# Package 'phenoCDM'

October 14, 2022

Analysis  Analysis
Version 0.1.3
<b>Date</b> 2018-05-01
Author Bijan Seyednasrollah, Jennifer J. Swenson, Jean-Christophe Domec, James S. Clark
Maintainer Bijan Seyednasrollah  bijan.s.nasr@gmail.com>
Description Using the Bayesian state-space approach, we developed a continuous development model to quantify dynamic incremental changes in the response variable. While the model was originally developed for daily changes in forest greenup, the model can be used to predict any similar process. The CDM can capture both timing and rate of nonlinear processes. Unlike statics methods, which aggregate variations into a single metric, our dynamic model tracks the changing impacts over time. The CDM accommodates nonlinear responses to variation in predictors, which changes throughout development.
<b>Depends</b> R (>= 3.3.0)
Imports rjags
License MIT + file LICENSE
Encoding UTF-8
LazyData true
RoxygenNote 6.0.1.9000
<pre>BugReports https://github.com/bnasr/phenoCDM/issues</pre>
Suggests knitr, rmarkdown
VignetteBuilder knitr
NeedsCompilation no
Repository CRAN
<b>Date/Publication</b> 2018-05-02 03:45:15 UTC
R topics documented:
fitCDM

2 fitCDM

	phenoSim																																
	phenoSimPlot plotPOGibbs																																
	plotPost	 •		•		•	•	•		•	•	•	•	•	 •	•	•	•	•	•	•	•	•	•	•	•	٠	•	•	•	•	•	/
Index																																	9
fitC	DM		Fit	t a	CI	)M	I N	10	de	·l																							

#### **Description**

This function fits a CDM model on the input data as it is described by the phenoSim function.

## Usage

## Arguments

x	Matrix of predictors [N x p].
Z	Vector of response values [N x 1].
connect	The connectivity matrix for the z vector [n x 2]. Each row contains the last and next elements of the time-series. NA values indicate not connected.
nGibbs	Number of MCMC itterations
nBurnin	Number of burn-in itterations.
n.adapt	Number of itterations for adaptive sampling
n.chains	Number of MCMC chains
quiet	logical value indicating whether to report the progress
calcLatentGibb	S
	logical value indicating whether to calculate the latent states
trend	time-series expected trend as -1:decreasing, +1:increasing, 0: not constrained

getGibbsSummary 3

getGibbsSummary

Summarize Output of the CDM Model

#### **Description**

This function return a summary of the output from the Gibbs-Sampling of the CDM model.

#### Usage

```
getGibbsSummary(ssOut, burnin = NULL, colNames = NULL,
   sigmaPerSeason = TRUE)
```

#### **Arguments**

ssOut CDM output list.

burnin Number of burnin itterations.

colNames vector of charachters includes names of each variable in the output.

sigmaPerSeason logical value indicating whether each site/season has a separate process error

phenoSim

phenoSim

Simulate Green-up Phenology Data

#### **Description**

This function return a set of simulated data for multiple green-up phenology time-series.

#### Usage

```
phenoSim(nSites = 1000, nTSet = c(3:6), p = 2, beta = NULL, sig = 0.1, tau = 0.01, miss = 0, plotFlag = FALSE, ymax = 1, trend = +1)
```

## Arguments

nSites	Number of sites/seasons
nTSet	A vector of integer values. Length of each time-series will be randomly sampled from this vector.
р	Number of predictors in the model.
beta	Beta coefficients
sig	Process error.
tau	Observation error.
miss	Fraction of missing data.
plotFlag	logical value indicating whether to plot the resulted time-series.
ymax	Asymptotic maximum values.
trend	time-series expected trend as -1:decreasing, +1:increasing, 0: not constrained

phenoSimPlot 5

#### **Examples**

phenoSimPlot

Plot Simulated Phenology Data

## Description

This function plots the time-series data described with a connectivity matrix.

#### Usage

#### **Arguments**

Z	A vector of time-series data [n x 1]
connect	The connectivity matrix for the z vector [n x 2]. Each row contains the last and next elements of the time-series. NA values means not connected.
add	logical value indicating whether the plot should be overlaid on the current panel.
col	The color variable as charachter
ylim	Range of the y axis
pch	pch value for the symbols
lwd	lwd value for line tickness

6 plotPOGibbs

plotPOGibbs

Plot Observed vs Predicted

#### Description

This function plot posterior distributions of the parameters.

#### Usage

```
plotPOGibbs(o, p, nburnin = NULL, xlim = range(o, na.rm = TRUE),
  ylim = range(p, na.rm = TRUE), xlab = "Observed", ylab = "Predicted",
  colSet = c("#fb8072", "#80b1d3", "black"), cex = 1, lwd = 2, pch = 19)
```

## Arguments

0	Observed vector
p	Predicted Gibbs samples
nburnin	numbe of burn-in itterations
xlim	x-axis range
ylim	y-axis range
xlab	x-axis label
ylab	y-axis label
colSet	vector of colors for points, bars and the 1:1 line
cex	cex value for size
lwd	line width
pch	pch value for symbols

```
ssSim <- phenoSim(nSites = 2, #number of sites
    nTSet = 30, #number of Time steps
    beta = c(1, 2), #beta coefficients
    sig = .01, #process error
    tau = .1, #observation error
    plotFlag = TRUE, #whether plot the data or not
    miss = 0.05, #fraction of missing data
    ymax = c(6, 3) #maximum of saturation trajectory</pre>
```

plotPost 7

```
)
ssOut <- fitCDM(x = ssSim$x, #predictors</pre>
                nGibbs = 200,
                nBurnin = 100,
                z = ssSim$z, #response
                connect = ssSim$connect, #connectivity of time data
                quiet=TRUE)
summ <- getGibbsSummary(ssOut, burnin = 100, sigmaPerSeason = FALSE)</pre>
colMeans(summ$ymax)
colMeans(summ$betas)
colMeans(summ$tau)
colMeans(summ$sigma)
par(mfrow = c(1,3), oma = c(1,1,3,1), mar=c(2,2,0,1), font.axis=2)
plotPost(chains = ssOut$chains[,c("beta.1", "beta.2")], trueValues = ssSim$beta)
plotPost(chains = ss0ut$chains[,c("ymax.1", "ymax.2")], trueValues = ssSim$ymax)
plotPost(chains = ssOut$chains[,c("sigma", "tau")], trueValues = c(ssSim$sig, ssSim$tau))
mtext('Posterior\ distributions\ of\ the\ parameters',\ side = 3,\ outer = TRUE,\ line = 1,\ font = 2)
legend('topleft', legend = c('posterior', 'true value'),
     col = c('black', 'red'), lty = 1, bty = 'n', cex=1.5, lwd =2)
yGibbs <- ssOut$latentGibbs
zGibbs <- ssOut$zpred
o <- ssOut$data$z
p <- apply(ssOut$rawsamples$y, 1, mean)</pre>
R2 \leftarrow cor(na.omit(cbind(o, p)))[1,2]^2
#Plot Observed vs Predicted
par(mar=c(4,4,1,1), font.axis=2)
plotPOGibbs(o = o , p = zGibbs,
            xlim = c(0,10), ylim=c(0,10),
            cex = .7, nburnin = 1000)
            points(o, p, pch = 3)
mtext(paste0('R^2 = ', signif(R2, 3)), line = -1, cex = 2, font = 2, side = 1, adj = .9)
legend('topleft', legend = c('mean', '95th percentile', '1:1 line', 'latent states'),
      col = c('#fb8072', '#80b1d3', 'black', 'black'),
      bty = 'n', cex=1.5,
      lty = c(NA, 1, 2, NA), lwd = c(NA, 2, 2, 2), pch = c(16, NA, NA, 3))
```

plotPost

Plot Posterior Distributions

#### **Description**

This function plot posterior distributions of the parameters.

8 plotPost

#### Usage

```
plotPost(chains, trueValues = NULL, outline = FALSE)
```

#### **Arguments**

chains Gibbs sampling chains
trueValues numeric vector of true values
outline logical value whether showing outliers

```
ssSim <- phenoSim(nSites = 2, #number of sites</pre>
                  nTSet = 30, #number of Time steps
                  beta = c(1, 2), #beta coefficients
                  sig = .01, #process error
                  tau = .1, #observation error
                  plotFlag = TRUE, #whether plot the data or not
                  miss = 0.05, #fraction of missing data
                  ymax = c(6, 3) \#maximum of saturation trajectory
)
ssOut <- fitCDM(x = ssSim$x, #predictors</pre>
                nGibbs = 200,
                nBurnin = 100,
                z = ssSim$z, #response
                connect = ssSim$connect, #connectivity of time data
                quiet=TRUE)
summ <- getGibbsSummary(ssOut, burnin = 100, sigmaPerSeason = FALSE)</pre>
colMeans(summ$ymax)
colMeans(summ$betas)
colMeans(summ$tau)
colMeans(summ$sigma)
par(mfrow = c(1,3), oma = c(1,1,3,1), mar=c(2,2,0,1), font.axis=2)
plotPost(chains = ssOut$chains[,c("beta.1", "beta.2")], trueValues = ssSim$beta)
plotPost(chains = ssOut$chains[,c("ymax.1", "ymax.2")], trueValues = ssSim$ymax)
plotPost(chains = ssOut$chains[,c("sigma", "tau")], trueValues = c(ssSim$sig, ssSim$tau))
mtext('Posterior distributions of the parameters', side = 3, outer = TRUE, line = 1, font = 2)
legend('topleft', legend = c('posterior', 'true value'), col = c('black', 'red'),
         lty = 1, bty = 'n', cex=1.5, lwd = 2)
```

## **Index**

* CDM	<pre>getGibbsSummary, 3</pre>
fitCDM, 2	
* Data	phenoSim, 4
phenoSim, 4	phenoSimPlot, 5
<pre>phenoSimPlot, 5</pre>	plotPOGibbs, 6
* Distributions	plotPost, 7
plotPost, 7	
* Fit	
fitCDM, 2	
* Gibbs	
<pre>getGibbsSummary, 3</pre>	
* Model	
fitCDM, 2	
* Observed	
plotPOGibbs, 6	
* Output	
<pre>getGibbsSummary, 3</pre>	
* Phenology	
phenoSim, 4	
<pre>phenoSimPlot, 5</pre>	
* Plot	
<pre>phenoSimPlot, 5</pre>	
plotPOGibbs, 6	
plotPost, 7	
* Posterior	
plotPost, 7	
* Predicted	
plotPOGibbs, 6	
* Sammary	
<pre>getGibbsSummary, 3</pre>	
* Sampling	
<pre>getGibbsSummary, 3</pre>	
* Simulated	
<pre>phenoSimPlot, 5</pre>	
* Simulate	
phenoSim, 4	
* VS	
plotPOGibbs, 6	
fitCDM, 2	