Raj Verma EV Vehicle Analysis

```
#Import required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.impute import SimpleImputer
import plotly.express as px

#Reading the .csv file
data=pd.read_csv("dataset.csv")
data.head()
```

```
   VIN (1-10)     County      City State  Postal Code  Model Year
Make  \
0  JTMEB3FV6N     Monroe  Key West    FL        33040        2022
TOYOTA
1  1G1RD6E45D      Clark  Laughlin    NV        89029        2013
CHEVROLET
2  JN1AZ0CP8B     Yakima    Yakima    WA        98901        2011
NISSAN
3  1G1FW6S08H     Skagit  Concrete    WA        98237        2017
CHEVROLET
4  3FA6P0SU1K  Snohomish   Everett    WA        98201        2019
FORD

        Model                   Electric Vehicle Type  \
0  RAV4 PRIME  Plug-in Hybrid Electric Vehicle (PHEV)
1        VOLT  Plug-in Hybrid Electric Vehicle (PHEV)
2        LEAF          Battery Electric Vehicle (BEV)
3     BOLT EV          Battery Electric Vehicle (BEV)
4      FUSION  Plug-in Hybrid Electric Vehicle (PHEV)

  Clean Alternative Fuel Vehicle (CAFV) Eligibility  Electric Range  \
0           Clean Alternative Fuel Vehicle Eligible              42
1           Clean Alternative Fuel Vehicle Eligible              38
2           Clean Alternative Fuel Vehicle Eligible              73
3           Clean Alternative Fuel Vehicle Eligible             238
4             Not eligible due to low battery range              26

   Base MSRP  Legislative District  DOL Vehicle ID  \
0          0                   NaN       198968248
1          0                   NaN         5204412
2          0                  15.0       218972519
3          0                  39.0       186750406
4          0                  38.0         2006714

              Vehicle Location       Electric Utility  2020 Census
Tract
```

```
0    POINT (-81.80023 24.5545)                     NaN
12087972100
1  POINT (-114.57245 35.16815)                     NaN
32003005702
2  POINT (-120.50721 46.60448)              PACIFICORP
53077001602
3   POINT (-121.7515 48.53892)  PUGET SOUND ENERGY INC
53057951101
4  POINT (-122.20596 47.97659)  PUGET SOUND ENERGY INC
53061041500
```

```python
#shape of the data
shape=data.shape
print("The Number of rows : {}".format(shape[0]))
print("The Number of columns : {}".format(shape[1]))
```

```
The Number of rows : 112634
The Number of columns : 17
```

```python
# Information about the data
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 112634 entries, 0 to 112633
Data columns (total 17 columns):
 #   Column                                             Non-Null Count
Dtype
---  ------                                             --------------
-----
 0   VIN (1-10)                                         112634 non-
null  object
 1   County                                             112634 non-
null  object
 2   City                                               112634 non-
null  object
 3   State                                              112634 non-
null  object
 4   Postal Code                                        112634 non-
null  int64
 5   Model Year                                         112634 non-
null  int64
 6   Make                                               112634 non-
null  object
 7   Model                                              112614 non-
null  object
 8   Electric Vehicle Type                              112634 non-
null  object
 9   Clean Alternative Fuel Vehicle (CAFV) Eligibility  112634 non-
null  object
 10  Electric Range                                     112634 non-
```

```
null  int64
 11  Base MSRP                                          112634 non-
null  int64
 12  Legislative District                               112348 non-
null  float64
 13  DOL Vehicle ID                                     112634 non-
null  int64
 14  Vehicle Location                                   112610 non-
null  object
 15  Electric Utility                                   112191 non-
null  object
 16  2020 Census Tract                                  112634 non-
null  int64
dtypes: float64(1), int64(6), object(10)
memory usage: 14.6+ MB
```

Exploratory data Analysis

Getting the insights from the data which includes

- Missing values.
- Duplicated Values.
- Outliers.
- Relationships.
- Distributions.

```
# Checking the Missing values
data.isna().sum()

VIN (1-10)                                            0
County                                                0
City                                                  0
State                                                 0
Postal Code                                           0
Model Year                                            0
Make                                                  0
Model                                                20
Electric Vehicle Type                                 0
Clean Alternative Fuel Vehicle (CAFV) Eligibility     0
Electric Range                                        0
Base MSRP                                             0
Legislative District                                286
DOL Vehicle ID                                        0
Vehicle Location                                     24
Electric Utility                                    443
2020 Census Tract                                     0
dtype: int64
```

Insights

- There are 20 missing values in Model column.
- 286 missing values in Legislative District.
- 443 Missing values in Electric Utility.

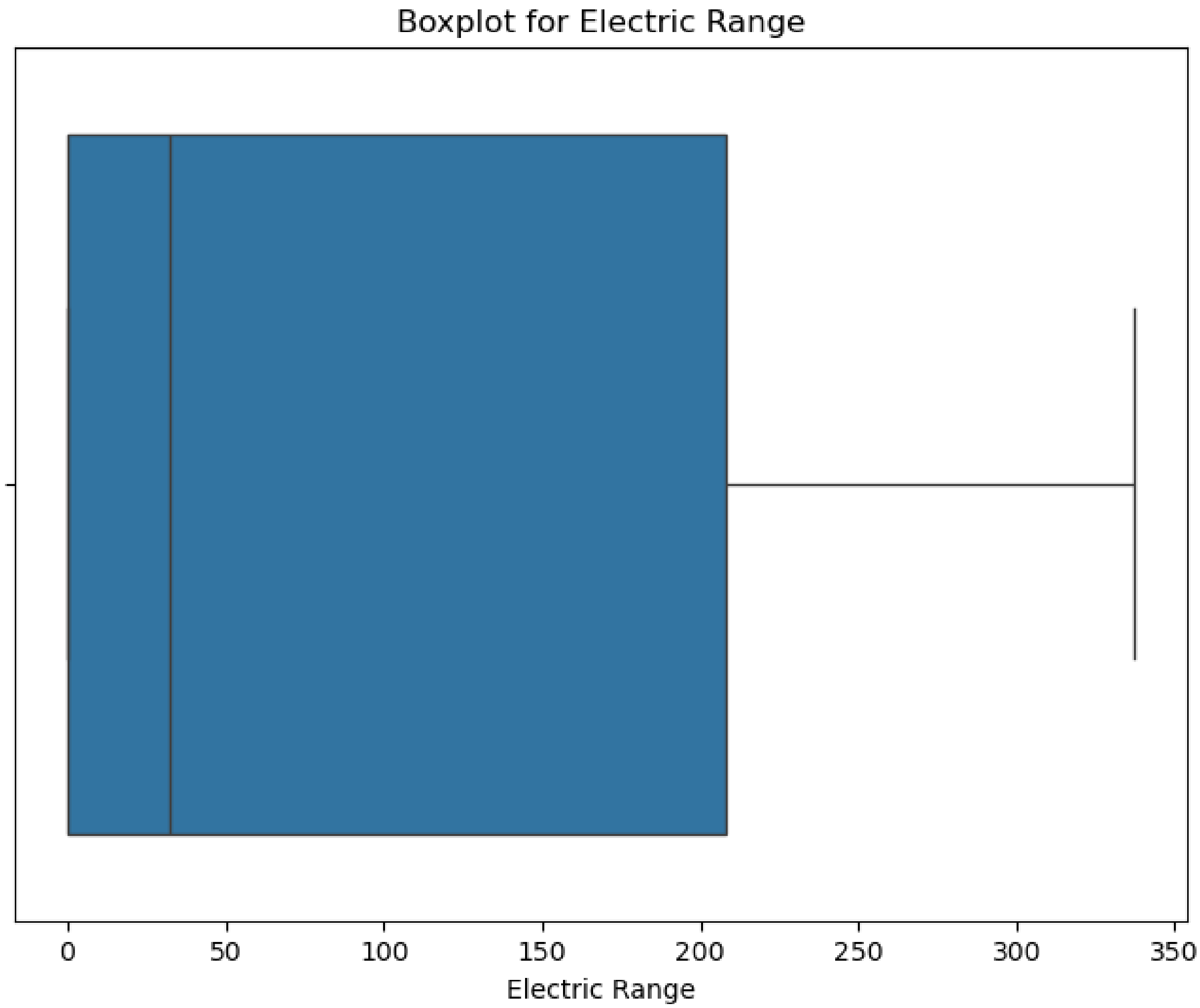
```
# Checking the Duplicated values
data.duplicated().sum()
```

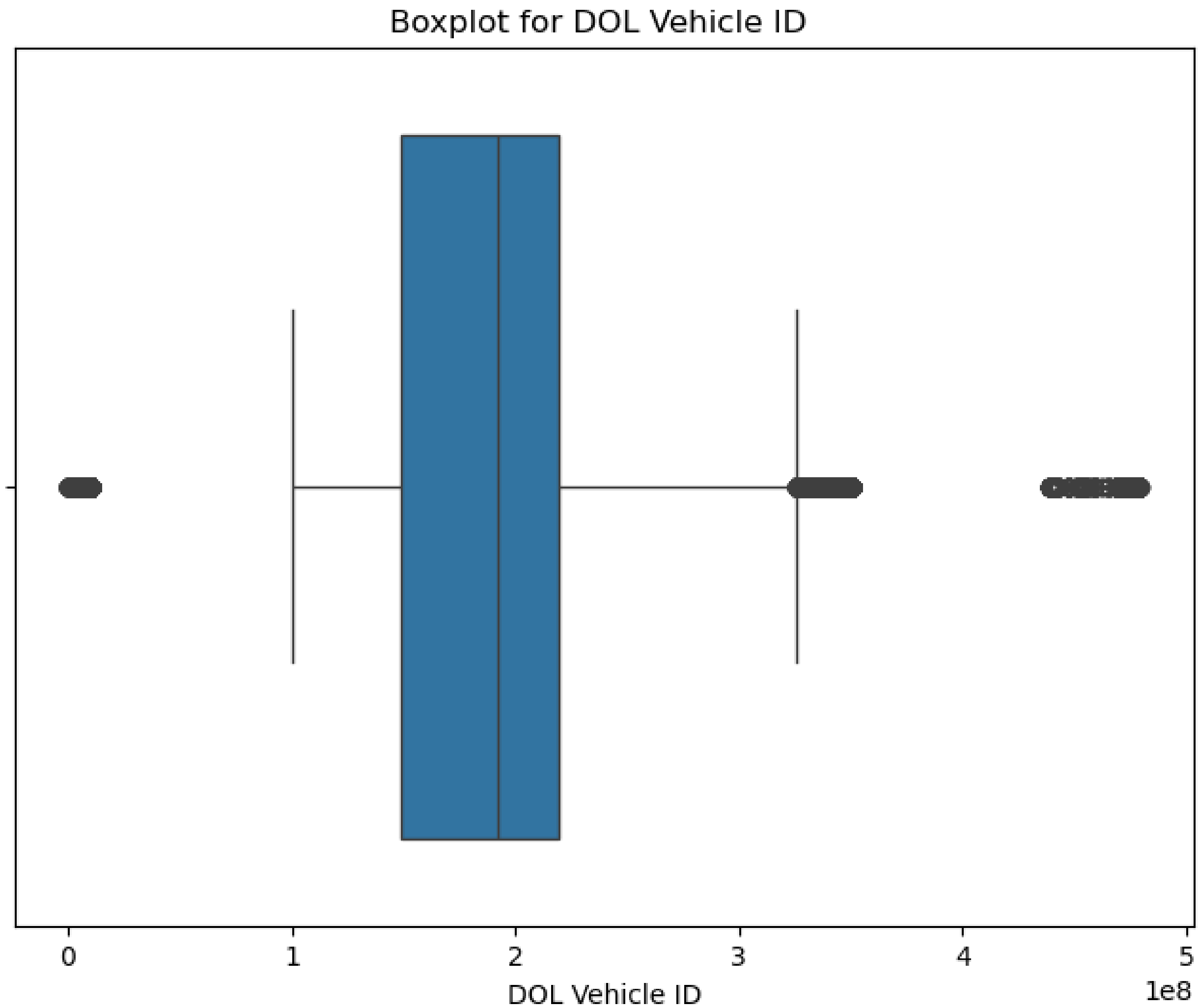
```
0
```

Insights

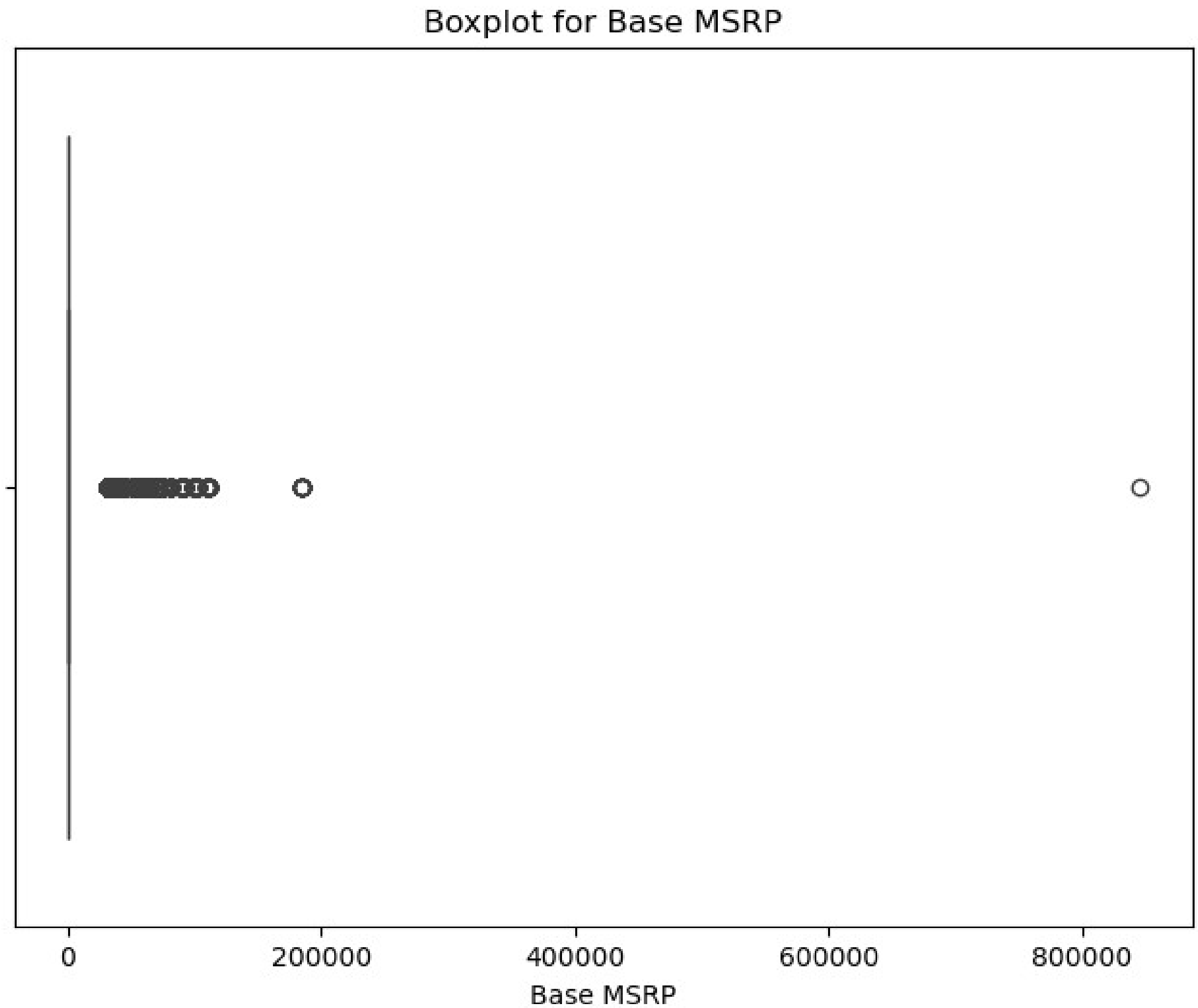
- There are no duplicated values in the data.

```
# Checking the outliers
plt.figure(figsize=(8,6))
sns.boxplot(x=data["Electric Range"])
plt.title("Boxplot for Electric Range")
plt.show()

plt.figure(figsize=(8,6))
sns.boxplot(x=data["DOL Vehicle ID"])
plt.title("Boxplot for DOL Vehicle ID ")
plt.show

plt.figure(figsize=(8,6))
sns.boxplot(x=data["Base MSRP"])
plt.title("Boxplot for Base MSRP")
plt.show()
```


Boxplot for Electric Range
0
50
100
150
200
250
300
350
Electric Range

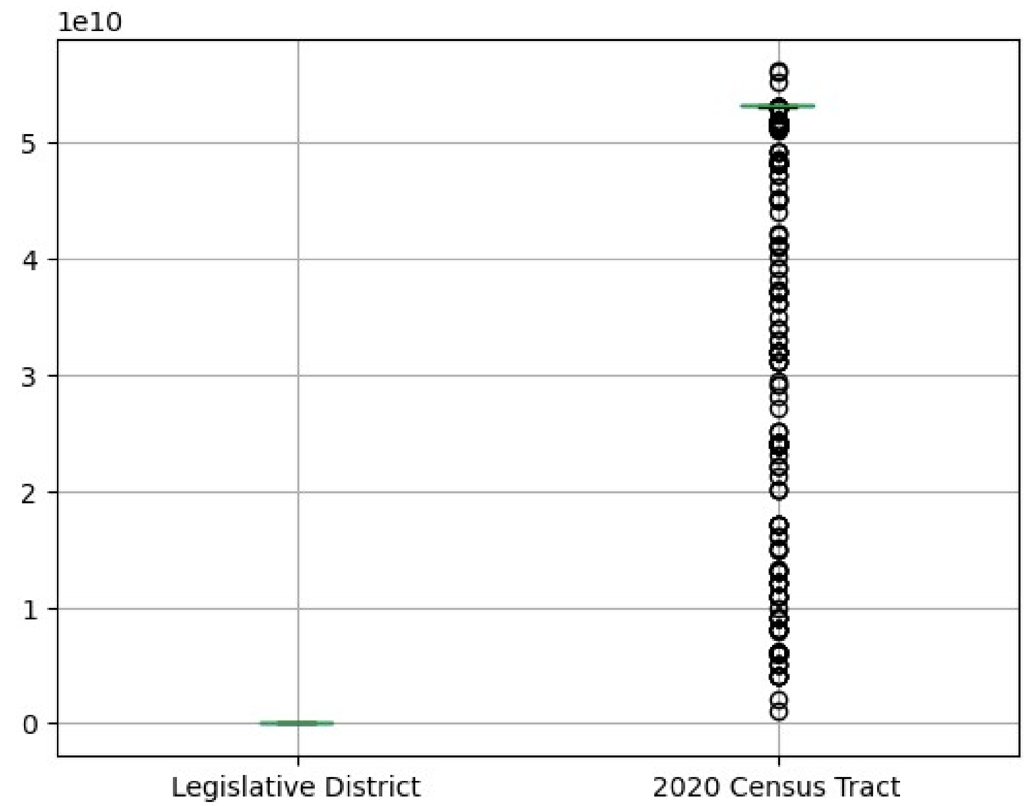


Boxplot for DOL Vehicle ID
0
1
2
3
4
5
1e8
DOL Vehicle ID



Imputing the missing values

```
Missing_columns=["Model","Legislative District","2020 Census Tract"]

SIM=SimpleImputer(strategy="most_frequent")
SIM

SimpleImputer(strategy='most_frequent')

data[["Model"]]=SIM.fit_transform(data[["Model"]])

data["Model"].isna().sum()

0

data[["Legislative District","2020 Census Tract"]].boxplot()
plt.show()
```




```
SIM=SimpleImputer(strategy="mean")
data[["2020 Census Tract"]]=SIM.fit_transform(data[["2020 Census
Tract"]])
data["2020 Census Tract"].isna().sum()

0

SIM=SimpleImputer(strategy="median")
data[["Legislative District"]]=SIM.fit_transform(data[["Legislative
District"]])
data["Legislative District"].isna().sum()

0
```

Univariate Analysis

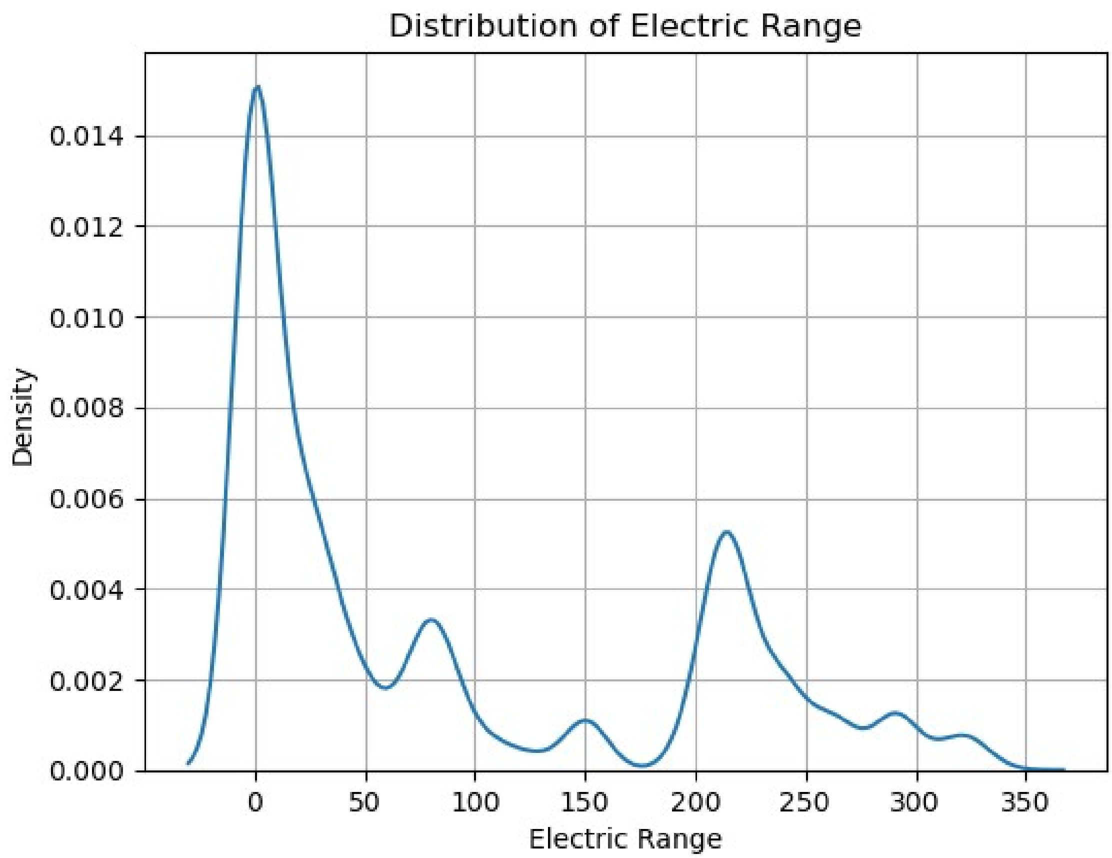
- Analysing the data using single feature.

```
data.columns

Index(['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'],
      dtype='object')
```

What is the distribution of Electric Range?

```
sns.kdeplot(x=data["Electric Range"])
plt.title("Distribution of Electric Range")
plt.grid()
plt.show()
```



Insights

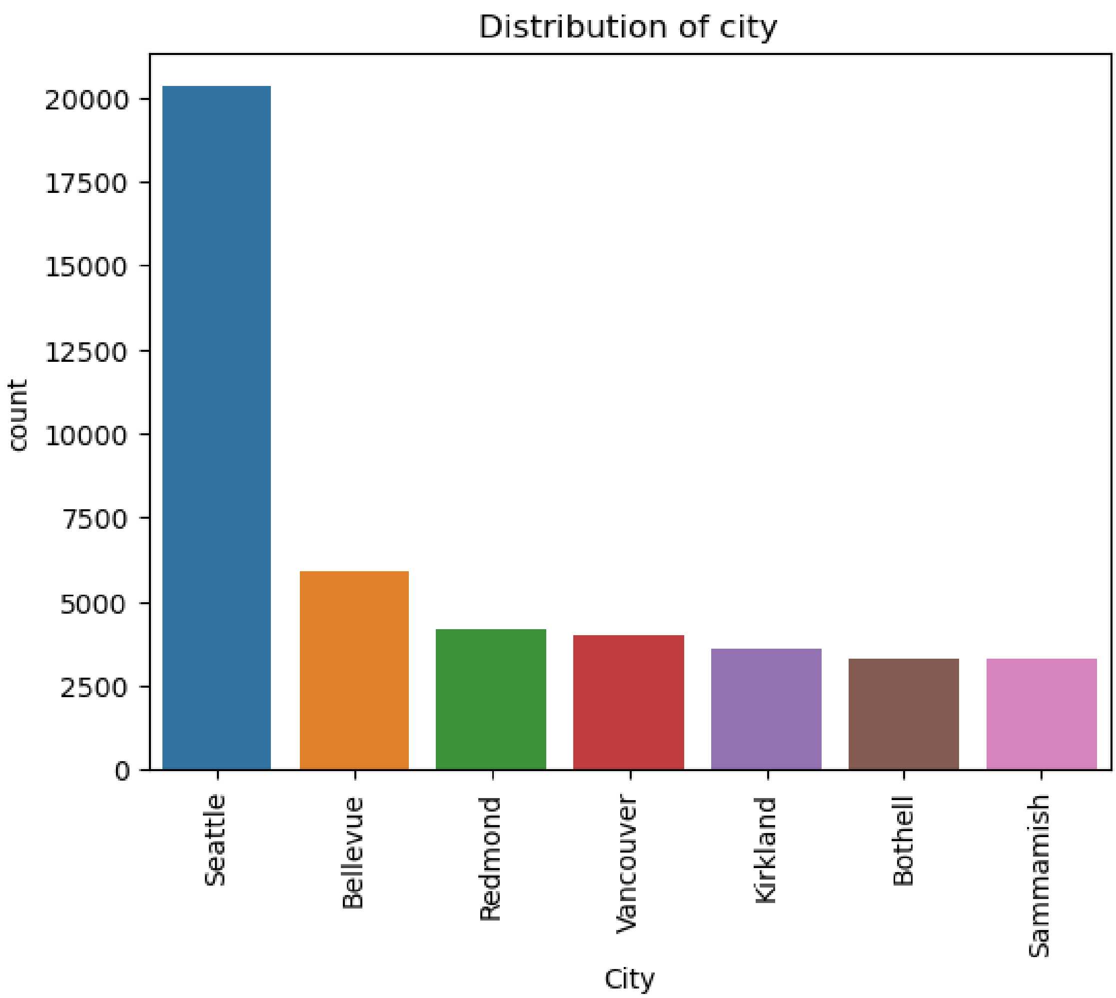
- In between 0 to 45 the electric range density is more compared to 5 to 100.
- Above 350 the electric range is decreasing.

Distribution of City?

```
d1=pd.DataFrame(data["City"].value_counts())
d1
```

```
                count
City                 
Seattle         20305
Bellevue         5921
Redmond          4201
Vancouver        4013
Kirkland         3598
...               ...
Hartline            1
Gaithersburg        1
El Paso             1
Klickitat           1
Worley              1

[629 rows x 1 columns]
```

```
sns.barplot(x=d1.index[:7],y=d1["count"][:7],hue=d1.index[:7])
plt.title("Distribution of city")
plt.xticks(rotation=90)
plt.show()
```



Insights

- Seattle is ranked more in distribution of cities.
- Worley is less compared to other cities.

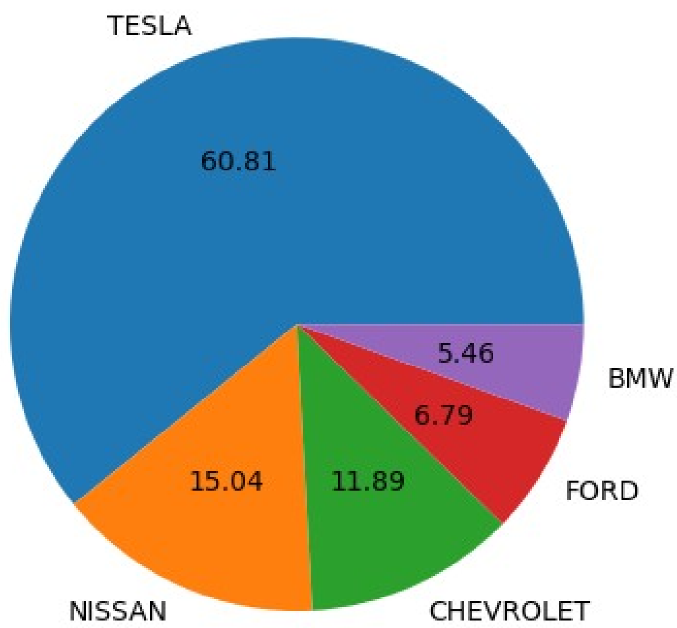
Dstribution of Make?

```
d2=pd.DataFrame(data["Make"].value_counts())
d2
```

Make	count
TESLA	52078
NISSAN	12880
CHEVROLET	10182
FORD	5819
BMW	4680
KIA	4483

```
TOYOTA              4405
VOLKSWAGEN          2514
AUDI                2332
VOLVO               2288
CHRYSLER            1794
HYUNDAI             1412
JEEP                1152
RIVIAN               885
FIAT                 822
PORSCHE              818
HONDA                792
MINI                 632
MITSUBISHI           588
POLESTAR             558
MERCEDES-BENZ        506
SMART                273
JAGUAR               219
LINCOLN              168
CADILLAC             108
LUCID MOTORS          65
SUBARU                59
LAND ROVER            38
LEXUS                 33
FISKER                20
GENESIS               18
AZURE DYNAMICS         7
TH!NK                  3
BENTLEY                3
```

```
plt.pie(x=d2["count"][:5],labels=d2.index[:5],autopct="%0.2f")
plt.show()
```



Insights

- Tesla has the highest propotion in the make compared to others.

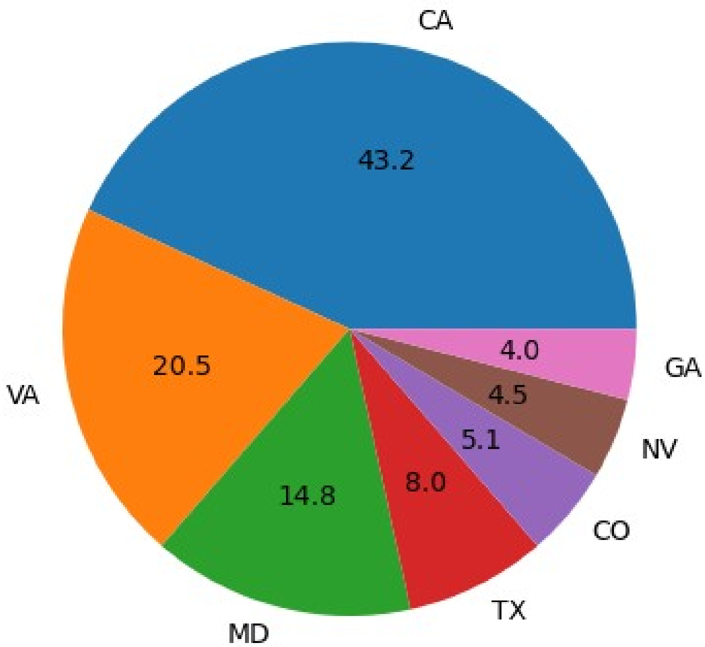
Distribution of State?

```
d3=pd.DataFrame(data["State"].value_counts())
d3
```

	count
State	
WA	112348
CA	76
VA	36
MD	26
TX	14
CO	9
NV	8
GA	7
NC	7
CT	6
DC	6
FL	6
AZ	6

```
IL          6
SC          5
OR          5
NE          5
HI          4
UT          4
AR          4
NY          4
TN          3
KS          3
MO          3
PA          3
MA          3
LA          3
NJ          3
NH          2
OH          2
WY          2
ID          2
KY          1
RI          1
ME          1
MN          1
SD          1
WI          1
NM          1
AK          1
MS          1
AL          1
DE          1
OK          1
ND          1
```

```python
plt.pie(x=d3["count"][1:8],labels=d3.index[1:8],autopct="%0.1f")
plt.show()
```



Bivariate Analysis

- Analysing the data using two features.

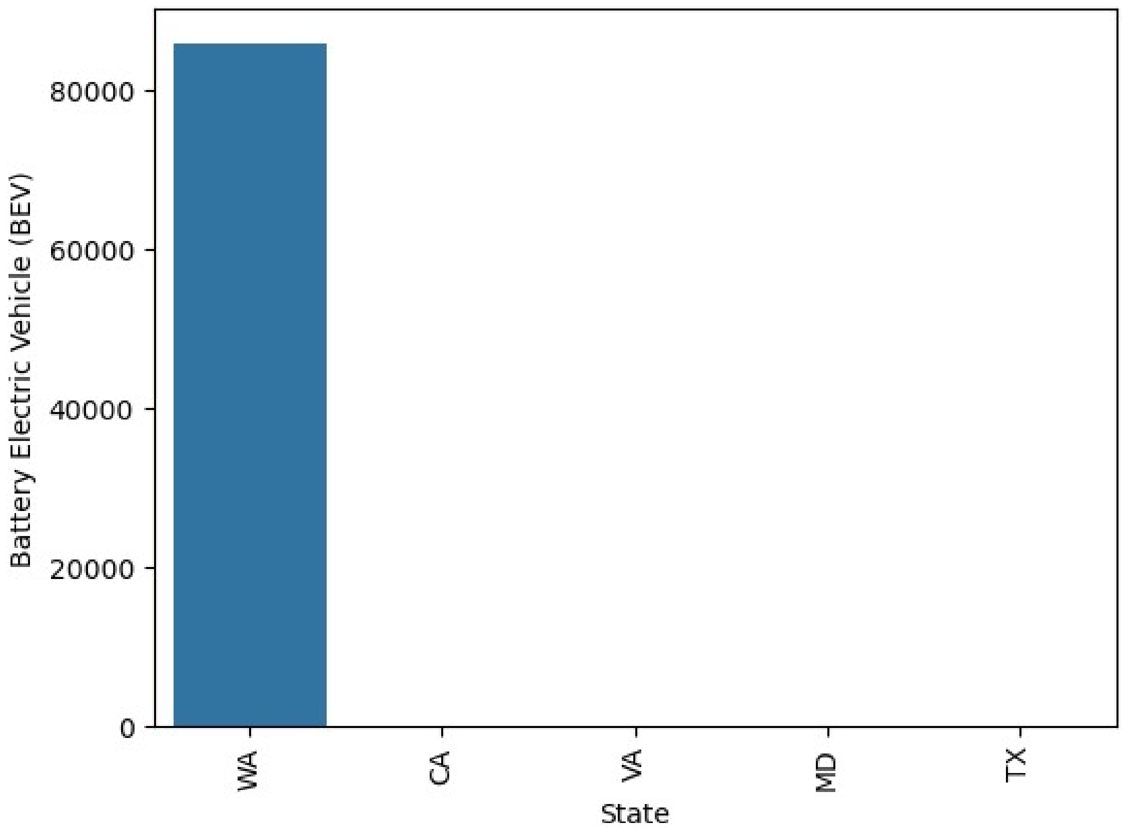
Which state has more Battery and least plug-in-hybrid electric type vehicles?

```
data.columns

Index(['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'],
      dtype='object')

g1=pd.crosstab(index=data["State"],columns=data["Electric Vehicle
Type"]).sort_values(by=["Battery Electric Vehicle (BEV)","Plug-in
Hybrid Electric Vehicle (PHEV)"],ascending=False)
g1.head()
len(g1)

45
```

```
g1.index
```

```
Index(['WA', 'CA', 'VA', 'MD', 'TX', 'CO', 'NV', 'IL', 'AZ', 'DC',
'SC', 'GA',
       'NC', 'FL', 'NE', 'AR', 'NY', 'PA', 'TN', 'OR', 'HI', 'UT',
'KS', 'LA',
       'MA', 'MO', 'ID', 'OH', 'WY', 'CT', 'NH', 'DE', 'MN', 'MS',
'NM', 'RI',
       'SD', 'WI', 'NJ', 'AK', 'AL', 'KY', 'ME', 'ND', 'OK'],
      dtype='object', name='State')
```

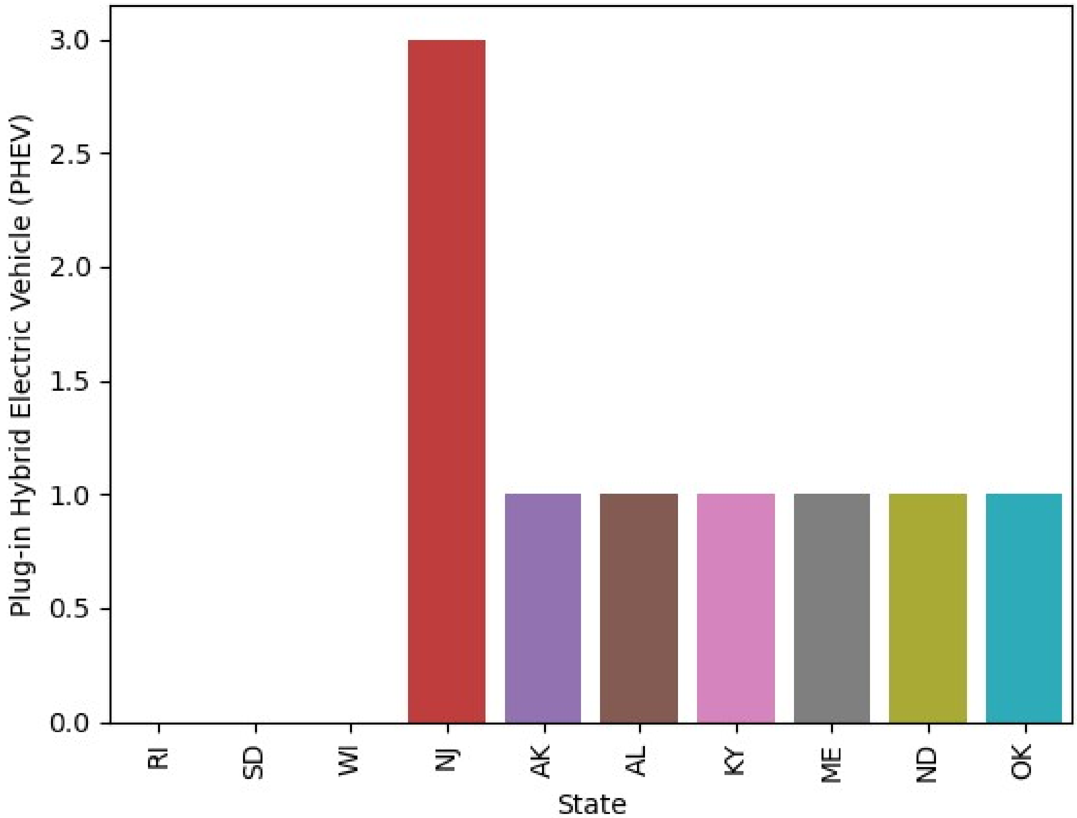
```
sns.barplot(x=g1.index[:5],y=g1["Battery Electric Vehicle (BEV)"]
[:5],hue=g1.index[:5])
plt.xticks(rotation=90)
plt.show()
```



Insights

- WA has more Battery Electric vehicles compared to other states.

```
sns.barplot(x=g1.index[35:45],y=g1["Plug-in Hybrid Electric Vehicle
(PHEV)"][35:45],hue=g1.index[35:45])
plt.xticks(rotation=90)
plt.show()
```



Insights

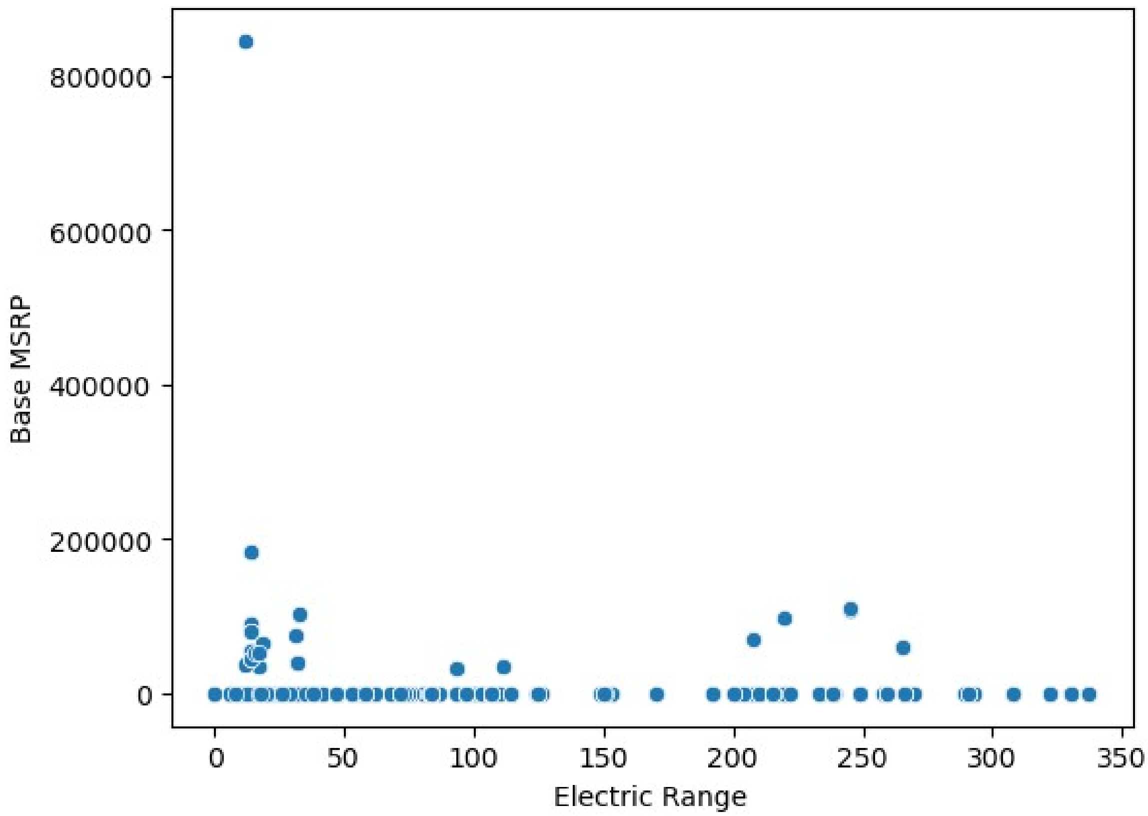
- OK,ND has less plug-in-hybrid electric vehicles.

What is the relationship between the Electric Range and Base MSRP of electric vehicles?

```
data[["Electric Range","Base MSRP"]].corr()
```

	Electric Range	Base MSRP
Electric Range	1.000000	0.085025
Base MSRP	0.085025	1.000000

```
sns.scatterplot(x=data["Electric Range"],y=data["Base MSRP"])
plt.show()
```

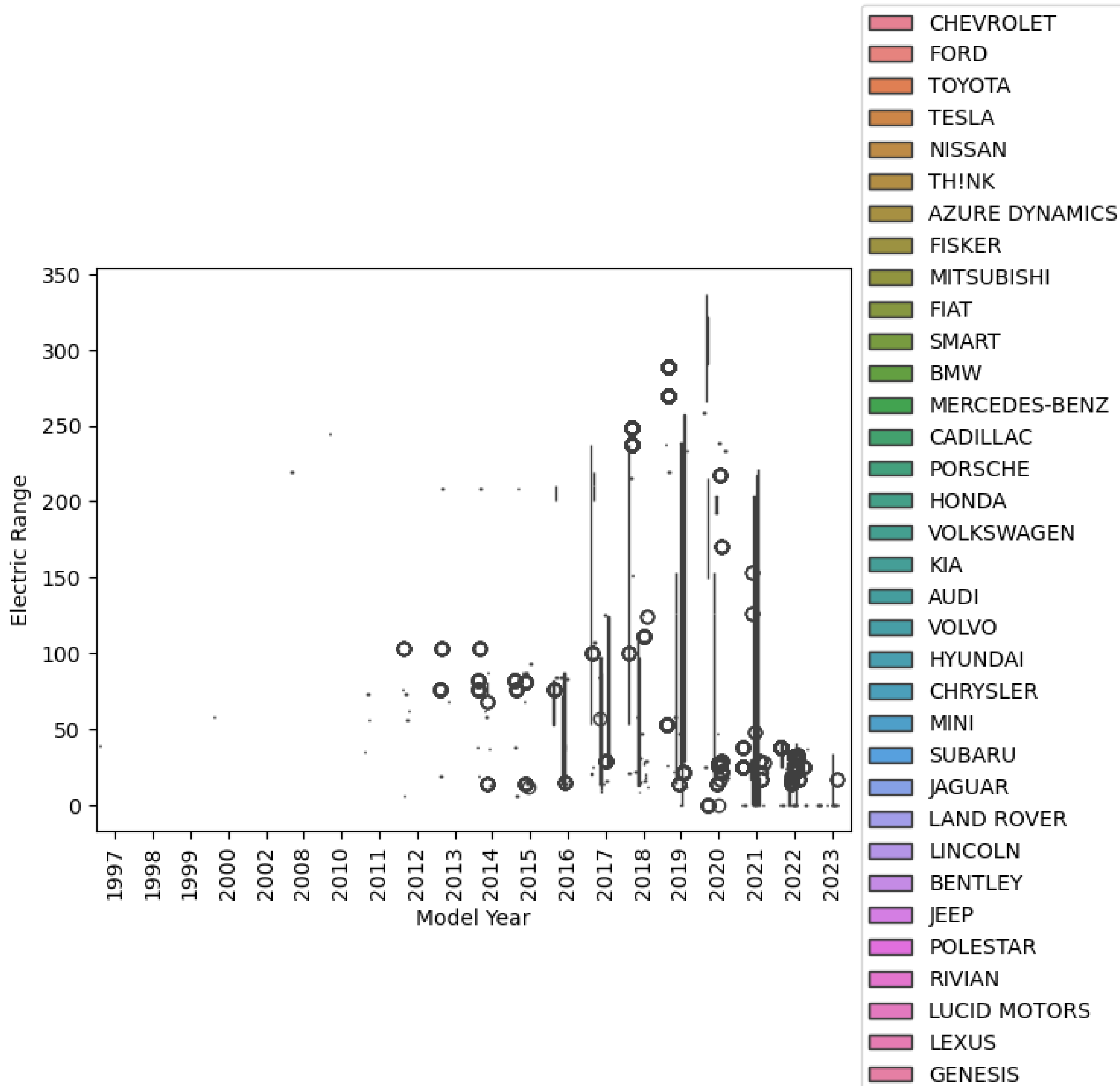


Insights

- Since the correlation is minimal, Electric Range is not a reliable predictor of the Base MSRP

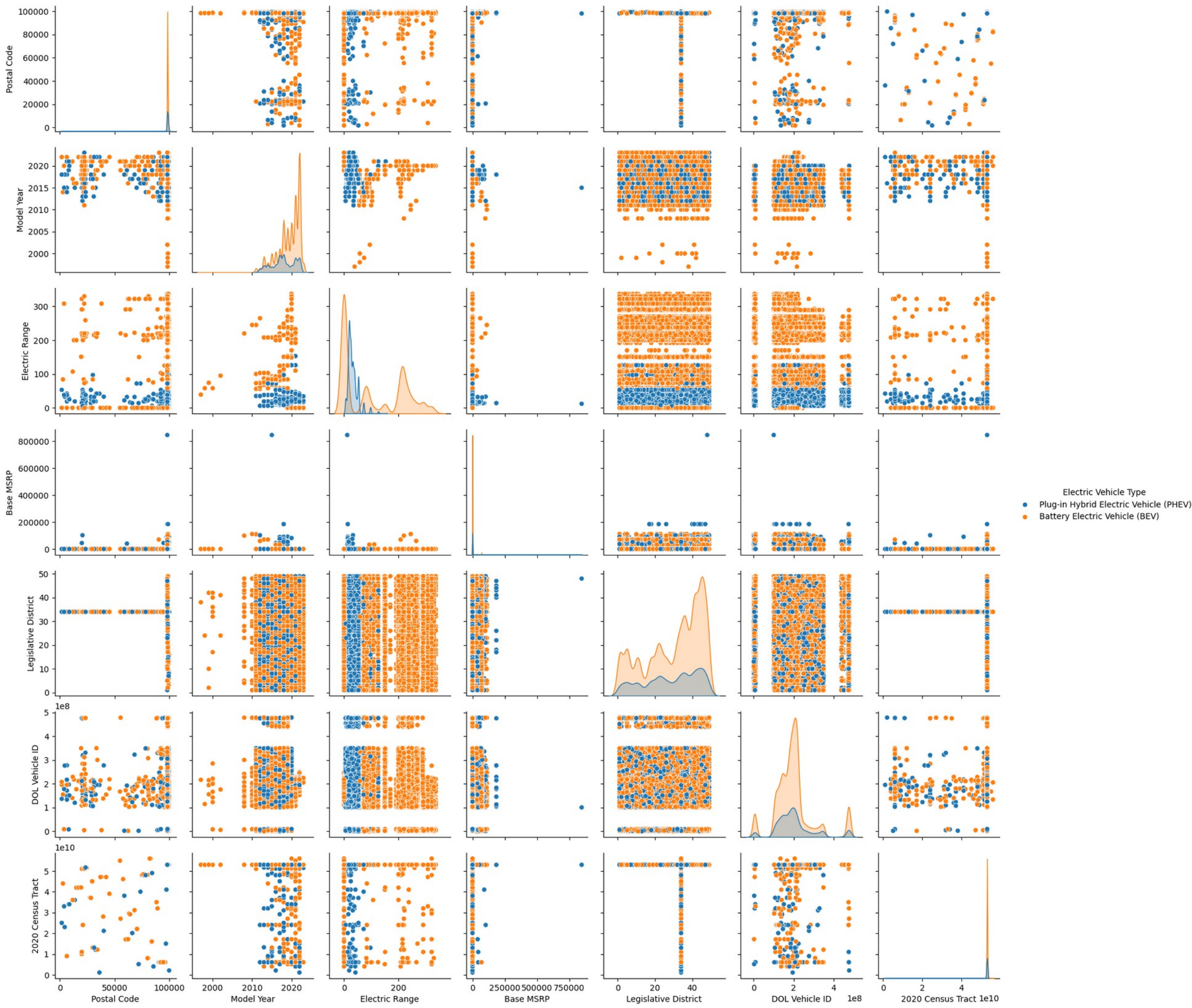
How does Model Year influence the Electric Range across different Make

```
sns.boxplot(x=data["Model Year"],y=data["Electric
Range"],hue=data["Make"])
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.xticks(rotation=90)
plt.show()
```



How do various numerical features (e.g., Electric Range, Base MSRP) interact with each other for different Electric Vehicle Type categories (BEV vs. PHEV)?

```
sns.pairplot(data, hue='Electric Vehicle Type', diag_kind='kde')
plt.show()
```



Create a Choropleth using plotly.express to display the number of EV vehicles based on location.

```
state_data = data.groupby('State')['VIN (1-10)'].count().reset_index()
state_data.columns = ['State', 'EV Count']

fig = px.choropleth(state_data,
                    locations='State',
                    locationmode='USA-states',
                    color='EV Count',
                    color_continuous_scale='greens',
                    scope='usa',
                    labels={'EV Count': 'Number of EV Vehicles'},
                    title='Number of Electric Vehicles by State')

fig.show()
```


```
!pip install bar-chart-race
```

```
Collecting bar-chart-race
  Downloading bar_chart_race-0.1.0-py3-none-any.whl.metadata (4.2 kB)
Requirement already satisfied: pandas>=0.24 in d:\jupyter\lib\site-
packages (from bar-chart-race) (2.2.2)
Requirement already satisfied: matplotlib>=3.1 in d:\jupyter\lib\site-
packages (from bar-chart-race) (3.8.4)
Requirement already satisfied: contourpy>=1.0.1 in d:\jupyter\lib\
site-packages (from matplotlib>=3.1->bar-chart-race) (1.2.0)
Requirement already satisfied: cycler>=0.10 in d:\jupyter\lib\site-
packages (from matplotlib>=3.1->bar-chart-race) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in d:\jupyter\lib\
site-packages (from matplotlib>=3.1->bar-chart-race) (4.51.0)
Requirement already satisfied: kiwisolver>=1.3.1 in d:\jupyter\lib\
site-packages (from matplotlib>=3.1->bar-chart-race) (1.4.4)
Requirement already satisfied: numpy>=1.21 in d:\jupyter\lib\site-
packages (from matplotlib>=3.1->bar-chart-race) (1.26.4)
Requirement already satisfied: packaging>=20.0 in d:\jupyter\lib\site-
packages (from matplotlib>=3.1->bar-chart-race) (23.2)
Requirement already satisfied: pillow>=8 in d:\jupyter\lib\site-
packages (from matplotlib>=3.1->bar-chart-race) (10.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in d:\jupyter\lib\
site-packages (from matplotlib>=3.1->bar-chart-race) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in d:\jupyter\lib\
site-packages (from matplotlib>=3.1->bar-chart-race) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in d:\jupyter\lib\site-
packages (from pandas>=0.24->bar-chart-race) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in d:\jupyter\lib\site-
packages (from pandas>=0.24->bar-chart-race) (2023.3)
Requirement already satisfied: six>=1.5 in d:\jupyter\lib\site-
packages (from python-dateutil>=2.7->matplotlib>=3.1->bar-chart-race)
(1.16.0)
Downloading bar_chart_race-0.1.0-py3-none-any.whl (156 kB)
   ---------------------------------------- 0.0/156.8 kB ? eta -:--:--
   ---------------------------------------- 0.0/156.8 kB ? eta -:--:--
   -- ------------------------------------- 10.2/156.8 kB ? eta
```

```
-:--:--
   -- ------------------------------------- 10.2/156.8 kB ? eta
-:--:--
   ---------- ---------------------------- 41.0/156.8 kB 281.8 kB/s
eta 0:00:01
   -------------------------------------  153.6/156.8 kB 919.0 kB/s
eta 0:00:01
   -------------------------------------- 156.8/156.8 kB 857.2 kB/s
eta 0:00:00
Installing collected packages: bar-chart-race
Successfully installed bar-chart-race-0.1.0
```

Create a Racing Bar Plot to display the animation of EV Make and its count each year

```
data.columns
```

```
Index(['State', 'VIN (1-10)'], dtype='object')
```

```
data
```

```
  State  VIN (1-10)
0    CA       15000
1    TX        7000
2    NY        6000
3    FL        8000
4    IL        5000
```

```
ev_make_by_year = data.groupby(['Model Year',
'Make']).size().reset_index(name='EV Count')

# Step 2: Create a list of all unique makes
unique_makes = data['Make'].unique()

# Step 3: Ensure all makes appear in every year by filling missing
combinations
all_years = pd.DataFrame({'Model Year': sorted(data['Model
Year'].unique())})
all_combinations = all_years.assign(key=1).merge(pd.DataFrame({'Make':
unique_makes, 'key':1}), on='key').drop('key', axis=1)
ev_make_by_year_full = all_combinations.merge(ev_make_by_year,
on=['Model Year', 'Make'], how='left').fillna(0)

# Step 4: Convert EV Count to integer (since it was NaN before)
ev_make_by_year_full['EV Count'] = ev_make_by_year_full['EV
Count'].astype(int)

# Step 5: Create the animated racing bar plot with increased height
fig = px.bar(
    ev_make_by_year_full,  # Data
```

```
    x='EV Count',  # X-axis shows the count of EVs
    y='Make',  # Y-axis shows the car Make
    color='Make',  # Color by car Make
    animation_frame='Model Year',  # Animation by year
    orientation='h',  # Horizontal bar chart
    title='Electric Vehicle Makes Over the Years',
    labels={'EV Count':'Number of EVs', 'Make':'Car Make'},  # Axis
labels
    range_x=[0, ev_make_by_year_full['EV Count'].max() * 1.1],  #
Dynamically set x-axis range
    height=800  # Increased height for better visibility
)

# Step 6: Show the plot
fig.show()
```