Package 'configural'

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Type Package

Title Multivariate Profile Analysis

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BugReports https://github.com/bwiernik/configural/issues

Description R functions for criterion profile analysis, Davison and Davenport (2002) <doi:10.1037/1082-989X.7.4.468> and meta-analytic criterion profile analysis, Wiernik, Wilmot, Davison, and Ones (2020) <doi:10.1037/met0000305>. Sensitivity analyses to aid in interpreting criterion profile analysis results are also included.

License GPL (>= 3)

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Suggests crayon

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R topics documented:

`configural-package` **configural**: *An R package for profile analysis*

Description

Overview of the **configural** package.

Details

The **configural** package provides tools for conducting configural and profile analyses. It currently supports criterion profile analysis (Davison & Davenport, 2002) and meta-analytic criterion profile analysis (Wiernik et al., 2019). Functions are provided to calculate criterion patterns and CPA variance decomposition, as well as for computing confidence intervals, shrinkage corrections, and fungible patterns.

Author(s)

Maintainer: Brenton M. Wiernik `<brenton@wiernik.org>`

See Also

Useful links:

- Report bugs at https://github.com/bwiernik/configural/issues `adjust_Rsq` *Adjust a regression model R-squared for overfitting*

Description

Estimate shrinkage for regression models

Usage

```
adjust_Rsq(Rsq, n, p, adjust = c("fisher", "pop", "cv"))
```

Arguments

`Rsq`	Observed model R-squared
`n`	Sample size
`p`	Number of predictors
`adjust`	Which adjustment to apply. Options are "fisher" for the Adjusted R-squared method used in `stats::lm()`, "pop" for the positive-part Pratt estimator of the population R-squared, and "cv" for the Browne/positive-part Pratt estimator of the cross-validity R-squared. Based on Shieh (2008), these are the estimators for the population and cross-validity R-squared values that show the least bias with a minimal increase in computational complexity.

Value

An adjusted R-squared value.

References

Shieh, G. (2008). Improved shrinkage estimation of squared multiple correlation coefficient and squared cross-validity coefficient. *Organizational Research Methods, 11*(2), 387–407. doi:10.1177/1094428106292901

Examples

```
adjust_Rsq(.55, 100, 6, adjust = "pop")
```

complete_matrix — *Make a matrix symmetric by averaging with its transpose*

Description

Makes a matrix symmetric by averaging the elements of the matrix and its transpose. When This function fills in NA elements of a matrix with the corresponding value from the matrix transpose, if available

Usage

```
complete_matrix(m, na.rm = TRUE)
```

Arguments

m	Numeric matrix to complete.
na.rm	Logical. Should missing values be dropped? (default: TRUE)

Value

A completed matrix.

Examples

```
predictors <- c('auto', 'skill_var', 'task_var', 'task_sig', 'task_id',
'fb_job', 'job_comp', 'interdep', 'fb_others', 'soc_support')
m <- jobchar$sevar_r[c('perform', predictors), c('perform', predictors)]
complete_matrix(m)
```

cor_covariance — *Calculate the asymptotic sampling covariance matrix for the unique elements of a correlation matrix*

Description

Calculate the asymptotic sampling covariance matrix for the unique elements of a correlation matrix

Usage

```
cor_covariance(r, n)
```

Arguments

r	A correlation matrix
n	The sample size

Value

The asymptotic sampling covariance matrix

Author(s)

Based on an internal function from the **fungible** package by Niels Waller

References

Nel, D. G. (1985). A matrix derivation of the asymptotic covariance matrix of sample correlation coefficients. *Linear Algebra and Its Applications, 67*, 137–145. doi:10.1016/00243795(85)901910

Examples

```
cor_covariance(matrix(c(1, .2, .3, .2, 1, .3, .3, .3, 1), ncol = 3), 100)
```

---

cor_covariance_meta *Estimate the asymptotic sampling covariance matrix for the unique elements of a meta-analytic correlation matrix*

Description

Estimate the asymptotic sampling covariance matrix for the unique elements of a meta-analytic correlation matrix

Usage

```
cor_covariance_meta(
  r,
  n,
  sevar,
  source = NULL,
  rho = NULL,
  sevar_rho = NULL,
  n_overlap = NULL
)
```

Arguments

`r`	A meta-analytic matrix of observed correlations (can be full or lower-triangular).
`n`	A matrix of total sample sizes for the meta-analytic correlations in `r` (can be full or lower-triangular).
`sevar`	A matrix of estimated sampling error variances for the meta-analytic correlations in `r` (can be full or lower-triangular).
`source`	A matrix indicating the sources of the meta-analytic correlations in `r` (can be full or lower-triangular). Used to estimate overlapping sample size for correlations when `n_overlap == NULL`.

`rho`	A meta-analytic matrix of corrected correlations (can be full or lower-triangular).
`sevar_rho`	A matrix of estimated sampling error variances for the meta-analytic corrected correlations in `rho` (can be full or lower-triangular).
`n_overlap`	A matrix indicating the overlapping sample size for the unique (lower triangular) values in `r` (can be full or lower-triangular). Values must be arranged in the order returned by `cor_labels(colnames(R))`.

Details

If both `source` and `n_overlap` are `NULL`, it is assumed that all meta-analytic correlations come from the the same source.

Value

The estimated asymptotic sampling covariance matrix

References

Nel, D. G. (1985). A matrix derivation of the asymptotic covariance matrix of sample correlation coefficients. *Linear Algebra and Its Applications, 67*, 137–145. doi:10.1016/00243795(85)901910

Wiernik, B. M. (2018). *Accounting for dependency in meta-analytic structural equations modeling: A flexible alternative to generalized least squares and two-stage structural equations modeling.* Unpublished manuscript.

Examples

```
cor_covariance_meta(r = mindfulness$r, n = mindfulness$n,
                    sevar = mindfulness$sevar_r, source = mindfulness$source)
```

`cor_labels` *Generate labels for correlations from a vector of variable names*

Description

This function returns a vector of labels for the unique correlations between pairs of variables from a supplied vector of variable names

Usage

```
cor_labels(var_names)
```

Arguments

`var_names`	A character vector of variable names

Value

A vector of correlation labels

Examples

```
cor_labels(colnames(mindfulness$r))
```

---

cpa_mat *Conduct criterion profile analysis using a correlation matrix*

Description

Conduct criterion profile analysis using a correlation matrix

Usage

```
cpa_mat(
  formula,
  cov_mat,
  n = NULL,
  se_var_mat = NULL,
  se_beta_method = c("normal", "lm"),
  adjust = c("fisher", "pop", "cv"),
  conf_level = 0.95,
  ...
)
```

Arguments

`formula`	Regression formula with a single outcome variable on the left-hand side and one or more predictor variables on the right-hand side (e.g., Y ~ X1 + X2).
`cov_mat`	Correlation matrix containing the variables to be used in the regression.
`n`	Sample size. Used to compute adjusted R-squared and, if `se_var_mat` is NULL, standard errors. If NULL and `se_var_mat` is specified, effective sample size is computed based on `se_var_mat` (cf. Revelle et al., 2017).
`se_var_mat`	Optional. The sampling error covariance matrix among the unique elements of `cov_mat`. Used to calculate standard errors. If not supplied, the sampling covariance matrix is calculated using `n`.
`se_beta_method`	Method to use to estimate the standard errors of standardized regression (beta) coefficients. Current options include "normal" (use the Jones-Waller, 2015, normal-theory approach) and "lm" (estimate standard errors using conventional regression formulas).
`adjust`	Method to adjust R-squared for overfitting. See `adjust_Rsq()` for details.
`conf_level`	Confidence level to use for confidence intervals.
`...`	Additional arguments.

Value

An object of class "cpa" containing the criterion pattern vector and CPA variance decomposition

References

Jones, J. A., & Waller, N. G. (2015). The normal-theory and asymptotic distribution-free (ADF) covariance matrix of standardized regression coefficients: Theoretical extensions and finite sample behavior. *Psychometrika, 80*(2), 365–378. doi:10.1007/s113360139380y

Revelle, W., Condon, D. M., Wilt, J., French, J. A., Brown, A., & Elleman, L. G. (2017). Web- and phone-based data collection using planned missing designs. In N. G. Fielding, R. M. Lee, & G. Blank, *The SAGE Handbook of Online Research Methods* (pp. 578–594). SAGE Publications. doi:10.4135/9781473957992.n33

Wiernik, B. M., Wilmot, M. P., Davison, M. L., & Ones, D. S. (2019). Meta-analytic criterion profile analysis. *Psychological Methods* doi:10.1037/met0000305

Examples

```
sevar <- cor_covariance_meta(mindfulness$r, mindfulness$n, mindfulness$sevar_r, mindfulness$source)
cpa_mat(mindfulness ~ ES + A + C + Ex + O,
          cov_mat = mindfulness$r,
          n = NULL,
          se_var_mat = sevar,
          adjust = "pop")
```

`cpa_scores` *Compute CPA level and pattern scores for a set of data*

Description

Compute CPA level and pattern scores for a set of data

Usage

```
cpa_scores(
  cpa_mod,
  newdata = NULL,
  augment = TRUE,
  cpa_names = c("cpa_lev", "cpa_pat"),
  scale = FALSE,
  scale_center = TRUE,
  scale_scale = TRUE
)
```

Arguments

`cpa_mod`	A model returned from `cpa_mat()` (a model of class "cpa")
`newdata`	A data frame or matrix containing columns with the same names as the predictors in `cpa_mod`.
`augment`	Should be CPA score columns be added to `newdata` (`TRUE`, default) or returned alone (`FALSE`)?

`cpa_names`	Character vector of length 2 giving the variable names to assign to the CPA score columns.
`scale`	Logical. Should the variables in `newdata` be scaled (standardized)?
`scale_center`	If `scale` is `TRUE`, passed to the `center` argument in `base::scale()`. Can be `TRUE` (center columns of `newdata` around the column means), `FALSE` (don't center), or a numeric vector of length equal to the number of predictors in `cpa_mod` containing the values to center around.
`scale_scale`	If `scale` is `TRUE`, passed to the `scale` argument in `base::scale()`. Can be `TRUE` (scale/standardize columns of `newdata` using the column standard deviations or root mean squares), `FALSE` (don't scale), or a numeric vector of length equal to the number of predictors in `cpa_mod` containing the values to scale by. See `base::scale()` for details.

Value

A data frame containing the CPA score variables.

Examples

```
sevar <- cor_covariance_meta(mindfulness$r, mindfulness$n, mindfulness$sevar_r, mindfulness$source)
cpa_mod <- cpa_mat(mindfulness ~ ES + A + C + Ex + O,
                   cov_mat = mindfulness$r,
                   n = NULL,
                   se_var_mat = sevar,
                   adjust = "pop")

newdata <- data.frame(ES = c(4.2, 3.2, 3.4, 4.2, 3.8, 4.0, 5.6, 2.8, 3.4, 2.8),
                      A  = c(4.0, 4.2, 3.8, 4.6, 4.0, 4.6, 4.6, 2.6, 3.6, 5.4),
                      C  = c(2.8, 4.0, 4.0, 3.0, 4.4, 5.6, 4.4, 3.4, 4.0, 5.6),
                      Ex = c(3.8, 5.0, 4.2, 3.6, 4.8, 5.6, 4.2, 2.4, 3.4, 4.8),
                      O  = c(3.0, 4.0, 4.8, 3.2, 3.6, 5.0, 5.4, 4.2, 5.0, 5.2)
                      )

newdata_cpa <- cpa_scores(cpa_mod, newdata, augment = FALSE)
newdata_augment <- cpa_scores(cpa_mod, newdata, augment = TRUE)
```

`disorders` *Meta-analytic correlations among Big Five personality traits and psychological disorders*

Description

Big Five intercorrelations from Davies et al. (2015). Big Five–psychological disorder correlations from Kotov et al. (2010). Note that there were several duplicate or missing values in the reported data table in the published article. These results are based on corrected data values.

Usage

```
data(disorders)
```

Format

list with entries `r` (mean observed correlations), `rho` (mean corrected correlations), `n` (sample sizes), `sevar_r` (sampling error variances for mean observed correlations), `sevar_rho` (sampling error variances for mean corrected correlations), and `source` (character labels indicating which meta-analytic correlations came from the same source)

References

Davies, S. E., Connelly, B. L., Ones, D. S., & Birkland, A. S. (2015). The general factor of personality: The "Big One," a self-evaluative trait, or a methodological gnat that won't go away? *Personality and Individual Differences, 81*, 13–22. doi:10.1016/j.paid.2015.01.006

Kotov, R., Gamez, W., Schmidt, F., & Watson, D. (2010). Linking "big" personality traits to anxiety, depressive, and substance use disorders: A meta-analysis. *Psychological Bulletin, 136*(5), 768–821. doi:10.1037/a0020327

Examples

```
data(disorders)
```

`fungible` *Locate extrema of fungible weights for regression and related models*

Description

Generates fungible regression weights (Waller, 2008) and related results using the method by Waller and Jones (2010).

Usage

```
fungible(
  object,
  theta = 0.005,
  Nstarts = 1000,
  MaxMin = c("min", "max"),
  silent = FALSE,
  ...
)
```

Arguments

`object`	A fitted model object. Currently supported classes are: "cpa"
`theta`	A vector of values to decrement from R-squared to compute families of fungible coefficients.
`Nstarts`	Maximum number of (max) minimizations from random starting configurations.

MaxMin	Should the cosine between the observed and alternative weights be maximized ("max") to find the maximally similar coefficients or minimized ("min") to find the maximally dissimilar coefficients?
silent	Should current optimization values be printed to the console (FALSE) or suppressed (TRUE)?
...	Additional arguments

Value

A list containing the alternative weights and other fungible weights estimation parameters

Author(s)

Niels Waller, Jeff Jones, Brenton M. Wiernik. Adapted from `fungible::fungibleExtrema()`.

References

Waller, N. G. (2008). Fungible weights in multiple regression. *Psychometrika, 73*(4), 691–703. doi:10.1007/s113360089066z

Waller, N. G., & Jones, J. A. (2009). Locating the extrema of fungible regression weights. *Psychometrika, 74*(4), 589–602. doi:10.1007/s1133600890877

Examples

```
mind <- cpa_mat(mindfulness ~ ES + A + C + Ex + O,
                cov_mat = mindfulness$r,
                n = harmonic_mean(vechs(mindfulness$n)),
                se_var_mat = cor_covariance_meta(mindfulness$r,
                                                 mindfulness$n,
                                                 mindfulness$sevar_r,
                                                 mindfulness$source),
                adjust = "pop")
mind_fung <- fungible(mind, Nstarts = 100)
```

`fungible.cpa` *Locate extrema of fungible criterion profile patterns*

Description

Identify maximally similar or dissimilar criterion patterns in criterion profile analysis

Usage

```
## S3 method for class 'cpa'
fungible(
  object,
  theta = 0.005,
  Nstarts = 1000,
  MaxMin = c("min", "max"),
  silent = FALSE,
  ...
)
```

Arguments

`object`	A fitted model object of class "cpa".
`theta`	A vector of values to decrement from R-squared to compute families of fungible coefficients.
`Nstarts`	Maximum number of (max) minimizations from random starting configurations.
`MaxMin`	Should the cosine between the observed and alternative weights be maximized ("max") to find the maximally similar coefficients or minimized ("min") to find the maximally dissimilar coefficients?
`silent`	Should current optimization values be printed to the console (`FALSE`) or suppressed (`TRUE`)?
`...`	Additional arguments

Value

A list containing the alternative weights and other fungible weights estimation parameters

References

Wiernik, B. M., Wilmot, M. P., Davison, M. L., & Ones, D. S. (2020). Meta-analytic criterion profile analysis. *Psychological Methods*. doi:10.1037/met0000305

Examples

```
mind <- cpa_mat(mindfulness ~ ES + A + C + Ex + O,
                cov_mat = mindfulness$r,
                n = harmonic_mean(vechs(mindfulness$n)),
                se_var_mat = cor_covariance_meta(mindfulness$r,
                                                 mindfulness$n,
                                                 mindfulness$sevar_r,
                                                 mindfulness$source),
                adjust = "pop")
mind_fung <- fungible(mind, Nstarts = 100)
```

fungible.lm *Locate extrema of fungible OLS regression weights*

Description

Identify maximally similar or dissimilar sets of fungible standardized regression coefficients from an OLS regression model

Usage

```
## S3 method for class 'lm'
fungible(
  object,
  theta = 0.005,
  Nstarts = 1000,
  MaxMin = c("min", "max"),
  silent = FALSE,
  ...
)
```

Arguments

`object`	A fitted model object of class "lm" or "summary.lm".
`theta`	A vector of values to decrement from R-squared to compute families of fungible coefficients.
`Nstarts`	Maximum number of (max) minimizations from random starting configurations.
`MaxMin`	Should the cosine between the observed and alternative weights be maximized ("max") to find the maximally similar coefficients or minimized ("min") to find the maximally dissimilar coefficients?
`silent`	Should current optimization values be printed to the console (`FALSE`) or suppressed (`TRUE`)?
`...`	Additional arguments

Value

A list containing the alternative weights and other fungible weights estimation parameters

References

Waller, N. G., & Jones, J. A. (2009). Locating the extrema of fungible regression weights. *Psychometrika, 74*(4), 589–602. doi:10.1007/s1133600890877

Examples

```
lm_mtcars <- lm(mpg ~ cyl + disp + hp + drat + wt + qsec + vs + am + gear + carb,
                data = mtcars)
lm_mtcars_fung <- fungible(lm_mtcars, Nstarts = 100)
```

`gre` *Meta-analytic correlations of Graduate Record Examination subtests with graduate grade point average*

Description

Correlations between GRE subtests and graduate student GPA from Kuncel et al. (2001).

Usage

```
data(gre)
```

Format

list with entries `r` (mean observed correlations), `rho` (mean corrected correlations), `n` (sample sizes), `sevar_r` (sampling error variances for mean observed correlations), `sevar_rho` (sampling error variances for mean corrected correlations), and `source` (character labels indicating which meta-analytic correlations came from the same source)

Details

GRE–GPA correlations in `rho` are corrected for direct range restriction on the GRE and unreliability in GPA. Subtest intercorrelations in `rho` are observed correlations computed among applicant norm samples. These values are also used in `r`. Due to compensatory selection on GRE scores, these values will not accurately reflect subtest intercorrelations in selected-student (range-restricted) samples. `sevar_rho` and`sevar_r` for GRE subtest intercorrelations are computed with an assumed SD_{ρ}SD_rho = .02.

References

Kuncel, N. R., Hezlett, S. A., & Ones, D. S. (2001). A comprehensive meta-analysis of the predictive validity of the graduate record examinations: Implications for graduate student selection and performance. *Psychological Bulletin, 127*(1), 162–181. doi:10.1037/00332909.127.1.162

Examples

```
data(gre)
```

harmonic_mean *Find the harmonic mean of a vector, matrix, or columns of a data.frame*

Description

The harmonic mean is merely the reciprocal of the arithmetic mean of the reciprocals.

Usage

```
harmonic_mean(x, na.rm = TRUE, zero = TRUE)
```

Arguments

x	A vector, matrix, or data.frame
na.rm	Logical. If TRUE, remove NA values before processing
zero	Logical, If TRUE, if there are any zeroes, return 0, else, return the harmonic mean of the non-zero elements

Value

The harmonic mean of x

Author(s)

Adapted from psych::harmonic.mean() by William Revelle

Examples

```
harmonic_mean(1:10)
```

hrm *Meta-analytic correlations of HRM practices with organizational financial performance*

Description

Human resource management practice–organizational financial performance correlations from Combs et al. (2006). Intercorrelations among HRM practices from Guest et al. (2004).

Usage

```
data(hrm)
```

Format

list with entries `r` (mean observed correlations), `rho` (mean corrected correlations), `n` (sample sizes), `sevar_r` (sampling error variances for mean observed correlations), `sevar_rho` (sampling error variances for mean corrected correlations), and `source` (character labels indicating which meta-analytic correlations came from the same source)

References

Combs, J., Liu, Y., Hall, A., & Ketchen, D. (2006). How much do high-performance work practices matter? A meta-analysis of their effects on organizational performance. *Personnel Psychology, 59*(3), 501–528. doi:10.1111/j.17446570.2006.00045.x

Guest, D., Conway, N., & Dewe, P. (2004). Using sequential tree analysis to search for 'bundles' of HR practices. *Human Resource Management Journal, 14*(1), 79–96. doi:10.1111/j.1748-8583.2004.tb00113.x

Examples

```
data(hrm)
```

---

jobchar — *Meta-analytic correlations of job characteristics with performance and satisfaction*

Description

Self-rated job characteristics intercorrelations and correlations with other-rated job performance and self-rated job satisfaction from Humphrey et al. (2007).

Usage

```
data(jobchar)
```

Format

list with entries `r` (mean observed correlations), `rho` (mean corrected correlations), `n` (sample sizes), `sevar_r` (sampling error variances for mean observed correlations), `sevar_rho` (sampling error variances for mean corrected correlations), and `source` (character labels indicating which meta-analytic correlations came from the same source)

References

Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: A meta-analytic summary and theoretical extension of the work design literature. *Journal of Applied Psychology, 92*(5), 1332–1356. doi:10.1037/0021-9010.92.5.1332

Examples

```
data(jobchar)
predictors <- c('auto', 'skill_var', 'task_var', 'task_sig', 'task_id',
                'fb_job', 'job_comp', 'interdep', 'fb_others', 'soc_support')
sevar_jobchar_perf <-
  cor_covariance_meta(
    r = jobchar$r[c('perform', predictors), c('perform', predictors)],
                    n = jobchar$n[c('perform', predictors), c('perform', predictors)],
             sevar = jobchar$sevar_r[c('perform', predictors), c('perform', predictors)],
                  rho = jobchar$rho[c('perform', predictors), c('perform', predictors)],
                    sevar_rho = jobchar$sevar_rho[c('perform', predictors),
                                                  c('perform', predictors)],
             source = jobchar$source[c('perform', predictors), c('perform', predictors)])
cpa_jobchar_perf <- cpa_mat(perform ~ auto + skill_var + task_var + task_sig +
                              task_id + fb_job + job_comp +
                              interdep + fb_others + soc_support,
                            cov_mat = jobchar$rho,
                         n = harmonic_mean(as.vector(jobchar$n[c('perform', predictors),
                                                             c('perform', predictors)])),
                            se_var_mat = sevar_jobchar_perf,
                            adjust = "pop", conf_level = .95)
```

---

mindfulness — *Meta-analytic correlations among Big Five personality traits and trait mindfulness*

Description

Big Five intercorrelations from Davies et al. (2015). Big Five–Mindfulness correlations from Hanley and Garland (2017). Coefficient alpha for mindfulness measures taken from Giluk (2009).

Usage

```
data(mindfulness)
```

Format

list with entries `r` (mean observed correlations), `rho` (mean corrected correlations), `n` (sample sizes), `sevar_r` (sampling error variances for mean observed correlations), `sevar_rho` (sampling error variances for mean corrected correlations), and `source` (character labels indicating which meta-analytic correlations came from the same source)

References

Davies, S. E., Connelly, B. L., Ones, D. S., & Birkland, A. S. (2015). The general factor of personality: The "Big One," a self-evaluative trait, or a methodological gnat that won't go away? *Personality and Individual Differences, 81*, 13–22. doi:10.1016/j.paid.2015.01.006

Giluk, T. L. (2009). Mindfulness, Big Five personality, and affect: A meta-analysis. *Personality and Individual Differences, 47*(8), 805–811. doi:10.1016/j.paid.2009.06.026

Hanley, A. W., & Garland, E. L. (2017). The mindful personality: A meta-analysis from a cybernetic perspective. *Mindfulness, 8*(6), 1456–1470. doi:10.1007/s1267101707368

Examples

```
data(mindfulness)
```

`n_effective_R2` *Effective sample size*

Description

Estimate an effective sample size for a statistic given the observed statistic and the estimated sampling error variance (cf. Revelle et al., 2017).

Usage

```
n_effective_R2(R2, var_R2, p)
```

Arguments

`R2`	Observed *R*^2^ value
`var_R2`	Estimated sampling error variance for *R*^2^
`p`	Number of predictors in the regression model

Details

`n_effective_R2` estimates the effective sample size for the *R*^2^ value from an OLS regression model, using the sampling error variance formula from Cohen et al. (2003).

Value

An effective sample size.

References

Revelle, W., Condon, D. M., Wilt, J., French, J. A., Brown, A., & Elleman, L. G. (2017). Web- and phone-based data collection using planned missing designs. In N. G. Fielding, R. M. Lee, & G. Blank, *The SAGE Handbook of Online Research Methods* (pp. 578–594). SAGE Publications. doi:10.4135/9781473957992.n33

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Routledge. doi:10.4324/9780203774441

Examples

```
n_effective_R2(0.3953882, 0.0005397923, 5)
```

`prejudice` *Correlations between study design moderators and effect sizes for prejudice reduction following intergroup contact*

Description

Correlations among study design moderators and study design moderator–observed prejudice reduction effect sizes from Pettigrew and Tropp (2008). Note that correlations with effect size have been reverse-coded so that a positive correlation indicates that a higher level of the moderator is associated with *larger* prejudice reduction.

Usage

```
data(prejudice)
```

Format

list with entries `r` (observed correlations among moderators) and `k` (number of samples in meta-analysis)

References

Pettigrew, T. F., & Tropp, L. R. (2006). A meta-analytic test of intergroup contact theory. *Journal of Personality and Social Psychology, 90*(5), 751–783. doi:10.1037/00223514.90.5.751

Examples

```
data(prejudice)
```

`team` *Meta-analytic correlations among team processes and team effectiveness*

Description

Team process intercorrelations and team process–team performance/affect correlations from LePine et al. (2008).

Usage

```
data(team)
```

Format

list with entries `r` (mean observed correlations), `rho` (mean corrected correlations), `n` (sample sizes), `sevar_r` (sampling error variances for mean observed correlations), `sevar_rho` (sampling error variances for mean corrected correlations), and `source` (character labels indicating which meta-analytic correlations came from the same source)

Details

Note that LePine et al. (2008) did not report confidence intervals, sampling error variances, or heterogeneity estimates for correlations among team processes; included sampling error variances in this list are based on total sample size only and do not include uncertainty stemming from any effect size heterogeneity.

References

LePine, J. A., Piccolo, R. F., Jackson, C. L., Mathieu, J. E., & Saul, J. R. (2008). A meta-analysis of teamwork processes: tests of a multidimensional model and relationships with team effectiveness criteria. *Personnel Psychology, 61*(2), 273–307. doi:10.1111/j.17446570.2008.00114.x

Examples

```
data(team)
```

`var_error_cpa` *Estimate the sampling error variance for criterion profile analysis parameters*

Description

Estimate the sampling error variance for criterion profile analysis parameters

Usage

```
var_error_cpa(
  Rxx,
  rxy,
  n = NULL,
  se_var_mat = NULL,
  adjust = c("fisher", "pop", "cv")
)
```

Arguments

`Rxx`	An intercorrelation matrix among the predictor variables
`rxy`	A vector of predictor–criterion correlations
`n`	The sample size. If NULL and `se_var_mat` is provided, `n` will be estimated as the effective sample size based on `se_var_mat`. See `n_effective_R2()`.
`se_var_mat`	A matrix of sampling covariance values for the elements of `Rxx` and `rxy`. If NULL, generated using the Normal theory covariance matrix based on `n`.
`adjust`	Method to adjust R-squared for overfitting. See `adjust_Rsq` for details.

Value

A list containing sampling covariance matrices or sampling error variance estimates for CPA parameters

Examples

```
var_error_cpa(mindfulness$rho[1:5, 1:5], mindfulness$rho[1:5, 6], n = 17060)
```

---

vech *Vectorize a matrix*

Description

`cvec` returns the column-wise vectorization of an input matrix (stacking the columns on one another). `rvec` returns the row-wise vectorization of an input matrix (concatenating the rows after each other). `vech` returns the column-wise half-vectorization of an input matrix (stacking the lower triangular elements of the matrix, including the diagonal). `vechs` returns the strict column-wise half-vectorization of an input matrix (stacking the lower triangular elements of the matrix, excluding the diagonal). All functions return the output as a vector.

Usage

```
vech(x)

vechs(x)

cvec(x)

rvec(x)
```

Arguments

x	A matrix

Value

A vector of values

Author(s)

Based on functions from the the **OpenMx** package

Examples

```
cvec(matrix(1:9, 3, 3))
rvec(matrix(1:9, 3, 3))
vech(matrix(1:9, 3, 3))
vechs(matrix(1:9, 3, 3))
vechs(matrix(1:12, 3, 4))
```

`vech2full` *Inverse vectorize a matrix*

Description

These functions return the symmetric matrix that produces the given half-vectorization result.

Usage

```
vech2full(x)

vechs2full(x, diagonal = 1)
```

Arguments

`x`	A vector
`diagonal`	A value or vector of values to enter on the diagonal for `vechs2full` (default = 1)

Details

The input consists of a vector of the elements in the lower triangle of the resulting matrix (for `vech2full`, including the elements along the diagonal of the matrix, as a column vector), filled column-wise. For `vechs2full`, the diagonal values are filled as 1 by default, alternative values can be specified using the `diag` argument. The inverse half-vectorization takes a vector and reconstructs a symmetric matrix such that vech2full(vech(x)) is identical to x if x is symmetric.

Value

A symmetric matrix

Author(s)

Based on functions from the the **OpenMx** package

Examples

```
vech2full(c(1, 2, 3, 5, 6, 9))
vechs2full(c(2, 3, 6), diagonal = 0)
```

wt_cov *Compute weighted covariances*

Description

Compute the weighted covariance among variables in a matrix or between the variables in two separate matrices/vectors.

Usage

```
wt_cov(
  x,
  y = NULL,
  wt = NULL,
  as_cor = FALSE,
  use = c("everything", "listwise", "pairwise"),
  unbiased = TRUE,
  df_type = c("count", "sum_wts")
)

wt_cor(x, y = NULL, wt = NULL, use = "everything")
```

Arguments

`x`	Vector or matrix of x variables.
`y`	Vector or matrix of y variables
`wt`	Vector of weights
`as_cor`	Logical scalar that determines whether the covariances should be standardized (TRUE) or unstandardized (FALSE).
`use`	Method for handling missing values. "everything" uses all values and does not account for missingness, "listwise" uses only complete cases, and "pairwise" uses pairwise deletion.
`unbiased`	Logical scalar determining whether variance should be unbiased (TRUE) or maximum-likelihood (FALSE).
`df_type`	Character scalar determining whether the degrees of freedom for unbiased estimates should be based on numbers of cases (n - 1; "count"; default) or squared sums of weights (1 - sum(w^2); "sum_wts").

Value

Scalar, vector, or matrix of covariances.

Author(s)

Jeffrey A. Dahlke

Examples

```
wt_cov(x = c(1, 0, 2), y = c(1, 2, 3), wt = c(1, 2, 2), as_cor = FALSE, use = "everything")
wt_cov(x = c(1, 0, 2), y = c(1, 2, 3), wt = c(1, 2, 2), as_cor = TRUE, use = "everything")
wt_cov(x = cbind(c(1, 0, 2), c(1, 2, 3)), wt = c(1, 2, 2), as_cor = FALSE, use = "everything")
wt_cov(x = cbind(c(1, 0, 2), c(1, 2, 3)), wt = c(1, 2, 2), as_cor = TRUE, use = "everything")
wt_cov(x = cbind(c(1, 0, 2, NA), c(1, 2, 3, 3)),
       wt = c(1, 2, 2, 1), as_cor = FALSE, use = "listwise")
wt_cov(x = cbind(c(1, 0, 2, NA), c(1, 2, 3, 3)),
       wt = c(1, 2, 2, 1), as_cor = TRUE, use = "listwise")
```

---

wt_dist — *Weighted descriptive statistics for a vector of numbers*

Description

Compute the weighted mean and variance of a vector of numeric values. If no weights are supplied, defaults to computing the unweighted mean and the unweighted maximum-likelihood variance.

Usage

```
wt_dist(
  x,
  wt = rep(1, length(x)),
  unbiased = TRUE,
  df_type = c("count", "sum_wts")
)

wt_mean(x, wt = rep(1, length(x)))

wt_var(
  x,
  wt = rep(1, length(x)),
  unbiased = TRUE,
  df_type = c("count", "sum_wts")
)
```

Arguments

x	Vector of values to be analyzed.
wt	Weights associated with the values in x.
unbiased	Logical scalar determining whether variance should be unbiased (TRUE) or maximum-likelihood (FALSE).
df_type	Character scalar determining whether the degrees of freedom for unbiased estimates should be based on numbers of cases ("count"; default) or sums of weights ("sum_wts").

Details

The weighted mean is computed as
$$\bar{x}_w = \frac{\Sigma_{i=1}^{k} x_i w_i}{\Sigma_{i=1}^{k} w_i}$$
where *x* is a numeric vector and *w* is a vector of weights.

The weighted variance is computed as

$$var_w(x) = \frac{\Sigma_{i=1}^{k} (x_i - \bar{x}_w)^2 w_i}{\Sigma_{i=1}^{k} w_i}$$

and the unbiased weighted variance is estimated by multiplying $var_w(x)$ by $\frac{k}{k-1}$.

Value

A weighted mean and variance if weights are supplied or an unweighted mean and variance if weights are not supplied.

Author(s)

Jeffrey A. Dahlke

Examples

```
wt_dist(x = c(.1, .3, .5), wt = c(100, 200, 300))
wt_mean(x = c(.1, .3, .5), wt = c(100, 200, 300))
wt_var(x = c(.1, .3, .5), wt = c(100, 200, 300))
```

## %&%	*Quadratic form matrix product*

Description

Calculate the quadratic form
$$Q = x'Ax$$

Usage

```
A %&% x
```

Arguments

A	A square matrix
x	A vector or matrix

Value

The quadratic product

Examples

```
diag(5) %&% 1:5
```

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