Package ‘ArchaeoChron’

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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.

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`ArchaeoChron` *Bayesian Modeling of Archaeological Chronologies*

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 manuel", 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
- combinationWithOutliers_Gauss() : A function for combining Gaussian dates using the outliers model described in Bronk Ramsey, 2009.
- 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

chronoEvents_Gauss — *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

```
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 coversion 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

P. Lanos and A. Philippe. Hierarchical Bayesian Modeling for Combining Dates in Archaeological Context. Journal de la SFdS, Vol. 158 (2) pp 72-88 2017.

Examples

```
### 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.evt[3] <-theta.evt[3] - 3 # stratigraphic inversion

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] ))
  }

sO2 = 1:Nevt
for (i in  1:Nevt) {
sO2[i]= 1/mean( 1/(s[pos[i]:(pos[i+1] -1)])^2 )
}

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

---

chronoOutliers_Gauss — *Bayesian chronologies of Gaussian dates using the outlier modelling of Oxcal software*

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

```
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 coversion 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

Bronk Ramsey C., Dealing with outliers and offsets in Radiocarbon dating, Radiocarbon, 2009, 51:1023-45.

Examples

```
### 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= Nevt)
theta.evt[3] <- theta.evt[3] - 3 # stratigraphic inversion

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),
outliersBernouilliProba=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

```
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
`refYear`	vector of year of reference for ages for coversion into calendar dates
`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

Examples

```
### 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] ))
```

```
  }

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

---

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

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(muj, sj^2)`
  - `muj <- theta + deltaj * phij`
  - `deltaj ~ N(0, sigma.deltaj^2)`
  - `phij ~ Bern(pj)`
- `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

References

Bronk Ramsey C., Dealing with outliers and offsets in Radiocarbon dating, Radiocarbon, 2009, 51:1023-45.

Examples

```
data(sunspot)
MCMC1 = combinationWithOutliers_Gauss(M=sunspot$Age[1:10], s= sunspot$Error[1:10],
refYear=rep(2016,10), outliersIndivVariance = rep(1,10),
outliersBernouilliProba=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),
outliersBernouilliProba=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

```
combinationWithRandomEffect_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(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

Congdom P. D., Bayesian Random Effect and Other Hierarchical Models: An Applied Perspective,Chapman and Hall/CRC, 2010

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)
```

---

combination_Gauss *Bayesian modeling for combining Gaussian dates*

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, sj^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 charcaol 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 charcaol

`Error` a numeric vector corresponding to the error on the radiocarbon measurement made on each charcaol

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

Vaschalde, C., Herve, G., Lanos, P., and Thiriot, J. (2014). La datation des structures de cuisson: integration de l'archeomagnetisme et du radiocarbone, apports de l'anthrazcologie. Archeologie Medievale, 44:1-16. P. Lanos and A. Philippe. Hierarchical Bayesian Modeling for Combining Dates in Archaeological Context. Journal de la SFdS, Vol. 158 (2) pp 72-88 2017.

Examples

```
data(cuers)
```

---

eventModel_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

P. Lanos and A. Philippe. Hierarchical Bayesian Modeling for Combining Dates in Archaeological Context. Journal de la SFdS, Vol. 158 (2) pp 72-88 2017.

Examples

```
 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)
```

eventModel_Gauss — *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 Nbobs measurements M associated with their error s, the model is the following one :

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

References

P. Lanos and A. Philippe. Hierarchical Bayesian Modeling for Combining Dates in Archaeological Context. Journal de la SFdS, Vol. 158 (2) pp 72-88 2017.

Examples

```
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)
```

---

intcal13 — *IntCal13 Northern Hemisphere Atmospheric Radiocarbon Calibration Curve*

Description

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

Usage

```
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

Reimer PJ, Bard E, Bayliss A, Beck JW, Blackwell PG, Bronk Ramsey C, Buck CE, Cheng H, Edwards RL, Friedrich M, Grootes PM, Guilderson TP, Haflidason H, Hajdas I, Hatte C, Heaton TJ, Hoffmann DL, Hogg AG, Hughen KA, Kaiser KF, Kromer B, Manning SW, Niu M, Reimer RW, Richards DA, Scott EM, Southon JR, Staff RA, Turney CSM, van der Plicht J. 2013. IntCal13 and Marine13 radiocarbon age calibration curves 0-50,000 years cal BP. Radiocarbon 55(4):1869-1887.

Examples

```
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

Reimer PJ, Bard E, Bayliss A, Beck JW, Blackwell PG, Bronk Ramsey C, Buck CE, Cheng H, Edwards RL, Friedrich M, Grootes PM, Guilderson TP, Haflidason H, Hajdas I, Hatte C, Heaton TJ, Hoffmann DL, Hogg AG, Hughen KA, Kaiser KF, Kromer B, Manning SW, Niu M, Reimer RW, Richards DA, Scott EM, Southon JR, Staff RA, Turney CSM, van der Plicht J. 2013. IntCal13 and Marine13 radiocarbon age calibration curves 0-50,000 years cal BP. Radiocarbon 55(4):1869-1887.

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

Reimer PJ, Bard E, Bayliss A, Beck JW, Blackwell PG, Bronk Ramsey C, Buck CE, Cheng H, Edwards RL, Friedrich M, Grootes PM, Guilderson TP, Haflidason H, Hajdas I, Hatte C, Heaton TJ, Hoffmann DL, Hogg AG, Hughen KA, Kaiser KF, Kromer B, Manning SW, Niu M, Reimer RW, Richards DA, Scott EM, Southon JR, Staff RA, Turney CSM, van der Plicht J. 2013. IntCal13 and Marine13 radiocarbon age calibration curves 0-50,000 years cal BP. Radiocarbon 55(4):1869-1887.

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)
```

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