The Determinants of Price in Used Cars using different GLMs

STAT478: Generalized Linear Model

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Abstract

Cars are a vital element of our daily lives. There are several types of automobiles created by various manufacturers; the customer must then make a selection. When an individual considers purchasing a car, there are various factors that may impact his/her decision on the type of automobile he/she is interested in. The decision that a buyer or driver makes is usually based on the price, safety, and how nice and spacious the automobile is. In the used automobile retail industry, this paper objectively assesses the influence of reference prices on customer purchase choices. Given the growing importance of the used vehicle market in internet auctions, this study adds on existing research on online auction markets to see how mileage and seller attributes influence the price premium on used cars (Richardson.M, 2009). The subject of the paper will be on relatively low-priced homogenous products and auction characteristics, as well as how to fit them into three distinct generic linear models.

Introduction

A car's features might vary greatly dependent on the model and the manufacturer. The three most important considerations for buyers are price, safety, and luxury. All of these factors have an important role in lowering the frequency of accidents. There are several fundamental aspects that must be considered while acquiring a car. Cars include a variety of performance enhancers, amenities, and safety features. Safety should be a top priority while shopping for a vehicle, convenience elements including a door, a luggage compartment, and maintenance are also included. In the short term, assessing the impact of these policies is difficult because of the complexity of the automobile industry (Urban, David, 2001). Automobiles are recognisable, long-lasting, and capable of having a wide range of lifespans. An "improvement" (such as better fuel efficiency) that is required in new car offerings at a high price can create a shift away from new cars and increase the value of older vehicles. The fleet's fuel efficiency may suffer in the near term if older vehicles are much less efficient than newer models. A positive reputation contributes to the establishment of the confidence essential for a transaction to occur. According to economic and marketing theory, a transaction will be effective only if the vendor and buyer have mutual trust. A positive reputation contributes to the establishment of the confidence essential for a transaction to occur. According to economic and marketing theory, a transaction will be effective only if the vendor and buyer have mutual trust. This combination may enable automobile owners to keep their vehicles' resale prices higher (Zhu.R, 2008). It's critical to understand the scale of the used-car industry when attempting to assess the issue's economic significance." Used-vehicle markets accounted for roughly 12.5 percent of overall retail sales in the United States in 1999, with $361 billion in sales. The number of used-vehicle sales topped the number of new-vehicle transactions by about three-to-one in terms of unit volume." I With the country's challenging economic conditions, the number of used car sales as a percentage of total automobile sales is projected to rise, making this an increasingly critical problem (Richardson.M, 2009).

Edmunds.com Inc. (stylized as edmunds) is an American online automotive resource that includes expert automobile reviews based on testing at the company's own facilities. Prices for new and used automobiles, dealer and inventory listings, a database of national and regional incentives and rebates, vehicle test drive evaluations, and tips and guidance on all areas of car purchases and ownership are all available on Edmunds.com. Edmunds.com's "True Market Value" pricing tools, which were established in 2000, give statistics. The Edmunds.com True Market Value New Vehicle Calculator shows the projected average price that people pay for new cars. Edmunds.com's True Market Value Used Vehicle Appraiser analyses actual transaction values for used automobiles purchased and sold by dealers and private individuals.

Edmunds.com has a feature over a million used cars for sale and no two vehicles have the same history, mileage, or condition, determining a used car's worth is more complicated. Prices for used automobiles may be found on a variety of websites that categorise them based on whether the transaction is with a dealer, a private party, a certified pre-owned vehicle, or a trade-in vehicle (Meghan R, 2019). Every automobile Edmunds.com offers is ranked from "Great Deals" to "Overpriced." TrueCar also utilises its own algorithms to provide a price label to automobiles that ranges from "Great Price" to "High Price" (Richardson.M, 2009). The price of a car isn't the only factor to consider when making a purchase. For most purchasers, a trade-in and the cost of financing are the two components of the deal. If you negotiate the price of the new car and the trade-in separately, you'll likely come out ahead. According to DeLorenzo, the pandemic prompted yet another change in the automotive industry: when automakers were forced to decrease the quantity of vehicles for sale last year, they realised that focusing on margins rather than volume would allow them to earn a reasonable profit. As a result, lower output is expected to continue in the near future. "On average, car costs will climb, and buyers will have a harder time finding what they want." Due to rising fuel prices, fuel economy is also of prime importance. Unfortunately, in practice, most people do not know exactly how much fuel their car consumes for each km driven.

This research expands on online auction marketplaces to evaluate how mileage and seller characteristics impact the price premium on used automobiles, given the increasing significance of the used car market in internet auctions. The paper will be focused on relatively low-priced homogeneous items and auction features; and how to fit them on three different general linear models.

Methodology

This study is perused at 5% significance. The data used is used car data taken from an Edmunds.com for buying and selling used cars, namely. From the online site sales data taken are sales of used cars in the United States of America in the period of 1968 - 2021 with 50 063 cars.

3.1. Variable identification and measurement

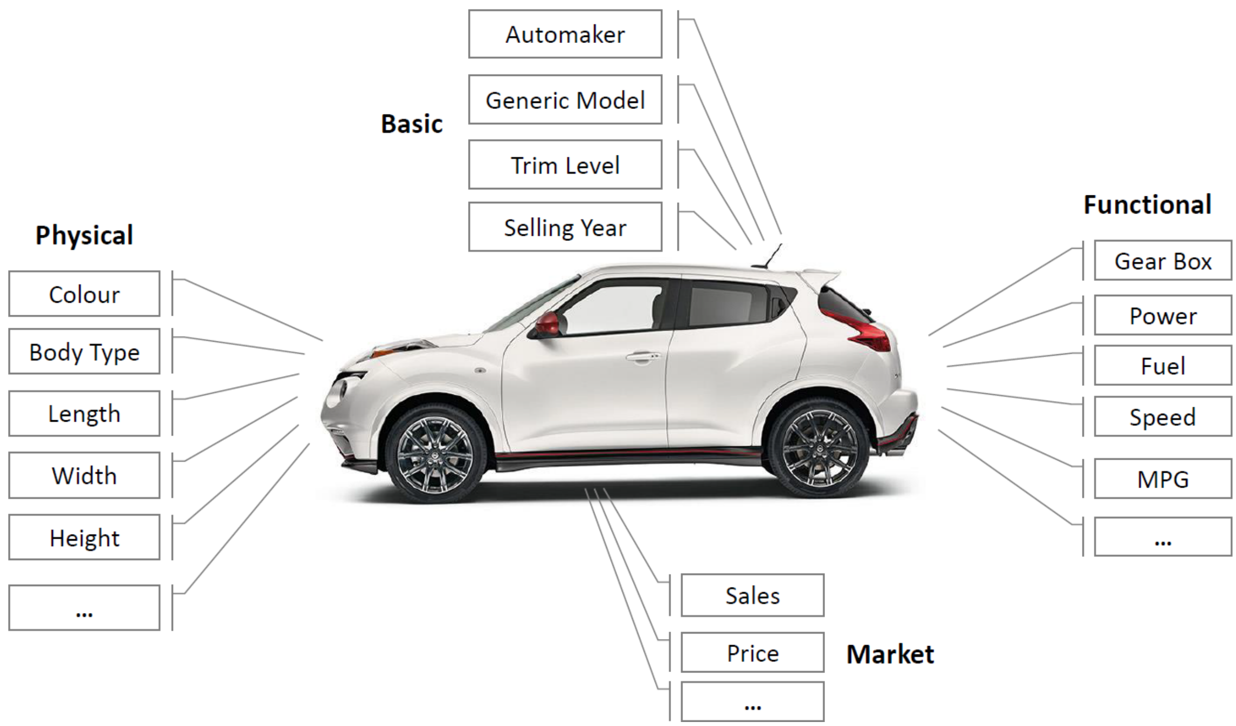


Figure 1 Data features collected

In this study, the variables used are:

- Car Age ($X1$) = Age of cars measured in years.
- Car Mileage ($X2$) = Mileage cars measured in km.
- Car Color ($X3$) = The color of each car.
- Car Transmission ($X4$) = Transmission of cars which are manual or automatic.
- Car Type ($X5$) = Type of car.
- City ($X6$) = Where to sell used cars
- Car Seats(X7) =Number of seats in car.
- Car doors (X8) = Number of car doors.
- Fuel type(X9) = Type of fuel in Car.
- Car Selling Price (Y) = Selling Price of cars in the period of 1968 - 2021.

3.2. Data Collection

This model will be based on quantitative and categorical data. Edmunds API was utilised as the source. That's what I used to obtain information from the website. With the help of these sources, data about the price of a car—both new and used—as well as its age, mileage, manufacture, condition, miles per gallon, safety ratings, and hybrid technology will be obtained. These variables will enable a generalized linear model to be performed and an equation to be calculated.

3.3. Statistical Methods

A generalised linear model (GLM) is a versatile version of conventional linear regression used in statistics. By enabling the linear model to be linked to the response variable through a link function and allowing the size of the variance of each measurement to be a function of its predicted value, the GLM generalises linear regression. We employed an inverse Gaussian regression model which is a type of generalised linear model (GLM) with a continuous, positively skewed, and not independently identically distributed mean response. The iterative reweighted least square approach is used to estimate the unknown regression coefficient of the IGRM using the standard maximum likelihood estimator (Feigl.P, 1965).

The majority of forecasts are based on regression modelling, which necessitates that the fitted model be acceptable for the data. One of the most prevalent regression model assumptions is that the dataset contains no outlier observations. However, in real-world applications, data frequently contain outliers, which have a significant impact on parameter estimate and inference. The GLM for the Gamma distribution is widely used in modelling continuous, non-negative, and positive-skewed data, such as insurance claims and survival data. GLM model selection, on the other hand, is based on AIC/BIC criterion, which is computationally inefficient for even a small number of variables.

The models we will be exploring how best to fit the data using a generalised linear model (GLM) on the car data that we found on the Edmunds API. We will explore the data with use of an inverse gaussian GLM, gamma GLM and a Tweedie GLM. We will employ diagnostic approaches to discover the best model for the analysis, such as AIC, Pseudo-R2, and dispersion to find the optimal model. Variables that take positive and continuous values often measure the amount of some physical quantity that is always present like the used car data. The two most common GLMs for this type of data are based on the gamma and inverse Gaussian distributions. Tweedie EDMs are distributions that generalize many of the EDMs already seen (the normal, Poisson, gamma and inverse Gaussian distributions are special cases) and include other distributions also (Dunn, P. K, 2008). The prototype response distributions for extended linear models are exponential dispersion models, which are linear exponential families with a dispersion parameter. The exponential dispersion models with power mean-variance connections belong to the Tweedie family. The Tweedie family includes the normal, Poisson, gamma, and inverse Gaussian distributions. Tweedie distributions do not have density functions that can be stated in closed form, except for these particular situations. Infinite summations produced from series expansions can be used to depict the densities instead (Gilchrist R, 1999).

3.4. Data analysis

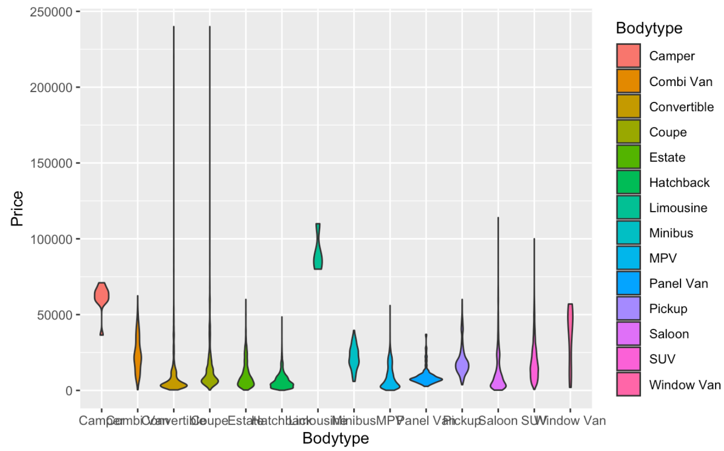


Figure 2 Violin Plot of Bodytype and price

Figure 2 of the violin plots shows that the majority of the automobiles, based on body type, are priced around $100,000 USD. The convertible and coupe also push the pricing point to its limit, since they both have the highest values. A fascinating statistic is that the majority of the values in the Camper body type are concentrated in a single price bracket.

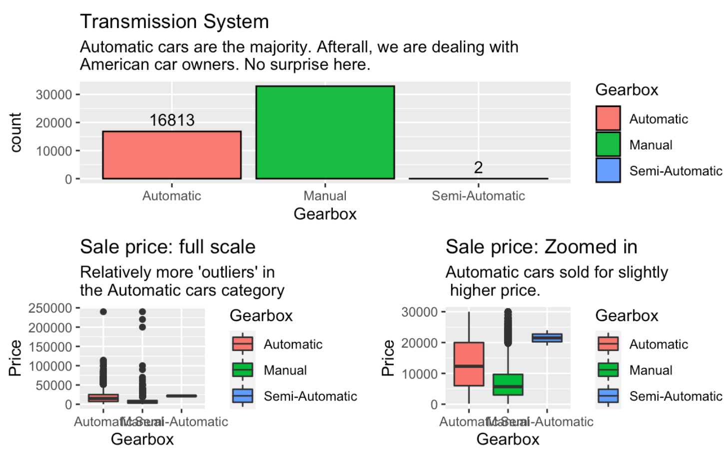


Figure 3 Transmission plot

We can see in figure 3 of the transmission plot that in the data we see the manual vehicles have a larger number than automatic and semi-automatic, but automatic vehicles considerably cost more.

The data analysis used in this study is generalised linear model and processed using R software in RStudio Build 351. This model was chosen to determine how much influence the independent variables have on the dependent variables either partially or together. The data used to find linear equations have independent variables and dependent variables. The independent variables are age, distance, color, transmission, type, doors, seats and mileage. While the dependent variable is the selling price of used cars. Three different models were used to predict the price: Inverse Gaussian GLM, Gamma GLM and Tweedie GLM.

Results

Inverse Gaussian model

```
glm(formula = Price ~ Fuel_type + Runned_Miles + Door_num + Seat_num +
    Bodytype + Reg_year, family = inverse.gaussian(link = "log"),
    data = d, maxit = 1000)

Deviance Residuals:
      Min         1Q     Median         3Q        Max
-0.097958  -0.003726  -0.001212   0.001488   0.124007

Coefficients:
                                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                              -2.111e+02  2.207e+00 -95.659  < 2e-16 ***
Fuel_typeDiesel                           9.107e-01  1.606e-01   5.672 1.42e-08 ***
Fuel_typeDiesel Hybrid                    1.025e+00  3.724e-01   2.751  0.00594 **
Fuel_typeElectric                         1.800e+00  1.883e+00   0.956  0.33915
Fuel_typeHybrid  Diesel/Electric          1.169e+00  1.356e+00   0.862  0.38891
Fuel_typeHybrid  Diesel/Electric Plug-in  1.263e+00  2.968e-01   4.256 2.08e-05 ***
Fuel_typeHybrid  Petrol/Electric          1.422e+00  1.643e-01   8.654  < 2e-16 ***
Fuel_typeHybrid  Petrol/Electric Plug-in  1.472e+00  2.097e-01   7.018 2.29e-12 ***
Fuel_typePetrol                           7.247e-01  1.606e-01   4.514 6.38e-06 ***
Fuel_typePetrol Ethanol                   6.783e-01  3.381e-01   2.006  0.04484 *
Fuel_typePetrol Hybrid                    1.013e+00  1.051e+00   0.964  0.33505
Fuel_typePetrol Plug-in Hybrid            1.068e+00  2.686e-01   3.975 7.04e-05 ***
Runned_Miles                             -7.118e-06  1.088e-07 -65.410  < 2e-16 ***
Door_num                                  3.099e-02  4.765e-03   6.503 7.92e-11 ***
Seat_num                                  9.304e-02  5.905e-03  15.756  < 2e-16 ***
BodytypeCombi Van                        -4.384e-01  7.312e-01  -0.600  0.54881
BodytypeConvertible                      -2.086e-01  7.250e-01  -0.288  0.77357
BodytypeCoupe                            -3.068e-01  7.250e-01  -0.423  0.67216
BodytypeEstate                           -9.548e-01  7.249e-01  -1.317  0.18777
BodytypeHatchback                        -1.345e+00  7.248e-01  -1.856  0.06344 .
BodytypeLimousine                         2.206e+00  1.692e+00   1.304  0.19228
BodytypeMinibus                          -2.575e-01  7.434e-01  -0.346  0.72907
BodytypeMPV                              -1.410e+00  7.249e-01  -1.946  0.05169 .
BodytypePanel Van                        -6.120e-01  7.282e-01  -0.840  0.40064
BodytypePickup                           -3.059e-01  7.270e-01  -0.421  0.67389
BodytypeSaloon                           -7.525e-01  7.249e-01  -1.038  0.29919
BodytypeSUV                              -4.759e-01  7.249e-01  -0.657  0.51144
BodytypeWindow Van                       -3.901e-01  7.761e-01  -0.503  0.61520
Reg_year                                  1.093e-01  1.032e-03 105.957  < 2e-16 ***
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for inverse.gaussian family taken to be 0.0001036823)

    Null deviance: 7.0777  on 49756  degrees of freedom
Residual deviance: 2.3133  on 49728  degrees of freedom
AIC: 968467

Number of Fisher Scoring iterations: 15
```

Figure 4 GLM: Inverse Gaussian

With a log link, the general linear model was utilised with an inverse gaussian as the distribution and performed to ascertain the effects of age, bodytype, door number, seat number, and fuel type on Price of car. The model explained 67.0 percent of the price variation (Nagelkerke R2). In comparison to the other cars, limousines (OR=9.08) had the biggest net increase for every dollar rise in price. Because the bodytypes were not statistically significant, they were not linked to price. Amongst the fueltype we found that electric vehicles have the highest per unit increase in price. We discovered a negative relationship between mileage and price. The GLM result shows an AIC of 968467, a model dispersion of 0.0001, and a pseudo-R2 of 0.67 in the inverse gaussian model.

Gamma Model

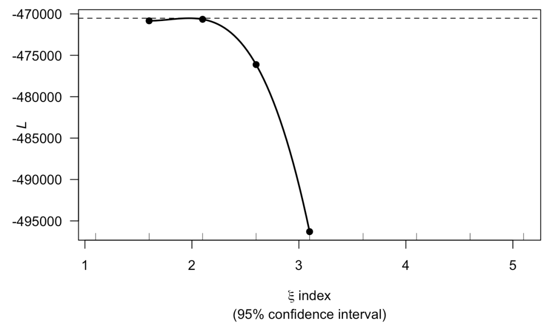
```
Call:
glm(formula = Price ~ Fuel_type + Runned_Miles + Door_num + Seat_num +
    Bodytype + Reg_year, family = Gamma(link = log), data = d)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4186  -0.3124  -0.0922   0.1573  10.0154

Coefficients:
                                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                              -1.973e+02  2.170e+00 -90.929  < 2e-16 ***
Fuel_typeDiesel                           9.200e-01  3.273e-01   2.811 0.004937 **
Fuel_typeDiesel Hybrid                    1.118e+00  3.437e-01   3.252 0.001148 **
Fuel_typeElectric                         1.857e+00  7.316e-01   2.538 0.011155 *
Fuel_typeHybrid  Diesel/Electric          1.134e+00  7.316e-01   1.550 0.121188
Fuel_typeHybrid  Diesel/Electric Plug-in  1.254e+00  3.467e-01   3.617 0.000298 ***
Fuel_typeHybrid  Petrol/Electric          1.309e+00  3.281e-01   3.989 6.63e-05 ***
Fuel_typeHybrid  Petrol/Electric Plug-in  1.594e+00  3.304e-01   4.824 1.41e-06 ***
Fuel_typePetrol                           7.331e-01  3.273e-01   2.240 0.025095 *
Fuel_typePetrol Ethanol                   6.723e-01  4.628e-01   1.453 0.146334
Fuel_typePetrol Hybrid                    1.095e+00  4.628e-01   2.365 0.018014 *
Fuel_typePetrol Plug-in Hybrid            1.169e+00  3.349e-01   3.491 0.000481 ***
Runned_Miles                             -6.948e-06  1.130e-07 -61.466  < 2e-16 ***
Door_num                                  3.082e-02  4.909e-03   6.278 3.45e-10 ***
Seat_num                                  1.016e-01  5.033e-03  20.195  < 2e-16 ***
BodytypeCombi Van                        -5.316e-01  1.942e-01  -2.738 0.006191 **
BodytypeConvertible                      -3.680e-01  1.899e-01  -1.938 0.052613 .
BodytypeCoupe                            -5.372e-01  1.894e-01  -2.837 0.004561 **
BodytypeEstate                           -1.005e+00  1.893e-01  -5.307 1.12e-07 ***
BodytypeHatchback                        -1.407e+00  1.891e-01  -7.438 1.04e-13 ***
BodytypeLimousine                         2.092e+00  3.780e-01   5.535 3.12e-08 ***
BodytypeMinibus                          -7.841e-01  2.019e-01  -3.884 0.000103 ***
BodytypeMPV                              -1.391e+00  1.896e-01  -7.335 2.24e-13 ***
BodytypePanel Van                        -6.802e-01  1.958e-01  -3.474 0.000514 ***
BodytypePickup                           -5.391e-01  1.910e-01  -2.822 0.004771 **
BodytypeSaloon                           -8.345e-01  1.893e-01  -4.408 1.05e-05 ***
BodytypeSUV                              -6.400e-01  1.892e-01  -3.383 0.000718 ***
BodytypeWindow Van                       -2.732e-01  2.258e-01  -1.210 0.226294
Reg_year                                  1.025e-01  1.061e-03  96.602  < 2e-16 ***
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Gamma family taken to be 0.4280841)

    Null deviance: 42441.9  on 49756  degrees of freedom
Residual deviance:  9083.3  on 49728  degrees of freedom
AIC: 940547

Number of Fisher Scoring iterations: 8
```

Figure 5 GLM: Gamma

The generic linear model was utilised, using a gamma distribution with a log link as the distribution. More Bodytype dummy variables became significant in the model when compared to the inverse gaussian model; we can also detect a shift in the model coefficients. The reported AIC from the model output (AIC= 940547), the dispersion=0.428084, and the pseudo-R2 = 0.785983 are all found in the gamma model.

Tweedie Model




```
MLE of xi CI for xi1 CI for xi2
 1.967347    1.998084    1.998084
```

We get the estimate of the value of the Tweedie index parameter, p, using the tweedie.profile function, and in the instance of the tweedie (ξ = 1.967347). as seen in the graph on figure when the plot reaches its highest point.

```
glm(formula = Price ~ Fuel_type + Runned_Miles + Door_num + Seat_num +
    Bodytype + Reg_year, family = tweedie(var.power = xi.est,
    link.power = 0), data = d)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.7083  -0.3613  -0.1066   0.1818  11.6623

Coefficients:
                                        Estimate Std. Error t value Pr(>|t|)
(Intercept)                           -1.972e+02  2.173e+00 -90.762  < 2e-16 ***
Fuel_typeDiesel                        9.179e-01  3.351e-01   2.739 0.006167 **
Fuel_typeDiesel Hybrid                 1.117e+00  3.502e-01   3.190 0.001425 **
Fuel_typeElectric                      1.856e+00  7.177e-01   2.586 0.009710 **
Fuel_typeHybrid  Diesel/Electric       1.130e+00  7.239e-01   1.561 0.118478
Fuel_typeHybrid  Diesel/Electric Plug-in 1.250e+00  3.533e-01   3.539 0.000402 ***
Fuel_typeHybrid  Petrol/Electric       1.302e+00  3.359e-01   3.876 0.000106 ***
Fuel_typeHybrid  Petrol/Electric Plug-in 1.593e+00  3.380e-01   4.714 2.44e-06 ***
Fuel_typePetrol                        7.312e-01  3.352e-01   2.182 0.029131 *
Fuel_typePetrol Ethanol                6.698e-01  4.698e-01   1.426 0.153988
Fuel_typePetrol Hybrid                 1.093e+00  4.608e-01   2.372 0.017700 *
Fuel_typePetrol Plug-in Hybrid         1.169e+00  3.422e-01   3.416 0.000635 ***
Runned_Miles                          -6.932e-06  1.131e-07 -61.293  < 2e-16 ***
Door_num                               3.037e-02  4.908e-03   6.189 6.11e-10 ***
Seat_num                               1.024e-01  4.988e-03  20.523  < 2e-16 ***
BodytypeCombi Van                     -5.350e-01  1.867e-01  -2.865 0.004165 **
BodytypeConvertible                   -3.717e-01  1.825e-01  -2.037 0.041658 *
BodytypeCoupe                         -5.420e-01  1.820e-01  -2.978 0.002900 **
BodytypeEstate                        -1.005e+00  1.819e-01  -5.525 3.32e-08 ***
BodytypeHatchback                     -1.408e+00  1.817e-01  -7.748 9.52e-15 ***
BodytypeLimousine                      2.090e+00  3.614e-01   5.782 7.41e-09 ***
BodytypeMinibus                       -7.960e-01  1.944e-01  -4.095 4.23e-05 ***
BodytypeMPV                           -1.389e+00  1.822e-01  -7.627 2.45e-14 ***
BodytypePanel Van                     -6.808e-01  1.886e-01  -3.610 0.000306 ***
BodytypePickup                        -5.440e-01  1.836e-01  -2.964 0.003042 **
BodytypeSaloon                        -8.355e-01  1.819e-01  -4.593 4.38e-06 ***
BodytypeSUV                           -6.443e-01  1.818e-01  -3.545 0.000394 ***
BodytypeWindow Van                    -2.712e-01  2.176e-01  -1.246 0.212825
Reg_year                               1.025e-01  1.062e-03  96.450  < 2e-16 ***
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Tweedie family taken to be 0.5661851)

    Null deviance: 56895  on 49756  degrees of freedom
Residual deviance: 12086  on 49728  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 8
```

Figure 6 GLM: Tweedie

With Tweedie, the coefficient findings are the same as in the other two models. When compared to the inverse gaussian and gamma models, more Bodytype dummy variables become significant in the model. We find the AIC in the Tweedie model using the AICTweedie function (AIC= 940372.9), as the model did not yield an AIC as shown in Figure 6. We observe that the model has a dispersion of 0.5662 and a pseudo-R2 of 0.7875824.

Residuals

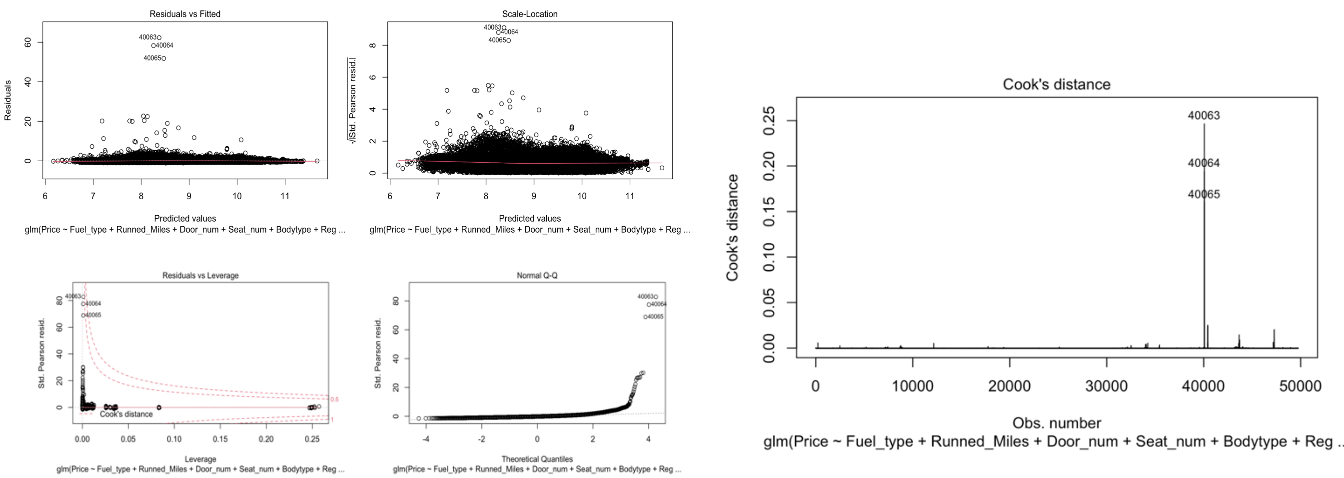


Figure 7: Residual of models

The residual plots of the various GLM models are identical, as seen in the figure 7 for all models. We can observe that the models do not violate any of the assumptions since there is no homoscedasticity in any of the model residuals. In the plots, especially the cooks distance plot, we see a recurrence of influential points (40063, 40064, and 40065). These residuals are mostly cars made in 1968, as their antics in the used car industry.

Discussion

Given the growing importance of the used vehicle market in internet auctions, this study adds on existing research on online auction markets to see how mileage and seller attributes influence the price premium on used cars. The subject of the paper will be on relatively low-priced homogenous products and auction characteristics, as well as how to fit them into three distinct generic linear models. The results showed that the Tweedie model was the most helpful model, as measured by the AIC (which was the lowest of the models) and pseudo R2. For the Tweedie regression, a stepwise regression was attempted but failed. What we can observe is that the AIC and the pseudo R2 of the Tweedie and the gamma are extremely comparable. So, in addition to the inverse gaussian distribution, we can use the gamma distribution as a better distribution to use.

The notion that the value of used automobiles is determined by a variety of variables is common information. The age of the automobile, its make and model, its origin, and its mileage are typically the most relevant the number of kilometres it has run (Wu. J. D, 2009). Other factors such as the type of fuel it uses, the interior style, the braking system, acceleration, the volume of its cylinders, safety index, the car's size, number of doors, paint colour, weight, consumer reviews, prestigious awards won by the car manufacturer, the car's physical state, whether it is a sports car, whether it has cruise control, whether it is automatic or manual transmission, and its physical state may all have an impact on the price. (Wu. J. D, 2009). We find that most of the electric cars to hybrid cars tend to hold value better, this is also likely due to the increase in price fuel in 2022; it maybe more economically better to use electric vehicles than fuel cars. A surprising fact for me was how limousines hold price cost longer than other vehicle body types.

Age and mileage are negative contributors to the resale value in that the older a car, or the more miles it has been driven will expend some of the vehicle's useful life and will lead to lower resale value. Fuel efficiency and its effect on resale value will fluctuate with gas prices as gas price go up, fuel efficiency becomes more important to resale value. In a time like today where the fuel price is high, a good Mile per gallon (MPG) rating can add value or subtract value depending on the rating (Meghan.R., 2019). A car receiving a good MPG rating will be more appealing in times of high gas prices and thus increase demand and value for the car. The opposite goes for vehicles with poor MPG ratings.

Limitations

One of the most significant issues with the models was fitting the GLM with all of the variables in the dataset, which caused the inverse gaussian and gamma models to fail to converge. I had to simplify the model to utilise fewer variables, and the model began to converge, however the model would occasionally output Na/NaN/inf, preventing the model from running. As a result, I was unable to create model interactions and was forced to utilise an additive model.

Future work

To be sure, the car industry is undergoing considerable transformation, and the sector's geography and makeup will alter. To stay afloat, automakers must put the needs of their customers first. Consumers are interested in automobiles that are regarded to be ecologically friendly, in addition to historical quality, fuel efficiency, and safety, according to this survey.

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