

Package ‘dream’

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Title Dynamic Relational Event Analysis and Modeling

Version 1.1.1

Maintainer Kevin A. Carson <kacarson@arizona.edu>

Description A set of tools for relational and event analysis, including two- and one-mode network brokerage and structural measures, and helper functions optimized for relational event analysis with large datasets, including creating relational risk sets, computing network statistics, estimating relational event models, and simulating relational event sequences. For more information on relational event models, see Butts (2008) <[doi:10.1111/j.1467-9531.2008.00203.x](https://doi.org/10.1111/j.1467-9531.2008.00203.x)>, Lerner and Lomi (2020) <[doi:10.1017/nws.2019.57](https://doi.org/10.1017/nws.2019.57)>, Bianchi et al. (2024) <[doi:10.1146/annurev-statistics-040722-060248](https://doi.org/10.1146/annurev-statistics-040722-060248)>, and Butts et al. (2023) <[doi:10.1017/nws.2023.9](https://doi.org/10.1017/nws.2023.9)>. In terms of the structural measures in this package, see Leal (2025) <[doi:10.1177/00491241251322517](https://doi.org/10.1177/00491241251322517)>, Burchard and Cornwell (2018) <[doi:10.1016/j.socnet.2018.04.001](https://doi.org/10.1016/j.socnet.2018.04.001)>, and Fujimoto et al. (2018) <[doi:10.1017/nws.2018.11](https://doi.org/10.1017/nws.2018.11)>. This package was developed with support from the National Science Foundation’s (NSF) Human Networks and Data Science Program (HNDS) under award number 2241536 (PI: Diego F. Leal). Any opinions, findings, and conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF.

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Imports collapse, data.table, foreach, parallel, doParallel, Rcpp, lifecycle

LinkingTo Rcpp

URL <https://github.com/kevinCarson/dream>

BugReports <https://github.com/kevinCarson/dream/issues>

NeedsCompilation yes

Author Kevin A. Carson [aut, cre] (ORCID: <<https://orcid.org/0009-0001-5762-2586>>),
Diego F. Leal [aut] (ORCID: <<https://orcid.org/0000-0001-9973-4626>>)

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create_riskset	<i>Process and Create Risk Sets for a One- and Two-Mode Relational Event Sequences</i>
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Description

[Deprecated]

create_riskset() has been deprecated starting on version 1.1.1 of the dream package. Please use the create_riskset_constant() function and see the NEWS.md file for more details.

This function creates one- and two-mode post-sampling eventset with options for case-control sampling (Vu et al. 2015) and sampling from the observed event sequence (Lerner and Lomi 2020). Case-control sampling samples an arbitrary m number of controls from the risk set for any event (Vu et al. 2015). Lerner and Lomi (2020) proposed sampling from the observed event sequence where observed events are sampled with probability p . Importantly, this function generates risk sets that assume that the risk set for each event is fixed across all time points, that is, all actors active at any time point across the event sequence are in the set of potential events. Users interested in generating time-varying risks sets should consult the [create_riskset_dynamic](#) function for one- and two-mode event sequences.

Usage

```
create_riskset(
  type = c("two-mode", "one-mode"),
  time,
  eventID,
  sender,
  receiver,
  p_samplingobserved = 1,
  n_controls,
  combine = TRUE,
  seed = 9999
)
```

Arguments

type	"two-mode" indicates that this is a two-mode event sequence. "one-mode" indicates that the event sequence is one-mode.
time	The vector of event time values from the observed event sequence.
eventID	The vector of event IDs from the observed event sequence (typically a numerical event sequence that goes from 1 to n).
sender	The vector of event senders from the observed event sequence.
receiver	The vector of event receivers from the observed event sequence.
p_samplingobserved	The numerical value for the probability of selection for sampling from the observed event sequence. Set to 1 by default indicating that all observed events from the event sequence will be included in the post-processing event sequence.

n_controls	The numerical value for the number of null event controls for each (sampled) observed event.
combine	TRUE/FALSE. TRUE indicates that the post-sampling (processing) event sequence should be merged with the pre-processing dataset. FALSE only returns the post-processing event sequence (that is, only the sampled events).
seed	The random number seed for user replication.

Details

This function processes observed events from the set E , where each event e_i is defined as:

$$e_i \in E = (s_i, r_i, t_i, G[E; t])$$

where:

- s_i is the sender of the event.
- r_i is the receiver of the event.
- t_i represents the time of the event.
- $G[E; t] = \{e_1, e_2, \dots, e_{t'} \mid t' < t\}$ is the network of past events, that is, all events that occurred prior to the current event, e_i .

Following Butts (2008) and Butts and Marcum (2017), for one-mode event sequences, the risk (support) set is defined as all possible events at time t , A_t , as the full Cartesian product of prior senders and receivers in the set $G[E; t]$ that could have occurred at time t . Formally:

$$A_t = \{(s, r) \mid s \in S \times r \in R\}$$

where S is the set of potential event senders and R is the set of potential event receivers. In this function, the full risk set is considered fixed across all time points.

For two-mode event sequences, the risk (support) set is defined as all possible events at time t , A_t , as the cross product of two disjoint sets, namely, prior senders and receivers, in the set $G[E; t]$ that could have occurred at time t . Formally:

$$A_t = \{(s, r) \mid s \in S \times r \in R\}$$

where S is the set of potential event senders and R is the set of potential event receivers. In this function, the full risk set is considered fixed across all time points.

Case-control sampling maintains the full set of observed events, that is, all events in E , and samples an arbitrary number m of non-events from the support set A_t (Vu et al. 2015; Lerner and Lomi 2020). This process generates a new support set, SA_t , for any relational event e_i contained in E given a network of past events $G[E; t]$. SA_t is formally defined as:

$$SA_t \subseteq \{(s, r) \mid s \in S \times r \in R\}$$

and in the process of sampling from the observed events, n number of observed events are sampled from the set E with known probability $0 < p \leq 1$. More formally, sampling from the observed set generates a new set $SE \subseteq E$.

Value

A post-processing data.table object with the following columns:

- time - The event time for the sampled and observed events.
- eventID - The numerical event sequence ID for the sampled and observed events.
- sender - The event senders of the sampled and observed events.
- receiver - The event targets (receivers) of the sampled and observed events.
- observed - Boolean indicating if the event is an observed or control event. (1 = observed; 0 = control)
- sampled - Boolean indicating if the event is sampled or not sampled. (1 = sampled; 0 = not sampled)

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.

Butts, Carter T. and Christopher Steven Marcum. 2017. "A Relational Event Approach to Modeling Behavioral Dynamics." In A. Pilny & M. S. Poole (Eds.), *Group processes: Data-driven computational approaches*. Springer International Publishing.

Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.

Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
data("WikiEvent2018.first100k")
WikiEvent2018.first100k$time <- as.numeric(WikiEvent2018.first100k$time)
### Creating the EventSet By Employing Case-Control Sampling With M = 10 and
### Sampling from the Observed Event Sequence with P = 0.01
EventSet <- create_riskset(
  type = "two-mode",
  time = WikiEvent2018.first100k$time, # The Time Variable
  eventID = WikiEvent2018.first100k$eventID, # The Event Sequence Variable
  sender = WikiEvent2018.first100k$user, # The Sender Variable
  receiver = WikiEvent2018.first100k$article, # The Receiver Variable
  p_samplingobserved = 0.01, # The Probability of Selection
  n_controls = 10, # The Number of Controls to Sample from the Full Risk Set
  seed = 9999) # The Seed for Replication

### Creating A New EventSet with more observed events and less control events
### Sampling from the Observed Event Sequence with P = 0.02
```

```

### Employing Case-Control Sampling With M = 2
EventSet1 <- create_riskset(
  type = "two-mode",
  time = WikiEvent2018.first100k$time, # The Time Variable
  eventID = WikiEvent2018.first100k$eventID, # The Event Sequence Variable
  sender = WikiEvent2018.first100k$user, # The Sender Variable
  receiver = WikiEvent2018.first100k$article, # The Receiver Variable
  p_samplingobserved = 0.02, # The Probability of Selection
  n_controls = 2, # The Number of Controls to Sample from the Full Risk Set
  seed = 9999) # The Seed for Replication

set.seed(9999)
events <- data.frame(time = sort(rexp(1:18)),
                    eventID = 1:18,
                    sender = c("A", "B", "C",
                              "A", "D", "E",
                              "F", "B", "A",
                              "F", "D", "B",
                              "G", "B", "D",
                              "H", "A", "D"),
                    target = c("B", "C", "D",
                              "E", "A", "F",
                              "D", "A", "C",
                              "G", "B", "C",
                              "H", "J", "A",
                              "F", "C", "B"))

# Creating a one-mode relational risk set with p = 1.00 (all true events)
# and 5 controls
eventSet <- create_riskset( type = "two-mode",
                          time = events$time,
                          eventID = events$eventID,
                          sender = events$sender,
                          receiver = events$target,
                          p_samplingobserved = 1.00,
                          n_controls = 5,
                          seed = 9999)

```

```
create_riskset_constant
```

Process and Create Risk Sets for a One- and Two-Mode Relational Event Sequences

Description

[Stable]

This function creates one- and two-mode post-sampling eventset with options for case-control sampling (Vu et al. 2015) and sampling from the observed event sequence (Lerner and Lomi 2020).

Case-control sampling samples an arbitrary m number of controls from the risk set for any event (Vu et al. 2015). Lerner and Lomi (2020) proposed sampling from the observed event sequence where observed events are sampled with probability p . Importantly, this function generates risk sets that assume that the risk set for each event is fixed across all time points, that is, all actors active at any time point across the event sequence are in the set of potential events. Users interested in generating time-varying risks sets should consult the `create_riskset_dynamic` function for one- and two-mode event sequences.

Usage

```
create_riskset_constant(
  type = c("two-mode", "one-mode"),
  time,
  eventID,
  sender,
  receiver,
  p_samplingobserved = 1,
  n_controls,
  combine = TRUE,
  seed = 9999
)
```

Arguments

<code>type</code>	"two-mode" indicates that this is a two-mode event sequence. "one-mode" indicates that the event sequence is one-mode.
<code>time</code>	The vector of event time values from the observed event sequence.
<code>eventID</code>	The vector of event IDs from the observed event sequence (typically a numerical event sequence that goes from 1 to n).
<code>sender</code>	The vector of event senders from the observed event sequence.
<code>receiver</code>	The vector of event receivers from the observed event sequence.
<code>p_samplingobserved</code>	The numerical value for the probability of selection for sampling from the observed event sequence. Set to 1 by default indicating that all observed events from the event sequence will be included in the post-processing event sequence.
<code>n_controls</code>	The numerical value for the number of null event controls for each (sampled) observed event.
<code>combine</code>	TRUE/FALSE. TRUE indicates that the post-sampling (processing) event sequence should be merged with the pre-processing dataset. FALSE only returns the post-processing event sequence (that is, only the sampled events).
<code>seed</code>	The random number seed for user replication.

Details

This function processes observed events from the set E , where each event e_i is defined as:

$$e_i \in E = (s_i, r_i, t_i, G[E; t])$$

where:

- s_i is the sender of the event.
- r_i is the receiver of the event.
- t_i represents the time of the event.
- $G[E; t] = \{e_1, e_2, \dots, e_{t'} \mid t' < t\}$ is the network of past events, that is, all events that occurred prior to the current event, e_i .

Following Butts (2008) and Butts and Marcum (2017), for one-mode event sequences, the risk (support) set is defined as all possible events at time t , A_t , as the full Cartesian product of prior senders and receivers in the set $G[E; t]$ that could have occurred at time t . Formally:

$$A_t = \{(s, r) \mid s \in S \times r \in R\}$$

where S is the set of potential event senders and R is the set of potential event receivers. In this function, the full risk set is considered fixed across all time points.

For two-mode event sequences, the risk (support) set is defined as all possible events at time t , A_t , as the cross product of two disjoint sets, namely, prior senders and receivers, in the set $G[E; t]$ that could have occurred at time t . Formally:

$$A_t = \{(s, r) \mid s \in S \times r \in R\}$$

where S is the set of potential event senders and R is the set of potential event receivers. In this function, the full risk set is considered fixed across all time points.

Case-control sampling maintains the full set of observed events, that is, all events in E , and samples an arbitrary number m of non-events from the support set A_t (Vu et al. 2015; Lerner and Lomi 2020). This process generates a new support set, SA_t , for any relational event e_i contained in E given a network of past events $G[E; t]$. SA_t is formally defined as:

$$SA_t \subseteq \{(s, r) \mid s \in S \times r \in R\}$$

and in the process of sampling from the observed events, n number of observed events are sampled from the set E with known probability $0 < p \leq 1$. More formally, sampling from the observed set generates a new set $SE \subseteq E$.

Value

A post-processing data.table object with the following columns:

- time - The event time for the sampled and observed events.
- eventID - The numerical event sequence ID for the sampled and observed events.
- sender - The event senders of the sampled and observed events.
- receiver - The event targets (receivers) of the sampled and observed events.
- observed - Boolean indicating if the event is an observed or control event. (1 = observed; 0 = control)
- sampled - Boolean indicating if the event is sampled or not sampled. (1 = sampled; 0 = not sampled)

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.
- Butts, Carter T. and Christopher Steven Marcum. 2017. "A Relational Event Approach to Modeling Behavioral Dynamics." In A. Pilny & M. S. Poole (Eds.), *Group processes: Data-driven computational approaches*. Springer International Publishing.
- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97–135.
- Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
data("WikiEvent2018.first100k")
WikiEvent2018.first100k$time <- as.numeric(WikiEvent2018.first100k$time)
### Creating the EventSet By Employing Case-Control Sampling With M = 10 and
### Sampling from the Observed Event Sequence with P = 0.01
EventSet <- create_riskset_constant(
  type = "two-mode",
  time = WikiEvent2018.first100k$time, # The Time Variable
  eventID = WikiEvent2018.first100k$eventID, # The Event Sequence Variable
  sender = WikiEvent2018.first100k$user, # The Sender Variable
  receiver = WikiEvent2018.first100k$article, # The Receiver Variable
  p_samplingobserved = 0.01, # The Probability of Selection
  n_controls = 10, # The Number of Controls to Sample from the Full Risk Set
  seed = 9999) # The Seed for Replication

### Creating A New EventSet with more observed events and less control events
### Sampling from the Observed Event Sequence with P = 0.02
### Employing Case-Control Sampling With M = 2
EventSet1 <- create_riskset_constant(
  type = "two-mode",
  time = WikiEvent2018.first100k$time, # The Time Variable
  eventID = WikiEvent2018.first100k$eventID, # The Event Sequence Variable
  sender = WikiEvent2018.first100k$user, # The Sender Variable
  receiver = WikiEvent2018.first100k$article, # The Receiver Variable
  p_samplingobserved = 0.02, # The Probability of Selection
  n_controls = 2, # The Number of Controls to Sample from the Full Risk Set
  seed = 9999) # The Seed for Replication

set.seed(9999)
events <- data.frame(time = sort(rexp(1:18)),
                    eventID = 1:18,
                    sender = c("A", "B", "C",
                              "A", "D", "E",
                              "F", "B", "A",
                              "F", "D", "B",
                              "G", "B", "D",
```

```

      "H", "A", "D"),
target = c("B", "C", "D",
          "E", "A", "F",
          "D", "A", "C",
          "G", "B", "C",
          "H", "J", "A",
          "F", "C", "B"))

# Creating a one-mode relational risk set with p = 1.00 (all true events)
# and 5 controls
eventSet <- create_riskset_constant( type = "two-mode",
                                   time = events$time,
                                   eventID = events$eventID,
                                   sender = events$sender,
                                   receiver = events$target,
                                   p_samplingobserved = 1.00,
                                   n_controls = 5,
                                   seed = 9999)

```

create_riskset_dynamic

Process and Create Time-Dynamic Risk Sets for a One- and Two-Mode Relational Event Sequences

Description

[Stable]

This function creates one- and two-mode time-dynamic post-sampling eventset with options for case-control sampling (Vu et al. 2015) and sampling from the observed event sequence (Lerner and Lomi 2020). Case-control sampling samples an arbitrary m number of controls from the risk set for any event (Vu et al. 2015). Lerner and Lomi (2020) proposed sampling from the observed event sequence where observed events are sampled with probability p . Importantly, this function generates risk sets that assume that the risk set for each event is fixed across all time points, that is, all actors active at any time point across the event sequence are in the set of potential events. Users interested in generating time non-varying risks sets should consult the `create_riskset` function for one- and two-mode event sequence.

Usage

```

create_riskset_dynamic(
  type = c("two-mode", "one-mode"),
  time,
  eventID,
  sender,
  receiver,
  p_samplingobserved = 1,

```

```

    n_controls,
    combine = TRUE,
    seed = 9999
)

```

Arguments

type	"two-mode" indicates that this is a two-mode event sequence. "one-mode" indicates that the event sequence is one-mode.
time	The vector of event time values from the observed event sequence.
eventID	The vector of event IDs from the observed event sequence (typically a numerical event sequence that goes from 1 to n).
sender	The vector of event senders from the observed event sequence.
receiver	The vector of event receivers from the observed event sequence.
p_samplingobserved	The numerical value for the probability of selection for sampling from the observed event sequence. Set to 1 by default indicating that all observed events from the event sequence will be included in the post-processing event sequence.
n_controls	The numerical value for the number of null event controls for each (sampled) observed event.
combine	TRUE/FALSE. TRUE indicates that the post-sampling (processing) event sequence should be merged with the pre-processing dataset. FALSE only returns the post-processing event sequence (that is, only the sampled events).
seed	The random number seed for user replication.

Details

This function processes observed events from the set E , where each event e_i is defined as:

$$e_i \in E = (s_i, r_i, t_i, G[E; t])$$

where:

- s_i is the sender of the event.
- r_i is the receiver of the event.
- t_i represents the time of the event.
- $G[E; t] = \{e_1, e_2, \dots, e_{t'} \mid t' < t\}$ is the network of past events, that is, all events that occurred prior to the current event, e_i .

Following Butts (2008) and Butts and Marcum (2017), for one-mode event sequences (i.e., type = "one-mode"), the risk (support) set at time t , that is, A_t , is defined as the full Cartesian product of all past actors who have been involved in a relational event at or before time t . Formally:

$$A_t = \{(s, r) \mid s \in N_t \times r \in N_t\}$$

where N_t is the set of potential event senders and targets at and time t .

Similarly, for two-mode event sequences (i.e., type = "one-mode"), the risk (support) set at time t , that is, A_t , is defined as the product of two disjoint sets, namely, prior senders and receivers, in the set $G[E; t]$ that could have occurred at time t . Formally:

$$A_t = \{(s, r) \mid s \in S_t \times r \in R_t\}$$

where S_t is the set of potential event senders that have sent a relational tie prior to or at time t and R is the set of potential event receivers that have received a relational tie prior to or at time t .

Case-control sampling maintains the full set of observed events, that is, all events in E , and samples an arbitrary number m of non-events from the support set A_t (Vu et al. 2015; Lerner and Lomi 2020). This process generates a new support set, SA_t , for any relational event e_i contained in E given a network of past events $G[E; t]$. SA_t is formally defined as:

$$SA_t \subseteq \{(s, r) \mid s \in S_t \times r \in R_t\}$$

and in the process of sampling from the observed events, n number of observed events are sampled from the set E with known probability $0 < p \leq 1$. More formally, sampling from the observed set generates a new set $SE \subseteq E$.

Value

A post-processing data.table object with the following columns:

- time - The event time for the sampled and observed events.
- eventID - The numerical event sequence ID for the sampled and observed events.
- sender - The event senders of the sampled and observed events.
- receiver - The event targets (receivers) of the sampled and observed events.
- observed - Boolean indicating if the event is an observed or control event. (1 = observed; 0 = control)
- sampled - Boolean indicating if the event is sampled or not sampled. (1 = sampled; 0 = not sampled)

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.
- Butts, Carter T. and Christopher Steven Marcum. 2017. "A Relational Event Approach to Modeling Behavioral Dynamics." In A. Pilny & M. S. Poole (Eds.), *Group processes: Data-driven computational approaches*. Springer International Publishing.
- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.
- Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```

data("WikiEvent2018.first100k")
WikiEvent2018.first100k$time <- as.numeric(WikiEvent2018.first100k$time)
### Creating the EventSet By Employing Case-Control Sampling With M = 10 and
### Sampling from the Observed Event Sequence with P = 0.01
EventSet <- create_riskset_dynamic(
  type = "two-mode",
  time = WikiEvent2018.first100k$time, # The Time Variable
  eventID = WikiEvent2018.first100k$eventID, # The Event Sequence Variable
  sender = WikiEvent2018.first100k$user, # The Sender Variable
  receiver = WikiEvent2018.first100k$article, # The Receiver Variable
  p_samplingobserved = 0.01, # The Probability of Selection
  n_controls = 10, # The Number of Controls to Sample from the Full Risk Set
  seed = 9999) # The Seed for Replication

### Creating A New EventSet with more observed events and less control events
### Sampling from the Observed Event Sequence with P = 0.02
### Employing Case-Control Sampling With M = 2
EventSet1 <- create_riskset_dynamic(
  type = "two-mode",
  time = WikiEvent2018.first100k$time, # The Time Variable
  eventID = WikiEvent2018.first100k$eventID, # The Event Sequence Variable
  sender = WikiEvent2018.first100k$user, # The Sender Variable
  receiver = WikiEvent2018.first100k$article, # The Receiver Variable
  p_samplingobserved = 0.02, # The Probability of Selection
  n_controls = 2, # The Number of Controls to Sample from the Full Risk Set
  seed = 9999) # The Seed for Replication

set.seed(9999)
events <- data.frame(time = sort(rexp(1:18)),
  eventID = 1:18,
  sender = c("A", "B", "C",
            "A", "D", "E",
            "F", "B", "A",
            "F", "D", "B",
            "G", "B", "D",
            "H", "A", "D"),
  target = c("B", "C", "D",
            "E", "A", "F",
            "D", "A", "C",
            "G", "B", "C",
            "H", "J", "A",
            "F", "C", "B"))

# Creating a one-mode relational risk set with p = 1.00 (all true events)
# and 5 controls
eventSet <- create_riskset_dynamic(type = "two-mode",
  time = events$time,
  eventID = events$eventID,

```

```

sender = events$sender,
receiver = events$target,
p_samplingobserved = 1.00,
n_controls = 5,
seed = 9999)

```

dream

dream: A Package for Dynamic Relational Event Analysis and Modeling

Description

The dream package provides users with helpful functions for relational and event analysis. In particular, dream provides users with helper functions for large relational event analysis, such as recently proposed sampling procedures for creating relational risk sets. Alongside the set of functions for relational event analysis, this package includes functions for the structural analysis of one- and two-mode networks, such as network constraint and effective size measures. This package was developed with support from the National Science Foundation's (NSF) Human Networks and Data Science Program (HNDS) under award number 2241536 (PI: Diego F. Leal). Any opinions, findings, and conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF.

dream functions

The dream package 'API' is structured into six categories, where the prefix identifies what category the specific function corresponds to (see below):

- dreamstats_
- netstats_om_
- netstats_tm_
- estimate_
- simulate_
- create_

The dreamstats_ functions compute relational/network statistics for relational event sequences. For instance, dreamstats_fourcycles computes the four-cycles network statistic for a two-mode relational event sequence. The create_ function creates a risk-set for one- and two-mode relational event sequences based on a set of sampling procedures. The netstats_om_ series of functions compute static network statics for one-mode networks (i.e., netstats_om_pib computes [Leal \(2025\)](#) measure for potential for intercultural brokerage). The netstats_om_ set of functions compute static network statics for two-mode networks (i.e., netstats_om_effective computes [Burchard and Cornwell \(2018\)](#) measure for two-mode ego effective size). The estimate_ functions estimate relational event models for relational event sequences. Currently, the only function in this set is estimate_rem_logit, which estimates the ordinal timing relational event model and, under certain conditions, can estimate a Cox-proportional hazard model for exact timing relational event models (see [Bianchi et al. \(2024\)](#) and [Butts \(2008\)](#) for more information on these models). Finally, the simulate_ functions simulate one-mode relational event sequences based upon results of a relational event model.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

See Also

Useful links:

- <https://github.com/kevinCarson/dream>
- Report bugs at <https://github.com/kevinCarson/dream/issues>

dreamstats_degree	<i>Compute Degree Network Statistics for Event Senders and Receivers in a Relational Event Sequence</i>
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Description**[Stable]**

The function computes the indegree network sufficient statistic for event senders in a relational event sequence (see Lerner and Lomi 2020; Butts 2008). This measure allows for indegree scores to be only computed for the sampled events, while creating the weights based on the full event sequence (see Lerner and Lomi 2020; Vu et al. 2015). The function also allows users to use two different weighting functions, return the counts of past events, reduce computational runtime, and specify a dyadic cutoff for relational relevancy.

Usage

```
dreamstats_degree(  
  formation = c("sender-indegree", "receiver-indegree", "sender-outdegree",  
    "receiver-outdegree"),  
  time,  
  sender,  
  receiver,  
  observed,  
  sampled,  
  halflife = 2,  
  counts = FALSE,  
  dyadic_weight = 0,  
  exp_weight_form = FALSE  
)
```

Arguments

formation	The degree statistic to be computed. "sender-indegree" computes the indegree statistic for the event senders. "receiver-indegree" computes the indegree statistic for the event receivers. "sender-outdegree" computes the outdegree statistic for the event senders. "receiver-outdegree" computes the outdegree statistic for the event receivers.
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time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
halflife	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).
counts	TRUE/FALSE. TRUE indicates that the counts of past events should be computed (see the details section). FALSE indicates that the temporal exponential weighting function should be used to downweigh past events (see the details section). Set to FALSE by default.
dyadic_weight	A numerical value for the dyadic cutoff weight that represents the numerical cutoff value for temporal relevancy based on the exponential weighting function. For example, a numerical value of 0.01, indicates that an exponential weight less than 0.01 will become 0 and that events with such value (or smaller values) will not be included in the sum of the past event weights (see the details section). Set to 0 by default.
exp_weight_form	TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default

Details

The function calculates sender indegree scores for relational event sequences based on the exponential weighting function used in either Lerner and Lomi (2020) or Lerner et al. (2013).

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset, and $T_{1/2}$ is the halflife parameter.

Sender-Indegree Statistic:

The formula for sender indegree for event e_i is:

$$senderindegree_{e_i} = w(s', s, t)$$

That is, all past events in which the event receiver is the current sender. Following Butts (2008), if the counts of the past events are requested, the formula for sender indegree for event e_i is:

$$\text{senderindegree}_{e_i} = d(r' = s, t')$$

Where, $d()$ is the number of past events where the event receiver, r' , is the current event sender s .

Sender-Outdegree Statistic:

The formula for sender outdegree for event e_i is:

$$\text{senderoutdegree}_{e_i} = w(s, r', t)$$

That is, all past events in which the past sender is the current sender and the event target can be any past user. Following Butts (2008), if the counts of the past events are requested, the formula for sender outdegree for event e_i is:

$$\text{senderoutdegree}_{e_i} = d(s = s', t')$$

Where, $d()$ is the number of past events where the sender s' is the current event sender, s

Receiver-Outdegree Statistic:

The formula for receiver outdegree for event e_i is:

$$\text{receiveroutdegree}_{e_i} = w(r', r, t)$$

Following Butts (2008), if the counts of the past events are requested, the formula for receiver outdegree for event e_i is:

$$\text{receiveroutdegree}_{e_i} = d(s' = r, t')$$

Where, $d()$ is the number of past events where the event sender, s' , is the current event receiver, r' .

Receiver-Indegree Statistic:

The formula for receiver indegree for event e_i is:

$$\text{recieverindegree}_{e_i} = w(s', r, t)$$

That is, all past events in which the event receiver is the current receiver. Following Butts (2008), if the counts of the past events are requested, the formula for receiver indegree for event e_i is:

$$\text{recieverindegree}_{e_i} = d(r' = r, t')$$

where, $d()$ is the number of past events where the past event receiver, r' , is the current event receiver (target).

Lastly, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022; Lerner and Lomi 2020) can specify the dyadic weight cutoff, that is, the minimum value for which the weight is considered relationally relevant. Users who do not know the specific dyadic cutoff value to use, can use the `remstats_dyadcut` function.

Value

The vector of degree statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.
- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.
- Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. "Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.
- Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
events <- data.frame(time = 1:18, eventID = 1:18,
                    sender = c("A", "B", "C",
                               "A", "D", "E",
                               "F", "B", "A",
                               "F", "D", "B",
                               "G", "B", "D",
                               "H", "A", "D"),
                    target = c("B", "C", "D",
                               "E", "A", "F",
                               "D", "A", "C",
                               "G", "B", "C",
                               "H", "J", "A",
                               "F", "C", "B"))

eventSet <- create_riskset_constant(type = "one-mode",
                                   time = events$time,
                                   eventID = events$eventID,
                                   sender = events$sender,
                                   receiver = events$target,
                                   p_samplingobserved = 1.00,
                                   n_controls = 1,
                                   seed = 9999)

#Computing the sender indegree statistic for the relational event sequence
eventSet$senderind <- dreamstats_degree(
  formation = "sender-indegree",
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
```

```

receiver = eventSet$receiver,
halflife = 2, #halflife parameter
dyadic_weight = 0,
exp_weight_form = FALSE)

#Computing the sender outdegree statistic for the relational event sequence
eventSet$senderout <- dreamstats_degree(
  formation = "sender-outdegree",
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#Computing the receiver outdegree statistic for the relational event sequence
eventSet$recieverout <- dreamstats_degree(
  formation = "receiver-outdegree",
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#Computing the receiver indegree statistic for the relational event sequence
eventSet$recieverind <- dreamstats_degree(
  formation = "receiver-indegree",
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

```

dreamstats_dyadcut	<i>A Helper Function to Assist Researchers in Finding Dyadic Weight Cutoff Values</i>
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Description**[Stable]**

A user-helper function to assist researchers in finding the dyadic cutoff value to compute sufficient statistics for relational event models based upon temporal dependency.

Usage

```
dreamstats_dyadcut(halfLife = 2, relationalWidth, exp_weight_form = FALSE)
```

Arguments

halfLife A numerical value that is the halfLife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).

relationalWidth The numerical value that corresponds to the time range for which the user specifies for temporal relevancy.

exp_weight_form TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default

Details

This function is specifically designed as a user-helper function to assist researchers in finding the dyadic cutoff value for creating sufficient statistics based upon temporal dependency. In other words, this function estimates a dyadic cutoff value for relational relevance, that is, the minimum dyadic weight for past events to be potentially relevant (i.e., to possibly have an impact) on the current event. All non-relevant events (i.e., events too distant in the past from the current event to be considered relevant, that is, those below the cutoff value) will have a weight of 0. This cutoff value is based upon two user-specified values: the events' halfLife (i.e., halfLife) and the relationally relevant event or time span (i.e., relationalWidth). Ideally, both the values for halfLife and relationalWidth would be based on the researcher's command of the relevant substantive literature. Importantly, halfLife and relationalWidth must be in the same units of measurement (e.g., days). If not, the function will not return the correct answer.

For example, let's say that the user defines the halfLife to be 15 days (i.e., two weeks) and the relationally relevant event or time span (i.e., relationalWidth) to be 30 days (i.e., events that occurred more than 1 month in the past are not considered relationally relevant for the current event). The user would then specify halfLife = 15 and relationalWidth = 30.

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset, and $T_{1/2}$ is the

halflife parameter. The task of this function is to find the weight, $w(s, r, t)$, that corresponds to the time difference provided by the user.

Value

The dyadic weight cutoff based on user specified values.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dfic@arizona.edu

References

Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.

Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. " Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.

Examples

```
#To replicate the example in the details section:
# with the Lerner et al. 2013 weighting function
dreamstats_dyadcut(halflife = 15,
                   relationalWidth = 30,
                   exp_weight_form = TRUE)

# without the Lerner et al. 2013 weighting function
dreamstats_dyadcut(halflife = 15,
                   relationalWidth = 30,
                   exp_weight_form = FALSE)

# A result to test the function (should come out to 0.50)
dreamstats_dyadcut(halflife = 30,
                   relationalWidth = 30,
                   exp_weight_form = FALSE)

# Replicating Lerner and Lomi (2020):
#"We set T1/2 to 30 days so that an event counts as (close to) one in the very next instant of time,
#it counts as 1/2 one month later, it counts as 1/4 two months after the event, and so on. To reduce
#the memory consumption needed to store the network of past events, we set a dyadic weight to
#zero if its value drops below 0.01. If a single event occurred in some dyad this would happen after
#6.64*T1/2, that is after more than half a year." (Lerner and Lomi 2020: 104).

# Based upon Lerner and Lomi (2020: 104), the result should be around 0.01. Since the
# time values in Lerner and Lomi (2020) are in milliseconds, we have to change
# all measurements into milliseconds
dreamstats_dyadcut(halflife = (30*24*60*60*1000), #30 days in milliseconds
                   relationalWidth = (6.64*30*24*60*60*1000), #Based upon the paper
                   #using the Lerner and Lomi (2020) weighting function
```

```
exp_weight_form = FALSE)
```

`dreamstats_fourcycles` *Compute the Four-Cycles Network Statistic for Event Dyads in a Relational Event Sequence*

Description

[Stable]

The function computes the four-cycles network sufficient statistic for a two-mode relational sequence with the exponential weighting function (Lerner and Lomi 2020). In essence, the four-cycles measure captures the tendency for clustering to occur in the network of past events, whereby an event is more likely to occur between a sender node a and receiver node b given that a has interacted with other receivers in past events who have received events from other senders that interacted with b (e.g., Duxbury and Haynie 2021, Lerner and Lomi 2020). The function also allows users to use two different weighting functions, return the counts of past events, reduce computational runtime, and specify a dyadic cutoff for relational relevancy.

Usage

```
dreamstats_fourcycles(  
  time,  
  sender,  
  receiver,  
  observed,  
  sampled,  
  halflife = 2,  
  counts = FALSE,  
  dyadic_weight = 0,  
  exp_weight_form = FALSE  
)
```

Arguments

<code>time</code>	The vector of event times from the post-processing event sequence.
<code>sender</code>	The vector of event senders from the post-processing event sequence.
<code>receiver</code>	The vector of event receivers from the post-processing event sequence
<code>observed</code>	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
<code>sampled</code>	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
<code>halflife</code>	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).

counts	TRUE/FALSE. TRUE indicates that the counts of past events should be computed (see the details section). FALSE indicates that the temporal exponential weighting function should be used to downweigh past events (see the details section). Set to FALSE by default.
dyadic_weight	A numerical value for the dyadic cutoff weight that represents the numerical cutoff value for temporal relevancy based on the exponential weighting function. For example, a numerical value of 0.01, indicates that an exponential weight less than 0.01 will become 0 and that events with such value (or smaller values) will not be included in the sum of the past event weights (see the details section). Set to 0 by default.
exp_weight_form	TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default.

Details

The function calculates the four-cycles network statistic for two-mode relational event models based on the exponential weighting function used in either Lerner and Lomi (2020) or Lerner et al. (2013).

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset (in this case, all events that have the same sender and receiver), and $T_{1/2}$ is the halflife parameter.

The formula for four-cycles for event e_i is:

$$fourcycles_{e_i} = \sqrt[3]{\sum_{s' \text{ and } r'} w(s', r, t) \cdot w(s, r', t) \cdot w(s', r', t)}$$

That is, the four-cycle measure captures all the past event structures in which the current event pair, sender s and target r close a four-cycle. In particular, it finds all events in which: a past sender s' had a relational event with target r , a past target r' had a relational event with current sender s , and finally, a relational event occurred between sender s' and target r' .

Four-cycles are computationally expensive, especially for large relational event sequences (see Lerner and Lomi 2020 for a discussion on this), therefore this function allows the user to input previously computed target indegree and sender outdegree scores to reduce the runtime. Relational events where either the event target or event sender were not involved in any prior relational events (i.e., a target indegree or sender outdegree score of 0) will close no-four cycles. This function exploits this feature.

Moreover, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022; Lerner and Lomi 2020) can specify the dyadic weight cutoff, that is, the minimum value for which the weight is considered relationally relevant. Users who do not know the specific dyadic cutoff value to use, can use the `remstats_dyadcut` function.

Following Lerner and Lomi (2020), if the counts of the past events are requested, the formula for four-cycles formation for event e_i is:

$$fourcycles_{e_i} = \sum_{i=1}^{|S'|} \sum_{j=1}^{|R'|} \min [d(s'_i, r, t), d(s, r'_j, t), d(s'_i, r'_j, t)]$$

where, $d()$ is the number of past events that meet the specific set operations, $d(s'_i, r, t)$ is the number of past events where the current event receiver received a tie from another sender s'_i , $d(s, r'_j, t)$ is the number of past events where the current event sender sent a tie to another receiver r'_j , and $d(s'_i, r'_j, t)$ is the number of past events where the sender s'_i sent a tie to the receiver r'_j . Moreover, the counting equation can leverage relational relevancy, by specifying the halflife parameter, exponential weighting function, and the dyadic cut off weight values (see the above sections for help with this). If the user is not interested in modeling relational relevancy, then those value should be left at their default values.

Value

The vector of four-cycle statistics for the two-mode relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Duxbury, Scott and Dana Haynie. 2021. "Shining a Light on the Shadows: Endogenous Trade Structure and the Growth of an Online Illegal Market." *American Journal of Sociology* 127(3): 787-827.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.
- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.
- Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. "Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.

Examples

```
data("WikiEvent2018.first100k")
WikiEvent2018 <- WikiEvent2018.first100k[1:1000,] #the first one thousand events
WikiEvent2018$time <- as.numeric(WikiEvent2018$time) #making the variable numeric
### Creating the EventSet By Employing Case-Control Sampling With M = 5 and
### Sampling from the Observed Event Sequence with P = 0.01
```

```

EventSet <-create_riskset_constant(type = "two-mode",
  time = WikiEvent2018$time, # The Time Variable
  eventID = WikiEvent2018$eventID, # The Event Sequence Variable
  sender = WikiEvent2018$user, # The Sender Variable
  receiver = WikiEvent2018$article, # The Receiver Variable
  p_samplingobserved = 0.01, # The Probability of Selection
  n_controls = 8, # The Number of Controls to Sample from the Full Risk Set
  combine = TRUE,
  seed = 9999) # The Seed for Replication

#Computing the four-cycles statistics for the relational event sequence with
#the exponential weights of past events returned
cycle4_weights <- dreamstats_fourcycles(
  time = EventSet$time,
  sender = EventSet$sender,
  receiver = EventSet$receiver,
  sampled = EventSet$sampled,
  observed = EventSet$observed,
  halflife = 2.592e+09, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#Computing the four-cycles statistics for the relational event sequence with
#the counts of past events returned
cycle4_counts <- dreamstats_fourcycles(
  time = EventSet$time,
  sender = EventSet$sender,
  receiver = EventSet$receiver,
  sampled = EventSet$sampled,
  observed = EventSet$observed,
  halflife = 2.592e+09, #halflife parameter
  dyadic_weight = 0,
  counts = TRUE)

cbind(cycle4_weights, cycle4_counts)

```

dreamstats_persistence

*Compute Butts' (2008) Persistence Network Statistic for Event Dyads
in a Relational Event Sequence*

Description

[Stable]

This function computes the persistence network sufficient statistic for a relational event sequence (see Butts 2008). Persistence measures the proportion of past ties sent from the event sender that

went to the current event receiver. Furthermore, this measure allows for persistence scores to be only computed for the sampled events, while creating the weights based on the full event sequence. Moreover, the function allows users to specify relational relevancy for the resulting statistic.

Usage

```
dreamstats_persistence(
  time,
  sender,
  target,
  sampled,
  observed,
  ref_sender = TRUE,
  nopastEvents = NA,
  dependency = FALSE,
  relationalTimeSpan = 0
)
```

Arguments

time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
target	The vector of event targets from the post-processing event sequence
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
ref_sender	TRUE/FALSE. TRUE indicates that the persistence statistic will be computed in reference to the sender's past relational history (see details section). FALSE indicates that the persistence statistic will be computed in reference to the target's past relational history (see details section). Set to TRUE by default.
nopastEvents	The numerical value that specifies what value should be given to events in which the sender has sent not past ties (i 's neighborhood when sender = TRUE) or has not received any past ties (j 's neighborhood when sender = FALSE). Set to NA by default.
dependency	TRUE/FALSE. TRUE indicates that temporal relevancy will be modeled (see the details section). FALSE indicates that temporal relevancy will not be modeled, that is, all past events are relevant (see the details section). Set to FALSE by default.
relationalTimeSpan	If dependency = TRUE, a numerical value that corresponds to the temporal span for relational relevancy, which must be the same measurement unit as the observed_time and processed_time objects. When dependency = TRUE, the relevant events are events that have occurred between current event time, t , and t -relationalTimeSpan. For example, if the time measurement is the number of days since the first event and the value for relationalTimeSpan is set to 10, then only those events which occurred in the past 10 days are included in the computation of the statistic.

Details

The function calculates the persistence network sufficient statistic for a relational event sequence based on Butts (2008).

The formula for persistence for event e_i with reference to the sender's past relational history is:

$$Persistence_{e_i} = \frac{d(s(e_i), r(e_i), A_t)}{d(s(e_i), A_t)}$$

where $d(s(e_i), r(e_i), A_t)$ is the number of past events where the current event sender sent a tie to the current event receiver, and $d(s(e_i), A_t)$ is the number of past events where the current sender sent a tie.

The formula for persistence for event e_i with reference to the target's past relational history is:

$$Persistence_{e_i} = \frac{d(s(e_i), r(e_i), A_t)}{d(r(e_i), A_t)}$$

where $d(s(e_i), r(e_i), A_t)$ is the number of past events where the current event sender sent a tie to the current event receiver, and $d(r(e_i), A_t)$ is the number of past events where the current receiver received a tie.

Moreover, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022) can specify the relational time span, that is, length of time for which events are considered relationally relevant. This should be specified via the option *relationalTimeSpan* with *dependency* set to TRUE.

Value

The vector of persistence network statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

Butts, Carter T. 2008. "A relational event framework for social action." *Sociological Methodology* 38(1): 155-200.

Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.

Examples

```
# A Dummy One-Mode Event Dataset
events <- data.frame(time = 1:18,
                     eventID = 1:18,
                     sender = c("A", "B", "C",
                                "A", "D", "E",
                                "F", "B", "A",
                                "F", "D", "B",
```

```

      "G", "B", "D",
      "H", "A", "D"),
target = c("B", "C", "D",
          "E", "A", "F",
          "D", "A", "C",
          "G", "B", "C",
          "H", "J", "A",
          "F", "C", "B"))

# Creating the Post-Processing Event Dataset with Null Events
eventSet <- create_riskset_constant(type = "one-mode",
                                   time = events$time,
                                   eventID = events$eventID,
                                   sender = events$sender,
                                   receiver = events$target,
                                   p_samplingobserved = 1.00,
                                   n_controls = 6,
                                   seed = 9999)

#Computing the persistence statistic for the relational event sequence
eventSet$remstats_persistence <- dreamstats_persistence(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  target = eventSet$receiver,
  ref_sender = TRUE)

```

dreamstats_prefattachment

Compute Butts' (2008) Preferential Attachment Network Statistic for Event Dyads in a Relational Event Sequence

Description

[Stable]

The function computes the preferential attachment network sufficient statistic for a relational event sequence (see Butts 2008). Preferential attachment measures the tendency towards a positive feedback loop in which actors involved in more past events are more likely to be involved in future events (see Butts 2008 for an empirical example and discussion). This measure allows for preferential attachment scores to be only computed for the sampled events, while creating the statistics based on the full event sequence. Moreover, the function allows users to specify relational relevancy for the resulting statistics.

Usage

```

dreamstats_prefattachment(
  time,

```

```

    sampled,
    observed,
    sender,
    receiver,
    dependency = FALSE,
    relationalTimeSpan = 0
)

```

Arguments

time	The vector of event times from the post-processing event sequence.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
dependency	TRUE/FALSE. TRUE indicates that temporal relevancy will be modeled (see the details section). FALSE indicates that temporal relevancy will not be modeled, that is, all past events are relevant (see the details section). Set to FALSE by default.
relationalTimeSpan	If dependency = TRUE, a numerical value that corresponds to the temporal span for relational relevancy, which must be the same measurement unit as the observed_time and processed_time objects. When dependency = TRUE, the relevant events are events that have occurred between current event time, t , and $t - relationalTimeSpan$. For example, if the time measurement is the number of days since the first event and the value for relationalTimeSpan is set to 10, then only those events which occurred in the past 10 days are included in the computation of the statistic.

Details

The function calculates preferential attachment for a relational event sequence based on Butts (2008).

Following Butts (2008), the formula for preferential attachment for event e_i is:

$$PA_{e_i} = \frac{d^+(r(e_i), A_t) + d^-(r(e_i), A_t)}{\sum_{i=1}^{|S|} (d^+(i, A_t) + d^-(i, A_t))}$$

where $d^+(r(e_i), A_t)$ is the past outdegree of the receiver for e_i , $d^-(r(e_i), A_t)$ is the past indegree of the receiver for e_i , $\sum_{i=1}^{|S|} (d^+(i, A_t) + d^-(i, A_t))$ is the sum of the past outdegree and indegree for all past event senders in the relational history.

Moreover, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022) can specify the relational time span, that is, length of time for which events are considered relationally relevant. This should be specified via the option *relationalTimeSpan* with *dependency* set to TRUE.

Value

The vector of event preferential attachment statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

Butts, Carter T. 2008. "A relational event framework for social action." *Sociological Methodology* 38(1): 155-200.

Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.

Examples

```
# A Dummy One-Mode Event Dataset
events <- data.frame(time = 1:18,
                    eventID = 1:18,
                    sender = c("A", "B", "C",
                              "A", "D", "E",
                              "F", "B", "A",
                              "F", "D", "B",
                              "G", "B", "D",
                              "H", "A", "D"),
                    target = c("B", "C", "D",
                              "E", "A", "F",
                              "D", "A", "C",
                              "G", "B", "C",
                              "H", "J", "A",
                              "F", "C", "B"))

# Creating the Post-Processing Event Dataset with Null Events
eventSet <- create_riskset_constant( type = "one-mode",
                                   time = events$time,
                                   eventID = events$eventID,
                                   sender = events$sender,
                                   receiver = events$target,
                                   p_samplingobserved = 1.00,
                                   n_controls = 6,
                                   seed = 9999)

#Computing the preferential attachment statistic for the relational event sequence
eventSet$pref <- dreamstats_prefattachment(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver)
```

dreamstats_recency *Compute Butts' (2008) Recency Network Statistic for Event Dyads in a Relational Event Sequence*

Description

[Stable]

This function computes the recency network sufficient statistic for a relational event sequence (see Butts 2008; Vu et al. 2015; Meijerink-Bosman et al. 2022). The recency statistic captures the tendency for more recent events (i.e., an exchange between two medical doctors) are more likely to re-occur in comparison to events that happened in the more distant past (see Butts 2008 for a discussion). This measure allows for recency scores to be only computed for the sampled events, while computing the statistics based on the full event sequence.

Usage

```
dreamstats_recency(
  time,
  sender,
  receiver,
  sampled,
  observed,
  type = c("raw.diff", "inv.diff.plus1", "rank.ordered.count"),
  i_neighborhood = TRUE,
  dependency = FALSE,
  relationalTimeSpan = NULL,
  nopastEvents = NA
)
```

Arguments

time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
type	A string value that specifies which recency formula will be used to compute the statistics. The options are "raw.diff", "inv.diff.plus1", "rank.ordered.count" (see details section).
i_neighborhood	TRUE/FALSE. TRUE indicates that the recency statistic will be computed in reference to the sender's past relational history (see details section). FALSE indicates that the recency statistic will be computed in reference to the target's past relational history (see details section). Set to TRUE by default.

dependency	TRUE/FALSE. TRUE indicates that temporal relevancy will be modeled (see details section). FALSE indicates that temporal relevancy will not be modeled, that is, all past events are relevant (see details section). Set to FALSE by default.
relationalTimeSpan	If dependency = TRUE, a numerical value that corresponds to the temporal span for relational relevancy, which must be the same measurement unit as the observed_time and processed_time objects. When dependency = TRUE, the relevant events are events that have occurred between current event time, t , and $t - relationalTimeSpan$. For example, if the time measurement is the number of days since the first event and the value for relationalTimeSpan is set to 10, then only those events which occurred in the past 10 days are included in the computation of the statistic.
nopastEvents	The numerical value that specifies what value should be given to events in which the sender was not active as a sender in the past (i 's neighborhood when $i_neighborhood = TRUE$) or was not the recipient of a past event (j 's neighborhood when $i_neighborhood = FALSE$). Set to NA by default.

Details

This function calculates the recency network sufficient statistic for a relational event based on Butts (2008), Vu et al. (2015), or Meijerink-Bosman et al. (2022). Depending on the type and neighborhood requested, different formulas will be used.

In the below equations, when $i_neighborhood$ is TRUE:

$$t^* = \max(t \in \{(s', r', t') \in E : s' = s \wedge r' = r \wedge t' < t\})$$

When $i_neighborhood$ is FALSE, the following formula is used:

$$t^* = \max(t \in \{(s', r', t') \in E : s' = r \wedge r' = s \wedge t' < t\})$$

The formula for recency for event e_i with type set to "raw.diff" and $i_neighborhood$ is TRUE (Vu et al. 2015):

$$recency_{e_i} = t_{e_i} - t^*$$

where t^* , is the most recent time in which the past event has the same receiver and sender as the current event. If there are no past events within the current dyad, then the value defaults to the *nopastEvents* argument.

The formula for recency for event e_i with type set to "raw.diff" and $i_neighborhood$ is FALSE (Vu et al. 2015):

$$recency_{e_i} = t_{e_i} - t^*$$

where t^* , is the most recent time in which the past event's sender is the current event receiver and the past event receiver is the current event sender. If there are no past events within the current dyad, then the value defaults to the *nopastEvents* argument.

The formula for recency for event e_i with type set to "inv.diff.plus1" and $i_neighborhood$ is TRUE (Meijerink-Bosman et al. 2022):

$$recency_{e_i} = \frac{1}{t_{e_i} - t^* + 1}$$

where t^* , is the most recent time in which the past event has the same receiver and sender as the current event. If there are no past events within the current dyad, then the value defaults to the *nopastEvents* argument.

The formula for recency for event e_i with type set to "inv.diff.plus1" and *i_neighborhood* is FALSE (Meijerink-Bosman et al. 2022):

$$recency_{e_i} = \frac{1}{t_{e_i} - t^* + 1}$$

where t^* , is the most recent time in which the past event's sender is the current event receiver and the past event receiver is the current event sender. If there are no past events within the current dyad, then the value defaults to the *nopastEvents* argument.

The formula for recency for event e_i with type set to "rank.ordered.count" and *i_neighborhood* is TRUE (Butts 2008):

$$recency_{e_i} = \rho(s(e_i), r(e_i), A_t)^{-1}$$

where $\rho(s(e_i), r(e_i), A_t)$, is the current event receiver's rank amongst the current sender's recent relational events. That is, as Butts (2008: 174) argues, " $\rho(s(e_i), r(e_i), A_t)$ is j's recency rank among i's in-neighborhood. Thus, if j is the last person to have called i, then $\rho(s(e_i), r(e_i), A_t)^{-1} = 1$. This falls to 1/2 if j is the second most recent person to call i, 1/3 if j is the third most recent person, etc." Moreover, if j is not in i's neighborhood, the value defaults to infinity. If there are no past events with the current sender, then the value defaults to the *nopastEvents* argument.

The formula for recency for event e_i with type set to "rank.ordered.count" and *i_neighborhood* is FALSE (Butts 2008):

$$recency_{e_i} = \rho(r(e_i), s(e_i), A_t)^{-1}$$

where $\rho(r(e_i), s(e_i), A_t)$, is the current event sender's rank amongst the current receiver's recent relational events. That is, this measure is the same as above where the dyadic pair is flipped for the past relational events. Moreover, if j is not in i's neighborhood, the value defaults to infinity. If there are no past events with the current sender, then the value defaults to the *nopastEvents* argument.

Finally, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022) can specify the relational time span, that is, length of time for which events are considered relationally relevant. This should be specified via the option *relationalTimeSpan* with *dependency* set to TRUE.

Value

The vector of recency network statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dfic@arizona.edu

References

- Butts, Carter T. 2008. "A relational event framework for social action." *Sociological Methodology* 38(1): 155-200.
- Meijerink-Bosman, Marlyne, Roger Leenders, and Joris Mulder. 2022. "Dynamic relational event modeling: Testing, exploring, and applying." *PLOS One* 17(8): e0272309.

Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.

Vu, Duy, Philippa Pattison, and Garry Robbins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
# A Dummy One-Mode Event Dataset
events <- data.frame(time = 1:18,
                    eventID = 1:18,
                    sender = c("A", "B", "C",
                              "A", "D", "E",
                              "F", "B", "A",
                              "F", "D", "B",
                              "G", "B", "D",
                              "H", "A", "D"),
                    target = c("B", "C", "D",
                              "E", "A", "F",
                              "D", "A", "C",
                              "G", "B", "C",
                              "H", "J", "A",
                              "F", "C", "B"))

# Creating the Post-Processing Event Dataset with Null Events
eventSet <- create_riskset_constant(type = "one-mode",
                                   time = events$time,
                                   eventID = events$eventID,
                                   sender = events$sender,
                                   receiver = events$target,
                                   p_samplingobserved = 1.00,
                                   n_controls = 6,
                                   seed = 9999)

#Computing the recency statistics (with raw time difference) for the relational event sequence
eventSet$recency_rawdiff <- dreamstats_recency(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  type = "raw.diff")

#Computing the recency statistics (with inverse of time difference) for the
#relational event sequence
eventSet$recency_rawdiff <- dreamstats_recency(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  type = "inv.diff.plus1")
```

```
#Computing the rank-based recency statistics for the relational event sequence
eventSet$recency_rawdiff <- dreamstats_recency(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  type = "rank.ordered.count")
```

dreamstats_reciprocity

Compute the Reciprocity Network Statistic for Event Dyads in a Relational Event Sequence

Description

[Stable]

This function calculates the reciprocity network sufficient statistic for a relational event sequence (see Lerner and Lomi 2020; Butts 2008). The reciprocity statistic captures the tendency for a sender a to ‘send a tie’ to (e.g., initiate a communication event with) receiver b given that b sent a tie to a in the past (i.e., an exchange between two medical doctors). This function allows for reciprocity scores to be only computed for the sampled events, while creating the weights based on the full event sequence (see Lerner and Lomi 2020; Vu et al. 2015). The function also allows users to use two different weighting functions, return the counts of past events, reduce computational runtime, and specify a dyadic cutoff for relational relevancy.

Usage

```
dreamstats_reciprocity(
  time,
  sender,
  receiver,
  observed,
  sampled,
  halflife = 2,
  counts = FALSE,
  dyadic_weight = 0,
  exp_weight_form = FALSE
)
```

Arguments

time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence

observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
halflife	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).
counts	TRUE/FALSE. TRUE indicates that the counts of past events should be computed (see the details section). FALSE indicates that the temporal exponential weighting function should be used to downweigh past events (see the details section). Set to FALSE by default.
dyadic_weight	A numerical value for the dyadic cutoff weight that represents the numerical cutoff value for temporal relevancy based on the exponential weighting function. For example, a numerical value of 0.01, indicates that an exponential weight less than 0.01 will become 0 and that events with such value (or smaller values) will not be included in the sum of the past event weights (see the details section). Set to 0 by default.
exp_weight_form	TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default.

Details

This function calculates reciprocity scores for relational event models based on the exponential weighting function used in either Lerner and Lomi (2020) or Lerner et al. (2013).

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset, and $T_{1/2}$ is the halflife parameter.

The formula for reciprocity for event e_i is:

$$reciprocity_{e_i} = w(r, s, t)$$

That is, all past events in which the past sender is the current receiver and the past receiver is the current sender.

Moreover, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022; Lerner and Lomi 2020) can specify the dyadic weight cutoff, that is, the minimum

value for which the weight is considered relationally relevant. Users who do not know the specific dyadic cutoff value to use, can use the `remstats_dyadcut` function.

Following Butts (2008), if the counts of the past events are requested, the formula for reciprocity for event e_i is:

$$reciprocity_{e_i} = d(r = s', s = r', t')$$

Where, $d()$ is the number of past events where the event sender, s' , is the current event receiver, r , and the event receiver (target), r' , is the current event sender, s . Moreover, the counting equation can be used in tandem with relational relevancy, by specifying the halflife parameter, exponential weighting function, and the dyadic cut off weight values. If the user is not interested in modeling relational relevancy, then those value should be left at their baseline values.

Value

The vector of reciprocity statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dffc@arizona.edu

References

- Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.
- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.
- Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. "Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.
- Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
events <- data.frame(time = 1:18, eventID = 1:18,
                    sender = c("A", "B", "C",
                               "A", "D", "E",
                               "F", "B", "A",
                               "F", "D", "B",
                               "G", "B", "D",
                               "H", "A", "D"),
                    target = c("B", "C", "D",
                               "E", "A", "F",
                               "D", "A", "C",
                               "G", "B", "C",
                               "H", "J", "A",
```

```

                                "F", "C", "B"))

eventSet <-create_riskset_constant(type = "one-mode",
                                time = events$time,
                                eventID = events$eventID,
                                sender = events$sender,
                                receiver = events$target,
                                p_samplingobserved = 1.00,
                                n_controls = 1,
                                seed = 9999)

#Computing the reciprocity statistics for the relational event sequence
eventSet$recip <- dreamstats_reciprocity(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

```

dreamstats_repetition *Compute Butts' (2008) Repetition Network Statistic for Event Dyads in a Relational Event Sequence*

Description

[Stable]

This function computes the repetition network sufficient statistic for a relational event sequence (see Lerner and Lomi 2020; Butts 2008). Repetition measures the increased tendency for events between S and R to occur given that S and R have interacted in the past. Furthermore, this function allows for repetition scores to be only computed for the sampled events, while creating the weights based on the full event sequence (see Lerner and Lomi 2020; Vu et al. 2015). The function also allows users to use two different weighting functions, return the counts of past events, reduce computational runtime, and specify a dyadic cutoff for relational relevancy.

Usage

```

dreamstats_repetition(
  time,
  sender,
  receiver,
  observed,
  sampled,
  halflife = 2,
  counts = FALSE,

```

```

    dyadic_weight = 0,
    exp_weight_form = FALSE
)

```

Arguments

time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
halflife	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).
counts	TRUE/FALSE. TRUE indicates that the counts of past events should be computed (see the details section). FALSE indicates that the temporal exponential weighting function should be used to downweigh past events (see the details section). Set to FALSE by default.
dyadic_weight	A numerical value for the dyadic cutoff weight that represents the numerical cutoff value for temporal relevancy based on the exponential weighting function. For example, a numerical value of 0.01, indicates that an exponential weight less than 0.01 will become 0 and that events with such value (or smaller values) will not be included in the sum of the past event weights (see the details section). Set to 0 by default.
exp_weight_form	TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default

Details

This function calculates the repetition scores for relational event models based on the exponential weighting function used in either Lerner and Lomi (2020) or Lerner et al. (2013).

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset (in this case, all events that have the same sender and receiver), and $T_{1/2}$ is the halflife parameter.

The formula for repetition for event e_i is:

$$\text{repetition}_{e_i} = w(s, r, t)$$

Moreover, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022; Lerner and Lomi 2020) can specify the dyadic weight cutoff, that is, the minimum value for which the weight is considered relationally relevant. Users who do not know the specific dyadic cutoff value to use, can use the `remstats_dyadcut` function.

Following Butts (2008), if the counts of the past events are requested, the formula for repetition for event e_i is:

$$\text{repetition}_{e_i} = d(s = s', r = r', t')$$

Where, $d()$ is the number of past events where the event sender, s' , is the current event sender, s , the event receiver (target), r' , is the current event receiver, r . Moreover, the counting equation can be used in tandem with relational relevancy, by specifying the halflife parameter, exponential weighting function, and the dyadic cut off weight values. If the user is not interested in modeling relational relevancy, then those value should be left at their baseline values.

Value

The vector of repetition statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.
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- Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
data("WikiEvent2018.first100k")
WikiEvent2018 <- WikiEvent2018.first100k[1:10000,] #the first ten thousand events
WikiEvent2018$time <- as.numeric(WikiEvent2018$time) #making the variable numeric
### Creating the EventSet By Employing Case-Control Sampling With M = 5 and
### Sampling from the Observed Event Sequence with P = 0.01
EventSet <- create_riskset_constant(type = "two-mode",
```

```

time = WikiEvent2018$time, # The Time Variable
eventID = WikiEvent2018$eventID, # The Event Sequence Variable
sender = WikiEvent2018$user, # The Sender Variable
receiver = WikiEvent2018$article, # The Receiver Variable
p_samplingobserved = 0.01, # The Probability of Selection
n_controls = 8, # The Number of Controls to Sample from the Full Risk Set
combine = TRUE,
seed = 9999) # The Seed for Replication

#Computing the repetition statistics for the relational event sequence with the
#weights of past events returned
rep_weights <- dreamstats_repetition(
  time = EventSet$time,
  sender = EventSet$sender,
  receiver = EventSet$receiver,
  sampled = EventSet$sampled,
  observed = EventSet$observed,
  halflife = 2.592e+09, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#Computing the repetition statistics for the relational event sequence with the
#counts of events returned
rep_counts <- dreamstats_repetition(
  time = EventSet$time,
  sender = EventSet$sender,
  receiver = EventSet$receiver,
  sampled = EventSet$sampled,
  observed = EventSet$observed,
  halflife = 2.592e+09, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

cbind(rep_weights, rep_counts)

```

dreamstats_triads *Compute Butts' (2008) Triadic Formation Statistics for Relational
Event Sequences*

Description

[Stable]

The function computes the set of one-mode triadic formation statistics discussed in Butts (2008) for a one-mode relational event sequence (see also Lerner and Lomi 2020). The function can compute the following triadic formations: 1) incoming shared partners (ISP), 2) outgoing shared partners (OSP), 3) incoming two-paths (ITP), and 4) outgoing two-paths (OTP). Importantly, this function

allows for the triadic formation statistics to be computed only for the sampled events, while creating the weights based on the full event sequence (see Lerner and Lomi 2020; Vu et al. 2015). The function also allows users to use two different weighting functions, return the counts of past events, reduce computational runtime, and specify a dyadic cutoff for relational relevancy.

Usage

```
dreamstats_triads(
  formation = c("ISP", "OSP", "ITP", "OTP"),
  time,
  sender,
  receiver,
  observed,
  sampled,
  halflife = 2,
  counts = FALSE,
  dyadic_weight = 0,
  exp_weight_form = FALSE
)
```

Arguments

formation	The specific triadic formation the statistic will be based on (see details section). "ISP" = incoming shared partners. "OSP" = outgoing shared partners. "OTP" = outgoing two-paths. "ITP" = incoming two-paths.
time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
halflife	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).
counts	TRUE/FALSE. TRUE indicates that the counts of past events should be computed (see the details section). FALSE indicates that the temporal exponential weighting function should be used to downweigh past events (see the details section). Set to FALSE by default.
dyadic_weight	A numerical value for the dyadic cutoff weight that represents the numerical cutoff value for temporal relevancy based on the exponential weighting function. For example, a numerical value of 0.01, indicates that an exponential weight less than 0.01 will become 0 and that events with such value (or smaller values) will not be included in the sum of the past event weights (see the details section). Set to 0 by default.

exp_weight_form

TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default

Details

The function calculates the triadic formation statistics discussed in Butts (2008) for relational event sequences based on the exponential weighting function used in either Lerner and Lomi (2020) or Lerner et al. (2013).

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset, and $T_{1/2}$ is the halflife parameter.

Outgoing Shared Partners:

The general formula for outgoing shared partners for event e_i is:

$$OSP_{e_i} = \sqrt{\sum_h w(s, h, t) \cdot w(r, h, t)}$$

That is, as discussed in Butts (2008), outgoing shared partners finds all past events where the current sender and target sent a relational tie (i.e., were a sender in a relational event) to the same h node.

Following Butts (2008), if the counts of the past events are requested, the formula for outgoing shared partners for event e_i is:

$$OSP_{e_i} = \sum_{i=1}^{|H|} \min [d(s, h, t), d(r, h, t)]$$

Where, $d()$ is the number of past events that meet the specific set operations. $d(s, h, t)$ is the number of past events where the current event sender sent a tie to a third actor, h , and $d(r, h, t)$ is the number of past events where the current event receiver sent a tie to a third actor, h . The sum loops through all unique actors that have formed past outgoing shared partners structures with the current event sender and receiver. Moreover, the counting equation can be used in tandem with relational relevancy, by specifying the halflife parameter, exponential weighting function, and the dyadic cut off weight values. If the user is not interested in modeling relational relevancy, then those value should be left at their defaults.

Outgoing Two-Paths:

The general formula for outgoing two-paths for event e_i is:

$$OTP_{e_i} = \sqrt{\sum_h w(s, h, t) \cdot w(h, r, t)}$$

That is, as discussed in Butts (2008), outgoing two-paths finds all past events where the current sender sends a relational tie to node h and the current target receives a relational tie from the same h node.

Following Butts (2008), if the counts of the past events are requested, the formula for outgoing two paths for event e_i is:

$$OTP_{e_i} = \sum_{i=1}^{|H|} \min [d(s, h, t), d(h, r, t)]$$

Where, $d()$ is the number of past events that meet the specific set operations. $d(s, h, t)$ is the number of past events where the current event sender sent a tie to a third actor, h , and $d(h, r, t)$ is the number of past events where the third actor h sent a tie to the current event receiver. The sum loops through all unique actors that have formed past outgoing two-path structures with the current event sender and receiver.

Incoming Two-Paths:

The general formula for incoming two-paths for event e_i is:

$$ITP_{e_i} = \sqrt{\sum_h w(r, h, t) \cdot w(h, s, t)}$$

That is, as discussed in Butts (2008), incoming two-paths finds all past events where the current sender was the receiver in a relational event where the sender was a node h and the current target was the sender in a past relational event where the target was the same node h .

Following Butts (2008), if the counts of the past events are requested, the formula for incoming two paths for event e_i is:

$$ITP_{e_i} = \sum_{i=1}^{|H|} \min [d(r, h, t), d(h, s, t)]$$

Where, $d()$ is the number of past events that meet the specific set operations. $d(r, h, t)$ is the number of past events where the current event receiver sent a tie to a third actor, h , and $d(h, s, t)$ is the number of past events where the third actor h sent a tie to the current event sender. The sum loops through all unique actors that have formed past incoming two-path structures with the current event sender and receiver.

Incoming Shared Partners:

The general formula for incoming shared partners for event e_i is:

$$ISP_{e_i} = \sqrt{\sum_h w(h, s, t) \cdot w(h, r, t)}$$

That is, as discussed in Butts (2008), incoming shared partners finds all past events where the current sender and target were themselves the target in a relational event from the same h node.

Following Butts (2008), if the counts of the past events are requested, the formula for incoming shared partners for event e_i is:

$$ISP_{e_i} = \sum_{i=1}^{|H|} \min [d(h, s, t), d(h, r, t)]$$

Where, $d()$ is the number of past events that meet the specific set operations, $d(h, s, t)$ is the number of past events where the current event sender received a tie from a third actor, h , and $d(h, r, t)$ is the number of past events where the current event receiver received a tie from a third actor, h . The sum loops through all unique actors that have formed past incoming shared partners structures with the current event sender and receiver.

Lastly, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022; Lerner and Lomi 2020) can specify the dyadic weight cutoff, that is, the minimum value for which the weight is considered relationally relevant. Users who do not know the specific dyadic cutoff value to use, can use the `remstats_dyadcut` function.

Value

The vector of triadic formation statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.
- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.
- Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. "Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.
- Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
events <- data.frame(time = 1:18,
                    eventID = 1:18,
                    sender = c("A", "B", "C",
                              "A", "D", "E",
                              "F", "B", "A",
                              "F", "D", "B",
                              "G", "B", "D",
```

```

                                "H", "A", "D"),
target = c("B", "C", "D",
           "E", "A", "F",
           "D", "A", "C",
           "G", "B", "C",
           "H", "J", "A",
           "F", "C", "B"))

eventSet <-create_riskset_constant(type = "one-mode",
                                  time = events$time,
                                  eventID = events$eventID,
                                  sender = events$sender,
                                  receiver = events$target,
                                  p_samplingobserved = 1.00,
                                  n_controls = 1,
                                  seed = 9999)

#compute the triadic statistic for the outgoing shared partners formation
eventSet$OSP <- dreamstats_triads(
  formation = "OSP", #outgoing shared partners argument
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#compute the triadic statistic for the incoming shared partners formation
eventSet$ISP <- dreamstats_triads(
  formation = "ISP", #incoming shared partners argument
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#compute the triadic statistic for the outgoing two-paths formation
eventSet$OTP <- dreamstats_triads(
  formation = "OTP", #outgoing two-paths argument
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

```

```
#compute the triadic statistic for the incoming two-paths formation
eventSet$ITP <- dreamstats_triads(
  formation = "ITP", #incoming two-paths argument
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)
```

estimate_rem_logit *Fit a Relational Event Model (REM) to Event Sequence Data*

Description

[Stable]

This function estimates the ordinal timing relational event model by maximizing the likelihood function given by Butts (2008) via maximum likelihood estimation. A nice outcome is that the ordinal timing relational event model is equivalent to the conditional logistic regression (see Greene 2003; for R functions, see [clogit](#)). In addition, based on this outcome and the structure of the data, this function can estimate the Cox proportional hazards model (see Box-Steffensmeier and Jones 2004; for R functions, see [coxph](#)) given that the likelihood functions are equivalent. An important assumption this model makes is that only one event occurs at each time point. If this is unfeasible for the user's specific dataset, we encourage the user to see the [clogit](#) function for the Breslow approximation technique (Box-Steffensmeier and Jones 2004). Future versions of the package will include options for interval timing relational event models and tied event data (e.g., multiple events at one time point).

Usage

```
estimate_rem_logit(
  formula,
  event.cluster,
  data,
  ordinal = TRUE,
  multiple.events = FALSE,
  newton.rhapon = TRUE,
  optim.method = "BFGS",
  optim.control = list(),
  tolerance = 1e-09,
  maxit = 20,
  starting.beta = NULL,
  ...
)
```

Arguments

<code>formula</code>	A formula object with the dependent variable on the left hand side of <code>~</code> and the covariates on the right hand side. This is the same argument found in <code>lm</code> and <code>glm</code> .
<code>event.cluster</code>	An integer or factor vector that groups each observed event with its corresponding control (null) events. This vector defines the strata in the event sequence, ensuring that each stratum contains one observed event and its associated null alternatives. It is used to structure the likelihood by stratifying events based on their occurrence in time.
<code>data</code>	The data.frame that contains the variable included in the formula argument.
<code>ordinal</code>	TRUE/FALSE. Currently, this function supports only the estimation of ordinal timing relational event models (see Butts 2008). Future versions of the package will include estimation options for interval timing relational event models. At this time, this argument is preset to TRUE and should not be modified by the user.
<code>multiple.events</code>	TRUE/FALSE. Currently, this function assumes that only one event occurs per event cluster (i.e., time point). Future versions of the package will include estimation options for multiple events per time point, commonly referred to as tied events, via the Breslow approximation technique (see Box-Steffensmeier and Jones 2004). At this moment, this argument is preset to FALSE and should not be modified by the user.
<code>newton.rhapson</code>	TRUE/FALSE. TRUE indicates an internal Newton-Rhapson iteration procedure with line searching is used to find the set of maximum likelihood estimates. FALSE indicates that the log likelihood function will be optimized via the <code>optim</code> function. The function defaults to TRUE.
<code>optim.method</code>	If <code>newton.rhapson</code> is FALSE, what <code>optim</code> method should be used in conjunction with the <code>optim</code> function. Defaults to "BFGS". See the <code>optim</code> function for the set of options.
<code>optim.control</code>	If <code>newton.rhapson</code> is FALSE, a list of control to be used in the <code>optim</code> function. See the <code>optim</code> function for the set of controls.
<code>tolerance</code>	If <code>newton.rhapson</code> is TRUE, the stopping criterion for the absolute difference in the log likelihoods for each Newton-Rhapson iteration. The optimization procedure stops when the absolute change in the log likelihoods is less than tolerance (see Greene 2003).
<code>maxit</code>	If <code>newton.rhapson</code> is TRUE, the maximum number of iterations for the Newton-Rhapson optimization procedure (see Greene 2003).
<code>starting.beta</code>	A numeric vector that represents the starting parameter estimates for the Newton-Rhapson optimization procedure. This may be a beneficial argument if the optimization procedure fails, since the Newton-Rhapson optimization procedure is sensitive to starting values. Preset to NULL.
<code>...</code>	Additional arguments.

Details

This function maximizes the ordinal timing relational event model likelihood function provided in the seminal REM paper by Butts (2008). The likelihood function is:

$$L(E|\beta) = \prod_{i=1}^{|E|} \frac{\lambda_{e_i}}{\sum_{e' \in RS_{e_i}} \lambda_{e'}}$$

where, following Butts (2008) and Duxbury (2020), E is the relational event sequence, λ_{e_i} is the hazard rate for event i , which is formulated to be equal to $\exp(\beta^T z(x, Y))$, that is, the linear combination of user-specific covariates, $z(x, Y)$, and associated REM parameters, β . Following Duxbury (2020), $z(x, Y)$ is a mapping function that represents the endogenous network statistics computed on the network of past events, x , and exogenous covariates, Y . The user provides these covariates via the `formula` argument.

This function provides two numerical optimization techniques to find the maximum likelihood estimates for the associated parameters. First, this function allows the user to use the `optim` function to find the associated parameters based on the above likelihood function. Secondly, and by default, this function employs a Newton-Raphson iteration algorithm with line-searching to find the unknown parameters (see Greene 2003 for a discussion of this algorithm). If desired, the user can provide the initial searching values for both algorithms with the `starting.beta` argument.

It's important to note that the modeling concerns of the conditional logistic regression apply to the ordinal timing relational event model, such as no within-sequence fixed effects, that is, a variable that does not vary within event cluster (i.e., a variable that is the same for both the null and observed events). The function internally checks for this and provides the user with a warning if any requested effects has no total within-event variance. Moreover, any observed events that have no associated control events are removed from the analysis as they provide no information to the log likelihood (see Greene 2003). The function removes these events from the sequence prior to estimation.

Value

An object of class "dream" as a list containing the following components:

optimization.method The optimization method used to find the parameters..

converged TRUE/FALSE. TRUE indicates that the REM converged.

loglikelihood.null The log likelihood of the null model (i.e., the model where the parameters are assumed to be 0).

loglikelihood.full The log likelihood of the estimated model.

chi.stat The chi-statistic of the likelihood ratio test.

loglikelihood.test The p-value of the likelihood ratio test.

df.null The degrees of freedom of the null model.

df.full The degrees of freedom of the full model.

parameters The MLE parameter estimates.

hessian The estimated hessian matrix.

gradient The estimated gradient vector.

se.parameter The standard errors of the MLE parameter estimates.


```

        sampled = post.processing$sampled,
        sender = post.processing$sender,
        receiver = post.processing$receiver,
        halflife = 2, #halflife parameter
        dyadic_weight = 0,
        exp_weight_form = FALSE)

#Computing the inertia/repetition statistic for the above post-processing
#one-mode relational event sequence
post.processing$inertia <- remstats_repetition(time = post.processing$time,
        observed = post.processing$observed,
        sampled = post.processing$sampled,
        sender = post.processing$sender,
        receiver = post.processing$receiver,
        halflife = 2, #halflife parameter
        dyadic_weight = 0,
        exp_weight_form = FALSE)

#Fitting a (ordinal) relational event model to the above one-mode relational
#event sequence
rem <- estimate_rem_logit(observed~ sender.outdegree + inertia,
        event.cluster = post.processing$time,
        data=post.processing)
summary(rem) #summary of the relational event model

#Fitting a (ordinal) relational event model to the above one-mode relational
#event sequence via the optim function
rem1 <- estimate_rem_logit(observed~ sender.outdegree + inertia,
        event.cluster = post.processing$time,
        data=post.processing,
        newton.rhapon=FALSE)
summary(rem1) #summary of the relational event model

```

netstats_om_constraint

Compute Burt's (1992) Constraint for Ego Networks from a Sociomatrix

Description

[Stable]

This function computes Burt's (1992) one-mode ego constraint based upon a sociomatrix.

Usage

```

netstats_om_constraint(
  net,
  inParallel = FALSE,

```

```

nCores = NULL,
isolates = NA,
pendants = 1
)

```

Arguments

<code>net</code>	A one-mode sociomatrix with network ties.
<code>inParallel</code>	TRUE/FALSE. TRUE indicates that parallel processing will be used to compute the statistic with the <i>foreach</i> package. FALSE indicates that parallel processing will not be used. Set to FALSE by default.
<code>nCores</code>	If <code>inParallel = TRUE</code> , the number of computing cores for parallel processing. If this value is not specified, then the function internally provides it by dividing the number of available cores in half.
<code>isolates</code>	What value should isolates be given? Set to NA by default.
<code>pendants</code>	What value should be given to pendant vertices? Set to 1 by default. Pendant vertices are those nodes who have one outgoing tie.

Details

The formula for Burt's (1992) one-mode ego constraint is:

$$c_{ij} = \left(p_{ij} + \sum_q p_{iq} p_{qj} \right)^2 \quad ; \quad q \neq i \neq j$$

where:

- p_{iq} is formulated as: $p_{iq} = \frac{z_{iq} + z_{qi}}{\sum_j (z_{ij} + z_{ji})}$; $i \neq j$

Finally, the aggregate constraint of an ego i is:

$$C_i = \sum_j c_{ij}$$

While this function internally locates isolates (i.e., nodes who have no ties) and pendants (i.e., nodes who only have one tie), the user should specify what values for constraint are returned for them via the *isolates* and *pendants* options. In particular, pendant vertices are those nodes who have one outgoing tie.

Lastly, this function allows users to compute the values in parallel via the *foreach*, *doParallel*, and *parallel* R packages.

Value

The vector of ego network constraint values.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dfle@arizona.edu

References

Burt, Ronald. 1992. *Structural Holes: The Social Structure of Competition*. Harvard University Press.

Examples

```
# For this example, we recreate the ego network provided in Burt (1992: 56):
BurtEgoNet <- matrix(c(
  0,1,0,0,1,1,1,
  1,0,0,1,0,0,1,
  0,0,0,0,0,0,1,
  0,1,0,0,0,0,1,
  1,0,0,0,0,0,1,
  1,0,0,0,0,0,1,
  1,0,0,0,0,0,1,
  1,1,1,1,1,1,0),
  nrow = 7, ncol = 7)
colnames(BurtEgoNet) <- rownames(BurtEgoNet) <- c("A", "B", "C", "D", "E",
  "F", "ego")
#the constraint value for the ego replicates that provided in Burt (1992: 56)
netstats_om_constraint(BurtEgoNet)
```

netstats_om_effective *Compute Burt's (1992) Effective Size for Ego Networks from a Sociomatrix*

Description

[Stable]

This function computes Burt's (1992) one-mode ego effective size based upon a sociomatrix (see details).

Usage

```
netstats_om_effective(
  net,
  inParallel = FALSE,
  nCores = NULL,
  isolates = NA,
  pendants = 1
)
```

Arguments

net The one-mode sociomatrix with network ties.

inParallel	TRUE/FALSE. TRUE indicates that parallel processing will be used to compute the statistic with the <i>foreach</i> package. FALSE indicates that parallel processing will not be used. Set to FALSE by default.
nCores	If inParallel = TRUE, the number of computing cores for parallel processing. If this value is not specified, then the function internally provides it by dividing the number of available cores in half.
isolates	The numerical value that represents what value will isolates be given. Set to NA by default.
pendants	The numerical value that represents what value will pendant vertices be given. Set to 1 by default. Pendant vertices are those nodes who have one outgoing tie.

Details

The formula for Burt's (1992; see also Borgatti 1997) one-mode ego effective size is:

$$E_i = \sum_j 1 - \sum_q p_{iq} m_{jq}; q \neq i \neq j$$

where E_i is the ego effective size for an ego i . p_{iq} is formulated as:

$$\frac{(z_{iq} + z_{qi})}{\sum_j (z_{ij} + z_{ji}); i \neq j}$$

and m_{jq} is:

$$m_{jq} = \frac{(z_{jq} + z_{qj})}{\max(z_{jk} + z_{kj})}$$

While this function internally locates isolates (i.e., nodes who have no ties) and pendants (i.e., nodes who only have one tie), the user should specify what values for constraint are returned for them via the *isolates* and *pendants* options. In particular, pendant vertices are those nodes who have one outgoing tie.

Value

The vector of ego network effective size values.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Burt, Ronald. 1992. *Structural Holes: The Social Structure of Competition*. Harvard University Press.
- Borgatti, Stephen. 1997. "Structural Holes: Unpacking Burt's Redundancy Measures." *Connections* 20(1): 35-38.

Examples

```

# For this example, we recreate the ego network provided in Borgatti (1997):
BorgattiEgoNet <- matrix(
  c(0,1,0,0,0,0,0,0,1,
    1,0,0,0,0,0,0,0,1,
    0,0,0,1,0,0,0,0,1,
    0,0,1,0,0,0,0,0,1,
    0,0,0,0,0,1,0,0,1,
    0,0,0,0,1,0,0,0,1,
    0,0,0,0,0,0,0,1,1,
    0,0,0,0,0,0,1,0,1,
    1,1,1,1,1,1,1,1,0),
  nrow = 9, ncol = 9, byrow = TRUE)
colnames(BorgattiEgoNet) <- rownames(BorgattiEgoNet) <- c("A", "B", "C",
  "D", "E", "F",
  "G", "H", "ego")

#the effective size value for the ego replicates that provided in Borgatti (1997)
netstats_om_effective(BorgattiEgoNet)

# For this example, we recreate the ego network provided in Burt (1992: 56):
BurtEgoNet <- matrix(c(
  0,1,0,0,1,1,1,
  1,0,0,1,0,0,1,
  0,0,0,0,0,0,1,
  0,1,0,0,0,0,1,
  1,0,0,0,0,0,1,
  1,0,0,0,0,0,1,
  1,1,1,1,1,1,0),
  nrow = 7, ncol = 7)
colnames(BurtEgoNet) <- rownames(BurtEgoNet) <- c("A", "B", "C", "D", "E",
  "F", "ego")

#the effective size value for the ego replicates that provided in Burt (1992: 56)
netstats_om_effective(BurtEgoNet)

```

netstats_om_nwalks *Compute the Number of Walks of Length K in a One-Mode Network*

Description**[Stable]**

This function calculates the number of walks of length k between any two vertices in an unweighted one-mode network.

Usage

```
netstats_om_nwalks(net, k)
```

Arguments

net An unweighted one-mode network adjacency matrix.
k A numerical value that corresponds to the length of the paths to be computed.

Details

A nice result from graph theory is that the number of walks of length k between vertices i and j can be found by:

$$A_{ij}^k$$

This function assumes that there are no self-loops (i.e., the diagonal of the matrix is 0).

Value

An $n \times n$ matrix of counts of paths.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

Examples

```
# For this example, we generate a random one-mode graph with the sna package.
#creating the random network with 10 actors
set.seed(9999)
rnet <- matrix(sample(c(0,1), 10*10, replace = TRUE, prob = c(0.8,0.2)),
               nrow = 10, ncol = 10, byrow = TRUE)
diag(rnet) <- 0 #setting self ties to 0
#counting the walks of length 2
netstats_om_nwalks(rnet, k = 2)
#counting the walks of length 5
netstats_om_nwalks(rnet, k = 5)
```

netstats_om_pib *Compute Potential for Intercultural Brokerage (PIB) Based on Leal (2025)*

Description**[Stable]**

Following Leal (2025), this function calculates node's Potential for Intercultural Brokerage (PIB) in a one-mode network, that is, brokerage based on nodes' distinct group memberships. For example, users can examine PIB based on actors' gender. The option count determines what is returned by the function. If count is TRUE, then the count of 'culturally' dissimilar pairs brokered by ego is included (i.e., ego's total count of brokered open triangles where the alters at the two endpoints of said open triangles are 'culturally' dissimilar from one another). If count is FALSE, the proportion of ego's brokered open triangles where the endpoints are 'culturally' dissimilar out of all of ego's brokered open triangles (regardless of the cultural identity of the alters) is returned. The formula for computing interpersonal brokerage is presented in the details section.

Usage

```
netstats_om_pib(
  net,
  g.mem,
  symmetric = TRUE,
  triad.type = NULL,
  count = TRUE,
  isolate = NA
)
```

Arguments

net	The one-mode adjacency matrix.
g.mem	The vector of membership values that the brokerage scores will be based on.
symmetric	TRUE/FALSE. TRUE indicates that network matrix will be treated as symmetric. FALSE indicates that the network matrix will be treated as asymmetric. Set to TRUE by default.
triad.type	The string value (or vector) that indicates what specific triadic (star) structures the potential for cultural brokerage will be computed for. Possible values are "ANY", "OTS", "ITS", "MTS" (see the details section). The function defaults to "ANY".
count	TRUE/FALSE. TRUE indicates that the number of culturally brokered open triangles will be returned. FALSE indicates that the proportion of culturally brokered open triangles to all open triangles will be returned (see the details section). Set to TRUE by default.
isolate	If count = FALSE, the numerical value that will be given to isolates. This value is set to NA by default, as 0/0 is undefined. The user can specify this value!

Details

Following Leal (2025), the formula for interpersonal brokerage is:

$$PIB_i = \sum_{j < k} \frac{S_{jik}}{S_{jk}} m_{jk}, \quad S_{jik} \neq 0 \text{ and } i \neq j \neq k$$

where:

- $S_{jik} = 1$ if there is an (un)directed two-path connecting actors j and k through actor i ; 0 otherwise.
- $m_{jk} = 1$ if actors j and k are on different sides of a symbolic boundary; 0 otherwise.
- Following Gould (1989), S_{jik} represents the total number of two-paths between actors j and k .

If the network is non-symmetric (i.e., the user specified `symmetric = FALSE`), then the function can compute the cultural brokerage scores for different star structures. The possible values are: "ANY", which computes the scores for all structures, where a tie exists between i and j , j and k , and one does not exist between i and k . "OTS" computes the values for outgoing two-stars ($i < j > k$) or

the 021D triad according to the M.A.N. notation; see Wasserman and Faust 1994), where j is the broker. "ITS" computes the values for incoming two-stars ($i \rightarrow j \leftarrow k$ or the 021U triad according to the M.A.N. notation; see Wasserman and Faust 1994), where j is the broker. "MTS" computes PIB for mixed triadic structures ($i \leftarrow j \leftarrow k$ or $i \rightarrow j \rightarrow k$ or the 021C triad according to the M.A.N. notation; see Wasserman and Faust 1994). If not specified, the function defaults to the "ANY" category. This function can also compute all of the formations at once.

Value

The vector of interpersonal cultural brokerage values for the one-mode network.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Gould, Roger. 1989. "Power and Social Structure in Community Elites." *Social Forces* 68(2): 531-552.
- Leal, Diego F. 2025. "Locating Cultural Holes Brokers in Diffusion Dynamics Across Bright Symbolic Boundaries." *Sociological Methods & Research* [doi:10.1177/00491241251322517](https://doi.org/10.1177/00491241251322517)
- Wasserman, Stanley and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*. Cambridge: Cambridge University Press.

Examples

```
# For this example, we recreate Figure 3 in Leal (2025)
LealNet <- matrix( c(
  0,1,0,0,0,0,0,
  1,0,1,1,0,0,0,
  0,1,0,0,1,1,0,
  0,1,0,0,1,0,0,
  0,0,1,1,0,0,0,
  0,0,1,0,0,0,1,
  0,0,0,0,0,1,0),
  nrow = 7, ncol = 7, byrow = TRUE)

colnames(LealNet) <- rownames(LealNet) <- c("A", "B", "C", "D",
                                             "E", "F", "G")

categorical_variable <- c(0,0,1,0,0,0,0)
#These values are exactly the same as reported by Leal (2025)
netstats_om_pib(LealNet,
  symmetric = TRUE,
  g.mem = categorical_variable)
```

 netstats_tm_constraint

Compute Burchard and Cornwell's (2018) Two-Mode Constraint

Description

[Stable]

This function calculates the values for two-mode network constraint for weighted and unweighted two-mode networks based on Burchard and Cornwell (2018).

Usage

```
netstats_tm_constraint(
  net,
  isolates = NA,
  returnCIJmat = FALSE,
  weighted = FALSE
)
```

Arguments

net	A two-mode adjacency matrix or affiliation matrix.
isolates	What value should isolates be given? Preset to be NA.
returnCIJmat	TRUE/FALSE. TRUE indicates that the full constraint matrix, that is, the network constraint from an alter j on node i , will be returned to the user. FALSE indicates that the total constraint will be returned. Set to FALSE by default.
weighted	TRUE/FALSE. TRUE indicates the resulting statistic will be based on the weighted formula (see the details section). FALSE indicates the statistic will be based on the original non-weighted formula. Set to FALSE by default.

Details

Following Burchard and Cornwell (2018), the formula for two-mode constraint is:

$$c_{ij} = \left(\frac{|\zeta(j) \cap \zeta(i)|}{|\zeta(i^*)|} \right)^2$$

where:

- c_{ij} is the constraint of ego i with respect to actor j .
- $|\zeta(j) \cap \zeta(i)|$ is the number of opposite-class contacts that i and j both share.
- The denominator, $|\zeta(i^*)|$, represents the total number of opposite-class contacts of ego i excluding pendants. Pendants are level 2 groups that only have one member (i.e., incoming tie).

The total constraint for ego i is given by:

$$C_i = \sum_{j \in \sigma(i)} c_{ij}$$

The function returns the aggregate constraint for each actor; however, the user can specify the function to return the constraint matrix by setting `returnCIJmat` to TRUE.

The function can also compute constraint for weighted two-mode networks by setting `weighted` to TRUE. The formula for two-mode weighted constraint is:

$$c_{ij} = \left(\frac{|\zeta(j) \cap \zeta(i)|}{|\zeta(i^*)|} \right)^2 \times w_t$$

where w_t is the average of the tie weights that i and j send to their shared opposite-class contacts.

Value

The vector of two-mode constraint scores for level 1 actors in a two-mode network.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

Burchard, Jake and Benjamin Cornwell. 2018. "Structural Holes and Bridging in Two-Mode Networks." *Social Networks* 55:11-20.

Examples

```
# For this example, we recreate Figure 2 in Burchard and Cornwell (2018: 13)
BCNet <- matrix(
  c(1,1,0,0,
    1,0,1,0,
    1,0,0,1,
    0,1,1,1),
  nrow = 4, ncol = 4, byrow = TRUE)
colnames(BCNet) <- c("1", "2", "3", "4")
rownames(BCNet) <- c("i", "j", "k", "m")
#library(sna) #To plot the two mode network, we use the sna R package
#gplot(BCNet, usearrows = FALSE,
#      gmode = "twomode", displaylabels = TRUE)
netstats_tm_constraint(BCNet)
```

```
#For this example, we recreate Figure 9 in Burchard and Cornwell (2018:18) for
#weighted two mode networks.
BCweighted <- matrix(c(1,2,1, 1,0,0,
                      0,2,1,0,0,1),
                    nrow = 4, ncol = 3,
                    byrow = TRUE)
rownames(BCweighted) <- c("i", "j", "k", "l")
netstats_tm_constraint(BCweighted, weighted = TRUE)
```

 netstats_tm_degrecent

Compute Degree Centrality Values for Two-Mode Networks

Description

[Stable]

This function computes the degree centrality values for two-mode networks following Knoke and Yang (2020). The computed degree centrality is based on the specified level. That is, in an affiliation matrix, the density can be computed on the symmetric $g \times g$ co-membership matrix of level 1 actors (e.g., medical doctors) or on the symmetric $h \times h$ shared actors matrix for level 2 groups (e.g., hospitals) based on their shared members.

Usage

```
netstats_tm_degrecent(net, level1 = TRUE)
```

Arguments

net	A two-mode adjacency matrix
level1	TRUE/FALSE. TRUE indicates that the degree centrality will be computed for level 1 nodes. FALSE indicates that the degree centrality will be computed for level 2 nodes. Set to TRUE by default.

Details

Following Knoke and Yang (2020), the computation of degree for two-mode affiliation networks is level specific. A two-mode affiliation matrix X with dimensions $g \times h$, where g is the number of level 1 nodes (e.g., medical doctors) and h is the number of level 2 nodes (i.e., hospitals). If the function is defined on the level 1 nodes, the degree centrality of an actor i is computed as:

$$X^G = XX^T$$

$$C_D^G(g_i) = \sum_{i=1}^g x_{ij}^g \quad (i \neq j)$$

In contrast, if it is defined on the level 2 nodes, the degree centrality of an actor i is computed as:

$$X^H = X^T X$$

$$C_D^H(h_i) = \sum_{i=1}^h x_{ij}^h \quad (i \neq j)$$

Value

The vector of two-mode level-specific degree centrality values.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

Knoke, David and Song Yang. 2020. *Social Network Analysis*. Sage: Quantitative Applications in the Social Sciences (154)

Examples

```
#Replicating the bipartite graph presented in Knoke and Yang (2020: 109)
knoke_yang_PC <- matrix(c(1,1,0,0, 1,1,0,0,
                        1,1,1,0, 0,0,1,1,
                        0,0,1,1), byrow = TRUE,
                        nrow = 5, ncol = 4)
colnames(knoke_yang_PC) <- c("Rubio-R", "McConnell-R", "Reid-D", "Sanders-D")
rownames(knoke_yang_PC) <- c("UPS", "MS", "HD", "SEU", "ANA")
netstats_tm_degrecent(knoke_yang_PC, level1 = TRUE) #this value matches the book
netstats_tm_degrecent(knoke_yang_PC, level1 = FALSE) #this value matches the book
```

netstats_tm_density *Compute Level-Specific Graph Density for Two-Mode Networks*

Description**[Stable]**

This function computes the density of a two-mode network following Wasserman and Faust (1994) and Knoke and Yang (2020). The density is computed based on the specified level. That is, in an affiliation matrix, density can be computed on the symmetric $g \times g$ matrix of co-membership for the level 1 actors or on the symmetric $h \times h$ matrix of shared actors for level 2 groups.

Usage

```
netstats_tm_density(net, binary = FALSE, level1 = TRUE)
```

Arguments

net	A two-mode adjacency matrix.
binary	TRUE/FALSE. TRUE indicates that the transposed matrices will be binarized (see Wasserman and Faust 1995: 316). FALSE indicates that the transposed matrices will not be binarized. Set to FALSE by default.
level1	TRUE/FALSE. TRUE indicates that the graph density will be computed for level 1 nodes. FALSE indicates that the graph density will be computed for level 2 nodes. Set to FALSE by default.

Details

Following Wasserman and Faust (1994) and Knoke and Yang (2020), the computation of density for two-mode networks is level specific. A two-mode matrix X with dimensions $g \times h$, where g is the number of level 1 nodes (e.g., medical doctors) and h is the number of level 2 nodes (i.e., hospitals). If the function is defined on the level 1 nodes, the density is computed as:

$$X^g = XX^T$$

$$D^g = \frac{\sum_{i=1}^g \sum_{j=1}^g x_{ij}^g}{g(g-1)}$$

In contrast, if it is defined on the level 2 nodes, the density is:

$$X^h = X^T X$$

$$D^h = \frac{\sum_{i=1}^h \sum_{j=1}^h x_{ij}^h}{h(h-1)}$$

Moreover, as discussed in Wasserman and Faust (1994: 316), the density can be based on the dichotomous relations instead of the shared membership values. This can be specified by *binary = TRUE*.

Value

The level-specific network density for the two-mode graph.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Wasserman, Stanley and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*. Cambridge University Press.
- Knoke, David and Song Yang. 2020. *Social Network Analysis*. Sage: Quantitative Applications in the Social Sciences (154).

Examples

```
#Replicating the bipartate graph presented in Knoke and Yang (2020: 109)
knoke_yang_PC <- matrix(c(1,1,0,0, 1,1,0,0,
                        1,1,1,0, 0,0,1,1,
                        0,0,1,1), byrow = TRUE,
                       nrow = 5, ncol = 4)
colnames(knoke_yang_PC) <- c("Rubio-R", "McConnell-R", "Reid-D", "Sanders-D")
rownames(knoke_yang_PC) <- c("UPS", "MS", "HD", "SEU", "ANA")
#compute two-mode density for level 1
#note: this value does not match that of Knoke and Yang (which we believe
#is a typo in that book), but does match that of Wasserman and
#Faust (1995: 317) for the ceo dataset.
netstats_tm_density(knoke_yang_PC, level1 = TRUE)
```

```
#compute two-mode density for level 2.
#note: this value matches that of the book
netstats_tm_density(knoke_yang_PC, level1 = FALSE)
```

netstats_tm_effective *Compute Burchard and Cornwell's (2018) Two-Mode Effective Size*

Description

[Stable]

This function calculates the values for two-mode effective size for weighted and unweighted two-mode networks based on Burchard and Cornwell (2018).

Usage

```
netstats_tm_effective(
  net,
  inParallel = FALSE,
  nCores = NULL,
  isolates = NA,
  weighted = FALSE
)
```

Arguments

net	A two-mode adjacency matrix or affiliation matrix
inParallel	TRUE/FALSE. TRUE indicates that parallel processing will be used to compute the statistic with the <i>foreach</i> package. FALSE indicates that parallel processing will not be used. Set to FALSE by default.
nCores	If inParallel = TRUE, the number of computing cores for parallel processing. If this value is not specified, then the function internally provides it by dividing the number of available cores in half.
isolates	What value should isolates be given? Preset to be NA.
weighted	TRUE/FALSE. TRUE indicates the resulting statistic will be based on the weighted formula (see the details section). FALSE indicates the statistic will be based on the original non-weighted formula. Set to FALSE by default.

Details

The formula for two-mode effective size is:

$$ES_i = |\sigma(i)| - \sum_{j \in \sigma(i)} r_{ij}$$

where:

- ES_i is the effective size of ego i .
- $|\sigma(i)|$ is the number of same-class contacts of ego i .
- $\sum_{j \in \sigma(i)} r_{ij}$ is the summation of the redundancy for each alter j in the two-mode ego network of i .

This function allows the user to compute the scores in parallel through the *foreach* and *doParallel* R packages. If the matrix is weighted, the user should specify *weighted = TRUE*. If the matrix is weighted, following Burchard and Cornwell (2018), the formula for two-mode weighted redundancy is:

$$r_{ij} = \frac{|\sigma(j) \cap \sigma(i)|}{|\sigma(i)| \times w_t}$$

where w_t is the average of the tie weights that i and j send to their shared opposite class contacts.

Value

The vector of two-mode effective size values for level 1 actors in a two-mode network.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dfle@arizona.edu

References

Burchard, Jake and Benjamin Cornwell. 2018. "Structural Holes and Bridging in Two-Mode Networks." *Social Networks* 55:11-20.

Examples

```
# For this example, we recreate Figure 2 in Burchard and Cornwell (2018: 13)
BCNet <- matrix(
  c(1,1,0,0,
    1,0,1,0,
    1,0,0,1,
    0,1,1,1),
  nrow = 4, ncol = 4, byrow = TRUE)
colnames(BCNet) <- c("1", "2", "3", "4")
rownames(BCNet) <- c("i", "j", "k", "m")
#library(sna) #To plot the two mode network, we use the sna R package
#gplot(BCNet, usearrows = FALSE,
#      gmode = "twomode", displaylabels = TRUE)
netstats_tm_effective(BCNet)
```

```
#In this example, we recreate Figure 9 in Burchard and Cornwell (2018:18)
#for weighted two mode networks.
BCweighted <- matrix(c(1,2,1, 1,0,0,
                      0,2,1,0,0,1),
                    nrow = 4, ncol = 3,
                    byrow = TRUE)
rownames(BCweighted) <- c("i", "j", "k", "l")
netstats_tm_effective(BCweighted, weighted = TRUE)
```

 netstats_tm_egodistance

Compute Fujimoto, Snijders, and Valente's (2018) Ego Homophily Distance for Two-Mode Networks

Description

[Stable]

This function computes the ego homophily distance in two-mode networks as proposed by Fujimoto, Snijders, and Valente (2018: 380). See Fujimoto, Snijders, and Valente (2018) for more details about this measure.

Usage

```
netstats_tm_egodistance(net, mem, standardize = FALSE)
```

Arguments

net	The two-mode adjacency matrix.
mem	The vector of membership values that the homophilous four cycles will be based on.
standardize	TRUE/FALSE. TRUE indicates that the scores will be standardized by the number of level 2 nodes the level 1 node is connected to. FALSE indicates that the scores will not be standardized. Set to FALSE by default.

Details

The formula for ego homophily distance in two-mode networks is:

$$Ego2Dist_i = \sum_a y_{ia} 1 - |v_i - p_{ia}|$$

where:

- \sum_a sums across all level 2 nodes in the network
- y_{ia} is the 1 if node i is tied to node a and 0 else.
- v_i is the value of the respondent. Within the function this is predefined to be 1 if there are multiple categories.
- p_{ia} is the proportion of same-category actors that are tied to node a not including the ego itself.
- $|v_i - p_{ia}|$ is equal to 1 if all the level 1 nodes that are tied to the level 2 node share the same categorical membership and 0 if all level 1 nodes are a different category.

If the ego is a level 2 isolate or a level 2 pendant, that is, only one level 1 node (e.g., patient) is connected to that specific level 2 node (e.g., medical doctor), then they are given a value of 0. In particular, the contribution to the ego distance for a pendant is 0. The ego distance value can be standardized by the number of groups which would provide the average ego distance as a proportion between 0 and 1.

Value

The vector of two-mode ego homophily distance.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

Fujimoto, Kayo, Tom A.B. Snijders, and Thomas W. Valente. 2018. "Multivariate dynamics of one-mode and two-mode networks: Explaining similarity in sports participation among friends." *Network Science* 6(3): 370-395.

Examples

```
# For this example, we use the Davis Southern Women's Dataset.
data("southern.women")
#creating a random binary membership vector
set.seed(9999)
membership <- sample(0:1, nrow(southern.women), replace = TRUE)
#the ego 2 mode distance non-standardized
netstats_tm_egodistance(southern.women, mem = membership)
#the ego 2 mode distance standardized
netstats_tm_egodistance(southern.women, mem = membership, standardize = TRUE)
```

netstats_tm_homfourcycles

Compute Fujimoto, Snijders, and Valente's (2018) Homophilous Four-Cycles for Two-Mode Networks

Description**[Stable]**

This function computes the number of homophilous four-cycles in a two-mode network as proposed by Fujimoto, Snijders, and Valente (2018: 380). See Fujimoto, Snijders, and Valente (2018) for more details about this measure.

Usage

```
netstats_tm_homfourcycles(net, mem)
```

Arguments

net	The two-mode adjacency matrix.
mem	The vector of membership values that the homophilous four-cycles will be based on.

Details

Following Fujimoto, Snijders, and Valente (2018: 380), the number of homophilous four-cycles for actor i is:

$$\sum_j \sum_{a \neq b} y_{ia} y_{ib} y_{ja} y_{jb} I v_i = v_j$$

where y is the two-mode adjacency matrix, v is the vector of membership scores (e.g., sports/club membership), a and b represent the level two groups, and $I v_i = v_j$ is the indicator function that is 1 if the values are the same and 0 if not.

Value

The vector of counts of homophilous four-cycles for the two-mode network.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

Fujimoto, Kayo, Tom A.B. Snijders, and Thomas W. Valente. 2018. "Multivariate dynamics of one-mode and two-mode networks: Explaining similarity in sports participation among friends." *Network Science* 6(3): 370-395.

Examples

```
# For this example, we use the Davis Southern Women's Dataset.
data("southern.women")
#creating a random binary membership vector
set.seed(9999)
membership <- sample(0:1, nrow(southern.women), replace = TRUE)
#the homophilous four-cycle values
netstats_tm_homfourcycles(southern.women, mem = membership)
```

netstats_tm_redundancy

Compute Burchard and Cornwell's (2018) Two-Mode Redundancy

Description**[Stable]**

This function calculates the values for two mode redundancy for weighted and unweighted two-mode networks based on Burchard and Cornwell (2018).

Usage

```
netstats_tm_redundancy(
  net,
  inParallel = FALSE,
  nCores = NULL,
  isolates = NA,
  weighted = FALSE
)
```

Arguments

<code>net</code>	A two-mode adjacency matrix or affiliation matrix.
<code>inParallel</code>	TRUE/FALSE. TRUE indicates that parallel processing will be used to compute the statistic with the <i>foreach</i> package. FALSE indicates that parallel processing will not be used. Set to FALSE by default.
<code>nCores</code>	If <code>inParallel = TRUE</code> , the number of computing cores for parallel processing. If this value is not specified, then the function internally provides it by dividing the number of available cores in half.
<code>isolates</code>	What value should isolates be given? Preset to be NA.
<code>weighted</code>	TRUE/FALSE. TRUE indicates the resulting statistic will be based on the weighted formula (see the details section). FALSE indicates the statistic will be based on the original non-weighted formula. Set to FALSE by default.

Details

The formula for two-mode redundancy is:

$$r_{ij} = \frac{|\sigma(j) \cap \sigma(i)|}{|\sigma(i)|}$$

where:

- r_{ij} is the redundancy of ego i with respect to actor j .
- $|\sigma(j) \cap \sigma(i)|$ is the number of same-class contacts (e.g., medical doctors in a hospital) that i and j both share.
- $|\sigma(i)|$ is the number of same-class contacts of ego i .

The two-mode redundancy is ego-bound, that is, the redundancy is only based on the two-mode ego network of i . Put differently, r_{ij} only considers the perspective of the ego. This function allows the user to compute the scores in parallel through the *foreach* and *doParallel* R packages. If the matrix is weighted, the user should specify `weighted = TRUE`. Following Burchard and Cornwell (2018), the formula for two-mode weighted redundancy is:

$$r_{ij} = \frac{|\sigma(j) \cap \sigma(i)|}{|\sigma(i)| \times w_t}$$

where w_t is the average of the tie weights that i and j send to their shared opposite class contacts.

Value

An $n \times n$ matrix with level 1 redundancy scores for actors in a two-mode network.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

Burchard, Jake and Benjamin Cornwell. 2018. "Structural Holes and bridging in two-mode networks." *Social Networks* 55:11-20.

Examples

```
# For this example, we recreate Figure 2 in Burchard and Cornwell (2018: 13)
BCNet <- matrix(
  c(1,1,0,0,
    1,0,1,0,
    1,0,0,1,
    0,1,1,1),
  nrow = 4, ncol = 4, byrow = TRUE)
colnames(BCNet) <- c("1", "2", "3", "4")
rownames(BCNet) <- c("i", "j", "k", "m")
#this values replicate those reported by Burchard and Cornwell (2018: 14)
netstats_tm_redundancy(BCNet)
```

```
#For this example, we recreate Figure 9 in Burchard and Cornwell (2018:18)
#for weighted two mode networks.
BCweighted <- matrix(c(1,2,1, 1,0,0,
                      0,2,1,0,0,1),
  nrow = 4, ncol = 3,
  byrow = TRUE)
rownames(BCweighted) <- c("i", "j", "k", "l")
netstats_tm_redundancy(BCweighted, weighted = TRUE)
```

print.dream

Print Method for Summary of dream Model

Description

Print Method for Summary of dream Model

Usage

```
## S3 method for class 'dream'
print(x, digits = 4, ...)
```

Arguments

x	An object of class "summary.dream".
digits	The number of digits to print after the decimal point.
...	Additional arguments (currently unused).

Value

No return value. Prints out the main results of a 'dream' object.

print.summary.dream *Print Method for dream Model*

Description

Print Method for dream Model

Usage

```
## S3 method for class 'summary.dream'
print(x, digits = 4, ...)
```

Arguments

x	An object of class "dream".
digits	The number of digits to print after the decimal point.
...	Additional arguments (currently unused).

Value

No return value. Prints out the main results of a 'dream' summary object.

remstats_degree *Compute Degree Network Statistics for Event Senders and Receivers in a Relational Event Sequence*

Description**[Deprecated]**

remstats_degree() has been deprecated starting on version 1.1.1 of the dream package. Please use the dreamstats_degree() function and see the NEWS.md file for more details.

The function computes the indegree network sufficient statistic for event senders in a relational event sequence (see Lerner and Lomi 2020; Butts 2008). This measure allows for indegree scores to be only computed for the sampled events, while creating the weights based on the full event sequence (see Lerner and Lomi 2020; Vu et al. 2015). The function also allows users to use two different weighting functions, return the counts of past events, reduce computational runtime, and specify a dyadic cutoff for relational relevancy.

Usage

```
remstats_degree(
  formation = c("sender-indegree", "receiver-indegree", "sender-outdegree",
    "receiver-outdegree"),
  time,
  sender,
  receiver,
  observed,
  sampled,
  halflife = 2,
  counts = FALSE,
  dyadic_weight = 0,
  exp_weight_form = FALSE
)
```

Arguments

formation	The degree statistic to be computed. "sender-indegree" computes the indegree statistic for the event senders. "receiver-indegree" computes the indegree statistic for the event receivers. "sender-outdegree" computes the outdegree statistic for the event senders. "receiver-outdegree" computes the outdegree statistic for the event receivers.
time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
halflife	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).
counts	TRUE/FALSE. TRUE indicates that the counts of past events should be computed (see the details section). FALSE indicates that the temporal exponential weighting function should be used to downweigh past events (see the details section). Set to FALSE by default.
dyadic_weight	A numerical value for the dyadic cutoff weight that represents the numerical cutoff value for temporal relevancy based on the exponential weighting function. For example, a numerical value of 0.01, indicates that an exponential weight less than 0.01 will become 0 and that events with such value (or smaller values) will not be included in the sum of the past event weights (see the details section). Set to 0 by default.
exp_weight_form	TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default

Details

The function calculates sender indegree scores for relational event sequences based on the exponential weighting function used in either Lerner and Lomi (2020) or Lerner et al. (2013).

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset, and $T_{1/2}$ is the halflife parameter.

Sender-Indegree Statistic:

The formula for sender indegree for event e_i is:

$$senderindegree_{e_i} = w(s', s, t)$$

That is, all past events in which the event receiver is the current sender. Following Butts (2008), if the counts of the past events are requested, the formula for sender indegree for event e_i is:

$$senderindegree_{e_i} = d(r' = s, t')$$

Where, $d()$ is the number of past events where the event receiver, r' , is the current event sender s .

Sender-Outdegree Statistic:

The formula for sender outdegree for event e_i is:

$$senderoutdegree_{e_i} = w(s, r', t)$$

That is, all past events in which the past sender is the current sender and the event target can be any past user. Following Butts (2008), if the counts of the past events are requested, the formula for sender outdegree for event e_i is:

$$senderoutdegree_{e_i} = d(s = s', t')$$

Where, $d()$ is the number of past events where the sender s' is the current event sender, s

Receiver-Outdegree Statistic:

The formula for receiver outdegree for event e_i is:

$$receiveroutdegree_{e_i} = w(r', r, t)$$

Following Butts (2008), if the counts of the past events are requested, the formula for receiver outdegree for event e_i is:

$$receiveroutdegree_{e_i} = d(s' = r, t')$$

Where, $d()$ is the number of past events where the event sender, s' , is the current event receiver, r .

Receiver-Indegree Statistic:

The formula for receiver indegree for event e_i is:

$$\text{recieverindegree}_{e_i} = w(s', r, t)$$

That is, all past events in which the event receiver is the current receiver. Following Butts (2008), if the counts of the past events are requested, the formula for receiver indegree for event e_i is:

$$\text{recieverindegree}_{e_i} = d(r' = r, t')$$

where, $d()$ is the number of past events where the past event receiver, r' , is the current event receiver (target).

Lastly, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022; Lerner and Lomi 2020) can specify the dyadic weight cutoff, that is, the minimum value for which the weight is considered relationally relevant. Users who do not know the specific dyadic cutoff value to use, can use the `remstats_dyadcut` function.

Value

The vector of degree statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dfic@arizona.edu

References

- Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.
- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.
- Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. "Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.
- Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
events <- data.frame(time = 1:18, eventID = 1:18,
                    sender = c("A", "B", "C",
                              "A", "D", "E",
                              "F", "B", "A",
                              "F", "D", "B",
                              "G", "B", "D",
                              "H", "A", "D"),
```

```

target = c("B", "C", "D",
           "E", "A", "F",
           "D", "A", "C",
           "G", "B", "C",
           "H", "J", "A",
           "F", "C", "B"))

eventSet <- create_riskset_constant(type = "one-mode",
                                   time = events$time,
                                   eventID = events$eventID,
                                   sender = events$sender,
                                   receiver = events$target,
                                   p_samplingobserved = 1.00,
                                   n_controls = 1,
                                   seed = 9999)

#Computing the sender indegree statistic for the relational event sequence
eventSet$senderind <- remstats_degree(
  formation = "sender-indegree",
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#Computing the sender outdegree statistic for the relational event sequence
eventSet$senderout <- remstats_degree(
  formation = "sender-outdegree",
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#Computing the receiver outdegree statistic for the relational event sequence
eventSet$recieverout <- remstats_degree(
  formation = "receiver-outdegree",
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

```

```
#Computing the receiver indegree statistic for the relational event sequence
eventSet$recieverind <- remstats_degree(
  formation = "receiver-indegree",
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)
```

remstats_dyadcut	<i>A Helper Function to Assist Researchers in Finding Dyadic Weight Cutoff Values</i>
------------------	---

Description

[Deprecated]

remstats_dyadcut() has been deprecated starting on version 1.1.1 of the dream package. Please use the dreamstats_dyadcut() function and see the NEWS.md file for more details.

A user-helper function to assist researchers in finding the dyadic cutoff value to compute sufficient statistics for relational event models based upon temporal dependency.

Usage

```
remstats_dyadcut(halflife = 2, relationalWidth, exp_weight_form = FALSE)
```

Arguments

halflife	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).
relationalWidth	The numerical value that corresponds to the time range for which the user specifies for temporal relevancy.
exp_weight_form	TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default

Details

This function is specifically designed as a user-helper function to assist researchers in finding the dyadic cutoff value for creating sufficient statistics based upon temporal dependency. In other words, this function estimates a dyadic cutoff value for relational relevance, that is, the minimum dyadic weight for past events to be potentially relevant (i.e., to possibly have an impact) on the current event. All non-relevant events (i.e., events too distant in the past from the current event to be considered relevant, that is, those below the cutoff value) will have a weight of 0. This cutoff value is based upon two user-specified values: the events' halflife (i.e, halflife) and the relationally relevant event or time span (i.e., relationalWidth). Ideally, both the values for halflife and relationalWidth would be based on the researcher's command of the relevant substantive literature. Importantly, halflife and relationalWidth must be in the same units of measurement (e.g., days). If not, the function will not return the correct answer.

For example, let's say that the user defines the halflife to be 15 days (i.e., two weeks) and the relationally relevant event or time span (i.e., relationalWidth) to be 30 days (i.e., events that occurred more than 1 month in the past are not considered relationally relevant for the current event). The user would then specify halflife = 15 and relationalWidth = 30.

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset, and $T_{1/2}$ is the halflife parameter. The task of this function is to find the weight, $w(s, r, t)$, that corresponds to the time difference provided by the user.

Value

The dyadic weight cutoff based on user specified values.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.
- Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. " Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.

Examples

```
#To replicate the example in the details section:
# with the Lerner et al. 2013 weighting function
remstats_dyadcut(halflife = 15,
                 relationalWidth = 30,
                 exp_weight_form = TRUE)

# without the Lerner et al. 2013 weighting function
remstats_dyadcut(halflife = 15,
                 relationalWidth = 30,
                 exp_weight_form = FALSE)

# A result to test the function (should come out to 0.50)
remstats_dyadcut(halflife = 30,
                 relationalWidth = 30,
                 exp_weight_form = FALSE)

# Replicating Lerner and Lomi (2020):
#"We set T1/2 to 30 days so that an event counts as (close to) one in the very next instant of time,
#it counts as 1/2 one month later, it counts as 1/4 two months after the event, and so on. To reduce
#the memory consumption needed to store the network of past events, we set a dyadic weight to
#zero if its value drops below 0.01. If a single event occurred in some dyad this would happen after
#6.64*T1/2, that is after more than half a year." (Lerner and Lomi 2020: 104).

# Based upon Lerner and Lomi (2020: 104), the result should be around 0.01. Since the
# time values in Lerner and Lomi (2020) are in milliseconds, we have to change
# all measurements into milliseconds
remstats_dyadcut(halflife = (30*24*60*60*1000), #30 days in milliseconds
                 relationalWidth = (6.64*30*24*60*60*1000), #Based upon the paper
                 #using the Lerner and Lomi (2020) weighting function
                 exp_weight_form = FALSE)
```

remstats_fourcycles *Compute the Four-Cycles Network Statistic for Event Dyads in a Relational Event Sequence*

Description

[Deprecated]

remstats_fourcycles() has been deprecated starting on version 1.1.1 of the dream package. Please use the dreamstats_fourcycles() function and see the NEWS.md file for more details.

The function computes the four-cycles network sufficient statistic for a two-mode relational sequence with the exponential weighting function (Lerner and Lomi 2020). In essence, the four-cycles measure captures the tendency for clustering to occur in the network of past events, whereby an event is more likely to occur between a sender node a and receiver node b given that a has interacted with other receivers in past events who have received events from other senders that interacted

with b (e.g., Duxbury and Haynie 2021, Lerner and Lomi 2020). The function also allows users to use two different weighting functions, return the counts of past events, reduce computational runtime, and specify a dyadic cutoff for relational relevancy.

Usage

```
remstats_fourcycles(
  time,
  sender,
  receiver,
  observed,
  sampled,
  halflife = 2,
  counts = FALSE,
  dyadic_weight = 0,
  exp_weight_form = FALSE
)
```

Arguments

time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
halflife	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).
counts	TRUE/FALSE. TRUE indicates that the counts of past events should be computed (see the details section). FALSE indicates that the temporal exponential weighting function should be used to downweigh past events (see the details section). Set to FALSE by default.
dyadic_weight	A numerical value for the dyadic cutoff weight that represents the numerical cutoff value for temporal relevancy based on the exponential weighting function. For example, a numerical value of 0.01, indicates that an exponential weight less than 0.01 will become 0 and that events with such value (or smaller values) will not be included in the sum of the past event weights (see the details section). Set to 0 by default.
exp_weight_form	TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default

Details

The function calculates the four-cycles network statistic for two-mode relational event models based on the exponential weighting function used in either Lerner and Lomi (2020) or Lerner et al. (2013). Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-\frac{(t-t') \cdot \ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-\frac{(t-t') \cdot \ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset (in this case, all events that have the same sender and receiver), and $T_{1/2}$ is the half-life parameter.

The formula for four-cycles for event e_i is:

$$fourcycles_{e_i} = \sqrt[3]{\sum_{s' \text{ and } r'} w(s', r, t) \cdot w(s, r', t) \cdot w(s', r', t)}$$

That is, the four-cycle measure captures all the past event structures in which the current event pair, sender s and target r close a four-cycle. In particular, it finds all events in which: a past sender s' had a relational event with target r , a past target r' had a relational event with current sender s , and finally, a relational event occurred between sender s' and target r' .

Four-cycles are computationally expensive, especially for large relational event sequences (see Lerner and Lomi 2020 for a discussion on this), therefore this function allows the user to input previously computed target indegree and sender outdegree scores to reduce the runtime. Relational events where either the event target or event sender were not involved in any prior relational events (i.e., a target indegree or sender outdegree score of 0) will close no-four cycles. This function exploits this feature.

Moreover, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022; Lerner and Lomi 2020) can specify the dyadic weight cutoff, that is, the minimum value for which the weight is considered relationally relevant. Users who do not know the specific dyadic cutoff value to use, can use the `remstats_dyadcut` function.

Following Lerner and Lomi (2020), if the counts of the past events are requested, the formula for four-cycles formation for event e_i is:

$$fourcycles_{e_i} = \sum_{i=1}^{|S'|} \sum_{j=1}^{|R'|} \min [d(s'_i, r, t), d(s, r'_j, t), d(s'_i, r'_j, t)]$$

where, $d()$ is the number of past events that meet the specific set operations, $d(s'_i, r, t)$ is the number of past events where the current event receiver received a tie from another sender s'_i , $d(s, r'_j, t)$ is the number of past events where the current event sender sent a tie to another receiver r'_j , and $d(s'_i, r'_j, t)$ is the number of past events where the sender s'_i sent a tie to the receiver r'_j . Moreover, the counting equation can leverage relational relevancy, by specifying the half-life parameter, exponential weighting function, and the dyadic cut off weight values (see the above sections for help with this). If the user is not interested in modeling relational relevancy, then those value should be left at their default values.

Value

The vector of four-cycle statistics for the two-mode relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

Duxbury, Scott and Dana Haynie. 2021. "Shining a Light on the Shadows: Endogenous Trade Structure and the Growth of an Online Illegal Market." *American Journal of Sociology* 127(3): 787-827.

Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.

Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.

Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. "Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.

Examples

```
data("WikiEvent2018.first100k")
WikiEvent2018 <- WikiEvent2018.first100k[1:1000,] #the first one thousand events
WikiEvent2018$time <- as.numeric(WikiEvent2018$time) #making the variable numeric
### Creating the EventSet By Employing Case-Control Sampling With M = 5 and
### Sampling from the Observed Event Sequence with P = 0.01
EventSet <- create_riskset_constant(type = "two-mode",
  time = WikiEvent2018$time, # The Time Variable
  eventID = WikiEvent2018$eventID, # The Event Sequence Variable
  sender = WikiEvent2018$user, # The Sender Variable
  receiver = WikiEvent2018$article, # The Receiver Variable
  p_samplingobserved = 0.01, # The Probability of Selection
  n_controls = 8, # The Number of Controls to Sample from the Full Risk Set
  combine = TRUE,
  seed = 9999) # The Seed for Replication

#Computing the four-cycles statistics for the relational event sequence with
#the exponential weights of past events returned
cycle4_weights <- remstats_fourcycles(
  time = EventSet$time,
  sender = EventSet$sender,
  receiver = EventSet$receiver,
  sampled = EventSet$sampled,
  observed = EventSet$observed,
  halflife = 2.592e+09, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)
```

```

#Computing the four-cycles statistics for the relational event sequence with
#the counts of past events returned
cycle4_counts <- remstats_fourcycles(
  time = EventSet$time,
  sender = EventSet$sender,
  receiver = EventSet$receiver,
  sampled = EventSet$sampled,
  observed = EventSet$observed,
  halflife = 2.592e+09, #halflife parameter
  dyadic_weight = 0,
  counts = TRUE)

cbind(cycle4_weights, cycle4_counts)

```

remstats_persistence *Compute Butts' (2008) Persistence Network Statistic for Event Dyads in a Relational Event Sequence*

Description

[Deprecated]

remstats_persistence() has been deprecated starting on version 1.1.1 of the dream package. Please use the dreamstats_persistence() function and see the NEWS.md file for more details.

This function computes the persistence network sufficient statistic for a relational event sequence (see Butts 2008). Persistence measures the proportion of past ties sent from the event sender that went to the current event receiver. Furthermore, this measure allows for persistence scores to be only computed for the sampled events, while creating the weights based on the full event sequence. Moreover, the function allows users to specify relational relevancy for the resulting statistic.

Usage

```

remstats_persistence(
  time,
  sender,
  target,
  sampled,
  observed,
  ref_sender = TRUE,
  nopastEvents = NA,
  dependency = FALSE,
  relationalTimeSpan = 0
)

```

Arguments

time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
target	The vector of event targets from the post-processing event sequence
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
ref_sender	TRUE/FALSE. TRUE indicates that the persistence statistic will be computed in reference to the sender's past relational history (see details section). FALSE indicates that the persistence statistic will be computed in reference to the target's past relational history (see details section). Set to TRUE by default.
nopastEvents	The numerical value that specifies what value should be given to events in which the sender has sent not past ties (i 's neighborhood when sender = TRUE) or has not received any past ties (j 's neighborhood when sender = FALSE). Set to NA by default.
dependency	TRUE/FALSE. TRUE indicates that temporal relevancy will be modeled (see the details section). FALSE indicates that temporal relevancy will not be modeled, that is, all past events are relevant (see the details section). Set to FALSE by default.
relationalTimeSpan	If dependency = TRUE, a numerical value that corresponds to the temporal span for relational relevancy, which must be the same measurement unit as the observed_time and processed_time objects. When dependency = TRUE, the relevant events are events that have occurred between current event time, t , and t -relationalTimeSpan. For example, if the time measurement is the number of days since the first event and the value for relationalTimeSpan is set to 10, then only those events which occurred in the past 10 days are included in the computation of the statistic.

Details

The function calculates the persistence network sufficient statistic for a relational event sequence based on Butts (2008).

The formula for persistence for event e_i with reference to the sender's past relational history is:

$$Persistence_{e_i} = \frac{d(s(e_i), r(e_i), A_t)}{d(s(e_i), A_t)}$$

where $d(s(e_i), r(e_i), A_t)$ is the number of past events where the current event sender sent a tie to the current event receiver, and $d(s(e_i), A_t)$ is the number of past events where the current sender sent a tie.

The formula for persistence for event e_i with reference to the target's past relational history is:

$$Persistence_{e_i} = \frac{d(s(e_i), r(e_i), A_t)}{d(r(e_i), A_t)}$$

where $d(s(e_i), r(e_i), A_t)$ is the number of past events where the current event sender sent a tie to the current event receiver, and $d(r(e_i), A_t)$ is the number of past events where the current receiver received a tie.

Moreover, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022) can specify the relational time span, that is, length of time for which events are considered relationally relevant. This should be specified via the option *relationalTimeSpan* with *dependency* set to TRUE.

Value

The vector of persistence network statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

Butts, Carter T. 2008. "A relational event framework for social action." *Sociological Methodology* 38(1): 155-200.

Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.

Examples

```
# A Dummy One-Mode Event Dataset
events <- data.frame(time = 1:18,
                    eventID = 1:18,
                    sender = c("A", "B", "C",
                              "A", "D", "E",
                              "F", "B", "A",
                              "F", "D", "B",
                              "G", "B", "D",
                              "H", "A", "D"),
                    target = c("B", "C", "D",
                              "E", "A", "F",
                              "D", "A", "C",
                              "G", "B", "C",
                              "H", "J", "A",
                              "F", "C", "B"))

# Creating the Post-Processing Event Dataset with Null Events
eventSet <- create_riskset_constant(type = "one-mode",
                                   time = events$time,
                                   eventID = events$eventID,
                                   sender = events$sender,
                                   receiver = events$target,
                                   p_samplingobserved = 1.00,
                                   n_controls = 6,
                                   seed = 9999)
```

```
#Computing the persistence statistic for the relational event sequence
eventSet$remstats_persistence <- remstats_persistence(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  target = eventSet$receiver,
  ref_sender = TRUE)
```

```
remstats_prefattachment
```

Compute Butts' (2008) Preferential Attachment Network Statistic for Event Dyads in a Relational Event Sequence

Description

[Deprecated]

remstats_prefattachment() has been deprecated starting on version 1.1.1 of the dream package. Please use the dreamstats_prefattachment() function and see the NEWS.md file for more details.

The function computes the preferential attachment network sufficient statistic for a relational event sequence (see Butts 2008). Preferential attachment measures the tendency towards a positive feedback loop in which actors involved in more past events are more likely to be involved in future events (see Butts 2008 for an empirical example and discussion). This measure allows for preferential attachment scores to be only computed for the sampled events, while creating the statistics based on the full event sequence. Moreover, the function allows users to specify relational relevancy for the resulting statistics.

Usage

```
remstats_prefattachment(
  time,
  sampled,
  observed,
  sender,
  receiver,
  dependency = FALSE,
  relationalTimeSpan = 0
)
```

Arguments

time	The vector of event times from the post-processing event sequence.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.

observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
dependency	TRUE/FALSE. TRUE indicates that temporal relevancy will be modeled (see the details section). FALSE indicates that temporal relevancy will not be modeled, that is, all past events are relevant (see the details section). Set to FALSE by default.
relationalTimeSpan	If dependency = TRUE, a numerical value that corresponds to the temporal span for relational relevancy, which must be the same measurement unit as the observed_time and processed_time objects. When dependency = TRUE, the relevant events are events that have occurred between current event time, t , and $t - relationalTimeSpan$. For example, if the time measurement is the number of days since the first event and the value for relationalTimeSpan is set to 10, then only those events which occurred in the past 10 days are included in the computation of the statistic.

Details

The function calculates preferential attachment for a relational event sequence based on Butts (2008).

Following Butts (2008), the formula for preferential attachment for event e_i is:

$$PA_{e_i} = \frac{d^+(r(e_i), A_t) + d^-(r(e_i), A_t)}{\sum_{i=1}^{|S|} (d^+(i, A_t) + d^-(i, A_t))}$$

where $d^+(r(e_i), A_t)$ is the past outdegree of the receiver for e_i , $d^-(r(e_i), A_t)$ is the past indegree of the receiver for e_i , $\sum_{i=1}^{|S|} (d^+(i, A_t) + d^-(i, A_t))$ is the sum of the past outdegree and indegree for all past event senders in the relational history.

Moreover, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022) can specify the relational time span, that is, length of time for which events are considered relationally relevant. This should be specified via the option *relationalTimeSpan* with *dependency* set to TRUE.

Value

The vector of event preferential attachment statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Butts, Carter T. 2008. "A relational event framework for social action." *Sociological Methodology* 38(1): 155-200.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.

Examples

```
# A Dummy One-Mode Event Dataset
events <- data.frame(time = 1:18,
                    eventID = 1:18,
                    sender = c("A", "B", "C",
                               "A", "D", "E",
                               "F", "B", "A",
                               "F", "D", "B",
                               "G", "B", "D",
                               "H", "A", "D"),
                    target = c("B", "C", "D",
                               "E", "A", "F",
                               "D", "A", "C",
                               "G", "B", "C",
                               "H", "J", "A",
                               "F", "C", "B"))

# Creating the Post-Processing Event Dataset with Null Events
eventSet <- create_riskset_constant( type = "one-mode",
                                   time = events$time,
                                   eventID = events$eventID,
                                   sender = events$sender,
                                   receiver = events$target,
                                   p_samplingobserved = 1.00,
                                   n_controls = 6,
                                   seed = 9999)

#Computing the preferential attachment statistic for the relational event sequence
eventSet$pref <- remstats_prefattachment(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver)
```

remstats_recency

Compute Butts' (2008) Recency Network Statistic for Event Dyads in a Relational Event Sequence

Description

[Deprecated]

remstats_recency() has been deprecated starting on version 1.1.1 of the dream package. Please use the dreamstats_recency() function and see the NEWS.md file for more details.

This function computes the recency network sufficient statistic for a relational event sequence (see Butts 2008; Vu et al. 2015; Meijerink-Bosman et al. 2022). The recency statistic captures the

tendency for more recent events (i.e., an exchange between two medical doctors) are more likely to re-occur in comparison to events that happened in the more distant past (see Butts 2008 for a discussion). This measure allows for recency scores to be only computed for the sampled events, while computing the statistics based on the full event sequence.

Usage

```
remstats_recency(
  time,
  sender,
  receiver,
  sampled,
  observed,
  type = c("raw.diff", "inv.diff.plus1", "rank.ordered.count"),
  i_neighborhood = TRUE,
  dependency = FALSE,
  relationalTimeSpan = NULL,
  nopastEvents = NA
)
```

Arguments

<code>time</code>	The vector of event times from the post-processing event sequence.
<code>sender</code>	The vector of event senders from the post-processing event sequence.
<code>receiver</code>	The vector of event receivers from the post-processing event sequence
<code>sampled</code>	A vector for the post-processing event sequence where <code>i</code> is equal to 1 if the observed dyadic event is sampled and 0 if not.
<code>observed</code>	A vector for the post-processing event sequence where <code>i</code> is equal to 1 if the dyadic event is observed and 0 if not.
<code>type</code>	A string value that specifies which recency formula will be used to compute the statistics. The options are "raw.diff", "inv.diff.plus1", "rank.ordered.count" (see details section).
<code>i_neighborhood</code>	TRUE/FALSE. TRUE indicates that the recency statistic will be computed in reference to the sender's past relational history (see details section). FALSE indicates that the recency statistic will be computed in reference to the target's past relational history (see details section). Set to TRUE by default.
<code>dependency</code>	TRUE/FALSE. TRUE indicates that temporal relevancy will be modeled (see details section). FALSE indicates that temporal relevancy will not be modeled, that is, all past events are relevant (see details section). Set to FALSE by default.
<code>relationalTimeSpan</code>	If <code>dependency = TRUE</code> , a numerical value that corresponds to the temporal span for relational relevancy, which must be the same measurement unit as the <code>observed_time</code> and <code>processed_time</code> objects. When <code>dependency = TRUE</code> , the relevant events are events that have occurred between current event time, t , and $t - \text{relationalTimeSpan}$. For example, if the time measurement is the number of days since the first event and the value for <code>relationalTimeSpan</code> is set to 10,

then only those events which occurred in the past 10 days are included in the computation of the statistic.

`nopastEvents` The numerical value that specifies what value should be given to events in which the sender was not active as a sender in the past (i 's neighborhood when `i_neighborhood = TRUE`) or was not the recipient of a past event (j 's neighborhood when `i_neighborhood = FALSE`). Set to NA by default.

Details

This function calculates the recency network sufficient statistic for a relational event based on Butts (2008), Vu et al. (2015), or Meijerink-Bosman et al. (2022). Depending on the type and neighborhood requested, different formulas will be used.

In the below equations, when `i_neighborhood` is TRUE:

$$t^* = \max(t \in \{(s', r', t') \in E : s' = s \wedge r' = r \wedge t' < t\})$$

When `i_neighborhood` is FALSE, the following formula is used:

$$t^* = \max(t \in \{(s', r', t') \in E : s' = r \wedge r' = s \wedge t' < t\})$$

The formula for recency for event e_i with type set to "raw.diff" and `i_neighborhood` is TRUE (Vu et al. 2015):

$$\text{recency}_{e_i} = t_{e_i} - t^*$$

where t^* , is the most recent time in which the past event has the same receiver and sender as the current event. If there are no past events within the current dyad, then the value defaults to the `nopastEvents` argument.

The formula for recency for event e_i with type set to "raw.diff" and `i_neighborhood` is FALSE (Vu et al. 2015):

$$\text{recency}_{e_i} = t_{e_i} - t^*$$

where t^* , is the most recent time in which the past event's sender is the current event receiver and the past event receiver is the current event sender. If there are no past events within the current dyad, then the value defaults to the `nopastEvents` argument.

The formula for recency for event e_i with type set to "inv.diff.plus1" and `i_neighborhood` is TRUE (Meijerink-Bosman et al. 2022):

$$\text{recency}_{e_i} = \frac{1}{t_{e_i} - t^* + 1}$$

where t^* , is the most recent time in which the past event has the same receiver and sender as the current event. If there are no past events within the current dyad, then the value defaults to the `nopastEvents` argument.

The formula for recency for event e_i with type set to "inv.diff.plus1" and `i_neighborhood` is FALSE (Meijerink-Bosman et al. 2022):

$$\text{recency}_{e_i} = \frac{1}{t_{e_i} - t^* + 1}$$

where t^* , is the most recent time in which the past event's sender is the current event receiver and the past event receiver is the current event sender. If there are no past events within the current dyad, then the value defaults to the *nopastEvents* argument.

The formula for recency for event e_i with type set to "rank.ordered.count" and *i_neighborhood* is TRUE (Butts 2008):

$$recency_{e_i} = \rho(s(e_i), r(e_i), A_t)^{-1}$$

where $\rho(s(e_i), r(e_i), A_t)$, is the current event receiver's rank amongst the current sender's recent relational events. That is, as Butts (2008: 174) argues, " $\rho(s(e_i), r(e_i), A_t)$ is j's recency rank among i's in-neighborhood. Thus, if j is the last person to have called i, then $\rho(s(e_i), r(e_i), A_t)^{-1} = 1$. This falls to 1/2 if j is the second most recent person to call i, 1/3 if j is the third most recent person, etc." Moreover, if j is not in i's neighborhood, the value defaults to infinity. If there are no past events with the current sender, then the value defaults to the *nopastEvents* argument.

The formula for recency for event e_i with type set to "rank.ordered.count" and *i_neighborhood* is FALSE (Butts 2008):

$$recency_{e_i} = \rho(r(e_i), s(e_i), A_t)^{-1}$$

where $\rho(r(e_i), s(e_i), A_t)$, is the current event sender's rank amongst the current receiver's recent relational events. That is, this measure is the same as above where the dyadic pair is flipped for the past relational events. Moreover, if j is not in i's neighborhood, the value defaults to infinity. If there are no past events with the current sender, then the value defaults to the *nopastEvents* argument.

Finally, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022) can specify the relational time span, that is, length of time for which events are considered relationally relevant. This should be specified via the option *relationalTimeSpan* with *dependency* set to TRUE.

Value

The vector of recency network statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Butts, Carter T. 2008. "A relational event framework for social action." *Sociological Methodology* 38(1): 155-200.
- Meijerink-Bosman, Marlyne, Roger Leenders, and Joris Mulder. 2022. "Dynamic relational event modeling: Testing, exploring, and applying." *PLOS One* 17(8): e0272309.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.
- Vu, Duy, Philippa Pattison, and Garry Robbins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```

# A Dummy One-Mode Event Dataset
events <- data.frame(time = 1:18,
                    eventID = 1:18,
                    sender = c("A", "B", "C",
                               "A", "D", "E",
                               "F", "B", "A",
                               "F", "D", "B",
                               "G", "B", "D",
                               "H", "A", "D"),
                    target = c("B", "C", "D",
                               "E", "A", "F",
                               "D", "A", "C",
                               "G", "B", "C",
                               "H", "J", "A",
                               "F", "C", "B"))

# Creating the Post-Processing Event Dataset with Null Events
eventSet <- create_riskset_constant(type = "one-mode",
                                   time = events$time,
                                   eventID = events$eventID,
                                   sender = events$sender,
                                   receiver = events$target,
                                   p_samplingobserved = 1.00,
                                   n_controls = 6,
                                   seed = 9999)

#Computing the recency statistics (with raw time difference) for the relational event sequence
eventSet$recency_rawdiff <- remstats_recency(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  type = "raw.diff")

#Computing the recency statistics (with inverse of time difference) for the
#relational event sequence
eventSet$recency_rawdiff <- remstats_recency(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  type = "inv.diff.plus1")

#Computing the rank-based recency statistics for the relational event sequence
eventSet$recency_rawdiff <- remstats_recency(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),

```

```
sender = eventSet$sender,
receiver = eventSet$receiver,
type = "rank.ordered.count")
```

remstats_reciprocity *Compute the Reciprocity Network Statistic for Event Dyads in a Relational Event Sequence*

Description

[Deprecated]

remstats_reciprocity() has been deprecated starting on version 1.1.1 of the dream package. Please use the dreamstats_reciprocity() function and see the NEWS.md file for more details.

This function calculates the reciprocity network sufficient statistic for a relational event sequence (see Lerner and Lomi 2020; Butts 2008). The reciprocity statistic captures the tendency for a sender a to ‘send a tie’ to (e.g., initiate a communication event with) receiver b given that b sent a tie to a in the past (i.e., an exchange between two medical doctors). This function allows for reciprocity scores to be only computed for the sampled events, while creating the weights based on the full event sequence (see Lerner and Lomi 2020; Vu et al. 2015). The function also allows users to use two different weighting functions, return the counts of past events, reduce computational runtime, and specify a dyadic cutoff for relational relevancy.

Usage

```
remstats_reciprocity(
  time,
  sender,
  receiver,
  observed,
  sampled,
  halflife = 2,
  counts = FALSE,
  dyadic_weight = 0,
  exp_weight_form = FALSE
)
```

Arguments

time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.

halflife	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).
counts	TRUE/FALSE. TRUE indicates that the counts of past events should be computed (see the details section). FALSE indicates that the temporal exponential weighting function should be used to downweigh past events (see the details section). Set to FALSE by default.
dyadic_weight	A numerical value for the dyadic cutoff weight that represents the numerical cutoff value for temporal relevancy based on the exponential weighting function. For example, a numerical value of 0.01, indicates that an exponential weight less than 0.01 will become 0 and that events with such value (or smaller values) will not be included in the sum of the past event weights (see the details section). Set to 0 by default.
exp_weight_form	TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default.

Details

This function calculates reciprocity scores for relational event models based on the exponential weighting function used in either Lerner and Lomi (2020) or Lerner et al. (2013).

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset, and $T_{1/2}$ is the halflife parameter.

The formula for reciprocity for event e_i is:

$$reciprocity_{e_i} = w(r, s, t)$$

That is, all past events in which the past sender is the current receiver and the past receiver is the current sender.

Moreover, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022; Lerner and Lomi 2020) can specify the dyadic weight cutoff, that is, the minimum value for which the weight is considered relationally relevant. Users who do not know the specific dyadic cutoff value to use, can use the [remstats_dyadcut](#) function.

Following Butts (2008), if the counts of the past events are requested, the formula for reciprocity for event e_i is:

$$reciprocity_{e_i} = d(r = s', s = r', t')$$

Where, $d()$ is the number of past events where the event sender, s' , is the current event receiver, r , and the event receiver (target), r' , is the current event sender, s . Moreover, the counting equation can be used in tandem with relational relevancy, by specifying the halflife parameter, exponential weighting function, and the dyadic cut off weight values. If the user is not interested in modeling relational relevancy, then those value should be left at their baseline values.

Value

The vector of reciprocity statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dfic@arizona.edu

References

- Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.
- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.
- Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. "Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.
- Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
events <- data.frame(time = 1:18, eventID = 1:18,
  sender = c("A", "B", "C",
    "A", "D", "E",
    "F", "B", "A",
    "F", "D", "B",
    "G", "B", "D",
    "H", "A", "D"),
  target = c("B", "C", "D",
    "E", "A", "F",
    "D", "A", "C",
    "G", "B", "C",
    "H", "J", "A",
    "F", "C", "B"))

eventSet <- create_riskset(type = "one-mode",
  time = events$time,
  eventID = events$eventID,
  sender = events$sender,
  receiver = events$target,
```

```

p_samplingobserved = 1.00,
n_controls = 1,
seed = 9999)

#Computing the reciprocity statistics for the relational event sequence
eventSet$recip <- remstats_reciprocity(
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

```

remstats_repetition	<i>Compute Butts' (2008) Repetition Network Statistic for Event Dyads in a Relational Event Sequence</i>
---------------------	--

Description

[Deprecated]

remstats_repetition() has been deprecated starting on version 1.1.1 of the dream package. Please use the dreamstats_repetition() function and see the NEWS.md file for more details.

This function computes the repetition network sufficient statistic for a relational event sequence (see Lerner and Lomi 2020; Butts 2008). Repetition measures the increased tendency for events between S and R to occur given that S and R have interacted in the past. Furthermore, this function allows for repetition scores to be only computed for the sampled events, while creating the weights based on the full event sequence (see Lerner and Lomi 2020; Vu et al. 2015). The function also allows users to use two different weighting functions, return the counts of past events, reduce computational runtime, and specify a dyadic cutoff for relational relevancy.

Usage

```

remstats_repetition(
  time,
  sender,
  receiver,
  observed,
  sampled,
  halflife = 2,
  counts = FALSE,
  dyadic_weight = 0,
  exp_weight_form = FALSE
)

```

Arguments

time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
halflife	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).
counts	TRUE/FALSE. TRUE indicates that the counts of past events should be computed (see the details section). FALSE indicates that the temporal exponential weighting function should be used to downweigh past events (see the details section). Set to FALSE by default.
dyadic_weight	A numerical value for the dyadic cutoff weight that represents the numerical cutoff value for temporal relevancy based on the exponential weighting function. For example, a numerical value of 0.01, indicates that an exponential weight less than 0.01 will become 0 and that events with such value (or smaller values) will not be included in the sum of the past event weights (see the details section). Set to 0 by default.
exp_weight_form	TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default

Details

This function calculates the repetition scores for relational event models based on the exponential weighting function used in either Lerner and Lomi (2020) or Lerner et al. (2013).

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-(t-t') \cdot \frac{\ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset (in this case, all events that have the same sender and receiver), and $T_{1/2}$ is the halflife parameter.

The formula for repetition for event e_i is:

$$repetition_{e_i} = w(s, r, t)$$

Moreover, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022; Lerner and Lomi 2020) can specify the dyadic weight cutoff, that is, the minimum value for which the weight is considered relationally relevant. Users who do not know the specific dyadic cutoff value to use, can use the `remstats_dyadcut` function.

Following Butts (2008), if the counts of the past events are requested, the formula for repetition for event e_i is:

$$repetition_{e_i} = d(s = s', r = r', t')$$

Where, $d()$ is the number of past events where the event sender, s' , is the current event sender, s , the event receiver (target), r' , is the current event receiver, r . Moreover, the counting equation can be used in tandem with relational relevancy, by specifying the half-life parameter, exponential weighting function, and the dyadic cut off weight values. If the user is not interested in modeling relational relevancy, then those value should be left at their baseline values.

Value

The vector of repetition statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dffc@arizona.edu

References

- Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.
- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.
- Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. "Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.
- Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
data("WikiEvent2018.first100k")
WikiEvent2018 <- WikiEvent2018.first100k[1:10000,] #the first ten thousand events
WikiEvent2018$time <- as.numeric(WikiEvent2018$time) #making the variable numeric
### Creating the EventSet By Employing Case-Control Sampling With M = 5 and
### Sampling from the Observed Event Sequence with P = 0.01
EventSet <- create_riskset_constant(type = "two-mode",
  time = WikiEvent2018$time, # The Time Variable
  eventID = WikiEvent2018$eventID, # The Event Sequence Variable
  sender = WikiEvent2018$user, # The Sender Variable
  receiver = WikiEvent2018$article, # The Receiver Variable
```

```

p_samplingobserved = 0.01, # The Probability of Selection
n_controls = 8, # The Number of Controls to Sample from the Full Risk Set
combine = TRUE,
seed = 9999) # The Seed for Replication

#Computing the repetition statistics for the relational event sequence with the
#weights of past events returned
rep_weights <- remstats_repetition(
  time = EventSet$time,
  sender = EventSet$sender,
  receiver = EventSet$receiver,
  sampled = EventSet$sampled,
  observed = EventSet$observed,
  halflife = 2.592e+09, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#Computing the repetition statistics for the relational event sequence with the
#counts of events returned
rep_counts <- remstats_repetition(
  time = EventSet$time,
  sender = EventSet$sender,
  receiver = EventSet$receiver,
  sampled = EventSet$sampled,
  observed = EventSet$observed,
  halflife = 2.592e+09, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

cbind(rep_weights, rep_counts)

```

remstats_triads	<i>Compute Butts' (2008) Triadic Formation Statistics for Relational Event Sequences</i>
-----------------	--

Description

[Deprecated]

remstats_triads() has been deprecated starting on version 1.1.1 of the dream package. Please use the dreamstats_triads() function and see the NEWS.md file for more details.

The function computes the set of one-mode triadic formation statistics discussed in Butts (2008) for a one-mode relational event sequence (see also Lerner and Lomi 2020). The function can compute the following triadic formations: 1) incoming shared partners (ISP), 2) outgoing shared partners (OSP), 3) incoming two-paths (ITP), and 4) outgoing two-paths (OTP). Importantly, this function allows for the triadic formation statistics to be computed only for the sampled events, while creating the weights based on the full event sequence (see Lerner and Lomi 2020; Vu et al. 2015). The

function also allows users to use two different weighting functions, return the counts of past events, reduce computational runtime, and specify a dyadic cutoff for relational relevancy.

Usage

```
remstats_triads(
  formation = c("ISP", "OSP", "ITP", "OTP"),
  time,
  sender,
  receiver,
  observed,
  sampled,
  halflife = 2,
  counts = FALSE,
  dyadic_weight = 0,
  exp_weight_form = FALSE
)
```

Arguments

formation	The specific triadic formation the statistic will be based on (see details section). "ISP" = incoming shared partners. "OSP" = outgoing shared partners. "OTP" = outgoing two-paths. "ITP" = incoming two-paths.
time	The vector of event times from the post-processing event sequence.
sender	The vector of event senders from the post-processing event sequence.
receiver	The vector of event receivers from the post-processing event sequence
observed	A vector for the post-processing event sequence where i is equal to 1 if the dyadic event is observed and 0 if not.
sampled	A vector for the post-processing event sequence where i is equal to 1 if the observed dyadic event is sampled and 0 if not.
halflife	A numerical value that is the halflife value to be used in the exponential weighting function (see details section). Preset to 2 (should be updated by the user based on substantive context).
counts	TRUE/FALSE. TRUE indicates that the counts of past events should be computed (see the details section). FALSE indicates that the temporal exponential weighting function should be used to downweigh past events (see the details section). Set to FALSE by default.
dyadic_weight	A numerical value for the dyadic cutoff weight that represents the numerical cutoff value for temporal relevancy based on the exponential weighting function. For example, a numerical value of 0.01, indicates that an exponential weight less than 0.01 will become 0 and that events with such value (or smaller values) will not be included in the sum of the past event weights (see the details section). Set to 0 by default.
exp_weight_form	TRUE/FALSE. TRUE indicates that the Lerner et al. (2013) exponential weighting function will be used (see the details section). FALSE indicates that the Lerner and Lomi (2020) exponential weighting function will be used (see the details section). Set to FALSE by default

Details

The function calculates the triadic formation statistics discussed in Butts (2008) for relational event sequences based on the exponential weighting function used in either Lerner and Lomi (2020) or Lerner et al. (2013).

Following Lerner and Lomi (2020), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-\frac{(t-t') \cdot \ln(2)}{T_{1/2}}}$$

Following Lerner et al. (2013), the exponential weighting function in relational event models is:

$$w(s, r, t) = e^{-\frac{(t-t') \cdot \ln(2)}{T_{1/2}}} \cdot \frac{\ln(2)}{T_{1/2}}$$

In both of the above equations, s is the current event sender, r is the current event receiver (target), t is the current event time, t' is the past event times that meet the weight subset, and $T_{1/2}$ is the halflife parameter.

Outgoing Shared Partners:

The general formula for outgoing shared partners for event e_i is:

$$OSP_{e_i} = \sqrt{\sum_h w(s, h, t) \cdot w(r, h, t)}$$

That is, as discussed in Butts (2008), outgoing shared partners finds all past events where the current sender and target sent a relational tie (i.e., were a sender in a relational event) to the same h node.

Following Butts (2008), if the counts of the past events are requested, the formula for outgoing shared partners for event e_i is:

$$OSP_{e_i} = \sum_{i=1}^{|H|} \min [d(s, h, t), d(r, h, t)]$$

Where, $d()$ is the number of past events that meet the specific set operations. $d(s, h, t)$ is the number of past events where the current event sender sent a tie to a third actor, h , and $d(r, h, t)$ is the number of past events where the current event receiver sent a tie to a third actor, h . The sum loops through all unique actors that have formed past outgoing shared partners structures with the current event sender and receiver. Moreover, the counting equation can be used in tandem with relational relevancy, by specifying the halflife parameter, exponential weighting function, and the dyadic cut off weight values. If the user is not interested in modeling relational relevancy, then those value should be left at their defaults.

Outgoing Two-Paths:

The general formula for outgoing two-paths for event e_i is:

$$OTP_{e_i} = \sqrt{\sum_h w(s, h, t) \cdot w(h, r, t)}$$

That is, as discussed in Butts (2008), outgoing two-paths finds all past events where the current sender sends a relational tie to node h and the current target receives a relational tie from the same h node.

Following Butts (2008), if the counts of the past events are requested, the formula for outgoing two paths for event e_i is:

$$OTPe_i = \sum_{i=1}^{|H|} \min [d(s, h, t), d(h, r, t)]$$

Where, $d()$ is the number of past events that meet the specific set operations. $d(s, h, t)$ is the number of past events where the current event sender sent a tie to a third actor, h , and $d(h, r, t)$ is the number of past events where the third actor h sent a tie to the current event receiver. The sum loops through all unique actors that have formed past outgoing two-path structures with the current event sender and receiver.

Incoming Two-Paths:

The general formula for incoming two-paths for event e_i is:

$$ITPe_i = \sqrt{\sum_h w(r, h, t) \cdot w(h, s, t)}$$

That is, as discussed in Butts (2008), incoming two-paths finds all past events where the current sender was the receiver in a relational event where the sender was a node h and the current target was the sender in a past relational event where the target was the same node h .

Following Butts (2008), if the counts of the past events are requested, the formula for incoming two paths for event e_i is:

$$ITPe_i = \sum_{i=1}^{|H|} \min [d(r, h, t), d(h, s, t)]$$

Where, $d()$ is the number of past events that meet the specific set operations. $d(r, h, t)$ is the number of past events where the current event receiver sent a tie to a third actor, h , and $d(h, s, t)$ is the number of past events where the third actor h sent a tie to the current event sender. The sum loops through all unique actors that have formed past incoming two-path structures with the current event sender and receiver.

Incoming Shared Partners:

The general formula for incoming shared partners for event e_i is:

$$ISPe_i = \sqrt{\sum_h w(h, s, t) \cdot w(h, r, t)}$$

That is, as discussed in Butts (2008), incoming shared partners finds all past events where the current sender and target were themselves the target in a relational event from the same h node.

Following Butts (2008), if the counts of the past events are requested, the formula for incoming shared partners for event e_i is:

$$ISPe_i = \sum_{i=1}^{|H|} \min [d(h, s, t), d(h, r, t)]$$

Where, $d()$ is the number of past events that meet the specific set operations, $d(h, s, t)$ is the number of past events where the current event sender received a tie from a third actor, h , and $d(h, r, t)$ is the

number of past events where the current event receiver received a tie from a third actor, h . The sum loops through all unique actors that have formed past incoming shared partners structures with the current event sender and receiver.

Lastly, researchers interested in modeling temporal relevancy (see Quintane, Mood, Dunn, and Falzone 2022; Lerner and Lomi 2020) can specify the dyadic weight cutoff, that is, the minimum value for which the weight is considered relationally relevant. Users who do not know the specific dyadic cutoff value to use, can use the `remstats_dyadcut` function.

Value

The vector of triadic formation statistics for the relational event sequence.

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dffc@arizona.edu

References

- Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38(1): 155-200.
- Quintane, Eric, Martin Wood, John Dunn, and Lucia Falzon. 2022. "Temporal Brokering: A Measure of Brokerage as a Behavioral Process." *Organizational Research Methods* 25(3): 459-489.
- Lerner, Jürgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: How to fit a relational event model to 360 million dyadic events." *Network Science* 8(1): 97-135.
- Lerner, Jürgen, Margit Bussman, Tom A.B. Snijders, and Ulrik Brandes. 2013. "Modeling Frequency and Type of Interaction in Event Networks." *The Corvinus Journal of Sociology and Social Policy* 4(1): 3-32.
- Vu, Duy, Philippa Pattison, and Garry Robins. 2015. "Relational event models for social learning in MOOCs." *Social Networks* 43: 121-135.

Examples

```
events <- data.frame(time = 1:18,
                    eventID = 1:18,
                    sender = c("A", "B", "C",
                               "A", "D", "E",
                               "F", "B", "A",
                               "F", "D", "B",
                               "G", "B", "D",
                               "H", "A", "D"),
                    target = c("B", "C", "D",
                               "E", "A", "F",
                               "D", "A", "C",
                               "G", "B", "C",
                               "H", "J", "A",
                               "F", "C", "B"))

eventSet <- create_riskset_constant(type = "one-mode",
```

```
        time = events$time,
        eventID = events$eventID,
        sender = events$sender,
        receiver = events$target,
        p_samplingobserved = 1.00,
        n_controls = 1,
        seed = 9999)

#compute the triadic statistic for the outgoing shared partners formation
eventSet$OSP <- remstats_triads(
  formation = "OSP", #outgoing shared partners argument
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#compute the triadic statistic for the incoming shared partners formation
eventSet$ISP <- remstats_triads(
  formation = "ISP", #incoming shared partners argument
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#compute the triadic statistic for the outgoing two-paths formation
eventSet$OTP <- remstats_triads(
  formation = "OTP", #outgoing two-paths argument
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
  dyadic_weight = 0,
  exp_weight_form = FALSE)

#compute the triadic statistic for the incoming two-paths formation
eventSet$IIP <- remstats_triads(
  formation = "IIP", #incoming two-paths argument
  time = as.numeric(eventSet$time),
  observed = eventSet$observed,
  sampled = rep(1,nrow(eventSet)),
  sender = eventSet$sender,
  receiver = eventSet$receiver,
  halflife = 2, #halflife parameter
```

```
dyadic_weight = 0,
exp_weight_form = FALSE)
```

simulate_rem_seq

Simulate a Random One-Mode Relational Event Sequence

Description

[Stable]

The function allows users to simulate a random one-mode relational event sequence between n actors for k events. This function follows the methods discussed in Butts (2008), Amati, Lomi, and Snijders (2024), and Scheter and Quintane (2021). See the details section for more information on this algorithm. Importantly, this function can be used to simulate a random event sequence to assess the goodness of fit for ordinal timing relational event models (see Amati, Lomi, and Snijders 2024), and simulate random outcomes for relational outcome models.

Usage

```
simulate_rem_seq(
  n_actors,
  n_events,
  inertia = FALSE,
  inertia_p = 0,
  recip = FALSE,
  recip_p = 0,
  sender_outdegree = FALSE,
  sender_outdegree_p = 0,
  sender_indegree = FALSE,
  sender_indegree_p = 0,
  target_outdegree = FALSE,
  target_outdegree_p = 0,
  target_indegree = FALSE,
  target_indegree_p = 0,
  assort = FALSE,
  assort_p = 0,
  trans_trips = FALSE,
  trans_trips_p = 0,
  three_cycles = FALSE,
  three_cycles_p = 0,
  starting_events = NULL,
  returnStats = FALSE,
  rseed = 9999
)
```

Arguments

n_actors	The number of potential actors in the event sequence.
n_events	The number of simulated events for the relational event sequence.
inertia	TRUE/FALSE. True indicates the effect will be included (see the details section). FALSE indicates the effect will not be included.
inertia_p	If <i>inertia</i> = TRUE, the numerical value that corresponds to the parameter weight for the inertia statistic.
recip	TRUE/FALSE. True indicates the effect will be included (see the details section). FALSE indicates the effect will not be included.
recip_p	If <i>recip</i> = TRUE, the numerical value that corresponds to the parameter weight for the reciprocity statistic.
sender_outdegree	TRUE/FALSE. True indicates the effect will be included (see the details section). FALSE indicates the effect will not be included.
sender_outdegree_p	If <i>sender_outdegree</i> = TRUE, the numerical value that corresponds to the parameter weight for the outdegree statistic.
sender_indegree	TRUE/FALSE. True indicates the effect will be included (see the details section). FALSE indicates the effect will not be included.
sender_indegree_p	If <i>sender_indegree</i> = TRUE, the numerical value that corresponds to the parameter weight for the indegree statistic.
target_outdegree	TRUE/FALSE. True indicates the effect will be included (see the details section). FALSE indicates the effect will not be included.
target_outdegree_p	If <i>target_outdegree</i> = TRUE, the numerical value that corresponds to the parameter weight for the outdegree statistic.
target_indegree	TRUE/FALSE. True indicates the effect will be included (see the details section). FALSE indicates the effect will not be included.
target_indegree_p	If <i>target_indegree</i> = TRUE, the numerical value that corresponds to the parameter weight for the indegree statistic.
assort	Boolean. TRUE/FALSE. True indicates the effect will be included (see the details section). FALSE indicates the effect will not be included.
assort_p	If <i>assort</i> = TRUE, the numerical value that corresponds to the parameter weight for the assortativity statistic.
trans_trips	TRUE/FALSE. True indicates the effect will be included (see the details section). FALSE indicates the effect will not be included.
trans_trips_p	If <i>trans_trips</i> = TRUE, the numerical value that corresponds to the parameter weight for the transitive triplets statistic.

three_cycles	TRUE/FALSE. True indicates the effect will be included (see the details section). FALSE indicates the effect will not be included.
three_cycles_p	If <i>three_cycles</i> = TRUE, the numerical value that corresponds to the parameter weight for the three cycles statistic.
starting_events	A $n \times 2$ dataframe with n starting events and 2 columns. The first column should be the sender and the second should be the target.
returnStats	TRUE/FALSE. TRUE indicates that the requested network statistics will be returned alongside the simulated relational event sequence. FALSE indicates that only the simulated relational event sequence will be returned. Set to FALSE by default.
rseed	A value for the starting seed for the random number generator. Set to 9999 by default.

Details

Following the authors listed in the descriptions section, the probability of selecting a new event for $t+1$ based on the past relational history, H_t , from $0 < t < t + 1$ is given by:

$$p(e_t) = \frac{\lambda_{ij}(t; \theta)}{\sum_{(u,v) \in R_t} \lambda_{uv}(t; \theta)}$$

where (i,j,t) is the triplet that corresponds to the dyadic pair with sender i and target j at time t contained in the full risk set, R_t , based on the past relational history. $\lambda_{ij}(t; \theta)$ is formulated as:

$$\lambda_{ij}(t; \theta) = e^{\sum_p \theta_p X_{ijp}(H_t)}$$

where θ_p corresponds to the specific parameter weight given by the user, and X_{ijp} represents the value of the specific statistic based on the current past relational history H_t .

Following Scheter and Quintane (2021) and Amati, Lomi, and Snijders (2024), the algorithm for simulating the random relational sequence for k events is:

- 1. Initialize the full risk set, R_t , which is the full Cartesian plot of actors.
- 2. Randomly sample the first event e_1 and add that event into the relational history, H_t .
- 3. Until $i = k$, compute the sufficient statistics for each event in the risk set, sample a new event e_i based on the probability function specified above, and add that element into the relational history.
- 4. End when $i > k$.

Currently, the function supports 6 statistics for one-mode networks. These are:

- Inertia: n_{ijt}
- Reciprocity: n_{jitt}
- Target Indegree: $\sum_k n_{kjt}$
- Target Outdegree: $\sum_k n_{jkt}$
- Sender Outdegree: $\sum_k n_{ikt}$

- Sender Indegree: $\sum_k n_{kit}$
- Assortativity: $\sum_k n_{kit} \cdot \sum_k n_{ikt}$
- Transitive Triplets: $\sum_k n_{ikt} \cdot n_{kjt}$
- Three Cycles: $\sum_k n_{jkt} \cdot n_{kit}$

Where n represents the counts of past events, i is the event sender, and j is the event target. See Scheter and Quintane (2021) and Butts (2008) for a further discussion of these statistics.

Users are allowed to insert a starting event sequence to base the simulation on. A few things are worth nothing. The starting event sequence should be a matrix with n rows indicating the number of starting events and 2 columns, with the first representing the event senders and the second column representing the event receivers. Internally, the number of actors is ignored, as the number of possible actors in the risk set is based only on the actors present in the starting event sequence. Finally, the sender and receiver actor IDs should be numerical values.

Value

A data frame that contains the simulated relational event sequence with the sufficient statistics (if requested).

Author(s)

Kevin A. Carson kacarson@arizona.edu, Diego F. Leal dflc@arizona.edu

References

- Amati, Viviana, Alessandro Lomi, and Tom A.B. Snijders. 2024. "A goodness of fit framework for relational event models." *Journal of the Royal Statistical Society Series A: Statistics in Society* 187(4): 967-988.
- Butts, Carter T. "A Relational Framework for Social Action." *Sociological Methodology* 38: 155-200.
- Schecter, Aaron and Eric Quintane. 2021 "The Power, Accuracy, and Precision of the Relational Event Model." *Organizational Research Methods* 24(4): 802-829.

Examples

```
#Creating a random relational sequence with 5 actors and 25 events
rem1<- simulate_rem_seq(n_actors = 25,
  n_events = 1000,
  inertia = TRUE,
  inertia_p = 0.12,
  recip = TRUE,
  recip_p = 0.08,
  sender_outdegree = TRUE,
  sender_outdegree_p = 0.09,
  target_indegree = TRUE,
  target_indegree_p = 0.05,
  assort = TRUE,
  assort_p = -0.01,
  trans_trips = TRUE,
```

```

        trans_trips_p = 0.09,
        three_cycles = TRUE,
        three_cycles_p = 0.04,
        starting_events = NULL,
        returnStats = TRUE)

rem1

#Creating a random relational sequence with 100 actors and 1000 events with
#only inertia and reciprocity
rem2 <- simulate_rem_seq(n_actors = 100,
                        n_events = 1000,
                        inertia = TRUE,
                        inertia_p = 0.12,
                        recip = TRUE,
                        recip_p = 0.08,
                        returnStats = TRUE)

rem2

#Creating a random relational sequence based on the starting sequence with
#only inertia and reciprocity
rem3 <- simulate_rem_seq(n_actors = 100, #does not matter can be any value, this is
                        #overridden by the starting event sequence
                        n_events = 100,
                        inertia = TRUE,
                        inertia_p = 0.12,
                        recip = TRUE,
                        recip_p = 0.08,
                        #a random starting event sequence
                        starting_events = matrix(c(1:10, 10:1),
                                                nrow = 10, ncol = 2, byrow = FALSE),
                        returnStats = TRUE)

rem3

```

southern.women

Davis Southern Women's Dataset

Description

Davis Southern Women's Dataset

Usage

```
data(southern.women)
```

Format

southern.women:

Two-Mode affiliation matrix from Davis et al.(1941) Southern Women study. 18 women x 14 events. Dataset is taken from the networkdata R package (Almquist 2014)

Source

Almqvist, Zach. 2014. *networkdata: Lin Freeman's Network Data Collection*. R package version 0.01, <https://github.com/Z-co/networkdata>.

Brieger, Ronald. 1974. "Duality of Persons and Groups." *Social Forces* 53(2): 181-190.

Davis, Allison, Burleigh B. Gardner, and Mary R. Gardner. 1941. *Deep South: A Social Anthropological Study of Caste and Class*. University of Chicago Press.

summary.dream

Summary Method for dream Objects

Description

Summarizes the results of an ordinal timing relational event model.

Usage

```
## S3 method for class 'dream'
summary(object, digits = 4, ...)
```

Arguments

object	An object of class "dream".
digits	The number of digits to print after the decimal point.
...	Additional arguments (currently unused).

Value

A list of summary statistics for the relational event model including parameter estimates, (null) likelihoods, and tests of significance for likelihood ratios and estimated parameters.

WikiEvent2018.first100k

Wikipedia Edit Event Sequence 2018

Description

The first 100,000 events of the (two-mode) Wikipedia edit event sequence, where an event is described as a Wikipedia user editing a Wikipedia article. The user column represents the unique event senders, the article column represents the unique event receivers (targets), and the time variable is in milliseconds.

Usage

```
data(WikiEvent2018.first100k)
```

Format

WikiEvent2018.first100k:

The first 100,000 events of the Wikipedia edit event sequence, where an event is described as a Wikipedia user editing a Wikipedia article. The user column represents the unique event senders, the article column represents the unique event receivers (targets), and the time variable is in milliseconds.

user the column that represents the unique event senders.

article the article column represents the unique event receivers.

time the event time variable in milliseconds.

eventID the numerical id for each event in the event sequence

Source

<https://zenodo.org/records/1626323>

Lerner, Jurgen and Alessandro Lomi. 2020. "Reliability of relational event model estimates under sampling: how to fit a relational event model to 360 million dyadic events." *Network Science* 8(1):97-135. (DOI: <https://doi.org/10.1017/nws.2019.57>)

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