Manual cars more fuel efficient: myth or reality?

In this report we address a long-debated and controversial issue concerning the fuel economy of automobiles with automatic or manual transmission: Which one is better in terms of MPG? How much is the difference? We analyzed design and performance data for a sample of 32 car models, european and american, high-end and economy, and can offer you some interesting points clarifying the fuel economy vs. transmission issue beyond common wisdom, urban legends, and *philosophical* biases ;-)

Executive Summary

A naive analysis, *not controlling* for other car features and performance metrics, would suggest that manual cars are more fuel-efficient, by about 7.2 miles per gallon, at a 99.86% confidence level (*2-sample t-test, 2-sided*). However, this assessment does not take into any consideration the heterogeneity of car models. Assuming that the data at our disposal are representative of the general car "population", our linear regression analysis leads us to conclude that in fact **there is NOT any significant difference in fuel efficiency between cars with automatic and manual transmission**. Most of the difference (variance) in fuel efficiency can be explained in terms of car weight and engine power.

The apparent better fuel economy of manual transmission emerges from a strong relationship between type of transmission and several other features (*e.g.* the cars with automatic transmission tend to be heavier, have larger and more powerful engines). Once the effect of these other "physical" factors is removed there is no residual difference between automatic and manual cars. This could actually be appreciated already by looking at the subset of cars in the narrow middle range of parameter values where both types of cars are present.

In the remainder of the report we summarize the methods and findings. Plots are presented in the Appendix. This report is being produced with a "live" R-markdown document, that I will post on my GitHub repo.

Data, Selection and Processing

The dataset comprises 32 car models. For each of them it reports its gas mileage in miles per gallon (MPG) and 10 other features encompassing various aspects of engine/powertrain design and measures of performance. Of the 10 potential *predictors*, five can be regarded as categorical either directly (*e.g.* `am`) or effectively (*e.g.* `carb`), and we treated them as *factors*. The other five take continuous numeric values.

MPG and **GP100M**: we performed our analysis on a transformed variable instead of directly on `mpg`, defining *gallons per 100 miles* (`gp100m <- 100/mpg`).
We decided to do this because `mpg`'s relationship with most continuous variables exhibits a marked curvature, which can potentially be an issue given our intent of working with linear models and hence it would recommend to transform the variables to mitigate its effect. The new variable exhibits much more "regular" (*i.e.* straighter) relationships with the predictors. Moreover, and likely related to the straightening of the relationships, `gp100m` *more transparently* represents what truly is the most important variable in the analysis, that is the amount of fuel used by a car.
It is also more intepretable with respect to many of the predictors: a *back-of-the-envelope* argument about energy $\propto$ force $\times$ distance, and in turn force $\propto$ weight would provide an explanation of the correlation between `gp100m` and `wt` (car weight). Also, correlations of `gp100m` with `disp` (the engine displacement volume) and `hp` (engine power) could be fairly promptly interpreted because both variables can be expected to have a proportional effect on fuel efficiency expressed in this way.

We first reviewed the relationship between the 10 variables by means of *pairs plots* (see Appendix) and correlation analyses, looking for potentially significant trends, such as correlations or noticeable differences between the two groups of *automatic* and *manual* transmission cars (coded in the `am` factor).

Based on this preliminary review, for what concerns categorical variables we decided to limit our analyses to `am` and `cyl` and to leave out `vs`, `gear` and `carb`. Among the continuous variables we left out `qsec` (the 1/4 mile time) because it did not show any significant relationship with any other variable, except with `hp` which is not surprising given `qsec` depends very directly on short-duration acceleration, hence engine power.

Findings – Exploratory Analysis : General Trends and Correlations

As the **pairs-plot** shows `gp100m` is strongly correlated with `wt` and `disp`, and between the two selected categorical variables `cyl` seems to exert a stronger influence than `am`.
This is illustrated also by the **interaction plots** showing that the mean `gp100m` within each `cyl` group is basically independent on `am`, and that the shift between automatic and manuals cars in each `cyl` group is very small. The **boxplots** further highlights that all "important" continuous variables exhibit systematic differences between `am` groups, similarly to `gp100m`, thus suggesting that the apparent correlation between these latter may not be truly a fundamental characteristic of automobiles.

Findings – Linear Regression Models

In this short report we focus on the results of the analysis based on what emerged as the most important continuous variables, `wt` and `hp`, combined with the two factor variables `am` and `cyl`. In particular we discuss three groups of models for explaining the variation in fuel efficiency, all based on a baseline model with `wt` as sole predictor. They are: **(1)** car weight with possible effect of type of transmission (`gp100m ~ wt*am`). **(2)** car weight with possible effect of number of cylinders (`gp100m ~ wt*cyl`). **(3)** car weight and engine power (`gp100m ~ wt + hp`). In each case we look at the model incrementally, for instance including only `wt`, the adding `am`, and finally adding the interaction between them (i.e. allowing for different slopes for each category-group).

In the models of **Case #1** the addition of `am`, even with interaction, is not accompanied by a statistically significant improvement, as it can be summarized by the adjusted-R^2 metric, which is 0.785, 0.79. 0.783, respectively. The *analysis of variance* of the nested models gives a $P(>F)$ of 0.216 and 0.68 for the `wt + am` and `wt*am` models. The `am` has no influence on the regression of `gp100m` on `wt`. The model is quite good, as illustrated by the *summary diagnostic plots*: it is worth noting that the residuals are distributed similarly for both `am` groups, visually showing that there is no additional "explanatory" effect by `am` after the effect of `wt` is subtracted.

Case #2 looks at the influence of `cyl` instead of `am`. Again, we compared a sequence of nested models `wt`, `wt + cyl`, `wt*cyl`. The adjusted-R^2 metric values are 0.785 (same as above, being the same *base model*), 0.812. 0.806, respectively, a modest improvement over the previous case. The *analysis of variance* of the nested models gives a $P(>F)$ of 0.062 and 0.589 which suggests that albeit at low statistical significance, in this case the addition of the factor variable does improve the model, but the extension with the interaction term does not yield any further improvement.

The models in final set, **Case #3**, are based on `wt` and `hp` only, one model with each of the separately, and one with them combined (no interaction). The adjusted-R^2 values are 0.785 (this is again the same *base model*), 0.568. 0.837, for `wt`, `hp` and `wt + hp` respectively. The model with `hp` alone provides a pretty poor fit, but the combined model achieves the highest reduction in variance of all the models we have tested that have up to three terms in the linear model (including possible interactions).

The *analysis of variance* of the nested `wt` and `wt+hp` models gives a $P(>F)$ of 0.003 which tells us that indeed the improvement of the model with addition of `hp` is statistically significant.

It is possible that a model with additional predictors might improve over the `wt+hp`, however looking at the regression plot and at the residuals plot, it is clear that there is no room left for a possible significant effect on `gp100m` explainable with `am`, which is the main issue of interest of this analysis.

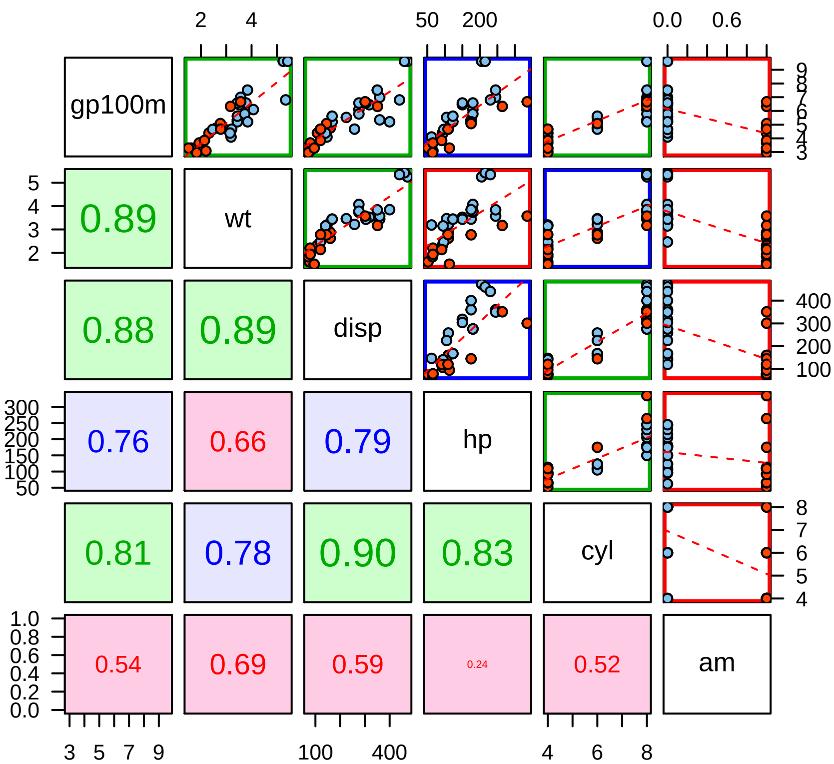
The best fit model has the form: gp100m = 0.6305 + 1.1485 wt + 0.0075 hp, or better still, shifting the reference point (*origin*) to `wt=2` and `hp=100` and scaling `hp` to 100:

$$\text{gp100m} = 3.6755 + 1.1485\ (\text{wt} - 2) + 0.7479\ (\text{hp} - 100)/100$$

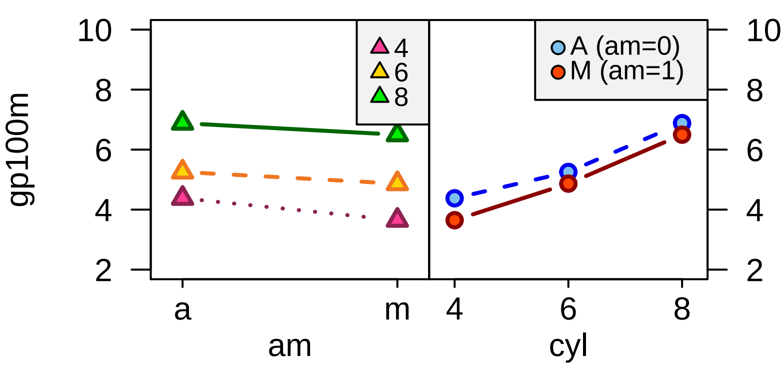
The fuel consumption in *gallons/100miles* of a car of 2000 lbs (`wt=2`) and 100 HP (`hp=100`) is predicted to be about 3.68 and to increase by 1.15 every 1000 lbs. and by 0.75 every 100 HP. It is important to keep in mind that `wt` and `hp` are correlated, with a slope of around 0.94, and therefore the increase in gas consumption will generally be a combination of the two components growing in similar proportions.

APPENDIX : SUPPLEMENTARY MATERIAL

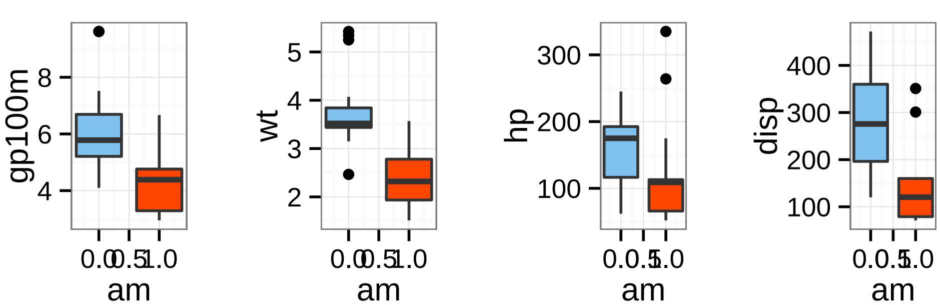
PAIRS PLOTS : Upper-right panels show the `y~x` scatterplots, with a `lm` line overlayed. Colors correspond to the `am` categories, blue `am=0` and red for `am=1` Lower-left panels report the (absolute) value of `cor(x,y)`.



INTERACTION PLOTS: Mean `gp100m` for the 6 groups resulting from combinations of `am` and `cyl`.



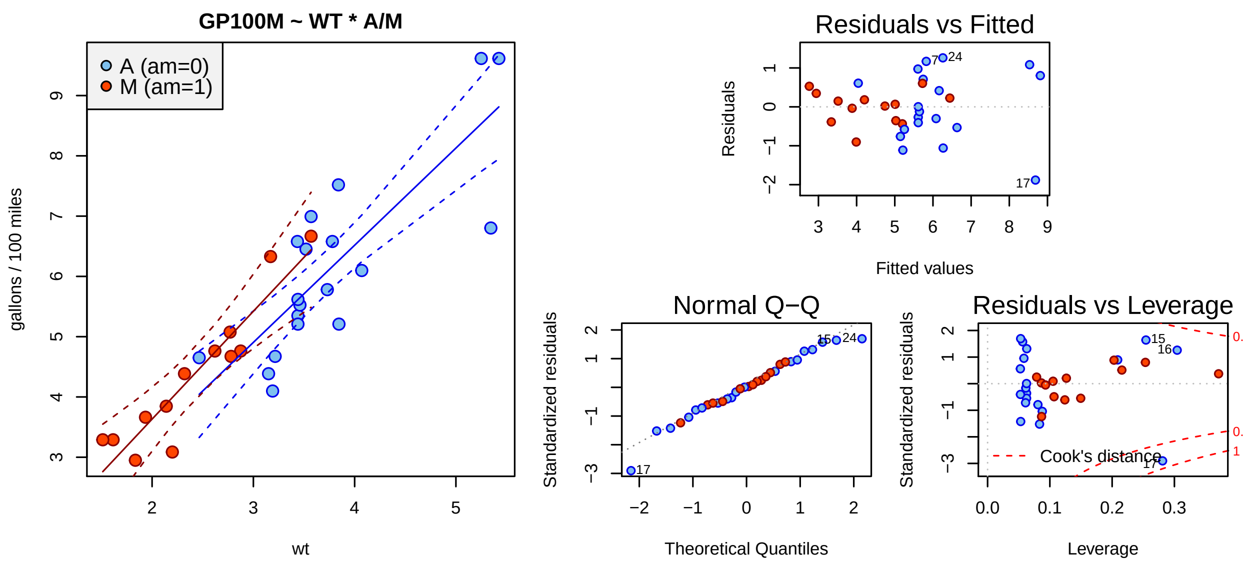
BOXPLOTS of gp100m, wt, hp, disp vs. am



LINEAR REGRESSION MODELS

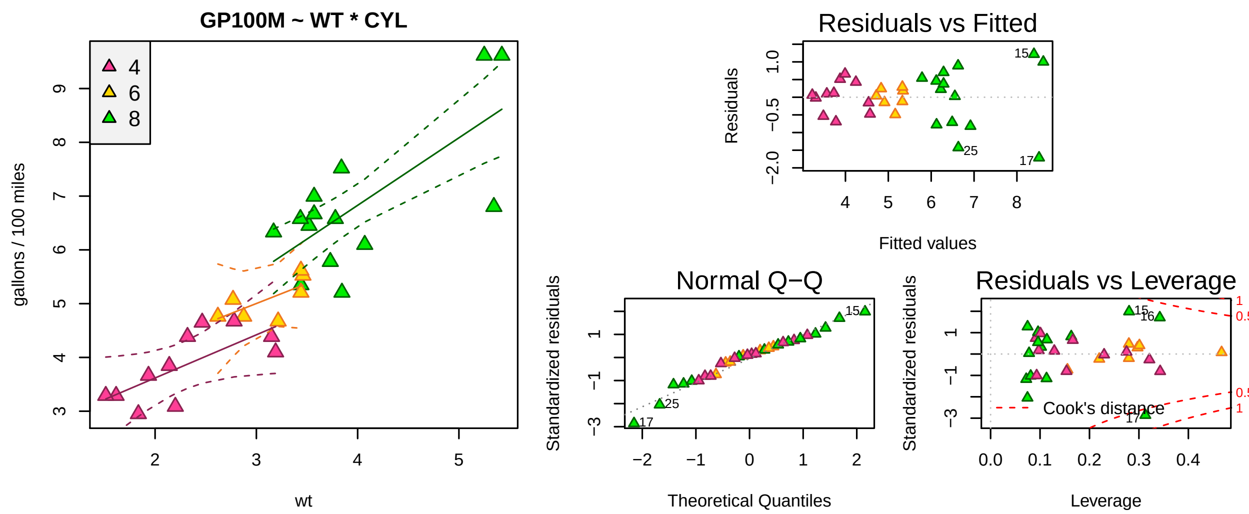
1. gp100m vs. wt by am (with interaction)

```
| MODEL : gp100m ~ wt
|       : adj. R^2 = 0.7850 /  F-stats: 114.168 on 1,30 Df,  p-value: 9.566e-12
| MODEL : gp100m ~ wt + amFac
|       : adj. R^2 = 0.7895 /  F-stats: 59.147 on 2,29 Df,  p-value: 5.836e-11
| MODEL : gp100m ~ wt + amFac + wt * amFac
|       : adj. R^2 = 0.7834 /  F-stats: 38.365 on 3,28 Df,  p-value: 4.726e-10

|   Res.Df  RSS Df Sum of Sq    F Pr(>F)
| 1     30 17.4
| 2     29 16.5  1     0.937 1.60   0.22
| 3     28 16.4  1     0.102 0.17   0.68
```



2. gp100m vs. wt by cyl (with interaction)

```
| MODEL : gp100m ~ wt
|       : adj. R^2 = 0.7850 /  F-stats: 114.168 on 1,30 Df,  p-value: 9.566e-12
| MODEL : gp100m ~ wt + cylFac
|       : adj. R^2 = 0.8125 /  F-stats: 45.774 on 3,28 Df,  p-value: 6.354e-11
| MODEL : gp100m ~ wt + cylFac + wt * cylFac
|       : adj. R^2 = 0.8061 /  F-stats: 26.780 on 5,26 Df,  p-value: 1.758e-09

|   Res.Df  RSS Df Sum of Sq    F Pr(>F)
| 1     30 17.4
| 2     28 14.2  2      3.24 3.10  0.062
| 3     26 13.6  2      0.57 0.54  0.589
```



3. gp100m vs. wt & hp [BEST MODEL]

```
| MODEL : gp100m ~ wt
|       : adj. R^2 = 0.7850 /  F-stats: 114.168 on 1,30 Df,  p-value: 9.566e-12
| MODEL : gp100m ~ hp
|       : adj. R^2 = 0.5682 /  F-stats: 41.786 on 1,30 Df,  p-value: 3.839e-07
| MODEL : gp100m ~ wt + hp
|       : adj. R^2 = 0.8365 /  F-stats: 80.326 on 2,29 Df,  p-value: 1.494e-12
|              Estimate     Std. Error    Pr(>|t|)     Signif
| (Intercept)  6.3051e-01   4.0936e-01    1.3435e-01
| wt           1.1485e+00   1.6201e-01    8.4494e-08   ***
| hp           7.4793e-03   2.3120e-03    3.0345e-03   **
|   Res.Df  RSS Df Sum of Sq    F Pr(>F)
| 1     30 17.4
| 2     29 12.8  1      4.61 10.5  0.003
```