Package 'fullfact'

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Version 1.0 Date 2015-12-01 Title Full Factorial Breeding Analysis Author Aimee Lee Houde [aut, cre], Trevor Pitcher [aut] Maintainer Aimee Lee Houde <aimee.lee.houde@gmail.com> **Depends** R $(>= 3.2.2)$, lme4, afex Description Package for the analysis of full factorial breeding designs. License GPL (>=2) URL <http://www.r-project.org>

BugReports Aimee Lee Houde <aimee.lee.houde@gmail.com> NeedsCompilation no

R topics documented:

fullfact-package *Full Factorial Breeding Analysis*

Description

Analysis of full factorial breeding designs. The package incorporates mixed-effects models suited for unbalanced experimental designs and non-normal data types. Extracts variance components and significance values for random and fixed effects. Calculates the amount of additive genetic, nonadditive genetic, and maternal variance explaining phenotypic traits. Produces confidence values using a bootstrap resampling routine and can apply bias and acceleration correction. Also includes an option for producing jackknife resampling confidence intervals. Calculates the power values of random and fixed effects.

Details

The DESCRIPTION file:

Index of help topics:

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References

Traditional full factorial breeding design analysis:

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Residual variance component values for generalized linear mixed-effects models:

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

Fixed effect variance component values for mixed-effects models:

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

Confidence intervals (bootstrap resampling, bias and acceleration correction, jackknife resampling):

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

Martin, H., Westad, F. & Martens, H. (2004). Imporved Jackknife Variance Estimates of Bilinear Model Parameters. COMPSTAT 2004 – Proceedings in Computational Statistics 16th Symposium Held in Prague, Czech Republic, 2004 (ed J. Antoch), pp. 261-275. Physica-Verlag HD, Heidelberg.

Data sources:

Pitcher TE, Neff BD. 2007. Genetic quality and offspring performance in Chinook salmon: implications for supportive breeding. Conservation Genetics 8(3):607-616. DOI: 10.1007/s10592-006- 9204-z

Examples

data(chinook_length) #Chinook salmon offspring length

Standard additive genetic, non-additive genetic, and maternal variance analysis

```
length_mod1<- observLmer(observ=chinook_length,dam="dam",sire="sire",response="length")
length_mod1
```
Confidence intervals

```
##Bootstrap resampling of data: replicates within family
#resampRepli(dat=chinook_length,copy=c(3:8),family="family",replicate="repli",iter=1000)
resampRepli(dat=chinook_length,copy=c(3:8),family="family",replicate="repli",iter=5)
#example of 5 iterations
#saves the files in working directory: one for each replicate and
#one final (combined) file "resamp_datR.csv"
```

```
##Import file
#length_datR<- read.csv("resamp_datR.csv")
data(chinook_resampL) #same as length_datR, 5 iterations
```

```
##Models for the resampled data: standard analysis
#length_rcomp<- resampLmer(resamp=length_datR,dam="dam",sire="sire",response="length",
#start=1,end=1000)
length_rcomp<- resampLmer(resamp=chinook_resampL,dam="dam",sire="sire",response="length",
start=1,end=5) #example of 5 models
```
barMANA 5

1. Uncorrected Bootstrap 95% confidence interval

```
#ciMANA(comp=length_rcomp)
data(chinook_bootL) #similar to length_rcomp, but 1,000 models
ciMANA(comp=chinook_bootL)
```
2. Bias and accelerated corrected Bootstrap 95% confidence interval

```
##Jackknife resampling of data, delete-one: for acceleration estimate
#length_jack<- JackLmer(observ=chinook_length.dam="dam",sire="sire",
#response="length")
length_jack<- JackLmer(observ=chinook_length,dam="dam",sire="sire",
response="length",first=10) #example of first 10 observations
```
#ciMANA(comp=length_rcomp,bias=c(0.0000000,0.7192253,0.2029684),accel=length_jack) data(chinook_jackL) #similar to length_jack, but all observations ciMANA(comp=chinook_bootL,bias=c(0.0000000,0.7192253,0.2029684),accel=chinook_jackL)

##3. Jackknife 95% confidence interval

```
#ciJack(comp=length_jack,full=c(0.0000000,0.7192253,0.2029684,1.0404425))
ciJack(comp=chinook_jackL,full=c(0.0000000,0.7192253,0.2029684,1.0404425))
```
barMANA *Bargraph of confidence intervals*

Description

A simple bargraph function for confidence intervals of additive genetic, non-additive genetic, and maternal variance components. Also, plots the median for the bootstrap resampling method or mean of the pseudo-values for the jackknife resampling method.

Usage

```
barMANA(ci_dat, type = "perc", bar_len = 0.1, ymax = NULL, ymin = NULL, yunit = NULL,
leg = "topright", cex_ylab = 1, cex_yaxis = 1, cex_names = 1)
```
Arguments

Details

Plots a bargraph with the median or mean as the top of the shaded bar and error bars covering the range of the confidence interval. Uses an object produced by any of the bootstrap resampling CI functions, i.e. *ciMANA*, *ciMANA2*, and *ciMANA3* or jackknife resampling functions, i.e. *ciJack*, *ciJack2*, and *ciJack3*. The median is plotted for bootstrap resampling and the mean of pseudovalue for jackknife resampling. Produces a simple legend. The function can plot several bar graphs grouped by *label* to visualize several phenotypic traits.

Examples

```
##Import bootstrap resampling results
data(chinook_bootS) #Chinook salmon offspring survival
#Extract un-corrected confidence interval
survival_ci<- ciMANA(comp=chinook_bootS,trait="survival")
survival_ci
#Default plot
barMANA(ci_dat=survival_ci)
#Add plot modifications
barMANA(ci_dat=survival_ci,bar_len=0.3,yunit=5,ymax=20,cex_ylab=1.3)
##Import jackknife resampling results
data(chinook_jackL) #Chinook salmon offspring length
#Extract jackknife confidence interval
length_ci<- ciJack2(comp=chinook_jackL,full=c(0.0000000,0.7192253,0.2029684,1.0404425,
0.1077423),position="tray",trait="length")
length_ci
#Default plot
barMANA(ci_dat=length_ci)
#Add plot modifications
barMANA(ci_dat=length_ci,bar_len=0.3,yunit=20,ymax=100,cex_ylab=1.3)
##Group survival and length together in the same plot
data(chinook_bootL) #Chinook salmon offspring length
length_ci2<- ciMANA2(comp=chinook_bootL,position="tray",trait="length")
length_ci2
#
comb_r<- rbind(survival_ci$raw,length_ci2$raw)
comb_p<- rbind(survival_ci$percentage,length_ci2$percentage)
comb_ci<- list(raw=comb_r,percentage=comb_p)
#Default plot
barMANA(ci_dat=comb_ci)
#Add plot modifications
barMANA(ci_dat=comb_ci,bar_len=0.3,yunit=20,ymax=100,cex_ylab=1.3,leg="topleft")
```
boxMANA *Boxplot of resampled results*

Description

A simple boxplot function for bootstrap and jackknife resampled results of additive genetic, nonadditive genetic, and maternal variance components.

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Usage

```
boxMANA(comp, type = "perc", ymax = NULL, ymin = NULL, yunit = NULL, leg = "topright",
cex_ylab = 1, cex_yaxis = 1, cex_znames = 1)
```
Arguments

Details

Plots an R boxplot. Uses an object produced by any of the bootstrap resampling functions, i.e. *resampLmer*, *resampLmer2*, *resampLmer3*, *resampGlmer*, *resampGlmer2*, and *resampGlmer3*. Or any of the jackknife resampling functions, i.e. *JackLmer*, *JackLmer2*, *JackLmer3*, *JackGlmer*, *Jack-Glmer2*, and *JackGlmer3*. Produces a simple legend.

Examples

#Import bootstrap resampled data model results data(chinook_bootL) #Chinook salmon offspring length

```
#Default plot
boxMANA(comp=chinook_bootL)
#Add plot modifications
boxMANA(comp=chinook_bootL,yunit=20,ymax=100,cex_ylab=1.3)
##Group length and survival together in the same plot
data(chinook_bootS) #Chinook salmon offspring survival
chinook_bootL$trait<- "length"
chinook_bootS$trait<- "survival"
colnames(chinook_bootL[,-2])
colnames(chinook_bootS)
#
comb_boot<- rbind(chinook_bootL[,-2],chinook_bootS) #remove 'tray'
comb_boot$trait<- as.factor(comb_boot$trait) #to form levels
#Default plot
boxMANA(comp=comb_boot)
```

```
#Add plot modifications
boxMANA(comp=comb_boot,yunit=20,ymax=100,cex_ylab=1.3)
```


Assign a binary number (i.e. '0' or '1') to two columns containing the number of offspring. Copy information by the number of times equal to the number of offspring.

Usage

buildBinary(dat, copy, one, zero)

Arguments

Details

Replicate-level data should be converted to the individual-level to not underestimate phenotypic variance, which can influence genetic and maternal estimates (see Puurtinen et al. 2009).

Value

A converted data frame with a number of row matching the total number of individuals.

References

Puurtinen M, Ketola T, Kotiaho JS. 2009. The good-genes and compatible-genes benefits of mate choice. The American Naturalist 174(5): 741-752. DOI: 10.1086/606024

See Also

[buildMulti](#page-8-1)

```
data(chinook_survival)
chinook_survival2<- buildBinary(dat=chinook_survival,copy=c(1:6,9),one="alive",zero="dead")
```


Assign multiple numbers to multiple columns containing the number of offspring. Copy information by the number of times equal to the number of offspring.

Usage

buildMulti(dat, copy, multi)

Arguments

Details

Replicate-level data should be converted to the individual-level to not underestimate phenotypic variance, which can influence genetic and maternal estimates (see Puurtinen et al. 2009).

Value

A converted data frame with a number of row matching the total number of individuals.

References

Puurtinen M, Ketola T, Kotiaho JS. 2009. The good-genes and compatible-genes benefits of mate choice. The American Naturalist 174(5): 741-752. DOI: 10.1086/606024

See Also

[buildBinary](#page-7-1)

```
data(chinook_survival)
chinook_survival$total<- chinook_survival$alive + chinook_survival$dead #create total column
chinook_survival3<- buildMulti(dat=chinook_survival,copy=c(1:6,9),multi=list(c(2,1,0),
c("total","alive","dead")))
```


Bootstrap resampled Chinook salmon fork length (mm) at hatch with the amount of additive genetic, non-additive genetic, and maternal variance calculations.

Usage

```
data("chinook_bootL")
```
Format

A data frame with 1000 observations on the following 9 variables.

dam.sire, a numeric vector.

tray, a numeric vector.

sire, a numeric vector.

dam, a numeric vector.

Residual, a numeric vector.

Total, a numeric vector.

additive, a numeric vector.

maternal, a numeric vector.

nonadd, a numeric vector.

Details

Also includes the calculations for the amount of variance explained by position (tray), dam by sire, sire, dam, residual,and total.

Source

http://link.springer.com.proxy1.lib.uwo.ca/article/10.1007

References

Pitcher TE, Neff BD. 2007. Genetic quality and offspring performance in Chinook salmon: implications for supportive breeding. Conservation Genetics 8(3):607-616. DOI: 10.1007/s10592-006- 9204-z

```
data(chinook_bootL)
## Extract bootstrap confidence interval
ciMANA(comp=chinook_bootL)
```


Bootstrap resampled Chinook salmon binary survival to hatch (1 is alive, 0 is dead) with the amount of additive genetic, non-additive genetic, and maternal variance calculations.

Usage

```
data("chinook_bootS")
```
Format

A data frame with 1000 observations on the following 8 variables.

dam.sire, a numeric vector.

sire, a numeric vector.

dam, a numeric vector.

Residual, a numeric vector.

Total, a numeric vector.

additive, a numeric vector.

maternal, a numeric vector.

nonadd, a numeric vector.

Details

Also includes the calculations for the amount of variance explained by dam by sire, sire, dam, residual, and total.

Source

http://link.springer.com.proxy1.lib.uwo.ca/article/10.1007

References

Pitcher TE, Neff BD. 2007. Genetic quality and offspring performance in Chinook salmon: implications for supportive breeding. Conservation Genetics 8(3):607-616. DOI: 10.1007/s10592-006- 9204-z

```
data(chinook_bootS)
## Extract bootstrap confidence interval
ciMANA(comp=chinook_bootS)
```


Jackknife resampled Chinook salmon fork length (mm) at hatch with the amount of additive genetic, non-additive genetic, and maternal variance calculations. Jackknife resampling was leave-out-one.

Usage

```
data("chinook_jackL")
```
Format

A data frame with 1210 observations on the following 9 variables.

dam.sire, a numeric vector.

tray, a numeric vector.

sire, a numeric vector.

dam, a numeric vector.

Residual, a numeric vector.

Total, a numeric vector.

additive, a numeric vector.

nonadd, a numeric vector.

maternal, a numeric vector.

Details

Also includes the calculations for the amount of variance explained by position (tray), dam by sire, sire, dam, residual, and total.

Source

http://link.springer.com.proxy1.lib.uwo.ca/article/10.1007

References

Pitcher TE, Neff BD. 2007. Genetic quality and offspring performance in Chinook salmon: implications for supportive breeding. Conservation Genetics 8(3):607-616. DOI: 10.1007/s10592-006- 9204-z

```
data(chinook_jackL)
## Extract jackknifed confidence interval
ciJack(comp=chinook_jackL,full=c(0.0000000,0.7192253,0.2029684,1.0404425))
```
chinook_length *Chinook salmon length, raw data*

Description

Raw Chinook salmon fork length (mm) at hatch for offspring produced using an 11 x 11 full factorial breeding design.

Usage

```
data("chinook_length")
```
Format

A data frame with 1210 observations on the following 8 variables.

family, a factor with levels: f1 f10 f100 f101 f102 f103 f104 f105 f106 f107 f108 f109 f11 f110 f111 f112 f113 f114 f115 f116 f117 f118 f119 f12 f120 f121 f13 f14 f15 f16 f17 f18 f19 f2 f20 f21 f22 f23 f24 f25 f26 f27 f28 f29 f3 f30 f31 f32 f33 f34 f35 f36 f37 f38 f39 f4 f40 f41 f42 f43 f44 f45 f46 f47 f48 f49 f5 f50 f51 f52 f53 f54 f55 f56 f57 f58 f59 f6 f60 f61 f62 f63 f64 f65 f66 f67 f68 f69 f7 f70 f71 f72 f73 f74 f75 f76 f77 f78 f79 f8 f80 f81 f82 f83 f84 f85 f86 f87 f88 f89 f9 f90 f91 f92 f93 f94 f95 f96 f97 f98 f99

repli, a factor with levels: r1 r2

dam, a factor with levels: d1 d10 d11 d2 d3 d4 d5 d6 d7 d8 d9

sire, a factor with levels: s1 s10 s11 s2 s3 s4 s5 s6 s7 s8 s9

tray, a factor with levels: t1 t10 t11 t12 t13 t14 t15 t16 t2 t3 t4 t5 t6 t7 t8 t9

cell, a factor with levels: 1A 1B 1C 1D 2A 2B 2C 2D 3A 3B 3C 3D 4A 4B 4C 4D

length, a numeric vector.

egg_size, a numeric vector.

Details

Also includes family identity, family replicate, incubator position (tray and cell), and average female egg size (mm) information.

Source

http://link.springer.com.proxy1.lib.uwo.ca/article/10.1007

References

Pitcher TE, Neff BD. 2007. Genetic quality and offspring performance in Chinook salmon: implications for supportive breeding. Conservation Genetics 8(3):607-616. DOI: 10.1007/s10592-006- 9204-z

```
data(chinook_length)
## Standard additive genetic, non-additive genetic, and maternal variance analysis
length_mod1<- observLmer(observ=chinook_length,dam="dam",sire="sire",response="length")
length_mod1
```


Bootstrap resampled Chinook salmon fork length (mm) at hatch. Number of iterations was 5.

Usage

data("chinook_resampL")

Format

A data frame with 1210 observations on the following 30 variables.

dam1, a numeric vector sire1, a numeric vector tray1, a numeric vector cell1, a numeric vector length1, a numeric vector egg_size1, a numeric vector dam2, a numeric vector sire2, a numeric vector tray2, a numeric vector cell2, a numeric vector length2, a numeric vector egg_size2, a numeric vector dam3, a numeric vector sire3, a numeric vector tray3, a numeric vector cell3, a numeric vector length3, a numeric vector egg_size3, a numeric vector dam4, a numeric vector sire4, a numeric vector tray4, a numeric vector cell4, a numeric vector length4, a numeric vector egg_size4, a numeric vector dam5, a numeric vector sire5, a numeric vector tray5, a numeric vector cell5, a numeric vector length5, a numeric vector egg_size5, a numeric vector

chinook_resampS 15

Source

Pitcher TE, Neff BD. 2007. Genetic quality and offspring performance in Chinook salmon: implications for supportive breeding. Conservation Genetics 8(3):607-616. DOI: 10.1007/s10592-006- 9204-z

Examples

```
data(chinook_resampL)
#the five models
length_rcomp1<- resampLmer(resamp=chinook_resampL,dam="dam",sire="sire",response="length",
start=1,end=5) #full analysis should use 1,000 models
```
chinook_resampS *Chinook salmon survival, bootstrap resampled*

Description

Bootstrap resampled Chinook salmon binary survival to hatch (1 is alive, 0 is dead). Number of iterations was 5.

Usage

```
data("chinook_resampS")
```
status1, a numeric vector

Format

A data frame with 36300 observations on the following 30 variables.

dam1, a numeric vector sire1, a numeric vector tray1, a numeric vector cell1, a numeric vector egg_size1, a numeric vector status2, a numeric vector dam2, a numeric vector sire2, a numeric vector tray2, a numeric vector cell2, a numeric vector egg_size2, a numeric vector status3, a numeric vector dam3, a numeric vector sire3, a numeric vector tray3, a numeric vector cell3, a numeric vector egg_size3, a numeric vector status4, a numeric vector dam4, a numeric vector sire4, a numeric vector tray4, a numeric vector cell4, a numeric vector egg_size4, a numeric vector status5, a numeric vector dam5, a numeric vector sire5, a numeric vector tray5, a numeric vector cell5, a numeric vector egg_size5, a numeric vector

Source

Pitcher TE, Neff BD. 2007. Genetic quality and offspring performance in Chinook salmon: implications for supportive breeding. Conservation Genetics 8(3):607-616. DOI: 10.1007/s10592-006- 9204-z

Examples

```
data(chinook_resampS)
survival_rcomp<- resampGlmer(resamp=chinook_resampS,dam="dam",sire="sire",response="status",
fam_link=binomial(logit),start=1,end=5) #full analysis should use 1,000 models
```
chinook_survival *Chinook salmon survival, raw data*

Description

Raw Chinook salmon numbers alive and dead to hatching of offspring produced using an 11 x 11 full factorial breeding design.

Usage

```
data("chinook_survival")
```
Format

A data frame with 242 observations on the following 9 variables.

family, a factor with levels: f1 f10 f100 f101 f102 f103 f104 f105 f106 f107 f108 f109 f11 f110 f111 f112 f113 f114 f115 f116 f117 f118 f119 f12 f120 f121 f13 f14 f15 f16 f17 f18 f19 f2 f20 f21 f22 f23 f24 f25 f26 f27 f28 f29 f3 f30 f31 f32 f33 f34 f35 f36 f37 f38 f39 f4 f40 f41 f42 f43 f44 f45 f46 f47 f48 f49 f5 f50 f51 f52 f53 f54 f55 f56 f57 f58 f59 f6 f60 f61 f62 f63 f64 f65 f66 f67 f68 f69 f7 f70 f71 f72 f73 f74 f75 f76 f77 f78 f79 f8 f80 f81 f82 f83 f84 f85 f86 f87 f88 f89 f9 f90 f91 f92 f93 f94 f95 f96 f97 f98 f99

repli, a factor with levels: r1 r2

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dam, a factor with levels: d1 d10 d11 d2 d3 d4 d5 d6 d7 d8 d9

sire, a factor with levels: s1 s10 s11 s2 s3 s4 s5 s6 s7 s8 s9

tray, a factor with levels: t1 t10 t11 t12 t13 t14 t15 t16 t2 t3 t4 t5 t6 t7 t8 t9

cell, a factor with levels: 1A 1B 1C 1D 2A 2B 2C 2D 3A 3B 3C 3D 4A 4B 4C 4D

alive, a numeric vector.

dead, a numeric vector.

egg_size, a numeric vector.

Details

Also includes family identity, family replicate, incubator position (tray and cell), and average female egg size (mm) information.

Source

http://link.springer.com.proxy1.lib.uwo.ca/article/10.1007

References

Pitcher TE, Neff BD. 2007. Genetic quality and offspring performance in Chinook salmon: implications for supportive breeding. Conservation Genetics 8(3):607-616. DOI: 10.1007/s10592-006- 9204-z

Examples

```
data(chinook_survival)
## Convert replicate-level recorded data to individual-level (binary) data
chinook_survival2<- buildBinary(dat=chinook_survival,copy=c(2:6,9),one="alive",zero="dead")
```

```
## Standard additive genetic, non-additive genetic, and maternal variance analysis
survival_mod1<- observGlmer(observ=chinook_survival2,dam="dam",sire="sire",
response="status",fam_link=binomial(logit))
survival_mod1
```
ciJack *Jackknife confidence intervals*

Description

Extracts jackknife confidence intervals for additive genetic, non-additive genetic, and maternal variance components.

Usage

```
cijack(comp, full, level = 95, rnd_r = 3, rnd_p = 1, trait = NULL)
```
Arguments

Details

Used for jackknife resampling results produced using *JackLmer* for normal data or *JackGlmer* for non-normal data. Jackknife confidence intervals, using pseudo-values are described by Efron and Tibshirani (1993). The standard errors are calculated from the pseudo-values and the Student's *t* distribution is used to provide the lower and upper confidence values. For delete-*d* jackknife resampling, *M* degrees of freedom are used for producing the confidence interval (Martin et al. 2004): $M = N / d$, where *N* is the total number of observations and d is the number of deleted observations. That is, *M* is the number of row in the jackknife resampling results. Large values of *M*, such as 1,000, can translate to the delete-d jackknife resampling method approaching bootstrap resampling expectations (Efron & Tibshirani 1993).

Value

Prints a data frame containing the lower, median, and upper values of the jackknife confidence interval for additive genetic, non-additive genetic, and maternal variance components. Values are presented as raw and percentages of the total variance value within each row.

References

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

Martin, H., Westad, F. & Martens, H. (2004). Imporved Jackknife Variance Estimates of Bilinear Model Parameters. COMPSTAT 2004 – Proceedings in Computational Statistics 16th Symposium Held in Prague, Czech Republic, 2004 (ed J. Antoch), pp. 261-275. Physica-Verlag HD, Heidelberg.

See Also

[ciJack2](#page-18-1), [ciJack3](#page-19-1)

Examples

data(chinook_jackL) #Chinook salmon offspring length, delete-one jackknife ciJack(chinook_jackL,c(0.0000000,0.7192253,0.2029684,1.0404425))

Extracts jackknife confidence intervals for additive genetic, non-additive genetic, and maternal variance components. Also extracts intervals for optional position and block variance components.

Usage

 cij ack2(comp, full, level = 95, $rnd_r = 3$, $rnd_p = 1$, $position = NULL$, $block = NULL$, trait = NULL)

Arguments

Details

Used for jackknife resampling results produced using *JackLmer2* for normal data or *JackGlmer2* for non-normal data. Jackknife confidence intervals, using pseudo-values are described by Efron and Tibshirani (1993). The standard errors are calculated from the pseudo-values and the Student's *t* distribution is used to provide the lower and upper confidence values. For delete-*d* jackknife resampling, *M* degrees of freedom are used for producing the confidence interval (Martin et al. 2004): $M = N / d$, where *N* is the total number of observations and d is the number of deleted observations. That is, *M* is the number of row in the jackknife resampling results. Large values of *M*, such as 1,000, can translate to the delete-d jackknife resampling method approaching bootstrap resampling expectations (Efron & Tibshirani 1993).

Value

Prints a data frame containing the lower, median, and upper values of the jackknife confidence interval for additive genetic, non-additive genetic, maternal variance components, and optional position and/or block variance components. Values are presented as raw and percentages of the total variance value within each row.

References

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York. Martin, H., Westad, F. & Martens, H. (2004). Imporved Jackknife Variance Estimates of Bilinear Model Parameters. COMPSTAT 2004 – Proceedings in Computational Statistics 16th Symposium Held in Prague, Czech Republic, 2004 (ed J. Antoch), pp. 261-275. Physica-Verlag HD, Heidelberg.

See Also

[ciJack](#page-16-1), [ciJack3](#page-19-1)

Examples

data(chinook_jackL) #Chinook salmon offspring length, delete-one jackknife ciJack2(chinook_jackL,c(0.0000000,0.7192253,0.2029684,1.0404425,0.1077423),position="tray")

ciJack3 *Jackknife confidence intervals 3*

Description

Extracts jackknife confidence intervals for additive genetic, non-additive genetic, and maternal variance components. Also extracts intervals for additional fixed and random effects.

Usage

ciJack3(comp, full, remain = NULL, level = 95, rnd_r = 3, rnd_p = 1, trait = NULL)

Arguments

Details

Used for jackknife resampling results produced using *JackLmer3* for normal data or *JackGlmer3* for non-normal data. Jackknife confidence intervals, using pseudo-values are described by Efron and Tibshirani (1993). The standard errors are calculated from the pseudo-values and the Student's *t* distribution is used to provide the lower and upper confidence values. For delete-*d* jackknife resampling, *M* degrees of freedom are used for producing the confidence interval (Martin et al. 2004): $M = N / d$, where *N* is the total number of observations and d is the number of deleted observations. That is, *M* is the number of row in the jackknife resampling results. Large values of *M*, such as 1,000, can translate to the delete-d jackknife resampling method approaching bootstrap resampling expectations (Efron & Tibshirani 1993).

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Value

Prints a data frame containing the lower, median, and upper values of the jackknife confidence interval for additive genetic, non-additive genetic, maternal variance components, and any additional fixed effect and random effect variance components. Values are presented as raw and percentages of the total variance value within each row.

References

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

Martin, H., Westad, F. & Martens, H. (2004). Imporved Jackknife Variance Estimates of Bilinear Model Parameters. COMPSTAT 2004 – Proceedings in Computational Statistics 16th Symposium Held in Prague, Czech Republic, 2004 (ed J. Antoch), pp. 261-275. Physica-Verlag HD, Heidelberg.

See Also

[ciJack](#page-16-1), [ciJack2](#page-18-1)

Examples

```
data(chinook_jackL) #Chinook salmon offspring length, delete-one jackknife
ciJack3(chinook_jackL,c(0.0000000,0.7192253,0.2029684,1.0404425,0.1077423,0.5499255),
remain=c("tray","Residual"))
```


 $Boostrap$ *confidence intervals*

Description

Extracts bootstrap-*t* confidence intervals for additive genetic, non-additive genetic, and maternal variance components.

Usage

 $ciMANA$ (comp, level = 95, $rnd_r = 3$, $rnd_p = 1$, bias = NULL, accel = NULL, trait = NULL)

Arguments

Details

Used for bootstrap resampling results produced using *resampLmer* for normal data or *resampGlmer* for non-normal data. Bootstrap-*t* confidence intervals, including bias and acceleration correction methods are described by Efron and Tibshirani (1993). Jackknife data model results for acceleration correction can be produced using *JackLmer*, for normal data or *JackGlmer* for non-normal data. The 'bias fail' warning is if the bias calculation is Inf or -Inf, e.g. *bias* contains a zero value, so the uncorrected confidence interval is displayed.

Value

Prints a data frame containing the lower, median, and upper values of the bootstrap-*t* confidence interval for additive genetic, non-additive genetic, and maternal variance components. Values are presented as raw and percentages of the total variance value within each row.

References

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

See Also

[ciMANA2](#page-21-1), [ciMANA3](#page-23-1)

Examples

#Import bootstrap resampled data model results data(chinook_bootL) #Chinook salmon offspring length

```
#Extract un-corrected confidence interval
ciMANA(comp=chinook_bootL)
```

```
#Extract bias corrected confidence interval
ciMANA(comp=chinook_bootL,bias=c(0.0000000,0.7192253,0.2029684))
#see details for 'bias' fail
```

```
#Extract bias and accelerated corrected confidence interval
#Import jackknife resampled data model results
data(chinook_jackL)
#
ciMANA(comp=chinook_bootL,bias=c(0.0000000,0.7192253,0.2029684),accel=chinook_jackL)
#see details for 'bias' fail
```
ciMANA2 *Bootstrap confidence intervals 2*

Description

Extracts bootstrap-*t* confidence intervals for additive genetic, non-additive genetic, and maternal variance components. Also extracts intervals for optional position and block variance components.

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Usage

```
ciMANA2(comp, level = 95, rnd_r = 3, rnd_p = 1, position = NULL, block = NULL,
bias = NULL, accel = NULL, trait = NULL)
```
Arguments

Details

Used for bootstrap resampling results produced using *resampLmer2* for normal data or*resampGlmer2* for non-normal data. Bootstrap-*t* confidence intervals, including bias and acceleration correction methods are described by Efron and Tibshirani (1993). Jackknife data model results for acceleration correction can be produced using *JackLmer2*, for normal data or *JackGlmer2* for non-normal data. The 'bias fail' warning is if the bias calculation is Inf or -Inf, e.g. *bias* contains a zero value, so the uncorrected confidence interval is displayed.

Value

Prints a data frame containing the lower, median, and upper values of the bootstrap-*t* confidence interval for additive genetic, non-additive genetic, maternal, and optional position and/or block variance components. Values are presented as raw and percentages of the total variance value within each row.

References

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

See Also

[ciMANA](#page-20-1), [ciMANA3](#page-23-1)

Examples

#Import bootstrap resampled data model results data(chinook_bootL) #Chinook salmon offspring length

#Extract un-corrected confidence interval ciMANA2(comp=chinook_bootL,position="tray")

```
#Extract bias corrected confidence interval
ciMANA2(comp=chinook_bootL,bias=c(0.0000000,0.7192253,0.2029684,0.1077423),position="tray")
#see details for 'bias' fail
#Extract bias and accelerated corrected confidence interval
#Import jackknife resampled data model results
data(chinook_jackL)
#
ciMANA2(comp=chinook_bootL,bias=c(0.0000000,0.7192253,0.2029684,0.1077423),
accel=chinook_jackL,position="tray")
#see details for 'bias' fail
```


ciMANA3 *Bootstrap confidence intervals 3*

Description

Extracts bootstrap-*t* confidence intervals for additive genetic, non-additive genetic, and maternal variance components. Also extracts intervals for additional fixed and random effects.

Usage

 $ciMANA3$ (comp, level = 95, rnd_r = 3, rnd_p = 1, bias = NULL, accel = NULL, remain = NULL, trait = NULL)

Arguments

Details

Used for bootstrap resampling results produced using *resampLmer3* for normal data or*resampGlmer3* for non-normal data. Bootstrap-*t* confidence intervals, including bias and acceleration correction methods are described by Efron and Tibshirani (1993). Jackknife data model results for acceleration correction can be produced using *JackLmer3*, for normal data or *JackGlmer3* for non-normal data. The 'bias fail' warning is if the bias calculation is Inf or -Inf, e.g. *bias* contains a zero value, so the uncorrected confidence interval is displayed.

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Value

Prints a data frame containing the lower, median, and upper values of the bootstrap-*t* confidence interval for additive genetic, non-additive genetic, maternal, and any additional fixed effect and random effect variance components. Values are presented as raw and percentages of the total variance value within each row.

References

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

See Also

[ciMANA](#page-20-1), [ciMANA2](#page-21-1)

Examples

```
#Import bootstrap resampled data model results
data(chinook_bootL) #Chinook salmon offspring length
```

```
#Extract un-corrected confidence interval
ciMANA3(comp=chinook_bootL,remain=c("tray","Residual"))
```

```
#Extract bias corrected confidence interval
ciMANA3(comp=chinook_bootL,bias=c(0.0000000,0.7192253,0.2029684,0.1077423,0.5499255),
remain=c("tray","Residual"))
#see details for 'bias' fail
```

```
#Extract bias and accelerated corrected confidence interval
#Import jackknife resampled data model results
data(chinook_jackL)
#
ciMANA3(comp=chinook_bootL,bias=c(0.0000000,0.7192253,0.2029684,0.1077423,0.5499255),
accel=chinook_jackL,remain=c("tray","Residual"))
```
JackGlmer *Jackknife components for non-normal data*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire.

Usage

```
JackGlmer(observ, dam, sire, response, fam_link, quasi = F, size = 1, first = NULL)
```
Arguments

Details

Uses delete-one jackknife resampling (Efron & Tibshirani 1993, p. 141-145). For the option of delete-*d* jackknife resampling, the rows of the observed data frame are shuffled and a block of observations of size *d* is deleted sequentially. Laplace approximation parameter estimation is used, which is a true likelihood method (Bolker et al. 2009). For the overdispersion option, an observation-level random effect is added to the model (Atkins et al. 2013). Extracts the dam, sire, dam, and dam by sire variance components. The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. The number of rows in the data frame matches the total number of observations (*N*) for delete-one jackknife resampling or *M* groups for delete-*d* jackknife resampling to the lowest integer. Each row represents a deleted single observation or deleted *d* observations group.

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Atkins DC, Baldwin SA, Zheng C, Gallop RJ, Neighbors C. 2013. A tutorial on count regression and zero-altered count models for longitudinal substance use data. Psychology of Addictive Behaviors 27(1): 166-177. DOI: 10.1037/a0029508

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Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[JackGlmer2](#page-26-1), [JackGlmer3](#page-28-1)

Examples

```
data(chinook_survival) #Chinook salmon offspring survival
## Convert replicate-level recorded data to individual-level (binary) data
chinook_survival2<- buildBinary(dat=chinook_survival,copy=c(1:6,9),one="alive",zero="dead")
#Delete-one
```

```
#survival_jack1<- JackGlmer(observ=chinook_survival2,dam="dam",sire="sire",
#response="status",fam_link=binomial(logit))
survival_jack1<- JackGlmer(observ=chinook_survival2,dam="dam",sire="sire",
response="status",fam_link=binomial(logit),first=2) #first 2, a few minutes
#Delete-d, d=36
#survival_jack1.2<- JackGlmer(observ=chinook_survival2,dam="dam",sire="sire",
#response="status",fam_link=binomial(logit),size=36)
survival_jack1.2<- JackGlmer(observ=chinook_survival2,dam="dam",sire="sire",
```
JackGlmer2 *Jackknife components for non-normal data 2*

response="status",fam_link=binomial(logit),size=36,first=2) #first 2, a few minutes

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire. Options to include one random position and/or one random block effect(s).

Usage

```
JackGlmer2(observ, dam, sire, response, fam_link, position = NULL, block = NULL,
quasi = F, size = 1, first = NULL)
```
Arguments

Details

Uses delete-one jackknife resampling (Efron & Tibshirani 1993, p. 141-145). For the option of delete-*d* jackknife resampling, the rows of the observed data frame are shuffled and a block of observations of size *d* is deleted sequentially. Laplace approximation parameter estimation is used, which is a true likelihood method (Bolker et al. 2009). For the overdispersion option, an observation-level random effect is added to the model (Atkins et al. 2013). Extracts the dam, sire, dam, and dam by sire variance components. Extracts optional position and block variance components. The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. Also columns containing the raw variance components for the options of position and/or block. The number of rows in the data frame matches the total number of observations (*N*) for delete-one jackknife resampling or *M* groups for delete-*d* jackknife resampling to the lowest integer. Each row represents a deleted single observation or deleted *d* observations group.

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

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References

Atkins DC, Baldwin SA, Zheng C, Gallop RJ, Neighbors C. 2013. A tutorial on count regression and zero-altered count models for longitudinal substance use data. Psychology of Addictive Behaviors 27(1): 166-177. DOI: 10.1037/a0029508

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[JackGlmer](#page-24-1), [JackGlmer3](#page-28-1)

Examples

```
data(chinook_survival) #Chinook salmon offspring survival
## Convert replicate-level recorded data to individual-level (binary) data
chinook_survival2<- buildBinary(dat=chinook_survival,copy=c(1:6,9),one="alive",zero="dead")
#Delete-one
```

```
#survival_jack2<- JackGlmer2(observ=chinook_survival2,dam="dam",sire="sire",
#response="status",fam_link=binomial(logit),position="tray")
survival_jack2<- JackGlmer2(observ=chinook_survival2,dam="dam",sire="sire",
response="status",fam_link=binomial(logit),position="tray",first=2)
#first 2, a few minutes
```

```
#Delete-d, d=36
#survival_jack2.2<- JackGlmer2(observ=chinook_survival2,dam="dam",sire="sire",
#response="status",fam_link=binomial(logit),position="tray",size=36)
survival_jack2.2<- JackGlmer2(observ=chinook_survival2,dam="dam",sire="sire",
response="status",fam_link=binomial(logit),position="tray",size=36,first=2)
#first 2, a few minutes
```
JackGlmer3 *Jackknife components for non-normal data 3*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, dam by sire, and any additional fixed and/or random effects.

Usage

JackGlmer3(observ, dam, sire, response, fam_link, remain, quasi = F, size = 1, $first = NULL)$

Arguments

Details

Uses delete-one jackknife resampling (Efron & Tibshirani 1993, p. 141-145). For the option of delete-*d* jackknife resampling, the rows of the observed data frame are shuffled and a block of observations of size *d* is deleted sequentially. Laplace approximation parameter estimation is used, which is a true likelihood method (Bolker et al. 2009). For the overdispersion option, an observation-level random effect is added to the model (Atkins et al. 2013). Extracts the dam, sire, dam, and dam by sire variance components. Extracts any additional fixed effect and random effect variance components. The fixed-effect variance component is as a single group using the method described by Nakagawa and Schielzeth (2013). The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. Also columns containing the raw variance components for remaining formula components. The number of rows in the data frame matches the total number of observations (*N*) for delete-one jackknife resampling or *M* groups for delete-*d* jackknife resampling to the lowest integer. Each row represents a deleted single observation or deleted *d* observations group.

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and

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binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Atkins DC, Baldwin SA, Zheng C, Gallop RJ, Neighbors C. 2013. A tutorial on count regression and zero-altered count models for longitudinal substance use data. Psychology of Addictive Behaviors 27(1): 166-177. DOI: 10.1037/a0029508

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[JackGlmer](#page-24-1), [JackGlmer2](#page-26-1)

Examples

```
data(chinook_survival) #Chinook salmon offspring survival
## Convert replicate-level recorded data to individual-level (binary) data
chinook_survival2<- buildBinary(dat=chinook_survival,copy=c(1:6,9),one="alive",zero="dead")
```

```
#Delete-one
#survival_jack3<- JackGlmer3(observ=chinook_survival2,dam="dam",sire="sire",
#response="status",fam_link=binomial(logit),remain="egg_size + (1|tray)")
survival_jack3<- JackGlmer3(observ=chinook_survival2,dam="dam",sire="sire"
response="status",fam_link=binomial(logit),remain="egg_size + (1|tray)",first=2)
#first 2, a few minutes
```

```
#Delete-d, d=36
#survival_jack3.2<- JackGlmer3(observ=chinook_survival2,dam="dam",sire="sire",
#response="status",fam_link=binomial(logit),remain="egg_size + (1|tray)",size=36)
survival_jack3.2<- JackGlmer3(observ=chinook_survival2.dam="dam".sire="sire",
response="status",fam_link=binomial(logit),remain="egg_size + (1|tray)",size=36,first=2)
#first 2, a few minutes
```
JackLmer *Jackknife components for normal data*

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire.

Usage

```
JackLmer(observ, dam, sire, response, ml = F, size = 1, first = NULL)
```
Arguments

Details

Uses delete-one jackknife resampling (Efron & Tibshirani 1993, p. 141-145). For the option of delete-*d* jackknife resampling, the rows of the observed data frame are shuffled and a block of observations of size *d* is deleted sequentially. Extracts the dam, sire, dam, dam by sire, and residual variance components. Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. The number of rows in the data frame matches the total number of observations (*N*) for delete-one jackknife resampling or *M* groups for delete-*d* jackknife resampling to the lowest integer. Each row represents a deleted single observation or deleted *d* observations group.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

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References

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York. Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

See Also

[JackLmer2](#page-32-1), [JackLmer3](#page-34-1)

Examples

data(chinook_length) #Chinook salmon offspring length

```
#Delete-one
#length_jack1<- JackLmer(observ=chinook_length,dam="dam",sire="sire",response="length")
length_jack1<- JackLmer(observ=chinook_length,dam="dam",sire="sire",response="length",
first=2) #first 2
```

```
#Delete-d, d=5
#length_jack1.2<- JackLmer(observ=chinook_length,dam="dam",sire="sire",response="length",
#size=5)
length_jack1.2<- JackLmer(observ=chinook_length,dam="dam",sire="sire",response="length",
size=5,first=2) #first 2
```


JackLmer2 *Jackknife components for normal data 2*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire. Options to include one random position and/or one random block effect(s).

Usage

JackLmer2(observ, dam, sire, response, position = NULL, block = NULL, ml = F, size = 1, $first = NULL)$

Arguments

first Number of initial sub-samples to run. Useful for examing if there is variation among sub-samples before jackknife resampling the entire data set. There can be little varitation for delete-one jackknife resampling with large data sets, and delete-*d* jackknife resampling should be considered.

Details

Uses delete-one jackknife resampling (Efron & Tibshirani 1993, p. 141-145). For the option of delete-*d* jackknife resampling, the rows of the observed data frame are shuffled and a block of observations of size *d* is deleted sequentially. Extracts the dam, sire, dam, dam by sire, and residual variance components. Extracts optional position and block variance components. Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. Also columns containing the raw variance components for the options of position and/or block. The number of rows in the data frame matches the total number of observations (*N*) for delete-one jackknife resampling or *M* groups for delete-*d* jackknife resampling to the lowest integer. Each row represents a deleted single observation or deleted *d* observations group.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

References

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

See Also

[JackLmer](#page-30-1), [JackLmer3](#page-34-1)

Examples

data(chinook_length) #Chinook salmon offspring length

```
#Delete-one
#length_jack2<- JackLmer2(observ=chinook_length,dam="dam",sire="sire",response="length",
#position="tray")
length_jack2<- JackLmer2(observ=chinook_length,dam="dam",sire="sire",response="length",
```
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```
position="tray",first=2) #first 2
#Delete-d, d=5
#length_jack2.2<- JackLmer2(observ=chinook_length,dam="dam",sire="sire",response="length",
#position="tray",size=5)
length_jack2.2<- JackLmer2(observ=chinook_length,dam="dam",sire="sire",response="length",
position="tray",size=5,first=2) #first 2
```
JackLmer3 *Jackknife components for normal data 3*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, dam by sire, and any additional fixed and/or random effects.

Usage

JackLmer3(observ, dam, sire, response, remain, ml = F, size = 1, first = NULL)

Arguments

Details

Uses delete-one jackknife resampling (Efron & Tibshirani 1993, p. 141-145). For the option of delete-*d* jackknife resampling, the rows of the observed data frame are shuffled and a block of observations of size *d* is deleted sequentially. Extracts the dam, sire, dam, dam by sire, and residual variance components. Extracts any additional fixed effect and random effect variance components. The fixed-effect variance component is as a single group using the method described by Nakagawa and Schielzeth (2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. Also columns containing the raw variance components for remaining formula components. The number of rows in the data frame matches the total number of observations (*N*) for delete-one jackknife resampling or *M* groups for delete-*d* jackknife resampling to the lowest integer. Each row represents a deleted single observation or deleted *d* observations group.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

References

Efron B, Tibshirani R. 1993. An introduction to the Bootstrap. Chapman and Hall, New York.

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[JackLmer](#page-30-1), [JackLmer2](#page-32-1)

Examples

data(chinook_length) #Chinook salmon offspring length

```
#Delete-one
#length_jack3<- JackLmer3(observ=chinook_length,dam="dam",sire="sire",response="length",
#remain="egg_size + (1|tray)")
length_jack3<- JackLmer3(observ=chinook_length,dam="dam",sire="sire",response="length",
remain="egg_size + (1|tray)",first=2) #first 2
```

```
#Delete-d, d=5
#length_jack3.2<- JackLmer3(observ=chinook_length,dam="dam",sire="sire",response="length",
#remain="egg_size + (1|tray)",size=5)
length_jack3.2<- JackLmer3(observ=chinook_length,dam="dam",sire="sire",response="length",
remain="egg_size + (1|tray)",size=5,first=2) #first 2
```


Value

Extracts additive genetic, non-additive genetic, and maternal variance components from a generalized linear mixed-effect model using the *glmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire.

Usage

```
observGlmer(observ, dam, sire, response, fam_link, quasi = F)
```
Arguments

Details

Laplace approximation parameter estimation is used, which is a true likelihood method (Bolker et al. 2009). For the overdispersion option, an observation-level random effect is added to the model (Atkins et al. 2013). Extracts the dam, sire, dam, and dam by sire variance components. The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009).

Value

A list object containing the raw variance components, the variance components as a percentage of the total variance component. Also, contains the difference in AIC and BIC, and likelihood ratio test Chi-square and p-value for all random effects.

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Atkins DC, Baldwin SA, Zheng C, Gallop RJ, Neighbors C. 2013. A tutorial on count regression and zero-altered count models for longitudinal substance use data. Psychology of Addictive Behaviors 27(1): 166-177. DOI: 10.1037/a0029508

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[observGlmer2](#page-37-1), [observGlmer3](#page-39-1)

Examples

data(chinook_survival) #Chinook salmon offspring survival ## Convert replicate-level recorded data to individual-level (binary) data chinook_survival2<- buildBinary(dat=chinook_survival,copy=c(2:6,9),one="alive",zero="dead") # survival_mod1<- observGlmer(observ=chinook_survival2,dam="dam",sire="sire",response="status", fam_link=binomial(logit)) #a few minutes survival_mod1

observGlmer2 *Variance components for non-normal data 2*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a generalized linear mixed-effect model using the *glmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire. Options to include one random position and/or one random block effect(s).

Usage

observGlmer2(observ, dam, sire, response, fam_link, position = NULL, block = NULL, quasi = F)

Arguments

observGlmer2 39

Details

Laplace approximation parameter estimation is used, which is a true likelihood method (Bolker et al. 2009). For the overdispersion option, an observation-level random effect is added to the model (Atkins et al. 2013). Extracts the dam, sire, dam, and dam by sire variance components. Extracts optional position and block variance components. The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009).

Value

A list object containing the raw variance components, the variance components as a percentage of the total variance component. Also, contains the difference in AIC and BIC, and likelihood ratio test Chi-square and p-value for all random effects.

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Atkins DC, Baldwin SA, Zheng C, Gallop RJ, Neighbors C. 2013. A tutorial on count regression and zero-altered count models for longitudinal substance use data. Psychology of Addictive Behaviors 27(1): 166-177. DOI: 10.1037/a0029508

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[observGlmer](#page-36-1), [observGlmer3](#page-39-1)

Examples

```
data(chinook_survival) #Chinook salmon offspring survival
## Convert replicate-level recorded data to individual-level (binary) data
chinook_survival2<- buildBinary(dat=chinook_survival,copy=c(2:6,9),one="alive",zero="dead")
#
survival_mod2<- observGlmer2(observ=chinook_survival2,dam="dam",sire="sire",
response="status",fam_link=binomial(logit),position="tray") #a few minutes
survival_mod2
```


observGlmer3 *Variance components for non-normal data 3*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a generalized linear mixed-effect model using the *glmer* function of the *lme4* package. Model random effects are dam, sire, dam by sire, and any additional fixed and/or random effects.

Usage

observGlmer3(observ, dam, sire, response, fam_link, remain, quasi = F, iter = 1000)

Arguments

Details

Laplace approximation parameter estimation is used, which is a true likelihood method (Bolker et al. 2009). For the overdispersion option, an observation-level random effect is added to the model (Atkins et al. 2013). Extracts the dam, sire, dam, and dam by sire variance components. Extracts any additional fixed effect and random effect variance components. The fixed-effect variance component is as a single group using the method described by Nakagawa and Schielzeth (2013). The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009). Significance values for any fixed effects are determined using likelihood ratio tests and a parametric bootstrap method (Bolker et al. 2009) from the *mixed* function of the *afex* package.

observGlmer3 41

Value

A list object containing the raw variance components, the variance components as a percentage of the total variance component. Contains the difference in AIC and BIC, likelihood ratio test Chi-square and p-value for both random and fixed effects. Also contains the parametric bootstrap p-value for fixed effects.

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Atkins DC, Baldwin SA, Zheng C, Gallop RJ, Neighbors C. 2013. A tutorial on count regression and zero-altered count models for longitudinal substance use data. Psychology of Addictive Behaviors 27(1): 166-177. DOI: 10.1037/a0029508

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[observGlmer](#page-36-1), [observGlmer2](#page-37-1)

Examples

```
data(chinook_survival) #Chinook salmon offspring survival
## Convert replicate-level recorded data to individual-level (binary) data
chinook_survival2<- buildBinary(dat=chinook_survival,copy=c(2:6,9),one="alive",zero="dead")
#just a few iterations for the p-value of fixed effect
survival_mod3<- observGlmer3(observ=chinook_survival2,dam="dam",sire="sire",
response="status",fam_link=binomial(logit),remain="egg_size + (1|tray)",iter=5)
#a few minutes
```
survival_mod3

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire.

Usage

observLmer(observ, dam, sire, response, ml = F)

Arguments

Details

Extracts the dam, sire, dam, dam by sire, and residual variance components. Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009).

Value

A list object containing the raw variance components, the variance components as a percentage of the total variance component. Also, contains the difference in AIC and BIC, and likelihood ratio test Chi-square and p-value for all random effects.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

observLmer2 43

References

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

See Also

[observLmer2](#page-42-1), [observLmer3](#page-43-1)

Examples

```
data(chinook_length) #Chinook salmon offspring length
length_mod1<- observLmer(observ=chinook_length,dam="dam",sire="sire",response="length")
length_mod1
```
observLmer2 *Variance components for normal data 2*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire. Options to include one random position and/or one random block effect(s).

Usage

```
observLmer2(observ, dam, sire, response, position = NULL, block = NULL, ml = F)
```
Arguments

Details

Extracts the dam, sire, dam, dam by sire, and residual variance components. Extracts optional position and block variance components. Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009).

A list object containing the raw variance components, the variance components as a percentage of the total variance component. Also, contains the difference in AIC and BIC, and likelihood ratio test Chi-square and p-value for all random effects.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

References

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

See Also

[observLmer](#page-41-1), [observLmer3](#page-43-1)

Examples

```
data(chinook_length) #Chinook salmon offspring length
length_mod2<- observLmer2(observ=chinook_length,dam="dam",sire="sire",response="length",
position="tray")
length_mod2
```
observLmer3 *Variance components for normal data 3*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, dam by sire, and any additional fixed and/or random effects.

Usage

```
observLmer3(observ, dam, sire, response, remain, ml = F, iter = 1000)
```
Value

observLmer3 45

Arguments

Details

Extracts the dam, sire, dam, dam by sire, and residual variance components. Extracts any additional fixed effect and random effect variance components. The fixed-effect variance component is as a single group using the method described by Nakagawa and Schielzeth (2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009). Significance values for any fixed effects are determined using likelihood ratio tests and a parametric bootstrap method (Bolker et al. 2009) from the *mixed* function of the *afex* package.

Value

A list object containing the raw variance components, the variance components as a percentage of the total variance component. Contains the difference in AIC and BIC, likelihood ratio test Chi-square and p-value for both random and fixed effects. Also contains the parametric bootstrap p-value for fixed effects.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

References

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[observLmer](#page-41-1), [observLmer2](#page-42-1)

Examples

```
data(chinook_length) #Chinook salmon offspring length
#just a few iterations for the p-value of fixed effect
length_mod3<- observLmer3(observ=chinook_length,dam="dam",sire="sire",response="length",
remain="egg_size + (1|tray)",iter=5)
length_mod3
```
powerGlmer *Power analysis for non-normal data*

Description

Extracts the power values of dam, sire, and dam by sire variance components from a generalized linear mixed-effect model using the *glmer* function of the *lme4* package.

Usage

```
powerGlmer(varcomp, nval, fam_link, alpha = 0.05, nsim = 100, poisLog = NULL)
```
Arguments

Details

Extracts the dam, sire, dam, and dam by sire power values. The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Power values are calculated by stochastically simulation data and then calculating the proportion of significance values less than *alpha* for each component (Bolker 2008). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009).

Value

A data frame with the sample sizes, variance component inputs, variance component outputs, and power values.

powerGlmer2 47

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Bolker BM. 2008. Ecological models and data in R. Princeton University Press, New Jersey.

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[powerGlmer2](#page-46-1), [powerGlmer3](#page-48-1)

Examples

```
#100 simulations
#pwr_G1<- powerGlmer(varcomp=c(1,0.15,0.11),nval=c(10,10,20),fam_link=binomial(logit))
#pwr_G1
#5 simulations
pwr_G1<- powerGlmer(varcomp=c(1,0.15,0.11),nval=c(10,10,20),fam_link=binomial(logit),
nsim=5)
pwr_G1
```
powerGlmer2 *Power analysis for non-normal data 2*

Description

Extracts the power values of dam, sire, and dam by sire variance components from a generalized linear mixed-effect model using the *glmer* function of the *lme4* package. Options to include one random position and/or one random block effect(s).

Usage

```
powerGlmer2(varcomp, nval, fam_link, alpha = 0.05, nsim = 100, position = NULL,
block = NULL, poisLog = NULL)
```
Arguments

Details

Extracts the dam, sire, dam, dam by sire, and position and/or block power values. The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Power values are calculated by stochastically simulation data and then calculating the proportion of significance values less than *alpha* for each component (Bolker 2008). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009).

Value

A data frame with the sample sizes, variance component inputs, variance component outputs, and power values.

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Bolker BM. 2008. Ecological models and data in R. Princeton University Press, New Jersey.

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

powerGlmer3 49

See Also

[powerGlmer](#page-45-1), [powerGlmer3](#page-48-1)

Examples

```
#100 simulations
#pwr_G2<- powerGlmer2(varcomp=c(1,0.15,0.11,0.5),nval=c(10,10,20,10),
#fam_link=binomial(logit),position=2)
#pwr_G2
#5 simulations
pwr_G2<- powerGlmer2(varcomp=c(1,0.15,0.11,0.5),nval=c(10,10,20,10),
fam_link=binomial(logit),position=2,nsim=5)
pwr_G2
```
powerGlmer3 *Power analysis for non-normal data 3*

Description

Extracts the power values of dam, sire, and dam by sire variance components from a generalized linear mixed-effect model using the *glmer* function of the *lme4* package. Model can include additional fixed and/or random effects.

Usage

powerGlmer3(var_rand, n_rand, design, remain, fam_link, var_fix = NULL, n_fix = NULL, alpha = 0.05 , nsim = 100 , poisLog = NULL, ftest = "LR", iter = NULL)

Arguments

Details

Extracts the dam, sire, dam, dam by sire, and any remaining random and fixed effects power values. The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Power values are calculated by stochastically simulation data and then calculating the proportion of significance values less than *alpha* for each component (Bolker 2008). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009). Significance values for any fixed effects are determined using likelihood ratio tests or parametric bootstrap method (Bolker et al. 2009) from the *mixed* function of the *afex* package.

Value

A data frame with the sample sizes, variance component inputs, variance component outputs, and power values.

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Bolker BM. 2008. Ecological models and data in R. Princeton University Press, New Jersey.

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[powerGlmer](#page-45-1), [powerGlmer2](#page-46-1)

powerLmer 51

Examples

```
##design object: 2 remaining random effects and 1 continous fixed effect
block=c(2,2); blocN=10; position=2; posN=10; offN=20
dam0<- stack(as.data.frame(matrix(1:(block[1]*blocN),ncol=blocN,nrow=block[1])))
sire0<- stack(as.data.frame(matrix(1:(block[2]*blocN),ncol=blocN,nrow=block[2])))
observ0<- merge(dam0,sire0, by="ind")
levels(observ0[,1])<- 1:blocN; colnames(observ0)<- c("block","dam","sire")
observ0$family<- 1:nrow(observ0) #add family
#expand for position
observ1<- do.call("rbind", replicate(position,observ0,simplify=FALSE));rm(observ0)
observ1$position<- sample(rep(1:posN,each=position)) #random assignment
#expand for offspring
observ<- do.call("rbind", replicate(offN,observ1,simplify=FALSE)); rm(observ1)
desn<- observ[,c(2,3,4,5,1)];rm(observ) #dam,sire,family,position,block
desn$egg_size<- 1:nrow(desn)
colnames(desn)[6]<- "egg_size"
#100 simulations
#pwr_G3<- powerGlmer3(var_rand=c(1,0.15,0.11,0.5,0.3),n_rand=c(20,20,40,10,10),
#fam_link=binomial(logit),var_fix=0.1,n_fix=1,design=desn,
#remain="(1|position)+(1|block)+egg_size")
#pwr_G3
#5 simulations
pwr_G3<- powerGlmer3(var_rand=c(1,0.15,0.11,0.5,0.3),n_rand=c(20,20,40,10,10),
fam_link=binomial(logit),var_fix=0.1,n_fix=1,design=desn,
remain="(1|position)+(1|block)+egg_size",nsim=5)
pwr_G3
```


powerLmer *Power analysis for normal data*

Description

Extracts the power values of dam, sire, and dam by sire variance components from a linear mixedeffect model using the *lmer* function of the *lme4* package.

Usage

```
powerLmer(varcomp, nval, alpha = 0.05, nsim = 100, ml = F)
```
Arguments

Details

Extracts the dam, sire, dam, and dam by sire power values. Power values are calculated by stochastically simulation data and then calculating the proportion of significance values less than *alpha* for each component (Bolker 2008). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009).

Value

A data frame with the sample sizes, variance component inputs, variance component outputs, and power values.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

References

Bolker BM. 2008. Ecological models and data in R. Princeton University Press, New Jersey.

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

See Also

[powerLmer2](#page-52-1), [powerLmer3](#page-53-1)

```
#100 simulations
#pwr_L1<- powerLmer(varcomp=c(0.19,0.03,0.02,0.76),nval=c(10,10,20))
#pwr_L1
#5simulations
pwr_L1<- powerLmer(varcomp=c(0.19,0.03,0.02,0.76),nval=c(10,10,20),nsim=5)
pwr_L1
```


Extracts the power values of dam, sire, and dam by sire variance components from a linear mixedeffect model using the *lmer* function of the *lme4* package. Options to include one random position and/or one random block effect(s).

Usage

```
powerLmer2(varcomp, nval, alpha = 0.05, nsim = 100, position = NULL, block = NULL,
ml = F
```
Arguments

Details

Extracts the dam, sire, dam, dam by sire, and position and/or block power values. Power values are calculated by stochastically simulation data and then calculating the proportion of significance values less than *alpha* for each component (Bolker 2008). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009).

Value

A data frame with the sample sizes, variance component inputs, variance component outputs, and power values.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

References

Bolker BM. 2008. Ecological models and data in R. Princeton University Press, New Jersey.

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

See Also

[powerLmer](#page-50-1), [powerLmer3](#page-53-1)

Examples

```
#100 simulations
#pwr_L2<- powerLmer2(varcomp=c(0.19,0.03,0.02,0.66,0.1),nval=c(10,10,20,10),position=2)
#pwr_L2
#5 simulations
pwr_L2<- powerLmer2(varcomp=c(0.19,0.03,0.02,0.66,0.1),nval=c(10,10,20,10),position=2,
nsim=5)
pwr_L2
```
powerLmer3 *Power analysis for normal data 3*

Description

Extracts the power values of dam, sire, and dam by sire variance components from a linear mixedeffect model using the *lmer* function of the *lme4* package. Model can include additional fixed and/or random effects.

Usage

```
powerLmer3(var_rand, n_rand, design, remain, var_fix = NULL, n_fix = NULL,
alpha = 0.05, nsim = 100, ml = F, ftest = "LR", iter = NULL)
```
Arguments

Details

Extracts the dam, sire, dam, dam by sire, and any remaining random and fixed effects power values. Power values are calculated by stochastically simulation data and then calculating the proportion of significance values less than *alpha* for each component (Bolker 2008). Significance values for the random effects are determined using likelihood ratio tests (Bolker et al. 2009). Significance values for any fixed effects are determined using likelihood ratio tests or parametric bootstrap method (Bolker et al. 2009) from the *mixed* function of the *afex* package.

Value

A data frame with the sample sizes, variance component inputs, variance component outputs, and power values.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

References

Bolker BM. 2008. Ecological models and data in R. Princeton University Press, New Jersey.

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

See Also

[powerLmer](#page-50-1), [powerLmer2](#page-52-1)

Examples

```
##design object: 2 remaining random effects and 1 continous fixed effect
block=c(2,2); blocN=10; position=2; posN=10; offN=20
dam0<- stack(as.data.frame(matrix(1:(block[1]*blocN),ncol=blocN,nrow=block[1])))
sire0 <- stack(as.data.frame(matrix(1:(block[2]*blocN),ncol=blocN,nrow=block[2])))
observ0<- merge(dam0,sire0, by="ind")
levels(observ0[,1])<- 1:blocN; colnames(observ0)<- c("block","dam","sire")
observ0$family<- 1:nrow(observ0) #add family
#expand for position
observ1<- do.call("rbind", replicate(position,observ0,simplify=FALSE));rm(observ0)
observ1$position<- sample(rep(1:posN,each=position)) #random assignment
#expand for offspring
observ<- do.call("rbind", replicate(offN,observ1,simplify=FALSE)); rm(observ1)
desn<- observ[,c(2,3,4,5,1)];rm(observ) #dam,sire,family,position,block
desn$egg_size<- 1:nrow(desn)
colnames(desn)[6]<- "egg_size"
#100 simulations
#pwr_L3<- powerLmer3(var_rand=c(0.19,0.03,0.02,0.51,0.1,0.05),n_rand=c(20,20,40,10,10),
#var_fix=0.1,n_fix=1,design=desn,remain="(1|position)+(1|block)+egg_size")
#pwr_L3
#5 simulations
pwr_L3<- powerLmer3(var_rand=c(0.19,0.03,0.02,0.51,0.1,0.05),n_rand=c(20,20,40,10,10),
var_fix=0.1,n_fix=1,design=desn,remain="(1|position)+(1|block)+egg_size",nsim=5)
pwr_L3
```
resampFamily *Bootstrap resample within families*

Description

Bootstrap resample observations grouped by family identities for a specified number of iterations to create a resampled data set.

Usage

```
resampFamily(dat, copy, family, iter)
```
resampGlmer 57

Arguments

Details

The resampled data can be used for producing bootstrap confidence intervals.

Value

Because of the large file sizes that can be produced, the resampling of each family X is saved separately as a common separated (X_resampF.csv) file in the working directory. These files are merged to create the final resampled data set (resamp_datF.csv).

See Also

[resampRepli](#page-66-1)

Examples

```
data(chinook_length) #Chinook salmon offspring length
#resampFamily(dat=chinook_length,copy=c(3:8),family="family",iter=1000)
resampFamily(dat=chinook_length,copy=c(3:8),family="family",iter=2)
#example with a couple iterations
```
resampGlmer *Bootstrap components for non-normal data*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a generalized linear mixed-effect model using the *glmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire.

Usage

```
resampGlmer(resamp, dam, sire, response, fam_link, start, end, quasi = F)
```
Arguments

Details

Used for bootstrap resampled data set produced using *resampRepli* or *resampFamily*. Laplace approximation parameter estimation is used, which is a true likelihood method (Bolker et al. 2009). For the overdispersion option, an observation-level random effect is added to the model (Atkins et al. 2013). Extracts the dam, sire, dam, and dam by sire variance components. The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. The number of rows in the data frame matches the number of iterations in the resampled data set and each row represents a model number.

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Atkins DC, Baldwin SA, Zheng C, Gallop RJ, Neighbors C. 2013. A tutorial on count regression and zero-altered count models for longitudinal substance use data. Psychology of Addictive Behaviors 27(1): 166-177. DOI: 10.1037/a0029508

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[resampGlmer2](#page-58-1), [resampGlmer3](#page-59-1)

Examples

data(chinook_resampS) #5 iterations

#survival_rcomp<- resampGlmer(resamp=survival_datR,dam="dam",sire="sire",response="status", #fam_link=binomial(logit),start=1,end=1000) survival_rcomp<- resampGlmer(resamp=chinook_resampS,dam="dam",sire="sire",response="status", fam_link=binomial(logit),start=1,end=2) #first 2 models, a few minutes

Extracts additive genetic, non-additive genetic, and maternal variance components from a generalized linear mixed-effect model using the *glmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire. Options to include one random position and/or one random block effect(s).

Usage

```
resampGlmer2(resamp, dam, sire, response, fam_link, start, end, position = NULL,
block = NULL, quasi = F)
```
Arguments

Details

Used for bootstrap resampled data set produced using *resampRepli* or *resampFamily*. Laplace approximation parameter estimation is used, which is a true likelihood method (Bolker et al. 2009). For the overdispersion option, an observation-level random effect is added to the model (Atkins et al. 2013). Extracts the dam, sire, dam, and dam by sire variance components. Extracts optional position and block variance components. The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. Also columns containing the raw variance components for the options of position and/or block. The number of rows in the data frame matches the number of iterations in the resampled data set and each row represents a model number.

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Atkins DC, Baldwin SA, Zheng C, Gallop RJ, Neighbors C. 2013. A tutorial on count regression and zero-altered count models for longitudinal substance use data. Psychology of Addictive Behaviors 27(1): 166-177. DOI: 10.1037/a0029508

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[resampGlmer](#page-56-1), [resampGlmer3](#page-59-1)

Examples

data(chinook_resampS) #5 iterations

```
#survival_rcomp2<- resampGlmer2(resamp=survival_datR,dam="dam",sire="sire",response="status",
#fam_link=binomial(logit),start=1,end=1000,position="tray")
survival_rcomp2<- resampGlmer2(resamp=chinook_resampS,dam="dam",sire="sire",response="status",
fam_link=binomial(logit),start=1,end=2,position="tray") #first 2 models, a few minutes
```
resampGlmer3 *Bootstrap components for non-normal data 3*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a generalized linear mixed-effect model using the *glmer* function of the *lme4* package. Model random effects are dam, sire, dam by sire, and any additional fixed and/or random effects.

Usage

```
resampGlmer3(resamp, dam, sire, response, fam_link, start, end, remain, quasi = F)
```


Note

resampGlmer3 61

Arguments

Details

Used for bootstrap resampled data set produced using *resampRepli* or *resampFamily*. Laplace approximation parameter estimation is used, which is a true likelihood method (Bolker et al. 2009). For the overdispersion option, an observation-level random effect is added to the model (Atkins et al. 2013). Extracts the dam, sire, dam, and dam by sire variance components. Extracts any additional fixed effect and random effect variance components. The fixed-effect variance component is as a single group using the method described by Nakagawa and Schielzeth (2013). The residual variance component for the *fam_links* are described by Nakagawa and Schielzeth (2010, 2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. Also columns containing the raw variance components for remaining formula components. The number of rows in the data frame matches the number of iterations in the resampled data set and each row represents a model number.

Note

The Laplace approximation is used because there were fewer disadvantages relative to penalized quasi-likelihood and Gauss-Hermite quadrature parameter estimation (Bolker et al. 2009). That is, penalized quasi-likelihood is not recommended for count responses with means less than 5 and binary responses with less than 5 successes per group. Gauss-Hermite quadrature is not recommended for more than two or three random effects because of the rapidly declining analytical speed with the increasing number of random effects.

References

Atkins DC, Baldwin SA, Zheng C, Gallop RJ, Neighbors C. 2013. A tutorial on count regression and zero-altered count models for longitudinal substance use data. Psychology of Addictive Behaviors 27(1): 166-177. DOI: 10.1037/a0029508

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

Nakagawa S, Schielzeth H. 2010. Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. Biological Reviews 85(4): 935-956. DOI: 10.1111/j.1469-185X.2010.00141.x

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[resampGlmer](#page-56-1), [resampGlmer2](#page-58-1)

Examples

data(chinook_resampS) #5 iterations

```
#survival_rcomp3<- resampGlmer3(resamp=survival_datR,dam="dam",sire="sire",
#response="status",fam_link=binomial(logit),start=1,end=1000,
#remain="egg_size# + (1|tray#)")
survival_rcomp3<- resampGlmer3(resamp=chinook_resampS,dam="dam",sire="sire",
response="status",fam_link=binomial(logit),start=1,end=2,
remain="egg_size# + (1|tray#)") #first 2 models, a few minutes
```


resampLmer *Bootstrap components for normal data*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire.

Usage

```
resampLmer(resamp, dam, sire, response, start, end, ml = F)
```
Arguments

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Details

Used for bootstrap resampled data set produced using *resampRepli* or *resampFamily*. Extracts the dam, sire, dam, dam by sire, and residual variance components. Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. The number of rows in the data frame matches the number of iterations in the resampled data set and each row represents a model number.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

References

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

See Also

[resampLmer2](#page-63-1), [resampLmer3](#page-64-1)

Examples

data(chinook_resampL) #5 iterations

```
#length_rcomp1<- resampLmer(resamp=length_datR,dam="dam",sire="sire",response="length",
#start=1,end=1000)
length_rcomp1<- resampLmer(resamp=chinook_resampL,dam="dam",sire="sire",response="length",
start=1,end=5)
```
Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, and dam by sire. Options to include one random position and/or one random block effect(s).

Usage

```
resampLmer2(resamp, dam, sire, response, start, end, position = NULL, block = NULL,
ml = F
```
Arguments

Details

Used for bootstrap resampled data set produced using *resampRepli* or *resampFamily*. Extracts the dam, sire, dam, dam by sire, and residual variance components. Extracts optional position and block variance components. Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. Also columns containing the raw variance components for the options of position and/or block. The number of rows in the data frame matches the number of iterations in the resampled data set and each row represents a model number.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if

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sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

References

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

See Also

[resampLmer](#page-61-1), [resampLmer3](#page-64-1)

Examples

data(chinook_resampL) #5 iterations

```
#length_rcomp2<- resampLmer2(resamp=length_datR,dam="dam",sire="sire",response="length",
#start=1,end=1000,position="tray")
length_rcomp2<- resampLmer2(resamp=chinook_resampL,dam="dam",sire="sire",response="length",
start=1,end=5,position="tray")
```
resampLmer3 *Bootstrap components for normal data 3*

Description

Extracts additive genetic, non-additive genetic, and maternal variance components from a linear mixed-effect model using the *lmer* function of the *lme4* package. Model random effects are dam, sire, dam by sire, and any additional fixed and/or random effects.

Usage

resampLmer3(resamp, dam, sire, response, start, end, remain, ml = F)

Arguments

Used for bootstrap resampled data set produced using *resampRepli* or *resampFamily*. Extracts the dam, sire, dam, dam by sire, and residual variance components. Extracts any additional fixed effect and random effect variance components. The fixed-effect variance component is as a single group using the method described by Nakagawa and Schielzeth (2013). Calculates the total variance component. Calculates the additive genetic, non-additive genetic, and maternal variance components (see Lynch and Walsh 1998, p. 603).

Value

A data frame with columns containing the raw variance components for dam, sire, dam by sire, residual, total, additive genetic, non-additive genetic, and maternal. Also columns containing the raw variance components for remaining formula components. The number of rows in the data frame matches the number of iterations in the resampled data set and each row represents a model number.

Note

Maximum likelihood (ML) estimates the parameters that maximize the likelihood of the observed data and has the advantage of using all the data and accounting for non-independence (Lynch and Walsh 1998, p. 779; Bolker et al. 2009). On the other hand, ML has the disadvantage of assuming that all fixed effects are known without error, producing a downward bias in the estimation of the residual variance component. This bias can be large if there are lots of fixed effects, especially if sample sizes are small. Restricted maximum likelihood (REML) has the advantage of not assuming the fixed effects are known and averages over the uncertainty, so there can be less bias in the estimation of the residual variance component. However, REML only maximizes a portion of the likelihood to estimate the effect parameters, but is the preferred method for analyzing large data sets with complex structure.

References

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White J-SS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends in Ecology and Evolution 24(3): 127-135. DOI: 10.1016/j.tree.2008.10.008

Lynch M, Walsh B. 1998. Genetics and Analysis of Quantitative Traits. Sinauer Associates, Massachusetts.

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(2): 133-142. DOI: 10.1111/j.2041-210x.2012.00261.x

See Also

[resampLmer](#page-61-1), [resampLmer2](#page-63-1)

Examples

```
data(chinook_resampL)
```

```
#length_rcomp3<- resampLmer3(resamp=length_datR,dam="dam",sire="sire",response="length",
#start=1,end=1000,remain="egg_size# + (1|tray#)")
length_rcomp3<- resampLmer3(resamp=chinook_resampL,dam="dam",sire="sire",response="length",
start=1,end=5,remain="egg_size# + (1|tray#)")
```


Details

Bootstrap resample observations grouped by replicate identities within family identities for a specified number of iterations to create a resampled data set.

Usage

resampRepli(dat, copy, family, replicate, iter)

Arguments

Details

The resampled data can be used for producing bootstrap confidence intervals.

Value

Because of the large file sizes that can be produced, the resampling of each replicate Y per family X is saved separately as a common separated (X_Y_resampR.csv) file in the working directory. These files are merged to create the final resampled data set (resamp_datR.csv).

See Also

[resampFamily](#page-55-1)

```
data(chinook_length) #Chinook salmon offspring length
#resampRepli(dat=chinook_length,copy=c(3:8),family="family",replicate="repli",iter=1000)
resampRepli(dat=chinook_length,copy=c(3:8),family="family",replicate="repli",iter=2)
#example with a couple iterations
```
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