Project Details

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

1)age: age of primary beneficiary

2)sex: insurance contractor gender, female, male

3)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

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

5)smoker: Smoking

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

7)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
```

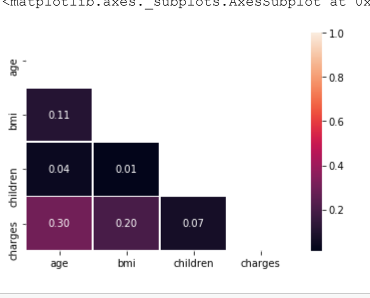
In [11]:
```
dataset.columns
```

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 0x24906118518>

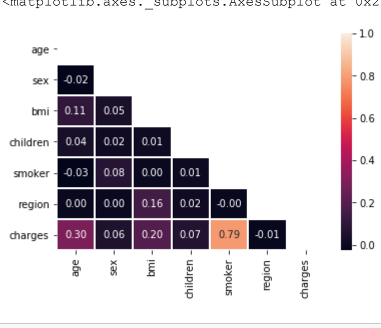


In [13]:
```
correlation_plot['charges'].sort_values()
```

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

In [44]:
```
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[44]: <matplotlib.axes._subplots.AxesSubplot at 0x2490a768be0>

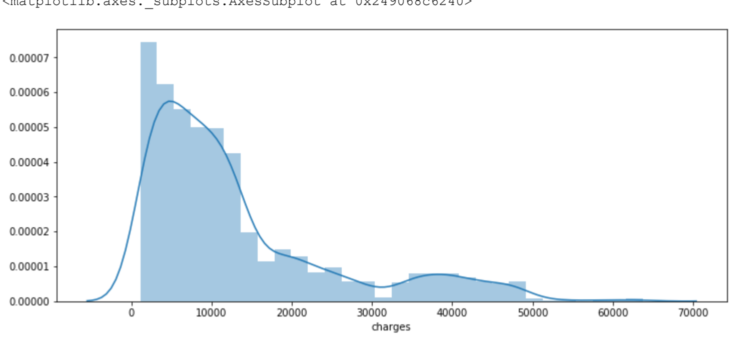


In [45]:
```
correlation_plot['charges'].sort_values()
```

Out[45]:
```
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
```

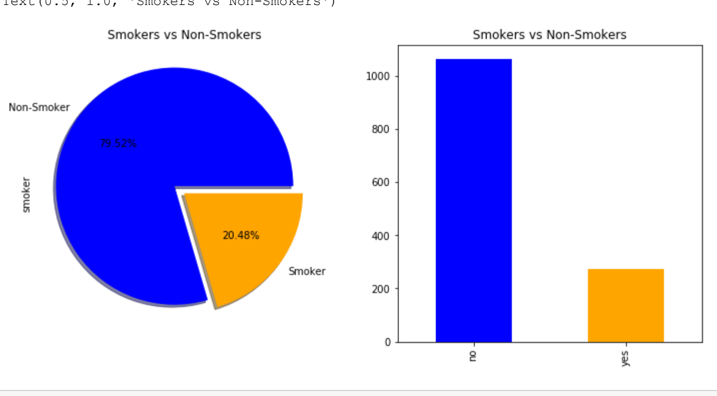
In [14]:
```
plt.figure(figsize=(12,5))
sns.distplot(dataset['charges'])
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x249068c6240>



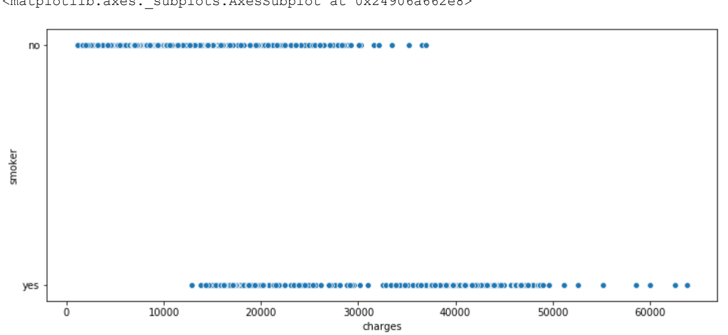
In [15]:
```
plt.figure(figsize=(12,12))
plt.subplot(2,2,1)
explode=(0.1,0)
color=['blue','orange']
label=['Non-Smoker','Smoker']
dataset['smoker'].value_counts().plot.pie(autopct='%.2f%%',shadow=True,explode=explode,colors=color,lab
els=label)
plt.title('Smokers vs Non-Smokers')
plt.subplot(2,2,2)
color=['blue','orange']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



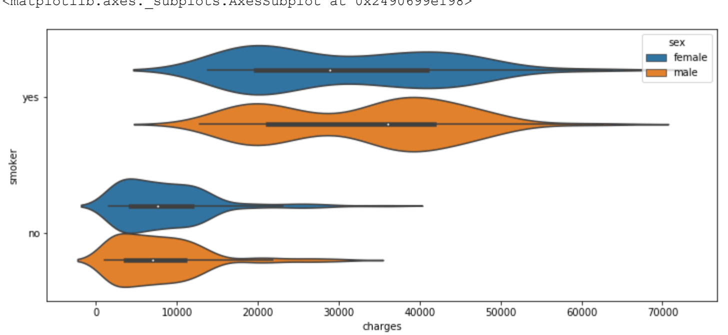
In [16]:
```
plt.figure(figsize=(12,5))

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

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x24906a662e8>



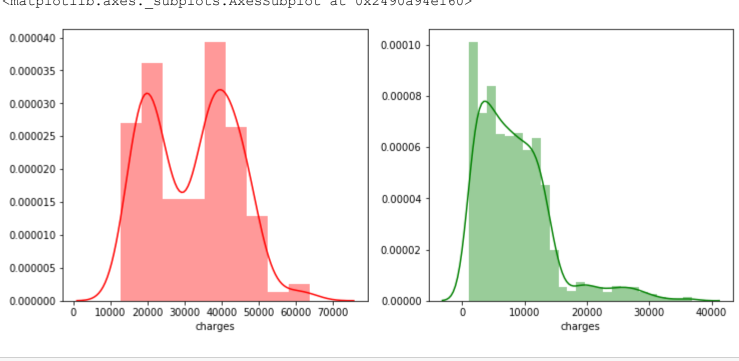
In [17]:
```
plt.figure(figsize=(12,5))

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

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x2490699e198>



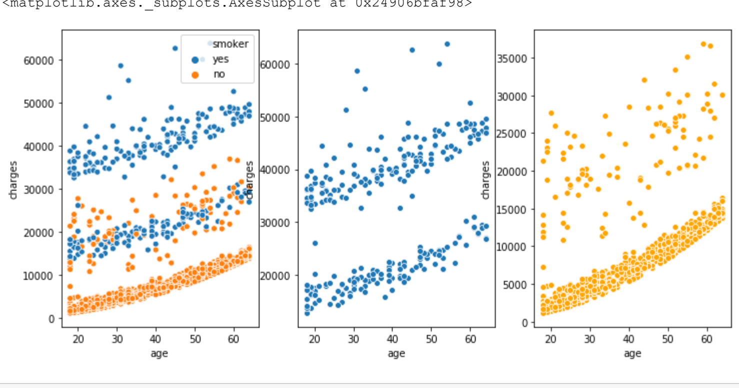
In [46]:
```
f=plt.figure(figsize=(12,5))
ax=f.add_subplot(121)
sns.distplot(dataset[(dataset.smoker==1)]['charges'],color='r',ax=ax)
ax=f.add_subplot(122)
sns.distplot(dataset[(dataset.smoker==0)]['charges'],color='g',ax=ax)
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x2490a94e160>



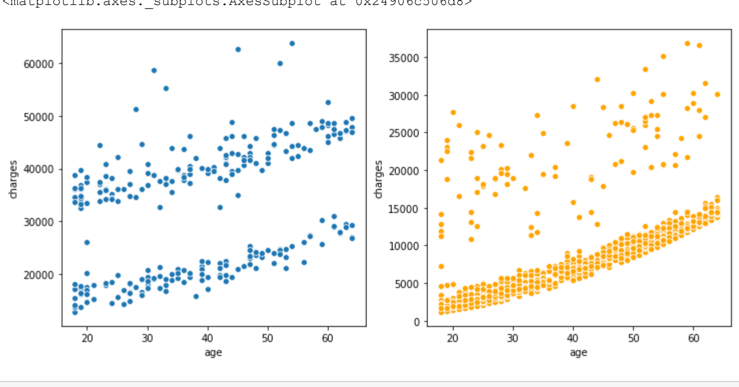
In [18]:
```
plt.figure(figsize=(12,12))
plt.subplot(2,3,1)
sns.scatterplot(dataset['age'],dataset['charges'],hue=dataset['smoker'])
plt.subplot(2,3,2)
smoker_dataset=dataset[dataset['smoker']=='yes']
non_smoker_dataset=dataset[dataset['smoker']=='no']
sns.scatterplot(smoker_dataset['age'],smoker_dataset['charges'])
plt.subplot(2,3,3)
sns.scatterplot(non_smoker_dataset['age'],non_smoker_dataset['charges'],color='orange')
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x24906bfaf98>



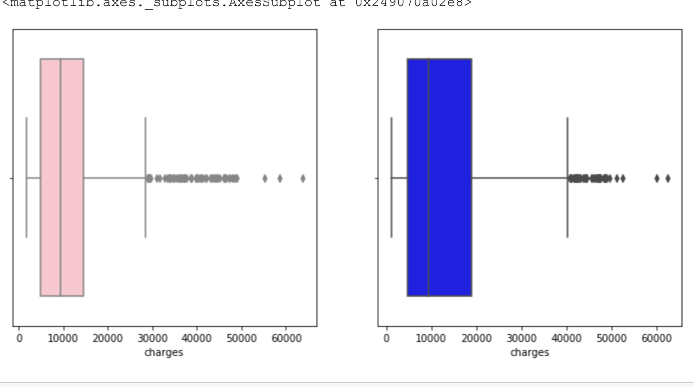
In [19]:
```
plt.figure(figsize=(12,12))
plt.subplot(2,2,1)
smoker_dataset=dataset[dataset['smoker']=='yes']
non_smoker_dataset=dataset[dataset['smoker']=='no']
sns.scatterplot(smoker_dataset['age'],smoker_dataset['charges'])
plt.subplot(2,2,2)
sns.scatterplot(non_smoker_dataset['age'],non_smoker_dataset['charges'],color='orange')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

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x24906c506d8>



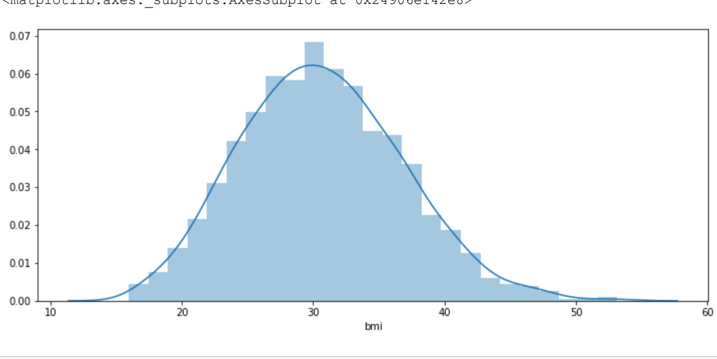
In [20]:
```
female_dataset=dataset[dataset['sex']=='female']
male_dataset=dataset[dataset['sex']=='male']
plt.figure(figsize=(12,12))
plt.subplot(2,2,1)
sns.boxplot(female_dataset['charges'],color='pink')
plt.subplot(2,2,2)
sns.boxplot(male_dataset['charges'],color='blue')
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x249070a02e8>



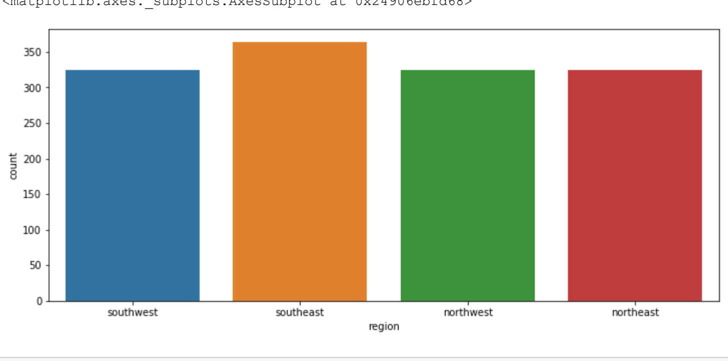
In [21]:
```
plt.figure(figsize=(12,5))

sns.distplot(dataset['bmi'])
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x24906e142e8>



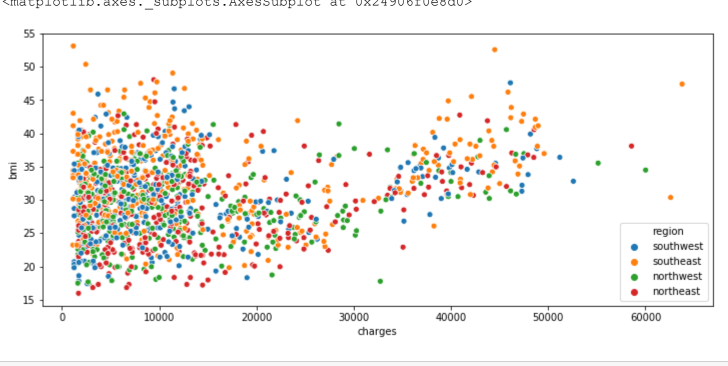
In [22]:
```
plt.figure(figsize=(12,5))

sns.countplot(dataset['region'])
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x24906ebfd68>



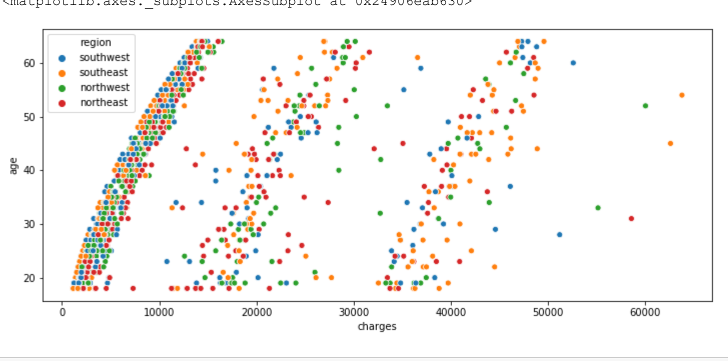
In [23]:
```
plt.figure(figsize=(12,5))

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

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x24906f0e8d0>



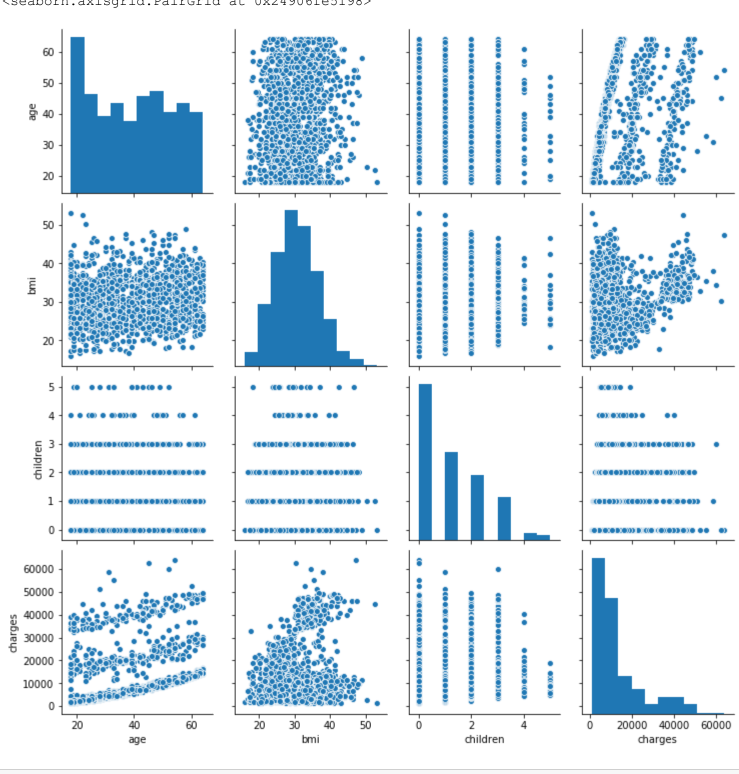
In [24]:
```
plt.figure(figsize=(12,5))

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

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x24906eab630>



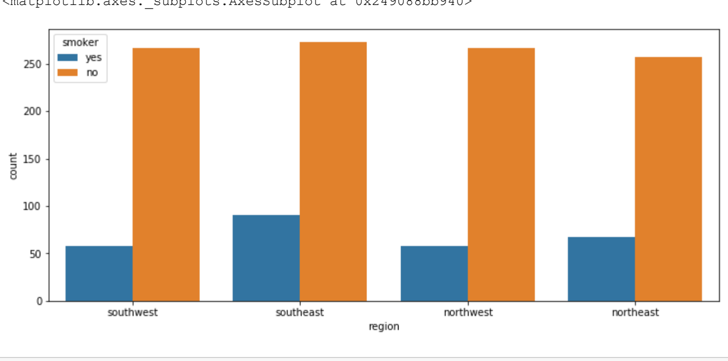
In [25]:
```
sns.pairplot(dataset)
```

Out[25]: <seaborn.axisgrid.PairGrid at 0x24906fe5198>



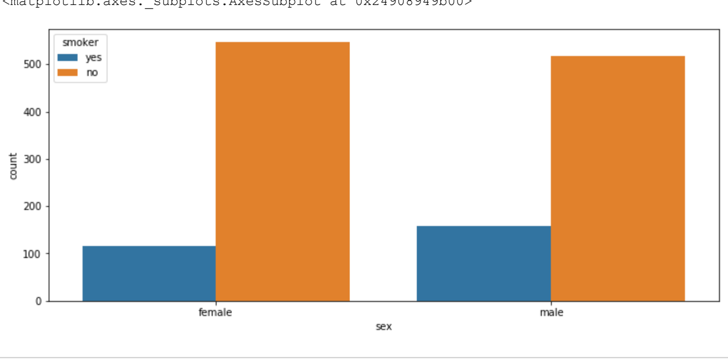
In [26]:
```
#Region wise Smoker
plt.figure(figsize=(12,5))

sns.countplot(dataset['region'],hue=dataset['smoker'])
```

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x249088bb940>



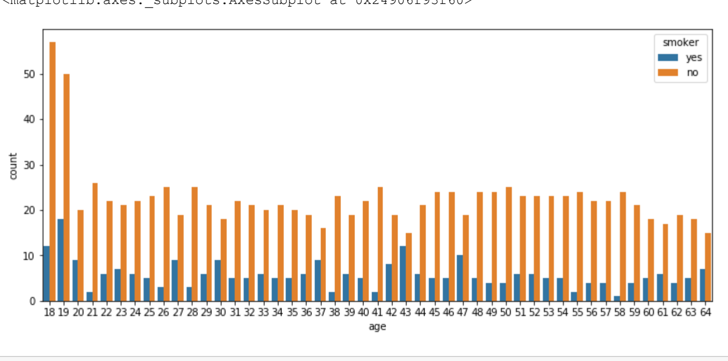
In [27]:
```
#Sex wise Smoker
plt.figure(figsize=(12,5))

sns.countplot(dataset['sex'],hue=dataset['smoker'])
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x24908949b00>



In [28]:
```
#Age wise Smoker
plt.figure(figsize=(12,5))
sns.countplot(dataset['age'],hue=dataset['smoker'])
```

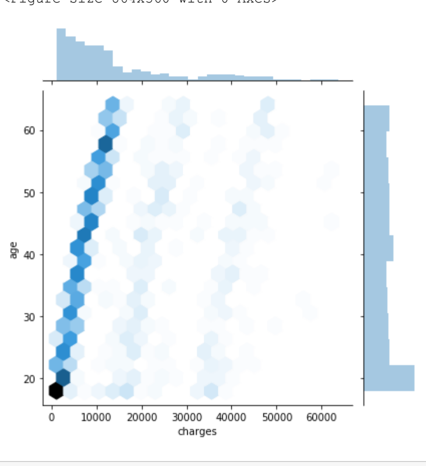
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x24906f93f60>



In [29]:
```
#Age, Charge, Smoker
plt.figure(figsize=(12,5))

sns.jointplot(data=dataset,x='charges',y='age',kind='hex')
```

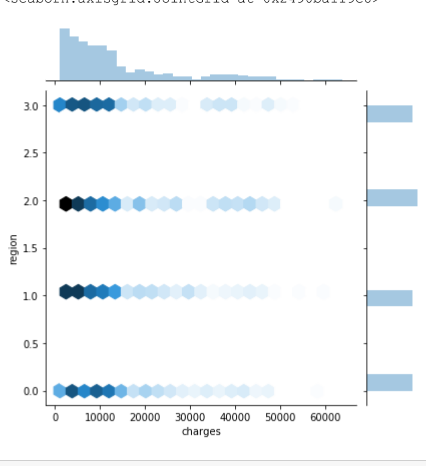
Out[29]: <seaborn.axisgrid.JointGrid at 0x24908da9048>

<Figure size 864x360 with 0 Axes>



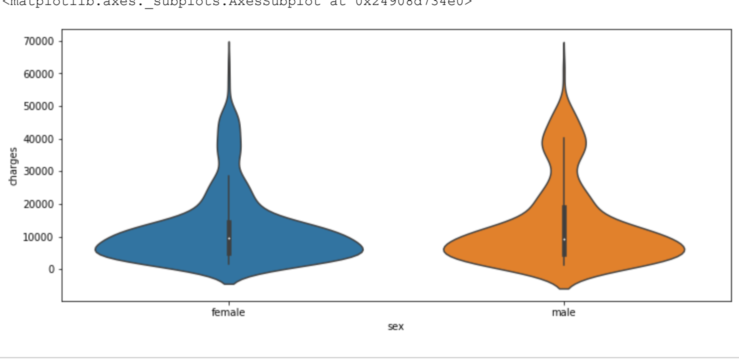
In [47]:
```
#Region, Charge, Smoker
sns.jointplot(data=dataset,x='charges',y='region',kind='hex')
```

Out[47]: <seaborn.axisgrid.JointGrid at 0x2490ba119e8>



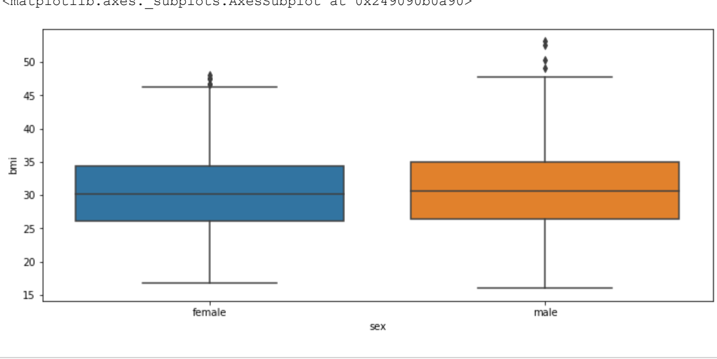
In [30]:
```
#Sex, Charge
plt.figure(figsize=(12,5))

sns.violinplot(dataset['sex'],dataset['charges'])
```

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x24908d734e0>



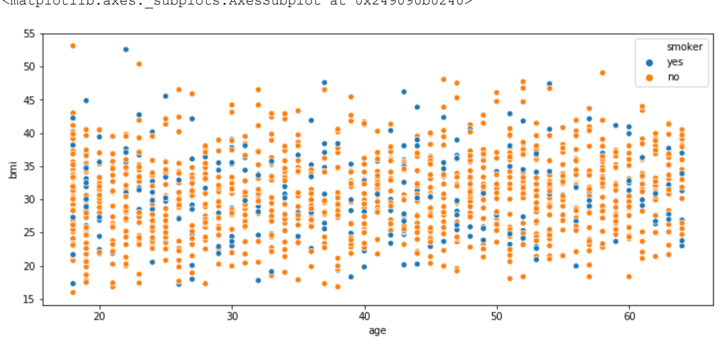
In [31]:
```
#Sex, BMI
plt.figure(figsize=(12,5))

sns.boxplot(dataset['sex'],dataset['bmi'])
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x249090b0a90>



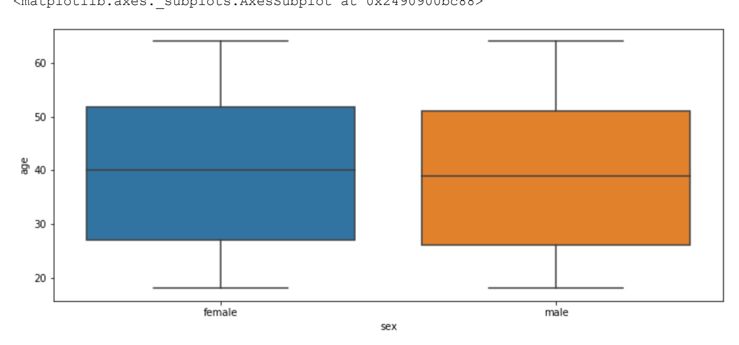
In [32]:
```
#Age, BMI
plt.figure(figsize=(12,5))

sns.scatterplot(dataset['age'],dataset['bmi'],hue=dataset['smoker'])
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x249090b0240>



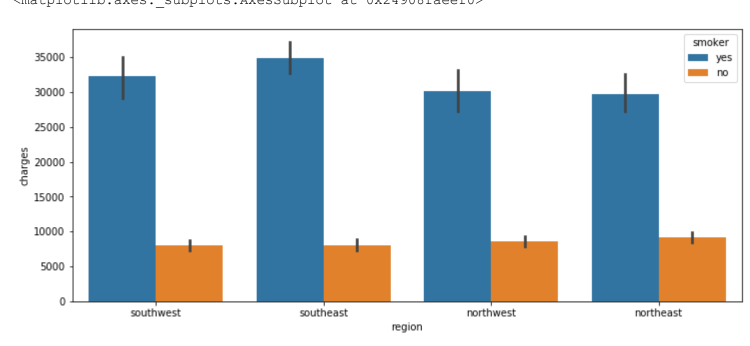
```
In [33]: #Age, Sex
         plt.figure(figsize=(12,5))

         sns.boxplot(dataset['sex'],dataset['age'])
```

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x2490900bc88>



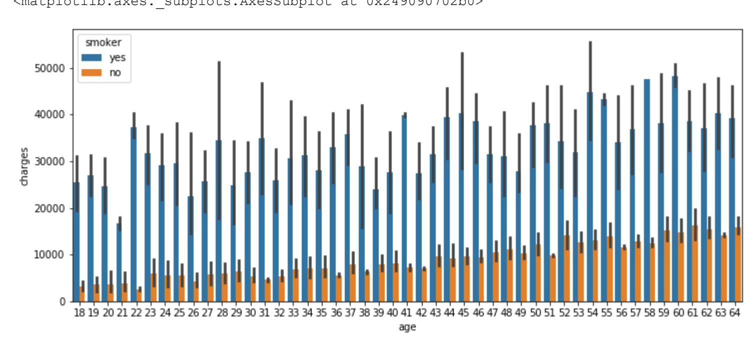

```
In [34]: plt.figure(figsize=(12,5))

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

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x24908faeef0>



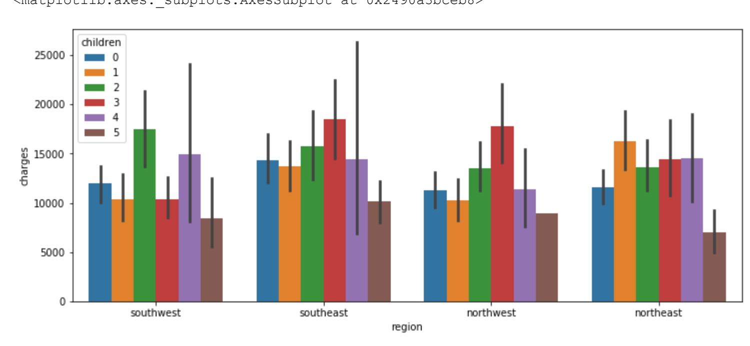

```
In [35]: plt.figure(figsize=(12,5))
         sns.barplot(dataset['age'],dataset['charges'],hue=dataset['smoker'])
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x249090702b0>



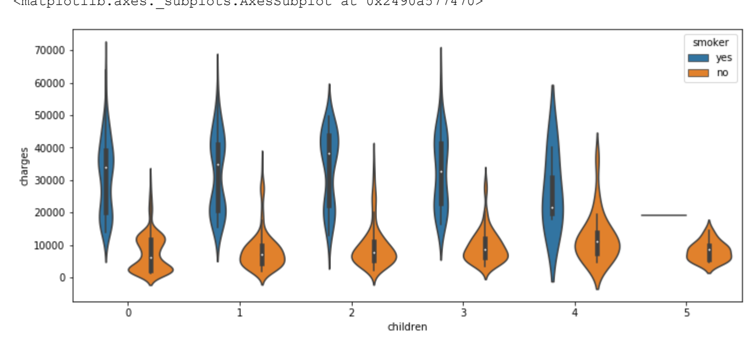

```
In [36]: plt.figure(figsize=(12,5))

         sns.barplot(dataset['region'],dataset['charges'],hue=dataset['children'])
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x2490a3bceb8>




```
In [37]: plt.figure(figsize=(12,5))

         sns.violinplot(dataset['children'],dataset['charges'],hue=dataset['smoker'])
```

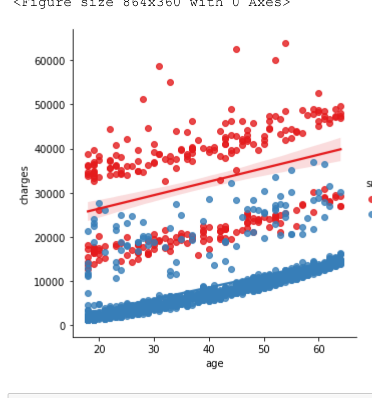
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x2490a577470>




```
In [38]: plt.figure(figsize=(12,5))

         sns.lmplot(x = 'age', y = 'charges', data=dataset, hue='smoker', palette='Set1')
```

Out[38]: <seaborn.axisgrid.FacetGrid at 0x2490a5d9a90>

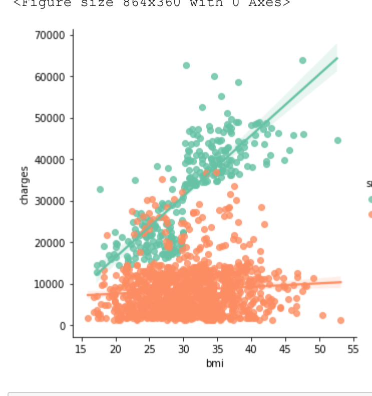
<Figure size 864x360 with 0 Axes>




```
In [39]: plt.figure(figsize=(12,5))

         sns.lmplot(x = 'bmi', y = 'charges', data=dataset, hue='smoker', palette='Set2')
```

Out[39]: <seaborn.axisgrid.FacetGrid at 0x2490a65f390>

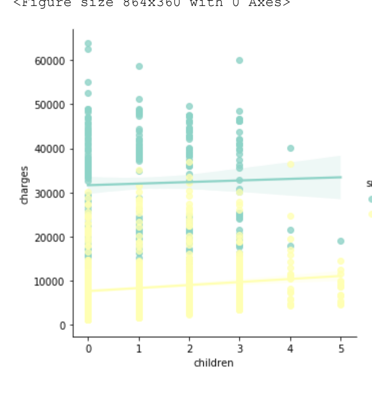
<Figure size 864x360 with 0 Axes>




```
In [40]: plt.figure(figsize=(12,5))

         sns.lmplot(x = 'children', y = 'charges', data=dataset, hue='smoker', palette='Set3')
```

Out[40]: <seaborn.axisgrid.FacetGrid at 0x2490a6e2978>

<Figure size 864x360 with 0 Axes>



Analysis

It is sad to see that people with age <25 have so much Insurance ChargeClearly Smokers in each region have really high Insurance ChargesIt shows that age is balanced for both male as well as femaleIt is clear that it won't much depend on the Sex of an IndividualMajority of people in dataset are from SouthEast, dataset looks almost balanced.""")We can see that distribution of BMI variable is almost Normal!For Smokers, charges are almost in the double range compared to Non-Smokers!According to the plots, it is clear smoking leads to higher Insurance Charges!We can see that majority of the people are Non-Smokers!According to the Heatmap ,it is clear that Smoker is the most important features related to Insurance Cost

Preparing

```
In [41]: #Label Encoding-Converting categorical data to numerical data
         #https://towardsdatascience.com/categorical-encoding-using-label-encoding-and-one-hot-encoder-911ef77fb
         5bd
```

```
In [42]: 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 [43]: dataset.head()
```

Out[43]:

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

```
In [49]: #backward elimination
```

```
In [50]: #forward selection
```

```
In [51]: #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 [52]: X
```

```
Out[52]: 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 [53]: y
```

```
Out[53]: array([16884.924 ,  1725.5523,  4449.462 , ...,  1629.8335,  2007.945 ,
                29141.3603])
```

```
In [54]: X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,random_state=0)
```

```
In [55]: X_train.shape
Out[55]: (1070, 6)
```

```
In [56]: X_test.shape
Out[56]: (268, 6)
```

```
In [57]: y_train.shape
Out[57]: (1070,)
```

```
In [58]: y_test.shape
Out[58]: (268,)
```

```
In [59]: #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)
```

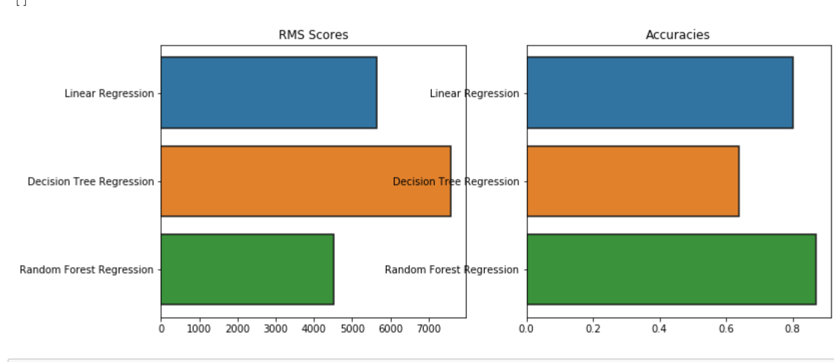
```
[  253.99185244   -24.32455098   328.40261701   443.72929547
 23568.87948381  -288.50857254] -11661.983908824392
```

Out[59]: 0.7998747145449959

```
In [60]: #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 : 7587.044613435255 0.6382626808537033
Random Forest Regression : 4517.5632021147185 0.8717502537718921
```

Out[60]: []




```
In [61]: #---------------------------------------------------------------------------------#
```

```
In [62]: #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[62]:

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:	Thu, 09 Dec 2021	Prob (F-statistic):	0.00
Time:	14:33:24	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 [63]: X_be2=X[:,[0,1,2,4,5]]
         regressor_OLS=sm.OLS(endog=y,exog=X_be2).fit()
         regressor_OLS.summary()
```

Out[63]:

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:	Thu, 09 Dec 2021	Prob (F-statistic):	0.00
Time:	14:33:30	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 [64]: X_be3=X[:,[0,1,4,5]]
         regressor_OLS=sm.OLS(endog=y,exog=X_be3).fit()
         regressor_OLS.summary()
```

Out[64]:

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:	Thu, 09 Dec 2021	Prob (F-statistic):	0.00
Time:	14:33:32	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 [65]: X_be4=X[:,[0,4,5]]
         regressor_OLS=sm.OLS(endog=y,exog=X_be4).fit()
         regressor_OLS.summary()
```

Out[65]:

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:	Thu, 09 Dec 2021	Prob (F-statistic):	0.00
Time:	14:33:32	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 [66]: #Best Features are Age, Smoker, Regions
```

```
In [67]: X=dataset.iloc[:,[0,4,5]].values
         y=dataset.iloc[:,6].values
```

```
In [68]: X
```

```
Out[68]: array([[19,  1,  3],
                [18,  0,  2],
                [28,  0,  2],
                ...,
                [18,  0,  2],
                [21,  0,  3],
                [61,  1,  1]], dtype=int64)
```

```
In [69]: y
```

```
Out[69]: array([16884.924 ,  1725.5523,  4449.462 , ...,  1629.8335,  2007.945 ,
                29141.3603])
```

```
In [70]: X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,random_state=0)
```

```
In [71]: X_train.shape
Out[71]: (1070, 3)
```

```
In [72]: X_test.shape
Out[72]: (268, 3)
```

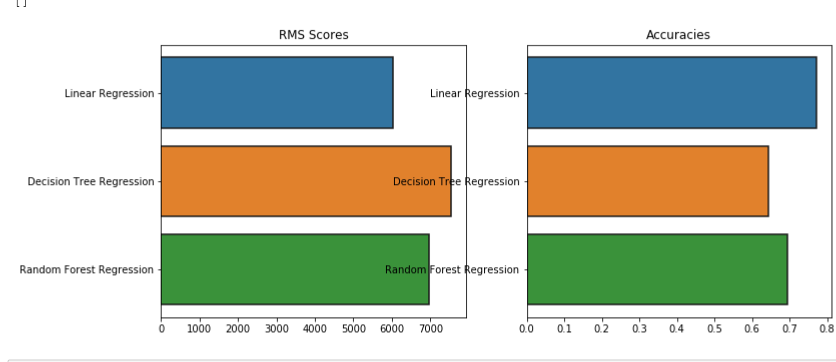
```
In [73]: y_train.shape
Out[73]: (1070,)
```

```
In [74]: y_test.shape
Out[74]: (268,)
```

```
In [75]: 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 : 6971.824533229763 0.6945494323454251
```

Out[75]: []




```
In [76]: #---------------------------------------------------------------------#
```

```
In [77]: #Forward Selection
```

```
In [78]: X_fs1=dataset.iloc[:,0].values
         y=dataset.iloc[:,-1].values
```

```
In [79]: X_fs1
Out[79]: array([19, 18, 28, ..., 18, 21, 61], dtype=int64)
```

```
In [80]: y
Out[80]: array([16884.924 ,  1725.5523,  4449.462 , ...,  1629.8335,  2007.945 ,
                29141.3603])
```

```
In [81]: X_fs1=dataset.iloc[:,0].values
         regressor_OLS=sm.OLS(endog=y,exog=X_fs1).fit()
         regressor_OLS.summary()
```

Out[81]:

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:	Thu, 09 Dec 2021	Prob (F-statistic):	3.95e-256
Time:	14:33:45	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 [82]: X_fs2=dataset.iloc[:,[0,1]].values
         regressor_OLS=sm.OLS(endog=y,exog=X_fs2).fit()
         regressor_OLS.summary()
```

Out[82]:

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:	Thu, 09 Dec 2021	Prob (F-statistic):	6.01e-257
Time:	14:33:45	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 [83]: X_fs3=dataset.iloc[:,[0,1,2]].values
         regressor_OLS=sm.OLS(endog=y,exog=X_fs3).fit()
         regressor_OLS.summary()
```

Out[83]:

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:	Thu, 09 Dec 2021	Prob (F-statistic):	6.55e-262
Time:	14:33:46	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 [84]: X_fs4=dataset.iloc[:,[0,2]].values
         regressor_OLS=sm.OLS(endog=y,exog=X_fs4).fit()
         regressor_OLS.summary()
```

Out[84]:

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:	Thu, 09 Dec 2021	Prob (F-statistic):	6.45e-263
Time:	14:33:46	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 [85]:
```
X_fs5=dataset.iloc[:,[0,2,3]].values
regressor_OLS=sm.OLS(endog=y,exog=X_fs5).fit()
regressor_OLS.summary()
```
Out[85]:

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:	Thu, 09 Dec 2021	**Prob (F-statistic):**	6.52e-262
Time:	14:33:47	**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	205.5096	20.605	9.974	0.000	165.088	245.931
x2	162.5084	28.007	5.802	0.000	107.566	217.451
x3	407.6827	257.331	1.584	0.113	-97.135	912.501

Omnibus:	369.789	**Durbin-Watson:**	2.018
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	750.403
Skew:	1.648	**Prob(JB):**	1.13e-163
Kurtosis:	4.610	**Cond. No.**	42.2

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

In [86]:
```
X_fs6=dataset.iloc[:,[0,2]].values
regressor_OLS=sm.OLS(endog=y,exog=X_fs6).fit()
regressor_OLS.summary()
```
Out[86]:

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:	Thu, 09 Dec 2021	**Prob (F-statistic):**	6.45e-263
Time:	14:33:47	**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 [87]:
```
X_fs7=dataset.iloc[:,[0,2,4]].values
regressor_OLS=sm.OLS(endog=y,exog=X_fs7).fit()
regressor_OLS.summary()
```
Out[87]:

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:	Thu, 09 Dec 2021	**Prob (F-statistic):**	0.00
Time:	14:33:47	**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 [88]:
```
X_fs8=dataset.iloc[:,[0,2,4,5]].values
regressor_OLS=sm.OLS(endog=y,exog=X_fs8).fit()
regressor_OLS.summary()
```
Out[88]:

OLS Regression Results

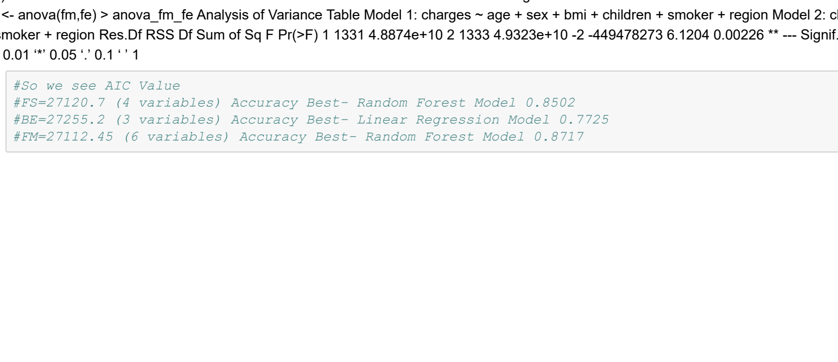
Dep. Variable:	y	**R-squared (uncentered):**	0.873
Model:	OLS	**Adj. R-squared (uncentered):**	0.873
Method:	Least Squares	**F-statistic:**	2294.
Date:	Thu, 09 Dec 2021	**Prob (F-statistic):**	0.00
Time:	14:33:48	**Log-Likelihood:**	-13625.
No. Observations:	1338	**AIC:**	2.726e+04
Df Residuals:	1334	**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 [89]:
```
X=dataset.iloc[:,[0,2,4,5]].values
y=dataset.iloc[:,6].values
```
In [90]:
```
X
```
Out[90]:
```
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 [91]:
```
y
```
Out[91]:
```
array([16884.924 ,  1725.5523,  4449.462 , ...,  1629.8335,  2007.945 ,
       29141.3603])
```
In [92]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,random_state=0)
```
In [93]:
```
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 : 7410.996011926145 0.6548553076534683
Random Forest Regression : 4882.032839653195 0.8502215151713243
```
Out[93]: []



R-Code to COmpare Models > fm <- lm(charges ~ age + sex + bmi + children + smoker + region, data=data) > summary(fm) Call: lm(formula = charges ~ age + sex + bmi + children + smoker + region, data = data) Residuals: Min 1Q Median 3Q Max -11343 -2807 -1017 1408 29752 Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -11815.45 955.13 -12.371 < 2e-16 *** age 257.29 11.89 21.647 < 2e-16 *** sex -131.11 332.81 -0.394 0.693681 bmi 332.57 27.72 11.997 < 2e-16 *** children 479.37 137.64 3.483 0.000513 *** smoker 23820.43 411.84 57.839 < 2e-16 *** region -353.64 151.93 -2.328 0.020077 * --- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 Residual standard error: 6060 on 1331 degrees of freedom Multiple R-squared: 0.7507, Adjusted R-squared: 0.7496 F-statistic: 668.1 on 6 and 1331 DF, p-value: < 2.2e-16 > AIC(fm) [1] 27112.45 > be <- lm(charges ~ age + smoker + region, data=data) > summary(be) Call: lm(formula = charges ~ age + smoker + region, data = data) Residuals: Min 1Q Median 3Q Max -16004.0 -2049.2 -1344.7 -249.1 28787.6 Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -2306.32 580.11 -3.976 7.39e-05 *** age 274.88 12.46 22.062 < 2e-16 *** smoker 23854.98 433.63 55.012 < 2e-16 *** region -56.47 158.39 -0.357 0.721 --- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 Residual standard error: 6399 on 1334 degrees of freedom Multiple R-squared: 0.7214, Adjusted R-squared: 0.7208 F-statistic: 1152 on 3 and 1334 DF, p-value: < 2.2e-16 > AIC(be) [1] 27255.2 > #Forward Selection > fe <- lm(charges ~ age + bmi + smoker + region, data=data) > summary(fe) Call: lm(formula = charges ~ age + bmi + smoker + region, data = data) Residuals: Min 1Q Median 3Q Max -11788 -3024 -998 1520 29147 Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -11442.01 941.85 -12.148 <2e-16 *** age 259.13 11.92 21.744 <2e-16 *** bmi 332.58 27.80 11.965 <2e-16 *** smoker 23820.70 412.23 57.785 <2e-16 *** region -345.30 152.49 -2.264 0.0237 * --- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 Residual standard error: 6083 on 1333 degrees of freedom Multiple R-squared: 0.7484, Adjusted R-squared: 0.7477 F-statistic: 991.5 on 4 and 1333 DF, p-value: < 2.2e-16 > AIC(fe) [1] 27120.7 > anova_fm_be <-anova(fm,be) > anova_fm_be Analysis of Variance Table Model 1: charges ~ age + sex + bmi + children + smoker + region Model 2: charges ~ age + smoker + region Res.Df RSS Df Sum of Sq F Pr(>F) 1 1331 4.8874e+10 2 1334 5.4621e+10 -3 -5746901759 52.169 < 2.2e-16 *** --- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 > anova_fm_fe <- anova(fm,fe) > anova_fm_fe Analysis of Variance Table Model 1: charges ~ age + sex + bmi + children + smoker + region Model 2: charges ~ age + bmi + smoker + region Res.Df RSS Df Sum of Sq F Pr(>F) 1 1331 4.8874e+10 2 1333 4.9323e+10 -2 -449478273 6.1204 0.00226 ** --- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

In [94]:
```
#So we see AIC Value
#FS=27120.7 (4 variables) Accuracy Best- Random Forest Model 0.8502
#BE=27255.2 (3 variables) Accuracy Best- Linear Regression Model 0.7725
#FM=27112.45 (6 variables) Accuracy Best- Random Forest Model 0.8717
```
Thank You