Electric Vehicle Market Segmentation – State Incentives

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GitHub Link

Problem Statement:

As a part of its bigger project of Electrifying Indian Mobility, Indian government and the constituent state authorities have been actively promoting the adoption of Electric Vehicles (EVs) with the help of a range of policy frameworks and incentives, aiming to reduce the vehicular pollution and boosting a sustainable and eco-friendly transportation ecosystem. As per the current scenario, the effectiveness and focus of these incentives vary significantly across different states. For a new entrant in the EV market, understanding these variations is crucial for developing targeted strategies that align with the regional policies and maximize the market penetration.

Here, in this segment, our primary objective will be to analyse state-wise policies and incentives related to EV adoption to identify distinct market segments. The goal is to uncover the insights that can contribute to the strategic decision-making for entering and expanding in the Indian Market. Our analysis will be specifically dedicated to answer the following questions:

1. How do different States in India vary in terms of the incentives and policies offered to promote EV adoption?
2. What are the common characteristics between the states that offer substantial support for EVs and those that provide minimal incentives?
3. How can these insights be used to develop targeted market entry and expansion strategies for a new EV company?

Data Sources:

The data for this analysis was sourced from several authoritative and reliable government portals and reports to ensure accuracy and relevance. The key data sources include the **Vahan Sewa Dashboard** (provided comprehensive vehicle registration data across different attributes for each state), **e-AMRIT** portal by NITI Aayog (useful for extracting information related to state-wise policies). Additionally, research from various reports by **PIB** (Press Information Bureau) and other sources were instrumental in obtaining information on state level incentives.

Combining necessary data acquired from these mentioned sources, we could have a data with variables as shown below for each Indian State:

```
1   df.columns
```

```
Index(['State', 'State_Code', '2W_22', '3W_22', '4W_22', 'Total_22', '2W_23',
       '3W_23', '4W_23', 'Total_23', '2W_24', '3W_24', '4W_24', 'Total_24',
       'Capital_subsidy_2W', 'Capital_subsidy_4W', 'Scrapping_Incentives',
       'Other_Incentives', 'SGST_Rem', 'Motor_Vehicle_Tax_Exe',
       'Registration_Fee_Exe', 'Road_Tax_Exe'],
      dtype='object')
```

**Other_Incentives include Retrofitting Incentive (RI), Interest Subvention (IS) and Early Bird Incentive (EBI).

Data Pre-processing:

As for the Data pre-processing part, there wasn't any null value present as inspected, hence we didn't need to impute our data. However, our data had some columns where a little cleaning was required. Some columns showing vehicle population were significantly large valued, hence required feature scaling. Finally, we tried PCA for dimensionality reduction and to have a clearer picture of our data capturing the maximum variance.

1. **Data Cleaning:**

- **Capital_subsidy_2W** and **Capital_subsidy_4W** columns had string " /kWh" that had to be removed to convert them into numeric column. A simple str.replace() function was used to achieve this.
- **Scrapping_Incentives** column had values in range like "5000-7000" which needed to be converted in appropriate format. Furthermore, "%" was creating problem to convert the column to numeric which advocated to be treated as well.
- **Other_Incentives** column had categories in the form of "RI", "IS", "EBI" which were encoded ordinally.
- **SGST_Rem, Motor_Vehicle_Tax_Exe, Registration_Fee_Exe, Road_Tax_Exe** columns had string "No" which was removed using **numpy**- np.where() function to substitute it with 0s.

2. **Feature Scaling:**

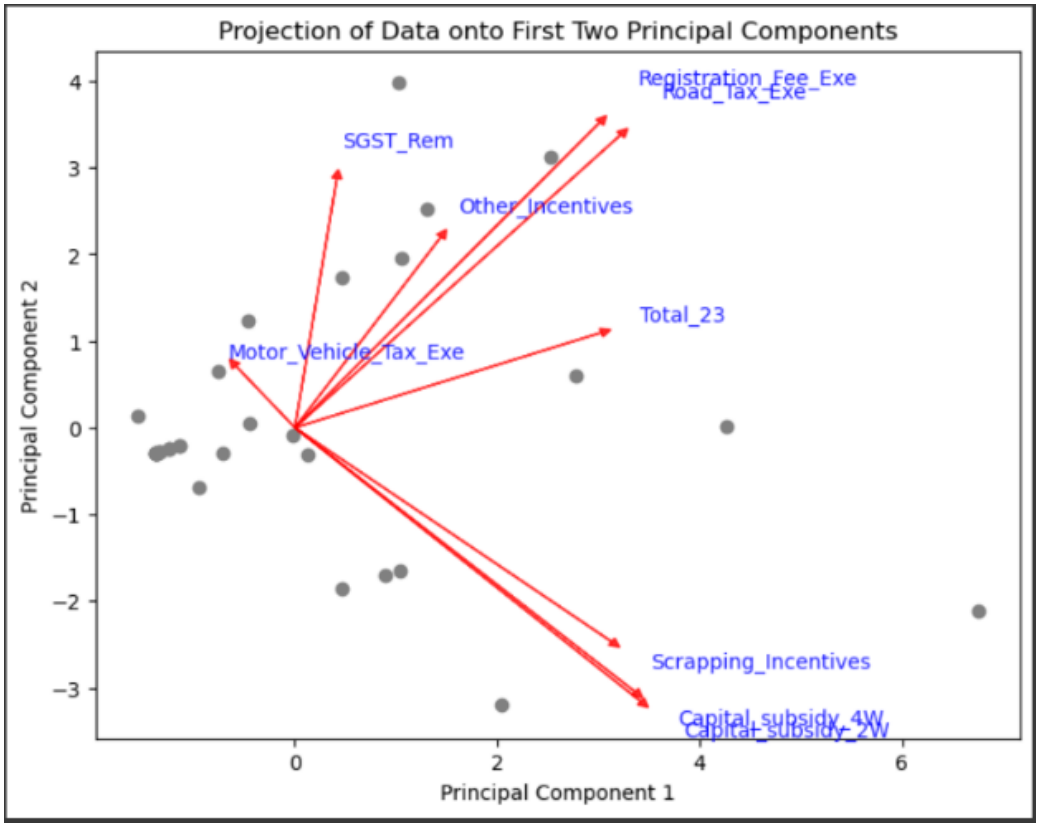
- To ensure that each feature could represent equally we sought to scale our data using the **"StandardScaler"** class of **"sklearn"** library, transforming them to have a mean of zero and standard deviation of one.

3. **Dimensionality Reduction using PCA:**

- By applying Principal Component Analysis (PCA) we were able to achieve dimensionality reduction which further enabled us to have a picture of our data in smaller dimensions (2D) which captured almost 60% of the total variance of our data.
- We were in turn able to analyse as to which features contributed the most to the variations in policy landscape of different states. This step not only simplified the

clustering process but also facilitated the visualization of the clusters, enabling us to interpret the result even more effectively.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Total_23	0.378469	0.137055	-0.243119	0.182861	-0.036310	0.861989	-0.023691	0.012906	-0.018980
Capital_subsidy_2W	0.427309	-0.394713	0.083596	-0.022226	0.169702	-0.093026	0.261915	0.740215	0.012499
Capital_subsidy_4W	0.420226	-0.380874	0.069135	-0.018771	0.204454	-0.070139	0.432682	-0.662766	-0.004512
Scrapping_Incentives	0.391309	-0.308673	0.154711	0.026877	-0.058310	-0.108797	-0.836170	-0.111418	-0.010437
Other_Incentives	0.180406	0.275153	-0.673293	0.016766	0.573636	-0.296775	-0.142387	0.001149	-0.027027
SGST_Rem	0.051818	0.359505	0.577683	-0.397088	0.578240	0.189039	-0.079642	0.004244	-0.014707
Motor_Vehicle_Tax_Exe	-0.072868	0.088924	0.300909	0.880127	0.282506	-0.067815	0.003188	0.004253	0.192813
Registration_Fee_Exe	0.376658	0.440265	0.158040	0.152910	-0.282191	-0.247358	0.106741	0.011412	-0.680879
Road_Tax_Exe	0.402545	0.422351	0.051250	-0.095018	-0.319091	-0.204861	0.080157	-0.008672	0.705432



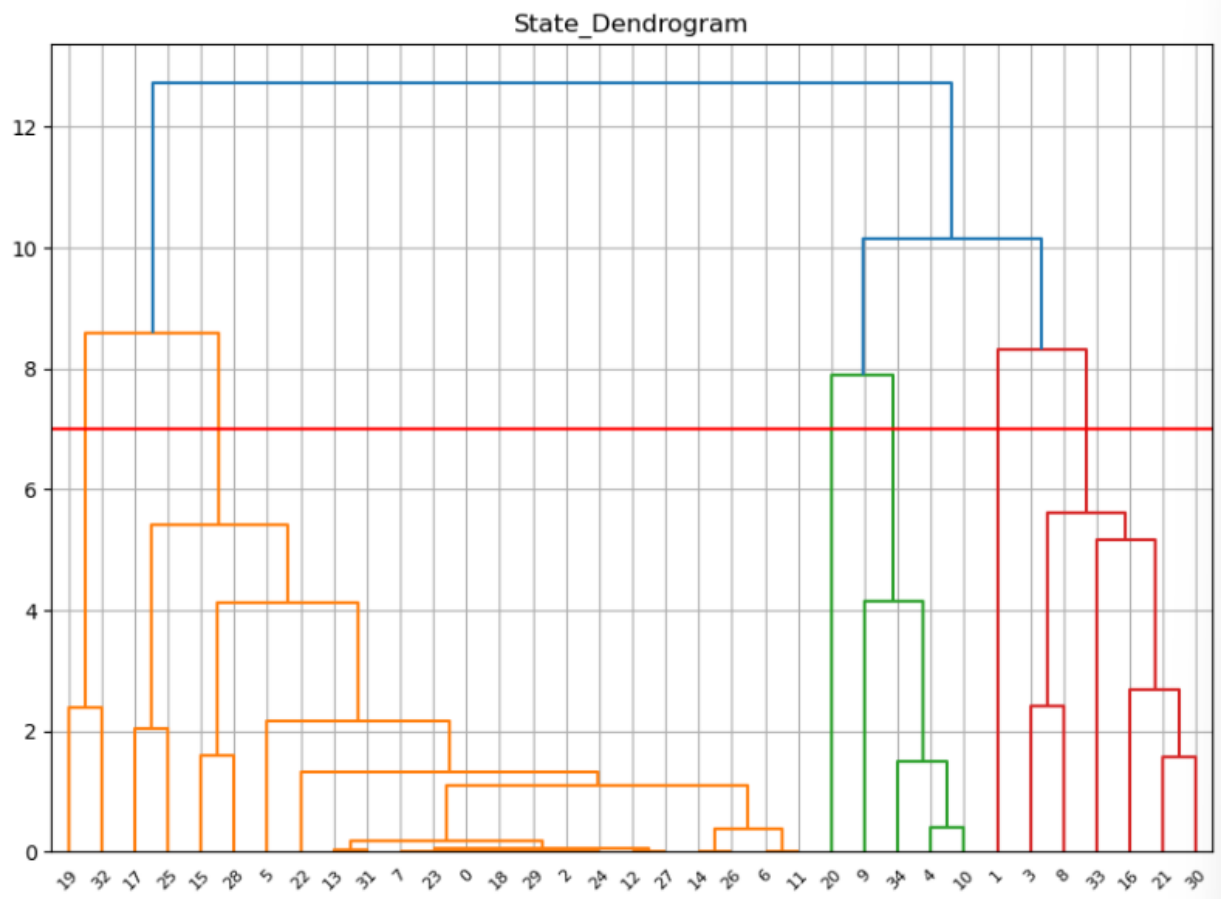
(Refer above two figures to visualize factor loading for each Principal Component so obtained and the scatter plot of the data with respect to the first two Principal Components)

Segment Extraction (ML Techniques Used):

To effectively segment Indian State based on their EV policies and incentives, we employed **"Agglomerative Hierarchical Clustering"** which is a powerful ML technique suitable for identifying the natural groupings in the data. This method was chosen for its ability to build

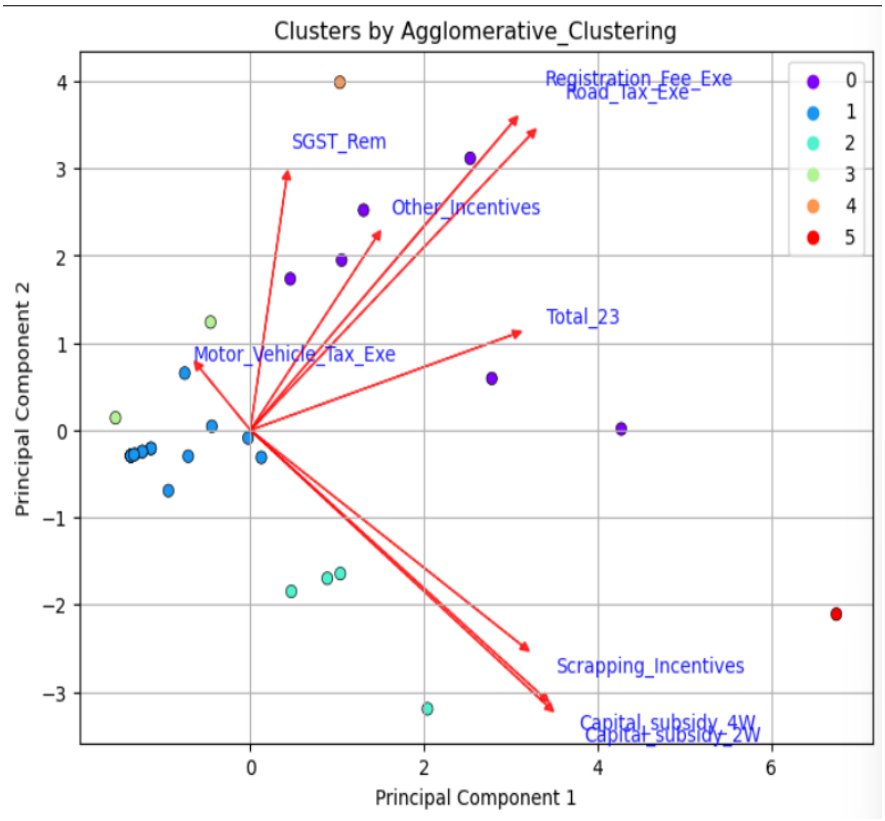
a hierarchy of clusters by iteratively merging and splitting existing clusters helping in understanding the underlying structure of the data. Another reason for choosing Agglomerative Clustering over **KMeans** clustering is that we got better and more meaningful clusters with the former than the later. This could be attributed to smaller data to work with.

We first created the **"Dendrogram"** by using **scipy.cluster.hierarchy's dendrogram()** function to understand the optimal number of clusters to be formed, which turned out to be six for our data.



The red line is where we cut the Dendrogram for number of clusters.

This Dendrogram also helped us to observe how individual states or smaller clusters were progressively merged into larger clusters. This becomes crucial when we particularly want to understand the relationship between the clusters and varying degrees of similarities among them. We finally fit our model for **n_clusters=6** to have our segments as shown in the figure below:

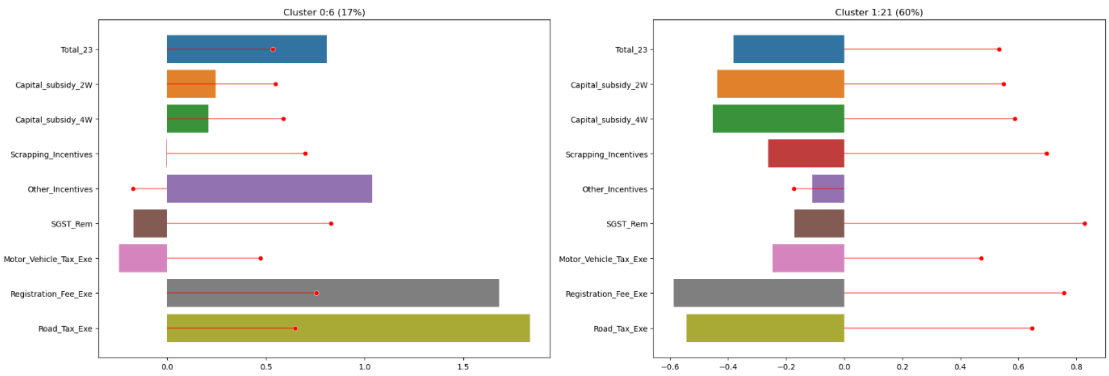


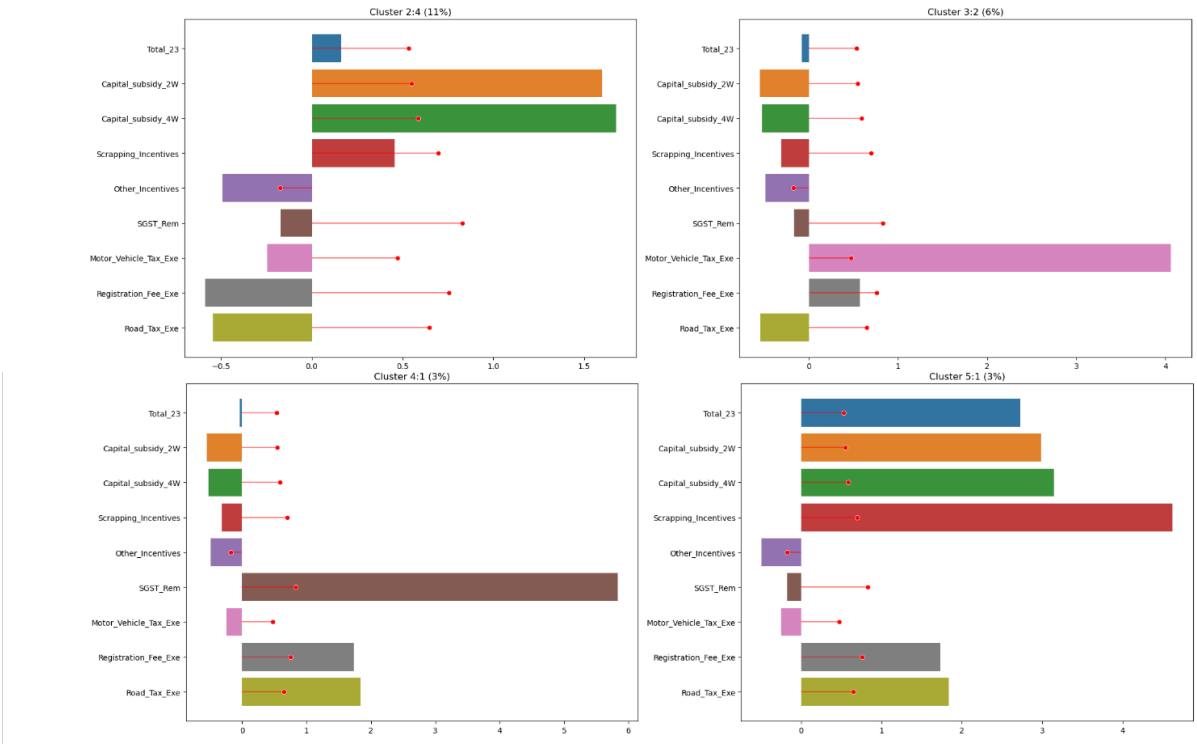
	Cluster	State
8	0	Delhi
21	0	Manipur
33	0	Uttar Pradesh
16	0	Kerala
30	0	Tamil Nadu
3	0	Assam
29	1	Sikkim
28	1	Rajasthan
27	1	Puducherry
26	1	Punjab
25	1	Odisha
24	1	Nagaland
23	1	Mizoram
22	1	Meghalaya
31	1	Tripura
18	1	Lakshadweep
0	1	Andaman & Nicobar Islands
17	1	Ladakh
14	1	Jharkhand
2	1	Arunachal Pradesh
5	1	Chandiagrh
6	1	Chhattisgarh
15	1	Karanataka
7	1	Dadra and Nagar Haveli and Diu and Daman
12	1	Himachal Pradesh
13	1	Jammu & Kashmir
11	1	Haryana
10	2	Gujarat
9	2	Goa
4	2	Bihar
34	2	West Bengal
19	3	Madhya Pradesh
32	3	Uttarakhand
1	4	Andhra Pradesh & Telangana
20	5	Maharashtra

To have clear picture as to which state fall under which cluster refer the adjacent table to the scatter plot.

Profiling and describing potential Segments:

Following visualizations highlight the distinct groupings of the states and allow us to interpret the clustering results in the context of the underlying features by presenting the Segment Profiles to understand each cluster constituent respectively.





With these Segment Profiles for each state, we are able to interpret how states varied in their approaches in encouraging the EV adoption.

Let us now try to answer the questions that we mentioned in the beginning of our analysis:

1. How do different States in India vary in terms of the incentives and policies offered to promote EV adoption?

Ans: States were grouped into six distinct clusters based on the level and type of support provided. Some states, particularly those in Cluster 2, show a comprehensive and aggressive approach, offering high capital subsidies for both two-wheelers and four-wheelers, significant scrapping incentives. In contrast, states in Clusters 3 and 4 offer moderate to low incentives, focusing primarily on limited tax exemptions with no capital subsidies and scrapping incentives which does not seem to be enough appeal the masses. Cluster 0 and 5, however, are even more aggressive in terms of their state support, with cluster 5 being one of the highest capital incentives providers along with scraping incentives to which the population seem to respond positively as well. Same with the cluster 0 where capital incentives aren't much but other state support in terms of other incentives, registration charge and road tax exemption are nudging the population to buy more EVs.

2. What are the common characteristics between the states that offer substantial support for EVs and those that provide minimal incentives?

Ans: States that offer substantial support for EV adoption, such as those in cluster 0, 2 and 5 tend to have comprehensive policies covering a wide range of incentives, including high

capital subsidies, scrapping incentives, and extensive tax exemptions. These states likely recognize the long-term benefits of EV adoption in terms of environmental impact and economic growth, thus investing heavily in creating a conducive environment for EV uptake. Conversely, states with no to minimal incentives, found in clusters 1, 3 and 4, often focus on limited tax exemptions and provide fewer direct financial incentives. These states might be facing budgetary constraints or have other policy priorities that limit their ability to offer extensive EV incentives. The common thread among supportive states is their proactive stance and willingness to invest significantly in EV infrastructure and incentives, while less supportive states exhibit a more cautious approach.

3. How can these insights be used to develop targeted market entry and expansion strategies for a new EV company?

Ans: Let's look at the insights cluster by cluster:

- **Cluster 1** – Here none of the incentives seem to be present in order to make the population buy the EVs. For this reason, we can consider this cluster as the most unfavourable for an EV start-up for its entry.
- **Cluster 3 and 4** – Even with certain level of state support the masses do not seem to be appealed for purchasing the EVs to that extent in these states. This advocates for further research in terms of the economic, demographic, behavioural and psycho-graphic analysis of these states to understand the market better (done in other segments of this report). Hence, we can look at these segments as a potential for business expansion subject to comprehensive research.
- **Cluster 2** – These are the states showing slightly better response to the policy support by their respective governments. Thus, we can look at the cluster 2 states appropriate for the expansion strategies for our business.
- **Cluster 0 and 5 –** For these clusters, there is comprehensive backing from the states which is not just limited to capital incentives or certain tax exemptions. Rather the policies span across different incentives which might be able to address different components of the populations. This might also be the reason which could push the masses to buy more EVs from different categories (2W, 3W, 4W, etc.). For example, UP shows maximum registered 3W EVs which could be attributed to one of these policy boosts. In conclusion, we can see these states as ideal for the Entry in the market.

In summary, our analysis has revealed significant variations in state-level incentives and policies for EV adoption across India, categorizing states into six distinct clusters based on the type and level of support provided. Clusters 0 and 5 stand out as the most aggressive in promoting EVs through comprehensive incentives, making them ideal for market entry. Conversely, cluster 1 presents the least favourable conditions due to the lack of incentives. Clusters 2, 3, and 4 show moderate support, suggesting potential for business expansion with further market research. These insights provide a strategic roadmap for a new EV

company to tailor its market entry and expansion efforts to align with state-specific policies, optimizing the chances for successful penetration and growth in the Indian EV market.