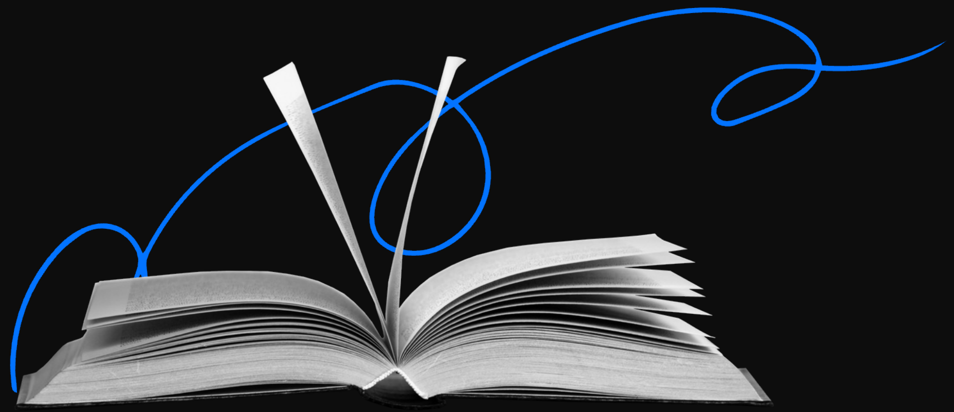
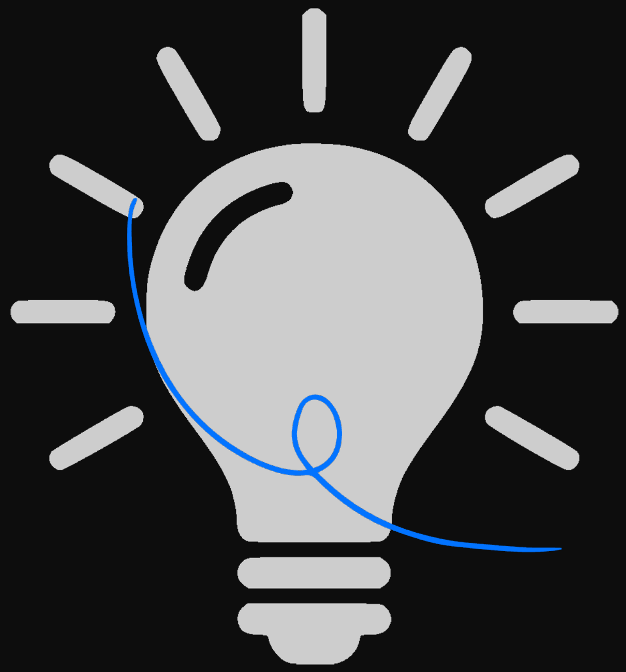
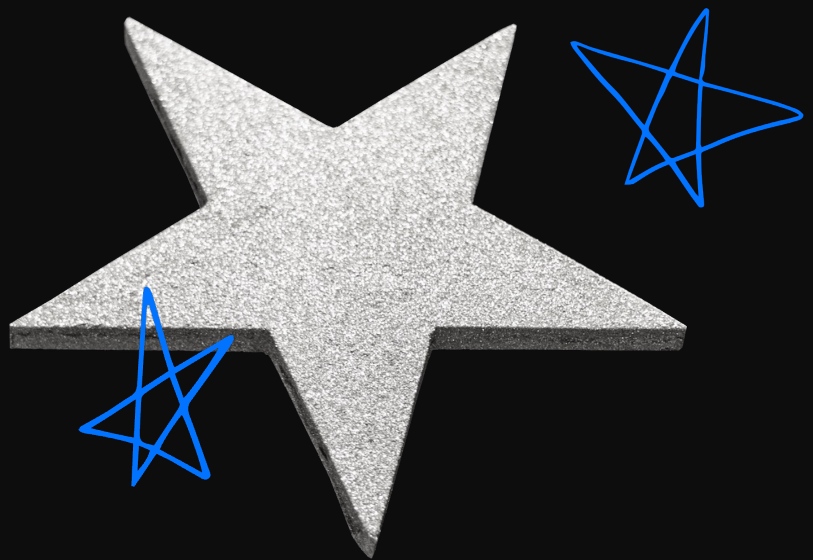
THE RISE OF ELECTRIC VEHICLES

AGENDA

Topics Covered







DATASET

- Electric Vehicle Population

INSIGHTS

- Data Analysis and Presentation

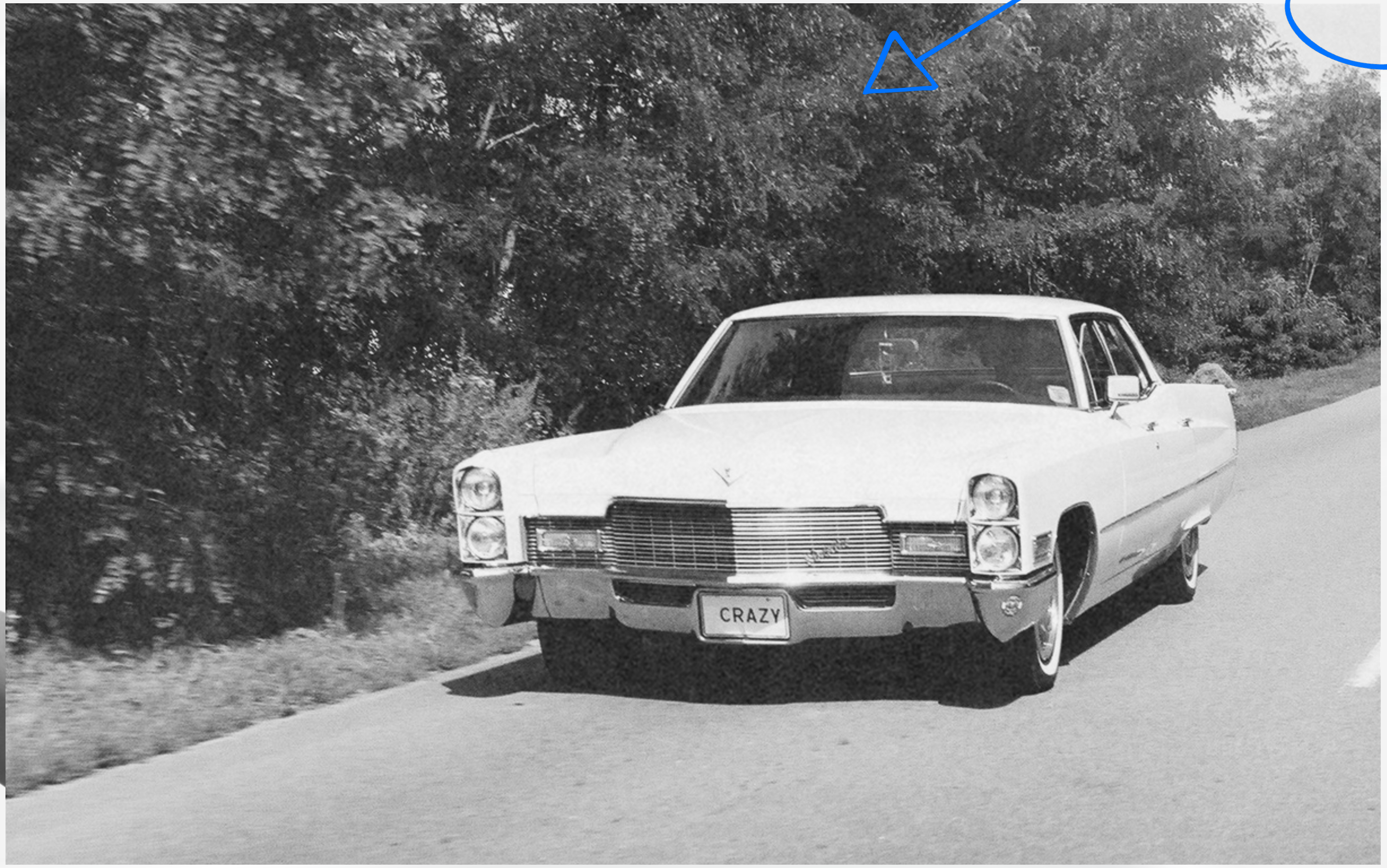
PREDICTIVE

- Linear Regression
- Multiple Regression
- Optimization

RECOMMEND

- Seven steps for A Successful EV GTM MODEL

PROBLEM STATEMENT



THE RISE OF EVs

How to Navigate the Market in WA?

DATASET

EV POPULATION DATA

DATASET

- *Data.gov.wa (Washington State Open Data Portal)*
- *mydf.shape:* (150482, 17)
- *mydf.keys():* 'VIN (1-10)', 'County', 'City', 'State', 'Postal Code', 'Model Year', 'Make', 'Model', 'Electric Vehicle Type', 'Clean Alternative Fuel Vehicle (CAFV) Eligibility', 'Electric Range', 'Base MSRP', 'Legislative District', 'DOL Vehicle ID', 'Vehicle Location', 'Electric Utility', '2020 Census Tract'

CLEAN DATASET

(1) EDF=mydf.dropna()

(2) EDF_ZeroRange=EDF[EDF['Electric Range']==0]

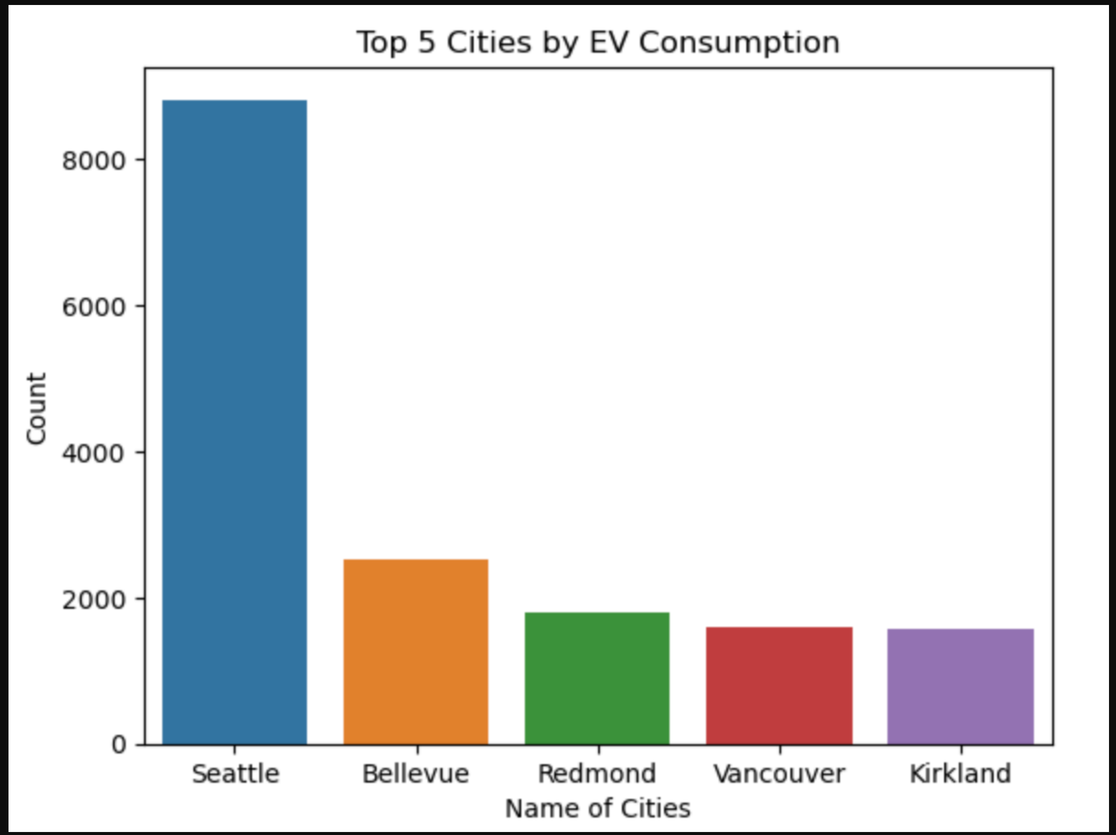
(3) EDF_ActualData = EDF[EDF['Electric Range']>0]

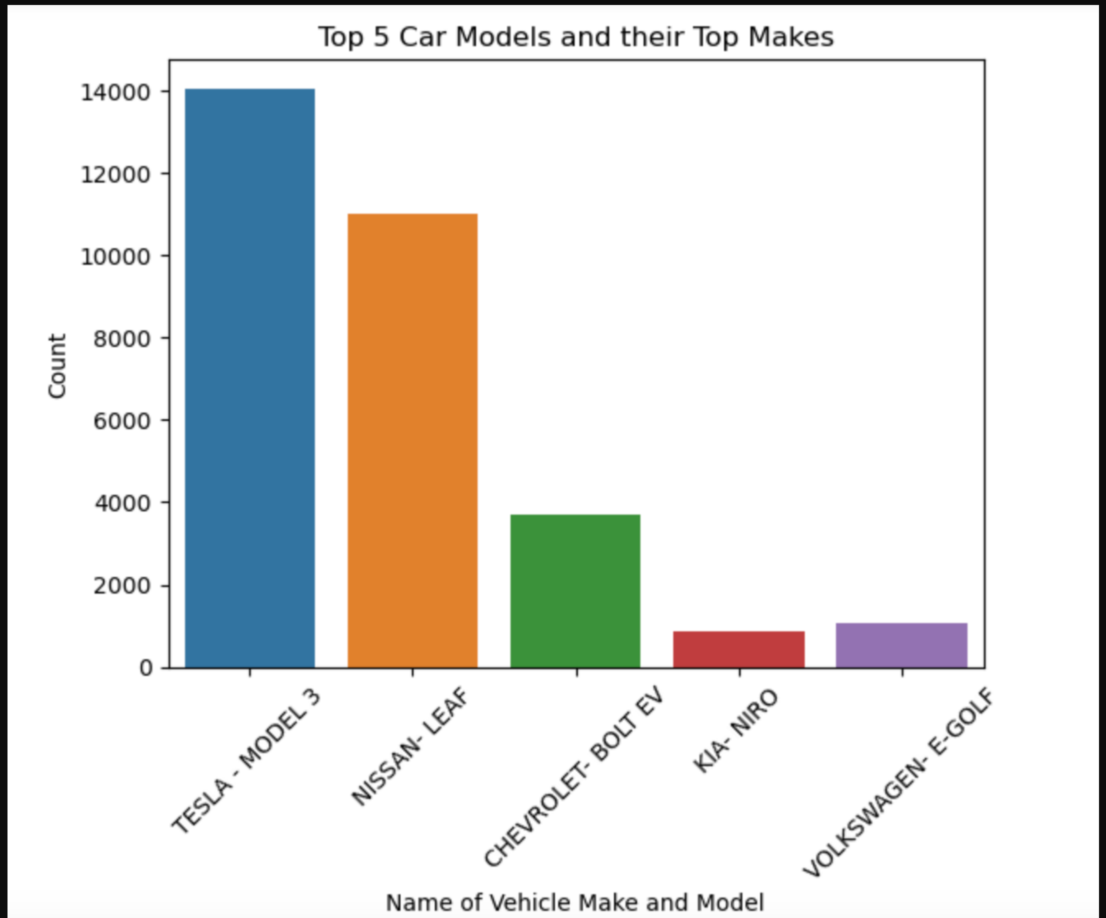
(4) EV_df=EDF_ActualData[EDF_ActualData['Electric Vehicle Type']=='Battery Electric Vehicle (BEV)']

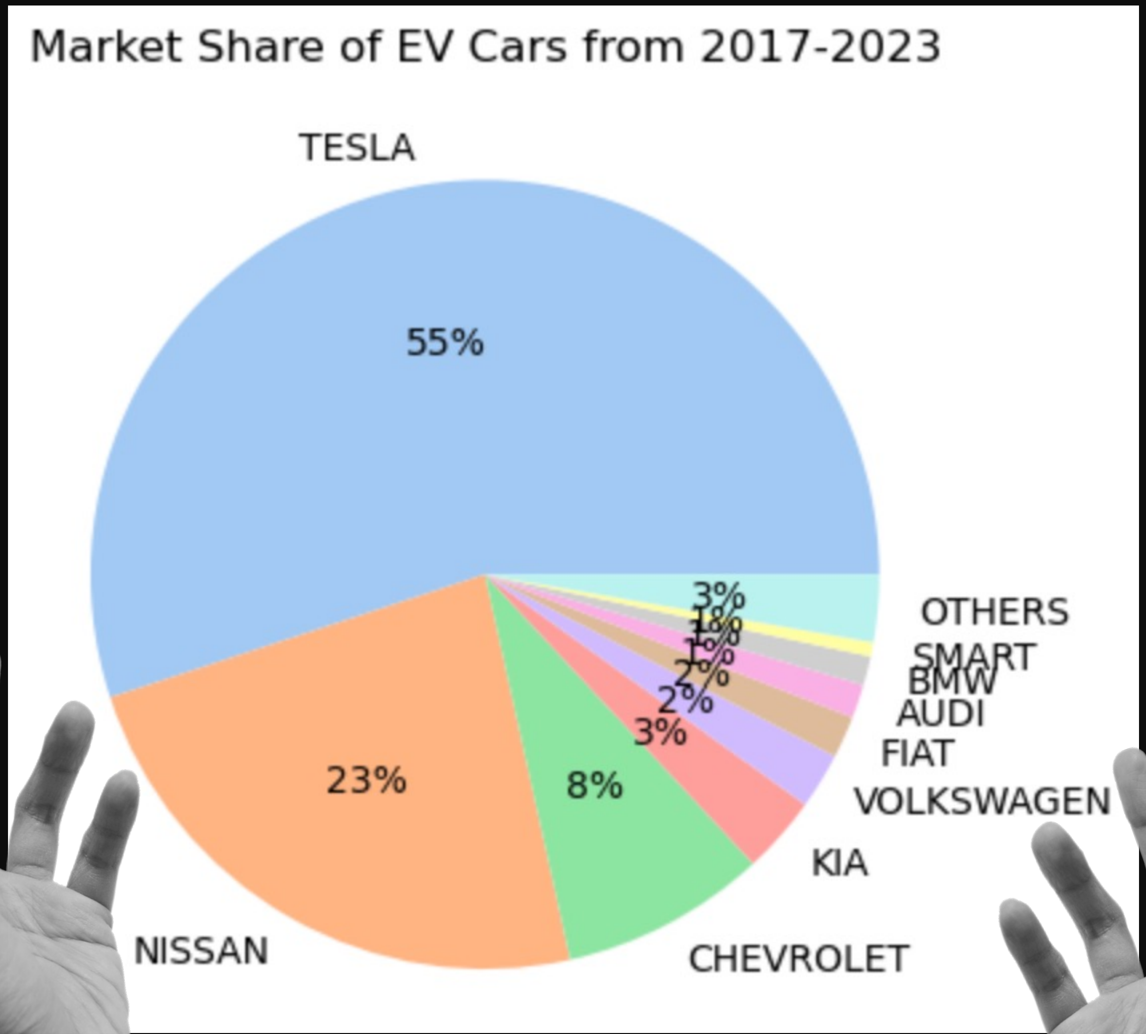
(5) EV_df.shape

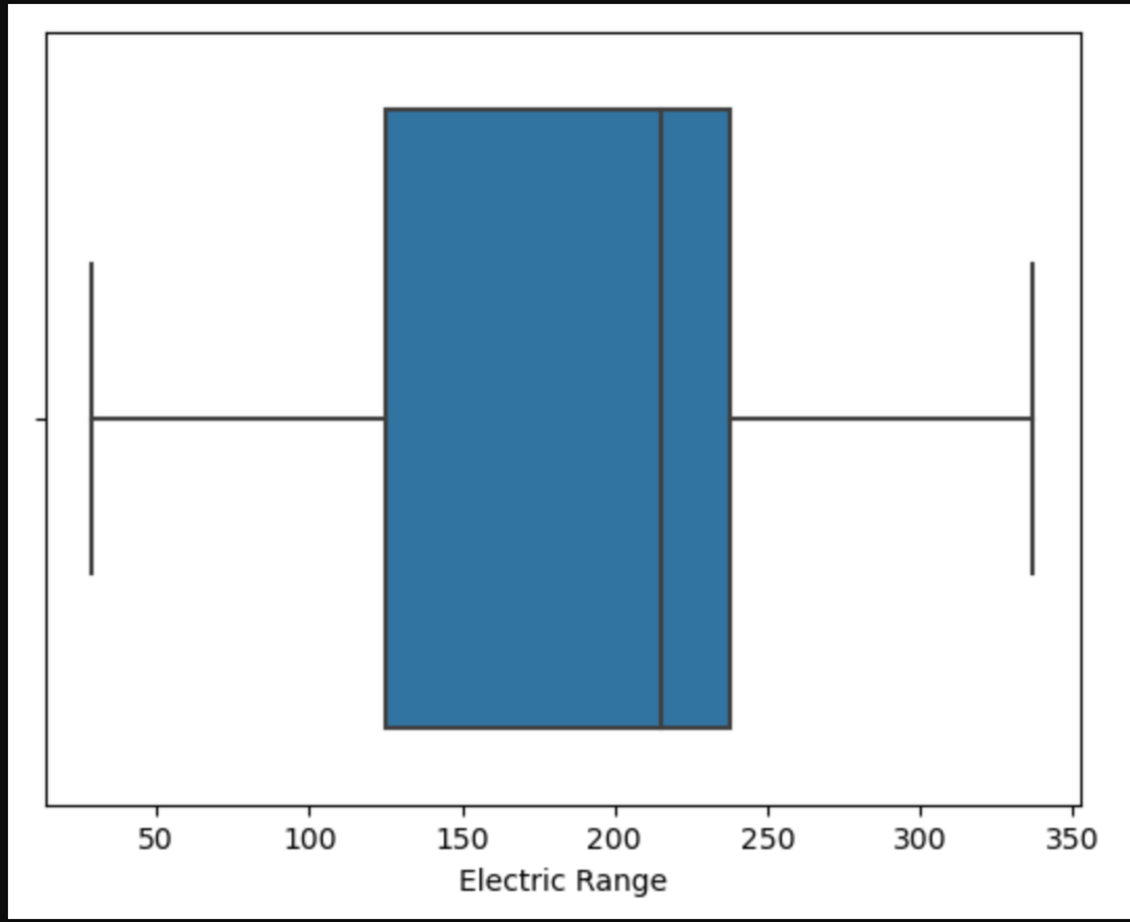
(6) EV_df[['Electric Vehicle Type']].value_counts()

DATA VISUALIZATIONS









TESLA HOLDS 55%

EV_Tesla=EV_df[EV_df['Make']=='TESLA']
EV_Tesla['Model'].value_counts()

```
MODEL 3      14056
MODEL S       6142
MODEL X       3303
MODEL Y       2272
ROADSTER        46
Name: Model, dtype: int64
```

NISSAN LEAF
2nd!

EV_Nissan=EV_df[EV_df['Make']=='NISSAN']
EV_Nissan['Model'].value_counts()

```
LEAF     10989
Name: Model, dtype: int64
```

NIRO FALLS SHORT

EV_Kia=EV_df[EV_df['Make']=='KIA']
EV_Kia['Model'].value_counts()

```
NIRO       848
SOUL       420
SOUL EV    225
Name: Model, dtype: int64
```

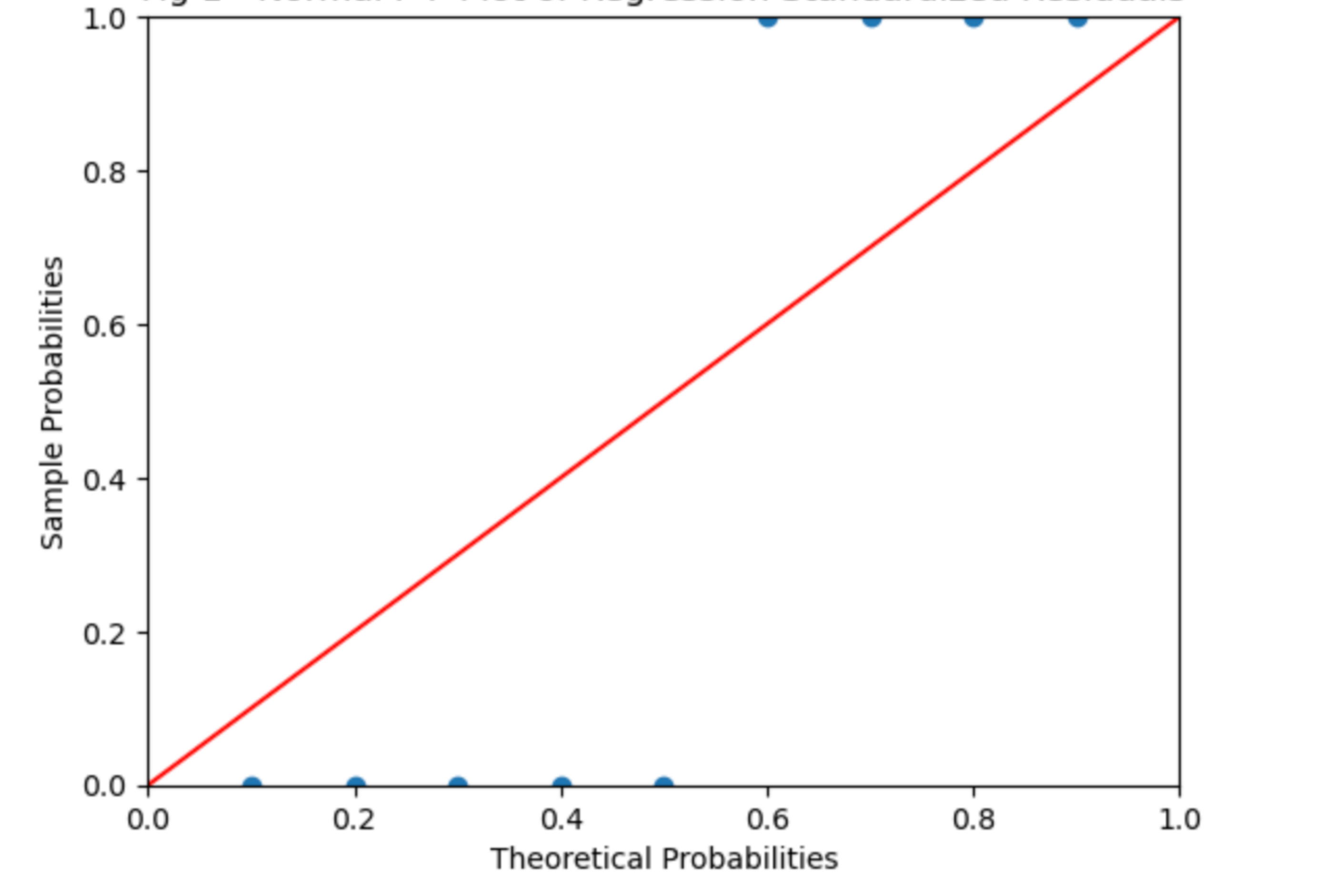
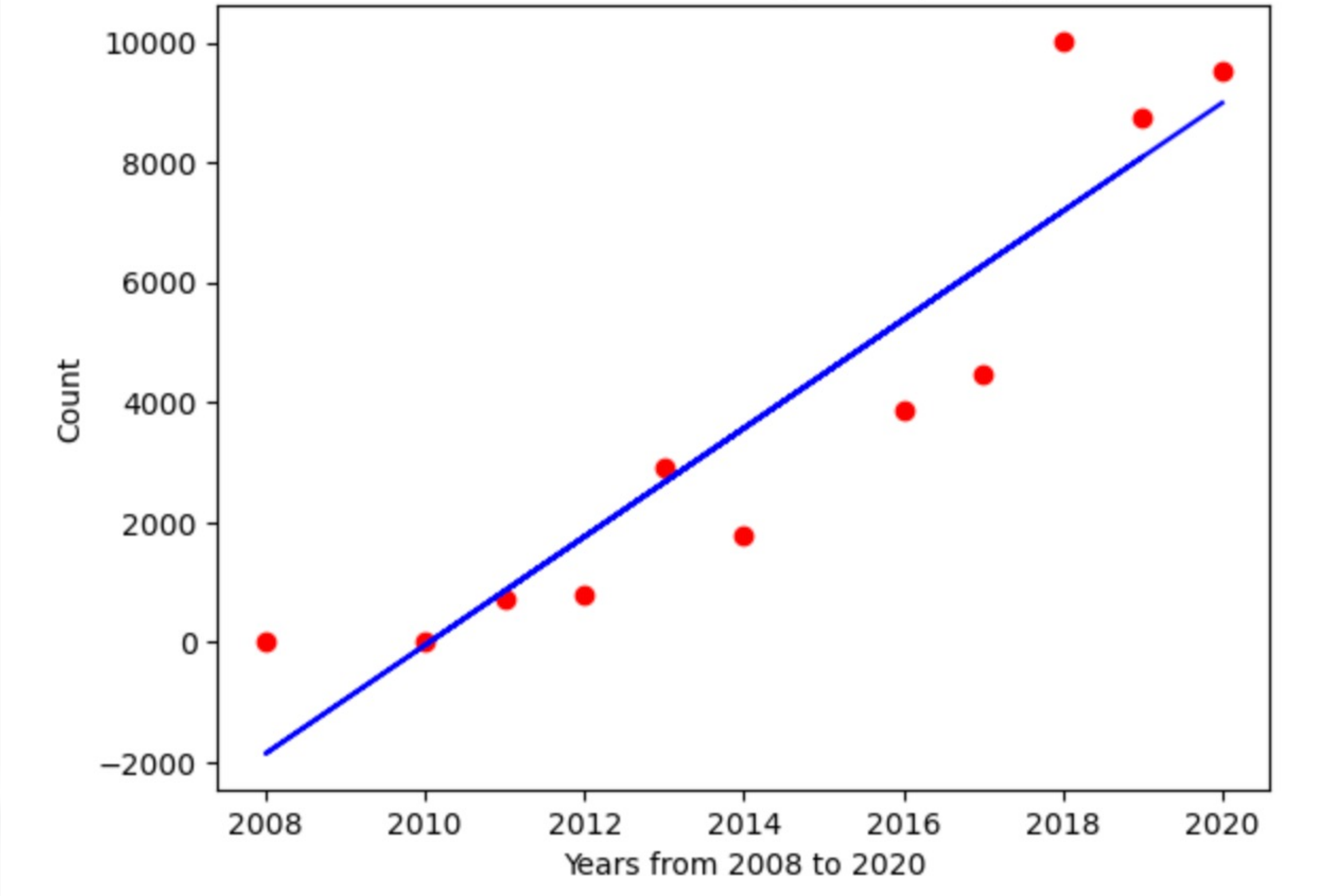


Fig 1 - Normal P-P Plot of Regression Standardized Residuals

LINEAR *REGRESSION*

y = 900.97x – 2,000,000

R-squared= 0.852



Model:	OLS	Adj. R-squared:	0.852
Dependent Variable:	Count	AIC:	156.7533
Date:	2023-10-03 16:38	BIC:	157.1477
No. Observations:	9	Log-Likelihood:	-76.377
Df Model:	1	F-statistic:	46.92
Df Residuals:	7	Prob (F-statistic):	0.000242
R-squared:	0.870	Scale:	1.7692e+06

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-1656566.5455	242362.9437	-6.8351	0.0002	-2229663.8398	-1083469.2511
Year	824.1545	120.3123	6.8501	0.0002	539.6611	1108.6480

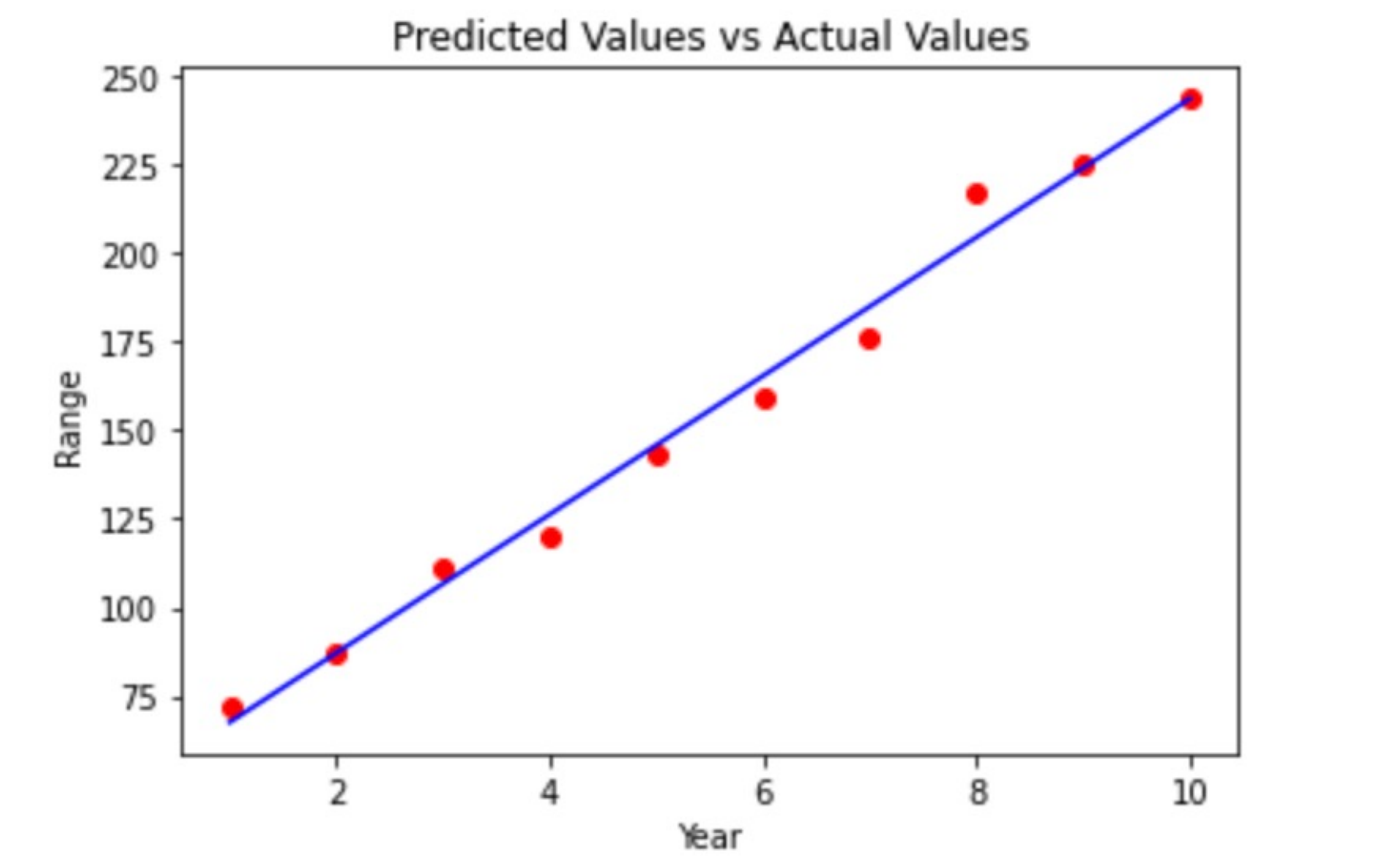
Omnibus:	3.310	Durbin-Watson:	2.003
Prob(Omnibus):	0.191	Jarque-Bera (JB):	0.988
Skew:	0.153	Prob(JB):	0.610
Kurtosis:	1.405	Condition No.:	1101180

MULTI REGRESSION

Model:	OLS	Adj. R-squared:	0.887
Dependent Variable:	Range	AIC:	91.7105
Date:	2023-10-04 14:57	BIC:	92.6183
No. Observations:	10	Log-Likelihood:	-42.855
Df Model:	2	F-statistic:	36.16
Df Residuals:	7	Prob (F-statistic):	0.000204
R-squared:	0.912	Scale:	441.35

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
const	39.8783	20.7489	1.9219	0.0961	-9.1851	88.9417
Year	14.4150	6.1619	2.3394	0.0519	-0.1555	28.9856
Count	0.0047	0.0053	0.9008	0.3976	-0.0077	0.0172

Omnibus:	0.706	Durbin-Watson:	1.733
Prob(Omnibus):	0.703	Jarque-Bera (JB):	0.460
Skew:	0.455	Prob(JB):	0.794
Kurtosis:	2.475	Condition No.:	18464



OPTIMIZATION

ACQUISTION VALUE

OBJECTIVE FUNCTION:

$MAX\ (TVA) = \sum_{i=1}^{n} R_i X_i y_i$

SUBJECT TO:

$$\sum_{i=1}^{n} x_{i=D}$$

$$X_i \le C_i \quad i = 1,2\,, \dots..n$$

$$X_i \ge MOQ_{i.}\ y_{i.}\ \ i = 1,2, \dots.n$$

$$X_i \ge 0$$

$$.\,y_i \in \{0:1\}$$

CRITERION	REASON FOR SELECTION	MEASUREMENT INDEX
Price	Select the price that generates the highest GP	$\frac{\mathrm{MIN[Price]}}{\text{Price to evaluated}}$
Electric Range	Select the shortest lead-time	$\frac{\text{[Electric Range]}}{\text{MAX[Electric Range\}}}$

***Note: We consider Weighing for the Criteria in the Objective function**

OPEN CONSTRAINTS:

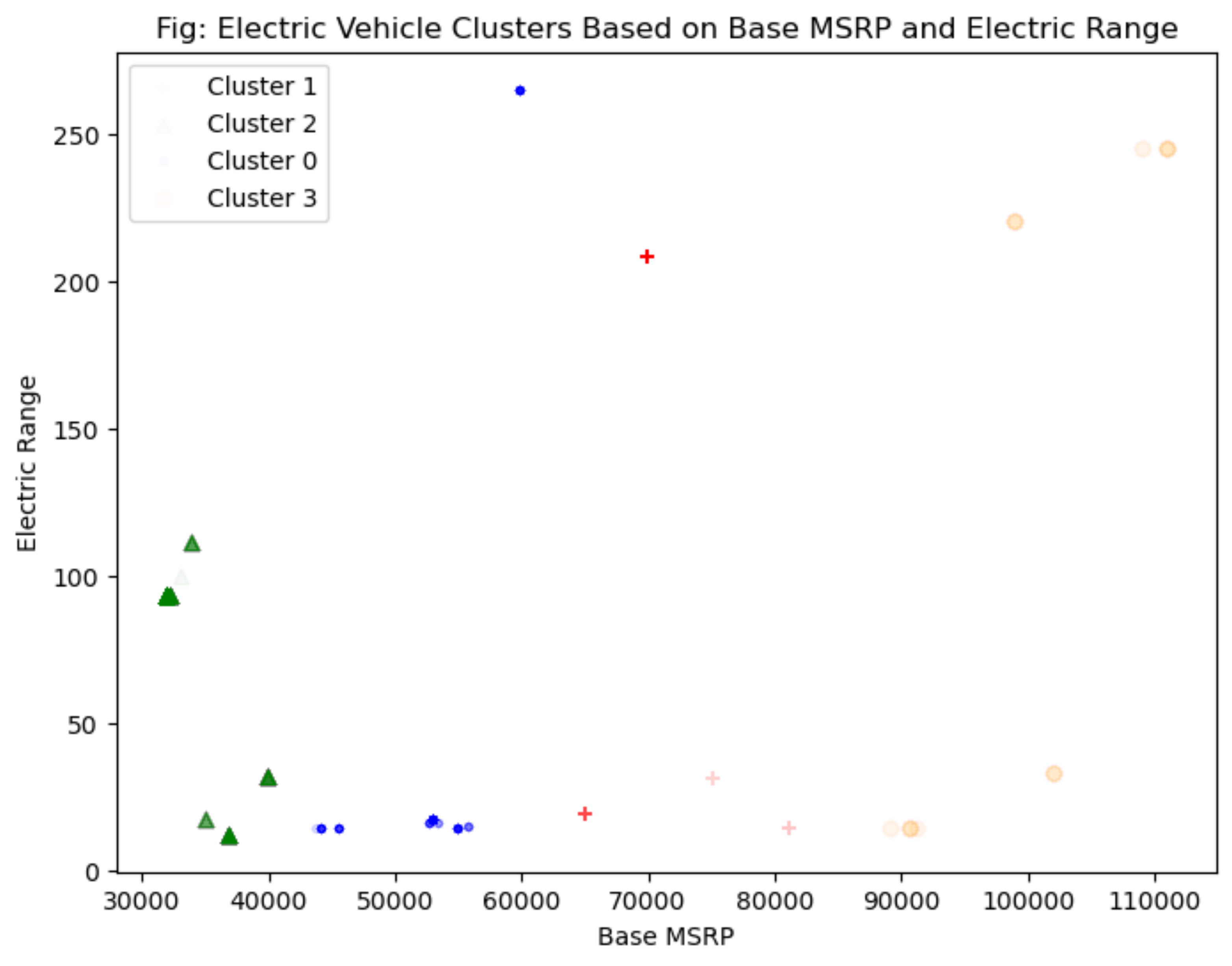
Capacity : If we have a fixed capacity per Car Brand/Make
Demand: If there is a Market Restrictions

OPTIMIZATION MODEL

```
In [252]: # We model the coefficient per each variable considering Prices & Electric Range

In [253]: #We weighted the criterias

In [284]: criteria_price=0.5
          criteria_elec=0.5

In [285]: x1=criteria_price*(filtered_df_1['Price'].min()/48300) + (criteria_elec*(153/337))
          x2=criteria_price*(filtered_df_1['Price'].min()/9999999) + (criteria_elec*(62/337))
          x3=criteria_price*(filtered_df_1['Price'].min()/27800) + (criteria_elec*(84/337))
          x4=criteria_price*(filtered_df_1['Price'].min()/47990) + (criteria_elec*(76/337))
          x5=criteria_price*(filtered_df_1['Price'].min()/23190) + (criteria_elec*(125/337))
          x6=criteria_price*(filtered_df_1['Price'].min()/29990)+ (criteria_elec*(110/337))
          x7=criteria_price*(filtered_df_1['Price'].min()/22440)+ (criteria_elec*(87/337))
          x8=criteria_price*(filtered_df_1['Price'].min()/104990)+ (criteria_elec*(337/337))
```

```
In [286]: #Since we need to optimize the acquisition value , which is a ratio, considering prices &Electric ranges

In [287]: obj = [-x1, -x2, -x3, -x4,-x5,-x6,-x7,-x8]

In [288]: # LHS matrix of inequality equations
          lhs = [[1,1,1,1,1,1,1,1],[0,0,0,0,1,0,0,0]]

In [289]: # RHS matrix of inequality equations, we set as demand a forecast for the bodytype, and a constraint for an specific brand-model
          rhs = [4000,100]

In [290]: from scipy.optimize import linprog

In [291]: lp_opt = linprog(c=obj,A_ub=lhs,b_ub=rhs,method = 'interior-point')

In [292]: lp_opt

Out[292]:  message: Optimization terminated successfully.
           success: True
            status: 0
               fun: -2520.341379205104
                 x: [ 5.247e-07  1.789e-07  9.008e-07  3.221e-07  1.000e+02
                      9.925e-07  3.900e+03  2.799e-06]
               nit: 6
```

CLUSTERING



Cluster	Base MSRP mean	Base MSRP std	Electric Range mean	Electric Range std
0	52648.611111	4955.887135	55.717391	92.025126
1	69822.897946	1758.112856	193.861361	49.651425
2	100225.000000	7970.458730	127.882979	108.132322
3	34120.176532	2822.702563	68.989616	36.539073

- *High variability in both ranges within clusters*
- *Highly subjective – consider other variables (e.g. brand, reliability, reviews, utility)*
- *Best overall value is in Cluster 1, relatively long range for price*
- *Cluster 3 is least expensive and offers a longer range on average*

WEB SCRAPING

7 Steps for a Successful GTM Model

McKinsey &Company

Code:

```
from bs4 import BeautifulSoup
import requests

url = 'https://www.mckinsey.com/industries/automotive-and-assembly/our

page = requests.get(url)
soup = BeautifulSoup(page.text,'html')

alltext= soup.find('div', class_='mdc-o-content-body mck-u-dropcap')
alltext
heading= alltext.find_all('h2')
subheadings = alltext.find_all('h3')

text = 'To date, electric vehicles (EVs)'
paragraphs = alltext.find_all('p')

#Printing the title tag for the post
match = soup.title.text
print(match)
print('')

date = soup.time.text
print(date)
print('')
lst = []
for para in subheadings:
    lst.append(para.text)

for i in range(5,len(lst)):
    print(lst[i])

print('')
print ("Read More at:", "https://www.mckinsey.com/industries/automotive-
```

Results:

```
Leaving the niche: Seven steps for a successful go-to-market model for electric vehicles | McKinsey

June 29, 2020

1. Reinvent brand positioning
2. Shape the charging ecosystem
3. Generate income from the life cycle
4. Massively reskill and refocus the sales force
5. Perfect the omnichannel approach
6. Upgrade after-sales customer-centricity and readiness
7. Transform the business model to achieve profitability at scale

Read More at: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/leaving-the-
for-a-successful-go-to-market-model-for-electric-vehicles
```

```
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7. Transform the business model to achieve profitability at scale
```

CITATIONS

1. *data_m2.csv, cars_us_22.csv,* ccarprice.com 2022/2023 new cars. validated web scrape by Tymoteusz Urban, WUT, Warsaw, Poland. https://www.kaggle.com/datasets/sidharth178/car-prices-dataset. Open Data Commons Open Database License.

2. *Electric Vehicle Population Data*. Washington State Department of Licensing, Research and Analysis Office (Updated September 14, 2023), https://data.wa.gov/Transportation/Electric-Vehicle-Population-Data/f6w7-q2d2. Open Data Commons Open Database License.

THANK

YOU!