Context

Machine Learning with R by Brett Lantz is a book that provides an introduction to machine learning using R. As far as I can tell, Packt Publishing does not make its datasets available online unless you buy the book and create a user account which can be a problem if you are checking the book out from the library or borrowing the book from a friend. All of these datasets are in the public domain but simply needed some cleaning up and recoding to match the format in the book.

Content Columns

age: age of primary beneficiary

sex: insurance contractor gender, female, male

bmi: Body mass index, providing an understanding of body, weights that are relatively high or low relative to height, objective index of body weight (kg / m ^ 2) using the ratio of height to weight, ideally 18.5 to 24.9

children: Number of children covered by health insurance / Number of dependents

smoker: Smoking

region: the beneficiary's residential area in the US, northeast, southeast, southwest, northwest.

charges: Individual medical costs billed by health insurance

Acknowledgements The dataset is available on GitHub here.

Inspiration Can you accurately predict insurance costs?

In [1]:
```
#We will try to analyse and visualuze the dataset and try to predict the insurance costs of different i
ndividuals
#using regression models and try to understand different variable selection techniques like
#backward elimination and forward selection
```

Importing Libraries

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as ps
%matplotlib inline
```

Getting Dataset

In [3]:
```
data_file=r'insurance.csv'
```

In [4]:
```
dataset=pd.read_csv(data_file)
```

Getting insights from Dataset

In [5]:
```
dataset
```

Out[5]:

	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 [6]:
```
dataset.head()
```

Out[6]:

	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 [7]:
```
dataset.tail()
```

Out[7]:

	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 [8]:
```
dataset.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 [9]:
```
dataset.describe(include='all')
```

Out[9]:

	age	sex	bmi	children	smoker	region	charges
count	1338.000000	1338	1338.000000	1338.000000	1338	1338	1338.000000
unique	NaN	2	NaN	NaN	2	4	NaN
top	NaN	male	NaN	NaN	no	southeast	NaN
freq	NaN	676	NaN	NaN	1064	364	NaN
mean	39.207025	NaN	30.663397	1.094918	NaN	NaN	13270.422265
std	14.049960	NaN	6.098187	1.205493	NaN	NaN	12110.011237
min	18.000000	NaN	15.960000	0.000000	NaN	NaN	1121.873900
25%	27.000000	NaN	26.296250	0.000000	NaN	NaN	4740.287150
50%	39.000000	NaN	30.400000	1.000000	NaN	NaN	9382.033000
75%	51.000000	NaN	34.693750	2.000000	NaN	NaN	16639.912515
max	64.000000	NaN	53.130000	5.000000	NaN	NaN	63770.428010

In [10]:
```
dataset.isnull().sum()
```

Out[10]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

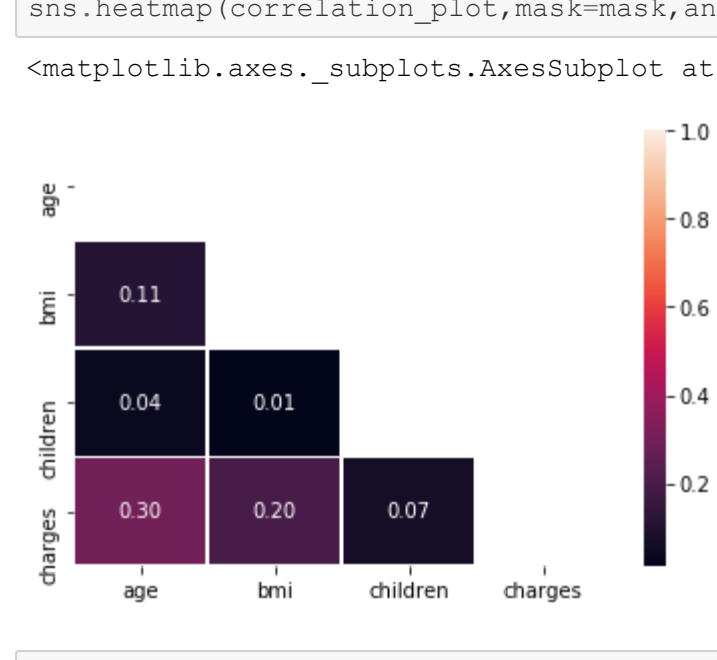
In [11]:
```
dataset.columns
```

Out[11]:
```
Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'], dtype='object')
```

Visualization

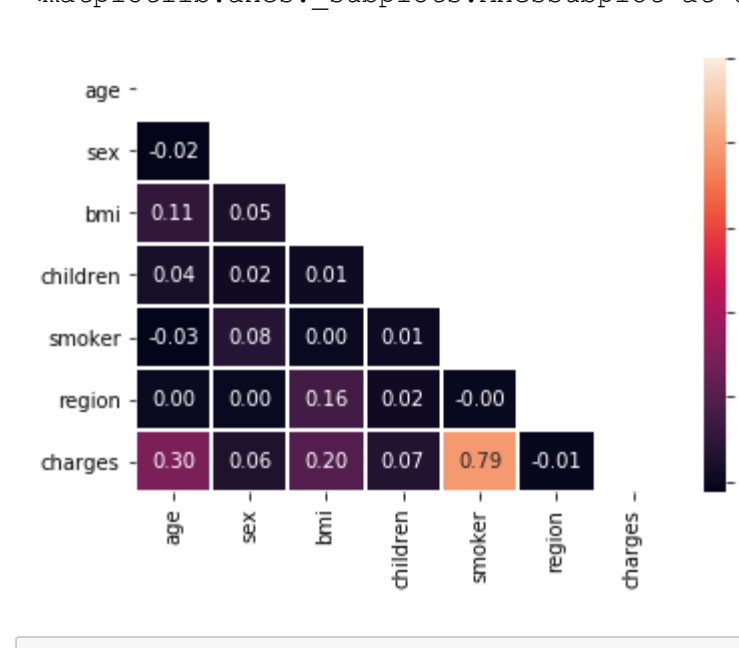
In [12]:
```
correlation_plot=dataset.corr()
mask = np.triu(np.ones_like(correlation_plot, dtype=np.bool))
sns.heatmap(correlation_plot,mask=mask,annot=True,fmt='0.2f',linewidth=0.8)
```

Out[12]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd8f1aa550>`



In [85]:
```
correlation_plot=dataset.corr()
mask = np.triu(np.ones_like(correlation_plot, dtype=np.bool))
sns.heatmap(correlation_plot,mask=mask,annot=True,fmt='0.2f',linewidth=0.8)
```

Out[85]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd967760b8>`



In [13]:
```
correlation_plot['charges'].sort_values()
```

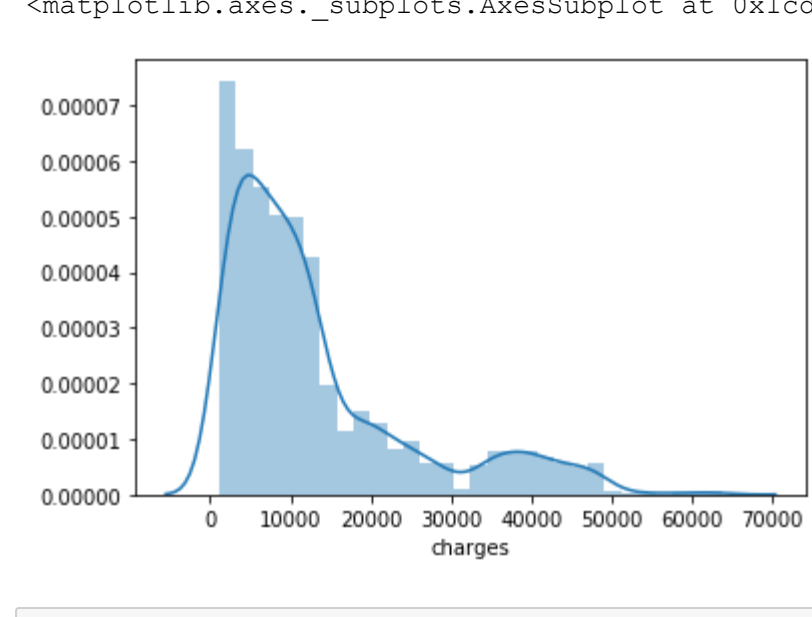
Out[13]:
```
children    0.067998
bmi         0.198341
age         0.299008
charges     1.000000
Name: charges, dtype: float64
```

In [86]:
```
correlation_plot['charges'].sort_values()
```

Out[86]:
```
region     -0.006208
sex         0.057292
children    0.067998
bmi         0.198341
age         0.299008
smoker      0.787251
charges     1.000000
Name: charges, dtype: float64
```

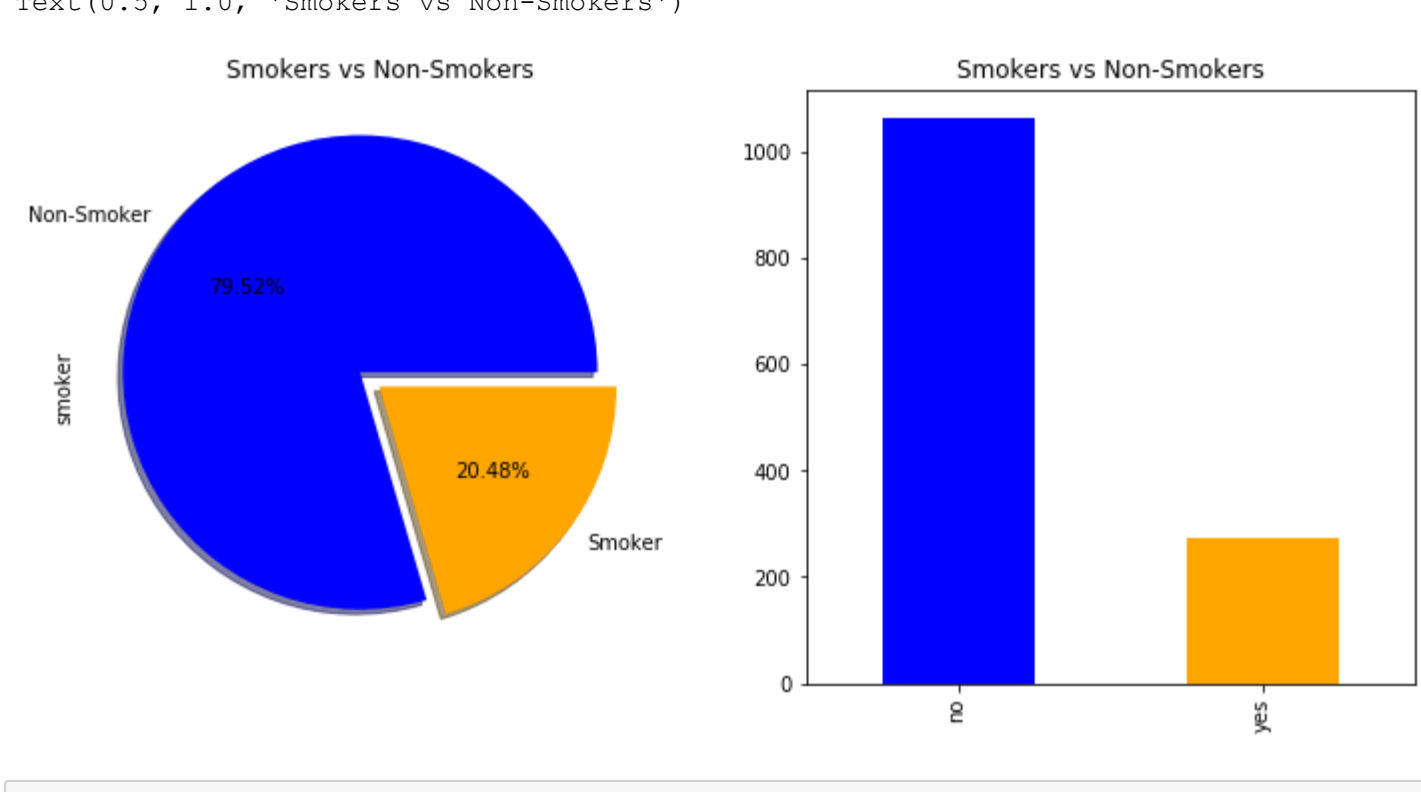
In [14]:
```
sns.distplot(dataset['charges'])
```

Out[14]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd8f953668>`



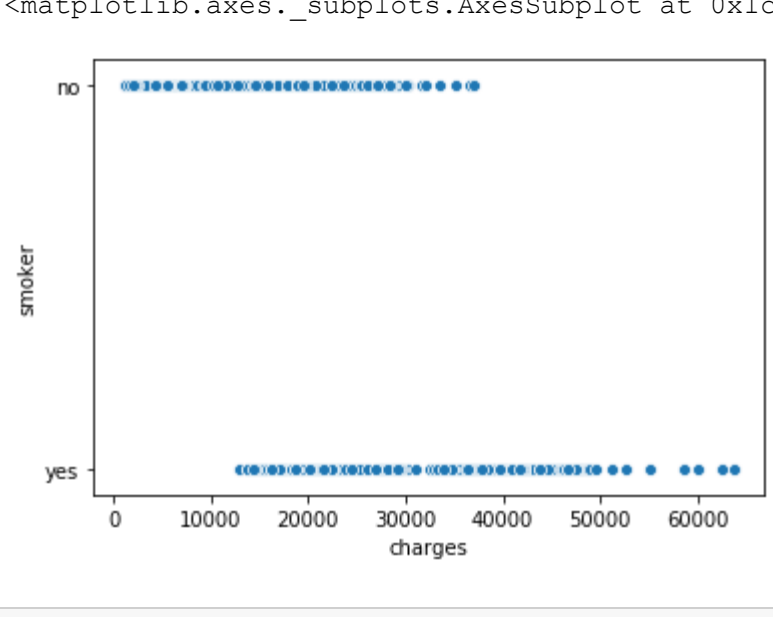
In [15]:
```
plt.figure(figsize=(12,12))
plt.subplot(2,2,1)
explode=(0.1,0)
color=['blue','orange']
label=['Non-Smoker','Smoker']
dataset['smoker'].value_counts().plot.pie(autopct='%.2f%%',shadow=True,explode=explode,colors=color,lab
els=label)
plt.title('Smokers vs Non-Smokers')
plt.subplot(2,2,2)
color=['blue','orange']
dataset['smoker'].value_counts().plot.bar(color=color)
plt.title('Smokers vs Non-Smokers')
```

Out[15]: `Text(0.5, 1.0, 'Smokers vs Non-Smokers')`



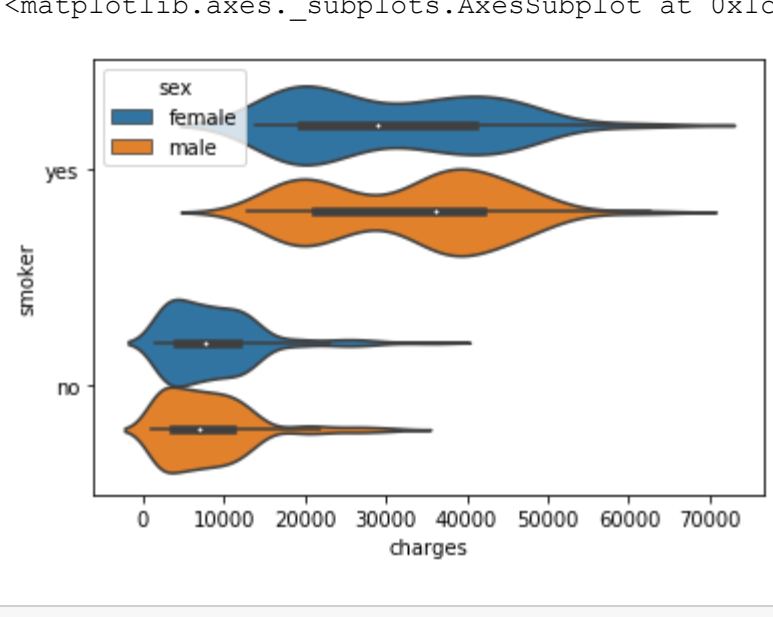
In [16]:
```
sns.scatterplot(dataset['charges'],dataset['smoker'])
```

Out[16]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd8fb20550>`



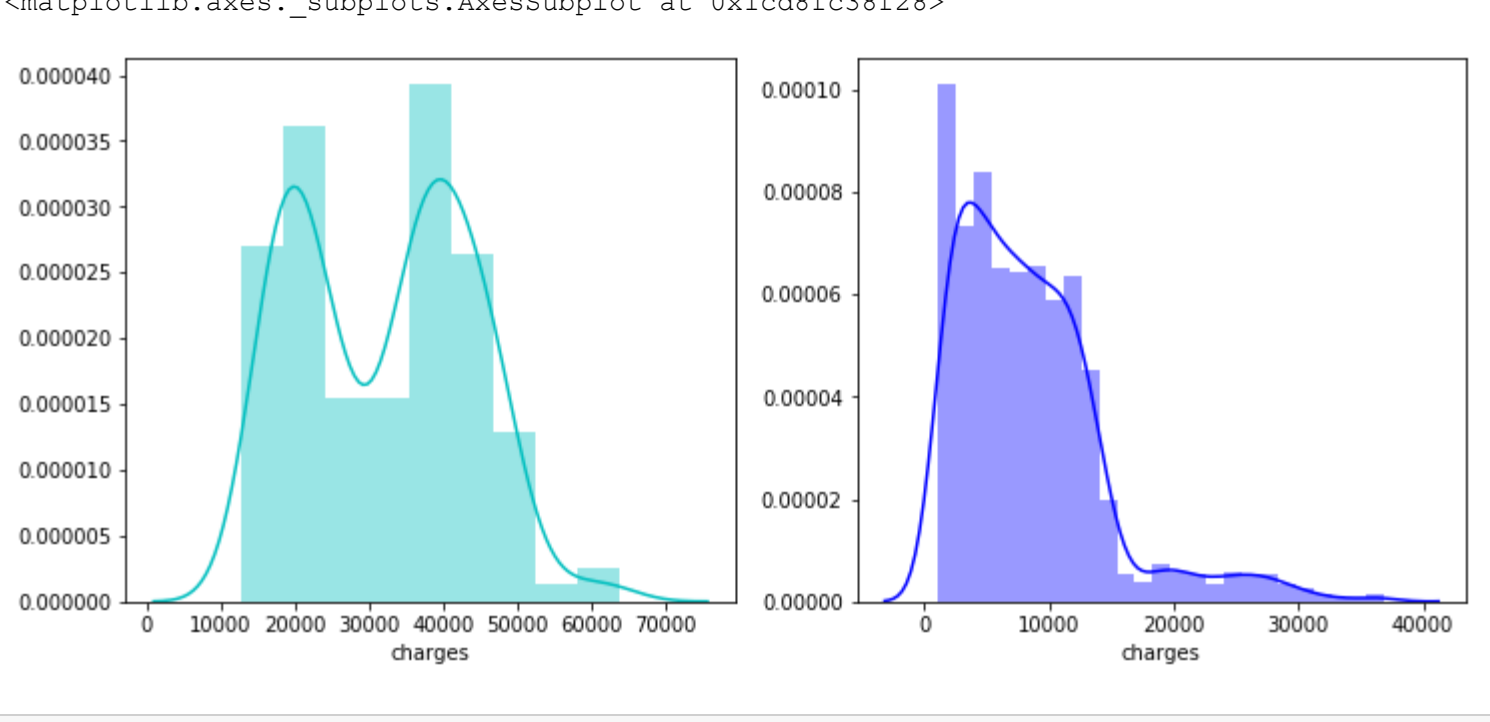
In [17]:
```
sns.violinplot(dataset['charges'],dataset['smoker'],hue=dataset['sex'])
```

Out[17]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd8fb4ad30>`



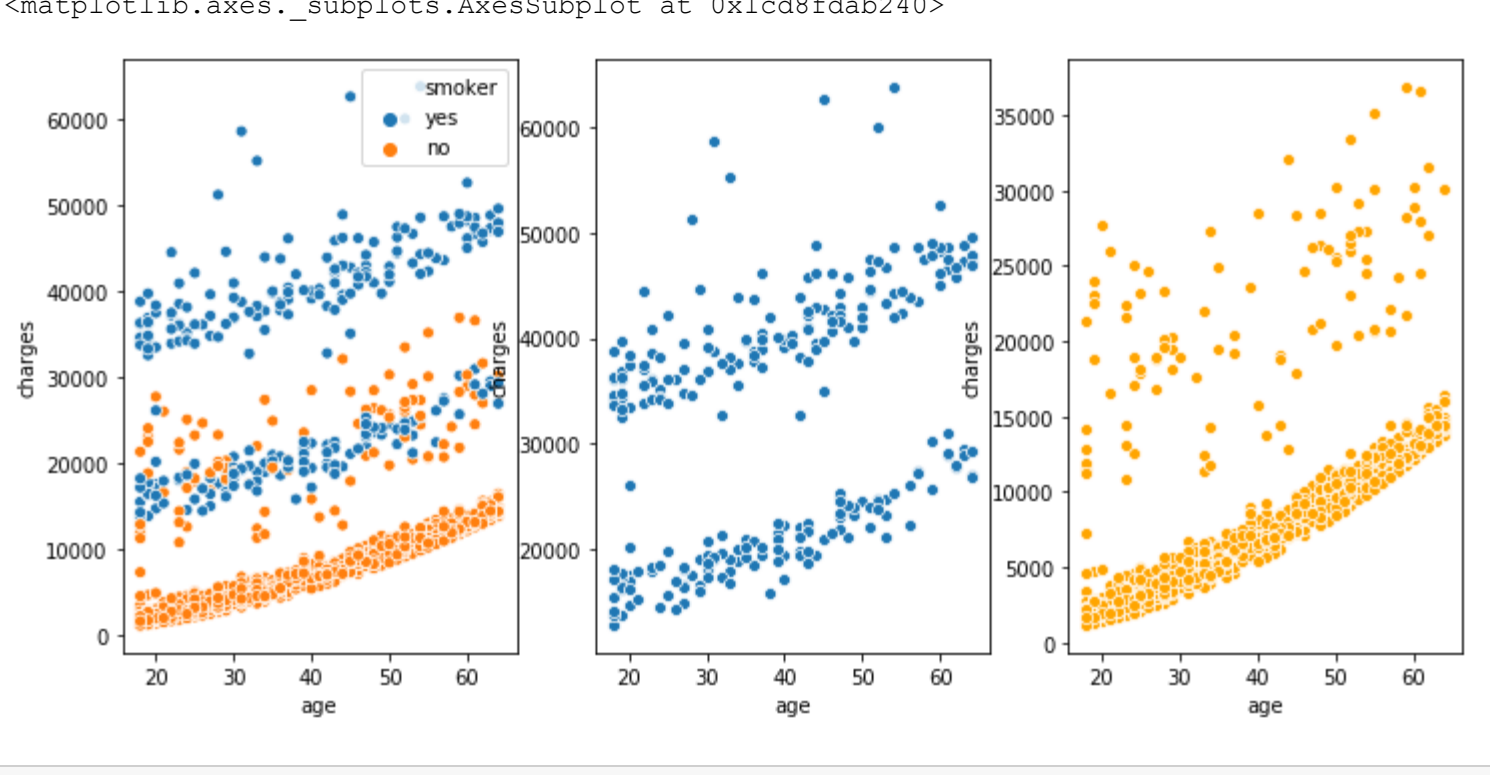
In [18]:
```
f=plt.figure(figsize=(12,5))
ax=f.add_subplot(121)
sns.distplot(dataset[(dataset.smoker=='yes')]['charges'],color='c',ax=ax)
ax=f.add_subplot(122)
sns.distplot(dataset[(dataset.smoker=='no')]['charges'],color='b',ax=ax)
```

Out[18]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd8fc38f28>`



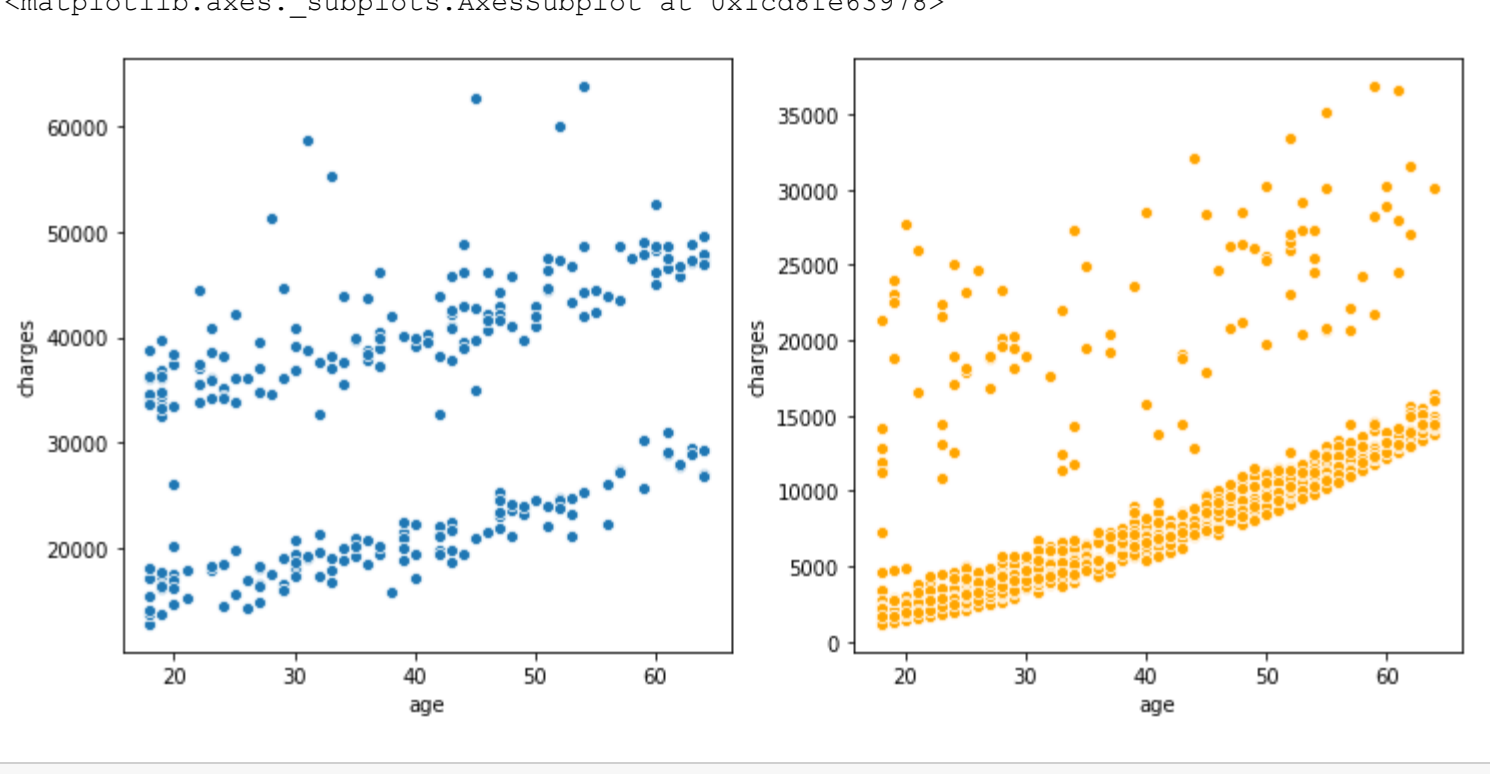
In [19]:
```
plt.figure(figsize=(12,12))
plt.subplot(2,3,1)
sns.scatterplot(dataset['age'],dataset['charges'],hue=dataset['smoker'])
plt.subplot(2,3,2)
smoker_dataset=dataset[dataset['smoker']=='yes']
non_smoker_dataset=dataset[dataset['smoker']=='no']
sns.scatterplot(smoker_dataset['age'],smoker_dataset['charges'])
plt.subplot(2,3,3)
sns.scatterplot(non_smoker_dataset['age'],non_smoker_dataset['charges'],color='orange')
```

Out[19]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd8fdab240>`



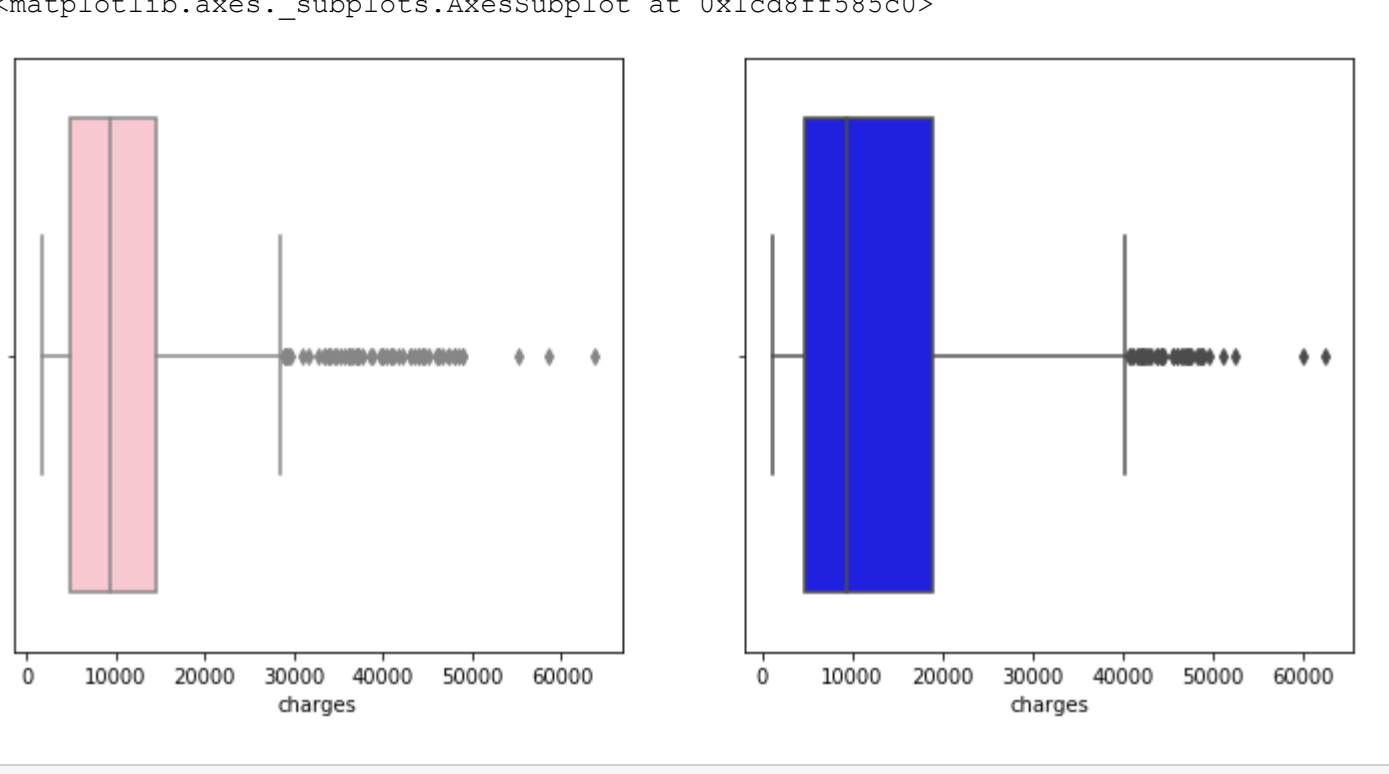
In [20]:
```
plt.figure(figsize=(12,12))
plt.subplot(2,2,1)
smoker_dataset=dataset[dataset['smoker']=='yes']
non_smoker_dataset=dataset[dataset['smoker']=='no']
sns.scatterplot(smoker_dataset['age'],smoker_dataset['charges'])
plt.subplot(2,2,2)
sns.scatterplot(non_smoker_dataset['age'],non_smoker_dataset['charges'],color='orange')
```

Out[20]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd8fe63978>`



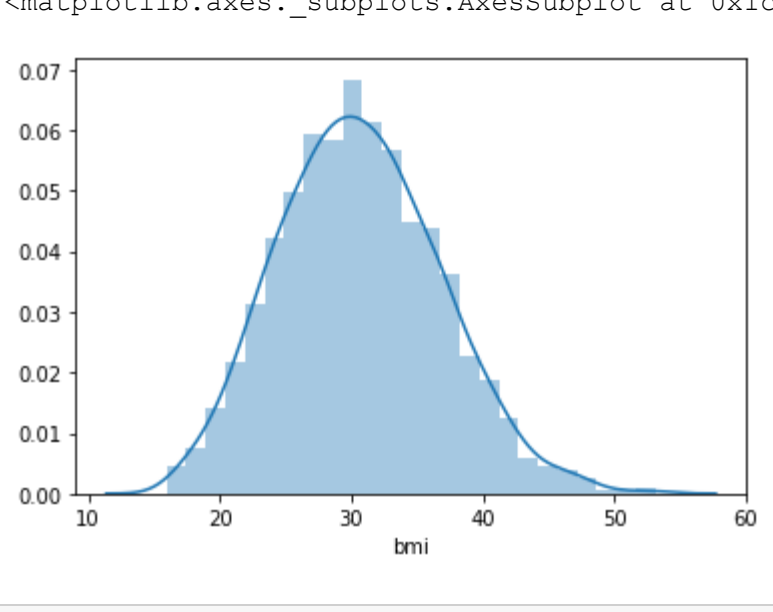
In [21]:
```
female_dataset=dataset[dataset['sex']=='female']
male_dataset=dataset[dataset['sex']=='male']
plt.figure(figsize=(12,12))
plt.subplot(2,2,1)
sns.boxplot(female_dataset['charges'],color='pink')
plt.subplot(2,2,2)
sns.boxplot(male_dataset['charges'],color='blue')
```

Out[21]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd8ff585c0>`



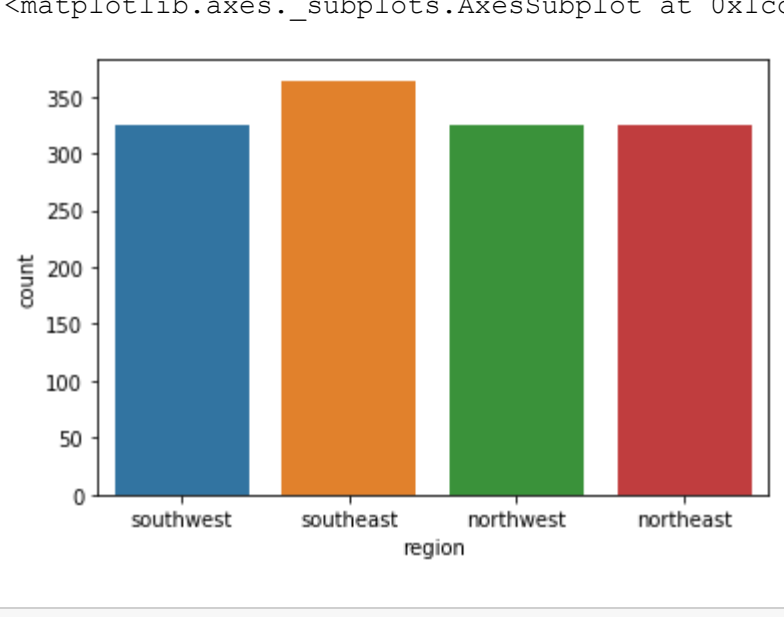
In [22]:
```
sns.distplot(dataset['bmi'])
```

Out[22]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd8ffca2e8>`



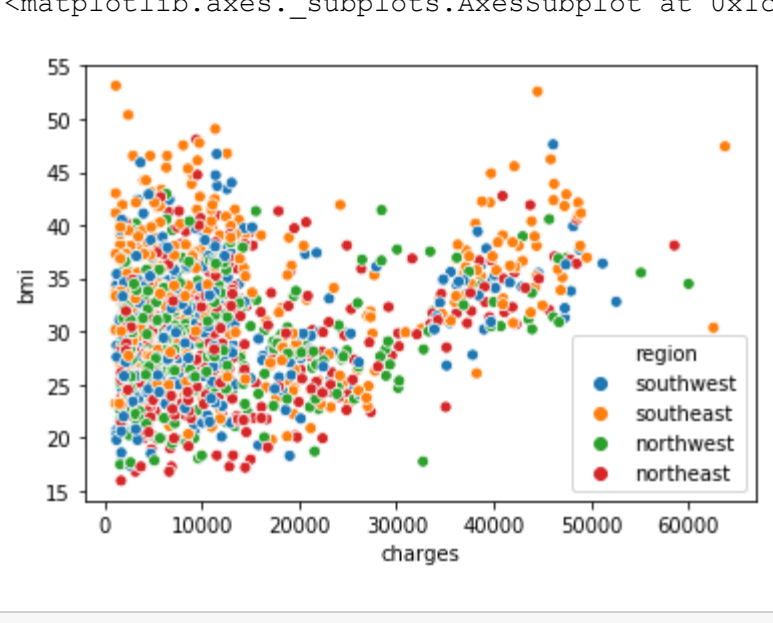
In [23]:
```
sns.countplot(dataset['region'])
```

Out[23]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd90097ef0>`



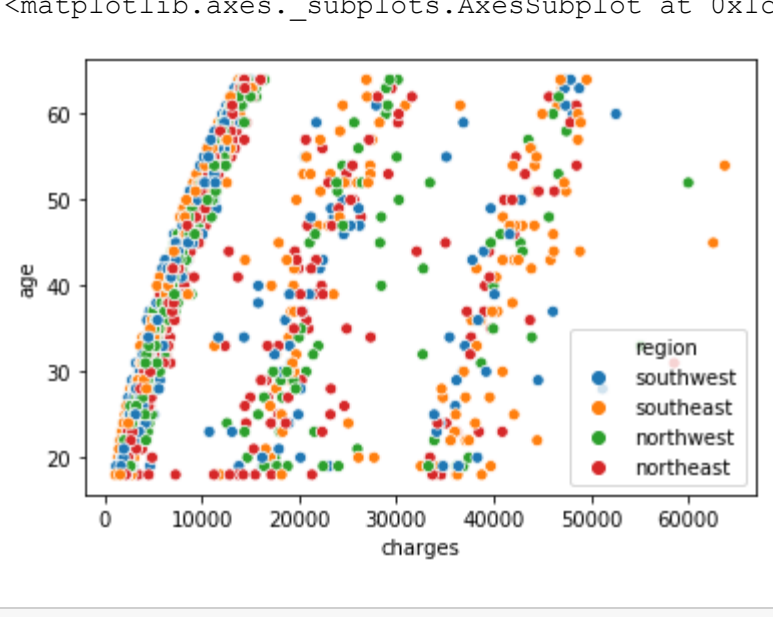
In [24]:
```
sns.scatterplot(dataset['charges'],dataset['bmi'],hue=dataset['region'])
```

Out[24]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd900f9320>`



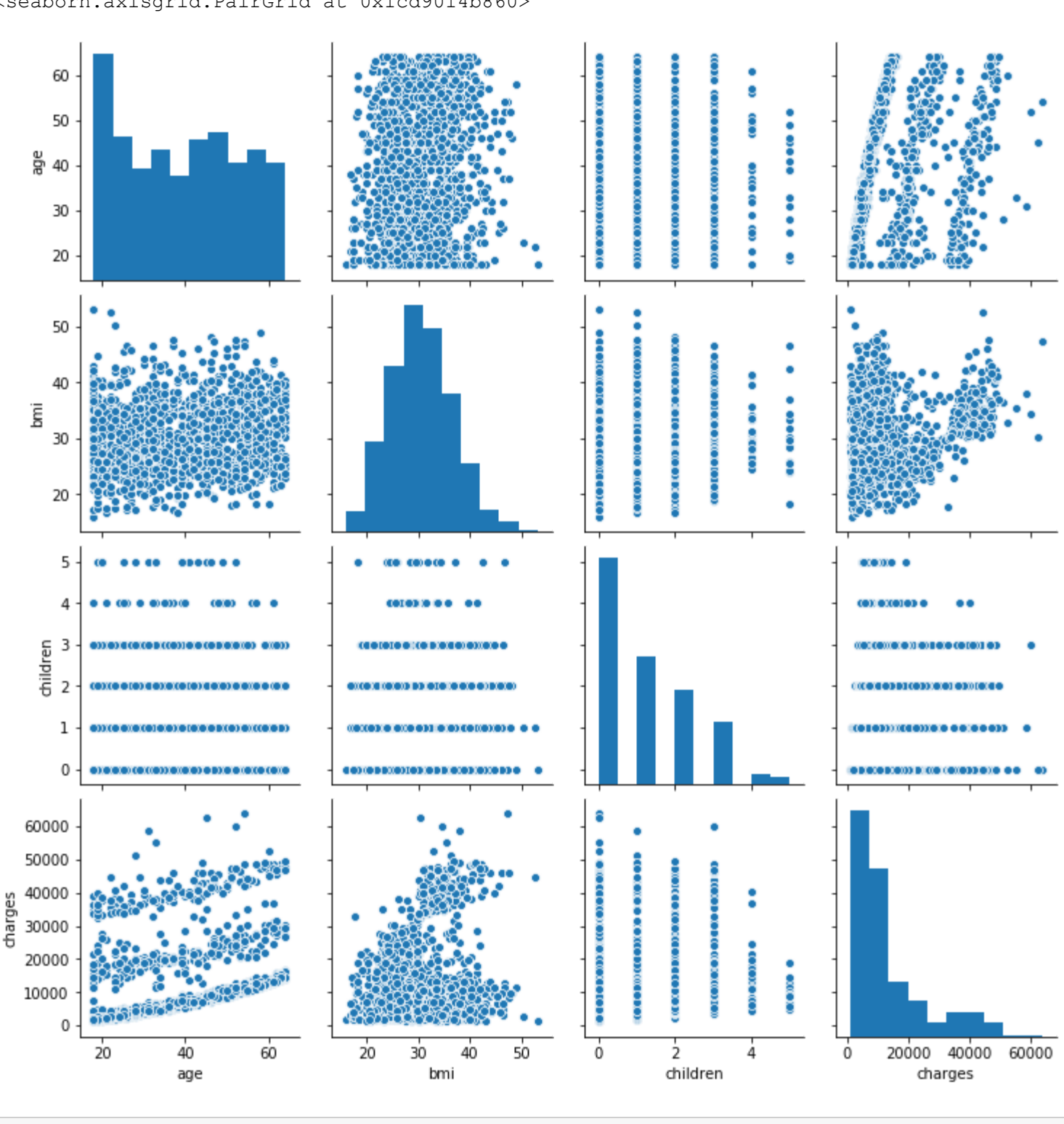
In [25]:
```
sns.scatterplot(dataset['charges'],dataset['age'],hue=dataset['region'])
```

Out[25]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd900f9f28>`



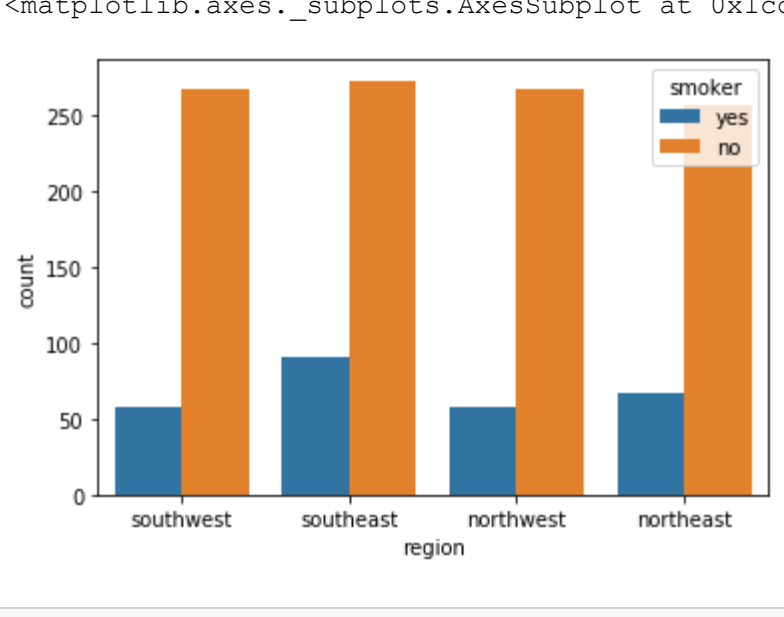
In [26]:
```
sns.pairplot(dataset)
```

Out[26]: `<seaborn.axisgrid.PairGrid at 0x1cd9014b860>`



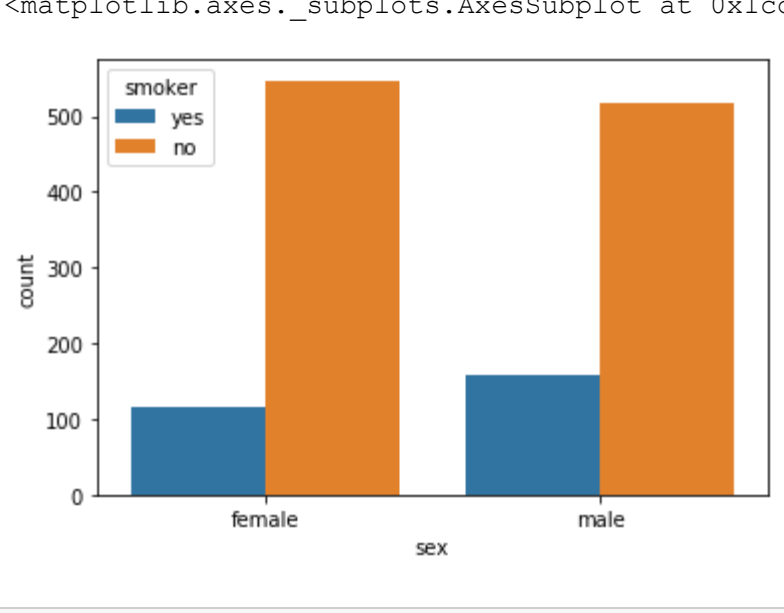
In [27]:
```
#Region wise Smoker
sns.countplot(dataset['region'],hue=dataset['smoker'])
```

Out[27]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd91a75dd8>`



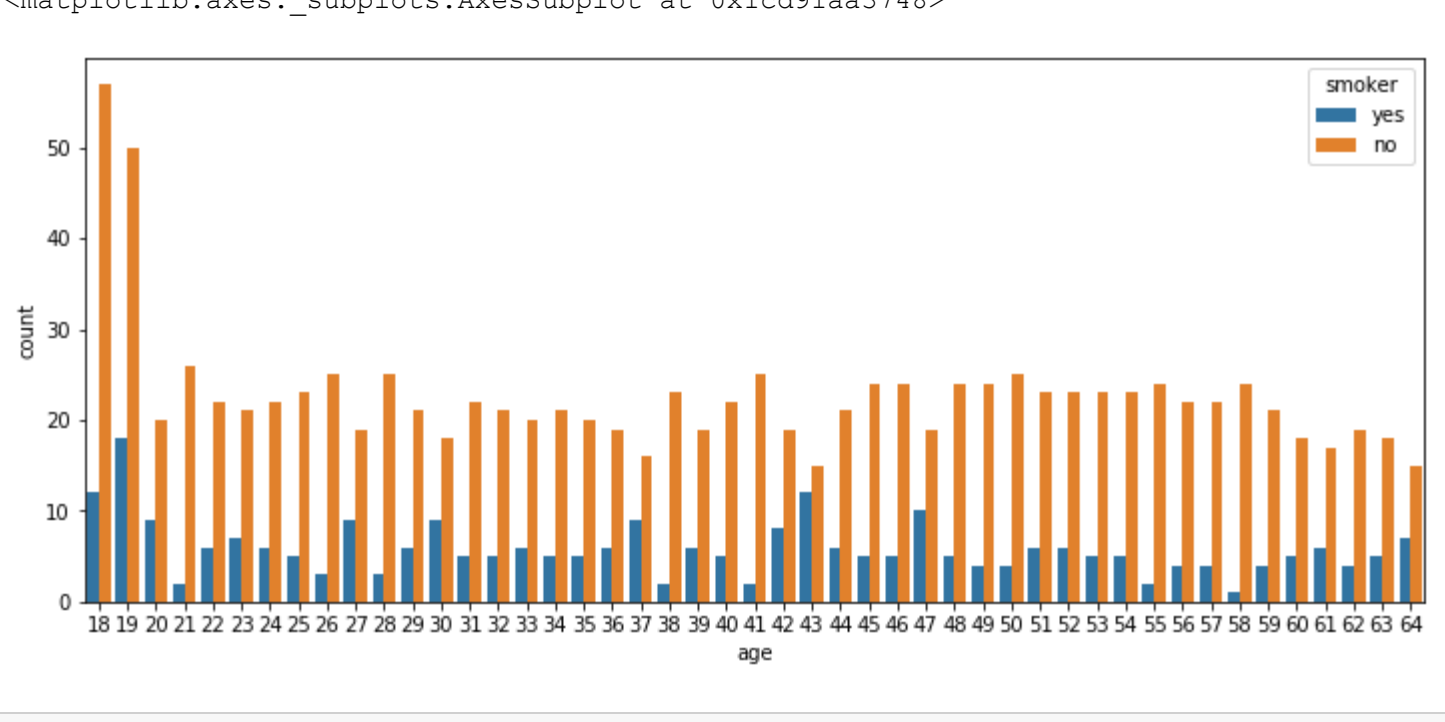
In [28]:
```
#Sex wise Smoker
sns.countplot(dataset['sex'],hue=dataset['smoker'])
```

Out[28]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd91d48320>`



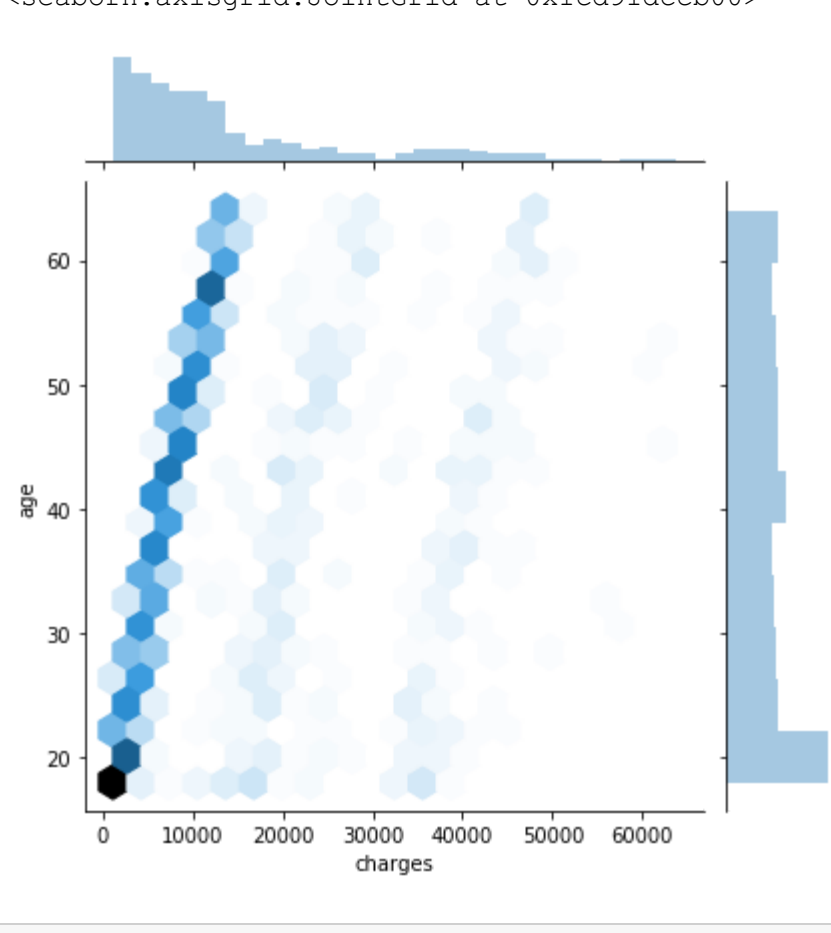
In [29]:
```
#Age wise Smoker
plt.figure(figsize=(12,5))
sns.countplot(dataset['age'],hue=dataset['smoker'])
```

Out[29]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd91aa3748>`



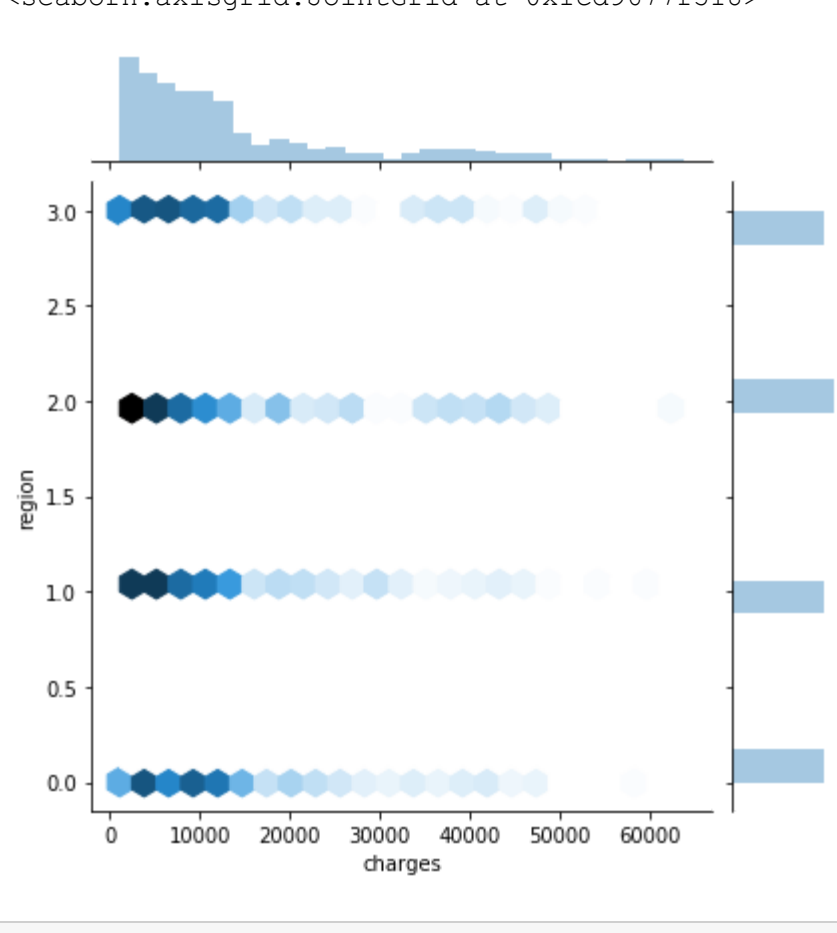
In [30]:
```
#Age, Charge, Smoker
sns.jointplot(data=dataset,x='charges',y='age',kind='hex')
```

Out[30]: `<seaborn.axisgrid.JointGrid at 0x1cd91dccb00>`



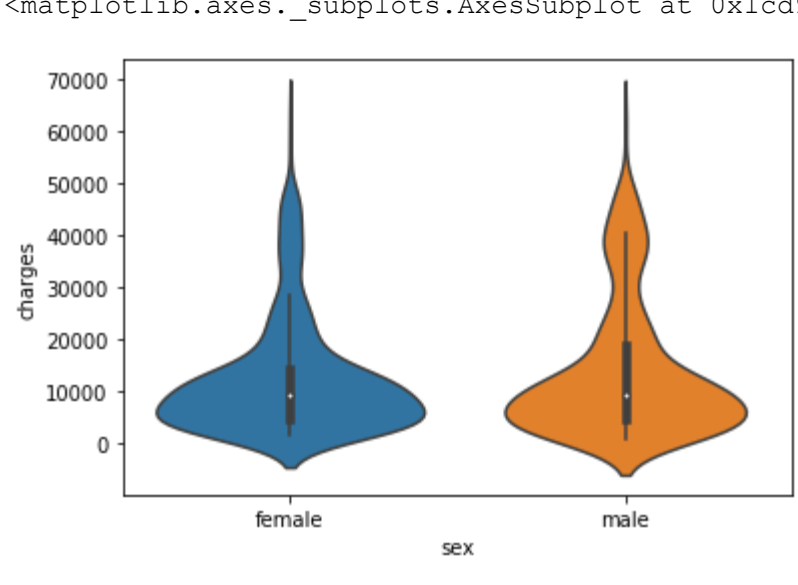
In [87]:
```
#Region, Charge, Smoker
sns.jointplot(data=dataset,x='charges',y='region',kind='hex')
```

Out[87]: `<seaborn.axisgrid.JointGrid at 0x1cd9677f518>`



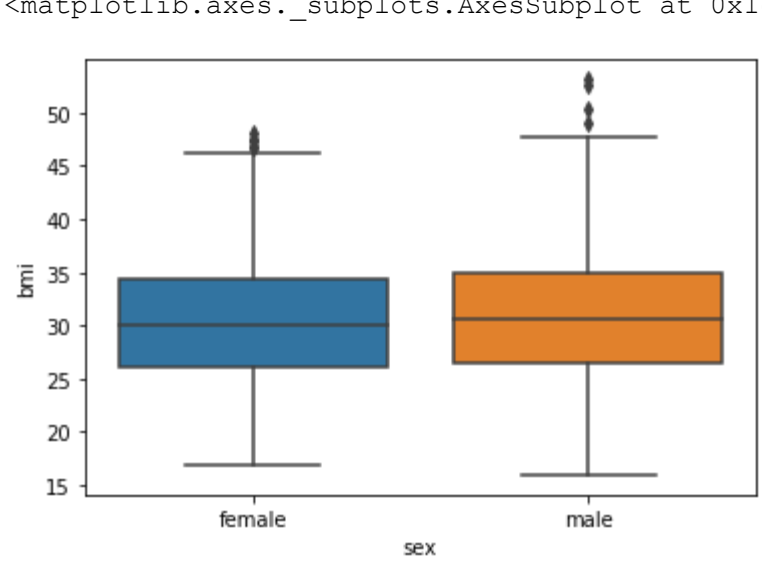
In [31]:
```
#Sex, Charge
sns.violinplot(dataset['sex'],dataset['charges'])
```

Out[31]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd920b8588>`



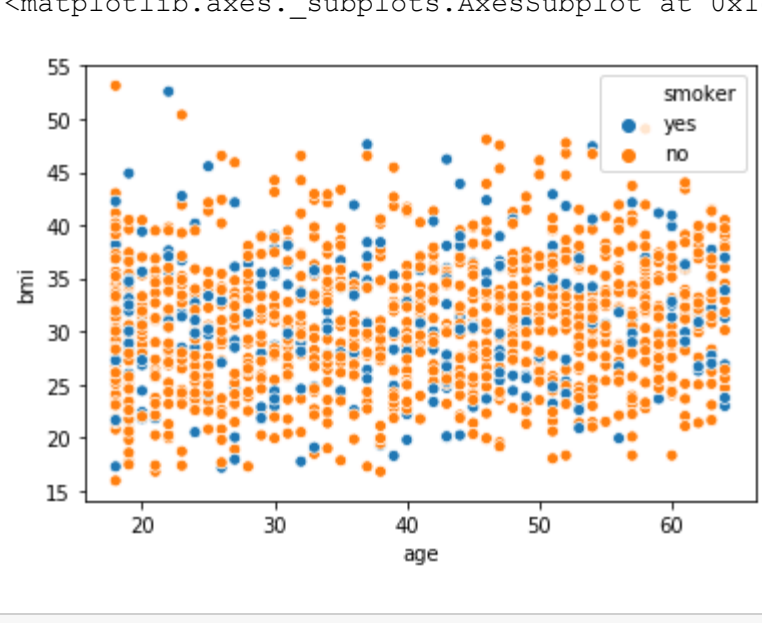
In [32]:
```
#Sex, BMI
sns.boxplot(dataset['sex'],dataset['bmi'])
```

Out[32]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd9215cdd8>`



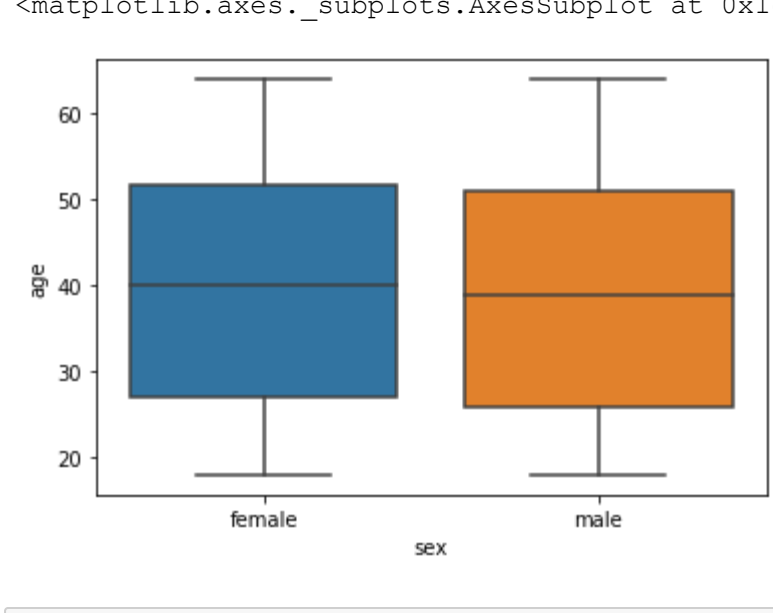
In [33]:
```
#Age, BMI
sns.scatterplot(dataset['age'],dataset['bmi'],hue=dataset['smoker'])
```

Out[33]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd920c70f0>`



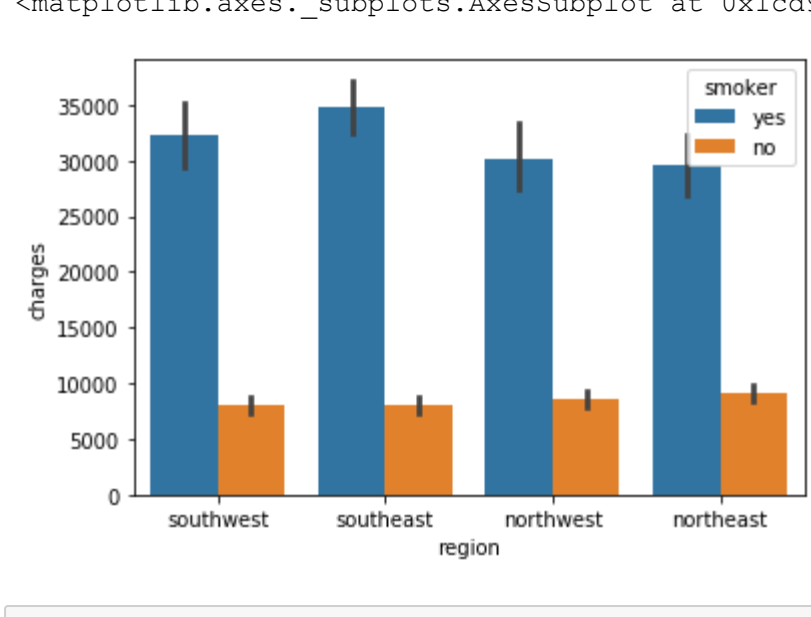
In [34]:
```
#Age, Sex
sns.boxplot(dataset['sex'],dataset['age'])
```

Out[34]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd922509e8>`



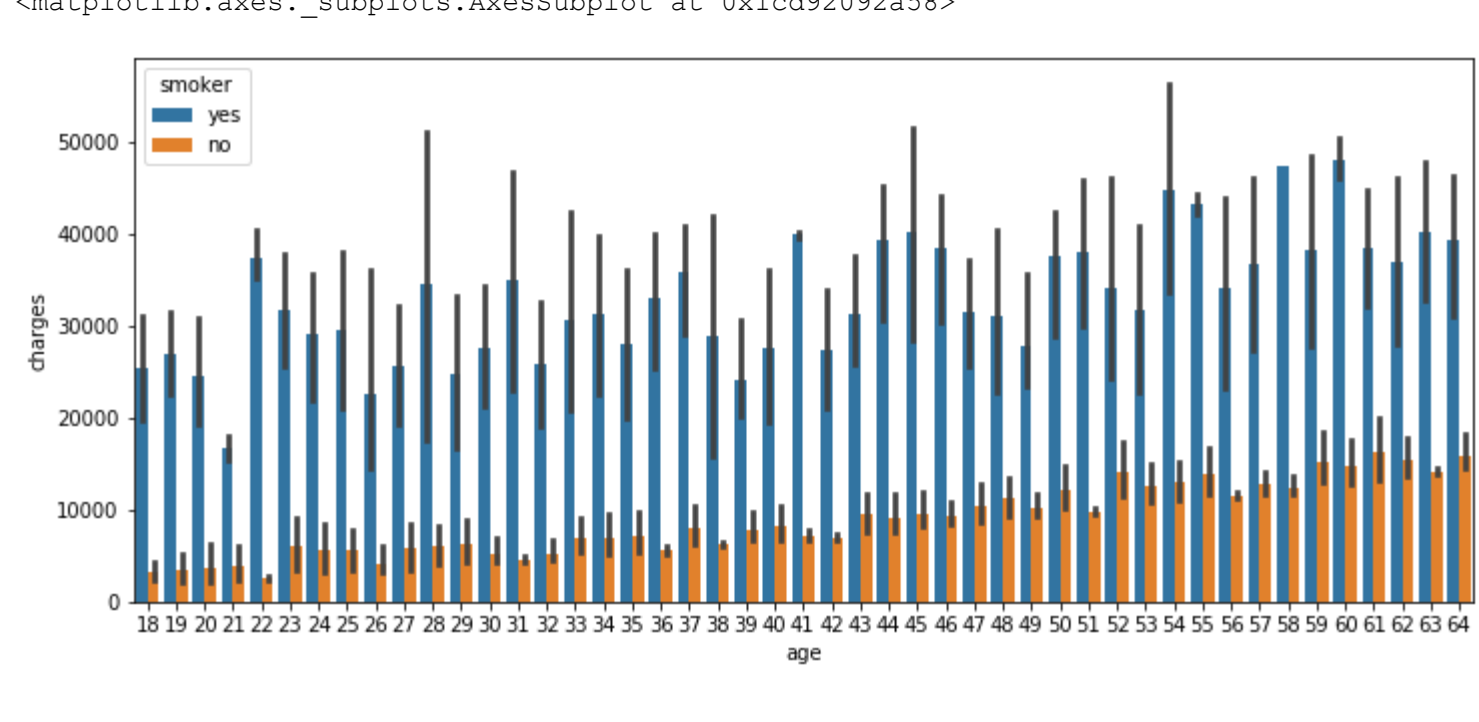
In [35]:
```
sns.barplot(dataset['region'],dataset['charges'],hue=dataset['smoker'])
```

Out[35]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd922b02e8>`

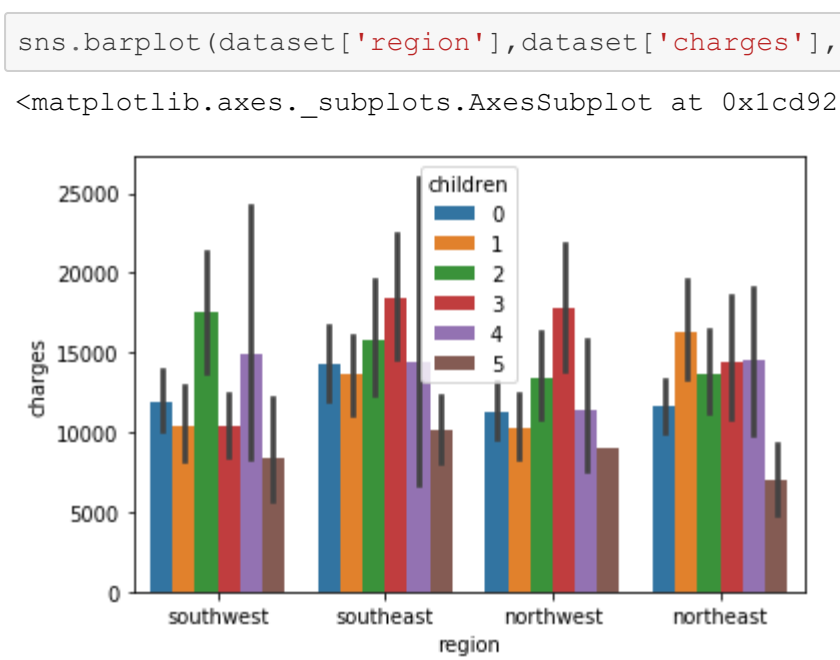


In [36]:
```
plt.figure(figsize=(12,5))
sns.barplot(dataset['age'],dataset['charges'],hue=dataset['smoker'])
```

Out[36]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd92092a58>`



In [37]:
```
sns.barplot(dataset['region'],dataset['charges'],hue=dataset['children'])
```
Out[37]: `<matplotlib.axes._subplots.AxesSubplot at 0x1cd925dd7f0>`



In [ ]:

Analysis

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Preparing

In [38]:
```
#Label Encoding-Converting categorical data to numerical data
#https://towardsdatascience.com/categorical-encoding-using-label-encoding-and-one-hot-encoder-911ef77fb
5bd
```

In [39]:
```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
le.fit(dataset.sex)
dataset.sex=le.transform(dataset.sex)
le.fit(dataset.smoker)
dataset.smoker=le.transform(dataset.smoker)
le.fit(dataset.region)
dataset.region=le.transform(dataset.region)
```

In [40]:
```
dataset.head()
```
Out[40]:

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

Modelling

In [41]:
```
#whole model(all 6 independent variables) used to predict the independent variable
```

In [42]:
```
#backward elimination
```

In [43]:
```
#forward selection
```

In [44]:
```
#splitting data into training and testing dataset
X=dataset.iloc[:,:-1].values
y=dataset.iloc[:,6].values
from sklearn.model_selection import train_test_split
```

In [45]:
```
X
```
Out[45]:
```
array([[19.  ,  0.  , 27.9 ,  0.  ,  1.  ,  3.  ],
       [18.  ,  1.  , 33.77,  1.  ,  0.  ,  2.  ],
       [28.  ,  1.  , 33.  ,  3.  ,  0.  ,  2.  ],
       ...,
       [18.  ,  0.  , 36.85,  0.  ,  0.  ,  2.  ],
       [21.  ,  0.  , 25.8 ,  0.  ,  0.  ,  3.  ],
       [61.  ,  0.  , 29.07,  0.  ,  1.  ,  1.  ]])
```

In [46]:
```
y
```
Out[46]:
```
array([16884.924 ,  1725.5523,  4449.462 , ...,  1629.8335,  2007.945 ,
       29141.3603])
```

In [47]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,random_state=0)
```

In [48]:
```
X_train.shape
```
Out[48]: `(1070, 6)`

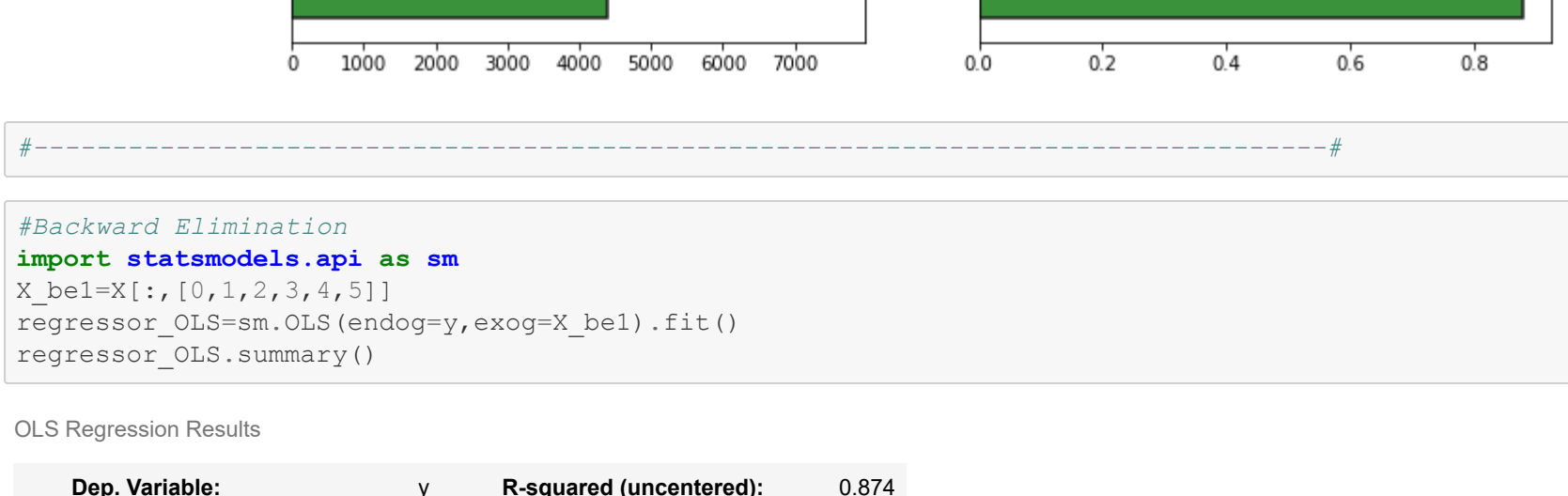
In [49]:
```
X_test.shape
```
Out[49]: `(268, 6)`

In [50]:
```
y_train.shape
```
Out[50]: `(1070,)`

In [51]:
```
y_test.shape
```
Out[51]: `(268,)`

In [52]:
```
#whole model:
from sklearn.linear_model import LinearRegression
lm1=LinearRegression()
lm1.fit(X_train,y_train)
lm1.predict(X_test)
print(lm1.coef_,lm1.intercept_)
lm1.score(X_test,y_test)
```
```
[  253.99185244   -24.32455098   328.40261701   443.72929547
 23568.87948381  -288.50857254] -11661.983908824392
```
Out[52]: `0.7998747145449959`

In [53]:
```
#Whole Model- Different Regression Models
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import accuracy_score,mean_squared_error

regressors=[['Linear Regression :',LinearRegression()],
       ['Decision Tree Regression :',DecisionTreeRegressor()],
       ['Random Forest Regression :',RandomForestRegressor()],
       ]
reg_pred=[]
accuracies=[]
print('Results...\n')
for name,model in regressors:
    model=model
    model.fit(X_train,y_train)
    predictions = model.predict(X_test)
    rms=np.sqrt(mean_squared_error(y_test, predictions))
    reg_pred.append(rms)
    accuracy= model.score(X_test,y_test)
    accuracies.append(accuracy)
    print(name,rms,accuracy)

y_ax=['Linear Regression' ,'Decision Tree Regression', 'Random Forest Regression' ]
x_ax=reg_pred

plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.barplot(x=x_ax,y=y_ax,linewidth=1.5,edgecolor="0.1")
plt.title('RMS Scores')
plt.plot()
plt.subplot(1,2,2)
sns.barplot(x=accuracies,y=y_ax,linewidth=1.5,edgecolor="0.1")
plt.title('Accuracies')
plt.plot()
```
```
Results...

Linear Regression : 5643.219748880902 0.7998747145449959
Decision Tree Regression : 7593.753566656418 0.6376226551579517
Random Forest Regression : 4379.540324009416 0.8794672406771654
```
Out[53]: `[]`



In [54]:
```
#----------------------------------------------------------------------------#
```

In [55]:
```
#Backward Elimination
import statsmodels.api as sm
X_be1=X[:,[0,1,2,3,4,5]]
regressor_OLS=sm.OLS(endog=y,exog=X_be1).fit()
regressor_OLS.summary()
```
Out[55]:

OLS Regression Results

Dep. Variable:	y	R-squared (uncentered):	0.874
Model:	OLS	Adj. R-squared (uncentered):	0.873
Method:	Least Squares	F-statistic:	1537.
Date:	Mon, 06 Dec 2021	Prob (F-statistic):	0.00
Time:	22:39:28	Log-Likelihood:	-13621.
No. Observations:	1338	AIC:	2.725e+04
Df Residuals:	1332	BIC:	2.729e+04
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	199.5462	11.538	17.295	0.000	176.912	222.180
x2	-693.5223	347.997	-1.993	0.046	-1376.205	-10.840
x3	62.3100	18.013	3.459	0.001	26.973	97.647
x4	265.5263	144.137	1.842	0.066	-17.234	548.286
x5	2.34e+04	433.195	54.006	0.000	2.25e+04	2.42e+04
x6	-553.9940	159.449	-3.474	0.001	-866.792	-241.196

Omnibus:	272.456	Durbin-Watson:	2.073
Prob(Omnibus):	0.000	Jarque-Bera (JB):	625.386
Skew:	1.120	Prob(JB):	1.58e-136
Kurtosis:	5.491	Cond. No.	128.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [56]:
```
X_be2=X[:,[0,1,2,4,5]]
regressor_OLS=sm.OLS(endog=y,exog=X_be2).fit()
regressor_OLS.summary()
```
Out[56]:

OLS Regression Results

Dep. Variable:	y	R-squared (uncentered):	0.873
Model:	OLS	Adj. R-squared (uncentered):	0.873
Method:	Least Squares	F-statistic:	1840.
Date:	Mon, 06 Dec 2021	Prob (F-statistic):	0.00
Time:	22:39:28	Log-Likelihood:	-13623.
No. Observations:	1338	AIC:	2.726e+04
Df Residuals:	1333	BIC:	2.728e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	201.6778	11.490	17.553	0.000	179.137	224.218
x2	-671.1566	348.098	-1.928	0.054	-1354.036	11.722
x3	67.9452	17.767	3.824	0.000	33.091	102.800
x4	2.341e+04	433.512	54.000	0.000	2.26e+04	2.43e+04
x5	-545.3991	159.523	-3.419	0.001	-858.344	-232.455

Omnibus:	271.652	Durbin-Watson:	2.069
Prob(Omnibus):	0.000	Jarque-Bera (JB):	618.351
Skew:	1.120	Prob(JB):	5.33e-135
Kurtosis:	5.465	Cond. No.	128.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [57]:
```
X_be3=X[:,[0,1,4,5]]
regressor_OLS=sm.OLS(endog=y,exog=X_be3).fit()
regressor_OLS.summary()
```
Out[57]:

OLS Regression Results

Dep. Variable:	y	R-squared (uncentered):	0.872
Model:	OLS	Adj. R-squared (uncentered):	0.872
Method:	Least Squares	F-statistic:	2273.
Date:	Mon, 06 Dec 2021	Prob (F-statistic):	0.00
Time:	22:39:28	Log-Likelihood:	-13630.
No. Observations:	1338	AIC:	2.727e+04
Df Residuals:	1334	BIC:	2.729e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	235.7394	7.296	32.313	0.000	221.427	250.051
x2	-317.3367	337.286	-0.941	0.347	-979.006	344.332
x3	2.36e+04	432.714	54.549	0.000	2.28e+04	2.45e+04
x4	-297.2862	146.476	-2.030	0.043	-584.635	-9.937

Omnibus:	264.736	Durbin-Watson:	2.077
Prob(Omnibus):	0.000	Jarque-Bera (JB):	616.743
Skew:	1.084	Prob(JB):	1.19e-134
Kurtosis:	5.523	Cond. No.	104.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [58]:
```
X_be4=X[:,[0,4,5]]
regressor_OLS=sm.OLS(endog=y,exog=X_be4).fit()
regressor_OLS.summary()
```
Out[58]:

OLS Regression Results

Dep. Variable:	y	R-squared (uncentered):	0.872
Model:	OLS	Adj. R-squared (uncentered):	0.872
Method:	Least Squares	F-statistic:	3031.
Date:	Mon, 06 Dec 2021	Prob (F-statistic):	0.00
Time:	22:39:28	Log-Likelihood:	-13630.
No. Observations:	1338	AIC:	2.727e+04
Df Residuals:	1335	BIC:	2.728e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	233.0209	6.699	34.786	0.000	219.880	246.162
x2	2.355e+04	429.299	54.864	0.000	2.27e+04	2.44e+04
x3	-316.1703	145.088	-2.179	0.029	-600.796	-31.544

Omnibus:	266.314	Durbin-Watson:	2.077
Prob(Omnibus):	0.000	Jarque-Bera (JB):	620.932
Skew:	1.089	Prob(JB):	1.47e-135
Kurtosis:	5.528	Cond. No.	102.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [59]:
```
#Best Features are Age, Smoker, Regions
```

In [60]:
```
X=dataset.iloc[:,[0,4,5]].values
y=dataset.iloc[:,6].values
```

In [61]:
```
X
```
Out[61]:
```
array([[19,  1,  3],
       [18,  0,  2],
       [28,  0,  2],
       ...,
       [18,  0,  2],
       [21,  0,  3],
       [61,  1,  1]], dtype=int64)
```

In [62]:
```
y
```
Out[62]:
```
array([16884.924 ,  1725.5523,  4449.462 , ...,  1629.8335,  2007.945 ,
       29141.3603])
```

In [63]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,random_state=0)
```

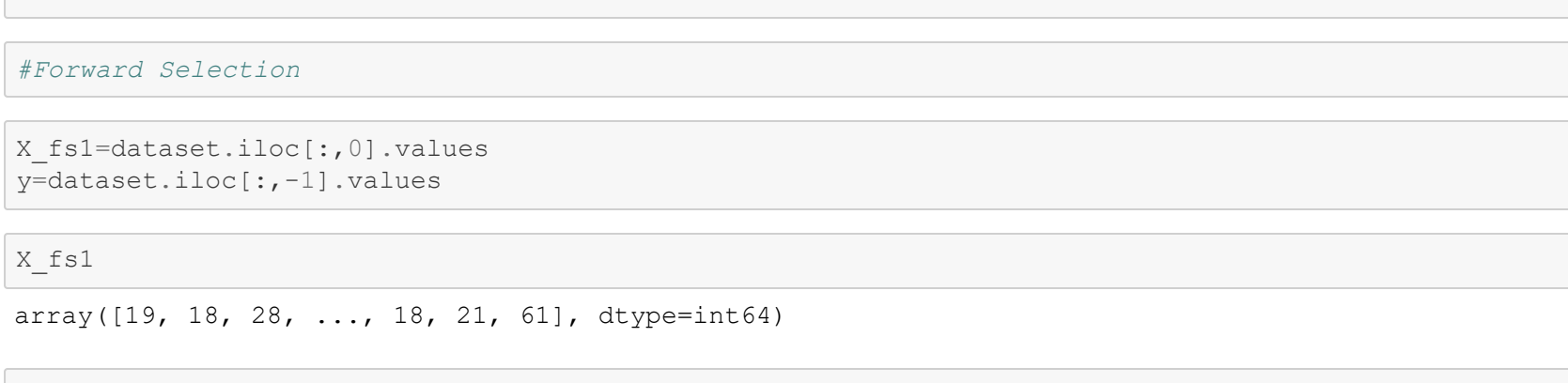
In [64]:
```
X_train.shape
```
Out[64]: `(1070, 3)`

In [65]:
```
X_test.shape
```
Out[65]: `(268, 3)`

In [66]:
```
y_train.shape
```
Out[66]: `(1070,)`

In [67]:
```
y_test.shape
```
Out[67]: `(268,)`

In [68]:
```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import accuracy_score,mean_squared_error

regressors=[['Linear Regression :',LinearRegression()],
       ['Decision Tree Regression :',DecisionTreeRegressor()],
       ['Random Forest Regression :',RandomForestRegressor()],
       ]
reg_pred=[]
accuracies=[]
print('Results...\n')
for name,model in regressors:
    model=model
    model.fit(X_train,y_train)
    predictions = model.predict(X_test)
    rms=np.sqrt(mean_squared_error(y_test, predictions))
    reg_pred.append(rms)
    accuracy= model.score(X_test,y_test)
    accuracies.append(accuracy)
    print(name,rms,accuracy)

y_ax=['Linear Regression' ,'Decision Tree Regression', 'Random Forest Regression' ]
x_ax=reg_pred

plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.barplot(x=x_ax,y=y_ax,linewidth=1.5,edgecolor="0.1")
plt.title('RMS Scores')
plt.plot()
plt.subplot(1,2,2)
sns.barplot(x=accuracies,y=y_ax,linewidth=1.5,edgecolor="0.1")
plt.title('Accuracies')
plt.plot()
```
```
Results...

Linear Regression : 6016.213695593682 0.7725454923581263
Decision Tree Regression : 7543.001912826166 0.6424502524438279
Random Forest Regression : 6983.6898703087745 0.6935088559505549
```
Out[68]: `[]`



In [69]:
```
#----------------------------------------------------------------------#
```

In [70]:
```
#Forward Selection
```

In [71]:
```
X_fs1=dataset.iloc[:,0].values
y=dataset.iloc[:,-1].values
```

In [72]:
```
X_fs1
```
Out[72]:
```
array([19, 18, 28, ..., 18, 21, 61], dtype=int64)
```

In [73]:
```
y
```
Out[73]:
```
array([16884.924 ,  1725.5523,  4449.462 , ...,  1629.8335,  2007.945 ,
       29141.3603])
```

In [74]:
```
X_fs1=dataset.iloc[:,0].values
regressor_OLS=sm.OLS(endog=y,exog=X_fs1).fit()
regressor_OLS.summary()
```
Out[74]:

OLS Regression Results

Dep. Variable:	y	R-squared (uncentered):	0.583
Model:	OLS	Adj. R-squared (uncentered):	0.583
Method:	Least Squares	F-statistic:	1868.
Date:	Mon, 06 Dec 2021	Prob (F-statistic):	3.95e-256
Time:	22:39:35	Log-Likelihood:	-14421.
No. Observations:	1338	AIC:	2.884e+04
Df Residuals:	1337	BIC:	2.885e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	329.2873	7.618	43.224	0.000	314.343	344.232

Omnibus:	393.480	Durbin-Watson:	2.037
Prob(Omnibus):	0.000	Jarque-Bera (JB):	840.455
Skew:	1.714	Prob(JB):	3.14e-183
Kurtosis:	4.823	Cond. No.	1.00

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [75]:
```
X_fs2=dataset.iloc[:,[0,1]].values
regressor_OLS=sm.OLS(endog=y,exog=X_fs2).fit()
regressor_OLS.summary()
```
Out[75]:

OLS Regression Results

Dep. Variable:	y	R-squared (uncentered):	0.587
Model:	OLS	Adj. R-squared (uncentered):	0.586
Method:	Least Squares	F-statistic:	947.6
Date:	Mon, 06 Dec 2021	Prob (F-statistic):	6.01e-257
Time:	22:39:36	Log-Likelihood:	-14415.
No. Observations:	1338	AIC:	2.883e+04
Df Residuals:	1336	BIC:	2.884e+04
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	306.1242	10.150	30.160	0.000	286.213	326.036
x2	2043.2674	594.697	3.436	0.001	876.626	3209.908

Omnibus:	387.299	Durbin-Watson:	2.052
Prob(Omnibus):	0.000	Jarque-Bera (JB):	819.051
Skew:	1.691	Prob(JB):	1.40e-178
Kurtosis:	4.803	Cond. No.	78.4

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [76]:
```
X_fs3=dataset.iloc[:,[0,1,2]].values
regressor_OLS=sm.OLS(endog=y,exog=X_fs3).fit()
regressor_OLS.summary()
```
Out[76]:

OLS Regression Results

Dep. Variable:	y	R-squared (uncentered):	0.596
Model:	OLS	Adj. R-squared (uncentered):	0.595
Method:	Least Squares	F-statistic:	655.7
Date:	Mon, 06 Dec 2021	Prob (F-statistic):	6.55e-262
Time:	22:39:36	Log-Likelihood:	-14400.
No. Observations:	1338	AIC:	2.881e+04
Df Residuals:	1335	BIC:	2.882e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	207.6709	20.510	10.125	0.000	167.436	247.906
x2	979.3428	619.212	1.582	0.114	-235.392	2194.078
x3	158.2079	28.739	5.505	0.000	101.830	214.586

Omnibus:	364.363	Durbin-Watson:	2.024
Prob(Omnibus):	0.000	Jarque-Bera (JB):	731.846
Skew:	1.631	Prob(JB):	1.21e-159
Kurtosis:	4.578	Cond. No.	102.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [77]:
```
X_fs4=dataset.iloc[:,[0,2]].values
regressor_OLS=sm.OLS(endog=y,exog=X_fs4).fit()
regressor_OLS.summary()
```
Out[77]:

OLS Regression Results

Dep. Variable:	y	R-squared (uncentered):	0.595
Model:	OLS	Adj. R-squared (uncentered):	0.594
Method:	Least Squares	F-statistic:	981.2
Date:	Mon, 06 Dec 2021	Prob (F-statistic):	6.45e-263
Time:	22:39:37	Log-Likelihood:	-14401.
No. Observations:	1338	AIC:	2.881e+04
Df Residuals:	1336	BIC:	2.882e+04
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	208.8632	20.507	10.185	0.000	168.633	249.094
x2	172.3943	27.318	6.311	0.000	118.803	225.986

Omnibus:	364.702	Durbin-Watson:	2.016
Prob(Omnibus):	0.000	Jarque-Bera (JB):	732.185
Skew:	1.634	Prob(JB):	1.02e-159
Kurtosis:	4.567	Cond. No.	5.51

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [78]:
```
X_fs5=dataset.iloc[:,[0,2,4]].values
regressor_OLS=sm.OLS(endog=y,exog=X_fs5).fit()
regressor_OLS.summary()
```
Out[78]:

OLS Regression Results

Dep. Variable:	y	R-squared (uncentered):	0.872
Model:	OLS	Adj. R-squared (uncentered):	0.872
Method:	Least Squares	F-statistic:	3031.
Date:	Mon, 06 Dec 2021	Prob (F-statistic):	0.00
Time:	22:39:37	Log-Likelihood:	-13631.
No. Observations:	1338	AIC:	2.727e+04
Df Residuals:	1335	BIC:	2.728e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	199.6458	11.535	17.307	0.000	177.017	222.275
x2	33.7512	15.580	2.166	0.030	3.188	64.315
x3	2.332e+04	433.987	53.745	0.000	2.25e+04	2.42e+04

Omnibus:	277.578	Durbin-Watson:	2.067
Prob(Omnibus):	0.000	Jarque-Bera (JB):	635.617
Skew:	1.141	Prob(JB):	9.49e-139
Kurtosis:	5.489	Cond. No.	126.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [79]:
```
X_fs6=dataset.iloc[:,[0,2,4,5]].values
regressor_OLS=sm.OLS(endog=y,exog=X_fs6).fit()
regressor_OLS.summary()
```
Out[79]:

OLS Regression Results

Dep. Variable:	y	R-squared (uncentered):	0.873
Model:	OLS	Adj. R-squared (uncentered):	0.873
Method:	Least Squares	F-statistic:	2294.
Date:	Mon, 06 Dec 2021	Prob (F-statistic):	0.00
Time:	22:39:38	Log-Likelihood:	-13625.
No. Observations:	1338	AIC:	2.726e+04
Df Residuals:	1334	BIC:	2.728e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	200.8988	11.495	17.478	0.000	178.349	223.448
x2	58.8403	17.145	3.432	0.001	25.205	92.475
x3	2.334e+04	432.249	53.987	0.000	2.25e+04	2.42e+04
x4	-549.2686	159.673	-3.440	0.001	-862.507	-236.031

Omnibus:	273.748	Durbin-Watson:	2.071
Prob(Omnibus):	0.000	Jarque-Bera (JB):	626.116
Skew:	1.126	Prob(JB):	1.10e-136
Kurtosis:	5.482	Cond. No.	126.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [80]:
```
X=dataset.iloc[:,[0,2,4,5]].values
y=dataset.iloc[:,6].values
```

In [81]:
```
X
```
Out[81]:
```
array([[19.  , 27.9 ,  1.  ,  3.  ],
       [18.  , 33.77,  0.  ,  2.  ],
       [28.  , 33.  ,  0.  ,  2.  ],
       ...,
       [18.  , 36.85,  0.  ,  2.  ],
       [21.  , 25.8 ,  0.  ,  3.  ],
       [61.  , 29.07,  1.  ,  1.  ]])
```

In [82]:
```
y
```
Out[82]:
```
array([16884.924 ,  1725.5523,  4449.462 , ...,  1629.8335,  2007.945 ,
       29141.3603])
```

In [83]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,random_state=0)
```

In [84]:
```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import accuracy_score,mean_squared_error

regressors=[['Linear Regression :',LinearRegression()],
       ['Decision Tree Regression :',DecisionTreeRegressor()],
       ['Random Forest Regression :',RandomForestRegressor()],
       ]
reg_pred=[]
accuracies=[]
print('Results...\n')
for name,model in regressors:
    model=model
    model.fit(X_train,y_train)
    predictions = model.predict(X_test)
    rms=np.sqrt(mean_squared_error(y_test, predictions))
    reg_pred.append(rms)
    accuracy= model.score(X_test,y_test)
    accuracies.append(accuracy)
    print(name,rms,accuracy)

y_ax=['Linear Regression' ,'Decision Tree Regression', 'Random Forest Regression' ]
x_ax=reg_pred

plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.barplot(x=x_ax,y=y_ax,linewidth=1.5,edgecolor="0.1")
plt.title('RMS Scores')
plt.plot()
plt.subplot(1,2,2)
sns.barplot(x=accuracies,y=y_ax,linewidth=1.5,edgecolor="0.1")
plt.title('Accuracies')
plt.plot()
```
```
Results...

Linear Regression : 5688.626766322956 0.7966412232221931
Decision Tree Regression : 7288.622287774011 0.6661595712170314
Random Forest Regression : 4756.618623274475 0.857817972196329
```
Out[84]: `[]`

In [ ]:

In [ ]: