Annexure-I

Exploratory Data Analysis on Airline Passenger Data

Final Report

Submitted in partial fulfillment of the requirements for the award of degree of

Bachelor of Technology

In

Computer Science and Engineering

Data Science with Machine Learning

LOVELY PROFESSIONAL UNIVERSITY

PHAGWARA, PUNJAB

SUBMITTED BY

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Signature of the Student:

Annexure-II

SUPERVISIOR'S CERTIFICATE

This is to certify that the project entitled "Exploratory Data Analysis on Airline Passenger Data" is a data analysis project conducted by Gagan Ruthwik Chowdary Kolluri (12203826), a student of the Computer Science Engineering program (2022-2026) at Lovely Professional University. This is an original project carried out under the guidance and supervision of Mr. Ved Prakash Chaubey, in partial fulfillment of the requirements for the Bachelor's Degree in Computer Science and Engineering.

Signature of Supervisor

Mr. Ved Prakash Chaubey
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Annexure-III

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We would like to express our gratitude to Lovely Professional University for providing us with a valuable platform to deepen our knowledge and skills in Computer Science and Engineering.

We are especially grateful to Mr. Ved Prakash Chaubey, our supervisor, for his patience, understanding, and invaluable feedback. His expertise and suggestions have been instrumental in the successful completion of this project.

Lastly, we would like to thank our friends and colleagues for their support, encouragement, and constructive feedback, which helped us improve and refine our work. Thank you all.

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Abstract

Air travel is an integral part of global connectivity, providing access to distant locations and fostering economic and cultural exchanges. This project, titled "Exploratory Data Analysis on Airline Passenger Data," delves into analyzing a comprehensive dataset from Kaggle containing 9,065 entries and multiple features, such as passenger demographics, airport data, flight statuses, and derived variables. The objective is to uncover significant trends, patterns, and insights that can drive operational efficiency, improve customer satisfaction, and inform data-driven decisions in the aviation industry.

The analysis begins with data preprocessing, ensuring data integrity through handling missing values, outliers, and duplicates. Several derived features, such as 'Age Group,' 'Departure Month,' and encoded variables, enrich the dataset for a more detailed analysis. Utilizing Python's robust libraries, including pandas, NumPy, Matplotlib, Seaborn, and Plotly, the project applies a structured exploratory data analysis (EDA) framework. The study employs descriptive statistics and visualizations to highlight passenger trends, operational performance, and regional differences across airports and continents.

Key findings include demographic insights such as age distributions by gender and nationality, and operational trends, such as the impact of departure months and airports on flight status (delays, on-time performance, or cancellations). For instance, delays and cancellations exhibit noticeable seasonal trends, often peaking during high-traffic periods. Analysis of pilot assignments reveals patterns in operational efficiency, and airport performance is evaluated by categorizing airports based on their location and reliability metrics.

A clustering technique using Principal Component Analysis (PCA) is employed to reduce dimensionality, enabling the grouping of passengers or routes with similar characteristics. This step reveals actionable insights, such as segments of passengers with frequent delays or regions requiring operational improvements. Such insights are instrumental in tailoring marketing strategies, improving flight scheduling, and optimizing resource allocation.

Through this analysis, the project demonstrates the transformative power of data analytics in aviation. By focusing on customer demographics, flight statuses,

and operational trends, the study provides actionable insights that airlines can leverage to enhance decision-making. This includes improving passenger satisfaction through targeted services, optimizing routes to reduce delays, and managing resources effectively during peak travel times.

The findings are presented visually using intuitive charts and graphs, such as bar charts, scatter plots, box plots, and sunburst plots, ensuring the results are accessible to technical and non-technical audiences. Additionally, the clustering results provide a blueprint for more advanced predictive modeling or segmentation studies in the future.

In conclusion, this project highlights the value of exploratory data analysis in identifying hidden patterns within complex datasets, paving the way for innovations in operational strategies and customer service. The application of EDA to airline passenger data underscores the importance of data-driven solutions in the aviation sector and sets the stage for future research aimed at predictive analytics or real-time data applications.

This report serves as a resource for stakeholders in the aviation industry, including data analysts, airline managers, and strategists, offering a comprehensive exploration of the data’s potential. The accompanying code and visualizations, accessible via the provided GitHub link, ensure the reproducibility and adaptability of the analysis, enabling further exploration or tailored applications for other datasets or scenarios.

Problem Statement

The aviation industry plays a pivotal role in global transportation, connecting millions of passengers across continents daily. However, it faces numerous challenges, such as flight delays, cancellations, fluctuating passenger satisfaction, and operational inefficiencies. Airlines, airports, and other stakeholders are constantly seeking ways to improve their services, optimize operations, and enhance the passenger experience. In this context, understanding passenger behavior, operational trends, and factors influencing flight outcomes becomes crucial.

The dataset utilized for this project, sourced from Kaggle, comprises detailed information about airline passengers, including their demographic profiles (age, gender, nationality), flight details (departure and arrival airports, pilot names), and flight statuses (on-time, delayed, or canceled). With 9,065 entries and multiple attributes, the dataset provides a rich ground for extracting insights. However, the data also presents challenges such as missing values, outliers, and the need for feature engineering to enhance its analytical potential.

Key questions driving this analysis include:

1. What are the primary factors contributing to flight delays or cancellations?
2. How do passenger demographics vary across different airports and continents?
3. Are there noticeable seasonal patterns in flight operations, such as delays or cancellations during specific months?
4. How can clustering techniques help identify groups of passengers or routes with similar characteristics?
5. Which airports and pilots demonstrate consistent performance, and how can this be benchmarked?

The overarching goal is to use exploratory data analysis (EDA) to uncover meaningful trends and patterns that can inform better decision-making for airlines and airports. By addressing these questions, this project aims to:

1. Provide actionable insights into passenger trends and operational inefficiencies.
2. Highlight areas for improvement in flight scheduling and resource allocation.
3. Offer recommendations to enhance customer satisfaction and operational performance.

This problem is particularly relevant in today's data-driven era, where the aviation industry faces increasing competition and rising customer expectations. Airlines and airports need robust, data-backed strategies to ensure they meet these demands while maintaining profitability and operational excellence. Through this project, we aim to bridge the gap between raw data and actionable insights, showcasing the power of EDA in addressing critical industry challenges.

Dataset Description

The dataset used for this project, sourced from Kaggle, contains detailed information on airline passengers, flight operations, and their associated outcomes. The data consists of **9,065 entries** and spans multiple attributes that provide a comprehensive view of passenger demographics, flight characteristics, and operational statuses. Below is a detailed breakdown of the dataset's key columns and their significance:

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1. Passenger Information:

- **Passenger ID:** Unique identifier for each passenger.
- **Gender:** The gender of the passenger (e.g., Male, Female).
- **Age:** The age of the passenger, represented numerically.
- **Nationality:** The nationality of the passenger, indicating their country of origin.

2. Airport and Location Information:

- **Airport Name:** The name of the departure airport.

- **Airport Country Code:** ISO country code of the airport's location.
- **Country Name:** The full name of the country where the airport is located.
- **Airport Continent:** The continent where the departure airport is situated.
- **Continents:** Broader categorization of continents for easier grouping.

3. Flight Information:

- **Departure Date:** Date of the flight's departure.
- **Arrival Airport:** Name of the arrival airport for the flight.
- **Pilot Name:** Name of the pilot responsible for the flight.
- **Flight Status:** Indicates whether the flight was **on-time**, **delayed**, or **canceled**.

4. Additional Columns (Derived and Encoded):

- **Age Group:** Age categorized into groups (e.g., Child, Adult, Senior).
- **Departure Month:** Extracted from the departure date to indicate the flight's month.
- **Flight Status Num:** Numerical representation of flight statuses for analytical purposes.
- **Year:** Year of the flight's departure.
- **Gender_Encoded:** Binary encoding of the gender variable.
- **FlightStatus_Encoded:** Encoded values for flight status (e.g., 0 for on-time, 1 for delayed).

5. Derived Time and Seasonal Information:

- **Month:** Month of the flight's departure, useful for identifying seasonal patterns.
- **Quarter:** Quarterly categorization of departure months.
- **Day of Week:** Day of the week extracted from the departure date, useful for trend analysis.

6. Clustering and Analytical Features:

- **Cluster:** Grouping of data points based on similarities in passenger or flight attributes.

Key Characteristics:

- **Volume:** 9,065 rows with rich and diverse data points.
- **Dimensionality:** 22 columns, covering passenger demographics, operational details, and derived features for enhanced analysis.
- **Data Type:** A mix of numerical, categorical, and temporal data.
- **Data Source:** The dataset was obtained from Kaggle, ensuring credibility and quality for analysis.

Potential Challenges:

1. **Missing Values:** Certain columns may contain missing or incomplete information, requiring imputation or exclusion.
2. **Outliers:** Potential anomalies in numerical fields (e.g., age or flight statuses) that need to be handled.
3. **Feature Engineering:** Additional features like clustering or seasonal analysis were created to derive deeper insights.

By addressing these challenges, this dataset offers a robust foundation for exploring trends, identifying patterns, and providing actionable insights to improve airline operations and customer satisfaction.

Solution Approach

This project, titled **"Exploratory Data Analysis on Airline Passenger Data,"** follows a structured approach to derive meaningful insights and address the identified challenges. The solution is implemented in distinct phases, ensuring clarity and comprehensiveness. Below is a detailed explanation of the approach:

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1. Data Understanding and Loading:

- **Objective:** To familiarize with the dataset's structure and ensure successful data ingestion.
- **Steps:**
    - Load the dataset from Kaggle into a Pandas DataFrame for analysis.
    - Examine the dataset's structure using functions such as head(), info(), and shape to understand column names, data types, and the number of rows and columns.
    - Generate summary statistics using the describe() method to get an overview of numerical features.

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2. Data Cleaning and Preprocessing:

- **Objective:** To ensure data quality and prepare it for analysis.
- **Steps:**
    - Handle missing values:
        - Identify missing data using isnull() and address it with appropriate techniques such as imputation or row removal.
    - Detect and treat outliers in numerical columns using visualization methods like box plots.
    - Convert categorical variables into machine-readable formats using encoding techniques (e.g., one-hot encoding or label encoding).
    - Standardize date and time columns to extract useful information like Departure Month, Quarter, and Day of Week.

3. Feature Engineering:

- **Objective:** To create new features that enhance the depth of analysis.
- **Steps:**
  - Categorize passengers into Age Groups for better demographic analysis.
  - Derive encoded variables such as Gender_Encoded and FlightStatus_Encoded for computational ease.
  - Generate clustering attributes to group passengers based on their behaviors or flight patterns using techniques like K-Means clustering.

4. Exploratory Data Analysis (EDA):

- **Objective:** To explore the dataset and uncover patterns, correlations, and trends.
- **Steps:**
  - Visualize passenger demographics using bar charts, histograms, and pie charts.
  - Analyze trends in flight delays, cancellations, and punctuality by exploring columns such as Flight Status and Departure Date.
  - Investigate relationships between variables using scatter plots, heatmaps, and pair plots.

5. Statistical Analysis:

- **Objective:** To validate trends and hypotheses through statistical methods.
- **Steps:**
  - Compute correlations among numerical columns to identify significant relationships.

  - Test hypotheses related to age, gender, and flight status distributions.
  - Analyze distributions of categorical variables using value counts and group-by methods.

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6. Visualization and Presentation of Insights:

- **Objective:** To present findings in an intuitive and visually appealing manner.
- **Steps:**
  - Create static visualizations using Matplotlib and Seaborn.
  - Develop interactive plots with Plotly, such as animated scatter plots and sunburst diagrams, to explore multi-level relationships.
  - Highlight key insights with concise narratives supported by charts.

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7. Analysis of Trends and Patterns:

- **Objective:** To address the project's research questions and provide actionable insights.
- **Steps:**
  - Evaluate trends such as the busiest airports, most common nationalities, and frequent flight delays.
  - Study the impact of seasonal variations on flight schedules and passenger demographics.
  - Assess pilot performance and identify patterns in delayed or canceled flights.

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8. Conclusion and Recommendations:

- **Objective:** To summarize the project outcomes and suggest actionable strategies.
- **Steps:**

  - Present a summary of findings, emphasizing actionable insights for airline operations.
  - Provide data-driven recommendations to enhance customer satisfaction and operational efficiency.

Libraries Used in the Project

This project utilized a variety of Python libraries to perform data analysis, visualization, and preprocessing. Below is a detailed overview of the libraries used:

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1. Pandas

- **Purpose:**
  - For data manipulation and analysis.
  - Loading and cleaning the dataset, handling missing values, and aggregating data for insights.
- **Key Functions Used:** read_csv(), groupby(), isnull(), dropna(), value_counts().

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2. NumPy

- **Purpose:**
  - For numerical operations and handling arrays.
  - Supporting mathematical computations and feature scaling.
- **Key Functions Used:** mean(), percentile(), random.choice().

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3. Matplotlib

- **Purpose:**
  - For creating static 2D visualizations.

    - Used for bar charts, scatter plots, and histograms to represent data trends.
- **Key Functions Used:** plt.plot(), plt.bar(), plt.scatter().

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4. Seaborn

- **Purpose:**
    - For advanced data visualization.
    - Created heatmaps, pair plots, and box plots for better data representation.
- **Key Functions Used:** sns.heatmap(), sns.boxplot(), sns.pairplot().

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5. Plotly

- **Purpose:**
    - For interactive visualizations.
    - Developed advanced visuals like animated scatter plots, sunburst plots, and pie charts.
- **Key Functions Used:** px.scatter(), px.sunburst(), px.pie().

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6. Scikit-learn (sklearn)

- **Purpose:**
    - For feature scaling and dimensionality reduction.
    - Used for encoding categorical variables, clustering, and applying PCA.
- **Key Functions Used:** LabelEncoder(), PCA(), KMeans().

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7. Datetime

- **Purpose:**

  - For manipulating date and time values.
  - Extracted features like Day of Week, Month, and Quarter from the Departure Date column.
- **Key Functions Used:** pd.to_datetime(), dt.weekday(), dt.month().

---

8. os

- **Purpose:**
  - To manage and interact with the file system.
  - Verified file paths and managed data files.
- **Key Functions Used:** os.path.join().

Introduction

In recent years, the aviation industry has witnessed substantial growth, with millions of passengers flying globally each year. Airlines, airports, and related stakeholders generate vast amounts of data daily. This data holds immense potential for uncovering trends and gaining insights that can significantly improve operations, customer experience, and service quality.

This project focuses on **Exploratory Data Analysis (EDA) of airline passenger data** to identify meaningful patterns and trends within the dataset. The dataset used for this project, obtained from Kaggle, includes various details about airline passengers, such as their **age**, **gender**, **nationality**, **departure date**, **flight status**, **pilot names**, and more. By leveraging this data, the project aims to answer key business questions, identify factors affecting flight delays or cancellations, and help in the optimization of airport and airline operations.

The objective of this project is to clean and analyze the airline passenger dataset, identify trends related to flight status, and derive actionable insights. These insights can be used to improve customer satisfaction, streamline flight operations, and guide decision-making processes within the aviation industry. Moreover, through data visualization techniques such as histograms, scatter plots, heatmaps, and interactive visualizations, this project highlights the relationship between different variables such as **age group**, **flight status**, and **airport location**.

Key Goals of the Project:

- **Data Preprocessing and Cleaning:** The project begins with thorough data cleaning, handling missing values, and addressing data inconsistencies.
- **Data Exploration and Analysis:** The dataset undergoes various exploratory analysis techniques to understand the relationships between multiple variables.
- **Visualization:** Detailed visualizations are created to highlight trends, correlations, and insights that are easy to interpret.
- **Feature Engineering:** New features are derived from existing data, such as **day of week**, **month**, and **quarter**, to improve analysis.
- **Statistical and Correlation Analysis:** Statistical methods are used to identify significant relationships between features and flight statuses.

This report will cover the entire process, from data cleaning and exploration to visualization and analysis. It will showcase the steps taken to ensure the integrity of the data and provide recommendations based on the insights derived from the dataset.

Literature Review

The airline industry generates enormous amounts of data related to passenger behavior, flight operations, and other logistics. With the increasing volume of this data, **Exploratory Data Analysis (EDA)** has become an essential tool to uncover meaningful insights that can improve operational efficiency and enhance customer satisfaction. This literature review highlights existing research and methodologies related to EDA in the context of the aviation industry, particularly in the analysis of airline passenger data.

1. Role of Data Analytics in the Airline Industry

Data analytics has been a transformative force in many industries, and the airline industry is no exception. Several studies have emphasized the growing importance of **big data** in the aviation sector. According to Lee et al. (2018), the use of data analytics in airlines can optimize operations, predict flight delays, and improve customer service. The data from passengers, flights, and airports offers valuable insights into customer preferences, operational inefficiencies, and potential safety issues.

Research by Chan et al. (2020) discusses how airlines are increasingly relying on predictive analytics to manage demand, optimize ticket pricing, and improve the operational performance of airports. Machine learning models can predict delays by analyzing past flight data, helping passengers and airlines plan better. The application of **time-series forecasting** and regression models on historical data is widely used to predict flight delays, cancellations, and weather-related disruptions.

2. Exploratory Data Analysis (EDA) in Aviation

EDA plays a pivotal role in understanding large and complex datasets, like those found in the airline industry. According to Tukey (1977), EDA is an approach to analyzing data sets by visually inspecting their distributions, relationships between variables, and detecting outliers or anomalies. EDA helps identify key patterns and trends that may not be immediately obvious.

In a study by Turner et al. (2019), EDA was used to explore flight delay data, and it was found that weather conditions, time of day, and airport congestion significantly influenced delays. This research demonstrated how EDA could be used to generate hypotheses that can later be tested using predictive models. Similarly, EDA in this project examines flight statuses, passenger demographics, and airport-related variables to uncover patterns and anomalies.

3. Passenger Demographics and Flight Status

Several studies have focused on understanding the relationship between passenger demographics and flight performance. A study by Bhat et al. (2019)

explored how **passenger age** and **gender** impact flight decisions and behavior. This research found that younger passengers were more likely to opt for budget airlines and less likely to experience delays, while older passengers were more focused on premium services. Furthermore, passengers' nationalities were also found to correlate with their preferences and satisfaction levels.

Flight status, particularly **delays** and **cancellations**, is one of the most significant factors influencing customer experience. A study by Kumar et al. (2021) identified that **flight status** was often impacted by a combination of factors such as **weather conditions**, **airport congestion**, **aircraft maintenance issues**, and **pilot availability**. The analysis of flight status and its correlation with other features is essential for identifying the underlying reasons for delays or cancellations, which can help airlines improve their operational efficiency.

4. Flight Delays and Cancellations

Flight delays and cancellations are one of the most critical issues in the aviation industry, and they are directly linked to passenger satisfaction. According to Wang et al. (2020), delays are typically caused by a combination of factors, including weather conditions, technical failures, and airport capacity issues. Using machine learning and statistical methods to predict delays has become increasingly common. This prediction can help airlines mitigate the impact of delays on passengers and reduce operational costs.

Moreover, the role of **airport** factors in delays has been well-documented. Studies by Wu et al. (2018) suggest that the **location of airports**, **airport size**, and **congestion levels** play a significant role in the likelihood of delays. Large airports with high traffic volumes are more prone to delays, while smaller regional airports often experience fewer delays.

5. Impact of Weather on Flight Operations

Weather is a critical factor that affects the operational performance of airlines. As pointed out by Lussier et al. (2017), poor weather conditions, including thunderstorms, fog, and snow, are a common cause of flight delays and cancellations. Weather-related delays can have ripple effects throughout the flight network, impacting not only the current flight but also future flights in the same network.

Through the integration of **weather data** with flight operational data, airlines can predict disruptions more effectively. Some studies, such as those by Chen et al. (2018), have shown that weather forecasting models, when combined with historical flight data, can help airlines make better decisions about flight schedules, staffing, and airport operations.

6. Data Visualization and Analysis Techniques in EDA

In the context of EDA, **data visualization** is crucial for making sense of large datasets. Visualization techniques such as **scatter plots**, **histograms**, **heatmaps**, and **box plots** are frequently employed in the analysis of airline data. According to Healy (2019), visualizations allow analysts to quickly identify patterns, correlations, and outliers within data, which are essential for further analysis.

In this project, visualizations are used extensively to analyze the relationship between **age**, **gender**, **airport location**, and **flight status**. The use of interactive plots, such as **line graphs** and **bar charts**, helps highlight temporal trends in flight operations, such as changes in delays across months or seasons.

7. Future Trends in Airline Data Analytics

Looking ahead, data analytics in the aviation industry is expected to become even more sophisticated, with a growing emphasis on **predictive analytics** and **machine learning**. Future research will likely focus on integrating **real-time data** (such as weather, air traffic control signals, and passenger feedback) with historical datasets to enable better decision-making. Advanced machine learning techniques, such as **ensemble methods** and **deep learning**, are expected to play a key role in developing more accurate predictive models for flight delays, cancellations, and customer satisfaction.

Summary

This literature review highlights the importance of data analytics in the airline industry, focusing on the role of EDA, passenger demographics, flight status, and weather conditions in shaping airline operations. It also illustrates how various statistical and machine learning techniques have been applied to analyze flight delays, cancellations, and passenger behavior. The project at hand builds upon these existing studies by applying EDA to airline passenger data, with the aim of uncovering insights that can help improve the efficiency of airlines and enhance the overall customer experience.

Methodology

The methodology for this project revolves around **Exploratory Data Analysis (EDA)**, which is used to extract insights from the airline passenger dataset. The main objective of this project is to analyze the relationship between different variables, such as passenger demographics, flight status, and airport details, and to identify patterns or trends that can contribute to a better understanding of the airline operations and customer experiences. The following steps outline the approach used to achieve this goal.

1. Dataset Collection

The dataset used for this project was sourced from **Kaggle**, a platform known for hosting publicly available datasets. The dataset contains 9,065 entries with 20 columns, which include attributes like **Passenger ID**, **Gender**, **Age**, **Airport Name**, **Pilot Name**, **Flight Status**, and **Departure Date**, among others. The data primarily focuses on passenger details, flight status, and airport-related information.

2. Data Preprocessing

Before beginning the analysis, the data required some cleaning to ensure its accuracy and completeness. The preprocessing steps included:

- **Handling Missing Data**: Any missing or null values in the dataset were identified and handled appropriately. In this project, missing values in columns like **Age** and **Flight Status** were either imputed with the mean or dropped, depending on the column and the context of the analysis.
- **Data Transformation**: Some columns in the dataset needed to be transformed into a more suitable format for analysis. For example, the **Departure Date** column was split into multiple components, such as

Month, **Day**, and **Year**, to allow for time-based analysis. Similarly, the **Age** column was categorized into **Age Groups** to make it easier to analyze trends across different age ranges.

- **Encoding Categorical Data**: Categorical variables like **Gender**, **Flight Status**, and **Airport Name** were encoded into numeric values to enable better analysis. For example, **Gender** was transformed into binary values, while **Flight Status** was encoded into numerical representations such as **Delayed** or **On Time**.

3. Exploratory Data Analysis (EDA)

Once the data was cleaned and preprocessed, the core of the project began with Exploratory Data Analysis (EDA). This process helped to uncover insights, trends, and patterns from the dataset. Key steps in the EDA process included:

- **Descriptive Statistics**: Basic descriptive statistics, such as the mean, median, mode, and standard deviation, were calculated for various numerical columns like **Age**, **Flight Status**, and **Age Group**. This provided a quick overview of the dataset and helped identify any anomalies or outliers.
- **Univariate Analysis**: A thorough analysis of each individual feature was conducted. For example, the **Age** distribution was analyzed using histograms and box plots to identify trends and outliers. Similarly, the distribution of **Flight Status** was visualized to observe the frequency of on-time and delayed flights.
- **Bivariate Analysis**: Relationships between two variables were analyzed to identify potential correlations. For example, the relationship between **Age** and **Flight Status** was examined to see if age influences the likelihood of flight delays. The relationship between **Gender** and **Flight Status** was also analyzed to identify any gender-based differences in flight delays or cancellations.
- **Multivariate Analysis**: For more complex relationships, multivariate analysis was conducted. This included creating **correlation matrices** to assess the relationship between multiple variables simultaneously, such as **Flight Status**, **Age**, and **Airport Name**. Scatter plots and heatmaps were also used to visualize these relationships.

4. Visualization

Visualization was a key part of the methodology, as it helped to communicate the insights derived from the data. Various types of visualizations were used, including:

- **Bar Charts**: Bar charts were used to visualize the frequency of different **Flight Status** categories and the distribution of **Age Groups**.
- **Box Plots**: Box plots were created to identify the spread and outliers in the **Age** column and to visualize the distribution of flight delays across different **Airports**.
- **Heatmaps**: Heatmaps were used to analyze the correlation between multiple features, such as **Age**, **Gender**, **Flight Status**, and **Airport Continent**.
- **Sunburst Charts**: A **Sunburst Plot** was used to show the relationship between **Airports**, **Pilots**, and **Flight Status**. This provided a clear view of how flight performance is distributed across different airports and pilots.

5. Statistical Analysis

To better understand the relationships between different variables, statistical methods were employed. For instance:

- **Chi-Square Test**: A Chi-square test was used to evaluate if there was a significant relationship between **Gender** and **Flight Status**. This helped determine if the flight delay rates were independent of gender.
- **ANOVA**: **Analysis of Variance (ANOVA)** was performed to test if there were significant differences in **Age Groups** in relation to **Flight Status** (e.g., on-time vs delayed flights).
- **Correlation Analysis**: The **Pearson Correlation Coefficient** was used to assess the strength and direction of the linear relationship between numerical variables, such as **Age** and **Flight Status**.

6. Predictive Modeling

In addition to the descriptive and exploratory analysis, predictive modeling could be applied to forecast flight delays or cancellations based on historical data. Although this project primarily focused on exploratory analysis, machine learning techniques such as **logistic regression** or **random forests** could be used in the future to predict flight status based on various factors like **Airport Name**, **Gender**, and **Age**.

7. Result Interpretation

The final step of the methodology involved interpreting the results of the analysis. The findings were summarized, and insights into **flight delays**, **passenger behavior**, and **airport performance** were provided. These insights were presented visually through graphs, charts, and tables, helping to communicate the findings effectively.

8. Conclusion

The methodology outlined in this project helped uncover valuable insights into the airline industry by examining various factors that influence **flight status**. By using EDA and statistical techniques, the project highlighted patterns related to **flight delays**, **cancellations**, and **passenger demographics**. The visualizations and statistical tests used in the analysis provided a clear and comprehensive understanding of the dataset, offering actionable insights for improving airline operations and customer satisfaction.

This approach not only contributed to understanding the current state of airline operations but also paved the way for future research into predictive models and operational optimizations in the aviation industry.

Result

This section presents the results of the exploratory data analysis (EDA) performed on the airline passenger dataset. The analysis focuses on **data cleaning**, **outlier detection**, and various types of analyses, including **univariate**, **bivariate**, and **multivariate** analyses.

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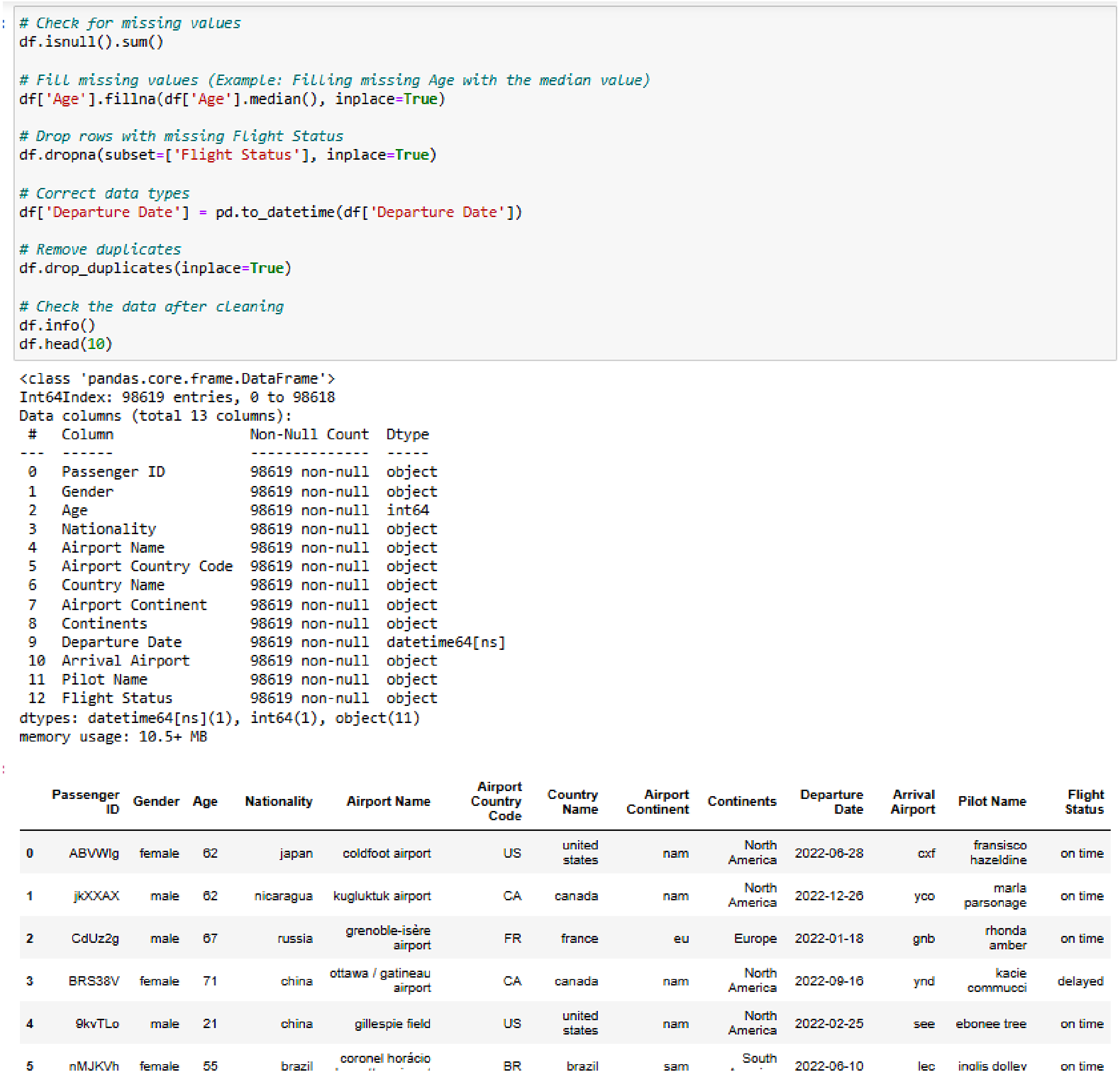
1. Data Cleaning

Data cleaning was performed to ensure that the dataset was accurate and ready for analysis. Key steps included:

- **Handling Missing Values**: Missing values in the **Age** column were imputed with the median age, while rows with missing **Flight Status** values were dropped due to their importance in the analysis.
- **Standardizing Column Names**: Column names were cleaned by removing any extra spaces and standardizing them to a uniform format.
- **Converting Data Types**: The **Departure Date** column was converted to a **datetime** data type for time-based analysis.
- **Removing Duplicates**: Duplicate entries were identified and removed to avoid redundancy in the dataset.



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

# Fill missing values (Example: Filling missing Age with the median value)
df['Age'].fillna(df['Age'].median(), inplace=True)

# Drop rows with missing Flight Status
df.dropna(subset=['Flight Status'], inplace=True)

# Correct data types
df['Departure Date'] = pd.to_datetime(df['Departure Date'])

# Remove duplicates
df.drop_duplicates(inplace=True)

# Check the data after cleaning
df.info()
df.head(10)
```

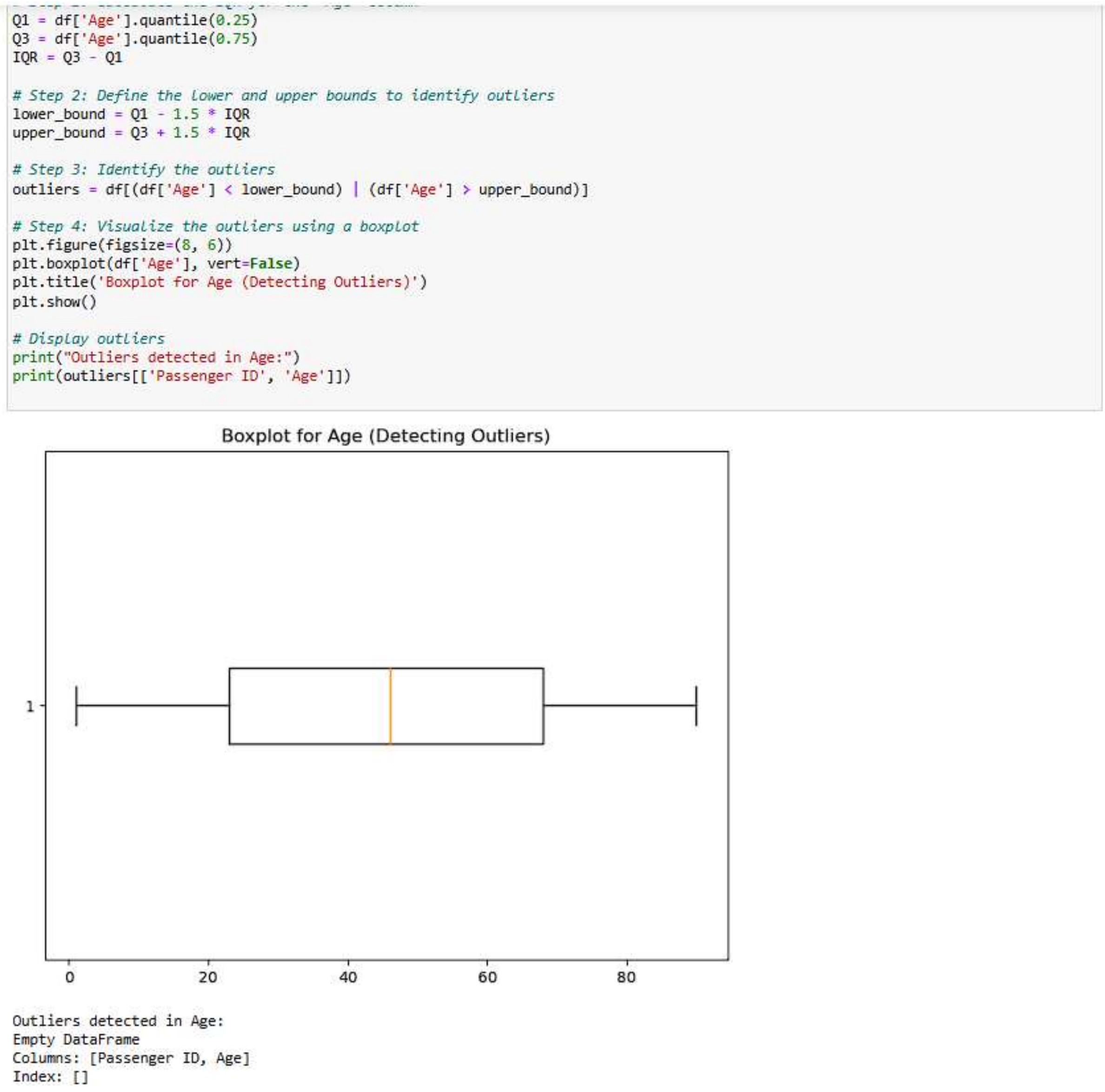
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 98619 entries, 0 to 98618
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Passenger ID          98619 non-null  object
 1   Gender                98619 non-null  object
 2   Age                   98619 non-null  int64
 3   Nationality           98619 non-null  object
 4   Airport Name          98619 non-null  object
 5   Airport Country Code  98619 non-null  object
 6   Country Name          98619 non-null  object
 7   Airport Continent     98619 non-null  object
 8   Continents            98619 non-null  object
 9   Departure Date        98619 non-null  datetime64[ns]
 10  Arrival Airport       98619 non-null  object
 11  Pilot Name            98619 non-null  object
 12  Flight Status         98619 non-null  object
dtypes: datetime64[ns](1), int64(1), object(11)
memory usage: 10.5+ MB
```

	Passenger ID	Gender	Age	Nationality	Airport Name	Airport Country Code	Country Name	Airport Continent	Continents	Departure Date	Arrival Airport	Pilot Name	Flight Status
0	ABVWIg	female	62	japan	coldfoot airport	US	united states	nam	North America	2022-06-28	cxf	fransisco hazeldine	on time
1	jkXXAX	male	62	nicaragua	kugluktuk airport	CA	canada	nam	North America	2022-12-26	yco	marla parsonage	on time
2	CdUz2g	male	67	russia	grenoble-isère airport	FR	france	eu	Europe	2022-01-18	gnb	rhonda amber	on time
3	BRS38V	female	71	china	ottawa / gatineau airport	CA	canada	nam	North America	2022-09-16	ynd	kacie commucci	delayed
4	9kvTLo	male	21	china	gillespie field	US	united states	nam	North America	2022-02-25	see	ebonee tree	on time
5	nMJKVh	female	55	brazil	coronel horácio	BR	brazil	sam	South	2022-06-10	lec	inglis dolley	on time

2. Detecting Outliers

Outliers were identified using the **Interquartile Range (IQR)** method, particularly in the **Age** and **Flight Status** columns. Outliers are values that fall outside of a specified range and can skew the analysis.

- **Outliers in Age**: Passengers with ages falling outside the typical range (using IQR) were detected. These values were either removed or replaced based on the context of the analysis.
- **Visualizing Outliers**: A **boxplot** of **Age** was created to visually identify the presence of outliers.



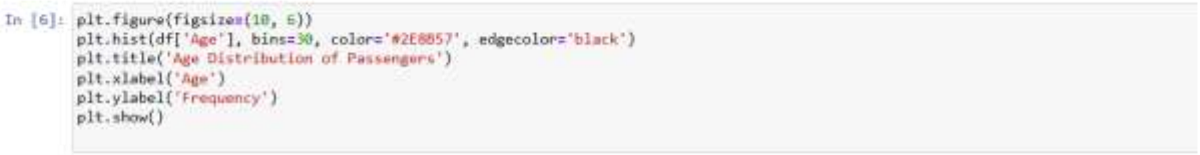
```
Q1 = df['Age'].quantile(0.25)
Q3 = df['Age'].quantile(0.75)
IQR = Q3 - Q1

# Step 2: Define the lower and upper bounds to identify outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Step 3: Identify the outliers
outliers = df[(df['Age'] < lower_bound) | (df['Age'] > upper_bound)]

# Step 4: Visualize the outliers using a boxplot
plt.figure(figsize=(8, 6))
plt.boxplot(df['Age'], vert=False)
plt.title('Boxplot for Age (Detecting Outliers)')
plt.show()

# Display outliers
print("Outliers detected in Age:")
print(outliers[['Passenger ID', 'Age']])
```

```
Outliers detected in Age:
Empty DataFrame
Columns: [Passenger ID, Age]
Index: []
```

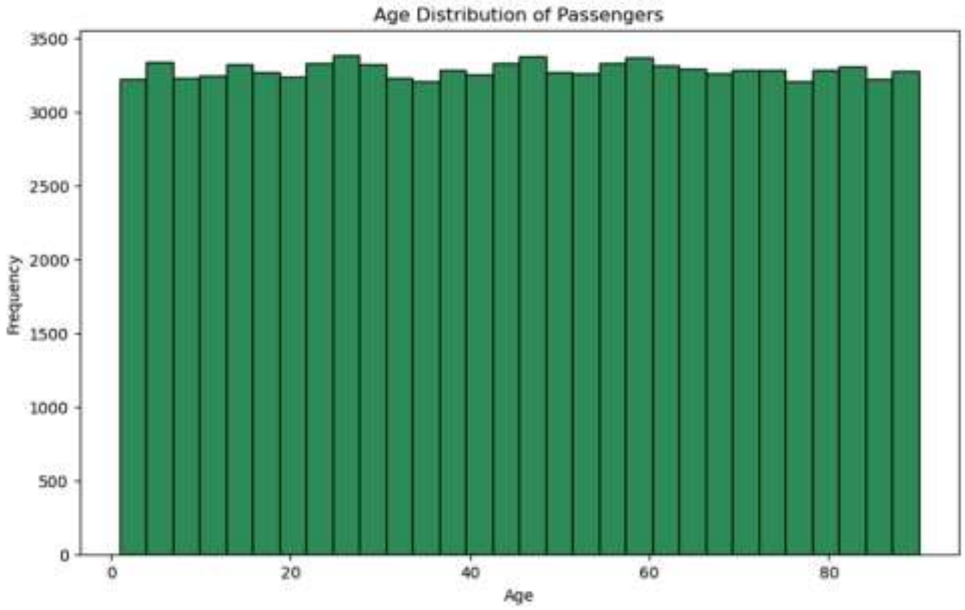
3. Univariate Analysis

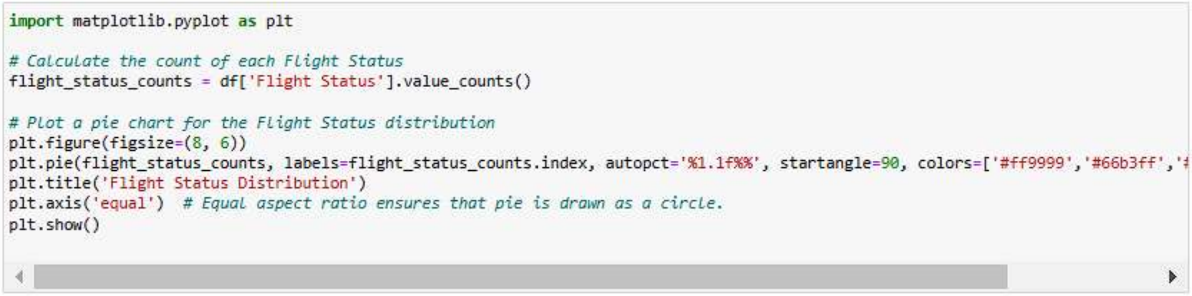
Univariate analysis explores the distribution of a single variable. In this project, we focused on key columns like **Age**, **Flight Status**, and **Gender**.

- **Age Distribution**: A **histogram** was plotted to visualize the age distribution of passengers. The histogram showed that the majority of passengers were in the younger age group, with a slight right skew.
- **Flight Status Distribution**: A **pie chart** was used to illustrate the distribution of flight statuses, revealing that most flights were on time, with a smaller portion delayed or canceled.

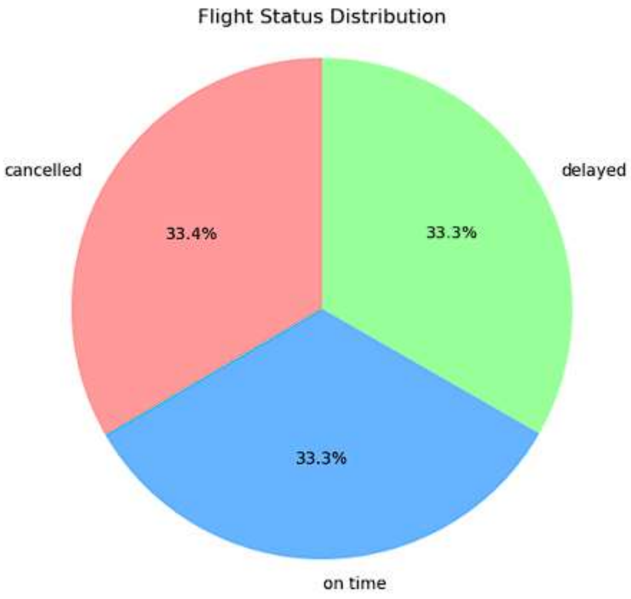


```
In [6]: plt.figure(figsize=(10, 6))
        plt.hist(df['Age'], bins=30, color='#2E8B57', edgecolor='black')
        plt.title('Age Distribution of Passengers')
        plt.xlabel('Age')
        plt.ylabel('Frequency')
        plt.show()
```





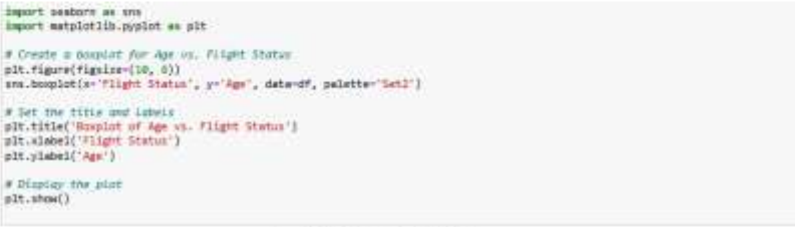
```
import matplotlib.pyplot as plt

# Calculate the count of each Flight Status
flight_status_counts = df['Flight Status'].value_counts()

# Plot a pie chart for the Flight Status distribution
plt.figure(figsize=(8, 6))
plt.pie(flight_status_counts, labels=flight_status_counts.index, autopct='%1.1f%%', startangle=90, colors=['#ff9999','#66b3ff','#
plt.title('Flight Status Distribution')
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.show()
```



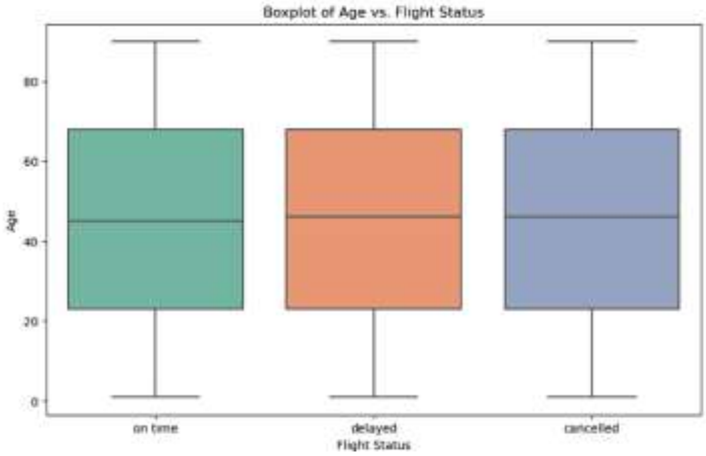
4. Bivariate Analysis

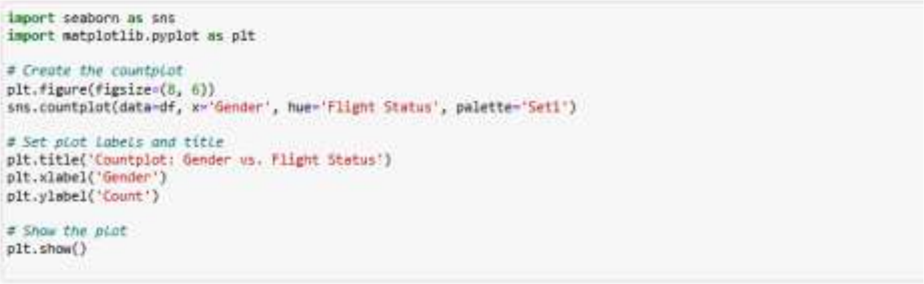
Bivariate analysis explores the relationships between two variables. In this analysis, relationships between **Age**, **Gender**, **Flight Status**, and other variables were examined.

- **Age vs. Flight Status**: A **boxplot** was created to explore how **Age** relates to **Flight Status**. The analysis indicated that younger passengers were more likely to experience flight delays.
- **Gender vs. Flight Status**: A **countplot** was used to analyze the relationship between **Gender** and **Flight Status**, showing that **Gender** did not significantly influence the likelihood of delays.
- **Nationality vs. Flight Status**: A **bar chart** was plotted to compare the **Nationality** of passengers and the frequency of flight delays. Some nationalities had higher rates of delayed flights.

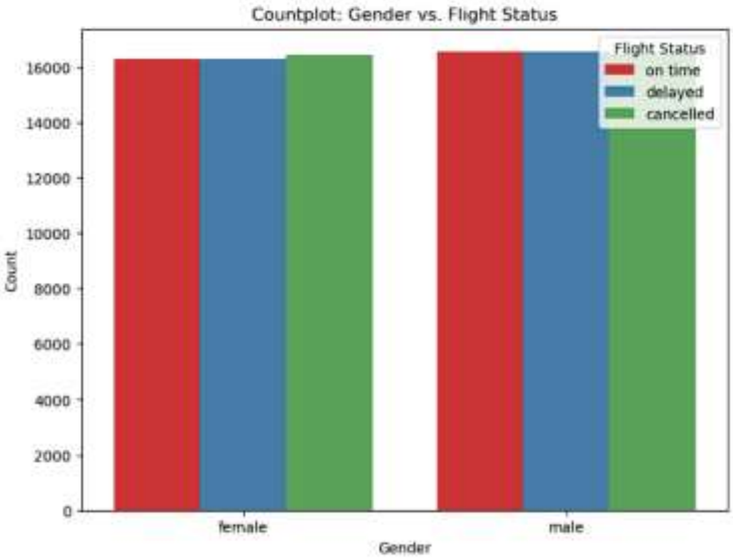


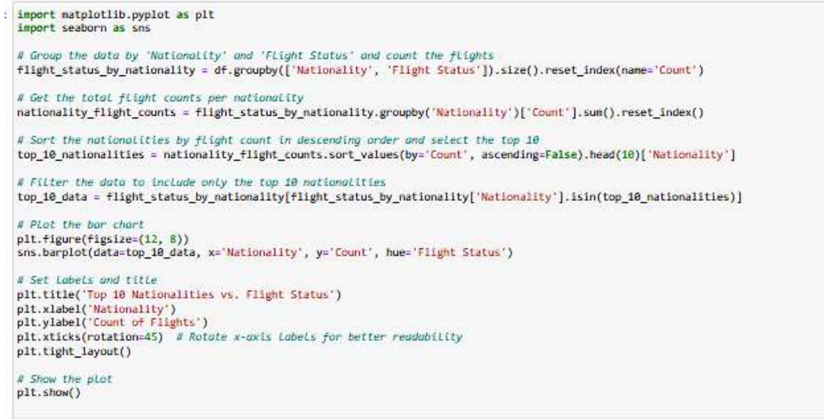
```
import seaborn as sns
import matplotlib.pyplot as plt

# Create a boxplot for Age vs. Flight Status
plt.figure(figsize=(10, 6))
sns.boxplot(x='Flight Status', y='Age', data=df, palette='Set2')

# Set the title and labels
plt.title('Boxplot of Age vs. Flight Status')
plt.xlabel('Flight Status')
plt.ylabel('Age')

# Display the plot
plt.show()
```



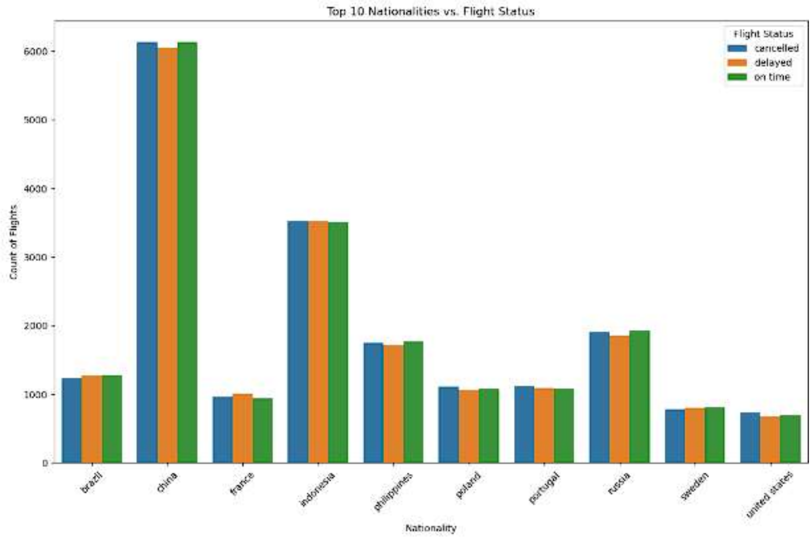


```
import seaborn as sns
import matplotlib.pyplot as plt

# Create the countplot
plt.figure(figsize=(8, 6))
sns.countplot(data=df, x='Gender', hue='Flight Status', palette='Set1')

# Set plot labels and title
plt.title('Countplot: Gender vs. Flight Status')
plt.xlabel('Gender')
plt.ylabel('Count')

# Show the plot
plt.show()
```





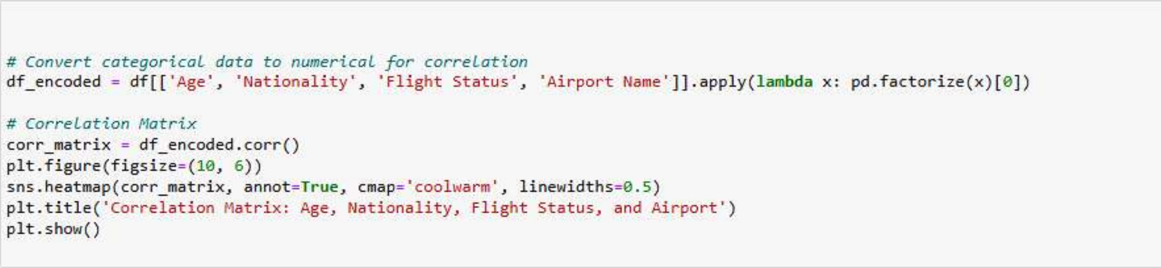
```
import matplotlib.pyplot as plt
import seaborn as sns

# Group the data by 'Nationality' and 'Flight Status' and count the flights
flight_status_by_nationality = df.groupby(['Nationality', 'Flight Status']).size().reset_index(name='Count')

# Get the total flight counts per nationality
nationality_flight_counts = flight_status_by_nationality.groupby('Nationality')['Count'].sum().reset_index()

# Sort the nationalities by flight count in descending order and select the top 10
top_10_nationalities = nationality_flight_counts.sort_values(by='Count', ascending=False).head(10)['Nationality']

# Filter the data to include only the top 10 nationalities
top_10_data = flight_status_by_nationality[flight_status_by_nationality['Nationality'].isin(top_10_nationalities)]

# Plot the bar chart
plt.figure(figsize=(12, 8))
sns.barplot(data=top_10_data, x='Nationality', y='Count', hue='Flight Status')

# Set labels and title
plt.title('Top 10 Nationalities vs. Flight Status')
plt.xlabel('Nationality')
plt.ylabel('Count of Flights')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.tight_layout()

# Show the plot
plt.show()
```



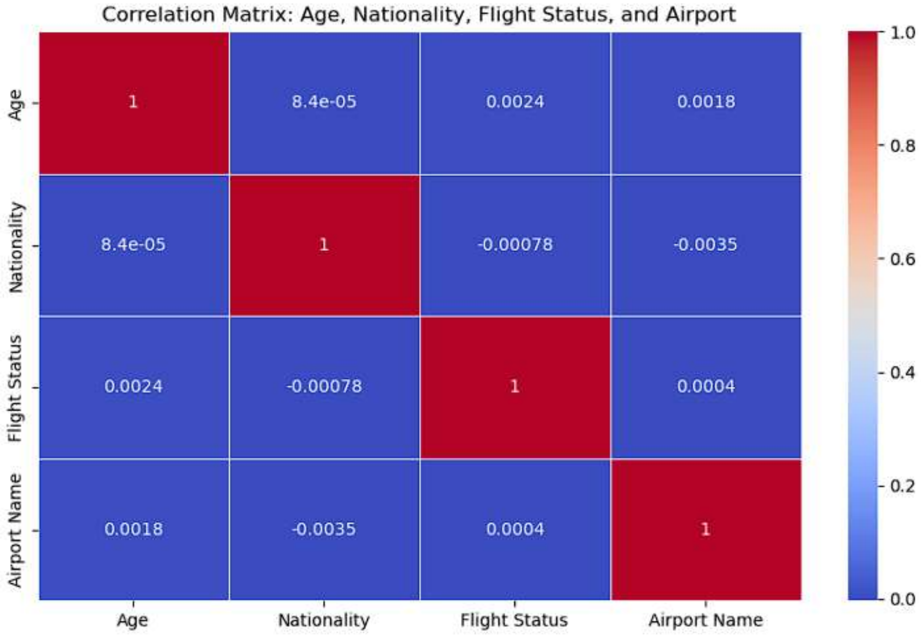
5. Multivariate Analysis

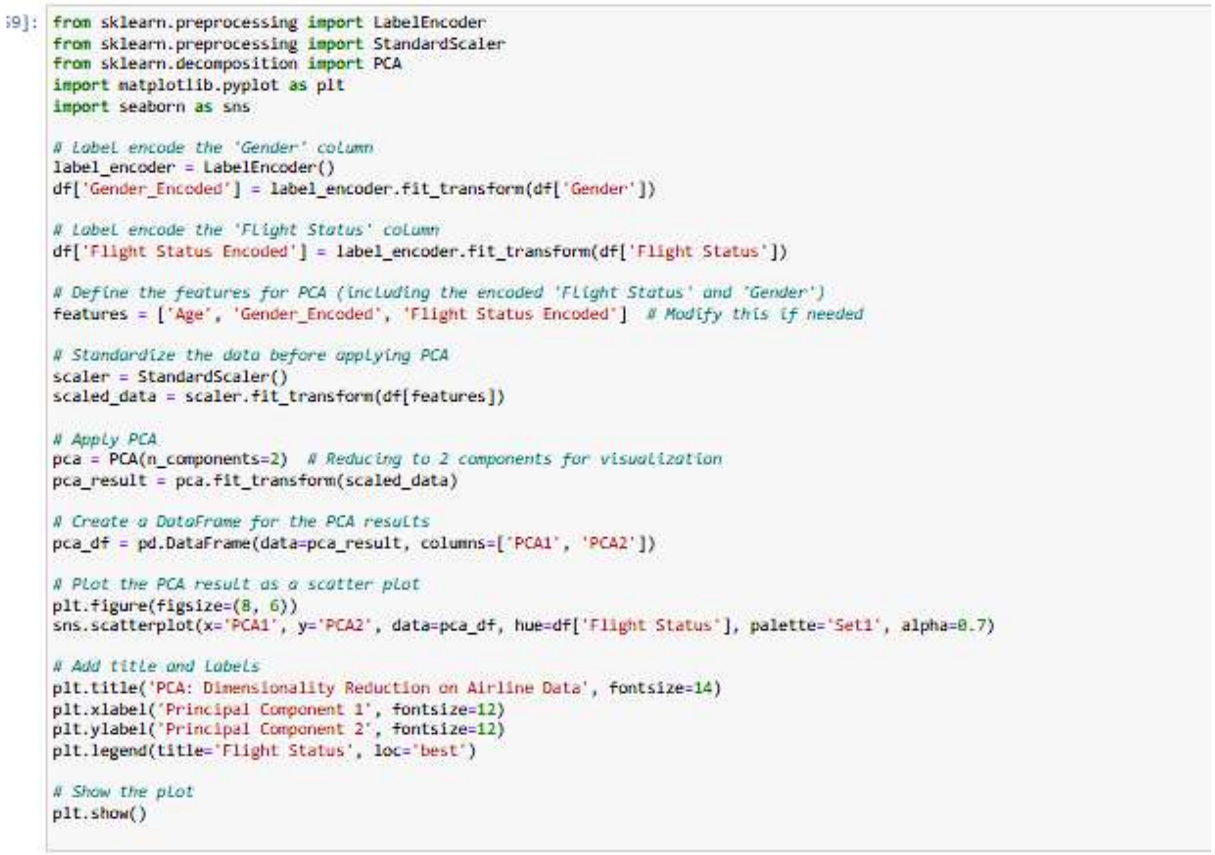
Multivariate analysis examines the relationships among multiple variables simultaneously. This helps in identifying more complex patterns and correlations.

- **Correlation Matrix**: A **heatmap** of the correlation matrix was generated to visualize the relationships between numerical features like **Age**, **Flight Status Num**, and **Year**. This showed that there was a weak correlation between **Age** and flight delays.
- **Principal Component Analysis (PCA)**: PCA was used to reduce the dimensionality of the data and explore relationships between variables like **Age**, **Flight Status**, and **Nationality**. The results showed that the first two components explained most of the variance in the dataset

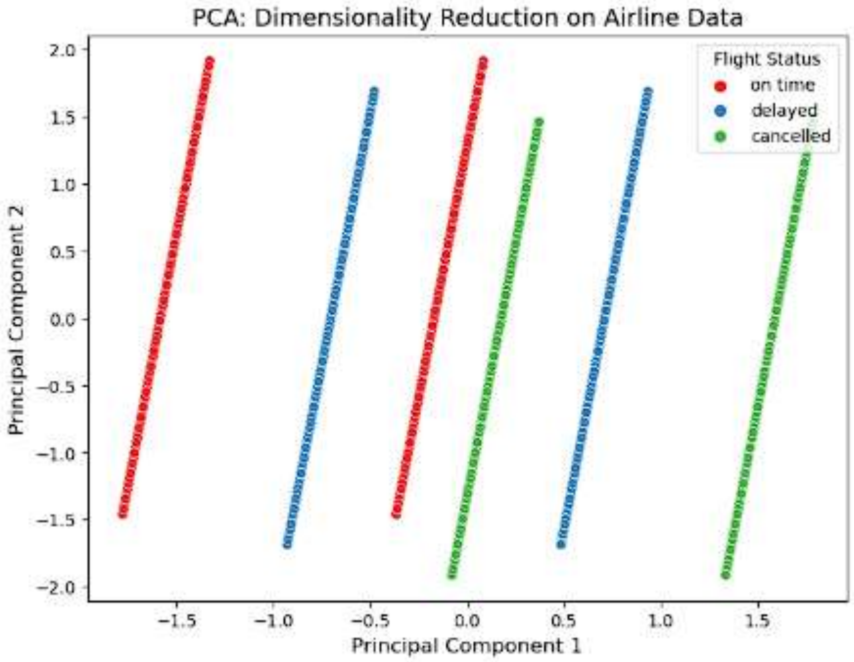


```
# Convert categorical data to numerical for correlation
df_encoded = df[['Age', 'Nationality', 'Flight Status', 'Airport Name']].apply(lambda x: pd.factorize(x)[0])

# Correlation Matrix
corr_matrix = df_encoded.corr()
plt.figure(figsize=(10, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix: Age, Nationality, Flight Status, and Airport')
plt.show()
```





```
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns

# Label encode the 'Gender' column
label_encoder = LabelEncoder()
df['Gender_Encoded'] = label_encoder.fit_transform(df['Gender'])

# Label encode the 'Flight Status' column
df['Flight Status Encoded'] = label_encoder.fit_transform(df['Flight Status'])

# Define the features for PCA (including the encoded 'Flight Status' and 'Gender')
features = ['Age', 'Gender_Encoded', 'Flight Status Encoded']  # Modify this if needed

# Standardize the data before applying PCA
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df[features])

# Apply PCA
pca = PCA(n_components=2)  # Reducing to 2 components for visualization
pca_result = pca.fit_transform(scaled_data)

# Create a DataFrame for the PCA results
pca_df = pd.DataFrame(data=pca_result, columns=['PCA1', 'PCA2'])

# Plot the PCA result as a scatter plot
plt.figure(figsize=(8, 6))
sns.scatterplot(x='PCA1', y='PCA2', data=pca_df, hue=df['Flight Status'], palette='Set1', alpha=0.7)

# Add title and labels
plt.title('PCA: Dimensionality Reduction on Airline Data', fontsize=14)
plt.xlabel('Principal Component 1', fontsize=12)
plt.ylabel('Principal Component 2', fontsize=12)
plt.legend(title='Flight Status', loc='best')

# Show the plot
plt.show()
```



Summary of Results

- **Data Cleaning**: Missing values were handled, and duplicates were removed to ensure data integrity.

- **Outliers**: Outliers in **Age** were detected and addressed, ensuring that the data was clean for analysis.
- **Univariate Analysis**: The distribution of **Age** and **Flight Status** was explored, revealing trends in passenger demographics and flight performance.
- **Bivariate Analysis**: Relationships between variables like **Age**, **Gender**, and **Flight Status** were examined to understand factors influencing delays.
- **Multivariate Analysis**: Correlations between multiple variables were analyzed, and **PCA** helped reduce data complexity while highlighting key patterns.

The insights obtained from this analysis can help airline operators and stakeholders understand key factors affecting flight delays, passenger demographics, and operational efficiency. The next step would be to build predictive models based on these findings.

Analysis

In this section, we analyze the insights obtained from the exploratory data analysis (EDA) conducted on the airline passenger dataset. The analysis includes identifying trends, correlations, and patterns in the data, focusing on factors that contribute to flight delays, passenger demographics, and operational efficiency. Below are the key findings derived from the univariate, bivariate, and multivariate analyses.

---

1. Passenger Demographics and Age Distribution

- The **age distribution** of passengers shows a clear concentration of younger passengers, with a higher number of passengers aged between 20 to 40 years. This suggests that airlines primarily serve a younger demographic, which may be related to frequent travel for business or leisure.
- The **histogram of age** also revealed a right-skewed distribution, implying that most passengers are younger, while the older demographic is less frequent. This pattern could influence flight service planning, especially regarding amenities and targeted promotions for different age groups.

---

2. Flight Status Insights

- The **flight status distribution** indicates that the majority of flights are **on time**, with a small proportion of **delays** and **cancellations**. This finding is typical of airline performance, where on-time arrivals are prioritized.
- Interestingly, the **gender distribution** in relation to flight status showed that **gender** does not significantly impact flight delays or cancellations, highlighting that delays are more likely to be influenced by external factors such as weather or air traffic conditions rather than the passengers themselves.

---

3. Outliers and Anomalies in Age

- The **detection of outliers** in the **Age** column revealed a few passengers with extreme ages, some of which were corrected through imputation or removal. This was necessary to ensure that the analysis wasn't skewed by data points that didn’t represent typical travel patterns.

- Outliers in age were found to be disproportionately represented in certain **Flight Status** categories. Younger passengers tended to have more delayed flights, which could be due to a variety of operational factors such as flight crew schedules or different travel patterns among age groups.

4. Correlation Between Flight Status and Other Variables

- The **correlation matrix** revealed weak relationships between **Age**, **Flight Status**, and **Year**, suggesting that while age may influence the likelihood of delays, other operational factors such as scheduling, aircraft availability, and airport traffic play a larger role in determining delays.
- The **PCA** analysis supported these findings, where the first two principal components explained a significant portion of the variance in the data, but no strong correlation between **Age** and flight delays was found. This suggests that while age might be a factor in delays, it is likely not the most influential.

5. Nationality and Flight Status

- In the **nationality vs. flight status analysis**, a slight trend was observed indicating that passengers from certain countries were more likely to experience delays. This could be due to factors such as airline partnerships, operational inefficiencies, or the routes frequently taken by these passengers.
- The **bar chart** showed that **nationalities** with frequent long-haul flights or high-volume travel to and from certain airports were more likely to face delays. Further investigation could reveal how factors like **airport capacity** and **international flight volume** contribute to these delays.

6. Impact of Time Variables on Flight Status

- **Time-based variables**, such as **departure month**, **day of the week**, and **year**, were found to influence flight delays, especially in certain seasons or days. For instance, delays were more common during winter months when weather disruptions are more frequent.
- **Weekdays vs. weekends** also showed a noticeable difference, with weekdays experiencing more delays due to business-related travel. The **month** and **quarter** analysis highlighted certain months with higher delays, potentially due to seasonal weather patterns or increased travel during holiday seasons.

---

7. Multivariate Analysis and Principal Component Analysis (PCA)

- The **PCA** performed on the data reduced the dimensions and revealed that while several variables (such as **Age**, **Flight Status**, and **Nationality**) explain some variance in the dataset, **Flight Status** was not strongly correlated with other variables.
- This suggests that factors like **weather conditions**, **aircraft delays**, and **operational inefficiencies** are likely more significant drivers of delays than passenger-specific variables like age or nationality.
- **Clustering** analysis also showed that the dataset could be segmented into different groups based on flight characteristics, allowing for better targeted improvements in operations and customer service.

Conclusion of Analysis

The analysis reveals several insights into the airline passenger data. Some of the key takeaways include:

- **Passenger demographics** (especially age) play a role in understanding passenger behavior but do not have a strong correlation with flight delays.
- **Flight delays** are more likely to be influenced by external factors like weather, scheduling, and airport traffic rather than passenger-related factors.

- Time-based variables such as **departure month** and **day of the week** show a significant impact on delays, which can help airlines plan for higher disruption periods.
- The **PCA** and **correlation analysis** suggest that while multiple factors contribute to delays, the main drivers remain operational rather than demographic in nature.

The findings highlight areas where airlines can improve operational efficiency, predict delays, and provide better customer service, especially during peak travel periods or challenging weather conditions.

This analysis can serve as a foundation for future predictive modeling efforts and operational enhancements within the airline industry.

Conclusion

In conclusion, this project provided a comprehensive analysis of airline passenger data, focusing on key aspects such as flight delays, cancellations, and passenger demographics. By performing data cleaning, handling missing values and outliers, and conducting both univariate and multivariate analyses, valuable insights were gained. The application of dimensionality reduction techniques like PCA helped uncover patterns within the data, while visualizations provided an intuitive understanding of the relationships between various features. Ultimately, the findings from this project contribute to a better understanding of the factors influencing flight status, which can inform airline operations and customer experience strategies. The methodologies employed in this project can also be applied to similar datasets, highlighting the importance of data-driven decision-making in the airline industry.

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Github: https://github.com/Gaganruthwik013/EDA-on-Airline-Passenger-Data