Package 'sindyr'

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sindyr-package

Sparse Identification of Nonlinear Dynamics

Description

This implements the Brunton et al (2016; PNAS, doi: 10.1073/pnas.1517384113) sparse identification algorithm for finding ordinary differential equations for a measured system from raw data (SINDy). The package includes a set of additional tools for working with raw data, with an emphasis on cognitive science applications (Dale and Bhat, 2018, doi: 10.1016/j.cogsys.2018.06.020). See https://github.com/racdale/sindyr for examples and updates.

Details

Package: sindyr
Type: Package
Version: 0.2.1
Date: 2018-09-10
License: GPL >= 2

sindy: Main function to infer coefficient matrix for set of ODEs.

windowed_sindy: Sliding window function to obtain SINDy results across segments of a time series.

features: Function for generation feature space from measured variables.

finite_differences: Numerical differentiation over multiple columns.

finite difference: Numerical differential of a vector.

Author(s)

Rick Dale and Harish S. Bhat

References

Dale, R. and Bhat, H. S. (2018). Equations of mind: data science for inferring nonlinear dynamics of socio-cognitive systems. Cognitive Systems Research, 52, 275-290.

Brunton, S. L., Proctor, J. L., and Kutz, J. N. (2016). Discovering governing equations from data by sparse identification of nonlinear dynamical systems. Proceedings of the National Academy of Sciences, 113(15), 3932-3937.

For further examples and links to other materials see: https://github.com/racdale/sindyr

Examples

example to reconstruct of

features 3

```
# the Lorenz system
library(sindyr)
set.seed(666)
dt = .001
numsteps = 10000; dt = dt; sigma = 10; r = 28; b = 2.6;
xs = data.frame(lorenzattractor(numsteps, dt, sigma, r, b))
colnames(xs) = list('x','y','z')
xs = xs[2000:nrow(xs),] # cut out initialization

Theta = features(xs,3) # grid of features
par(mfrow=c(7,3),oma = c(2,0,0,0) + 0.1,mar = c(1,1,1,1) + 0.1)
for (i in 2:ncol(Theta)) {
   plot(Theta[,i],xlab='t',main=gsub(':','',colnames(Theta)[i]),type='l',xaxt='n',yaxt='n')
}
sindy.obj = sindy(xs=xs,dt=dt,lambda=.5) # let's reconstruct
sindy.obj$B # Lorenz equations
```

features

Build a matrix of features for SINDy

Description

Takes a raw matrix of data and converts into polynomial features

Arguments

x Raw data to be converted into features

polyorder Order of polynomials (including k-th self products)

intercept Include column of 1s in features to represent intercept (default = TRUE)

Details

Expands raw data into a set of polynomial features.

Value

Returns a new matrix of data with features from raw data

Author(s)

Rick Dale and Harish S. Bhat

finite_differences

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finite	difference	Est

Estimate derivative of variable with finite differences

Description

Estimates first-order derivatives of a vector

Arguments

- x Raw data to be differentiated
- S Sample rate of data to return derivatives using raw time

Details

Uses simplest version of finite-difference method (window size 2) to numerically estimate derivative of a time series.

Value

Returns first-order numerical derivatives estimated from data.

Author(s)

Rick Dale and Harish S. Bhat

finite_differences

Estimate derivatives of multiple variables with finite differences

Description

Estimates first-order derivatives of column vectors of a matrix

Arguments

xs Raw data to be differentiated (matrix)

S Sample rate of data to return derivatives using raw time

Details

Uses simplest version of finite-difference method (window size 2) to numerically estimate derivative of multiple columnar time series.

Value

Returns first-order numerical derivatives estimated from data.

lorenzattractor 5

Author(s)

Rick Dale and Harish S. Bhat

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Description

An implementation of the Lorenz dynamical system, which describes the motion of a possible particle, which will neither converge to a steady state, nor diverge to infinity; but rather stay in a bounded but 'chaotically' defined region, i.e., an attractor.

Usage

```
lorenzattractor(numsteps, dt, sigma, r, b)
```

Arguments

numsteps	The number of simulated points
dt	System parameter
sigma	System parameter
r	System parameter
b	System parameter

Value

It returns a matrix with the 3 dimensions of the Lorenz

Author(s)

Moreno I. Coco (moreno.cocoi@gmail.com)

References

Lorenz, Edward Norton (1963). Deterministic nonperiodic flow. Journal of the Atmospheric Sciences 20(2) 130-141.

Examples

```
## initialize the parameters
numsteps = 2 ^ 11; dt = .01; sigma = 10; r = 28; b = 8/3;
res = lorenzattractor(numsteps, dt, sigma, r, b)
```

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sindy	Run main SINDy function	
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Description

Estimates coefficients for set of ordinary differential equations governing system variables.

Arguments

XS	Matrix of raw data
dx	Matrix of main system variable dervatives; if NULL, it estimates with finite differences from xs
dt	Sample interval, if data continuously sampled; default = 1
Theta	Matrix of features; if not supplied, assumes polynomial features of order 3
lambda	Threshold to use for iterated least squares sparsification (Brunton et al.)
B.expected	The function will compute a goodness of fit if supplied with an expected coefficient matrix B; default = NULL
verbose	Verbose mode outputs Theta and dx values in their entirety; default = FALSE
fit.its	Number of iterations to conduct the least-square threshold sparsification; default = 10
plot.eq.graph	When set to TRUE, prints an igraph plot of variables as a graph structure; default = FALSE

Details

Uses the "left-division" approach of Brunton et al. (2016), and implements least-squares sparsification, and outputs coefficients after iterations stabilize.

Value

Returns a matrix B of coefficients specifying the relationship between dx and Theta

Author(s)

Rick Dale and Harish S. Bhat

References

Dale, R. and Bhat, H. S. (in press). Equations of mind: data science for inferring nonlinear dynamics of socio-cognitive systems. Cognitive Systems Research.

Brunton, S. L., Proctor, J. L., and Kutz, J. N. (2016). Discovering governing equations from data by sparse identification of nonlinear dynamical systems. Proceedings of the National Academy of Sciences, 113(15), 3932-3937.

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windowed_sindy	Run SINDy over time windows	
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Description

Run SINDy on raw data with a sliding window approach

Arguments

xs	Matrix of raw data
dx	Matrix of main system variable dervatives; if NULL, it estimates with finite differences from xs
dt	Sample interval, if data continuously sampled; default = 1
Theta	Matrix of features; if not supplied, assumes polynomial features of order 3
lambda	Threshold to use for iterated least squares sparsification (Brunton et al.)
fit.its	Number of iterations to conduct the least-square threshold sparsification; default = 10
B.expected	The function will compute a goodness of fit if supplied with an expected coefficient matrix B; default = NULL
window.size	Size of window to segment raw data as separate time series; defaults to deciles
window.shift	Step sizes across windows, permitting overlap; defaults to deciles

Details

A convenience function for extracting a list of coefficients on segments of a time series. This facilitates using SINDy output as source of descriptive measures of dynamics.

Value

It returns a list of coefficients Bs containing B coefficients at each window

Author(s)

Rick Dale and Harish S. Bhat

References

Dale, R. and Bhat, H. S. (in press). Equations of mind: data science for inferring nonlinear dynamics of socio-cognitive systems. Cognitive Systems Research.

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