Exploring Electric Vehicle Adoption Trends in Washington State

Literature Review

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Github Repository: https://github.com/acherungotTMU/TMU_Capstone

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Introduction

The rise in electric vehicle (EV) adoption is a key component in the transition to sustainable transportation. This literature review aims to provide a comprehensive analysis of the factors influencing EV adoption in Washington State, focusing on geographic and infrastructure related factors, and to evaluate the use of machine learning models in predicting future EV adoption trends.

1. **What is already known about the topic?**

   Electric vehicle adoption is influenced by a variety of factors, including environmental concerns, government policies, financial incentives, and advancements in EV technology. Socio-economic factors such as income, education, and occupation also play significant roles. Apart from these factors, geographic location and infrastructure such as electric utility provider also plays an important role in deciding the adoption rates of electric vehicles.

2. **Critical analysis of what is already known?**

   Existing studies have established that financial incentives and government policies significantly impact EV adoption. However, there is a gap in understanding the combined effect of geographic and infrastructure related factors, particularly in Washington State. Moreover, the application of machine learning models for predicting EV adoption trends based on these factors is relatively underexplored.

3. **Has Anyone Else Ever Done Anything Exactly the Same?**

   No studies have been found that exactly replicate the current research focus on Washington State using the same dataset and machine learning approaches. However, similar studies have been conducted in other regions, focusing on different aspects of EV adoption.

4. **Has Anyone Else Done Anything That is Related?**

   Yes, related studies include:

   1. https://www.sciencedirect.com/science/article/abs/pii/S0301421512005162 - Egbue, O., & Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions

  - Summary: This paper compares the performance of Random Forest and SVM classifiers in the context of regional land cover mapping using satellite imagery. The study highlights the strengths and weaknesses of each method in terms of accuracy, precision, and computational efficiency.

  - Relevance: The comparison of Random Forest and SVM in this paper provides valuable insights into the strengths and weaknesses of these two machine learning techniques. This knowledge is crucial for the project as it helps in selecting the most appropriate model for predicting the likelihood of choosing BEVs or PHEVs and understanding the trade-offs involved.

2. https://link.springer.com/article/10.1007/BF00994018 - Cortes, C., & Vapnik, V. (1995). Support-vector networks.

  - Summary: This seminal paper introduces the Support Vector Machine (SVM) algorithm, a powerful tool for classification tasks. The SVM algorithm aims to find the optimal hyperplane that separates data points of different classes with the maximum margin.

  - Relevance: SVM is one of the machine learning techniques proposed for classifying the likelihood of choosing BEVs or PHEVs. Understanding the theoretical foundation and practical applications of SVM helps in effectively implementing and interpreting the results of this classification method in the project.

3. https://www.researchgate.net/publication/358119990_Comparison_of_Random_Forest_and_Support_Vector_Machine_Classifiers_for_Regional_Land_Cover_Mapping_Using_Coarse_Resolution_FY-3C_Images - Xu, W., Adugna, T., & Fan, J. (2022). Comparison of Random Forest and Support Vector Machine Classifiers for Regional Land Cover Mapping Using Coarse Resolution FY-3C Images

  - Summary: This paper compares the performance of Random Forest and SVM classifiers in the context of regional land cover mapping using satellite imagery. The study highlights the strengths and weaknesses of each method in terms of accuracy, precision, and computational efficiency.

  - Relevance: The comparison of Random Forest and SVM in this paper provides valuable insights into the strengths and weaknesses of these two machine learning techniques. This knowledge is crucial for the project as it helps in selecting the most appropriate model for predicting the likelihood of choosing BEVs or PHEVs and understanding the trade-offs involved.

4. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0176729 - Zhang, Y., Zhong, M., Geng, N., & Jiang, Y. (2017). Forecasting electric vehicles sales with univariate and multivariate time series models: The case of China

    - Summary: This study uses univariate and multivariate time series models to forecast electric vehicle sales in China. The authors compare different time series models to identify the best approach for accurate prediction.

    - Relevance: This paper is relevant as it provides methodologies for forecasting EV adoption using time series models. Although focused on China, the techniques can be adapted for predicting future EV adoption trends in Washington State.

5. https://www.sciencedirect.com/science/article/pii/S0965856416302208 - Hardman, S., Shiu, E., & Steinberger-Wilckens, R. (2016). Comparing high-end and low-end early adopters of battery electric vehicles. Transportation Research Part A: Policy and Practice, 88, 40-57

    - Summary: This paper examines the characteristics of high-end and low-end early adopters of battery electric vehicles (BEVs). The study analyzes factors influencing adoption and provides insights into the demographics and preferences of different adopter groups.

    - Relevance: Understanding the characteristics of early adopters can inform the feature engineering process in the project. The methodologies used in this study for analyzing adoption patterns can be applied to predict future EV adoption trends in Washington State.

6. https://www.mdpi.com/2073-4441/15/22/3940 - Ehteram, M., & Banadkooki, F. B. (2023). A Developed Multiple Linear Regression (MLR) Model for Monthly Groundwater Level Prediction. Water

    - Summary: This paper presents a multiple linear regression (MLR) model developed to predict monthly groundwater levels. The study demonstrates how MLR can be effectively used for predictive modeling in environmental science by evaluating various factors influencing groundwater levels.

    - Relevance: This paper is relevant because it provides an example of using multiple linear regression for predictive modeling, which is one of the techniques proposed for predicting future EV adoption trends in

Washington State. The methodologies used in this study can be adapted to analyze the relationship between demographic, socio-economic factors, and EV adoption rates.

7. https://www.atlantis-press.com/proceedings/iserss-19/125911091 - Xiaodong Wu, Yuzhu Zeng and Xiaodong Wu (2019). Using Apriori Algorithm on Students' Performance Data for Association Rules Mining

    - Summary: This paper applies the Apriori algorithm to mine association rules from students' performance data. The study demonstrates how association rule mining can uncover hidden patterns and relationships in data.

    - Relevance: The Apriori algorithm can be used to identify associations between geographic location, electric utilities, and EV adoption patterns. This approach helps understand the impact of local infrastructure on EV adoption.

5. <u>Where Does my Work Fit in With What Has Gone Before?</u>

This research builds on existing studies by focusing specifically on Washington State and using a comprehensive dataset from the Department of Licensing. The application of machine learning models to predict EV adoption based on demographic and socio-economic factors is a novel contribution.

6. <u>Why is this Research Worth Doing in the Light of What Has Already Been Done?</u>

Understanding the factors driving EV adoption in Washington State can help policymakers and businesses develop targeted strategies to promote EV adoption. Predictive models can provide valuable insights into future trends, aiding in infrastructure planning and policy formulation. The analysis will be grouped based on city, county and legislative districts as these variables will be necessary to give an insight to the respective policy makers of the state.

Based on my research, policy makers can have an insight on the growth rate of electric vehicles. From these insights, they can make important decisions related to changes in electric vehicle registration policy, number of new charging stations to be installed, design new plans and policies to boost electric vehicle use in respective location and what changes electric utility companies can make in the future based on the growth rate of electric vehicles.

Descriptive Statistics and Exploratory Data Analysis (EDA)

The dataset includes over 181,000 observations with variables such as VIN, County, City, State, Postal Code, Model Year, Make, Model, Electric Vehicle Type, CAFV Eligibility, Electric Range, Base MSRP, Legislative District, DOL Vehicle ID, Vehicle Location, Electric Utility, and 2020 Census Tract.

Description of Variables:

- VIN (1-10): The first ten characters of the Vehicle Identification Number, which uniquely identifies each vehicle.
- County: This is the geographic region of a state that a vehicle's owner is listed to reside within. Vehicles registered in Washington state may be located in other states.
- City: The city in which the registered owner resides.
- State: This is the geographic region of the country associated with the record. These addresses may be located in other states.
- Postal Code: The 5-digit zip code in which the registered owner resides.
- Model Year: The model year of the vehicle, determined by decoding the Vehicle Identification Number (VIN).
- Make: The manufacturer of the vehicle, determined by decoding the Vehicle Identification Number (VIN).
- Model: The model of the vehicle, determined by decoding the Vehicle Identification Number (VIN).
- Electric Vehicle Type: Indicates whether the vehicle is a Battery Electric Vehicle (BEV) or a Plug-in Hybrid Electric Vehicle (PHEV), distinguishing between different types of electric vehicles.
- Clean Alternative Fuel Vehicle (CAFV) Eligibility: This categorizes vehicle as Clean Alternative Fuel Vehicles (CAFVs) based on the fuel requirement and electric-only range requirement in House Bill 2042 as passed in the 2019 legislative session.
- Electric Range: Describes how far a vehicle can travel purely on its electric charge.

- Base MSRP: This is the lowest Manufacturer's Suggested Retail Price (MSRP) for any trim level of the model in question.

- Legislative District: The specific section of Washington State that the vehicle's owner resides in, as represented in the state legislature.

- DOL Vehicle ID: An identification number assigned by the Washington State Department of Licensing, serving as a unique identifier within the licensing system.

- Vehicle Location: The center of the ZIP Code for the registered vehicle.

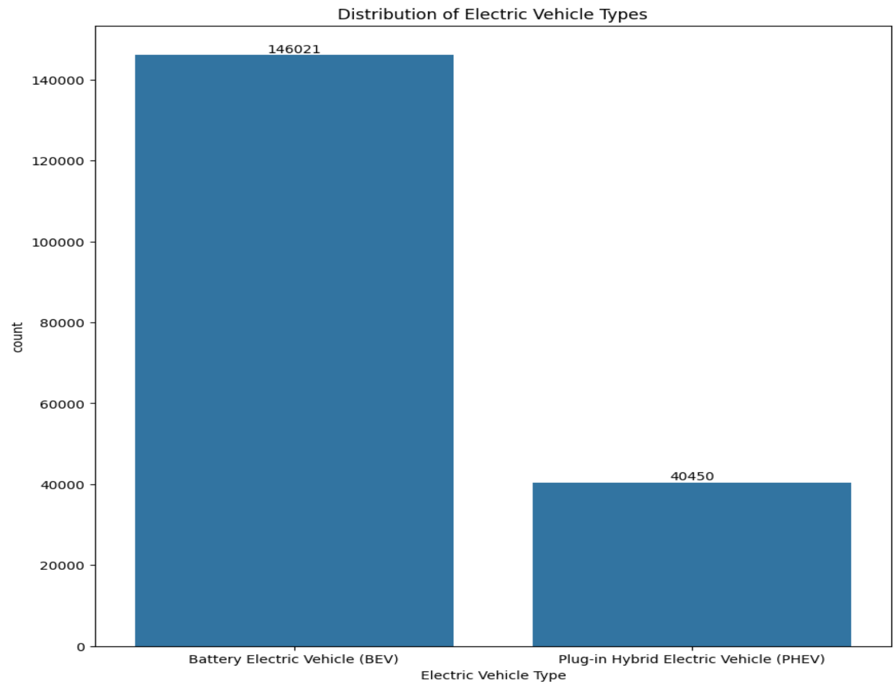
- Electric Utility: This is the electric power retail service territories serving the address of the registered vehicle. All ownership types for areas in Washington are included: federal, investor owned, municipal, political subdivision, and cooperative. If the address for the registered vehicle falls into an area with overlapping electric power retail service territories, then a single pipe | delimits utilities of same TYPE and a double pipe || delimits utilities of different types.
- 2020 Census Tract: The census tract identifier is a combination of the state, county, and census tract codes as assigned by the United States Census Bureau in the 2020 census, also known as Geographic Identifier (GEOID).

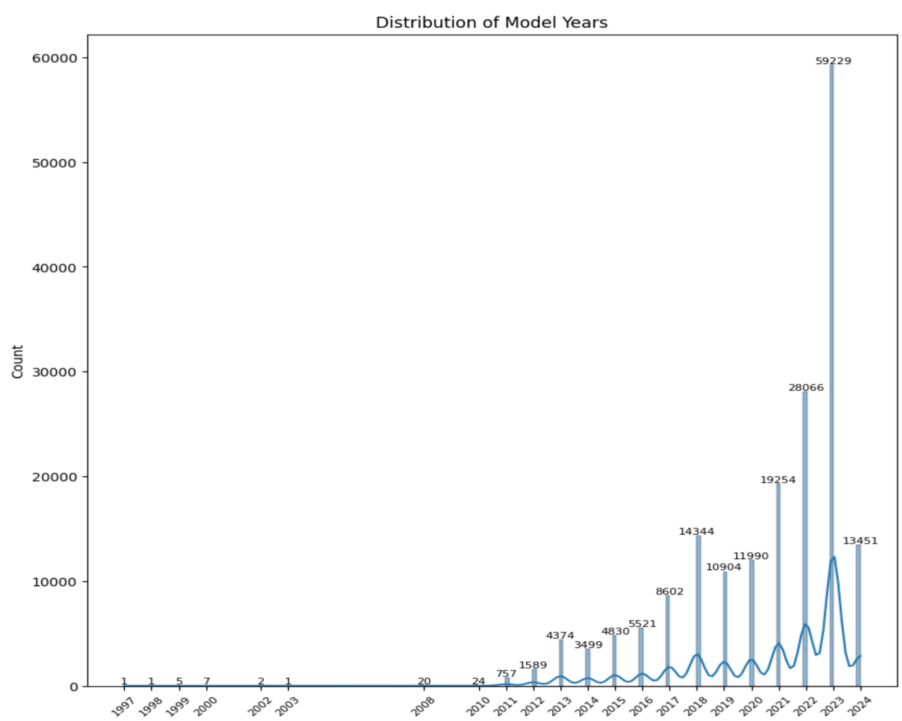
Univariate Analysis and Bivariate Analysis:

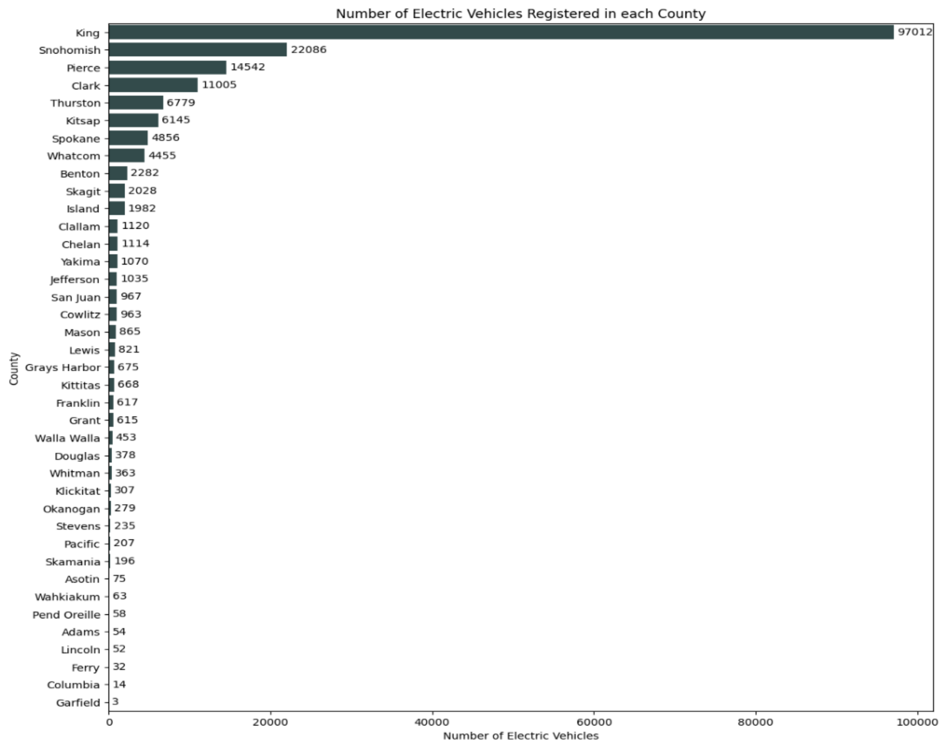
A descriptive statistic including data types of each variable, missing values, correlations and data distribution is done using the y-data profiling library in python. The output, in HTML format is uploaded in GitHub repository.

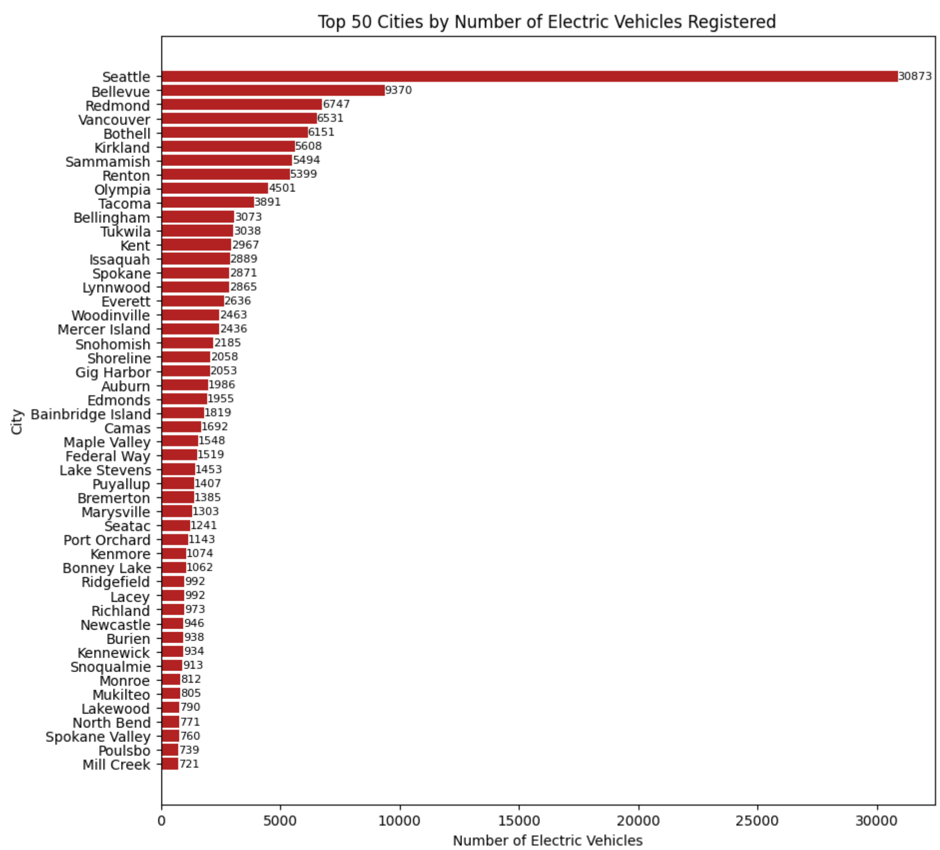
To draw a better picture, visualization tools of python have been used to depict the univariate and bivariate analysis of electric vehicle population data and the same are mentioned below. This will help in understanding the variable fluctuations and relationships:

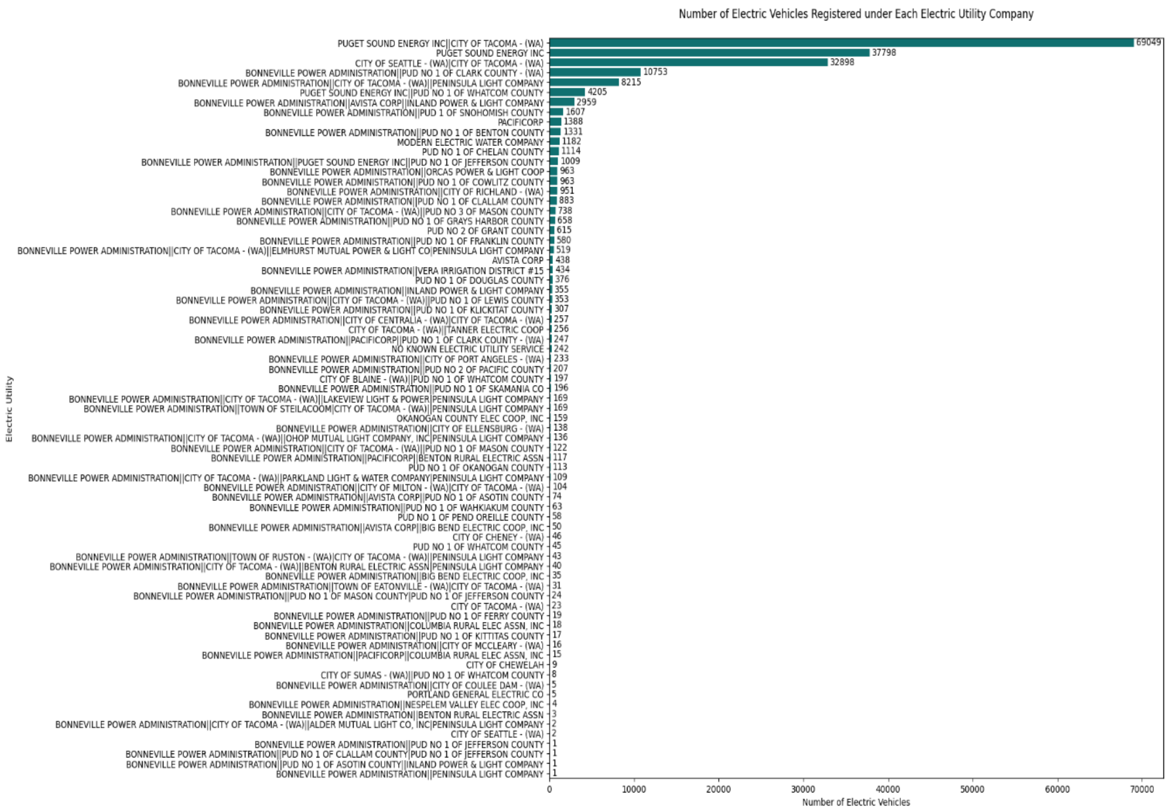
Univariate Analysis:

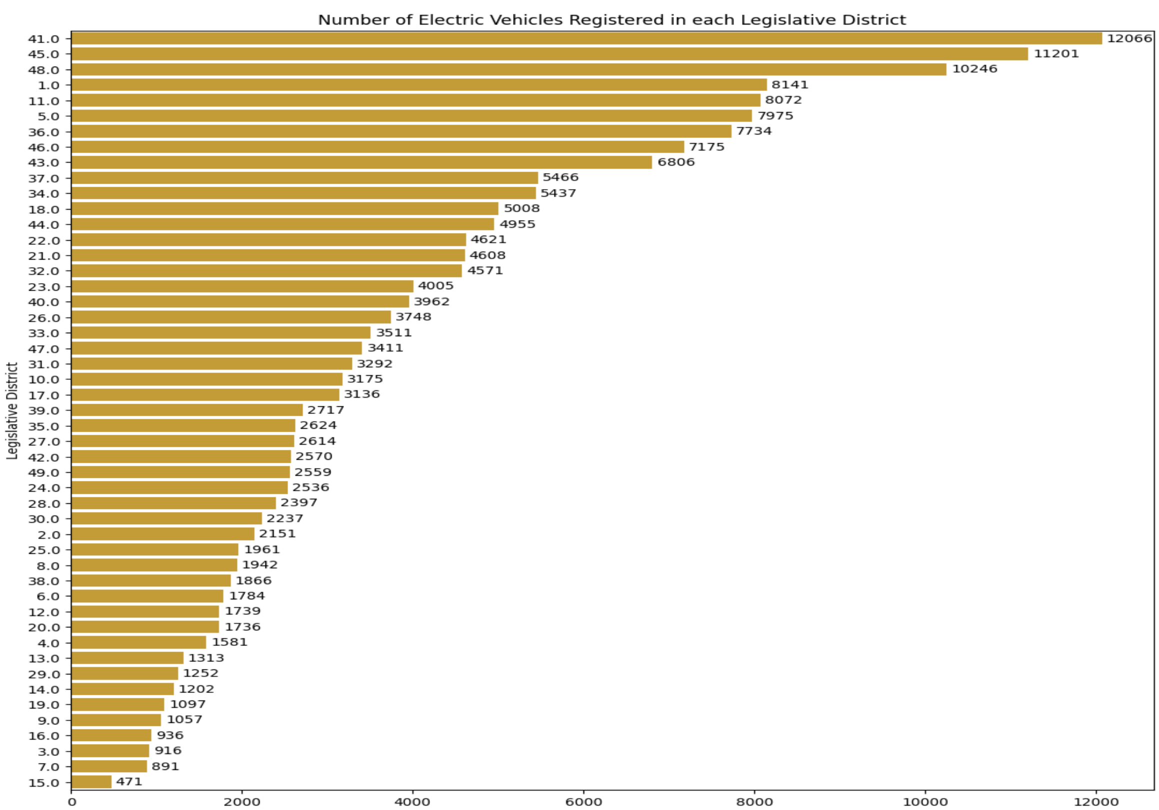




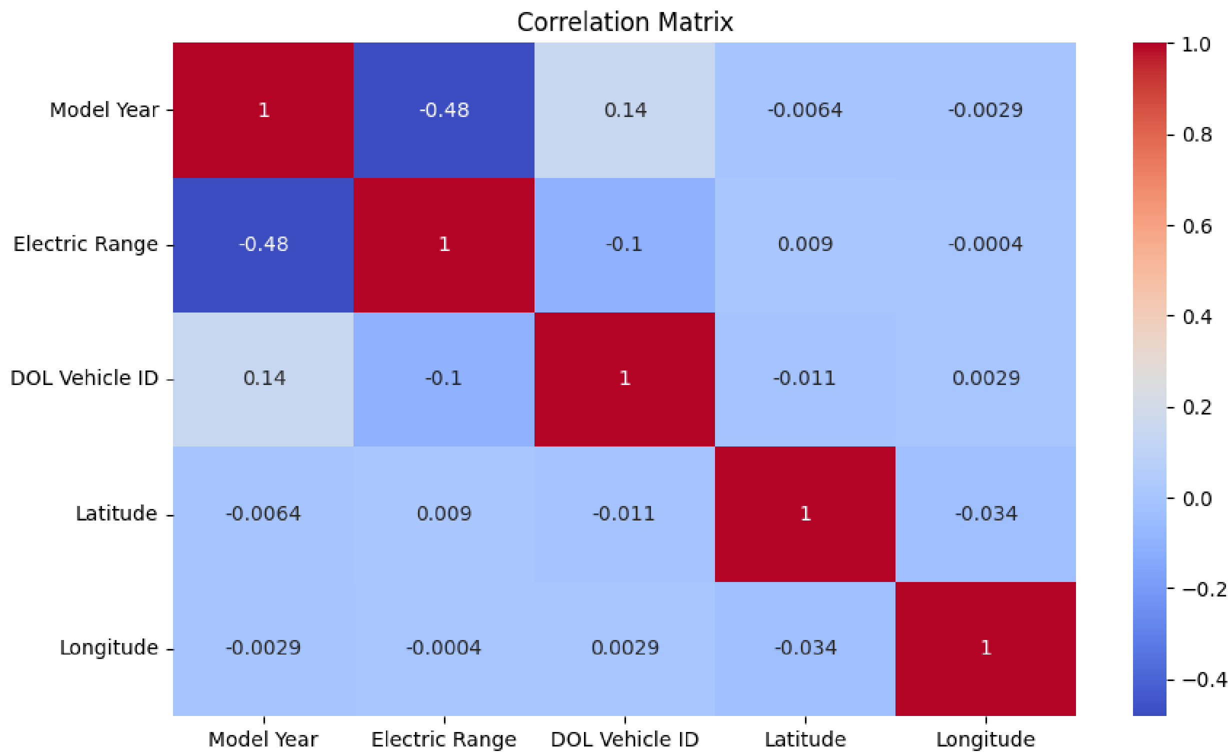

Number of Electric Vehicles Registered in each County
King 97012
Snohomish 22086
Pierce 14542
Clark 11005
Thurston 6779
Kitsap 6145
Spokane 4856
Whatcom 4455
Benton 2282
Skagit 2028
Island 1982
Clallam 1120
Chelan 1114
Yakima 1070
Jefferson 1035
San Juan 967
Cowlitz 963
Mason 865
Lewis 821
Grays Harbor 675
Kittitas 668
Franklin 617
Grant 615
Walla Walla 453
Douglas 378
Whitman 363
Klickitat 307
Okanogan 279
Stevens 235
Pacific 207
Skamania 196
Asotin 75
Wahkiakum 63
Pend Oreille 58
Adams 54
Lincoln 52
Ferry 32
Columbia 14
Garfield 3
County
0
20000
40000
60000
80000
100000
Number of Electric Vehicles


Top 50 Cities by Number of Electric Vehicles Registered
Seattle 30873
Bellevue 9370
Redmond 6747
Vancouver 6531
Bothell 6151
Kirkland 5608
Sammamish 5494
Renton 5399
Olympia 4501
Tacoma 3891
Bellingham 3073
Tukwila 3038
Kent 2967
Issaquah 2889
Spokane 2871
Lynnwood 2865
Everett 2636
Woodinville 2463
Mercer Island 2436
Snohomish 2185
Shoreline 2058
Gig Harbor 2053
Auburn 1986
Edmonds 1955
Bainbridge Island 1819
Camas 1692
Maple Valley 1548
Federal Way 1519
Lake Stevens 1453
Puyallup 1407
Bremerton 1385
Marysville 1303
Seatac 1241
Port Orchard 1143
Kenmore 1074
Bonney Lake 1062
Ridgefield 992
Lacey 992
Richland 973
Newcastle 946
Burien 938
Kennewick 934
Snoqualmie 913
Monroe 812
Mukilteo 805
Lakewood 790
North Bend 771
Spokane Valley 760
Poulsbo 739
Mill Creek 721
City
0
5000
10000
15000
20000
25000
30000
Number of Electric Vehicles


Number of Electric Vehicles Registered under Each Electric Utility Company
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA) 69049
PUGET SOUND ENERGY INC 37798
CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA) 32898
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLARK COUNTY - (WA) 10753
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PENINSULA LIGHT COMPANY 8215
PUGET SOUND ENERGY INC||PUD NO 1 OF WHATCOM COUNTY 4205
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||INLAND POWER & LIGHT COMPANY 2959
BONNEVILLE POWER ADMINISTRATION||PUD 1 OF SNOHOMISH COUNTY 1607
PACIFICORP 1388
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF BENTON COUNTY 1331
MODERN ELECTRIC WATER COMPANY 1182
PUD NO 1 OF CHELAN COUNTY 1114
BONNEVILLE POWER ADMINISTRATION||PUGET SOUND ENERGY INC||PUD NO 1 OF JEFFERSON COUNTY 1009
BONNEVILLE POWER ADMINISTRATION||ORCAS POWER & LIGHT COOP 963
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF COWLITZ COUNTY 963
BONNEVILLE POWER ADMINISTRATION||CITY OF RICHLAND - (WA) 951
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLALLAM COUNTY 883
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO 3 OF MASON COUNTY 738
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF GRAYS HARBOR COUNTY 658
PUD NO 2 OF GRANT COUNTY 615
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF FRANKLIN COUNTY 580
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||ELMHURST MUTUAL POWER & LIGHT CO|PENINSULA LIGHT COMPANY 519
AVISTA CORP 438
BONNEVILLE POWER ADMINISTRATION||VERA IRRIGATION DISTRICT #15 434
PUD NO 1 OF DOUGLAS COUNTY 376
BONNEVILLE POWER ADMINISTRATION||INLAND POWER & LIGHT COMPANY 355
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO 1 OF LEWIS COUNTY 353
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF KLICKITAT COUNTY 307
BONNEVILLE POWER ADMINISTRATION||CITY OF CENTRALIA - (WA)|CITY OF TACOMA - (WA) 257
CITY OF TACOMA - (WA)||TANNER ELECTRIC COOP 256
BONNEVILLE POWER ADMINISTRATION||PACIFICORP||PUD NO 1 OF CLARK COUNTY - (WA) 247
NO KNOWN ELECTRIC UTILITY SERVICE 242
BONNEVILLE POWER ADMINISTRATION||CITY OF PORT ANGELES - (WA) 233
BONNEVILLE POWER ADMINISTRATION||PUD NO 2 OF PACIFIC COUNTY 207
CITY OF BLAINE - (WA)||PUD NO 1 OF WHATCOM COUNTY 197
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF SKAMANIA CO 196
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||LAKEVIEW LIGHT & POWER|PENINSULA LIGHT COMPANY 169
BONNEVILLE POWER ADMINISTRATION||TOWN OF STEILACOOM|CITY OF TACOMA - (WA)||PENINSULA LIGHT COMPANY 169
OKANOGAN COUNTY ELEC COOP, INC 159
BONNEVILLE POWER ADMINISTRATION||CITY OF ELLENSBURG - (WA) 138
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||OHOP MUTUAL LIGHT COMPANY, INC|PENINSULA LIGHT COMPANY 136
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PUD NO 1 OF MASON COUNTY 122
BONNEVILLE POWER ADMINISTRATION||PACIFICORP||BENTON RURAL ELECTRIC ASSN 117
PUD NO 1 OF OKANOGAN COUNTY 113
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PARKLAND LIGHT & WATER COMPANY|PENINSULA LIGHT COMPANY 109
BONNEVILLE POWER ADMINISTRATION||CITY OF MILTON - (WA)|CITY OF TACOMA - (WA) 104
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||PUD NO 1 OF ASOTIN COUNTY 74
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF WAHKIAKUM COUNTY 63
PUD NO 1 OF PEND OREILLE COUNTY 58
BONNEVILLE POWER ADMINISTRATION||AVISTA CORP||BIG BEND ELECTRIC COOP, INC 50
CITY OF CHENEY - (WA) 46
PUD NO 1 OF WHATCOM COUNTY 45
BONNEVILLE POWER ADMINISTRATION||TOWN OF RUSTON - (WA)|CITY OF TACOMA - (WA)||PENINSULA LIGHT COMPANY 43
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||BENTON RURAL ELECTRIC ASSN|PENINSULA LIGHT COMPANY 40
BONNEVILLE POWER ADMINISTRATION||BIG BEND ELECTRIC COOP, INC 35
BONNEVILLE POWER ADMINISTRATION||TOWN OF EATONVILLE - (WA)|CITY OF TACOMA - (WA) 31
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF MASON COUNTY|PUD NO 1 OF JEFFERSON COUNTY 24
CITY OF TACOMA - (WA) 23
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF FERRY COUNTY 19
BONNEVILLE POWER ADMINISTRATION||COLUMBIA RURAL ELEC ASSN, INC 18
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF KITTITAS COUNTY 17
BONNEVILLE POWER ADMINISTRATION||CITY OF MCCLEARY - (WA) 16
BONNEVILLE POWER ADMINISTRATION||PACIFICORP||COLUMBIA RURAL ELEC ASSN, INC 15
CITY OF CHEWELAH 9
CITY OF SUMAS - (WA)||PUD NO 1 OF WHATCOM COUNTY 8
BONNEVILLE POWER ADMINISTRATION||CITY OF COULEE DAM - (WA) 5
PORTLAND GENERAL ELECTRIC CO 5
BONNEVILLE POWER ADMINISTRATION||NESPELEM VALLEY ELEC COOP, INC 4
BONNEVILLE POWER ADMINISTRATION||BENTON RURAL ELECTRIC ASSN 3
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||ALDER MUTUAL LIGHT CO, INC|PENINSULA LIGHT COMPANY 2
CITY OF SEATTLE - (WA) 2
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF JEFFERSON COUNTY 1
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLALLAM COUNTY|PUD NO 1 OF JEFFERSON COUNTY 1
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF ASOTIN COUNTY||INLAND POWER & LIGHT COMPANY 1
BONNEVILLE POWER ADMINISTRATION||PENINSULA LIGHT COMPANY 1
Electric Utility
0
10000
20000
30000
40000
50000
60000
70000
Number of Electric Vehicles


Number of Electric Vehicles Registered in each Legislative District
41.0 12066
45.0 11201
48.0 10246
1.0 8141
11.0 8072
5.0 7975
36.0 7734
46.0 7175
43.0 6806
37.0 5466
34.0 5437
18.0 5008
44.0 4955
22.0 4621
21.0 4608
32.0 4571
23.0 4005
40.0 3962
26.0 3748
33.0 3511
47.0 3411
31.0 3292
10.0 3175
17.0 3136
39.0 2717
35.0 2624
27.0 2614
42.0 2570
49.0 2559
24.0 2536
28.0 2397
30.0 2237
2.0 2151
25.0 1961
8.0 1942
38.0 1866
6.0 1784
12.0 1739
20.0 1736
4.0 1581
13.0 1313
29.0 1252
14.0 1202
19.0 1097
9.0 1057
16.0 936
3.0 916
7.0 891
15.0 471
Legislative District
0
2000
4000
6000
8000
10000
12000
Number of Electric Vehicles

Bivariate Analysis:



Approach

The approach adopted for the three research questions are as follows:

Cleaning of Data:

1. After carefully summarising the data, 398 observations having the registration details of states other than Washington were removed.'
2. The vehicle location variable having geographical coordinates of the registered vehicle location, has been cleaned and split into two named Latitude and Longitude.

3. As Postal Code, Legislative District and 2020 Census Tract are categorical variables, they have been converted to string data type.
4. Base MSRP variable was removed as 98% of its data have the value 0.
5. No duplicate values were found in the data.

Research Question	**Definition**	**Approach**
1.What makes people in Washington State decide to buy BEVs and PHEVs?	This question aims to identify the factors that influence the decision to purchase Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) in Washington State.	**Feature Selection:** Use features like County, City, Electric Vehicle Type, Electric Range, Legislative District and Electric Utility Company **Machine Learning:** Use Logistic Regression, Random Forest Classifier and Support Vector Machine (SVM) to classify the likelihood of choosing BEVs and PHEVs **Testing:** Split the data into 80% training and 20% testing sets **Variables:** Dependent Variable – Electric Vehicle Type (BEV or PHEV) Independent Variable- County, City, Electric Range, Legislative District and Electric Utility company **Hypothesis Testing:** Perform Logistic Regression coefficients analysis to determine the significance of independent variables **Comparison:** Compare model performance using accuracy,

		precision, recall and F1-score and identify the best performing models based on these metrics. **References:** Egbue, O., & Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy, 48,* 717-729. Wenbo Xu, & Tesfaye Adugna. (2022). Comparison of Random Forest and Support Vector Machine Classifiers for Regional Land Cover Mapping Using Coarse Resolution FY-3C Images Cortes, C., & Vapnik, V. (1995). Support-vector networks.
2. Can we use machine learning to predict how many more people will start using electric cars in the future, based on	This question explores the feasibility of using machine learning models to forecast the adoption of	**Feature Engineering:** Create features like the number of EVs registered per year, average Electric Range per year, etc. **Variables:** Dependent: Number of EVs registered (Future EV Adoption) Independent: County, City, Electric Vehicle Type, Electric

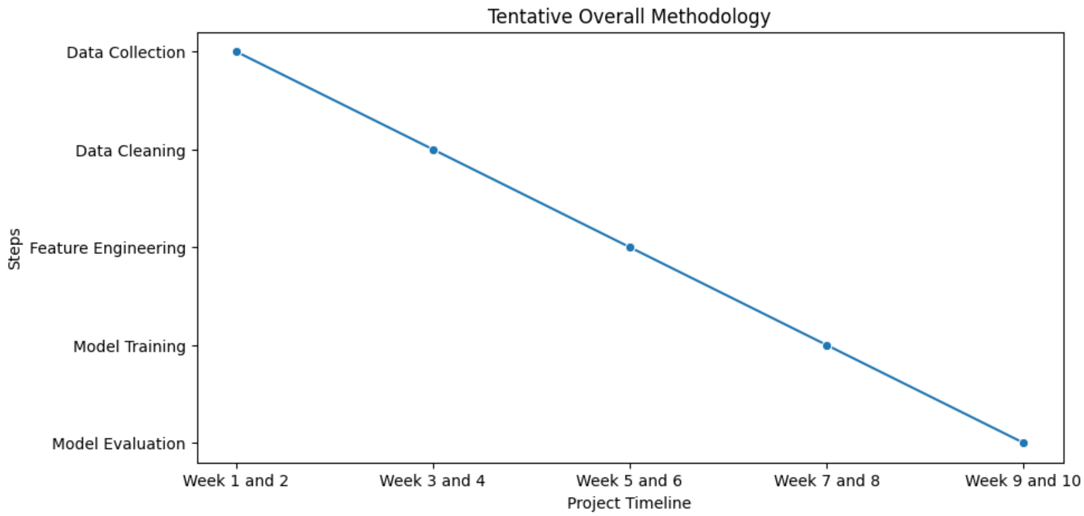
things like where they live and how much money they make?	electric vehicles based on geographic and infrastructure related data.	Range, Model Year, Electric Utility Company, Legislative District **Machine Learning:** Linear Regression for trend analysis. Random forest for Prediction **Training and Testing:** Split the dataset into training (80%) and testing (20%) **Hypothesis Testing:** Perform t-tests to compare means of continuous variables (e.g., Electric Range) between different groups (e.g., Electric Vehicle Type). **Model Evaluation:** Use mean squared error (MSE) and R-squared values to evaluate regression models. **References:** - Bai, S., Wang, H., & Liu, X. (2020). Forecasting electric vehicle sales with univariate and multivariate time series models. - Zhang, Y., Jiang, M., & Zhong, N. (2017). A study on machine learning methods for prediction of chronic diseases. Journal of Biomedical Informatics, 69, 237-244.
3. How do geographic location and local infrastructure (electric	This question investigates the influence of geographic factors and the availability of local infrastructure, like	**Feature Engineering:**

utilities) impact EV adoption in Washington?	electric utilities, on the adoption rates of electric vehicles.	- Create features like the number of EVs per county, city, or utility area. - Use latitude and longitude to create spatial features such as proximity to urban centers or other relevant locations. **Variable:** Dependent- - EV Adoption Rate (number of EVs registered in each location). Independent- - County, City, Electric Utility, Electric Range, Model Year, Latitude, Longitude. **Machine Learning:** - Multiple Linear Regression to account for geographic dependencies. - K-means Clustering to identify patterns and group similar areas. - Apriori Algorithm to identify associations between geographic location, electric utilities, and EV adoption patterns. **Training and Testing:** Split the dataset into training (80%) and testing (20%) sets. Hypothesis Testing: Perform ANOVA to compare means across different categories of geographic locations.

		Model Evaluation: **-** Evaluate models using adjusted R-squared and clustering accuracy. - Interpret geographic patterns using visualizations like heat maps and scatter plots. **References:** - Ehteram, M., & Banadkooki, F. B. (2023). A Developed Multiple Linear Regression (MLR) Model for Monthly Groundwater Level Prediction. *Water* - Xiaodong Wu, Yuzhu Zeng and Xiaodong Wu (2019). Using Apriori Algorithm on Students' Performance Data for Association Rules Mining

Tentative overall Methodology

This structured timeline ensures a systematic approach to the project, covering all critical stages from data collection to model evaluation. Each phase is allocated sufficient time to thoroughly address its objectives, ensuring the final model is robust and reliable. This detailed approach will provide a comprehensive understanding of EV adoption trends in Washington State, supporting future strategic planning and policy-making efforts.



References

1. Egbue, O., & Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy*. Retrieved from https://www.sciencedirect.com/science/article/abs/pii/S0301421512005162

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