

# Package ‘GPoM’

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**Type** Package

**Title** Generalized Polynomial Modelling

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**Description** Platform dedicated to the Global Modelling technique. Its aim is to obtain ordinary differential equations of polynomial form directly from time series. It can be applied to single or multiple time series under various conditions of noise, time series lengths, sampling, etc. This platform is developed at the Centre d'Etudes Spatiales de la Biosphere (CESBIO), UMR 5126 UPS/CNRS/CNES/IRD, 18 av. Edouard Belin, 31401 TOULOUSE, FRANCE. The developments were funded by the French program Les Enveloppes Fluides et l'Environnement (LEFE, MANU, projets GloMo, SpatioGloMo and MoMu). The French program Defi InFiNiTi (CNRS) and PNTS are also acknowledged (projects Crops'IChaos and Musc & SlowFast).

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 GPoM-package

*GPoM package: Generalized Polynomial Modelling*


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## Description

GPoM is a platform dedicated to the Global Modelling technique. Its aim is to obtain deterministic models of Ordinary Differential Equations from observational time series. It applies to single and to multiple time series. With single time series, it can be used: to detect low-dimensional determinism and low-dimensional (deterministic) chaos. It can also be used to characterize the observed behavior, using the obtained models as a proxy of the original dynamics, as far as the model validation could be checked. With multiple time series, it can be used: to detect couplings between observed variables, to infer causal networks, and to reformulate the original equations of the observed system (retro-modelling). The present package focuses on models in Ordinary Differential Equations of polynomial form. The package was designed to model weakly predictable dynamical behaviors (such as chaotic behaviors). Of course, it can also apply to more of fully predictable behavior, either linear or nonlinear. Several vignettes are associated to the package which can be used as a tutorial, and it also provides an overlook of the diversity of applications and at the performances of the tools. Users are kindly asked to quote the corresponding references when using the package (see hereafter).

## Note

### FOR USERS

This package was developed at Centre d'Etudes Spatiales de la Biosphere (Cesbio, UMR 5126, UPS-CNRS-CNES-IRD, <http://www.cesbio.ups-tlse.fr>). An important part of the developments were funded by the French program Les Enveloppes Fluides et l'Environnement (LEFE, MANU, projets GloMo, SpatioGloMo and MoMu). The French program Défi InFiNiTi (CNRS) and PNTS are also acknowledged (projects Crops'IChaos and Musc & SlowFast).

If you apply this package to single time series, please quote [6]. If you apply it to multivariate time series, please quote [10]. If you apply it to infer couplings among time series, please quote [8]. If you apply it to classification, please quote [11].

### HISTORICAL BACKGROUND

The global modelling technique was initiated during the early 1990s [1-3]. It takes its background from the Theory of Nonlinear Dynamical Systems. Earlier investigations can also be found in the fields of Electrical Engineering and Statistics but these mainly focused on linear problems [4]. The approach became applicable to the analysis of real world environmental behaviours by the end of the 2000s [5-7]. Recent works have shown that the approach could be applied to numerous other dynamical behaviors [8-10]. Global modelling aims to obtain deterministic models directly from observed time series.

**Author(s)**

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**References**

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- [9] Mangiarotti S., Peyre M. & Huc M., A chaotic model for the epidemic of Ebola Virus Disease in West Africa (2013-2016). *Chaos*, 26, 113112, 2016.
- [10] Mangiarotti S., 2014. Modelisation globale et Caracterisation Topologique de dynamiques environnementales - de l'analyse des enveloppes fluides et du couvert de surface de la Terre a la caracterisation topodynamique du chaos. Habilitation to Direct Research, University of Toulouse 3, France.
- [11] Mangiarotti S., Sharma A.K., Corgne S., Hubert-Moy L., Ruiz L., Sekhar M., Kerr Y., Can the global modelling technique be used for crop classification? *Chaos, Solitons & Fractals*, in press.

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allMod\_nVar3\_dMax2 data set

*Numerical description of a list of eighteen three-dimensional chaotic systems (see vignette 7\_Retro-Modelling)*

---

**Description**

A list named allMod\_nVar3\_dMax2 of matrix providing the numerical description of eighteen three-dimensional chaotic systems:

Lorenz-1963 (\$L63), Rössler-1976 (\$R76), Burke & shaw 1981 (\$BS81), Lorenz-1984 (\$L84), Nosé

& Hoer 1986 (`$NH86`), Genesis & Tosi 1992 (`$GT92`), Spott systems 1994 (`$SprF`, `$SprH`, `$SprK`, `$SprO`, `$SprP`, `$SprG`, `$SprM`, `$SprQ`, `$SprS`), Chlouverakis & Sprott 2004 (`$CS2004`), Li 2007 (`$Li2007`) and the Cord system by Aguirre & Letellier 2012 (`$Cord2012`). Each dynamical system is provided as a matrix: each column corresponds to one equation, each lines to the polynomial coefficients which order is following the convention defined by function `poLabs(nVar = 3, dMax = 2)`.

### Usage

```
allMod_nVar3_dMax2
```

### Format

An object of class `list` of length 18.

### Author(s)

Sylvain Mangiarotti, Mireille Huc.

### References

All the references are provided in vignette `7_retro-modelling`.

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<code>allToTest</code>	<i>A list providing the description of six models tested by the function <code>autoGPoMoTest</code>.</i>
------------------------	--

---

### Description

List of 6 models available for tests (by `autoGPoMoTest`). Each model (`$mToTest1`, `$mToTest2`, etc.) is provided as a matrix of dimension  $10 * 3$ . Each column corresponds to one equation. The order of the coefficients follows the conventions defined by `poLabs(nVar = 3, dMax = 2)`.

### Usage

```
allToTest
```

### Format

An object of class `list` of length 6.

### Author(s)

Sylvain Mangiarotti, Mireille Huc

**Examples**

```
#####
# example #
#####
data("allToTest")
# 6 models are available in this list:
names(allToTest)
# The parameter of their formulation (nVar and dMax)
# can be retrieved:
nVar <- dim(allToTest$mToTest6)[2]
dMax <- p2dMax(nVar = 3, pMaxKnown = dim(allToTest$mToTest6)[1])
# Their equation can be edited as follows:
visuEq(allToTest$mToTest6, nVar, dMax, approx = 2)
```

---

autoGPoMoSearch

*Automatic search of polynomial Equations*


---

**Description**

This algorithm aims to get an ensemble of possible models which integrability will be tested later with function `autoGPoMoTest`. By default, all the terms are considered available (Some of the terms can be excluded intentionally using the option `filterReg`). The maximum size of the equation depends on the model dimension `nVar`, and on the maximum polynomial degree `dMax`. The algorithm removes polynomial terms one by one using a leave-one-out method.

**Usage**

```
autoGPoMoSearch(
  data,
  dt,
  nVar = nVar,
  dMax = dMax,
  weight = NULL,
  show = 0,
  underSamp = NULL,
  filterReg = NULL
)
```

**Arguments**

<code>data</code>	Input Time series: Each column is one time series that corresponds to one variable.
<code>dt</code>	Time sampling of the input series.
<code>nVar</code>	Number of variables considered in the polynomial formulation.
<code>dMax</code>	Maximum degree of the polynomial formulation.

weight	A vector providing the binary weighting function of the input data series (0 or 1). By default, all the values are set to 1.
show	Provide (2) or not (0-1) visual output during the running process.
underSamp	Number of points used for undersampling the data. For undersamp = 1 the complete time series is used. For undersamp = 2, only one data out of two is kept, etc.
filterReg	A vector that specifies the template for the equation structure (for one single equation). The convention defined by poLabs is used. Value is 1 if the regressor is available, 0 if it is not.

**Value**

A list of two matrices:

\$filtMemo describes the selected terms (1 if the term is used, 0 if not)

\$KMemo provides the corresponding coefficients

**Author(s)**

Sylvain Mangiarotti, Flavie Le Jean

**See Also**

[autoGPoMoTest](#), [gPoMo](#), [findAllSets](#), [poLabs](#)

**Examples**

```
# Load data
data('RosYco')
# Search for potential models
filt = autoGPoMoSearch(RosYco[,2], nVar = 3, dMax = 2,
                      dt = 1/125, show = 1)
# As an example, the equations of the fourth line has the following terms:
poLabs(nVar = 3, dMax = 2)[filt$filtMemo[5,] != 0]
# which coefficients correspond to
cbind(filt$KMemo[5,], poLabs(nVar = 3, dMax = 2))[filt$filtMemo[5,] != 0,]
```

---

autoGPoMoTest	<i>Tests the numerical integrability of models and classify their dynamical regime</i>
---------------	--

---

**Description**

Tests the numerical integrability of provided models (these may have been obtained with function `autoGPoMoSearch`), and classify these models as Divergent, Fixed Points, Periodic or not Unclassified (potentially chaotic).

**Usage**

```

autoGPoMoTest(
  data,
  tin = NULL,
  dt = NULL,
  nVar = nVar,
  dMax = dMax,
  show = 1,
  verbose = 1,
  allKL = allKL,
  numValidIC = 1,
  weight = NULL,
  IstepMin = 10,
  IstepMax = 10000,
  tooFarThr = 4,
  FxPtThr = 1e-08,
  LimCyclThr = 1e-06,
  method = "rk4"
)

```

**Arguments**

data	Input Time series: Each column is one time series that corresponds to one variable.
tin	Input date vector which length should correspond to the input time series.
dt	Sampling time of the input time series.
nVar	Number of variables considered in the polynomial formulation.
dMax	Maximum degree of the polynomial formulation.
show	Provide (2) or not (0-1) visual output during the running process.
verbose	Gives information (if set to 1) about the algorithm progress and keeps silent if set to 0.
allKL	A list of all the models \$mToTest1, \$mToTest2, etc. to be tested. Each model is provided as a matrix.
numValidIC	Line number of the first valid initial conditions, that is, such as weight is not equal to zero.
weight	A vector providing the binary weighting function of the input data series (0 or 1). By default, all the values are set to 1.
IstepMin	The minimum number of integration step to start of the analysis (by default IstepMin = 10).
IstepMax	The maximum number of integration steps for stopping the analysis (by default IstepMax = 10000).
tooFarThr	Divergence threshold, maximum value of the model trajectory compared to the data standard deviation. By default a trajectory is too far if the distance to the center is larger than four times the variance of the input data.





---

bDrvFilt	<i>Builds the derivative filter</i>
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---

**Description**

Build the Savitzky-Golay derivative filter (Savitzky-Golay, 1964).

**Usage**

```
bDrvFilt(nDrv, tstep, winL = 9)
```

**Arguments**

nDrv	The number of derivatives to be computed.
tstep	Sampling time.
winL	The local window length to be used for computing the derivatives [1].

**Author(s)**

Sylvain Mangiarotti

**References**

[1] Savitzky, A.; Golay, M.J.E., Smoothing and Differentiation of Data by Simplified Least Squares Procedures. *Analytical Chemistry* 36 (8), 1627-1639, 1964.

---

cano2M	<i>cano2M : Converts a model in canonical form into a matrix form</i>
--------	---

---

**Description**

Converts the vectorial formulation of canonical models into a matrix formulation (that is, including explicitey all the equations). For both input, the list of terms follows the convention defined by poLabs.

**Usage**

```
cano2M(nVar, dMax, poly)
```

**Arguments**

nVar	The number of variables
dMax	The maximum degree allowed in the formulation
poly	A vector of coefficients corresponding to the regressor of the canonical function

**Author(s)**

Sylvain Mangiarotti, Mireille Huc

**See Also**

[drvSucc](#), [gPoMo](#), [poLabs](#)

**Examples**

```
# A vector of polynomial terms corresponding to a canonical form:
polyTerms <- c(0.2,0,-1,0.5,0,0,0,0,0)
# Convert this vector into a matrix formulation with all the equations:
K <- cano2M(3,2,polyTerms)
# Visualize the equations:
visuEq(K,3,2)
```

---

 combiEq

*combiEq : Combine Equations from different sources*


---

**Description**

Combines equations of different sources into a single system. During this combination, the polynomial maximal degree can be either imposed or optimized to reduce the model size. All the input have to follow the convention defined by poLabs.

**Usage**

```
combiEq(
  inK,
  inXnote = NULL,
  eqNum = NULL,
  XnoteOut = NULL,
  nVarOut = NULL,
  dMaxOut = NULL
)
```

**Arguments**

inK	A list of models, each provided as a matrix. A single matrix can also be provided, it will be transformed into a list containing a single matrix.
inXnote	A list of vectors with the names of the input variables for each model. If not provided, default notation is used: "X1", "X2", etc. A single matrix can also be provided, it will be transformed into a list containing a single matrix.
eqNum	A list of vector, providing each the equations number (relating to the input models) to be kept in the output equation system. If not provided, all the equations are kept. A single matrix can also be provided, it will be transformed into a list containing a single matrix.

XnoteOut	A vector with the names of the output variables. If not provided, default notation is used considering that the variables of the input models are all different
nVarOut	The dimension of the output equation system (if not provided, this degree is deduced from the input models)
dMaxOut	The maximal polynomial degree of the output equation system (if not provided, this degree is deduced from the input models)

**Author(s)**

Sylvain Mangiarotti

**See Also**[gPoMo](#), [poLabs](#)**Examples**

```
# Load models
data("allMod_nVar3_dMax2")
# Display equations of system 1
visuEq(nVar = 3, dMax = 2, K = allMod_nVar3_dMax2$NH86, substit = 1)
# Display equations of system 2
visuEq(nVar = 3, dMax = 2, K = allMod_nVar3_dMax2$R76, substit = 1)
# put the two systems in a list
allK <- list()
allK[[1]] <- allMod_nVar3_dMax2$NH86
allK[[2]] <- allMod_nVar3_dMax2$R76

# Example 1: reformulate two autonomous system in a single matrix
visuEq(K = allK[[1]], substit = c('u', 'v', 'w'))
visuEq(K = allK[[2]], substit = c('X', 'Y', 'Z'))
Knew <- combiEq(allK)
visuEq(K = Knew, substit = c('u', 'v', 'w', 'X', 'Y', 'Z'))

# Example 2
inXnote = list()
inXnote[[1]] <- c('u', 'v', 'w')
inXnote[[2]] <- c('X', 'Y', 'Z')
visuEq(K = allK[[1]], substit = inXnote[[1]])
visuEq(K = allK[[2]], substit = inXnote[[2]])
XnoteOut = c('X', 'Y', 'Z', 'u', 'v', 'w')
Knew2 <- combiEq(allK, inXnote = inXnote, XnoteOut = XnoteOut)
visuEq(K = Knew2, substit = XnoteOut)

# Example 3
inXnote = list()
inXnote[[1]] <- c('u', 'v', 'w')
inXnote[[2]] <- c('X', 'Y', 'Z')
visuEq(K = allK[[1]], substit = inXnote[[1]])
visuEq(K = allK[[2]], substit = inXnote[[2]])
XnoteOut = c('u', 'X', 'v', 'Y', 'w', 'Z')
```

```
Knew3 <- combiEq(allK, inXnote = inXnote, XnoteOut = XnoteOut, dMaxOut = 3)
visuEq(K = Knew3, substit = XnoteOut)

# Example 4
dim(Knew3)
inXnote = c('x', 'X', 'y', 'Y', 'z', 'Z')
visuEq(K = Knew3, substit = inXnote)
XnoteOut = c('X', 'Y', 'Z')
Knew4 <- combiEq(Knew3, inXnote = inXnote, XnoteOut = XnoteOut)
dim(Knew4)
visuEq(K = Knew4, substit = XnoteOut)
```

---

compDeriv

*Computes the successive derivatives of a time series*

---

### Description

Computes the successive derivatives from one single time series, with the Savitzky-Golay approach (1964).

### Usage

```
compDeriv(TS, nDrv, tstep, winL = 9)
```

### Arguments

TS	A single time series provided as a single vector.
nDrv	The number of derivatives to be computed from the input series. The resulting number of output time series will thus be $nVar = nDrv + 1$ .
tstep	Sampling Time of the input time series TS.
winL	The local window length used for computing the derivatives [1-2].

### Value

A matrix containing the original variable (smoothed by the filtering process) and its `nDrv` first derivatives (note that `winL` values of the original time series will be lost both at the beginning and the end of the time series due to boundary effect).

### Author(s)

Sylvain Mangiarotti

### References

- [1] Savitzky, A.; Golay, M.J.E., Smoothing and Differentiation of Data by Simplified Least Squares Procedures. *Analytical Chemistry* 36 (8), 1627-1639, 1964.
- [2] Steinier J., Termonia Y., Deltour, J. Comments on smoothing and differentiation of data by simplified least square procedure. *Analytical Chemistry* 44 (11): 1906-1909, 1972.

**See Also**

[gloMoId](#), [gPoMo](#), [poLabs](#)

---

concat

*Concat Concatenates separated time series*

---

**Description**

The aim of this code is to provide, from a set of multiple time series, a single concatenated time series for applying the global modeling technique to all the time time series in association.

**Usage**

```
concat(svr1TS, winL = 9)
```

**Arguments**

svr1TS	All separated time series.
winL	Total number of points used for computing the derivatives of the input time series. This parameter will be used as an input in function <code>drvSucc</code> to compute the derivatives.

**Value**

concaTS The concatenated time series.

**Author(s)**

Sylvain Mangiarotti, Mireille Huc

**References**

S. Mangiarotti, F. Le Jean, M. Huc & C. Letellier, 2016. Global modeling of aggregated and associated chaotic dynamics, *Chaos, Solitons & Fractals*, 83, 82-96.

**Examples**

```
# load data
data("svr1TS")
# Concatenate the data set into a single time series
winL = 55
concaTS <- concat(svr1TS, winL = winL)
# Plot the concatenated time series
plot(concaTS$sglTS$TS[,1], concaTS$sglTS$TS[,2],
     main = 'Concatenated time series',
     xlab = 'Time (concatenated)', ylab = 'y(t)',
     type = 'l', col = 'gray')
lines(concaTS$sglTS$TS[concaTS$sglTS$W == 1,1],
```

```

      concatS$sglTS$TS[concatS$sglTS$W == 1,2], type = 'p', col = 'green', cex = 0.5)
lines(concatS$sglTS$TS[concatS$sglTS$W == 0,1],
      concatS$sglTS$TS[concatS$sglTS$W == 0,2], type = 'p', col = 'red', cex = 0.5)
lines(concatS$sglTS$TS[,1], concatS$sglTS$W, type = 'l')
## Not run:
# The concatenated data set can be used for global modelling:
GPout1 <- gPoMo(data = concatS$sglTS$TS[,2], tin = concatS$sglTS$TS[,1],
               dMax = 2, nS = 3, winL = winL, weight = concatS$sglTS$W, show = 1,
               IstepMin = 10, IstepMax = 6000, nPmin = 11, nPmax = 11, method = 'rk4')

## End(Not run)

```

---

concatMultS	<i>ConcatMultS Concatenates separated time series (of single or multiples variables)</i>
-------------	--

---

### Description

The aim of this code is to provide, from multiple sets of (single or multiple) time series, a single concatenated set of time series for applying the global modeling technique to all the time time series in association.

### Usage

```
concatMultS(svrITS, winL = 9)
```

### Arguments

svrITS	All separated sets of time series.
winL	Total number of points used for computing the derivatives of the input time series. This parameter will be used as an input in function drvSucc to compute the derivatives.

### Value

concatS A single set of concatenated time series.

### Author(s)

Sylvain Mangiarotti, Mireille Huc

### References

S. Mangiarotti, F. Le Jean, M. Huc & C. Letellier, 2016. Global modeling of aggregated and associated chaotic dynamics, *Chaos, Solitons & Fractals*, 83, 82-96.

**Examples**

```

# load data
data("svr1TS")
# Concatenate the data set into a single time series
winL = 55
concaTS <- concat(svr1TS, winL = winL)
# Plot the concatenated time series
plot(concaTS$sglTS$TS[,1], concaTS$sglTS$TS[,2],
     main = 'Concatenated time series',
     xlab = 'Time (concatenated)', ylab = 'y(t)',
     type = 'l', col = 'gray')
lines(concaTS$sglTS$TS[concaTS$sglTS$W == 1,1],
      concaTS$sglTS$TS[concaTS$sglTS$W == 1,2], type = 'p', col = 'green', cex = 0.5)
lines(concaTS$sglTS$TS[concaTS$sglTS$W == 0,1],
      concaTS$sglTS$TS[concaTS$sglTS$W == 0,2], type = 'p', col = 'red', cex = 0.5)
lines(concaTS$sglTS$TS[,1], concaTS$sglTS$W, type = 'l')
## Not run:
# The concatenated data set can be used for global modelling:
GPout1 <- gPoMo(data = concaTS$sglTS$TS[,2], tin = concaTS$sglTS$TS[,1],
               dMax = 2, nS = 3, winL = winL, weight = concaTS$sglTS$W, show = 1,
               IstepMin = 10, IstepMax = 6000, nPmin = 11, nPmax = 11, method = 'rk4')

## End(Not run)

```

---

d2pMax

*Provides the number of polynomial terms pMax given dMax and nVar*


---

**Description**

Computes the number of polynomial terms pMax used to formulate an equation given the maximal polynomial degree dMax and the number of variables nVar following the conventions as defined by fuction poLabs.

**Usage**

```
d2pMax(nVar, dMaxKnown)
```

**Arguments**

nVar	Number of variables considered in the polynomial formulation.
dMaxKnown	The maximum polynomial degree dMax

**Value**

The number pMax of polynomial terms used to code a polynomial equation



**Author(s)**

Sylvain Mangiarotti

**See Also**

[gloMoId](#), [gPoMo](#), [poLabs](#)

**Examples**

```
#####  
# Example 1 #  
#####  
# Maximum polynomial degree ?  
# number of variables:  
nVar <- 3  
# polynomial degree:  
dMax <- 3  
# The maximal polynomial degree used for coding the polynomial is:  
d2pMax(nVar,dMax)
```

---

data\_vignetteIII data set

*Output of the vignette III\_Modelling*

---

**Description**

To reduce the computation time, the outputs of the simulations presented in vignette VI have been run beforehand and saved in this file.

**Usage**

```
data_vignetteIII
```

**Format**

An object of class list of length 12.

**Author(s)**

Sylvain Mangiarotti, Mireille Huc.

---

data\_vignetteVI data set

*Output of the vignette VI\_Sensitivity*

---

**Description**

To reduce the computation time, the outputs of the simulations presented in vignette VI have been run beforehand and saved in this file.

**Usage**

data\_vignetteVI

**Format**

An object of class list of length 6.

**Author(s)**

Sylvain Mangiarotti, Mireille Huc.

---

data\_vignetteVII data set

*Output of the vignette VII\_Retro-Modelling*

---

**Description**

To reduce the computation time, the outputs of the simulations presented in vignette VII have been run beforehand and saved in this file.

**Usage**

data\_vignetteVII

**Format**

An object of class list of length 29.

**Author(s)**

Sylvain Mangiarotti, Mireille Huc.

---

derivODE2	<i>A subfonction for the numerical integration of polynomial equations provided in a generic form following the convention defined by function poLabs.</i>
-----------	--

---

### Description

This function provides the one step integration of polynomial Ordinary Differential Equations (ODE). This function requires the function ode (deSolve package).

### Usage

```
derivODE2(t, x, K, regS = NULL)
```

### Arguments

t	All the dates for which the result of the numerical integration of the model must be provided
x	Current state vector (input from which the next state will be estimated)
K	A matrix providing the model description: each column corresponds to one equation which polynomial organisation is following the convention defined by function poLabs.
regS	Current states of each polynomial terms used in poLabs. These states can be deduced from the current state vector x (using the function regSeries). When available, it can be provided as an input to avoid unnecessary computation.

### Author(s)

Sylvain Mangiarotti

### See Also

[numicano](#), [numinousy](#)

---

derivODEwMultiX	<i>derivODEwMultiX : A Subfonction for the numerical integration of polynomial equations in the generic form defined by function poLabs and with External Forcing F(t)</i>
-----------------	--

---

### Description

This function provides the one step integration of polynomial Ordinary Differential Equations (ODE). This function requires the function ode ("deSolve" package). This function has to be run with the Runge-Kutta method (method = 'rk4')

**Usage**

```
derivODEwMultiX(t, x, K, extF, regS = NULL)
```

**Arguments**

t	All the dates for which the result of the numerical integration of the model will have to be provided
x	Current state vector (input from which the next state will be estimated)
K	is the model: each column corresponds to one equation which organisation is following the convention given by function poLabs which requires the definition of the model dimension nVar (i.e. the number of variables) and the maximum polynomial degree dMax allowed. The last Equation correspond to the forcing variable that is artificially set to 0.
extF	is the external forcing. It is defined by two columns. The first column correspond to time t. The second column to F(t) the forcing at time t. Note that when launching the integration function ode, the forcing F(t) should be provided with a sampling time twice the sampling time used in t (because rk4 method will always use an intermediate time step).
regS	Current states of each polynomial terms used in poLabs. These states can be deduced from the current state vector x (using function regSeries). When available, it can be provided as an input to avoid unnecessary computation.

**Author(s)**

Sylvain Mangiarotti

**Examples**

```
# build a non autonomous model
nVar = 4
dMax = 3
omega = 0.2
gamma = 0.05
Kdf=matrix(0, nrow = d2pMax(nVar = nVar, dMax = dMax), ncol = nVar)
Kdf[11,1] = 1
Kdf[2,2] = 1
Kdf[5,2] = 1
Kdf[11,2] = -gamma
Kdf[35,2] = -1
Kdf[2,3] = NA
Kdf[2,4] = NA
visuEq(K = Kdf, substit = c('x', 'y', 'u', 'v'))
#
# Prepare the external forcing
# number of integration time step
Istep <- 500
# time step
smp1 <- 1 / 20
# output time vector
```

```

dater <- (0:Istep) * smp1
# hald step time vector (for Runge-Kutta integration)
daterdbl <- (0:(Istep*2 + 1)) * smp1 / 2
# generate the forcing (here variables u and v)
extF = cbind(daterdbl, -0.1 * cos(daterdbl * omega), 0.05 * cos(daterdbl * 16/3*omega))
#
# Initial conditions to be used (external variables can be set to 0)
etatInit <- c(-0.616109362 , -0.126882584 , 0, 0)
#
# Numerical integration
reconstr2 <- ode(etatInit, dater, derivODEwMultiX,
                Kdf, extF = extF, method = 'rk4')
# Reconstruction of the output
nVarExt <- dim(extF)[2] - 1
reconstr2[, (nVar - nVarExt + 2):(nVar + 1)] <- extF[(0:Istep+1)*2, 2:(nVarExt+1)]

```

---

detectP1limCycl

*Detection of limit cycles of period-1*


---

### Description

This algorithm aim to detect period-1 limit cycles from trajectories in the phase sapce considered in a bidimensional projection.

### Usage

```
detectP1limCycl(data, LimCyclThreshold = 0.01, show = 2)
```

### Arguments

data	A matrix of the trajectory in a 2D space (if more than two columns are provided, only the two first columns are considered)
LimCyclThreshold	The detection threshold
show	Indicates the deepness of the feedback (from 0 to 2)

### Value

Indicates if a limit cycle is detected (1) or not (0)

### Author(s)

Sylvain Mangiarotti

### See Also

[autoGPoMoTest](#)

---

 drvSucc

*drvSucc : Computes the successive derivatives of a time series*


---

### Description

Computes the successive derivatives from one single time series, using the Savitzky-Golay algorithm (1964).

### Usage

```
drvSucc(tin = NULL, serie, nDeriv, weight = NULL, tstep = NULL, winL = 9)
```

### Arguments

tin	Input date vector which length should correspond to the input time series.
serie	A single time series provided as a single vector.
nDeriv	The number of derivatives to be computed from the input time series. The resulting number of time series obtained in output will be $nDeriv + 1$ .
weight	A vector providing the binary weighting function of the input data series (0 or 1). By default, all the values are set to 1.
tstep	Sampling time of the input time series. Used only if time vector tin is not provided.
winL	Number (exclusively odd number) of points of the local window used for computing the derivatives along the input time series. The Savitzky-Golay filter is used for this purpose [1,2].

### Value

A list containing:

\$serie The original time serie

\$tin The time vector containing the dates corresponding to the original time series

\$tstep The time step (assumed to be regular)

\$tout The time vector of the output series

seriesDeriv A matrix containing the original time series (smoothed by the filtering process) in the first column and its  $nDeriv + 1$  successive derivatives in the next ones. Note that winL values of the original time series will be lost, that is  $(winL - 1)/2$  at the beginning and  $(winL - 1)/2$  at the end of the time series due to a computation boundary effect).

### Author(s)

Sylvain Mangiarotti, Mireille Huc

## References

- [1] Savitzky, A.; Golay, M.J.E., Smoothing and Differentiation of Data by Simplified Least Squares Procedures. *Analytical Chemistry* 36 (8), 1627-1639, 1964.
- [2] Steinier J., Termonia Y., Deltour, J. Comments on smoothing and differentiation of data by simplified least square procedure. *Analytical Chemistry* 44 (11): 1906-1909, 1972.

## See Also

[gloMoId](#), [gPoMo](#), [poLabs](#), [compDeriv](#)

## Examples

```
#####
# Example 1 #
#####
# Generate a time series:
tin <- seq(0, 5, by = 0.01)
data <- 2 * sin(5*tin)
dev.new()
par(mfrow = c(3, 1))
# Compute its derivatives:
drv <- drvSucc(tin = tin, nDeriv = 2, serie = data, winL = 5)
#
# plot original and filtered series
plot(tin, data, type='l', col = 'black', xlab = 't', ylab = 'x(t)')
lines(drv$tout, drv$seriesDeriv[,1], lty = 3, lwd = 3, col = 'green')
#
# analytic 1st derivative
firstD <- 10 * cos(5 * tin)
# plot both
plot(tin, firstD, type = 'l', col = 'black', xlab = 't', ylab = 'dx/dt')
lines(drv$tout, drv$seriesDeriv[,2], lty = 3, lwd = 3, col = 'green')
#
# analytic 2nd derivative
scdD <- -50 * sin(5 * tin)
# plot both
plot(tin, scdD, type = 'l', col = 'black', xlab = 't', ylab = 'd2x/dt2')
lines(drv$tout, drv$seriesDeriv[,3], lty=3, lwd = 3, col = 'green')

#####
# Example 2 #
#####
# load data:
data("Ross76")
tin <- Ross76[,1]
data <- Ross76[,2]

# Compute the derivatives
drvOut <- drvSucc(tin, data, nDeriv=4)
dev.new()
par(mfrow = c(3, 1))
```

```

# original and smoothed variable:
plot(drvOut$tin, drvOut$serie,
      type='p', cex = 1, xlab = 'time', ylab = 'x(t)')
lines(drvOut$tout, drvOut$seriesDeriv[,1], type='p', col='red')
lines(drvOut$tout, drvOut$seriesDeriv[,1], type='l', col='red')
# 1st derivative:
plot(drvOut$tout, drvOut$seriesDeriv[,2],
      type='p', col='red', xlab = 'time', ylab = 'dx(t)/dt')
lines(drvOut$tout, drvOut$seriesDeriv[,2], type='l', col='red')
# 2nd derivative:
plot(drvOut$tout, drvOut$seriesDeriv[,3],
      type='p', col='red', xlab = 'time', ylab = 'd2x(t)/dt2')
lines(drvOut$tout, drvOut$seriesDeriv[,3], type='l', col='red')

```

---

findAllSets

*Find all possible sets of equation combinations considering an ensemble of possible equation.*

---

### Description

For each equation to be retrieved, an ensemble of potential formulation is given. For instance, if three possible formulations are provided for equation (1), one for equation (2) and two for equation (3). In this case, six (i.e.  $3 \times 1 \times 2$ ) possible sets of equations can be obtained from these potential formulations. The aim of this program is to formulate all the potential systems from the individual formulations provided of the individual equations.

### Usage

```
findAllSets(allFilt, nS = c(3), nPmin = 1, nPmax = 14)
```

### Arguments

allFilt	A list with: (1) A matrix allFilt\$Xi of possible formulations for each equation (corresponding to variable Xi); And (2) a vector allFilt\$Npi providing the number of polynomial terms contained in each formulation.
nS	A vector providing the number of dimensions used for each input variables (see Examples 1 and 2). The dimension of the resulting model will be $nVar = \text{sum}(nS)$ .
nPmin	Corresponds to the minimum number of parameters (and thus of polynomial term) allowed.
nPmax	Corresponds to the maximum number of parameters (and thus of polynomial) allowed.

### Author(s)

Sylvain Mangiarotti



**See Also**[autoGPoMoSearch](#)**Examples**

```
#####
# Example 1 #
#####
# We build an example
allFilt <- list()
# For equation 1 (variable X1)
allFilt$Np1 <- 1 # only one formulation with one single parameter
# For equation 2 (variable X2)
allFilt$Np2 <- c(3, 4) # two potential formulations, with respectively three and four parameters
# For equation 3 (variable X3)
allFilt$Np3 <- c(2, 4) # two potential formulations, with respectively two and four parameters
# Formulations for variables Xi:
# For X1:
allFilt$X1 <- t(as.matrix(c(0,0,0,1,0,0,0,0,0,0)))
# For X2:
allFilt$X2 <- t(matrix(c(0,-0.85,0,-0.27,0,0,0,0.46,0,0,
                        0,-0.64,0,0,0,0,0.43,0,0),
                      ncol=2, nrow=10))
# For X3:
allFilt$X3 <- t(matrix(c(0, 0.52, 0, -1.22e-05, 0, 0, 0.99, 5.38e-05, 0, 0,
                        0, 0.52, 0, 0, 0, 0, 0.99, 0, 0, 0),
                      ncol=2, nrow=10))
# From these individual we can retrieve all possible formulations
findAllSets(allFilt, nS=c(3), nPmin=1, nPmax=14)
# if only formulations with seven maximum number of terms are expected:
findAllSets(allFilt, nS=c(3), nPmin=1, nPmax=7)
```

**Description**

Algorithm for global modelling in polynomial and canonical formulation of Ordinary Differential Equations. Univariate Global modeling aims to obtain multidimensional models from single time series (Gouesbet & Letellier 1994, Mangiarotti et al. 2012). An example of such application can be found in Mangiarotti et al. (2014) For a multivariate application, see GPoMo (Mangiarotti 2015, Mangiarotti et al. 2016).

**Example:**

For a model dimension nVar=3, the global model will read:

$$dX1/dt = X2$$

$$dX2/dt = X3$$

$$dX3/dt = P(X1, X2, X3).$$

**Usage**

```

gloMoId(
  series,
  tin = NULL,
  dt = NULL,
  nVar = NULL,
  dMax = 1,
  weight = NULL,
  show = 1,
  filterReg = NULL,
  winL = 9
)

```

**Arguments**

series	The original data set: either a single vector corresponding to the original variable; Or a matrix containing the original variable in the first column and its successive derivatives in the next columns. In the latter case, for the construction of n-dimensional model, series should have $nVar + 1$ columns since one more derivative will be necessary to identify the model parameters. Variable nVar will be set equal to n. In the former case, that is when only a single vector is provided, the derivatives will be automatically recomputed. Therefore, the dimension nVar expected for the model has to be provided.
tin	Input date vector which length should correspond to the input time series.
dt	Sampling time of the input time series.
nVar	Number of variables considered in the polynomial formulation.
dMax	Maximum degree of the polynomial formulation.
weight	A vector providing the binary weighting function of the input data series (0 or 1). By default, all the values are set to 1.
show	Provide (2) or not (0-1) visual output during the running process.
filterReg	A vector that specifies the template for the equation structure (for one single equation). The convention defined by poLabs is used. Value is 1 if the regressor is available, 0 if it is not.
winL	Total number of points used for computing the derivatives of the input time series. This parameter will be used as an input in function drvSucc to compute the derivatives.

**Value**

A list of five elements :

`$init` The original time series and the successive derivatives used for the modeling.

`$filterReg` The structure of the output model. Value is 1 if the regressor is available, 0 if it is not. The terms order is given by function poLabs.

\$K Values of the identified coefficients corresponding to the regressors defined in filterReg.

\$resTot The variance of the residual signal of the model.

\$resSsMod The variance of the residual signal of the closer submodels.

\$finalWeight Weighting series after boundary values were removed.

### Author(s)

Sylvain Mangiarotti, Laurent Drapeau, Mireille Huc

### References

- [1] Gouesbet G., Letellier C., Global vector-field reconstruction by using a multivariate polynomial L2 approximation on nets, *Physical Review E*, 49 (6), 4955-4972, 1994.
- [2] Mangiarotti S., Coudret R., Drapeau L., & Jarlan L., Polynomial search and global modeling : Two algorithms for modeling chaos, *Physical Review E*, 86, 046205, 2012.
- [3] Mangiarotti S., Drapeau L. & Letellier C., Two chaotic models for cereal crops observed from satellite in northern Morocco. *Chaos*, 24(2), 023130, 2014.
- [4] Mangiarotti S., Low dimensional chaotic models for the plague epidemic in Bombay (1896-1911), *Chaos, Solitons & Fractals*, 81(A), 184-196, 2015.
- [5] Mangiarotti S., Peyre M. & Huc M., A chaotic model for the epidemic of Ebola Virus Disease in West Africa (2013-2016). *Chaos*, 26, 113112, 2016.

### See Also

[gPoMo](#), [autoGPoMoSearch](#), [autoGPoMoTest](#), [poLabs](#)

### Examples

```
#####
# Example 1 #
#####
# load data
data("Ross76")
tin <- Ross76[,1]
data <- Ross76[,2:3]

# Polynomial identification
reg <- gloMoId(data[0:500,2], dt=1/100, nVar=2, dMax=2, show=0)

#####
# Example 2 #
#####
# load data
data(NDVI)
```

```

# Definition of the Model structure
terms <- c(1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1)
poLabs(3,3,terms==1)
reg <- gloMoId(NDVI [,1:1], dt=1/125, nVar=3, dMax=3,
              show=0, filterReg=terms==1)

## Not run:
#####
# Example 3 #
#####
# load data
data("Ross76")
# time vector
tin <- Ross76[1:500,1]
# single time series
series <- Ross76[1:500,3]
# some noise is added
series[1:100] <- series[1:100] + 0.01 * runif(1:100, min = -1, max = 1)
series[301:320] <- series[301:320] + 0.05 * runif(1:20, min = -1, max = 1)
# weighting function
W <- tin * 0 + 1
W[1:100] <- 0 # the first hundred values will not be considered
W[301:320] <- 0 # twenty other values will not be considered either
reg <- gloMoId(series, dt=1/100, weight = W, nVar=3, dMax=2, show=1)
visuEq(reg$K, 3, 2, approx = 4)
# first weight which value not equal to zero:
i1 = which(reg$finalWeight == 1)[1]
v0 <- reg$init[i1,1:3]

reconstr <- numicano(nVar=3, dMax=2, Istep=5000, onestep=1/250, PolyTerms=reg$K,
                  v0=v0, method="ode45")
plot(reconstr$reconstr[,2], reconstr$reconstr[,3], type='l', lwd = 3,
     main='phase portrait', xlab='time t', ylab = 'x(t)', col='orange')

# original data:
lines(reg$init[,1], reg$init[,2], type='l',
      main='phase portrait', xlab='x', ylab = 'dx/dt', col='black')
# initial condition
lines(v0[1], v0[2], type = 'p', col = 'red')

## End(Not run)

```

**Description**

Algorithm for a Generalized Polynomial formulation of multivariate Global Modeling. Global modeling aims to obtain multidimensional models from single time series [1-2]. In the generalized

(polynomial) formulation provided in this function, it can also be applied to multivariate time series [3-4].

Example:

Note that nS provides the number of dimensions used from each variable

case I

For nS=c(2, 3) means that 2 dimensions are reconstructed from variable 1: the original variable X1 and its first derivative X2), and 3 dimensions are reconstructed from variable 2: the original variable X3 and its first and second derivatives X4 and X5. The generalized model will thus be such as:

$$dX1/dt = X2$$

$$dX2/dt = P1(X1, X2, X3, X4, X5)$$

$$dX3/dt = X4$$

$$dX4/dt = X5$$

$$dX5/dt = P2(X1, X2, X3, X4, X5).$$

case II

For nS=c(1, 1, 1, 1) means that only the original variables X1, X2, X3 and X4 will be used. The generalized model will thus be such as:

$$dX1/dt = P1(X1, X2, X3, X4)$$

$$dX2/dt = P2(X1, X2, X3, X4)$$

$$dX3/dt = P3(X1, X2, X3, X4)$$

$$dX4/dt = P4(X1, X2, X3, X4).$$

## Usage

```
gPoMo(
  data,
  tin = NULL,
  dtFixe = NULL,
  dMax = 2,
  nS = c(3),
  winL = 9,
  weight = NULL,
  show = 1,
  verbose = 1,
  underSamp = NULL,
  EqS = NULL,
  AndManda = NULL,
  OrMandaPerEq = NULL,
  IstepMin = 2,
  IstepMax = 2000,
  nPmin = 1,
  nPmax = 14,
  tooFarThr = 4,
  FxPtThr = 1e-08,
  LimCyclThr = 1e-06,
  nPminPerEq = 1,
  nPmaxPerEq = NULL,
```

```

    method = "rk4"
)

```

### Arguments

data	Input Time series: Each column is one time series that corresponds to one variable.
tin	Input date vector which length should correspond to the input time series.
dtFixe	Time step used for the analysis. It should correspond to the sampling time of the input data. Note that for very large and very small time steps, alternative units may be used in order to stabilize the numerical computation.
dMax	Maximum degree of the polynomial formulation.
nS	A vector providing the number of dimensions used for each input variables (see Examples 1 and 2). The dimension of the resulting model will be $nVar = \text{sum}(nS)$ .
winL	Total number of points used for computing the derivatives of the input time series. This parameter will be used as an input in function <code>drvSucc</code> to compute the derivatives.
weight	A vector providing the binary weighting function of the input data series (0 or 1). By default, all the values are set to 1.
show	Provide (2) or not (0-1) visual output during the running process.
verbose	Gives information (if set to 1) about the algorithm progress and keeps silent if set to 0.
underSamp	Number of points used for undersampling the data. For <code>undersamp = 1</code> the complete time series is used. For <code>undersamp = 2</code> , only one data out of two is kept, etc.
EqS	Model template including all allowed regressors. Each column corresponds to one equation. Each line corresponds to one polynomial term as defined by function <code>poLabs</code> .
AndManda	AND-mandatory terms in the equations (all the provided terms should be in the equations).
OrMandaPerEq	OR-mandatory terms per equations (at least one of the provided terms should be in each equation).
IstepMin	The minimum number of integration step to start of the analysis (by default <code>IstepMin = 10</code> ).
IstepMax	The maximum number of integration steps for stopping the analysis (by default <code>IstepMax = 10000</code> ).
nPmin	Corresponds to the minimum number of parameters (and thus of polynomial term) allowed.
nPmax	Corresponds to the maximum number of parameters (and thus of polynomial) allowed.
tooFarThr	Divergence threshold, maximum value of the model trajectory compared to the data standard deviation. By default a trajectory is too far if the distance to the center is larger than four times the variance of the input data.

FxPtThr	Threshold used to detect fixed points.
LimCyclThr	Threshold used to detect the limit cycle.
nPminPerEq	Corresponds to the minimum number of parameters (and thus of polynomial term) allowed per equation.
nPmaxPerEq	Corresponds to the maximum number of parameters (and thus of polynomial) allowed per equation.
method	The integration technique used for the numerical integration. By default, the fourth-order Runge-Kutta method (method = 'rk4') is used. Other methods such as 'ode45' or 'lsoda' may also be chosen. See package deSolve for details.

### Value

A list containing:

`$tin` The time vector of the input time series

`$inputdata` The input time series

`$tfiltdata` The time vector of the filtered time series (boundary removed)

`$filtdata` A matrix of the filtered time series with its derivatives

`$okMod` A vector classifying the models: diverging models (0), periodic models of period-1 (-1), unclassified models (1).

`$coeff` A matrix with the coefficients of one selected model

`$models` A list of all the models to be tested `$mToTest1`, `$mToTest2`, etc. and all selected models `$model1`, `$model2`, etc.

`$tout` The time vector of the output time series (vector length corresponding to the longest numerical integration duration)

`$stockoutreg` A list of matrices with the integrated trajectories (variable X1 in column 1, X2 in 2, etc.) of all the models `$model1`, `$model2`, etc.

### Author(s)

Sylvain Mangiarotti, Flavie Le Jean, Mireille Huc

### References

- [1] Gouesbet G. & Letellier C., 1994. Global vector-field reconstruction by using a multivariate polynomial L2 approximation on nets, *Physical Review E*, 49 (6), 4955-4972.
- [2] Mangiarotti S., Coudret R., Drapeau L. & Jarlan L., Polynomial search and Global modelling: two algorithms for modeling chaos. *Physical Review E*, 86(4), 046205.
- [3] Mangiarotti S., Le Jean F., Huc M. & Letellier C., Global Modeling of aggregated and associated chaotic dynamics. *Chaos, Solitons and Fractals*, 83, 82-96.
- [4] S. Mangiarotti, M. Peyre & M. Huc, 2016. A chaotic model for the epidemic of Ebola virus disease in West Africa (2013-2016). *Chaos*, 26, 113112.

**See Also**

[gloMoId](#), [autoGPoMoSearch](#), [autoGPoMoTest](#)  
[autoGPoMoSearch](#), [autoGPoMoTest](#), [visuOutGP](#), [poLabs](#), [predictab](#), [drvSucc](#)

**Examples**

```
#Example 1
data("Ross76")
tin <- Ross76[,1]
data <- Ross76[,3]
dev.new()
out1 <- gPoMo(data, tin = tin, dMax = 2, nS=c(3), show = 1,
              IstepMax = 1000, nPmin = 9, nPmax = 11)
visuEq(out1$models$model1, approx = 4)

## Not run:
#Example 2
data("Ross76")
tin <- Ross76[,1]
data <- Ross76[,3]
# if some data are not valid (vector 'weight' with zeros)
W <- tin * 0 + 1
W[1:100] <- 0
W[700:1500] <- 0
W[2000:2800] <- 0
W[3000:3500] <- 0
dev.new()
out2 <- gPoMo(data, tin = tin, weight = W,
              dMax = 2, nS=c(3), show = 1,
              IstepMax = 6000, nPmin = 9, nPmax = 11)
visuEq(out2$models$model3, approx = 4)

## End(Not run)

## Not run:
#Example 3
data("Ross76")
tin <- Ross76[,1]
data <- Ross76[,2:4]
dev.new()
out3 <- gPoMo(data, tin=tin, dMax = 2, nS=c(1,1,1), show = 1,
              IstepMin = 10, IstepMax = 3000, nPmin = 7, nPmax = 8)
# the simplest model able to reproduce the observed dynamics is model #5
visuEq(out3$models$model5, approx = 3, substit = 1) # the original Rossler system is thus retrieved

## End(Not run)

## Not run:
#Example 4
data("Ross76")
```



```

tin <- Ross76[,1]
data <- Ross76[,2:3]
# model template:
EqS <- matrix(1, ncol = 3, nrow = 10)
EqS[,1] <- c(0,0,0,1,0,0,0,0,0,0)
EqS[,2] <- c(1,1,0,1,0,1,1,1,1,1)
EqS[,3] <- c(0,1,0,0,0,0,1,1,0,0)
visuEq(EqS, substit = c('X','Y','Z'))
dev.new()
out4 <- gPoMo(data, tin=tin, dMax = 2, nS=c(2,1), show = 1,
             EqS = EqS, IstepMin = 10, IstepMax = 2000,
             nPmin = 9, nPmax = 11)
visuEq(out4$models$model2, approx = 2, substit = c("Y","Y2","Z"))

## End(Not run)

## Not run:
#Example 5
# load data
data("TSallMod_nVar3_dMax2")
#multiple (six) time series
tin <- TSallMod_nVar3_dMax2$SprK$reconstr[1:400,1]
TSRo76 <- TSallMod_nVar3_dMax2$R76$reconstr[,2:4]
TSSprK <- TSallMod_nVar3_dMax2$SprK$reconstr[,2:4]
data <- cbind(TSRo76,TSSprK)[1:400,]
dev.new()
# generalized Polynomial modelling
out5 <- gPoMo(data, tin = tin, dMax = 2, nS = c(1,1,1,1,1,1),
             show = 0, method = 'rk4',
             IstepMin = 2, IstepMax = 3,
             nPmin = 13, nPmax = 13)

# the original Rossler (variables x, y and z) and Sprott (variables u, v and w)
# systems are retrieved:
visuEq(out5$models$model347, approx = 4,
      substit = c('x', 'y', 'z', 'u', 'v', 'w'))
# to check the robustness of the model, the integration duration
# should be chosen longer (at least IstepMax = 4000)

## End(Not run)

```

---

GSproc

*Gram-Schmidt procedure*


---

### Description

Computes regressors coefficients using the Gram-Schmidt procedure.

**Usage**

```
GSproc(polyK, ivec, weight = NULL)
```

**Arguments**

polyK	One list including \$Y and \$phy with: \$Y a matrix for which the ith column will be used to add one orthogonal vector to the (i-1)th vectors of the current orthogonal base; and \$phy such as the current orthogonal base is given by the (i-1)th first columns of matrix polyK\$phy.
ivec	Defines i, the current vector of polyK\$Y and the current orthogonal base of pParam\$phy.
weight	The weighing vector.

**Value**

uNew The model parameterization, that is: The residual orthogonal vector that can be included into the current orthogonal base. If the current base is empty, uNew is equal to the input vector of \$Y; if the base is complete, uNew equals 0.

**Author(s)**

Sylvain Mangiarotti

---

NDVI

*A time series of vegetation index measured from satellite*

---

**Description**

A time series of 28 years of Normalized Difference Vegetation Index measured from space by the Advanced Very High Resolution Radiometer (AVHRR) sensor from 1982 to 2008 (see reference [1] for details).

**Usage**

```
NDVI
```

**Format**

An object of class `data.frame` with 9618 rows and 4 columns.

**Author(s)**

Sylvain Mangiarotti, Flavie Le Jean

**References**

[1] Mangiarotti S., Drapeau L. & Letellier C., 2014. Two chaotic models for cereal crops observed from satellite in northern Morocco.

---

 numicano

*Numerical Integration of models in ODE of polynomial form*


---

**Description**

Function for the numerical integration of Ordinary Differential Equations of polynomial form.

**Usage**

```
numicano(
  nVar,
  dMax,
  Istep = 1000,
  onestep = 1/125,
  KL = NULL,
  PolyTerms = NULL,
  v0 = NULL,
  method = "rk4"
)
```

**Arguments**

nVar	Number of variables considered in the polynomial formulation.
dMax	Maximum degree of the polynomial formulation.
Istep	The number of integration time steps
onestep	Time step length
KL	Matrix formulation of the model to integrate numerically
PolyTerms	Vectorial formulation of the model (only for models of canonical form)
v0	The initial conditions (a vector which length should correspond to the model dimension nVar)
method	The integration method (See package deSolve), by default method = 'rk4'.

**Value**

A list of two variables:

\$KL The model in its matrix formulation

\$reconst The integrated trajectory (first column is the time, next columns are the model variables)

**Author(s)**

Sylvain Mangiarotti



```

poLabs(nVar, dMax, PolyTerms!=0)
# initial conditions
v0 <- c(0.54, 3.76, -90, -5200)
# model integration
reconstr <- numicano(nVar, dMax, Istep=500, onestep=1/250, PolyTerms=PolyTerms,
                    v0=v0, method="ode45")
# Plot of the simulated time series obtained
plot(reconstr$reconstr[,2], reconstr$reconstr[,3], type='l',
     main='phase portrait', xlab='x', ylab = 'dx/dt')
# Edition of the equations
visuEq(reconstr$KL, nVar, dMax)

## End(Not run)

```

---

numiMultiX	<i>Numerical Integration polynomial ODEs with Multiple eXternal forcing</i>
------------	---

---

## Description

Function for the numerical integration of Ordinary Differential Equations of polynomial form including single or Multiple external forcing

## Usage

```

numiMultiX(
  nVar,
  dMax,
  Istep = 1000,
  onestep = 1/125,
  Kdf,
  extF = extF,
  v0 = NULL,
  method = "rk4"
)

```

## Arguments

nVar	Number of variables considered in the polynomial formulation.
dMax	Maximum degree of the polynomial formulation.
Istep	The number of integration time steps. By default, Istep = 1000
onestep	The time step to be used for numerical integration
Kdf	The nonautonomous model in its matrix formulation, NA (i.e. not available) values should be provided for forcing variables provided as an external signal
extF	A matrix providing the time vector in the first column, and time series of each forcing in the next ones

`v0` The initial conditions. Its length should be in agreement with the dynamical system dimension. Therefore, 0 or NA can be provided for external forcing

`method` integration method. By default 'rk4' is used

### Value

A list of two variables:

`$Kdf` The nonautonomous model in its matrix formulation

`$reconstr` The integrated trajectory (first column is the time, next columns are the model variables)

### Author(s)

Sylvain Mangiarotti

### See Also

[derivODE2](#), [numicano](#), [numinoisy](#)

### Examples

```
#####
# Example 1 #
#####
# build a non autonomous model
nVar = 4
dMax = 3
gamma = 0.05
Kdf=matrix(0, nrow = d2pMax(nVar = nVar, dMax = dMax), ncol = nVar)
Kdf[11,1] = 1
Kdf[2,2] = 1
Kdf[5,2] = 1
Kdf[11,2] = -gamma
Kdf[35,2] = -1
Kdf[2,3] = NA
Kdf[2,4] = NA
visuEq(K = Kdf, substit = c('x', 'y', 'u', 'v'))

# build an external forcing
# number of integration time step
Istep <- 500

# time step
smp1 <- 1 / 20

# output time vector
tvec <- (0:(Istep-1)) * smp1

# angular frequency (for periodic forcing)
omega = 0.2
```

```

# half step time vector (for Runge-Kutta integration)
tvecX <- (0:(Istep*2-2)) * smp1 / 2
# generate the forcing (here variables u and v)
extF = cbind(tvecX, -0.1 * cos(tvecX * omega), 0.05 * cos(tvecX * 16/3*omega))

# decimate the data
extFrs <- extF[seq(1,dim(extF)[1],by=50),]
extFrs <- rbind(extFrs,extF[dim(extF)[1],])

# Initial conditions to be used (external variables can be set to 0)
etatInit <- c(-0.616109362, -0.126882584, NA, NA)
# model integration
out <- numiMultiX(nVar, dMax, Istep=Istep, onestep=smp1, Kdf=Kdf,
                 extF,
                 v0=etatInit, method="rk4")
outrs <- numiMultiX(nVar, dMax, Istep=Istep, onestep=smp1, Kdf=Kdf,
                  extFrs,
                  v0=etatInit, method="rk4")

dev.new()
par(mfrow = c(2, 2), # 2 x 2 pictures on one plot
    pty = "s")
plot(out$reconstr[,2],out$reconstr[,3],
     xlab = 'x(t)', ylab = 'y(t)', type = 'l', col = 'red')
lines(outrs$reconstr[,2],outrs$reconstr[,3],
     xlab = 'x(t)', ylab = 'y(t)', type = 'l', col = 'green')
plot(out$reconstr[,2],out$reconstr[,4],
     xlab = 'x(t)', ylab = 'u(t)', type = 'l', col = 'red')
plot(out$reconstr[,4],out$reconstr[,5],
     xlab = 'u(t)', ylab = 'v(t)', type = 'l', col = 'red')

```

---

numinoisy

*Generates time series of deterministic-behavior with stochastic perturbations (measurement and/or dynamical noise)*


---

### Description

Generates time series from Ordinary Differential Equations perturbed by dynamical and/or measurement noises

### Usage

```

numinoisy(
  x0,
  t,
  K,
  varData = NULL,
  txVarBruitA = NULL,

```

```

txVarBruitM = NULL,
varBruitA = NULL,
varBruitM = NULL,
taux = NULL,
freq = NULL,
variables = NULL,
method = NULL
)

```

### Arguments

<code>x0</code>	The initial conditions. Should be a vector which size must be equal to the model dimension $\dim(K)[2]$ (the number of variables of the model defined by matrix <code>K</code> ).
<code>t</code>	A vector providing all the dates for which the output are expected.
<code>K</code>	The Ordinary Differential Equations used to model the dynamics. The number of column should correspond to the number of variables, the number of lines to the number of parameters following the convention defined by <code>poLabs(nVar, dMax)</code> .
<code>varData</code>	A vector of size <code>nVar</code> providing the characteristic variances of each variable of the dynamical systems in ODE defined by matrix <code>K</code> . If not provided, this variance is automatically estimated.
<code>txVarBruitA</code>	A vector defining the ratio of ADDITIVE noise for each variable of the dynamical system in ODE. The additive noise is added at the end of the numerical integration process. The ratio is defined relatively to the signal variance of each variable.
<code>txVarBruitM</code>	A vector defining the ratio of DYNAMICAL noise for each variable of the dynamical system in ODE. This noise is a perturbation added at each numerical integration step. The ratio is defined relatively to the signal variance of each variable.
<code>varBruitA</code>	A vector defining the variance of ADDITIVE noise for each variable of the dynamical system in ODE. The additive noise is added at the end of the numerical integration process.
<code>varBruitM</code>	A vector defining the variance of DYNAMICAL noise for each variable of the dynamical system in ODE. This noise is a perturbation added at each numerical integration step.
<code>taux</code>	Generates random gaps in time series. Parameter <code>taux</code> defines the ratio of data to be kept (e.g. for <code>taux = 0.75</code> , 75 percents of the data are kept).
<code>freq</code>	Subsamples the time series. Parameter <code>freq</code> defines the periodicity of data kept (e.g. for <code>freq = 3</code> , 1 data out of 3 is kept).
<code>variables</code>	Defines which variables must be generated.
<code>method</code>	Defines the numerical integration method to be used. The fourth-order Runge-Kutta method is used by default ( <code>method = 'rk4'</code> ). Other method may be used (such as <code>'ode45'</code> or <code>'lsoda'</code> ), see function <code>ode</code> from package <code>deSolve</code> for details.



**Value**

A list of two variables:

\$donnees The integrated trajectory (first column is the time, next columns are the model variables)

\$bruitM The level of dynamical noise

\$bruitA The level of additive noise

\$vectBruitM The vector of the dynamical noise used to produce the time series

\$vectBruitA The vector of the additive noise used to produce the time series

\$cart\_type The level standard deviation

**Author(s)**

Sylvain Mangiarotti, Malika Chassan

**Examples**

```
#####
# Example 1 #
#####
# Rossler Model formulation
# The model dimension
nVar = 3
# maximal polynomial degree
dMax = 2
a = 0.520
b = 2
c = 4
Eq1 <- c(0,-1, 0,-1, 0, 0, 0, 0, 0, 0)
Eq2 <- c(0, 0, 0, a, 0, 0, 1, 0, 0, 0)
Eq3 <- c(b,-c, 0, 0, 0, 0, 0, 1, 0, 0)
K <- cbind(Eq1, Eq2, Eq3)
# Edit the equations
visuEq(K, nVar, dMax)
# initial conditions
v0 <- c(-0.6, 0.6, 0.4)
# output time required
timeOut = (0:800)/50
# variance of additive noise
varBruitA = c(0,0,0)^2
# variance of multiplitive noise
varBruitM = c(2E-2, 0, 2E-2)^2
# numerical integration with noise
intgr <- numinoisy(v0, timeOut, K, varBruitA = varBruitA, varBruitM = varBruitM, freq = 1)
```

```

# Plot of the simulated time series obtained
dev.new()
plot(intgr$donnees[,2], intgr$donnees[,3], type='l',
     main='phase portrait', xlab='x(t)', ylab = 'y(t)')
dev.new()
par(mfrow = c(3, 1))
plot(intgr$donnees[,1], intgr$donnees[,2], type='l',
     main='phase portrait', xlab='x(t)', ylab = 'y(t)')
lines(intgr$donnees[,1], intgr$vectBruitM[,2]*10, type='l',
      main='phase portrait', xlab='x(t)', ylab = 'e(t)*10', col='red')
plot(intgr$donnees[,1], intgr$donnees[,3], type='l',
     main='phase portrait', xlab='x(t)', ylab = 'y(t)')
lines(intgr$donnees[,1], intgr$vectBruitM[,3]*10, type='l',
      main='phase portrait', xlab='x(t)', ylab = 'e(t)*10', col='red')
plot(intgr$donnees[,1], intgr$donnees[,4], type='l',
     main='phase portrait', xlab='x(t)', ylab = 'y(t)')
lines(intgr$donnees[,1], intgr$vectBruitM[,4]*10, type='l',
      main='phase portrait', xlab='x(t)', ylab = 'e(t)*10', col='red')

```

---

odeBruitMult2

*For the numerical integration of ordinary differential equations with dynamical noise.*

---

## Description

A subfunction for the numerical integration of Ordinary Differential Equations provided in a generic polynomial form. Model formulation follows the convention defined by function `poLabs`.

## Usage

```

odeBruitMult2(
  x0,
  t,
  K,
  varData = NULL,
  txVarBruitM = NULL,
  varBruitM = NULL,
  method = NULL
)

```

## Arguments

<code>x0</code>	Initial conditions
<code>t</code>	All the dates for which the result of the numerical integration of the model must be provided
<code>K</code>	A matrix providing the model description: each column corresponds to one equation which polynomial organisation is following the convention defined by function <code>poLabs</code> .

varData	A vector of size nVar providing the characteristic variances of each variable of the dynamical systems in ODE defined by matrix K. If not provided, this variance is automatically estimated.
txVarBruitM	A vector defining the ratio of DYNAMICAL noise for each variable of the dynamical system in ODE. This noise is a perturbation added at each numerical integration step. The ratio is defined relatively to the signal variance of each variable.
varBruitM	A vector defining the variance of DYNAMICAL noise for each variable of the dynamical system in ODE. This noise is a perturbation added at each numerical integration step.
method	Numerical method used in the integration process. (see ode function in deSolve package for details).

**Author(s)**

Sylvain Mangiarotti, Malika Chassan

**See Also**

[numinousy](#)

---

P1FxCh

*A data set for testing periodicity*


---

**Description**

A matrix of 6 columns corresponding to six time series, two resulting from a Period-1 limit cycle, two from regime converging to fixed point, and two relating to a chaotic behavior

**Usage**

P1FxCh

**Format**

An object of class `matrix` with 1000 rows and 6 columns.

**Author(s)**

Sylvain Mangiarotti, Mireille Huc.

---

P1FxChP2

*A data set for testing periodicity*


---

**Description**

Trajectories for testing periodicity. The following regimes are made available: Period-1 in columns 1:2, Fixed Point in 3:4, chaotic in 5:6, Period-2 in 7:8

**Usage**

P1FxChP2

**Format**

An object of class `matrix` with 1000 rows and 8 columns.

**Author(s)**

Sylvain Mangiarotti, Mireille Huc.

---

p2dMax

*p2dMax : provides the maximum polynomial degree dMax given the number of variables nVar and the number of possible polynomial terms pMax.*


---

**Description**

Find the maximum polynomial degree dMax given the number of polynomial terms pMax and the system dimension nVar.

**Usage**

`p2dMax(nVar, pMaxKnown)`

**Arguments**

`nVar`            Number of variables considered in the polynomial formulation.  
`pMaxKnown`      The number of polynomial terms

**Value**

`dMax` The maximum polynomial degree

**Author(s)**

Sylvain Mangiarotti, Laurent Drapeau

**See Also**

[gloMoId](#), [gPoMo](#), [poLabs](#)

**Examples**

```
#####
# Example 1 #
#####
# Maximum polynomial degree ?
# number of variables:
nVar <- 3
# size of the polynomial vector:
pMax <- 10
# The maximal polynomial degree used for coding the polynomial is:
p2dMax(nVar,pMax)

#####
# Example 2 #
#####
# for pMax = 462 and nVar = 6, then dMax is:
p2dMax(6,462)
# indeed:
length(poLabs(nVar=6, dMax=5))
```

---

 paramId

*For parameter Identification*


---

**Description**

Estimate the polynomial coefficients.

**Usage**

```
paramId(allForK, drv, weight)
```

**Arguments**

allForK	The list of input parameters
drv	The derivative (on the equation left hand)
weight	The weighting series

**Value**

allForK The initial list completed with the model parameters.

**Author(s)**

Sylvain Mangiarotti

---

 poLabs

*Polynomial labels order*


---

### Description

Defines the order of the polynomial labels given the number of variables nVar and the maximum polynomial degree dMax.

### Usage

```
poLabs(nVar, dMax, findIt = NULL, Xnote = "X")
```

### Arguments

nVar	The number of variables
dMax	The maximum degree allowed in the formulation
findIt	A vector of selected terms.
Xnote	Enables to defines the notation used for the variable, by default Xnote = 'X'.

### Value

lbls A vector of characters. Each element is the expression of one polynomial term, such as  $X_1^2 X_3 X_4$

### Author(s)

Sylvain Mangiarotti

### See Also

[visuEq](#)

### Examples

```
#Regressor order for three variables \eqn{(X1,X2,X3)} (nVar = 3) for a maximum
#polynomial degree equal to 2 (dMax = 2): poLabs(3,2)
#and for two variables only : poLabs(2,2)

# For a quadratic equation of two variables,
# the polynomial \deqn{P(X1,X2) = 0.5 + 0.3 X1 -0.25 X1 X2}
# could thus be written as a vector Pvec such as:
Pvec = c(0.5, 0, 0, 0.3, -0.25, 0)
# considering the convention corresponding to
poLabs(2,2)
# Indeed:
poLabs(2, 2, findIt = Pvec!=0)
# An alternative notation can be used with parameter Xnote
poLabs(2, 2, findIt = Pvec!=0, Xnote = 'w')
```

```
# or also
poLabs(2, 2, findIt = Pvec!=0, Xnote = c('x','y'))
```

---

predictab	<i>Estimate the models performance obtained with GPoMo in term of predictability</i>
-----------	--

---

### Description

The algorithm aims to estimate automatically the forecasting performances of the models obtained with gPoMo.

### Usage

```
predictab(
  ogp,
  fullt = NULL,
  fulldata = NULL,
  hp = NULL,
  Nech = 50,
  show = 1,
  selecmod = NULL,
  id = 1,
  selV = 1,
  na.rm = FALSE
)
```

### Arguments

ogp	The output list obtained from function gPoMo.
fullt	Time vector of the data set for which predictability will be tested
fulldata	Data set for which predictability will be tested
hp	Time vector of the horizon of prediction
Nech	Number of simulations
show	Provide (2) or not (0-1) visual output during the running process.
selecmod	A vector of the model selected.
id	The type of model to identify. id = 1 corresponds to unidentified models, that is, potentially chaotic.
selV	Selected variable for the analysis
na.rm	Indicates if the NA should be removed (na.rm = TRUE) or not (na.rm = FALSE).

**Value**

ErrmodAll A list of matrix \$Predmod1, \$Predmod2, etc. and \$Errmod1, \$Errmod2, etc. providing respectively the forecasting and the forecasting error of models 1, 2, etc. Each column corresponds to one simulation starting from a specific initial condition. Each line corresponds to one horizon of prediction. Vectors corresponding to the initial condition time tE and the horizon of prediction hpE are also provided in \$tE and \$hpE, respectively.

**Author(s)**

Sylvain Mangiarotti, Mireille Huc

**Examples**

```
# load data
data("Ross76")
# time vector
tin <- Ross76[seq(1, 3000, by = 8), 1]
# single time series
data <- Ross76[seq(1, 3000, by = 8), 3]
# dev.new()
# plot(tin, data, xlab = 'time', ylab = 'y(t)')

# global modelling
# results are put in list outputGPoM
outputGPoM <- gPoMo(data[1:300], tin = tin[1:300], dMax = 2, nS=c(3),
                    show = 0, method = 'rk4',
                    nPmin = 10, nPmax = 12,
                    IstepMin = 150, IstepMax = 151)
#
visuOutGP(outputGPoM)

#####
# and test predictability #
#####
outpred <- predictab(outputGPoM, hp = 15, Nech = 30)

# manual visualisation of the outputs (e.g. for model 1):
dev.new()
image(outpred$tE, outpred$hpE, t(outpred$Errmod1),
      xlab = 't', ylab = 'hp', main = 'Errmod1')
```

**Description**

Estimate the parameters variations of a model of canonical form considering a sliding window on an external dataset.



**Usage**

```
pTimEv(
  TS,
  nVar,
  dMax,
  TSdate,
  whatTerms = NULL,
  wlength = 1000,
  onestep = 100,
  removeExtr = 1
)
```

**Arguments**

TS	The time series to be tested
nVar	Number of variables considered in the polynomial formulation.
dMax	Maximum degree of the polynomial formulation.
TSdate	The time vector
whatTerms	The terms to be considered in the analysis. Note that these are organised following the convention defined by <code>poLabs(nVar,dMax)</code> . Since only the structure is required, if coefficients are provided, these are transformed to 1.
wlength	The window length
onestep	Step length between two estimations
removeExtr	Ratio of estimated values to be removed (if chosen equal to 0.1, only 90 disersion will be kept)

**Value**

A list containing:

`$slidingoutGM` An  $n*(pMax+1)$  matrix presenting the  $pMax$  estimated parameters  $p1(t)$ ,  $p2(t)$  etc. column by column. The residual signal  $\epsilon(t)$  is provided in the last (i.e.  $pMax + 1$ ) column. Each line correspond to one date provided in `$TSdate`

`$TSdate` A time vector relating to the estimates presented in `$slidingoutGM`

`$W` A vector providing the output values that can kept (=1) or must be removed (=0)

`$whatTerms` A vector recalling the terms taken into account in the analysis (their order refers to `poLabs(nVar, dMax)` function)

`$param` A vector with the parameter values used to apply the function: `nVar`, `dMax`, `wlength`, `onestep`, `removeExtr`

**Author(s)**

Sylvain Mangiarotti

**See Also**

[autoGPoMoSearch](#), [gPoMo](#), [poLabs](#)

## Examples

```
#Example
data(TS)
plot(TS[,1], TS[,2], type='l')
nVar <- 3
dMax <- 2
pMax <- choose(nVar+dMax,dMax)
whatTerms <- c(1,1,0,1,1,1,1,1,1,1)

# apply pTimEv
statio <- pTimEv(TS[,2], nVar, dMax, TS[,1], whatTerms = whatTerms,
                wlength = 1000, onestep = 20, removeExtr = 0.15)
# Plot the results
dev.new()
layout(matrix(1:12, nrow=4, ncol=3, byrow = TRUE))
what <- which(statio$whatTerms!=0)
for (i in what) {
  plot(statio$TSdate[statio$W==1], statio$slidingoutGM[statio$W==1,i],
       xlab='TSdate', ylab='coeff', main=poLabs(nVar,dMax)[i])
}
plot(statio$TSdate[statio$W==1], statio$slidingoutGM[statio$W==1,pMax+1],
     xlab='date', ylab='Epsilon', main='Resid', log = 'y')
```

---

regOrd

*Generate the conventional order for polynomial terms in a the polynomial formulation*

---

## Description

Generate the conventional order of the polynomial terms for the polynomial description. It is formulated as a matrix of exponents: Each column of the matrix (a,b,c, ...) corresponds to a product of the nVar available variables X1, X2, X3, etc., that is,  $X1^a X2^b X3^c$ , etc.

## Usage

```
regOrd(nVar, dMax)
```

## Arguments

nVar	The number of variables
dMax	The maximum degree allowed in the formulation

## Value

A matrix of exponents. Each column corresponds to one polynomial term. Each line correspond to the exponent of one variable. For example, a column of three exponents (0, 2, 1) corresponds to the monomial  $X1^0 * X2^2 * X3^1$ , that is  $X2^2 X3$ .

**Author(s)**

Sylvain Mangiarotti

**See Also**[poLabs](#)

---

**regSeries***Estimates the monomial time series*

---

**Description**

Creates time series by multiplying given time series among them.

**Usage**

```
regSeries(nVar, dMax, series, pReg = NULL)
```

**Arguments**

nVar	Number of variables considered in the polynomial formulation.
dMax	Maximum degree of the polynomial formulation.
series	A matrix containing the original time series from which the monomials are built. Each column corresponds to one given variable.
pReg	A matrix filled, for each column, with powers of time series used to create.

**Value**

rpFull A matrix of time series. Each column corresponds to one regressor such as  $X_1^2 X_3 X_4$

**Author(s)**

Sylvain Mangiarotti

**Examples**

```
data(TSallMod_nVar3_dMax2)
sprttK <- as.matrix(TSallMod_nVar3_dMax2$SprK$reconstr)[,2:4]
dMax <- 2
nVar <- dim(sprttK)[2]

#Example 1
polySeries2 <- regSeries(nVar, dMax, sprttK)

#Example 2
p <- c(1,3,1)
polySeries2 <- regSeries(nVar, dMax, sprttK, pReg=p)
```

---

Rossler-1976 data set *Time series of the Rossler-1976 system*

---

### Description

The Rössler system is the 3-dimensional chaotic system

$$dx/dt = -y - z$$

$$dy/dt = x + ay$$

$$dz/dt = b + z(x - c),$$

discovered by Otto E. Rössler in 1976 [1]. The following parameters and initial conditions were used to produce the present data set:

$$a = 0.520, b = 2, c = 4$$

$$\text{and } (x_0, y_0, z_0) = (-0.04298734, 1.025536, 0.09057987).$$

The following four columns are provided:

(1) time  $t$ , (2)  $x(t)$ , (3)  $y(t)$  and (4)  $z(t)$ .

For this parameterization, the Rössler system produces a chaotic behavior characterized by a regime non-coherent in phase (oscillations duration can be very different from one oscillation to another).

### Usage

Ross76

### Format

An object of class `deSolve` (inherits from `matrix`) with 4000 rows and 4 columns.

### Author(s)

Sylvain Mangiarotti, Flavie Le Jean, Malika Chassan, Laurent Drapeau, Mireille Huc.

### References

[1] O. Rössler, 1976. An Equation for Continuous Chaos, *Physics Letters*, 71A, 2-3, 155-157.

---

RosYco

*Twelve Rossler-1976 time series (exclusively variable y)*

---

### Description

Twelve independant Rossler-1976 time series (variable  $y$ ). The parameters used to generate the time series correspond to a phase coherent behavior. Details can be found in [1]

### Usage

RosYco

**Format**

An object of class `matrix` with 3000 rows and 12 columns.

**Details**

Another set of time series of the Rossler-1976 chaotic system

**Author(s)**

Sylvain Mangiarotti, Flavie Le Jean.

**References**

[1] Mangiarotti S., Le Jean F., Huc M. & Letellier C., Global Modeling of aggregated and associated chaotic dynamics. *Chaos, Solitons and Fractals*, 83, 82-96.

---

subSysD

*subSysD : Sub-systems Disentangling*

---

**Description**

Detect, disentangle and reformulate Sub-systems from an ensemble of equations.

**Usage**

```
subSysD(inK, inXnote = NULL)
```

**Arguments**

<code>inK</code>	A list of models, each provided as a matrix. A single matrix can also be provided, it will be transformed into a list containing a single matrix.
<code>inXnote</code>	A vector with the names of the input variables. If not provided, default notation is used: "X1", "X2", etc.

**Author(s)**

Sylvain Mangiarotti

**See Also**

[gPoMo](#), [poLabs](#), [combiEq](#)

## Examples

```

# Load models
data("allMod_nVar3_dMax2")
# Display equations of system 1
visuEq(nVar = 3, dMax = 2, K = allMod_nVar3_dMax2$NH86, subtit = 1)
# Display equations of system 2
visuEq(nVar = 3, dMax = 2, K = allMod_nVar3_dMax2$R76, subtit = 1)
# put the two systems in a list
allK <- list()
allK[[1]] <- allMod_nVar3_dMax2$NH86
allK[[2]] <- allMod_nVar3_dMax2$R76

# Example 1 (two independant subsystems)
# take two separate systems and mix them
inXnote = list()
inXnote[[1]] <- c('u', 'v', 'w')
inXnote[[2]] <- c('X', 'Y', 'Z')
visuEq(K = allK[[1]], subtit = inXnote[[1]])
visuEq(K = allK[[2]], subtit = inXnote[[2]])
XnoteOut = c('u', 'X', 'v', 'Y', 'w', 'Z')
Knew3 <- combiEq(allK, inXnote = inXnote, XnoteOut = XnoteOut, dMaxOut = 3)
visuEq(K = Knew3, subtit = XnoteOut)
# Disentangle the subsystems from the mixed equations
dstgl <- subSysD(Knew3, inXnote = XnoteOut)
## Optional
# library(igraph)
# g1<-graph.adjacency(dstgl$FM);
# l <- layout_with_fr(g1)
# plot(g1, edge.arrow.siez = .4, edge.curved=.4, vertex.label=XnoteOut, layout = 1)

# Example 2 (one subsystem included in the other)
Kduff <- matrix(0, ncol = 4, nrow = 35)
Kduff[[11,1]] <- Kduff[[5,2]] <- Kduff[[2,3]] <- 1
Kduff[[35,2]] <- -1
Kduff[[11,2]] <- -0.05
Kduff[[5,4]] <- 2 * acos(-1) / 6.2
Xnote <- c("x", "y", "u", "v")
visuEq(Kduff, subtit = Xnote)
dstgl2 <- subSysD(Kduff, inXnote = Xnote)

```

---

svr/TS

*A data set for the global modeling of time series in association*


---

## Description

This data set aims to test the global modelling technique when several time series of different sizes are available. Four time series are provided, all derived from the Rössler-1976 system.

**Usage**

```
svrITS
```

**Format**

An object of class `list` of length 4.

**Author(s)**

Sylvain Mangiarotti, Mireille Huc.

**References**

S. Mangiarotti, F. Le Jean, M. Huc & C. Letellier, 2016. Global modeling of aggregated and associated chaotic dynamics, *Chaos, Solitons & Fractals*, 83, 82-96.

---

testP	<i>Periodic solution test</i>
-------	-------------------------------

---

**Description**

Tests if a trajectory is periodic.

**Usage**

```
testP(data, wthresh = 0.1, fxPtThresh = 1e-04, show = 0)
```

**Arguments**

data	Input Time series: Each column is one time series that corresponds to one variable.
wthresh	Threshold used to detect the limit cycle.
fxPtThresh	Threshold used to detect fixed points.
show	Provide (2) or not (0-1) visual output during the running process.

**Value**

periodic An integer classifying the models: diverging or unclassified trajectory (0), period-1 trajectory (-1), period-2 trajectory (-2) and fixed Point (2).

**Author(s)**

Sylvain Mangiarotti, Flavie Le Jean

**See Also**

[autoGPoMoTest](#), [gPoMo](#)

**Examples**

```
#Example
# Load data:
data('P1FxChP2')
# Test a period-1 trajectory
testP(P1FxChP2[,1:2], wthresh=0.1, fxPtThresh = 1e-6, show=0)
# Test a Fixed Point trajectory
testP(P1FxChP2[,3:4], wthresh=0.1, fxPtThresh = 1e-6, show=0)
# Test a chaotic trajectory
testP(P1FxChP2[,5:6], wthresh=0.1, fxPtThresh = 1e-6, show=0)
# Test a period-2 trajectory
testP(P1FxChP2[,7:8], wthresh=0.1, fxPtThresh = 1e-6, show=0)
```

---

TS	<i>Time series resulting from the integration of a non stationary system</i>
----	--

---

**Description**

A 2\*6001 matrix with the time vector in column one and a time series resulting from the integration of a non stationary Rössler system – parameter a varying in time: a(t) – in column two.

**Usage**

TS

**Format**

An object of class `matrix` with 6001 rows and 2 columns.

**Author(s)**

Sylvain Mangiarotti, Mireille Huc.

---

TSallMod_nVar3_dMax2 data set	<i>Time series of three-dimensional chaotic systems (for vignette VII_Retro-Modelling)</i>
-------------------------------	--

---

**Description**

A list of matrix providing the time series in a list named `TSallMod_nVar3_dMax2` of eighteen three-dimensional chaotic systems: Lorenz-1963 (`$L63`), Rössler-1976 (`$R76`), Burke & shaw 1981 (`$BS81`), Lorenz-1984 (`$L84`), Nosé & Hooer 1986 (`$NH86`), Genesio & Tosi 1992 (`$GT92`), Spott systems 1994 (`$SprF`, `$SprH`, `$SprK`, `$SprO`, `$SprP`, `$SprG`, `$SprM`, `$SprQ`, `$SprS`), Chlouverakis & Sprott 2004 (`$CS2004`), Li 2007 (`$Li2007`) and the Cord system by Aguirre & Letellier 2012 (`$Cord2012`). Time series are provided in a matrix in which each column corresponds to one variable of the dynamical systems.



**Usage**

```
TSallMod_nVar3_dMax2
```

**Format**

An object of class list of length 18.

**Author(s)**

Sylvain Mangiarotti, Mireille Huc.

**References**

References for the systems are provided in vignette ‘VII\_retro-modelling’.

---

visuEq	<i>Displays the models Equations</i>
--------	--------------------------------------

---

**Description**

Displays the model equations for a polynomial model which description is provided as a matrix K, each column corresponding to one equation. The coefficients of the polynomial terms are given following the order defined by function poLabs. The matrix can also be provided in a list K, in this case, the matrix should be located in K\$model[[selecmod]] where selecmod should be provided as input parameter.

**Usage**

```
visuEq(
  K,
  nVar = NULL,
  dMax = NULL,
  substit = 0,
  approx = FALSE,
  selecmod = NULL
)
```

**Arguments**

K	A matrix providing the model description: each column corresponds to one equation which polynomial organisation is following the convention defined by function poLabs.
nVar	The number of variables
dMax	The maximum degree allowed in the formulation

substit	Applies substitutions to the default values: for <code>substit = 0</code> (default value), variables are chosen as <code>X1, X2, ...</code> for <code>substit = 1</code> , variable <code>X1, X2, ...</code> will be replaced by <code>x, y, z, ...</code> for <code>substit = 2</code> , the codes provides a LaTeX-like formulation of the model. The variables name can also be defined explicetely as follows: for <code>substit = c('x', 'H', 'T1')</code> , variables <code>X1, X2, X3 ...</code> will be replaced by <code>x, H and T1</code> .
approx	The number of extra digits to be used: for <code>approx = FALSE</code> (default value) digits are edited with double precision; for <code>approx = TRUE</code> , only the minimum number of digits is edited (in order to have all the terms different from 0) for <code>approx = 1, 2, etc.</code> then respectively <code>1, 2, etc.</code> digits are added to the minimum number of digits corresponding to <code>approx = TRUE</code> .
selecmo	An integer providing the number in the sublist when the model matrix is provided in a list. Should not be provided (or <code>NULL</code> ) if the model matrix is provided directly.

### Author(s)

Sylvain Mangiarotti

### Examples

```
#EQUATIONS VISUALISATION
# number of variables:
nVar <- 3
# maximum polynomial degree:
dMax <- 2
# polynomial organization:
poLabs(nVar,dMax)
# model construction
KL = matrix(0, ncol = 3, nrow = 10)
KL[1,1] <- KL[2,2] <- 1
KL[4,1] <- -1
KL[5,3] <- -0.123456789
# Equations visualisation:
# (a) by default, variables names X1, X2, X3 are used
visuEq(KL, nVar, dMax)
# (b) for substit=1, variables names x, y, y are used instead
visuEq(KL, nVar, dMax, approx = TRUE, substit=1)
# (c) the name of the variables can also be chosen manually
visuEq(KL, nVar, dMax, approx = 3, substit=c('U', 'V', 'W'))

# A canonical model can be provided as a single vector
polyTerms <- c(0.2,0,-1,0.5,0,0,0,0,0,0)
visuEq(KL, 3,2)
```

---

visuOutGP

*visuOutGP : get a quick information of gPoMo output*


---

### Description

The algorithm aims to get a quick information about the outputs obtained with gPoMo.

### Usage

```
visuOutGP(
  ogp,
  selecmod = NULL,
  id = 1,
  prioMinMax = "data",
  opt3D = "TRUE",
  maxPages = NULL,
  seeEq = 1
)
```

### Arguments

ogp	The output list obtained from gPoMo.
selecmod	A vector of the selected model. Maximum 24 models can be presented at the same time.
id	The type of model to identify. id = 1 corresponds to the unidentified models, that is, potentially chaotic models).
prioMinMax	Gives the priority for the plots among: "data", "model", "dataonly" and "modelonly".
opt3D	Provides a 3D plot (x,y,z) when opt = 'TRUE' (the rgl library is required).
maxPages	The maximum of pages to be displayed (4 by default, but this may be insufficient when too many models remain)
seeEq	Indicates if equations should be displayed (seeEq = 1, by default) or not (seeEq = 0).

### Value

A Matrix describing the terms composing each model by row. The first row corresponds to the model detection (1 unclarified, 2 diverging, 0 is fixed point, -n with n an integer, is period-n cycle' )

### Author(s)

Sylvain Mangiarotti

**Examples**

```

# load data
data("Ross76")
# # time vector
tin <- Ross76[seq(1, 3000, by = 8), 1]
# single time series
data <- Ross76[seq(1, 3000, by = 8), 3]
dev.new()
plot(tin, data, type = 'l', main = 'Observed time series')
# global modelling
# results are put in list outputGPoM
outputGPoM <- gPoMo(data, tin=tin, dMax = 2, nS=c(3), show = 0,
                    nPmin = 9, nPmax = 12, method = 'rk4',
                    IstepMin = 200, IstepMax = 201)
visuOutGP(outputGPoM)

```

---

wInProd

*Weighted inner product*


---

**Description**

Computes weighted inner products.

**Usage**

```
wInProd(A1, A2, weight = NULL)
```

**Arguments**

A1	The input matrix 1.
A2	The input matrix 2.
weight	The weighting vector.

**Value**

inP The weighted inner product.

**Examples**

```

#####
#Example 1 #
#####
A1 = c(0,1,2,0,1,3)
A2 = c(1,2,0,0,4,1)
wInProd(A1, A2)

#####

```

```
#Example 2 #  
#####  
A1 = c(0,1,2,0,1,3)  
A2 = c(1,2,0,0,4,1)  
w = c(0,0,0,1,1,1)  
wInProd(A1, A2, weight = w)
```

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