Feynn Labs Project II

EV MARKET

Analysde the Electric Vehicle market in India using Segmentation analysis to come up with a feasible strategy to enter the market, targeting the segments most likely to use Electric vehicles.

by

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Abstract:

The electric vehicle (EV) market has experienced considerable growth, yet it continues to confront various challenges and issues. It's crucial to note that conditions may have evolved since this information was gathered, so considering the latest developments is essential. Below are some of the key challenges currently affecting the EV market:

Limited Range: Many consumers are concerned about the shorter driving range of electric vehicles compared to traditional gasoline-powered cars. Ongoing initiatives aim to address this issue through the expansion of charging infrastructure and advancements in battery technology.

Charging Infrastructure: The absence of a comprehensive network of charging stations makes it difficult for electric vehicle owners to find convenient charging locations. This issue is particularly pronounced for individuals who frequently travel or live in remote areas.

Cost Factors: Electric vehicles remain more expensive than their gasoline counterparts, which may deter some potential buyers. However, prices are gradually decreasing and are expected to continue this trend as EV adoption increases.

Environmental Considerations: The environmental benefits of electric vehicles can vary based on factors such as the energy source used for power generation. To maximize their positive impact on the environment, a shift towards renewable energy sources in electricity generation is necessary.

K-Means Clustering:

K-Means is an unsupervised machine learning technique used for clustering data points into groups based on their similarities. It can also analyze latitude and longitude data to identify geographic patterns and group nearby areas. The process involves the following steps:

Data Preparation: The initial step is to select the latitude and longitude attributes that we want to cluster.

Feature Scaling: Since latitude and longitude variables typically have different scales, it is important to scale or normalize them. This ensures that each variable contributes equally during the clustering process.

Determining the Number of Clusters (K): Before applying K-Means, we need to decide on the optimal number of clusters (K) for the dataset. This can be achieved by assessing the quality of clustering results for various K values using techniques such as the Elbow Method or the Silhouette Score.

Implementing K-Means: After selecting K, we can execute the K-Means algorithm to organize the data into K clusters. Each cluster will consist of locations that are geographically similar.

Interpreting Results: Examine the clustering outcomes to identify geographic trends. Visualizing the clusters on a map can help illustrate how locations are grouped.

Principal Component Analysis (PCA)

Dimensionality reduction method that simplifies the complexity of geographic data while maintaining critical information. It is especially beneficial when working with high-dimensional datasets, such as pairs of latitude and longitude. The application of PCA involves the following steps:

Data Preparation: Begin by selecting the latitude and longitude attributes for analysis using PCA. Typically, the data is structured in a matrix format where each row corresponds to a specific location, and each column represents either latitude or longitude.

Standardization: Standardize the dataset by subtracting the mean and scaling the values to achieve unit variance. This step ensures that both latitude and longitude have an equal impact on the analysis.

PCA Computation: Apply PCA to the standardized dataset to calculate the principal components. PCA identifies linear combinations of latitude and longitude that capture the most significant variations within the data.

Choosing Principal Components: Review the explained variance ratio to determine the number of principal components to retain. You can select a subset of the most significant components that account for a substantial portion of the variance in the dataset.

Interpreting Results: The principal components can be interpreted to reveal patterns or trends within the geographic data. They represent directions in the original feature space that maximize variance.

Conclusion and Insights Gained from the Research/Analysis:

In this research, we utilized two distinct datasets: one focusing on the Indian automobile buying behavior and the other on electric vehicle charging stations.

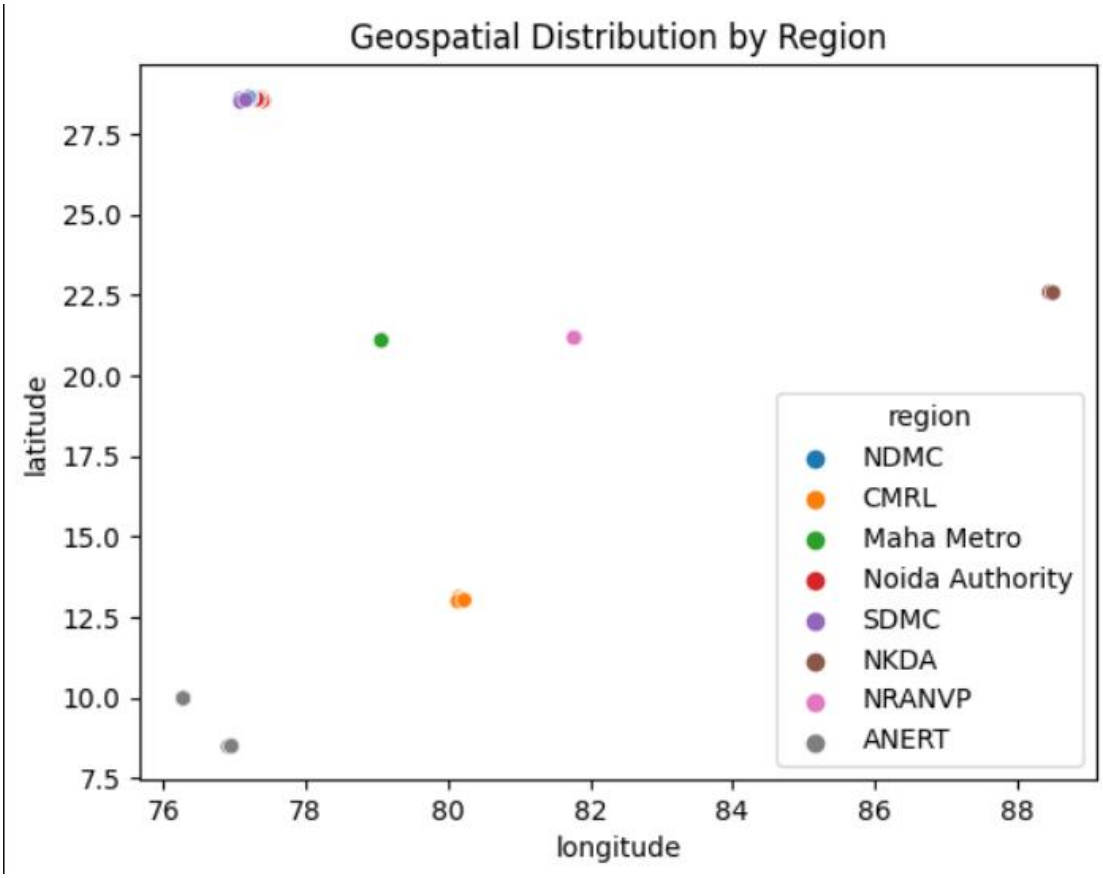
- Although the electric vehicle market is still in its nascent stage, it is experiencing rapid growth. The attributes identified in the analysis can be leveraged to segment the electric vehicle market and discern various consumer segments. By comprehending the unique needs and preferences of each segment, businesses can tailor their marketing and sales strategies to align with these specific requirements.
- Our findings indicate that younger individuals, professionals, and those with higher educational qualifications are more inclined to adopt electric vehicles early. Additionally, consumers with fewer dependents or those with a working spouse may show a greater likelihood of purchasing an electric vehicle. Factors such as the make of the vehicle and pricing are also critical considerations.
- Through further research and analysis, businesses can enhance their understanding of the electric vehicle market, enabling them to devise more effective marketing and sales strategies that resonate with diverse consumer segments.

DATASET 1

ev.csv

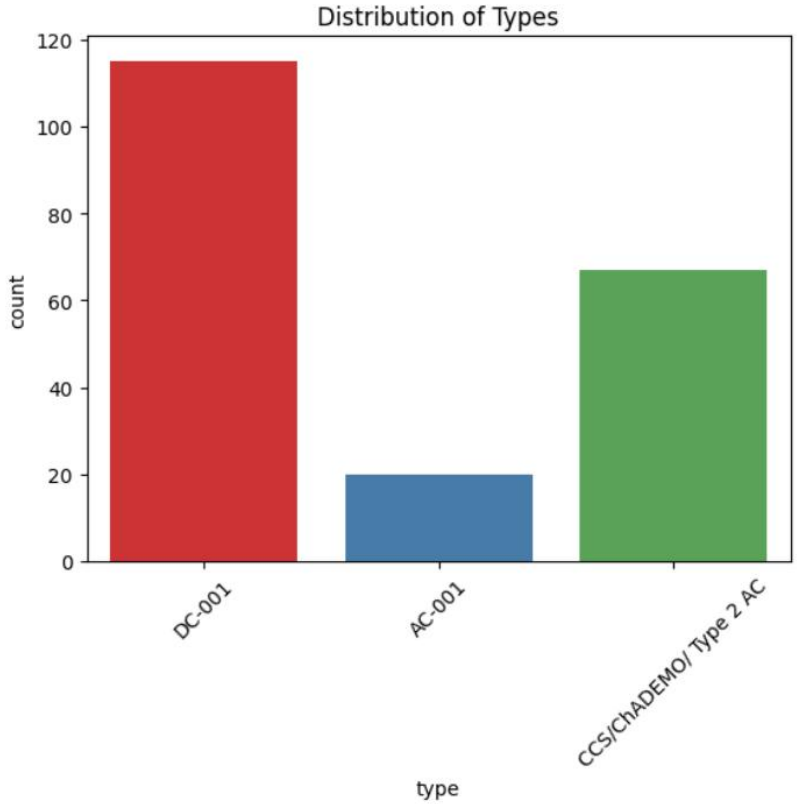
no	region	address	aux addres	latitude	longitude	type	power	service
1	NDMC	Prithviraj Mi	Electric Vehi	28.6007255	77.2262524	DC-001	15 kW	Self Service
2	NDMC	Prithviraj Mi	Electric Vehi	28.6007255	77.2262524	DC-001	15 kW	Self Service
3	NDMC	Outside RW	Electric Vehi	28.5883031	77.2176972	DC-001	15 kW	Self Service
4	NDMC	Opposite Dc	Electric Vehi	28.5826538	77.2200872	DC-001	15 kW	Self Service
5	NDMC	Opposite Gc	Electric Vehi	28.584485	77.220316	DC-001	15 kW	Self Service
6	NDMC	Dharma Ma	Electric Vehi	28.6023562	77.1866178	DC-001	15 kW	Self Service
7	NDMC	Outside We	Electric Vehi	28.6336861	77.2181403	DC-001	15 kW	Self Service
8	NDMC	Near NDMC	Electric Vehi	28.6304482	77.2255578	DC-001	15 kW	Self Service
9	NDMC	Near Bikane	Electric Vehi	28.5838828	77.163408	DC-001	15 kW	Self Service
10	NDMC	Khan Marke	Electric Vehi	28.6003333	77.2268889	DC-001	15 kW	Self Service
11	NDMC	Outside Dev	Electric Vehi	28.633675	77.2234929	DC-001	15 kW	Self Service
12	NDMC	Opposite HI	Electric Vehi	28.6325843	77.2229787	DC-001	15 kW	Self Service
13	NDMC	Outside Orie	Electric Vehi	28.6317294	77.2221076	DC-001	15 kW	Self Service
14	NDMC	Outside Jain	Electric Vehi	28.633841	77.2074439	DC-001	15 kW	Self Service
15	NDMC	NDMC Parki	Electric Vehi	28.6281626	77.2155151	DC-001	15 kW	Self Service
16	NDMC	NDMC Parki	Electric Vehi	28.6281626	77.2155151	DC-001	15 kW	Self Service
17	NDMC	Next to PVR	Electric Vehi	28.6350113	77.2196112	DC-001	15 kW	Self Service
18	NDMC	Opposite So	Electric Vehi	28.6338828	77.2215424	DC-001	15 kW	Self Service
19	NDMC	Opposite HF	Electric Vehi	28.6318964	77.2215824	DC-001	15 kW	Self Service

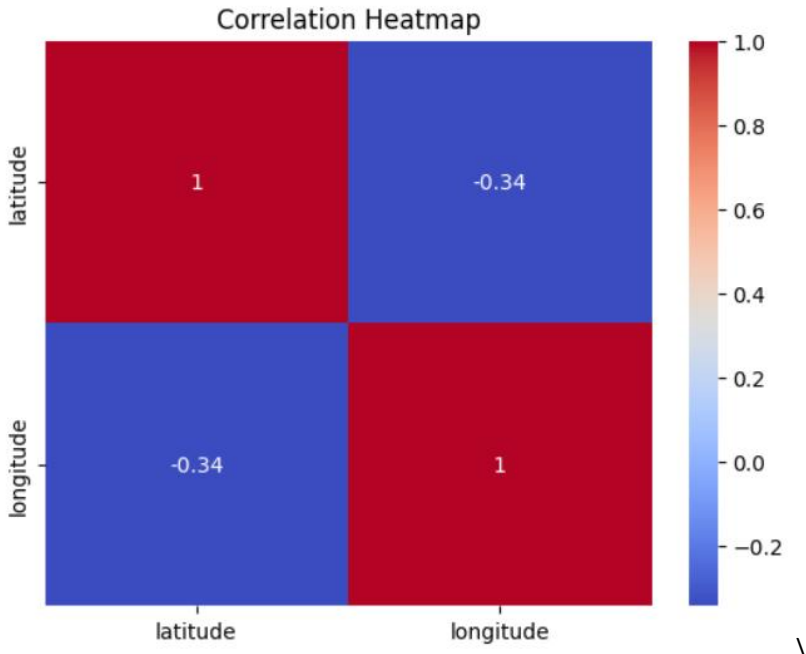
202x9



The plot visually represents the geographic distribution of data points based on their latitude and longitude coordinates. By color-coding the data points according to

their 'region' attribute, viewers can quickly identify which points belong to each region, making it easier to understand the geographic spread of data across different areas. Additionally, the plot reveals spatial patterns and trends related to geographic locations, allowing for the identification of regions with denser concentrations of data points compared to others.





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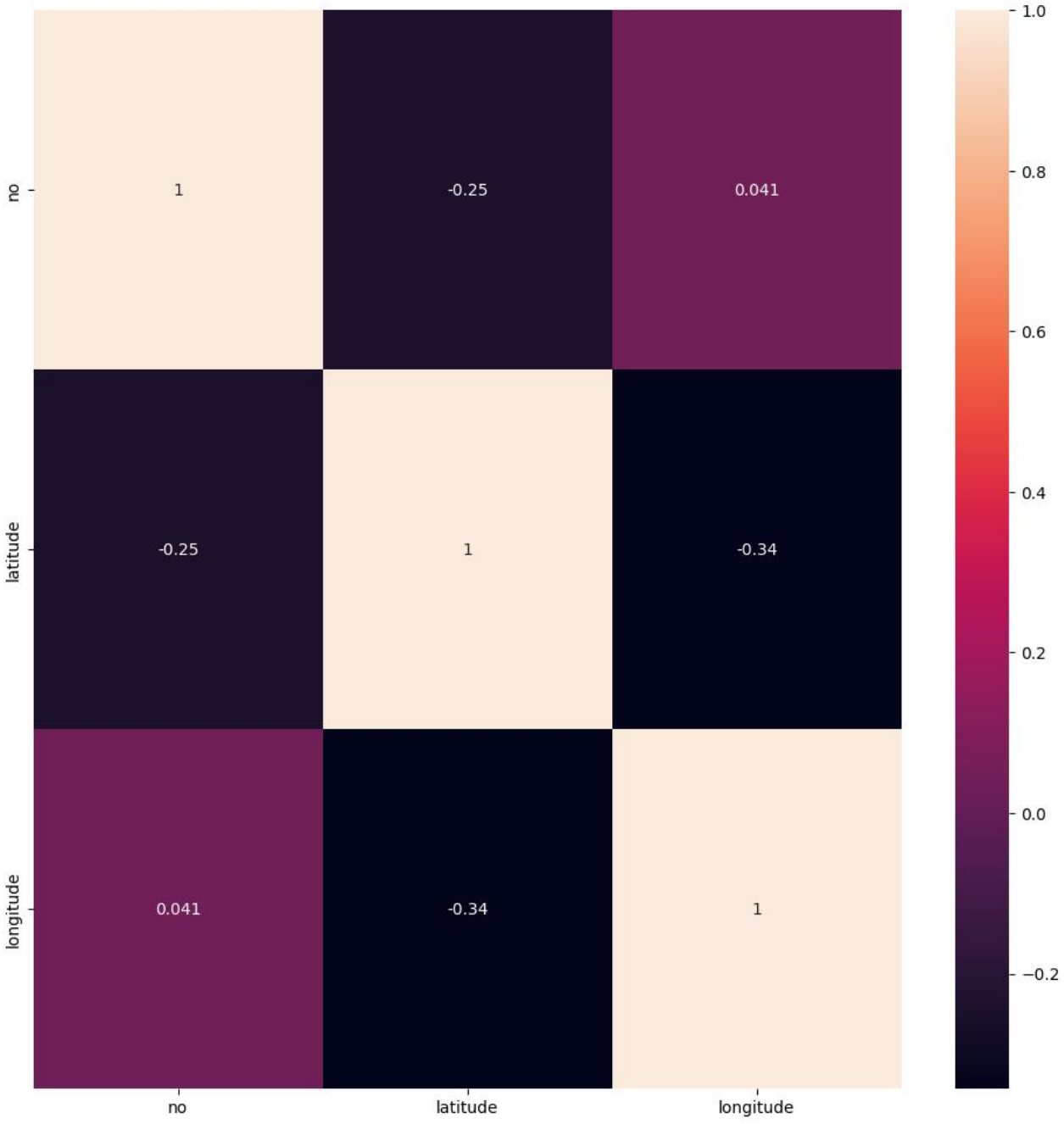
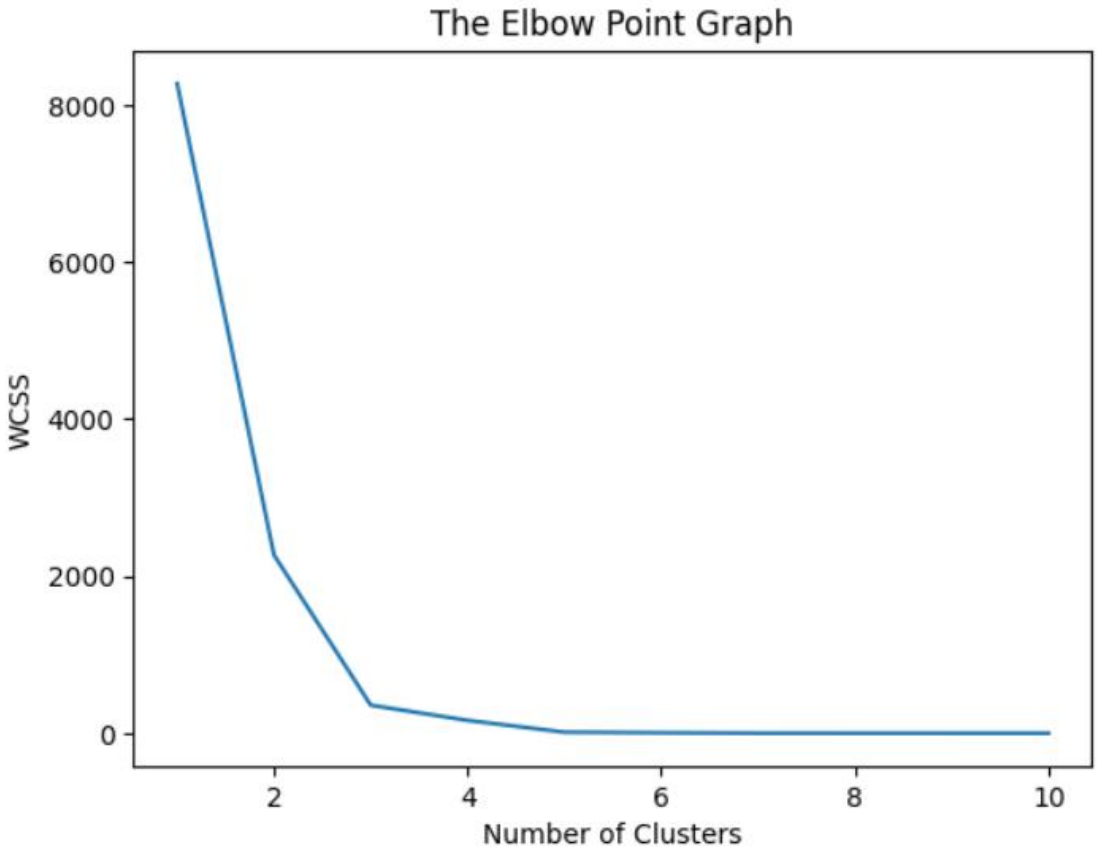

no
latitude
longitude
1
-0.25
0.041
-0.25
1
-0.34
0.041
-0.34
1
no
latitude
longitude
1.0
0.8
0.6
0.4
0.2
0.0
−0.2



The insight derived from this plot pertains to determining the optimal number of clusters for the K-means clustering algorithm. The key concept is to identify the "elbow point" on the plot, where the Within-Cluster Sum of Squares (WCSS) begins to decline at a slower rate. This point typically indicates a favorable balance between the number of clusters and the variance explained by those clusters. In essence, it marks the stage at which adding more clusters does not significantly enhance clustering quality. When examining the plot, we should focus on the point where the curve starts to bend or form an "elbow." This indicates the optimal number of clusters for the K-means algorithm, aiding in making an informed decision about the appropriate number of clusters to apply to the data.

K-MEANS

:

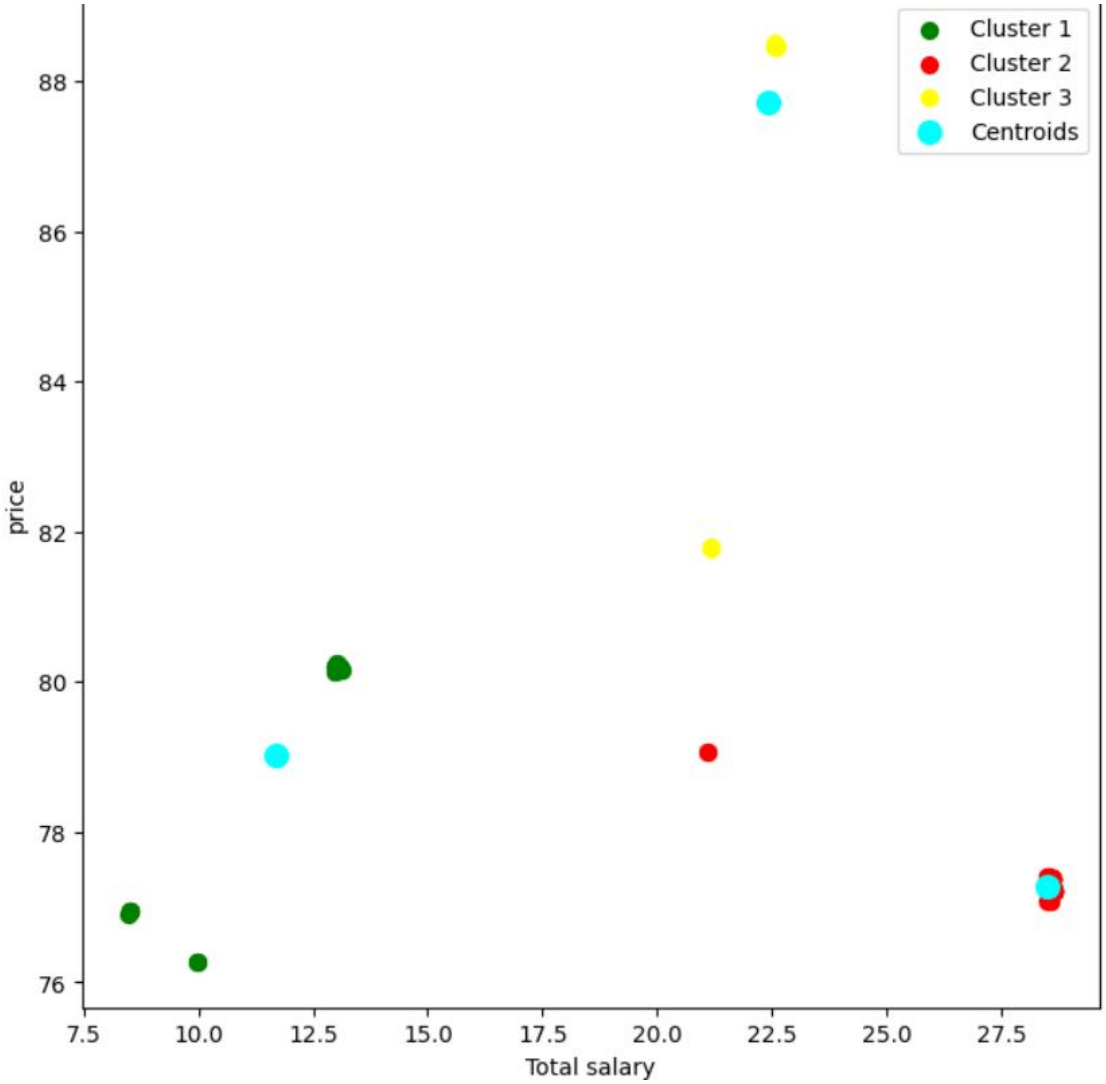
```
from sklearn.cluster import KMeans

n_clusters = 3
n_init = 20  # Set n_init explicitly

kmeans = KMeans(n_clusters=n_clusters, n_init=n_init)
kmeans = KMeans(n_clusters =3, init='k-means++', random_state=0)
# return a label for each data point based on their cluster
Y = kmeans.fit_predict(X)

print(Y)
```

```
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 1 1 1 1 1 1 1 1 2 2
 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1
 1 1 0 0 0 0 1 1 2 2 2 2 0 0 0 0 1]
```



The key insights derived from this plot include:

Cluster Separation: It allows us to assess how well-separated the clusters are in the feature space. Ideally, clusters should be distinct and clearly separated from one another.

Cluster Size and Density: We can evaluate the size of each cluster (the number of data points) and its density by observing the concentration of points in each region.

Centroids: The centroids, represented in cyan, indicate the mean positions of the clusters, marking the center of each cluster.

Cluster Interpretation: By analyzing the distribution of data points within each cluster, we can gain insights into the characteristics of customers or data points in each segment.

Outliers: The plot may reveal any outliers—data points that are significantly distant from the centroids or other cluster members.

Overall, this visualization aids in understanding the outcomes of K-Means clustering, providing a clear representation of how data points are grouped into clusters based on their features.

PCA :

	PCA_Component_1	PCA_Component_2
0	-0.605905	-0.060469
1	-0.605905	-0.060469
2	-0.606295	-0.056944
3	-0.605035	-0.056777
4	-0.605213	-0.057061
..	...	...
197	1.870473	2.539483
198	1.861824	2.550801
199	1.527740	2.507268
200	1.870473	2.539483
201	-0.616160	-0.039343

CLASSIFICATION REPORT FOR DATASET 1 :

Accuracy: 0.49

Classification Report:

	precision	recall	f1-score	support
10(3.3 kW each)	0.31	0.80	0.44	5
142kW	0.44	0.54	0.48	13
15 kW	0.75	0.39	0.51	23
accuracy			0.49	41
macro avg	0.50	0.58	0.48	41
weighted avg	0.60	0.49	0.50	41

Confusion Matrix:

```
[[4 1 0]
 [3 7 3]
 [6 8 9]]
```

DATASET 2
Indian automoble buying behavour study 1.0.csv

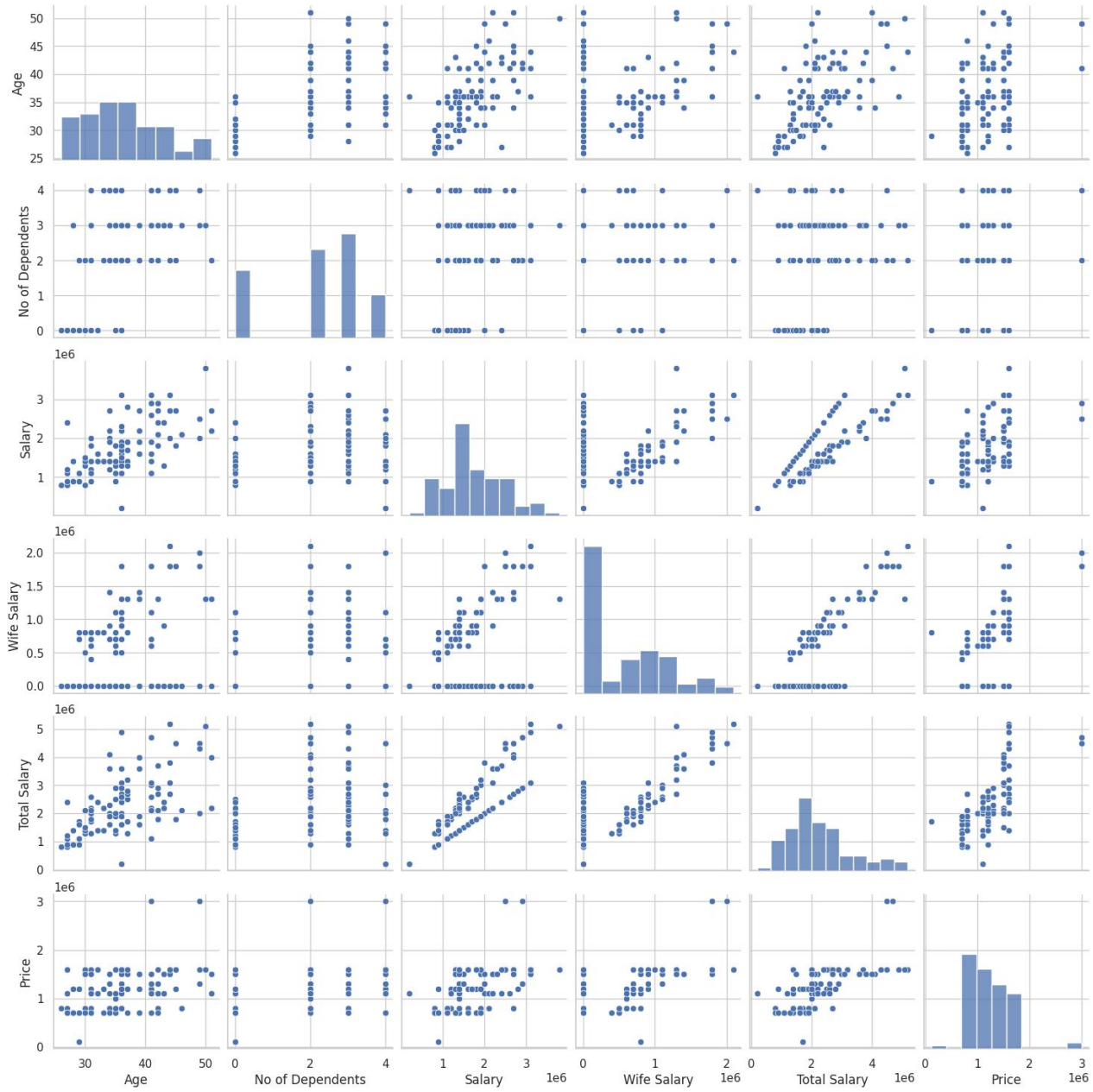
Age	Profession	Marrital Sta	Education	No of Depe	Personal lo	House Loan	Wife Work	Salary	Wife Salary	Total Salary	Make	Price
27	Salaried	Single	Post Gradu	0	Yes	No	No	800000	0	800000	i20	800000
35	Salaried	Married	Post Gradu	2	Yes	Yes	Yes	1400000	600000	2000000	Ciaz	1000000
45	Business	Married	Graduate	4	Yes	Yes	No	1800000	0	1800000	Duster	1200000
41	Business	Married	Post Gradu	3	No	No	Yes	1600000	600000	2200000	City	1200000
31	Salaried	Married	Post Gradu	2	Yes	No	Yes	1800000	800000	2600000	SUV	1600000
28	Salaried	Married	Graduate	3	Yes	Yes	No	900000	0	900000	Baleno	700000
31	Salaried	Married	Graduate	4	No	No	Yes	1200000	600000	1800000	City	1200000
33	Business	Married	Post Gradu	4	No	No	No	1400000	0	1400000	Baleno	700000
34	Business	Married	Post Gradu	4	No	No	No	2000000	0	2000000	Verna	1100000
34	Salaried	Married	Graduate	3	Yes	Yes	Yes	1200000	700000	1900000	i20	800000
35	Salaried	Married	Post Gradu	4	No	No	Yes	1300000	700000	2000000	SUV	1600000
35	Salaried	Married	Graduate	4	Yes	Yes	m	1400000	0	1400000	Baleno	700000
29	Salaried	Married	Post Gradu	0	No	No	Yes	900000	800000	1700000	Verna	110000
30	Business	Single	Post Gradu	2	Yes	No	No	1400000	0	1400000	i20	800000
31	Business	Married	Graduate	3	Yes	Yes	Yes	900000	400000	1300000	Baleno	700000
49	Salaried	Married	Post Gradu	4	No	No	Yes	2500000	2000000	4500000	Luxuray	3000000
26	Salaried	Single	Post Gradu	0	No	No	No	800000	0	800000	i20	800000
27	Salaried	Single	Graduate	0	Yes	No	Yes	800000	0	800000	Baleno	700000
29	Salaried	Single	Post Gradu	2	No	No	No	900000	0	900000	City	1200000
30	Salaried	Married	Graduate	0	No	No	Yes	800000	500000	1300000	Baleno	700000
37	Salaried	Married	Post Gradu	3	No	Yes	Yes	1700000	800000	2500000	City	1200000
35	Business	Married	Graduate	3	No	Yes	Yes	1100000	800000	1900000	i20	800000
36	Business	Married	Graduate	3	No	No	Yes	1400000	1000000	2400000	SUV	1600000
35	Business	Married	Post Gradu	4	No	No	Yes	900000	500000	1400000	Baleno	700000
35	Salaried	Married	Graduate	3	Yes	No	Yes	1400000	600000	2000000	Ciaz	1100000
35	Salaried	Married	Graduate	2	No	No	Yes	1800000	1100000	2900000	SUV	1600000
35	Salaried	Married	Post Gradu	4	Yes	Yes	No	1300000	0	1300000	Baleno	700000
36	Business	Married	Graduate	3	No	No	No	1600000	0	1600000	i20	800000
36	Salaried	Married	Post Gradu	3	Yes	Yes	Yes	1700000	900000	2600000	Verna	1200000
36	Salaried	Married	Post Gradu	2	No	No	Yes	1800000	900000	2700000	SUV	1600000
41	Business	Married	Graduate	3	No	No	No	1100000	0	1100000	Baleno	700000
41	Salaried	Married	Graduate	3	No	No	Yes	1400000	700000	2100000	Duster	1300000
41	Salaried	Married	Post Gradu	4	No	Yes	Yes	1900000	1100000	3000000	Creata	1500000
43	Business	Married	Graduate	3	No	No	Yes	1300000	900000	2200000	Creata	1500000
42	Salaried	Married	Graduate	4	Yes	Yes	No	2100000	0	2100000	Ciaz	1100000
42	Salaried	Married	Post Gradu	3	No	No	Yes	2400000	1300000	3700000	SUV	1600000
29	Business	Married	Post Gradu	0	No	No	Yes	900000	700000	1600000	City	1200000

99x13

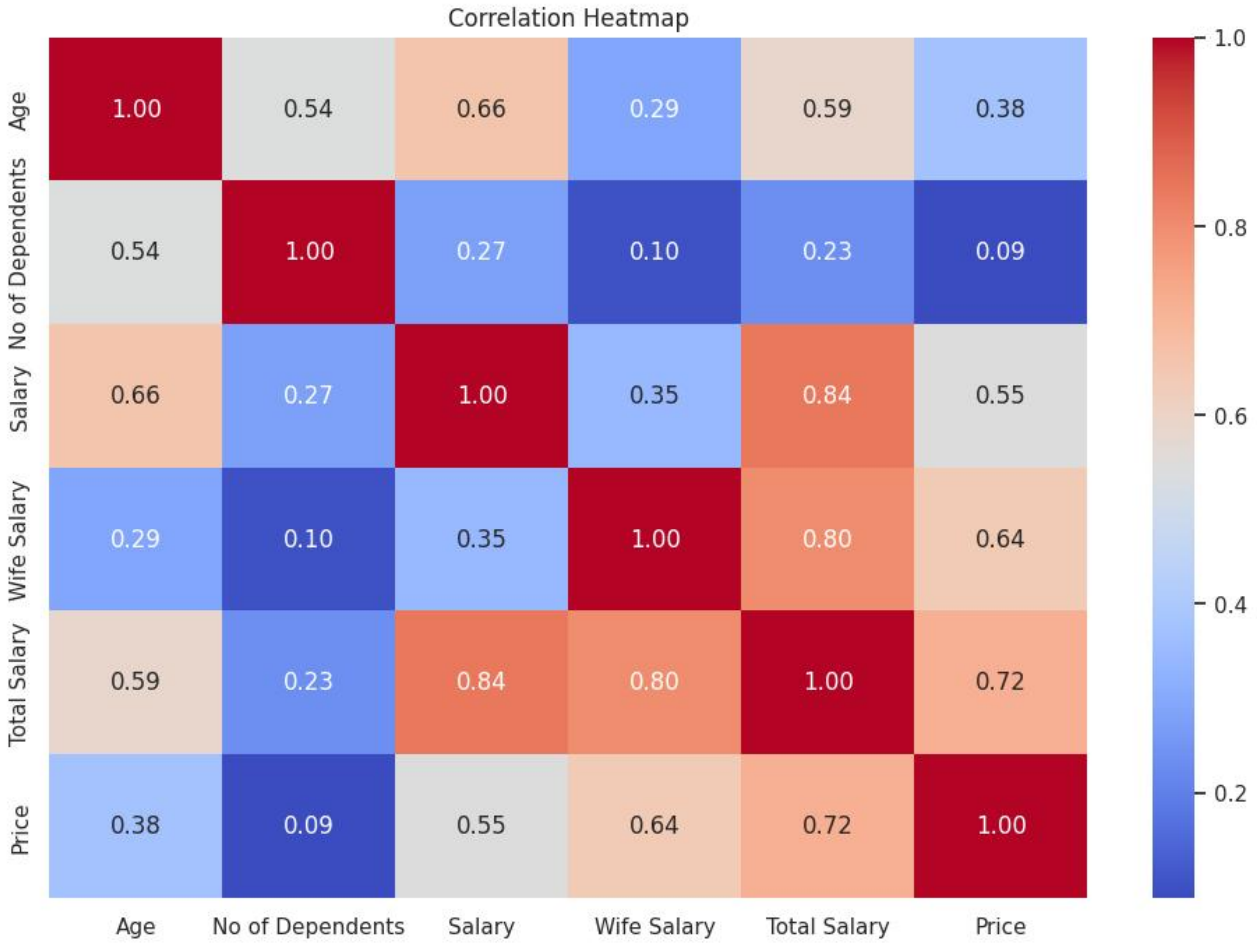
```
print(data_frame.dtypes)
```

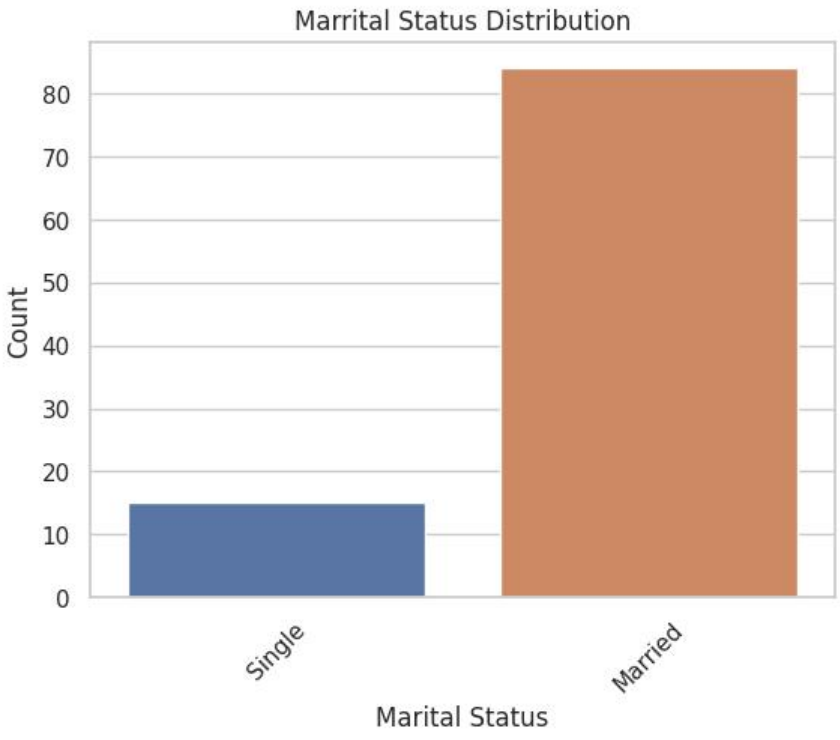
```
Age                   int64
Profession           object
Marrital Status      object
Education            object
No of Dependents      int64
Personal loan        object
House Loan           object
Wife Working         object
Salary                int64
Wife Salary           int64
Total Salary          int64
Make                 object
Price                 int64
dtype: object
```

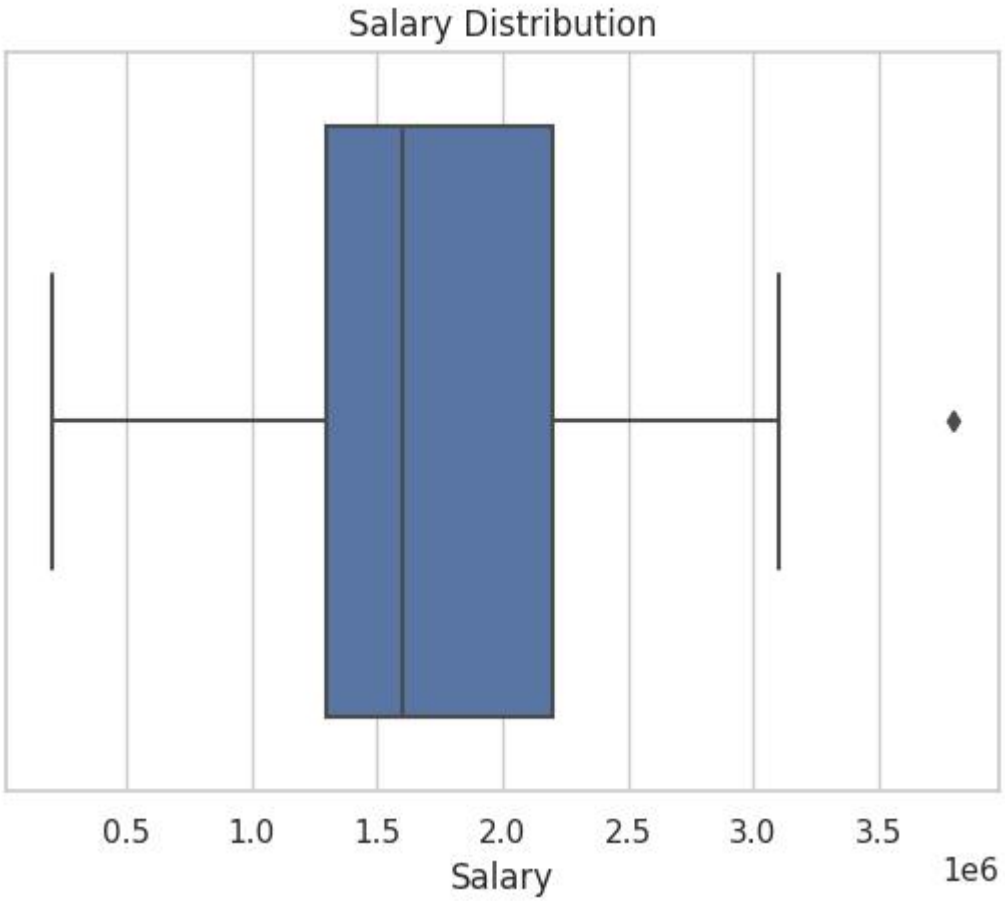
PAIRPLOT:

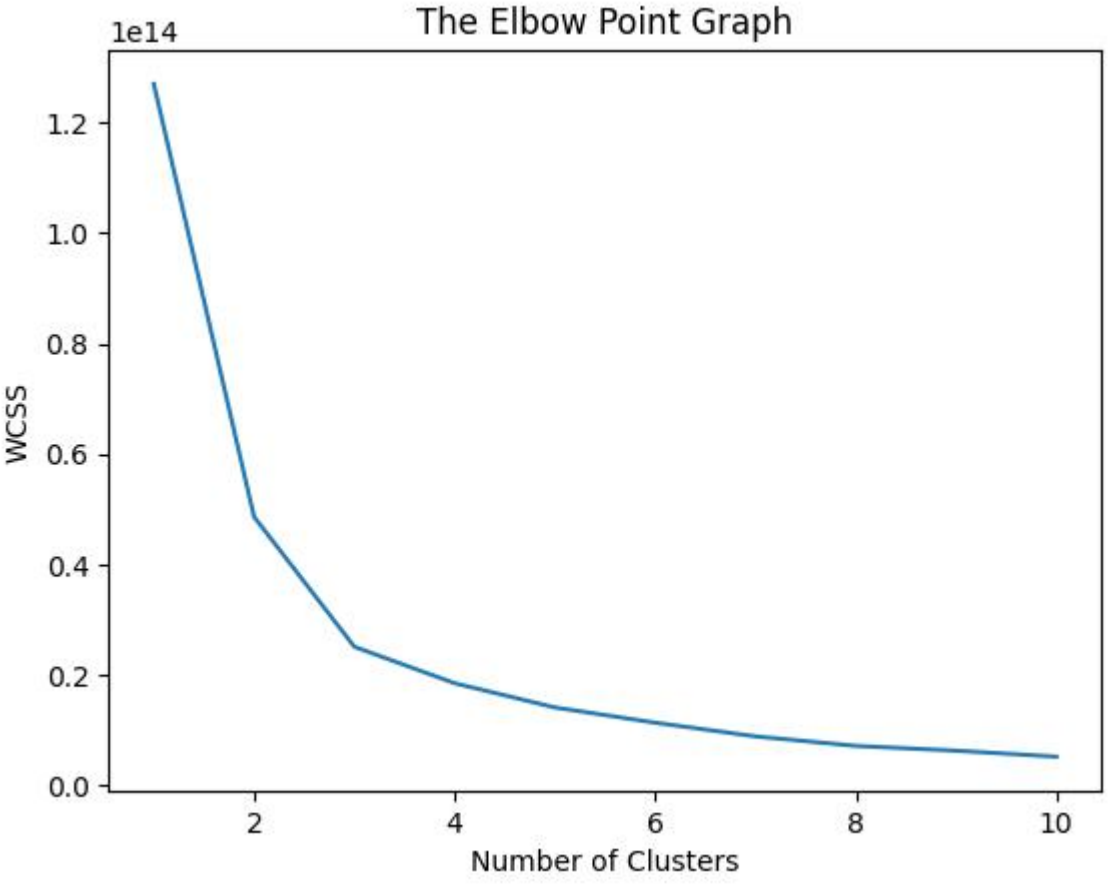

Age
No of Dependents
Salary
Wife Salary
Total Salary
Price
1e6

CORRELATION HEATMAP:






Salary Distribution
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Salary
1e6


The Elbow Point Graph
1e14
1.2
1.0
0.8
0.6
0.4
0.2
0.0
WCSS
2
4
6
8
10
Number of Clusters

K MEANS :

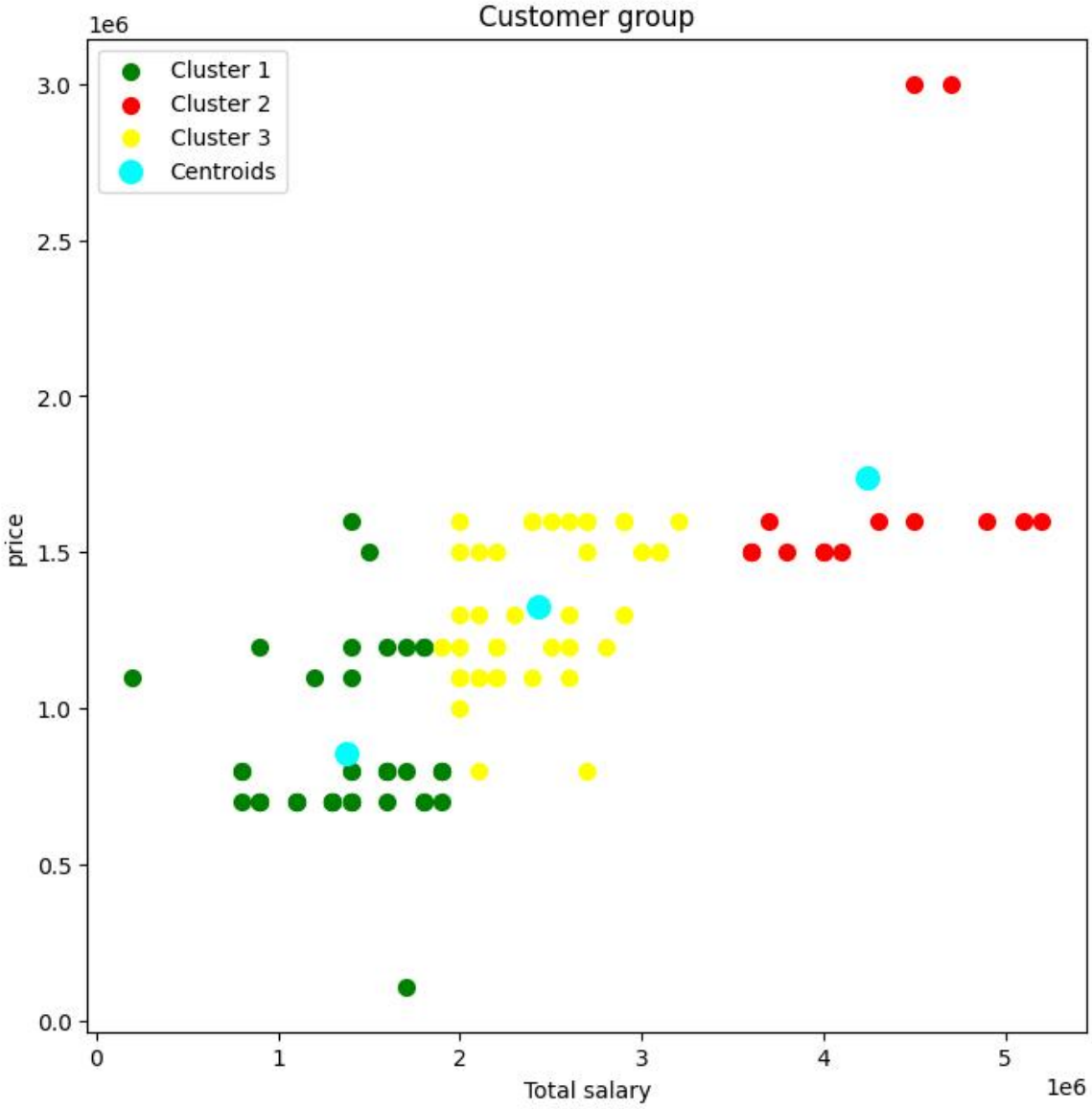
```
from sklearn.cluster import KMeans

n_clusters = 3
n_init = 20  # Set n_init explicitly

kmeans = KMeans(n_clusters=n_clusters, n_init=n_init)
kmeans = KMeans(n_clusters =3, init='k-means++', random_state=0)
# return a label for each data point based on their cluster
Y = kmeans.fit_predict(X)

print(Y)
```

```
[0 2 0 2 2 0 0 0 2 0 2 0 0 0 0 1 0 0 0 0 2 0 2 0 2 2 0 0 2 2 0 2 2 2 2 1 0
 2 0 2 0 0 2 2 0 1 0 2 0 2 2 1 2 1 1 2 2 0 0 0 0 0 2 0 2 0 1 2 1 0 2 2 0 2
 2 1 0 2 2 1 2 1 2 2 2 0 0 2 1 0 0 1 2 0 2 1 2 1 2]
```



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PCA :

```
<bound method NDFrame.head of     PCA_Component_1  PCA_Component_2
0         -1.634550         0.354909
1         -0.498168        -0.131976
2         -0.308691         0.328045
3         -0.038147         0.057500
4          0.881895         0.436453
..              ...              ...
94         0.746623         0.571726
95         2.572799        -1.254450
96        -0.200521        -0.104874
97         1.666427        -0.672827
98        -0.200521        -0.104874
```

CLASSIFICATION REPORT :

```
Classification Report:
              precision    recall  f1-score   support

          27       0.17      1.00      0.29         1
          29       0.00      0.00      0.00         2
          30       0.00      0.00      0.00         0
          31       0.00      0.00      0.00         4
          32       0.00      0.00      0.00         1
          33       0.00      0.00      0.00         0
          34       0.00      0.00      0.00         2
          35       0.00      0.00      0.00         3
          36       0.00      0.00      0.00         3
          37       0.00      0.00      0.00         0
          39       0.00      0.00      0.00         0
          41       0.00      0.00      0.00         1
          42       0.00      0.00      0.00         1
          50       0.00      0.00      0.00         1
          51       0.00      0.00      0.00         1

    accuracy                           0.05        20
   macro avg       0.01      0.07      0.02        20
weighted avg       0.01      0.05      0.01        20

Confusion Matrix:
[[1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [1 0 1 0 0 0 0 0 1 0 0 0 0 0 0 1]
 [1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0]
 [1 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0]]
```

Improving the Electric Vehicle (EV) market segmentation project by allocating additional time and budget for data collection can significantly enhance the accuracy and depth of the results. Here are several strategies to elevate the project:

Enhanced Data Collection:

Geographic Data: Gather detailed geographic information such as population density, traffic patterns, proximity to public transportation, and the availability of charging infrastructure. This will provide a more comprehensive understanding of regions and their readiness for EV adoption.

Consumer Surveys: Conduct targeted surveys to gain specific insights into consumer preferences, attitudes, and barriers related to EV adoption. Questions should cover income, environmental awareness, and willingness to pay for EVs.

Government Policies: Collect information on government policies, incentives, and regulations concerning EVs at the regional level to assess how these measures impact market segmentation.

Competitor Data: Acquire data on competitors' EV sales, marketing strategies, and pricing models to gain insights into market dynamics and competition.

Expanded Data Attributes:

Additional Demographic Data: Gather more detailed demographic information, including age groups, education levels, and occupation types.

Psychographic Data: Investigate consumer lifestyles, values, and behaviors that influence EV adoption decisions, including environmental consciousness and tech-savviness.

Charging Station Data: Include real-time information on charging station availability, utilization rates, and charging speeds, which is essential for evaluating infrastructure readiness.

Advanced Machine Learning Models:

Random Forest and Gradient Boosting: Utilize these ensemble methods to capture complex interactions between attributes, which are effective for multi-class classification tasks like market segmentation.

Neural Networks: Employ deep learning models for intricate pattern recognition in large datasets, which can reveal hidden relationships between various attributes.

Price Optimization: Implement pricing models that consider factors such as consumer willingness to pay, competitor pricing, and government incentives, optimizing pricing strategies for different market segments.

Charging Infrastructure Planning: Use predictive analytics to identify areas with potential gaps in charging infrastructure and strategically plan the expansion of charging networks.

Customer Segmentation:

Behavioral Segmentation: Analyze customer behavior data to segment consumers based on actual purchasing patterns, such as repeat buyers, first-time buyers, or those who consider EVs but do not purchase.

Lifetime Value Analysis: Assess the lifetime value of different customer segments to inform marketing and retention strategies.

By integrating these enhancements, we can develop a more sophisticated and actionable market segmentation analysis, allowing us to tailor marketing strategies, product offerings, and infrastructure investments to meet the specific needs and preferences of diverse customer segments within the EV market.

The estimated Market Size for this Electric Vehicle Market Domain (non-segmented) in Numbers?

The estimated market size for the global electric vehicle (EV) market was approximately **$165.8 billion** in **2022**. Projections indicate that this market is expected to grow to around **$823.75 billion** by **2030**, achieving a **compound annual growth rate (CAGR)** of **18.2%** from 2022 to 2030.

Factors Driving Growth in the EV Market:

Government Incentives: Various governments worldwide are implementing incentives to encourage EV adoption, including tax breaks, subsidies, and access to high-occupancy vehicle (HOV) lanes.

Rising Fuel Prices: Increasing gasoline prices are making electric vehicles a more appealing choice for consumers seeking cost-effective alternatives.

Improvements in EV Technology: Rapid advancements in EV technology are leading to longer battery ranges and faster charging times, enhancing the overall user experience.

Growing Environmental Awareness: A rising consciousness about environmental issues is driving consumers to consider the ecological benefits of electric vehicles.

Market Segmentation:

- **By Vehicle Type:** The market is categorized into passenger cars, commercial vehicles, and two-wheelers.
- **By Propulsion Type:** This segment includes battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and hybrid electric vehicles (HEVs).
- **By Battery Type:** The battery segment is divided into lithium-ion batteries and lead-acid batteries.
- **By Region:** The market spans across North America, Europe, Asia Pacific, and the Rest of the World.

Regional Insights:

The EV market is experiencing rapid growth across all regions, with particularly strong expansion in **Asia Pacific**. This growth is attributed to the region's burgeoning economies and increasing governmental support for electric vehicles.

Overall, the electric vehicle market presents significant growth potential, driven by various factors that are expected to sustain its rapid expansion in the coming years.

Here are the top four variables/features that can be used to create the most optimal market segments for the electric vehicle (EV) market:

Income: The income level of potential EV buyers is a significant factor influencing their decision to purchase an electric vehicle. Higher-income individuals are more likely to afford the upfront costs of an EV and the associated electricity costs for charging.

Age: Younger consumers tend to be early adopters of new technologies, including electric vehicles. They often show greater environmental consciousness and a willingness to pay a premium for sustainable options, making age a critical variable in market segmentation.

Location: The geographical location of potential buyers plays a crucial role in their likelihood of purchasing an EV. Urban residents are more likely to have access to charging infrastructure and services necessary for supporting EV ownership, which can influence their purchasing decisions.

Environmental Awareness: Individuals who possess a strong awareness of the environmental benefits associated with electric vehicles are generally more inclined to consider purchasing one. This is especially relevant in regions where government regulations aim to reduce greenhouse gas emissions, creating a favorable environment for EV adoption.

Additional Variables to Consider:

- **Occupation:** Certain professions, such as engineers and scientists, may exhibit a higher interest in EVs due to their familiarity with technology and sustainability.
- **Family Size:** Smaller families might prefer EVs, as they typically require less space than larger vehicles, making them more suitable for their needs.
- **Interest in Technology:** Consumers with a keen interest in technology are more likely to embrace the innovations and features offered by electric vehicles.
- **Brand Preference:** Some individuals may have specific preferences for certain EV brands, such as Tesla or BMW, which can influence their purchasing decisions.
- **Driving Habits:** Consumers who frequently drive short distances may find electric vehicles more appealing due to their suitability for daily commutes and lower operational costs.

By analyzing these variables, businesses can create precise market segments that cater to the unique needs and preferences of each group. This approach will enhance the effectiveness of marketing and sales strategies in the electric vehicle market.

GITHUB :

https://github.com/Mukhilan22/Mukhilan-EV-MARKET-FeynnLabs

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