FUEL CONSUMPTION: MANUAL VS AUTOMATIC CARS

EXECUTIVE SUMMARY

This report aims at investigating the following questions:

1. Is an automatic or manual transmission better for MPG (miles per gallons)

2. Quantify the MPG difference between automatic and manual transmissions

The conclusion of the analysis is that the type of transmission does not affect the fuel consumption and that the weight of the car and the number of cylinders are much more accurate predictors. It is developed a model based on these two predictors and the following table summarises the predictions of fuel consumption in miles per gallons, depending on weight and number of cylinders:

Weight (tons)	4 cyl	6 cyl	8 cyl
2	27.96	25.66	23.36
3	22.74	20.44	18.14
4	19.14	16.84	14.54
5	17.16	14.86	12.56

The analysis is carried out on the dataset mtcars. Due to the small number of models and the age of the dataset, the results cannot be generalised to the current population of cars, but can give an insight within the set of cars considered.

REPORT

The database contains **32** car models of which **19** have automatic transmission and **13** have manual. The variable "am" is **0** for automatic transmission and **1** for manual.

A simple t-test confirm that the two transmissions are not from the same population as the interval does not contain 0 and the p-value **0.0014** is sufficiently low (see *Appendix 2*), therefore there is a statistcally significant difference between the "mpg" of the two groups.

We consider a linear model with "am" as a predictor and "mpg" as a response (see *Appendix 3*). The model performs poorly: R-squared **0.36** is very low (1 being best fit, 0 being no fit at all) and this, together with a Residual Standard Error (RSE) of **4.822**, suggests that the model is not accurate.

We look therefore at other variables that might be confounders. Let's call primary the variables that refer to technical specifications of the car and the engine ("cyl", "disp", "drat", "wt", "vs", "am", "gear", "carb") and secondary the ones that refer to performance of the car ("mpg", "hp", "qsec") and therefore consequences of the primary ones. We are interested in the outcome of a secondary variable ("mpg") with primary variables as predictors. Based on a brief literature review, the variables that can be relevant to our analysis are weight ("wt"), the number of cylinders ("cyl") and the displacement ("disp"). The rear axle ratio ("drat") is also mentioned as having an impact on fuel consumption. The weight and the number of cylinders can tell a lot about a car because they are related to the size and power of the engine and therefore the size and the type of car. Displacement (the amount of fuel burnt per stroke of the engine) gives similar information about the engine but in this case it is correlated with cylinders (see *Appendix 4*) and we therefore use interaction rather than confounding.
We will proceed at setting up 5 nested models, verifying the best fit and then drop redundant variables through an ANOVA test.

If we look at the "wt" plot of *Appendix 1*, we can imagine two groups of cars: one of light and manual cars and the other of heavy and automatic cars. The plot in *Appendix 5* suggests that there are indeed two groups with different reaction to the increase in weight. Rather than automatic/manuals having different "mpg" trend based on the weight, we suggest that there is a quadratic relationship between "wt" and "mpg", that is the slope changes with the weight (steeper on the left side of the graph, flatter on the right). This would explain why mpg in manuals cars, that are on the left of the graph, have a steeper slope than automatic ones. Let's have *model1* with the linear predictor "wt" and *model2* where we add "wt^2". Indeed model2 better explains the relationship between "wt" and "mpg", as the R-squared goes from **0.75** to **0.82** with a reduced RSE from **3.05** to **2.65** and improved p-value (see *appendix 6*). In *model 3* we add the variable "cyl". In *model4* we introduce the variable "am", to try to answer the initial question and its interaction with "wt" (see *Appendix 5*). In *model5*, we introduce the interaction between "cyl" and "disp", plus the variable "drat". We can now run an anova test to verify which of these variale can be dropped without loss of relevant information.

```
a <- anova(fit_wt, fit_wt2, fit_wt2_cyl, fit_wt2_cyl_am, fit_wt2_cyl_am_disp_drat)
```

The Anova test reveals that the impact of manual/automatic transmission on "mpg", with a p-value of 0.15 is not statistically significant (the variable "am" can be dropped) and that the most relevant variables of the dataset at predicting fuel consumption are the weight and the number of cylinders. We propose *model3* as the most accurate in predicting the fuel consumption based on primary variables, as below:

mpg_i = 47.86 + -9.27wt_i + 0.81wt_i^2 + -1.15cyl_i

The model explains ***86%*** of the variation in fuel consumption with a residual standard error of ***2.4 miles per gallon***. All of the coefficients are significant at 0.05 significant level. We look at the plots of the residuals (see *Appendix 8*) in order to verify the following assumptions:

1. The variables are indipendent : the Residuals vs Fitted shows no pattern and confirm indipendency;
2. Normality of the residuals: the Normal Q-Q plot shows the standardised residuals laying on the line and confirm normality;
3. Constant variance: the Scale-Location plot shows the points randomly distributed and confirm the variance is constant;
4. In the Residuals vs Leverage plot all the points fall within the 0.5 band and confirm that there are no outliers.

As a final check, we verify the presence of outliers that can influence the model. In *model3* the number of observations with a dfbeta coefficient bigger than 1 is 0, therefore the model meets the all the basic assumptions of linear regression.

CONCLUSIONS

In conclusion, it is found that the type of transmission does not significantly affect the fuel consumption. The sole distinction between manual and automatic cars is a poor predictor of the fuel consumption and other factors more influential have to be taken into account for a more precise prediction. We make a distinction between primary variables (car and engine's technical specifications) and secondary variables (variables describing a performance, which are the result of the primary technical specifications). We propose a model to predict fuel consumption using primary variables. The model takes into account weight and numer of cylinders can explain 86% of the variation in miles per gallons with a residual standard error of 2.39.

NOTES

In order to reduce the lenght of the report I have omitted several tables. The code to replicate the analisys and read the tables is in the appendix. This pdf document has been created with Knitr from

a Markdown document in R Studio. The complete code can be found as a repository at the address: https://github.com/duccioa/CourseraRegression-Project

APPENDIX

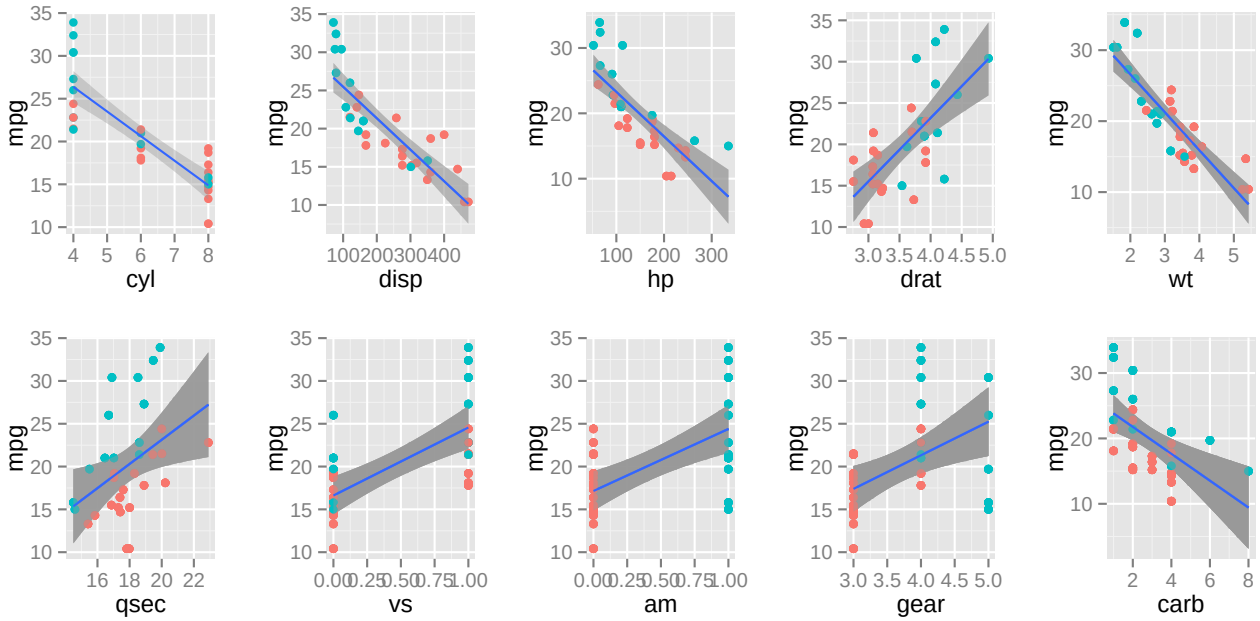
Appendix 1

Exploratory graphs

```
##Print multiple exploratory graphs with ggplot using grid.arrange
names_var <- names(select(mtcars, -mpg))
out <- NULL
g <- ggplot(mtcars, aes(y = mpg))
for(i in 1:length(names_var)){

    g <- g + aes_string(x = names_var[i]) +
        geom_point(aes(colour = factor(am))) +
        geom_smooth(method = "lm", aes(group = 1)) +
        guides(colour = FALSE)

    out[[i]] <- g # creates a list with all the plots
}
grid.arrange(out[[1]], out[[2]], out[[3]], out[[4]],
             out[[5]], out[[6]], out[[7]], out[[8]],
             out[[9]], out[[10]], nrow = 2)
```



Appendix 2

```
t.test(mtcars$mpg ~ mtcars$am)
```

Appendix 3

```
fit_am <- lm(mpg ~ am, mtcars)
summary(fit_am)
```

Appendix 4

```
attach(mtcars)
cor(cyl, disp)
t.test(disp[cyl == 4], disp[cyl == 6])
t.test(disp[cyl == 6], disp[cyl == 8])
summary(lm(disp ~ cyl))
detach(mtcars)
```

Appendix 5

```
fit_interaction <- lm(mpg ~ am + wt + am*wt, mtcars)
summary(fit_interaction)$coef
plot(mtcars$wt, mtcars$mpg, col = as.factor(mtcars$am))
abline(fit_interaction$coef[1],  fit_interaction$coef[3])
abline(fit_interaction$coef[1] + fit_interaction$coef[2],
       fit_interaction$coef[3] + fit_interaction$coef[4], col = "red")
```

Appendix 6

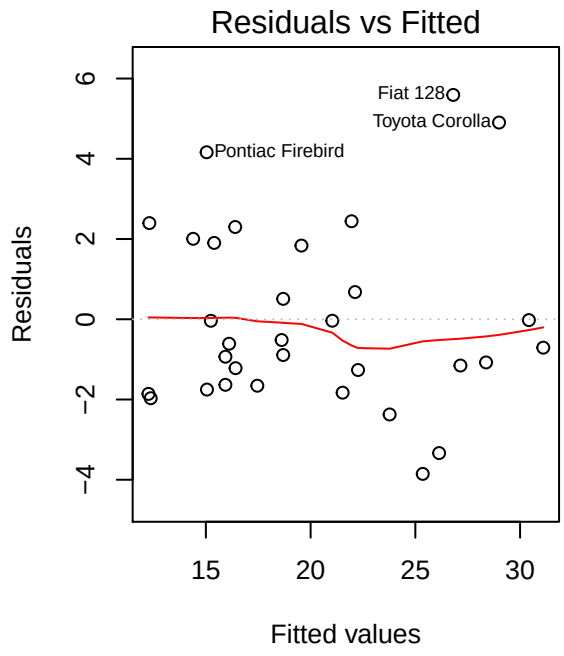
```
summary(fit_wt)
summary(fit_wt2)
```

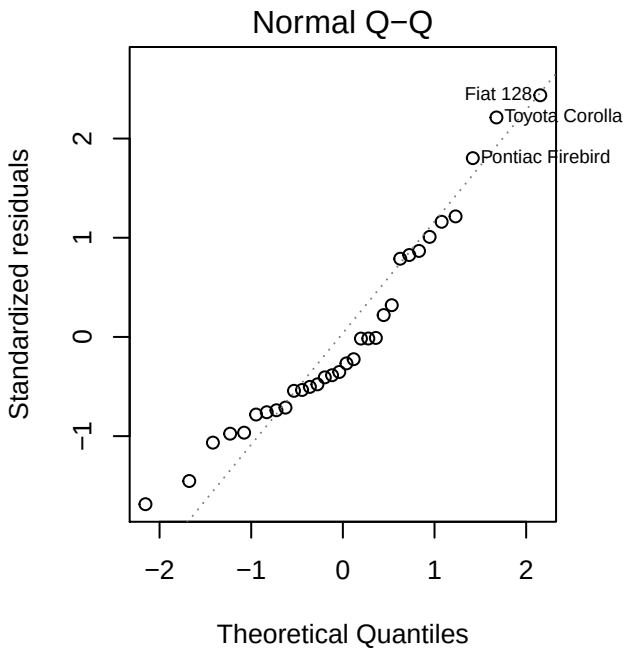
Appendix 7

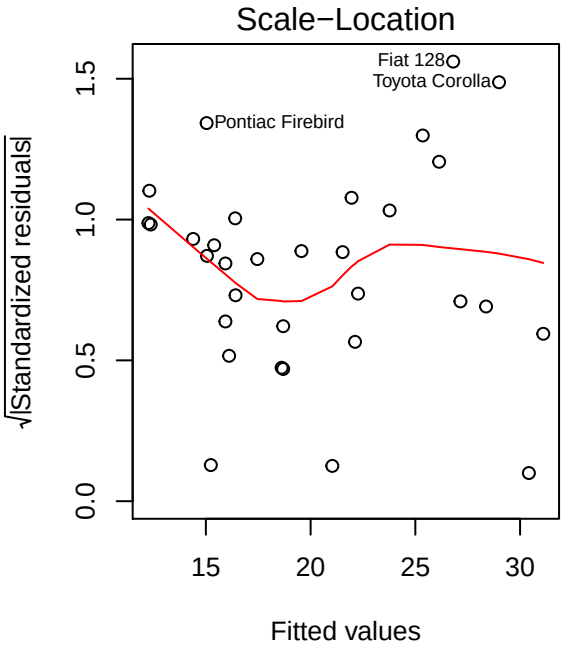
```
attach(mtcars)
cor(wt, am)
t.test(wt[am == 0], wt[am == 1])
summary(lm(wt ~ am))
detach(mtcars)
```

Appendix 8

```
par(mfrow=c(2,2))
plot(fit_wt2_cyl)
```


Residuals vs Fitted
Residuals
Fitted values
Fiat 128
Toyota Corolla
Pontiac Firebird


Normal Q−Q
Standardized residuals
Theoretical Quantiles
Fiat 128
Toyota Corolla
Pontiac Firebird


Scale−Location
√|Standardized residuals|
Fitted values
Fiat 128
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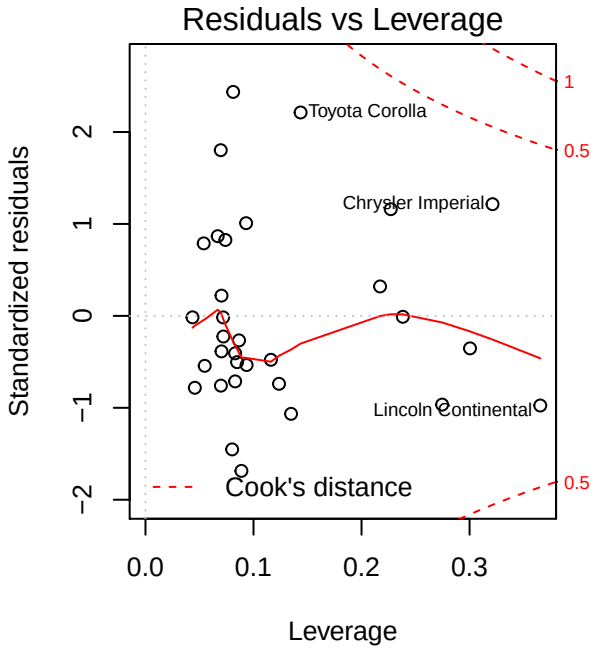
Pontiac Firebird


Residuals vs Leverage
Standardized residuals
Leverage
Toyota Corolla
Chrysler Imperial
Lincoln Continental
Cook's distance
1
0.5
0.5