Rationale for MASSExtra

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Preamble

This extension package to the classical `MASS` package (Venables & Ripley, of ancient lineage), whose origins go back to nearly 30 years, comes about for a number of reasons.

Firstly, in my teaching I found I was using some of the old functions in the package with consistently different argument settings to the defaults. I was also interested in supplying various convenience extensions that simplified teaching and including various tweaks to improve the interface. Examples follow below.

Secondly, I wanted to provide a few functions that were mainly useful as programming examples. For example, the function `zs` and its allies `zu`, `zq` and `zr` are mainly alternatives to `base::scale`, but they can be used to show how to write functions that can be used in fitting models in such a way that they work as they should when the fitted model object is used for prediction with new data.

Masking `select` from other packages

Finally, there is the perennial `select` problem. When `MASS` is used with other packages, such as `dplyr` the `select` function can easly be masked, causing confusion with users. `MASS::select` is rarely used, but `dplyr::select` is fundamental. There are standard ways of managing this kind of masking, but what we have done in `MASSExtra` is to export the more common functions used from `MASS` along with the extensions, in such a way that users will not need to have `MASS` attached to the search path at all, and hence masking is unlikely.

The remainder of this document will do a walk-through of some of the new functions provided by the package. We begin by setting the computational context:

```
suppressPackageStartupMessages({
  library(ggwebthemes) ## https://gitlab.com/peterbar/ggwebthemes/
  library(visreg)
  library(knitr)
  library(tidyverse)
  library(patchwork)
  library(MASSExtra)
})
options(knitr.kable.NA = "")
theme_set(theme_web_bw() + theme(title = element_text(hjust = 0.5)))
```

Amble

We now consider some of the extensions that the package offers to the originals. Most of the extensions will have a name that includes an underscore of two somewhere to distinguish it from the V&R original. Note that the original version is *also* exported so that scripts that use it may do so without change, via the new package.

The `box_cox` extensions

This original version, `boxcox` has a fairly rigid display for the plotted output which has been changed to give a more easily appreciated result. The $y-$axis has been changed to give the likelihood-ratio statistic rather

than the log-likelihood, and for the $x-$axis some attempt has been made to focus on the crucial region for the transformation parameter, λ,

The following example shows the old and new plot versions for a simple example.

```
par(mfrow = c(1, 2))
mod0 <- lm(MPG.city ~ Weight, Cars93)
boxcox(mod0)  ## MASS
box_cox(mod0) ## MASSExtra tweak
```

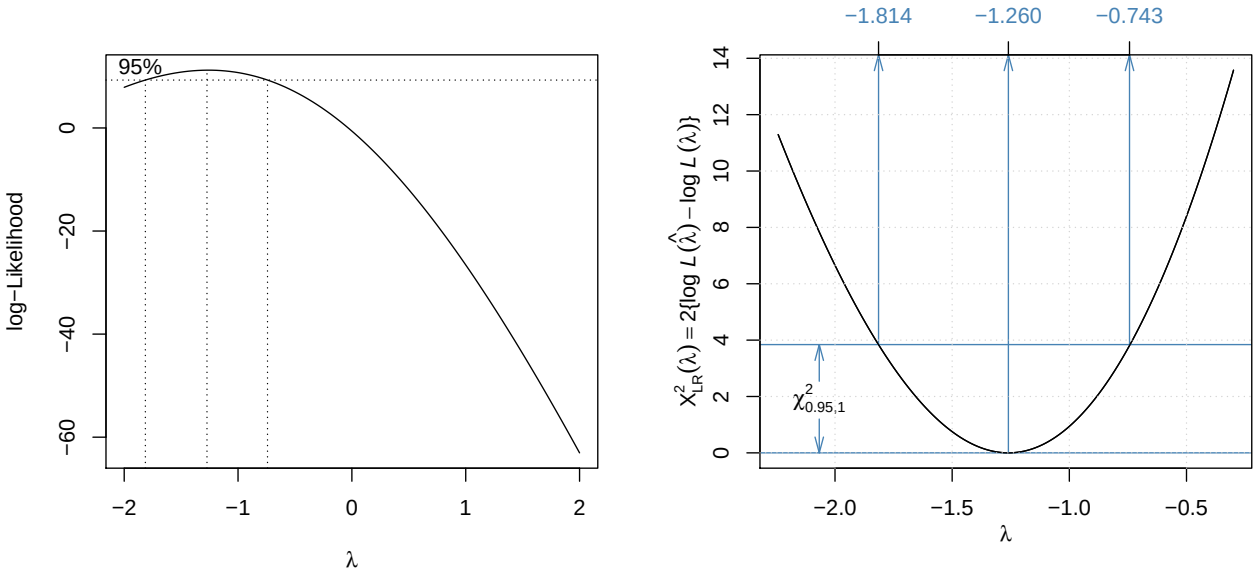


Figure 1: Box-cox, old and new displays

In addition, there are functions `bc` to evaluate the transformation for a given exponent, and a function `lambda` which finds the optimum exponent (not that a precise exponent will usually be needed).

It is interesting to see how in this instance the transformation can both straighten the relationship and provide a scale in which the variance is more homogeneous. See Figure 2.

```
p0 <- ggplot(Cars93) + aes(x = Weight) + geom_point(colour = "#2297E6")  + xlab("Weight (lbs)") +
  geom_smooth(se = FALSE, method = "loess", formula = y ~ x, size=0.7, colour = "black")
p1 <- p0 + aes(y = MPG.city) + ylab("Miles per gallon (MPG)") + ggtitle("Untransformed response")
p2 <- p0 + aes(y = bc(MPG.city, lambda(mod0))) + ggtitle("Transformed response") +
  ylab(bquote(bc(MPG, .(round(lambda(mod0), 2)))))
p1 + p2
```

A more natural scale to use, consistent with the Box-Cox suggestion, would be the reciprocal. For example we could use GPM = 100/MPG the "gallons per 100 miles" scale, which would have the added benefit of being more-or-less what the rest of the world uses to gauge fuel efficiency outside the USA. Readers should try this for themselves.

Stepwise model building extensions

The primary `MASS` functions for refining linear models and their allies are `dropterm` and `stepAIC`. The package provides a few extensions to these, but mainly a change of defaults in the argument settings.

1. `drop_term` is a front-end to `MASS::dropterm` with a few tweaks. By default the result is arranged in sorted order, i.e. with `sorted = TRUE`, and also by default with `test = TRUE` (somewhat in defiance of much advice to the contrary given by experienced practitioners: *caveat emptor!*).

   The user may specify the test to use in the normal way, but the default test is decided by an ancillary

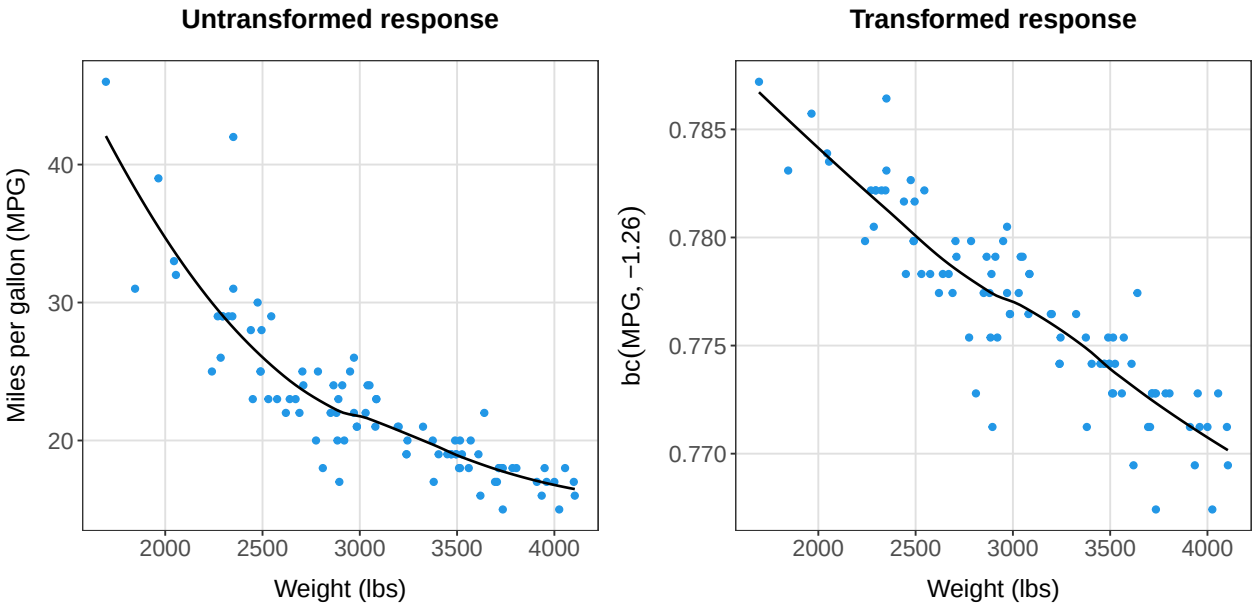


Figure 2: The Box-Cox transformation effect

generic function, `default_test`, which guesses the appropriate test from the object itself. This is an S3 generic and further methods can be supplied for new fitted model objects.

In addition `drop_term` returns and object which retains information on the criterion used, `AIC`, `BIC`, `GIC` (see below) or some specific penalty value `k`. The object also has a class `"drop_term"` for which a `plot` method is provided. Both the `plot` and `print` methods display the criterion. See the example below for how this is done.

2. `step_AIC` is a front-end to `MASS::stepAIC` with the default argument `trace = FALSE` set. This may of course be over-ruled, but it seems the most frequent choice by users, anyway. In addition the actual criterion used, by dafault `k = 2`, i.e. AIC, is retained with the result and passed on to methods in much the same say as for `drop_term` above.

   Since the (default) criterion name is encoded in the function name, two further versions are supplied, namely `step_BIC` and `step_GIC` (again, see below), which use a different, and obvious, default criterion.

   In any of `step_AIC`, `step_BIC` or `step_GIC` a different value of `k` may be specified in which case that value of `k` is retained with the object and displayed as appropriate in further methods.

   Finally in any of these functions `k` may be specified either as a numeric penalty, such as `k = 4` for example, or by character string `k = "AIC"` or `k = "BIC"` with an obvious meaning in either case.

3. Criteria. The **Akaike Information Criterion**, AIC, corresponds to a penalty `k = 2` and the **Bayesian Information Criterion**, BIC, corresponds to `k = log(n)` where `n` is the sample size. In addition to these two the present functions offer an intermediate default penalty `k = (2 + log(n))/2` which is "not too strong and not too weak", making it the **Goldilocks Information Criterion**, GIC. There is also a standalone function `GIC` to evaluate this `k` if need be.

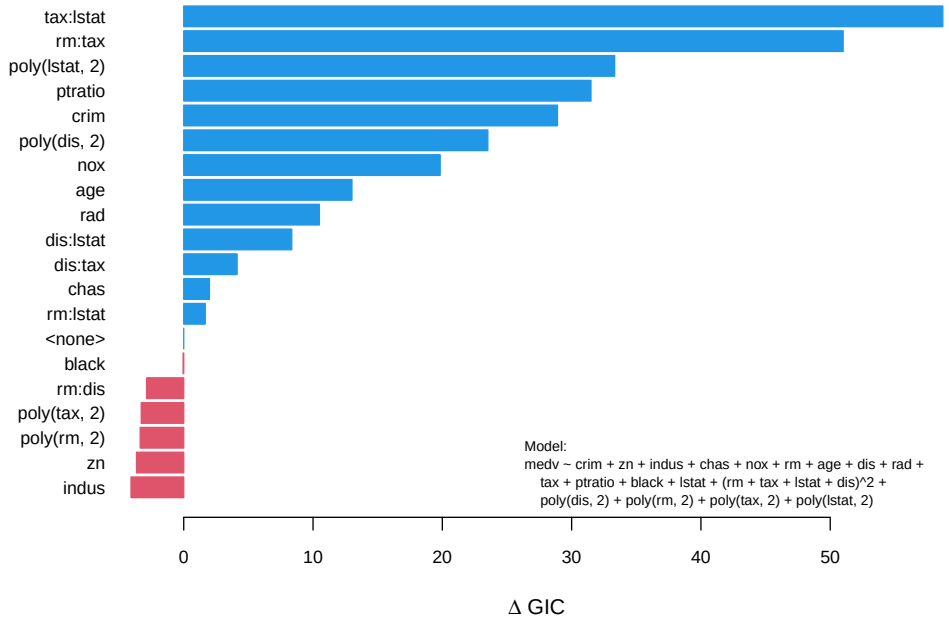
   This suggestion appears to be original, but *no particular claim is made for it* other than with intermediate to largish data sets it has proved useful for exploratory purposes in our experience.

   Our strong advice is that these tools should ***only*** be used for exploratory purposes in any case, and should ***never*** be used in isolation. They have a well-deserved very negative reputation when misused, as they commonly are.

Examples

We consider the well-known (and much maligned) Boston house price data. See `?Boston`. We begin by fitting a model that has more terms in it than the usual model, as it contains a few extra quadratic terms, including some key linear by linear interactions.

```
big_model <- lm(medv ~ . + (rm + tax + lstat + dis)^2 + poly(dis, 2) + poly(rm, 2) +
                  poly(tax, 2) + poly(lstat, 2), Boston)
big_model %>% drop_term(k = "GIC") %>% plot() %>% kable(booktabs=TRUE, digits=3)
```



	Df	Sum of Sq	RSS	delta_GIC	F Value	Pr(F)
tax:lstat	1	728.695	6241.320	58.707	63.714	0.000
rm:tax	1	634.356	6146.981	51.000	55.465	0.000
poly(lstat, 2)	1	423.361	5935.985	33.327	37.017	0.000
ptratio	1	401.916	5914.540	31.495	35.142	0.000
crim	1	371.709	5884.334	28.905	32.501	0.000
poly(dis, 2)	1	309.410	5822.034	23.519	27.053	0.000
nox	1	267.160	5779.784	19.833	23.359	0.000
age	1	189.742	5702.366	13.010	16.590	0.000
rad	1	161.441	5674.065	10.492	14.116	0.000
dis:lstat	1	137.523	5650.148	8.355	12.024	0.001
dis:tax	1	90.529	5603.153	4.129	7.915	0.005
chas	1	66.861	5579.485	1.987	5.846	0.016
rm:lstat	1	63.305	5575.929	1.664	5.535	0.019
			5512.624	0.000		
black	1	44.479	5557.103	-0.047	3.889	0.049
rm:dis	1	13.525	5526.149	-2.873	1.183	0.277
poly(tax, 2)	1	9.012	5521.636	-3.287	0.788	0.375
poly(rm, 2)	1	8.130	5520.755	-3.368	0.711	0.400
zn	1	5.035	5517.659	-3.651	0.440	0.507
indus	1	0.405	5513.029	-4.076	0.035	0.851

Unlike `MASS::dropterm`, the table shows the terms beginning with the most important ones, that is those which, if dropped, would *increase* the criterion and ending with those of least looking importance, that is those whose removal would most *decrease* the criterion. And also note that here we are using the `GIC`, which is

displayed in the output.

Note particularly that rather than give the *value* of the criterion by default the table and plot show *change* in the criterion which would result if the term is removed from the model at that point. This is a more meaningful quantity, and invariant with respect to the way in which the log-likelihood is defined.

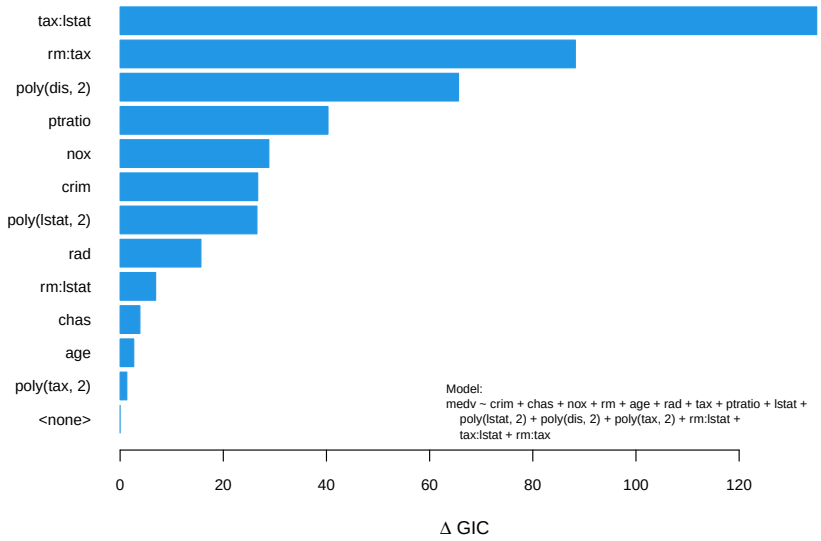
The `plot` method gives a graphical view of the same key bits of information, in the same vertical order as given in the table. Terms whose removal would (at this point) improve the model are shown in *red* and those which would not, and hence should (again, at this point) be retained are shown in *blue*.

With all stepwise methods it is critically important to notice that the whole picture can change once any change is made to the current model. This terms which appear "promising" at this stage may not seem so once any variable is removed from the model or some other variable brought into it. This is a notoriously tricky area for the inexperienced.

Notice that the `plot` method returns the original object, which can then be passed on via a pipe to more operations. (`kable` does not, so this pipe sequence cannot be changed.)

We now consider a refinement of this model by stepwise means, but rather than use the large model as the starting point, we begin with a more modest one which has no quadratic terms.

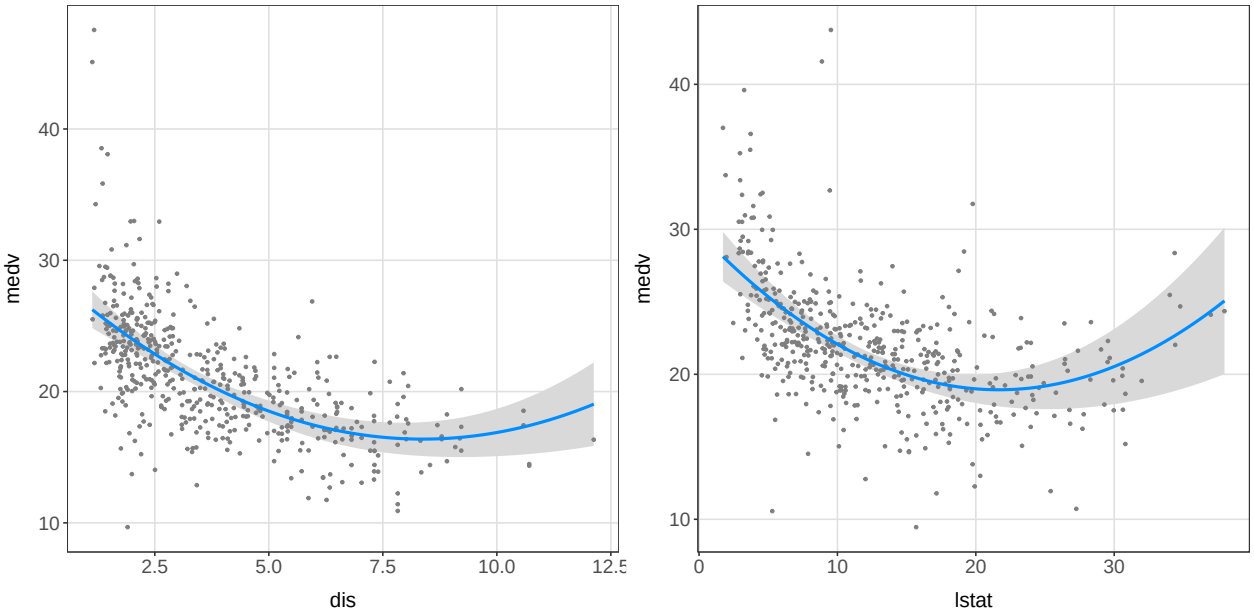
```
base_model <- lm(medv ~ ., Boston)
gic_model <- step_GIC(base_model, scope = list(lower = ~1, upper = formula(big_model)))
drop_term(gic_model) %>% plot() %>% kable(booktabs = TRUE, digits = 3)
```



	Df	Sum of Sq	RSS	delta_GIC	F Value	Pr(F)
tax:lstat	1	1853.126	7707.733	135.034	154.780	0.000
rm:tax	1	1172.351	7026.958	88.244	97.919	0.000
poly(dis, 2)	2	919.601	6774.208	65.596	38.404	0.000
ptratio	1	537.017	6391.624	40.293	44.854	0.000
nox	1	393.819	6248.426	28.828	32.893	0.000
crim	1	367.257	6221.864	26.672	30.675	0.000
poly(lstat, 2)	1	365.333	6219.940	26.516	30.514	0.000
rad	1	233.292	6087.899	15.658	19.486	0.000
rm:lstat	1	128.612	5983.219	6.882	10.742	0.001
chas	1	92.617	5947.224	3.829	7.736	0.006
age	1	78.635	5933.242	2.638	6.568	0.011
poly(tax, 2)	1	62.892	5917.499	1.293	5.253	0.022
			5854.607	0.000		

The model is likely to be over-fitted. To follow up on this we could look at profiles of the fitted terms as an informal way of model 'criticism'.

```
capture.output(suppressWarnings({
   g1 <- visreg(gic_model, "dis", plot = FALSE, ylim = c(5,50))
   g2 <- visreg(gic_model, "lstat", plot = FALSE, ylim = c(5,50))
   plot(g1, gg = TRUE) + plot(g2, gg = TRUE)
})) -> junk
```



The case for curvature appears to be fairly weak, in each case with departure from a straight line dependence depending on a relatively few observations with high values for the predictor. (Notice how hard you have to work to prevent `visreg` from generating unwanted output.)