```
In [147]: w# Import necessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [148]: insurancedata = pd.read\_csv(r'C:\Users\alharbi\Downloads\insurance.csv')

In [149]: insurancedata.head(5)

Out[149]:

	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	NaN	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

In [150]: insurancedata.shape

Out[150]: (1338, 7)

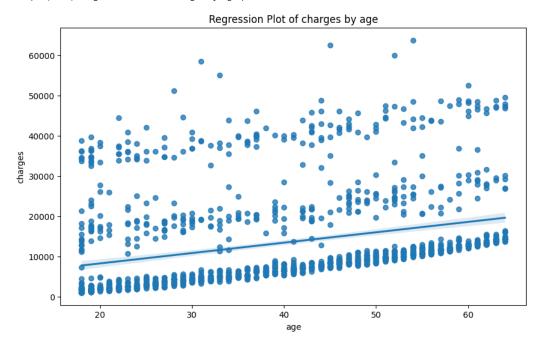
In [151]: insurancedata.describe()

Out[151]:

	age	bmi	children	charges
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.663397	1.094918	13270.422265
std	14.049960	6.098187	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.693750	2.000000	16639.912515
max	64.000000	53.130000	5.000000	63770.428010

```
In [228]: plt.figure(figsize=(10, 6))
    sns.regplot(x='age', y='charges', data=insurancedata)
    plt.title('Regression Plot of charges by age')
```

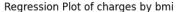
Out[228]: Text(0.5, 1.0, 'Regression Plot of charges by age')

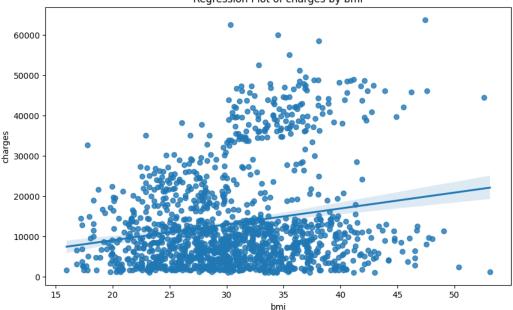


```
In [225]: from scipy import stats
    pearson_coef_age, p_value_age = stats.pearsonr(insurancedata['age'], insurancedata['charges'])
    print("The Pearson Correlation Coefficient between age and charges is", pearson_coef_age, "with a P-value of P=", p_value_age)
```

```
In [229]: plt.figure(figsize=(10, 6))
    sns.regplot(x='bmi', y='charges', data=insurancedata)
    plt.title('Regression Plot of charges by bmi')
```

Out[229]: Text(0.5, 1.0, 'Regression Plot of charges by bmi')



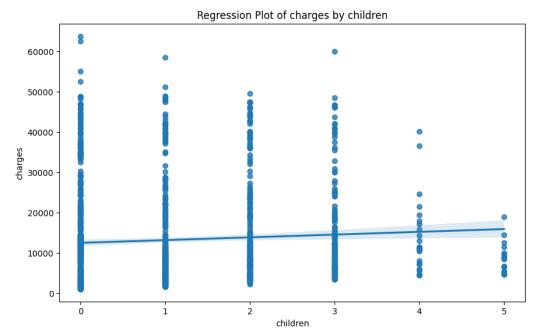


```
In [90]: pearson_coef_bmi, p_value_bmi = stats.pearsonr(insurancedata['bmi'], insurancedata['charges'])
print("The Pearson Correlation Coefficient between bmi and charges is", pearson_coef_bmi, "with a P-value of P=", p_value_bmi)
```

The Pearson Correlation Coefficient between bmi and charges is 0.19834096883362878 with a P-value of P= 2.459085535116766e-13

```
In [230]: plt.figure(figsize=(10, 6))
    sns.regplot(x='children', y='charges', data=insurancedata)
    plt.title('Regression Plot of charges by children')
```

 ${\tt Out[230]:}$  Text(0.5, 1.0, 'Regression Plot of charges by children')



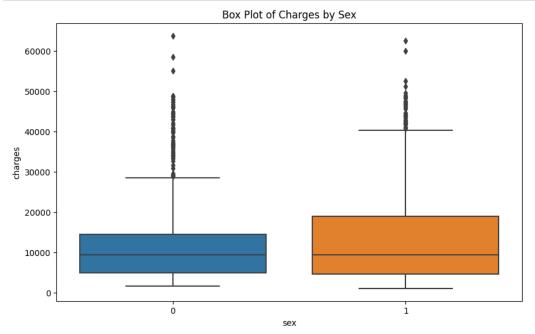
```
In [231]: pearson_coef_children, p_value_children = stats.pearsonr(insurancedata['children'], insurancedata['charges'])
print("The Pearson Correlation Coefficient between children and charges is", pearson_coef_children, "with a P-value of P=", p_value_children)

...
```

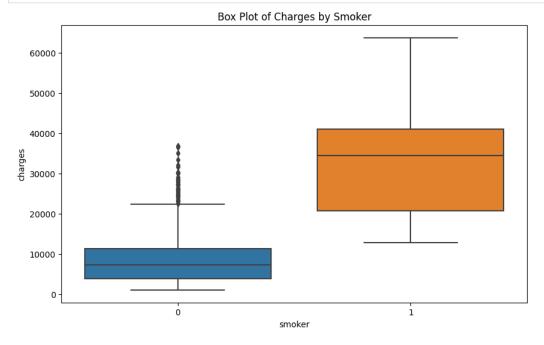
The Pearson Correlation Coefficient between children and charges is 0.06799822684790464 with a P-value of P= 0.012852128520136508

```
In [232]: import seaborn as sns import matplotlib.pyplot as plt
```

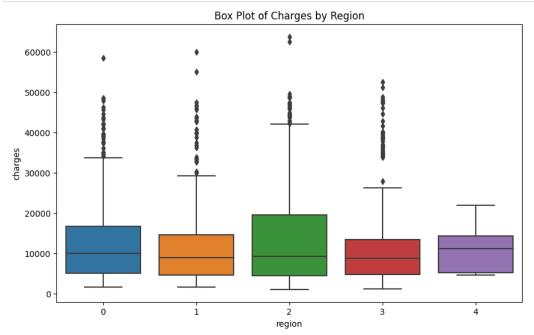
```
In [233]: plt.figure(figsize=(10, 6))
    sns.boxplot(x='sex', y='charges', data=insurancedata)
    plt.title('Box Plot of Charges by Sex')
    plt.show()
```



```
In [234]: plt.figure(figsize=(10, 6))
    sns.boxplot(x='smoker', y='charges', data=insurancedata)
    plt.title('Box Plot of Charges by Smoker')
    plt.show()
```



```
In [235]: plt.figure(figsize=(10, 6))
    sns.boxplot(x='region', y='charges', data=insurancedata)
    plt.title('Box Plot of Charges by Region')
    plt.show()
```



```
In [236]: data = insurancedata.drop(['region', 'sex', 'smoker'], axis=1)
```

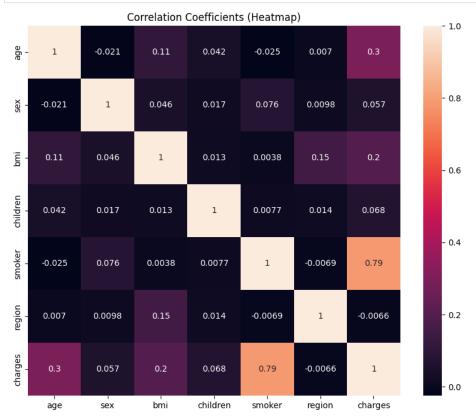
In [237]: data.head(5)

Out[237]:

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

In [238]: import matplotlib.pyplot as plt import seaborn as sns

```
In [226]:
plt.figure(figsize=(10, 8))
sns.heatmap(data.corr(), annot=True)
plt.title('Correlation Coefficients (Heatmap)')
plt.show()
```



In [165]: insurancedata.head(5)

Out[165]:

	age	sex	ıma	children	smoker	region	cnarges
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	NaN	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

In [166]: insurancedata.shape

Out[166]: (1338, 7)

In [170]: # Check for missing values

print(insurancedata.isnull().sum())

age 0
sex 0
bmi 0
children 0
smoker 0
region 5
charges 0
dtype: int64

In [173]: data=insurancedata.dropna()

In [175]: # Check for missing values
print(data.isnull().sum())

age 0 sex 0 bmi 0 children 0 smoker 0 region 0 charges 0

dtype: int64

```
In [176]: data.dtypes
Out[176]: age
                            int64
                           object
            bmi
                          float64
            children
                            int64
                           object
            smoker
            region
                           object
                          float64
            charges
            dtype: object
In [177]: from sklearn.preprocessing import LabelEncoder
            # Label encoding
            label_encoder = LabelEncoder()
           insurancedata['sex'] = label_encoder.fit_transform(insurancedata['sex'])
insurancedata['smoker'] = label_encoder.fit_transform(insurancedata['smoker'])
insurancedata['region'] = label_encoder.fit_transform(insurancedata['region'])
In [178]: data.head(10)
Out[178]:
                age
                        Sex
                             hmi children smoker
                                                      region
                                                                 charges
                            27.90
                                                              16884.92400
                  19
                     female
                                                    southwest
                  18
                       male 33.77
                                                no
                                                    southeast
                                                               1725.55230
                 28
                            33.00
                                         3
                                                    southeast
                                                               4449.46200
                       male
                                                no
                 32
                      male 28.88
                                         0
                                                no
                                                    northwest
                                                              3866.85520
                                                    southeast
                                                              3756.62160
                                                              8240.58960
                     female
                            33.44
                                                no
                                                    southeast
                            27.74
                                                    northwest
                                                              7281.50560
                                         2
                                                               6406.41070
                            29.83
                                                    northeast
                                                no
                 60
                     female 25.84
                                         Ω
                                                no northwest 28923.13692
                25
                                                no northeast 2721.32080
                      male 26.22
In [243]: import scipy.stats as stats
            data = stats.zscore(insurancedata)
In [244]: data
Out[244]:
                                                 children
                        age
                                                                      region
                0 -1.438764 -1.010519 -0.453320 -0.908614
                                                          1.970587
                                                                    1.324162
                                                                              0.298584
                1 -1.509965 0.989591
                                       0.509621 -0.078767
                                                          -0.507463
                                                                    0.425719 -0.953689
               2 -0.797954 0.989591 0.383307 1.580926 -0.507463 0.425719 -0.728675
                3 -0.441948 0.989591 -1.305531 -0.908614 -0.507463 2.222604 0.719843
                4 -0.513149  0.989591 -0.292556 -0.908614 -0.507463 -0.472723 -0.776802
                  1333
             1334 -1.509965 -1.010519 0.206139 -0.908614 -0.507463 -1.371165 -0.914002
                  -1.509965 -1.010519 1.014878 -0.908614 -0.507463 0.425719 -0.961596
            1336 -1.296362 -1.010519 -0.797813 -0.908614 -0.507463 1.324162 -0.930362
             1337
                  1.551686 -1.010519 -0.261388 -0.908614 1.970587 -0.472723 1.311053
            1338 rows × 7 columns
In [259]: import pandas as pd
           from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Lasso
            from sklearn.ensemble import RandomForestRegressor
            from sklearn.metrics import mean_squared_error
            import seaborn as sns
            import matplotlib.pyplot as plt
In [260]: X = insurancedata.drop(['charges'], axis=1)
           y = insurancedata['charges']
In [261]: # Split the data into training and testing datasets
            X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
In [262]: # Multiple Linear Regression
            lr = LinearRegression()
            lr.fit(X_train, y_train)
Out[262]: LinearRegression
            LinearRegression()
```

```
In [263]: # Making predictions
              y_pred_lr = lr.predict(X_test)
In [264]: # Evaluate the model
              mse_lr = mean_squared_error(y_test, y_pred_lr)
              print('MSE for Linear Regression: ', mse_lr)
              MSE for Linear Regression: 31882830.66682946
In [265]: # Random Forest Regressor
              rf = RandomForestRegressor()
              rf.fit(X_train, y_train)
Out[265]:
              ▼ RandomForestRegressor
              RandomForestRegressor()
In [266]: # Making predictions
y_pred_rf = rf.predict(X_test)
In [267]: # Evaluate the model
              mse_rf = mean_squared_error(y_test, y_pred_rf)
print('MSE for Random Forest: ', mse_rf)
              MSE for Random Forest: 19699405.91022278
In [268]: # LASSO Regression
lasso = Lasso()
              lasso.fit(X_train, y_train)
Lasso()
In [269]: # Making predictions
              y_pred_lasso = lasso.predict(X_test)
In [270]: # Evaluate the model
    mse_lasso = mean_squared_error(y_test, y_pred_lasso)
    print('MSE for LASSO is: ', mse_lasso)
              MSE for LASSO is: 31887412.635049313
In [271]: # Compare performance of models using bar plot
mse_scores = [('Linear Regression', mse_lr), ('Random Forest', mse_rf), ('LASSO', mse_lasso)]
mse_df = pd.DataFrame(data = mse_scores, columns=['Model', 'MSE Score'])
mse_df.sort_values(by='MSE Score', ascending=True, inplace=True)
In [272]: f, axe = plt.subplots(1,1, figsize=(10,5))
sns.barplot(x = mse_df['Model'], y = mse_df['MSE Score'], ax = axe)
              plt.title('MSE Comparison')
              plt.xlabel('Model')
              plt.ylabel('MSE')
              plt.show()
                                                                              MSE Comparison
                         1e7
                   3.0
                   2.5
                   2.0
                MSE
                   1.5
                   1.0
                   0.5
                   0.0
                                                                               Linear Regression
                                      Random Forest
                                                                                                                                  LASSO
                                                                                       Model
   In [ ]:
   In [ ]:
```