

Package: Greymodels (via r-universe)

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Type Package

Title Shiny App for Grey Forecasting Model

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Description The 'Greymodels' Shiny app is an interactive interface for statistical modelling and forecasting using grey-based models. It covers several state-of-the-art univariate and multivariate grey models. A user friendly interface allows users to easily compare the performance of different models for prediction and among others, visualize graphical plots of predicted values within user chosen confidence intervals. Chang, C. (2019) <doi:10.24818/18423264/53.1.19.11>, Li, K., Zhang, T. (2019) <doi:10.1007/s12667-019-00344-0>, Ou, S. (2012) <doi:10.1016/j.compag.2012.03.007>, Li, S., Zhou, M., Meng, W., Zhou, W. (2019) <doi:10.1080/23307706.2019.1666310>, Xie, N., Liu, S. (2009) <doi:10.1016/j.apm.2008.01.011>, Shao, Y., Su, H. (2012) <doi:10.1016/j.aasri.2012.06.003>, Xie, N., Liu, S., Yang, Y., Yuan, C. (2013) <doi:10.1016/j.apm.2012.10.037>, Li, S., Miao, Y., Li, G., Ikram, M. (2020) <doi:10.1016/j.matcom.2019.12.020>, Che, X., Luo, Y., He, Z. (2013) <doi:10.4028/www.scientific.net/AMM.364.207>, Zhu, J., Xu, Y., Leng, H., Tang, H., Gong, H., Zhang, Z. (2016) <doi:10.1109/appeec.2016.7779929>, Luo, Y., Liao, D. (2012) <doi:10.4028/www.scientific.net/AMR.507.265>, Bilgil, H. (2020) <doi:10.3934/math.2021091>, Li, D., Chang, C., Chen, W., Chen, C. (2011) <doi:10.1016/j.apm.2011.04.006>, Chen, C. (2008) <doi:10.1016/j.chaos.2006.08.024>, Zhou, W., Pei, L. (2020) <doi:10.1007/s00500-019-04248-0>, Xiao, X., Duan, H. (2020) <doi:10.1016/j.engappai.2019.103350>, Xu, N., Dang, Y. (2015) <doi:10.1155/2015/606707>, Chen, P., Yu, H. (2014) <doi:10.1155/2014/242809>, Zeng, B., Li, S., Meng, W., Zhang, D. (2019) <doi:10.1371/journal.pone.0221333>, Liu, L., Wu, L. (2021) <doi:10.1016/j.apm.2020.08.080>, Hu, Y. (2020) <doi:10.1007/s00500-020-04765-3>, Zhou, P., Ang, B., Poh, K. (2006) <doi:10.1016/j.energy.2005.12.002>, Cheng, M., Li, J.,

Liu, Y., Liu, B. (2020) <doi:10.3390/su12020698>, Wang, H., Wang, P., Senel, M., Li, T. (2019) <doi:10.1155/2019/9049815>, Ding, S., Li, R. (2020) <doi:10.1155/2020/4564653>, Zeng, B., Li, C. (2018) <doi:10.1016/j.cie.2018.02.042>, Xie, N., Liu, S. (2015) <doi:10.1109/JSEE.2015.00013>, Zeng, X., Yan, S., He, F., Shi, Y. (2019) <doi:10.1016/j.apm.2019.11.032>.

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URL <https://github.com/havishaJ/Greymodels>

Encoding UTF-8

LazyData true

Depends R (>= 4.0.0), dplyr, Metrics, cmna, plotly

Imports shiny, shinydashboard, shinyWidgets, ggplot2, readxl, particle.swarm.optimisation, scales, expm

Config/pak/sysreqs cmake libfreetype6-dev libglu1-mesa-dev make texlive libicu-dev libpng-dev libuv1-dev libgl1-mesa-dev libssl-dev zlib1g-dev

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Contents

app_server	3
BackgroundValues	4
CombinedModels	6
ConfidenceInterval	8
ExtendedForms	10
IntervalMultivariable	13
Multivariable	16
Optimization	19
ParametersEstimation	22
Plots	24
ResidualModification	27

Index	31
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app_server	<i>Runs the Shiny app</i>
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Description

Runs the greymodels Shiny app

Usage

```
ui()  
server(input, output)  
run_app()
```

Arguments

ui	Controls the layout and appearance of the greymodels shiny app
input	Stores the current values of all of the widgets in the app
output	Contains all of the code needed to update the R objects in the app
server	Contains the instructions to build the greymodels shiny app

Value

No return value, runs the app

Examples

```
# Only run this example in interactive R sessions  
  
if (interactive()) {  
  
  library("shiny")  
  library("shinydashboard")  
  library("shinyWidgets")  
  library("readxl")  
  library("Metrics")  
  library("particle.swarm.optimisation")  
  library("cmna")  
  library("expm")  
  library("plotly")  
  library("ggplot2")  
  library("scales")  
  library("dplyr")  
  
  run_app <- function(){  
  
    shiny::shinyApp(ui, server, options = list(launch.browser = TRUE))  
  }  
  
}
```

BackgroundValues	<i>Improved background values</i>
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Description

A collection of grey forecasting models with improvements to the underlying background value z.

Usage

gm11(x0)
epgm11(x0)
tbgm11(x0)
igm11(x0)
gm114(x0)

Arguments

x0	Raw data
gm11	Basic grey model
epgm11	Extrapolation-based grey model
tbgm11	Data transformation-based grey model
igm11	Improved grey model
gm114	Grey model with single variable, one first-order variable, four background values

Value

fitted and predicted values

References

Chang C (2019). Extrapolation-based Grey Model for Small-Dataset Forecasting. Economic Computation and Economic Cybernetics Studies and Research, 53(1), 171-182. DOI:10.24818/18423264/53.1.19.11.

Li K, Zhang T (2019). A Novel Grey Forecasting Model and its Application in Forecasting the Energy Consumption in Shanghai. Energy Systems, pp. 1-16. DOI:10.1007/s12667-019-00344-0.

Ou S (2012). Forecasting Agricultural Output with an Improved Grey Forecasting Model based on the Genetic Algorithm. Computers and Electronics in Agriculture, 85, 33-39. DOI:10.1016/j.compag.2012.03.007.

Li S, Zhou M, Meng W, Zhou W (2019). A new Prediction Model for Forecasting the Automobiles Ownership in China. Journal of Control and Decision, 8(2), 155-164. DOI:10.1080/23307706.2019.1666310.

Examples

```

# GM(1,1) model

# x0 is the original data sequence
x0 <- c(2350,2465,2557,2577,2689,2739,2797,2885,2937,2996)

# Calculate AGO
x1 <- cumsum(x0)

# Determine length of x0
n <- length(x0)

# Generate background value sequence Z
b <- numeric(n)

for (i in 1:n){
  b[i] <- -(0.5*x1[i + 1] + 0.5*x1[i])
}

b1 <- b[1:n-1]

# Create a matrix B
B <- matrix(1,nrow=n-1,ncol=2)
B[,1] <- t(t(b1[1:n-1]))

# Create matrix yn
yn <- matrix(c(x0),ncol=1)
yn <- t(t(x0[2:n]))

# Estimate parameters a and b by ordinary least squares method (OLS)
xcap <- solve (t(B)%*% B)%*% t(B) %*% yn
a <- xcap[1,1]
b <- xcap[2,1]

# Calculate fitted values
scale_with <- function(k)
{
  (x0[1] - (b/a)) * exp(-a*k) * (1 - exp(a))
}
fitted <- scale_with(1:n)
x0cap <- c(x0[1],fitted[1:n-1])
x0cap

# A is the number of forecast values
A <- 4

# Predicted values
x0cap4 <- scale_with(1 : n+A-1)
x0cap5 <- tail(x0cap4,A)
x0cap5

# Fitted and predicted values

```

```
x0cap2 <- c(x0cap,x0cap5)
x0cap2
```

CombinedModels

Combined models

Description

A collection of hybrid grey forecasting models.

Usage

```
ngbm11(x0)
ggvm11(x0)
tfdgm11(x0)
```

Arguments

x0	Raw data
ngbm11	Non-linear grey Bernoulli model
ggvm11	Grey generalized Verhulst model
tfdgm11	Traffic flow mechanics grey model

Value

fitted and predicted values

References

Chen C (2008). Application of the Novel Nonlinear Grey Bernoulli Model for Forecasting Unemployment Rate. *Chaos, Solitons and Fractals*, 37(1), 278-287. DOI:10.1016/j.chaos.2006.08.024.

Zhou W, Pei L (2020). The Grey Generalized Verhulst model and its Application for Forecasting Chinese Pig Price Index. *Soft Computing*, 24, 4977-4990. DOI:10.1007/s00500-019-04248-0.

Xiao X, Duan H (2020). A New Grey Model for Traffic Flow Mechanisms. *Engineering Applications of Artificial Intelligence*, 88(2020), 103350. DOI:10.1016/j.engappai.2019.103350.

Examples

```
#TFDGM (1, 1) model: Traffic flow mechanics grey model

# Input data x0
x0 <- c(129,151,132,144,119,125,127,132)
# AGO
x1 <- cumsum(x0)

n <- length(x0)
```

```

z <- numeric(n)
for (i in 1:n){
  z[i] <- 0.5*(x1[i+1] + x1[i])
}
z1 <- z[1:n-1]

mat2 <- matrix(c(z1),ncol=1)

for (i in 1:n){
  z[i] <- (0.5*(x1[i+1] + x1[i]))^2
}
z2 <- z[1:n-1]

mat1 <- matrix(c(z2),ncol=1)
mat3 <- matrix(1,nrow=n-1,ncol=1)

B <- cbind(mat1, mat2, mat3)

y <- matrix(c(x0),ncol=1)
y <- t(t(x0[2:n]))

pcap <- (solve (t(B) %*% B)) %*% t(B) %*% y
a <- pcap[1,1]
b <- pcap[2,1]
lambda <- pcap[3,1]

p <- b/(2*a)
q <- ((b^2)/(4*(a^2))) - (lambda/a)

forecast <- numeric(n)
for (k in 1:n){
  if (q == 0){
    C2 <- (-1 / (x0[1] + p)) - a
    forecast[k] <- ( -1 / ((a*k) + C2) ) - p
  } else if (q < 0) {
    c3 <- (1/sqrt(-q)) * atan( (x0[1]+p) / sqrt(-q) ) - a
    forecast[k] <- sqrt(-q)* tan( sqrt(-q) * ( (a*k) + c3 ) ) - p
  }
}
x1cap <- c(forecast)

x0cap <- numeric(n)
for (i in 1:n){
  x0cap[i] <- x1cap[i+1] - x1cap[i]
}
x0cap1 <- x0cap[1:n-1]
x0cap <- c(x0[1],x0cap1)
# Fitted values
x0cap

A <- 4

```

```

forecasta <- numeric(n)
for (k in 1:n+A){
  if (q == 0){
    C2 <- (-1 / (x0[1] + p)) - a
    forecast[k] <- ( -1 / ((a*k) + C2) ) - p
  } else if (q < 0) {
    c3 <- (1/sqrt(-q)) * atan( (x0[1]+p) / sqrt(-q) ) - a
    forecasta[k] <- sqrt(-q)* tan( sqrt(-q) * ( (a*k) + c3 ) ) - p
  }
}
x1cap4 <- c(forecasta)

t4 <- length(x1cap4)

x0cap4 <- numeric(t4)
for (i in 1:t4-1) {
  x0cap4[i] <- x1cap4[i+1] - x1cap4[i]
}
x0cap4 <- c(x0[1],x0cap4[1:t4-1])

# Predicted values
x0cap5 <- tail(x0cap4,A)
x0cap5

# Fitted & Predicted values
x0cap2 <- c(x0cap,x0cap5)
x0cap2

```

ConfidenceInterval	<i>Confidence interval of predicted values</i>
--------------------	--

Description

The CValue, CI_rm and CI_mdbgm functions calculate the confidence interval of the predicted values.

Usage

```

CValue(fp1,actual1,x,ci)
CI_rm(fp1,actual1,x,ci)
CI_nhmgmp(fp1,x01,x02,x,ci)
CI_igndgm(fp1,actual1,x,ci)
CI_mdbgm(fp1,actual1,x,ci)

```

Arguments

fp1	Fitted and predicted values
actual1	Raw data

x01	Raw data of variable 1
x02	Raw data of variable 2
x	Number of forecasts chosen by the user
ci	The confidence level chosen by the user. Values range between 90%, 95% and 99%.

Value

confidence interval of predicted values

Examples

```
# Confidence interval of predicted values for EPGM (1, 1) model

# fp1 is the sequence of fitted and predicted values

fp1<-c(560,541.4,517.8,495.3,473.7,453.1,433.4,414.5,396.5)

# actual1 is the original data

actual1<-c(560,540,523,500,475)

fp2 <- t(fp1)

w <- length(fp2)

actual2 <- t(actual1)

n <- length(actual2)

fitted1 <- fp2[1:n]

fitted2 <- tail(fp1,4)

# x is the number of values to predict

x <- 4

predicted <- t(fitted2[1:x])

t <- length(predicted)

# Performance error - Root mean square error (rmse)

require("Metrics")

s <- rmse(actual2, fitted1)

sse <- sum((actual2 - fitted1)^2)

mse <- sse / (n - 2)
```

```

# ci is the confidence level (90, 95, 99)

ci <- 95

cc <- (ci + 100)/200

t.val <- qt(cc, n - 2)

# Calculate prediction interval

u <- numeric(t)
l <- numeric(t)

for (i in 1:t) {
  u[i] = predicted[i] + (t.val * (sqrt(mse) * sqrt(i)))
  l[i] = predicted[i] - (t.val * (sqrt(mse) * sqrt(i)))
}

UpperBound <- c(u[1:t])
LowerBound <- c(l[1:t])

CIsset <- data.frame(LowerBound,UpperBound)
CIsset

```

ExtendedForms

Extended forms of grey models

Description

A collection of extended grey forecasting models.

Usage

```

dgm11(x0)
dgm21(x0)
odgm21(x0)
ndgm11(x0)
vssgm11(x0)
gom11(x0)
gomia11(x0)
ungom11(x0)
exgm11(x0)
egm11(k,x0,k_A,x0_A)

```

Arguments

`x0` Raw data

k	Data index of raw data
x0_A	Raw data (testing set)
k_A	Data index (testing set)
dgm11	Discrete grey model with single variable, first order differential equation
dgm21	Discrete grey model with single variable, second order differential equation model
odgm21	Optimized discrete grey model with single variable, second order differential equation
ndgm11	Non-homogeneous discrete grey model
vssgm11	Variable speed and adaptive structure-based grey model
gom11	Grey opposite-direction model based on inverse accumulation and traditional interpolation method
gomia11	Grey opposite-direction model based on inverse accumulation
ungom11	Unbiased grey opposite-direction model based on inverse accumulation
exgm11	Exponential grey model
egm11	Extended grey model

Value

fitted and predicted values

References

Xie N, Liu S (2009). Discrete Grey Forecasting Model and its Application. *Applied Mathematical Modelling*, 33(2), 1173-1186. DOI:10.1016/j.apm.2008.01.011.

Shao Y, Su H (2012). On Approximating Grey Model DGM (2, 1). 2012 AASRI Conference on Computational Intelligence and Bioinformatics, 1, 8-13. DOI:10.1016/j.aasri.2012.06.003.

Xie N, Liu S, Yang Y, Yuan C (2013). On Novel Grey Forecasting Model based on Non-homogeneous Index Sequence. *Applied Mathematical Modelling*, 37, 5059-5068. DOI:10.1016/j.apm.2012.10.037.

Li S, Miao Y, Li G, Ikram M (2020). A Novel Varistructure Grey Forecasting Model with Speed Adaptation and its Application. *Mathematical and Computers in Simulation*, 172, 45-70. DOI:10.1016/j.matcom.2019.12.020.

Che X, Luo Y, He Z (2013). Grey New Information GOM (1, 1) Model based Opposite-Direction Accumulated Generating and its Application. *Applied Mechanics and Materials*, 364, 207-210. DOI:10.4028/www.scientific.net/AMM.364.207.

Power Load Forecasting based on GOM (1, 1) Model under the Condition of Missing Data. 2016 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), pp. 2461-2464. DOI:10.1109/appeec.2016.7779929.

Luo Y, Liao D (2012). Grey New Information Unbiased GOM (1, 1) Model based on Opposite-Direction Accumulated Generating and its Application. *Advanced Materials Research*, 507, 265-268. DOI:10.4028/www.scientific.net/AMR.507.265.

Bilgil H (2020). New Grey Forecasting Model with its Application and Computer Code. AIMS Mathematics, 6(2), 1497-1514. DOI: 10.3934/math.2021091.

An Extended Grey Forecasting Model for Omnidirectional Forecasting considering Data Gap Difference. Applied Mathematical Modeling, 35, 5051-5058. DOI:10.1016/j.apm.2011.04.006.

Examples

```
# EXGM (1, 1): Exponential grey model

# Input data x0
x0 <- c(2028,2066,2080,2112,2170,2275,2356,2428)

# Calculate accumulated generating operation (AGO)
x1 <- cumsum(x0)

# n is the length of sequence x0
n <- length(x0)

# Create matrix y
y <- matrix(c(x0),ncol=1)
y <- t(t(x0[2:n]))

b <- numeric(n)
for (i in 1:n){
  b[i] <- -0.5*(x1[i+1] + x1[i])
}
b1 <- b[1:n-1]

# Create matrix B2
mat1 <- matrix(c(b1),ncol=1)
mat2 <- matrix(1,nrow=n-1,ncol=1)
f <- numeric(n)
for (i in 1:n){
  f[i] <- ( exp(1) - 1 ) * exp(-i)
}
f1 <- f[2:n]

mat3 <- matrix(c(f1),ncol=1)
B2 <- cbind(mat1, mat2, mat3)

# Parameters estimation (a, b and c) by ordinary least squares method (OLS)
rcap <- (solve (t(B2) %*% B2)) %*% t(B2) %*% y
a <- rcap[1,1]
b <- rcap[2,1]
c <- rcap[3,1]

scale_with <- function(k)
{
  ( x1[1] - (b/a) - ( ( c/(a-1) ) * exp(-1) ) ) * exp(a*(1-k)) + (b/a) + ( c/(a-1) ) * exp(-k)
}
```

```

forecast1 <- scale_with(1:n)
x1cap <- c(forecast1)
x0cap1 <- numeric(n)
for (i in 1:n){
  x0cap1[i] <- x1cap[i+1] - x1cap[i]
}
x0cap <- c(x0[1],x0cap1[1:n-1])
# Fitted values
x0cap

# A is the number of forecast values
A <- 4

x1cap4 <- scale_with(1 : n+A )
t4 <- length(x1cap4)
x0cap4 <- numeric(t4-1)
for (i in 1:t4-1) {
  x0cap4[i] <- x1cap4[i+1] - x1cap4[i]
}
x0cap4 <- c(x0[1],x0cap4[1:t4-1])
x0cap5 <- tail(x0cap4,A)
# Predicted values
x0cap5

x0cap2 <- c(x0cap,x0cap5)
# Fitted and predicted values
x0cap2

```

IntervalMultivariable *Multivariate interval sequences*

Description

A collection of multivariate grey forecasting models based on interval number sequences.

Usage

```

igndgm12(LB,UB)
mdbgm12(x01L,x01U,x02L,x02U,x01La,x01Ua,x02La,x02Ua)

```

Arguments

LB, UB	Lower and upper bound of interval sequence
x01L, x01U	Lower and upper bound of first interval sequence (training set)
x02L, x02U	Lower and upper bound of second interval sequence (training set)
x01La, x01Ua	Lower and upper bound of first interval sequence (testing set)
x02La, x02Ua	Lower and upper bound of second interval sequence (testing set)
igndgm12	Interval grey number sequence based on non-homogeneous discrete grey model
mdbgm12	Multivariate grey model based on dynamic background algorithm

Value

fitted and predicted values

References

Xie N, Liu S (2015). Interval Grey Number Sequence Prediction by using Nonhomogeneous Exponential Discrete Grey Forecasting Model. *Journal of Systems Engineering and Electronics*, 26(1), 96-102. DOI:10.1109/JSEE.2015.00013.

Zeng X, Yan S, He F, Shi Y (2019). Multivariable Grey Model based on Dynamic Background Algorithm for Forecasting the Interval Sequence. *Applied Mathematical Modelling*, 80(23). DOI:10.1016/j.apm.2019.11.032.

Examples

#MDBGM (1, 2) model: Multivariate grey model based on dynamic background algorithm.

```
# Input data
#x01 Lower and upper bound of sequence 1
#x02 Lower and upper bound of sequence 2

# x01L is the lower bound of sequence 1
x01L <- c(2721,3136,3634,3374,3835,3595,3812,4488)

# x01U is the upper bound of sequence 1
x01U <- c(3975,4349,4556,5103,5097,5124,5631,6072)

# x02L is the lower bound of sequence
x02L <- c(24581,30070,36656,36075,42173,42074,45537,55949)

# x02U is the upper bound of sequence 2
x02U <- c(41731,49700,55567,61684,68295,68342,73989,78194)

x01 <- cbind(x01L,x01U)
x02 <- cbind(x02L,x02U)

# AGO
x11L <- cumsum(x01L)
x11U <- cumsum(x01U)

x11 <- cbind(x11L,x11U)

x12L <- cumsum(x02L)
x12U <- cumsum(x02U)

x12 <- cbind(x12L,x12U)

# Length of sequence
n <- length(x01L)

# Background values
b <- numeric(n)
```

```

for (i in 1:n){
  b[i] <- (0.5*x11L[i + 1] + 0.5*x11L[i])
  b1 <- b[1:n-1]
}
z1L <- matrix(c(b1),ncol=1)

n <- length(x01L)
d <- numeric(n)
for (i in 1:n){
  d[i] <- (0.5*x11U[i + 1] + 0.5*x11U[i])
  d1 <- d[1:n-1]
}
z1U <- matrix(c(d1),ncol=1)

# Create matrix Y
YL <- matrix(c(x01L[2:n]),ncol=1)
YU <- matrix(c(x01U[2:n]),ncol=1)

# Create matrix X
mat1 <- matrix(c(x12L[2:n]),ncol=1)
mat2 <- matrix(c(x12U[2:n]),ncol=1)
mat3 <- matrix(c(x11L[1:n-1]),ncol=1)
mat4 <- matrix(c(x11U[1:n-1]),ncol=1)
mat5 <- matrix(2:n,nrow=n-1,ncol=1)
mat6 <- matrix(1,nrow=n-1,ncol=1)

X <- cbind(mat1,mat2,mat3,mat4,mat5,mat6)

# Parameters estimation by OLS - Lower
A1 <- solve (t(X) %*% X) %*% t(X) %*% YL
miu11 <- A1[1,1]
miu12 <- A1[2,1]
gamma11 <- A1[3,1]
gamma12 <- A1[4,1]
g1 <- A1[5,1]
h1 <- A1[6,1]

# Parameters estimation by OLS - Upper
A2 <- solve (t(X) %*% X) %*% t(X) %*% YU
miu21 <- A2[1,1]
miu22 <- A2[2,1]
gamma21 <- A2[3,1]
gamma22 <- A2[4,1]
g2 <- A2[5,1]
h2 <- A2[6,1]

# Fitted values - Lower
scale_with <- function(k)
{
  (miu11*x12L[k]) + (miu12*x12U[k]) + (gamma11*x11L[k-1]) + (gamma12*x11U[k-1]) + (g1*k) + h1
}
forecast_L <- scale_with(2:n)
x0cap1L <- c(x01L[1],forecast_L)

```

```

# Fitted values - Upper
scale_with <- function(k)
{
  (miu21*x12L[k]) + (miu22*x12U[k]) + (gamma21*x11L[k-1]) + (gamma22*x11U[k-1]) + (g2*k) + h2
}
forecast_U <- scale_with(2:n)
x0cap1U <- c(x01U[1],forecast_U)

# Matrix of fitted values (lower and upper)
x0cap <- matrix(c(cbind(x0cap1L,x0cap1U)),ncol=2)
x0cap

```

Multivariable

Multivariate sequences

Description

A collection of grey forecasting models based on multiple variables.

Usage

```

gm13(x1,x2,x3)
igm13(x1,x2,x3)
nhmgm1(x01,x02)
nhmgm2(x01,x02)
gmcg12(x01,x02,dat_a)
gmc12(x01,x02,dat_a)
dbgm12(x01,x02,dat_a)

```

Arguments

x1, x2, x3	Raw data of 3 variables (training set)
x01, x02	Raw data of 2 variables (training set)
dat_a	Raw data of x02 (testing set)
gm13	Grey multivariate model with first order differential equation and 3 variables
igm13	Improved grey multivariate model with first order differential equation and 3 variables
nhmgm1	Non-homogeneous multivariate grey model with first order differential equation and 2 variables with $p = 1$
nhmgm2	Non-homogeneous multivariate grey model with first order differential equation and 2 variables with $p = 2$
gmcg12	Multivariate grey convolution model with first order differential equation and 2 variables using the Gaussian rule

gmc12	Multivariate grey convolution model with first order differential equation and 2 variables using the trapezoidal rule
dbgm12	Multivariate grey model with dynamic background value, first order differential equation and 2 variables using the Gaussian rule

Value

fitted and predicted values

References

- Cheng M, Li J, Liu Y, Liu B (2020). Forecasting Clean Energy Consumption in China by 2025: Using Improved Grey Model GM (1, N). Sustainability, 12(2), 1-20. DOI:10.3390/su12020698.
- Wang H, Wang P, Senel M, Li T (2019). On Novel Non-homogeneous Multivariable Grey Forecasting Model NHMGM. Mathematical Problems in Engineering, 2019, 1-13. DOI:10.1155/2019/9049815.
- Ding S, Li R (2020). A New Multivariable Grey Convolution model based on Simpson's rule and its Application. Complexity, pp. 1-14. DOI:10.1155/2020/4564653.
- Zeng B, Li C (2018). Improved Multivariable Grey Forecasting Model and with a Dynamic Background Value Coefficient and its Application. Computers and Industrial Engineering, 118, 278-290. DOI:10.1016/j.cie.2018.02.042.

Examples

```
# GMC_g (1, 2) model

# Input raw data
x01 <- c(897,897,890,876,848,814)
x02 <- c(514,495,444,401,352,293)
dat_a <- c(514,495,444,401,352,293,269,235,201,187)

# AGO
x11 <- cumsum(x01)
x12 <- cumsum(x02)

n <- length(x01)

b11 <- numeric(n)
b12 <- numeric(n)

for (i in 1:n){
  b11[i] <- -(0.5*x11[i + 1] + 0.5*x11[i])
  b12[i] <- (0.5*x12[i + 1] + 0.5*x12[i])
}
b11a <- b11[1:n-1]
b12a <- b12[1:n-1]

mat1 <- matrix(c(b11a),ncol=1)
mat2 <- matrix(c(b12a),ncol=1)
```

```

mat3 <- matrix(1,nrow=n-1,ncol=1)

B <- cbind(mat1, mat2, mat3)

yn <- matrix(c(x01),ncol=1)
yn <- t(t(x01[2:n]))

xcap <- solve (t(B) %*% B) %*% t(B) %*% yn

beta1 <- xcap[1,1]
beta2 <- xcap[2,1]
u <- xcap[3,1]

fe <- numeric(n)
for (i in 1:n){
  fe[i] <- beta2 * x12[i] + u
}
E <- matrix(c(fe[1:n]),ncol =1)
xrG <- replicate(n,0)
for (t in 2:n){
  sm <- 0
  for (e in 2:t){
    sm <- sm + ( (exp(-beta1*(t - e + 0.5)))) * ( 0.5 * (E[e]+ E[e-1]) )
  }
  xrG[t] <- ( x01[1]*exp(-beta1*(t-1)) ) + sm
}
xcap1G <- c(x01[1],xrG[2:n])
fG <- numeric(n-1)
for (i in 1:n-1){
  fG[i] <- (xcap1G[i+1] - xcap1G[i])
}
f1G <- fG[1:n-1]
x0cap <- matrix(c(x01[1],f1G[1:n-1]),ncol=1)
# Fitted values
x0cap

A <- 4

newx02 <- as.numeric(unlist(dat_a))
m <- length(newx02)
newx12 <- cumsum(newx02)
fe_A <- numeric(m)
for (i in 1:m){
  fe_A[i] <- beta2 * newx12[i] + u
}
E_A <- matrix(c(fe_A[1:m]),ncol =1)
xrG_A <- replicate(m,0)
for (t in 2:m){
  sm <- 0
  for (e in 2:t){
    sm <- sm + ( (exp(-beta1*(t - e + 0.5)))) * ( 0.5 * (E_A[e]+ E_A[e-1]) )
  }
  xrG_A[t] <- ( x01[1]*exp(-beta1*(t-1)) ) + sm
}

```

```

}
x0cap1G_A <- c(x01[1],xrG_A[2:m])

fG_A <- numeric(m-1)
for (i in 1:m-1){
  fG_A[i] <- (x0cap1G_A[i+1] - x0cap1G_A[i])
}
f1G_A <- fG_A[1:m-1]

x0cap4 <- matrix(c(x01[1],f1G_A[1:m-1]),ncol=1)

x0cap5 <- tail(x0cap4,A)
# Predicted values
x0cap5

# Fitted & Predicted values
x0cap2 <- c(x0cap,x0cap5 )
x0cap2

```

Optimization

Optimization-based grey models

Description

A collection of grey forecasting models using optimization techniques to find optimal parameters of grey models.

Usage

```

optim_psogm(x0)
psogm11(x0)
optim_andgm(x0)
andgm11(x0)
optim_egm11r(x0)
egm11r(x0)

```

Arguments

x0	Raw data
optim_psogm	Parameters optimization (a and b) by particle swarm optimization(PSO)
psogm11	Particle swarm optimization-based grey model
optim_andgm	Parameters optimization (r) by PSO
andgm11	Adjacent non-homogeneous discrete grey model
optim_egm11r	Parameters optimization (r) by PSO
egm11r	Even form of grey model with one variable and one first order equation with accumulating generation of order r

Value

fitted and predicted values

References

Zeng B, Li S, Meng W, Zhang D (2019). An Improved Grey Prediction Model for China's Beef Consumption Forecasting. PLOS ONE, 14(9), 1-18. DOI:10.1371/journal.pone.0221333.

Liu L, Wu L (2021). Forecasting the Renewable Energy Consumption of the European Countries by an Adjacent Non-homogeneous Grey Model. Applied Mathematical Modelling, 89, 1932-1948. DOI:10.1016/j.apm.2020.08.080.

Examples

```
# Input raw data
x0 <- c(2.8,3.8,4.6,5.2,5.7,6.0,6.2,6.92,7.77,8.92,10.06)

# Parameter optimization

library(particle.swarm.optimisation)

fitness_function <- function(value)
{
  r <- value[1]

  n <- length(x0)

  xr1 <- numeric(n)

  for (i in 1:n){
    xr1[i] <- ( (r-1)/r ) * sum(x0[1:i]) + (1/r)*x0[i+1]
  }
  xr <- c(x0[1],xr1[1:n-1])

  mat1 <-matrix(xr[1:n-1], nrow=n-1,ncol=1)
  mat2 <-matrix(2:n-1, nrow=n-1,ncol=1)
  mat3 <- matrix(1,nrow=n-1,ncol=1)

  B <- cbind(mat1, mat2, mat3)

  y <- t(t(xr[2:n]))

  rcap <- (solve (t(B) %*% B)) %*% t(B) %*% y
  beta1 <- rcap[1,1]
  beta2 <- rcap[2,1]
  beta3 <- rcap[3,1]

  scale_with <- function(k)
  {
    ( beta1^k * x0[1] ) + ( ( 1 - beta1^k )/( 1 - beta1 ) ) * (beta2*k + beta3)
  }
}
```

```

forecast1 <- scale_with(1:n)

xrcap <- c(x0[1],forecast1)

matrix2 <- matrix("",1,n)
matrix2 <- as.numeric(matrix2)
matrix2[1] <- x0[1]

for (i in 2:length(matrix2+1)) {
  matrix2[i] <- r*xrcap[i] - (r-1)*sum(matrix2[1:i-1])
}
particule_result <- matrix2
fitness <- -(1/n)*sum(abs((x0-particule_result)/x0)*100, na.rm=TRUE)
return(fitness)
}
values_ranges <- list(c(0.001,5))
swarm <- ParticleSwarm$new(pop_size = 100,
  values_names = list("r"),
  fitness_function = fitness_function,
  max_it = 100,
  acceleration_coefficient_range = list(c(0.5,1.5),c(0.5,1.5)),
  inertia = 0.7,
  ranges_of_values = values_ranges)
swarm$run(plot = FALSE,verbose = FALSE,save_file = FALSE)
swarm$swarm_best_values

opt_r <- swarm$swarm_best_values[1]
opt_r

n <- length(x0)

xr1r <- numeric(n)
for (i in 1:n){
  xr1r[i] <- ( (opt_r-1)/opt_r ) * sum(x0[1:i]) + (1/opt_r)*x0[i+1]
}
xoptr <- c(x0[1],xr1r[1:n-1])

mat1r <-matrix(xoptr[1:n-1], nrow=n-1,ncol=1)
mat2r <-matrix(2:n-1, nrow=n-1,ncol=1)
mat3r <- matrix(1,nrow=n-1,ncol=1)

Br <- cbind(mat1r, mat2r, mat3r)

yr <- t(t(xoptr[2:n]))

rcapr <- (solve (t(Br) %*% Br)) %*% t(Br) %*% yr
beta1r <- rcapr[1,1]
beta2r <- rcapr[2,1]
beta3r <- rcapr[3,1]

scale_with <- function(k)
{
  ( beta1r^k * x0[1] ) + ( ( 1 - beta1r^k )/( 1 - beta1r ) ) * (beta2r*k + beta3r)
}

```

```

}
forecast1r <- scale_with(1:n)

xrcapr <- c(x0[1],forecast1r)

matrix2r <- matrix("",1,n)
matrix2r <- as.numeric(matrix2r)

matrix2r[1] <- x0[1]

for (i in 2:length(matrix2r+1)) {
  matrix2r[i] <- opt_r*xrcapr[i] - (opt_r-1)*sum(matrix2r[1:i-1])
}
x0cap <- c(matrix2r)
# Fitted values
x0cap

A <- 4

# Predicted values
n <- length(x0)
nn <- n + A
scale_with <- function(k)
{
  ( beta1r^k * x0[1] ) + ( ( 1 - beta1r^k )/( 1 - beta1r ) ) * (beta2r*k + beta3r)
}
forecast1ra <- scale_with(1:nn)

xrcapra <- c(x0[1],forecast1ra)
matrix2ra <- matrix("",1,nn)
matrix2ra <- as.numeric(matrix2ra)
matrix2ra[1] <- x0[1]

for (i in 2:length(matrix2ra+1)) {
  matrix2ra[i] <- opt_r*xrcapra[i] - (opt_r-1)*sum(matrix2ra[1:i-1])
}
x0cap4 <- c(matrix2ra)
x0cap5 <- tail(x0cap4,A)
# Predicted values
x0cap5

# Fitted & Predicted values
x0cap2 <- c(x0cap,x0cap5)
x0cap2

```

ParametersEstimation *Parameters estimation*

Description

A collection of grey forecasting models based on parameters estimation.

Usage

```
sogm21(x0)
ngm11k(x0)
ngm11kc(x0)
ongm11kc(x0)
```

Arguments

x0	Raw data
sogm21	Structured optimized grey model with single variable and second order differential equation
ngm11k	Nonlinear grey model
ngm11kc	Nonlinear grey model
ongm11kc	Optimized nonlinear grey model

Value

fitted and predicted values

References

Xu N, Dang Y (2015). An Optimized Grey GM (2, 1) Model and Forecasting of Highway Subgrade Settlement. Mathematical Problems in Engineering, 2015(1), 1-6. DOI:10.1155/2015/606707.

Chen P, Yu H (2014). Foundation Settlement Prediction based on a Novel NGM Model. Mathematical Problems in Engineering 2014, 242809. DOI:10.1155/2014/242809.

Examples

```
# ONGM (1, 1, k, c) model: Nonlinear grey model

# Input data x0
x0 <- c(23.36,43.19,58.73,70.87,83.71,92.91,99.73,105.08,109.73,112.19,113.45)

# AGO
x1 <- cumsum(x0)

tm <- length(x0)

# Create matrix y
y <- matrix(c(x0),ncol=1)
y <- t(t(x0[2:tm]))

b <- numeric(tm)
for (i in 1:tm){
  b[i] <- -0.5*(x1[i+1] + x1[i])
}
b1 <- b[1:tm-1]
```

```

# Create matrix B2
mat1 <- matrix(c(b1),ncol=1)
mat2 <-matrix(2:tm, nrow=tm-1,ncol=1)
mat3 <- matrix(1,nrow=tm-1,ncol=1)

B2 <- cbind(mat1, mat2, mat3)

# Parameters estimation by OLS
rcap <- (solve (t(B2) %*% B2)) %*% t(B2) %*% y
a <- rcap[1,1]
b <- rcap[2,1]
c <- rcap[3,1]

m <- log ((2+a)/(2-a))
n <- (m*b)/a
p <- (m*c)/a - (n/a) + (n/2) + (n/m)

scale_with <- function(k)
{
  (1-exp(a))*(x1[1]-(n/m)+(n/(m^2))-(p/m))*exp(-m*(k-1))+(n/m)
}
forecast1 <- scale_with(2:tm)

x0cap <- c(x0[1],forecast1)
# Fitted values
x0cap

A <- 4

x0cap4 <- scale_with(1 : tm+A )

x0cap5 <- tail(x0cap4,A)
# Predicted values
x0cap5

# Fitted & Predicted values
x0cap2 <- c(x0cap,x0cap5)
x0cap2

```

Plots

plots

Description

The plots function gives an interactive plot of the model.

Usage

```
plots(x0,x0cap2,ci,model)
```

```

plotrm(x0,x0cap2,ci,model)
plotsmv1(actual1,fp1,ci,model)
plotsmv2(actual1,fitted,ci,model)
plotsigndgm(actual,pred,ci,model)
plots_mdbgm12(actual,pred,ci,model)

```

Arguments

<code>x0</code>	Raw data
<code>x0cap2</code>	Fitted and predicted data
<code>actual</code>	Raw data of interval sequences
<code>actual1</code>	Raw data of multi-variate sequences
<code>fp1</code>	Fitted and predicted data of first variable
<code>fitted</code>	Fitted data of multi-variate sequences
<code>pred</code>	Fitted and predicted data of interval sequences
<code>ci</code>	The confidence level chosen by the user. Values range between 90%, 95% and 99%.
<code>model</code>	The model under consideration

Value

plots

Examples

```

# Plots - EPGM (1, 1) model

x0cap2<-c(560,541.4,517.8,495.3,473.7,453.1,433.4,414.5,396.5)

x0<-c(560,540,523,500,475)

# length of x0
n <- length(x0)

fitted2 <- t(x0cap2)

x0cap <- x0cap2[1:n]

# Last 4 values of x0cap2
fitted3 <- tail(x0cap2,4)

x0cap5 <- fitted3

w <- length(x0cap2)
t <- length(x0cap5)

# Performance errors
# Root mean square error

```

```

s <- rmse(x0, x0cap)

# Sum of square error
sse <- sum((x0 - x0cap)^2)

# Mean square error
mse <- sse / (n - 2)

# Calculate confidence interval
ci <- 95
cc <- (ci + 100)/200

t.val <- qt(cc, n - 2)

u <- numeric(t)
l <- numeric(t)
for (i in 1:t) {
  u[i] = x0cap5[i] + (t.val * (sqrt(mse) * sqrt(i)))
  l[i] = x0cap5[i] - (t.val * (sqrt(mse) * sqrt(i)))
}
UB <- c(u[1:t])
LB <- c(l[1:t])

LB1 <- c(x0cap[n],LB)
UB2 <- c(x0cap[n],UB)

l1 <- length(LB1)
d3 <- seq(1, l1, 1)
u1 <- length(UB2)
d4 <- seq(1, u1, 1)

set3 <- data.frame(x=d3, y=LB1)
set4 <- data.frame(x=d4, y=UB2)

d0 <- seq(1, n, 1)
xy1 <- data.frame(x=d0, y=x0)

d1 <- seq(1, w, 1)
xy2 <- data.frame(x=d1, y=x0cap2)

# Create data frame
df <- rbind(xy1, xy2, set3, set4)

# Plots
colors <- c("Raw Data"="red", "Fitted&Forecasts"="blue", "LowerBound"="green", "UpperBound"="yellow")
CI <- c(n:w)

x=y=NULL

p <- ggplot(df) +
  theme_bw() +
  labs(title = 'EPGM (1, 1) model', x = 'Number of observation', y = 'Data Forecast & Prediction') +
  scale_x_continuous(breaks=1:w) +

```

```

scale_y_continuous(labels = scales::comma) +
geom_point(data = xy1, aes(x = x, y = y), shape = 24, color = "black") +
geom_point(data = xy2, aes(x = x, y = y), shape = 21, color = "black") +
geom_point(data = set3, aes(x = CI, y = y), shape = 23, color = "black") +
geom_point(data = set4, aes(x = CI, y = y), shape = 23, color = "black") +
geom_line(data = xy1, aes(x = x, y = y,color = "Raw Data")) +
geom_line(data = xy2, aes(x = x, y = y,color = "Fitted&Forecasts")) +
geom_line(data = set3, aes(x = CI, y = y,color = "LowerBound"), linetype=2) +
geom_line(data = set4, aes(x = CI, y = y,color = "UpperBound"), linetype=2) +
scale_color_manual(name = "Label",values = colors)
r <- ggplotly(p)
r

```

ResidualModification *Residual modification*

Description

A collection of grey forecasting models based on residual grey models.

Usage

```

remnantgm11(x0,x0_A)
tgm11(x0,x0_A)

```

Arguments

<code>x0</code>	Raw data (training set)
<code>x0_A</code>	Raw data (testing set)
<code>remnantgm11</code>	Residual-based grey model
<code>tgm11</code>	Trigonometric grey model

Value

fitted and predicted values

References

Hu Y (2020). Energy Demand Forecasting using a Novel Remnant GM (1, 1) Model. Soft Computing, pp. 13903-13912. DOI:10.1007/s00500-020-04765-3.

Zhou P, Ang B, Poh K (2006). A Trigonometric Grey Prediction Approach to Forecasting Electricity Demand. Energy, 31(14), 2839-2847. DOI:10.1016/j.energy.2005.12.002.

Examples

```

# TGM (1, 1) model: Trigonometric grey model

x0 <- c(2350,2465,2557,2577,2689,2739,2797,2885,2937,2996)
x0_A <- c(3042,3120,3132,3237)

x1 <- cumsum(x0)

n <- length(x0)

b <- numeric(n)
for (i in 1:n){
  b[i] <- -(0.5*x1[i + 1] + 0.5*x1[i])
}
b1 <- b[1:n-1]

B <- matrix(1,nrow=n-1,ncol=2)
B[,1] <- t(t(b1[1:n-1]))

yn <- matrix(c(x0),ncol=1)
yn <- t(t(x0[2:n]))

xcap <- solve (t(B) %*% B) %*% t(B) %*% yn
a <- xcap[1,1]
b <- xcap[2,1]

scale_with <- function(k)
{
  (x0[1] - (b/a)) * exp(-a*k) * (1 - exp(a))
}
fitted <- scale_with(1:n)

x0cap <- c(x0[1],fitted[1:n-1])

x0cap_GM <- c(x0cap)

n <- length(x0)

r0 <- numeric(n)

for (i in 1:n){
  r0[i] <-x0[i] - x0cap_GM[i]
}
R <- r0[2:n]

rn <- matrix(c(R),ncol=1)

m <- length(rn)

L <- 23

mat1 <- matrix(1,nrow=n-1,ncol=1)

```

```

mat2 <- matrix(1:m, nrow=m, ncol=1)

s <- replicate(n, 0)
for (i in 1:n){
  s[i] <- sin( (2*(i-1)*pi)/L )
}
mat3 <- matrix(c(s[2:n]), ncol=1)

c <- replicate(n, 0)
for (i in 1:n){
  c[i] <- cos( (2*(i-1)*pi)/L )
}
mat4 <- matrix(c(c[2:n]), ncol=1)

B <- cbind(mat1, mat2, mat3, mat4)

rcap <- (solve (t(B) %*% B)) %*% t(B) %*% rn
b0 <- rcap[1,1]
b1 <- rcap[2,1]
b2 <- rcap[3,1]
b3 <- rcap[4,1]

scale_with <- function(k)
{
  b0 + (b1*k) + (b2*sin( (2*pi*k)/L )) + (b3*cos( (2*pi*k)/L ))
}
forecast <- scale_with(1:m)

r0cap <- c(0, forecast)

xcap_tr <- r0cap + x0cap_GM

A <- 4
scale_with <- function(k)
{
  (x0[1] - (b/a)) * exp(-a*k) * (1 - exp(a))
}
fitted_a <- scale_with(1 : n+A-1)

x0cap_GMa <- c(fitted_a)

predicted_a <- tail(x0cap_GMa, A)

n_a <- length(x0_A)

r0_a <- numeric(n_a)
for (i in 1:n_a){
  r0_a[i] <- x0_A[i] - x0cap_GMa[i]
}
R_a <- r0_a[1:n_a]

rn_a <- matrix(c(R_a), ncol=1)

```

```
scale_with <- function(k)
{
  b0 + (b1*k) + (b2*sin( (2*pi*k)/L )) + (b3*cos( (2*pi*k)/L ))
}
forecast_a <- scale_with(1:m+A)

r0cap_a <- tail(forecast_a,A)

xcap_tra <- r0cap_a + predicted_a

x0cap5 <- c(xcap_tra)
x0cap2 <- c(xcap_tr,x0cap5 )
# Fitted and predicted values
x0cap2
```

Index

andgm11 (Optimization), 19
app_server, 3
BackgroundValues, 4
CI_igndgm (ConfidenceInterval), 8
CI_mdbgm (ConfidenceInterval), 8
CI_nhmgmp (ConfidenceInterval), 8
CI_rm (ConfidenceInterval), 8
CValue (ConfidenceInterval), 8
CombinedModels, 6
ConfidenceInterval, 8
dbgm12 (Multivariable), 16
dgm11 (ExtendedForms), 10
dgm21 (ExtendedForms), 10
egm11 (ExtendedForms), 10
egm11r (Optimization), 19
epgm11 (BackgroundValues), 4
exgm11 (ExtendedForms), 10
ExtendedForms, 10
ggvm11 (CombinedModels), 6
gm11 (BackgroundValues), 4
gm114 (BackgroundValues), 4
gm13 (Multivariable), 16
gmc12 (Multivariable), 16
gmcg12 (Multivariable), 16
gom11 (ExtendedForms), 10
gomia11 (ExtendedForms), 10
igm11 (BackgroundValues), 4
igm13 (Multivariable), 16
igndgm12 (IntervalMultivariable), 13
IntervalMultivariable, 13
mdbgm12 (IntervalMultivariable), 13
Multivariable, 16
ndgm11 (ExtendedForms), 10
ngbm11 (CombinedModels), 6
ngm11k (ParametersEstimation), 22
ngm11kc (ParametersEstimation), 22
nhmgm1 (Multivariable), 16
nhmgm2 (Multivariable), 16
odgm21 (ExtendedForms), 10
ongm11kc (ParametersEstimation), 22
optim_andgm (Optimization), 19
optim_egm11r (Optimization), 19
optim_psogm (Optimization), 19
Optimization, 19
ParametersEstimation, 22
plotrm (Plots), 24
Plots, 24
plots (Plots), 24
plots_mdbgm12 (Plots), 24
plotsigndgm (Plots), 24
plotsmv1 (Plots), 24
plotsmv2 (Plots), 24
psogm11 (Optimization), 19
remnantgm11 (ResidualModification), 27
ResidualModification, 27
run_app (app_server), 3
server (app_server), 3
sogm21 (ParametersEstimation), 22
tbgm11 (BackgroundValues), 4
tfdgm11 (CombinedModels), 6
tgm11 (ResidualModification), 27
ui (app_server), 3
ungom11 (ExtendedForms), 10
vssgm11 (ExtendedForms), 10