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signnet: An R package for analyzing signed networks

David Schoch [1]

1 GESIS - Leibniz Institute for the Social Sciences

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Summary

Network analysis usually deals with relations among entities which are positive, such as friendship, or advice seeking. Most analytic tools are constructed with this assumption, be that centrality indices, or clustering tools. However, not all conceivable relationships are positive. People can be friends but also enemies. A signed network is a network where both, positive and negative relationships may occur. Common network analytic tools are not applicable to such networks without adapting for the existence of negative ties. The R package `signnet` brings together methods that have been developed to analyze signed networks. This includes known blockmodeling techniques, centrality indices and tools for two-mode networks, as well as unique analytic techniques surrounding structural balance theory.

Statement of need

Signed networks are increasingly popular in empirical network science since many phenomena can be modeled with positive and negative ties. Examples include studies of polarization (Neal, 2020), collaborations on Wikipedia (Brandes et al., 2009), international relations (Estrada, 2019), and relations on social media (Kunegis et al., 2009). General purpose packages for network analysis such as `igraph` (Csardi & Nepusz, 2006) and `sna` (Butts, 2008) implement all commonly used network analytic methods but do not offer any functionality for signed networks. `signnet` closes this gap and makes many tools for signed networks available in R. The package has already found its place in empirical research (Capozzi et al., 2022; Fritz et al., 2022) and the R package `backbone` (Neal, 2022) uses the data structure suggested by `signnet` for signed backbones of networks.

Implementation details

The package is modeled with `igraph` compatibility in mind and follows its function naming scheme. All functions in the package assume that an `igraph` object is a signed network if it has an edge attribute "sign" with values 1 (positive) or -1 (negative). If a function from `igraph` was adapted for signed networks, it can be called via `<igraph_name>_signed()`. Prominent examples include `as_adj_signed()`, `graph_from_adjacency_matrix_signed()`, `degree_signed()`, and `triad_census_signed()`.

Functionalities

This section highlights some of the main methods implemented in the package. For more details for each subsection see the respective package vignette or consult http://signnet.schochastics.net/.

```
install.packages("signnet")
library(signnet)
```

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```r
data("tribes") # dataset included in signnet
```

Structural balance

In its simplest form, structural balance is defined via triangles (Heider, 1946). A triangle in a network is balanced if all ties are positive ("the friend of a friend is a friend") or only one tie is positive ("the enemy of my enemy is my friend"). The remaining configurations are said to be unbalanced. A whole network is balanced if it can be partitioned into two node sets, such that intra-group edges are all positive and inter-group edges are all negative (Cartwright & Harary, 1956).

Determining if a network is balanced or not is easy, but measuring the degree of "balancedness" (i.e. how close is a network to be balanced?) is not. `signnet` implements several methods to calculate balance scores(Aref & Wilson, 2018). All are defined such that a value of one indicates perfect balance and zero perfect imbalance.

```r
balance_score(tribes, method = "triangles")
#> 0.867647
```

The method based on triangles simply counts the fraction of triangles that are balanced. Alternatively, the frustration index can be used, which computes the minimum number of edges whose removal results in a balance network (Aref & Wilson, 2019). To use the function `frustation_exact()`, `ompr` and its auxiliary packages need to be installed first (Schumacher, 2022).

```r
install.packages(c("ompr", "ompr.roi", "ROI", "ROI.plugin.glpk"))
frustration_exact(tribes)
#> $frustration
#> [1] 7
#>
#> $partition
#>  [1] 0 0 1 1 1 1 1 1 1 1 1 1 1 1 0 0
```

The return value `partition` gives the optimal partition into the two node sets for which the optimal frustration is achieved. The implemented algorithm can deal with fairly large networks, even though the problem is NP hard (Aref & Neal, 2020).

Blockmodeling

In signed blockmodeling, the goal is to determine k blocks of nodes such that all intra-block edges are positive and inter-block edges are negative (Doreian & Mrvar, 1996). The function `signed_blockmodel()` is used to construct such a model. The parameter k is the number of desired blocks. α is a trade-off parameter. The function minimizes $P(C) = \alpha N + (1 - \alpha)P$, where N is the total number of negative ties within blocks and P be the total number of positive ties between blocks.

```r
tribe_blocks <- signed_blockmodel(tribes, k = 3,
                                  alpha = 0.5, annealing = TRUE)
tribe_blocks
#> $membership
#> [1] 2 2 1 1 3 1 1 1 3 3 1 1 3 3 2 2
#>
#> $criterion
#> [1] 2
```

The result can be visualized with `ggblock`, as shown in Figure 1.

```r
ggblock(tribes, tribe_blocks$membership, show_blocks = TRUE)
```

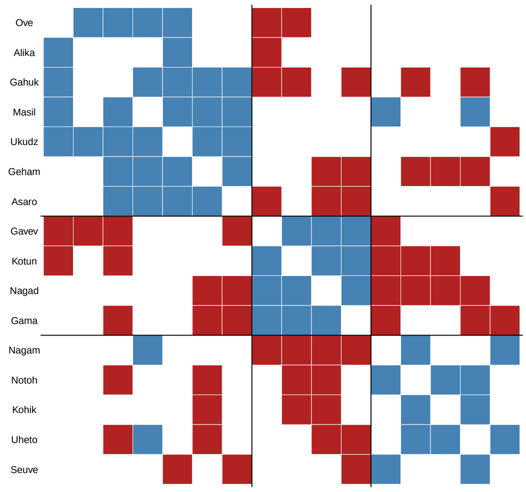

Figure 1: Blocks of the tribes network. Blue squares indicate positive and red squares negative ties.

Centrality

There exist hundreds of indices for networks with only positive ties, but for signed networks they are rather scarce. The signnet package implements three indices. Versions of degree and eigenvector centrality (Bonacich & Lloyd, 2004), and PN centrality (Everett & Borgatti, 2014). The PN index is very similar to Katz status for networks with only positive ties (Katz, 1953). The technical details can be found in the paper by Everett & Borgatti.

The below example illustrates all indices with a network where signed degree can not distinguish vertices.

```
A <- matrix(c( 0,  1,  0,  1,  0,  0,  0, -1, -1,  0,
               1,  0,  1, -1,  1, -1, -1,  0,  0,  0,
               0,  1,  0,  1, -1,  0,  0,  0, -1,  0,
               1, -1,  1,  0,  1, -1, -1,  0,  0,  0,
               0,  1, -1,  1,  0,  1,  0, -1,  0, -1,
               0, -1,  0, -1,  1,  0,  1,  0,  1, -1,
               0, -1,  0, -1,  0,  1,  0,  1, -1,  1,
              -1,  0,  0,  0, -1,  0,  1,  0,  1,  0,
              -1,  0, -1,  0,  0,  1, -1,  1,  0,  1,
               0,  0,  0,  0, -1, -1,  1,  0,  1,  0),10,10)

g <- graph_from_adjacency_matrix_signed(A, "undirected")

degree_signed(g, type = "ratio")
#> [1] 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5
eigen_centrality_signed(g)
#> [1] 0.6221496 1.0000000 0.7451885 1.0000000 0.8999004 0.6428959 0.3582816
#> [8] 0.3747192 0.2808741 0.0783457
pn_index(g)
#> [1] 0.900975 0.861348 0.907700 0.861348 0.841066 0.849656 0.861732
#> [8] 0.901591 0.850985 0.907293
```

Signed two-mode networks

A common analytic tool for two-mode networks is to project the network onto on relevant mode. This is easily done using the adjacency matrix A. AA^T yields the row projection and

$A^T A$ the column projection. The resulting networks will thus be weighted. Several methods exist to turn a weighted projection into an unweighted network where only the most significant edges are included (Neal, 2022). Projecting signed networks is not as straightforward, because "nullification" of edges can occur. Schoch (2021) introduces two methods to deal with this issue which are implemented in `signnet`. The trick is to convert the signed network into an a special unsigned one with `as_unsigned_2mode()`, do the projection as usual and the turn it back to a signed graph with `as_signed_proj()`. The details can be found in the original paper and in two designated vignettes.

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