Importing Libraries

In [1]:
```
import numpy as np # linear algebra
import pandas as pd # for data processing like in this project csv loading
import matplotlib.pyplot as plt  # for data visualization
import seaborn as sns # for data visualization i.e pairplot
from sklearn import metrics # for calculating rootmean square
```

Data Loading and Insites

In [2]:
```
# reading the data

df = pd.read_csv('insurance.csv')

# checking the shape
print(df.shape)
```

```
(1338, 8)
```

In [3]:
```
# checking data points
print(df.size)
```

```
10704
```

In [4]:
```
# previewing 1st 5 dataset checking wether its loaded or not sucessfully
df.head()
```

Out[4]:

	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 [ ]:

In [5]:
```
#description about data set

df.describe()
```

Out[5]:

	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 [6]:
```
#checing information about data

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 [7]:
```
# checking number of null value in this data
df.isnull().sum()
```

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

In [8]:
```
# checking if any null value is present or not
df.isnull().any()
```

Out[8]:
```
age               False
sex               False
bmi               False
children          False
smoker            False
region            False
charges           False
insuranceclaim    False
dtype: bool
```

from this data we can get insites that :

1. data belongs to middle age people (mostly)

2. maximum age of any person is 64 where as minimum age is 18 only

3. maximum bmi is 53.13 which is a deep sign of obasity

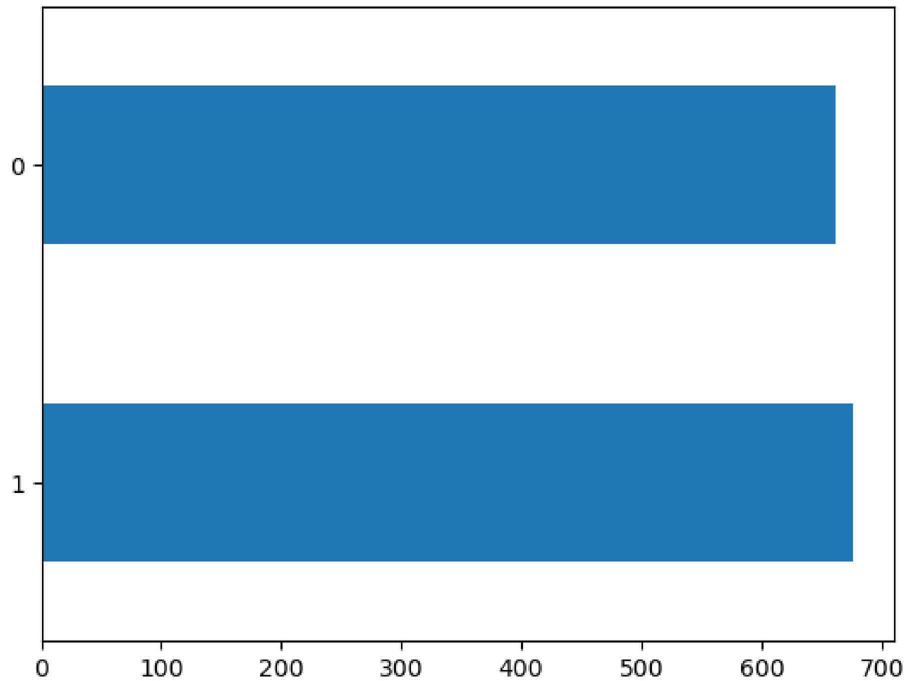
4. there is no null value in this data

5. There are 676 male and 662 female

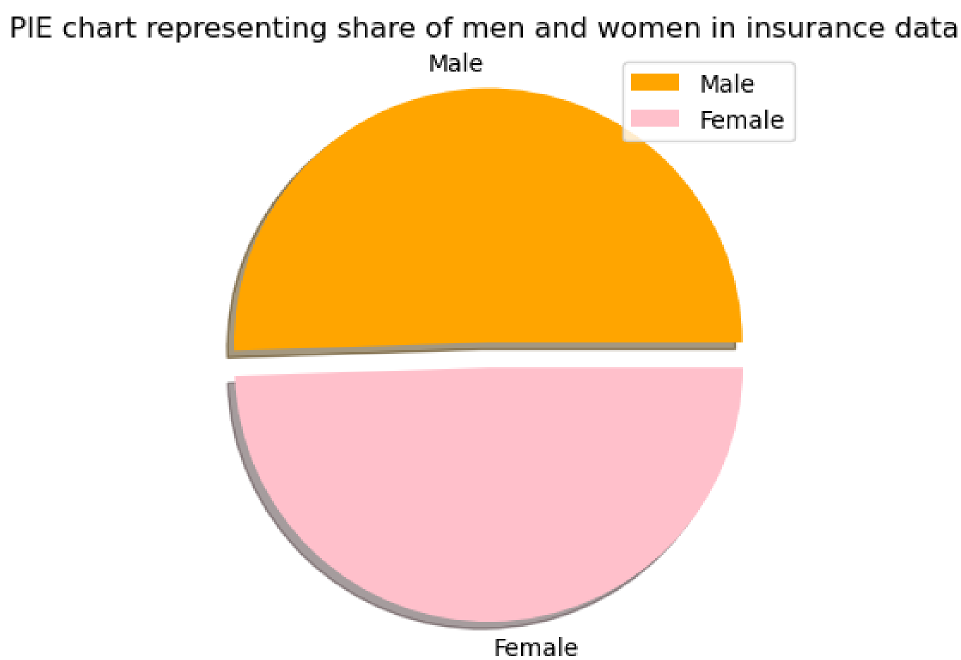
In [10]:
```
# checking value count of male and female in data
df['sex'].value_counts()
```

Out[10]:
```
1    676
0    662
Name: sex, dtype: int64
```

In [11]:
```
# ploting a bar graph showing about number of male and female
df.sex.value_counts(normalize=False).plot.barh()
plt.show()
```



In [12]:
```
#pie chart: with Label and explode
mylables=["Male","Female"] # here label is "Male - is 1 where as Female - is 0"
colors = ['orange', 'pink']
myexplode=[0.10,0]
size = [676, 662]
plt.pie(size,colors = colors,labels =mylables,explode = myexplode, shadow = True)
plt.title('PIE chart representing share of men and women in insurance data ')
plt.legend()
plt.show()
```

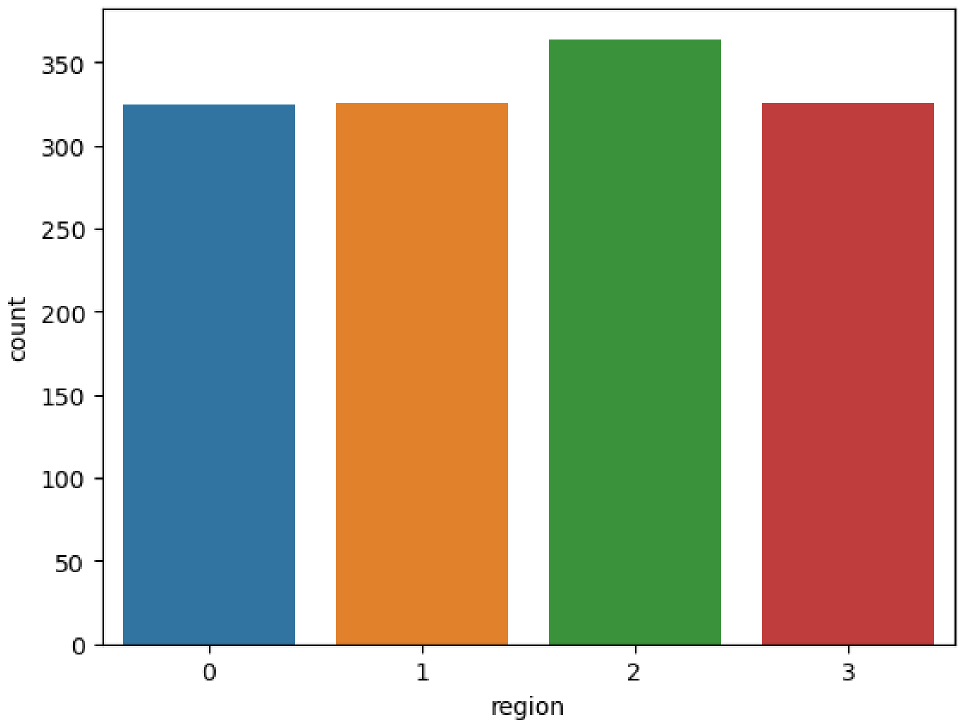


In [13]:
```python
# checking customer belonging
df['region'].value_counts()
```

Out[13]:
```
2    364
3    325
1    325
0    324
Name: region, dtype: int64
```

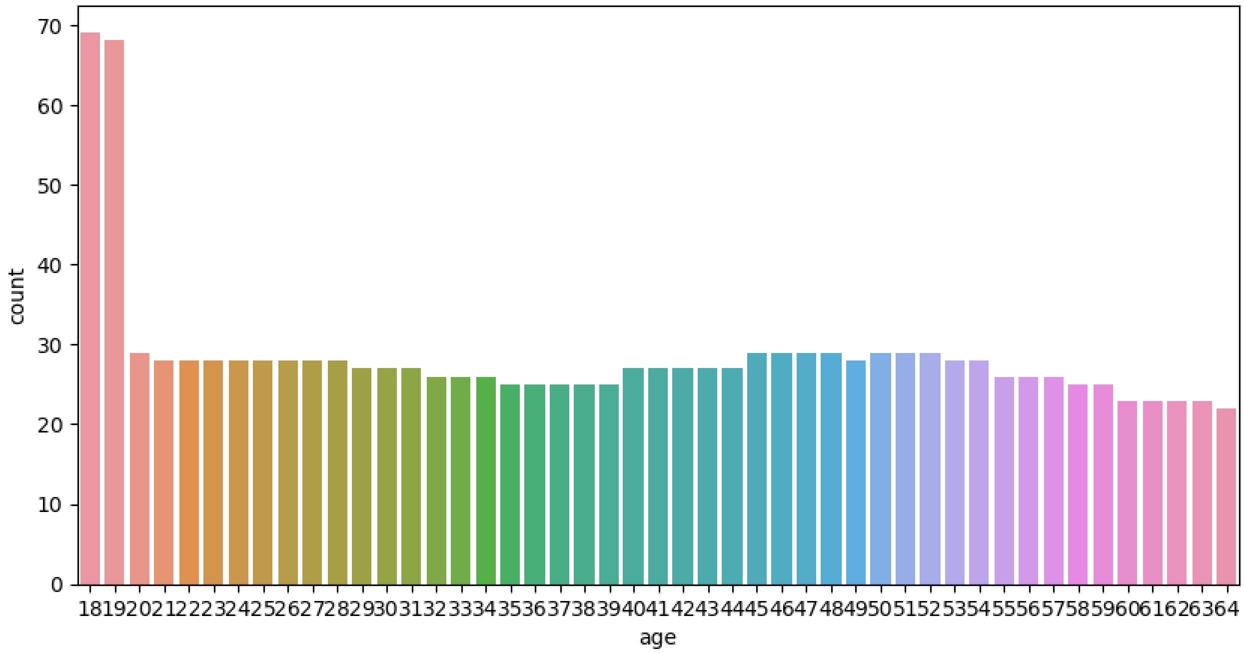
In [14]:
```python
#ploting a Countplot showing region
sns.countplot("region",data = df)
plt.show()
```

```
D:\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following var
iable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data
`, and passing other arguments without an explicit keyword will result in an error or misinterp
retation.
  warnings.warn(
```

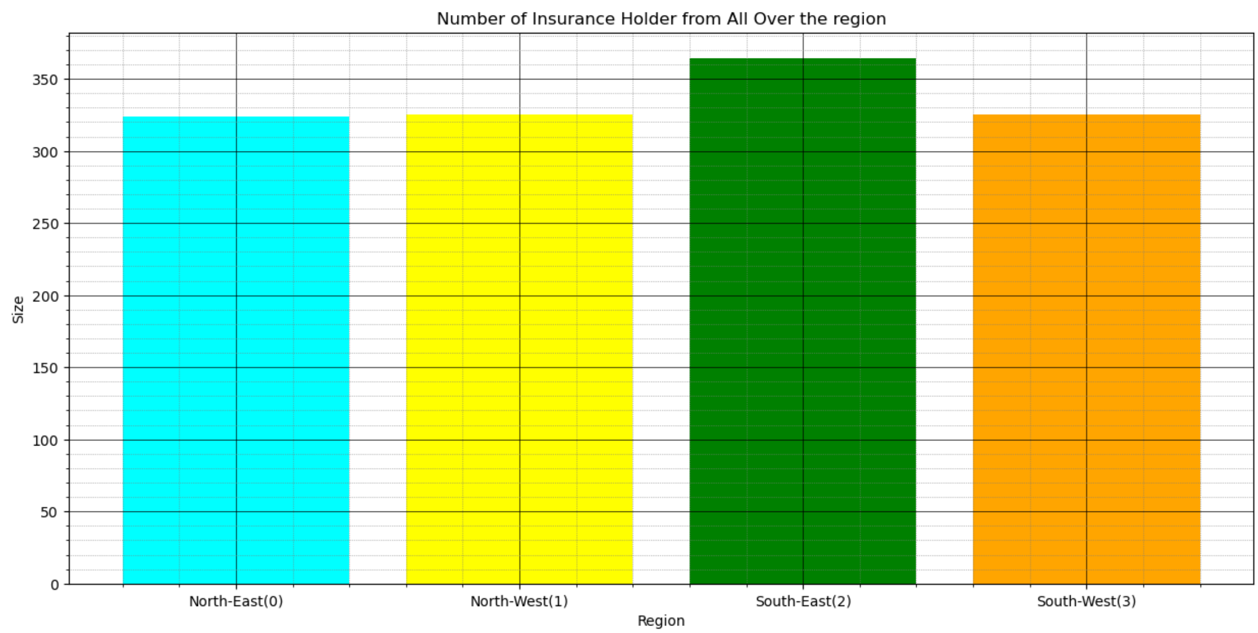


In [15]:
```python
#ploting a Countplot showing age
plt.figure(figsize = (10,5))
sns.countplot("age",data = df)
plt.show()
```

```
D:\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following var
iable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data
`, and passing other arguments without an explicit keyword will result in an error or misinterp
retation.
  warnings.warn(
```



In [16]:
```
# ploting a bar graph showing about region wise with labels grid and minor grids and title

x = ['North-East(0)', 'North-West(1)', 'South-East(2)', 'South-West(3)']
size = [324, 325, 364, 325]
plt.figure(figsize = (15,7))
x_pos = [i for i, _ in enumerate(x)]
plt.bar(x_pos, size, color=['cyan', 'yellow', 'green', 'orange'])
plt.xlabel("Region")
plt.ylabel("Size")
plt.title("Number of Insurance Holder from All Over the region")
plt.xticks(x_pos, x)
# Turn on the grid
plt.minorticks_on()
plt.grid(which='major', linestyle='-', linewidth='0.5', color='black')
# Customize the minor grid
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='grey')
plt.show()
```



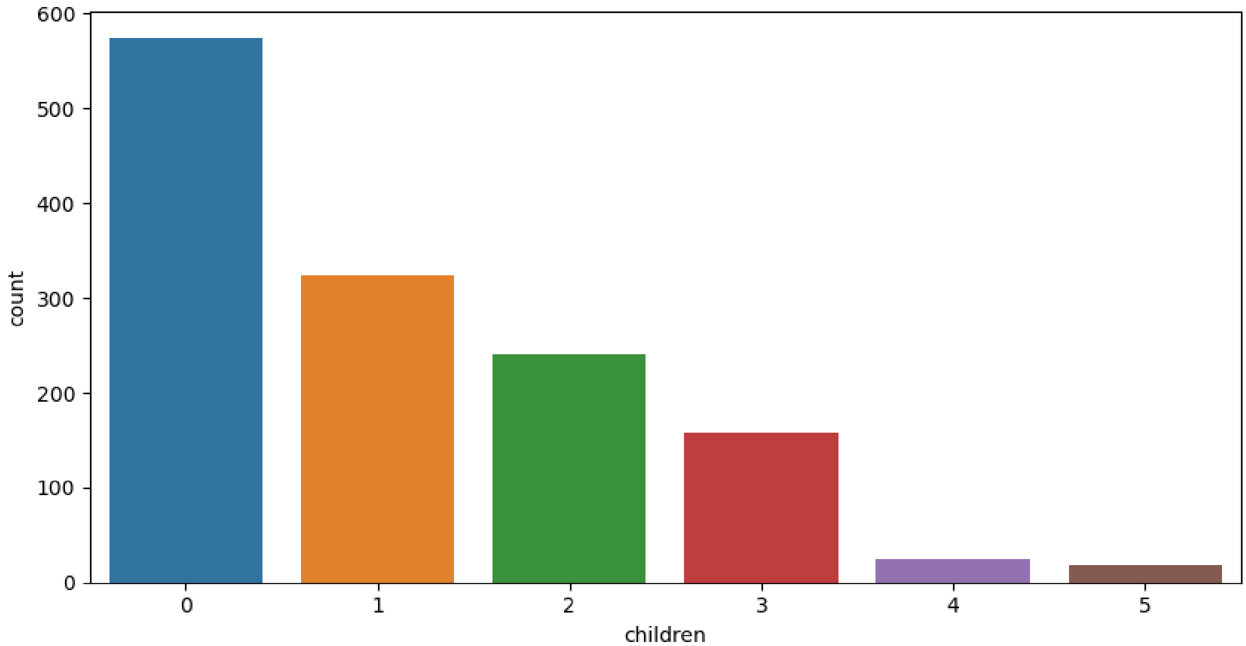
Insites-6. People belonging residential area from northeast(0) are 324 person ; northwest(1) are 325 person ; southeast(2) are 364 person ; southwest(3) are 325 person

In [18]:
```
# checking children count
df['children'].value_counts()
```

Out[18]:
```
0    574
1    324
2    240
3    157
4     25
5     18
Name: children, dtype: int64
```

In [19]:
```
#ploting a Countplot showing number of children
plt.figure(figsize = (10,5))
sns.countplot("children",data = df)
plt.show()
```

```
D:\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following var
iable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data
`, and passing other arguments without an explicit keyword will result in an error or misinterp
retation.
  warnings.warn(
```



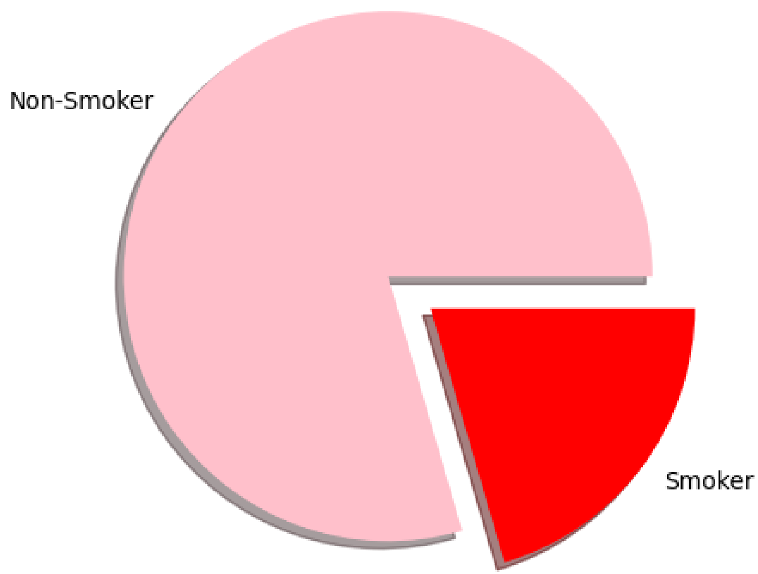
In [ ]:
```
# pie chart: with Label and explode
plt.figure(figsize = (10,5))
mylables=["No Children","1 Child","2 Children","3 Children","4 Children","5 Children"]
colors = ['orange','pink','purple','cyan','yellow','blue']
myexplode=[0.10,0,0,0,0,0]
size = [574, 324,240,157,25,18]
plt.pie(size,colors = colors,labels =mylables,explode = myexplode, shadow = True)
plt.title('PIE chart representing share of person per chidren as per given data ')
plt.legend()
plt.show()
```

In [21]:
```
# 7. count of people having no children are 574 ; with 1 children are 324 ; with 2 children are 2
```

In [22]:
```
# checking number of smokers
df['smoker'].value_counts()
```

Out[22]:
```
0    1064
1     274
Name: smoker, dtype: int64
```

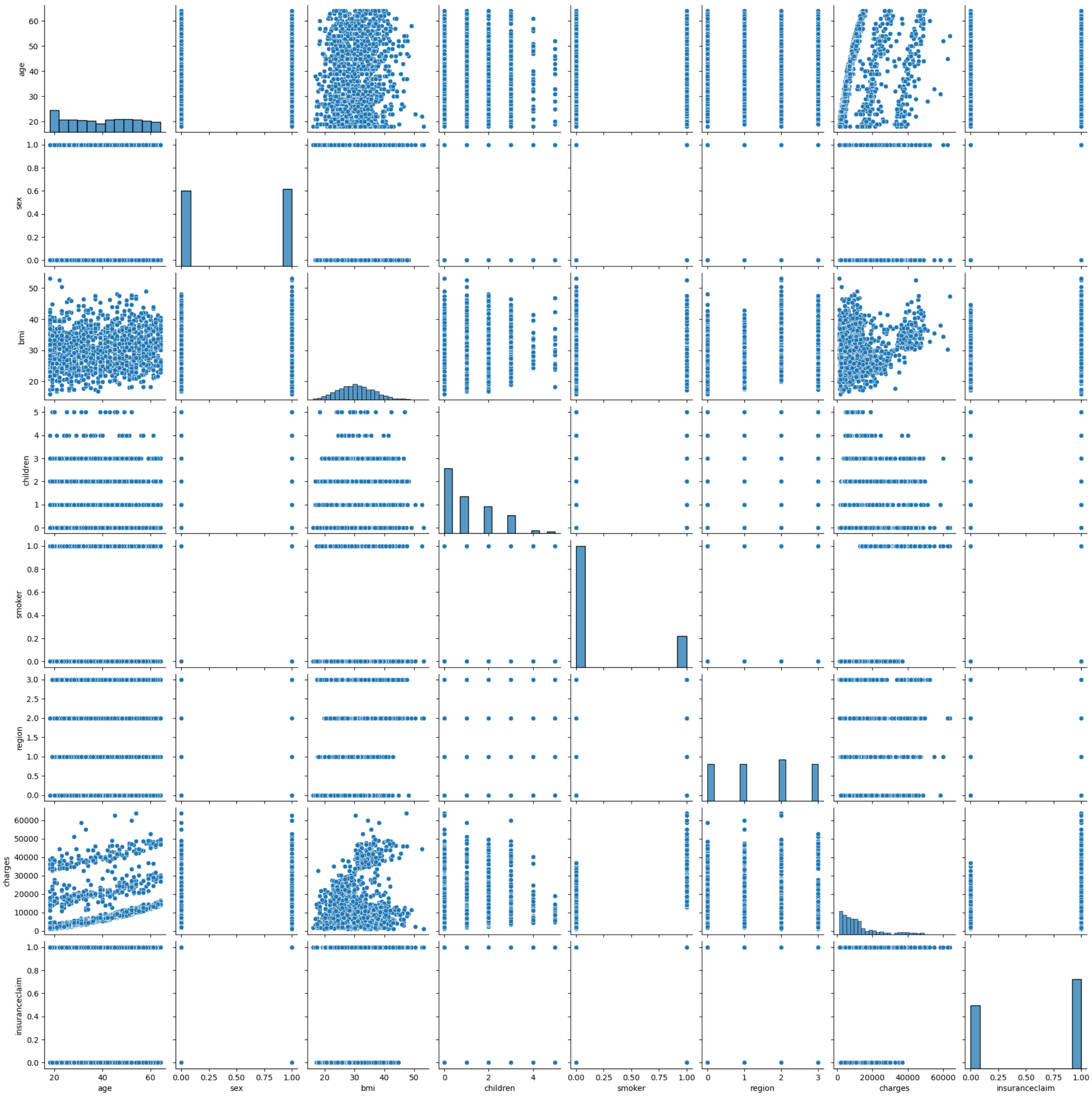
In [23]:
```python
#ploting a bar grap showing number of smoker
plt.figure(figsize = (10,5))
mylables=['Non-Smoker','Smoker']
colors = ['pink','Red']
myexplode=[0.10,0.10]
size = [1064,274]
plt.pie(size,colors = colors,labels =mylables,explode = myexplode, shadow = True)

plt.show()
```



In [24]:
```python
# 8. count of non smokers are represented as 0 which is 1064 where as 274 peopple are smoker
```

In [25]:
```python
# pairplot
sns.pairplot(df)
```

Out[25]: <seaborn.axisgrid.PairGrid at 0x1c48c044310>



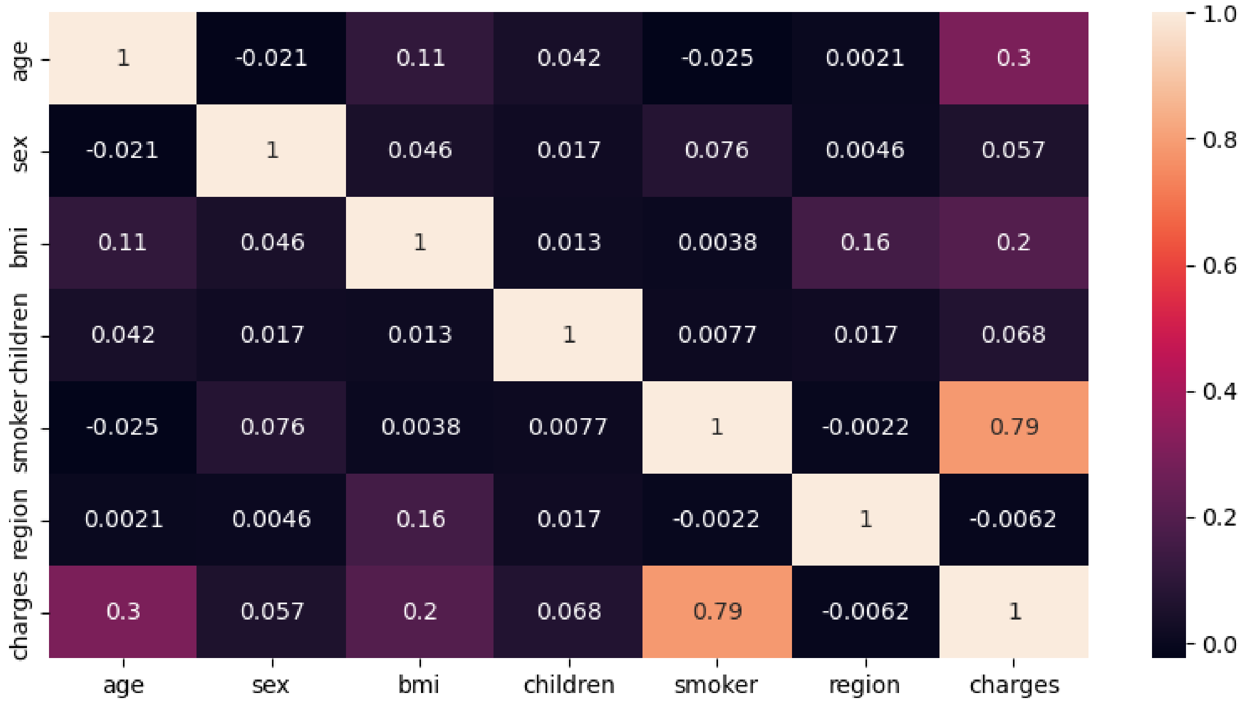
In [26]:
```python
# Corelation Between Diffrent Feature
df[['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges']].corr()
```

Out[26]:

	age	sex	bmi	children	smoker	region	charges
age	1.000000	-0.020856	0.109272	0.042469	-0.025019	0.002127	0.299008
sex	-0.020856	1.000000	0.046371	0.017163	0.076185	0.004588	0.057292
bmi	0.109272	0.046371	1.000000	0.012759	0.003750	0.157566	0.198341
children	0.042469	0.017163	0.012759	1.000000	0.007673	0.016569	0.067998
smoker	-0.025019	0.076185	0.003750	0.007673	1.000000	-0.002181	0.787251
region	0.002127	0.004588	0.157566	0.016569	-0.002181	1.000000	-0.006208
charges	0.299008	0.057292	0.198341	0.067998	0.787251	-0.006208	1.000000

Insite from this Corelation are : 1. Charges are Dependent Upon Age (Higher the Age More will be Insurance Charges) ; 2. Charges are Dependent upon Smokers and BMI

In [28]:
```
#plot the correlation matrix of salary, balance and age in data dataframe.
plt.figure(figsize = (10,5))
sns.heatmap(df[['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges']].corr(), annot=Tr
plt.show()
```



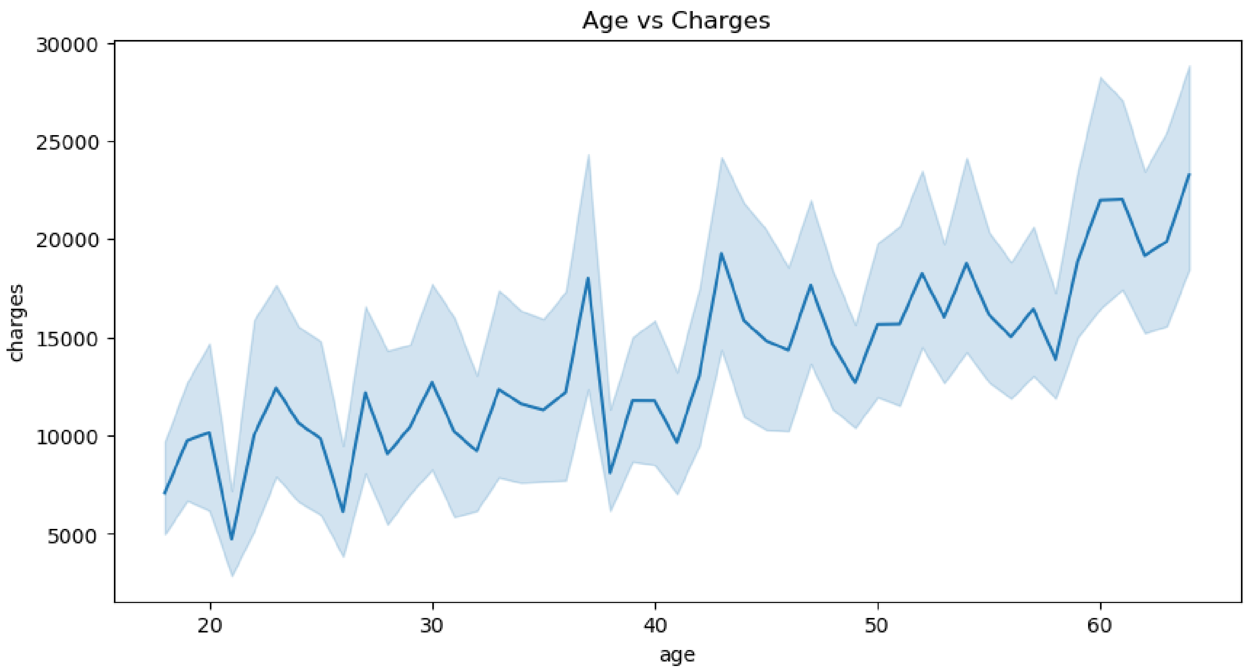
In [29]:
```
df.columns
```

Out[29]:
```
Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges',
       'insuranceclaim'],
      dtype='object')
```

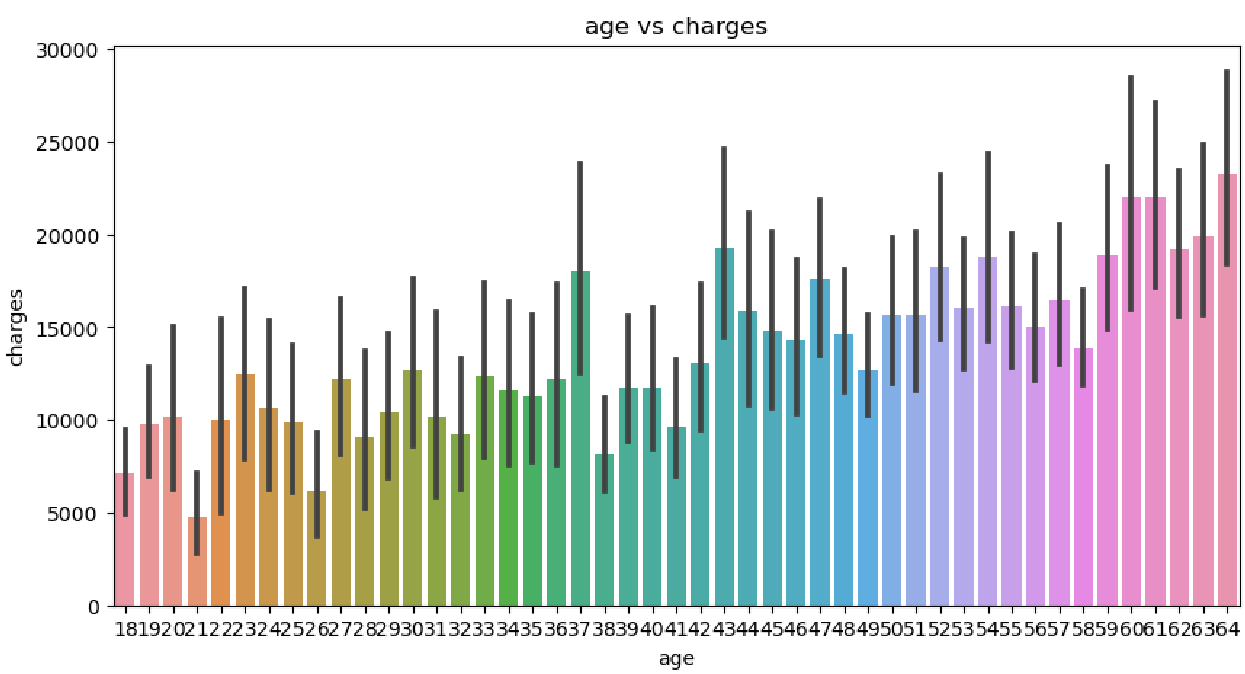
Insites From this Heat Map :- 1. Smoker Tends to Pay More Insurance Charges; 2. Age is Positively Related to Charge; 3. Charges are also propotional to bmi

In [ ]:

In [31]:
```python
# Age vs Charges
# the more the age the more will be insurance charge (roughly estimated)

plt.figure(figsize = (10, 5))
sns.lineplot(x = 'age', y = 'charges', data = df)

plt.title("Age vs Charges")
plt.show()
```

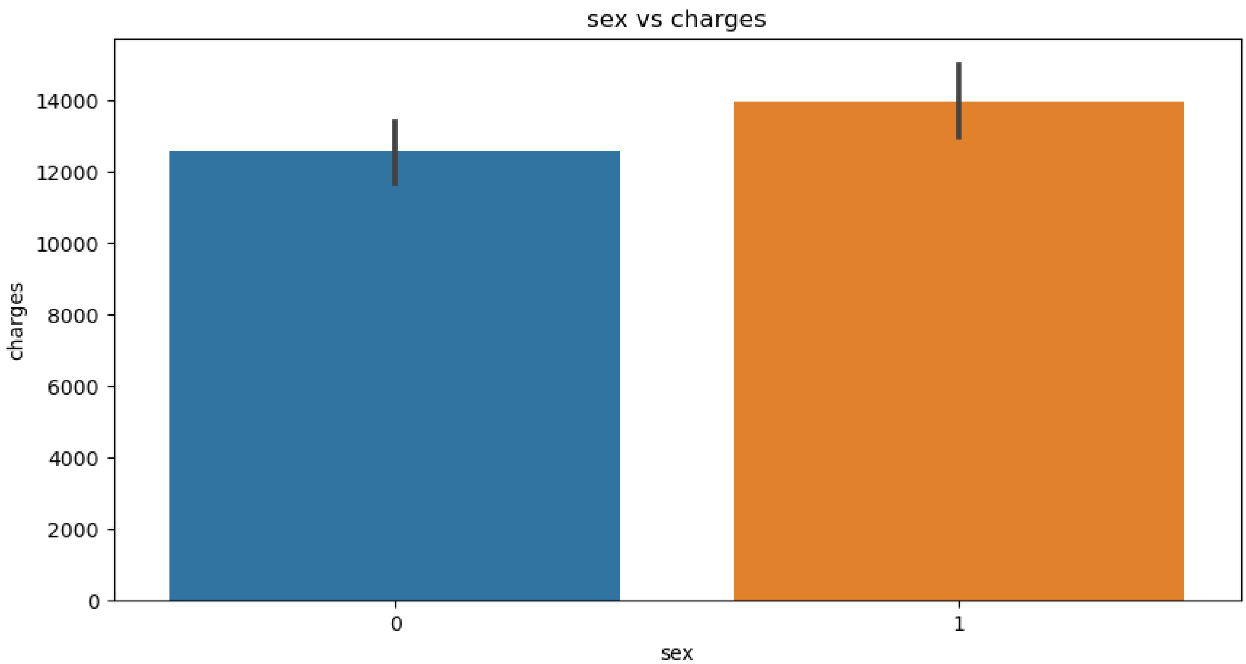


In [32]:
```python
#bax plot for age vs charge

plt.figure(figsize = (10, 5))
sns.barplot(x = 'age', y = 'charges', data = df)

plt.title('age vs charges')
plt.show()
```

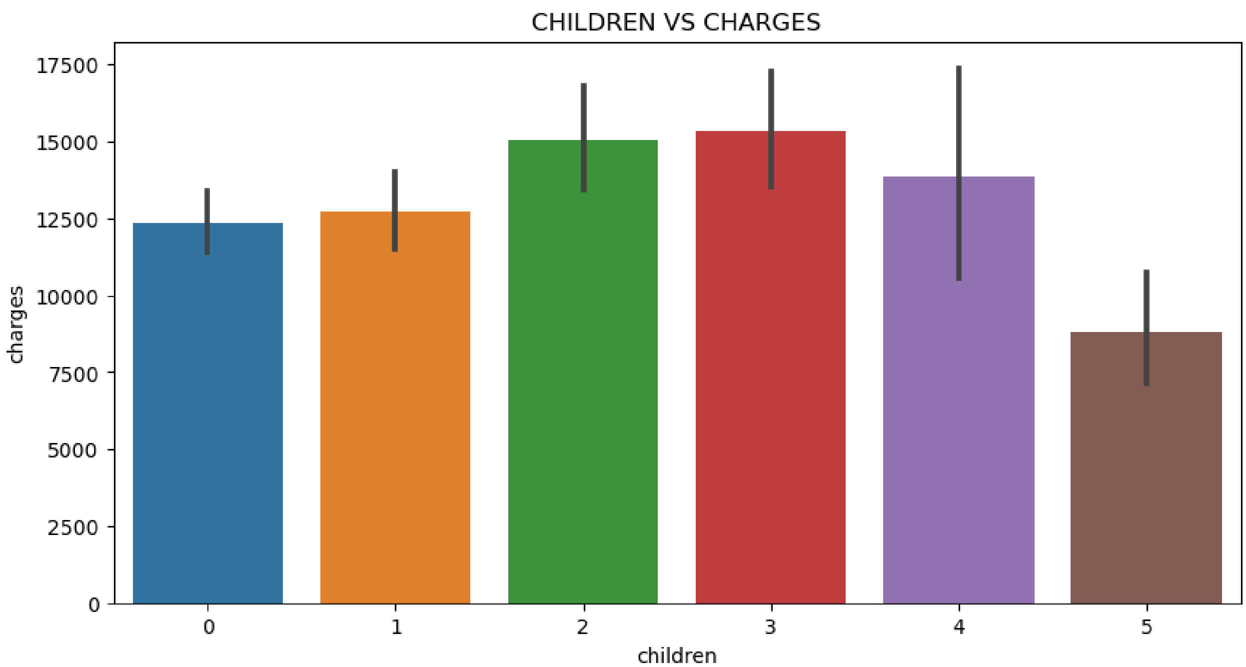


In [33]:

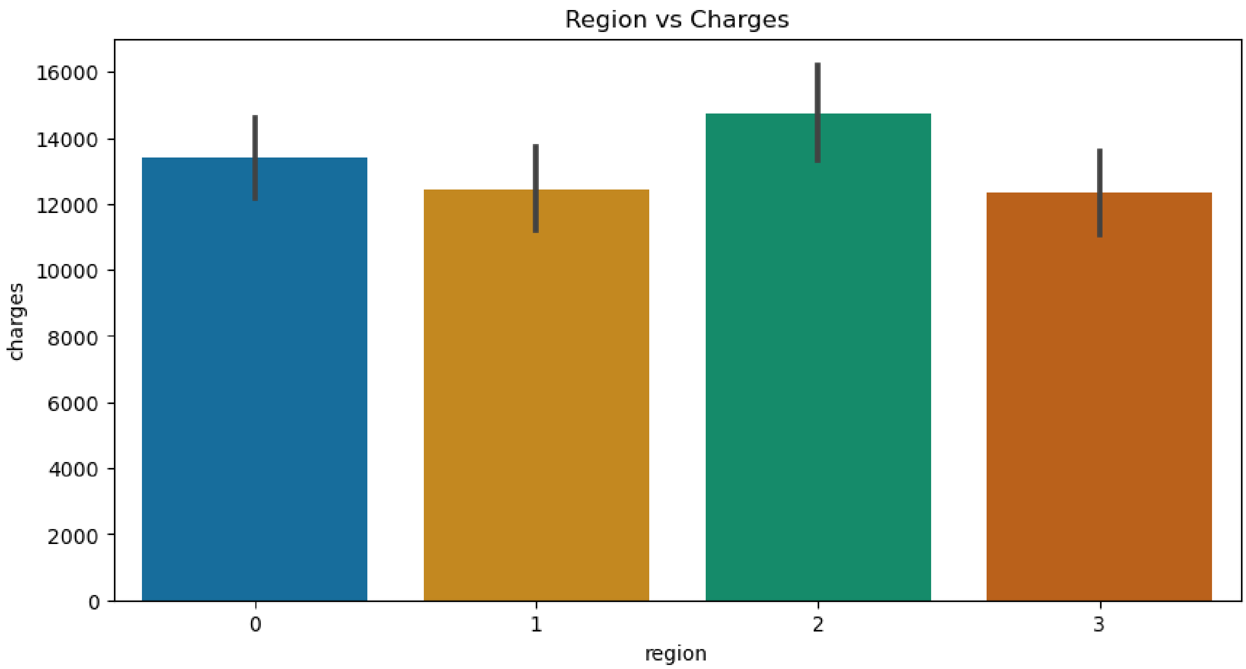
```python
#plot the box plot of sex and charges
# as 1 belongs to men : it shows that men are paying more insurance charges then Women (in genera
#bar plot

plt.figure(figsize = (10, 5))
sns.barplot(x = 'sex', y = 'charges', data = df)

plt.title('sex vs charges')
plt.show()
```



In [34]:
```
# children vs charges
# no. of childrens of a person has a weird dependency on insurance charge. i.e(parents of more cl

plt.figure(figsize = (10, 5))
sns.barplot(x = 'children', y = 'charges', data = df)

plt.title('CHILDREN VS CHARGES')
plt.show()
```

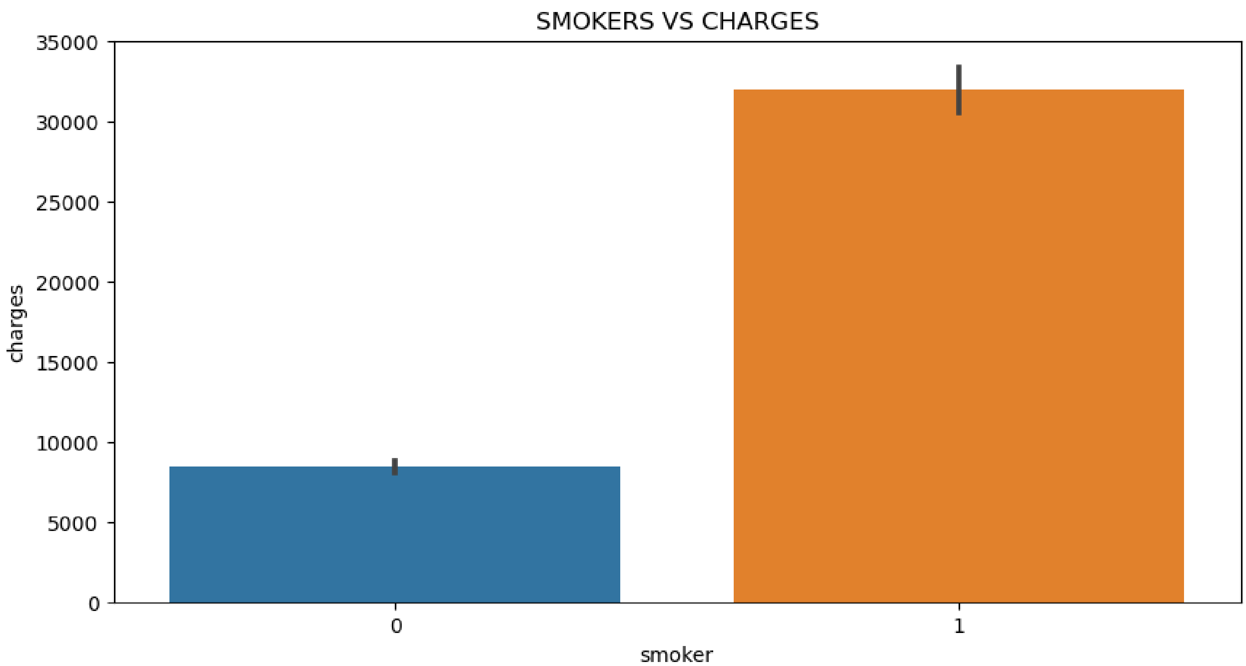


In [35]:
```
# region vs charges BAR GRAPh

plt.figure(figsize = (10, 5))
sns.barplot(x = 'region', y = 'charges', data = df, palette = 'colorblind')

plt.title('Region vs Charges')
plt.show()
```



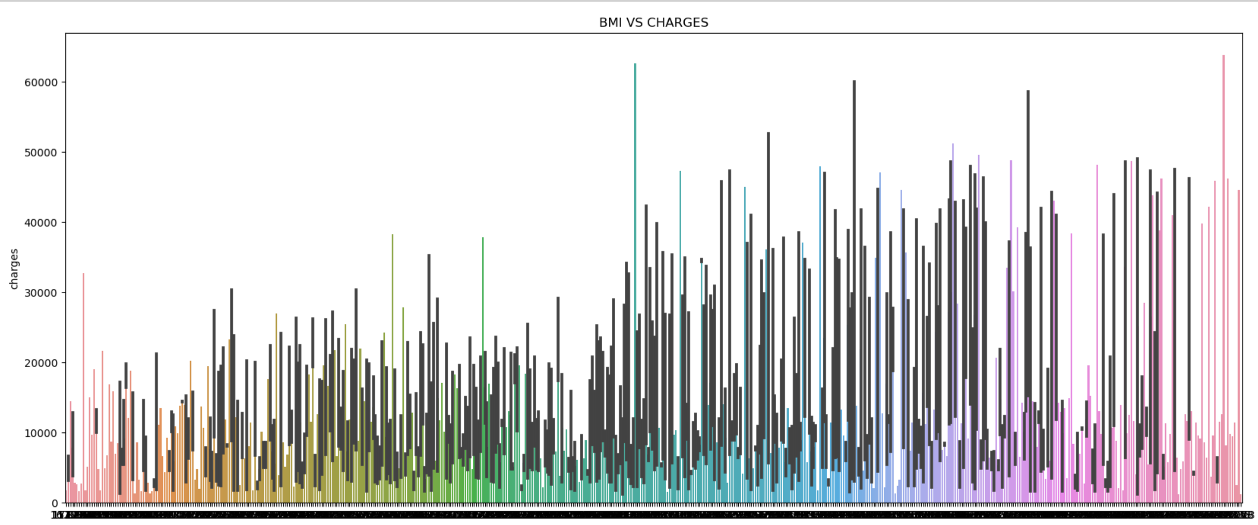
In [36]:
```
# from the graph we can clearly state that region dont play any role in charges it is highly inde
```

In [37]:
```
# smoker vs charges
plt.figure(figsize = (10, 5))
sns.barplot(x = 'smoker', y = 'charges', data = df)

plt.title('SMOKERS VS CHARGES')
plt.show()
```



In [38]:
```
# from the graph where 0 represents non smoker and 1 represent smoker it is clear that smoker ter
```

In [39]:
```
# BMI vs charges
plt.figure(figsize = (20,8))
sns.barplot(x = 'bmi', y = 'charges', data = df)

plt.title('BMI VS CHARGES')
plt.show()
```



In [40]:
```
# From Graph we can canclude that higher the BMI more will be Insurance Premium Charges
```

Data Cleaning

In [41]:
```
# removing un required columns from the insurance data
# As from the above grph we can clearly state that region dont play any role in charges it is hig

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

In [42]:
```
df.shape
```

Out[42]: (1338, 7)

In [43]:
```
#as earlier there was 10704 data point the new one has 9366 data point after removing region
df.size
```

Out[43]: 9366

In [44]:
```
# seperate out features and target value from dataset

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

In [45]:
```
X.shape
```

Out[45]: (1338, 6)

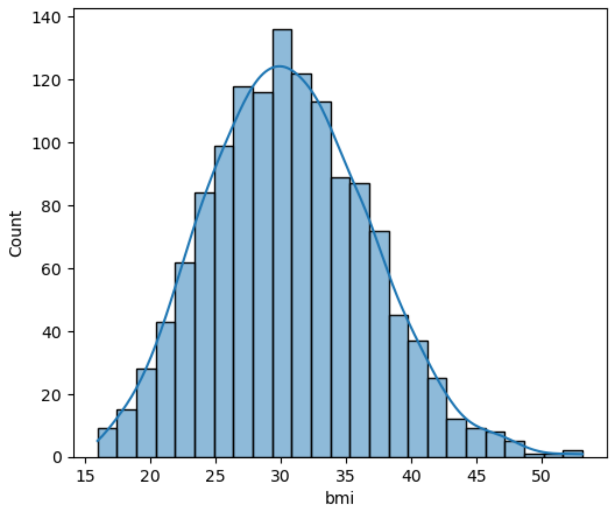
In [46]:
```
y.shape
```

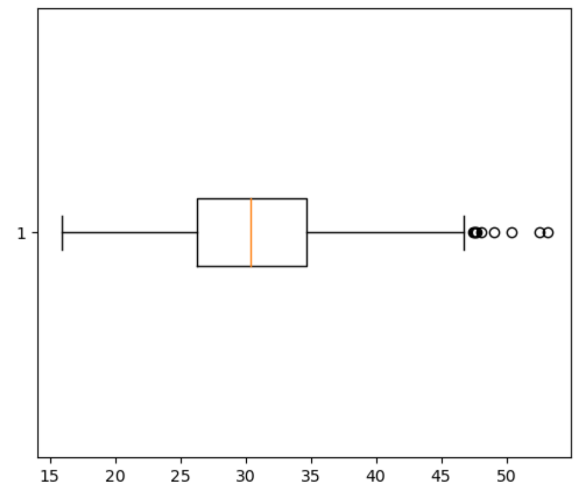
Out[46]: (1338,)

Finding an Outlier

In [86]:
```
#bmi outlier

# For BMI feature
print("BMI: ")
print("Skewness : ",round(df['bmi'].skew(),3))
plt.figure(figsize=(13,5))
plt.subplot(1,2,1)
sns.histplot(data=df['bmi'],kde=True)
plt.subplot(1,2,2)
plt.boxplot(x=df['bmi'],vert=False)
plt.show()
```

```
BMI:
Skewness :  0.284
```





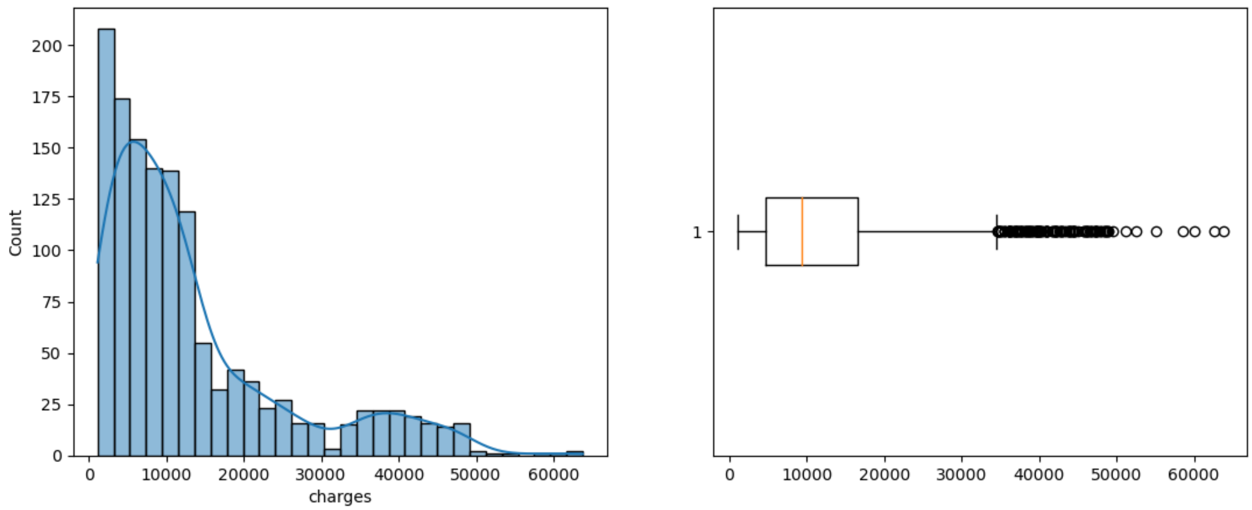
In [88]:
```
# Finding Position of Outlier
#position plot of outlier

print(np.where(df["bmi"]>45))
```

```
(array([ 116,  286,  292,  401,  438,  454,  543,  547,  549,  582,  660,
        847,  860,  930,  941, 1024, 1047, 1088, 1131, 1317], dtype=int64),)
```

bmi can be more or less as per medical condition of person so no need to treat it as per this data

In [50]:
```
#Charges outlier
print("charges: ")
print("Skewness : ",round(df['charges'].skew(),3))
plt.figure(figsize=(13,5))
plt.subplot(1,2,1)
sns.histplot(data=df['charges'],kde=True)
plt.subplot(1,2,2)
plt.boxplot(x=df['charges'],vert=False)
plt.show()
```

```
charges:
Skewness :  1.516
```



Charges can be More or less as per required by insurance company

Spliting Data (Training and Testing Data) and Importing Sklearn Modules

In [52]:
```
#spliting data into training and testing data set

from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.3, random_state =0)  # for op
```

Scaling by Standardization

In [53]:
```
from sklearn.preprocessing import StandardScaler
```

In [54]:
```
ss = StandardScaler()
X=ss.fit_transform(X)
```

In [55]:
```
print("X_train shape : " , X_train.shape)
print("X_test shape : ", X_test.shape)
print("y_train shape : " , y_train.shape)
print("y_test shape : ", y_test.shape)
```

```
X_train shape :  (936, 6)
X_test shape :  (402, 6)
y_train shape :  (936,)
y_test shape :  (402,)
```

Importing and Using Decision Tree (Supervised Learning) Algorithm

In [56]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [76]:
```
# model

dtc = DecisionTreeClassifier(max_depth=5)

#fitting

dtc.fit(X_train,y_train)
```

Out[76]:
```
DecisionTreeClassifier(max_depth=5)
```

In [ ]:
```
# predicting via Decision Tree Algorithm

y_pred=dtc.predict(X_test)

y_pred
```

In [78]:
```
#Calculating RMSE Root MEan Square Error

rmse= np.sqrt(metrics.mean_squared_error(y_test,y_pred))
print("Root Mean Square Error = ",rmse)
```

```
Root Mean Square Error =  0.3419289734514642
```

Checking Out Training and Testing Data Accuracy (Actual vs Predicted)

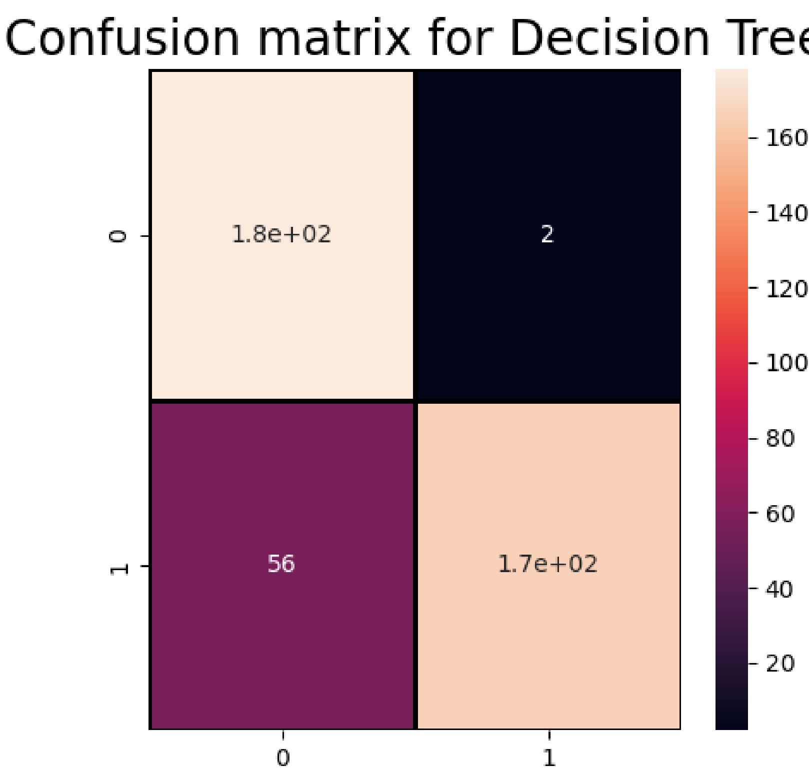
In [79]:
```
# compute accuracy on training set

dtc_train= dtc.score(X_train,y_train)

print("Training Data Accuracy by Decision Tree Algorithm is : " , dtc_train)

# compute accuracy on testing set

dtc_test= dtc.score(X_test,y_test)

print("Testing Data Accuracy by Decision Tree Algorithm is : " , dtc_test)
```

```
Training Data Accuracy by Decision Tree Algorithm is :  0.9123931623931624
Testing Data Accuracy by Decision Tree Algorithm is :  0.8830845771144279
```

In [61]:
```
# calculating the mean squared error
mse = np.mean((y_test - y_pred)**2, axis = None)
print("MSE :", mse)

# Calculating the root mean squared error
rmse = np.sqrt(mse)
print("RMSE :", rmse)
```

```
MSE : 0.14427860696517414
RMSE : 0.37984023873883366
```

In [62]:
```
# lets find out our model performance

from sklearn.metrics import confusion_matrix

#Lets print the confusion metrix for this model

plt.rcParams['figure.figsize']=(5,5)
cm=confusion_matrix(y_test,y_pred)
sns.heatmap(cm,annot=True,linewidths=1,linecolor='black',cbar=True)
plt.title("Confusion matrix for Decision Tree",fontsize=20)
plt.show()

from sklearn.metrics import confusion_matrix
# confusion matrix calculation
tn,fp,fn,tp=confusion_matrix(y_test,y_pred).ravel()
# print the confusion matrix
print("Confusion Matrix:")
print("True Negative = ",tn,"False Positive =",fp)
print("False Negative = ",fn,"True Positive =",tp)
```




```
Confusion Matrix:
True Negative =  178 False Positive = 2
False Negative =  56 True Positive = 166
```

In [63]:
```
df.head()
```

Out[63]:

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

In [81]:
```
# what is the process the model uses to generate its predictions, Lets Check?
Lets Check[32,0,44,0,1,7000] means Age =32 ; sex = Female ; Bmi = 44; Children = 0; Smoker= Yes;
new_check = dtc.predict((np.array([[32,0,44,0,1,7000]])))
print("Provide Wether insurance claim for given condition (should claim be given or not) : ",new_
```

```
Provide Wether insurance claim for given condition (should claim be given or not) :  [1]
```

In [82]:
```
# here 1 means insurance can be given where as 0 mean not to give
```

In [66]:
```
# what is the process the model uses to generate its predictions, Lets Check?
new_check = dtc.predict((np.array([[25,1,66,3,0,1000]])))
print("Provide Wether insurance claim for given condition (should claim be given or not) : ",new_
```

```
Provide Wether insurance claim for given condition (should claim be given or not) :  [0]
```

Deciding a Model

Usually We Select Only Those Model Whisch Has Highest Accuracy Among All those Prediction Results

We applied many models to the data, but decision tree gave the best accuracy among all of

Decision Tree Classifier - It gives 88% on testing and 91% on training data

Naive Bayes - It gives 75-76% Accuracy

Logistic Regression - It gives 82% accuracy on testing and 88% on training data

Support Vector Classification - It gives 87% accuracy

In [69]:
```
# Lets print the classifiction report also
from sklearn.metrics import classification_report
cr =classification_report(y_test,y_pred)
print(cr)
```

```
              precision    recall  f1-score   support

           0       0.76      0.99      0.86       180
           1       0.99      0.75      0.85       222

    accuracy                           0.86       402
   macro avg       0.87      0.87      0.86       402
weighted avg       0.89      0.86      0.86       402
```

High precision indicates that the model is making less but some false positive predicions also

While high recall signifies that the model is making lesser false negative predictions

We can conclude our model is working eficiently, recall and f1-score

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In [ ]:
```

```