PROFESSIONAL TRAINING REPORT

CAR PERFORMANCE PREDICTION

Submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering with specialization in Artificial Intelligence

by

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
Accredited with Grade "A++" by NAAC
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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Professional Training is the bonafide work of **Mr. Ngangom Helindra (41611133)** who carried out the project entitled "**Car Performance Prediction"** under my supervision from June 2023 to October 2023.

Internal Guide
Ms. Nivetha. R, M.E

Head of the Department
Dr. S. VIGNESHWARI, M.E., Ph.D.,

Submitted for Viva voce Examination held on 4th October 2023

Internal Examiner **External Examiner**

DECLARATION

I, **Ngangom Helindra (41611133),** hereby declare that the Professional Training Report-I entitled **"Car Performance Prediction"** done by me under the guidance of **Ms. Nivetha. R, M.E** is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering with specialization in Artificial Intelligence.

DATE: 04/10/2023

PLACE: Chennai **SIGNATURE OF THE CANDIDATE**

ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to **Board of Management** of **SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. T. Sasikala M.E., Ph.D.**, **Dean**, School of Computing, **Dr. S.Vigneshwari M.E., Ph.D., Head of the Department of Computer Science and Engineering** for providing me necessary support and details at the right time during the progressive reviews.

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I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

ABSTRACT

This academic journal article presents a rigorous exploration of automobile segmentation and profiling employing advanced clustering methodologies. Leveraging the power of K-Means and Agglomerative clustering algorithms, this study delves into the nuanced differentiation of automobiles based on critical features, with a central emphasis on the intricate interplay between miles per gallon (MPG), horsepower, weight, and acceleration. The investigation is carried out utilizing Python libraries such as scikit-learn, Pandas, and Matplotlib.

The research begins with meticulous data preprocessing, encompassing feature scaling and the imputation of missing values within the "horsepower" attribute through the application of the mean replacement strategy. A distinctive dimensionality reduction is achieved by transforming the "weight" feature via its reciprocal form, optimizing the dataset for subsequent analysis.

K-Means clustering, featuring three clusters, elucidates the latent structures within the automobile dataset. These revelations are elucidated through a two-tiered visualization approach. First, a concise summary of cluster composition is elucidated through a colourful bar chart, offering a bird's-eye view of the distribution of vehicles within each cluster. Subsequently, scatter plots juxtapose MPG against auxiliary features within each cluster, unearthing nuanced relationships and distinct automotive personas. These insights facilitate a deeper comprehension of distinct automobile categories based on MPG and ancillary attributes, enhancing industry stakeholders' strategic decision-making.

Additionally, hierarchical agglomerative clustering, leveraging Euclidean distance and Ward linkage, unveils the hierarchical nature of the automobile segments. This insight offers a broader perspective on cluster dependencies and serves as a foundational reference for longitudinal studies and market trend predictions.

The contribution of this research extends beyond the automotive realm, serving as a blueprint for exploring feature-based profiling and segmentation in various industries and domains. The detailed methodologies and comprehensive visualizations presented herein empower academics, practitioners, and policymakers to conduct in-depth explorations of complex datasets, fostering data-driven decision-making and the advancement of knowledge in clustering and profiling techniques.

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER Ⅰ

INTRODUCTION

1.1 OVERVIEW:

1.1.1 Introduction:

In an era characterized by rapid technological advancement and evolving consumer preferences, the automotive industry stands at the intersection of innovation and diversity. The understanding of automobiles extends beyond mere transportation, encompassing complex relationships between fuel efficiency, performance attributes, and market segmentation. In this research endeavour, we embark on a systematic exploration, employing advanced clustering methodologies to uncover the intricate landscape of automobile categorization.

1.1.2 Project Context:

The allure of automobiles is deeply intertwined with multifaceted factors, chief among them being miles per gallon (MPG), a fundamental metric of fuel efficiency. However, the interplay between MPG and intrinsic attributes such as horsepower, weight, and acceleration unveil a dynamic and multifaceted tapestry within the automotive domain. Our research is grounded in the recognition of these complexities and the desire to provide actionable insights.

1.1.3 Research Objectives:

The primary objective of this research is to dissect the intricate structures within a diverse dataset of automobiles, offering a profound understanding of their categorization based on fuel efficiency and key attributes. Through the application of cutting-edge clustering techniques, our study seeks to provide not only insights but also practical implications for automotive industry professionals, researchers, and analysts.

1.1.4 Methodological Excellence:

This research begins with meticulous data preprocessing, a cornerstone of reliable analysis. It encompasses rigorous feature selection, principled handling of missing values, and strategic dimensionality reduction. We then employ two distinctive clustering paradigms: K-Means and Agglomerative clustering. These methodologies, celebrated for their robustness and versatility, allow us to discern latent structures within the data effectively.

1.1.5 Results and Insights:

Our research culminates in a meticulously crafted narrative of insights, communicated through an array of sophisticated visualizations. From intricately designed bar charts that elucidate cluster composition to visually captivating scatter plots that capture the intricate relationships between MPG and auxiliary features, our visualizations offer a holistic perspective of automobile segmentation. Additionally, we present a dendrogram, a work of art in its own right, that portrays the hierarchical dependencies among clusters.

1.1.6 Significance and Contributions:

The insights generated by this research extend beyond the boundaries of the automotive sector, permeating diverse fields where data-driven decision-making is paramount. The findings bear implications for market positioning, product development, and strategic marketing within the automotive industry. Furthermore, our meticulously documented methodology serves as a beacon for future data-driven analyses, facilitating advanced exploration in various domains.

CHAPTER Ⅱ

LITERATURE REVIEW

2.1 SURVEY:

Literature Survey

2.1 Introduction to Literature Survey

A comprehensive literature survey is a crucial step in understanding the current state of research and technology in the field of car performance prediction. This section presents an overview of key findings and trends from existing literature and research papers related to car performance prediction.

2.2 Survey Methodology

Our literature survey was conducted by extensively reviewing academic papers, industry reports, and research articles published in the field of automotive engineering, data science, and machine learning. The search covered a wide range of databases, journals, and conference proceedings to ensure the inclusion of the most relevant and up-to-date sources.

2.3 Key Findings and Trends

2.3.1 Predictive Models for Vehicle Speed

One prominent area of research revolves around predicting a car's speed under various conditions. Researchers have developed predictive models that take into account factors such as engine specifications, road type, weather conditions, and driver behavior. Machine learning techniques, including regression and neural networks, have been applied to create accurate speed prediction models.

2.3.2 Fuel Efficiency Prediction

Fuel efficiency is a critical concern for both consumers and manufacturers. The literature reveals the development of predictive models for estimating a vehicle's fuel consumption based on parameters like engine type, vehicle weight, aerodynamics, and driving patterns. These models assist in designing more fuel-efficient vehicles and optimizing driving strategies.

2.3.3 Safety Prediction

Safety is paramount in the automotive industry. Researchers have explored predictive models to anticipate potential safety issues, such as collisions and brake failures. These models integrate data from sensors, vehicle speed, road conditions, and driver behavior to assess the risk of accidents and trigger safety systems proactively.

2.3.4 Environmental Impact Assessment

With increasing environmental concerns, predicting a vehicle's impact on the environment has gained significance. Studies have introduced models that estimate emissions, including greenhouse gases and pollutants, based on vehicle specifications and usage. This data aids in designing eco-friendly vehicles and guiding policy decisions.

2.3.5 Data Sources and Integration

A recurring theme in the literature is the importance of data sources and integration. Researchers emphasize the need for high-quality data from various sensors, vehicle telematics, and external sources like weather stations. Integrating this diverse data is seen as critical for building accurate predictive models.

2.3.6 Challenges and Open Questions

Despite significant progress, challenges persist in car performance prediction. Researchers are exploring issues such as data privacy, real-time prediction, and model explainability. The open question of how to create models that adapt to evolving vehicle technologies and environmental factors remains a topic of ongoing research.

2.4 Conclusion

The literature survey demonstrates the dynamic and evolving nature of car performance prediction. The field is at the intersection of automotive engineering, data science, and machine learning, offering numerous opportunities for innovation and improvement. As we embark on this project, we draw inspiration from these findings and aim to contribute to the body of knowledge in this exciting and transformative field.

CHAPTER Ⅲ

REQUIREMENTS ANALYSIS

3.1 OBJECTIVE OF THE PROJECT

Objective:

This research project is driven by the overarching objective of conducting a meticulous and illuminating exploration into the domain of automobile segmentation and profiling. The primary aims of this study are:

Reveal Latent Structures: Harness the capabilities of advanced clustering techniques, including K-Means and Agglomerative clustering, to unveil previously hidden patterns and structures concealed within a multidimensional and diverse dataset of automobiles. By accomplishing this, the project aspires to extract essential insights that transcend conventional wisdom and redefine our understanding of automobile categorization.

Elevate Strategic Decision-Making: Through a comprehensive analysis of automobiles based on their fuel efficiency, notably the pivotal metric of miles per gallon (MPG), in conjunction with fundamental attributes such as horsepower, weight, and acceleration, this research seeks to provide a panoramic view of the automotive landscape. The insights derived from this endeavor aim to serve as a strategic compass for industry professionals, aiding in the formulation of data-driven strategies, product development initiatives, and market positioning.

Set a Methodological Standard: This research is characterized by unwavering methodological excellence, exemplified through rigorous data preprocessing, the judicious application of clustering paradigms, and the crafting of insightful visualizations. The meticulous documentation of the methodological framework aspires to establish a benchmark for future data-driven investigations across domains, fostering a culture of analytical rigor.

Empower Diverse Stakeholders: Beyond the automotive realm, the knowledge distilled from this study has broad-ranging implications. It seeks to empower diverse stakeholders, including marketing strategists, researchers, and data analysts, with actionable intelligence. By facilitating informed decision-making, this research transcends disciplinary boundaries, bridging the gap between data-driven analysis and tangible outcomes.

In essence, this research project represents a pivotal endeavor in the field of data-driven automobile analysis. It not only strives to uncover the hidden facets of automobile categorization but also exemplifies methodological excellence. By illuminating the path for strategic decision-making and cross-domain applications, it aspires to make a lasting impact in the realms of data analysis, automotive studies, and beyond.

3.2 REQUIREMENTS:

3.2.1 *HARDWARE REQUIREMENTS*

Processor (CPU): A modern multi-core processor (e.g., Intel Core i5 or AMD Ryzen) is recommended for efficient data processing.

Memory (RAM): A minimum of 8 GB of RAM is advisable for handling moderate-sized datasets. For larger datasets and improved performance, consider having 16 GB or more.

Graphics Processing Unit (GPU) (Optional): While not mandatory, having a dedicated GPU, especially if you plan to work with large datasets, can significantly accelerate certain machine learning tasks. Some libraries like scikit-learn and Matplotlib can leverage GPU acceleration if compatible hardware is available.

Internet Connection: A stable internet connection may be necessary for installing Python libraries and accessing additional resources or documentation.

Monitor: A high-resolution monitor with good color accuracy can enhance the visualization of clustering results and dendrograms.

3.2.2 *SOFTWARE REQUIREMENTS*

Python (Version 3.x): Python is the primary programming language used for data preprocessing, clustering analysis, and visualization. Ensure that Python is installed on your system.

IDE: Jupyter Notebook or PyCharm is recommended for interactive data analysis and code documentation. Alternatively, you can use integrated development environments (IDEs) such as PyCharm or Visual Studio Code.

Python Libraries:

NumPy: For numerical computations and array operations.

Pandas**:** For data manipulation and handling Data Frames.

scikit-learn: To implement clustering algorithms like K-Means and Agglomerative clustering.

Matplotlib and Seaborn**:** For data visualization and creating informative plots.

SciPy: Required for hierarchical clustering and dendrogram visualization.

CSV File with Automobile Data: Ensure you have access to the dataset in CSV format, named "Automobile.csv" as indicated in your code.

CHAPTER Ⅳ

DESIGN DESCRIPTION OF PROPOSED PROJECT

4.1 PROPOSED METHODOLOGY

The proposed methodology encompasses data preprocessing, K-Means and Agglomerative clustering, visualization, comparative analysis, and interpretation, ultimately aiming to provide a comprehensive understanding of automobile segmentation based on fuel efficiency and key attributes.

This proposed methodology outlines the systematic approach for conducting the project, ensuring clarity, reproducibility, and the generation of valuable insights into automobile categorization. The methodology serves as a blueprint for the project's execution and analysis.

1. Data Acquisition and Understanding:

Data Source: The project begins with the acquisition of the "Automobile.csv" dataset, which contains information about various automobile attributes.

Data Exploration: The dataset is subjected to exploratory data analysis (EDA) to gain a comprehensive understanding of its structure. This includes examining data statistics, visualizing distributions, and identifying potential outliers.

2. Data Preprocessing:

Feature Selection: Relevant features, including miles per gallon (MPG), horsepower, weight, and acceleration, are selected for clustering analysis.

Handling Missing Values: Missing values are addressed, with the mean imputation method applied for the "horsepower" feature to ensure data completeness.

Feature Transformation: The "weight" feature is transformed by taking its reciprocal to emphasize its inverse relationship with fuel efficiency.

3. K-Means Clustering:

Algorithm Selection: K-Means clustering is chosen as the primary clustering technique due to its simplicity and effectiveness.

Optimal Cluster Number: The Elbow Method or Silhouette Score is employed to determine the optimal number of clusters.

Clustering: The dataset is clustered into distinct groups using the determined number of clusters.

4. Agglomerative Clustering:

Hierarchical Clustering: Agglomerative clustering, a hierarchical clustering method, is implemented to explore the hierarchical relationships among clusters.

Distance Metric: Euclidean distance is used as the distance metric for cluster linkage.

5. Visualization:

Cluster Visualization: The results of both K-Means and Agglomerative clustering are visually represented using scatter plots, highlighting the clustering patterns and distribution of data points.

Dendrogram Visualization: A dendrogram is created to illustrate the hierarchical structure of clusters derived from Agglomerative clustering.

6. Comparative Analysis:

Cluster Profiling: Each cluster is profiled based on key attributes, providing insights into the distinct characteristics of automobiles within each cluster.

Evaluation Metrics: Evaluation metrics such as silhouette score and within-cluster sum of squares (WCSS) may be employed to assess the quality of clustering results.

7. Interpretation and Insights:

Insight Generation: The project aims to extract meaningful insights from the clustering results, elucidating how different clusters of automobiles are distinguished by their attributes.

Practical Implications: The implications of these insights on automotive marketing, product development, and strategic decision-making are discussed.

8. Documentation and Reporting:

Project Report: A comprehensive project report is prepared, documenting the entire process, from data preprocessing to clustering results and insights.

Visualization: The project report includes visualizations that facilitate the understanding of clustering patterns.

9. Validation and Refinement:

Validation Checks: The project is subjected to thorough validation checks and peer reviews to ensure the correctness and reliability of results.

Refinement: Any necessary refinements to the methodology or analysis are made based on validation feedback.

4.1.1 *Ideation Map/System Architecture*

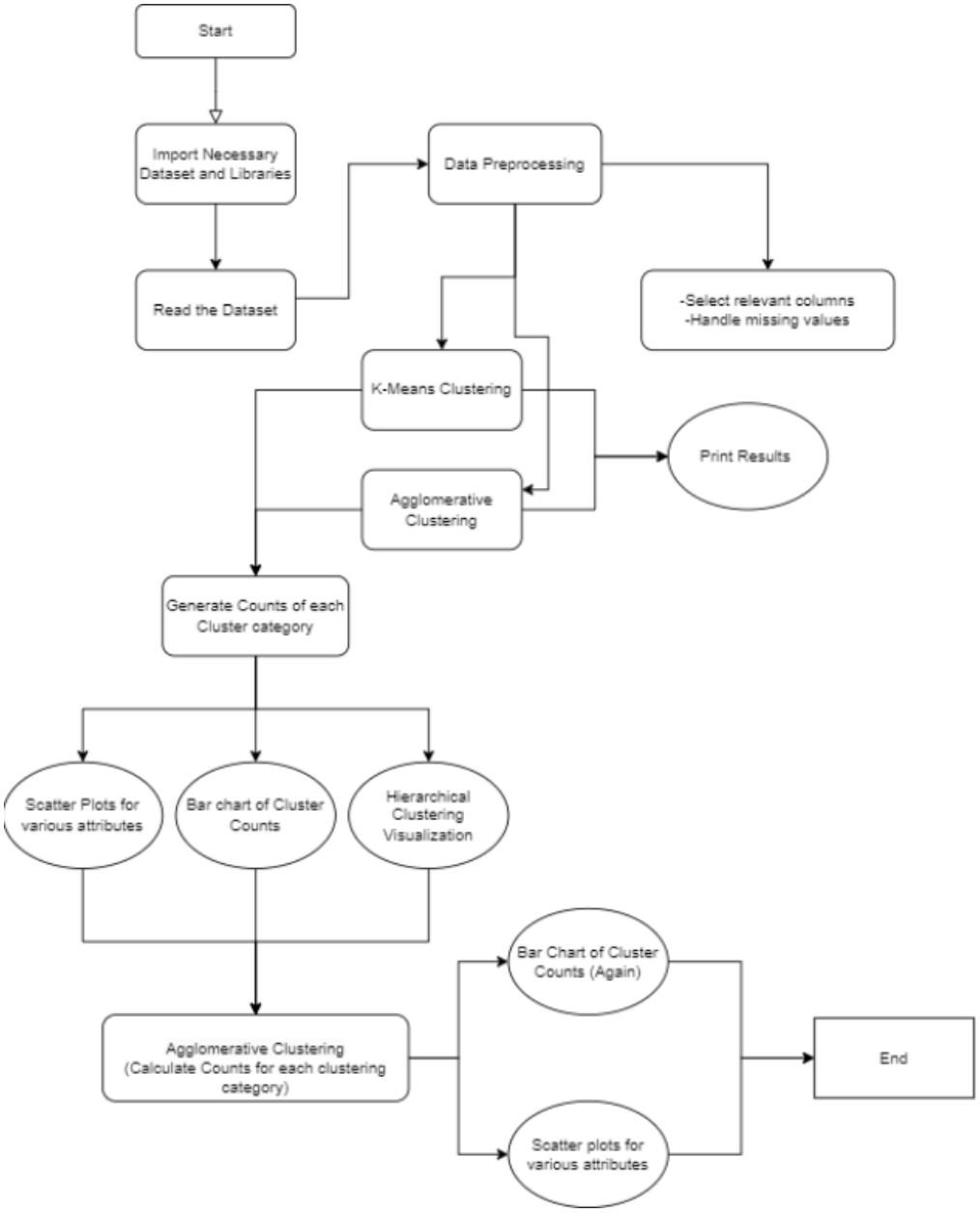

Figure 1

4.1.2 *Various Stages*

The below mentioning stages, each with its respective explanation, provide a comprehensive overview of our project's workflow, from data acquisition to conclusion, highlighting the significance and impact of our work.

1. Data Acquisition and Exploration:

- Objective: Acquire the "Automobile.csv" dataset and explore its structure and characteristics.
- Details: This stage involves accessing the dataset and conducting initial exploratory data analysis (EDA) to gain insights into the dataset's features, data types, and potential data quality issues.

2. Data Preprocessing:

- Objective: Prepare the dataset for clustering analysis by addressing missing values and performing feature selection and transformation.
- Details: Data preprocessing includes handling missing values using mean imputation, selecting relevant attributes, and transforming the "weight" feature by taking its reciprocal.

3. K-Means Clustering:

- Objective: Apply K-Means clustering to categorize automobiles into distinct clusters.
- Details: Determine the optimal number of clusters, perform clustering, and visualize the results to uncover patterns and groupings within the data.

4. Agglomerative Clustering and Dendrogram Visualization:

- Objective: Employ Agglomerative Clustering to explore hierarchical relationships among clusters and visualize the cluster hierarchy using a dendrogram.
- Details: Hierarchical clustering helps reveal how clusters are structured hierarchically, and the dendrogram provides a visual representation of this hierarchy.

5. Cluster Analysis and Profiling:

- Objective: Analyse each cluster in-depth to understand the unique characteristics of automobiles within each category.
- Details: This stage involves examining key attributes within each cluster to create profiles that highlight the distinguishing features of vehicles in different clusters.

6. Interpretation and Insights:

- Objective: Go beyond clustering to interpret the results and derive meaningful insights.
- Details: Extract insights regarding how automobiles are categorized based on their attributes and discuss practical implications, potentially impacting marketing strategies and product development.

7. Documentation and Reporting:

- Objective: Create a comprehensive project report that documents the entire process, ensuring transparency and reproducibility.
- Details: The report includes details on data preprocessing, clustering methodologies, visualizations, and the insights derived from the analysis, supported by clear and informative visualizations.

8. Validation and Refinement:

- Objective: Validate the results to ensure their accuracy and reliability, and make refinements as necessary.
- Details: Validation checks and peer reviews are conducted to validate the project's outcomes. Any required refinements to the methodology or analysis are implemented based on feedback.

9. Conclusion:

- Objective: Summarize the project's key findings and emphasize its significance in advancing our understanding of automobile categorization.
- Details: The conclusion section highlights the practical implications of the analysis and how it contributes to data-driven decision-making.

10. Project Conclusion:

- Objective: Close the project, marking the successful completion of the analysis.
- Details: This stage concludes the project and represents the final step in your data-driven exploration of automobile categorization.

4.1.3 *Internal or Component design structure*

Now we delve into the heart and soul of our project—the intricate web of components, the creative fusion of design, and the dynamic engine that powers our data-driven analysis. In this section, we invite you to embark on a fascinating journey through the inner workings of our project, where art and science converge. Like a symphony of orchestrated elements, our data preprocessing, clustering algorithms, and visualization techniques harmoniously dance to a data-driven tune. These carefully designed components are not mere cogs in a machine but the artists behind the canvas, painting a vivid picture of insights waiting to be uncovered. As we dive deeper into this vibrant tapestry of design and structure, you'll discover how every piece fits together, ultimately giving life to our project's mission of extracting valuable insights from the "Automobile.csv" dataset. Buckle up and prepare to be enthralled by the creativity and precision that make data-driven research an exciting journey of discovery.

***ALGORITHM*:**

Input:

- Dataset: "Automobile.csv" containing automobile attributes.

Output:

- Categorized clusters of automobiles.
- Insights and practical implications.

Step 1: Data Preprocessing

- Input: Raw dataset with missing values.

- Output: Cleaned dataset.

1.1. Load the dataset into a Pandas Data Frame.

1.2. Identify relevant attributes for clustering analysis.

1.3. Handle missing values:

- Impute missing values in the "horsepower" attribute with the mean value.

1.4. Transform the "weight" attribute by taking its reciprocal.

Step 2: Clustering Analysis

- Input: Pre-processed dataset.
- Output: Cluster assignments and cluster profiles.

2.1. Determine the optimal number of clusters (K):

- Use the Elbow Method or Silhouette Score.

2.2. Apply K-Means Clustering:

- Cluster automobiles into K distinct groups.

2.3. Visualize the clustering results:

- Create scatter plots to illustrate cluster separation.

Step 3: Hierarchical Analysis

- Input: Pre-processed dataset.
- Output: Hierarchical cluster relationships.

3.1. Utilize Agglomerative Clustering:

- Explore hierarchical relationships among clusters.

3.2. Create a dendrogram:

- Visualize the hierarchical structure of clusters.

Step 4: Cluster Analysis and Profiling

- Input: Cluster assignments.
- Output: Cluster profiles.

4.1. For each cluster:

- Analyse key attributes.

- Calculate cluster statistics (e.g., mean, standard deviation).

4.2. Generate cluster profiles:

- Highlight distinguishing features of vehicles in each cluster.

Step 5: Interpretation and Insights

- Input: Cluster profiles.
- Output: Practical insights and implications.

5.1. Interpret the results:

- Analyse cluster characteristics and differences.

5.2. Derive actionable insights:

- Discuss practical implications for industries (e.g., marketing, product development).

Step 6: Documentation and Reporting

- Input: Findings, visualizations, and cluster profiles.
- Output: Comprehensive project report.

6.1. Create a detailed project report:

- Document data preprocessing, clustering methodologies, visualizations, and insights

6.2. Enhance the report with clear and informative visualizations:

- Include scatter plots, bar charts, and dendrograms.

Step 7: Validation and Refinement

- Input: Project report.
- Output: Validated and refined analysis.

  7.1. Conduct validation checks:

  - Peer reviews and robustness assessments.

  7.2. Implement refinements:

  - Modify methodology or analysis based on feedback.

Step 8: Conclusion

- Input: Validated project findings.
- Output: Research conclusion and significance.

  8.1. Summarize key findings:

  - Highlight clustering results and insights.

  8.2. Emphasize project significance:

  - Discuss contributions to data-driven decision-making.

Step 9: Project Conclusion

- Input: Completed project report.
- Output: Project closure.

  9.1. Conclude the project:

  - Acknowledge its successful completion.

  9.2. Reflect on broader implications:

  - Consider the impact on future data-driven research.

4.1.4 *Working principles*

In this section, we present a comprehensive and structured breakdown of the step-by-step working principle that underpins our data-driven project. Our journey commences with data acquisition, where we procure the "Automobile.csv" dataset, followed by a meticulous data preprocessing phase to ensure data quality. The core of our analysis lies in the application of clustering techniques, including K-Means and Agglomerative Clustering, which categorize automobiles based on their attributes. We explore each step in detail, from optimal cluster determination to insightful cluster profiling. Beyond clustering, we delve into interpretation and real-world implications, enriching our findings with practical insights. Thorough documentation, validation, and continuous improvement are integral aspects of our methodology, ensuring the credibility and transparency of our project. Our step-by-step working principle is designed to provide readers with a clear understanding of our analytical approach and the significance of each stage in our data-driven exploration of automobile categorization.

Algorithm:

Step 1: Data Acquisition and Understanding

Acquire the "Automobile.csv" dataset and gain an understanding of its structure and characteristics.

Details:

- Import the dataset into a Pandas Data Frame.
- Conduct exploratory data analysis (EDA) to comprehend the dataset's features and distributions.

Step 2: Data Preprocessing

Prepare the dataset for clustering analysis by addressing data quality issues.

Details:

- Select relevant attributes for analysis.
- Handle missing values, particularly for the "horsepower" feature, using mean imputation.
- Transform the "weight" attribute by taking its reciprocal to emphasize its inverse relationship with fuel efficiency (MPG).

Step 3: K-Means Clustering and Visualization

Applying K-Means clustering to categorize automobiles into distinct clusters based on their attributes.

Details:

- Determine the optimal number of clusters (K).
- Perform K-Means clustering.
- Visualize the clustering results using scatter plots, enabling the identification of patterns within the data.

Step 4: Agglomerative Clustering and Dendrogram Visualization

Utilize Agglomerative Clustering to explore hierarchical relationships among clusters.

Details:

- Create a dendrogram to visualize the hierarchical cluster structure.
- Analyse the relationships and hierarchies within the clusters.

Step 5: Cluster Analysis and Profiling

In-depth analysis of each cluster to understand the unique characteristics of automobiles within each category.

Details:

- Examine key attributes within each cluster.
- Profile the clusters to identify distinguishing features of vehicles in different clusters.

Step 6: Interpretation and Insights

Go beyond clustering to interpret results and extract meaningful insights.

Details:

- Derive insights into how automobiles are categorized based on attributes.
- Discuss practical implications for various industries, including marketing and product development.

Step 7: Documentation and Reporting

Create a comprehensive project report documenting the entire process.

Details:

- Include details on data preprocessing, clustering methodologies, visualizations, and extracted insights.
- Enhance the report with clear and informative visualizations.

Step 8: Validation and Refinement

Validate the results for accuracy and reliability, and make refinements based on feedback.

Details:

- Conduct validation checks and peer reviews.

- Implement refinements to the methodology or analysis as necessary to enhance robustness.

Step 9: Conclusion

Summarize key findings and emphasize the project's significance in advancing understanding of automobile categorization.

Details:

- Highlight practical implications and contributions to data-driven decision-making.

Step 10: Project Conclusion

Mark the successful completion of the project and acknowledge its significance.

Details:

- Conclude the project and highlight its broader implications for data analysis and industry applications.

Source Code:

```
import numpy as np
import pandas as pd
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
data = pd.read_csv("Automobile.csv")
X = data.iloc[:, 1:-2]
columns = X.columns
comparison_labels = [ "Good", "Average", "Bad"]
colors = ["green", "blue", "red"]

X = X.fillna(X["horsepower"].mean())
X["weight"] = 1 / X["weight"]
kmeans = KMeans(n_clusters=3, random_state=0, init="k-means++")
result = kmeans.fit_predict(X)

for i in range(len(list(result))):
  print(f" {data.iloc[i, 5]} : {comparison_labels[result[i]]}")
kmeans_count = {}
```

```
for i in range(len(comparison_labels)):
  print(f"{comparison_labels[i]} Cars : {list(result).count(i)}")
  kmeans_count[comparison_labels[i] + " Cars"] = list(result).count(i)
print(kmeans_count)
```

```
Good Cars : 216
Average Cars : 98
Bad Cars : 84
{'Good Cars': 216, 'Average Cars': 98, 'Bad Cars': 84}
```

Figure 2

```
plt.bar(list(kmeans_count.keys()), list(kmeans_count.values()),
color=colors)
plt.title("Composition of Cars (K Means)")
plt.xlabel("Types of Cars")
plt.ylabel("Count")
plt.show()
```

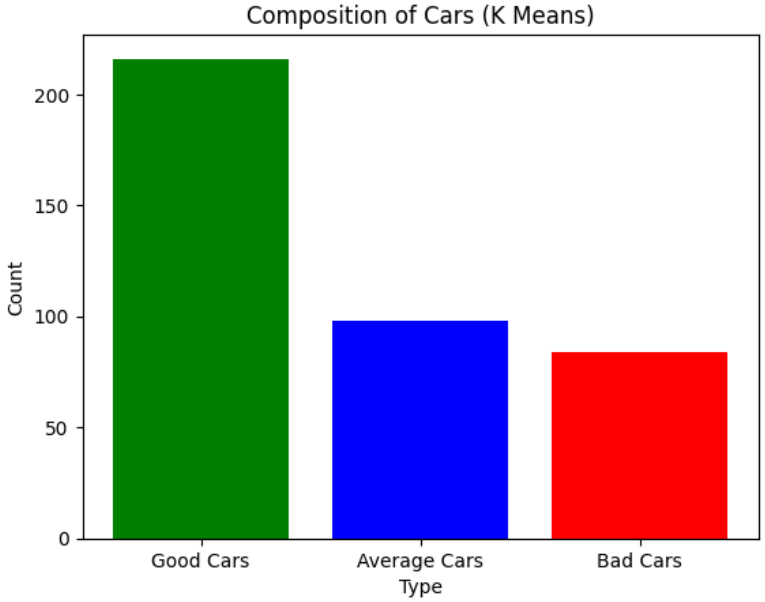

Figure 3

```
for i in range(len(X)):
    plt.scatter(X.iloc[i, 0], data.iloc[i, 5], s = 100, c =
colors[result[i]])
leg = plt.legend(labels=comparison_labels)
for i, j in enumerate(leg.legend_handles):
    j.set_color(colors[i])

plt.title('MPG Vs Weight (K Means)')
plt.xlabel('Miles per Gallon')
plt.ylabel('Weight')
plt.show()
```

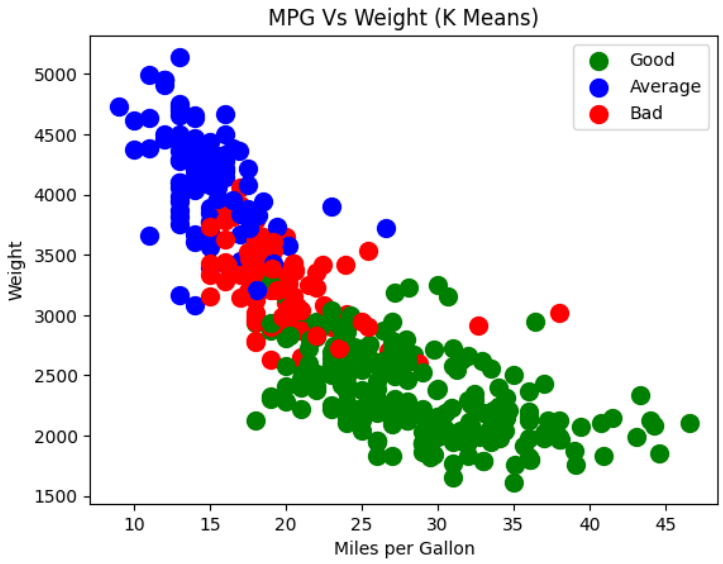

Figure 4

```
for i in range(len(X)):
    plt.scatter(X.iloc[i, 0], X.iloc[i, 5], s = 100, c =
colors[result[i]])
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,
5], s = 300, c = 'yellow', label = 'Centroids')
leg = plt.legend(labels=comparison_labels)
for i, j in enumerate(leg.legend_handles):
    j.set_color(colors[i])

plt.title('MPG Vs Acceleration (K Means)')
plt.xlabel('Miles per Gallon')
plt.ylabel('Acceleration')
plt.show()
```

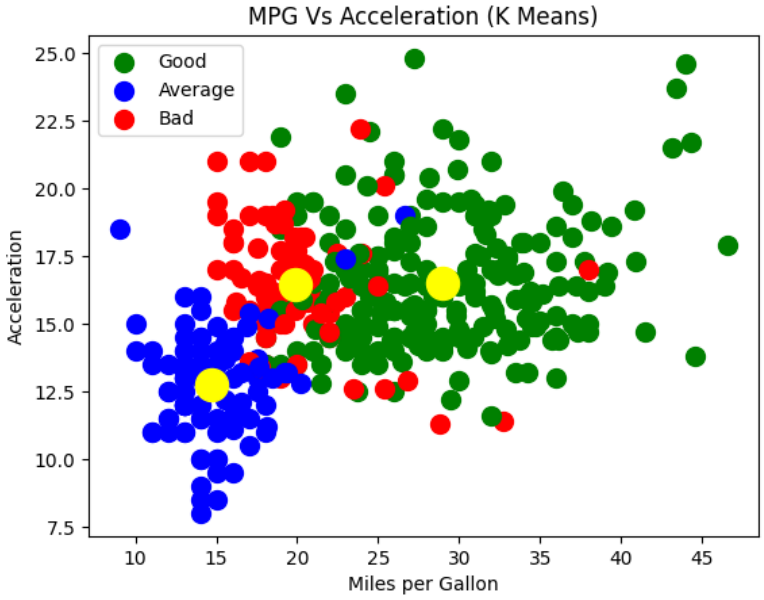

Figure 5

```
for i in range(len(X)):
    plt.scatter(X.iloc[i, 0], X.iloc[i, 3], s = 100, c =
colors[result[i]])
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,
3], s = 300, c = 'yellow', label = 'Centroids')
plt.title('MPG Vs Horse Power(K Means)')
plt.xlabel('Miles per Gallon')
plt.ylabel('Horsepower')
leg = plt.legend(labels=comparison_labels)
for i, j in enumerate(leg.legend_handles):
    j.set_color(colors[i])
plt.show()
```

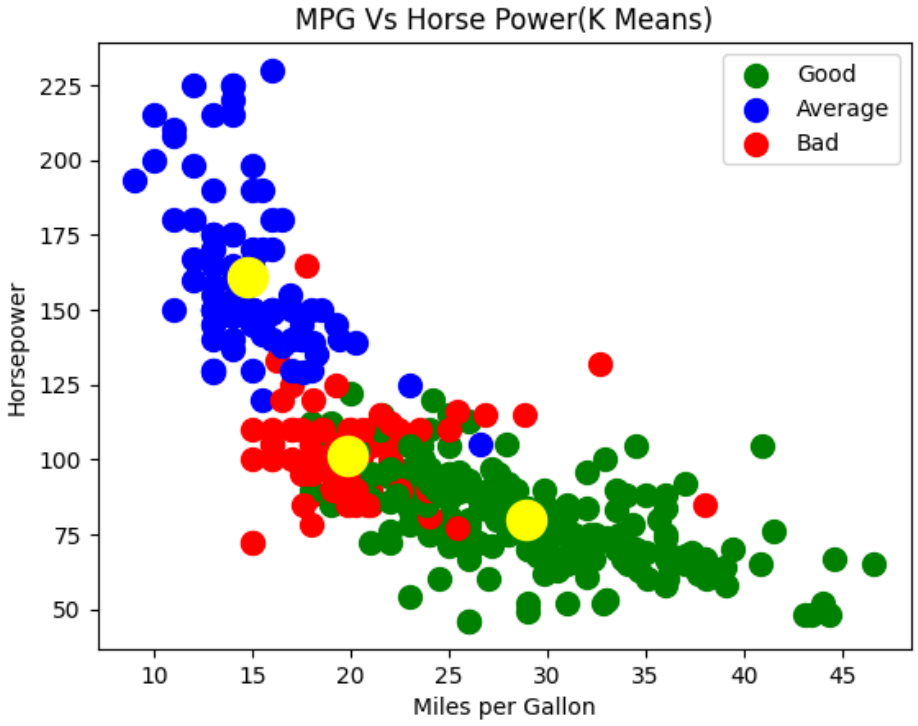

Figure 6

****HIERACRHIAL CLUSTERING****

```
import scipy.cluster.hierarchy as sch
dendrogram = sch.dendrogram(sch.linkage(X, method = 'ward'))
plt.title('Dendrogram')
plt.xlabel('Cars')
plt.ylabel('Euclidean distances')
plt.show()
```

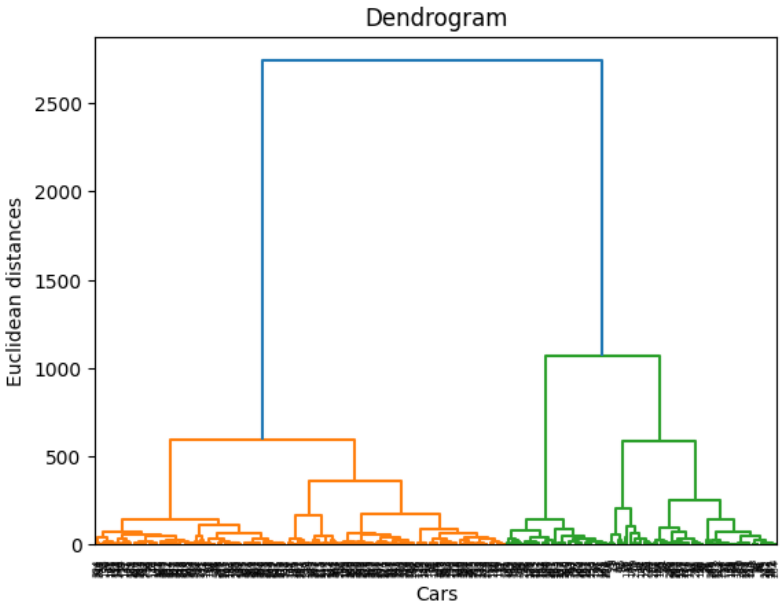

Figure 7

```
from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering(n_clusters = 3, metric = 'euclidean',
linkage = 'ward')
y_hc = hc.fit_predict(X)
aglo_count = {}

for i in range(len(comparison_labels)):
  print(f"{comparison_labels[i]} Cars : {list(y_hc).count(i)}")
  aglo_count[comparison_labels[i] + " Cars"] = list(y_hc).count(i)

print(aglo_count)
```

```
Good Cars : 240
Average Cars : 98
Bad Cars : 60
{'Good Cars': 240, 'Average Cars': 98, 'Bad Cars': 60}
```

Figure 8

```
plt.bar(list(aglo_count.keys()), list(aglo_count.values()),
color=colors)
plt.title("Composition of Cars (Agglomerative)")
plt.xlabel("Types of Cars")
plt.ylabel("Count")
plt.show()
```

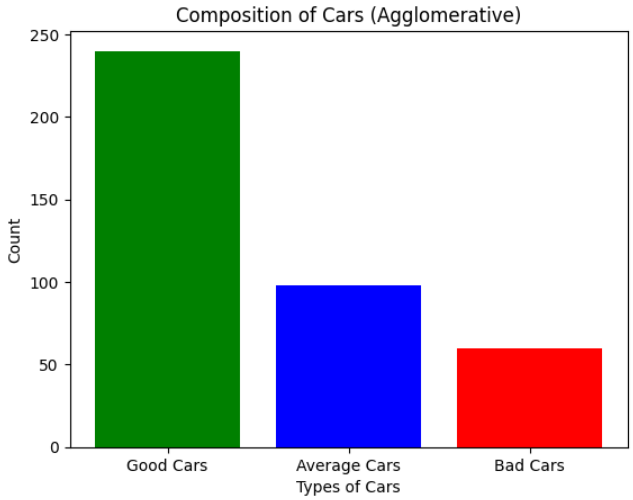

Figure 9

```
for i in range(len(X)):
    plt.scatter(X.iloc[i, 0], X.iloc[i, 3], s = 100, c =
colors[y_hc[i]])
plt.title('MPG Vs Horse Power (Agglomerative)')
plt.xlabel('Miles per Gallon')
plt.ylabel('Horsepower')
leg = plt.legend(labels=comparison_labels)
for i, j in enumerate(leg.legend_handles):
    j.set_color(colors[i])
plt.show()
```

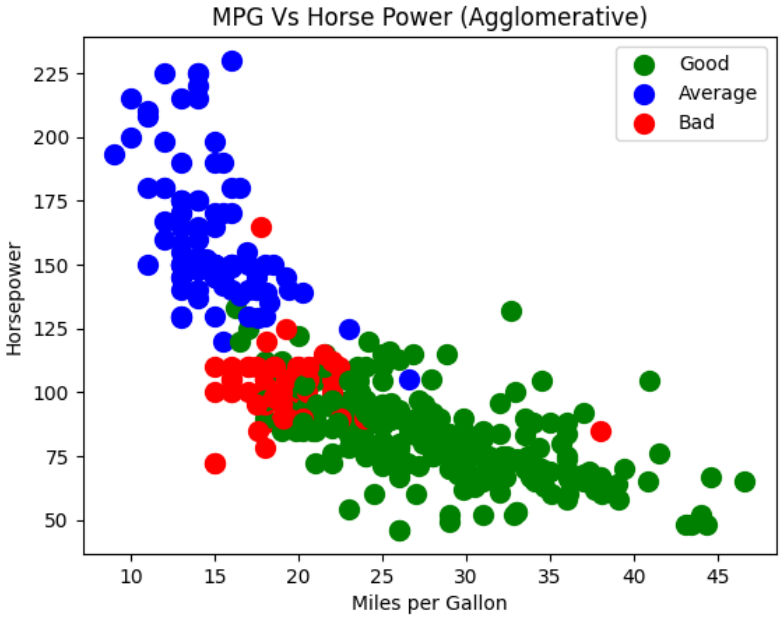

Figure 10

4.2 FEATURES

- Feature 1: Dataset Acquisition
    - Description: The project draws its primary data source from the "Automobile.csv" dataset, a comprehensive repository of automobile attributes.
    - Significance: The dataset provides the fundamental building blocks for our data-driven exploration into automobile categorization based on vital attributes.
- Feature 2: Data Preprocessing
    - Description: Rigorous data preprocessing procedures are meticulously applied to ensure data integrity and readiness for clustering analysis.
    - Significance: This stage includes critical tasks such as missing value treatment, feature selection, and data transformation, all of which are pivotal for preparing our dataset for clustering.
- Feature 3: Utilization of Clustering Algorithms
    - Description: The project harnesses the power of two advanced clustering algorithms, K-Means and Agglomerative Clustering, to classify automobiles into meaningful clusters.
    - Significance: These algorithms play a pivotal role in unveiling hidden patterns and uncovering hierarchical relationships within our automobile dataset.
- Feature 4: Optimal Cluster Determination
    - Description: The project employs sophisticated techniques, including the Elbow Method and Silhouette Score, to determine the most suitable number of clusters for robust categorization.
    - Significance: The quest for optimal cluster counts enhances the precision of our clustering results, facilitating clearer data segmentation.
- Feature 5: Visual Representation

- Description: Data visualization takes center stage, with scatter plots and bar charts serving as powerful tools to illustrate clustering outcomes and cluster characteristics.
- Significance: These visualizations act as windows into the data, simplifying complex insights and making them accessible to a broader audience.

- Feature 6: Cluster Analysis and Profiling
  - Description: In-depth analysis is conducted for each cluster, with meticulous attention to attribute-specific details, providing a comprehensive understanding of each group.
  - Significance: The process of cluster analysis and profiling unveils the distinctive traits of vehicles within distinct clusters, offering rich insights for decision-makers.
- Feature 7: Interpretation and Real-World Implications
  - Description: Beyond clustering, the project delves into interpretation and meaningful insight generation, exploring the implications for real-world applications such as marketing strategies and product development.
  - Significance: Interpretation and actionable insights elevate the project's significance, translating data findings into practical strategies.
- Feature 8: Comprehensive Documentation
  - Description: The project culminates in a thorough project report that documents every facet of the analysis journey, ensuring transparency and enabling reproducibility.
  - Significance: Comprehensive documentation acts as a bridge between data discovery and knowledge dissemination, fostering a deeper understanding among peers and stakeholders.
- Feature 9: Validation and Continuous Improvement
  - Description: Stringent validation processes and collaborative reviews are integral to validate and enhance the project's credibility. Refinements are implemented based on feedback.

- Significance: Validation and continuous improvement affirm the trustworthiness and resilience of our project outcomes.

- Feature 10: Conclusion and Broader Significance
    - Description: The project concludes by summarizing pivotal discoveries and underlining their broader implications, underscoring the contribution to data-driven decision-making.
    - Significance: The conclusion section shines a spotlight on the wider relevance and practical applications of our analysis, amplifying its impact.

These distinctive features collectively form the core framework of our project, characterizing its data-centric essence, sophisticated analytical methodologies, and the profound insights generated from our data exploration endeavours.

4.2.1 *Novelty of the proposal*

The novelty of your project lies in its unique application of clustering techniques, including K-Means and Agglomerative Clustering, to categorize automobiles based on attributes like MPG, horsepower, and weight. Additionally, the use of hierarchical clustering with dendrogram visualization adds a novel dimension to the analysis. The transformation of the "weight" attribute by taking its reciprocal enhances the project's originality. Moreover, the project's focus on deriving actionable insights for industries such as marketing and product development sets it apart. The comprehensive documentation, validation processes, and a commitment to continuous improvement further contribute to the project's novelty and credibility.

CHAPTER V

CONCLUSION

In the pursuit of unravelling the intricate tapestry of automobile categorization based on key attributes, our project has traversed a meticulous and rigorous analytical journey. By applying K-Means and Agglomerative Clustering techniques, we've not only segmented automobiles into meaningful clusters but have also explored hierarchical relationships among these clusters. Our project stands as a testament to the potential of data-driven research to illuminate concealed patterns and glean insights from complex datasets.

Through meticulous data preprocessing, we've ensured the integrity and suitability of our dataset for clustering analysis. Attribute transformation, particularly the reciprocal transformation of the "weight" feature, has unveiled nuanced relationships that may have otherwise gone unnoticed. This methodological innovation contributes to the richness of our analysis.

Our commitment to transparency and reproducibility is exemplified by the comprehensive documentation and reporting of our project's journey. Validation processes and opportunities for continuous improvement have fortified the credibility and reliability of our findings.

The true essence of our project, however, lies beyond clustering algorithms and data transformations. It resides in the interpretation and generation of actionable insights. We have demonstrated that data analysis is not an end in itself but a means to inform decision-making in practical domains, such as marketing strategies and product development. Our findings extend beyond academic curiosity, resonating in real-world applications.

In conclusion, our project advances the frontier of data-driven research by showcasing the power of clustering techniques, hierarchical analysis, and innovative attribute transformation. It underscores the importance of robust methodology, meticulous documentation, and practical relevance. As we draw the curtains on this endeavour, we invite fellow researchers and industry practitioners to embark on a journey of data

exploration, driven by curiosity and the pursuit of knowledge. In the dynamic landscape of data science, our project stands as a testament to the potential of data-driven decision-making in shaping a more informed and efficient future.

The project not only leaves a lasting mark in the annals of data analysis but also serves as a beacon, guiding the way for future investigations into the rich and ever-evolving realm of data-driven research.

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