Developed an automated machine learning model to estimate insurance premiums for new medical insurance policies. The model leverages key input features, including age, gender, BMI, number of dependents, smoking status, and region of residence, to accurately predict premium charges.


```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sn
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRFRegressor
```

```
df = pd.read_csv("/content/sample_data/insurance.csv")
```

```
df.head()
```

	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

```
# number of rows and columns
df.shape
```

```
(1338, 7)
```

```
df.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
```

Categorical Variables

Sex

Smoker

Region

```
# checking for missing values
df.isnull().sum()
```

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

dtype: int64

```
df.describe()
```

	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

```
import plotly.express as px
import matplotlib
import seaborn as sns
%matplotlib inline
```

The following settings will improve the default style and font sizes for our charts.

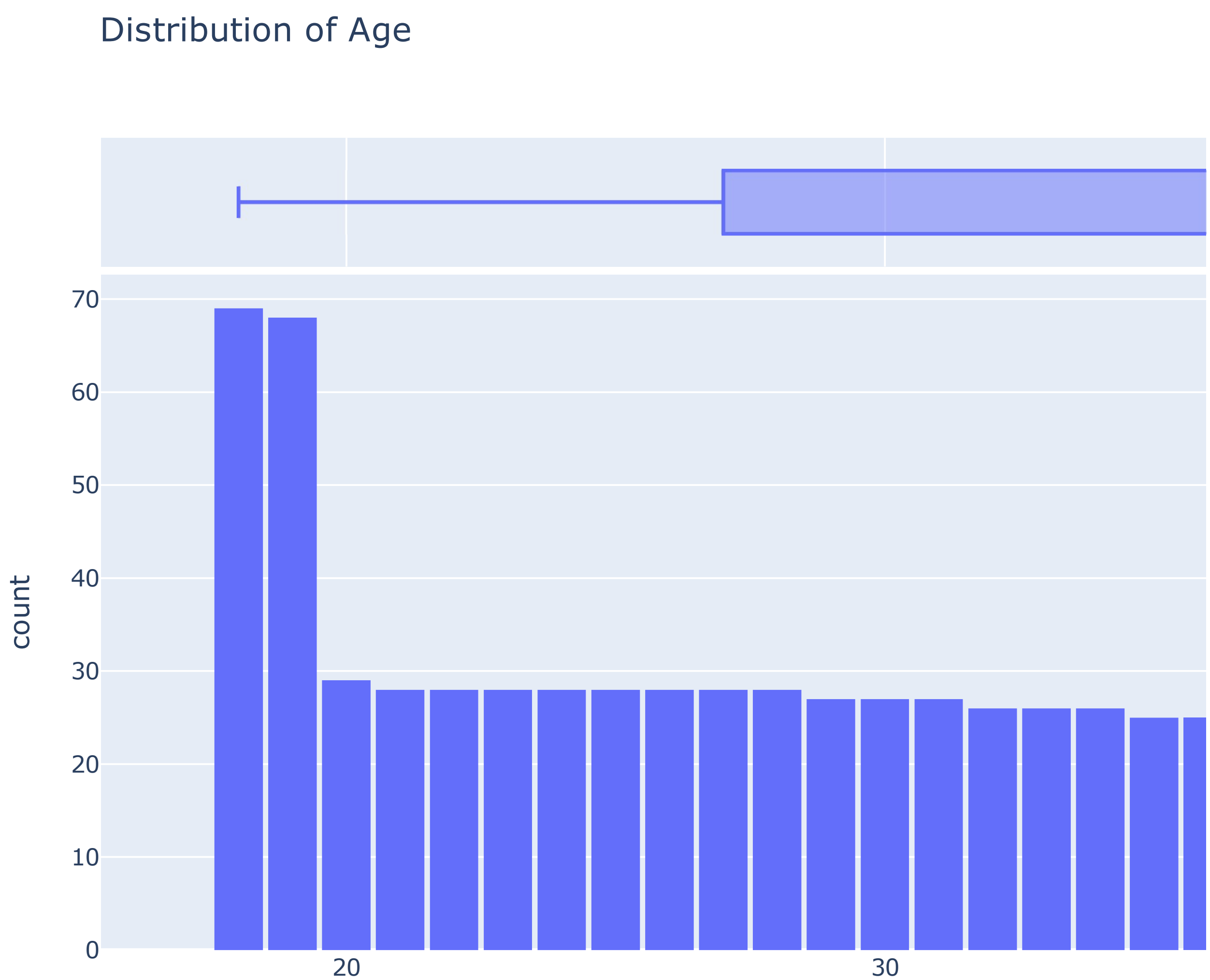
```
df.age.describe()
```

	age
count	1338.000000
mean	39.207025
std	14.049960
min	18.000000
25%	27.000000
50%	39.000000
75%	51.000000
max	64.000000

dtype: float64

```
fig = px.histogram(df,
                   x='age',
                   marginal='box',
                   nbins=57,
                   title='Distribution of Age')
```

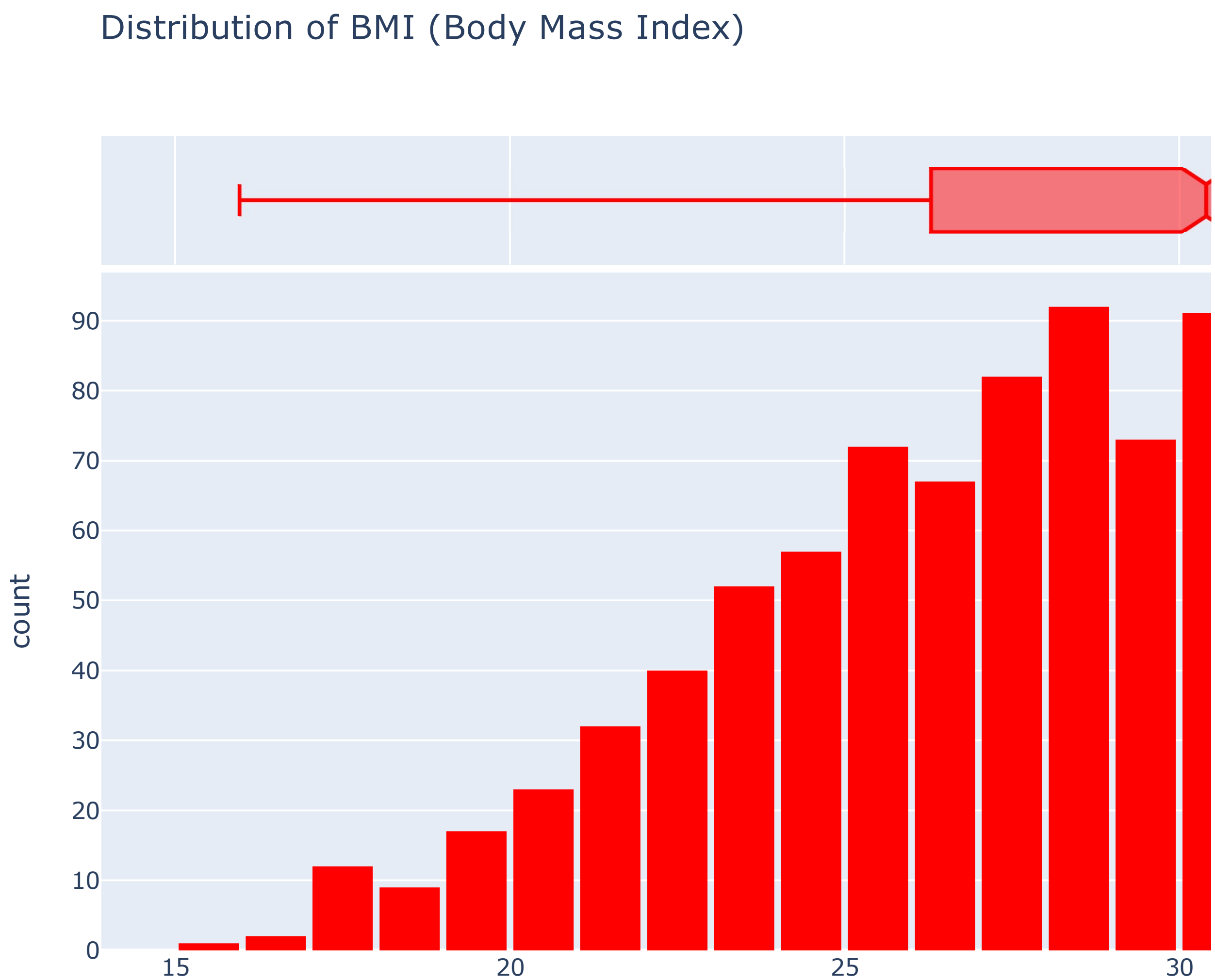
```
fig.update_layout(bargap=0.1, height=600)
fig.show()
```



Body Mass Index

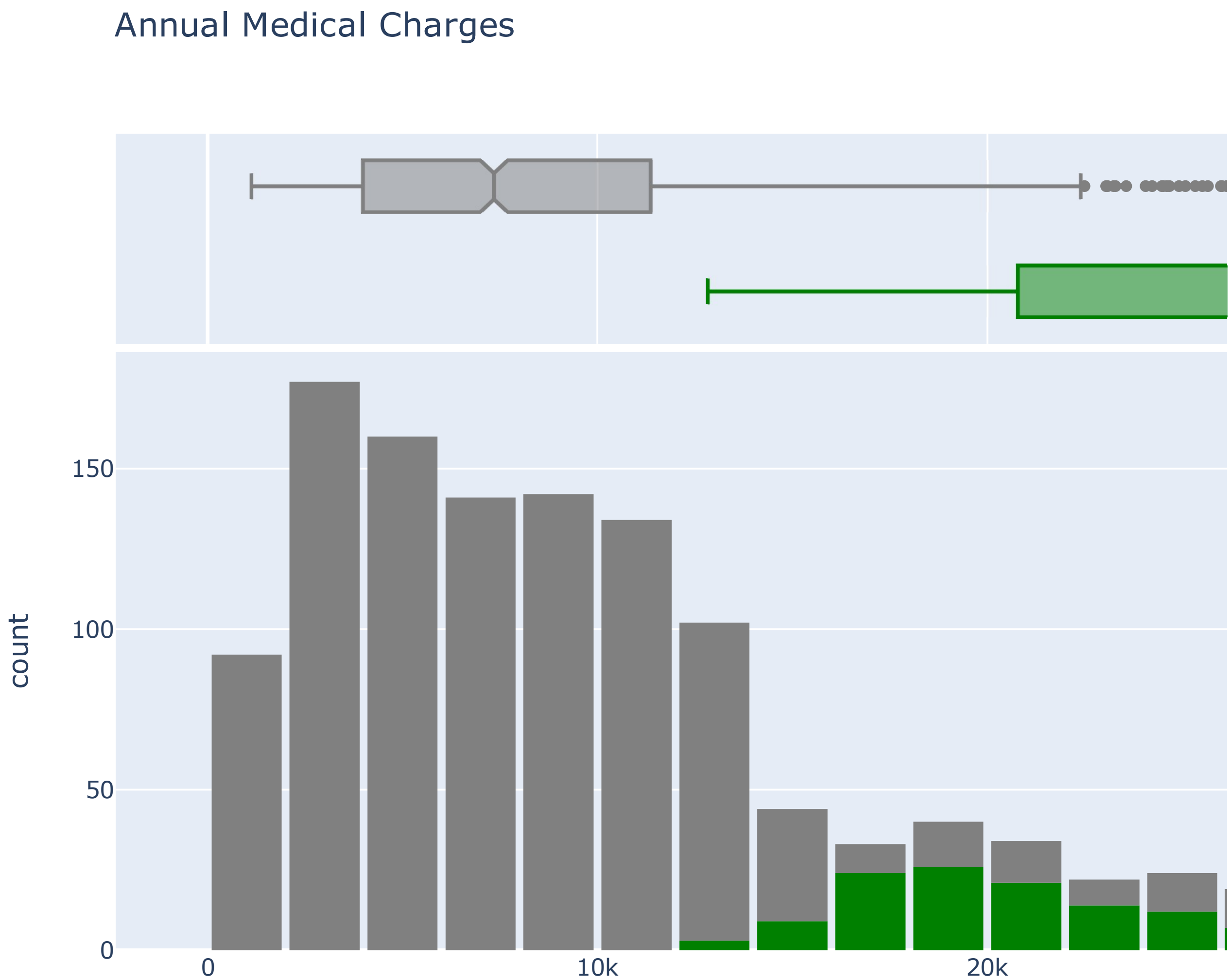
The distribution of BMI (Body Mass Index) of customers, using a histogram and box plot.

```
fig = px.histogram(df,
                   x='bmi',
                   marginal='box',
                   color_discrete_sequence=['red'],
                   title='Distribution of BMI (Body Mass Index)')
fig.update_layout(bargap=0.1, height=600)
fig.show()
```



The measurements of body mass index seem to form a Gaussian distribution centered around the value 30, with a few outliers towards the right.

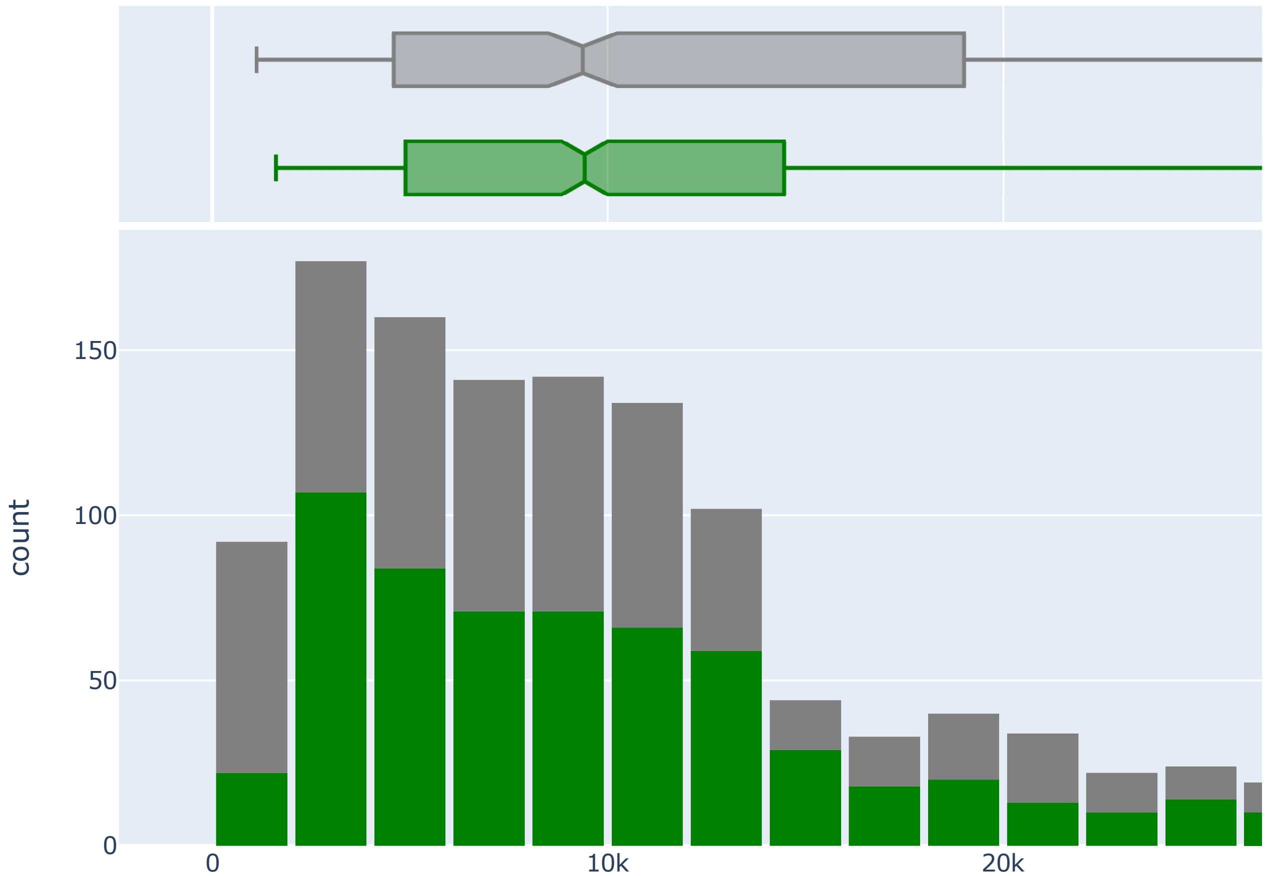
```
fig = px.histogram(df,
                   x='charges',
                   marginal='box',
                   color='smoker',
                   color_discrete_sequence=['green', 'grey'],
                   title='Annual Medical Charges')
fig.update_layout(bargap=0.1, height=600)
fig.show()
```



most customers, the annual medical charges are under $10,000. Only a small fraction of customer have higher medical expenses, possibly due to accidents, major illnesses and genetic diseases. The distribution follows a "power law" There is a significant difference in medical expenses between smokers and non-smokers.

```
fig = px.histogram(df,
                   x='charges',
                   marginal='box',
                   color='sex',
                   color_discrete_sequence=['green', 'grey'],
                   title='Annual Medical Charges')
fig.update_layout(bargap=0.1, height=600)
fig.show()
```

Annual Medical Charges



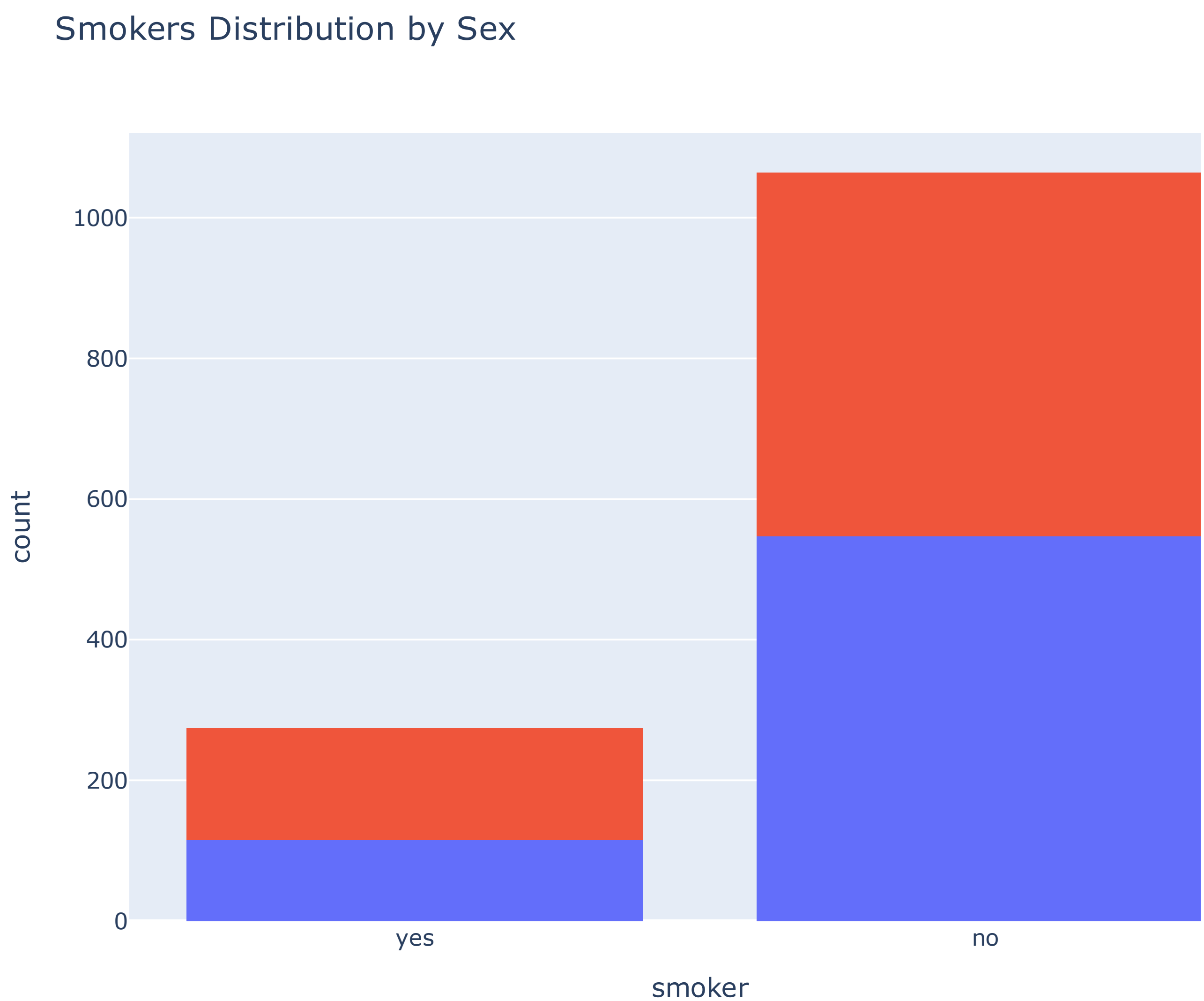

```
#Smoker
df.smoker.value_counts()
```

smoker	count
no	1064
yes	274

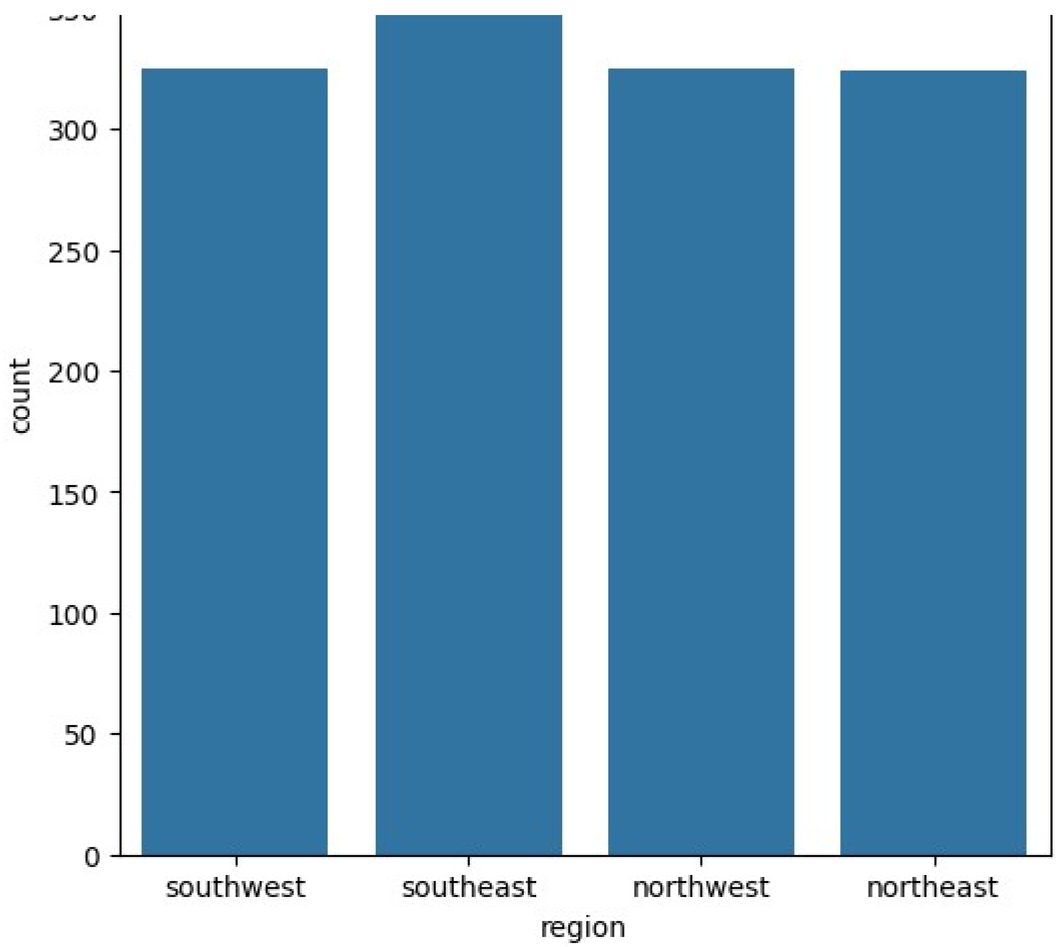
dtype: int64

```
#Smokers Distribution by Sex
fig = px.histogram(
    df,
    x='smoker',
    color='sex',
    title='Smokers Distribution by Sex'
)
```

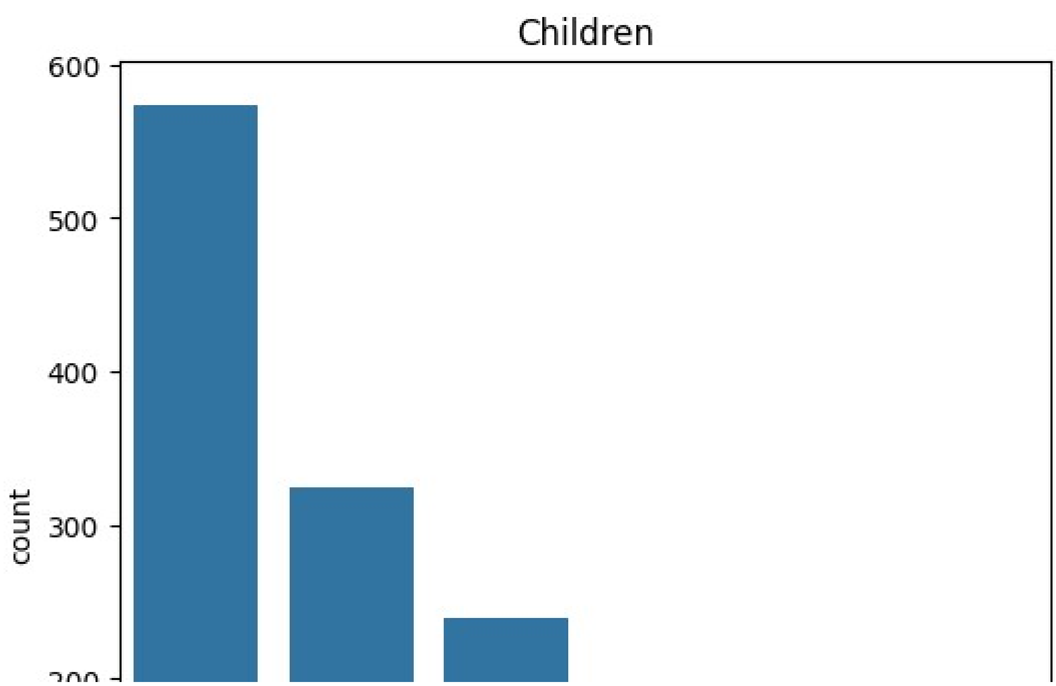
```
fig.update_layout(
    width=800,
    height=600
)

fig.show()
```

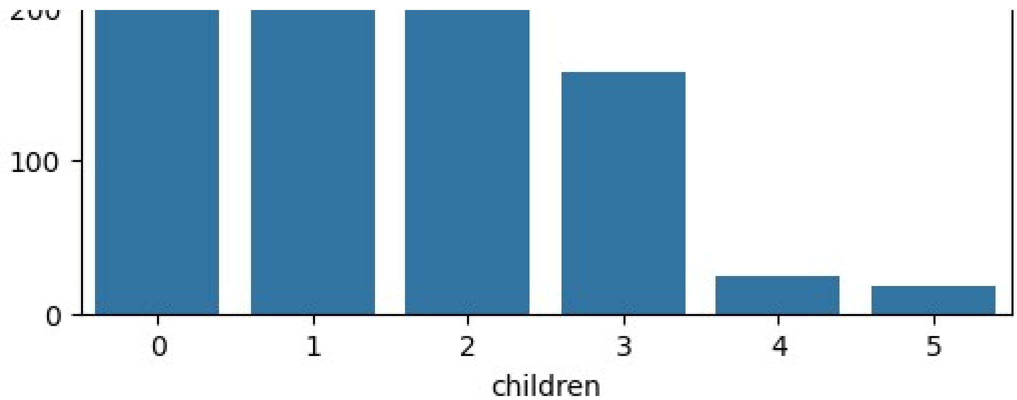



```
# region column
plt.figure(figsize=(6,6))
sn.countplot(x='region', data=df)
plt.title('region')
plt.show()
```




```
# children column
plt.figure(figsize=(6,6))
sn.countplot(x='children', data=df)
plt.title('Children')
plt.show()
```



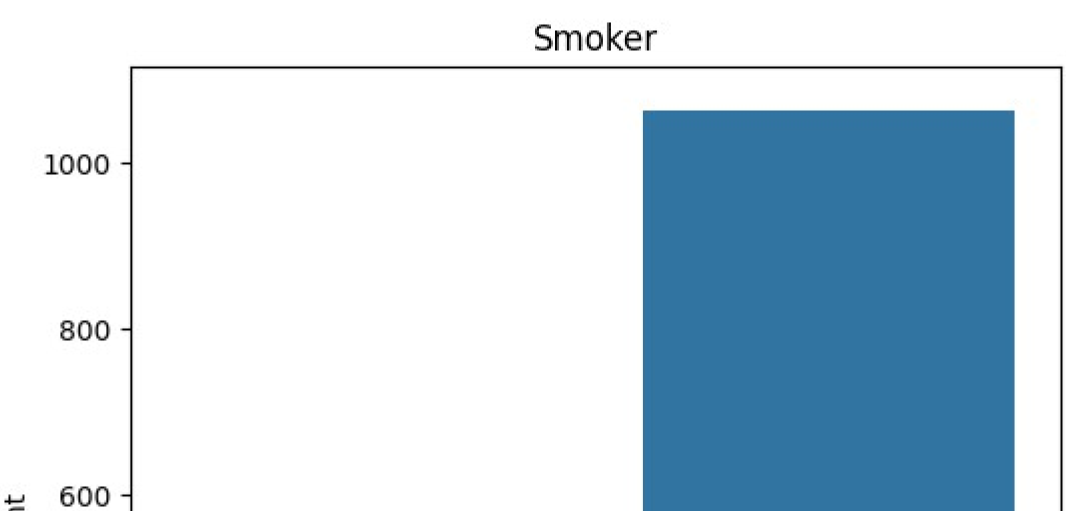


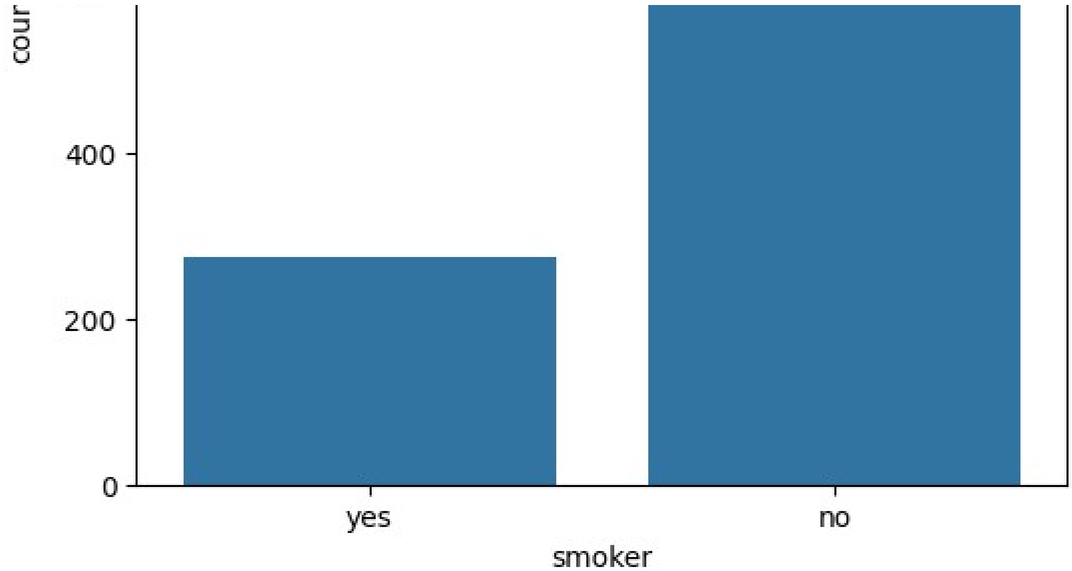

```
df['children'].value_counts()
```

children	count
0	574
1	324
2	240
3	157
4	25
5	18

dtype: int64

```
# region column
plt.figure(figsize=(6,6))
sn.countplot(x='smoker', data=df)
plt.title('Smoker')
plt.show()
```



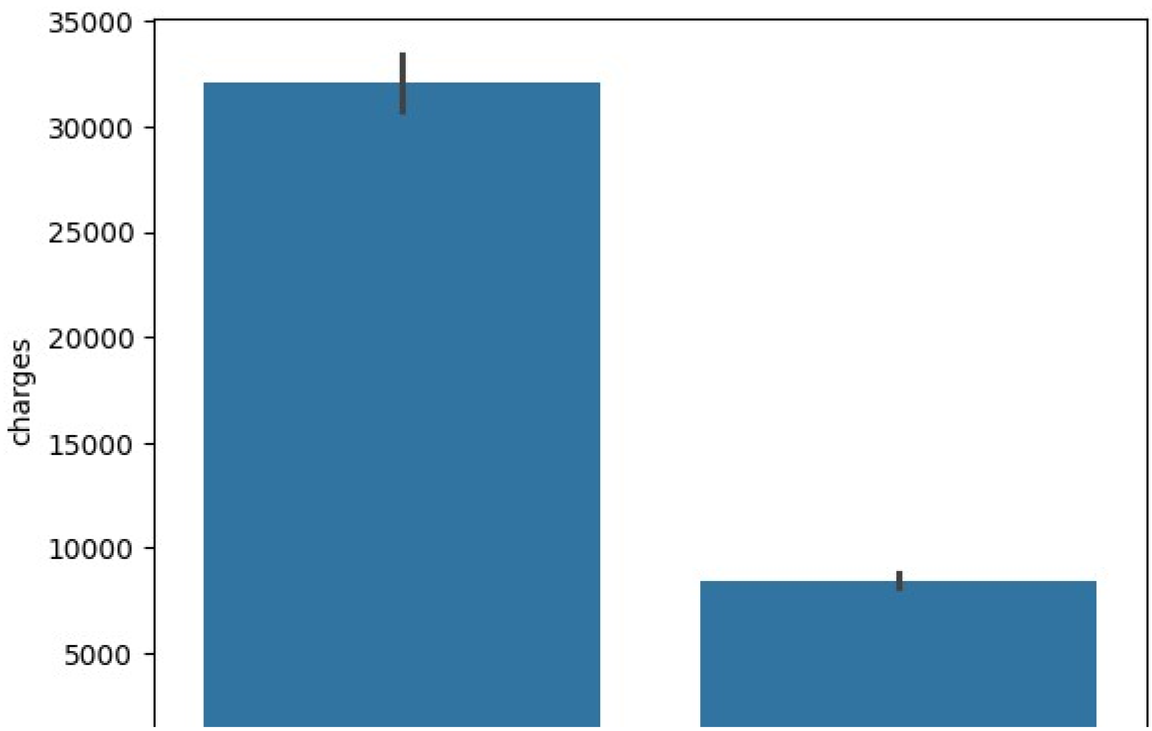



```
df['smoker'].value_counts()
```

smoker	count
no	1064
yes	274

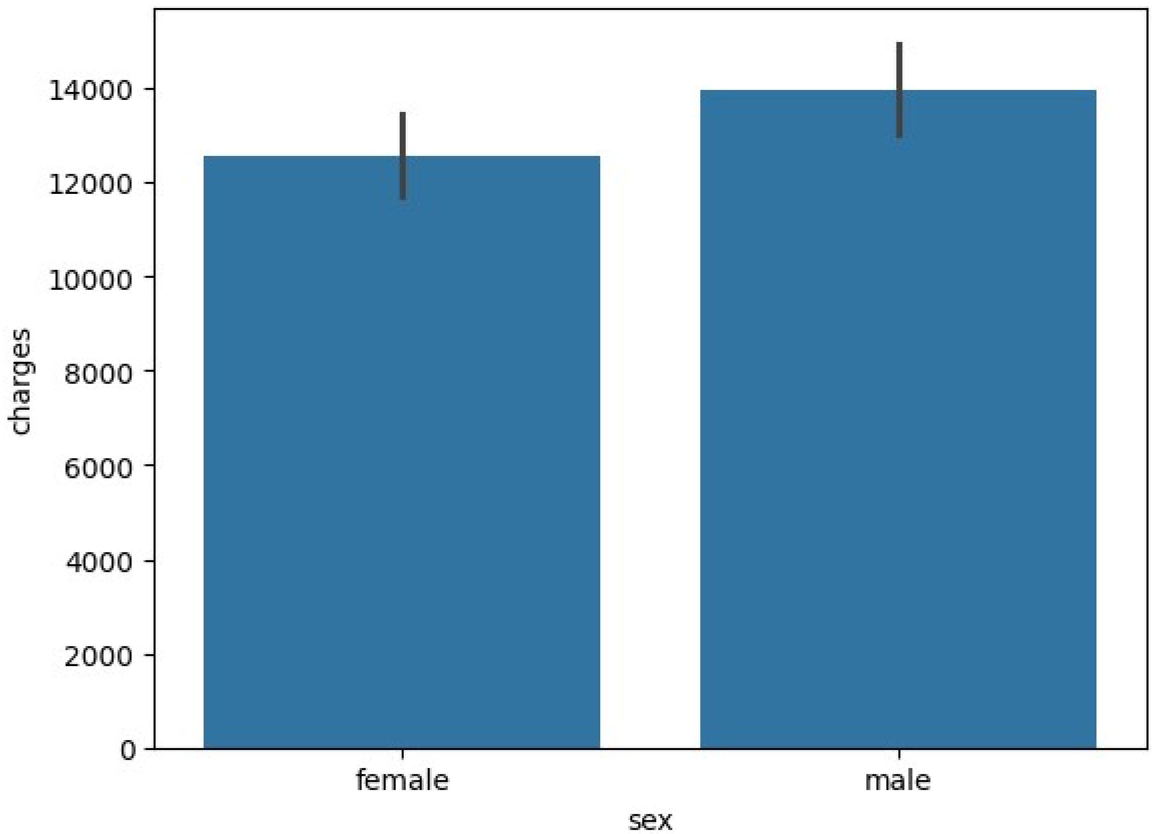
dtype: int64

```
sns.barplot(data=df, x='smoker', y='charges');
```

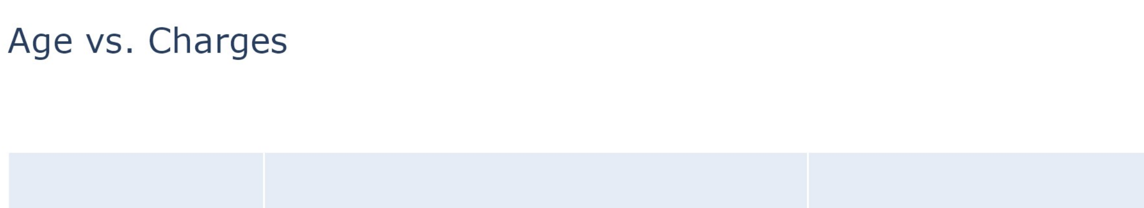


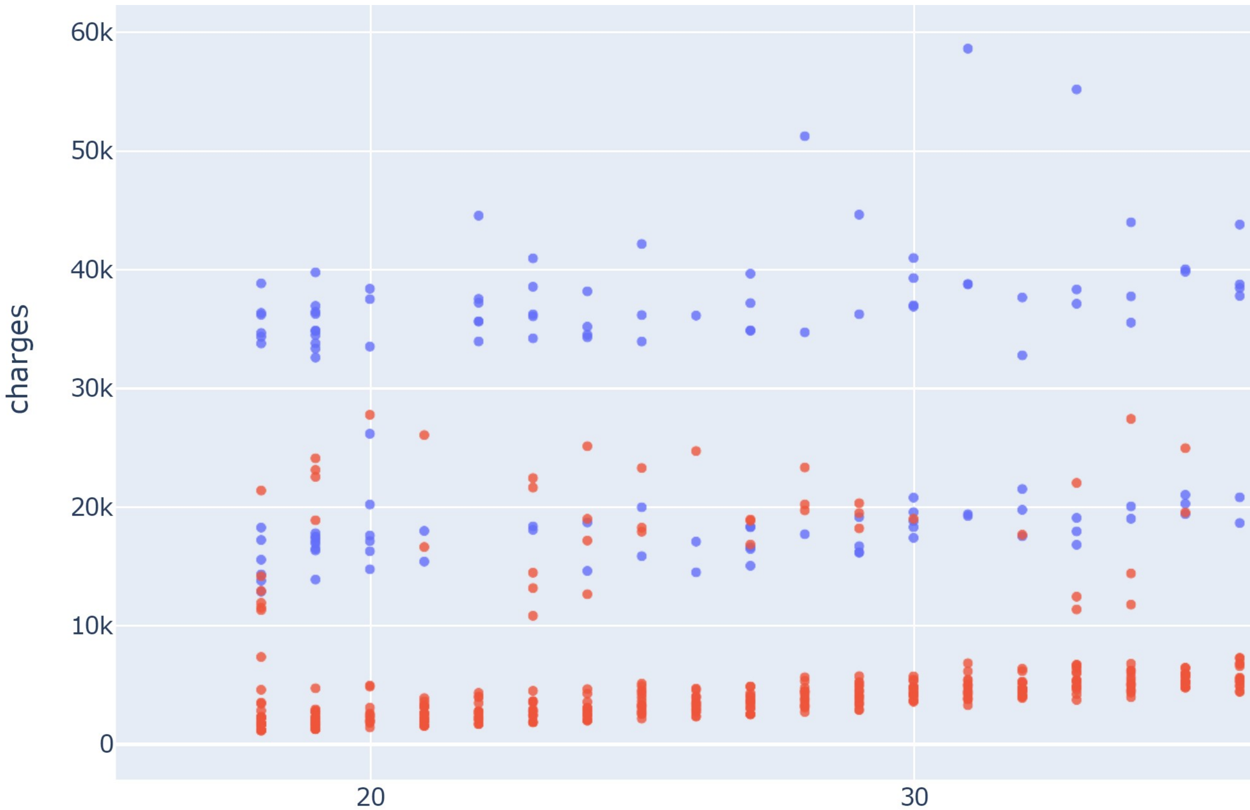

```
sns.barplot(data=df, x='sex', y='charges')
```

<Axes: xlabel='sex', ylabel='charges'>

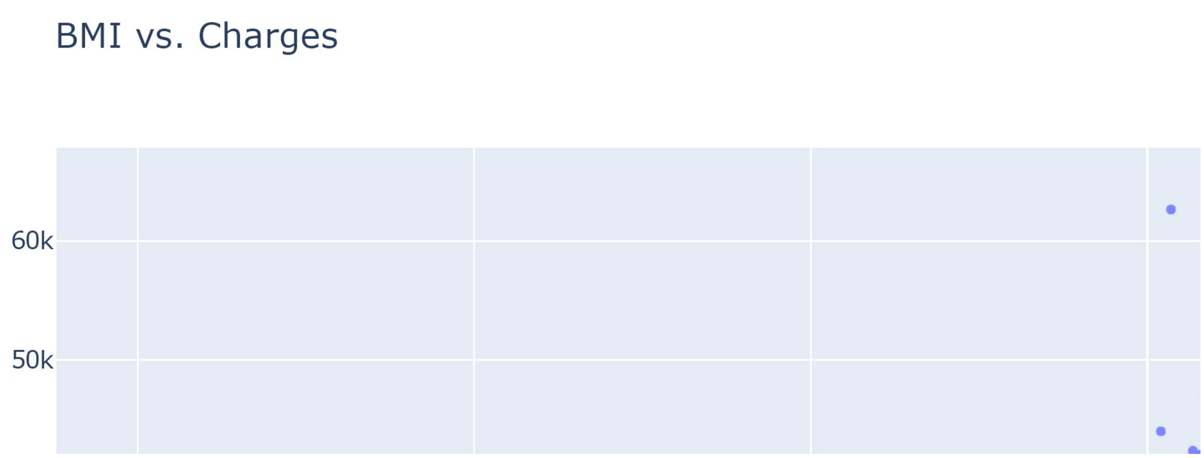


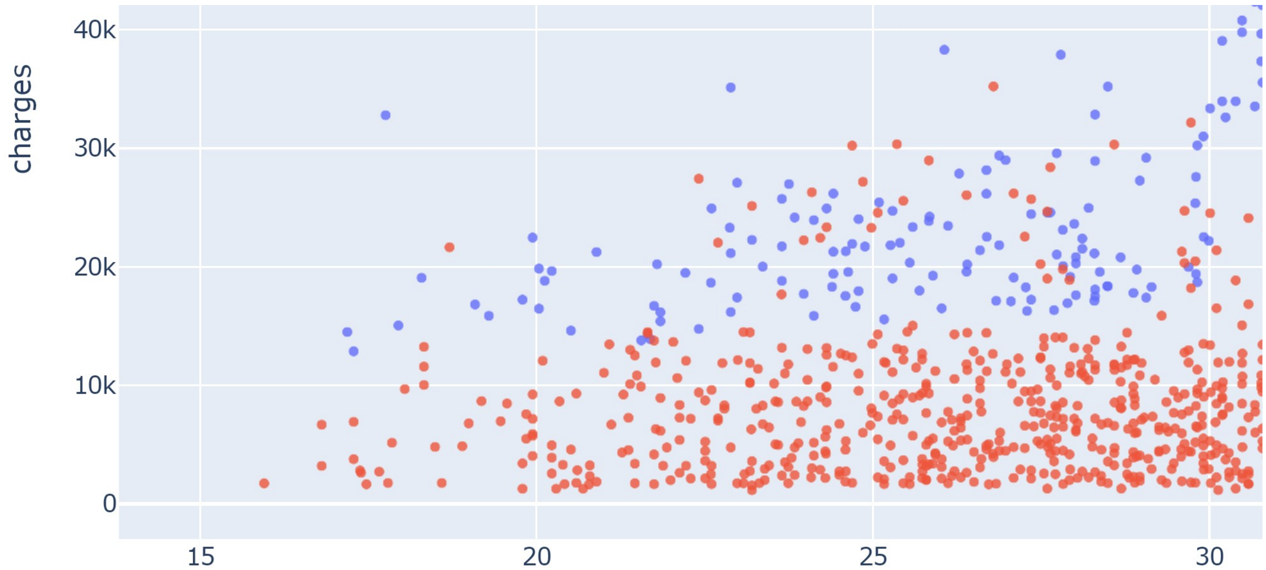

```
fig = px.scatter(df,
                 x='age',
                 y='charges',
                 color='smoker',
                 opacity=0.8,
                 hover_data=['sex'],
                 height=600,
                 title='Age vs. Charges')
fig.update_traces(marker_size= 5)
fig.show()
```






```
fig = px.scatter(df,
                 x='bmi',
                 y='charges',
                 color='smoker',
                 opacity=0.8,
                 hover_data=['sex'],
                 height=600,
                 title='BMI vs. Charges')
fig.update_traces(marker_size=5)
fig.show()
```






```
smoker_values = {'no': 0, 'yes': 1}
smoker_numeric = df.smoker.map(smoker_values)
df.charges.corr(smoker_numeric)
```

```
0.787251430498478
```

```
sex_values = {'male': 0, 'female': 1}
sex_numeric = df.sex.map(sex_values)
df.charges.corr(sex_numeric)
```

```
-0.057292062202025484
```

```
# Encode non-numeric columns
for column in df.select_dtypes(include=['object']).columns:
    encoder = LabelEncoder()
    df[column] = encoder.fit_transform(df[column])
```

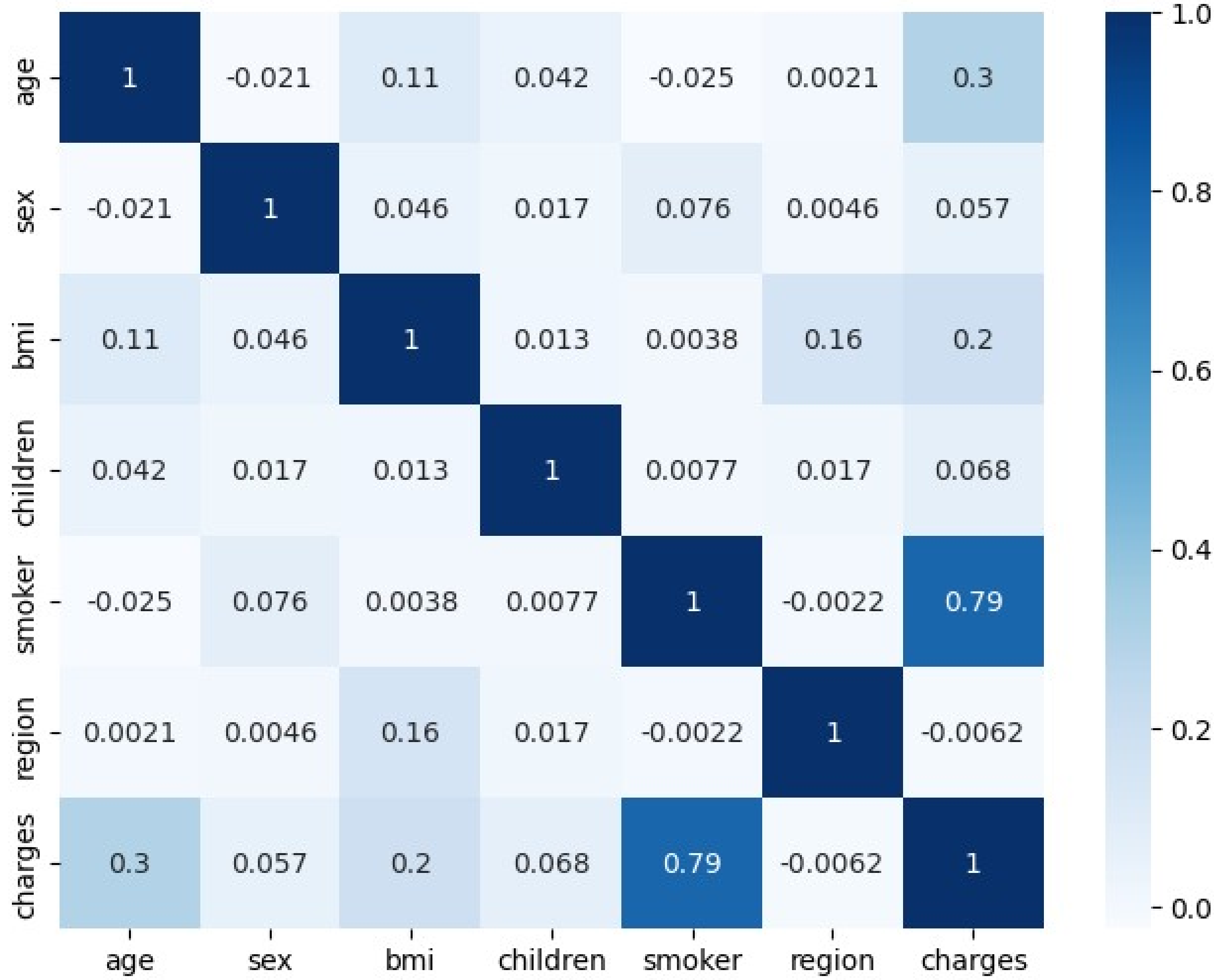
```
df.corr()
```

	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

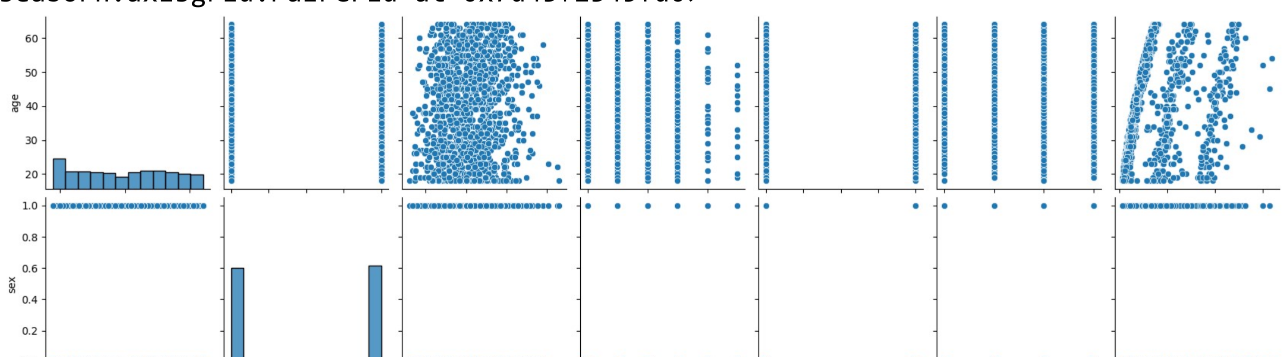
```
#Heatmap
plt.figure(figsize=(8,6))
sn.heatmap(df.corr(), annot=True, cmap='Blues')
```

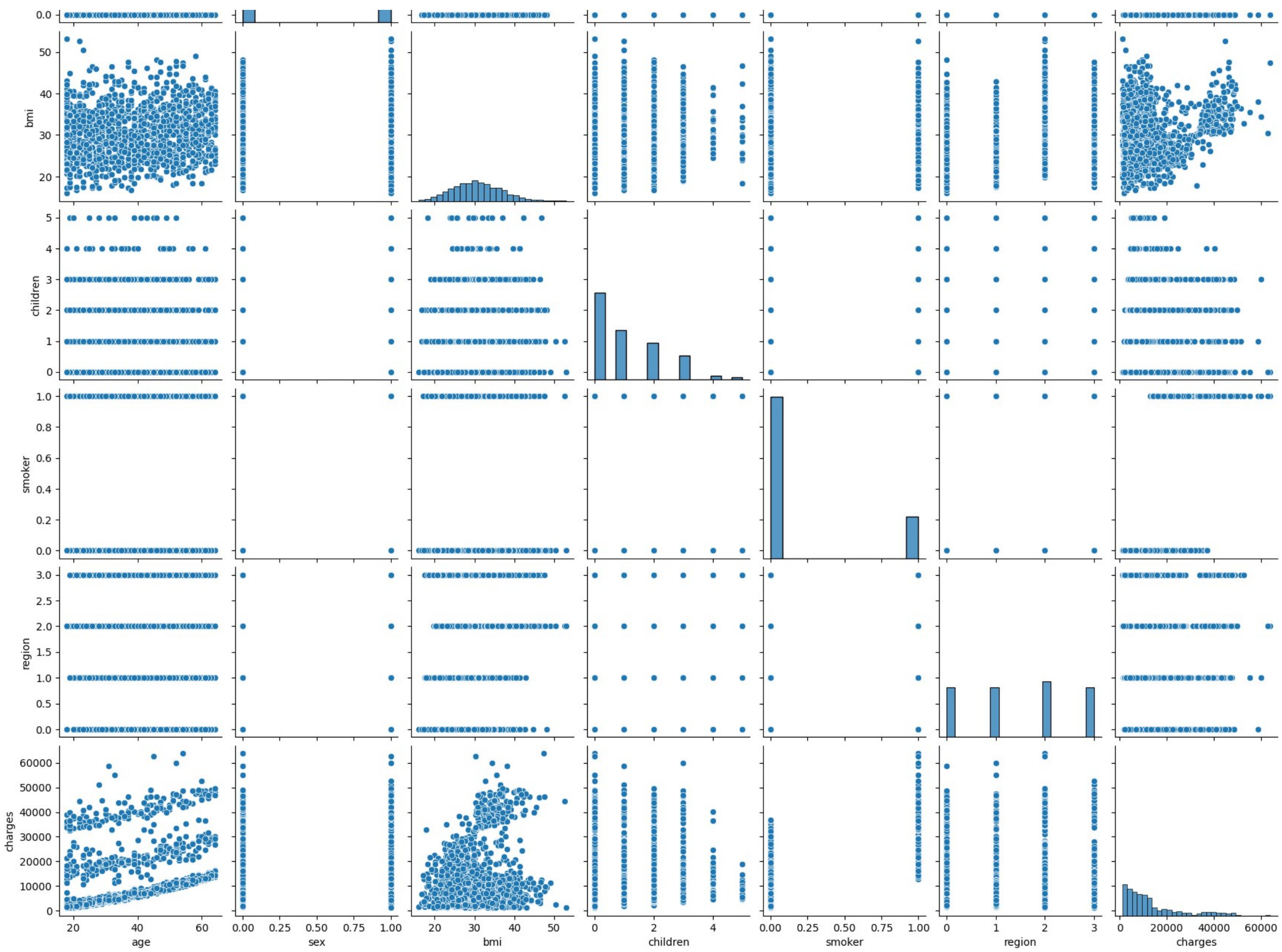
<Axes: >




```
sn.pairplot(df)
```

<seaborn.axisgrid.PairGrid at 0x7d43f2345fd0>




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

```
df.head()
```

	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

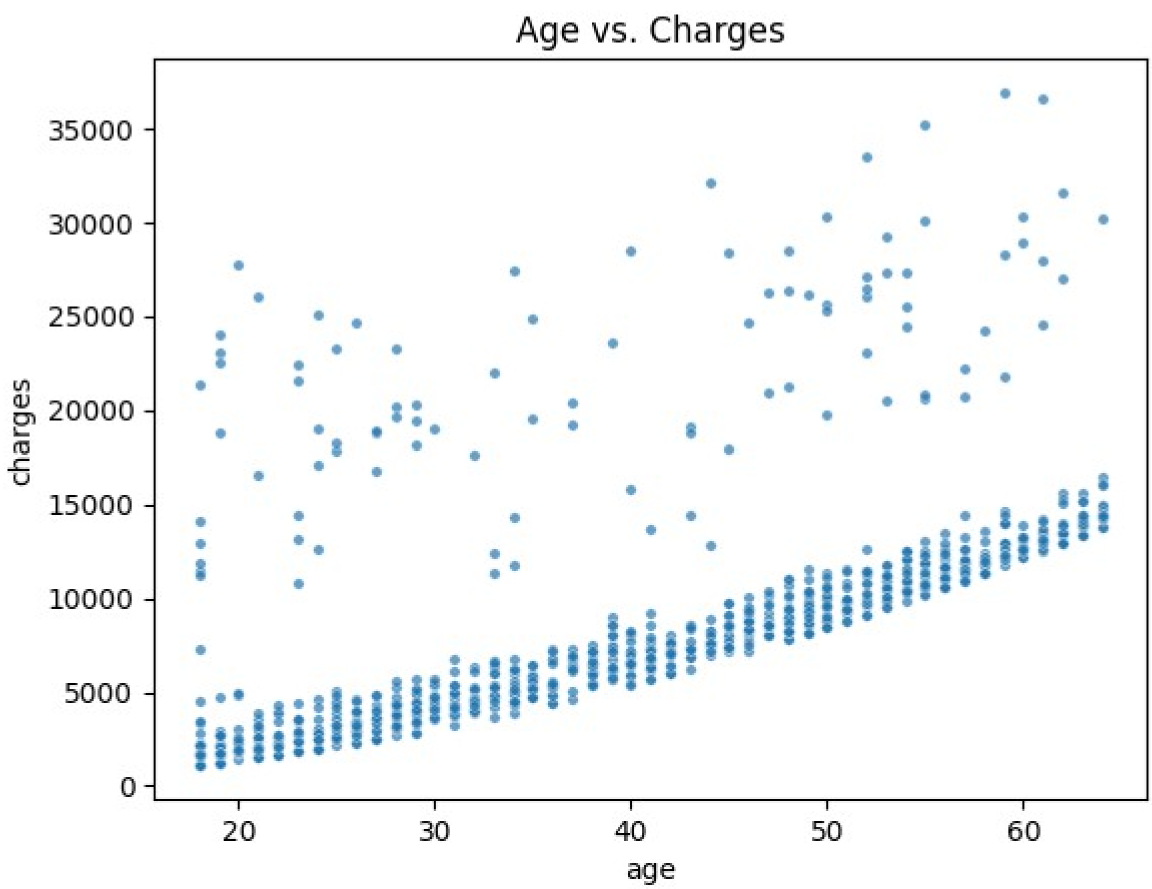
```
non_smoker_df = df[df.smoker == 0]
```

```
non_smoker_df.head(4)
```

	age	sex	bmi	children	smoker	region	charges
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

```
plt.title('Age vs. Charges')
sns.scatterplot(data=non_smoker_df, x='age', y='charges', alpha=0.7, s=15);
```



Model

In the above case, the x axis shows "age" and the y axis shows "charges". Thus, we're assuming the following relationship between the two:

charges=w×age+b

We'll try determine ww and bb for the line that best fits the data.

```
This technique is called linear regression, and we call the above equation a linear regression model,

The numbers ww and bb are called the parameters or weights of the model.

The values in the "age" column of the dataset are called the inputs to the model and the values in th
```

Let define a helper function estimate_charges, to compute charges, given age, w and b.

```
#create a function
def estimate_charges(age, w, b):
    return w * age + b
```

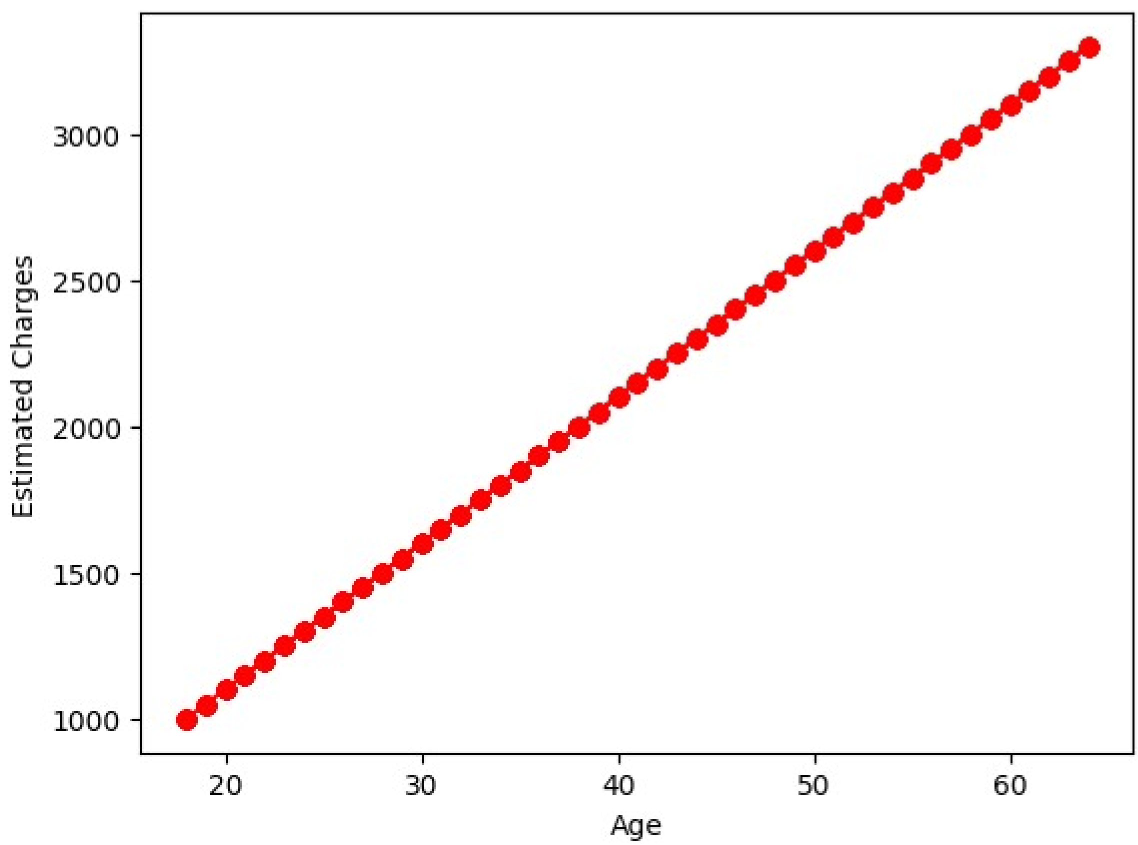
The estimate_charges function is our very first model.

Let's guess the values for w and b and use them to estimate the value for charges.

```
w = 50
b = 100
```

```
ages = non_smoker_df.age
estimated_charges = estimate_charges(ages, w, b)
```

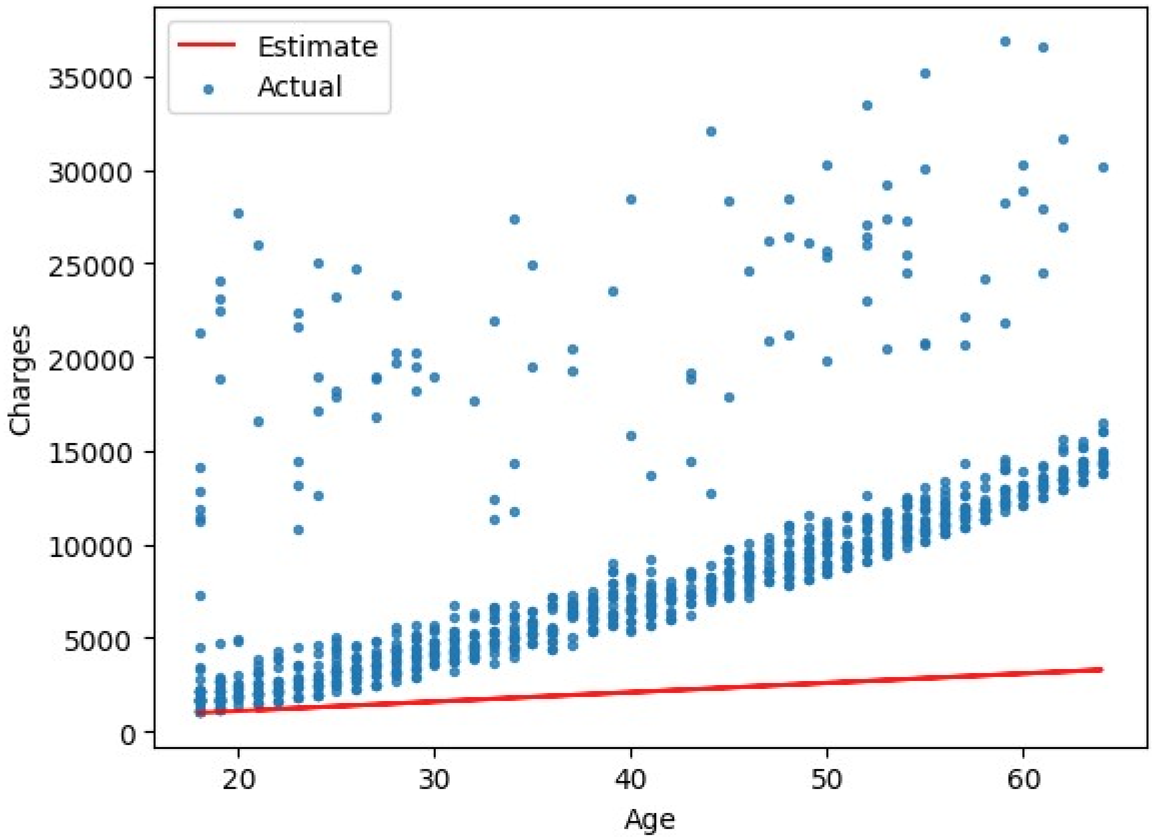
```
plt.plot(ages, estimated_charges, 'r-o');
plt.xlabel('Age');
plt.ylabel('Estimated Charges');
```



As expected, the points lie on a straight line.

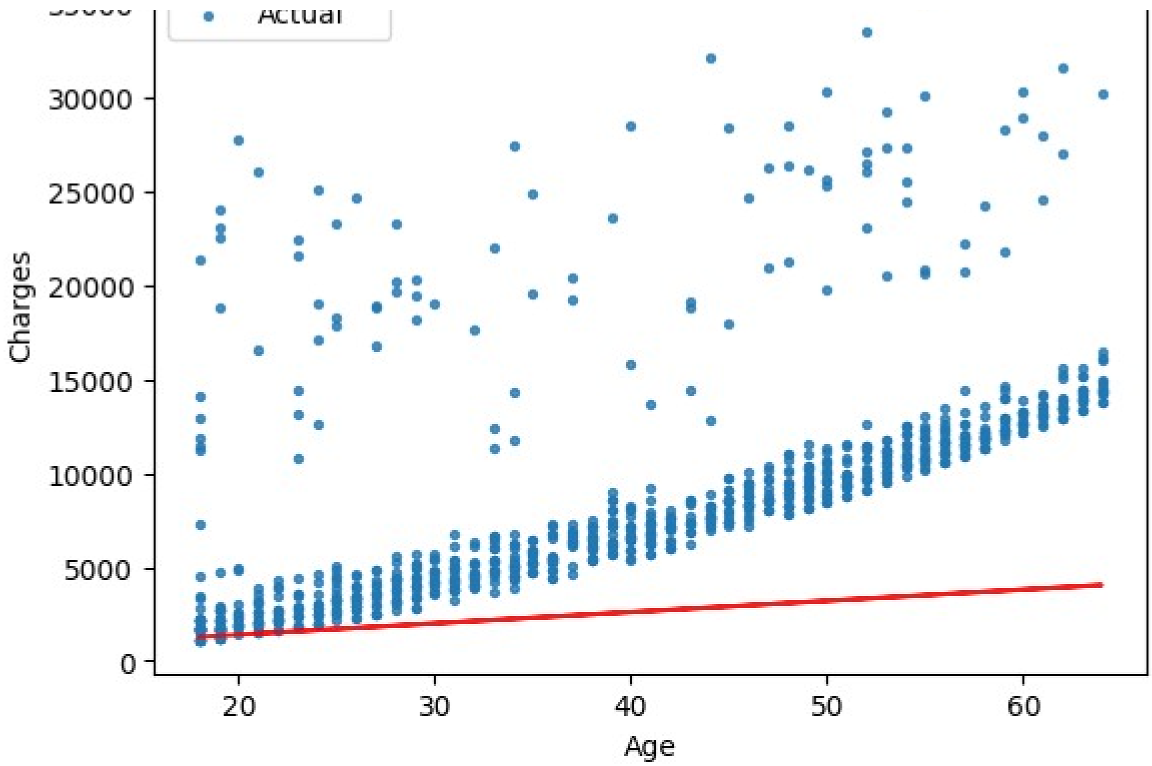
We can overlay this line on the actual data, so see how well our model fits the data.

```
target = non_smoker_df.charges

plt.plot(ages, estimated_charges, 'r', alpha=0.9);
plt.scatter(ages, target, s=8,alpha=0.8);
plt.xlabel('Age');
plt.ylabel('Charges')
plt.legend(['Estimate', 'Actual']);
```




```
def try_parameters(w, b):
    ages = non_smoker_df.age
    target = non_smoker_df.charges

    estimated_charges = estimate_charges(ages, w, b)

    plt.plot(ages, estimated_charges, 'r', alpha=0.9);
    plt.scatter(ages, target, s=8,alpha=0.8);
    plt.xlabel('Age');
    plt.ylabel('Charges')
    plt.legend(['Estimate', 'Actual']);
```

```
try_parameters(60, 200)
```



Loss/Cost Function

We can compare our model's predictions with the actual targets using the following method:

```
Calculate the difference between the targets and predictions (the differenced is called the "residual
Square all elements of the difference matrix to remove negative values.
Calculate the average of the elements in the resulting matrix.
Take the square root of the result
```

The result is a single number, known as the root mean squared error (RMSE). The above description can be stated mathematically as follows: WCanPkA.png

Geometrically, the residuals can be visualized as follows: Il3NL80.png

Let's define a function to compute the RMSE.

```
def rmse(targets, predictions):
    return np.sqrt(np.mean(np.square(targets - predictions)))
```

Let's compute the RMSE for our model with a sample set of weights

```
targets = non_smoker_df['charges']
```

```
predicted = estimate_charges(non_smoker_df.age, w, b)
```

```
rmse(targets, predicted)
```

```
8461.949562575493
```

Linear Regression using Scikit-learn

In practice, you'll never need to implement either of the above methods yourself. You can use a library like scikit-learn to do this for you.

```
model = LinearRegression()
```

```
inputs = non_smoker_df[['age']]
targets = non_smoker_df.charges
print('inputs.shape :', inputs.shape)
print('targes.shape :', targets.shape)
```

```
inputs.shape : (1064, 1)
targes.shape : (1064,)
```

Model for Non-Smokers

```
#Let's fit the model to the data.

model.fit(inputs, targets)
```

```
▾ LinearRegression  i ?
LinearRegression()
```

```
## We can now make predictions using the model. Let's try predicting the charges for t
model.predict(np.array([[23],
                        [37],
                        [61]]))
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/base.py:439: UserWarning:

X does not have valid feature names, but LinearRegression was fitted with feature

array([ 4055.30443855,  7796.78921819, 14210.76312614])
```

```
predictions = model.predict(inputs)
```

```
predictions
```

```
array([2719.0598744 , 5391.54900271, 6727.79356686, ..., 2719.0598744 ,
       2719.0598744 , 3520.80661289])
```

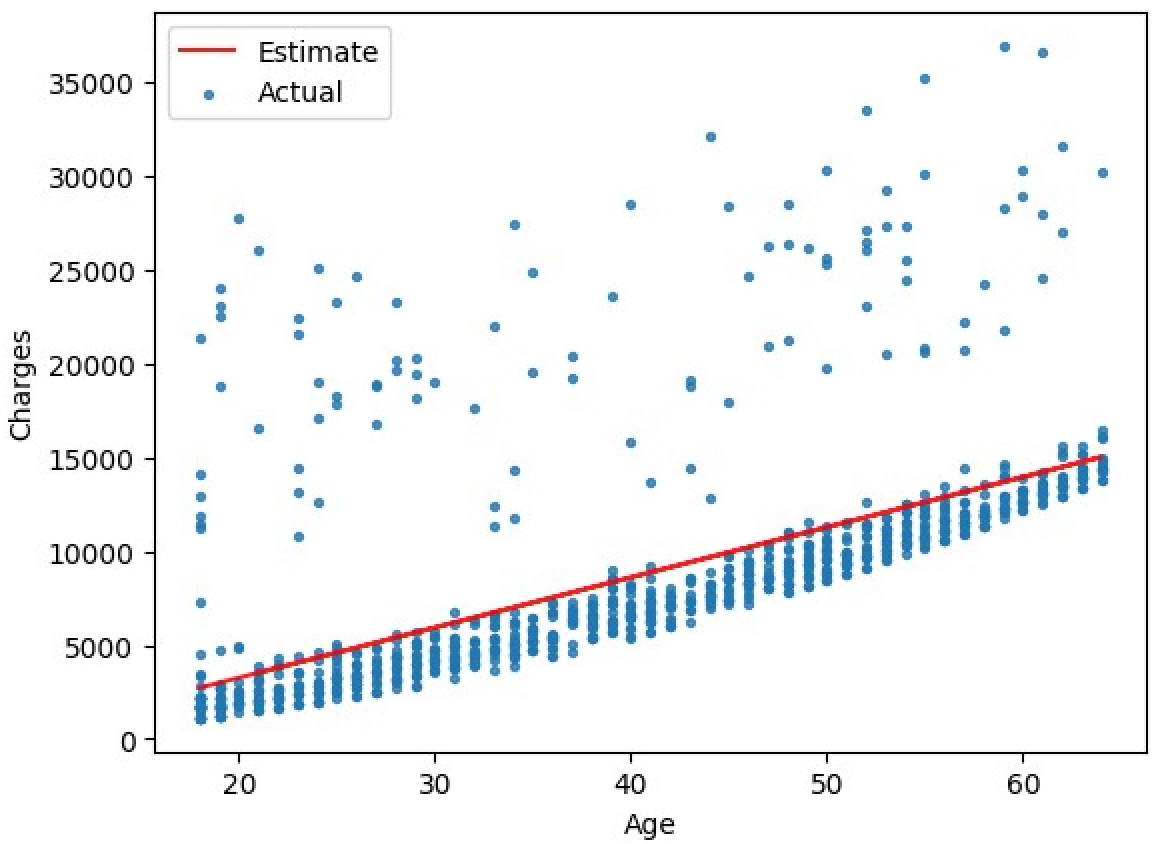
```
rmse(targets, predictions)
```

```
4662.505766636395
```

```
# w & b
model.coef_,model.intercept_
```

```
(array([267.24891283]), -2091.4205565650864)
```

```
try_parameters(model.coef_, model.intercept_)
```




```
X = df.drop(columns='charges', axis=1)
Y = df['charges']
```

```
print('X :', X.shape)
print('Y :', Y.shape)
```

```
X : (1338, 6)
Y : (1338,)
```

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=
```

```
print(X_train.shape, X_test.shape)
```

```
(1070, 6) (268, 6)
```

```
# loading the Linear Regression model
model2 = LinearRegression()
```

First complete Model

```
model2.fit(X_train, Y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
# w & b
model2.coef_,model2.intercept_
```

```
(array([  251.36689613,   -35.4338166 ,   330.76133485,   589.05862101,
        23905.96516848,  -323.62760276]),
 -11747.4671720888)
```

```
cat_cols = ['smoker', 'sex']
categorical_data = df[cat_cols].values
```

```
from sklearn.preprocessing import StandardScaler
```

```
numeric_cols = ['age', 'bmi', 'children', 'region']
scaler = StandardScaler()
scaler.fit(df[numeric_cols])
```

```
▾ StandardScaler
StandardScaler()
```

```
weights_df = pd.DataFrame({
    'feature': np.append(numeric_cols + cat_cols, 'Intercept'),
    'weight': np.append(model2.coef_, model2.intercept_)
```

```
    weight : np.append(model2.coef_, model2.intercept_)
})

# Sort the DataFrame by weight
weights_df = weights_df.sort_values('weight', ascending=False)
print(weights_df)
```

```
     feature        weight
4     smoker  23905.965168
3     region    589.058621
2   children    330.761335
0        age    251.366896
1        bmi    -35.433817
5        sex   -323.627603
6  Intercept -11747.467172
```

```
# prediction on training data
training_data_prediction =model2.predict(X_train)
```

```
# R squared value
r2_train = metrics.r2_score(Y_train, training_data_prediction)
print('R squared vale : ', r2_train)
```

```
R squared vale :  0.7519923667088932
```

```
# Compute loss to evalute the model
loss = rmse(Y_train, training_data_prediction)
print('Train Loss:', loss)
```

```
Train Loss: 6008.670641259382
```

```
# prediction on test data
test_data_prediction =model2.predict(X_test)
```

```
# R squared value
r2_test = metrics.r2_score(Y_test, test_data_prediction)
print('R squared vale : ', r2_test)
```

```
R squared vale :  0.7445422986536503
```

```
# Compute loss to evalute the model
loss = rmse(Y_test, test_data_prediction)
print('Test Loss:', loss)
```

```
Test Loss: 6193.935113523997
```

Because different columns have different ranges, we run into two issues:

```
We can't compare the weights of different column to identify which features are important
A column with a larger range of inputs may disproportionately affect the loss and dominate the optimi
```

For this reason, it's common practice to scale (or standardize) the values in numeric column by subtracting the mean and dividing by the standard deviation.

dT5fLFI.png

We can apply scaling using the StandardScaler class from scikit-learn.

```
df
```

	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
...	...	...	...	...	...	...	...
1333	50	1	30.970	3	0	1	10600.54830
1334	18	0	31.920	0	0	0	2205.98080
1335	18	0	36.850	0	0	2	1629.83350
1336	21	0	25.800	0	0	3	2007.94500
1337	61	0	29.070	0	1	1	29141.36030

1338 rows × 7 columns

```
scaler.mean_
```

```
array([39.20702541, 30.66339686,  1.09491779,  1.51569507])
```

```
scaler.var_
```

```
array([197.25385199,  37.16008997,   1.45212664,   1.2198583 ])
```

```
scaled_inputs = scaler.transform(df[numeric_cols])
scaled_inputs
```

```
array([[-1.43876426, -0.45332   , -0.90861367,  1.34390459],
```

```
       [-1.50996545,  0.5096211 , -0.07876719,  0.43849455],
       [-0.79795355,  0.38330685,  1.58092576,  0.43849455],
       ...,
       [-1.50996545,  1.0148781 , -0.90861367,  0.43849455],
       [-1.29636188, -0.79781341, -0.90861367,  1.34390459],
       [ 1.55168573, -0.26138796, -0.90861367, -0.46691549]])
```

```
scaled_df = pd.DataFrame(scaled_inputs, columns=numeric_cols)
scaled_df
```

	age	bmi	children	region
0	-1.438764	-0.453320	-0.908614	1.343905
1	-1.509965	0.509621	-0.078767	0.438495
2	-0.797954	0.383307	1.580926	0.438495
3	-0.441948	-1.305531	-0.908614	-0.466915
4	-0.513149	-0.292556	-0.908614	-0.466915
...	...	...	...	...
1333	0.768473	0.050297	1.580926	-0.466915
1334	-1.509965	0.206139	-0.908614	-1.372326
1335	-1.509965	1.014878	-0.908614	0.438495
1336	-1.296362	-0.797813	-0.908614	1.343905
1337	1.551686	-0.261388	-0.908614	-0.466915

1338 rows × 4 columns

Second Model After Regularisation of (age bmi children region)data

```
inputs = np.concatenate((scaled_inputs, categorical_data), axis=1)
targets = df.charges

# Create and train the model
model3 = LinearRegression().fit(inputs, targets)
r_squared = model3.score(inputs, targets)
# Generate predictions
predictions = model3.predict(inputs)

# Compute loss to evalute the model
loss = rmse(targets, predictions)
```

```
print('Loss:', loss)
print(f"R-squared (model3.score): {r_squared}")
```

```
Loss: 6043.811701706331
R-squared (model3.score): 0.7507372027994937
```

Model Specification

$$charges = b_1 \times age + b_2 \times bmi + b_3 \times children + b_4 \times smoker + b_5 \times sex + b_6 \times region + b$$

```
# 0=female; 1= male
# 0=No; 1=Yes
#4 = northeast; 3 =southwest; 2 = southeast; 1 = northwest
df_inputs = pd.DataFrame(inputs, columns=["age","sex","bmi","children","smoker","regic
pd.concat([df_inputs, targets], axis=1)
```

	age	sex	bmi	children	smoker	region	charges
0	-1.438764	-0.453320	-0.908614	1.343905	1.0	0.0	16884.92400
1	-1.509965	0.509621	-0.078767	0.438495	0.0	1.0	1725.55230
2	-0.797954	0.383307	1.580926	0.438495	0.0	1.0	4449.46200
3	-0.441948	-1.305531	-0.908614	-0.466915	0.0	1.0	21984.47061
4	-0.513149	-0.292556	-0.908614	-0.466915	0.0	1.0	3866.85520
...	...	...	...	...	...	...	...
1333	0.768473	0.050297	1.580926	-0.466915	0.0	1.0	10600.54830
1334	-1.509965	0.206139	-0.908614	-1.372326	0.0	0.0	2205.98080
1335	-1.509965	1.014878	-0.908614	0.438495	0.0	0.0	1629.83350
1336	-1.296362	-0.797813	-0.908614	1.343905	0.0	0.0	2007.94500
1337	1.551686	-0.261388	-0.908614	-0.466915	1.0	0.0	29141.36030

1338 rows × 7 columns

Building a Predictive System

```
input_data = (-1.438764,-0.453320,  -0.908614,  1.343905,   1.0,    0.0)

# changing input_data to a numpy array
input_data_as_numpy_array = np.asarray(input_data)
```

```
# reshape the array
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)

prediction = model3.predict(input_data_reshaped)
print(prediction)

print('The insurance cost is USD ', prediction[0])
```

```
[25111.24245598]
The insurance cost is USD  25111.242455983163
```

Random Forest¶

```
dt=RandomForestRegressor(n_estimators=10)
dt.fit(X_train,Y_train)
```

```
▾        RandomForestRegressor
RandomForestRegressor(n_estimators=10)
```

```
y_pred=dt.predict(X_train)
train_acc=metrics.r2_score(Y_train,y_pred)

train_acc
```

```
0.9695788225361871
```

```
y1_pred=dt.predict(X_test)
test_acc=metrics.r2_score(Y_test,y1_pred)

test_acc
```

```
0.8257546158063296
```

XGBoost

```
xb=XGBRFRegressor()
xb.fit(X_train,Y_train)
```

```
▾                                   XGBRFRegressor
XGBRFRegressor(base_score=None, booster=None, callbacks=None,
               colsample_bylevel=None, colsample_bytree=None, device=None,
               early_stopping_rounds=None, enable_categorical=False,
               eval_metric=None, feature_types=None, gamma=None,
               grow_policy=None, importance_type=None,
```

```
                   interaction_constraints=None, max_bin=None,
                   max_cat_threshold=None, max_cat_to_onehot=None,
                   max_delta_step=None, max_depth=None, max_leaves=None,
                   min_child_weight=None, missing=nan, monotone_constraints=None,
                   multi_strategy=None, n_estimators=None, n_jobs=None,
                   num_parallel_tree=None, objective='reg:squarederror',
```

```
x_pred=xb.predict(X_train)
trainn_acc=metrics.r2_score(Y_train,x_pred)
```

```
trainn_acc
```

```
0.9059801279335391
```

```
x1_pred=xb.predict(X_test)
testt_acc=metrics.r2_score(Y_test,x1_pred)
```

```
testt_acc
```

```
0.8652226300368335
```

Decision Tree

```
mt=DecisionTreeRegressor()
mt.fit(X_train,Y_train)
```

```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

```
d_pred=mt.predict(X_train)
trainnn_acc=metrics.r2_score(Y_train,d_pred)
```

```
trainnn_acc
```

```
1.0
```

```
d1_pred=mt.predict(X_test)
testd_df=metrics.r2_score(Y_test,d1_pred)
```

```
testd_df
```

```
0.7612620918295904
```

```
df
```

	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
...	...	...	...	...	...	...	...
1333	50	1	30.970	3	0	1	10600.54830
1334	18	0	31.920	0	0	0	2205.98080
1335	18	0	36.850	0	0	2	1629.83350
1336	21	0	25.800	0	0	3	2007.94500
1337	61	0	29.070	0	1	1	29141.36030

1338 rows × 7 columns

```
input_data = (19,   0 , 27.900,     0,  1,  3)

# changing input_data to a numpy array
input_data_as_numpy_array = np.asarray(input_data)

# reshape the array
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)

prediction = dt.predict(input_data_reshaped)
print(prediction)

print('The insurance cost is USD ', prediction[0])
```

```
[16904.5396]
The insurance cost is USD  16904.5396
/usr/local/lib/python3.11/dist-packages/sklearn/base.py:439: UserWarning:

X does not have valid feature names, but RandomForestRegressor was fitted with fea
```

```
input_data = (19,   0 , 27.900,     0,  1,  3)

# changing input_data to a numpy array
input_data_as_numpy_array = np.asarray(input_data)

# reshape the array
```

```
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)

prediction = xb.predict(input_data_reshaped)
print(prediction)

print('The insurance cost is USD ', prediction[0])
```

```
[18362.865]
The insurance cost is USD  18362.865
```

The objective of this section is to demonstrate how to visualize the impact of independent variables on the target variable (Charges) for research purposes.

```
import statsmodels.api as sm


# Add a constant to inputs for the intercept
inputs = sm.add_constant(inputs)

# Fit the model
model = sm.OLS(targets, inputs).fit()

# Display summary
print(model.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                charges   R-squared:                       0.751
Model:                            OLS   Adj. R-squared:                  0.750
Method:                 Least Squares   F-statistic:                     668.1
Date:                Wed, 29 Jan 2025   Prob (F-statistic):               0.00
Time:                        12:44:28   Log-Likelihood:                -13548.
No. Observations:                1338   AIC:                         2.711e+04
Df Residuals:                    1331   BIC:                         2.715e+04
Df Model:                           6                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       8458.6374    246.361     34.334      0.000    7975.340    8941.935
x1          3613.5362    166.932     21.647      0.000    3286.058    3941.014
x2          2027.3168    168.992     11.997      0.000    1695.798    2358.836
x3           577.6603    165.867      3.483      0.001     252.271     903.050
x4          -390.5855    167.799     -2.328      0.020    -719.764     -61.407
x5          2.382e+04    411.843     57.839      0.000      2.3e+04    2.46e+04
x6          -131.1106    332.811     -0.394      0.694    -784.001     521.780
==============================================================================
Omnibus:                      299.003   Durbin-Watson:                   2.088
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              713.975
```

```
Skew:                           1.207   Prob(JB):                    9.17e-156
Kurtosis:                       5.642   Cond. No.                         2.97
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly s
```

```
# Define feature names
feature_names = ["const","age", "sex", "bmi", "children", "smoker", "region"]

# Convert inputs to a DataFrame with feature names
inputs_df = pd.DataFrame(inputs, columns=feature_names)

# Add a constant to inputs for the intercept
inputs_df = sm.add_constant(inputs_df)

# Flatten the target array to 1D
targets = targets.ravel()

# Fit the model
model = sm.OLS(targets, inputs_df).fit()

# Display the summary
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.751
Model:                            OLS   Adj. R-squared:                  0.750
Method:                 Least Squares   F-statistic:                     668.1
Date:                Wed, 29 Jan 2025   Prob (F-statistic):               0.00
Time:                        12:44:38   Log-Likelihood:                -13548.
No. Observations:                1338   AIC:                         2.711e+04
Df Residuals:                    1331   BIC:                         2.715e+04
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       8458.6374    246.361     34.334      0.000    7975.340    8941.935
age         3613.5362    166.932     21.647      0.000    3286.058    3941.014
sex         2027.3168    168.992     11.997      0.000    1695.798    2358.836
bmi          577.6603    165.867      3.483      0.001     252.271     903.050
children    -390.5855    167.799     -2.328      0.020    -719.764     -61.407
smoker      2.382e+04    411.843     57.839      0.000      2.3e+04    2.46e+04
region      -131.1106    332.811     -0.394      0.694    -784.001     521.780
==============================================================================
Omnibus:                      299.003   Durbin-Watson:                   2.088
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              713.975
Skew:                           1.207   Prob(JB):                    9.17e-156
Kurtosis:                       5.642   Cond. No.                         2.97
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly s
<ipython-input-93-1438cb63339b>:11: FutureWarning:

Series.ravel is deprecated. The underlying array is already 1D, so ravel is not ne
```

The Ordinary Least Squares (OLS) regression model explains 75.1% of the variation in the dependent variable (R-squared = 0.751), indicating a good fit. The adjusted R-squared (0.750) confirms this fit while accounting for the number of predictors. The F-statistic of 668.1 ($p < 0.001$) shows the overall model is statistically significant. Among the predictors, age, sex, BMI, and smoker status are statistically significant ($p < 0.05$), with smoker status showing the strongest positive effect (coefficient = 23,820). In contrast, region is not statistically significant ($p = 0.694$), suggesting it does not contribute meaningfully to the model. The intercept (8458.64) represents the baseline value of the dependent variable when all predictors are zero. Diagnostic tests indicate potential non-normality of residuals (Omnibus and Jarque-Bera tests, $p < 0.001$), but the Durbin-Watson statistic (2.088) suggests no significant autocorrelation.

Start coding or generate with AI.