ass1

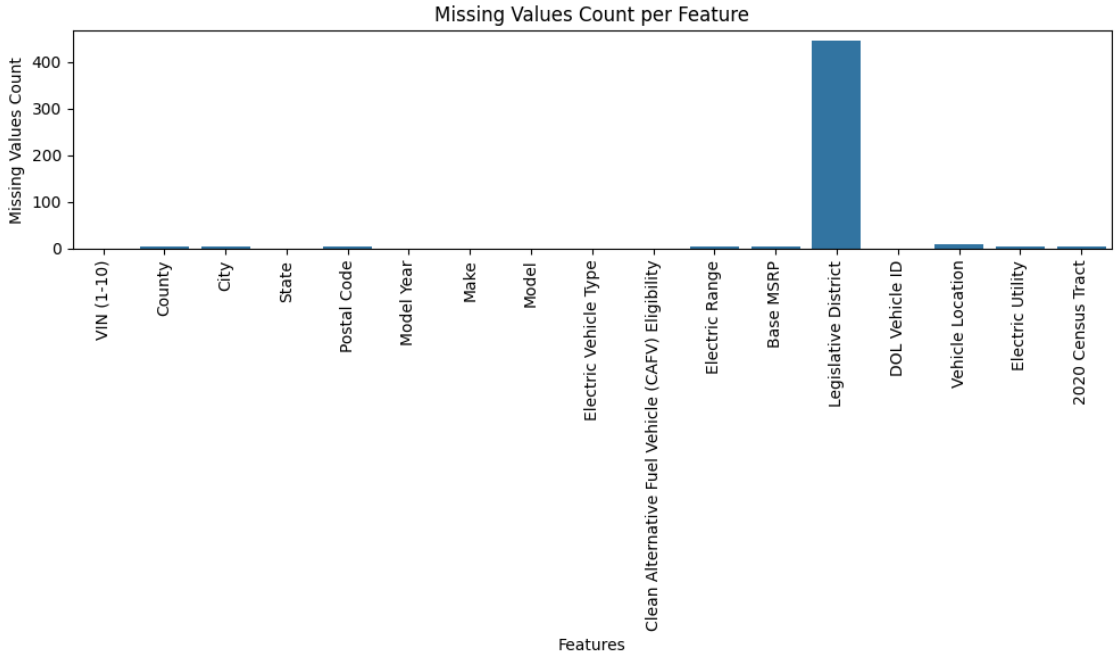
October 26, 2024

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import folium
from folium.plugins import HeatMap

print("Document Missing Values: Check for missing values and document their␣
 ↪frequency and distribution across features\n")
missing_values = ["n/a", "na", "--"]
df = pd.read_csv("Electric_Vehicle_Population_Data.csv",␣
 ↪na_values=missing_values)
missing_values_count = df.isnull().sum()
missing_values_percentage = (missing_values_count / len(df)) * 100

missing_values_table = pd.DataFrame({
    'Missing Values Count': missing_values_count,
    'Missing Values Percentage': missing_values_percentage
})
print(missing_values_table)

plt.figure(figsize=(10, 6))
sns.barplot(x=missing_values_count.index, y=missing_values_count.values)
plt.xticks(rotation=90)
plt.title("Missing Values Count per Feature")
plt.xlabel("Features")
plt.ylabel("Missing Values Count")
plt.tight_layout()
plt.show()
```

```
Document Missing Values: Check for missing values and document their frequency
and distribution across features

                                                Missing Values Count  \
VIN (1-10)                                                         0
County                                                             4
City                                                               4
State                                                              0
Postal Code                                                        4
```

Model Year	0
Make	0
Model	0
Electric Vehicle Type	0
Clean Alternative Fuel Vehicle (CAFV) Eligibility	0
Electric Range	5
Base MSRP	5
Legislative District	445
DOL Vehicle ID	0
Vehicle Location	10
Electric Utility	4
2020 Census Tract	4

	Missing Values Percentage
VIN (1-10)	0.000000
County	0.001903
City	0.001903
State	0.000000
Postal Code	0.001903
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	0.002379
Base MSRP	0.002379
Legislative District	0.211738
DOL Vehicle ID	0.000000
Vehicle Location	0.004758
Electric Utility	0.001903
2020 Census Tract	0.001903



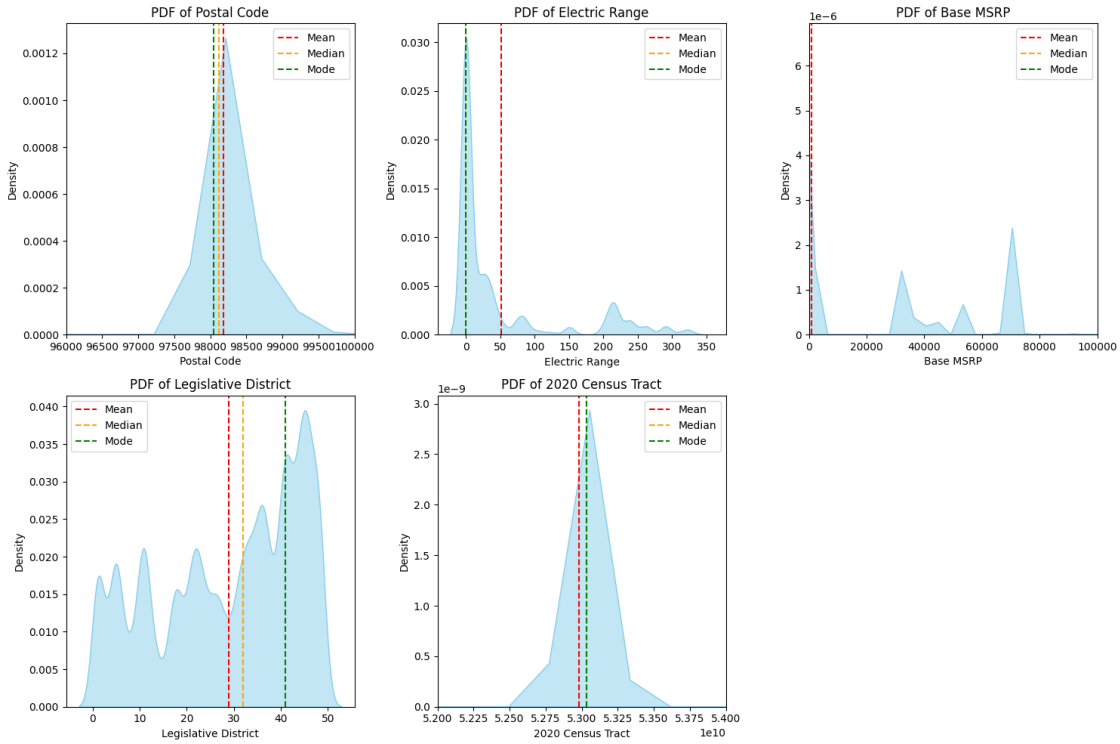
[3]:
```
print("Missing Value Strategies: If missing values are present, apply multiple␣
 ↪strategies (e.g., mean/median imputation, dropping rows) and compare their␣
 ↪impact on the analysis.")

numerical_columns = df.select_dtypes(include='number').columns.tolist()
df_numeric = df[numerical_columns]

summary_stats = {}

for column in numerical_columns:
    if missing_values_count[column] > 0:  # Check if the column has missing␣
 ↪values

        mean_value = df[column].mean().round().astype(int)
        median_value = df[column].median().round().astype(int)
        mode_value = df[column].mode().iloc[0].round().astype(int)
        std_dev_value = df[column].std().round().astype(int)

        summary_stats[column] = {
            'Mean': mean_value,
            'Median': median_value,
            'Mode': mode_value,
            'Standard Deviation': std_dev_value
        }
```

```
summary_stats_df = pd.DataFrame(summary_stats).T
print("\nMissing Value Strategies:")
print("Summary Statistics for Columns with Missing Values:\n", summary_stats_df)

plt.figure(figsize=(15, 10))
for i, column in enumerate(summary_stats_df.index[:6]):  # Only take the first␣
 ↪6 columns
    plt.subplot(2, 3, i + 1)
    sns.kdeplot(df[column], fill=True, color='skyblue', alpha=0.5)
    plt.axvline(summary_stats_df.loc[column, 'Mean'], color='red',␣
 ↪linestyle='--', label='Mean')
    plt.axvline(summary_stats_df.loc[column, 'Median'], color='orange',␣
 ↪linestyle='--', label='Median')
    plt.axvline(summary_stats_df.loc[column, 'Mode'], color='green',␣
 ↪linestyle='--', label='Mode')
    plt.title(f'PDF of {column}')
    plt.xlabel(column)
    plt.ylabel('Density')
    plt.legend()
    if column == 'Postal Code':
        plt.xlim(96000, 100000)
    if column == 'Base MSRP':
        plt.xlim(0, 100000)
    if column == '2020 Census Tract':
        plt.xlim(52000000000, 54000000000)

plt.tight_layout()
plt.show()
```

Missing Value Strategies: If missing values are present, apply multiple strategies (e.g., mean/median imputation, dropping rows) and compare their impact on the analysis.

```
Missing Value Strategies:
Summary Statistics for Columns with Missing Values:
                              Mean       Median         Mode  \
Postal Code                  98178        98125        98052
Electric Range                  51            0            0
Base MSRP                      898            0            0
Legislative District            29           32           41
2020 Census Tract     52979294366  53033030101  53033028200

                      Standard Deviation
Postal Code                         2445
Electric Range                        87
Base MSRP                           7654
Legislative District                  15
```

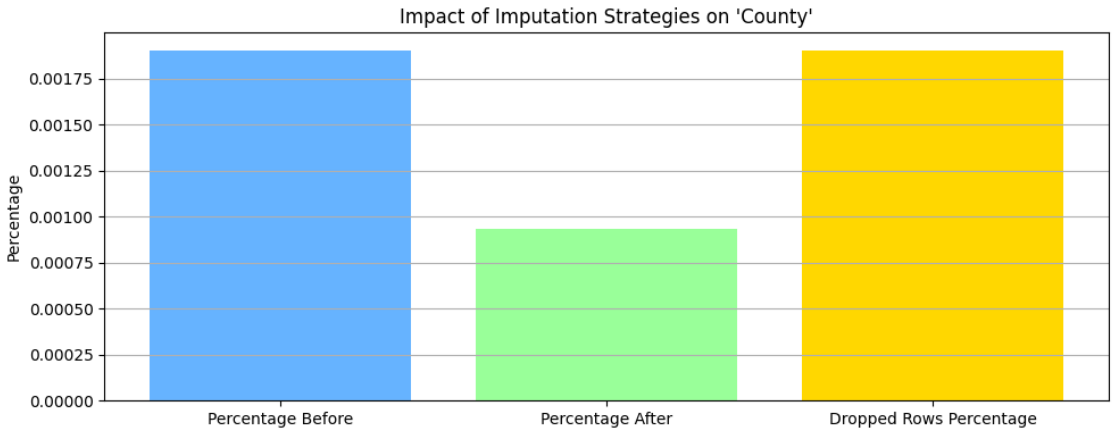
```
2020 Census Tract              1551466456
```



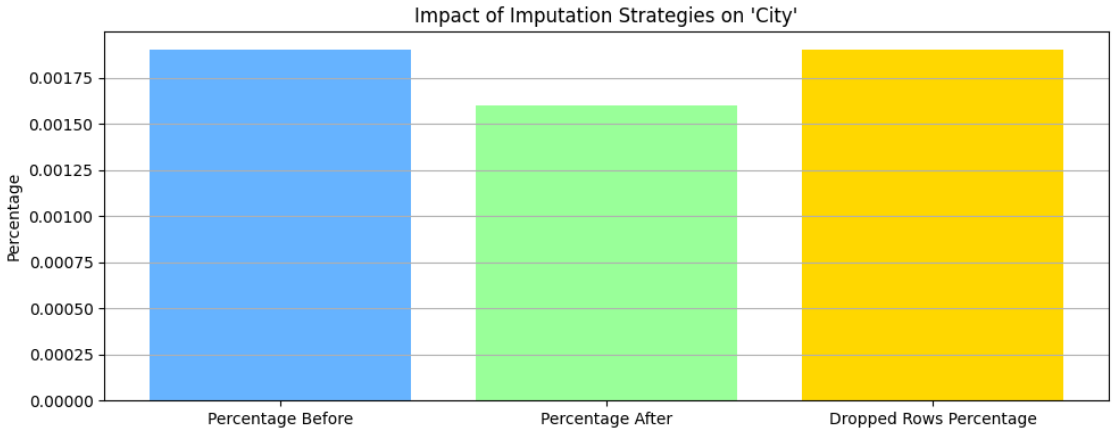
[3]:
```python
import pandas as pd
import matplotlib.pyplot as plt

non_numerical_columns = df.select_dtypes(include=['object']).columns.tolist()

df_mode_imputed = df.copy()
df_placeholder_imputed = df.copy()

for column in non_numerical_columns:
    if missing_values_count[column] > 0:
        original_value_counts = df[column].value_counts(normalize=True)

        missing_before = df[column].isnull().sum()

        mode_value = df[column].mode()[0]
        df_mode_imputed[column] = df_mode_imputed[column].fillna(mode_value)
        mode_value_counts = df_mode_imputed[column].value_counts(normalize=True)

        df_dropped_rows = df.dropna(subset=[column])

        num_dropped_rows = len(df) - len(df_dropped_rows)
        dropped_rows_percentage = (num_dropped_rows / len(df)) * 100
```

```
        original_top_value = original_value_counts.index[0]
        original_top_percentage = original_value_counts.iloc[0] * 100
        mode_top_percentage = mode_value_counts[mode_value] * 100

        # Print results without using DataFrame
        print(f"Impact of Missing Value Handling on '{column}' Column:")
        print("Missing Values Before: ", missing_before)
        print("Mode Value: ", mode_value)
        print("Percentage Before: ", original_top_percentage)
        print("Percentage After: ", mode_top_percentage)
        print("different : ", mode_top_percentage - original_top_percentage)
        print("Dropped Rows Percentage: ", dropped_rows_percentage)
        print("_______________________________")  # Separator line


        plt.figure(figsize=(10, 4))
        plt.bar(['Percentage Before', 'Percentage After', 'Dropped Rows␣
↪Percentage'],
                [(missing_before / len(df)) * 100 ,␣
↪mode_top_percentage-original_top_percentage, dropped_rows_percentage],
                color=['#66B3FF', '#99FF99', '#FFD700'])
        plt.title(f"Impact of Imputation Strategies on '{column}'")
        plt.ylabel('Percentage')
        plt.grid(axis='y')
        plt.tight_layout()
        plt.show()
```

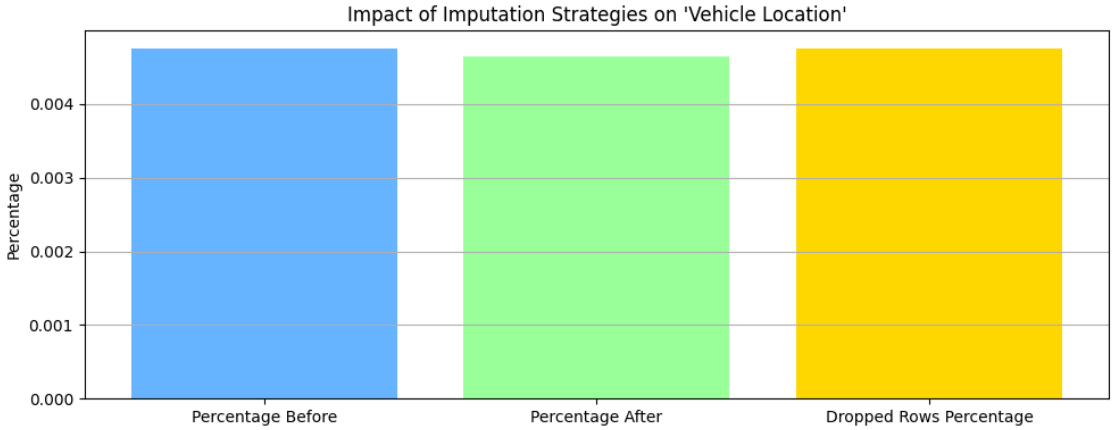
```
Impact of Missing Value Handling on 'County' Column:
Missing Values Before:  4
Mode Value:  King
Percentage Before:  50.96806733884974
Percentage After:  50.96900054718911
different :  0.0009332083393687185
Dropped Rows Percentage:  0.001903266481098185
-------------------------------
```



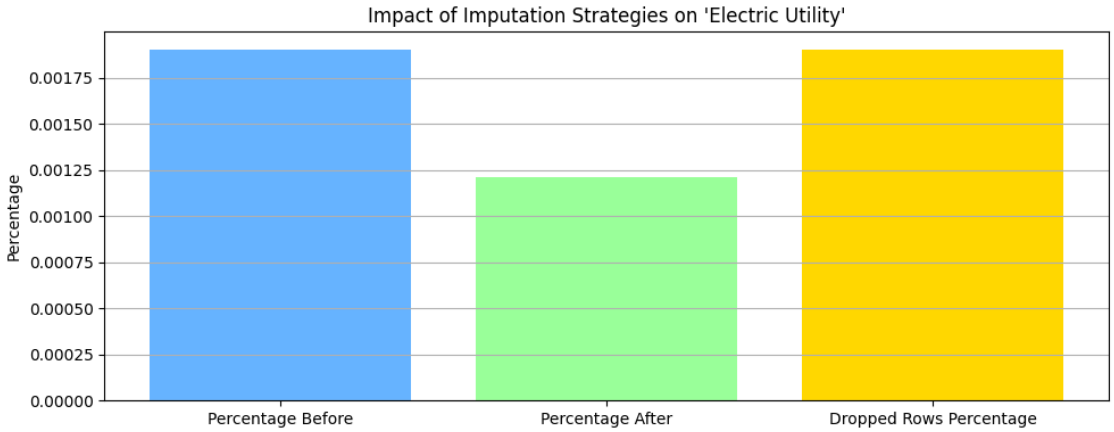

```
Impact of Missing Value Handling on 'City' Column:
Missing Values Before:  4
Mode Value:  Seattle
Percentage Before:  16.10860245240554
Percentage After:  16.110199129255584
different :  0.0015966768500454975
Dropped Rows Percentage:  0.001903266481098185
------------------------------
```




```
Impact of Missing Value Handling on 'Vehicle Location' Column:
Missing Values Before:  10
Mode Value:  POINT (-122.13158 47.67858)
Percentage Before:  2.501011158430682
Percentage After:  2.5056503223657605
different :  0.004639163935078461
Dropped Rows Percentage:  0.004758166202745461
------------------------------
```




```
Impact of Missing Value Handling on 'Electric Utility' Column:
Missing Values Before:  4
Mode Value:  PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)
Percentage Before:  36.45110177435395
Percentage After:  36.45231127923299
different :  0.0012095048790357055
Dropped Rows Percentage:  0.001903266481098185
------------------------------
```



[27]:
```
print("Feature Encoding:\n Encode categorical features (e.g., Make, Model) using techniques like one-hot encoding")
categorical_columns = ['Make', 'Model', 'Electric Vehicle Type', 'Clean Alternative Fuel Vehicle (CAFV) Eligibility', 'Electric Utility']
print("Categorical Columns:", categorical_columns)

for column in categorical_columns:
```

```
    if column in df.columns:
        one_hot_encoded = pd.get_dummies(df[column], prefix=column,␣
↪drop_first=True)
        print(f'One-Hot Encoding for {column}:\n', one_hot_encoded)
        print(f'Number of columns after encoding for {column}: {one_hot_encoded.
↪shape[1]}')
        print("\n\n")
```

```
Feature Encoding: Encode categorical features (e.g., Make, Model) using
techniques like one-hot encoding
Categorical Columns: ['Make', 'Model', 'Electric Vehicle Type', 'Clean
Alternative Fuel Vehicle (CAFV) Eligibility', 'Electric Utility']
One-Hot Encoding for Make:
         Make_ALFA ROMEO  Make_AUDI  Make_AZURE DYNAMICS  Make_BENTLEY  \
0                  False      False                False         False
1                  False      False                False         False
2                  False      False                False         False
3                  False      False                False         False
4                  False      False                False         False
…                  …          …                    …             …
210160             False      False                False         False
210161             False      False                False         False
210162             False      False                False         False
210163             False      False                False         False
210164             False      False                False         False

        Make_BMW  Make_CADILLAC  Make_CHEVROLET  Make_CHRYSLER  Make_DODGE  \
0           True          False           False          False       False
1          False          False           False          False       False
2          False          False           False          False       False
3          False          False           False          False       False
4          False          False           False          False       False
…          …              …               …              …           …
210160     False          False           False          False       False
210161     False          False           False          False       False
210162     False          False           False          False       False
210163     False          False           False          False       False
210164     False          False           False          False       False

        Make_FIAT  …  Make_ROLLS-ROYCE  Make_SMART  Make_SUBARU  Make_TESLA  \
0           False  …              False       False        False       False
1           False  …              False       False        False        True
2           False  …              False       False        False       False
3           False  …              False       False        False        True
4           False  …              False       False        False       False
…           …      …              …           …            …           …
210160      False  …              False       False        False       False
```

```
210161      False  …             False       False        False       False
210162      False  …             False       False        False       False
210163      False  …             False       False        False        True
210164      False  …             False       False        False        True

        Make_TH!NK  Make_TOYOTA  Make_VINFAST  Make_VOLKSWAGEN  Make_VOLVO  \
0            False        False         False            False       False
1            False        False         False            False       False
2            False        False         False            False       False
3            False        False         False            False       False
4            False        False         False            False       False
…                …            …             …                …           …
210160       False        False         False            False       False
210161       False        False         False            False       False
210162       False         True         False            False       False
210163       False        False         False            False       False
210164       False        False         False            False       False

        Make_WHEEGO ELECTRIC CARS
0                           False
1                           False
2                           False
3                           False
4                           False
…                           …
210160                      False
210161                      False
210162                      False
210163                      False
210164                      False

[210165 rows x 42 columns]
Number of columns after encoding for Make: 42



One-Hot Encoding for Model:
         Model_500  Model_500E  Model_530E  Model_740E  Model_745E  \
0           False       False       False       False       False
1           False       False       False       False       False
2           False       False       False       False       False
3           False       False       False       False       False
4           False       False       False       False       False
…               …           …           …           …           …
210160      False       False       False       False       False
210161      False       False       False       False       False
210162      False       False       False       False       False
210163      False       False       False       False       False
```

```
210164      False       False       False       False       False

        Model_745LE  Model_750E  Model_918  Model_A3  Model_A7 E  …  \
0             False       False      False     False       False  …
1             False       False      False     False       False  …
2             False       False      False     False       False  …
3             False       False      False     False       False  …
4             False       False      False     False       False  …
…               …           …          …         …           …  …
210160        False       False      False     False       False  …
210161        False       False      False     False       False  …
210162        False       False      False     False       False  …
210163        False       False      False     False       False  …
210164        False       False      False     False       False  …

        Model_VOLT  Model_WHEEGO  Model_WRANGLER  Model_X3  Model_X5  \
0            False         False           False     False      True
1            False         False           False     False     False
2            False         False           False     False     False
3            False         False           False     False     False
4            False         False           False     False     False
…              …             …               …         …         …
210160       False         False           False     False     False
210161       False         False           False     False     False
210162       False         False           False     False     False
210163       False         False           False     False     False
210164       False         False           False     False     False

        Model_XC40  Model_XC60  Model_XC90  Model_XM  Model_ZDX
0            False       False       False     False      False
1            False       False       False     False      False
2            False       False       False     False      False
3            False       False       False     False      False
4            False       False       False     False      False
…              …           …           …         …
210160       False       False       False     False      False
210161       False       False       False     False      False
210162       False       False       False     False      False
210163       False       False       False     False      False
210164       False       False       False     False      False

[210165 rows x 152 columns]
Number of columns after encoding for Model: 152



One-Hot Encoding for Electric Vehicle Type:
         Electric Vehicle Type_Plug-in Hybrid Electric Vehicle (PHEV)
```

```
0                                                    True
1                                                   False
2                                                    True
3                                                   False
4                                                   False
…                                                   …
210160                                               True
210161                                               True
210162                                               True
210163                                              False
210164                                              False

[210165 rows x 1 columns]
Number of columns after encoding for Electric Vehicle Type: 1



One-Hot Encoding for Clean Alternative Fuel Vehicle (CAFV) Eligibility:
         Clean Alternative Fuel Vehicle (CAFV) Eligibility_Eligibility unknown
as battery range has not been researched  \
0                                                   False
1                                                   False
2                                                   False
3                                                   False
4                                                   False
…                                                   …
210160                                              False
210161                                              False
210162                                              False
210163                                               True
210164                                               True

        Clean Alternative Fuel Vehicle (CAFV) Eligibility_Not eligible due to
low battery range
0                                                   False
1                                                   False
2                                                    True
3                                                   False
4                                                   False
…                                                   …
210160                                               True
210161                                               True
210162                                              False
210163                                              False
210164                                              False

[210165 rows x 2 columns]
Number of columns after encoding for Clean Alternative Fuel Vehicle (CAFV)
```

```
Eligibility: 2



One-Hot Encoding for Electric Utility:
         Electric Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||BIG BEND
ELECTRIC COOP, INC  \
0                                                    False
1                                                    False
2                                                    False
3                                                    False
4                                                    False
…                                                    …
210160                                               False
210161                                               False
210162                                               False
210163                                               False
210164                                               False

        Electric Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||INLAND
POWER & LIGHT COMPANY  \
0                                                    False
1                                                    False
2                                                    False
3                                                    False
4                                                    False
…                                                    …
210160                                               False
210161                                               False
210162                                               False
210163                                               False
210164                                                True

        Electric Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||PUD NO 1
OF ASOTIN COUNTY  \
0                                                    False
1                                                    False
2                                                    False
3                                                    False
4                                                    False
…                                                    …
210160                                               False
210161                                               False
210162                                               False
210163                                               False
210164                                               False

        Electric Utility_BONNEVILLE POWER ADMINISTRATION||BENTON RURAL ELECTRIC
```

```
ASSN  \
0                                                    False
1                                                    False
2                                                    False
3                                                    False
4                                                    False
…                                                    …
210160                                               False
210161                                               False
210162                                               False
210163                                               False
210164                                               False

       Electric Utility_BONNEVILLE POWER ADMINISTRATION||BIG BEND ELECTRIC
COOP, INC  \
0                                                    False
1                                                    False
2                                                    False
3                                                    False
4                                                    False
…                                                    …
210160                                               False
210161                                               False
210162                                               False
210163                                               False
210164                                               False

       Electric Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF CENTRALIA -
(WA)|CITY OF TACOMA - (WA)  \
0                                                    False
1                                                    False
2                                                    False
3                                                    False
4                                                    False
…                                                    …
210160                                               False
210161                                               False
210162                                               False
210163                                               False
210164                                               False

       Electric Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF COULEE DAM -
(WA)  \
0                                                    False
1                                                    False
2                                                    False
3                                                    False
4                                                    False
```

```
…                                                    …
210160                                               False
210161                                               False
210162                                               False
210163                                               False
210164                                               False

       Electric Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF ELLENSBURG -
(WA)  \
0                                                    False
1                                                    False
2                                                    False
3                                                    False
4                                                    False
…                                                    …
210160                                               False
210161                                               False
210162                                               False
210163                                               False
210164                                               False

       Electric Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF MCCLEARY -
(WA)  \
0                                                    False
1                                                    False
2                                                    False
3                                                    False
4                                                    False
…                                                    …
210160                                               False
210161                                               False
210162                                               False
210163                                               False
210164                                               False

       Electric Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF MILTON -
(WA)|CITY OF TACOMA - (WA)  \
0                                                    False
1                                                    False
2                                                    False
3                                                    False
4                                                    False
…                                                    …
210160                                               False
210161                                               False
210162                                               False
210163                                               False
210164                                               False
```

```
        …  Electric Utility_PORTLAND GENERAL ELECTRIC CO  \
0       …                                          False
1       …                                          False
2       …                                          False
3       …                                          False
4       …                                          False
…     …                                            …
210160  …                                          False
210161  …                                          False
210162  …                                          False
210163  …                                          False
210164  …                                          False

        Electric Utility_PUD NO 1 OF CHELAN COUNTY  \
0                                            False
1                                            False
2                                            False
3                                            False
4                                            False
…                                            …
210160                                       False
210161                                       False
210162                                       False
210163                                       False
210164                                       False

        Electric Utility_PUD NO 1 OF DOUGLAS COUNTY  \
0                                             False
1                                             False
2                                             False
3                                             False
4                                             False
…                                             …
210160                                        False
210161                                        False
210162                                        False
210163                                        False
210164                                        False

        Electric Utility_PUD NO 1 OF OKANOGAN COUNTY  \
0                                              False
1                                              False
2                                              False
3                                              False
4                                              False
…                                              …
210160                                         False
```

```
210161                                          False
210162                                          False
210163                                          False
210164                                          False

        Electric Utility_PUD NO 1 OF PEND OREILLE COUNTY  \
0                                                   False
1                                                   False
2                                                   False
3                                                   False
4                                                   False
…                                                   …
210160                                              False
210161                                              False
210162                                              False
210163                                              False
210164                                              False

        Electric Utility_PUD NO 1 OF WHATCOM COUNTY  \
0                                             False
1                                             False
2                                             False
3                                             False
4                                             False
…                                             …
210160                                        False
210161                                        False
210162                                        False
210163                                        False
210164                                        False

        Electric Utility_PUD NO 2 OF GRANT COUNTY  \
0                                           False
1                                           False
2                                           False
3                                           False
4                                           False
…                                           …
210160                                       True
210161                                      False
210162                                      False
210163                                      False
210164                                      False

        Electric Utility_PUGET SOUND ENERGY INC  \
0                                          True
1                                          True
2                                          True
```

```
3                                          True
4                                         False
…                                         …
210160                                    False
210161                                     True
210162                                    False
210163                                    False
210164                                    False

        Electric Utility_PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)  \
0                                                         False
1                                                         False
2                                                         False
3                                                         False
4                                                          True
…                                                         …
210160                                                    False
210161                                                    False
210162                                                    False
210163                                                     True
210164                                                    False

        Electric Utility_PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY
0                                                         False
1                                                         False
2                                                         False
3                                                         False
4                                                         False
…                                                         …
210160                                                    False
210161                                                    False
210162                                                    False
210163                                                    False
210164                                                    False

[210165 rows x 73 columns]
Number of columns after encoding for Electric Utility: 73
```

[15]:
```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

print("\n\nNormalization:")
# Print max and min values
```

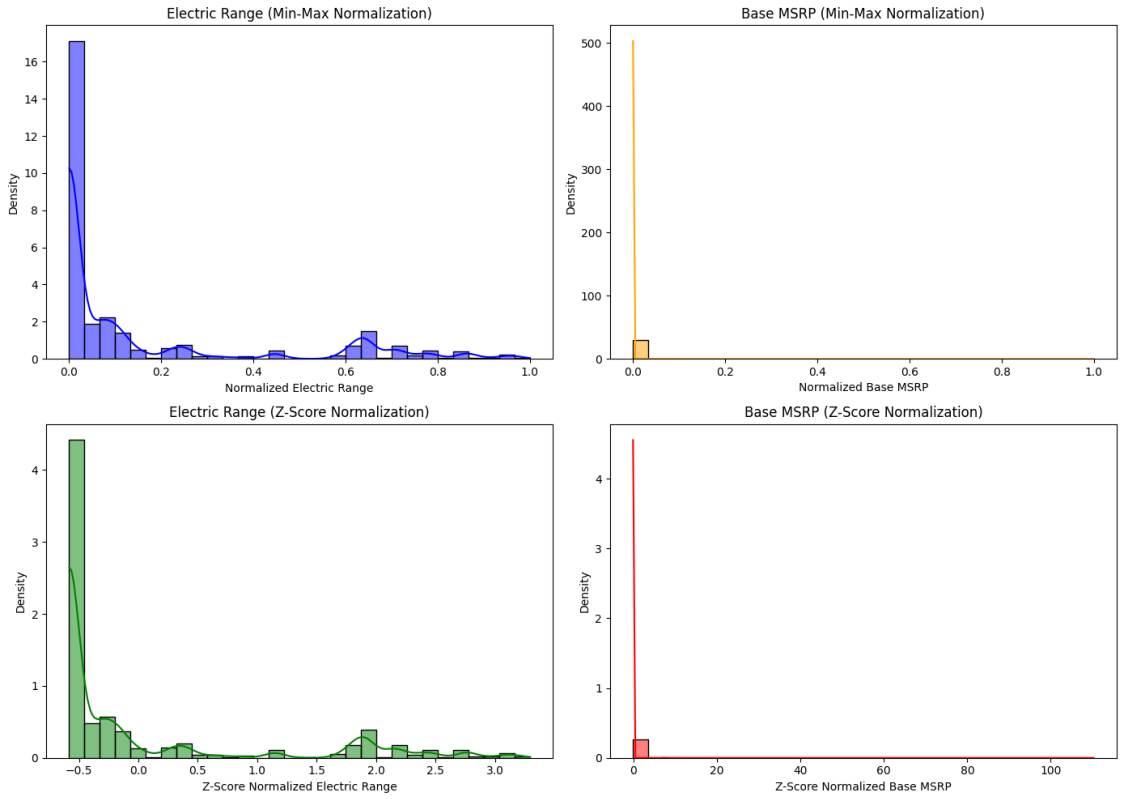
```
print("Max and Min Values after Capping:")
print(f"Electric Range - Max: {df['Electric Range'].max()}, Min: {df['Electric␣
 ↪Range'].min()}")
print(f"Base MSRP - Max: {df['Base MSRP'].max()}, Min: {df['Base MSRP'].min()}")

df['Electric Range MinMax'] = (df['Electric Range'] - df['Electric Range'].
 ↪min()) / (df['Electric Range'].max() - df['Electric Range'].min())
df['Base MSRP MinMax'] = (df['Base MSRP'] - df['Base MSRP'].min()) / (df['Base␣
 ↪MSRP'].max() - df['Base MSRP'].min())

def z_score(column):
    return (column - column.mean()) / column.std()

# Apply the Z-Score function
df['Electric Range ZScore'] = z_score(df['Electric Range'])
df['Base MSRP ZScore'] = z_score(df['Base MSRP'])

print("\nZ-score Calculations for Electric Range and Base MSRP:")
print(f"Electric Range Z-score: z = (Electric Range - {df['Electric Range'].
 ↪mean():.2f}) / {df['Electric Range'].std():.2f}")
print(f"Base MSRP Z-score: z = (Base MSRP - {df['Base MSRP'].mean():.2f}) /␣
 ↪{df['Base MSRP'].std():.2f}")
print("\n\n")
print(df[['Electric Range', 'Base MSRP', 'Electric Range MinMax', 'Base MSRP␣
 ↪MinMax', 'Electric Range ZScore', 'Base MSRP ZScore']].head())

plt.figure(figsize=(14, 10))

plt.subplot(2, 2, 1)
sns.histplot(df['Electric Range MinMax'], bins=30, kde=True, color='blue',␣
 ↪stat="density")
plt.title('Electric Range (Min-Max Normalization)')
plt.xlabel('Normalized Electric Range')
plt.ylabel('Density')

plt.subplot(2, 2, 2)
sns.histplot(df['Base MSRP MinMax'], bins=30, kde=True, color='orange',␣
 ↪stat="density")
plt.title('Base MSRP (Min-Max Normalization)')
plt.xlabel('Normalized Base MSRP')
plt.ylabel('Density')

# Z-Score Normalization plots
plt.subplot(2, 2, 3)
sns.histplot(df['Electric Range ZScore'], bins=30, kde=True, color='green',␣
 ↪stat="density")
```

```
plt.title('Electric Range (Z-Score Normalization)')
plt.xlabel('Z-Score Normalized Electric Range')
plt.ylabel('Density')

plt.subplot(2, 2, 4)
sns.histplot(df['Base MSRP ZScore'], bins=30, kde=True, color='red',␣
 ↪stat="density")
plt.title('Base MSRP (Z-Score Normalization)')
plt.xlabel('Z-Score Normalized Base MSRP')
plt.ylabel('Density')

plt.tight_layout()
plt.show()
```

```
Normalization:
Max and Min Values after Capping:
Electric Range - Max: 337.0, Min: 0.0
Base MSRP - Max: 845000.0, Min: 0.0

Z-score Calculations for Electric Range and Base MSRP:
Electric Range Z-score: z = (Electric Range - 50.60) / 86.97
Base MSRP Z-score: z = (Base MSRP - 897.68) / 7653.59
```

	Electric Range	Base MSRP	Electric Range MinMax	Base MSRP MinMax	\
0	30.0	0.0	0.089021	0.0	
1	215.0	0.0	0.637982	0.0	
2	15.0	0.0	0.044510	0.0	
3	215.0	0.0	0.637982	0.0	
4	150.0	0.0	0.445104	0.0	

	Electric Range ZScore	Base MSRP ZScore
0	-0.236880	-0.117288
1	1.890211	-0.117288
2	-0.409347	-0.117288
3	1.890211	-0.117288
4	1.142855	-0.117288



[14]:
```
import folium
from folium.plugins import HeatMap

print("\n\nSpatial Distribution:")
df['Latitude'] = df['Vehicle Location'].apply(lambda x: float(x.split()[2].
 ↪strip(')')) if isinstance(x, str) else None)
df['Longitude'] = df['Vehicle Location'].apply(lambda x: float(x.split()[1].
 ↪strip('(')) if isinstance(x, str) else None)


m = folium.Map(location=[df['Latitude'].mean(), df['Longitude'].mean()],␣
 ↪zoom_start=10)
heat_data = [[row['Latitude'], row['Longitude']] for _, row in df.iterrows() if␣
 ↪pd.notna(row['Latitude']) and pd.notna(row['Longitude'])]
HeatMap(heat_data).add_to(m)

m.save('ev_location_map.html')
m
```

```
Spatial Distribution:
```

[14]: <folium.folium.Map at 0x773a7d2adf90>

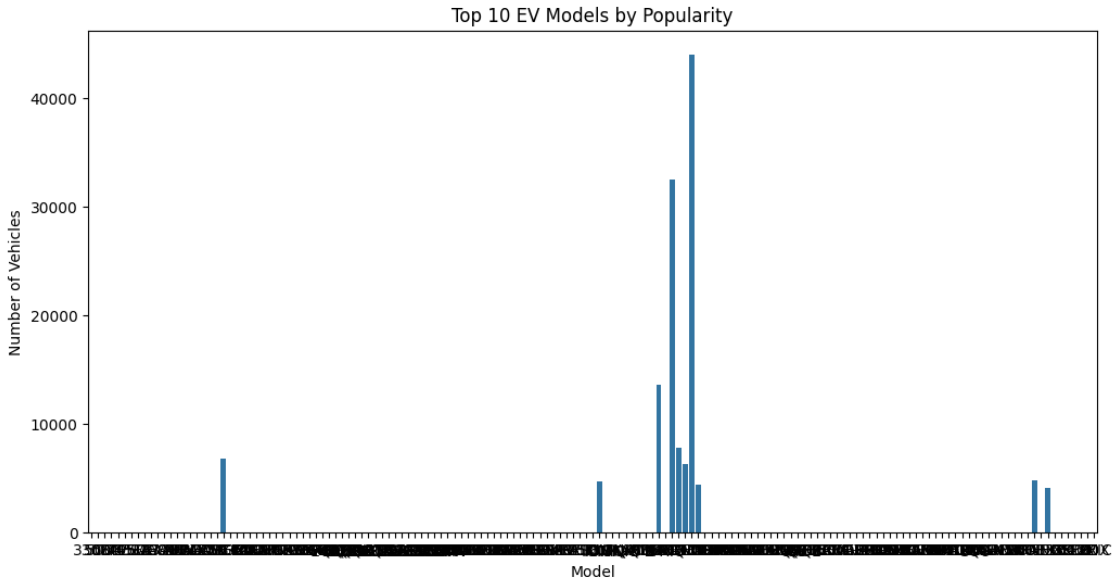
[4]:
```
# Load the data from a CSV file (replace 'your_file.csv' with your actual file␣
 ↪path)
df = pd.read_csv('Electric_Vehicle_Population_Data.csv')

# Convert categorical fields to category dtype
categorical_cols = ['County', 'City', 'State', 'Make', 'Model', 'Electric␣
 ↪Vehicle Type', 'Clean Alternative Fuel Vehicle (CAFV) Eligibility']
for col in categorical_cols:
    df[col] = df[col].astype('category')
# Count the number of occurrences of each model
model_popularity = df['Model'].value_counts().reset_index()
model_popularity.columns = ['Model', 'Count']

# Display the popularity data
print(model_popularity)


# Set up the matplotlib figure
plt.figure(figsize=(12, 6))
# Create a bar plot for model popularity
sns.barplot(data=model_popularity.head(10), x='Model', y='Count')     # Top 10␣
 ↪models
plt.title('Top 10 EV Models by Popularity')
plt.ylabel('Number of Vehicles')
plt.xlabel('Model')
plt.show()
# Count vehicles per model year
year_trends = df.groupby(['Model Year', 'Model'], observed=True).size().
 ↪unstack(fill_value=0)

# Plot trends over years
plt.figure(figsize=(14, 7))
year_trends.plot(kind='line', marker='o')
plt.title('Trends in EV Model Popularity Over Years')
plt.xlabel('Model Year')
plt.ylabel('Number of Vehicles')
plt.legend(title='Model', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid()
plt.show()

# Pie chart for Clean Alternative Fuel Vehicle (CAFV) Eligibility
cafv_counts = df['Clean Alternative Fuel Vehicle (CAFV) Eligibility'].
 ↪value_counts()
plt.figure(figsize=(8, 8))
```

```
plt.pie(cafv_counts, labels=cafv_counts.index, autopct='%1.1f%%',␣
 ↪startangle=90, colors=sns.color_palette('viridis', len(cafv_counts)))
plt.title('Proportion of CAFV Eligibility')
plt.axis('equal')  # Equal aspect ratio ensures that pie chart is circular
plt.show()

# Grouped bar plot for EV counts by Make and Electric Vehicle Type
plt.figure(figsize=(14, 7))
sns.countplot(data=df, x='Make', hue='Electric Vehicle Type', palette='viridis')
plt.title('Count of Electric Vehicles by Make and Type')
plt.xlabel('Make')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Electric Vehicle Type')
plt.show()


# Bar plot for average Base MSRP by Electric Vehicle Type
avg_msrp_by_type = df.groupby('Electric Vehicle Type', observed=True)['Base␣
 ↪MSRP'].mean().reset_index()
plt.figure(figsize=(12, 6))
sns.barplot(data=avg_msrp_by_type, x='Electric Vehicle Type', y='Base MSRP')
plt.title('Average Base MSRP by Electric Vehicle Type')
plt.xlabel('Electric Vehicle Type')
plt.ylabel('Average Base MSRP')
plt.xticks(rotation=45)
plt.show()


# Electric Range Histogram
plt.figure(figsize=(8, 5))
sns.histplot(df['Electric Range'], bins=30, kde=True)
plt.title('Distribution of Electric Range')
plt.xlabel('Electric Range (miles)')
plt.ylabel('Frequency')
plt.show()

# Base MSRP Histogram
plt.figure(figsize=(8, 5))
sns.histplot(df['Base MSRP'], bins=30, kde=True)
plt.title('Distribution of Base MSRP')
plt.xlabel('Base MSRP ($)')
plt.ylabel('Frequency')
plt.show()

# Box plot for Base MSRP by Make
plt.figure(figsize=(12, 6))
```

```
sns.boxplot(data=df, x='Make', y='Base MSRP')
plt.title('Base MSRP Distribution by EV Make')
plt.xlabel('Make')
plt.ylabel('Base MSRP')
plt.xticks(rotation=45)
plt.show()

# Bar chart for number of EVs in each city
plt.figure(figsize=(12, 6))
city_counts = df['City'].value_counts().head(10)  # Show top 10 cities
sns.barplot(x=city_counts.index, y=city_counts.values)
plt.title('Distribution of EVs Across Top 10 Cities')
plt.xlabel('City')
plt.ylabel('Number of EVs')
plt.xticks(rotation=45)
plt.show()


# Bar chart for number of EVs in each county
plt.figure(figsize=(12, 6))
county_counts = df['County'].value_counts().head(10)  # Show top 10 counties
sns.barplot(x=county_counts.index, y=county_counts.values)
plt.title('Distribution of EVs Across Top 10 Counties')
plt.xlabel('County')
plt.ylabel('Number of EVs')
plt.xticks(rotation=45)
plt.show()


# Pivot table for stacking Electric Vehicle Type by City
city_ev_type = df.pivot_table(index='City', columns='Electric Vehicle Type',␣
 ↪aggfunc='size', fill_value=0, observed=False).head(10)

# Stacked bar chart
city_ev_type.plot(kind='bar', stacked=True, figsize=(12, 6))
plt.title('Distribution of EV Types Across Top 10 Cities')
plt.xlabel('City')
plt.ylabel('Number of EVs')
plt.xticks(rotation=45)
plt.legend(title='Electric Vehicle Type')
plt.show()


# Pivot table for stacking Electric Vehicle Type by County
county_ev_type = df.pivot_table(index='County', columns='Electric Vehicle␣
 ↪Type', aggfunc='size', fill_value=0, observed=False).head(10)
```

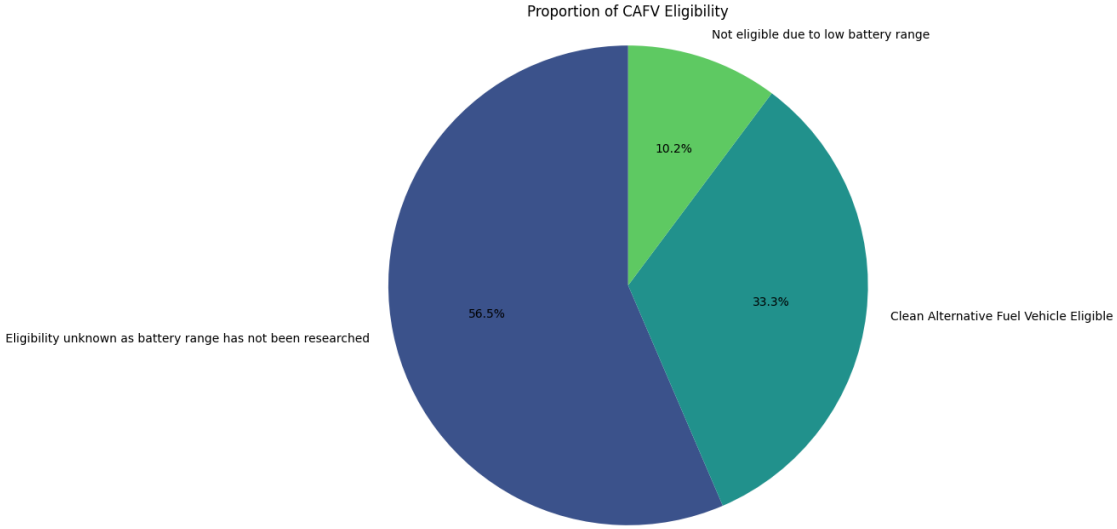
```
# Stacked bar chart
county_ev_type.plot(kind='bar', stacked=True, figsize=(12, 6))
plt.title('Distribution of EV Types Across Top 10 Counties')
plt.xlabel('County')
plt.ylabel('Number of EVs')
plt.xticks(rotation=45)
plt.legend(title='Electric Vehicle Type')
plt.show()
```

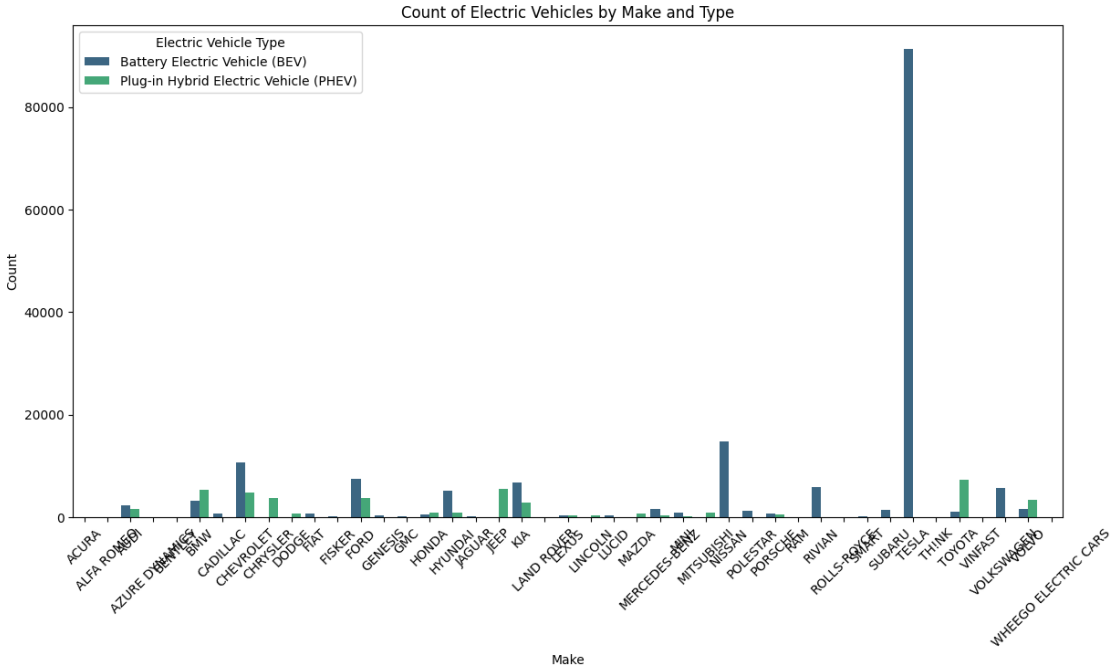
```
              Model  Count
0           MODEL Y  44038
1           MODEL 3  32520
2              LEAF  13606
3           MODEL S   7795
4           BOLT EV   6780
..              ...    ...
148            750E      2
149         SPECTRE      2
150  PROMASTER 3500      2
151             918      1
152           VF 8       1

[153 rows x 2 columns]
```

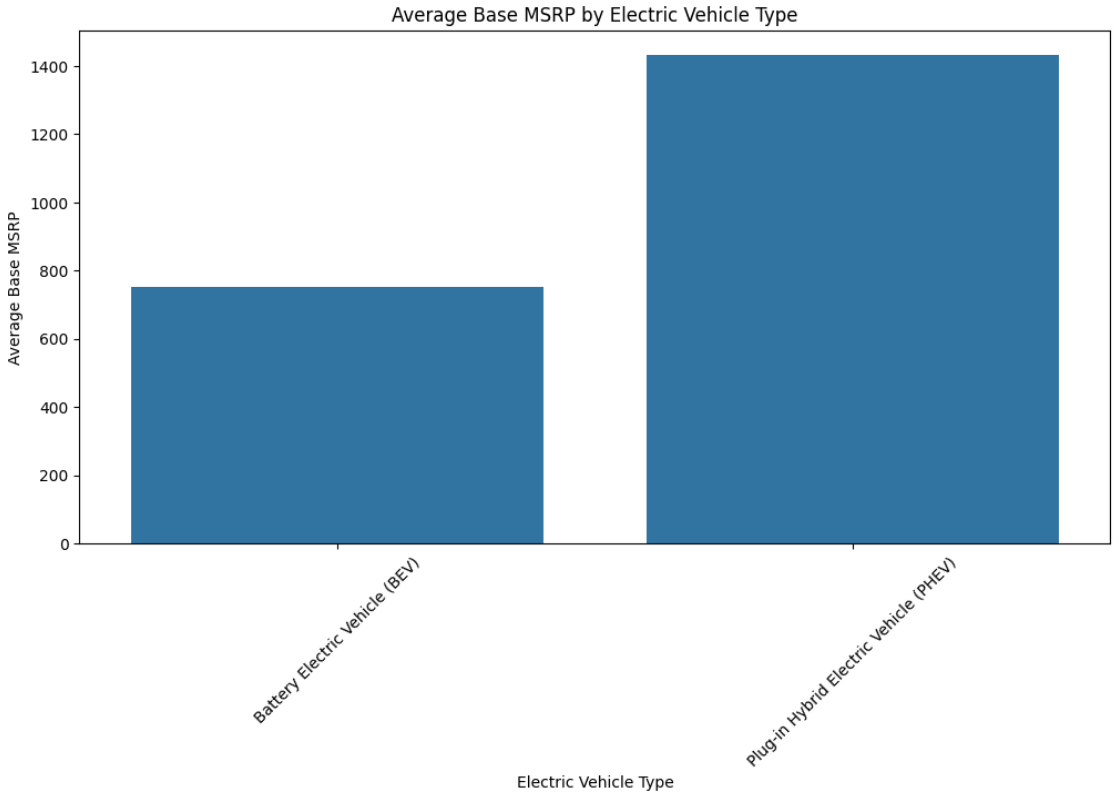


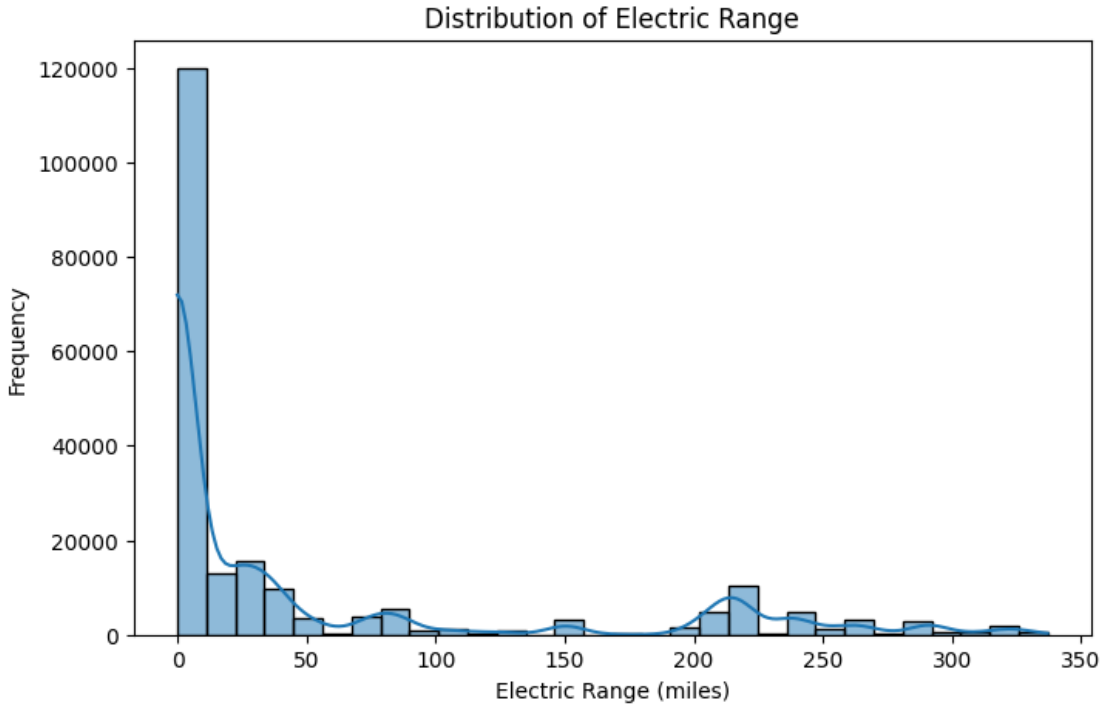

```
<Figure size 1400x700 with 0 Axes>
```

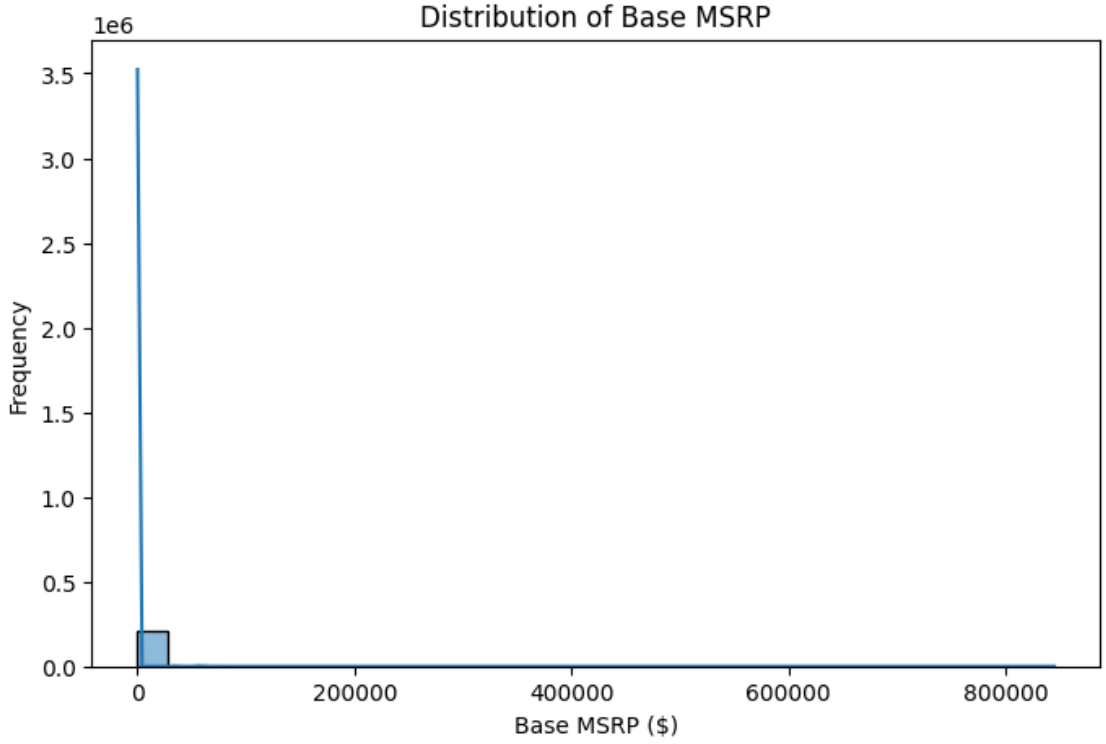

Trends in EV Model Popularity Over Years
Number of Vehicles
Model Year
0
2500
5000
7500
10000
12500
15000
17500
2000
2005
2010
2015
2020
2025
Model
330E
500
500E
530E
740E
745E
745LE
750E
918
A3
A7 E
A8 E
ACCORD
AIR
ARIYA
AVIATOR
B-CLASS
BENTAYGA
BLAZER EV
BOLT EUV
BOLT EV
BZ4X
C-CLASS
C-MAX
C40
CAYENNE
CITY
CLARITY
CORSAIR
COUNTRYMAN
CR-V
CROSSTREK
CT6
CX-70
CX-90
CYBERTRUCK
E-GOLF
E-TRON
E-TRON GT
E-TRON SPORTBACK
EDV
ELR
EQ FORTWO
EQB-CLASS
EQE-CLASS SEDAN
EQE-CLASS SUV
EQS-CLASS SEDAN
EQS-CLASS SUV
EQUINOX EV
ESCAPE
ESPRINTER
EV6
EV9
EX40
F-150
FLYING SPUR
FOCUS
FORTWO
FORTWO ELECTRIC DRIVE
FUSION
G80
GLC-CLASS
GLE-CLASS
GRAND CHEROKEE
GV60
GV70
HARDTOP
HORNET
HUMMER EV PICKUP
HUMMER EV SUV
I-MIEV
I-PACE
I3
I4
I5
I7
I8
ID.4
IONIQ
IONIQ 5
IONIQ 5 N
IONIQ 6
IX
KARMA
KONA
KONA ELECTRIC
LEAF
LYRIQ
MODEL 3
MODEL S
MODEL X
MODEL Y
MUSTANG MACH-E
MX-30
NIRO
NX
OCEAN
OPTIMA
OUTLANDER
PACIFICA
PANAMERA
PRIUS PLUG-IN
PRIUS PRIME
PROLOGUE
PROMASTER 3500
PS2
Q4
Q5
Q5 E
Q8
R1S
R1T
RANGE ROVER
RANGE ROVER SPORT
RANGER
RAV4
RAV4 PRIME
ROADSTER
RS E-TRON GT
RX
RZ
S-CLASS
S60
S90
SANTA FE
SILVERADO EV
SOLTERRA
SONATA
SORENTO
SOUL
SOUL EV
SPARK
SPECTRE
SPORTAGE
SQ8
TAYCAN
TONALE
TRANSIT
TRANSIT CONNECT ELECTRIC
TUCSON
TX
V60
VF 8
VOLT
WHEEGO
WRANGLER
X3
X5
XC40
XC60
XC90
XM
ZDX

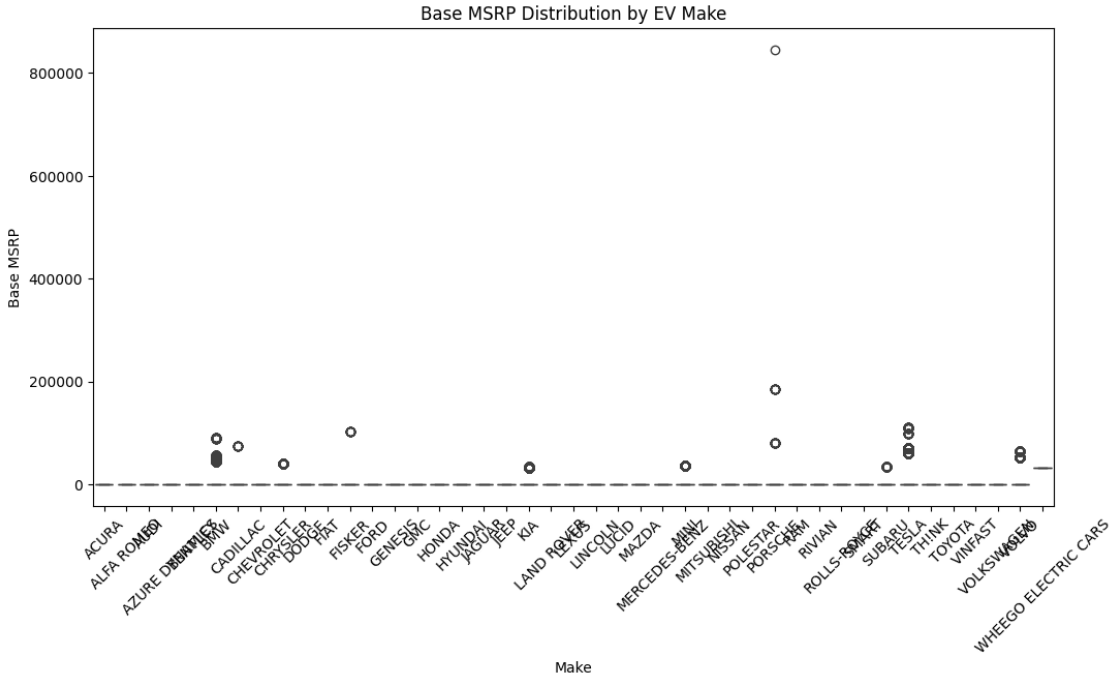

Proportion of CAFV Eligibility
Not eligible due to low battery range
10.2%
33.3%
Clean Alternative Fuel Vehicle Eligible
56.5%
Eligibility unknown as battery range has not been researched

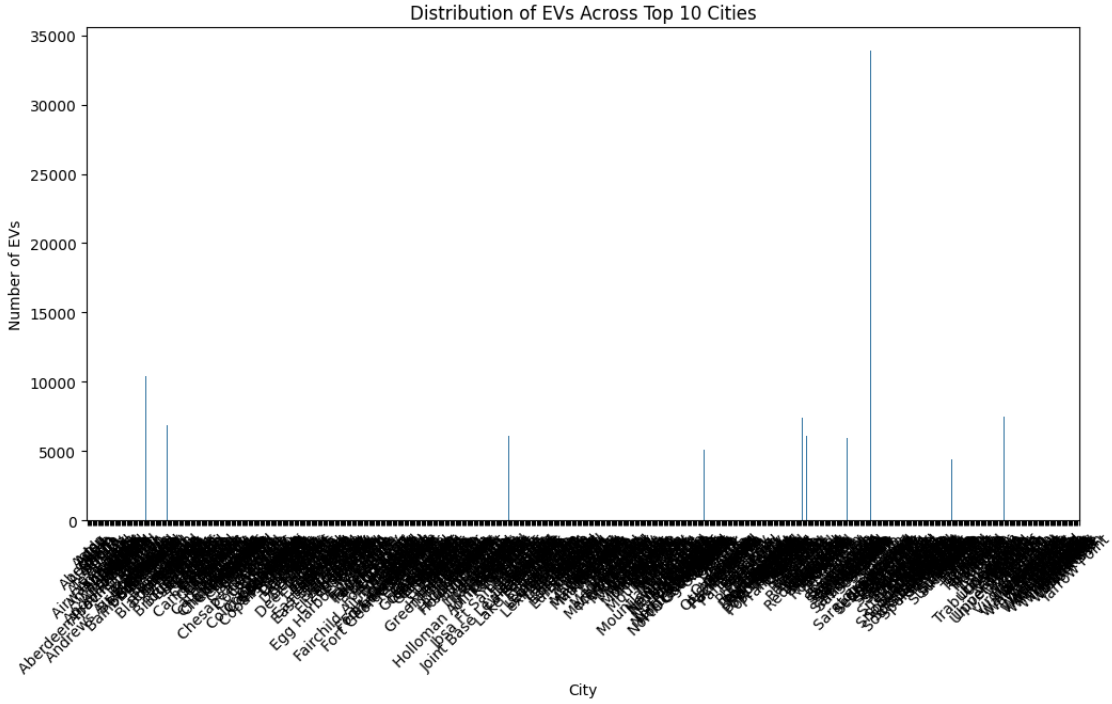

Count of Electric Vehicles by Make and Type
Electric Vehicle Type
Battery Electric Vehicle (BEV)
Plug-in Hybrid Electric Vehicle (PHEV)
Count
0
20000
40000
60000
80000
Make
ACURA
ALFA ROMEO
AUDI
BMW
CADILLAC
CHEVROLET
CHRYSLER
DODGE
FIAT
FISKER
FORD
GENESIS
GMC
HONDA
HYUNDAI
JAGUAR
JEEP
KIA
LAND ROVER
LEXUS
LINCOLN
LUCID
MAZDA
MERCEDES-BENZ
MITSUBISHI
NISSAN
POLESTAR
PORSCHE
RAM
RIVIAN
SUBARU
TESLA
THINK
TOYOTA
VINFAST
VOLKSWAGEN
VOLVO
WHEEGO ELECTRIC CARS

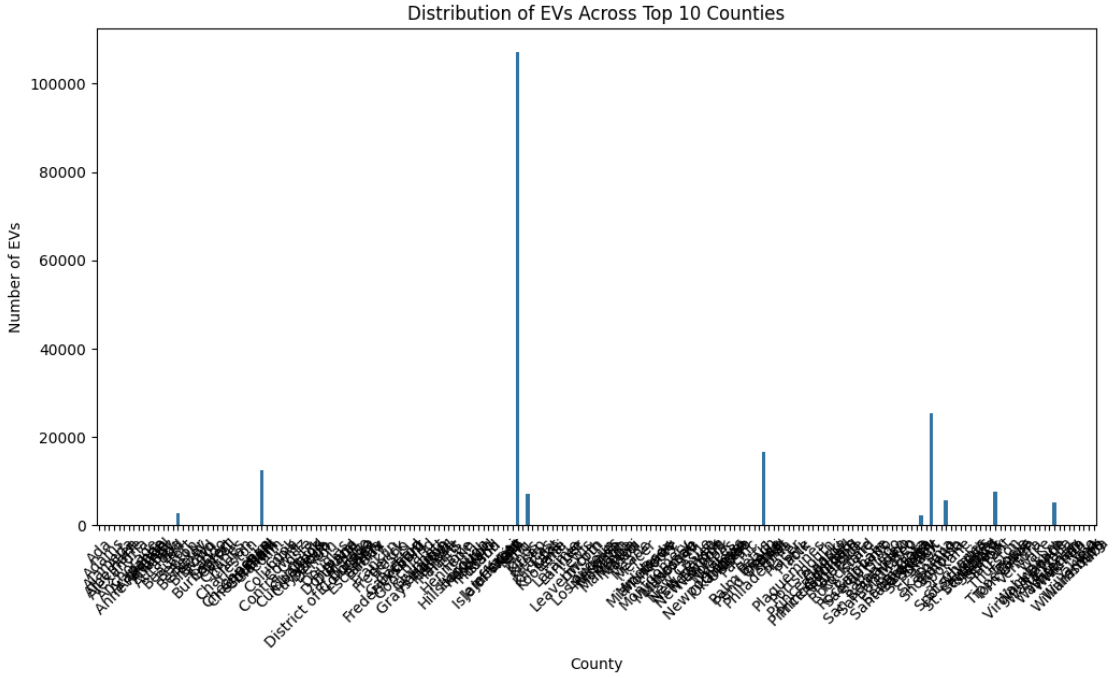

Average Base MSRP by Electric Vehicle Type
Average Base MSRP
0
200
400
600
800
1000
1200
1400
Battery Electric Vehicle (BEV)
Plug-in Hybrid Electric Vehicle (PHEV)
Electric Vehicle Type

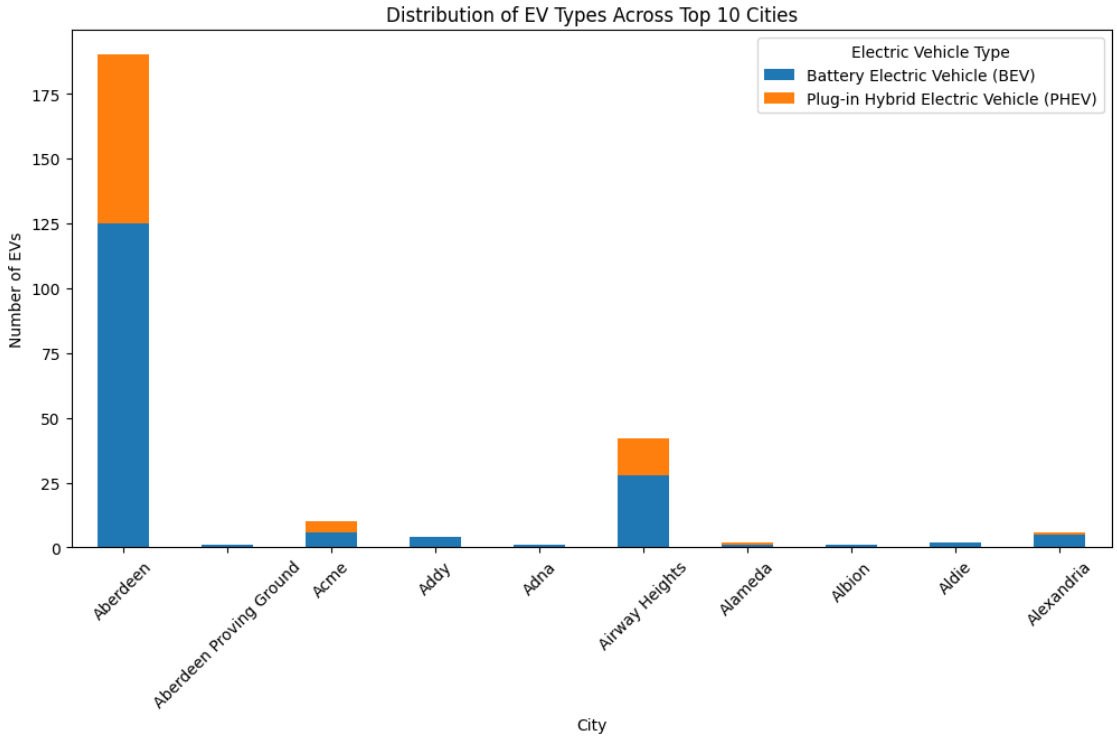

Distribution of Electric Range
Frequency
0
20000
40000
60000
80000
100000
120000
0
50
100
150
200
250
300
350
Electric Range (miles)

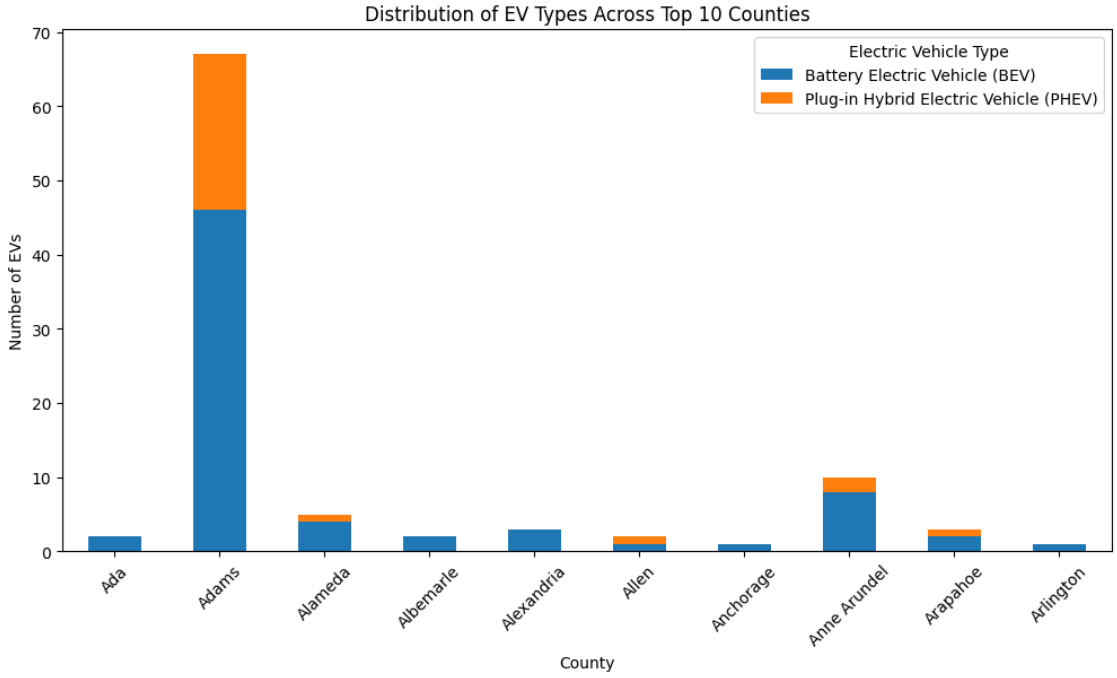

Distribution of Base MSRP
1e6
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Frequency
0
200000
400000
600000
800000
Base MSRP ($)


Base MSRP Distribution by EV Make
800000
600000
400000
200000
0
Base MSRP
ACURA
ALFA ROMEO
AUDI
AZURE DYNAMICS
BENTLEY
BMW
CADILLAC
CHEVROLET
CHRYSLER
DODGE
FIAT
FISKER
FORD
GENESIS
GMC
HONDA
HYUNDAI
JAGUAR
JEEP
KIA
LAND ROVER
LEXUS
LINCOLN
LUCID
MAZDA
MERCEDES-BENZ
MINI
MITSUBISHI
NISSAN
POLESTAR
PORSCHE
RAM
RIVIAN
ROLLS-ROYCE
SMART
SUBARU
TESLA
THINK
TOYOTA
VINFAST
VOLKSWAGEN
VOLVO
WHEEGO ELECTRIC CARS
Make


Distribution of EVs Across Top 10 Cities
Number of EVs
City

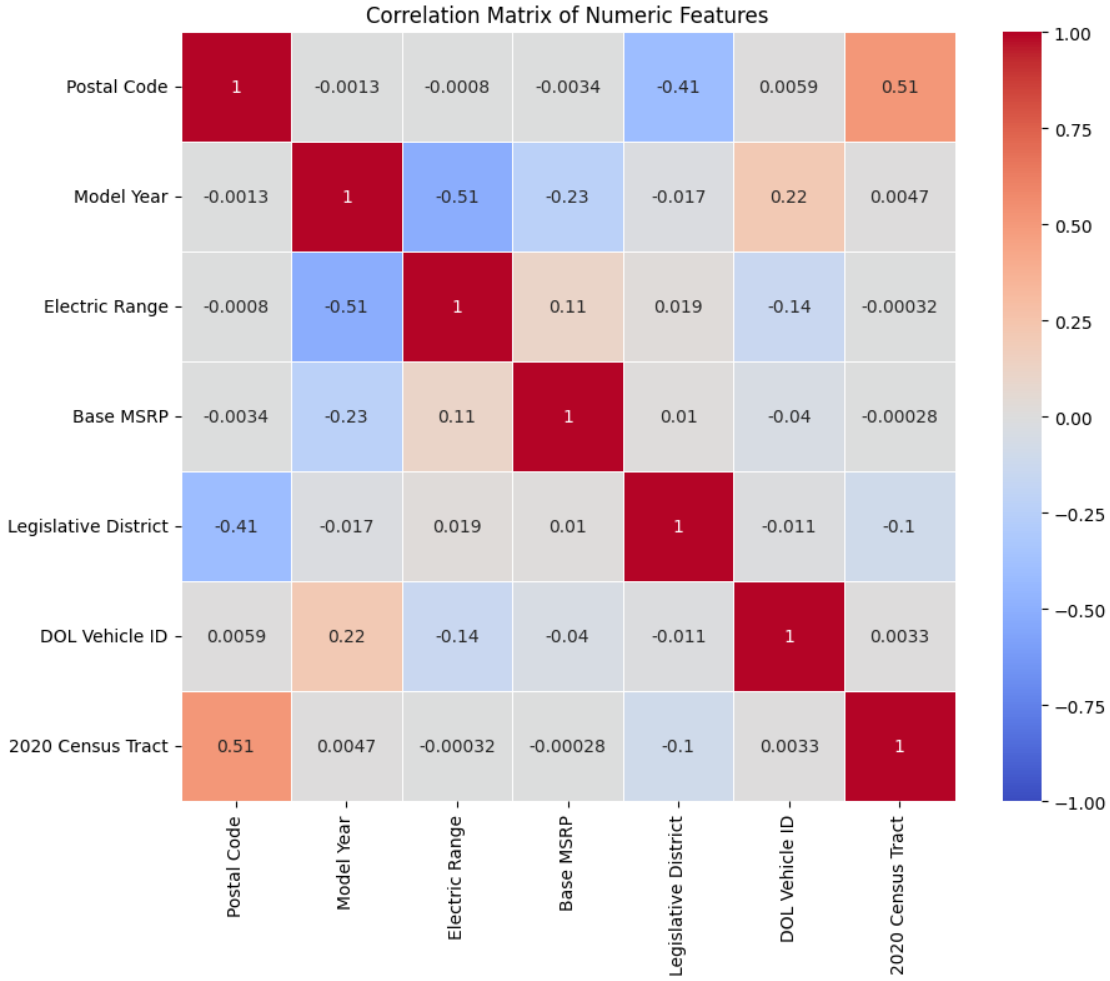

Distribution of EVs Across Top 10 Counties
Number of EVs
County

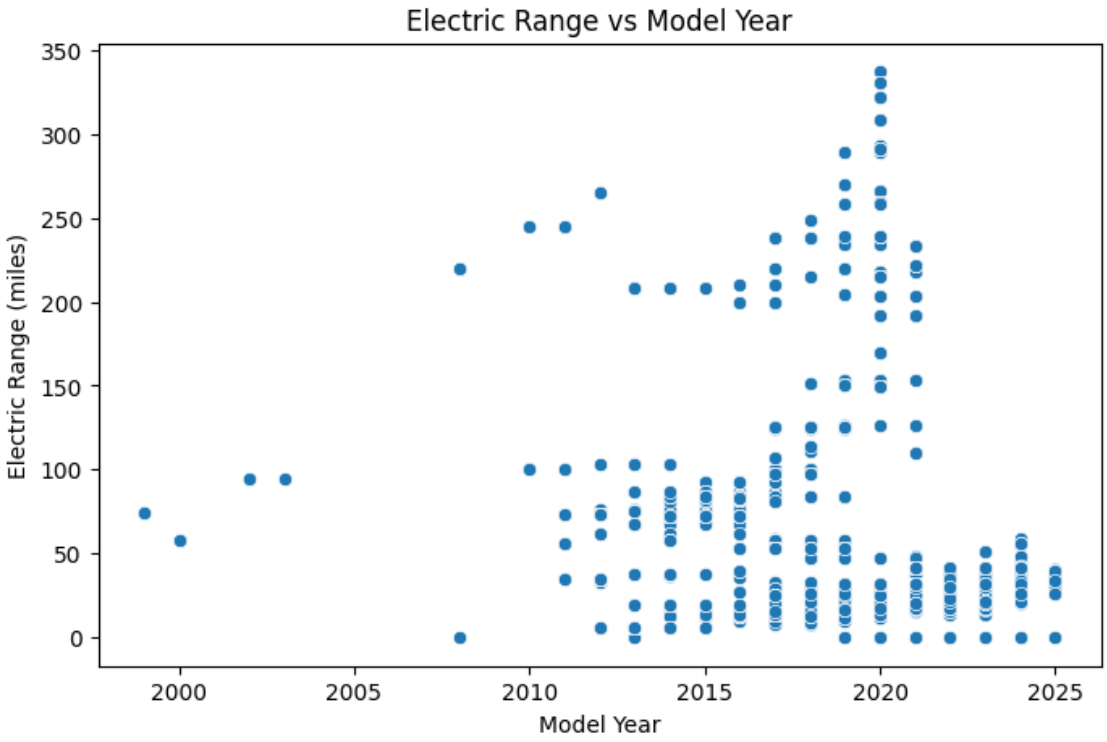

Distribution of EV Types Across Top 10 Cities
Electric Vehicle Type
Battery Electric Vehicle (BEV)
Plug-in Hybrid Electric Vehicle (PHEV)
Number of EVs
0
25
50
75
100
125
150
175
Aberdeen
Aberdeen Proving Ground
Acme
Addy
Adna
Airway Heights
Alameda
Albion
Aldie
Alexandria
City

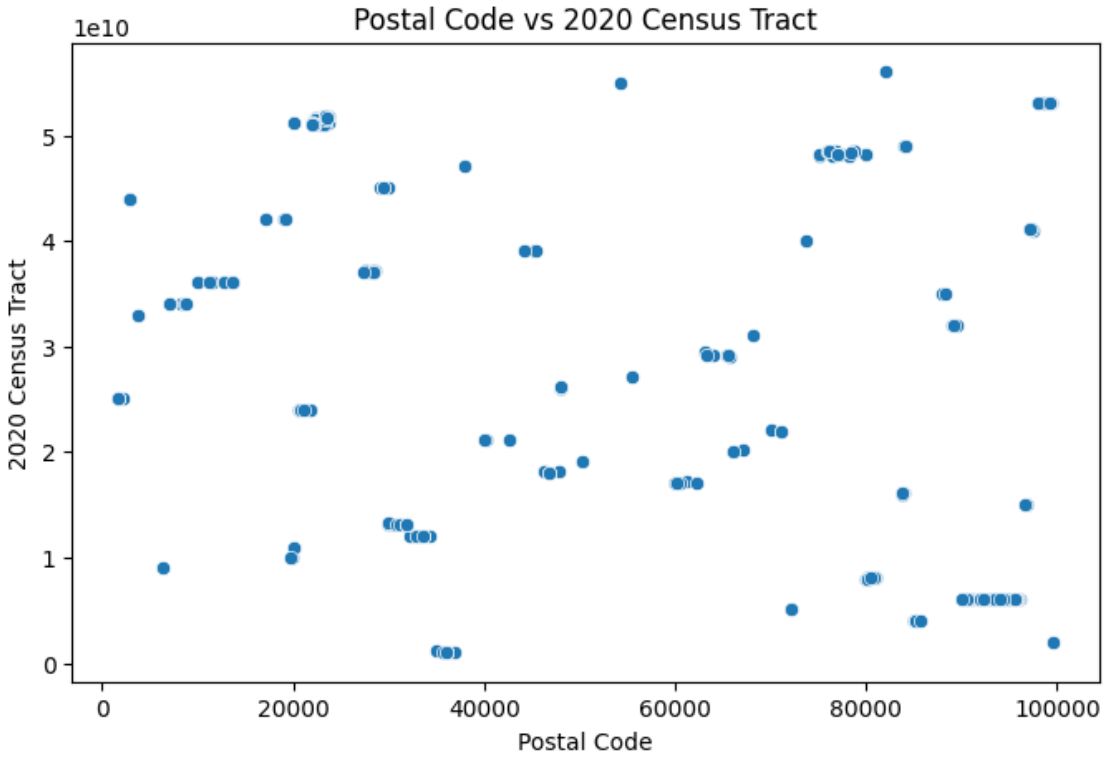

Distribution of EV Types Across Top 10 Counties
Electric Vehicle Type
Battery Electric Vehicle (BEV)
Plug-in Hybrid Electric Vehicle (PHEV)
Number of EVs
0
10
20
30
40
50
60
70
Ada
Adams
Alameda
Albemarle
Alexandria
Allen
Anchorage
Anne Arundel
Arapahoe
Arlington
County

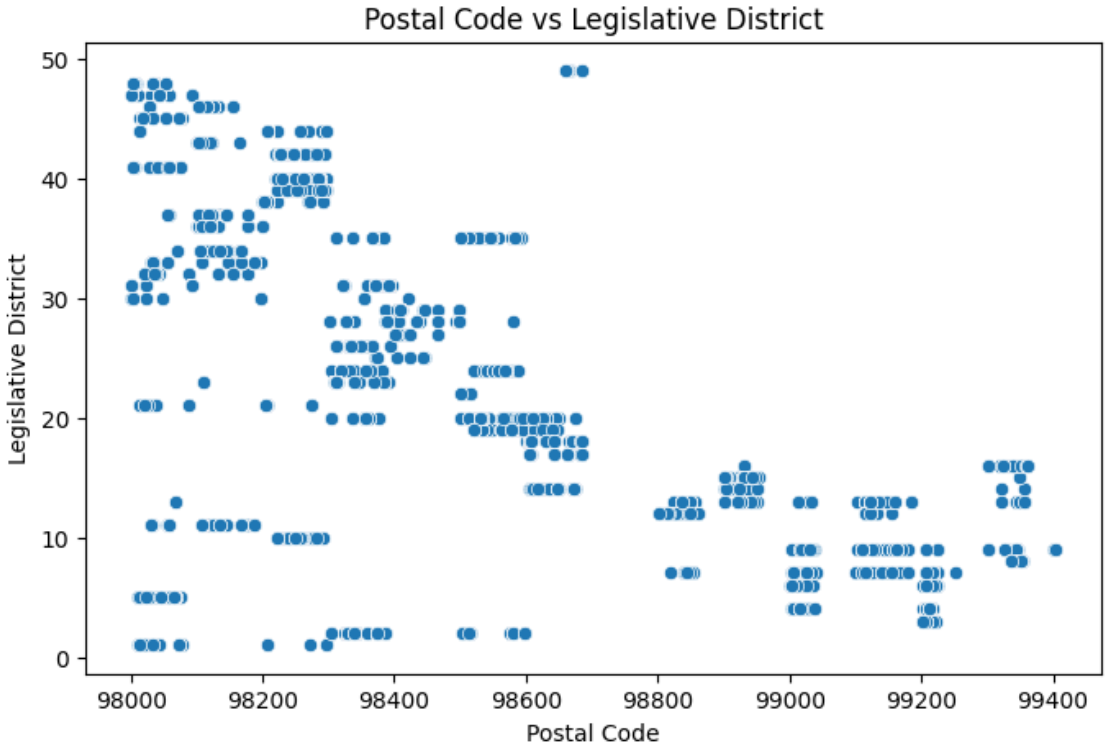
[3]:
```
##correlation

# Select only numeric features from the dataset
numeric_features = df.select_dtypes(include=['float64', 'int64'])

# Calculate the correlation matrix
correlation_matrix = numeric_features.corr()

# Plot the heatmap to visualize correlations
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1,␣
 ↪linewidths=0.5)
plt.title('Correlation Matrix of Numeric Features')
plt.show()


# Scatter plot between 'Electric Range' and 'Model Year'
plt.figure(figsize=(8, 5))
sns.scatterplot(x='Model Year', y='Electric Range', data=df)
plt.title('Electric Range vs Model Year')
plt.xlabel('Model Year')
plt.ylabel('Electric Range (miles)')
plt.show()

# Scatter plot between 'Postal Code' and '2020 Census Tract'
plt.figure(figsize=(8, 5))
sns.scatterplot(x='Postal Code', y='2020 Census Tract', data=df)
plt.title('Postal Code vs 2020 Census Tract')
plt.xlabel('Postal Code')
plt.ylabel('2020 Census Tract')
plt.show()

# Scatter plot between 'Postal Code' and 'Legislative District'
plt.figure(figsize=(8, 5))
sns.scatterplot(x='Postal Code', y='Legislative District', data=df)
plt.title('Postal Code vs Legislative District')
plt.xlabel('Postal Code')
plt.ylabel('Legislative District')
plt.show()

'''
# Scatter plot between 'Electric Range' and 'Base MSRP'
plt.figure(figsize=(8, 5))
sns.scatterplot(x='Base MSRP', y='Electric Range', data=df)
plt.title('Electric Range vs Base MSRP')
plt.xlabel('Base MSRP ($)')
plt.ylabel('Electric Range (miles)')
```

```
plt.show()

# Scatter plot between 'Model Year' and 'Base MSRP'
plt.figure(figsize=(8, 5))
sns.scatterplot(x='Base MSRP', y='Model Year', data=df)
plt.title('Model Year vs Base MSRP')
plt.xlabel('Base MSRP ($)')
plt.ylabel('Model Year')
plt.show()
'''
```




Electric Range vs Model Year
Electric Range (miles)
Model Year
0
50
100
150
200
250
300
350
2000
2005
2010
2015
2020
2025


Postal Code vs 2020 Census Tract
1e10
2020 Census Tract
Postal Code
0
1
2
3
4
5
0
20000
40000
60000
80000
100000



[3]:
```
"\n# Scatter plot between 'Electric Range' and 'Base
MSRP'\nplt.figure(figsize=(8, 5))\nsns.scatterplot(x='Base MSRP', y='Electric
Range', data=df)\nplt.title('Electric Range vs Base MSRP')\nplt.xlabel('Base
MSRP ($)')\nplt.ylabel('Electric Range (miles)')\nplt.show()\n\n# Scatter plot
between 'Model Year' and 'Base MSRP'\nplt.figure(figsize=(8,
5))\nsns.scatterplot(x='Base MSRP', y='Model Year', data=df)\nplt.title('Model
Year vs Base MSRP')\nplt.xlabel('Base MSRP ($)')\nplt.ylabel('Model
Year')\nplt.show()\n"
```

[ ]: