Package 'MonotonicityTest'

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Type Package

Title Nonparametric Bootstrap Test for Regression Monotonicity

Version 1.0

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Description Implements nonparametric bootstrap tests for detecting monotonicity in regression functions from Hall, P. and Heckman, N. (2000) <doi:10.1214/aos/1016120363> Includes tools for visualizing results using Nadaraya-Watson kernel regression and supports efficient computation with C++.

License GPL

Encoding UTF-8

RoxygenNote 7.3.2

LinkingTo Rcpp, RcppEigen

Imports Rcpp (>= 1.0.13-1), parallel, stats, graphics, grDevices

Suggests testthat (>= 3.0.0)

Config/testthat/edition 3

NeedsCompilation yes

Contents

`create_kernel_plot` *Generate Kernel Plot*

Description

Creates a scatter plot of the input vectors X and Y, and overlays a Nadaraya-Watson kernel regression curve using the specified bandwidth.

Usage

```
create_kernel_plot(X, Y, bandwidth = bw.nrd(X) * (length(X)^-0.1))
```

Arguments

`X`	Vector of x values.
`Y`	Vector of y values.
`bandwidth`	Kernel bandwidth used for the Nadaraya-Watson estimator. Default is calculated as `bw.nrd(X) * (length(X) ^ -0.1)`.

Value

A recorded plot object containing the scatter plot with the kernel regression curve.

References

Nadaraya, E. A. (1964). On estimating regression. *Theory of Probability and Its Applications*, **9**(1), 141–142.

Watson, G. S. (1964). Smooth estimates of regression functions. *Sankhyā: The Indian Journal of Statistics, Series A*, 359-372.

Examples

```
# Example 1: Basic plot on quadratic function
seed <- 42
set.seed(seed)
# Generate sample data
X <- runif(500)
Y <- X ^ 2 + rnorm(500, sd = 0.1)

# Plot with default bandwidth
plot <- create_kernel_plot(X, Y, bandwidth = bw.nrd(X) * (length(X) ^ -0.1))
plot
```

`monotonicity_test` *Perform Monotonicity Test*

Description

Performs a monotonicity test between the vectors X and Y as described in Hall and Heckman (2000). This function uses a bootstrap approach to test for monotonicity in a nonparametric regression setting.

Usage

```
monotonicity_test(
  X,
  Y,
  bandwidth = bw.nrd(X) * (length(X)^-0.1),
  boot_num = 200,
  m = floor(0.05 * length(X)),
  ncores = 1,
  negative = FALSE,
  seed = NULL
)
```

Arguments

`X`	Numeric vector of predictor variable values. Must not contain missing or infinite values.
`Y`	Numeric vector of response variable values. Must not contain missing or infinite values.
`bandwidth`	Numeric value for the kernel bandwidth used in the Nadaraya-Watson estimator. Default is calculated as `bw.nrd(X) * (length(X) ^ -0.1)`.
`boot_num`	Integer specifying the number of bootstrap samples. Default is `200`.
`m`	Integer parameter used in the calculation of the test statistic. Corresponds to the minimum window size to calculate the test statistic over or a "smoothing" parameter. Lower values increase the sensitivity of the test to local deviations from monotonicity. Default is `floor(0.05 * length(X))`.
`ncores`	Integer specifying the number of cores to use for parallel processing. Default is `1`.
`negative`	Logical value indicating whether to test for a monotonic decreasing (negative) relationship. Default is `FALSE`.
`seed`	Optional integer for setting the random seed. If NULL (default), the global random state is used.

Details

The test evaluates the following hypotheses:

H_0: The regression function is monotonic

- *Non-decreasing* if `negative = FALSE`
- *Non-increasing* if `negative = TRUE`

H_A: The regression function is not monotonic

Value

A list with the following components:

`p` The p-value of the test. A small p-value (e.g., < 0.05) suggests evidence against the null hypothesis of monotonicity.

`dist` The distribution of test statistic under the null from bootstrap samples. The length of `dist` is equal to `boot_num`.

`stat` The test statistic calculated from the original data.

Note

For large datasets (e.g., $n \geq 6500$) this function may require significant computation time due to having to compute the statistic for every possible interval. Consider reducing `boot_num`, using a subset of the data, or using parallel processing with `ncores` to improve performance.

In addition to this, a minimum of 300 observations is recommended for kernel estimates to be reliable.

References

Hall, P., & Heckman, N. E. (2000). Testing for monotonicity of a regression mean by calibrating for linear functions. *The Annals of Statistics*, **28**(1), 20–39.

Examples

```
# Example 1: Usage on monotonic increasing function
# Generate sample data
seed <- 42
set.seed(seed)
# Generate sample data
X <- runif(500)
Y <- 4 * X + rnorm(500, sd = 1)

monotonicity_test(X, Y, boot_num=25, seed=seed)

# Example 2: Usage on non-monotonic function
seed <- 42
set.seed(seed)
# Generate sample data
X <- runif(500)
Y <- (X - 0.5) ^ 2 + rnorm(500, sd = 0.5)

monotonicity_test(X, Y, boot_num=25, seed=seed)
```

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