Package ‘ArchaeoChron’

November 17, 2017

Type  Package
Title  Bayesian Modeling of Archaeological Chronologies
Version  0.1
Date  2017-11-16
Author  Anne Philippe [aut, cre],
        Marie-Anne Vibet [aut]
Maintainer  Anne Philippe <anne.philippe@univ-nantes.fr>
Description  Provides a list of functions for the Bayesian modeling of archaeological chronologies. The Bayesian models are implemented in 'JAGS' ('JAGS' stands for Just Another Gibbs Sampler. It is a program for the analysis of Bayesian hierarchical models using Markov Chain Monte Carlo (MCMC) simulation. See <http://mcmc-jags.sourceforge.net/> and ``JAGS Version 4.3.0 user manual'', Martin Plummer (2017) <https://sourceforge.net/projects/mcmc-jags/files/Manuals/>.). The inputs are measurements with their associated standard deviations and the study period. The output is the MCMC sample of the posterior distribution of the event date with or without radiocarbon calibration.
License  GPL-3
Depends  R (>= 2.10), coda, rjags, ArchaeoPhases
Imports  stats, utils, graphics, grDevices, Bchron
Suggests  knitr, rmarkdown
VignetteBuilder  knitr
RoxygenNote  5.0.1
NeedsCompilation  no
Repository  CRAN
Date/Publication  2017-11-17 12:15:57 UTC

R topics documented:

<table>
<thead>
<tr>
<th>Topic</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ArchaeoChron</td>
<td>2</td>
</tr>
<tr>
<td>chronoEvents_Gauss</td>
<td>3</td>
</tr>
<tr>
<td>chronoOutliers_Gauss</td>
<td>4</td>
</tr>
</tbody>
</table>
Description

This package provides a list of functions for the Bayesian modeling of archaeological chronologies. The Bayesian models are implemented in JAGS (JAGS stands for Just Another Gibbs Sampler). It is a program for the analysis of Bayesian hierarchical models using Markov Chain Monte Carlo (MCMC) simulation. See <http://mcmc-jags.sourceforge.net/> and "JAGS Version 4.3.0 user manual", Martin Plummer (2017) <https://sourceforge.net/projects/mcmc-jags/files/Manuals/>.). The inputs are measurements with their associated standard deviations and the study period. The output is the MCMC sample of the posterior distribution of the event date with or without radiocarbon calibration.

ArchaeoChron functions

- `combination_Gauss()`: A function for a simple combination of Gaussian dates
- `combinationWithRandomEffect_Gauss()`: A function for combining Gaussian dates introducing a random effect (see Congdom, 2010)
- `eventModel_Gauss()`: A function for combining Gaussian dates introducing an individual random effect (see Lanos and Philippe, 2017)
- `chrono_Gauss()`: A function for a simple chronology of Gaussian dates
- `chronoOutliers_Gauss()`: A function for the chronology of Gaussian dates associated with an outlier modeling (Bronk Ramsey, 2009)
- `chronoEvents_Gauss()`: A function for the chronology of events combining Gaussian dates (Lanos and Philippe, 2017)
- `eventModel_C14()`: A function for combining radiocarbon dates
Bayesian chronologies of Gaussian dates using the Event Model

Description

Bayesian modeling for combining Gaussian dates. These dates are assumed to be contemporaneous of the event date. The posterior distribution of the event date is sampled by MCMC algorithm as well as those of all parameters of the Bayesian model as described in Lanos & Philippe (2017).

Usage

```r
chronoEvents_Gauss(m, s, refYear=NULL, measurementsPerEvent, studyPeriodMin, studyPeriodMax, numberChains = 2, numberAdapt = 10000, numberUpdate = 10000, variable.names = c("theta"), numberSample = 50000, thin = 10)
```

Arguments

- `M`: vector of measurement
- `s`: vector of measurement errors
- `refYear`: vector of year of reference for ages for conversion into calendar dates
- `measurementsPerEvent`: vector containing the number of measurements associated with the first event, then the second ...
- `studyPeriodMin`: numerical value corresponding to the start of the study period in BC/AD format
- `studyPeriodMax`: numerical value corresponding to the end of the study period in BC/AD format
- `numberChains`: number of Markov chains simulated
- `numberAdapt`: number of iterations in the Adapt period of the MCMC algorithm
- `numberUpdate`: number of iterations in the Update period of the MCMC algorithm
- `variable.names`: names of the variables whose Markov chains are kept
- `numberSample`: number of iterations in the Acquire period of the MCMC algorithm
- `thin`: step between consecutive iterations finally kept

Value

This function returns a Markov chain of the posterior distribution. The MCMC chain is in date format BC/AD, that is the reference year is 0. Only values for the variables defined by `variable.names` are given.

Author(s)

Anne Philippe & Marie-Anne Vibet
**References**


**Examples**

```r
### simulated data

# Number of events
Nevt = 3

# number of dates by events
measurementsPerEvent = c(2,3,2)

# positions
pos = 1 + c(0, cumsum(measurementsPerEvent))

# simulation of data
theta.evt = seq(1,10, length.out= Nevt)

theta = NULL
for(i in 1:Nevt ){
  theta[1] = c(theta, rep(theta.evt[i],measurementsPerEvent[i]))
}

s = seq(1,1, length.out= sum(measurementsPerEvent))

M=NULL
for( i in 1:sum(measurementsPerEvent)){
  M[i] = c(M, rnorm(1, theta[i], s[i] ))
}

s02 = 1:Nevt
for (i in 1:Nevt) {
  s02[i]= 1/mean( 1/(s[pos[i]:(pos[i+1])])^2 )
}

MCMCSample = chronOOutliers_Gauss( M=M, s=s, measurementsPerEvent=measurementsPerEvent, studyPeriodMin=-10, studyPeriodMax=30)
plot(MCMCSample)
```

**Description**

Bayesian modeling for combining Gaussian dates. These dates are assumed to be contemporaneous of the event date. The posterior distribution is sampled by a MCMC algorithm as well as those of all parameters of the Bayesian model.
**chronoOutliers_Gauss**

### Usage

```r
chronoOutliers_Gauss(M, s, refYear=NULL, outliersIndivVariance, outliersBernouilliProba, studyPeriodMin, studyPeriodMax, numberChains = 2, numberAdapt = 10000, numberUpdate = 10000, variable.names = c("theta"), numberSample = 50000, thin = 10)
```

### Arguments

- `M`: vector of measurement
- `s`: vector of measurement errors
- `refYear`: vector of year of reference for ages for conversion into calendar dates
- `outliersIndivVariance`: vector of individual variance for delta[i]
- `outliersBernouilliProba`: vector of Bernouilli probability for each date. Reflects a prior assumption that the date is an outlier.
- `studyPeriodMin`: numerical value corresponding to the start of the study period in BC/AD format
- `studyPeriodMax`: numerical value corresponding to the end of the study period in BC/AD format
- `numberChains`: number of Markov chains simulated
- `numberAdapt`: number of iterations in the Adapt period of the MCMC algorithm
- `numberUpdate`: number of iterations in the Update period of the MCMC algorithm
- `variable.names`: names of the variables whose Markov chains are kept
- `numberSample`: number of iterations in the Acquire period of the MCMC algorithm
- `thin`: step between consecutive iterations finally kept

### Value

This function returns a Markov chain of the posterior distribution. The MCMC chain is in date format BC/AD, that is the reference year is 0. Only values for the variables defined by 'variable.names' are given.

### Author(s)

Anne Philippe & Marie-Anne Vibet

### References

Examples

```r
### simulated data (see examples(chronoEvent_Gauss))

# Number of event
Nevt = 3
# number of dates by events
measurementsPerEvent = c(2,3,2)
# positions
pos = 1 + c(0, cumsum(measurementsPerEvent))

# simulation of data
theta.evt = seq(1,10, length.out= Nevts)

theta = NULL
for(i in 1:Nevt ){
  theta = c(theta, rep(theta.evt[i],measurementsPerEvent[i]))
}

s = seq(1,1, length.out= sum(measurementsPerEvent))

M=NULL
for( i in 1:sum(measurementsPerEvent)){
  M= c(M, rnorm(1, theta[i], s[i]))
}

MCMCSample = chronoOutliers_Gauss(M, s, outliersIndivVariance = rep(5,7),
        outliersBernoulliProba=rep(0.2,7), studyPeriodMin=-10, studyPeriodMax=30,
        numberAdapt = 1000, numberUpdate = 1000, numberSample = 5000)
plot(MCMCSample)
```

---

**chrono_Gauss**

*Bayesian chronologies of Gaussian dates*

**Description**

Bayesian modeling for combining Gaussian dates. These dates are assumed to be contemporaneous of the event date. The posterior distribution is sampled by a MCMC algorithm as well as those of all parameters of the Bayesian model.

**Usage**

```r
chrono_Gauss(M, s, refYear=NULL, studyPeriodMin, studyPeriodMax,
        numberChains = 2, numberAdapt = 10000, numberUpdate = 10000,
        variable.names = c("theta"), numberSample = 50000, thin = 10)
```
Arguments

- \( M \): vector of measurement
- \( s \): vector of measurement errors
- \( \text{refYear} \): vector of year of reference for ages for conversion into calendar dates
- \( \text{studyPeriodMin} \): numerical value corresponding to the start of the study period in BC/AD format
- \( \text{studyPeriodMax} \): numerical value corresponding to the end of the study period in BC/AD format
- \( \text{numberChains} \): number of Markov chains simulated
- \( \text{numberAdapt} \): number of iterations in the Adapt period of the MCMC algorithm
- \( \text{numberUpdate} \): number of iterations in the Update period of the MCMC algorithm
- \( \text{variableNames} \): names of the variables whose Markov chains are kept
- \( \text{numberSample} \): number of iterations in the Acquire period of the MCMC algorithm
- \( \text{thin} \): step between consecutive iterations finally kept

Value

This function returns a Markov chain of the posterior distribution. The MCMC chain is in date format BC/AD, that is the reference year is 0. Only values for the variables defined by ‘variableNames’ are given.

Author(s)

Anne Philippe & Marie-Anne Vibet

Examples

```r
### simulated data (see examples(chronoEvent_Gauss))

# Number of events
Nevt = 3

# number of dates by events
measurementsPerEvent = c(2, 3, 2)

# positions
pos = 1 + c(0, cumsum(measurementsPerEvent))

# simulation of data
theta evt = seq(1, 10, length.out= Nevt)

theta = NULL
for(i in 1:Nevt ){
  theta = c(theta, rep(theta evt[i], measurementsPerEvent[i]))
}

s = seq(1, 1, length.out= sum(measurementsPerEvent))

M=NULL
for( i in 1:sum(measurementsPerEvent)){
  M= c(M, rnorm(1, theta[i], s[i]))
}
combinationWithoutliers_Gauss

Bayesian modeling for combining Gaussian dates and handling outliers

Description

Bayesian modeling for combining Gaussian dates with known variance and that may be outliers. These dates are assumed to be contemporaneous of the target date and have non identical distributions as the variance may be different for each date. The posterior distribution of the modeling is sampled by a MCMC algorithm implemented in JAGS.

Usage

combinationWithoutliers_Gauss(M, s, refYear=NULL, outliersIndivVariance, outliersBernouilliProba, studyPeriodMin, studyPeriodMax, numberChains = 2, numberAdapt = 10000, numberUpdate = 10000, variable.names = c("theta"), numberSample = 50000, thin = 10)

Arguments

M     vector of measurement
s     vector of measurement errors
refYear     vector of year of reference for ages
outliersIndivVariance     vector of individual variance for delta[i]
outliersBernouilliProba     vector of Bernouilli probability for each date. Reflects a prior assumption that the date is an outlier.
studyPeriodMin     numerical value corresponding to the start of the study period in BC/AD format
studyPeriodMax     numerical value corresponding to the end of the study period in BC/AD format
numberChains     number of Markov chains simulated
numberAdapt     number of iterations in the Adapt period of the MCMC algorithm
numberUpdate     number of iterations in the Update period of the MCMC algorithm
variable.names     names of the variables whose Markov chains are kept
numberSample     number of iterations in the Acquire period of the MCMC algorithm
thin     step between consecutive iterations finally kept

MCMCSample = chrono_Gauss(M, s, studyPeriodMin=-10, studyPeriodMax=30)
plot(MCMCSample)
Details

If there are Nbobs measurements $M$ associated with their error $s$, the model is the following one:

- for $j$ in $(1: Nbobs)$
  - $M_j \sim N(m_j, s_j^2)$
  - $m_j \leftarrow \theta + \delta_j \phi_j$
  - $\delta_j \sim N(0, \sigma_{\delta_j}^2)$
  - $\phi_j \sim \text{Bern}(p_j)$
- $\theta \sim U(t_a, t_b)$

Value

This function returns a Markov chain of the posterior distribution. The MCMC chain is in date format BC/AD, that is the reference year is 0. Only values for the variables defined by 'variable.names' are given.

Author(s)

Anne Philippe & Marie-Anne Vibet

References


Examples

data(sunspot)
MCMC1 = combinationWithOutliers_Gauss(M=sunspot$Age[1:10], s= sunspot$Error[1:10],
refYear=rep(2016,10), outliersIndivVariance = rep(1,10),
outliersBernoulliProba=rep(0.2, 10), studyPeriodMin=800, studyPeriodMax=1500,
variable.names = c('theta'))
plot(MCMC1)
gelman.diag(MCMC1)

# Influence of outliersIndivVariance
MCMC2 = combinationWithOutliers_Gauss(M=sunspot$Age[1:10], s= sunspot$Error[1:10],
refYear=rep(2016,10), outliersIndivVariance = rep(10,10),
outliersBernoulliProba=rep(0.2, 10), studyPeriodMin=800, studyPeriodMax=1500,
variable.names = c('theta'))
plot(MCMC2)
gelman.diag(MCMC2)
**combinationWithRandomEffect_Gauss**

*Bayesian modeling for combining Gaussian dates with a random effect*

**Description**

Bayesian modeling for combining Gaussian dates with known variance and with the addition of a random effect. These dates are assumed to be contemporaneous of the target date and have non identical distributions as the variance may be different for each date. In addition, a random effect is introduced in the modelling by a shrinkage distribution as defined by Congdom (2010). The posterior distribution of the modeling is sampled by a MCMC algorithm implemented in JAGS.

**Usage**

```r
combinationWithRandomEffect_Gauss(mL, sL, refYear=NULL, studyPeriodMin, studyPeriodMax, numberChains = 2, numberAdapt = 10000, numberUpdate = 10000, variable.names = c("theta"), numberSample = 50000, thin = 10)
```

**Arguments**

- `M` vector of measurement
- `s` vector of measurement errors
- `refYear` vector of year of reference for ages
- `studyPeriodMin` numerical value corresponding to the start of the study period in BC/AD format
- `studyPeriodMax` numerical value corresponding to the end of the study period in BC/AD format
- `numberChains` number of Markov chains simulated
- `numberAdapt` number of iterations in the Adapt period of the MCMC algorithm
- `numberUpdate` number of iterations in the Update period of the MCMC algorithm
- `variable.names` names of the variables whose Markov chains are kept
- `numberSample` number of iterations in the Acquire period of the MCMC algorithm
- `thin` step between consecutive iterations finally kept

**Details**

If there are Nobs measurements `M` associated with their error `s`, the model is the following one:

- for `j` in (1:Nobs)
  - `Mj ~ N(muj, sj^2)`
  - `muj ~ N(theta, sigmai^2)`
- `theta ~ U(ta, tb)`
- `sigma ~ UniformShrinkage`
Value
This function returns a Markov chain of the posterior distribution. The MCMC chain is in date format BC/AD, that is the reference year is 0. Only values for the variables defined by 'variable.names' are given.

Author(s)
Anne Philippe & Marie-Anne Vibet

References

Examples
data(sunspot)
MCMC = combinationWithRandomEffect_Gauss(M=sunspot$Age[1:10], s= sunspot$Error[1:10], refYear=rep(2016, 10), studyPeriodMin=0, studyPeriodMax=1500, variable.names = c('theta'))
plot(MCMC)
gelman.diag(MCMC)

Description
Simple Bayesian modeling for combining Gaussian dates with known variance. These dates are assumed to be contemporaneous of the target date and have non identical distributions as the variance may be different for each date. The posterior distribution of the modeling is sampled by a MCMC algorithm implemented in JAGS.

Usage
combination_Gauss(M, s, refYear=NULL, studyPeriodMin, studyPeriodMax, numberChains = 2, numberAdapt = 10000, numberUpdate = 10000, variable.names = c("theta"), numberSample = 50000, thin = 10)

Arguments
M vector of measurement
s vector of measurement errors
refYear vector of year of reference for ages
studyPeriodMin numerical value corresponding to the start of the study period in BC/AD format
studyPeriodMax numerical value corresponding to the end of the study period in BC/AD format
numberChains number of Markov chains simulated
numberAdapt  number of iterations in the Adapt period of the MCMC algorithm
numberUpdate number of iterations in the Update period of the MCMC algorithm
variable.names names of the variables whose Markov chains are kept
numberSample number of iterations in the Acquire period of the MCMC algorithm
thin step between consecutive iterations finally kept

Details

If there are Nbobs measurements M associated with their error s, the model is the following one:

- for j in (1:Nbobs), Mj ~ N(\theta, s_j^2)
- \theta ~ U(ta, tb)

Value

This function returns a Markov chain of the posterior distribution. The MCMC chain is in date format BC/AD, that is the reference year is 0. Only values for the variables defined by ‘variable.names’ are given.

Author(s)

Anne Philippe & Marie-Anne Vibet

Examples

data(sunspot)
MCMC = combination_gauss(M=sunspot$Age[1:10], s= sunspot$Error[1:10], refYear=rep(2016,10), studyPeriodMin=900, studyPeriodMax=1500, variable.names = c('theta'))
plot(MCMC)
gelman.diag(MCMC)

cuers

Dating the Last Firing of the Medieval or Modern Lime Kiln of Cuers
(Provence, France)

Description

Radiocarbon dates and errors associated with the last firing of the kiln. These dates are measured on two charcoal found in the kiln and assumed to have burnt during the last firing.

Usage

data("cuers")
Format

A data frame with 2 observations on the following 3 variables.

- **SampleName**: name of the charcoal
- **Age**: a numeric vector corresponding to the radiocarbon measurement made on each charcoal
- **Error**: a numeric vector corresponding to the error on the radiocarbon measurement made on each charcoal

Details

The last firing date of lime kiln of Cuers (Provence, France), Pas-Redon site (Vaschalde et al. (2014)), has been determined using walls baked clay (AM dating) and charcoals (14C dating). Here the dating is only based on the 2 radiocarbon datings (Poz-42876 and Ly-16086) only.

Source


Examples

data(cuers)

dataModel_C14

Bayesian modeling for combining radiocarbon dates using the Event Model

Description

Bayesian modeling for combining radiocarbon dates. These dates are assumed to be contemporaneous of the event date. The posterior distribution of the event date is sampled by MCMC algorithm as well as those of all parameters of the Bayesian model as described in Lanos & Philippe (2017).

Usage

eventModel_C14(M, s, calibCurve='intcal13', studyPeriodMin, studyPeriodMax, numberChains = 2, numberAdapt = 10000, numberUpdate = 10000, variable.names = c("theta"), numberSample = 50000, thin = 10)
Arguments

- **M**: vector of radiocarbon measurements in date format Before Present (Ages before 1950)
- **s**: vector of measurement errors
- **calibCurve**: the name of the calibration curve associated with the M radiocarbon measurements
- **studyPeriodMin**: numerical value corresponding to the start of the study period in BC/AD format
- **studyPeriodMax**: numerical value corresponding to the end of the study period in BC/AD format
- **numberChains**: number of Markov chains simulated
- **numberAdapt**: number of iterations in the Adapt period of the MCMC algorithm
- **numberUpdate**: number of iterations in the Update period of the MCMC algorithm
- **variable.names**: names of the variables whose Markov chains are kept
- **numberSample**: number of iterations in the Acquire period of the MCMC algorithm
- **thin**: step between consecutive iterations finally kept

Value

This function returns a Markov chain of the posterior distribution. The MCMC chain is in date format BC/AD, that is the reference year is 0. Only values for the variables defined by `variable.names` are given.

Author(s)

Anne Philippe & Marie-Anne Vibet

References


Examples

```r
data(cuers)
MCMC = eventModel_C14(M=cuers$Age, s=cuers$Error, calibCurve = 'intcal13',
studyPeriodMin = 1000, studyPeriodMax = 2000, variable.names = c('theta'), numberAdapt = 1000,
numberUpdate = 1000, numberSample = 3000)
plot(MCMC)
```
Bayesian modeling for combining Gaussian dates using the Event Model

Description

Bayesian modeling for combining Gaussian dates. These dates are assumed to be contemporaneous of the event date. The posterior distribution of the event date is sampled by MCMC algorithm as well as those of all parameters of the Bayesian model as described in Lanos & Philippe (2017).

Usage

```
eventModel_Gauss(M, s, refYear=NULL, studyPeriodMin, studyPeriodMax, numberChains = 2,
numberAdapt = 10000, numberUpdate = 10000, variable.names = c("theta"),
numberSample = 50000, thin = 10)
```

Arguments

- `M` vector of measurement
- `s` vector of measurement errors
- `refYear` vector of year of reference for ages
- `studyPeriodMin` numerical value corresponding to the start of the study period in BC/AD format
- `studyPeriodMax` numerical value corresponding to the end of the study period in BC/AD format
- `numberChains` number of Markov chains simulated
- `numberAdapt` number of iterations in the Adapt period of the MCMC algorithm
- `numberUpdate` number of iterations in the Update period of the MCMC algorithm
- `variable.names` names of the variables whose Markov chains are kept
- `numberSample` number of iterations in the Acquire period of the MCMC algorithm
- `thin` step between consecutive iterations finally kept

Details

If there are Nobs measurements M associated with their error s, the model is the following one:

- for j in (1:Nobs)
  - Mj ~ N(muj, sj^2)
  - muj ~ N(theta, sigmai^2)
  - sigmai ~ UniformShrinkage

Value

This function returns a Markov chain of the posterior distribution. The MCMC chain is in date format BC/AD, that is the reference year is 0. Only values for the variables defined by 'variable.names' are given.
**Author(s)**

Anne Philippe & Marie-Anne Vibet

**References**


**Examples**

```r
data(sunspot)
MCMC = eventModel_Gauss(M=sunspot$Age[1:10], s= sunspot$Error[1:10], refYear=rep(2016,10),
studyPeriodMin=900, studyPeriodMax=1500, variable.names = c('theta'))
plot(MCMC)
gelman.diag(MCMC)
```

**Description**

IntCal13 northern hemisphere atmospheric radiocarbon calibration curve published by Reimer et al.

**Usage**

```r
data("intcal13")
```

**Format**

A data frame with 5141 observations on the following 3 variables.

- `CALBP` a numeric vector of calibrated age in year before present (before 1950)
- `14Cage` a numeric vector of radiocarbon age in year before present (before 1950)
- `Error` a numeric vector of calibrated age in year before present (before 1950)

**References**


**Examples**

```r
data(intcal13)
```
marine13

Marine Radiocarbon Calibration Curve

Description

Marine radiocarbon calibration curve published by Reimer et al.

Usage

data("marine13")

Format

A data frame with 4801 observations on the following 3 variables.

CALBP a numeric vector of calibrated age in year before present (before 1950)
14Cage a numeric vector of radiocarbon age in year before present (before 1950)
Error a numeric vector of calibrated age in year before present (before 1950)

References


Examples

data(marine13)

shcal13

Southern Hemisphere Atmospheric Radiocarbon Calibration Curve

Description

Southern Hemisphere atmospheric radiocarbon calibration curve published by Reimer et al.

Usage

data("shcal13")
Format
A data frame with 5141 observations on the following 3 variables.

- CalBP  a numeric vector of calibrated age in year before present (before 1950)
- 14Cage  a numeric vector of radiocarbon age in year before present (before 1950)
- Error  a numeric vector of calibrated age in year before present (before 1950)

References

Examples
data(shcal13)

sunspot  Dated impacts on the sun corresponding to a unique archaeological event (Fictive data)

Description
Fictive data corresponding to dated impacts on the sun

Usage
data("sunspot")

Format
A data frame with 171 observations on the following 2 variables.

- Age  a numeric vector corresponding to the dated impact (ages in date before 2016)
- Error  a numeric vector corresponding to the error made on the measurement

Examples
data(sunspot)
Index

*Topic **Chronology** of dates
  chrono_Gauss, 6
*Topic **Chronology**
  chrono_Gauss, 6
  chronoEvents_Gauss, 3
  chronoOutliers_Gauss, 4
*Topic **Combination** of dates
  combination_Gauss, 11
  combinationWithOutliers_Gauss, 8
  combinationWithRandomEffect_Gauss, 10
  eventModel_C14, 13
  eventModel_Gauss, 15
*Topic **Event Model**
  chronoEvents_Gauss, 3
  eventModel_C14, 13
  eventModel_Gauss, 15
*Topic **Gaussian dates**
  chrono_Gauss, 6
  chronoEvents_Gauss, 3
  chronoOutliers_Gauss, 4
  combination_Gauss, 11
  combinationWithOutliers_Gauss, 8
  combinationWithRandomEffect_Gauss, 10
  eventModel_Gauss, 15
*Topic **Outliers**
  combinationWithOutliers_Gauss, 8
*Topic **Oxcal**
  chronoOutliers_Gauss, 4
*Topic **Radiocarbon dates**
  eventModel_C14, 13
*Topic **Random effect**
  combinationWithRandomEffect_Gauss, 10
  eventModel_C14, 13
  eventModel_Gauss, 15
*Topic **datasets**
  cuers, 12

ArchaeoChron, 2
ArchaeoChron-package (ArchaeoChron), 2
chrono_Gauss, 6
chronoEvents_Gauss, 3
chronoOutliers_Gauss, 4
combination_Gauss, 11
combinationWithOutliers_Gauss, 8
combinationWithRandomEffect_Gauss, 10
cuers, 12
eventModel_C14, 13
eventModel_Gauss, 15
intcal13, 16
marine13, 17
shcal13, 17
sunspot, 18