Regression Models Final Assignment : mtcars analysis

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Introduction

This document is my submission for the final assignment of the Regression Models course from the Coursera Data Science specialization by the John Hopkins University.

Instructions

You work for Motor Trend, a magazine about the automobile industry. Looking at a data set of a collection of cars, they are interested in exploring the relationship between a set of variables and miles per gallon (MPG) (outcome). They are particularly interested in the following two questions:

- "Is an automatic or manual transmission better for MPG"
- "Quantify the MPG difference between automatic and manual transmissions"

Take the `mtcars` data set and write up an analysis to answer their question using regression models and exploratory data analyses.

Author's note

Since we're doing many significance tests in this study, we have to correct for this. in order to avoid getting p-values by pure luck. Since we estimate the number of significance tests in the study to be of the order of 10, the Bonferroni correction tells us to look for p-values under 0.005.

Exploratory analysis

We first get a grip of the data by using basic R commands.

It appears that some of the variables are naturally discrete. We thus convert them to factor variables.

```
mtcars_fac <- mutate(mtcars, cyl = factor(cyl),
                     vs = factor(vs, labels = c("V engine", "Straigth engine")),
                     am = factor(am, labels = c("Automatic", "Manual")),
                     gear = factor(gear),
                     carb = factor(carb))
```

We then plot a pair graph of the original `mtcars` data to get a grip of the correlation between the variables. `mpg` seems to decrease when `cyl`, `disp`, `hp`, `wt` increase, and seems to be higher among V engines than among Straigth engines, and higher among automatic transmission cars than among manual transmission cars as well.
Some of those relations make sense : a heavier car will naturally use more gas, and a car designer will have to sacrifice some efficiency in order to achieve higher horsepower. The others, however, are more obscure.

Since we are especially interested in the relationship between variables `mpg` and `am`, we plot a boxplot of the value of `mpg` for automatic and manual transmission. It appears that cars with manual transmission have a notably higher mpg than those with automatic transmission.

```
fit <- lm(mpg ~ am, mtcars_fac)
```

Fitting a first model we find that the average value of `mpg` is 17.15 for automatic cars and 7.24 for manual cars. Both p-values are low enough for us to reject the null hypothesis that the actual coefficients are zero. However, the model's R-squared is only 0.36 which is not satisfying. We thus have to try adding other variables in order to explain `mpg`'s variance.

Model Selection

As our first model is not satisfying, we will search for other significant variables in the modelling of `mpg`. We start with a model including all variables and use the AIC (Akaike information criterion) to eliminate variables down to a better model.

```
fit_all <- lm(mpg ~.,data=mtcars_fac)
fit_step <- step(fit_all, trace = 0)
```

This new model is not fully satisfying, however. The p-values for the `cyl8` coefficient is 0.35, which is far from enough to attest for its significance. The p-value for the `am` coefficient is 0.21 which is not good enough either.

Since these coefficients are not significative, let us fit two models, each with one of these variable dropped. We also fit a model where we drop both the `cyl` and `am` variables and compare these models to our previous one.

```
fit_no_am <- lm(mpg ~ wt + hp + cyl, mtcars_fac)
fit_no_cyl <- lm(mpg ~ wt + hp + am, mtcars_fac)
fit_no_am_no_cyl <- lm(mpg ~ wt + hp, mtcars_fac)
anova(fit_step, fit_no_am)
```

```
## Analysis of Variance Table
##
## Model 1: mpg ~ cyl + hp + wt + am
## Model 2: mpg ~ wt + hp + cyl
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1     26 151.03
## 2     27 160.78 -1    -9.752 1.6789 0.2065
```

```
anova(fit_step, fit_no_cyl)
```

```
## Analysis of Variance Table
##
## Model 1: mpg ~ cyl + hp + wt + am
## Model 2: mpg ~ wt + hp + am
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1     26 151.03
## 2     28 180.29 -2   -29.265 2.5191    0.1 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(fit_step, fit_no_am_no_cyl)
```

```
## Analysis of Variance Table
##
## Model 1: mpg ~ cyl + hp + wt + am
```

```
## Model 2: mpg ~ wt + hp
##   Res.Df    RSS Df Sum of Sq      F  Pr(>F)
## 1     26 151.03
## 2     29 195.05 -3   -44.022 2.5262 0.07947 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The model without either `am` or `cyl` seems to be the only one improving on the previous one. It seems to be a pretty satisfying model since the p-values are better than previously, being under our Bonferroni threshold of 0.005!
So the two remaining variables are horsepower and weight. But those two seem intuitively related : cars that have higher horsepower will be heavier. We thus try correcting for the interaction between the two variables.

```
fit_final <- lm(mpg ~ wt + hp + wt*hp, mtcars_fac)
anova(fit_no_am_no_cyl, fit_final)
```

```
## Analysis of Variance Table
##
## Model 1: mpg ~ wt + hp
## Model 2: mpg ~ wt + hp + wt * hp
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1     29 195.05
## 2     28 129.76  1    65.286 14.088 0.0008108 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The improvement obtained by adding the interaction term seems like a good idea. This model actually explains *almost* as much variance (R-squared = 0.88) than the model containing all the variables (R-squared = 0.89) which many less variables, *and* this time the coefficients of all the terms are highly significant.

Residuals

We observe no particular pattern in the various plots of the residuals, and they seem to be normally distributed : our model presents no obvious weakness.

Conclusion

Our study showed that, if the mtcars sample is representative, the transmission mode does not have a significant influence on the MPG, which is mainly explained by weight and horsepower. Therefore, the interaction between the transmission mode and the MPG is not quantifiable : the difference in MPG between the automatic cars and the manual cars is explained by their weight and horsepower.

Appendices

mtcars data

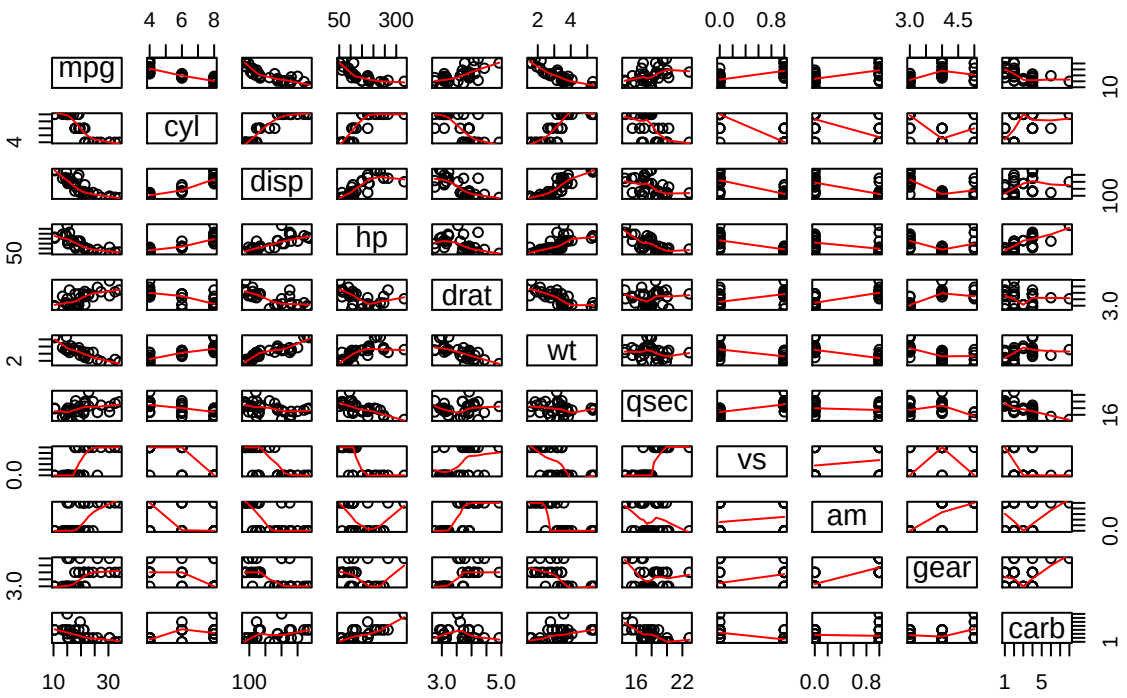
```
##                   mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4         21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag     21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710        22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
## Hornet 4 Drive    21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
## Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
## Valiant           18.1   6  225 105 2.76 3.460 20.22  1  0    3    1
```

```
## 'data.frame':    32 obs. of  11 variables:
##  $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
##  $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
##  $ disp: num  160 160 108 258 360 ...
##  $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
##  $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
##  $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
##  $ qsec: num  16.5 17 18.6 19.4 17 ...
##  $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
##  $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
##  $ gear: num  4 4 4 3 3 3 3 4 4 4 ...
##  $ carb: num  4 4 1 1 2 1 4 2 2 4 ...
```

```
##       mpg             cyl             disp             hp       
##  Min.   :10.40   Min.   :4.000   Min.   : 71.1   Min.   : 52.0  
##  1st Qu.:15.43   1st Qu.:4.000   1st Qu.:120.8   1st Qu.: 96.5  
##  Median :19.20   Median :6.000   Median :196.3   Median :123.0  
##  Mean   :20.09   Mean   :6.188   Mean   :230.7   Mean   :146.7  
##  3rd Qu.:22.80   3rd Qu.:8.000   3rd Qu.:326.0   3rd Qu.:180.0  
##  Max.   :33.90   Max.   :8.000   Max.   :472.0   Max.   :335.0  
##       drat             wt             qsec             vs        
##  Min.   :2.760   Min.   :1.513   Min.   :14.50   Min.   :0.0000  
##  1st Qu.:3.080   1st Qu.:2.581   1st Qu.:16.89   1st Qu.:0.0000  
##  Median :3.695   Median :3.325   Median :17.71   Median :0.0000  
##  Mean   :3.597   Mean   :3.217   Mean   :17.85   Mean   :0.4375  
##  3rd Qu.:3.920   3rd Qu.:3.610   3rd Qu.:18.90   3rd Qu.:1.0000  
##  Max.   :4.930   Max.   :5.424   Max.   :22.90   Max.   :1.0000  
##        am              gear            carb      
##  Min.   :0.0000   Min.   :3.000   Min.   :1.000  
##  1st Qu.:0.0000   1st Qu.:3.000   1st Qu.:2.000  
##  Median :0.0000   Median :4.000   Median :2.000  
##  Mean   :0.4062   Mean   :3.688   Mean   :2.812  
##  3rd Qu.:1.0000   3rd Qu.:4.000   3rd Qu.:4.000  
##  Max.   :1.0000   Max.   :5.000   Max.   :8.000
```

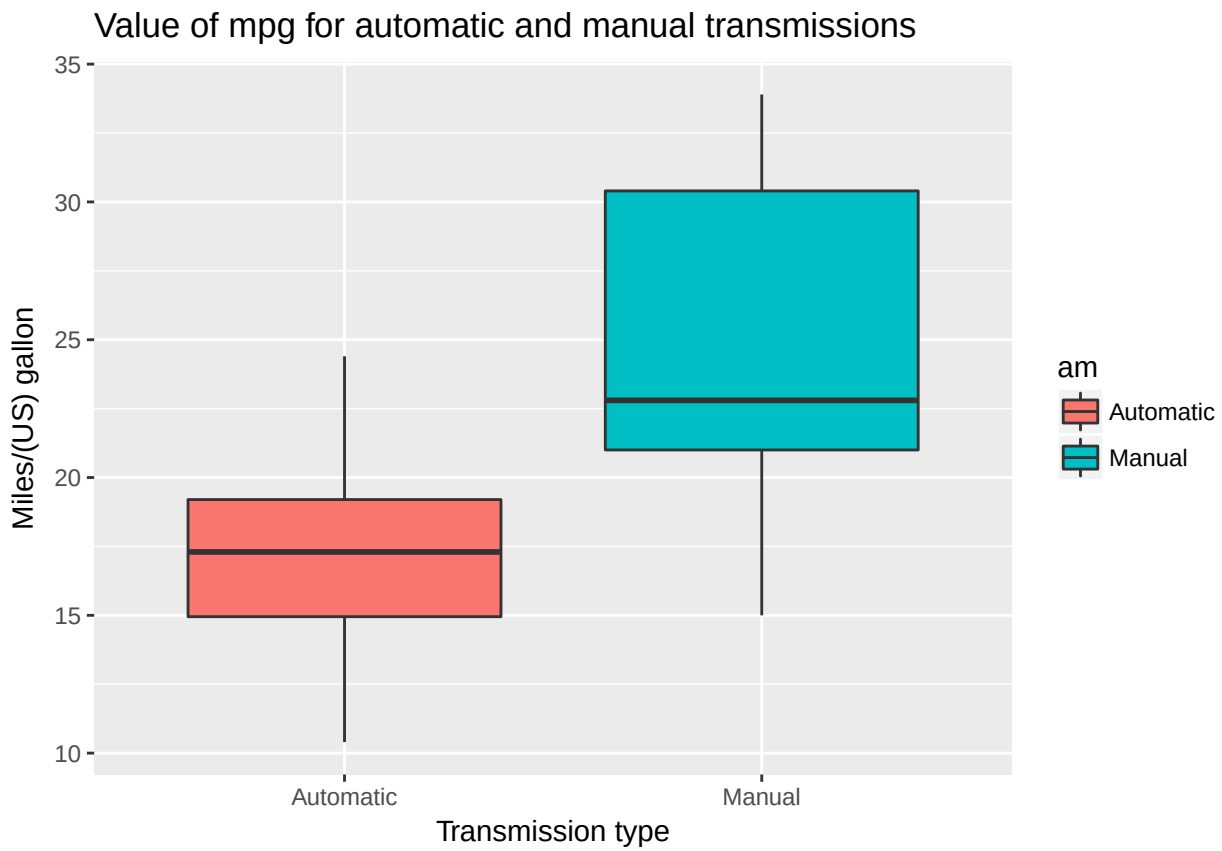
Pair graph

```
pairs(mtcars, panel=panel.smooth, main="Pair graph for mtcars data")
```



Boxplot

```
g <- ggplot(mtcars_fac, aes(am, mpg)) +
    geom_boxplot(aes(fill = am)) +
    labs(title = "Value of mpg for automatic and manual transmissions",
         x = "Transmission type",
         y = "Miles/(US) gallon")
print(g)
```



Models

Simple Model

```
summary(fit)
```

```
##
## Call:
## lm(formula = mpg ~ am, data = mtcars_fac)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.3923 -3.0923 -0.2974  3.2439  9.5077
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   17.147      1.125  15.247 1.13e-15 ***
## amManual       7.245      1.764   4.106 0.000285 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.902 on 30 degrees of freedom
## Multiple R-squared:  0.3598, Adjusted R-squared:  0.3385
## F-statistic: 16.86 on 1 and 30 DF,  p-value: 0.000285
```

Model with all variables

```
summary(fit_all)
```

```
##
## Call:
## lm(formula = mpg ~ ., data = mtcars_fac)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.5087 -1.3584 -0.0948  0.7745  4.6251
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       23.87913   20.06582   1.190   0.2525
## cyl6              -2.64870    3.04089  -0.871   0.3975
## cyl8              -0.33616    7.15954  -0.047   0.9632
## disp               0.03555    0.03190   1.114   0.2827
## hp                -0.07051    0.03943  -1.788   0.0939 .
## drat               1.18283    2.48348   0.476   0.6407
## wt                -4.52978    2.53875  -1.784   0.0946 .
## qsec               0.36784    0.93540   0.393   0.6997
## vsStraigth engine  1.93085    2.87126   0.672   0.5115
## amManual           1.21212    3.21355   0.377   0.7113
## gear4              1.11435    3.79952   0.293   0.7733
## gear5              2.52840    3.73636   0.677   0.5089
## carb2             -0.97935    2.31797  -0.423   0.6787
## carb3              2.99964    4.29355   0.699   0.4955
## carb4              1.09142    4.44962   0.245   0.8096
## carb6              4.47757    6.38406   0.701   0.4938
## carb8              7.25041    8.36057   0.867   0.3995
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.833 on 15 degrees of freedom
## Multiple R-squared:  0.8931, Adjusted R-squared:  0.779
## F-statistic:  7.83 on 16 and 15 DF,  p-value: 0.000124
```

Model obtained with AIC

```
summary(fit_step)
```

```
##
## Call:
## lm(formula = mpg ~ cyl + hp + wt + am, data = mtcars_fac)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9387 -1.2560 -0.4013  1.1253  5.0513
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 33.70832    2.60489  12.940 7.73e-13 ***
```

```
## cyl6        -3.03134    1.40728  -2.154  0.04068 *
## cyl8        -2.16368    2.28425  -0.947  0.35225
## hp          -0.03211    0.01369  -2.345  0.02693 *
## wt          -2.49683    0.88559  -2.819  0.00908 **
## amManual     1.80921    1.39630   1.296  0.20646
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.41 on 26 degrees of freedom
## Multiple R-squared:  0.8659, Adjusted R-squared:  0.8401
## F-statistic: 33.57 on 5 and 26 DF,  p-value: 1.506e-10
```

Model with only `wt` and `hp`

```
summary(fit_no_am_no_cyl)
```

```
##
## Call:
## lm(formula = mpg ~ wt + hp, data = mtcars_fac)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -3.941 -1.600 -0.182  1.050  5.854
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 37.22727    1.59879  23.285  < 2e-16 ***
## wt          -3.87783    0.63273  -6.129 1.12e-06 ***
## hp          -0.03177    0.00903  -3.519  0.00145 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.593 on 29 degrees of freedom
## Multiple R-squared:  0.8268, Adjusted R-squared:  0.8148
## F-statistic: 69.21 on 2 and 29 DF,  p-value: 9.109e-12
```

Final Model with `wt`, `hp` and their interaction

```
summary(fit_final)
```

```
##
## Call:
## lm(formula = mpg ~ wt + hp + wt * hp, data = mtcars_fac)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.0632 -1.6491 -0.7362  1.4211  4.5513
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 49.80842    3.60516  13.816 5.01e-14 ***
## wt          -8.21662    1.26971  -6.471 5.20e-07 ***
```

```
## hp          -0.12010    0.02470  -4.863 4.04e-05 ***
## wt:hp        0.02785    0.00742   3.753 0.000811 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.153 on 28 degrees of freedom
## Multiple R-squared:  0.8848, Adjusted R-squared:  0.8724
## F-statistic: 71.66 on 3 and 28 DF,  p-value: 2.981e-13
```

Residuals

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