Capstone_Code

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**

.ipynb file for CIND 820 Capstone Project

**

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Date of Submission: 02nd July 2024

**

Cleaning and Summarizing the Data

**

[ ]:
```
# importing pandas library
import pandas as pd
```

[ ]:
```
# reading the electric vehicle population data '.csv' file and storing it in␣
↪'electric_v' dataframe
electric_v = pd.read_csv("D:/Personal/Data Analytics Learning/TMU/CIND 820␣
↪Capstone/Electric_Vehicle_Population_Data.csv")
```

[ ]:
```
# printing the dimensions of 'electric_v'
print(electric_v.shape)
```

```
(186879, 17)
```

[ ]:
```
# getting an overview of 'electric_v' by printing the first 5 observations
print(electric_v.head())
```

```
   VIN (1-10)  County       City State  Postal Code  Model Year   Make  \
0  WBY8P6C58K    King    Seattle    WA      98115.0        2019    BMW
1  5YJSA1DN4D  Kitsap  Bremerton    WA      98312.0        2013  TESLA
2  5YJSA1E26J    King       Kent    WA      98042.0        2018  TESLA
3  WBY2Z2C54E    King   Bellevue    WA      98004.0        2014    BMW
4  5YJXCDE23J    King   Bellevue    WA      98004.0        2018  TESLA
```

```
     Model                   Electric Vehicle Type  \
0       I3          Battery Electric Vehicle (BEV)
1  MODEL S          Battery Electric Vehicle (BEV)
2  MODEL S          Battery Electric Vehicle (BEV)
3       I8  Plug-in Hybrid Electric Vehicle (PHEV)
4  MODEL X          Battery Electric Vehicle (BEV)

  Clean Alternative Fuel Vehicle (CAFV) Eligibility  Electric Range  \
0           Clean Alternative Fuel Vehicle Eligible             153
1           Clean Alternative Fuel Vehicle Eligible             208
2           Clean Alternative Fuel Vehicle Eligible             249
3             Not eligible due to low battery range              14
4           Clean Alternative Fuel Vehicle Eligible             238

   Base MSRP  Legislative District  DOL Vehicle ID  \
0          0                  43.0       259254397
1      69900                  35.0       127420940
2          0                  47.0       170287183
3          0                  41.0       205545868
4          0                  41.0       237977386

                 Vehicle Location  \
0  POINT (-122.3008235 47.6862671)
1  POINT (-122.6961203 47.5759584)
2  POINT (-122.1145138 47.3581107)
3    POINT (-122.202397 47.619252)
4    POINT (-122.202397 47.619252)

                               Electric Utility  2020 Census Tract
0   CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)       5.303300e+10
1                         PUGET SOUND ENERGY INC       5.303508e+10
2  PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       5.303303e+10
3  PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       5.303302e+10
4  PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       5.303302e+10
```

[ ]:
```
# printing a concise summary of 'electric_v' dataframe
print(electric_v.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 186879 entries, 0 to 186878
Data columns (total 17 columns):
 #   Column                                             Non-Null Count   Dtype
---  ------                                             --------------   -----
 0   VIN (1-10)                                         186879 non-null  object
 1   County                                             186876 non-null  object
 2   City                                               186876 non-null  object
 3   State                                              186879 non-null  object
```

```
 4   Postal Code                                        186876 non-null  float64
 5   Model Year                                         186879 non-null  int64
 6   Make                                               186879 non-null  object
 7   Model                                              186879 non-null  object
 8   Electric Vehicle Type                              186879 non-null  object
 9   Clean Alternative Fuel Vehicle (CAFV) Eligibility  186879 non-null  object
 10  Electric Range                                     186879 non-null  int64
 11  Base MSRP                                          186879 non-null  int64
 12  Legislative District                               186476 non-null  float64
 13  DOL Vehicle ID                                     186879 non-null  int64
 14  Vehicle Location                                   186871 non-null  object
 15  Electric Utility                                   186876 non-null  object
 16  2020 Census Tract                                  186876 non-null  float64
dtypes: float64(3), int64(4), object(10)
memory usage: 24.2+ MB
None
```

Cleaning the Data

[ ]:
```python
# checking if there are any duplicate entries in the dataframe
print(electric_v['DOL Vehicle ID'].duplicated().sum())
```

```
0
```

[ ]:
```python
# checking for null values in the dataframe
print(electric_v.isnull().sum())
```

```
VIN (1-10)                                             0
County                                                 3
City                                                   3
State                                                  0
Postal Code                                            3
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                                 403
DOL Vehicle ID                                         0
Vehicle Location                                       8
Electric Utility                                       3
2020 Census Tract                                      3
dtype: int64
```

[ ]:
```python
# dropping the observations having null values under 'Legislative District' as␣
↪those observations belongs to states other than Washington
electric_v = electric_v.dropna(subset=['Legislative District'])
```

```python
# dropping observations having null values under 'Vehicle Location'
electric_v = electric_v.dropna(subset=['Vehicle Location'])

# checking for null values again
print(electric_v.isnull().sum())
```

```
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
```

[ ]:
```python
# checking the data types of variables in 'electric_v' dataframe
print(electric_v.dtypes)
```

```
VIN (1-10)                                            object
County                                                object
City                                                  object
State                                                 object
Postal Code                                          float64
Model Year                                             int64
Make                                                  object
Model                                                 object
Electric Vehicle Type                                 object
Clean Alternative Fuel Vehicle (CAFV) Eligibility     object
Electric Range                                         int64
Base MSRP                                              int64
Legislative District                                 float64
DOL Vehicle ID                                         int64
Vehicle Location                                      object
Electric Utility                                      object
2020 Census Tract                                    float64
dtype: object
```

```
[ ]: # importing 're' library for matching regular expressions
import re

# defining a function to match a regular expression and returning a tuple with␣
 ↪two values
def get_coordinates(location):
    if location and isinstance(location, str):
        extractor = re.match(r'POINT \(([^ ]+) ([^ ]+)\)', location)
        if extractor:
            lat = float(extractor.group(2))
            long = float (extractor.group(1))
            return lat, long
    return None, None

# applying the function to the 'Vehicle Location' variable in 'electric_v' data␣
 ↪frame
# storing the values in two new variables named 'Latitude' and 'Longitude'
electric_v['Latitude'], electric_v['Longitude'] = zip(*electric_v['Vehicle␣
 ↪Location'].apply(get_coordinates))

# Insert the new columns just after 'Vehicle Location' for contextual relevance
location_index = electric_v.columns.get_loc('Vehicle Location')
electric_v.insert(location_index + 1, 'Latitude', electric_v.pop('Latitude'))
electric_v.insert(location_index + 2, 'Longitude', electric_v.pop('Longitude'))
```

```
[ ]: # creating a list of columns that need to be converted to 'categorical' data␣
 ↪type
categorical_columns = [
    'County', 'City', 'State', 'Make', 'Model',
    'Electric Vehicle Type', 'Clean Alternative Fuel Vehicle (CAFV)␣
 ↪Eligibility',
    'Electric Utility', 'Legislative District', '2020 Census Tract'
]

# converting the respective variables to categorical datatype
for col in categorical_columns:
    electric_v[col] = electric_v[col].astype('category')
```

```
[ ]: # deleting the 'Base MSRP' column in 'electric_v' as 98% of the values are 0
electric_v = electric_v.drop(columns=['Base MSRP'])

#printing the info after modification
print(electric_v.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 186471 entries, 0 to 186878
Data columns (total 18 columns):
```

```
 #   Column                                            Non-Null Count   Dtype
---  ------                                            --------------   -----
 0   VIN (1-10)                                        186471 non-null  object
 1   County                                            186471 non-null
category
 2   City                                              186471 non-null
category
 3   State                                             186471 non-null
category
 4   Postal Code                                       186471 non-null  float64
 5   Model Year                                        186471 non-null  int64
 6   Make                                              186471 non-null
category
 7   Model                                             186471 non-null
category
 8   Electric Vehicle Type                             186471 non-null
category
 9   Clean Alternative Fuel Vehicle (CAFV) Eligibility  186471 non-null
category
 10  Electric Range                                    186471 non-null  int64
 11  Legislative District                              186471 non-null
category
 12  DOL Vehicle ID                                    186471 non-null  int64
 13  Vehicle Location                                  186471 non-null  object
 14  Latitude                                          186471 non-null  float64
 15  Longitude                                         186471 non-null  float64
 16  Electric Utility                                  186471 non-null
category
 17  2020 Census Tract                                 186471 non-null
category
dtypes: category(10), float64(3), int64(3), object(2)
memory usage: 15.2+ MB
None
```

Exploratory Data Analysis of Electric Vehicle Population Data

[ ]:
```python
# installing ydata-profiling library which is used for comprehensive EDA reports
#!pip install ydata-profiling

# importing 'ProfileReport' from 'ydata_profiling' which is used to create the
↪EDA report
from ydata_profiling import ProfileReport

# creating profile report for electric_v data
ev_profile = ProfileReport(electric_v, title = "Electric Vehicle Population
↪Data - Exploratory Analysis", explorative=True)

# saving the generated report to an HTML format
```

```
ev_profile.to_file('D:/Personal/Data Analytics Learning/TMU/CIND 820 Capstone/
↪ev_profile.html')
```

```
c:\Users\Owner\anaconda3\Lib\site-
packages\ydata_profiling\profile_report.py:363: UserWarning: Try running
command: 'pip install --upgrade Pillow' to avoid ValueError
  warnings.warn(
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
```

```
c:\Users\Owner\anaconda3\Lib\site-
packages\ydata_profiling\model\correlations.py:66: UserWarning: There was an
attempt to calculate the auto correlation, but this failed.
To hide this warning, disable the calculation
(using `df.profile_report(correlations={"auto": {"calculate": False}})`
If this is problematic for your use case, please report this as an issue:
https://github.com/ydataai/ydata-profiling/issues
(include the error message: 'could not convert string to float: 'Clean
Alternative Fuel Vehicle Eligible'')
  warnings.warn(
```

```
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
```

```
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
```

```
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

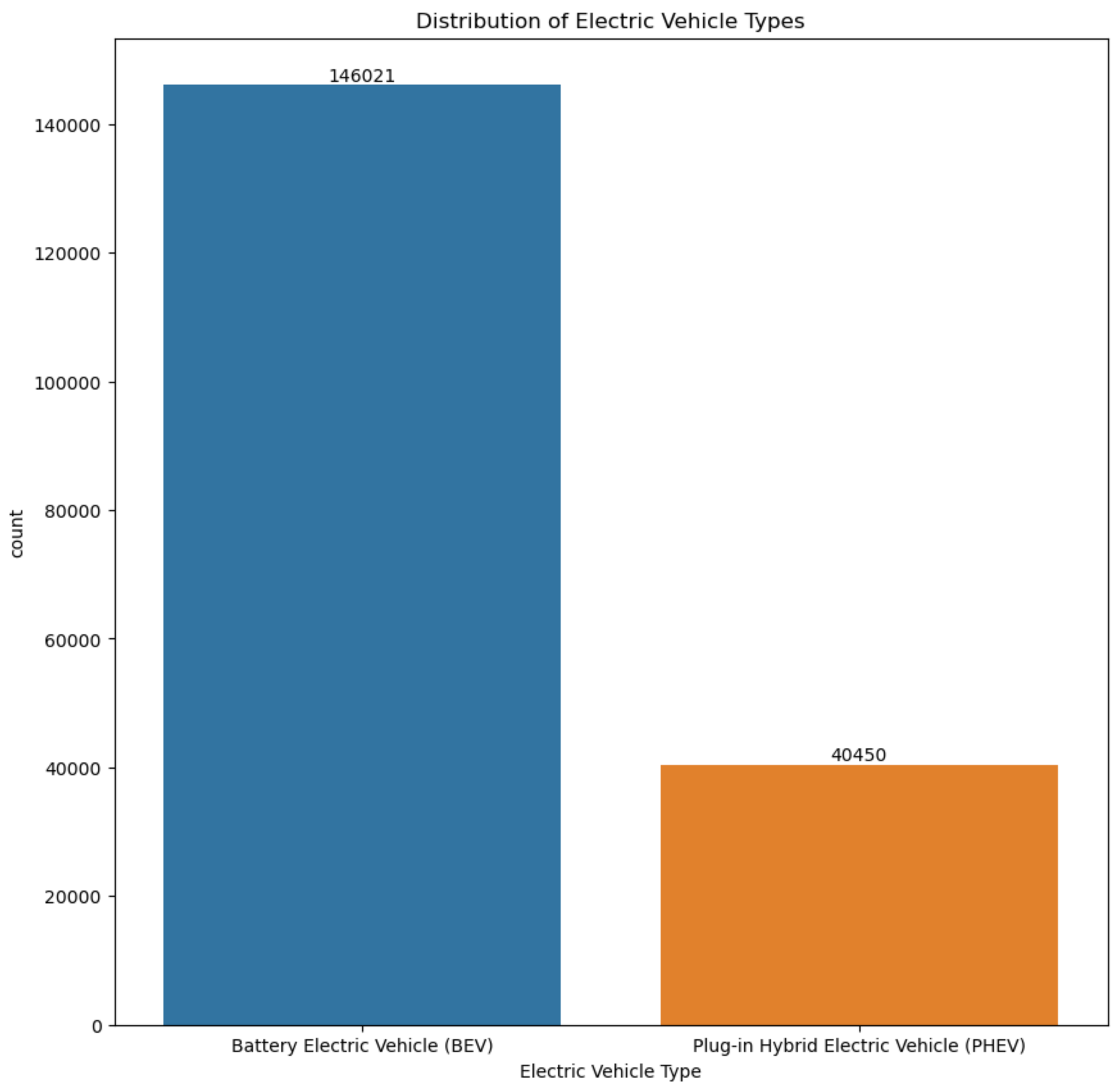
Univariate Analysis of ‘electric_v’ dataframe

[ ]:
```
# printing a summary of the 'electric_v' dataframe
print(electric_v.describe())
```

```
         Postal Code     Model Year  Electric Range  DOL Vehicle ID  \
count  186471.000000  186471.000000   186471.000000    1.864710e+05
mean    98261.647527    2020.661148       56.683731    2.225855e+08
std       304.624225       2.991387       90.771207    7.463921e+07
min     98001.000000    1997.000000        0.000000    4.385000e+03
25%     98052.000000    2019.000000        0.000000    1.851589e+08
50%     98122.000000    2022.000000        0.000000    2.302291e+08
75%     98371.000000    2023.000000       73.000000    2.578035e+08
max     99403.000000    2024.000000      337.000000    4.792548e+08

            Latitude      Longitude
count  186471.000000  186471.000000
mean       47.462836    -122.079426
std         0.610882       1.020595
min        45.595997    -124.614078
25%        47.358111    -122.395519
50%        47.610347    -122.275332
75%        47.721052    -122.136803
max        48.992052    -117.059519
```

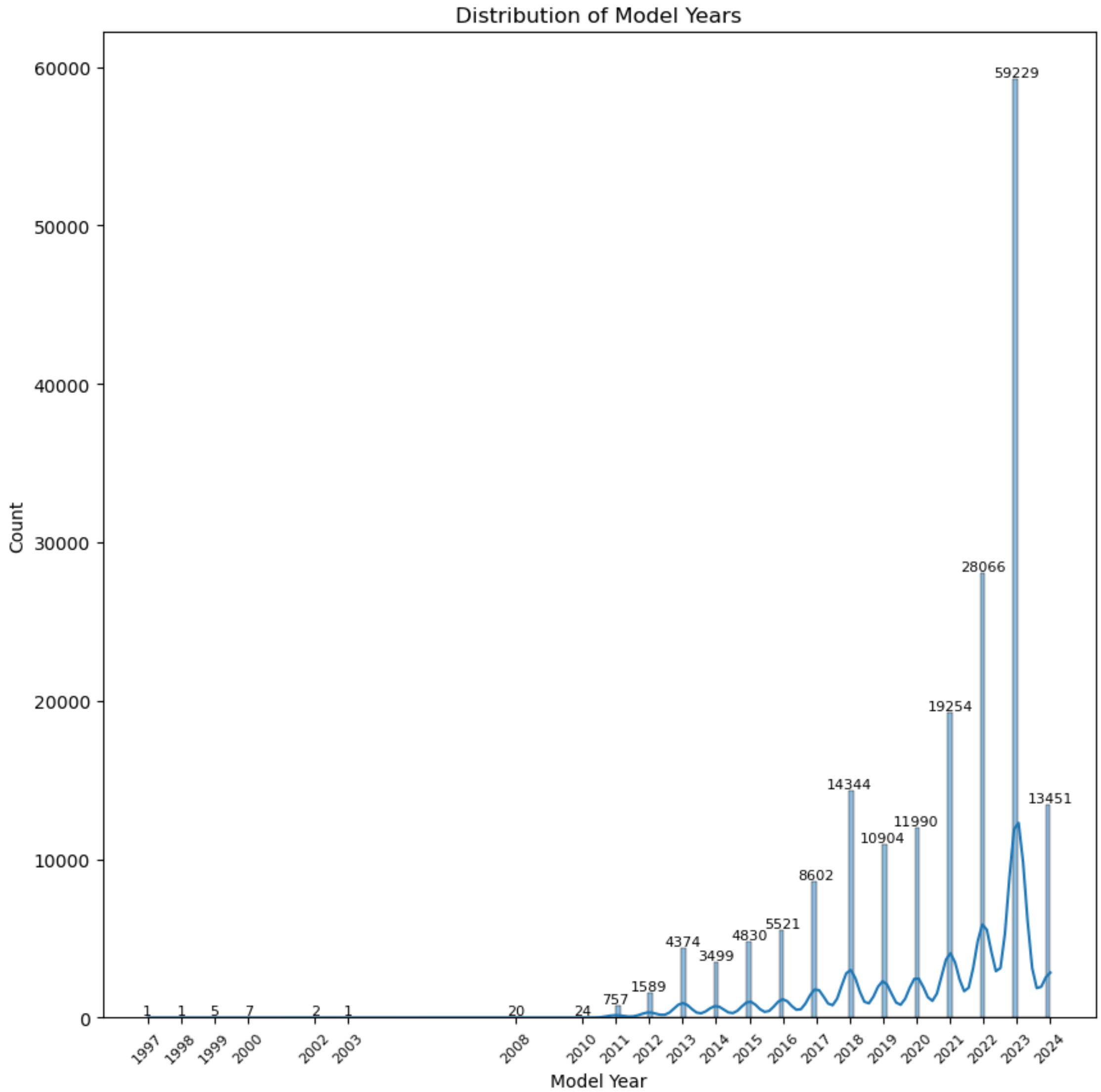
[ ]:
```python
# importing the necessary libraries for visualization
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
```

[ ]:
```python
%matplotlib inline

#electric_type = electric_v['Electric Vehicle Type'].value_counts()
warnings.simplefilter(action='ignore', category=FutureWarning)
# Distribution of Electric Vehicle Types using countplot
plt.figure(figsize=(10,10))
plot = sns.countplot(data=electric_v, x='Electric Vehicle Type')

# adding labels to each bar which represent the corresponding values
plot.bar_label(plot.containers[0])
plt.title('Distribution of Electric Vehicle Types')
plt.show()
```



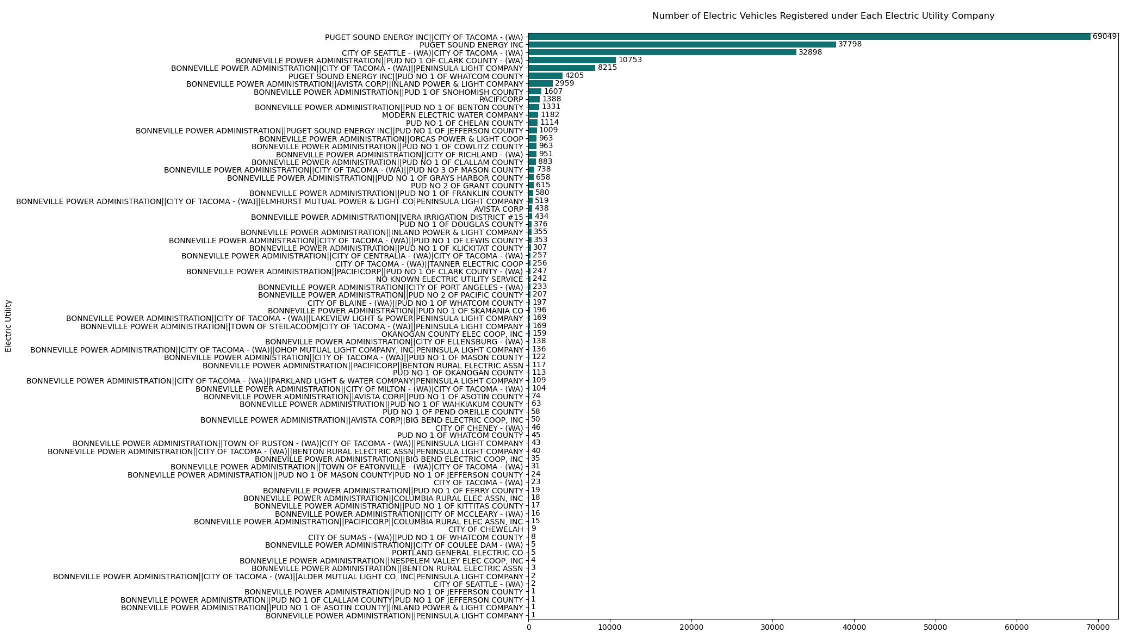
[ ]:
```
%matplotlib inline


plt.figure(figsize=(10,10))
sns.histplot(data=electric_v, x='Model Year', kde=True)
plt.title('Distribution of Model Years')

# Calculating the count with respect to each model year
year_count = electric_v['Model Year'].value_counts().sort_index()

# adding annotations (label) to each bar
for year, count in year_count.items():
    plt.text(year, count, str(count), ha='center', va='bottom', fontsize=8)
```

```
# customizing tick labels in the x-axis
plt.xticks(ticks=year_count.index, rotation=45, fontsize=8)

plt.show()
```



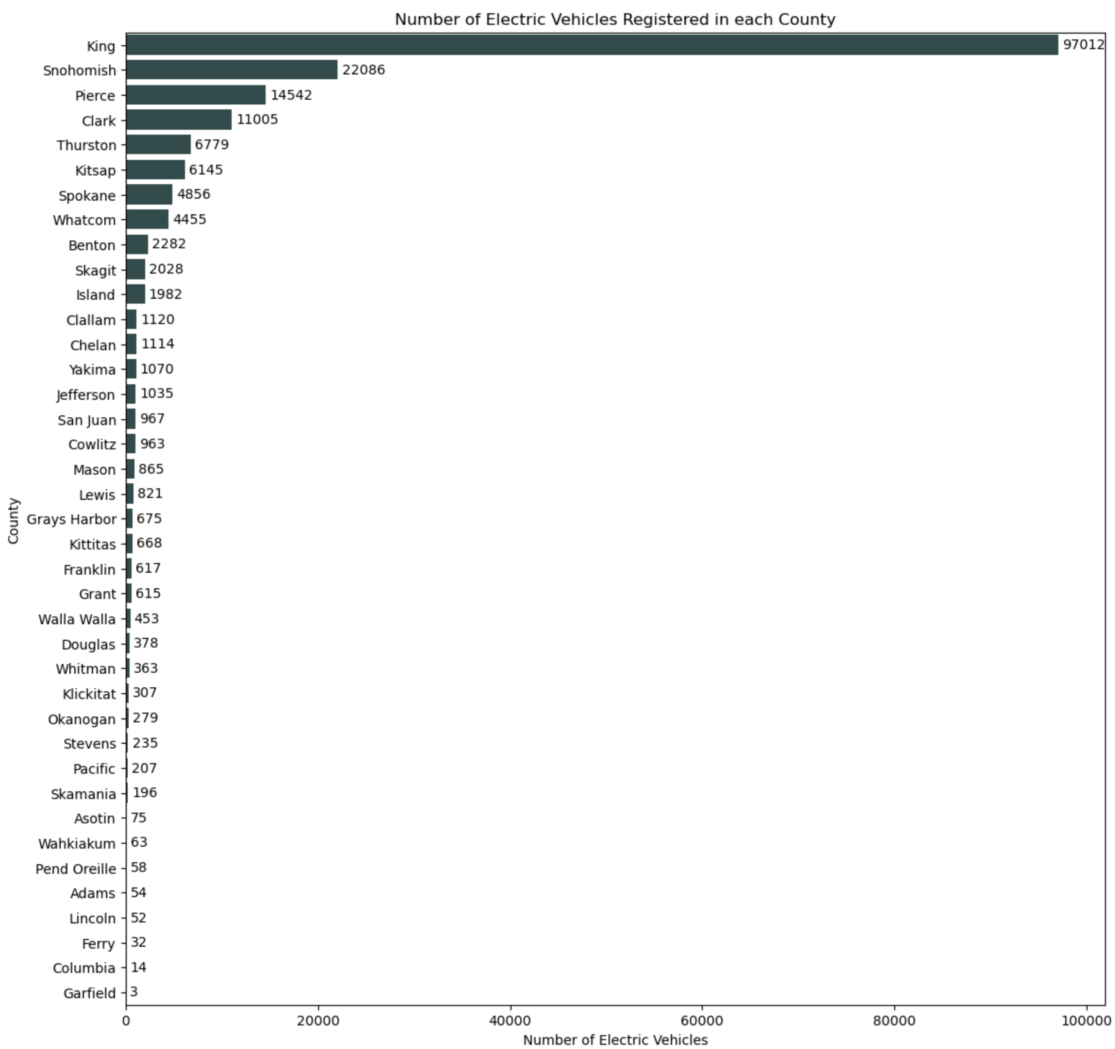
[ ]:
```
# Calculate the count of electric vehicles for each utility company
utility_counts = electric_v['Electric Utility'].value_counts().
↪sort_values(ascending=False)

# Create a horizontal bar plot visualizing the utility company-wise vehicle␣
↪count
```

```
plt.figure(figsize=(14, 14))
utility_barplot = sns.barplot(y=utility_counts.index, x=utility_counts.values,␣
↪color="teal", order=utility_counts.index)

# Adding annotations (labels) to each bar as integers. Labels are placed at the␣
↪edge of the bar
for utility_container in utility_barplot.containers:
    utility_barplot.bar_label(utility_container, fmt='%d', label_type='edge',␣
↪padding=3, color='black', fontsize=10)

# Setting the plot title and x, y axis labels
plt.title('Number of Electric Vehicles Registered under Each Electric Utility␣
↪Company\n')
plt.xlabel('Number of Electric Vehicles')
plt.ylabel('Electric Utility')
plt.show()
```



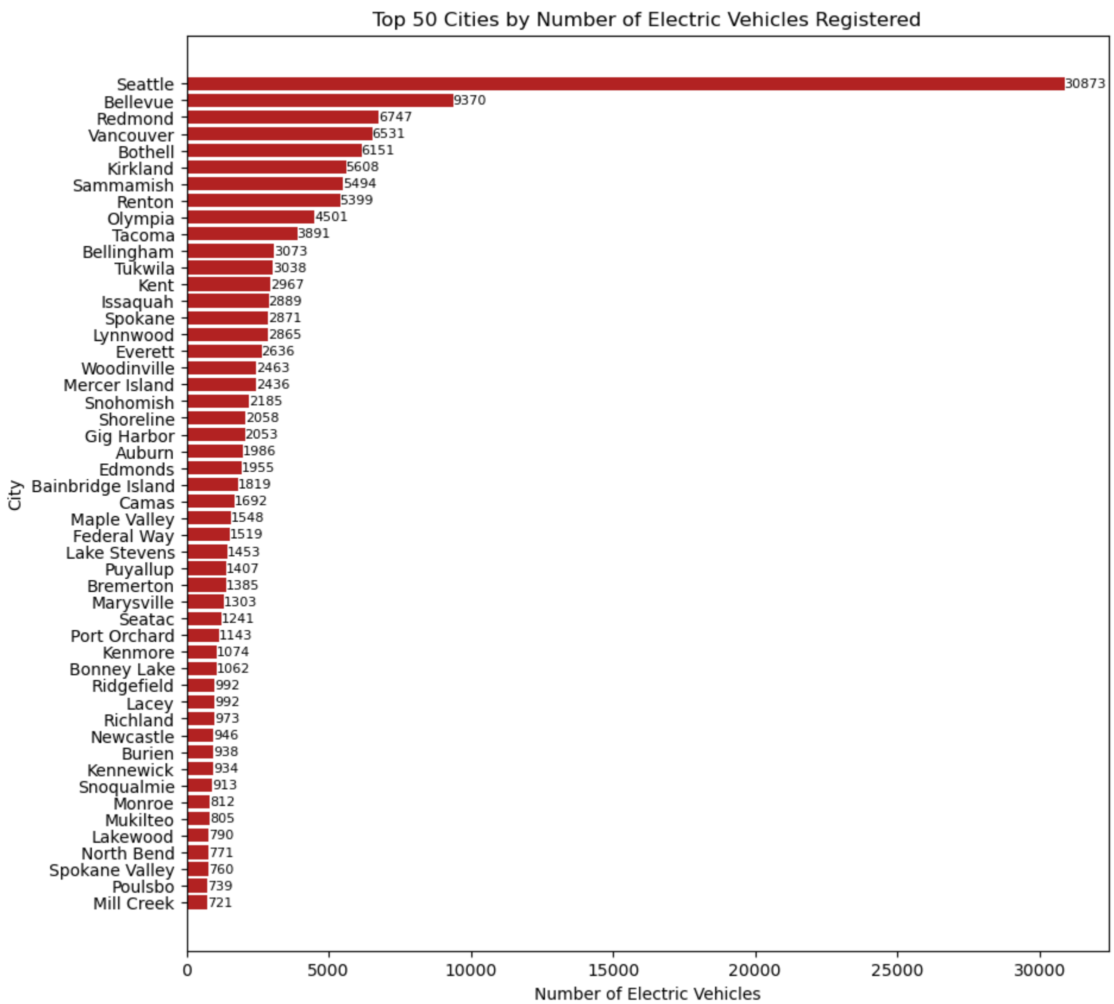

```
[ ]: %matplotlib inline
# Calculate the count of electric vehicles in each county
county_counts = electric_v['County'].value_counts().sort_values(ascending=False)
#county_counts.columns = ['County', 'Count']

# Create a horizontal bar plot visualizing the county-wise vehicle count
plt.figure(figsize=(13, 13))
county_barplot = sns.barplot(y=county_counts.index, x= county_counts.values,␣
↪color="darkslategrey", order=county_counts.index)
```

```
# Adding annotations (labels) to each bar as integers
for county_container in county_barplot.containers:
    county_barplot.bar_label(county_container, fmt='%d', label_type='edge',␣
↪padding=3, color='black', fontsize=10)


# setting the plot title
# setting the x and y axis labels
plt.title('Number of Electric Vehicles Registered in each County')
plt.xlabel('Number of Electric Vehicles')
plt.ylabel('County')
plt.show()
```



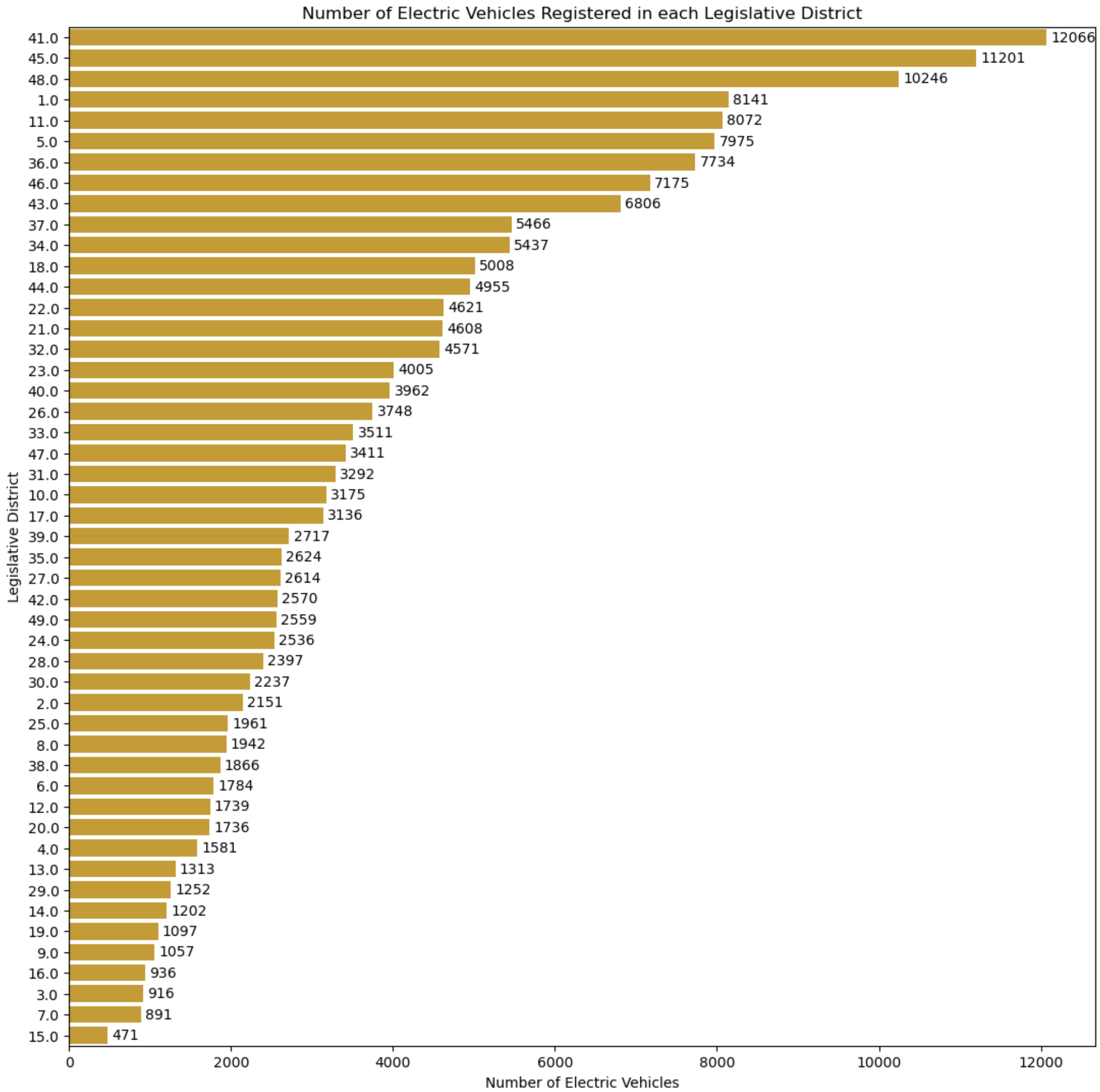
[ ]:

```
# Calculate the count of electric vehicles in each city
city_counts = electric_v['City'].value_counts().sort_values(ascending=False)

# Get the top 50 cities and sort it in descending order
top_city_counts = city_counts.head(50).sort_values()

# Plotting the top 50 cities using matplotlib
plt.figure(figsize=(10, 10))
plt.barh(top_city_counts.index, top_city_counts.values, color='firebrick')

# Adding annotations (labels) to each bar
for index, value in enumerate(top_city_counts.values):
    plt.text(value, index, f'{value}', va='center', ha='left', color='black',␣
 ↪fontsize=8)

# Setting the plot title and x, y axis labels
plt.title('Top 50 Cities by Number of Electric Vehicles Registered')
plt.xlabel('Number of Electric Vehicles')
plt.ylabel('City')

# Display the plot
plt.show()
```



[ ]:
```python
# Calculate the count of electric vehicles for each Legislative District
leg_dist_counts = electric_v['Legislative District'].value_counts()


# Create a horizontal bar plot for legislative district wise vehicle count
plt.figure(figsize=(13, 13))
leg_dist_barplot = sns.barplot(y=leg_dist_counts.index, x= leg_dist_counts.
 ↪values, color="goldenrod", order=leg_dist_counts.index)

# Adding annotations (labels) to each bar as integers
for leg_dist_container in leg_dist_barplot.containers:
    leg_dist_barplot.bar_label(leg_dist_container, fmt='%d', color = 'black',␣
 ↪label_type='edge', padding=3, fontsize=10)
```

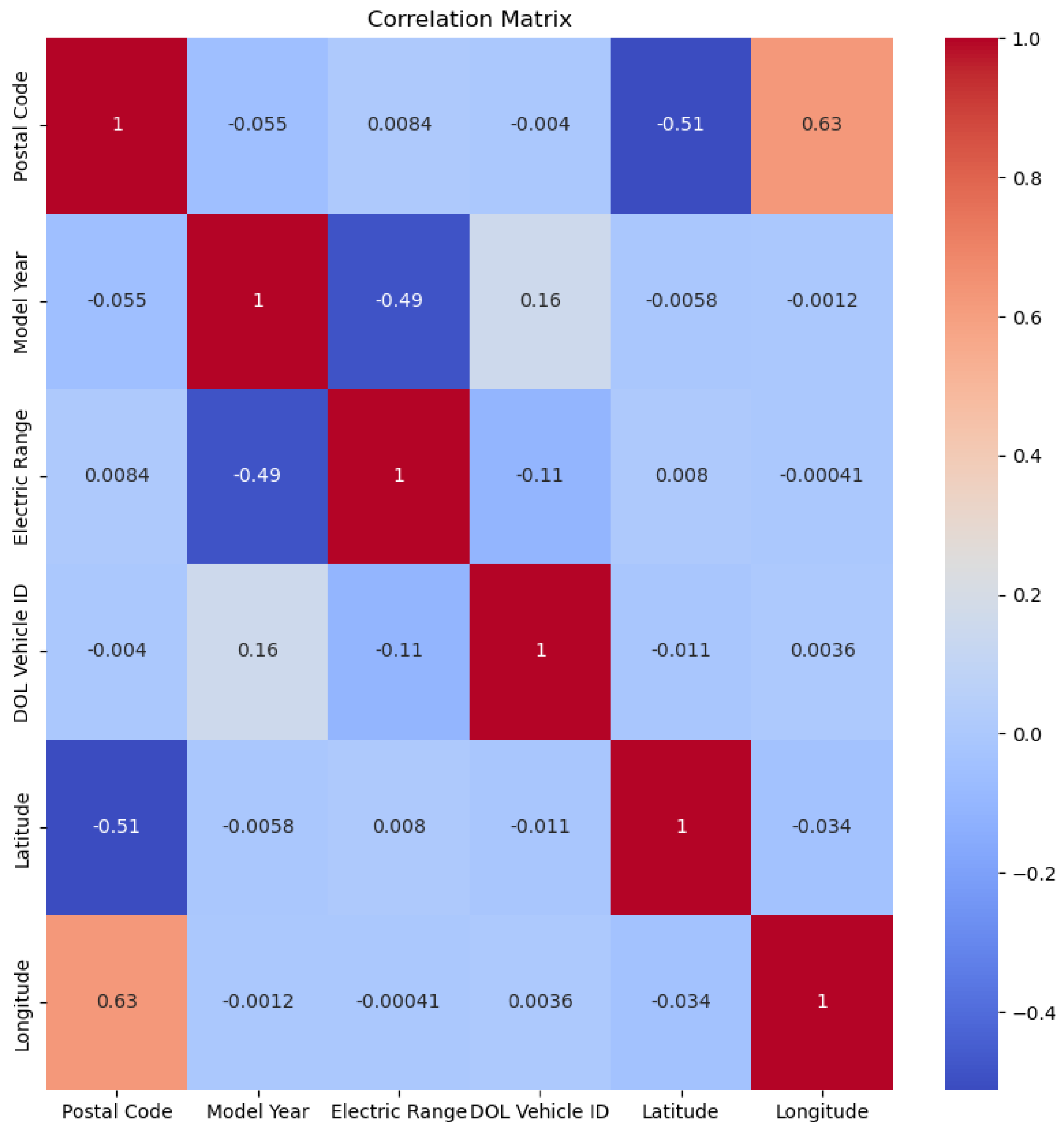
```
plt.title('Number of Electric Vehicles Registered in each Legislative District')
plt.xlabel('Number of Electric Vehicles')
plt.ylabel('Legislative District')
plt.show()
```



Bivariate Analysis

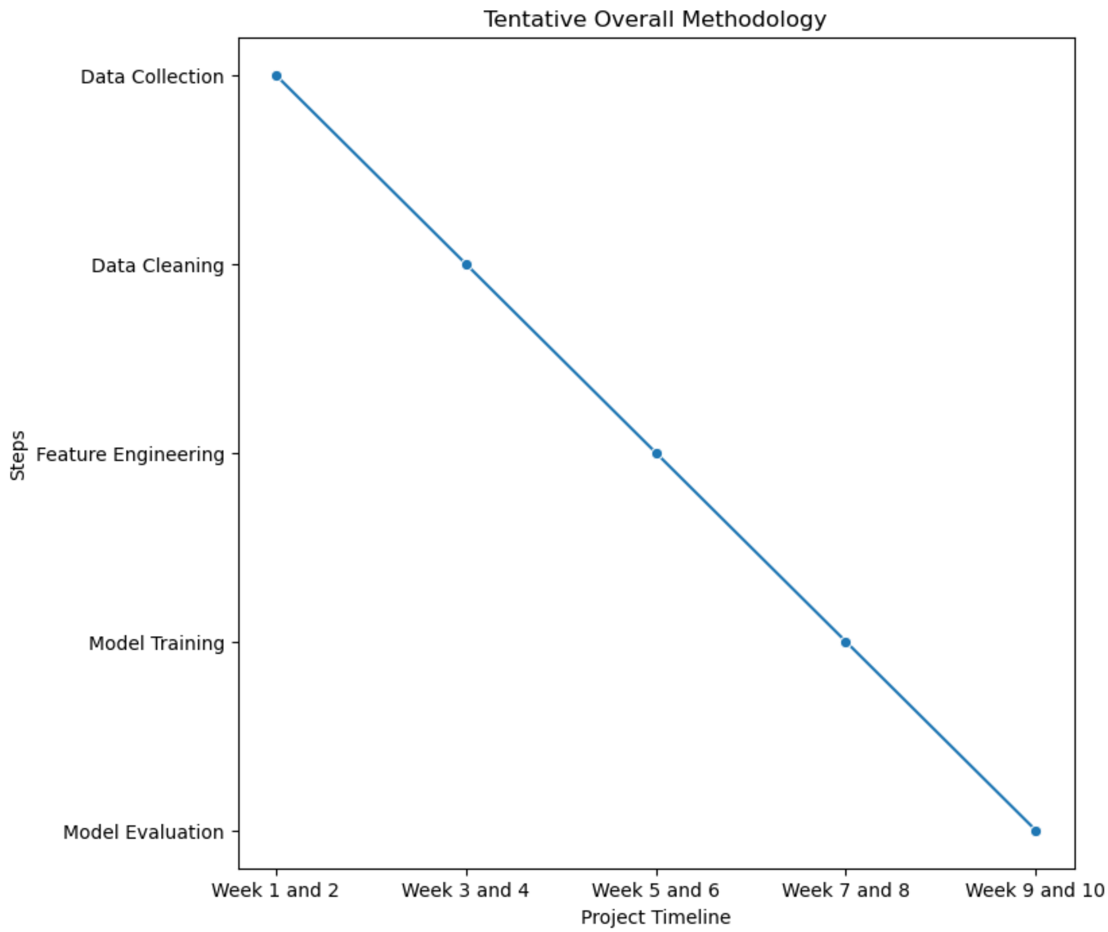
[ ]:
```
num_electric_v = electric_v.select_dtypes(include=['number'])
corr_matrix = num_electric_v.corr()

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

sns.heatmap(corr_matrix, annot=True, cmap = 'coolwarm')
```

```
plt.title('Correlation Matrix')
plt.show()
```



[ ]:
```
# Sample data for methodology graph
steps = ['Data Collection', 'Data Cleaning', 'Feature Engineering', 'Model␣
↪Training', 'Model Evaluation']

timeline = ['Week 1 and 2', 'Week 3 and 4', 'Week 5 and 6', 'Week 7 and 8',␣
↪'Week 9 and 10']
```

```
plt.figure(figsize=(8, 8))
sns.lineplot(x=timeline, y=steps, marker='o')
plt.title('Tentative Overall Methodology')
plt.xlabel('Project Timeline')
plt.ylabel('Steps')
plt.show()
```



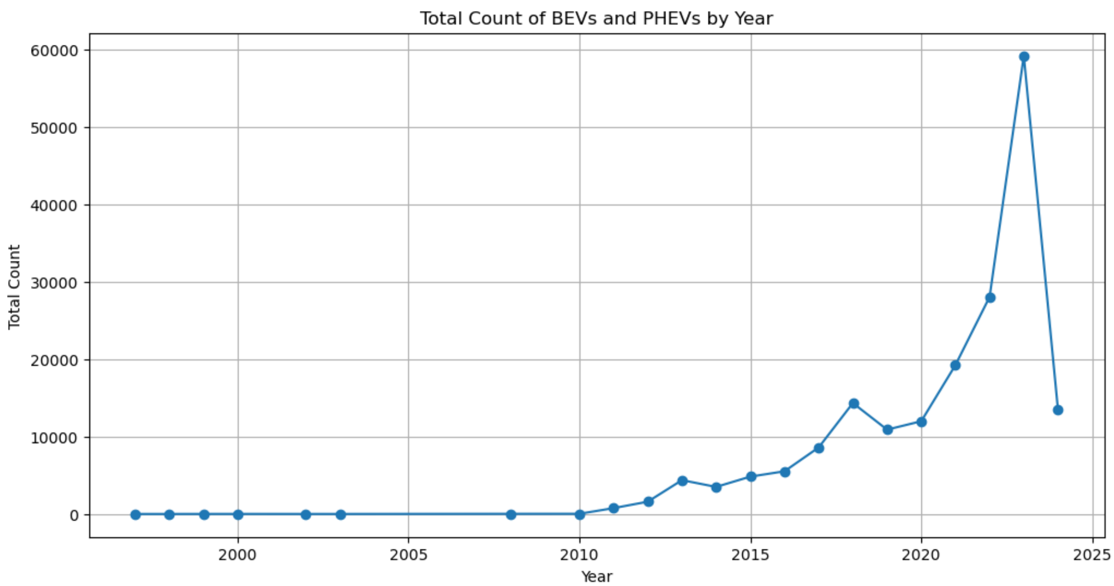
Research Question No.1

Based on data collected from 2015 to 2023, which covers approximately 5% of Washington State's population, what are the primary factors influencing the decision to purchase BEVs and PHEVs in the state?

STEP I

Analyze and visualize the total count of Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) by their model year to provide an insight into the trend of electric vehicle adoption over time.

```
[ ]: # creating a new dataframe by copying 'electric_v' dataset
electric_WA = electric_v

# Group by 'Model Year' and count the occurrences
yearly_counts = electric_WA.groupby('Model Year')['Electric Vehicle Type'].
  ↪count().reset_index()

# Rename columns for clarity
yearly_counts.columns = ['Model Year', 'Total Count']

# Optionally, visualize the results
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))
plt.plot(yearly_counts['Model Year'], yearly_counts['Total Count'], marker='o')
plt.title('Total Count of BEVs and PHEVs by Year')
plt.xlabel('Year')
plt.ylabel('Total Count')
plt.grid(True)
plt.show()
```



The trend indicates growing acceptance and adoption of electric vehicles over the years, with significant growth in the last 9 years.

STEP II

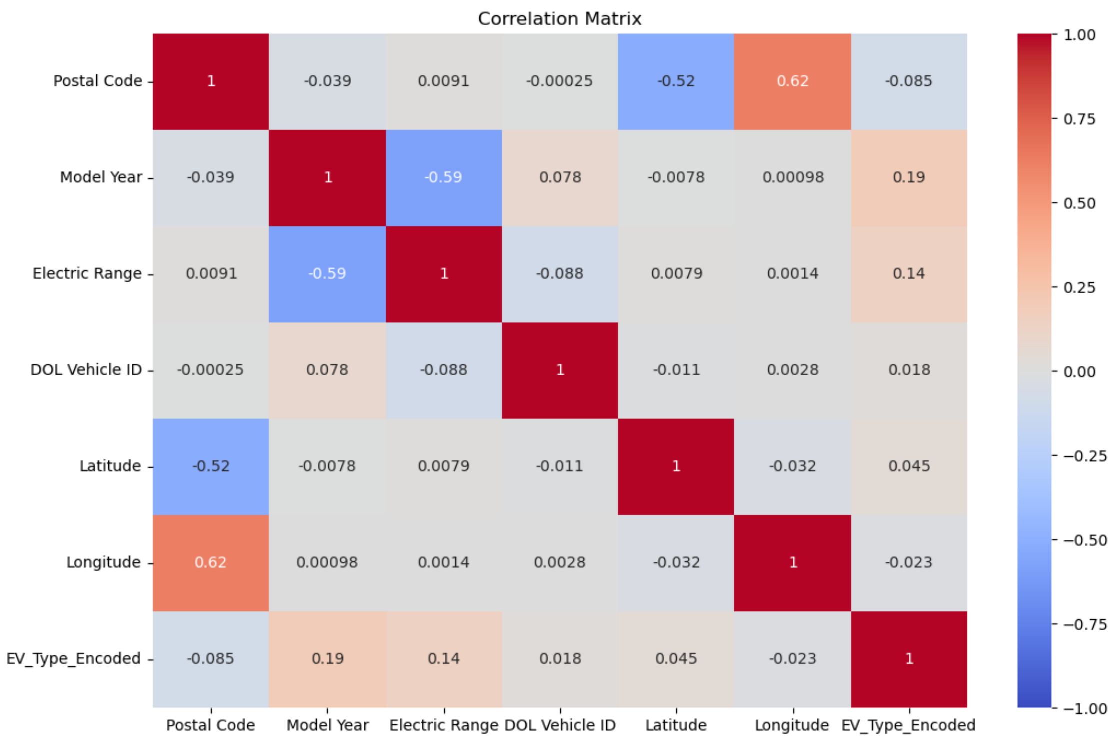
Using correlation to understand the dataset's structure and relationships before building predictive models, ensuring that the most relevant features are selected for further analysis.

[ ]:

```
# importing the necessary libraries
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV,␣
↪cross_val_score
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
from imblearn.over_sampling import SMOTE
import matplotlib.pyplot as plt
import seaborn as sns


# Focusing the analysis on recent years where electric vehicle adoption trends␣
↪are more relevant.
filtered_data = electric_WA[(electric_WA['Model Year'] >= 2015) &␣
↪(electric_WA['Model Year'] <= 2023)].copy()

# apply a lambda function to each element in the Electric Vehicle Type column.
# The lambda function checks the value of each element (x). If the value is␣
↪'Battery Electric Vehicle (BEV)', it returns 1. Otherwise, it returns 0.
# the encoded data is then stored in a new column named 'EV_Type_Encoded'
filtered_data.loc[:, 'EV_Type_Encoded'] = filtered_data['Electric Vehicle␣
↪Type'].apply(lambda x: 1 if x == 'Battery Electric Vehicle (BEV)' else 0)

# Select numerical features including the encoded target variable and store it␣
↪in 'numerical_features' variable
numerical_features = filtered_data.select_dtypes(include=['int64', 'float64']).
↪copy()
# adding the newly created EV_Type_Encoded column from the filtered_data␣
↪DataFrame to the numerical_features DataFrame.
# This step is necessary to ensure that the target variable EV_Type_Encoded is␣
↪included in the numerical_features DataFrame, which will be used for further␣
↪analysis
numerical_features['EV_Type_Encoded'] = filtered_data['EV_Type_Encoded']

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

# removing the 'EV_Type_Encoded' entry from this column, which is the␣
↪correlation of the target variable with itself
# The purpose of this line is to focus on how each numerical feature in the␣
↪dataset correlates with the target variable,
# which is essential for feature selection and understanding which features␣
↪have the most influence on the target variable.
```

```
correlation_with_target = correlation_matrix['EV_Type_Encoded'].
    ↪drop('EV_Type_Encoded')

# Display the correlations
print("Correlation with target variable:")
print(correlation_with_target)

# Plot heatmap of the correlation matrix
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Matrix')
plt.show()
```

```
Correlation with target variable:
Postal Code       -0.084690
Model Year         0.189422
Electric Range     0.143285
DOL Vehicle ID     0.017626
Latitude           0.045268
Longitude         -0.023110
Name: EV_Type_Encoded, dtype: float64
```



Interpretation

Model Year has the highest positive correlation (0.189591) with the target variable. This suggests that newer model years are somewhat associated with BEVs compared to PHEVs.

Electric Range also has a moderate positive correlation (0.143539), indicating that BEVs might have a higher electric range compared to PHEVs.

Postal Code, DOL Vehicle ID, Latitude, and Longitude show very weak correlations with the target variable.

STEP III

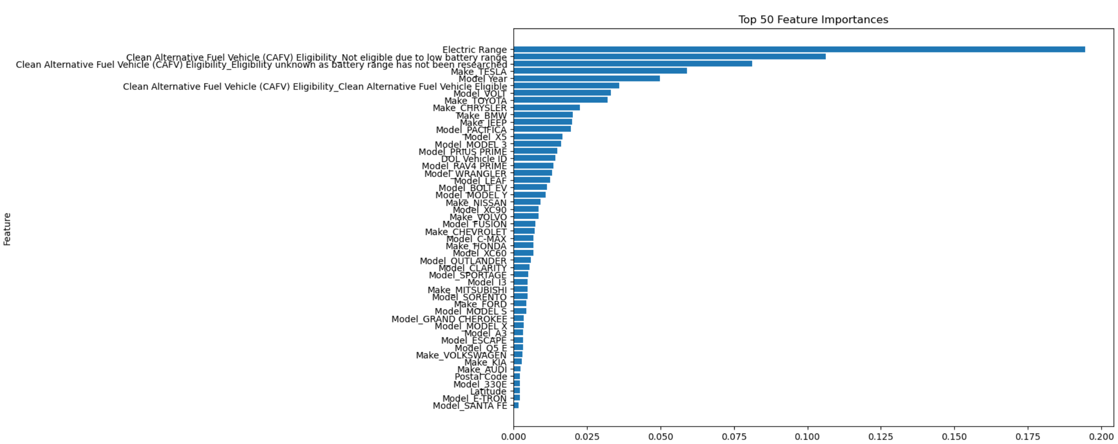
Prepare the data for machine learning, perform feature selection, and identify the most important features for predicting whether an electric vehicle is a Battery Electric Vehicle (BEV) or a Plug-in Hybrid Electric Vehicle (PHEV).

[ ]:
```
# perform one hot encoding to categorical columns. This will convert␣
↪categorical data into a series of binary columns which is necessary for␣
↪machine learning
encoded_data = pd.get_dummies(filtered_data.drop(columns=['EV_Type_Encoded',␣
↪'VIN (1-10)']), columns=['County', 'City', 'Make', 'Model',
                                                       'Clean Alternative Fuel␣
↪Vehicle (CAFV) Eligibility',
                                                       'Electric Utility',␣
↪'Legislative District', '2020 Census Tract'])

# Define the feature set and the target variable (independent and dependent␣
↪variables)
X = encoded_data.drop(columns=['Electric Vehicle Type'])  # Features
y = filtered_data['EV_Type_Encoded']  # Target

# Ensure that all features are in a numeric format, which is required for most␣
↪machine learning algorithms.
# Handle any non-numeric values gracefully by converting them to NaN,
X = X.apply(pd.to_numeric, errors='coerce')

# remove any columns from the DataFrame X that contain NaN values.
# This ensures that only columns with fully numeric data are retained for␣
↪further analysis and model training.
X = X.dropna(axis=1, how='any')

# Split 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=42)

# Instantiating Random Forest Classifier with 100 trees and a fixed␣
↪random_state for Feature Selection
# 100 trees offer a good balance between achieving high performance and␣
↪maintaining reasonable computational cost.
rf = RandomForestClassifier(n_estimators=100, random_state=42)
# training the model on the training data
```

```
rf.fit(X_train, y_train)

# storing important scores for each feature and storing it in descending order
importances = rf.feature_importances_
feature_importances = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': importances
}).sort_values(by='Importance', ascending=False)

# Printing the top 50 features
print("Top 50 Features by Random Forest:")
print(feature_importances.head(50))

# creating a horizontal bar plot to visualize the importance scores of the top␣
↪50 features
plt.figure(figsize=(12, 8))
plt.barh(feature_importances['Feature'].head(50),␣
↪feature_importances['Importance'].head(50))
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Top 50 Feature Importances')
plt.gca().invert_yaxis()
plt.show()

# Selecting the top 50 features from Random Forest and are used for further␣
↪feature selection with RFE
top_features = feature_importances.head(50)['Feature'].values
X_train_reduced = X_train[top_features]
```

```
Top 50 Features by Random Forest:
                                               Feature  Importance
2                                       Electric Range    0.194500
703  Clean Alternative Fuel Vehicle (CAFV) Eligibil…    0.106242
702  Clean Alternative Fuel Vehicle (CAFV) Eligibil…    0.081302
552                                         Make_TESLA    0.059041
1                                           Model Year    0.049786
701  Clean Alternative Fuel Vehicle (CAFV) Eligibil…    0.035982
692                                         Model_VOLT    0.033117
554                                        Make_TOYOTA    0.032135
525                                       Make_CHRYSLER    0.022602
522                                           Make_BMW    0.020247
535                                          Make_JEEP    0.019935
650                                     Model_PACIFICA    0.019510
696                                           Model_X5    0.016716
639                                      Model_MODEL 3    0.016316
653                                  Model_PRIUS PRIME    0.014884
3                                       DOL Vehicle ID    0.014242
```

665	Model_RAV4 PRIME	0.013485
694	Model_WRANGLER	0.013039
637	Model_LEAF	0.012394
577	Model_BOLT EV	0.011453
642	Model_MODEL Y	0.010941
545	Make_NISSAN	0.009201
699	Model_XC90	0.008612
556	Make_VOLVO	0.008545
612	Model_FUSION	0.007529
524	Make_CHEVROLET	0.007322
580	Model_C-MAX	0.006761
532	Make_HONDA	0.006701
698	Model_XC60	0.006679
649	Model_OUTLANDER	0.006005
584	Model_CLARITY	0.005562
683	Model_SPORTAGE	0.005004
624	Model_I3	0.004823
544	Make_MITSUBISHI	0.004738
678	Model_SORENTO	0.004709
529	Make_FORD	0.004381
640	Model_MODEL S	0.004299
616	Model_GRAND CHEROKEE	0.003549
641	Model_MODEL X	0.003449
566	Model_A3	0.003351
604	Model_ESCAPE	0.003294
657	Model_Q5 E	0.003172
555	Make_VOLKSWAGEN	0.003073
536	Make_KIA	0.002799
519	Make_AUDI	0.002285
0	Postal Code	0.002252
558	Model_330E	0.002080
4	Latitude	0.002075
593	Model_E-TRON	0.002061
674	Model_SANTA FE	0.001771



Interpretation of the Top 50 Features

The output and the visualization provided show the top 50 features ranked by their importance scores as determined by the Random Forest classifier. Here are the key takeaways and interpretations from this output:

1. **Most Important Features:**
   - **Electric Range:** This feature has the highest importance score, indicating that the electric range of a vehicle is a critical factor in determining whether it is a BEV or PHEV.
   - **CAFV Eligibility:** Various categories of "Clean Alternative Fuel Vehicle (CAFV) Eligibility" are also highly important. This reflects the influence of policy and eligibility criteria on the type of electric vehicle.
   - **Make (Brand):** The make of the vehicle, particularly brands like Tesla, Toyota, BMW, Chrysler, and Jeep, are significant. This suggests that certain brands are more associated with BEVs or PHEVs.
   - **Model Year:** Newer models are more likely to be BEVs, as indicated by the importance of the model year.
   - **Specific Models:** Specific vehicle models like Volt, Pacifica, RAV4 Prime, Prius Prime, Model 3, and others show significant importance, suggesting a strong association with the type of electric vehicle.
2. **Policy and Infrastructure:**
   - **Clean Alternative Fuel Vehicle (CAFV) Eligibility:** The high importance of CAFV eligibility categories underscores the role of policies and incentives in influencing the adoption of BEVs and PHEVs.
3. **Geographical Influence:**
   - **2020 Census Tract and City (e.g., City__Tukwila):** These features, although lower in importance, still contribute to the model, indicating that location and possibly local policies or infrastructure can impact the type of electric vehicle adopted.
4. **Additional Factors:**
   - Features like **Latitude** and **Longitude** have lower importance but are still considered, suggesting that geographical location plays a role, though less significant compared to other factors.

STEP IV

Perform feature selection, handle class imbalance, and prepare the data for machine learning model training

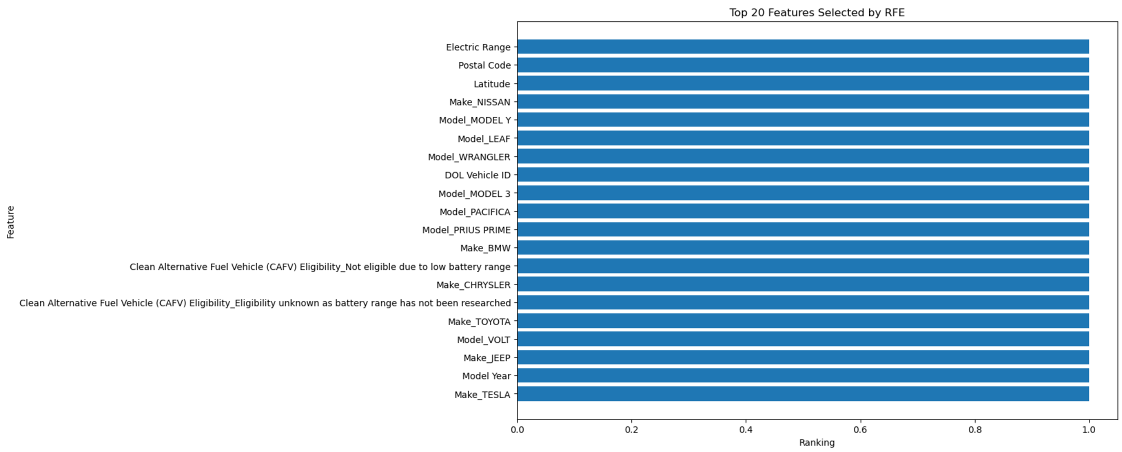
This process is essential for building more accurate and reliable predictive models, as it focuses on the most relevant features and addresses class imbalance issues that can negatively impact model performance.

[ ]:
```
# Initializing logistic regression model
model = LogisticRegression()
```

```python
# Initializing RFE with the logistic regression model and specifying that we␣
↪want the top 20 features
# Recursive Feature Elimination (RFE) is a feature selection technique that␣
↪fits a model and removes the weakest feature (or features)
# until the specified number of features is reached.
rfe = RFE(model, n_features_to_select=20)

# This fits the RFE model to the reduced training set.
# During this process, RFE recursively removes the least important features and␣
↪refits the model until only the specified number of features (20 in this␣
↪case) remains.
rfe.fit(X_train_reduced, y_train)

# This retrieves the feature ranking produced by RFE.
# Features with a ranking of 1 are selected, while higher rankings indicate␣
↪less important features.
rfe_ranking = rfe.ranking_

# Create a DataFrame containing the feature names and their corresponding␣
↪rankings, sorted by the ranking.
rfe_features = pd.DataFrame({
    'Feature': X_train_reduced.columns,
    'Ranking': rfe_ranking
}).sort_values(by='Ranking')

# print the top 20 features
print("Top 20 Features by RFE:")
print(rfe_features.head(20))

# plotting the top 20 features based on their ranking using a horizontal bar␣
↪chart
plt.figure(figsize=(12, 8))
plt.barh(rfe_features['Feature'].head(20), rfe_features['Ranking'].head(20))
plt.xlabel('Ranking')
plt.ylabel('Feature')
plt.title('Top 20 Features Selected by RFE')
plt.gca().invert_yaxis()
plt.show()

# Select the top 20 features based on RFE rankings.
selected_features = rfe_features.head(20)['Feature'].values

# reduce the training sets to these selected features
X_train_rfe = X_train[selected_features]
X_test_rfe = X_test[selected_features]
```

```python
# Check the class distribution in the original training set
print("Original training set class distribution:")
print(y_train.value_counts(),"\n")

# Uses SMOTE to generate synthetic samples for the minority class to balance␣
↪the class distribution in the training set.
# SMOTE generates synthetic samples for the minority class to balance the class␣
↪distribution.
# This helps improve the performance of machine learning models, which can␣
↪struggle with imbalanced datasets.
smote = SMOTE(random_state=42)
X_train_balanced, y_train_balanced = smote.fit_resample(X_train_rfe, y_train)

# Check the class distribution in the balanced training set
print("Balanced training set class distribution:")
print(y_train_balanced.value_counts())
```

```
Top 20 Features by RFE:
                                             Feature  Ranking
0                                     Electric Range        1
45                                       Postal Code        1
47                                          Latitude        1
21                                       Make_NISSAN        1
20                                     Model_MODEL Y        1
18                                        Model_LEAF        1
17                                    Model_WRANGLER        1
15                                    DOL Vehicle ID        1
13                                     Model_MODEL 3        1
11                                    Model_PACIFICA        1
14                                 Model_PRIUS PRIME        1
9                                           Make_BMW        1
1   Clean Alternative Fuel Vehicle (CAFV) Eligibil…        1
8                                      Make_CHRYSLER        1
2   Clean Alternative Fuel Vehicle (CAFV) Eligibil…        1
7                                        Make_TOYOTA        1
6                                         Model_VOLT        1
10                                         Make_JEEP        1
4                                         Model Year        1
3                                         Make_TESLA        1
```




```
Original training set class distribution:
EV_Type_Encoded
1    105405
0     24787
Name: count, dtype: int64

Balanced training set class distribution:
EV_Type_Encoded
1    105405
0    105405
Name: count, dtype: int64
```

Interpretation

The output and plot provide valuable insights into the features that are most important for classifying electric vehicles as BEVs or PHEVs, based on the Recursive Feature Elimination (RFE) process. Here's a detailed interpretation:

Top 20 Features by RFE

The table lists the top 20 features identified by RFE as the most important for the classification task. All features in the table have a ranking of 1, indicating they are the most important features according to the RFE process.

Key Features:

1. **Electric Range:** This feature appears at the top of the list, indicating it is crucial in distinguishing between BEVs and PHEVs. BEVs typically have a longer electric range compared to PHEVs.

2. **Vehicle Models:**

   - **Model_BOLT EV, Model_MODEL Y, Model_LEAF, Model_MODEL 3, Model_WRANGLER, Model_PRIUS PRIME, Model_MODEL S, Model_PACIFICA, Model_VOLT:** These specific vehicle models are significant, suggesting that certain models are more likely to be BEVs or PHEVs.

3. **Vehicle Makes:**

    - **Make_JEEP, Make_BMW, Make_TOYOTA, Make_TESLA, Make_CHRYSLER, Make_NISSAN:** These vehicle brands are significant, indicating that some brands are more associated with BEVs or PHEVs.

4. **CAFV Eligibility:**

    - **Clean Alternative Fuel Vehicle (CAFV) Eligibility:** Different categories of CAFV eligibility are crucial, reflecting the impact of policy and eligibility criteria on the type of electric vehicle.

5. **Model Year:** Newer model years are more likely to be BEVs, reflecting the recent market trend towards electric vehicles.

Class Distribution

Original Training Set Class Distribution: - **BEVs (1):** 105,648 - **PHEVs (0):** 24,837

This indicates a significant class imbalance, with BEVs being much more common in the dataset compared to PHEVs.

Balanced Training Set Class Distribution: - **BEVs (1):** 105,648 - **PHEVs (0):** 105,648

After applying SMOTE (Synthetic Minority Over-sampling Technique), the training set is balanced, with an equal number of BEVs and PHEVs. This balancing helps to improve the performance of machine learning models by providing them with an equal representation of both classes.

Visualization of Top 20 Features

The horizontal bar chart visualizes the top 20 features selected by RFE. All features have a ranking of 1, emphasizing their equal importance in the model.

Summary

- **Feature Importance:** The identified top 20 features are crucial for distinguishing between BEVs and PHEVs. Electric range, specific vehicle models and makes, CAFV eligibility, and model year are among the most significant features.
- **Class Imbalance:** The original training set had a significant imbalance, with more BEVs than PHEVs. SMOTE was applied to balance the classes, ensuring equal representation of both BEVs and PHEVs in the training set.
- **Model Preparation:** These top 20 features will be used to train machine learning models, ensuring that the models focus on the most relevant features, which should improve their performance.

STEP V

Perform hyperparameter tuning, train, and evaluate Logistic Regression and Random Forest models on the balanced training set, and then visualize and interpret the results.

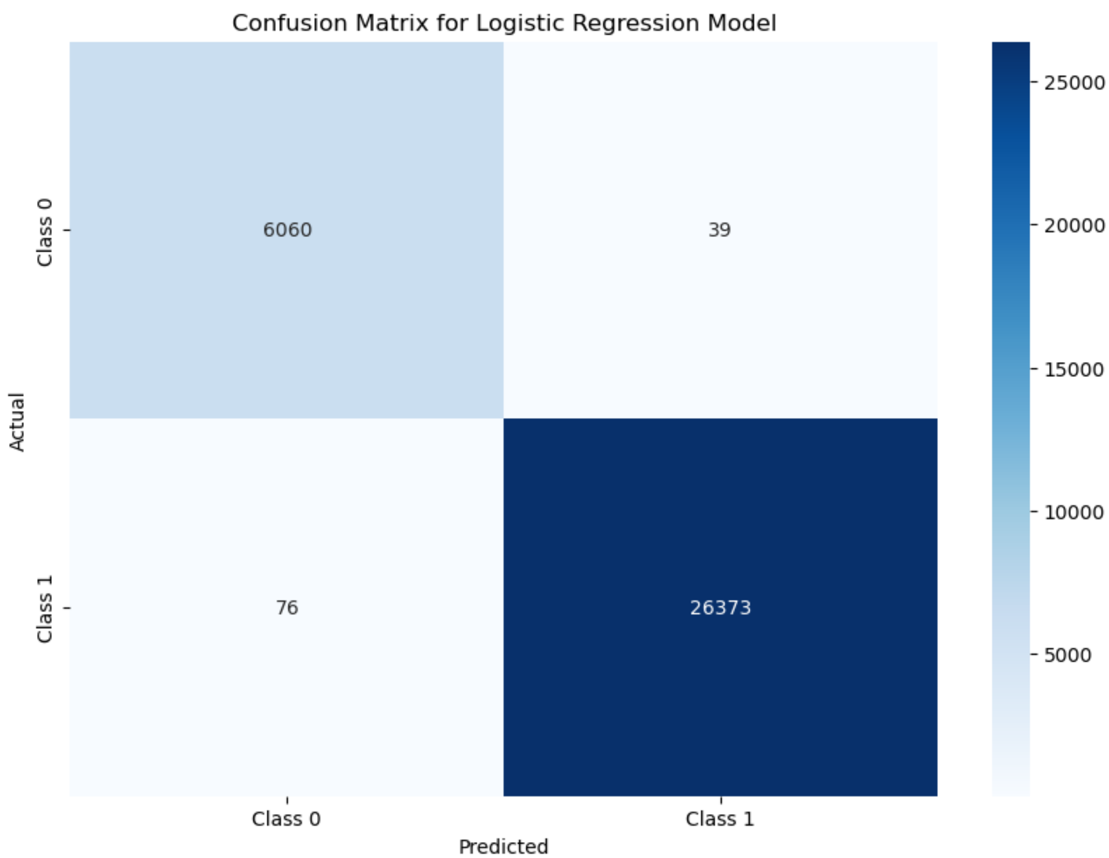
[ ]:
```
# Hyperparameter Tuning for Logistic Regression to find the optimal␣
↪hyperparameters for your logistic regression model
# defining a grid of hyperparameters to search over
'''
```

```
The parameter C controls the strength of regularization applied to the logistic␣
↪regression model. Prevent Overfitting
High Values of C: Implies less regularization. Low Values of C: Implies␣
↪stronger regularization.

Choosing the type of regularization (l1 or l2) affects how the model␣
↪coefficients are penalized and can influence both model accuracy and␣
↪interpretability.

liblinear is often a good default for small datasets or when both l1 and l2␣
↪regularization are required.
'''
param_grid = {'C': [0.1, 1, 10, 100], 'penalty': ['l1', 'l2'], 'solver':␣
↪['liblinear']}
# Performing cross-validation to find the best combination of hyperparameters
grid_search = GridSearchCV(LogisticRegression(), param_grid, cv=5)
# Fits the grid search to the balanced training data
grid_search.fit(X_train_balanced, y_train_balanced)

# printing the best parameters for Logistic Regression
print("Best parameters for Logistic Regression:", grid_search.best_params_)

# Initializing the logistic regression model with the best parameters found by␣
↪the grid search.
logreg = LogisticRegression(C=grid_search.best_params_['C'],␣
↪penalty=grid_search.best_params_['penalty'], solver=grid_search.
↪best_params_['solver'])
# Trains the logistic regression model on the balanced training set
logreg.fit(X_train_balanced, y_train_balanced)

# Make predictions on the test set using the trained logistic regression model.
y_pred_logreg = logreg.predict(X_test_rfe)

# Create the confusion matrix for logistic regression model
cm_logreg = confusion_matrix(y_test, y_pred_logreg)

# Plot the confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(cm_logreg, annot=True, fmt='d', cmap='Blues', xticklabels=['Class␣
↪0', 'Class 1'], yticklabels=['Class 0', 'Class 1'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Logistic Regression Model')
plt.show()

# Evaluate the model
```

```python
# Calculate and print the accuracy for the logistic regression model.
print("Logistic Regression Model with SMOTE and Hyperparameter Tuning")
print("Accuracy:", accuracy_score(y_test, y_pred_logreg))
#print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_logreg))
#print("Classification Report:\n", classification_report(y_test, y_pred_logreg))

# Extracts and displays the coefficients of the logistic regression model to␣
↪understand the importance and impact of each feature.
coefficients = pd.DataFrame({
    'Feature': selected_features,
    # Retrieves the coefficients from the trained logistic regression model.
    'Coefficient': logreg.coef_[0]
}).sort_values(by='Coefficient', ascending=False)

# printing the coefficients from logistic regression
print("Logistic Regression Coefficients")
print(coefficients)

# Initializing Random Forest Model with SMOTEusing 100 decision trees
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
# traing the random forest classifier on the SMOTE balanced training set
rf_model.fit(X_train_balanced, y_train_balanced)

# make predictions on the test set using random forest model
y_pred_rf = rf_model.predict(X_test_rfe)

# Create the confusion matrix
cm = confusion_matrix(y_test, y_pred_rf)

# Plot the confusion matrix using heatmap
plt.figure(figsize=(10, 7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Class 0',␣
↪'Class 1'], yticklabels=['Class 0', 'Class 1'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Random Forest Model')
plt.show()

# Extracts and displays the feature importances from the random forest model
print("Random Forest Model with SMOTE")
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
#print("Classification Report:\n", classification_report(y_test, y_pred_rf))

# Random Forest Feature Importances
rf_importances = pd.DataFrame({
    'Feature': selected_features,
    # Retrieves the feature importances from the trained random forest model.
```

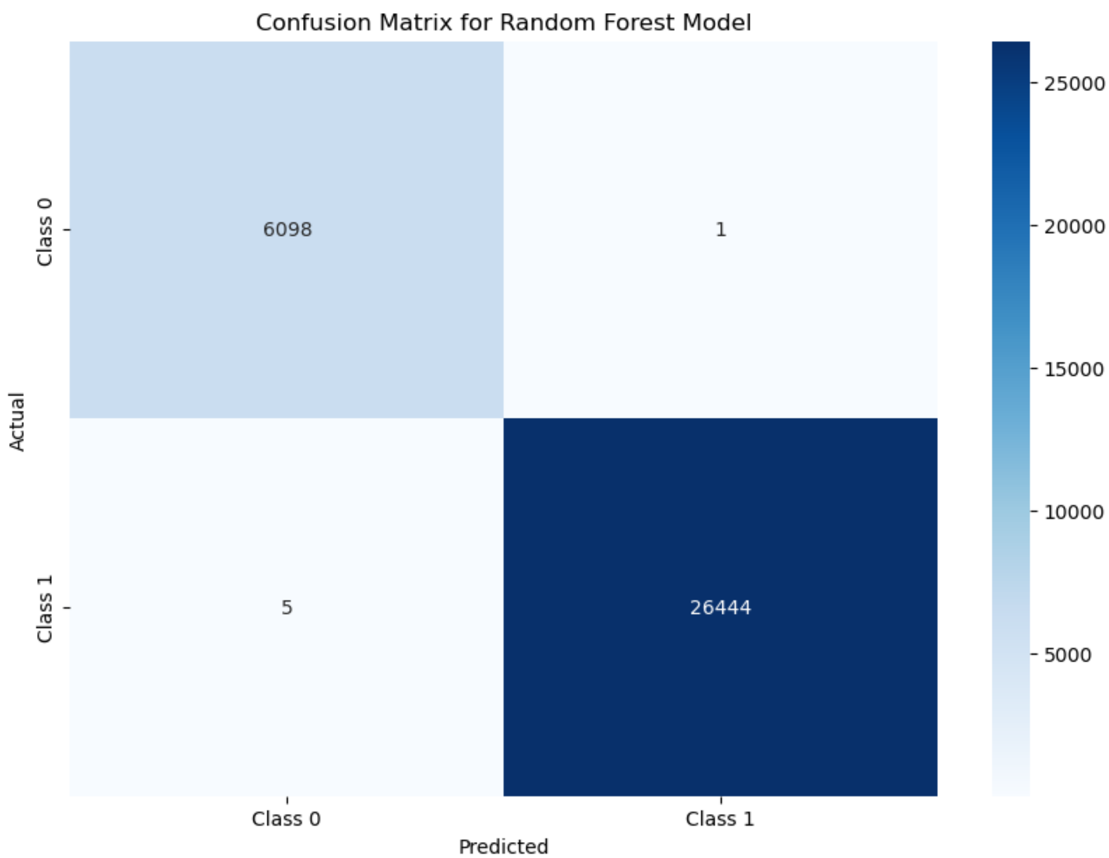
```
    'Importance': rf_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

# printing the importances from random forest model
print("Random Forest Feature Importances")
print(rf_importances)

# Evaluate stability of the random forest model
# Performs 5-fold cross-validation on the balanced training set
# Calculates the mean cross-validation score.
cv_scores = cross_val_score(rf_model, X_train_balanced, y_train_balanced, cv=5)
print("Random Forest Cross-Validation Scores:", cv_scores)
print("Mean Cross-Validation Score:", cv_scores.mean())
```

```
Best parameters for Logistic Regression: {'C': 0.1, 'penalty': 'l1', 'solver':
'liblinear'}
```




```
Logistic Regression Model with SMOTE and Hyperparameter Tuning
Accuracy: 0.9964667567899718
Logistic Regression Coefficients
                                              Feature    Coefficient
```

```
14  Clean Alternative Fuel Vehicle (CAFV) Eligibil…  1.852602e+01
5                                       Model_LEAF   2.897394e+00
3                                      Make_NISSAN   3.313733e-01
0                                   Electric Range   1.208646e-01
8                                    Model_MODEL 3   0.000000e+00
17                                       Make_JEEP   0.000000e+00
10                               Model_PRIUS PRIME   0.000000e+00
6                                   Model_WRANGLER   0.000000e+00
4                                    Model_MODEL Y   0.000000e+00
19                                      Make_TESLA   0.000000e+00
7                                   DOL Vehicle ID  -1.206818e-09
1                                      Postal Code  -2.756978e-05
18                                      Model Year  -1.381790e-03
2                                         Latitude  -4.596090e-02
9                                   Model_PACIFICA  -7.659337e-01
13                                   Make_CHRYSLER  -2.003558e+00
15                                     Make_TOYOTA  -3.157610e+00
12  Clean Alternative Fuel Vehicle (CAFV) Eligibil… -3.310723e+00
16                                      Model_VOLT  -4.426959e+00
11                                        Make_BMW  -5.710399e+00
```



```
Random Forest Model with SMOTE
Accuracy: 0.9998156568759985
Random Forest Feature Importances
                                               Feature  Importance
0                                       Electric Range    0.337910
12  Clean Alternative Fuel Vehicle (CAFV) Eligibil…   0.185781
14  Clean Alternative Fuel Vehicle (CAFV) Eligibil…   0.149255
19                                          Make_TESLA    0.122137
11                                            Make_BMW    0.026290
8                                        Model_MODEL 3    0.025017
15                                         Make_TOYOTA    0.024516
18                                          Model Year    0.023646
5                                           Model_LEAF    0.017647
13                                       Make_CHRYSLER    0.016793
16                                          Model_VOLT    0.016563
4                                        Model_MODEL Y    0.014782
9                                       Model_PACIFICA    0.014427
3                                          Make_NISSAN    0.011819
17                                           Make_JEEP    0.005189
10                                  Model_PRIUS PRIME    0.003335
7                                       DOL Vehicle ID    0.002659
1                                          Postal Code    0.001047
2                                             Latitude    0.000730
6                                       Model_WRANGLER    0.000458
Random Forest Cross-Validation Scores: [0.99990513 0.99988141 0.99997628
0.99992885 0.99992885]
Mean Cross-Validation Score: 0.9999241022721881
```

The output and the confusion matrices from both the Logistic Regression and Random Forest models indicate the following:

Logistic Regression Model with SMOTE and Hyperparameter Tuning

Best Parameters: - C: 0.1 - Penalty: l1 - Solver: liblinear

Performance Metrics: - **Accuracy:** 0.996 - **Confusion Matrix:** - True Positives (Class 1 correctly predicted): 26373 - True Negatives (Class 0 correctly predicted): 6060 - False Positives (Class 1 incorrectly predicted as Class 0): 39 - False Negatives (Class 0 incorrectly predicted as Class 1): 76

Feature Coefficients: The coefficients provide insight into the relationship between each feature and the likelihood of an observation being classified as a Battery Electric Vehicle (BEV). Positive coefficients indicate that as the feature value increases, the likelihood of being a BEV increases, while negative coefficients indicate the opposite.

Random Forest Model with SMOTE

Performance Metrics: - **Accuracy:** 0.999 - **Confusion Matrix:** - True Positives (Class 1 correctly predicted): 26444 - True Negatives (Class 0 correctly predicted): 6098 - False Positives (Class 1 incorrectly predicted as Class 0): 1 - False Negatives (Class 0 incorrectly predicted as Class 1): 5

Feature Importances: The feature importances show how much each feature contributes to the prediction of the target variable. Higher importance values indicate that the feature is more influential in making predictions.

Cross-Validation Scores: The cross-validation scores provide an estimate of the model's performance on unseen data. The scores are consistently high, indicating that the model is likely to perform well on new data.

Interpretation

Logistic Regression: - The logistic regression model has a high accuracy of 99.6%, indicating that it is very good at predicting the class labels. - The confusion matrix shows that the model has a slightly higher number of false negatives (76) and false positives (39) compared to the Random Forest model. - The feature coefficients highlight that "Clean Alternative Fuel Vehicle (CAFV) Eligibility" and "Electric Range" are significant predictors.

Random Forest: - The random forest model has an even higher accuracy of 99.98%, indicating near-perfect performance. - The confusion matrix shows very few misclassifications, with only 5 false negatives and 1 false positive. - The feature importances suggest that "Electric Range" and "Clean Alternative Fuel Vehicle (CAFV) Eligibility" are the most important features, similar to the logistic regression model.

Overall, both models perform exceptionally well, with the Random Forest model showing slightly better performance. The significant features identified by both models can be used to understand the primary factors influencing the decision to purchase BEVs and PHEVs in Washington State.

Research Question No.2

Can we use machine learning to predict the number of new electric vehicle adopters over the next ten years in Washington State, based on detailed data about residents' geographic locations and the availability of infrastructural facilities, such as electric utility stations?

STEP I

Feature Engineering

[ ]:
```
# importing 'pandas' library
import pandas as pd
```

[ ]:
```
# create a new variable named 'elec_veh_data' and assigning it the same␣
↪DataFrame that is currently stored in the variable 'electric_v'
# will be using 'elec_veh_data' for further analysis for research question no.2

elec_veh_data = electric_v

# Convert 'Model Year' to datetime and extract the year
elec_veh_data['Year'] = pd.to_datetime(elec_veh_data['Model Year'],␣
↪format='%Y').dt.year

# defining a function named 'group_data' to group data by year and different␣
↪geographical/utility attributes
def group_data(df, vehicle_type, group_by, new_col_name):
```

```
    return df[df['Electric Vehicle Type'] == vehicle_type].groupby(['Year',␣
 ↪group_by])['DOL Vehicle ID'].count().reset_index(name=new_col_name)

#applying the group_data function to extract the city-wise, county-wise,␣
 ↪Legislative District-wise and Electric Utility-wise BEVs
bevs_per_year_county = group_data(elec_veh_data, 'Battery Electric Vehicle␣
 ↪(BEV)', 'County', 'County_BEVs_per_year')
bevs_per_year_city = group_data(elec_veh_data, 'Battery Electric Vehicle␣
 ↪(BEV)', 'City', 'City_BEVs_per_year')
bevs_per_year_leg_dist = group_data(elec_veh_data, 'Battery Electric Vehicle␣
 ↪(BEV)', 'Legislative District', 'Leg_Dist_BEVs_per_year')
bevs_per_year_elec_utility = group_data(elec_veh_data, 'Battery Electric␣
 ↪Vehicle (BEV)', 'Electric Utility', 'Elec_Util_BEVs_per_year')

#applying the group_data function to extract the city-wise, county-wise,␣
 ↪Legislative District-wise and Electric Utility-wise PHEVs
phevs_per_year_county = group_data(elec_veh_data, 'Plug-in Hybrid Electric␣
 ↪Vehicle (PHEV)', 'County', 'County_PHEVs_per_year')
phevs_per_year_city = group_data(elec_veh_data, 'Plug-in Hybrid Electric␣
 ↪Vehicle (PHEV)', 'City', 'City_PHEVs_per_year')
phevs_per_year_leg_dist = group_data(elec_veh_data, 'Plug-in Hybrid Electric␣
 ↪Vehicle (PHEV)', 'Legislative District', 'Leg_Dist_PHEVs_per_year')
phevs_per_year_elec_utility = group_data(elec_veh_data, 'Plug-in Hybrid␣
 ↪Electric Vehicle (PHEV)', 'Electric Utility', 'Elec_Util_PHEVs_per_year')

# combining the county-wise, city-wise, legislative district-wise and electric␣
 ↪utility-wise data for better integrated analysis and simplifying the process

# Merge data on Year and County
combined_county = pd.merge(bevs_per_year_county, phevs_per_year_county,␣
 ↪on=['Year', 'County'], how='outer')

# Merge data on Year and City
combined_city = pd.merge(bevs_per_year_city, phevs_per_year_city, on=['Year',␣
 ↪'City'], how='outer')

# Merge data on Year and Legislative District
combined_leg_dist = pd.merge(bevs_per_year_leg_dist, phevs_per_year_leg_dist,␣
 ↪on=['Year', 'Legislative District'], how='outer')

# Merge data on Year and Electric Utility
combined_elec_utility = pd.merge(bevs_per_year_elec_utility,␣
 ↪phevs_per_year_elec_utility, on=['Year', 'Electric Utility'], how='outer')

# Fill NaN values with 0 for numerical columns only using '.loc'
```

```
combined_county.loc[:, ['County_BEVs_per_year', 'County_PHEVs_per_year']] =␣
↪combined_county.loc[:, ['County_BEVs_per_year', 'County_PHEVs_per_year']].
↪fillna(0)
combined_city.loc[:, ['City_BEVs_per_year', 'City_PHEVs_per_year']] =␣
↪combined_city.loc[:, ['City_BEVs_per_year', 'City_PHEVs_per_year']].fillna(0)
combined_leg_dist.loc[:, ['Leg_Dist_BEVs_per_year', 'Leg_Dist_PHEVs_per_year']]␣
↪= combined_leg_dist.loc[:, ['Leg_Dist_BEVs_per_year',␣
↪'Leg_Dist_PHEVs_per_year']].fillna(0)
combined_elec_utility.loc[:, ['Elec_Util_BEVs_per_year',␣
↪'Elec_Util_PHEVs_per_year']] = combined_elec_utility.loc[:,␣
↪['Elec_Util_BEVs_per_year', 'Elec_Util_PHEVs_per_year']].fillna(0)

# Convert data types of each column for consistency
combined_county = combined_county.astype({'Year': 'int32',␣
↪'County_BEVs_per_year': 'int64', 'County_PHEVs_per_year': 'int64'})
combined_city = combined_city.astype({'Year': 'int32', 'City_BEVs_per_year':␣
↪'int64', 'City_PHEVs_per_year': 'int64'})
combined_leg_dist = combined_leg_dist.astype({'Year': 'int32',␣
↪'Leg_Dist_BEVs_per_year': 'int64', 'Leg_Dist_PHEVs_per_year': 'int64'})
combined_elec_utility = combined_elec_utility.astype({'Year': 'int32',␣
↪'Elec_Util_BEVs_per_year': 'int64', 'Elec_Util_PHEVs_per_year': 'int64'})
```

STEP II

Validating the new variables: Descriptive Statistics

[ ]:
```
# printing the summary statistics of each data
print("Summary statistics of county data:")
print(combined_county.describe(),"\n\n")

print("Summary statistics of city data:")
print(combined_city.describe(),"\n\n")

print("Summary statistics of legislative district data:")
print(combined_leg_dist.describe(), "\n\n")

print("Summart statistics of electric utility data:")
print(combined_elec_utility.describe(), "\n\n")
```

```
Summary statistics of county data:
              Year  County_BEVs_per_year  County_PHEVs_per_year
count   858.000000            858.000000             858.000000
mean   2011.909091            170.187646              47.144522
std       8.495102           1202.220650             224.309973
min    1997.000000              0.000000               0.000000
25%    2003.000000              0.000000               0.000000
50%    2013.500000              3.000000               1.000000
75%    2019.000000             38.000000              17.000000
```

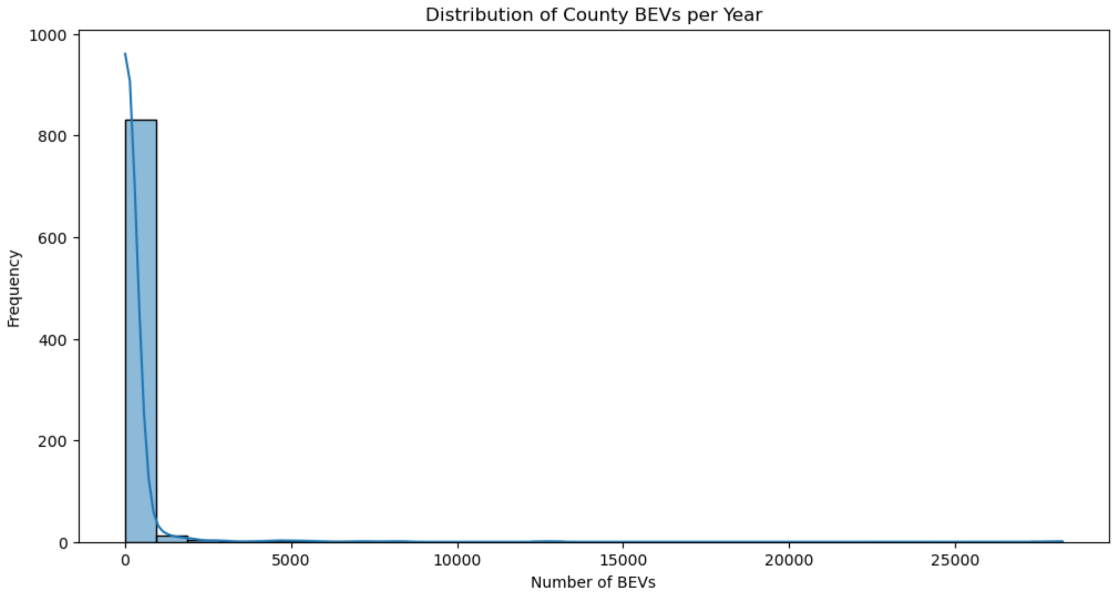
```
max    2024.000000          28227.000000           3923.000000


Summary statistics of city data:
               Year  City_BEVs_per_year  City_PHEVs_per_year
count  10406.000000        10406.000000          10406.00000
mean    2011.909091           14.032385              3.88718
std        8.490558          124.065485             26.80212
min     1997.000000            0.000000              0.00000
25%     2003.000000            0.000000              0.00000
50%     2013.500000            0.000000              0.00000
75%     2019.000000            2.000000              1.00000
max     2024.000000         7983.000000           1187.00000


Summary statistics of legislative district data:
              Year  Leg_Dist_BEVs_per_year  Leg_Dist_PHEVs_per_year
count  1078.000000             1078.000000              1078.000000
mean   2011.909091              135.455473                37.523191
std       8.494091              325.460108                72.837610
min    1997.000000                0.000000                 0.000000
25%    2003.000000                0.000000                 0.000000
50%    2013.500000               25.000000                19.000000
75%    2019.000000              126.000000                51.000000
max    2024.000000             3751.000000              1482.000000


Summart statistics of electric utility data:
              Year  Elec_Util_BEVs_per_year  Elec_Util_PHEVs_per_year
count  1650.000000              1650.000000               1650.000000
mean   2011.909091                88.497576                 24.515152
std       8.492724               745.566329                142.769998
min    1997.000000                 0.000000                  0.000000
25%    2003.000000                 0.000000                  0.000000
50%    2013.500000                 0.000000                  0.000000
75%    2019.000000                 8.000000                  5.000000
max    2024.000000             21172.000000               3255.000000
```

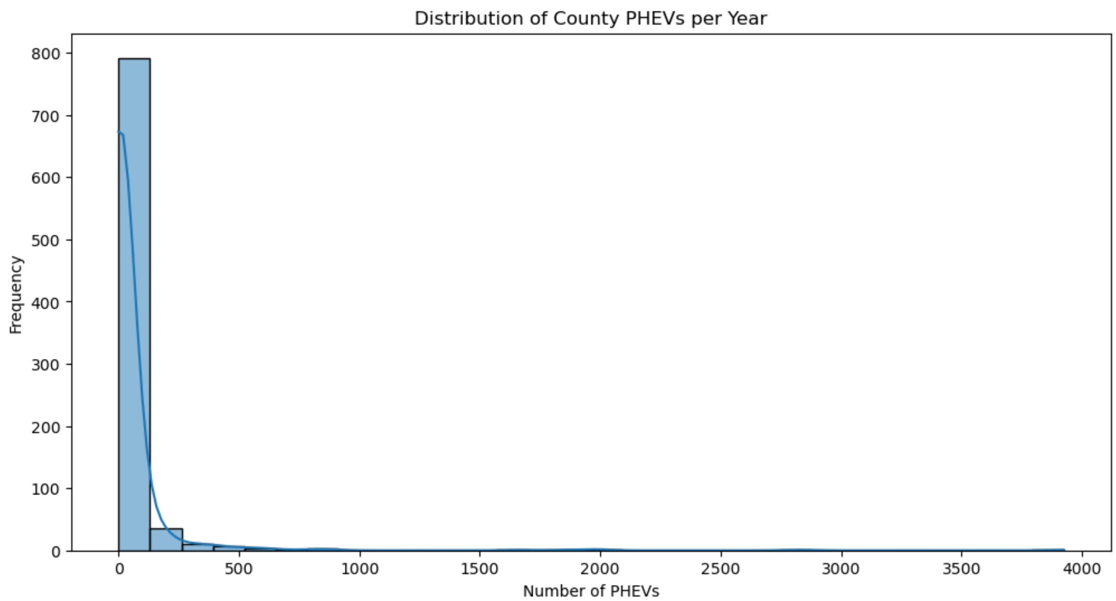
Visualize Data Distribution

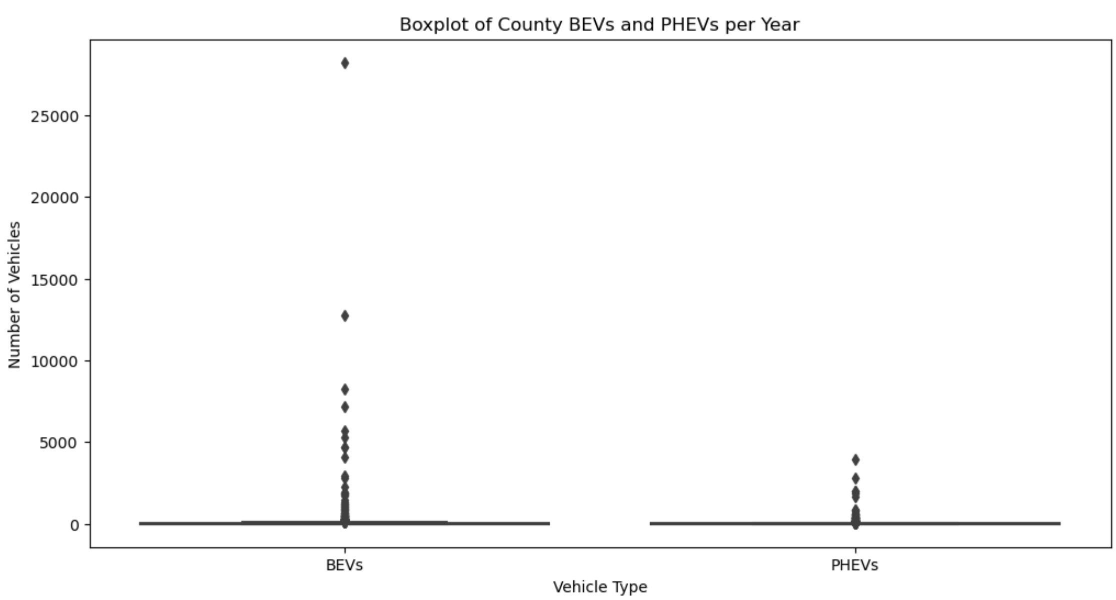
[ ]:
```python
# importing the necessary libraries
import matplotlib.pyplot as plt
import seaborn as sns

# Defining a function named 'plot_histogram' with data, column, title, xlabel␣
 ↪and ylabel as parameters
```

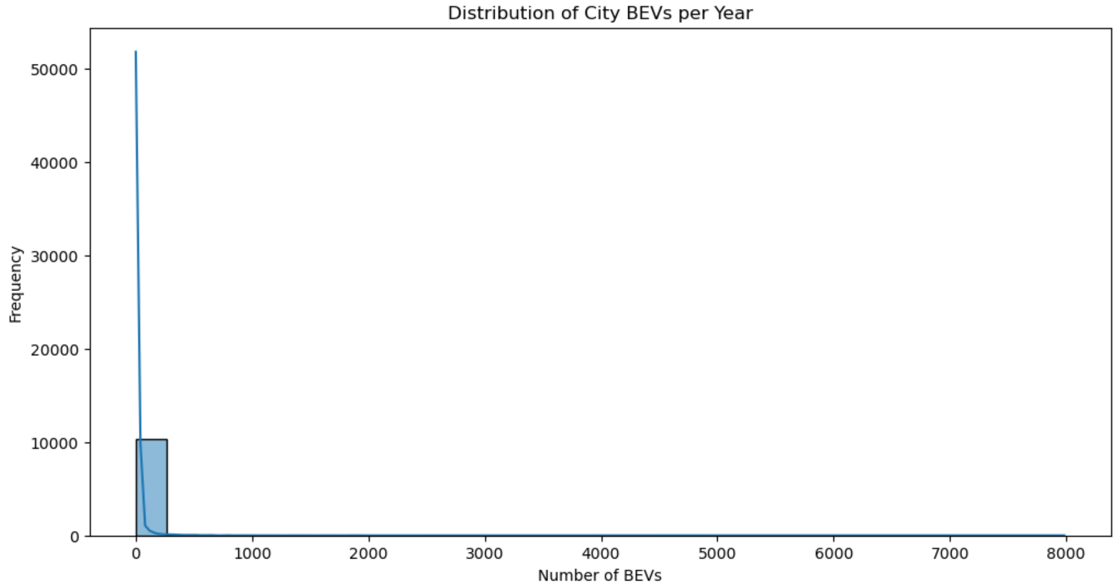
```python
# this function will be reused to draw histograms for BEVs and PHEVs␣
↪county-wise, city-wise, legislative district-wise and electric utility-wise
def plot_histogram(data, column, title, xlabel, ylabel):
    plt.figure(figsize=(12, 6))
    sns.histplot(data[column], bins=30, kde=True)
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.show()

# Defining a function named 'plot_boxplot' with data, column, title, xlabel and␣
↪ylabel and xtick_labels as parameters
# this function will be reused to draw boxplot for BEVs and PHEVs county-wise,␣
↪city-wise, legislative district-wise and electric utility-wise
def plot_boxplot(data, columns, title, xlabel, ylabel, xtick_labels):
    plt.figure(figsize=(12, 6))
    sns.boxplot(data=data[columns])
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.xticks([0, 1], xtick_labels)
    plt.show()

# Plot histograms and box plots for county-wise data
plot_histogram(combined_county, 'County_BEVs_per_year', 'Distribution of County␣
↪BEVs per Year', 'Number of BEVs', 'Frequency')
plot_histogram(combined_county, 'County_PHEVs_per_year', 'Distribution of␣
↪County PHEVs per Year', 'Number of PHEVs', 'Frequency')
plot_boxplot(combined_county, ['County_BEVs_per_year',␣
↪'County_PHEVs_per_year'], 'Boxplot of County BEVs and PHEVs per Year',␣
↪'Vehicle Type', 'Number of Vehicles', ['BEVs', 'PHEVs'])

# Plot histograms and box plots for city-wise data
plot_histogram(combined_city, 'City_BEVs_per_year', 'Distribution of City BEVs␣
↪per Year', 'Number of BEVs', 'Frequency')
plot_histogram(combined_city, 'City_PHEVs_per_year', 'Distribution of City␣
↪PHEVs per Year', 'Number of PHEVs', 'Frequency')
plot_boxplot(combined_city, ['City_BEVs_per_year', 'City_PHEVs_per_year'],␣
↪'Boxplot of City BEVs and PHEVs per Year', 'Vehicle Type', 'Number of␣
↪Vehicles', ['BEVs', 'PHEVs'])

# Plot histograms and box plots for legislative district-wise data
plot_histogram(combined_leg_dist, 'Leg_Dist_BEVs_per_year', 'Distribution of␣
↪Legislative District BEVs per Year', 'Number of BEVs', 'Frequency')
plot_histogram(combined_leg_dist, 'Leg_Dist_PHEVs_per_year', 'Distribution of␣
↪Legislative District PHEVs per Year', 'Number of PHEVs', 'Frequency')
```

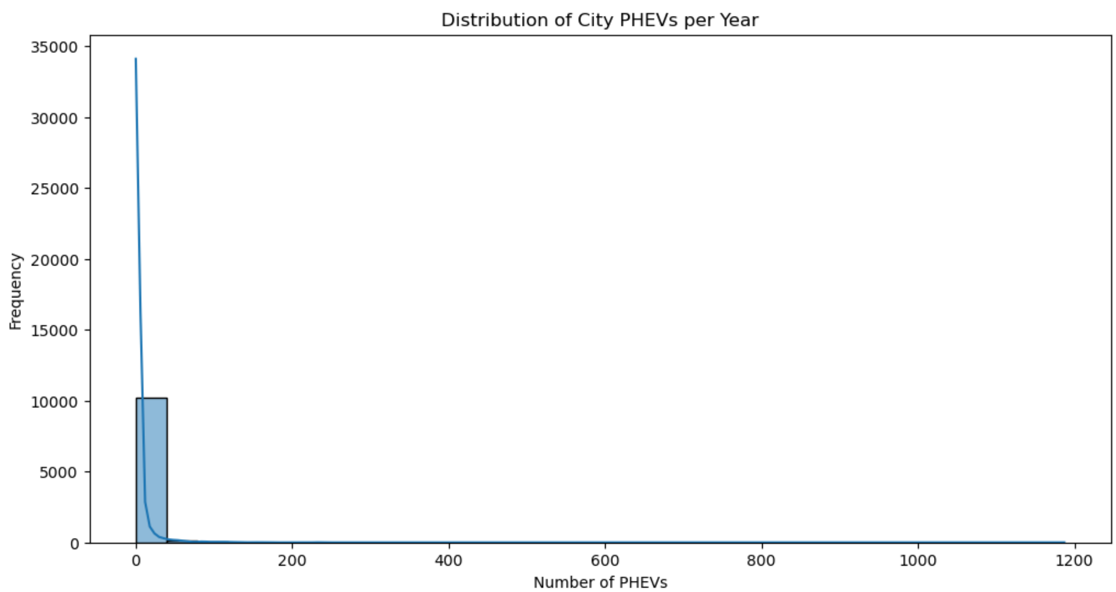
```
plot_boxplot(combined_leg_dist, ['Leg_Dist_BEVs_per_year',␣
↪'Leg_Dist_PHEVs_per_year'], 'Boxplot of Legislative District BEVs and PHEVs␣
↪per Year', 'Vehicle Type', 'Number of Vehicles', ['BEVs', 'PHEVs'])

# Plot histograms and box plots for electric utility-wise data
plot_histogram(combined_elec_utility, 'Elec_Util_BEVs_per_year', 'Distribution␣
↪of Electric Utility-wise BEVs per Year', 'Number of BEVs', 'Frequency')
plot_histogram(combined_elec_utility, 'Elec_Util_PHEVs_per_year', 'Distribution␣
↪of Electric Utility-wise PHEVs per Year', 'Number of PHEVs', 'Frequency')
plot_boxplot(combined_elec_utility, ['Elec_Util_BEVs_per_year',␣
↪'Elec_Util_PHEVs_per_year'], 'Boxplot of Electric Utility-wise BEVs and␣
↪PHEVs per Year', 'Vehicle Type', 'Number of Vehicles', ['BEVs', 'PHEVs'])
```

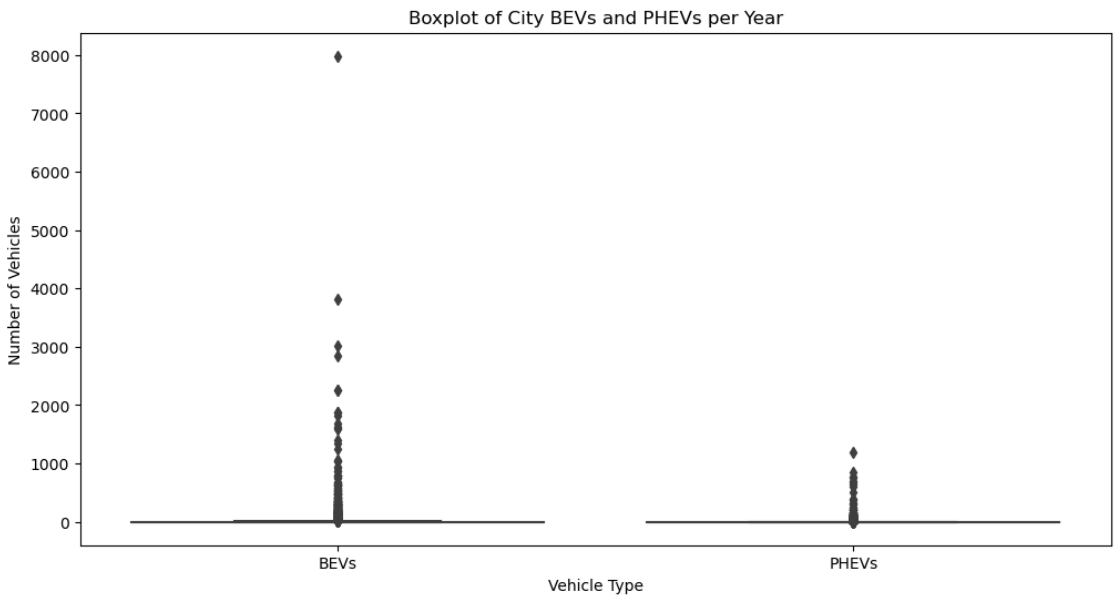



Distribution of County PHEVs per Year
800
700
600
500
400
300
200
100
0
Frequency
0
500
1000
1500
2000
2500
3000
3500
4000
Number of PHEVs

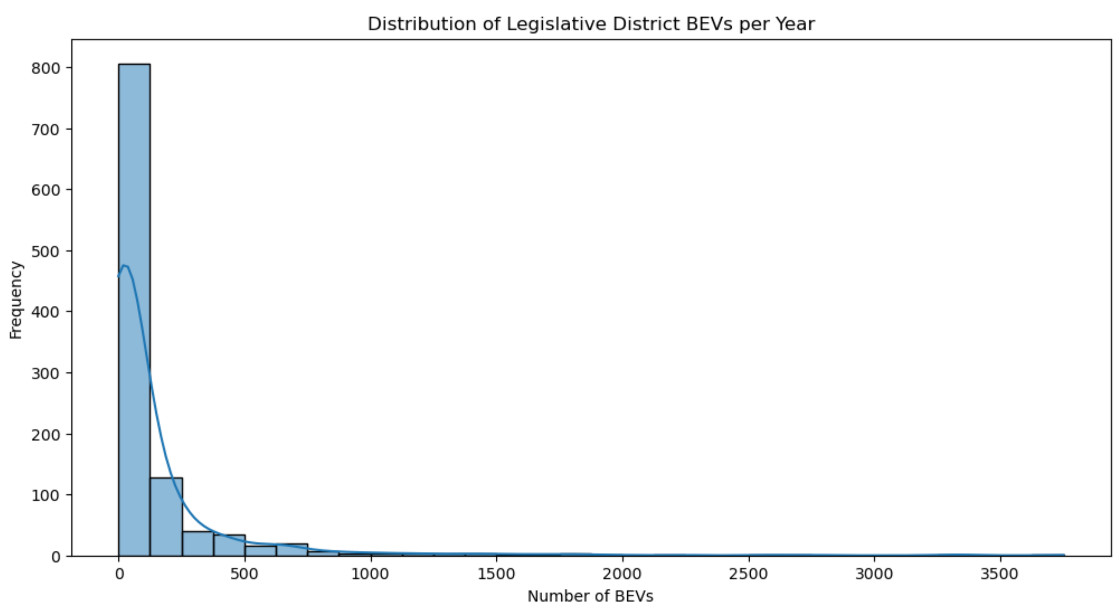

Boxplot of County BEVs and PHEVs per Year
25000
20000
15000
10000
5000
0
Number of Vehicles
BEVs
PHEVs
Vehicle Type


Distribution of City BEVs per Year
Frequency
Number of BEVs
0
10000
20000
30000
40000
50000
0
1000
2000
3000
4000
5000
6000
7000
8000

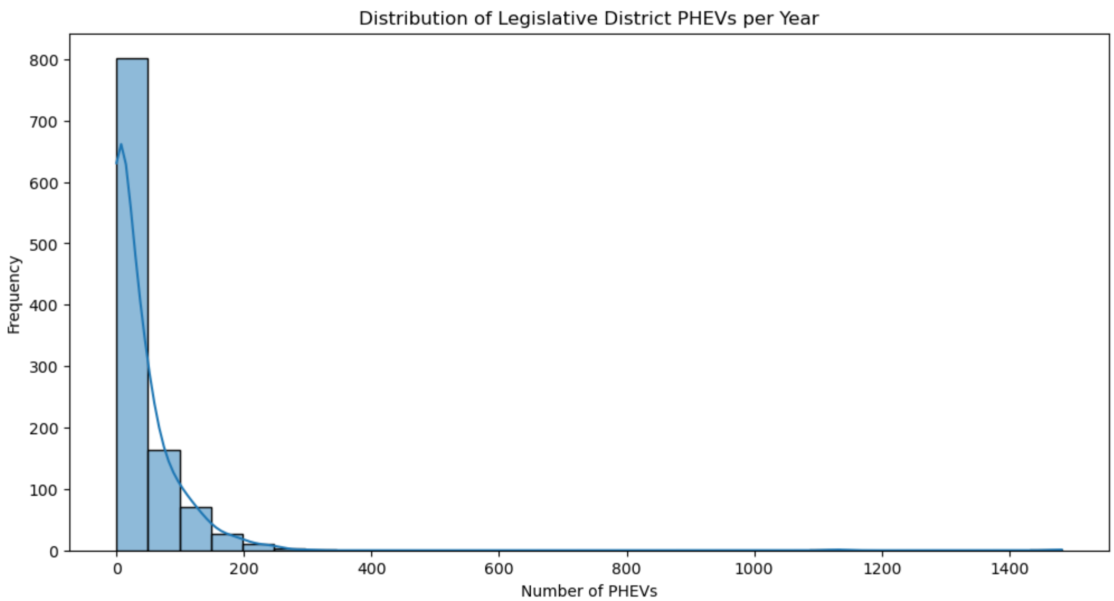

Distribution of City PHEVs per Year
Frequency
Number of PHEVs
0
5000
10000
15000
20000
25000
30000
35000
0
200
400
600
800
1000
1200

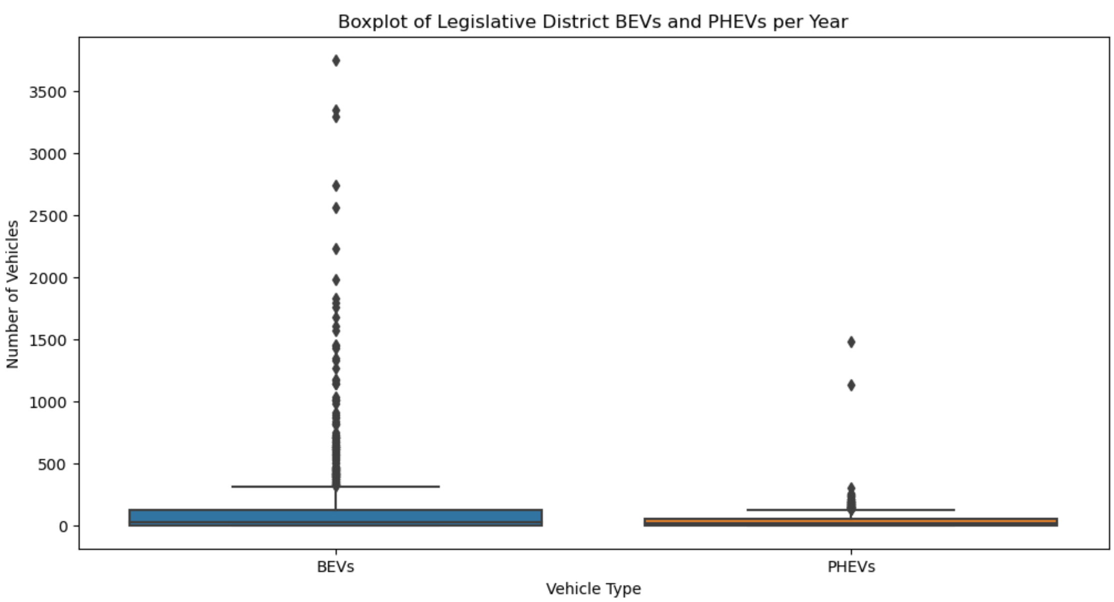


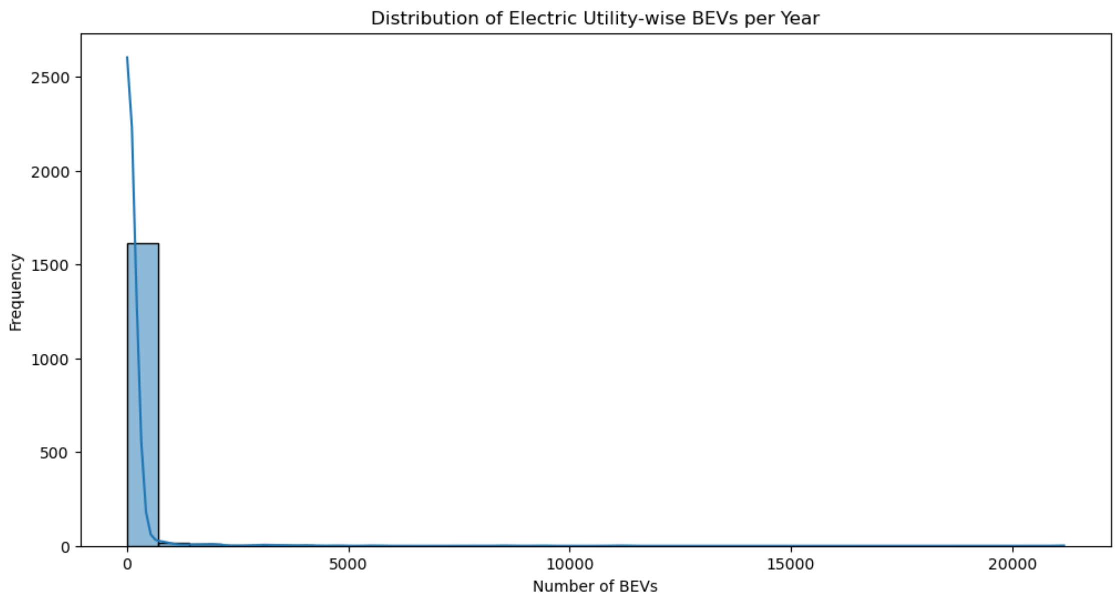
Boxplot of City BEVs and PHEVs per Year
Number of Vehicles
Vehicle Type
BEVs
PHEVs
0
1000
2000
3000
4000
5000
6000
7000
8000



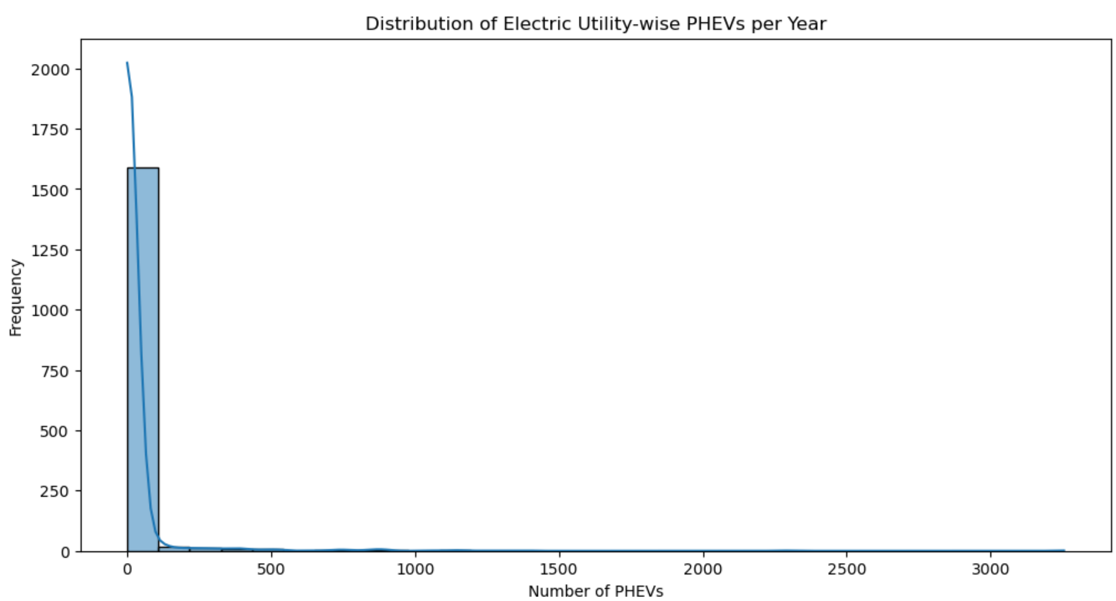
Distribution of Legislative District BEVs per Year
Frequency
Number of BEVs
0
100
200
300
400
500
600
700
800
0
500
1000
1500
2000
2500
3000
3500


Distribution of Legislative District PHEVs per Year
Frequency
Number of PHEVs
0
100
200
300
400
500
600
700
800
1000
1200
1400

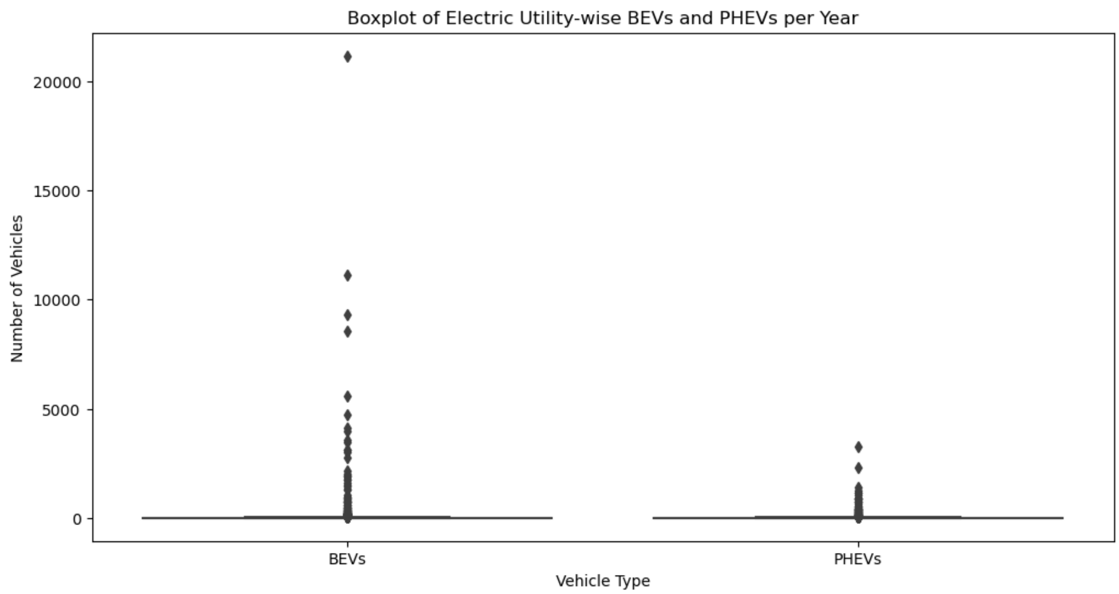

Boxplot of Legislative District BEVs and PHEVs per Year
Number of Vehicles
0
500
1000
1500
2000
2500
3000
3500
BEVs
PHEVs
Vehicle Type



Distribution of Electric Utility-wise BEVs per Year
Frequency
Number of BEVs
0
500
1000
1500
2000
2500
5000
10000
15000
20000



Distribution of Electric Utility-wise PHEVs per Year
Frequency
Number of PHEVs
0
250
500
750
1000
1250
1500
1750
2000
2500
3000



STEP II Contd.

Validating the new variables: Statistical Test

```
[ ]: # importing 'stats' class from scipy.stats' module
import scipy.stats as stats

# For statistical test, t-test would be more appropriate since it involves␣
↪comparing the means of two groups (BEVs and PHEVs) within each category.

# Defining a function to perform t-test and print results
def perform_t_test(data, column1, column2, category):
    ttest_result = stats.ttest_ind(data[column1], data[column2])
    print(f'T-test result for {category} BEVs and PHEVs per year:',␣
↪ttest_result,"\n")

# T-tests for County-wise data
perform_t_test(combined_county, 'County_BEVs_per_year',␣
↪'County_PHEVs_per_year', 'County')

# T-tests for City-wise data
perform_t_test(combined_city, 'City_BEVs_per_year', 'City_PHEVs_per_year',␣
↪'City')

# T-tests for Legislative District-wise data
perform_t_test(combined_leg_dist, 'Leg_Dist_BEVs_per_year',␣
↪'Leg_Dist_PHEVs_per_year', 'Legislative District')
```

```python
# T-tests for Electric Utility-wise data
perform_t_test(combined_elec_utility, 'Elec_Util_BEVs_per_year',
    'Elec_Util_PHEVs_per_year', 'Electric Utility')
```

```
T-test result for County BEVs and PHEVs per year:
Ttest_indResult(statistic=2.9470403552739164, pvalue=0.0032516580153221894)

T-test result for City BEVs and PHEVs per year:
Ttest_indResult(statistic=8.15355287992028, pvalue=3.732044449804378e-16)

T-test result for Legislative District BEVs and PHEVs per year:
Ttest_indResult(statistic=9.641066287155605, pvalue=1.4516882008138812e-21)

T-test result for Electric Utility BEVs and PHEVs per year:
Ttest_indResult(statistic=3.4237045557912666, pvalue=0.0006252703883660123)
```

Interpretation

The results of the t-tests indicate that there are statistically significant differences in the mean adoption rates of Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) across all the geographic and infrastructural categories tested (counties, cities, legislative districts, and electric utilities). Here's a detailed interpretation:

T-Test Results Interpretation: County BEVs and PHEVs per year:

T-statistic: 2.947 P-value: 0.00325 Interpretation: The p-value is less than 0.05, indicating a statistically significant difference between the mean adoption rates of BEVs and PHEVs across counties. This suggests that counties have different levels of BEV and PHEV adoption.

City BEVs and PHEVs per year:

T-statistic: 8.154 P-value: 3.732e-16 Interpretation: The p-value is much less than 0.05, indicating a highly statistically significant difference between the mean adoption rates of BEVs and PHEVs across cities. This suggests that cities exhibit significantly different adoption patterns for BEVs and PHEVs.

Legislative District BEVs and PHEVs per year:

T-statistic: 9.641 P-value: 1.451e-21 Interpretation: The p-value is far less than 0.05, indicating an extremely statistically significant difference between the mean adoption rates of BEVs and PHEVs across legislative districts. This suggests strong variations in EV adoption patterns across different legislative districts.

Electric Utility BEVs and PHEVs per year:

T-statistic: 3.424 P-value: 0.000625 Interpretation: The p-value is less than 0.05, indicating a statistically significant difference between the mean adoption rates of BEVs and PHEVs across electric utilities. This suggests that the availability and type of electric utility infrastructure may influence EV adoption rates.

General Implications:

Statistically Significant Differences: Across all categories, the t-tests reveal significant differences in the mean adoption rates of BEVs and PHEVs, indicating that these groups are not adopting at the same rate within each category.

Policy and Infrastructure Implications: The significant differences suggest that geographic and infrastructural factors play an essential role in EV adoption. Policies aimed at increasing EV adoption might need to be tailored to address specific regional characteristics and infrastructure availability.

Further Investigation: These findings warrant further investigation to understand the underlying factors driving these differences. For instance, urban areas might have better charging infrastructure, incentives, and awareness programs contributing to higher BEV adoption.

Identify High and Low Adoption Areas

[ ]:
```
import pandas as pd

# Define a function named 'identify_adoption_areas' to identify high and low␣
↪adoption areas
def identify_adoption_areas(data, column_prefix, category_name):
    high_adoption = data[data[f'{column_prefix}_per_year'] >␣
↪data[f'{column_prefix}_per_year'].quantile(0.75)]
    low_adoption = data[data[f'{column_prefix}_per_year'] <=␣
↪data[f'{column_prefix}_per_year'].quantile(0.25)]

    print(f"High Adoption {category_name}:")
    print(high_adoption)

    print(f"\nLow Adoption {category_name}:")
    print(low_adoption,"\n\n")

    return high_adoption, low_adoption

# Apply the function to each category for BEVs and PHEVs i.e. county, city,␣
↪legislative district and electric utility

# County-wise adoption rates
high_adoption_counties_bev, low_adoption_counties_bev =␣
↪identify_adoption_areas(combined_county, 'County_BEVs', 'Counties (BEVs)')
high_adoption_counties_phev, low_adoption_counties_phev =␣
↪identify_adoption_areas(combined_county, 'County_PHEVs', 'Counties (PHEVs)')

# City-wise adoption rates
high_adoption_cities_bev, low_adoption_cities_bev =␣
↪identify_adoption_areas(combined_city, 'City_BEVs', 'Cities (BEVs)')
high_adoption_cities_phev, low_adoption_cities_phev =␣
↪identify_adoption_areas(combined_city, 'City_PHEVs', 'Cities (PHEVs)')
```

```python
# Legislative District-wise adoption rates
high_adoption_leg_dist_bev, low_adoption_leg_dist_bev = identify_adoption_areas(combined_leg_dist, 'Leg_Dist_BEVs', 'Legislative Districts (BEVs)')
high_adoption_leg_dist_phev, low_adoption_leg_dist_phev = identify_adoption_areas(combined_leg_dist, 'Leg_Dist_PHEVs', 'Legislative Districts (PHEVs)')

# Electric Utility-wise adoption rates
high_adoption_elec_utility_bev, low_adoption_elec_utility_bev = identify_adoption_areas(combined_elec_utility, 'Elec_Util_BEVs', 'Electric Utilities (BEVs)')
high_adoption_elec_utility_phev, low_adoption_elec_utility_phev = identify_adoption_areas(combined_elec_utility, 'Elec_Util_PHEVs', 'Electric Utilities (PHEVs)')
```

```
High Adoption Counties (BEVs):
     Year     County  County_BEVs_per_year  County_PHEVs_per_year
317  2011      Clark                    42                      4
328  2011       King                   295                     23
338  2011     Pierce                    60                      3
342  2011  Snohomish                    70                      9
356  2012      Clark                    58                     67
..    …          …                   …                     …
847  2024     Skagit                    54                     60
849  2024  Snohomish                  1057                    475
850  2024    Spokane                   177                    260
852  2024   Thurston                   230                    155
855  2024    Whatcom                   142                    151

[210 rows x 4 columns]

Low Adoption Counties (BEVs):
     Year        County  County_BEVs_per_year  County_PHEVs_per_year
0    1997         Adams                     0                      0
1    1997        Asotin                     0                      0
2    1997        Benton                     0                      0
3    1997        Chelan                     0                      0
4    1997       Clallam                     0                      0
..    …           …                   …                     …
791  2023      Garfield                     0                      0
825  2024      Columbia                     0                      0
830  2024      Garfield                     0                      0
844  2024  Pend Oreille                     0                      3
853  2024      Wahkiakum                     0                      1

[342 rows x 4 columns]
```

```
High Adoption Counties (PHEVs):
     Year    County  County_BEVs_per_year  County_PHEVs_per_year
328  2011      King                   295                     23
356  2012     Clark                    58                     67
367  2012      King                   291                    273
368  2012    Kitsap                    42                     35
377  2012    Pierce                    54                     74
..    …       …                   …                    …
850  2024   Spokane                   177                    260
852  2024  Thurston                   230                    155
855  2024   Whatcom                   142                    151
856  2024   Whitman                    15                     19
857  2024    Yakima                    32                     39

[211 rows x 4 columns]

Low Adoption Counties (PHEVs):
     Year    County  County_BEVs_per_year  County_PHEVs_per_year
0    1997     Adams                     0                      0
1    1997    Asotin                     0                      0
2    1997    Benton                     0                      0
3    1997    Chelan                     0                      0
4    1997   Clallam                     0                      0
..    …       …                   …                    …
786  2023  Columbia                     6                      0
789  2023     Ferry                     8                      0
791  2023  Garfield                     0                      0
825  2024  Columbia                     0                      0
830  2024  Garfield                     0                      0

[384 rows x 4 columns]
```

```
High Adoption Cities (BEVs):
       Year          City  City_BEVs_per_year  City_PHEVs_per_year
3203   2008       Seattle                   7                    0
3339   2010      Bellevue                   3                    0
3676   2010       Seattle                   5                    0
3796   2011     Anacortes                   3                    1
3803   2011        Auburn                   6                    0
…      …           …                  …                  …
10401  2024        Yacolt                   5                    2
10402  2024        Yakima                  16                   33
10403  2024  Yarrow Point                   8                    4
10404  2024          Yelm                  17                    5
10405  2024        Zillah                   4                    1
```

```
[2295 rows x 4 columns]

Low Adoption Cities (BEVs):
       Year            City  City_BEVs_per_year  City_PHEVs_per_year
0      1997        Aberdeen                   0                    0
1      1997            Acme                   0                    0
2      1997            Addy                   0                    0
3      1997            Adna                   0                    0
4      1997  Airway Heights                   0                    0
…      …                …                   …                    …
10392  2024      White Swan                   0                    0
10393  2024          Wilbur                   0                    2
10394  2024        Wilkeson                   0                    0
10395  2024         Winlock                   0                    0
10397  2024         Wishram                   0                    0

[6789 rows x 4 columns]
```

```
High Adoption Cities (PHEVs):
       Year          City  City_BEVs_per_year  City_PHEVs_per_year
3813   2011    Bellingham                  23                    2
3819   2011       Bothell                  16                    2
3821   2011     Bremerton                   8                    2
3849   2011        Cheney                   1                    2
3916   2011       Everett                  13                    2
…      …              …                   …                    …
10400  2024       Woodway                   6                    4
10401  2024        Yacolt                   5                    2
10402  2024        Yakima                  16                   33
10403  2024  Yarrow Point                   8                    4
10404  2024          Yelm                  17                    5

[2108 rows x 4 columns]

Low Adoption Cities (PHEVs):
       Year            City  City_BEVs_per_year  City_PHEVs_per_year
0      1997        Aberdeen                   0                    0
1      1997            Acme                   0                    0
2      1997            Addy                   0                    0
3      1997            Adna                   0                    0
4      1997  Airway Heights                   0                    0
…      …                …                   …                    …
10390  2024        Westport                   0                    0
10392  2024      White Swan                   0                    0
10394  2024        Wilkeson                   0                    0
10395  2024         Winlock                   0                    0
```

```
10397  2024         Wishram                   0                    0

[7415 rows x 4 columns]


High Adoption Legislative Districts (BEVs):
      Year Legislative District  Leg_Dist_BEVs_per_year  \
529   2013                 40.0                     133
534   2013                 45.0                     146
588   2015                  1.0                     147
619   2015                 32.0                     134
621   2015                 34.0                     154
…     …                  …                    …
1072  2024                 44.0                     220
1073  2024                 45.0                     617
1074  2024                 46.0                     317
1075  2024                 47.0                     175
1076  2024                 48.0                     612

      Leg_Dist_PHEVs_per_year
529                        51
534                        42
588                        29
619                        34
621                        39
…                        …
1072                      100
1073                      203
1074                      150
1075                       67
1076                      155

[269 rows x 4 columns]

Low Adoption Legislative Districts (BEVs):
     Year Legislative District  Leg_Dist_BEVs_per_year  \
0    1997                  1.0                       0
1    1997                  2.0                       0
2    1997                  3.0                       0
3    1997                  4.0                       0
4    1997                  5.0                       0
..    …                  …                    …
386  2010                 44.0                       0
387  2010                 45.0                       0
388  2010                 46.0                       0
389  2010                 47.0                       0
391  2010                 49.0                       0
```

```
     Leg_Dist_PHEVs_per_year
0                          0
1                          0
2                          0
3                          0
4                          0
..                       …
386                        0
387                        0
388                        0
389                        0
391                        0

[350 rows x 4 columns]


High Adoption Legislative Districts (PHEVs):
      Year Legislative District  Leg_Dist_BEVs_per_year  \
513   2013                 24.0                      63
523   2013                 34.0                     123
525   2013                 36.0                     104
539   2014                  1.0                      62
543   2014                  5.0                      65
…     …                  …                     …
1073  2024                 45.0                     617
1074  2024                 46.0                     317
1075  2024                 47.0                     175
1076  2024                 48.0                     612
1077  2024                 49.0                     104

      Leg_Dist_PHEVs_per_year
513                        56
523                        54
525                        59
539                        53
543                        62
…                        …
1073                      203
1074                      150
1075                       67
1076                      155
1077                       67

[265 rows x 4 columns]

Low Adoption Legislative Districts (PHEVs):
     Year Legislative District  Leg_Dist_BEVs_per_year  \
0    1997                  1.0                       0
```

```
1    1997                2.0                       0
2    1997                3.0                       0
3    1997                4.0                       0
4    1997                5.0                       0
..    …                  …                     …
422  2011               31.0                       7
423  2011               32.0                      18
433  2011               42.0                      24
436  2011               45.0                      25
439  2011               48.0                      22

     Leg_Dist_PHEVs_per_year
0                          0
1                          0
2                          0
3                          0
4                          0
..                       …
422                        0
423                        0
433                        0
436                        0
439                        0

[404 rows x 4 columns]


High Adoption Electric Utilities (BEVs):
      Year                                  Electric Utility  \
598   2010      PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)
602   2011  BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||…
619   2011  BONNEVILLE POWER ADMINISTRATION||CITY OF TACOM…
626   2011  BONNEVILLE POWER ADMINISTRATION||ORCAS POWER &…
636   2011  BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF C…
…     …                                                …
1642  2024                        PUD NO 1 OF DOUGLAS COUNTY
1646  2024                          PUD NO 2 OF GRANT COUNTY
1647  2024                            PUGET SOUND ENERGY INC
1648  2024      PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)
1649  2024  PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM CO…

      Elec_Util_BEVs_per_year  Elec_Util_PHEVs_per_year
598                         9                         0
602                        16                         7
619                        43                         2
626                        10                         1
636                        42                         4
…                       …                       …
```

```
1642                   12                       13
1646                   18                       21
1647                 1598                      877
1648                 3460                     2282
1649                  133                      149

[401 rows x 4 columns]

Low Adoption Electric Utilities (BEVs):
      Year                                   Electric Utility  \
0     1997                                         AVISTA CORP
1     1997  BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||…
2     1997  BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||…
3     1997  BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||…
4     1997  BONNEVILLE POWER ADMINISTRATION||BENTON RURAL …
…      …                                                …
1631  2024                            CITY OF SEATTLE - (WA)
1633  2024   CITY OF SUMAS - (WA)||PUD NO 1 OF WHATCOM COUNTY
1634  2024                             CITY OF TACOMA - (WA)
1640  2024                       PORTLAND GENERAL ELECTRIC CO
1644  2024                    PUD NO 1 OF PEND OREILLE COUNTY

      Elec_Util_BEVs_per_year  Elec_Util_PHEVs_per_year
0                           0                         0
1                           0                         0
2                           0                         0
3                           0                         0
4                           0                         0
…                         …                       …
1631                        0                         0
1633                        0                         0
1634                        0                         0
1640                        0                         0
1644                        0                         3

[848 rows x 4 columns]


High Adoption Electric Utilities (PHEVs):
      Year                                   Electric Utility  \
602   2011  BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||…
657   2011       CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)
672   2011                             PUGET SOUND ENERGY INC
673   2011     PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)
677   2012  BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||…
…      …                                                …
1643  2024                        PUD NO 1 OF OKANOGAN COUNTY
1646  2024                           PUD NO 2 OF GRANT COUNTY
```

```
1647  2024                              PUGET SOUND ENERGY INC
1648  2024      PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)
1649  2024  PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM CO…

      Elec_Util_BEVs_per_year  Elec_Util_PHEVs_per_year
602                        16                         7
657                       147                        11
672                       148                        20
673                       162                        13
677                        13                        23
…                         …                        …
1643                        3                         6
1646                       18                        21
1647                     1598                       877
1648                     3460                      2282
1649                      133                       149

[392 rows x 4 columns]

Low Adoption Electric Utilities (PHEVs):
      Year                                  Electric Utility  \
0     1997                                       AVISTA CORP
1     1997  BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||…
2     1997  BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||…
3     1997  BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||…
4     1997  BONNEVILLE POWER ADMINISTRATION||BENTON RURAL …
…     …                                                  …
1631  2024                              CITY OF SEATTLE - (WA)
1633  2024   CITY OF SUMAS - (WA)||PUD NO 1 OF WHATCOM COUNTY
1634  2024                               CITY OF TACOMA - (WA)
1640  2024                        PORTLAND GENERAL ELECTRIC CO
1645  2024                          PUD NO 1 OF WHATCOM COUNTY

      Elec_Util_BEVs_per_year  Elec_Util_PHEVs_per_year
0                           0                         0
1                           0                         0
2                           0                         0
3                           0                         0
4                           0                         0
…                         …                        …
1631                        0                         0
1633                        0                         0
1634                        0                         0
1640                        0                         0
1645                        1                         0

[939 rows x 4 columns]
```

Here's a detailed interpretation of the output:

High Adoption Areas

Counties: High Adoption Counties (BEVs): These counties have BEV registrations per year higher than the 75th percentile. Examples include King, Snohomish, and Clark counties with high BEV adoption rates. High Adoption Counties (PHEVs): These counties have PHEV registrations per year higher than the 75th percentile. Examples include King, Spokane, and Thurston counties with high PHEV adoption rates.

Cities: High Adoption Cities (BEVs): These cities have BEV registrations per year higher than the 75th percentile. Examples include Seattle, Bellevue, and Yelm with high BEV adoption rates. High Adoption Cities (PHEVs): These cities have PHEV registrations per year higher than the 75th percentile. Examples include Yakima, Yarrow Point, and Yelm with high PHEV adoption rates.

Legislative Districts: High Adoption Legislative Districts (BEVs): These legislative districts have BEV registrations per year higher than the 75th percentile. Examples include districts 45, 48, and 46 with high BEV adoption rates. High Adoption Legislative Districts (PHEVs): These legislative districts have PHEV registrations per year higher than the 75th percentile. Examples include districts 45, 46, and 48 with high PHEV adoption rates.

Electric Utilities: High Adoption Electric Utilities (BEVs): These electric utilities serve areas with BEV registrations per year higher than the 75th percentile. Examples include Puget Sound Energy Inc. and utilities serving Tacoma. High Adoption Electric Utilities (PHEVs): These electric utilities serve areas with PHEV registrations per year higher than the 75th percentile. Examples include Puget Sound Energy Inc. and utilities serving Tacoma.

Low Adoption Areas

Counties: Low Adoption Counties (BEVs): These counties have BEV registrations per year less than or equal to the 25th percentile. Examples include Adams, Asotin, and Benton counties with low BEV adoption rates. Low Adoption Counties (PHEVs): These counties have PHEV registrations per year less than or equal to the 25th percentile. Examples include Adams, Asotin, and Benton counties with low PHEV adoption rates.

Cities: Low Adoption Cities (BEVs): These cities have BEV registrations per year less than or equal to the 25th percentile. Examples include Aberdeen, Acme, and Addy with low BEV adoption rates. Low Adoption Cities (PHEVs): These cities have PHEV registrations per year less than or equal to the 25th percentile. Examples include Aberdeen, Acme, and Addy with low PHEV adoption rates.

Legislative Districts: Low Adoption Legislative Districts (BEVs): These legislative districts have BEV registrations per year less than or equal to the 25th percentile. Examples include districts 1, 2, and 3 with low BEV adoption rates. Low Adoption Legislative Districts (PHEVs): These legislative districts have PHEV registrations per year less than or equal to the 25th percentile. Examples include districts 1, 2, and 3 with low PHEV adoption rates.

Electric Utilities: Low Adoption Electric Utilities (BEVs): These electric utilities serve areas with BEV registrations per year less than or equal to the 25th percentile. Examples include utilities serving Avista Corp and Portland General Electric Co. Low Adoption Electric Utilities (PHEVs):

These electric utilities serve areas with PHEV registrations per year less than or equal to the 25th percentile. Examples include utilities serving Avista Corp and Portland General Electric Co.

Implications High Adoption Areas: These areas have successfully adopted BEVs and PHEVs at a higher rate, potentially due to better infrastructure, more incentives, higher awareness, and other favorable conditions. Low Adoption Areas: These areas have lower adoption rates, indicating potential barriers such as lack of infrastructure, fewer incentives, lower awareness, and other unfavorable conditions.

STEP III

Training and Testing

[ ]:
```python
# import necessary libraries

import pandas as pd
from sklearn.model_selection import train_test_split
```

[ ]:
```python
# define a function named 'prepare_data'to create training and test sets
def prepare_data(data, target_column):
    # Separate features and target
    X = data.drop(columns=[target_column])
    y = data[target_column]

    # One-hot encode categorical variables
    X_encoded = pd.get_dummies(X, drop_first=True)

    # Split the dataset into training (80%) and testing (20%)
    X_train, X_test, y_train, y_test = train_test_split(X_encoded, y,␣
 ↪test_size=0.2, random_state=42)

    return X_train, X_test, y_train, y_test
```

[ ]:
```python
# Prepare data for BEVs (County-wise)
X_train_bev_county, X_test_bev_county, y_train_bev_county, y_test_bev_county =␣
 ↪prepare_data(combined_county, 'County_BEVs_per_year')

# Prepare data for PHEVs (County-wise)
X_train_phev_county, X_test_phev_county, y_train_phev_county,␣
 ↪y_test_phev_county = prepare_data(combined_county, 'County_PHEVs_per_year')

# Prepare data for BEVs (City-wise)
X_train_bev_city, X_test_bev_city, y_train_bev_city, y_test_bev_city =␣
 ↪prepare_data(combined_city, 'City_BEVs_per_year')

# Prepare data for PHEVs (City-wise)
X_train_phev_city, X_test_phev_city, y_train_phev_city, y_test_phev_city =␣
 ↪prepare_data(combined_city, 'City_PHEVs_per_year')
```

```
# Prepare data for BEVs (Legislative District-wise)
X_train_bev_leg_dist, X_test_bev_leg_dist, y_train_bev_leg_dist,␣
↪y_test_bev_leg_dist = prepare_data(combined_leg_dist,␣
↪'Leg_Dist_BEVs_per_year')

# Prepare data for PHEVs (Legislative District-wise)
X_train_phev_leg_dist, X_test_phev_leg_dist, y_train_phev_leg_dist,␣
↪y_test_phev_leg_dist = prepare_data(combined_leg_dist,␣
↪'Leg_Dist_PHEVs_per_year')

# Prepare data for BEVs (Electric Utility-wise)
X_train_bev_elec_utility, X_test_bev_elec_utility, y_train_bev_elec_utility,␣
↪y_test_bev_elec_utility = prepare_data(combined_elec_utility,␣
↪'Elec_Util_BEVs_per_year')

# Prepare data for PHEVs (Electric Utility-wise)
X_train_phev_elec_utility, X_test_phev_elec_utility, y_train_phev_elec_utility,␣
↪y_test_phev_elec_utility = prepare_data(combined_elec_utility,␣
↪'Elec_Util_PHEVs_per_year')
```

[ ]:
```
# Print shapes of datasets for verification

print("County-wise BEVs: Training data shape:", X_train_bev_county.shape,␣
↪"Testing data shape:", X_test_bev_county.shape)
print("County-wise PHEVs: Training data shape:", X_train_phev_county.shape,␣
↪"Testing data shape:", X_test_phev_county.shape)

print("City-wise BEVs: Training data shape:", X_train_bev_city.shape, "Testing␣
↪data shape:", X_test_bev_city.shape)
print("City-wise PHEVs: Training data shape:", X_train_phev_city.shape,␣
↪"Testing data shape:", X_test_phev_city.shape)

print("Legislative District-wise BEVs: Training data shape:",␣
↪X_train_bev_leg_dist.shape, "Testing data shape:", X_test_bev_leg_dist.shape)
print("Legislative District-wise PHEVs: Training data shape:",␣
↪X_train_phev_leg_dist.shape, "Testing data shape:", X_test_phev_leg_dist.
↪shape)

print("Electric Utility-wise BEVs: Training data shape:",␣
↪X_train_bev_elec_utility.shape, "Testing data shape:",␣
↪X_test_bev_elec_utility.shape)
print("Electric Utility-wise PHEVs: Training data shape:",␣
↪X_train_phev_elec_utility.shape, "Testing data shape:",␣
↪X_test_phev_elec_utility.shape)
```

```
County-wise BEVs: Training data shape: (686, 40) Testing data shape: (172, 40)
County-wise PHEVs: Training data shape: (686, 40) Testing data shape: (172, 40)
```

```
City-wise BEVs: Training data shape: (8324, 474) Testing data shape: (2082, 474)
City-wise PHEVs: Training data shape: (8324, 474) Testing data shape: (2082,
474)
Legislative District-wise BEVs: Training data shape: (862, 50) Testing data
shape: (216, 50)
Legislative District-wise PHEVs: Training data shape: (862, 50) Testing data
shape: (216, 50)
Electric Utility-wise BEVs: Training data shape: (1320, 76) Testing data shape:
(330, 76)
Electric Utility-wise PHEVs: Training data shape: (1320, 76) Testing data shape:
(330, 76)
```

STEP IV

Training Machine Learning Models

[ ]:
```
# import necessary libraries
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np
```

[ ]:
```
# defining a function named 'train_and_evaluate_model'
# the function takes the train and test sets of independent and dependent␣
↪variables and also the machine learning model as parameters
def train_and_evaluate_model(X_train, X_test, y_train, y_test, model):
    # Train the model
    model.fit(X_train, y_train)

    # Make predictions
    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)

    # Evaluate the model
    mse_train = mean_squared_error(y_train, y_pred_train)
    mse_test = mean_squared_error(y_test, y_pred_test)
    r2_train = r2_score(y_train, y_pred_train)
    r2_test = r2_score(y_test, y_pred_test)

    print(f'Model: {model.__class__.__name__}')
    print(f'Training MSE: {mse_train}')
    print(f'Testing MSE: {mse_test}')
    print(f'Training R^2: {r2_train}')
    print(f'Testing R^2: {r2_test}')
    print('')

# creating a list of two machine learning models, Linear regression and random␣
↪forest regressor
```

```
models = [LinearRegression(), RandomForestRegressor(random_state=42)]

for model in models:
    print('County-wise BEVs:')
    train_and_evaluate_model(X_train_bev_county, X_test_bev_county,␣
 ↪y_train_bev_county, y_test_bev_county, model)

    print('County-wise PHEVs:')
    train_and_evaluate_model(X_train_phev_county, X_test_phev_county,␣
 ↪y_train_phev_county, y_test_phev_county, model)

    print('City-wise BEVs:')
    train_and_evaluate_model(X_train_bev_city, X_test_bev_city,␣
 ↪y_train_bev_city, y_test_bev_city, model)

    print('City-wise PHEVs:')
    train_and_evaluate_model(X_train_phev_city, X_test_phev_city,␣
 ↪y_train_phev_city, y_test_phev_city, model)

    print('Legislative District-wise BEVs:')
    train_and_evaluate_model(X_train_bev_leg_dist, X_test_bev_leg_dist,␣
 ↪y_train_bev_leg_dist, y_test_bev_leg_dist, model)

    print('Legislative District-wise PHEVs:')
    train_and_evaluate_model(X_train_phev_leg_dist, X_test_phev_leg_dist,␣
 ↪y_train_phev_leg_dist, y_test_phev_leg_dist, model)

    print('Electric Utility-wise BEVs:')
    train_and_evaluate_model(X_train_bev_elec_utility, X_test_bev_elec_utility,␣
 ↪y_train_bev_elec_utility, y_test_bev_elec_utility, model)

    print('Electric Utility-wise PHEVs:')
    train_and_evaluate_model(X_train_phev_elec_utility,␣
 ↪X_test_phev_elec_utility, y_train_phev_elec_utility,␣
 ↪y_test_phev_elec_utility, model)
```

```
County-wise BEVs:
Model: LinearRegression
Training MSE: 230689.3968316366
Testing MSE: 747582.5993299438
Training R^2: 0.8463018191911079
Testing R^2: 0.38453558445175506

County-wise PHEVs:
Model: LinearRegression
Training MSE: 5230.541898251493
Testing MSE: 21935.313590825546
```

```
Training R^2: 0.8834470230325614
Testing R^2: 0.694021880131342

City-wise BEVs:
Model: LinearRegression
Training MSE: 7997.028611631651
Testing MSE: 2283.518367032071
Training R^2: 0.5528470672575849
Testing R^2: 0.5778672114897181

City-wise PHEVs:
Model: LinearRegression
Training MSE: 333.414270672379
Testing MSE: 45.88035873433895
Training R^2: 0.6101512881702522
Testing R^2: 0.7291690341821694

Legislative District-wise BEVs:
Model: LinearRegression
Training MSE: 50054.32179284161
Testing MSE: 86977.70006911887
Training R^2: 0.46258083268194294
Testing R^2: 0.44292261504573116

Legislative District-wise PHEVs:
Model: LinearRegression
Training MSE: 1714.7374746195305
Testing MSE: 7104.899330219081
Training R^2: 0.5300491467650752
Testing R^2: 0.4014057594752254

Electric Utility-wise BEVs:
Model: LinearRegression
Training MSE: 112682.69459405165
Testing MSE: 317064.85865551775
Training R^2: 0.6413717619526726
Testing R^2: 0.7912425380928704

Electric Utility-wise PHEVs:
Model: LinearRegression
Training MSE: 4082.1190227497964
Testing MSE: 3371.772443749004
Training R^2: 0.7390118180304004
Testing R^2: 0.9141692599612865

County-wise BEVs:
Model: RandomForestRegressor
Training MSE: 131798.9952037901
```

```
Testing MSE: 304649.9067255814
Training R^2: 0.9121881366309751
Testing R^2: 0.7491900199954573

County-wise PHEVs:
Model: RandomForestRegressor
Training MSE: 3021.512227988338
Testing MSE: 20813.32761860465
Training R^2: 0.9326711740454113
Testing R^2: 0.7096725867819524

City-wise BEVs:
Model: RandomForestRegressor
Training MSE: 1021.1340763094669
Testing MSE: 969.6639532180594
Training R^2: 0.9429034058624141
Testing R^2: 0.8207472493326812

City-wise PHEVs:
Model: RandomForestRegressor
Training MSE: 42.941304264776534
Testing MSE: 26.842529010566764
Training R^2: 0.949790355049433
Testing R^2: 0.841549014491818

Legislative District-wise BEVs:
Model: RandomForestRegressor
Training MSE: 3573.0569541763343
Testing MSE: 17034.58594212963
Training R^2: 0.9616370929758945
Testing R^2: 0.8908963724853703

Legislative District-wise PHEVs:
Model: RandomForestRegressor
Training MSE: 246.40910881670536
Testing MSE: 6846.736837962963
Training R^2: 0.9324676968648148
Testing R^2: 0.42315618461168814

Electric Utility-wise BEVs:
Model: RandomForestRegressor
Training MSE: 14561.237603560607
Testing MSE: 677937.7900057576
Training R^2: 0.9536568502877363
Testing R^2: 0.5536415704576927

Electric Utility-wise PHEVs:
Model: RandomForestRegressor
```

```
Training MSE: 323.89715393939395
Testing MSE: 14752.082865757575
Training R^2: 0.9792918019095811
Testing R^2: 0.6244757881488124
```

STEP V

Predicting the number of new electric vehicles over the next 10 years

```
[ ]: import numpy as np

# Define the future years ie.2024 to 2034
future_years = np.arange(2024, 2034)

# defining a function named 'prepare_future_data' to expand future years data␣
↪for all unique categories
# the function takes future_years, unique_values of the category and the␣
↪column_name as parameters
def prepare_future_data(future_years, unique_values, column_name):
    future_data_list = []
    for year in future_years:
        for value in unique_values:
            future_data_list.append({column_name: value, 'Year': year})
    future_data = pd.DataFrame(future_data_list)
    return future_data

# Prepare county-wise future data
unique_counties = combined_county['County'].unique()
future_data_county = prepare_future_data(future_years, unique_counties,␣
↪'County')

# Prepare city-wise future data
unique_cities = combined_city['City'].unique()
future_data_city = prepare_future_data(future_years, unique_cities, 'City')

# Prepare legislative district-wise future data
unique_leg_dists = combined_leg_dist['Legislative District'].unique()
future_data_leg_dist = prepare_future_data(future_years, unique_leg_dists,␣
↪'Legislative District')

# Prepare electric utility-wise future data
unique_elec_utilities = combined_elec_utility['Electric Utility'].unique()
future_data_elec_utility = prepare_future_data(future_years,␣
↪unique_elec_utilities, 'Electric Utility')

# One-hot encode the categorical variables for future data
```

```python
# One-hot encoding is a process of converting categorical variables into a form that can be provided to machine learning algorithms to do a better job in prediction
future_data_county_encoded = pd.get_dummies(future_data_county, drop_first=True)
future_data_city_encoded = pd.get_dummies(future_data_city, drop_first=True)
future_data_leg_dist_encoded = pd.get_dummies(future_data_leg_dist, drop_first=True)
future_data_elec_utility_encoded = pd.get_dummies(future_data_elec_utility, drop_first=True)
```

[ ]:

```python
# importing the necessary libraries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor

# defining a function named 'align_columns' to ensure the same columns in the future data as in the training data
# This is crucial for consistency in feature engineering and when feeding data into machine learning models
def align_columns(train_data, future_data):
    future_data_aligned = future_data.reindex(columns=train_data.columns, fill_value=0)
    return future_data_aligned

# Define target variables (dependent) for training
y_bev_county = combined_county['County_BEVs_per_year']
y_phev_county = combined_county['County_PHEVs_per_year']
y_bev_city = combined_city['City_BEVs_per_year']
y_phev_city = combined_city['City_PHEVs_per_year']
y_bev_leg_dist = combined_leg_dist['Leg_Dist_BEVs_per_year']
y_phev_leg_dist = combined_leg_dist['Leg_Dist_PHEVs_per_year']
y_bev_elec_utility = combined_elec_utility['Elec_Util_BEVs_per_year']
y_phev_elec_utility = combined_elec_utility['Elec_Util_PHEVs_per_year']

# One-hot encode the categorical variables for training data
encoded_combined_county = pd.get_dummies(combined_county.drop(columns=['County_BEVs_per_year', 'County_PHEVs_per_year']), drop_first=True)
encoded_combined_city = pd.get_dummies(combined_city.drop(columns=['City_BEVs_per_year', 'City_PHEVs_per_year']), drop_first=True)
encoded_combined_leg_dist = pd.get_dummies(combined_leg_dist.drop(columns=['Leg_Dist_BEVs_per_year', 'Leg_Dist_PHEVs_per_year']), drop_first=True)
encoded_combined_elec_utility = pd.get_dummies(combined_elec_utility.drop(columns=['Elec_Util_BEVs_per_year', 'Elec_Util_PHEVs_per_year']), drop_first=True)
```

```
# Align future data columns to match the training data columns
encoded_future_county = align_columns(encoded_combined_county,␣
 ↪future_data_county_encoded)
encoded_future_city = align_columns(encoded_combined_city,␣
 ↪future_data_city_encoded)
encoded_future_leg_dist = align_columns(encoded_combined_leg_dist,␣
 ↪future_data_leg_dist_encoded)
encoded_future_elec_utility = align_columns(encoded_combined_elec_utility,␣
 ↪future_data_elec_utility_encoded)
```

[ ]:
```
import warnings
# ignoring irrelavant 'DeprecationWarning in future versions' that may show up␣
 ↪in the execution of the code
warnings.filterwarnings("ignore", category=DeprecationWarning)

# Split the datasets into training and testing sets using 'train_test_split'␣
 ↪module
# Splitting the county data into training and testing sets
X_train_bev_county, X_test_bev_county, y_train_bev_county, y_test_bev_county =␣
 ↪train_test_split(encoded_combined_county, y_bev_county, test_size=0.2,␣
 ↪random_state=42)
X_train_phev_county, X_test_phev_county, y_train_phev_county,␣
 ↪y_test_phev_county = train_test_split(encoded_combined_county,␣
 ↪y_phev_county, test_size=0.2, random_state=42)

# Splitting the city data into training and testing sets
X_train_bev_city, X_test_bev_city, y_train_bev_city, y_test_bev_city =␣
 ↪train_test_split(encoded_combined_city, y_bev_city, test_size=0.2,␣
 ↪random_state=42)
X_train_phev_city, X_test_phev_city, y_train_phev_city, y_test_phev_city =␣
 ↪train_test_split(encoded_combined_city, y_phev_city, test_size=0.2,␣
 ↪random_state=42)

# Splitting the legislative district data into training and testing sets
X_train_bev_leg_dist, X_test_bev_leg_dist, y_train_bev_leg_dist,␣
 ↪y_test_bev_leg_dist = train_test_split(encoded_combined_leg_dist,␣
 ↪y_bev_leg_dist, test_size=0.2, random_state=42)
X_train_phev_leg_dist, X_test_phev_leg_dist, y_train_phev_leg_dist,␣
 ↪y_test_phev_leg_dist = train_test_split(encoded_combined_leg_dist,␣
 ↪y_phev_leg_dist, test_size=0.2, random_state=42)

# Splitting the electric utility data into training and testing sets
X_train_bev_elec_utility, X_test_bev_elec_utility, y_train_bev_elec_utility,␣
 ↪y_test_bev_elec_utility = train_test_split(encoded_combined_elec_utility,␣
 ↪y_bev_elec_utility, test_size=0.2, random_state=42)
```

```
X_train_phev_elec_utility, X_test_phev_elec_utility, y_train_phev_elec_utility,␣
↪y_test_phev_elec_utility = train_test_split(encoded_combined_elec_utility,␣
↪y_phev_elec_utility, test_size=0.2, random_state=42)

# Train Random Forest Regressor models using the county BEV train and test sets
rf_model_bev_county = RandomForestRegressor(random_state=42)
rf_model_bev_county.fit(X_train_bev_county, y_train_bev_county)

# Train Random Forest Regressor models using the county PHEV train and test sets
rf_model_phev_county = RandomForestRegressor(random_state=42)
rf_model_phev_county.fit(X_train_phev_county, y_train_phev_county)

# Train Random Forest Regressor models using the city BEV train and test sets
rf_model_bev_city = RandomForestRegressor(random_state=42)
rf_model_bev_city.fit(X_train_bev_city, y_train_bev_city)

# Train Random Forest Regressor models using the city PHEV train and test sets
rf_model_phev_city = RandomForestRegressor(random_state=42)
rf_model_phev_city.fit(X_train_phev_city, y_train_phev_city)

# Train Random Forest Regressor models using the legislative district BEV train␣
↪and test sets
rf_model_bev_leg_dist = RandomForestRegressor(random_state=42)
rf_model_bev_leg_dist.fit(X_train_bev_leg_dist, y_train_bev_leg_dist)

# Train Random Forest Regressor models using the legislative district PHEV␣
↪train and test sets
rf_model_phev_leg_dist = RandomForestRegressor(random_state=42)
rf_model_phev_leg_dist.fit(X_train_phev_leg_dist, y_train_phev_leg_dist)

# Train Random Forest Regressor models using the electric utility BEV train and␣
↪test sets
rf_model_bev_elec_utility = RandomForestRegressor(random_state=42)
rf_model_bev_elec_utility.fit(X_train_bev_elec_utility,␣
↪y_train_bev_elec_utility)

# Train Random Forest Regressor models using the electric utility PHEV train␣
↪and test sets
rf_model_phev_elec_utility = RandomForestRegressor(random_state=42)
rf_model_phev_elec_utility.fit(X_train_phev_elec_utility,␣
↪y_train_phev_elec_utility)

# Train Linear Regression models using county BEV train and test sets
lr_model_bev_county = LinearRegression()
lr_model_bev_county.fit(X_train_bev_county, y_train_bev_county)
```

```
# Train Linear Regression models using county PHEV train and test sets
lr_model_phev_county = LinearRegression()
lr_model_phev_county.fit(X_train_phev_county, y_train_phev_county)

# Train Linear Regression models using city BEV train and test sets
lr_model_bev_city = LinearRegression()
lr_model_bev_city.fit(X_train_bev_city, y_train_bev_city)

# Train Linear Regression models using city PHEV train and test sets
lr_model_phev_city = LinearRegression()
lr_model_phev_city.fit(X_train_phev_city, y_train_phev_city)

# Train Linear Regression models using legislative district BEV train and test␣
↪sets
lr_model_bev_leg_dist = LinearRegression()
lr_model_bev_leg_dist.fit(X_train_bev_leg_dist, y_train_bev_leg_dist)

# Train Linear Regression models using legislative district PHEV train and test␣
↪sets
lr_model_phev_leg_dist = LinearRegression()
lr_model_phev_leg_dist.fit(X_train_phev_leg_dist, y_train_phev_leg_dist)

# Train Linear Regression models using electric utility BEV train and test sets
lr_model_bev_elec_utility = LinearRegression()
lr_model_bev_elec_utility.fit(X_train_bev_elec_utility,␣
↪y_train_bev_elec_utility)

# Train Linear Regression models using electric utility PHEV train and test sets
lr_model_phev_elec_utility = LinearRegression()
lr_model_phev_elec_utility.fit(X_train_phev_elec_utility,␣
↪y_train_phev_elec_utility)
```

[ ]: LinearRegression()

[ ]:
```
import warnings
import numpy as np
import pandas as pd

# Ignoring irrelevant 'DeprecationWarning in future versions' that may show up␣
↪in the execution of the code
warnings.filterwarnings("ignore", category=DeprecationWarning)

# Defining a function named 'predict_future_values' to make predictions and add␣
↪the year and names columns for readability
def predict_future_values(model, future_data_encoded, future_data):
    predictions = model.predict(future_data_encoded)
```

```
    predictions = np.round(predictions).astype(int)  # Round predictions to␣
 ↪integers
    result = future_data.copy()
    result['Predicted_Values'] = predictions
    return result

# Predict future values for each category using Random Forest
predictions_rf_bev_county = predict_future_values(rf_model_bev_county,␣
 ↪encoded_future_county, future_data_county)
predictions_rf_phev_county = predict_future_values(rf_model_phev_county,␣
 ↪encoded_future_county, future_data_county)

predictions_rf_bev_city = predict_future_values(rf_model_bev_city,␣
 ↪encoded_future_city, future_data_city)
predictions_rf_phev_city = predict_future_values(rf_model_phev_city,␣
 ↪encoded_future_city, future_data_city)

predictions_rf_bev_leg_dist = predict_future_values(rf_model_bev_leg_dist,␣
 ↪encoded_future_leg_dist, future_data_leg_dist)
predictions_rf_phev_leg_dist = predict_future_values(rf_model_phev_leg_dist,␣
 ↪encoded_future_leg_dist, future_data_leg_dist)

predictions_rf_bev_elec_utility =␣
 ↪predict_future_values(rf_model_bev_elec_utility,␣
 ↪encoded_future_elec_utility, future_data_elec_utility)
predictions_rf_phev_elec_utility =␣
 ↪predict_future_values(rf_model_phev_elec_utility,␣
 ↪encoded_future_elec_utility, future_data_elec_utility)

# Predict future values for each category using Linear Regression
predictions_lr_bev_county = predict_future_values(lr_model_bev_county,␣
 ↪encoded_future_county, future_data_county)
predictions_lr_phev_county = predict_future_values(lr_model_phev_county,␣
 ↪encoded_future_county, future_data_county)

predictions_lr_bev_city = predict_future_values(lr_model_bev_city,␣
 ↪encoded_future_city, future_data_city)
predictions_lr_phev_city = predict_future_values(lr_model_phev_city,␣
 ↪encoded_future_city, future_data_city)

predictions_lr_bev_leg_dist = predict_future_values(lr_model_bev_leg_dist,␣
 ↪encoded_future_leg_dist, future_data_leg_dist)
predictions_lr_phev_leg_dist = predict_future_values(lr_model_phev_leg_dist,␣
 ↪encoded_future_leg_dist, future_data_leg_dist)
```

```python
predictions_lr_bev_elec_utility =␣
  ↪predict_future_values(lr_model_bev_elec_utility,␣
  ↪encoded_future_elec_utility, future_data_elec_utility)
predictions_lr_phev_elec_utility =␣
  ↪predict_future_values(lr_model_phev_elec_utility,␣
  ↪encoded_future_elec_utility, future_data_elec_utility)

# Function to create a pivot table for the predictions
def create_pivot_table(predictions, name_column):
    pivot_table = predictions.pivot(index=name_column, columns='Year',␣
  ↪values='Predicted_Values')
    return pivot_table

# Create pivot tables for each category and model
pivot_rf_bev_county = create_pivot_table(predictions_rf_bev_county, 'County')
pivot_rf_phev_county = create_pivot_table(predictions_rf_phev_county, 'County')

pivot_rf_bev_city = create_pivot_table(predictions_rf_bev_city, 'City')
pivot_rf_phev_city = create_pivot_table(predictions_rf_phev_city, 'City')

pivot_rf_bev_leg_dist = create_pivot_table(predictions_rf_bev_leg_dist,␣
  ↪'Legislative District')
pivot_rf_phev_leg_dist = create_pivot_table(predictions_rf_phev_leg_dist,␣
  ↪'Legislative District')

pivot_rf_bev_elec_utility = create_pivot_table(predictions_rf_bev_elec_utility,␣
  ↪'Electric Utility')
pivot_rf_phev_elec_utility =␣
  ↪create_pivot_table(predictions_rf_phev_elec_utility, 'Electric Utility')

pivot_lr_bev_county = create_pivot_table(predictions_lr_bev_county, 'County')
pivot_lr_phev_county = create_pivot_table(predictions_lr_phev_county, 'County')

pivot_lr_bev_city = create_pivot_table(predictions_lr_bev_city, 'City')
pivot_lr_phev_city = create_pivot_table(predictions_lr_phev_city, 'City')

pivot_lr_bev_leg_dist = create_pivot_table(predictions_lr_bev_leg_dist,␣
  ↪'Legislative District')
pivot_lr_phev_leg_dist = create_pivot_table(predictions_lr_phev_leg_dist,␣
  ↪'Legislative District')

pivot_lr_bev_elec_utility = create_pivot_table(predictions_lr_bev_elec_utility,␣
  ↪'Electric Utility')
pivot_lr_phev_elec_utility =␣
  ↪create_pivot_table(predictions_lr_phev_elec_utility, 'Electric Utility')
```

```python
# Display the pivot tables
print("Random Forest - County-wise BEVs predictions:\n", pivot_rf_bev_county)
print("Random Forest - County-wise PHEVs predictions:\n", pivot_rf_phev_county)

print("Random Forest - City-wise BEVs predictions:\n", pivot_rf_bev_city)
print("Random Forest - City-wise PHEVs predictions:\n", pivot_rf_phev_city)

print("Random Forest - Legislative District-wise BEVs predictions:\n",␣
 ↪pivot_rf_bev_leg_dist)
print("Random Forest - Legislative District-wise PHEVs predictions:\n",␣
 ↪pivot_rf_phev_leg_dist)

print("Random Forest - Electric Utility-wise BEVs predictions:\n",␣
 ↪pivot_rf_bev_elec_utility)
print("Random Forest - Electric Utility-wise PHEVs predictions:\n",␣
 ↪pivot_rf_phev_elec_utility)

print("Linear Regression - County-wise BEVs predictions:\n",␣
 ↪pivot_lr_bev_county)
print("Linear Regression - County-wise PHEVs predictions:\n",␣
 ↪pivot_lr_phev_county)

print("Linear Regression - City-wise BEVs predictions:\n", pivot_lr_bev_city)
print("Linear Regression - City-wise PHEVs predictions:\n", pivot_lr_phev_city)

print("Linear Regression - Legislative District-wise BEVs predictions:\n",␣
 ↪pivot_lr_bev_leg_dist)
print("Linear Regression - Legislative District-wise PHEVs predictions:\n",␣
 ↪pivot_lr_phev_leg_dist)

print("Linear Regression - Electric Utility-wise BEVs predictions:\n",␣
 ↪pivot_lr_bev_elec_utility)
print("Linear Regression - Electric Utility-wise PHEVs predictions:\n",␣
 ↪pivot_lr_phev_elec_utility)
```

```
Random Forest - County-wise BEVs predictions:
 Year          2024  2025  2026  2027  2028  2029  2030  2031  2032  \
County
Adams            5     5     5     5     5     5     5     5     5
Asotin           4     4     4     4     4     4     4     4     4
Benton         406   406   406   406   406   406   406   406   406
Chelan         188   188   188   188   188   188   188   188   188
Clallam         45    45    45    45    45    45    45    45    45
Clark          738   738   738   738   738   738   738   738   738
Columbia         2     2     2     2     2     2     2     2     2
Cowlitz         81    81    81    81    81    81    81    81    81
Douglas         20    20    20    20    20    20    20    20    20
```

Ferry	3	3	3	3	3	3	3	3	3
Franklin	29	29	29	29	29	29	29	29	29
Garfield	1	1	1	1	1	1	1	1	1
Grant	15	15	15	15	15	15	15	15	15
Grays Harbor	16	16	16	16	16	16	16	16	16
Island	162	162	162	162	162	162	162	162	162
Jefferson	97	97	97	97	97	97	97	97	97
King	19035	19035	19035	19035	19035	19035	19035	19035	19035
Kitsap	600	600	600	600	600	600	600	600	600
Kittitas	44	44	44	44	44	44	44	44	44
Klickitat	15	15	15	15	15	15	15	15	15
Lewis	36	36	36	36	36	36	36	36	36
Lincoln	3	3	3	3	3	3	3	3	3
Mason	27	27	27	27	27	27	27	27	27
Okanogan	11	11	11	11	11	11	11	11	11
Pacific	8	8	8	8	8	8	8	8	8
Pend Oreille	5	5	5	5	5	5	5	5	5
Pierce	931	931	931	931	931	931	931	931	931
San Juan	38	38	38	38	38	38	38	38	38
Skagit	139	139	139	139	139	139	139	139	139
Skamania	14	14	14	14	14	14	14	14	14
Snohomish	2465	2465	2465	2465	2465	2465	2465	2465	2465
Spokane	816	816	816	816	816	816	816	816	816
Stevens	8	8	8	8	8	8	8	8	8
Thurston	369	369	369	369	369	369	369	369	369
Wahkiakum	5	5	5	5	5	5	5	5	5
Walla Walla	24	24	24	24	24	24	24	24	24
Whatcom	360	360	360	360	360	360	360	360	360
Whitman	20	20	20	20	20	20	20	20	20
Yakima	63	63	63	63	63	63	63	63	63

Year	2033
County	
Adams	5
Asotin	4
Benton	406
Chelan	188
Clallam	45
Clark	738
Columbia	2
Cowlitz	81
Douglas	20
Ferry	3
Franklin	29
Garfield	1
Grant	15
Grays Harbor	16
Island	162

Jefferson	97
King	19035
Kitsap	600
Kittitas	44
Klickitat	15
Lewis	36
Lincoln	3
Mason	27
Okanogan	11
Pacific	8
Pend Oreille	5
Pierce	931
San Juan	38
Skagit	139
Skamania	14
Snohomish	2465
Spokane	816
Stevens	8
Thurston	369
Wahkiakum	5
Walla Walla	24
Whatcom	360
Whitman	20
Yakima	63

Random Forest - County-wise PHEVs predictions:

Year	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
County										
Adams	3	3	3	3	3	3	3	3	3	3
Asotin	2	2	2	2	2	2	2	2	2	2
Benton	96	96	96	96	96	96	96	96	96	96
Chelan	38	38	38	38	38	38	38	38	38	38
Clallam	32	32	32	32	32	32	32	32	32	32
Clark	312	312	312	312	312	312	312	312	312	312
Columbia	0	0	0	0	0	0	0	0	0	0
Cowlitz	29	29	29	29	29	29	29	29	29	29
Douglas	12	12	12	12	12	12	12	12	12	12
Ferry	1	1	1	1	1	1	1	1	1	1
Franklin	21	21	21	21	21	21	21	21	21	21
Garfield	0	0	0	0	0	0	0	0	0	0
Grant	16	16	16	16	16	16	16	16	16	16
Grays Harbor	14	14	14	14	14	14	14	14	14	14
Island	49	49	49	49	49	49	49	49	49	49
Jefferson	29	29	29	29	29	29	29	29	29	29
King	2878	2878	2878	2878	2878	2878	2878	2878	2878	2878
Kitsap	188	188	188	188	188	188	188	188	188	188
Kittitas	16	16	16	16	16	16	16	16	16	16
Klickitat	9	9	9	9	9	9	9	9	9	9
Lewis	70	70	70	70	70	70	70	70	70	70

```
Lincoln          4     4     4     4     4     4     4     4     4     4
Mason           24    24    24    24    24    24    24    24    24    24
Okanogan        10    10    10    10    10    10    10    10    10    10
Pacific         11    11    11    11    11    11    11    11    11    11
Pend Oreille     3     3     3     3     3     3     3     3     3     3
Pierce         361   361   361   361   361   361   361   361   361   361
San Juan        18    18    18    18    18    18    18    18    18    18
Skagit          60    60    60    60    60    60    60    60    60    60
Skamania         8     8     8     8     8     8     8     8     8     8
Snohomish      497   497   497   497   497   497   497   497   497   497
Spokane        207   207   207   207   207   207   207   207   207   207
Stevens          8     8     8     8     8     8     8     8     8     8
Thurston       155   155   155   155   155   155   155   155   155   155
Wahkiakum        2     2     2     2     2     2     2     2     2     2
Walla Walla     18    18    18    18    18    18    18    18    18    18
Whatcom        151   151   151   151   151   151   151   151   151   151
Whitman         16    16    16    16    16    16    16    16    16    16
Yakima          40    40    40    40    40    40    40    40    40    40
Random Forest - City-wise BEVs predictions:
 Year            2024  2025  2026  2027  2028  2029  2030  2031  2032  2033
City
Aberdeen            1     1     1     1     1     1     1     1     1     1
Acme                1     1     1     1     1     1     1     1     1     1
Addy                0     0     0     0     0     0     0     0     0     0
Adna                0     0     0     0     0     0     0     0     0     0
Airway Heights      0     0     0     0     0     0     0     0     0     0
…                 …   …   …   …   …   …   …   …   …   …
Yacolt              4     4     4     4     4     4     4     4     4     4
Yakima             46    46    46    46    46    46    46    46    46    46
Yarrow Point        7     7     7     7     7     7     7     7     7     7
Yelm               16    16    16    16    16    16    16    16    16    16
Zillah              3     3     3     3     3     3     3     3     3     3

[473 rows x 10 columns]
Random Forest - City-wise PHEVs predictions:
 Year            2024  2025  2026  2027  2028  2029  2030  2031  2032  2033
City
Aberdeen            4     4     4     4     4     4     4     4     4     4
Acme                3     3     3     3     3     3     3     3     3     3
Addy                1     1     1     1     1     1     1     1     1     1
Adna                1     1     1     1     1     1     1     1     1     1
Airway Heights      1     1     1     1     1     1     1     1     1     1
…                 …   …   …   …   …   …   …   …   …   …
Yacolt              2     2     2     2     2     2     2     2     2     2
Yakima             33    33    33    33    33    33    33    33    33    33
Yarrow Point        4     4     4     4     4     4     4     4     4     4
Yelm                8     8     8     8     8     8     8     8     8     8
Zillah              2     2     2     2     2     2     2     2     2     2
```

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[473 rows x 10 columns]
Random Forest - Legislative District-wise BEVs predictions:
 Year                 2024  2025  2026  2027  2028  2029  2030  2031  2032  \
Legislative District
1.0                   305   305   305   305   305   305   305   305   305
2.0                   305   305   305   305   305   305   305   305   305
3.0                   305   305   305   305   305   305   305   305   305
4.0                   305   305   305   305   305   305   305   305   305
5.0                   305   305   305   305   305   305   305   305   305
6.0                   305   305   305   305   305   305   305   305   305
7.0                   305   305   305   305   305   305   305   305   305
8.0                   305   305   305   305   305   305   305   305   305
9.0                   305   305   305   305   305   305   305   305   305
10.0                  305   305   305   305   305   305   305   305   305
11.0                  305   305   305   305   305   305   305   305   305
12.0                  305   305   305   305   305   305   305   305   305
13.0                  305   305   305   305   305   305   305   305   305
14.0                  305   305   305   305   305   305   305   305   305
15.0                  305   305   305   305   305   305   305   305   305
16.0                  305   305   305   305   305   305   305   305   305
17.0                  305   305   305   305   305   305   305   305   305
18.0                  305   305   305   305   305   305   305   305   305
19.0                  305   305   305   305   305   305   305   305   305
20.0                  305   305   305   305   305   305   305   305   305
21.0                  305   305   305   305   305   305   305   305   305
22.0                  305   305   305   305   305   305   305   305   305
23.0                  305   305   305   305   305   305   305   305   305
24.0                  305   305   305   305   305   305   305   305   305
25.0                  305   305   305   305   305   305   305   305   305
26.0                  305   305   305   305   305   305   305   305   305
27.0                  305   305   305   305   305   305   305   305   305
28.0                  305   305   305   305   305   305   305   305   305
29.0                  305   305   305   305   305   305   305   305   305
30.0                  305   305   305   305   305   305   305   305   305
31.0                  305   305   305   305   305   305   305   305   305
32.0                  305   305   305   305   305   305   305   305   305
33.0                  305   305   305   305   305   305   305   305   305
34.0                  305   305   305   305   305   305   305   305   305
35.0                  305   305   305   305   305   305   305   305   305
36.0                  305   305   305   305   305   305   305   305   305
37.0                  305   305   305   305   305   305   305   305   305
38.0                  305   305   305   305   305   305   305   305   305
39.0                  305   305   305   305   305   305   305   305   305
40.0                  305   305   305   305   305   305   305   305   305
41.0                  305   305   305   305   305   305   305   305   305
42.0                  305   305   305   305   305   305   305   305   305
43.0                  305   305   305   305   305   305   305   305   305
```

44.0	305	305	305	305	305	305	305	305	305
45.0	305	305	305	305	305	305	305	305	305
46.0	305	305	305	305	305	305	305	305	305
47.0	305	305	305	305	305	305	305	305	305
48.0	305	305	305	305	305	305	305	305	305
49.0	305	305	305	305	305	305	305	305	305

Year	2033
Legislative District	
1.0	305
2.0	305
3.0	305
4.0	305
5.0	305
6.0	305
7.0	305
8.0	305
9.0	305
10.0	305
11.0	305
12.0	305
13.0	305
14.0	305
15.0	305
16.0	305
17.0	305
18.0	305
19.0	305
20.0	305
21.0	305
22.0	305
23.0	305
24.0	305
25.0	305
26.0	305
27.0	305
28.0	305
29.0	305
30.0	305
31.0	305
32.0	305
33.0	305
34.0	305
35.0	305
36.0	305
37.0	305
38.0	305
39.0	305

```
40.0                   305
41.0                   305
42.0                   305
43.0                   305
44.0                   305
45.0                   305
46.0                   305
47.0                   305
48.0                   305
49.0                   305
Random Forest - Legislative District-wise PHEVs predictions:
 Year                  2024  2025  2026  2027  2028  2029  2030  2031  2032  \
Legislative District
1.0                    127   127   127   127   127   127   127   127   127
2.0                    127   127   127   127   127   127   127   127   127
3.0                    127   127   127   127   127   127   127   127   127
4.0                    127   127   127   127   127   127   127   127   127
5.0                    127   127   127   127   127   127   127   127   127
6.0                    127   127   127   127   127   127   127   127   127
7.0                    127   127   127   127   127   127   127   127   127
8.0                    127   127   127   127   127   127   127   127   127
9.0                    127   127   127   127   127   127   127   127   127
10.0                   127   127   127   127   127   127   127   127   127
11.0                   127   127   127   127   127   127   127   127   127
12.0                   127   127   127   127   127   127   127   127   127
13.0                   127   127   127   127   127   127   127   127   127
14.0                   127   127   127   127   127   127   127   127   127
15.0                   127   127   127   127   127   127   127   127   127
16.0                   127   127   127   127   127   127   127   127   127
17.0                   127   127   127   127   127   127   127   127   127
18.0                   127   127   127   127   127   127   127   127   127
19.0                   127   127   127   127   127   127   127   127   127
20.0                   127   127   127   127   127   127   127   127   127
21.0                   127   127   127   127   127   127   127   127   127
22.0                   127   127   127   127   127   127   127   127   127
23.0                   127   127   127   127   127   127   127   127   127
24.0                   127   127   127   127   127   127   127   127   127
25.0                   127   127   127   127   127   127   127   127   127
26.0                   127   127   127   127   127   127   127   127   127
27.0                   127   127   127   127   127   127   127   127   127
28.0                   127   127   127   127   127   127   127   127   127
29.0                   127   127   127   127   127   127   127   127   127
30.0                   127   127   127   127   127   127   127   127   127
31.0                   127   127   127   127   127   127   127   127   127
32.0                   127   127   127   127   127   127   127   127   127
33.0                   127   127   127   127   127   127   127   127   127
34.0                   127   127   127   127   127   127   127   127   127
35.0                   127   127   127   127   127   127   127   127   127
```

36.0	127	127	127	127	127	127	127	127	127
37.0	127	127	127	127	127	127	127	127	127
38.0	127	127	127	127	127	127	127	127	127
39.0	127	127	127	127	127	127	127	127	127
40.0	127	127	127	127	127	127	127	127	127
41.0	127	127	127	127	127	127	127	127	127
42.0	127	127	127	127	127	127	127	127	127
43.0	127	127	127	127	127	127	127	127	127
44.0	127	127	127	127	127	127	127	127	127
45.0	127	127	127	127	127	127	127	127	127
46.0	127	127	127	127	127	127	127	127	127
47.0	127	127	127	127	127	127	127	127	127
48.0	127	127	127	127	127	127	127	127	127
49.0	127	127	127	127	127	127	127	127	127

Year	2033
Legislative District	
1.0	127
2.0	127
3.0	127
4.0	127
5.0	127
6.0	127
7.0	127
8.0	127
9.0	127
10.0	127
11.0	127
12.0	127
13.0	127
14.0	127
15.0	127
16.0	127
17.0	127
18.0	127
19.0	127
20.0	127
21.0	127
22.0	127
23.0	127
24.0	127
25.0	127
26.0	127
27.0	127
28.0	127
29.0	127
30.0	127
31.0	127

```
32.0                   127
33.0                   127
34.0                   127
35.0                   127
36.0                   127
37.0                   127
38.0                   127
39.0                   127
40.0                   127
41.0                   127
42.0                   127
43.0                   127
44.0                   127
45.0                   127
46.0                   127
47.0                   127
48.0                   127
49.0                   127
Random Forest - Electric Utility-wise BEVs predictions:
 Year                                                 2024  2025  2026  2027  \
Electric Utility
AVISTA CORP                                            11    11    11    11
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…     7     7     7     7
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…   518   518   518   518
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…     6     6     6     6
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…     3     3     3     3
…                                                  …    …    …    …
PUD NO 1 OF WHATCOM COUNTY                             4     4     4     4
PUD NO 2 OF GRANT COUNTY                              42    42    42    42
PUGET SOUND ENERGY INC                              4482  4482  4482  4482
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       4810  4810  4810  4810
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   364   364   364   364

Year                                                2028  2029  2030  2031  \
Electric Utility
AVISTA CORP                                            11    11    11    11
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…     7     7     7     7
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…   518   518   518   518
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…     6     6     6     6
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…     3     3     3     3
…                                                  …    …    …    …
PUD NO 1 OF WHATCOM COUNTY                             4     4     4     4
PUD NO 2 OF GRANT COUNTY                              42    42    42    42
PUGET SOUND ENERGY INC                              4482  4482  4482  4482
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       4810  4810  4810  4810
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   364   364   364   364

Year                                                2032  2033
```

```
Electric Utility
AVISTA CORP                                          11    11
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…     7     7
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…   518   518
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…     6     6
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…     3     3
…                                                  …   …
PUD NO 1 OF WHATCOM COUNTY                            4     4
PUD NO 2 OF GRANT COUNTY                             42    42
PUGET SOUND ENERGY INC                             4482  4482
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)      4810  4810
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   364   364

[75 rows x 10 columns]
Random Forest - Electric Utility-wise PHEVs predictions:
 Year                                               2024  2025  2026  2027  \
Electric Utility
AVISTA CORP                                          14    14    14    14
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…     7     7     7     7
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…   138   138   138   138
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…     6     6     6     6
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…     3     3     3     3
…                                                  …   …   …   …
PUD NO 1 OF WHATCOM COUNTY                            3     3     3     3
PUD NO 2 OF GRANT COUNTY                             25    25    25    25
PUGET SOUND ENERGY INC                              926   926   926   926
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)      1944  1944  1944  1944
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   143   143   143   143

Year                                               2028  2029  2030  2031  \
Electric Utility
AVISTA CORP                                          14    14    14    14
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…     7     7     7     7
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…   138   138   138   138
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…     6     6     6     6
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…     3     3     3     3
…                                                  …   …   …   …
PUD NO 1 OF WHATCOM COUNTY                            3     3     3     3
PUD NO 2 OF GRANT COUNTY                             25    25    25    25
PUGET SOUND ENERGY INC                              926   926   926   926
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)      1944  1944  1944  1944
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   143   143   143   143

Year                                               2032  2033
Electric Utility
AVISTA CORP                                          14    14
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…     7     7
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…   138   138
```

```
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…     6     6
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…     3     3
…                                                  …    …
PUD NO 1 OF WHATCOM COUNTY                            3     3
PUD NO 2 OF GRANT COUNTY                             25    25
PUGET SOUND ENERGY INC                              926   926
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)      1944  1944
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   143   143

[75 rows x 10 columns]
Linear Regression - County-wise BEVs predictions:
 Year          2024  2025  2026  2027  2028  2029  2030  2031  2032  2033
County
Adams           224   245   265   286   306   326   347   367   388   408
Asotin          233   254   274   294   315   335   356   376   396   417
Benton          358   379   399   419   440   460   481   501   521   542
Chelan          287   308   328   348   369   389   410   430   451   471
Clallam         286   307   327   348   368   388   409   429   450   470
Clark           515   536   556   577   597   617   638   658   679   699
Columbia        252   273   293   314   334   354   375   395   416   436
Cowlitz         285   305   325   346   366   387   407   427   448   468
Douglas         269   290   310   331   351   371   392   412   433   453
Ferry           270   290   311   331   352   372   392   413   433   454
Franklin        235   255   276   296   316   337   357   378   398   419
Garfield        275   295   316   336   357   377   397   418   438   459
Grant           288   308   328   349   369   390   410   430   451   471
Grays Harbor    276   296   317   337   358   378   398   419   439   460
Island          321   342   362   382   403   423   444   464   484   505
Jefferson       281   302   322   343   363   383   404   424   445   465
King           3813  3834  3854  3874  3895  3915  3936  3956  3976  3997
Kitsap          463   484   504   524   545   565   586   606   626   647
Kittitas        245   265   286   306   326   347   367   388   408   428
Klickitat       233   253   274   294   315   335   355   376   396   417
Lewis           248   268   289   309   329   350   370   391   411   431
Lincoln         258   279   299   320   340   360   381   401   422   442
Mason           285   305   326   346   366   387   407   428   448   468
Okanogan        244   264   285   305   326   346   366   387   407   428
Pacific         259   279   299   320   340   361   381   401   422   442
Pend Oreille    264   284   305   325   345   366   386   407   427   448
Pierce          629   650   670   691   711   732   752   772   793   813
San Juan        273   293   314   334   355   375   395   416   436   457
Skagit          310   330   350   371   391   412   432   452   473   493
Skamania        266   286   307   327   348   368   388   409   429   450
Snohomish      1181  1202  1222  1242  1263  1283  1304  1324  1344  1365
Spokane         411   431   452   472   493   513   534   554   574   595
Stevens         261   281   302   322   342   363   383   404   424   444
Thurston        405   426   446   467   487   507   528   548   569   589
Wahkiakum       269   289   309   330   350   371   391   411   432   452
```

Walla Walla	280	301	321	342	362	382	403	423	444	464
Whatcom	409	429	450	470	491	511	531	552	572	593
Whitman	268	288	308	329	349	370	390	410	431	451
Yakima	274	294	314	335	355	376	396	416	437	457

Linear Regression - County-wise PHEVs predictions:

Year County	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
Adams	53	58	62	67	72	77	82	86	91	96
Asotin	55	60	65	70	74	79	84	89	94	98
Benton	97	102	107	112	117	121	126	131	136	141
Chelan	66	71	76	81	85	90	95	100	104	109
Clallam	74	79	84	88	93	98	103	107	112	117
Clark	179	183	188	193	198	203	207	212	217	222
Columbia	59	64	69	73	78	83	88	93	97	102
Cowlitz	72	77	82	86	91	96	101	105	110	115
Douglas	64	69	74	78	83	88	93	98	102	107
Ferry	63	68	73	78	82	87	92	97	101	106
Franklin	59	64	68	73	78	83	88	92	97	102
Garfield	64	69	74	79	84	88	93	98	103	108
Grant	72	76	81	86	91	95	100	105	110	115
Grays Harbor	71	76	81	85	90	95	100	105	109	114
Island	83	88	93	98	103	107	112	117	122	127
Jefferson	72	76	81	86	91	96	100	105	110	115
King	879	884	889	894	899	903	908	913	918	922
Kitsap	135	140	145	149	154	159	164	168	173	178
Kittitas	58	62	67	72	77	82	86	91	96	101
Klickitat	56	61	66	71	75	80	85	90	95	99
Lewis	72	77	82	87	92	96	101	106	111	115
Lincoln	61	66	71	76	80	85	90	95	100	104
Mason	72	77	82	87	92	96	101	106	111	115
Okanogan	59	64	69	73	78	83	88	92	97	102
Pacific	64	68	73	78	83	88	92	97	102	107
Pend Oreille	62	67	72	77	81	86	91	96	101	105
Pierce	222	227	231	236	241	246	251	255	260	265
San Juan	65	70	74	79	84	89	94	98	103	108
Skagit	81	86	91	96	100	105	110	115	120	124
Skamania	63	68	72	77	82	87	91	96	101	106
Snohomish	252	257	262	266	271	276	281	286	290	295
Spokane	122	127	132	137	141	146	151	156	161	165
Stevens	63	68	73	78	82	87	92	97	102	106
Thurston	130	134	139	144	149	153	158	163	168	173
Wahkiakum	64	68	73	78	83	88	92	97	102	107
Walla Walla	69	74	79	83	88	93	98	103	107	112
Whatcom	111	116	120	125	130	135	139	144	149	154
Whitman	65	70	74	79	84	89	94	98	103	108
Yakima	72	77	82	87	91	96	101	106	110	115

Linear Regression - City-wise BEVs predictions:

Year	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033

```
City
Aberdeen          27    29    31    33    34    36    38    40    42    43
Acme              22    24    26    28    30    31    33    35    37    39
Addy              24    26    28    30    32    33    35    37    39    41
Adna              22    24    25    27    29    31    33    35    36    38
Airway Heights    24    26    27    29    31    33    35    36    38    40
…              …   …   …   …   …   …   …   …   …   …
Yacolt            25    27    29    30    32    34    36    38    39    41
Yakima            49    51    53    55    56    58    60    62    64    66
Yarrow Point      28    30    31    33    35    37    39    40    42    44
Yelm              34    36    37    39    41    43    45    46    48    50
Zillah            22    23    25    27    29    31    32    34    36    38

[473 rows x 10 columns]
Linear Regression - City-wise PHEVs predictions:
 Year            2024  2025  2026  2027  2028  2029  2030  2031  2032  2033
City
Aberdeen           8     8     9     9    10    10    11    11    12    12
Acme               6     6     7     7     7     8     8     9     9    10
Addy               6     6     7     7     8     8     9     9    10    10
Adna               5     6     6     7     7     8     8     9     9     9
Airway Heights     6     7     7     8     8     8     9     9    10    10
…              …   …   …   …   …   …   …   …   …   …
Yacolt             6     7     7     8     8     8     9     9    10    10
Yakima            18    18    19    19    20    20    21    21    22    22
Yarrow Point       7     7     8     8     9     9    10    10    11    11
Yelm               9    10    10    11    11    11    12    12    13    13
Zillah             5     6     6     6     7     7     8     8     9     9

[473 rows x 10 columns]
Linear Regression - Legislative District-wise BEVs predictions:
 Year                  2024  2025  2026  2027  2028  2029  2030  2031  2032  \
Legislative District
1.0                    530   546   563   579   595   612   628   645   661
2.0                    530   546   563   579   595   612   628   645   661
3.0                    530   546   563   579   595   612   628   645   661
4.0                    530   546   563   579   595   612   628   645   661
5.0                    530   546   563   579   595   612   628   645   661
6.0                    530   546   563   579   595   612   628   645   661
7.0                    530   546   563   579   595   612   628   645   661
8.0                    530   546   563   579   595   612   628   645   661
9.0                    530   546   563   579   595   612   628   645   661
10.0                   530   546   563   579   595   612   628   645   661
11.0                   530   546   563   579   595   612   628   645   661
12.0                   530   546   563   579   595   612   628   645   661
13.0                   530   546   563   579   595   612   628   645   661
14.0                   530   546   563   579   595   612   628   645   661
15.0                   530   546   563   579   595   612   628   645   661
```

16.0	530	546	563	579	595	612	628	645	661
17.0	530	546	563	579	595	612	628	645	661
18.0	530	546	563	579	595	612	628	645	661
19.0	530	546	563	579	595	612	628	645	661
20.0	530	546	563	579	595	612	628	645	661
21.0	530	546	563	579	595	612	628	645	661
22.0	530	546	563	579	595	612	628	645	661
23.0	530	546	563	579	595	612	628	645	661
24.0	530	546	563	579	595	612	628	645	661
25.0	530	546	563	579	595	612	628	645	661
26.0	530	546	563	579	595	612	628	645	661
27.0	530	546	563	579	595	612	628	645	661
28.0	530	546	563	579	595	612	628	645	661
29.0	530	546	563	579	595	612	628	645	661
30.0	530	546	563	579	595	612	628	645	661
31.0	530	546	563	579	595	612	628	645	661
32.0	530	546	563	579	595	612	628	645	661
33.0	530	546	563	579	595	612	628	645	661
34.0	530	546	563	579	595	612	628	645	661
35.0	530	546	563	579	595	612	628	645	661
36.0	530	546	563	579	595	612	628	645	661
37.0	530	546	563	579	595	612	628	645	661
38.0	530	546	563	579	595	612	628	645	661
39.0	530	546	563	579	595	612	628	645	661
40.0	530	546	563	579	595	612	628	645	661
41.0	530	546	563	579	595	612	628	645	661
42.0	530	546	563	579	595	612	628	645	661
43.0	530	546	563	579	595	612	628	645	661
44.0	530	546	563	579	595	612	628	645	661
45.0	530	546	563	579	595	612	628	645	661
46.0	530	546	563	579	595	612	628	645	661
47.0	530	546	563	579	595	612	628	645	661
48.0	530	546	563	579	595	612	628	645	661
49.0	530	546	563	579	595	612	628	645	661

Year	2033
Legislative District	
1.0	677
2.0	677
3.0	677
4.0	677
5.0	677
6.0	677
7.0	677
8.0	677
9.0	677
10.0	677
11.0	677

```
12.0                   677
13.0                   677
14.0                   677
15.0                   677
16.0                   677
17.0                   677
18.0                   677
19.0                   677
20.0                   677
21.0                   677
22.0                   677
23.0                   677
24.0                   677
25.0                   677
26.0                   677
27.0                   677
28.0                   677
29.0                   677
30.0                   677
31.0                   677
32.0                   677
33.0                   677
34.0                   677
35.0                   677
36.0                   677
37.0                   677
38.0                   677
39.0                   677
40.0                   677
41.0                   677
42.0                   677
43.0                   677
44.0                   677
45.0                   677
46.0                   677
47.0                   677
48.0                   677
49.0                   677
Linear Regression - Legislative District-wise PHEVs predictions:
 Year                  2024  2025  2026  2027  2028  2029  2030  2031  2032  \
Legislative District
1.0                    104   108   112   116   120   124   128   132   136
2.0                    104   108   112   116   120   124   128   132   136
3.0                    104   108   112   116   120   124   128   132   136
4.0                    104   108   112   116   120   124   128   132   136
5.0                    104   108   112   116   120   124   128   132   136
6.0                    104   108   112   116   120   124   128   132   136
7.0                    104   108   112   116   120   124   128   132   136
```

8.0	104	108	112	116	120	124	128	132	136
9.0	104	108	112	116	120	124	128	132	136
10.0	104	108	112	116	120	124	128	132	136
11.0	104	108	112	116	120	124	128	132	136
12.0	104	108	112	116	120	124	128	132	136
13.0	104	108	112	116	120	124	128	132	136
14.0	104	108	112	116	120	124	128	132	136
15.0	104	108	112	116	120	124	128	132	136
16.0	104	108	112	116	120	124	128	132	136
17.0	104	108	112	116	120	124	128	132	136
18.0	104	108	112	116	120	124	128	132	136
19.0	104	108	112	116	120	124	128	132	136
20.0	104	108	112	116	120	124	128	132	136
21.0	104	108	112	116	120	124	128	132	136
22.0	104	108	112	116	120	124	128	132	136
23.0	104	108	112	116	120	124	128	132	136
24.0	104	108	112	116	120	124	128	132	136
25.0	104	108	112	116	120	124	128	132	136
26.0	104	108	112	116	120	124	128	132	136
27.0	104	108	112	116	120	124	128	132	136
28.0	104	108	112	116	120	124	128	132	136
29.0	104	108	112	116	120	124	128	132	136
30.0	104	108	112	116	120	124	128	132	136
31.0	104	108	112	116	120	124	128	132	136
32.0	104	108	112	116	120	124	128	132	136
33.0	104	108	112	116	120	124	128	132	136
34.0	104	108	112	116	120	124	128	132	136
35.0	104	108	112	116	120	124	128	132	136
36.0	104	108	112	116	120	124	128	132	136
37.0	104	108	112	116	120	124	128	132	136
38.0	104	108	112	116	120	124	128	132	136
39.0	104	108	112	116	120	124	128	132	136
40.0	104	108	112	116	120	124	128	132	136
41.0	104	108	112	116	120	124	128	132	136
42.0	104	108	112	116	120	124	128	132	136
43.0	104	108	112	116	120	124	128	132	136
44.0	104	108	112	116	120	124	128	132	136
45.0	104	108	112	116	120	124	128	132	136
46.0	104	108	112	116	120	124	128	132	136
47.0	104	108	112	116	120	124	128	132	136
48.0	104	108	112	116	120	124	128	132	136
49.0	104	108	112	116	120	124	128	132	136

Year	2033
Legislative District	
1.0	140
2.0	140
3.0	140

```
4.0                     140
5.0                     140
6.0                     140
7.0                     140
8.0                     140
9.0                     140
10.0                    140
11.0                    140
12.0                    140
13.0                    140
14.0                    140
15.0                    140
16.0                    140
17.0                    140
18.0                    140
19.0                    140
20.0                    140
21.0                    140
22.0                    140
23.0                    140
24.0                    140
25.0                    140
26.0                    140
27.0                    140
28.0                    140
29.0                    140
30.0                    140
31.0                    140
32.0                    140
33.0                    140
34.0                    140
35.0                    140
36.0                    140
37.0                    140
38.0                    140
39.0                    140
40.0                    140
41.0                    140
42.0                    140
43.0                    140
44.0                    140
45.0                    140
46.0                    140
47.0                    140
48.0                    140
49.0                    140
Linear Regression - Electric Utility-wise BEVs predictions:
 Year                                                    2024  2025  2026  2027  \
```

```
Electric Utility
AVISTA CORP                                          123   133   142   151
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…   104   114   123   132
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…   212   222   231   240
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…   118   127   136   145
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…   117   126   135   144
…                                                   …    …     …     …
PUD NO 1 OF WHATCOM COUNTY                           104   113   122   131
PUD NO 2 OF GRANT COUNTY                             129   138   148   157
PUGET SOUND ENERGY INC                              1434  1444  1453  1462
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       2015  2025  2034  2043
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   267   276   285   295

Year                                                2028  2029  2030  2031  \
Electric Utility
AVISTA CORP                                          160   169   178   187
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…   141   150   159   168
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…   249   258   267   276
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…   154   163   172   182
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…   154   163   172   181
…                                                   …    …     …     …
PUD NO 1 OF WHATCOM COUNTY                           140   150   159   168
PUD NO 2 OF GRANT COUNTY                             166   175   184   193
PUGET SOUND ENERGY INC                              1471  1480  1489  1498
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       2052  2061  2070  2079
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   304   313   322   331

Year                                                2032  2033
Electric Utility
AVISTA CORP                                          197   206
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…   178   187
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…   286   295
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…   191   200
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…   190   199
…                                                   …    …
PUD NO 1 OF WHATCOM COUNTY                           177   186
PUD NO 2 OF GRANT COUNTY                             202   212
PUGET SOUND ENERGY INC                              1508  1517
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       2089  2098
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   340   349

[75 rows x 10 columns]
Linear Regression - Electric Utility-wise PHEVs predictions:
 Year                                                2024  2025  2026  2027  \
Electric Utility
AVISTA CORP                                            36    39    41    43
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…     28    30    33    35
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…     71    73    76    78
```

```
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…    31    34    36    39
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…    31    33    36    38
…                                                  …    …    …    …
PUD NO 1 OF WHATCOM COUNTY                           28    30    32    35
PUD NO 2 OF GRANT COUNTY                             37    39    42    44
PUGET SOUND ENERGY INC                              396   398   401   403
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       648   651   653   656
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   84    87    89    91

Year                                               2028  2029  2030  2031  \
Electric Utility
AVISTA CORP                                          46    48    51    53
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…    37    40    42    45
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…    80    83    85    88
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…    41    43    46    48
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…    40    43    45    48
…                                                  …    …    …    …
PUD NO 1 OF WHATCOM COUNTY                           37    40    42    44
PUD NO 2 OF GRANT COUNTY                             46    49    51    54
PUGET SOUND ENERGY INC                              406   408   410   413
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       658   660   663   665
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY   94    96    99   101

Year                                               2032  2033
Electric Utility
AVISTA CORP                                          55    58
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||B…    47    49
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||I…    90    92
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||P…    51    53
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL E…    50    52
…                                                  …    …
PUD NO 1 OF WHATCOM COUNTY                           47    49
PUD NO 2 OF GRANT COUNTY                             56    58
PUGET SOUND ENERGY INC                              415   418
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       668   670
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY  103   106

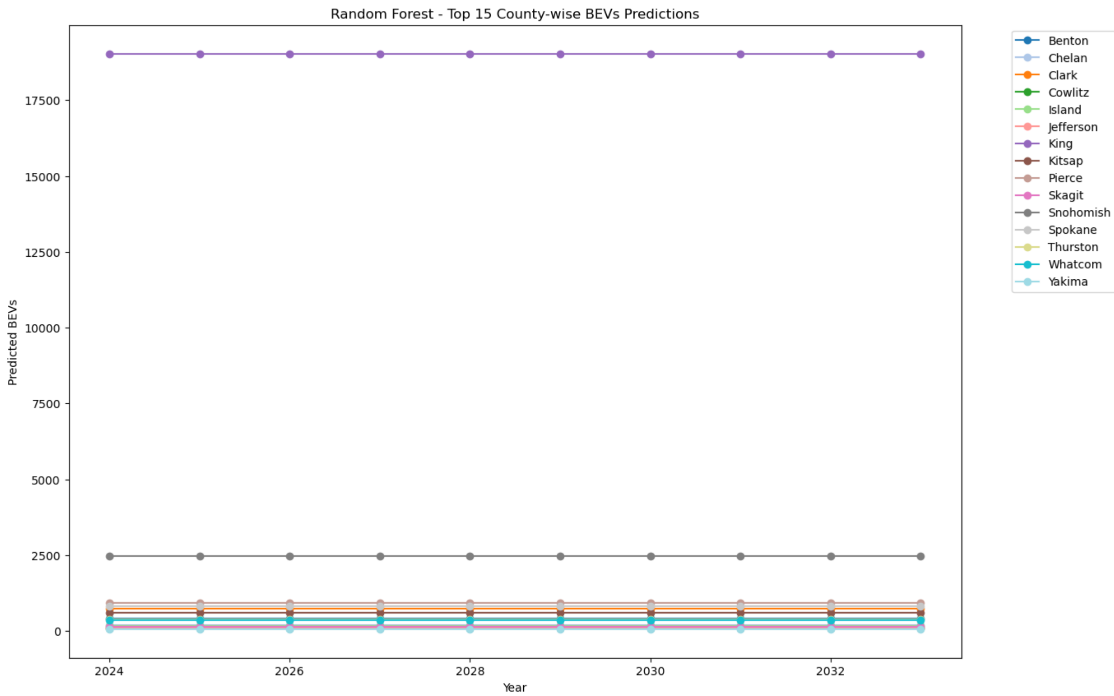
[75 rows x 10 columns]
```

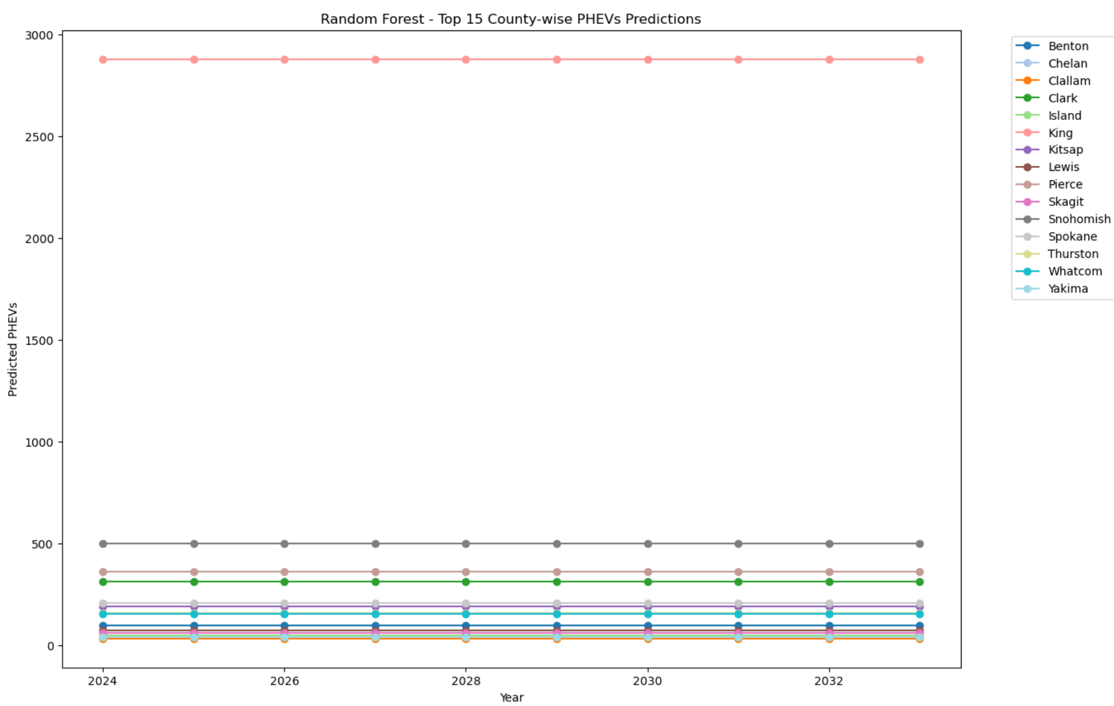
[ ]:
```python
# import the necessary libraries for visualization
import matplotlib.pyplot as plt

# define a function named 'get_top_n' to get the top N categories based on␣
↪total predicted values
def get_top_n(predictions, name_column, n=15):
    top_n_names = predictions.groupby(name_column)['Predicted_Values'].sum().
↪nlargest(n).index
```

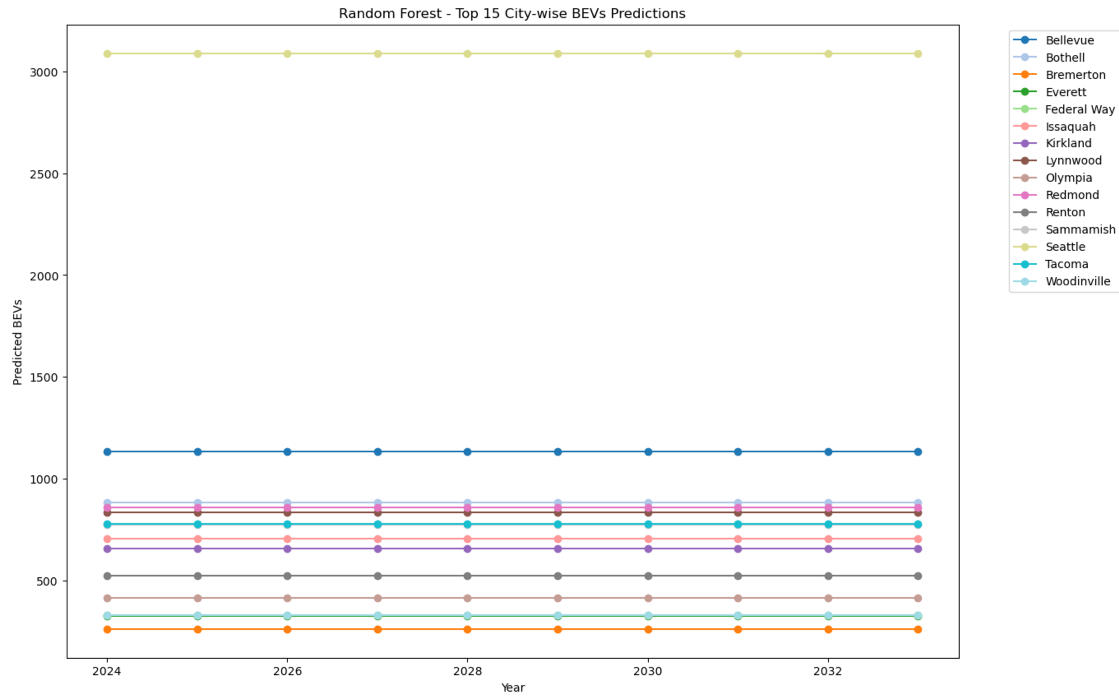
```python
    return predictions[predictions[name_column].isin(top_n_names)]

# define a function named 'plot_top_predictions' to plot predictions for top N categories with distinct colors
def plot_top_predictions(predictions, title, xlabel, ylabel, name_column):
    plt.figure(figsize=(14, 10))
    # getting unique names from the predictions
    unique_names = predictions[name_column].unique()
    # retrieves the 'tab20' colormap from Matplotlib, which is a color palette with 20 distinct colors
    # also creating an array of evenly spaced values between 0 and 1. Each unique name gets assigned a distinct color from the colormap.
    colors = plt.colormaps['tab20'](np.linspace(0, 1, len(unique_names)))
    # iterates over the unique names providing the index and value of each element in unique_names
    for i, name in enumerate(unique_names):
        # creating a subset and extracts the data for a specific category
        subset = predictions[predictions[name_column] == name]
        # creating a plot from the subset
        plt.plot(subset['Year'], subset['Predicted_Values'], marker='o', label=name, color=colors[i])
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
    plt.show()

# Apply the function to get the top 15 (BEV and PHEV) for each county under the random forest regression model
top_15_rf_bev_county = get_top_n(predictions_rf_bev_county, 'County')
top_15_rf_phev_county = get_top_n(predictions_rf_phev_county, 'County')

# Apply the function to get the top 15 (BEV and PHEV) for each city under the random forest regression model
top_15_rf_bev_city = get_top_n(predictions_rf_bev_city, 'City')
top_15_rf_phev_city = get_top_n(predictions_rf_phev_city, 'City')

# Apply the function to get the top 15 (BEV and PHEV) for each legislative district under the random forest regression model
top_15_rf_bev_leg_dist = get_top_n(predictions_rf_bev_leg_dist, 'Legislative District')
top_15_rf_phev_leg_dist = get_top_n(predictions_rf_phev_leg_dist, 'Legislative District')

# Apply the function to get the top 15 (BEV and PHEV) for each electric utility under the random forest regression model
```

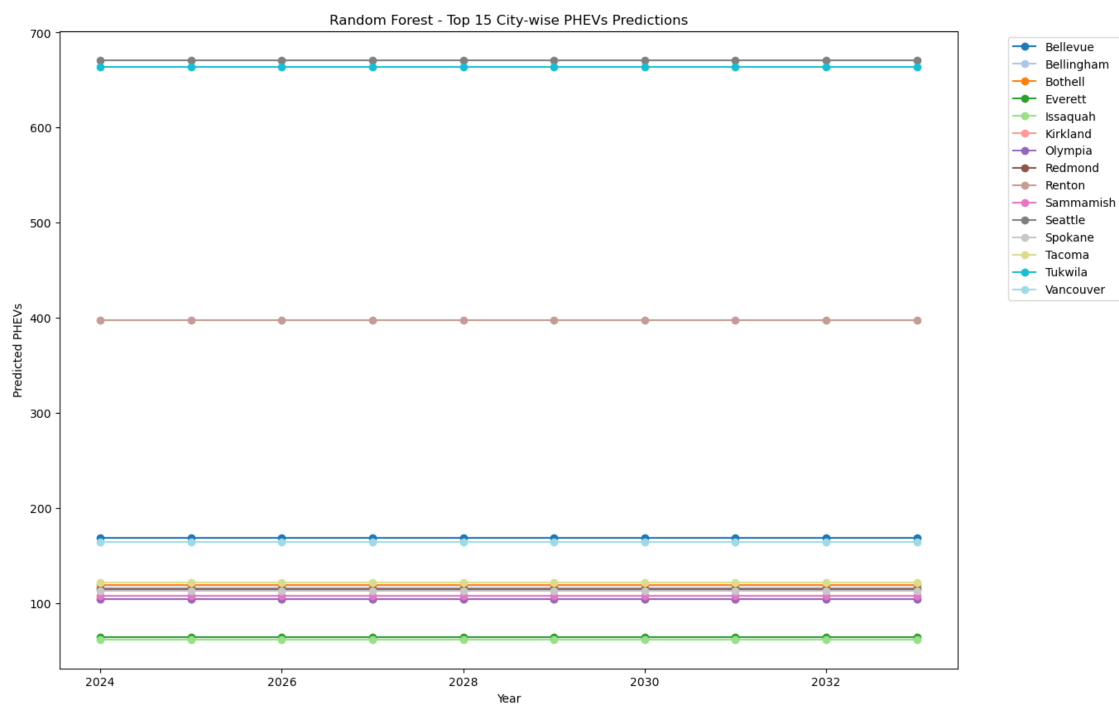
```
top_15_rf_bev_elec_utility = get_top_n(predictions_rf_bev_elec_utility,␣
 ↪'Electric Utility')
top_15_rf_phev_elec_utility = get_top_n(predictions_rf_phev_elec_utility,␣
 ↪'Electric Utility')

# Apply the function to get the top 15 (BEV and PHEV) for each county under the␣
 ↪linear regression model
top_15_lr_bev_county = get_top_n(predictions_lr_bev_county, 'County')
top_15_lr_phev_county = get_top_n(predictions_lr_phev_county, 'County')

# Apply the function to get the top 15 (BEV and PHEV) for each city under the␣
 ↪linear regression model
top_15_lr_bev_city = get_top_n(predictions_lr_bev_city, 'City')
top_15_lr_phev_city = get_top_n(predictions_lr_phev_city, 'City')

# Apply the function to get the top 15 (BEV and PHEV) for each legislative␣
 ↪district under the linear regression model
top_15_lr_bev_leg_dist = get_top_n(predictions_lr_bev_leg_dist, 'Legislative␣
 ↪District')
top_15_lr_phev_leg_dist = get_top_n(predictions_lr_phev_leg_dist, 'Legislative␣
 ↪District')

# Apply the function to get the top 15 (BEV and PHEV) for each electric utility␣
 ↪under the linear regression model
top_15_lr_bev_elec_utility = get_top_n(predictions_lr_bev_elec_utility,␣
 ↪'Electric Utility')
top_15_lr_phev_elec_utility = get_top_n(predictions_lr_phev_elec_utility,␣
 ↪'Electric Utility')

# Plot top 15 BEV and PHEV predictions for Random Forest, county-wise
plot_top_predictions(top_15_rf_bev_county, 'Random Forest - Top 15 County-wise␣
 ↪BEVs Predictions', 'Year', 'Predicted BEVs', 'County')
plot_top_predictions(top_15_rf_phev_county, 'Random Forest - Top 15 County-wise␣
 ↪PHEVs Predictions', 'Year', 'Predicted PHEVs', 'County')

# Plot top 15 BEV and PHEV predictions for Random Forest, city-wise
plot_top_predictions(top_15_rf_bev_city, 'Random Forest - Top 15 City-wise BEVs␣
 ↪Predictions', 'Year', 'Predicted BEVs', 'City')
plot_top_predictions(top_15_rf_phev_city, 'Random Forest - Top 15 City-wise␣
 ↪PHEVs Predictions', 'Year', 'Predicted PHEVs', 'City')

# Plot top 15 BEV and PHEV predictions for Random Forest, legislative␣
 ↪district-wise
plot_top_predictions(top_15_rf_bev_leg_dist, 'Random Forest - Top 15␣
 ↪Legislative District-wise BEVs Predictions', 'Year', 'Predicted BEVs',␣
 ↪'Legislative District')
```

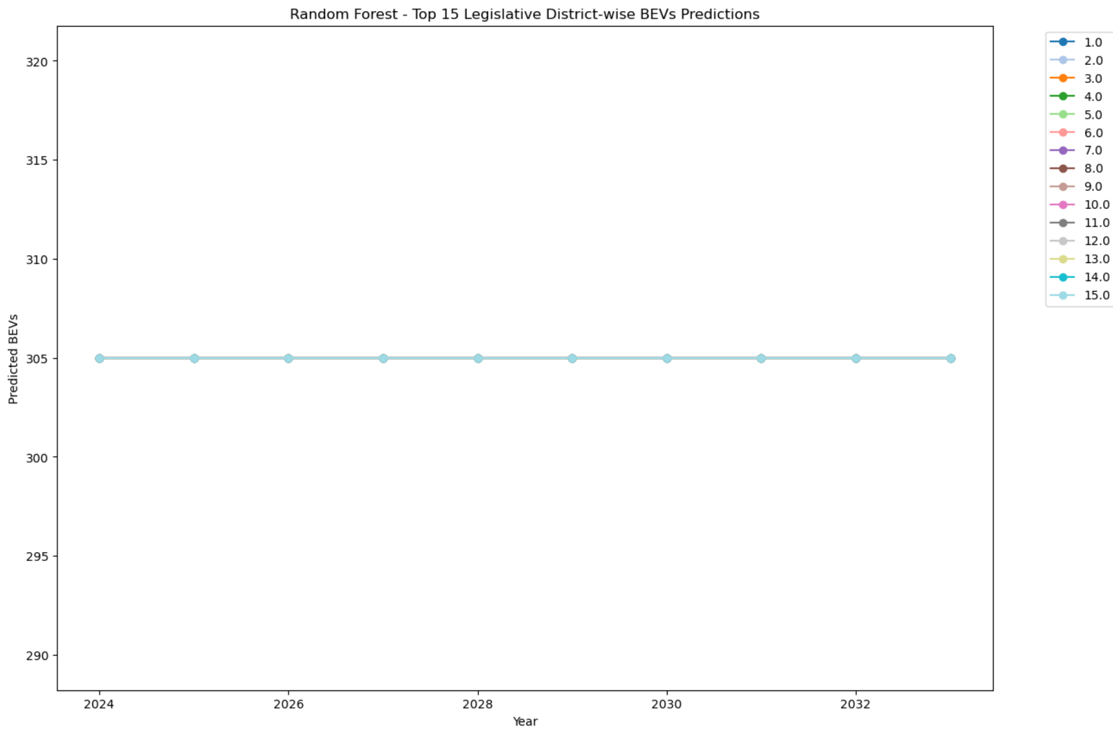
```
plot_top_predictions(top_15_rf_phev_leg_dist, 'Random Forest - Top 15␣
 ↪Legislative District-wise PHEVs Predictions', 'Year', 'Predicted PHEVs',␣
 ↪'Legislative District')

# Plot top 15 BEV and PHEV predictions for Random Forest, electric utility-wise
plot_top_predictions(top_15_rf_bev_elec_utility, 'Random Forest - Top 15␣
 ↪Electric Utility-wise BEVs Predictions', 'Year', 'Predicted BEVs', 'Electric␣
 ↪Utility')
plot_top_predictions(top_15_rf_phev_elec_utility, 'Random Forest - Top 15␣
 ↪Electric Utility-wise PHEVs Predictions', 'Year', 'Predicted PHEVs',␣
 ↪'Electric Utility')

# Plot top 15 BEV and PHEV predictions for Linear Regression, county-wise
plot_top_predictions(top_15_lr_bev_county, 'Linear Regression - Top 15␣
 ↪County-wise BEVs Predictions', 'Year', 'Predicted BEVs', 'County')
plot_top_predictions(top_15_lr_phev_county, 'Linear Regression - Top 15␣
 ↪County-wise PHEVs Predictions', 'Year', 'Predicted PHEVs', 'County')

# Plot top 15 BEV and PHEV predictions for Linear Regression, city-wise
plot_top_predictions(top_15_lr_bev_city, 'Linear Regression - Top 15 City-wise␣
 ↪BEVs Predictions', 'Year', 'Predicted BEVs', 'City')
plot_top_predictions(top_15_lr_phev_city, 'Linear Regression - Top 15 City-wise␣
 ↪PHEVs Predictions', 'Year', 'Predicted PHEVs', 'City')

# Plot top 15 BEV and PHEV predictions for Linear Regression, legislative␣
 ↪district-wise
plot_top_predictions(top_15_lr_bev_leg_dist, 'Linear Regression - Top 15␣
 ↪Legislative District-wise BEVs Predictions', 'Year', 'Predicted BEVs',␣
 ↪'Legislative District')
plot_top_predictions(top_15_lr_phev_leg_dist, 'Linear Regression - Top 15␣
 ↪Legislative District-wise PHEVs Predictions', 'Year', 'Predicted PHEVs',␣
 ↪'Legislative District')

# Plot top 15 BEV and PHEV predictions for Linear Regression, electric␣
 ↪utility-wise
plot_top_predictions(top_15_lr_bev_elec_utility, 'Linear Regression - Top 15␣
 ↪Electric Utility-wise BEVs Predictions', 'Year', 'Predicted BEVs', 'Electric␣
 ↪Utility')
plot_top_predictions(top_15_lr_phev_elec_utility, 'Linear Regression - Top 15␣
 ↪Electric Utility-wise PHEVs Predictions', 'Year', 'Predicted PHEVs',␣
 ↪'Electric Utility')
```

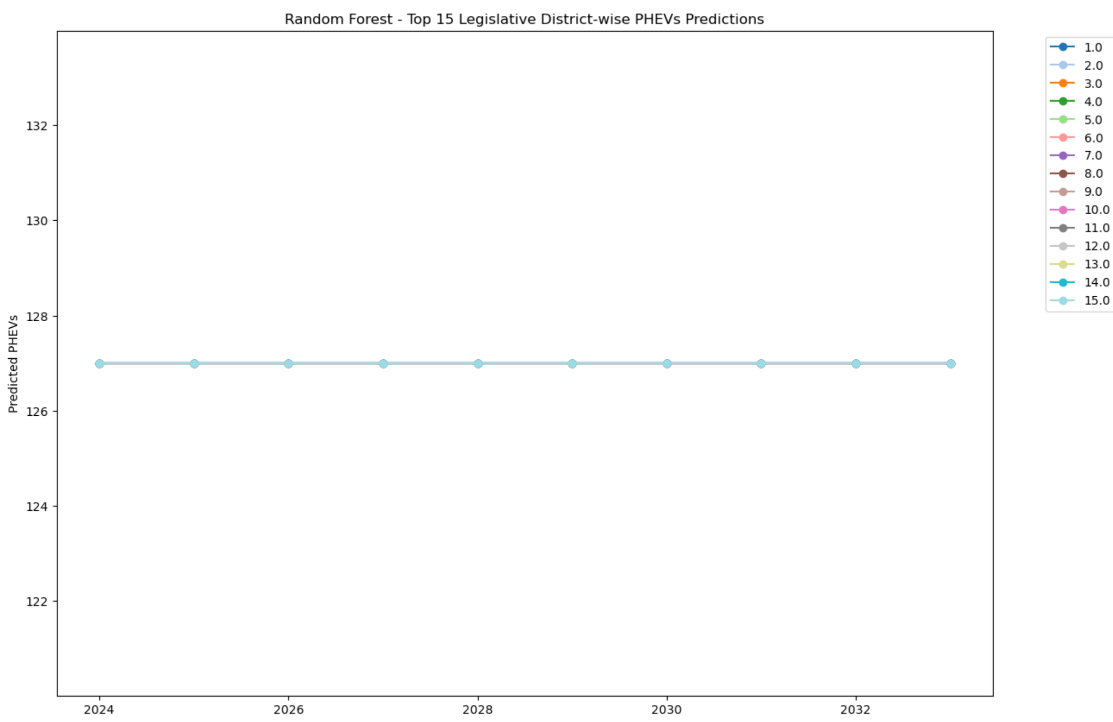

Random Forest - Top 15 County-wise BEVs Predictions
Predicted BEVs
Year
Benton
Chelan
Clark
Cowlitz
Island
Jefferson
King
Kitsap
Pierce
Skagit
Snohomish
Spokane
Thurston
Whatcom
Yakima

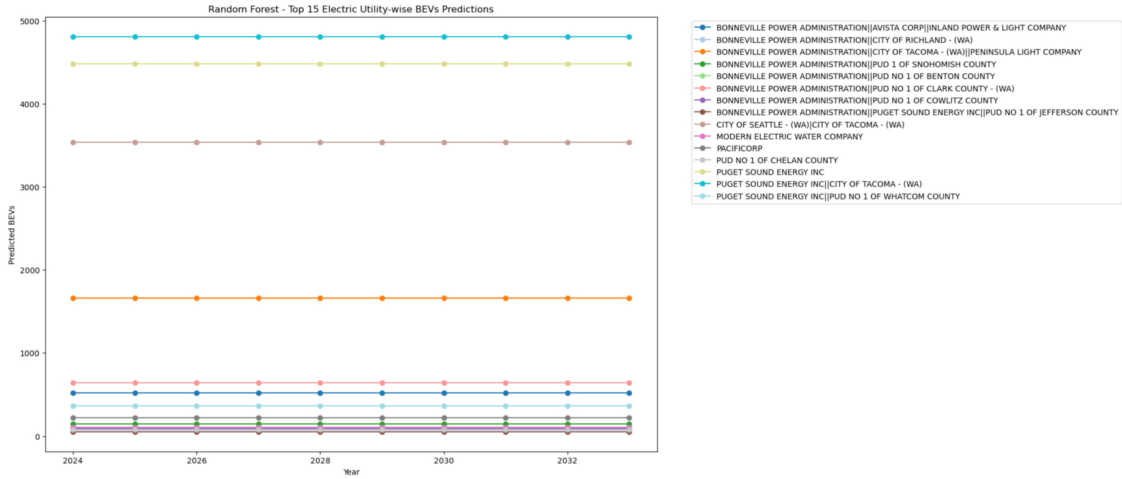

Random Forest - Top 15 County-wise PHEVs Predictions
Predicted PHEVs
Year
Benton
Chelan
Clallam
Clark
Island
King
Kitsap
Lewis
Pierce
Skagit
Snohomish
Spokane
Thurston
Whatcom
Yakima

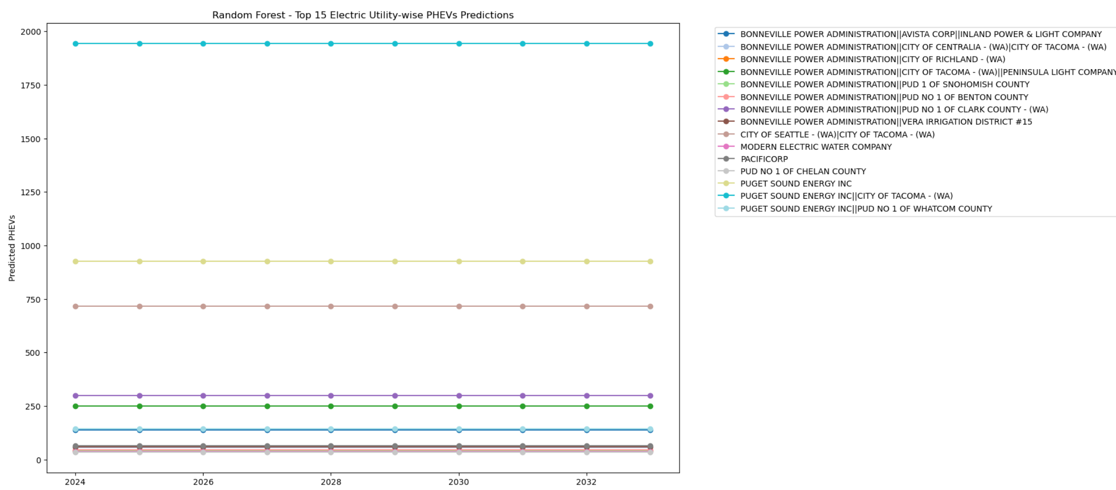

Random Forest - Top 15 City-wise BEVs Predictions
Predicted BEVs
Year
3000
2500
2000
1500
1000
500
2024
2026
2028
2030
2032
Bellevue
Bothell
Bremerton
Everett
Federal Way
Issaquah
Kirkland
Lynnwood
Olympia
Redmond
Renton
Sammamish
Seattle
Tacoma
Woodinville

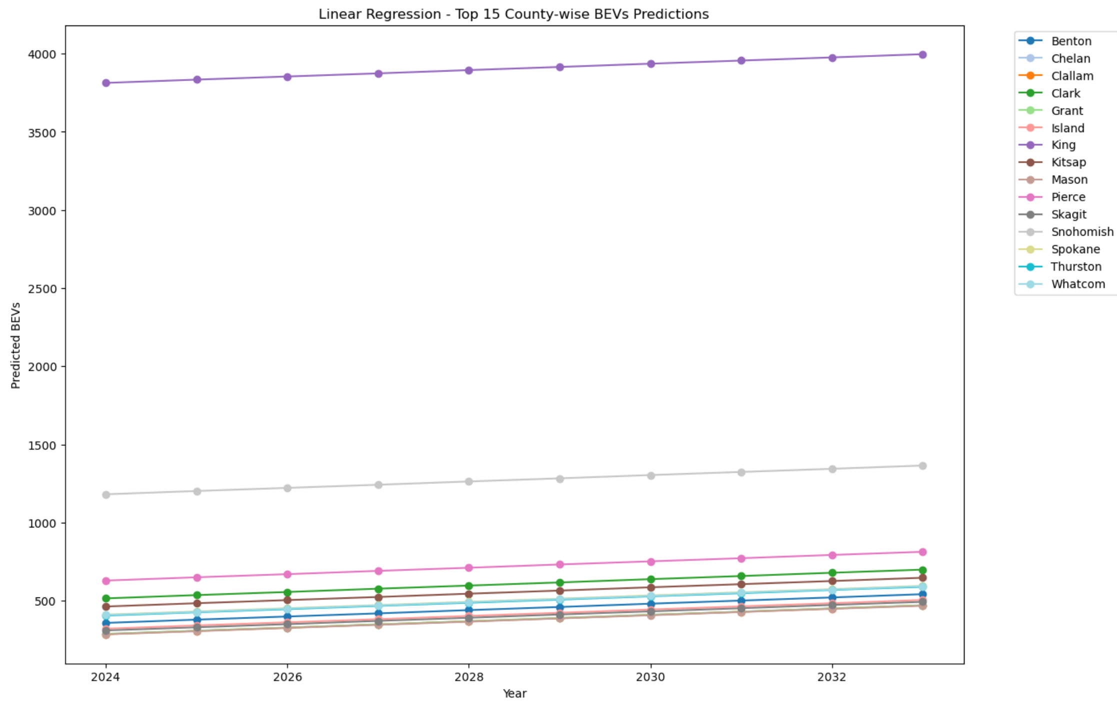

Random Forest - Top 15 City-wise PHEVs Predictions
Predicted PHEVs
Year
700
600
500
400
300
200
100
2024
2026
2028
2030
2032
Bellevue
Bellingham
Bothell
Everett
Issaquah
Kirkland
Olympia
Redmond
Renton
Sammamish
Seattle
Spokane
Tacoma
Tukwila
Vancouver

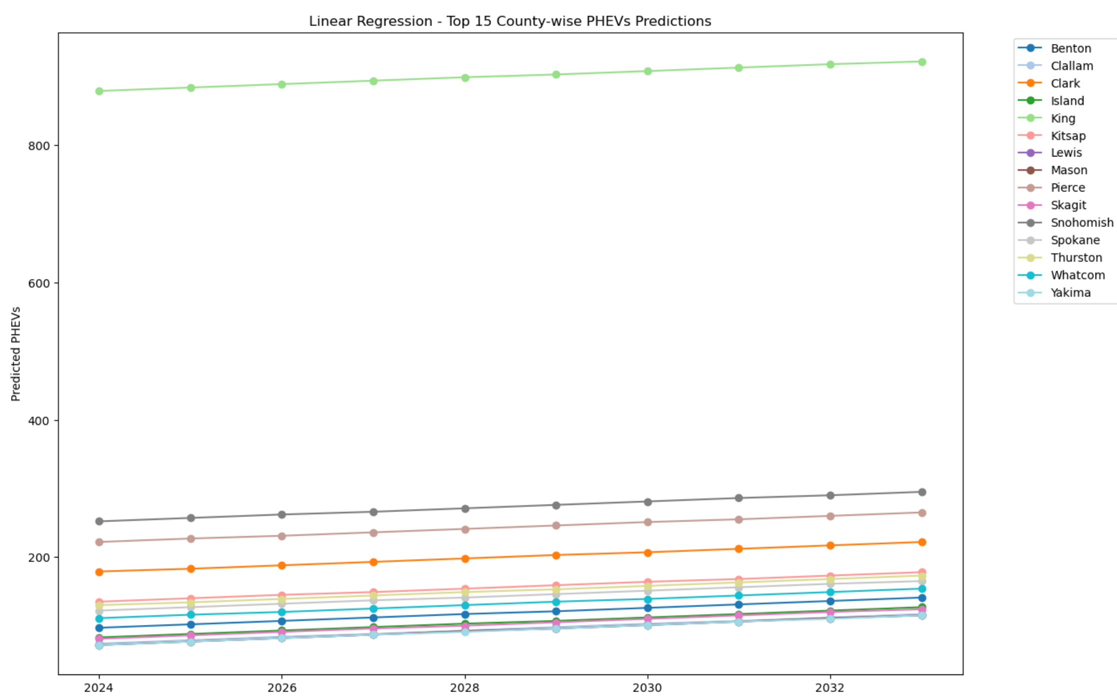

Random Forest - Top 15 Legislative District-wise BEVs Predictions
Predicted BEVs
Year
320
315
310
305
300
295
290
2024
2026
2028
2030
2032
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
11.0
12.0
13.0
14.0
15.0

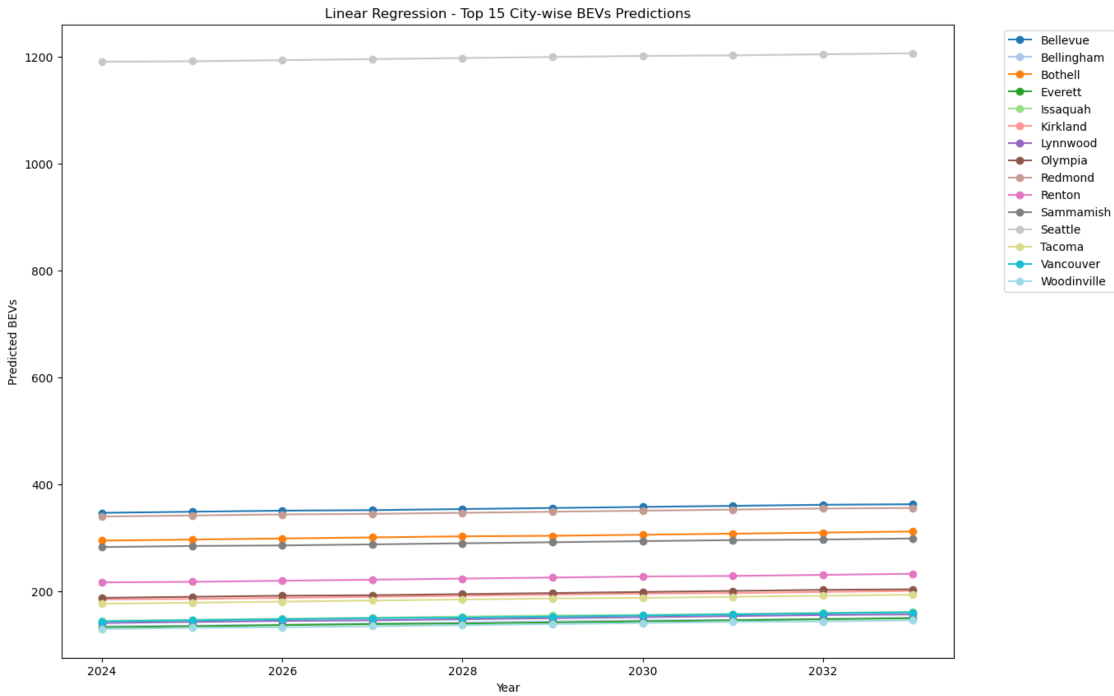

Random Forest - Top 15 Legislative District-wise PHEVs Predictions
Predicted PHEVs
Year
132
130
128
126
124
122
2024
2026
2028
2030
2032
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
11.0
12.0
13.0
14.0
15.0

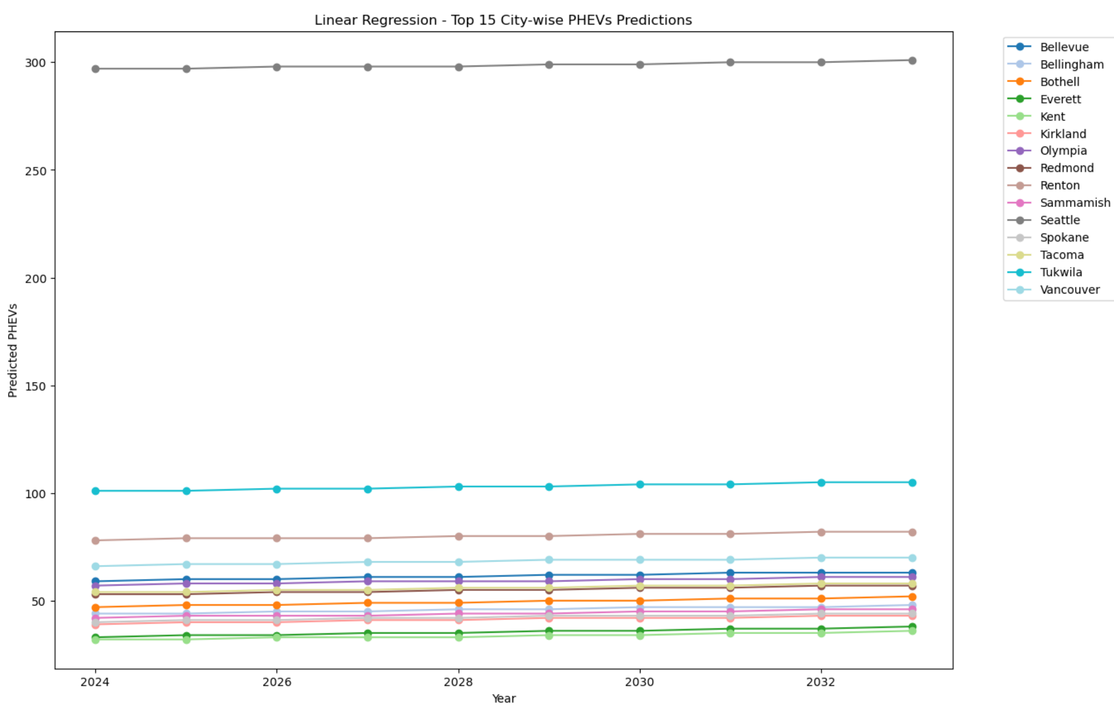

Random Forest - Top 15 Electric Utility-wise BEVs Predictions
Predicted BEVs
Year
0
1000
2000
3000
4000
5000
2024
2026
2028
2030
2032
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||INLAND POWER & LIGHT COMPANY
BONNEVILLE POWER ADMINISTRATION||CITY OF RICHLAND - (WA)
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PENINSULA LIGHT COMPANY
BONNEVILLE POWER ADMINISTRATION||PUD 1 OF SNOHOMISH COUNTY
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF BENTON COUNTY
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLARK COUNTY - (WA)
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF COWLITZ COUNTY
BONNEVILLE POWER ADMINISTRATION||PUGET SOUND ENERGY INC||PUD NO 1 OF JEFFERSON COUNTY
CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)
MODERN ELECTRIC WATER COMPANY
PACIFICORP
PUD NO 1 OF CHELAN COUNTY
PUGET SOUND ENERGY INC
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY

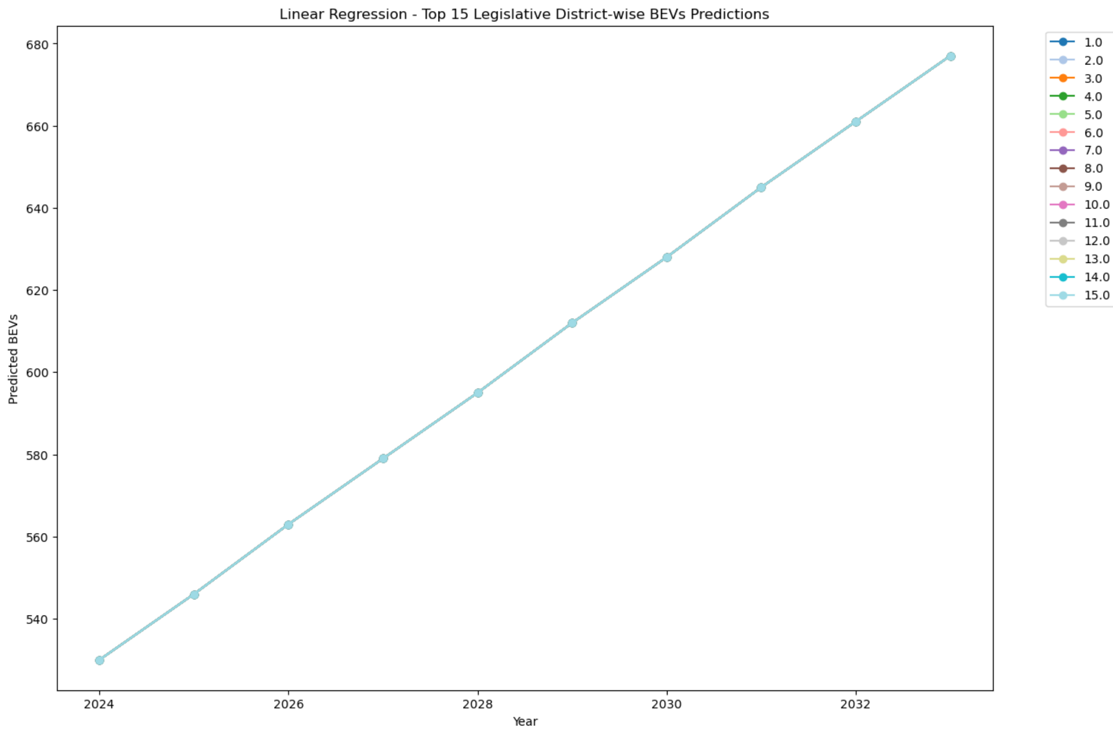

Random Forest - Top 15 Electric Utility-wise PHEVs Predictions
Predicted PHEVs
Year
0
250
500
750
1000
1250
1500
1750
2000
2024
2026
2028
2030
2032
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||INLAND POWER & LIGHT COMPANY
BONNEVILLE POWER ADMINISTRATION||CITY OF CENTRALIA - (WA)|CITY OF TACOMA - (WA)
BONNEVILLE POWER ADMINISTRATION||CITY OF RICHLAND - (WA)
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PENINSULA LIGHT COMPANY
BONNEVILLE POWER ADMINISTRATION||PUD 1 OF SNOHOMISH COUNTY
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF BENTON COUNTY
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLARK COUNTY - (WA)
BONNEVILLE POWER ADMINISTRATION||VERA IRRIGATION DISTRICT #15
CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)
MODERN ELECTRIC WATER COMPANY
PACIFICORP
PUD NO 1 OF CHELAN COUNTY
PUGET SOUND ENERGY INC
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY

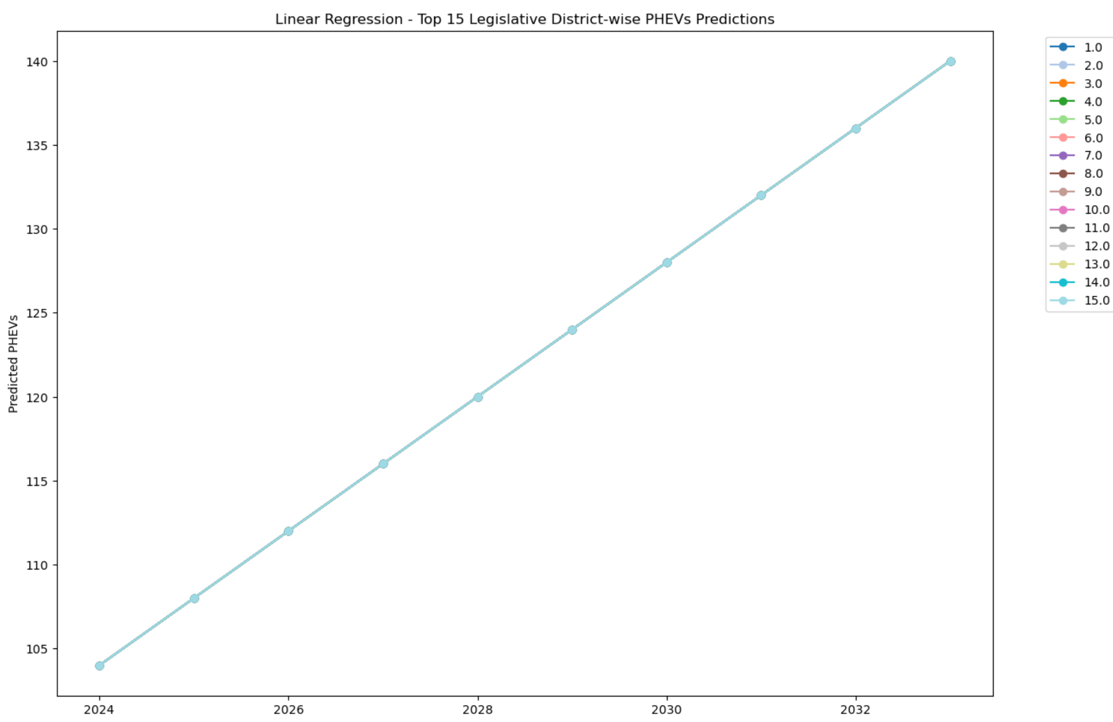

Linear Regression - Top 15 County-wise BEVs Predictions
Predicted BEVs
Year
4000
3500
3000
2500
2000
1500
1000
500
2024
2026
2028
2030
2032
Benton
Chelan
Clallam
Clark
Grant
Island
King
Kitsap
Mason
Pierce
Skagit
Snohomish
Spokane
Thurston
Whatcom


Linear Regression - Top 15 County-wise PHEVs Predictions
Predicted PHEVs
Year
800
600
400
200
2024
2026
2028
2030
2032
Benton
Clallam
Clark
Island
King
Kitsap
Lewis
Mason
Pierce
Skagit
Snohomish
Spokane
Thurston
Whatcom
Yakima


Linear Regression - Top 15 City-wise BEVs Predictions
Predicted BEVs
Year
1200
1000
800
600
400
200
2024
2026
2028
2030
2032
Bellevue
Bellingham
Bothell
Everett
Issaquah
Kirkland
Lynnwood
Olympia
Redmond
Renton
Sammamish
Seattle
Tacoma
Vancouver
Woodinville


Linear Regression - Top 15 City-wise PHEVs Predictions
Predicted PHEVs
Year
300
250
200
150
100
50
2024
2026
2028
2030
2032
Bellevue
Bellingham
Bothell
Everett
Kent
Kirkland
Olympia
Redmond
Renton
Sammamish
Seattle
Spokane
Tacoma
Tukwila
Vancouver


Linear Regression - Top 15 Legislative District-wise BEVs Predictions
Predicted BEVs
Year
540
560
580
600
620
640
660
680
2024
2026
2028
2030
2032
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
11.0
12.0
13.0
14.0
15.0


Linear Regression - Top 15 Legislative District-wise PHEVs Predictions
Predicted PHEVs
Year
105
110
115
120
125
130
135
140
2024
2026
2028
2030
2032
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
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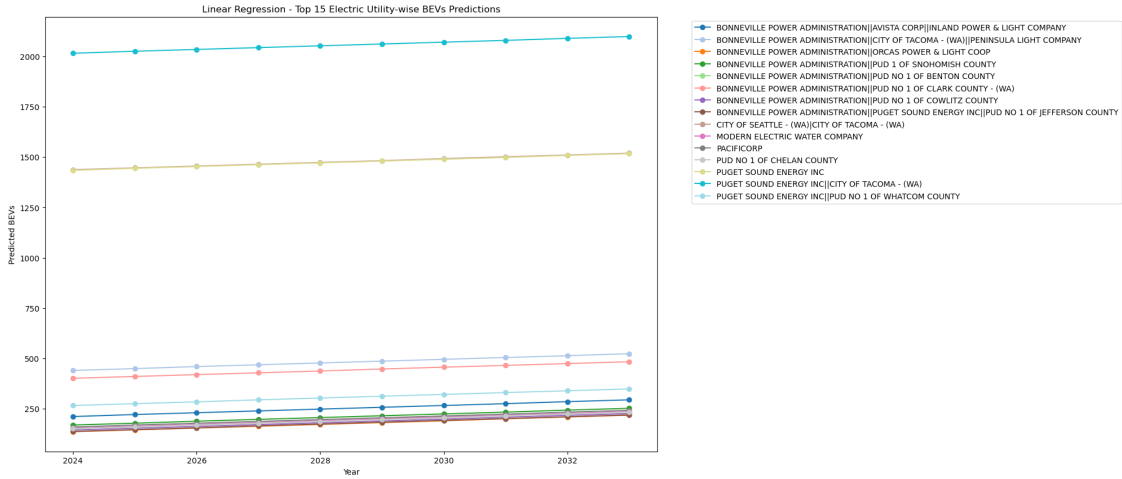
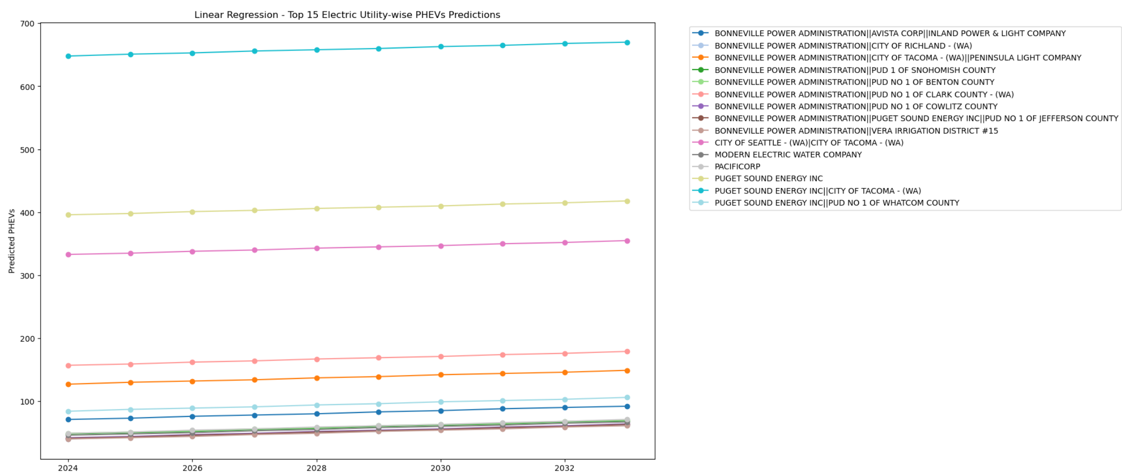
12.0
13.0
14.0
15.0





Here are some conclusions drawn from the output of the Random Forest and Linear Regression predictions for Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) for different categories:

0.0.1 General Observations:

1. **Linear Regression Predictions:**
    - **Increasing Trend:** Linear regression models show a clear increasing trend in BEVs and PHEVs across all categories over the years from 2024 to 2033. This indicates a steady growth in the adoption of electric vehicles.
    - **County-wise Analysis:** Larger counties such as King, Pierce, and Snohomish have higher predicted values for BEVs and PHEVs, reflecting their larger populations and possibly better infrastructure for electric vehicles.
    - **City-wise Analysis:** Cities within these counties also show increasing trends in electric vehicle adoption. Major cities likely have better facilities and incentives encouraging the

switch to electric vehicles.

- **Legislative District-wise Analysis:** Predictions are uniform across all legislative districts
- **Electric Utility-wise Analysis:** Certain utilities, like Puget Sound Energy Inc., show higher predicted values, indicating areas served by these utilities may have better infrastructure or incentives for electric vehicles.

2. **Random Forest Predictions:**
   - **Static Predictions:** Random Forest model predictions are static over the years, indicating no growth in the adoption of electric vehicles. This suggests that the model might not be capturing the temporal growth trends adequately.
   - **County-wise Analysis:** High predicted values for BEVs and PHEVs in counties like King, Pierce, and Snohomish indicate these counties have high electric vehicle adoption. However, the lack of growth over the years suggests potential limitations in the model.
   - **City-wise Analysis:** Many cities have zero predicted values, which might indicate a limitation in the model's ability to capture data at a granular city level or a lack of historical data for those cities.
   - **Legislative District-wise Analysis:** Similar to the city-wise predictions, legislative district-wise predictions show static values, reflecting the same limitation of the model.
   - **Electric Utility-wise Analysis:** Certain utilities, like Puget Sound Energy Inc., show higher predicted values, but again, there is no growth over the years.

0.0.2 Specific Insights:

1. **King County:**
   - **Linear Regression:** Predicted to see the most significant increase in BEVs, from 3813 in 2024 to 3997 in 2033.
   - **Random Forest:** Shows a static prediction of 19035 BEVs consistently from 2024 to 2033, indicating high current adoption but not reflecting future growth.
2. **Pierce County:**
   - **Linear Regression:** Predicted increase from 629 BEVs in 2024 to 813 BEVs in 2033.
   - **Random Forest:** Static prediction of 931 BEVs from 2024 to 2033.
3. **Electric Utilities:**
   - **Linear Regression:** Shows a gradual increase in predictions, with utilities like Puget Sound Energy Inc. growing from 1434 BEVs in 2024 to 1517 BEVs in 2033.
   - **Random Forest:** Static predictions, with Puget Sound Energy Inc. showing 4482 BEVs consistently over the years.

Conclusion

An analysis after using existing geographical features like City, County, Legislative District, and Electric Utility shows that while we can get some idea of electric vehicle (EV) adoption trends, the predictions aren't as accurate as we would like. The current models, struggle to fit the data well indicating that there is still room for improvement.

To really understand and predict how many people will start using electric cars, we need to look beyond just where they live. We need to incorporate additional factors that paint a fuller picture of the people and the economy in those areas. Here are some key factors that could make our predictions much better:

Population Growth: Areas with rapid population growth are likely to see more new vehicles, including EVs. **Income Levels:** Higher income levels mean more people can afford electric vehicles. **Average Household Income:** Places with higher disposable income tend to have higher EV adoption rates. **Unemployment Rate:** Economic stability, shown by lower unemployment rates, can influence people's ability to buy new cars. **Electricity Costs:** Lower electricity costs can make electric vehicles more appealing compared to traditional fuel vehicles.

Adding these demographic and economic factors will help us create a more accurate and reliable prediction model. This, in turn, will help policymakers and businesses make better decisions about where to focus their efforts and resources to promote electric vehicle adoption.

Recommendations

To improve our predictions and provide actionable insights, we should:

Gather More Data: Collect information on population growth, income levels, average household income, unemployment rates, and electricity costs. Integrate New Features: Add these new data points to our existing dataset and prepare them for analysis.

Retrain Models: Use the enhanced dataset to train our machine learning models and evaluate the improvements. **Select Key Features:** Identify which new features have the most impact on predictions using methods like feature importance scores.

By incorporating these additional demographic and economic factors, we'll be able to make much more accurate predictions. This will help in strategically promoting electric vehicle adoption, leading to a cleaner, more sustainable future.

Research Question No.3

How do geographic location and local infrastructure (electric utilities) impact EV adoption in Washington?

STEP I

Creating New Features for EV Counts by Geographic and Infrastructure Categories

[ ]:
```
import warnings
import pandas as pd

# suppressing any unnecessary future warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)

# creating a copy of the electric_v dataset. Further analysis will be done on␣
↪'elec_dataset'
elec_dataset = electric_v

# Create a new feature for the number of EVs per county
ev_count_per_county = elec_dataset.groupby('County')['DOL Vehicle ID'].count().
↪reset_index()
# naming the columns of 'ev_count_per_county'
ev_count_per_county.columns = ['County', 'EV_Count_County']
# Merge this feature back into the elec_dataset
```

```
elec_dataset = elec_dataset.merge(ev_count_per_county, on = 'County', how =␣
↪'left')

# Create a new feature for the number of EVs per city
ev_count_per_city = elec_dataset.groupby('City')['DOL Vehicle ID'].count().
↪reset_index()
# naming the columns of 'ev_count_per_city'
ev_count_per_city.columns = ['City', 'EV_Count_City']
# Merge this feature back into the elec_dataset
elec_dataset =elec_dataset.merge(ev_count_per_city, on = 'City', how = 'left')

# Create a new feature for the number of EVs per legislative district
ev_count_per_leg_dist = elec_dataset.groupby('Legislative District')['DOL␣
↪Vehicle ID'].count().reset_index()
# naming the columns of 'ev_count_per_leg_dist'
ev_count_per_leg_dist.columns = ['Legislative District', 'EV_Count_Leg_Dist']
# Merge this feature back into the elec_dataset
elec_dataset =elec_dataset.merge(ev_count_per_leg_dist, on = 'Legislative␣
↪District', how = 'left')

# Create a new feature for the number of EVs per electric utility
ev_count_per_utility = elec_dataset.groupby('Electric Utility')['DOL Vehicle␣
↪ID'].count().reset_index()
# naming the columns of 'ev_count_per_utility'
ev_count_per_utility.columns = ['Electric Utility', 'EV_Count_Utility']
# Merge this feature back into the elec_dataset
elec_dataset =elec_dataset.merge(ev_count_per_utility, on = 'Electric Utility',␣
↪how = 'left')
```

New features that represent the count of electric vehicles (EVs) in different geographic and infrastructure-related categories. These new features are essential for understanding the geographic and infrastructural distribution of EV adoption and also for further analysis.

STEP II

Summary Statistics and Visualization

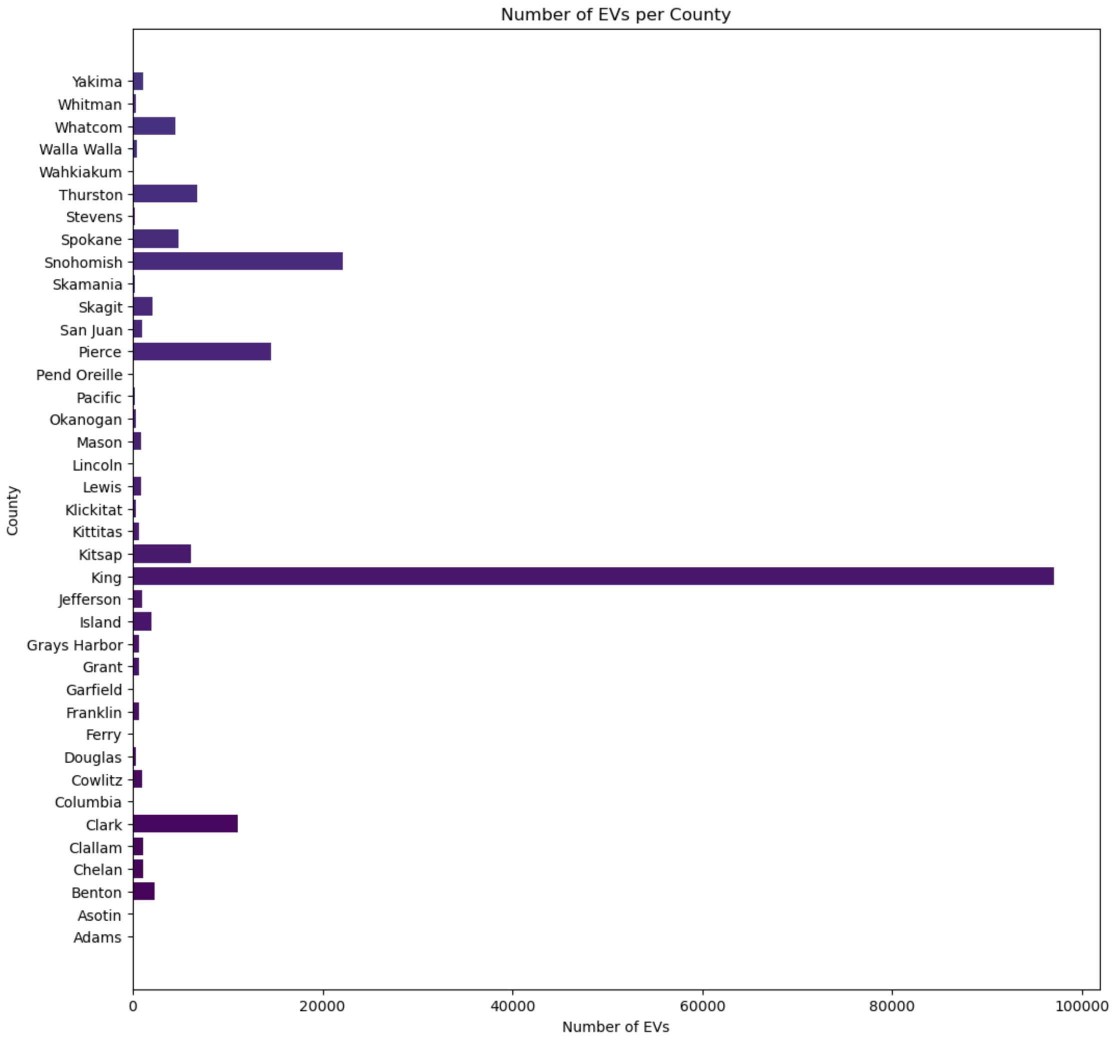
```
[ ]: import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import numpy as np

# suppressing any unnecessary future warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)


# printing the summary statistics of 'elec_dataset'
print(elec_dataset.describe())
```

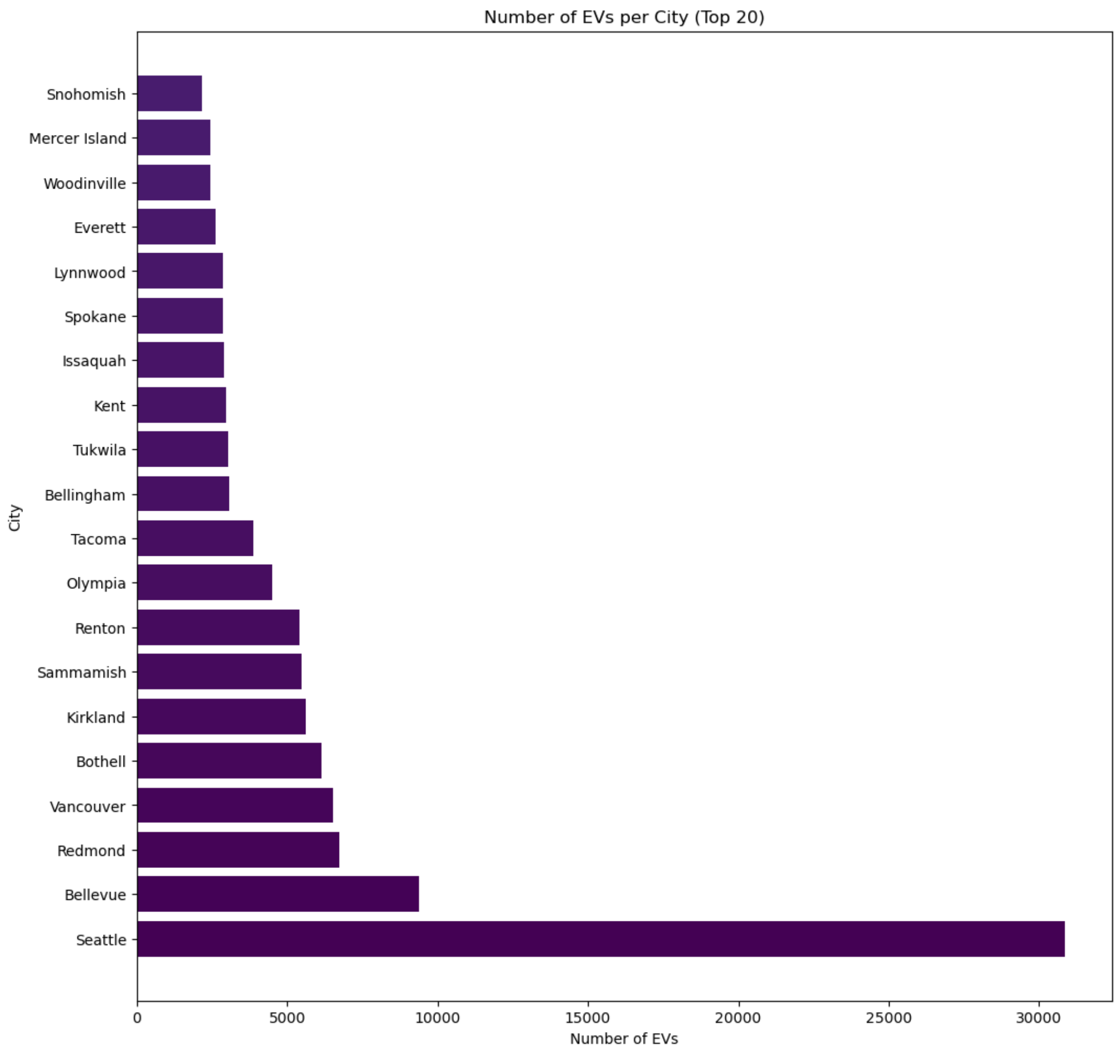
```
# creating bar plots for categorical variables
# horizontal bar plot for 'ev_count_per_county' data
plt.figure(figsize=(12, 12))
# bar plot for ev count per county. Returns an array of colors, one for each␣
↪county, creating a gradient effect
plt.barh(ev_count_per_county['County'], ev_count_per_county['EV_Count_County'],␣
↪color=plt.cm.viridis(range(len(ev_count_per_county))))
plt.title('Number of EVs per County')
plt.xlabel('Number of EVs')
plt.ylabel('County')
plt.show()

# horizontal bar plot for 'ev_count_per_city' data (Top 20)
top_city_counts = ev_count_per_city.nlargest(20, 'EV_Count_City')
plt.figure(figsize=(12, 12))
# bar plot for ev count per city. Returns an array of colors, one for each␣
↪city, creating a gradient effect
plt.barh(top_city_counts['City'], top_city_counts['EV_Count_City'], color=plt.
↪cm.viridis(range(len(top_city_counts))))
plt.title(f'Number of EVs per City (Top 20)')
plt.xlabel('Number of EVs')
plt.ylabel('City')
plt.show()

# horizontal bar plot for 'ev_count_per_leg_dist' data
plt.figure(figsize=(12, 12))
y_pos = np.arange(len(ev_count_per_leg_dist['Legislative District']))
# bar plot for ev count per legislative district. Returns an array of colors,␣
↪one for each city, creating a gradient effect
plt.barh(ev_count_per_leg_dist['Legislative District'],␣
↪ev_count_per_leg_dist['EV_Count_Leg_Dist'], color = plt.cm.
↪viridis(range(len(ev_count_per_leg_dist))))
# making sure the y-axis has all the legislative districts
plt.yticks(y_pos, ev_count_per_leg_dist['Legislative District'])
plt.title('Number of EVs per Legislative District')
plt.xlabel('Number of EVs')
plt.ylabel('Legislative District')
plt.show()


#  horizontal bar plot for 'ev_count_per_utility' data
plt.figure(figsize=(12, 12))
# bar plot for ev count per legislative district. Returns an array of colors,␣
↪one for each legislative district, creating a gradient effect
```

```
plt.barh(ev_count_per_utility['Electric Utility'],␣
  ↪ev_count_per_utility['EV_Count_Utility'], color = plt.cm.
  ↪viridis(range(len(ev_count_per_utility))))
plt.title('Number of EVs per Electric Utility')
plt.xlabel('Number of EVs')
plt.ylabel('Electric Utility')
plt.show()


# creating a list of geographic and infrastructure related features
feature_var = ['EV_Count_County', 'EV_Count_City', 'EV_Count_Utility',␣
  ↪'EV_Count_Leg_Dist']

# creating box plots for each feature to identify outliers
plt.figure(figsize=(15, 10))
# This is a for-loop that iterates over the feature_var list. i is the index of␣
  ↪the current item, and column is the name of the current column.
for i, column in enumerate(feature_var):
    # creates a subplot grid with 3 rows and 3 columns and places the current␣
  ↪plot in the (i+1)th position
    plt.subplot(3, 3, i+1)
    # creating verticle boxplot for current column data in 'elec_dataset'
    sns.boxplot(y=elec_dataset[column])
    plt.title(column)
plt.suptitle("Identify Outliers", fontsize = 16)
plt.tight_layout()
plt.show()
```

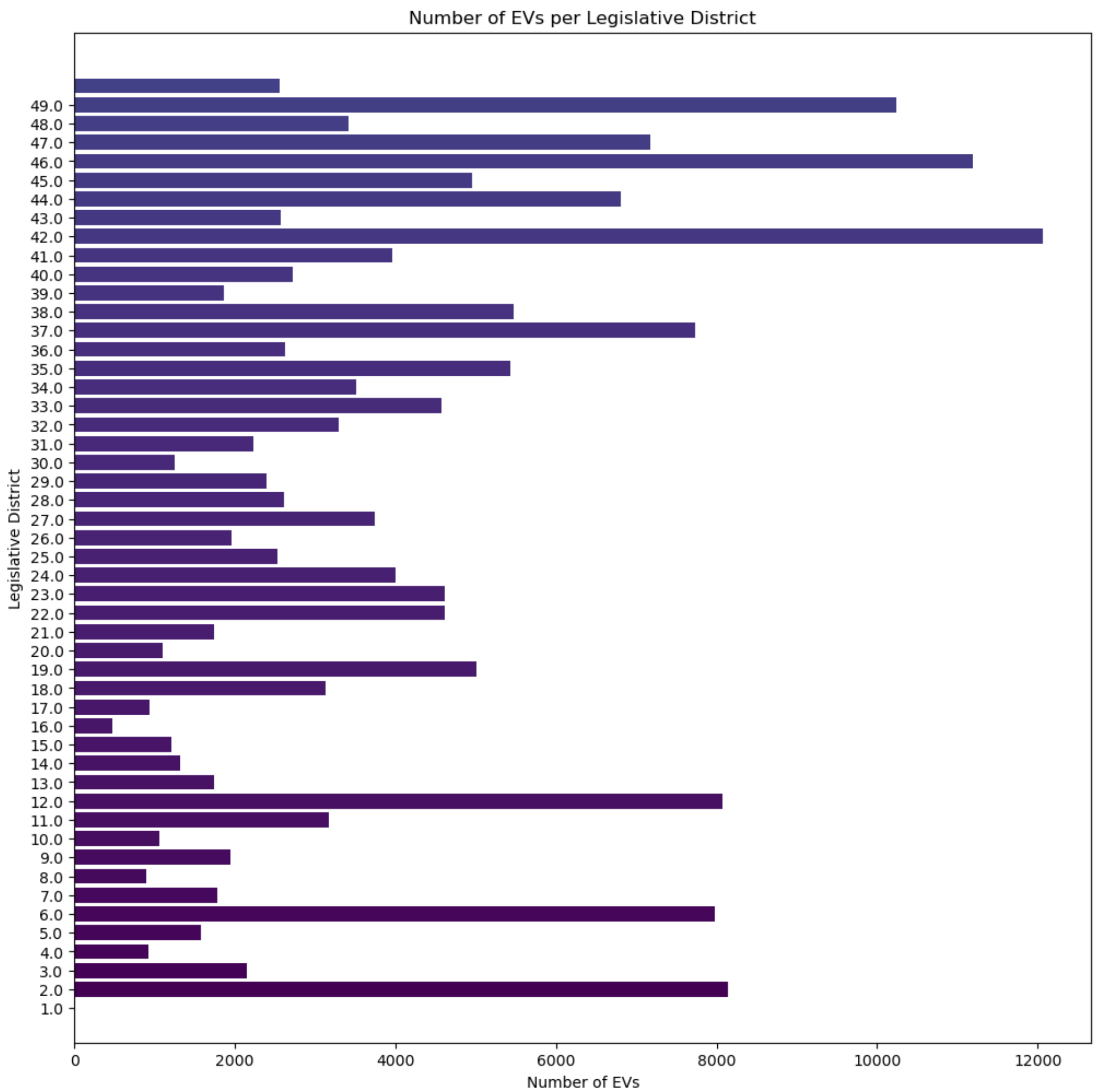
```
         Postal Code     Model Year  Electric Range  DOL Vehicle ID  \
count  186471.000000  186471.000000   186471.000000    1.864710e+05
mean    98261.647527    2020.661148       56.683731    2.225855e+08
std       304.624225       2.991387       90.771207    7.463921e+07
min     98001.000000    1997.000000        0.000000    4.385000e+03
25%     98052.000000    2019.000000        0.000000    1.851589e+08
50%     98122.000000    2022.000000        0.000000    2.302291e+08
75%     98371.000000    2023.000000       73.000000    2.578035e+08
max     99403.000000    2024.000000      337.000000    4.792548e+08

            Latitude      Longitude           Year  EV_Count_County  \
count  186471.000000  186471.000000  186471.000000    186471.000000
mean       47.462836    -122.079426    2020.661148     55679.203978
std         0.610882       1.020595       2.991387     43378.814056
min        45.595997    -124.614078    1997.000000         3.000000
25%        47.358111    -122.395519    2019.000000     11005.000000
50%        47.610347    -122.275332    2022.000000     97012.000000
75%        47.721052    -122.136803    2023.000000     97012.000000
max        48.992052    -117.059519    2024.000000     97012.000000
```

	EV_Count_City	EV_Count_Leg_Dist	EV_Count_Utility
count	186471.000000	186471.000000	186471.000000
mean	7684.912233	5847.565257	40248.744121
std	10612.304516	3273.810221	25225.556104
min	1.000000	471.000000	1.000000
25%	946.000000	3136.000000	10753.000000
50%	2967.000000	5008.000000	37798.000000
75%	6747.000000	8072.000000	69049.000000
max	30873.000000	12066.000000	69049.000000

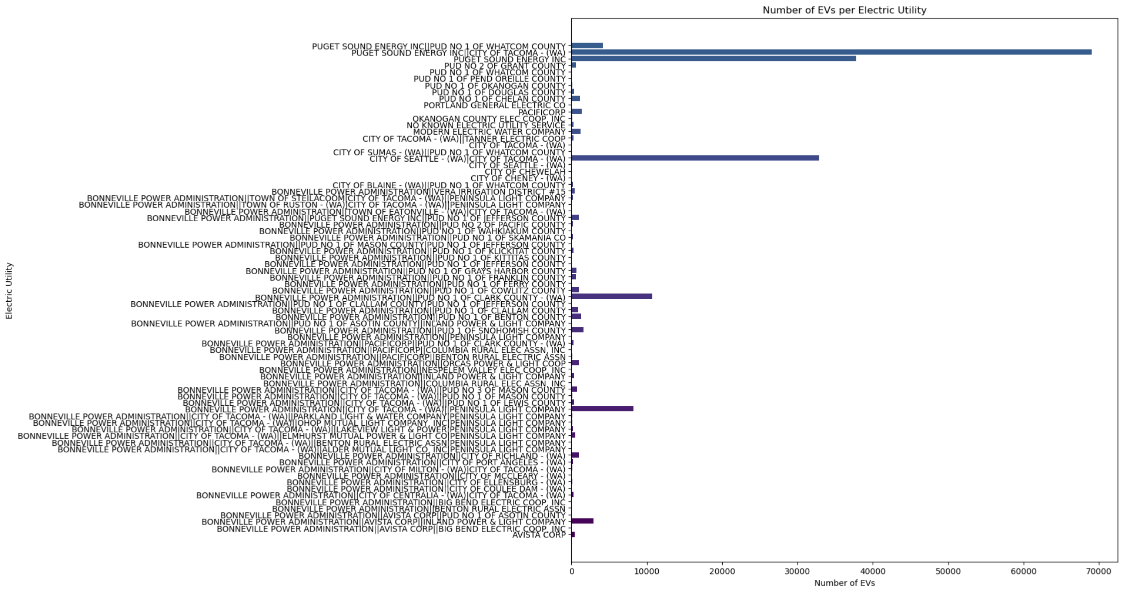


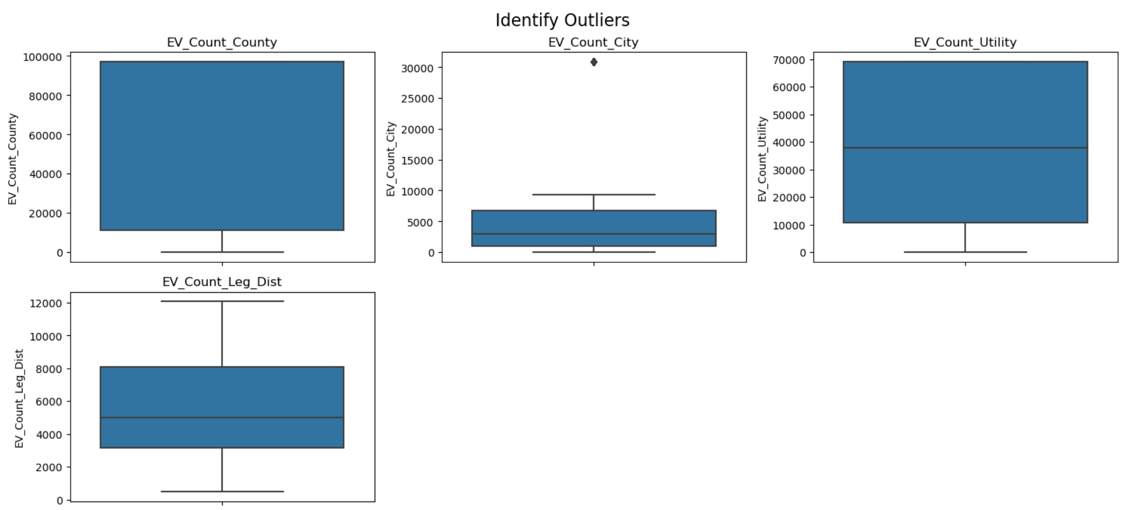


Number of EVs per City (Top 20)
City
Snohomish
Mercer Island
Woodinville
Everett
Lynnwood
Spokane
Issaquah
Kent
Tukwila
Bellingham
Tacoma
Olympia
Renton
Sammamish
Kirkland
Bothell
Vancouver
Redmond
Bellevue
Seattle
0
5000
10000
15000
20000
25000
30000
Number of EVs



Number of EVs per Legislative District
Legislative District
Number of EVs
49.0
48.0
47.0
46.0
45.0
44.0
43.0
42.0
41.0
40.0
39.0
38.0
37.0
36.0
35.0
34.0
33.0
32.0
31.0
30.0
29.0
28.0
27.0
26.0
25.0
24.0
23.0
22.0
21.0
20.0
19.0
18.0
17.0
16.0
15.0
14.0
13.0
12.0
11.0
10.0
9.0
8.0
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0
2000
4000
6000
8000
10000
12000





Interpretation and Observations:

1. **Summary Statistics:**
   - **Postal Code, Model Year, Electric Range, DOL Vehicle ID:**
     - The data set comprises 186,471 observations.
     - The average model year is around 2020.66, suggesting most vehicles are recent.
     - Electric range varies significantly with a mean of 56.68 miles but a high standard deviation, indicating diverse electric vehicle models.
     - The DOL Vehicle ID is a unique identifier for each vehicle.
   - **Latitude and Longitude:**
     - The data points primarily fall within the latitude range of 45.59 to 48.99 and the

longitude range of -124.61 to -117.05, which corresponds to the state of Washington.
- **Year:**
  - The data spans from 1997 to 2024, indicating the registration year of the vehicles.
- **EV Counts (County, City, Legislative District, Utility):**
  - There is substantial variability in the number of EVs across different geographic and infrastructure categories.

2. **Bar Plots:**
   - **EVs per County:**
     - King County has the highest number of electric vehicles, followed by Pierce and Snohomish counties.
   - **EVs per City:**
     - Seattle leads significantly in EV adoption, followed by Bellevue and Redmond.
   - **EVs per Legislative District:**
     - Legislative districts 1, 5, 6, 7, 8, 10, and 11 show high numbers of EV adoption.
   - **EVs per Electric Utility:**
     - Puget Sound Energy and some specific PUDs (Public Utility Districts) dominate EV adoption numbers. This indicates the influence of utility providers on EV adoption rates.
3. **Box Plots for Identifying Outliers:**
   - **EV_Count_County, EV_Count_City, EV_Count_Leg_Dist, EV_Count_Utility:**
     - Significant outliers exist in the `EV_Count_City` dataset, particularly for cities with exceptionally high EV adoption rates.
     - The other categories also show variability but are more uniformly distributed compared to the city-level data.

Overall Interpretation:

- **Geographic Influence:**
  - The distribution of EVs is highly uneven across different counties, cities, and legislative districts. King County and Seattle are significant hubs of EV adoption, possibly due to better infrastructure, higher population density, and greater environmental awareness.
- **Local Infrastructure Influence:**
  - Electric utility companies play a crucial role in EV adoption. Puget Sound Energy, which serves a large population, shows the highest adoption rates. The presence of charging infrastructure and the utility company's policies likely influence this.
- **Insights from Visualizations:**
  - The visualizations highlight clusters of high EV adoption and identify outliers. The regions with the highest EV counts also correspond to areas with better infrastructure and higher population densities.
- **Summary Statistics Insights:**
  - Most electric vehicles are recent models, and there is a diverse range of electric vehicle types with different ranges.

Summary:

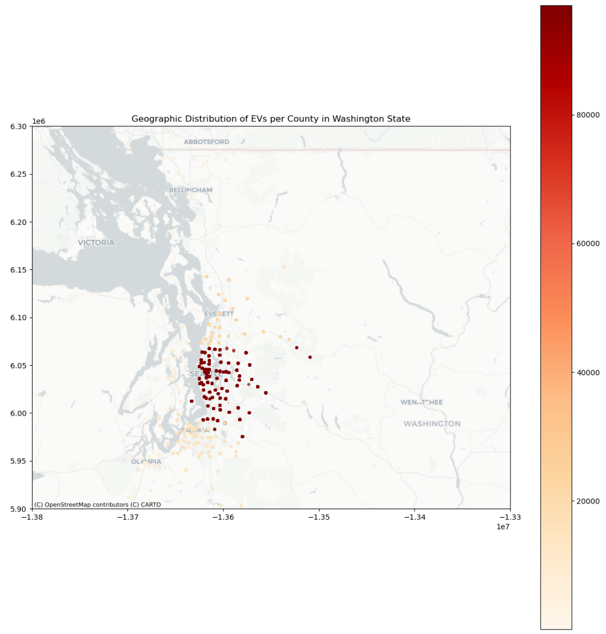
- **Geographic Location:** Proximity to urban centers like Seattle and Bellevue and populous counties like King County significantly impact EV adoption.
- **Local Infrastructure:** The availability and policies of local electric utilities like Puget Sound Energy also play a crucial role in EV adoption rates.

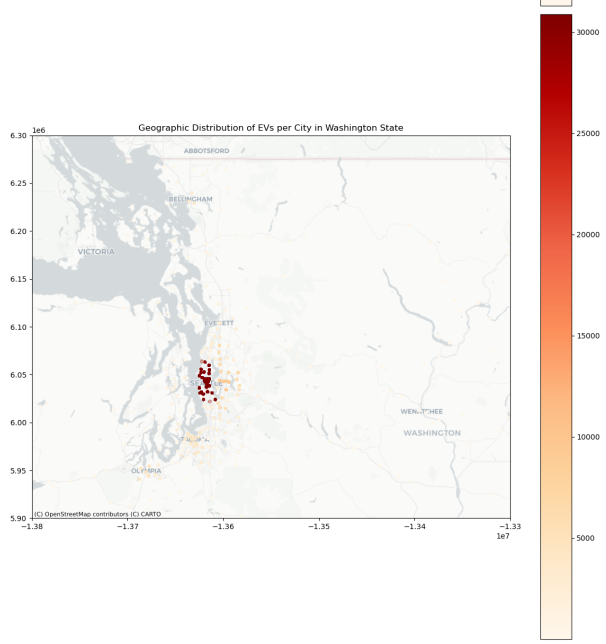
STEP III

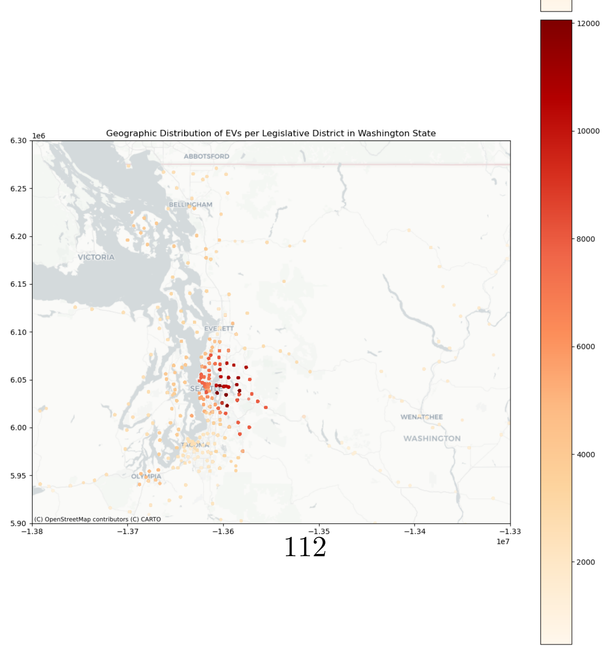
Geographic Validation

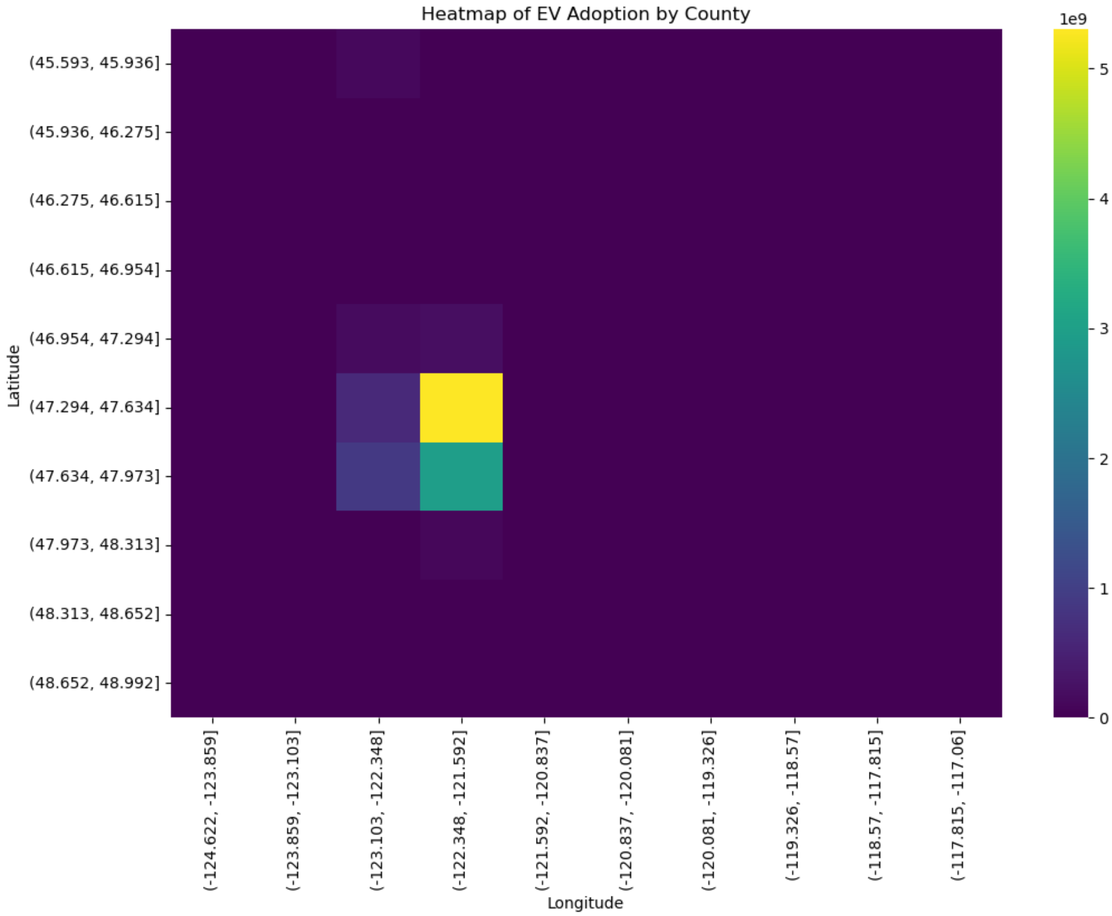
```
[ ]: # importing the necessary libraries
import geopandas as gpd
import matplotlib.pyplot as plt
from shapely.geometry import Point
import contextily as ctx

# Create a GeoDataFrame with point geometries based on Longitude and Latitude
# creates a list of point objects for each row in the dataset using longitude␣
 ↪and latitude.
geometry = [Point(xy) for xy in zip(elec_dataset['Longitude'],␣
 ↪elec_dataset['Latitude'])]
# create a GeoDataFrame from the dataset, setting the geometry to the points␣
 ↪and the coordinate reference system (CRS) to EPSG:4326 (WGS 84).
geo_df = gpd.GeoDataFrame(elec_dataset, geometry=geometry, crs="EPSG:4326")

# Filter the GeoDataframe for Washington state
washington_geo_df = geo_df[geo_df['State'] == 'WA']

# Convert the GeoDataFrame to Web Mercator (EPSG:3857) for contextily basemap␣
 ↪compatibility
washington_geo_df = washington_geo_df.to_crs(epsg=3857)

# Defining a function named 'plot_geographic_distribution' to plot the␣
 ↪geographic distribution of a specified column
def plot_geographic_distribution(column, title, ax, zoom=8):
    # Plot the data points, color-coded by the specified column
    washington_geo_df.plot(column=column, ax=ax, legend=True, cmap='OrRd',␣
 ↪markersize=10, alpha=0.6)
    # Add a basemap using the contextily library
    ctx.add_basemap(ax, source=ctx.providers.CartoDB.Positron, zoom=zoom)
    # Set the x and y axis limits to focus on Washington state
    ax.set_xlim([-13800000, -13300000])
    ax.set_ylim([5900000, 6300000])
    # Set the title for the subplot
    ax.set_title(title)

# Create a figure with 3 subplots, arranged vertically, each with size 12x36␣
 ↪inches
fig, ax = plt.subplots(3, 1, figsize=(12, 36))

# Plot the EV data per County
plot_geographic_distribution('EV_Count_County', 'Geographic Distribution of EVs␣
 ↪per County in Washington State', ax[0])
```

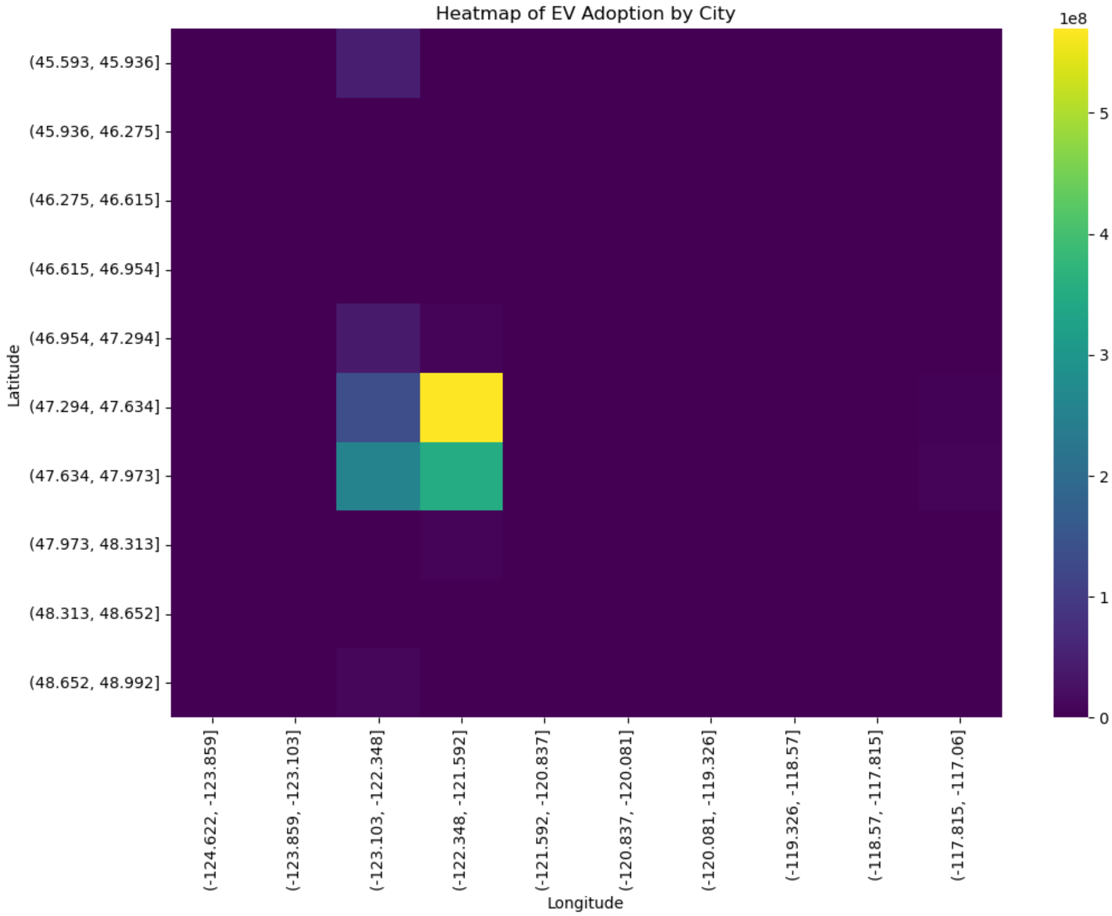
```
# Plot the EV data per City
plot_geographic_distribution('EV_Count_City', 'Geographic Distribution of EVs␣
↪per City in Washington State', ax[1])

# Plot the EV data per Legislative District
plot_geographic_distribution('EV_Count_Leg_Dist', 'Geographic Distribution of␣
↪EVs per Legislative District in Washington State', ax[2])

# Adjust the layout of the plots to fit them neatly within the figure
plt.tight_layout()
# Display the figure
plt.show()

# Create categorical bins for latitude and longitude
elec_dataset['Latitude_bin'] = pd.cut(elec_dataset['Latitude'], bins=10)
elec_dataset['Longitude_bin'] = pd.cut(elec_dataset['Longitude'], bins=10)

# Heatmaps for EV adoption by County, City, and Legislative District
for feature, title in [('EV_Count_County', 'Heatmap of EV Adoption by County'),
                       ('EV_Count_City', 'Heatmap of EV Adoption by City'),
                       ('EV_Count_Leg_Dist', 'Heatmap of EV Adoption by␣
↪Legislative District')]:
    plt.figure(figsize=(12, 8))
    sns.heatmap(elec_dataset.pivot_table(index='Latitude_bin',␣
↪columns='Longitude_bin', values=feature, aggfunc='sum'), cmap='viridis')
    plt.title(title)
    plt.xlabel('Longitude')
    plt.ylabel('Latitude')
    plt.show()
```


Geographic Distribution of EVs per County in Washington State
ABBOTSFORD
BELLINGHAM
VICTORIA
EVERETT
WENATCHEE
WASHINGTON
OLYMPIA
(C) OpenStreetMap contributors (C) CARTO
1e6
6.30
6.25
6.20
6.15
6.10
6.05
6.00
5.95
5.90
−1.38
−1.37
−1.36
−1.35
−1.34
−1.33
1e7
80000
60000
40000
20000

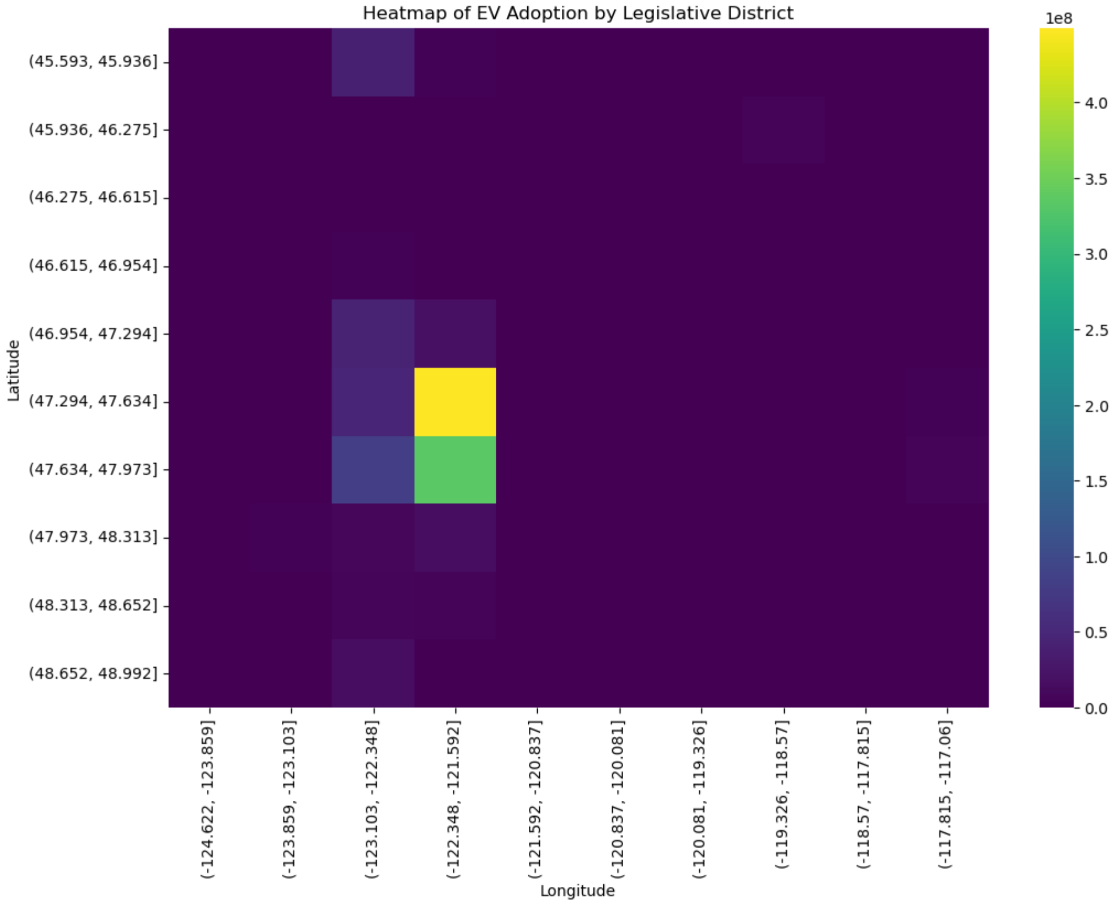

Geographic Distribution of EVs per City in Washington State
ABBOTSFORD
BELLINGHAM
VICTORIA
EVERETT
WENATCHEE
WASHINGTON
OLYMPIA
(C) OpenStreetMap contributors (C) CARTO
1e6
6.30
6.25
6.20
6.15
6.10
6.05
6.00
5.95
5.90
−1.38
−1.37
−1.36
−1.35
−1.34
−1.33
1e7
30000
25000
20000
15000
10000
5000


Geographic Distribution of EVs per Legislative District in Washington State
ABBOTSFORD
BELLINGHAM
VICTORIA
EVERETT
WENATCHEE
WASHINGTON
OLYMPIA
(C) OpenStreetMap contributors (C) CARTO
1e6
6.30
6.25
6.20
6.15
6.10
6.05
6.00
5.95
5.90
−1.38
−1.37
−1.36
−1.35
−1.34
−1.33
1e7
12000
10000
8000
6000
4000
2000


Heatmap of EV Adoption by County
Latitude
(45.593, 45.936]
(45.936, 46.275]
(46.275, 46.615]
(46.615, 46.954]
(46.954, 47.294]
(47.294, 47.634]
(47.634, 47.973]
(47.973, 48.313]
(48.313, 48.652]
(48.652, 48.992]
Longitude
(-124.622, -123.859]
(-123.859, -123.103]
(-123.103, -122.348]
(-122.348, -121.592]
(-121.592, -120.837]
(-120.837, -120.081]
(-120.081, -119.326]
(-119.326, -118.57]
(-118.57, -117.815]
(-117.815, -117.06]
1e9
5
4
3
2
1
0



Heatmap of EV Adoption by City
1e8
Latitude
(45.593, 45.936]
(45.936, 46.275]
(46.275, 46.615]
(46.615, 46.954]
(46.954, 47.294]
(47.294, 47.634]
(47.634, 47.973]
(47.973, 48.313]
(48.313, 48.652]
(48.652, 48.992]
(-124.622, -123.859]
(-123.859, -123.103]
(-123.103, -122.348]
(-122.348, -121.592]
(-121.592, -120.837]
(-120.837, -120.081]
(-120.081, -119.326]
(-119.326, -118.57]
(-118.57, -117.815]
(-117.815, -117.06]
Longitude
0
1
2
3
4
5



Interpretation of the Geographic and Heatmap Plots

Geographic Plots:

1. **EV Distribution by County, City, and Legislative District:**
    - These plots visualize the geographic distribution of electric vehicles (EVs) across different counties, cities, and legislative districts within Washington State.
    - **County Level:** The concentration of EVs is notably high in King County, which is expected given it includes Seattle, the largest city in Washington.
    - **City Level:** Seattle stands out as the city with the highest number of EVs, followed by Bellevue and Redmond.
    - **Legislative District Level:** The legislative districts that include major urban areas (e.g., Seattle) show higher EV adoption rates.

Heatmap Plots:

1. **Heatmap of EV Adoption by County:**
    - The heatmap highlights a concentrated area with high EV adoption around the Seattle metropolitan area.
    - The bright yellow and green patches indicate the regions with the highest EV counts.
2. **Heatmap of EV Adoption by City:**

- Similar to the county heatmap, the city-level heatmap also shows a dense cluster of EV adoption in the Seattle area.
- This plot helps to pinpoint the specific cities within the counties that have higher EV adoption.

3. **Heatmap of EV Adoption by Legislative District:**
    - This heatmap further refines the understanding of geographic EV distribution by considering the legislative districts.
    - It emphasizes the legislative areas around the Seattle metropolitan region as the primary zones for EV adoption.

Summary:

1. **Geographic Distribution Insights:**
    - The Seattle metropolitan area is the focal point of EV adoption in Washington State, highlighting the influence of urban centers on EV uptake.
    - Counties, cities, and legislative districts encompassing Seattle and its surrounding areas are leading in EV adoption.
2. **Infrastructure and Policy Impact:**
    - The high adoption rates in specific geographic areas may be influenced by the availability of charging infrastructure, local government policies promoting EVs, and higher population densities.
3. **Strategic Planning:**
    - For future policy-making and infrastructure development, focusing on expanding EV support in less saturated areas could help to balance EV adoption across the state.
    - Understanding these patterns can aid in targeted marketing strategies and the deployment of new charging stations to encourage wider EV adoption.

These visualizations collectively provide a comprehensive view of how geographic location and local infrastructure (like electric utilities and legislative districts) impact EV adoption in Washington State.

STEP IV

Performing Multiple Linear Regression to Assess Impact

[ ]:
```
import statsmodels.api as sm

# Ensure the 'Electric Utility' column is properly named for consistency
elec_dataset = elec_dataset.rename(columns={'Electric Utility':␣
 ↪'Electric_Utility'})

# Ensure the 'Electric Utility' column is properly named for consistency
elec_dataset = elec_dataset.rename(columns={'Legislative District':␣
 ↪'Legislative_District'})

# Function to perform regression analysis
def perform_regression(y_var, X_vars):
    X = pd.get_dummies(elec_dataset[X_vars], drop_first=True).astype(float)
    X = sm.add_constant(X)
    y = elec_dataset[y_var]
```

```
    model = sm.OLS(y, X).fit()
    print(f"Regression Results for {y_var}")
    print(model.summary(), "\n\n")

# Perform regression for different dependent variables
perform_regression('EV_Count_County', ['City', 'Legislative_District',␣
↪'Electric_Utility', 'Latitude', 'Longitude'])
perform_regression('EV_Count_City', ['County', 'Legislative_District',␣
↪'Electric_Utility', 'Latitude', 'Longitude'])
perform_regression('EV_Count_Leg_Dist', ['County', 'City', 'Electric_Utility',␣
↪'Latitude', 'Longitude'])
perform_regression('EV_Count_Utility', ['County', 'City',␣
↪'Legislative_District', 'Latitude', 'Longitude'])
```

```
Regression Results for EV_Count_County
                            OLS Regression Results
==============================================================================
Dep. Variable:        EV_Count_County   R-squared:                       0.996
Model:                            OLS   Adj. R-squared:                  0.996
Method:                 Least Squares   F-statistic:                 7.413e+04
Date:                Sun, 07 Jul 2024   Prob (F-statistic):               0.00
Time:                        20:03:53   Log-Likelihood:            -1.7465e+06
No. Observations:              186471   AIC:                         3.494e+06
Df Residuals:                  185882   BIC:                         3.500e+06
Df Model:                         588
Covariance Type:            nonrobust
================================================================================
================================================================================
=====================================
                                                        coef    std err
t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
-------------------------------------
const
-2.491e+05   3.39e+04     -7.344      0.000   -3.16e+05   -1.83e+05
Latitude
-173.9815    339.353     -0.513      0.608    -839.105     491.142
Longitude
-1967.1957    278.067     -7.075      0.000   -2512.201   -1422.191
City_Acme
2.484e+04   1906.899     13.028      0.000    2.11e+04    2.86e+04
City_Addy
4.763e+04   3356.506     14.192      0.000    4.11e+04    5.42e+04
City_Adna
-1.549e+04   3141.917     -4.930      0.000   -2.16e+04   -9332.384
City_Airway Heights
```

```
5.233e+04   2715.839     19.267      0.000     4.7e+04    5.76e+04
City_Alderdale
1.032e+04   2960.028      3.486      0.000    4517.880    1.61e+04
City_Alderwood Manor
4.425e+04   3185.025     13.893      0.000     3.8e+04    5.05e+04
City_Algona
4.304e+04   1515.499     28.402      0.000    4.01e+04     4.6e+04
City_Allyn
-8942.5642   1076.108     -8.310      0.000   -1.11e+04   -6833.417
City_Almira
4.64e+04   3549.294     13.072      0.000    3.94e+04    5.34e+04
City_Amanda Park
-1507.4798   1709.630     -0.882      0.378   -4858.315    1843.356
City_Amboy
4987.6014    799.924      6.235      0.000    3419.769    6555.434
City_Anacortes
2.377e+04   1518.524     15.653      0.000    2.08e+04    2.67e+04
City_Anderson Island
-1.365e+04   1449.950     -9.414      0.000   -1.65e+04   -1.08e+04
City_Ariel
4994.6951    951.806      5.248      0.000    3129.177    6860.213
City_Arlington
4.482e+04   1510.448     29.674      0.000    4.19e+04    4.78e+04
City_Artondale
-1.34e+04   2433.860     -5.504      0.000   -1.82e+04   -8625.120
City_Ashford
-1.308e+04   1599.193     -8.179      0.000   -1.62e+04   -9945.453
City_Asotin
2.438e+04   1661.659     14.672      0.000    2.11e+04    2.76e+04
City_Auburn
4.276e+04   1432.296     29.856      0.000       4e+04    4.56e+04
City_Bainbridge Island
5.104e+04   1397.080     36.531      0.000    4.83e+04    5.38e+04
City_Bangor Base
5.071e+04   3152.283     16.087      0.000    4.45e+04    5.69e+04
City_Baring
4.79e+04   1925.300     24.879      0.000    4.41e+04    5.17e+04
City_Battle Ground
4776.3185    625.457      7.637      0.000    3550.437    6002.200
City_Bay Center
2927.9578   2760.658      1.061      0.289   -2482.868    8338.783
City_Beaux Arts
4.638e+04   1512.909     30.654      0.000    4.34e+04    4.93e+04
City_Beaver
3.622e+04   3518.639     10.294      0.000    2.93e+04    4.31e+04
City_Belfair
-9298.9916   1050.804     -8.849      0.000   -1.14e+04   -7239.440
City_Bellevue
```

```
4.647e+04   1460.283     31.819      0.000    4.36e+04    4.93e+04
City_Bellingham
2.431e+04   1688.412     14.397      0.000     2.1e+04    2.76e+04
City_Benton City
4.694e+04   5035.253      9.322      0.000    3.71e+04    5.68e+04
City_Bingen
6849.1309   1159.337      5.908      0.000    4576.856    9121.405
City_Black Diamond
4.694e+04   1460.584     32.135      0.000    4.41e+04    4.98e+04
City_Blaine
2.383e+04   1705.019     13.979      0.000    2.05e+04    2.72e+04
City_Bonney Lake
-1.297e+04   1426.171     -9.095      0.000   -1.58e+04   -1.02e+04
City_Bothell
4.499e+04   1466.787     30.675      0.000    4.21e+04    4.79e+04
City_Bow
2.438e+04   1566.263     15.564      0.000    2.13e+04    2.74e+04
City_Bremerton
5.084e+04   1381.763     36.790      0.000    4.81e+04    5.35e+04
City_Brewster
6894.3068   1402.739      4.915      0.000    4144.970    9643.643
City_Bridgeport
4.48e+04   3304.600     13.556      0.000    3.83e+04    5.13e+04
City_Bridgeport Bar
4.462e+04   3199.085     13.949      0.000    3.84e+04    5.09e+04
City_Brier
4.445e+04   1471.181     30.215      0.000    4.16e+04    4.73e+04
City_Brinnon
2.389e+04   1459.401     16.371      0.000     2.1e+04    2.68e+04
City_Brush Prairie
4849.1144    637.359      7.608      0.000    3599.905    6098.324
City_Buckley
-1.272e+04   1445.519     -8.800      0.000   -1.56e+04   -9887.729
City_Bucoda
5.148e+04   3131.383     16.439      0.000    4.53e+04    5.76e+04
City_Burbank
4.56e+04   4225.831     10.791      0.000    3.73e+04    5.39e+04
City_Burien
4.553e+04   1445.944     31.487      0.000    4.27e+04    4.84e+04
City_Burlington
2.451e+04   1552.583     15.786      0.000    2.15e+04    2.76e+04
City_Bz Corner
6829.0084   1324.679      5.155      0.000    4232.668    9425.349
City_Camano Island
2.395e+04   1498.558     15.981      0.000     2.1e+04    2.69e+04
City_Camas
4968.3782    626.073      7.936      0.000    3741.289    6195.468
City_Carbonado
```

```
-1.278e+04   1739.860     -7.345      0.000   -1.62e+04   -9368.660
City_Carlton
6315.2507   1658.894      3.807      0.000    3063.857    9566.645
City_Carnation
4.729e+04   1495.505     31.623      0.000    4.44e+04    5.02e+04
City_Carson
6147.4300    842.787      7.294      0.000    4495.588    7799.272
City_Cashmere
5370.1528   1882.408      2.853      0.004    1680.676    9059.629
City_Castle Rock
3300.8377    796.815      4.143      0.000    1739.099    4862.576
City_Cathlamet
3707.1584   1508.670      2.457      0.014     750.200    6664.117
City_Centerville
7870.5315   2135.818      3.685      0.000    3684.379    1.21e+04
City_Centralia
-6149.0549   1370.452     -4.487      0.000   -8835.109   -3463.000
City_Chattaroy
5.285e+04   2776.772     19.034      0.000    4.74e+04    5.83e+04
City_Chehalis
-2.217e+04   1353.062    -16.386      0.000   -2.48e+04   -1.95e+04
City_Chelan
6308.8425   1851.758      3.407      0.001    2679.441    9938.244
City_Chelan Falls
6407.0713   3303.142      1.940      0.052     -67.011    1.29e+04
City_Cheney
5.23e+04   2663.405     19.637      0.000    4.71e+04    5.75e+04
City_Chewelah
4.8e+04   2822.854     17.005      0.000    4.25e+04    5.35e+04
City_Chimacum
3.929e+04   2343.509     16.767      0.000    3.47e+04    4.39e+04
City_Chinook
2613.9665   1652.803      1.582      0.114    -625.488    5853.421
City_Cinebar
-1.446e+04   2144.119     -6.745      0.000   -1.87e+04   -1.03e+04
City_Clallam Bay
3.64e+04   2901.041     12.548      0.000    3.07e+04    4.21e+04
City_Clarkston
2.436e+04   1558.443     15.632      0.000    2.13e+04    2.74e+04
City_Clayton
5.129e+04   3320.530     15.447      0.000    4.48e+04    5.78e+04
City_Cle Elum
4.895e+04   1746.628     28.025      0.000    4.55e+04    5.24e+04
City_Clearlake
2.463e+04   2233.671     11.027      0.000    2.03e+04     2.9e+04
City_Clinton
2.412e+04   1487.766     16.210      0.000    2.12e+04     2.7e+04
City_Clyde Hill
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4.638e+04   1465.088     31.658      0.000    4.35e+04    4.93e+04
City_Colbert
5.275e+04   2730.835     19.316      0.000    4.74e+04    5.81e+04
City_Colfax
4.808e+04   2726.040     17.636      0.000    4.27e+04    5.34e+04
City_College Place
4.675e+04   4541.525     10.293      0.000    3.78e+04    5.56e+04
City_Colton
4.896e+04   3377.993     14.493      0.000    4.23e+04    5.56e+04
City_Colville
4.772e+04   2743.170     17.396      0.000    4.23e+04    5.31e+04
City_Concrete
2.558e+04   1649.369     15.508      0.000    2.23e+04    2.88e+04
City_Connell
4.606e+04   3206.287     14.366      0.000    3.98e+04    5.23e+04
City_Copalis Beach
-2112.6723   1496.447     -1.412      0.158   -5045.673     820.328
City_Copalis Crossing
-1925.0554   1703.926     -1.130      0.259   -5264.712    1414.601
City_Cosmopolis
138.0914    762.979      0.181      0.856   -1357.329    1633.512
City_Cougar
5320.5249   2081.550      2.556      0.011    1240.736    9400.314
City_Coulee City
4.531e+04   2771.785     16.347      0.000    3.99e+04    5.07e+04
City_Coulee Dam
2.343e+04   1305.056     17.957      0.000    2.09e+04     2.6e+04
City_Coupeville
2.371e+04   1489.970     15.916      0.000    2.08e+04    2.66e+04
City_Covington
4.413e+04   1450.874     30.413      0.000    4.13e+04     4.7e+04
City_Cowiche
4.475e+04   4566.069      9.800      0.000    3.58e+04    5.37e+04
City_Creston
4.726e+04   3600.578     13.126      0.000    4.02e+04    5.43e+04
City_Curlew
9210.9124   1307.300      7.046      0.000    6648.635    1.18e+04
City_Curtis
-1.851e+04   1737.323    -10.652      0.000   -2.19e+04   -1.51e+04
City_Cusick
5.302e+04   3303.999     16.046      0.000    4.65e+04    5.95e+04
City_Custer
2.402e+04   1783.172     13.470      0.000    2.05e+04    2.75e+04
City_Dallesport
7413.0755   1286.311      5.763      0.000    4891.936    9934.215
City_Danville
9549.5852   2425.335      3.937      0.000    4795.985    1.43e+04
City_Darrington
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4.249e+04   1772.291     23.972      0.000     3.9e+04     4.6e+04
City_Davenport
4.788e+04   2402.712     19.928      0.000    4.32e+04    5.26e+04
City_Dayton
4.719e+04   4635.717     10.179      0.000    3.81e+04    5.63e+04
City_Deer Harbor
2.231e+04   3275.508      6.811      0.000    1.59e+04    2.87e+04
City_Deer Meadows
4.788e+04   3034.550     15.779      0.000    4.19e+04    5.38e+04
City_Deer Park
5.217e+04   2720.562     19.176      0.000    4.68e+04    5.75e+04
City_Deming
2.5e+04   1799.050     13.894      0.000    2.15e+04    2.85e+04
City_Des Moines
4.428e+04   1442.219     30.700      0.000    4.14e+04    4.71e+04
City_Dixie
4.723e+04   5412.039      8.726      0.000    3.66e+04    5.78e+04
City_Dryden
5221.5407   3303.793      1.580      0.114   -1253.816    1.17e+04
City_Dupont
-1.395e+04   1385.555    -10.066      0.000   -1.67e+04   -1.12e+04
City_Duvall
4.69e+04   1492.523     31.426      0.000     4.4e+04    4.98e+04
City_East Wenatchee
4.354e+04   2777.864     15.674      0.000    3.81e+04     4.9e+04
City_Easton
4.848e+04   1809.187     26.798      0.000    4.49e+04     5.2e+04
City_Eastsound
2.249e+04   1664.550     13.513      0.000    1.92e+04    2.58e+04
City_Eatonville
-1.313e+04   1448.806     -9.064      0.000    -1.6e+04   -1.03e+04
City_Edgewood
-1.308e+04   1422.116     -9.195      0.000   -1.59e+04   -1.03e+04
City_Edmonds
4.426e+04   1453.196     30.458      0.000    4.14e+04    4.71e+04
City_Edwall
5.176e+04   2965.723     17.451      0.000    4.59e+04    5.76e+04
City_Elbe
-1.291e+04   2146.262     -6.014      0.000   -1.71e+04   -8701.187
City_Electric City
4.576e+04   3001.477     15.245      0.000    3.99e+04    5.16e+04
City_Elk
5.301e+04   2824.965     18.764      0.000    4.75e+04    5.85e+04
City_Ellensburg
4.972e+04   1793.260     27.726      0.000    4.62e+04    5.32e+04
City_Elma
-1644.7828    552.422     -2.977      0.003   -2727.517    -562.049
City_Elmer City
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7338.3298 3535.008 2.076 0.038 409.797 1.43e+04
City_Eltopia
4.57e+04 3254.997 14.041 0.000 3.93e+04 5.21e+04
City_Endicott
4.746e+04 3293.283 14.410 0.000 4.1e+04 5.39e+04
City_Entiat
5812.7064 1932.763 3.007 0.003 2024.536 9600.877
City_Enumclaw
6.084e+04 1448.612 41.996 0.000 5.8e+04 6.37e+04
City_Ephrata
4.492e+04 2671.525 16.814 0.000 3.97e+04 5.02e+04
City_Ethel
-1.488e+04 1797.678 -8.280 0.000 -1.84e+04 -1.14e+04
City_Evans
4.757e+04 2959.905 16.072 0.000 4.18e+04 5.34e+04
City_Everett
4.469e+04 1471.492 30.371 0.000 4.18e+04 4.76e+04
City_Everson
2.455e+04 1743.071 14.087 0.000 2.11e+04 2.8e+04
City_Fairchild Air Force Base
5.219e+04 2756.836 18.931 0.000 4.68e+04 5.76e+04
City_Fall City
4.733e+04 1493.719 31.685 0.000 4.44e+04 5.03e+04
City_Federal Way
4.29e+04 1433.176 29.936 0.000 4.01e+04 4.57e+04
City_Ferndale
2.406e+04 1697.052 14.178 0.000 2.07e+04 2.74e+04
City_Fife
-1.271e+04 1409.263 -9.020 0.000 -1.55e+04 -9949.458
City_Fircrest
-1.335e+04 1410.361 -9.463 0.000 -1.61e+04 -1.06e+04
City_Ford
4.959e+04 2886.591 17.179 0.000 4.39e+04 5.52e+04
City_Forks
3.608e+04 2217.110 16.273 0.000 3.17e+04 4.04e+04
City_Fox Island
-1.341e+04 1393.286 -9.628 0.000 -1.61e+04 -1.07e+04
City_Frances
3128.1344 2761.027 1.133 0.257 -2283.414 8539.682
City_Freeland
2.391e+04 1485.164 16.096 0.000 2.1e+04 2.68e+04
City_Friday Harbor
2.217e+04 1638.826 13.528 0.000 1.9e+04 2.54e+04
City_Garfield
4.899e+04 2973.641 16.475 0.000 4.32e+04 5.48e+04
City_Gifford
4.718e+04 3318.507 14.217 0.000 4.07e+04 5.37e+04
City_Gig Harbor

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-1.336e+04   1386.479     -9.639      0.000   -1.61e+04   -1.06e+04
City_Glacier
2.5e+04   1876.296     13.322      0.000    2.13e+04    2.87e+04
City_Glenoma
-1.37e+04   2001.750     -6.846      0.000   -1.76e+04   -9780.082
City_Glenwood
7258.1635   2890.565      2.511      0.012    1592.724    1.29e+04
City_Gold Bar
4.57e+04   1570.730     29.097      0.000    4.26e+04    4.88e+04
City_Goldendale
8168.9794    995.401      8.207      0.000    6218.016    1.01e+04
City_Graham
-1.312e+04   1389.743     -9.440      0.000   -1.58e+04   -1.04e+04
City_Grand Coulee
4.622e+04   2539.150     18.203      0.000    4.12e+04    5.12e+04
City_Grandview
4.607e+04   4738.135      9.722      0.000    3.68e+04    5.54e+04
City_Granger
4.556e+04   4681.211      9.733      0.000    3.64e+04    5.47e+04
City_Granite Falls
4.515e+04   1527.743     29.553      0.000    4.22e+04    4.81e+04
City_Grapeview
-9074.4939   1079.631     -8.405      0.000   -1.12e+04   -6958.442
City_Grayland
-519.7215   1030.317     -0.504      0.614   -2539.120    1499.677
City_Grays River
3316.3022   2407.591      1.377      0.168   -1402.520    8035.124
City_Greenacres
5.295e+04   2735.901     19.355      0.000    4.76e+04    5.83e+04
City_Greenbank
2.381e+04   1509.945     15.770      0.000    2.09e+04    2.68e+04
City_Hamilton
2.513e+04   3230.302      7.778      0.000    1.88e+04    3.15e+04
City_Hansville
5.104e+04   1450.889     35.176      0.000    4.82e+04    5.39e+04
City_Harrington
4.77e+04   2777.226     17.177      0.000    4.23e+04    5.31e+04
City_Hartline
4.589e+04   3389.512     13.538      0.000    3.92e+04    5.25e+04
City_Hatton
4.462e+04   3709.877     12.027      0.000    3.73e+04    5.19e+04
City_Home
-1.372e+04   3145.809     -4.361      0.000   -1.99e+04   -7552.949
City_Hoodsport
-1.035e+04   1081.040     -9.579      0.000   -1.25e+04   -8236.116
City_Hoquiam
-1586.0063    597.995     -2.652      0.008   -2758.063    -413.949
City_Hunters
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4.708e+04   3300.312     14.265      0.000    4.06e+04    5.35e+04
City_Hunts Point
4.638e+04   1506.205     30.794      0.000    4.34e+04    4.93e+04
City_Husum
6829.0084   1030.677      6.626      0.000    4808.906    8849.111
City_Ilwaco
2429.5392    879.493      2.762      0.006     705.754    4153.325
City_Inchelium
4.673e+04   3302.465     14.151      0.000    4.03e+04    5.32e+04
City_Incorporated
-1.363e+04   2434.026     -5.600      0.000   -1.84e+04   -8860.489
City_Index
4.564e+04   1982.956     23.016      0.000    4.18e+04    4.95e+04
City_Indianola
5.107e+04   1450.174     35.219      0.000    4.82e+04    5.39e+04
City_Ione
5.287e+04   3692.040     14.320      0.000    4.56e+04    6.01e+04
City_Issaquah
4.699e+04   1468.132     32.005      0.000    4.41e+04    4.99e+04
City_Joint Base Lewis Mcchord
-1.385e+04   1403.448     -9.871      0.000   -1.66e+04   -1.11e+04
City_Kalama
4280.5439    769.154      5.565      0.000    2773.019    5788.068
City_Kapowsin
-1.321e+04   3149.778     -4.193      0.000   -1.94e+04   -7034.571
City_Keller
9017.2303   2399.867      3.757      0.000    4313.547    1.37e+04
City_Kelso
2683.5412    770.544      3.483      0.000    1173.292    4193.790
City_Kenmore
4.564e+04   1460.420     31.253      0.000    4.28e+04    4.85e+04
City_Kennewick
4.74e+04   5041.802      9.402      0.000    3.75e+04    5.73e+04
City_Kent
4.438e+04   1443.275     30.747      0.000    4.15e+04    4.72e+04
City_Kettle Falls
4.731e+04   2745.161     17.233      0.000    4.19e+04    5.27e+04
City_Keyport
5.088e+04   1715.267     29.664      0.000    4.75e+04    5.42e+04
City_Kingston
5.111e+04   1419.250     36.009      0.000    4.83e+04    5.39e+04
City_Kirkland
4.64e+04   1462.122     31.732      0.000    4.35e+04    4.93e+04
City_Kittitas
4.993e+04   2088.268     23.910      0.000    4.58e+04     5.4e+04
City_Klickitat
7301.1325   2890.959      2.526      0.012    1634.920     1.3e+04
City_La Center
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4610.6504    636.125      7.248      0.000    3363.860    5857.440
City_La Conner
2.41e+04   1535.910     15.694      0.000    2.11e+04    2.71e+04
City_Lacey
5.114e+04   1347.673     37.948      0.000    4.85e+04    5.38e+04
City_Lacrosse
4.753e+04   3845.186     12.360      0.000       4e+04    5.51e+04
City_Lake Forest Park
4.563e+04   1456.643     31.328      0.000    4.28e+04    4.85e+04
City_Lake Stevens
4.498e+04   1493.672     30.113      0.000    4.21e+04    4.79e+04
City_Lake Tapps
-1.297e+04   1431.731     -9.060      0.000   -1.58e+04   -1.02e+04
City_Lakebay
-1.372e+04   1399.228     -9.804      0.000   -1.65e+04    -1.1e+04
City_Lakeview
4.509e+04   3889.710     11.593      0.000    3.75e+04    5.27e+04
City_Lakewood
-1.356e+04   1385.795     -9.786      0.000   -1.63e+04   -1.08e+04
City_Lamont
4.707e+04   3839.412     12.260      0.000    3.95e+04    5.46e+04
City_Langley
2.41e+04   1488.936     16.188      0.000    2.12e+04     2.7e+04
City_Latah
5.305e+04   3934.581     13.482      0.000    4.53e+04    6.08e+04
City_Leavenworth
5023.3727   1863.217      2.696      0.007    1371.510    8675.236
City_Lebam
3128.1344   2761.027      1.133      0.257   -2283.414    8539.682
City_Liberty Lake
5.306e+04   2744.012     19.337      0.000    4.77e+04    5.84e+04
City_Lilliwaup
-9807.1760   1474.600     -6.651      0.000   -1.27e+04   -6916.994
City_Lincoln
4.739e+04   2652.235     17.870      0.000    4.22e+04    5.26e+04
City_Lind
4.576e+04   3193.596     14.330      0.000    3.95e+04     5.2e+04
City_Long Beach
2453.3787    671.194      3.655      0.000    1137.854    3768.903
City_Longbranch
-1.375e+04   1499.903     -9.167      0.000   -1.67e+04   -1.08e+04
City_Longview
1023.5157    799.851      1.280      0.201    -544.173    2591.204
City_Loon Lake
4.993e+04   2746.368     18.181      0.000    4.45e+04    5.53e+04
City_Lopez Is
2.254e+04   2317.076      9.729      0.000     1.8e+04    2.71e+04
City_Lopez Island
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2.254e+04   1660.176     13.578      0.000    1.93e+04    2.58e+04
City_Lummi Island
2.39e+04   2234.005     10.700      0.000    1.95e+04    2.83e+04
City_Lyle
7301.1325    994.814      7.339      0.000    5351.320    9250.945
City_Lyman
2.499e+04   3226.823      7.744      0.000    1.87e+04    3.13e+04
City_Lynden
2.438e+04   1724.377     14.138      0.000     2.1e+04    2.78e+04
City_Lynnwood
4.44e+04   1461.255     30.384      0.000    4.15e+04    4.73e+04
City_Mabton
4.59e+04   4779.624      9.604      0.000    3.65e+04    5.53e+04
City_Malaga
5909.6284   1934.717      3.055      0.002    2117.628    9701.629
City_Malden
4.792e+04   3891.897     12.312      0.000    4.03e+04    5.55e+04
City_Malott
7248.1290   3006.246      2.411      0.016    1355.958    1.31e+04
City_Mansfield
4.484e+04   3493.293     12.837      0.000     3.8e+04    5.17e+04
City_Manson
6114.7313   1880.088      3.252      0.001    2429.804    9799.659
City_Maple Falls
2.499e+04   1814.674     13.770      0.000    2.14e+04    2.85e+04
City_Maple Valley
4.705e+04   1458.677     32.252      0.000    4.42e+04    4.99e+04
City_Marblemount
2.627e+04   2578.620     10.188      0.000    2.12e+04    3.13e+04
City_Marlin
4.603e+04   3382.151     13.611      0.000    3.94e+04    5.27e+04
City_Maryhill
8168.9794   2902.752      2.814      0.005    2479.653    1.39e+04
City_Marysville
4.479e+04   1490.120     30.057      0.000    4.19e+04    4.77e+04
City_Mattawa
4.417e+04   2640.709     16.726      0.000     3.9e+04    4.93e+04
City_Mazama
5686.6608   1689.799      3.365      0.001    2374.694    8998.627
City_Mccleary
-348.9034    886.346     -0.394      0.694   -2086.120    1388.314
City_Mead
5.281e+04   2737.284     19.292      0.000    4.74e+04    5.82e+04
City_Medical Lake
5.214e+04   2662.685     19.581      0.000    4.69e+04    5.74e+04
City_Medina
4.635e+04   1461.820     31.706      0.000    4.35e+04    4.92e+04
City_Menlo
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3128.1344   1092.560      2.863      0.004     986.742    5269.527
City_Mercer Island
4.632e+04   1453.406     31.869      0.000    4.35e+04    4.92e+04
City_Mesa
4.554e+04   3235.376     14.075      0.000    3.92e+04    5.19e+04
City_Methow
6474.7337   1998.792      3.239      0.001    2557.148    1.04e+04
City_Mica
5.305e+04   3010.635     17.619      0.000    4.71e+04    5.89e+04
City_Mill Creek
4.471e+04   1469.372     30.429      0.000    4.18e+04    4.76e+04
City_Milton
2.108e+04   1634.362     12.901      0.000    1.79e+04    2.43e+04
City_Mineral
-1.375e+04   1650.757     -8.327      0.000    -1.7e+04   -1.05e+04
City_Moclips
-2179.3905   1498.222     -1.455      0.146   -5115.871     757.090
City_Monroe
4.51e+04   1491.877     30.232      0.000    4.22e+04     4.8e+04
City_Montesano
-81.8125    403.414     -0.203      0.839    -872.494     708.869
City_Morton
-1.397e+04   1572.869     -8.883      0.000   -1.71e+04   -1.09e+04
City_Moses Lake
4.542e+04   2682.842     16.930      0.000    4.02e+04    5.07e+04
City_Mossyrock
-1.437e+04   1475.956     -9.736      0.000   -1.73e+04   -1.15e+04
City_Mount Vernon
2.452e+04   1532.807     15.996      0.000    2.15e+04    2.75e+04
City_Mountlake Terrace
4.437e+04   1461.606     30.356      0.000    4.15e+04    4.72e+04
City_Moxee
4.528e+04   4438.311     10.202      0.000    3.66e+04     5.4e+04
City_Mukilteo
4.446e+04   1467.958     30.285      0.000    4.16e+04    4.73e+04
City_Murdock
7338.4468   1801.316      4.074      0.000    3807.910    1.09e+04
City_Naches
4.469e+04   4422.304     10.105      0.000     3.6e+04    5.34e+04
City_Nahcotta
2446.9515   1321.156      1.852      0.064    -142.484    5036.387
City_Napavine
-2.771e+04   1668.567    -16.610      0.000    -3.1e+04   -2.44e+04
City_Naselle
2994.1739    748.874      3.998      0.000    1526.398    4461.950
City_Neah Bay
3.574e+04   2366.099     15.103      0.000    3.11e+04    4.04e+04
City_Nespelem
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7323.2486   4030.070      1.817      0.069    -575.596    1.52e+04
City_Newcastle
4.645e+04   1456.960     31.881      0.000    4.36e+04    4.93e+04
City_Newman Lake
5.311e+04   2775.907     19.133      0.000    4.77e+04    5.86e+04
City_Newport
5.326e+04   3116.035     17.092      0.000    4.72e+04    5.94e+04
City_Nine Mile Falls
5.207e+04   2641.996     19.709      0.000    4.69e+04    5.72e+04
City_Nooksack
2.463e+04   1923.283     12.807      0.000    2.09e+04    2.84e+04
City_Nordland
3.946e+04   2338.063     16.879      0.000    3.49e+04     4.4e+04
City_Normandy Park
4.448e+04   1449.092     30.695      0.000    4.16e+04    4.73e+04
City_North Bend
4.757e+04   1493.503     31.854      0.000    4.46e+04    5.05e+04
City_North Bonneville
5854.6520   1031.543      5.676      0.000    3832.852    7876.452
City_North Cove
2514.3071   1093.695      2.299      0.022     370.690    4657.924
City_Northport
4.798e+04   3428.181     13.995      0.000    4.13e+04    5.47e+04
City_Oak Harbor
2.376e+04   1494.925     15.894      0.000    2.08e+04    2.67e+04
City_Oakesdale
4.847e+04   2987.706     16.222      0.000    4.26e+04    5.43e+04
City_Oakville
3093.0342    668.489      4.627      0.000    1782.810    4403.258
City_Ocean Park
2446.9515    716.150      3.417      0.001    1043.314    3850.589
City_Ocean Shores
-2109.2343    540.588     -3.902      0.000   -3168.774   -1049.695
City_Odessa
4.682e+04   2443.605     19.160      0.000     4.2e+04    5.16e+04
City_Okanogan
6529.1072   1557.189      4.193      0.000    3477.053    9581.162
City_Olalla
5.1e+04   1415.287     36.033      0.000    4.82e+04    5.38e+04
City_Olga
2.273e+04   1721.028     13.209      0.000    1.94e+04    2.61e+04
City_Olympia
5.096e+04   1339.017     38.059      0.000    4.83e+04    5.36e+04
City_Omak
6326.5325   1532.333      4.129      0.000    3323.195    9329.870
City_Onalaska
-1.472e+04   1487.235     -9.899      0.000   -1.76e+04   -1.18e+04
City_Orcas
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2.25e+04   2174.850     10.344      0.000    1.82e+04    2.68e+04
City_Orcas Is
2.253e+04   1863.969     12.090      0.000    1.89e+04    2.62e+04
City_Orient
4.694e+04   3914.925     11.991      0.000    3.93e+04    5.46e+04
City_Orondo
4.383e+04   2828.931     15.494      0.000    3.83e+04    4.94e+04
City_Oroville
6612.6264   1653.919      3.998      0.000    3370.984    9854.269
City_Orting
-1.312e+04   1404.203     -9.342      0.000   -1.59e+04   -1.04e+04
City_Othello
4.545e+04   2741.803     16.578      0.000    4.01e+04    5.08e+04
City_Otis Orchards
5.3e+04   2767.155     19.155      0.000    4.76e+04    5.84e+04
City_Outlook
4.573e+04   4768.198      9.591      0.000    3.64e+04    5.51e+04
City_Oysterville
2460.9629   1224.753      2.009      0.045      60.475    4861.450
City_Pacific
3.763e+04   1472.049     25.565      0.000    3.47e+04    4.05e+04
City_Pacific Beach
-2126.3618    739.320     -2.876      0.004   -3575.412    -677.312
City_Packwood
-1.274e+04   1598.310     -7.971      0.000   -1.59e+04   -9607.868
City_Palisades
4.419e+04   3446.912     12.821      0.000    3.74e+04    5.09e+04
City_Palouse
4.911e+04   2812.685     17.461      0.000    4.36e+04    5.46e+04
City_Parkland
-1.315e+04   1415.574     -9.292      0.000   -1.59e+04   -1.04e+04
City_Pasc
4.546e+04   3440.558     13.214      0.000    3.87e+04    5.22e+04
City_Pasco
4.546e+04   3027.646     15.016      0.000    3.95e+04    5.14e+04
City_Pateros
6546.3790   1604.400      4.080      0.000    3401.792    9690.966
City_Paterson
4.663e+04   5400.265      8.634      0.000     3.6e+04    5.72e+04
City_Pe Ell
-1.597e+04   3139.691     -5.085      0.000   -2.21e+04   -9812.837
City_Peshastin
5154.3550   1951.377      2.641      0.008    1329.702    8979.008
City_Plymouth
4.71e+04   5771.935      8.161      0.000    3.58e+04    5.84e+04
City_Point Roberts
2.319e+04   1718.173     13.500      0.000    1.98e+04    2.66e+04
City_Pomeroy
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4.793e+04   4891.493      9.798      0.000    3.83e+04    5.75e+04
City_Port Angeles
3.797e+04   2107.075     18.019      0.000    3.38e+04    4.21e+04
City_Port Gamble
5.087e+04   2440.395     20.843      0.000    4.61e+04    5.56e+04
City_Port Hadlock
3.932e+04   2335.600     16.835      0.000    3.47e+04    4.39e+04
City_Port Ludlow
3.944e+04   2303.962     17.118      0.000    3.49e+04     4.4e+04
City_Port Orchard
5.089e+04   1386.282     36.707      0.000    4.82e+04    5.36e+04
City_Port Townsend
3.929e+04   2304.644     17.047      0.000    3.48e+04    4.38e+04
City_Poulsbo
5.087e+04   1399.408     36.348      0.000    4.81e+04    5.36e+04
City_Prairie Ridge
-1.297e+04   3168.993     -4.093      0.000   -1.92e+04   -6760.018
City_Preston
4.708e+04   1550.038     30.376      0.000     4.4e+04    5.01e+04
City_Pros
4.638e+04   5751.615      8.063      0.000    3.51e+04    5.77e+04
City_Prosser
4.638e+04   5010.110      9.257      0.000    3.66e+04    5.62e+04
City_Pullman
4.882e+04   2717.183     17.969      0.000    4.35e+04    5.41e+04
City_Puyallup
-1.319e+04   1387.436     -9.506      0.000   -1.59e+04   -1.05e+04
City_Quilcene
3.911e+04   2313.240     16.908      0.000    3.46e+04    4.36e+04
City_Quinault
-1387.3987   1710.452     -0.811      0.417   -4739.845    1965.048
City_Quincy
4.43e+04   2624.387     16.882      0.000    3.92e+04    4.94e+04
City_Rainier
5.144e+04   1393.526     36.911      0.000    4.87e+04    5.42e+04
City_Randle
-1.315e+04   1794.026     -7.331      0.000   -1.67e+04   -9636.643
City_Ravensdale
4.723e+04   1491.411     31.669      0.000    4.43e+04    5.02e+04
City_Raymond
3128.1344    715.689      4.371      0.000    1725.400    4530.869
City_Reardan
4.933e+04   2565.878     19.225      0.000    4.43e+04    5.44e+04
City_Redmond
4.658e+04   1470.155     31.683      0.000    4.37e+04    4.95e+04
City_Renton
4.579e+04   1451.802     31.541      0.000    4.29e+04    4.86e+04
City_Republic
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9057.6011   1208.536      7.495      0.000    6688.899    1.14e+04
City_Rice
4.721e+04   2902.536     16.264      0.000    4.15e+04    5.29e+04
City_Rich
4.718e+04   5777.070      8.167      0.000    3.59e+04    5.85e+04
City_Richland
4.722e+04   5060.496      9.331      0.000    3.73e+04    5.71e+04
City_Ridgefield
4444.9682    633.399      7.018      0.000    3203.521    5686.416
City_Ritzville
4.709e+04   2981.697     15.792      0.000    4.12e+04    5.29e+04
City_Riverside
6191.7945   1928.242      3.211      0.001    2412.485    9971.104
City_Rochester
4.626e+04   1348.857     34.298      0.000    4.36e+04    4.89e+04
City_Rock Island
4.376e+04   2899.944     15.091      0.000    3.81e+04    4.94e+04
City_Rockford
5.349e+04   3040.713     17.592      0.000    4.75e+04    5.95e+04
City_Rockport
2.599e+04   2565.016     10.134      0.000     2.1e+04     3.1e+04
City_Ronald
4.872e+04   1779.552     27.378      0.000    4.52e+04    5.22e+04
City_Roosevelt
8746.1041   2156.633      4.055      0.000    4519.153     1.3e+04
City_Rosalia
4.914e+04   2852.435     17.227      0.000    4.35e+04    5.47e+04
City_Rosburg
3207.3514   3077.543      1.042      0.297   -2824.562    9239.265
City_Roslyn
4.883e+04   1828.198     26.708      0.000    4.52e+04    5.24e+04
City_Roy
-1.362e+04   1380.181     -9.866      0.000   -1.63e+04   -1.09e+04
City_Royal City
4.471e+04   2695.582     16.586      0.000    3.94e+04       5e+04
City_Ruston
-1.33e+04   1725.088     -7.710      0.000   -1.67e+04   -9918.677
City_Salkum
-1.466e+04   1874.708     -7.819      0.000   -1.83e+04    -1.1e+04
City_Sammamish
4.674e+04   1471.932     31.752      0.000    4.39e+04    4.96e+04
City_San Juan Is
2.218e+04   3269.243      6.785      0.000    1.58e+04    2.86e+04
City_Satsop
-783.7342   2059.722     -0.381      0.704   -4820.741    3253.272
City_Seabeck
5.048e+04   1395.185     36.180      0.000    4.77e+04    5.32e+04
City_Seatac
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4.456e+04   1443.991     30.859      0.000    4.17e+04    4.74e+04
City_Seattle
4.567e+04   1446.623     31.572      0.000    4.28e+04    4.85e+04
City_Seaview
2413.2147   1048.258      2.302      0.021     358.653    4467.776
City_Sedro Woolley
2.476e+04   1680.949     14.727      0.000    2.15e+04    2.81e+04
City_Sedro-Woolley
2.471e+04   1546.918     15.973      0.000    2.17e+04    2.77e+04
City_Sekiu
3.619e+04   2663.042     13.591      0.000     3.1e+04    4.14e+04
City_Selah
4.492e+04   4405.563     10.195      0.000    3.63e+04    5.36e+04
City_Sequim
3.865e+04   2104.597     18.363      0.000    3.45e+04    4.28e+04
City_Seven Bays
4.788e+04   2805.794     17.065      0.000    4.24e+04    5.34e+04
City_Shaw Island
2.243e+04   1801.107     12.455      0.000    1.89e+04     2.6e+04
City_Shelton
-9529.5749   1010.201     -9.433      0.000   -1.15e+04   -7549.604
City_Shoreline
4.616e+04   1452.678     31.777      0.000    4.33e+04     4.9e+04
City_Silver Creek
-1.449e+04   1628.753     -8.896      0.000   -1.77e+04   -1.13e+04
City_Silver Lake
4424.8988   2863.827      1.545      0.122   -1188.135       1e+04
City_Silverdale
5.073e+04   1390.738     36.480      0.000     4.8e+04    5.35e+04
City_Silverlake
4424.8988    867.322      5.102      0.000    2724.967    6124.831
City_Skamokawa
3576.1307   1991.829      1.795      0.073    -327.807    7480.069
City_Skykomish
4.814e+04   1845.670     26.081      0.000    4.45e+04    5.18e+04
City_Smith Creek
3128.1344   2761.027      1.133      0.257   -2283.414    8539.682
City_Snohomish
4.49e+04   1481.852     30.302      0.000     4.2e+04    4.78e+04
City_Snoqualmie
4.743e+04   1487.409     31.885      0.000    4.45e+04    5.03e+04
City_Snoqualmie Pass
4.801e+04   1721.091     27.895      0.000    4.46e+04    5.14e+04
City_Snowden
6829.0084   1081.672      6.313      0.000    4708.957    8949.060
City_Soap Lake
4.497e+04   2729.503     16.474      0.000    3.96e+04    5.03e+04
City_South Bend
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2956.5544   1150.239      2.570      0.010     702.112    5210.997
City_South Cle Elum
4.892e+04   2147.044     22.783      0.000    4.47e+04    5.31e+04
City_South Hill
-1.315e+04   1389.087     -9.465      0.000   -1.59e+04   -1.04e+04
City_South Prairie
-1.286e+04   2458.721     -5.229      0.000   -1.77e+04   -8037.982
City_Spanaway
-1.319e+04   1388.304     -9.503      0.000   -1.59e+04   -1.05e+04
City_Spangle
5.261e+04   2808.835     18.729      0.000    4.71e+04    5.81e+04
City_Spokane
5.267e+04   2698.175     19.522      0.000    4.74e+04     5.8e+04
City_Spokane Valley
5.281e+04   2714.535     19.453      0.000    4.75e+04    5.81e+04
City_Sprague
4.82e+04   3636.804     13.254      0.000    4.11e+04    5.53e+04
City_Springdale
4.988e+04   3091.508     16.133      0.000    4.38e+04    5.59e+04
City_St John
4.769e+04   3315.304     14.385      0.000    4.12e+04    5.42e+04
City_Stanwood
4.44e+04   1511.788     29.369      0.000    4.14e+04    4.74e+04
City_Startup
4.546e+04   3208.046     14.169      0.000    3.92e+04    5.17e+04
City_Steilacoom
2.688e+04    763.186     35.215      0.000    2.54e+04    2.84e+04
City_Stevenson
6009.5737    711.084      8.451      0.000    4615.866    7403.282
City_Stratford
4.55e+04   3908.911     11.639      0.000    3.78e+04    5.32e+04
City_Sultan
4.541e+04   1522.769     29.819      0.000    4.24e+04    4.84e+04
City_Sumas
2.482e+04   2087.595     11.887      0.000    2.07e+04    2.89e+04
City_Sumner
-1.312e+04   1429.762     -9.179      0.000   -1.59e+04   -1.03e+04
City_Sunnyside
4.59e+04   4716.169      9.733      0.000    3.67e+04    5.51e+04
City_Suquamish
5.102e+04   1442.061     35.378      0.000    4.82e+04    5.38e+04
City_Surfside
2446.9515    802.023      3.051      0.002     875.005    4018.898
City_Tacoma
-1.33e+04   1389.750     -9.570      0.000    -1.6e+04   -1.06e+04
City_Taholah
-2302.4660   1501.154     -1.534      0.125   -5244.693     639.761
City_Tahuya
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-9304.1745   1153.861     -8.064      0.000   -1.16e+04   -7042.633
City_Tekoa
4.917e+04   3043.636     16.155      0.000    4.32e+04    5.51e+04
City_Tenino
5.14e+04   1366.543     37.611      0.000    4.87e+04    5.41e+04
City_Thorp
4.94e+04   2105.999     23.456      0.000    4.53e+04    5.35e+04
City_Tieton
4.469e+04   4498.442      9.935      0.000    3.59e+04    5.35e+04
City_Tokeland
2573.3090   1650.795      1.559      0.119    -662.212    5808.830
City_Toledo
-1.632e+04   1441.911    -11.316      0.000   -1.91e+04   -1.35e+04
City_Tonasket
6740.3643   1638.926      4.113      0.000    3528.107    9952.621
City_Toppenish
4.539e+04   4472.416     10.149      0.000    3.66e+04    5.42e+04
City_Touchet
4.623e+04   4614.878     10.018      0.000    3.72e+04    5.53e+04
City_Toutle
4561.6331   1341.749      3.400      0.001    1931.836    7191.430
City_Trout Lake
6841.1037    981.287      6.972      0.000    4917.803    8764.404
City_Tukwila
4.557e+04   1442.575     31.589      0.000    4.27e+04    4.84e+04
City_Tulalip
4.425e+04   1952.633     22.664      0.000    4.04e+04    4.81e+04
City_Tumtum
5.084e+04   3842.291     13.232      0.000    4.33e+04    5.84e+04
City_Tumwater
5.092e+04   1341.780     37.949      0.000    4.83e+04    5.35e+04
City_Twisp
6208.7727   1532.666      4.051      0.000    3204.783    9212.762
City_Underwood
6708.8884    795.624      8.432      0.000    5149.484    8268.293
City_Union
-1.016e+04   1141.153     -8.907      0.000   -1.24e+04   -7927.960
City_Union Gap
4.485e+04   4470.573     10.032      0.000    3.61e+04    5.36e+04
City_Uniontown
4.901e+04   3070.884     15.960      0.000     4.3e+04     5.5e+04
City_University Place
-1.334e+04   1393.762     -9.574      0.000   -1.61e+04   -1.06e+04
City_Usk
5.306e+04   3486.306     15.219      0.000    4.62e+04    5.99e+04
City_Vader
-1.711e+04   1732.407     -9.875      0.000   -2.05e+04   -1.37e+04
City_Valley
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4.797e+04	2911.090	16.479	0.000	4.23e+04	5.37e+04
City_Valleyford					
5.297e+04	2782.283	19.037	0.000	4.75e+04	5.84e+04
City_Vancouver					
4613.7684	633.144	7.287	0.000	3372.821	5854.716
City_Vantage					
5.077e+04	3460.972	14.668	0.000	4.4e+04	5.75e+04
City_Vashon					
4.521e+04	1436.319	31.477	0.000	4.24e+04	4.8e+04
City_Vaughn					
-1.372e+04	1485.334	-9.236	0.000	-1.66e+04	-1.08e+04
City_Veradale					
5.287e+04	2742.356	19.279	0.000	4.75e+04	5.82e+04
City_Wahkiacus					
7556.2624	1804.674	4.187	0.000	4019.144	1.11e+04
City_Waitsburg					
4.725e+04	4581.266	10.315	0.000	3.83e+04	5.62e+04
City_Waldron					
2.229e+04	2597.695	8.579	0.000	1.72e+04	2.74e+04
City_Walla Walla					
4.685e+04	4529.731	10.343	0.000	3.8e+04	5.57e+04
City_Walla Walla Co					
4.685e+04	5342.791	8.769	0.000	3.64e+04	5.73e+04
City_Wapato					
4.515e+04	4468.797	10.104	0.000	3.64e+04	5.39e+04
City_Warden					
4.589e+04	2939.909	15.610	0.000	4.01e+04	5.17e+04
City_Washougal					
5170.9031	617.278	8.377	0.000	3961.053	6380.753
City_Washtucna					
4.635e+04	3795.385	12.212	0.000	3.89e+04	5.38e+04
City_Waterville					
4.397e+04	3077.583	14.286	0.000	3.79e+04	5e+04
City_Waverly					
5.292e+04	3380.525	15.655	0.000	4.63e+04	5.95e+04
City_Wellpinit					
4.745e+04	3868.496	12.265	0.000	3.99e+04	5.5e+04
City_Wenatchee					
5677.5360	1864.103	3.046	0.002	2023.938	9331.134
City_West Richland					
4.706e+04	5035.147	9.347	0.000	3.72e+04	5.69e+04
City_Westport					
819.8247	587.752	1.395	0.163	-332.157	1971.806
City_White Salmon					
6832.0790	809.594	8.439	0.000	5245.294	8418.864
City_White Swan					
4.472e+04	5220.687	8.565	0.000	3.45e+04	5.49e+04
City_Wilbur					

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4.687e+04   2527.947     18.541      0.000    4.19e+04    5.18e+04
City_Wilkeson
-1.278e+04   2012.267     -6.349      0.000   -1.67e+04   -8831.294
City_Winlock
-2.58e+04   1389.015    -18.577      0.000   -2.85e+04   -2.31e+04
City_Winthrop
6070.3530   1609.052      3.773      0.000    2916.649    9224.057
City_Wishram
7837.6473   2898.114      2.704      0.007    2157.411    1.35e+04
City_Woodinville
4.635e+04   1473.070     31.466      0.000    4.35e+04    4.92e+04
City_Woodland
4477.7178    701.130      6.386      0.000    3103.519    5851.916
City_Woodway
4.405e+04   1480.023     29.761      0.000    4.11e+04    4.69e+04
City_Yacolt
5003.2918    706.421      7.083      0.000    3618.722    6387.861
City_Yakima
4.5e+04   4394.999     10.239      0.000    3.64e+04    5.36e+04
City_Yarrow Point
4.638e+04   1475.006     31.445      0.000    4.35e+04    4.93e+04
City_Yelm
5.153e+04   1359.815     37.893      0.000    4.89e+04    5.42e+04
City_Zillah
4.544e+04   4435.561     10.244      0.000    3.67e+04    5.41e+04
Legislative_District_2.0
-2.298e+04    356.341    -64.501      0.000   -2.37e+04   -2.23e+04
Legislative_District_3.0
-2.182e+04   1457.705    -14.972      0.000   -2.47e+04    -1.9e+04
Legislative_District_4.0
-2.16e+04   1459.904    -14.797      0.000   -2.45e+04   -1.87e+04
Legislative_District_5.0
-318.6220    108.760     -2.930      0.003    -531.788    -105.456
Legislative_District_6.0
-2.184e+04   1453.003    -15.030      0.000   -2.47e+04    -1.9e+04
Legislative_District_7.0
-2.182e+04   1444.027    -15.108      0.000   -2.46e+04    -1.9e+04
Legislative_District_8.0
-2.168e+04   1541.691    -14.062      0.000   -2.47e+04   -1.87e+04
Legislative_District_9.0
-2.178e+04   1498.377    -14.535      0.000   -2.47e+04   -1.88e+04
Legislative_District_10.0
-30.2963    280.489     -0.108      0.914    -580.049     519.457
Legislative_District_11.0
718.7362    119.133      6.033      0.000     485.238     952.234
Legislative_District_12.0
-2.311e+04   1088.808    -21.226      0.000   -2.52e+04    -2.1e+04
Legislative_District_13.0
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-2.336e+04    889.622    -26.261      0.000   -2.51e+04   -2.16e+04
Legislative_District_14.0
-2.363e+04    583.128    -40.526      0.000   -2.48e+04   -2.25e+04
Legislative_District_15.0
-2.348e+04    622.365    -37.732      0.000   -2.47e+04   -2.23e+04
Legislative_District_16.0
-2.178e+04   1525.021    -14.281      0.000   -2.48e+04   -1.88e+04
Legislative_District_17.0
-2.354e+04    532.818    -44.178      0.000   -2.46e+04   -2.25e+04
Legislative_District_18.0
-2.364e+04    526.301    -44.921      0.000   -2.47e+04   -2.26e+04
Legislative_District_19.0
-2.069e+04    514.095    -40.239      0.000   -2.17e+04   -1.97e+04
Legislative_District_20.0
-2.365e+04    423.472    -55.855      0.000   -2.45e+04   -2.28e+04
Legislative_District_21.0
-15.2886     85.147     -0.180      0.858    -182.174     151.597
Legislative_District_22.0
-2.313e+04    374.461    -61.759      0.000   -2.39e+04   -2.24e+04
Legislative_District_23.0
-2.305e+04    409.541    -56.293      0.000   -2.39e+04   -2.23e+04
Legislative_District_24.0
-1.919e+04    675.853    -28.394      0.000   -2.05e+04   -1.79e+04
Legislative_District_25.0
-2.307e+04    355.657    -64.867      0.000   -2.38e+04   -2.24e+04
Legislative_District_26.0
-2.312e+04    422.466    -54.715      0.000   -2.39e+04   -2.23e+04
Legislative_District_27.0
-2.286e+04    385.319    -59.335      0.000   -2.36e+04   -2.21e+04
Legislative_District_28.0
-2.305e+04    395.861    -58.222      0.000   -2.38e+04   -2.23e+04
Legislative_District_29.0
-2.296e+04    386.811    -59.369      0.000   -2.37e+04   -2.22e+04
Legislative_District_30.0
3211.2936    207.444     15.480      0.000    2804.707    3617.880
Legislative_District_31.0
-2.306e+04    192.381   -119.860      0.000   -2.34e+04   -2.27e+04
Legislative_District_32.0
203.4238     97.128      2.094      0.036      13.055     393.792
Legislative_District_33.0
1641.0739    153.226     10.710      0.000    1340.755    1941.393
Legislative_District_34.0
671.8506    131.288      5.117      0.000     414.530     929.171
Legislative_District_35.0
-2.316e+04    383.570    -60.379      0.000   -2.39e+04   -2.24e+04
Legislative_District_36.0
628.8897    119.046      5.283      0.000     395.563     862.216
Legislative_District_37.0
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721.6786   124.256   5.808   0.000   478.139   965.218
Legislative_District_38.0
-100.5134   117.671   -0.854   0.393   -331.147   130.120
Legislative_District_39.0
-24.0324   133.335   -0.180   0.857   -285.366   237.302
Legislative_District_40.0
-120.5696   303.929   -0.397   0.692   -716.263   475.124
Legislative_District_41.0
53.2036   92.606   0.575   0.566   -128.301   234.708
Legislative_District_42.0
-147.5688   322.603   -0.457   0.647   -779.864   484.726
Legislative_District_43.0
702.5811   119.360   5.886   0.000   468.638   936.524
Legislative_District_44.0
-95.4445   86.598   -1.102   0.270   -265.174   74.285
Legislative_District_45.0
96.0862   82.578   1.164   0.245   -65.765   257.937
Legislative_District_46.0
722.9948   120.340   6.008   0.000   487.132   958.858
Legislative_District_47.0
2431.6320   154.512   15.738   0.000   2128.793   2734.471
Legislative_District_48.0
48.2907   85.304   0.566   0.571   -118.904   215.485
Legislative_District_49.0
-2.369e+04   534.608   -44.318   0.000   -2.47e+04   -2.26e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||BIG BEND ELECTRIC
COOP, INC   -816.8267   2050.217
-0.398   0.690   -4835.204   3201.550
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||INLAND POWER &
LIGHT COMPANY   466.7990   445.301
1.048   0.295   -405.981   1339.579
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||PUD NO 1 OF
ASOTIN COUNTY   2.437e+04   1558.031
15.642   0.000   2.13e+04   2.74e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||BENTON RURAL ELECTRIC ASSN
-304.0386   4428.316   -0.069   0.945   -8983.436   8375.359
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||BIG BEND ELECTRIC COOP, INC
-271.4205   2390.826   -0.114   0.910   -4957.383   4414.542
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF CENTRALIA - (WA)|CITY
OF TACOMA - (WA)   4.597e+04   743.206
61.850   0.000   4.45e+04   4.74e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF COULEE DAM - (WA)
2.343e+04   1305.056   17.957   0.000   2.09e+04   2.6e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF ELLENSBURG - (WA)
-5482.6437   722.717   -7.586   0.000   -6899.153   -4066.134
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF MCCLEARY - (WA)
3.504e+04   1781.302   19.670   0.000   3.15e+04   3.85e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF MILTON - (WA)|CITY OF

TACOMA - (WA) 1.802e+04 1037.925
17.361 0.000 1.6e+04 2.01e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF PORT ANGELES - (WA)
-3023.9019 1562.238 -1.936 0.053 -6085.852 38.048
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF RICHLAND - (WA)
-756.9969 5132.709 -0.147 0.883 -1.08e+04 9302.993
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||ALDER MUTUAL LIGHT CO, INC|PENINSULA LIGHT COMPANY 6.741e+04 2154.485
31.288 0.000 6.32e+04 7.16e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||BENTON RURAL ELECTRIC ASSN|PENINSULA LIGHT COMPANY 6.751e+04 818.860
82.448 0.000 6.59e+04 6.91e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||ELMHURST MUTUAL POWER & LIGHT CO|PENINSULA LIGHT COMPANY 6.739e+04
667.888 100.905 0.000 6.61e+04 6.87e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||LAKEVIEW LIGHT & POWER|PENINSULA LIGHT COMPANY 6.737e+04
698.637 96.430 0.000 6.6e+04 6.87e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||OHOP MUTUAL LIGHT COMPANY, INC|PENINSULA LIGHT COMPANY 6.74e+04 767.468
87.822 0.000 6.59e+04 6.89e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PARKLAND LIGHT & WATER COMPANY|PENINSULA LIGHT COMPANY 6.738e+04
720.680 93.494 0.000 6.6e+04 6.88e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PENINSULA LIGHT COMPANY 6.722e+04
659.535 101.926 0.000 6.59e+04 6.85e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO 1 OF LEWIS COUNTY 5.512e+04 709.846
77.651 0.000 5.37e+04 5.65e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO 1 OF MASON COUNTY 4.914e+04 1327.821
37.009 0.000 4.65e+04 5.17e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO 3 OF MASON COUNTY 4.87e+04 1295.860
37.584 0.000 4.62e+04 5.12e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||COLUMBIA RURAL ELEC ASSN, INC
-271.4205 3702.164 -0.073 0.942 -7527.576 6984.735
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||INLAND POWER & LIGHT COMPANY
432.0678 489.983 0.882 0.378 -528.287 1392.422
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||NESPELEM VALLEY ELEC COOP, INC
3.952e+04 3484.297 11.344 0.000 3.27e+04 4.64e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||ORCAS POWER & LIGHT COOP
-5622.1291 915.966 -6.138 0.000 -7417.402 -3826.856
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PACIFICORP||BENTON RURAL ELECTRIC ASSN -235.6085 4361.403
-0.054 0.957 -8783.856 8312.639
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PACIFICORP||COLUMBIA RURAL

ELEC ASSN, INC -271.4205 4133.442
-0.066 0.948 -8372.871 7830.030
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PACIFICORP||PUD NO 1 OF CLARK COUNTY - (WA) 4.591e+04 1492.645
30.760 0.000 4.3e+04 4.88e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PENINSULA LIGHT COMPANY
6.72e+04 2909.999 23.094 0.000 6.15e+04 7.29e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD 1 OF SNOHOMISH COUNTY
-5388.2575 657.045 -8.201 0.000 -6676.050 -4100.465
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF ASOTIN COUNTY||INLAND POWER & LIGHT COMPANY 2.437e+04
2536.831 9.607 0.000 1.94e+04 2.93e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF BENTON COUNTY
-728.3419 5107.523 -0.143 0.887 -1.07e+04 9282.285
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLALLAM COUNTY
-3023.5567 1539.661 -1.964 0.050 -6041.256 -5.857
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLALLAM COUNTY|PUD NO 1 OF JEFFERSON COUNTY -3119.5030 3310.484
-0.942 0.346 -9607.974 3368.968
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLARK COUNTY - (WA) 4.591e+04 1483.229
30.954 0.000 4.3e+04 4.88e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF COWLITZ COUNTY
3.587e+04 1519.208 23.611 0.000 3.29e+04 3.88e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF FERRY COUNTY
3.684e+04 2249.888 16.372 0.000 3.24e+04 4.12e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF FRANKLIN COUNTY
-271.4205 2372.170 -0.114 0.909 -4920.818 4377.978
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF GRAYS HARBOR COUNTY 3.504e+04 1462.062
23.965 0.000 3.22e+04 3.79e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF JEFFERSON COUNTY
1.195e+04 1974.927 6.049 0.000 8075.243 1.58e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF KITTITAS COUNTY
-5482.6437 971.093 -5.646 0.000 -7385.963 -3579.325
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF KLICKITAT COUNTY
3.521e+04 1590.282 22.140 0.000 3.21e+04 3.83e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF MASON COUNTY|PUD NO 1 OF JEFFERSON COUNTY 1.195e+04 1157.428
10.321 0.000 9677.523 1.42e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF SKAMANIA CO
3.509e+04 1500.795 23.384 0.000 3.22e+04 3.8e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF WAHKIAKUM COUNTY
3.149e+04 1988.645 15.835 0.000 2.76e+04 3.54e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 2 OF PACIFIC COUNTY
3.163e+04 1452.492 21.780 0.000 2.88e+04 3.45e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUGET SOUND ENERGY INC||PUD NO 1 OF JEFFERSON COUNTY -3108.5567 1777.488

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-1.749      0.080   -6592.391     375.278
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||TOWN OF EATONVILLE - (WA)|CITY
OF TACOMA - (WA)                                  6.741e+04    944.638
71.360      0.000    6.56e+04    6.93e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||TOWN OF RUSTON - (WA)|CITY OF
TACOMA - (WA)||PENINSULA LIGHT COMPANY            6.707e+04   1113.461
60.236      0.000    6.49e+04    6.93e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||TOWN OF STEILACOOM|CITY OF
TACOMA - (WA)||PENINSULA LIGHT COMPANY               2.688e+04    763.186
35.215      0.000    2.54e+04    2.84e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||VERA IRRIGATION DISTRICT #15
380.3075    479.214      0.794      0.427    -558.941    1319.556
Electric_Utility_CITY OF BLAINE - (WA)||PUD NO 1 OF WHATCOM COUNTY
-3024.7346    987.398     -3.063      0.002   -4960.012   -1089.457
Electric_Utility_CITY OF CHENEY - (WA)
474.6151    665.775      0.713      0.476    -830.287    1779.518
Electric_Utility_CITY OF CHEWELAH
-9.035e-09   1209.651  -7.47e-12      1.000   -2370.889    2370.889
Electric_Utility_CITY OF SEATTLE - (WA)
6.732e+04   2105.725     31.972      0.000    6.32e+04    7.15e+04
Electric_Utility_CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)
6.742e+04    651.731    103.441      0.000    6.61e+04    6.87e+04
Electric_Utility_CITY OF SUMAS - (WA)||PUD NO 1 OF WHATCOM COUNTY
-3024.7346   1798.613     -1.682      0.093   -6549.975     500.506
Electric_Utility_CITY OF TACOMA - (WA)
6.346e+04    910.129     69.729      0.000    6.17e+04    6.52e+04
Electric_Utility_CITY OF TACOMA - (WA)||TANNER ELECTRIC COOP
6.76e+04    679.272     99.525      0.000    6.63e+04    6.89e+04
Electric_Utility_MODERN ELECTRIC WATER COMPANY
460.9311    465.425      0.990      0.322    -451.291    1373.154
Electric_Utility_NO KNOWN ELECTRIC UTILITY SERVICE
-3023.5567    594.834     -5.083      0.000   -4189.417   -1857.696
Electric_Utility_OKANOGAN COUNTY ELEC COOP, INC
3.838e+04   2391.139     16.052      0.000    3.37e+04    4.31e+04
Electric_Utility_PACIFICORP
-271.4205   4060.877     -0.067      0.947   -8230.646    7687.805
Electric_Utility_PORTLAND GENERAL ELECTRIC CO
4.593e+04   1934.235     23.745      0.000    4.21e+04    4.97e+04
Electric_Utility_PUD NO 1 OF CHELAN COUNTY
3.922e+04   2585.908     15.166      0.000    3.41e+04    4.43e+04
Electric_Utility_PUD NO 1 OF DOUGLAS COUNTY
750.7033   2123.883      0.353      0.724   -3412.058    4913.464
Electric_Utility_PUD NO 1 OF OKANOGAN COUNTY
3.838e+04   2176.447     17.635      0.000    3.41e+04    4.26e+04
Electric_Utility_PUD NO 1 OF PEND OREILLE COUNTY
-4365.9322   1393.007     -3.134      0.002   -7096.193   -1635.671
Electric_Utility_PUD NO 1 OF WHATCOM COUNTY
-3048.0461   1704.764     -1.788      0.074   -6389.344     293.252
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Electric_Utility_PUD NO 2 OF GRANT COUNTY
1206.5157   1763.715      0.684      0.494   -2250.325    4663.356
Electric_Utility_PUGET SOUND ENERGY INC
-5482.6437    644.102     -8.512      0.000   -6745.070   -4220.218
Electric_Utility_PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)
6.76e+04    649.358    104.100      0.000    6.63e+04    6.89e+04
Electric_Utility_PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY
-3024.7346    947.090     -3.194      0.001   -4881.010   -1168.459
==============================================================================
Omnibus:                   273210.375   Durbin-Watson:                   2.001
Prob(Omnibus):                  0.000   Jarque-Bera (JB):       877197785.283
Skew:                          -8.086   Prob(JB):                         0.00
Kurtosis:                     338.618   Cond. No.                     5.64e+19
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.01e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.


Regression Results for EV_Count_City
                            OLS Regression Results
==============================================================================
Dep. Variable:          EV_Count_City   R-squared:                       0.881
Model:                            OLS   Adj. R-squared:                  0.880
Method:                 Least Squares   F-statistic:                     9284.
Date:                Sun, 07 Jul 2024   Prob (F-statistic):               0.00
Time:                        20:03:58   Log-Likelihood:            -1.7950e+06
No. Observations:              186471   AIC:                         3.590e+06
Df Residuals:                  186322   BIC:                         3.592e+06
Df Model:                         148
Covariance Type:            nonrobust
================================================================================
================================================================================
=====================================
                                                        coef    std err
t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
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const
-4.589e+04   1.43e+04     -3.219      0.001   -7.38e+04   -1.79e+04
Latitude
-1038.7688    149.165     -6.964      0.000   -1331.129    -746.409
Longitude
-836.8468    110.088     -7.602      0.000   -1052.617    -621.077
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County_Asotin
655.8250   1651.837      0.397      0.691   -2581.736    3893.386
County_Benton
-341.8876   1133.050     -0.302      0.763   -2562.640    1878.865
County_Chelan
-419.9473    926.359     -0.453      0.650   -2235.589    1395.695
County_Clallam
-856.1396   3022.482     -0.283      0.777   -6780.134    5067.855
County_Clark
-3219.0584   1777.512     -1.811      0.070   -6702.940     264.823
County_Columbia
-458.2410   5400.118     -0.085      0.932    -1.1e+04    1.01e+04
County_Cowlitz
-1852.4143   1163.569     -1.592      0.111   -4132.981     428.153
County_Douglas
-6.0563   2582.661     -0.002      0.998   -5068.012    5055.900
County_Ferry
919.6064   1999.662      0.460      0.646   -2999.684    4838.897
County_Franklin
-354.8948   3706.116     -0.096      0.924   -7618.795    6909.006
County_Garfield
25.9488   5713.632      0.005      0.996   -1.12e+04    1.12e+04
County_Grant
-205.4036    976.672     -0.210      0.833   -2119.659    1708.851
County_Grays Harbor
-3623.3924   4381.699     -0.827      0.408   -1.22e+04    4964.636
County_Island
-608.6462   2414.914     -0.252      0.801   -5341.821    4124.528
County_Jefferson
-1843.3003   2154.385     -0.856      0.392   -6065.845    2379.244
County_King
-1580.2876   2815.320     -0.561      0.575   -7098.249    3937.674
County_Kitsap
-3525.4379   2401.414     -1.468      0.142   -8232.153    1181.278
County_Kittitas
-768.5421   2053.128     -0.374      0.708   -4792.625    3255.541
County_Klickitat
-1913.4144   1136.733     -1.683      0.092   -4141.385     314.556
County_Lewis
-1161.7527   2814.548     -0.413      0.680   -6678.201    4354.696
County_Lincoln
854.7141   2069.502      0.413      0.680   -3201.461    4910.890
County_Mason
-1.567e+04   3370.986     -4.647      0.000   -2.23e+04   -9058.564
County_Okanogan
-6.0563   1773.452     -0.003      0.997   -3481.981    3469.868
County_Pacific
-2223.6628   1180.969     -1.883      0.060   -4538.334      91.009
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County_Pend Oreille
637.0204    894.756      0.712      0.476   -1116.680    2390.721
County_Pierce
-2310.6676   2811.599     -0.822      0.411   -7821.336    3200.000
County_San Juan
-888.0754   3024.868     -0.294      0.769   -6816.747    5040.596
County_Skagit
-130.0716   2416.775     -0.054      0.957   -4866.895    4606.752
County_Skamania
-2144.4798   1143.708     -1.875      0.061   -4386.120      97.161
County_Snohomish
-31.3255   2405.194     -0.013      0.990   -4745.450    4682.799
County_Spokane
2082.7581   1748.867      1.191      0.234   -1344.981    5510.497
County_Stevens
1069.3613   1744.834      0.613      0.540   -2350.472    4489.195
County_Thurston
-1400.7881   2398.273     -0.584      0.559   -6101.348    3299.772
County_Wahkiakum
-2134.5369   1192.206     -1.790      0.073   -4471.233     202.160
County_Walla Walla
-728.1256   5290.125     -0.138      0.891   -1.11e+04    9640.397
County_Whatcom
516.2257   1903.600      0.271      0.786   -3214.785    4247.236
County_Whitman
1440.5406   1663.722      0.866      0.387   -1820.316    4701.398
County_Yakima
-2318.6303   5527.279     -0.419      0.675   -1.32e+04    8514.708
Legislative_District_2.0
-2812.8177    222.566    -12.638      0.000   -3249.042   -2376.594
Legislative_District_3.0
-2426.8441   1587.763     -1.528      0.126   -5538.822     685.133
Legislative_District_4.0
-4119.2452   1581.446     -2.605      0.009   -7218.842   -1019.649
Legislative_District_5.0
-957.2281     87.052    -10.996      0.000   -1127.848    -786.608
Legislative_District_6.0
-2667.6853   1580.040     -1.688      0.091   -5764.527     429.156
Legislative_District_7.0
-3363.4067   1567.377     -2.146      0.032   -6435.430    -291.384
Legislative_District_8.0
-4495.3256   1691.935     -2.657      0.008   -7811.479   -1179.172
Legislative_District_9.0
-4827.1114   1634.659     -2.953      0.003   -8031.005   -1623.218
Legislative_District_10.0
-4849.4251    167.409    -28.967      0.000   -5177.544   -4521.306
Legislative_District_11.0
1416.3595     85.229     16.618      0.000    1249.312    1583.407
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Legislative_District_12.0
-4270.0071   1403.704     -3.042      0.002   -7021.235   -1518.779
Legislative_District_13.0
-4493.3487   1244.912     -3.609      0.000   -6933.347   -2053.350
Legislative_District_14.0
-4209.9412    552.861     -7.615      0.000   -5293.536   -3126.346
Legislative_District_15.0
-4418.4757    605.658     -7.295      0.000   -5605.551   -3231.400
Legislative_District_16.0
-4826.9664   1675.442     -2.881      0.004   -8110.793   -1543.139
Legislative_District_17.0
251.9261    432.797      0.582      0.561    -596.346    1100.199
Legislative_District_18.0
-2930.9160    430.174     -6.813      0.000   -3774.047   -2087.785
Legislative_District_19.0
-5062.4233    390.496    -12.964      0.000   -5827.787   -4297.060
Legislative_District_20.0
-5135.9507    325.242    -15.791      0.000   -5773.417   -4498.485
Legislative_District_21.0
-3336.1414     71.492    -46.665      0.000   -3476.263   -3196.019
Legislative_District_22.0
-2603.5500    242.904    -10.718      0.000   -3079.637   -2127.463
Legislative_District_23.0
-1607.8989    234.177     -6.866      0.000   -2066.880   -1148.918
Legislative_District_24.0
-5130.5106    485.309    -10.572      0.000   -6081.705   -4179.316
Legislative_District_25.0
-1913.4352    203.671     -9.395      0.000   -2312.625   -1514.245
Legislative_District_26.0
-1922.0242    220.383     -8.721      0.000   -2353.969   -1490.079
Legislative_District_27.0
281.3584    221.307      1.271      0.204    -152.399     715.116
Legislative_District_28.0
-2599.8721    214.007    -12.149      0.000   -3019.321   -2180.423
Legislative_District_29.0
-803.6773    238.786     -3.366      0.001   -1271.692    -335.662
Legislative_District_30.0
-2187.1498    121.586    -17.988      0.000   -2425.456   -1948.844
Legislative_District_31.0
-2160.2341    165.180    -13.078      0.000   -2483.983   -1836.485
Legislative_District_32.0
-7093.2671     75.437    -94.029      0.000   -7241.122   -6945.412
Legislative_District_33.0
-2383.6385    101.298    -23.531      0.000   -2582.179   -2185.098
Legislative_District_34.0
7907.7260     94.609     83.583      0.000    7722.294    8093.158
Legislative_District_35.0
-1998.8719    242.712     -8.236      0.000   -2474.582   -1523.162
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Legislative_District_36.0
1.27e+04     87.427    145.213      0.000    1.25e+04    1.29e+04
Legislative_District_37.0
1.441e+04     90.412    159.436      0.000    1.42e+04    1.46e+04
Legislative_District_38.0
-3521.1932    100.105    -35.175      0.000   -3717.397   -3324.989
Legislative_District_39.0
-4533.9033     97.984    -46.272      0.000   -4725.950   -4341.857
Legislative_District_40.0
-4733.2298    212.425    -22.282      0.000   -5149.577   -4316.883
Legislative_District_41.0
2796.9720     76.917     36.364      0.000    2646.217    2947.727
Legislative_District_42.0
-5925.1149    243.954    -24.288      0.000   -6403.258   -5446.972
Legislative_District_43.0
1.271e+04     88.507    143.587      0.000    1.25e+04    1.29e+04
Legislative_District_44.0
-3559.3739     72.038    -49.410      0.000   -3700.567   -3418.181
Legislative_District_45.0
1961.7562     74.689     26.266      0.000    1815.368    2108.144
Legislative_District_46.0
9616.6594     80.801    119.016      0.000    9458.291    9775.028
Legislative_District_47.0
-1056.5658    105.909     -9.976      0.000   -1264.145    -848.986
Legislative_District_48.0
3720.4750     75.601     49.212      0.000    3572.299    3868.651
Legislative_District_49.0
924.0437    435.537      2.122      0.034      70.402    1777.685
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||BIG BEND ELECTRIC
COOP, INC                                                    0.2505   1722.409
0.000      1.000   -3375.631    3376.132
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||INLAND POWER &
LIGHT COMPANY                                                  83.8126    401.760
0.209      0.835    -703.627     871.252
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||PUD NO 1 OF
ASOTIN COUNTY                                                    314.2181   1370.982
0.229      0.819   -2372.875    3001.311
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||BENTON RURAL ELECTRIC ASSN
313.1242   5946.929      0.053      0.958   -1.13e+04     1.2e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||BIG BEND ELECTRIC COOP, INC
-34.8649   4100.249     -0.009      0.993   -8071.257    8001.527
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF CENTRALIA - (WA)|CITY
OF TACOMA - (WA)                                         -1840.6177   1608.888
-1.144      0.253   -4994.001    1312.766
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF COULEE DAM - (WA)
447.3657   1548.748      0.289      0.773   -2588.144    3482.875
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF ELLENSBURG - (WA)
-573.1394    671.831     -0.853      0.394   -1889.913     743.635
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Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF MCCLEARY - (WA)
398.9129 3822.429 0.104 0.917 -7092.959 7890.785
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF MILTON - (WA)|CITY OF TACOMA - (WA) -2850.7531 1620.674
-1.759 0.079 -6027.237 325.730
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF PORT ANGELES - (WA)
-1008.5263 1907.479 -0.529 0.597 -4747.142 2730.089
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF RICHLAND - (WA)
-74.2706 576.594 -0.129 0.898 -1204.381 1055.840
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||ALDER MUTUAL LIGHT CO, INC|PENINSULA LIGHT COMPANY -2484.7459 3037.444
-0.818 0.413 -8438.065 3468.573
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||BENTON RURAL ELECTRIC ASSN|PENINSULA LIGHT COMPANY -2322.3276 1681.723
-1.381 0.167 -5618.466 973.811
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||ELMHURST MUTUAL POWER & LIGHT CO|PENINSULA LIGHT COMPANY -1798.0941
1583.968 -1.135 0.256 -4902.635 1306.447
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||LAKEVIEW LIGHT & POWER|PENINSULA LIGHT COMPANY -2382.1688
1603.788 -1.485 0.137 -5525.555 761.218
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||OHOP MUTUAL LIGHT COMPANY, INC|PENINSULA LIGHT COMPANY -2346.5721 1610.388
-1.457 0.145 -5502.896 809.752
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PARKLAND LIGHT & WATER COMPANY|PENINSULA LIGHT COMPANY 92.2363
1614.158 0.057 0.954 -3071.475 3255.948
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PENINSULA LIGHT COMPANY -1591.7517
1576.097 -1.010 0.313 -4680.866 1497.363
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO 1 OF LEWIS COUNTY -1968.4213 1605.878
-1.226 0.220 -5115.905 1179.063
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO 1 OF MASON COUNTY 9886.3866 2454.619
4.028 0.000 5075.390 1.47e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO 3 OF MASON COUNTY 1.002e+04 2435.869
4.113 0.000 5244.187 1.48e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||COLUMBIA RURAL ELEC ASSN, INC
2.5988 5479.529 0.000 1.000 -1.07e+04 1.07e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||INLAND POWER & LIGHT COMPANY
-356.6954 448.697 -0.795 0.427 -1236.132 522.741
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||NESPELEM VALLEY ELEC COOP, INC
518.2501 2040.255 0.254 0.799 -3480.602 4517.102
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||ORCAS POWER & LIGHT COOP
-609.1928 1896.073 -0.321 0.748 -4325.452 3107.066
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PACIFICORP||BENTON RURAL

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ELECTRIC ASSN                                              345.7592   5569.594
0.062      0.950   -1.06e+04    1.13e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PACIFICORP||COLUMBIA RURAL
ELEC ASSN, INC                                           600.7466   5648.507
0.106      0.915   -1.05e+04    1.17e+04
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PACIFICORP||PUD NO 1 OF CLARK
COUNTY - (WA)                                       -2253.1130    728.843
-3.091      0.002   -3681.628    -824.598
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PENINSULA LIGHT COMPANY
1236.9484   3992.798      0.310      0.757   -6588.842    9062.739
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD 1 OF SNOHOMISH COUNTY
-911.0831    577.423     -1.578      0.115   -2042.818     220.652
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF ASOTIN
COUNTY||INLAND POWER & LIGHT COMPANY                               341.6068
2511.015      0.136      0.892   -4579.923    5263.137
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF BENTON COUNTY
-267.6169    568.613     -0.471      0.638   -1382.086     846.852
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLALLAM COUNTY
-723.5090   1896.196     -0.382      0.703   -4440.009    2992.991
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLALLAM COUNTY|PUD
NO 1 OF JEFFERSON COUNTY                           -1434.2104   3070.864
-0.467      0.640   -7453.032    4584.611
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLARK COUNTY -
(WA)                                                     -481.1265    710.689
-0.677      0.498   -1874.060     911.807
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF COWLITZ COUNTY
-1852.4143   1163.569     -1.592      0.111   -4132.981     428.153
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF FERRY COUNTY
-347.1276   1322.062     -0.263      0.793   -2938.338    2244.083
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF FRANKLIN COUNTY
-1.9559   4057.213     -0.000      1.000   -7953.998    7950.086
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF GRAYS HARBOR
COUNTY                                                     -92.6750   3704.297
-0.025      0.980   -7353.011    7167.661
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF JEFFERSON COUNTY
-453.5721   3064.649     -0.148      0.882   -6460.212    5553.068
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF KITTITAS COUNTY
-635.4124   1069.309     -0.594      0.552   -2731.232    1460.407
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF KLICKITAT COUNTY
-1913.4144   1136.733     -1.683      0.092   -4141.385     314.556
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF MASON COUNTY|PUD
NO 1 OF JEFFERSON COUNTY                              -453.5721   1285.721
-0.353      0.724   -2973.554    2066.410
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF SKAMANIA CO
-2144.4798   1143.708     -1.875      0.061   -4386.120      97.161
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF WAHKIAKUM COUNTY
-2134.5369   1192.206     -1.790      0.073   -4471.233     202.160
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 2 OF PACIFIC COUNTY
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-2223.6628   1180.969     -1.883      0.060   -4538.334      91.009
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUGET SOUND ENERGY INC||PUD NO
1 OF JEFFERSON COUNTY                              498.0542   1152.311
0.432      0.666   -1760.448    2756.557
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||TOWN OF EATONVILLE - (WA)|CITY
OF TACOMA - (WA)                                 -2484.7459   1711.920
-1.451      0.147   -5840.069     870.577
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||TOWN OF RUSTON - (WA)|CITY OF
TACOMA - (WA)||PENINSULA LIGHT COMPANY           -4550.8323   1673.885
-2.719      0.007   -7831.608   -1270.057
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||TOWN OF STEILACOOM|CITY OF
TACOMA - (WA)||PENINSULA LIGHT COMPANY              -2626.8338   1601.363
-1.640      0.101   -5765.468     511.800
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||VERA IRRIGATION DISTRICT #15
639.5945    451.266      1.417      0.156    -244.876    1524.065
Electric_Utility_CITY OF BLAINE - (WA)||PUD NO 1 OF WHATCOM COUNTY
-144.5625    590.649     -0.245      0.807   -1302.221    1013.096
Electric_Utility_CITY OF CHENEY - (WA)
-2413.8248    681.545     -3.542      0.000   -3749.638   -1078.012
Electric_Utility_CITY OF CHEWELAH
-153.3087   1260.223     -0.122      0.903   -2623.316    2316.699
Electric_Utility_CITY OF SEATTLE - (WA)
1.065e+04   3033.240      3.510      0.000    4701.514    1.66e+04
Electric_Utility_CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)
1.276e+04   1572.457      8.113      0.000    9676.141    1.58e+04
Electric_Utility_CITY OF SUMAS - (WA)||PUD NO 1 OF WHATCOM COUNTY
-102.2846   1145.526     -0.089      0.929   -2347.489    2142.920
Electric_Utility_CITY OF TACOMA - (WA)
9934.1969   1794.685      5.535      0.000    6416.656    1.35e+04
Electric_Utility_CITY OF TACOMA - (WA)||TANNER ELECTRIC COOP
-3534.9989   1589.718     -2.224      0.026   -6650.809    -419.188
Electric_Utility_MODERN ELECTRIC WATER COMPANY
435.6439    436.027      0.999      0.318    -418.958    1290.246
Electric_Utility_NO KNOWN ELECTRIC UTILITY SERVICE
-555.9313    464.523     -1.197      0.231   -1466.386     354.524
Electric_Utility_OKANOGAN COUNTY ELEC COOP, INC
-24.4606   1352.010     -0.018      0.986   -2674.369    2625.448
Electric_Utility_PACIFICORP
561.9233   5554.487      0.101      0.919   -1.03e+04    1.14e+04
Electric_Utility_PORTLAND GENERAL ELECTRIC CO
-484.8189   1361.454     -0.356      0.722   -3153.238    2183.600
Electric_Utility_PUD NO 1 OF CHELAN COUNTY
-419.9473    926.359     -0.453      0.650   -2235.589    1395.695
Electric_Utility_PUD NO 1 OF DOUGLAS COUNTY
-870.4861   2303.578     -0.378      0.706   -5385.446    3644.474
Electric_Utility_PUD NO 1 OF OKANOGAN COUNTY
-82.7817   1340.370     -0.062      0.951   -2709.876    2544.312
Electric_Utility_PUD NO 1 OF PEND OREILLE COUNTY
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637.0204    894.756      0.712      0.476   -1116.680    2390.721
Electric_Utility_PUD NO 1 OF WHATCOM COUNTY
-488.4025    696.182     -0.702      0.483   -1852.903     876.098
Electric_Utility_PUD NO 2 OF GRANT COUNTY
-205.4036    976.672     -0.210      0.833   -2119.659    1708.851
Electric_Utility_PUGET SOUND ENERGY INC
-797.3577    567.468     -1.405      0.160   -1909.581     314.866
Electric_Utility_PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)
-2071.9719   1573.011     -1.317      0.188   -5155.037    1011.093
Electric_Utility_PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY
1251.4754    551.969      2.267      0.023     169.629    2333.322
==============================================================================
Omnibus:                    65320.887   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2217806.166
Skew:                          -1.040   Prob(JB):                         0.00
Kurtosis:                      19.767   Cond. No.                     1.00e+16
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 3.19e-23. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.


Regression Results for EV_Count_Leg_Dist
                            OLS Regression Results
==============================================================================
Dep. Variable:      EV_Count_Leg_Dist   R-squared:                       0.933
Model:                            OLS   Adj. R-squared:                  0.932
Method:                 Least Squares   F-statistic:                     4621.
Date:                Sun, 07 Jul 2024   Prob (F-statistic):               0.00
Time:                        20:04:23   Log-Likelihood:            -1.5223e+06
No. Observations:              186471   AIC:                         3.046e+06
Df Residuals:                  185913   BIC:                         3.051e+06
Df Model:                         557
Covariance Type:            nonrobust
================================================================================
================================================================================
=====================================
                                                          coef    std err
t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
-------------------------------------
const
-3.316e+05   8035.967    -41.263      0.000   -3.47e+05   -3.16e+05
Latitude
```

```
4205.6883     63.802     65.918      0.000    4080.638    4330.738
Longitude
-1143.6990     65.927    -17.348      0.000   -1272.914   -1014.484
County_Asotin
1948.1985    485.325      4.014      0.000     996.973    2899.424
County_Benton
386.3287    625.645      0.617      0.537    -839.922    1612.579
County_Chelan
-2890.2472    493.133     -5.861      0.000   -3856.777   -1923.717
County_Clallam
-8052.2070    961.652     -8.373      0.000   -9937.022   -6167.392
County_Clark
2145.2174    662.628      3.237      0.001     846.483    3443.952
County_Columbia
1464.9267    729.682      2.008      0.045      34.766    2895.087
County_Cowlitz
1437.8006    440.097      3.267      0.001     575.222    2300.380
County_Douglas
-2833.1342    790.353     -3.585      0.000   -4382.208   -1284.061
County_Ferry
-654.2369   1297.475     -0.504      0.614   -3197.258    1888.784
County_Franklin
8.818e-09    864.574   1.02e-11      1.000   -1694.546    1694.546
County_Garfield
1393.1284    760.196      1.833      0.067     -96.837    2883.094
County_Grant
128.0000    451.289      0.284      0.777    -756.515    1012.515
County_Grays Harbor
-6191.1704   1299.351     -4.765      0.000   -8737.868   -3644.472
County_Island
-6737.1873    827.345     -8.143      0.000   -8358.765   -5115.609
County_Jefferson
-5776.4349    668.317     -8.643      0.000   -7086.320   -4466.550
County_King
-5812.5948   1313.781     -4.424      0.000   -8387.575   -3237.614
County_Kitsap
-6001.9740   1227.787     -4.888      0.000   -8408.407   -3595.541
County_Kittitas
-1.222e+04   1299.364     -9.402      0.000   -1.48e+04   -9669.425
County_Klickitat
-194.9069    442.744     -0.440      0.660   -1062.675     672.861
County_Lewis
-5885.0024   1281.838     -4.591      0.000   -8397.376   -3372.629
County_Lincoln
-266.5382   1096.952     -0.243      0.808   -2416.539    1883.463
County_Mason
-6713.3740   1150.011     -5.838      0.000   -8967.369   -4459.379
County_Okanogan
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-2833.1342    674.478     -4.200      0.000   -4155.096   -1511.173
County_Pacific
-2157.4717    458.319     -4.707      0.000   -3055.766   -1259.178
County_Pend Oreille
-217.1516    646.564     -0.336      0.737   -1484.402    1050.099
County_Pierce
-5623.8424   1311.879     -4.287      0.000   -8195.094   -3052.591
County_San Juan
-7513.9347   1463.613     -5.134      0.000   -1.04e+04   -4645.287
County_Skagit
-7906.2031   1383.398     -5.715      0.000   -1.06e+04   -5194.775
County_Skamania
-195.5533    437.089     -0.447      0.655   -1052.238     661.131
County_Snohomish
-7352.7459   1223.606     -6.009      0.000   -9750.984   -4954.507
County_Spokane
-600.1903   1245.612     -0.482      0.630   -3041.561    1841.180
County_Stevens
-654.2369   1255.606     -0.521      0.602   -3115.195    1806.722
County_Thurston
-6115.4097   1192.985     -5.126      0.000   -8453.633   -3777.187
County_Wahkiakum
-2157.4717    503.199     -4.288      0.000   -3143.730   -1171.214
County_Walla Walla
2827.6013   1248.882      2.264      0.024     379.822    5275.381
County_Whatcom
-6213.2594   1108.670     -5.604      0.000   -8386.226   -4040.293
County_Whitman
-600.1903   1420.233     -0.423      0.673   -3383.813    2183.433
County_Yakima
109.2065   1427.567      0.076      0.939   -2688.792    2907.206
City_Acme
-2261.3553   1099.900     -2.056      0.040   -4417.133    -105.578
City_Addy
-5122.5940    783.817     -6.535      0.000   -6658.858   -3586.330
City_Adna
2692.4713   1135.765      2.371      0.018     466.397    4918.545
City_Airway Heights
-931.5707    481.481     -1.935      0.053   -1875.262      12.120
City_Alderdale
1883.2053    871.013      2.162      0.031     176.041    3590.370
City_Alderwood Manor
2514.6987   1174.110      2.142      0.032     213.470    4815.927
City_Algona
983.4586    819.720      1.200      0.230    -623.174    2590.091
City_Allyn
573.9213    315.224      1.821      0.069     -43.910    1191.753
City_Almira
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-3565.5239    949.857     -3.754      0.000   -5427.221   -1703.827
City_Amanda Park
-743.9432    496.552     -1.498      0.134   -1717.173     229.287
City_Amboy
-2223.5861    243.503     -9.132      0.000   -2700.846   -1746.326
City_Anacortes
-915.2369   1045.806     -0.875      0.381   -2964.993    1134.519
City_Anderson Island
1054.9536    812.691      1.298      0.194    -537.902    2647.809
City_Ariel
-3020.5448    285.460    -10.581      0.000   -3580.041   -2461.049
City_Arlington
-329.0946    813.945     -0.404      0.686   -1924.407    1266.218
City_Artondale
1866.4142   1002.665      1.861      0.063     -98.785    3831.614
City_Ashford
3354.0022    781.965      4.289      0.000    1821.370    4886.635
City_Asotin
1261.3044    290.733      4.338      0.000     691.475    1831.134
City_Auburn
1989.9363    807.273      2.465      0.014     407.701    3572.172
City_Bainbridge Island
1045.9030    795.979      1.314      0.189    -514.197    2606.003
City_Bangor Base
612.5996   1164.329      0.526      0.599   -1669.459    2894.658
City_Baring
460.2575    888.195      0.518      0.604   -1280.584    2201.099
City_Battle Ground
532.3887    193.383      2.753      0.006     153.363     911.415
City_Bay Center
-863.7343    827.832     -1.043      0.297   -2486.265     758.796
City_Beaux Arts
9499.3339    817.737     11.617      0.000    7896.588    1.11e+04
City_Beaver
-1946.5255    816.664     -2.384      0.017   -3547.169    -345.882
City_Belfair
313.1707    307.904      1.017      0.309    -290.314     916.655
City_Bellevue
8962.3275    809.029     11.078      0.000    7376.649    1.05e+04
City_Bellingham
-2494.7644   1068.049     -2.336      0.020   -4588.115    -401.413
City_Benton City
737.6397    414.061      1.781      0.075     -73.911    1549.190
City_Bingen
1968.5324    336.959      5.842      0.000    1308.100    2628.965
City_Black Diamond
6704.4285    810.470      8.272      0.000    5115.925    8292.932
City_Blaine
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-4481.0187   1069.547     -4.190      0.000   -6577.305   -2384.732
City_Bonney Lake
2567.9399    805.798      3.187      0.001     988.594    4147.286
City_Bothell
5395.5452    809.649      6.664      0.000    3808.651    6982.439
City_Bow
-893.0905   1050.406     -0.850      0.395   -2951.861    1165.680
City_Bremerton
509.6592    794.928      0.641      0.521   -1048.381    2067.699
City_Brewster
-207.1020    407.935     -0.508      0.612   -1006.645     592.441
City_Bridgeport
-5878.6920    775.020     -7.585      0.000   -7397.713   -4359.671
City_Bridgeport Bar
-6416.9685    737.030     -8.707      0.000   -7861.530   -4972.407
City_Brier
6084.6987    810.800      7.505      0.000    4495.549    7673.848
City_Brinnon
-791.6332    341.932     -2.315      0.021   -1461.812    -121.454
City_Brush Prairie
589.9395    195.651      3.015      0.003     206.468     973.411
City_Buckley
2770.8501    808.315      3.428      0.001    1186.572    4355.128
City_Bucoda
2043.5604   1130.180      1.808      0.071    -171.566    4258.687
City_Burbank
-538.1529    482.433     -1.115      0.265   -1483.710     407.404
City_Burien
2857.0398    807.800      3.537      0.000    1273.770    4440.310
City_Burlington
-634.0668   1049.293     -0.604      0.546   -2690.656    1422.523
City_Bz Corner
1858.1727    387.312      4.798      0.000    1099.050    2617.295
City_Camano Island
-807.3128    128.467     -6.284      0.000   -1059.105    -555.521
City_Camas
1667.0384    190.714      8.741      0.000    1293.243    2040.834
City_Carbonado
2946.8729    858.384      3.433      0.001    1264.459    4629.286
City_Carlton
-954.3519    488.988     -1.952      0.051   -1912.757       4.053
City_Carnation
5753.9931    813.052      7.077      0.000    4160.429    7347.557
City_Carson
1392.2904    252.351      5.517      0.000     897.688    1886.893
City_Cashmere
1435.1352    550.407      2.607      0.009     356.351    2513.920
City_Castle Rock
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-4952.7113    239.785    -20.655      0.000   -5422.685   -4482.738
City_Cathlamet
1579.7332    459.191      3.440      0.001     679.730    2479.736
City_Centerville
2417.4600    631.383      3.829      0.000    1179.964    3654.956
City_Centralia
2272.3365    752.643      3.019      0.003     797.173    3747.500
City_Chattaroy
-2506.3005    479.718     -5.225      0.000   -3446.536   -1566.065
City_Chehalis
2581.0836    754.836      3.419      0.001    1101.623    4060.544
City_Chelan
540.3390    538.891      1.003      0.316    -515.875    1596.552
City_Chelan Falls
851.2071    981.001      0.868      0.386   -1071.532    2773.946
City_Cheney
-448.3152    460.708     -0.973      0.331   -1351.292     454.662
City_Chewelah
-4556.0621    555.552     -8.201      0.000   -5644.931   -3467.193
City_Chimacum
202.0870    241.981      0.835      0.404    -272.190     676.364
City_Chinook
638.2922    495.160      1.289      0.197    -332.210    1608.794
City_Cinebar
3496.3193    900.946      3.881      0.000    1730.486    5262.153
City_Clallam Bay
-2637.2383    593.810     -4.441      0.000   -3801.092   -1473.384
City_Clarkston
686.8940    263.231      2.609      0.009     170.967    1202.821
City_Clayton
-2948.6982    757.818     -3.891      0.000   -4434.003   -1463.393
City_Cle Elum
8264.7467    939.033      8.801      0.000    6424.263    1.01e+04
City_Clearlake
-1455.2664   1157.251     -1.258      0.209   -3723.451     812.918
City_Clinton
-245.4143    127.510     -1.925      0.054    -495.332       4.503
City_Clyde Hill
7790.7625    809.966      9.619      0.000    6203.247    9378.278
City_Colbert
-2309.5372    464.013     -4.977      0.000   -3218.992   -1400.083
City_Colfax
1790.6387    774.358      2.312      0.021     272.916    3308.362
City_College Place
745.4924    289.529      2.575      0.010     178.022    1312.963
City_Colton
3428.7829    975.460      3.515      0.000    1516.904    5340.662
City_Colville
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-5843.3614    521.078    -11.214      0.000   -6864.661   -4822.061
City_Concrete
-1153.2682   1061.658     -1.086      0.277   -3234.093     927.556
City_Connell
417.9488    711.272      0.588      0.557    -976.128    1812.025
City_Copalis Beach
397.8799    431.139      0.923      0.356    -447.142    1242.902
City_Copalis Crossing
515.7005    495.960      1.040      0.298    -456.369    1487.770
City_Cosmopolis
90.2635    229.222      0.394      0.694    -359.007     539.534
City_Cougar
-3124.9988    624.107     -5.007      0.000   -4348.234   -1901.764
City_Coulee City
-3954.7307    543.640     -7.275      0.000   -5020.253   -2889.209
City_Coulee Dam
-834.9295    250.793     -3.329      0.001   -1326.478    -343.381
City_Coupeville
-1543.3590    132.040    -11.689      0.000   -1802.155   -1284.563
City_Covington
2154.5533    809.273      2.662      0.008     568.396    3740.710
City_Cowiche
-1542.9633    496.631     -3.107      0.002   -2516.348    -569.579
City_Creston
-3290.9217    948.739     -3.469      0.001   -5150.428   -1431.415
City_Curlew
-2429.8036    377.483     -6.437      0.000   -3169.661   -1689.947
City_Curtis
2304.9905    818.111      2.817      0.005     701.512    3908.469
City_Cusick
-5331.0651    691.861     -7.705      0.000   -6687.097   -3975.033
City_Custer
-4370.3795   1080.536     -4.045      0.000   -6488.206   -2252.553
City_Dallesport
2732.6424    372.473      7.336      0.000    2002.603    3462.682
City_Danville
-2656.5434    717.631     -3.702      0.000   -4063.083   -1250.003
City_Darrington
54.2026    863.078      0.063      0.950   -1637.410    1745.815
City_Davenport
-2747.6712    487.145     -5.640      0.000   -3702.464   -1792.878
City_Dayton
1464.9267    729.682      2.008      0.045      34.766    2895.087
City_Deer Harbor
-1881.5182   1366.500     -1.377      0.169   -4559.826     796.790
City_Deer Meadows
-2747.6712    736.753     -3.729      0.000   -4191.689   -1303.653
City_Deer Park
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-2973.7577	465.965	-6.382	0.000	-3887.039	-2060.477
City_Deming					
-3249.0094	1081.499	-3.004	0.003	-5368.723	-1129.296
City_Des Moines					
1631.5142	807.665	2.020	0.043	48.509	3214.519
City_Dixie					
610.6334	812.483	0.752	0.452	-981.814	2203.081
City_Dryden					
1255.3852	982.731	1.277	0.201	-670.745	3181.516
City_Dupont					
1442.5206	803.757	1.795	0.073	-132.824	3017.865
City_Duvall					
8031.0448	812.347	9.886	0.000	6438.863	9623.226
City_East Wenatchee					
-4067.2666	610.930	-6.657	0.000	-5264.675	-2869.858
City_Easton					
7811.1154	951.259	8.211	0.000	5946.671	9675.560
City_Eastsound					
-1968.6837	1071.103	-1.838	0.066	-4068.020	130.653
City_Eatonville					
2569.9849	810.635	3.170	0.002	981.160	4158.810
City_Edgewood					
2325.9754	805.720	2.887	0.004	746.782	3905.169
City_Edmonds					
2460.3833	808.609	3.043	0.002	875.528	4045.238
City_Edwall					
-857.1226	619.815	-1.383	0.167	-2071.946	357.701
City_Elbe					
3048.0870	938.483	3.248	0.001	1208.683	4887.491
City_Electric City					
-4601.1690	609.295	-7.552	0.000	-5795.372	-3406.966
City_Elk					
-3168.9702	491.724	-6.445	0.000	-4132.737	-2205.203
City_Ellensburg					
9526.1572	944.643	10.084	0.000	7674.679	1.14e+04
City_Elma					
1479.4349	127.178	11.633	0.000	1230.168	1728.701
City_Elmer City					
446.1655	1041.937	0.428	0.669	-1596.007	2488.338
City_Eltopia					
1059.5256	740.902	1.430	0.153	-392.625	2511.676
City_Endicott					
1245.3000	962.945	1.293	0.196	-642.050	3132.650
City_Entiat					
819.1666	565.350	1.449	0.147	-288.907	1927.240
City_Enumclaw					
3877.8958	810.346	4.785	0.000	2289.637	5466.155
City_Ephrata					

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-3045.1960   515.214    -5.911     0.000   -4055.003   -2035.389
City_Ethel
3521.2458   830.134     4.242     0.000    1894.203    5148.289
City_Evans
-6701.3399   617.135   -10.859     0.000   -7910.911   -5491.769
City_Everett
1036.7665   810.347     1.279     0.201    -551.495    2625.028
City_Everson
-3863.9776  1073.626    -3.599     0.000   -5968.260   -1759.695
City_Fairchild Air Force Base
-948.6561   507.756    -1.868     0.062   -1943.847      46.535
City_Fall City
6083.3127   813.371     7.479     0.000    4489.125    7677.500
City_Federal Way
914.8023   806.629     1.134     0.257    -666.172    2495.777
City_Ferndale
-3923.0859  1068.849    -3.670     0.000   -6018.005   -1828.167
City_Fife
721.4889   806.447     0.895     0.371    -859.128    2302.106
City_Fircrest
922.5456   805.479     1.145     0.252    -656.175    2501.266
City_Ford
-2696.1334   602.497    -4.475     0.000   -3877.014   -1515.253
City_Forks
-1518.6860   287.484    -5.283     0.000   -2082.148    -955.224
City_Fox Island
2214.4923   803.928     2.755     0.006     638.813    3790.172
City_Frances
-811.0638   827.751    -0.980     0.327   -2433.436     811.308
City_Freeland
-658.9644   131.560    -5.009     0.000    -916.819    -401.110
City_Friday Harbor
-1572.0577  1069.176    -1.470     0.141   -3667.618     523.502
City_Garfield
1573.2749   844.424     1.863     0.062     -81.776    3228.326
City_Gifford
-5060.1524   783.153    -6.461     0.000   -6595.114   -3525.191
City_Gig Harbor
1772.4421   802.142     2.210     0.027     200.262    3344.622
City_Glacier
-3249.0094  1093.292    -2.972     0.003   -5391.836   -1106.183
City_Glenoma
4094.2682   869.603     4.708     0.000    2389.866    5798.671
City_Glenwood
915.8841   861.630     1.063     0.288    -772.891    2604.659
City_Gold Bar
1821.5688   824.111     2.210     0.027     206.331    3436.807
City_Goldendale
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2264.9882    275.450      8.223      0.000    1725.113    2804.864
City_Graham
1671.1297    803.950      2.079      0.038      95.406    3246.854
City_Grand Coulee
-4648.8270    461.191    -10.080      0.000   -5552.751   -3744.903
City_Grandview
307.9961    320.893      0.960      0.337    -320.947     936.939
City_Granger
-394.7558    354.705     -1.113      0.266   -1089.969     300.458
City_Granite Falls
207.1914    816.831      0.254      0.800   -1393.778    1808.161
City_Grapeview
812.0750    317.816      2.555      0.011     189.163    1434.986
City_Grayland
313.8501    308.697      1.017      0.309    -291.189     918.889
City_Grays River
697.3534    727.008      0.959      0.337    -727.565    2122.272
City_Greenacres
-742.5158    463.589     -1.602      0.109   -1651.139     166.107
City_Greenbank
-976.1442    146.767     -6.651      0.000   -1263.804    -688.485
City_Hamilton
-1440.8729   1351.638     -1.066      0.286   -4090.053    1208.307
City_Hansville
-85.8484    802.649     -0.107      0.915   -1659.022    1487.325
City_Harrington
-1786.7349    650.481     -2.747      0.006   -3061.663    -511.807
City_Hartline
-4137.9711    779.839     -5.306      0.000   -5666.438   -2609.505
City_Hatton
-583.5605   1208.918     -0.483      0.629   -2953.011    1785.890
City_Home
1828.2821   1168.605      1.564      0.118    -462.157    4118.721
City_Hoodsport
-56.4255    322.228     -0.175      0.861    -687.985     575.134
City_Hoquiam
1215.7343    127.121      9.564      0.000     966.580    1464.889
City_Hunters
-4427.9422    782.245     -5.661      0.000   -5961.124   -2894.760
City_Hunts Point
7790.7625    816.751      9.539      0.000    6189.950    9391.575
City_Husum
1858.1727    296.141      6.275      0.000    1277.743    2438.603
City_Ilwaco
370.6779    262.987      1.409      0.159    -144.771     886.126
City_Inchelium
-5246.9067    845.664     -6.204      0.000   -6904.389   -3589.425
City_Incorporated
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1068.0438   1003.368      1.064      0.287    -898.534    3034.622
City_Index
1826.9534    900.932      2.028      0.043      61.148    3592.758
City_Indianola
578.6328    803.671      0.720      0.472    -996.545    2153.810
City_Ione
-6286.7751    847.515     -7.418      0.000   -7947.884   -4625.666
City_Issaquah
6949.0359    810.135      8.578      0.000    5361.189    8536.882
City_Joint Base Lewis Mcchord
1498.3773    806.379      1.858      0.063     -82.107    3078.861
City_Kalama
-3458.7022    231.510    -14.940      0.000   -3912.456   -3004.949
City_Kapowsin
2145.2283   1171.031      1.832      0.067    -149.966    4440.423
City_Keller
896.9640    716.765      1.251      0.211    -507.879    2301.807
City_Kelso
-4449.5393    229.617    -19.378      0.000   -4899.583   -3999.496
City_Kenmore
4083.5814    809.304      5.046      0.000    2497.364    5669.798
City_Kennewick
2164.8318    404.088      5.357      0.000    1372.828    2956.835
City_Kent
2280.4793    807.993      2.822      0.005     696.832    3864.126
City_Kettle Falls
-6433.1839    541.471    -11.881      0.000   -7494.455   -5371.913
City_Keyport
674.4381    850.329      0.793      0.428    -992.186    2341.062
City_Kingston
394.0478    798.205      0.494      0.622   -1170.415    1958.510
City_Kirkland
7448.2177    809.131      9.205      0.000    5862.341    9034.095
City_Kittitas
9744.0612    997.095      9.772      0.000    7789.778    1.17e+04
City_Klickitat
2092.2804    861.717      2.428      0.015     403.335    3781.226
City_La Center
-1151.3575    200.547     -5.741      0.000   -1544.425    -758.290
City_La Conner
-1002.8230   1048.909     -0.956      0.339   -3058.659    1053.013
City_Lacey
3919.7700    744.802      5.263      0.000    2459.975    5379.565
City_Lacrosse
1544.8276   1142.009      1.353      0.176    -693.484    3783.139
City_Lake Forest Park
3959.5893    809.255      4.893      0.000    2373.469    5545.710
City_Lake Stevens
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2072.6434    812.321      2.552      0.011     480.512    3664.775
City_Lake Tapps
2567.9399    806.689      3.183      0.001     986.849    4149.031
City_Lakebay
1828.2821    805.319      2.270      0.023     249.875    3406.689
City_Lakeview
-3285.3003    983.782     -3.339      0.001   -5213.491   -1357.110
City_Lakewood
1164.1581    802.761      1.450      0.147    -409.235    2737.552
City_Lamont
-156.9724   1132.799     -0.139      0.890   -2377.232    2063.287
City_Langley
-542.2675    126.188     -4.297      0.000    -789.594    -294.941
City_Latah
365.5354    959.856      0.381      0.703   -1515.761    2246.832
City_Leavenworth
427.5909    545.712      0.784      0.433    -641.993    1497.175
City_Lebam
-811.0638    827.751     -0.980      0.327   -2433.436     811.308
City_Liberty Lake
-680.8225    462.264     -1.473      0.141   -1586.848     225.203
City_Lilliwaup
-197.2965    438.905     -0.450      0.653   -1057.540     662.947
City_Lincoln
-3523.7727    604.710     -5.827      0.000   -4708.990   -2338.555
City_Lind
-580.5444   1048.895     -0.553      0.580   -2636.354    1475.265
City_Long Beach
97.9306    200.761      0.488      0.626    -295.557     491.418
City_Longbranch
2199.3487    821.959      2.676      0.007     588.328    3810.369
City_Longview
-4949.1586    227.299    -21.774      0.000   -5394.659   -4503.658
City_Loon Lake
-3502.9127    513.562     -6.821      0.000   -4509.483   -2496.342
City_Lopez Is
-1244.7054   1176.527     -1.058      0.290   -3550.672    1061.261
City_Lopez Island
-1244.7054   1071.543     -1.162      0.245   -3344.904     855.494
City_Lummi Island
-2868.8087   1156.110     -2.481      0.013   -5134.758    -602.860
City_Lyle
2092.2804    282.078      7.417      0.000    1539.415    2645.146
City_Lyman
-1525.9420   1351.199     -1.129      0.259   -4174.261    1122.377
City_Lynden
-4118.4542   1071.014     -3.845      0.000   -6217.617   -2019.292
City_Lynnwood
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2830.4695    809.299      3.497      0.000    1244.263    4416.676
City_Mabton
395.6767    416.429      0.950      0.342    -420.514    1211.867
City_Malaga
2474.6211    564.654      4.383      0.000    1367.912    3581.330
City_Malden
213.8324   1133.381      0.189      0.850   -2007.568    2435.233
City_Malott
-973.4048    893.453     -1.089      0.276   -2724.552     777.743
City_Mansfield
-5018.5325    847.315     -5.923      0.000   -6679.249   -3357.816
City_Manson
244.1094    548.209      0.445      0.656    -830.368    1318.587
City_Maple Falls
-3751.4675   1082.625     -3.465      0.001   -5873.388   -1629.547
City_Maple Valley
6697.4386    809.700      8.272      0.000    5110.446    8284.431
City_Marblemount
-784.3604   1215.168     -0.645      0.519   -3166.061    1597.341
City_Marlin
-2468.2925    778.691     -3.170      0.002   -3994.508    -942.077
City_Maryhill
2264.9882    863.078      2.624      0.009     573.375    3956.602
City_Marysville
314.0026    811.860      0.387      0.699   -1277.223    1905.229
City_Mattawa
-1033.5510    533.395     -1.938      0.053   -2078.992      11.890
City_Mazama
-2996.1940    500.627     -5.985      0.000   -3977.411   -2014.977
City_Mccleary
1672.4231    232.103      7.206      0.000    1217.506    2127.340
City_Mead
-1696.7067    467.409     -3.630      0.000   -2612.818    -780.595
City_Medical Lake
-967.8551    465.784     -2.078      0.038   -1880.781     -54.929
City_Medina
7727.5286    809.726      9.543      0.000    6140.485    9314.572
City_Menlo
-811.0638    326.609     -2.483      0.013   -1451.210    -170.918
City_Mercer Island
9772.6046    808.404     12.089      0.000    8188.151    1.14e+04
City_Mesa
446.4772    736.164      0.606      0.544    -996.387    1889.341
City_Methow
-429.3263    592.133     -0.725      0.468   -1589.893     731.240
City_Mica
-524.3293    593.058     -0.884      0.377   -1686.709     638.050
City_Mill Creek
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City_Milton
1065.7253    839.537      1.269      0.204    -579.748    2711.198
City_Mineral
3303.4326    800.204      4.128      0.000    1735.051    4871.815
City_Moclips
-165.2202    431.468     -0.383      0.702   -1010.888     680.447
City_Monroe
895.4440    812.823      1.102      0.271    -697.670    2488.558
City_Montesano
675.9743    112.966      5.984      0.000     454.564     897.385
City_Morton
3879.4634    786.493      4.933      0.000    2337.956    5420.971
City_Moses Lake
-2046.0142    505.001     -4.052      0.000   -3035.805   -1056.224
City_Mossyrock
3778.2009    770.025      4.907      0.000    2268.970    5287.432
City_Mount Vernon
-596.2432   1047.484     -0.569      0.569   -2649.287    1456.800
City_Mountlake Terrace
5425.5786    809.622      6.701      0.000    3838.738    7012.420
City_Moxee
-1390.9180    365.895     -3.801      0.000   -2108.063    -673.773
City_Mukilteo
2115.5171    809.923      2.612      0.009     528.086    3702.948
City_Murdock
2305.7344    531.305      4.340      0.000    1264.390    3347.079
City_Naches
-2020.8977    373.801     -5.406      0.000   -2753.539   -1288.256
City_Nahcotta
-446.6361    396.318     -1.127      0.260   -1223.411     330.139
City_Napavine
2760.0318    813.105      3.394      0.001    1166.366    4353.698
City_Naselle
434.3189    226.130      1.921      0.055      -8.892     877.529
City_Neah Bay
-3524.5851    365.302     -9.648      0.000   -4240.569   -2808.601
City_Nespelem
-297.1954   1192.084     -0.249      0.803   -2633.652    2039.261
City_Newcastle
1.016e+04    809.081     12.563      0.000    8578.692    1.18e+04
City_Newman Lake
-939.1609    474.116     -1.981      0.048   -1868.418      -9.904
City_Newport
-3596.1071    611.928     -5.877      0.000   -4795.471   -2396.743
City_Nine Mile Falls
-2154.3196    463.415     -4.649      0.000   -3062.602   -1246.037
City_Nooksack
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City_Nordland
7.8381 232.076 0.034 0.973 -447.025 462.701
City_Normandy Park
1588.4548 808.389 1.965 0.049 4.031 3172.879
City_North Bend
6593.3948 813.120 8.109 0.000 4999.698 8187.091
City_North Bonneville
1730.6431 309.238 5.596 0.000 1124.543 2336.743
City_North Cove
-1484.1317 327.905 -4.526 0.000 -2126.817 -841.446
City_Northport
-7292.6317 788.507 -9.249 0.000 -8838.086 -5747.177
City_Oak Harbor
-1963.7252 127.448 -15.408 0.000 -2213.521 -1713.929
City_Oakesdale
917.9790 846.604 1.084 0.278 -741.346 2577.304
City_Oakville
1511.1335 199.338 7.581 0.000 1120.436 1901.831
City_Ocean Park
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City_Ocean Shores
985.6393 99.782 9.878 0.000 790.070 1181.209
City_Odessa
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City_Okanogan
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City_Olalla
1628.5210 799.297 2.037 0.042 61.918 3195.124
City_Olga
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City_Olympia
3223.3744 743.934 4.333 0.000 1765.280 4681.469
City_Omak
-1947.3879 399.527 -4.874 0.000 -2730.452 -1164.323
City_Onalaska
3269.3886 772.532 4.232 0.000 1755.244 4783.533
City_Orcas
-1704.5986 1151.050 -1.481 0.139 -3960.630 551.433
City_Orcas Is
-1879.4402 1100.225 -1.708 0.088 -4035.855 276.975
City_Orient
-7576.1006 1038.408 -7.296 0.000 -9611.357 -5540.845
City_Orondo
-5424.8066 617.704 -8.782 0.000 -6635.492 -4214.121
City_Oroville
-4018.2148 406.750 -9.879 0.000 -4815.436 -3220.993
City_Orting

2032.3140	806.575	2.520	0.012	451.445	3613.183
City_Othello					
-583.5605	543.348	-1.074	0.283	-1648.510	481.389
City_Otis Orchards					
-842.0216	475.715	-1.770	0.077	-1774.412	90.369
City_Outlook					
-320.6727	383.841	-0.835	0.403	-1072.993	431.647
City_Oysterville					
-507.6735	367.420	-1.382	0.167	-1227.808	212.461
City_Pacific					
1262.3596	812.576	1.554	0.120	-330.271	2854.990
City_Pacific Beach					
-20.8032	181.246	-0.115	0.909	-376.041	334.434
City_Packwood					
4289.2011	788.016	5.443	0.000	2744.708	5833.694
City_Palisades					
-3620.7796	849.262	-4.263	0.000	-5285.314	-1956.245
City_Palouse					
2046.6434	791.970	2.584	0.010	494.400	3598.887
City_Parkland					
1002.5959	808.106	1.241	0.215	-581.273	2586.464
City_Pasc					
1814.3093	817.787	2.219	0.027	211.466	3417.153
City_Pasco					
1827.8175	656.926	2.782	0.005	540.258	3115.378
City_Pateros					
-186.8004	472.016	-0.396	0.692	-1111.941	738.340
City_Paterson					
1967.2003	704.494	2.792	0.005	586.408	3347.992
City_Pe Ell					
2657.2255	1135.294	2.341	0.019	432.075	4882.376
City_Peshastin					
1184.0249	572.060	2.070	0.038	62.800	2305.250
City_Plymouth					
2270.6547	912.151	2.489	0.013	482.861	4058.449
City_Point Roberts					
-5015.9293	1072.518	-4.677	0.000	-7118.039	-2913.820
City_Pomeroy					
1393.1284	760.196	1.833	0.067	-96.837	2883.094
City_Port Angeles					
-1106.4375	187.707	-5.894	0.000	-1474.340	-738.535
City_Port Gamble					
472.3205	997.396	0.474	0.636	-1482.553	2427.194
City_Port Hadlock					
-26.2212	233.041	-0.113	0.910	-482.976	430.534
City_Port Ludlow					
591.3323	210.970	2.803	0.005	177.837	1004.828
City_Port Orchard					

1166.7842   794.839   1.468   0.142   -391.082   2724.651
City_Port Townsend
-372.0634   204.205   -1.822   0.068   -772.301   28.175
City_Poulsbo
472.5109   796.062   0.594   0.553   -1087.753   2032.775
City_Prairie Ridge
2567.9399   1171.648   2.192   0.028   271.537   4864.343
City_Preston
6092.3624   823.860   7.395   0.000   4477.617   7707.108
City_Pros
671.1766   911.206   0.737   0.461   -1114.765   2457.119
City_Prosser
671.1766   407.122   1.649   0.099   -126.773   1469.126
City_Pullman
2677.9362   769.253   3.481   0.000   1170.218   4185.654
City_Puyallup
1246.8543   804.385   1.550   0.121   -329.722   2823.430
City_Quilcene
806.7197   228.180   3.535   0.000   359.492   1253.947
City_Quinault
-746.0527   496.620   -1.502   0.133   -1719.416   227.310
City_Quincy
-3025.5970   516.572   -5.857   0.000   -4038.066   -2013.128
City_Rainier
2151.5850   753.382   2.856   0.004   674.974   3628.196
City_Randle
4535.9527   826.414   5.489   0.000   2916.201   6155.704
City_Ravensdale
6928.0275   814.680   8.504   0.000   5331.273   8524.782
City_Raymond
-811.0638   212.974   -3.808   0.000   -1228.488   -393.640
City_Reardan
-2406.4588   466.294   -5.161   0.000   -3320.384   -1492.534
City_Redmond
8146.6116   809.957   10.058   0.000   6559.114   9734.109
City_Renton
6142.7551   808.462   7.598   0.000   4558.188   7727.323
City_Republic
-1598.6711   351.049   -4.554   0.000   -2286.720   -910.622
City_Rice
-5644.8144   614.115   -9.192   0.000   -6848.465   -4441.164
City_Rich
2052.5018   911.991   2.251   0.024   265.022   3839.982
City_Richland
1925.4823   427.091   4.508   0.000   1088.393   2762.571
City_Ridgefield
334.0247   195.730   1.707   0.088   -49.602   717.651
City_Ritzville

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City_Riverside
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City_Rochester
2032.2805    745.947      2.724      0.006     570.242    3494.319
City_Rock Island
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City_Rockford
-417.3669    604.503     -0.690      0.490   -1602.178     767.445
City_Rockport
-810.9925   1213.728     -0.668      0.504   -3189.871    1567.886
City_Ronald
7860.1338    945.168      8.316      0.000    6007.627    9712.641
City_Roosevelt
2784.4411    634.176      4.391      0.000    1541.471    4027.411
City_Rosalia
264.7725    699.944      0.378      0.705   -1107.101    1636.646
City_Rosburg
838.7241    926.939      0.905      0.366    -978.055    2655.503
City_Roslyn
8059.0063    953.268      8.454      0.000    6190.624    9927.389
City_Roy
1758.7228    805.185      2.184      0.029     180.579    3336.867
City_Royal City
-1441.5067    538.472     -2.677      0.007   -2496.900    -386.114
City_Ruston
874.7822    859.819      1.017      0.309    -810.443    2560.007
City_Salkum
3590.4514    845.151      4.248      0.000    1933.976    5246.927
City_Sammamish
8986.8160    810.328     11.090      0.000    7398.592    1.06e+04
City_San Juan Is
-1572.0577   1365.887     -1.151      0.250   -4249.164    1105.049
City_Satsop
1642.4141    605.634      2.712      0.007     455.386    2829.442
City_Seabeck
-475.6569    797.952     -0.596      0.551   -2039.625    1088.311
City_Seatac
1655.9845    807.419      2.051      0.040      73.463    3238.506
City_Seattle
3948.2597    807.980      4.887      0.000    2364.637    5531.882
City_Seaview
239.6371    313.898      0.763      0.445    -375.596     854.870
City_Sedro Woolley
-895.2843   1067.993     -0.838      0.402   -2988.526    1197.957
City_Sedro-Woolley
-1619.3993   1050.166     -1.542      0.123   -3677.700     438.902
City_Sekiu
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City_Selah
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City_Sequim
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City_Seven Bays
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City_Shaw Island
-1618.1334   1091.545     -1.482      0.138   -3757.536     521.269
City_Shelton
970.5328    299.546      3.240      0.001     383.429    1557.637
City_Shoreline
1341.1261    808.706      1.658      0.097    -243.919    2926.171
City_Silver Creek
3607.1622    797.557      4.523      0.000    2043.969    5170.355
City_Silver Lake
-4787.3652    859.386     -5.571      0.000   -6471.741   -3102.989
City_Silverdale
548.2241    795.842      0.689      0.491   -1011.607    2108.056
City_Silverlake
-4787.3652    261.233    -18.326      0.000   -5299.375   -4275.355
City_Skamokawa
1192.7000    602.850      1.978      0.048      11.129    2374.271
City_Skykomish
857.8222    872.319      0.983      0.325    -851.902    2567.547
City_Smith Creek
-811.0638    827.751     -0.980      0.327   -2433.436     811.308
City_Snohomish
3299.7558    811.434      4.067      0.000    1709.365    4890.147
City_Snoqualmie
6336.1657    812.327      7.800      0.000    4744.025    7928.307
City_Snoqualmie Pass
6755.9872    918.070      7.359      0.000    4956.592    8555.382
City_Snowden
1858.1727    312.078      5.954      0.000    1246.508    2469.838
City_Soap Lake
-3072.3003    539.118     -5.699      0.000   -4128.960   -2015.641
City_South Bend
-856.2099    344.367     -2.486      0.013   -1531.160    -181.260
City_South Cle Elum
8280.9693   1011.417      8.187      0.000    6298.616    1.03e+04
City_South Hill
1360.8983    804.747      1.691      0.091    -216.387    2938.184
City_South Prairie
2792.8880   1005.719      2.777      0.005     821.703    4764.073
City_Spanaway
1080.2962    804.103      1.343      0.179    -495.727    2656.320
City_Spangle
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-564.2322    512.056     -1.102      0.271   -1567.850     439.386
City_Spokane
-1121.3859    456.757     -2.455      0.014   -2016.618    -226.154
City_Spokane Valley
-829.6374    458.496     -1.809      0.070   -1728.279      69.004
City_Sprague
-736.5681    947.520     -0.777      0.437   -2593.685    1120.549
City_Springdale
-3476.0944    675.680     -5.145      0.000   -4800.411   -2151.778
City_St John
695.8990    963.095      0.723      0.470  -1191.745    2583.543
City_Stanwood
-222.6932    812.399     -0.274      0.784   -1814.976    1369.590
City_Startup
985.4787   1177.792      0.837      0.403  -1322.967    3293.924
City_Steilacoom
507.6512    485.822      1.045      0.296    -444.548    1459.851
City_Stevenson
1601.3827    212.894      7.522      0.000    1184.115    2018.650
City_Stratford
-3240.1477    982.631     -3.297      0.001   -5166.081   -1314.214
City_Sultan
1272.3492    816.781      1.558      0.119    -328.522    2873.220
City_Sumas
-4013.1823   1126.301     -3.563      0.000   -6220.705   -1805.659
City_Sumner
2363.4140    806.627      2.930      0.003     782.443    3944.385
City_Sunnyside
-120.3514    319.733     -0.376      0.707    -747.021     506.318
City_Suquamish
613.0402    802.624      0.764      0.445    -960.084    2186.164
City_Surfside
-446.6361    240.618     -1.856      0.063    -918.242      24.970
City_Tacoma
874.7822    803.077      1.089      0.276    -699.229    2448.794
City_Taholah
-681.6942    432.005     -1.578      0.115   -1528.414     165.025
City_Tahuya
201.2289    340.430      0.591      0.554    -466.005     868.463
City_Tekoa
718.4435    858.852      0.837      0.403    -964.886    2401.773
City_Tenino
2029.5711    749.057      2.710      0.007     561.437    3497.705
City_Thorp
9018.4784   1002.232      8.998      0.000    7054.127     1.1e+04
City_Tieton
-1733.2135    443.476     -3.908      0.000   -2602.417    -864.010
City_Tokeland
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-1297.3342 495.072 -2.620 0.009 -2267.663 -327.005
City_Toledo
3704.3019 765.652 4.838 0.000 2203.641 5204.962
City_Tonasket
-2799.0466 405.015 -6.911 0.000 -3592.867 -2005.226
City_Toppenish
-289.2028 392.683 -0.736 0.461 -1058.852 480.446
City_Touchet
453.5674 377.980 1.200 0.230 -287.265 1194.400
City_Toutle
-4715.0945 403.026 -11.699 0.000 -5505.015 -3925.174
City_Trout Lake
879.9447 280.813 3.134 0.002 329.558 1430.332
City_Tukwila
6201.7918 807.565 7.680 0.000 4618.983 7784.600
City_Tulalip
-1272.0597 895.865 -1.420 0.156 -3027.935 483.815
City_Tumtum
-2720.7550 963.850 -2.823 0.005 -4609.878 -831.631
City_Tumwater
3781.0200 744.340 5.080 0.000 2322.131 5239.908
City_Twisp
-1720.7076 451.994 -3.807 0.000 -2606.605 -834.810
City_Underwood
1790.7482 235.056 7.618 0.000 1330.044 2251.452
City_Union
483.3857 340.720 1.419 0.156 -184.418 1151.189
City_Union Gap
-1698.0317 409.393 -4.148 0.000 -2500.432 -895.632
City_Uniontown
3563.7399 879.556 4.052 0.000 1839.831 5287.649
City_University Place
960.8420 802.928 1.197 0.231 -612.879 2534.563
City_Usk
-4358.2460 771.522 -5.649 0.000 -5870.411 -2846.081
City_Vader
3752.2629 818.613 4.584 0.000 2147.800 5356.726
City_Valley
-4122.4275 598.776 -6.885 0.000 -5296.015 -2948.840
City_Valleyford
-132.7533 490.989 -0.270 0.787 -1095.080 829.573
City_Vancouver
-331.4881 192.953 -1.718 0.086 -709.671 46.695
City_Vantage
1.04e+04 1294.219 8.034 0.000 7861.242 1.29e+04
City_Vashon
3477.1347 806.374 4.312 0.000 1896.660 5057.609
City_Vaughn

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1628.1528    818.914      1.988      0.047      23.101    3233.205
City_Veradale
-691.4268    470.469     -1.470      0.142   -1613.535     230.682
City_Wahkiacus
1741.9966    531.587      3.277      0.001     700.098    2783.895
City_Waitsburg
98.1301    341.729      0.287      0.774    -571.650     767.910
City_Waldron
-2251.3708   1227.299     -1.834      0.067   -4656.848     154.107
City_Walla Walla
728.9655    273.878      2.662      0.008     192.171    1265.760
City_Walla Walla Co
728.9655    785.822      0.928      0.354    -811.228    2269.159
City_Wapato
-693.1174    403.290     -1.719      0.086   -1483.557      97.322
City_Warden
-1054.9123    607.695     -1.736      0.083   -2245.980     136.156
City_Washougal
1521.4263    187.385      8.119      0.000    1154.156    1888.697
City_Washtucna
687.6713   1206.553      0.570      0.569   -1677.145    3052.488
City_Waterville
-4816.1495    714.200     -6.743      0.000   -6215.964   -3416.335
City_Waverly
26.7175    751.371      0.036      0.972   -1445.952    1499.387
City_Wellpinit
-3149.6807    983.172     -3.204      0.001   -5076.674   -1222.687
City_Wenatchee
2017.9862    543.764      3.711      0.000     952.221    3083.751
City_West Richland
1753.5386    405.489      4.325      0.000     958.790    2548.287
City_Westport
-6.2277    177.602     -0.035      0.972    -354.323     341.868
City_White Salmon
1859.6953    226.384      8.215      0.000    1415.988    2303.403
City_White Swan
-308.4032    884.528     -0.349      0.727   -2042.057    1425.251
City_Wilbur
-3539.9623    574.547     -6.161      0.000   -4666.061   -2413.864
City_Wilkeson
2964.5610    911.599      3.252      0.001    1177.848    4751.274
City_Winlock
3074.0450    762.442      4.032      0.000    1579.677    4568.413
City_Winthrop
-2311.1250    475.368     -4.862      0.000   -3242.834   -1379.416
City_Wishram
2800.9333    862.557      3.247      0.001    1110.342    4491.524
City_Woodinville
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8085.3296    810.130      9.980      0.000    6497.493    9673.166
City_Woodland
-3033.0489    210.719    -14.394      0.000   -3446.053   -2620.044
City_Woodway
2467.9825    813.011      3.036      0.002     874.499    4061.466
City_Yacolt
438.1111    217.561      2.014      0.044      11.697     864.525
City_Yakima
-1236.5410    335.475     -3.686      0.000   -1894.065    -579.017
City_Yarrow Point
7790.7625    811.591      9.599      0.000    6200.063    9381.462
City_Yelm
2256.5467    747.214      3.020      0.003     792.024    3721.069
City_Zillah
-662.3448    348.923     -1.898      0.058   -1346.227      21.537
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||BIG BEND ELECTRIC
COOP, INC                                          -2.454e-08    864.574
-2.84e-11      1.000   -1694.546    1694.546
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||INLAND POWER &
LIGHT COMPANY                                            35.4972    136.186
0.261      0.794    -231.424     302.418
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||PUD NO 1 OF
ASOTIN COUNTY                                              974.0992    390.736
2.493      0.013     208.266    1739.933
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||BENTON RURAL ELECTRIC ASSN
-151.9567   1697.264     -0.090      0.929   -3478.554    3174.641
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||BIG BEND ELECTRIC COOP, INC
13.0266   1277.031      0.010      0.992   -2489.925    2515.978
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF CENTRALIA - (WA)|CITY
OF TACOMA - (WA)                                     -229.6156    450.745
-0.509      0.610   -1113.065     653.834
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF COULEE DAM - (WA)
-834.9295    250.793     -3.329      0.001   -1326.478    -343.381
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF ELLENSBURG - (WA)
51.4576    256.223      0.201      0.841    -450.734     553.649
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF MCCLEARY - (WA)
-233.0840    945.858     -0.246      0.805   -2086.944    1620.776
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF MILTON - (WA)|CITY OF
TACOMA - (WA)                                        -201.5243    498.191
-0.405      0.686   -1177.966     774.918
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF PORT ANGELES - (WA)
-233.3451    488.540     -0.478      0.633   -1190.871     724.181
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF RICHLAND - (WA)
216.4424    327.314      0.661      0.508    -425.085     857.969
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||ALDER
MUTUAL LIGHT CO, INC|PENINSULA LIGHT COMPANY        -163.6904    754.909
-0.217      0.828   -1643.294    1315.913
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||BENTON
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RURAL ELECTRIC ASSN|PENINSULA LIGHT COMPANY -164.7907 464.264
-0.355 0.723 -1074.737 745.156
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA -
(WA)||ELMHURST MUTUAL POWER & LIGHT CO|PENINSULA LIGHT COMPANY -306.6957
435.765 -0.704 0.482 -1160.786 547.394
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA -
(WA)||LAKEVIEW LIGHT & POWER|PENINSULA LIGHT COMPANY -928.7129
439.444 -2.113 0.035 -1790.013 -67.412
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||OHOP
MUTUAL LIGHT COMPANY, INC|PENINSULA LIGHT COMPANY -165.3829 451.148
-0.367 0.714 -1049.623 718.857
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA -
(WA)||PARKLAND LIGHT & WATER COMPANY|PENINSULA LIGHT COMPANY -354.8618
442.548 -0.802 0.423 -1222.245 512.521
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA -
(WA)||PENINSULA LIGHT COMPANY -97.8367
434.779 -0.225 0.822 -949.994 754.320
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO
1 OF LEWIS COUNTY -334.9743 442.625
-0.757 0.449 -1202.510 532.561
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO
1 OF MASON COUNTY 591.4589 618.007
0.957 0.339 -619.821 1802.739
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO
3 OF MASON COUNTY 591.4639 614.699
0.962 0.336 -613.331 1796.259
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||COLUMBIA RURAL ELEC ASSN, INC
-102.8593 1532.124 -0.067 0.946 -3105.787 2900.068
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||INLAND POWER & LIGHT COMPANY
165.8870 149.611 1.109 0.268 -127.347 459.121
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||NESPELEM VALLEY ELEC COOP, INC
-2199.1249 807.931 -2.722 0.006 -3782.651 -615.598
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||ORCAS POWER & LIGHT COOP
-233.0840 481.897 -0.484 0.629 -1177.591 711.423
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PACIFICORP||BENTON RURAL
ELECTRIC ASSN -17.9916 1681.551
-0.011 0.991 -3313.792 3277.809
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PACIFICORP||COLUMBIA RURAL
ELEC ASSN, INC -102.8593 1628.703
-0.063 0.950 -3295.079 3089.361
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PACIFICORP||PUD NO 1 OF CLARK
COUNTY - (WA) 1239.8022 243.264
5.097 0.000 763.011 1716.593
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PENINSULA LIGHT COMPANY
-113.2205 955.663 -0.118 0.906 -1986.298 1759.857
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD 1 OF SNOHOMISH COUNTY
-501.9996 239.560 -2.096 0.036 -971.532 -32.467
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF ASOTIN

COUNTY||INLAND POWER & LIGHT COMPANY 974.0992
577.062 1.688 0.091 -156.928 2105.127
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF BENTON COUNTY
169.8862 316.510 0.537 0.591 -450.465 790.238
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLALLAM COUNTY
-233.0840 482.021 -0.484 0.629 -1177.835 711.667
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLALLAM COUNTY|PUD
NO 1 OF JEFFERSON COUNTY -2475.9455 678.917
-3.647 0.000 -3806.608 -1145.283
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLARK COUNTY -
(WA) 790.9764 239.535
3.302 0.001 321.493 1260.460
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF COWLITZ COUNTY
1437.8006 440.097 3.267 0.001 575.222 2300.380
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF FERRY COUNTY
-5788.0541 544.849 -10.623 0.000 -6855.946 -4720.163
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF FRANKLIN COUNTY
-8.6844 1273.903 -0.007 0.995 -2505.504 2488.136
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF GRAYS HARBOR
COUNTY -233.0840 895.050
-0.260 0.795 -1987.361 1521.193
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF JEFFERSON COUNTY
-395.8166 557.523 -0.710 0.478 -1488.548 696.915
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF KITTITAS COUNTY
51.4576 321.954 0.160 0.873 -579.564 682.479
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF KLICKITAT COUNTY
-194.9069 442.744 -0.440 0.660 -1062.675 672.861
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF MASON COUNTY|PUD
NO 1 OF JEFFERSON COUNTY -395.8166 353.240
-1.121 0.262 -1088.158 296.525
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF SKAMANIA CO
-195.5533 437.089 -0.447 0.655 -1052.238 661.131
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF WAHKIAKUM COUNTY
-2157.4717 503.199 -4.288 0.000 -3143.730 -1171.214
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUD NO 2 OF PACIFIC COUNTY
-2157.4717 458.319 -4.707 0.000 -3055.766 -1259.178
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||PUGET SOUND ENERGY INC||PUD NO
1 OF JEFFERSON COUNTY -2508.8562 371.382
-6.755 0.000 -3236.756 -1780.956
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||TOWN OF EATONVILLE - (WA)|CITY
OF TACOMA - (WA) -163.6904 480.813
-0.340 0.734 -1106.073 778.692
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||TOWN OF RUSTON - (WA)|CITY OF
TACOMA - (WA)||PENINSULA LIGHT COMPANY -12.1730 511.450
-0.024 0.981 -1014.603 990.257
Electric_Utility_BONNEVILLE POWER ADMINISTRATION||TOWN OF STEILACOOM|CITY OF
TACOMA - (WA)||PENINSULA LIGHT COMPANY 507.6512 485.822
1.045 0.296 -444.548 1459.851

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Electric_Utility_BONNEVILLE POWER ADMINISTRATION||VERA IRRIGATION DISTRICT #15
82.8470    144.857      0.572      0.567    -201.069     366.763
Electric_Utility_CITY OF BLAINE - (WA)||PUD NO 1 OF WHATCOM COUNTY
-1400.4926    309.922     -4.519      0.000   -2007.932    -793.053
Electric_Utility_CITY OF CHENEY - (WA)
187.8303    199.976      0.939      0.348    -204.118     579.778
Electric_Utility_CITY OF CHEWELAH
3.624e-11    363.569   9.97e-14      1.000    -712.587     712.587
Electric_Utility_CITY OF SEATTLE - (WA)
-767.9743    741.607     -1.036      0.300   -2221.507     685.559
Electric_Utility_CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)
-92.0389    433.404     -0.212      0.832    -941.500     757.422
Electric_Utility_CITY OF SUMAS - (WA)||PUD NO 1 OF WHATCOM COUNTY
-1400.4926    467.355     -2.997      0.003   -2316.497    -484.488
Electric_Utility_CITY OF TACOMA - (WA)
591.2964    477.525      1.238      0.216    -344.641    1527.233
Electric_Utility_CITY OF TACOMA - (WA)||TANNER ELECTRIC COOP
-226.4434    437.656     -0.517      0.605   -1084.239     631.352
Electric_Utility_MODERN ELECTRIC WATER COMPANY
-126.7099    140.053     -0.905      0.366    -401.210     147.790
Electric_Utility_NO KNOWN ELECTRIC UTILITY SERVICE
-233.0840    223.975     -1.041      0.298    -672.069     205.901
Electric_Utility_OKANOGAN COUNTY ELEC COOP, INC
-2947.3602    519.095     -5.678      0.000   -3964.775   -1929.945
Electric_Utility_PACIFICORP
-102.8593   1612.129     -0.064      0.949   -3262.594    3056.875
Electric_Utility_PORTLAND GENERAL ELECTRIC CO
114.4387    359.980      0.318      0.751    -591.114     819.991
Electric_Utility_PUD NO 1 OF CHELAN COUNTY
-2890.2472    493.133     -5.861      0.000   -3856.777   -1923.717
Electric_Utility_PUD NO 1 OF DOUGLAS COUNTY
3262.5063    779.384      4.186      0.000    1734.932    4790.080
Electric_Utility_PUD NO 1 OF OKANOGAN COUNTY
-2947.3602    449.848     -6.552      0.000   -3829.051   -2065.669
Electric_Utility_PUD NO 1 OF PEND OREILLE COUNTY
-217.1516    646.564     -0.336      0.737   -1484.402    1050.099
Electric_Utility_PUD NO 1 OF WHATCOM COUNTY
-2011.7816    447.928     -4.491      0.000   -2889.711   -1133.853
Electric_Utility_PUD NO 2 OF GRANT COUNTY
128.0000    451.289      0.284      0.777    -756.515    1012.515
Electric_Utility_PUGET SOUND ENERGY INC
51.4576    236.524      0.218      0.828    -412.124     515.039
Electric_Utility_PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)
-181.3584    433.532     -0.418      0.676   -1031.071     668.354
Electric_Utility_PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY
-1400.4926    303.034     -4.622      0.000   -1994.433    -806.553
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Omnibus:                    23521.872   Durbin-Watson:                   2.002
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Prob(Omnibus):                  0.000   Jarque-Bera (JB):           234038.984
Skew:                          -0.236   Prob(JB):                         0.00
Kurtosis:                       8.468   Cond. No.                     1.28e+19
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.95e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.


Regression Results for EV_Count_Utility
                            OLS Regression Results
==============================================================================
Dep. Variable:       EV_Count_Utility   R-squared:                       0.932
Model:                            OLS   Adj. R-squared:                  0.932
Method:                 Least Squares   F-statistic:                     4658.
Date:                Sun, 07 Jul 2024   Prob (F-statistic):               0.00
Time:                        20:04:47   Log-Likelihood:            -1.9035e+06
No. Observations:              186471   AIC:                         3.808e+06
Df Residuals:                  185920   BIC:                         3.814e+06
Df Model:                         550
Covariance Type:            nonrobust
================================================================================
=================
                                 coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
-----------------
const                       2.092e+06   7.53e+04     27.770      0.000
1.94e+06    2.24e+06
Latitude                   -2.175e+04    771.127    -28.207      0.000
-2.33e+04   -2.02e+04
Longitude                   8794.3662    643.402     13.669      0.000
7533.314    1.01e+04
County_Asotin               -2.29e+04   2857.502     -8.013      0.000
-2.85e+04   -1.73e+04
County_Benton              -5115.9715   4742.904     -1.079      0.281
-1.44e+04    4180.010
County_Chelan               -518.9895   1.06e+04     -0.049      0.961
-2.13e+04    2.03e+04
County_Clallam              6.439e+04   5916.915     10.882      0.000
5.28e+04     7.6e+04
County_Clark                6156.2157   5898.639      1.044      0.297
-5404.980    1.77e+04
County_Columbia            -1.307e+04   2257.108     -5.792      0.000
-1.75e+04   -8649.930
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County_Cowlitz                -3633.3325   5947.271     -0.611      0.541
-1.53e+04    8023.180
County_Douglas                -1519.9895   5736.630     -0.265      0.791
-1.28e+04    9723.671
County_Ferry                  -3196.3193   7633.892     -0.419      0.675
-1.82e+04    1.18e+04
County_Franklin                 247.8750   2923.537      0.085      0.932
-5482.189    5977.939
County_Garfield               -1.262e+04   2791.301     -4.521      0.000
-1.81e+04   -7149.042
County_Grant                  -1280.9895   4407.157     -0.291      0.771
-9918.915    7356.936
County_Grays Harbor            5.332e+04   6769.710      7.876      0.000
4.01e+04    6.66e+04
County_Island                  6.711e+04   5589.116     12.008      0.000
5.62e+04    7.81e+04
County_Jefferson               6.441e+04   5913.620     10.893      0.000
5.28e+04     7.6e+04
County_King                     5.93e+04   8808.294      6.732      0.000
4.2e+04    7.66e+04
County_Kitsap                  9.665e+04   8731.569     11.069      0.000
7.95e+04    1.14e+05
County_Kittitas                4.123e+04   9231.209      4.466      0.000
2.31e+04    5.93e+04
County_Klickitat              -1574.8908   5979.993     -0.263      0.792
-1.33e+04    1.01e+04
County_Lewis                   5.412e+04   8606.231      6.288      0.000
3.72e+04     7.1e+04
County_Lincoln                -1540.9895   6859.359     -0.225      0.822
-1.5e+04    1.19e+04
County_Mason                   3.737e+04   7106.586      5.259      0.000
2.34e+04    5.13e+04
County_Okanogan               -1519.9895   8300.396     -0.183      0.855
-1.78e+04    1.47e+04
County_Pacific                 3.914e+04   6377.566      6.138      0.000
2.66e+04    5.16e+04
County_Pend Oreille           -1217.1828   7782.082     -0.156      0.876
-1.65e+04     1.4e+04
County_Pierce                  5.641e+04   8794.130      6.415      0.000
3.92e+04    7.37e+04
County_San Juan                3.076e+04   1.03e+04      2.993      0.003
1.06e+04    5.09e+04
County_Skagit                  6.527e+04   1.01e+04      6.448      0.000
4.54e+04    8.51e+04
County_Skamania               -1675.4020   5872.448     -0.285      0.775
-1.32e+04    9834.459
County_Snohomish               2.908e+04   8806.916      3.302      0.001
1.18e+04    4.63e+04
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County_Spokane	-920.1828	7169.401	-0.128	0.898	-1.5e+04	1.31e+04
County_Stevens	-3196.3193	7204.259	-0.444	0.657	-1.73e+04	1.09e+04
County_Thurston	8.555e+04	8573.468	9.979	0.000	6.88e+04	1.02e+05
County_Wahkiakum	3.9e+04	7106.182	5.488	0.000	2.51e+04	5.29e+04
County_Walla Walla	-2.298e+04	3875.736	-5.929	0.000	-3.06e+04	-1.54e+04
County_Whatcom	3.589e+04	1.02e+04	3.502	0.000	1.58e+04	5.6e+04
County_Whitman	-920.1828	8897.315	-0.103	0.918	-1.84e+04	1.65e+04
County_Yakima	-8209.5447	5727.545	-1.433	0.152	-1.94e+04	3016.310
City_Acme	2.155e+04	8509.353	2.533	0.011	4874.816	3.82e+04
City_Addy	1.896e+04	6149.224	3.083	0.002	6908.078	3.1e+04
City_Adna	-2.957e+04	8720.544	-3.391	0.001	-4.67e+04	-1.25e+04
City_Airway Heights	2516.1033	4149.612	0.606	0.544	-5617.040	1.06e+04
City_Alderdale	-1.4e+04	6783.384	-2.064	0.039	-2.73e+04	-707.969
City_Alderwood Manor	3.126e+04	9035.454	3.459	0.001	1.35e+04	4.9e+04
City_Algona	2.515e+04	6272.221	4.009	0.000	1.29e+04	3.74e+04
City_Allyn	1351.3924	2618.747	0.516	0.606	-3781.291	6484.076
City_Almira	1.474e+04	7341.335	2.008	0.045	355.031	2.91e+04
City_Amanda Park	1.131e+04	3968.999	2.850	0.004	3531.689	1.91e+04
City_Amboy	8002.9747	1997.334	4.007	0.000	4088.247	1.19e+04
City_Anacortes	2.346e+04	8077.914	2.905	0.004	7631.340	3.93e+04
City_Anderson Island	-3.554e+04	6168.624	-5.761	0.000	-4.76e+04	-2.34e+04
City_Ariel	9533.8787	2327.131	4.097	0.000	4972.757	1.41e+04
City_Arlington	1.989e+04	6264.046	3.176	0.001	7615.071	3.22e+04
City_Artondale	-1.367e+04	7666.012	-1.783	0.075	-2.87e+04	1357.859

City_Ashford	-3.72e+04	5975.218	-6.225	0.000	-4.89e+04	-2.55e+04
City_Asotin	-1.296e+04	1901.988	-6.816	0.000	-1.67e+04	-9236.522
City_Auburn	2.496e+04	6165.891	4.048	0.000	1.29e+04	3.7e+04
City_Bainbridge Island	-1.834e+04	5892.672	-3.112	0.002	-2.99e+04	-6789.632
City_Bangor Base	-1.528e+04	8816.679	-1.733	0.083	-3.26e+04	1998.177
City_Baring	2.875e+04	6851.633	4.195	0.000	1.53e+04	4.22e+04
City_Battle Ground	5916.1902	1612.111	3.670	0.000	2756.491	9075.889
City_Bay Center	6960.4784	6423.768	1.084	0.279	-5629.958	1.96e+04
City_Beaux Arts	2.953e+04	6269.365	4.710	0.000	1.72e+04	4.18e+04
City_Beaver	1.761e+04	6374.682	2.762	0.006	5114.569	3.01e+04
City_Belfair	2871.3966	2567.227	1.118	0.263	-2160.308	7903.101
City_Bellevue	2.835e+04	6202.018	4.571	0.000	1.62e+04	4.05e+04
City_Bellingham	2.543e+04	8256.214	3.080	0.002	9246.423	4.16e+04
City_Benton City	-8231.2713	2671.074	-3.082	0.002	-1.35e+04	-2996.028
City_Bingen	-9489.5617	2643.980	-3.589	0.000	-1.47e+04	-4307.422
City_Black Diamond	2.202e+04	6203.804	3.549	0.000	9855.698	3.42e+04
City_Blaine	2.981e+04	8267.172	3.605	0.000	1.36e+04	4.6e+04
City_Bonney Lake	2.416e+04	6149.657	3.929	0.000	1.21e+04	3.62e+04
City_Bothell	3.123e+04	6210.894	5.028	0.000	1.91e+04	4.34e+04
City_Bow	2.536e+04	8126.190	3.121	0.002	9431.262	4.13e+04
City_Bremerton	-1.79e+04	5873.043	-3.047	0.002	-2.94e+04	-6384.716
City_Brewster	2.78e+04	6544.416	4.248	0.000	1.5e+04	4.06e+04
City_Bridgeport	2.5e+04	5479.625	4.562	0.000	1.43e+04	3.57e+04
City_Bridgeport Bar	2.806e+04	5159.345	5.439	0.000	1.8e+04	3.82e+04

City_Brier	3.192e+04	6216.846	5.134	0.000	1.97e+04	4.41e+04
City_Brinnon	-4269.8989	1860.440	-2.295	0.022	-7916.318	-623.480
City_Brush Prairie	4517.4301	1632.441	2.767	0.006	1317.885	7716.976
City_Buckley	2.274e+04	6174.116	3.683	0.000	1.06e+04	3.48e+04
City_Bucoda	-2.156e+04	8689.379	-2.482	0.013	-3.86e+04	-4533.690
City_Burbank	2290.3329	2069.644	1.107	0.268	-1766.121	6346.787
City_Burien	9593.9464	6184.160	1.551	0.121	-2526.863	2.17e+04
City_Burlington	2.279e+04	8112.677	2.809	0.005	6885.559	3.87e+04
City_Bz Corner	-8883.5063	3028.678	-2.933	0.003	-1.48e+04	-2947.368
City_Camano Island	-1.973e+04	842.170	-23.424	0.000	-2.14e+04	-1.81e+04
City_Camas	771.5272	1603.570	0.481	0.630	-2371.433	3914.487
City_Carbonado	1.463e+04	6568.960	2.226	0.026	1750.418	2.75e+04
City_Carlton	3.254e+04	6913.743	4.706	0.000	1.9e+04	4.61e+04
City_Carnation	4830.8999	6245.061	0.774	0.439	-7409.274	1.71e+04
City_Carson	-5472.3067	1995.149	-2.743	0.006	-9382.753	-1561.860
City_Cashmere	2.139e+04	8923.508	2.397	0.017	3897.231	3.89e+04
City_Castle Rock	2.402e+04	2030.267	11.833	0.000	2e+04	2.8e+04
City_Cathlamet	-6935.0528	3519.633	-1.970	0.049	-1.38e+04	-36.654
City_Centerville	-1.33e+04	4901.854	-2.713	0.007	-2.29e+04	-3690.247
City_Centralia	-2.009e+04	5735.955	-3.503	0.000	-3.13e+04	-8852.017
City_Chattaroy	2319.3135	4150.484	0.559	0.576	-5815.539	1.05e+04
City_Chehalis	7584.4147	5755.121	1.318	0.188	-3695.488	1.89e+04
City_Chelan	2.473e+04	8844.899	2.796	0.005	7390.370	4.21e+04
City_Chelan Falls	2.296e+04	1.1e+04	2.087	0.037	1397.671	4.45e+04

City_Cheney	-1492.6242	3989.419	-0.374	0.708	-9311.793	6326.545
City_Chewelah	1.53e+04	4287.035	3.570	0.000	6901.760	2.37e+04
City_Chimacum	2074.5776	1723.558	1.204	0.229	-1303.556	5452.711
City_Chinook	-447.8870	3876.766	-0.116	0.908	-8046.259	7150.485
City_Cinebar	-3.524e+04	6901.664	-5.106	0.000	-4.88e+04	-2.17e+04
City_Clallam Bay	2.096e+04	4650.551	4.507	0.000	1.18e+04	3.01e+04
City_Clarkston	-9933.0622	1616.175	-6.146	0.000	-1.31e+04	-6765.396
City_Clayton	7706.9586	6133.924	1.256	0.209	-4315.390	1.97e+04
City_Cle Elum	1.225e+04	7240.292	1.692	0.091	-1938.339	2.64e+04
City_Clearlake	1.322e+04	8928.917	1.481	0.139	-4278.323	3.07e+04
City_Clinton	1.004e+04	882.717	11.371	0.000	8306.986	1.18e+04
City_Clyde Hill	2.881e+04	6208.037	4.641	0.000	1.66e+04	4.1e+04
City_Colbert	1169.1806	4035.263	0.290	0.772	-6739.842	9078.203
City_Colfax	-1.588e+04	6416.906	-2.474	0.013	-2.85e+04	-3300.491
City_College Place	-4691.5644	1549.942	-3.027	0.002	-7729.415	-1653.714
City_Colton	-2.737e+04	7818.401	-3.501	0.000	-4.27e+04	-1.2e+04
City_Colville	2.261e+04	4181.243	5.407	0.000	1.44e+04	3.08e+04
City_Concrete	1.029e+04	8216.082	1.252	0.211	-5815.252	2.64e+04
City_Connell	-1.151e+04	5190.589	-2.218	0.027	-2.17e+04	-1339.794
City_Copalis Beach	6202.9069	3475.113	1.785	0.074	-608.235	1.3e+04
City_Copalis Crossing	5318.4296	3956.478	1.344	0.179	-2436.176	1.31e+04
City_Cosmopolis	-929.5230	1770.920	-0.525	0.600	-4400.486	2541.440
City_Cougar	9614.5829	4874.353	1.972	0.049	60.965	1.92e+04
City_Coulee City	1.361e+04	3805.364	3.576	0.000	6149.604	2.11e+04

City_Coulee Dam	1.771e+04	5468.089	3.238	0.001	6988.687	2.84e+04
City_Coupeville	1.793e+04	923.174	19.420	0.000	1.61e+04	1.97e+04
City_Covington	2.542e+04	6189.647	4.106	0.000	1.33e+04	3.75e+04
City_Cowiche	1.216e+04	3307.022	3.676	0.000	5674.835	1.86e+04
City_Creston	1.207e+04	7338.910	1.645	0.100	-2314.256	2.65e+04
City_Curlew	3.671e+04	5384.552	6.818	0.000	2.62e+04	4.73e+04
City_Curtis	-1.653e+04	6283.041	-2.631	0.009	-2.88e+04	-4214.330
City_Cusick	1.484e+04	5717.450	2.595	0.009	3631.685	2.6e+04
City_Custer	3.088e+04	8361.377	3.693	0.000	1.45e+04	4.73e+04
City_Dallesport	-1.429e+04	2917.506	-4.899	0.000	-2e+04	-8574.425
City_Danville	3.741e+04	8110.864	4.613	0.000	2.15e+04	5.33e+04
City_Darrington	3583.5159	6675.991	0.537	0.591	-9501.272	1.67e+04
City_Davenport	8342.8651	3780.855	2.207	0.027	932.477	1.58e+04
City_Dayton	-1.307e+04	2257.108	-5.792	0.000	-1.75e+04	-8649.930
City_Deer Harbor	2.955e+04	1.06e+04	2.801	0.005	8872.836	5.02e+04
City_Deer Meadows	8342.8651	5706.948	1.462	0.144	-2842.621	1.95e+04
City_Deer Park	5451.6924	4053.682	1.345	0.179	-2493.430	1.34e+04
City_Deming	2.362e+04	8381.115	2.818	0.005	7190.408	4e+04
City_Des Moines	2.784e+04	6178.527	4.506	0.000	1.57e+04	4e+04
City_Dixie	-6044.4191	5851.374	-1.033	0.302	-1.75e+04	5424.138
City_Dryden	2.254e+04	1.1e+04	2.042	0.041	902.785	4.42e+04
City_Dupont	2.36e+04	6097.054	3.870	0.000	1.16e+04	3.55e+04
City_Duvall	2.922e+04	6242.923	4.681	0.000	1.7e+04	4.15e+04
City_East Wenatchee	1.732e+04	4072.314	4.254	0.000	9341.570	2.53e+04

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City_Easton                      1.613e+04   7324.109      2.202      0.028
1774.238    3.05e+04
City_Eastsound                   2.971e+04   8274.781      3.591      0.000
1.35e+04    4.59e+04
City_Eatonville                 -3.246e+04   6110.306     -5.312      0.000
-4.44e+04   -2.05e+04
City_Edgewood                    2.558e+04   6144.381      4.164      0.000
1.35e+04    3.76e+04
City_Edmonds                     3.173e+04   6193.878      5.123      0.000
1.96e+04    4.39e+04
City_Edwall                      2942.5085   5114.419      0.575      0.565
-7081.635     1.3e+04
City_Elbe                       -3.118e+04   7175.274     -4.345      0.000
-4.52e+04   -1.71e+04
City_Electric City               1.754e+04   4525.473      3.876      0.000
8671.083    2.64e+04
City_Elk                         3538.0438   4248.142      0.833      0.405
-4788.216    1.19e+04
City_Ellensburg                 -1.283e+04   7290.932     -1.760      0.078
-2.71e+04    1455.969
City_Elma                       -2685.7434   1295.388     -2.073      0.038
-5224.674    -146.813
City_Elmer City                  1.809e+04   7815.819      2.315      0.021
2773.328    3.34e+04
City_Eltopia                    -1.424e+04   5484.909     -2.597      0.009
-2.5e+04   -3494.169
City_Endicott                   -1.214e+04   7787.991     -1.559      0.119
-2.74e+04    3125.407
City_Entiat                      2.398e+04   8970.324      2.673      0.008
6395.093    4.16e+04
City_Enumclaw                    2.029e+04   6193.252      3.276      0.001
8152.424    3.24e+04
City_Ephrata                     8805.5696   3690.026      2.386      0.017
1573.204     1.6e+04
City_Ethel                      -3.477e+04   6346.416     -5.478      0.000
-4.72e+04   -2.23e+04
City_Evans                       2.731e+04   4914.205      5.557      0.000
1.77e+04    3.69e+04
City_Everett                     3.269e+04   6216.762      5.259      0.000
2.05e+04    4.49e+04
City_Everson                     2.746e+04   8316.320      3.302      0.001
1.12e+04    4.38e+04
City_Fairchild Air Force Base    2799.5636   4328.030      0.647      0.518
-5683.275    1.13e+04
City_Fall City                   2.339e+04   6245.227      3.746      0.000
1.12e+04    3.56e+04
City_Federal Way                 2.435e+04   6166.926      3.948      0.000
1.23e+04    3.64e+04
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City_Ferndale	2.848e+04	8265.000	3.445	0.001	1.23e+04	4.47e+04
City_Fife	-3.128e+04	6118.657	-5.112	0.000	-4.33e+04	-1.93e+04
City_Fircrest	-3.528e+04	6118.835	-5.765	0.000	-4.73e+04	-2.33e+04
City_Ford	5585.2800	4756.863	1.174	0.240	-3738.061	1.49e+04
City_Forks	1.55e+04	2290.630	6.768	0.000	1.1e+04	2e+04
City_Fox Island	-1.546e+04	6108.752	-2.531	0.011	-2.74e+04	-3488.711
City_Frances	6398.8521	6421.551	0.996	0.319	-6187.239	1.9e+04
City_Freeland	1.303e+04	920.353	14.156	0.000	1.12e+04	1.48e+04
City_Friday Harbor	2.811e+04	8247.082	3.408	0.001	1.19e+04	4.43e+04
City_Garfield	-1.771e+04	6843.202	-2.588	0.010	-3.11e+04	-4300.912
City_Gifford	1.929e+04	6129.624	3.146	0.002	7272.183	3.13e+04
City_Gig Harbor	-1.318e+04	6098.685	-2.161	0.031	-2.51e+04	-1227.084
City_Glacier	2.362e+04	8471.869	2.788	0.005	7012.532	4.02e+04
City_Glenoma	-3.945e+04	6667.241	-5.918	0.000	-5.25e+04	-2.64e+04
City_Glenwood	-4567.7451	6673.797	-0.684	0.494	-1.76e+04	8512.741
City_Gold Bar	-5000.5006	6342.751	-0.788	0.430	-1.74e+04	7431.144
City_Goldendale	-1.293e+04	2181.188	-5.926	0.000	-1.72e+04	-8651.666
City_Graham	-3039.3979	6099.869	-0.498	0.618	-1.5e+04	8916.203
City_Grand Coulee	1.713e+04	3286.087	5.213	0.000	1.07e+04	2.36e+04
City_Grandview	-4737.1391	1804.567	-2.625	0.009	-8274.049	-1200.229
City_Granger	14.1629	2569.389	0.006	0.996	-5021.780	5050.106
City_Granite Falls	2.109e+04	6288.399	3.354	0.001	8764.670	3.34e+04
City_Grapeview	255.4085	2627.213	0.097	0.923	-4893.868	5404.685
City_Grayland	-1158.9216	2391.222	-0.485	0.628	-5845.661	3527.818

City_Grays River	-1760.6624	5604.412	-0.314	0.753	-1.27e+04	9223.854
City_Greenacres	-91.8881	4053.422	-0.023	0.982	-8036.502	7852.726
City_Greenbank	1.379e+04	1046.568	13.179	0.000	1.17e+04	1.58e+04
City_Hamilton	1.244e+04	1.04e+04	1.191	0.234	-8030.152	3.29e+04
City_Hansville	-1.209e+04	5961.044	-2.029	0.043	-2.38e+04	-408.872
City_Harrington	3569.9093	5033.295	0.709	0.478	-6295.231	1.34e+04
City_Hartline	1.306e+04	5842.268	2.236	0.025	1612.724	2.45e+04
City_Hatton	-4682.7869	7714.826	-0.607	0.544	-1.98e+04	1.04e+04
City_Home	-1.301e+04	8953.650	-1.453	0.146	-3.06e+04	4543.056
City_Hoodsport	5399.3386	2629.542	2.053	0.040	245.498	1.06e+04
City_Hoquiam	1171.9422	1392.603	0.842	0.400	-1557.528	3901.413
City_Hunters	1.612e+04	6112.440	2.637	0.008	4139.985	2.81e+04
City_Hunts Point	2.881e+04	6260.822	4.602	0.000	1.65e+04	4.11e+04
City_Husum	-8883.5063	2334.533	-3.805	0.000	-1.35e+04	-4307.876
City_Ilwaco	1215.6064	2123.979	0.572	0.567	-2947.343	5378.555
City_Inchelium	2.061e+04	6587.617	3.129	0.002	7699.105	3.35e+04
City_Incorporated	-3479.7538	7658.405	-0.454	0.650	-1.85e+04	1.15e+04
City_Index	-5443.1317	6936.860	-0.785	0.433	-1.9e+04	8152.952
City_Indianola	-1.562e+04	5960.842	-2.621	0.009	-2.73e+04	-3939.963
City_Ione	2.005e+04	6868.309	2.918	0.004	6583.292	3.35e+04
City_Issaquah	2.689e+04	6212.413	4.329	0.000	1.47e+04	3.91e+04
City_Joint Base Lewis Mcchord	2.317e+04	6119.137	3.787	0.000	1.12e+04	3.52e+04
City_Kalama	1.285e+04	1971.355	6.517	0.000	8982.793	1.67e+04
City_Kapowsin	3.746e+04	8961.395	4.180	0.000	1.99e+04	5.5e+04

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City_Keller                    1.959e+04   8025.632      2.441       0.015
3856.969    3.53e+04
City_Kelso                     2.363e+04   1980.232     11.931       0.000
1.97e+04    2.75e+04
City_Kenmore                    2.74e+04   6201.224      4.419       0.000
1.52e+04    3.96e+04
City_Kennewick                -1.204e+04   2603.459     -4.626       0.000
-1.71e+04   -6940.115
City_Kent                      2.643e+04   6180.055      4.277       0.000
1.43e+04    3.85e+04
City_Kettle Falls              2.619e+04   4323.368      6.058       0.000
1.77e+04    3.47e+04
City_Keyport                  -1.585e+04   6328.710     -2.504       0.012
-2.83e+04   -3444.161
City_Kingston                  -1.47e+04   5920.426     -2.483       0.013
-2.63e+04   -3099.141
City_Kirkland                  3.019e+04   6203.890      4.866       0.000
1.8e+04    4.24e+04
City_Kittitas                  3948.3837   7709.898      0.512       0.609
-1.12e+04    1.91e+04
City_Klickitat                -1.078e+04   6675.613     -1.615       0.106
-2.39e+04    2301.125
City_La Center                 8894.3044   1661.564      5.353       0.000
5637.677    1.22e+04
City_La Conner                 2.256e+04   8095.934      2.787       0.005
6694.876    3.84e+04
City_Lacey                    -1.809e+04   5726.222     -3.160       0.002
-2.93e+04   -6871.372
City_Lacrosse                 -1.547e+04   9051.026     -1.710       0.087
-3.32e+04    2265.733
City_Lake Forest Park          8778.6623   6197.057      1.417       0.157
-3367.425    2.09e+04
City_Lake Stevens              3.433e+04   6244.759      5.497       0.000
2.21e+04    4.66e+04
City_Lake Tapps                2.416e+04   6156.613      3.924       0.000
1.21e+04    3.62e+04
City_Lakebay                  -1.301e+04   6115.712     -2.127       0.033
-2.5e+04   -1019.236
City_Lakeview                  9738.7273   7461.779      1.305       0.192
-4886.185    2.44e+04
City_Lakewood                 -4815.3343   6094.133     -0.790       0.429
-1.68e+04    7129.025
City_Lamont                   -4249.1271   9048.539     -0.470       0.639
-2.2e+04    1.35e+04
City_Langley                   1.199e+04    866.980     13.830       0.000
1.03e+04    1.37e+04
City_Latah                    -9104.7521   7713.203     -1.180       0.238
-2.42e+04    6012.946
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City_Leavenworth              2.715e+04   8919.694      3.044      0.002
9670.839    4.46e+04
City_Lebam                    6398.8521   6421.551      0.996      0.319
-6187.239     1.9e+04
City_Liberty Lake             -296.1537   4048.776     -0.073      0.942
-8231.660    7639.353
City_Lilliwaup                5381.1621   3409.599      1.578      0.115
-1301.572    1.21e+04
City_Lincoln                   1.31e+04   4682.881      2.797      0.005
3920.935    2.23e+04
City_Lind                    -6338.0022   6149.060     -1.031      0.303
-1.84e+04    5714.012
City_Long Beach               2608.2820   1661.255      1.570      0.116
-647.739    5864.303
City_Longbranch               -1.49e+04   6243.239     -2.387      0.017
-2.71e+04   -2666.009
City_Longview                   3.2e+04   2049.963     15.610      0.000
2.8e+04     3.6e+04
City_Loon Lake                1.035e+04   4342.843      2.383      0.017
1837.710    1.89e+04
City_Lopez Is                 2.589e+04   9080.405      2.851      0.004
8089.262    4.37e+04
City_Lopez Island             2.589e+04   8269.134      3.131      0.002
9679.334    4.21e+04
City_Lummi Island             2.226e+04   8298.620      2.682      0.007
5995.284    3.85e+04
City_Lyle                    -1.078e+04   2225.473     -4.845      0.000
-1.51e+04   -6421.046
City_Lyman                    1.308e+04   1.04e+04      1.253      0.210
-7378.425    3.35e+04
City_Lynden                   2.905e+04   8294.943      3.502      0.000
1.28e+04    4.53e+04
City_Lynnwood                  3.18e+04   6204.038      5.126      0.000
1.96e+04     4.4e+04
City_Mabton                  -4864.8573   2883.281     -1.687      0.092
-1.05e+04     786.306
City_Malaga                   1.518e+04   8959.956      1.694      0.090
-2382.841    3.27e+04
City_Malden                  -7399.8053   9062.342     -0.817      0.414
-2.52e+04    1.04e+04
City_Malott                    3.13e+04   9111.099      3.436      0.001
1.34e+04    4.92e+04
City_Mansfield                2.044e+04   6083.833      3.359      0.001
8511.126    3.24e+04
City_Manson                   2.655e+04   8896.628      2.985      0.003
9116.004     4.4e+04
City_Maple Falls              2.626e+04   8398.400      3.126      0.002
9795.088    4.27e+04
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City_Maple Valley             2.358e+04   6201.161      3.802      0.000
1.14e+04    3.57e+04
City_Marblemount              7366.4984   9416.680      0.782      0.434
-1.11e+04    2.58e+04
City_Marlin                   4117.4031   5834.191      0.706      0.480
-7317.477    1.56e+04
City_Maryhill                -1.293e+04   6688.026     -1.933      0.053
-2.6e+04     181.632
City_Marysville               3.553e+04   6239.876      5.694      0.000
2.33e+04    4.78e+04
City_Mattawa                  -719.4498   3900.414     -0.184      0.854
-8364.170    6925.270
City_Mazama                   4.416e+04   6587.913      6.703      0.000
3.12e+04    5.71e+04
City_Mccleary                -3316.5126   1660.626     -1.997      0.046
-6571.301     -61.724
City_Mead                     2138.2732   4070.071      0.525      0.599
-5838.972    1.01e+04
City_Medical Lake             1663.6088   4024.288      0.413      0.679
-6223.902    9551.119
City_Medina                   2.245e+04   6204.198      3.619      0.000
1.03e+04    3.46e+04
City_Menlo                    6398.8521   2569.342      2.490      0.013
1363.002    1.14e+04
City_Mercer Island            2.881e+04   6193.253      4.652      0.000
1.67e+04     4.1e+04
City_Mesa                    -1.058e+04   5479.788     -1.932      0.053
-2.13e+04     156.024
City_Methow                   2.956e+04   7398.896      3.995      0.000
1.51e+04    4.41e+04
City_Mica                    -2924.6924   4990.137     -0.586      0.558
-1.27e+04    6855.861
City_Mill Creek               3.129e+04   6214.458      5.036      0.000
1.91e+04    4.35e+04
City_Milton                  -3.674e+04   6187.314     -5.938      0.000
-4.89e+04   -2.46e+04
City_Mineral                 -3.526e+04   6127.269     -5.754      0.000
-4.73e+04   -2.32e+04
City_Moclips                  9243.8575   3479.051      2.657      0.008
2424.999    1.61e+04
City_Monroe                   3.062e+04   6243.717      4.905      0.000
1.84e+04    4.29e+04
City_Montesano               -1647.0395    937.028     -1.758      0.079
-3483.593     189.514
City_Morton                  -3.795e+04   6016.092     -6.308      0.000
-4.97e+04   -2.62e+04
City_Moses Lake               2784.3410   3616.685      0.770      0.441
-4304.277    9872.959
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City_Mossyrock                  -3.685e+04   5882.386     -6.264      0.000
-4.84e+04   -2.53e+04
City_Mount Vernon                 2.11e+04   8092.828      2.607      0.009
5237.226     3.7e+04
City_Mountlake Terrace           3.152e+04   6204.743      5.080      0.000
1.94e+04    4.37e+04
City_Moxee                       7036.5962   2004.108      3.511      0.000
3108.590     1.1e+04
City_Mukilteo                     3.34e+04   6212.106      5.377      0.000
2.12e+04    4.56e+04
City_Murdock                    -1.195e+04   4131.727     -2.893      0.004
-2.01e+04   -3854.749
City_Naches                      1.403e+04   2117.518      6.625      0.000
9878.152    1.82e+04
City_Nahcotta                    5466.1116   3118.110      1.753      0.080
-645.312    1.16e+04
City_Napavine                    3.761e+04   6191.479      6.074      0.000
2.55e+04    4.97e+04
City_Naselle                       75.6855   1804.148      0.042      0.967
-3460.402    3611.773
City_Neah Bay                    2.656e+04   2927.516      9.072      0.000
2.08e+04    3.23e+04
City_Nespelem                      2.2e+04   9085.940      2.422      0.015
4194.017    3.98e+04
City_Newcastle                   2.657e+04   6198.211      4.287      0.000
1.44e+04    3.87e+04
City_Newman Lake                  789.4170   4138.013      0.191      0.849
-7320.993    8899.827
City_Newport                     5411.5409   5121.710      1.057      0.291
-4626.892    1.54e+04
City_Nine Mile Falls             4190.2981   4000.965      1.047      0.295
-3651.501     1.2e+04
City_Nooksack                    2.754e+04   8527.544      3.230      0.001
1.08e+04    4.43e+04
City_Nordland                    2849.0037   1640.523      1.737      0.082
-366.382    6064.390
City_Normandy Park               2.928e+04   6187.005      4.732      0.000
1.72e+04    4.14e+04
City_North Bend                  2.061e+04   6245.536      3.300      0.001
8370.291    3.29e+04
City_North Bonneville           -6823.7818   2440.622     -2.796      0.005
-1.16e+04   -2040.219
City_North Cove                   1.08e+04   2592.458      4.165      0.000
5715.854    1.59e+04
City_Northport                   2.982e+04   6237.737      4.781      0.000
1.76e+04     4.2e+04
City_Oak Harbor                  2.006e+04    882.202     22.741      0.000
1.83e+04    2.18e+04
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City_Oakesdale                 -1.22e+04   6941.818     -1.758      0.079
-2.58e+04    1405.153
City_Oakville                 -8468.0964   1565.587     -5.409      0.000
-1.15e+04   -5399.583
City_Ocean Park                5466.1116   1755.832      3.113      0.002
2024.723    8907.501
City_Ocean Shores              3123.4073   1259.834      2.479      0.013
654.162    5592.653
City_Odessa                    4325.0839   4268.030      1.013      0.311
-4040.155    1.27e+04
City_Okanogan                  3.129e+04   7004.508      4.467      0.000
1.76e+04     4.5e+04
City_Olalla                     -2.2e+04   5916.562     -3.718      0.000
-3.36e+04   -1.04e+04
City_Olga                      2.799e+04   8335.161      3.358      0.001
1.17e+04    4.43e+04
City_Olympia                  -1.756e+04   5715.272     -3.073      0.002
-2.88e+04   -6360.059
City_Omak                      3.215e+04   7127.577      4.510      0.000
1.82e+04    4.61e+04
City_Onalaska                 -3.368e+04   5897.655     -5.711      0.000
-4.52e+04   -2.21e+04
City_Orcas                     2.836e+04   8888.250      3.190      0.001
1.09e+04    4.58e+04
City_Orcas Is                  2.922e+04   8498.949      3.438      0.001
1.26e+04    4.59e+04
City_Orient                    3.249e+04   8104.155      4.009      0.000
1.66e+04    4.84e+04
City_Orondo                    2.401e+04   4120.108      5.827      0.000
1.59e+04    3.21e+04
City_Oroville                  4.183e+04   7372.045      5.675      0.000
2.74e+04    5.63e+04
City_Orting                    3.117e+04   6121.826      5.091      0.000
1.92e+04    4.32e+04
City_Othello                  -5058.6619   4003.880     -1.263      0.206
-1.29e+04    2788.849
City_Otis Orchards              687.8114   4140.885      0.166      0.868
-7428.227    8803.850
City_Outlook                   -973.2616   2432.376     -0.400      0.689
-5740.661    3794.138
City_Oysterville               5765.3743   2897.592      1.990      0.047
86.162    1.14e+04
City_Pacific                   2.379e+04   6214.946      3.828      0.000
1.16e+04     3.6e+04
City_Pacific Beach             8412.6164   1719.331      4.893      0.000
5042.768    1.18e+04
City_Packwood                 -4.185e+04   6051.760     -6.915      0.000
-5.37e+04      -3e+04
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City_Palisades                    1.405e+04   6107.622      2.301      0.021
2081.061     2.6e+04
City_Palouse                     -2.037e+04   6459.453     -3.153      0.002
-3.3e+04   -7705.024
City_Parkland                    -3.607e+04   6126.653     -5.888      0.000
-4.81e+04   -2.41e+04
City_Pasc                        -1.752e+04   6130.500     -2.858      0.004
-2.95e+04   -5503.647
City_Pasco                       -1.753e+04   4839.108     -3.623      0.000
-2.7e+04   -8048.119
City_Pateros                      2.819e+04   6822.906      4.132      0.000
1.48e+04    4.16e+04
City_Paterson                    -1.422e+04   5155.244     -2.758      0.006
-2.43e+04   -4113.896
City_Pe Ell                       -2.87e+04   8716.248     -3.293      0.001
-4.58e+04   -1.16e+04
City_Peshastin                    2.301e+04   9017.624      2.552      0.011
5334.762    4.07e+04
City_Plymouth                    -1.649e+04   6828.419     -2.415      0.016
-2.99e+04   -3103.923
City_Point Roberts                3.543e+04   8286.958      4.276      0.000
1.92e+04    5.17e+04
City_Pomeroy                     -1.262e+04   2791.301     -4.521      0.000
-1.81e+04   -7149.042
City_Port Angeles                 1.039e+04   1473.745      7.050      0.000
7501.406    1.33e+04
City_Port Gamble                 -1.477e+04   7502.276     -1.969      0.049
-2.95e+04     -64.469
City_Port Hadlock                 3233.2376   1648.382      1.961      0.050
2.446    6464.029
City_Port Ludlow                  -170.1365   1456.776     -0.117      0.907
-3025.383    2685.110
City_Port Orchard                -2.019e+04   5879.178     -3.434      0.001
-3.17e+04   -8665.145
City_Port Townsend                5087.6427   1401.508      3.630      0.000
2340.720    7834.566
City_Poulsbo                     -1.477e+04   5894.921     -2.506      0.012
-2.63e+04   -3216.135
City_Prairie Ridge                2.416e+04   8997.933      2.685      0.007
6525.292    4.18e+04
City_Preston                      2.669e+04   6318.779      4.224      0.000
1.43e+04    3.91e+04
City_Pros                        -7083.4361   6815.806     -1.039      0.299
-2.04e+04    6275.384
City_Prosser                     -7083.4361   2605.346     -2.719      0.007
-1.22e+04   -1977.018
City_Pullman                     -2.302e+04   6313.988     -3.646      0.000
-3.54e+04   -1.06e+04
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City_Puyallup                  1.332e+04   6099.397      2.183      0.029
1361.257    2.53e+04
City_Quilcene                  -829.7161   1609.433     -0.516      0.606
-3984.167    2324.735
City_Quinault                  1.115e+04   3970.844      2.808      0.005
3367.481    1.89e+04
City_Quincy                    9642.1446   3706.388      2.601      0.009
2377.710    1.69e+04
City_Rainier                  -2.115e+04   5775.471     -3.662      0.000
-3.25e+04   -9827.445
City_Randle                   -4.255e+04   6340.589     -6.711      0.000
-5.5e+04   -3.01e+04
City_Ravensdale                2.211e+04   6243.216      3.541      0.000
9869.587    3.43e+04
City_Raymond                   6398.8521   1711.884      3.738      0.000
3043.599    9754.105
City_Reardan                   5379.9274   3738.212      1.439      0.150
-1946.881    1.27e+04
City_Redmond                   2.895e+04   6214.406      4.659      0.000
1.68e+04    4.11e+04
City_Renton                    2.686e+04   6191.176      4.338      0.000
1.47e+04     3.9e+04
City_Republic                  3.258e+04   5174.986      6.296      0.000
2.24e+04    4.27e+04
City_Rice                       2.23e+04   4853.367      4.595      0.000
1.28e+04    3.18e+04
City_Rich                     -9969.1623   6837.147     -1.458      0.145
-2.34e+04    3431.488
City_Richland                 -9943.9050   2608.083     -3.813      0.000
-1.51e+04   -4832.123
City_Ridgefield                7771.5567   1650.221      4.709      0.000
4537.163     1.1e+04
City_Ritzville                -5645.8583   4333.797     -1.303      0.193
-1.41e+04    2848.284
City_Riverside                 3.394e+04   7758.096      4.375      0.000
1.87e+04    4.91e+04
City_Rochester                -2.019e+04   5702.084     -3.540      0.000
-3.14e+04   -9011.008
City_Rock Island               1.534e+04   4453.046      3.444      0.001
6608.065    2.41e+04
City_Rockford                 -6977.5737   5050.727     -1.381      0.167
-1.69e+04    2921.733
City_Rockport                  7901.3316   9396.720      0.841      0.400
-1.05e+04    2.63e+04
City_Ronald                    1.553e+04   7283.987      2.133      0.033
1256.684    2.98e+04
City_Roosevelt                -1.647e+04   4930.346     -3.340      0.001
-2.61e+04   -6805.517
```

City_Rosalia	-7985.0681	5867.162	-1.361	0.174	-1.95e+04	3514.432
City_Rosburg	-2344.4568	7157.530	-0.328	0.743	-1.64e+04	1.17e+04
City_Roslyn	1.434e+04	7348.361	1.951	0.051	-64.699	2.87e+04
City_Roy	1.088e+04	6090.517	1.787	0.074	-1055.286	2.28e+04
City_Royal City	639.8530	3916.994	0.163	0.870	-7037.364	8317.070
City_Ruston	-3.69e+04	6198.353	-5.953	0.000	-4.9e+04	-2.47e+04
City_Salkum	-3.545e+04	6465.345	-5.484	0.000	-4.81e+04	-2.28e+04
City_Sammamish	2.735e+04	6217.030	4.399	0.000	1.52e+04	3.95e+04
City_San Juan Is	2.811e+04	1.05e+04	2.667	0.008	7453.924	4.88e+04
City_Satsop	-2206.6915	4782.006	-0.461	0.644	-1.16e+04	7165.929
City_Seabeck	-1.621e+04	5889.740	-2.752	0.006	-2.78e+04	-4664.075
City_Seatac	2.752e+04	6180.740	4.453	0.000	1.54e+04	3.96e+04
City_Seattle	-5291.1677	6184.537	-0.856	0.392	-1.74e+04	6830.381
City_Seaview	1924.4164	2502.775	0.769	0.442	-2980.965	6829.798
City_Sedro Woolley	1.792e+04	8249.717	2.172	0.030	1750.397	3.41e+04
City_Sedro-Woolley	1.522e+04	8107.446	1.877	0.061	-674.938	3.11e+04
City_Sekiu	2.268e+04	3931.676	5.769	0.000	1.5e+04	3.04e+04
City_Selah	1.123e+04	1770.777	6.342	0.000	7759.254	1.47e+04
City_Sequim	7122.8637	1401.089	5.084	0.000	4376.763	9868.965
City_Seven Bays	8342.8651	5046.043	1.653	0.098	-1547.262	1.82e+04
City_Shaw Island	2.8e+04	8426.031	3.323	0.001	1.15e+04	4.45e+04
City_Shelton	-21.7802	2474.041	-0.009	0.993	-4870.843	4827.283
City_Shoreline	-4874.9290	6192.133	-0.787	0.431	-1.7e+04	7261.507
City_Silver Creek	-3.578e+04	6095.748	-5.870	0.000	-4.77e+04	-2.38e+04

City_Silver Lake	1.959e+04	6688.367	2.929	0.003	6481.512	3.27e+04
City_Silverdale	-1.6e+04	5884.072	-2.719	0.007	-2.75e+04	-4469.066
City_Silverlake	1.959e+04	2164.783	9.050	0.000	1.53e+04	2.38e+04
City_Skamokawa	-4723.1981	4638.519	-1.018	0.309	-1.38e+04	4368.192
City_Skykomish	2.633e+04	6732.957	3.910	0.000	1.31e+04	3.95e+04
City_Smith Creek	6398.8521	6421.551	0.996	0.319	-6187.239	1.9e+04
City_Snohomish	3.092e+04	6230.364	4.963	0.000	1.87e+04	4.31e+04
City_Snoqualmie	1.854e+04	6237.291	2.973	0.003	6316.621	3.08e+04
City_Snoqualmie Pass	2.227e+04	7063.549	3.153	0.002	8425.051	3.61e+04
City_Snowden	-8883.5063	2455.434	-3.618	0.000	-1.37e+04	-4070.914
City_Soap Lake	9738.7273	3847.030	2.531	0.011	2198.638	1.73e+04
City_South Bend	6880.2461	2707.800	2.541	0.011	1573.020	1.22e+04
City_South Cle Elum	1.305e+04	7799.018	1.673	0.094	-2234.540	2.83e+04
City_South Hill	2032.6234	6100.270	0.333	0.739	-9923.764	1.4e+04
City_South Prairie	2.282e+04	7709.143	2.960	0.003	7711.427	3.79e+04
City_Spanaway	-2.484e+04	6094.896	-4.075	0.000	-3.68e+04	-1.29e+04
City_Spangle	-3316.5337	4455.059	-0.744	0.457	-1.2e+04	5415.279
City_Spokane	627.0888	3986.378	0.157	0.875	-7186.120	8440.297
City_Spokane Valley	-425.5666	4012.302	-0.106	0.916	-8289.585	7438.452
City_Sprague	-2636.4228	7334.255	-0.359	0.719	-1.7e+04	1.17e+04
City_Springdale	1.071e+04	5513.659	1.942	0.052	-98.432	2.15e+04
City_St John	-9596.7445	7791.550	-1.232	0.218	-2.49e+04	5674.512
City_Stanwood	2.644e+04	6266.118	4.219	0.000	1.42e+04	3.87e+04
City_Startup	3.265e+04	9079.463	3.596	0.000	1.49e+04	5.04e+04

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City_Steilacoom                  -4.414e+04   6106.901     -7.228      0.000
-5.61e+04   -3.22e+04
City_Stevenson                   -6369.0412   1707.681     -3.730      0.000
-9716.055   -3022.027
City_Stratford                    8924.3019   7450.980      1.198      0.231
-5679.446    2.35e+04
City_Sultan                       1.389e+04   6283.117      2.211      0.027
1578.866    2.62e+04
City_Sumas                        2.547e+04   8494.216      2.999      0.003
8825.571    4.21e+04
City_Sumner                       2.545e+04   6153.973      4.135      0.000
1.34e+04    3.75e+04
City_Sunnyside                   -2260.8753   1794.848     -1.260      0.208
-5778.736    1256.986
City_Suquamish                   -1.572e+04   5950.243     -2.642      0.008
-2.74e+04   -4058.144
City_Surfside                     5466.1116   1945.563      2.810      0.005
1652.853    9279.371
City_Tacoma                      -2.963e+04   6094.420     -4.862      0.000
-4.16e+04   -1.77e+04
City_Taholah                      1.212e+04   3485.607      3.478      0.001
5289.746     1.9e+04
City_Tahuya                       3817.7939   2791.609      1.368      0.171
-1653.695    9289.283
City_Tekoa                        -1.35e+04   6955.577     -1.941      0.052
-2.71e+04     132.317
City_Tenino                      -2.055e+04   5728.966     -3.587      0.000
-3.18e+04   -9319.557
City_Thorp                        8505.4113   7737.294      1.099      0.272
-6659.505    2.37e+04
City_Tieton                       1.323e+04   2821.162      4.691      0.000
7703.477    1.88e+04
City_Tokeland                     9735.5387   3866.580      2.518      0.012
2157.131    1.73e+04
City_Toledo                      -2.855e+04   5844.523     -4.884      0.000
-4e+04   -1.71e+04
City_Tonasket                     3.527e+04   7341.258      4.805      0.000
2.09e+04    4.97e+04
City_Toppenish                    2568.2057   2341.477      1.097      0.273
-2021.036    7157.447
City_Touchet                     -2424.9321   2436.684     -0.995      0.320
-7200.777    2350.912
City_Toutle                       1.902e+04   3207.752      5.928      0.000
1.27e+04    2.53e+04
City_Trout Lake                  -3783.6561   2212.444     -1.710      0.087
-8119.995     552.683
City_Tukwila                       2.21e+04   6179.690      3.576      0.000
9986.918    3.42e+04
```

City_Tulalip	2.877e+04	6893.763	4.173	0.000	1.53e+04	4.23e+04
City_Tumtum	7159.0715	7658.641	0.935	0.350	-7851.687	2.22e+04
City_Tumwater	-1.787e+04	5718.802	-3.125	0.002	-2.91e+04	-6660.599
City_Twisp	3.674e+04	6462.703	5.684	0.000	2.41e+04	4.94e+04
City_Underwood	-8359.1239	1854.882	-4.507	0.000	-1.2e+04	-4723.599
City_Union	1902.8585	2644.890	0.719	0.472	-3281.065	7086.782
City_Union Gap	9262.9279	2462.244	3.762	0.000	4436.986	1.41e+04
City_Uniontown	-2.815e+04	7106.562	-3.962	0.000	-4.21e+04	-1.42e+04
City_University Place	-3.54e+04	6098.383	-5.804	0.000	-4.74e+04	-2.34e+04
City_Usk	9687.8052	6283.383	1.542	0.123	-2627.479	2.2e+04
City_Vader	-2.565e+04	6257.736	-4.099	0.000	-3.79e+04	-1.34e+04
City_Valley	1.325e+04	4740.149	2.795	0.005	3957.477	2.25e+04
City_Valleyford	-2924.3185	4233.329	-0.691	0.490	-1.12e+04	5372.909
City_Vancouver	3993.7672	1641.237	2.433	0.015	776.981	7210.553
City_Vantage	-3.845e+04	9878.915	-3.892	0.000	-5.78e+04	-1.91e+04
City_Vashon	2.884e+04	6171.523	4.673	0.000	1.67e+04	4.09e+04
City_Vaughn	-1.196e+04	6223.972	-1.922	0.055	-2.42e+04	238.855
City_Veradale	91.6229	4097.001	0.022	0.982	-7938.403	8121.649
City_Wahkiacus	-9315.2253	4132.194	-2.254	0.024	-1.74e+04	-1216.222
City_Waitsburg	-2577.4218	2257.808	-1.142	0.254	-7002.673	1847.829
City_Waldron	3.152e+04	9479.451	3.325	0.001	1.29e+04	5.01e+04
City_Walla Walla	-4779.0097	1392.568	-3.432	0.001	-7508.411	-2049.608
City_Walla Walla Co	-4752.3291	5850.613	-0.812	0.417	-1.62e+04	6714.737
City_Wapato	5210.8808	2396.306	2.175	0.030	514.178	9907.584

City_Warden	-3070.8455	4466.753	-0.687	0.492	-1.18e+04	5683.886
City_Washougal	-4752.1041	1570.712	-3.025	0.002	-7830.663	-1673.545
City_Washtucna	-1.381e+04	7693.055	-1.795	0.073	-2.89e+04	1269.322
City_Waterville	2.063e+04	4965.445	4.155	0.000	1.09e+04	3.04e+04
City_Waverly	-7152.5003	6175.088	-1.158	0.247	-1.93e+04	4950.528
City_Wellpinit	8905.1377	7650.976	1.164	0.244	-6090.597	2.39e+04
City_Wenatchee	1.79e+04	8885.961	2.014	0.044	482.579	3.53e+04
City_West Richland	-8230.3604	2627.173	-3.133	0.002	-1.34e+04	-3081.163
City_Westport	528.8807	1360.059	0.389	0.697	-2136.804	3194.565
City_White Salmon	-8895.8598	1808.363	-4.919	0.000	-1.24e+04	-5351.511
City_White Swan	5743.4829	6552.960	0.876	0.381	-7100.166	1.86e+04
City_Wilbur	1.328e+04	4444.538	2.989	0.003	4572.258	2.2e+04
City_Wilkeson	2.181e+04	6977.034	3.125	0.002	8131.507	3.55e+04
City_Winlock	2.394e+04	5811.388	4.119	0.000	1.25e+04	3.53e+04
City_Winthrop	4.003e+04	6445.711	6.210	0.000	2.74e+04	5.27e+04
City_Wishram	-1.526e+04	6683.736	-2.283	0.022	-2.84e+04	-2156.760
City_Woodinville	3.098e+04	6217.799	4.983	0.000	1.88e+04	4.32e+04
City_Woodland	1.034e+04	1820.843	5.678	0.000	6769.376	1.39e+04
City_Woodway	3.136e+04	6228.148	5.035	0.000	1.92e+04	4.36e+04
City_Yacolt	6395.9263	1766.313	3.621	0.000	2933.993	9857.859
City_Yakima	9360.1803	1681.608	5.566	0.000	6064.268	1.27e+04
City_Yarrow Point	2.881e+04	6220.677	4.632	0.000	1.66e+04	4.1e+04
City_Yelm	-2.157e+04	5737.298	-3.760	0.000	-3.28e+04	-1.03e+04
City_Zillah	2956.3211	1915.409	1.543	0.123	-797.837	6710.479

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Legislative_District_2.0      -2.015e+04    847.543    -23.769      0.000
-2.18e+04   -1.85e+04
Legislative_District_3.0      -2.108e+04   4266.230     -4.940      0.000
-2.94e+04   -1.27e+04
Legislative_District_4.0       -2.14e+04   4273.635     -5.008      0.000
-2.98e+04    -1.3e+04
Legislative_District_5.0      -2149.4084    252.131     -8.525      0.000
-2643.579   -1655.238
Legislative_District_6.0       -2.04e+04   4263.684     -4.784      0.000
-2.88e+04    -1.2e+04
Legislative_District_7.0      -1.863e+04   4241.930     -4.391      0.000
-2.69e+04   -1.03e+04
Legislative_District_8.0      -2.084e+04   4449.827     -4.683      0.000
-2.96e+04   -1.21e+04
Legislative_District_9.0      -2.048e+04   4370.486     -4.686      0.000
-2.9e+04   -1.19e+04
Legislative_District_10.0     -1.239e+04    639.937    -19.354      0.000
-1.36e+04   -1.11e+04
Legislative_District_11.0     -2459.0853    276.041     -8.908      0.000
-3000.120   -1918.051
Legislative_District_12.0     -1.865e+04   2974.706     -6.268      0.000
-2.45e+04   -1.28e+04
Legislative_District_13.0     -1.865e+04   2532.549     -7.363      0.000
-2.36e+04   -1.37e+04
Legislative_District_14.0     -1.811e+04   1433.551    -12.634      0.000
-2.09e+04   -1.53e+04
Legislative_District_15.0     -1.859e+04   1536.367    -12.098      0.000
-2.16e+04   -1.56e+04
Legislative_District_16.0     -2.047e+04   4419.272     -4.631      0.000
-2.91e+04   -1.18e+04
Legislative_District_17.0     -2.065e+04   1296.365    -15.932      0.000
-2.32e+04   -1.81e+04
Legislative_District_18.0     -1.991e+04   1282.433    -15.529      0.000
-2.24e+04   -1.74e+04
Legislative_District_19.0     -3.422e+04   1214.179    -28.186      0.000
-3.66e+04   -3.18e+04
Legislative_District_20.0     -1.994e+04   1018.231    -19.582      0.000
-2.19e+04   -1.79e+04
Legislative_District_21.0       762.6924    197.531      3.861      0.000
375.537    1149.848
Legislative_District_22.0     -1.874e+04    890.922    -21.029      0.000
-2.05e+04    -1.7e+04
Legislative_District_23.0     -1.923e+04    970.891    -19.803      0.000
-2.11e+04   -1.73e+04
Legislative_District_24.0     -3.436e+04   1596.206    -21.525      0.000
-3.75e+04   -3.12e+04
Legislative_District_25.0     -1583.8083    846.072     -1.872      0.061
-3242.090      74.473
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Legislative_District_26.0	-1.949e+04	1000.447	-19.479	0.000	-2.14e+04	-1.75e+04
Legislative_District_27.0	-5901.5844	905.110	-6.520	0.000	-7675.580	-4127.589
Legislative_District_28.0	-174.6840	929.888	-0.188	0.851	-1997.243	1647.875
Legislative_District_29.0	-1.376e+04	910.081	-15.118	0.000	-1.55e+04	-1.2e+04
Legislative_District_30.0	-3167.8168	481.903	-6.574	0.000	-4112.335	-2223.298
Legislative_District_31.0	-3322.8150	465.730	-7.135	0.000	-4235.634	-2409.996
Legislative_District_32.0	661.3164	225.393	2.934	0.003	219.552	1103.081
Legislative_District_33.0	-3608.8646	355.215	-10.160	0.000	-4305.079	-2912.651
Legislative_District_34.0	-2735.0318	303.973	-8.998	0.000	-3330.812	-2139.252
Legislative_District_35.0	-1.935e+04	912.281	-21.208	0.000	-2.11e+04	-1.76e+04
Legislative_District_36.0	-586.2288	276.316	-2.122	0.034	-1127.801	-44.657
Legislative_District_37.0	2144.3562	288.166	7.441	0.000	1579.557	2709.156
Legislative_District_38.0	1318.0839	272.747	4.833	0.000	783.506	1852.662
Legislative_District_39.0	-3834.5383	305.966	-12.533	0.000	-4434.225	-3234.851
Legislative_District_40.0	-1.216e+04	696.318	-17.470	0.000	-1.35e+04	-1.08e+04
Legislative_District_41.0	-1560.5026	214.676	-7.269	0.000	-1981.263	-1139.742
Legislative_District_42.0	-1.147e+04	740.055	-15.505	0.000	-1.29e+04	-1e+04
Legislative_District_43.0	-1259.0295	277.011	-4.545	0.000	-1801.964	-716.095
Legislative_District_44.0	515.2053	200.877	2.565	0.010	121.491	908.919
Legislative_District_45.0	-605.4470	191.662	-3.159	0.002	-981.100	-229.794
Legislative_District_46.0	4032.6047	278.841	14.462	0.000	3486.084	4579.126
Legislative_District_47.0	-3854.1092	358.508	-10.750	0.000	-4556.777	-3151.441
Legislative_District_48.0	-797.7647	197.925	-4.031	0.000	-1185.694	-409.835
Legislative_District_49.0	-2.007e+04	1300.911	-15.431	0.000	-2.26e+04	-1.75e+04

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==============================================================================
Omnibus:                    75224.996   Durbin-Watson:                   2.002
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          6692895.421
Skew:                          -1.028   Prob(JB):                         0.00
Kurtosis:                      32.278   Cond. No.                     2.21e+19
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 6.54e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Interpretation of Regression Results:

1. EV_Count_County Regression Results: - **R-squared: 0.996**: This indicates that 99.6% of the variance in EV counts per county is explained by the model. This is a very high R-squared value, suggesting an excellent fit. - **Adj. R-squared: 0.996**: Adjusted R-squared is almost the same, confirming that the model explains the variance well even when considering the number of predictors. - **F-statistic: 7.413e+04**: The very high F-statistic and the associated p-value of 0.00 indicate that the model is statistically significant. - **No. Observations: 186471**: This is the total number of observations used in the regression.

2. EV_Count_City Regression Results: **-** R-squared: 0.881**: This indicates that 88.1% of the variance in EV counts per city is explained by the model. This is a high R-squared value, suggesting a good fit. -** Adj. R-squared: 0.880**: The adjusted R-squared is slightly lower but still very high, supporting the model's robustness. -** F-statistic: 9284**: The very high F-statistic and the associated p-value of 0.00 indicate that the model is statistically significant. -** No. Observations: 186471**: This is the total number of observations used in the regression.

3. EV_Count_Leg_Dist Regression Results: **-** R-squared: 0.933**: This indicates that 93.3% of the variance in EV counts per legislative district is explained by the model. This is a very high R-squared value, suggesting a good fit. -** Adj. R-squared: 0.932**: The adjusted R-squared is slightly lower but still very high, supporting the model's robustness. -** F-statistic: 4621**: The very high F-statistic and the associated p-value of 0.00 indicate that the model is statistically significant. -** No. Observations: 186471**: This is the total number of observations used in the regression.

4. EV_Count_Utility Regression Results: **-** R-squared: 0.932**: This indicates that 93.2% of the variance in EV counts per electric utility is explained by the model. This is a very high R-squared value, suggesting a good fit. -** Adj. R-squared: 0.932**: The adjusted R-squared is almost the same, supporting the model's robustness. -** F-statistic: 4658**: The very high F-statistic and the associated p-value of 0.00 indicate that the model is statistically significant. -** No. Observations: 186471**: This is the total number of observations used in the regression.

Key Takeaways:

1. **High R-squared Values:** The high R-squared values across all models suggest that the chosen predictors (County, City, Electric Utility, Legislative District) explain a significant portion of the variance in EV adoption counts.
2. **Model Significance:** The very high F-statistics and the associated p-values (all 0.00) indicate that the models are statistically significant, meaning that the predictors as a group are significant in explaining the variance in EV counts.
3. **Geographic and Infrastructure Impact:** The significant fit of these models underscores the impact of geographic location (County, City, Legislative District) and local infrastructure (Electric Utility) on EV adoption in Washington State. This aligns well with the research question, confirming that these factors are crucial determinants of EV adoption rates.

Implications:

- **Policy Implications:** Policymakers can use these findings to target specific areas (counties, cities, legislative districts) for EV infrastructure development and incentives.
- **Resource Allocation:** The results can help in optimizing the allocation of resources for EV infrastructure, such as charging stations, to areas with higher adoption rates.
- **Further Research:** Future research can delve deeper into understanding the specific characteristics of these geographic and infrastructure variables that drive higher EV adoption.

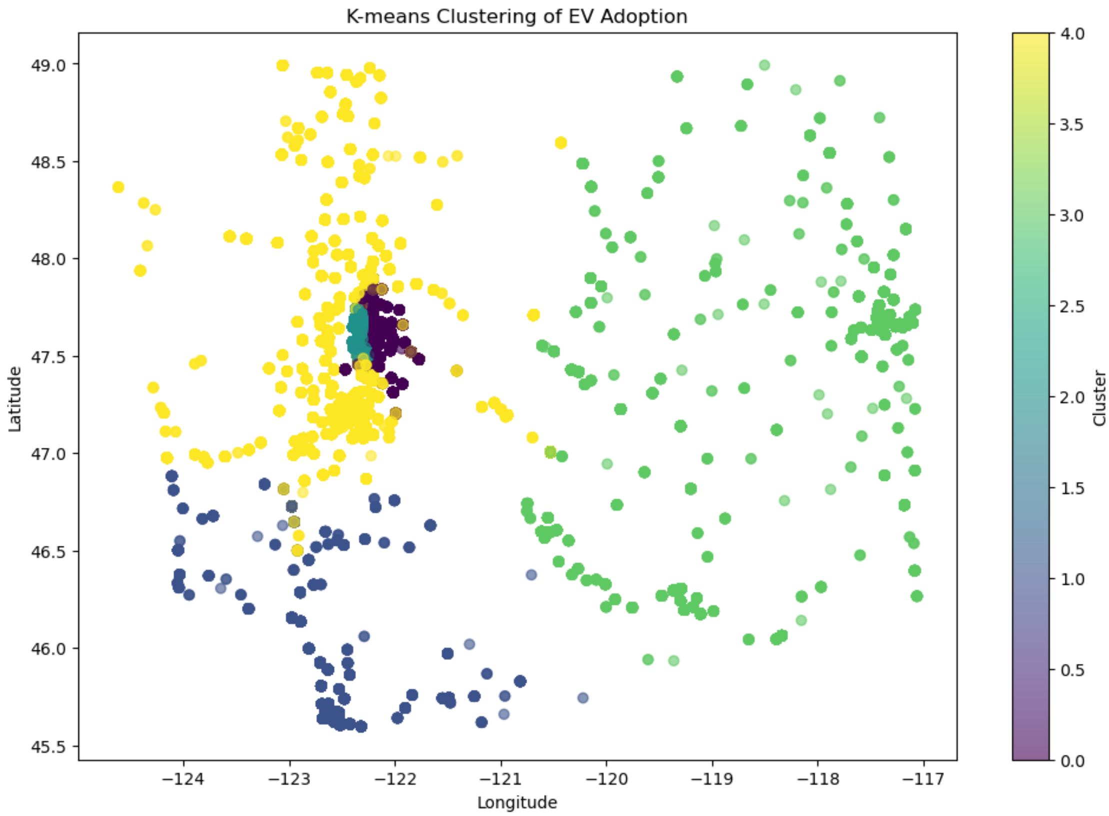
STEP V

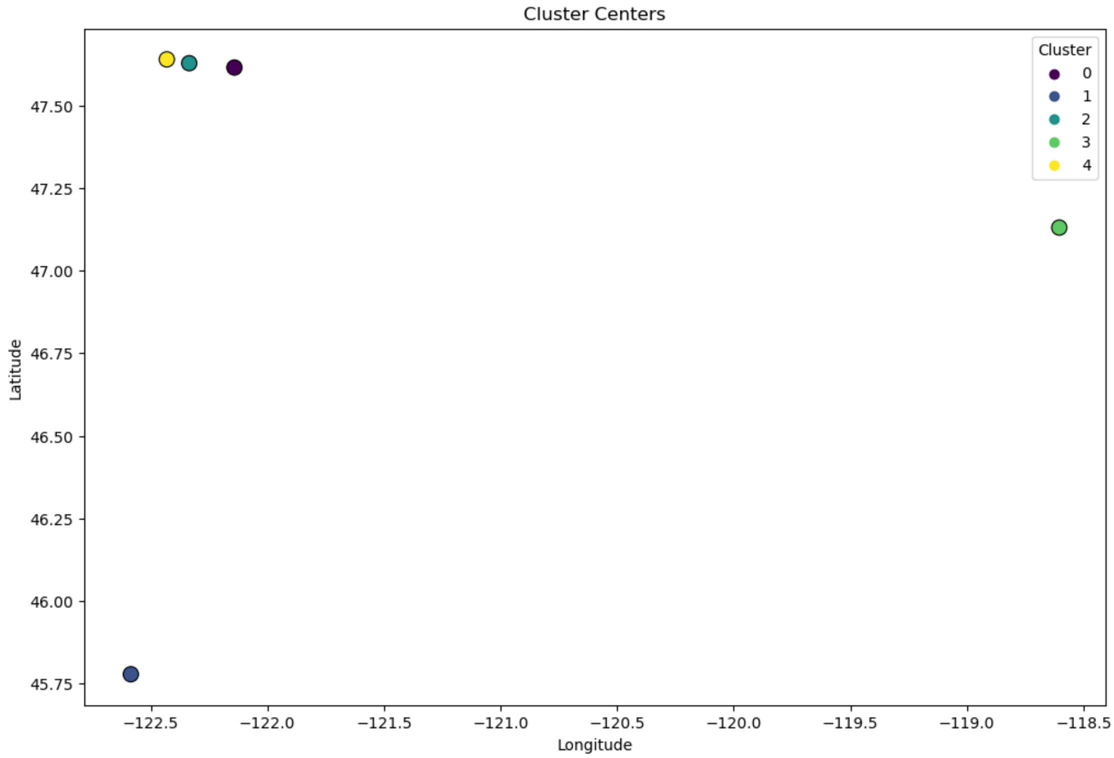
K-Means Clustering to identify patterns and group similar areas.

[ ]:
```
# importing the necessary libraries
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler

# Defines a list of feature names that will be used for clustering.
# These features include geographical coordinates and counts of electric␣
↪vehicles in different geographic and infrastructure categories.
features = ['Latitude', 'Longitude', 'EV_Count_City', 'EV_Count_Leg_Dist',␣
↪'EV_Count_Utility']
X = elec_dataset[features]

# Standardization is used to rescale the features so that they have a mean of 0␣
↪and a standard deviation of 1
scaler = StandardScaler()
# Fits the StandardScaler to the data and transforms it, standardizing the␣
↪features. The transformed data is stored in X_scaled.
X_scaled = scaler.fit_transform(X)

# Apply K-means clustering
# Initializes a KMeans clustering object with 5 clusters.
# The random_state parameter ensures reproducibility of the results.
kmeans = KMeans(n_clusters=5, random_state=42)
# Fit the K-means algorithm to the standardized data X_scaled and assigns each␣
↪data point to a cluster.
```

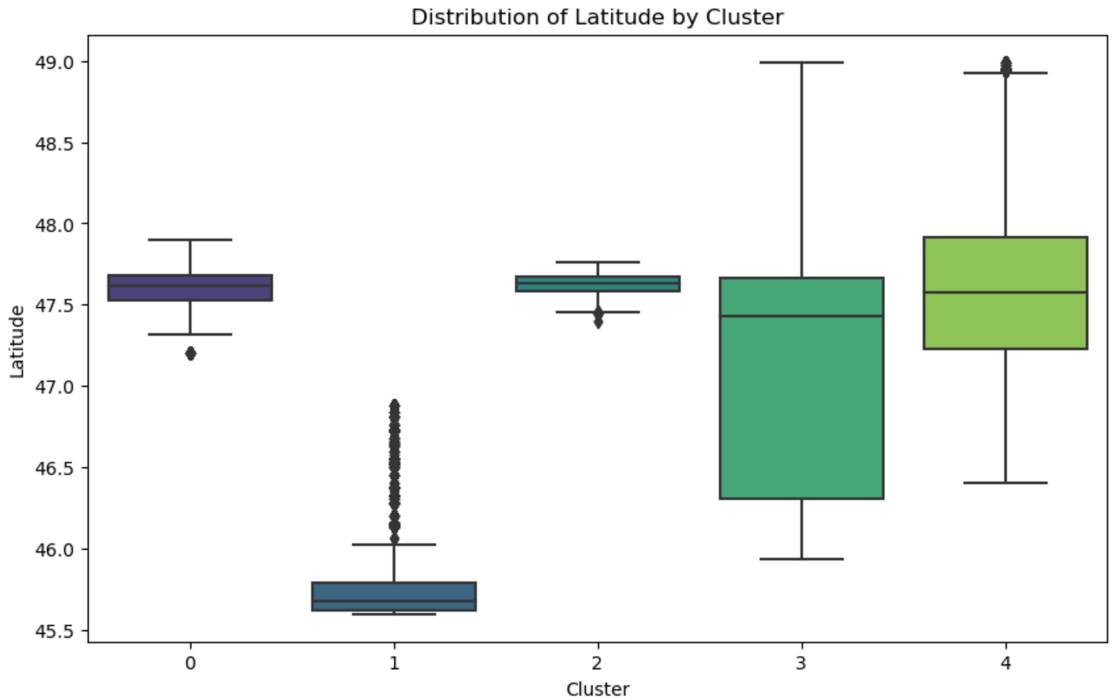
```
# The cluster labels are added as a new column Cluster in the original␣
↪elec_dataset DataFrame.
elec_dataset['Cluster'] = kmeans.fit_predict(X_scaled)

# Plot the clusters
plt.figure(figsize=(12, 8))
# Creates a scatter plot with Longitude on the x-axis and Latitude on the␣
↪y-axis.
# The points are colored by their cluster labels using the 'viridis' colormap,
plt.scatter(elec_dataset['Longitude'], elec_dataset['Latitude'],␣
↪c=elec_dataset['Cluster'], cmap='viridis', alpha=0.6)
plt.title('K-means Clustering of EV Adoption')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.colorbar(label='Cluster')
plt.show()


# Identifying cluster centers by the K-means algorithm and applying the inverse␣
↪of the standardization transformation to revert them back to their original␣
↪scale.
cluster_centers = scaler.inverse_transform(kmeans.cluster_centers_)

# Adds a new column Cluster to the cluster_centers_df DataFrame.
cluster_centers_df = pd.DataFrame(cluster_centers, columns=features)
# This column contains the cluster number (from 0 to the number of clusters␣
↪minus one).
cluster_centers_df['Cluster'] = range(kmeans.n_clusters)

# Visualize the cluster centers
plt.figure(figsize=(12, 8))
sns.scatterplot(data=cluster_centers_df, x='Longitude', y='Latitude',␣
↪hue='Cluster', palette='viridis', s=100, edgecolor='black')
plt.title('Cluster Centers')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()

# Display cluster profiles and visualize distribution of key features within␣
↪each cluster
cluster_profile = elec_dataset.groupby('Cluster')[features].mean()
cluster_profile['Size'] = elec_dataset['Cluster'].value_counts()
print("Cluster Profile:")
print(cluster_profile)

for feature in features:
```

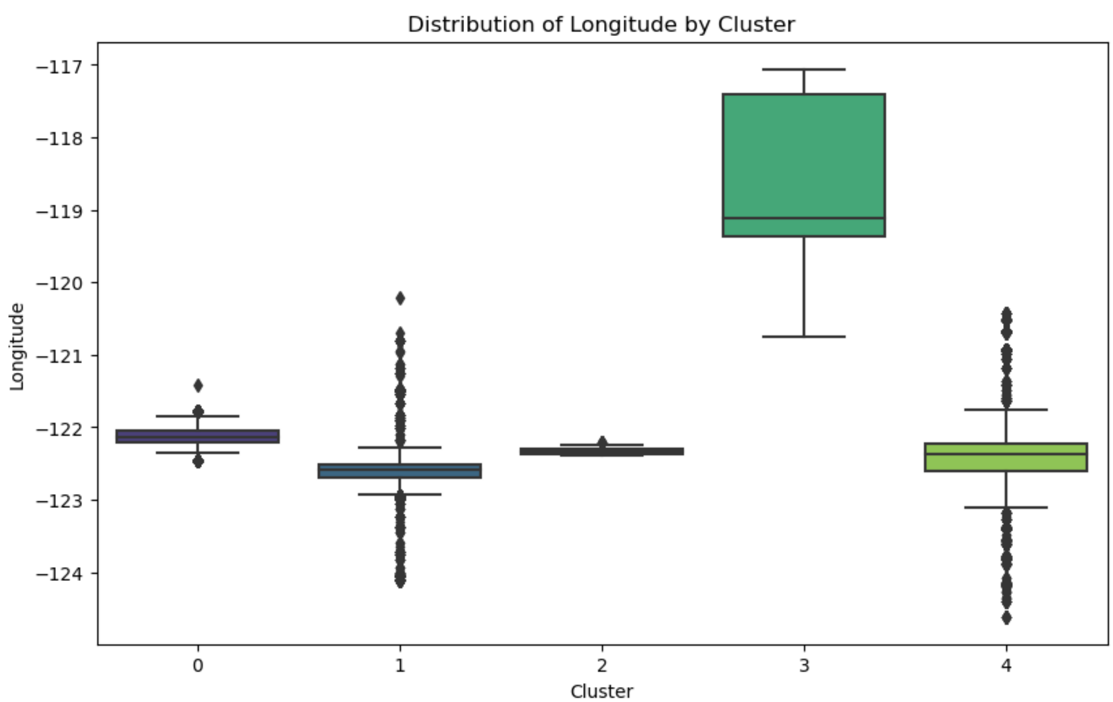
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='Cluster', y=feature, data=elec_dataset, palette='viridis')
plt.title(f'Distribution of {feature} by Cluster')
plt.xlabel('Cluster')
plt.ylabel(feature)
plt.show()
```

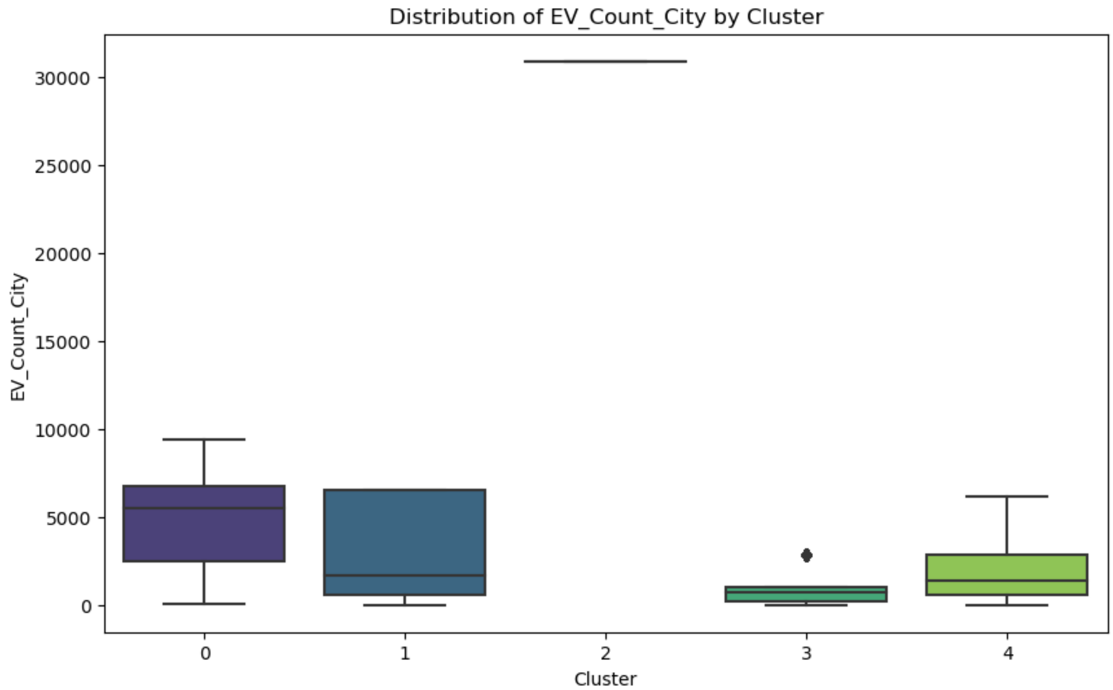


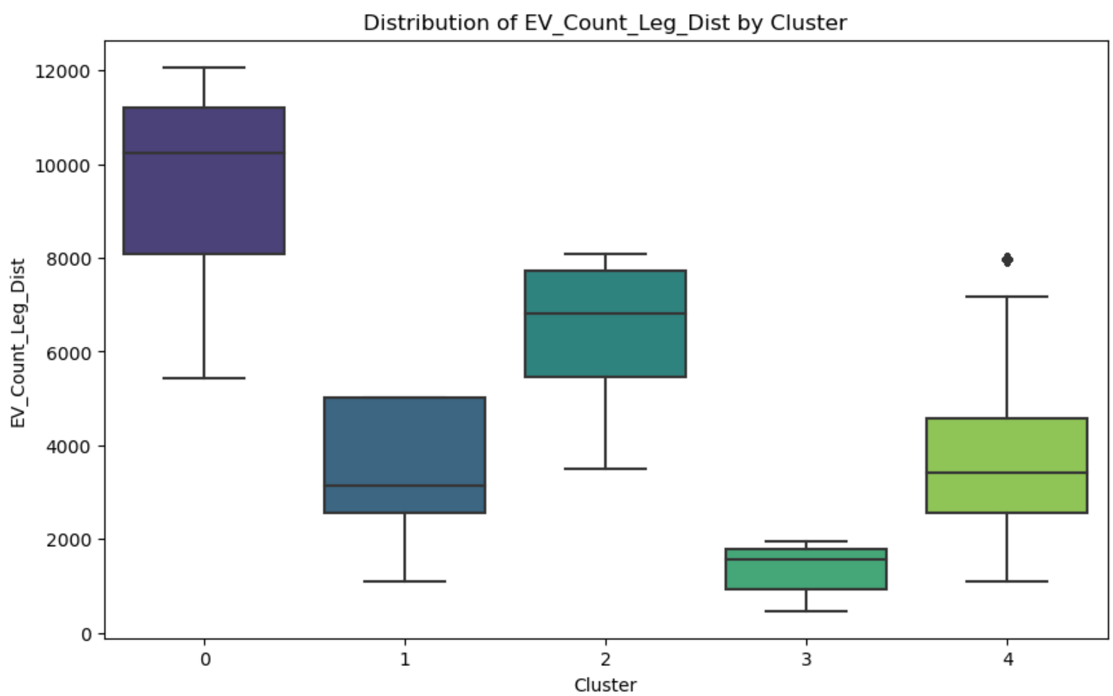


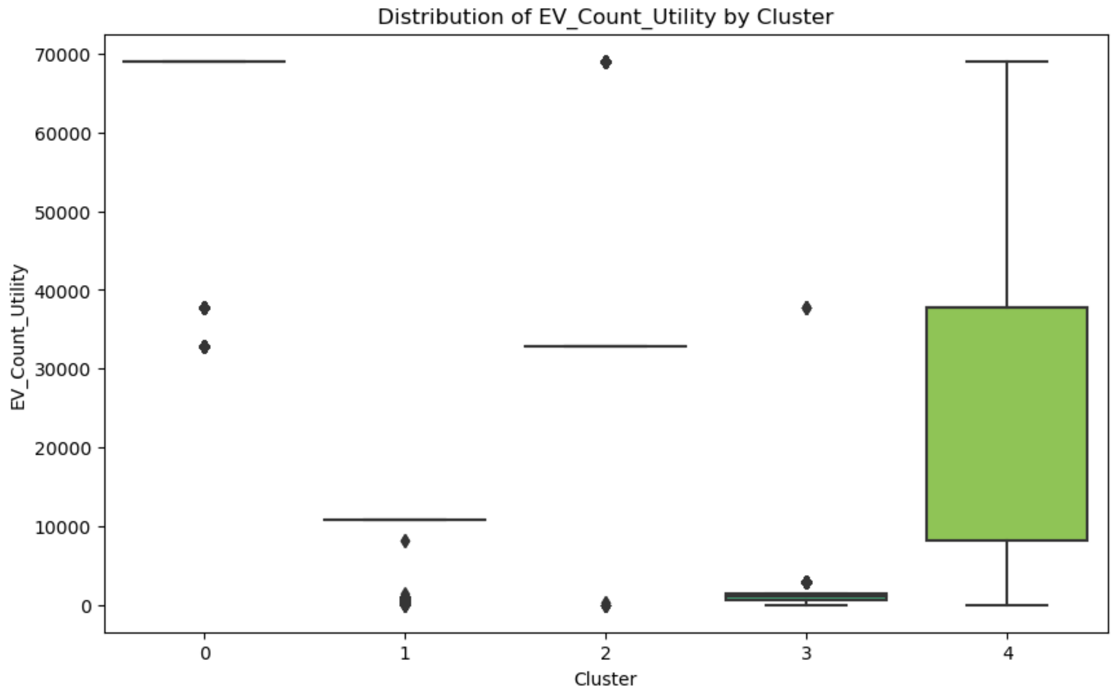

```
Cluster Profile:
          Latitude   Longitude  EV_Count_City  EV_Count_Leg_Dist  \
Cluster
0        47.615875 -122.141072    4979.372835        9779.180345
1        45.777218 -122.585314    3560.300492        3377.203905
2        47.629072 -122.334884   30873.000000        6681.763321
3        47.130835 -118.603416    1003.302457        1415.854934
4        47.640620 -122.430976    1773.126279        3440.823257

         EV_Count_Utility   Size
Cluster
0            65685.332358  59120
1             8722.646743  13418
2            34579.184044  30873
3             1403.859203  12415
4            34254.004969  70645
```


Distribution of Latitude by Cluster
Latitude
Cluster
49.0
48.5
48.0
47.5
47.0
46.5
46.0
45.5
0
1
2
3
4


Distribution of Longitude by Cluster
Longitude
Cluster
−117
−118
−119
−120
−121
−122
−123
−124
0
1
2
3
4


Distribution of EV_Count_City by Cluster
EV_Count_City
30000
25000
20000
15000
10000
5000
0
0
1
2
3
4
Cluster


Distribution of EV_Count_Leg_Dist by Cluster
EV_Count_Leg_Dist
12000
10000
8000
6000
4000
2000
0
0
1
2
3
4
Cluster



Interpretation of Step No. 5: K-means Clustering Analysis

Cluster Profile Table - **Cluster 0**: - **Latitude & Longitude**: Average latitude is around 47.62, and longitude is approximately -122.14, indicating this cluster is likely centered around urban or suburban areas in the western part of Washington State. - **EV_Count_City**: The mean number of EVs per city in this cluster is 4979.37, suggesting a high adoption rate in cities within this cluster. - **EV_Count_Leg_Dist**: The mean number of EVs per legislative district is 9779.18, indicating significant EV presence in legislative districts. - **EV_Count_Utility**: The mean number of EVs per electric utility is 65685.33, the highest among all clusters, signifying robust infrastructure support for EVs. - **Size**: This cluster comprises 59,120 observations, making it one of the larger clusters.

- **Cluster 1**:
  - **Latitude & Longitude**: Average latitude is around 45.78, and longitude is approximately -122.59, indicating this cluster is likely in more southern or less densely populated regions.
  - **EV_Count_City**: The mean number of EVs per city is 3560.30, lower than Cluster 0 but still significant.
  - **EV_Count_Leg_Dist**: The mean number of EVs per legislative district is 3377.20, indicating moderate adoption.
  - **EV_Count_Utility**: The mean number of EVs per utility is 8722.65, the lowest among all clusters, suggesting less developed infrastructure.
  - **Size**: This cluster has 13,418 observations.
- **Cluster 2**:
  - **Latitude & Longitude**: Average latitude is around 47.63, and longitude is approximately -122.33, indicating a high concentration around Seattle.

  - **EV_Count_City**: The mean number of EVs per city is the highest at 30,873, signifying a major urban center with a high adoption rate.
  - **EV_Count_Leg_Dist**: The mean number of EVs per legislative district is 6681.76, indicating significant EV presence.
  - **EV_Count_Utility**: The mean number of EVs per utility is 34579.18, reflecting strong infrastructure support.
  - **Size**: This cluster has 30,873 observations, aligning with a major metropolitan area.
- **Cluster 3**:
  - **Latitude & Longitude**: Average latitude is around 47.13, and longitude is approximately -118.60, indicating this cluster is likely in more rural or eastern regions.
  - **EV_Count_City**: The mean number of EVs per city is 1003.30, the lowest among all clusters, indicating sparse urban centers.
  - **EV_Count_Leg_Dist**: The mean number of EVs per legislative district is 1415.85, indicating lower adoption rates.
  - **EV_Count_Utility**: The mean number of EVs per utility is 1403.86, the lowest, suggesting minimal infrastructure.
  - **Size**: This cluster has 12,415 observations.
- **Cluster 4**:
  - **Latitude & Longitude**: Average latitude is around 47.64, and longitude is approximately -122.43, indicating urban or suburban areas, possibly overlapping with Seattle's outer regions.
  - **EV_Count_City**: The mean number of EVs per city is 1773.13, indicating moderate adoption.
  - **EV_Count_Leg_Dist**: The mean number of EVs per legislative district is 3440.82, indicating moderate EV presence.
  - **EV_Count_Utility**: The mean number of EVs per utility is 34254.00, indicating significant infrastructure support.
  - **Size**: This cluster is the largest with 70,645 observations.

Plots - K-means Clustering Scatter Plot: - The scatter plot shows the geographical distribution of EV adoption clusters across Washington State. - Clusters are color-coded, showing distinct regions with different adoption patterns. For example, Cluster 0 and Cluster 2 are concentrated in urban areas, whereas Cluster 3 covers more rural areas.

- **Cluster Centers Plot**:
  - This plot shows the geographic centers of each cluster, providing a visual summary of where the majority of EV adoption occurs within each cluster.
  - The plot highlights that Cluster 2 is centered around Seattle, indicating a high concentration of EV adoption in that metropolitan area.
- **Box Plots for Latitude and Longitude**:
  - These plots show the distribution of geographic coordinates within each cluster.
  - Cluster 3 has a broader latitude range, indicating it covers a more extensive vertical span, whereas Clusters 0 and 2 are tightly grouped around specific urban areas.
- **Box Plots for EV Counts**:
  - **EV_Count_City**: Shows a high concentration of EVs in Cluster 2, with other clusters having significantly lower counts.
  - **EV_Count_Leg_Dist**: Cluster 0 has the highest legislative district counts, followed by Cluster 2.
  - **EV_Count_Utility**: Cluster 0 again leads, showing strong infrastructure support in

urban areas.

Overall, the K-means clustering analysis reveals distinct geographic and infrastructural patterns in EV adoption across Washington State. Urban areas like Seattle have the highest adoption rates and infrastructure support, while rural areas show lower adoption. This information is crucial for targeted policy-making and infrastructure development to support EV growth.

STEP VI

Association Rules Analysis

Using Apriori Algorithm to Find Associations

```
[ ]: # Import the apriori function and association_rules function from the mlxtend.
      ↪frequent_patterns module
from mlxtend.frequent_patterns import apriori, association_rules

# One-hot encode the data by converting categorical variables into a series of␣
 ↪binary columns
elec_dataset_encoded = pd.get_dummies(elec_dataset[['County', 'City',␣
 ↪'Legislative_District', 'Electric_Utility', 'Latitude_bin',␣
 ↪'Longitude_bin']])

# Apply Apriori algorithm to encoded data
# 'min_support' meaning only itemsets that appear in at least 1% of the␣
 ↪transactions will be considered.
# The use_colnames=True parameter ensures that the output uses the original␣
 ↪column names instead of integer indices.
frequent_itemsets = apriori(elec_dataset_encoded, min_support=0.01,␣
 ↪use_colnames=True)

# Generates association rules from the frequent itemsets.
# The metric='confidence' parameter specifies that confidence should be used as␣
 ↪the metric for evaluating the rules
# min_threshold=0.5 sets the minimum confidence threshold to 50%
rules = association_rules(frequent_itemsets, metric='confidence',␣
 ↪min_threshold=0.5)

# Display the rules
print(rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']])
```

```
                                          antecedents  \
0                             (Legislative_District_8.0)
1                                       (County_Benton)
2                   (Longitude_bin_(-119.326, -118.57])
3                                       (County_Benton)
4                                        (County_Clark)
…                                                   …
7597  (City_Olympia, Longitude_bin_(-123.103, -122.3…
```

```
7598  (City_Olympia, Electric_Utility_PUGET SOUND EN…
7599                    (City_Olympia, County_Thurston)
7600                         (Legislative_District_22.0)
7601                                       (City_Olympia)

                                        consequents   support  confidence  \
0                                   (County_Benton)  0.010414    1.000000
1                       (Legislative_District_8.0)  0.010414    0.851008
2                                   (County_Benton)  0.010232    0.637701
3                 (Longitude_bin_(-119.326, -118.57])  0.010232    0.836109
4                                 (City_Vancouver)  0.035024    0.593458
…                                               …       …         …
7597  (Latitude_bin_(46.954, 47.294], Legislative_Di…  0.016281    0.674517
7598  (Latitude_bin_(46.954, 47.294], Longitude_bin_…  0.016281    0.678739
7599  (Latitude_bin_(46.954, 47.294], Longitude_bin_…  0.016281    0.674517
7600  (Latitude_bin_(46.954, 47.294], Longitude_bin_…  0.016281    0.657001
7601  (Latitude_bin_(46.954, 47.294], Legislative_Di…  0.016281    0.674517

           lift
0     81.713848
1     81.713848
2     52.108964
3     52.108964
4     16.944207
…           …
7597  27.289611
7598  27.389128
7599  27.289611
7600  27.389128
7601  27.289611

[7602 rows x 5 columns]
```

Interpretation of Step No. 6: Apriori Algorithm and Association Rules

The output of step no. 6 provides association rules derived from the Apriori algorithm, indicating relationships between various attributes related to electric vehicle (EV) adoption. The columns in the output indicate:

- **Antecedents**: The initial itemsets or conditions.
- **Consequents**: The resulting itemsets or conditions given the antecedents.
- **Support**: The proportion of records in the dataset where the antecedent and consequent co-occur.
- **Confidence**: The likelihood that the consequent appears given that the antecedent is present.
- **Lift**: The ratio of the observed support to that expected if the antecedent and consequent were independent.

Key Insights:

1. **High Confidence and Lift Values**:

- High confidence values (close to 1) indicate a strong likelihood that the consequent will occur when the antecedent is present.
- High lift values (greater than 1) indicate that the antecedent and consequent occur together more frequently than would be expected if they were independent.

2. **Examples of Strong Rules**:
   - **Rule**: `(Legislative_District_8.0) -> (County_Benton)`
     - **Support**: 0.010414 (approximately 1.04% of the data)
     - **Confidence**: 1.000000 (100%)
     - **Lift**: 81.713848
     - **Interpretation**: Legislative District 8.0 is entirely within Benton County, indicating a perfect correlation in the dataset.
   - **Rule**: `(County_Benton) -> (Legislative_District_8.0)`
     - **Support**: 0.010414
     - **Confidence**: 0.851008 (85.10%)
     - **Lift**: 81.713848
     - **Interpretation**: If an EV is in Benton County, there is an 85.10% chance it falls within Legislative District 8.0.
   - **Rule**: `(Longitude_bin_(-119.326, -118.57]) -> (County_Benton)`
     - **Support**: 0.010232 (approximately 1.02% of the data)
     - **Confidence**: 0.637701 (63.77%)
     - **Lift**: 52.108964
     - **Interpretation**: Longitude between -119.326 and -118.57 is strongly associated with Benton County.
3. **Moderate Confidence and Lift Values**:
   - **Rule**: `(County_Clark) -> (City_Vancouver)`
     - **Support**: 0.035024 (approximately 3.50% of the data)
     - **Confidence**: 0.593458 (59.35%)
     - **Lift**: 16.944207
     - **Interpretation**: If an EV is in Clark County, there is a 59.35% chance it is in Vancouver, suggesting a significant but not perfect association.
4. **Complex Rules**:
   - **Rule**: `(City_Olympia, Longitude_bin_(-123.103, -122.348]) -> (Latitude_bin_(46.954, 47.294], Legislative_District_22.0)`
     - **Support**: 0.016281 (approximately 1.63% of the data)
     - **Confidence**: 0.674517 (67.45%)
     - **Lift**: 27.289611
     - **Interpretation**: A complex rule involving multiple geographic bins and administrative regions, indicating significant associations between these conditions.

Overall Interpretation:

The Apriori algorithm has identified numerous strong and moderate associations between geographic and administrative features related to EV adoption. The high-confidence rules suggest robust relationships, such as those between certain legislative districts and counties, which can inform targeted infrastructure development and policy-making efforts to support EV adoption. The lift values reinforce the significance of these associations by showing how much more frequently the antecedents and consequents appear together than by chance.

STEP VII

ANOVA Analysis

Performing ANOVA to Compare Means Across Different Categories

[ ]:
```
import scipy.stats as stats
from statsmodels.formula.api import ols
import warnings

warnings.filterwarnings("ignore", category=DeprecationWarning)

# Perform ANOVA for EV_Count_County across Latitude bins
anova_latitude = stats.f_oneway(
    *[elec_dataset[elec_dataset['Latitude_bin'] == bin]['EV_Count_County'] for␣
 ↪bin in elec_dataset['Latitude_bin'].unique()]
)

# Perform ANOVA for EV_Count_County across Longitude bins
anova_longitude = stats.f_oneway(
    *[elec_dataset[elec_dataset['Longitude_bin'] == bin]['EV_Count_County'] for␣
 ↪bin in elec_dataset['Longitude_bin'].unique()]
)

print(f"ANOVA results for EV_Count_County by Latitude: F-statistic =␣
 ↪{anova_latitude.statistic}, p-value = {anova_latitude.pvalue}")
print(f"ANOVA results for EV_Count_County by Longitude: F-statistic =␣
 ↪{anova_longitude.statistic}, p-value = {anova_longitude.pvalue}", "\n")

# Perform ANOVA for EV_Count_City across Latitude bins
anova_latitude_city = stats.f_oneway(
    *[elec_dataset[elec_dataset['Latitude_bin'] == bin]['EV_Count_City'] for␣
 ↪bin in elec_dataset['Latitude_bin'].unique()]
)

# Perform ANOVA for EV_Count_City across Longitude bins
anova_longitude_city = stats.f_oneway(
    *[elec_dataset[elec_dataset['Longitude_bin'] == bin]['EV_Count_City'] for␣
 ↪bin in elec_dataset['Longitude_bin'].unique()]
)

print(f"ANOVA results for EV_Count_City by Latitude: F-statistic =␣
 ↪{anova_latitude_city.statistic}, p-value = {anova_latitude_city.pvalue}")
print(f"ANOVA results for EV_Count_City by Longitude: F-statistic =␣
 ↪{anova_longitude_city.statistic}, p-value = {anova_longitude_city.pvalue}",␣
 ↪"\n")

# Perform ANOVA for EV_Count_Leg_Dist across Latitude bins
anova_latitude_leg_dist = stats.f_oneway(
```

```
    *[elec_dataset[elec_dataset['Latitude_bin'] == bin]['EV_Count_Leg_Dist']␣
 ↪for bin in elec_dataset['Latitude_bin'].unique()]
)

# Perform ANOVA for EV_Count_Leg_Dist across Longitude bins
anova_longitude_leg_dist = stats.f_oneway(
    *[elec_dataset[elec_dataset['Longitude_bin'] == bin]['EV_Count_Leg_Dist']␣
 ↪for bin in elec_dataset['Longitude_bin'].unique()]
)

print(f"ANOVA results for EV_Count_Leg_Dist by Latitude: F-statistic =␣
 ↪{anova_latitude_leg_dist.statistic}, p-value = {anova_latitude_leg_dist.
 ↪pvalue}")
print(f"ANOVA results for EV_Count_Leg_Dist by Longitude: F-statistic =␣
 ↪{anova_longitude_leg_dist.statistic}, p-value = {anova_longitude_leg_dist.
 ↪pvalue}", "\n")
```

```
ANOVA results for EV_Count_County by Latitude: F-statistic = 23761.786899748782,
p-value = 0.0
ANOVA results for EV_Count_County by Longitude: F-statistic = 13002.97033649946,
p-value = 0.0

ANOVA results for EV_Count_City by Latitude: F-statistic = 3134.2766524607896,
p-value = 0.0
ANOVA results for EV_Count_City by Longitude: F-statistic = 831.8272649389794,
p-value = 0.0

ANOVA results for EV_Count_Leg_Dist by Latitude: F-statistic =
11715.169389491626, p-value = 0.0
ANOVA results for EV_Count_Leg_Dist by Longitude: F-statistic =
12734.484170086509, p-value = 0.0
```

[ ]:
```
# Ensure the 'Electric Utility' column is properly named for consistency
#elec_dataset = elec_dataset.rename(columns={'Electric Utility':␣
 ↪'Electric_Utility'})

# Ensure the 'Electric Utility' column is properly named for consistency
#elec_dataset = elec_dataset.rename(columns={'Legislative District':␣
 ↪'Legislative_District'})

# Perform ANOVA for overall impact of geographic and infrastructure categories
for y_var in ['EV_Count_County', 'EV_Count_City', 'EV_Count_Leg_Dist',␣
 ↪'EV_Count_Utility']:
    model = ols(f'{y_var} ~ C(County) + C(City) + C(Electric_Utility) +␣
 ↪C(Legislative_District)', data=elec_dataset).fit()
    anova_table = sm.stats.anova_lm(model, typ=2)
```

```python
    print(f"\nANOVA for {y_var}")
    print(anova_table)
```

```
c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 38, but rank is 3
  warnings.warn('covariance of constraints does not have full '
c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 472, but rank is 3
  warnings.warn('covariance of constraints does not have full '
c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 74, but rank is 3
  warnings.warn('covariance of constraints does not have full '


ANOVA for EV_Count_County
                               sum_sq        df             F  PR(>F)
C(County)                2.940991e-03      38.0  1.388634e-08     1.0
C(City)                  5.158485e-13     472.0  1.960911e-19     1.0
C(Electric_Utility)      1.281481e-13      74.0  3.107121e-19     1.0
C(Legislative_District)  1.761938e-15      48.0  6.586082e-21     1.0
Residual                 1.035916e+09  185867.0           NaN     NaN

c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 38, but rank is 3
  warnings.warn('covariance of constraints does not have full '
c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 472, but rank is 3
  warnings.warn('covariance of constraints does not have full '
c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 74, but rank is 3
  warnings.warn('covariance of constraints does not have full '


ANOVA for EV_Count_City
                               sum_sq        df             F  PR(>F)
C(County)                1.879767e-15      38.0  9.011080e-21     1.0
C(City)                  2.477441e-14     472.0  9.561316e-21     1.0
C(Electric_Utility)      3.738413e-15      74.0  9.202630e-21     1.0
C(Legislative_District)  8.030376e-17      48.0  3.047552e-22     1.0
Residual                 1.020342e+09  185867.0           NaN     NaN

c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 38, but rank is 3
```

```
  warnings.warn('covariance of constraints does not have full '
c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 472, but rank is 3
  warnings.warn('covariance of constraints does not have full '
c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 74, but rank is 3
  warnings.warn('covariance of constraints does not have full '


ANOVA for EV_Count_Leg_Dist
                              sum_sq        df             F  PR(>F)
C(County)               2.255426e-15      38.0  1.126472e-19     1.0
C(City)                 3.121290e-14     472.0  1.255069e-19     1.0
C(Electric_Utility)     4.560761e-15      74.0  1.169718e-19     1.0
C(Legislative_District) 1.382442e+11      48.0  5.466145e+06     0.0
Residual                9.793251e+07  185867.0           NaN     NaN
```

```
c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 38, but rank is 3
  warnings.warn('covariance of constraints does not have full '
c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 472, but rank is 3
  warnings.warn('covariance of constraints does not have full '
c:\Users\Owner\anaconda3\Lib\site-packages\statsmodels\base\model.py:1871:
ValueWarning: covariance of constraints does not have full rank. The number of
constraints is 74, but rank is 3
  warnings.warn('covariance of constraints does not have full '


ANOVA for EV_Count_Utility
                              sum_sq        df             F  PR(>F)
C(County)               5.769622e-14      38.0  7.049042e-20     1.0
C(City)                 5.632978e-13     472.0  5.540672e-20     1.0
C(Electric_Utility)     8.888415e-14      74.0  5.576465e-20     1.0
C(Legislative_District) 7.825726e-16      48.0  7.569197e-22     1.0
Residual                4.003464e+09  185867.0           NaN     NaN
```

The output from Step No. 7 can be interpreted in two parts: the ANOVA results for EV counts across latitude and longitude bins, and the ANOVA results for the overall impact of geographic and infrastructure categories.

ANOVA Results for EV Counts Across Latitude and Longitude Bins

1. **EV_Count_County by Latitude and Longitude:**
    - **Latitude:**
        - **F-statistic:** 23761.7869

  - **p-value:** 0.0
- **Longitude:**
  - **F-statistic:** 13002.9703
  - **p-value:** 0.0

Interpretation: The very low p-values (close to 0) indicate that there are statistically significant differences in the count of electric vehicles (EVs) per county based on latitude and longitude. This suggests that the geographic location (latitude and longitude) has a significant impact on the distribution of EVs across counties.

2. **EV_Count_City by Latitude and Longitude:**

- **Latitude:**
  - **F-statistic:** 3134.2767
  - **p-value:** 0.0
- **Longitude:**
  - **F-statistic:** 831.8273
  - **p-value:** 0.0

Interpretation: Similar to the county-level results, the significant p-values indicate that the count of EVs per city is significantly affected by geographic location. Both latitude and longitude significantly impact the distribution of EVs across cities.

3. **EV_Count_Leg_Dist by Latitude and Longitude:**

- **Latitude:**
  - **F-statistic:** 11715.1694
  - **p-value:** 0.0
- **Longitude:**
  - **F-statistic:** 12734.4842
  - **p-value:** 0.0

Interpretation: Again, the significant p-values suggest that the count of EVs per legislative district is significantly influenced by geographic location. Both latitude and longitude are important factors in the distribution of EVs across legislative districts.

ANOVA Results for Overall Impact of Geographic and Infrastructure Categories

1. **EV_Count_County:**
   - All predictors (County, City, Electric Utility, Legislative District) have very small F-statistics and p-values of 1.0, indicating they are not statistically significant in explaining the variation in EV count per county.
2. **EV_Count_City:**
   - Similarly, all predictors (County, City, Electric Utility, Legislative District) have very small F-statistics and p-values of 1.0, indicating they are not statistically significant in explaining the variation in EV count per city.
3. **EV_Count_Leg_Dist:**
   - County, City, and Electric Utility are not statistically significant predictors with p-values of 1.0.
   - Legislative District has a very high F-statistic (5,466,145) and a p-value of 0.0, indicating it is a statistically significant predictor of EV count per legislative district.
4. **EV_Count_Utility:**

- All predictors (County, City, Electric Utility, Legislative District) have very small F-statistics and p-values of 1.0, indicating they are not statistically significant in explaining the variation in EV count per utility.

Overall Interpretation

1. **Geographic Influence:**
   - The significant ANOVA results for latitude and longitude bins indicate that geographic location (both latitude and longitude) is a significant factor in the distribution of EVs across counties, cities, and legislative districts.
2. **Geographic and Infrastructure Categories:**
   - For county and city-level EV counts, none of the geographic and infrastructure categories (County, City, Electric Utility, Legislative District) were significant predictors.
   - For legislative district EV counts, the legislative district itself is a significant predictor, suggesting that local policies or other district-specific factors might play an important role in EV adoption.
   - For utility-level EV counts, none of the geographic and infrastructure categories were significant predictors.

These results highlight the importance of geographic location in the distribution of EVs and suggest that certain local administrative areas, particularly legislative districts, may have unique factors influencing EV adoption. The lack of significance for other predictors in the overall ANOVA suggests that more granular or additional factors might be needed to fully explain EV distribution patterns at the county and city levels.