21BDS0273
Anshika Singh

Module 1: Introduction to Exploratory Data Analysis

Objective:

- Introduce the concept of EDA and understand the initial steps in data exploration.

Key Operations:

- Importing necessary libraries like `numpy`, `pandas`, `matplotlib`, and `seaborn`.
- Loading the dataset (`auto-mpg.csv`) into a pandas DataFrame.
- Displaying the first few rows using `df.head()`, checking for random samples using `df.sample()`, and getting summary information using `df.info()`.
- Analyzing the dataset structure, which consists of 398 records and 9 columns (mpg, cylinders, displacement, horsepower, weight, acceleration, model year, origin, car name).

Summary: This module helps in understanding the data's structure and determining the types of variables (numeric, categorical) before diving deeper into analysis.

Module 2: Data Transformation

Objective:

- Clean and prepare the dataset for analysis.

Key Operations:

1. **Removing Duplicates:**
    - Checking for and removing duplicate records.
2. **Handling Missing Values:**
    - Replacing missing values represented as '?' with `NaN` and filling the missing 'horsepower' values using forward fill (`ffill`).
    - Using `df.isna().sum()` to get the total count of missing values and filling missing entries.
3. **Transforming Variables:**
    - Converting the 'horsepower' column to numeric, dealing with potential errors using `pd.to_numeric()`.
    - Creating a new categorical column `horsepower_bins` based on 'horsepower' ranges (Low, Medium, High).

Summary: This module focuses on cleaning the data by addressing missing values and ensuring that columns are in the correct format for analysis.

Module 3: Correlation Analysis and Time Series Analysis

Objective:

- Understand relationships between numerical features and analyze time-dependent patterns.

Key Operations:

1. **Correlation Analysis:**
    - Using the `corr()` method to compute correlation coefficients between numerical features.
    - Visualizing the correlation matrix using a heatmap with `seaborn` to identify which variables have strong correlations (e.g., mpg and weight).
2. **Time Series Analysis:**
    - Plotting the trend of average miles per gallon (`mpg`) over the model years to analyze how fuel efficiency has changed over time using `groupby()` and `plot()`.

Summary: This module helps in understanding how different numerical features relate to each other and how trends evolve over time.

Module 4: Data Summarization and Visualization

Objective:

- Summarize the dataset with descriptive statistics and visualize distributions.

Key Operations:

1. **Descriptive Statistics:**
    - Using `describe()` to summarize numerical columns and get insights such as mean, standard deviation, min, and max values.
2. **Visualization:**
    - Plotting histograms for numerical variables like 'mpg', 'horsepower', 'weight', and 'displacement' to understand their distributions.
    - Using bar charts to visualize categorical variables (e.g., the distribution of cylinders and horsepower categories).
    - Additional analyses include plotting the MPG distribution and a scatter plot for horsepower vs. mpg.

Summary: This module highlights how to extract summary statistics and visualize the data using various plots, helping to identify patterns and distributions in the data.

Module 5: Clustering Algorithms

Objective:

- Apply clustering techniques to group the data based on similarities.

Key Operations:

1. **Preprocessing:**
   - Preparing the dataset for clustering by selecting relevant features (e.g., mpg, cylinders, model year, origin) and scaling the features using `StandardScaler`.
2. **Clustering Models:**
   - **Agglomerative Clustering**: Hierarchical clustering method used to form clusters.
   - **Gaussian Mixture Models (GMM)**: A probabilistic model used for clustering with a Gaussian distribution assumption.
   - **Minimum Spanning Tree (MST) Clustering**: Based on distance measures between points to form clusters.
3. **Evaluation:**
   - Evaluating the clustering results using the silhouette score, which measures how similar objects are within the same cluster compared to other clusters.

Summary: This module demonstrates how to apply different clustering algorithms to group similar instances and how to evaluate the performance of these algorithms.

Module 6: Data Visualization for Clusters

Objective:

- Visualize the results of clustering and understand cluster structures.

Key Operations:

1. **Visualizing Clusters:**
   - Scatter plots and pair plots for clustered data, helping to visually identify how different clusters are distributed across the feature space.
   - Using `sns.pairplot()` to see pairwise relationships in the dataset for the selected features.
2. **Cluster Comparison:**
   - Visualizing the mean MPG for each cluster to compare performance metrics between clusters.
   - Additional plots like boxplots for understanding the spread of 'mpg' by origin.

Summary: This module focuses on visualizing the clusters formed in the previous module to understand their characteristics and differences.

Module 7: Advanced Analysis and Model Evaluation

Objective:

- Apply advanced techniques for analysis and evaluate model performance.

Key Operations:

1. **Advanced Statistical Analysis:**
    - Exploring statistical measures like variance, mean, and skewness in features.
    - Using advanced visualizations to compare features within each cluster, such as box plots and strip plots.
2. **Model Evaluation:**
    - Evaluating the performance of different clustering models using the silhouette score, which indicates how well the data points fit their clusters.
    - Tuning models and adjusting hyperparameters to improve the quality of clustering.

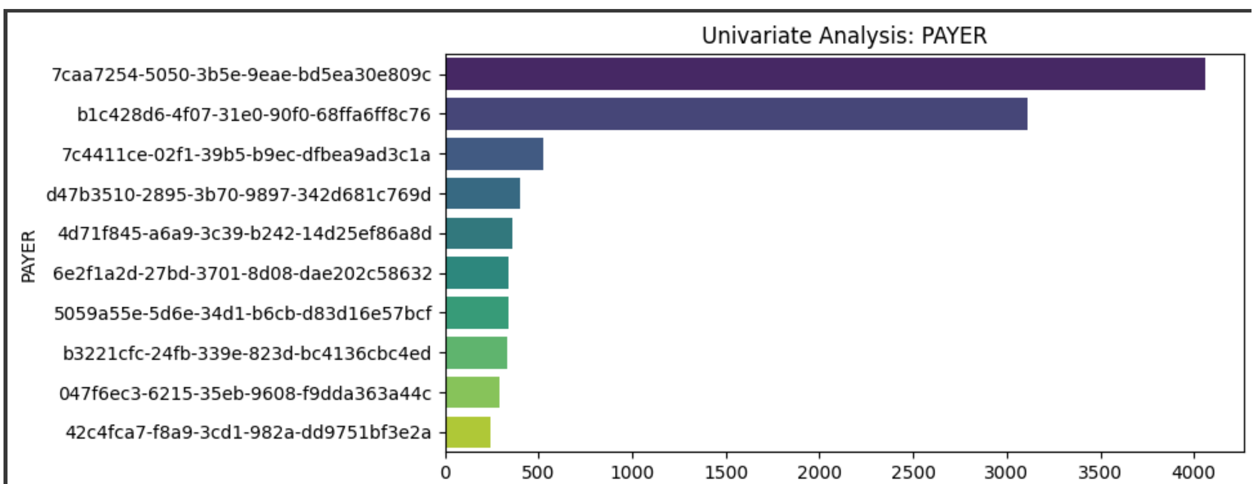
Summary: This final module applies advanced methods to analyze clusters in more detail and evaluates the quality of clustering models through performance metrics like the silhouette score.

Final Thoughts:

This detailed breakdown covers the core steps of Exploratory Data Analysis (EDA) and the clustering analysis that follows. Each module progresses logically from loading and cleaning the data to complex analysis and model evaluation, with the goal of gaining actionable insights from the dataset.

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

```
  sns.barplot(y=value_counts.index, x=value_counts.values, palette='viridis')
```



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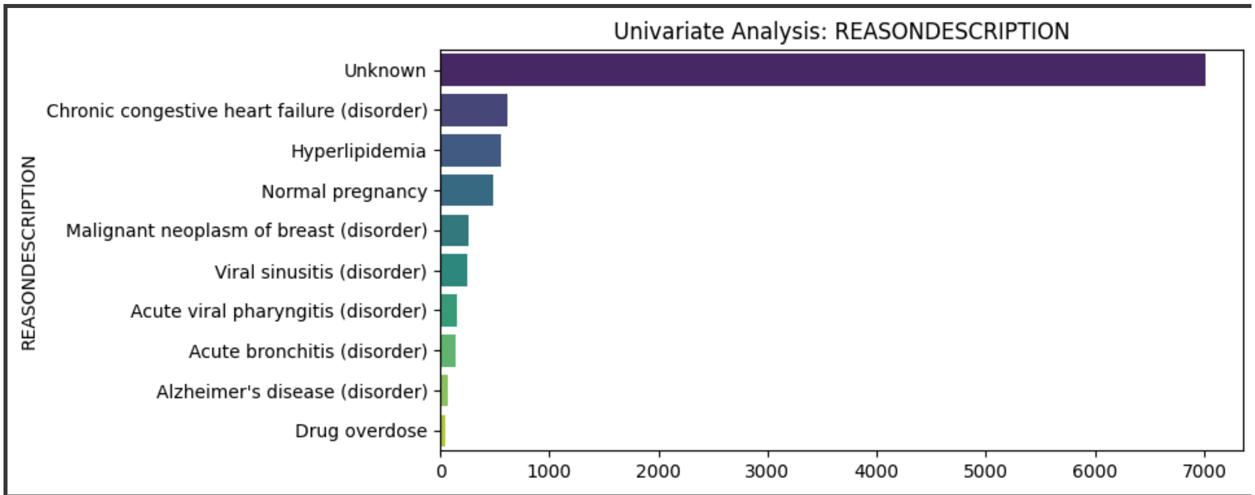

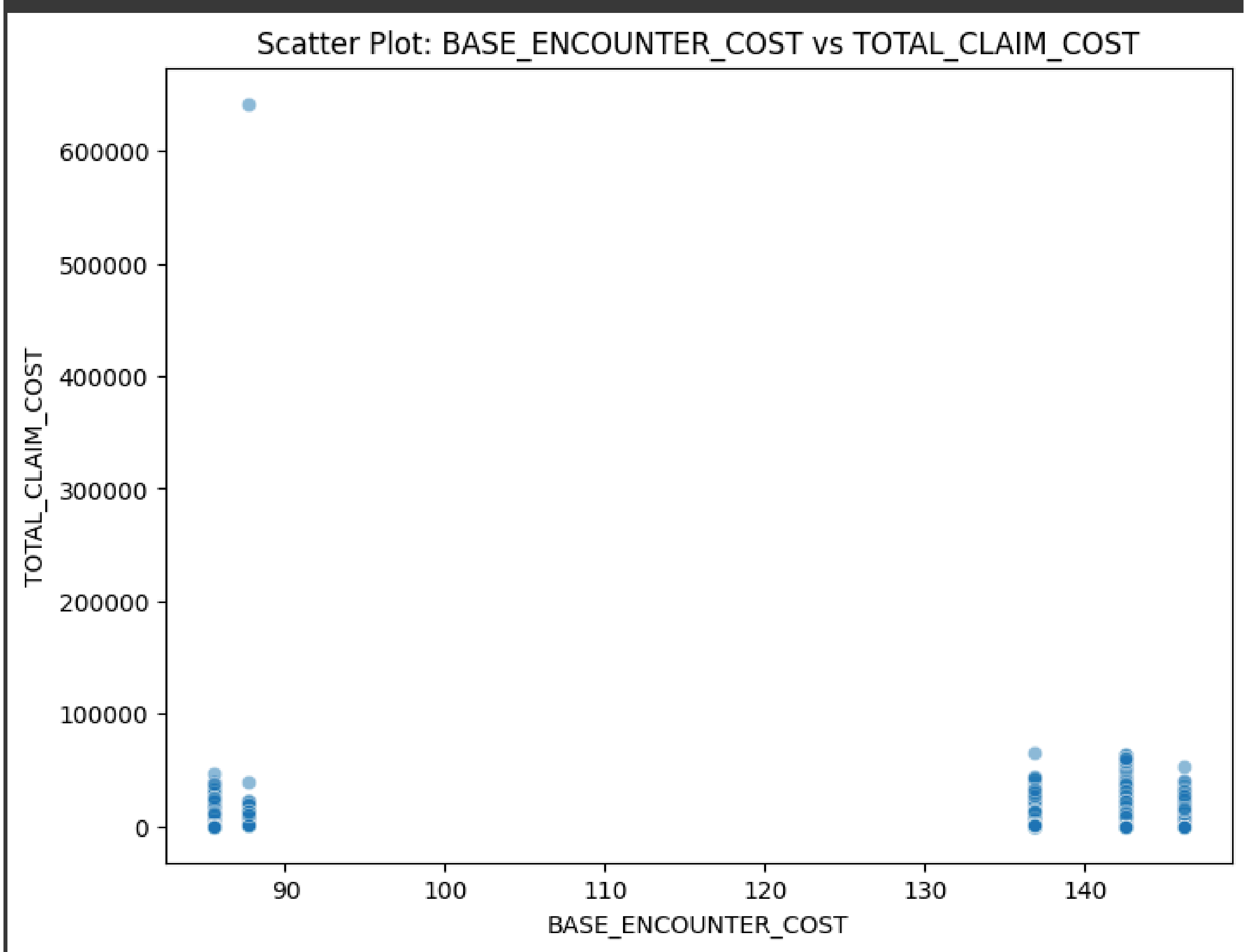

https://github.com/anshikazzzz/EDA_DA

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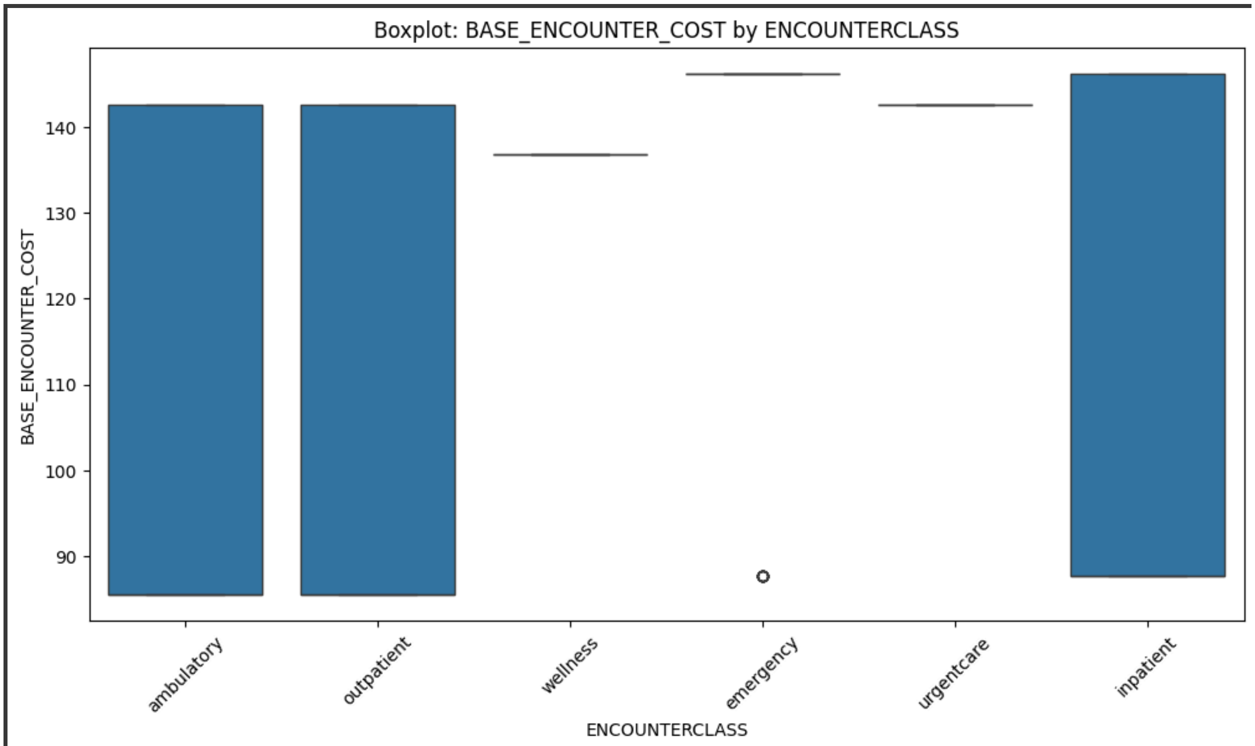

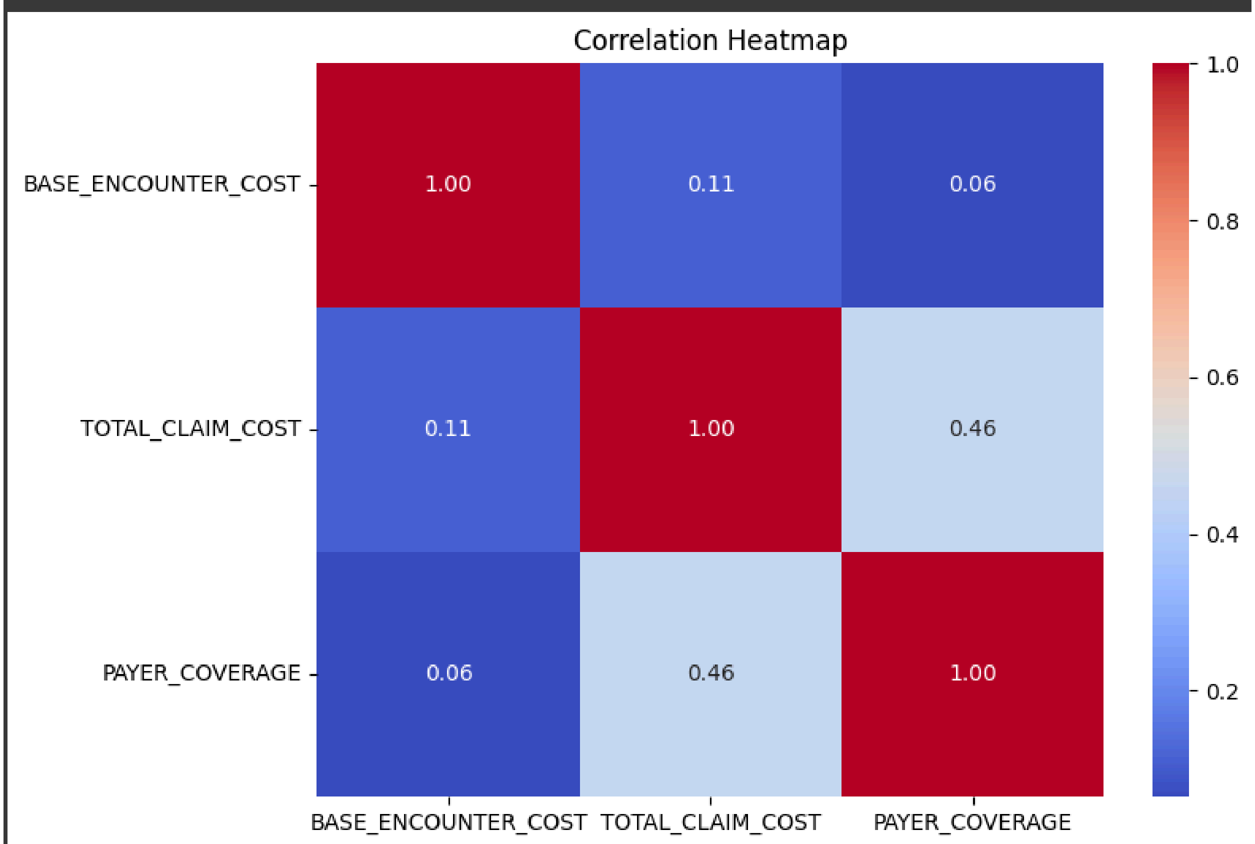

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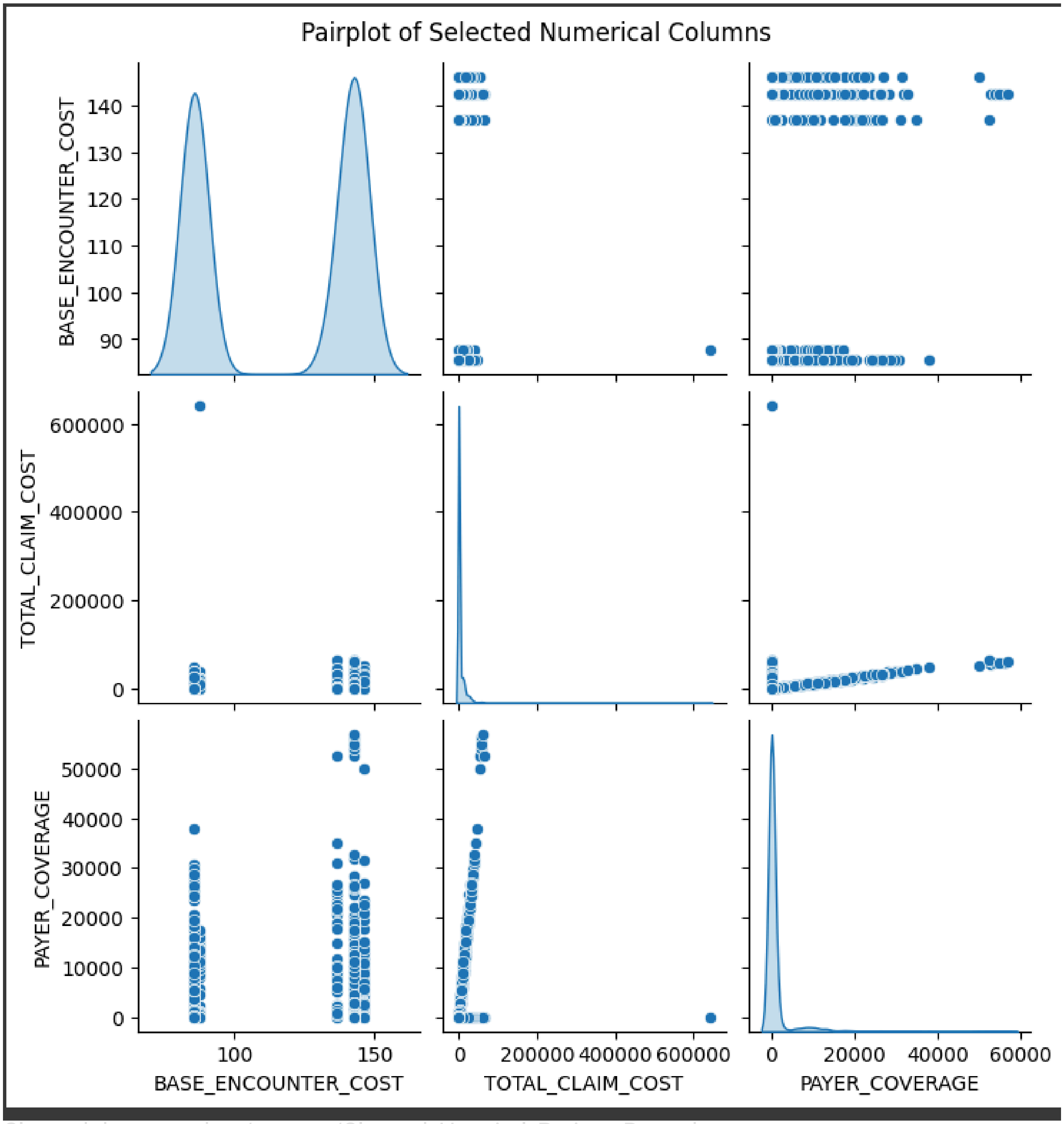

Cleaned data saved to /content/Cleaned_Hospital_Patient_Records.csv
Dataset Dimensions (Rows, Columns): (10000, 14)

Dataset Summary:

	Id	START \
count	10000	10000
unique	10000	9943
top	45e12044-bee7-0cf6-1fa4-22cf463aa876	2012-07-23T17:55:09Z
freq	1	2
mean	NaN	NaN

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```
std                        NaN            NaN
min                        NaN            NaN
25%                        NaN            NaN
50%                        NaN            NaN
75%                        NaN            NaN
max                        NaN            NaN

                    STOP                        PATIENT  \
count              10000                          10000
unique              9979                            847
top     2016-11-09T09:18:33Z  1712d26d-822d-1e3a-2267-0a9dba31d7c8
freq                   2                            497
mean                 NaN                            NaN
std                  NaN                            NaN
min                  NaN                            NaN
25%                  NaN                            NaN
50%                  NaN                            NaN
75%                  NaN                            NaN
max                  NaN                            NaN

                           ORGANIZATION  \
count                             10000
unique                                1
top     d78e84ec-30aa-3bba-a33a-f29a3a454662
freq                              10000
mean                                NaN
std                                 NaN
min                                 NaN
25%                                 NaN
50%                                 NaN
75%                                 NaN
max                                 NaN

                                  PAYER ENCOUNTERCLASS         CODE  \
count                             10000          10000  1.000000e+04
unique                               10              6           NaN
top     7caa7254-5050-3b5e-9eae-bd5ea30e809c    ambulatory           NaN
freq                               4061           4512           NaN
mean                                NaN            NaN  2.944941e+08
std                                 NaN            NaN  1.998256e+08
min                                 NaN            NaN  1.505002e+06
25%                                 NaN            NaN  1.853450e+08
50%                                 NaN            NaN  1.853490e+08
75%                                 NaN            NaN  4.104100e+08
```

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```
max                          NaN         NaN  7.029270e+08

                   DESCRIPTION  BASE_ENCOUNTER_COST  \
count                        10000         10000.000000
unique                          50                  NaN
top     Encounter for problem (procedure)                NaN
freq                          1574                  NaN
mean                           NaN          115.872884
std                            NaN           28.443555
min                            NaN           85.550000
25%                            NaN           85.550000
50%                            NaN          136.800000
75%                            NaN          142.580000
max                            NaN          146.180000

       TOTAL_CLAIM_COST  PAYER_COVERAGE    REASONCODE  \
count      10000.000000    10000.000000  2.992000e+03
unique              NaN             NaN           NaN
top                 NaN             NaN           NaN
freq                NaN             NaN           NaN
mean        3670.142553     1119.613660  2.456104e+11
std        10497.436123     4688.193825  4.350989e+12
min            0.000000        0.000000  5.602001e+06
25%          142.580000        0.000000  5.582200e+07
50%          278.580000       24.270000  7.549800e+07
75%         1391.400000      155.770000  1.956620e+08
max       641882.700000   188453.170000  1.241710e+14

                          REASONDESCRIPTION
count                                  2992
unique                                   64
top     Chronic congestive heart failure (disorder)
freq                                    611
mean                                    NaN
std                                     NaN
min                                     NaN
25%                                     NaN
50%                                     NaN
75%                                     NaN
max                                     NaN

Missing Values:
 Id                    0
START                  0
```

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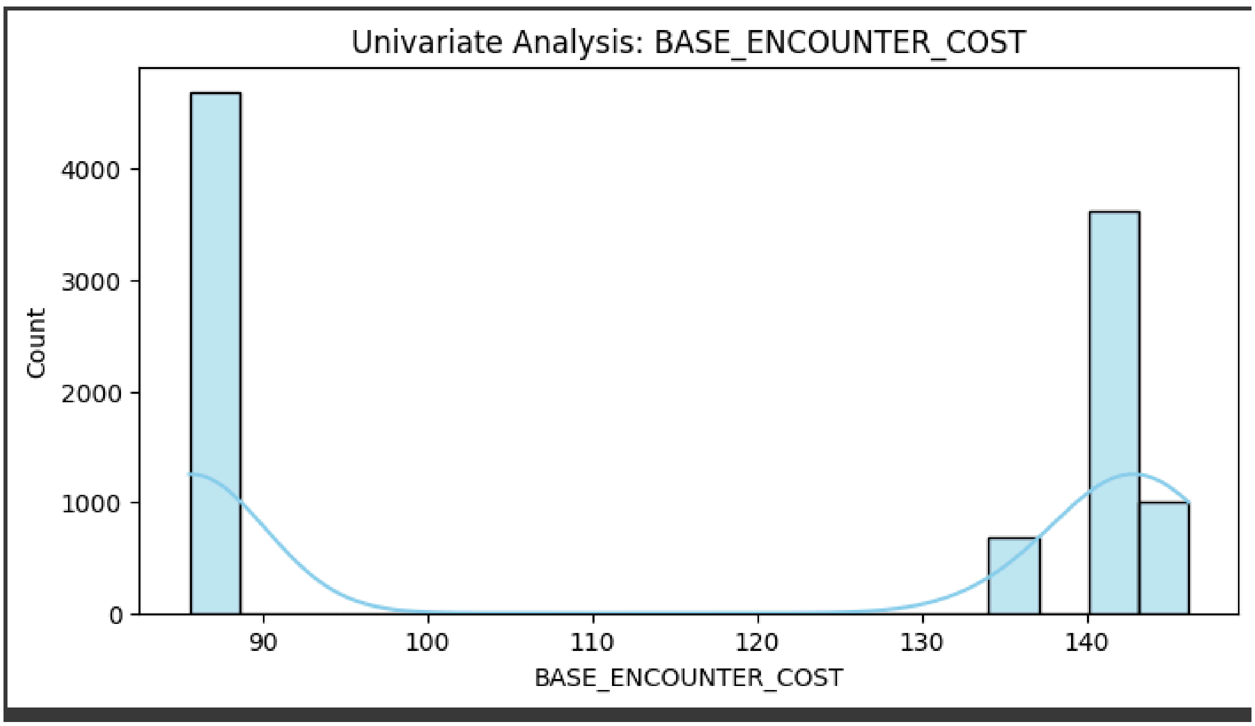
```
STOP                  0
PATIENT               0
ORGANIZATION          0
PAYER                 0
ENCOUNTERCLASS        0
CODE                  0
DESCRIPTION           0
BASE_ENCOUNTER_COST   0
TOTAL_CLAIM_COST      0
PAYER_COVERAGE        0
REASONCODE         7008
REASONDESCRIPTION  7008
dtype: int64
```



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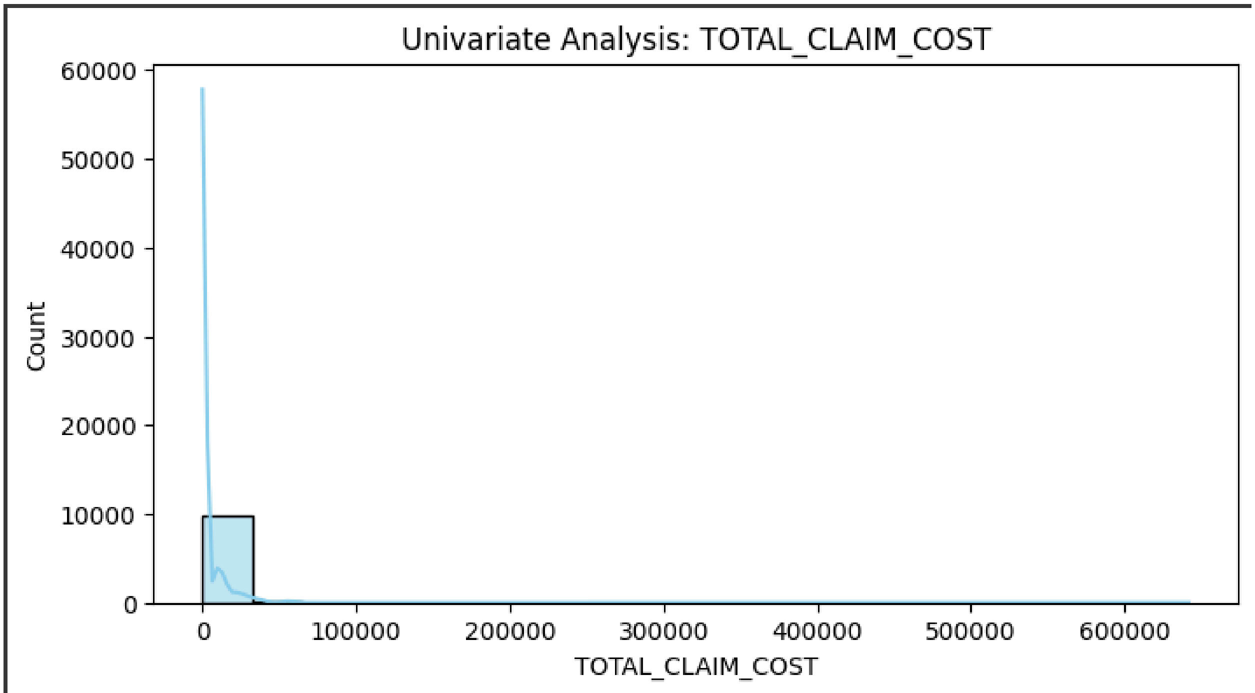

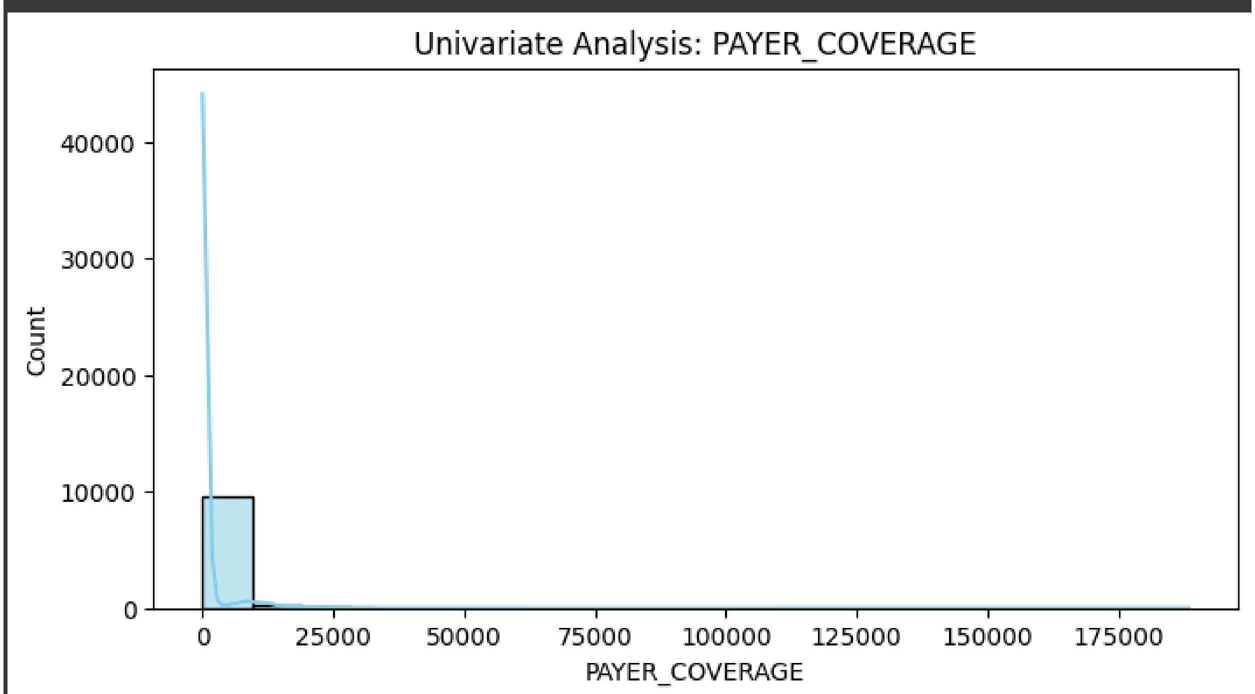

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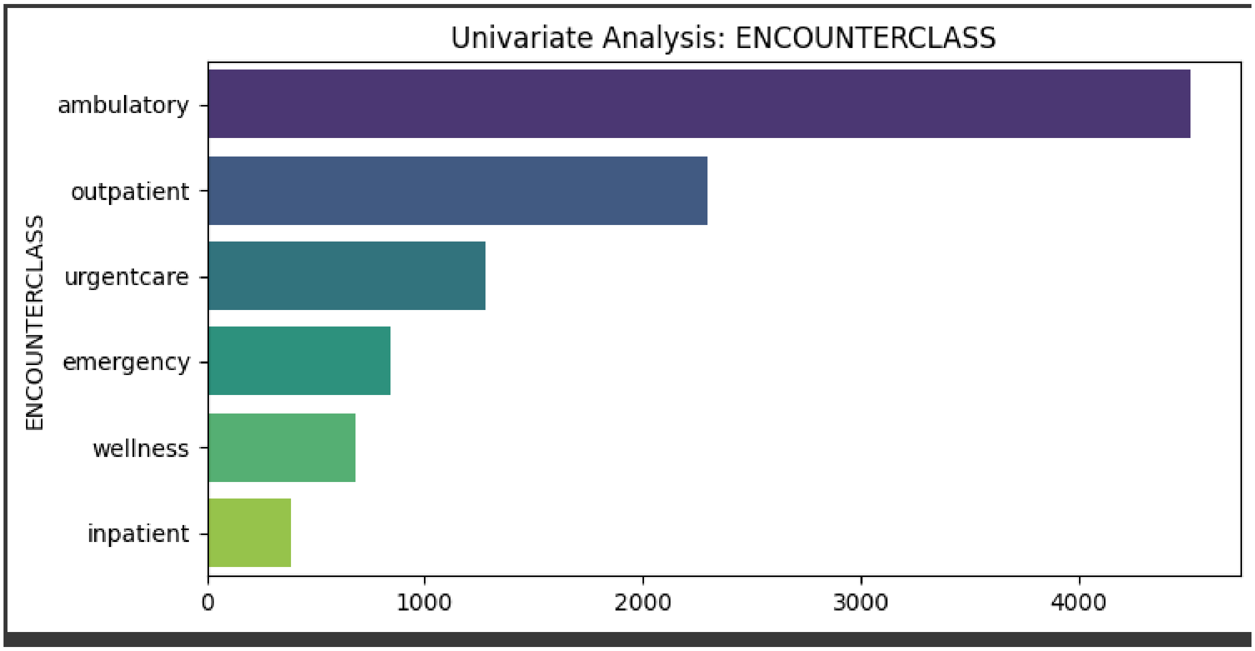

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