Analysis of Electrical Vehicles

A system for predicting the best Electrical vehicle price for the customer

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Abstract*—The number of electrical vehicles is increasing exponentially every year. People are buying electrical vehicles as they are eco-friendly and pollution free. Because of this a lot of companies have different models of electrical vehicles with different varieties of features. People have difficulties in selecting which electrical vehicle to buy with required features. Here we focus on predicting the best price value for the electrical vehicle suitable for a person according to their requirements. Usually the price of the electrical vehicles mainly depend on their battery, make, model and range. So we focus on predicting appropriate price values for vehicles for a person depending on the data collected from their places.

***Keywords*—Electrical vehicle price predictions, Data analytics, Decision tree regression model**

I. Introduction

Electrical vehicle price prediction provides an important insight to the most appropriate vehicle which is suitable for the customer. This price prediction system can provide a suggested price of the vehicle which has the best battery performance and range.

The most important thing in an electrical vehicle is the battery and the range of the vehicle. So we have taken a data set of the electrical vehicles in the United States of America containing information about different types of electrical vehicles in that region with their performance, range and cost. This data set Also contains the distribution of different make and model across different years which were sold in the state with their prices.

We used this data set to predict prices with appropriate electrical vehicles which will be suitable for their use according to their requirements. This model can also be used to study the distribution of electrical vehicles across different parts of the state and decide which car is suitable For that particular region.

The attributes present in the dataset are vehicle number, County, City, State, Zip code, Model year, Make, Model, Electric vehicle type, Fuel vehicle eligibility, Electric range, Base MSRP, Legislative district, Vehicle id, vehicle location.

This paper documents our approach to build a price prediction model to predict appropriate electrical vehicles price to individuals based on their requirements. The data set chosen for this project is “Electrical vehicle population data” from Kaggle which has electrical vehicle details of different companies which were brought by the people in that region.

II. LITERATURE REVIEW

A. *Model-Based Range Prediction for Electric Cars and Trucks under Real-World Conditions [1]*

By: Manfred Dollinger and Gerhard Fischerauer

The further improvement of electric portability requires major logical endeavors to get solid information for vehicle and drive advancement. Commonsense experience has more than once shown that vehicle information sheets don't contain sensible utilization and reach figures. Since the dread of low reach is a huge hindrance to the acknowledgment of electric portability, a solid information base can give designers extra bits of knowledge and make certainty among vehicle clients. This model takes utilization pertinent boundaries, like occasional impacts, landscape character, and driving conduct, into account.Some of the conclusions that the model predicted are almost impossible to obtain experimentally. Quantitative results also reveal the important contributions of operation and rolling resistance towards the overall energy project.

This model considers air resistance, rolling resistance, gravity, mass inertia, electric motor, inverter, battery, recuperation and vehicle accessories to predict correctly.

The conclusions obtained from this prediction model were that winter conditions reduce the range by 8% hilly Terrain reduces the range by 7% individual driving behaviour reduces range by 20%.

This model has shown that, despite the complexity of BEV consumption data determination, a remarkable agreement with empirical data is possible with a model that only works with parameter values known a priori and that can be implemented with common desktop computer software.

B. *Energy Consumption Prediction for Electric Vehicles Based on Real-World Data [2]*

By:Cedric De Cauwer,Joeri Van Mierlo,Thierry Coosemans

Electric vehicle (EV) energy utilization is variable and depends on various outer factors like street geography, traffic, driving style, encompassing temperature, and so forth The objective of this paper is to recognize and evaluate connections between the kinematic boundaries of the vehicle and its energy utilization. In view of the vehicle element's condition as the basic actual model, various straight relapses are utilized to build three models. Each model uses an alternate degree of collection of the information boundaries, permitting expectations utilizing various kinds of accessible info boundaries.

Energy Model

The objective is to develop EV energy utilization models dependent on certifiable estimations. The proposed models are factual models dependent on the fundamental actual standards of the vehicle elements and kinematics.Energy misfortunes in the energy inventory network before the battery are not considered as they don't affect the scope of the EV. Accordingly, framework misfortunes and charging misfortunes are excluded from this model.The battery-to-wheel utilization of an electric vehicle is a component of the necessary mechanical energy at the wheels, dictated by the kinematic boundaries over a direction, the drivetrain effectiveness, and the energy utilization of helpers to make this model material, this nitty gritty degree of info must be extricated and anticipated from street, ecological, and traffic circumstances. In spite of these downsides for the third model, notwithstanding a lower relationship coefficient and high steady term (so there is less inconstancy represented), the forecast of the utilization over a total excursion had comparable precision to the next two models, which shows the capability of this strategy.

C. Predicting the Price of Used Cars using Machine Learning Techniques [3]
By: Sameerchand Pudaruth

This paper clarifies about the regulated AI methods to anticipate the cost of pre-owned vehicles in Mauritius. The forecasts depend on recorded information gathered from everyday papers. Various procedures like numerous straight relapse investigation, k-closest neighbors, innocent bayes and choice trees have been utilized to make the expectations. The expectations are then assessed and contrasted all together with observing those which give the best exhibitions. An apparently simple issue ended up being for sure undeniably challenging to determine with high exactness.
Foreseeing the cost of pre-owned vehicles is both a significant and fascinating issue. As per information acquired from the Public Vehicle Authority, the quantity of vehicles enrolled somewhere in the range of 2003 and 2013 has seen an astounding increment of 234%. From 68, 524 vehicles enlisted in 2003, this number has now reached 160, 701. With troublesome financial conditions, almost certainly, deals of second-hand imported (reconditioned) vehicles and pre-owned vehicles will increase. It is accounted for in
that the deals of new vehicles has enrolled a diminishing of 8% in 2013.

In Various Straight Relapse Investigation, Pearson connection coefficient was processed between various sets of elements to get the summed up outcomes. The worth of r was viewed as - 0.33 among year and mileage.
In K-Closest Neighbors, information is contrasted with every one of the current records to find the best matches. This model inferred that kNN works essentially preferable for Nissan vehicles over for Toyota vehicles.
In Decision Trees Only Nissan and Toyota cars were considered for building the decision tree. The prices were grouped into six nominal categories as most of the popular decision tree algorithms cannot handle numeric outputs.
In this paper, four different machine learning techniques have been used to forecast the price of used cars in Mauritius. The mean error with linear regression was about Rs51, 000 while for kNN it was about Rs27, 000 for Nissan cars and about Rs45, 000 for Toyota cars. J48 and NaiveBayes accuracy dangled between 60-70% for different combinations of parameters.

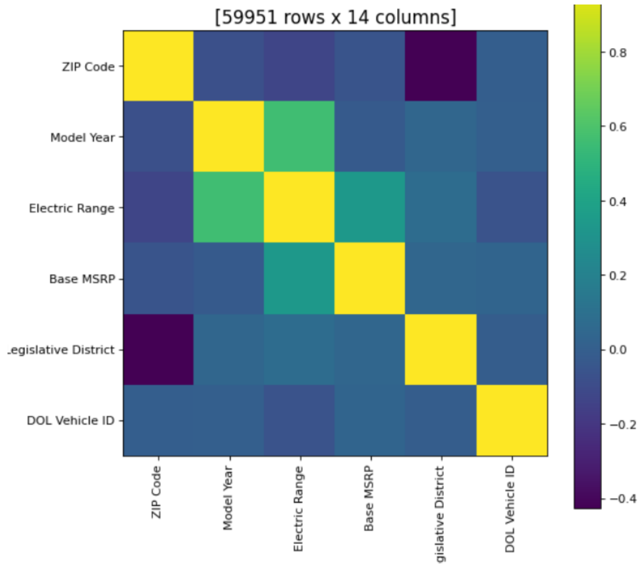
III. Exploratory data analysis

Dataset

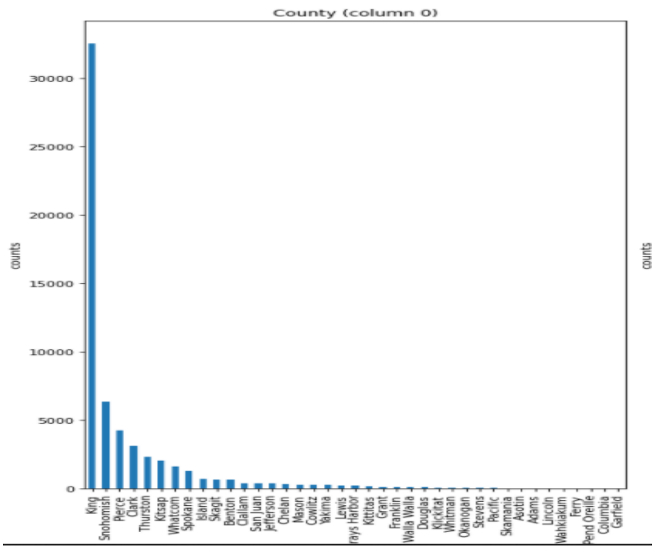
Name: Electrical vehicle population data.
Source:
https://www.kaggle.com/vijayakishoredusi/ev population?select=Electric_Vehicle_Population_Data.csv
Number of columns:15
Number of samples: 62261
Number of quantitative attributes: 5
Number of qualitative attributes: 10
Attributes: vehicle number, County, City, State, Zip code, Model year, Make, Model, Electric vehicle type, Fuel vehicle eligibility, Electric range, Base MSRP, Legislative district, Vehicle id, vehicle location.

Exploratory data analysis summary

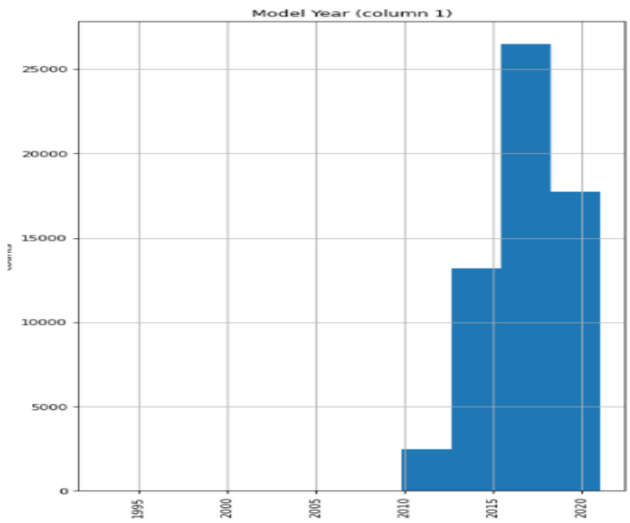
Correlation heat maps showed a high correlation between Electric range and model year. Few columns like vehicle number, city, state, zip code, vehicle id, vehicle location were of no importance for our study. They were deleted from the dataset. Base MSRP column had missing values, but it was important for the study, so we replaced the missing values with the mean of the respective column.



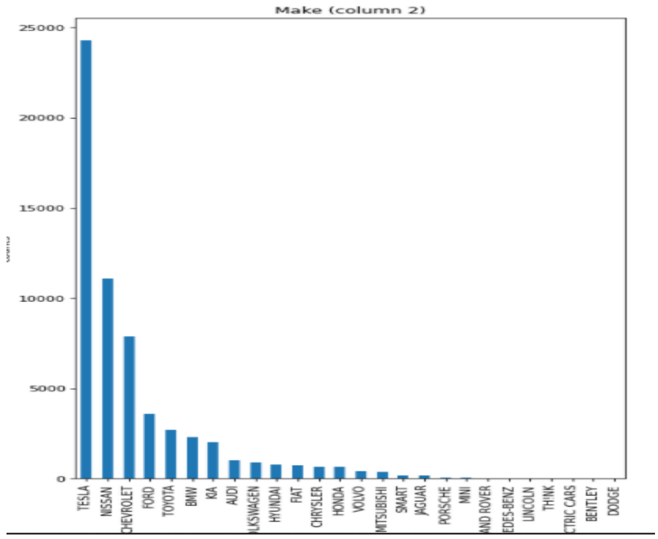
County plot showed us that a lot of vehicles in the dataset belonged to the king county.



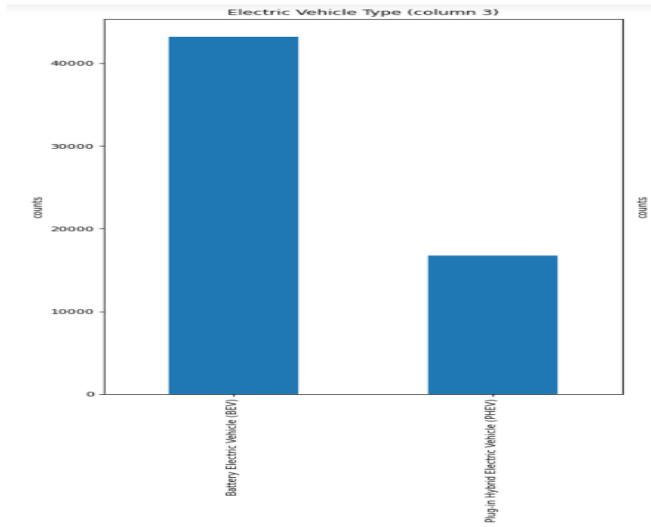
Model year plot showed us that a lot of vehicles in the dataset were from the years between 2010-2020.



Make plot showed us that the major shareholders of vehicle data in the dataset were Tesla, Nissan and Chevrolet.



Plot of Electrical vehicle type showed us that a lot more vehicles belonged to Battery electric vehicles compared to plug-in hybrid electric vehicles.



IV. PRE-PROCESSING

The selected dataset is electrical vehicle population data from the United Nations of America. Initially we check for the null values present in the dataset. We drop all the null values. The missing values are being replaced with the mean of the respective column. We drop the columns which are not necessary.

We use electrical vehicle type, clean alternative fuel vehicle(CAFP), eligibility, model, make, model year columns are the required columns for the model. The first four columns mentioned above are categorical data types. We use encoding techniques to encode these columns and add the encoded columns for the current dataset.

V. Building the model

The data set we got after the preprocessing step is split into two parts as training and testing sets. Since we have more categorical data type columns, we use the well known decision tree model for regression. Decision tree classifier is just like a flowchart to the terminal nodes of presenting classification of outputs. We use entropy to find a way to split the dataset until all the data belongs to the same class. There are several algorithms like ID3, C4.5 and CART to build decision trees. We use the training set to fit the model.

VI. Conclusion

We were able to successfully analyse the dataset and gain several insights. We also developed a model using a Decision tree where we predict the vehicle price for the required specifications.After the model is trained we use the test data set to test the model accuracy. The accuracy we got from the model was 99%.

VII. References

[1] Manfred Dollinger and Gerhard Fischerauer, "Model-Based Range Prediction for Electric Cars and Trucks under Real-World Conditions" 2021. Available: https://www.mdpi.com/1996-1073/14/18/5804/pdf

[2] Cedric De Cauwer, Joeri Van Mierlo, Thierry Coosemans, "Energy Consumption Prediction for Electric Vehicles Based on Real-World Data", 2015. [Online]. Available: https://econpapers.repec.org/article/gamjeners/v_3a8_3ay_3a2015_3ai_3a8_3ap_3a8573-8593_3ad_3a54101.htm

[3] Sameerchand Pudaruth, "Predicting the Price of Used Cars using Machine Learning Techniques", 2014. [Online]. Available: http://ripublication.com/irph/ijict_spl/ijictv4n7spl_17.pdf