

# Descriptive Analytics for Mixed Data

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

```
In [ ]: # Load data
df = pd.read_excel('descriptive.xlsx')
```

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

```
Out[ ]:
```

	id	calcium	iron	protein	vitamin A	vitamin C	age	sex	bmi	children	smoker
0	1	522.29	10.188	42.561	349.13	54.141	38	male	19.300	0	yes
1	2	343.32	4.113	67.793	266.99	24.839	41	female	31.600	0	no
2	3	858.26	13.741	59.933	667.90	155.455	30	male	25.460	0	no
3	4	575.98	13.245	42.215	792.23	224.688	18	female	30.115	0	no
4	5	1927.50	18.919	111.316	740.27	80.961	61	female	29.920	3	yes

## Data Cleaning

```
In [ ]: # remove unwanted columns
df.drop(columns='id',inplace=True)
```

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

```
Out[ ]:
```

	calcium	iron	protein	vitamin A	vitamin C	age	sex	bmi	children	smoker	region
0	522.29	10.188	42.561	349.13	54.141	38	male	19.300	0	yes	south
1	343.32	4.113	67.793	266.99	24.839	41	female	31.600	0	no	south
2	858.26	13.741	59.933	667.90	155.455	30	male	25.460	0	no	north
3	575.98	13.245	42.215	792.23	224.688	18	female	30.115	0	no	north
4	1927.50	18.919	111.316	740.27	80.961	61	female	29.920	3	yes	south

## Task 1: Quantitative Data Analysis

- Compute average, median, and mode values for the quantitative.
- Construct a sales (charges) data frequency distribution.
- Ascertain data spread by calculating range, variance, and standard deviation.
- Develop visual aids like histograms, box plots, or bar graphs to depict sales figures.

```
In [ ]: # df.dtypes
# df.columns.to_list()
```

- Compute average, median, and mode values for the quantitative.

```
In [ ]: Quantitative_columns = ['calcium', 'iron', 'protein', 'vitamin A', 'vitamin C', 'age', 'bmi']
Qualitative_columns = ['sex', 'smoker', 'region']
```

```
In [ ]: quantitative_data = df[Quantitative_columns]

average_values = quantitative_data.mean()
median_values = quantitative_data.median()
mode_values = quantitative_data.mode().iloc[0]

# Create a DataFrame for better presentation
summary_table = pd.DataFrame({
    'Average': average_values,
    'Median': median_values,
    'Mode': mode_values
})

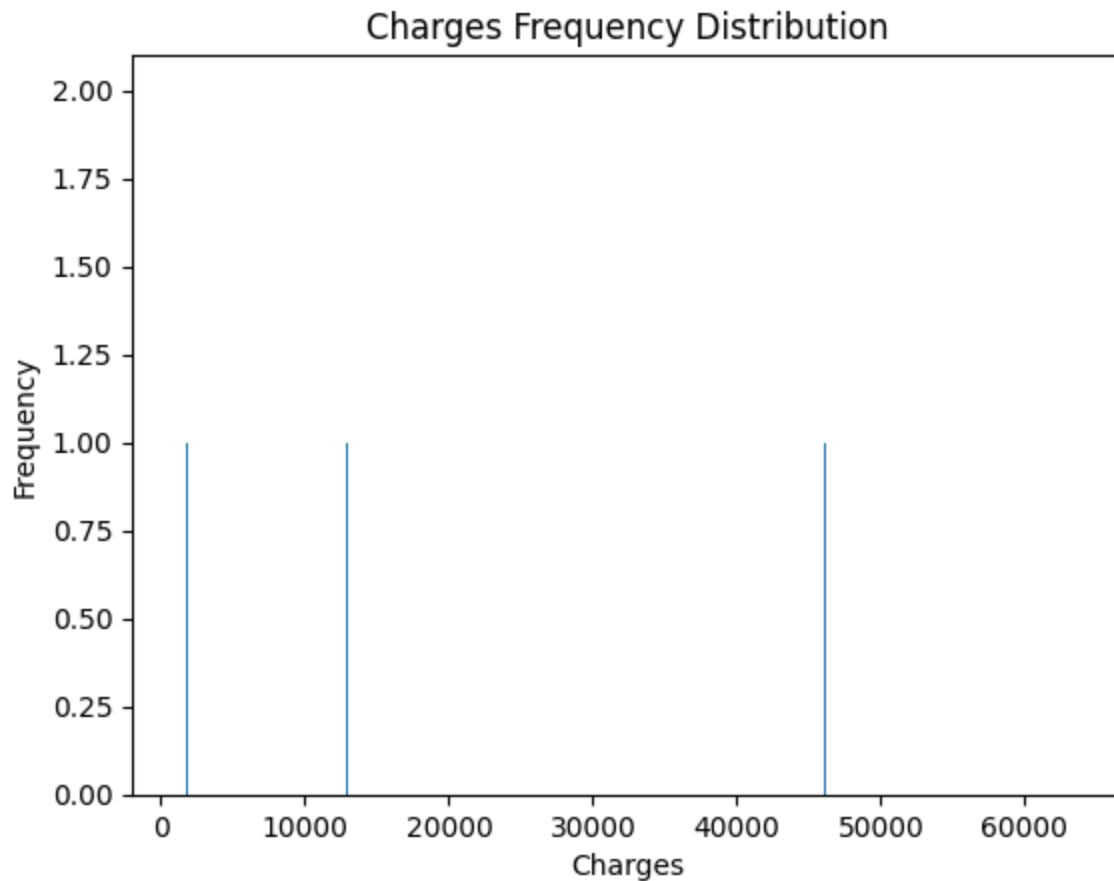
print("Summary of Quantitative Data:")
print(summary_table)
```

```
Summary of Quantitative Data:
           Average  Median  Mode
calcium    624.338219  549.3800  7.440
iron        11.136673   10.0925  7.136
protein     65.990699   61.4285 73.267
vitamin A   841.556055  525.2750  0.000
vitamin C    78.458196   53.5850  0.000
age         39.593151   40.0000 19.000
bmi         30.963404   30.6900 32.300
children    1.071233    1.0000  0.000
```

- Construct a sales (charges) data frequency distribution:

```
In [ ]: charges_frequency = df['charges'].value_counts().sort_index()

plt.bar(charges_frequency.index, charges_frequency.values)
plt.xlabel('Charges')
plt.ylabel('Frequency')
plt.title('Charges Frequency Distribution')
plt.show()
```



- Ascertain data spread by calculating range, variance, and standard deviation:

```
In [ ]: data_spread = pd.DataFrame({
    'Range': quantitative_data.max() - quantitative_data.min(),
    'Variance': quantitative_data.var(),
    'Standard Deviation': quantitative_data.std()
})

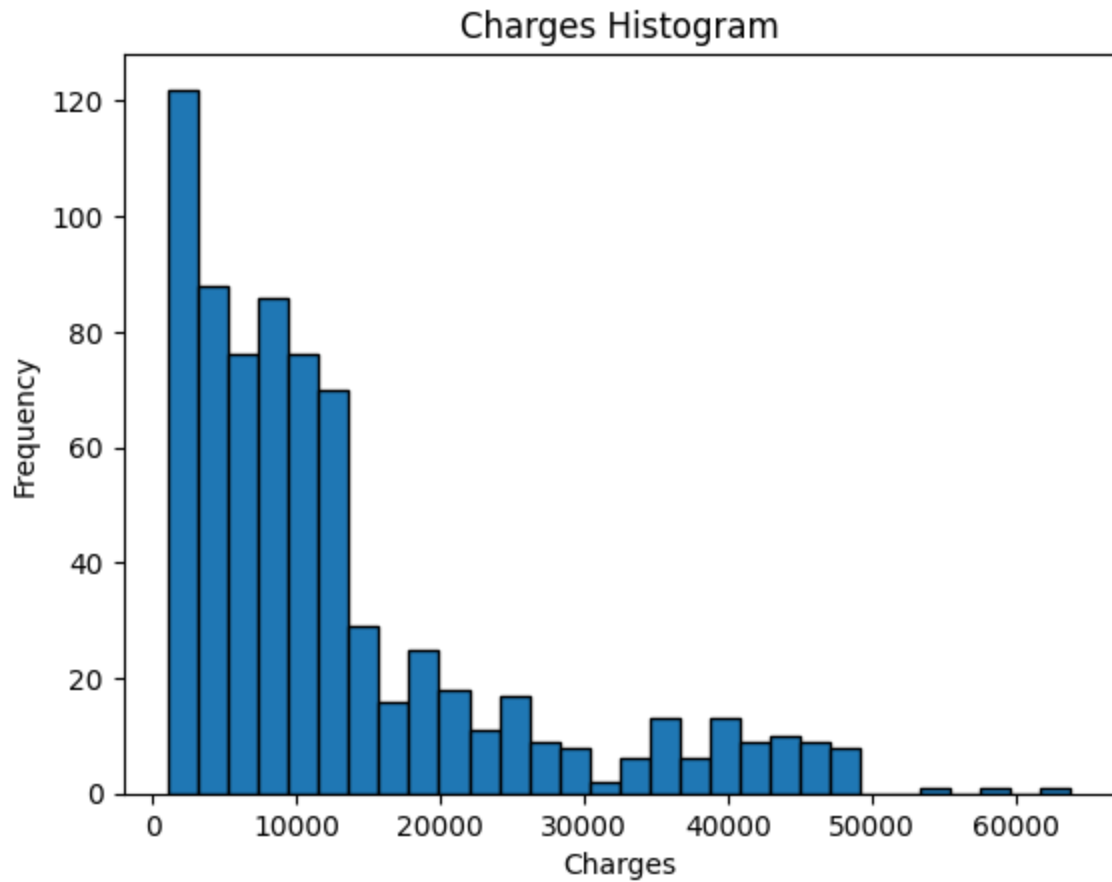
print(data_spread)
```

	Range	Variance	Standard Deviation
calcium	2859.000	1.565989e+05	395.725745
iron	58.668	3.571731e+01	5.976396
protein	251.012	9.310199e+02	30.512619
vitamin A	34434.270	2.689709e+06	1640.033257
vitamin C	433.339	5.337309e+03	73.056887
age	46.000	2.011799e+02	14.183791
bmi	33.100	3.670461e+01	6.058433
children	5.000	1.383122e+00	1.176062

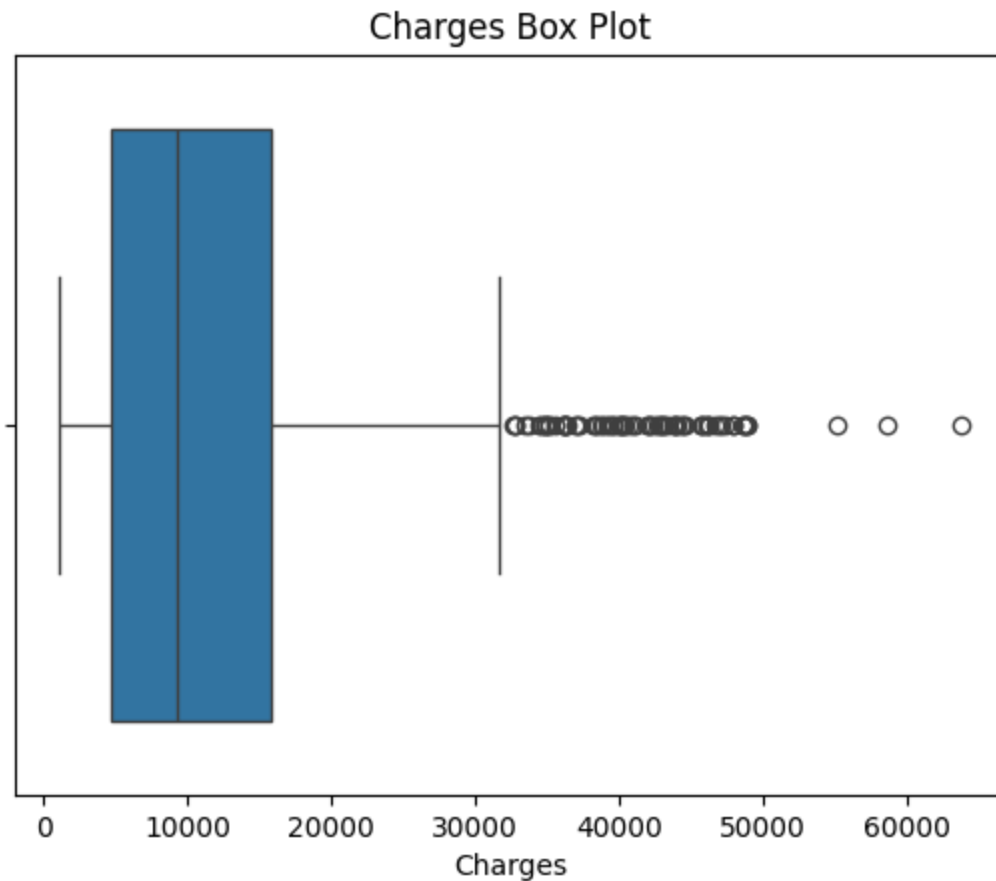
- Develop visual aids like histograms, box plots, or bar graphs to depict sales figures:

```
In [ ]: # Histogram:
plt.hist(df['charges'], bins=30, edgecolor='black')
plt.xlabel('Charges')
plt.ylabel('Frequency')
```

```
plt.title('Charges Histogram')  
plt.show()
```



```
In [ ]: # Box Plot:  
sns.boxplot(x='charges', data=df)  
plt.xlabel('Charges')  
plt.title('Charges Box Plot')  
plt.show()
```



## Task 2: Qualitative Data Analysis

- Review categorical data.
- Quantify and visualize the categorical data with meaningful categories and charts.
- Create dummy variables for region and smoker, and one other categorical data.
- Compile your discoveries into a narrative, emphasizing major insights and potential links to the sales figures.
- Analyze correlations between different attributes, if exists.

- Review categorical data.

```
In [ ]: # Extracting categorical data
categorical_data = df[Qualitative_columns]
```

- Quantify and visualize the categorical data with meaningful categories and charts.

```
In [ ]: # Quantify and visualize categorical data
for column in categorical_data.columns:
    print(f"\n{column.capitalize()} Data:")
    print(categorical_data[column].value_counts())

# Visualize using a bar chart
```

```
plt.figure(figsize=(8, 5))
sns.countplot(x=column, data=df)
plt.xlabel(column.capitalize())
plt.ylabel('Count')
plt.title(f'{column.capitalize()} Distribution')
plt.show()
```

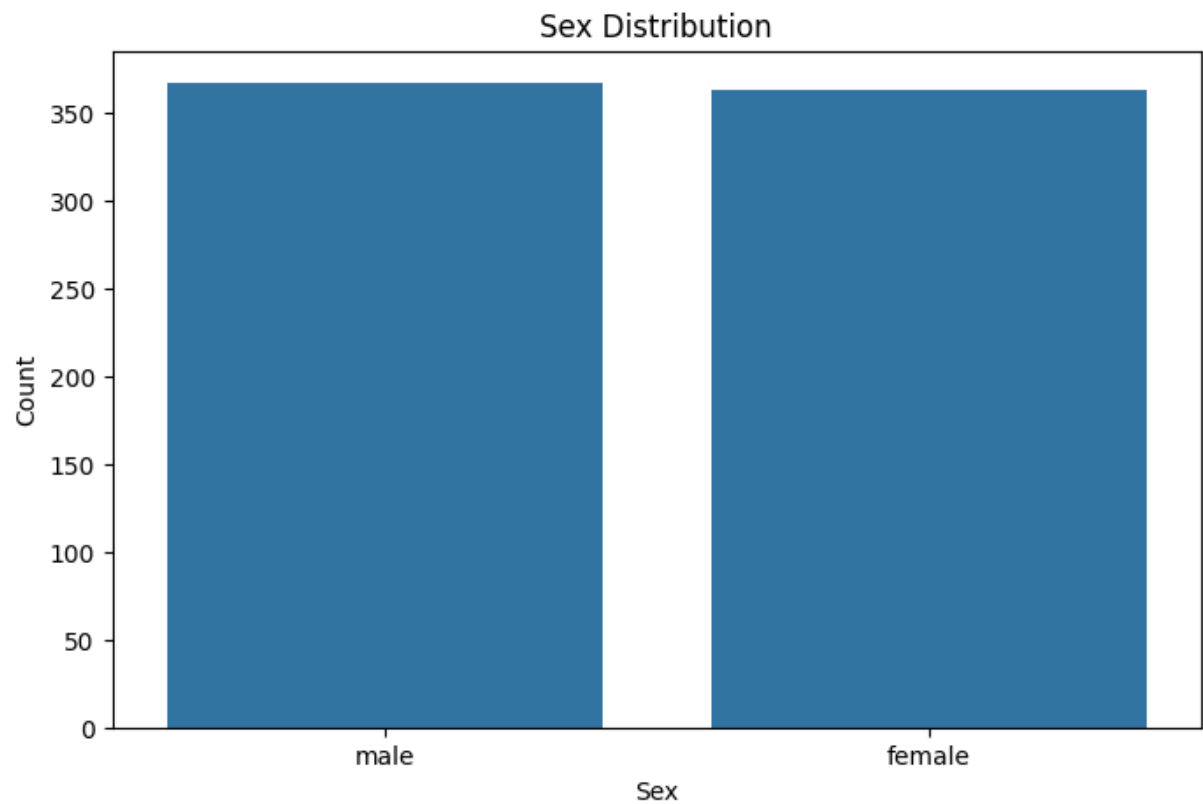
Sex Data:

sex

male 367

female 363

Name: count, dtype: int64



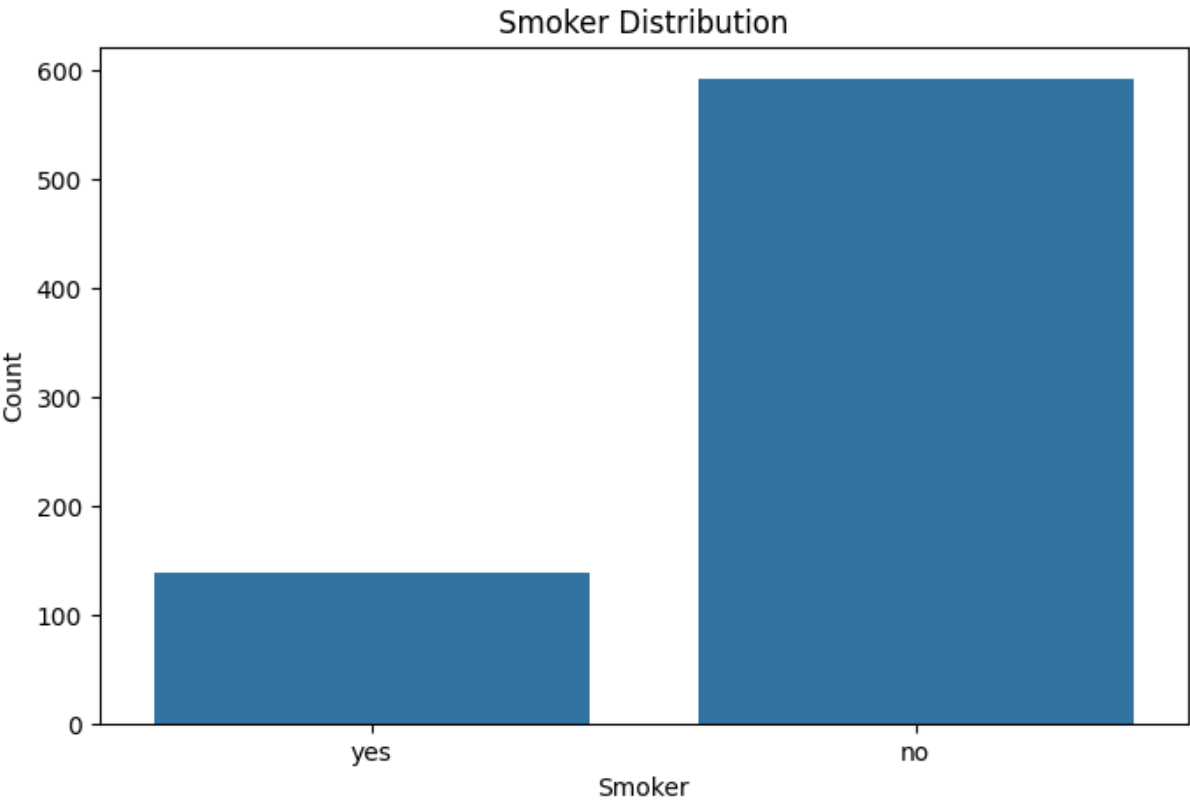
Smoker Data:

smoker

no 592

yes 138

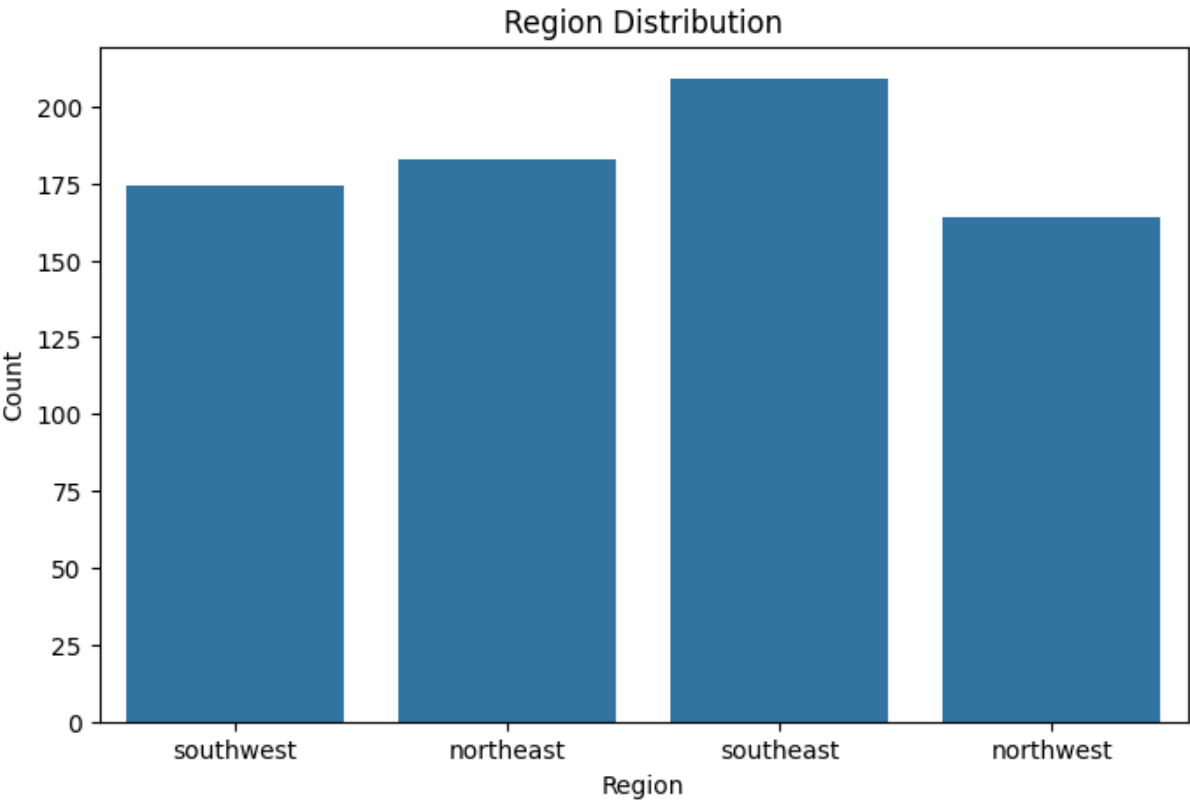
Name: count, dtype: int64



Region Data:

region	count
southeast	209
northeast	183
southwest	174
northwest	164

Name: count, dtype: int64



- Create dummy variables for region and smoker, and one other categorical data.

```
In [ ]: # Create dummy variables for 'region', 'smoker', and one other categorical data
df_dummies = pd.get_dummies(df, columns=['region', 'smoker', 'sex'], drop_first=True)
```

```
In [ ]: df_dummies.head()
```

```
Out [ ]:
```

	calcium	iron	protein	vitamin A	vitamin C	age	bmi	children	charges	region_nc
0	522.29	10.188	42.561	349.13	54.141	38	19.300	0	15820.6990	
1	343.32	4.113	67.793	266.99	24.839	41	31.600	0	6186.1270	
2	858.26	13.741	59.933	667.90	155.455	30	25.460	0	3645.0894	
3	575.98	13.245	42.215	792.23	224.688	18	30.115	0	21344.8467	
4	1927.50	18.919	111.316	740.27	80.961	61	29.920	3	30942.1918	

## Narrative Analysis of Categorical Variables and Sales Figures:

1. Sex Distribution: The dataset includes information about the gender distribution of individuals. The bar chart reveals a relatively balanced representation of males and females. This indicates that the dataset is not skewed towards one gender, which is crucial for unbiased analyses.
2. Smoker Status: The 'smoker' category shows a significant disparity, with a notable proportion of smokers compared to non-smokers. The countplot emphasizes the importance of considering the impact of smoking habits on health-related variables and, potentially, on insurance charges.
3. Regional Distribution: The 'region' variable provides insights into the geographic distribution of the dataset. The countplot illustrates that the data is not evenly distributed across regions. For a comprehensive analysis, it's essential to understand how regional differences may influence health-related parameters and, consequently, insurance charges.

- Analyze correlations between different attributes, if exists.

```
In [ ]: # Analyze correlations between different attributes
correlation_matrix = df_dummies.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=
```



```
plt.title('Correlation Matrix')
plt.show()
```

