Statistical Analysis of Used Cars Data

Welbeck Achiampong, Muhyadin Yusuf, Minh Pham, and Jordan Addo

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```r
# set your global options here and load your packages
knitr::opts_chunk$set(fig.width = 10, fig.height = 5, echo = TRUE, eval = TRUE)
library(knitr)
library(tidyverse)
used_cars <- read.csv("used_cars_data.csv") #redirect
```

1 Introduction

This project aims to explore the used car market by analyzing the factors that influence the pricing of used cars. With the increasing demand for used vehicles, understanding how various features like the manufacturer, model, year, engine type, and kilometers driven impact the price can help consumers and dealers alike make informed decisions. The dataset, `used_cars_data.csv`, contains information on these attributes, offering insights into how different features contribute to the sale price of a car. By developing a predictive model, we can provide a more accurate estimate of a used car's value based on its characteristics, making this research valuable for both buyers and sellers in the used car market.

To address this, we will build a linear regression model to estimate the price based on these features. The model will follow the general equation $Y = B_0 + B_1x_1 + B_2x_2$ where Y is the response variable(pricted price) and the $B's$ represents the coefficients and the $x's$ are the input variables. Through pre-processing the data and ensuring it is clean and normalized yo be able to accurately predict the price of used cars.

1.1 Reserach questions

Our research question is to determine whether a model can effectively predict the price of a used car using variables such as the year of the car, kilometers driven, engine capacity, and fuel type.

1.2 Data set desription

The dataset, used_cars_data.csv, contains information about used cars and their sale prices. There are several variables present in the dataset, including:

- Manufacturer: the car manufacturer (e.g. Toyota, Ford, Honda, etc.)
- Model: the specific car model (e.g. Corolla, Mustang, Accord, etc.)

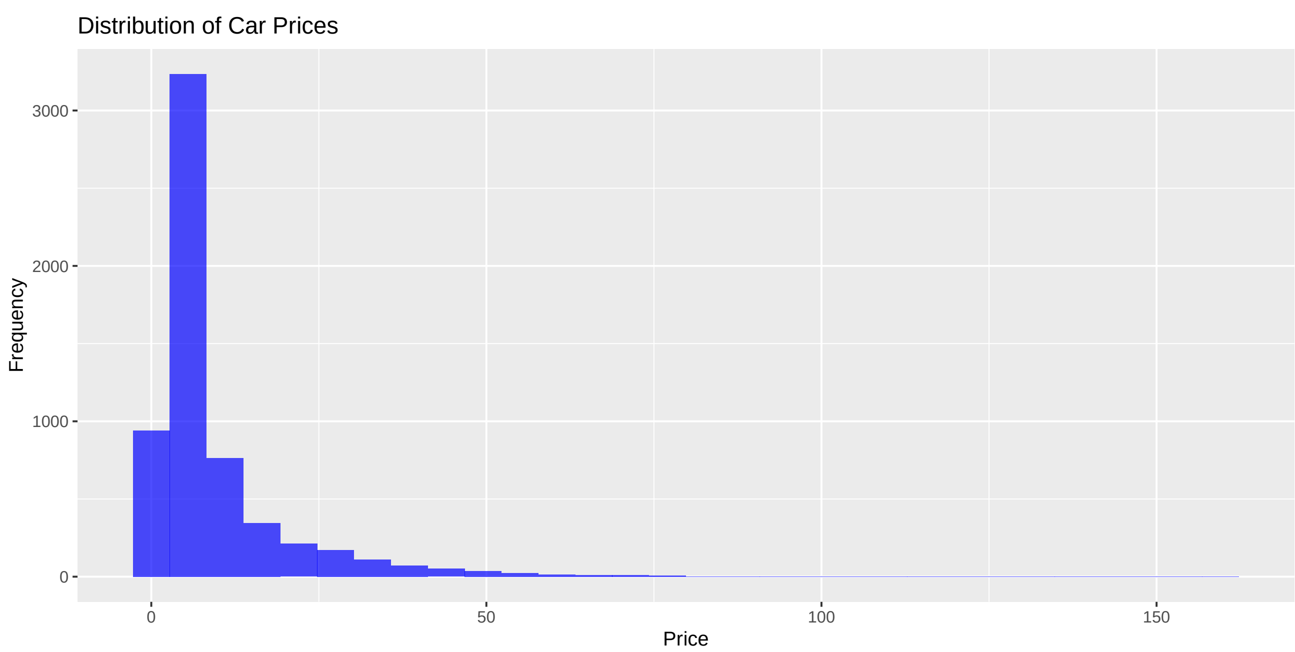
- Location: The place of the car (e.g. Mumbai, Pune, Jaipur, etc.)
- Year: the year the car was released (e.g. 2010, 2014, 2015, etc.)
- Engine: the number of cylinders in the engine
- Fuel_type : the type of fuel the car uses (e.g. gas, diesel, electric)
- Kilometer_Driven: the total distance the car has traveled
- Transmission: the type of transmission (e.g. automatic, manual)

Using this data, we can develop a model to predict the sale price of a used car based on these variables.

2 Exploratory Data Analysis

```
ggplot(used_cars, aes(x = Price)) +
  geom_histogram(bins = 30, fill = "blue", alpha = 0.7) +
  labs(title = "Distribution of Car Prices", x = "Price", y = "Frequency")
```

```
## Warning: Removed 1234 rows containing non-finite outside the scale range
## (‘stat_bin()‘).
```



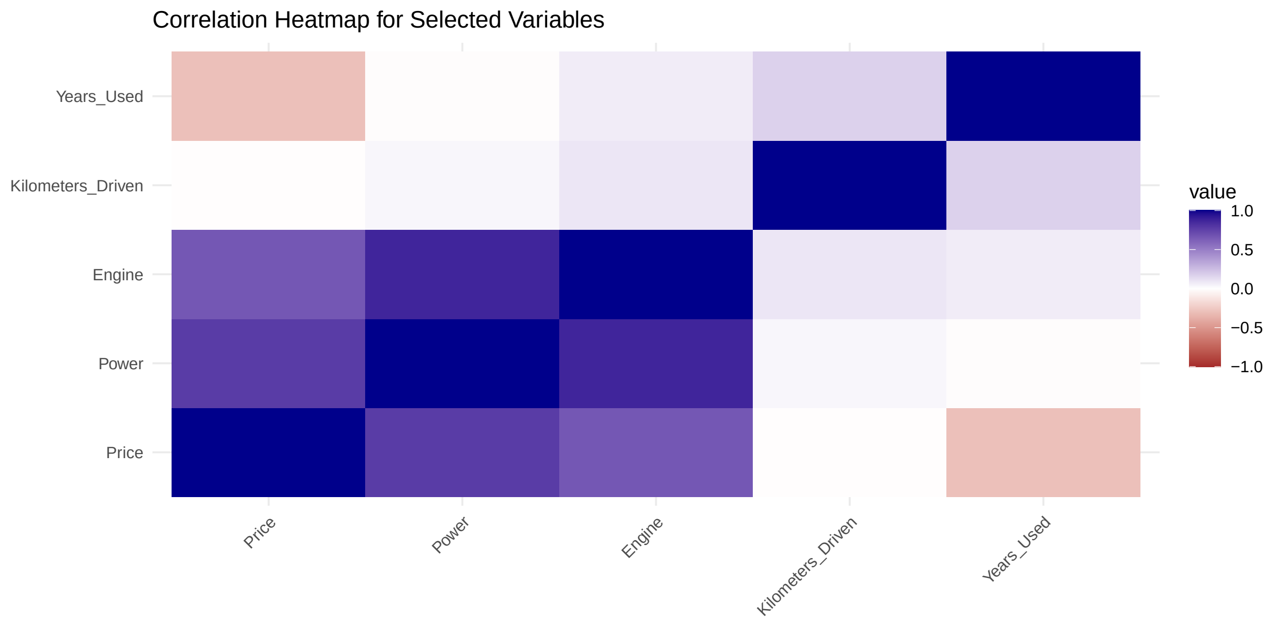
In our exploratory of the data, we observe that the price range of most used cars is around $10,000 USD.

```r
# Load necessary libraries
library(ggplot2)
library(reshape2)
```

```
##
## Attaching package: 'reshape2'

## The following object is masked from 'package:tidyr':
##
##     smiths
```

```r
library(dplyr)

# Assuming the 'Mileage' column needs cleaning
used_cars$Mileage <- as.numeric(gsub("[^0-9.]", "", used_cars$Mileage))
used_cars$Engine <- as.numeric(gsub("[^0-9.]", "", used_cars$Engine))
used_cars$Power <- as.numeric(gsub("[^0-9.]", "", used_cars$Power))

# Calculate 'Years_Used'
used_cars$Years_Used <- 2024 - used_cars$Year

# Filter the data to include only the selected columns
selected_data <- used_cars[, c("Price", "Power", "Engine", "Kilometers_Driven", "Years_Use

# Remove rows with missing values
selected_data <- na.omit(selected_data)

# Create a correlation matrix
cor_matrix <- cor(selected_data, use = "complete.obs")

# Melt the correlation matrix for ggplot
cor_melted <- melt(cor_matrix)

# Plot the heatmap with a blue-white-green color gradient and scale set from -1 to 1
ggplot(cor_melted, aes(Var1, Var2, fill = value)) +
  geom_tile() +
  scale_fill_gradient2(low = "brown", mid = "white", high = "darkblue", midpoint = 0, lim
```

```r
theme_minimal() +
labs(title = "Correlation Heatmap for Selected Variables", x = "", y = "") +
theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Jordan :Need explain the correlation graph

3 Statistical Methods

3.1 Regression

What are the two statistical techniques you plan to use to answer your regression question? Give details here. Name variables, write out models (using β_i's), let me know if you're using CV, backward selection, etc. Write formulas. Explain why you chose to use these two techniques.

Explain Regression(Jordan) Regression is a statistical method used to understand the relationship between different variables.The goal of regression is to understand how the dependent variable changes when the independent variables are varied. This helps in predicting future values of the dependent variable. Our statistical approach will be to create a linear regression model

4 Results

4.1 Regression

```
library(dplyr)
library(ggplot2)

used_cars_data <- read.csv("used_cars_data.csv")

used_cars_data$Mileage <- as.numeric(gsub(" km/kg| kmpl", "", used_cars_data$Mileage))
used_cars_data$Engine <- as.numeric(gsub(" CC", "", used_cars_data$Engine))
used_cars_data$Power <- as.numeric(gsub(" bhp", "", used_cars_data$Power))
```

```
## Warning: NAs introduced by coercion
```

```
used_cars_data <- used_cars_data %>%
  mutate(across(where(is.numeric), ~ ifelse(is.na(.), median(., na.rm = TRUE), .)))

used_cars_data$Fuel_Type <- as.factor(used_cars_data$Fuel_Type)
used_cars_data$Transmission <- as.factor(used_cars_data$Transmission)
used_cars_data$Location <- as.factor(used_cars_data$Location)

used_cars_data$Year <- factor(used_cars_data$Year)

unique_years <- sort(unique(used_cars_data$Year))
used_cars_data$Year <- factor(used_cars_data$Year, levels = unique_years)

model <- lm(Price ~  Kilometers_Driven  + Fuel_Type +  Mileage + Transmission + Power, dat
summary(model)
```

```
##
## Call:
## lm(formula = Price ~ Kilometers_Driven + Fuel_Type + Mileage +
##     Transmission + Power, data = used_cars_data)
##
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -63.635  -2.479  -0.102   2.007 131.384
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)        -3.636e+00  1.168e+00  -3.112 0.001864 **
## Kilometers_Driven  -3.666e-06  1.007e-06  -3.642 0.000273 ***
## Fuel_TypeDiesel     3.079e-01  9.240e-01   0.333 0.738975
## Fuel_TypeElectric   7.613e+00  5.140e+00   1.481 0.138613
## Fuel_TypeLPG        4.350e-01  2.258e+00   0.193 0.847217
## Fuel_TypePetrol    -1.595e+00  9.286e-01  -1.718 0.085927 .
## Mileage             1.258e-01  2.258e-02   5.572 2.61e-08 ***
## TransmissionManual -3.360e+00  2.431e-01 -13.823  < 2e-16 ***
## Power               1.191e-01  2.397e-03  49.660  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.142 on 7244 degrees of freedom
## Multiple R-squared:  0.5191, Adjusted R-squared:  0.5186
## F-statistic: 977.6 on 8 and 7244 DF,  p-value: < 2.2e-16
```

```r
predicted_prices <- predict(model, used_cars_data)
used_cars_data$Predicted_Price <- predicted_prices
head(used_cars_data)
```

```
##   S.No.                             Name   Location Year Kilometers_Driven
## 1     0           Maruti Wagon R LXI CNG     Mumbai 2010             72000
## 2     1 Hyundai Creta 1.6 CRDi SX Option       Pune 2015             41000
## 3     2                     Honda Jazz V    Chennai 2011             46000
## 4     3                Maruti Ertiga VDI    Chennai 2012             87000
## 5     4  Audi A4 New 2.0 TDI Multitronic Coimbatore 2013             40670
## 6     5  Hyundai EON LPG Era Plus Option  Hyderabad 2012             75000
##   Fuel_Type Transmission Owner_Type Mileage Engine  Power Seats New_Price Price
## 1       CNG       Manual      First   26.60    998  58.16     5            1.75
## 2    Diesel       Manual      First   19.67   1582 126.20     5           12.50
## 3    Petrol       Manual      First   18.20   1199  88.70     5 8.61 Lakh  4.50
## 4    Diesel       Manual      First   20.77   1248  88.76     7            6.00
```

```
## 5    Diesel    Automatic     Second   15.20   1968 140.80     5              17.74
## 6       LPG       Manual      First   21.10    814  55.20     5               2.35
##   Predicted_Price
## 1        3.009842
## 2       10.660176
## 3        4.089619
## 4        6.172488
## 5       15.197553
## 6        2.389628
```

Write estimated final models. Give details. Interpret models and/or coefficients. What do your models say? Do the two models send the same message? What are the important inputs?

4.2 Final Estimated Model

$Price = -3.636e+00 - 3.666e-06 * Kilometers_Driven + 3.079e-01 * Fuel_TypeDiesel + 7.613e+00 * Fuel_TypeElectric + 4.350e-01 * Fuel_TypeLPG - 1.595e+00 * Fuel_TypePetrol + 1.258e-01 * Mileage - 3.360e+00 * TransmissionManual + 1.191e-01 * Power + \epsilon$

The estimated model for the price of a used car considering the different variables such as Kilometer Driven, Fuel type(Diesel,Electric,LPG,Petrol), Mileage, Transmission and power. The co-efficient in out model tells us the change in our price by one unit. In other words, as the price of a used car increases, the imput variables changes based on their respective co-efficient.

4.3 Model Interpertation

- Intercept (-3.636e+00) : Tells us the price of a used car, assuming the the other variables equals zero.
- Kilometer Driven (-3.666e-06) :
- Fuel type
- Mileage
- Transmission

Make plots of your models if possible.

```r
ggplot(used_cars_data, aes(x = Price, y = predicted_prices)) +
  geom_point(color = "blue") +
  geom_abline(slope = 1, intercept = 0, color = "red", linetype = "dashed") +
```

```r
ggtitle("Actual vs Predicted Prices") +
xlab("Actual Price") +
ylab("Predicted Price") +
theme_minimal()
```

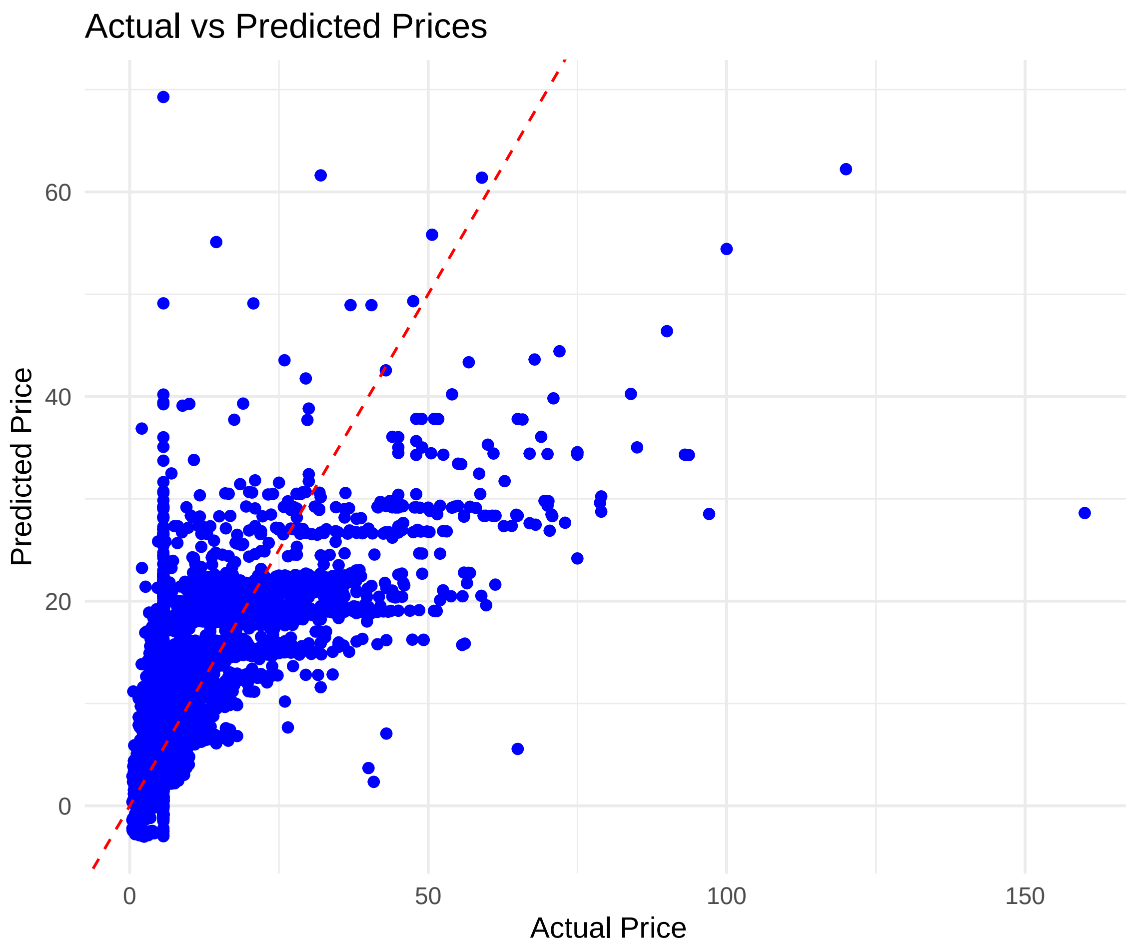


Figure 1: The relationship between sepal and petal lenghts

5 Conclusions

What did you learn? What else would you have wanted to know but couldn't? Is something looking weird / surprising / unexpected?

Don't use formulas here or be too statistical. This section is for the wider audience.

Everybody should write three to four sentences.

6 Appendix A

If you need it.