A Statistical Approach to Used Car Price Prediction

12/09/2024

Steven Qie
Statistics and Computer Science
University of Illinois Urbana-Champaign
qie2@illinois.edu

Brian Gong
Statistics and Computer Science
University of Illinois Urbana-Champaign
brianhg2@illinois.edu

William Yeh
Statistics and Computer Science
University of Illinois Urbana-Champaign
wy16@illinois.edu

Introduction

With the used car market being significantly larger than the new car market, many consumers are realizing that used cars provide a more affordable option. It plays a significant role in the growth and stability of the U.S. economy, driven by changing consumer preferences, economic factors, and the availability of certain cars. Accurately predicting the price of a used car is a challenging but essential task for buyers, sellers, and market analysts/economists alike.

This report aims to develop various predictive models for used car prices using the Used Car Price Prediction Dataset from Kaggle. This dataset comprises of 4,009 data points, representing unique vehicle listings, as well as nine distinct features that serve as key indicators influencing the value of a used car. We follow a very structured and standard approach, including data exploration, preprocessing, model training, and evaluation using relevant performance metrics. By leveraging these methods, we aim to uncover valuable insights into the world of automobiles and the various factors that are driving used car prices.

Need a section on key findings....

Abstract—

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We utilized AI tools in this report to enhance and assist in our writing. These tools helped play a big role in ensuring clarity, conciseness, and professionalism. We also utilized AI tools to help us with syntax help when writing code in R, as well as discovering potential bugs in our code.

Literature Review

This literature review aims to summarize key findings and approaches from a few noteworthy research papers focused on used car price prediction.

"Price Prediction of Used Cars Using Machine Learning", written by Chuyang Jin of the University of Sydney, presents a model that can predict a used vehicle's price given their year of production, mileage, tax, miles per gallon, He hopes that his model can benefit and save time for both sellers and buyers who are looking to sell or serach for second-hand vehicles. Jin used a CSV dataset containing 100,000 records of used cars in the UK, focusing specifically on the Mercedes brand. The nine factors that he considered were the following: model, year, selling price, transmission, mileage, fuel type, tax, miles per gallon (mpg), and engine size. While doing exploratory data analysis and preprocessing, Jin noted that many many predictors had skewed distributions. For example, the overwhelming majority of prices fell in the 0-75,000 range, limiting the model's potential effectiveness for higher price ranges. Jin deemed these data points as outliers and excluded them to ensure that the model would be more accurate and usable. After testing various forms of regression, namely linear, polynomial, SVR, Decision Trees, and Random Forests, Jin found Random Forest Regression yielded the best R squared value of 0.90416.

"Used Car Price Prediction using Machine Learning: A Case Study", written by Mustapha Hankar, Marouane Birjali, and Abderrahim Beni-Hssane, applies several supervised machine learning algorithms to predict used car price prices based on features from a dataset collected from an online eCommerce website called Avito. During preprocessing, the authors of this paper performed recursive feature elimination to maintain only the most relevant features to car prices: year of manufacture, mileage, mark, fuel type, fiscal power, and model. Along with a baseline multiple linear regression model, the study also looked at K-nearest neighbors, Random Forest, Gradient Boosting, and Artificial Neural Networks. The study utilized 2 different performance metrics, R^2 and RMSE, and concluded that the Gradient Boosting Regression Model achieved the best results, with a R^2 of 0.8 and RMSE of 44516.20.

"Car Price Prediction using Supervised and Unsupervised Learning Models and Deep Learning" by Thomas Nsiah approached the problem of car price prediction from a supervised and unsupervised lenses. While supervised models allow a consumer to understand the key factors and predictors that influence pricing of used cars, unsupervised learning oftentimes uncovers hidden connections and patterns within the data. In his paper, Nsiah used a mock dataset of 50,000 UK second hand car sales with features similar to the previous 2 studies, such as model, engine size, fuel type, year, and mileage. Supervised learning models that Nsiah tried included simple linear regression, polynomial regression, and random forest, evaluated using mean absolute error (MAE) and R-squared metrics. He concluded that out of the supervised models, random forest performed best with an R-squared of 0.99849 and a MAE of 289.0691. For unsupervised learning techniques, Nsiah applied K-Means and DBSCAN clustering to identify price patterns, evaluated using the Davis Boudlin Index and the Silhouette Coefficient. He concluded that K-Means clustering for the year of manufacture vs price produced the best clustering results.

Overall, these three studies demonstrate the effectiveness that machinie learning can have on accurately predicting used car prices. The next section will outline our own approach and findings.

Citations:

- C. Jin, "Price Prediction of Used Cars Using Machine Learning," in 2021 IEEE International Conference on Emergency Science and Information Technology (ICESIT), Chongqing, China, 2021, pp. 223-230, doi: 10.1109/ICESIT53460.2021.9696839.
- M. Hankar, M. Birjali, and A. Beni-Hssane, "Used Car Price Prediction using Machine Learning: A Case Study," in 2022 11th International Symposium on Signal, Image, Video and Communications (ISIVC), El Jadida, Morocco, 2022, pp. 1-4, doi: 10.1109/ISIVC54825.2022.9800719.
- T. Nsiah, "Car Price Prediction using Supervised and Unsupervised Learning Models and Deep Learning," unpublished, 2024.

Data Processing and Summary Statistics

First, we will import the dataset and libraries into our workspace

#Preliminary Data Cleaning/Modifications First, we will removed the dollar sign and comma in price to enable numeric operations

Corrected the spelling of mileage from milage to mileage. Removed mi. and , to enable numeric operations.

The Engine columns contains very useful information such as the horsepower, displacement, cylinders, engine type, and fuel type. We turn these all into new columns.

```
##      brand                           model model_year mileage fuel_type
## 1     Ford Utility Police Interceptor Base       2013   51000 Flex Fuel
## 2  Hyundai                    Palisade SEL       2021   34742      <NA>
## 3    Lexus                  RX 350 RX 350       2022   22372      <NA>
## 4 INFINITI               Q50 Hybrid Sport       2015   88900  Electric
## 5     Audi       Q3 45 S line Premium Plus       2021    9835      <NA>
## 6    Acura                         ILX 2.4L       2016  136397      <NA>
##        transmission               ext_col int_col
## 1       6-Speed A/T                 Black   Black
## 2 8-Speed Automatic        Moonlight Cloud    Gray
## 3         Automatic                  Blue   Black
## 4       7-Speed A/T                 Black   Black
## 5 8-Speed Automatic Glacier White Metallic   Black
## 6                 F                Silver  Ebony.
##                                accident clean_title price horsepower
## 1 At least 1 accident or damage reported         Yes 10300        300
## 2 At least 1 accident or damage reported         Yes 38005         NA
## 3                         None reported             54598         NA
## 4                         None reported         Yes 15500        354
## 5                         None reported             34999         NA
## 6                         None reported             14798         NA
##   displacement  cylinders engine_type
## 1          3.7 6 Cylinder        <NA>
## 2          3.8       <NA>        DOHC
## 3           NA       <NA>        DOHC
## 4          3.5 6 Cylinder        <NA>
## 5          2.0       <NA>        DOHC
## 6           NA       <NA>        <NA>
```

Looking at each column's type and unique count

```
##        brand        model   model_year      mileage    fuel_type transmission
##  "character"  "character"    "integer"    "numeric"  "character"  "character"
##      ext_col      int_col     accident  clean_title        price   horsepower
##  "character"  "character"  "character"  "character"    "numeric"    "numeric"
## displacement    cylinders  engine_type
##    "numeric"  "character"  "character"
```

```
##        brand        model   model_year      mileage    fuel_type transmission
##           57         1898           NA           NA            7           62
##      ext_col      int_col     accident  clean_title        price   horsepower
##          319          156            3            2           NA           NA
## displacement    cylinders  engine_type
##           NA            8            6
```

Let's examine columns that include NA or Empty String entries.

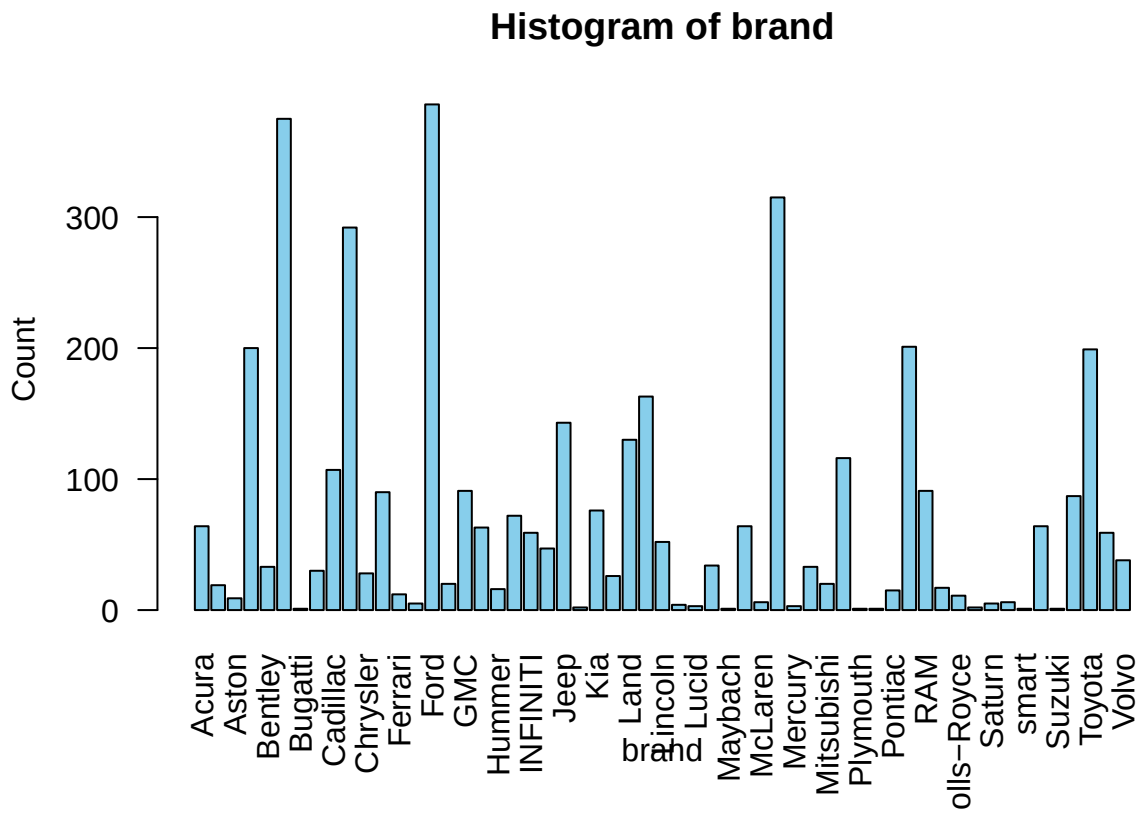
```
## [1] "fuel_type"    "accident"     "clean_title"  "horsepower"   "displacement"
## [6] "cylinders"    "engine_type"
```

#Analyzing categorical variables Categorical variables with various unique values include brand, model, transmission, ext_col, int_col. Let's examine all of them

First, we look at the "brand" and the "model" columns. Through analysis shown below, we have decided to omit both of these columns. Our reasoning and visualizations are shown below.

There are 57 unique brands with the frequency histogram not showing much dominance in a certain brand. To reduce the dimensionality, we will just omit this column

```
## [1] 57
```

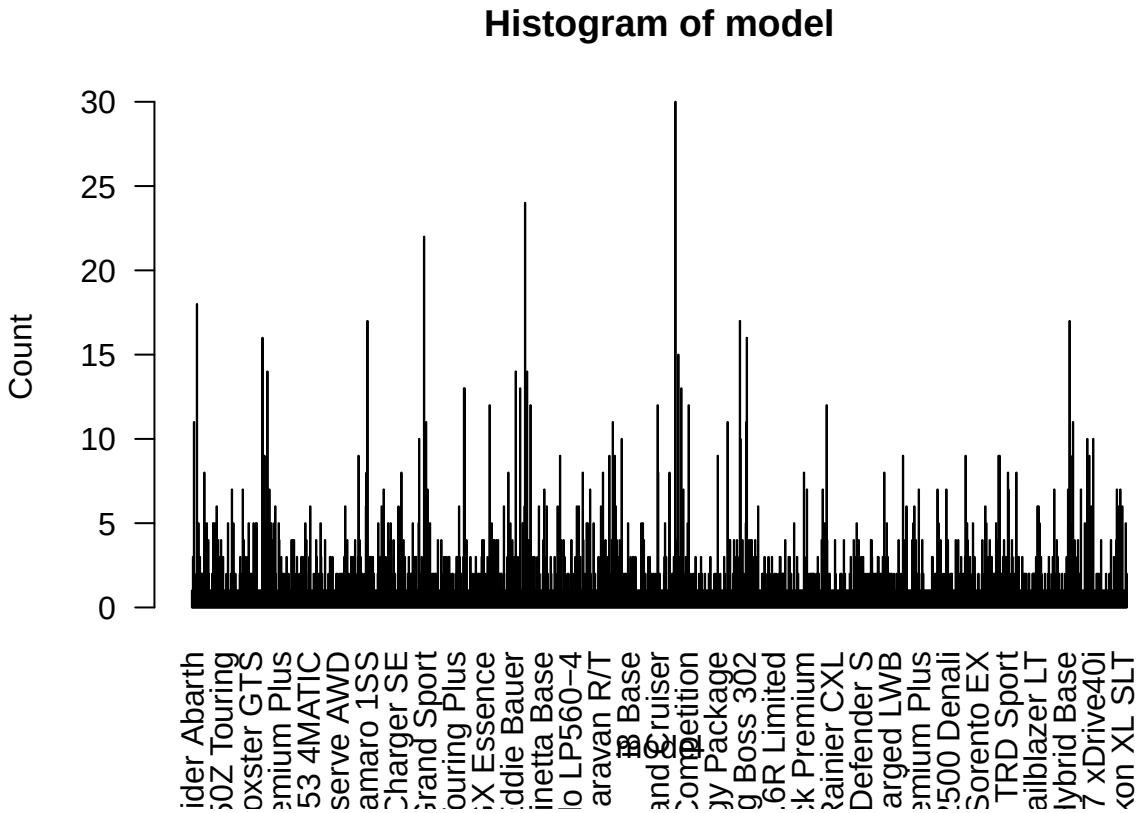



```
## # A tibble: 57 x 4
##    brand         medianprice averageprice count
##    <chr>               <dbl>        <dbl> <int>
##  1 Ford               32378.       36241.   386
##  2 BMW                32999        41072.   375
##  3 Mercedes-Benz      38598        52076.   315
##  4 Chevrolet          31992.       36723.   292
##  5 Porsche            59900        88751.   201
##  6 Audi               34498.       39907.   200
##  7 Toyota             27999        30026    199
```

```
##  8 Lexus              30000        35669.   163
##  9 Jeep               30000        31100.   143
## 10 Land               44924        55764.   130
## # i 47 more rows
```

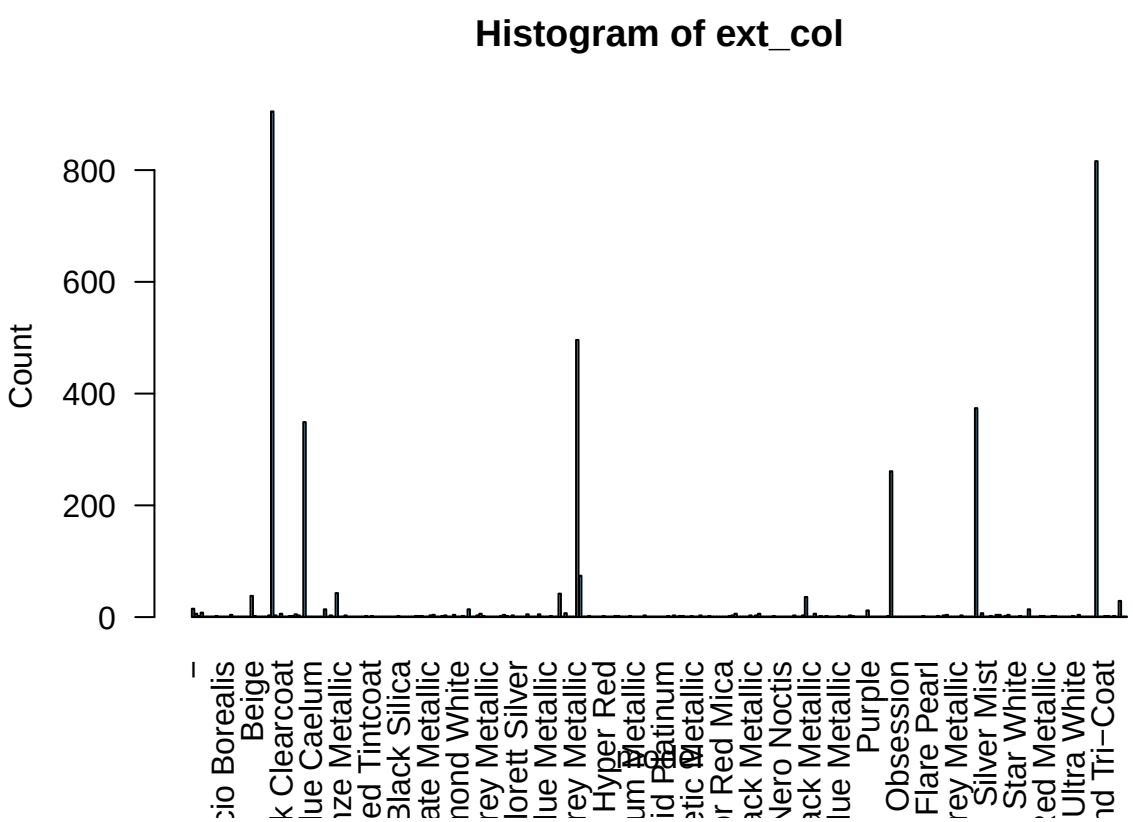
This problem is seen even more in the model column. We also omit this column from the dataset

```
## [1] 1898
```



Now, let's examine colors. There are both intcol and extcol variables. Having too many unique color names can introduce noise into your classification model and make it harder for the model to generalize effectively. Grouping the colors into broader, more general categories can help improve model performance by reducing the dimensionality of the feature and making patterns more apparent.

```
## [1] 319
```

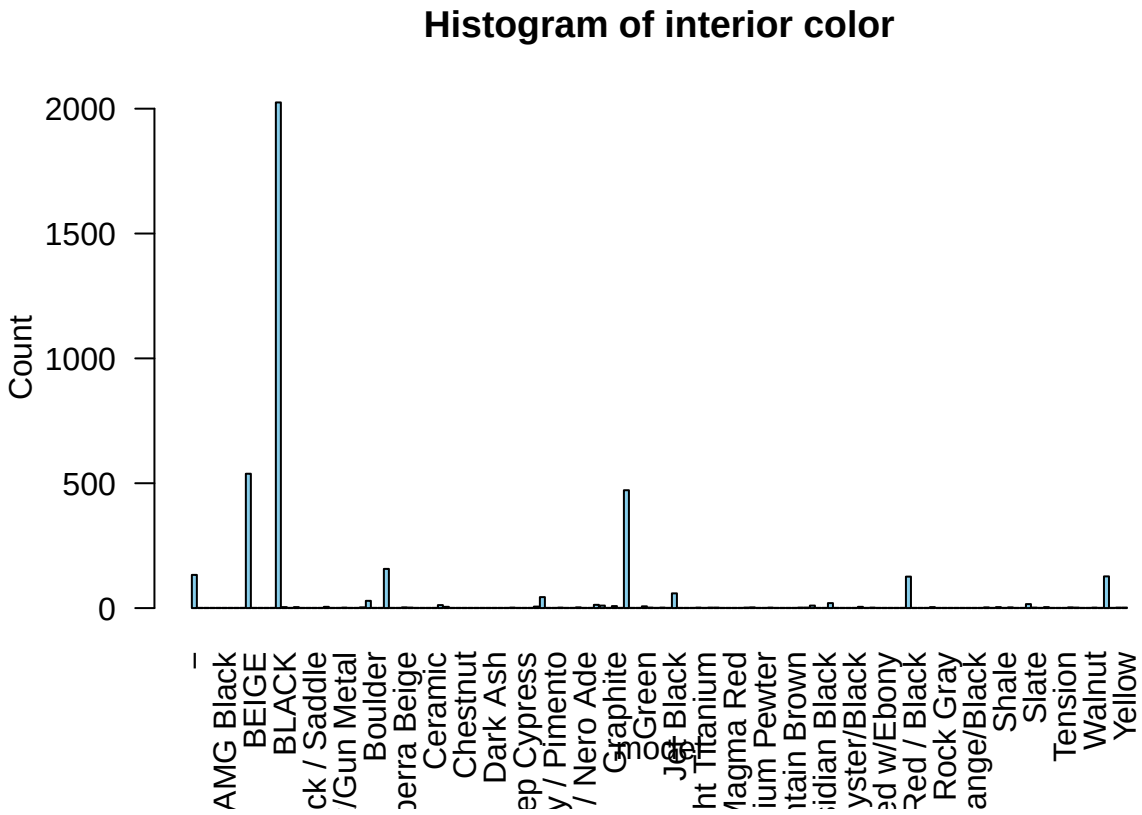


Let's apply the generalization function to simply the different colors

```
## [1] "Black" "Other" "White" "Gray"  "Gold"  "Brown"
```

The same thing happens to int_col, but looking at the dataset we will have 4 categories.

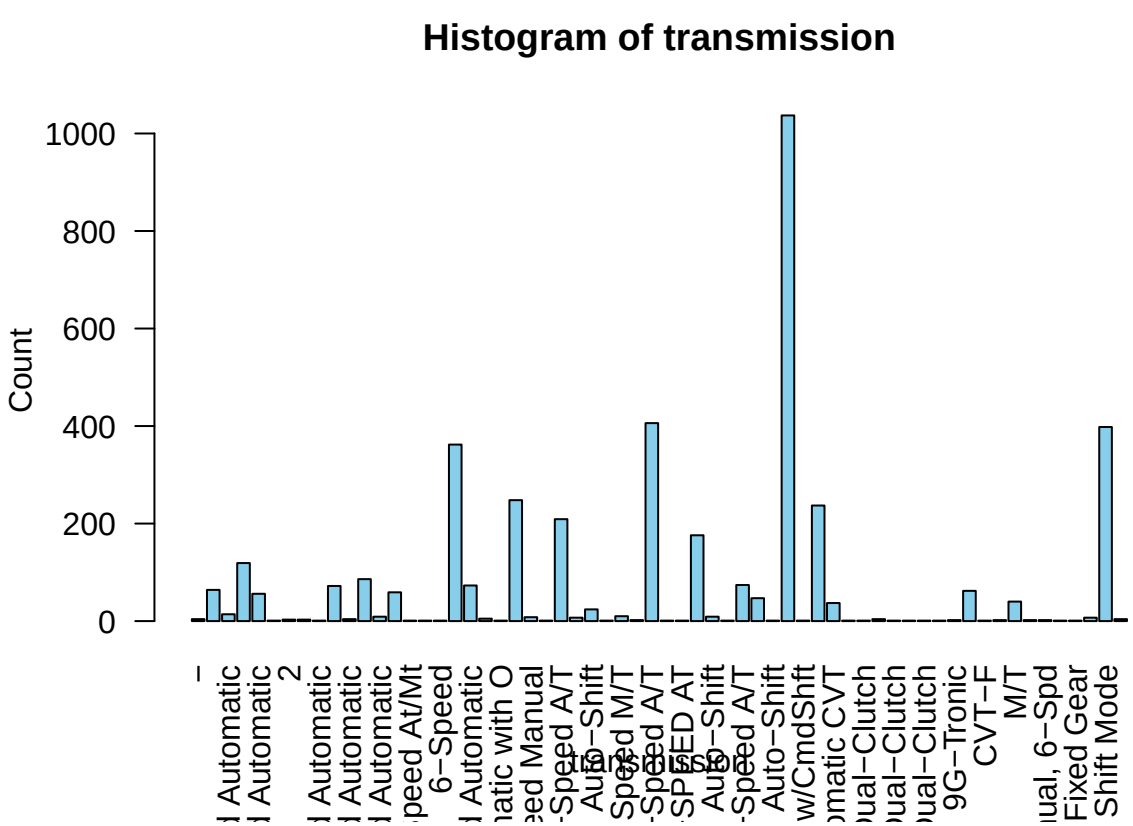
```
## [1] 156
```




```
## [1] "Black"       "Gray"        "Other"       "Beige/Ivory"
```

Examining the transmission column now

```
## [1] 62
```




```
## # A tibble: 62 x 4
##    transmission                    medianprice averageprice count
##    <chr>                                 <dbl>        <dbl> <int>
##  1 A/T                                   20500       31508.  1037
##  2 8-Speed A/T                           39625       51126.   406
##  3 Transmission w/Dual Shift Mode        34000       54711.   398
##  4 6-Speed A/T                           20900       25450.   362
##  5 6-Speed M/T                           26450       39282.   248
##  6 Automatic                             47541       63105.   237
##  7 7-Speed A/T                           32999       47250.   209
##  8 8-Speed Automatic                     41599       66072.   176
##  9 10-Speed A/T                          57000       60915.   119
## 10 5-Speed A/T                           15000       17607.    86
## # i 52 more rows
```

```
## [1] "A/T"                           "8-Speed A/T"
## [3] "Transmission w/Dual Shift Mode" "6-Speed A/T"
## [5] "6-Speed M/T"                   "Automatic"
## [7] "7-Speed A/T"
```

Now, we have looked at all the categorical variables with many many unique values, we will now one-hot encode the cagtegorical vairables. # One-hot encoding categorical variables

After looking at histograms for both Brand and Transmission, it seems Brand is more uniformly distributed while Transmission has a few salient categories. After exploring the categories of transmissions we found that the top 7 most frequent transmissions account for approximately 67-70% of the data points. Therefore we

will one hot encode these 7 categories + an "Other" category for Transmission for a total of 8 transmission categories. We will also one hot encode "fuel type" and "cylinders" since those are categorical variables as well.

Transmission

#Analyzing Null/Empty Values We will first look at the problem with NA and Empty values, something that this dataset has a lot of. We will first handle both NA and Empty " " values by replacing them to "NA" to make it easier to preprocess and analyze.

```
## [1] "fuel_type"    "accident"     "clean_title"  "horsepower"   "displacement"
## [6] "cylinders"    "engine_type"
```

```
## NULL
```

```
## NULL
```

```
##   [1]  300   NA  354  292  282  311  534  715  382  400  375  305  287  550  120
##  [16]  355  276  445  362  345  383  180  211  173  240  552  536  310  228  268
##  [31]  503  325  208  250  200  420  302  306  237  248  425  582  444  335  424
##  [46]  340  225  365  315  199  560  326  165  835  241  215  130  288  369  195
##  [61]  285  485  132  416  360  280  620  265  469  169  330  275  303  450  651
##  [76]  255  455  182  236  370  212  565  230  171  252  220  188  235  320  138
##  [91]  291  523  440  181  429  263  210  404  670  563  283  150  266  328  304
## [106]  381  493  641  760  329  239  160  402  166  390  147  357  271  350  611
## [121]  295  603  454  490  301  395  272  437  323  256  140  600  409  640  204
## [136]  316  591  219  505  403  170  115  562  106  201  496  475  184  407  543
## [151]  333  553  471  380  247  349  190  410  260  245  332  261  107  577  290
## [166]  453  293  139  389  567  221  518  630  218  385  174  134  273  172  542
## [181]  571  601  500  270  161  394  520  164  205  308  226  227  412  158  414
## [196]  177  346  111  573  277  191  318  411  244  605  192  207  155  189  185
## [211]  162  187  313  557  281  463  186  797  214  449  153  296  650  759  286
## [226]  525  246  526  397  645  575  401  348  510  122  179  167  691  202  136
## [241]  151  617  146  294  317  175  717  435  405  616  137  152  206  415  460
## [256]  707  319  426  555  480  121  430  159  378  321  344  133  232  142  278
## [271]   78  258  264  118   76  788  131  148  203  253  312  467  168  156  353
## [286]  545  422  451  197  386  778  521  495  621  456  279  540  104  372  366
## [301]  284  556  193  393  198  298  145  242  243   70  610  141  217  533  262
## [316]  342  483  109  231  473  324  443  101  322  126  638  710  154  808  143
## [331]  602  363  178  580  624  379  502  470 1020  572  702  660  341  222  729
## [346]  417  482  224  176
```

```
##  [1] 3.70 3.80   NA 3.50 2.00 4.40 5.20 3.00 5.00 3.60 2.20 5.30 5.70 2.40 2.70
## [16] 6.00 4.00 1.50 6.10 1.60 2.90 3.30 3.40 2.50 1.80 6.20 4.30 6.75 5.50 5.60
## [31] 6.30 5.40 6.70 4.60 4.50 4.70 1.30 2.30 3.20 5.80 6.80 6.40 8.00 4.20 1.20
## [46] 3.90 1.70 7.00 2.80 6.60 1.40 4.80 7.40 5.90 8.10 6.50 8.40 0.65 8.30 2.10
## [61] 7.30 1.00
```

```
## NULL
```

```
## NULL
```

```
## [1] 810
```

```
## [1] 396
```

```
##
## 0.65    1  1.2  1.3  1.4  1.5  1.6  1.7  1.8    2  2.1  2.2  2.3  2.4  2.5  2.7
##    5    1    3    8   16   38   59    1   46  471    2    5   35   99  175   46
##  2.8  2.9    3  3.2  3.3  3.4  3.5  3.6  3.7  3.8  3.9    4  4.2  4.3  4.4  4.5
##    5   16  432   31   26   30  333  235   62  105   15  182   26   15   82    2
##  4.6  4.7  4.8    5  5.2  5.3  5.4  5.5  5.6  5.7  5.8  5.9    6  6.1  6.2  6.3
##   70   54   28  112   29  104   23   28   35  129    3    4   67    4  173    6
##  6.4  6.5  6.6  6.7 6.75  6.8    7  7.3  7.4    8  8.1  8.3  8.4
##   28    7   26   52    2    7    3    4    1    1    2    3    1
```

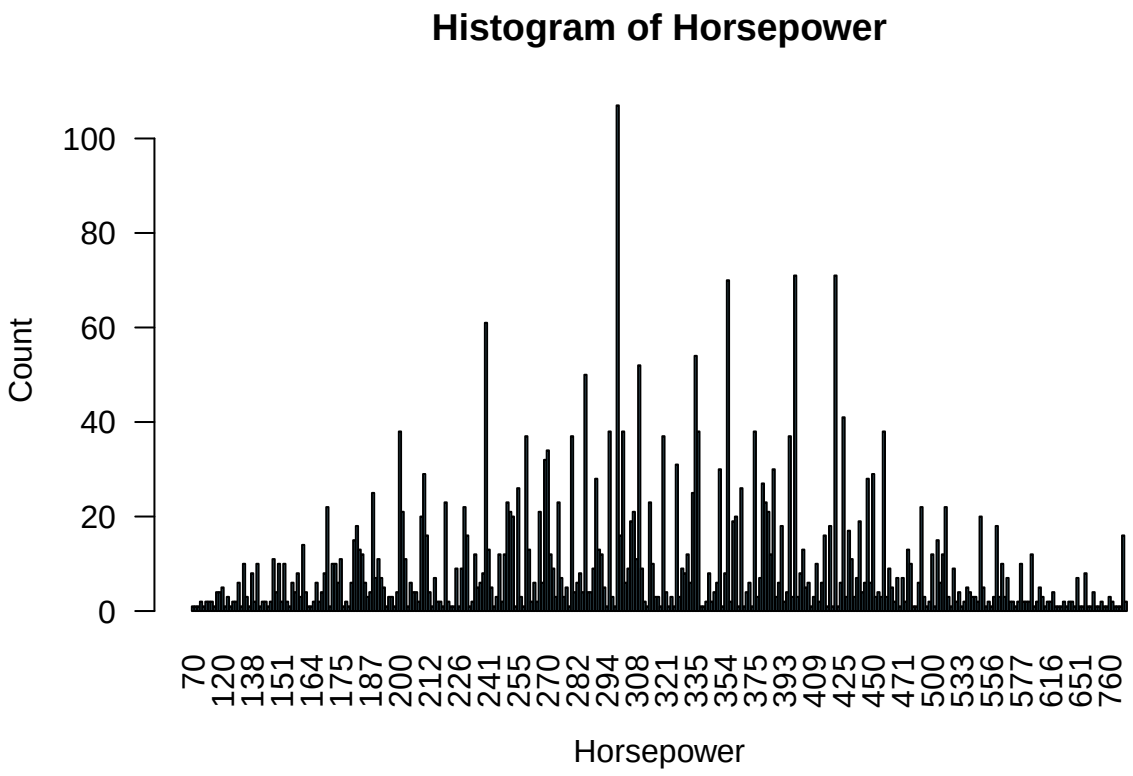
```
##    model_year      mileage        fuel_type         transmission
##  Min.   :1974   Min.   :   100   Length:4009        Length:4009
##  1st Qu.:2012   1st Qu.: 23044   Class :character   Class :character
##  Median :2017   Median : 52775   Mode  :character   Mode  :character
##  Mean   :2016   Mean   : 64718
##  3rd Qu.:2020   3rd Qu.: 94100
##  Max.   :2024   Max.   :405000
##
##    ext_col            int_col            accident         clean_title
##  Length:4009        Length:4009        Length:4009        Length:4009
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##      price           horsepower      displacement    cylinders
##  Min.   :   2000   Min.   :  70.0   Min.   :0.650   Length:4009
##  1st Qu.:  17200   1st Qu.: 248.0   1st Qu.:2.500   Class :character
##  Median :  31000   Median : 310.0   Median :3.500   Mode  :character
##  Mean   :  44553   Mean   : 332.3   Mean   :3.711
##  3rd Qu.:  49990   3rd Qu.: 400.0   3rd Qu.:4.700
##  Max.   :2954083   Max.   :1020.0   Max.   :8.400
##                    NA's   :810      NA's   :396
##  engine_type
##  Length:4009
##  Class :character
##  Mode  :character
##
##
##
##
```

There are five columns with empty strings/NA values. Let's examine all five of them to discover if we can find any patterns.

horsepower

```
## [1] 348
```

```
## [1] 810
```



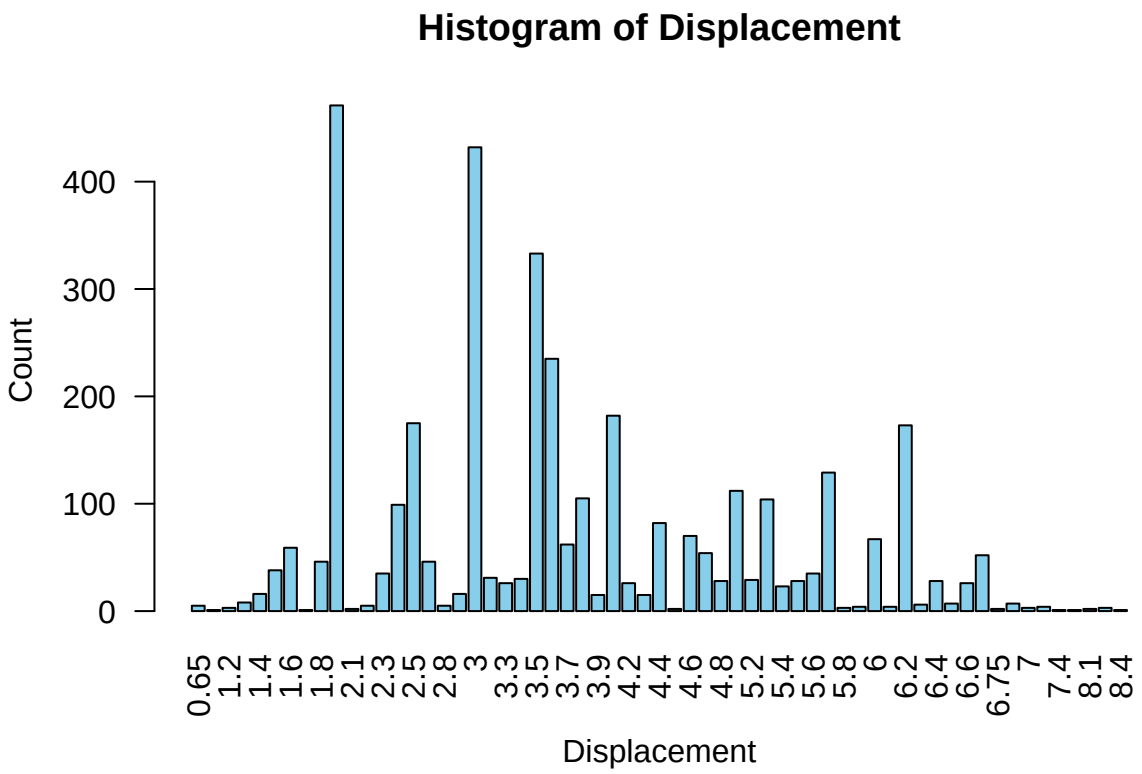

```
## [1] 0
```

Since there are 348 unique values in horsepower, we can consider horsepower as a continuous variable rather than categorical. However, there are 810 null values in a dataset with 4009 entries which is over 20% null values. This is too many to simply drop, so we want to perform some form of imputation. Looking at the distribution of horsepowers, we can see that the median is a good representative approximation for the distribution so we will use **median imputation**.

displacement (engine size)

```
## [1] 61
```

```
## [1] 396
```




```
## [1] 0
```

There are 61 unique values in displacement (engine size). Although these appear to be discretized measurements (ex: size = 0.8 or size = 3.71 may not make sense), we can treat it as a more continuous predictor for now. There are 396 null values in displacement which is just under 10% null values, so we could consider dropping these. However since the median already exists in the dataset (median = 3.5) we can also proceed with median imputation which is what we did.

```
## # A tibble: 7 x 4
##   fuel_type            medianprice averageprice count
##   <chr>                      <dbl>        <dbl> <int>
## 1 Diesel                     45450        48878.   114
## 2 Electric                   42000.       46884.   238
## 3 Flex Fuel                  18650        22156.   128
## 4 Gasoline                   27000        38733.  2731
## 5 Hybrid                     37999        45063.    17
## 6 Plug-In Electric/Gas       44945        45946.    34
## 7 <NA>                       41599        68192.   747
```

The NA values for fuel_type have a higher median price and average price than other types, and makes up a significant count of observations so we are going to treat it as a separate category.

#cylinder

```
## # A tibble: 8 x 4
```

```
##   cylinders   medianprice averageprice count
##   <chr>             <dbl>        <dbl> <int>
## 1 10 Cylinder     100000       166530.    23
## 2 12 Cylinder      81330       140259.    37
## 3 3 Cylinder       32000        45281.    13
## 4 4 Cylinder       19000        22476.   739
## 5 5 Cylinder       10150.       18584.    20
## 6 6 Cylinder       27999        35935.  1225
## 7 8 Cylinder       34500        46401.  1007
## 8 <NA>             42599        64844.   945
```

#accident

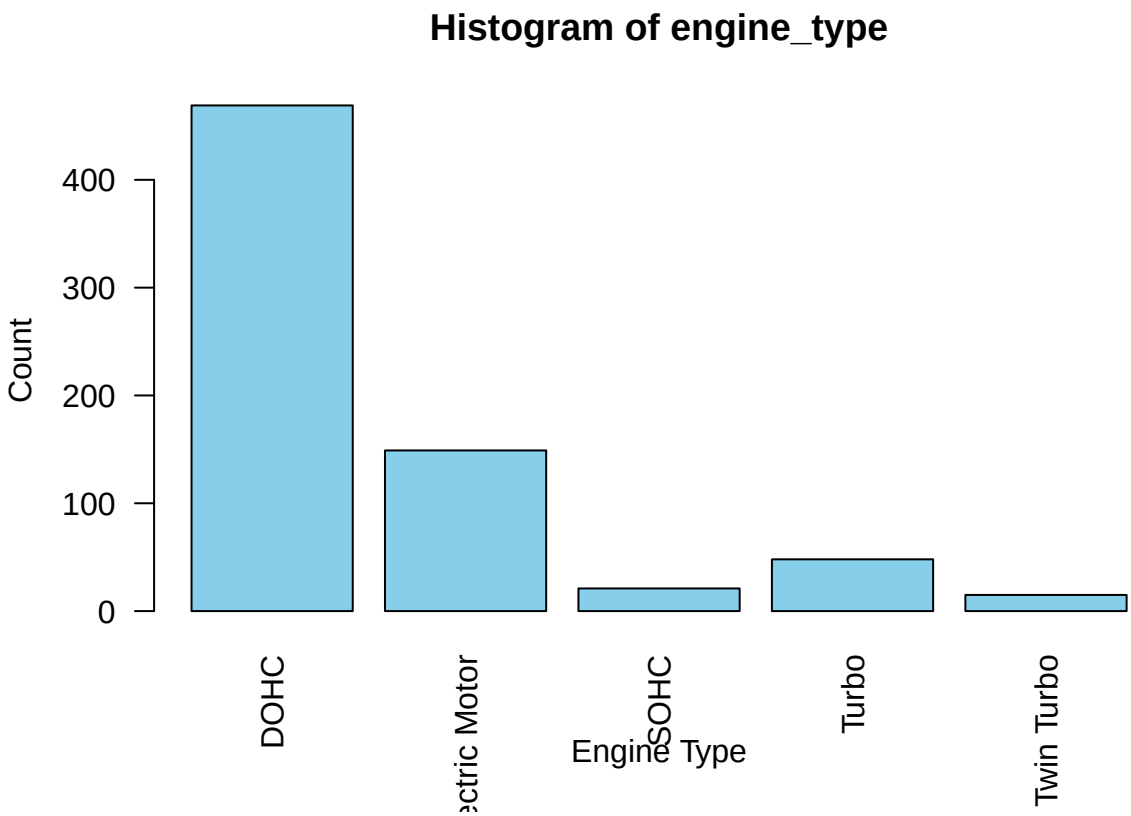
```
## # A tibble: 3 x 4
##   accident                                  medianprice averageprice count
##   <chr>                                           <dbl>        <dbl> <int>
## 1 ""                                              36500        50788.   113
## 2 "At least 1 accident or damage reported"        20900        28832.   986
## 3 "None reported"                                 35668.       49638.  2910
```

The NA/Empty values for accident exhibit very similar properties to the None reported category, with median price and average price being pretty similar, not to mention a very small percentage of data is represented by this value. Therefore, we replace and combine these observations with the None reported category. Because accident only has 2 unique values now, no accidents and 1 or more accidents, we changed it to 1,0 to be useful for models.

```
## # A tibble: 2 x 4
##   clean_title medianprice averageprice count
##   <chr>             <dbl>        <dbl> <int>
## 1 ""                42996.       60695.   596
## 2 "Yes"             29000        41734.  3413
```

The NA values for clean_title clearly have a significantly higher median price and will be treated as a separate category. We apply similar reasoning from accident to clean_title. Since there is only “Yes” and NA, we treat all the yes’s to 1 and all the NA values to 0.

```
## [1] 1 0
```



#engine type

```
## # A tibble: 6 x 4
##   engine_type    medianprice averageprice count
##   <chr>                <dbl>        <dbl> <int>
## 1 DOHC                39244        77951.   469
## 2 Electric Motor      47800        54439.   149
## 3 SOHC                38998        38676.    21
## 4 Turbo               49940.       51767.    48
## 5 Twin Turbo          85998        89258.    15
## 6 <NA>                28250        39101.  3307
```

#Removing Outliers We remove outliers with 1.5*IQR value.

```
## [1] "Number of outliers:  244 and average price of these cars:  214826.76"
```

```
##    model_year      mileage        fuel_type         transmission
##  Min.   :1992   Min.   :   100   Length:3765        Length:3765
##  1st Qu.:2012   1st Qu.: 26600   Class :character   Class :character
##  Median :2017   Median : 57237   Mode  :character   Mode  :character
##  Mean   :2015   Mean   : 68075
##  3rd Qu.:2020   3rd Qu.: 97000
##  Max.   :2024   Max.   :405000
##    ext_col            int_col            accident       clean_title
##  Length:3765        Length:3765        Min.   :0.0000   Min.   :0.0000
##  Class :character   Class :character   1st Qu.:0.0000   1st Qu.:1.0000
##  Mode  :character   Mode  :character   Median :0.0000   Median :1.0000
```

```
##                                      Mean   :0.2595   Mean   :0.8608
##                                      3rd Qu.:1.0000   3rd Qu.:1.0000
##                                      Max.   :1.0000   Max.   :1.0000
##      price         horsepower      displacement    cylinders
##  Min.   : 2000   Min.   :  70.0   Min.   :0.650   Length:3765
##  1st Qu.:16500   1st Qu.: 263.0   1st Qu.:2.500   Class :character
##  Median :29600   Median : 310.0   Median :3.500   Mode  :character
##  Mean   :33518   Mean   : 320.9   Mean   :3.648
##  3rd Qu.:45500   3rd Qu.: 375.0   3rd Qu.:4.400
##  Max.   :99000   Max.   :1020.0   Max.   :8.300
##  engine_type
##  Length:3765
##  Class :character
##  Mode  :character
##
##
##
```

#turning each categorial column into a factor type

#one hot encoding Some models will require one hot encoding. For these models, we create a new dataset and apply this one hot encoding

#Final Summary Statistics

```
## [1] 3765   46
```

```
##    model_year      mileage       fuel_type.Diesel  fuel_type.Electric
##  Min.   :1992   Min.   :   100   Min.   :0.00000   Min.   :0.00000
##  1st Qu.:2012   1st Qu.: 26600   1st Qu.:0.00000   1st Qu.:0.00000
##  Median :2017   Median : 57237   Median :0.00000   Median :0.00000
##  Mean   :2015   Mean   : 68075   Mean   :0.02895   Mean   :0.06135
##  3rd Qu.:2020   3rd Qu.: 97000   3rd Qu.:0.00000   3rd Qu.:0.00000
##  Max.   :2024   Max.   :405000   Max.   :1.00000   Max.   :1.00000
##  fuel_type.Flex Fuel fuel_type.Gasoline fuel_type.Hybrid   fuel_type.NA
##  Min.   :0.000       Min.   :0.0000     Min.   :0.00000   Min.   :0.0000
##  1st Qu.:0.000       1st Qu.:0.0000     1st Qu.:0.00000   1st Qu.:0.0000
##  Median :0.000       Median :1.0000     Median :0.00000   Median :0.0000
##  Mean   :0.034       Mean   :0.6887     Mean   :0.00425   Mean   :0.1737
##  3rd Qu.:0.000       3rd Qu.:1.0000     3rd Qu.:0.00000   3rd Qu.:0.0000
##  Max.   :1.000       Max.   :1.0000     Max.   :1.00000   Max.   :1.0000
##  fuel_type.Plug-In Electric/Gas transmission.6-Speed A/T
##  Min.   :0.00000                Min.   :0.00000
##  1st Qu.:0.00000                1st Qu.:0.00000
##  Median :0.00000                Median :0.00000
##  Mean   :0.00903                Mean   :0.09535
##  3rd Qu.:0.00000                3rd Qu.:0.00000
##  Max.   :1.00000                Max.   :1.00000
##  transmission.6-Speed M/T transmission.7-Speed A/T transmission.8-Speed A/T
##  Min.   :0.00000          Min.   :0.00000          Min.   :0.00000
##  1st Qu.:0.00000          1st Qu.:0.00000          1st Qu.:0.00000
##  Median :0.00000          Median :0.00000          Median :0.00000
##  Mean   :0.06348          Mean   :0.05206          Mean   :0.09854
##  3rd Qu.:0.00000          3rd Qu.:0.00000          3rd Qu.:0.00000
```

```
##  Max.   :1.00000          Max.   :1.00000          Max.   :1.00000
##  transmission.A/T transmission.Automatic transmission.Other
##  Min.   :0.0000   Min.   :0.00000        Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.00000        1st Qu.:0.0000
##  Median :0.0000   Median :0.00000        Median :0.0000
##  Mean   :0.2667   Mean   :0.05657        Mean   :0.2709
##  3rd Qu.:1.0000   3rd Qu.:0.00000        3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :1.00000        Max.   :1.0000
##  transmission.Transmission w/Dual Shift Mode ext_col.Black   ext_col.Brown
##  Min.   :0.00000                             Min.   :0.000   Min.   :0.00000
##  1st Qu.:0.00000                             1st Qu.:0.000   1st Qu.:0.00000
##  Median :0.00000                             Median :0.000   Median :0.00000
##  Mean   :0.09641                             Mean   :0.255   Mean   :0.02125
##  3rd Qu.:0.00000                             3rd Qu.:1.000   3rd Qu.:0.00000
##  Max.   :1.00000                             Max.   :1.000   Max.   :1.00000
##   ext_col.Gold      ext_col.Gray    ext_col.Other    ext_col.White
##  Min.   :0.00000   Min.   :0.0000   Min.   :0.0000   Min.   :0.000
##  1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.000
##  Median :0.00000   Median :0.0000   Median :0.0000   Median :0.000
##  Mean   :0.01116   Mean   :0.2653   Mean   :0.2133   Mean   :0.234
##  3rd Qu.:0.00000   3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:0.000
##  Max.   :1.00000   Max.   :1.0000   Max.   :1.0000   Max.   :1.000
##  int_col.Beige/Ivory int_col.Black     int_col.Gray    int_col.Other
##  Min.   :0.0000      Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000      1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.0000      Median :1.0000   Median :0.0000   Median :0.0000
##  Mean   :0.1392      Mean   :0.5214   Mean   :0.1246   Mean   :0.2149
##  3rd Qu.:0.0000      3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:0.0000
##  Max.   :1.0000      Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##     accident       clean_title         price         horsepower
##  Min.   :0.0000   Min.   :0.0000   Min.   : 2000   Min.   :  70.0
##  1st Qu.:0.0000   1st Qu.:1.0000   1st Qu.:16500   1st Qu.: 263.0
##  Median :0.0000   Median :1.0000   Median :29600   Median : 310.0
##  Mean   :0.2595   Mean   :0.8608   Mean   :33518   Mean   : 320.9
##  3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:45500   3rd Qu.: 375.0
##  Max.   :1.0000   Max.   :1.0000   Max.   :99000   Max.   :1020.0
##   displacement   cylinders.10 Cylinder cylinders.12 Cylinder
##  Min.   :0.650   Min.   :0.000000      Min.   :0.000000
##  1st Qu.:2.500   1st Qu.:0.000000      1st Qu.:0.000000
##  Median :3.500   Median :0.000000      Median :0.000000
##  Mean   :3.648   Mean   :0.002922      Mean   :0.005578
##  3rd Qu.:4.400   3rd Qu.:0.000000      3rd Qu.:0.000000
##  Max.   :8.300   Max.   :1.000000      Max.   :1.000000
##  cylinders.3 Cylinder cylinders.4 Cylinder cylinders.5 Cylinder
##  Min.   :0.000000     Min.   :0.0000       Min.   :0.000000
##  1st Qu.:0.000000     1st Qu.:0.0000       1st Qu.:0.000000
##  Median :0.000000     Median :0.0000       Median :0.000000
##  Mean   :0.003453     Mean   :0.1958       Mean   :0.005312
##  3rd Qu.:0.000000     3rd Qu.:0.0000       3rd Qu.:0.000000
##  Max.   :1.000000     Max.   :1.0000       Max.   :1.000000
##  cylinders.6 Cylinder cylinders.8 Cylinder  cylinders.NA    engine_type.DOHC
##  Min.   :0.0000       Min.   :0.000        Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000       1st Qu.:0.000        1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.0000       Median :0.000        Median :0.0000   Median :0.0000
```

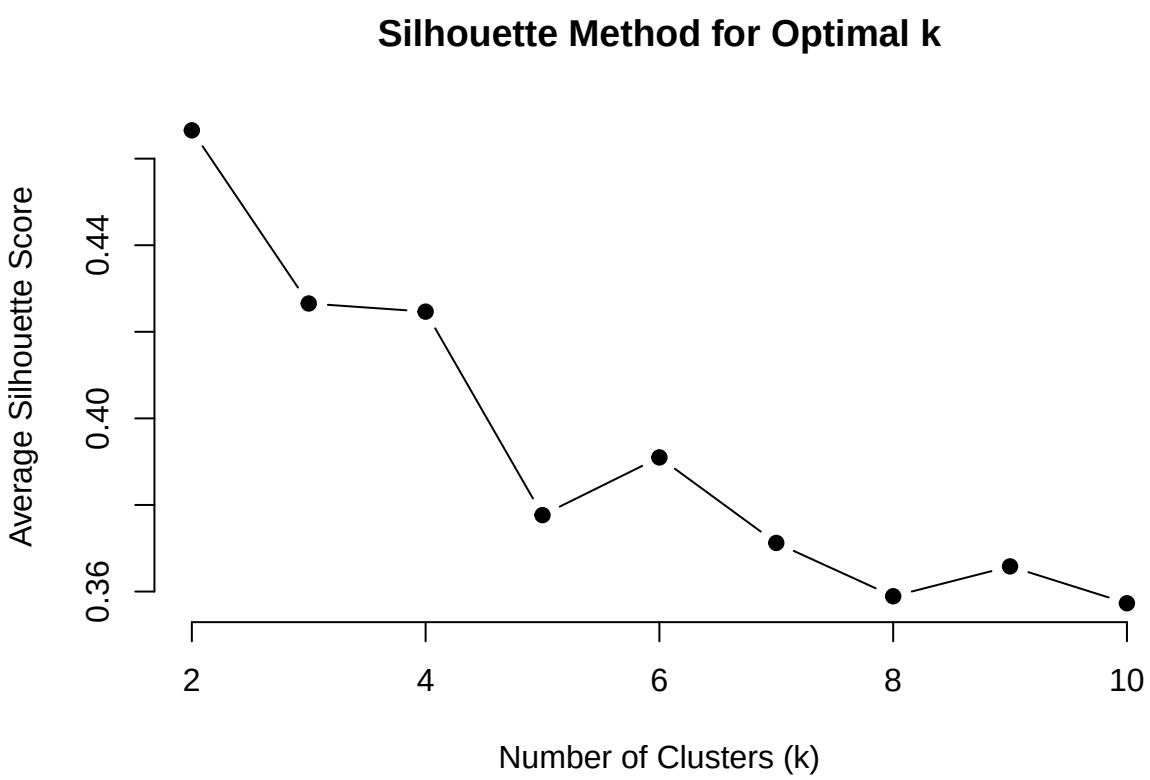
```
##  Mean   :0.3118       Mean   :0.251        Mean   :0.2242   Mean   :0.1039
##  3rd Qu.:1.0000       3rd Qu.:1.000        3rd Qu.:0.0000   3rd Qu.:0.0000
##  Max.   :1.0000       Max.   :1.000        Max.   :1.0000   Max.   :1.0000
##  engine_type.Electric Motor engine_type.NA   engine_type.SOHC
##  Min.   :0.00000            Min.   :0.0000   Min.   :0.000000
##  1st Qu.:0.00000            1st Qu.:1.0000   1st Qu.:0.000000
##  Median :0.00000            Median :1.0000   Median :0.000000
##  Mean   :0.03825            Mean   :0.8369   Mean   :0.005578
##  3rd Qu.:0.00000            3rd Qu.:1.0000   3rd Qu.:0.000000
##  Max.   :1.00000            Max.   :1.0000   Max.   :1.000000
##  engine_type.Turbo engine_type.Twin Turbo
##  Min.   :0.00000   Min.   :0.000000
##  1st Qu.:0.00000   1st Qu.:0.000000
##  Median :0.00000   Median :0.000000
##  Mean   :0.01275   Mean   :0.002656
##  3rd Qu.:0.00000   3rd Qu.:0.000000
##  Max.   :1.00000   Max.   :1.000000
```

Unsupervised Learning

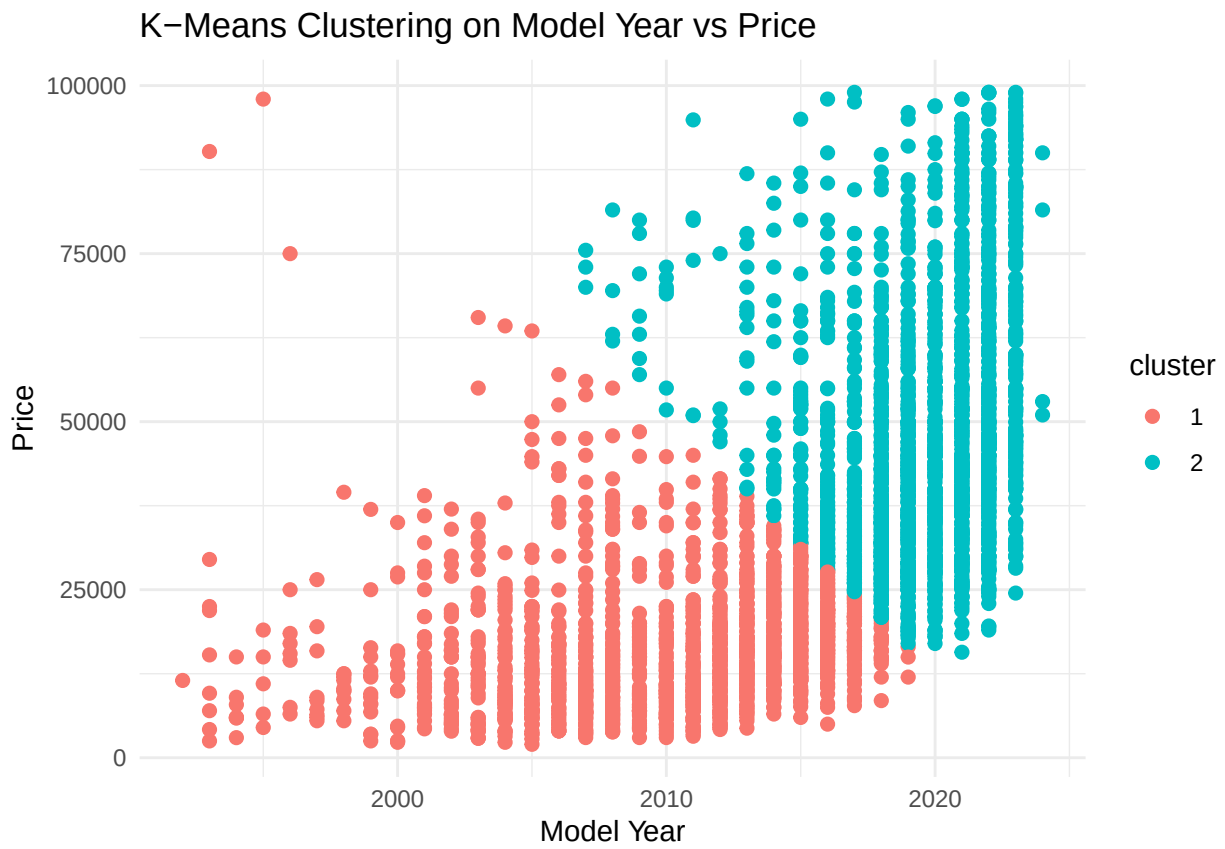
Apply at least three clustering algorithms to the processed dataset. Determine the appropriate number of clusters and discuss the interpretability of these clusters. Do they hold any meaningful distinctions? Examine whether the clustering results are associated with your outcome variable.

1. KMeans Clustering

We decided to use kmeans to examine the relation between model_year and price, as we noticed a similar examination in one of the papers while doing the literature review. Because K-means utilizes distance metrics, we scale the data before clustering.



We decided to use the Silhouette Method to determine the optimal number of clusters. This method essentially uses distance measures calculating how close clusters are to themselves and how far away they are to other clusters to judge the optimal number of clusters. In this case, 2 has the highest average silhouette score so we will use k=2.

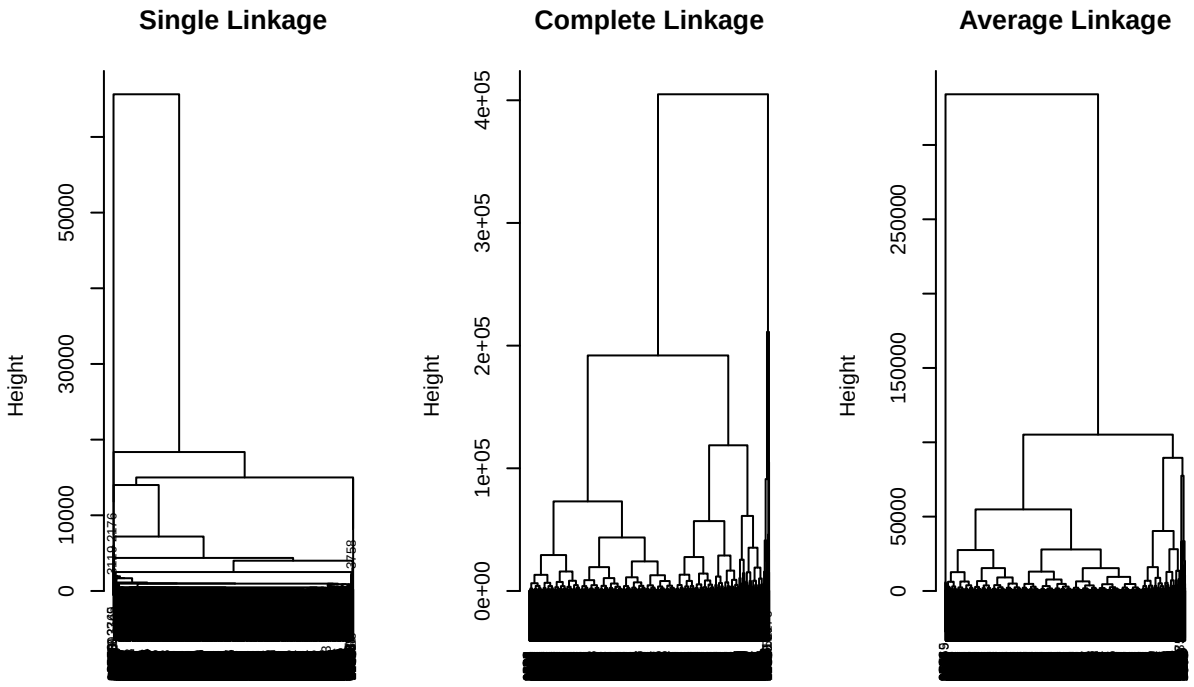


There seems to be a pretty solid relationship between a more recent model_year and higher price. Although the 2 clusters seem to be mostly dominated by model year, it's clear that the average price of cluster 2 is higher than cluster 1.

2. Hierarchical Clustering

Next, we will try hierarchical clustering with three different linkage methods(single, complete, and average) using euclidean distance. Hierarchical Clustering begins with each data point starting as its own cluster. The goal is to progressively group them together until there is only one group. The process involves choosing the closest two groups, calculated through a specific distance metric.

Removing non-numeric features as clustering requires numeric features. Also, removed the target feature price.




```
##
##    1    2
## 3674   91
```

```
## # A tibble: 2 x 7
##   cluster avg_price avg_model_year avg_accident avg_mileage avg_horsepower count
##   <fct>       <dbl>          <dbl>        <dbl>       <dbl>          <dbl> <int>
## 1 1          34086.          2015.        0.254      64111.           322.  3674
## 2 2          10588.          2007.        0.484     228100.           267.    91
```

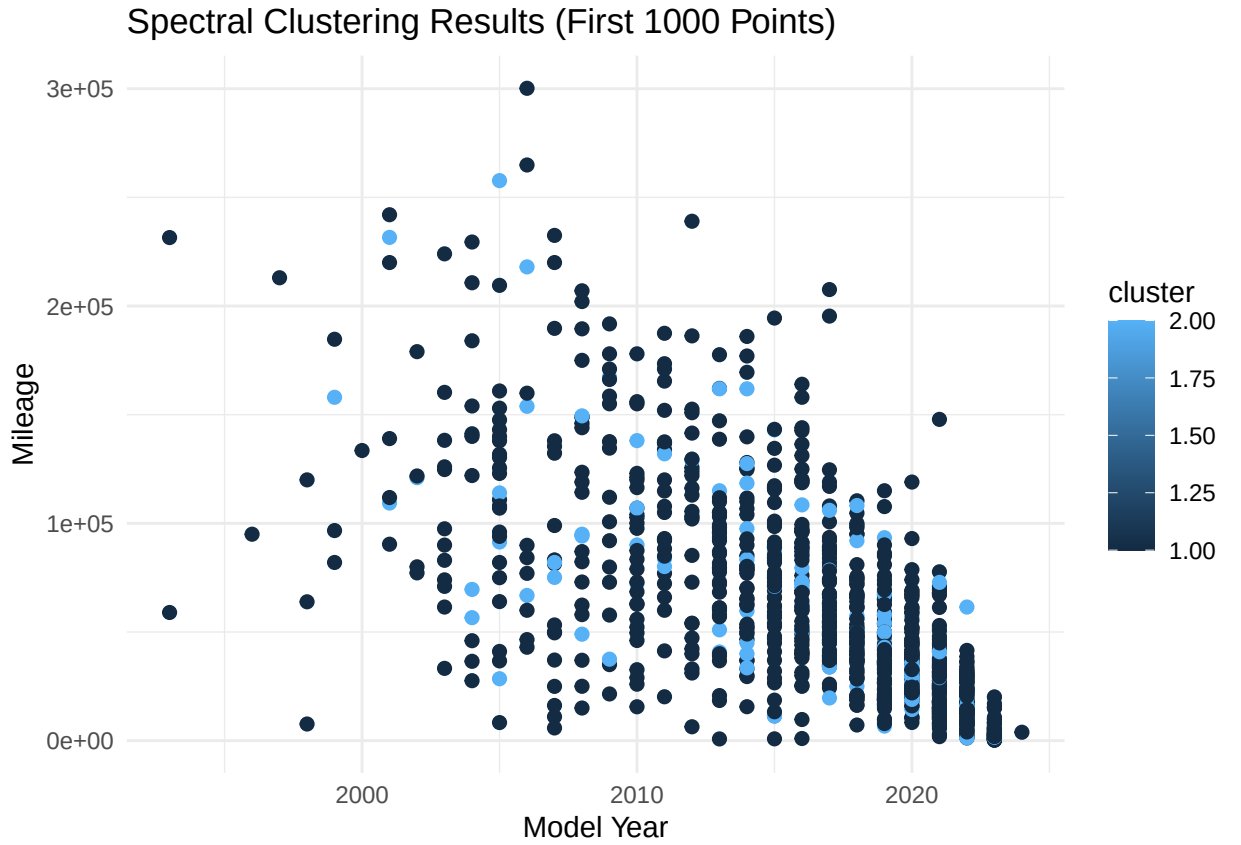
There are a lot of correlations here that make sense between the 2 clusters. Cluster 1, with a more recent avg_model_year, also has a lower avg_mileage and a lower avg_accident rate, probably because the car has been driven for less time, this cluster also has a much higher avg_price in comparison to cluster 2. The data isn't distributed very well however as a vast majority of the points sit in cluster 1, perhaps suggesting that hierarchical clustering isn't suitable for this dataset.

3. Spectral Clustering

Finally, we will try spectral clustering, which aims to group observations based on their proximity information. This method involves 2 main steps, the first being using the eigenvalues of a similarity matrix to perform dimension reduction, followed by applying a clustering algorithm like K-means.

```
## # A tibble: 2 x 6
##   cluster avg_model_year avg_mileage avg_accident avg_horsepower count
```

```
##     <int>          <dbl>       <dbl>        <dbl>          <dbl> <int>
## 1       1          2016.      60899.        0.246          325.   859
## 2       2          2016.      60429.        0.220          329.   141
```



Similar to Cluster 1, with a more recent avg_model_year, also has a lower avg_mileage and a lower avg_accident rate, this cluster also has a much higher avg_price in comparison to cluster 2. The distribution of data points between the 2 clusters seem to be more even in comparison to heirarchicaly clustering, meaning that perhaps spectral clustering is more suitable for this dataset.

Prediction Models

For all the supervised models below, we will split the data into training sets for model training and testing sets to evaluate performance and accuracy

```
##   model_year mileage fuel_type.Diesel fuel_type.Electric fuel_type.Flex Fuel
## 1       2013   51000                0                  0                   1
## 2       2021   34742                0                  0                   0
## 3       2022   22372                0                  0                   0
## 4       2015   88900                0                  1                   0
## 5       2021    9835                0                  0                   0
## 6       2016  136397                0                  0                   0
##   fuel_type.Gasoline fuel_type.Hybrid fuel_type.NA
## 1                  0                0           0
## 2                  0                0           1
## 3                  0                0           1
## 4                  0                0           0
```

```
## 5                  0               0           1
## 6                  0               0           1
##   fuel_type.Plug-In Electric/Gas transmission.6-Speed A/T
## 1                             0                       1
## 2                             0                       0
## 3                             0                       0
## 4                             0                       0
## 5                             0                       0
## 6                             0                       0
##   transmission.6-Speed M/T transmission.7-Speed A/T transmission.8-Speed A/T
## 1                        0                       0                       0
## 2                        0                       0                       0
## 3                        0                       0                       0
## 4                        0                       1                       0
## 5                        0                       0                       0
## 6                        0                       0                       0
##   transmission.A/T transmission.Automatic transmission.Other
## 1                0                      0                 0
## 2                0                      0                 1
## 3                0                      1                 0
## 4                0                      0                 0
## 5                0                      0                 1
## 6                0                      0                 1
##   transmission.Transmission w/Dual Shift Mode ext_col.Black ext_col.Brown
## 1                                           0             1             0
## 2                                           0             0             0
## 3                                           0             0             0
## 4                                           0             1             0
## 5                                           0             0             0
## 6                                           0             0             0
##   ext_col.Gold ext_col.Gray ext_col.Other ext_col.White int_col.Beige/Ivory
## 1            0            0             0             0                   0
## 2            0            0             1             0                   0
## 3            0            0             1             0                   0
## 4            0            0             0             0                   0
## 5            0            0             0             1                   0
## 6            0            1             0             0                   0
##   int_col.Black int_col.Gray int_col.Other accident clean_title horsepower
## 1             1            0             0        1           1        300
## 2             0            1             0        1           1        310
## 3             1            0             0        0           0        310
## 4             1            0             0        0           1        354
## 5             1            0             0        0           0        310
## 6             0            0             1        0           0        310
##   displacement cylinders.10 Cylinder cylinders.12 Cylinder cylinders.3 Cylinder
## 1          3.7                     0                     0                    0
## 2          3.8                     0                     0                    0
## 3          3.5                     0                     0                    0
## 4          3.5                     0                     0                    0
## 5          2.0                     0                     0                    0
## 6          3.5                     0                     0                    0
##   cylinders.4 Cylinder cylinders.5 Cylinder cylinders.6 Cylinder
## 1                    0                   0                   1
## 2                    0                   0                   0
```

```
## 3                    0                    0                    0
## 4                    0                    0                    1
## 5                    0                    0                    0
## 6                    0                    0                    0
##   cylinders.8 Cylinder cylinders.NA engine_type.DOHC engine_type.Electric Motor
## 1                    0            0                0                           0
## 2                    0            1                1                           0
## 3                    0            1                1                           0
## 4                    0            0                0                           0
## 5                    0            1                1                           0
## 6                    0            1                0                           0
##   engine_type.NA engine_type.SOHC engine_type.Turbo engine_type.Twin Turbo
## 1              1                0                0                        0
## 2              0                0                0                        0
## 3              0                0                0                        0
## 4              1                0                0                        0
## 5              0                0                0                        0
## 6              1                0                0                        0
```

1. Linear Model. There are mainly three possible linear models: Lasso, Ridge, and Elastic Net. We will try all three models and see which one performs the best. Lasso, Ridge, and Elastic Net all benefit from feature scaling because these models involve regularization. which will penalize the size of coefficients of the model to avoid overfitting. All 3 models also involving a tuning parameter, and so we will use k-fold cross validation to find the best parameters. cv.glmnet will automatically scale and center the data as well.

Training our ridge model

```
## [1] 1368.33
```

```
## [1] 12017.06
```

Training our lasso model

```
## [1] 82.02921
```

```
## [1] 11992.87
```

Training our elastic net model

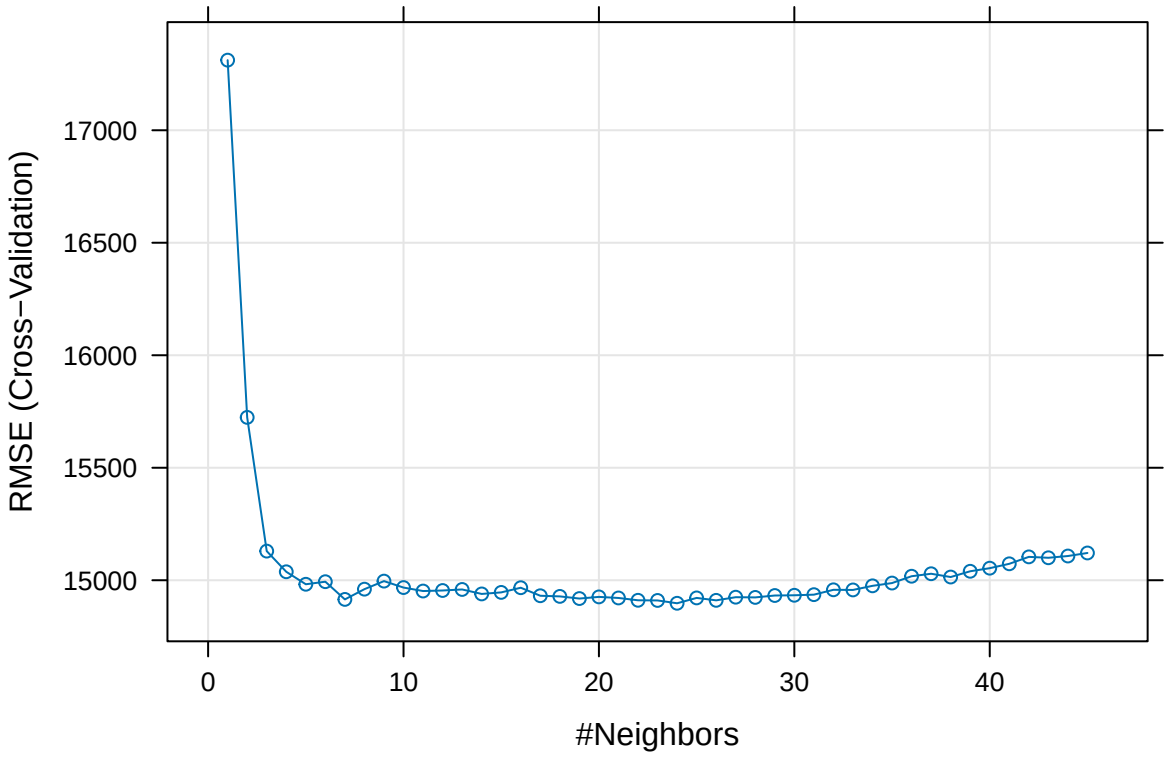
```
## [1] 149.4839
```

```
## [1] 11993.98
```

Out of our 3 linear models, Ridge performed the best, with a RMSE of 12261.19

2. K Nearest Neighbors(KNN) regression works by calculating the k nearest training set data points to the test point and predicting the target value by taking the average of their target values. KNN is sensitive to feature scaling, so we will need to scale the data. The reason behind this is for example, if one feature has ranges from 1-10 and another one has 1-10000, distance calcualtions will be biased and results will suffer as a result. KNN is also sensitive to the choice of k. To find the optimal value of k, we will perform k-fold cross validation.

```
## Number of components to retain: 32
```




```
## [1] "The best value of k based on cross-validation is:  24"
```

```
## [1] "Prediction errort:  39760.6901508748"
```

3. Random Forest
4. SVM? does this count as a linear model
5. Gradient Boosting Regressor

Open-Ended Question/Conclusion

A researcher has reached out and is interested in estimating the original price of the cars in our dataset as if they were brand new.

To solve this problem, we will follow a similar approach by building a machine learning model using the most features that are typically related to depreciation. Additionally, modeling depreciation is usually something that is not linear. A car brand's value might lose a large portion of it's value in the first year and then depreciates more slowly afterward, while another model might hold it's value better in the long run. Also, for example, if a car get's in an accident, suddenly it's price will plummet. Therefore, we will try non-linear models such as random forest and use the following features that we deemed to be especially important for understanding depreciation.

1. Brand. Some brands might hold their value better than others. Economy brands like Ford and Toyota may display a more linear depreciation, while luxary brands like BMW and Mercedes might see a more

steep initial depreciation. Whether or not a brand is a luxary or economy is pretty benefifical, as luxary brands will typically have higher starting prices than economy brands. This is why we decide to include this for calcalitng new prices and decided to omit it in our prediction models above.

2. Age. Age is one of the most fundamental factors in depreciation. Generally, cars will lose value over time since newer models with updated features get released. In out dataset, since we are only given the model_year of when the car was manufactured, we create a new column called "Age" that is simply current_year - model_year + 1. This gives us the number of years that have passed since the car was new.
3. Mileage. Mileage is another fundamental factor in depreciation. It is a indicator of how much the car has been used. Generally, higher mileage correlates with lower value, as more maintenance may be required to keep it healthy and running.
4. Accident History. Accidents will significantly decrease the value of the car, which contributes to depreciation.

5. Clean Title. A clean title indicates that there has been no legal/insurance issues with the car. Similar to accident history, a car without a clean title may depreciate more quickly because of the higher perceived risk.

The task of estimating brand new car prices using only a dataset of used car data can be challenging. The biggest limitating factor is that because the model has never actually seen cars at zero age and zero mileage, it has to infer and extrapolate what the car might have cost when it was first bought, leading to potential inaccuracies. There are also a lot of other external factors that the dataset doesn't capture, such as inflation, competition, technological advancements, and special promotions all have the ability to shift pricing strategies and patterns. For example, a certain used car's price might have been during a time of inflation, which may not align with the pricing logic for the car's original release date.

To avoid model complexity that arises from having to one-hot encoding every single brand and practicality reasons, we will train our model on a subset of the data, mainly used cars that belong to the 7 most common brands in the dataset: Ford, BMW, Mercedes-Benz, Chevrolet, Porsche, Audi, Toyota. This is a good mix of both luxary and economy brands.

```
##               price          brand.Audi           brand.BMW     brand.Chevrolet
##           "numeric"           "numeric"           "numeric"           "numeric"
##          brand.Ford brand.Mercedes-Benz       brand.Porsche        brand.Toyota
##           "numeric"           "numeric"           "numeric"           "numeric"
##             mileage            accident         clean_title                 Age
##           "numeric"           "numeric"           "numeric"           "numeric"
```

lasso model

Let's do the task of selecting three cars from your dataset and estimating their price as if they were new. Let's first select a random toyota car

```
##       brand             model model_year     milage fuel_type
## 1374 Toyota Corolla Hybrid LE       2022 44,459 mi.    Hybrid
##                                                 engine transmission ext_col
## 1374 121.0HP 1.8L 4 Cylinder Engine Gas/Electric Hybrid          A/T  Silver
##      int_col      accident clean_title   price
## 1374    Gray None reported         Yes $22,945
```

```
## [1] "the new price is  44874.8338414634"
```