Model Plots

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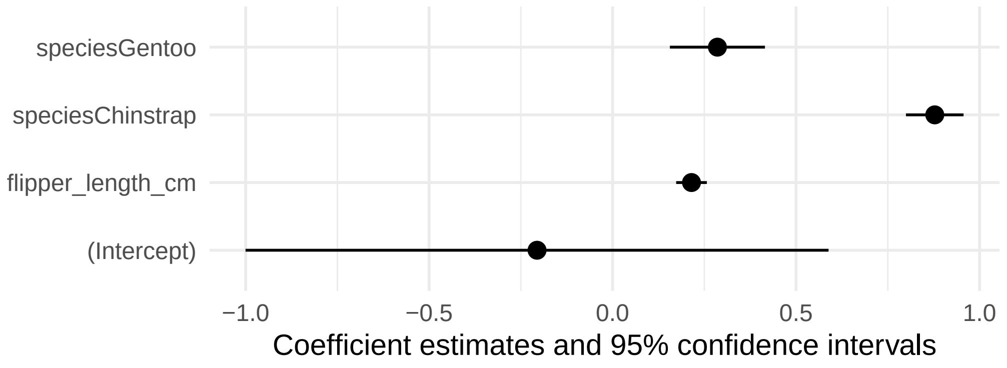
`modelplot` is a function from the `modelsummary` package. It allows you to plot model estimates and confidence intervals. It makes it easy to subset, rename, reorder, and customize plots using same mechanics as in `modelsummary`.

To illustrate how the function works, we fit a linear model to data about the Palmer Penguins:

```r
url <- 'https://vincentarelbundock.github.io/Rdatasets/csv/palmerpenguins/penguins.csv'
dat <- read.csv(url)

# rescale mm -> cm
dat$bill_length_cm <- dat$bill_length_mm / 10
dat$flipper_length_cm <- dat$flipper_length_mm / 10

mod <- lm(bill_length_cm ~ flipper_length_cm + species, data = dat)
```

Then, we load the `modelsummary` library and call `modelplot`:

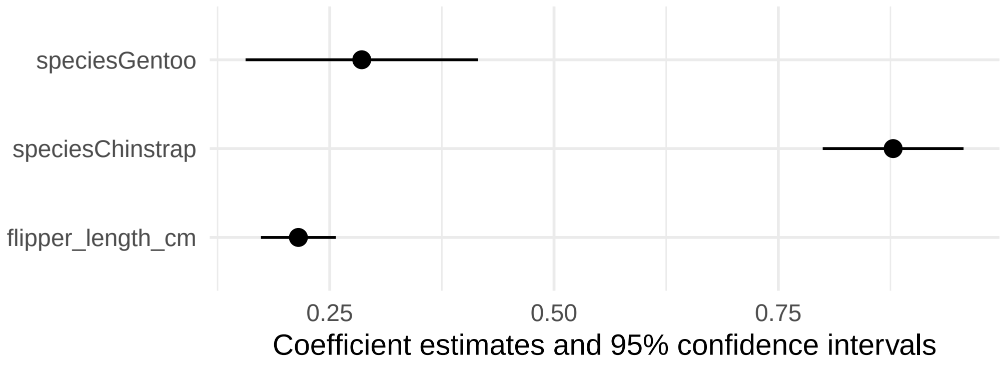
```r
library(modelsummary)

modelplot(mod)
```



1 Rename, reorder, subset

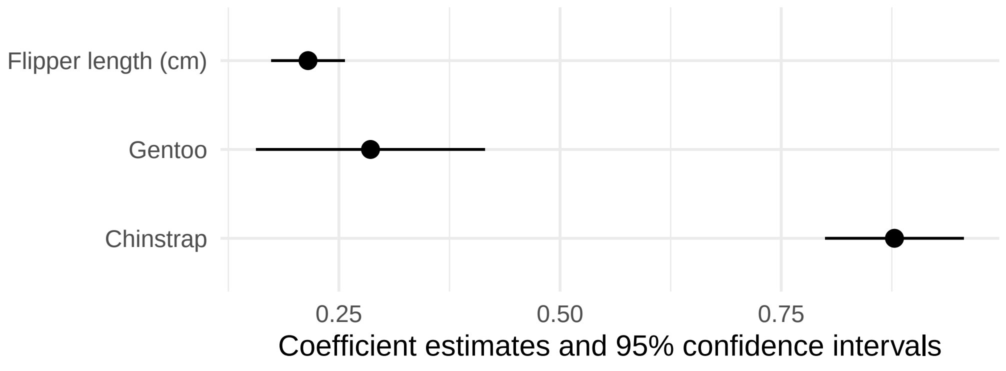
`modelplot` uses the same mechanics as `modelsummary` to rename, reorder, and subset estimates. First, you can use the `coef_omit` argument. This will omit any coefficient that matches a string or regular expression. To omit the intercept, for example, we can type:

```r
modelplot(mod, coef_omit = 'Interc')
```



Second, you can use the `coef_map` argument. `coef_map` is a named character vector, where names correspond to the original term names, and values correspond the names you want to assign. Any variable that is *not* included in `coef_map` will be excluded. Variables will also be drawn in the same order as in `coef_map`:

```r
cm <- c('speciesChinstrap' = 'Chinstrap',
        'speciesGentoo' = 'Gentoo',
        'flipper_length_cm' = 'Flipper length (cm)')

modelplot(mod, coef_map = cm)
```



2 Several models

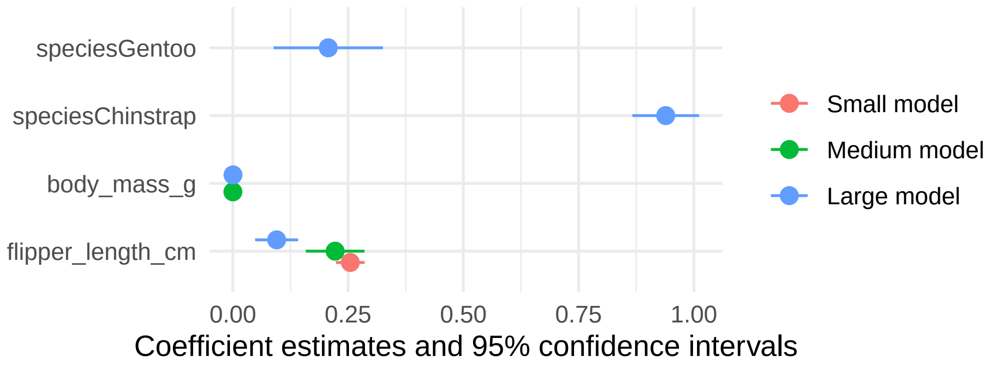
The main `modelsummary` functions allows you to create a table with the results of several models side-by-side, by storing them in a (potentially named) list:

```r
models <- list(
  "Small model" = lm(bill_length_cm ~ flipper_length_cm, data = dat),
  "Medium model" = lm(bill_length_cm ~ flipper_length_cm + body_mass_g, data = dat),
  "Large model" = lm(bill_length_cm ~ flipper_length_cm + body_mass_g + species, data = dat)

modelsummary(models, statistic = 'conf.int')
```

	Small model	Medium model	Large model
(Intercept)	−0.726	−0.344	0.984
	[−1.356, −0.097]	[−1.245, 0.557]	[0.215, 1.752]
flipper_length_cm	0.255	0.222	0.095
	[0.224, 0.286]	[0.158, 0.285]	[0.048, 0.142]
body_mass_g		0.000	0.000
		[0.000, 0.000]	[0.000, 0.000]
speciesChinstrap			0.939
			[0.867, 1.011]
speciesGentoo			0.207
			[0.088, 0.326]
Num.Obs.	342	342	342
R2	0.431	0.433	0.817
R2 Adj.	0.429	0.430	0.815
AIC	369.0	369.6	−12.6
BIC	380.5	385.0	10.4
Log.Lik.	−181.499	−180.813	12.313
F	257.092	129.365	375.333
RMSE	0.41	0.41	0.23

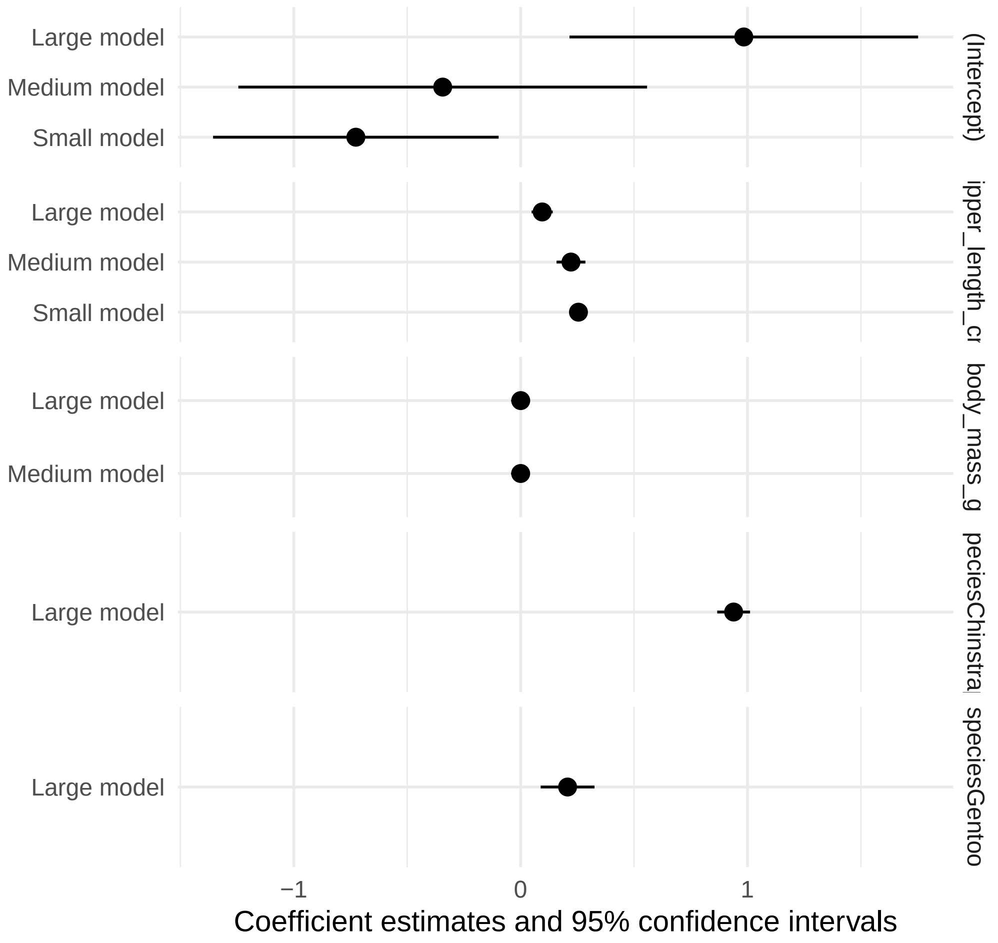
`modelplot` works the same way:

```r
modelplot(models, coef_omit = 'Interc')
```



Instead of displaying results with “dodged” side-by-side lines, you can also use `facet`:

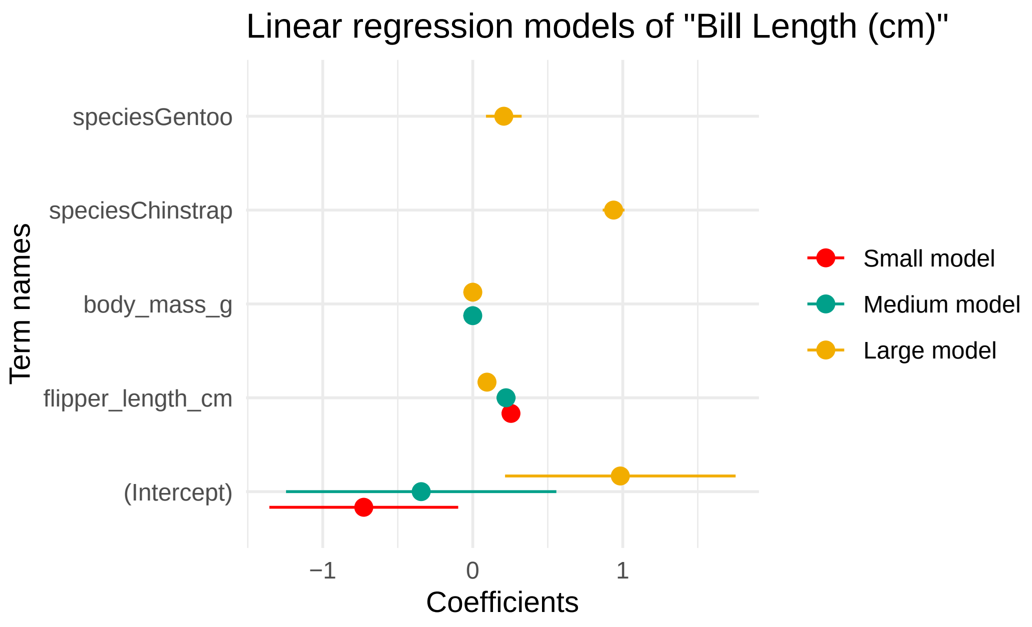
```r
modelplot(models, facet = TRUE)
```



3 Customizing plots

The graphs produced by `modelplot` are simple `ggplot2` objects. You can thus post-process them using the normal suite of functions available for all objects of this type. Here, we change the axis labels, add a title and a caption, and use a color scheme inspired by Wes Anderson's *Darjeeling Limited*:

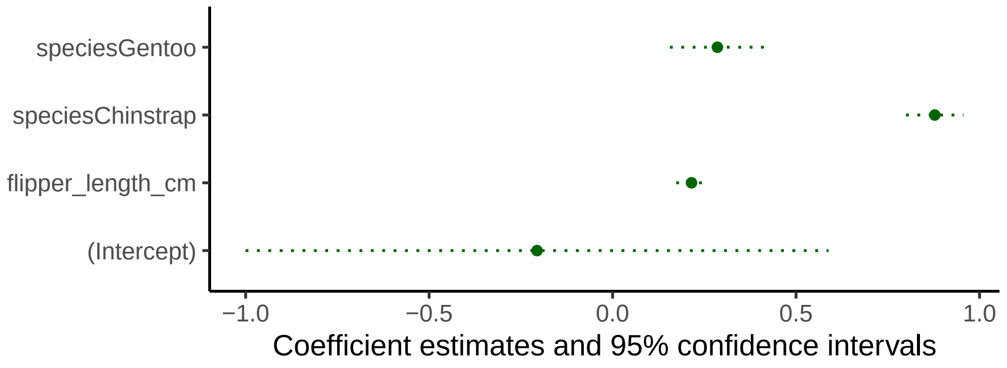
```r
library(wesanderson)
library(ggplot2)

modelplot(models) +
    labs(x = 'Coefficients',
         y = 'Term names',
         title = 'Linear regression models of "Bill Length (cm)"',
         caption = "Data source: Gorman, Williams & Fraser (2014), packaged for R by @apreshi
    scale_color_manual(values = wes_palette('Darjeeling1'))
```



iams & Fraser (2014), packaged for R by @apreshill and @allison_horst

In `ggplot2`, some visual choices must be made when calling the "geom", rather than with post-processing functions. For instance, the `size`, `color`, `fatten`, `linetype` arguments must all be specified inside the `geom_pointrange` function for them to take effect. `modelplot` will pass any unknown argument to `geom_pointrange`, so users can simply call:

```
modelplot(mod, size = 1, fatten = .7, color = 'darkgreen', linetype = 'dotted') +
    theme_classic()
```

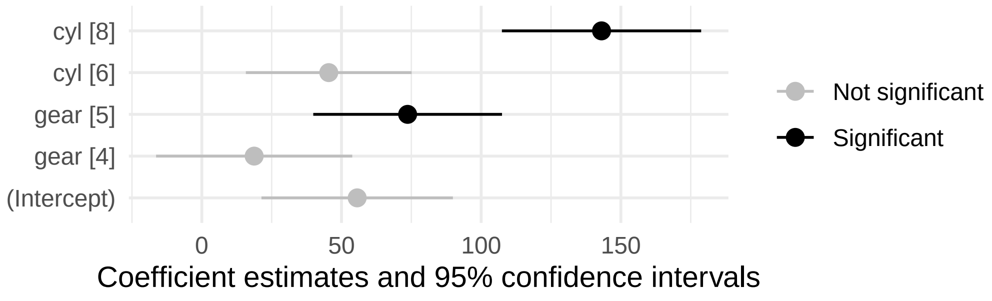


3.1 Conditional colors and shape

Note: This section requires a version of `modelsummary` greater than 1.2.0 or the development version.

In a very nice Stack Overflow answer, Allan Cameron shows how we can use the `aes()` function from `ggplot2` to add conditional aesthetics. For example, if we want to display statistically significant coefficients in a different color:

```r
library(ggplot2)
mod <- lm(hp ~ factor(gear) + factor(cyl), data = mtcars)

modelplot(mod, coef_rename = TRUE) +
  aes(color = ifelse(p.value < 0.001, "Significant", "Not significant")) +
  scale_color_manual(values = c("grey", "black"))
```



3.2 Example: Using facets to compare models

Customizing plots with `ggplot2` makes `modelplot` very flexible. For example, imagine you want to compare the coefficients of three models with different dependent variables. First, we load the packages and estimate our models:

```r
library(ggplot2)
library(modelsummary)

models <- list(
  lm(vs ~ carb + mpg + cyl, data = mtcars),
  lm(disp ~ carb + mpg + cyl, data = mtcars),
  lm(hp ~ carb + mpg + cyl, data = mtcars))
```

Then, we use the `dvnames` function to rename our list with names matching the the dependent variable in each model:

```r
models <- dvnames(models)
```

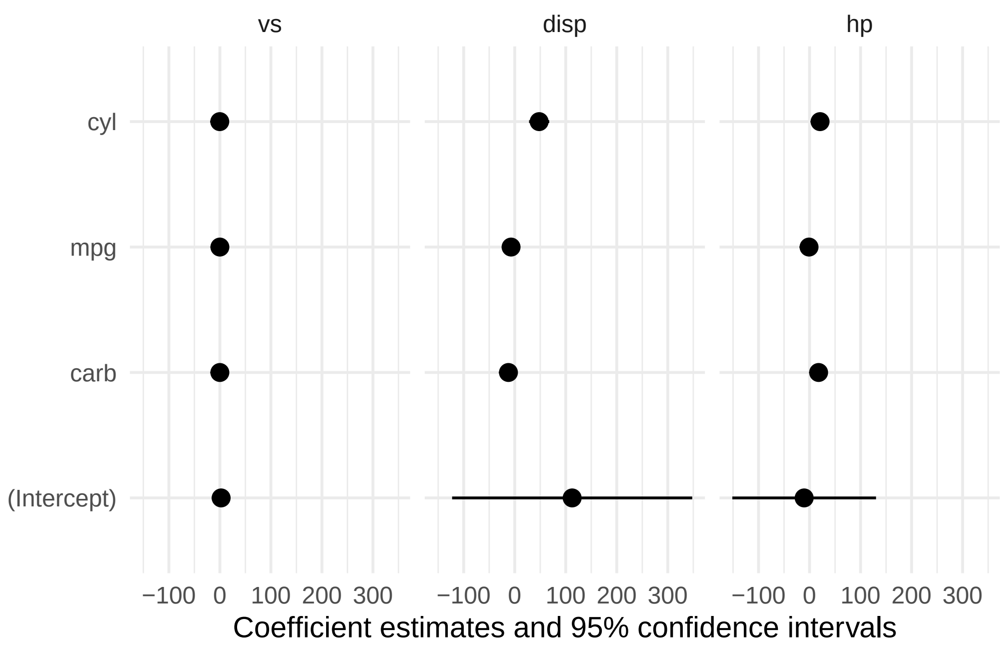
By calling `modelplot` with the `draw=FALSE` argument, we see the raw data used to draw the plot. Here, we see that there is a `model` column:

```r
modelplot(models, draw = FALSE)
```

```
          term model    estimate   std.error     conf.low   conf.high      p.value
1  (Intercept)    vs   2.41742511  0.67622094   1.03224931  3.80260091 1.296718e-03
5  (Intercept)  disp 112.57276339 114.86315481 -122.71374324 347.85927003 3.354494e-01
9  (Intercept)    hp -10.56116383  68.75946117 -151.40853516 130.28620751 8.790301e-01
2         carb    vs  -0.06945116  0.03943402  -0.15022810  0.01132577 8.912324e-02
6         carb  disp -12.30144724  6.69827859  -26.02224894  1.41935446 7.692105e-02
10        carb    hp  17.75593287  4.00972816   9.54237706 25.96948867 1.320972e-04
3          mpg    vs  -0.01513960  0.01716410  -0.05029868  0.02001947 3.852593e-01
7          mpg  disp  -7.14964651  2.91550156  -13.12178072 -1.17751230 2.068858e-02
11         mpg    hp  -1.00486469  1.74527956  -4.57990780  2.57017842 5.693755e-01
4          cyl    vs  -0.23926135  0.05687969  -0.35577411 -0.12274859 2.410214e-04
8          cyl  disp  47.90105842  9.66160634  28.11015499 67.69196184 3.111898e-05
12         cyl    hp  20.60581208  5.78363747   8.75856779 32.45305638 1.338485e-03
```

Finally, we use the `model` column as our identifier in `ggplot2`'s `facet_grid` command to display models side by side:

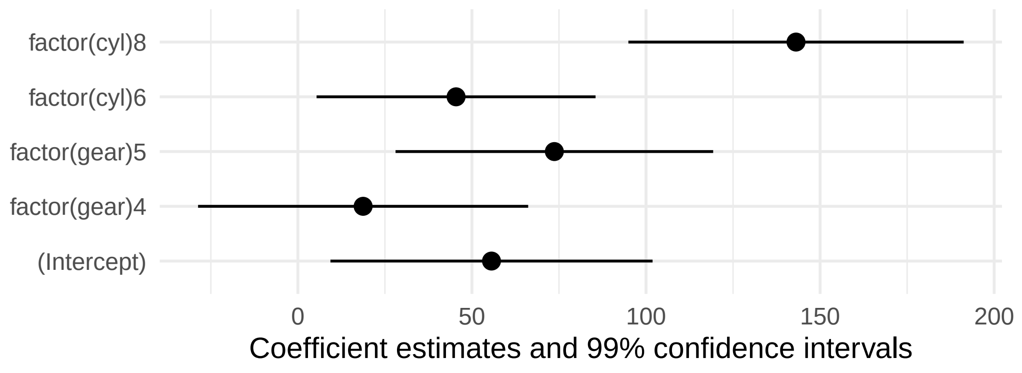
```r
modelplot(models, color = "black") + facet_grid(~model)
```



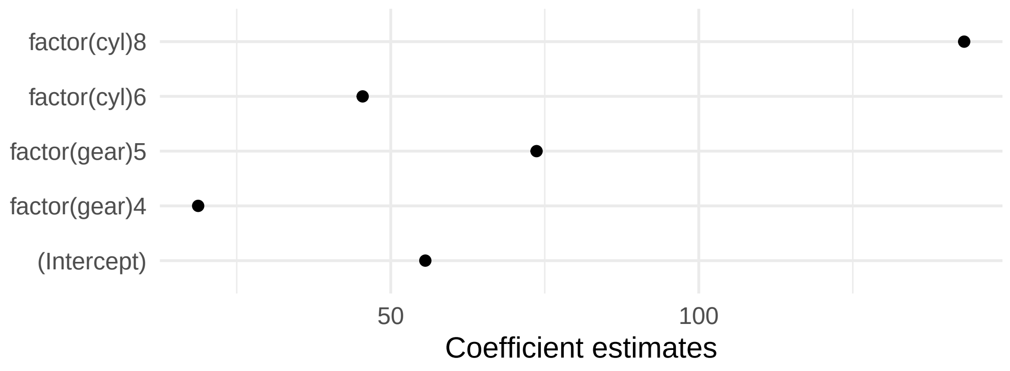
4 Confidence intervals

You can change the α level of your confidence intervals by changing the `conf_level` argument:

```
modelplot(mod, conf_level = .99)
```



```
modelplot(mod, conf_level = NULL)
```

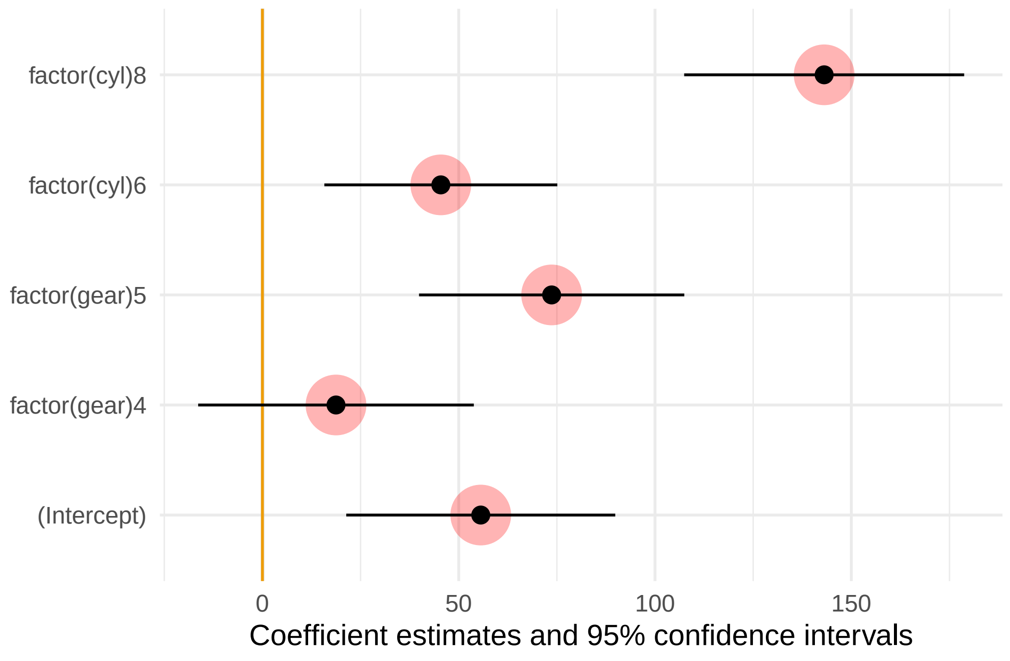


5 Background annotations

Sometimes, you want to display annotations on a plot, but you would like to draw these annotations *behind* the `geom_pointrange` which displays the estimates. Since `modelplot` draws the `geom_pointrange` automatically, any `ggplot2` annotation you add to the plot using `+` will be added on *top* of the existing ones.

To add your annotations in the background, you can pass them as a list of `ggplot2` “geoms”:

```
library(ggplot2)

b <- list(geom_vline(xintercept = 0, color = 'orange'),
          annotate("rect", alpha = .1,
                   xmin = -.5, xmax = .5,
                   ymin = -Inf, ymax = Inf),
          geom_point(aes(y = term, x = estimate), alpha = .3,
                     size = 10, color = 'red'))

modelplot(mod, background = b)
```



6 Raw data and customization

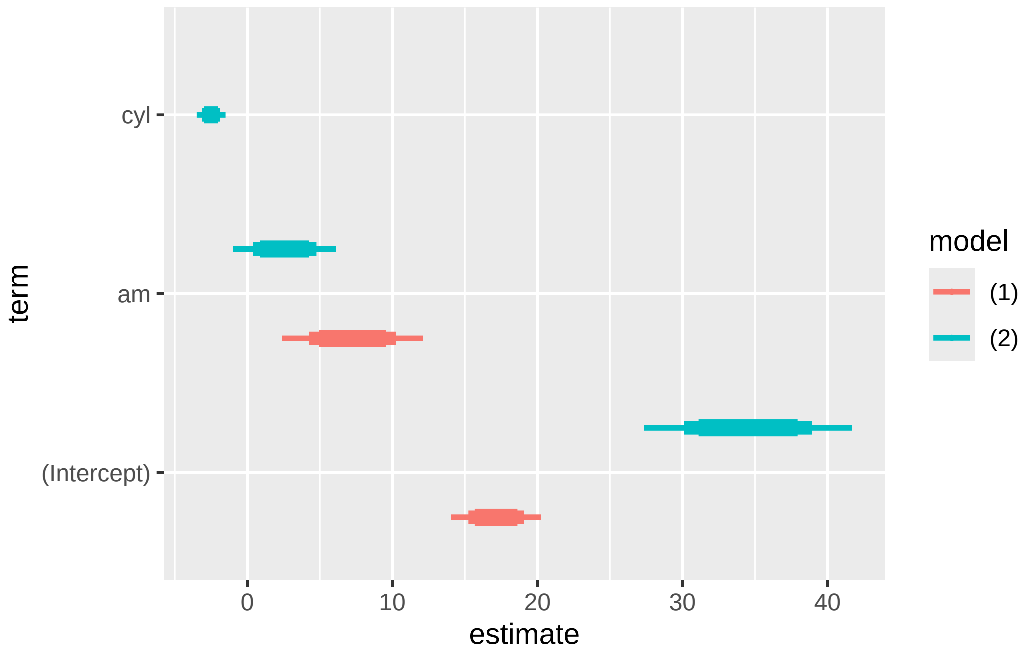
If you would like to customize the plots even more than what `modelplot` allows, you can obtain the raw data used to draw the plots by setting `draw=FALSE`:

```
modelplot(models, draw = FALSE)
```

```
          term model     estimate    std.error      conf.low    conf.high      p.value
1  (Intercept)    vs   2.41742511   0.67622094    1.03224931   3.80260091 1.296718e-03
5  (Intercept)  disp 112.57276339 114.86315481 -122.71374324 347.85927003 3.354494e-01
9  (Intercept)    hp -10.56116383  68.75946117 -151.40853516 130.28620751 8.790301e-01
2         carb    vs  -0.06945116   0.03943402   -0.15022810   0.01132577 8.912324e-02
6         carb  disp -12.30144724   6.69827859  -26.02224894   1.41935446 7.692105e-02
10        carb    hp  17.75593287   4.00972816    9.54237706  25.96948867 1.320972e-04
3          mpg    vs  -0.01513960   0.01716410   -0.05029868   0.02001947 3.852593e-01
7          mpg  disp  -7.14964651   2.91550156  -13.12178072  -1.17751230 2.068858e-02
11         mpg    hp  -1.00486469   1.74527956   -4.57990780   2.57017842 5.693755e-01
4          cyl    vs  -0.23926135   0.05687969   -0.35577411  -0.12274859 2.410214e-04
8          cyl  disp  47.90105842   9.66160634   28.11015499  67.69196184 3.111898e-05
12         cyl    hp  20.60581208   5.78363747    8.75856779  32.45305638 1.338485e-03
```

This allows users to use external tools such as the powerful `ggdist` package. In this example, we use the `purrr::map_dfr` function to call `modelplot` several times with different confidence levels. Then, we draw a plot where the different confidence intervals are drawn with different thicknesses:

```r
library(tidyverse)
library(modelsummary)
library(ggdist)

# fit
models <- list(
  lm(mpg ~ am, mtcars),
  lm(mpg ~ am + cyl, mtcars))

# summarize
dat <- map_dfr(c(.8, .9, .99), function(x) {
  modelplot(models, conf_level = x, draw = FALSE) %>%
  mutate(.width = x)
})

# plot
ggplot(dat, aes(
    y = term, x = estimate,
    xmin = conf.low, xmax = conf.high,
    color = model)) +
  ggdist::geom_pointinterval(
    position = "dodge",
    interval_size_range = c(1, 3),
    fatten_point = .1)
```


cyl
am
(Intercept)
term
0
10
20
30
40
estimate
model
(1)
(2)