

# Package ‘rr2’

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**Type** Package

**Title** R2s for Regression Models

**Version** 1.0.2

**Description** Three methods to calculate R2 for models with correlated errors, including Phylogenetic GLS, Phylogenetic Logistic Regression, Linear Mixed Models (LMMs), and Generalized Linear Mixed Models (GLMMs). See details in Ives 2018 <doi:10.1093/sysbio/syy060>.

**License** GPL-3

**Depends** R (>= 3.0), stats

**Encoding** UTF-8

**LazyData** true

**Imports** lme4, phylolm, ape, utils, Matrix, nlme

**RoxygenNote** 6.1.1

**Suggests** testthat

**URL** <https://github.com/arives/rr2>

**BugReports** <https://github.com/arives/rr2/issues>

**NeedsCompilation** no

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**Repository** CRAN

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binaryPGLMM	<i>Phylogenetic GLM for binary data</i>
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## Description

Fitting phylogenetic generalized linear models for binary data (0 and 1).

## Usage

```
binaryPGLMM(formula, data = list(), phy, s2.init = 0.1,
             B.init = NULL, tol.pql = 10^-6, maxit.pql = 200,
             maxit.reml = 100)
```

## Arguments

formula	Regression formula.
data	Data frame to fit the model with.
phy	Phylogenetic tree of type phylo with branch lengths.
s2.init	Initial variance values for random terms, default is 0.1.
B.init	Initial coefficient values for fixed terms, if not provided, will use those from lm.
tol.pql	Tolerance value, default is 10 <sup>-6</sup> .
maxit.pql	The number of iterations, default is 200.
maxit.reml	The number of iterations for optim, default is 100.

## Value

A large list with class as binaryPGLMM.

---

inv.logit	<i>Invert logit function</i>
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**Description**

Convert numeric values between 0 and 1.

**Usage**

```
inv.logit(x)
```

**Arguments**

x	A numeric vector.
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partialR2	<i>Partial R2</i>
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**Description**

Get partial R2 by comparing a model and its reduced model.

**Usage**

```
partialR2(mod, mod.r)
```

**Arguments**

mod	A linear regression model.
mod.r	A reduced model based on mod.

**Value**

R2 value between 0 and 1.

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partialR2adj	<i>Adjusted partial R2</i>
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### Description

Get adjusted partial R2 by comparing a model and its reduced model.

### Usage

```
partialR2adj(mod, df.f = summary(mod)$df[1], mod.r,
             df.r = summary(mod.r)$df[1])
```

### Arguments

mod	A linear regression model.
df.f	Degree of freedom of the mod.
mod.r	A reduced model based on mod.
df.r	Degree of freedom of the reduced mod.r.

### Value

A list of both R2 and adjusted R2 , the latter is not necessary to be between 0 and 1.

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R2	<i>Calculate R2.lik, R2.resid, and R2.pred</i>
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### Description

This is a wrapper for calculating three R2s – R2.lik, R2.resid, and R2.pred – for LMMs and GLMMs, and phylogenetic LMMs (PLMMs) and GLMMs (PGLMMs). Note that the individual functions R2.lik(), R2.resid(), and R2.pred() can be called separately. This is preferable if you are only interested in one R2; for example, for phylo1m() called from 'R2' you need to specify 'phy' (phylo object for the phylogeny), while R2.lik() does not require this.

### Usage

```
R2(mod = NULL, mod.r = NULL, phy = NULL, sigma2_d = c("s2w", "NS",
             "rNS"), lik = TRUE, resid = TRUE, pred = TRUE)
```

**Arguments**

<code>mod</code>	A regression model with one of the following classes: 'lm', 'glm', 'lmerMod', 'glmerMod', 'phylolm', 'gls', 'binaryPGLMM', or 'communityPGLMM'.
<code>mod.r</code>	A reduced model; if not provided, the total R2 will be given by setting 'mod.r' to the model corresponding to 'mod' with the intercept as the only predictor.
<code>phy</code>	The phylogeny for phylogenetic models (as a 'phylo' object), which is not required to be specified for <code>R2.lik()</code> of non-phylogenetic models.
<code>sigma2_d</code>	Distribution-specific variance $\sigma_d^2$ (see Details) used in <code>R2.resid()</code> . For binomial GLMs, GLMMs and PGLMMs with logit link functions, options are c('s2w', 'NS', 'rNS'). For binomial GLMs, GLMMs and PGLMMs with probit link functions, options are c('s2w', 'NS'). Other families use 's2w'.
<code>lik</code>	Whether to calculate <code>R2.lik</code> ; default is TRUE.
<code>resid</code>	Whether to calculate <code>R2.resid</code> ; default is TRUE.
<code>pred</code>	Whether to calculate <code>R2.pred</code> ; default is TRUE.

**Details**

Details about the methods are provided under the separate functions for `R2.lik()`, `R2.resid()`, and `R2.pred()`. There are also many worked examples.

**Value**

A vector, with all three R2s by default.

**Author(s)**

Daijiang Li and Anthony R. Ives

**References**

Ives A.R. and Li D. 2018. rr2: An R package to calculate R2s for regression models. Journal of Open Source Software. DOI:10.21105/joss.01028

Ives A.R. 2018. R2s for Correlated Data: Phylogenetic Models, LMMs, and GLMMs. Systematic Biology. DOI:10.1093/sysbio/syy060

**See Also**

MuMIn, lme4, ape, phylolm, pez

**Examples**

```
library(ape)
library(phylolm)
library(lme4)
library(nlme)

#####
# LMM with two fixed and two random effects
```

```

p1 <- 10
nsample <- 10
n <- p1 * nsample

d <- data.frame(x1 = 0, x2 = 0, y = 0, u1 = rep(1:p1, each = nsample),
               u2 = rep(1:p1, times = nsample))
d$u1 <- as.factor(d$u1)
d$u2 <- as.factor(d$u2)

b1 <- 1
b2 <- -1
sd1 <- 1.5

d$x1 <- rnorm(n = n)
d$x2 <- rnorm(n = n)
d$y <- b1 * d$x1 + b2 * d$x2 + rep(rnorm(n = p1, sd = sd1), each = nsample) +
  rep(rnorm(n = p1, sd = sd1), times = nsample) + rnorm(n = n)

z.f <- lmer(y ~ x1 + x2 + (1 | u1) + (1 | u2), data = d, REML = FALSE)
z.x <- lmer(y ~ x1 + (1 | u1) + (1 | u2), data = d, REML = FALSE)
z.v <- lmer(y ~ 1 + (1 | u2), data = d, REML = FALSE)
z.0 <- lm(y ~ 1, data = d)

R2(z.f, z.x)
R2(z.f, z.v)
R2(z.f)

#####
# GLMM with one fixed and one random effect

p1 <- 10
nsample <- 10
n <- p1 * nsample

d <- data.frame(x = 0, y = 0, u = rep(1:p1, each = nsample))
d$u <- as.factor(d$u)

b1 <- 1
sd1 <- 1.5

d$x <- rnorm(n = n)
prob <- inv.logit(b1 * d$x + rep(rnorm(n = p1, sd = sd1), each = nsample))
d$y <- rbinom(n = n, size = 1, prob = prob)

z.f <- glmer(y ~ x + (1 | u), data = d, family = 'binomial')
z.x <- glmer(y ~ 1 + (1 | u), data = d, family = 'binomial')
z.v <- glm(y ~ x, data = d, family = 'binomial')

R2(z.f, z.x)
R2(z.f, z.v)
R2(z.f)

# These give different results for R2.resid.

```

```

R2(z.f, sigma2_d = 's2w')
R2(z.f, sigma2_d = 'NS')
R2(z.f, sigma2_d = 'rNS')

#####
# PGLS with a single fixed effect

n <- 100
d <- data.frame(x = array(0, dim = n), y = 0)

b1 <- 1.5
signal <- 0.7

phy <- compute.brLen(rtree(n = n), method = 'Grafen', power = 1)
phy.x <- compute.brLen(phy, method = 'Grafen', power = .0001)

# Generate random data
x <- rTraitCont(phy.x, model = 'BM', sigma = 1)
e <- signal^0.5 * rTraitCont(phy, model = 'BM', sigma = 1) + (1-signal)^0.5 * rnorm(n = n)
d$x <- x[match(names(e), names(x))]
d$y <- b1 * x + e
rownames(d) <- phy$tip.label

z.x <- phyloLm(y ~ 1, phy = phy, data = d, model = 'lambda')
z.f <- phyloLm(y ~ x, phy = phy, data = d, model = 'lambda')
z.v <- lm(y ~ x, data = d)

R2(z.f, z.x, phy = phy)
R2(z.f, z.v, phy = phy)
R2(z.f, phy = phy)

# This also works for models fit with gls() in {nlme}
z.x <- gls(y ~ 1, data = d, correlation = corPagel(1, phy), method = "ML")
z.f <- gls(y ~ x, data = d, correlation = corPagel(1, phy), method = "ML")
z.v <- lm(y ~ x, data = d)

R2(z.f, z.x)
R2(z.f, z.v)
R2(z.f)

# But note that you need to define weights for gls() with non-ultrametric trees;
# if not, you will get a error from R2.resid, "Matrix is not block-diagonal"

phy.nu <- rtree(n = n)
# Generate random data
e <- signal^0.5 * rTraitCont(phy.nu, model = 'BM', sigma = 1) + (1-signal)^0.5 * rnorm(n = n)
d$x <- x[match(names(e), names(x))]
d$y <- b1 * x + e
rownames(d) <- phy.nu$tip.label

weights <- diag(vcv.phylo(phy.nu))
z.x <- gls(y ~ 1, data = d,
          correlation = corPagel(1, phy.nu),

```

```

        weights=varFixed(~weights), method = "ML")
z.f <- gls(y ~ x,data = d,
          correlation = corPagel(1, phy.nu),
          weights=varFixed(~weights), method = "ML")
z.v <- lm(y ~ x, data = d)

R2(z.f, z.x)
R2(z.f, z.v)
R2(z.f)

#####
# PGLMM with one fixed effect

n <- 100
b1 <- 1.5
signal <- 2

phy <- compute.brLen(rtree(n = n), method = 'Grafen', power = 1)
phy.x <- compute.brLen(phy, method = 'Grafen', power = .0001)

# Generate random data
x <- rnorm(n)
d <- data.frame(x = x, y = 0)

e <- signal * rTraitCont(phy, model = 'BM', sigma = 1)
e <- e[match(phy$tip.label, names(e))]

d$y <- rbinom(n = n, size = 1, prob = inv.logit(b1 * d$x + e))
rownames(d) <- phy$tip.label

# Use the function binaryPGLMM() from the rr2 package rather than ape.
z.f <- rr2::binaryPGLMM(y ~ x, data = d, phy = phy)
z.x <- rr2::binaryPGLMM(y ~ 1, data = d, phy = phy)
z.v <- glm(y ~ x, data = d, family = 'binomial')

# R2.lik is not produced, because binaryPGLMM() does not generate a likelihood.
R2(z.f, z.x, phy = phy)
R2(z.f, z.v, phy = phy)
R2(z.f, phy = phy)

```

---

R2.lik

*Calculate R2.lik*


---

## Description

Calculate partial and total R2s for LMM, GLMM, PGLS, and PGLMM using R2.lik, an R2 based on the likelihood of observing the data.



**Usage**

```
R2.lik(mod = NULL, mod.r = NULL)
```

**Arguments**

**mod** A regression model with one of the following classes: 'lm', 'glm', 'lmerMod', 'glmerMod', 'phylolm', 'phyloglm', 'gls', or 'communityPGLMM'.

**mod.r** A reduced model; if not provided, the total R2 will be given by setting 'mod.r' to the model corresponding to 'mod' with the intercept as the only predictor.

**Details**

R2.lik() works with classes 'lm', 'glm', 'lmerMod', 'glmerMod', 'phylolm', 'phyloglm', and 'communityPGLMM' (family = 'gaussian' only). It is implemented as

$$partialR2 = 1 - exp(-2/n * (logLik(mod.f) - logLik(mod.r)))$$

where 'mod.f' and 'mod.r' are the full and reduced models, respectively. The total R2 is given when 'mod.r' is the model corresponding to mod.f that contains only the intercept. For GLMMs and PGLMMs, R2.lik() is standardized to have a maximum of one following Nagelkerke (1991).

Note that phyloglm() can have difficulties in finding solutions when there is no phylogenetic signal. Therefore, when the estimate of alpha is >50, indicating no phylogenetic signal, the model is refit with the corresponding GLM.

R2.lik() is also computed for LMMs and GLMMs in the MuMIn package.

**Value**

R2.lik value.

**Author(s)**

Anthony R. Ives

**References**

- Ives A.R. and Li D. 2018. rr2: An R package to calculate R2s for regression models. Journal of Open Source Software. DOI:10.21105/joss.01028
- Ives A.R. 2018. R2s for Correlated Data: Phylogenetic Models, LMMs, and GLMMs. Systematic Biology. DOI:10.1093/sysbio/syy060
- Nagelkerke 1991. A note on a general definition of the coefficient of determination. Biometrika 78:691–692.

**See Also**

MuMIn, lme4, ape, phylolm, pez

**Examples**

```

library(ape)
library(phyloilm)
library(lme4)
library(nlme)

#####
# LMM with two fixed and two random effects
p1 <- 10
nsample <- 10
n <- p1 * nsample

d <- data.frame(x1 = 0, x2 = 0, y = 0, u1 = rep(1:p1, each = nsample),
               u2 = rep(1:p1, times = nsample))
d$u1 <- as.factor(d$u1)
d$u2 <- as.factor(d$u2)

b1 <- 1
b2 <- -1
sd1 <- 1.5

d$x1 <- rnorm(n = n)
d$x2 <- rnorm(n = n)
d$y <- b1 * d$x1 + b2 * d$x2 + rep(rnorm(n = p1, sd = sd1), each = nsample) +
  rep(rnorm(n = p1, sd = sd1), times = nsample) + rnorm(n = n)

z.f <- lmer(y ~ x1 + x2 + (1 | u1) + (1 | u2), data = d, REML = FALSE)
z.x <- lmer(y ~ x1 + (1 | u1) + (1 | u2), data = d, REML = FALSE)
z.v <- lmer(y ~ 1 + (1 | u2), data = d, REML = FALSE)
z.0 <- lm(y ~ 1, data = d)

R2.lik(z.f, z.x)
R2.lik(z.f, z.v)
R2.lik(z.f)

# These give the same results.
R2.lik(z.f, z.0)
R2.lik(z.f)

#####
# GLMM with one fixed and one random effect

p1 <- 10
nsample <- 10
n <- p1 * nsample

d <- data.frame(x = 0, y = 0, u = rep(1:p1, each = nsample))
d$u <- as.factor(d$u)

b1 <- 1
sd1 <- 1.5

```

```

d$x <- rnorm(n = n)
prob <- inv.logit(b1 * d$x + rep(rnorm(n = p1, sd = sd1), each = nsample))
d$y <- rbinom(n = n, size = 1, prob = prob)

z.f <- glmer(y ~ x + (1 | u), data = d, family = 'binomial')
z.x <- glmer(y ~ 1 + (1 | u), data = d, family = 'binomial')
z.v <- glm(y ~ x, data = d, family = 'binomial')

R2.lik(z.f, z.x)
R2.lik(z.f, z.v)
R2.lik(z.f)

#####
# PGLS with a single fixed effect

n <- 100
d <- data.frame(x = array(0, dim = n), y = 0)

b1 <- 1.5
signal <- 0.7

phy <- compute.brLen(rtree(n = n), method = 'Grafen', power = 1)
phy.x <- compute.brLen(phy, method = 'Grafen', power = .0001)

# Generate random data
x <- rTraitCont(phy.x, model = 'BM', sigma = 1)
e <- signal^0.5 * rTraitCont(phy, model = 'BM', sigma = 1) + (1-signal)^0.5 * rnorm(n = n)
d$x <- x[match(names(e), names(x))]
d$y <- b1 * x + e
rownames(d) <- phy$tip.label

z.x <- phylolm(y ~ 1, phy = phy, data = d, model = 'lambda')
lam.x <- round(z.x$optpar, digits = 4)
z.f <- phylolm(y ~ x, phy = phy, data = d, model = 'lambda')
z.v <- lm(y ~ x, data = d)

R2.lik(z.f, z.x)
R2.lik(z.f, z.v)
R2.lik(z.f)

# This also works for models fit with gls() in {nlme}
z.x <- gls(y ~ 1, data = d, correlation = corPagel(1, phy), method = "ML")
z.f <- gls(y ~ x, data = d, correlation = corPagel(1, phy), method = "ML")
z.v <- lm(y ~ x, data = d)
R2.lik(z.f, z.x)
R2.lik(z.f, z.v)
R2.lik(z.f)

#####
# PGLMM with one fixed effect

n <- 100
b1 <- 1.5

```

```

signal <- 2

phy <- compute.brLen(rtree(n = n), method = 'Grafen', power = 1)
phy.x <- compute.brLen(phy, method = 'Grafen', power = .0001)

# Generate random data
x <- rnorm(n)
d <- data.frame(x = x, y = 0)

e <- signal * rTraitCont(phy, model = 'BM', sigma = 1)
e <- e[match(phy$tip.label, names(e))]

d$y <- rbinom(n = n, size = 1, prob = inv.logit(b1 * d$x + e))
rownames(d) <- phy$tip.label

z.f <- phyloglm(y ~ x, data = d, start.alpha = 1, phy = phy)
z.x <- phyloglm(y ~ 1, data = d, phy = phy, start.alpha = min(20, z.f$alpha))
z.v <- glm(y ~ x, data = d, family = 'binomial')

R2.lik(z.f, z.x)
R2.lik(z.f, z.v)
R2.lik(z.f)

```

---

R2.pred

*Calculate R2.pred*


---

## Description

Calculate partial and total R2s for LMM, GLMM, PGLS, and PGLMM using R2.pred, an R2 based on the variance of the difference between the observed and predicted values of a fitted model.

## Usage

```
R2.pred(mod = NULL, mod.r = NULL, phy = NULL)
```

## Arguments

mod	A regression model with one of the following classes: 'lm', 'glm', 'lmerMod', 'glmerMod', 'phylolm', 'gls', 'binaryPGLMM', or 'communityPGLMM'.
mod.r	A reduced model; if not provided, the total R2 will be given by setting 'mod.r' to the model corresponding to 'mod' with the intercept as the only predictor.
phy	The phylogeny for phylogenetic models (as a 'phylo' object), which must be specified for models of class 'phylolm'.

## Details

R2.pred works with classes 'lm', 'glm', 'lmerMod', 'glmerMod', 'phylolm', 'phyloglm', 'gls', 'binaryPGLMM', and 'communityPGLMM' (family = gaussian and binomial).

**LMM (lmerMod), GLMM (glmerMod), PGLMM (binaryPGLMM and communityPGLMM):**

$$partialR2 = 1 - var(y - y.fitted.f)/var(y - y.fitted.r)$$

where y are the observed data, and y.fitted.f and y.fitted.r are the fitted (predicted) values from the full and reduced models. For GLMMs and PGLMMs, the values of y.fitted are in the space of the raw data (as opposed to the 'Normal' or 'latent' space). When the reduced model 'mod.r' is not specified, the total R2 is computing using the reduced model with only the intercept.

Note that the version of binaryPGLMM() in the package ape is replaced by a version contained within rr2 that outputs all of the required information for the calculation of R2.resid.

**PGLS (phylolm and gls):**

For PGLS, the total R2.pred is computed by removing each datum one at a time, predicting its value from the fitted model, repeating this for all data points, and then calculating the variance of the difference between observed and fitted values. The predictions are calculated as

$$res.predicted[j] = V[j, -j]solve(V[-j, -j])res[-j]$$

where res[-j] is a vector of residuals with datum j removed, V[-j,-j] is the phylogenetic covariance matrix with row and column j removed, and V[j, -j] is row j of covariance matrix V with element j removed. The partial R2.pred is calculated from the total R2.pred from full and reduced models as

$$partialR2 = 1 - (1 - R2.pred.f)/(1 - R2.pred.r)$$

Note that phylolm() can have difficulties in finding solutions when there is no phylogenetic signal; when the estimate indicates no phylogenetic signal, you should refit the model with the corresponding LM.

**LM (lm) and GLM (glm):**

For compatibility and generating reduced models, rr2 will compute R2.pred for LM and GLM that correspond to LMM/PGLS and GLMM/PGLMM.

## Value

R2.pred value.

## Author(s)

Anthony R. Ives

## References

- Ives A.R. and Li D. 2018. rr2: An R package to calculate R2s for regression models. Journal of Open Source Software. DOI:10.21105/joss.01028
- Ives A.R. 2018. R2s for Correlated Data: Phylogenetic Models, LMMs, and GLMMs. Systematic Biology. DOI:10.1093/sysbio/syy060

**See Also**

MuMIn, lme4, ape, phylolm, pez

**Examples**

```

library(ape)
library(phylolm)
library(lme4)
library(nlme)

#####
# LMM with two fixed and two random effects
p1 <- 10
nsample <- 10
n <- p1 * nsample

d <- data.frame(x1 = 0, x2 = 0, y = 0, u1 = rep(1:p1, each = nsample),
               u2 = rep(1:p1, times = nsample))
d$u1 <- as.factor(d$u1)
d$u2 <- as.factor(d$u2)

b1 <- 1
b2 <- -1
sd1 <- 1.5

d$x1 <- rnorm(n = n)
d$x2 <- rnorm(n = n)
d$y <- b1 * d$x1 + b2 * d$x2 + rep(rnorm(n = p1, sd = sd1), each = nsample) +
  rep(rnorm(n = p1, sd = sd1), times = nsample) + rnorm(n = n)

z.f <- lmer(y ~ x1 + x2 + (1 | u1) + (1 | u2), data = d, REML = FALSE)
z.x <- lmer(y ~ x1 + (1 | u1) + (1 | u2), data = d, REML = FALSE)
z.v <- lmer(y ~ 1 + (1 | u2), data = d, REML = FALSE)
z.0 <- lm(y ~ 1, data = d)

R2.pred(z.f, z.x)
R2.pred(z.f, z.v)
R2.pred(z.f)

#####
# GLMM with one fixed and one random effect

p1 <- 10
nsample <- 10
n <- p1 * nsample

d <- data.frame(x = 0, y = 0, u = rep(1:p1, each = nsample))
d$u <- as.factor(d$u)

b1 <- 1
sd1 <- 1.5

```

```

d$x <- rnorm(n = n)
prob <- inv.logit(b1 * d$x + rep(rnorm(n = p1, sd = sd1), each = nsample))
d$y <- rbinom(n = n, size = 1, prob = prob)

z.f <- glmer(y ~ x + (1 | u), data = d, family = 'binomial')
z.x <- glmer(y ~ 1 + (1 | u), data = d, family = 'binomial')
z.v <- glm(y ~ x, data = d, family = 'binomial')

R2.pred(z.f, z.x)
R2.pred(z.f, z.v)
R2.pred(z.f)

#####
# PGLS with a single fixed effect

n <- 100
d <- data.frame(x = array(0, dim = n), y = 0)

b1 <- 1.5
signal <- 0.7

phy <- compute.brLen(rtree(n = n), method = 'Grafen', power = 1)
phy.x <- compute.brLen(phy, method = 'Grafen', power = .0001)

# Generate random data
x <- rTraitCont(phy.x, model = 'BM', sigma = 1)
e <- signal^0.5 * rTraitCont(phy, model = 'BM', sigma = 1) + (1-signal)^0.5 * rnorm(n = n)
d$x <- x[match(names(e), names(x))]
d$y <- b1 * x + e
rownames(d) <- phy$tip.label

z.x <- gls(y ~ 1, data = d, correlation = corPagel(1, phy), method = "ML")
z.f <- gls(y ~ x, data = d, correlation = corPagel(1, phy), method = "ML")
z.v <- lm(y ~ x, data = d)

R2.pred(z.f, z.x)
R2.pred(z.f, z.v)
R2.pred(z.f)

#####
# PGLMM with one fixed effect

n <- 100
b1 <- 1.5
signal <- 2

phy <- compute.brLen(rtree(n = n), method = 'Grafen', power = 1)
phy.x <- compute.brLen(phy, method = 'Grafen', power = .0001)

# Generate random data
x <- rnorm(n)
d <- data.frame(x = x, y = 0)

```

```
e <- signal * rTraitCont(phy, model = 'BM', sigma = 1)
e <- e[match(phy$tip.label, names(e))]

d$y <- rbinom(n = n, size = 1, prob = inv.logit(b1 * d$x + e))
rownames(d) <- phy$tip.label

# Use the function binaryPGLMM() from the rr2 package rather than ape.
z.f <- rr2::binaryPGLMM(y ~ x, data = d, phy = phy)
z.x <- rr2::binaryPGLMM(y ~ 1, data = d, phy = phy)
z.v <- glm(y ~ x, data = d, family = 'binomial')

R2.pred(z.f, z.x)
R2.pred(z.f, z.v)
R2.pred(z.f)
```

---

R2.resid

---

*Calculate R2.resid*


---

## Description

Calculate partial and total R2s for LMM, GLMM, PGLS, and PGLMM using R2.resid, an extension of ordinary least-squares (OLS) R2s. For LMMs and GLMMs, R2.resid is related to the method proposed by Nakagawa and Schielzeth (2013).

## Usage

```
R2.resid(mod = NULL, mod.r = NULL, phy = NULL, sigma2_d = c("s2w",
  "NS", "rNS"))
```

## Arguments

mod	A regression model with one of the following classes: 'lm', 'glm', 'lmerMod', 'glmerMod', 'phylolm', 'gls', or 'binaryPGLMM'. For 'glmerMod', only family = c('binomial', 'poisson') are supported.
mod.r	A reduced model; if not provided, the total R2 will be given by setting 'mod.r' to the model corresponding to 'mod' with the intercept as the only predictor.
phy	The phylogeny for phylogenetic models (as a 'phylo' object), which must be specified for models of class 'phylolm'.
sigma2_d	Distribution-specific variance $\sigma_d^2$ (see Details). For binomial GLMs, GLMMs and PGLMMs with logit link functions, options are c('s2w', 'NS', 'rNS'). For binomial GLMs, GLMMs and PGLMMs with probit link functions, options are c('s2w', 'NS'). Other families use 's2w'.



**Details**

R2.resid works with classes 'lm', 'glm', 'lmerMod', 'glmerMod', 'phylolm', and 'binaryPGLMM'.

**LMM (lmerMod):**

$$partialR^2 = 1 - \sigma_{e.f}^2 / \sigma_{e.r}^2$$

$$totalR^2 = 1 - \sigma_{e.f}^2 / var(y)$$

where  $\sigma_{e.f}^2$  and  $\sigma_{e.r}^2$  are the estimated residual variances from the full and reduced LMM, and  $var(y)$  is the total variance of the response (dependent) variable.

**GLMM (glmerMod):**

$$totalR^2 = 1 - \sigma_d^2 / (\sigma_x^2 + \sigma_b^2 + \sigma_d^2)$$

where  $\sigma_x^2$  and  $\sigma_b^2$  are the estimated variances associated with the fixed and random effects.  $\sigma_d^2$  is a term that scales the implied 'residual variance' of the GLMM (see Ives 2018, Appendix 1). The default used for  $\sigma_d^2$  is  $\sigma_w^2$  which is computed from the iterative weights of the GLMM. Specifically,

$$\sigma_w^2 = var(g'(\mu) * (y - \mu))$$

where  $g'()$  is the derivative of the link function, and  $(y - \mu)$  is the difference between the data  $y$  and their predicted values  $\mu$ . This is the default option specified by `sigma2_d = 's2w'`. For binomial models with a logit link function, `sigma2_d = 'NS'` gives the scaling  $\sigma_d^2 = \pi^2/3$ , and `sigma2_d = 'rNS'` gives  $\sigma_d^2 = 0.8768809 * \pi^2/3$ . For binomial models with a probit link function, `sigma2_d = 'NS'` gives the scaling  $\sigma_d^2 = 1$ . In general option `sigma2_d = 's2w'` will give values lower than `sigma2_d = 'NS'` and `'rNS'`, but the values will be closer to `R2.lik()` and `R2.pred()`. For other forms of `sigma2_d` from Nakagawa and Schielzeth (2013) and Nakagawa et al. (2017), see the MuMIn package.

Partial R2s are given by the standard formula

$$partialR^2 = 1 - (1 - R_f^2) / (1 - R_r^2)$$

where  $R_f$  and  $R_r$  are the total R2s for full and reduced models, respectively.

**PGLS (phylolm):**

$$partialR^2 = 1 - c.f * \sigma_f^2 / (c.r * \sigma_r^2)$$

where  $\sigma_f^2$  and  $\sigma_r^2$  are the variances estimated for the PGLS full and reduced models, and  $c.f$  and  $c.r$  are the scaling values for full and reduce models that equal the total sum of phylogenetic branch length estimates. Note that the phylogeny needs to be specified in R2.resid.

Note that `phylolm()` can have difficulties in finding solutions when there is no phylogenetic signal; when the estimate indicates no phylogenetic signal, you should refit the model with the corresponding LM.

**PGLMM (binaryPGLMM):**

The binary PGLMM is computed in the same way as the binomial GLMM, with options `sigma_d = c('s2w', 'NS', 'rNS')`. The estimated variance of the random effect associated with the phylogeny,  $\sigma_b^2$ , is multiplied by the diagonal elements of the phylogenetic covariance matrix. For binary models, this covariance matrix should be standardized so that all diagonal elements are the same (a contemporaneous or ultrametric phylogenetic tree) (Ives and Garland 2014). In case this is not done, however, the code takes the geometric average of the diagonal elements.

Note that the version of `binaryPGLMM()` in the package `ape` is replaced by a version contained within `rr2` that outputs all of the required information for the calculation of `R2.resid()`

**LM (lm) and GLM (glm):**

For compatibility and generating reduced models, `rr2` will compute `R2.resid()` for LM and GLM that correspond to LMM/PGLS and GLMM/PGLMM.

**Value**

`R2.resid` value.

**Author(s)**

Anthony R. Ives

**References**

- Ives A.R. and Li D. 2018. `rr2`: An R package to calculate R2s for regression models. *Journal of Open Source Software*. DOI:10.21105/joss.01028
- Ives A.R. 2018. R2s for Correlated Data: Phylogenetic Models, LMMs, and GLMMs. *Systematic Biology*. DOI:10.1093/sysbio/syy060
- Ives A. R., Garland T., Jr. 2014. Phylogenetic regression for binary dependent variables. In: Garamszegi LZ editor. *Modern Phylogenetic Comparative Methods and Their Application in Evolutionary Biology*. Berlin Heidelberg, Springer-Verlag, p. 231-261.
- Nakagawa S., Schielzeth H. 2013. A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution*, 4:133-142.
- Nakagawa S., Johnson P. C. D., Schielzeth H. 2017. The coefficient of determination R2 and intra-class correlation coefficient from generalized linear mixed-effects models revisited and expanded. *Journal of the Royal Society Interface*, 14.

**See Also**

`MuMIn`, `lme4`, `ape`, `phylolm`, `pez`

`MuMIn`

**Examples**

```
library(ape)
library(phylolm)
library(lme4)
library(nlme)
```

```
#####
# LMM with two fixed and two random effects
p1 <- 10
nsample <- 10
n <- p1 * nsample

d <- data.frame(x1 = 0, x2 = 0, y = 0, u1 = rep(1:p1, each = nsample),
               u2 = rep(1:p1, times = nsample))
d$u1 <- as.factor(d$u1)
d$u2 <- as.factor(d$u2)

b1 <- 1
b2 <- -1
sd1 <- 1.5

d$x1 <- rnorm(n = n)
d$x2 <- rnorm(n = n)
d$y <- b1 * d$x1 + b2 * d$x2 + rep(rnorm(n = p1, sd = sd1), each = nsample) +
  rep(rnorm(n = p1, sd = sd1), times = nsample) + rnorm(n = n)

z.f <- lmer(y ~ x1 + x2 + (1 | u1) + (1 | u2), data = d, REML = FALSE)
z.x <- lmer(y ~ x1 + (1 | u1) + (1 | u2), data = d, REML = FALSE)
z.v <- lmer(y ~ 1 + (1 | u2), data = d, REML = FALSE)
z.0 <- lm(y ~ 1, data = d)

R2.resid(z.f, z.x)
R2.resid(z.f, z.v)
R2.resid(z.f)

#####
# GLMM with one fixed and one random effect

p1 <- 10
nsample <- 10
n <- p1 * nsample

d <- data.frame(x = 0, y = 0, u = rep(1:p1, each = nsample))
d$u <- as.factor(d$u)

b1 <- 1
sd1 <- 1.5

d$x <- rnorm(n = n)
prob <- inv.logit(b1 * d$x + rep(rnorm(n = p1, sd = sd1), each = nsample))
d$y <- rbinom(n = n, size = 1, prob = prob)

z.f <- glmer(y ~ x + (1 | u), data = d, family = 'binomial')
z.x <- glmer(y ~ 1 + (1 | u), data = d, family = 'binomial')
z.v <- glm(y ~ x, data = d, family = 'binomial')

R2.resid(z.f, z.x)
R2.resid(z.f, z.v)
```

```

R2.resid(z.f)

#####
# PGLS with a single fixed effect

n <- 100
d <- data.frame(x = array(0, dim = n), y = 0)

b1 <- 1.5
signal <- 0.7

phy <- compute.brLen(rtree(n = n), method = 'Grafen', power = 1)
phy.x <- compute.brLen(phy, method = 'Grafen', power = .0001)

# Generate random data
x <- rTraitCont(phy.x, model = 'BM', sigma = 1)
e <- signal^0.5 * rTraitCont(phy, model = 'BM', sigma = 1) + (1-signal)^0.5 * rnorm(n = n)
d$x <- x[match(names(e), names(x))]
d$y <- b1 * x + e
rownames(d) <- phy$tip.label

z.x <- phyloLm(y ~ 1, phy = phy, data = d, model = 'lambda')
lam.x <- round(z.x$optpar, digits = 4)
z.f <- phyloLm(y ~ x, phy = phy, data = d, model = 'lambda')
z.v <- lm(y ~ x, data = d)

R2.resid(z.f, z.x, phy = phy)
R2.resid(z.f, z.v, phy = phy)
R2.resid(z.f, phy = phy)

# This also works for models fit with gls() in {nlme}
z.x <- gls(y ~ 1, data = d, correlation = corPagel(1, phy), method = "ML")
z.f <- gls(y ~ x, data = d, correlation = corPagel(1, phy), method = "ML")
z.v <- lm(y ~ x, data = d)

R2.resid(z.f, z.x)
R2.resid(z.f, z.v)
R2.resid(z.f)

# But note that you need to define weights for gls() with non-ultrametric trees;
# if not, you will get a error "Matrix is not block-diagonal"

phy.nu <- rtree(n = n)

# Generate random data
e <- signal^0.5 * rTraitCont(phy.nu, model = 'BM', sigma = 1) + (1-signal)^0.5 * rnorm(n = n)
d$x <- x[match(names(e), names(x))]
d$y <- b1 * x + e
rownames(d) <- phy.nu$tip.label

weights <- diag(vcv.phylo(phy.nu))
z.x <- gls(y ~ 1, data = d,
          correlation = corPagel(1, phy.nu),

```

```

        weights=varFixed(~weights), method = "ML")
z.f <- gls(y ~ x,data = d,
          correlation = corPagel(1, phy.nu),
          weights=varFixed(~weights), method = "ML")
z.v <- lm(y ~ x, data = d)

R2.resid(z.f, z.x)
R2.resid(z.f, z.v)
R2.resid(z.f)

#####
# PGLMM with one fixed effect

n <- 100
b1 <- 1.5
signal <- 2

phy <- compute.brLen(rtree(n = n), method = 'Grafen', power = 1)
phy.x <- compute.brLen(phy, method = 'Grafen', power = .0001)

# Generate random data
x <- rnorm(n)
d <- data.frame(x = x, y = 0)

e <- signal * rTraitCont(phy, model = 'BM', sigma = 1)
e <- e[match(phy$tip.label, names(e))]

d$y <- rbinom(n = n, size = 1, prob = inv.logit(b1 * d$x + e))
rownames(d) <- phy$tip.label

# Use the function binaryPGLMM() from the rr2 package rather than ape.
z.f <- rr2::binaryPGLMM(y ~ x, data = d, phy = phy)
z.x <- rr2::binaryPGLMM(y ~ 1, data = d, phy = phy)
z.v <- glm(y ~ x, data = d, family = 'binomial')

R2.resid(z.f, z.x, phy = phy)
R2.resid(z.f, z.v, phy = phy)
R2.resid(z.f, phy = phy)

```

**Description**

The rr2 package provides methods to calculate R2 for models with correlated errors, including Phylogenetic GLS, Phylogenetic Logistic Regression, LMMs, GLMM, and PGLMM.

---

transf_phy	<i>Transform a phylogeny based on a phylolm model</i>
------------	---

---

**Description**

Using a fitted phylolm model to transform branch lengths of a phylogeny

**Usage**

```
transf_phy(phylolmMod, phy)
```

**Arguments**

phylolmMod	A fitted phylolm model.
phy	A phylogeny with class 'phylo'.

**Value**

A transformed phylogeny.

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