Package: plotMElm (via r-universe)

November 1, 2024

Type Package

Title Plot Marginal Effects from Linear Models

Description Plot marginal effects for interactions estimated from linear models.

Version 0.1.6

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BugReports https://github.com/christophergandrud/plotMElm/issues

License GPL (>= 3)

Imports ggplot2, interactionTest

LazyData TRUE

RoxygenNote 6.0.1

Repository https://christophergandrud.r-universe.dev

RemoteUrl https://github.com/christophergandrud/plotmelm

RemoteRef HEAD

RemoteSha 8199266364fb56d40cf9163881808f5cc49dd2a9

Contents

`plot_me` *Plot marginal effects from two-way interactions in linear regressions*

Description

Plot marginal effects from two-way interactions in linear regressions

Usage

```
plot_me(obj, term1, term2, fitted2, ci = 95, ci_type = "standard",
  t_statistic, plot = TRUE)
```

Arguments

obj	fitted model object from lm.
term1	character string of the first constitutive term of the interaction's variable name.
term2	character string of the second constitutive term of the interaction's variable name.
fitted2	numeric vector of fitted values of term2 to plot for. If unspecified, then all unique observed values are used.
ci	numeric. confidence interval level, expressed on the]0, 100[interval. The default is 95.
ci_type	character string specifying the type of confidence interval to find and plot. If 'standard' then standard confidence intervals (e.g. those suggested by Brambor, Clark, and Golder 2006) are found. If fdr then confidence intervals are found using critical t-statistics to limit the false discovery rate (limit over confidence).
t_statistic	numeric. Custom t-statistic for finding the confidence interval. May be useful if the user want to use a funciton like findMultiLims to find the t-statistic.
plot	boolean. return plot if TRUE; return data.frame of marginal effects estimates if FALSE.

Value

a gg class ggplot2 object

Source

Inspired by: http://www.statsblogs.com/2013/08/27/creating-marginal-effect-plots-for-linear-regressior

Benjamini, Yoav, and Yosef Hochberg. 1995. "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing". Journal of the Royal Statistical Society, Series B 57(1): 289–300.

Brambor, Thomas, William Roberts Clark, and Matt Golder. "Understanding interaction models: Improving empirical analyses". Political Analysis 14.1 (2006): 63-82.

Esarey, Justin, and Jane Lawrence Sumner. 2015. "Marginal Effects in Interaction Models: Determining and Controlling the False Positive Rate". URL: http://jee3.web.rice.edu/interaction-overconfidence.pdf.

Examples

```
## Continuous Term1 and Term2
# Estimate model
states <- as.data.frame(state.x77)
m1 <- lm(Murder ~ Income * Population, data = states)
```

```
# Plot marginal effect of Income across the observed range of Population
# on the Murder rate
plot_me(m1, 'Income', 'Population', ci = 95)

# CI created using false discovery rate limiting t-statistic
plot_me(m1, 'Income', 'Population', ci_type = 'fdr')

# Return marginal effects as a data frame
plot_me(m1, 'Income', 'Population', plot = FALSE)

## Term 2 with <= 5 unique values
# Estimate model
m2 <- lm(mpg ~ wt * cyl, data = mtcars)

# Plot marginal effect of Weight across the Number of Cylinders (continuous)
plot_me(m2, 'wt', 'cyl')

## Categorical (factor) Term2
# Set Term 2 as a factor variable
mtcars$cyl <- factor(mtcars$cyl,
                 labels = c('4 Cyl', '6 Cyl', '8 Cyl'))

# Estimate model
m3 <- lm(mpg ~ wt * cyl, data = mtcars)

# Plot marginal effect of Weight across the Number of Cylinders (factor)
plot_me(m3, 'wt', 'cyl')
```

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