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Research Paper

New Car price prediction model using AI before launch: Forward selection Regression

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Abstract: It is very important to predict car price before launching it in the market. In the research, regression models are developed to predict the price of the car. Three models have been developed in the research paper: Backward Elimination, Backward Elimination with VIF, and forward selection. The data is taken from Kaggle. The most important factors are decided by correlating other variables with the car price. A linear regression model is finally developed, with engine size as the most influencing factor, the type of driver as the second influencing factor, and the type of the car body as the third influencing factor. Linear regression model predicts the car price with good model accuracy. The exploratory data analysis is done to know about the data set. The variables having variance influence factor r more than ten are omitted to avoid the problem of multicollinearity. The first model developed is forward selection, in which engine size is used to build the first regression model having a single variable. The value of adjusted R^2 is 0.764, and the aim is to increase the value of this factor, and all the coefficients in this model are statistically significant. The second variable included is the type of carburetor (2bbl) that is incorporated in the model, and a regression model is developed. The adjusted R^2 is 0.778 and all the coefficients are statistically significant. The third regression model is developed by incorporating types of the drive (Reverse drive), and the value of adjusted R^2 is 0.802, and all the coefficients are statistically significant.

Further, it was tried by the hit and trial method incorporated the other variables in the model to increase the model accuracy and adjusted R^2, but there was no benefit. The types of variables are selected based on correlation and VIF. The second approach adopted to build the regression model is backward elimination, in which all the variables are included and eliminated one by one based on VIF and statistical significance. The adjusted R^2 is 0.919, but some variables are statistically insignificant as the p-value is more than 0.05 with a 95% confidence interval. After eliminating all the variables having VIF of more than ten and statistically significant, the final regression model has adjusted R^2 is 0.863. The third approach adopted is backward elimination, where only statistically significant factors are considered. The final regression model with backward elimination has adjusted R^2 is 0.863. Finally, we recommend the forward selection method of regression to predict the price of the car as it has less omitted variables bias.

Keywords: Linear regression, correlation, forward selection, backward elimination, data analysis, Backward elimination

1. Introduction

Artificial Intelligence plays an important role in prediction of the car price of newly launch car with the help of machine learning algorithm. Whenever a company is planning to launch a new car, there is a need to predict the car price in given market with given countries. Various researchers have used several machine learning algorithms for the prediction of car price with the supervised machine learning algorithms. The research works lacks in deciding the methods of selecting the input parameters of the newly launch car. There is a need to find the way of incorporating the parameters in the model of machine learning. There are various machine learning models available for the prediction of price like regression, support vector machine etc. Regression plays an important role for the prediction of car price of a newly launch car. There are various types of regression models available but there is a need for finding the correct way of selecting the independent variables. According research there should be the minimum number of independent variables to be incorporated in the model for better prediction of dependent variables. The various class of machine learning is given below.

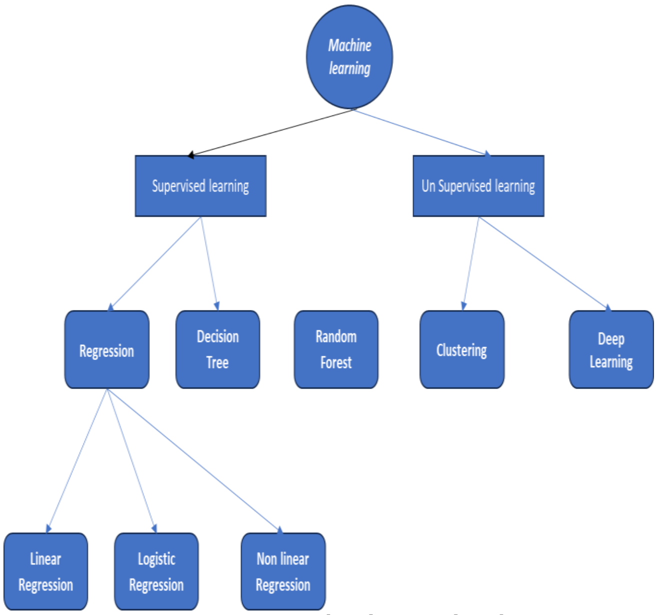


Figure 1: Various machine learning algorithms

Regression has been used extensively for building the machine learning models in various field of science and technology. Linear regression is found easy to build models of machine learning. For the complex problem there is a need to go with non linear regression model.

2. Related Work

The transport sector plays an important role in the economy of the world. In developed and developing nations, the automobile industry is called the "Industry of Industries" [1]. The automobile sectors are changing significantly due to developments in e-commerce, direct sales, and electric vehicles [2]. The expectation of a vehicle's worth is a fascinating and well-known topic. Machine learning plays a vital role in predicting the price of newly launch car. Now a days various researchers are doing modelling based on artificial intelligence and machine learning to discover the new area [3]. Regression can be used to predict the output based on various suitable input. Multiple linear regression is used to build an automobile price forecasting model. They might predict 98% of predictability. The researcher has built the model for prediction based on machine learning [4]. To estimate the cost of a secondhand car, another study proposed a model that would be created using ANNs (Artificial Neural Networks). He gave Mark, estimated automobile life and passed miles some thought. With increased accuracy, the nonlinear model could predict automobile prices better than conventional linear models [5]. Researchers used a knowledge-based neuro-fuzzy technique to analyze the assessment of automotive prices. This approach details the best car prices and the location where the highest quality can be acquired. The speed of a car was predicted using a regression model with a neighboring k-nearest machine learning technique. Since it has traded more than two million vehicles, this program appears very effective [6-7]. Richardson [8] provided a specific technique in his thesis research. He anticipated that automakers would produce more durable vehicles. Richardson used numerous regression models and discovered that the value of electric vehicles has remained stable longer than conventional automobiles. This provides greater fuel efficiency, which stems from concerns about urban warming. The car price was predicted with the help of common supervised learning [10]. Linear regression was used to estimate the car price of a launching car by splitting the data set into training and testing set [11]. The heteroscedasticity is considered while building the regression model for prediction [12]. To incorporate the sustainability the regression model is used for better prediction of a car [13]. Sparse regression is used to build the regression model for the prediction of car [14]. [15] has developed model for the prediction of used car and important independent variables are considered for better prediction of the model. Apart from regression, the k-based neighborhood can be used for building the machine learning model [16]. The resale value of any commodities can be predicted with the help of regression as shown by [17]. Thus, from the literature it is desired to select the method to identify the methods how to build regression model specially for prediction of car price.

3. Theory/Calculation

The data set is obtained from Kaggle for the existing car company including price and other input variables. Data and notebooks are available for data scientists and analysts on the open-source machine learning and data science platform Kaggle. Before utilizing any algorithm to anticipate the price, the necessary data is cleaned and pre-processed using supervised learning (Multiple linear regression). The data is splitted into the training and testing sets following pre-processing and cleaning. Regression models are created in the study to forecast the cost of the car. By using forward selection, backward elimination, and backward Elimination with VIF, a straightforward linear regression model and prediction are created. In order to select the best algorithms for the prediction, all three results are finally compared [7-9]

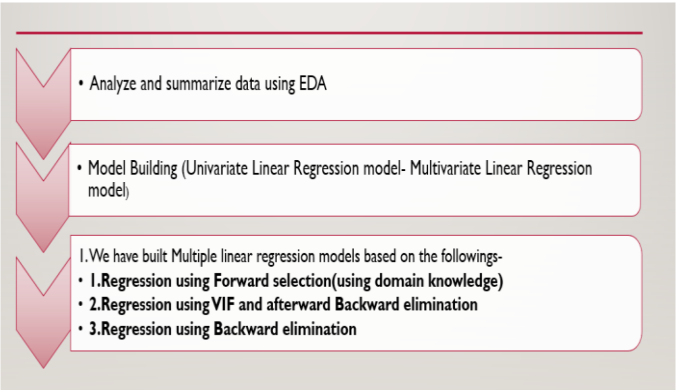


Figure 2: The layout of the work

The various types of independent variables have been incorporated in the regression model for the prediction of car price. The car price has very strong correlation with engine size. Correlation is an important mathematical way to find the associations between two variables. The horse power is also having the strong correlation with car price. If we incorporate engine size and horse power then this will create the problem of VIF in the regression model. It is desired to have a way of incorporating the suitable methods of regression. Forward selection and backward elimination may play an important role in deciding the regression model for good incorporation of independent variables in the model.

Experimental method and procedure

The following three types of regression models are formulated based on the linear regression model- multivariate Linear Regression.

i. Regression using Forward selection (using domain knowledge)
ii. Regression using VIF and, afterward, Backward Elimination
iii. .Regression using Backward Elimination

The statistic from the given car data set is below in Table 1.

Table 1: Different statistical aggregations in the dataset

	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stroke
count	205.0000	205.0000	205.0000	205.0000	205.0000	205.0000	205.0000	205.0000
mean	98.7566	174.0493	65.9078	53.7249	2555.5659	126.9073	3.3298	3.2554
std	6.0218	12.3373	2.1452	2.4435	520.6802	41.6427	0.2708	0.3136
min	86.6000	141.1000	60.3000	47.8000	1488.0000	61.0000	2.5400	2.0700
25%	94.5000	166.3000	64.1000	52.0000	2145.0000	97.0000	3.1500	3.1100
50%	97.0000	173.2000	65.5000	54.1000	2414.0000	120.0000	3.3100	3.2900
75%	102.4000	183.1000	66.9000	55.5000	2935.0000	141.0000	3.5800	3.4100
max	120.9000	208.1000	72.3000	59.8000	4066.0000	326.0000	3.9400	4.1700

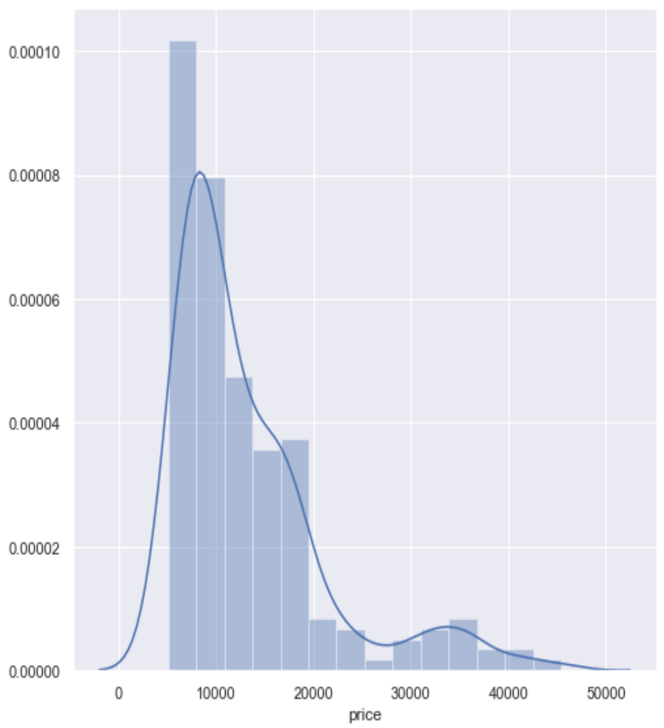


Figure 3: Car price distribution plot

Based on the scatter plot of the horsepower, engine size, Car weight, car width shows a positive correlation. Highway mileage, city milage shows a negative correlation with the car price. The correlation of price with various input variables are shown in the figure below. It was plotted with the help of python programming language. Correlation helps to find the variable to be included in the regression model. We can see from the figure that car price has the positive correlation with car length, car width, car Hight and car weigh. It is not advisable to incorporate all the variables at a time because it will create the problem of valance inflation factor. There is a need to find a way to get rid of this situation. One way is to avoid the variables with more than 10 VIF.

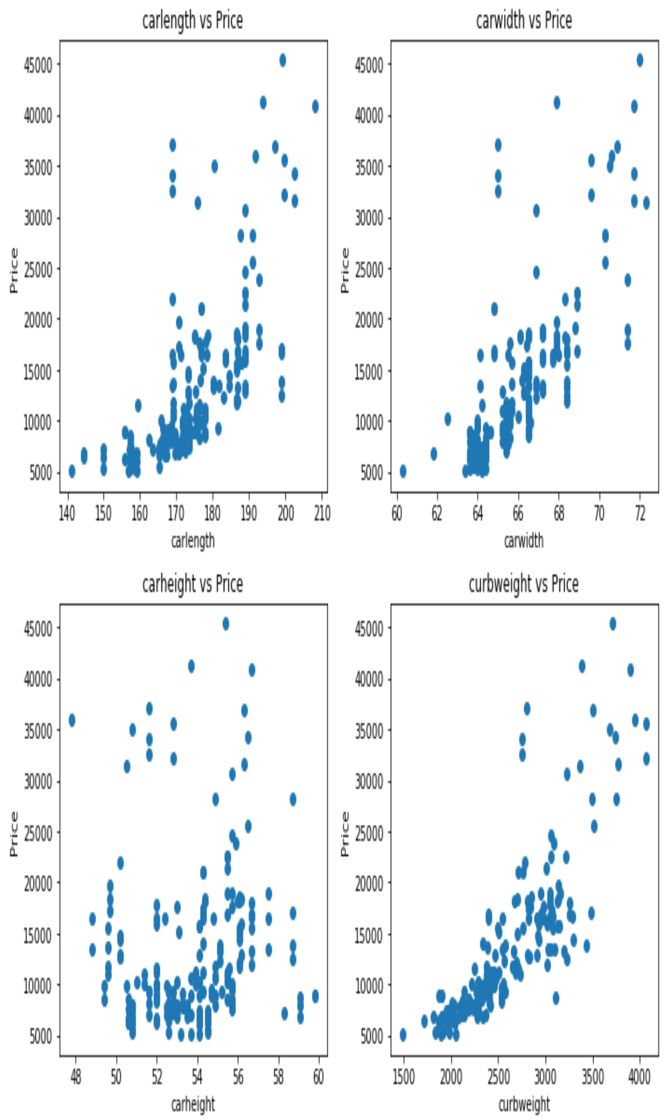


Figure 4: Scatter Plot of price and a different variable

The box plot is showing the outliers in the data set so the data sets are discarded from the model to increase the model accuracy. It is found that there are many outliers present in the data set. We have pre-processed the data set and incorporated the outliers. The data after deleting all the outliers is used in the model. Other way is to use some machine learning models to predict the missing data.

Figure 5: Box plot for price having outliers

4. Results and Discussion

4.1 Regression using Forward selection

Price=-8000.44+167.69*engine-size

Adjusted R^2= 0.764

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.764
Model:                            OLS   Adj. R-squared:                  0.763
Method:                 Least Squares   F-statistic:                     657.6
Date:                Thu, 23 Sep 2021   Prob (F-statistic):           1.35e-65
Time:                        11:30:54   Log-Likelihood:                -1984.4
No. Observations:                 205   AIC:                             3973.
Df Residuals:                     203   BIC:                             3979.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -8005.4455    873.221     -9.168      0.000   -9727.191   -6283.700
enginesize   167.6984      6.539     25.645      0.000     154.805     180.592
==============================================================================
Omnibus:                       23.788   Durbin-Watson:                   0.768
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               33.092
Skew:                           0.717   Prob(JB):                     6.52e-08
Kurtosis:                       4.348   Cond. No.                         429.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

     Features    VIF
0       const  10.33
1  enginesize   1.00
```

Figure 6: Regression using Forward selection

4.2 Model 2

price=-5689.10+155.60*enginesize-2428.92*2bbl

Adjusted R^2= 0.780

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.780
Model:                            OLS   Adj. R-squared:                  0.778
Method:                 Least Squares   F-statistic:                     359.0
Date:                Fri, 24 Sep 2021   Prob (F-statistic):           3.15e-67
Time:                        18:54:46   Log-Likelihood:                -1977.1
No. Observations:                 205   AIC:                             3960.
Df Residuals:                     202   BIC:                             3970.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -5689.1075   1034.870     -5.497      0.000   -7729.641   -3648.574
enginesize   155.6081      7.053     22.062      0.000     141.701     169.515
2bbl       -2428.9209    627.100     -3.873      0.000   -3665.422   -1192.420
==============================================================================
Omnibus:                       20.701   Durbin-Watson:                   0.731
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               31.770
Skew:                           0.593   Prob(JB):                     1.26e-07
Kurtosis:                       4.521   Cond. No.                         565.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

     Features    VIF
0       const  15.51
1  enginesize   1.24
2        2bbl   1.24
```

Figure 7: Regression using Forward selection

Model 3

*Price=-5079.79+139.87*enginesize-1598.35.97*2bbl-3022.11*rwd*

Adjusted R^2= 0.802

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.801
Model:                            OLS   Adj. R-squared:                  0.798
Method:                 Least Squares   F-statistic:                     270.3
Date:                Sat, 25 Sep 2021   Prob (F-statistic):           2.92e-70
Time:                        00:38:52   Log-Likelihood:                -1966.8
No. Observations:                 205   AIC:                             3942.
Df Residuals:                     201   BIC:                             3955.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -5079.7904    995.649     -5.102      0.000   -7043.048   -3116.533
enginesize   139.8714      7.546     18.537      0.000     124.993     154.750
2bbl       -1598.3523    624.635     -2.559      0.011   -2830.031    -366.674
rwd         3022.1121    656.979      4.600      0.000    1726.657    4317.567
==============================================================================
Omnibus:                       19.543   Durbin-Watson:                   0.749
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               37.116
Skew:                           0.479   Prob(JB):                     8.72e-09
Kurtosis:                       4.851   Cond. No.                         566.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

     Features    VIF
0       const  15.79
3         rwd   1.60
1  enginesize   1.57
2        2bbl   1.36
```

Figure 8: Regression using Forward selection

Model 4

price = -4361.52+ 137.36*engine size-1572.28*2bbl-2987.51*rwd-1115.07*hatchback

Adjusted R^2= 0.806

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.806
Model:                            OLS   Adj. R-squared:                  0.802
Method:                 Least Squares   F-statistic:                     207.6
Date:                Sat, 25 Sep 2021   Prob (F-statistic):           5.27e-70
Time:                        00:45:51   Log-Likelihood:                -1964.5
No. Observations:                 205   AIC:                             3939.
Df Residuals:                     200   BIC:                             3956.
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -4361.5203   1041.357     -4.188      0.000   -6414.968   -2308.073
enginesize   137.3625      7.568     18.151      0.000     122.440     152.285
2bbl       -1572.2874    619.149     -2.539      0.012   -2793.185    -351.390
rwd         2987.5108    651.282      4.587      0.000    1703.250    4271.772
hatchback  -1158.0791    536.721     -2.158      0.032   -2216.437     -99.721
==============================================================================
Omnibus:                       20.116   Durbin-Watson:                   0.745
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               39.022
Skew:                           0.486   Prob(JB):                     3.36e-09
Kurtosis:                       4.903   Cond. No.                         597.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

     Features    VIF
0       const  17.59
3         rwd   1.61
1  enginesize   1.60
2        2bbl   1.36
4   hatchback   1.05
```

Figure 9: Regression using Forward selection

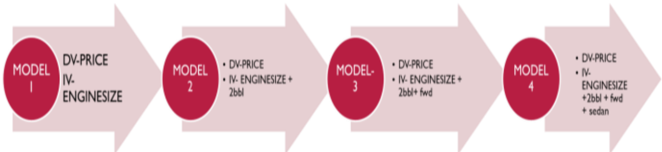


Figure 5: Flowchart of model using forward selection

4.2 Regression using VIF and, afterward backward Elimination

In this model, we have tested the multicollinearity assumption using VIF (Variance Inflation Factor). For VIF > 10, we have eliminated independent variables step by step. The following independent variables remain, and afterward, the backward elimination technique is used based on the p-value at a 5% significance level.

```
                Features      VIF
0                  const  1866.27
1             enginesize     9.65
4                citympg     5.79
2              wheelbase     4.27
3              boreratio     3.84
20                  ohcf     3.10
19                   ohc     2.82
21                  ohcv     2.65
6                    fwd     2.65
14      compressionratio     2.62
11                   two     2.60
13                stroke     2.56
9                    six     2.45
16             hatchback     2.13
5                  turbo     2.01
18                  rear     1.97
12                   two     1.89
22                  2bbl     1.89
10                twelve     1.68
24                  spdi     1.68
8                   five     1.59
15               hardtop     1.52
17                 wagon     1.23
7                  dohcv     1.21
23                   mfi     1.14
25                  spfi     1.05
```

Figure 10: Regression using VIF and afterward backward elimination

Final model with backward elimination

Adjusted R^2=0.863

Regression equation:

*Price= -72370 +103.71 *engine size + 1283.53 car width -3167.35 bore ratio -3048.33 fwd + 15200 rear*

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.863
Model:                            OLS   Adj. R-squared:                  0.859
Method:                 Least Squares   F-statistic:                     250.1
Date:                Wed, 22 Sep 2021   Prob (F-statistic):           9.53e-84
Time:                        21:15:09   Log-Likelihood:                -1928.9
No. Observations:                 205   AIC:                             3870.
Df Residuals:                     199   BIC:                             3890.
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -7.237e+04   9598.743     -7.540      0.000   -9.13e+04   -5.34e+04
enginesize   103.7102      8.273     12.536      0.000      87.396     120.025
carwidth    1283.5381    157.682      8.140      0.000     972.595    1594.481
boreratio  -3167.3580   1073.561     -2.950      0.004   -5284.374   -1050.342
fwd        -3048.3354    544.913     -5.594      0.000   -4122.880   -1973.791
rear         1.52e+04   1890.294      8.039      0.000    1.15e+04    1.89e+04
==============================================================================
Omnibus:                       50.442   Durbin-Watson:                   0.868
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              171.301
Skew:                           0.957   Prob(JB):                     6.35e-38
Kurtosis:                       7.048   Cond. No.                     6.80e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.8e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

     Features      VIF
0       const  2102.90
1  enginesize     2.70
2    carwidth     2.60
3   boreratio     1.92
4         fwd     1.64
5        rear     1.18
```

Figure 11: Final model with backward elimination

4.3 Regression using Backward Elimination

In this model, all the independent variables are considered at first and then dropped one by one with the help of VIF and value of p.

- In this model, all the independent variables are considered first and then dropped one by one based on p values and VIF.

Model building criteria

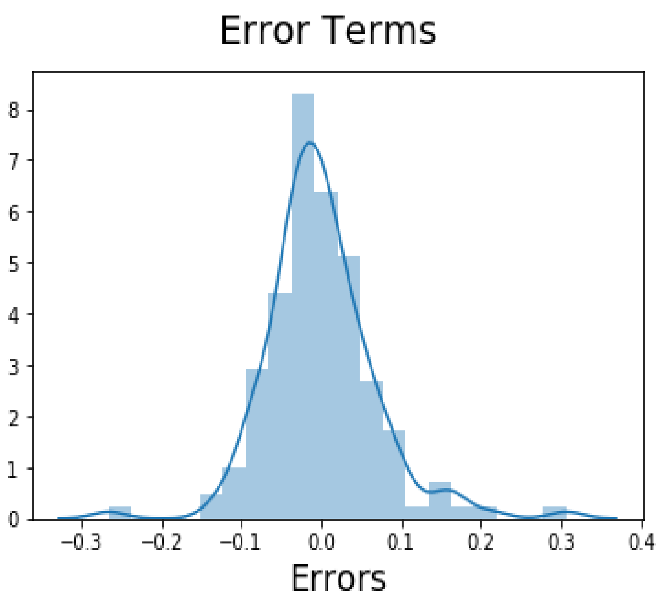
The threshold p-value and VIF value is as follows:

- The independent variables having p values more than 0.05 (i.e., 95 percent of confidence).
- VIF should be less than 10 to avoid the problem of multi collinearity.

After having a significant model, we found that the numbers of independent variables were large, so we applied Occam's Razor Principle to the model.

Table 2: Comparison of different models

	MODEL A	MODEL B	MODEL C
Dependent variable	Price	price	price
Independent variables	engine size,2bbl, rwd, hatchback	engine size, car width, bore ratio, fwd, rear	engine size, car width, ohcv, stroke, turbo, four
R^2	0.806	0.863	0.867
Adjusted R^2	0.802	0.859	0.863
Regression equation	*price = -4361.52+ 137.36*engine size- 1572.28*2bbl- 2987.51*rwd- 1115.07*hatchback*	*price= -72370 +103.71 *engine size + 1283.53* car width -3167.35* bore ratio - 3048.33* fwd + 15200* rear*	*price=-2.768 +138.39* enginesize+ 613.06* car width – 6962 *ohcv - 3913.02 *stroke+ 1497.31 *turbo – 5288.83 *four*



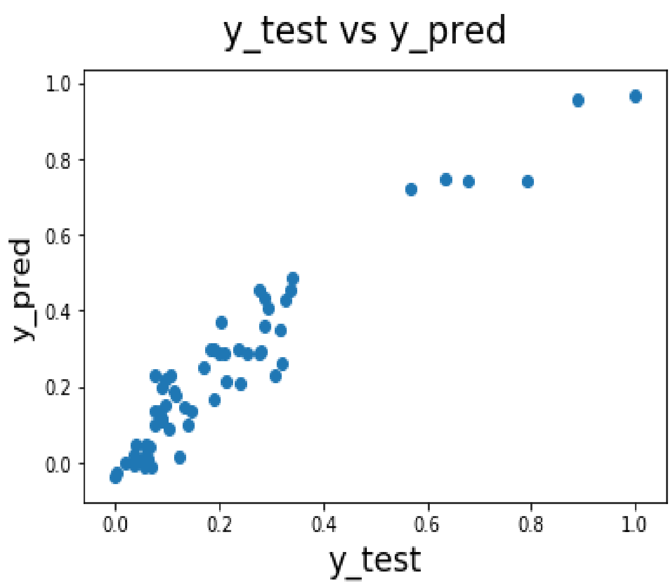


Figure 12: Error terms in regression model following Normal distribution.

5. Conclusion

It is easy to predict the price of a car with the help of regression but it is very difficult to decide the various input parameters required for prediction. Model A is the best model to predict the independent variables that demonstrate causation with the price of the car after applying a variety of regression methods to the model. The novelty of the research paper is to select the input variable to estimate the car price. Model A, forward selection should be used to select the input variables and one by one variables should be included in the model to estimate the demand. Our model suggest that for a new car the manufacturers can select engine size, types of carburator, types of drive and car body to estimate the car price directly in the U.S market. The model is generic can be applied for any country. The training and testing set has to be given the real data of that particular company. The research papers is lefting out the direction for future work for other types of products for predicting the price using forward selection regression model. The final model is given below.
price = -4361.52+ 137.36*engine size-1572.28*2bbl-2987.51*rwd-1115.07*hatchback.

The research paper can also be used to predict the price of other commodities like electronics and electrical items (TV, Fridge, mobile phone). The future work will be to develop the model foe predict the price of Electrical products.

Conflict of Interest
The authors declare that they do not have any conflict of interest.

Authors' Contributions
Author-1 Conceived the study, involved in protocol development and data analysis. Author-2&3 literature survey and wrote the first draft of the manuscript. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

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