Regression Models Project — MPG Analysis Using Mtcars Data Set

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Summary

This analysis uses a data set of a collection of cars to explore the relationship between a set of car features and MPG. Specifically, it answers 2 questions concerning the influence of transmission type on MPG. Data are first divided into a subset of numeric variables and another of factor variables for rudimentary exploration. Subsequent feature selection is utilizes a stepwise algorithm based on AIC. Regression model comparison, coefficient interpretation and potential problems are presented in the third part of this analysis.

```
library(rmarkdown)
library(knitr)
library(dplyr)
library(ggplot2)
library(magrittr)
library(stargazer)
library(ggfortify)
```

Exploratory Analysis

Correlation Matrix of Numeric Variables

Check the correlation of each pair of the numeric variables. But keep in mind that variables that have a high correlation with MPG do not necessarily cause a high or low MPG.

```
data("mtcars")
kable(head(mtcars))
```

	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

```
sapply(mtcars, class)
```

```
##
        {\tt mpg}
                   cyl
                            disp
                                        hp
                                                drat
                                                            wt
                                                                     qsec
                                           "numeric" "numeric" "numeric"
  "numeric" "numeric" "numeric"
##
##
         vs
                    am
                            gear
                                      carb
## "numeric" "numeric" "numeric" "numeric"
```

```
mtcars[ , c('cyl', 'vs', 'am')] %<>% lapply(function(x) as.factor(x))
# Should not use sapply().
mtcars_numeric <- select_if(mtcars, is.numeric)
kable(cor(mtcars_numeric))</pre>
```

	mpg	disp	hp	drat	wt	qsec	gear	carb
mpg	1.0000000	-0.8475514	-0.7761684	0.6811719	-0.8676594	0.4186840	0.4802848	-0.5509251
disp	-0.8475514	1.0000000	0.7909486	-0.7102139	0.8879799	-0.4336979	-0.5555692	0.3949769
hp	-0.7761684	0.7909486	1.0000000	-0.4487591	0.6587479	-0.7082234	-0.1257043	0.7498125
drat	0.6811719	-0.7102139	-0.4487591	1.0000000	-0.7124406	0.0912048	0.6996101	-0.0907898
wt	-0.8676594	0.8879799	0.6587479	-0.7124406	1.0000000	-0.1747159	-0.5832870	0.4276059
qsec	0.4186840	-0.4336979	-0.7082234	0.0912048	-0.1747159	1.0000000	-0.2126822	-0.6562492
gear	0.4802848	-0.5555692	-0.1257043	0.6996101	-0.5832870	-0.2126822	1.0000000	0.2740728
carb	-0.5509251	0.3949769	0.7498125	-0.0907898	0.4276059	-0.6562492	0.2740728	1.0000000

Factor Variable Exploration

Violin plots are created to show the MPG distribution dependent on transmission types (am). Furthermore, 2 additional violin plots are drawn to reveal the abovementioned distribution when either engine type (vs) or number of cylinders (cyl) is taken into consideration. (Please see "Violin Plot of MPG on Transmission Type (1) - (3)" in Appendix.)

```
mtcars_factor <- select(mtcars, mpg, cyl, vs, am)</pre>
levels(mtcars_factor$vs) <- c('V-shape', 'Straight')</pre>
levels(mtcars_factor$am) <- c('Automatic', 'Manual')</pre>
theme_format <- theme(plot.margin = unit(c(1,1,1,1), "cm"),</pre>
                                                           plot.title = element_text(hjust = 0.5, size = 16),
                                                           axis.text = element_text(size = 12),
                                                           axis.title = element_text(size = 14))
am_only \leftarrow ggplot(mtcars_factor, aes(x = am, y = mpg)) +
                              geom_violin(trim = FALSE) + geom_boxplot(width = 0.2) +
                              labs(x = "Transmission Type", y = "MPG", title = "Violin Plot of MPG on Transmission Type (1)") +
                             theme format
am vs <- ggplot(mtcars factor, aes(x = am, y = mpg, fill = vs)) + geom violin(trim = FALSE) +
                         labs(x = "Transmission Type", y = "MPG", title = "Violin Plot of MPG on Transmission Type (2)") +
                        theme_format + scale_fill_manual(values = c("lightsteelblue1", "mistyrose"), name = "Engine Type")
am_cyl \leftarrow ggplot(mtcars_factor, aes(x = am, y = mpg, fill = cyl)) + geom_violin(trim = FALSE) + geom_violin(trim 
                           labs(x = "Transmission Type", y = "MPG", title = "Violin Plot of MPG on Transmission Type (3)") +
                           theme_format + scale_fill_manual(values = c("thistle1", "lightsteelblue3", "navajowhite"),
                                                                                                                   name = "Number of Cylinders")
am_only
am_vs
am_cyl
```

Regression Models

Model Selection

In this analysis, only OLS models will be built and compared.

First, select a formula-based model by AIC. This gives us a basic model that yields the best performance when interaction terms are not taken into consideration. Then we run two more regressions of MPG on the variables selected, but with different variable interactions added.

```
basic_model <- step(lm(mpg~., data = mtcars), trace = 0)
all.vars(formula(basic_model))</pre>
```

[1] "mpg" "wt" "qsec" "am"

Regression Results

	Dependent variable:					
		MPG				
	(1)	(2)	(3)			
Weight	-3.917***	-3.777***	-2.937***			
	(0.711)	(0.671)	(0.666)			
Manual Transmission * 1/4 Mile Time	Э	1.060**				
		(0.487)				
1/4 Mile Time	1.226***	0.817**	1.017***			
	(0.289)	(0.330)	(0.252)			
Manual Transmission * Weight			-4.141***			
			(1.197)			
Manual Transmission	2.936**	-15.614 [*]	14.079***			
	(1.411)	(8.624)	(3.435)			
Constant	9.618	16.529**	9.723			
	(6.960)	(7.267)	(5.899)			
Observations	32	32	32			
R^2	0.850	0.872	0.896			
Adjusted R ²	0.834	0.853	0.880			
Residual Std. Error	2.459 (df = 28)	2.309 (df = 27)	2.084 (df = 27)			
F Statistic	52.750**** (df = 3; 28)	46.029*** (df = 4; 27)	58.061*** (df = 4; 27)			
Note:		p<	:0.1; p<0.05; p<0.01			

Based on the above result, the third model (with interaction between transmission type and weight) is selected for MPG prediction because it has the largest F-stat as well as largest adjusted R-squared. Also we see that the regressors in this model all have significant coefficients.

Residual Plotting

Four types of residual plots are created to show potential pitfalls in the model. But judging from the plots, the model does not appear to have significant problems such as heteroskedasticity or high leverage points.

(Please see "Residual Plots" in Appendix.)

```
autoplot(inter_am_wt, label.size = 3)
```

Coefficient Interpretation & Potential Problems

The model fomula is:

 $\mathring{MPG} = 9.723 + 14.079 \times Manual_Transmission - 2.937 \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.141 \times Manual_Transmission \times Weight + 1.017 \times (1/4_Mile_Time) - 4.011 \times (1/4_Mile_Time) - 4.0$

Holding other things constant, the predicted MPG for a car with automatic transmission is given by:

$$\stackrel{\frown}{MPG}_{automatic} = 9.723 - 2.937 \times Weight + 1.017 \times (1/4_Mile_Time)$$

while that for a car with manual transmission is:

$$MPG_{manual} = 23.802 - 7.078 \times Weight + 1.017 \times (1/4_Mile_Time)$$

Question 1: Quantify the MPG difference between automatic and manual transmissions.

The difference is measured by:

$$\stackrel{\wedge}{MPG}_{automatic} - \stackrel{\wedge}{MPG}_{manual} = -14.079 + 4.141 \times Weight$$

Question 2: Is an automatic or manual transmission better for MPG?

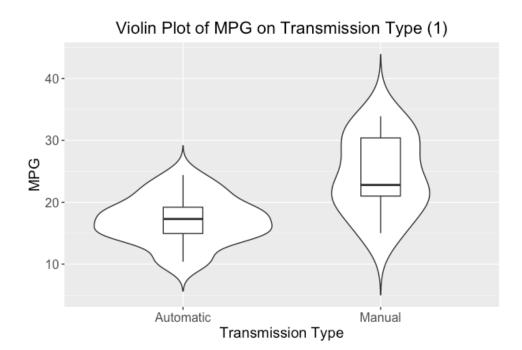
That depends. When a car is no heavier than $(14.079/4.141 \times 1000 \approx)$ 3,399.90 lbs, manual transmission has an edge in terms of MPG. If its weight exceeds 3,399.90 lbs, than automatic transmission is better for MPG.

Question 3: How about the uncertainties?

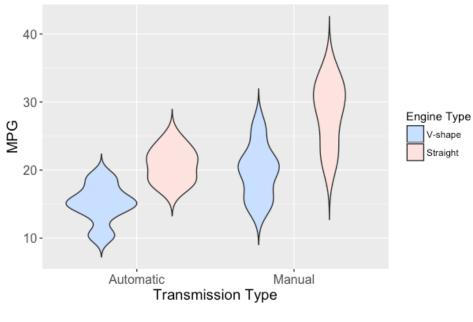
In this analysis, a potentially fatal problem is that the number of observations is way too small compared to the number of features. A small change in any observation of our data set can have a great influence in our model selection and robustness. Because of the lack of observations, we cannot determine with certainty whether the features not included in this analysis are actually influential or not.

Appendix

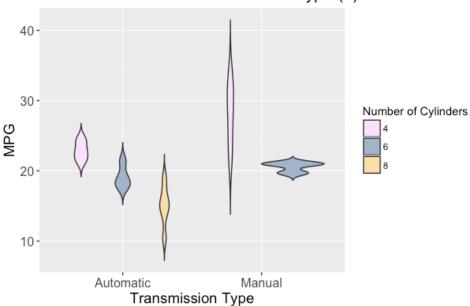
MPG on Transmission:



Violin Plot of MPG on Transmission Type (2)



Violin Plot of MPG on Transmission Type (3)



Residual Plots:

