Electric vehicle market in India

Market Segmentation

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I. Fermi Estimation (Breakdown of Problem Statement)

a. Class of vehicle
b. Battery quality
c. Safety
d. Price of vehicle
e. Power of vehicle
f. Range(mileage) of vehicle

II. Data Sources

a. https://www.kaggle.com/
   i. Kaggle -> Vehicle dataset
b. https://www.business-standard.com/
c. businesstoday.in

III. Data pre-processing (steps and libraries used)

a. Libraries Used for Data Preprocessing:
   i. NumPy (import NumPy as np)
   ii. Pandas (import pandas as pd)
   iii. Matplotlib (import matplotlib.pyplot as plt)
   iv. Seaborn (import seaborn as sns)
b. Steps:
   i. Import libraries
   ii. Import dataset
   iii. Checking null values
   iv. Filling out null values by mean and mode

```python
[43] import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
```

```python
[32] x = pd.read_csv('Car details v3.csv')
```

```python
[33] x.head()
```

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	torque	seats
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	23.4 kmpl	1248 CC	74 bhp	190Nm@ 2000rpm	5.0
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	21.14 kmpl	1498 CC	103.52 bhp	250Nm@ 1500-2500rpm	5.0
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	17.7 kmpl	1497 CC	78 bhp	12.7@ 2,700(kgm@ rpm)	5.0
3	Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	23.0 kmpl	1396 CC	90 bhp	22.4 kgm at 1750-2750rpm	5.0
4	Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	16.1 kmpl	1298 CC	88.2 bhp	11.5@ 4,500(kgm@ rpm)	5.0

```python
[34] x.describe()
```

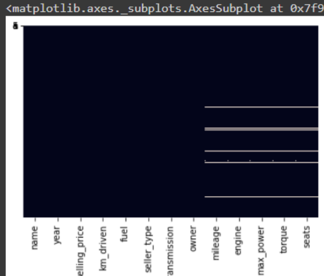
	year	selling_price	km_driven	seats
count	8128.000000	8.128000e+03	8.128000e+03	7907.000000
mean	2013.804011	6.382718e+05	6.981951e+04	5.416719
std	4.044249	8.062534e+05	5.655055e+04	0.959588
min	1983.000000	2.999900e+04	1.000000e+00	2.000000
25%	2011.000000	2.549990e+05	3.500000e+04	5.000000
50%	2015.000000	4.500000e+05	6.000000e+04	5.000000
75%	2017.000000	6.750000e+05	9.800000e+04	5.000000
max	2020.000000	1.000000e+07	2.360457e+06	14.000000

```python
[35] x.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8128 entries, 0 to 8127
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   name           8128 non-null   object
 1   year           8128 non-null   int64
 2   selling_price  8128 non-null   int64
 3   km_driven      8128 non-null   int64
 4   fuel           8128 non-null   object
 5   seller_type    8128 non-null   object
 6   transmission   8128 non-null   object
 7   owner          8128 non-null   object
 8   mileage        7907 non-null   object
 9   engine         7907 non-null   object
 10  max_power      7913 non-null   object
 11  torque         7906 non-null   object
 12  seats          7907 non-null   float64
dtypes: float64(1), int64(3), object(9)
memory usage: 825.6+ KB
```

```python
[36] sns.heatmap(x.isna(), yticklabels='False',cbar = False)

     # heatmap of null values in train data
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f90def941d0>
```




```python
[37] x.isna().any().value_counts()#number of columns having null values in data
```

```
False    8
True     5
dtype: int64
```

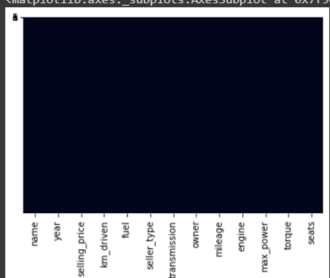
```python
[38] for i in x:
       if x[i].isna().any():
         print(i,  x[i].isna().value_counts()[1],x[i].dtype)

     # shows column name , null values in it, and data type of train
```

```
mileage 221 object
engine 221 object
max_power 215 object
torque 222 object
seats 221 float64
```

```
[39] for i in x:
       if x[i].any() :
         if x[i].dtype == 'float64':
           x[i].fillna(value=x[i].mean(),inplace=True)

         else:
           x[i].fillna(value=x[i].mode()[0],inplace=True)

     # fills null values
     # if column is having float data type then it will fill null values by geting mean of column
     # and if column in having object data type then it will fill out by taking mode
```

```
[40] x.info()

     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 8128 entries, 0 to 8127
     Data columns (total 13 columns):
      #   Column         Non-Null Count  Dtype
     ---  ------         --------------  -----
      0   name           8128 non-null   object
      1   year           8128 non-null   int64
      2   selling_price  8128 non-null   int64
      3   km_driven      8128 non-null   int64
      4   fuel           8128 non-null   object
      5   seller_type    8128 non-null   object
      6   transmission   8128 non-null   object
      7   owner          8128 non-null   object
      8   mileage        8128 non-null   object
      9   engine         8128 non-null   object
      10  max_power      8128 non-null   object
      11  torque         8128 non-null   object
      12  seats          8128 non-null   float64
     dtypes: float64(1), int64(3), object(9)
     memory usage: 825.6+ KB
```

```
[41] sns.heatmap(x.isna(), yticklabels='False',cbar = False)

     # heatmap of null values in train data

     <matplotlib.axes._subplots.AxesSubplot at 0x7f90cd16b0d0>
```



IV. Segment extraction

a. For this project I have used many ML techniques as:

i. Boxplot: Boxplots are a measure of how well distributed the data in a data set is. It divides the data set into three quartiles. This graph represents the minimum, maximum, median, first quartile and third quartile in the data set.

ii. Pairplot: To plot multiple pairwise bivariate distributions in a dataset, you can use the pairplot() function. This shows the relationship for (n, 2) combination of variable in a DataFrame as a matrix of plots and the diagonal plots are the univariate plots.

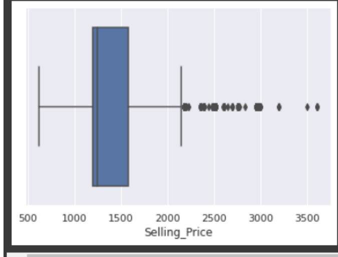
iii. Correlation: Correlation Matrix is basically a covariance matrix. Also known as the auto-covariance matrix, dispersion matrix, variance matrix, or variance-covariance matrix. It is a matrix in which i-j position defines the correlation between the ith and jth parameter of the given data-set.

```
x['engine']=x['engine'].replace(' CC','',regex=True).str.replace(',', '')
```

```
x['engine'] = pd.to_numeric(x['engine'])
```

```
sns.boxplot(x['engine'])
sns.set(style="darkgrid")

plt.xlabel('Selling_Price')
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional ar
  FutureWarning
```

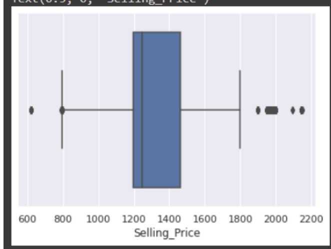



```
Q1 = x['engine'].quantile(0.25)
Q3 = x['engine'].quantile(0.75)
IQR = Q3 - Q1

upper_limit = Q3 + 1.5 * IQR
lower_limit = Q1 - 1.5 * IQR

x[x['engine']> upper_limit]
x[x['engine']< lower_limit]

x = x[x['engine'] < upper_limit]
x.shape
```

```
(6945, 13)
```

```
sns.boxplot(x['engine'])
plt.xlabel('Selling_Price')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argume
  FutureWarning
Text(0.5, 0, 'Selling_Price')
```



```
x['mileage']=x['mileage'].replace(' km/kg','',regex=True).str.replace(',', '')
x['mileage']=x['mileage'].replace(' kmpl','',regex=True).str.replace(',', '')

x['mileage'] = pd.to_numeric(x['mileage'])
```

```
sns.boxplot(x['mileage'])
plt.xlabel('Selling_Price')
```

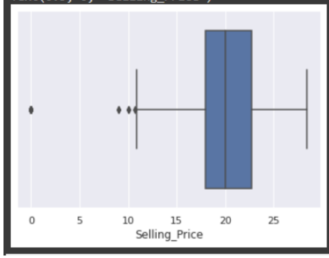
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional a
  FutureWarning
Text(0.5, 0, 'Selling_Price')
```


```
Q1 = x['mileage'].quantile(0.25)
Q3 = x['mileage'].quantile(0.75)
IQR = Q3 - Q1

upper_limit = Q3 + 1.5 * IQR
lower_limit = Q1 - 1.5 * IQR

x[x['mileage']> upper_limit]
x[x['mileage']< lower_limit]

x = x[x['mileage'] < upper_limit]
x.shape
```

```
(6936, 13)
```

```
sns.boxplot(x['mileage'])
plt.xlabel('Selling_Price')
```

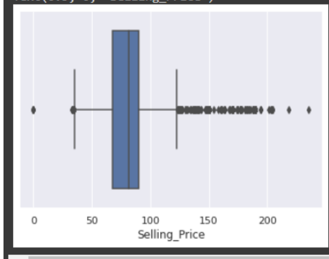
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional arg
  FutureWarning
Text(0.5, 0, 'Selling_Price')
```



```
x[ max_power ]=x[ max_power ].replace( bhp , ,regex=True).str.replace( , , )
x['max_power'] = pd.to_numeric(x['max_power'])
```

```
sns.boxplot(x['max_power'])
plt.xlabel('Selling_Price')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional arg
  FutureWarning
Text(0.5, 0, 'Selling_Price')
```

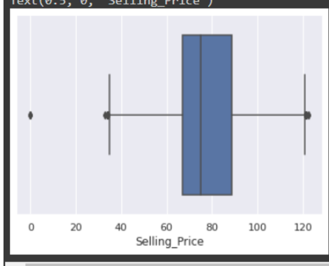



```
Q1 = x['max_power'].quantile(0.25)
Q3 = x['max_power'].quantile(0.75)
IQR = Q3 - Q1

upper_limit = Q3 + 1.5 * IQR
lower_limit = Q1 - 1.5 * IQR

x[x['max_power']> upper_limit]
x[x['max_power']< lower_limit]

x = x[x['max_power'] < upper_limit]
x.shape
```

```
(6322, 13)
```

```
sns.boxplot(x['max_power'])
plt.xlabel('Selling_Price')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional ar
  FutureWarning
Text(0.5, 0, 'Selling_Price')
```



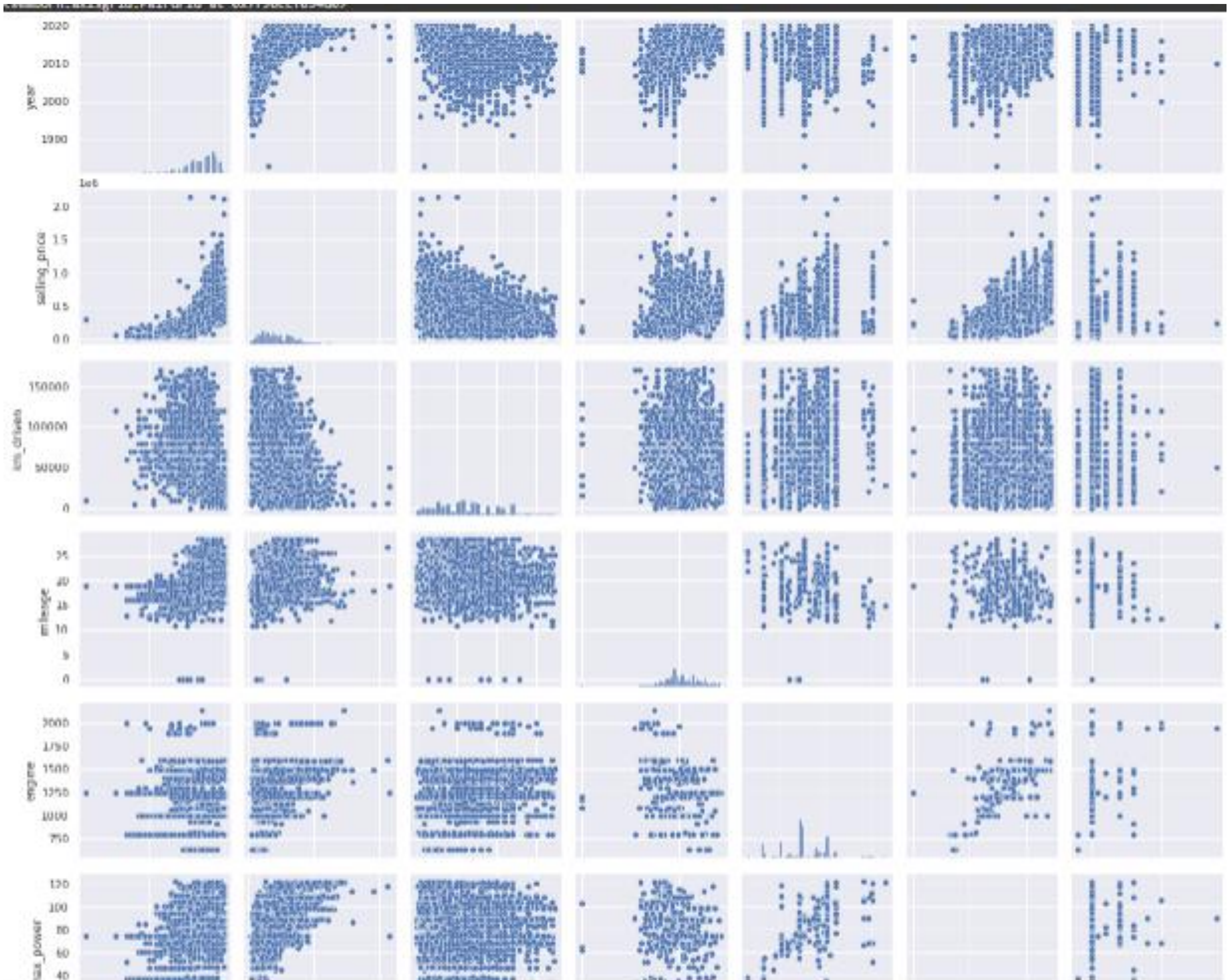

```
sns.boxplot(x['km_driven'])
plt.xlabel('Selling_Price')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional arg
  FutureWarning
Text(0.5, 0, 'Selling_Price')
```


```
Q1 = x['km_driven'].quantile(0.25)
Q3 = x['km_driven'].quantile(0.75)
IQR = Q3 - Q1

upper_limit = Q3 + 1.5 * IQR
lower_limit = Q1 - 1.5 * IQR

x[x['km_driven']> upper_limit]
x[x['km_driven']< lower_limit]

x = x[x['km_driven'] < upper_limit]
x.shape
```

```
(6189, 13)
```

```
sns.pairplot(x)
```

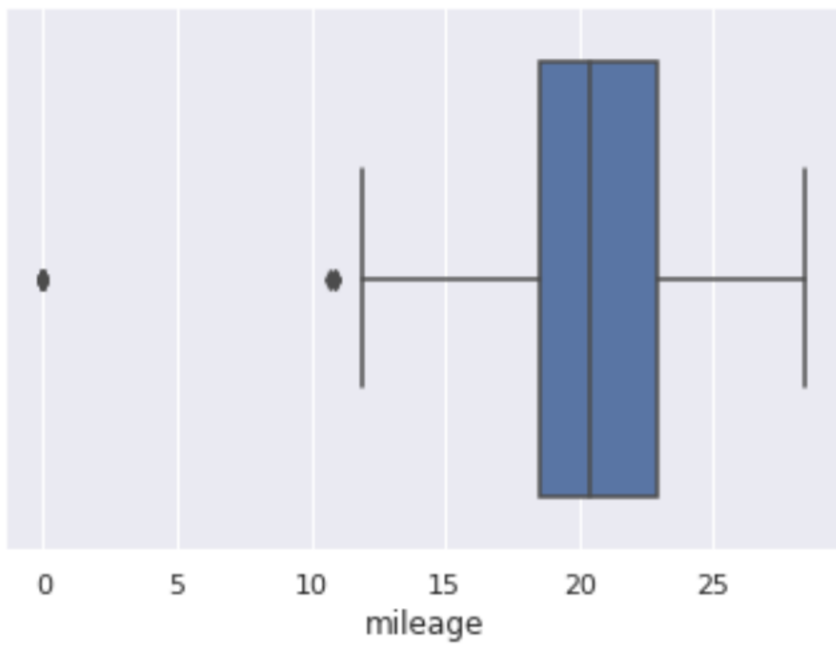



```
correlation = x.corr()
correlation
```

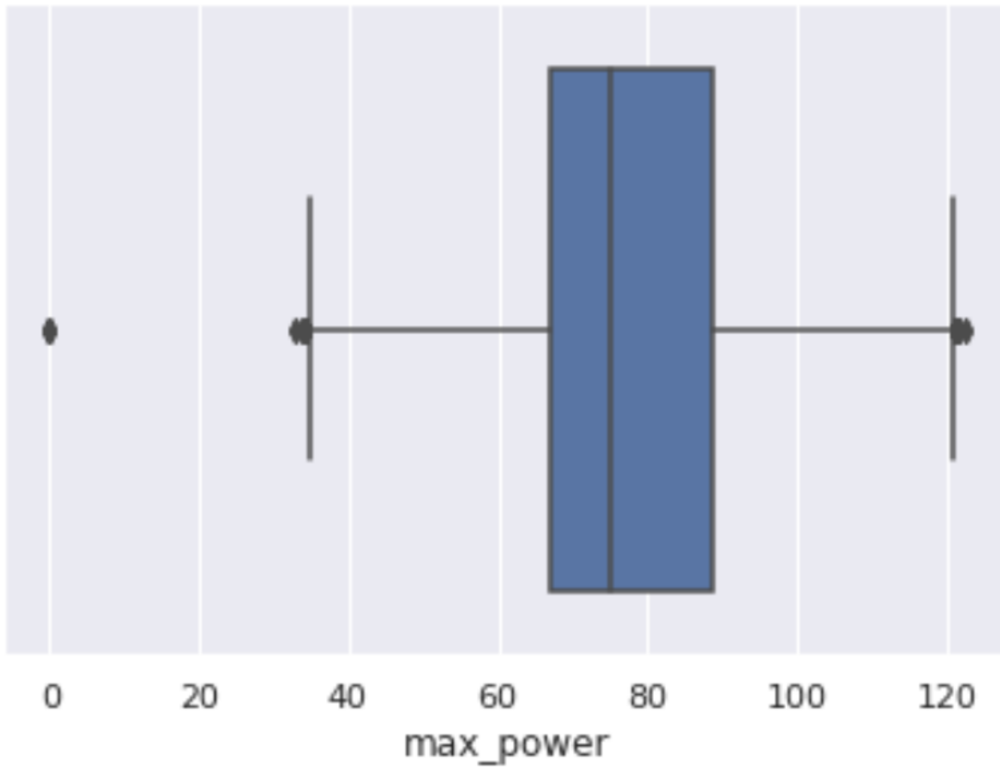
	year	selling_price	km_driven	mileage	engine	max_power	seats
year	1.000000	0.708742	-0.488131	0.396822	0.085382	0.296652	0.116750
selling_price	0.708742	1.000000	-0.380615	0.255069	0.408757	0.601289	0.188563
km_driven	-0.488131	-0.380615	1.000000	-0.074276	0.184925	-0.046016	0.049573
mileage	0.396822	0.255069	-0.074276	1.000000	-0.154489	-0.114272	-0.117702
engine	0.085382	0.408757	0.184925	-0.154489	1.000000	0.787895	0.227209
max_power	0.296652	0.601289	-0.046016	-0.114272	0.787895	1.000000	0.170921
seats	0.116750	0.188563	0.049573	-0.117702	0.227209	0.170921	1.000000

V. Profiling and describing potential segment

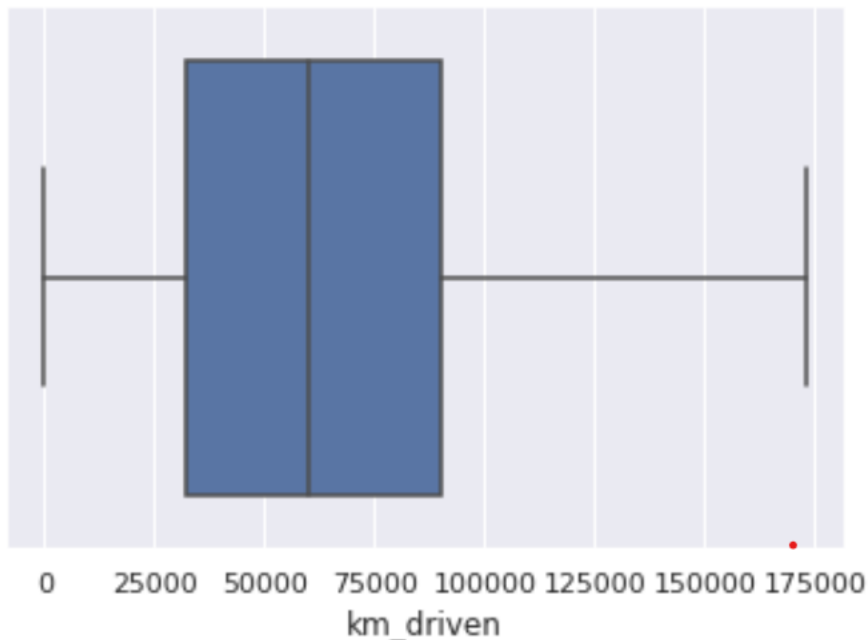
a. According to mileage data the mileage of the vehicle should be around 20. This data shows us that 50% of vehicles has mileage from 17 to 23 kmpl. So we should also design our vehicle in such a way that our vehicle should give same experience as an conventional vehicle,



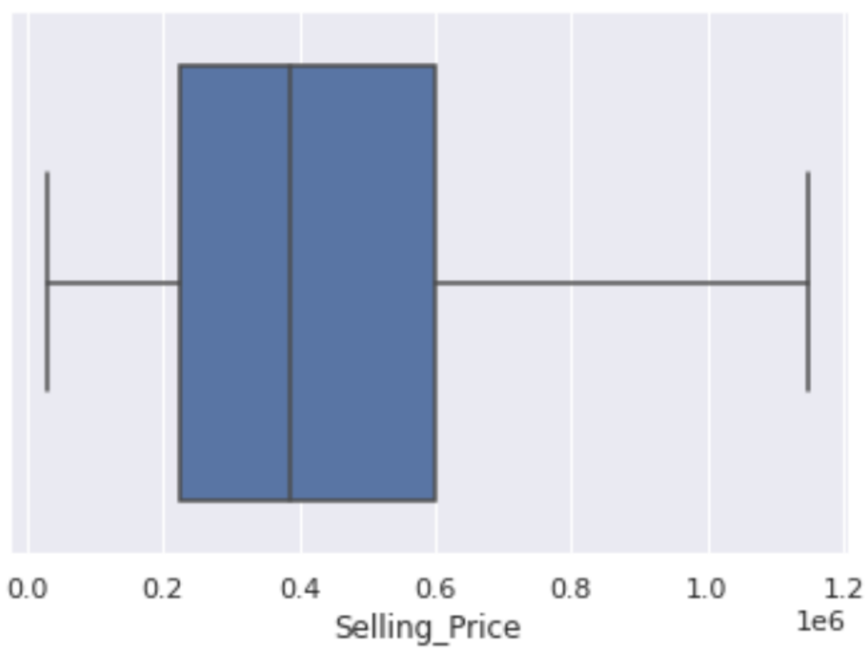
b. According to power: design of vehicle should be fullfill basic power need of a user and power of conventional vehicle is: range(67bhp – 90 bhp), median 76bhp.



c. According to KM a vehicle can drive across his lifespan: it should averagely last for around 61000 km’s and 50% of vehicles last in range of (29000 to 90000km’s)

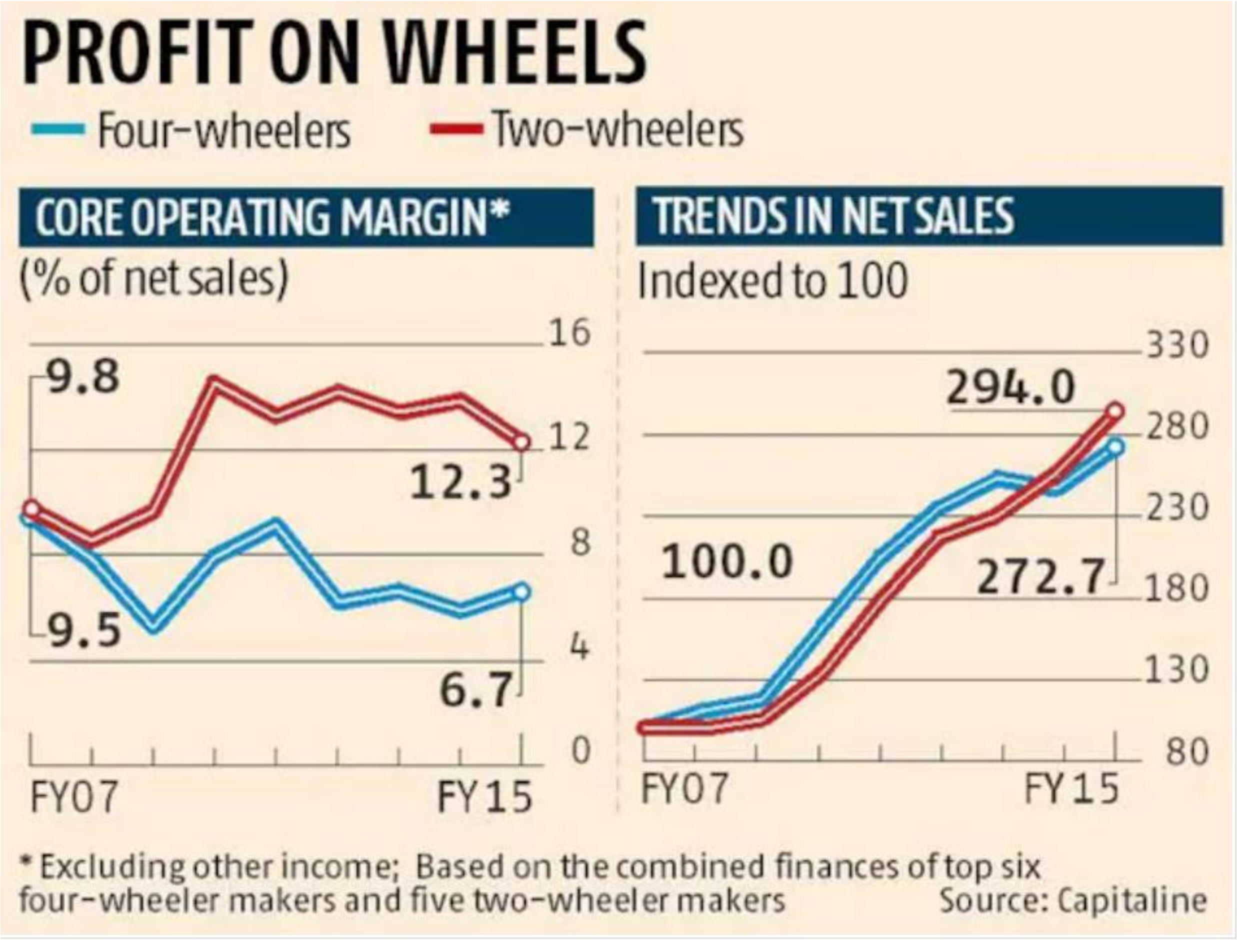


d. According to selling price : the price of product should be around 4lakhs according to data,



VI. Selection of target segment

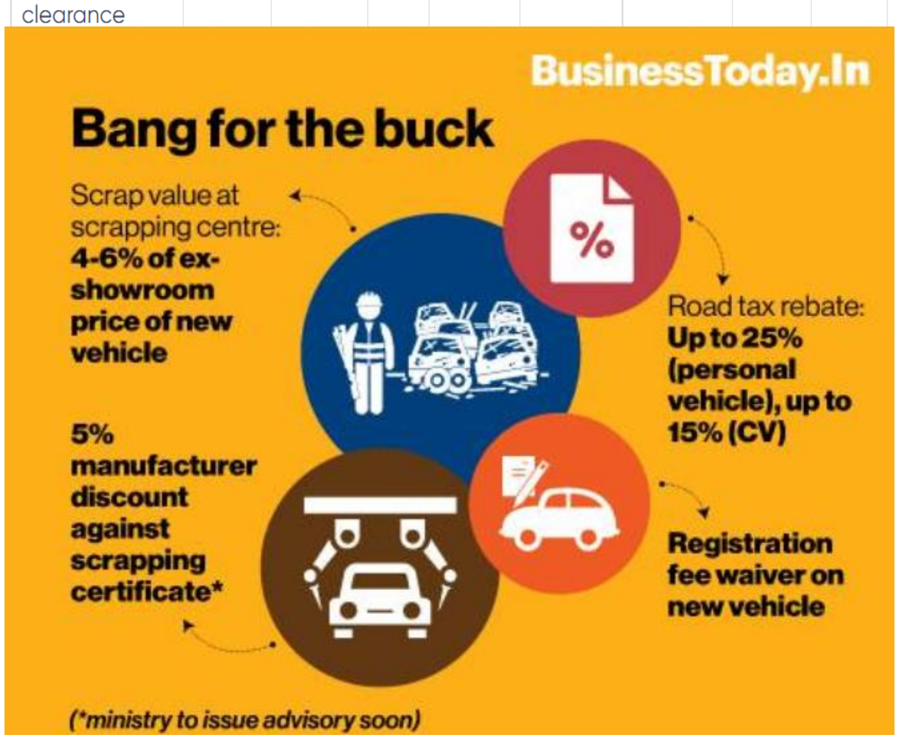
a. According to this given data you can clearly see that 2 wheelers has very high margins compare to 4 wheelers and its sales have crossed 4 wheelers.



b. Bad government policies for 4 wheelers.

i. Very high taxes: it has very high taxes for example if you want to buy fortuner that you have to give 55.3 of tax i.e

Segment	Excise	*Nccd +auto cess	VAT	*Road tax	*Motor vehicle tax	Total	CGST	SGST	TOTAL	Difference
Small Cars <1200cc	12.50%	1.1%	14%	State based	State based	28% (approx)	9%	9%	18%	10%
Mid-SizeCars from 1200cc to 1500cc	24%	1.1%	14%	State based	State based	39%	9%	9%	18%	21%
Luxury Cars>1500cc	27%	1.1%	14%	State based	State based	42%	14%	14%	28%	14%
SUV's >1500cc, >170mm ground clearance	30%	1.1%	14%	State based	State based	45%	14%	14%	28%	17%



VII. Customizing the marketing mix

a. According to data and our analysis we have come up to the conclusion that our product should target middle class people of out population. Because majority of our drivers are riders, and our vehicle should have two categories: bikes and scooters.

VIII. GITHUB link:

a. https://github.com/UjasAdepal/Electric-vehicle-market-in-India/blob/8b0be73fda3aa3241dc41e21cf24262f6b41b465/Electric_vehicle_market_in_India.ipynb