Package ‘CINNA’

April 7, 2022

Title Deciphering Central Informative Nodes in Network Analysis

Version 1.2.0

Date 2022-04-06

Description Functions for computing, comparing and demonstrating top informative centrality measures within a network <doi:10.1093/bioinformatics/bty819>.

License GPL-3

Encoding UTF-8

LazyData true

VignetteBuilder knitr

Suggests knitr, rmarkdown

Imports igraph, network, sna, centiserve, FactoMineR, factoextra, GGally, pheatmap, corrplot, dendextend, viridis, ggplot2, Rtsne, qdapTools, plyr, circlize, intergraph

RoxygenNote 7.1.1

NeedsCompilation no

Author Minoo Ashtiani [aut, cre], Mehdi Mirzaie [ctb], Mohieddin Jafari [ctb]

Maintainer Minoo Ashtiani <ashtiani.minoo@gmail.com>

Repository CRAN

Date/Publication 2022-04-07 15:12:31 UTC

R topics documented:

`calculate_centralities` *Centrality measure calculation*

Description

This function computes multitude centrality measures of an igraph object.

Usage

```
calculate_centralities(x, except = NULL, include = NULL, weights = NULL)
```

Arguments

`x`	the component of a network as an igraph object
`except`	A vector containing names of centrality measures which could be omitted from the calculations.
`include`	A vector including names of centrality measures which should be computed.
`weights`	A character scalar specifying the edge attribute to use.(default=NULL)

Details

This function calculates various types of centrality measures which are applicable to the network topology and returns the results as a list. In "except" argument, you can specify centrality measures which is not necessary to calculate.

Value

A list concluding centrality measure values in which the columns indicate centralities and the rows show the vertices.

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

Bonacich, P., & Lloyd, P. (2001). Eigenvector like measures of centrality for asymmetric relations. Social Networks, 23(3), 191–201.

Bonacich, P. (1972). Factoring and weighting approaches to status scores and clique identification. The Journal of Mathematical Sociology, 2(1), 113–120.

Bonacich, P. (1987). Power and Centrality: A Family of Measures. American Journal of Sociology, 92(5), 1170–1182.

Burt, R. S. (2004). Structural Holes and Good Ideas. American Journal of Sociology, 110(2), 349–399.

Batagelj, V., & Zaversnik, M. (2003). An O(m) Algorithm for Cores Decomposition of Networks, 1–9. Retrieved from

Seidman, S. B. (1983). Network structure and minimum degree. Social Networks, 5(3), 269–287.

Kleinberg, J. M. (1999). Authoritative sources in a hyperlinked environment. Journal of the ACM, 46(5), 604–632.

Wasserman, S., & Faust, K. (1994). Social network analysis : methods and applications. American Ethnologist (Vol. 24). Barrat, A., Barthélemy, M., Pastor Satorras, R., & Vespignani, A. (2004). The architecture of complex weighted networks. Proceedings of the National Academy of Sciences of the United States of America , 101(11), 3747–3752.

Brin, S., & Page, L. (2010). The Anatomy of a Large Scale Hypertextual Web Search Engine The Anatomy of a Search Engine. Search, 30(June 2000), 1–7.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. Social Networks, 1(3), 215–239.

Brandes, U. (2001). A faster algorithm for betweenness centrality*. The Journal of Mathematical Sociology, 25(2), 163–177.

Estrada E., Rodriguez-Velazquez J. A.: Subgraph centrality in Complex Networks. Physical Review E 71, 056103.

Freeman, L. C., Borgatti, S. P., & White, D. R. (1991). Centrality in valued graphs: A measure of betweenness based on network flow. Social Networks, 13(2), 141–154.

Brandes, U., & Erlebach, T. (Eds.). (2005). Network Analysis (Vol. 3418). Berlin, Heidelberg: Springer Berlin Heidelberg.

Stephenson, K., & Zelen, M. (1989). Rethinking centrality: Methods and examples. Social Networks, 11(1), 1–37.

Wasserman, S., & Faust, K. (1994). Social network analysis : methods and applications. American Ethnologist (Vol. 24).

Brandes, U. (2008). On variants of shortest path betweenness centrality and their generic computation. Social Networks, 30(2), 136–145.

Goh, K.-I., Kahng, B., & Kim, D. (2001). Universal Behavior of Load Distribution in Scale Free Networks. Physical Review Letters, 87(27), 278701.

Shimbel, A. (1953). Structural parameters of communication networks. The Bulletin of Mathematical Biophysics, 15(4), 501–507.

Assenov, Y., Ramrez, F., Schelhorn, S.-E., Lengauer, T., & Albrecht, M. (2008). Computing topological parameters of biological networks. Bioinformatics, 24(2), 282–284.

Diekert, V., & Durand, B. (Eds.). (2005). STACS 2005 (Vol. 3404). Berlin, Heidelberg: Springer Berlin Heidelberg.

Gräßler, J., Koschützki, D., & Schreiber, F. (2012). CentiLib: comprehensive analysis and exploration of network centralities. Bioinformatics (Oxford, England), 28(8), 1178–9.

Latora, V., & Marchiori, M. (2001). Efficient Behavior of Small World Networks. Physical Review Letters, 87(19), 198701.

Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. Social Networks, 32(3), 245–251.

Estrada, E., Higham, D. J., & Hatano, N. (2009). Communicability betweenness in complex networks. Physica A: Statistical Mechanics and Its Applications, 388(5), 764–774.

Hagberg, Aric, Pieter Swart, and Daniel S Chult. Exploring network structure, dynamics, and function using NetworkX. No. LA-UR-08-05495; LA-UR-08-5495. Los Alamos National Laboratory (LANL), 2008.

Kalinka, A. T., & Tomancak, P. (2011). linkcomm: an R package for the generation, visualization, and analysis of link communities in networks of arbitrary size and type. Bioinformatics, 27(14), 2011–2012.

Faghani, M. R., & Nguyen, U. T. (2013). A Study of XSS Worm Propagation and Detection Mechanisms in Online Social Networks. IEEE Transactions on Information Forensics and Security, 8(11), 1815–1826.

Brandes, U., & Erlebach, T. (Eds.). (2005). Network Analysis (Vol. 3418). Berlin, Heidelberg: Springer Berlin Heidelberg.

Lin, C.-Y., Chin, C.-H., Wu, H.-H., Chen, S.-H., Ho, C.-W., & Ko, M.-T. (2008). Hubba: hub objects analyzer–a framework of interactome hubs identification for network biology. Nucleic Acids Research, 36(Web Server), W438–W443.

Chin, C., Chen, S., & Wu, H. (2009). cyto Hubba: A Cytoscape Plug in for Hub Object Analysis in Network Biology. Genome Informatics . . . , 5(Java 5), 2–3.

Qi, X., Fuller, E., Wu, Q., Wu, Y., & Zhang, C.-Q. (2012). Laplacian centrality: A new centrality measure for weighted networks. Information Sciences, 194, 240–253.

Joyce, K. E., Laurienti, P. J., Burdette, J. H., & Hayasaka, S. (2010). A New Measure of Centrality for Brain Networks. PLoS ONE, 5(8), e12200.

Lin, C.-Y., Chin, C.-H., Wu, H.-H., Chen, S.-H., Ho, C.-W., & Ko, M.-T. (2008). Hubba: hub objects analyzer–a framework of interactome hubs identification for network biology. Nucleic Acids Research, 36(Web Server), W438–W443.

Hubbell, C. H. (1965). An Input Output Approach to Clique Identification. Sociometry, 28(4), 377.

Dangalchev, C. (2006). Residual closeness in networks. Physica A: Statistical Mechanics and Its Applications, 365(2), 556–564.

Brandes, U. & Erlebach, T. (2005). Network Analysis: Methodological Foundations, U.S. Government Printing Office.

Korn, A., Schubert, A., & Telcs, A. (2009). Lobby index in networks. Physica A: Statistical Mechanics and Its Applications, 388(11), 2221–2226.

White, S., & Smyth, P. (2003). Algorithms for estimating relative importance in networks. In Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining KDD '03 (p. 266). New York, New York, USA: ACM Press.

Cornish, A. J., & Markowetz, F. (2014). SANTA: Quantifying the Functional Content of Molecular Networks. PLoS Computational Biology, 10(9), e1003808.

Scardoni, G., Petterlini, M., & Laudanna, C. (2009). Analyzing biological network parameters with CentiScaPe. Bioinformatics, 25(21), 2857–2859.

Lin, N. (1976). Foundations of Social Research. Mcgraw Hill.

Borgatti, S. P., & Everett, M. G. (2006). A Graph theoretic perspective on centrality. Social Networks, 28(4), 466–484.

Newman, M. (2010). Networks. Oxford University Press.

Junker, Bjorn H., Dirk Koschutzki, and Falk Schreiber(2006). "Exploration of biological network centralities with CentiBiN." BMC bioinformatics 7.1 : 219.

Pal, S. K., Kundu, S., & Murthy, C. A. (2014). Centrality measures, upper bound, and influence maximization in large scale directed social networks. Fundamenta Informaticae, 130(3), 317–342.

Lin, C.-Y., Chin, C.-H., Wu, H.-H., Chen, S.-H., Ho, C.-W., & Ko, M.-T. (2008). Hubba: hub objects analyzer–a framework of interactome hubs identification for network biology. Nucleic Acids Research, 36(Web Server), W438–W443.

Scardoni, G., Petterlini, M., & Laudanna, C. (2009). Analyzing biological network parameters with CentiScaPe. Bioinformatics, 25(21), 2857–2859.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. Social Networks, 1(3), 215–239.

Chen, D.-B., Gao, H., L?, L., & Zhou, T. (2013). Identifying Influential Nodes in Large Scale Directed Networks: The Role of Clustering. PLoS ONE, 8(10), e77455.

Jana Hurajova, S. G. and T. M. (2014). Decay Centrality. In 15th Conference of Kosice Mathematicians. Herlany.

Viswanath, M. (2009). ONTOLOGY BASED AUTOMATIC TEXT SUMMARIZATION. Vishweshwaraiah Institute of Technology.

Przulj, N., Wigle, D. A., & Jurisica, I. (2004). Functional topology in a network of protein interactions. Bioinformatics, 20(3), 340–348.

del Rio, G., Koschtzki, D., & Coello, G. (2009). How to identify essential genes from molecular networks BMC Systems Biology, 3(1), 102.

Scardoni, G. and Carlo Laudanna, C.B.M.C., 2011. Network centralities for Cytoscape. University of Verona.

BOLDI, P. & VIGNA, S. 2014. Axioms for centrality. Internet Mathematics, 00-00.

MARCHIORI, M. & LATORA, V. 2000. Harmony in the small-world. Physica A: Statistical Mechanics and its Applications, 285, 539-546.

OPSAHL, T., AGNEESSENS, F. & SKVORETZ, J. 2010. Node centrality in weighted networks: Generalizing degree and shortest paths. Social Networks, 32, 245-251.

OPSAHL, T. 2010. Closeness centrality in networks with disconnected components (http://toreopsahl.com/2010/03/20/closen
centrality-in-networks-with-disconnected-components/)

Michalak, T.P., Aadithya, K.V., Szczepanski, P.L., Ravindran, B. and Jennings, N.R., 2013. Efficient computation of the Shapley value for game-theoretic network centrality. Journal of Artificial Intelligence Research, 46, pp.607-650.

Macker, J.P., 2016, November. An improved local bridging centrality model for distributed network analytics. In Military Communications Conference, MILCOM 2016-2016 IEEE (pp. 600-605). IEEE. DOI: 10.1109/MILCOM.2016.7795393

DANGALCHEV, C. 2006. Residual closeness in networks. Physica A: Statistical Mechanics and its Applications, 365, 556-564. DOI: 10.1016/j.physa.2005.12.020

Alain Barrat, Marc Barthelemy, Romualdo Pastor-Satorras, Alessandro Vespignani: The architecture of complex weighted networks, Proc. Natl. Acad. Sci. USA 101, 3747 (2004)

See Also

`alpha.centrality`, `bonpow`, `constraint`, `centr_degree`, `eccentricity`, `eigen_centrality`, `coreness`, `authority_score`, `hub_score`, `transitivity`, `page_rank`, `betweenness`, `subgraph.centrality`, `flowbet`, `infocent`, `loadcent`, `stresscent`, `graphcent`, `topocoefficient`, `closeness.currentflow`, `closeness.latora`, `communibet`, `communitycent`, `crossclique`, `entropy`, `epc`, `laplacian`, `leverage`, `mnc`, `hubbell`, `semilocal`, `closeness.vitality`, `closeness.residual`, `lobby`, `markovcent`, `radiality`, `lincent`, `geokpath`, `katzcent`, `diffusion.degree`, `dmnc`, `centroid`, `closeness.freeman`, `clusterrank`, `decay`, `barycenter`, `bottleneck`, `averagedis`, `local_bridging_centrality`, `wiener_index_centrali`
`group_centrality`, `dangalchev_closeness_centrality`, `harmonic_centrality`, `strength`

Examples

```
data("zachary")
```

```
p <- proper_centralities(zachary)
calculate_centralities(zachary, include = "Degree Centrality")
```

---

cortex *Macaque Visual Cortex Network*

Description

A graph describing the macaque visual cortex network. Nodes are neocortical areas, 25 of them are participated in visual function in the macaque, and 7 of which are associated with them

Usage

```
data("cortex")
```

Format

an igraph object with "gml" format

References

D.J. Felleman and D.C. van Essen, "Distributed hierarchical processing in the primate cerebral cortex." Cerebral Cortex 1(1), 1-47 (1991).

Examples

```
data("cortex")
print(cortex)
```

---

dangalchev_closeness_centrality
Dangalchev Closeness Centrality

Description

This function computes Dangalchev Closeness Centrality. This can be access by computing a network resistance. More specifically, it measures the closeness by removing nodes and edges. The evalauation of this measure of closeness will be easier and this can be useful for unconnected graphs too.

Usage

```
dangalchev_closeness_centrality(
  x,
  vids = V(x),
  mode = c("all", "out", "in"),
  weights = NULL
)
```

Arguments

x	An igraph or a network object
vids	Nodes to be considered in the calculation
mode	A Character value, indicating whether the shortest paths "in" or "out" of the nodes in the directed graphs should be considered. For undirected graphs we use "all".
weights	Numeric vector indicating weights of the edges

Value

a vector including centrality values for each node

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

DANGALCHEV, C. 2006. Residual closeness in networks. Physica A: Statistical Mechanics and its Applications, 365, 556-564. DOI: 10.1016/j.physa.2005.12.020

See Also

closeness.residual

Examples

```
data(zachary)

dangalchev_closeness_centrality(zachary)
```

---

drugTarget *Drug Target Network*

Description

A bipartite graph extracted from DrugBank 1.0 database. The network includes two set of nodes including Food and Drug Administration (FDA)-approved drugs and their corresponding protein targets designated by their Uniprot ID. The 1080 drugs and their 519 target proteins nodes are connected via 3766 interactions. Please note that it is a shrunken network in which metabolizing enzymes, carriers and transporters associated with drug metabolism are filtered and solely targets directly related to their pharmacological effects are included. It is also an example of unconnected graphs.

Usage

```
drugTarget
```

Format

an igraph object with "gml" format

References

Barneh, F., Jafari, M., & Mirzaie, M. (2015). Updates on drug–target network; facilitating polypharmacology and data integration by growth of DrugBank database. Briefings in Bioinformatics, bbv094. https://doi.org/10.1093/bib/bbv094

Examples

```
data("drugTarget")
print(drugTarget)
```

`giant_component_extract`

Giant component extraction of a graph

Description

This function extracts the largest connected or the giant component of the input graph which can be an "igraph" object or a "network" object and convert them as "igraph" objects. For the bipartite graph, this will apply projection before extracting the components.

Usage

```
giant_component_extract(
  x,
  directed = TRUE,
  bipartite_proj = FALSE,
  num_proj = 1
)
```

Arguments

`x`	An igraph or a network object
`directed`	Whether to create a directed graph(default=TRUE)
`bipartite_proj`	Whether the bipartite network must be projected or not(default=FALSE)
`num_proj`	A number which shows the number of projects especifically for bipartite graphs.(default=1)

Details

This function distinguishes the largest component of an "igraph" or a "network" object and illustrates them as a list which contains the edgelist of the giant component. If the input graph was bipartite and the "bipartite_proj" was TRUE, it will projet it and you can decide to which project you want to continue to work with that.

Value

a list contatining the giant componet of the input graph. The first element is an igraph object and the second is the edgelist of that.

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

Newman, M. (2010). Networks. Oxford University Press.

See Also

induced.subgraph,clusters

Examples

```
# a graph with 4 vertices

data(zachary)
giant_component_extract(zachary)
```

---

graph_extract_components

Component extraction of a graph

Description

This function extracts all connected components of the input which can be an "igraph" object or a "network" object and convert them as "igraph" objects.

Usage

```
graph_extract_components(
  x,
  directed = TRUE,
  bipartite_proj = FALSE,
  num_proj = 1
)
```

Arguments

x	An igraph or a network object
directed	Whether to create a directed graph(default=TRUE)
bipartite_proj	Whether the bipartite network must be projected or not(default=FALSE)
num_proj	Numbers 1 or 2 which shows the number of projects for bipartite graphs.(default=1)

Details

This function seperates different components of an "igraph" or a "network" object and illustrates them as a list of independent graphs. If the input graph was bipartite and the "bipartite_proj" was TRUE, it will project it and you can decide in which project you want to continue to work with.

Value

a list including the components of the input as igraph objects

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

See Also

induced.subgraph,components

Examples

```
data(zachary)

graph_extract_components(zachary)
```

---

group_centrality *Group Centrality*

Description

This function computes group Centrality. So, it considers a consistent ranking of each node to be calculated such that scores diverse possible synergies among possible groups of vertices.

Usage

```
group_centrality(x, vids = V(x))
```

Arguments

`x`	An igraph or a network object
`vids`	Nodes to be considered in the calculation

Value

a vector including centrality values for each node

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

Michalak, T.P., Aadithya, K.V., Szczepanski, P.L., Ravindran, B. and Jennings, N.R., 2013. Efficient computation of the Shapley value for game-theoretic network centrality. Journal of Artificial Intelligence Research, 46, pp.607-650.

https://www.civilica.com/Paper-IBIS07-IBIS07_127.html

Examples

```
data(zachary)

group_centrality(zachary)
```

`harmonic_centrality` *Harmonic Centrality*

Description

This function computes Harmonic Centrality. The harmonic metric defines as the denormalized reciprocal of the harmonic mean of all distances.

Usage

```
harmonic_centrality(
  x,
  vids = V(x),
  mode = c("all", "out", "in"),
  weights = NULL
)
```

Arguments

`x`	An igraph or a network object
`vids`	Nodes to be considered in the calculation
`mode`	a character value, "out" for out-degree, "in" for in-degree or "total" for the sum of the two. For undirected graphs this argument is ignored. "all" is a synonym of "total".
`weights`	Numeric vector indicating weights of the edges

Value

a vector including centrality values for each node

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

BOLDI, P. & VIGNA, S. 2014. Axioms for centrality. Internet Mathematics, 00-00.

MARCHIORI, M. & LATORA, V. 2000. Harmony in the small-world. Physica A: Statistical Mechanics and its Applications, 285, 539-546.

OPSAHL, T., AGNEESSENS, F. & SKVORETZ, J. 2010. Node centrality in weighted networks: Generalizing degree and shortest paths. Social Networks, 32, 245-251.

OPSAHL, T. 2010. Closeness centrality in networks with disconnected components (http://toreopsahl.com/2010/03/20/closer centrality-in-networks-with-disconnected-components/)

Examples

```
data(zachary)

harmonic_centrality(zachary)
```

`kangaroo` *Kangaroo Network*

Description

An undirected graph based on interactions between free-ranging grey kangaroos. A node displays a kangaroo and an edge between two kangaroos demonstrates an interaction. The weights indicate the total count of interactions.

Usage

```
kangaroo
```

Format

an igraph object with "gml" format

References

Kangaroo network dataset – KONECT, October 2016.

TR Grant. Dominance and association among members of a captive and a free-ranging group of grey kangaroos (Macropus giganteus). Animal Behaviour, 21(3):449–456, 1973.

Examples

```
data("kangaroo")
print(kangaroo)
```

---

local_bridging_centrality

Local Bridging Centrality

Description

This function computes Local Bridging Centrality. This classifies nodes regarding their structural links among the dense components.

Usage

```
local_bridging_centrality(x, vids = V(x))
```

Arguments

`x`	An igraph or a network object
`vids`	Nodes to be considered in the calculation

Value

a vector including centrality values for each node

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

Macker, J.P., 2016, November. An improved local bridging centrality model for distributed network analytics. In Military Communications Conference, MILCOM 2016-2016 IEEE (pp. 600-605). IEEE. DOI: 10.1109/MILCOM.2016.7795393

See Also

betweenness

Examples

```
data(zachary)

local_bridging_centrality(zachary)
```

---

misc_extract_components

Component extraction of miscellaneous graph formats

Description

This function extracts all components of the input with various formats and convert them as "igraph" objects.

Usage

```
misc_extract_components(
  x,
  directed = TRUE,
  mode = "directed",
  weighted = NULL,
  unibipartite = FALSE,
  diag = TRUE
)
```

Arguments

x	The input could be an edgelist and an adjacency matrix
directed	Whether to create a directed graph.(default=TRUE)
mode	Character scalar, explain how should demonstrate the supplied matrix. Possible values are: directed, undirected, upper, lower, max, min, plus.(default="directed")
weighted	An argument for specifying whether the graph should be weighted or not. If it is NULL then an unweighted graph is created.(default=NULL)
unibipartite	A boolean parameter describing whether the input edge list is corresponding to a bipartite graph. TRUE value specifies the biprtite graph and vice versa.(default=FALSE)
diag	Logical scalar, whether to consider the diagonal of the matrix or not. If it was FALSE then the diagonal spotted as zeros.(default=TRUE)

Details

This function assert components of the input object which can be an edgelist, an adjacency matrix and a graphNEL object. The result would be a list including components as seperated graphs.

Value

a list including the components of the input graph as igraph objects

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

See Also

induced.subgraph,components, graph_from_adjacency_matrix

---

pca_centralities *Ranking centrality measure based on contributions*

Description

This function demonstrates ranks of centrality measures in order of information levels.

Usage

```
pca_centralities(
  x,
  scale.unit = TRUE,
  cut.off = 80,
  ncp = 5,
  graph = FALSE,
  axes = c(1, 2)
)
```

Arguments

x	a list containg the computed centrality values
scale.unit	a boolean constant, whether data should be scaled to unit variance(default=TRUE)
cut.off	The intensity that must be exceeded in cumulative percentage of variance of eigen values.(default=80)
ncp	number of dimensions in final results (default=5)
graph	a boolean constant, whether the graph shoul be displayed
axes	a length 2 vector describing the number of components to plot(default=c(1,2))

Details

This function represents centralities in the ranking list based on variable contribution to make principal components. PCA is a method for drawing out important variables from a data set. It helps user to reduced the dimensions in high dimensional data. It is more common to use for more than 3 dimensional datasets.

Value

a plot illustrating significant centralities in the order of contribution

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

Husson, F., Lê, S., & Pagès, J. (2010). Exploratory Multivariate Analysis by Example using R. Chapman & Hall/CRC Computer Science & Data Analysis, 40(April), 240.

http://www.sthda.com/english/

See Also

PCA

---

print_calculate_centralities

Print computed centrality measures results into a file

Description

This function prints all centrality measure results into a file

Usage

```
print_calculate_centralities(x, file = NULL)
```

Arguments

x	a list containing the centrality measure values
file	A character string naming the .pdf file to print into. If NULL the result would be printed to the exist directory.(default=NULL)

Value

Print out calculate_centralitiesfunction will be saved in the given directory.

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

`print_visualize_association` *Print pairwise association plot among centrality measures into a file*

Description

This function prints regression plot between pair of centrality measures

Usage

```
print_visualize_association(x, y, scale = TRUE, file = NULL)
```

Arguments

`x`	a vector containing a centrality values as independent variable
`y`	a vector containing a centrality values as dependent variable
`scale`	Whether the centrality values should be scaled or not(default=TRUE)
`file`	A character string naming the file to print into. If NULL the result would be printed to the exist directory(default=NULL)

Value

The resulted plot of `visualize_association`function will be saved in the given directory.

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

`print_visualize_correlations` *Print centrality correlation plot*

Description

This function prints a plot including all pairwise correlation between centrality measures

Usage

```
print_visualize_correlations(
  x,
  scale = TRUE,
  method = c("pearson", "kendall", "spearman"),
  file = NULL
)
```

Arguments

x	a list indicating calculated centrality measures which is the output of "calculate_centralities" function
scale	Whether the centrality values should be scaled or not(default=TRUE)
method	character string describing the type of correlation coefficient (or covariance) to be computed. The proper values are "pearson", "kendall", or "spearman". (default="pearson")
file	A character string naming the .pdf file to print into. If NULL the result would be printed to the exist directory.(default=NULL)

Value

The resulted plot of visualize_correlationsfunction will be saved in the given directory.#' @importFrom igraph alpha.centrality

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

---

print_visualize_dendrogram

Print dendrogram plot of a graph

Description

This function prints dendrogram plot of a graph based on predefined centrality measures.

Usage

```
print_visualize_dendrogram(
  x,
  centrality.type = "Degree Centrality",
  computed_centrality_value = NULL,
  k = 4,
  file = NULL
)
```

Arguments

x	an igraph object
centrality.type	The type of centrality which should be calculated(default="Degree Centrality")
computed_centrality_value	A vector containing the values of calculated centrality measure for each node(default=NULL)
k	number of clusters
file	A character string naming the .pdf file to print into. If NULL the result would be printed to the exist directory.(default=NULL)

Value

The resulted plot of `visualize_dendrogram`function will be saved in the given directory.#' @importFrom igraph alpha.centrality

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

---

print_visualize_graph *Print visualized based on centrality values graph*

Description

This function prints visualized based on centrality values graph.

Usage

```
print_visualize_graph(
  x,
  computed_centrality_value = NULL,
  centrality.type = "Degree Centrality",
  file = NULL
)
```

Arguments

`x` an igraph object

`computed_centrality_value`
A vector containing the values of calculated centrality measure for each node(default=NULL)

`centrality.type`
The type of centrality which should be calculated(default="Degree Centrality")

`file` A character string naming the .pdf file to print into. If NULL the result would be printed to the exist directory.(default=NULL)

Value

The resulted plot of `visualize_graph`function will be saved in the given directory.#' @importFrom igraph alpha.centrality

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

---

print_visualize_heatmap
Print the heatmap plot of centrality measures

Description

This function prints the heatmap plot

Usage

```
print_visualize_heatmap(x, scale = TRUE, file = NULL)
```

Arguments

x	a list indicating calculated centrality measures
scale	Whether the centrality values should be scaled or not(default=TRUE)
file	A character string naming the .pdf file to print into. If NULL the result would be printed to the exist directory.(default=NULL)

Value

The resulted plot of `visualize_heatmap`function will be saved in the given directory.

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

---

print_visualize_pair_correlation
Print pairwise correlation and histogram plots between two centrality measures

---

Description

This function prints pairwise correlation of centrality measures and histogram plot.

Usage

```
print_visualize_pair_correlation(x, y, scale = TRUE, file = NULL)
```

Arguments

x	a vector containing a centrality measure
y	a vector containing another centrality measure
scale	Whether the centrality values should be scaled or not(default=TRUE)
file	A character string naming the .pdf file to print into. If NULL the result would be printed to the exist directory.

Value

The resulted plot of `visualize_pair_correlation`function will be saved in the given directory.

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

`proper_centralities` *Proper centrality measure representation*

Description

This function indicates proper centrality measures of an igraph object based on the network topology

Usage

```
proper_centralities(x)
```

Arguments

`x`	an igraph object

Details

This function represents a list including the names of centrality measures which are applicable for the input graph based on the topology

Value

a list including the name of centrality measures which are suitable for the input graph

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

See Also

`calculate_centralities`

Examples

```
data("zachary")
proper_centralities(zachary)
```

`rhesus` *Moreno Rhesus Network*

Description

A directed graph including observed grooming episodes between free ranging rhesus macaques (Macaca mulatta) in Cayo Santiago during a two month period in 1963. Cayo Santiago is an island off the coast of Puerto Rico, which also is named as Isla de los monos (Island of the monkeys). A node indicates a monkey and a directed edge in which a rhesus macaque groomed another rhesus macaque. The weights of edges demonstrates how often this behaviour was seen.

Usage

```
rhesus
```

Format

an igraph object with "gml" format

References

Rhesus network dataset – KONECT, October 2016.

DS Sade. Sociometrics of macaca mulatta I. linkages and cliques in grooming matrices. Folia Primatologica, 18(3-4):196–223, 1972.

Examples

```
data("rhesus")
print(rhesus)
```

`summary_calculate_centralities` *Summarize centrality measure calculation results*

Description

This function computes minimum, first quater, median, mean, third qarter and maximum values of computed centrality measures.

Usage

```
summary_calculate_centralities(x)
```

Arguments

`x`	centrality measure calculation results

Value

a list concluding summary results for each centrality measure value

The result values of calculate_centralitiesfunction will be saved in the given directory.#' @importFrom igraph alpha.centrality

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

`summary_graph_extract_components`
Summarize component extraction of a graph

Description

This function summarizes all components of the input which can be an "igraph" object or a "network" object

Usage

```
summary_graph_extract_components(
  x,
  directed = TRUE,
  bipartite_proj = FALSE,
  num_proj = 1
)
```

Arguments

x	An igraph or a network object
directed	a boolean constant, Whether to create a directed graph(default=TRUE)
bipartite_proj	Whether the bipartite network must be projected or not(default=FALSE)
num_proj	A number which shows the number of projects especifically for bipartite graphs.(default=1)

Value

The result values of graph_extract_componentsfunction will be saved in the given directory.#' @importFrom igraph alpha.centrality

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

summary_pca_centralities *Summarize PCA result related to centrality measures*

Description

This function summarizes PCA result related to centrality measures.

Usage

```
summary_pca_centralities(x, scale.unit = TRUE, ncp = 5)
```

Arguments

x	a list containg the computed centrality values
scale.unit	a boolean constant, whether data should be scaled to unit variance(default=TRUE)
ncp	number of dimensions in final results (default=5)

Value

The result values of `pca_centralities`function will be saved in the given directory.#' @importFrom igraph alpha.centrality

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

summary_tsne_centralities *Summarize t-Distributed Stochastic Neighbor Embedding (t-SNE) on centrality measures*

Description

This function summarize tsne analysis results on centrality measures

Usage

```
summary_tsne_centralities(x, dims = 2, perplexity = 5, scale = TRUE)
```

Arguments

x	a list containg the computed cetrality values
dims	integer; number of the outpu dimensions(default=2)
perplexity	numeric; A flexible measure of the efficient number of neighbors. The performance of SNE is fairly robust to changes in the perplexity, and typical values are between 5 and 50.(default=5)
scale	Whether the centrality values should be scaled or not(default=TRUE)

Value

It resturns a list containing below values:

Y Matrix containing the new representations for the objects

costs The cost for every object after the final iteration

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

See Also

Rtsne

---

tsne_centralities *t-Distributed Stochastic Neighbor Embedding (t-SNE) on centrality measures*

Description

This function applies t-SNE, dimensionality reduction algorithm, on centrality measures.

Usage

```
tsne_centralities(x, dims = 2, perplexity = 5, scale = TRUE)
```

Arguments

x	a list containg the computed cetrality values
dims	integer; number of the outpu dimensions(default=2)
perplexity	numeric; A flexible measure of the efficient number of neighbors. The performance of SNE is fairly robust to changes in the perplexity, and typical values are between 5 and 50.(default=5)
scale	Whether the centrality values should be scaled or not(default=TRUE)

Details

t-SNE is a non-linear dimensionality reduction algorithm used for exploring high-dimensional data. Here, It maps multi-dimensional centrality measure data to less dimensions suitable to work with it.

Value

It resturns cost plot of tsne results which displays centralities in order of their corresponding costs.

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

van der Maaten, L. (2014). Accelerating t SNE using Tree Based Algorithms. Journal of Machine Learning Research, 15, 3221–3245. Van Der Maaten, L. J. P., & Hinton, G. E. (2008). Visualizing high dimensional data using t sne. Journal of Machine Learning Research, 9, 2579–2605.

See Also

`Rtsne`

`visualize_association` *Pairwise association plot between centrality measures*

Description

This function computes regression between pair of centrality measures to show more details of association among them.

Usage

```
visualize_association(x, y, scale = TRUE)
```

Arguments

`x`	a vector containing a centrality measure as independent variable
`y`	a vector containing a centrality measure as dependent variable
`scale`	Whether the centrality values should be scaled or not

Details

This function applies regression analysis on two different centrality values in order to find out the corresponding association between them. Regression analysis is a kind of statitiscal method for approximation the association between variables.It asserts that the value of dependent variable changes when the value of independent variable varies.

Value

The regression plot, and the values resulted by the regression process.

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

CHAMBERS, & M., J. (1992). Statistical Models in S. Wadsworth. Pacific Grove, California. Retrieved from

Wilkinson, G. N., & Rogers, C. E. (1973). Symbolic Description of Factorial Models for Analysis of Variance. Applied Statistics, 22(3), 392.

---

visualize_correlations

Correlation plot between centrality measures

Description

This function draw correlation plot between pair of centrality measures

Usage

```
visualize_correlations(x, scale = TRUE, method = "pearson")
```

Arguments

`x`	a list indicating calculated centrality measures
`scale`	Whether the centrality values should be scaled or not(default=TRUE)
`method`	a character string describing the type of correlation coefficient (or covariance) to be computed. The proper values are "pearson", "kendall", or "spearman". (default="pearson")

Details

This function illustrates pairwise correlation plot of computed centrality measures. The names of centralities shown in the result plot is abbreviated and compelete names can be seen in "proper_centralities" function. Colors from red to blue indicate the intensity of correlation value. If two centrality measures have an inverse relationship then their correspnding color in plot have to be red and vice versa.

Value

The pairwise correlation plot

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

See Also

ggpairs

---

visualize_dendrogram *Dendrogram plot among centrality measures*

Description

This function demonstrates the vertice dendrogram of a graph based on a centrality type.

Usage

```
visualize_dendrogram(
  x,
  centrality.type = "Degree Centrality",
  computed_centrality_value = NULL,
  k = 4
)
```

Arguments

`x` an igraph object

`centrality.type`
The type of centrality which should be considered.(default="Degree Centrality")

`computed_centrality_value`
A vector containing the values of calculated centrality measure for each node.(default=NULL)

`k` number of clusters(default=4)

Details

This function represents node dendrogram of a graph based on a centrality measure. If the favor centrality is not computed yet, by specifying the name of that it will compute it and show the result.

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

Galili, T. (2015). dendextend: an R package for visualizing, adjusting and comparing trees of hierarchical clustering. Bioinformatics, 31(22), 3718–3720.

See Also

dendrogram

`visualize_graph` *Graph visualization based on a specific centrality measure*

Description

This function demonstrates the input graph in which the size of nodes indicates calculated centrality value.

Usage

```
visualize_graph(
  x,
  computed_centrality_value = NULL,
  centrality.type = "Degree Centrality"
)
```

Arguments

`x` an igraph object

`computed_centrality_value`
A vector containing the values of calculated centrality measure for each node.

`centrality.type`
The type of centrality which should be calculated.

Details

This function represents the graph in which size of nodes are based on computed centrality value. If the values of wanted centrality measure were computed then by placing them in computed_centrality_value argument to use it for drawing the plot. Otherwise, by only giving the name of favorite centrality measure in centrality.type argument, this function will calculate it and then demonstrates the corresponding graph.

Value

a plot illustrating the graph

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

visualize_heatmap — *Heatmap plot between centrality measures*

Description

This function draws heatmap between pair of centrality measures

Usage

```
visualize_heatmap(x, scale = TRUE)
```

Arguments

x	a list indicating calculated centrality measures
scale	Whether the centrality values should be scaled or not

Details

This function illustrates the heatmap plot of computed centrality measures.

Value

The correlation plot

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

visualize_pair_correlation — *Pairwise correlation plot between two centrality measures*

Description

This function computes and plots correlation between pair of centrality measures and histogram plots.

Usage

```
visualize_pair_correlation(x, y, scale = TRUE)
```

Arguments

x	a vector containing a centrality measure
y	a vector containing another centrality measure
scale	Whether the centrality values should be scaled or not

Details

This function illustrates the correlation value between two centrality measures and their corresponding scatterplot and histograms.

Value

The correlation plot

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

Emerson, J. W., Green, W. A., Schloerke, B., Crowley, J., Cook, D., Hofmann, H., & Wickham, H. (2013). The Generalized Pairs Plot. Journal of Computational and Graphical Statistics, 22(1), 79–91.

See Also

ggpairs

---

wiener_index_centrality   *Wiener Index Centrality*

Description

This function computes Wiener Index Centrality. The Wiener index computes the sum of the all shortest paths between a node v and all other related nodes in the graph. Fundementally, it's like to the closeness but here since the reciprocal is not computed, the value has the opposite meaning.

Usage

```
wiener_index_centrality(
  x,
  vids = V(x),
  mode = c("all", "out", "in"),
  weights = NULL
)
```

Arguments

x	An igraph or a network object
vids	Nodes to be considered in the calculation
mode	A Character value, indicating whether the shortest paths "in" or "out" of the nodes in the directed graphs should be considered. For undirected graphs we use "all".
weights	Numeric vector indicating weights of the edges

Value

a vector including centrality values for each node

Author(s)

Minoo Ashtiani, Mehdi Mirzaie, Mohieddin Jafari

References

Scardoni, G. and Carlo Laudanna, C.B.M.C., 2011. Network centralities for Cytoscape. University of Verona.

Examples

```
data(zachary)

wiener_index_centrality(zachary)
```

`zachary` *Zachary Karate Club Network*

Description

A graph describing friendships among members of a university karate club. Includes metadata for faction membership after a social partition.

Usage

```
zachary
```

Format

an igraph object with "gml" format

References

W. W. Zachary, "An information flow model for conflict and fission in small groups." Journal of Anthropological Research 33, 452-473 (1977).

Examples

```
data("zachary")
print(zachary)
```

Index