Machine learning with tidymodels

Regression analysis of electric vehicle ranges

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2024-10-06

Introduction

The report aims to analyze the average effect on the range in miles based on electric vehicle type (battery electric vehicle or plug-in hybrid). A linear regression model was trained using tidymodels and evaluated on a testing split. Correlation analysis was also performed to identify features with a linear relationship to longer range. Through regression analysis, the main goal is to answer the question:

What is the effect on range in miles for electric vehicles depending on whether they are battery electric vehicles or plug-in hybrids?

Solution summary

The regression model achieved an RMSE of 53.8, an R-squared value of 0.705, and an MAE of 36.1 when evaluated on the testing split. There is a statistically significant difference in range in miles between plug in hybrids and battery electric vehicle types, with an average decrease of 167 miles for plug in hybrids compared to battery electric vehicles. Through correlation analysis, it was concluded that Tesla models such as the Bolt EV and Model 3 are the most strongly correlated with the range bin of 215 to infinity. Chevrolet and Tesla were the only manufacturers positively correlated with the highest range bin within this analysis.

#Core syntax for analysis

```r
#CORE LIBRARIES

#Data analysis
library(tidyverse)
library(correlationfunnel)
library(skimr)
library(janitor)

#Machine learning
library(tidymodels)
```

```r
#Loading data --
electric_tbl <- read_csv("data.csv")
```

```
## Rows: 205439 Columns: 17
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (10): VIN (1-10), County, City, State, Make, Model, E.V_Type, CAFV, Vehi...
## dbl  (7): Postal Code, Model Year, Electric Range, Base MSRP, Legislative Di...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
#Data exploration --

electric_tbl %>% glimpse()
```

```
## Rows: 205,439
## Columns: 17
## $ `VIN (1-10)`           <chr> "JTMAB3FV3P", "1N4AZ1CP6J", "5YJ3E1EA4L", "1N4A~
## $ County                 <chr> "Kitsap", "Kitsap", "King", "King", "Thurston",~
## $ City                   <chr> "Seabeck", "Bremerton", "Seattle", "Seattle", "~
## $ State                  <chr> "WA", "WA", "WA", "WA", "WA", "WA", "WA", "WA",~
## $ `Postal Code`          <dbl> 98380, 98312, 98101, 98125, 98597, 98036, 98370~
## $ `Model Year`           <dbl> 2023, 2018, 2020, 2014, 2017, 2020, 2022, 2023,~
## $ Make                   <chr> "TOYOTA", "NISSAN", "TESLA", "NISSAN", "CHEVROL~
## $ Model                  <chr> "RAV4 PRIME", "LEAF", "MODEL 3", "LEAF", "BOLT ~
## $ E.V_Type               <chr> "PHEV", "BEV", "BEV", "BEV", "BEV", "BEV", "PHE~
## $ CAFV                   <chr> "known", "known", "known", "known", "known", "k~
## $ `Electric Range`       <dbl> 42, 151, 266, 84, 238, 291, 31, 0, 291, 84, 238~
## $ `Base MSRP`            <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 31950, 0, 0~
## $ `Legislative District` <dbl> 35, 35, 43, 46, 20, 21, 23, 39, 47, 45, 26, 35,~
## $ `DOL Vehicle ID`       <dbl> 240684006, 474183811, 113120017, 108188713, 176~
## $ `Vehicle Location`     <chr> "POINT (-122.8728334 47.5798304)", "POINT (-122~
## $ `Electric Utility`     <chr> "PUGET SOUND ENERGY INC", "PUGET SOUND ENERGY I~
## $ `2020 Census Tract`    <dbl> 53035091301, 53035080700, 53033007302, 53033000~
```

```
electric_tbl %>% sample_n(20)
```

```
## # A tibble: 20 x 17
##    `VIN (1-10)` County    City      State `Postal Code` `Model Year` Make  Model
##    <chr>        <chr>     <chr>     <chr>         <dbl>        <dbl> <chr> <chr>
##  1 7SAYGDEF9R   King      Seattle   WA            98112         2024 TESLA MODE~
##  2 YV4ED3ULXP   King      Seattle   WA            98109         2023 VOLVO XC40
##  3 3FMTK3SU2M   King      Mercer I~ WA            98040         2021 FORD  MUST~
##  4 5YJ3E1EB6P   Clark     Ridgefie~ WA            98642         2023 TESLA MODE~
##  5 7SAYGDEE8N   King      Bellevue  WA            98006         2022 TESLA MODE~
##  6 7PDSGABA1P   King      Seattle   WA            98105         2023 RIVI~ R1S
##  7 7SAYGDED2R   Kitsap    Poulsbo   WA            98370         2024 TESLA MODE~
##  8 5YJYGDEF7L   King      Issaquah  WA            98029         2020 TESLA MODE~
##  9 7SAYGDEE6P   King      Woodinvi~ WA            98072         2023 TESLA MODE~
## 10 1FTBW1YK7P   Snohomish Everett   WA            98201         2023 FORD  TRAN~
## 11 5YJ3E1EB6M   Pierce    Tacoma    WA            98403         2021 TESLA MODE~
## 12 5YJ3E1EB6N   King      Seattle   WA            98118         2022 TESLA MODE~
## 13 KM8HC3A62R   King      Shoreline WA            98133         2024 HYUN~ KONA~
## 14 7SAYGAEE8P   Thurston  Olympia   WA            98501         2023 TESLA MODE~
## 15 5YJSA1E25G   King      Woodinvi~ WA            98072         2016 TESLA MODE~
## 16 5YJ3E1EA7P   Lewis     Centralia WA            98531         2023 TESLA MODE~
## 17 5YJ3E1EB3P   King      Seattle   WA            98101         2023 TESLA MODE~
## 18 5YJ3E1EBXR   King      Seattle   WA            98119         2024 TESLA MODE~
## 19 1G1RA6S54J   King      Seattle   WA            98126         2018 CHEV~ VOLT
## 20 WBY7Z4C57J   Clark     Vancouver WA            98682         2018 BMW   I3
## # i 9 more variables: E.V_Type <chr>, CAFV <chr>, `Electric Range` <dbl>,
## #   `Base MSRP` <dbl>, `Legislative District` <dbl>, `DOL Vehicle ID` <dbl>,
## #   `Vehicle Location` <chr>, `Electric Utility` <chr>,
## #   `2020 Census Tract` <dbl>
```

```
#Cleaning var names --
electric_tbl <- electric_tbl %>% clean_names()
```

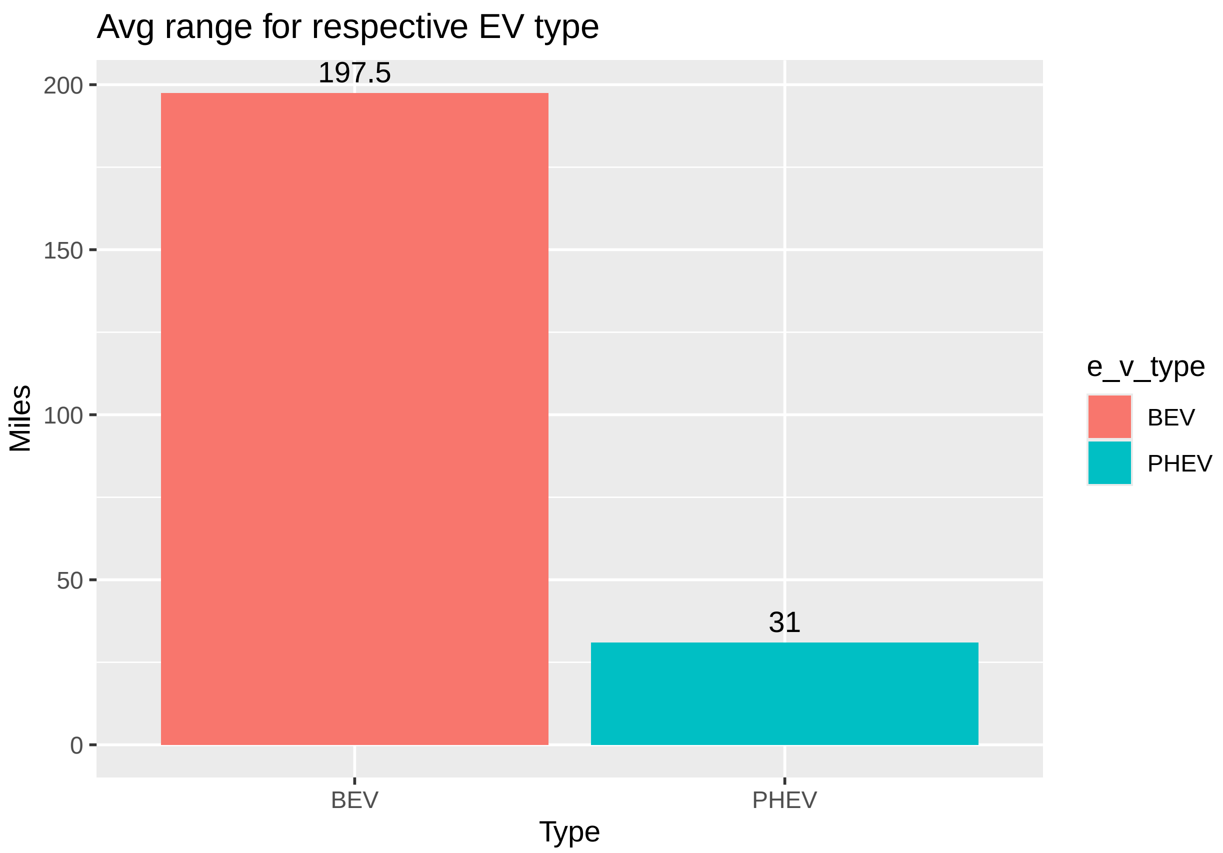
```
#EXPLORATORY DATA ANALYSIS --

# Count n vehicles where distance = 0  --
electric_tbl %>%
  filter(electric_range==0) %>%
  count()
```

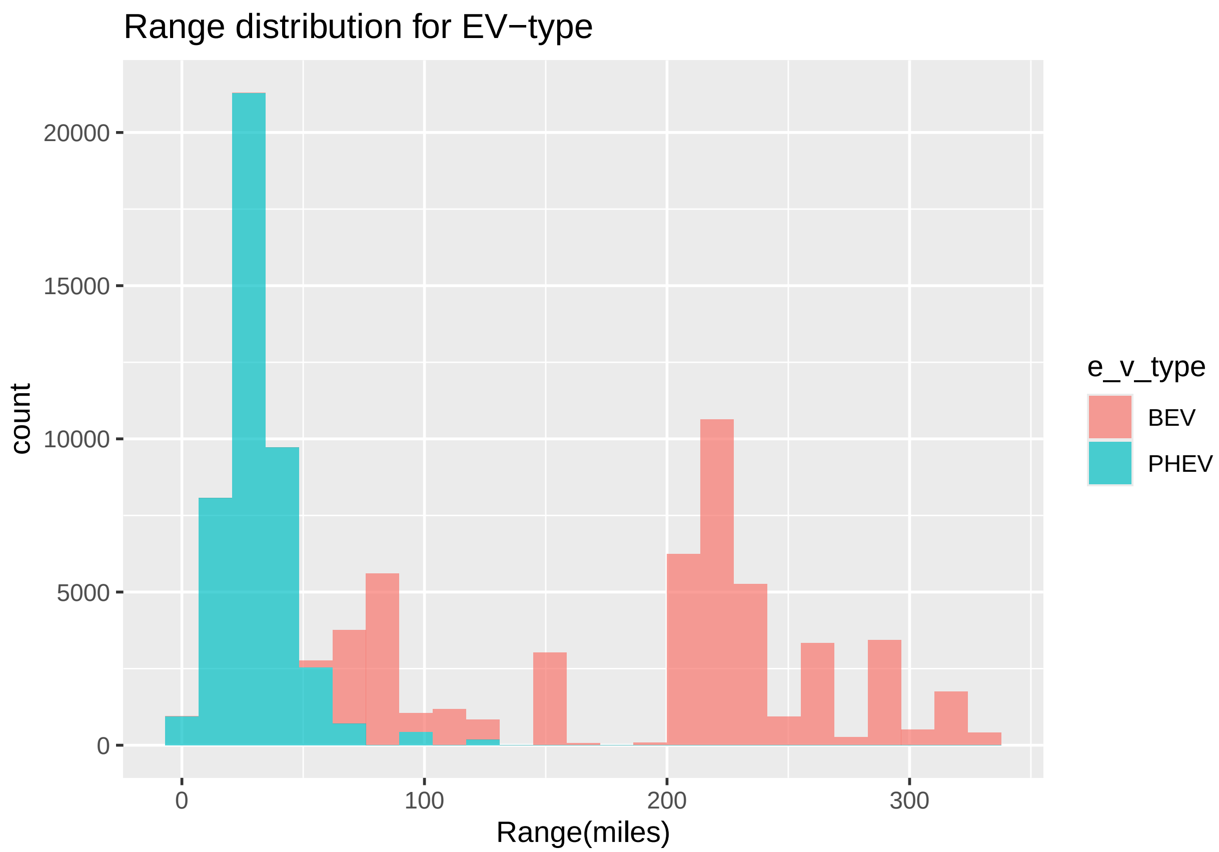
```
## # A tibble: 1 x 1
##        n
##    <int>
## 1 114172
```

```
# Basic mean values for  electric range by EV type --

electric_tbl %>%
  filter(electric_range!=0) %>%
  group_by(e_v_type) %>%
  summarise(avg_electric_range=mean(electric_range)) %>%
  ggplot(aes(e_v_type,avg_electric_range,fill=e_v_type))+
  geom_col()+
  geom_text(aes(label=round(avg_electric_range,1)),
            vjust=-0.5)+
  labs(title="Avg range for respective EV type",
       x="Type",y="Miles")
```



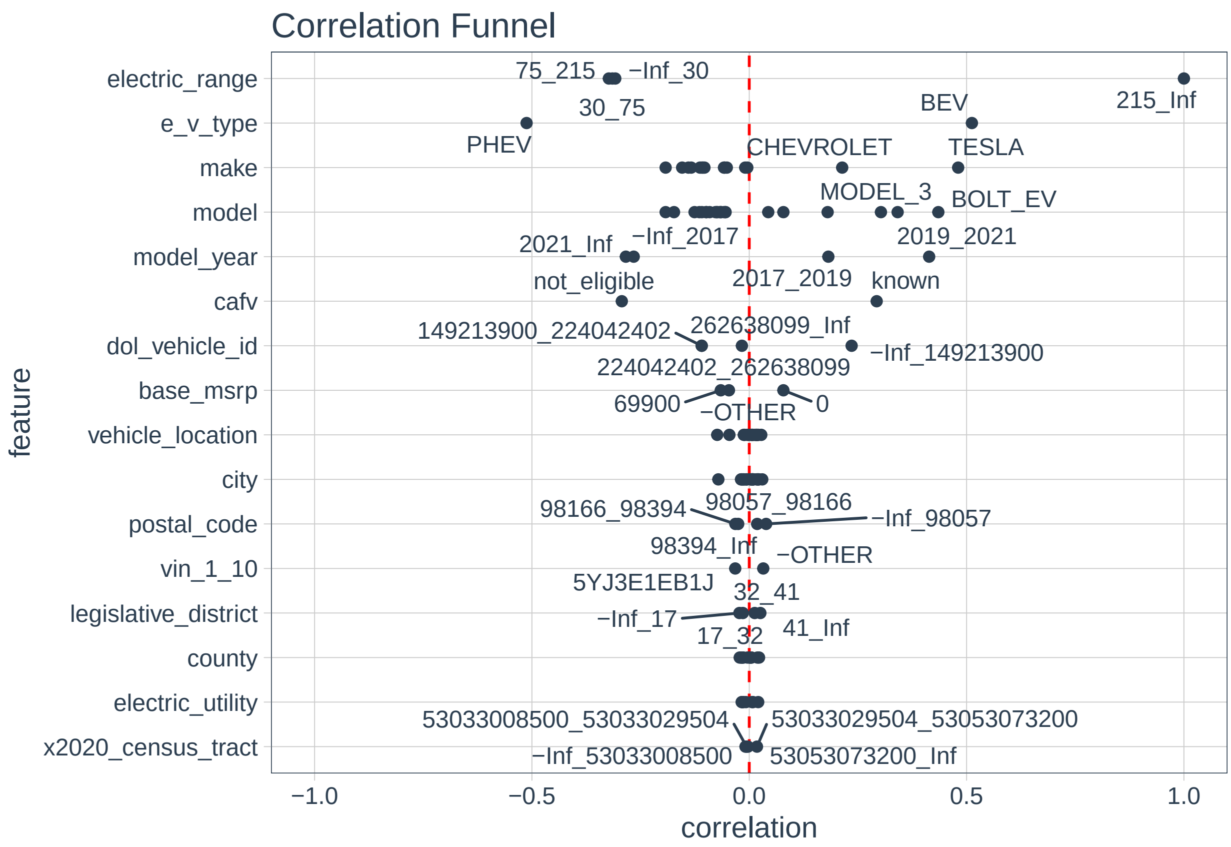
```
#Histogram for respective group --
electric_tbl %>%
  filter(electric_range!=0) %>%
  ggplot(aes(electric_range,fill=e_v_type))+
  geom_histogram(alpha=0.7,bins=25)+
  labs(title="Range distribution for EV-type",
       x="Range(miles)")
```



```
#Correlation analysis --

electric_tbl %>%
  filter(electric_range!=0) %>%
  na.omit() %>%
  binarize() %>%
  correlate(electric_range__215_Inf) %>%
  plot_correlation_funnel()
```

```
## Warning: ggrepel: 96 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



```
# Simple linear reg feature selection -- avg. electric range effect of EV-type**

ev_type_tbl <- electric_tbl %>%
  filter(electric_range!=0) %>%
  select(electric_range,e_v_type) %>%
  mutate(e_v_type=as.factor(e_v_type))

# Train / test split
set.seed(123)
simple_lm_split <- initial_split(data=ev_type_tbl,prop=0.8)
lm_training <- training(simple_lm_split)
lm_testing <- testing(simple_lm_split)

#Regression recipe --
lm_model_rec  <- recipe(electric_range~e_v_type,data=lm_training)

# Linear model spec --
lm_model_spec<-linear_reg() %>%
  set_engine("lm")

#Combind into workflow --

lm_wf <- workflow() %>%
  add_recipe(lm_model_rec) %>%
  add_model(lm_model_spec)
```

```
# Training linear model --

lm_model_fit <- fit(lm_wf,data=lm_training)

#Results --
lm_model_fit %>%
  extract_fit_parsnip() %>%
  tidy()
```

```
## # A tibble: 2 x 5
##   term         estimate std.error statistic p.value
##   <chr>           <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      198.     0.275      718.       0
## 2 e_v_typePHEV    -167.     0.397     -420.       0
```

```
#Model evaluation -- (Examined on testing data)
ev_predict <- predict(lm_model_fit,new_data=lm_testing)

#Combinding actual vs. predicted values --
actvspred_lm<- lm_testing %>% select(electric_range) %>%
  bind_cols(ev_predict)

lm_evaluation <-metrics(data=actvspred_lm,truth=electric_range,estimate=.pred)

#Final linear reg. model metrics --
lm_evaluation
```

```
## # A tibble: 3 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard      53.8
## 2 rsq     standard       0.705
## 3 mae     standard      36.1
```