Consumer Behavior Analysis for Electric Vehicle Adoption using Digital Twins

Import Libraries

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import missingno as msno
from prettytable import PrettyTable
import warnings
warnings.filterwarnings('ignore')

# Modeling
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
from sklearn.svm import SVR, SVC
from sklearn.cluster import KMeans

# Splitting data and model evaluation
from sklearn.metrics import accuracy_score, f1_score, roc_auc_score, make_scorer, clas
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score, KFold
from sklearn.model_selection import GridSearchCV

# Sampling
from imblearn.under_sampling import NearMiss
from collections import Counter

# Feature importance
import shap
```

Load Dataset

In [3]:
```
data = pd.read_csv('Electric_Vehicle_Population_Data (2).csv')
```

In [4]:
```
data.head()
```

Out[4]:

	VIN (1-10)	County	City	State	Postal Code	Model Year	Make	Model	Electric Vehicle Type	Clean Alternative Fuel Vehicle (CAFV) Eligibility	E
0	5YJYGDEE1L	King	Seattle	WA	98122.0	2020	TESLA	MODEL Y	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eligible	
1	7SAYGDEE9P	Snohomish	Bothell	WA	98021.0	2023	TESLA	MODEL Y	Battery Electric Vehicle (BEV)	Eligibility unknown as battery range has not b...	
2	5YJSA1E4XK	King	Seattle	WA	98109.0	2019	TESLA	MODEL S	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eligible	
3	5YJSA1E27G	King	Issaquah	WA	98027.0	2016	TESLA	MODEL S	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eligible	
4	5YJYGDEE5M	Kitsap	Suquamish	WA	98392.0	2021	TESLA	MODEL Y	Battery Electric Vehicle (BEV)	Eligibility unknown as battery range has not b...	

Data Preprocessing

In [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 177866 entries, 0 to 177865
Data columns (total 17 columns):
 #   Column                                             Non-Null Count   Dtype  
---  ------                                             --------------   -----  
 0   VIN (1-10)                                         177866 non-null  object 
 1   County                                             177861 non-null  object 
 2   City                                               177861 non-null  object 
 3   State                                              177866 non-null  object 
 4   Postal Code                                        177861 non-null  float64
 5   Model Year                                         177866 non-null  int64  
 6   Make                                               177866 non-null  object 
 7   Model                                              177866 non-null  object 
 8   Electric Vehicle Type                              177866 non-null  object 
 9   Clean Alternative Fuel Vehicle (CAFV) Eligibility  177866 non-null  object 
 10  Electric Range                                     177866 non-null  int64  
 11  Base MSRP                                          177866 non-null  int64  
 12  Legislative District                               177477 non-null  float64
 13  DOL Vehicle ID                                     177866 non-null  int64  
 14  Vehicle Location                                   177857 non-null  object 
 15  Electric Utility                                   177861 non-null  object 
 16  2020 Census Tract                                  177861 non-null  float64
dtypes: float64(3), int64(4), object(10)
memory usage: 23.1+ MB
```

In [6]:

```
# initialize category and numeric data
category = [i for i in data.columns if data[i].dtype == 'object']
#numerical = [i for i in data.columns if data[i].dtype != 'object']
```

In [7]:

```
data.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	
Postal Code	177861.0	9.817245e+04	2.442451e+03	1.545000e+03	9.805200e+04	9.812200e+04	9.83700(
Model Year	177866.0	2.020516e+03	2.989384e+00	1.997000e+03	2.019000e+03	2.022000e+03	2.02300(
Electric Range	177866.0	5.884216e+01	9.198130e+01	0.000000e+00	0.000000e+00	0.000000e+00	7.50000(
Base MSRP	177866.0	1.073109e+03	8.358625e+03	0.000000e+00	0.000000e+00	0.000000e+00	0.00000(
Legislative District	177477.0	2.912748e+01	1.489217e+01	1.000000e+00	1.800000e+01	3.300000e+01	4.20000(
DOL Vehicle ID	177866.0	2.202313e+08	7.584987e+07	4.385000e+03	1.814743e+08	2.282522e+08	2.54844!
2020 Census Tract	177861.0	5.297672e+10	1.578047e+09	1.001020e+09	5.303301e+10	5.303303e+10	5.30530(

In [8]:

```
# show statistical summary of category data
data[category].describe().T
```

Out[8]:

	count	unique	top	freq
VIN (1-10)	177866	10830	7SAYGDEE6P	1239
County	177861	196	King	92740
City	177861	723	Seattle	29447
State	177866	46	WA	177477
Make	177866	40	TESLA	79659
Model	177866	139	MODEL Y	35989
Electric Vehicle Type	177866	2	Battery Electric Vehicle (BEV)	139210
Clean Alternative Fuel Vehicle (CAFV) Eligibility	177866	3	Eligibility unknown as battery range has not b...	91950
Vehicle Location	177857	861	POINT (-122.12302 47.67668)	4574
Electric Utility	177861	76	PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)	65990

In [103…

```
# Checking the data shape
shape_of_data = data.shape
print(shape_of_data)
```

```
(177861, 955)
```

MIssing Values

In [10]:

```
# show missing values of data
data.isnull().sum()
```

Out[10]:

```
VIN (1-10)                                             0
County                                                 5
City                                                   5
State                                                  0
Postal Code                                            5
Model Year                                             0
Make                                                   0
Model                                                  0
Electric Vehicle Type                                  0
Clean Alternative Fuel Vehicle (CAFV) Eligibility      0
Electric Range                                         0
Base MSRP                                              0
Legislative District                                 389
DOL Vehicle ID                                         0
Vehicle Location                                       9
Electric Utility                                       5
2020 Census Tract                                      5
dtype: int64
```

In [11]:

```
# Null values checking
data.isna()
data.isna().sum()
data.isna().sum()/len(data)*100
data.isna().sum()/len(data)*1000
```

```
Out[11]: VIN (1-10)                                           0.000000
County                                               0.028111
City                                                 0.028111
State                                                0.000000
Postal Code                                          0.028111
Model Year                                           0.000000
Make                                                 0.000000
Model                                                0.000000
Electric Vehicle Type                                0.000000
Clean Alternative Fuel Vehicle (CAFV) Eligibility    0.000000
Electric Range                                       0.000000
Base MSRP                                            0.000000
Legislative District                                 2.187040
DOL Vehicle ID                                       0.000000
Vehicle Location                                     0.050600
Electric Utility                                     0.028111
2020 Census Tract                                    0.028111
dtype: float64
```

In [12]:
```
# Duplicat values check
Checking_duplicate_values=data.duplicated().sum()
print(f'The data set contains the {Checking_duplicate_values} values')
```

```
The data set contains the 0 values
```

In [13]:
```
# drop the missing values on the subset County and City
data.dropna(subset=['County', 'City'], inplace=True)

# show missing values of data
data.isnull().sum()
```

```
Out[13]: VIN (1-10)                                             0
County                                                 0
City                                                   0
State                                                  0
Postal Code                                            0
Model Year                                             0
Make                                                   0
Model                                                  0
Electric Vehicle Type                                  0
Clean Alternative Fuel Vehicle (CAFV) Eligibility      0
Electric Range                                         0
Base MSRP                                              0
Legislative District                                 384
DOL Vehicle ID                                         0
Vehicle Location                                       4
Electric Utility                                       0
2020 Census Tract                                      0
dtype: int64
```

Imputation

In [14]:
```
# define a procudure to impute missing values for numeric data
def impute_numeric_data(data, columns, mode):
    for col in columns:
        if mode == 'median':
            value = data[col].median()
        elif mode == 'mean':
            value = data[col].mean()
```

```
        data[col].fillna(value, inplace=True)

# define a procudure to impute missing values for category data
def impute_categoric_data(data, columns):
    for col in columns:
        mode_value = data[col].mode().iloc[0]
        data[col].fillna(mode_value, inplace=True)

# apply imputation procedure for numeric and category data
impute_numeric_data(data, ['Legislative District'], 'median')
impute_categoric_data(data, ['Model', 'Vehicle Location'])

# show missing values of data
data.isnull().sum()
```

Out[14]:

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

Feature Engineering

In [15]:

```
# update values in 'Electric Vehicle Type' column
data['Electric Vehicle Type'] = data['Electric Vehicle Type'].apply(lambda x: \
                                                                x.replace('Plug-in Hyb
                                                                .replace('Battery Elec

# rename column 'Clean Alternative Fuel Vehicle (CAFV) Eligibility' to 'Clean Alternat
data.rename(columns={'Clean Alternative Fuel Vehicle (CAFV) Eligibility': 'Clean Alter

# define a function to extract longitude and latitude from 'Vehicle Location' column
def extract_coordinates(point_string):
    coordinates = point_string.replace('POINT', '').replace('(', '').replace(')', '')
    longitude, latitude = coordinates.split()
    return float(longitude), float(latitude)

# apply the 'extract_coordinates' function to 'Vehicle Location' column and create new
data[['Longitude', 'Latitude']] = data['Vehicle Location'].apply(extract_coordinates).
data = data.drop('Vehicle Location', axis=1)

# define a function to map state codes to state names
def state_mapping(state_code):
    state_mapping = {
        'AL': 'Alabama', 'AK': 'Alaska', 'AZ': 'Arizona', 'AR': 'Arkansas',
        'CA': 'California', 'CO': 'Colorado', 'CT': 'Connecticut', 'DE': 'Delaware',
```

```
        'FL': 'Florida', 'GA': 'Georgia', 'HI': 'Hawaii', 'ID': 'Idaho',
        'IL': 'Illinois', 'IN': 'Indiana', 'IA': 'Iowa', 'KS': 'Kansas',
        'KY': 'Kentucky', 'LA': 'Louisiana', 'ME': 'Maine', 'MD': 'Maryland',
        'MA': 'Massachusetts', 'MI': 'Michigan', 'MN': 'Minnesota', 'MS': 'Mississippi
        'MO': 'Missouri', 'MT': 'Montana', 'NE': 'Nebraska', 'NV': 'Nevada',
        'NH': 'New Hampshire', 'NJ': 'New Jersey', 'NM': 'New Mexico', 'NY': 'New York
        'NC': 'North Carolina', 'ND': 'North Dakota', 'OH': 'Ohio', 'OK': 'Oklahoma',
        'OR': 'Oregon', 'PA': 'Pennsylvania', 'RI': 'Rhode Island', 'SC': 'South Carol
        'SD': 'South Dakota', 'TN': 'Tennessee', 'TX': 'Texas', 'UT': 'Utah',
        'VT': 'Vermont', 'VA': 'Virginia', 'WA': 'Washington', 'WV': 'West Virginia',
        'WI': 'Wisconsin', 'WY': 'Wyoming'
    }

    return state_mapping.get(state_code, 'Unknown')

# apply the 'state_mapping' function to 'State' column
data['State'] = data['State'].apply(state_mapping)

# define a function to extract the first substring from a column
def extract_substring(data, column_name):
    data[column_name] = data[column_name].str.split('-|\\|').str[0].str.strip()

# apply the 'extract_substring' function to 'Electric Utility' column
extract_substring(data, 'Electric Utility')
```

In [16]:

```
data.head()
```

Out[16]:

	VIN (1-10)	County	City	State	Postal Code	Model Year	Make	Model	Electric Vehicle Type	Cle Alternat F Vehi Eligibi
0	5YJYGDEE1L	King	Seattle	Washington	98122.0	2020	TESLA	MODEL Y	BEV	Cle Alternat F Veh Eligi
1	7SAYGDEE9P	Snohomish	Bothell	Washington	98021.0	2023	TESLA	MODEL Y	BEV	Eligibi unkno as batt range not
2	5YJSA1E4XK	King	Seattle	Washington	98109.0	2019	TESLA	MODEL S	BEV	Cle Alternat F Veh Eligi
3	5YJSA1E27G	King	Issaquah	Washington	98027.0	2016	TESLA	MODEL S	BEV	Cle Alternat F Veh Eligi
4	5YJYGDEE5M	Kitsap	Suquamish	Washington	98392.0	2021	TESLA	MODEL Y	BEV	Eligibi unkno as batt range not

In [17]:

```
data.shape
```

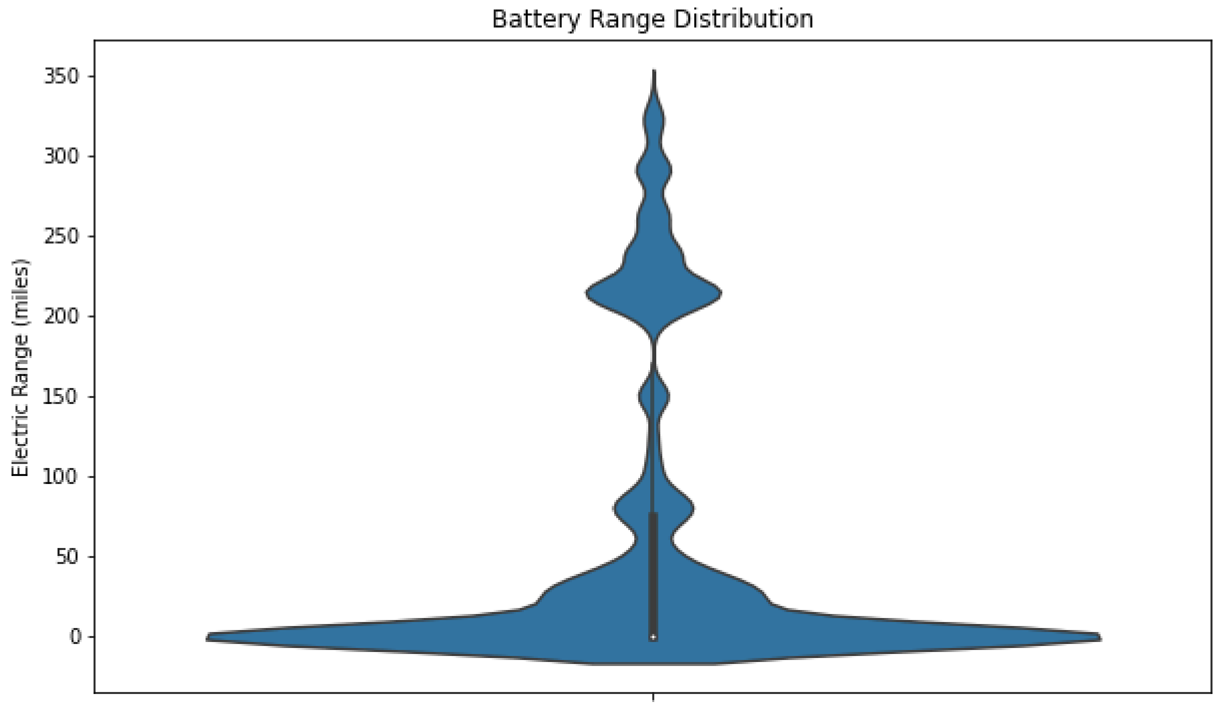
Out[17]:

```
(177861, 18)
```

EDA

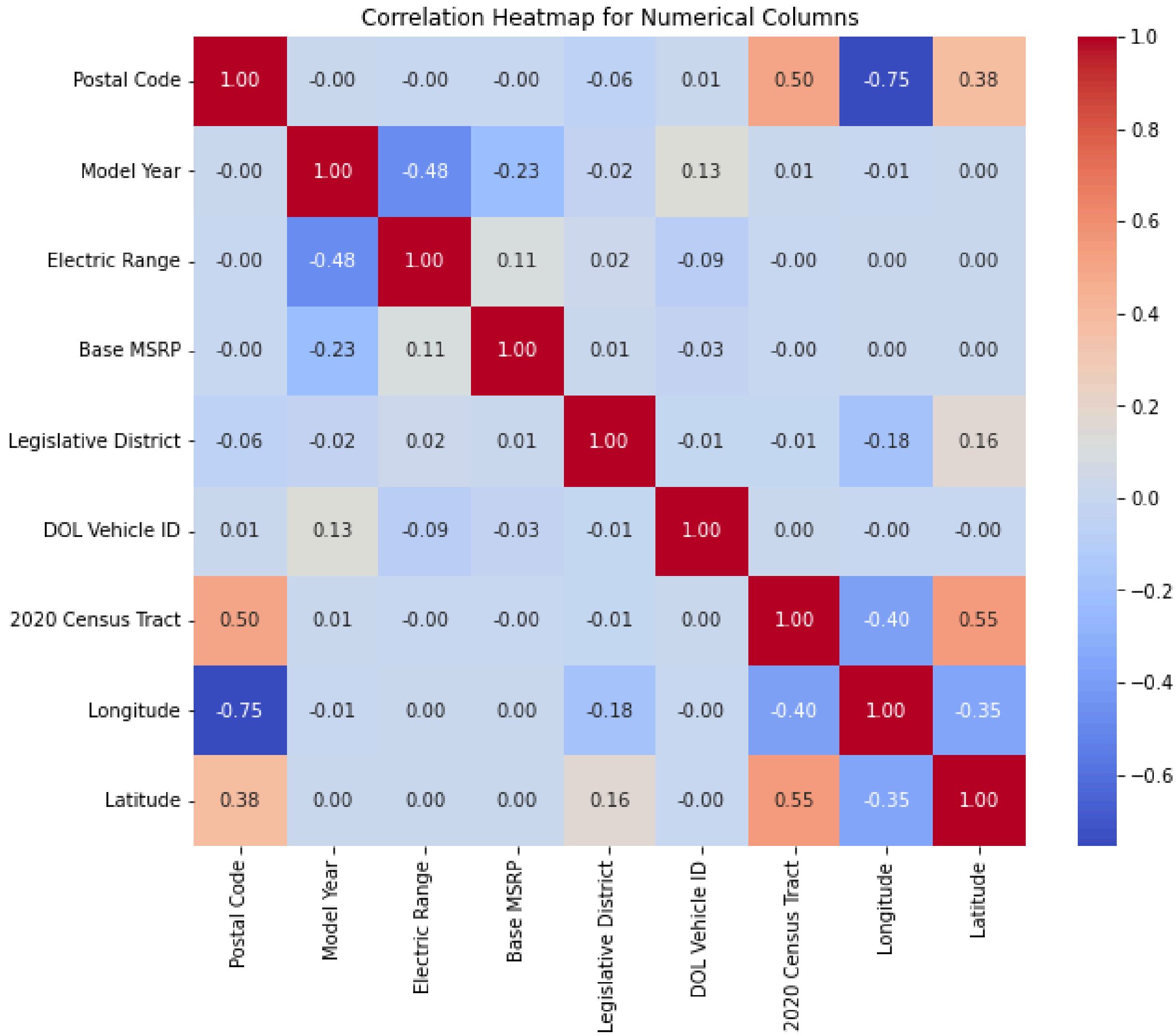
In [18]:

```
# Visualizing Battery Range using Violin Plot
plt.figure(figsize=(10, 6))
sns.violinplot(data=data, y='Electric Range')
plt.title('Battery Range Distribution')
plt.ylabel('Electric Range (miles)')
plt.show()
```



In [19]:
```
# Selecting only numerical columns
numerical_data = data.select_dtypes(include=['float64', 'int64'])
```

In [20]:
```
# Heatmap for Correlation with all numerical columns
plt.figure(figsize=(10, 8))
sns.heatmap(numerical_data.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap for Numerical Columns')
plt.show()
```



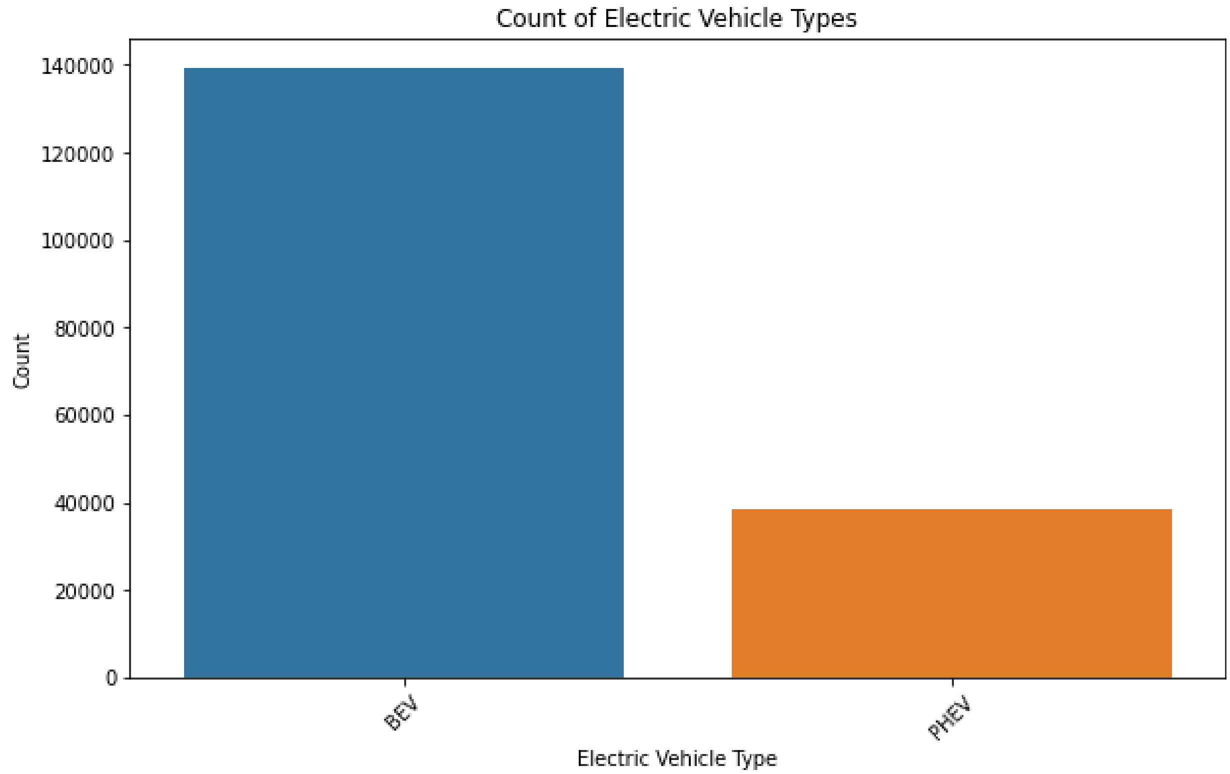
In [21]:

```
column_names = data.columns
print("Column names of EV DataFrame:", column_names)
```

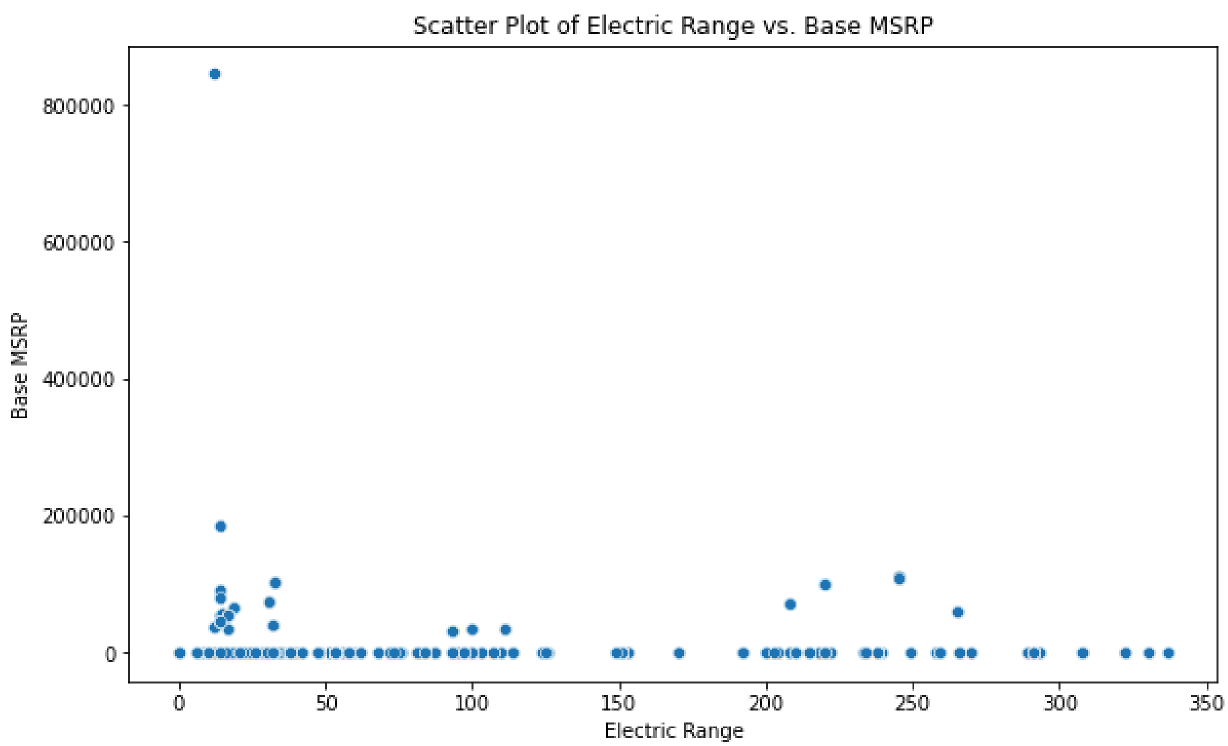
```
Column names of EV DataFrame: Index(['VIN (1-10)', 'County', 'City', 'State', 'Postal
Code', 'Model Year',
       'Make', 'Model', 'Electric Vehicle Type',
       'Clean Alternative Fuel Vehicle Eligibility', 'Electric Range',
       'Base MSRP', 'Legislative District', 'DOL Vehicle ID',
       'Electric Utility', '2020 Census Tract', 'Longitude', 'Latitude'],
      dtype='object')
```

In [22]:

```
# Count of each Electric Vehicle Type
plt.figure(figsize=(10, 6))
sns.countplot(x='Electric Vehicle Type', data=data)
plt.title('Count of Electric Vehicle Types')
plt.xlabel('Electric Vehicle Type')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```

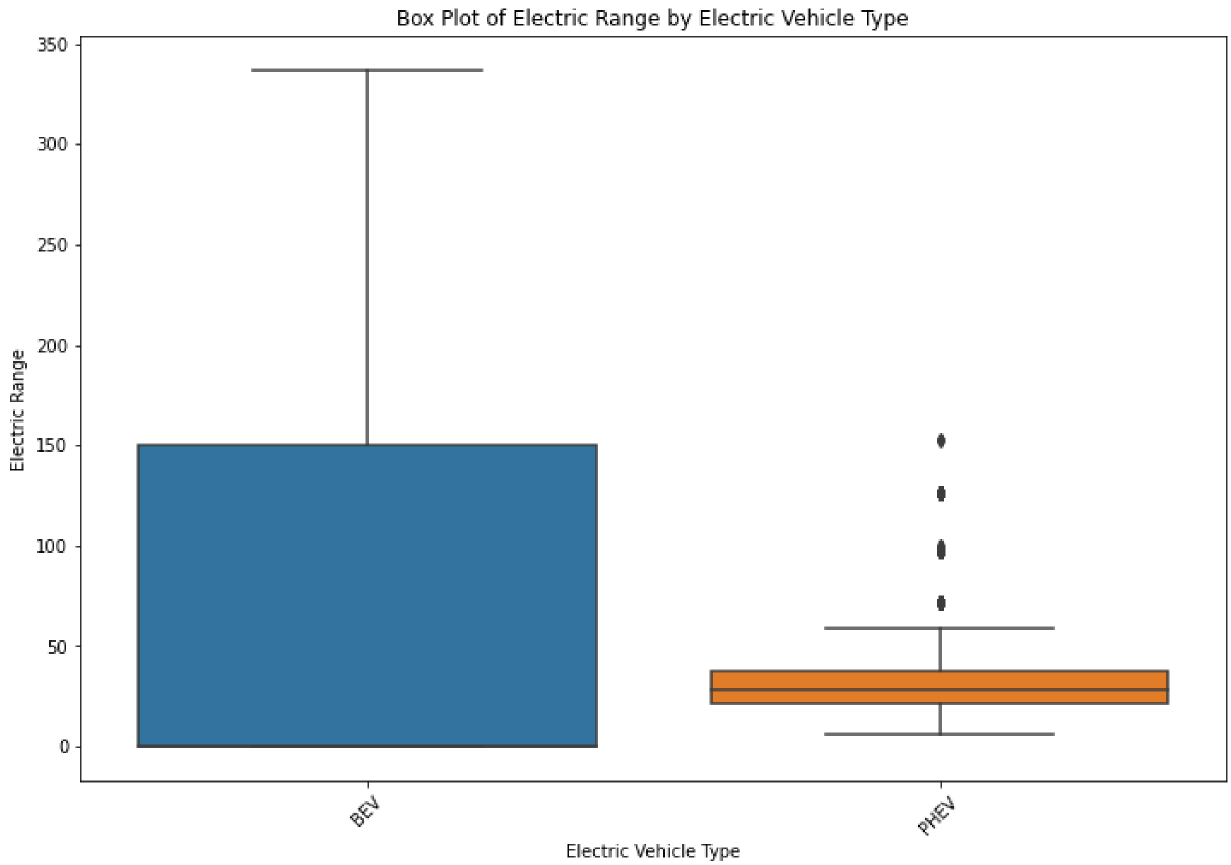


In [23]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Electric Range', y='Base MSRP', data=data)
plt.title('Scatter Plot of Electric Range vs. Base MSRP')
plt.xlabel('Electric Range')
plt.ylabel('Base MSRP')
plt.show()
```

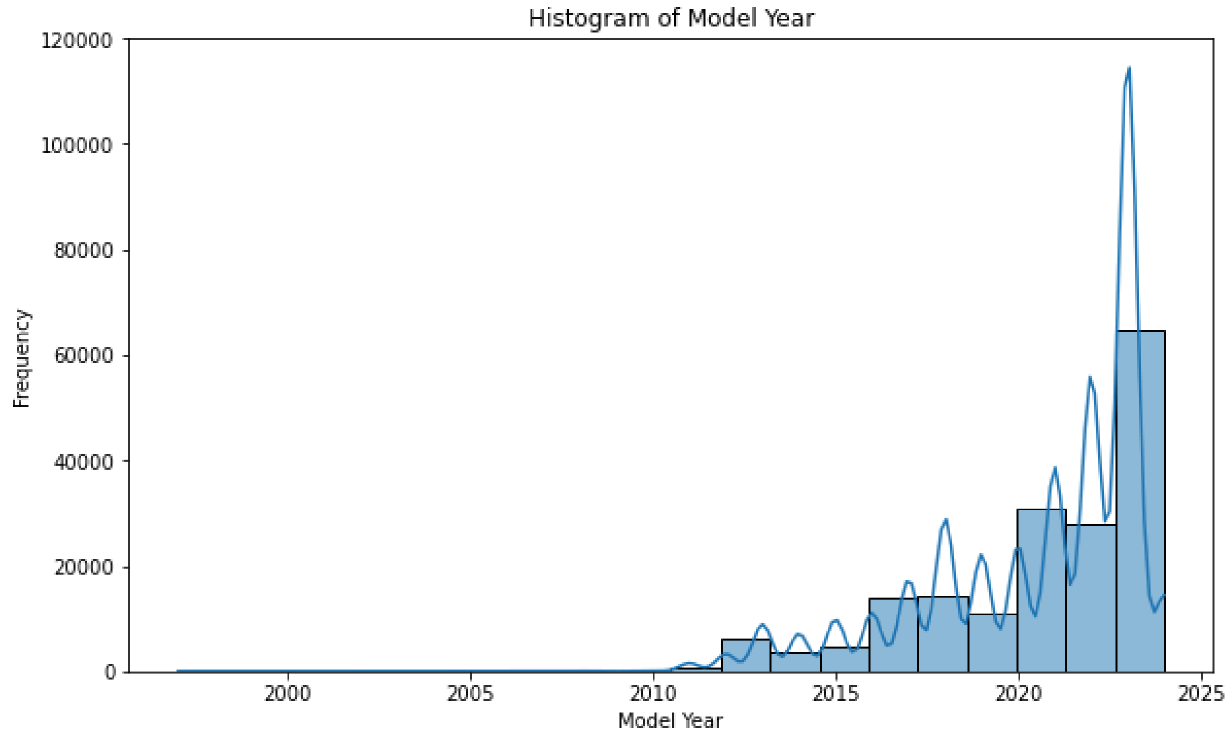


In [24]:
```
plt.figure(figsize=(12, 8))
sns.boxplot(x='Electric Vehicle Type', y='Electric Range', data=data)
plt.title('Box Plot of Electric Range by Electric Vehicle Type')
```

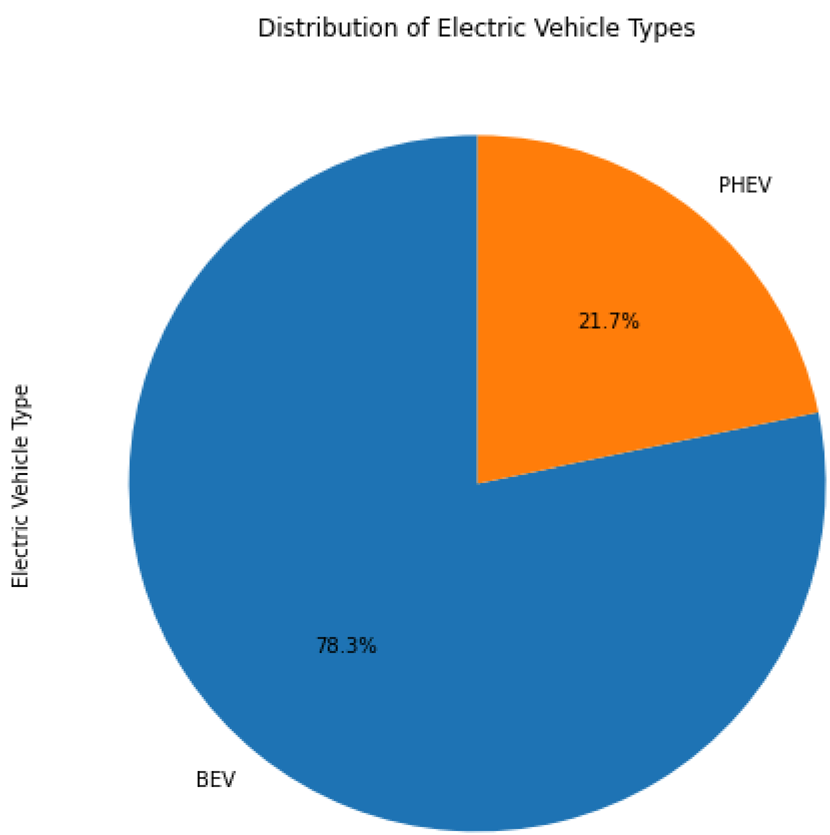
```
plt.xlabel('Electric Vehicle Type')
plt.ylabel('Electric Range')
plt.xticks(rotation=45)
plt.show()
```



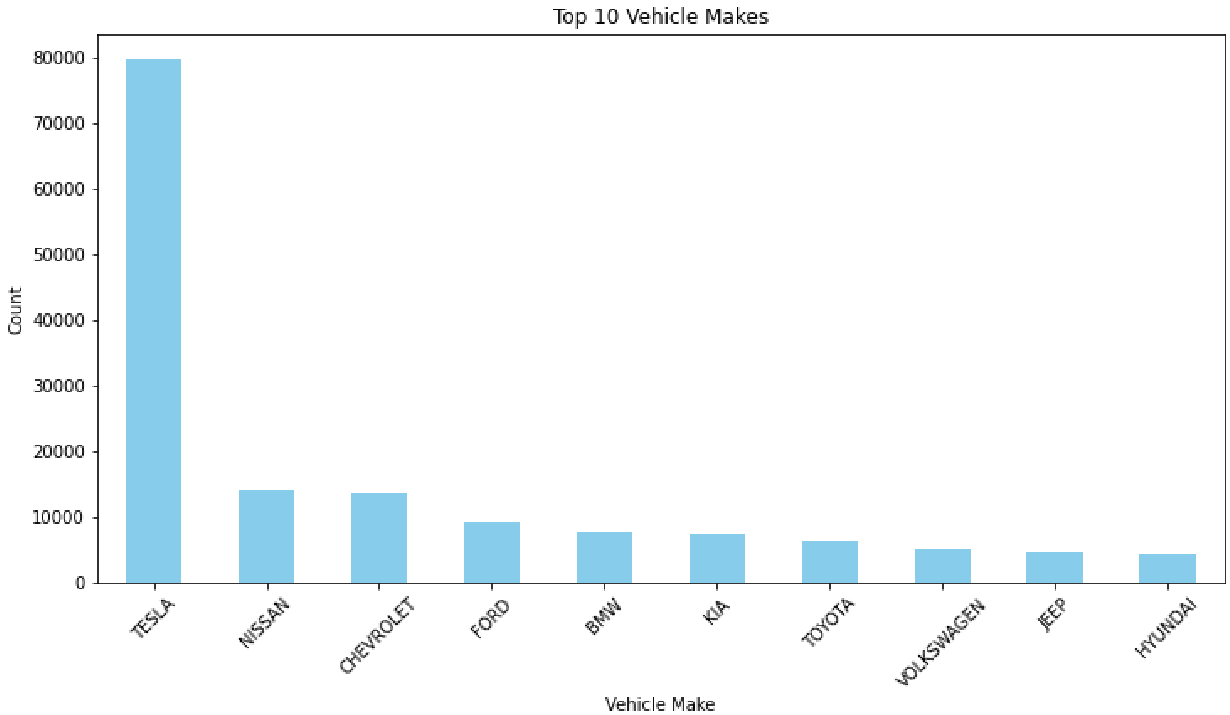
In [25]:
```
plt.figure(figsize=(10, 6))
sns.histplot(data['Model Year'], bins=20, kde=True)
plt.title('Histogram of Model Year')
plt.xlabel('Model Year')
plt.ylabel('Frequency')
plt.show()
```



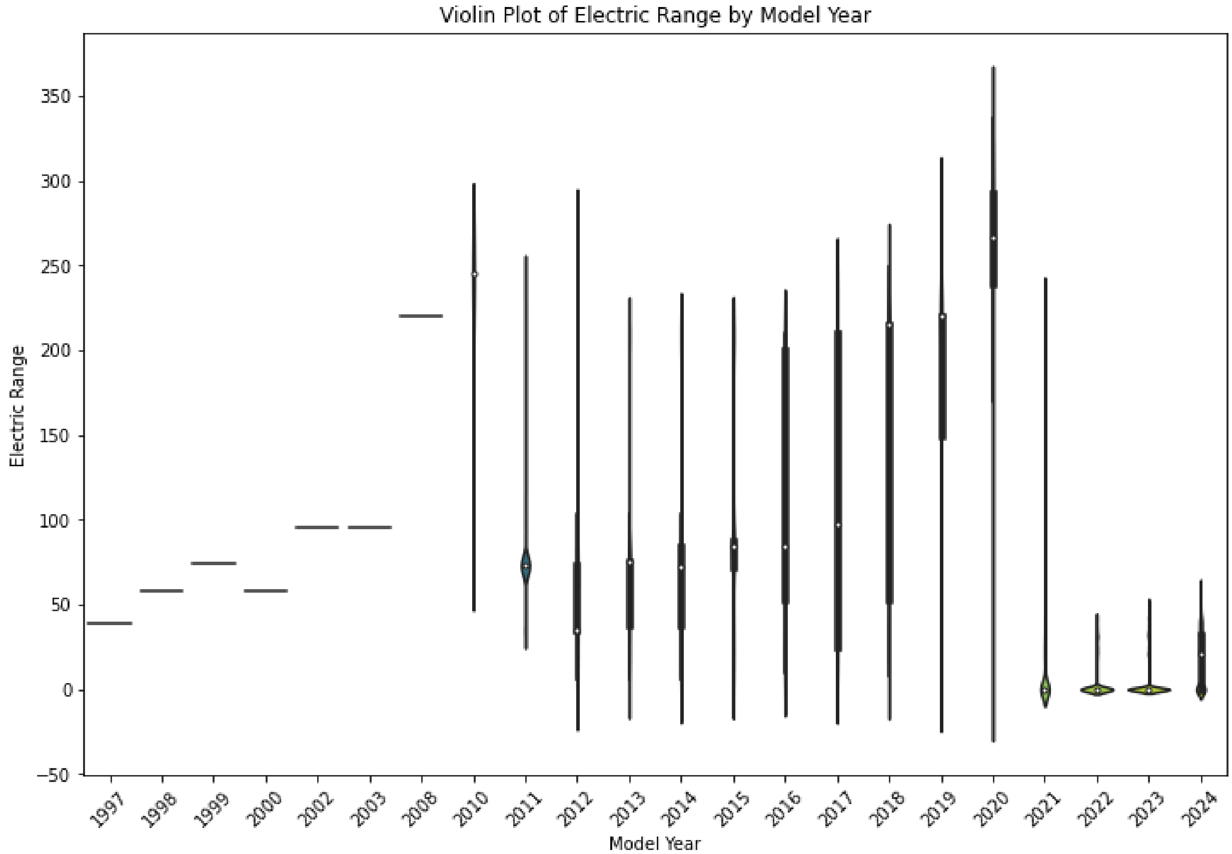
In [26]:
```
plt.figure(figsize=(8, 8))
data['Electric Vehicle Type'].value_counts().plot.pie(autopct='%1.1f%%', startangle=90
plt.title('Distribution of Electric Vehicle Types')
plt.show()
```



In [27]:
```
plt.figure(figsize=(12, 6))
top_makes = data['Make'].value_counts().nlargest(10)
top_makes.plot(kind='bar', color='skyblue')
plt.title('Top 10 Vehicle Makes')
plt.xlabel('Vehicle Make')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```

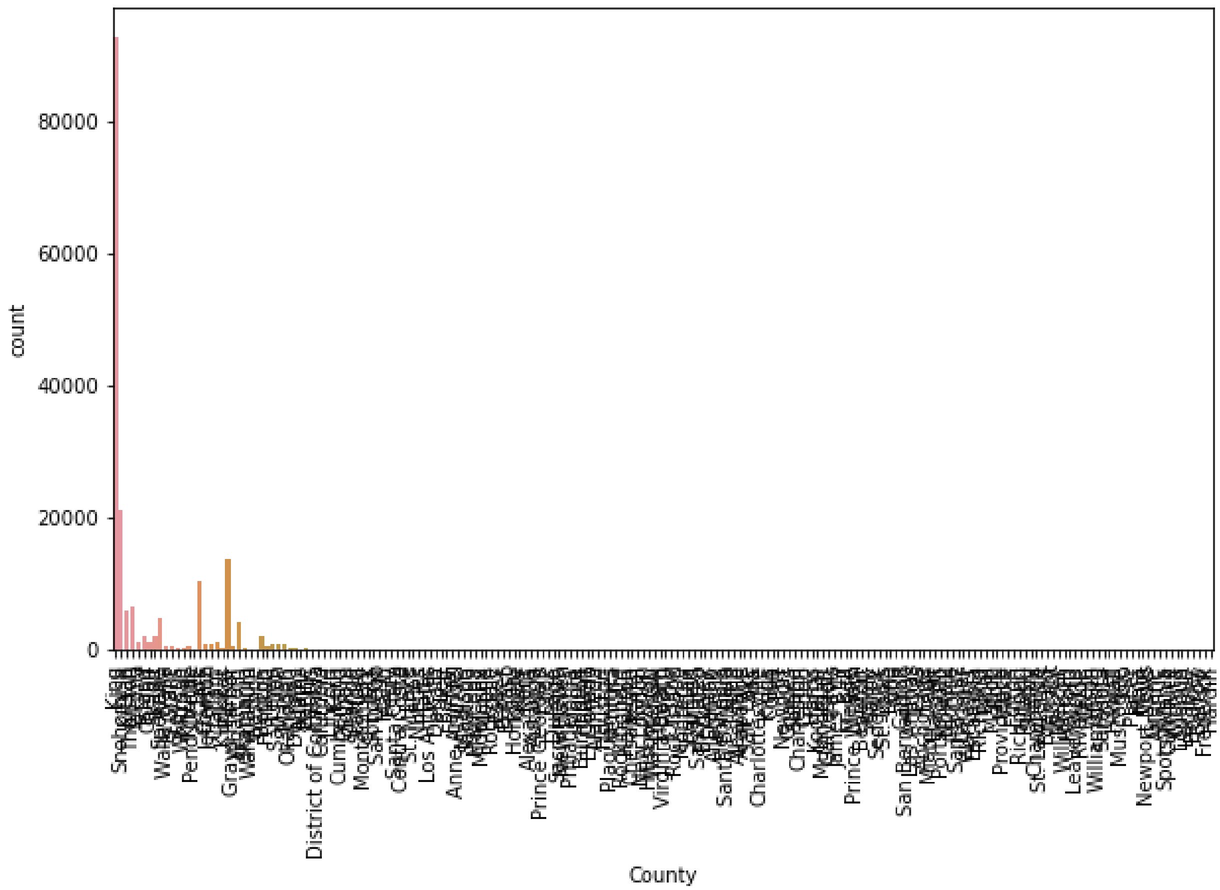


In [28]:
```
plt.figure(figsize=(12, 8))
sns.violinplot(x='Model Year', y='Electric Range', data=data, palette='viridis')
plt.title('Violin Plot of Electric Range by Model Year')
plt.xlabel('Model Year')
plt.ylabel('Electric Range')
plt.xticks(rotation=45)
plt.show()
```



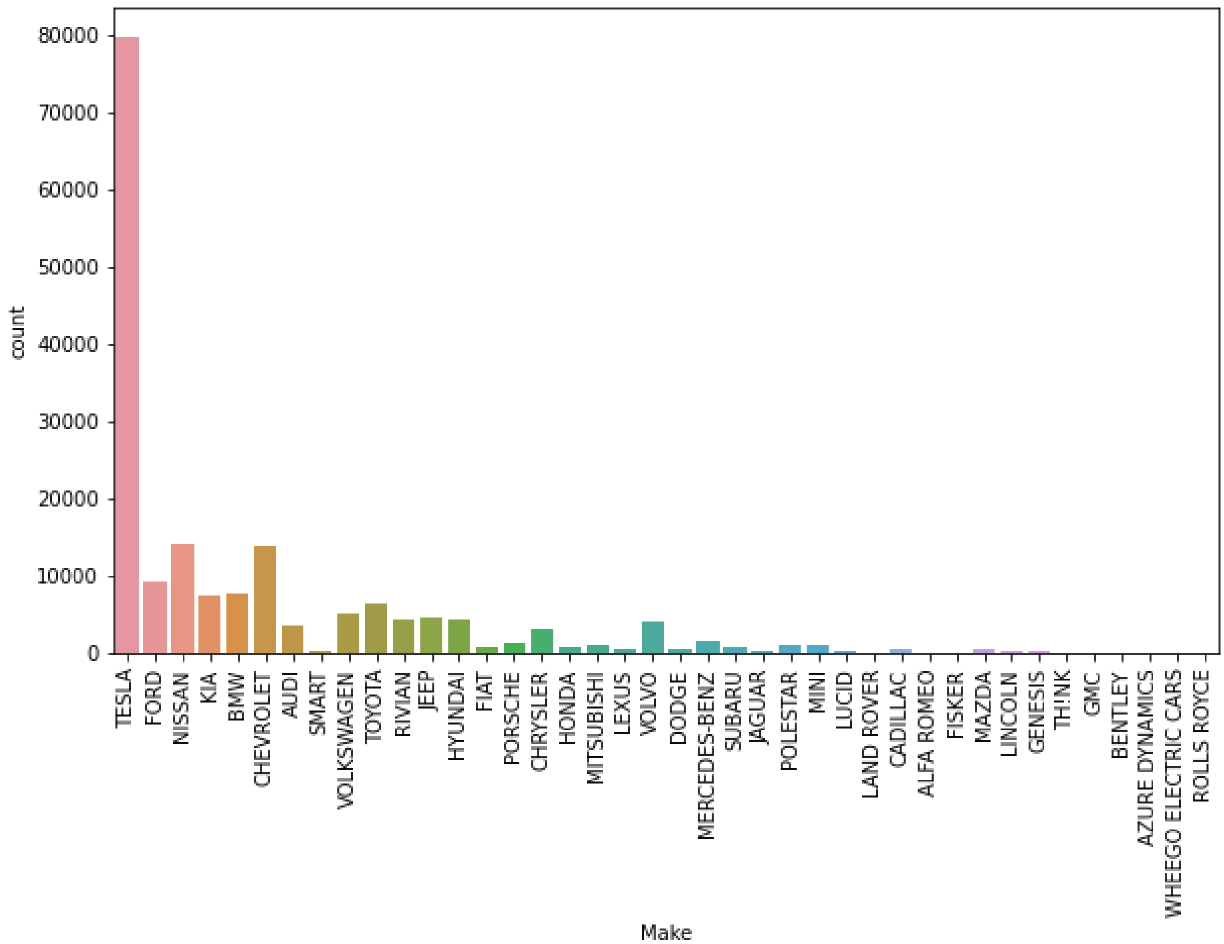
In [29]:
```
# Cleaning Null Values
data.dropna(inplace=True)

# Checking Duplicate Value
data.duplicated().sum()

# Removing Column
data['State'].value_counts()

# State column has only one value i.e WA means Washington D.C. So we can remove 'state
data.drop(columns='State',inplace=True)
```

In [30]:
```
plt.figure(figsize=(10,6))
sns.countplot(x='County',data=data)
plt.xticks(rotation=90);
```



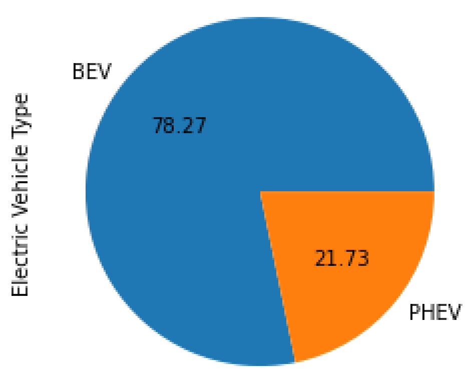
In [31]:

```
plt.figure(figsize=(10,6))
sns.countplot(x='Make',data=data)
plt.xticks(rotation=90);
```

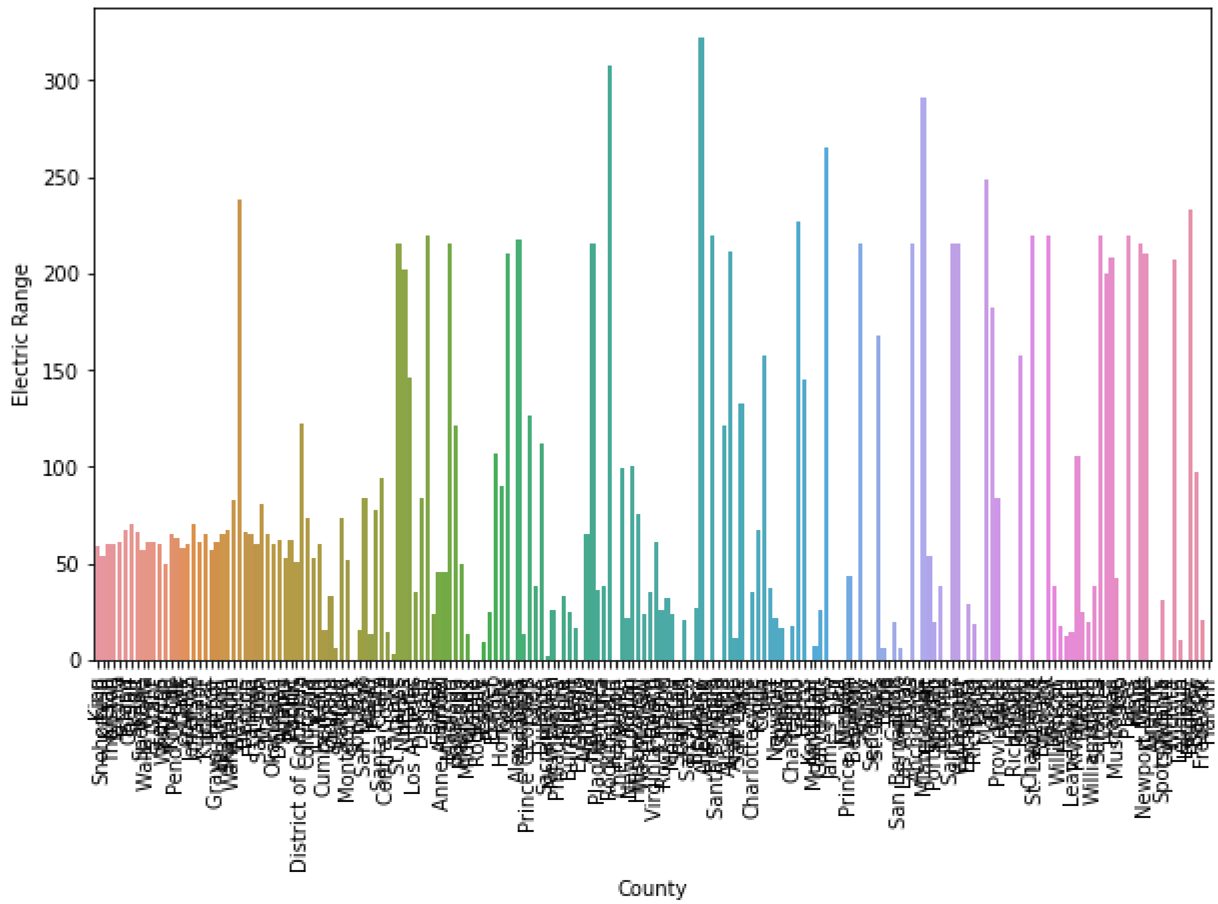


In [32]:
```
data['Electric Vehicle Type'].value_counts().plot(kind='pie',autopct='%.2f')
```

Out[32]:
```
<AxesSubplot:ylabel='Electric Vehicle Type'>
```

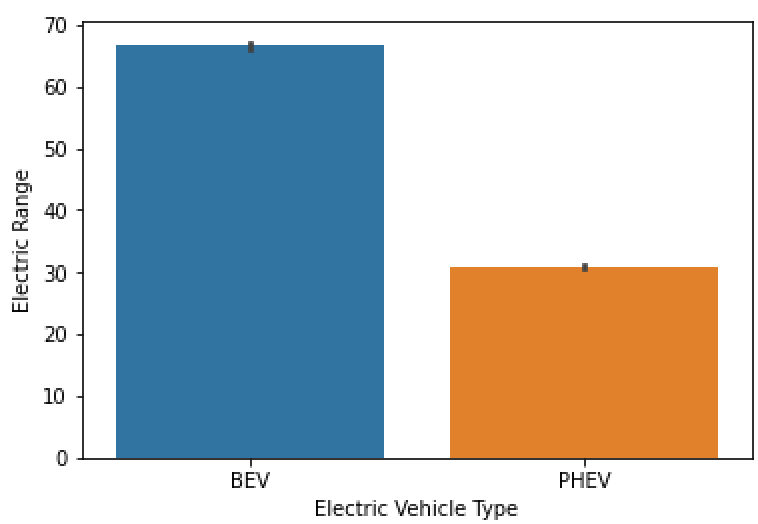


In [33]:
```
# Bivariate Analysis
plt.figure(figsize=(10,6))
sns.barplot(x='County',y='Electric Range',data=data,ci=None)
plt.xticks(rotation=90);
```

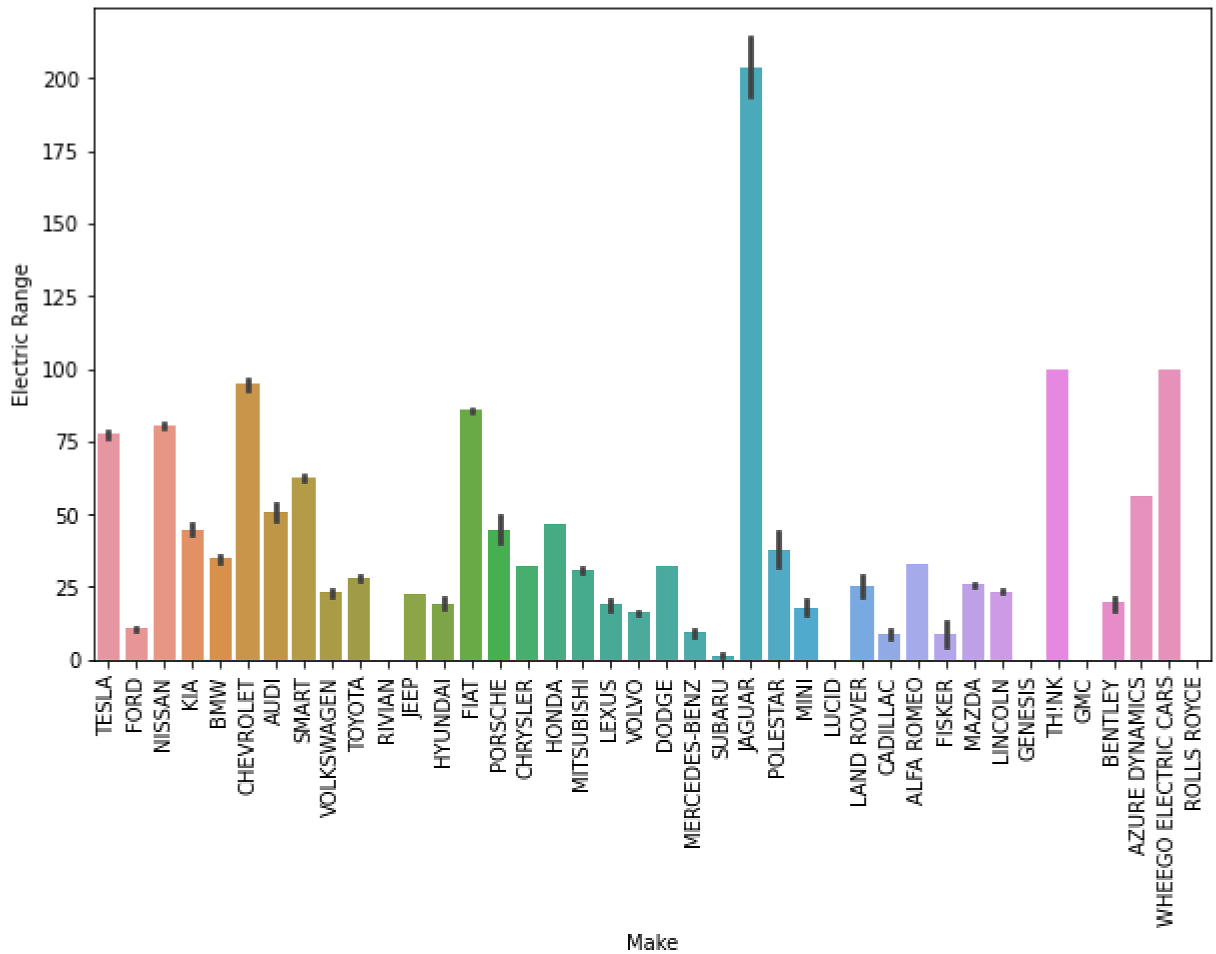


In [34]:
```
sns.barplot(x='Electric Vehicle Type',y='Electric Range',data=data)
```

Out[34]:
```
<AxesSubplot:xlabel='Electric Vehicle Type', ylabel='Electric Range'>
```

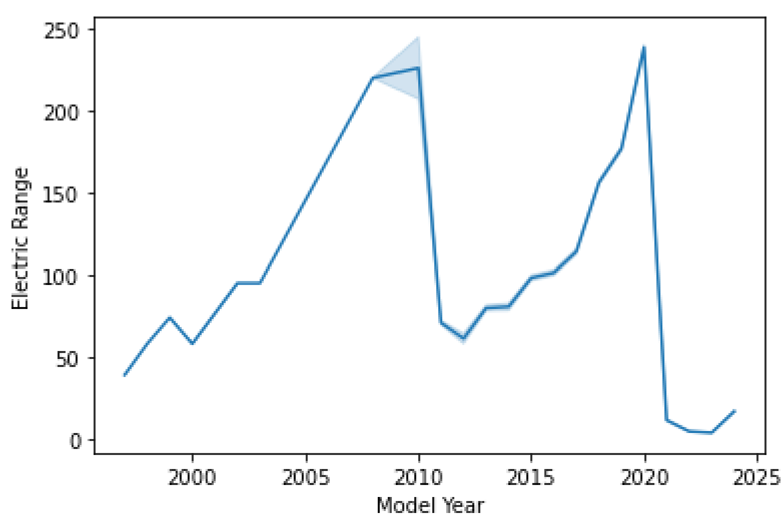


In [35]:
```
plt.figure(figsize=(10,6))
sns.barplot(x='Make',y='Electric Range',data=data)
plt.xticks(rotation=90);
```

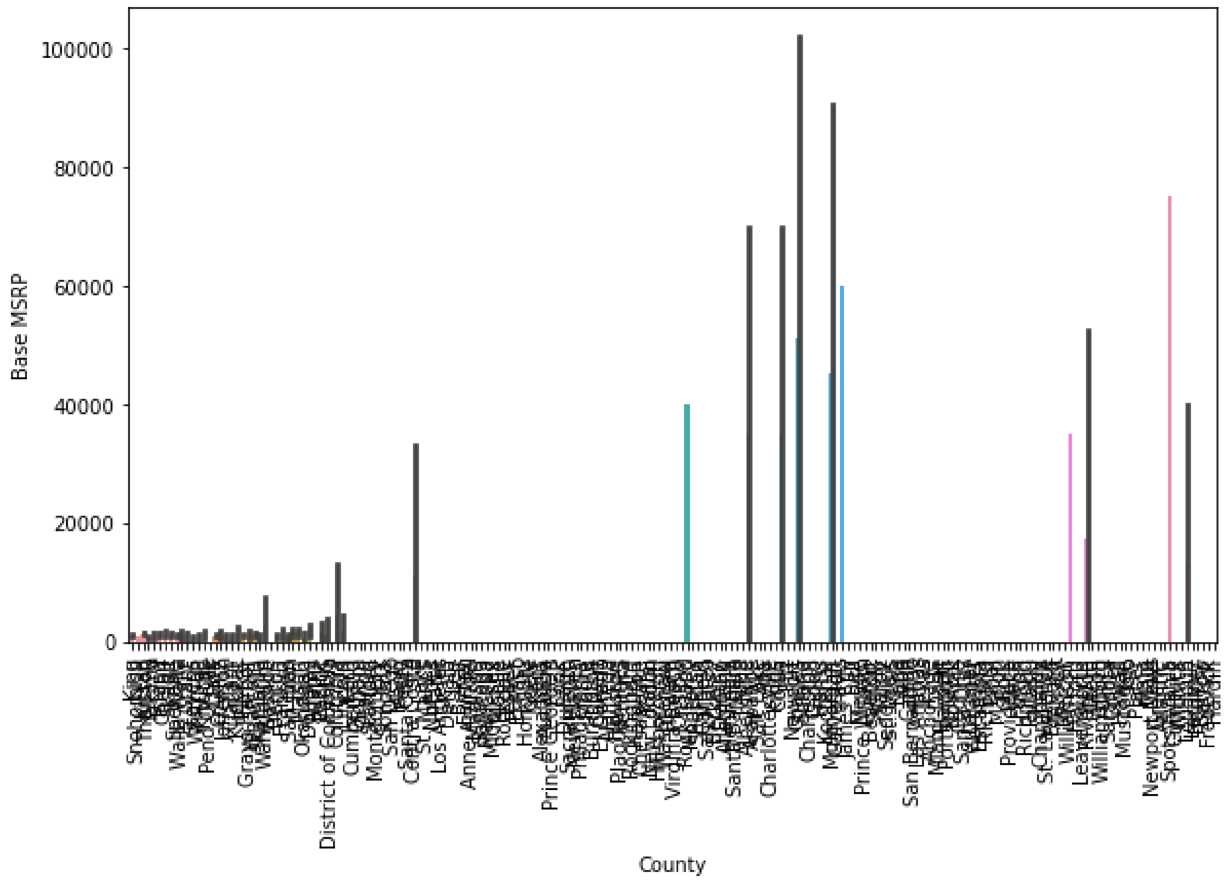


In [36]:
```python
sns.lineplot(x='Model Year',y='Electric Range',data=data)
```

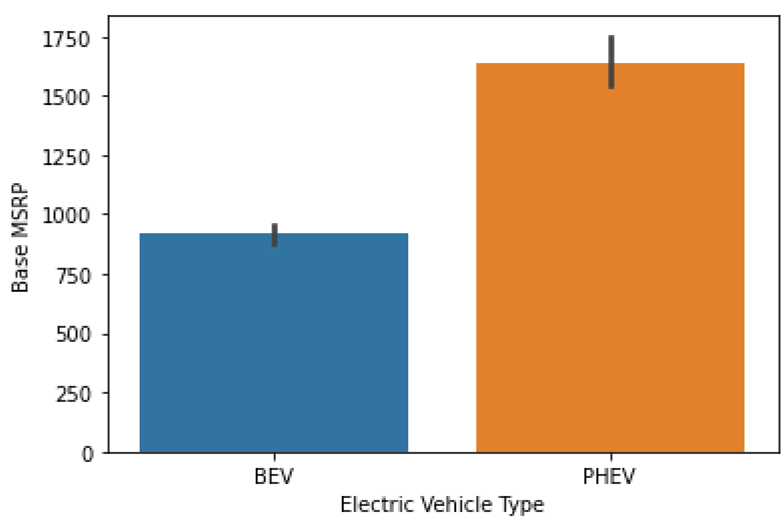
Out[36]: <AxesSubplot:xlabel='Model Year', ylabel='Electric Range'>



In [37]:
```python
plt.figure(figsize=(10,6))
sns.barplot(x='County',y='Base MSRP',data=data)
plt.xticks(rotation=90);
```



In [38]:
```python
sns.barplot(x='Electric Vehicle Type',y='Base MSRP',data=data)
```
Out[38]:
```
<AxesSubplot:xlabel='Electric Vehicle Type', ylabel='Base MSRP'>
```



In [39]:
```python
# Q1:Which counties and cities in Washington State have the highest electric vehicle r
# Lets start by grouping our data according to Cities and Counties since our dataset c
county_city_registrations = data.groupby(['County', 'City']).size().reset_index(name='
county_city_registrations.head(2)
```

Out[39]:

	County	City	Registrations
0	Ada	Boise	2
1	Adams	Aurora	1

In [40]:
```
# Then we need to arrange the grouped data in Descending order
highest_registrations = county_city_registrations.sort_values(by='Registrations', asce
highest_registrations.head(2)
```

Out[40]:

	County	City	Registrations
277	King	Seattle	29447
244	King	Bellevue	8930

In [41]:
```
# What are the most popular electric vehicle makes and models in Washington State?
# To identify the most popular electric vehicle makes and models in Washington State b
# can follow these steps: Group the data by "Make" and "Model" columns to aggregate re

make_model_distribution = data.groupby(['Make', 'Model']).size().reset_index(name='Reg
make_model_distribution.head(2)
```

Out[41]:

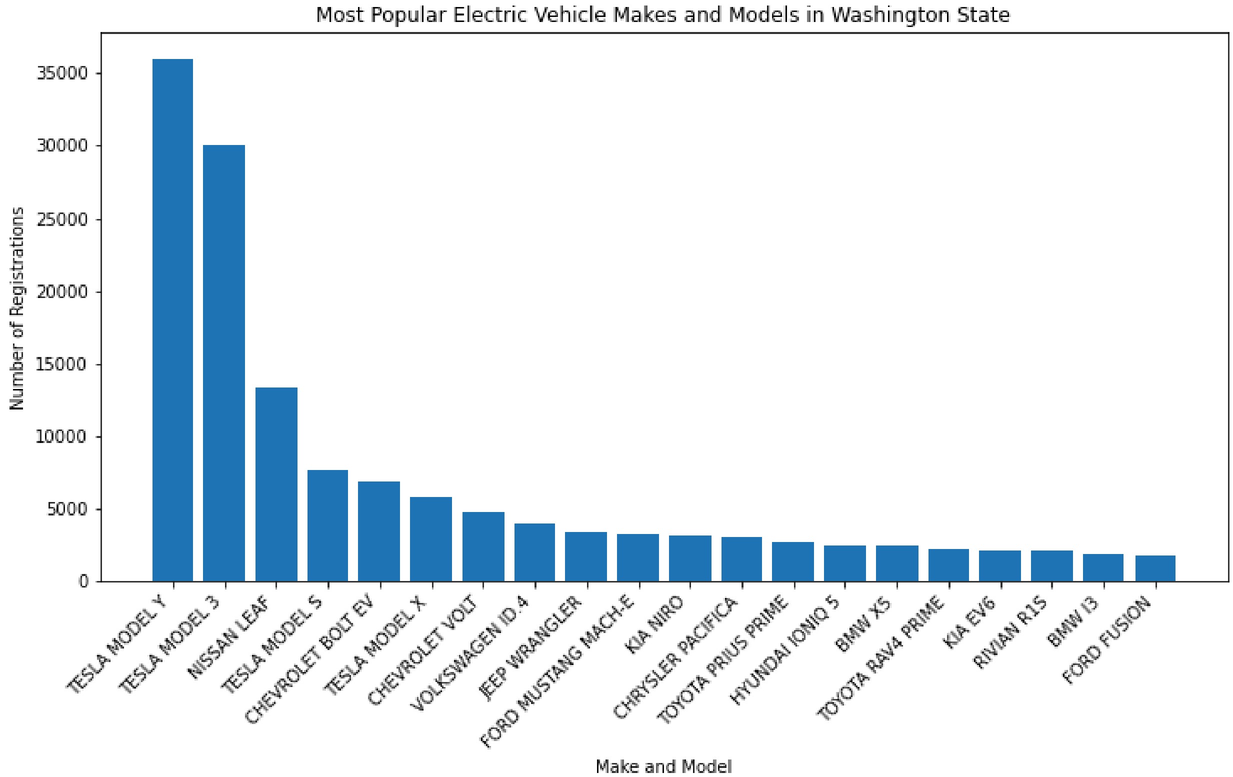
	Make	Model	Registrations
0	ALFA ROMEO	TONALE	39
1	AUDI	A3	548

In [42]:
```
# Sort the DataFrame in descending order based on the number of registrations to ident
popular_make_model = make_model_distribution.sort_values(by='Registrations', ascending
popular_make_model.head(2)
```

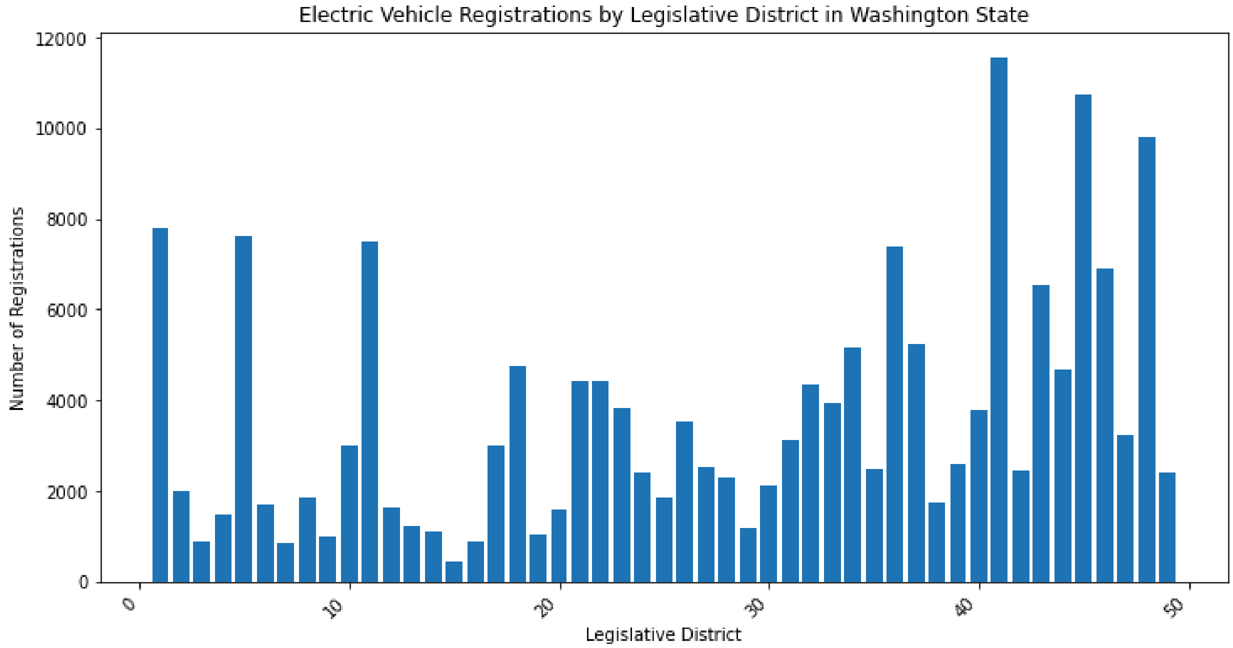
Out[42]:

	Make	Model	Registrations
120	TESLA	MODEL Y	35989
117	TESLA	MODEL 3	30091

In [43]:
```
# Create visualizations, such as bar charts or tables, to illustrate the distribution

x=popular_make_model.head(20)
plt.figure(figsize=(12, 6))
plt.bar(x['Make'] + ' ' + x['Model'], x['Registrations'])
plt.xlabel('Make and Model')
plt.ylabel('Number of Registrations')
plt.title('Most Popular Electric Vehicle Makes and Models in Washington State')
plt.xticks(rotation=45, ha='right')
plt.show()
```



In [44]:
```
# Group by Legislative District
district_distribution = data.groupby('Legislative District').size().reset_index(name='

# Sort by Registrations
popular_districts = district_distribution.sort_values(by='Registrations', ascending=Fa

# Plot a bar chart
plt.figure(figsize=(12, 6))
plt.bar(popular_districts['Legislative District'], popular_districts['Registrations'])
plt.xlabel('Legislative District')
plt.ylabel('Number of Registrations')
plt.title('Electric Vehicle Registrations by Legislative District in Washington State'
plt.xticks(rotation=45, ha='right')
plt.show()

# Calculate and display the correlation coefficient
correlation_coefficient = data['Legislative District'].corr( popular_districts['Regist
print(f"Correlation Coefficient: {correlation_coefficient}")
```




```
Correlation Coefficient: -0.05435021249664533
```

In [45]:

```
# Filter for electric vehicles that are eligible as CAFV

eligible_vehicles = data[data['Clean Alternative Fuel Vehicle Eligibility'] == 'Clean

# Calculate the percentage
percentage_eligible_vehicles = (len(eligible_vehicles) / len(data)) * 100

print(f"Percentage of Electric Vehicles Eligible as CAFV: {percentage_eligible_vehicle
```

```
Percentage of Electric Vehicles Eligible as CAFV: 37.29%
```

In [ ]:

In [46]:

```
data.head()
```

Out[46]:

	VIN (1-10)	County	City	Postal Code	Model Year	Make	Model	Electric Vehicle Type	Clean Alternative Fuel Vehicle Eligibility	Electric Range
0	5YJYGDEE1L	King	Seattle	98122.0	2020	TESLA	MODEL Y	BEV	Clean Alternative Fuel Vehicle Eligible	291
1	7SAYGDEE9P	Snohomish	Bothell	98021.0	2023	TESLA	MODEL Y	BEV	Eligibility unknown as battery range has not b...	0
2	5YJSA1E4XK	King	Seattle	98109.0	2019	TESLA	MODEL S	BEV	Clean Alternative Fuel Vehicle Eligible	270
3	5YJSA1E27G	King	Issaquah	98027.0	2016	TESLA	MODEL S	BEV	Clean Alternative Fuel Vehicle Eligible	210
4	5YJYGDEE5M	Kitsap	Suquamish	98392.0	2021	TESLA	MODEL Y	BEV	Eligibility unknown as battery range has not b...	0

In [ ]:

In [ ]:

In [47]:

```
from sklearn.preprocessing import LabelEncoder

# Now you can use LabelEncoder
label_encoder = LabelEncoder()
data['Electric Vehicle Type'] = label_encoder.fit_transform(data['Electric Vehicle Typ
data['Make'] = label_encoder.fit_transform(data['Make'])
```

In [48]:

```
# Encoding categorical variables
label_encoder = LabelEncoder()
data['Electric Vehicle Type'] = label_encoder.fit_transform(data['Electric Vehicle Typ
data['Make'] = label_encoder.fit_transform(data['Make'])
data['Model'] = label_encoder.fit_transform(data['Model'])
```

In [ ]:

In [49]:

```
# Split the data into features (X) and target variable (y)
#X = data[['Electric Range', 'Base MSRP', 'Electric Vehicle Type', 'Make', 'Model']]
```

```
#y = data['Model']
```

In [50]:
```
# Splitting the data into training and testing sets
#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state
```

In [ ]:

In [51]:
```
# Drop irrelevant columns
data.drop("VIN (1-10)", axis=1, inplace=True)
```

In [96]:
```
data[['Postal Code', 'Model Year', 'Make', 'Model', 'Electric Range', 'Base MSRP']]
```

Out[96]:

	Postal Code	Model Year	Make	Model	Electric Range	Base MSRP
0	98122.0	2020	34	81	291	0
1	98021.0	2023	34	81	0	0
2	98109.0	2019	34	79	270	0
3	98027.0	2016	34	79	210	0
4	98392.0	2021	34	81	0	0
...	...	...	...	...	...	...
177861	98391.0	2022	34	81	0	0
177862	98584.0	2023	15	75	0	0
177863	98848.0	2021	34	81	0	0
177864	98010.0	2021	37	68	0	0
177865	98422.0	2021	34	78	0	0

177861 rows × 6 columns

In [95]:
```
print(data.columns[:0])
```

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

In [ ]:

Train Test Splitting

In [82]:
```
#sns.set_theme(style="white")

X = data[['Postal Code', 'Model Year', 'Make', 'Model', 'Electric Range', 'Base MSRP']
y = data['Electric Vehicle Type'].values


# split the data into train and test sets with a test size of 30%
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, stratify=y, r
```

In [83]:
```
# count the occurrences of target value in the 'Electric Vehicle Type' column
data['Electric Vehicle Type'].value_counts()
```

Out[83]:
```
0    139205
1     38656
Name: Electric Vehicle Type, dtype: int64
```

In [ ]:

Naive Bayes

In [84]:
```
# initialize the Naive Bayes classifier and fit it to the resampled training data
NB_classifier = GaussianNB()
NB_classifier.fit(X_train, y_train)

# make predictions on the test data
y_pred = NB_classifier.predict(X_test)

# calculate metric evaluation and confusion matrix
accurary = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)

# print the result
print("="*55)
print("Accuracy     :", accurary)
print("ROC AUC Score:", roc_auc_score(y_test, y_pred))

print("="*55)
print("Classification Report:\n\n", classification_report(y_test, y_pred))
print("="*55)

print("Confusion Matrix:\n\n", cm)
print("="*55)
```

```
=======================================================
Accuracy     : 0.896437339530351
ROC AUC Score: 0.8193302711926629
=======================================================
Classification Report:

               precision    recall  f1-score   support

           0       0.92      0.96      0.94     41762
           1       0.81      0.68      0.74     11597

    accuracy                           0.90     53359
   macro avg       0.86      0.82      0.84     53359
weighted avg       0.89      0.90      0.89     53359

=======================================================
Confusion Matrix:

 [[39913  1849]
 [ 3677  7920]]
=======================================================
```

Logistic Regression

In [90]:
```
# initialize the Logistic Regression classifier and fit it to the resampled training d
LR_classifier = LogisticRegression()
```

```
LR_classifier.fit(X_train, y_train)

# make predictions on the test data
y_pred = LR_classifier.predict(X_test)

# calculate metric evaluation and confusion matrix
accurary = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)

# print the result
print("="*55)
print("Accuracy     :", accurary)
print("ROC AUC Score:", roc_auc_score(y_test, y_pred))

print("="*55)
print("Classification Report:\n\n", classification_report(y_test, y_pred))
print("="*55)

print("Confusion Matrix:\n\n", cm)
print("="*55)
```

```
=======================================================
Accuracy     : 0.834423433722521
ROC AUC Score: 0.6884668793554423
=======================================================
Classification Report:

               precision    recall  f1-score   support

           0       0.86      0.95      0.90     41762
           1       0.69      0.43      0.53     11597

    accuracy                           0.83     53359
   macro avg       0.77      0.69      0.71     53359
weighted avg       0.82      0.83      0.82     53359

=======================================================
Confusion Matrix:

 [[39534  2228]
 [ 6607  4990]]
=======================================================
```

Random Forest Classifier

In [98]:

```
# initialize the Random Forest classifier and fit it to the resampled training data
RF_classifier = RandomForestClassifier(n_estimators=100)
RF_classifier.fit(X_train, y_train)

# make predictions on the test data
y_pred = RF_classifier.predict(X_test)

# calculate metric evaluation and confusion matrix
accurary = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)

# print the result
print("="*55)
```

```python
print("Accuracy     :", accurary)
print("ROC AUC Score:", roc_auc_score(y_test, y_pred))

print("="*55)
print("Classification Report:\n\n", classification_report(y_test, y_pred))
print("="*55)

print("Confusion Matrix:\n\n", cm)
print("="*55)
```

```
=======================================================
Accuracy     : 0.9999062950954853
ROC AUC Score: 0.9998155689989119
=======================================================
Classification Report:

               precision    recall  f1-score   support

           0       1.00      1.00      1.00     41762
           1       1.00      1.00      1.00     11597

    accuracy                           1.00     53359
   macro avg       1.00      1.00      1.00     53359
weighted avg       1.00      1.00      1.00     53359

=======================================================
Confusion Matrix:

 [[41761     1]
 [    4 11593]]
=======================================================
```