

Package ‘netdiffuseR’

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Title Analysis of Diffusion and Contagion Processes on Networks

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Description Empirical statistical analysis, visualization and simulation of diffusion and contagion processes on networks. The package implements algorithms for calculating network diffusion statistics such as transmission rate, hazard rates, exposure models, network threshold levels, infectiousness (contagion), and susceptibility. The package is inspired by work published in Valente, et al., (2015) <DOI:10.1016/j.socscimed.2015.10.001>; Valente (1995) <ISBN: 9781881303213>, Myers (2000) <DOI:10.1086/303110>, Iyengar and others (2011) <DOI:10.1287/mksc.1100.0566>, Burt (1987) <DOI:10.1086/228667>; among others.

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'plot_diffnet2.r' 'rewire.r' 'random_graph.R' 'rdiffnet.r'
 'read_write_foreign.r' 'select_egoalter.R' 'spatial.R'
 'stats.R' 'struct_equiv.R' 'struct_test.R'
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approx_geodesic	<i>Approximate Geodesic Distances</i>
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Description

Computes approximate geodesic distance matrix using graph powers and keeping the amount of memory used low.

Usage

```
approx_geodesic(graph, n = 6L, warn = FALSE)
```

```
approx_geodist(graph, n = 6L, warn = FALSE)
```

Arguments

graph	Any class of accepted graph format (see netdiffuseR-graphs).
n	Integer scalar. Degree of approximation. Bigger values increase precision (see details).
warn	Logical scalar. When TRUE, it warns if the algorithm performs less steps than required.

Details

While both **igraph** and **sna** offer very good and computationally efficient routines for computing geodesic distances, both functions return dense matrices, i.e. not sparse, which can be troublesome. Furthermore, from the perspective of social network analysis, path lengths of more than 6 steps, for example, may not be meaningful, or at least, relevant for the researcher. In such cases, `approx_geodesic` serves as a solution to this problem, computing geodesics up to the number of steps, n , desired, hence, if $n = 6$, once the algorithm finds all paths of 6 or less steps it will stop, returning a sparse matrix with zeros for those pairs of vertices for which it was not able to find a path with less than n steps.

Depending on the graph size and density, `approx_geodesic`'s performance can be compared to that of `sna::geodist`. Although, as n increases, `geodist` becomes a better alternative.

The algorithm was implemented using power graphs. At each iteration i the power graph of order i is computed, and its values are compared to the current values of the geodesic matrix (which is initialized in zero).

1. Initialize the output `ans(n, n)`
2. For $i=1$ to $i < n$ do
 - (a) Iterate through the edges of G^i , if `ans` has a zero value in the corresponding row+column, replace it with i

(b) next

3. Replace all diagonal elements with a zero and return.

This implementation can be more memory efficient than the aforementioned ones, but at the same time it can be significantly slower.

approx_geodist is just an alias for approx_geodesic.

Value

A sparse matrix of class `dgCMatrix` of size $\text{nnodes}(\text{graph})^2$ with geodesic distances up to n .

Examples

```
# A very simple example -----
g <- ring_lattice(10, 3)
approx_geodesic(g, 6)
sna::geodist(as.matrix(g))[[2]]
igraph::distances(
  igraph::graph_from_adjacency_matrix(g, mode = "directed"),
  mode = "out"
)
```

<code>as.array.diffnet</code>	<i>Coerce a diffnet graph into an array</i>
-------------------------------	---------------------------------------------

Description

Coerce a diffnet graph into an array

Usage

```
## S3 method for class 'diffnet'
as.array(x, ...)
```

Arguments

<code>x</code>	A diffnet object.
<code>...</code>	Ignored.

Details

The function takes the list of sparse matrices stored in `x` and creates an array with them. Attributes and other elements from the diffnet object are dropped.

`dimnames` are obtained from the metadata of the diffnet object.

Value

A three-dimensional array of T matrices of size $n \times n$.

See Also

[diffnet](#).

Other diffnet methods: [%*%](#), [c.diffnet](#), [diffnet-arithmetic](#), [diffnet-class](#), [diffnet_index](#), [plot.diffnet](#), [summary.diffnet](#)

Examples

```
# Creating a random diffnet object
set.seed(84117)
mydiffnet <- rdiffnet(30, 5)

# Coercing it into an array
as.array(mydiffnet)
```

as_dgCMatrix

Coerce a matrix-like objects to dgCMatrix (sparse matrix)

Description

This helper function allows easy coercion to sparse matrix objects from the **Matrix** package, [dgCMatrix](#).

Usage

```
as_dgCMatrix(x, make.dimnames = TRUE, ...)

as.dgCMatrix(x, make.dimnames = TRUE, ...)

as_spmat(x, make.dimnames = TRUE, ...)

## Default S3 method:
as_dgCMatrix(x, make.dimnames = TRUE, ...)

## S3 method for class 'diffnet'
as_dgCMatrix(x, make.dimnames = TRUE, ...)

## S3 method for class 'array'
as_dgCMatrix(x, make.dimnames = TRUE, ...)

## S3 method for class 'igraph'
as_dgCMatrix(x, make.dimnames = TRUE, ...)

## S3 method for class 'network'
```

```
as_dgMatrix(x, make.dimnames = TRUE, ...)  
  
## S3 method for class 'list'  
as_dgMatrix(x, make.dimnames = TRUE, ...)
```

Arguments

`x` An object to be coerced into a sparse matrix.
`make.dimnames` Logical scalar. When TRUE, it makes sure that the returned object has dimnames.
`...` Further arguments passed to the method.

Details

In the case of the `igraph` and `network` methods, `...` is passed to `as_adj` and `as.matrix.network` respectively.

Value

Either a list with `dgMatrix` objects or a `dgMatrix` object.

Examples

```
set.seed(1231)  
x <- rgraph_er(10)  
  
# From matrix object  
as_dgMatrix(as.matrix(x))  
  
# From a network object  
as_dgMatrix(network::as.network(as.matrix(x)))  
  
# From igraph object  
as_dgMatrix(igraph::graph_from_adjacency_matrix(x))  
  
# From array  
myarray <- array(dim=c(10,10,2))  
myarray[, ,1] <- as.matrix(x)  
myarray[, ,2] <- as.matrix(x)  
  
myarray  
as_dgMatrix(myarray)  
  
# From a diffnet object  
ans <- as_dgMatrix(medInnovationsDiffNet)  
str(ans)
```

bass

*Bass Model***Description**

Fits the Bass Diffusion model. In particular, fits an observed curve of proportions of adopters to $F(t)$, the proportion of adopters at time t , finding the corresponding coefficients p , Innovation rate, and q , imitation rate.

Usage

```
fitbass(dat, ...)

## S3 method for class 'diffnet'
fitbass(dat, ...)

## Default S3 method:
fitbass(dat, ...)

## S3 method for class 'diffnet_bass'
plot(x, y = 1:length(x$m$lhs()), add = FALSE,
     pch = c(21, 24), main = "Bass Diffusion Model",
     ylab = "Proportion of adopters", xlab = "Time", type = c("b", "b"),
     lty = c(2, 1), col = c("black", "black"), bg = c("lightblue", "gray"),
     include.legend = TRUE, ...)

bass_F(Time, p, q)

bass_dF(p, q, Time)

bass_f(Time, p, q)
```

Arguments

<code>dat</code>	Either a <code>diffnet</code> object, or a numeric vector. Observed cumulative proportion of adopters.
<code>...</code>	Further arguments passed to the method.
<code>x</code>	An object of class <code>diffnet_bass</code> .
<code>y</code>	Integer vector. Time (label).
<code>add</code>	Passed to <code>matplot</code> .
<code>pch</code>	Passed to <code>matplot</code> .
<code>main</code>	Passed to <code>matplot</code> .
<code>ylab</code>	Character scalar. Label of the y axis.
<code>xlab</code>	Character scalar. Label of the x axis.

type	Passed to <code>matplot</code> .
lty	Passed to <code>matplot</code> .
col	Passed to <code>matplot</code> .
bg	Passed to <code>matplot</code> .
include.legend	Logical scalar. When TRUE, draws a legend.
Time	Integer vector with values greater than 0. The t parameter.
p	Numeric scalar. Coefficient of innovation.
q	Numeric scalar. Coefficient of imitation.

Details

The function fits the bass model with parameters $[p, q]$ for values $t = 1, 2, \dots, T$, in particular, it fits the following function:

$$F(t) = \frac{1 - \exp -(p + q)t}{1 + \frac{q}{p} \exp -(p + q)t}$$

Which is implemented in the `bass_F` function. The proportion of adopters at time t , $f(t)$ is:

$$f(t) = \begin{cases} F(t), & t = 1 \\ F(t) - F(t - 1), & t > 1 \end{cases}$$

and it's implemented in the `bass_f` function.

For testing purposes only, the gradient of F with respect to p and q is implemented in `bass_dF`.

The estimation is done using `nls`.

Value

An object of class `nls` and `diffnet_bass`. For more details, see `nls` in the `stats` package.

Author(s)

George G. Vega Yon

References

Bass's Basement Institute Institute. The Bass Model. (2010). Available at: <http://www.bassbasement.org/BassModel/Default.aspx>. (Accessed: 29th March 2017)

See Also

Other statistics: `classify_adopters`, `cumulative_adopt_count`, `dgr`, `ego_variance`, `exposure`, `hazard_rate`, `infection`, `moran`, `struct_equiv`, `threshold`, `vertex_covariate_dist`

Examples

```
# Fitting the model for the Brazilian Farmers Data -----
data(brfarmersDiffNet)
ans <- fitbass(brfarmersDiffNet)

# All the methods that work for the -nls- object work here
ans
summary(ans)
coef(ans)
vcov(ans)

# And the plot method returns both, fitted and observed curve
plot(ans)
```

bootnet

*Network Bootstrapping***Description**

Implements the bootstrapping method described in Snijders and Borgatti (1999). This function is essentially a wrapper of [boot](#).

Usage

```
resample_graph(graph, self = NULL, useR = FALSE, ...)

bootnet(graph, statistic, R, resample.args = list(self = FALSE), ...)

## S3 method for class 'diffnet_bootnet'
c(..., recursive = FALSE)

## S3 method for class 'diffnet_bootnet'
print(x, ...)

## S3 method for class 'diffnet_bootnet'
hist(x,
      main = "Empirical Distribution of Statistic", xlab = expression(Values ~
        of ~ t), breaks = 20, annotated = TRUE, b0 = expression(atop(plain(""))
        %up% plain("")), t[0]), b = expression(atop(plain("")) %up% plain("")),
      t[]), ask = TRUE, ...)
```

Arguments

graph	Any class of accepted graph format (see netdiffuser-graphs).
self	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).

useR	Logical scalar. When TRUE, autolinks are filled using an R based routine. Otherwise it uses the Rcpp implementation (default). This is intended for testing only.
...	Further arguments passed to the method (see details).
statistic	A function that returns a vector with the statistic(s) of interest. The first argument must be the graph, and the second argument a vector of indices (see details)
R	Number of reps
resample.args	List. Arguments to be passed to resample_graph
recursive	Ignored
x	A <code>diffnet_bootnet</code> class object.
main	Character scalar. Title of the histogram.
xlab	Character scalar. x-axis label.
breaks	Passed to hist .
annotated	Logical scalar. When TRUE marks the observed data average and the simulated data average.
b0	Character scalar. When annotated=TRUE, label for the value of b0.
b	Character scalar. When annotated=TRUE, label for the value of b.
ask	Logical scalar. When TRUE, asks the user to type <Enter> to see each plot (as many as statistics where computed).

Details

Just like the `boot` function of the **boot** package, the `statistic` that is passed must have as arguments the original data (the graph in this case), and a vector of indices. In each repetition, the graph that is passed is a resampled version generated as described in Snijders and Borgatti (1999).

When `self = FALSE`, for pairs of individuals that haven been drawn more than once the algorithm, in particular, `resample_graph`, takes care of filling these pseudo autolinks that are not in the diagonal of the network. By default it is assumed that these pseudo-autolinks depend on whether the original graph had any, hence, if the diagonal has any non-zero value the algorithm assumes that `self = TRUE`, skipping the 'filling algorithm'. It is important to notice that, in order to preserve the density of the original network, when assigning an edge value to a pair of the form (i, i) (pseudo-autolinks), such is done with probability proportional to the density of the network, in other words, before choosing from the existing list of edge values, the algorithm decides whether to set a zero value first.

The vector of indices that is passed to `statistic`, an integer vector with range 1 to n , corresponds to the drawn sample of nodes, so the user can, for example, use it to get a subset of a `data.frame` that will be used with the graph.

Value

A list of class `diffnet_bootnet` containing the following:

graph	The graph passed to <code>bootnet</code> .
-------	--------------------------------------------

p.value	The resulting p-value of the test (see details).
t0	The observed value of the statistic.
mean_t	The average value of the statistic applied to the simulated networks.
var_t	A vector of length length(t0). Bootstrap variances.
R	Number of simulations.
statistic	The function statistic passed to bootnet.
boot	A boot class object as return from the call to boot.
resample.args	The list resample.args passed to bootnet.

References

Snijders, T. A. B., & Borgatti, S. P. (1999). Non-Parametric Standard Errors and Tests for Network Statistics. *Connections*, 22(2), 1–10. Retrieved from https://insna.org/PDF/Connections/v22/1999_I-2_61-70.pdf

See Also

Other Functions for inference: [moran](#), [struct_test](#)

Examples

```
#
set.seed(13)
g <- rgraph_ba(t=99)

ans <- bootnet(g, function(w, ...) length(w@x), R=100)
ans
```

brfarmers

Brazilian Farmers

Description

From Valente (1995) “In the mid-1960s, Rogers and others conducted an ambitious ‘three country study’ to determine influences on adoption of farm practices in Nigeria, India and Brazil. [...] Only in Brazil, and only for hybrid corn, did adoption of the innovation reach more than a small proportion of the farmers.”

Usage

```
brfarmers
```

Format

A data frame with 692 rows and 148 columns:

village village number

idold respondent id

age respondent's age

liveout Lived outside of community

visits # of visits to large city

contact # of contacts with relatives

coop membership in coop

orgs membership in organizations

patry Patriarchalism score

liter Literate

news1 # of newspapers or mags pr mon

subs subscribe to news

radio1 Own radio

radio2 Frequency radio listening

radio3 program preference

tv frequency Tv viewing

movie freq movie attendance

letter freq letter writing

source total # of sources used for ag

practA Ever used practice A

practB Ever used practice B

practC Ever used practice C

practD Ever used practice D

practE Ever used practice E

practF Ever used practice F

practG Ever used practice G

practH Ever used practice H

practI Ever used practice I

practJ Ever used practice J

practK Ever used practice K

practL Ever used practice L

yrA A year of adoption

yrB B year of adoption

yrC C year of adoption

yrD D year of adoption

yrE E year of adoption
yrF F year of adoption
yrG G year of adoption
yrH H year of adoption
yrI I year of adoption
yrJ J year of adoption
yrK K year of adoption
yrL L year of adoption
curA A Current use
curB B Current use
curC C Current use
curD D Current use
curE E Current use
curF F Current use
curG G Current use
curH H Current use
curI I Current use
curJ J Current use
curK K Current use
curL L Current use
srce1 Source of aware in A
timeA Years ago 1st aware
src2 Source of more info on A
src3 Most influential source
use use during trial stage
total total # of practices adopted
futatt Future attitude
achiev Achievement Score
attcred Attitude toward credit
littest Score on functional literacy t
acarcomm Communication with ACAR repres
econk Economic knowledge
caact recognize any change agent act
hfequip # of home & farm equipments owned
politk political knowledge score
income income
land1 total land area in pasture

land2 total land area planted
cows # of cows giving milk
land3 total land owned
respf respondent named as friend
respa respondent named as ag adv
resppa respondent named for practic A
resppb respondent named for practic B
resppc respondent named for practic C
poly polymorphic OL for 3 practices
respl respondent named for loan
resppi resp named for price info
repsccp resp named for coop comm proj
counter counterfactuality score
opinion opinionness score
school years of schooling by resp
pk1 political know 1
pk2 political know 2
pk3 political know 3
pk4 political know 4
pk5 political know 5
innovtim innovativeness time
adoptpet adoption percent
discon # of practices discontinued
mmcred Mass media credibility
trust Trust
stusincn Status inconsistency
nach N achievement motivation
attcred2 Attitude toward credit
risk Risk taking
socpart Social participate
patriarc patriarchy
crdit2 attit to credit for product
visicit visitin cities
nondep non-dependence on farming
oltotal OL total 7 items t-score
innov overall innovativeness score
icosmo cosmo index

immexp mass media exposure index
iempath empathy index
iach5 achievement motivation index 5
iach7 achievement motivation index 7
ipk political knowledge index
immc mass media credibility index
iol OL index
yr Actual Year of Adoption
fs — MISSING INFO —
ado Time of Adoption
tri Triangular values used as appro
hlperc high low percent of diffusion
hlperc1 — MISSING INFO —
new new or old villages
card1 card number
sour1 Source: radio
sour2 Source: TV
sour3 Source: Newspaper
sour4 Source: Magazine
sour5 Source: ACAR Bulletin
sour6 Source: Agronomist
sour7 Source: Neighbor
source6 — MISSING INFO —
adopt — MISSING INFO —
net31 nomination friend 1
net32 nomination friend 2
net33 nomination friend 3
net21 nomination influential 1
net22 nomination influential 2
net23 nomination influential 3
net11 nomination practice A
net12 nomination practice B
net13 nomination practice C
net41 nomination coop comm proj
id — MISSING INFO —
commun Number of community
toa Time of Adoption
test — MISSING INFO —
study Number of study in Valente (1995)

Details

The dataset has 692 respondents (farmers) from 11 communities. Collected during 1966, it spans 20 years of farming practices.

Source

The Brazilian Farmers data were collected as part of a USAID-funded study of farming practicing in the three countries, India, Nigeria, and Brazil. There was only one wave of data that contained survey questions regarding social networks, and only in Brazil did diffusion of the studied farming innovations reach an appreciable saturation level- that was for hybrid seed corn. The data were stored along with hundreds of other datasets by the University of Wisconsin library and I, Tom Valente, paid a fee to have the disks mailed to me in the early 1990s.

References

Rogers, E. M., Ascroft, J. R., & Röling, N. (1970). Diffusion of Innovation in Brazil, Nigeria, and India. Unpublished Report. Michigan State University, East Lansing.

Valente, T. W. (1995). Network models of the diffusion of innovations (2nd ed.). Cresskill N.J.: Hampton Press.

See Also

Other diffusion datasets: [brfarmersDiffNet](#), [diffusion-data](#), [fakeDynEdgelist](#), [fakeEdgelist](#), [fakesurveyDyn](#), [fakesurvey](#), [kfamilyDiffNet](#), [kfamily](#), [medInnovationsDiffNet](#), [medInnovations](#)

brfarmersDiffNet	<i>diffnet version of the Brazilian Farmers data</i>
------------------	------------------------------------------------------

Description

A directed dynamic graph with 692 vertices and 21 time periods. The attributes in the graph are static and described in [brfarmers](#).

Format

A [diffnet](#) class object.

See Also

Other diffusion datasets: [brfarmers](#), [diffusion-data](#), [fakeDynEdgelist](#), [fakeEdgelist](#), [fakesurveyDyn](#), [fakesurvey](#), [kfamilyDiffNet](#), [kfamily](#), [medInnovationsDiffNet](#), [medInnovations](#)

c.diffnet

Combine diffnet objects

Description

Combining [diffnet](#) objects that share time periods and attributes names, but vertices ids (only valid for diffnet objects that have an empty intersection between vertices ids).

Usage

```
## S3 method for class 'diffnet'
c(..., recursive = FALSE)
```

Arguments

... diffnet objects to be concatenated.
recursive Ignored.

Details

The diffnet objects in ... must fulfill the following conditions:

1. Have the same time range,
2. have the same vertex attributes, and
3. have an empty intersection of vertices ids,

The meta data regarding `undirected`, `value`, and `multiple` are set to `TRUE` if any of the concatenating diffnet objects has that meta equal to `TRUE`.

The resulting diffnet object's columns in the vertex attributes ordering (both dynamic and static) will coincide with the first diffnet's ordering.

Value

A new diffnet object with as many vertices as the sum of each concatenated diffnet objects' number of vertices.

See Also

Other diffnet methods: [%*%](#), [as.array.diffnet](#), [diffnet-arithmetic](#), [diffnet-class](#), [diffnet_index](#), [plot.diffnet](#), [summary.diffnet](#)

Examples

```
# Calculate structural equivalence exposure by city -----
data(medInnovationsDiffNet)

# Subsetting diffnets
city1 <- medInnovationsDiffNet[medInnovationsDiffNet[["city"]] == 1]
city2 <- medInnovationsDiffNet[medInnovationsDiffNet[["city"]] == 2]
city3 <- medInnovationsDiffNet[medInnovationsDiffNet[["city"]] == 3]
city4 <- medInnovationsDiffNet[medInnovationsDiffNet[["city"]] == 4]

# Computing exposure in each one
city1[["expo_se"]] <- exposure(city1, alt.graph="se", valued=TRUE)
city2[["expo_se"]] <- exposure(city2, alt.graph="se", valued=TRUE)
city3[["expo_se"]] <- exposure(city3, alt.graph="se", valued=TRUE)
city4[["expo_se"]] <- exposure(city4, alt.graph="se", valued=TRUE)

# Concatenating all
diffnet <- c(city1, city2, city3, city4)
diffnet
```

classify_adopters	<i>Classify adopters accordingly to Time of Adoption and Threshold levels.</i>
-------------------	--------------------------------------------------------------------------------

Description

Adopters are classified as in Valente (1995). In general, this is done depending on the distance in terms of standard deviations from the mean of Time of Adoption and Threshold.

Usage

```
classify_adopters(...)

classify(...)

## S3 method for class 'diffnet'
classify_adopters(graph, include_censored = FALSE, ...)

## Default S3 method:
classify_adopters(graph, toa, t0 = NULL, t1 = NULL,
  expo = NULL, include_censored = FALSE, ...)

## S3 method for class 'diffnet_adopters'
ftable(x, as.pcent = TRUE, digits = 2, ...)

## S3 method for class 'diffnet_adopters'
```

```
as.data.frame(x, row.names = NULL,
  optional = FALSE, ...)

## S3 method for class 'diffnet_adopters'
plot(x, y = NULL, ftable.args = list(),
  table.args = list(), ...)
```

Arguments

...	Further arguments passed to the method.
graph	A dynamic graph.
include_censored	Logical scalar, passed to threshold .
toa	Integer vector of length n with times of adoption.
t0	Integer scalar passed to threshold and toa_mat .
t1	Integer scalar passed to toa_mat .
expo	Numeric matrix of size $n \times T$ with network exposures.
x	A <code>diffnet_adopters</code> class object.
as.pcent	Logical scalar. When TRUE returns a table with percentages instead.
digits	Integer scalar. Passed to round .
row.names	Passed to as.data.frame .
optional	Passed to as.data.frame .
y	Ignored.
ftable.args	List of arguments passed to ftable .
table.args	List of arguments passed to table .

Details

Classifies (only) adopters according to time of adoption and threshold as described in Valente (1995). In particular, the categories are defined as follow:

For Time of Adoption, with `toa` as the vector of times of adoption:

- *Early Adopters*: $toa[i] \leq \text{mean}(toa) - \text{sd}(toa)$,
- *Early Majority*: $\text{mean}(toa) - \text{sd}(toa) < toa[i] \leq \text{mean}(toa)$,
- *Late Majority*: $\text{mean}(toa) < toa[i] \leq \text{mean}(toa) + \text{sd}(toa)$, and
- *Laggards*: $\text{mean}(toa) + \text{sd}(toa) < toa[i]$.

For Threshold levels, with `thr` as the vector of threshold levels:

- *Very Low Thresh.*: $thr[i] \leq \text{mean}(thr) - \text{sd}(thr)$,
- *Low Thresh.*: $\text{mean}(thr) - \text{sd}(thr) < thr[i] \leq \text{mean}(thr)$,
- *High Thresh.*: $\text{mean}(thr) < thr[i] \leq \text{mean}(thr) + \text{sd}(thr)$, and
- *Very High. Thresh.*: $\text{mean}(thr) + \text{sd}(thr) < thr[i]$.

By default threshold levels are not computed for left censored data. These will have a NA value in the thr vector.

The plot method, `plot.diffnet_adopters`, is a wrapper for the `plot.table` method. This generates a `mosaicplot` plot.

Value

A list of class `diffnet_adopters` with the following elements:

<code>toa</code>	A factor vector of length n with 4 levels: "Early Adopters", "Early Majority", "Late Majority", and "Laggards"
<code>thr</code>	A factor vector of length n with 4 levels: "Very Low Thresh.", "Low Thresh.", "High Thresh.", and "Very High Thresh."

Author(s)

George G. Vega Yon

References

Valente, T. W. (1995). "Network models of the diffusion of innovations" (2nd ed.). Cresskill N.J.: Hampton Press.

See Also

Other statistics: `bass`, `cumulative_adopt_count`, `dgr`, `ego_variance`, `exposure`, `hazard_rate`, `infection`, `moran`, `struct_equiv`, `threshold`, `vertex_covariate_dist`

Examples

```
# Classifying brfarmers -----
x <- brfarmersDiffNet
diffnet.toa(x)[x$toa==max(x$toa, na.rm = TRUE)] <- NA
out <- classify_adopters(x)

# This is one way
round(
with(out, ftable(toa, thr, dnn=c("Time of Adoption", "Threshold")))/
  nnodes(x[!is.na(x$toa)])*100, digits=2)

# This is other
ftable(out)

# Can be coerced into a data.frame, e.g. -----
## Not run:
View(classify(brfarmersDiffNet))
cbind(as.data.frame(classify(brfarmersDiffNet)), brfarmersDiffNet$toa)

## End(Not run)
```

```
# Creating a mosaic plot with the medical innovations -----
x <- classify(medInnovationsDiffNet)
plot(x)
```

classify_graph	Analyze an R object to identify the class of graph (if any)
----------------	-------------------------------------------------------------

Description

Analyze an R object to identify the class of graph (if any)

Usage

```
classify_graph(graph)
```

Arguments

graph Any class of accepted graph format (see [netdiffuseR-graphs](#)).

Details

This function analyzes an R object and tries to classify it among the accepted classes in **netdiffuseR**. If the object fails to fall in one of the types of graphs the function returns with an error indicating what (and when possible, where) the problem lies.

The function was designed to be used with [as_diffnet](#).

Value

When the object fits any of the accepted graph formats, a list of attributes including

type	Character scalar. Whether is a static or a dynamic graph
class	Character scalar. The class of the original object
ids	Character vector. Labels of the vertices
pers	Integer vector. Labels of the time periods
nper	Integer scalar. Number of time periods
n	Integer scalar. Number of vertices in the graph

Otherwise returns with error.

Author(s)

George G. Vega Yon

See Also

[as_diffnet](#), [netdiffuseR-graphs](#)

 cumulative_adopt_count

Cummulative count of adopters

Description

For each time period, calculates the number of adopters, the proportion of adopters, and the adoption rate.

Usage

```
cumulative_adopt_count(obj)
```

Arguments

obj A $n \times T$ matrix (Cumulative adoption matrix obtained from [toa_mat](#)) or a [diffnet](#) object.

Details

The rate of adoption—returned in the 3rd row out the resulting matrix—is calculated as

$$\frac{q_t - q_{t-1}}{q_{t-1}}$$

where q_i is the number of adopters in time t . Note that it is only calculated for $t > 1$.

Value

A $3 \times T$ matrix, where its rows contain the number of adoptes, the proportion of adopters and the rate of adoption respectively, for each period of time.

Author(s)

George G. Vega Yon & Thomas W. Valente

See Also

Other statistics: [bass](#), [classify_adopters](#), [dgr](#), [ego_variance](#), [exposure](#), [hazard_rate](#), [infection](#), [moran](#), [struct_equiv](#), [threshold](#), [vertex_covariate_dist](#)

dgr *Indegree, outdegree and degree of the vertices*

Description

Computes the requested degree measure for each node in the graph.

Usage

```
dgr(graph, cmode = "degree", undirected = getOption("diffnet.undirected",
  FALSE), self = getOption("diffnet.self", FALSE),
  valued = getOption("diffnet.valued", FALSE))
```

```
## S3 method for class 'diffnet_degSeq'
plot(x, breaks = min(100L, nrow(x)/5),
  freq = FALSE, y = NULL, log = "xy", hist.args = list(),
  slice = ncol(x), xlab = "Degree", ylab = "Freq", ...)
```

Arguments

graph	Any class of accepted graph format (see netdiffuseR-graphs).
cmode	Character scalar. Either "indegree", "outdegree" or "degree".
undirected	Logical scalar. When TRUE only the lower triangle of the adjacency matrix will be considered (faster).
self	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).
valued	Logical scalar. When TRUE weights will be considered. Otherwise non-zero values will be replaced by ones.
x	An <code>diffnet_degSeq</code> object
breaks	Passed to hist .
freq	Logical scalar. When TRUE the y-axis will reflex counts, otherwise densities.
y	Ignored
log	Passed to plot (see par).
hist.args	Arguments passed to hist .
slice	Integer scalar. In the case of dynamic graphs, number of time point to plot.
xlab	Character scalar. Passed to plot .
ylab	Character scalar. Passed to plot .
...	Further arguments passed to plot .

Value

A numeric matrix of size $n \times T$. In the case of `plot`, returns an object of class [histogram](#).

Author(s)

George G. Vega Yon

See Also

Other statistics: [bass](#), [classify_adopters](#), [cumulative_adopt_count](#), [ego_variance](#), [exposure](#), [hazard_rate](#), [infection](#), [morán](#), [struct_equiv](#), [threshold](#), [vertex_covariate_dist](#)

Other visualizations: [diffusionMap](#), [drawColorKey](#), [grid_distribution](#), [hazard_rate](#), [plot_adopters](#), [plot_diffnet2](#), [plot_diffnet](#), [plot_infectsuscep](#), [plot_threshold](#), [rescale_vertex_igraph](#)

Examples

```
# Comparing degree measurements -----
# Creating an undirected graph
graph <- rgraph_ba()
graph

data.frame(
  In=dgr(graph, "indegree", undirected = FALSE),
  Out=dgr(graph, "outdegree", undirected = FALSE),
  Degree=dgr(graph, "degree", undirected = FALSE)
)

# Testing on Korean Family Planning (weighted graph) -----
data(kfamilyDiffNet)
d_unvalued <- dgr(kfamilyDiffNet, valued=FALSE)
d_valued   <- dgr(kfamilyDiffNet, valued=TRUE)

any(d_valued!=d_unvalued)

# Classic Scale-free plot -----
set.seed(1122)
g <- rgraph_ba(t=1e3-1)
hist(dgr(g))

# Since by default uses logscale, here we suppress the warnings
# on points been discarded for <=0.
suppressWarnings(plot(dgr(g)))
```

diag_expand

*Creates a square matrix suitable for spatial statistics models.***Description**

Creates a square matrix suitable for spatial statistics models.

Usage

```
diag_expand(...)

## S3 method for class 'list'
diag_expand(graph, self = getOption("diffnet.self"),
  valued = getOption("diffnet.valued"), ...)

## S3 method for class 'diffnet'
diag_expand(graph, self = getOption("diffnet.self"),
  valued = getOption("diffnet.valued"), ...)

## S3 method for class 'matrix'
diag_expand(graph, nper, self = getOption("diffnet.self"),
  valued = getOption("diffnet.valued"), ...)

## S3 method for class 'array'
diag_expand(graph, self = getOption("diffnet.self"),
  valued = getOption("diffnet.valued"), ...)

## S3 method for class 'dgCMatrix'
diag_expand(graph, nper, self = getOption("diffnet.self"),
  valued = getOption("diffnet.valued"), ...)
```

Arguments

...	Further arguments to be passed to the method.
graph	Any class of accepted graph format (see netdiffuseR-graphs).
self	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).
valued	Logical scalar. When TRUE weights will be considered. Otherwise non-zero values will be replaced by ones.
nper	Integer scalar. Number of time periods of the graph.

Value

A square matrix of class [dgCMatrix](#) of size $(\text{nnode}(g) * \text{nper})^2$

Examples

```
# Simple example -----
set.seed(23)
g <- rgraph_er(n=10, p=.5, t=2, undirected=TRUE)

# What we've done: A list with 2 bernoulli graphs
g

# Expanding to a 20*20 matrix with structural zeros on the diagonal
# and on cell 'off' adjacency matrix
diag_expand(g)
```

diffnet-arithmetic diffnet *Arithmetic and Logical Operators*

Description

Addition, subtraction, network power of diffnet and logical operators such as & and | as objects

Usage

```
## S3 method for class 'diffnet'
x ^ y

graph_power(x, y, valued = getOption("diffnet.valued", FALSE))

## S3 method for class 'diffnet'
y / x

## S3 method for class 'diffnet'
x - y

## S3 method for class 'diffnet'
x * y

## S3 method for class 'diffnet'
x & y

## S3 method for class 'diffnet'
x | y
```

Arguments

x	A diffnet class object.
y	Integer scalar. Power of the network
valued	Logical scalar. When FALSE all non-zero entries of the adjacency matrices are set to one.

Details

Using binary operators, ease data management process with diffnet.

By default the binary operator ^ assumes that the graph is valued, hence the power is computed using a weighted edges. Otherwise, if more control is needed, the user can use graph_power instead.

Value

A diffnet class object

See Also

Other diffnet methods: [%*%](#), [as.array.diffnet](#), [c.diffnet](#), [diffnet-class](#), [diffnet_index](#), [plot.diffnet](#), [summary.diffnet](#)

Examples

```
# Computing two-steps away threshold with the Brazilian farmers data -----
data(brfarmersDiffNet)

expo1 <- threshold(brfarmersDiffNet)
expo2 <- threshold(brfarmersDiffNet^2)

# Computing correlation
cor(expo1,expo2)

# Drawing a qqplot
qqplot(expo1, expo2)

# Working with inverse -----
brf2_step <- brfarmersDiffNet^2
brf2_step <- 1/brf2_step

# Removing the first 3 vertex of medInnovationsDiffnet -----
data(medInnovationsDiffNet)

# Using a diffnet object
first3Diffnet <- medInnovationsDiffNet[1:3,,]
medInnovationsDiffNet - first3Diffnet

# Using indexes
medInnovationsDiffNet - 1:3

# Using ids
medInnovationsDiffNet - as.character(1001:1003)
```

diffnet-class

Creates a diffnet class object

Description

diffnet objects contain diffusion networks. With adjacency matrices and time of adoption (toa) vector as its main components, most of the package's functions have methods for this class of objects.

Usage

```
as_diffnet(graph, ...)
```

```
## Default S3 method:
```

```

as_diffnet(graph, ...)

## S3 method for class 'networkDynamic'
as_diffnet(graph, toavar, ...)

new_diffnet(graph, toa, t0 = min(toa, na.rm = TRUE), t1 = max(toa, na.rm =
  TRUE), vertex.dyn.attrs = NULL, vertex.static.attrs = NULL,
  id.and.per.vars = NULL, graph.attrs = NULL,
  undirected = getOption("diffnet.undirected"),
  self = getOption("diffnet.self"),
  multiple = getOption("diffnet.multiple"), name = "Diffusion Network",
  behavior = "Unspecified")

## S3 method for class 'diffnet'
as.data.frame(x, row.names = NULL, optional = FALSE,
  attr.class = c("dyn", "static"), ...)

diffnet.attrs(graph, element = c("vertex", "graph"), attr.class = c("dyn",
  "static"), as.df = FALSE)

diffnet.attrs(graph, element = "vertex", attr.class = "static") <- value

diffnet.toa(graph)

diffnet.toa(graph, i) <- value

## S3 method for class 'diffnet'
print(x, ...)

nodes(graph)

diffnetLapply(graph, FUN, ...)

## S3 method for class 'diffnet'
str(object, ...)

## S3 method for class 'diffnet'
dimnames(x)

## S3 method for class 'diffnet'
t(x)

## S3 method for class 'diffnet'
dim(x)

```

Arguments

`graph` A dynamic graph (see [netdiffuseR-graphs](#)).

...	Further arguments passed to the jmethod.
toavar	Character scalar. Name of the variable that holds the time of adoption.
toa	Numeric vector of size n . Times of adoption.
t0	Integer scalar. Passed to <code>toa_mat</code> .
t1	Integer scalar. Passed to <code>toa_mat</code> .
vertex.dyn.attrs	Vertices dynamic attributes (see details).
vertex.static.attrs	Vertices static attributes (see details).
id.and.per.vars	A character vector of length 2. Optionally specified to check the order of the rows in the attribute data.
graph.attrs	Graph dynamic attributes (not supported yet).
undirected	Logical scalar. When TRUE only the lower triangle of the adjacency matrix will be considered (faster).
self	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).
multiple	Logical scalar. When TRUE allows multiple edges.
name	Character scalar. Name of the diffusion network (descriptive).
behavior	Character scalar. Name of the behavior being analyzed (innovation).
x	A <code>diffnet</code> object.
row.names	Ignored.
optional	Ignored.
attr.class	Character vector/scalar. Indicates the class of the attribute, either dynamic ("dyn"), or static ("static").
element	Character vector/scalar. Indicates what to retrieve/alter.
as.df	Logical scalar. When TRUE returns a <code>data.frame</code> .
value	In the case of <code>diffnet.toa</code> , replacement, otherwise see below.
i	Indices specifying elements to replace. See Extract .
FUN	a function to be passed to <code>lapply</code>
object	A <code>diffnet</code> object.

Details

`diffnet` objects hold both, static and dynamic vertex attributes. When creating `diffnet` objects, these can be specified using the arguments `vertex.static.attrs` and `vertex.dyn.attrs`; depending on whether the attributes to specify are static or dynamic, **netdiffuseR** currently supports the following objects:

Class	Dimension	Check sorting
<i>Static attributes</i> matrix	with n rows	id

data.frame	with n rows	id
vector	of length n	-
<i>Dynamic attributes</i>		
matrix	with $n \times T$ rows	id, per
data.frame	with $n \times T$ rows	id, per
vector	of length $n \times T$	-
list	of length T with matrices or data.frames of n rows	id, per

The last column, **Check sorting**, lists the variables that the user should specify if he wants the function to check the order of the rows of the attributes (notice that this is not possible for the case of vectors). By providing the name of the vertex id variable, `id`, and the time period id variable, `per`, the function makes sure that the attribute data is presented in the right order. See the example below. If the user does not provide the names of the vertex id and time period variables then the function does not check the way the rows are sorted, further it assumes that the data is in the correct order.

Value

A list of class `diffnet` with the following elements:

<code>graph</code>	A list of length T . Containing sparse square matrices of size n and class <code>dgCMatrix</code> .
<code>toa</code>	An integer vector of size T with times of adoption.
<code>adopt</code> , <code>cumadopt</code>	Numeric matrices of size $n \times T$ as those returned by <code>toa_mat</code> .
<code>vertex.static.attrs</code>	If not NULL, a data frame with n rows with vertex static attributes.
<code>vertex.dyn.attrs</code>	A list of length T with data frames containing vertex attributes through time (dynamic).
<code>graph.attrs</code>	A data frame with T rows.
<code>meta</code>	A list of length 9 with the following elements: <ul style="list-style-type: none"> • <code>type</code>: Character scalar equal to "dynamic". • <code>class</code>: Character scalar equal to "list". • <code>ids</code>: Character vector of size n with vertices' labels. • <code>pers</code>: Integer vector of size T. • <code>nper</code>: Integer scalar equal to T. • <code>n</code>: Integer scalar equal to n. • <code>self</code>: Logical scalar. • <code>undirected</code>: Logical scalar. • <code>multiple</code>: Logical scalar. • <code>name</code>: Character scalar. • <code>behavior</code>: Character scalar.

Auxiliary functions

`diffnet.attrs` Allows retrieving network attributes. In particular, by default returns a list of length T with data frames with the following columns:

1. `per` Indicating the time period to which the observation corresponds.
2. `toa` Indicating the time of adoption of the vertex.
3. Further columns depending on the vertex and graph attributes.

Each vertex static attributes' are repeated T times in total so that these can be binded (`rbind`) to dynamic attributes.

When `as.df=TRUE`, this convenience function is useful as it can be used to create event history (panel data) datasets used for model fitting.

Conversely, the replacement method allows including new vertex or graph attributes either dynamic or static (see examples below).

`diffnet.toa(graph)` works as an alias of `graph$toa`. The replacement method, `diffnet.toa<-used as diffnet.toa(graph)<- . . ., is the right way of modifying times of adoption as when doing so it performs several checks on the time ranges, and recalculates adoption and cumulative adoption matrices using toa_mat.`

`nodes(graph)` is an alias for `graph$meta$ids`.

Author(s)

George G. Vega Yon

See Also

Default options are listed at [netdiffuseR-options](#)

Other diffnet methods: [%*%](#), [as.array.diffnet](#), [c.diffnet](#), [diffnet-arithmetic](#), [diffnet_index](#), [plot.diffnet](#), [summary.diffnet](#)

Other data management functions: [edgelist_to_adjmat](#), [egonet_attrs](#), [isolated](#), [survey_to_diffnet](#)

Examples

```
# Creating a random graph
set.seed(123)
graph <- rgraph_ba(t=9)
graph <- lapply(1:5, function(x) graph)

# Pretty TOA
names(graph) <- 2001L:2005L
toa <- sample(c(2001L:2005L,NA), 10, TRUE)

# Creating diffnet object
diffnet <- new_diffnet(graph, toa)
diffnet
summary(diffnet)
```



```

# Plotting slice 4
plot(diffnet, t=4)

# ATTRIBUTES -----

# Retrieving attributes
diffnet.attrs(diffnet, "vertex", "static")

# Now as a data.frame (only static)
diffnet.attrs(diffnet, "vertex", "static", as.df = TRUE)

# Now as a data.frame (all of them)
diffnet.attrs(diffnet, as.df = TRUE)
as.data.frame(diffnet) # This is a wrapper

# Unsorted data -----
# Loading example data
data(fakesurveyDyn)

# Creating a diffnet object
fs_diffnet <- survey_to_diffnet(
  fakesurveyDyn, "id", c("net1", "net2", "net3"), "toa", "group",
  timevar = "time", keep.isolates=TRUE, warn.coercion=FALSE)

# Now, we extract the graph data and create a diffnet object from scratch
graph <- fs_diffnet$graph
ids <- fs_diffnet$meta$ids
graph <- Map(function(g) {
  dimnames(g) <- list(ids,ids)
  g
}, g=graph)
attrs <- diffnet.attrs(fs_diffnet, as.df=TRUE)
toa <- diffnet.toa(fs_diffnet)

# Lets apply a different sorting to the data to see if it works
n <- nrow(attrs)
attrs <- attrs[order(runif(n)),]

# Now, recreating the old diffnet object (notice -id.and.per.vars- arg)
fs_diffnet_new <- new_diffnet(graph, toa=toa, vertex.dyn.attrs=attrs,
  id.and.per.vars = c("id", "per"))

# Now, retrieving attributes. The 'new one' will have more (repeated)
attrs_new <- diffnet.attrs(fs_diffnet_new, as.df=TRUE)
attrs_old <- diffnet.attrs(fs_diffnet, as.df=TRUE)

# Comparing elements!
tocompare <- intersect(colnames(attrs_new), colnames(attrs_old))
all(attrs_new[,tocompare] == attrs_old[,tocompare], na.rm = TRUE) # TRUE!

# diffnetLapply -----

data(medInnovationsDiffNet)

```

```
diffnetLapply(medInnovationsDiffNet, function(x, cumadopt, ...) {sum(cumadopt)})
```

```
diffnet_check_attr_class
```

Infer whether value is dynamic or static.

Description

Intended for internal use only, this function is used in [diffnet_index](#) methods.

Usage

```
diffnet_check_attr_class(value, meta)
```

Arguments

value	Either a matrix, data frame or a list. Attribute values.
meta	A list. A diffnet object's meta data.

Value

The value object either as a data frame (if static) or as a list of data frames (if dynamic). If value does not follow the permitted types of [diffnet_index](#), then returns with error.

```
diffnet_index
```

Indexing diffnet objects (on development)

Description

Access and assign (replace) elements from the adjacency matrices or the vertex attributes data frames.

Usage

```
## S3 method for class 'diffnet'
x[[name, as.df = FALSE]]

## S3 replacement method for class 'diffnet'
x[[i, j]] <- value

## S3 method for class 'diffnet'
x[i, j, k, drop = FALSE]

## S3 replacement method for class 'diffnet'
x[i, j, k] <- value
```

Arguments

x	A diffnet class object.
name	String vector. Names of the vertices attributes.
as.df	Logical scalar. When TRUE returns a data frame, otherwise a list of length T .
i	Index of the i-th row of the adjacency matrix (see details).
j	Index of the j-th column of the adjacency matrix (see details)
value	Value to assign (see details)
k	Index of the k-th slice of the adjacency matrix (see details).
drop	Logical scalar. When TRUE returns an adjacency matrix, otherwise a filtered diffnet object.
...	Further argumnets to be passed to the method (on development)

Details

The `[[.diffnet` methods provides access to the diffnet attributes data frames, static and dynamic. By providing the name of the corresponding attribute, depending on whether it is static or dynamic the function will return either a data frame–static attributes–or a list of these–dynamic attributes. For the assigning method, `[[<-.diffnet`, the function will infer what kind of attribute is by analyzing the dimensions of value, in particular we have the following possible cases:

Class	Dimension	Inferred
matrix	$n \times T$	Dynamic
matrix	$n \times 1$	Static
matrix	$(n \times T) \times 1$	Dynamic
data.frame	$n \times T$	Dynamic
data.frame	$n \times 1$	Static
data.frame	$(n \times T) \times 1$	Dynamic
vector	n	Static
vector	$n \times T$	Dynamic
list*	T data.frames/matrices/vectors	Dynamic

*: With $n \times 1$ data.frame/matrix or n length vector.

Other cases will return with error.

In the case of the slices index k , either an integer vector with the positions, a character vector with the labels of the time periods or a logical vector of length T can be used to specify which slices to retrieve. Likewise, indexing vertices works in the same way with the only difference that, instead of time period labels and a logical vector of length T , vertices ids labels and a logical vector of length n should be provided.

When subsetting slices, the function modifies the `toa` vector as well as the `adopt` and `cumadopt` matrices collapsing network tinning. For example, if a network goes from time 1 to 20 and we set `k=3:10`, all individuals who adopted prior to time 3 will be set as adopters at time 3, and all individuals who adopted after time 10 will be set as adopters at time 10, changing the adoption and cumulative adoption matrices. Importantly, k have no gaps, and it should be within the graph time period range.

Value

In the case of the assigning methods, a diffnet object. Otherwise, for `[.diffnet` a vector extracted from one of the attributes data frames, and for `[.diffnet` a list of length `length(k)` with the corresponding `[i, j]` elements from the adjacency matrix.

Author(s)

George G. Vega Yon

See Also

Other diffnet methods: [%%](#), [as.array.diffnet](#), [c.diffnet](#), [diffnet-arithmetic](#), [diffnet-class](#), [plot.diffnet](#), [summary.diffnet](#)

Examples

```
# Creating a random diffusion network -----
set.seed(111)
graph <- rdiffnet(100,5)

# Accessing to a static attribute
graph[["real_threshold"]]

# Accessing to subsets of the adjacency matrix
graph[1,,1:3, drop=TRUE]
graph[,1:3, drop=TRUE][[1]]

# ... Now, as diffnet objects (the default)
graph[1,,1:3, drop=FALSE]
graph[,1:3, drop=FALSE]

# Changing values in the adjacency matrix
graph[1, , , drop=TRUE]
graph[1,,] <- -5
graph[1, , , drop=TRUE]

# Adding attributes (dynamic) -----
# Preparing the data
set.seed(1122)
x <- rdiffnet(30, 5, seed.p.adopt=.15)

# Calculating exposure, and storing it diffe
expoM <- exposure(x)
expoL <- lapply(seq_len(x$meta$nper), function(x) expoM[,x,drop=FALSE])
expoD <- do.call(rbind, expoL)

# Adding data (all these are equivalent)
x[["expoM"]] <- expoM
x[["expoL"]] <- expoL
x[["expoD"]] <- expoD
```

```
# Lets compare
identical(x[["expoM"]], x[["expoL"]]) # TRUE
identical(x[["expoM"]], x[["expoD"]]) # TRUE
```

diffreg

Diffusion regression model

Description

A wrapper of `glm`, this function estimates a lagged regression model of adoption as a function of exposure and other controls as specified by the user.

Usage

```
diffreg(model, type = c("logit", "probit"))
```

Arguments

model	An object of class <code>formula</code> where the right-hand-side is an object of class <code>diffnet</code>
type	Character scalar. Either "probit" or "logit".

Details

The model must be in the following form:

```
<diffnet object> ~ exposure + covariate1 + covariate2 + ...
```

Where exposure can be specified either as a simple term, or as a call to the exposure function, e.g. to compute exposure with a lag of length 2, the formula could be:

```
<diffnet object> ~ exposure(lags = 2) + covariate1 + covariate2 + ...
```

When no argument is passed to exposure, the function sets a lag of length 1 by default (see the *Lagged regression* section).

This is a wrapper of `glm`. The function does the following steps:

1. Compute exposure by calling exposure on the LHS.
2. Modify the formula so that the model is on adoption as a function of exposure and whatever covariates the user specifies.
3. Selects either "probit" or "logit" and prepares the call to `glm`. This includes passing the following line:

```
subset = ifelse(is.na(toa), TRUE, toa >= per)
```

This results in including observations that either did not adopted or up to the time of adoption.

4. Estimates the model.

The data passed to `glm` is obtained by using `as.data.frame.diffnet`.

Value

An object of class `glm`.

Lagged regression

The model estimated is a lagged regression model that has two main assumptions:

1. The network is exogenous to the behavior (no selection effect)
2. The influence effect (diffusion) happens in a lagged fashion, hence, exposure is computed lagged.

If either of these two assumptions is not met, then the model becomes endogenous, and so inference becomes invalid.

In the case of the first assumption, the user can overcome the non-exogeneity problem by providing an alternative network. This can be done by specifying `alt.graph` in the `exposure` function so that the network becomes exogenous to the adoption.

Examples

```
data("medInnovationsDiffNet")

# Default model
ans <- diffreg(
  medInnovationsDiffNet ~ exposure + factor(city) + proage + per)
summary(ans)
```

diffusion-data

Diffusion Network Datasets

Description

Diffusion Network Datasets

Details

The three classic network diffusion datasets included in `netdiffuseR` are the medical innovation data originally collected by Coleman, Katz & Menzel (1966); the Brazilian Farmers collected as part of the three country study implemented by Everett Rogers (Rogers, Ascroft, & Röling, 1970), and Korean Family Planning data collected by researchers at the Seoul National University's School of Public (Rogers & Kincaid, 1981). The table below summarizes the three datasets:

	Medical Innovation	Brazilian Farmers	Korean Family Planning
<i>Country</i>	USA	Brazil	Korean
<i># Respondents</i>	125 Doctors	692 Farmers	1,047 Women
<i># Communities</i>	4	11	25
<i>Innovation</i>	Tetracycline	Hybrid Corn Seed	Family Planning
<i>Time for Diffusion</i>	18 Months	20 Years	11 Years
<i>Year Data Collected</i>	1955-1956	1966	1973

<i>Ave. Time to 50%</i>	6	16	7
<i>Highest Saturation</i>	0.89	0.98	0.83
<i>Lowest Saturation</i>	0.81	0.29	0.44
<i>Citation</i>	Coleman et al (1966)	Rogers et al (1970)	Rogers & Kincaid (1981)

All datasets include a column called *study* which is coded as (1) Medical Innovation (2) Brazilian Farmers, (3) Korean Family Planning.

Right censored data

By convention, non-adopting actors are coded as one plus the last observed time of adoption. Prior empirical event history approaches have used this approach (Valente, 2005; Marsden and Podolny, 1990) and studies have shown that omitting such observations leads to biased results (van den Bulte & Iyengar, 2011).

Author(s)

Thomas W. Valente

References

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See Also

Other diffusion datasets: [brfarmersDiffNet](#), [brfarmers](#), [fakeDynEdgelist](#), [fakeEdgelist](#), [fakesurveyDyn](#), [fakesurvey](#), [kfamilyDiffNet](#), [kfamily](#), [medInnovationsDiffNet](#), [medInnovations](#)

diffusionMap	<i>Creates a heatmap based on a graph layout and a vertex attribute</i>
--------------	-------------------------------------------------------------------------

Description

Using bi-dimensional kernel smoothers, creates a heatmap based on a graph layout and colored accordingly to x . This visualization technique is intended to be used with large graphs.

Usage

```
diffusionMap(graph, ...)

diffmap(graph, ...)

## Default S3 method:
diffusionMap(graph, x, x.adj = round_to_seq,
  layout = NULL, jitter.args = list(), kde2d.args = list(n = 100),
  sharp.criter = function(x, w) { wvar(x, w) > (max(x, na.rm = TRUE) -
  min(x, na.rm = TRUE))^2/12 }, ...)

## S3 method for class 'diffnet'
diffusionMap(graph, slice = nslices(graph), ...)

## S3 method for class 'diffnet_diffmap'
image(x, ...)

## S3 method for class 'diffnet_diffmap'
print(x, ...)

## S3 method for class 'diffnet_diffmap'
plot(x, y = NULL, ...)
```

Arguments

graph	A square matrix of size $n \times n$.
...	Arguments passed to method.
x	An vector of length n . Usually a toa vector.
x.adj	Function to adjust x . If not NULL then it is applied to x at the beginning (see details).
layout	Either a $n \times 2$ matrix of coordinates or a layout function applied to graph (must return coordinates).

<code>jitter.args</code>	A list including arguments to be passed to jitter .
<code>kde2d.args</code>	A list including arguments to be passed to kde2d .
<code>sharp.criter</code>	A function choose whether to apply a weighted mean for each cell, or randomize over the values present in that cell (see details).
<code>slice</code>	Integer scalar. Slice of the network to be used as baseline for drawing the graph.
<code>y</code>	Ignored.

Details

The image is created using the function `kde2d` from the **MASS** package. The complete algorithm follows:

1. `x` is coerced into integer and the range is adjusted to start from 1. NA are replaced by zero.
2. If no layout is passed, layout is computed using [layout_nicely](#) from **igraph**
3. Then, a `kde2d` map is computed for each level of `x`. The resulting matrices are added up as a weighted sum. This only holds if at the cell level the function `sharp.criter` returns FALSE.
4. The jitter function is applied to the repeated coordinates.
5. 2D kernel is computed using `kde2d` over the coordinates.

The function `sharp.criter` must take two values, a vector of levels and a vector of weights. It must return a logical scalar with value equal to TRUE when a randomization at the cell level must be done, in which case the final value of the cell is chosen using `sample(x, 1, prob=w)`.

The resulting matrix can be passed to [image](#) or similar.

The argument `x.adj` uses by default the function [round_to_seq](#) which basically maps `x` to a fix length sequence of numbers such that `x.adj(x)` resembles an integer sequence.

Value

A list of class `diffnet_diffmap`

<code>coords</code>	A matrix of size $n \times 2$ of vertices coordinates.
<code>map</code>	Output from <code>kde2d</code> . This is a list with 3 elements, vectors <code>x</code> , <code>y</code> and matrix <code>z</code> of size $n \times n$ (passed via <code>kde2d.args</code>).
<code>h</code>	Bandwidth passed to <code>kde2d</code> .

Author(s)

George G. Vega Yon

References

Vega Yon, George G., and Valente, Thomas W., Visualizing Large Annotated Networks as Heatmaps using Weighted Averages based on Kernel Smoothers (Working paper).

See Also

Other visualizations: [dgr](#), [drawColorKey](#), [grid_distribution](#), [hazard_rate](#), [plot_adopters](#), [plot_diffnet2](#), [plot_diffnet](#), [plot_infetsuscep](#), [plot_threshold](#), [rescale_vertex_igraph](#)

Examples

```

# Example with a random graph -----

## Not run:
set.seed(1231)

# Random scale-free diffusion network
x <- rdiffnet(1000, 4, seed.graph="scale-free", seed.p.adopt = .025,
             rewire = FALSE, seed.nodes = "central",
             rgraph.arg=list(self=FALSE, m=4),
             threshold.dist = function(id) runif(1,.2,.4))

# Diffusion map (no random toa)
dm0 <- diffusionMap(x, kde2d.args=list(n=150, h=.5), layout=igraph::layout_with_fr)

# Random
diffnet.toa(x) <- sample(x$toa, size = nnodes(x))

# Diffusion map (random toa)
dm1 <- diffusionMap(x, layout = dm0$coords, kde2d.args=list(n=150, h=.5))

oldpar <- par(no.readonly = TRUE)
col <- colorRampPalette(blues9)(100)
par(mfrow=c(1,2), oma=c(1,0,0,0))
image(dm0, col=col, main="Non-random Times of Adoption\nAdoption from the core.")
image(dm1, col=col, main="Random Times of Adoption")
par(mfrow=c(1,1))
mtext("Both networks have the same distribution on times of adoption", 1,
      outer = TRUE)
par(oldpar)

## End(Not run)

# Example with Brazilian Farmers -----
## Not run:
dn <- brfarmersDiffNet

# Setting last TOA as NA
diffnet.toa(dn)[dn$toa == max(dn$toa)] <-
  NA

# Coordinates
coords <- sna::gplot.layout.fruchtermanreingold(
  as.matrix(dn$graph[[1]]), layout.par=NULL
)

# Plotting diffusion
plot_diffnet2(dn, layout=coords, vertex.size = 300)

# Adding diffusion map
out <- diffusionMap(dn, layout=coords, kde2d.args=list(n=100, h=50))

```

```
col <- adjustcolor(colorRampPalette(c("white", "lightblue", "yellow", "red"))(100), .5)
with(out$map, .filled.contour(x,y,z,pretty(range(z), 100),col))

## End(Not run)
```

drawColorKey

Draw a color key in the current device

Description

Draw a color key in the current device

Usage

```
drawColorKey(x, tick.marks = pretty_within(x), labels = tick.marks,
  main = NULL, key.pos = c(0.925, 0.975, 0.05, 0.95), pos = 2,
  nlevels = length(tick.marks), color.palette = viridis::viridis(nlevels),
  tick.width = c(0.01, 0.0075), add.box = TRUE, na.col = NULL,
  na.height = 0.1, na.lab = "n/a", ...)
```

Arguments

x	A numeric vector with the data (it is used to extract the range).
tick.marks	A numeric vector indicating the levels to be included in the axis.
labels	Character vector. When provided, specifies using different labels for the tick marks than those provided by tick.marks.
main	Character scalar. Title of the key.
key.pos	A numeric vector of length 4 with relative coordinates of the key (as % of the plotting area, see par("usr"))
pos	Integer scalar. Position of the axis as in text .
nlevels	Integer scalar. Number of levels (colors) to include in the color key.
color.palette	Color palette of length(nlevels).
tick.width	Numeric vector of length 2 indicating the length of the inner and outer tick marks as percentage of the axis.
add.box	Logical scalar. When TRUE adds a box around the key.
na.col	Character scalar. If specified, adds an additional box indicating the NA color.
na.height	Numeric scalar. Relative height of the NA box. Only use if na.col is not NULL.
na.lab	Character scalar. Label of the NA block. Only use if na.col is not NULL.
...	Further arguments to be passed to rect

Value

Invisible NULL.

Author(s)

George G. Vega Yon

See Also

Other visualizations: [dgr](#), [diffusionMap](#), [grid_distribution](#), [hazard_rate](#), [plot_adopters](#), [plot_diffnet2](#), [plot_diffnet](#), [plot_infetsuscep](#), [plot_threshold](#), [rescale_vertex_igraph](#)

Examples

```
set.seed(166)
x <- rnorm(100)
col <- colorRamp(c("lightblue", "yellow", "red"))((x - min(x))/(max(x) - min(x)))
col <- rgb(col, maxColorValue = 255)
plot(x, col=col, pch=19)
drawColorKey(x, nlevels = 100, border="transparent",
  main="Key\nLike A\nBoss")
```

edgelist_to_adjmat *Conversion between adjacency matrix and edgelist*

Description

Generates adjacency matrix from an edgelist and vice versa.

Usage

```
edgelist_to_adjmat(edgelist, w = NULL, t0 = NULL, t1 = NULL, t = NULL,
  simplify = TRUE, undirected = getOption("diffnet.undirected"),
  self = getOption("diffnet.self"),
  multiple = getOption("diffnet.multiple"), keep.isolates = TRUE,
  recode.ids = TRUE)
```

```
adjmat_to_edgelist(graph, undirected = getOption("diffnet.undirected", FALSE),
  keep.isolates = getOption("diffnet.keep.isolates", TRUE))
```

Arguments

edgelist	Two column matrix/data.frame in the form of ego -source- and alter -target- (see details).
w	Numeric vector. Strength of ties (optional).
t0	Integer vector. Starting time of the ties (optional).
t1	Integer vector. Finishing time of the ties (optional).
t	Integer scalar. Repeat the network t times (if no t0, t1 are provided).
simplify	Logical scalar. When TRUE and times=NULL it will return an adjacency matrix, otherwise an array of adjacency matrices. (see details).

<code>undirected</code>	Logical scalar. When TRUE only the lower triangle of the adjacency matrix will be considered (faster).
<code>self</code>	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).
<code>multiple</code>	Logical scalar. When TRUE allows multiple edges.
<code>keep.isolates</code>	Logical scalar. When FALSE, rows with NA/NULL values (isolated vertices unless have autolink) will be dropped (see details).
<code>recode.ids</code>	Logical scalar. When TRUE ids are recoded using <code>as.factor</code> (see details).
<code>graph</code>	Any class of accepted graph format (see <code>netdiffuseR-graphs</code>).

Details

When converting from edgelist to adjmat the function will `recode` the edgelist before starting. The user can keep track after the recording by checking the resulting adjacency matrices' `row.names`. In the case that the user decides skipping the recoding (because wants to keep vertices index numbers, implying that the resulting graph will have isolated vertices), he can override this by setting `recode.ids=FALSE` (see example).

When multiple edges are included, `multiple=TRUE`, each vertex between $\{i, j\}$ will be counted as many times it appears in the edgelist. So if a vertex $\{i, j\}$ appears 2 times, the adjacency matrix element (i, j) will be 2.

Edges with incomplete information (missing data on `w` or `times`) are not included on the graph. Incomplete cases are tagged using `complete.cases` and can be retrieved by the user by accessing the attribute `incomplete`.

Were the case that either `ego` or `alter` are missing (i.e. NA values), the function will either way include the non-missing vertex. See below for an example of this.

The function performs several checks before starting to create the adjacency matrix. These are:

- Dimensions of the inputs, such as number of columns and length of vectors
- Having complete cases. If any edge has a non-numeric value such as NAs or NULL in either `times` or `w`, it will be removed. A full list of such edges can be retrieved from the attribute `incomplete`
- Nodes and times ids coding

`recode.ids=FALSE` is useful when the vertices ids have already been coded. For example, after having use `adjmat_to_edgelist`, ids are correctly encoded, so when going back (using `edgelist_to_adjmat`) `recode.ids` should be FALSE.

Value

In the case of `edgelist_to_adjmat` either an adjacency matrix (if `times` is NULL) or an array of these (if `times` is not null). For `adjmat_to_edgelist` the output is an edgelist with the following columns:

<code>ego</code>	Origin of the tie.
<code>alter</code>	Target of the tie.
<code>value</code>	Value in the adjacency matrix.
<code>time</code>	Either a 1 (if the network is static) or the time stamp of the tie.

Author(s)

George G. Vega Yon & Thomas W. Valente

See Also

Other data management functions: [diffnet-class](#), [egonet_attrs](#), [isolated](#), [survey_to_diffnet](#)

Examples

```
# Base data
set.seed(123)
n <- 5
edgelist <- rgraph_er(n, as.edgelist=TRUE, p=.2)[,c("ego","alter")]
times <- sample.int(3, nrow(edgelist), replace=TRUE)
w <- abs(rnorm(nrow(edgelist)))

# Simple example
edgelist_to_adjmat(edgelist)
edgelist_to_adjmat(edgelist, undirected = TRUE)

# Using w
edgelist_to_adjmat(edgelist, w)
edgelist_to_adjmat(edgelist, w, undirected = TRUE)

# Using times
edgelist_to_adjmat(edgelist, t0 = times)
edgelist_to_adjmat(edgelist, t0 = times, undirected = TRUE)

# Using times and w
edgelist_to_adjmat(edgelist, t0 = times, w = w)
edgelist_to_adjmat(edgelist, t0 = times, undirected = TRUE, w = w)

# Not recoding -----
# Notice that vertices 3, 4 and 5 are not present in this graph.
graph <- matrix(c(
  1,2,6,
  6,6,7
), ncol=2)

# Generates an adjmat of size 4 x 4
edgelist_to_adjmat(graph)

# Generates an adjmat of size 7 x 7
edgelist_to_adjmat(graph, recode.ids=FALSE)

# Dynamic with spells -----
edgelist <- rbind(
  c(1,2,NA,1990),
  c(2,3,NA,1991),
  c(3,4,1991,1992),
  c(4,1,1992,1993),
  c(1,2,1993,1993)
```

```

)

graph <- edgelist_to_adjmat(edgelist[,1:2], t0=edgelist[,3], t1=edgelist[,4])

# Creating a diffnet object with it so we can apply the plot_diffnet function
diffnet <- as_diffnet(graph, toa=1:4)
plot_diffnet(diffnet, label=rownames(diffnet))

# Missing alter in the edgelist -----
data(fakeEdgelist)

# Notice that edge 202 is isolated
fakeEdgelist

# The function still includes vertex 202
edgelist_to_adjmat(fakeEdgelist[,1:2])

edgelist

```

edges_coords	<i>Compute ego/alter edge coordinates considering alter's size and aspect ratio</i>
--------------	-------------------------------------------------------------------------------------

Description

Given a graph, vertices' positions and sizes, calculates the absolute positions of the endpoints of the edges considering the plot's aspect ratio.

Usage

```
edges_coords(graph, toa, x, y, vertex_cex, undirected = TRUE,
  no_contemporary = TRUE, dev = as.numeric(c()), ran = as.numeric(c()),
  curved = as.logical(c()))
```

Arguments

graph	A square matrix of size n . Adjacency matrix.
toa	Integer vector of size n . Times of adoption.
x	Numeric vector of size n . x-coordinta of vertices.
y	Numeric vector of size n . y-coordinta of vertices.
vertex_cex	Numeric vector of size n . Vertices' sizes in terms of the x-axis (see symbols).
undirected	Logical scalar. Whether the graph is undirected or not.
no_contemporary	Logical scalar. Whether to return (compute) edges' coordiantes for vertices with the same time of adoption (see details).
dev	Numeric vector of size 2. Height and width of the device (see details).

ran	Numeric vector of size 2. Range of the x and y axis (see details).
curved	Logical vector.

Details

In order to make the plot's visualization more appealing, this function provides a straight forward way of computing the tips of the edges considering the aspect ratio of the axes range. In particular, the following corrections are made at the moment of calculating the edges coords:

- Instead of using the actual distance between ego and alter, a relative one is calculated as follows

$$d' = [(x_0 - x_1)^2 + (y'_0 - y'_1)^2]^{\frac{1}{2}}$$

$$\text{where } y'_i = y_i \times \frac{\max x - \min x}{\max y - \min y}$$

- Then, for the relative elevation angle, `alpha`, the relative distance d' is used, $\alpha' = \arccos((x_0 - x_1)/d')$
- Finally, the edge's endpoint's (alter) coordinates are computed as follows:

$$x'_1 = x_1 + \cos(\alpha') \times v_1$$

$$y'_1 = y_1 - \sin(\alpha') \times v_1 \times \frac{\max y - \min y}{\max x - \min x}$$

Where v_1 is alter's size in terms of the x-axis, and the sign of the second term in y'_1 is negative iff $y_0 < y_1$.

The same process (with sign inverted) is applied to the edge starting point. The resulting values, x'_1, y'_1 can be used with the function `arrows`. This is the workhorse function used in `plot_threshold`.

The `dev` argument provides a reference to rescale the plot accordingly to the device, and former, considering the size of the margins as well (this can be easily fetched via `par("pin")`, plot area in inches).

On the other hand, `ran` provides a reference for the adjustment according to the range of the data, this is `range(x)[2] - range(x)[1]` and `range(y)[2] - range(y)[1]` respectively.

Value

A numeric matrix of size $m \times 5$ with the following columns:

<code>x0, y0</code>	Edge origin
<code>x1, y1</code>	Edge target
<code>alpha</code>	Relative angle between (x_0, y_0) and (x_1, y_1) in terms of radians

With m as the number of resulting edges.

Examples

```

# -----
data(medInnovationsDiffNet)
library(sna)

# Computing coordinates
set.seed(79)
coords <- sna::gplot(as.matrix(medInnovationsDiffNet$graph[[1]]))

# Getting edge coordinates
vcex <- rep(1.5, nnodes(medInnovationsDiffNet))
ecoords <- edges_coords(
  medInnovationsDiffNet$graph[[1]],
  diffnet.toa(medInnovationsDiffNet),
  x = coords[,1], y = coords[,2],
  vertex_cex = vcex,
  dev = par("pin")
)

ecoords <- as.data.frame(ecoords)

# Plotting
symbols(coords[,1], coords[,2], circles=vcex,
  inches=FALSE, xaxs="i", yaxs="i")

with(ecoords, arrows(x0,y0,x1,y1, length=.1))

```

egonet_attr

*Retrieve alter's attributes (network effects)***Description**

For a given set of vertices V , retrieves each vertex's alter's attributes. This function enables users to calculate exposure on variables other than the attribute that is diffusing. Further, it enables the specification of alternative functions to use to characterize ego's personal network including calculating the mean, maximum, minimum, median, or sum of the alters' attributes. These measures may be static or dynamic over the interval of diffusion and they may be binary or valued.

Usage

```

egonet_attr(graph, attrs, V = NULL, direction = "outgoing",
  fun = function(x) x, as.df = FALSE, self = getOption("diffnet.self"),
  valued = getOption("diffnet.valued"), ...)

```

Arguments

graph	Any class of accepted graph format (see netdiffuseR-graphs).
attrs	If graph is static, Numeric matrix with n rows, otherwise a list of numeric matrices with n rows.

<code>V</code>	Integer vector. Set of vertices from which the attributes will be retrieved.
<code>direction</code>	Character scalar. Either "outgoing", "incoming".
<code>fun</code>	Function. Applied to each
<code>as.df</code>	Logical scalar. When TRUE returns a data.frame instead of a list (see details).
<code>self</code>	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).
<code>valued</code>	Logical scalar. When TRUE weights will be considered. Otherwise non-zero values will be replaced by ones.
<code>...</code>	Further arguments to be passed to fun.

Details

By indexing inner/outer edges, this function retrieves ego network attributes for all $v \in V$, which by default is the complete set of vertices in the graph.

When `as.df=TRUE` the function returns a data.frame of size $(|V| \times T) \times k$ where T is the number of time periods and k is the number of columns generated by the function.

The function can be used to create network effects as those in the **RSiena** package. The difference here is that the definition of the statistic directly relies on the user. For example, in the **RSiena** package, the dyadic covariate effect *37. covariate (centered) main effect (X)*

$$s_{i37}(x) = \sum_j x_{ij}(w_{ij} - \bar{w})$$

Which, having a diffnet object with attributes named `x` and `w`, can be calculated as

```
egonet_attrs(diffnet, as.df=TRUE, fun=function(dat) {
  sum(dat[, "x"]*(dat[, "w"] - mean(dat[, "w"])))
})
```

Furthermore, we could use the *median* centered instead, for example

```
egonet_attrs(diffnet, as.df=TRUE, fun=function(dat) {
  sum(dat[, "x"]*(dat[, "w"] - median(dat[, "w"])))
})
```

Where for each i , `dat` will be a matrix with as many rows as individuals in his egonet. Such matrix holds the column names of the attributes in the network.

When `self = TRUE`, it will include ego's attributes, regardless the network has loops or not.

Value

A list with ego alters's attributes. By default, if the graph is static, the output is a list of length $\text{length}(V)$ with matrices having the following columns:

value	Either the corresponding value of the tie.
id	Alter's id
...	Further attributes contained in <code>attrs</code>

On the other hand, if graph is dynamic, the output is list of length T of lists of length $\text{length}(V)$ with data frames having the following columns:

value	The corresponding value of the adjacency matrix.
id	Alter's id
per	Time id
...	Further attributes contained in <code>attrs</code>

Author(s)

George G. Vega Yon

See Also

Other data management functions: [diffnet-class](#), [edgelist_to_adjmat](#), [isolated](#), [survey_to_diffnet](#)

Examples

```
# Simple example with diffnet -----
set.seed(1001)
diffnet <- rdiffnet(150, 5, seed.graph="small-world")

# Adding attributes
indeg <- dgr(diffnet, cmode="indegree")
head(indeg)
diffnet[["indegree"]] <- indeg

# Retrieving egonet's attributes (vertices 1 and 20)
egonet_attrs(diffnet, V=c(1,20))

# Example with a static network -----

set.seed(1231)
n <- 20
net <- rgraph_ws(n = n, k = 4, p = .5)
someattr <- matrix(rnorm(n * 2), ncol= 2, dimnames = list(NULL, c("a", "b")))

# Maximum of -a- in ego network
ans <- egonet_attrs(net, someattr, fun = function(x) max(x[, "a"]))
ans

# checking it worked, taking a look at node 1, 2, and 3
```

```

max(someattr[which(net[1,] == 1), "a"]) == ans[1] # TRUE
max(someattr[which(net[2,] == 1), "a"]) == ans[2] # TRUE
max(someattr[which(net[3,] == 1), "a"]) == ans[3] # TRUE

```

ego_variance *Computes variance of Y at ego level*

Description

Computes variance of Y at ego level

Usage

```
ego_variance(graph, Y, funname, all = FALSE)
```

Arguments

graph A matrix of size $n \times n$ of class dgMatrix.
Y A numeric vector of length n .
funname Character scalar. Comparison to make (see [vertex_covariate_compare](#)).
all Logical scalar. When FALSE (default) f_i is mean at ego level. Otherwise is fix for all i (see details).

Details

For each vertex i the variance is computed as follows

$$\left(\sum_j a_{ij}\right)^{-1} \sum_j a_{ij} [f(y_i, y_j) - f_i]^2$$

Where a_{ij} is the ij -th element of graph, f is the function specified in funname, and, if all=FALSE $f_i = \sum_j a_{ij} f(y_i, y_j) / \sum_j a_{ij}$, otherwise $f_i = f_j = \frac{1}{n^2} \sum_{i,j} f(y_i, y_j)$

This is an auxiliary function for [struct_test](#). The idea is to compute an adjusted measure of dissimilarity between vertices, so the closest in terms of f is i to its neighbors, the smaller the relative variance.

Value

A numeric vector of length n .

See Also

[struct_test](#)

Other statistics: [bass](#), [classify_adopters](#), [cumulative_adopt_count](#), [dgr](#), [exposure](#), [hazard_rate](#), [infection](#), [moran](#), [struct_equiv](#), [threshold](#), [vertex_covariate_dist](#)

exposure	<i>Ego exposure</i>
----------	---------------------

Description

Calculates exposure to adoption over time via multiple different types of weight matrices. The basic model is exposure to adoption by immediate neighbors (outdegree) at the time period prior to ego's adoption. This exposure can also be based on (1) incoming ties, (2) structural equivalence, (3) indirect ties, (4) attribute weighted (5) network-metric weighted (e.g., central nodes have more influence), and attribute-weighted (e.g., based on homophily or tie strength).

Usage

```
exposure(graph, cumadopt, attrs = NULL, alt.graph = NULL,
         outgoing = getOption("diffnet.outgoing", TRUE),
         valued = getOption("diffnet.valued", FALSE), normalized = TRUE,
         groupvar = NULL, self = getOption("diffnet.self"), lags = 0L, ...)
```

Arguments

graph	A dynamic graph (see netdiffuseR-graphs).
cumadopt	$n \times T$ matrix. Cumulative adoption matrix obtained from toa_mat
attrs	Either a character scalar (if graph is diffnet), or a numeric matrix of size $n \times T$. Weighting for each time, period (see details).
alt.graph	Either a graph that should be used instead of graph, or "se" (see details).
outgoing	Logical scalar. When TRUE, computed using outgoing ties.
valued	Logical scalar. When TRUE weights will be considered. Otherwise non-zero values will be replaced by ones.
normalized	Logical scalar. When TRUE, the exposure will be between zero and one (see details).
groupvar	Passed to struct_equiv .
self	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).
lags	Integer scalar. When different from 0, the resulting exposure matrix will be the lagged exposure as specified (see examples).
...	Further arguments passed to struct_equiv (only used when alt.graph="se").

Details

Exposure is calculated as follows:

$$E_t = (S_t \times [x_t \circ A_t]) / (S_t \times x_t)$$

Where S_t is the graph in time t , x_t is an attribute vector of size n at time t , A_t is the t -th column of the cumulative adopters matrix (a vector of length n with $a_{ti} = 1$ if i has adopted at or prior to t), \circ is the kronecker product (element-wise), and \times is the matrix product.

By default the graph used for this calculation, S , is the social network. Alternatively, in the case of `diffnet` objects, the user can provide an alternative graph using `alt.graph`. An example of this would be using $1/SE$, the element-wise inverse of the structural equivalence matrix (see example below). Furthermore, if `alt.graph="se"`, the inverse of the structural equivalence is computed via `struct_equiv` and used instead of the provided graph. Notice that when using a valued graph the option `valued` should be equal to `TRUE`, this check is run automatically when running the model using structural equivalence.

If the `alt.graph` is static, then the function will warn about it and will recycle the graph to compute exposure at each time point.

An important remark is that when calculating **structural equivalence** the function **assumes that this is to be done to the entire graph** regardless of disconnected communities (as in the case of the medical innovations data set). Hence, structural equivalence for individuals for two different communities may not be zero. If the user wants to calculate structural equivalence separately by community, he should create different `diffnet` objects and do so (see example below). Alternatively, for the case of `diffnet` objects, by using the option `groupvar` (see `struct_equiv`), the user can provide the function with the name of a grouping variable—which should one in the set of static vertex attributes—so that the algorithm is done by group (or community) instead of in an aggregated way.

If the user does not specify a particular weighting attribute in `attrs`, the function sets this as a matrix of ones. Otherwise the function will return an attribute weighted exposure. When graph is of class `diffnet`, `attrs` can be a character scalar specifying the name of any of the graph's attributes, both dynamic and static. See the examples section for a demonstration using degree.

When `outgoing=FALSE`, S is replaced by its transposed, so in the case of a social network exposure will be computed based on the incoming ties.

If `normalize=FALSE` then denominator, $S_t \times x_t$, is not included. This can be useful when, for example, exposure needs to be computed as a count instead of a proportion. A good example of this can be found at the examples section of the function `rdiffnet`.

Value

A matrix of size $n \times T$ with exposure for each node.

Author(s)

George G. Vega Yon & Thomas W. Valente

References

- Burt, R. S. (1987). "Social Contagion and Innovation: Cohesion versus Structural Equivalence". *American Journal of Sociology*, 92(6), 1287. <http://doi.org/10.1086/228667>
- Valente, T. W. (1995). "Network models of the diffusion of innovations" (2nd ed.). Cresskill N.J.: Hampton Press.

See Also

Other statistics: [bass](#), [classify_adopters](#), [cumulative_adopt_count](#), [dgr](#), [ego_variance](#), [hazard_rate](#), [infection](#), [moran](#), [struct_equiv](#), [threshold](#), [vertex_covariate_dist](#)

Examples

```
# Calculating lagged exposure -----
set.seed(8)
graph <- rdifffnet(20, 4)

expo0 <- exposure(graph)
expo1 <- exposure(graph, lags = 1)

# These should be equivalent
stopifnot(all(expo0[, -4] == expo1[, -1])) # No stop!

# Calculating the exposure based on Structural Equivalence -----
set.seed(113132)
graph <- rdifffnet(100, 10)

SE <- lapply(struct_equiv(graph), "[[", "SE")
SE <- lapply(SE, function(x) {
  x <- 1/x
  x[!is.finite(x)] <- 0
  x
})

# Recall setting valued equal to TRUE!
expo_se <- exposure(graph, alt.graph=SE , valued=TRUE)

# These three lines are equivalent to:
expo_se2 <- exposure(graph, alt.graph="se", valued=TRUE)
# Notice that we are setting valued=TRUE, but this is not necessary since when
# alt.graph = "se" the function checks this to be setted equal to TRUE

# Weighted Exposure using degree -----
eDE <- exposure(graph, attrs=dgr(graph))

# Which is equivalent to
graph[["deg"]] <- dgr(graph)
eDE2 <- exposure(graph, attrs="deg")

# Comparing using incoming edges -----
eIN <- exposure(graph, outgoing=FALSE)

# Structural equivalence for different communities -----
data(medInnovationsDiffNet)

# METHOD 1: Using the c.difffnet method:
```

```

# Creating subsets by city
cities <- unique(medInnovationsDiffNet[["city"]])

diffnet <- medInnovationsDiffNet[medInnovationsDiffNet[["city"]] == cities[1]]
diffnet[["expo_se"]] <- exposure(diffnet, alt.graph="se", valued=TRUE)

for (v in cities[-1]) {
  diffnet_v <- medInnovationsDiffNet[medInnovationsDiffNet[["city"]] == v]
  diffnet_v[["expo_se"]] <- exposure(diffnet_v, alt.graph="se", valued=TRUE)
  diffnet <- c(diffnet, diffnet_v)
}

# We can set the original order (just in case) of the data
diffnet <- diffnet[medInnovationsDiffNet$meta$ids]
diffnet

# Checking everything is equal
test <- summary(medInnovationsDiffNet, no.print=TRUE) ==
  summary(diffnet, no.print=TRUE)

stopifnot(all(test[!is.na(test)]))

# METHOD 2: Using the 'groupvar' argument
# Further, we can compare this with using the groupvar
diffnet[["expo_se2"]] <- exposure(diffnet, alt.graph="se",
  groupvar="city", valued=TRUE)

# These should be equivalent
test <- diffnet[["expo_se", as.df=TRUE]] == diffnet[["expo_se2", as.df=TRUE]]
stopifnot(all(test[!is.na(test)]))

# METHOD 3: Computing exposure, rbind and then adding it to the diffnet object
expo_se3 <- NULL
for (v in unique(cities))
  expo_se3 <- rbind(
    expo_se3,
    exposure(
      diffnet[diffnet[["city"]] == v],
      alt.graph = "se", valued=TRUE
    )
  )

# Just to make sure, we sort the rows
expo_se3 <- expo_se3[diffnet$meta$ids,]

diffnet[["expo_se3"]] <- expo_se3

test <- diffnet[["expo_se", as.df=TRUE]] == diffnet[["expo_se3", as.df=TRUE]]
stopifnot(all(test[!is.na(test)]))

# METHOD 4: Using the groupvar in struct_equiv
se <- struct_equiv(diffnet, groupvar="city")
se <- lapply(se, "[", "SE")

```



```
se <- lapply(se, function(x) {
  x <- 1/x
  x[!is.finite(x)] <- 0
  x
})

diffnet[["expo_se4"]] <- exposure(diffnet, alt.graph=se, valued=TRUE)

test <- diffnet[["expo_se", as.df=TRUE]] == diffnet[["expo_se4", as.df=TRUE]]
stopifnot(all(test[!is.na(test)]))
```

fakeDynEdgelist

Fake dynamic edgelist

Description

A data frame used for examples in reading edgelist format networks. This edgelist can be merged with the dataset [fakesurveyDyn](#).

Format

A data frame with 22 rows and 4 variables

ego Nominating individual

alter Nominated individual

value Strength of the tie

time Integer with the time of the spell

Author(s)

George G. Vega Yon

Source

Generated for the package

See Also

Other diffusion datasets: [brfarmersDiffNet](#), [brfarmers](#), [diffusion-data](#), [fakeEdgelist](#), [fakesurveyDyn](#), [fakesurvey](#), [kfamilyDiffNet](#), [kfamily](#), [medInnovationsDiffNet](#), [medInnovations](#)

fakeEdgelist *Fake static edgelist*

Description

A data frame used for examples in reading edgelist format networks. This edgelist can be merged with the dataset [fakesurvey](#).

Format

A data frame with 11 rows and 3 variables

ego Nominating individual

alter Nominated individual

value Strength of the tie

Author(s)

George G. Vega Yon

Source

Generated for the package

See Also

Other diffusion datasets: [brfarmersDiffNet](#), [brfarmers](#), [diffusion-data](#), [fakeDynEdgelist](#), [fakesurveyDyn](#), [fakesurvey](#), [kfamilyDiffNet](#), [kfamily](#), [medInnovationsDiffNet](#), [medInnovations](#)

fakesurvey *Fake survey data*

Description

This data frame is used to illustrate some of the functions of the package, in particular, the [survey_to_diffnet](#) function. This dataset can be merged with the [fakeEdgelist](#).

Format

A data frame with 9 rows and 9 variables

id Unique id at group level

toa Time of adoption

group Group id

net1 Network nomination 1

net2 Network nomination 2
net3 Network nomination 3
age Age of the respondent
gender Gende of the respondent
note Descroption of the respondent

Author(s)

George G. Vega Yon

Source

Generated for the package.

See Also

Other diffusion datasets: [brfarmersDiffNet](#), [brfarmers](#), [diffusion-data](#), [fakeDynEdgelist](#), [fakeEdgelist](#), [fakesurveyDyn](#), [kfamilyDiffNet](#), [kfamily](#), [medInnovationsDiffNet](#), [medInnovations](#)

fakesurveyDyn

Fake longitudinal survey data

Description

This data frame is used to illustrate some of the functions of the package, in particular, the [survey_to_diffnet](#) function. This dataset can be merged with the [fakeDynEdgelist](#).

Format

A data frame with 18 rows and 10 variables

id Unique id at group level
toa Time of adoption
group Group id
net1 Network nomination 1
net2 Network nomination 2
net3 Network nomination 3
age Age of the respondent
gender Gende of the respondent
note Descroption of the respondent
time Timing of the wave

Author(s)

George G. Vega Yon

Source

Generated for the package.

See Also

Other diffusion datasets: [brfarmersDiffNet](#), [brfarmers](#), [diffusion-data](#), [fakeDynEdgelist](#), [fakeEdgelist](#), [fakesurvey](#), [kfamilyDiffNet](#), [kfamily](#), [medInnovationsDiffNet](#), [medInnovations](#)

grid_distribution *Distribution over a grid*

Description

Distribution of pairs over a grid of fix size.

Usage

```
grid_distribution(x, y, nlevels = 100L)
```

Arguments

x	Numeric vector of size n
y	Numeric vector of size n
nlevels	Integer scalar. Number of bins to return

Details

This function ment for internal use only.

Value

Returns a list with three elements

x	Numeric vector of size nlevels with the class marks for x
y	Numeric vector of size nlevels with the class marks for y
z	Numeric matrix of size nlevels by nlevels with the distribution of the elements in terms of frequency

Examples

```
# Generating random vectors of size 100
x <- rnorm(100)
y <- rnorm(100)

# Calculating distribution
grid_distribution(x,y,20)
```

See Also

Used by [plot_infetsuscep](#)

Other visualizations: [dgr](#), [diffusionMap](#), [drawColorKey](#), [hazard_rate](#), [plot_adopters](#), [plot_diffnet2](#), [plot_diffnet](#), [plot_infetsuscep](#), [plot_threshold](#), [rescale_vertex_igraph](#)

hazard_rate

Network Hazard Rate

Description

The hazard rate is the instantaneous probability of adoption at each time representing the likelihood members will adopt at that time (Allison 1984). The shape of the hazard rate indicates the pattern of new adopters over time. Rapid diffusion with convex cumulative adoption curves will have hazard functions that peak early and decay over time whereas slow concave cumulative adoption curves will have hazard functions that are low early and rise over time. Smooth hazard curves indicate constant adoption whereas those that oscillate indicate variability in adoption behavior over time.

Usage

```
hazard_rate(obj, no.plot = FALSE, include.grid = TRUE, ...)
```

```
plot_hazard(x, ...)
```

```
## S3 method for class 'diffnet_hr'
plot(x, y = NULL, main = "Hazard Rate",
     xlab = "Time", ylab = "Hazard Rate", type = "b", include.grid = TRUE,
     bg = "lightblue", pch = 21, add = FALSE, ylim = c(0, 1), ...)
```

Arguments

obj	A $n \times T$ matrix (Cumulative adoption matrix obtained from toa_mat) or a diffnet object.
no.plot	Logical scalar. When TRUE, suppress plotting (only returns hazard rates).
include.grid	Logical scalar. When TRUE includes a grid on the plot.
...	further arguments to be passed to the method.
x	An object of class <code>diffnet_hr</code> .
y	ignored.
main	Character scalar. Title of the plot
xlab	Character scalar. x-axis label.
ylab	Character scalar. y-axis label.
type	Character scalar. See par .
bg	Character scalar. Color of the points.
pch	Integer scalar. See par .
add	Logical scalar. When TRUE it adds the hazard rate to the current plot.
ylim	Numeric vector. See plot .

Details

This function computes hazard rate, plots it and returns the hazard rate vector invisible (so is not printed on the console). For $t > 1$, hazard rate is calculated as

$$\frac{q_t - q_{t-1}}{n - q_{t-1}}$$

where q_i is the number of adopters in time t , and n is the number of vertices in the graph.

In survival analysis, hazard rate is defined formally as

$$\lambda(t) = \lim_{h \rightarrow +0} \frac{F(t+h) - F(t)}{h} \frac{1}{1 - F(t)}$$

Then, by approximating $h = 1$, we can rewrite the equation as

$$\lambda(t) = \frac{F(t+1) - F(t)}{1 - F(t)}$$

Furthermore, we can estimate $F(t)$, the probability of not having adopted the innovation in time t , as the proportion of adopters in that time, this is $F(t) \sim q_t/n$, so now we have

$$\lambda(t) = \frac{q_{t+1}/n - q_t/n}{1 - q_t/n} = \frac{q_{t+1} - q_t}{n - q_t}$$

As showed above.

The `plot_hazard` function is an alias for the `plot_diffnet_hr` method.

Value

A row vector of size T with hazard rates for $t > 1$ of class `diffnet_hr`. The class of the object is only used by the S3 plot method.

Author(s)

George G. Vega Yon & Thomas W. Valente

References

Allison, P. (1984). Event history analysis regression for longitudinal event data. Beverly Hills: Sage Publications.

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data (2nd ed.). Cambridge: MIT Press.

See Also

Other statistics: [bass](#), [classify_adopters](#), [cumulative_adopt_count](#), [dgr](#), [ego_variance](#), [exposure](#), [infection](#), [moran](#), [struct_equiv](#), [threshold](#), [vertex_covariate_dist](#)

Other visualizations: [dgr](#), [diffusionMap](#), [drawColorKey](#), [grid_distribution](#), [plot_adopters](#), [plot_diffnet2](#), [plot_diffnet](#), [plot_infetsuscep](#), [plot_threshold](#), [rescale_vertex_igraph](#)

Examples

```
# Creating a random vector of times of adoption
toa <- sample(2000:2005, 20, TRUE)

# Computing cumulative adoption matrix
cumadopt <- toa_mat(toa)$cumadopt

# Visualizing the hazard rate
hazard_rate(cumadopt)
```

igraph *Coercion between graph classes*

Description

Coercion between graph classes

Usage

```
diffnet_to_igraph(graph, slices = 1:nslices(graph))

igraph_to_diffnet(graph = NULL, graph.list = NULL, toavar, t0 = NULL,
  t1 = NULL, ...)
```

Arguments

graph	Either a diffnet or igraph graph object.
slices	An integer vector indicating the slices to subset.
graph.list	A list of igraph objects.
toavar	Character scalar. Name of the attribute that holds the times of adoption.
t0	Integer scalar. Passed to new_diffnet .
t1	Integer scalar. Passed to new_diffnet .
...	Further arguments passed to as_diffnet .

Value

Either a list of length(slices) [igraph](#) ([diffnet_to_igraph](#)), or a [diffnet](#) object ([igraph_to_diffnet](#)) objects.

See Also

Other Foreign: [network](#), [read_pajek](#), [read_ucinet_head](#)

Examples

```
# Reading the medical innovation data into igraph -----
x <- diffnet_to_igraph(medInnovationsDiffNet)

# Fetching the times of adoption
igraph::vertex_attr(x[[1]], "toa")
```

infection

*Susceptibility and Infection***Description**

Calculates infectiousness and susceptibility for each node in the graph

Usage

```
infection(graph, toa, t0 = NULL, normalize = TRUE, K = 1L, r = 0.5,
  expdiscount = FALSE, valued = getOption("diffnet.valued", FALSE),
  outgoing = getOption("diffnet.outgoing", TRUE))

susceptibility(graph, toa, t0 = NULL, normalize = TRUE, K = 1L, r = 0.5,
  expdiscount = FALSE, valued = getOption("diffnet.valued", FALSE),
  outgoing = getOption("diffnet.outgoing", TRUE))
```

Arguments

graph	A dynamic graph (see netdiffuseR-graphs).
toa	Integer vector of length n with the times of adoption.
t0	Integer scalar. See toa_mat .
normalize	Logical. Whether or not to normalize the outcome
K	Integer scalar. Number of time periods to consider
r	Numeric scalar. Discount rate used when <code>expdiscount=TRUE</code>
expdiscount	Logical scalar. When TRUE, exponential discount rate is used (see details).
valued	Logical scalar. When TRUE weights will be considered. Otherwise non-zero values will be replaced by ones.
outgoing	Logical scalar. When TRUE, computed using outgoing ties.

Details

Normalization, `normalize=TRUE`, is applied by dividing the resulting number from the infectiousness/susceptibility stat by the number of individuals who adopted the innovation at time t .

Given that node i adopted the innovation in time t , its Susceptibility is calculated as follows

$$S_i = \frac{\sum_{k=1}^K \sum_{j=1}^n x_{ij(t-k+1)} z_j(t-k) \times \frac{1}{w_k}}{\sum_{k=1}^K \sum_{j=1}^n x_{ij(t-k+1)} z_j(1 \leq t \leq t-k) \times \frac{1}{w_k}} \quad \text{for } i, j = 1, \dots, n \quad i \neq j$$

where $x_{ij(t-k+1)}$ is 1 whenever there's a link from i to j at time $t - k + 1$, $z_{j(t-k)}$ is 1 whenever individual j adopted the innovation at time $t - k$, $z_{j(1 \leq t \leq t-k)}$ is 1 whenever j had adopted the innovation up to $t - k$, and w_k is the discount rate used (see below).

Similarly, infectiousness is calculated as follows

$$I_i = \frac{\sum_{k=1}^K \sum_{j=1}^n x_{ji(t+k-1)} z_{j(t+k)} \times \frac{1}{w_k}}{\sum_{k=1}^K \sum_{j=1}^n x_{ji(t+k-1)} z_{j(t+k \leq t \leq T)} \times \frac{1}{w_k}} \quad \text{for } i, j = 1, \dots, n \quad i \neq j$$

It is worth noticing that, as we can see in the formulas, while susceptibility is from alter to ego, infection is from ego to alter.

When `outgoing=FALSE` the algorithms are based on incoming edges, this is the adjacency matrices are transposed swapping the indexes (i, j) by (j, i) . This can be useful for some users.

Finally, by default both are normalized by the number of individuals who adopted the innovation in time $t - k$. Thus, the resulting formulas, when `normalize=TRUE`, can be rewritten as

$$S'_i = \frac{S_i}{\sum_{k=1}^K \sum_{j=1}^n z_{j(t-k)} \times \frac{1}{w_k}} \quad I'_i = \frac{I_i}{\sum_{k=1}^K \sum_{j=1}^n z_{j(t-k)} \times \frac{1}{w_k}}$$

For more details on these measurements, please refer to the vignette titled *Time Discounted Infection and Susceptibility*.

Value

A numeric column vector (matrix) of size n with either infection/susceptibility rates.

Discount rate

Discount rate, w_k in the formulas above, can be either exponential or linear. When `expdiscount=TRUE`, $w_k = (1 + r)^{k-1}$, otherwise it will be $w_k = k$.

Note that when $K = 1$, the above formulas are equal to the ones presented in Valente et al. (2015).

Author(s)

George G. Vega Yon

References

Thomas W. Valente, Stephanie R. Dyal, Kar-Hai Chu, Heather Wipfli, Kayo Fujimoto Diffusion of innovations theory applied to global tobacco control treaty ratification, *Social Science & Medicine*, Volume 145, November 2015, Pages 89-97, ISSN 0277-9536 <http://dx.doi.org/10.1016/j.socscimed.2015.10.001>

Myers, D. J. (2000). The Diffusion of Collective Violence: Infectiousness, Susceptibility, and Mass Media Networks. *American Journal of Sociology*, 106(1), 173–208. <https://doi.org/10.1086/303110>

See Also

The user can visualize the distribution of both statistics by using the function [plot_infectsuscep](#)

Other statistics: [bass](#), [classify_adopters](#), [cumulative_adopt_count](#), [dgr](#), [ego_variance](#), [exposure](#), [hazard_rate](#), [moran](#), [struct_equiv](#), [threshold](#), [vertex_covariate_dist](#)

Examples

```
# Creating a random dynamic graph
set.seed(943)
graph <- rgraph_er(n=100, t=10)
toa <- sample.int(10, 100, TRUE)

# Computing infection and susceptibility (K=1)
infection(graph, toa)
susceptibility(graph, toa)

# Now with K=4
infection(graph, toa, K=4)
susceptibility(graph, toa, K=4)
```

 isolated

Find and remove isolated vertices

Description

Find and remove unconnected vertices from the graph.

Usage

```
isolated(graph, undirected = getOption("diffnet.undirected", FALSE),
  self = getOption("diffnet.self", FALSE))

drop_isolated(graph, undirected = getOption("diffnet.undirected", FALSE),
  self = getOption("diffnet.self", FALSE))
```

Arguments

graph	Any class of accepted graph format (see netdiffuseR-graphs).
undirected	Logical scalar. When TRUE only the lower triangle of the adjacency matrix will be considered (faster).
self	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).

Value

When graph is an adjacency matrix:

`isolated` an matrix of size $n \times 1$ with 1's where a node is isolated
`drop_isolated` a modified graph excluding isolated vertices.

Otherwise, when graph is a list

`isolated` an matrix of size $n \times T$ with 1's where a node is isolated
`drop_isolated` a modified graph excluding isolated vertices.

Author(s)

George G. Vega Yon

See Also

Other data management functions: [diffnet-class](#), [edgelist_to_adjmat](#), [egonet_attrs](#), [survey_to_diffnet](#)

Examples

```
# Generating random graph
set.seed(123)
adjmat <- rgraph_er()

# Making nodes 1 and 4 isolated
adjmat[c(1,4),] <- 0
adjmat[,c(1,4)] <- 0
adjmat

# Finding isolated nodes
iso <- isolated(adjmat)
iso

# Removing isolated nodes
drop_isolated(adjmat)

# Now with a dynamic graph
graph <- rgraph_er(n=10, t=3)

# Making 1 and 5 isolated
graph <- lapply(graph, "[<-", i=c(1,5), j=1:10, value=0)
graph <- lapply(graph, "[<-", i=1:10, j=c(1,5), value=0)
graph

isolated(graph)
drop_isolated(graph)
```

kfamily

*Korean Family Planning***Description**

From Valente (1995) “Scholars at Seoul National University’s School of Public Health (Park, Chung, Han & Lee, 1974) collected data on the adoption of family planning methods among all married women of child-bearing age 25 in Korea villages in 1973 (N = 1,047).”

Format

A data frame with 1,047 rows and 432 columns:

village Village of residence

id Respondent ID number

recno1 Card number NA

studno1 Study number NA

area1 Village of residence

id1 Respondent ID number

nimage1 Number males age 0

nimage2 Number males age 0-4

nimage3 Number males age 5-9

nimage4 Number males age 10-14

nimage5 Number males age 15-19

nimage6 Number males age 20-24

nimage7 Number males age 25-29

nimage8 Number males age 30-34

nimage9 Number males age 35-39

nimage10 Number males age 40-44

nimage11 Number males age 45-49

nimage12 Number males age 50-54

nimage13 Number males age 55-59

nimage14 Number males age 60-64

nimage15 Number males age 65-69

nimage16 Number males age 70-74

nimage17 Number males age 75-79

nimage18 Number males age 80+

nfage1 Number females age 0

nfage2 Number females age 0-4

nfage3 Number females age 5-9
nfage4 Number females age 10-14
nfage5 Number females age 15-19
nfage6 Number females age 20-24
nfage7 Number females age 25-29
nfage8 Number females age 30-34
nfage9 Number females age 35-39
nfage10 Number females age 40-44
nfage11 Number females age 45-49
nfage12 Number females age 50-54
nfage13 Number females age 55-59
nfage14 Number females age 60-64
nfage15 Number females age 65-69
nfage16 Number females age 70-74
nfage17 Number females age 75-79
nfage18 Number females age 80+
pregs total pregnancies
pregs1 number normal deliveries
pregs2 number of induced abortions
pregs3 number of spontaneous abortions
pregs4 number of still births
pregs5 number of deaths after live birth
pregs6 currently pregnant
sons number of sons
daughts number of daughters
planning Ever heard of FP or birth control
loop1 Awareness of Loop
loop2 Detailed knowledge of Loop
loop3 Attitudes toward Loop
loop4 Knowledge of Loop used by neighbors
loop5 Knowledge of place of service for Loop
pill1 Awareness of Pill
pill2 Detailed knowledge of Pill
pill3 Attitudes toward Pill
pill4 Knowledge of Pill used by neighbors
pill5 Knowledge of place of service for Pill
vase1 Awareness of Vasectomy

vase2 Detailed knowledge of Vasectomy
vase3 Attitudes toward Vasectomy
vase4 Knowledge of Vasectomy used by neighbors
vase5 Knowledge of place of service for Vasectomy
cond1 Awareness of Condoms
cond2 Detailed knowledge Condoms
cond3 Attitudes toward Condoms
cond4 Knowledge of Condoms used by neighbors
cond5 Knowledge of place of service for Condoms
rhyt1 Awareness of Rhythm
rhyt2 Detailed knowledge Rhythm
rhyt3 Attitudes toward Rhythm
rhyt4 Knowledge of Rhythm used by neighbors
bbt1 Awareness of Basic Body Temperature
bbt2 Detailed knowledge Basic Body Temperature
bbt3 Attitudes toward BBT
recno2 Record Number NA
studno2 Study Number NA
area2 village number
id2 id number
bbt4 Knowledge of BBT used by neighbors
diap1 Awareness of Diaphragm
diap2 Detailed knowledge Diaphragm
diap3 Attitudes toward Diaphragm
diap4 Knowledge of Diaphragm used by neighbors
with1 Awareness of Withdrawal
with2 Detailed knowledge Withdrawal
with3 Attitudes toward Withdrawal
with4 Knowledge of Withdrawal used by neighbors
tuba1 Awareness of Tubal Ligation
tuba2 Detailed knowledge TL
tuba3 Attitudes toward TL
tuba4 Knowledge of TL used by neighbors
fp1 Experience with an FP practice
fp2 Reasons for not practicing
fp3 What would you do if problem was solved
fp4 Any other reason for not practicing

- fp5** Reasons for practicing
- fp6** time between decision and adoption
- fp7** reasons for time lag
- fp8** Ever discontinued practicing
- fp9** Reasons for discontinuing
- fp10** Attitude toward FP
- child1** Ideal number of sons
- child2** Ideal number of daughters
- child3** Ideal number of children regardless of sex
- child4** what do if kept having girls
- comop1** Spousal communication on # of children
- comop2** Spousal communication on FP
- comop3** Consensus on opinion between couple
- comop4** What was the difference
- comop5** Opinion on who should practice
- comop6** Different opinions on who should practice
- comop7** Who should make final decision
- comop8** Residence in old age
- net11** Neighbors talk to about FP- 1
- net12** Neighbors talk to about FP- 2
- net13** Neighbors talk to about FP- 3
- net14** Neighbors talk to about FP- 4
- net15** Neighbors talk to about FP- 5
- famawe1** Family members of FP Practice
- famawe2** Parents awareness of FP Practice
- famawe3** How did parents-in-law become aware
- famawe4** How did parents become aware
- famawe5** How did husband become aware
- advic1** Advice given to neighbors where to go
- advic2** Advice given on method
- advic3** Ever met persons who give advice on FP
- advic4** Credibility of person advising on FP
- advic5** Counter advice given to others
- rumor1** Rumors on Loop
- rumor2** Rumors on Pill
- rumor3** Rumors on Vasectomy
- rumor4** Rumors on Condom

rumor5 Rumors on Tuballigation
media1 Possession of Radio
media2 Possession of TV
media3 Subscription to Newspaper
media4 Subscription to Happy Home
media5 Subscription to other magazine
media6 Radio exposure to FP
media7 TV exposure to FP
media8 Daily paper exposure to FP
media9 Happy Home exposure to FP
media10 Magazine exposure to FP
media11 Movie or slide exposure to FP
media12 Poster exposure to FP
media13 Pamphlet exposure to FP
media14 FP Meeting exposure to FP
recno3 Record number NA
studno3 Study number NA
area3 village
id3 id
media15 Public lecture exposure to FP
media16 Mobile van exposure to FP
media17 Neighbors exposure to FP
media18 Workers home visiting exposure to FP
media19 Husband exposure to FP
club1 Awareness of clubs in community
club2 Membership in club
club3 Reasons for not becoming a member
club4 Feeling of necessity of club
club5 Visit of mobile van to area
club6 Service received from van
club7 Decision-making on FP on # children
club8 Decision-making on important goods
club9 Decision-making on childrens discipline
club10 Decision making on purchase wife clothes
net21 Closest neighbor most frequently met
n1adv Advice received from neighbor 1
n1prac practice of FP by neighbor 1

net22 Closest neighbor person 2
n2adv Advice received from neighbor 2
n2prac Practice of FP by neighbor 2
net23 Closest neighbor person 3
n3adv Advice received from neighbor 3
n3prac Practice of FP by neighbor 3
net24 Closest neighbor 4
n4adv Advice received from neighbor 4
n4prac Practice of FP by neighbor 4
net25 Closest neighbor 5
n5adv Advice received from neighbor 5
n5prac Practice of FP by neighbor 5
stand Standard living of above neighbors
educ Education level of named neighbors
net31 Advice on FP sought from 1
net32 Advice on FP sought from 2
net33 Advice on FP sought from 3
net34 Advice on FP sought from 4
net35 Advice on FP sought from 5
net41 Information provided on FP by 1
net42 Information provided on FP by 1
net43 Information provided on FP by 1
net44 Information provided on FP by 1
net45 Information provided on FP by 1
net51 Seek advice on induced abortion 1
net52 Seek advice on induced abortion 2
net53 Seek advice on induced abortion 3
net54 Seek advice on induced abortion 4
net55 Seek advice on induced abortion 5
age Age of respondent
agemar Age at first marriage
recno4 Rec no NA
studno4 Study no NA
area4 village
id4 id
net61 Advice on health sought from 1
net62 Advice on health sought from 2

net63 Advice on health sought from 3
net64 Advice on health sought from 4
net65 Advice on health sought from 5
net71 Advice on purchase of goods 1
net72 Advice on purchase of goods 2
net73 Advice on purchase of goods 3
net74 Advice on purchase of goods 4
net75 Advice on purchase of goods 5
net81 Advice on childrens education 1
net82 Advice on childrens education 2
net83 Advice on childrens education 3
net84 Advice on childrens education 4
net85 Advice on childrens education 5
rfampl1 Advice on FP sought by 1
rfampl2 Advice on FP sought by 2
rfampl3 Advice on FP sought by 3
rfampl4 Advice on FP sought by 4
rfampl5 Advice on FP sought by 5
rfampll Leadership score - indegree FP
rabort1 Advice on abortion sought by 1
rabort2 Advice on abortion sought by 2
rabort3 Advice on abortion sought by 3
rabort4 Advice on abortion sought by 4
rabort5 Advice on abortion sought by 5
rabortl Leadership score - indegree abortion
rhealth1 Advice on health sought by 1
rhealth2 Advice on health sought by
rhealth3 Advice on health sought by
rhealth4 Advice on health sought by
rhealth5 Advice on health sought by
rhealthl Leadership score - indegree health
recno5 rec no NA
studno5 study no NA
area5 village
id5 id
rgoods1 Advice on purchases sought by 1
rgoods2 Advice on purchases sought by 2

rgoods3 Advice on purchases sought by 3
rgoods4 Advice on purchases sought by 4
rgoods5 Advice on purchases sought by 5
rgoods1 Leadership score - indegree purchases
reduc1 Advice on education sought by 1
reduc2 Advice on education sought by 2
reduc3 Advice on education sought by 3
reduc4 Advice on education sought by 4
reduc5 Advice on education sought by 5
reduc1 Leadership score - indegree education
hub1 Husbands friend 1
hub2 Husbands friend 2
hub3 Husbands friend 3
hub4 Husbands friend 4
hub5 Husbands friend 5
hubed Husbands education
wifeed Wifes education
wiferel Wifes religion
hubocc Husbands occupation
wifeocc Wifes occupation
know1 Can you insert a loop yourself
know2 Can you remove it alone
know3 Can a man use a loop
know4 How long can a loop be used
know5 Which doctor
know6 Doctor or nurse
know7 Oral pill method
know8 Can men take pills
know9 Long term use
know10 Time required for vasectomy
know11 Does vasectomy = castration
know12 Can any doctor do vasectomies
pref1 Who prefer use: Husband or wife
pref2 Reasons for preferring FP practice by wife
pref3 Reasons for preferring FP practice by husband
ageend Ideal age to end childbearing
cfp Current status of FP

cfatt1 Husbands attitude
cfatt2 In-laws attitude
cfatt3 Own parents attitude
cbyr Start of period from year
cbmnth Start of period from month
ceyr End of period year
cemnth End of period month
clngth Length of period
cawe1 FP contact
cawe2 Awareness of contraceptive method at the time
cawe3 Awareness of service site
cawe4 Credibility
recno6 rec no NA
studno6 study no NA
area6 village
id6 id
fpt1 FP Status time 1
fatt1t1 Husbands attitude T1
fatt2t1 In-laws attitude T1
fatt3t1 Own parents attitude T1
byrt1 Start of Time 1 from year
lnght1 Length of Time 1
awe1t1 FP Contact Time 1
awe2t1 Methods known at Time 1
awe3t1 Knowledge of service sites Time 1
awe4t1 Credibility of service site Time 1
fpt2 FP Status time 2
fatt1t2 Husbands attitude T2
fatt2t2 In-laws attitude T2
fatt3t2 Own parents attitude T2
byrt2 Start of Time 2 from year
lnght2 Length of Time 2
awe1t2 FP Contact Time 2
awe2t2 Methods known at Time 2
awe3t2 Knowledge of service sites Time 2
awe4t2 Credibility of service site Time 2
fpt3 FP Status time 3

fatt1t3 Husbands attitude T3
fatt2t3 In-laws attitude T3
fatt3t3 Own parents attitude T3
byrt3 Start of Time 3 from year
lnght3 Length of Time 3
awe1t3 FP Contact Time 3
awe2t3 Methods known at Time 3
awe3t3 Knowledge of service sites Time 3
awe4t3 Credibility of service site Time 3
fpt4 FP Status time 4
fatt1t4 Husbands attitude T4
fatt2t4 In-laws attitude T4
fatt3t4 Own parents attitude T4
byrt4 Start of Time 4 from year
lnght4 Length of Time 4
awe1t4 FP Contact Time 4
awe2t4 Methods known at Time 4
awe3t4 Knowledge of service sites Time 4
awe4t4 Credibility of service site Time 4
fpt5 FP Status time 5
fatt1t5 Husbands attitude T5
fatt2t5 In-laws attitude T5
fatt3t5 Own parents attitude T5
byrt5 Start of Time 5 from year
lnght5 Length of Time 5
awe1t5 FP Contact Time 5
awe2t5 Methods known at Time 5
awe3t5 Knowledge of service sites Time 5
awe4t5 Credibility of service site Time 5
fpt6 FP Status time 6
fatt1t6 Husbands attitude T6
fatt2t6 In-laws attitude T6
fatt3t6 Own parents attitude T6
byrt6 Start of Time 6 from year
lnght6 Length of Time 6
awe1t6 FP Contact Time 6
awe2t6 Methods known at Time 6

awe3t6 Knowledge of service sites Time 6
awe4t6 Credibility of service site Time 6
recno7 rec no NA
studno7 study no NA
area7 village
id7 id
fpt7 FP Status time 7
fatt1t7 Husbands attitude T7
fatt2t7 In-laws attitude T7
fatt3t7 Own parents attitude T7
byrt7 Start of Time 7 from year
lnght7 Length of Time 7
awe1t7 FP Contact Time 7
awe2t7 Methods known at Time 7
awe3t7 Knowledge of service sites Time 7
awe4t7 Credibility of service site Time 7
fpt8 FP Status time 8
fatt1t8 Husbands attitude T8
fatt2t8 In-laws attitude T8
fatt3t8 Own parents attitude T8
byrt8 Start of Time 8 from year
lnght8 Length of Time 8
awe1t8 FP Contact Time 8
awe2t8 Methods known at Time 8
awe3t8 Knowledge of service sites Time 8
awe4t8 Credibility of service site Time 8
fpt9 FP Status time 9
fatt1t9 Husbands attitude T9
fatt2t9 In-laws attitude T9
fatt3t9 Own parents attitude T9
byrt9 Start of Time 9 from year
lnght9 Length of Time 9
awe1t9 FP Contact Time 9
awe2t9 Methods known at Time 9
awe3t9 Knowledge of service sites Time 9
awe4t9 Credibility of service site Time 9
fpt10 FP Status time 10

fatt1t10 Husbands attitude T10
fatt2t10 In-laws attitude T10
fatt3t10 Own parents attitude T10
byrt10 Start of Time 10 from year
lnght10 Length of Time 10
awe1t10 FP Contact Time 10
awe2t10 Methods known at Time 10
awe3t10 Knowledge of service sites Time 10
awe4t10 Credibility of service site Time 10
fpt11 FP Status time 11
fatt1t11 Husbands attitude T11
fatt2t11 In-laws attitude T11
fatt3t11 Own parents attitude T11
byrt11 Start of Time 11 from year
lnght11 Length of Time 11
awe1t11 FP Contact Time 11
awe2t11 Methods known at Time 11
awe3t11 Knowledge of service sites Time 11
awe4t11 Credibility of service site Time 11
fpt12 FP Status time 12
fatt1t12 Husbands attitude T12
fatt2t12 In-laws attitude T12
fatt3t12 Own parents attitude T12
byrt12 Start of Time 12 from year
lnght12 Length of Time 12
awe1t12 FP Contact Time 12
awe2t12 Methods known at Time 12
awe3t12 Knowledge of service sites Time 12
awe4t12 Credibility of service site Time 12
ado adopt times years converted to 1=63
ado1
ado2
ado3
commun Village number
toa Time of Adoption
study Study (for when multiple diff studies used)

Details

The dataset has 1,047 respondents (women) from 25 communities. Collected during 1973 it spans 11 years of data.

Source

The Korean Family Planning data were stored on a Vax tape that Rogers had given to Marc Granovetter who then gave it to his colleague Roland Soong (see Granovetter & Soong, 1983). Granovetter instructed Song to send the tape to me and I had it loaded on the Vax machine at USC in 1990 and was able to download the data to a PC. The first two datasets were acquired for my dissertation (Valente, 1991) and the third added as I completed my book on Network Models of the Diffusion of Innovations (Valente, 1995; also see Valente, 2005).

References

Everett M. Rogers, & Kincaid, D. L. (1981). *Communication Networks: Toward a New Paradigm for Research*. (C. Macmillan, Ed.). New York; London: Free Press.

Valente, T. W. (1995). *Network models of the diffusion of innovations* (2nd ed.). Cresskill N.J.: Hampton Press.

See Also

Other diffusion datasets: [brfarmersDiffNet](#), [brfarmers](#), [diffusion-data](#), [fakeDynEdgelist](#), [fakeEdgelist](#), [fakesurveyDyn](#), [fakesurvey](#), [kfamilyDiffNet](#), [medInnovationsDiffNet](#), [medInnovations](#)

kfamilyDiffNet

diffnet version of the Korean Family Planning data

Description

A directed dynamic graph with 1,047 vertices and 11 time periods. The attributes in the graph are static and described in [kfamily](#).

Format

A [diffnet](#) class object.

See Also

Other diffusion datasets: [brfarmersDiffNet](#), [brfarmers](#), [diffusion-data](#), [fakeDynEdgelist](#), [fakeEdgelist](#), [fakesurveyDyn](#), [fakesurvey](#), [kfamily](#), [medInnovationsDiffNet](#), [medInnovations](#)

matrix_compare	<i>Non-zero element-wise comparison between two sparse matrices</i>
----------------	---------------------------------------------------------------------

Description

Taking advantage of matrix sparseness, the function only evaluates fun between pairs of elements of A and B where either A or B have non-zero values. This can be helpful to implement other binary operators between sparse matrices that may not be implemented in the **Matrix** package.

Usage

```
matrix_compare(A, B, fun)
```

```
compare_matrix(A, B, fun)
```

Arguments

A	A matrix of size n*m of class <code>dgCMatrix</code> .
B	A matrix of size n*m of class <code>dgCMatrix</code> .
fun	A function that receives 2 arguments and returns a scalar.

Details

Instead of comparing element by element, the function loops through each matrix non-zero elements to make the comparisons, which in the case of sparse matrices can be more efficient (faster). Algorithmically it can be described as follows:

```
# Matrix initialization
init ans[n,m];

# Looping through non-zero elements of A
for e_A in E_A:
  ans[e_A] = fun(A[e_A], B[e_A])

# Looping through non-zero elements of B and applying the function
# in e_B only if it was not applied while looping in E_A.
for e_B in E_B:
  if (ans[e_B] == Empty)
    ans[e_B] = fun(A[e_B], B[e_B])
```

compare_matrix is just an alias for matrix_compare.

Value

An object of class `dgCMatrix` of size n*m.

See Also

Other dyadic-level comparison functions: [vertex_covariate_compare](#), [vertex_covariate_dist](#)

Examples

```
# These two should yield the same results -----

# Creating two random matrices
set.seed(89)
A <- rgraph_ba(t = 9, m = 4)
B <- rgraph_ba(t = 9, m = 4)
A;B

# Comparing
ans0 <- matrix_compare(A,B, function(a,b) (a+b)/2)

ans1 <- matrix(0, ncol=10, nrow=10)
for (i in 1:10)
  for (j in 1:10)
    ans1[i,j] <- mean(c(A[i,j], B[i,j]))

# Are these equal?
all(ans0[] == ans1[]) # Should yield TRUE

# More elaborated example (speed) -----
## Not run:

set.seed(123123123)
A <- rgraph_ba(t = 5e3, m = 2)
B <- rgraph_ba(t = 5e3, m = 2)

Am <- as.matrix(A)
Bm <- as.matrix(B)

compfun <- function(a,b)
  ifelse(a > b, a, b)

microbenchmark::microbenchmark(
  diffnet = matrix_compare(A, B, compfun),
  R       = matrix(ifelse(Am > Bm, Am, Bm), ncol=ncol(Am)),
  times   = 10
)
# Unit: milliseconds
#   expr      min       lq      mean   median      uq      max neval
# diffnet 352.7989 355.0193 583.5366 357.7138 364.7604 2493.914   10
#         R 1648.9607 1744.6762 2491.2435 1947.4344 2729.1274 6260.011   10

## End(Not run)
```

 medInnovations

 Medical Innovation

Description

From Valente (1995) “Coleman, Katz and Menzel from Columbia University’s Bureau of Applied Research studied the adoption of tetracycline by physicians in four Illinois communities in 1954.[...] Tetracycline was a powerful and useful antibiotic just introduced in the mid-1950s”

Format

A data frame with 125 rows and 59 columns:

city city id
id sequential respondent id
detail detail man
meet meetings, lectures, hospitals
coll colleagues
attend attend professional meets
proage professional age
length length of reside in community
here only practice here
science science versus patients
position position in home base
journ2 journal subscriptions
paadico Percent alter adoption date imp
ado adoption month 1 to 18
thresh threshold
ctl corrected tl tl-exp level
catbak category 1-init 2-marg 3-low tl
sourinfo source of information
origid original respondent id
adopt adoption date 1= 11/53
recon reconstructed med innov
date date became aware
info information source
most most important info source
journ journals
drug drug houses

net1_1 advisor nomination1
net1_2 advisor nomination2
net1_3 advisor nomination3
net2_1 discuss nomination1
net2_2 discuss nomination2
net2_3 discuss nomination3
net3_1 friends nomination1
net3_2 friends nomination2
net3_3 friends nomination3
nojourn number of pro journals receive
free free time companions
social med discussions during social
club club membership
friends friends are doctors
young young patients
nonpoor nonpoverty patients
office office visits
house house calls
tend tendency to prescribe drugs
reltend relative tendency to prescribe
perc perceived drug competition
proximty physical proximity to other doc
home home base hospital affiliation
special specialty
belief belief in science
proage2 professional age 2
presc prescription prone
detail2 contact with detail man
dichot dichotomous personal preference
expect adoption month expected
recall recalls adopting
commun Number of community
toa Time of Adoption
study Number of study in Valente (1995)

Details

The collected dataset has 125 respondents (doctors), and spans 17 months of data collected in 1955. Time of adoption of non-adopters has been set to month 18 (see the manual entry titled [Difussion Network Datasets](#)).

Source

The Medical Innovation data were stored in file cabinets in a basement building at Columbia University. Ron Burt (1987) acquired an NSF grant to develop network diffusion models and retrieve the original surveys and enter them into a database. He distributed copies of the data on diskette and sent one to me, Tom Valente, and I imported onto a PC environment.

References

Coleman, J., Katz, E., & Menzel, H. (1966). *Medical innovation: A diffusion study* (2nd ed.). New York: Bobbs-Merrill

Valente, T. W. (1995). *Network models of the diffusion of innovations* (2nd ed.). Cresskill N.J.: Hampton Press.

See Also

Other diffusion datasets: [brfarmersDiffNet](#), [brfarmers](#), [diffusion-data](#), [fakeDynEdgelist](#), [fakeEdgelist](#), [fakesurveyDyn](#), [fakesurvey](#), [kfamilyDiffNet](#), [kfamily](#), [medInnovationsDiffNet](#)

medInnovationsDiffNet *diffnet version of the Medical Innovation data*

Description

A directed dynamic graph with 125 vertices and 18 time periods. The attributes in the graph are static and described in [medInnovations](#).

Format

A [diffnet](#) class object.

See Also

Other diffusion datasets: [brfarmersDiffNet](#), [brfarmers](#), [diffusion-data](#), [fakeDynEdgelist](#), [fakeEdgelist](#), [fakesurveyDyn](#), [fakesurvey](#), [kfamilyDiffNet](#), [kfamily](#), [medInnovations](#)

mentor_matching *Optimal Leader/Mentor Matching*

Description

Implements the algorithm described in Valente and Davis (1999)

Usage

```
mentor_matching(graph, n, cmode = "indegree", lead.ties.method = "average",
  geodist.args = list())
```

```
leader_matching(graph, n, cmode = "indegree", lead.ties.method = "average",
  geodist.args = list())
```

```
## S3 method for class 'diffnet_mentor'
plot(x, y = NULL, vertex.size = "degree",
  minmax.relative.size = getOption("diffnet.minmax.relative.size", c(0.01,
  0.04)), lead.cols = grDevices::topo.colors(attr(x, "nleaders")),
  vshapes = c(Leader = "square", Follower = "circle"), add.legend = TRUE,
  main = "Mentoring Network", ...)
```

Arguments

graph	Any class of accepted graph format (see netdiffuser-graphs).
n	Number of leaders
cmode	Passed to dgr .
lead.ties.method	Passed to rank
geodist.args	Passed to approx_geodesic .
x	An object of class <code>diffnet_mentor</code> .
y	Ignored.
vertex.size	Either a numeric scalar or vector of size n , or any of the following values: "indegree", "degree", or "outdegree" (see details).
minmax.relative.size	Passed to rescale_vertex_igraph .
lead.cols	Character vector of length <code>attr(x, "nleaders")</code> . Colors to be applied to each group. (see details)
vshapes	Character scalar of length 2. Shapes to identify leaders (mentors) and followers respectively.
add.legend	Logical scalar. When TRUE generates a legend to distinguish between leaders and followers.
main	Character scalar. Passed to title
...	Further arguments passed to plot.igraph

Details

The algorithm works as follows:

1. Find the top n individuals ranking them by `dgr(graph, cmode)`. The rank is computed by the function `rank`. Denote this set M .
2. Compute the geodesic matrix.
3. For each v in V do:
 - (a) Find the mentor m in M such that is closest to v
 - (b) Were there a tie, choose the mentor that minimizes the average path length from v 's direct neighbors to m .
 - (c) If there are no paths to any member of M , or all have the same average path length to v 's neighbors, then assign one randomly.

Plotting is done via the function `plot.igraph`.

When `vertex.size` is either of "degree", "indegree", or "outdegree", `vertex.size` will be replaced with `dgr(. , cmode =)` so that the vertex size reflects the desired degree.

The argument `minmax.relative.size` is passed to `rescale_vertex_igraph` which adjusts `vertex.size` so that the largest and smallest vertices have a relative size of `minmax.relative.size[2]` and `minmax.relative.size[1]` respectively with respect to the x-axis.

Value

An object of class `diffnet_mentor` and `data.frame` with the following columns:

<code>name</code>	Character. Labels of the vertices
<code>degree</code>	Numeric. Degree of each vertex in the graph
<code>iselader</code>	Logical. TRUE when the vertex was picked as a leader.
<code>match</code>	Character. The corresponding matched leader.

The object also contains the following attributes:

<code>nleaders</code>	Integer scalar. The resulting number of leaders (could be greater than n)
<code>.</code>	
<code>graph</code>	The original graph used to run the algorithm.

References

Valente, T. W., & Davis, R. L. (1999). Accelerating the Diffusion of Innovations Using Opinion Leaders. *The ANNALS of the American Academy of Political and Social Science*, 566(1), 55–67.
<http://journals.sagepub.com/doi/abs/10.1177/000271629956600105>

Examples

```
# A simple example -----
set.seed(1231)
graph <- rgraph_ws(n=50, k = 4, p = .5)

# Looking for 3 mentors
ans <- mentor_matching(graph, n = 3)

head(ans)
table(ans$match) # We actually got 9 b/c of ties

# Visualizing the mentor network
plot(ans)
```

moran

Computes Moran's I correlation index

Description

Natively built for computing Moran's I on `dgCMatrix` objects, this routine allows computing the I on large sparse matrices (graphs). Part of its implementation was based on [ape::Moran.I](#), which computes the I for dense matrices.

Usage

```
moran(x, w, normalize.w = TRUE, alternative = "two.sided")
```

Arguments

<code>x</code>	Numeric vector of size n .
<code>w</code>	Numeric matrix of size $n \times n$. Weights. It can be either a object of class <code>matrix</code> or <code>dgCMatrix</code> from the <code>Matrix</code> package.
<code>normalize.w</code>	Logical scalar. When TRUE normalizes rowsums to one (or zero).
<code>alternative</code>	Character String. Specifies the alternative hypothesis that is tested against the null of no autocorrelation; must be of one "two.sided", "less", or "greater".

Details

In the case that the vector `x` is close to constant (degenerate random variable), the statistic becomes irrelevant, and furthermore, the standard error tends to be undefined (NaN).

Value

A list of class `diffnet_moran` with the following elements:

<code>observed</code>	Numeric scalar. Observed correlation index.
<code>expected</code>	Numeric scalar. Expected correlation index equal to $-1/(N - 1)$.
<code>sd</code>	Numeric scalar. Standard error under the null.
<code>p.value</code>	Numeric scalar. p-value of the specified alternative.

Author(s)

George G. Vega Yon

References

Moran's I. (2015, September 3). In Wikipedia, The Free Encyclopedia. Retrieved 06:23, December 22, 2015, from https://en.wikipedia.org/w/index.php?title=Moran%27s_I&oldid=679297766

See Also

Other statistics: [bass](#), [classify_adopters](#), [cumulative_adopt_count](#), [dgr](#), [ego_variance](#), [exposure](#), [hazard_rate](#), [infection](#), [struct_equiv](#), [threshold](#), [vertex_covariate_dist](#)

Other Functions for inference: [bootnet](#), [struct_test](#)

Examples

```
## Not run:

# Generating a small random graph
set.seed(123)
graph <- rgraph_ba(t = 4)
w <- approx_geodesic(graph)
x <- rnorm(5)

# Computing Moran's I
moran(x, w)

# Comparing with the ape's package version
ape::Moran.I(x, as.matrix(w))

## End(Not run)
```

netdiffuseR

netdiffuseR

Description

Statistical analysis, visualization and simulation of diffusion and contagion processes on networks. The package implements algorithms for calculating stats such as innovation threshold levels, infectiousness (contagion) and susceptibility, and hazard rates as presented in Burt (1987), Valente (1995), and Myers (2000) (among others).

You can access to the project website at <https://github.com/USCCANA/netdiffuseR>

Details

Analysis of Diffusion and Contagion Processes on Networks

Acknowledgements

netdiffuseR was created with the support of grant R01 CA157577 from the National Cancer Institute/National Institutes of Health.

Workshops and Tutorials

Online you can find several learning resources:

- Sunbelt 2016 <https://github.com/USCCANA/netdiffuser-sunbelt2016>
- NASN 2017 <https://github.com/USCCANA/netdiffuser-nasn2017>
- Sunbelt 2018 <https://github.com/USCCANA/netdiffuser-sunbelt2018>

Author(s)

George G. Vega Yon & Thomas W. Valente

netdiffuseR-graphs

Network data formats

Description

List of accepted graph formats

Details

The **netdiffuseR** package can handle different types of graph objects. Two general classes are defined across the package's functions: static graphs, and dynamic graphs.

- In the case of **static graphs**, these are represented as adjacency matrices of size $n \times n$ and can be either `matrix` (dense matrices) or `dgMatrix` (sparse matrix from the **Matrix** package). While most of the package functions are defined for both classes, the default output graph is sparse, i.e. `dgMatrix`.
- With respect to **dynamic graphs**, these are represented by either a `diffnet` object, an `array` of size $n \times n \times T$, or a list of size T with sparse matrices (class `dgMatrix`) of size $n \times n$. Just like the static graph case, while most of the functions accept both graph types, the default output is `dgMatrix`.

diffnet objects

In the case of `diffnet`-class objects, the following arguments can be omitted when calling functions suitable for graph objects:

- `toa`: Time of Adoption vector
- `adopt`: Adoption Matrix
- `cumadopt`: Cumulative Adoption Matrix
- `undirected`: Whether the graph is directed or not

Objects' names

When possible, **netdiffuseR** will try to reuse graphs dimensional names, this is, `rownames`, `colnames`, `dimnames` and `names` (in the case of dynamic graphs as lists). Otherwise, when no names are provided, these will be created from scratch.

Author(s)

George G. Vega Yon

netdiffuseR-options **netdiffuseR** *default options*

Description

netdiffuseR default options

Details

Set of default options used by the package. These can be retrieved via `getOption` using the prefix `diffnet` (see examples)

Value

The full list of options follows:

```
undirected      FALSE
self            FALSE
multiple        FALSE
tol             1e-8 (used for package testing)
valued          FALSE
outgoing        TRUE
keep.isolates  TRUE
minmax.relative.size
                c(0.025, 0.05)
```

Author(s)

George G. Vega Yon

Examples

```
getOption("diffnet.undirected")
getOption("diffnet.multiple")
getOption("diffnet.self")
```

netmatch

Matching Estimators with Network Data

Description

WARNING: This function is still in development and has not been tested throughly. Following Aral et al. (2009), netmatch computes matching estimators for network data. The function netmatch_prepare, which prepares the data to be used with [matchit](#) from the **MatchIt** package, is called by netmatch.

Usage

```
netmatch_prepare(dat, graph, timevar, depvar, covariates, treat_thr = rep(1L,
  length(graph)), adopt_thr = rep(1L, length(graph)), expo_pcent = FALSE,
  expo_lag = 0L)
```

```
netmatch(dat, graph, timevar, depvar, covariates, treat_thr = rep(1L,
  length(graph)), adopt_thr = rep(1L, length(graph)), expo_pcent = FALSE,
  expo_lag = 0L, ...)
```

Arguments

dat	data.frame with dynamic data. Must be of <code>nrow(dat)==nslices(graph)*nnodes(graph)</code> .
graph	List with sparse matrices.
timevar	Character scalar. Name of time variable
depvar	Character scalar. Name of the dependent variable
covariates	Character vector. Name(s) of the control variable(s).
treat_thr	Either a numeric scalar or vector of length <code>nslices(graph)</code> . Sets the threshold of exposure at which it is considered that an observation is treated.
adopt_thr	Either a numeric scalar or vector of length <code>nslices(graph)</code> . Sets the threshold of depvar at which it is considered that an observation has adopted a behavior.
expo_pcent	Logical scalar. When TRUE, exposure is computed non-normalized (so it is a count rather than a percentage).
expo_lag	Integer scalar. Number of lags to consider when computing exposure. <code>expo_lag=1</code> defines exposure in T considering behavior and network at T-1.
...	Further arguments to be passed to <code>matchit</code> .

Details

In Aral et al. (2009), the matching estimator is used as a response to the fact that the observed network is homophilous. Essentially, using exposure as a treatment indicator, which is known to be endogenous, we can apply the same principle of matching estimators in which, after controlling for characteristics (covariates), individuals from the treated group (exposed to some behavior) can be compared to individuals from the control group (not exposed to that behavior), as the only difference between the two is the exposure.

As pointed out in King & Nielsen (2015), it is suggested that, contrary to what Aral et al. (2009), the matching is not performed over propensity score since it is known that the later can increase imbalances in the data and thus obtaining exactly the opposed outcome that matching based estimators pursue.

A couple of good references for matching estimators are Imbens and Wooldridge (2009), and Sekhon (2008).

Value

In the case of `netmatch_prepare`

dat	A data.frame with the original data (covariates), plus the following new variables: <code>treat</code> , <code>adopt</code> , <code>exposure</code> .
match_model	A formula to be passed to <code>netmatch</code>

`netmatch` returns the following:

fATT	A numeric vector of length N_1 (number of treated used in the matching process). Treatment effects on the treated at the individual level
match_obj	The output from <code>matchit</code> .

Author(s)

George G. Vega Yon

References

- Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences of the United States of America*, 106(51), 21544–21549. doi: [10.1073/pnas.0908800106](https://doi.org/10.1073/pnas.0908800106)
- Imbens, G. W., & Wooldridge, J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature*, 47(1), 5–86. doi: [10.1257/jel.47.1.5](https://doi.org/10.1257/jel.47.1.5)
- King, G., & Nielsen, R. (2015). Why Propensity Scores Should Not Be Used for.
- Sekhon, J. S. (2008). The Neyman-Rubin Model of Causal Inference and Estimation Via Matching Methods. *The Oxford Handbook of Political Methodology*. doi: [10.1093/oxfordhb/9780199286546.003.0011](https://doi.org/10.1093/oxfordhb/9780199286546.003.0011)

network

*Coercion between diffnet, network and networkDynamic***Description**

Coercion between diffnet, network and networkDynamic

Usage

```
diffnet_to_network(graph, slices = 1:nslices(graph), ...)
diffnet_to_networkDynamic(graph, slices = 1:nslices(graph),
  diffnet2net.args = list(), netdyn.args = list())
networkDynamic_to_diffnet(graph, toavar)
network_to_diffnet(graph = NULL, graph.list = NULL, toavar, t0 = NULL,
  t1 = NULL)
```

Arguments

graph	An object of class diffnet
slices	An integer vector indicating the slices to subset
...	Further arguments passed to networkDynamic
diffnet2net.args	List of arguments passed to <code>diffnet_to_network</code> .
netdyn.args	List of arguments passed to networkDynamic
toavar	Character scalar. Name of the vertex attribute that holds the times of adoption.
graph.list	A list of network objects.
t0	Integer scalar. Passed to new_diffnet .
t1	Integer scalar. Passed to new_diffnet .

Details

`diffnet_to_networkDynamic` calls `diffnet_to_network` and uses the output to call `networkDynamic`, passing the resulting list of network objects as `network.list` (see [networkDynamic](#)).

By default, `diffnet_to_networkDynamic` passes `net.obs.period` as

```
net.obs.period = list(
  observations = list(range(graph$meta$pers)),
  mode="discrete",
  time.increment = 1,
  time.unit = "step"
)
```

By default, `networkDynamic_to_diffnet` uses the first slice as reference for vertex attributes and times of adoption.

By default, `network_to_diffnet` uses the first element of `graph` (a list) as reference for vertex attributes and times of adoption.

Value

`diffnet_to_network` returns a list of length `length(slices)` in which each element is a [network](#) object corresponding a slice of the graph (`diffnet` object). The attributes list will include `toa` (time of adoption).

An object of class `networkDynamic`.

Caveats

Since `diffnet` does not support edges attributes, these will be lost when converting from network-type objects. The same applies to network attributes.

See Also

Other Foreign: [igraph](#), [read_pajek](#), [read_ucinet_head](#)

Examples

```
# Cohersing a diffnet to a list of networks -----
set.seed(1)
ans <- diffnet_to_network(rdifffnet(20, 2))
ans

# and back
network_to_diffnet(graph.list = ans, toavar="toa")

# If it was static, we can use -graph- instead
network_to_diffnet(ans[[1]], toavar="toa")

# A random diffusion network -----
set.seed(87)
dn <- rdifffnet(50, 4)
```

```
ans <- diffnet_to_networkDynamic(dn)

# and back
networkDynamic_to_diffnet(ans, toavar = "toa")
```

nvertices

Count the number of vertices/edges/slices in a graph

Description

Count the number of vertices/edges/slices in a graph

Usage

```
nvertices(graph)

nnodes(graph)

nedges(graph)

nlinks(graph)

nslices(graph)
```

Arguments

graph Any class of accepted graph format (see [netdiffuseR-graphs](#)).

Details

nnodes and nlinks are just aliases for nvertices and nedges respectively.

Value

For nvertices and nslices, an integer scalar equal to the number of vertices and slices in the graph. Otherwise, from nedges, either a list of size t with the counts of edges (non-zero elements in the adjacency matrices) at each time period, or, when graph is static, a single scalar with such number.

Examples

```
# Creating a dynamic graph (we will use this for all the classes) -----
set.seed(13133)
diffnet <- rdiffnet(100, 4)

# Lets use the first time period as a static graph
graph_mat <- diffnet$graph[[1]]
graph_dgCMatrix <- methods::as(graph_mat, "dgCMatrix")
```



```

# Now lets generate the other dynamic graphs
graph_list <- diffnet$graph
graph_array <- as.array(diffnet) # using the as.array method for diffnet objects

# Now we can compare vertices counts
nvertices(diffnet)
nvertices(graph_list)
nvertices(graph_array)

nvertices(graph_mat)
nvertices(graph_dgCMatrix)

# ... and edges count
nedges(diffnet)
nedges(graph_list)
nedges(graph_array)

nedges(graph_mat)
nedges(graph_dgCMatrix)

```

permutate_graph

Permute the values of a matrix

Description

permutate_graph Shuffles the values of a matrix either considering *loops* and *multiple* links (which are processed as cell values different than 1/0). `rewire_qap` generates a new graph `graph'` that is isomorphic to `graph`.

Usage

```
permutate_graph(graph, self = FALSE, multiple = FALSE)
```

```
rewire_permute(graph, self = FALSE, multiple = FALSE)
```

```
rewire_qap(graph)
```

Arguments

<code>graph</code>	Any class of accepted graph format (see netdiffuseR-graphs).
<code>self</code>	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).
<code>multiple</code>	Logical scalar. When TRUE allows multiple edges.

Value

A permuted version of `graph`.

Author(s)

George G. Vega Yon

References

Anderson, B. S., Butts, C., & Carley, K. (1999). The interaction of size and density with graph-level indices. *Social Networks*, 21(3), 239–267. [http://dx.doi.org/10.1016/S0378-8733\(99\)00011-8](http://dx.doi.org/10.1016/S0378-8733(99)00011-8)

Mantel, N. (1967). The detection of disease clustering and a generalized regression approach. *Cancer Research*, 27(2), 209–20. http://cancerres.aacrjournals.org/content/27/2_Part_1/209

See Also

This function can be used as null distribution in `struct_test`

Other simulation functions: `rdiffnet`, `rewire_graph`, `rgraph_ba`, `rgraph_er`, `rgraph_ws`, `ring_lattice`

Examples

```
# Simple example -----
set.seed(1231)
g <- rgraph_ba(t=9)
g

# These preserve the density
permute_graph(g)
permute_graph(g)

# These are isomorphic to g
rewire_qap(g)
rewire_qap(g)
```

plot.diffnet

S3 plotting method for diffnet objects.

Description

S3 plotting method for diffnet objects.

Usage

```
## S3 method for class 'diffnet'
plot(x, y = NULL, t = 1, vertex.color = c(adopt =
  "steelblue", noadopt = "white"), vertex.size = "degree",
  main = "Diffusion network in time %d",
  minmax.relative.size = getOption("diffnet.minmax.relative.size", c(0.01,
  0.04)), ...)
```

Arguments

x	An object of class <code>diffnet</code>
y	Ignored.
t	Integer scalar indicating the time slice to plot.
vertex.color	Character scalar/vector. Color of the vertices.
vertex.size	Either a numeric scalar or vector of size n , or any of the following values: "indegree", "degree", or "outdegree" (see details).
main	Character. A title template to be passed to <code>sprintf</code> .
minmax.relative.size	Passed to <code>rescale_vertex_igraph</code> .
...	Further arguments passed to <code>plot_igraph</code> .

Details

Plotting is done via the function `plot_igraph`.

When `vertex.size` is either of "degree", "indegree", or "outdegree", `vertex.size` will be replaced with `dgr(, cmode =)` so that the vertex size reflects the desired degree.

The argument `minmax.relative.size` is passed to `rescale_vertex_igraph` which adjusts `vertex.size` so that the largest and smallest vertices have a relative size of `minmax.relative.size[2]` and `minmax.relative.size[1]` respectively with respect to the x-axis.

Value

A matrix with the coordinates of the vertices.

Author(s)

George G. Vega Yon

See Also

Other `diffnet` methods: `%*`, `as.array.diffnet`, `c.diffnet`, `diffnet-arithmetic`, `diffnet-class`, `diffnet_index`, `summary.diffnet`

Examples

```
data(medInnovationsDiffNet)
plot(medInnovationsDiffNet)
```

plot_adopters

Visualize adopters and cumulative adopters

Description

Visualize adopters and cumulative adopters

Usage

```
plot_adopters(obj, freq = FALSE, what = c("adopt", "cumadopt"),
  add = FALSE, include.legend = TRUE, include.grid = TRUE, pch = c(21,
  24), type = c("b", "b"), ylim = if (!freq) c(0, 1) else NULL, lty = c(1,
  1), col = c("black", "black"), bg = c("tomato", "gray"), xlab = "Time",
  ylab = ifelse(freq, "Frequency", "Proportion"),
  main = "Adopters and Cumulative Adopters", ...)
```

Arguments

obj	Either a diffnet object or a cumulative adoption matrix.
freq	Logical scalar. When TRUE frequencies are plotted instead of proportions.
what	Character vector of length 2. What to plot.
add	Logical scalar. When TRUE lines and dots are added to the current graph.
include.legend	Logical scalar. When TRUE a legend of the graph is plotted.
include.grid	Logical scalar. When TRUE, the grid of the graph is drawn
pch	Integer vector of length 2. See matplot .
type	Character vector of length 2. See matplot .
ylim	Numeric vector of length 2. Sets the plotting limit for the y-axis.
lty	Numeric vector of length 2. See matplot .
col	Character vector of length 2. See matplot .
bg	Character vector of length 2. See matplot .
xlab	Character scalar. Name of the x-axis.
ylab	Character scalar. Name of the y-axis.
main	Character scalar. Title of the plot
...	Further arguments passed to matplot .

Value

A matrix as described in [cumulative_adopt_count](#).

Author(s)

George G. Vega Yon

See Also

Other visualizations: [dgr](#), [diffusionMap](#), [drawColorKey](#), [grid_distribution](#), [hazard_rate](#), [plot_diffnet2](#), [plot_diffnet](#), [plot_infectsuscep](#), [plot_threshold](#), [rescale_vertex_igraph](#)

Examples

```
# Generating a random diffnet -----
set.seed(821)
diffnet <- rdiffnet(100, 5, seed.graph="small-world", seed.nodes="central")

plot_adopters(diffnet)

# Alternatively, we can use a TOA Matrix
toa <- sample(c(NA, 2010L,2015L), 20, TRUE)
mat <- toa_mat(toa)
plot_adopters(mat$cumadopt)
```

plot_diffnet	<i>Plot the diffusion process</i>
--------------	-----------------------------------

Description

Creates a colored network plot showing the structure of the graph through time (one network plot for each time period) and the set of adopter and non-adopters in the network.

Usage

```
plot_diffnet(...)

## S3 method for class 'diffnet'
plot_diffnet(graph, ...)

## Default S3 method:
plot_diffnet(graph, cumadopt, slices = NULL,
  vertex.color = c("white", "tomato", "steelblue"),
  vertex.shape = c("square", "circle", "circle"), vertex.size = "degree",
  mfrow.par = NULL, main = c("Network in period %s", "Diffusion Network"),
  legend.args = list(),
  minmax.relative.size = getOption("diffnet.minmax.relative.size", c(0.01,
  0.04)), background = NULL, ...)
```

Arguments

...	Further arguments to be passed to plot.igraph .
graph	A dynamic graph (see netdiffuseR-graphs).
cumadopt	$n \times T$ matrix.
slices	Integer vector. Indicates what slices to plot. By default all are plotted.

vertex.color	A character vector of size 3 with colors names.
vertex.shape	A character vector of size 3 with shape names.
vertex.size	Either a numeric scalar or vector of size n , or any of the following values: "indegree", "degree", or "outdegree" (see details).
mfrow.par	Vector of size 2 with number of rows and columns to be passed to <code>par</code> .
main	Character scalar. A title template to be passed to <code>sprintf</code> .
legend.args	List of arguments to be passed to <code>legend</code> .
minmax.relative.size	Passed to <code>rescale_vertex_igraph</code> .
background	Either a function to be called before plotting each slice, a color to specify the background color, or NULL (in which case nothing is done).

Details

Plotting is done via the function `plot.igraph`.

When `vertex.size` is either of "degree", "indegree", or "outdegree", `vertex.size` will be replaced with `dgr(., cmode =)` so that the vertex size reflects the desired degree.

The argument `minmax.relative.size` is passed to `rescale_vertex_igraph` which adjusts `vertex.size` so that the largest and smallest vertices have a relative size of `minmax.relative.size[2]` and `minmax.relative.size[1]` respectively with respect to the x-axis.

Plotting is done via the function `plot.igraph`.

In order to center the attention on the diffusion process itself, the positions of each vertex are computed only once by aggregating the networks through time, this is, instead of computing the layout for each time t , the function creates a new graph accumulating links through time.

The `mfrow.par` sets how to arrange the plots on the device. If $T = 5$ and `mfrow.par=c(2, 3)`, the first three networks will be in the top of the device and the last two in the bottom.

The argument `vertex.color` contains the colors of non-adopters, new-adopters, and adopters respectively. The new adopters (default color "tomato") have a different color than the adopters when the graph is at their time of adoption, hence, when the graph has been plotted is in $t = 2$ and $toa = 2$ the vertex will be plotted in red.

`legend.args` has the following default parameter:

```
x          "bottom"
legend     c("Non adopters", "New adopters", "Adopters")
pch        sapply(vertex.shape, switch, circle = 21, square = 22, 21)
bty        "n"
horiz      TRUE
```

Value

Calculated coordinates for the grouped graph (invisible).

Author(s)

George G. Vega Yon

See Also

Other visualizations: [dgr](#), [diffusionMap](#), [drawColorKey](#), [grid_distribution](#), [hazard_rate](#), [plot_adopters](#), [plot_diffnet2](#), [plot_infectsuscep](#), [plot_threshold](#), [rescale_vertex_igraph](#)

Examples

```
# Generating a random graph
set.seed(1234)
n <- 6
nper <- 5
graph <- rgraph_er(n,nper, p=.3, undirected = FALSE)
toa <- sample(2000:(2000+nper-1), n, TRUE)
adopt <- toa_mat(toa)

plot_diffnet(graph, adopt$cumadopt)
```

plot_diffnet2

Another way of visualizing diffusion

Description

Another way of visualizing diffusion

Usage

```
plot_diffnet2(graph, ...)

## S3 method for class 'diffnet'
plot_diffnet2(graph, toa, slice = nslices(graph), ...)

## Default S3 method:
plot_diffnet2(graph, toa, pers = min(toa, na.rm =
  TRUE):max(toa, na.rm = TRUE),
  color.ramp = grDevices::colorRamp(viridis::magma(20)), layout = NULL,
  key.width = 0.1, key.args = list(), main = "Diffusion dynamics",
  add.map = NULL, diffmap.args = list(kde2d.args = list(n = 100)),
  diffmap.alpha = 0.5, include.white = "first", vertex.size = "degree",
  minmax.relative.size = getOption("diffnet.minmax.relative.size", c(0.01,
  0.04)), no.graph = FALSE, ...)
```

Arguments

graph	Any class of accepted graph format (see netdiffuseR-graphs).
...	Further arguments passed to plot.igraph .
toa	Integer vector of length n with the times of adoption.
slice	Integer scalar. Number of slice to use as baseline for drawing the graph.
pers	Integer vector of length T indicating the time periods of the data.
color.ramp	A function as returned by colorRamp .
layout	Passed to plot.igraph .
key.width	Numeric scalar. Sets the proportion of the plot (x-axis) that the key uses.
key.args	List. Further arguments to be passed to drawColorKey .
main	Character scalar. Title of the graph.
add.map	Character scalar. When "first" plots a diffusionMap before the graph itself. If "last" then it adds it at the end. When NULL adds nothing.
diffmap.args	List. If add.map=TRUE, arguments passed to diffusionMap .
diffmap.alpha	Numeric scalar between [0,1]. Alpha level for the map.
include.white	Character scalar. Includes white in the color palette used in the map. When include.white=NULL then it won't include it.
vertex.size	Either a numeric scalar or vector of size n , or any of the following values: "in-degree", "degree", or "outdegree" (see details).
minmax.relative.size	Passed to rescale_vertex_igraph .
no.graph	Logical scala. When TRUE the graph is not drawn. This only makes sense when the option add.map is active.

Details

Plotting is done via the function [plot.igraph](#).

When `vertex.size` is either of "degree", "indegree", or "outdegree", `vertex.size` will be replaced with `dgr(., cmode =)` so that the vertex size reflects the desired degree.

The argument `minmax.relative.size` is passed to [rescale_vertex_igraph](#) which adjusts `vertex.size` so that the largest and smallest vertices have a relative size of `minmax.relative.size[2]` and `minmax.relative.size[1]` respectively with respect to the x-axis.

If `key.width` ≤ 0 then no key is created.

By default, the function passes the following values to [plot.igraph](#):

- `vertex.label` equals to ""
- `vertex.frame.color` equals to "white"
- `add` equals to TRUE
- `rescale` equals to FALSE
- `vertex.size` equals to `rescale.fun(vertex.size)`

Value

A list with the following elements

layout	A numeric matrix with vertex coordinates.
vertex.color	A character vector with computed colors for each vertex.
vertex.label	The value passed to plot_diffnet2.
vertex.shape	A character vector with assigned shapes.
vertex.size	A numeric vector with vertices sizes
diffmap	If add.map=TRUE, the returned values from diffmap

Author(s)

George G. Vega Yon

See Also

Other visualizations: [dgr](#), [diffusionMap](#), [drawColorKey](#), [grid_distribution](#), [hazard_rate](#), [plot_adopters](#), [plot_diffnet](#), [plot_infectsuscep](#), [plot_threshold](#), [rescale_vertex_igraph](#)

plot_infectsuscep *Plot distribution of infect/suscep*

Description

After calculating infectiousness and susceptibility of each individual on the network, it creates an nlevels by nlevels matrix indicating the number of individuals that lie within each cell, and draws a heatmap.

Usage

```
plot_infectsuscep(graph, toa, t0 = NULL, normalize = TRUE, K = 1L,
  r = 0.5, expdiscount = FALSE, bins = 20, nlevels = round(bins/2),
  h = NULL, logscale = TRUE,
  main = "Distribution of Infectiousness and\nSusceptibility",
  xlab = "Infectiousness of ego", ylab = "Susceptibility of ego",
  sub = ifelse(logscale, "(in log-scale)", NA),
  color.palette = viridis::viridis_pal(), include.grid = TRUE,
  exclude.zeros = FALSE, valued = getOption("diffnet.valued", FALSE), ...)
```

Arguments

graph	A dynamic graph (see netdiffuser-graphs).
toa	Integer vector of length n with the times of adoption.
t0	Integer scalar. See toa_mat .
normalize	Logical scalar. Passed to infection/susceptibility.

K	Integer scalar. Passed to infection/susceptibility.
r	Numeric scalar. Passed to infection/susceptibility.
expdiscount	Logical scalar. Passed to infection/susceptibility.
bins	Integer scalar. Size of the grid (n).
nlevels	Integer scalar. Number of levels to plot (see filled.contour).
h	Numeric vector of length 2. Passed to kde2d in the MASS package.
logscale	Logical scalar. When TRUE the axis of the plot will be presented in log-scale.
main	Character scalar. Title of the graph.
xlab	Character scalar. Title of the x-axis.
ylab	Character scalar. Title of the y-axis.
sub	Character scalar. Subtitle of the graph.
color.palette	a color palette function to be used to assign colors in the plot (see filled.contour).
include.grid	Logical scalar. When TRUE, the grid of the graph is drawn.
exclude.zeros	Logical scalar. When TRUE, observations with zero values
valued	Logical scalar. When FALSE non-zero values in the adjmat are set to one. in infect or suscep are excluded from the graph. This is done explicitly when logscale=TRUE.
...	Additional parameters to be passed to filled.contour .

Details

This plotting function was inspired by Aral, S., & Walker, D. (2012).

By default the function will try to apply a kernel smooth function via [kde2d](#). If not possible (because not enough data points), then the user should try changing the parameter `h` or set it equal to zero.

`toa` is passed to `infection/susceptibility`.

Value

A list with three elements:

infect	A numeric vector of size n with infectiousness levels
suscep	A numeric vector of size n with susceptibility levels
coords	A list containing the class marks and counts used to draw the plot via filled.contour (see grid.distribution)
complete	A logical vector with TRUE when the case was included in the plot. (this is relevant whenever <code>logscale=TRUE</code>)

Author(s)

George G. Vega Yon

References

Aral, S., & Walker, D. (2012). "Identifying Influential and Susceptible Members of Social Networks". *Science*, 337(6092), 337–341. <http://doi.org/10.1126/science.1215842>

See Also

Infectiousness and susceptibility are computed via [infection](#) and [susceptibility](#).

Other visualizations: [dgr](#), [diffusionMap](#), [drawColorKey](#), [grid_distribution](#), [hazard_rate](#), [plot_adopters](#), [plot_diffnet2](#), [plot_diffnet](#), [plot_threshold](#), [rescale_vertex_igraph](#)

Examples

```
# Generating a random graph -----
set.seed(1234)
n <- 100
nper <- 20
graph <- rgraph_er(n,nper, p=.2, undirected = FALSE)
toa <- sample(1:(1+nper-1), n, TRUE)

# Visualizing distribution of suscep/infect
out <- plot_infetsuscep(graph, toa, K=3, logscale = FALSE)
```

plot_threshold *Threshold levels through time*

Description

Draws a graph where the coordinates are given by time of adoption, x-axis, and threshold level, y-axis.

Usage

```
plot_threshold(graph, expo, ...)

## S3 method for class 'diffnet'
plot_threshold(graph, expo, ...)

## S3 method for class 'array'
plot_threshold(graph, expo, ...)

## Default S3 method:
plot_threshold(graph, expo, toa, include_censored = FALSE,
  t0 = min(toa, na.rm = TRUE), attrs = NULL,
  undirected = getOption("diffnet.undirected"), no.contemporary = TRUE,
  main = "Time of Adoption by\nNetwork Threshold", xlab = "Time",
  ylab = "Threshold", vertex.size = "degree", vertex.color = NULL,
  vertex.label = "", vertex.label.pos = NULL, vertex.label.cex = 1,
  vertex.label.adj = c(0.5, 0.5), vertex.label.color = NULL,
  vertex.sides = 40L, vertex.rot = 0, edge.width = 2, edge.color = NULL,
  arrow.width = NULL, arrow.length = NULL, arrow.color = NULL,
  include.grid = FALSE, vertex.frame.color = NULL, bty = "n",
  jitter.factor = c(1, 1), jitter.amount = c(0.25, 0.025), xlim = NULL,
  ylim = NULL, edge.curved = NULL, background = NULL, ...)
```

Arguments

graph	A dynamic graph (see netdiffuseR-graphs).
expo	$n \times T$ matrix. Exposure to the innovation obtained from exposure
...	Additional arguments passed to plot .
toa	Integer vector of length n with the times of adoption.
include_censored	Logical scalar. Passed to threshold .
t0	Integer scalar. Passed to threshold .
attrs	Passed to exposure (via threshold).
undirected	Logical scalar. When TRUE only the lower triangle of the adjacency matrix will be considered (faster).
no.contemporary	Logical scalar. When TRUE, edges for vertices with the same toa won't be plotted.
main	Character scalar. Title of the plot.
xlab	Character scalar. x-axis label.
ylab	Character scalar. y-axis label.
vertex.size	Numeric vector of size n . Relative size of the vertices.
vertex.color	Either a vector of size n or a scalar indicating colors of the vertices.
vertex.label	Character vector of size n . Labels of the vertices.
vertex.label.pos	Integer value to be passed to text via pos.
vertex.label.cex	Either a numeric scalar or vector of size n . Passed to text .
vertex.label.adj	Passed to text .
vertex.label.color	Passed to text .
vertex.sides	Either a vector of size n or a scalar indicating the number of sides of each vertex (see details).
vertex.rot	Either a vector of size n or a scalar indicating the rotation in radians of each vertex (see details).
edge.width	Numeric. Width of the edges.
edge.color	Character. Color of the edges.
arrow.width	Numeric value to be passed to arrows .
arrow.length	Numeric value to be passed to arrows .
arrow.color	Color.
include.grid	Logical. When TRUE, the grid of the graph is drawn.
vertex.frame.color	Either a vector of size n or a scalar indicating colors of vertices' borders.
btty	See par .

jitter.factor	Numeric vector of size 2 (for x and y) passed to jitter .
jitter.amount	Numeric vector of size 2 (for x and y) passed to jitter .
xlim	Passed to plot .
ylim	Passed to plot .
edge.curved	Logical scalar. When curved, generates curved edges.
background	TBD

Details

When `vertex.label=NULL` the function uses vertices ids as labels. By default `vertex.label=""` plots no labels.

Vertices are drawn using an internal function for generating polygons. Polygons are inscribed in a circle of radius `vertex.size`, and can be rotated using `vertex.rot`. The number of sides of each polygon is set via `vertex.sides`.

Author(s)

George G. Vega Yon

See Also

Use [threshold](#) to retrieve the corresponding threshold obtained returned by [exposure](#).

Other visualizations: [dgr](#), [diffusionMap](#), [drawColorKey](#), [grid_distribution](#), [hazard_rate](#), [plot_adopters](#), [plot_diffnet2](#), [plot_diffnet](#), [plot_infectsuscep](#), [rescale_vertex_igraph](#)

Examples

```
# Generating a random graph
set.seed(1234)
n <- 6
nper <- 5
graph <- rgraph_er(n,nper, p=.3, undirected = FALSE)
toa <- sample(2000:(2000+nper-1), n, TRUE)
adopt <- toa_mat(toa)

# Computing exposure
expos <- exposure(graph, adopt$cumadopt)

plot_threshold(graph, expos, toa)

# Calculating degree (for sizing the vertices)
plot_threshold(graph, expos, toa, vertex.size = "indegree")
```

```
pretty_within          Pretty numbers within a range.
```

Description

A wrapper for `pretty`.

Usage

```
pretty_within(x, min.n = 5, xrange = range(x, na.rm = TRUE), ...)
```

Arguments

<code>x</code>	Numeric vector passed to <code>pretty</code> .
<code>min.n</code>	Integer scalar passed to <code>pretty</code> .
<code>xrange</code>	Numeric vector of length 2. Indicates the range in which the output vector should lie on.
<code>...</code>	Further arguments passed to the method.

The only difference with `pretty` is that this function subsets the resulting vector as

```
tick[(tick >= xrange[1]) & (tick <= xrange[2])]
```

Examples

```
# Simple example -----
set.seed(3331)
x <- runif(10)
pretty(x)
pretty_within(x)
range(x)
```

```
rdiffnet              Random diffnet network
```

Description

Simulates a diffusion network by creating a random dynamic network and adoption threshold levels.

Usage

```
rdiffnet_multiple(R, statistic, ..., ncpus = 1L, cl = NULL)
```

```
rdiffnet(n, t, seed.nodes = "random", seed.p.adopt = 0.05,
  seed.graph = "scale-free", rgraph.args = list(), rewire = TRUE,
  rewire.args = list(), threshold.dist = runif(n), exposure.args = list(),
  name = "A diffusion network", behavior = "Random contagion",
  stop.no.diff = TRUE)
```

Arguments

R	Integer scalar. Number of simulations to be done.
statistic	A Function to be applied to each simulated diffusion network.
...	Further arguments to be passed to rdiffnet.
ncpus	Integer scalar. Number of processors to be used (see details).
cl	An object of class <code>c("SOCKcluster", "cluster")</code> (see details).
n	Integer scalar. Number of vertices.
t	Integer scalar. Time length.
seed.nodes	Either a character scalar or a vector. Type of seed nodes (see details).
seed.p.adopt	Numeric scalar. Proportion of early adopters.
seed.graph	Baseline graph used for the simulation (see details).
rgraph.args	List. Arguments to be passed to rgraph.
rewire	Logical scalar. When TRUE, network slices are generated by rewiring (see rewire_graph).
rewire.args	List. Arguments to be passed to rewire_graph .
threshold.dist	Either a function to be applied via sapply , a numeric scalar, or a vector/matrix with n elements. Sets the adoption threshold for each node.
exposure.args	List. Arguments to be passed to exposure .
name	Character scalar. Passed to as_diffnet .
behavior	Character scalar. Passed to as_diffnet .
stop.no.diff	Logical scalar. When TRUE, the function will return with error if there was no diffusion. Otherwise it throws a warning.

Details

Instead of randomizing whether an individual adopts the innovation or not, this toy model randomizes threshold levels, seed adopters and network structure, so an individual adopts the innovation in time T iff his exposure is above or equal to his threshold. The simulation is done in the following steps:

1. Using `seed.graph`, a baseline graph is created.
2. Given the baseline graph, the set of initial adopters is defined using `seed.nodes`.

3. Afterwards, if `rewire=TRUE` $t - 1$ slices of the network are created by iteratively rewiring the baseline graph.
4. The `threshold.dist` function is applied to each node in the graph.
5. Simulation starts at $t = 2$ assigning adopters in each time period accordingly to each vertex's threshold and exposure.

When `seed.nodes` is a character scalar it can be "marginal", "central" or "random", So each of these values sets the initial adopters using the vertices with lowest degree, with highest degree or completely randomly. The number of early adoptes is set as `seed.p.adopt * n`. Please note that when marginal nodes are set as seed it may be the case that no diffusion process is attained as the chosen set of first adopters can be isolated. Any other case will be considered as an index (via [`<-` methods]), hence the user can manually set the set of initial adopters, for example if the user sets `seed.nodes=c(1, 4, 7)` then nodes 1, 4 and 7 will be selected as initial adopters.

The argument `seed.graph` can be either a function that generates a graph (Any class of accepted graph format (see `netdiffuseR-graphs`)), a graph itself or a character scalar in which the user sets the algorithm used to generate the first network (network in $t=1$), this can be either "scale-free" (Barabasi-Albert model using the `rgraph_ba` function, the default), "bernoulli" (Erdos-Renyi model using the `rgraph_er` function), or "small-world" (Watts-Strogatz model using the `rgraph_ws` function). The list `rgraph.args` passes arguments to the chosen algorithm.

When `rewire=TRUE`, the networks that follow $t=1$ will be generated using the `rewire_graph` function as $G(t) = R(G(t - 1))$, where R is the rewiring algorithm.

If a function, the argument `threshold.dist` sets the threshold for each vertex in the graph. It is applied using `sapply` as follows

```
sapply(1:n, threshold.dist)
```

By default sets the threshold to be random for each node in the graph.

If `seed.graph` is provided, no random graph is generated and the simulation is applied using that graph instead.

`rewire.args` has the following default options:

```
p          .1
undirected  getOption("diffnet.undirected", FALSE)
self       getOption("diffnet.self", FALSE)
```

`exposure.args` has the following default options:

```
outgoing    TRUE
valued      getOption("diffnet.valued", FALSE)
normalized  TRUE
```

The function `rdiffnet_multiple` is a wrapper of `rdiffnet` wich allows simulating multiple diffusion networks with the same parameters and apply the same function to all of them. This function is designed to allow the user to perform larger simulation studies in which the distribution of a particular statistic is observed.

When `cl` is provided, then simulations are done via `parSapply`. If `ncpus` is greater than 1, then the function creates a cluster via `makeCluster` which is stopped (removed) once the process is complete.

Value

A random `diffnet` class object.

`rdiffnet_multiple` returns either a vector or an array depending on what statistic is (see `sapply` and `parSapply`).

Author(s)

George G. Vega Yon

See Also

Other simulation functions: `permute_graph`, `rewire_graph`, `rgraph_ba`, `rgraph_er`, `rgraph_ws`, `ring_lattice`

Examples

```
# A simple example -----
set.seed(123)
z <- rdiffnet(100,10)
z
summary(z)

# A more complex example: Adopt if at least one neighbor has adopted -----
y <- rdiffnet(100, 10, threshold.dist=function(x) 1,
  exposure.args=list(valued=FALSE, normalized=FALSE))

# Re thinking the Adoption of Tetracycline -----
newMI <- rdiffnet(seed.graph = medInnovationsDiffNet$graph,
  threshold.dist = threshold(medInnovationsDiffNet), rewiring=FALSE)

# Simulation study comparing the diffusion with diff sets of seed nodes -----

# Random seed nodes
set.seed(1)
ans0 <- rdiffnet_multiple(R=50, statistic=function(x) sum(!is.na(x$toa)),
  n = 100, t = 4, seed.nodes = "random", stop.no.diff=FALSE)

# Central seed nodes
set.seed(1)
ans1 <- rdiffnet_multiple(R=50, statistic=function(x) sum(!is.na(x$toa)),
  n = 100, t = 4, seed.nodes = "central", stop.no.diff=FALSE)

boxplot(cbind(Random = ans0, Central = ans1), main="Number of adopters")
```

read_pajek	<i>Read foreign graph formats</i>
------------	-----------------------------------

Description

Reading pajek and Ucinet files, this function returns weighted edgelists in the form of data frames including a data frame of the vertices. (function on development)

Usage

```
read_pajek(x)
```

```
read_ml(x)
```

Arguments

`x` Character scalar. Path to the file to be imported.

Details

Since .net files allow working with multi-relational networks (more than one class of edge), the function returns lists of edges and edgelist with the corresponding tag on the .net file. For example, if the .net file contains

```
*Arcslist :9 "SAMPPR"
...
*Arcslist :10 "SAMNPR"
```

The output will include data frames of edgelists with those tags.

Value

In the case of `read_pajek`, a list with three elements

vertices	A data frame with n rows and two columns: id and label
edges	If not null, a list of data frames with three columns: ego, alter, w (weight)
edgelist	If not null, a list of data frame with three columns: ego, alter, w (weight)

For `read_ml`, a list with two elements:

adjmat	An array with the graph
meta	A list with metadata

Author(s)

George G. Vega Yon

Source

From the pajek manual <http://mrvar.fdv.uni-lj.si/pajek/pajekman.pdf>

See Also

Other Foreign: [igraph](#), [network](#), [read_ucinet_head](#)

Examples

```
# From .net: Sampson monastery data from UCINET dataset -----
# Reading the arcs/edges format
path <- system.file("extdata", "SAMPSON.NET", package = "netdiffuseR")
SAMPSON <- read_pajek(path)

# Reading the arcslist/edgelist format
path <- system.file("extdata", "SAMPSONL.NET", package = "netdiffuseR")
SAMPSONL <- read_pajek(path)

# From DL (UCINET): Sampson monastery data (again) -----
path <- system.file("extdata", "SAMPSON.DAT", package = "netdiffuseR")
SAMPSONL <- read_ml(path)
```

read_ucinet_head	<i>Reads UCINET files</i>
------------------	---------------------------

Description

Reads UCINET files

Read UCINET files (binary)

Usage

```
read_ucinet_head(f)
```

```
read_ucinet(f, echo = FALSE)
```

Arguments

f Character scalar. Name of the header file. e.g. mydata.##h.

echo Logical scalar. When TRUE shows a message.

Value

An array including dimnames (if there are) and the following attributes:

headerversion	Character scalar
year	Integer. Year the file was created
month	Integer. Month of the year the file was created.
day	Integer. Day of the month the file was created.
dow	Integer. Day of the week the file was created.
labtype	
infile.dt	Character scalar. Type of data of the array.
dim	Integer vector. Dimensions of the array.
tit	Character scalar. Title of the file.
haslab	Logical vector. Whether each dim has a label.

See Also

Other Foreign: [igraph](#), [network](#), [read_pajek](#)

recode

Recodes an edgelist such that ids go from 1 to n

Description

Recodes an edgelist such that ids go from 1 to n

Usage

```
recode(data, ...)
```

```
## S3 method for class 'data.frame'
```

```
recode(data, ...)
```

```
## S3 method for class 'matrix'
```

```
recode(data, ...)
```

Arguments

data	Edgelist as either a matrix or dataframe with ego and alter
...	Further arguments for the method (ignored)

Details

Required for using most of the package's functions, as ids are used as a reference for accessing elements in adjacency matrices.

Value

A recoded edgelist as a two-column matrix/data.frame depending on the class of data. The output includes an attribute called "recode" which contains a two column data.frame providing a mapping between the previous code and the new code (see the examples)

Author(s)

George G. Vega Yon

See Also

[edgelist_to_adjmat](#)

Examples

```
# Simple example -----
edgelist <- cbind(c(1,1,3,6),c(4,3,200,1))
edgelist
recoded_edgelist <- recode(edgelist)
recoded_edgelist

# Retrieving the "recode" attribute
attr(recoded_edgelist, "recode")
```

`rescale_vertex_igraph` Rescale vertex size to be used in `plot.igraph`.

Description

This function rescales a vertex size before passing it to `plot.igraph` so that the resulting vertices have the desired size relative to the x-axis.

Usage

```
rescale_vertex_igraph(vertex.size, par.usr = par("usr"),
  minmax.relative.size = getOption("diffnet.minmax.relative.size", c(0.01,
  0.04)), adjust = 200)

igraph_vertex_rescale(vertex.size, par.usr = par("usr"),
  minmax.relative.size = getOption("diffnet.minmax.relative.size", c(0.01,
  0.04)), adjust = 200)

vertex_rescale_igraph(vertex.size, par.usr = par("usr"),
  minmax.relative.size = getOption("diffnet.minmax.relative.size", c(0.01,
  0.04)), adjust = 200)
```

Arguments

<code>vertex.size</code>	Numeric vector of unscaled vertices' sizes. This is unit-free.
<code>par.usr</code>	Integer vector of length 4 with the coordinates of plotting region. by default uses <code>par("usr")</code> .
<code>minmax.relative.size</code>	A numeric vector of length 2. Represents the desired min and max vertex sizes relative to the x-axis in terms of percentage (see details).
<code>adjust</code>	Numeric scalar. Adjustment made to the resulting adjusted size (see details).

Details

`minmax.relative.size` limits the minimum and maximum size that a vertex can take in the plot relative to the x-axis scale. The values for the x-axis scale are by default retrieved by accessing to `par("usr")`. By default the vertex are rescaled to be at least 1% of the size of the plotting region and no more than 5% of the plotting region, `minmax.relative.size=c(.01, .05)`.

The default value for `adjust` is taken from [igraph](#) version 1.0.1. In particular, the function `igraph:::igraph.shape.circle.plot`, in which before passing the `vertex.size` to the function `symbols`, the vertex size is reduced by 200.

The rescaling is as follows:

$$v' = \frac{v - \underline{v}}{\bar{v} - \underline{v}} \times (\bar{s} - \underline{s}) + \underline{s}$$

Where v is the vertex size, \bar{v} and \underline{v} are the max and min values of v respectively, and \bar{s} and \underline{s} are the max and min size that vertices take in terms of `minmax.relative.size` and `par.usr`. The adjusted value v' is then multiplied by `adjust`.

`igraph_vertex_rescale` and `vertex_rescale_igraph` are aliases.

Value

An integer vector of the same length as `vertex.size` with rescaled values.

Author(s)

George G. Vega Yon

See Also

Other visualizations: [dgr](#), [diffusionMap](#), [drawColorKey](#), [grid_distribution](#), [hazard_rate](#), [plot_adopters](#), [plot_diffnet2](#), [plot_diffnet](#), [plot_infetsuscep](#), [plot_threshold](#)

Examples

```
library(igraph)

# Random graph and coordinates
set.seed(2134)
g <- barabasi.game(10)
```

```

coords <- layout_nicely(g)

# Random size and figures
size <- runif(10)
size <- cbind(size, size)
shap <- sample(c("circle", "square"),10,TRUE)

# Plotting
oldpar <- par(no.readonly = TRUE)
par(mfrow=c(2,2), mai=rep(.5,4))
for (i in seq(1, 1000, length.out = 4)) {
  # New plot-window
  plot.new()
  plot.window(xlim=range(coords[,1]*i), ylim=range(coords[,2]*i))

  # plotting graph
  plot(g, layout=coords*i, add=TRUE, rescale=FALSE,
       vertex.shape = shap,
       vertex.size = rescale_vertex_igraph(size) # HERE WE RESCALE!
  )

  # Adding some axis
  axis(1, lwd=0, lwd.ticks = 1)
  axis(2, lwd=0, lwd.ticks = 1)
  box()
}

par(oldpar)

```

rewire_graph

Graph rewiring algorithms

Description

Changes the structure of a graph by altering ties.

Usage

```

rewire_graph(graph, p, algorithm = "endpoints", both.ends = FALSE,
             self = FALSE, multiple = FALSE,
             undirected = getOption("diffnet.undirected"), pr.change = ifelse(self,
             0.5, 1), copy.first = TRUE, althexagons = FALSE)

```

Arguments

graph	Any class of accepted graph format (see netdiffuser-graphs).
p	Either a [0,1] vector with rewiring probabilities (algorithm="endpoints"), or an integer vector with number of iterations (algorithm="swap").

algorithm	Character scalar. Either "swap", "endpoints", or "qap" (see rewire_qap).
both.ends	Logical scalar. When TRUE rewires both ends.
self	Logical scalar. When TRUE, allows loops (self edges).
multiple	Logical scalar. When TRUE allows multiple edges.
undirected	Logical scalar. When TRUE only the lower triangle of the adjacency matrix will be considered (faster).
pr.change	Numeric scalar. Probability ([0,1]) of doing a rewire (see details).
copy.first	Logical scalar. When TRUE and graph is dynamic uses the first slice as a baseline for the rest of slices (see details).
althexagons	Logical scalar. When TRUE uses the compact alternating hexagons algorithm (currently ignored [on development]).

Details

The algorithm "qap" is described in [rewire_qap](#), and only uses graph from the arguments (since it is simply relabelling the graph).

In the case of "swap" and "endpoints", both algorithms are implemented sequentially, this is, edge-wise checking self edges and multiple edges over the changing graph; in other words, at step m (in which either a new endpoint or edge is chosen, depending on the algorithm), the algorithms verify whether the proposed change creates either multiple edges or self edges using the resulting graph at step $m - 1$.

The main difference between the two algorithms is that the "swap" algorithm preserves the degree sequence of the graph and "endpoints" does not. The "swap" algorithm is specially useful to assess the non-randomness of a graph's structural properties, furthermore it is this algorithm the one used in the [struct_test](#) routine implemented in **netdiffuseR**.

Rewiring assumes a weighted network, hence $G(i, j) = k = G(i', j')$, where i', j' are the new endpoints of the edge and k may not be equal to one.

In the case of dynamic graphs, when `copy.first=TRUE`, after rewiring the first slice $t = 1$ —the rest of slices are generated by rewiring the rewired version of the first slice. Formally:

$$G(t)' = \begin{cases} R(G(t)) & \text{if } t = 1 \\ R(G(1)') & \text{otherwise} \end{cases}$$

Where $G(t)$ is the t -th slice, $G(t)'$ is the t -th rewired slice, and R is the rewiring function. Otherwise, `copy.first=FALSE` (default), The rewiring function is simply $G(t)' = R(G(t))$.

The following sections describe the way both algorithms were implemented.

Swap algorithm

The "swap" algorithm chooses randomly two edges (a, b) and (c, d) and swaps the 'right' endpoint of both such that we get (a, d) and (c, b) (considering self and multiple edges).

Following Milo et al. (2004) testing procedure, the algorithm shows to be well behaved in terms of being unbiased, so after each iteration each possible structure of the graph has the same probability of being generated. The algorithm has been implemented as follows:

Let E be the set of edges of the graph G . For $i = 1$ to p , do:

1. With probability $1 - \text{pr. change}$ go to the last step.
2. Choose $e_0 = (a, b)$ from E . If $! \text{self} \ \& \ a == b$ then go to the last step.
3. Choose $e_1 = (c, d)$ from E . If $! \text{self} \ \& \ c == d$ then go to the last step.
4. Define $e_0' = (a, d)$ and $e_1' = (c, b)$. If $! \text{multiple} \ \& \ [G[e_0']] != 0 \ | \ [G[e_1']] != 0$ then go to the last step.(*)
5. Define $v_0 = G[e_0]$ and $v_1 = G[e_1]$, set $G[e_0] = 0$ and $G[e_1] = 0$ (and the same to the diagonally opposed coordinates in the case of undirected graphs)
6. Set $G[e_0'] = v_0$ and $G[e_1'] = v_1$ (and so with the diagonally opposed coordinates in the case of undirected graphs).
7. Next i .

(*) When `altheaxagons=TRUE`, the algorithm changes and applies what Rao et al. (1996) describe as Compact Alternating Hexagons. This modification assures the algorithm to be able to achieve any structure. The algorithm consists on doing the following swapping: $(i_1i_2, i_1i_3, i_2i_3, i_2i_1, i_3i_1, i_3i_2)$ with values $(1, 0, 1, 0, 1, 0)$ respectively with $i_1! = i_2! = i_3$. See the examples and references.

In Milo et al. (2004) is suggested that in order for the rewired graph to be independent from the original one researchers usually iterate around $nlinks(\text{graph}) * 100$ times, so $p = nlinks(\text{graph}) * 100$. On the other hand in Ray et al (2012) it is shown that in order to achive such it is needed to perform $nlinks(\text{graph}) * \log(1/\text{eps})$, where $\text{eps} \sim 1e-7$, in other words, around $nlinks(\text{graph}) * 16$. We set the default to be 20.

In the case of Markov chains, the variable `pr.change` allows making the algorithm aperiodic. This is relevant only if the probability self-loop to a particular state is null, for example, if we set `self=TRUE` and `multiple=TRUE`, then in every step the algorithm will be able to change the state. For more details see Stanton and Pinar (2012) [p. 3.5:9].

Endpoints algorithm

This reconnect either one or both of the endpoints of the edge randomly. As a big difference with the swap algorithm is that this does not preserves the degree sequence of the graph (at most the outgoing degree sequence). The algorithm is implemented as follows:

Let G be the baseline graph and G' be a copy of it. Then, For $l = 1$ to $|E|$ do:

1. Pick the l -th edge from E , define it as $e = (i, j)$.
2. Draw r from $U(0, 1)$, if $r > p$ go to the last step.
3. If $! \text{undirected} \ \& \ i < j$ go to the last step.
4. Randomly select a vertex j' (and i' if `both_ends==TRUE`). And define $e' = (i, j')$ (or $e' = (i', j')$ if `both_ends==TRUE`).
5. If $! \text{self} \ \& \ i == j'$ (or if `both_ends==TRUE \ \& \ i' == j'`) go to the last step.
6. If $! \text{multiple} \ \& \ G'[e'] != 0$ then go to the last step.
7. Define $v = G[e]$, set $G'[e] = 0$ and $G'[e'] = v$ (and the same to the diagonally opposed coordinates in the case of undirected graphs).
8. Next l .

The endpoints algorithm is used by default in `rdiffnet` and used to be the default in `struct_test` (now swap is the default).

Author(s)

George G. Vega Yon

References

- Watts, D. J., & Strogatz, S. H. (1998). Collectivedynamics of "small-world" networks. *Nature*, 393(6684), 440–442. <http://doi.org/10.1038/30918>
- Milo, R., Kashtan, N., Itzkovitz, S., Newman, M. E. J., & Alon, U. (2004). On the uniform generation of random graphs with prescribed degree sequences. *Arxiv Preprint condmat0312028*, condmat/0, 1–4. Retrieved from <http://arxiv.org/abs/cond-mat/0312028>
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- A . Ramachandra Rao, R. J. and S. B. (1996). A Markov Chain Monte Carlo Method for Generating Random (0 , 1) -Matrices with Given Marginals. *The Indian Journal of Statistics*, 58, 225–242.
- Stanton, I., & Pinar, A. (2012). Constructing and sampling graphs with a prescribed joint degree distribution. *Journal of Experimental Algorithmics*, 17(1), 3.1. <http://doi.org/10.1145/2133803.2330086>

See AlsoOther simulation functions: [permute_graph](#), [rdiffnet](#), [rgraph_ba](#), [rgraph_er](#), [rgraph_ws](#), [ring_lattice](#)**Examples**

```
# Checking the consistency of the "swap" -----

# A graph with known structure (see Milo 2004)
n <- 5
x <- matrix(0, ncol=n, nrow=n)
x <- as(x, "dgCMatrix")
x[1,c(-1,-n)] <- 1
x[c(-1,-n),n] <- 1

x

# Simulations (increase the number for more precision)
set.seed(8612)
nsim <- 1e4
w <- sapply(seq_len(nsim), function(y) {
  # Creating the new graph
  g <- rewire_graph(x,p=nlinks(x)*100, algorithm = "swap")

  # Categorizing (tag of the generated structure)
  paste0(as.vector(g), collapse="")
})
```

```

# Counting
coded <- as.integer(as.factor(w))

plot(table(coded)/nsim*100, type="p", ylab="Frequency %", xlab="Class of graph", pch=3,
      main="Distribution of classes generated by rewiring")

# Marking the original structure
baseline <- paste0(as.vector(x), collapse="")
points(x=7,y=table(as.factor(w))[baseline]/nsim*100, pch=3, col="red")

```

rgraph_ba

Scale-free and Homophilic Random Networks

Description

Generates a scale-free random graph based on Bollabas et al. (2001), also known as *Linearized Chord Diagram (LCD)* which has nice mathematical properties. And also scale-free homophilic networks when a vertex attribute `eta` is passed.

Usage

```
rgraph_ba(m0 = 1L, m = 1L, t = 10L, graph = NULL, self = TRUE,
          eta = NULL)
```

Arguments

<code>m0</code>	Integer scalar. Number of initial vertices in the graph.
<code>m</code>	Integer scalar. Number of new edges per vertex added.
<code>t</code>	Integer scalar. Number of time periods (steps).
<code>graph</code>	Any class of accepted graph format (see netdiffuseR-graphs).
<code>self</code>	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).
<code>eta</code>	Numeric vector of length $t+m0$. When specified, it generates a scale-free homophilic network (see details).

Details

Based on Ballobás et al. (2001) creates a directed random graph of size $t + m0$. A big difference with B-A model is that this allows for loops (self/auto edges) and further multiple links, nevertheless, as t increases, the number of such cases reduces.

By default, the degree of the first $m0$ vertices is set to be 2 (loops). When $m>1$, as described in the paper, each new link from the new vertex is added one at a time “counting ‘outward half’ of the edge being added as already contributing to the degrees”.

When `self=FALSE`, the generated graph is created without autolinks. This means that at the beginning, if the number of links equals zero, all vertices have the same probability of receiving a new link.

When `eta` is passed, it implements the model specified in De Almeida et al. (2013), a scale-free homophilic network. To do so `eta` is rescaled to be between 0 and 1 and the probability that the node i links to node j is as follows:

$$\frac{(1 - A_{ij})k_j}{\sum_j (1 - A_{ij})k_j}$$

Where $A_{ij} = |\eta_i - \eta_j|$ and k_j is the degree of the j -th vertex.

Value

If graph is not provided, a static graph, otherwise an expanded graph (t additional vertices) of the same class as graph.

The resulting graph will have `graph$meta$undirected = FALSE` if it is of class `diffnet` and `attr(graph, "undirected")=FALSE` otherwise.

Author(s)

George G. Vega Yon

References

- Bollobás, B., Riordan, O., Spencer, J., & Tusnády, G. (2001). The degree sequence of a scale-free random graph process. *Random Structures & Algorithms*, 18(3), 279–290. <http://doi.org/10.1002/rsa.1009>
- Albert-László Barabási, & Albert, R. (1999). Emergence of Scaling in Random Networks. *Science*, 286(5439), 509–512. <http://doi.org/10.1126/science.286.5439.509>
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- De Almeida, M. L., Mendes, G. A., Madras Viswanathan, G., & Da Silva, L. R. (2013). Scale-free homophilic network. *European Physical Journal B*, 86(2). <http://doi.org/10.1140/epjb/e2012-30802-x>

See Also

Other simulation functions: [permute_graph](#), [rdiffnet](#), [rewire_graph](#), [rgraph_er](#), [rgraph_ws](#), [ring_lattice](#)

Examples

```
# Using another graph as a base graph -----
graph <- rgraph_ba()
graph

graph <- rgraph_ba(graph=graph)
```

```

# Generating a scale-free homophilic graph (no loops) -----
set.seed(112)
eta <- rep(c(1,1,1,1,2,2,2,2), 20)
ans <- rgraph_ba(t=length(eta) - 1, m=3, self=FALSE, eta=eta)

# Converting it to igraph (so we can plot it)
ig <- igraph::graph_from_adjacency_matrix(ans)

# Neat plot showing the output
oldpar <- par(no.readonly = TRUE)
par(mfrow=c(1,2))
plot(ig, vertex.color=c("red","blue")[factor(eta)], vertex.label=NA,
      vertex.size=5, main="Scale-free homophilic graph")
suppressWarnings(plot(dgr(ans), main="Degree distribution"))
par(oldpar)

```

rgraph_er

Erdos-Renyi model

Description

Generates a bernoulli random graph.

Usage

```

rgraph_er(n = 10, t = 1, p = 0.01,
          undirected = getOption("diffnet.undirected"), weighted = FALSE,
          self = getOption("diffnet.self"), as.edgelist = FALSE)

```

Arguments

n	Integer. Number of vertices
t	Integer. Number of time periods
p	Double. Probability of a link between ego and alter.
undirected	Logical scalar. Whether the graph is undirected or not.
weighted	Logical. Whether the graph is weighted or not.
self	Logical. Whether it includes self-edges.
as.edgelist	Logical. When TRUE the graph is presented as an edgelist instead of an adjacency matrix.

Details

For each pair of nodes $\{i, j\}$, an edge is created with probability p , this is, $Pr\{Link\ i - j\} = Pr\{x < p\}$, where x is drawn from a *Uniform*(0, 1).

When `weighted=TRUE`, the strength of ties is given by the random draw x used to compare against p , hence, if $x < p$ then the strength will be set to x .

In the case of dynamic graphs, the algorithm is repeated t times, so the networks are uncorrelated.

Value

A graph represented by an adjacency matrix (if `t=1`), or an array of adjacency matrices (if `t>1`).

Note

The resulting adjacency matrix is store as a dense matrix, not as a sparse matrix, hence the user should be careful when choosing the size of the network.

Author(s)

George G. Vega Yon

References

Barabasi, Albert-Laszlo. "Network science book" Retrieved November 1 (2015) <http://barabasi.com/book/network-science>.

See Also

Other simulation functions: [permute_graph](#), [rdiffnet](#), [rewire_graph](#), [rgraph_ba](#), [rgraph_ws](#), [ring_lattice](#)

Examples

```
## Not run:
# Setting the seed
set.seed(123)

# Generating an directed graph
rgraph_er(undirected=FALSE)

# Comparing P(tie)
x <- rgraph_er(1000, p=.1)
sum(x)/length(x)

# Several period random gram
rgraph_er(t=5)

## End(Not run)
```

rgraph_ws	<i>Watts-Strogatz model</i>
-----------	-----------------------------

Description

Generates a small-world random graph.

Usage

```
rgraph_ws(n, k, p, both.ends = FALSE, self = FALSE, multiple = FALSE,
          undirected = FALSE)
```

Arguments

n	Integer scalar. Set the size of the graph.
k	Integer scalar. Set the initial degree of the ring (must be less than n).
p	Numeric scalar/vector of length T . Set the probability of changing an edge.
both.ends	Logical scalar. When TRUE rewires both ends.
self	Logical scalar. When TRUE, allows loops (self edges).
multiple	Logical scalar. When TRUE allows multiple edges.
undirected	Logical scalar. Passed to ring_lattice

Details

Implemented as in Watts and Strogatz (1998). Starts from an undirected ring with n vertices all with degree k (so it must be an even number), and then rewire each edge by setting the endpoint (so now you treat it as a digraph) randomly any vertex in $N \setminus i$ avoiding multiple links (by default) using the rewiring algorithm described on the paper.

Value

A random graph of size $n \times n$ following the small-world model. The resulting graph will have `attr(graph, "undirected")=FALSE`.

Author(s)

George G. Vega Yon

References

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of "small-world" networks. *Nature*, 393(6684), 440–2. <http://dx.doi.org/10.1038/30918>

Newman, M. E. J. (2003). The Structure and Function of Complex Networks. *SIAM Review*, 45(2), 167–256. <http://doi.org/10.1137/S003614450342480>

See Also

Other simulation functions: [permute_graph](#), [rdiffnet](#), [rewire_graph](#), [rgraph_ba](#), [rgraph_er](#), [ring_lattice](#)

Examples

```
library(igraph)
set.seed(7123)
x0 <- graph_from_adjacency_matrix(rgraph_ws(10,2, 0))
x1 <- graph_from_adjacency_matrix(rgraph_ws(10,2, .3))
x2 <- graph_from_adjacency_matrix(rgraph_ws(10,2, 1))

oldpar <- par(no.readonly=TRUE)
par(mfrow=c(1,3))
plot(x0, layout=layout_in_circle, edge.curved=TRUE, main="Regular")
plot(x1, layout=layout_in_circle, edge.curved=TRUE, main="Small-world")
plot(x2, layout=layout_in_circle, edge.curved=TRUE, main="Random")
par(oldpar)
```

ring_lattice

Ring lattice graph

Description

Creates a ring lattice with n vertices, each one of degree (at most) k as an undirected graph. This is the basis of [rgraph_ws](#).

Usage

```
ring_lattice(n, k, undirected = FALSE)
```

Arguments

n	Integer scalar. Size of the graph.
k	Integer scalar. Out-degree of each vertex.
undirected	Logical scalar. Whether the graph is undirected or not.

Details

when undirected=TRUE, the degree of each node always even. So if k=3, then the degree will be 2.

Value

A sparse matrix of class [dgMatrix](#) of size $n \times n$.

References

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of “small-world” networks. *Nature*, 393(6684), 440–2. <http://doi.org/10.1038/30918>

See Also

Other simulation functions: [permute_graph](#), [rdiffnet](#), [rewire_graph](#), [rgraph_ba](#), [rgraph_er](#), [rgraph_ws](#)

round_to_seq	<i>Takes a numeric vector and maps it into a finite length sequence</i>
--------------	-------------------------------------------------------------------------

Description

Takes a numeric vector and maps it into a finite length sequence

Usage

```
round_to_seq(x, nlevels = 20, as_factor = FALSE)
```

Arguments

x	A numeric or integer vector.
nlevels	Integer scalar. Length of the sequence to be map onto.
as_factor	Logical scalar. When TRUE the resulting vector is factor.

Value

A vector of length `length(x)` with values mapped to a sequence with `nlevels` unique values

See Also

Used in [diffmap](#) and [plot_diffnet2](#)

Examples

```
x <- rnorm(100)
w <- data.frame(as.integer(round_to_seq(x, as_factor = TRUE)),x)
plot(w,x)
```

select_egoalter	<i>Calculate the number of adoption changes between ego and alter.</i>
-----------------	------------------------------------------------------------------------

Description

This function calculates the 16 possible configurations between ego and alter over two time points in terms of their behavior and tie changes. From time one to time two, given a binary state of behavior, ego and alter can be related in 16 different ways. The function `adopt_changes` is just an alias for `select_egoalter`.

Usage

```
select_egoalter(graph, adopt, period = NULL)

adopt_changes(graph, adopt, period = NULL)

## S3 method for class 'diffnet_adoptChanges'
summary(object, ...)
```

Arguments

graph	A dynamic graph (see netdiffuseR-graphs).
adopt	$n \times T$ matrix. Cumulative adoption matrix obtained from <code>toa_mat</code> .
period	Integer scalar. Optional to make the count for a particular period of time.
object	An object of class <code>diffnet_adoptChanges</code> .
...	Ignored.

Details

The 16 possibilities are summarized in this matrix:

				Alter			
				$t - 1$	No	Yes	Yes
Ego	$t - 1$	t	No	Yes	No	Yes	
	No	No	1	2	9	10	
		Yes	3	4	11	12	
	Yes	No	5	6	13	14	
	Yes	7	8	15	16		

The first two Yes/No columns represent Ego's adoption of the innovation in $t - 1$ and t ; while the first two Yes/No rows represent Alter's adoption of the innovation in $t - 1$ and t respectively. So for example, number 4 means that while neither of the two had adopted the innovation in $t - 1$, both have in t . At the same time, number 12 means that ego adopted the innovation in t , but alter had already adopted in $t - 1$ (so it has it in both, t and $t - 1$).

Value

An object of class `diffnet_adoptChanges` and `data.frame` with $n \times (T - 1)$ rows and $2 + 16 \times 3$ columns. The column names are:

<code>time</code>	Integer representing the time period
<code>id</code>	Node id
<code>select_a_01, . . . , select_a_16</code>	Number of new links classified between categories 1 to 16.
<code>select_d_01, . . . , select_d_16</code>	Number of remove links classified between categories 1 to 16.
<code>select_s_01, . . . , select_s_16</code>	Number of unchanged links classified between categories 1 to 16.

Author(s)

George G. Vega Yon & Thomas W. Valente

References

Thomas W. Valente, Stephanie R. Dyal, Kar-Hai Chu, Heather Wipfli, Kayo Fujimoto, *Diffusion of innovations theory applied to global tobacco control treaty ratification*, *Social Science & Medicine*, Volume 145, November 2015, Pages 89-97, ISSN 0277-9536 (<http://dx.doi.org/10.1016/j.socscimed.2015.10.001>)

Examples

```
# Simple example -----
set.seed(1312)
dn <- rdifffnet(20, 5, seed.graph="small-world")

ans <- adopt_changes(dn)
str(ans)
summary(ans)
```

struct_equiv	<i>Structural Equivalence</i>
--------------	-------------------------------

Description

Computes structural equivalence between ego and alter in a network

Usage

```
struct_equiv(graph, v = 1, inf.replace = 0, groupvar = NULL, ...)

## S3 method for class 'diffnet_se'
print(x, ...)
```

Arguments

graph	Any class of accepted graph format (see netdiffuseR-graphs).
v	Numeric scalar. Cohesion constant (see details).
inf.replace	Deprecated.
groupvar	Either a character scalar (if graph is diffnet), or a vector of size n .
...	Further arguments to be passed to approx_geodesic (not valid for the print method).
x	A <code>diffnet_se</code> class object.

Details

Structure equivalence is computed as presented in Valente (1995), and Burt (1987), in particular

$$SE_{ij} = \frac{(dmax_i - d_{ji})^v}{\sum_{k \neq i}^n (dmax_i - d_{ki})^v}$$

with the summation over $k \neq i$, and d_{ji} , Euclidian distance in terms of geodesics, is defined as

$$d_{ji} = \left[(z_{ji} - z_{ij})^2 + \sum_k^n (z_{jk} - z_{ik})^2 + \sum_k^n (z_{ki} - z_{kj})^2 \right]^{\frac{1}{2}}$$

with z_{ij} as the geodesic (shortest path) from i to j , and $dmax_i$ equal to largest Euclidean distance between i and any other vertex in the network. All summations are made over $k \notin \{i, j\}$

Here, the value of v is interpreted as cohesion level. The higher its value, the higher will be the influence that the closest alters will have over ego (see Burt's paper in the reference).

Structural equivalence can be computed either for the entire graph or by groups of vertices. When, for example, the user knows before hand that the vertices are distributed across separated communities, he can make this explicit to the function and provide a `groupvar` variable that accounts for this. Hence, when `groupvar` is not NULL the algorithm will compute structural equivalence within communities as marked by `groupvar`.

Value

If graph is a static graph, a list with the following elements:

SE	Matrix of size $n \times n$ with Structural equivalence
d	Matrix of size $n \times n$ Euclidean distances
gdist	Matrix of size $n \times n$ Normalized geodesic distance

In the case of dynamic graph, is a list of size `t` in which each element contains a list as described before. When `groupvar` is specified, the resulting matrices will be of class `dgCMatrix`, otherwise will be of class `matrix`.

Author(s)

George G. Vega Yon & Thomas W. Valente

References

- Burt, R. S. (1987). "Social Contagion and Innovation: Cohesion versus Structural Equivalence". *American Journal of Sociology*, 92(6), 1287–1335. <http://doi.org/10.1086/228667>
- Valente, T. W. (1995). "Network models of the diffusion of innovations" (2nd ed.). Cresskill N.J.: Hampton Press.

See Also

Other statistics: [bass](#), [classify_adopters](#), [cumulative_adopt_count](#), [dgr](#), [ego_variance](#), [exposure](#), [hazard_rate](#), [infection](#), [moran](#), [threshold](#), [vertex_covariate_dist](#)

Examples

```
# Computing structural equivalence for the fakedata -----
data(fakesurvey)

# Coercing it into a diffnet object
fakediffnet <- survey_to_diffnet(
  fakesurvey, "id", c("net1", "net2", "net3"), "toa", "group"
)

# Computing structural equivalence without specifying group
se_all <- struct_equiv(fakediffnet)

# Notice that pairs of individuals from different communities have
# non-zero values
se_all
se_all[[1]]$SE

# ... Now specifying a groupvar
se_group <- struct_equiv(fakediffnet, groupvar="group")

# Notice that pairs of individuals from different communities have
# only zero values.
se_group
se_group[[1]]$SE
```

struct_test

Structure dependence test

Description

Test whether or not a network estimates can be considered structurally dependent, i.e. a function of the network structure. By rewiring the graph and calculating a particular statistic t , the test compares the observed mean of t against the empirical distribution of it obtained from rewiring the network.

Usage

```

n_rewires(graph, p = c(20L, rep(0.1, nslices(graph) - 1)))

struct_test(graph, statistic, R, rewire.args = list(), ...)

## S3 method for class 'diffnet_struct_test'
c(..., recursive = FALSE)

## S3 method for class 'diffnet_struct_test'
print(x, ...)

## S3 method for class 'diffnet_struct_test'
hist(x,
      main = "Empirical Distribution of Statistic", xlab = expression(Values ~
        of ~ t), breaks = 20, annotated = TRUE, b0 = expression(atop(plain(""))
        %up% plain("")), t[0]), b = expression(atop(plain("")) %up% plain("")),
        t[]), ask = TRUE, ...)

struct_test_asymp(graph, Y, statistic_name = "distance", p = 2, ...)

```

Arguments

graph	A diffnet graph.
p	Either a Numeric scalar or vector of length <code>nslices(graph)-1</code> with the number of rewires per links.
statistic	A function that returns either a scalar or a vector.
R	Integer scalar. Number of repetitions.
rewire.args	List. Arguments to be passed to rewire_graph
...	Further arguments passed to the method (see details).
recursive	Ignored
x	A <code>diffnet_struct_test</code> class object.
main	Character scalar. Title of the histogram.
xlab	Character scalar. x-axis label.
breaks	Passed to hist .
annotated	Logical scalar. When TRUE marks the observed data average and the simulated data average.
b0	Character scalar. When <code>annotated=TRUE</code> , label for the value of <code>b0</code> .
b	Character scalar. When <code>annotated=TRUE</code> , label for the value of <code>b</code> .
ask	Logical scalar. When TRUE, asks the user to type <Enter> to see each plot (as many as statistics where computed).
Y	Numeric vector of length n .
statistic_name	Character scalar. Name of the metric to compute. Currently this can be either "distance", ">", "<", "=", ">=", or "<=".

Details

struct_test computes the test by generating the null distribution using Monte Carlo simulations (rewiring). struct_test_asymp computes the test using an asymptotic approximation. While available, we do not recommend using the asymptotic approximation since it has not shown good results when compared to the MC approximation. Furthermore, the asymptotic version has only been implemented for graph as static graph.

The output from the hist method is the same as [hist.default](#).

struct_test is a wrapper for the function `boot` from the `boot` package. Instead of resampling data-vertices or edges—in each iteration the function rewires the original graph using `rewire_graph` and applies the function defined by the user in `statistic`.

The default values to `rewire_graph` via `rewire.args` are:

<code>p</code>	Number or Integer with default <code>n_rewires(graph)</code> .
<code>undirected</code>	Logical scalar with default <code>getOption("diffnet.undirected", FALSE)</code> .
<code>copy.first</code>	Logical scalar with <code>TRUE</code> .
<code>algorithm</code>	Character scalar with default <code>"swap"</code> .

In `struct_test ...` are passed to `boot`, otherwise are passed to the corresponding method (`hist` for instance).

From the `print` method, p-value for the null of the statistic been equal between graph and its rewired versions is computed as follows

$$p(\tau) = 2 \times \min(\Pr(t \leq \tau), \Pr(t \geq \tau))$$

Where $\Pr\{\cdot\}$ is approximated using the Empirical Distribution Function retrieved from the simulations.

For the case of the asymptotic approximation, under the null we have

$$\sqrt{n} \left(\hat{\beta}(Y, G) - \mu_{\beta} \right) \sim^d \mathbf{N} \left(0, \sigma_{\beta}^2 \right)$$

The test is actually on development by Vega Yon and Valente. A copy of the working paper can be distributed upon request to g.vegayon@gmail.com.

The function `n_rewires` proposes a vector of number of rewirings that are performed in each iteration.

Value

A list of class `diffnet_struct_test` containing the following:

<code>graph</code>	The graph passed to <code>struct_test</code> .
<code>p.value</code>	The resulting p-value of the test (see details).
<code>t0</code>	The observed value of the statistic.
<code>mean_t</code>	The average value of the statistic applied to the simulated networks.
<code>R</code>	Number of simulations.

statistic The function `statistic` passed to `struct_test`.
boot A boot class object as return from the call to `boot`.
rewire.args The list `rewire.args` passed to `struct_test`.

Author(s)

George G. Vega Yon

References

Vega Yon, George G. and Valente, Thomas W. (On development).
 Davidson, R., & MacKinnon, J. G. (2004). *Econometric Theory and Methods*. New York: Oxford University Press.

See Also

Other Functions for inference: [bootnet](#), [moran](#)

Examples

```

# Creating a random graph
set.seed(881)
diffnet <- rdiffnet(100, 5, seed.graph="small-world")

# Testing structure-dependency of threshold
res <- struct_test(diffnet, function(g) mean(threshold(g), na.rm=TRUE), R=100)
res
hist(res)

# Adding a legend
legend("topright", bty="n",
  legend=c(
    expression(t[0]:~Baseline),
    expression(t:~Rewired~average)
  )
)

# Concatenating results
c(res, res)

# Running in parallel fashion
## Not run:
res <- struct_test(diffnet, function(g) mean(threshold(g), na.rm=TRUE), R=100,
  ncpus=4, parallel="multicore")
res
hist(res)

## End(Not run)

```

summary.diffnet *Summary of diffnet objects*

Description

Summary of diffnet objects

Usage

```
## S3 method for class 'diffnet'
summary(object, slices = NULL, no.print = FALSE,
        skip.moran = FALSE, valued = getOption("diffnet.valued", FALSE), ...)
```

Arguments

object	An object of class diffnet .
slices	Either an integer or character vector. While integer vectors are used as indexes, character vectors are used jointly with the time period labels.
no.print	Logical scalar. When TRUE suppress screen messages.
skip.moran	Logical scalar. When TRUE Moran's I is not reported (see details).
valued	Logical scalar. When TRUE weights will be considered. Otherwise non-zero values will be replaced by ones.
...	Further arguments to be passed to approx_geodesic .

Details

Moran's I is calculated over the cumulative adoption matrix using as weighting matrix the inverse of the geodesic distance matrix. All this via [moran](#). For each time period t , this is calculated as:

$$m = \text{moran}(C[, t], G^{(-1)})$$

Where $C[, t]$ is the t -th column of the cumulative adoption matrix, $G^{(-1)}$ is the element-wise inverse of the geodesic matrix at time t , and [moran](#) is **netdiffuseR**'s moran's I routine. When `skip.moran=TRUE` Moran's I is not reported. This can be useful for both: reducing computing time and saving memory as geodesic distance matrix can become large. Since version 1.18.0, geodesic matrices are approximated using [approx_geodesic](#) which, as a difference from [geodist](#) from the **sna** package, and [distances](#) from the **igraph** package returns a matrix of class `dgCMatrix` (more details in [approx_geodesic](#)).

Value

A data frame with the following columns:

adopt	Integer. Number of adopters at each time point.
cum_adopt	Integer. Number of cumulative adopters at each time point.

cum_adopt_pcent	Numeric. Proportion of cumulative adopters at each time point.
hazard	Numeric. Hazard rate at each time point.
density	Numeric. Density of the network at each time point.
moran_obs	Numeric. Observed Moran's I.
moran_exp	Numeric. Expected Moran's I.
moran_sd	Numeric. Standard error of Moran's I under the null.
moran_pval	Numeric. P-value for the observed Moran's I.

Author(s)

George G. Vega Yon

See Also

Other diffnet methods: [%*%](#), [as.array.diffnet](#), [c.diffnet](#), [diffnet-arithmetic](#), [diffnet-class](#), [diffnet_index](#), [plot.diffnet](#)

Examples

```
data(medInnovationsDiffNet)
summary(medInnovationsDiffNet)
```

survey_to_diffnet *Convert survey-like data and edgelist to a diffnet object*

Description

These convenient functions turn network nomination datasets and edgelist with vertex attributes datasets into diffnet objects. Both work as wrappers of [edgelist_to_adjmat](#) and [new_diffnet](#).

Usage

```
survey_to_diffnet(dat, idvar, netvars, toavar, groupvar = NULL,
  no.unsurveyed = TRUE, timevar = NULL, t = NULL,
  undirected = getOption("diffnet.undirected", FALSE),
  self = getOption("diffnet.self", FALSE),
  multiple = getOption("diffnet.multiple", FALSE), keep.isolates = TRUE,
  recode.ids = TRUE, warn.coercion = TRUE, ...)

edgelist_to_diffnet(edgelist, w = NULL, t0 = NULL, t1 = NULL, dat, idvar,
  toavar, timevar = NULL, undirected = getOption("diffnet.undirected",
  FALSE), self = getOption("diffnet.self", FALSE),
  multiple = getOption("diffnet.multiple", FALSE), fill.missing = NULL,
  keep.isolates = TRUE, recode.ids = TRUE, warn.coercion = TRUE)
```

Arguments

<code>dat</code>	A data frame.
<code>idvar</code>	Character scalar. Name of the id variable.
<code>netvars</code>	Character vector. Names of the network nomination variables.
<code>toavar</code>	Character scalar. Name of the time of adoption variable.
<code>groupvar</code>	Character scalar. Name of cohort variable (e.g. city).
<code>no.unsurveyed</code>	Logical scalar. When TRUE the nominated individuals that do not show in <code>idvar</code> are set to NA (see details).
<code>timevar</code>	Character scalar. In the case of longitudinal data, name of the time var.
<code>t</code>	Integer scalar. Repeat the network <code>t</code> times (if no <code>t0</code> , <code>t1</code> are provided).
<code>undirected</code>	Logical scalar. When TRUE only the lower triangle of the adjacency matrix will be considered (faster).
<code>self</code>	Logical scalar. When TRUE autolinks (loops, self edges) are allowed (see details).
<code>multiple</code>	Logical scalar. When TRUE allows multiple edges.
<code>keep.isolates</code>	Logical scalar. When FALSE, rows with NA/NULL values (isolated vertices unless have autolink) will be dropped (see details).
<code>recode.ids</code>	Logical scalar. When TRUE ids are recoded using as.factor (see details).
<code>warn.coercion</code>	Logical scalar. When TRUE warns coercion from numeric to integer.
<code>...</code>	Further arguments to be passed to new_diffnet .
<code>edgelist</code>	Two column matrix/data.frame in the form of ego -source- and alter -target- (see details).
<code>w</code>	Numeric vector. Strength of ties (optional).
<code>t0</code>	Integer vector. Starting time of the ties (optional).
<code>t1</code>	Integer vector. Finishing time of the ties (optional).
<code>fill.missing</code>	Character scalar. In the case of having unmatching ids between <code>dat</code> and <code>edgelist</code> , fills the data (see details).

Details

All of `netvars`, `toavar` and `groupvar` must be integers. Were these numeric they are coerced into integers, otherwise, when neither of both, the function returns with error. `idvar`, on the other hand, should only be integer when calling `survey_to_diffnet`, on the contrary, for `edgelist_to_diffnet`, `idvar` may be character.

In field work it is not unusual that some respondents nominate unsurveyed individuals. In such case, in order to exclude them from the analysis, the user can set `no.unsurveyed=TRUE` (the default), telling the function to exclude such individuals from the adjacency matrix. This is done by setting variables in `netvars` equal to NA when the nominated id can't be found in `idvar`.

If the network nomination process was done in different groups (location for example) the survey id numbers may be define uniquely within each group but not across groups (there may be many individuals with `id=1`, for example). To encompass this issue, the user can tell the function what variable can be used to distinguish between groups through the `groupvar` argument. When `groupvar` is provided, function redefines `idvar` and the variables in `netvars` as follows:

```
dat[[idvar]] <- dat[[idvar]] + dat[[groupvar]]*z
```

Where $z = 10^{\text{nchar}(\max(\text{dat}[[\text{idvar}]])}$.

For longitudinal data, it is assumed that the `toavar` holds the same information through time, this is, time-invariable. This as the package does not yet support variable times of adoption.

The `fill.missing` option can take any of these three values: "edgelist", "dat", or "both". This argument works as follows:

1. When `fill.missing="edgelist"` (or "both") the function will check which vertices show in `dat` but do not show in `edgelist`. If there is any, the function will include these in `edgelist` as ego to NA (so they have no link to anyone), and, if specified, will fill the `t0`, `t1` vectors with NAs for those cases. If `w` is also specified, the new vertices will be set to `min(w, na.rm=TRUE)`.
2. When `fill.missing="dat"` (or "both") the function checks which vertices show in `edgelist` but not in `dat`. If there is any, the function will include these in `dat` by adding one row per individual.

Value

A `diffnet` object.

Author(s)

Vega Yon

See Also

[fakesurvey](#), [fakesurveyDyn](#)

Other data management functions: [diffnet-class](#), [edgelist_to_adjmat](#), [egonet_attrs](#), [isolated](#)

Examples

```
# Loading a fake survey (data frame)
data(fakesurvey)

# Diffnet object keeping isolated vertices -----
dn1 <- survey_to_diffnet(fakesurvey, "id", c("net1", "net2", "net3"), "toa",
  "group", keep.isolates=TRUE)

# Diffnet object NOT keeping isolated vertices
dn2 <- survey_to_diffnet(fakesurvey, "id", c("net1", "net2", "net3"), "toa",
  "group", keep.isolates=FALSE)

# dn1 has an extra vertex than dn2
dn1
dn2

# Loading a longitudinal survey data (two waves) -----
data(fakesurveyDyn)

groupvar <- "group"
```

```

x <- survey_to_diffnet(
  fakesurveyDyn, "id", c("net1", "net2", "net3"), "toa", "group" ,
  timevar = "time", keep.isolates = TRUE, warn.coercion=FALSE)

plot_diffnet(x, vertex.label = rownames(x))

# Reproducing medInnovationsDiffNet object -----
data(medInnovations)

# What are the netvars
netvars <- names(medInnovations)[grepl("^net", names(medInnovations))]

medInnovationsDiffNet2 <- survey_to_diffnet(
  medInnovations,
  "id", netvars, "toa", "city",
  warn.coercion=FALSE)

medInnovationsDiffNet2

# Comparing with the package's version
all(diffnet.toa(medInnovationsDiffNet2) == diffnet.toa(medInnovationsDiffNet)) #TRUE
all(
  diffnet.attrs(medInnovationsDiffNet2, as.df = TRUE) ==
  diffnet.attrs(medInnovationsDiffNet, as.df = TRUE),
  na.rm=TRUE) #TRUE

```

threshold

Retrive threshold levels from the exposure matrix

Description

Thresholds are each vertexes exposure at the time of adoption. Substantively it is the proportion of adopters required for each ego to adopt. (see [exposure](#)).

Usage

```
threshold(obj, toa, t0 = min(toa, na.rm = TRUE), include_censored = FALSE,
  lags = 0L, ...)
```

Arguments

obj	Either a $n \times T$ matrix (eposure to the innovation obtained from exposure) or a diffnet object.
toa	Integer vector. Indicating the time of adoption of the innovation.
t0	Integer scalar. See toa_mat .
include_censored	Logical scalar. When TRUE (default), threshold

lags Integer scalar. Number of lags to consider when computing thresholds. lags=1 defines threshold as exposure at $T - 1$, where T is time of adoption. levels are not reported for observations adopting in the first time period.

... Further arguments to be passed to [exposure](#).

Details

By default exposure is not computed for vertices adopting at the first time period, `include_censored=FALSE`, as estimating threshold for left censored data may yield biased outcomes.

Value

A vector of size n indicating the threshold for each node.

Author(s)

George G. Vega Yon & Thomas W. Valente

See Also

Threshold can be visualized using [plot_threshold](#)

Other statistics: [bass](#), [classify_adopters](#), [cumulative_adopt_count](#), [dgr](#), [ego_variance](#), [exposure](#), [hazard_rate](#), [infection](#), [morán](#), [struct_equiv](#), [vertex_covariate_dist](#)

Examples

```
# Generating a random graph with random Times of Adoption
set.seed(783)
toa <- sample.int(4, 5, TRUE)
graph <- rgraph_er(n=5, t=max(toa) - min(toa) + 1)

# Computing exposure using Structural Equivalence
adopt <- toa_mat(toa)
se <- struct_equiv(graph)
se <- lapply(se, function(x) methods::as((x$SE)^(-1), "dgCMatrix"))
expo <- exposure(graph, adopt$cumadopt, alt.graph=se)

# Retrieving threshold
threshold(expo, toa)

# We can do the same by creating a diffnet object
diffnet <- as_diffnet(graph, toa)
threshold(diffnet, alt.graph=se)
```

`toa_diff`*Difference in Time of Adoption (TOA) between individuals*

Description

Creates $n \times n$ matrix indicating the difference in times of adoption between each pair of nodes

Usage

```
toa_diff(obj, t0 = NULL, labels = NULL)
```

Arguments

`obj` Either an integer vector of size n containing time of adoption of the innovation, or a `diffnet` object.

`t0` Integer scalar. Sets the lower bound of the time window (e.g. 1955).

`labels` Character vector of size n . Labels (ids) of the vertices.

Details

Each cell ij of the resulting matrix is calculated as $toa_j - toa_i$, so that whenever its positive it means that the j -th individual (alter) adopted the innovation sooner.

Value

An $n \times n$ symmetric matrix indicating the difference in times of adoption between each pair of nodes.

Author(s)

George G. Vega Yon & Thomas W. Valente

Examples

```
# Generating a random vector of time
set.seed(123)
times <- sample(2000:2005, 10, TRUE)

# Computing the TOA differences
toa_diff(times)
```

toa_mat	<i>Time of adoption matrix</i>
---------	--------------------------------

Description

Creates two matrices recording times of adoption of the innovation. One matrix records the time period of adoption for each node with zeros elsewhere. The second records the cumulative time of adoption such that there are ones for the time of adoption and every time period thereafter.

Usage

```
toa_mat(obj, labels = NULL, t0 = NULL, t1 = NULL)
```

Arguments

obj	Either an integer vector of size n containing time of adoption of the innovation, or a <code>diffnet</code> object.
labels	Character vector of size n . Labels (ids) of the vertices.
t0	Integer scalar. Sets the lower bound of the time window (e.g. 1955).
t1	Integer scalar. Sets the upper bound of the time window (e.g. 2000).

Details

In order to be able to work with time ranges other than $1, \dots, T$ the function receives as input the boundary labels of the time windows through the variables `t0` and `t1`. While by default the function assumes that the boundaries are given by the range of the `times` vector, the user can set a personalized time range exceeding the one given by the `times` vector. For instance, times of adoption may range between 2001 and 2005 but the actual data, the network, is observed between 2000 and 2005 (so there is not left censoring in the data), hence, the user could write:

```
adopmats <- toa_mat(times, t0=2000, t1=2005)
```

That way the resulting `cumadopt` and `adopt` matrices would have $2005 - 2000 + 1 = 6$ columns instead of $2005 - 2001 + 1 = 5$ columns, with the first column of the two matrices containing only zeros (as the first adoption happend after the year 2000).

Value

A list of two $n \times T$

<code>cumadopt</code>	has 1's for all years in which a node indicates having the innovation.
<code>adopt</code>	has 1's only for the year of adoption and 0 for the rest.

Author(s)

George G. Vega Yon & Thomas W. Valente

Examples

```
# Random set of times of adoptions
times <- sample(c(NA, 2001:2005), 10, TRUE)

toa_mat(times)

# Now, suppose that we observe the graph from 2000 to 2006
toa_mat(times, t0=2000, t1=2006)
```

transformGraphBy	<i>Apply a function to a graph considering non-diagonal structural zeros</i>
------------------	------------------------------------------------------------------------------

Description

When there are structural zeros given by groups, this function applies a particular transformation function of a graph by groups returning a square matrix of the same size of the original one with structural zeros and the function applied by INDICES.

Usage

```
transformGraphBy(graph, INDICES, fun = function(g, ...) g, ...)

## S3 method for class 'diffnet'
transformGraphBy(graph, INDICES, fun = function(g, ...) g,
  ...)

## S3 method for class 'dgCMatrix'
transformGraphBy(graph, INDICES, fun = function(g, ...) g,
  ...)
```

Arguments

graph	A graph
INDICES	A vector of length n .
fun	A function. This function must return a matrix of class <code>dgCMatrix</code> with the same dimension as <code>dim(g)</code> .
...	Further arguments passed to fun

Details

The transformation function fun must return a square matrix of size $m \times m$, where m is the size of the subgroup given by INDICES. See examples below

Examples

```

# Rewiring a graph by community -----

# Two Random graphs of different size
set.seed(123)
g0 <- rgraph_ba(m=2, self=FALSE)
g1 <- rgraph_ba(m=3, t=19, self=FALSE)

# Need a place to store both networks together!
G <- methods::new(
  Class = "dgCMatrix",
  Dim   = c(1L,1L)*(nnodes(g0) + nnodes(g1)),
  p     = rep(0L, (nnodes(g0) + nnodes(g1)) + 1L)
)

# Filling the matrix
G[1:nnodes(g0),1:nnodes(g0)] <- g0
G[(nnodes(g0) + 1):nnodes(G), (nnodes(g0) + 1):nnodes(G)] <- g1

# Creating an index (community)
indx <- c(rep(1, nnodes(g0)), rep(2, nnodes(g1)))

# Apply the rewiring algorithm per group
ans <- transformGraphBy(G, indx, function(g, ...) {
  rewire_graph(g, 100, "swap")
})

ans

```

vertex_covariate_compare

Comparisons at dyadic level

Description

Comparisons at dyadic level

Usage

```
vertex_covariate_compare(graph, X, funname)
```

Arguments

graph	A matrix of size $n \times n$ of class dgCMatrix.
X	A numeric vector of length n .
funname	Character scalar. Comparison to make (see details).

Details

This auxiliary function takes advantage of the sparseness of graph and applies a function in the form of $f_{unname}(x_i, x_j)$ only to (i, j) that have no empty entry. In other words, applies a compares elements of X only between vertices that have a link; making $nlinks(\text{graph})$ comparisons instead of looping through $n \times n$, which is much faster.

`funname` can take any of the following values: "distance", "^2" or "quaddistance", ">" or "greater", "<" or "smaller", ">=" or "greaterequal", "<=" or "smallerequal", "==" or "equal".

Value

A matrix `dgCMatrix` of size $n \times n$ with values in the form of $f_{unname}(x_i, x_j)$.

See Also

Other dyadic-level comparison functions: [matrix_compare](#), [vertex_covariate_dist](#)

Examples

```
# Basic example -----
set.seed(1313)
G <- rgraph_ws(10, 4, .2)
x <- rnorm(10)

vertex_covariate_compare(G, x, "distance")
vertex_covariate_compare(G, x, "^2")
vertex_covariate_compare(G, x, ">=")
vertex_covariate_compare(G, x, "<=")
```

`vertex_covariate_dist` *Computes covariate distance between connected vertices*

Description

Computes covariate distance between connected vertices

Usage

```
vertex_covariate_dist(graph, X, p = 2)
```

```
vertex_mahalanobis_dist(graph, X, S)
```

Arguments

<code>graph</code>	A square matrix of size n of class <code>dgCMatrix</code> .
<code>X</code>	A numeric matrix of size $n \times K$. Vertices attributes
<code>p</code>	Numeric scalar. Norm to compute
<code>S</code>	Square matrix of size <code>ncol(x)</code> . Usually the var-covar matrix.

Details

Faster than `dist`, these functions compute distance metrics between pairs of vertices that are connected (otherwise skip).

The function `vertex_covariate_dist` is the simil of `dist` and returns p-norms (Minkowski distance). It is implemented as follows (for each pair of vertices):

$$D_{ij} = \left(\sum_{k=1}^K |X_{ik} - X_{jk}|^p \right)^{1/p} \quad \text{if } graph_{i,j} \neq 0$$

In the case of mahalanobis distance, for each pair of vertex (i, j) , the distance is computed as follows:

$$D_{ij} = ((X_i - X_j) \times S \times (X_i - X_j)')^{1/2} \quad \text{if } graph_{i,j} \neq 0$$

Value

A matrix of size $n \times n$ of class `dgCMatrix`. Will be symmetric only if graph is symmetric.

Author(s)

George G. Vega Yon

References

Mahalanobis distance. (2016, September 27). In Wikipedia, The Free Encyclopedia. Retrieved 20:31, September 27, 2016, from https://en.wikipedia.org/w/index.php?title=Mahalanobis_distance&oldid=741488252

See Also

`mahalanobis` in the stats package.

Other statistics: `bass`, `classify_adopters`, `cumulative_adopt_count`, `dgr`, `ego_variance`, `exposure`, `hazard_rate`, `infection`, `moran`, `struct_equiv`, `threshold`

Other dyadic-level comparison functions: `matrix_compare`, `vertex_covariate_compare`

Examples

```
# Distance (aka p norm) -----
set.seed(123)
G <- rgraph_ws(20, 4, .1)
X <- matrix(runif(40), ncol=2)

vertex_covariate_dist(G, X)

# Mahalanobis distance -----
S <- var(X)

M <- vertex_mahalanobis_dist(G, X, S)
```

```

# Example with diffnet objects -----
data(medInnovationsDiffNet)
X <- cbind(
  medInnovationsDiffNet[["proage"]],
  medInnovationsDiffNet[["attend"]]
)

S <- var(X, na.rm=TRUE)
ans <- vertex_mahalanobis_dist(medInnovationsDiffNet, X, S)

```

weighted_var	<i>Computes weighted variance</i>
--------------	-----------------------------------

Description

Computes weighted variance

Usage

```
weighted_var(x, w)
```

```
wvar(x, w)
```

Arguments

`x` A numeric vector of length n .
`w` A numeric vector of length n .

Details

`weighted_variance` implements weighted variance computation in the following form:

$$\frac{\sum_i w'_i (x_i - \bar{x})^2}{(1 - n)}$$

where $w'_i = w_i / \sum_i w_i$, and $\bar{x} = \sum_i w'_i x_i$.

Value

Numeric scalar with the weighted variance.

See Also

This function is used in [diffmap](#).

%*% *Matrix multiplication*

Description

Matrix multiplication methods, including [diffnet](#) objects. This function creates a generic method for %*% allowing for multiplying diffnet objects.

Usage

```
x %*% y

## Default S3 method:
x %*% y

## S3 method for class 'diffnet'
x %*% y
```

Arguments

x Numeric or complex matrices or vectors, or diffnet objects.
y Numeric or complex matrices or vectors, or diffnet objects.

Details

This function can be useful to generate alternative graphs, for example, users could compute the n-steps graph by doing `net %*% net` (see examples).

Value

In the case of diffnet objects performs matrix multiplication via [mapply](#) using `x$graph` and `y$graph` as arguments, returning a diffnet. Otherwise returns the default according to %*%.

See Also

Other diffnet methods: [as.array.diffnet](#), [c.diffnet](#), [diffnet-arithmetic](#), [diffnet-class](#), [diffnet_index](#), [plot.diffnet](#), [summary.diffnet](#)

Examples

```
# Finding the Simmelian Ties network -----

# Random diffnet graph
set.seed(773)
net <- rdiffnet(100, 4, seed.graph='small-world', rgraph.args=list(k=8))
netsim <- net

# According to Dekker (2006), Simmelian ties can be computed as follows
```

%%*

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```
netsim <- net * t(net) # Keeping mutal
netsim <- netsim * (netsim %*% netsim)

# Checking out differences (netsim should have less)
nlinks(net)
nlinks(netsim)

mapply(`-`, nlinks(net), nlinks(netsim))
```

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