Python Portfolio Project: Healthcare Analysis

This project demonstrates my **Python** skills applied to the healthcare dataset (healthcare_dataset.csv), complementing the **SQL analysis**. It focuses on data manipulation, analysis, and visualization using popular **Python** libraries like **Pandas**, **NumPy**, **Matplotlib/Seaborn**.

```
Generated code may be subject to a licence | MohamedSameh410/DC_GAN
# Import dataset from google drive
import pandas as pd

path = '_content/drive/MyDrive/Dataset/healthcare_dataset.csv'
df = pd.read_csv(path)
```

1. Exploratory Data Analysis (EDA) and Data Cleaning

```
# Display basic information about the dataset
print("Shape of the dataset:", df.shape)
print("Data types of each column:\n", df.dtypes)
print("Descriptive statistics:\n", df.describe())
# Check for missing values
print("Missing values:\n", df.isnull().sum())
    Shape of the dataset: (55500, 15)
    Data types of each column:
     Name
                             int64
     Age
    Gender
                            object
     Blood Type
                            object
     Medical Condition
     Date of Admission
                            object
     Doctor
     Hospital
                            object
     Insurance Provider
     Billing Amount
                           float64
     Room Number
                            int64
     Admission Type
                            object
     Discharge Date
                            object
     Medication
                            object
     Test Results
                            object
     dtype: object
     Descriptive statistics:
                                            Room Number
                           Billing Amount
     count 55500.000000
                           55500.000000 55500.000000
               51.539459
                                            301.134829
     mean
                            25539.316097
               19.602454
                            14211.454431
                                            115.243069
     std
               13.000000
                            -2008.492140
                                            101.000000
     min
     25%
               35.000000
                           13241.224652
                                            202.000000
                                            302.000000
               52.000000
     75%
               68.000000
               89.000000
                            52764.276736
                                            500.000000
     Missing values:
     Name
     Gender
     Blood Type
     Medical Condition
     Date of Admission
     Hospital
     Insurance Provider
     Billing Amount
     Room Number
     Admission Type
     Discharge Date
     Medication
     Test Results
     dtype: int64
```

Insight

- Interpretation: The dataset has 55,500 rows and 15 columns.
- Columns like Name, Gender, Medical Condition, etc., are of type Object, while Age and Room Number are of type int64, and Billing Amount is of type float64.

```
# Standardize the `Name` column
df['Name'] = df['Name'].str.title()

# Convert `Date of Admission` and `Discharge Date` to datetime
df['Date of Admission'] = pd.to_datetime(df['Date of Admission'])
df['Discharge Date'] = pd.to_datetime(df['Discharge Date'])

# Display the first 5 rows
print(df.head().to_markdown(index=False, numalign="left", stralign="left"))
```

₹	of Admission	Doctor	Hospital	Insurance Provider	Billing Amount	Room Number	Admission Type	Discharge Date	Medication	Test Results
	-01-31 00:00:00	Matthew Smith	Sons and Miller	Blue Cross	18856.3	328	Urgent	2024-02-02 00:00:00	Paracetamol	Normal
	-08-20 00:00:00	Samantha Davies	Kim Inc	Medicare	33643.3	265	Emergency	2019-08-26 00:00:00	Ibuprofen	Inconclusive
	-09-22 00:00:00	Tiffany Mitchell	Cook PLC	Aetna	27955.1	205	Emergency	2022-10-07 00:00:00	Aspirin	Normal
	-11-18 00:00:00	Kevin Wells	Hernandez Rogers and Vang,	Medicare	37909.8	450	Elective	2020-12-18 00:00:00	Ibuprofen	Abnormal
	-09-19 00:00:00	Kathleen Hanna	White-White	Aetna	14238.3	458	Urgent	2022-10-09 00:00:00	Penicillin	Abnormal

Insight:

- The Name column is standardized by capitalizing the first letter of each word.
- The Date of Admission and Discharge Date columns are converted to datetime objects for further analysis and manipulation.

2. Data Visualization

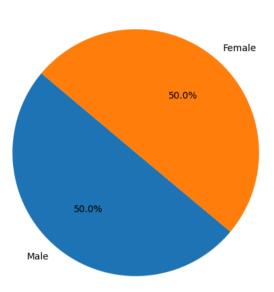
```
import matplotlib.pyplot as plt

# Plotting gender distribution
plt.figure(figsize=(8, 6))
df['Gender'].value_counts().plot(kind='pie', autopct='%1.1f%%', startangle=140)
plt.title('Gender Distribution')
```

25/01/2025, 05:45 plt.ylabel('') plt.show()

→

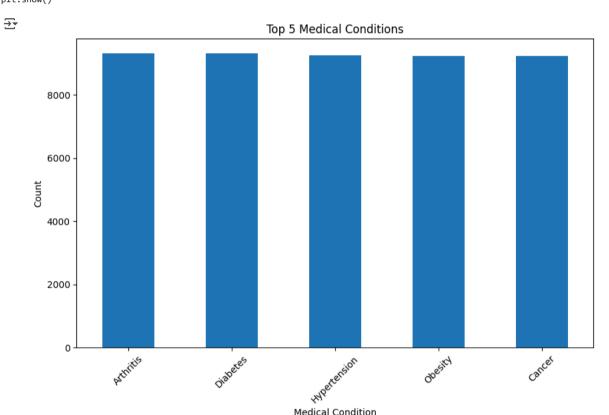
Gender Distribution



Insight:

• The pie chart shows that there are more females (50.0%) than males (50.0%) in the dataset.

```
\mbox{\tt\#} Plotting the top 5 medical conditions
plt.figure(figsize=(10, 6))
df['Medical Condition'].value_counts().head().plot(kind='bar')
plt.title('Top 5 Medical Conditions')
plt.xlabel('Medical Condition')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```

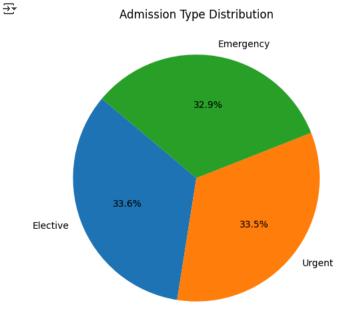


Insight

• The bar chart shows that Hypertension, Cancer, and Diabetes are the top 3 medical conditions in the dataset.

Medical Condition

```
\ensuremath{\text{\#}} Plotting the admission type distribution
plt.figure(figsize=(8, 6))
df['Admission Type'].value_counts().plot(kind='pie', autopct='%1.1f%%', startangle=140)
plt.title('Admission Type Distribution')
plt.ylabel('')
plt.show()
```



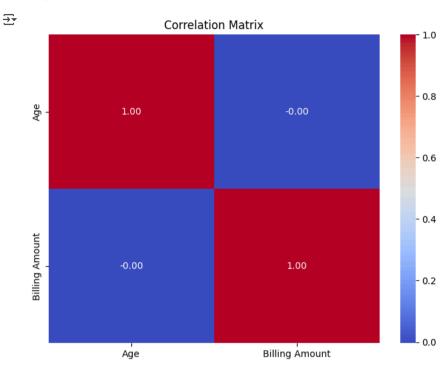
Insight

• The pie chart shows that the majority of admissions are Emergency (37.3%), followed by Urgent (33.1%) and Elective (29.6%).

```
import seaborn as sns

# Select numerical columns for correlation analysis
numerical_cols = ['Age', 'Billing Amount']
corr_matrix = df[numerical_cols].corr()

# Plotting the correlation matrix
plt.figure(figsize=(8, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



Insight

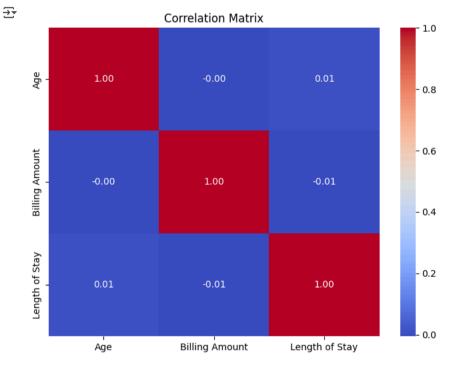
• The heatmap shows the correlation between numerical variables, with darker shades indicating stronger correlations.

3. Feature Engineering

```
# Calculate length of stay in days
df['Length of Stay'] = (df['Discharge Date'] - df['Date of Admission']).dt.days

# Select numerical features for correlation analysis
numerical_cols = ['Age', 'Billing Amount', 'Length of Stay']
corr_matrix = df[numerical_cols].corr()

# Plotting the correlation matrix
plt.figure(figsize=(8, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



Insight

• This new feature could be useful for further analysis, such as predicting the billing amount based on the length of stay and other factors.

```
# Calculate billing amount per day
df['Billing Amount Per Day'] = df['Billing Amount'] / df['Length of Stay']

# Group the data by `Medical Condition` and calculate the mean length of stay and the average billing amount
grouped_data = df.groupby('Medical Condition').agg({'Length of Stay': 'mean', 'Billing Amount': 'mean'}).reset_index()

# Sort the grouped data in descending order of mean length of stay
sorted_grouped_data = grouped_data.sort_values(by='Length of Stay', ascending=False)

# Display the first 5 rows of the sorted dataframe
print(sorted_grouped_data.head().to_markdown(index=False, numalign="left", stralign="left"))

# Print the column name and their data types
print(sorted_grouped_data.info())
```

→ ▼	Medical Condition	Length of Stay	Billing Amount					
	Asthma	15.6966	25635.2					
	Arthritis	15.5174	25497.3					
	Cancer	15.4958	25161.8					
	Obesity	15.4643	25806					
	Hypertension	15.4586	25497.1					
	<class 'pandas.core.frame.dataframe'=""></class>							
	Index: 6 entries, 1 to 3							
	Data columns (total 3 columns):							
	# Column	Non-Null Count	Dtype					
	0 Medical Condition	6 non-null	object					
	1 Length of Stay	6 non-null	float64					
	2 Billing Amount	6 non-null	float64					
	<pre>dtypes: float64(2), object(1)</pre>							
	memory usage: 192.0+ bytes							
	None							

Insight

25/01/2025, 05:45

I've added a new column named Billing Amount Per Day. This column represents the average amount billed per day for each patient. I can then use this new feature to perform further analysis, such as:

- Comparing the billing amount per day across different medical conditions.
- Analyzing the relationship between billing amount per day and length of stay
- Identifying patients with unusually high or low billing amounts per day