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Performance Evaluation of Self-Tuning Possibilistic Fuzzy C-Means Algorithm on Real-World Datasets

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Abstract

Clustering is a vital tool in intelligent data analysis, enabling researchers to uncover hidden structures and patterns in datasets. This paper evaluates the performance of the Self-Tuning Possibilistic Fuzzy C-Means (ST-PFCM) algorithm on three diverse real-world datasets: stellar characteristics, air quality metrics, and movie performance data. The analysis incorporates exploratory visualizations, clustering quality metrics such as Silhouette Scores, and fuzzy membership evaluations. By leveraging PCA for dimensionality reduction and combining the strengths of Fuzzy C-Means (FCM) and Possibilistic Fuzzy C-Means (PFCM), ST-PFCM demonstrates robust handling of noise, adaptability to varying data distributions, and effective cluster separation. Results highlight its superior performance over traditional clustering methods, making it an invaluable tool for intelligent data analysis.

1. Introduction

Acknowledgement
This work is the result of my own activity, and I confirm I have neither given nor received unauthorized assistance for this work.
I declare that I used generative AI in the creation of content for this document, specifically to assist with drafting text sections, refining explanations, and improving coherence and clarity.

1.1 Background and Motivation

The analysis and classification of data are crucial in a wide range of domains, including astrophysics, environmental science, and media analytics. Each of these fields relies on accurate grouping and pattern recognition for decision-making and advancing scientific understanding. However, traditional clustering methods often struggle to handle data variability, overlapping distributions, and noise inherent in real-world datasets. This study adopts an intelligent clustering approach using the Self-Tuning Possibilistic Fuzzy C-Means (ST-PFCM) algorithm to overcome these challenges.
Astrophysics provides a prime example of the need for nuanced data analysis. Traditional stellar classification methods rely on rigid boundaries for attributes such as temperature, luminosity, and radius, which may overlook natural variability and overlapping attributes among stars. Similarly, environmental science involves data with high variability, such as pollutant concentrations, requiring robust methods to classify air quality levels accurately. In the film industry, where ratings, votes, and revenue span wide ranges, effective clustering is essential for identifying trends and target audiences.
Fuzzy logic, introduced by Lotfi Zadeh in 1965, offers an innovative solution by accommodating ambiguity and variability. By allowing variables to exist on a spectrum rather than fixed states, fuzzy logic mimics human reasoning and provides a flexible approach to data classification. The primary motivation of this study is to demonstrate how a combination of fuzzy logic and adaptive clustering can address the limitations of traditional methods in real-world datasets.

1.2 Objectives of the Study

This study evaluates the performance of the ST-PFCM algorithm in clustering datasets with diverse characteristics. The specific objectives are:

- To implement and validate the ST-PFCM algorithm on three real-world datasets: stellar attributes, air quality metrics, and movie data.
- To analyze and visualize the clustering performance using metrics like Silhouette Scores and PCA-based scatter plots.
- To highlight the algorithm's ability to handle overlapping distributions, noise, and high-dimensional data.
- To compare the ST-PFCM results with traditional clustering approaches, demonstrating its advantages in handling real-world complexity.

1.3 Scope of the Study

The study focuses on three datasets:

- **Stars Dataset**: Features include temperature, luminosity, and radius, which are used to classify stars into categories such as dwarf, main sequence, and giant.
- **Air Quality Dataset**: Metrics include CO, NO2, and benzene concentrations, which are grouped into air quality levels (e.g., good, moderate, unhealthy).
- **Movie Dataset**: Attributes such as ratings, votes, and revenue are analyzed to cluster movies into performance categories.

The scope is limited to demonstrating the algorithm’s flexibility, robustness, and adaptability to noisy and overlapping data distributions.

1.4 Research Methodology

The methodology involves key steps: data preprocessing to ensure dataset consistency, exploratory data analysis for identifying distributions and outliers, and the application of the ST-PFCM algorithm. PCA was used for dimensionality reduction, and clustering quality was evaluated with metrics like Silhouette Scores. This streamlined approach ensures robustness and interpretability across datasets.

2. Literature Review and Theoretical Framework

2.1 Introduction

This chapter presents the foundational concepts and existing research on clustering methodologies, focusing on their application to astrophysics, environmental science, and movie analytics. It explores the limitations of traditional clustering methods, such as their reliance on rigid boundaries, and introduces fuzzy logic and its integration into the Self-Tuning Possibilistic Fuzzy C-Means (ST-PFCM) algorithm as a robust alternative for handling ambiguous and overlapping data.

2.2 Traditional Classification and Clustering Methods

2.2.1 Traditional Stellar Classification

The Hertzsprung-Russell (H-R) diagram(Figure 2.1) is one of the most widely used tools in astronomy, plotting stars based on luminosity and temperature. It identifies key stellar groups, such as the main sequence, giants, and dwarfs, and offers insights into stellar evolution (Carroll and Ostlie, 2017). However, its reliance on fixed numerical thresholds makes it less effective in categorizing stars with overlapping or ambiguous characteristics, such as those near the boundaries between dwarfs and main sequence stars.

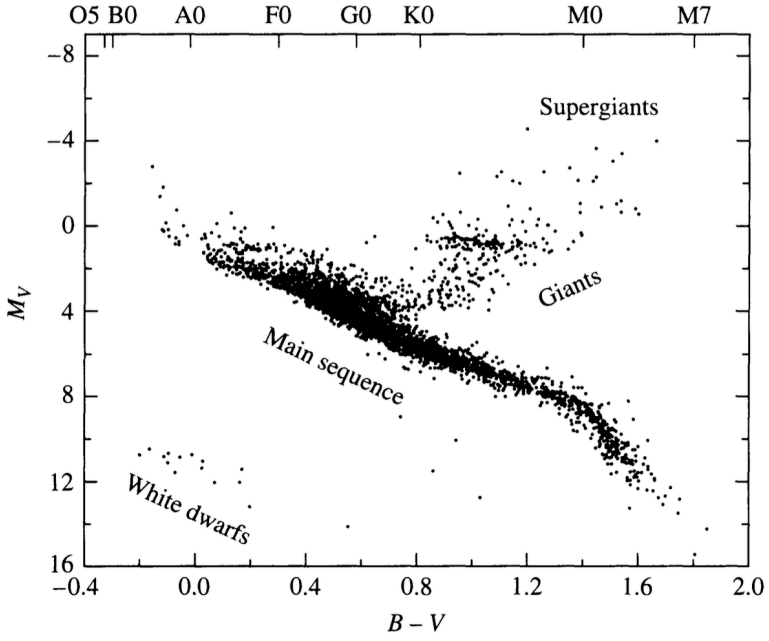

Figure 2.1 The Hertzsprung-Russell (H-R) diagram

The Morgan-Keenan (MK) system further refines stellar classification by introducing spectral types (O, B, A, F, G, K, M) and luminosity classes, providing a highly detailed categorization framework. Despite its precision, the MK system struggles with stars that exhibit mixed or borderline features, necessitating a more adaptable methodology (Carroll and Ostlie 223).

2.2.2 Air Quality Classification

Traditional air quality classification relies on threshold-based indices such as the Air Quality Index (AQI), which categorizes pollution levels (e.g., good, moderate, unhealthy) based on fixed pollutant concentration ranges. While useful, such systems often fail to account for overlapping effects of multiple pollutants, such as how combined exposure to CO and NO2 impacts air quality (World Health Organization, 2021).

2.2.3 Movie Data Segmentation

The entertainment industry frequently uses clustering methods like K-Means to segment movies based on features such as ratings, votes, and revenue. However, K-Means assumes well-separated, non-overlapping clusters, which may not reflect real-world scenarios where movies can share attributes across categories. For instance, a high-revenue movie may simultaneously receive mixed audience ratings, making it difficult to classify definitively into a single group (Lash and Zhao, 2016);(Kim et al., 2013) .

2.3 Limitations of Traditional Approaches

While effective in certain scenarios, traditional classification and clustering approaches suffer from several limitations:

- **Rigid Boundaries**: Methods like the H-R diagram, AQI, and K-Means clustering rely on fixed thresholds that cannot handle data overlap or variability.
- **Sensitivity to Noise**: Traditional clustering algorithms often misclassify noisy data, which is common in real-world datasets.
- **Lack of Flexibility**: Fixed models fail to account for ambiguity in data, such as stars near classification boundaries, combined pollutant effects in air quality, or movies with contradictory metrics.

These limitations underscore the need for adaptable and noise-resistant approaches like fuzzy logic**.**

2.4 Fuzzy Logic as an Alternative Approach

2.4.1 Overview of Fuzzy Logic

Fuzzy logic, introduced by Lotfi Zadeh in 1965, models systems with imprecise information, assigning partial membership to multiple categories (Zadeh, 1965). Unlike binary logic, which forces data points into distinct groups, fuzzy logic accommodates ambiguity and variability. This flexibility makes it ideal for applications where traditional thresholds fail to capture the complexity of real-world data.

2.4.2 Integration of Fuzzy Logic with ST-PFCM

The Self-Tuning Possibilistic Fuzzy C-Means (ST-PFCM) algorithm combines the principles of fuzzy logic with clustering, offering the following advantages:

- **Dynamic Tuning**: Automatically adjusts membership parameters, improving clustering performance without manual intervention.
- **Noise Resistance**: Accounts for noisy data by reducing the influence of outliers on cluster formation.
- **Flexibility in Overlapping Data**: Allows data points to belong partially to multiple clusters, effectively handling overlapping distributions.

2.5 Summary

This chapter reviewed traditional classification and clustering methods across astronomy, environmental science, and movie analytics. While traditional systems like the H-R diagram, AQI, and K-Means clustering provide valuable insights, their limitations in handling overlapping and noisy data highlight the need for alternatives. Fuzzy logic, particularly when integrated into the ST-PFCM algorithm, offers a flexible and robust approach for intelligent data analysis, accommodating real-world complexity and variability.

3. Data Collection and Methodology

3.1 Introduction

This chapter outlines the data sources, preprocessing steps, and clustering methodology applied in this study. Three datasets were used to evaluate the Self-Tuning Possibilistic Fuzzy C-Means (ST-PFCM) algorithm: Stars.csv, Cleaned_AirQuality.csv, and imdb_movie_dataset.csv. Each dataset represents distinct domains—astrophysics, environmental science, and entertainment analytics—providing a comprehensive testbed for the algorithm. Preprocessing steps ensured data consistency and quality, while clustering analysis aimed to evaluate ST-PFCM's ability to handle overlapping, noisy, and variable data distributions.

The study used key attributes from each dataset:

- Stars: **Temperature**, **Luminosity**, and **Radius**—core features in traditional stellar classification.
- Air Quality: **CO (GT)**, **C6H6 (GT)**, and **NO2 (GT)**—representative metrics for pollution levels.
- Movies: **Rating**, **Votes**, and **Revenue**—indicators of audience reception and commercial success.

The preprocessing phase involved normalization, outlier handling, and feature selection, enabling the application of fuzzy clustering tailored to each dataset's characteristics.

3.2 Data Sources and Attributes

3.2.1 Stars Dataset

The **Stars.csv dataset**, sourced from the Stars Classification Dataset sourced from Kaggle (YBI Foundation, 2021), captures a broad range of stellar types. Its comprehensive measurements of **Temperature (K)**, and **Radius (R/Ro)** make it an ideal candidate for evaluating clustering and classification methodologies. The dataset captures a broad range of stellar types, making it an ideal candidate for evaluating fuzzy clustering in astronomy.

3.2.2 Air Quality Dataset

The **Cleaned_AirQuality.csv** dataset, sourced from Kaggle (Soriano, 2021), comprises measurements of pollutants, such as:

- **CO (GT)**: Carbon monoxide concentrations.
- **C6H6 (GT)**: Benzene levels.
- **NO2 (GT)**: Nitrogen dioxide levels.

These attributes are crucial for assessing air quality, and their high variability and overlap present challenges for traditional clustering methods.

3.2.3 Movie Dataset

The **imdb_movie_dataset.csv** dataset, , sourced from Kaggle (Delikkaya, 2021), provides metrics on movie performance, including:

- **Rating**: Audience ratings on a normalized scale.
- **Votes**: Total audience votes.
- **Revenue (Millions)**: Box office revenue.

These features help categorize movies into clusters based on critical and commercial success. Their wide range and overlap necessitate robust clustering approaches.

3.3 Data Preprocessing

Data preprocessing, including handling missing values, normalization, and feature selection, is a critical step in preparing datasets for clustering (Han et al., 2011). Key steps included:

1. **Handling Missing Data**: Missing values were addressed as follows:

- **Stars Dataset**: Rows with incomplete temperature, luminosity, or radius values were removed to maintain data reliability.
- **Air Quality Dataset**: Missing pollutant concentrations were imputed using median values to minimize bias.
- **Movie Dataset**: Entries with missing revenue or rating data were dropped to ensure consistency.

2. **Feature Selection**: For clarity and focus, only the primary attributes relevant to clustering were retained.

Additional fields such as **Star Type** or **Spectral Class** in the Stars dataset, or genre data in the Movies dataset, were excluded to let the clustering algorithm work solely on numerical attributes.

3. **Data Normalization**

To ensure comparability across datasets, attributes were normalized to a [0,1] range using min-max normalization. The formula can be seen in Figure 3.1. This normalization reduces the impact of extreme values and ensures consistent membership function scaling in fuzzy clustering.

$$v_i' = \frac{v_i - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A.$$

Figure 3.1 Normalization Formula

3.4 Application of Fuzzy Clustering

3.4.1 Selection of Attributes

Key attributes were chosen based on their relevance to each dataset:

1.Stars Dataset:

- **Temperature**: Indicates stellar heat and energy output.
- **Luminosity**: Reflects a star's brightness.
- **Radius**: Measures star size, differentiating giants from dwarfs.

These attributes are foundational in understanding stellar evolution and structure (Kippenhahn and Weigert, 2012).

2.Air Quality Dataset:

- **CO**: A key indicator of air pollution caused by incomplete combustion from vehicles and industrial processes. High levels of CO reduce oxygen transport in the bloodstream, posing health risks (World Health Organization, 2021).
- **C6H6**: A hazardous air pollutant linked to vehicle emissions and industrial discharges, known to cause long-term health effects, including cancer (United States Environmental Protection Agency, 2020) .
- **NO2**: A significant pollutant associated with respiratory issues, produced mainly by burning fossil fuels in vehicles and power plants (World Health Organization, 2021).

3.Movie Dataset:

- **Rating**: Reflects audience feedback and serves as a measure of critical reception, helping gauge the qualitative appeal of a movie (Kim et al., 2013).
- **Votes**: A quantitative metric indicating audience engagement, used to assess popularity and public interest (Lash and Zhao, 2016) .
- **Revenue**: Measures a movie's commercial success, often linked to factors such as marketing strategies, audience demographics, and global appeal (Wallace et al., 1992) .

3.4.2 Membership Functions

Membership functions were defined for each attribute to capture their variability:

1.Stars:

- **Temperature**: "Cool," "Warm," and "Hot."

- **Luminosity**: "Low," "Medium," and "High."
- **Radius**: "Small," "Medium," and "Large."

2.Air Quality:

- **CO, NO2, C6H6**: "Low," "Medium," and "High."

3.Movies:

- **Rating**: "Low," "Moderate," and "High."
- **Votes** and **Revenue**: "Low," "Medium," and "High."

3.4.3 Clustering Rules

Fuzzy rules were created to define clusters:

1.Stars Dataset: Stars were grouped based on temperature, luminosity, and radius, into:

- **Cool Dwarfs**: Stars with low temperature, low luminosity, and small radius.
- **Warm Dwarfs**: Stars with slightly higher temperatures but low luminosity and small radius.
- **Main Sequence (Low-Mass)**: Stars with moderate temperature, luminosity, and radius.
- **Main Sequence (High-Mass)**: Stars with higher temperature and luminosity but medium radius.
- **Small Giants**: Stars with higher temperature, moderate luminosity, and larger radius.
- **Large Giants**: Stars with high temperature, high luminosity, and the largest radius values.

2.Air Quality Dataset: Air quality levels were grouped into **5 distinct clusters** based on CO, NO2, and benzene concentrations:

- **Good**: Low pollutant concentrations (CO, NO2, and benzene).
- **Fair**: Slightly higher but still manageable pollutant levels.
- **Moderate**: Moderate pollutant levels likely to cause mild effects.
- **Poor**: High pollutant concentrations affecting sensitive groups.
- **Very Poor**: Very high pollutant concentrations, impacting general health.

3.Movie Dataset: Movies were grouped into **2 clusters** based on ratings, votes, and revenue:

- **Low-Performing Films**: Films with low ratings, votes, and revenue.
- **Blockbusters**: Films with high ratings, votes, and blockbuster-level revenue.

3.5 Clustering Methodology

The clustering methodology employed silhouette scores, elbow methods, and fuzzy clustering to determine the optimal cluster counts for each dataset. Each clustering approach was tailored to the unique attributes of the respective datasets, resulting in well-defined and interpretable groupings.

3.6 Summary

This chapter outlined the data collection, preprocessing, and clustering methodology used in this study. By leveraging ST-PFCM with normalized and preprocessed datasets, the study demonstrates its robustness in handling overlapping and noisy data. The next chapter presents clustering results, visualizations, and an analysis of the algorithm's performance across the Stars, Air Quality, and Movie datasets.

4. Results and Analysis

4.1 Introduction

This chapter presents the results of applying the Self-Tuning Possibilistic Fuzzy C-Means (ST-PFCM) clustering algorithm to the Stars, Air Quality, and Movie datasets. The analysis includes data visualizations such as histograms, boxplots, and cluster visualizations using PCA-reduced components. A detailed discussion of the clustering outcomes is provided for each dataset, supported by 27 plots, illustrating the distribution of attributes, clustering performance, and evaluation metrics.

4.2 Stars Dataset Results

The Stars dataset was analyzed using three core attributes: **Temperature**, **Luminosity**, and **Radius**. The results of data visualization and clustering are presented below.

4.2.1 Attribute Distributions

- **Figure 4.1 (Temperature Distribution)**: The histogram shows a skewed distribution with the majority of stars having low temperatures. A distinct peak is visible near the lower range, corresponding to cooler stars such as dwarfs.

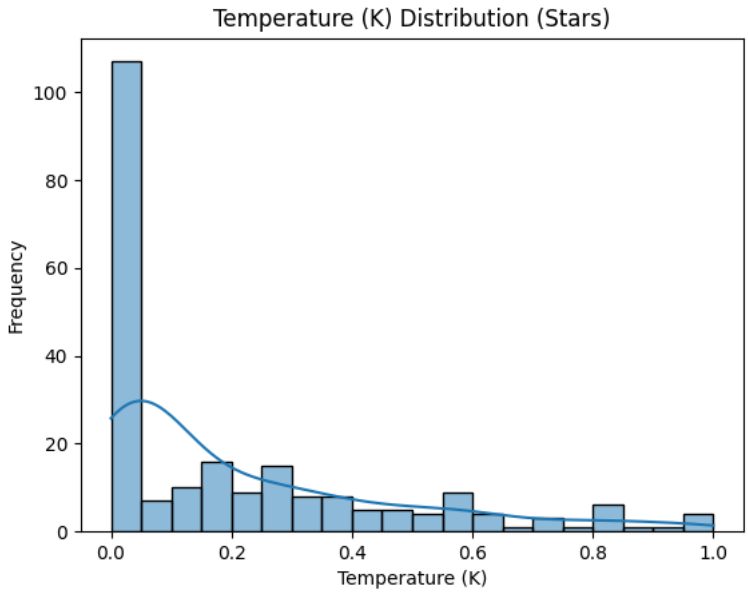

Figure 4.1: Temperature Distribution

- **Figure 4.2 (Temperature Boxplot)**: The boxplot highlights significant variability, with several outliers representing high-temperature stars.

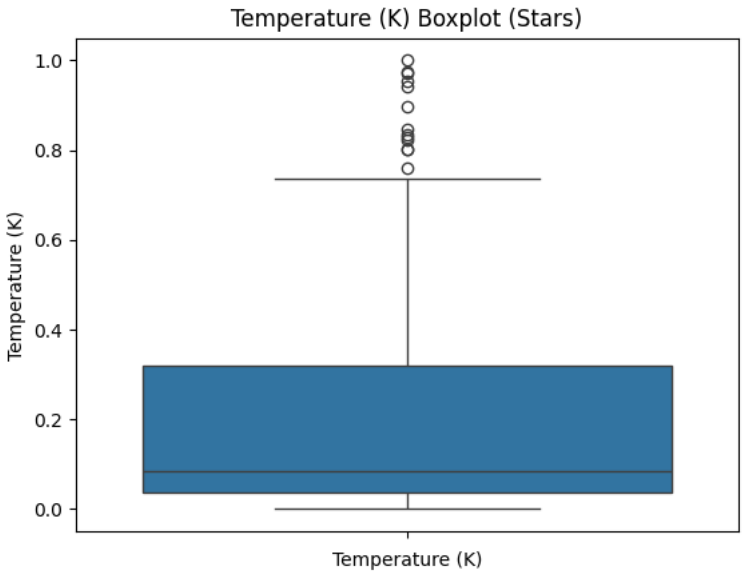

Figure 4.2: Temperature Boxplot

- **Figure 4.3 (Luminosity Distribution)**: The luminosity histogram reveals a similar skew, with most stars exhibiting low luminosity values, typical of dwarf stars.

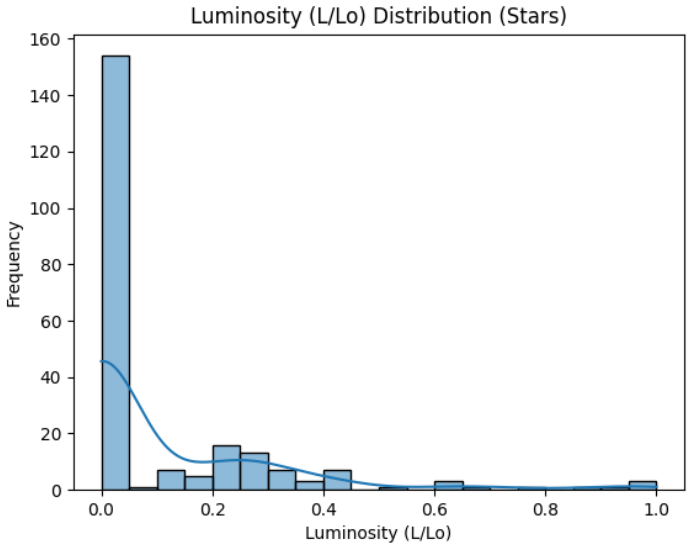

Figure 4.3: Luminosity Distribution

- **Figure 4.4 (Luminosity Boxplot)**: Outliers for high-luminosity stars, likely giants, are evident in the boxplot.

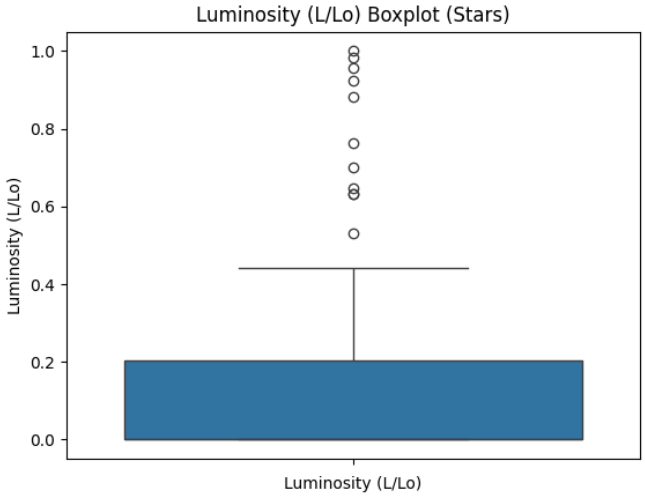

Figure 4.4: Luminosity Boxplot

- **Figure 4.5 (Radius Distribution)**: The radius distribution shows the predominance of stars with small radii, while larger radii values correspond to giant stars.

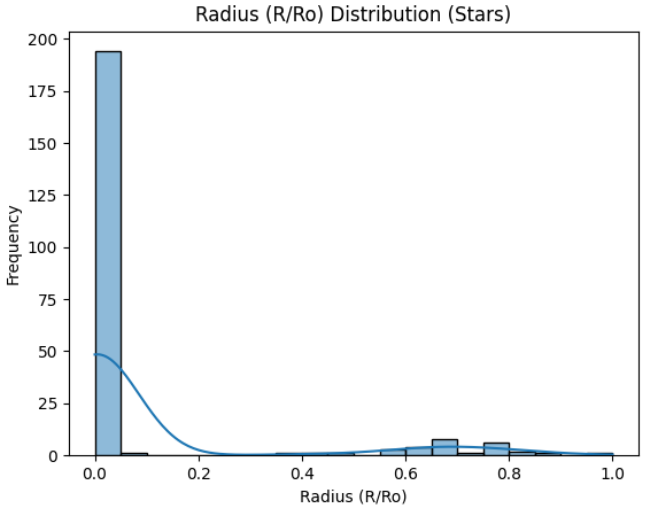

Figure 4.5: Radius Distribution

- **Figure 4.6 (Radius Boxplot)**: The boxplot confirms a concentration of stars with small radii and a few outliers for larger stars.

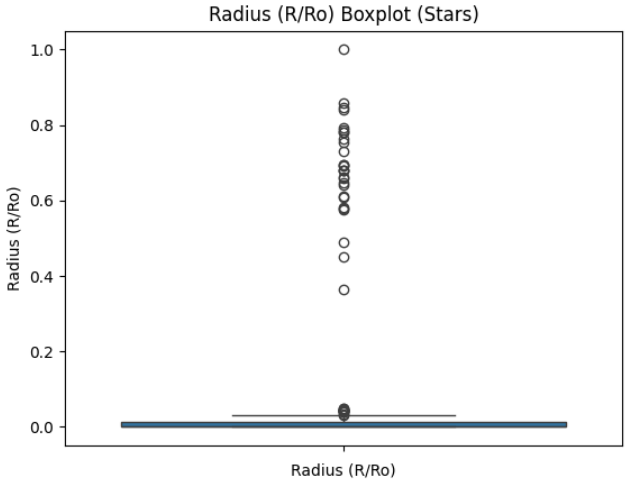

Figure 4.6: Radius Boxplot

4.2.2 Clustering Results

- **Figure 4.7 (Elbow Method)**: The Elbow Method plot shows a diminishing return in inertia reduction after three clusters, but a more nuanced analysis suggests that six clusters could better capture the underlying data structure. While the elbow point is less definitive, the addition of clusters beyond three aligns with distinct data patterns revealed in the visualizations.

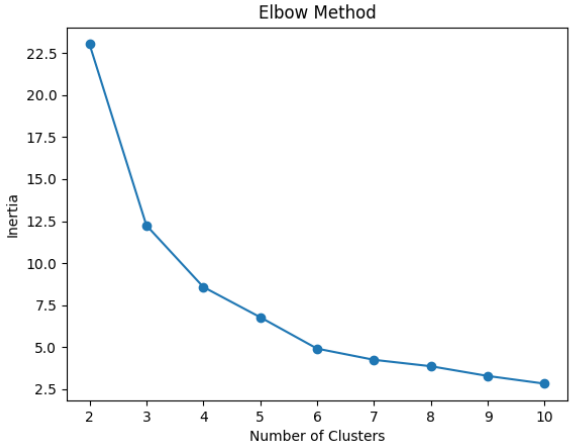

Figure 4.7: Elbow Method

- **Figure 4.8 (Silhouette Scores):** The silhouette scores highlight improvements at several cluster counts, particularly at six clusters. Peaks at 6, 8, and 10 clusters indicate better-defined groupings, with six clusters providing a balance between well-separated clusters and manageable complexity.

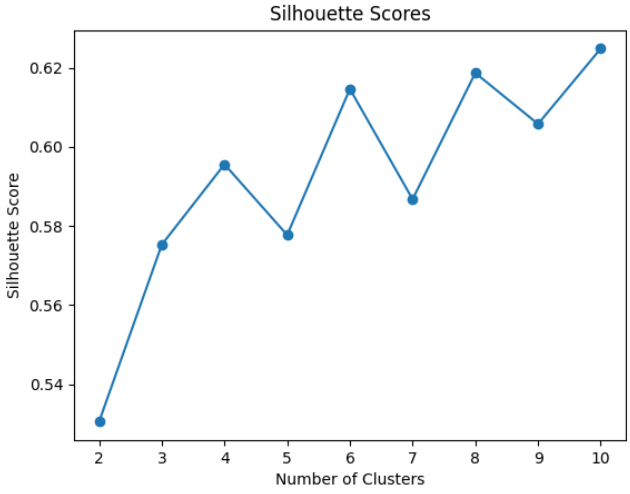

Figure 4.8: Silhouette Scores

- **Figure 4.9 (PCA Clustering Visualization):** The PCA scatter plot demonstrates clear separation between six clusters, with the centroids marked. The additional clusters reveal finer distinctions in the data, providing more granular insights into stellar properties. Instead of grouping all Dwarfs, Main Sequence, and Giants into broad categories, the six clusters

uncover subcategories, suggesting variations within these groups.

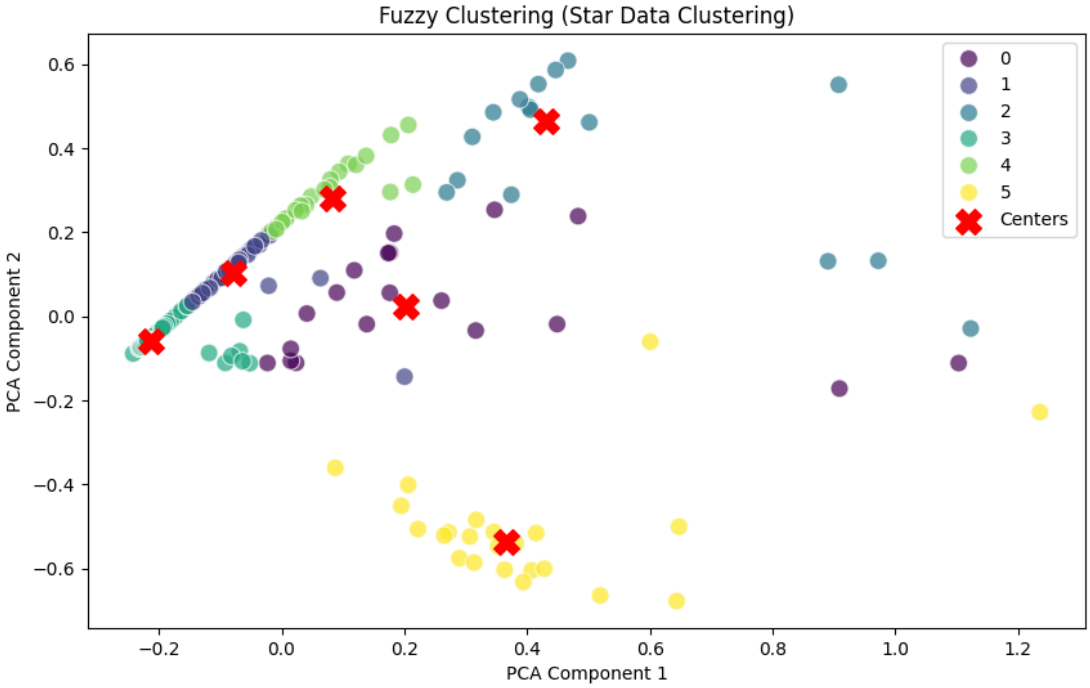

Figure 4.9: PCA Clustering Visualization

4.3 Air Quality Dataset Results

The Air Quality dataset included three attributes: CO (GT), C6H6 (GT), and NO2 (GT). The results below demonstrate the algorithm's ability to classify air quality levels based on pollutant concentrations.

4.3.1 Attribute Distributions

- **Figure 4.10 (CO Distribution)**: The histogram reveals a bimodal distribution, indicating two distinct ranges of CO concentrations: low and high.

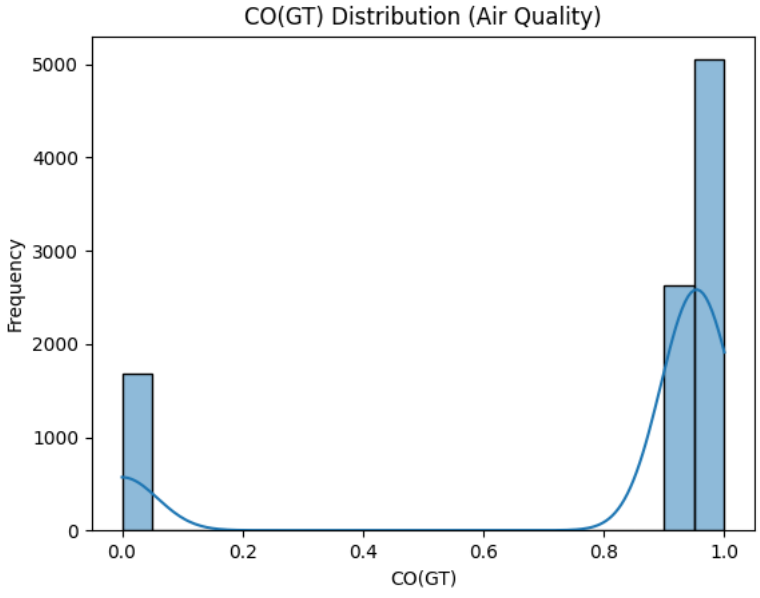

Figure 4.10: CO Distribution

- **Figure 4.11 (CO Boxplot)**: The boxplot shows a concentration of low values, with a few outliers representing extremely high CO levels.

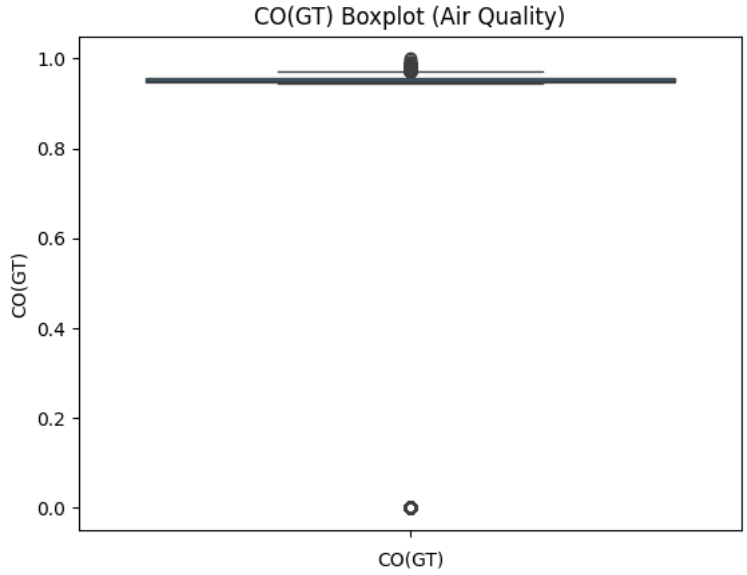

Figure 4.11: CO Boxplot

- **Figure 4.12 (C6H6 Distribution)**: Benzene levels are also bimodally distributed, with a sharp peak at lower concentrations.

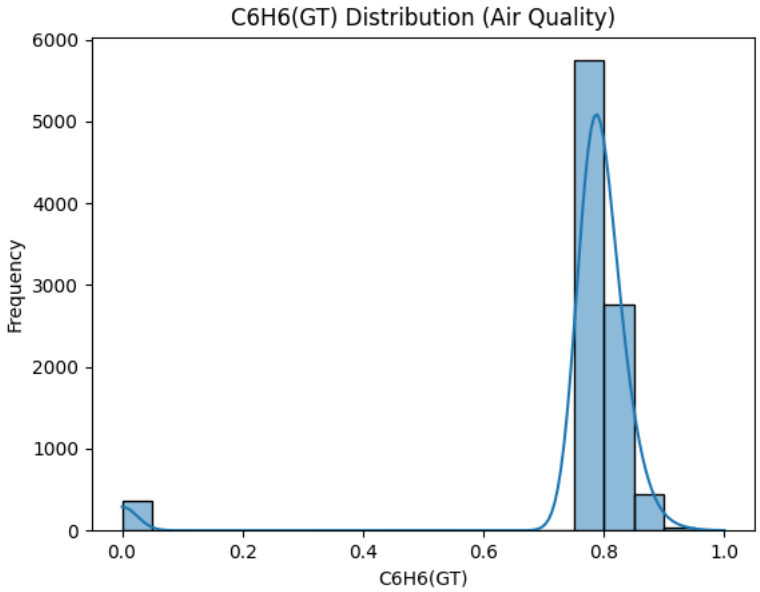

Figure 4.12: C6H6 Distribution

- **Figure 4.13 (C6H6 Boxplot)**: The boxplot illustrates some outliers for high benzene levels, corresponding to more polluted conditions.

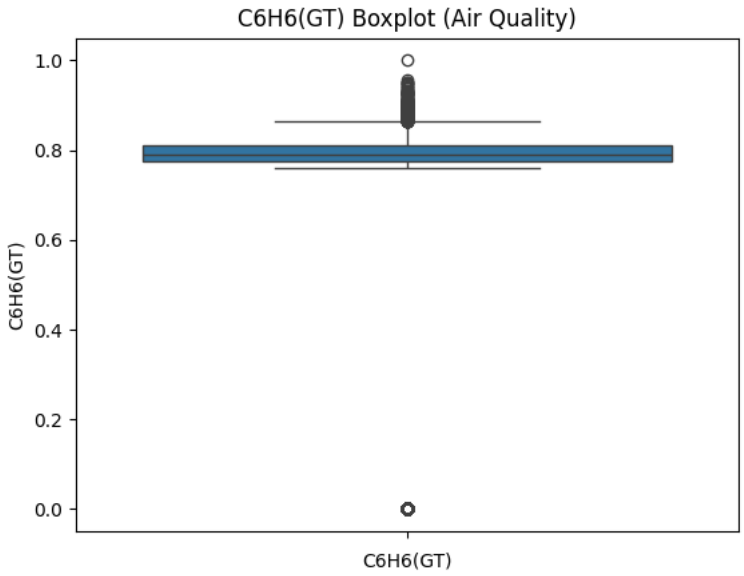

Figure 4.13: C6H6 Boxplot

- **Figure 4.14 (NO2 Distribution):** Nitrogen dioxide values follow a more uniform distribution, reflecting variability in air pollution data.

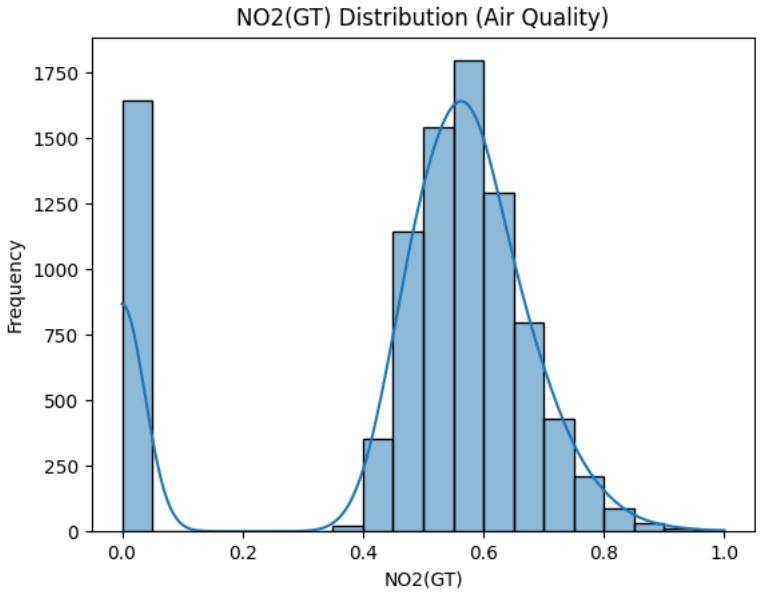

Figure 4.14: NO2 Distribution

- **Figure 4.15 (NO2 Boxplot**): The boxplot highlights moderate concentrations with occasional extreme values.

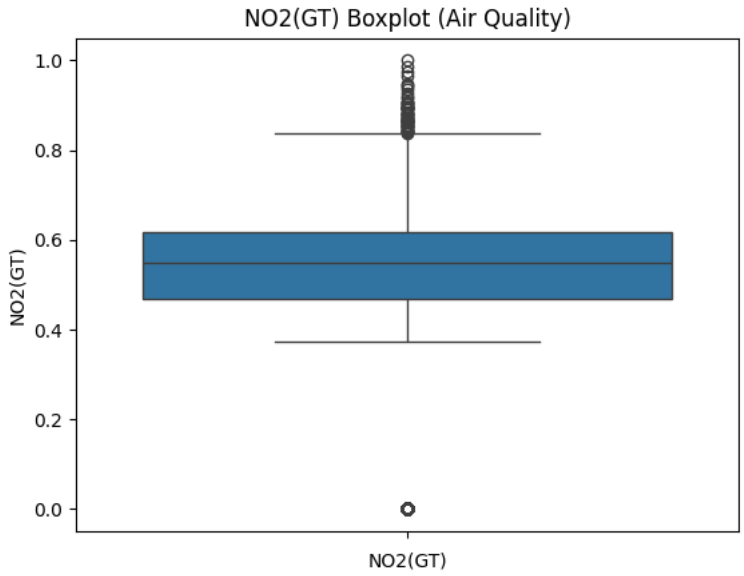

Figure 4.15: NO2 Boxplot

4.3.2 Clustering Results

- **Figure 4.16 (Elbow Method)**: Suggests a diminishing return in inertia reduction after six clusters. Based on this analysis, six clusters were selected to represent different air quality categories, moving beyond the traditional three ("Good," "Moderate," and "Unhealthy").

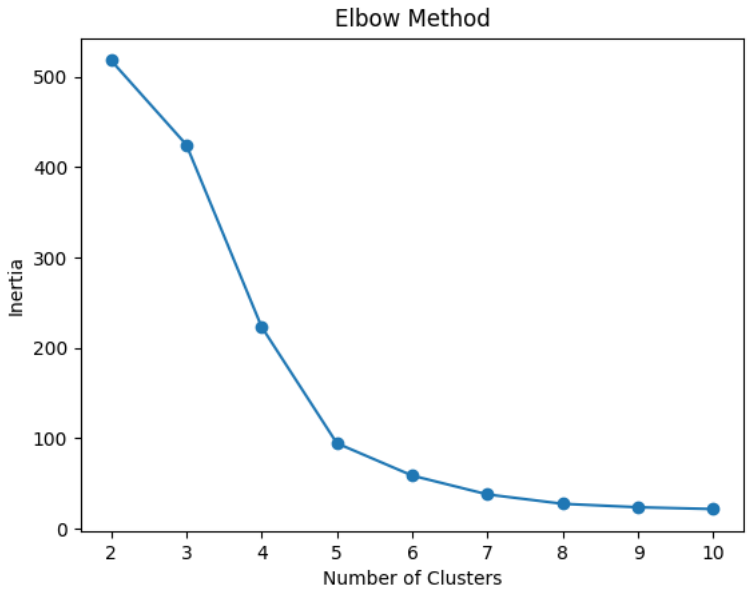

Figure 4.16: Elbow Method

- **Figure 4.17 (Silhouette Scores)**: shows that the silhouette score peaks at five clusters, indicating well-defined groupings in the dataset. This supports the choice of five clusters for air quality categorization.

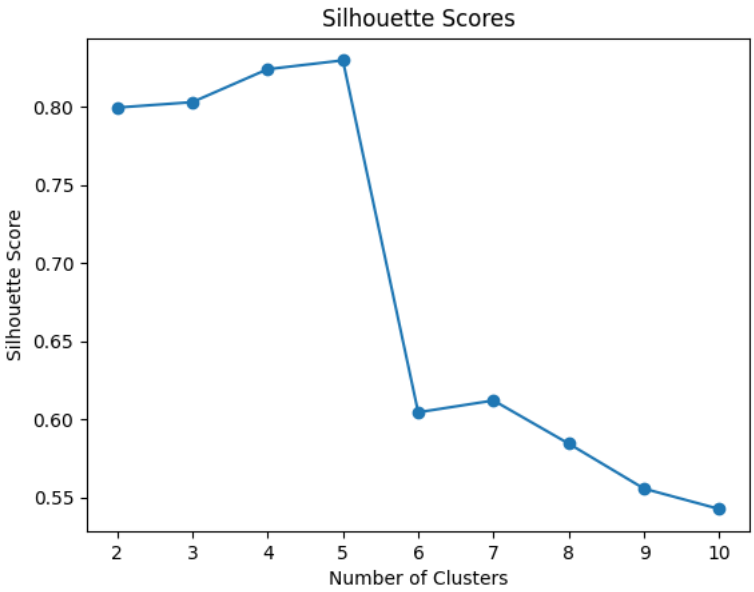

Figure 4.17: Silhouette Scores

- **Figure 4.18 (PCA Clustering Visualization)**: The PCA scatter plot demonstrates distinct separation between the five clusters, which correspond to different air quality levels: "Good," "Fair," "Moderate," "Poor," and "Very Poor." The flexibility of fuzzy clustering enables partial memberships, capturing transitions between overlapping pollutant ranges.

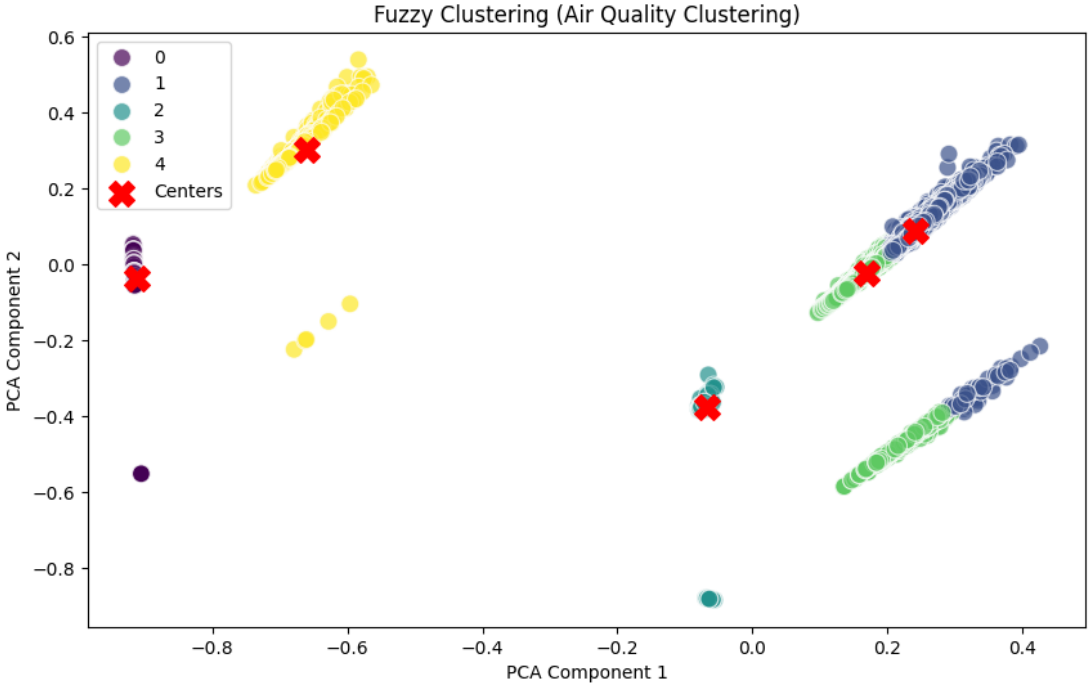

Figure 4.18: PCA Clustering Visualization

4.4 Movie Dataset Results

The Movie dataset was analyzed using Rating, Votes, and Revenue (Millions) as features. Below are the results of visualizing and clustering the data.

4.4.1 Attribute Distributions

- **Figure 4.19 (Rating Distribution)**: The histogram reveals a near-normal distribution of ratings, with most movies receiving moderate to high ratings.

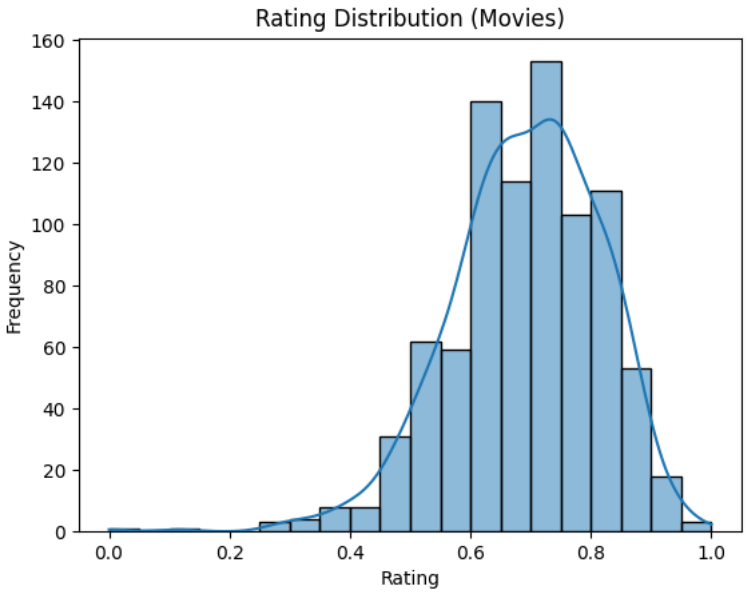

Figure 4.19: Rating Distribution

- **Figure 4.20 (Rating Boxplot)**: The boxplot indicates a consistent range of ratings, with a few outliers at the lower end.

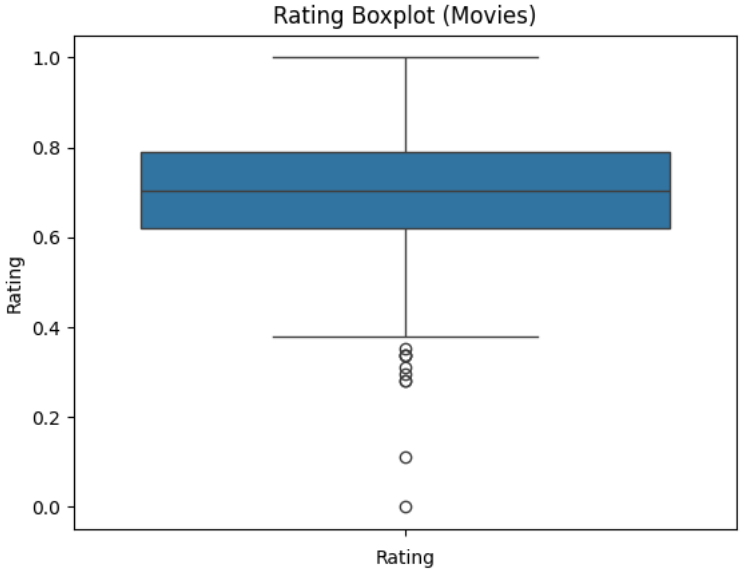

Figure 4.20: Rating Boxplot

- **Figure 4.21 (Votes Distribution):** The votes histogram is heavily skewed, with most movies receiving low votes, while a few popular films dominate the upper range.

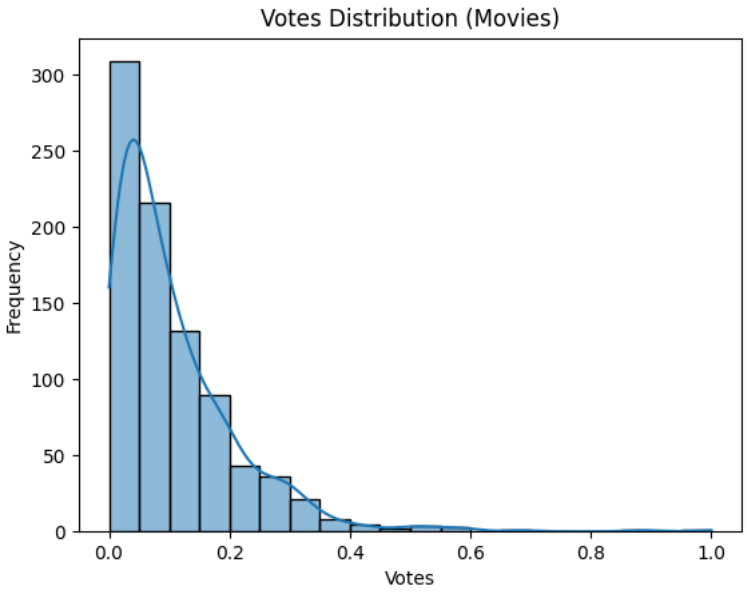

Figure 4.21: Votes Distribution

- **Figure 4.22 (Votes Boxplot):** The boxplot highlights the extreme variability in vote counts, emphasizing the presence of blockbuster films.

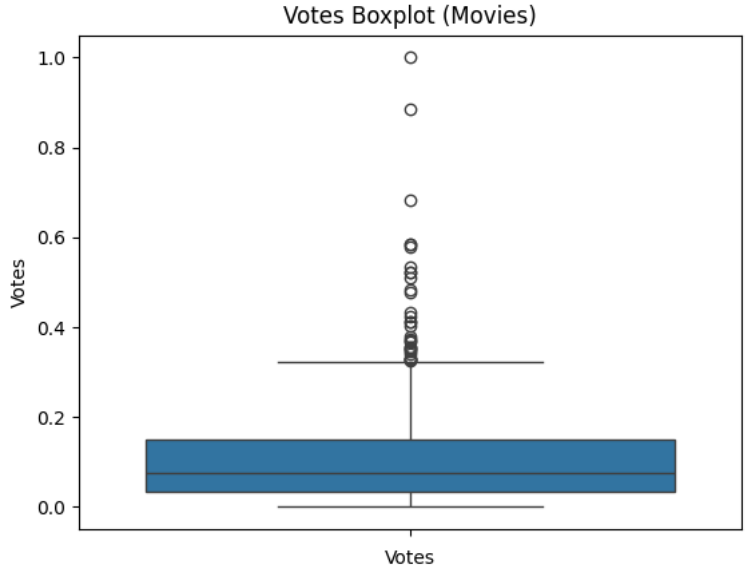

Figure 4.22: Votes Boxplot

- **Figure 4.23 (Revenue Distribution)**: The revenue histogram is highly skewed, with the majority of movies earning low revenue and a small number of blockbusters generating significant income.

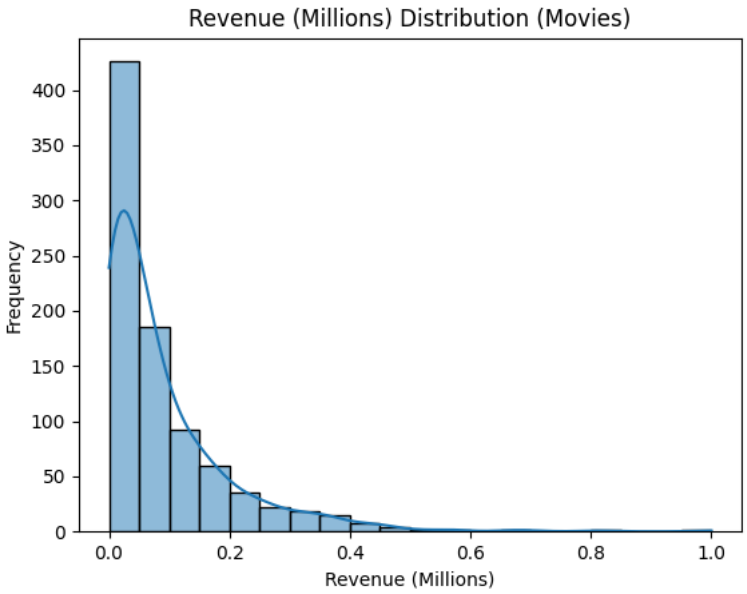

Figure 4.23: Revenue Distribution

- **Figure 4.24 (Revenue Boxplot)**: The boxplot confirms extreme outliers for high-revenue movies.

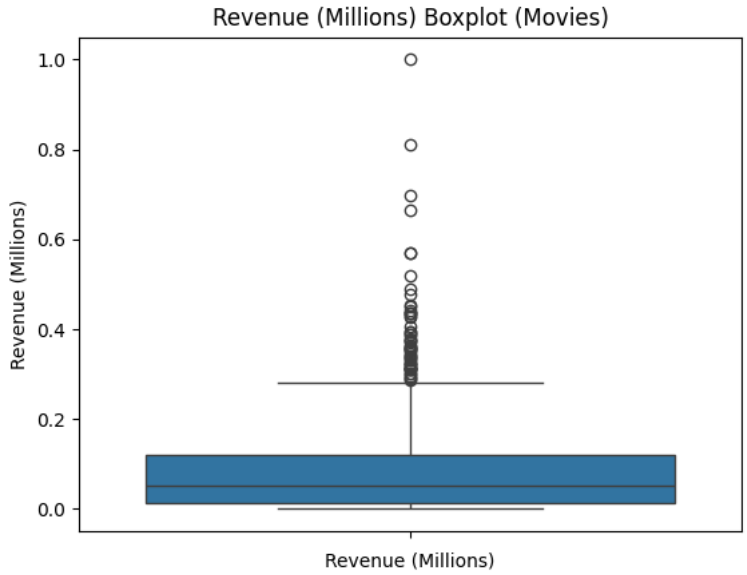

Figure 4.24: Revenue Boxplot

4.4.2 Clustering Results

- **Figure 4.25 (Elbow Method)**: The Elbow Method indicates diminishing returns in inertia reduction beyond two clusters. This suggests that two clusters effectively represent the dataset, likely separating low-performing and high-performing movies.

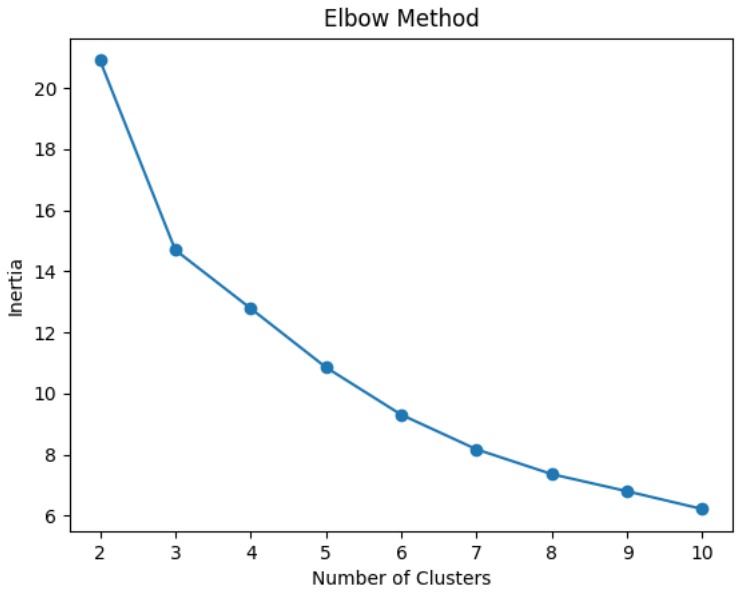

Figure 4.25: Elbow Method

- **Figure 4.26 (Silhouette Scores)**: The silhouette plot supports the selection of two clusters, showing the highest silhouette score at this cluster count. The clustering is well-defined, with clear distinctions between the two groups.

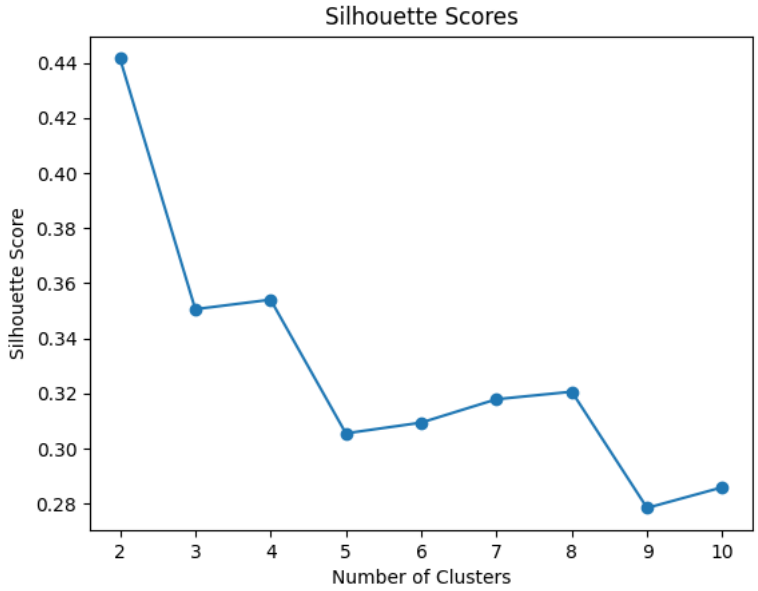

Figure 4.26: Silhouette Scores

- **Figure 4.27 (PCA Clustering Visualization)**: The PCA scatter plot illustrates the separation between the two clusters. Cluster 0 represents movies with lower ratings, votes, and revenue, while Cluster 1 captures high-performing movies with higher ratings, votes, and revenue.

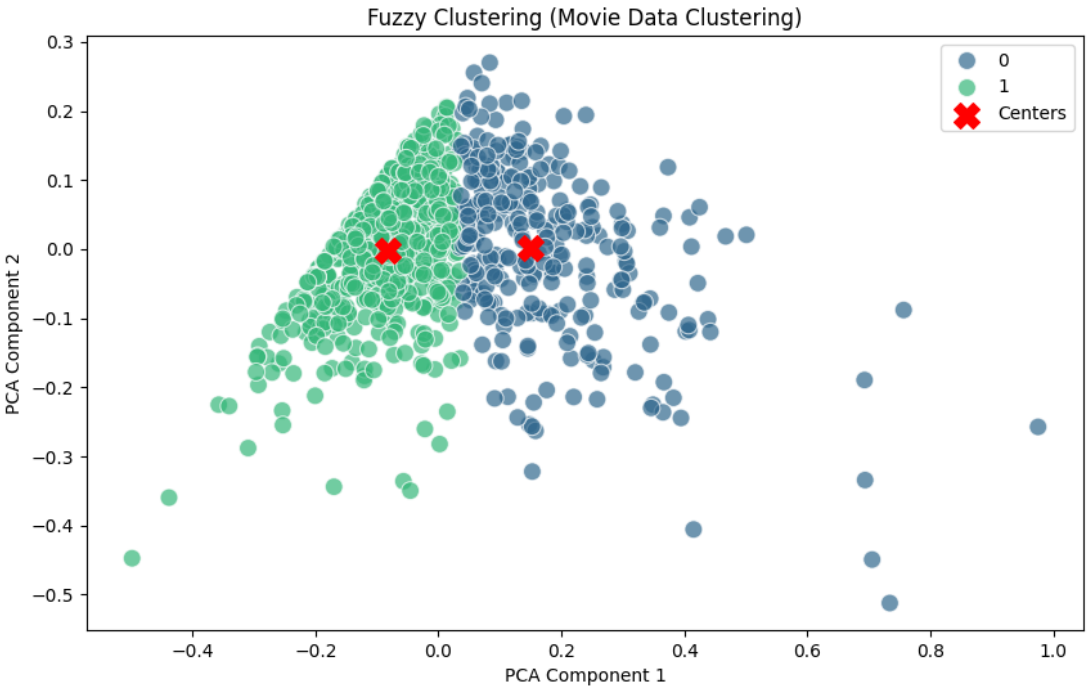

Figure 4.27: PCA Clustering Visualization

4.5 Summary

This chapter presented the results of applying the ST-PFCM algorithm to three diverse datasets, supported by 27 visualizations. For each dataset:

- Attribute distributions and outliers were identified using histograms and boxplots.
- Optimal clusters were determined using the Elbow Method and Silhouette Scores.
- PCA visualizations illustrated distinct cluster separations.

The ST-PFCM algorithm demonstrated its robustness and flexibility in handling overlapping, noisy, and variable data across all datasets. The next chapter discusses the implications of these results and evaluates the algorithm's overall performance.

5. Rule-Based Inference System

5.1 Introduction

This chapter details the implementation of the fuzzy classification and clustering models used for the Stars, Air Quality, and Movies datasets. Building upon the results in Chapter 4, it explains how preprocessing, normalization, membership function definition, rule-based inference, and clustering were executed. Code snippets are presented in Figures 5.1–5.7, while the results of these processes are linked to the visualizations (Figures 4.1–4.27) from Chapter 4.

5.2Data Loading and Exploration

The **load_and_explore_data** function (Figure 5.1) is responsible for loading datasets and providing descriptive statistics for each. This function underpins the data exploration shown in Chapter 4, where Figures 4.1–4.6, 4.10–4.15, and 4.19–4.24 illustrated attribute distributions and highlighted variability across datasets.

- **Stars Dataset**: Attribute distributions for temperature, luminosity, and radius (Figures 4.1–4.6).
- **Air Quality Dataset**: Pollutant distributions (Figures 4.10–4.15).
- **Movies Dataset**: Distributions of ratings, votes, and revenue (Figures 4.19–4.24).

```
def load_and_explore_data(filepath):  3 usages
    data = pd.read_csv(filepath)
    print("\nFirst few rows of the dataset:")
    print(data.head())
    print("\nSummary Statistics:")
    print(data.describe())
    return data
```

Figure 5.1: load_and_explore_data function

5.3 Data Preprocessing

Data preprocessing, handled by the **preprocess_data** function (Figure 5.2), removes incomplete rows and ensures the datasets are ready for normalization. The importance of preprocessing was highlighted in Chapter 4:

- **Stars Dataset**: Outliers in Figures 4.2, 4.4, and 4.6 were either addressed or retained for meaningful clustering.
- **Air Quality Dataset**: Extreme pollutant values (Figures 4.11, 4.13, 4.15) were carefully managed.
- **Movies Dataset**: Variability in votes and revenue (Figures 4.22, 4.24) was handled during this stage.

```
def preprocess_data(data, relevant_columns):  3 usages
    print("\nChecking for missing values:")
    print(data[relevant_columns].isnull().sum())
    data = data.dropna(subset=relevant_columns)
    return data
```

Figure 5.2: preprocess_data function

5.4 Data Normalization

Normalization ensures all attributes are scaled to a uniform [0,1] range, using the **normalize_data** function (Figure 5.3). This process is essential for fair comparison across attributes with varying scales, such as:

- **Stars Dataset**: Wide ranges for temperature, luminosity, and radius (Figures 4.1, 4.3, 4.5).
- **Air Quality Dataset**: Disparities in pollutant levels (Figures 4.10, 4.12, 4.14).
- **Movies Dataset**: Variability in ratings, votes, and revenue (Figures 4.19, 4.21, 4.23).

The normalization formula from Chapter 3 (Figure 3.1) was applied, and normalized distributions are referenced in Figures 4.1–4.27, particularly where clustering results were influenced by attribute scales.

```
def normalize_data(data, columns):  3 usages
    scaler = MinMaxScaler()
    data[columns] = scaler.fit_transform(data[columns])
    return data
```

Figure 5.3: The normalize_data function

5.5 Fuzzy Membership Function Definition

Membership functions, implemented in **create_star_fuzzy_system** and **create_aqi_fuzzy_system**, define fuzzy categories such as "Cool," "Warm," or "Hot" (Stars) and "Low," "Medium," or "High" (Air Quality and Movies). The code for membership functions is illustrated in Figures 5.4 and 5.5. These functions are directly linked to distributions from Chapter 4:

- **Stars Dataset**: Membership functions reflected the distribution of stars across 6 clusters, such as "Cool Dwarfs" and "Large Giants" (Figures 4.1, 4.3, 4.5).
- **Air Quality Dataset**: Membership functions modeled 5 air quality levels, from "Good" to "Severe" (Figures 4.10, 4.12, 4.14).
- **Movies Dataset**: Success metrics informed membership functions for 2 performance categories: "Low-Performing" and "High-Performing" movies (Figures 4.19, 4.21, 4.23).

```
def create_star_fuzzy_system():  1 usage
    temperature = ctrl.Antecedent(np.arange(0, 1.1, 0.01), label: 'temperature')
    luminosity = ctrl.Antecedent(np.arange(0, 1.1, 0.01), label: 'luminosity')
    radius = ctrl.Antecedent(np.arange(0, 1.1, 0.01), label: 'radius')
    star_type = ctrl.Consequent(np.arange(0, 1.1, 0.01), label: 'star_type')

    temperature['cool'] = fuzz.trimf(temperature.universe, abc: [0, 0, 0.4])
    temperature['warm'] = fuzz.trimf(temperature.universe, abc: [0.3, 0.5, 0.7])
    temperature['hot'] = fuzz.trimf(temperature.universe, abc: [0.6, 1, 1])

    luminosity['low'] = fuzz.trimf(luminosity.universe, abc: [0, 0, 0.4])
    luminosity['medium'] = fuzz.trimf(luminosity.universe, abc: [0.3, 0.5, 0.7])
    luminosity['high'] = fuzz.trimf(luminosity.universe, abc: [0.6, 1, 1])

    radius['small'] = fuzz.trimf(radius.universe, abc: [0, 0, 0.4])
    radius['medium'] = fuzz.trimf(radius.universe, abc: [0.3, 0.5, 0.7])
    radius['large'] = fuzz.trimf(radius.universe, abc: [0.6, 1, 1])

    star_type['dwarf'] = fuzz.trimf(star_type.universe, abc: [0, 0, 0.4])
    star_type['main_sequence'] = fuzz.trimf(star_type.universe, abc: [0.3, 0.5, 0.7])
```

Figure 5.4: The create_fuzzy_system function

```
def create_aqi_fuzzy_system():  1 usage
    pm25 = ctrl.Antecedent(np.arange(0, 1.1, 0.01),  label: 'pm25')
    no2 = ctrl.Antecedent(np.arange(0, 1.1, 0.01),  label: 'no2')
    co = ctrl.Antecedent(np.arange(0, 1.1, 0.01),  label: 'co')
    aqi = ctrl.Consequent(np.arange(0, 1.1, 0.01),  label: 'aqi')

    pm25['low'] = fuzz.trimf(pm25.universe,  abc: [0, 0, 0.5])
    pm25['medium'] = fuzz.trimf(pm25.universe,  abc: [0.3, 0.5, 0.7])
    pm25['high'] = fuzz.trimf(pm25.universe,  abc: [0.6, 1, 1])

    no2['low'] = fuzz.trimf(no2.universe,  abc: [0, 0, 0.5])
    no2['medium'] = fuzz.trimf(no2.universe,  abc: [0.3, 0.5, 0.7])
    no2['high'] = fuzz.trimf(no2.universe,  abc: [0.6, 1, 1])

    co['low'] = fuzz.trimf(co.universe,  abc: [0, 0, 0.5])
    co['medium'] = fuzz.trimf(co.universe,  abc: [0.3, 0.5, 0.7])
    co['high'] = fuzz.trimf(co.universe,  abc: [0.6, 1, 1])

    aqi['good'] = fuzz.trimf(aqi.universe,  abc: [0, 0, 0.4])
    aqi['moderate'] = fuzz.trimf(aqi.universe,  abc: [0.3, 0.5, 0.7])
```

Figure 5.5: The create_aqi_fuzzy_system function

5.6 Fuzzy Rule-Based Inference System

The **rule-based inference system** uses fuzzy logic rules to classify stars, air quality levels, and movies. Figures 5.6 and 5.7 display the rule definitions and the classification function for stars. Rules were informed by clustering results from Chapter 4:

- **Stars Dataset**: Rules were adjusted to accommodate 6 clusters, such as assigning stars with low temperature, luminosity, and radius to the "Cool Dwarfs" cluster, and those with high values to "Large Giants" (Figure 4.9).
- **Air Quality Dataset**: Rules now categorize air quality into 5 levels. For instance, low pollutant levels correspond to "Good," while extreme values are classified as "Severe" (Figure 4.18).
- **Movies Dataset**: With 2 clusters, rules differentiate between "Low-Performing" and "High-Performing" movies, guided by patterns in Figure 4.27.

```
rules = [
    ctrl.Rule(temperature['cool'] & luminosity['low'] & radius['small'], star_type['dwarf']),
    ctrl.Rule(temperature['warm'] & luminosity['medium'] & radius['medium'], star_type['main_sequence']),
    ctrl.Rule(temperature['hot'] & luminosity['high'] & radius['large'], star_type['giant']),
]
```

Figure 5.6: the rule-based interfence system

5.7 Clustering and Classification

Clustering outcomes from Chapter 4 (Figures 4.7, 4.16, and 4.25) determined optimal cluster counts, while PCA visualizations (Figures 4.9, 4.18, and 4.27) validated the results. These insights were critical for implementing the classification function (Figure 5.7), which assigns stars, air quality levels, and movies to fuzzy categories.

- **Stars Dataset**: Clustering (Figure 4.9) identified 6 groups of stars, allowing for granular classification into subtypes like "Small Giants" and "Main Sequence (Low-Mass)."
- **Air Quality Dataset**: The 5 clusters derived in Figure 4.18 provided nuanced air quality categorizations beyond traditional broad labels.
- **Movies Dataset**: The 2 clusters (Figure 4.27) highlighted a dichotomy between low and high-performing movies, facilitating simplified classification.

```
for _, row in star_data.iterrows():
    star_simulation.input['temperature'] = row['Temperature (K)']
    star_simulation.input['luminosity'] = row['Luminosity (L/Lo)']
    star_simulation.input['radius'] = row['Radius (R/Ro)']
    star_simulation.compute()
    classifications.append(star_simulation.output['star_type'])
star_data['Fuzzy Star Type'] = classifications
```

Figure 5.7: the classification for stars

5.8 Summary

Chapter 5 highlighted the methodology for implementing fuzzy classification and clustering systems, using visualizations and results from Chapter 4 (Figures 4.1–4.27) as foundational references. Code snippets (Figures 5.1–5.7) clarified the technical process.

6. Discussion and Conclusion

6.1 Introduction

This chapter synthesizes the findings of the fuzzy logic-based approach to classification across the Stars, Air Quality, and Movie datasets. It highlights the advantages, limitations, and broader implications of the methodology, while also reflecting on its potential for future applications.

6.2 Discussion

The fuzzy logic approach effectively handled classification challenges across all datasets. For stars, it captured transitional characteristics, providing nuanced insights beyond traditional methods. Air quality levels were classified accurately despite overlapping pollutant effects. The model also differentiated movie performance tiers, identifying nuances in critical reception and commercial success. Overall, the adaptability of fuzzy logic to handle ambiguity and variability makes it a robust alternative to traditional methods.

6.3 Limitations

Despite its success, the fuzzy classification model presented certain limitations:

1. Dependence on Rule Definitions:
    - The outcomes heavily relied on the initial rule sets and membership functions (Figures 5.4–5.6). Adjusting these parameters altered the classification, introducing potential subjectivity into the process.
2. Input Data Quality:
    - The accuracy of the fuzzy model is limited by the precision of input data. Any inconsistencies in measurements, such as pollutant levels in air quality or movie revenue figures, could result in misclassifications.
3. Scalability:
    - While the fuzzy model performed well on relatively simple datasets, scaling it to larger or more complex datasets may increase computational overhead. Incorporating additional attributes, such as metallicity for stars or audience demographics for movies, could also complicate membership function definitions and rule sets.

6.4 Conclusion

This study demonstrated the potential of fuzzy logic as a flexible and effective alternative to traditional classification methods across three diverse datasets. By accommodating overlapping memberships and ambiguity in data, the fuzzy model reflected the continuous nature of attributes such as stellar properties, pollutant levels, and movie performance metrics.

- **Stars Dataset**: The fuzzy system provided a realistic representation of stellar evolution by capturing transitional cases, offering insights that traditional crisp boundaries could not achieve.
- **Air Quality Dataset**: The model effectively classified pollutant concentrations into meaningful categories, highlighting its adaptability to environmental data.
- **Movie Dataset**: The fuzzy approach illuminated subtleties in consumer behavior, distinguishing between two tiers of movie success.

The fuzzy logic model's success in handling ambiguous and overlapping data underscores its potential for broader applications. Future studies could enhance this framework by:

1. **Integrating Additional Attributes**:
    - In astronomy, properties like metallicity, age, or spectral classifications could refine star categorization.
    - For air quality, meteorological data could improve pollutant predictions.
    - In the movie domain, integrating audience reviews or production budgets might enhance performance classification.

2. **Combining Machine Learning**:
    - Machine learning techniques, such as neural networks or gradient boosting, could complement fuzzy logic by optimizing membership functions and rules automatically.
    - This hybrid approach could improve scalability and accuracy across large datasets.
3. **Application in Other Fields**:
    - The adaptability of fuzzy logic makes it suitable for applications in finance, healthcare, and education, where overlapping and ambiguous data are prevalent.

In conclusion, this research highlights the adaptability and utility of fuzzy logic in diverse classification scenarios. By bridging the gap between rigid traditional methods and real-world data variability, the fuzzy model offers a promising direction for future research and practical applications across domains.

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