Package ‘networkscaleup’

April 6, 2022

Title Network Scale-Up Models for Aggregated Relational Data

Version 0.1-1

Description Provides a variety of Network Scale-up Models for researchers to analyze Aggregated Relational Data, mostly through the use of Stan. In this version, the package implements models from Laga, I., Bao, L., and Niu, X (2021) <arXiv:2109.10204>, Zheng, T., Salganik, M. J., and Gelman, A. (2006) <doi:10.1198/016214505000001168>, Killworth, P. D., Johnsen, E. C., McCarty, C., Shelley, G. A., and Bernard, H. R. (1998) <doi:10.1016/S0378-8733(96)00305-X>, and Killworth, P. D., McCarty, C., Bernard, H. R., Shelley, G. A., and Johnsen, E. C. (1998) <doi:10.1177/0193841X9802200205>.

License GPL (>= 3)

Encoding UTF-8

RoxygenNote 7.1.2

Biarch true

Depends R (>= 3.4.0)

Imports methods, Rcpp (>= 0.12.0), RcppParallel (>= 5.0.1), rstan (>= 2.18.1), rstantools (>= 2.1.1), LaplacesDemon (>= 16.1.6)

LinkingTo BH (>= 1.66.0), Rcpp (>= 0.12.0), RcppEigen (>= 0.3.3.3.0), RcppParallel (>= 5.0.1), rstan (>= 2.18.1), StanHeaders (>= 2.18.0)

SystemRequirements GNU make

Suggests rmarkdown, knitr

VignetteBuilder knitr

LazyData true

NeedsCompilation yes

Author Ian Laga [aut, cre] (<https://orcid.org/0000-0002-5164-4856>),
Le Bao [aut],
Xiaoyue Niu [aut]

Maintainer Ian Laga <ilaga25@gmail.com>

Repository CRAN

Date/Publication 2022-04-06 07:10:02 UTC

R topics documented:

`networkscaleup-package` *The 'networkscaleup' package.*

Description

Provides a variety of Network Scale-up Models for researchers to analyze Aggregated Relational Data, mostly through the use of Stan.

References

Stan Development Team (2021). RStan: the R interface to Stan. R package version 2.21.3. https://mc-stan.org

Laga, I., Bao, L., and Niu, X (2021). A Correlated Network Scaleup Model: Finding the Connection Between Subpopulations

Zheng, T., Salganik, M. J., and Gelman, A. (2006). How many people do you know in prison, *Journal of the American Statistical Association*, **101:474**, 409–423

Killworth, P. D., Johnsen, E. C., McCarty, C., Shelley, G. A., and Bernard, H. R. (1998). A Social Network Approach to Estimating Seroprevalence in the United States, *Social Networks*, **20**, 23–50

Killworth, P. D., McCarty, C., Bernard, H. R., Shelley, G. A., and Johnsen, E. C. (1998). Estimation of Seroprevalence, Rape and Homelessness in the United States Using a Social Network Approach, *Evaluation Review*, **22**, 289–308

`correlatedStan` *Fit ARD using the uncorrelated or correlated model in Stan This function fits the ARD using either the uncorrelated or correlated model in Laga et al. (2021) in Stan. The population size estimates and degrees are scaled using a post-hoc procedure.*

Description

Fit ARD using the uncorrelated or correlated model in Stan This function fits the ARD using either the uncorrelated or correlated model in Laga et al. (2021) in Stan. The population size estimates and degrees are scaled using a post-hoc procedure.

Usage

```
correlatedStan(
  ard,
  known_sizes = NULL,
  known_ind = NULL,
  N = NULL,
  model = c("correlated", "uncorrelated"),
  scaling = c("all", "overdispersed", "weighted", "weighted_sq"),
  x = NULL,
  z_global = NULL,
  z_subpop = NULL,
  G1_ind = NULL,
  G2_ind = NULL,
  B2_ind = NULL,
  chains = 3,
  cores = 1,
  warmup = 1000,
  iter = 1500,
  thin = 1,
  return_fit = FALSE,
  ...
)
```

Arguments

`ard`	The n_i x n_k matrix of non-negative ARD integer responses, where the (i,k)th element corresponds to the number of people that respondent `i` knows in subpopulation `k`.
`known_sizes`	The known subpopulation sizes corresponding to a subset of the columns of `ard`.
`known_ind`	The indices that correspond to the columns of `ard` with known_sizes. By default, the function assumes the first `n_known` columns, where `n_known` corresponds to the number of `known_sizes`.
`N`	The known total population size.
`model`	A character vector denoting which of the two models should be fit, either 'uncorrelated' or 'correlated'. More details of these models are provided below. The function decides which covariate model is needed based on the covariates provided below.
`scaling`	An optional character vector providing the name of scaling procedure should be performed in order to transform estimates to degrees and subpopulation sizes. If `NULL`, the parameters will be returned unscaled. Alternatively, scaling may be performed independently using the scaling function. Scaling options are `NULL`, `overdispersed`, `all`, `weighted`, or `weighted_sq` (`weighted` and `weighted_sq` are only available if `model = "correlated"`. Further details are provided in the Details section.
`x`	A matrix with dimensions n_i x `n_unknown`, where `n_unknown` refers to the number of unknown subpopulation sizes. In the language of Teo et al. (2019), these represent the individual's perception of each hidden population.

z_global	A matrix with dimensions n_i x p_global, where p_global is the number of demographic covariates used. This matrix represents the demographic information about the respondents in order to capture the barrier effects.
z_subpop	A matrix with dimensions n_i x p_subpop, where p_subpop is the number of demographic covariates used. This matrix represents the demographic information about the respondents in order to capture the barrier effects.
G1_ind	A vector of indices denoting the columns of ard that correspond to the primary scaling groups, i.e. the collection of rare girls' names in Zheng, Salganik, and Gelman (2006). By default, all known_sizes are used. If G2_ind and B2_ind are not provided, C = C_1, so only G1_ind are used. If G1_ind is not provided, no scaling is performed.
G2_ind	A vector of indices denoting the columns of ard that correspond to the subpopulations that belong to the first secondary scaling groups, i.e. the collection of somewhat popular girls' names.
B2_ind	A vector of indices denoting the columns of ard that correspond to the subpopulations that belong to the second secondary scaling groups, i.e. the collection of somewhat popular boys' names.
chains	A positive integer specifying the number of Markov chains.
cores	A positive integer specifying the number of cores to use to run the Markov chains in parallel.
warmup	A positive integer specifying the total number of samples for each chain (including warmup). Matches the usage in stan.
iter	A positive integer specifying the number of warmup samples for each chain. Matches the usage in stan.
thin	A positive integer specifying the interval for saving posterior samples. Default value is 1 (i.e. no thinning).
return_fit	A logical indicating whether the fitted stanfit object should be return. Defaults to FALSE.
...	Additional arguments to be passed to stan.

Details

This function currently fits a variety of models proposed in Laga et al. (2022+). The user may provide any combination of x, z_global, and z_subpop. Additionally, the user may choose to fit a uncorrelated version of the model, where the correlation matrix is equal to the identity matrix.

The scaling options are described below:

NULL No scaling is performed

overdispersed The scaling procedure outlined in Zheng et al. (2006) is performed. In this case, at least Pg1_ind must be provided. See overdispersedStan for more details.

all All subpopulations with known sizes are used to scale the parameters, using a modified scaling procedure that standardizes the sizes so each population is weighted equally. Additional details are provided in Laga et al. (2022+).

weighted All subpopulations with known sizes are weighted according their correlation with the unknown subpopulation size. Additional details are provided in Laga et al. (2022+)

weighted_sq Same as `weighted`, except the weights are squared, providing more relative weight to subpopulations with higher correlation.

Value

Either the full fitted Stan model if `return_fit = TRUE`, else a named list with the estimated parameters extracted using extract (the default). The estimated parameters are named as follows (if estimated in the corresponding model), with additional descriptions as needed:

delta Raw delta parameters

sigma_delta Standard deviation of delta

rho Log prevalence, if scaled, else raw rho parameters

mu_rho Mean of rho

sigma_rho Standard deviation of rho

alpha Slope parameters corresponding to z

beta_global Slope parameters corresponding to x_global

beta_subpop Slope parameters corresponding to x_subpop

tau_N Standard deviation of random effects b

Corr Correlation matrix, if `Correlation = TRUE`

If scaled, the following additional parameters are included:

log_degrees Scaled log degrees

degree Scaled degrees

log_prevalences Scaled log prevalences

sizes Subpopulation size estimates

References

Laga, I., Bao, L., and Niu, X (2021). A Correlated Network Scaleup Model: Finding the Connection Between Subpopulations

Examples

```
## Not run:
data(example_data)

x = example_data$x
z_global = example_data$z[,1:2]
z_subpop = example_data$z[,3:4]

basic_corr_est = correlatedStan(example_data$ard,
     known_sizes = example_data$subpop_sizes[c(1, 2, 4)],
     known_ind = c(1, 2, 4),
     N = example_data$N,
     model = "correlated",
     scaling = "weighted",
```

```
     chains = 1,
     cores = 1,
     warmup = 50,
     iter = 100)

cov_uncorr_est = correlatedStan(example_data$ard,
     known_sizes = example_data$subpop_sizes[c(1, 2, 4)],
     known_ind = c(1, 2, 4),
     N = example_data$N,
     model = "uncorrelated",
     scaling = "all",
     x = x,
     z_global = z_global,
     z_subpop = z_subpop,
     chains = 1,
     cores = 1,
     warmup = 50,
     iter = 100)

cov_corr_est = correlatedStan(example_data$ard,
     known_sizes = example_data$subpop_sizes[c(1, 2, 4)],
     known_ind = c(1, 2, 4),
     N = example_data$N,
     model = "correlated",
     scaling = "all",
     x = x,
     z_subpop = z_subpop,
     chains = 1,
     cores = 1,
     warmup = 50,
     iter = 100)

# Compare size estimates
round(data.frame(true = example_data$subpop_sizes,
     corr_basic = colMeans(basic_corr_est$sizes),
     uncorr_x_zsubpop_zglobal = colMeans(cov_uncorr_est$sizes),
     corr_x_zsubpop = colMeans(cov_corr_est$sizes)))

# Look at z slope parameters
colMeans(cov_uncorr_est$beta_global)
colMeans(cov_corr_est$beta_subpop)
colMeans(cov_uncorr_est$beta_subpop)

# Look at x slope parameters
colMeans(cov_uncorr_est$alpha)
colMeans(cov_corr_est$alpha)

## End(Not run)
```

example_data — *Simulated ARD data set with z and x.*

Description

A simulated data set to demonstrate and test the NSUM methods. The data was simulated from the basic Killworth Binomial model.

Usage

```
example_data
```

Format

A named list for an ARD survey from 100 respondents about 5 subpopulations.

ard A 100 x 5 matrix with integer valued respondents

x A 100 x 5 matrix with simulated answers from a 1-5 Likert scale

z A 100 x 4 matrix with answers for each respondents about 4 demographic questions

N An integer specifying the total population size

subpop_size A vector with the 5 true subpopulation sizes

degrees A vector with the 100 true respondent degrees

---

killworth — *Fit Killworth models to ARD. This function estimates the degrees and population sizes using the plug-in MLE and MLE estimator.*

Description

Fit Killworth models to ARD. This function estimates the degrees and population sizes using the plug-in MLE and MLE estimator.

Usage

```
killworth(
  ard,
  known_sizes = NULL,
  known_ind = 1:length(known_sizes),
  N = NULL,
  model = c("MLE", "PIMLE")
)
```

Arguments

`ard`	The n_i x n_k matrix of non-negative ARD integer responses, where the (i,k)th element corresponds to the number of people that respondent `i` knows in subpopulation `k`.
`known_sizes`	The known subpopulation sizes corresponding to a subset of the columns of `ard`.

known_ind — The indices that correspond to the columns of `ard` with known_sizes. By default, the function assumes the first `n_known` columns, where `n_known` corresponds to the number of `known_sizes`.

N — The known total population size.

model — A character string corresponding to either the plug-in MLE (PIMLE) or the MLE (MLE). The function assumes MLE by default.

Value

A named list with the estimated degrees and sizes.

References

Killworth, P. D., Johnsen, E. C., McCarty, C., Shelley, G. A., and Bernard, H. R. (1998). A Social Network Approach to Estimating Seroprevalence in the United States, *Social Networks*, **20**, 23–50

Killworth, P. D., McCarty, C., Bernard, H. R., Shelley, G. A., and Johnsen, E. C. (1998). Estimation of Seroprevalence, Rape and Homelessness in the United States Using a Social Network Approach, *Evaluation Review*, **22**, 289–308

Laga, I., Bao, L., and Niu, X. (2021). Thirty Years of the Network Scale-up Method, *Journal of the American Statistical Association*, **116:535**, 1548–1559

Examples

```
# Analyze an example ard data set using the killworth function
data(example_data)

ard = example_data$ard
subpop_sizes = example_data$subpop_sizes
N = example_data$N

mle.est = killworth(ard,
known_sizes = subpop_sizes[c(1, 2, 4)],
known_ind = c(1, 2, 4),
N = N, model = "MLE")

pimle.est = killworth(ard,
known_sizes = subpop_sizes[c(1, 2, 4)],
known_ind = c(1, 2, 4),
N = N, model = "PIMLE")

## Compare estimates with the truth
plot(mle.est$degrees, example_data$degrees)

data.frame(true = subpop_sizes[c(3, 5)],
mle = mle.est$sizes,
pimle = pimle.est$sizes)
```

overdispersed *Fit Overdispersed model to ARD (Gibbs-Metropolis)*

Description

This function fits the ARD using the Overdispersed model using the original Gibbs-Metropolis Algorithm provided in Zheng, Salganik, and Gelman (2006). The population size estimates and degrees are scaled using a post-hoc procedure. For the Stan implementation, see overdispersedStan.

Usage

```
overdispersed(
  ard,
  known_sizes = NULL,
  known_ind = NULL,
  G1_ind = NULL,
  G2_ind = NULL,
  B2_ind = NULL,
  N = NULL,
  warmup = 1000,
  iter = 1500,
  refresh = NULL,
  thin = 1,
  verbose = FALSE,
  alpha_tune = 0.4,
  beta_tune = 0.2,
  omega_tune = 0.2,
  init = "MLE"
)
```

Arguments

`ard`	The n_i x n_k matrix of non-negative ARD integer responses, where the (i,k)th element corresponds to the number of people that respondent `i` knows in subpopulation `k`.
`known_sizes`	The known subpopulation sizes corresponding to a subset of the columns of `ard`.
`known_ind`	The indices that correspond to the columns of `ard` with known_sizes. By default, the function assumes the first `n_known` columns, where `n_known` corresponds to the number of `known_sizes`.
`G1_ind`	A vector of indices denoting the columns of `ard` that correspond to the primary scaling groups, i.e. the collection of rare girls' names in Zheng, Salganik, and Gelman (2006). By default, all known_sizes are used. If G2_ind and B2_ind are not provided, `C = C_1`, so only G1_ind are used. If G1_ind is not provided, no scaling is performed.

G2_ind	A vector of indices denoting the columns of ard that correspond to the subpopulations that belong to the first secondary scaling groups, i.e. the collection of somewhat popular girls' names.
B2_ind	A vector of indices denoting the columns of ard that correspond to the subpopulations that belong to the second secondary scaling groups, i.e. the collection of somewhat popular boys' names.
N	The known total population size.
warmup	A positive integer specifying the number of warmup samples.
iter	A positive integer specifying the total number of samples (including warmup).
refresh	An integer specifying how often the progress of the sampling should be reported. By default, resorts to every 10%. Suppressed if verbose = FALSE.
thin	A positive integer specifying the interval for saving posterior samples. Default value is 1 (i.e. no thinning).
verbose	Logical value, specifying whether sampling progress should be reported.
alpha_tune	A positive numeric indicating the standard deviation used as the jumping scale in the Metropolis step for alpha. Defaults to 0.4, which has worked well for other ARD datasets.
beta_tune	A positive numeric indicating the standard deviation used as the jumping scale in the Metropolis step for beta Defaults to 0.2, which has worked well for other ARD datasets.
omega_tune	A positive numeric indicating the standard deviation used as the jumping scale in the Metropolis step for omega Defaults to 0.2, which has worked well for other ARD datasets.
init	A named list with names corresponding to the first-level model parameters, name 'alpha', 'beta', and 'omega'. By default the 'alpha' and 'beta' parameters are initialized at the values corresponding to the Killworth MLE estimates (for the missing 'beta'), with all 'omega' set to 20. Alternatively, init = 'random' simulates 'alpha' and 'beta' from a normal random variable with mean 0 and standard deviation 1. By default, init = 'MLE' initializes values at the Killworth et al. (1998b) MLE estimates for the degrees and sizes and simulates the other parameters.

Details

This function fits the overdispersed NSUM model using the Metropolis-Gibbs sampler provided in Zheng et al. (2006).

Value

A named list with the estimated posterior samples. The estimated parameters are named as follows, with additional descriptions as needed:

alphas Log degree, if scaled, else raw alpha parameters

betas Log prevalence, if scaled, else raw beta parameters

inv_omegas Inverse of overdispersion parameters

sigma_alpha Standard deviation of alphas

mu_beta Mean of betas

sigma_beta Standard deviation of betas

omegas Overdispersion parameters

If scaled, the following additional parameters are included:

mu_alpha Mean of log degrees

degrees Degree estimates

sizes Subpopulation size estimates

References

Zheng, T., Salganik, M. J., and Gelman, A. (2006). How many people do you know in prison, *Journal of the American Statistical Association*, **101:474**, 409–423

Examples

```
# Analyze an example ard data set using Zheng et al. (2006) models
# Note that in practice, both warmup and iter should be much higher
data(example_data)

ard = example_data$ard
subpop_sizes = example_data$subpop_sizes
known_ind = c(1, 2, 4)
N = example_data$N

overdisp.est = overdispersed(ard,
known_sizes = subpop_sizes[known_ind],
known_ind = known_ind,
G1_ind = 1,
G2_ind = 2,
B2_ind = 4,
N = N,
warmup = 50,
iter = 100)

# Compare size estimates
data.frame(true = subpop_sizes,
basic = colMeans(overdisp.est$sizes))

# Compare degree estimates
plot(example_data$degrees, colMeans(overdisp.est$degrees))

# Look at overdispersion parameter
colMeans(overdisp.est$omegas)
```

overdispersedStan *Fit ARD using the Overdispersed model in Stan*

Description

This function fits the ARD using the Overdispersed model in Stan. The population size estimates and degrees are scaled using a post-hoc procedure. For the Gibbs-Metropolis algorithm implementation, see overdispersed.

Usage

```
overdispersedStan(
  ard,
  known_sizes = NULL,
  known_ind = NULL,
  G1_ind = NULL,
  G2_ind = NULL,
  B2_ind = NULL,
  N = NULL,
  chains = 3,
  cores = 1,
  warmup = 1000,
  iter = 1500,
  thin = 1,
  return_fit = FALSE,
  ...
)
```

Arguments

`ard`	The n_i x n_k matrix of non-negative ARD integer responses, where the (i,k)th element corresponds to the number of people that respondent `i` knows in subpopulation `k`.
`known_sizes`	The known subpopulation sizes corresponding to a subset of the columns of `ard`.
`known_ind`	The indices that correspond to the columns of `ard` with known_sizes. By default, the function assumes the first `n_known` columns, where `n_known` corresponds to the number of `known_sizes`.
`G1_ind`	A vector of indices denoting the columns of `ard` that correspond to the primary scaling groups, i.e. the collection of rare girls' names in Zheng, Salganik, and Gelman (2006). By default, all known_sizes are used. If G2_ind and B2_ind are not provided, `C = C_1`, so only G1_ind are used. If G1_ind is not provided, no scaling is performed.
`G2_ind`	A vector of indices denoting the columns of `ard` that correspond to the subpopulations that belong to the first secondary scaling groups, i.e. the collection of somewhat popular girls' names.

B2_ind	A vector of indices denoting the columns of ard that correspond to the subpopulations that belong to the second secondary scaling groups, i.e. the collection of somewhat popular boys' names.
N	The known total population size.
chains	A positive integer specifying the number of Markov chains.
cores	A positive integer specifying the number of cores to use to run the Markov chains in parallel.
warmup	A positive integer specifying the total number of samples for each chain (including warmup). Matches the usage in stan.
iter	A positive integer specifying the number of warmup samples for each chain. Matches the usage in stan.
thin	A positive integer specifying the interval for saving posterior samples. Default value is 1 (i.e. no thinning).
return_fit	A logical indicating whether the fitted Stan model should be returned instead of the rstan::extracted and scaled parameters. This is FALSE by default.
...	Additional arguments to be passed to stan.

Details

This function fits the overdispersed NSUM model using the Gibbs-Metropolis algorithm provided in Zheng et al. (2006).

Value

Either the full fitted Stan model if `return_fit = TRUE`, else a named list with the estimated parameters extracted using extract (the default). The estimated parameters are named as follows, with additional descriptions as needed:

alphas Log degree, if `scaling = TRUE`, else raw alpha parameters

betas Log prevalence, if `scaling = TRUE`, else raw beta parameters

inv_omegas Inverse of overdispersion parameters

sigma_alpha Standard deviation of alphas

mu_beta Mean of betas

sigma_beta Standard deviation of betas

omegas Overdispersion parameters

If `scaling = TRUE`, the following additional parameters are included:

mu_alpha Mean of log degrees

degrees Degree estimates

sizes Subpopulation size estimates

References

Zheng, T., Salganik, M. J., and Gelman, A. (2006). How many people do you know in prison, *Journal of the American Statistical Association*, **101:474**, 409–423

Examples

```
# Analyze an example ard data set using Zheng et al. (2006) models
# Note that in practice, both warmup and iter should be much higher
## Not run:
data(example_data)

ard = example_data$ard
subpop_sizes = example_data$subpop_sizes
known_ind = c(1, 2, 4)
N = example_data$N

overdisp.est = overdispersedStan(ard,
known_sizes = subpop_sizes[known_ind],
known_ind = known_ind,
G1_ind = 1,
G2_ind = 2,
B2_ind = 4,
N = N,
chains = 1,
cores = 1,
warmup = 250,
iter = 500)

# Compare size estimates
round(data.frame(true = subpop_sizes,
basic = colMeans(overdisp.est$sizes)))

# Compare degree estimates
plot(example_data$degrees, colMeans(overdisp.est$degrees))

# Look at overdispersion parameter
colMeans(overdisp.est$omegas)

## End(Not run)
```

`scaling` *Scale raw log degree and log prevalence estimates*

Description

This function scales estimates from either the overdispersed model or from the correlated models. Several scaling options are available.

Usage

```
scaling(
  log_degrees,
  log_prevalences,
  scaling = c("all", "overdispersed", "weighted", "weighted_sq"),
```

```
    known_sizes = NULL,
    known_ind = NULL,
    Correlation = NULL,
    G1_ind = NULL,
    G2_ind = NULL,
    B2_ind = NULL,
    N = NULL
  )
```

Arguments

`log_degrees` The matrix of estimated raw log degrees from either the overdispersed or correlated models.

`log_prevalences` The matrix of estimates raw log prevalences from either the overdispersed or correlated models.

`scaling` An character vector providing the name of scaling procedure should be performed in order to transform estimates to degrees and subpopulation sizes. Scaling options are `overdispersed`, `all` (the default), `weighted`, or `weighted_sq` (`weighted` and `weighted_sq` are only available if `Correlation` is provided. Further details are provided in the Details section.

`known_sizes` The known subpopulation sizes corresponding to a subset of the columns of `ard`.

`known_ind` The indices that correspond to the columns of `ard` with known_sizes. By default, the function assumes the first `n_known` columns, where `n_known` corresponds to the number of `known_sizes`.

`Correlation` The estimated correlation matrix used to calculate scaling weights. Required if `scaling = weighted` or `scaling = weighted_sq`.

`G1_ind` If `scaling = overdispersed`, a vector of indices corresponding to the subpopulations that belong to the primary scaling groups, i.e. the collection of rare girls' names in Zheng, Salganik, and Gelman (2006). By default, all known_sizes are used. If G2_ind and B2_ind are not provided, `C = C_1`, so only G1_ind are used. If G1_ind is not provided, no scaling is performed.

`G2_ind` If `scaling = overdispersed`, a vector of indices corresponding to the subpopulations that belong to the first secondary scaling groups, i.e. the collection of somewhat popular girls' names.

`B2_ind` If `scaling = overdispersed`, a vector of indices corresponding to the subpopulations that belong to the second secondary scaling groups, i.e. the collection of somewhat popular boys' names.

`N` The known total population size.

Details

The `scaling` options are described below:

NULL No scaling is performed

overdispersed The scaling procedure outlined in Zheng et al. (2006) is performed. In this case, at least `Pg1_ind` must be provided. See overdispersedStan for more details.

all All subpopulations with known sizes are used to scale the parameters, using a modified scaling procedure that standardizes the sizes so each population is weighted equally. Additional details are provided in Laga et al. (2021).

weighted All subpopulations with known sizes are weighted according their correlation with the unknown subpopulation size. Additional details are provided in Laga et al. (2021)

weighted_sq Same as `weighted`, except the weights are squared, providing more relative weight to subpopulations with higher correlation.

Value

The named list containing the scaled log degree, degree, log prevalence, and size estimates

References

Zheng, T., Salganik, M. J., and Gelman, A. (2006). How many people do you know in prison, *Journal of the American Statistical Association*, **101:474**, 409–423

Laga, I., Bao, L., and Niu, X (2021). A Correlated Network Scaleup Model: Finding the Connection Between Subpopulations

Index