**Student Declaration of Authorship**

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**Data Mining and Machine Learning** (Course Code: **F21DL**)

**Airline Survey Analysis**

**(Course Work – I)**

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# Overview

Airline Survey analysis project is taken for machine learning to answer two question as mentioned below.

**Question 1:** To predict Customer Loyaltyfromprovided data [Appendix](#_Appendix) Dataset 1 & 2.

**Question 2:** To provideCustomer Reaction Analysis based on image-based identification where we will classify customers based on facial reactions.

# Data Analysis and Exploration

Dataset 1 & 2: Dataset 1 & 2 are excel data as plotted below. The input CSV file contains 25 columns of customer data with variables capturing demographic details (e.g., Age, Gender), travel specifics (e.g., Flight Distance, Type of Travel), and service experience ratings across multiple aspects such as Online Boarding, Seat Comfort, and Food and Drink. The dataset also includes columns reflecting customer satisfaction and customer type from which Loyalty column is derived. This structured data is used to identify loyal customers.

## Data Quality and Missing Values

The dataset includes various customer attributes and satisfaction metrics aimed at predicting customer loyalty, segmented into four classes derived from **Customer Type** and **Satisfaction** ratings. To ensure data quality, an initial analysis was conducted to assess the completeness of each feature. While most features were complete, a few had minor data gaps. Specifically, **Arrival Delay** showed approximately 0.3% missing values, **Ease of Online Booking** had 4.37% missing values, and **Departure and Arrival Time Convenience** exhibited a 5.1% gap. Additionally, some in-flight service ratings, such as **Leg Room Service**, **In-flight Wifi Service**, and **Food and Drink**, had small data deficiencies.

A screenshot of a computer

Description automatically generatedA screenshot of a computer screen

Description automatically generatedA screenshot of a graph

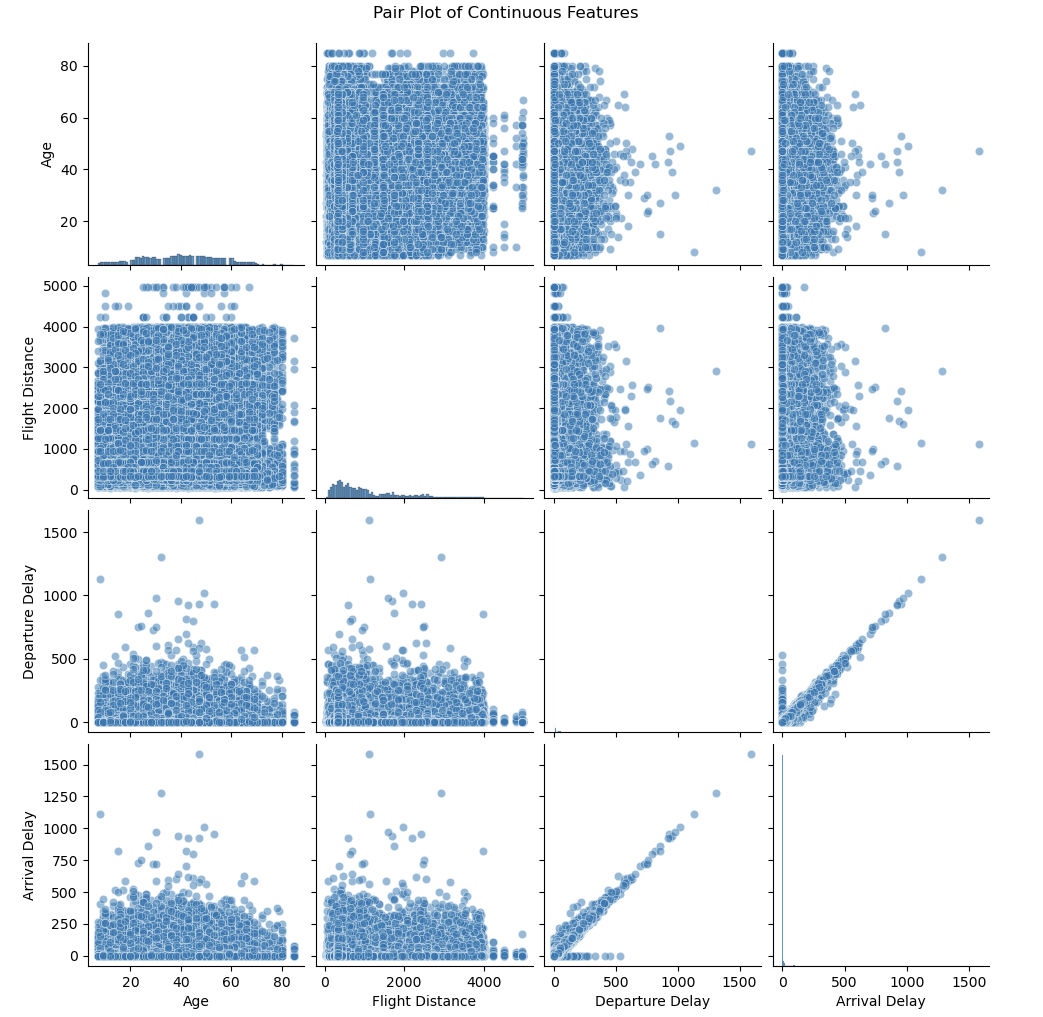
Description automatically generated

Figure 1

A customized imputation strategy was employed to address these missing values effectively. For continuous features like **Arrival Delay** and **Departure Delay**, missing values were filled using the median, a robust choice against outliers. In cases where certain satisfaction metrics were recorded as zero due to missing feedback, these were replaced with the median of available responses, ensuring consistency in representation and reducing bias introduced by missing feedback.

## Feature Types and Encoding

The dataset contains both categorical and continuous variables, each requiring specific handling to prepare them for clustering and predictive modeling. Categorical features, including Gender, Customer Type, Type of Travel, and Class, were label-encoded to convert them into numerical representations that clustering algorithms can process. For example, Gender was transformed into binary values, while Type of Travel (Business or Personal) and Class (Business, Economy, Economy Plus) were similarly encoded to capture their distinct values numerically.

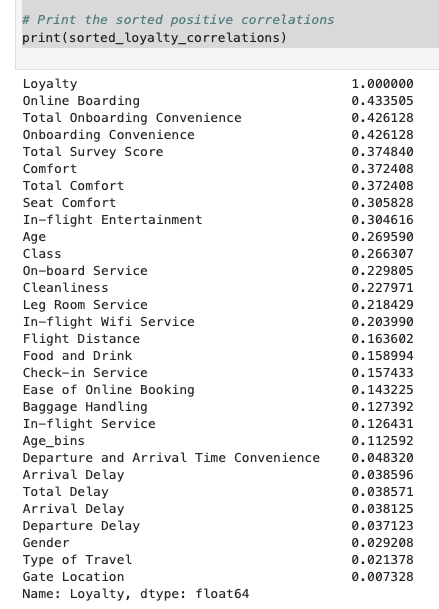
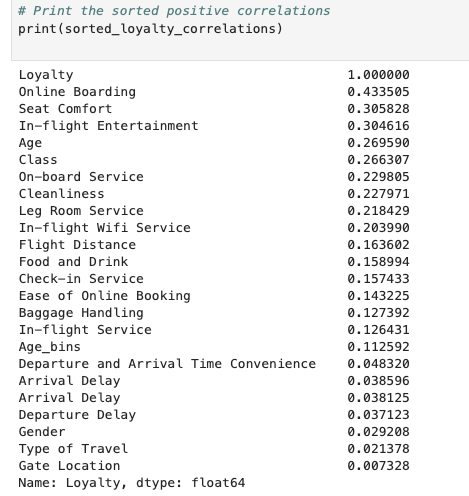
A graph of a line

Description automatically generated with medium confidence

Continuous features, such as Flight Distance, Departure Delay, and Arrival Delay, were transformed to enhance their interpretability and reduce skewness. Binning was applied to the delay features based on quantiles to better capture the natural distribution of delays without excessive variance. Additionally, Age was binned into broader categories (e.g., young adults, middle-aged, seniors), simplifying age-related analysis and providing a more structured way to analyze demographic patterns.

## Feature Engineering

Feature engineering played a crucial role in enhancing the dataset’s predictive power by generating broader survey-based metrics and interaction terms. Key features were aggregated to form new variables like **Total Onboarding Convenience**, **Overall Comfort**, **In-flight Service Quality**, and **Cleanliness**. For instance, **Total Onboarding Convenience** was constructed by combining scores from **Ease of Online Booking**, **Check-in Service**, and **Gate Location**, encapsulating the entire boarding experience into a single metric. This not only simplified the data but also highlighted the comprehensive impact of the boarding process on customer satisfaction.



To capture complex relationships, interaction terms were created, particularly for features expected to influence customer loyalty when combined. These interaction terms included **Online Boarding x Comfort**, **Departure Delay x Total Survey Score**, and others that helped highlight combined service effects. Notably, these engineered interaction terms exhibited higher correlation scores with loyalty, emphasizing the importance of customer experiences formed by multiple factors working together.

Correlation analysis further revealed positive relationships between features such as **Online Boarding** (0.43), **Onboarding Convenience** (0.42), and **Seat Comfort** (0.30) with loyalty scores. Variance Inflation Factor (VIF) analysis was also conducted to detect multicollinearity. Delay-related features like **Departure Delay** and **Arrival Delay** showed high VIF values, indicating close correlations. By introducing feature scaling and strategically adding interaction terms, multicollinearity was effectively mitigated, ensuring that feature dependencies did not overly influence clustering outcomes.

These refined features provided a well-balanced and insightful dataset optimized for loyalty prediction. They allowed clustering algorithms to identify meaningful customer segments characterized by flight experience, service ratings, and convenience factors, offering deeper insights into the drivers of customer loyalty. This comprehensive preparation facilitated a more structured and robust predictive analysis, capturing both individual service ratings and broader experience impacts.

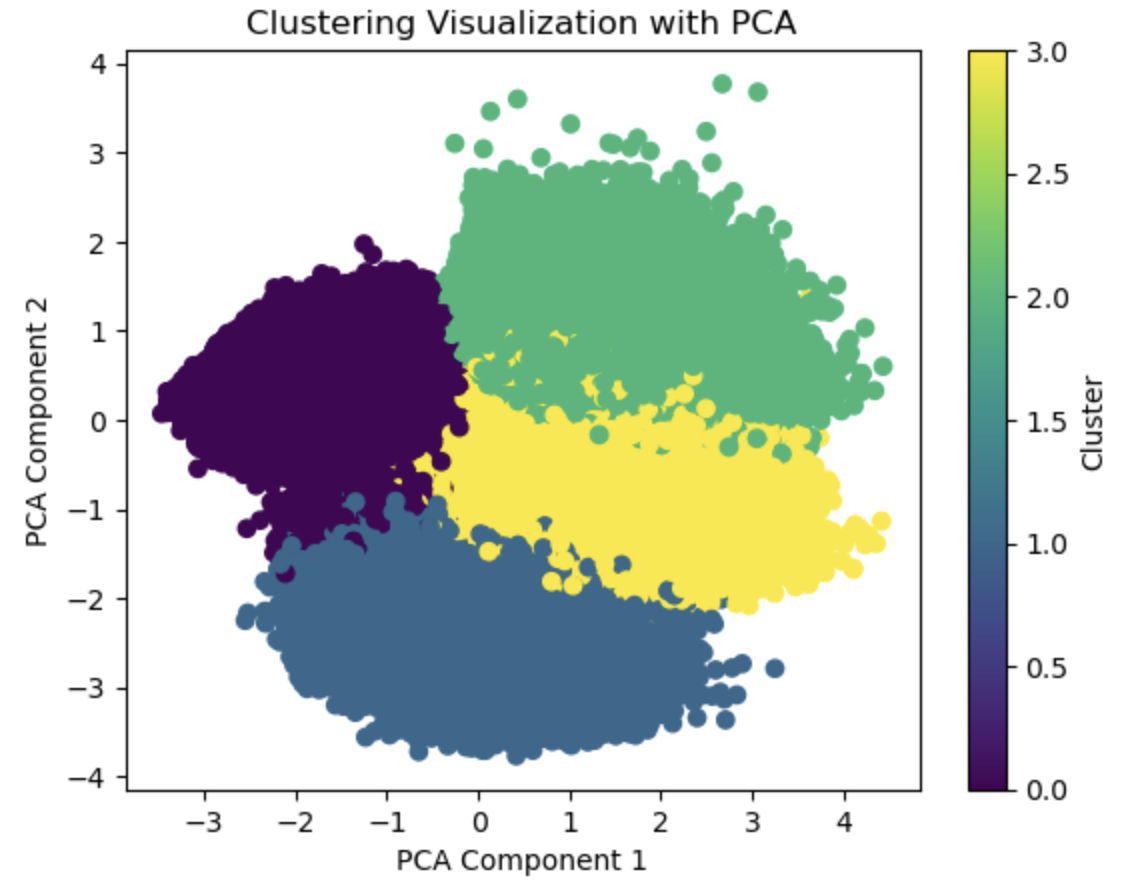
# Clustering

## Rationale for K-Means Selection and Data Preparation

For customer segmentation, K-Means clustering was selected due to its efficiency in handling high-dimensional, continuous data. Our dataset, consisting of metrics on customer service experience (e.g., Online Boarding, Seat Comfort) and demographics, was well-suited to K-Means, which allows for meaningful segmentation based solely on feature similarity without the need for labeled data.

Data standardization was essential, as K-Means relies on Euclidean distance; without standardization, features with larger scales might dominate clustering. We applied StandardScaler to normalize the data, followed by the Elbow Method to determine an optimal cluster count by plotting within-cluster sum of squares (inertia) for clusters ranging from 1 to 10. An “elbow” was observed at 4 clusters, indicating an optimal balance between compactness and simplicity. Silhouette Scores, which measure the separation between clusters, confirmed that 4 clusters provided clear distinctions between customer groups. This was further visualized using PCA for dimensionality reduction, enabling us to view the clusters on a two-dimensional plot for clearer interpretation.

A graph of a number of clusters

Description automatically generated

## Cluster Profiles and Key Insights

The clustering revealed four distinct customer segments with varying service expectations and demographic characteristics.

**Cluster 0** predominantly includes middle-aged customers who prioritize convenience, rating Online Boarding and Leg Room Service highly. This suggests a loyalty driver centered on ease and comfort during onboarding. **Cluster 1** comprises older, mostly business travelers who often take long-haul flights. They rate Food and Drink service well, indicating that in-flight amenities are important to this group’s loyalty. **Cluster 2** represents younger customers on shorter flights, with lower ratings for Online Boarding and On-board Service, suggesting potential gaps in meeting their expectations. These customers may be less loyal, representing an opportunity for targeted improvements. **Cluster 3** includes young leisure travelers who value Leg Room Service, suggesting that targeted offers on comfort and affordability may appeal strongly to this group.

This segmentation allows us to identify loyalty drivers specific to each group. Correlation analysis shows Online Boarding, Total Onboarding Convenience, and Seat Comfort as key factors associated with loyalty, which align with the needs identified within each cluster. By understanding these profiles, we can develop tailored loyalty programs and service improvements that directly address the preferences of each customer segment, enhancing retention and satisfaction across the board.

# Baseline Training and Evaluation Experiments

## Models Implemented

In this analysis, three distinct machine learning models were implemented: Decision Tree, Naive Bayes, and k-Nearest Neighbors (k-NN). Each model was chosen for its unique strengths in handling classification tasks. The Decision Tree Classifier is a powerful model that splits data based on feature criteria, making it adept at capturing non-linear patterns in the dataset. The Naive Bayes model, specifically the Gaussian Naive Bayes, leverages probabilistic methods, assuming conditional independence among features, which often performs well on smaller datasets. Lastly, the k-NN model was used as a non-parametric method that classifies samples based on their proximity to labeled data points, with k set to 5 to balance complexity and performance.

A screenshot of a graph

Description automatically generated

## 4.2 Model Output and Evaluation

Each model’s performance was evaluated using standard classification metrics, including accuracy, precision, recall, and F1 score. The Decision Tree model yielded the highest accuracy of 80%, with corresponding F1, precision, and recall values around 0.81, suggesting it effectively captured the patterns in the data. Naive Bayes produced a lower accuracy of 71%, with an F1 score of 0.73, indicating some limitations in modeling this dataset due to its independence assumption. The k-NN model achieved an accuracy of 77% with an F1 score of 0.77, performing reasonably well though slightly lower than the Decision Tree. Confusion matrices illustrated the models’ performance in detail, with the Decision Tree showing the most balanced results, suggesting that it might be the most reliable model for this dataset.

# Neural Networks

# Conclusion

# Appendix

* GITHUB Repository Link: <https://github.com/HWHospital2024/HW_Hospital_App>
* Dataset Source Details:
  1. Dataset 1: Airline Passenger Satisfaction Dataset
     + Link: <https://www.kaggle.com/datasets/teejmahal20/airline-passenger-satisfaction/data>
     + File name: airline\_passenger\_satisfaction.csv
  2. Dataset 2: Airline Passenger Satisfaction
     + Link: <https://www.kaggle.com/datasets/mysarahmadbhat/airline-passenger-satisfaction/data>
     + File Name: train.csv & test.scv
  3. Dataset 3: VGGFace2 Dataset
     + Link: <https://www.kaggle.com/datasets/jonathanoheix/face-expression-recognition-dataset>
     + Folder name: "train" & "Validate" folders