Market Segmentation Analysis of Electric Vehicles Market in India

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Fynn Labs: Project 2

Link: *https://github.com/Nethranandps/feynn_intern*

1. IMG

Problem Statement

Task is to analyse the Electric Vehicles Market in India using *Segmentation* analysis and come up with a feasible strategy to enter the market, targeting the segments most likely to use their product in terms of Geographic, Demographic, Psychographic, and Behavioural.

In this report we analyse the Electric Vehicles Market in India using segments such as region, price, charging facility, type of vehicles (e.g., 2 wheelers, 3 wheelers, 4 wheelers

etc.), retail outlets, manufacturers, body type (e.g., Hatchback, Sedan, SUV, Autorickshaw etc.), safety, plug types and much more.

Fermi Estimation

Wild Guess: Around 8-10% people will have electric vehicles by the end of 2023 in India.
Educated Guess:

Employment rate = it is the ratio of number of available labor force to the population of People in the working age.

We think there are about 1.5 billion Indians in the world. Let's assume the only people over18 and under 60 works, assuming that they account for around 60% of the population then that would make 0.9 billion Indians in the working class. Out of the 0.9 billion people not all are employed, assuming only 2023 had 45% employment rate that would bring the number around 405 million.

Since, not everyone can afford an electric vehicle, let’s assume only people above middle class can afford an electric vehicle, that would be 40 million. Not everyone buys an electric vehicle. Let’s assume out of these 40 million only 10 million are willing to buy an electric vehicle.

Variables and Formulas:

Let E(x) be the employment rate of the year x (in %). Let P(x) be the population of the year x.

Let A(x) be the number of available Labor in the year x.

Let r be the ratio of Indians between the age of 18 and 60 to the total population of India.

E(x) = (A(x)*100)/(P(x)*r)

This formula will formulate the Employment ratio for the year x.

Gathering More Information:

Estimation for the population of the year 2022 can be obtained by the increase in population each year

P (2019) = 1.3676 billion

P (2020) = 1.3786 billion

P (2021) = 1.39199 billion

P (2020)-P (2019) =
11million P (2021)-P
(2020) = 13.39 million
the mean would be
12.195 million

thus P (2022) = 1.44185 billion assuming A(x) is
constant every year= 471,688,990r=0.6 C=0.75
E (2022) = (471,688,990/(1,441,850,000*0.6))*0.75 E (2022) = 42%

Conclusion: By this analysis, we conclude that by the end of the year 2024 there would a Employment rate of 42%. That would make 42% of 405 million i.e., 170 million. Out of these 170 million only 10% afford EV'S. So around 17 million people will have EV's by the end of 2024"

Data Collection

Data was extracted from the various websites mentioned below for EV market segmentation.

Link for data extraction:

- https://pib.gov.in/PressReleasePage.aspx?PRID=1842704
  https://www.ibef.org/blogs/electricvehicles-market-in-india
  https://evreporter.com/indias-region-wise-ev-market-jan-may-2022/
- https://www.india-briefing.com/news/indias-ev-manufacturing-capacity-and-marketpreferences- progress-25840.html/
- https://github.com/Marisha18/Market-Segmentation-for-Electric-Vehicles-in-India/blob/main/Market_Segmentation.ipynb https://github.com/Ashwini3535/EV-MARKETIN-INDIA

Data from those links are extracted by Google play scraper available on libraries package. There are multiple datasets get extracted from those websites in CSV and Excel formats. There are some pdfs also which contains valuable information regarding the EV market. We have extracted data from those pdfs as well.

Raw data generated:

- https://github.com/ShubhamNavghare/FeyNN_Labs_Project_2EV_Market_Segmentation/tree/main/Dataset
- https://github.com/ShubhamNavghare/FeyNN_Labs_Project_2-EV_Market_Segmentation/tree/main/PDF

Columns explanations:

1. ‘Brand’ and tells the manufacturers of electric vehicles.

2. ‘model’ tells the various of electric vehicles.
3. ‘Accuse’, ‘Top Speed’, ’Power Train’ tells specification about the vehicles.
4. ‘Range’, ‘Fast Charge’, ‘Plug_type’ and ‘ Bodystyle’ tells us about range of vehicle per full charge,fast charging is provided or not, type of charging plug and body style of vehicle respectively.
5. ‘Seats’ and ‘Price’ tells about the number of seats available on vehicle and their price.
6. ‘Region’ and ‘State/UT’ tells about the states of India.
7. ‘EV Charging Facility’ and ‘Chargers’ tells about the facility of charging in the respective states.
8. ‘2V’, ‘3V’, ‘4V’, ‘Bus’ tells about the type of vehicles in the market.

Data Preprocessing

Steps taken to preprocess the scraped raw data:

1. Ordinal encoded 'PowerTrain'
2. Label encoded 'RapidCharge’
3. Used Label Encoder and Standard Scaler package for preprocessing of the dataset.

Exploratory Data Analysis

An Exploratory Data Analysis or EDA is a thorough examination meant to uncover the underlying structure of a data set and is important for a company because it exposes trends, patterns, and relationships that are not readily apparent.

We analyzed our dataset using *univariate* (analyze data over a single variable/column from a dataset), *bivariate* (analyze data by taking two variables/columns into consideration from a dataset) and *multivariate* (analyze data by taking more than two variables/columns into consideration from a dataset) analysis.

The bar graph below shows the diversity of the data geographically. We can see that we have the maximum amount of data of states *Karnataka* and *Maharashtra*; and minimum amount of data for *Sikkim, Meghalaya, Lakshadweep, Ladakh,* and *Dadra and Nagar Haveli and Daman and Diu*. There are a total of 1536 rows of data distributed among the cities shown in the graph.

IMPLEMENTATION CODE

DATASET-1

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
```

In [14]:

```
df1 = pd.read_csv('1_ev_charger_dataset.csv')
df1.head()
```

Out[14]:

	Region	2W	3W	4W	Bus	Chargers
0	Uttar Pradesh	9852	42881	458	197	207
1	Maharastra	38558	893	1895	186	317
2	Karnataka	32844	568	589	57	172
3	Tamil Nadu	25642	396	426	0	256
4	Gujarat	22359	254	423	22	228

In [15]:

```
print('DF1 Shape: ', df1.shape)
```

```
DF1 Shape:  (24, 6)
```

In [16]:

```
print(' <<< DATASET 1 ------------------------------------------------------
------')
print(df1.info())
```

```
 <<< DATASET 1 ------------------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24 entries, 0 to 23
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Region    24 non-null     object
 1   2W        24 non-null     int64
 2   3W        24 non-null     int64
 3   4W        24 non-null     int64
 4   Bus       24 non-null     int64
 5   Chargers  24 non-null     int64
dtypes: int64(5), object(1)
memory usage: 1.2+ KB
None
```

In [17]:

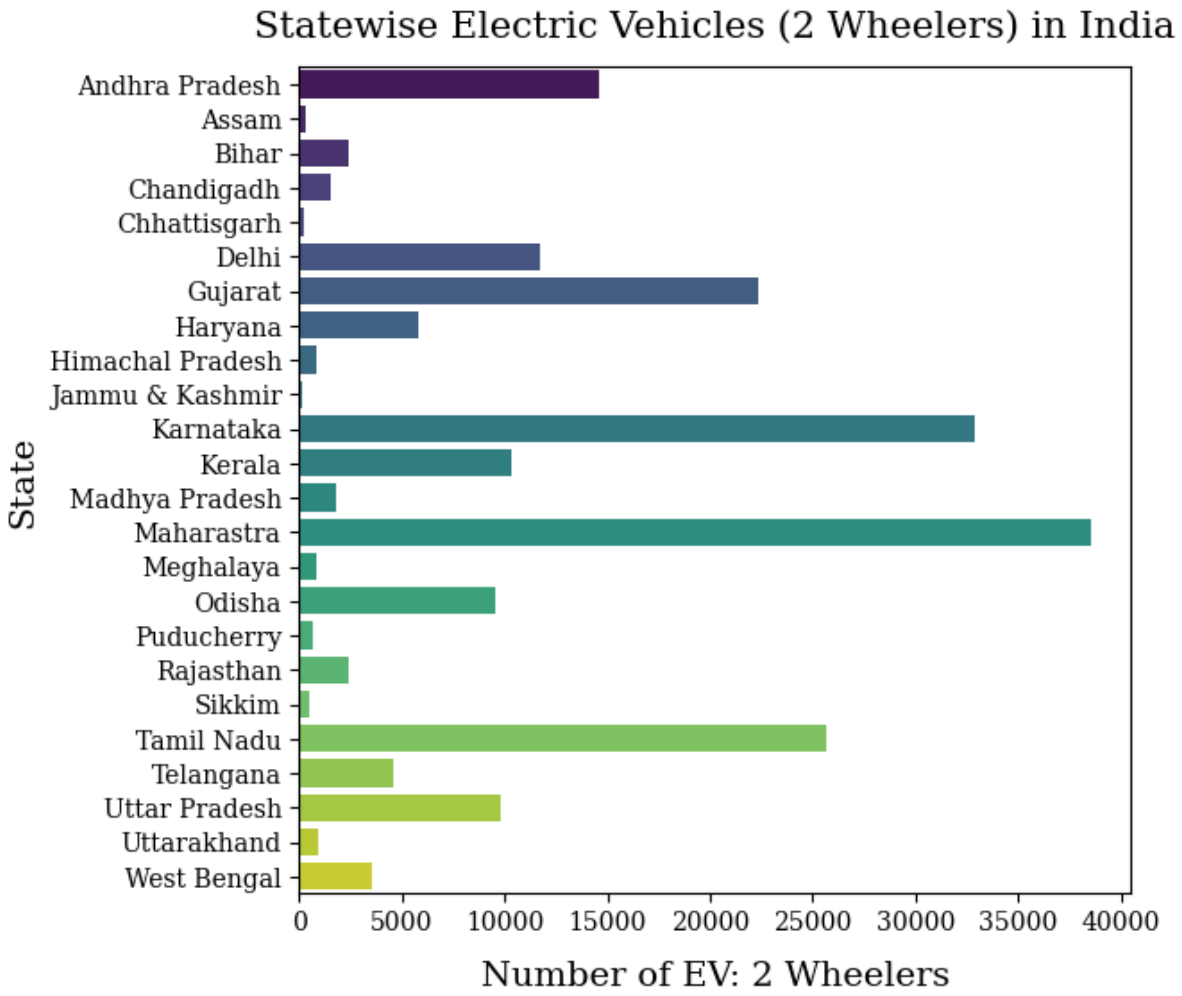
```
d1 = df1.describe()
display('<<< DATASET 1 >>>', d1,)
```

'<<< DATASET 1 >>>'

	2W	3W	4W	Bus	Chargers
count	24.000000	24.000000	24.000000	24.000000	24.000000
mean	8421.458333	3853.166667	334.041667	28.500000	106.791667
std	10942.261145	8850.690961	476.930628	63.771331	96.623869
min	187.000000	234.000000	12.000000	0.000000	10.000000
25%	848.000000	512.750000	34.750000	0.000000	25.000000
50%	2967.500000	931.000000	129.000000	0.000000	67.500000
75%	10697.750000	2659.250000	434.000000	5.500000	180.250000
max	38558.000000	42881.000000	1895.000000	197.000000	317.000000

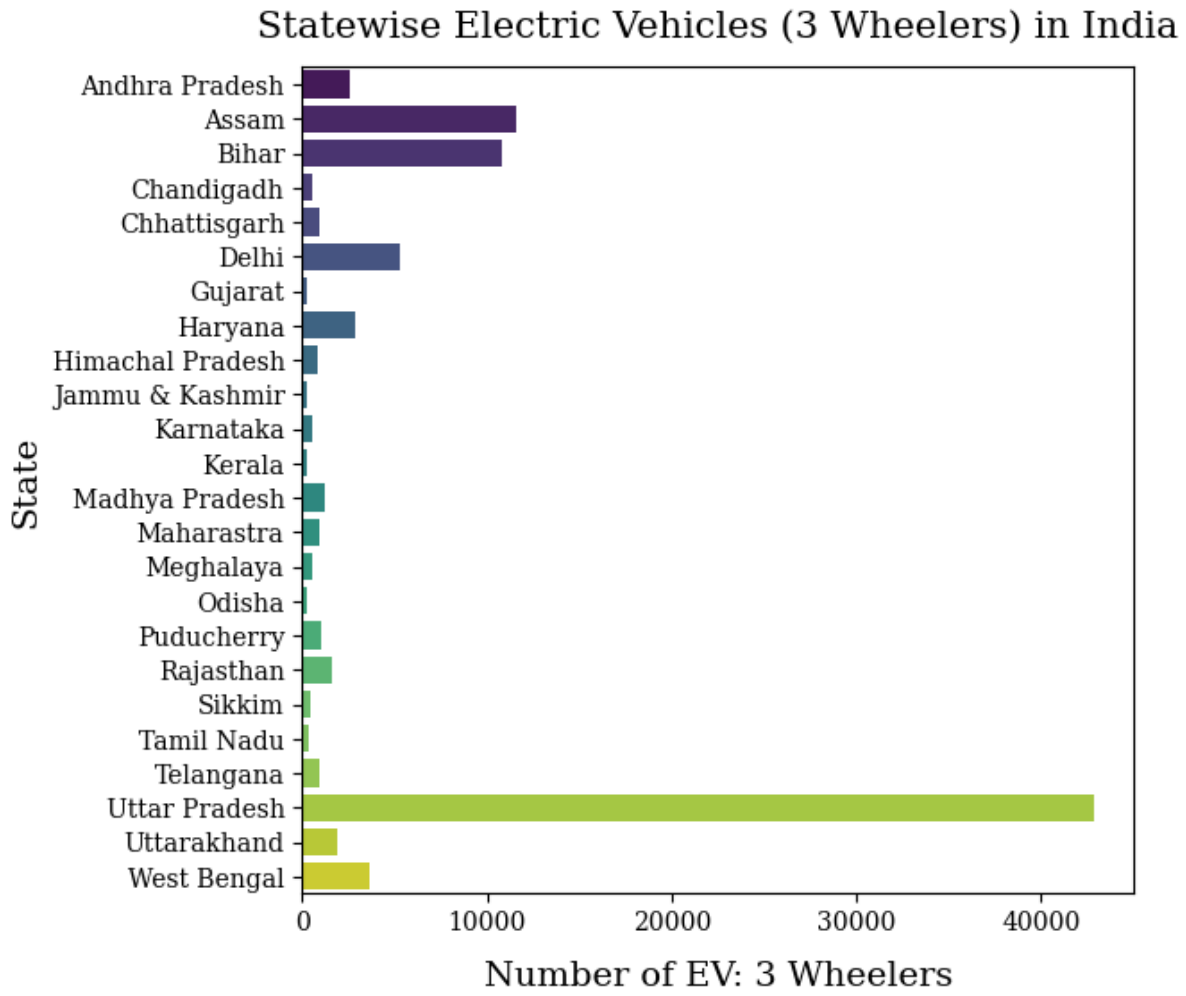
In [18]:

```
plt.figure(figsize=(6, 6))
sns.barplot(data=df1, y=df1['Region'].sort_values(ascending=True), x='2W',
palette='viridis')
plt.ylabel('State', fontsize=14, family='serif')
plt.xlabel('Number of EV: 2 Wheelers', family='serif', fontsize=14,
labelpad=10)
plt.xticks(family='serif')
plt.yticks(family='serif')
plt.title(label='Statewise Electric Vehicles (2 Wheelers) in India',
weight=200, family='serif', size=15, pad=12)
plt.show()
```



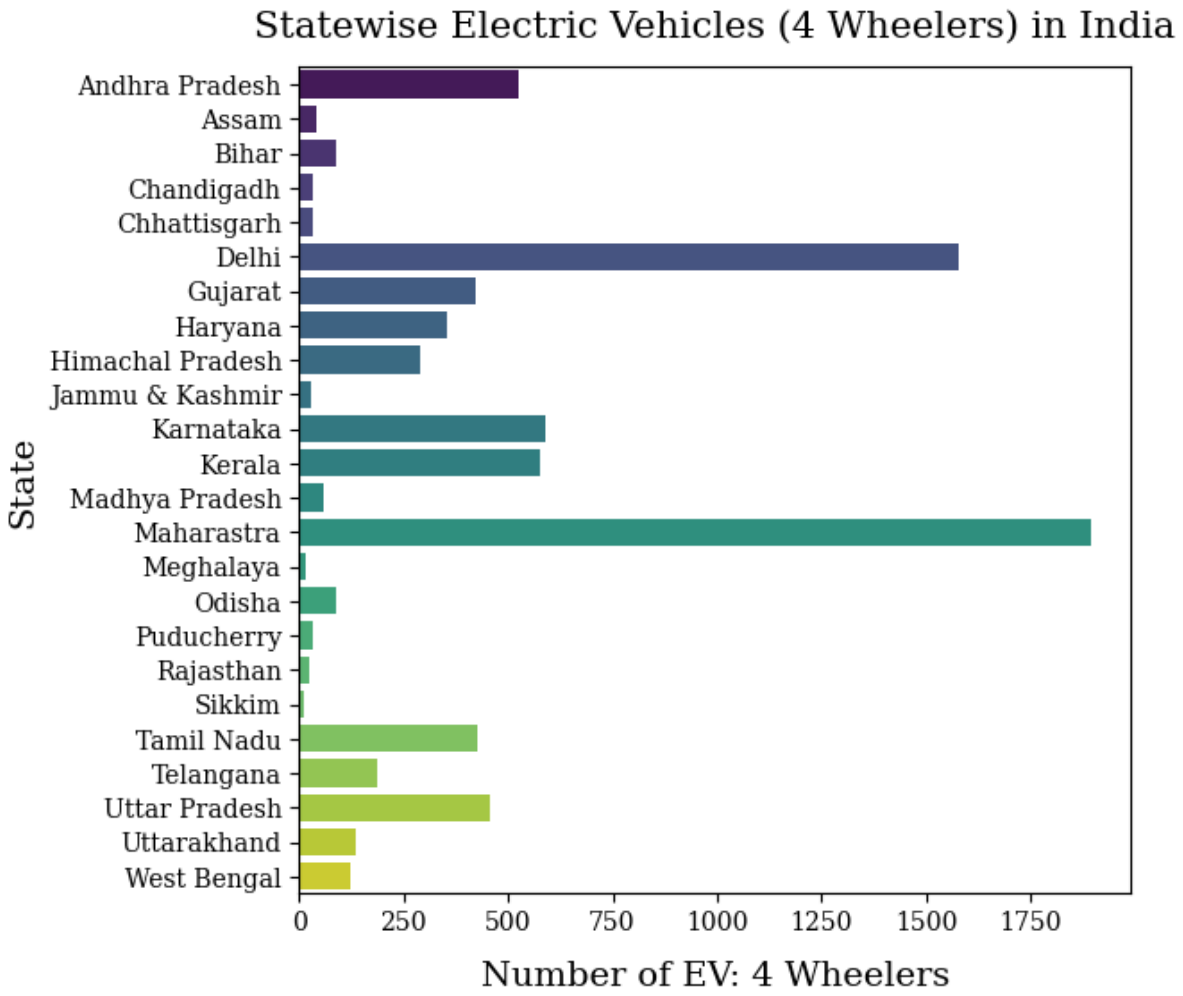
In [19]:

```
plt.figure(figsize=(6, 6))
sns.barplot(data=df1, y=df1['Region'].sort_values(ascending=True), x='3W',
palette='viridis')
plt.ylabel('State', fontsize=14, family='serif')
plt.xlabel('Number of EV: 3 Wheelers', family='serif', fontsize=14,
labelpad=10)
plt.xticks(family='serif')
plt.yticks(family='serif')
plt.title(label='Statewise Electric Vehicles (3 Wheelers) in India',
weight=200, family='serif', size=15, pad=12)
plt.show()
```



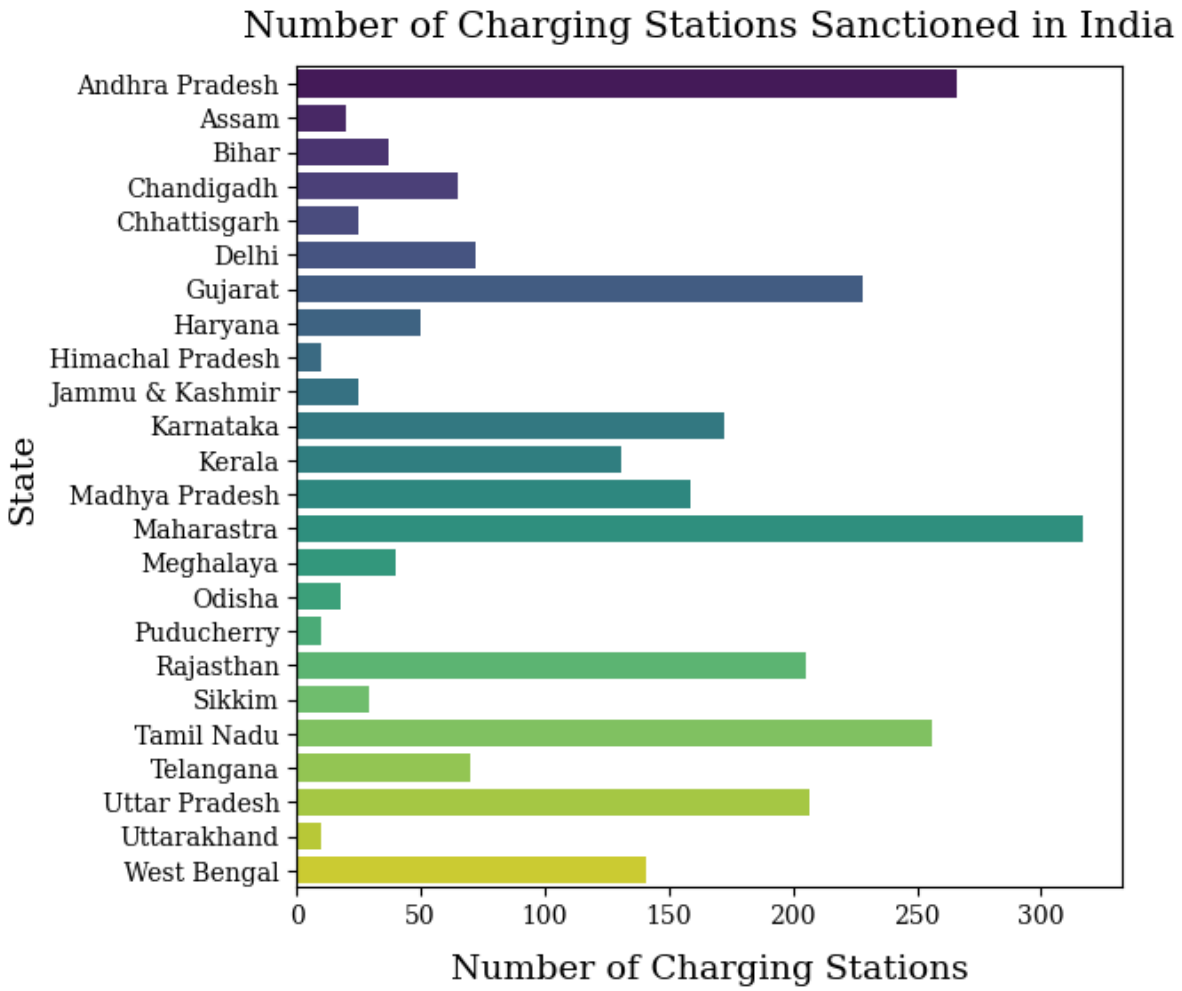
In [20]:

```
plt.figure(figsize=(6, 6))
sns.barplot(data=df1, y=df1['Region'].sort_values(ascending=True), x='4W',
palette='viridis')
plt.ylabel('State', fontsize=14, family='serif')
plt.xlabel('Number of EV: 4 Wheelers', family='serif', fontsize=14,
labelpad=10)
plt.xticks(family='serif')
plt.yticks(family='serif')
plt.title(label='Statewise Electric Vehicles (4 Wheelers) in India',
weight=200, family='serif', size=15, pad=12)
plt.show()
```



In [21]:

```
plt.figure(figsize=(6, 6))
sns.barplot(data=df1, y=df1['Region'].sort_values(ascending=True),
x='Chargers', palette='viridis')
plt.ylabel('State', fontsize=14, family='serif')
plt.xlabel('Number of Charging Stations', family='serif', fontsize=14,
labelpad=10)
plt.xticks(family='serif')
plt.yticks(family='serif')
plt.title(label='Number of Charging Stations Sanctioned in India',
weight=200, family='serif', size=15, pad=12)
plt.show()
```



In [23]:

```
plt.figure(figsize=(6,6))
sns.heatmap(data=df1.corr(), annot=True, cmap='Purples', cbar=False,
square=True, fmt='.2f', linewidths=.3)
plt.title('Correlation Matrix', family='serif', size=15, pad=12);
```

```
C:\Users\Nethranand PS\AppData\Local\Temp\ipykernel_7840\1643327926.py:2: F
utureWarning: The default value of numeric_only in DataFrame.corr is deprec
ated. In a future version, it will default to False. Select only valid colu
mns or specify the value of numeric_only to silence this warning.
  sns.heatmap(data=df1.corr(), annot=True, cmap='Purples', cbar=False, squa
re=True, fmt='.2f', linewidths=.3)
```

In [27]:

```
X = df1[['Region','2W','3W','4W', 'Bus', 'Chargers']]
```

In [30]:

```
from sklearn.preprocessing import StandardScaler, LabelEncoder
data=X
label_encoder = LabelEncoder()
data['Region'] = label_encoder.fit_transform(data['Region'])
data['2W'] = label_encoder.fit_transform(data['2W'])
data['3W'] = label_encoder.fit_transform(data['3W'])
data['4W'] = label_encoder.fit_transform(data['4W'])
data['Bus'] = label_encoder.fit_transform(data['Bus'])
data['Chargers'] = label_encoder.fit_transform(data['Chargers'])


# Scale numerical variables
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data)

# Convert back to DataFrame
data_scaled = pd.DataFrame(data_scaled, columns=data.columns)
```

In [32]:

```
kmean = KMeans(n_clusters=4, init='k-means++', random_state=90)
kmean.fit(data)
```

```
C:\Users\Nethranand PS\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.
py:870: FutureWarning: The default value of `n_init` will change from 10 to
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
C:\Users\Nethranand PS\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.
py:1382: UserWarning: KMeans is known to have a memory leak on Windows with
MKL, when there are less chunks than available threads. You can avoid it by
setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

Out[32]:

KMeans

KMeans(n_clusters=4, random_state=90)

In [33]:

```
print(kmean.labels_)
```

```
[2 3 3 3 3 1 1 1 3 0 1 2 2 2 2 0 1 0 0 0 0 2 0 0]
```

In [34]:

```
pd.Series(kmean.labels_).value_counts()
```

Out[34]:

```
0    8
2    6
3    5
1    5
dtype: int64
```

In [35]:

```
df1['clusters'] = kmean.labels_
```

In [47]:

```
from sklearn.model_selection import train_test_split
data = data.dropna()
x=data['2W']
y=data['Chargers']
X_train, X_test, y_train, y_test = train_test_split(x,y, test_size=0.2,
random_state=42)
```

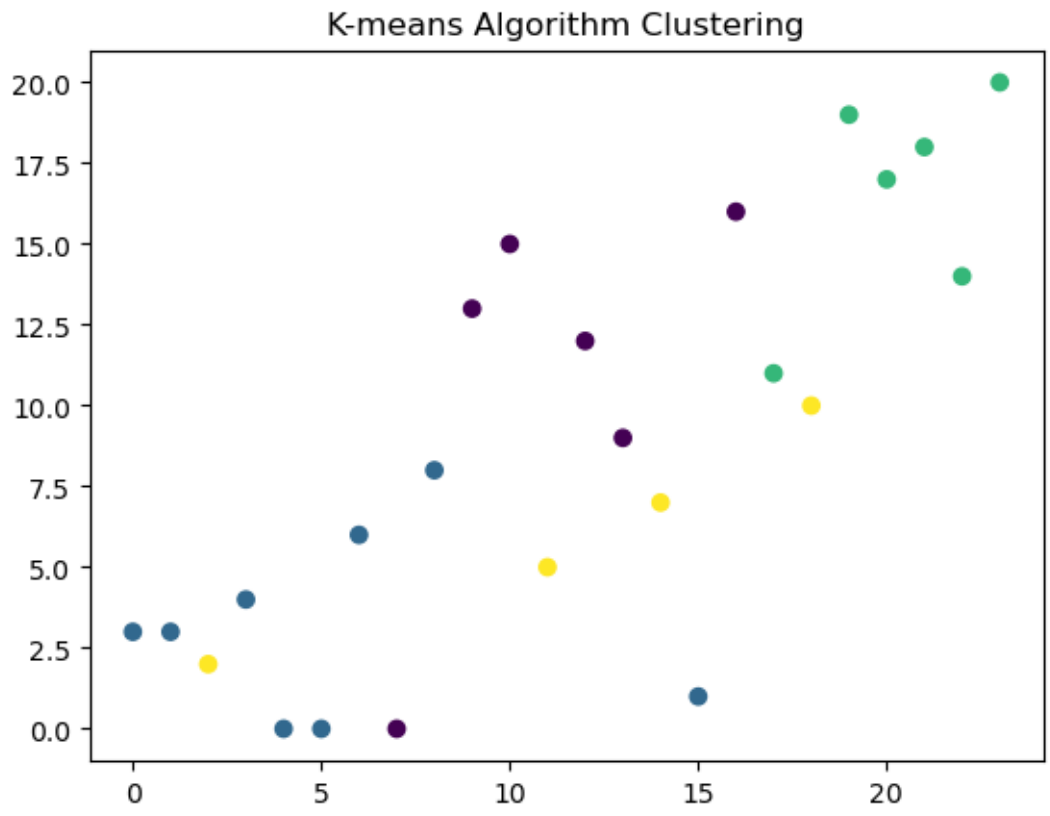
In [51]:

```
from sklearn.cluster import KMeans
kmeans_model = KMeans(n_clusters=4)
kmeans_model.fit(data)
kmeans_labels = kmeans_model.predict(data)
```

```
C:\Users\Nethranand PS\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.
py:870: FutureWarning: The default value of `n_init` will change from 10 to
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
C:\Users\Nethranand PS\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.
py:1382: UserWarning: KMeans is known to have a memory leak on Windows with
MKL, when there are less chunks than available threads. You can avoid it by
setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

In [52]:

```
plt.scatter(data['2W'], data['Chargers'], c=kmeans_labels, cmap='viridis')
plt.title('K-means Algorithm Clustering')
plt.show()
```



In [1]:

Dataset-2

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
```

In [2]:

```
df2 = pd.read_csv('ElectricCarData_Clean.csv')
df2.head()
```

Out[2]:

	Brand	Model	AccelSec	TopSpeed_KmH	Range_Km	Efficiency_WhKm	FastCharge_KmH	RapidCharge	PowerTrain	PlugType	BodyStyle	Segment	Seats	PriceEuro
0	Tesla	Model 3 Long Range Dual Motor	4.6	233	450	161	940	Yes	AWD	Type 2 CCS	Sedan	D	5	55480
1	Volkswagen	ID.3 Pure	10.0	160	270	167	250	Yes	RWD	Type 2 CCS	Hatchback	C	5	30000
2	Polestar	2	4.7	210	400	181	620	Yes	AWD	Type 2 CCS	Liftback	D	5	56440
3	BMW	iX3	6.8	180	360	206	560	Yes	RWD	Type 2 CCS	SUV	D	5	68040
4	Honda	e	9.5	145	170	168	190	Yes	RWD	Type 2 CCS	Hatchback	B	4	32997

In [3]:

```
print('DF2 Shape: ', df2.shape)
```

```
DF2 Shape:  (103, 14)
```

In [5]:

```
print(' <<< DATASET 1 ------------------------------------------------------
------')
print(df2.info())
```

```
 <<< DATASET 1 ------------------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103 entries, 0 to 102
```

```
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Brand            103 non-null    object
 1   Model            103 non-null    object
 2   AccelSec         103 non-null    float64
 3   TopSpeed_KmH     103 non-null    int64
 4   Range_Km         103 non-null    int64
 5   Efficiency_WhKm  103 non-null    int64
 6   FastCharge_KmH   103 non-null    object
 7   RapidCharge      103 non-null    object
 8   PowerTrain       103 non-null    object
 9   PlugType         103 non-null    object
 10  BodyStyle        103 non-null    object
 11  Segment          103 non-null    object
 12  Seats            103 non-null    int64
 13  PriceEuro        103 non-null    int64
dtypes: float64(1), int64(5), object(8)
memory usage: 11.4+ KB
None
```

In [9]:

```
d2 = df2.describe()
display('<<< DATASET 2 >>>', d2)
```

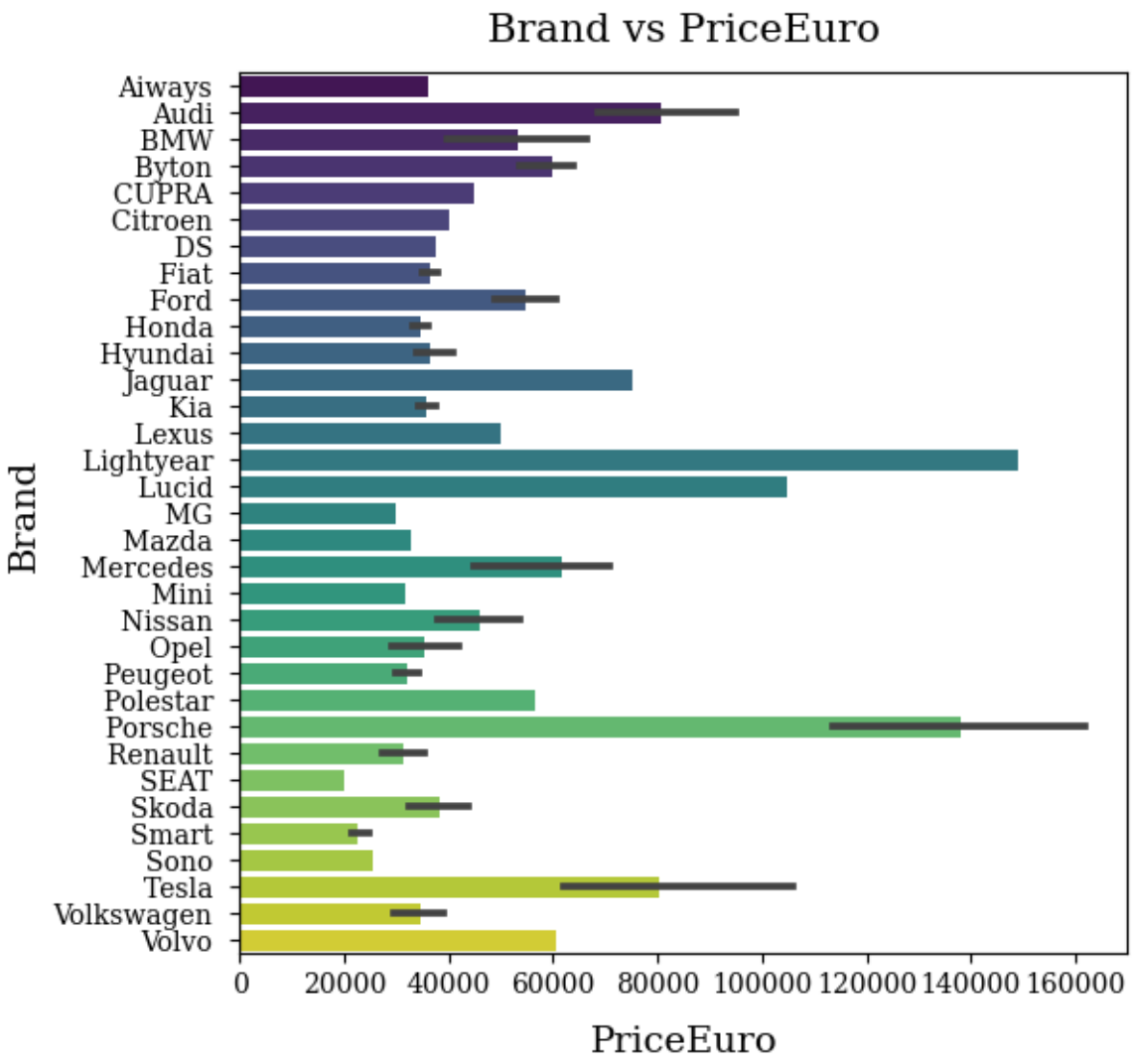
'<<< DATASET 2 >>>'

	AccelSec	TopSpeed_KmH	Range_Km	Efficiency_WhKm	Seats	PriceEuro
count	103.000000	103.000000	103.000000	103.000000	103.000000	103.000000
mean	7.396117	179.194175	338.786408	189.165049	4.883495	55811.563107
std	3.017430	43.573030	126.014444	29.566839	0.795834	34134.665280
min	2.100000	123.000000	95.000000	104.000000	2.000000	20129.000000
25%	5.100000	150.000000	250.000000	168.000000	5.000000	34429.500000
50%	7.300000	160.000000	340.000000	180.000000	5.000000	45000.000000
75%	9.000000	200.000000	400.000000	203.000000	5.000000	65000.000000
max	22.400000	410.000000	970.000000	273.000000	7.000000	215000.000000

In [10]:

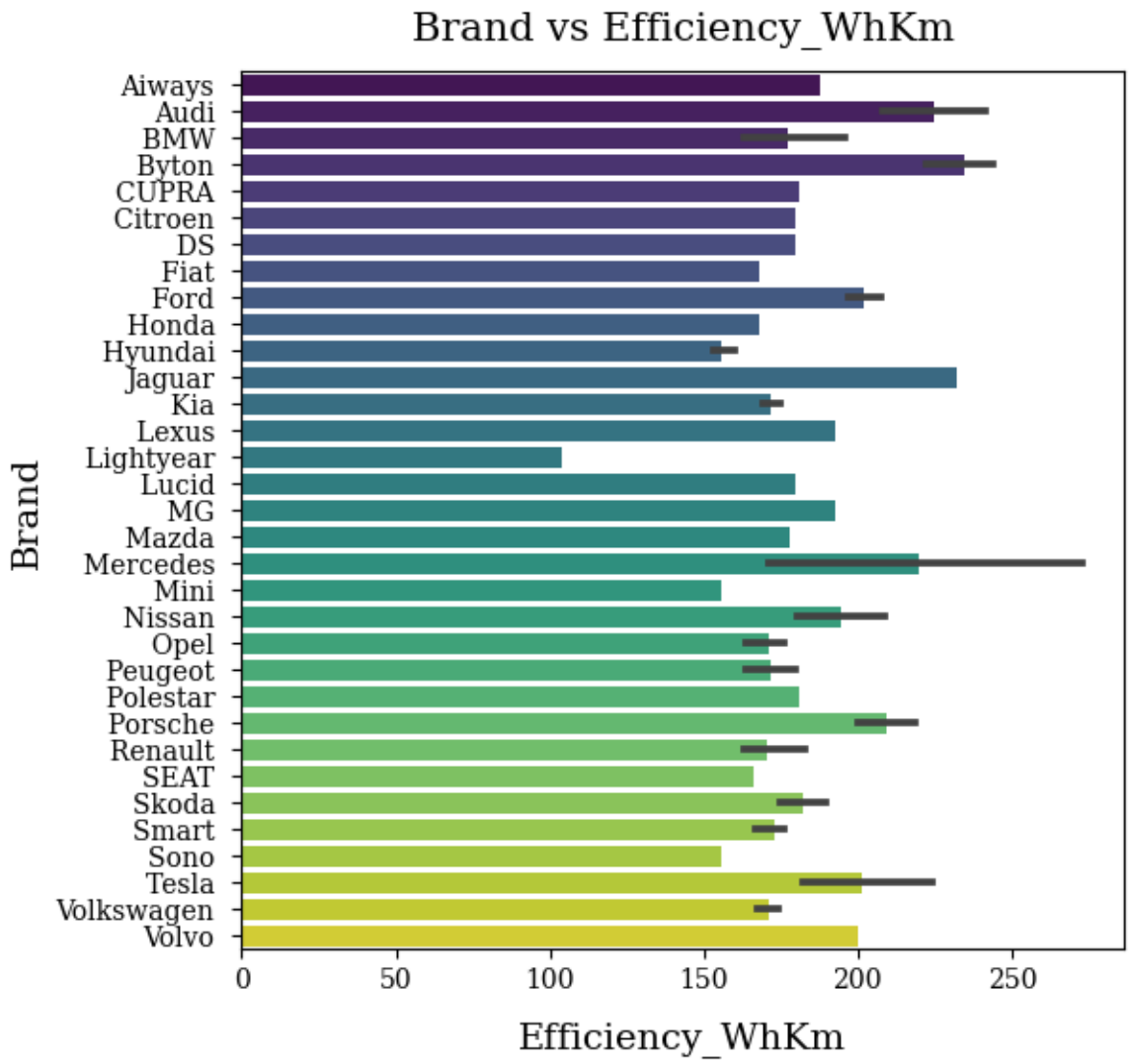
```
plt.figure(figsize=(6, 6))
sns.barplot(data=df2, y=df2['Brand'].sort_values(ascending=True),
x='PriceEuro', palette='viridis')
plt.ylabel('Brand', fontsize=14, family='serif')
plt.xlabel('PriceEuro', family='serif', fontsize=14, labelpad=10)
plt.xticks(family='serif')
```

```
plt.yticks(family='serif')
plt.title(label='Brand vs PriceEuro', weight=200, family='serif', size=15,
pad=12)
plt.show()
```



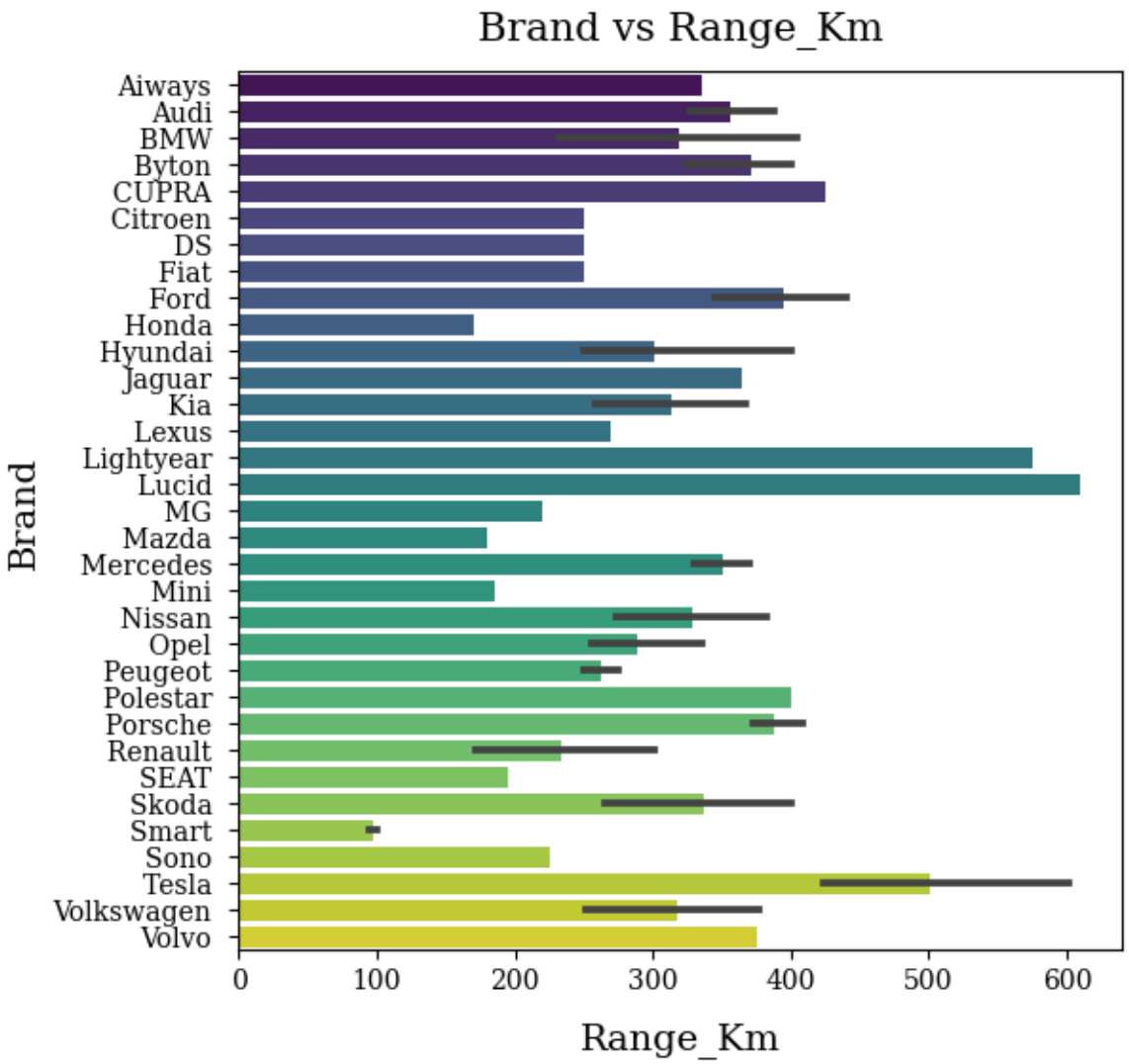
In [12]:

```
plt.figure(figsize=(6, 6))
sns.barplot(data=df2, y=df2['Brand'].sort_values(ascending=True),
x='Efficiency_WhKm', palette='viridis')
plt.ylabel('Brand', fontsize=14, family='serif')
plt.xlabel('Efficiency_WhKm', family='serif', fontsize=14, labelpad=10)
plt.xticks(family='serif')
plt.yticks(family='serif')
plt.title(label='Brand vs Efficiency_WhKm', weight=200, family='serif',
size=15, pad=12)
plt.show()
```



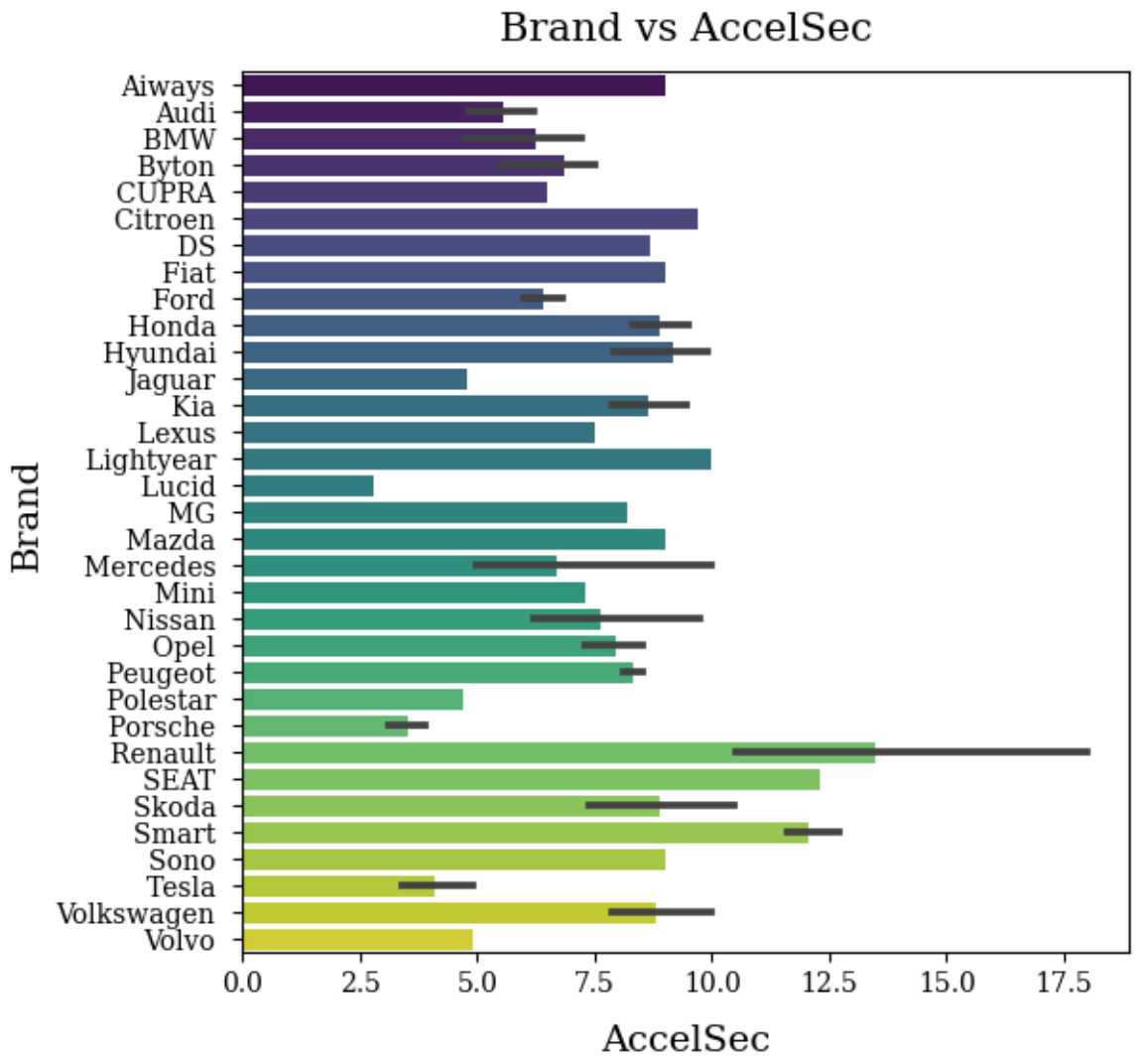
In [13]:

```
plt.figure(figsize=(6, 6))
sns.barplot(data=df2, y=df2['Brand'].sort_values(ascending=True),
x='Range_Km', palette='viridis')
plt.ylabel('Brand', fontsize=14, family='serif')
plt.xlabel('Range_Km', family='serif', fontsize=14, labelpad=10)
plt.xticks(family='serif')
plt.yticks(family='serif')
plt.title(label='Brand vs Range_Km', weight=200, family='serif', size=15,
pad=12)
plt.show()
```



In [14]:

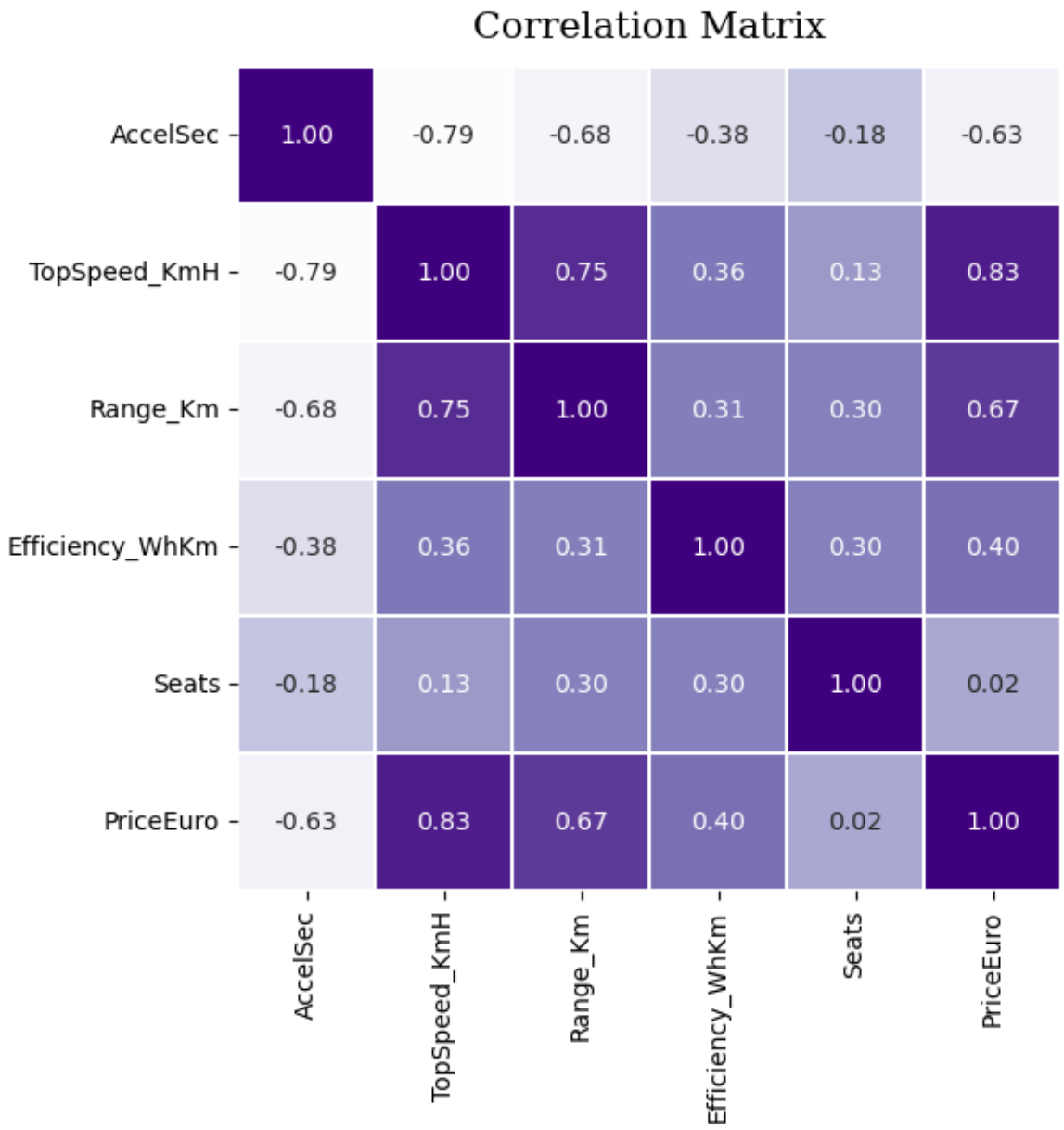
```
plt.figure(figsize=(6, 6))
sns.barplot(data=df2, y=df2['Brand'].sort_values(ascending=True),
x='AccelSec', palette='viridis')
plt.ylabel('Brand', fontsize=14, family='serif')
plt.xlabel('AccelSec', family='serif', fontsize=14, labelpad=10)
plt.xticks(family='serif')
plt.yticks(family='serif')
plt.title(label='Brand vs AccelSec', weight=200, family='serif', size=15,
pad=12)
plt.show()
```



In [15]:

```
plt.figure(figsize=(6,6))
sns.heatmap(data=df2.corr(), annot=True, cmap='Purples', cbar=False,
square=True, fmt='.2f', linewidths=.3)
plt.title('Correlation Matrix', family='serif', size=15, pad=12);
```

```
C:\Users\Nethranand PS\AppData\Local\Temp\ipykernel_5136\3985166321.py:2: F
utureWarning: The default value of numeric_only in DataFrame.corr is deprec
ated. In a future version, it will default to False. Select only valid colu
mns or specify the value of numeric_only to silence this warning.
  sns.heatmap(data=df2.corr(), annot=True, cmap='Purples', cbar=False, squa
re=True, fmt='.2f', linewidths=.3)
```


Correlation Matrix
AccelSec
TopSpeed_KmH
Range_Km
Efficiency_WhKm
Seats
PriceEuro
1.00 -0.79 -0.68 -0.38 -0.18 -0.63
-0.79 1.00 0.75 0.36 0.13 0.83
-0.68 0.75 1.00 0.31 0.30 0.67
-0.38 0.36 0.31 1.00 0.30 0.40
-0.18 0.13 0.30 0.30 1.00 0.02
-0.63 0.83 0.67 0.40 0.02 1.00
AccelSec
TopSpeed_KmH
Range_Km
Efficiency_WhKm
Seats
PriceEuro