```
Linear, Logistic, KNN, SVM, Random Forest
```

In [317]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import sklearn
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, classification_report
```

In [318]:
```
data = pd.read_csv("Insurance.csv")
data
```

Out[318]:

	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 [319]:
```
data.columns
```

Out[319]:
```
Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'], dtype
='object')
```

In [320]:
```
data['age'].unique()
```

Out[320]:
```
array([19, 18, 28, 33, 32, 31, 46, 37, 60, 25, 62, 23, 56, 27, 52, 30, 34,
       59, 63, 55, 22, 26, 35, 24, 41, 38, 36, 21, 48, 40, 58, 53, 43, 64,
       20, 61, 44, 57, 29, 45, 54, 49, 47, 51, 42, 50, 39], dtype=int64)
```

In [321]:
```
data['sex'].unique()
```

Out[321]:
```
array(['female', 'male'], dtype=object)
```

In [322]:
```
data['bmi'].unique()
```

Out[322]:
```
array([27.9  , 33.77 , 33.   , 22.705, 28.88 , 25.74 , 33.44 , 27.74 ,
       29.83 , 25.84 , 26.22 , 26.29 , 34.4  , 39.82 , 42.13 , 24.6  ,
       30.78 , 23.845, 40.3  , 35.3  , 36.005, 32.4  , 34.1  , 31.92 ,
       28.025, 27.72 , 23.085, 32.775, 17.385, 36.3  , 35.6  , 26.315,
       28.6  , 28.31 , 36.4  , 20.425, 32.965, 20.8  , 36.67 , 39.9  ,
       26.6  , 36.63 , 21.78 , 30.8  , 37.05 , 37.3  , 38.665, 34.77 ,
       24.53 , 35.2  , 35.625, 33.63 , 28.   , 34.43 , 28.69 , 36.955,
       31.825, 31.68 , 22.88 , 37.335, 27.36 , 33.66 , 24.7  , 25.935,
       22.42 , 28.9  , 39.1  , 36.19 , 23.98 , 24.75 , 28.5  , 28.1  ,
       32.01 , 27.4  , 34.01 , 29.59 , 35.53 , 39.805, 26.885, 38.285,
       37.62 , 41.23 , 34.8  , 22.895, 31.16 , 27.2  , 26.98 , 39.49 ,
       24.795, 31.3  , 38.28 , 19.95 , 19.3  , 31.6  , 25.46 , 30.115,
       29.92 , 27.5  , 28.4  , 30.875, 27.94 , 35.09 , 29.7  , 35.72 ,
       32.205, 28.595, 49.06 , 27.17 , 23.37 , 37.1  , 23.75 , 28.975,
       31.35 , 33.915, 28.785, 28.3  , 37.4  , 17.765, 34.7  , 26.505,
       22.04 , 35.9  , 25.555, 28.05 , 25.175, 31.9  , 36.   , 32.49 ,
       25.3  , 29.735, 38.83 , 30.495, 37.73 , 37.43 , 24.13 , 37.145,
       39.52 , 24.42 , 27.83 , 36.85 , 39.6  , 29.8  , 29.64 , 28.215,
       37.   , 33.155, 18.905, 41.47 , 30.3  , 15.96 , 33.345, 37.7  ,
       27.835, 29.2  , 26.41 , 30.69 , 41.895, 30.9  , 32.2  , 32.11 ,
       31.57 , 26.2  , 30.59 , 32.8  , 18.05 , 39.33 , 32.23 , 24.035,
       36.08 , 22.3  , 26.4  , 31.8  , 26.73 , 23.1  , 23.21 , 33.7  ,
       33.25 , 24.64 , 33.88 , 38.06 , 41.91 , 31.635, 36.195, 17.8  ,
       24.51 , 22.22 , 38.39 , 29.07 , 22.135, 26.8  , 30.02 , 35.86 ,
       20.9  , 17.29 , 34.21 , 25.365, 40.15 , 24.415, 25.2  , 26.84 ,
       24.32 , 42.35 , 19.8  , 32.395, 30.2  , 29.37 , 34.2  , 27.455,
       27.55 , 20.615, 24.3  , 31.79 , 21.56 , 28.12 , 40.565, 27.645,
       31.2  , 26.62 , 48.07 , 36.765, 33.4  , 45.54 , 28.82 , 22.99 ,
       27.7  , 25.41 , 34.39 , 22.61 , 37.51 , 38.   , 33.33 , 34.865,
       33.06 , 35.97 , 31.4  , 25.27 , 40.945, 34.105, 36.48 , 33.8  ,
       36.7  , 36.385, 34.5  , 32.3  , 27.6  , 29.26 , 35.75 , 23.18 ,
       25.6  , 35.245, 43.89 , 20.79 , 30.5  , 21.7  , 21.89 , 24.985,
       32.015, 30.4  , 21.09 , 22.23 , 32.9  , 24.89 , 31.46 , 17.955,
       30.685, 43.34 , 39.05 , 30.21 , 31.445, 19.855, 31.02 , 38.17 ,
       20.6  , 47.52 , 20.4  , 38.38 , 24.31 , 23.6  , 21.12 , 30.03 ,
       17.48 , 20.235, 17.195, 23.9  , 35.15 , 35.64 , 22.6  , 39.16 ,
       27.265, 29.165, 16.815, 33.1  , 26.9  , 33.11 , 31.73 , 46.75 ,
       29.45 , 32.68 , 33.5  , 43.01 , 36.52 , 26.695, 25.65 , 29.6  ,
       38.6  , 23.4  , 46.53 , 30.14 , 30.   , 38.095, 28.38 , 28.7  ,
       33.82 , 24.09 , 32.67 , 25.1  , 32.56 , 41.325, 39.5  , 34.3  ,
       31.065, 21.47 , 25.08 , 43.4  , 25.7  , 27.93 , 39.2  , 26.03 ,
       30.25 , 28.93 , 35.7  , 35.31 , 31.   , 44.22 , 26.07 , 25.8  ,
       39.425, 40.48 , 38.9  , 47.41 , 35.435, 46.7  , 46.2  , 21.4  ,
       23.8  , 44.77 , 32.12 , 29.1  , 37.29 , 43.12 , 36.86 , 34.295,
       23.465, 45.43 , 23.65 , 20.7  , 28.27 , 35.91 , 29.   , 19.57 ,
       31.13 , 21.85 , 40.26 , 33.725, 29.48 , 32.6  , 37.525, 23.655,
       37.8  , 19.   , 21.3  , 33.535, 42.46 , 38.95 , 36.1  , 29.3  ,
       39.7  , 38.19 , 42.4  , 34.96 , 42.68 , 31.54 , 29.81 , 21.375,
       40.81 , 17.4  , 20.3  , 18.5  , 26.125, 41.69 , 24.1  , 36.2  ,
       40.185, 39.27 , 34.87 , 44.745, 29.545, 23.54 , 40.47 , 40.66 ,
       36.6  , 35.4  , 27.075, 28.405, 21.755, 40.28 , 30.1  , 32.1  ,
       23.7  , 35.5  , 29.15 , 27.   , 37.905, 22.77 , 22.8  , 34.58 ,
       27.1  , 19.475, 26.7  , 34.32 , 24.4  , 41.14 , 22.515, 41.8  ,
       26.18 , 42.24 , 26.51 , 35.815, 41.42 , 36.575, 42.94 , 21.01 ,
       24.225, 17.67 , 31.5  , 31.1  , 32.78 , 32.45 , 50.38 , 47.6  ,
       25.4  , 29.9  , 43.7  , 24.86 , 28.8  , 29.5  , 29.04 , 38.94 ,
       44.   , 20.045, 40.92 , 35.1  , 29.355, 32.585, 32.34 , 39.8  ,
```

```
       24.605, 33.99 , 28.2  , 25.   , 33.2  , 23.2  , 20.1  , 32.5  ,
       37.18 , 46.09 , 39.93 , 35.8  , 31.255, 18.335, 42.9  , 26.79 ,
       39.615, 25.9  , 25.745, 28.16 , 23.56 , 40.5  , 35.42 , 39.995,
       34.675, 20.52 , 23.275, 36.29 , 32.7  , 19.19 , 20.13 , 23.32 ,
       45.32 , 34.6  , 18.715, 21.565, 23.   , 37.07 , 52.58 , 42.655,
       21.66 , 32.   , 18.3  , 47.74 , 22.1  , 19.095, 31.24 , 29.925,
       20.35 , 25.85 , 42.75 , 18.6  , 23.87 , 45.9  , 21.5  , 30.305,
       44.88 , 41.1  , 40.37 , 28.49 , 33.55 , 40.375, 27.28 , 17.86 ,
       33.3  , 39.14 , 21.945, 24.97 , 23.94 , 34.485, 21.8  , 23.3  ,
       36.96 , 21.28 , 29.4  , 27.3  , 37.9  , 37.715, 23.76 , 25.52 ,
       27.61 , 27.06 , 39.4  , 34.9  , 22.   , 30.36 , 27.8  , 53.13 ,
       39.71 , 32.87 , 44.7  , 30.97 ])
```

In [323]:
```
data['children'].unique()
```

Out[323]:
```
array([0, 1, 3, 2, 5, 4], dtype=int64)
```

In [324]:
```
data['smoker'].unique()
```

Out[324]:
```
array(['yes', 'no'], dtype=object)
```

In [325]:
```
data['region'].unique()
```

Out[325]:
```
array(['southwest', 'southeast', 'northwest', 'northeast'], dtype=object)
```

In [326]:
```
data['charges'].unique()
```

Out[326]:
```
array([16884.924 ,  1725.5523,  4449.462 , ...,  1629.8335,  2007.945 ,
       29141.3603])
```

In [327]:
```
len(data['charges'])
```

Out[327]:
```
1338
```

In [328]:
```
data.head()
```

Out[328]:

	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 [329]:
```
data.tail()
```

Out[329]:

	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 [330]:
```
len(data)
```

Out[330]:
```
1338
```

In [331]:
```
data.index
```

Out[331]:
```
RangeIndex(start=0, stop=1338, step=1)
```

In [332]:
```
data.dtypes
```

Out[332]:
```
age            int64
sex           object
bmi          float64
children       int64
smoker        object
region        object
charges      float64
dtype: object
```

In [333]:
```
data.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   bmi       1338 non-null   float64
 3   children  1338 non-null   int64  
 4   smoker    1338 non-null   object 
 5   region    1338 non-null   object 
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

In [334]:
```
data.describe()
```

Out[334]:

	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

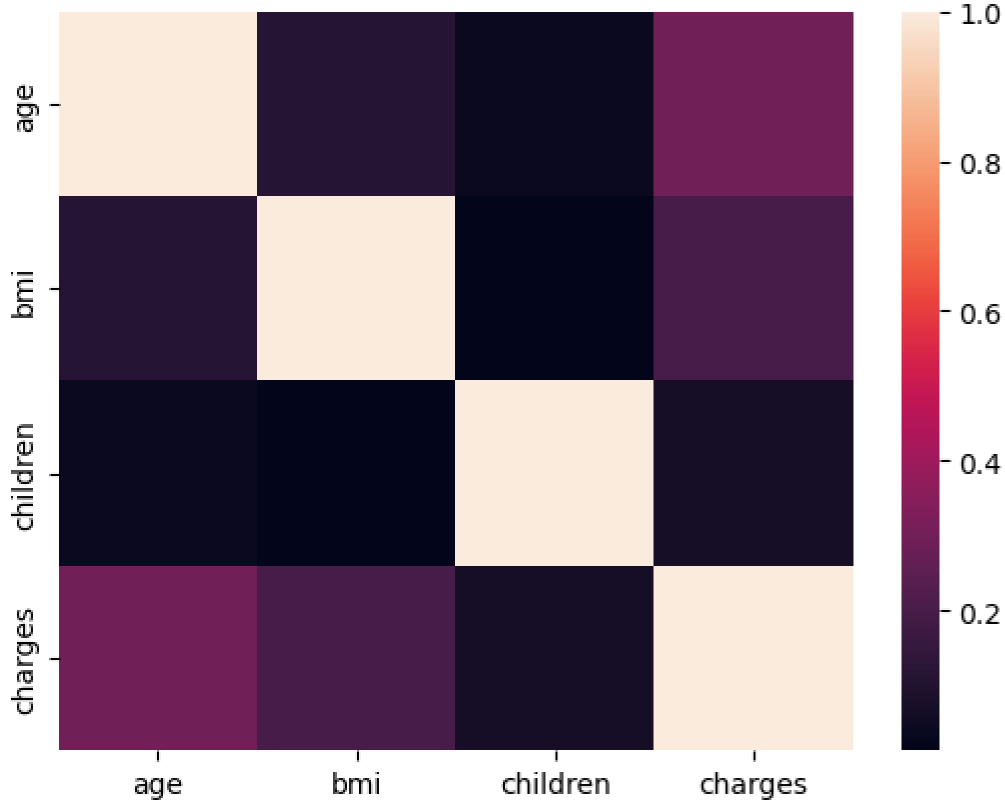
In [335]:
```
corr = data.corr()
corr
```

Out[335]:

	age	bmi	children	charges
age	1.000000	0.109272	0.042469	0.299008
bmi	0.109272	1.000000	0.012759	0.198341
children	0.042469	0.012759	1.000000	0.067998
charges	0.299008	0.198341	0.067998	1.000000

In [336]:
```
sns.heatmap(corr)
```

Out[336]: <AxesSubplot:>



In [337]:
```
data.isna()
```

Out[337]:

	age	sex	bmi	children	smoker	region	charges
0	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...
1333	False	False	False	False	False	False	False
1334	False	False	False	False	False	False	False
1335	False	False	False	False	False	False	False
1336	False	False	False	False	False	False	False
1337	False	False	False	False	False	False	False

In [338]:
```
data.isna().sum()
```

Out[338]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

In [339]:
```
data.isnull()
```

Out[339]:

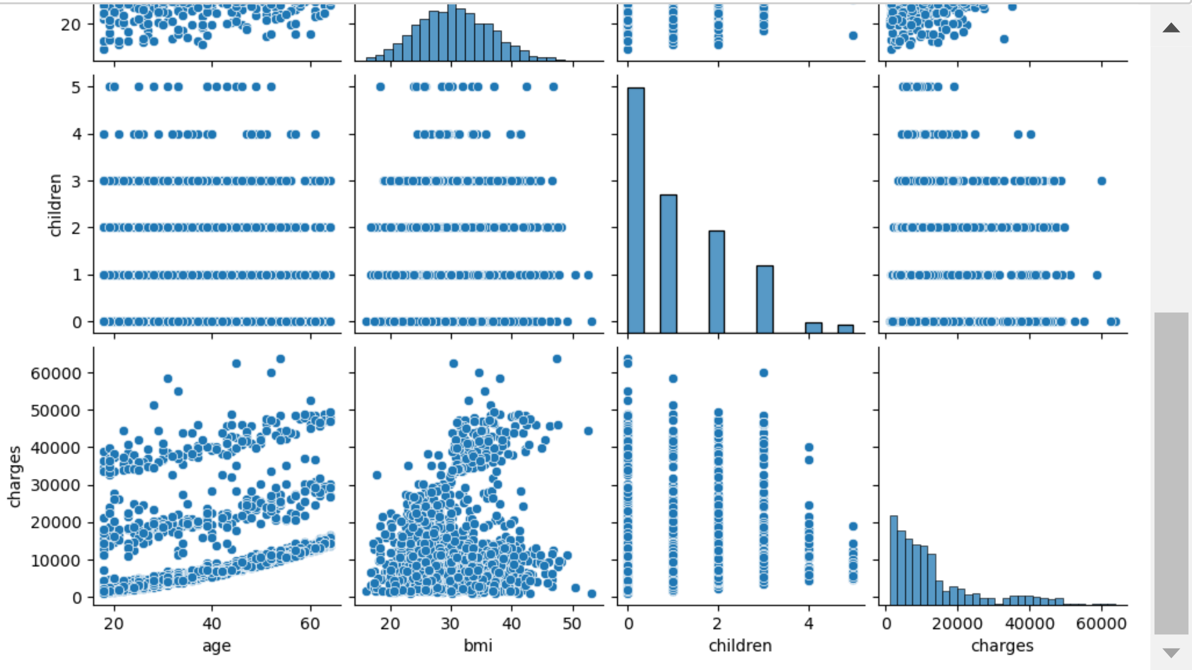
	age	sex	bmi	children	smoker	region	charges
0	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...
1333	False	False	False	False	False	False	False
1334	False	False	False	False	False	False	False
1335	False	False	False	False	False	False	False
1336	False	False	False	False	False	False	False
1337	False	False	False	False	False	False	False

1338 rows × 7 columns

In [340]:
```
data.isnull().sum()
```

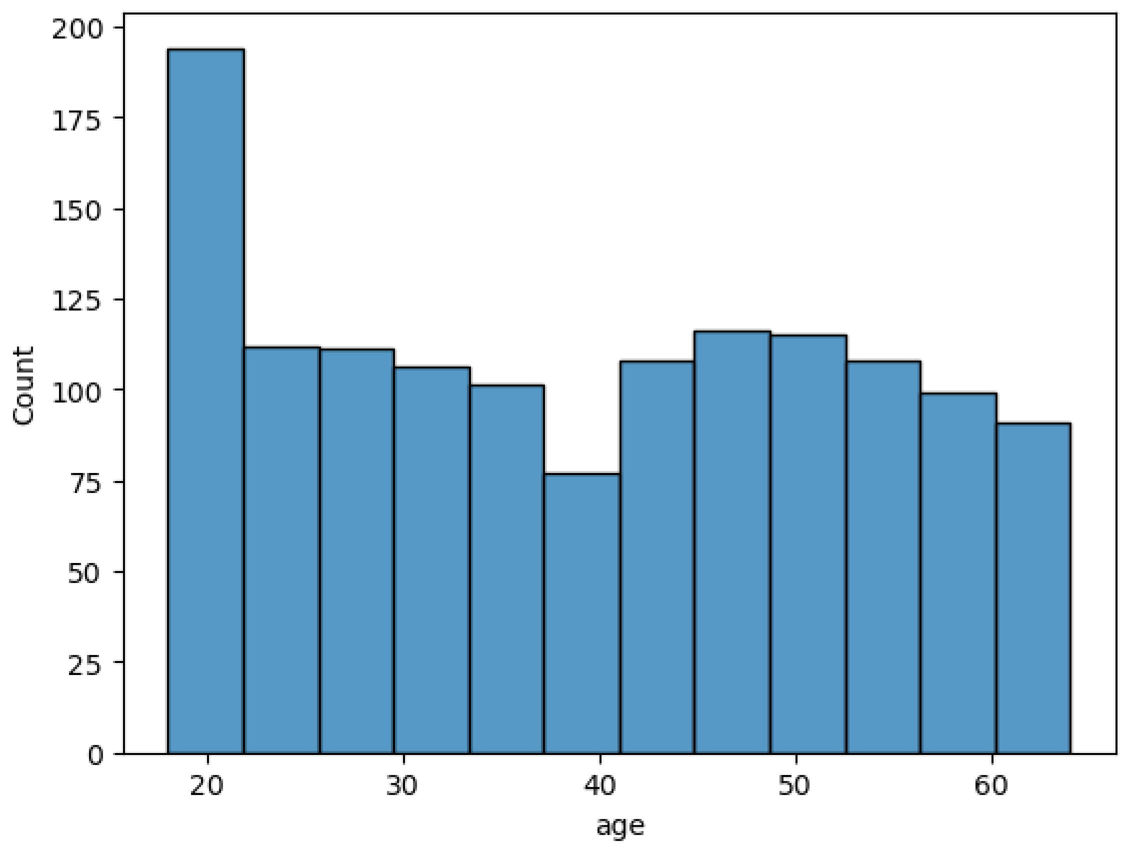
Out[340]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

In [341]:
```
sns.pairplot(data)
```



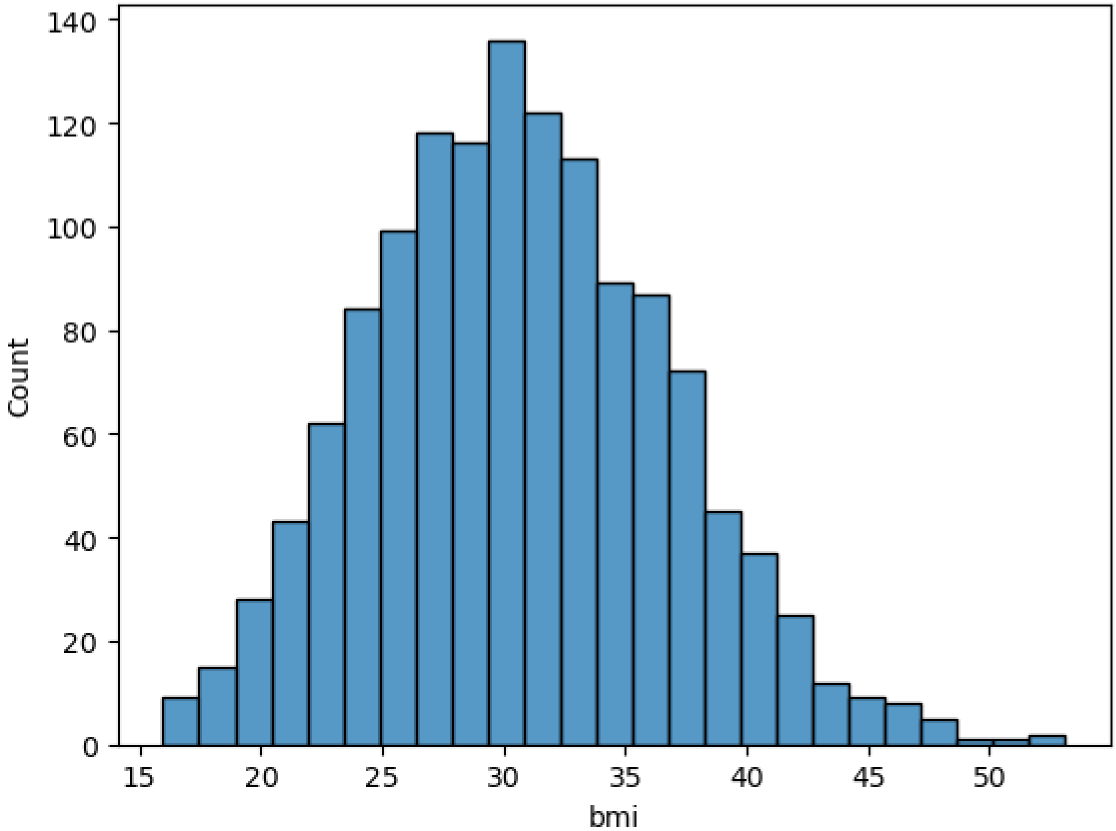
In [342]:
```
sns.histplot(x=data['age'],data=data)
```

Out[342]: <AxesSubplot:xlabel='age', ylabel='Count'>



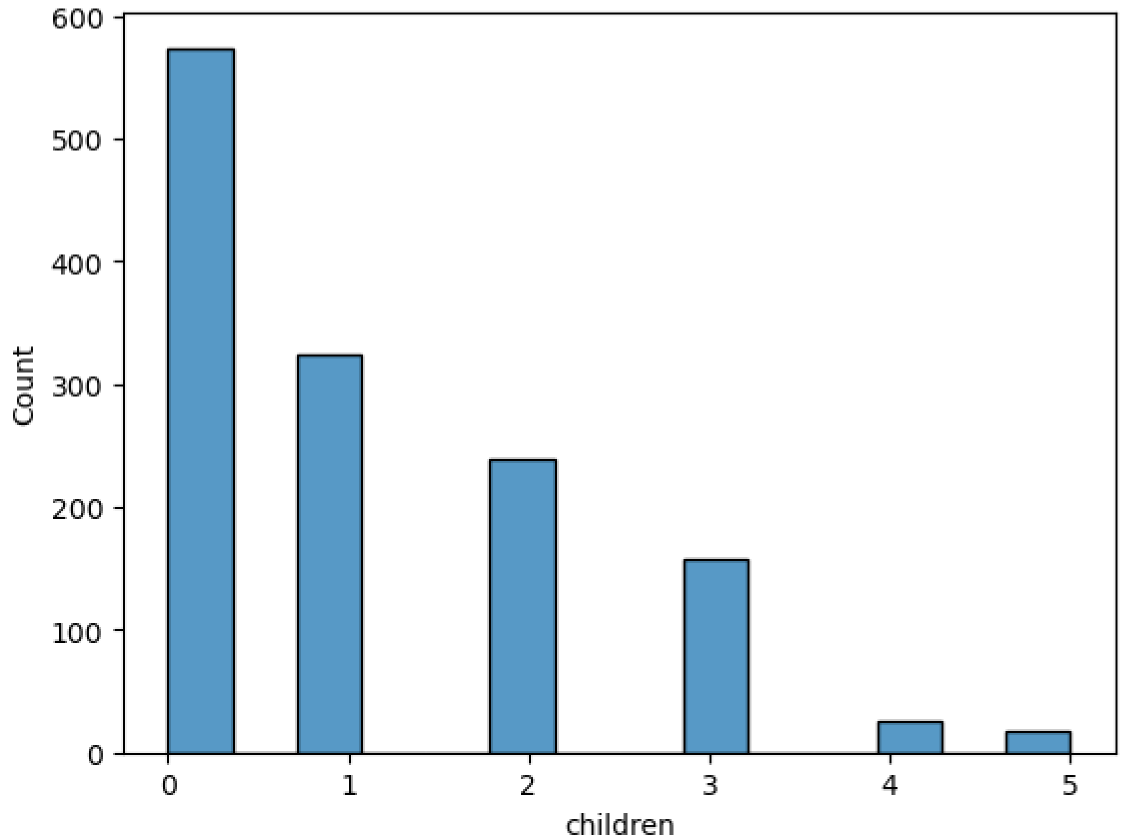
In [343]:
```
sns.histplot(x=data['bmi'],data=data)
```

Out[343]: <AxesSubplot:xlabel='bmi', ylabel='Count'>



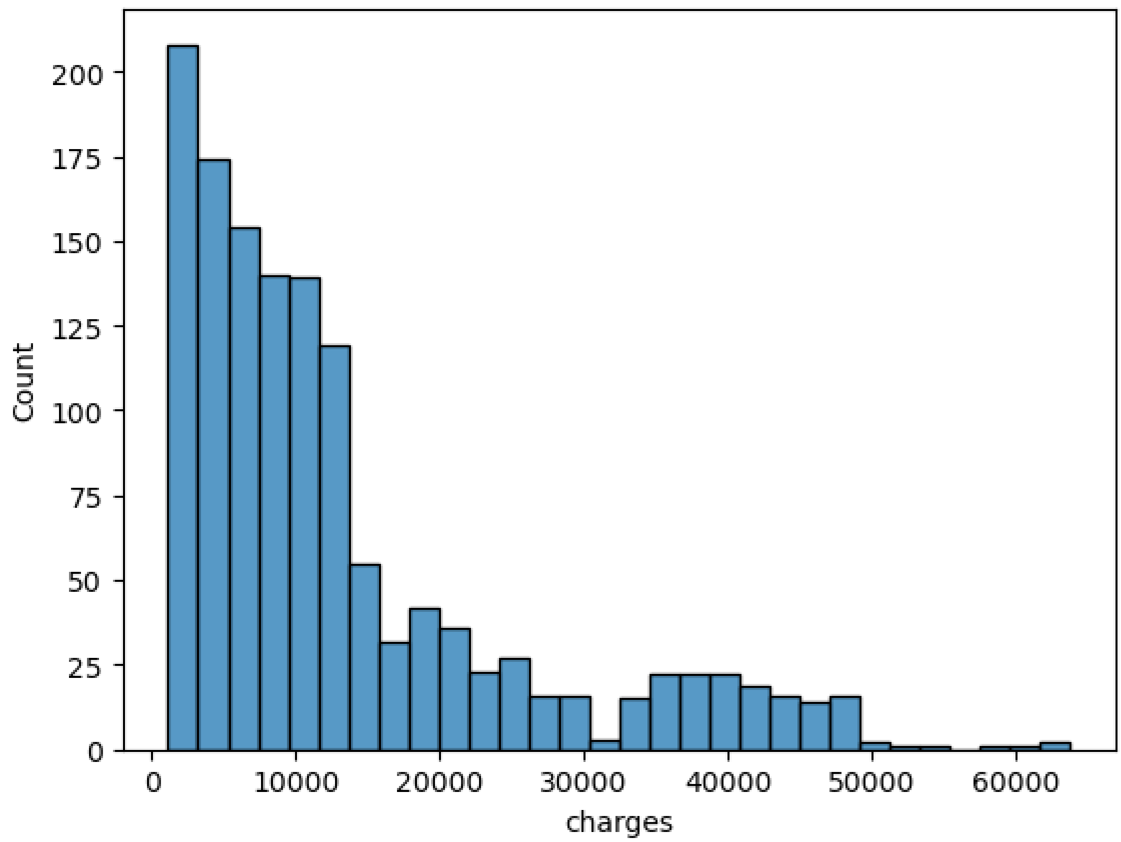
In [344]:
```
sns.histplot(x=data['children'],data=data)
```

Out[344]: <AxesSubplot:xlabel='children', ylabel='Count'>



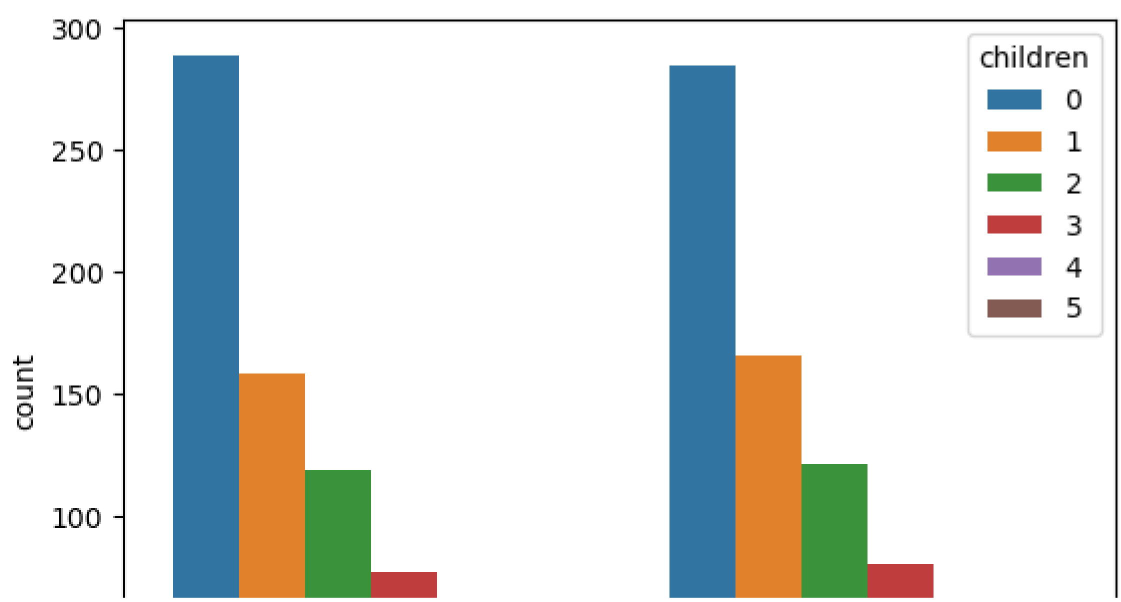
In [345]:
```
sns.histplot(x=data['charges'],data=data)
```

Out[345]: <AxesSubplot:xlabel='charges', ylabel='Count'>



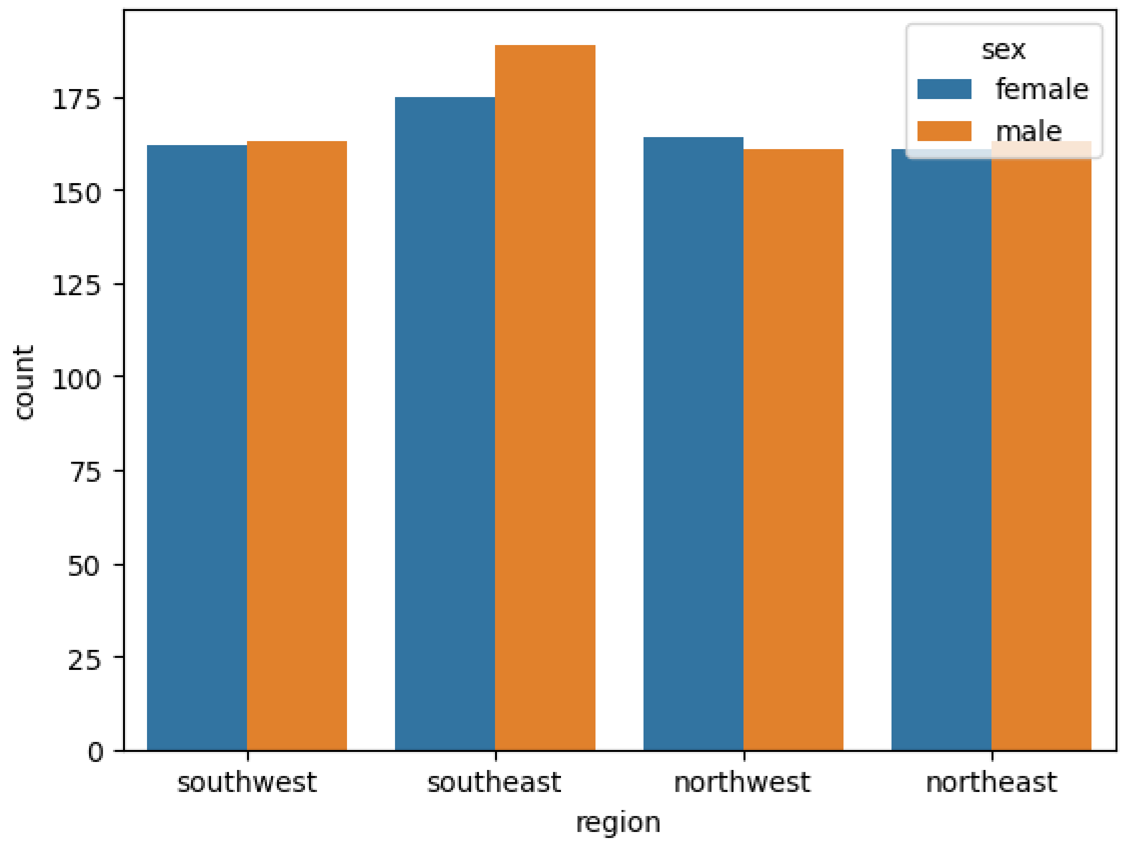
In [346]:
```
sns.countplot(x = 'sex', data = data, hue = 'children')
```

Out[346]: <AxesSubplot:xlabel='sex', ylabel='count'>

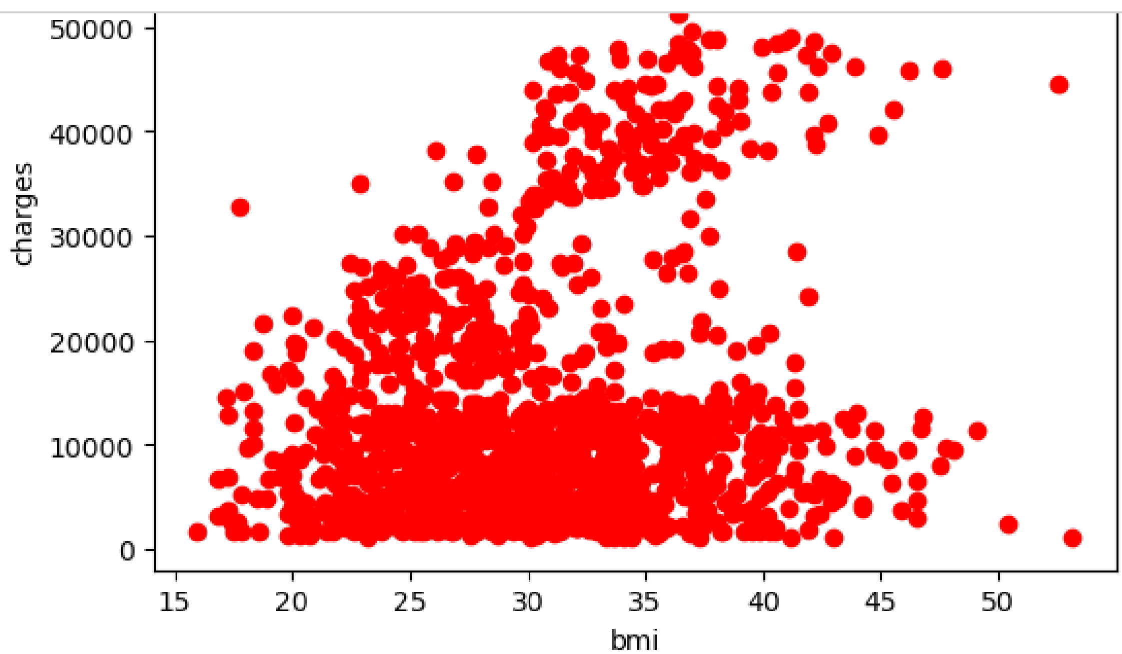


In [347]:
```
sns.countplot(x='region',data=data,hue='sex')
```

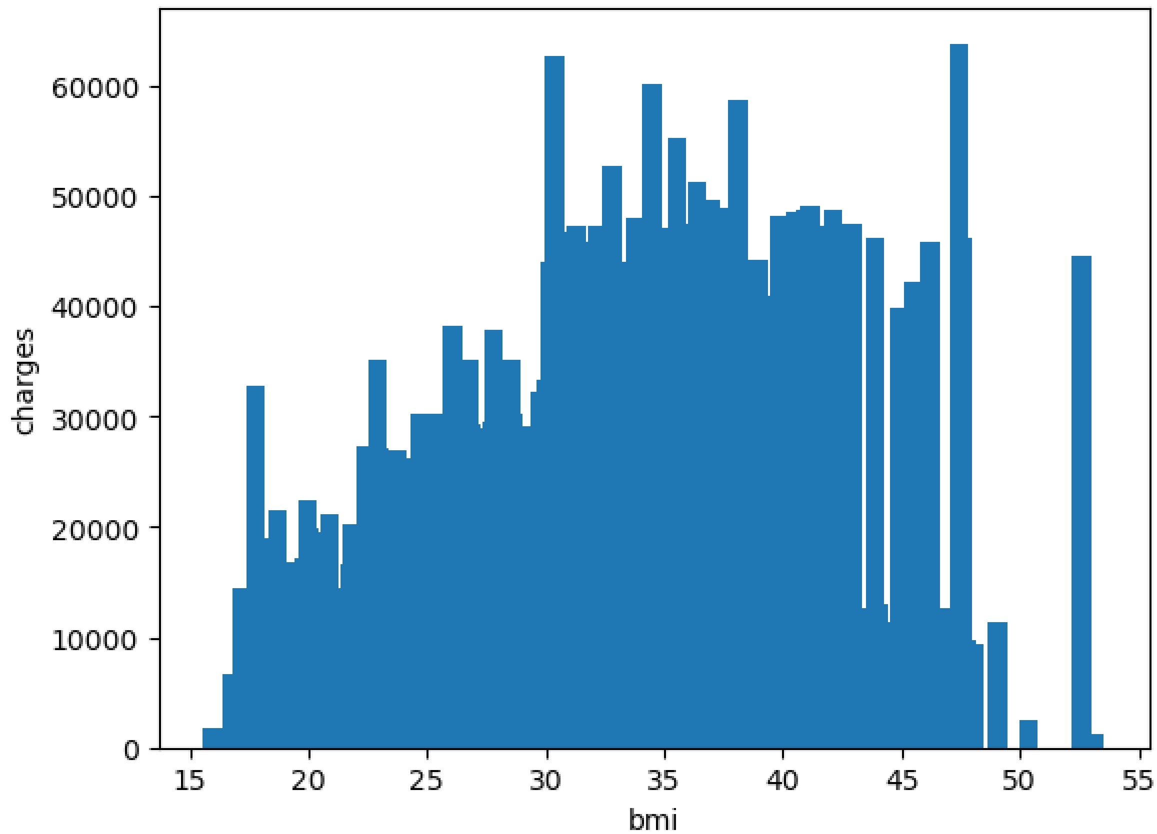
Out[347]: <AxesSubplot:xlabel='region', ylabel='count'>



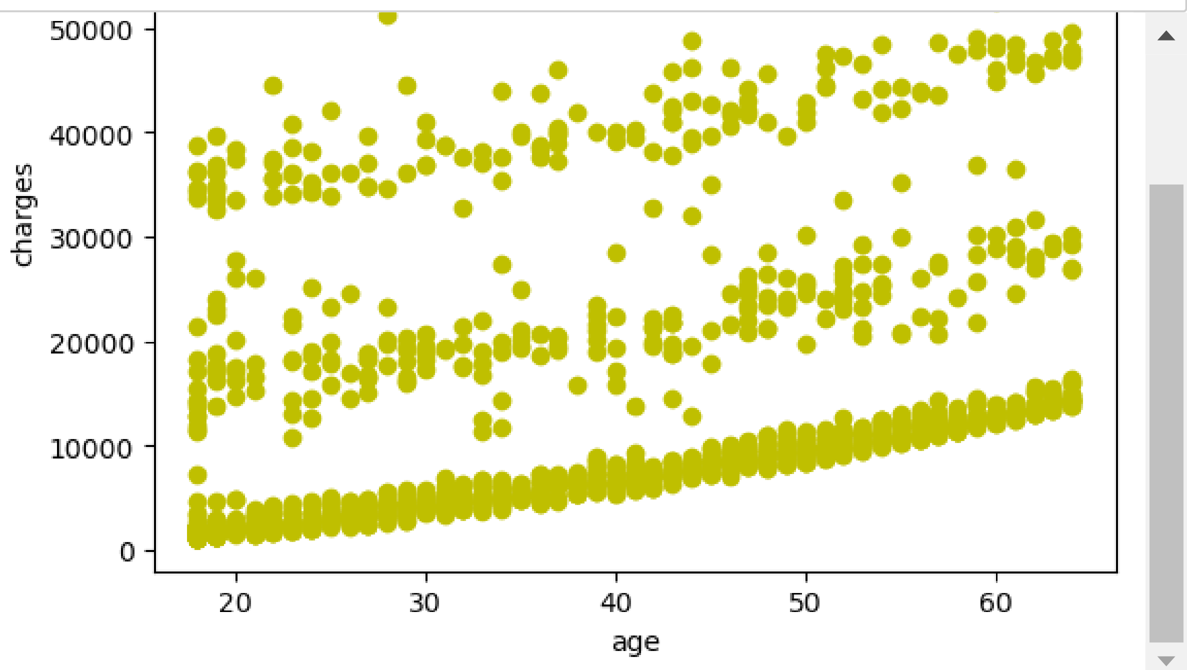
In [348]:
```
plt.scatter(x=data['bmi'],y=data['charges'],c='r')
plt.xlabel('bmi')
plt.ylabel('charges')
plt.show()
```



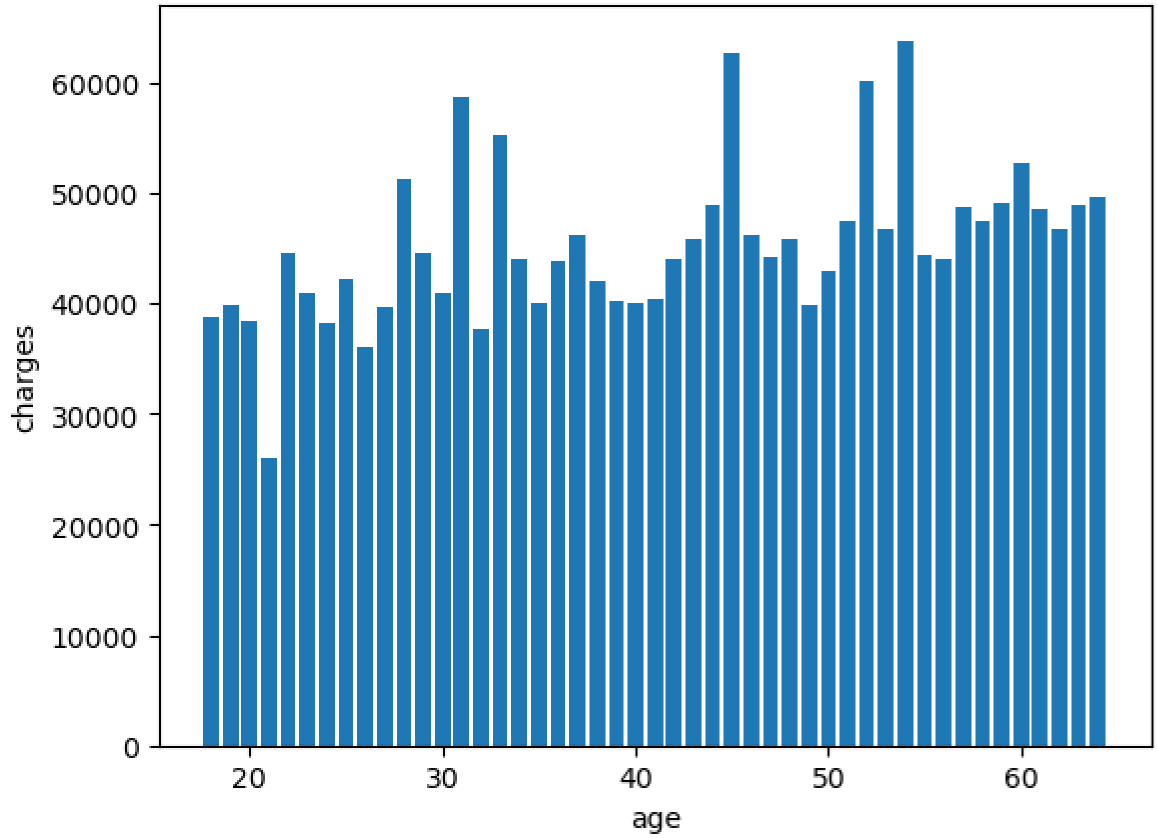
In [349]:
```
plt.bar(data['bmi'],data['charges'])
plt.xlabel('bmi')
plt.ylabel('charges')
plt.show()
```



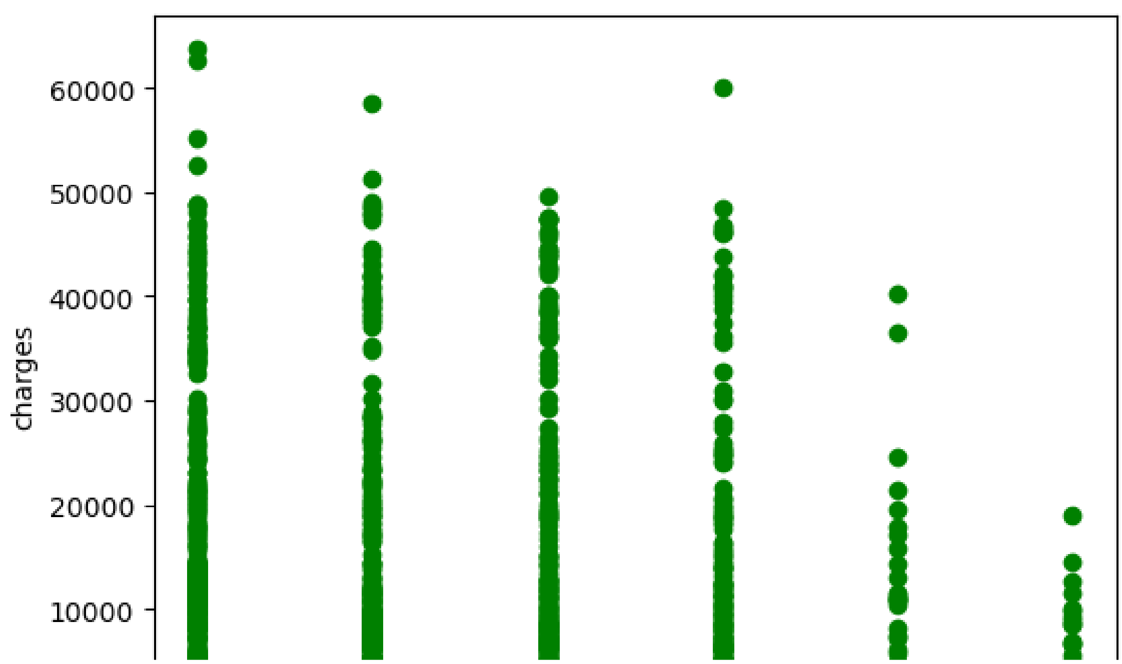
In [350]:
```
plt.scatter(x=data['age'],y=data['charges'],c='y')
plt.xlabel('age')
plt.ylabel('charges')
plt.show()
```



In [351]:
```
plt.bar(data['age'],data['charges'])
plt.xlabel('age')
plt.ylabel('charges')
plt.show()
```

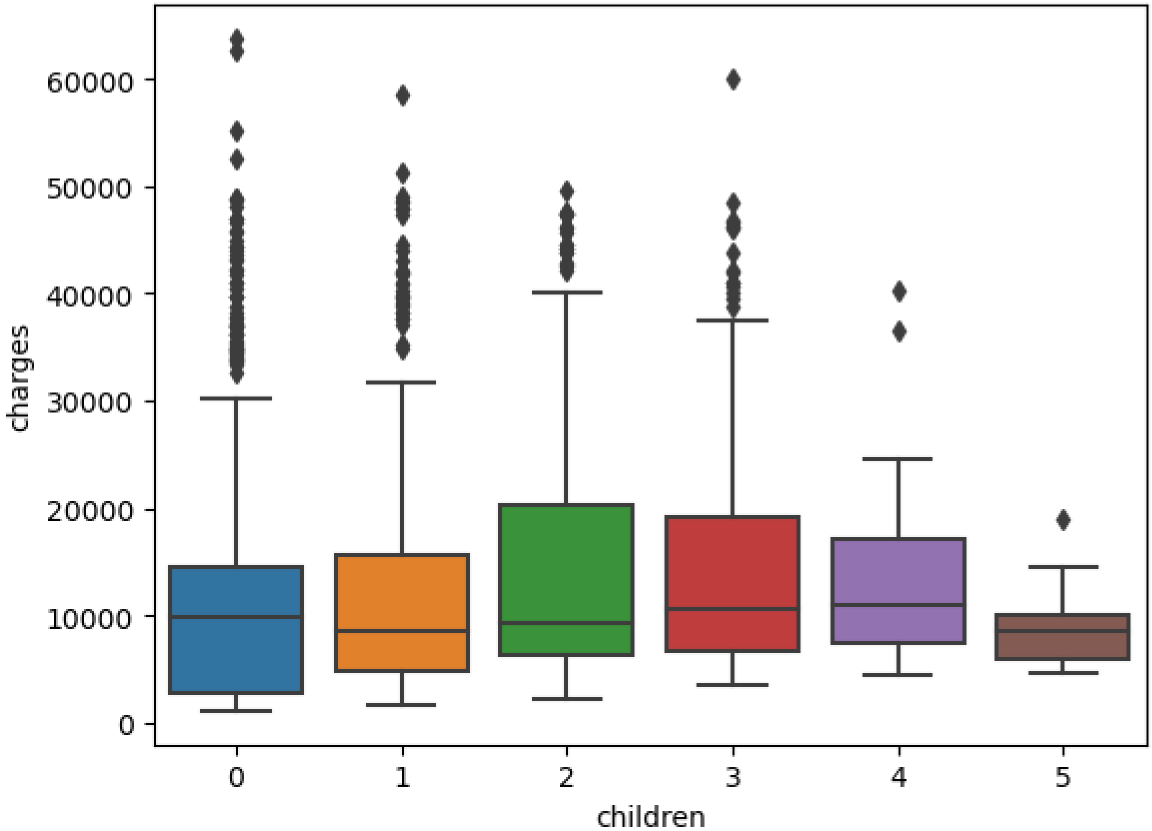


In [352]:
```
plt.scatter(x=data['children'],y=data['charges'],c='g')
plt.xlabel('children')
plt.ylabel('charges')
plt.show()
```

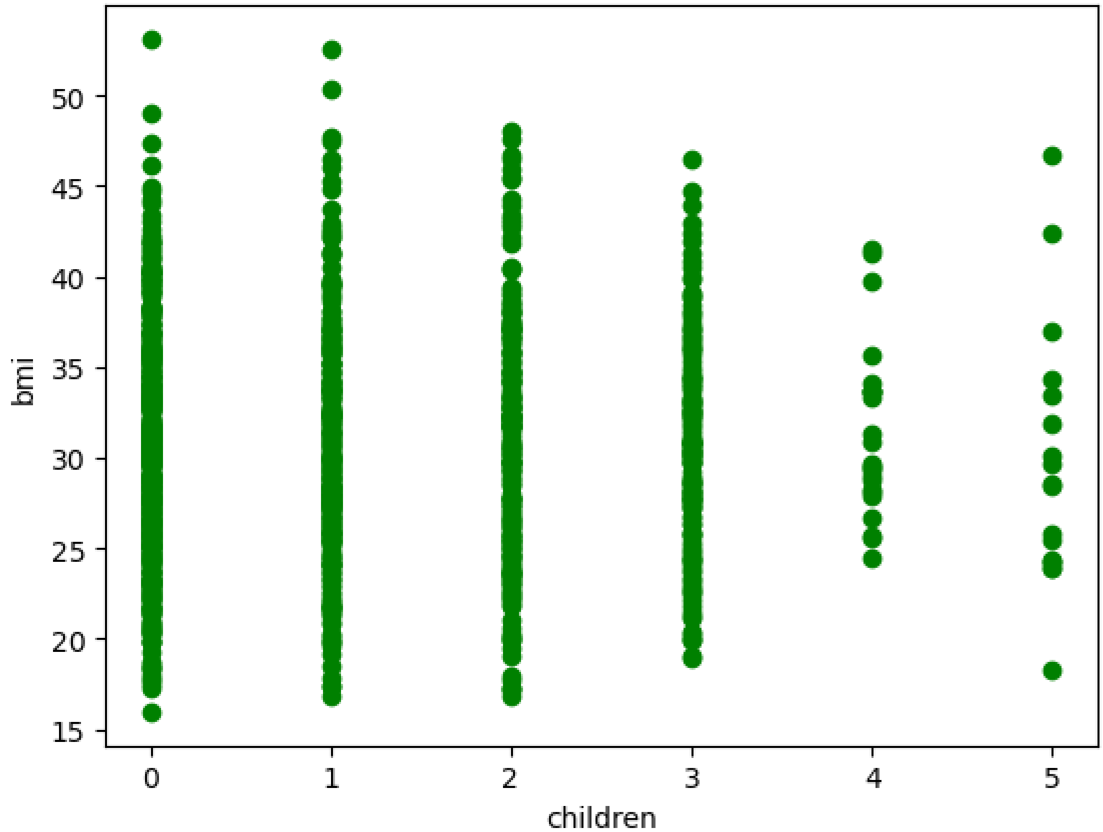


In [353]:
```
sns.boxplot(x=data["children"], y=data["charges"], data=data)
```

Out[353]: <AxesSubplot:xlabel='children', ylabel='charges'>

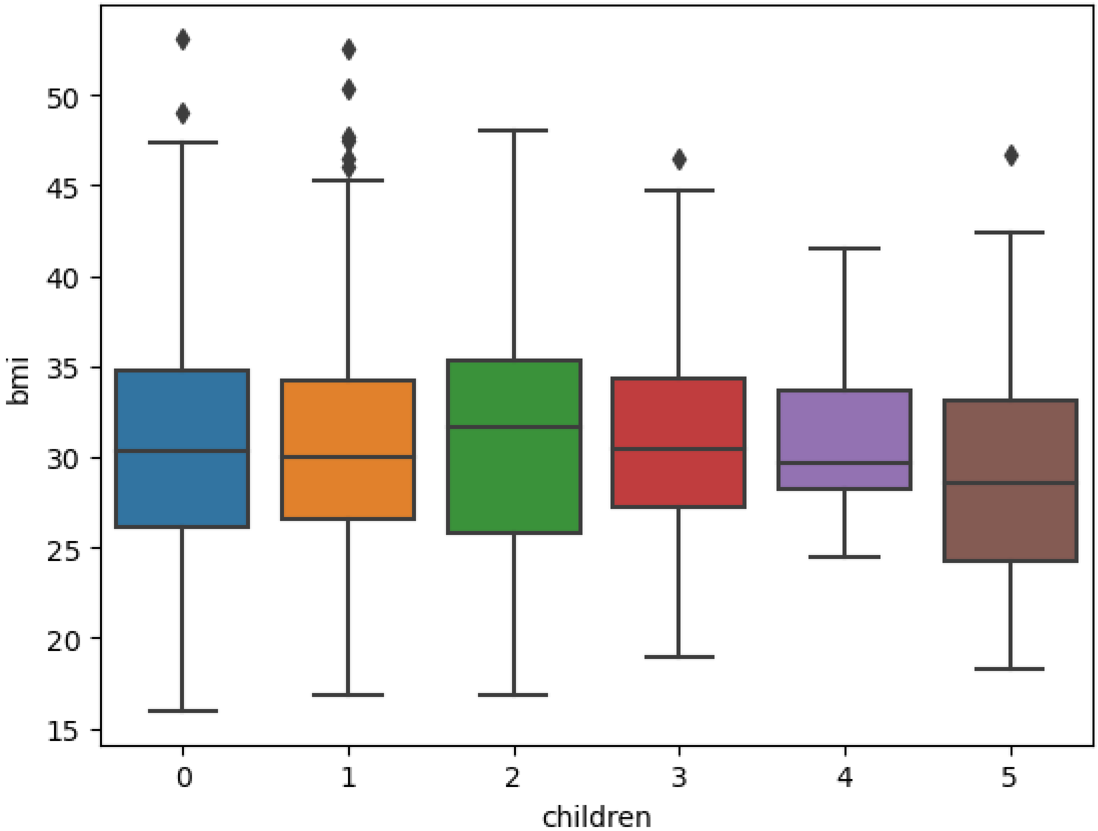


In [354]:
```
plt.scatter(x=data['children'],y=data['bmi'],c='g')
plt.xlabel('children')
plt.ylabel('bmi')
plt.show()
```



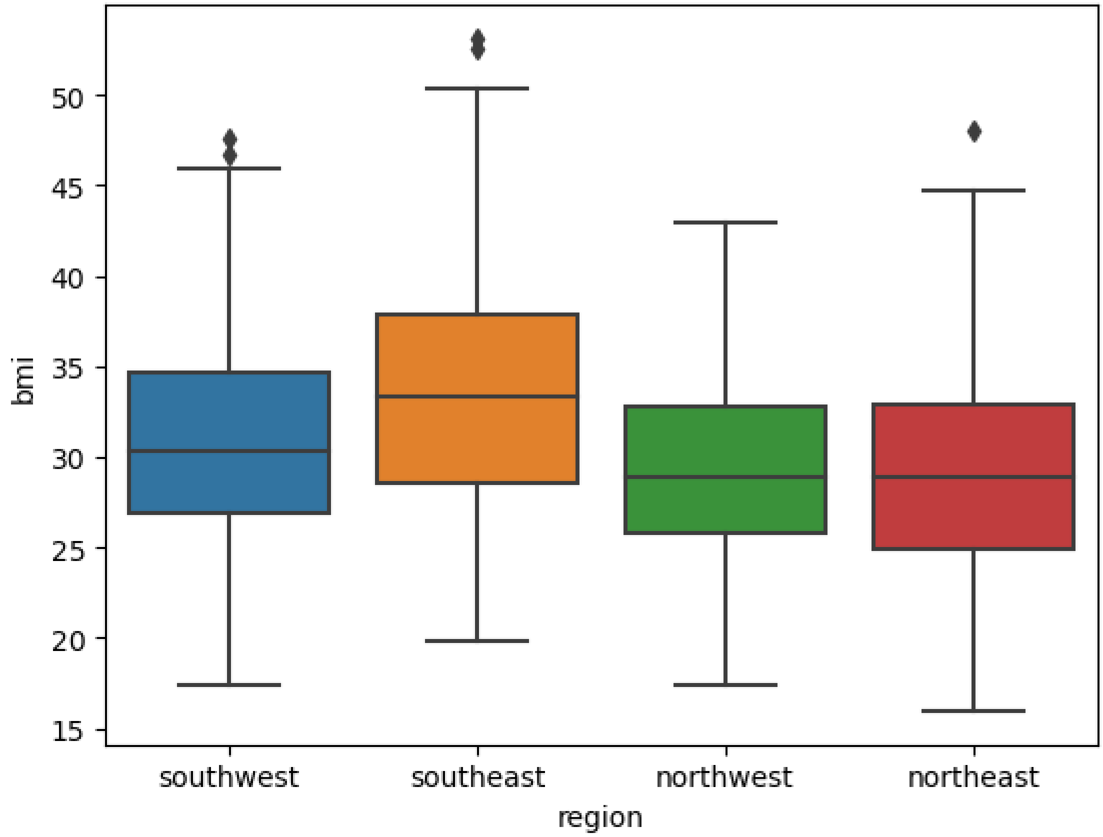
In [355]:
```
sns.boxplot(x=data["children"], y=data["bmi"], data=data)
```

Out[355]: <AxesSubplot:xlabel='children', ylabel='bmi'>



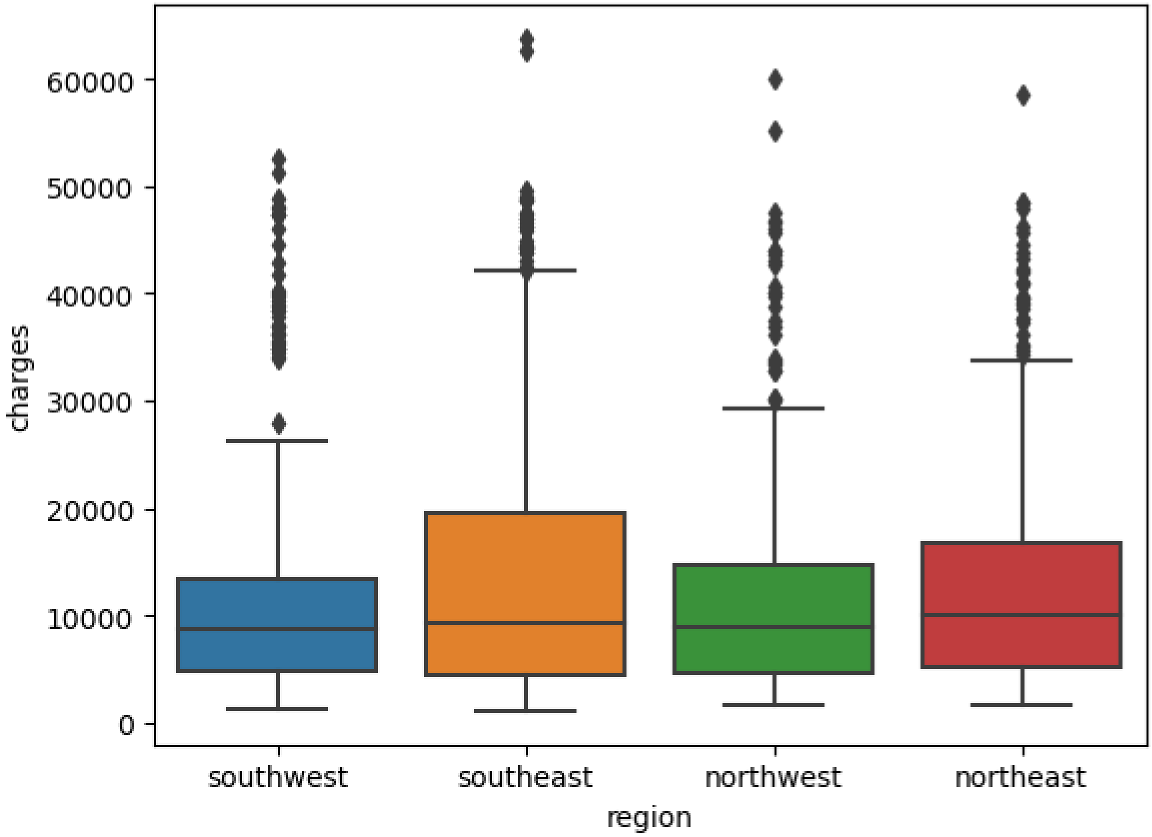
In [356]:
```
sns.boxplot(x=data["region"], y=data["bmi"], data=data)
```

Out[356]: <AxesSubplot:xlabel='region', ylabel='bmi'>



In [357]:
```
sns.boxplot(x=data["region"], y=data["charges"], data=data)
```

Out[357]: <AxesSubplot:xlabel='region', ylabel='charges'>



In [358]:
```
print(f"Our data has dimensions: {data.shape[0]} by {data.shape[1]}")
```

```
Our data has dimensions: 1338 by 7
```

In [359]:
```
x = data['age']
y = data['charges']
```

In [360]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_stat
```

In [361]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1070,)
(268,)
(1070,)
(268,)
```

In [362]:
```
x_train=x_train.values.reshape(-1,1)
```

In [363]:
```
x_test=x_test.values.reshape(-1,1)
```

In [364]:
```
model = LinearRegression()
```

In [365]:
```
model.fit(x_train,y_train)
```

Out[365]:
```
LinearRegression()
```

In [366]:
```
model.score(x_test,y_test)
```

Out[366]:
```
0.07899146595873285
```

In [367]:
```
print(f"intercept: {model.intercept_}")
```

```
intercept: 2998.5777306780055
```

In [368]:
```
print(f"slope: {model.coef_}")
```

```
slope: [262.31687345]
```

In [369]:
```
y_pred = model.intercept_ + model.coef_*x_test
print(f"y_pred : {y_pred}")
```

```
y_pred : [[ 7982.59832619]
 [17950.63951722]
 [16376.73827653]
 [15852.10452963]
 [ 8507.23207309]
 [11130.40080757]
 [15852.10452963]
 [17688.32264377]
 [10081.13331377]
 [12704.30204826]
 [18737.59013756]
 [17163.68889687]
 [13228.93579515]
 [14015.8864155 ]
 [ 7720.28145274]
 [15589.78765618]
 [11655.03455446]
 [12179.66830136]
 [18475.27326411]
 [19262.22388446]
 [16639.05514998]
 [10868.08393412]
 [15065.15390929]
 [16114.42140308]
 [ 7720.28145274]
 [13753.56954205]
 [14278.20328894]
 [15589.78765618]
 [11655.03455446]
 [10868.08393412]
 [17688.32264377]
 [11917.35142791]
 [16901.37202342]
 [ 7982.59832619]
 [15589.78765618]
 [16901.37202342]
 [10868.08393412]
 [ 8507.23207309]
 [18212.95639066]
 [14802.83703584]
 [10343.45018722]
 [18212.95639066]
 [16114.42140308]
 [18475.27326411]
 [11130.40080757]
 [18737.59013756]
 [ 8244.91519964]
 [10343.45018722]
 [16376.73827653]
 [17950.63951722]
 [18999.90701101]
 [17426.00577032]
 [ 9294.18269343]
 [14802.83703584]
 [ 7720.28145274]
 [11392.71768101]
 [14278.20328894]
```

```
[18737.59013756]
[ 9031.86581998]
[ 7720.28145274]
[10605.76706067]
[18999.90701101]
[ 9031.86581998]
[ 9031.86581998]
[18737.59013756]
[15589.78765618]
[15852.10452963]
[17950.63951722]
[ 7982.59832619]
[ 9294.18269343]
[16639.05514998]
[11130.40080757]
[ 7982.59832619]
[17163.68889687]
[19262.22388446]
[14278.20328894]
[ 9031.86581998]
[10605.76706067]
[17688.32264377]
[16114.42140308]
[ 8507.23207309]
[17426.00577032]
[16901.37202342]
[ 9294.18269343]
[13491.2526686 ]
[ 9556.49956688]
[14015.8864155 ]
[14540.52016239]
[15852.10452963]
[13753.56954205]
[12179.66830136]
[15852.10452963]
[18737.59013756]
[15589.78765618]
[ 7982.59832619]
[16901.37202342]
[16376.73827653]
[17688.32264377]
[18212.95639066]
[12179.66830136]
[17950.63951722]
[ 9556.49956688]
[10868.08393412]
[ 7982.59832619]
[19786.85763135]
[ 9031.86581998]
[ 7982.59832619]
[14802.83703584]
[ 7720.28145274]
[17426.00577032]
[11917.35142791]
[ 9818.81644033]
[ 7982.59832619]
[19524.5407579 ]
```

```
[ 9294.18269343]
[ 7982.59832619]
[11655.03455446]
[19524.5407579 ]
[12179.66830136]
[ 8244.91519964]
[16114.42140308]
[15589.78765618]
[12966.6189217 ]
[15065.15390929]
[17688.32264377]
[15589.78765618]
[17426.00577032]
[12179.66830136]
[14015.8864155 ]
[14540.52016239]
[ 7720.28145274]
[ 7982.59832619]
[12966.6189217 ]
[11655.03455446]
[15065.15390929]
[ 7982.59832619]
[ 7982.59832619]
[ 7720.28145274]
[16639.05514998]
[14802.83703584]
[19262.22388446]
[12179.66830136]
[11917.35142791]
[19786.85763135]
[18212.95639066]
[17426.00577032]
[ 7720.28145274]
[13753.56954205]
[ 7720.28145274]
[12704.30204826]
[14540.52016239]
[ 9818.81644033]
[16639.05514998]
[17426.00577032]
[15589.78765618]
[14015.8864155 ]
[16376.73827653]
[16376.73827653]
[15589.78765618]
[ 9031.86581998]
[11655.03455446]
[19786.85763135]
[18212.95639066]
[ 9818.81644033]
[11392.71768101]
[ 8507.23207309]
[12441.98517481]
[17163.68889687]
[17688.32264377]
[12441.98517481]
[11392.71768101]
```

```
[10343.45018722]
[17688.32264377]
[18475.27326411]
[10081.13331377]
[12966.6189217 ]
[ 9031.86581998]
[18475.27326411]
[10343.45018722]
[12179.66830136]
[18737.59013756]
[18999.90701101]
[15852.10452963]
[14015.8864155 ]
[ 9556.49956688]
[10081.13331377]
[ 8769.54894653]
[15327.47078274]
[15065.15390929]
[13753.56954205]
[18999.90701101]
[16639.05514998]
[11130.40080757]
[ 7982.59832619]
[12966.6189217 ]
[16376.73827653]
[12441.98517481]
[ 7982.59832619]
[16376.73827653]
[15065.15390929]
[13753.56954205]
[13753.56954205]
[17163.68889687]
[13228.93579515]
[12966.6189217 ]
[ 7720.28145274]
[13491.2526686 ]
[14015.8864155 ]
[ 8244.91519964]
[17950.63951722]
[10868.08393412]
[16901.37202342]
[ 9294.18269343]
[ 9818.81644033]
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[19786.85763135]
[17426.00577032]
[ 8769.54894653]
[ 7720.28145274]
[14540.52016239]
[ 8244.91519964]
[16901.37202342]
[17426.00577032]
[10081.13331377]
[ 7982.59832619]
[ 9294.18269343]
[11392.71768101]
[ 9031.86581998]
```

```
 [ 7982.59832619]
 [19524.5407579 ]
 [ 8507.23207309]
 [18475.27326411]
 [16376.73827653]
 [11917.35142791]
 [17163.68889687]
 [17426.00577032]
 [10868.08393412]
 [ 7982.59832619]
 [15065.15390929]
 [11392.71768101]
 [15327.47078274]
 [ 8507.23207309]
 [19262.22388446]
 [ 9294.18269343]
 [17426.00577032]
 [16639.05514998]
 [14278.20328894]
 [15327.47078274]
 [ 9556.49956688]
 [19786.85763135]
 [16901.37202342]
 [11130.40080757]
 [18737.59013756]
 [16376.73827653]
 [ 9818.81644033]
 [ 8769.54894653]
 [ 7720.28145274]
 [13491.2526686 ]
 [ 7982.59832619]
 [18999.90701101]
 [14540.52016239]
 [14015.8864155 ]
 [15065.15390929]
 [13228.93579515]
 [14540.52016239]
 [15327.47078274]
 [ 7982.59832619]
 [12179.66830136]]
```

In [370]:
```
print(x_train.shape)
print(y_test.shape)
print(y_pred.shape)
```

```
(1070, 1)
(268,)
(268, 1)
```

In [371]:
```
y_test = y_test.values.reshape(-1,1)
```

In [372]:
```
print(y_test.shape)
```

```
(268, 1)
```

In [373]:
```
rss = np.sum((y_test - y_pred) ** 2)
```

In [374]:
```
print("RSS:", rss)
```

```
RSS: 36846983136.88877
```

In [375]:
```
x1 = data['bmi']
y = data['charges']
```

In [376]:
```
x1_train, x1_test, y_train, y_test = train_test_split(x1, y, test_size = 0.2,
```

In [377]:
```
print(x1_train.shape)
print(x1_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1070,)
(268,)
(1070,)
(268,)
```

In [378]:
```
x1_train = x1_train.values.reshape(-1,1)
```

In [379]:
```
x1_test = x1_test.values.reshape(-1,1)
```

In [380]:
```
model1 = LinearRegression()
```

In [381]:
```
model1.fit(x1_train,y_train)
```

Out[381]:
```
LinearRegression()
```

In [382]:
```
model1.score(x1_test,y_test)
```

Out[382]:
```
0.05716373981200229
```

In [383]:
```
print(f"intercept: {model1.intercept_}")
print(f"slope: {model.coef_}")
```

```
intercept: 2001.129553376486
slope: [262.31687345]
```

In [384]:
```
y1_pred = model1.coef_*x1_test + model1.intercept_
print(f"y1_pred: {y1_pred}")
```

```
y1_pred: [[15009.47211896]
 [13548.64220518]
 [15547.67261351]
 [15412.20718291]
 [10165.667668  ]
 [14592.09214359]
 [15734.39523407]
 [12470.41060215]
 [11531.30565757]
 [11666.77108818]
 [10982.12147946]
 [19099.06363198]
 [13841.54043351]
 [12618.69033024]
 [14606.73705501]
 [13058.03767273]
 [10313.94739609]
 [12142.73070921]
 [15371.93367651]
 [14156.40602896]
 [14174.71216823]
 [16298.2243236 ]
 [12157.37562062]
 [11739.99564526]
 [13026.91723597]
 [12400.84727292]
 [12018.24896217]
 [14204.00199106]
 [14046.56919333]
 [11322.61566989]
 [15108.32527102]
 [11886.44475942]
 [10279.16573148]
 [13687.76886363]
 [11465.4035562 ]
 [10905.23569452]
 [14925.26387832]
 [11410.48513839]
 [16298.2243236 ]
 [13166.04389443]
 [14083.18147188]
 [14592.09214359]
 [12190.32667131]
 [15584.28489205]
 [10641.62728903]
 [12470.41060215]
 [14928.92510617]
 [13599.89939514]
 [ 8609.64583001]
 [12539.97393138]
 [13559.62588874]
 [12874.97628003]
 [10661.76404223]
 [11410.48513839]
 [12018.24896217]
 [18191.07912416]
 [13922.0874463 ]
```

```
 [14852.03932123]
 [10870.45402991]
 [17748.07055382]
 [15009.47211896]
 [14279.05716207]
 [12431.96770968]
 [12296.50227908]
 [15531.19708817]
 [13826.89552209]
 [12505.19226676]
 [10780.75394749]
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 [ 9513.96910997]
 [14626.87380821]
 [15948.57706353]
 [12582.0780517 ]
 [11009.58068837]
 [12992.13557136]
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 [12018.24896217]
 [12230.60017771]
 [11264.03602423]
 [11600.8689868 ]
 [ 8157.48419003]
 [14279.05716207]
 [11079.14401759]
 [12728.52716586]
 [14000.80384516]
 [18674.3612009 ]
 [11264.03602423]
 [18070.25860498]
 [14209.49383284]
 [14105.148839  ]
 [12261.72061447]
 [10731.32737146]
 [14123.45497827]
 [13801.26692711]
 [10279.16573148]
 [12794.42926724]
 [11447.09741693]
 [15734.39523407]
 [15357.2887651 ]
 [10592.200713  ]
 [14452.96548514]
 [10835.6723653 ]
 [10934.52551736]
 [14742.20248561]
 [10418.29238993]
 [12366.06560831]
 [11044.36235298]
 [13058.03767273]
 [15653.84822128]
 [12922.57224213]
 [12150.05316492]
 [12955.52329282]
 [11218.27067605]
 [17131.15366041]
```

```
 [11809.55897448]
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 [16539.86536197]
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 [11287.83400528]
 [10941.84797307]
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 [15584.28489205]
 [15976.03627244]
 [ 9653.09576843]
 [12192.15728524]
 [15090.01913175]
 [12106.11843067]
 [ 9543.2589328 ]
 [11357.3973345 ]
 [16016.30977883]
 [ 8713.99082385]
 [16018.14039276]
 [13618.20553441]
 [14566.46354861]
 [11264.03602423]
 [15170.56614454]
 [13652.98719902]
 [12122.59395601]
 [12754.15576084]
 [13936.73235771]
 [14888.65159977]
 [10557.41904839]
 [15935.76276604]
 [13305.17055288]
 [15739.88707585]
 [13861.6771867 ]
 [16700.95938755]
 [11849.83248088]
 [13826.89552209]
 [12157.37562062]
 [12018.24896217]
 [14595.75337145]
 [13076.343812  ]
 [15533.02770209]
 [13720.71991432]
 [12984.81311565]
 [14139.93050361]
 [15492.7541957 ]
 [14888.65159977]
 [12691.91488732]
 [11959.6693165 ]
 [12157.37562062]
 [12911.58855857]
```

```
[14731.21880205]
[ 9305.27912229]
[10661.76404223]
[ 9861.78575611]
[11983.46729755]
[14888.65159977]
[13861.6771867 ]
[ 8331.3925131 ]
[17868.891073  ]
[12853.0089129 ]
[10070.47574379]
[12957.35390674]
[17131.15366041]
[10244.38406686]
[12673.60874805]
[12270.8736841 ]
[18593.81418811]
[ 9270.49745767]
[12853.0089129 ]
[13826.89552209]
[17305.06198347]
[ 9470.03437572]
[10974.79902375]
[ 9131.37079922]
[ 9543.2589328 ]
[12633.33524166]
[14870.3454605 ]
[10940.01735914]
[12270.8736841 ]
[14526.19004222]
[15584.28489205]
[10421.95361778]
[14485.91653582]
[12713.88225445]
[11787.59160736]
[14487.74714975]
[11586.22407539]
[16818.11867888]
[12508.85349462]
[12226.93894985]
[10378.01888354]
[14313.83882668]
[14522.52881437]
[14888.65159977]
[13460.77273668]
[12609.5372606 ]
[13358.25835677]
[14324.82251024]
[13058.03767273]
[13200.82555904]
[ 9653.09576843]
[14000.80384516]
[ 8922.68081153]
[12192.15728524]
[10568.40273195]
[12887.79057751]
[14229.63058604]
```

```
 [12362.40438045]
 [15492.7541957 ]
 [14313.83882668]
 [12190.32667131]
 [17707.79704742]
 [ 8957.46247615]
 [12574.75559599]
 [12948.20083711]
 [10418.29238993]
 [13200.82555904]
 [16435.52036813]
 [12995.79679921]
 [19399.28431601]
 [16459.31834918]
 [15496.41542355]
 [13720.71991432]
 [14083.18147188]
 [10905.23569452]
 [14928.92510617]
 [13717.05868647]
 [13801.26692711]
 [15879.01373431]
 [15705.10541124]
 [11844.3406391 ]
 [11425.13004981]
 [14204.00199106]
 [12783.44558367]
 [16574.64702658]
 [14279.05716207]
 [12296.50227908]
 [ 9479.18744536]
 [15322.50710048]
 [12915.24978642]
 [11635.65065142]
 [14244.27549745]
 [14925.26387832]
 [16261.61204506]
 [16257.9508172 ]
 [15392.07042971]
 [11566.08732219]]
```

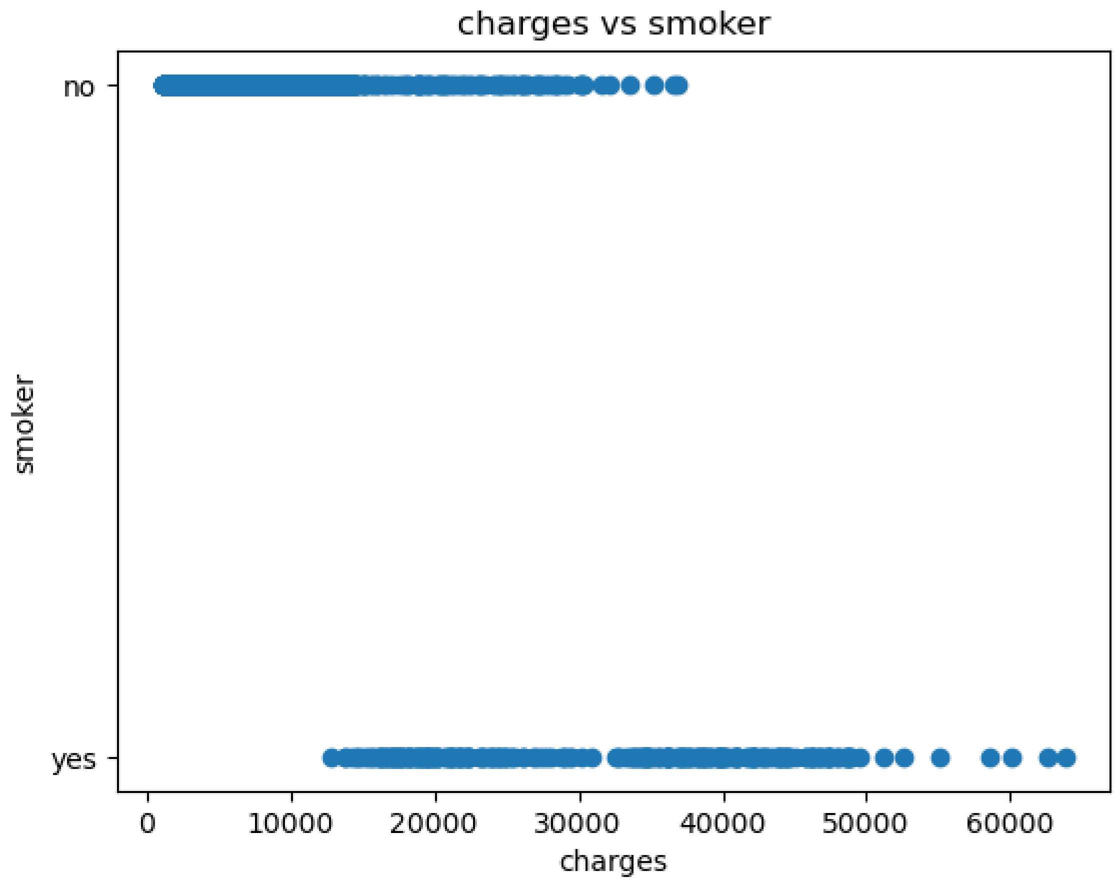
In [385]:
```
y_test = y_test.values.reshape(-1,1)
```

In [386]:
```
RSS1 = np.sum((y_test - y1_pred) ** 2)
```

In [387]:
```
print(f"RSS :{RSS1}")
```

```
RSS :37720249591.561134
```

In [388]:
```
plt.scatter(x=data['charges'],y=data['smoker'])
plt.xlabel("charges")
plt.ylabel("smoker")
plt.title("charges vs smoker")
plt.show()
```



In [389]:
```
smoke = pd.get_dummies(data['smoker'],drop_first=True)
```

In [390]:
```
data['smoke'] = smoke
```

In [391]:
```
data.head()
```

Out[391]:

	age	sex	bmi	children	smoker	region	charges	smoke
0	19	female	27.900	0	yes	southwest	16884.92400	1
1	18	male	33.770	1	no	southeast	1725.55230	0
2	28	male	33.000	3	no	southeast	4449.46200	0
3	33	male	22.705	0	no	northwest	21984.47061	0
4	32	male	28.880	0	no	northwest	3866.85520	0

In [392]:
```
xa = data['charges']
ya = data['smoke']
```

In [393]:
```
xa_train, xa_test, ya_train, ya_test = train_test_split(xa,ya,test_size=0.2,ra
```

In [394]:
```
print(xa_train.shape)
print(xa_test.shape)
print(ya_train.shape)
print(ya_test.shape)
```

```
(1070,)
(268,)
(1070,)
(268,)
```

In [395]:
```
xa_train = xa_train.values.reshape(-1,1)
xa_test = xa_test.values.reshape(-1,1)
```

In [396]:
```
modela = LogisticRegression()
modela.fit(xa_train,ya_train)
```

Out[396]:
```
LogisticRegression()
```

In [397]:
```
modela.score(xa_test,ya_test)
```

Out[397]:
```
0.9104477611940298
```

In [398]:
```
print(f"intercept: {modela.intercept_}")
print(f"slope: {modela.coef_}")
```

```
intercept: [-5.65519559]
slope: [[0.00025126]]
```

In [399]:
```
modela.classes_
```

Out[399]:
```
array([0, 1], dtype=uint8)
```

In [400]:
```
modela.predict_proba(xa_test)
```

Out[400]:
```
array([[9.94735580e-01, 5.26442035e-03],
       [9.42812396e-01, 5.71876039e-02],
       [9.69064287e-01, 3.09357129e-02],
       [9.54639685e-01, 4.53603154e-02],
       [9.94099298e-01, 5.90070182e-03],
       [1.66198820e-02, 9.83380118e-01],
       [9.65015950e-01, 3.49840505e-02],
       [9.38539065e-01, 6.14609354e-02],
       [9.92487229e-01, 7.51277130e-03],
       [6.78235221e-01, 3.21764779e-01],
       [9.22852359e-01, 7.71476405e-02],
       [9.40251179e-01, 5.97488210e-02],
       [9.83087762e-01, 1.69122385e-02],
       [9.79838602e-01, 2.01613981e-02],
       [9.95364614e-01, 4.63538622e-03],
       [9.67759830e-01, 3.22401699e-02],
       [5.32771446e-01, 4.67228554e-01],
       [9.82766883e-01, 1.72331167e-02],
       [1.89608694e-01, 8.10391306e-01],
```

In [401]:
```
ya_pred = modela.predict(x_test)
```

In [402]:
```
print(f"ya_pred :{ya_pred}")
```

```
ya_pred :[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0]
```

In [403]:
```
pd.DataFrame(confusion_matrix(ya_test,ya_pred),columns=['Predicted No','Predic
```

Out[403]:

	Predicted No	Predicted Yes
No	214	0
Yes	54	0

In [404]:
```
print(classification_report(ya_test,ya_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      1.00      0.89       214
           1       0.00      0.00      0.00        54

    accuracy                           0.80       268
   macro avg       0.40      0.50      0.44       268
weighted avg       0.64      0.80      0.71       268


C:\Users\Noah\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:
1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\Noah\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:
1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\Noah\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:
1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [405]:
```
gender = pd.get_dummies(data['sex'],drop_first=True)
```

In [406]:
```
data['gender'] = gender
```

In [407]:
```
data.head()
```

Out[407]:

	age	sex	bmi	children	smoker	region	charges	smoke	gender
0	19	female	27.900	0	yes	southwest	16884.92400	1	0
1	18	male	33.770	1	no	southeast	1725.55230	0	1
2	28	male	33.000	3	no	southeast	4449.46200	0	1
3	33	male	22.705	0	no	northwest	21984.47061	0	1
4	32	male	28.880	0	no	northwest	3866.85520	0	1

In [408]:
```
xb = data['charges']
yb = data['gender']
```

In [409]:
```
xb_train, xb_test, yb_train, yb_test = train_test_split(xb, yb, test_size = 0.
```

In [410]:
```
print(xb_train.shape)
print(xb_test.shape)
print(yb_train.shape)
print(yb_test.shape)
```

```
(1070,)
(268,)
(1070,)
(268,)
```

In [411]:
```
xb_train = xb_train.values.reshape(-1,1)
xb_test = xb_test.values.reshape(-1,1)
```

In [412]:
```
modelb = LogisticRegression()
```

In [413]:
```
modelb.fit(xb_train,yb_train)
```

Out[413]:
```
LogisticRegression()
```

In [414]:
```
modelb.score(xb_test,yb_test)
```

Out[414]:
```
0.48880597014925375
```

In [415]:
```
modelb.classes_
```

Out[415]:
```
array([0, 1], dtype=uint8)
```

In [416]:
```
print(f"intercept: {modelb.intercept_}")
print(f"slope: {modelb.coef_}")
```

```
intercept: [-2.47525154e-10]
slope: [[5.74297972e-06]]
```

In [417]:
```
modelb.predict_proba(xb_test)
```

Out[417]:
```
array([[0.49763616, 0.50236384],
       [0.48370543, 0.51629457],
       [0.48737015, 0.51262985],
       [0.48509926, 0.51490074],
       [0.49698055, 0.50301945],
       [0.44459853, 0.55540147],
       [0.486644  , 0.513356  ],
       [0.48326817, 0.51673183],
       [0.49559122, 0.50440878],
       [0.47197603, 0.52802397],
       [0.48187464, 0.51812536],
       [0.48343983, 0.51656017],
       [0.49090114, 0.50909886],
       [0.48987846, 0.51012154],
       [0.49836689, 0.50163311],
       [0.48712661, 0.51287339],
       [0.46847777, 0.53152223],
       [0.49079192, 0.50920808],
       [0.45947488, 0.54052512],
```

In [418]:
```
yb_pred = modelb.predict(xb_test)
```

In [419]:
```
print(f"yb_pred:{yb_pred}")
```

```
yb_pred:[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1]
```

In [420]:
```
pd.DataFrame(confusion_matrix(yb_test,yb_pred),columns=['Predicted No','Predic
```

Out[420]:

	Predicted No	Predicted Yes
No	0	137
Yes	0	131

In [421]:
```
print(classification_report(yb_test,yb_pred))
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       137
           1       0.49      1.00      0.66       131

    accuracy                           0.49       268
   macro avg       0.24      0.50      0.33       268
weighted avg       0.24      0.49      0.32       268


C:\Users\Noah\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:
1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\Noah\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:
1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\Noah\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:
1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division` parameter
to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [422]:
```
xc = data['bmi']
yc = data['gender']
```

In [423]:
```
xc_train, xc_test, yc_train, yc_test = train_test_split(xc, yc, test_size=0.2,
```

In [424]:
```
print(xc_train.shape)
print(xc_test.shape)
print(yc_train.shape)
print(yc_test.shape)
```

```
(1070,)
(268,)
(1070,)
(268,)
```

In [425]:
```
xc_train = xc_train.values.reshape(-1,1)
xc_test = xc_test.values.reshape(-1,1)
```

In [426]:
```
modelc = LogisticRegression()
```

In [427]:
```
modelc.fit(xc_train,yc_train)
```

Out[427]:
```
LogisticRegression()
```

In [428]:
```
modelc.score(xc_test,yc_test)
```

Out[428]:
```
0.5223880597014925
```

In [429]:
```
modelc.classes_
```

Out[429]:
```
array([0, 1], dtype=uint8)
```

In [430]:
```
print(f"modelc intercept: {modelc.intercept_}")
```

```
modelc intercept: [-0.33149167]
```

In [431]:
```
print(f"modelc slope: {modelc.coef_}")
```

```
modelc slope: [[0.01202926]]
```

In [432]:
```python
modelc.predict_proba(xc_test)
```

Out[432]:
```
array([[0.47604136, 0.52395864],
       [0.48802447, 0.51197553],
       [0.47163274, 0.52836726],
       [0.472742  , 0.527258  ],
       [0.51580451, 0.48419549],
       [0.4794629 , 0.5205371 ],
       [0.47010421, 0.52989579],
       [0.49687877, 0.50312123],
       [0.50459236, 0.49540764],
       [0.50347973, 0.49652027],
       [0.50910246, 0.49089754],
       [0.44268433, 0.55731567],
       [0.4856203 , 0.5143797 ],
       [0.49566087, 0.50433913],
       [0.47934281, 0.52065719],
       [0.49205266, 0.50794734],
       [0.51458768, 0.48541232],
       [0.49957028, 0.50042972],
       [0.47307183, 0.52692817],
```

In [433]:
```python
yc_pred = modelc.predict(xc_test)
```

In [434]:
```python
pd.DataFrame(confusion_matrix(yc_test,yc_pred), columns = ['Predicted No','Pre
```

Out[434]:

	Predicted No	Predicted Yes
No	45	92
Yes	36	95

In [435]:
```python
print(classification_report(yc_test,yc_pred))
```

```
              precision    recall  f1-score   support

           0       0.56      0.33      0.41       137
           1       0.51      0.73      0.60       131

    accuracy                           0.52       268
   macro avg       0.53      0.53      0.51       268
weighted avg       0.53      0.52      0.50       268
```

In [436]:
```python
from sklearn.neighbors import KNeighborsClassifier
```

In [437]:
```
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
data['region'] = label_encoder.fit_transform(data['region'])
print(data.head())
```

```
   age     sex     bmi  children smoker  region      charges  smoke  gender
0   19  female  27.900         0    yes       3  16884.92400      1       0
1   18    male  33.770         1     no       2   1725.55230      0       1
2   28    male  33.000         3     no       2   4449.46200      0       1
3   33    male  22.705         0     no       1  21984.47061      0       1
4   32    male  28.880         0     no       1   3866.85520      0       1
```

In [438]:
```
xk = data['bmi']
yk = data['region']
xk
yk
```

Out[438]:
```
0       3
1       2
2       2
3       1
4       1
       ..
1333    1
1334    0
1335    2
1336    3
1337    1
Name: region, Length: 1338, dtype: int32
```

In [439]:
```
xk_train,xk_test,yk_train,yk_test = train_test_split(xk,yk,test_size=0.2,randc
```

In [440]:
```
print(xk_train.shape)
print(xk_test.shape)
print(yk_train.shape)
print(yk_test.shape)
```

```
(1070,)
(268,)
(1070,)
(268,)
```

In [441]:
```
xk_train = xk_train.values.reshape(-1,1)
xk_test = xk_test.values.reshape(-1,1)
```

In [442]:
```
NN = KNeighborsClassifier(n_neighbors=5)
```

In [443]:
```
NN.fit(xk_train,yk_train)
```

Out[443]:
```
KNeighborsClassifier()
```

In [444]:
```
NN.score(xk_test,yk_test)
```

```
C:\Users\Noah\anaconda3\lib\site-packages\sklearn\neighbors\_classification.p
y:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosi
s`), the default behavior of `mode` typically preserves the axis it acts alon
g. In SciPy 1.11.0, this behavior will change: the default value of `keepdims
` will become False, the `axis` over which the statistic is taken will be eli
minated, and the value None will no longer be accepted. Set `keepdims` to Tru
e or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

Out[444]:
```
0.40298507462686567
```

In [445]:
```
yNN_pred = NN.predict(xk_test)
```

```
C:\Users\Noah\anaconda3\lib\site-packages\sklearn\neighbors\_classification.p
y:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosi
s`), the default behavior of `mode` typically preserves the axis it acts alon
g. In SciPy 1.11.0, this behavior will change: the default value of `keepdims
` will become False, the `axis` over which the statistic is taken will be eli
minated, and the value None will no longer be accepted. Set `keepdims` to Tru
e or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

In [446]:
```
print(f"yNN_pred : {yNN_pred}")
```

```
yNN_pred : [2 3 1 1 0 3 3 1 0 1 3 2 0 0 2 3 0 2 1 0 0 2 0 1 1 3 0 2 0 0 1 0 1
0 1 1 0
 2 2 1 2 3 1 3 0 1 3 0 0 0 3 2 1 2 0 3 0 2 3 2 2 2 0 1 1 1 3 0 3 3 2 2 3 3
 1 0 0 1 0 1 0 2 0 2 1 2 0 3 0 3 0 3 2 3 1 2 3 3 1 0 2 1 1 3 0 1 1 3 2 0 2
 2 0 0 2 3 2 0 3 0 3 1 0 0 2 2 1 1 0 3 0 2 1 2 3 3 3 0 3 0 0 2 0 2 0 1 3 2
 2 0 2 1 2 0 2 1 1 0 0 3 1 1 0 1 0 2 2 2 1 0 3 3 1 1 3 0 2 0 0 3 0 0 2 0 0
 1 0 2 0 0 1 2 0 2 3 3 1 2 1 0 2 3 0 3 2 3 1 1 1 3 1 0 1 3 2 1 0 2 2 3 1 2
 1 0 1 0 1 3 1 2 1 1 2 0 1 2 0 1 3 1 2 2 2 0 2 1 3 0 3 3 3 1 2 2 2 2 2 1 0
 3 2 1 3 0 2 2 1 0]
```

In [447]:
```
pd.DataFrame(confusion_matrix(yk_test,yNN_pred),columns=['Predicted 0','Predic
```

Out[447]:

	Predicted 0	Predicted 1	Predicted 2	Predicted 3
Actual 0	29	20	6	6
Actual 1	17	23	11	15
Actual 2	16	14	37	15
Actual 3	15	10	15	19

In [448]:
```
print(classification_report(yk_test,yNN_pred))
```

```
              precision    recall  f1-score   support

           0       0.38      0.48      0.42        61
           1       0.34      0.35      0.35        66
           2       0.54      0.45      0.49        82
           3       0.35      0.32      0.33        59

    accuracy                           0.40       268
   macro avg       0.40      0.40      0.40       268
weighted avg       0.41      0.40      0.40       268
```

In [449]:
```
xk1 = data['charges']
xk1
```

Out[449]:
```
0       16884.92400
1        1725.55230
2        4449.46200
3       21984.47061
4        3866.85520
           ...
1333    10600.54830
1334     2205.98080
1335     1629.83350
1336     2007.94500
1337    29141.36030
Name: charges, Length: 1338, dtype: float64
```

In [450]:
```
yk = data['region']
yk
```

Out[450]:
```
0       3
1       2
2       2
3       1
4       1
       ..
1333    1
1334    0
1335    2
1336    3
1337    1
Name: region, Length: 1338, dtype: int32
```

In [451]:
```
xk1_train, xk1_test, yk_train, yk_test = train_test_split(xk1,yk,test_size=0.2
```

In [452]:
```
print(xk1_test.shape)
print(xk1_train.shape)
print(yk_test.shape)
print(yk_train.shape)
```

```
(268,)
(1070,)
(268,)
(1070,)
```

In [453]:
```
xk1_test = xk1_test.values.reshape(-1,1)
xk1_train = xk1_train.values.reshape(-1,1)
```

In [454]:
```
NN1 = KNeighborsClassifier(n_neighbors=5)
```

In [455]:
```
NN1.fit(xk1_train,yk_train)
```

Out[455]:
```
KNeighborsClassifier()
```

In [456]:
```
NN1.score(xk1_test,yk_test)
```

```
C:\Users\Noah\anaconda3\lib\site-packages\sklearn\neighbors\_classification.p
y:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosi
s`), the default behavior of `mode` typically preserves the axis it acts alon
g. In SciPy 1.11.0, this behavior will change: the default value of `keepdims
` will become False, the `axis` over which the statistic is taken will be eli
minated, and the value None will no longer be accepted. Set `keepdims` to Tru
e or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

Out[456]:
```
0.332089552238806
```

In [457]:
```
yNN1_pred = NN1.predict(xk1_test)
```

```
C:\Users\Noah\anaconda3\lib\site-packages\sklearn\neighbors\_classification.p
y:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosi
s`), the default behavior of `mode` typically preserves the axis it acts alon
g. In SciPy 1.11.0, this behavior will change: the default value of `keepdims
` will become False, the `axis` over which the statistic is taken will be eli
minated, and the value None will no longer be accepted. Set `keepdims` to Tru
e or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

In [458]:
```
print(f"yNN1_pred : {yNN1_pred}")
```

```
yNN1_pred : [2 3 3 0 1 0 0 0 0 2 1 0 1 0 2 1 1 1 1 2 0 0 1 1 0 0 0 3 1 3 0 0
0 0 1 0 2
 0 3 2 0 0 0 0 1 1 0 3 3 0 1 2 0 2 2 1 0 2 3 2 2 0 1 1 0 3 1 2 1 0 2 2 3 1
 1 0 1 1 1 0 1 1 3 3 0 2 0 2 0 1 0 1 0 0 2 0 3 1 1 1 3 3 1 3 2 0 3 1 0 1 1
 2 2 0 1 3 0 1 2 0 0 3 2 3 1 0 3 2 1 1 3 2 3 2 2 3 2 2 0 0 0 3 3 1 0 1 2 0
 2 0 2 0 0 2 2 2 0 3 0 2 2 2 0 2 1 2 0 0 1 2 1 3 3 0 2 1 0 1 2 2 0 0 1 2 3
 1 3 2 1 1 2 2 0 1 0 0 1 1 0 2 3 3 1 0 2 2 3 0 3 1 1 0 2 2 0 2 3 3 2 0 2 3
 1 2 2 3 0 3 2 1 3 0 3 0 1 1 1 2 0 1 3 1 1 3 0 0 1 0 1 3 2 0 1 2 2 0 3 3 2
 2 2 0 2 1 2 2 1 3]
```

In [459]:
```
pd.DataFrame(confusion_matrix(yk_test,yNN1_pred),columns=['Predicted 0','Predi
```

Out[459]:

	Predicted 0	Predicted 1	Predicted 2	Predicted 3
Actual 0	25	11	12	13
Actual 1	20	22	14	10
Actual 2	18	21	30	13
Actual 3	18	16	13	12

In [460]:
```
print(classification_report(yk_test,yNN1_pred))
```

```
              precision    recall  f1-score   support

           0       0.31      0.41      0.35        61
           1       0.31      0.33      0.32        66
           2       0.43      0.37      0.40        82
           3       0.25      0.20      0.22        59

    accuracy                           0.33       268
   macro avg       0.33      0.33      0.32       268
weighted avg       0.34      0.33      0.33       268
```

KNN not good on large datasets

In [461]:
```
data.head()
```

Out[461]:

	age	sex	bmi	children	smoker	region	charges	smoke	gender
0	19	female	27.900	0	yes	3	16884.92400	1	0
1	18	male	33.770	1	no	2	1725.55230	0	1
2	28	male	33.000	3	no	2	4449.46200	0	1
3	33	male	22.705	0	no	1	21984.47061	0	1
4	32	male	28.880	0	no	1	3866.85520	0	1

In [462]:
```
from sklearn import svm
```

In [463]:
```
xs = data['charges']
```

In [464]:
```
ys = data['smoke']
```

In [465]:
```
print(xs)
```

```
0       16884.92400
1        1725.55230
2        4449.46200
3       21984.47061
4        3866.85520
           ...
1333    10600.54830
1334     2205.98080
1335     1629.83350
1336     2007.94500
1337    29141.36030
Name: charges, Length: 1338, dtype: float64
```

In [466]:
```
print(ys)
```

```
0       1
1       0
2       0
3       0
4       0
       ..
1333    0
1334    0
1335    0
1336    0
1337    1
Name: smoke, Length: 1338, dtype: uint8
```

In [467]:
```
xs_train, xs_test, ys_train, ys_test = train_test_split(xs,ys,test_size=0.2,ra
```

In [468]:
```
print(xs_train.shape)
print(xs_test.shape)
print(ys_train.shape)
print(ys_test.shape)
```

```
(1070,)
(268,)
(1070,)
(268,)
```

In [469]:
```
xs_train = xs_train.values.reshape(-1,1)
xs_test = xs_test.values.reshape(-1,1)
```

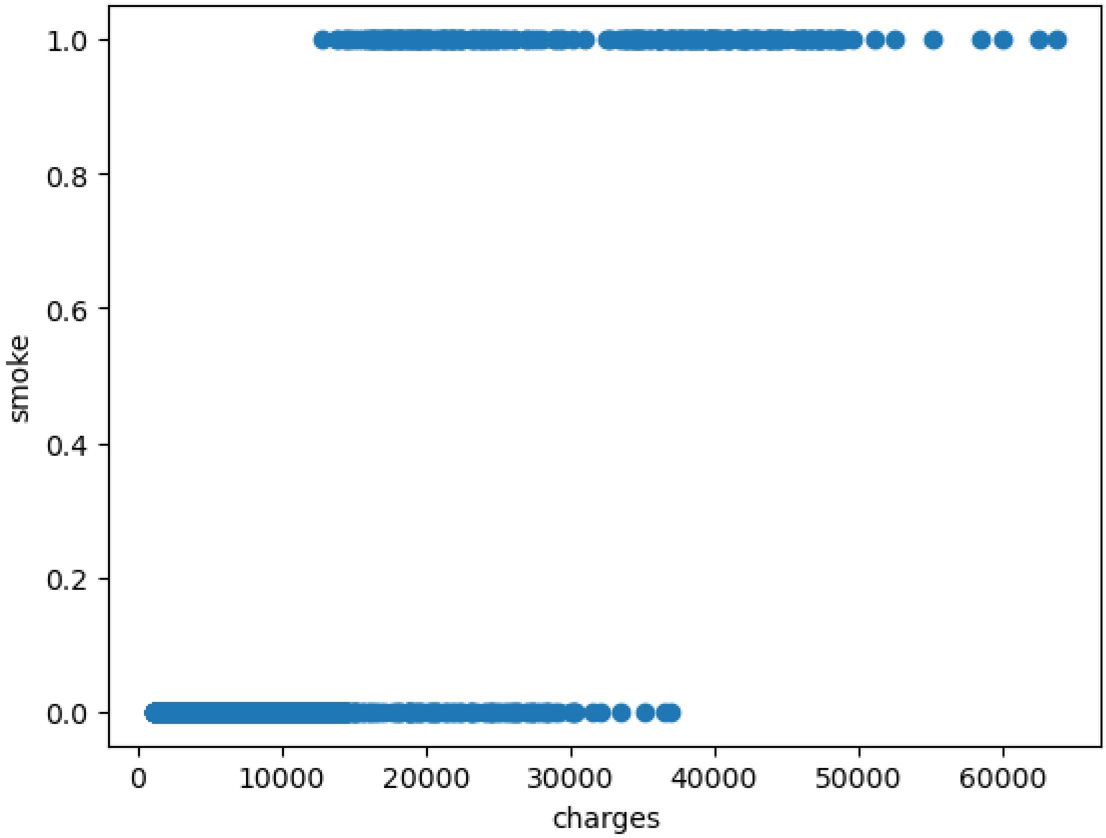
In [470]:
```
models = svm.SVC()
models.fit(xs_train,ys_train)
```

Out[470]:
```
SVC()
```

In [471]:
```
models.score(xs_test,ys_test)
```

Out[471]:
```
0.9328358208955224
```

In [472]:
```
plt.scatter(x = data['charges'],y = data['smoke'])
plt.xlabel('charges')
plt.ylabel("smoke")
plt.show()
```



In [473]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [476]:
```
regressor = RandomForestRegressor(n_estimators = 500, random_state = 1)
regressor.fit(xs_train,ys_train)
```

Out[476]:
```
RandomForestRegressor(n_estimators=500, random_state=1)
```

In [477]:
```
regressor.score(xs_train,ys_train)
```

Out[477]:
```
0.9414024055614973
```