

# Package ‘JM’

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**Title** Joint Modeling of Longitudinal and Survival Data

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**Author** Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**Maintainer** Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**Description** Shared parameter models for the joint modeling of longitudinal and time-to-event data.

**Depends** R (>= 2.11.0), MASS, nlme, splines, survival

**Enhances** xtable

**LazyLoad** yes

**LazyData** yes

**License** GPL (>= 2)

**URL** <http://rwiki.sciviews.org/doku.php?id=packages:cran:jm>

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aids	<i>Didanosine versus Zalcitabine in HIV Patients</i>
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## Description

A randomized clinical trial in which both longitudinal and survival data were collected to compare the efficacy and safety of two antiretroviral drugs in treating patients who had failed or were intolerant of zidovudine (AZT) therapy.

## Format

A data frame with 1408 observations on the following 9 variables.

patient patients identifier; in total there are 467 patients.

Time the time to death or censoring.

death a numeric vector with 0 denoting censoring and 1 death.

CD4 the CD4 cells count.

obstime the time points at which the CD4 cells count was recorded.

drug a factor with levels ddC denoting zalcitabine and ddI denoting didanosine.

gender a factor with levels female and male.

prevOI a factor with levels AIDS denoting previous opportunistic infection (AIDS diagnosis) at study entry, and noAIDS denoting no previous infection.

AZT a factor with levels intolerance and failure denoting AZT intolerance and AZT failure, respectively.

## Note

The data frame `aids.id` contains the first CD4 cell count measurement for each patient. This data frame is used to fit the survival model.

**Source**

<http://www.biostat.umn.edu/~brad/data.html>, <http://www.biostat.umn.edu/~brad/software.html>

**References**

Goldman, A., Carlin, B., Crane, L., Launer, C., Korvick, J., Deyton, L. and Abrams, D. (1996) Response of CD4+ and clinical consequences to treatment using ddI or ddC in patients with advanced HIV infection. *Journal of Acquired Immune Deficiency Syndromes and Human Retrovirology* **11**, 161–169.

Guo, X. and Carlin, B. (2004) Separate and joint modeling of longitudinal and event time data using standard computer packages. *The American Statistician* **58**, 16–24.

**Examples**

```
summary(aids.id)
```

---

 anova

---

*Anova Method for Fitted Joint Models*


---

**Description**

Produces marginal Wald tests or Performs a likelihood ratio test between two nested joint models.

**Usage**

```
## S3 method for class 'jointModel'
anova(object, object2, test = TRUE,
       process = c("both", "Longitudinal", "Event"), L = NULL, ...)
```

**Arguments**

object	an object inheriting from class <code>jointModel</code> , nested in <code>object2</code> .
object2	an object inheriting from class <code>jointModel</code> .
test	logical; if TRUE the likelihood ratio test is performed.
process	for which of the two submodels to produce the marginal Wald tests table.
L	a numeric matrix of appropriate dimensions defining the contrasts of interest.
...	additional arguments; currently none is used.

**Value**

An object of class `aov.jointModel` with components,

<code>nam0</code>	the name of object.
<code>L0</code>	the log-likelihood under the null hypothesis (object).
<code>aic0</code>	the AIC value for the model given by object.
<code>bic0</code>	the BIC value for the model given by object.
<code>nam1</code>	the name of object2.
<code>L1</code>	the log-likelihood under the alternative hypothesis (object2).
<code>aic1</code>	the AIC value for the model given by object2.
<code>bic1</code>	the BIC value for the model given by object2.
<code>df</code>	the degrees of freedom for the test (i.e., the difference in the number of parameters).
<code>LRT</code>	the value of the Likelihood Ratio Test statistic (returned if <code>test = TRUE</code> ).
<code>p.value</code>	the <i>p</i> -value of the test (returned if <code>test = TRUE</code> ).
<code>aovTab.Y</code>	a data.frame with the marginal Wald tests for the longitudinal process; produced only when object2 is missing.
<code>aovTab.T</code>	a data.frame with the marginal Wald tests for the event process; produced only when object2 is missing.
<code>aovTab.L</code>	a data.frame with the marginal Wald tests for the user-defined contrasts matrix; produced only when object2 is missing and L is not NULL.

**Warning**

The code minimally checks whether the models are nested! The user is responsible to supply nested models in order the LRT to be valid.

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**References**

Rizopoulos, D. (2010) JM: An R Package for the Joint Modelling of Longitudinal and Time-to-Event Data. *Journal of Statistical Software* **35** (9), 1–33. <http://www.jstatsoft.org/v35/i09/>

**See Also**

[jointModel](#)

## Examples

```
## Not run:
# linear mixed model fit without treatment effect
fitLME.null <- lme(sqrt(CD4) ~ obstime,
  random = ~ 1 | patient, data = aids)
# cox model fit without treatment effect
fitCOX.null <- coxph(Surv(Time, death) ~ 1,
  data = aids.id, x = TRUE)
# joint model fit without treatment effect
fitJOINT.null <- jointModel(fitLME.null, fitCOX.null,
  timeVar = "obstime", method = "weibull-PH-aGH")

# linear mixed model fit with treatment effect
fitLME.alt <- lme(sqrt(CD4) ~ obstime * drug - drug,
  random = ~ 1 | patient, data = aids)
# cox model fit with treatment effect
fitCOX.alt <- coxph(Surv(Time, death) ~ drug,
  data = aids.id, x = TRUE)
# joint model fit with treatment effect
fitJOINT.alt <- jointModel(fitLME.alt, fitCOX.alt, timeVar = "obstime",
  method = "weibull-PH-aGH")

# likelihood ratio test for treatment effect
anova(fitJOINT.null, fitJOINT.alt)

## End(Not run)
```

---

coef

*Estimated Coefficients for Joint Models*


---

## Description

Extracts estimated coefficients from fitted joint models.

## Usage

```
## S3 method for class 'jointModel'
coef(object, process = c("Longitudinal", "Event"),
  include.splineCoefs = FALSE, ...)
## S3 method for class 'jointModel'
fixef(object, process = c("Longitudinal", "Event"),
  include.splineCoefs = FALSE, ...)
```

## Arguments

object	an object inheriting from class jointModel.
process	for which model (i.e., linear mixed model or survival model) to extract the estimated coefficients.

```
include.splineCoefs
    logical; if TRUE and the method argument in jointModel() is "ch-Laplace",
    the estimated B-spline coefficients are included as well.
...
    additional arguments; currently none is used.
```

### Details

When `process = "Event"` both methods return the same output. However, for `process = "Longitudinal"`, the `coef()` method returns the subject-specific coefficients, whereas `fixef()` only the fixed effects.

### Value

A numeric vector or a matrix of the estimated parameters for the fitted model.

### Author(s)

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

### See Also

[ranef.jointModel](#)

### Examples

```
## Not run:
# linear mixed model fit
fitLME <- lme(sqrt(CD4) ~ obstime * drug - drug,
  random = ~ 1 | patient, data = aids)
# cox model fit
fitCOX <- coxph(Surv(Time, death) ~ drug, data = aids.id, x = TRUE)

# joint model fit
fitJOINT <- jointModel(fitLME, fitCOX,
  timeVar = "obstime")

# fixed effects for the longitudinal process
fixef(fitJOINT)

# fixed effects + random effects estimates for the longitudinal
# process
coef(fitJOINT)

# fixed effects for the event process
fixef(fitJOINT, process = "Event")
coef(fitJOINT, process = "Event")

## End(Not run)
```

---

`crLong`*Transform Competing Risks Data in Long Format*

---

**Description**

In a competing risks setting this function expands the data frame with a single row per subject to the a data frame in long format in which each subject has as many rows as the number of competing events.

**Usage**

```
crLong(data, statusVar, censLevel,  
       nameStrata = "strata", nameStatus = "status2")
```

**Arguments**

<code>data</code>	the data frame containing the competing risk data with a single row per subject.
<code>statusVar</code>	a character string denoting the name of the variable in data that identifies the status variable which equals 1 if the subject had any of the competing events and 0 otherwise.
<code>censLevel</code>	a character string or a scalar denoting the censoring level in the <code>statusVar</code> variable of data.
<code>nameStrata</code>	a character string denoting the variable that will be added in the long version of data denoting the various causes of event.
<code>nameStatus</code>	a character string denoting the variable that will be added in the long version of data denoting if the subject experience any of the competing events.

**Value**

A data frame in the long format with multiple rows per subject.

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**References**

Putter, H., Fiocco, M., and Geskus, R. (2007). Tutorial in biostatistics: Competing risks and multi-state models. *Statistics in Medicine* **26**, 2389–2430.

**Examples**

```
head(crLong(pbc2.id, "status", "alive"))
```

---

 dynC

*Dynamic Discrimination Index for Joint Models*


---

## Description

It computes the dynamic discrimination index presented in Rizopoulos (2010).

## Usage

```
dynC(object, ...)
```

```
## S3 method for class 'jointModel'
dynC(object, dt, data, idVar = "id", times = NULL,
      nt = 10, simulate = FALSE, estimator = c("median", "mean"),
      M = 10, validate = FALSE, B = 10, verbose = FALSE, ...)
```

## Arguments

object	an object inheriting from class <code>jointModel</code> .
dt	a numeric value indicating the length of the interval of primary interest within which we want to distinguish between subjects who died within the interval from subjects who survived longer than that.
data	a data frame that contains all variables use in the fit of the joint model. This should include both the variables for the longitudinal and survival parts.
idVar	a character string identifying the variable in data that distinguishes between subjects.
times	at which time points to compute the AUCs in order to obtain the dynamic C index.
nt	the number of time points to compute the AUCs, if the number of unique visit times in the sample is greater than nt.
simulate	the <code>simulate</code> argument of <code>survfitJM</code> .
estimator	the <code>estimator</code> argument of <code>survfitJM</code> .
M	the <code>M</code> argument of <code>survfitJM</code> .
validate	logical; if TRUE the Bootstrap validated index is produced – <b>this feature is not yet implemented.</b>
B	numeric value indicating how many Bootstrap samples to use – <b>this feature is not yet implemented.</b>
verbose	logical; if TRUE information is printed after each Bootstrap sample – <b>this feature is not yet implemented.</b>
...	extra arguments; currently none is used.

## Details

(**Note:** the following contain some math formulas, which are better viewed in the pdf version of the manual accessible at <http://cran.r-project.org/web/packages/JM/JM.pdf>.)

Function dynC computes the following discrimination index

$$C_{dyn}^{\Delta t} = \int \text{AUC}(t, \Delta t) \Pr\{\mathcal{E}(t, \Delta t)\} dt / \int \Pr\{\mathcal{E}(t, \Delta t)\} dt,$$

where

$$\text{AUC}(t, \Delta t) = \Pr[\pi_i(t + \Delta t | t) < \pi_j(t + \Delta t | t) | \{T_i^* \in (t, t + \Delta t]\} \cap \{T_j^* > t + \Delta t\}],$$

and

$$\mathcal{E}(t, \Delta t) = [\{T_i^* \in (t, t + \Delta t]\} \cap \{T_j^* > t + \Delta t\}],$$

with  $i$  and  $j$  denote to randomly selected subjects, and  $\pi_i(t + \Delta t | t)$  denotes the conditional survival probabilities calculated by `survfitJM`, calculated for different time windows  $\Delta t$  specified by argument `dt`.

Index  $C_{dyn}^{\Delta t}$  is in the spirit of Harrell's  $c$ -index, that is for the comparable subjects (i.e., the ones whose observed event times can be ordered), we compare their dynamic survival probabilities calculated by `survfitJM`.

As with Harrell's  $c$ -index,  $C_{dyn}^{\Delta t}$  does not take into account censoring, and therefore is expected to mask the true discriminative capability of the joint model under heavy censoring.

## Value

An object of class dynC is a list with components,

AUCt	A numeric matrix with the values of the Area Under the ROC Curve for the different time points.
dynC	the value of the dynamic C index.

## Author(s)

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

## References

- Antolini, L., Boracchi, P., and Biganzoli, E. (2005). A time-dependent discrimination index for survival data. *Statistics in Medicine* **24**, 3927–3944.
- Harrell, F., Kerry, L. and Mark, D. (1996). Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. *Statistics in Medicine* **15**, 361–387.
- Rizopoulos, D. (2011). Dynamic predictions and prospective accuracy in joint models for longitudinal and time-to-event data. *Biometrics* **67**, 819–829.

## See Also

[survfitJM](#), [rocJM](#), [jointModel](#)

## Examples

```
## Not run:
fitLME <- lme(sqrt(CD4) ~ obstime + obstime:(drug + AZT + prevOI + gender),
  random = ~ obstime | patient, data = aids)
fitSURV <- coxph(Surv(Time, death) ~ drug + AZT + prevOI + gender,
  data = aids.id, x = TRUE)
fit.aids <- jointModel(fitLME, fitSURV, timeVar = "obstime",
  method = "piecewise-PH-aGH")

# the following will take some time to execute...
C.JMaids1 <- dynC(fit.aids, dt = 2, data = aids, idVar = "patient")
C.JMaids1

C.JMaids2 <- dynC(fit.aids, dt = 6, data = aids, idVar = "patient")
C.JMaids2

C.JMaids3 <- dynC(fit.aids, dt = 8, data = aids, idVar = "patient")
C.JMaids3

## End(Not run)
```

---

fitted

*Fitted Values for Joint Models*

---

## Description

Calculates fitted values for joint models.

## Usage

```
## S3 method for class 'jointModel'
fitted(object, process = c("Longitudinal", "Event"),
  type = c("Marginal", "Subject", "EventTime", "Slope"), scale = c("survival",
  "cumulative-Hazard", "log-cumulative-Hazard"), M = 200, ...)
```

## Arguments

object	an object inheriting from class jointModel.
process	for which model (i.e., linear mixed model or survival model) to calculate the fitted values.
type	what type of fitted values to calculate for the survival outcome. See <b>Details</b> .
scale	in which scale to calculate; relevant only when process = "Event".
M	how many times to simulate random effects; see <b>Details</b> for more info.
...	additional arguments; currently none is used.

## Details

For process = "Longitudinal", let  $X$  denote the design matrix for the fixed effects  $\beta$ , and  $Z$  the design matrix for the random effects  $b$ . Then for type = "Marginal" the fitted values are  $X\hat{\beta}$ , whereas for type = "Subject" they are  $X\hat{\beta} + Z\hat{b}$ . For type = "EventTime" is the same as type = "Subject" but evaluated at the observed event times. Finally, type = "Slope" returns  $Xs\hat{\beta} + Zs\hat{b}$  where  $Xs$  and  $Zs$  denote the fixed- and random-effects design matrices corresponding to the slope term which is specified in the `derivForm` argument of `jointModel`.

For process = "Event" and type = "Subject" the linear predictor conditional on the random effects estimates is calculated for each sample unit. Depending on the value of the scale argument the fitted survival function, cumulative hazard function or log cumulative hazard function is returned. For type = "Marginal", random effects values for each sample unit are simulated  $M$  times from a normal distribution with zero mean and covariance matrix the estimated covariance matrix for the random effects. The marginal survival function for the  $i$ th sample unit is approximated by

$$S_i(t) = \int S_i(t|b_i)p(b_i)db_i \approx (1/M) \sum_{m=1}^M S_i(t|b_{im}),$$

where  $p(b_i)$  denotes the normal probability density function, and  $b_{im}$  the  $m$ th simulated value for the random effect of the  $i$ th sample unit. The cumulative hazard and log cumulative hazard functions are calculated as  $H_i(t) = -\log S_i(t)$  and  $\log H_i(t) = \log\{-\log S_i(t)\}$ , respectively.

## Value

a numeric vector of fitted values.

## Author(s)

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

## References

Rizopoulos, D. (2010) JM: An R Package for the Joint Modelling of Longitudinal and Time-to-Event Data. *Journal of Statistical Software* **35** (9), 1–33. <http://www.jstatsoft.org/v35/i09/>

## See Also

`residuals.jointModel`

## Examples

```
## Not run:
# linear mixed model fit
fitLME <- lme(log(serBilir) ~ drug * year,
  random = ~ 1 | id, data = pbc2)
# survival regression fit
fitSURV <- survreg(Surv(years, status2) ~ drug,
  data = pbc2.id, x = TRUE)
# joint model fit, under the (default) Weibull model
fitJOINT <- jointModel(fitLME, fitSURV, timeVar = "year")
```

```

# fitted for the longitudinal process
head(cbind(
  "Marg" = fitted(fitJOINT),
  "Subj" = fitted(fitJOINT, type = "Subject")
))

# fitted for the event process - survival function
head(cbind(
  "Marg" = fitted(fitJOINT, process = "Ev"),
  "Subj" = fitted(fitJOINT, process = "Ev", type = "Subject")
))

# fitted for the event process - cumulative hazard function
head(cbind(
  "Marg" = fitted(fitJOINT, process = "Ev",
    scale = "cumulative-Hazard"),
  "Subj" = fitted(fitJOINT, process = "Ev", type = "Subject",
    scale = "cumulative-Hazard")
))

## End(Not run)

```

---

JM

*Joint Modelling of Longitudinal and Time-to-Event Data in R*


---

## Description

This package fits shared parameter models for the joint modelling of normal longitudinal responses and event times under a maximum likelihood approach. Various options for the survival model and optimization/integration algorithms are provided.

## Details

```

Package: JM
Type: Package
Version: 0.9-2
Date: 2011-11-28
License: GPL

```

The package has a single model-fitting function called `jointModel`, which accepts as main arguments a linear mixed effects object fit returned by function `lme()` of package **nlme**, and a survival object fit returned by either function `coxph()` or function `survreg()` of package **survival**. In addition, the method argument of `jointModel()` specifies the type of the survival submodel to be fitted and the type of the numerical integration technique; available options are:

"Cox-PH-GH" the time-dependent version of a proportional hazards model with unspecified base-

line hazard function. The Gauss-Hermite integration rule is used to approximate the required integrals. (This option corresponds to the joint model proposed by Wulfsohn and Tsiatis, 1997)

"weibull-PH-GH" the Weibull model under the proportional hazards formulation. The Gauss-Hermite integration rule is used to approximate the required integrals.

"weibull-AFT-GH" the Weibull model under the accelerated failure time formulation. The Gauss-Hermite integration rule is used to approximate the required integrals.

"piecewise-PH-GH" a proportional hazards model with a piecewise constant baseline risk function. The Gauss-Hermite integration rule is used to approximate the required integrals.

"spline-PH-GH" a proportional hazards model, in which the log baseline hazard is approximated using B-splines. The Gauss-Hermite integration rule is used to approximate the required integrals.

"ch-Laplace" an additive log cumulative hazard model, in which the log cumulative baseline hazard is approximated using B-splines. A fully exponential Laplace approximation method is used to approximate the required integrals (Rizopoulos et al., 2009).

For all the above mentioned options (except the last one), a pseudo-adaptive Gauss-Hermite integration rule is also available (Rizopoulos, 2011b). This is much faster than the classical Gauss-Hermite rule, and in several simulations it has been shown to perform equally well (though its performance is still under investigation).

The package also offers several utility functions that can extract useful information from fitted joint models. The most important of those are included in the **See also** section below.

#### Author(s)

Dimitris Rizopoulos

Maintainer: Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

#### References

Henderson, R., Diggle, P. and Dobson, A. (2000) Joint modelling of longitudinal measurements and event time data. *Biostatistics* **1**, 465–480.

Rizopoulos, D. (2011a) Dynamic predictions and prospective accuracy in joint models for longitudinal and time-to-event data. *Biometrics* **67**, 819–829.

Rizopoulos, D. (2011b) Fast fitting of joint models for longitudinal and event time Data using a pseudo-adaptive Gaussian quadrature rule. *Computational Statistics and Data Analysis*, to appear.

Rizopoulos, D. (2010) JM: An R package for the joint modelling of longitudinal and time-to-event data. *Journal of Statistical Software* **35** (9), 1–33. <http://www.jstatsoft.org/v35/i09/>

Rizopoulos, D., Verbeke, G. and Lesaffre, E. (2009) Fully exponential Laplace approximation for the joint modelling of survival and longitudinal data. *Journal of the Royal Statistical Society, Series B* **71**, 637–654.

Rizopoulos, D., Verbeke, G. and Molenberghs, G. (2010) Multiple-imputation-based residuals and diagnostic plots for joint models of longitudinal and survival outcomes. *Biometrics* **66**, 20–29.

Tsiatis, A. and Davidian, M. (2004) Joint modeling of longitudinal and time-to-event data: an overview. *Statistica Sinica* **14**, 809–834.

Wulfsohn, M. and Tsiatis, A. (1997) A joint model for survival and longitudinal data measured with error. *Biometrics* **53**, 330–339.

### See Also

[jointModel](#), [survfitJM](#), [rocJM](#), [dynC](#), [predict](#)

---

jointModel

*Joint Models for Longitudinal and Survival Data*

---

### Description

This function fits shared parameter models for the joint modelling of normal longitudinal responses and time-to-event data under a maximum likelihood approach. Various options for the survival model are available.

### Usage

```
jointModel(lmeObject, survObject, timeVar,
  parameterization = c("value", "slope", "both"),
  method = c("weibull-PH-aGH", "weibull-PH-GH", "weibull-AFT-aGH",
    "weibull-AFT-GH", "piecewise-PH-aGH", "piecewise-PH-GH",
    "Cox-PH-aGH", "Cox-PH-GH", "spline-PH-aGH", "spline-PH-GH",
    "ch-Laplace"),
  interFact = NULL, derivForm = NULL, lag = 0, scaleWB = NULL,
  CompRisk = FALSE, init = NULL, control = list(), ...)
```

### Arguments

lmeObject	an object inheriting from class <code>lme</code> (see also <b>Note</b> ).
survObject	an object inheriting from class <code>coxph</code> or class <code>survreg</code> . In the call to <code>coxph()</code> or <code>survreg()</code> , you need to specify the argument <code>x = TRUE</code> such that the design matrix is contained in the object fit. See <b>Examples</b> .
timeVar	a character string indicating the time variable in the linear mixed effects model.
parameterization	a character string indicating the type of parameterization. See <b>Details</b>
method	a character string specifying the type of joint model to fit. See <b>Details</b> .
interFact	a list with components <code>value</code> a formula for the interaction terms corresponding to the value parameterization, <code>slope</code> a formula for the interaction terms corresponding to the slope parameterization, <code>data</code> a data frame containing these variables (this should have the same number of rows and ordering of subjects, as the one in <code>survObject</code> ).

derivForm	a list with components <code>fixed</code> a formula representing the derivative of the fixed-effects part of the liner mixed model with respect to time, <code>indFixed</code> a numeric vector indicating which fixed effects of <code>lmeObject</code> correspond to the derivative, <code>random</code> a formula representing the derivative of the random-effects part of the liner mixed model with respect to time, and <code>indRandom</code> a numeric vector indicating which random effects of <code>lmeObject</code> correspond to the derivative. When a random intercepts linear mixed model is assumed, then <code>random</code> = <code>~ 1</code> and <code>indRandom</code> = <code>FALSE</code> . Required only when <code>parameterization</code> == <code>"slope"</code> or <code>parameterization</code> == <code>"both"</code> . See <b>Examples</b> .
lag	a numeric scalar denoting a lag effect in the time-dependent covariate represented by the mixed model; default is 0.
scaleWB	a numeric scalar denoting a fixed value for the scale parameter of the Weibull hazard; used only when <code>method</code> = <code>"weibull-AFT-GH"</code> or <code>method</code> = <code>"weibull-PH-GH"</code> . The default <code>NULL</code> means that the scale parameter is estimated.
CompRisk	logical; should a competing risks joint model be fitted.
init	a list of user-specified initial values. The initial values list must have the following components: <b>betas</b> the vector of fixed effects for the linear mixed effects model. <b>sigma</b> the measurement error standard deviation for the linear mixed effects model. <b>D</b> the variance-covariance matrix of the random effects. <b>gammas</b> the vector of baseline covariates for the survival model. For <code>method</code> = <code>"ch-Laplace"</code> this vector should first contain initial values for the sorted B-spline coefficients used to model the log cumulative baseline hazard. <b>alpha</b> the association parameters. <b>Dalpha</b> the association parameters for the true slopes parameterization <b>xi</b> the vector of baseline risk function values within the intervals specified by the knots; specified only when <code>method</code> = <code>"piecewise-PH-GH"</code> . <b>gammas.bs</b> the vector of spline coefficients; specified only when <code>method</code> = <code>"spline-PH-GH"</code> . <b>sigma.t</b> the scale parameter for the Weibull baseline risk function; specified only when <code>method</code> = <code>"weibull-AFT-GH"</code> or <code>method</code> = <code>"weibull-PH-GH"</code> . <b>lambda0</b> a vector of the baseline hazard values at the sorted unique event times; specified only when <code>method</code> = <code>"Cox-PH-GH"</code> . If the user-specified list of initial values does not contain some of these components or contains components not of the appropriate length, then the default initial values are used instead.
control	a list of control values with components: <b>only.EM</b> logical; if <code>TRUE</code> only the EM algorithm is used in the optimization, otherwise if convergence has not been achieved a quasi-Newton algorithm is initiated. Default is <code>FALSE</code> except for <code>method</code> = <code>"Cox-PH-GH"</code> for which only the EM algorithm is available. <b>iter.EM</b> the number of EM iterations. Default is 50 except for <code>method</code> = <code>"Cox-PH-GH"</code> for which the default is 200.

- iter.qN** the number of quasi-Newton iterations. Default is 150.
- optimizer** a character string indicating which optimizer to use; options are "optim" (default) and "nlminb".
- tol1** tolerance value for convergence in the parameters; see **Details**. Default is 1e-03.
- tol2** tolerance value for convergence in the parameters; see **Details**. Default is 1e-04.
- tol3** tolerance value for convergence in the log-likelihood; see **Details**. Default is  $\sqrt{.Machine\$double.eps}$ .
- numeriDeriv** a character string indicating which type of numerical derivative to use to compute the Hessian matrix; options are "fd" (default) denoting the forward difference approximation, and "cd" denoting the central difference approximation.
- eps.Hes** tolerance value used in the numerical derivative method. Default is 1e-06; if you choose `numeriDeriv = "cd"` a larger value (e.g., 1e-04) is suggested.
- parscale** the `parscale` control argument for `optim()`, or the `scale` argument for `nlminb()`. It should be a numeric vector of length equal to the number of parameters. Default is 0.01 for all parameters.
- step.max** tolerance value for the maximum step size in the Newton-Raphson algorithm used to update the parameters of the survival submodel for `method = "ch-Laplace"`. Default is 0.1.
- backtrackSteps** the number of backtrack steps to use when updating the parameters of the survival submodel under `method = "ch-Laplace"`.
- knots** a numeric vector of the knots positions for the piecewise constant baseline risk function of for the log times used in the B-splines approximation of the log cumulative baseline hazard; therefore, this argument is relevant only when `method = "piecewise-PH-GH"`, `method = "spline-PH-GH"` or `method = "ch-Laplace"`. The default is to place equally-spaced  $\text{lng.in.kn}$  knots in the quantiles of the observed event times. For stratified models fitted with `method = "spline-PH-GH"` this should be a list with elements numeric vectors of knots positions for each strata.
- lng.in.kn** the number of internal knots; relevant only when when `method = "piecewise-PH-GH"` where it denotes the number of internal knots for the piecewise constant baseline risk function or when `method = "spline-PH-GH"` or `method = "ch-Laplace"` where it denotes the number of internal knots for B-splines approximation of the log baseline hazard. Default is 6 when `method = "piecewise-PH-GH"` and 5 otherwise.
- equal.strata.knots** logical; if TRUE (the default), then the same knots are used in the approximation of the baseline risk function in different strata when `method = "spline-PH-GH"`.
- ord** a positive integer denoting the order of the B-splines used to approximate the log cumulative hazard (default is 4); relevant only when `method = "spline-PH-GH"` or `method = "ch-Laplace"`.
- typeGH** a character string indicating the type of Gauss-Hermite rule to be used. Options are "simple" and "adaptive". The default is "simple" but it is turned

to adaptive when the user specifies in the method argument an option that contains aGH.

**GHk** the number of Gauss-Hermite quadrature points used to approximate the integrals over the random effects. The default is 15 for one- or two-dimensional integration and for  $N < 2000$ , and 9 otherwise for the simple Gauss-Hermite rule, and 5 for one-, two-dimensional or three-dimensional integration and for  $N < 2000$ , and 3 otherwise for the pseudo adaptive Gauss-Hermite rule, where  $N$  denotes the total number of longitudinal measurements.

**GKk** the number of Gauss-Kronrod points used to approximate the integral involved in the calculation of the survival function. Two options are available, namely 7 or 15. For method = "weibull-PH-GH", method = "weibull-AFT-GH" and method = "spline-PH-GH" 15 are used, whereas for method = "piecewise-PH-GH" 7.

**verbose** logical; if TRUE, the parameter estimates and the log-likelihood value are printed during the optimization procedure. Default is FALSE.

... options passed to the control argument.

## Details

Function `jointModel` fits joint models for longitudinal and survival data (more detailed information about the formulation of these models can be found in Rizopoulos (2010)). For the longitudinal responses the linear mixed effects model represented by the `lmeObject` is assumed. For the survival times let  $w_i$  denote the vector of baseline covariates in `survObject`, with associated parameter vector  $\gamma$ ,  $m_i(t)$  the value of the longitudinal outcome at time point  $t$  as approximated by the linear mixed model (i.e.,  $m_i(t)$  equals the fixed-effects part + random-effects part of the linear mixed effects model for sample unit  $i$ ),  $\alpha$  the association parameter for  $m_i(t)$ ,  $m'_i(t)$  the derivative of  $m_i(t)$  with respect to  $t$ , and  $\alpha_d$  the association parameter for  $m'_i(t)$ . Then, for method = "weibull-AFT-GH" a time-dependent Weibull model under the accelerated failure time formulation is assumed. For method = "weibull-PH-GH" a time-dependent relative risk model is postulated with a Weibull baseline risk function. For method = "piecewise-PH-GH" a time-dependent relative risk model is postulated with a piecewise constant baseline risk function. For method = "spline-PH-GH" a time-dependent relative risk model is assumed in which the log baseline risk function is approximated using B-splines. For method = "ch-Laplace" an additive model on the log cumulative hazard scale is assumed (see Rizopoulos et al., 2009 for more info). Finally, for method = "Cox-PH-GH" a time-dependent relative risk model is assumed where the baseline risk function is left unspecified (Wulfsohn and Tsiatis, 1997). For all these options the linear predictor for the survival submodel is written as

$$\eta = \gamma^\top w_i + \alpha m_i\{\max(t - k, 0)\},$$

when parameterization = "value",

$$\eta = \gamma^\top w_i + \alpha_s m'_i\{\max(t - k, 0)\},$$

when parameterization = "slope", and

$$\eta = \gamma^\top w_i + \alpha m_i\{\max(t - k, 0)\} + \alpha_s m'_i\{\max(t - k, 0)\},$$

when parameterization = "both", where in all the above the value of  $k$  is specified by the `lag` argument and  $m'_i(t) = dm_i(t)/dt$ . If `interFact` is specified, then  $m_i\{\max(t - k, 0)\}$  and/or

$m'_i\{\max(t - k, 0)\}$  are multiplied with the design matrices derived from the formulas supplied as the first two arguments of `interFact`, respectively. In this case  $\alpha$  and/or  $\alpha_s$  become vectors of association parameters.

For `method = "spline-PH-GH"` it is also allowed to include stratification factors. These should be included in the specification of the `survObject` using function `strata()`. Note that in this case `survObject` must only be a 'coxph' object.

For all survival models except for the time-dependent proportional hazards model, the optimization algorithm starts with EM iterations, and if convergence is not achieved, it switches to quasi-Newton iterations (i.e., BFGS in `optim()` or `nlmminb()`, depending on the value of the optimizer control argument). For `method = "Cox-PH-GH"` only the EM algorithm is used. During the EM iterations, convergence is declared if either of the following two conditions is satisfied: (i)  $L(\theta^{it}) - L(\theta^{it-1}) < tol_3\{|L(\theta^{it-1})| + tol_3\}$ , or (ii)  $\max\{|\theta^{it} - \theta^{it-1}| / (|\theta^{it-1}| + tol_1)\} < tol_2$ , where  $\theta^{it}$  and  $\theta^{it-1}$  is the vector of parameter values at the current and previous iterations, respectively, and  $L(\cdot)$  is the log-likelihood function. The values for  $tol_1$ ,  $tol_2$  and  $tol_3$  are specified via the `control` argument. During the quasi-Newton iterations, the default convergence criteria of either `optim()` or `nlmminb()` are used.

The required integrals are approximated using the standard Gauss-Hermite quadrature rule when the chosen option for the method argument contains the string "GH", and the (pseudo) adaptive Gauss-Hermite rule when the chosen option for the method argument contains the string "aGH". For `method = "ch-Laplace"` the fully exponential Laplace approximation described in Rizopoulos et al. (2009) is used. The (pseudo) adaptive Gauss-Hermite and the Laplace approximation are particularly useful when high-dimensional random effects vectors are considered (e.g., when modelling nonlinear subject-specific trajectories with splines or high-order polynomials).

## Value

See [jointModelObject](#) for the components of the fit.

## Note

1. The `lmeObject` argument should represent a linear mixed model object with a simple random-effects structure, i.e., only the `pdDiag()` class is currently allowed.
2. The `lmeObject` object should not contain any within-group correlation structure (i.e., `correlation` argument of `lme()`) or within-group heteroscedasticity structure (i.e., `weights` argument of `lme()`).
3. It is assumed that the linear mixed effects model `lmeObject` and the survival model `survObject` have been fitted to the same subjects. Moreover, it is assumed that the ordering of the subjects is the same for both `lmeObject` and `survObject`, i.e., that the first line in the data frame containing the event times corresponds to the first set of lines identified by the grouping variable in the data frame containing the repeated measurements, and so on.
4. In the `print` and `summary` generic functions for class `jointModel`, the estimated coefficients (and standard errors for the `summary` generic) for the event process are augmented with the element "Assoct" that corresponds to the association parameter  $\alpha$  and the element "Assoct.s" that corresponds to the parameter  $\alpha_s$  when parameterization is "slope" or "both" (see **Details**).
5. The standard errors returned by the `summary` generic function for class `jointModel` when `method = "Cox-PH-GH"` are based on the profile score vector (i.e., given the NPMLE for the unspecified baseline hazard). Hsieh et al. (2006) have noted that these standard errors are underestimated.

6. As it is the case for all types of mixed models that require numerical integration, it is advisable (especially in difficult datasets) to check the stability of the maximum likelihood estimates with an increasing number of Gauss-Hermite quadrature points.

7. For more examples and additional material check <http://rwiki.sciviews.org/doku.php?id=packages:cran:jm>.

### Author(s)

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

### References

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Tsiatis, A. and Davidian, M. (2004) Joint modeling of longitudinal and time-to-event data: an overview. *Statistica Sinica* **14**, 809–834.

Wulfsohn, M. and Tsiatis, A. (1997) A joint model for survival and longitudinal data measured with error. *Biometrics* **53**, 330–339.

### See Also

[jointModelObject](#), [anova.jointModel](#), [coef.jointModel](#), [fixef.jointModel](#), [ranef.jointModel](#), [fitted.jointModel](#), [residuals.jointModel](#), [plot.jointModel](#), [survfitJM](#), [rocJM](#), [dynC](#)

### Examples

```
# linear mixed model fit (random intercepts)
fitLME <- lme(log(serBilir) ~ drug * year, random = ~ 1 | id, data = pbc2)
# survival regression fit
fitSURV <- survreg(Surv(years, status2) ~ drug, data = pbc2.id, x = TRUE)
# joint model fit, under the (default) Weibull model
fitJOINT <- jointModel(fitLME, fitSURV, timeVar = "year")
fitJOINT
summary(fitJOINT)
```

```

## Not run:
# linear mixed model fit (random intercepts + random slopes)
fitLME <- lme(log(serBilir) ~ drug * year, random = ~ year | id, data = pbc2)
# survival regression fit
fitSURV <- survreg(Surv(years, status2) ~ drug, data = pbc2.id, x = TRUE)
# joint model fit, under the (default) Weibull model
fitJOINT <- jointModel(fitLME, fitSURV, timeVar = "year")
fitJOINT
summary(fitJOINT)

# we also include an interaction term of log(serBilir) with drug
fitJOINT <- jointModel(fitLME, fitSURV, timeVar = "year",
  interFact = list(value = ~ drug, data = pbc2.id))
fitJOINT
summary(fitJOINT)

# a joint model in which the risk for an event depends both on the true value of
# marker and the true value of the slope of the longitudinal trajectory
lmeFit <- lme(sqrt(CD4) ~ obstime * drug, random = ~ obstime | patient, data = aids)
coxFit <- coxph(Surv(Time, death) ~ drug, data = aids.id, x = TRUE)

# to fit this model we need to specify the 'derivForm' argument, which is a list
# with first component the derivative of the fixed-effects formula of 'lmeFit' with
# respect to 'obstime', second component the indicator of which fixed-effects
# coefficients correspond to the previous defined formula, third component the
# derivative of the random-effects formula of 'lmeFit' with respect to 'obstime',
# and fourth component the indicator of which random-effects correspond to the
# previous defined formula
dForm <- list(fixed = ~ 1 + drug, indFixed = c(2, 4), random = ~ 1, indRandom = 2)
jointModel(lmeFit, coxFit, timeVar = "obstime", method = "spline-PH-aGH",
  parameterization = "both", derivForm = dForm)

# Competing Risks joint model
# we first expand the PBC dataset in the competing risks long format
# with two competing risks being death and transplantation
pbc2.idCR <- crLong(pbc2.id, "status", "alive")

# we fit the linear mixed model as before
lmeFit.pbc <- lme(log(serBilir) ~ drug * ns(year, 3),
  random = list(id = pdDiag(form = ~ ns(year, 3))), data = pbc2)

# however, for the survival model we need to use the data in the long
# format, and include the competing risks indicator as a stratification
# factor. We also take interactions of the baseline covariates with the
# stratification factor in order to allow the effect of these covariates
# to be different for each competing risk
coxCRFit.pbc <- coxph(Surv(years, status2) ~ (drug + sex)*strata + strata(strata),
  data = pbc2.idCR, x = TRUE)

# the corresponding joint model is fitted simply by including the above

```

```

# two submodels as main arguments, setting argument CompRisk to TRUE,
# and choosing as method = "spline-PH-aGH". Similarly as above, we also
# include strata as an interaction factor to allow serum bilirubin to
# have a different effect for each of the two competing risks
jmCRFit.pbc <- jointModel(lmeFit.pbc, coxCRFit.pbc, timeVar = "year",
  method = "spline-PH-aGH",
  interFact = list(value = ~ strata, data = pbc2.idCR),
  CompRisk = TRUE)
summary(jmCRFit.pbc)

## End(Not run)

# linear mixed model fit
fitLME <- lme(sqrt(CD4) ~ obstime * drug - drug,
  random = ~ 1 | patient, data = aids)
# cox model fit
fitCOX <- coxph(Surv(Time, death) ~ drug, data = aids.id, x = TRUE)
# joint model fit with a spline-approximated baseline hazard function
fitJOINT <- jointModel(fitLME, fitCOX,
  timeVar = "obstime", method = "spline-PH-aGH")
fitJOINT
summary(fitJOINT)

```

---

jointModelObject

*Fitted jointModel Object*


---

## Description

An object returned by the `jointModel` function, inheriting from class `jointModel` and representing a fitted joint model for longitudinal and time-to-event data. Objects of this class have methods for the generic functions `anova`, `coef`, `fitted`, `fixed.effects`, `logLik`, `plot`, `print`, `random.effects`, `residuals`, `summary`, and `vcov`.

## Value

The following components must be included in a legitimate `jointModel` object.

**coefficients** a list with the estimated coefficients. The components of this list are:

- betas** the vector of fixed effects for the linear mixed effects model.
- sigma** the measurement error standard deviation for the linear mixed effects model.
- gammas** the vector of baseline covariates for the survival model.
- alpha** the association parameter(s).
- Dalpha** the association parameter(s) corresponding to the slope of the true trajectory.
- sigma.t** the scale parameter for the Weibull survival model; returned only when `method = "weibull-PH-GH"` or `method = "weibull-AFT-GH"`.

	<p><b>xi</b> the parameter of the piecewise constant baseline hazard; returned only when <code>method = "piecewise-PH-GH"</code>.</p> <p><b>gamma.bs</b> the coefficients of the B-splines use to approximate the baseline hazard; returned only when <code>method = "spline-PH-GH"</code>.</p> <p><b>lambda0</b> a two-column numeric matrix with the first column containing the estimated baseline hazard values, and the second the unique sorted event times; returned only when <code>method = "Cox-PH-GH"</code>.</p> <p><b>D</b> the variance-covariance matrix of the random effects.</p>
Hessian	the Hessian matrix evaluated at the estimated parameter values.
logLik	the log-likelihood value.
EB	<p>a list with components:</p> <p><b>post.b</b> the estimated random effects values.</p> <p><b>post.vb</b> the estimated variance for the random effects estimates.</p> <p><b>Zb</b> the estimated random effects part of the linear predictor for the longitudinal outcome (i.e., <math>Z</math> is the design matrix for the random effects <math>b</math>).</p> <p><b>Ztimeb</b> the estimated random effects part of the linear predictor for the survival outcome (i.e., evaluated at the observed event times).</p> <p><b>Ztime2b</b> the estimated random effects part of the linear predictor for the survival outcome (i.e., for the <math>i</math>th sample unit is evaluated at all event times that are less or equal to the <math>i</math>th observed event time); returned only when <code>method = "Cox-PH-GH"</code>.</p>
knots	the numeric vector of the knots positions; returned only when <code>method = "spline-PH-GH"</code> , <code>method = "piecewise-PH-GH"</code> or <code>method = "ch-Laplace"</code> .
iters	the number of iterations in the optimization algorithm.
convergence	convergence identifier: 0 corresponds to successful convergence, whereas 1 to a problem (i.e., when 1, usually more iterations are required).
n	the number of sample units.
N	the total number of repeated measurements for the longitudinal outcome.
ni	a vector with the number of repeated measurements for each sample unit.
d	a numeric vector with 0 denoting censored observation and 1 events.
id	the grouping vector for the longitudinal responses.
x	a list with the design matrices for the longitudinal and event processes.
y	a list with the response vectors for the longitudinal and event processes.
data.id	a <code>data.frame</code> containing the variables for the linear mixed effects model at the time of the event.
method	the value of the <code>method</code> argument.
termsY	the terms component of the <code>lmeObject</code> .
termsT	the terms component of the <code>survObject</code> .
formYx	the formula for the fixed effects part of the longitudinal model.
formYz	the formula for the random effects part of the longitudinal model.
formT	the formula for the survival model.

timeVar            the value of the timeVar argument  
 control            the value of the control argument.  
 parameterization            the value of the parameterization argument.  
 interFact            the value of the interFact argument  
 derivForm            the value of the derivForm argument.  
 lag                the value of the lag argument.  
 call                the matched call.

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**See Also**

[jointModel](#)

---

pbc2

*Mayo Clinic Primary Biliary Cirrhosis Data*

---

**Description**

Followup of 312 randomised patients with primary biliary cirrhosis, a rare autoimmune liver disease, at Mayo Clinic.

**Format**

A data frame with 1945 observations on the following 20 variables.

id patients identifier; in total there are 312 patients.

years number of years between registration and the earlier of death, transplantation, or study analysis time.

status a factor with levels alive, transplanted and dead.

drug a factor with levels placebo and D-penicil.

age at registration in years.

sex a factor with levels male and female.

year number of years between enrollment and this visit date, remaining values on the line of data refer to this visit.

ascites a factor with levels No and Yes.

hepatomegaly a factor with levels No and Yes.

spiders a factor with levels No and Yes.

edema a factor with levels No edema (i.e., no edema and no diuretic therapy for edema), edema no diuretics (i.e., edema present without diuretics, or edema resolved by diuretics), and edema despite diuretics (i.e., edema despite diuretic therapy).

serBilir serum bilirubin in mg/dl.

serChol serum cholesterol in mg/dl.

albumin albumin in gm/dl.

alkaline alkaline phosphatase in U/liter.

SGOT SGOT in U/ml.

platelets platelets per cubic ml / 1000.

prothrombin prothrombin time in seconds.

histologic histologic stage of disease.

status2 a numeric vector with the value 1 denoting if the patient was transplanted or dead, and 0 if the patient was alive.

### Note

The data frame `pb2.id` contains the first measurement for each patient. This data frame is used to fit the survival model.

### Source

<http://lib.stat.cmu.edu/datasets/pbcseq>

### References

Fleming, T. and Harrington, D. (1991) *Counting Processes and Survival Analysis*. Wiley, New York.

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### Examples

```
summary(pbc2.id)
```

---

plot

*Plot Diagnostics for Joint Models*

---

### Description

Produces a variety of plots for fitted joint models.

**Usage**

```
## S3 method for class 'jointModel'
plot(x, which = 1:4, caption = c("Residuals vs Fitted",
  "Normal Q-Q", "Marginal Survival", "Marginal Cumulative Hazard",
  "Marginal log Cumulative Hazard", "Baseline Hazard",
  "Cumulative Baseline Hazard", "Subject-specific Survival",
  "Subject-specific Cumulative Hazard",
  "Subject-specific log Cumulative Hazard"), survTimes = NULL,
  main = "",
  ask = prod(par("mfcol")) < length(which) && dev.interactive(),
  ..., ids = NULL, add.smooth = getOption("add.smooth"),
  add.qqline = TRUE, add.KM = FALSE, cex.caption = 1, return = FALSE)
```

**Arguments**

<code>x</code>	an object inheriting from class <code>jointModel</code> .
<code>which</code>	which types of plots to produce, specify a subset of the numbers 1:10.
<code>caption</code>	captions to appear above the plots defined by argument <code>which</code> .
<code>survTimes</code>	a vector of survival times for which the survival, cumulative hazard or log cumulative hazard will be computed. Default is <code>seq(minT, maxT, length = 15)</code> , where <code>minT</code> and <code>maxT</code> are the minimum and maximum observed survival times, respectively.
<code>main</code>	a character string specifying the title in the plot.
<code>ask</code>	logical; if TRUE, the user is asked before each plot, see <code>par(ask=.)</code> .
<code>...</code>	other parameters to be passed through to plotting functions.
<code>ids</code>	a numeric vector specifying which subjects, the subject-specific plots will include; default is all subjects.
<code>add.smooth</code>	logical; if TRUE a smooth line is superimposed in the "Residuals vs Fitted" plot.
<code>add.qqline</code>	logical; if TRUE a qq-line is superimposed in the "Normal Q-Q" plot.
<code>add.KM</code>	logical; if TRUE the Kaplan-Meier estimate of the survival function is superimposed in the "Marginal Survival" plot.
<code>cex.caption</code>	magnification of captions.
<code>return</code>	logical; if TRUE and <code>which</code> takes in values in <code>c(3:5, 8:10)</code> , then the values used to create the plot are returned.

**Note**

The plots of the baseline hazard and the cumulative baseline hazard are only produced when the joint model has been fitted using `method = "Cox-PH-GH"`.

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

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

```
## Not run:
# linear mixed model fit
fitLME <- lme(log(serBilir) ~ drug * year, random = ~ 1 | id, data = pbc2)
# survival regression fit
fitSURV <- survreg(Surv(years, status2) ~ drug, data = pbc2.id, x = TRUE)
# joint model fit, under the (default) Weibull model
fitJOINT <- jointModel(fitLME, fitSURV, timeVar = "year")

plot(fitJOINT, 3, add.KM = TRUE, col = "red", lwd = 2)

par(mfrow = c(2, 2))
plot(fitJOINT)

## End(Not run)
```

plot.rocJM

*Plot Method for rocJM Objects***Description**

Produces plots of ROC curves and the corresponding areas under the curve.

**Usage**

```
## S3 method for class 'rocJM'
plot(x, which = NULL, type = c("ROC", "AUC"),
     ndt = "all", main = NULL, caption = NULL, xlab = NULL,
     ylab = NULL, ask = NULL, legend = FALSE, lx = NULL, ly = NULL,
     lty = NULL, col = NULL, cex.caption = 0.8, cex.axis = NULL,
     cex.lab = NULL, cex.main = NULL, ...)
```

**Arguments**

x	an object inheriting from class rocJM.
which	a numeric vector specifying for which generic subjects to produce the plots. This refers to the different cases identified by the idVar argument in <a href="#">rocJM</a> .
type	a character string specifying which plot to produce the ROC curves or the areas under the ROC curves.
ndt	the character string "all" or a numeric scalar specifying for which time windows (dt argument of <a href="#">rocJM</a> ) to produce the plots.
main	a character string specifying the title in the plot.

caption	a character string specifying a caption in the plot.
xlab	a character string specifying the x-axis label in the plot.
ylab	a character string specifying the y-axis label in the plot.
ask	logical; if TRUE, the user is asked before each plot, see par().
legend	logical; if TRUE, a legend is included in the plot.
lx,ly	the x and y arguments of legend().
lty	what types of lines to use.
col	which colors to use.
cex.caption	font size for the caption.
cex.axis, cex.lab, cex.main	graphical parameters; see par for more info.
...	extra graphical parameters passed to plot().

### Author(s)

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

### References

Rizopoulos, D. (2011). Dynamic predictions and prospective accuracy in joint models for longitudinal and time-to-event data. *Biometrics* **67**, 819–829.

More examples can be found at <http://rwiki.sciviews.org/doku.php?id=packages:cran:jm>.

### See Also

[rocJM](#)

### Examples

```
## Not run:
fitLME <- lme(sqrt(CD4) ~ obstime + obstime:(drug + AZT + prevOI + gender),
  random = ~ obstime | patient, data = aids)
fitSURV <- coxph(Surv(Time, death) ~ drug + AZT + prevOI + gender,
  data = aids.id, x = TRUE)
fit.aids <- jointModel(fitLME, fitSURV, timeVar = "obstime",
  method = "piecewise-PH-aGH")

ND <- aids[aids$patient == "7", ]
roc <- rocJM(fit.aids, dt = c(2, 4, 8), ND, idVar = "patient")
plot(roc, lwd = 2, legend = TRUE)
plot(roc, type = "AUC")

## End(Not run)
```

---

plot.survfitJM                      *Plot Method for survfitJM Objects*

---

## Description

Produces plots of conditional probabilities of survival.

## Usage

```
## S3 method for class 'survfitJM'
plot(x, estimator = c("both", "mean", "median"),
     which = NULL, fun = NULL, conf.int = FALSE,
     add.last.time.axis.tick = FALSE, include.y = FALSE, main = NULL,
     xlab = NULL, ylab = NULL, ylab2 = NULL, lty = NULL, col = NULL,
     lwd = NULL, pch = NULL, ask = NULL, legend = FALSE, ...,
     cex.axis.z = 1, cex.lab.z = 1)
```

## Arguments

x	an object inheriting from class <code>survfitJM</code> .
estimator	character string specifying, whether to include in the plot the mean of the conditional probabilities of survival, the median or both. The mean and median are taken as estimates of these conditional probabilities over the M replications of the Monte Carlo scheme described in <a href="#">survfitJM</a> .
which	a numeric or character vector specifying for which subjects to produce the plot. If a character vector, then it should contain a subset of the values of the <code>idVar</code> variable of the <code>newdata</code> argument of <a href="#">survfitJM</a> .
fun	a vectorized function defining a transformation of the survival curve. For example with <code>fun=log</code> the log-survival curve is drawn.
conf.int	logical; if TRUE, then a pointwise confidence interval is included in the plot.
add.last.time.axis.tick	logical; if TRUE, a tick is added in the x-axis for the last available time point for which a longitudinal measurement was available.
include.y	logical; if TRUE, two plots are produced per subject, i.e., the plot of conditional probabilities of survival and a scatterplot of his longitudinal measurements.
main	a character string specifying the title in the plot.
xlab	a character string specifying the x-axis label in the plot.
ylab	a character string specifying the y-axis label in the plot.
ylab2	a character string specifying the y-axis label in the plot when <code>include.y = TRUE</code> .
lty	what types of lines to use.
col	which colors to use.
lwd	the thickness of the lines.

pch	the type of points to use.
ask	logical; if TRUE, the user is asked before each plot, see <code>par()</code> .
legend	logical; if TRUE, a legend is included in the plot.
cex.axis.z, cex.lab.z	the par cex argument for the axis at side 4, when <code>include.y = TRUE</code> .
...	extra graphical parameters passed to <code>plot()</code> .

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**References**

- Rizopoulos, D. (2010) JM: An R Package for the Joint Modelling of Longitudinal and Time-to-Event Data. *Journal of Statistical Software* **35** (9), 1–33. <http://www.jstatsoft.org/v35/i09/>
- Rizopoulos, D. (2011). Dynamic predictions and prospective accuracy in joint models for longitudinal and time-to-event data. *Biometrics* **67**, 819–829.

**See Also**

[survfitJM](#)

**Examples**

```
# linear mixed model fit
fitLME <- lme(sqrt(CD4) ~ obstime + obstime:drug,
  random = ~ 1 | patient, data = aids)
# cox model fit
fitCOX <- coxph(Surv(Time, death) ~ drug, data = aids.id, x = TRUE)

# joint model fit
fitJOINT <- jointModel(fitLME, fitCOX,
  timeVar = "obstime", method = "weibull-PH-aGH")

# sample of the patients who are still alive
ND <- aids[aids$patient == "141", ]
ss <- survfitJM(fitJOINT, newdata = ND, idVar = "patient", M = 50)
plot(ss)
plot(ss, include.y = TRUE, add.last.time.axis.tick = TRUE, legend = TRUE)
```

---

predict

*Predictions for Joint Models*

---

**Description**

Calculates predicted values for the longitudinal part of a joint model.

**Usage**

```
## S3 method for class 'jointModel'
predict(object, newdata, type = c("Marginal", "Subject"),
        interval = c("none", "confidence", "prediction"), level = 0.95, idVar = "id",
        FtTimes = NULL, M = 300, returnData = FALSE, scale = 1.6, ...)
```

**Arguments**

object	an object inheriting from class jointModel.
newdata	a data frame in which to look for variables with which to predict.
type	a character string indicating the type of predictions to compute, marginal or subject-specific. See <b>Details</b> .
interval	a character string indicating what type of intervals should be computed.
level	a numeric scalar denoting the tolerance/confidence level.
idVar	a character string indicating the name of the variable in newdata that corresponds to the subject identifier; required when type = "Subject".
FtTimes	a list with components numeric vectors denoting the time points for which we wish to compute subject-specific predictions after the last available measurement provided in newdata. For each subject in newdata the default is a sequence of 25 equally spaced time points from the last available measurement to the maximum follow-up time of all subjects (plus a small quantity). This argument is only used when type = "Subject".
M	numeric scalar denoting the number of Monte Carlo samples. See <b>Details</b> .
returnData	logical; if TRUE the data frame supplied in newdata is returned augmented with the outputs of the function.
scale	a numeric value setting the scaling of the covariance matrix of the empirical Bayes estimates in the Metropolis step during the Monte Carlo sampling.
...	additional arguments; currently none is used.

**Details**

When type = "Marginal", this function computes predicted values for the fixed-effects part of the longitudinal submodel. In particular, let  $X$  denote the fixed-effects design matrix calculated using newdata. The predict() calculates  $\hat{y} = X\hat{\beta}$ , and if interval = "confidence",  $\text{var}(\hat{y}) = XVX^t$ , with  $V$  denoting the covariance matrix of  $\hat{\beta}$ . The confidence interval is based on a normal approximation. Confidence intervals are constructed under the normal approximation.

When type = "Subject", this functions computes subject-specific predictions for the longitudinal outcome based on the joint model. This accomplished with a Monte Carlo simulation scheme, similar to the one described in [survfitJM](#). The only difference is in Step 3, where for interval = "confidence"  $y_i^* = X_i\beta^* + Z_ib_i^*$ , whereas for interval = "prediction"  $y_i^*$  is a random vector from a normal distribution with mean  $X_i\beta^* + Z_ib_i^*$  and standard deviation  $\sigma^*$ . Based on this Monte Carlo simulation scheme we take as estimate of  $\hat{y}_i$  the average of the  $M$  estimates  $y_i^*$  from each Monte Carlo sample. Confidence intervals are constructed using the percentiles of  $y_i^*$  from the Monte Carlo samples.

**Value**

If `se.fit = FALSE` a numeric vector of predicted values, otherwise a list with components `pred` the predicted values, `se.fit` the standard error for the fitted values, and `low` and `upp` the lower and upper limits of the confidence interval. If `returnData = TRUE`, it returns the data frame `newdata` with the previously mentioned components added.

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**See Also**

[jointModel](#)

**Examples**

```
## Not run:
# linear mixed model fit
fitLME <- lme(log(serBilir) ~ drug * year,
  random = ~ year | id, data = pbc2)
# survival regression fit
fitSURV <- survreg(Surv(years, status2) ~ drug,
  data = pbc2.id, x = TRUE)
# joint model fit, under the (default) Weibull model
fitJOINT <- jointModel(fitLME, fitSURV, timeVar = "year")

DF <- with(pbc2, expand.grid(drug = levels(drug),
  year = seq(min(year), max(year), len = 100)))
Ps <- predict(fitJOINT, DF, interval = "confidence", return = TRUE)
require(lattice)
xyplot(pred + low + upp ~ year | drug, data = Ps,
  type = "l", col = c(2,1,1), lty = c(1,2,2), lwd = 2,
  ylab = "Average log serum Bilirubin")

# Subject-specific predictions
ND <- pbc2[pbc2$id == 2, ]
Ps.ss <- predict(fitJOINT, ND, type = "Subject",
  interval = "confidence", return = TRUE)
require(lattice)
xyplot(pred + low + upp ~ year | id, data = Ps.ss,
  type = "l", col = c(2,1,1), lty = c(1,2,2), lwd = 2,
  ylab = "Average log serum Bilirubin")

## End(Not run)
```

---

 prothro

*Prednisone versus Placebo in Liver Cirrhosis Patients*


---

**Description**

A randomized trial on 488 liver cirrhosis patients

**Format**

Two data frames with the following variable.

id patients identifier; in total there are 467 patients.

pro prothrombin measurements.

time for data frame prothro the time points at which the prothrombin measurements were taken;  
for data frame prothros the time to death or censoring.

death a numeric vector with 0 denoting censoring and 1 death.

treat randomized treatment; a factor with levels "placebo" and "prednisone".

**Source**

<http://www.gllamm.org/books/readme.html#14.6>,

**References**

Andersen, P. K., Borgan, O., Gill, R. D. and Keiding, N. (1993). *Statistical Models Based on Counting Processes*. New York: Springer.

**Examples**

```
summary(prothros)
```

---

 ranef

*Random Effects Estimates for Joint Models*


---

**Description**

Extracts the random effects estimates from a fitted joint model.

**Usage**

```
## S3 method for class 'jointModel'
ranef(object, type = c("mean", "mode"), postVar = FALSE, ...)
```

**Arguments**

object	an object inheriting from class <code>jointModel</code> .
type	what type of empirical Bayes estimates to compute, the mean of the posterior distribution or the mode of the posterior distribution.
postVar	logical; if TRUE the variance of the posterior distribution is also returned. When <code>type == "mode"</code> , then this equals $\{-\partial^2 \log p(b_i T_i, \delta_i, y_i) / \partial b_i^\top \partial b_i\}^{-1}$ .
...	additional arguments; currently none is used.

**Value**

a numeric matrix with rows denoting the individuals and columns the random effects (e.g., intercepts, slopes, etc.). If `postVar = TRUE`, the numeric matrix has an extra attribute "postVar".

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**See Also**

[coef.jointModel](#), [fixef.jointModel](#)

**Examples**

```
## Not run:
# linear mixed model fit
fitLME <- lme(log(serBilir) ~ drug * year, random = ~ 1 | id, data = pbc2)
# survival regression fit
fitSURV <- survreg(Surv(years, status2) ~ drug, data = pbc2.id, x = TRUE)

# joint model fit, under the (default) Weibull model
fitJOINT <- jointModel(fitLME, fitSURV, timeVar = "year")
ranef(fitJOINT)

## End(Not run)
```

---

residuals

*Residuals for Joint Models*


---

**Description**

Calculates residuals for joint models.

**Usage**

```
## S3 method for class 'jointModel'
residuals(object, process = c("Longitudinal", "Event"),
  type = c("Marginal", "Subject", "stand-Marginal",
    "stand-Subject", "Martingale", "CoxSnell", "AFT"),
  MI = FALSE, M = 50, time.points = NULL, return.data = FALSE,
  ...)
```

**Arguments**

object	an object inheriting from class <code>jointModel</code> .
process	for which model (i.e., linear mixed model or survival model) to calculate residuals.
type	what type of residuals to calculate. See <b>Details</b> .
MI	logical; if TRUE multiple-imputation-based residuals are calculated.
M	integer denoting how many imputations to use for the MI residuals.
time.points	for fixed visit times, this should be a numeric vector with the unique times points at which longitudinal measurements are supposed to be taken; if NULL, then the code attempts to extract these unique time points using the design matrix for the fixed effects of the longitudinal model and the value of the <code>timeVar</code> argument of <code>jointModel</code> . For random visit times, this should be an object of class <code>weibull.frailty</code> that represents the fit of Weibull model with Gamma frailties for the visiting process. The user may also augment the object <code>weibull.frailty</code> with the following two attributes: <code>"prev.y"</code> denoting the variable name for the previous longitudinal responses, and <code>"tmax"</code> denoting the end of the study.
return.data	logical; if TRUE and MI = TRUE and fixed visit times are considered, then the multiply imputed data sets are returned.
...	additional arguments; currently none is used.

**Details**

When `process = "Longitudinal"`, residuals are calculated for the longitudinal outcomes. In particular, if `type = "Marginal"` these are  $e_{ij} = y_{ij} - x_{ij}^T \hat{\beta}$ , whereas for `type = "Subject"`,  $e_{ij} = y_{ij} - x_{ij}^T \hat{\beta} - z_{ij}^T b_i$ , where  $i$  denotes the subject and  $j$  the measurement,  $y_{ij}$  the longitudinal responses,  $x_{ij}^T$  and  $z_{ij}^T$  the corresponding rows of the fixed and random effects design matrices, respectively, and  $\beta$  and  $b_i$  denote the fixed effects and random effects components. If `type = "stand-Marginal"` or `type = "stand-Subject"`, the above defined residuals are divided by the estimated standard deviation of the corresponding error term. If `MI = TRUE`, multiple-imputation-based residuals are calculated for the longitudinal process; for more information regarding these residuals, check Rizopoulos et al. (2009).

When `process = "Event"`, residuals are calculated for the survival outcome. Martingale residuals are available for all options for the survival submodel (for the different options of survival submodel, check the method argument of `jointModel`). Cox-Snell residuals (Cox and Snell, 1968) are available for the Weibull model and the additive log cumulative hazard model. AFT residuals are only available for the Weibull model.

**Value**

If `MI = FALSE`, a numeric vector of residual values. Otherwise a list with components:

<code>fitted.values</code>	the fitted values for the observed data.
<code>residuals</code>	the residuals for the observed data.
<code>fitted.valsM</code>	the fitted values for the missing data.
<code>resid.valsM</code>	the multiply imputed residuals for the missing longitudinal responses.
<code>mean.resid.valsM</code>	the average of the multiply imputed residuals for the missing longitudinal responses; returned only if fixed visit times are considered.
<code>dataM</code>	if <code>return.data = TRUE</code> and fixed visit times are considered, then it returns the data set with the simulated response values for the longitudinal outcome, for each of the multiple imputations.

**Note**

The multiple-imputation-based residuals are not available for joint models with `method = "Cox-PH-GH"`.

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**References**

Cox, D. and Snell, E. (1968) A general definition of residuals. *Journal of the Royal Statistical Society, Series B* **30**, 248–275.

Rizopoulos, D., Verbeke, G. and Molenberghs, G. (2010) Multiple-imputation-based residuals and diagnostic plots for joint models of longitudinal and survival outcomes. *Biometrics* **66**, 20–29.

Rizopoulos, D. (2010) JM: An R Package for the Joint Modelling of Longitudinal and Time-to-Event Data. *Journal of Statistical Software* **35** (9), 1–33. <http://www.jstatsoft.org/v35/i09/>

**See Also**

[fitted.jointModel](#)

**Examples**

```
## Not run:
# linear mixed model fit
fitLME <- lme(sqrt(CD4) ~ obstime * drug - drug,
  random = ~ 1 | patient, data = aids)
# cox model fit
fitCOX <- coxph(Surv(Time, death) ~ drug, data = aids.id, x = TRUE)

# joint model fit, under the additive log cumulative hazard model
fitJOINT <- jointModel(fitLME, fitCOX,
  timeVar = "obstime")
```

```

# residuals for the longitudinal outcome
head(cbind(
  "Marginal" = residuals(fitJOINT),
  "std-Marginal" = residuals(fitJOINT, type = "stand-Marginal"),
  "Subject" = residuals(fitJOINT, type = "Subject"),
  "std-Subject" = residuals(fitJOINT, type = "stand-Subject")
))

# residuals for the survival outcome
head(cbind(
  "Martingale" = residuals(fitJOINT, process = "Event", type = "Martingale"),
  "CoxSnell" = residuals(fitJOINT, process = "Event", type = "CoxSnell")
))

## End(Not run)

```

---

rocJM	<i>Predictive Accuracy Measures for Longitudinal Markers under a Joint Modelling Framework</i>
-------	--

---

## Description

It computes sensitivity, specificity, ROC and AUC measures for joint models.

## Usage

```

rocJM(object, dt, data, idVar = "id", directionSmaller = NULL, cc = NULL, min.cc = NULL,
  max.cc = NULL, optThr = c("sens*spec", "youden"),
  diffType = c("absolute", "relative"), abs.diff = 0, rel.diff = 1,
  M = 300, burn.in = 100, scale = 1.6)

```

## Arguments

object	an object inheriting from class <code>jointModel</code> .
dt	a numeric vector indicating the lengths of the time intervals of primary interest within which we want to distinguish between subjects who died within the intervals from subjects who survived longer than that.
data	a data frame that contains the baseline covariates for the longitudinal and survival submodels, including a case identifier (i.e., the variable denoted by the argument <code>idVar</code> ), the time points on which longitudinal measurements are assumed to be taken (this should have the same name as in the argument <code>timeVar</code> of <code>jointModel</code> ).
idVar	the name of the variable in <code>data</code> that identifies the different generic subjects to be considered.
directionSmaller	logical; if TRUE, then smaller values for the longitudinal outcome are associated with higher risk for an event.

cc	a numeric vector of threshold values for the longitudinal marker; if NULL, this is computed using a regular sequence based on percentiles of the observed marker values.
min.cc	the start of the regular sequence for the threshold values for the longitudinal marker; see argument cc above.
max.cc	the end of the regular sequence for the threshold values for the longitudinal marker; see argument cc above.
optThr	character string defining how the optimal threshold is to be computed. The default chooses the cut-point for the marker that maximizes the product of sensitivity and specificity. Option "youden" chooses the cut-point that maximizes Youden's index that equals sensitivity + specificity - 1.
diffType	character string defining the type of prediction rule. See <b>Details</b> .
abs.diff	a numeric vector of absolute differences in the definition of composite prediction rules.
rel.diff	a numeric vector of relative differences in the definition of composite prediction rules.
M	a numeric scalar denoting the number of Monte Carlo samples.
burn.in	a numeric scalar denoting the iterations to discard.
scale	a numeric scalar that controls the acceptance rate of the Metropolis-Hastings algorithm. See <b>Details</b> .

## Details

(**Note:** the following contain some math formulas, which are better viewed in the pdf version of the manual accessible at <http://cran.r-project.org/package=JM>.)

Assume that we have collected longitudinal measurements  $Y_i(t) = \{y_i(s); 0 \leq s \leq t\}$  up to time point  $t$  for subject  $i$ . We are interested in events occurring in the medically relevant time frame  $(t, t + \Delta t]$  within which the physician can take an action to improve the survival chance of the patient. Using an appropriate function of the marker history  $Y_i(t)$ , we can define a prediction rule to discriminate between patients of high and low risk for an event. For instance, for in HIV infected patients, we could consider values of CD4 cell count smaller than a specific threshold as predictive for death. Since we are in a longitudinal context, we have the flexibility of determining which values of the longitudinal history of the patient will contribute to the specification of the prediction rule. That is, we could define a composite prediction rule that is not based only on the last available measurement but rather on the last two or last three measurements of a patient. Furthermore, it could be of relevance to consider different threshold values for each of these measurements, for instance, we could define as success the event that the pre-last CD4 cell count is  $c$  and the last one  $0.5c$ , indicating that a 50% decrease is strongly indicative for death. Under this setting we define sensitivity and specificity as,

$$Pr\{\mathcal{S}_i(t, k, c) \mid T_i^* > t, T_i^* \in (t, t + \Delta t]\},$$

and

$$Pr\{\mathcal{F}_i(t, k, c) \mid T_i^* > t, T_i^* > t + \Delta t\},$$

respectively, where we term  $\mathcal{S}_i(t, k, c) = \{y_i(s) \leq c_s; k \leq s \leq t\}$  as success (i.e., occurrence of the event of interest), and  $\mathcal{F}_i(t, k, c) = \{y_i(s) > c_s; k \leq s \leq t\}$  as a failure,  $T_i^*$  denotes the

time-to-event, and  $\Delta t$  the length of the medically relevant time window (specified by argument `dt`). The cut values for the marker  $c$  are specified by the `cc`, `min.cc` and `max.cc` arguments. Two types of composite prediction rules can be defined depending on the value of the `diffType` argument. Absolute prediction rules in which, between successive measurements there is an absolute difference of between the cut values, and relative prediction rules in which there is a relative difference between successive measurements of the marker. The lag values for these differences are defined by the `abs.diff` and `rel.diff` arguments. Some illustrative examples:

**Ex1:** keeping the defaults we define a simple rule that is only based on the last available marker measurement.

**Ex2:** to define a prediction rule that is based on the last two available measurements using the same cut values (e.g., if a patient had two successive measurements below a medically relevant threshold), we need to set `abs.diff = c(0, 0)`.

**Ex3:** to define a prediction rule that is based on the last two available measurements using a drop of 5 units between the cut values (e.g., the pre-last measurement is  $c$  and the last  $c - 5$ ), we need to set `abs.diff = c(0, -5)`.

**Ex4:** to define a prediction rule that is based on the last two available measurements using a drop of 20% units between the cut values (e.g., the pre-last measurement is  $c$  and the last  $0.8c$ ), we need to set `diffType = "relative"` and `rel.diff = c(0, 0.8)`.

The estimation of the above defined probabilities is achieved with a Monte Carlo scheme similar to the one described in [survfitJM](#). The number of Monte Carlo samples is defined by the `M` argument, and the burn-in iterations for the Metropolis-Hastings algorithm using the `burn.in` argument.

More details can be found in Rizopoulos (2011).

## Value

An object of class `rocJM` is a list with components,

<code>MCresults</code>	a list of length the number of distinct cases in data. Each component of this list is again a list with four components the estimated Sensitivity <code>Sens</code> and its standard error <code>seSens</code> , and the estimated Specificity <code>Spec</code> and its standard error <code>seSpec</code> . All these four components are matrices with rows corresponding to the different <code>dt</code> values and columns corresponding to the different <code>cc</code> values.
<code>AUCs</code>	a numeric vector of estimated areas under the ROC curves for the different values of <code>dt</code> .
<code>optThr</code>	a numeric vector with the optimal threshold values for the markers for the different <code>dt</code> under the choice made in argument <code>optThr</code> .
<code>times</code>	a list of length the number of distinct cases in data with components numeric vectors of the time points at which longitudinal measurements are supposed to be taken.
<code>dt</code>	a copy of the <code>dt</code> argument.
<code>M</code>	a copy of the <code>M</code> argument.
<code>diffType</code>	a copy of the <code>diffType</code> argument.
<code>abs.diff</code>	a copy of the <code>abs.diff</code> argument.
<code>rel.diff</code>	a copy of the <code>rel.diff</code> argument.

cc	a copy of the cc argument.
min.cc	a copy of the min.cc argument.
max.cc	a copy of the max.cc argument.
success.rate	a numeric matrix with the success rates of the Metropolis-Hastings algorithm described above.

### Author(s)

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

### References

Heagerty, P. and Zheng, Y. (2005). Survival model predictive accuracy and ROC curves. *Biometrics* **61**, 92–105.

Rizopoulos, D. (2011). Dynamic predictions and prospective accuracy in joint models for longitudinal and time-to-event data. *Biometrics* **67**, 819–829.

Rizopoulos, D. (2010) JM: An R package for the joint modelling of longitudinal and time-to-event data. *Journal of Statistical Software* **35** (9), 1–33. <http://www.jstatsoft.org/v35/i09/>

Zheng, Y. and Heagerty, P. (2007). Prospective accuracy for longitudinal markers. *Biometrics* **63**, 332–341.

### See Also

[plot.rocJM](#), [survfitJM](#), [dynC](#), [jointModel](#)

### Examples

```
## Not run:
fitLME <- lme(sqrt(CD4) ~ obstime * (drug + AZT + prevOI + gender),
  random = ~ obstime | patient, data = aids)
fitSURV <- coxph(Surv(Time, death) ~ drug + AZT + prevOI + gender,
  data = aids.id, x = TRUE)
fit.aids <- jointModel(fitLME, fitSURV, timeVar = "obstime",
  method = "piecewise-PH-aGH")

# the following will take some time to execute...
ND <- aids[aids$patient == "7", ]
roc <- rocJM(fit.aids, dt = c(2, 4, 8), ND, idVar = "patient")
roc

## End(Not run)
```

simulate

*Simulate from Joint Models.***Description**

simulate longitudinal responses and event times from joint models

**Usage**

```
simulateJM(nsim, nsub, thetas, times, formulas, Data = NULL,
           method = c("weibull-PH", "weibull-AFT", "piecewise-PH", "spline-PH"),
           lag = 0, censoring = "uniform", max.FUtime = NULL, seed = NULL,
           return.ranef = FALSE)
## S3 method for class 'jointModel'
simulate(object, nsim, seed = NULL, times = NULL,
         Data = NULL, ...)
```

**Arguments**

nsim	number of data sets to be simulated.
nsub	the number of subjects in each data set.
thetas	a list with the parameter values. This should be of the same structure as the coefficients component returned by <code>jointModel()</code> .
times	a numeric vector denoting the time points at which longitudinal measurements are planned to be taken.
formulas	a list with components: <code>Yfixed</code> a formula for the fixed-effects part of the linear mixed model, <code>Yrandom</code> a formula for the random-effects part of the linear mixed model, <code>Tfixed</code> a formula for the baseline covariates part of the survival submodel, <code>timeVar</code> a character string indicating the name of the time variable in the linear mixed model.
Data	a data frame containing any covariates used in the formulas defined in the <code>formulas</code> argument.
method	a character string indicating from what type of survival submodel to simulate. There are the same options as the ones provided by <code>jointModel</code> .
lag	a numeric value denoting a lagged effect; the same as the <code>lag</code> argument of <code>jointModel</code> .
censoring	a character string or a numeric vector.
max.FUtime	a numeric value denoting the maximum follow-up time for the study. The default is <code>max(times) + 2 * IQR(times)</code> .
seed	an object specifying if and how the random number generator should be initialized ('seeded'). It could be either <code>NULL</code> or an integer that will be used in a call to <code>set.seed()</code> before simulating the response vectors. If set, the value is saved as the "seed" attribute of the returned value.

return.ranef      logical; if TRUE, each component of the returned list has the attributed "ranef" that contains the random-effects values used in the simulation.

object            an object inheriting from class jointModel.

...                additional arguments; currently none is used.

### Value

A list of length nsim of data frames that contains the simulated responses for the longitudinal process "y", the simulated event times "Time", the event indicator "Event", and the subject identification number "id". If extra covariates were assumed, these are also included.

### Author(s)

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

### See Also

[jointModel](#)

### Examples

```
## Not run:
prothro$t0 <- as.numeric(prothro$time == 0)
lmeFit <- lme(pro ~ treat * (time + t0), random = ~ time | id, data = prothro)
survFit <- coxph(Surv(Time, death) ~ treat, data = prothros, x = TRUE)
jointFit <- jointModel(lmeFit, survFit, timeVar = "time",
  method = "weibull-PH-aGH")

newData <- simulate(jointFit, nsim = 1, times = seq(0, 11, len = 15))
newData

## End(Not run)
```

---

summary.weibull.frailty

*Summary Method for weibull.frailty Objects*

---

### Description

Summarizes the fit of a Weibull model with Gamma frailties

### Usage

```
## S3 method for class 'weibull.frailty'
summary(object, sand.se = FALSE, ...)
```

**Arguments**

object	an object inheriting from class <code>weibull.frailty</code> .
sand.se	logical; if TRUE, sandwich standard errors are also produced.
...	additional arguments; currently none is used.

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**See Also**

[weibull.frailty](#)

**Examples**

```
fit <- weibull.frailty(Surv(time, status) ~ age + sex, kidney)
summary(fit)
summary(fit, TRUE)
```

---

survfitJM

*Prediction in Joint Models*

---

**Description**

This function computes the conditional probability of surviving later times than the last observed time for which a longitudinal measurement was available.

**Usage**

```
survfitJM(object, newdata, idVar = "id", simulate = TRUE, survTimes = NULL,
last.time = NULL, M = 200, CI.levels = c(0.025, 0.975), scale = 1.6)
```

**Arguments**

object	an object inheriting from class <code>jointModel</code> .
newdata	a data frame that contains the longitudinal and covariate information for the subjects for which prediction of survival probabilities is required. The names of the variables in this data frame must be the same as in the data frames that were used to fit the linear mixed effects model (using <code>lme()</code> ) and the survival model (using <code>coxph()</code> or <code>survreg()</code> ) that were supplied as the two first argument of <a href="#">jointModel</a> . In addition, this data frame should contain a variable that identifies the different subjects (see also argument <code>idVar</code> ).
idVar	the name of the variable in <code>newdata</code> that identifies the different subjects.
simulate	logical; if TRUE, a Monte Carlo approach is used to estimate survival probabilities. If FALSE, a first order estimator is used instead. (see <b>Details</b> )

survTimes	a numeric vector of times for which prediction survival probabilities are to be computed.
last.time	a numeric vector or character string. This specifies the known time at which each of the subjects in newdat was known to be alive. If NULL, then this is automatically taken as the last time each subject provided a longitudinal measurement. If a numeric vector, then it is assumed to contain this last time point for each subject. If a character string, then it should be a variable in the data frame newdata.
M	integer denoting how many Monte Carlo samples to use – see <b>Details</b> .
CI.levels	a numeric vector of length two that specifies which quantiles to use for the calculation of confidence interval for the predicted probabilities – see <b>Details</b> .
scale	a numeric scalar that controls the acceptance rate of the Metropolis-Hastings algorithm – see <b>Details</b> .

### Details

Based on a fitted joint model (represented by object), and a history of longitudinal responses  $\tilde{y}_i(t) = \{y_i(s), 0 \leq s \leq t\}$  and a covariates vector  $x_i$  (stored in newdata), this function provides estimates of  $Pr(T_i > u | T_i > t, \tilde{y}_i(t), x_i)$ , i.e., the conditional probability of surviving time  $u$  given that subject  $i$ , with covariate information  $x_i$ , has survived up to time  $t$  and has provided longitudinal the measurements  $\tilde{y}_i(t)$ .

To estimate  $Pr(T_i > u | T_i > t, \tilde{y}_i(t), x_i)$  and if `simulate = TRUE`, a Monte Carlo procedure is followed with the following steps:

**Step 1:** Simulate new parameter values, say  $\theta^*$ , from  $N(\hat{\theta}, C(\hat{\theta}))$ , where  $\hat{\theta}$  are the MLEs and  $C(\hat{\theta})$  their large sample covariance matrix, which are extracted from object.

**Step 2:** Simulate random effects values, say  $b_i^*$ , from their posterior distribution given survival up to time  $t$ , the vector of longitudinal responses  $\tilde{y}_i(t)$  and  $\theta^*$ . This is achieved using a Metropolis-Hastings algorithm with independent proposals from a properly centered and scaled multivariate  $t$  distribution. The `scale` argument controls the acceptance rate for this algorithm.

**Step 3** Using  $\theta^*$  and  $b_i^*$ , compute  $Pr(T_i > u | T_i > t, b_i^*, x_i; \theta^*)$ .

**Step 4:** Repeat Steps 1-3  $M$  times.

Based on the  $M$  estimates of the conditional probabilities, we compute useful summary statistics, such as their mean, median, and quantiles (to produce a confidence interval).

If `simulate = FALSE`, then survival probabilities are estimated using the formula

$$Pr(T_i > u | T_i > t, \hat{b}_i, x_i; \hat{\theta}),$$

where  $\hat{\theta}$  denotes the MLEs as above, and  $\hat{b}_i$  denotes the empirical Bayes estimates.

### Value

A list of class `survfitJM` with components:

summaries	a list with elements numeric matrices with numeric summaries of the predicted probabilities for each subject.
-----------	---

survTimes	a copy of the survTimes argument.
last.time	a numeric vector with the time of the last available longitudinal measurement of each subject.
obs.times	a list with elements numeric vectors denoting the timings of the longitudinal measurements for each subject.
y	a list with elements numeric vectors denoting the longitudinal responses for each subject.
full.results	a list with elements numeric matrices with predicted probabilities for each subject in each replication of the Monte Carlo scheme described above.
success.rate	a numeric vector with the success rates of the Metropolis-Hastings algorithm described above for each subject.
scale	a copy of the scale argument.

**Note**

Predicted probabilities are not computed for joint models with `method = "ch-Laplace"` and `method = "Cox-PH-GH"`.

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**References**

- Rizopoulos, D. (2010) JM: An R Package for the Joint Modelling of Longitudinal and Time-to-Event Data. *Journal of Statistical Software* **35** (9), 1–33. <http://www.jstatsoft.org/v35/i09/>
- Rizopoulos, D. (2011). Dynamic predictions and prospective accuracy in joint models for longitudinal and time-to-event data. *Biometrics* **67**, 819–829.

**See Also**

[jointModel](#), [plot.survfitJM](#)

**Examples**

```
# linear mixed model fit
fitLME <- lme(sqrt(CD4) ~ obstime + obstime:drug,
  random = ~ 1 | patient, data = aids)
# cox model fit
fitCOX <- coxph(Surv(Time, death) ~ drug, data = aids.id, x = TRUE)

# joint model fit
fitJOINT <- jointModel(fitLME, fitCOX,
  timeVar = "obstime", method = "weibull-PH-aGH")

# sample of the patients who are still alive
ND <- aids[aids$patient == "141", ]
ss <- survfitJM(fitJOINT, newdata = ND, idVar = "patient", M = 50)
ss
```

---

`wald.strata`*Wald Test for Stratification Factors*

---

**Description**

It performs a Wald test to test the hypothesis of equal spline coefficients among strata in the approximation of baseline risk function.

**Usage**

```
wald.strata(fit)
```

**Arguments**

`fit` an object of class `jointModel` with `method = "spline-PH-GH"` and with a strata specification in the survival part.

**Value**

an object of class `wald.strata` with components:

`alternative` a character string naming the alternative.

`Result` a numeric matrix with the results of the Wald test.

**Note**

This test is valid when the same knots have been used across strata.

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**Examples**

```
## Not run:
fitLME <- lme(log(serBilir) ~ drug * year - drug, random = ~ year | id,
             data = pbc2)
fitSURV <- coxph(Surv(years, status2) ~ drug + strata(hepatomegaly),
                data = pbc2.id, x = TRUE)
fit.pbc <- jointModel(fitLME, fitSURV, timeVar = "year", method = "spline-PH-aGH")
wald.strata(fit.pbc)

## End(Not run)
```

weibull.frailty

*Weibull Model with Gamma Frailties***Description**

Fits a Weibull model with Gamma frailties for multivariate survival data under maximum likelihood

**Usage**

```
weibull.frailty(formula = formula(data), data = parent.frame(),
               id = "id", subset, na.action, init, control = list())
```

**Arguments**

formula	an object of class formula: a symbolic description of the model to be fitted. The response must be a survival object as returned by function <code>Surv()</code> .
data	an optional data frame containing the variables specified in the model.
id	either a character string denoting a variable name in data or a numeric vector specifying which event times belong to the same cluster (e.g., hospital, patient, etc.).
subset	an optional vector specifying a subset of observations to be used in the fitting process.
na.action	what to do with missing values.
init	a numeric vector of length $p + 3$ of initial values. The first $p$ elements should correspond to the regression coefficients for the covariates, and the last 3 to log-scale, log-shape, and log-frailty-variance, respectively. See <b>Details</b> .
control	a list of control values with components: <ul style="list-style-type: none"> <li><b>optimizer</b> a character string indicating which optimizer to use; options are "optim" (default) and "nlminb".</li> <li><b>parscale</b> the parscale control argument for <code>optim()</code>, or the scale argument for <code>nlminb()</code>. It should be a numeric vector of length equal to the number of parameters. Default is 0.01 for all parameters.</li> <li><b>maxit</b> the maximum number of iterations. Default is 500.</li> <li><b>numeriDeriv</b> a character string indicating which type of numerical derivative to use to compute the Hessian matrix; options are "fd" denoting the forward difference approximation, and "cd" (default) denoting the central difference approximation.</li> <li><b>eps.Hes</b> tolerance value used in the numerical derivative method. Default is 1e-03.</li> </ul>

**Details**

The fitted model is defined as follows:

$$\lambda(t_i|\omega_i) = \lambda_0(t_i)\omega_i \exp(x_i^T \beta),$$

where  $i$  denotes the subject,  $\lambda(\cdot)$  denotes the hazard function, conditionally on the frailty  $\omega_i$ ,  $x_i$  is a vector of covariates with corresponding regression coefficients  $\beta$ , and  $\lambda_0(\cdot)$  is the Weibull baseline hazard defined as  $\lambda_0(t) = \text{shape} * \text{scale} * t^{\text{shape}-1}$ . Finally, for the frailties we assume  $\omega_i \sim \text{Gamma}(\eta, \eta)$ , with  $\eta^{-1}$  denoting the unknown variance of  $\omega_i$ 's.

**Value**

an object of class `weibull.frailty` with components:

<code>coefficients</code>	a list with the estimated coefficients values. The components of this list are: <code>betas</code> , <code>scale</code> , <code>shape</code> , and <code>var.frailty</code> , and correspond to the coefficients with the same name.
<code>hessian</code>	the hessian matrix at convergence. For the <code>shape</code> , <code>scale</code> , and <code>var-frailty</code> parameters the Hessian is computed on the log scale.
<code>logLik</code>	the log-likelihood value.
<code>control</code>	a copy of the <code>control</code> argument.
<code>y</code>	an object of class <code>Surv</code> containing the observed event times and the censoring indicator.
<code>x</code>	the design matrix of the model.
<code>id</code>	a numeric vector specifying which event times belong to the same cluster.
<code>nam.id</code>	the value of argument <code>id</code> , if that was a character string.
<code>terms</code>	the term component of the fitted model.
<code>data</code>	a copy of data or the created <code>model.frame</code> .
<code>call</code>	the matched call.

**Note**

`weibull.frailty()` currently supports only right-censored data.

**Author(s)**

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

**Examples**

```
weibull.frailty(Surv(time, status) ~ age + sex, kidney)
```

---

xtable	<i>xtable Method from Joint Models.</i>
--------	---

---

### Description

produces a LaTeX table with the results of a joint model using package xtable.

### Usage

```
## S3 method for class 'jointModel'
xtable(x, caption = NULL, label = NULL, align = NULL,
       digits = NULL, display = NULL, which = c("all", "Longitudinal", "Event"),
       varNames.Long = NULL, varNames.Event = NULL, p.values = TRUE,
       digits.pval = 4, ...)
```

### Arguments

x	a object inheriting from class jointModel.
caption	the caption argument of xtable().
label	the label argument of xtable().
align	the align argument of xtable().
digits	the digits argument of xtable().
display	the display argument of xtable().
which	a character string indicating which results to include in the LaTeX table. Options are all results, the results of longitudinal submodel or the results of the survival submodel.
varNames.Long	a character vector of the variable names for the longitudinal submodel.
varNames.Event	a character vector of the variable names for the survival submodel.
p.values	logical; should p-values be included in the table.
digits.pval	a numeric scalare denoting the number of significance digits in the <i>p</i> -value.
...	additional arguments; currently none is used.

### Value

A LaTeX code chunk with the results of the joint modeling analysis.

### Author(s)

Dimitris Rizopoulos <d.rizopoulos@erasmusmc.nl>

### See Also

[jointModel](#)

**Examples**

```
## Not run:
require(xtable)
prothro$t0 <- as.numeric(prothro$time == 0)
lmeFit <- lme(pro ~ treat * (time + t0), random = ~ time | id, data = prothro)
survFit <- coxph(Surv(Time, death) ~ treat, data = prothros, x = TRUE)
jointFit <- jointModel(lmeFit, survFit, timeVar = "time",
  method = "weibull-PH-aGH")

xtable(jointFit, math.style.negative = TRUE)

## End(Not run)
```

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