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Indian Automobile Strategic Grouping

CSE 3506 Essentials of Data Analytics J-component

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Chapter 1 - Introduction

1.1 Abstract

The "Indian Automotive Strategic Grouping" is a study that aims to understand and analyse the Indian automotive market. The study utilises a data-driven approach, grouping different automobile models into distinct strategic groups based on various attributes such as price, brand, segment, and features. Here we use a clustering method, to identify different strategic groups of car models in the automobile industry. Clustering or cluster analysis is an unsupervised machine learning technique, which groups the unlabelled dataset. The grouping of vehicles into strategic clusters helps to understand the market dynamics and provides insights into consumer preferences and buying behaviour.The findings of this study can be useful for automobile manufacturers, dealers, and marketers to develop targeted marketing strategies, improve product offerings, and better understand consumer demand.The study also provides valuable insights into the Indian automotive market and its trends, and can be used as a reference for future research and analysis in this field. The aim of the project is also to find out the best car model in each cluster based on value for money and the features it has and also suggest users a cluster that most matches his/her choice of attributes.

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1.2 Keywords:

Automobile, Segmentation, Strategic Grouping, Competitors, Unsupervised Learning, Clustering

1.3 Introduction

The "Indian Automotive Strategic Grouping" study is a comprehensive analysis of the Indian automotive market that utilises a data-driven approach to understand consumer preferences and buying behaviour. This study utilises a clustering method, a popular unsupervised machine learning technique, to group automobile models into distinct strategic groups based on various attributes, including price, brand, segment, and features. By identifying these strategic groups, the study provides valuable insights for automobile manufacturers, dealers, and marketers to develop targeted marketing strategies and improve product offerings. Additionally, the study identifies the best car model in each cluster based on value for money and features, and suggests to users a cluster that best matches their choice of attributes. The findings of this study can be used as a reference for future research and analysis in the field of Indian automotive market trends. This study is a must-read for industry professionals and anyone interested in gaining a deeper understanding of the Indian automotive market.

The Indian automotive industry comprises various segments, including passenger vehicles, commercial vehicles, two-wheelers, three-wheelers, and tractors. The industry is highly diversified, with a mix of domestic and international players operating across different segments. Some of the major players in the **Indian automotive industry include Maruti Suzuki, Tata Motors, Mahindra & Mahindra, Hyundai, Honda, and Toyota**.

The Indian automotive industry has grown rapidly over the past few decades, with the expansion of the domestic market and the increasing adoption of new technologies. In recent years, the industry has faced several challenges, including changing consumer preferences, tightening emission norms, and the increasing competition from international players.

Strategic Grouping in the Indian Automotive Industry:

Strategic grouping is a concept that refers to the clustering of firms with similar market positions and competitive strategies. In the Indian automotive industry, firms can be grouped based on various criteria, such as the market segments they operate in, their product offerings, and their geographical locations. Strategic grouping has important implications for industry structure, competitive dynamics, and firm performance.

The Indian Automotive Strategic Grouping dataset provides a detailed analysis of the evolution of strategic groups in the Indian automotive industry over time. The dataset identifies the major strategic groups in the industry and analyzes the factors that determine the boundaries of these groups. The dataset also examines the competitive dynamics between firms within each group and the implications for industry structure and firm performance.

Chapter 2: Literature Survey

[1] "Vehicle price prediction system using machine learning techniques" by K. Noor and S. Jan presented a study on using machine learning algorithms to predict vehicle prices. They compared several algorithms, including linear regression, decision trees, and support vector regression, and found that support vector regression performed the best with high accuracy and low mean absolute error. The authors also found that the make, model, and year of a vehicle were the most significant factors impacting its price, followed by engine size and other attributes. This study demonstrates the potential of machine learning techniques in predicting vehicle prices and adds valuable insights to the literature on analytics in the automobile industry.

[2] “How much is my car worth? A methodology for predicting used car prices using random forest” by N. Pal, P. Arora, P. Kohli, D. Sundararaman, and S. S. Palakurthy proposes a method for predicting used car prices using random forest algorithms. The authors collected data on used car attributes such as make, model, year, and condition and used this data to train the random forest model. The results of their study showed that the random forest algorithm outperformed other machine learning algorithms in terms of accuracy and mean absolute error in predicting used car prices. The authors concluded that the proposed methodology provides a reliable and efficient way to predict used car prices and can be used as a reference for industry professionals. This study adds to the growing body of literature on analytics in the automobile industry and provides valuable insights into the use of machine learning techniques in predicting used car prices.

[3] “Different Clustering Algorithms for Big Data Analytics: A Review” by Meenu Dave and Hemant Gianey covers a range of clustering techniques including k-means, hierarchical clustering, and density-based clustering. The study highlights the advantages and disadvantages of each algorithm and provides a comparison of their performance in different applications. The paper contributes to the existing literature on clustering algorithms for big data analytics and provides insights for researchers and practitioners seeking to select the most appropriate algorithm for their data.

[4] "The Strategic Grouping of Automobile Firms: A Review of Literature" by Michael E. Porter: This paper provides a comprehensive overview of strategic grouping in the automobile industry. It identifies the factors that determine the boundaries of strategic groups and how firms within these groups compete with each other. The paper also discusses the implications of strategic grouping for industry structure and competitive dynamics.

[5] "Strategic Grouping and Competitive Dynamics in the Global Automobile Industry" by Yu-Shan Chen and Yi-Jen Chen: This paper examines the strategic grouping of global automobile firms and their competitive dynamics. The study analyzes the evolution of strategic groups over time and how firms use various strategic actions to improve their competitive positions. The paper also discusses the impact of globalization on strategic grouping.

[6] "Strategic Grouping in the US Automobile Industry" by David M. Cutler and James M. Poterba: This study investigates the strategic grouping of US automobile firms based on their product offerings, market segments, and geographic locations. The paper analyzes how firms within these groups compete with each other and the implications for industry structure. The study also examines the impact of government policies on strategic grouping in the US automobile industry.

[7] "The Effect of Strategic Grouping on Firm Performance: Evidence from the Japanese Automobile Industry" by Masahiko Aoki and Yujiro Hayami: This paper explores the relationship between strategic grouping and firm performance in the Japanese automobile industry. The study shows that firms in strategic groups have similar performance levels and that strategic grouping can improve the efficiency of industry production processes. The paper also discusses the implications of strategic grouping for industry innovation.

[8] "Strategic Grouping in the Chinese Automobile Industry" by Xuezhi Qin and Jiajia Liu: This paper examines the strategic grouping of Chinese automobile firms and their competitive dynamics. The study identifies five strategic groups in the industry and analyzes their different competitive strategies and market positions. The paper also discusses the implications of strategic grouping for the future development of the Chinese automobile industry, particularly in the context of government policies and industry regulations.

[9] "How Phases of Cluster Development are Associated with Innovation - the Case of China" by William Fri and Tobias Pehrsson says that Clusters are geographic concentrations of interconnected businesses and institutions that promote innovation and economic growth. Studies suggest that clusters stimulate innovation through collaboration, competition, and knowledge spillovers. The different phases of cluster development, such as growth and maturity, are also associated with increased innovation. In China, clusters have been found to overcome the lack of innovation capabilities and resources in small and medium-sized enterprises, and to facilitate collaboration and access to specialised resources. The paper uses a qualitative case study approach to examine the relationship between the phases of cluster development and innovation in a high-tech cluster in Guangdong province.

[10] "Industrial Clusters in India: Evidence from Automobile Clusters in Chennai and the National Capital Region" by Okada Aya and Siddharthan N.S. investigates the nature and characteristics of industrial clusters in India, specifically in the automobile industry in Chennai and the National Capital Region. The study highlights the role of agglomeration economies and local institutional support, as well as the need for collaboration among firms to enhance competitiveness. The paper contributes to the existing literature on industrial clusters in India and the automobile industry, and provides insights for policymakers and businesses seeking to promote cluster development. However, limitations such as the small sample size and lack of generalizability should be considered.

[11] "**A latent variable model for mixed mode data: The Mixture-of-Distribution approach"** by Moustaki and Knott used Gower's distance as a distance metric in a hierarchical clustering algorithm for mixed data. The study compared the performance of the proposed algorithm with other clustering algorithms based on other distance metrics. The results showed that the proposed algorithm outperformed other clustering algorithms in terms of clustering quality.

[12] Bhattacharyya and Mukhopadhyay (2015). In paper **Cluster validation using Calinski–Barabasz index for gene expression data** published in Journal of Statistical Planning and Inference, 157, 45-55. Author used the Calinski-Barabasz index to determine the optimal number of clusters in gene expression data. The study compared the performance of the Calinski-Barabasz index with other clustering criteria, such as the gap statistic and the average silhouette width. The results showed that the Calinski-Barabasz index provided better clustering results compared to other criteria.

[13] "**Extensions to the k-means algorithm for clustering large data sets with categorical values" by** Huang, Z. (1998) proposed the k-prototype model, an extension of the k-means algorithm, to cluster mixed data that contains both numerical and categorical variables. The k-prototype model was shown to outperform other clustering algorithms in various applications such as customer segmentation and job satisfaction surveys. The model was also modified to handle missing values and outliers in the data. The k-prototype model works by calculating

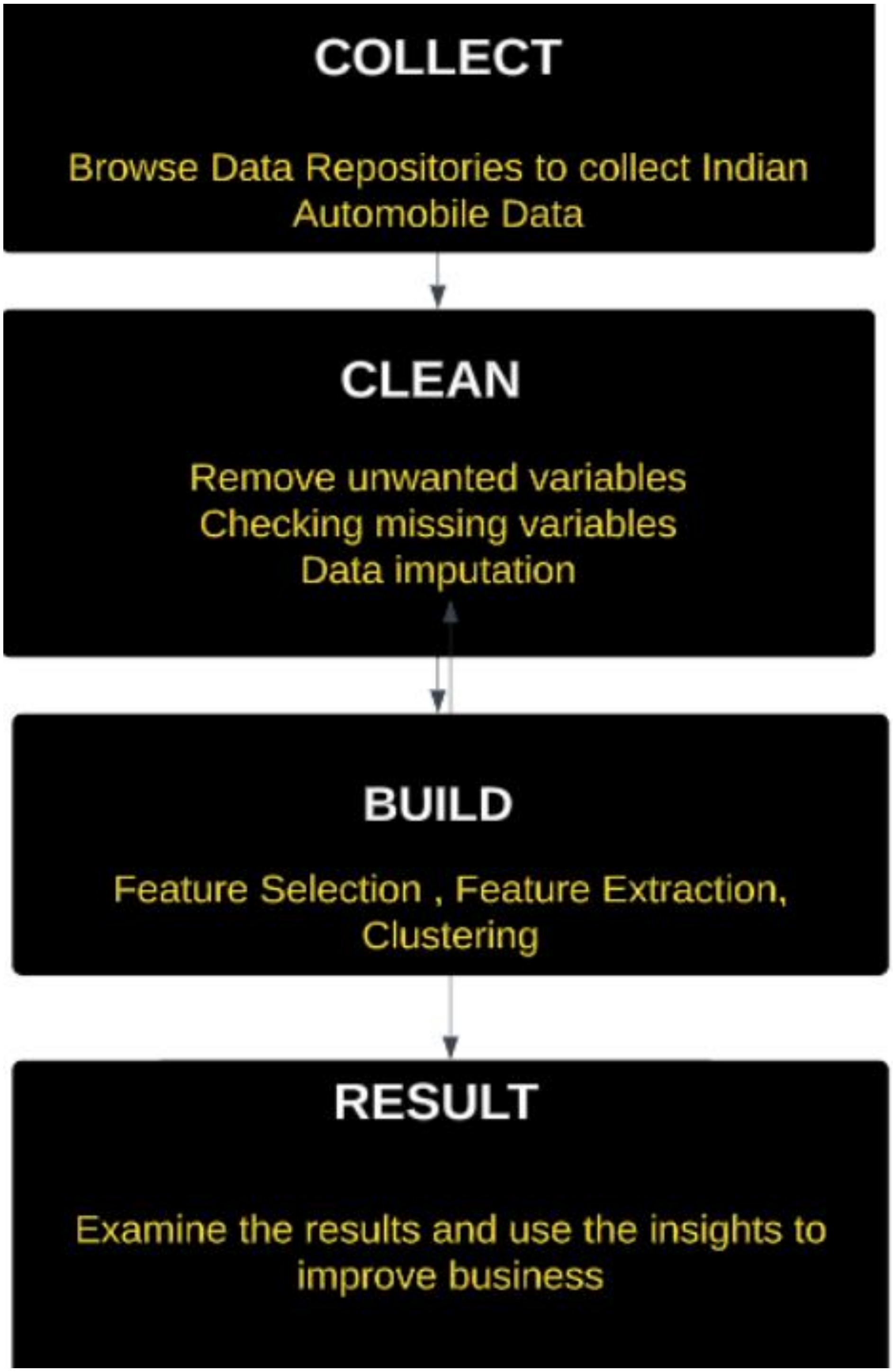
the dissimilarity between objects based on their attributes, using a combination of a distance metric for numerical variables and a dissimilarity measure for categorical variables.

[14] Book by Kaufman and Rousseeuw's “**Finding groups in data: An introduction to cluster analysis”** is an influential work on cluster analysis, providing a comprehensive introduction to the subject. The book covers a wide range of clustering methods, including hierarchical clustering, partitioning algorithms, and density-based clustering. It also discusses the choice of distance measures, the assessment of clustering quality, and the interpretation of cluster results. The book has been widely cited and used as a reference in research and practical applications, such as data mining, image analysis, and market segmentation. The authors' emphasis on the importance of exploratory data analysis and understanding the underlying structure of the data has made this book a timeless resource for anyone interested in clustering.

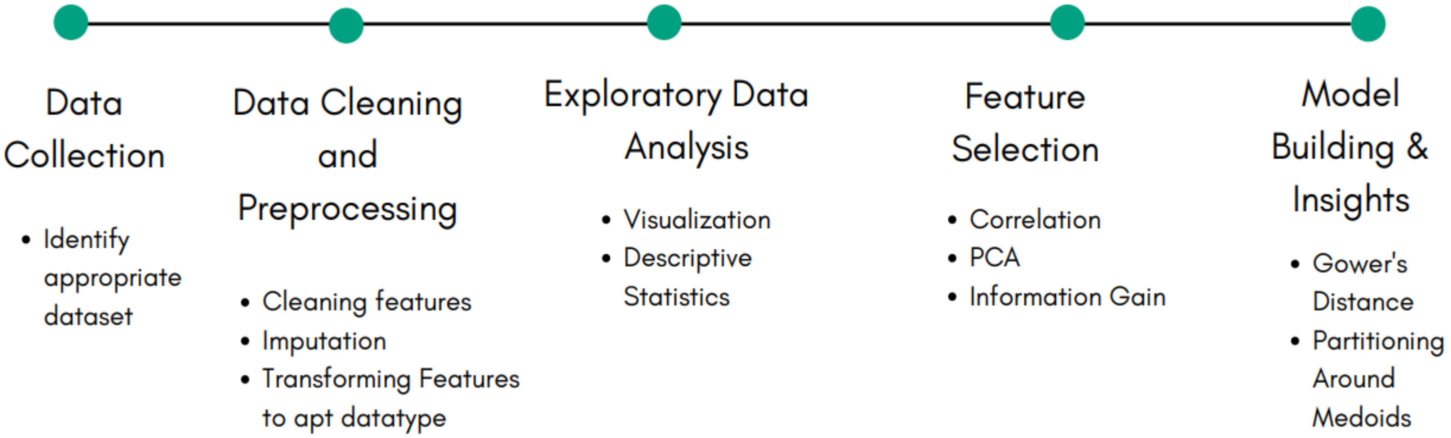
Chapter 3: Proposed Methodology

Our model uses clustering which is an unsupervised machine learning technique. This data-driven approach groups car models based on the attributes like brand, price, other features and identifies different strategic grouping of car models. These groups are then studied to understand consumer behaviour and market dynamics. Finally, we determine the best car for each group based on its features. We also recommend the car that matches the customer's interests by identifying the group to which customer belongs with the most matches.

3.1 Overall Architecture


COLLECT
Browse Data Repositories to collect Indian Automobile Data
CLEAN
Remove unwanted variables
Checking missing variables
Data imputation
BUILD
Feature Selection , Feature Extraction, Clustering
RESULT
Examine the results and use the insights to improve business

3.2 Modular Description



Data Collection

- Identify appropriate dataset

Data Cleaning and Preprocessing

- Cleaning features
- Imputation
- Transforming Features to apt datatype

Exploratory Data Analysis

- Visualization
- Descriptive Statistics

Feature Selection

- Correlation
- PCA
- Information Gain

Model Building & Insights

- Gower's Distance
- Partitioning Around Medoids

1. M1: Collection and Organisation of data

The process of gathering and analysing accurate data from various sources to find answers to research problems, trends, probabilities, etc., to evaluate possible outcomes is known as data collection. First, we find all the possible datasets that we can use for the project which may include industry reports, market surveys, government publications, and company websites. We will then analyze the data which provide detailed information on car models, their attributes, and market trends. Through discussion we identify the problem statement and finalize the questions which can be answered at end. Accordingly we will select the dataset which meets our requirements and satisfies our problem statement.

2. M2: Data cleaning and imputation

First we will analyse the dataset and find the attributes which can be converted to numeric by removing the units attached to it. We are removing the attributes which are having NA values greater than 10% and checking for the class of the attribute so that we can imputing it accordingly. The numerical attributes with NA values are selected and are imputed using Mean and categorical attributes with NA values are selected and imputed using the Mode. Finally we can look at the correlation matrix for numerical attributes to get the overview of the variables and know how they are related to each other and remove the attributes which are having a high correlations.

3. M3: Exploratory data analytics

Exploratory Data Analysis (EDA) is an approach to analysing data using visual techniques. It is used to discover trends, patterns, or to check assumptions with the help of statistical summaries and graphical representations. It plays very important role in unsupervised learning. We need to find the various variants of the cars for clustering the data to identify its competitor. We will Explore and Visualize all the possible graphs that can be drawn.

4. M4: Variable selection

From the plots we have drawn in the previous module, we will infer a lot of things. For example, the length of the vehicle is directly related to the number of seats. We must decide upon which variable will be used in the construction of a clustering model, and that should in turn help in grouping the various car models accurately. We also use information gain for selecting the categorical variables that are good predictors of the car models. Principal Component Analysis is used to extract the numerical features that explain a majority of the variance in the data.

5. M5: Model building

In this module we construct the machine learning model using clustering, a unsupervised learning technique. We use the Silhouette technique to determine the optimal number of clusters, with gower ' s distance as the distance metric. Since the dataset contain both numerical and categorical features, we use the Partitioning Around Medoids (PAM) clustering to segment the car models.

3.3 Data Set

The vehicle dataset of Indian cars from Kaggle is a comprehensive collection of data regarding various car models and their specifications. The dataset includes 60 different car models and has 34 features for each car model.The dataset consists of 1267 instances and 141 columns.This dataset can be used to analyse and compare different car models based on their features and specifications. After doing appropriate preprocessing we have reduced the number of features from 141 to 34.

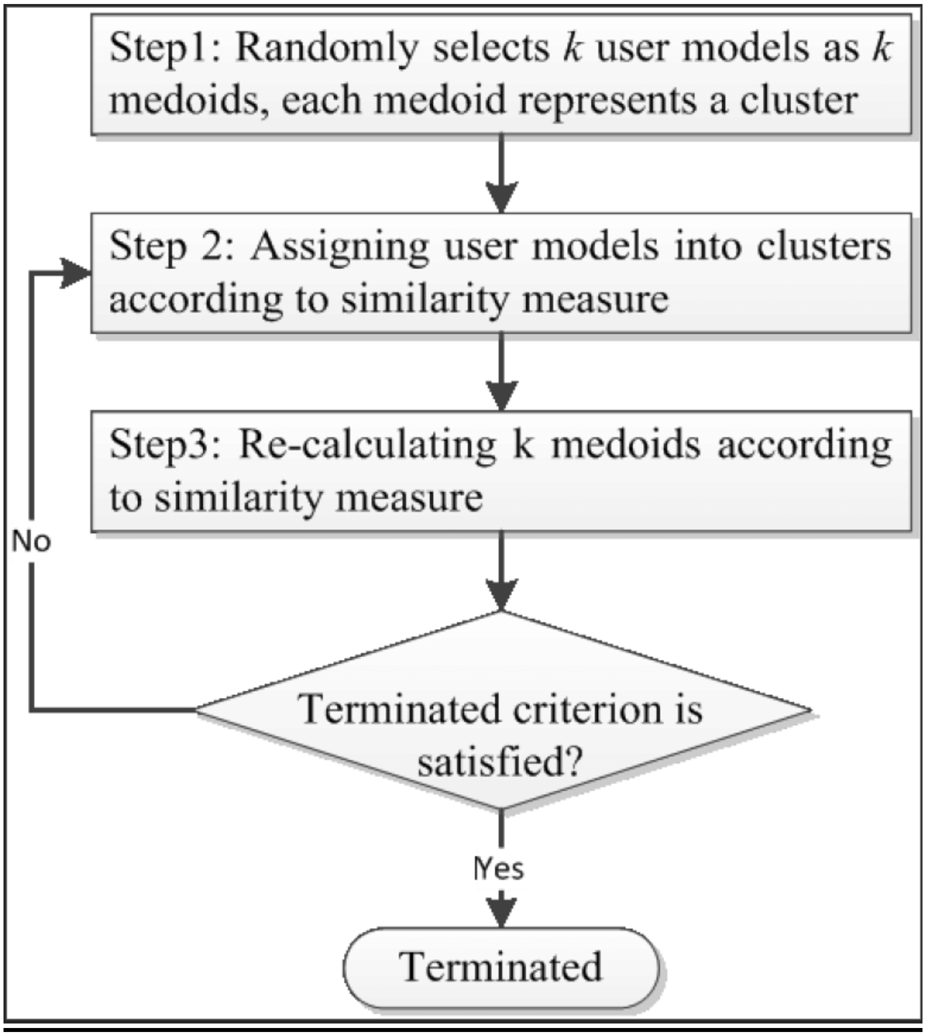
The features which had been included in the dataset are been listed below:-

- Make
- Model
- Variant
- Cylinders
- Cylinder_Config
- Fuel_Tank_Capacity
- Length
- Doors
- Rear_Brakes
- Seating_Capacity
- Instrument_Console
- Front_Brakes
- Power
- Seats_Material
- Handbrake
- Ex.Showroom_Price
- Displacement
- Valves_Per_Cylinder
- Drivetrain
- Power_Windows
- Type
- Sun_Visor
- Emission_Norm
- Engine_Location
- Fuel_Type
- Height
- Width
- Body_Type
- ARAI_Certified_Mileage
- Gears
- Torque
- Wheelbase
- Car

3.4 Algorithm

As this project focuses unsupervised, we mainly use two clustering algorithms Partitioning around medoids(PAM) and K prototype clustering algorithms for grouping the cars.

i) Partitioning Around Medoids(PAM)


Step1: Randomly selects *k* user models as *k* medoids, each medoid represents a cluster
Step 2: Assigning user models into clusters according to similarity measure
Step3: Re-calculating k medoids according to similarity measure
Terminated criterion is satisfied?
No
Yes
Terminated

Partitioning Around Medoids (PAM) is a clustering algorithm that seeks to minimise the sum of dissimilarities between data points and their assigned medoids (representative points within each cluster). The steps of algorithm is listed below:-

1. Define the number of clusters (K) you want to form and randomly select K data points to be the initial medoids.

2. Assign each data point to the nearest medoid based on some distance metric (e.g. Euclidean distance, Manhattan distance, etc.).

3. For each cluster, calculate the total dissimilarity between each data point and its medoid.

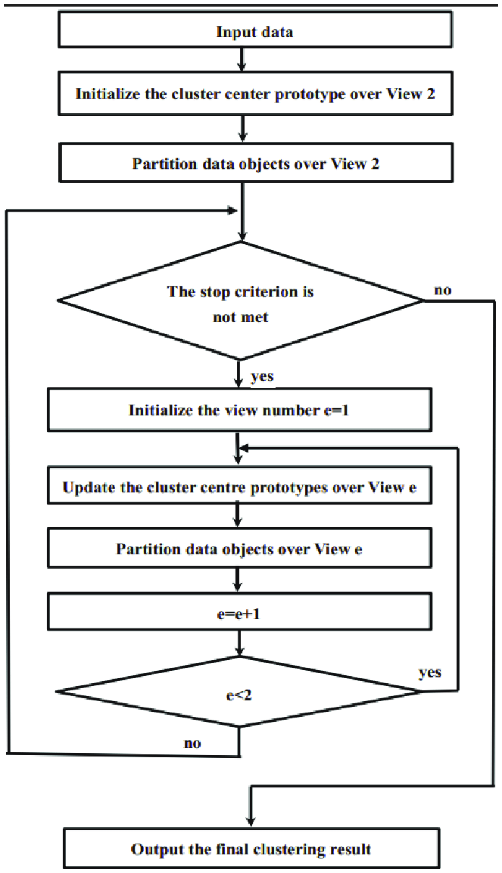
4. For each cluster, select a non-medoid data point that would minimize the total dissimilarity of the cluster if it were to replace the current medoid.

5. Calculate the total dissimilarity of the new set of medoids.

6. If the total dissimilarity is lower than the previous set of medoids, update the medoids and go back to step 2. If the total dissimilarity is not lower, stop the algorithm and return the final set of medoids and their assigned data points.

7. Repeat steps 2-6 until the algorithm converges (i.e. the medoids no longer change).

ii) **K Prototype Clustering**


Input data
Initialize the cluster center prototype over View 2
Partition data objects over View 2
The stop criterion is not met
no
yes
Initialize the view number e=1
Update the cluster centre prototypes over View e
Partition data objects over View e
e=e+1
e<2
yes
no
Output the final clustering result

K-Prototype Clustering is a variant of K-means algorithm that can handle mixed data types by using a combination of categorical and numerical distance metrics. Here's a step-by-step algorithm for K-Prototype Clustering:

1. Define the number of clusters (K) you want to form and randomly select K data points to be the initial centroids.

2. Assign each data point to the nearest centroid based on the combination of categorical and numerical distance metrics. The categorical distance metric is usually a dissimilarity measure such as Hamming distance, while the numerical distance metric is typically the Euclidean distance.

3. For each cluster, calculate the average dissimilarity between each data point and its centroid. The average dissimilarity is the sum of the categorical dissimilarity and numerical distance divided by the number of data points in the cluster.

4. For each centroid, select a data point that would minimize the average dissimilarity of the cluster if it were to replace the current centroid. The selection process is based on a combination of the categorical and numerical distances.

5. Calculate the total average dissimilarity of the new set of centroids.

6. If the total average dissimilarity is lower than the previous set of centroids, update the centroids and go back to step 2. If the total average dissimilarity is not lower, stop the algorithm and return the final centroids and their assigned data points.

7. Repeat steps 2-6 until the algorithm converges (i.e. the centroids no longer change).

Chapter 4 - Results And Discussions

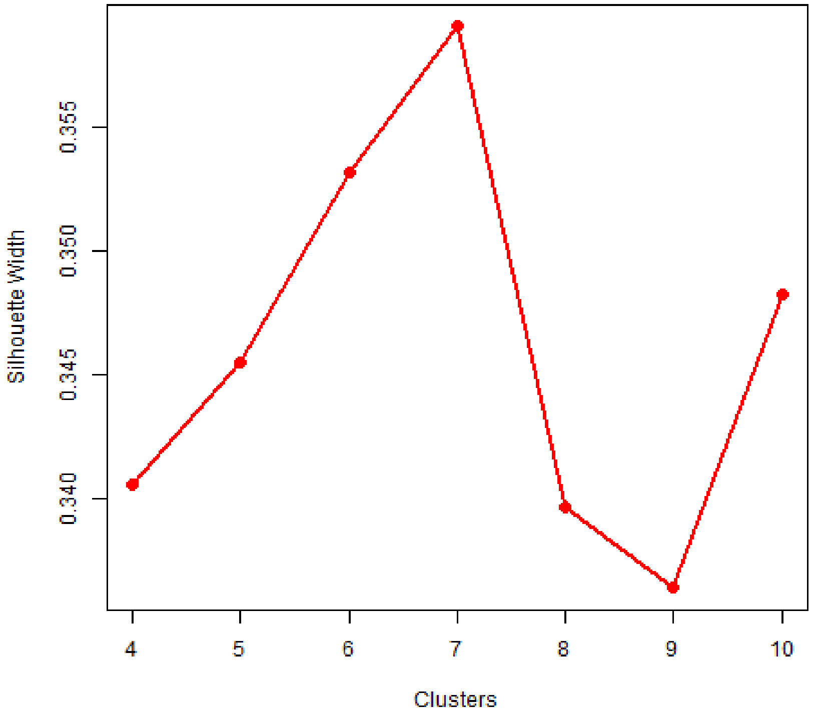
4.1 Result & Output

4.1.1 Partitioning Around Medoids

The dataset to be clustered had both numerical and categorical data. Hence Partitioning Around Medoids, a.k.a the K-Medoids algorithm was used with Gower's Distance as the distance metric to cluster the car models. The results of the K-Medoids clustering was a model-wise segmentation of car models from multiple brands. By this, a car manufacturer would get to know a competitive car model of another brand for a particular car model.

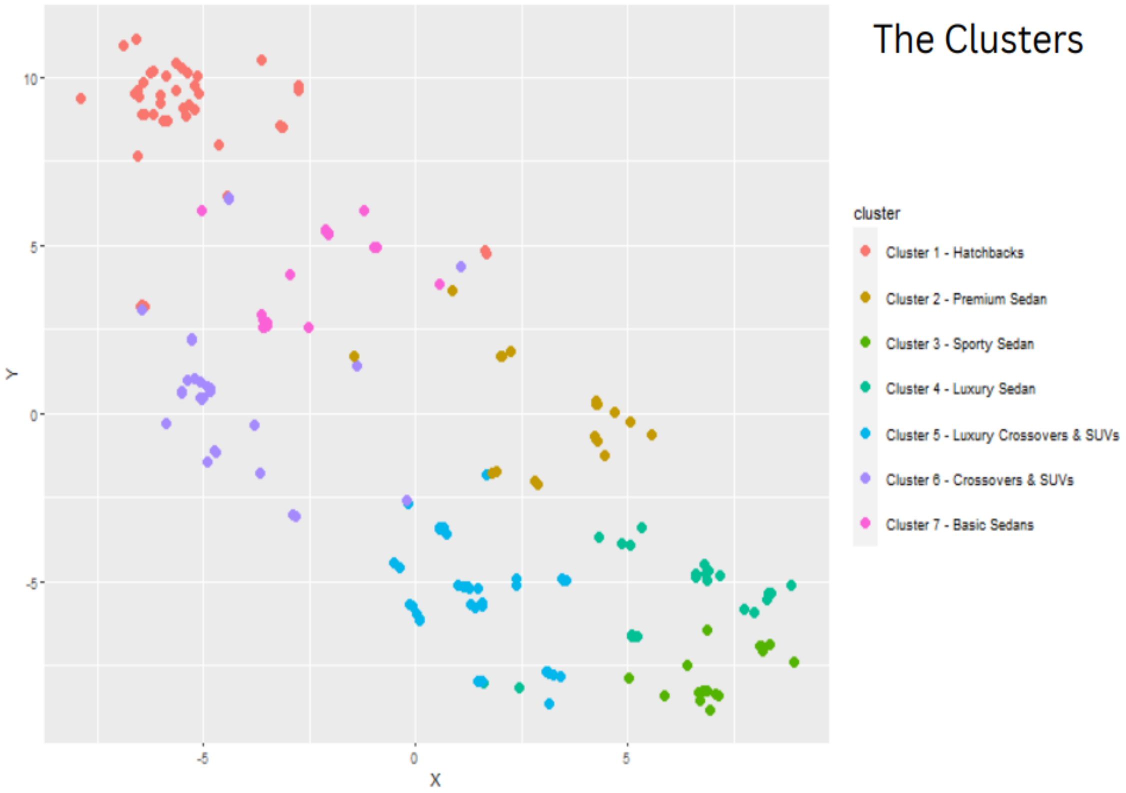
I. **Silhouette Graph -**

A silhouette graph was plotted with the number of clusters on the x-axis and the silhouette width on the y-axis to find out the optimal number of clusters. It is a measure of the quality of clustering for various number of clusters. The silhouette width ranges between -1 and 1 and higher the value, better the clustering. A peak was observed at K=7 and hence having 7 clusters would be optimum.



II. Cluster Visualisation -

The t-Distributed Neighbor Embedding (t-SNE) a statistical method that is mainly used to visualize high-dimensional data was used to plot the clusters.



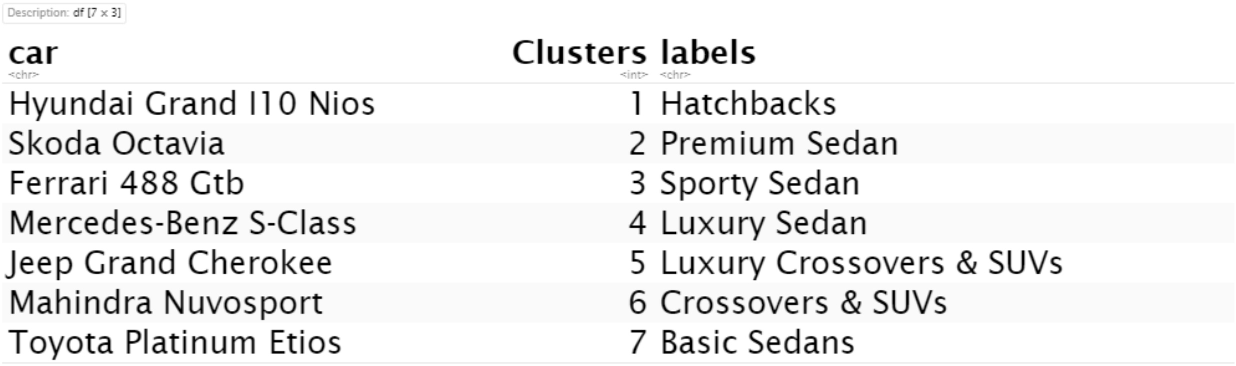
III. Cluster Representatives

Medoids

The Seven Clusters were named based on the car's price range, luxury level and body type. The cluster names are -

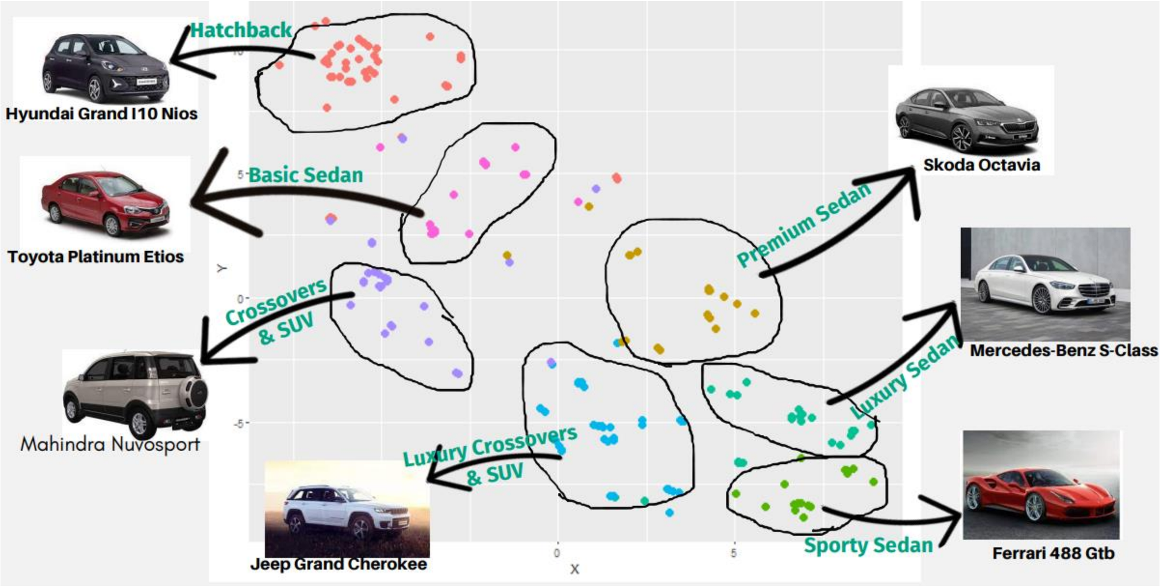
1. Cluster 1 - Hatchback
2. Cluster 2- Premium Sedan
3. Cluster 3 - Sporty Sedan
4. Cluster 4 - Luxury Sedan
5. Cluster 5 - Luxury Crossovers & SUV
6. Cluster 6 - Crossovers & SUV
7. Cluster 7 - Basic Sedan

The cluster representatives - the medoid car model of each cluster are tabulated below.



Description: df [7 x 3]

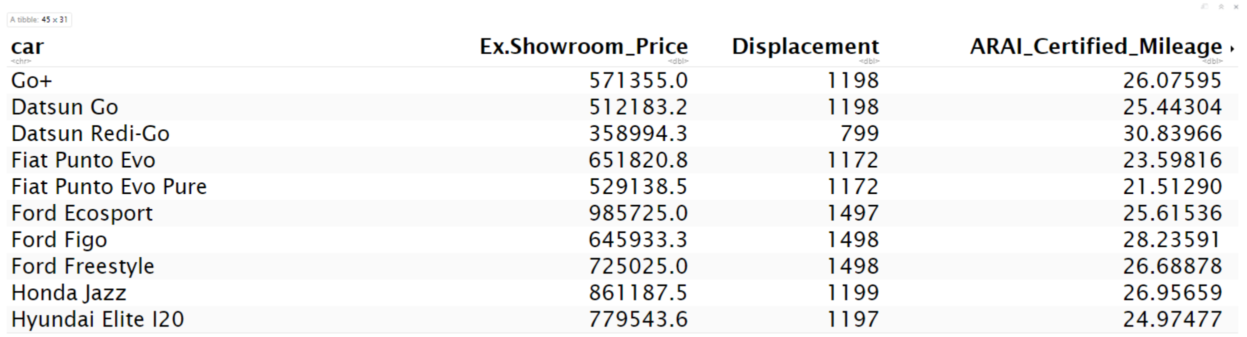
car	Clusters	labels
<chr>	<int>	<chr>
Hyundai Grand I10 Nios	1	Hatchbacks
Skoda Octavia	2	Premium Sedan
Ferrari 488 Gtb	3	Sporty Sedan
Mercedes-Benz S-Class	4	Luxury Sedan
Jeep Grand Cherokee	5	Luxury Crossovers & SUVs
Mahindra Nuvosport	6	Crossovers & SUVs
Toyota Platinum Etios	7	Basic Sedans



The samples from each cluster are tabulated below -

Cluster -1 (Hatchbacks)

Cluster -1 consists of Hatchback car models. A total of 45 car models belong to this cluster.

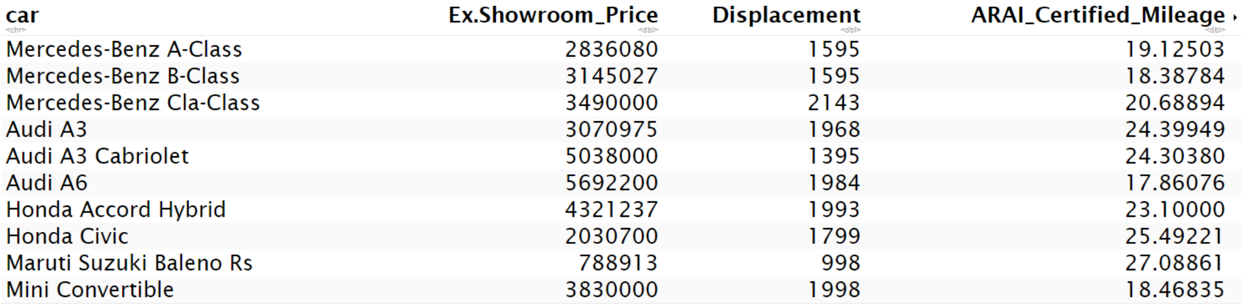


A tibble: 45 x 31

car	Ex.Showroom_Price	Displacement	ARAI_Certified_Mileage ▸
<chr>	<dbl>	<dbl>	<dbl>
Go+	571355.0	1198	26.07595
Datsun Go	512183.2	1198	25.44304
Datsun Redi-Go	358994.3	799	30.83966
Fiat Punto Evo	651820.8	1172	23.59816
Fiat Punto Evo Pure	529138.5	1172	21.51290
Ford Ecosport	985725.0	1497	25.61536
Ford Figo	645933.3	1498	28.23591
Ford Freestyle	725025.0	1498	26.68878
Honda Jazz	861187.5	1199	26.95659
Hyundai Elite I20	779543.6	1197	24.97477

Cluster - 2 (Premium Sedans)

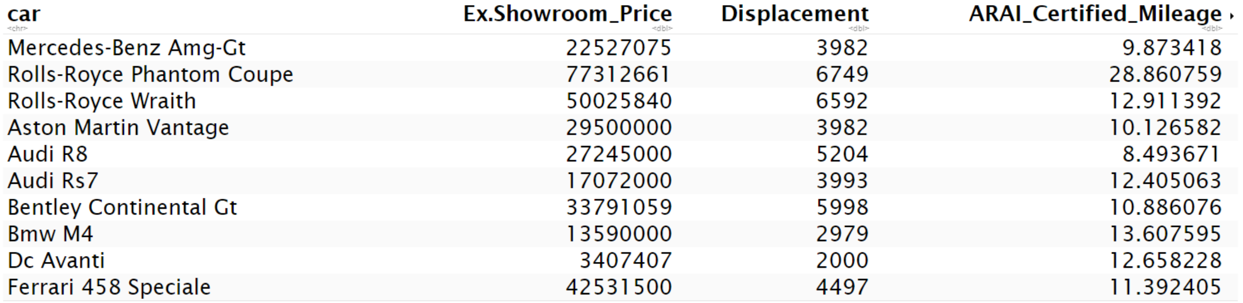
Cluster -2 consists of Sedans from a premium range. Their prices are higher than the Basic Sedans (Cluster - 7). A total of 21 car models belong to this cluster.



car	Ex.Showroom_Price	Displacement	ARAI_Certified_Mileage ▸
<chr>	<dbl>	<dbl>	<dbl>
Mercedes-Benz A-Class	2836080	1595	19.12503
Mercedes-Benz B-Class	3145027	1595	18.38784
Mercedes-Benz Cla-Class	3490000	2143	20.68894
Audi A3	3070975	1968	24.39949
Audi A3 Cabriolet	5038000	1395	24.30380
Audi A6	5692200	1984	17.86076
Honda Accord Hybrid	4321237	1993	23.10000
Honda Civic	2030700	1799	25.49221
Maruti Suzuki Baleno Rs	788913	998	27.08861
Mini Convertible	3830000	1998	18.46835

Cluster - 3 (Sporty Sedans)

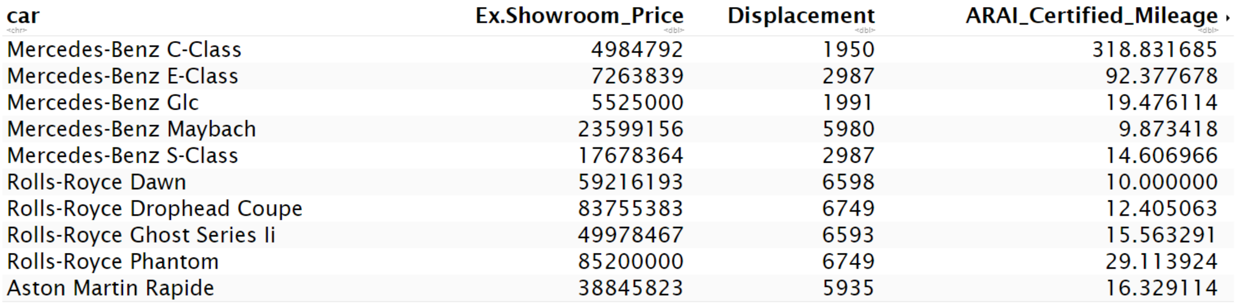
Cluster - 3 consists of Sporty Sedans with higher price than the Basic Sedans (Cluster - 7). Sporty Sedans are characterised by a lower height, higher number of cylinders, usually 8 or 12 and upto 8 gears. A total of 19 car models belong to this cluster.



car	Ex.Showroom_Price	Displacement	ARAI_Certified_Mileage ▸
<chr>	<dbl>	<dbl>	<dbl>
Mercedes-Benz Amg-Gt	22527075	3982	9.873418
Rolls-Royce Phantom Coupe	77312661	6749	28.860759
Rolls-Royce Wraith	50025840	6592	12.911392
Aston Martin Vantage	29500000	3982	10.126582
Audi R8	27245000	5204	8.493671
Audi Rs7	17072000	3993	12.405063
Bentley Continental Gt	33791059	5998	10.886076
Bmw M4	13590000	2979	13.607595
Dc Avanti	3407407	2000	12.658228
Ferrari 458 Speciale	42531500	4497	11.392405

Cluster - 4 (Luxury Sedans)

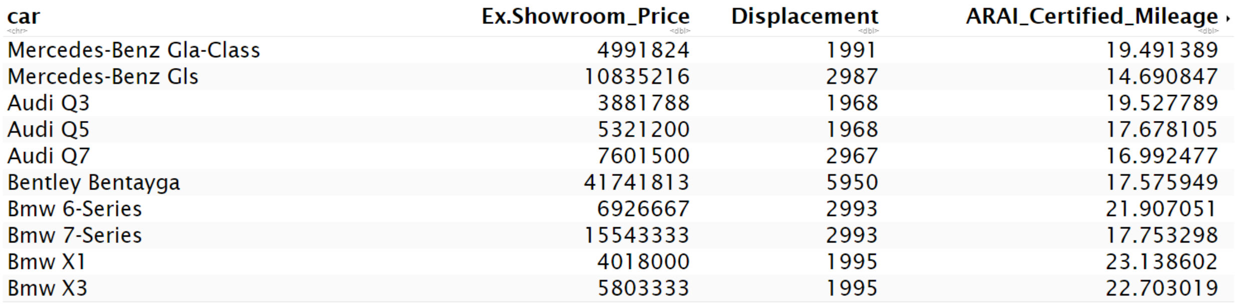
Cluster -4 consists of high end luxury sedan models from top brands that are known for their luxury and lavishness. Their prices are much higher than the Basic Sedans (Cluster - 7). A total of 25 car models belong to this cluster.



car	Ex.Showroom_Price	Displacement	ARAI_Certified_Mileage ▸
<chr>	<dbl>	<dbl>	<dbl>
Mercedes-Benz C-Class	4984792	1950	318.831685
Mercedes-Benz E-Class	7263839	2987	92.377678
Mercedes-Benz Glc	5525000	1991	19.476114
Mercedes-Benz Maybach	23599156	5980	9.873418
Mercedes-Benz S-Class	17678364	2987	14.606966
Rolls-Royce Dawn	59216193	6598	10.000000
Rolls-Royce Drophead Coupe	83755383	6749	12.405063
Rolls-Royce Ghost Series Ii	49978467	6593	15.563291
Rolls-Royce Phantom	85200000	6749	29.113924
Aston Martin Rapide	38845823	5935	16.329114

Cluster - 5 (Luxury Crossovers & SUVs)

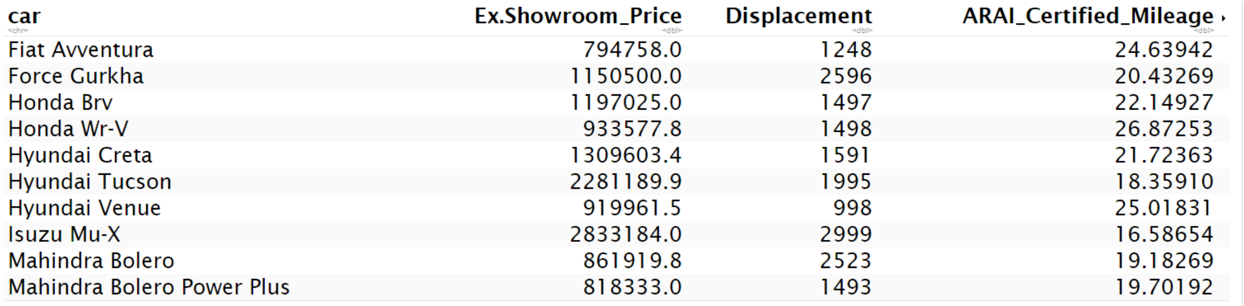
Cluster -5 consists of crossovers and SUVs from top brands that are known for luxury. Their prices are higher than the Basic Crossovers & SUVs (Cluster - 6). Crossovers and SUVs are distinguished from other car types by a higher height, displacement and drive-train (4 wheel drive). A total of 38 car models belong to this cluster.



car	Ex.Showroom_Price	Displacement	ARAI_Certified_Mileage ▸
<chr>	<dbl>	<dbl>	<dbl>
Mercedes-Benz Gla-Class	4991824	1991	19.491389
Mercedes-Benz Gls	10835216	2987	14.690847
Audi Q3	3881788	1968	19.527789
Audi Q5	5321200	1968	17.678105
Audi Q7	7601500	2967	16.992477
Bentley Bentayga	41741813	5950	17.575949
Bmw 6-Series	6926667	2993	21.907051
Bmw 7-Series	15543333	2993	17.753298
Bmw X1	4018000	1995	23.138602
Bmw X3	5803333	1995	22.703019

Cluster - 6 (Crossovers & SUVs)

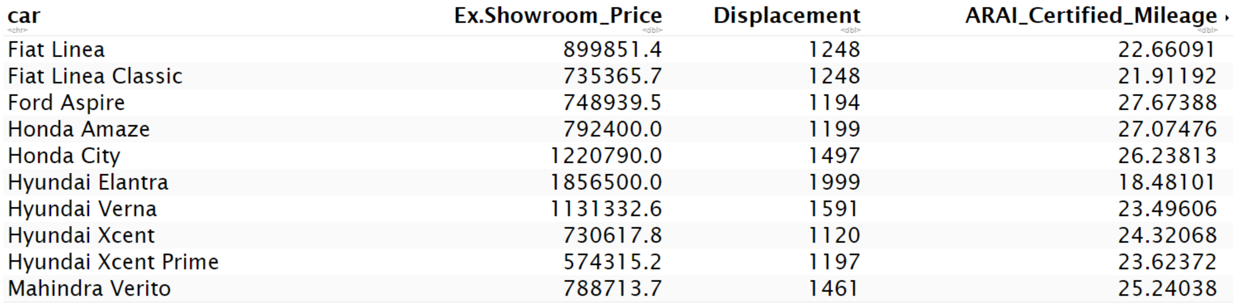
Cluster - 6 consists of Crossovers & SUVs that are cheaper in price. They are characterised by a larger displacement, height and weight than the hatchbacks. A total of 28 car models belong to this cluster.



car	Ex.Showroom_Price	Displacement	ARAI_Certified_Mileage ▸
<chr>	<dbl>	<dbl>	<dbl>
Fiat Avventura	794758.0	1248	24.63942
Force Gurkha	1150500.0	2596	20.43269
Honda Brv	1197025.0	1497	22.14927
Honda Wr-V	933577.8	1498	26.87253
Hyundai Creta	1309603.4	1591	21.72363
Hyundai Tucson	2281189.9	1995	18.35910
Hyundai Venue	919961.5	998	25.01831
Isuzu Mu-X	2833184.0	2999	16.58654
Mahindra Bolero	861919.8	2523	19.18269
Mahindra Bolero Power Plus	818333.0	1493	19.70192

Cluster - 7 (Basic Sedans)

Cluster - 7 consists of Basic Sedans. A total of 23 car models belong to this cluster.

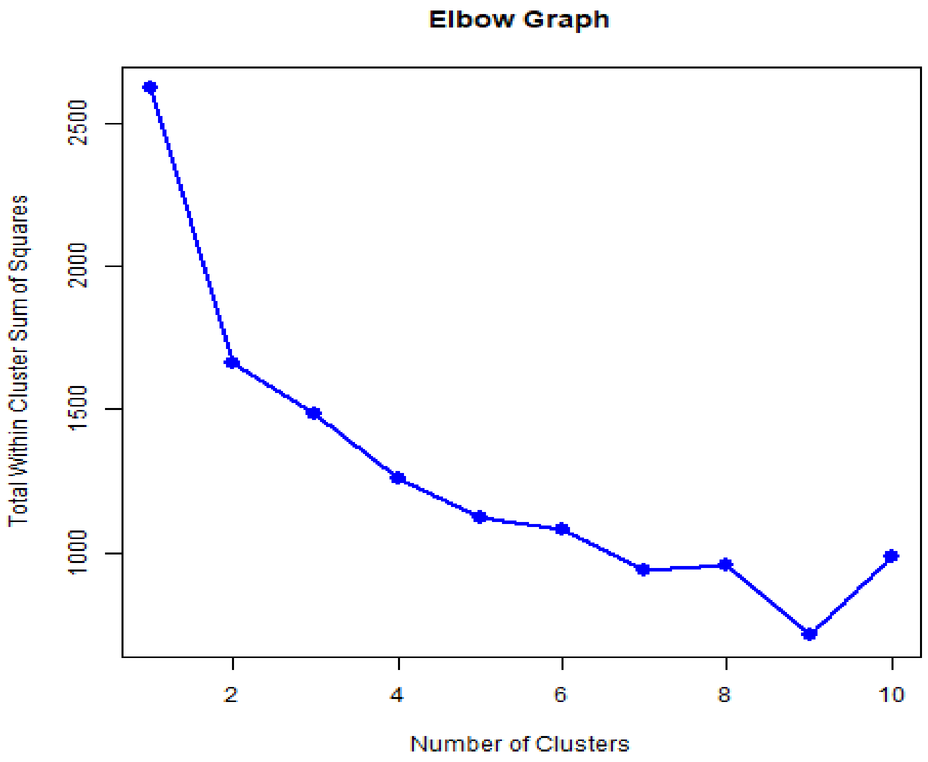


car <chr>	Ex.Showroom_Price <dbl>	Displacement <dbl>	ARAI_Certified_Mileage <dbl>
Fiat Linea	899851.4	1248	22.66091
Fiat Linea Classic	735365.7	1248	21.91192
Ford Aspire	748939.5	1194	27.67388
Honda Amaze	792400.0	1199	27.07476
Honda City	1220790.0	1497	26.23813
Hyundai Elantra	1856500.0	1999	18.48101
Hyundai Verna	1131332.6	1591	23.49606
Hyundai Xcent	730617.8	1120	24.32068
Hyundai Xcent Prime	574315.2	1197	23.62372
Mahindra Verito	788713.7	1461	25.24038

4.1.2 K-Protoype

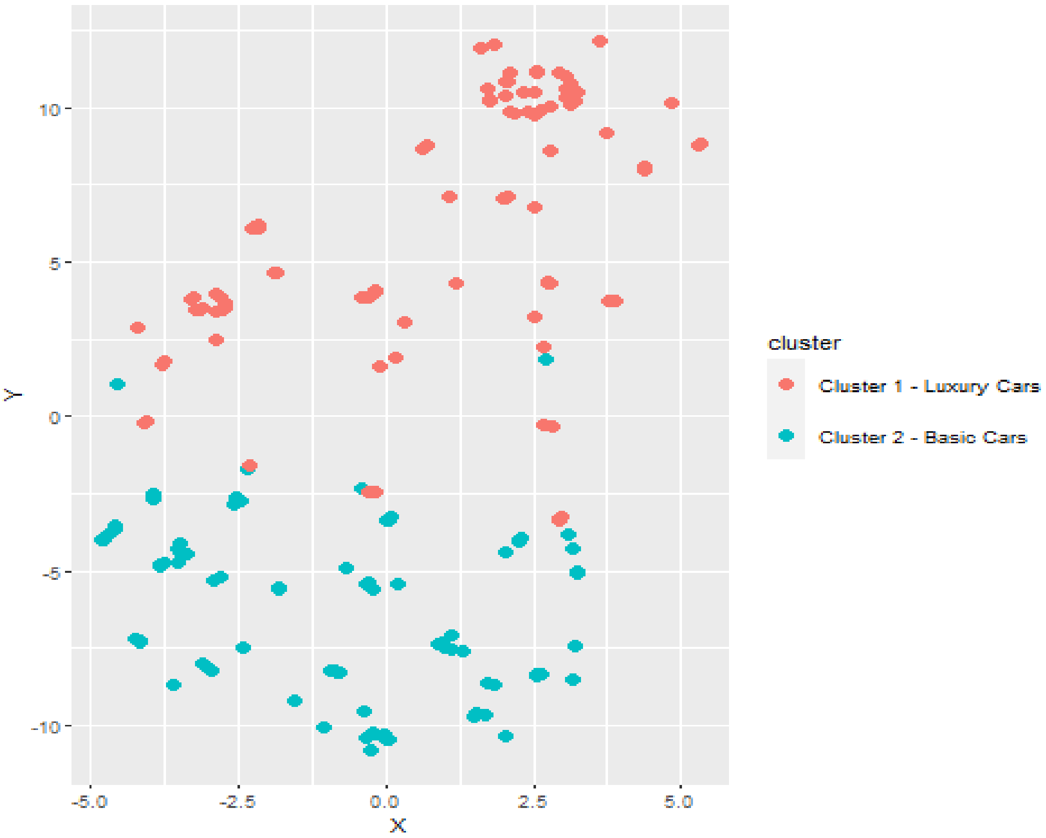
The K-Prototype algorithm provides segmentation based on brands. All the luxurious and extravagant brands are grouped together while the basic and economic brands fall into a group. The automobile market segmentation is at the brand level. A manufacturer can get to know their competitors in the Indian Market.

I. **Elbow Graph -**
An elbow graph with Number of Clusters on the x-axis and the Total Within-Cluster Sum of Squares on the y-axis was plotted to find the optimal number of clusters. The elbow bend occurs for Number of Clusters = 2 and hence the optimal number of clusters for the K-prototype model is fixed to be 2.



II. Cluster Visualisation -

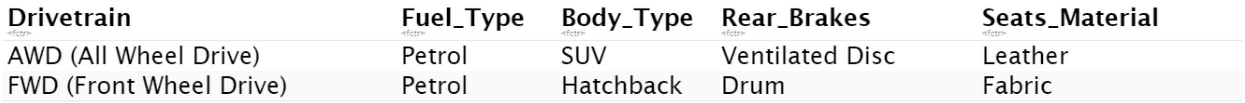
The t-Distributed Neighbor Embedding (t-SNE) a statistical method that is mainly used to visualize high-dimensional data was used to plot the clusters. The Cluster-1 represents Luxury Cars while the Cluster-2 represents economic cars.



III. Cluster Representatives

Centroids

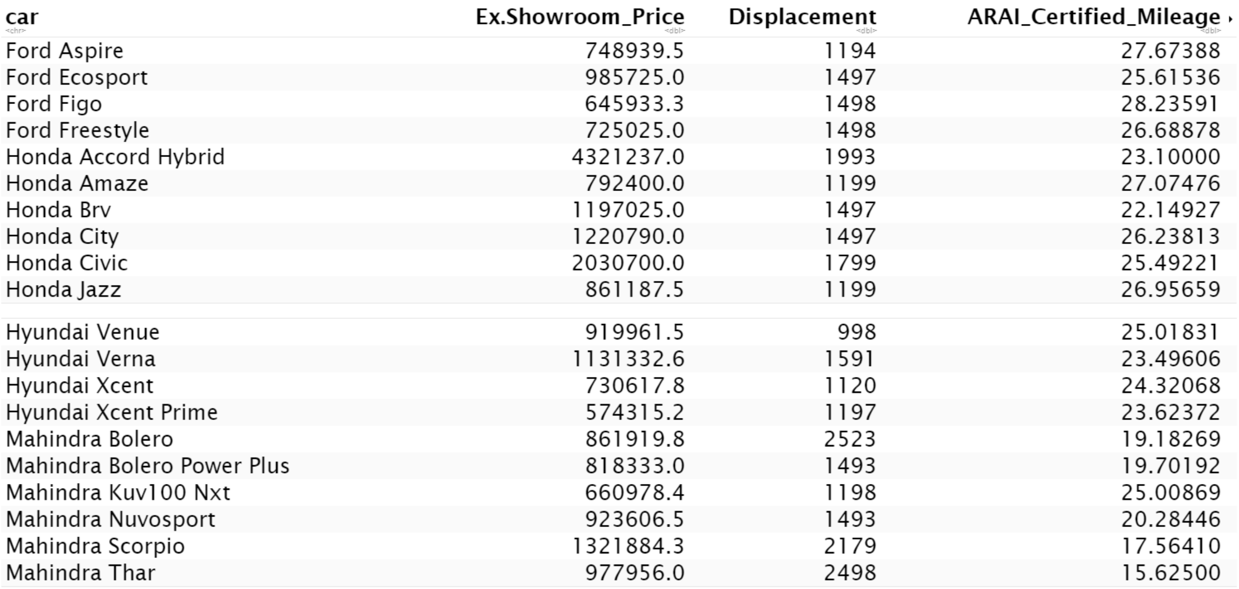
The k-Prototype algorithm computes cluster centroids rather than assigning a data instance as medoid. The cluster centroids are -



Drivetrain	Fuel_Type	Body_Type	Rear_Brakes	Seats_Material
<fctr>	<fctr>	<fctr>	<fctr>	<fctr>
AWD (All Wheel Drive)	Petrol	SUV	Ventilated Disc	Leather
FWD (Front Wheel Drive)	Petrol	Hatchback	Drum	Fabric

Cluster - 1 (Basic Brands)

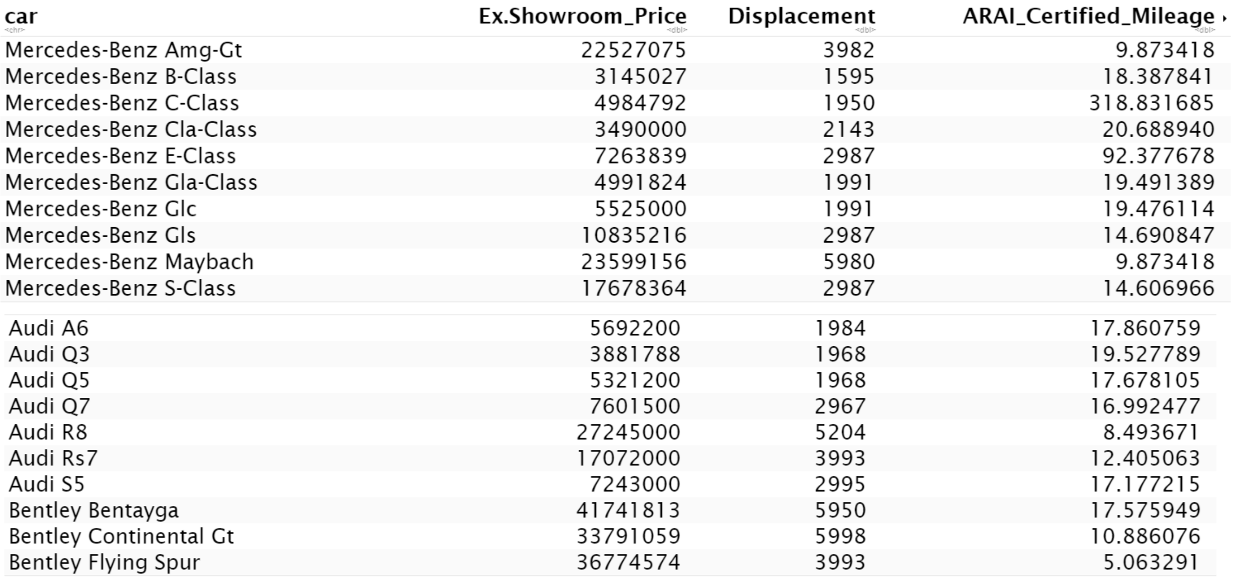
Cluster - 1 consists of car models from Economic Brands. This group consists of multiple body-types, and are characterized by their cheaper price. A total of 102 car models belong to this cluster. A few of the car models belonging to this cluster are-



car	Ex.Showroom_Price	Displacement	ARAI_Certified_Mileage ›
<chr>	<dbl>	<dbl>	<dbl>
Ford Aspire	748939.5	1194	27.67388
Ford Ecosport	985725.0	1497	25.61536
Ford Figo	645933.3	1498	28.23591
Ford Freestyle	725025.0	1498	26.68878
Honda Accord Hybrid	4321237.0	1993	23.10000
Honda Amaze	792400.0	1199	27.07476
Honda Brv	1197025.0	1497	22.14927
Honda City	1220790.0	1497	26.23813
Honda Civic	2030700.0	1799	25.49221
Honda Jazz	861187.5	1199	26.95659
Hyundai Venue	919961.5	998	25.01831
Hyundai Verna	1131332.6	1591	23.49606
Hyundai Xcent	730617.8	1120	24.32068
Hyundai Xcent Prime	574315.2	1197	23.62372
Mahindra Bolero	861919.8	2523	19.18269
Mahindra Bolero Power Plus	818333.0	1493	19.70192
Mahindra Kuv100 Nxt	660978.4	1198	25.00869
Mahindra Nuvosport	923606.5	1493	20.28446
Mahindra Scorpio	1321884.3	2179	17.56410
Mahindra Thar	977956.0	2498	15.62500

Cluster - 2 (Luxury Brands)

Cluster - 2 consists of car models from Luxury Brands. This group consists of multiple body-types, and are characterized by their high price. A total of 97 car models belong to this cluster. A few of the car models belonging to this cluster are-



car	Ex.Showroom_Price	Displacement	ARAI_Certified_Mileage ›
<chr>	<dbl>	<dbl>	<dbl>
Mercedes-Benz Amg-Gt	22527075	3982	9.873418
Mercedes-Benz B-Class	3145027	1595	18.387841
Mercedes-Benz C-Class	4984792	1950	318.831685
Mercedes-Benz Cla-Class	3490000	2143	20.688940
Mercedes-Benz E-Class	7263839	2987	92.377678
Mercedes-Benz Gla-Class	4991824	1991	19.491389
Mercedes-Benz Glc	5525000	1991	19.476114
Mercedes-Benz Gls	10835216	2987	14.690847
Mercedes-Benz Maybach	23599156	5980	9.873418
Mercedes-Benz S-Class	17678364	2987	14.606966
Audi A6	5692200	1984	17.860759
Audi Q3	3881788	1968	19.527789
Audi Q5	5321200	1968	17.678105
Audi Q7	7601500	2967	16.992477
Audi R8	27245000	5204	8.493671
Audi Rs7	17072000	3993	12.405063
Audi S5	7243000	2995	17.177215
Bentley Bentayga	41741813	5950	17.575949
Bentley Continental Gt	33791059	5998	10.886076
Bentley Flying Spur	36774574	3993	5.063291

4.1.3 Performance Evaluation

The cluster statistics for both the K-Medoids and K-Prototype algorithm are summarised below -

Metric	K - Medoid	K - Prototype
Number of Clusters	7	2
Average between cluster distance	0.4118	0.4875
Average within cluster distance	0.1596	0.2566
Maximum cluster diameter	0.5500	0.6523
Minimum Separation	0.0066	0.0124
Average Silhouette width	0.3590	0.4557
Dunn Index	0.0121	0.0190
Calinski Harabasz Index	120.184	208.517

Based on the Calinski Harabasz Index and the Dunn Index, K-Prototype algorithm seems to perform well than the K-Medoids algorithm with minimum between cluster similarities. Higher values of Calinski Harabasz Index and the Dunn Index support this.

4.2 Inference

4.2.1 Inferences from K-Medoids Clustering

1) **Brands Positions**

Maruti Suzuki, Tata, Mahindra, Hyundai have clearly positioned themselves only in the economic and basic segment, largely targeting middle class consumers. It can be clearly seen from the clustering results that the above Makers occur only in the Basic Sedans, Hatchbacks and thus they are strong competitors of each other when it comes to the economic market. Likewise, Mercedes, BMW, Audi, Porsche and Jaguar compete with each other in the Luxury segment. They are prime manufacturers of sporty and luxury sedans.

2) **Honda City vs Honda Amaze**

Honda City is a higher priced and premium sedan than Honda Amaze, but that does not seem true from the clustering results. Both car models are grouped into the same segment, which may not be the desired target market perceived by Honda. This suggests that Honda City being a premium car model than a more basic Honda Amaze, may often be perceived alike by most consumers.

3) **Unpopularity of Isuzu Mu-X**

Isuzu, a Japanese car manufacturer, did not make much in the Indian automobile market. From 2013 until March 2022, only 2598 units of the car were sold. This could possibly be because of tough competitors in its cluster like Toyota Innova Crysta and Hyundai Creta which are highly sought after by buyers. Isuzu ' s failure may be because of their choice of target market - the SUV segment ruled by well established brands like Toyota and Hyundai.

4) Volkswagen Ameo is a perfect successor to Volkswagen Vento

Volkswagen wanted to introduce Ameo as a replacement to Volkswagen Vento, which seems successful from the clustering results. Both the car models occur in the low end sedan segment and hence indicates how Volkswagen continues its hold in the low end sedan segment.

5) Toyota Fortuner vs Ford Endeavour

The clustering result suggests a tough competition between Toyota Fortuner and Ford Endeavour. Both occurring in the Luxury Crossovers & SUVs segment, Ford' s Endeavour competes with Toyota ' s Fortuner in every aspect including price, displacement and mileage.

6) Skoda Superb's Competitors

Skoda Superb competes with Volkswagen Passat and even the basic models from Mercedes and Audi in the luxury sedan segment. Because of an equal competition in the market between the cars in this segment, none outstands the other. This segment is equally held by makers like Mercedes, Volkswagen, Skoda and Audi.

7) Hyundai Creta vs Hyundai Tucson

Hyundai is a competitor to itself when it comes to Creta vs Tucson. The newly launched Tucson is not as sought after as Creta. Annual sales of Creta was 1,40,895 in 2022 while Tuscon was only a few thousands. Both occur in the Crossover & SUV segment and hence the same target market. This means that trying to increase the sales of one model will bring down the sales of the other.

8) Maruti Suzuki's Monopoly

Clearly seen from the Clustering results, Maruti Suzuki dominates the Hatchback segment with a total of 15 car models and contributes a 33% market share in this strategic group. Maruti Suzuki thus holds a major share in the Indian automobile market, primarily dominating the hatchback segment.

4.2.2 Inferences from K-Prototype Clustering

1) Brand Segmentation

The K-Prototype Clustering provides a segmentation of brands. It results in grouping the Indian Automobile Brands into two strategic groups -

1. Luxury Brands - The luxury brands consist of Mercedes, Audi, Porsche, Rolls Royes to name a few. They are leading manufacturers of luxury cars across the globe. These brands are sought after by the well off consumers.

2. Economic Brands - Brands like Maruti, Mahindra, Hyundai, Honda, Fiat, Ford, etc. fall under this segment. Their cars are economical and are widely sought after by the Indian automobile consumer market. They dominate the automobile market in terms of their sales. The consumers of these brands belong to middle and upper middle class.

4.3 Performance Analysis

K-medoids tends to have higher computational complexity compared to k-prototype because it involves finding the best medoid from a set of data points in each iteration, which can be computationally expensive, especially for large datasets. K-prototype, on the other hand, involves updating centroids based on numerical means and categorical modes, which can be computationally more efficient.

- The time complexity of the k-prototypes algorithm : **O(k*p*n**)
- The time complexity of K-medoids algorithm is : **O(k * (n-k)^2)**

where ‘n’ is the number of data points, ‘k’ is the number of clusters and ‘p’ is the number of features

Chapter 5: Conclusion

The "Indian Automotive Strategic Grouping" study represents a valuable contribution to the field of Indian automotive market analysis. With its utilisation of a data-driven approach and a clustering method, the study provides a comprehensive and nuanced understanding of consumer preferences and buying behaviour. By grouping automobile models into distinct strategic groups based on various attributes, including price, brand, segment, and features, the study offers valuable insights for automobile manufacturers, dealers, and marketers seeking to develop targeted marketing strategies and improve product offerings.Customers can use this information to make informed purchasing decisions, identifying the car models that best match their preferred attributes and provide the best value for money.Additionally, the study identifies the best car model in each cluster based on value for money and features, providing customers with a clear idea of which models offer the most desirable features for the best price. Overall, this study can help customers make informed purchasing decisions, by providing valuable insights into the Indian automotive market, and identifying the car models that best match their needs and preferences. As such, the study is highly recommended for anyone with an interest in the Indian automotive market or automotive market analysis more broadly.

Chapter 6: Future Scope

The "Indian Automotive Strategic Grouping" study offers valuable insights into the Indian automotive market, providing a comprehensive and nuanced understanding of consumer preferences and buying behaviour. As such, it has several future scopes that can enhance its value and contribute to the field of Indian automotive market analysis. Some of the feature scope has been discussed below:-

1. The study could be updated regularly to reflect changes in the Indian automotive market, such as the introduction of new car models or changes in consumer preferences. This would ensure that the study remains relevant and up-to-date, providing valuable insights for industry professionals and customers alike.
2. This could also be expanded to include a more comprehensive analysis of the Indian automotive market, covering aspects such as sales trends, market share, and competitive landscape. This would provide a more complete understanding of the Indian automotive market, helping industry professionals make informed decisions and enhancing the study's overall value.
3. Finally, the study's insights could be applied to develop new products and services that cater to the needs and preferences of Indian consumers. For instance, manufacturers could use the study's clustering method to develop targeted marketing strategies or new car models that offer features and attributes that are most valued by Indian consumers. This could help manufacturers improve their market position and competitiveness in the Indian automotive market.

Overall, the "Indian Automotive Strategic Grouping" study has several future scopes that can enhance its value and contribute to the field of Indian automotive market analysis. Its insights can help industry professionals and customers make informed decisions, and its application can lead to the development of new products and services that better cater to Indian consumers' needs and preferences.

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