Network Estimation and Visualization with Nestimate + cograph

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25 November 2026

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Introduction

Nestimate (Saqr, López-Pernas, & Misiejuk, 2026) estimates networks from sequence and panel data, and cograph draws them. The two packages divide the work: Nestimate computes the networks, their resampling, comparisons and clusterings, and returns objects that cograph's `splot()` draws directly. This tutorial follows one dataset through the steps of a transition network analysis (Saqr et al., 2025; Saqr, López-Pernas, & Tikka, 2025), which has been used, for example, to map students' self-regulated learning tactics (Peeters, Saqr, & Viberg, 2020): estimating the network, checking the stability of its edges and centralities, comparing groups, and grouping the states into clusters.

Step	Nestimate	cograph
Estimate a network	`build_network()`	`splot()`
Stability of the edges	`bootstrap_network()`	`splot()`, `plot_bootstrap_forest()`
Stability of the centralities	`centrality_stability()`	`splot()`
Networks per group	`build_network(group = )`	`splot()`
Compare groups	`permutation()`	`splot()`
Clusters of states	`build_mcml()`, `as_tna()`	`splot()`

Data

`group_regulation_long` records the regulation actions of students working in groups, one row per action, with the student (`Actor`), the time (`Time`) and the action (`Action`). It is generated synthetically from the `group_regulation` dataset of the tna package (Tikka, López-Pernas, & Saqr, 2025). The nine actions, `adapt`, `cohesion`, `consensus`, `coregulate`, `discuss`, `emotion`, `monitor`, `plan` and `synthesis`, are the nodes of the networks below. `Achiever` marks each student as a high or a low achiever.

```
library(Nestimate)
library(cograph)
```

```
##
## Attaching package: 'cograph'

## The following objects are masked from 'package:Nestimate':
##
##     as_tna, centrality, get_theme
```

```
head(group_regulation_long)
```

```
##   Actor Achiever Group Course                Time    Action
## 1     1     High     1      A 2025-01-01 10:27:07  cohesion
## 2     1     High     1      A 2025-01-01 10:35:20 consensus
## 3     1     High     1      A 2025-01-01 10:42:18   discuss
## 4     1     High     1      A 2025-01-01 10:50:00 synthesis
## 5     1     High     1      A 2025-01-01 10:52:25     adapt
## 6     1     High     1      A 2025-01-01 10:57:31 consensus
```

Estimating networks

A transition network

`build_network()` estimates a network from the data. With `method = "relative"`, the weight of the edge from one action to another is the probability that the second follows the first, so each row of the weight matrix sums to 1.

```
net <- build_network(group_regulation_long, action = "Action",
                     actor = "Actor", time = "Time", method = "relative")
net
```

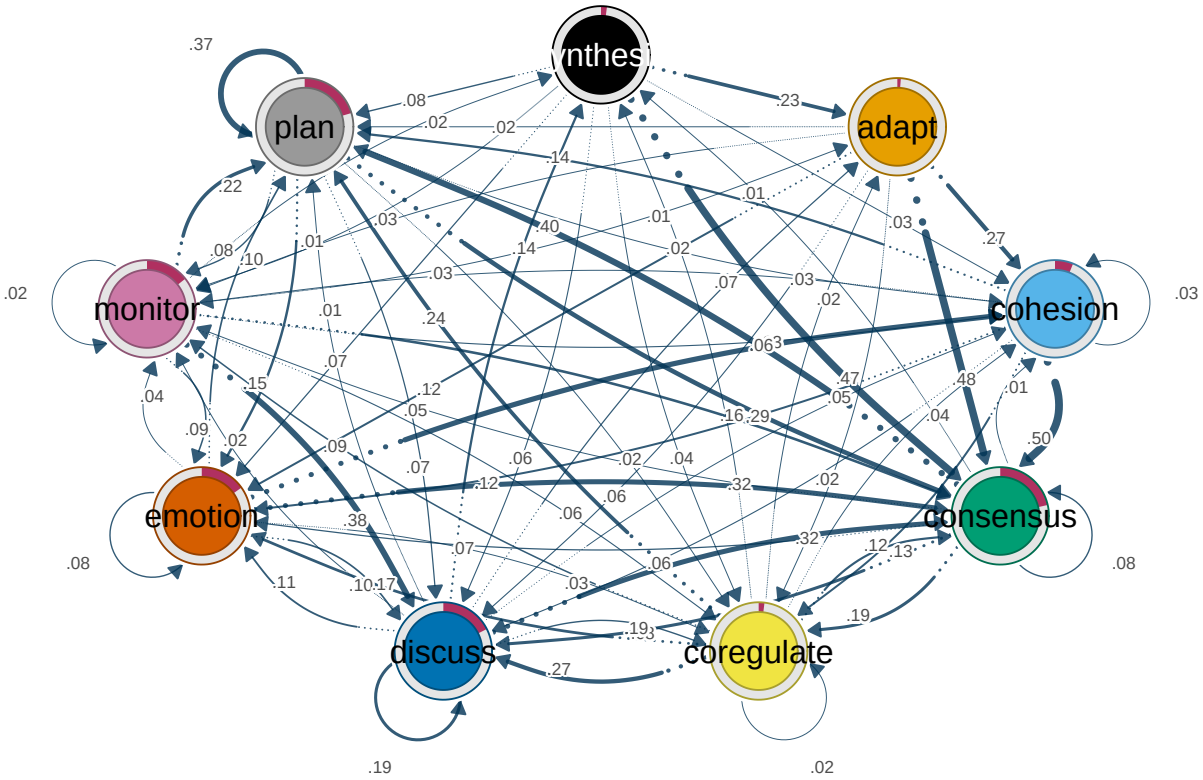
```
## Transition Network (relative probabilities) [directed]
##   Weights: [0.001, 0.498]  |  mean: 0.115
##
##   Strongest edges (10 of 78):
##    from      to        weight
##    cohesion  consensus 0.498
##    adapt     consensus 0.477
##    synthesis consensus 0.466
##    consensus plan      0.396
##    monitor   discuss   0.375
##    plan      plan      0.374
##    emotion   cohesion  0.325
##    discuss   consensus 0.321
##    emotion   consensus 0.320
##    plan      consensus 0.290
##
##  extract_edges(include_self = TRUE) lists every edge; extract_transition_matrix() gives the weight matrix;
##   extract_initial_probs() the initial probabilities.
```

```
extract_initial_probs(net)
```

```
##      adapt   cohesion  consensus coregulate    discuss    emotion
##     0.0115     0.0605     0.2140     0.0190     0.1755     0.1515
##    monitor       plan  synthesis
##     0.1440     0.2045     0.0195
```

The strongest transitions lead to `consensus`: from `cohesion` (0.50), from `adapt` (0.48) and from `synthesis` (0.47). `consensus` is also the most frequent first action (0.21), followed by `plan` (0.20). The network is a `netobject`, which inherits from `cograph_network`, so `splot()` draws it.

```
splot(net)
```



Other estimators

`method` selects the estimator; `list_estimators()` lists them.

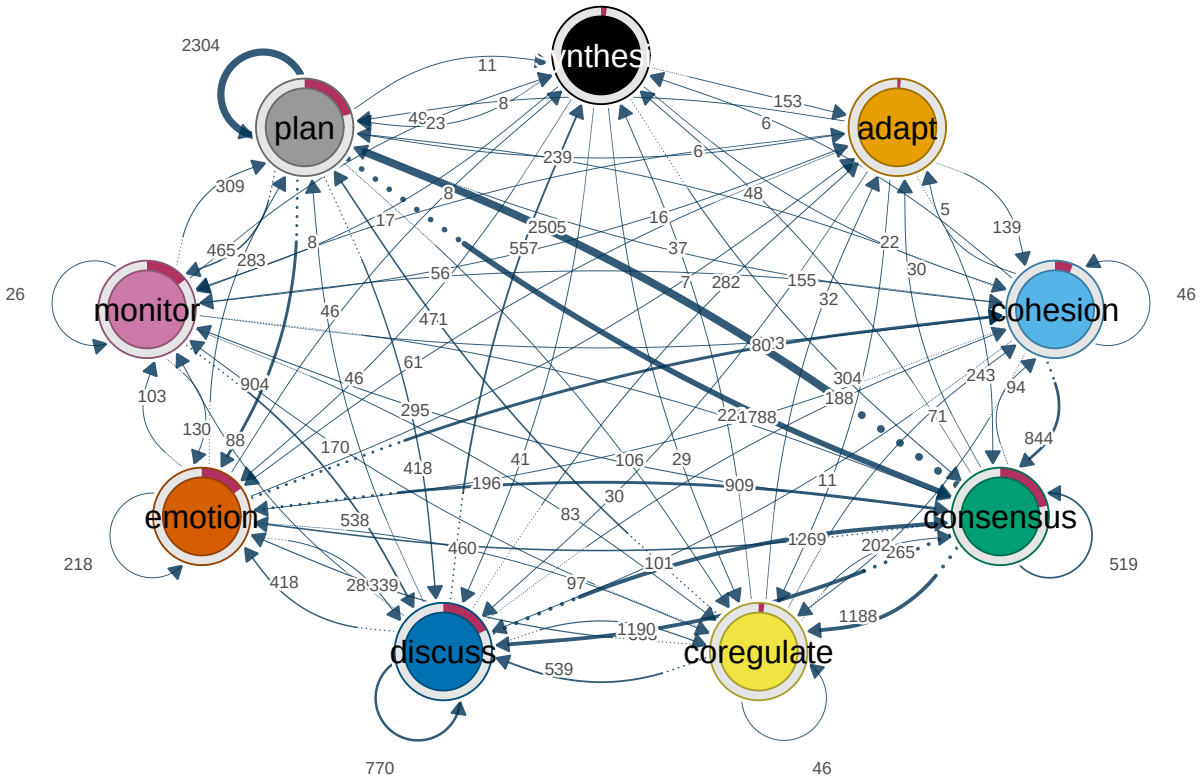
```
list_estimators()
```

```
##                 name
## 1          attention
## 2      co_occurrence
## 3                cor
## 4          frequency
## 5                gap
## 6             glasso
## 7              ising
## 8            latency
## 9                mgm
## 10             ngram
## 11              pcor
## 12          relative
## 13           reverse
## 14              wtna
## 15 wtna_cooccurrence
##                                                 description directed
## 1                        Decay-weighted attention transitions     TRUE
```

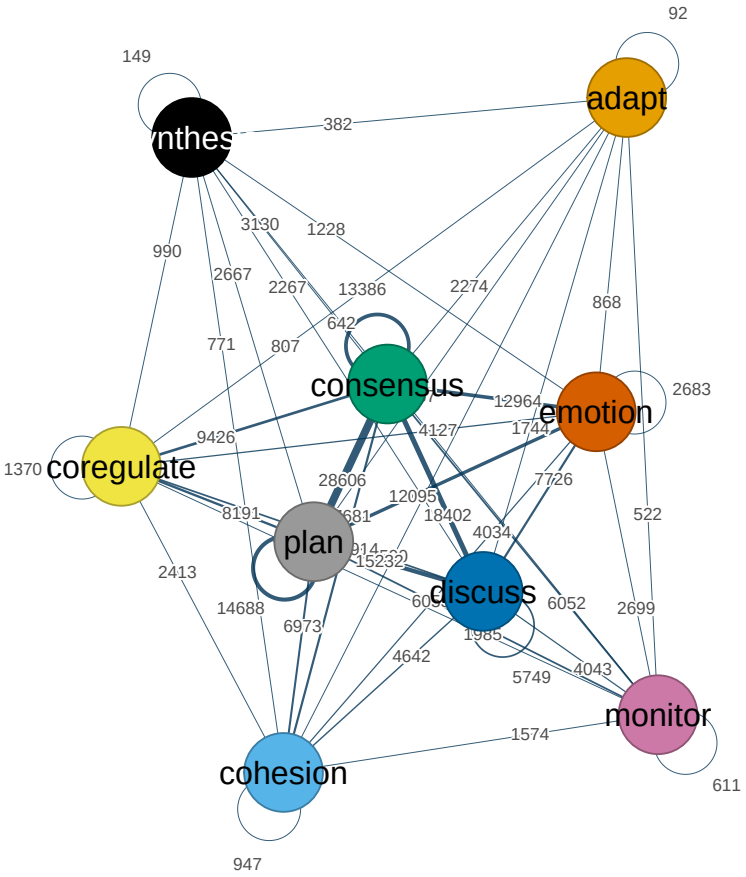
```
## 2                              Co-occurrence within sequences    FALSE
## 3                                Pairwise correlation network    FALSE
## 4                             Raw transition frequency counts     TRUE
## 5               Gap-allowed transitions weighted by 1/distance     TRUE
## 6                  EBICglasso regularized partial correlations    FALSE
## 7               Ising model (L1-penalized logistic regression)    FALSE
## 8           Reply network weighted by response speed (latency)     TRUE
## 9  Mixed Graphical Model (nodewise lasso, EBIC, LW threshold)    FALSE
## 10      n-gram transitions (adjacent pairs per n-gram window)     TRUE
## 11                          Unregularized partial correlations    FALSE
## 12                   Row-normalized transition probabilities     TRUE
## 13        Reverse (reply) transitions: transpose of frequency     TRUE
## 14                    Window-based TNA transitions (one-hot)     TRUE
## 15                  Window-based TNA co-occurrence (one-hot)    FALSE
```

Fifteen estimators are available. The directed ones (`relative`, `frequency`, `attention`, `ngram`, `gap`, `reverse`, `latency`, `wtna`) describe which action follows which; the undirected ones (`cor`, `pcor`, `glasso`, `ising`, `mgm`, `co_occurrence`, `wtna_cooccurrence`) describe which actions or variables go together (Saqr, Beck, & López-Pernas, 2024). `frequency` keeps the counts of the transitions instead of their probabilities, and `co_occurrence` counts how often two actions occur in the same sequence.

```
frequency_net <- build_network(group_regulation_long, action = "Action",
                               actor = "Actor", time = "Time",
                               method = "frequency")
splot(frequency_net)
```



```
co_occurrence_net <- build_network(group_regulation_long, action = "Action",
                                   actor = "Actor", time = "Time",
                                   method = "co_occurrence")
splot(co_occurrence_net, layout = "spring")
```



Stability of the edges

An edge estimated from one sample may not hold in another. `bootstrap_network()` resamples the sequences with replacement, re-estimates the network in each resample and reports, for each edge, its mean, its 95% interval and a p-value (Saqr et al., 2025). By default the p-value is the share of resamples in which the edge's weight falls outside a consistency range of 0.75 to 1.25 times its original weight, so an edge with a small p-value keeps its size across resamples.

```
set.seed(265)
boot <- bootstrap_network(net, iter = 1000)
boot
```

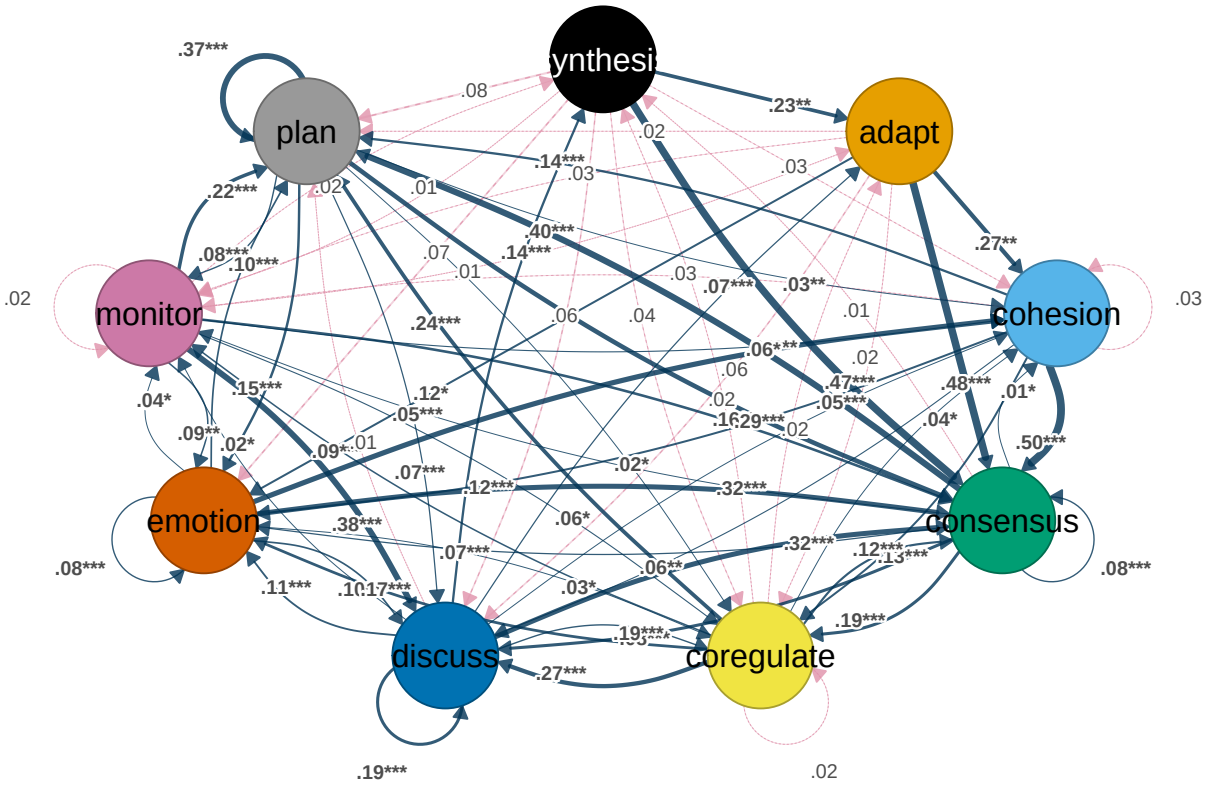
```
##   Edge                    Mean     95% CI          p
##   ----------------------------------------------
##   cohesion → consensus    0.498  [0.474, 0.521]  ***
##   adapt → consensus       0.478  [0.430, 0.523]  ***
##   synthesis → consensus   0.466  [0.427, 0.507]  ***
```

```
##   consensus → plan        0.396  [0.383, 0.407]  ***
##   monitor → discuss       0.375  [0.351, 0.401]  ***
##   ... and 46 more significant edges
##
## Bootstrap Network  [Transition Network (relative) | directed]
##   Iterations : 1000  |  Nodes : 9
##   Edges      : 51 significant / 78 total
##   CI         : 95%  |  Inference: stability  |  CR [0.75, 1.25]
```

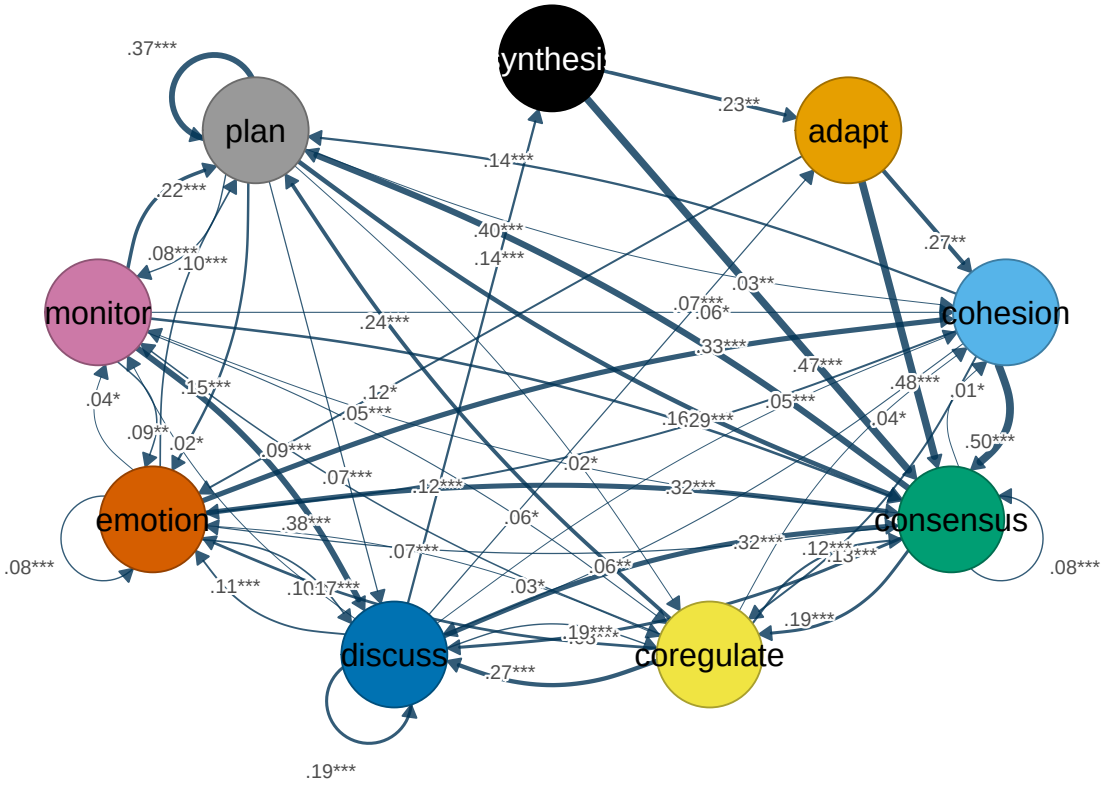
Of the 78 edges, 51 are stable at the 5% level. The strongest transitions are also the most precise: `cohesion` to `consensus` has a mean of 0.50 and an interval of [0.47, 0.52].

`splot()` draws the stable edges solid and the others dashed; `display = "significant"` draws only the stable edges, `display = "full"` all edges alike, and `show_stars = TRUE` or `show_ci = TRUE` add the significance stars or the intervals to the edge labels.

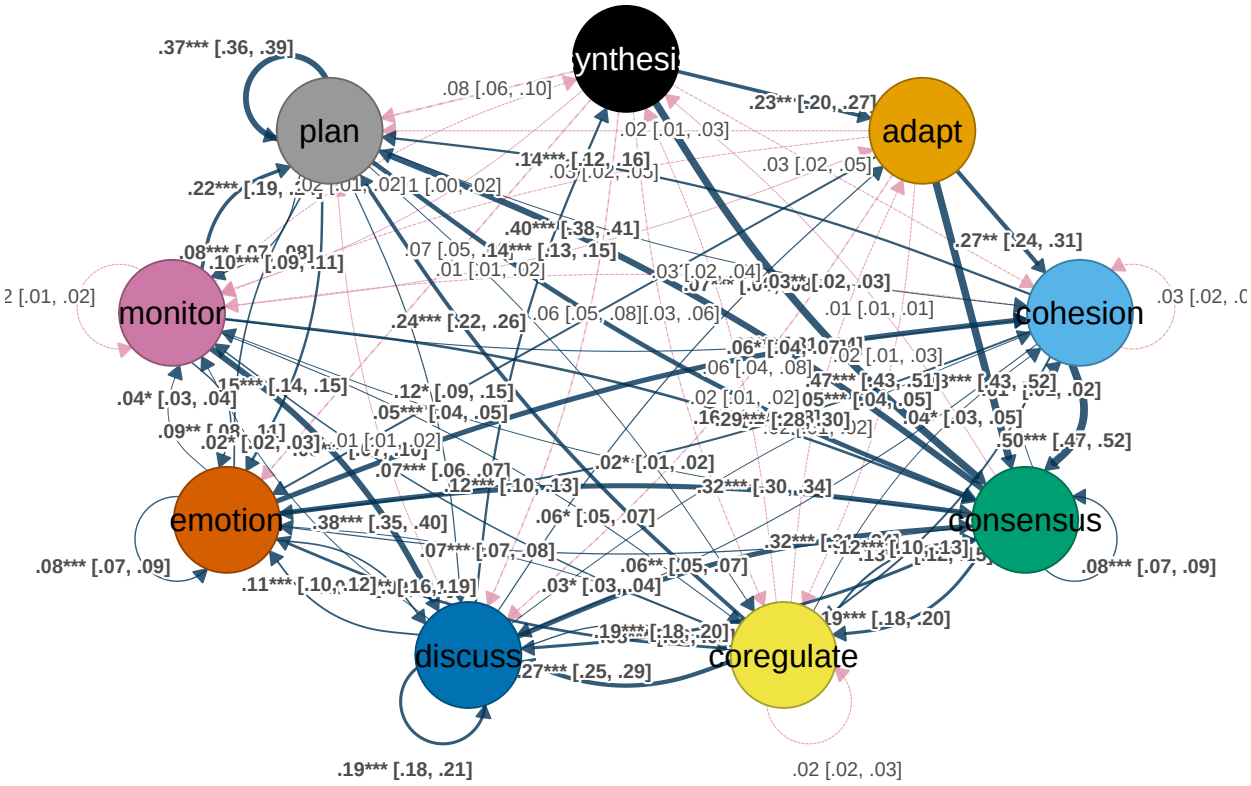
```
splot(boot)
```



```
splot(boot, display = "significant")
```

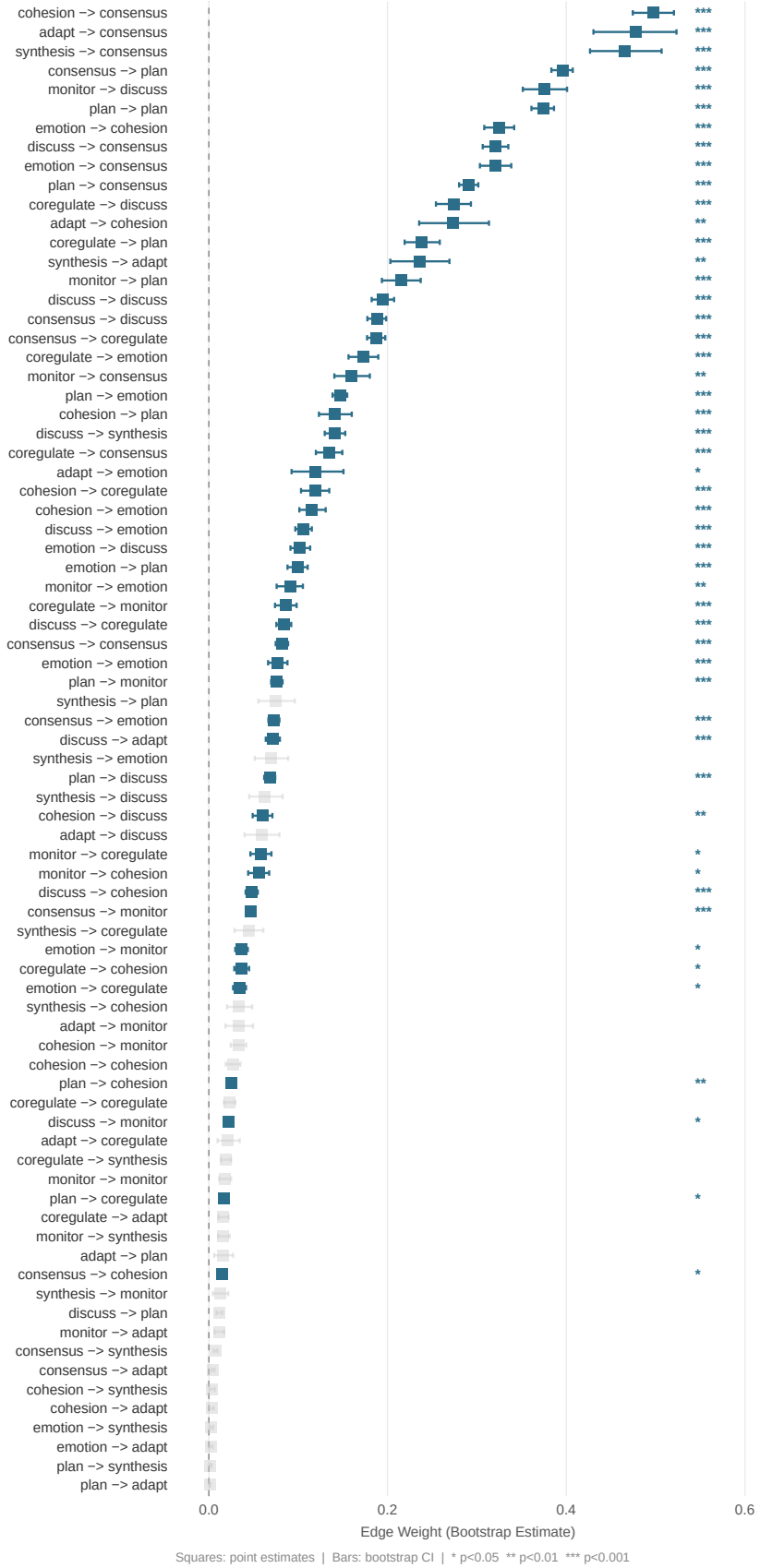



```
splot(boot, show_ci = TRUE)
```



A forest plot shows the estimate and the interval of every edge; `layout` arranges the edges in a list, a circle or groups.

```
plot_bootstrap_forest(boot, show_ci = TRUE)
```



Squares: point estimates | Bars: bootstrap CI | * p<0.05 ** p<0.01 *** p<0.001

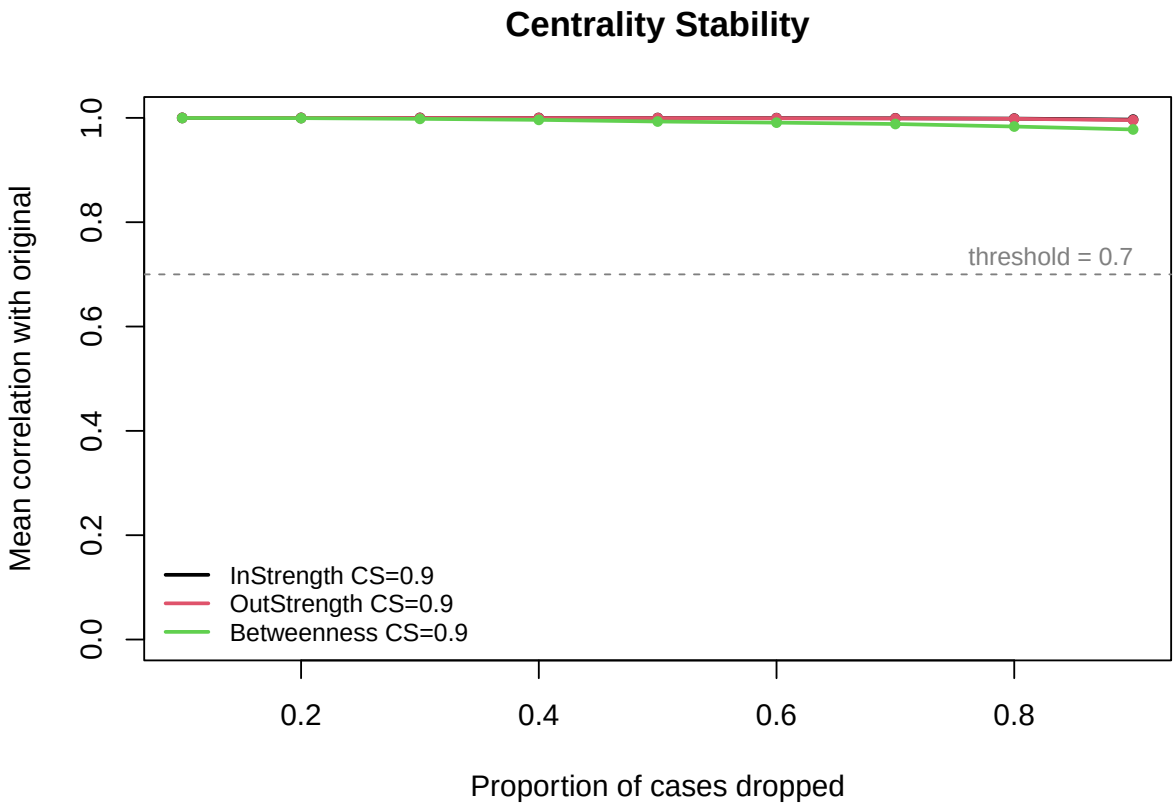
Stability of the centralities

Centrality measures summarise each node's position in the network. `centrality_stability()` drops increasing proportions of the sequences, recomputes the centralities, and correlates them with the centralities of the full data (Epskamp, Borsboom, & Fried, 2018). The CS-coefficient is the largest proportion of sequences that can be dropped while the correlation stays above 0.7 in 95% of the resamples; Epskamp et al. (2018) treat values above 0.5 as acceptable.

```
set.seed(265)
cs <- centrality_stability(net, iter = 500)
cs
```

```
## Centrality Stability (500 iterations, threshold = 0.7)
##   Drop proportions: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9
##
##   CS-coefficients:
##     InStrength       0.90
##     OutStrength      0.90
##     Betweenness      0.90
```

```
splot(cs)
```



The CS-coefficients of in-strength, out-strength and betweenness are all 0.90: the ranking of the actions by these measures holds when 90% of the sequences are removed.

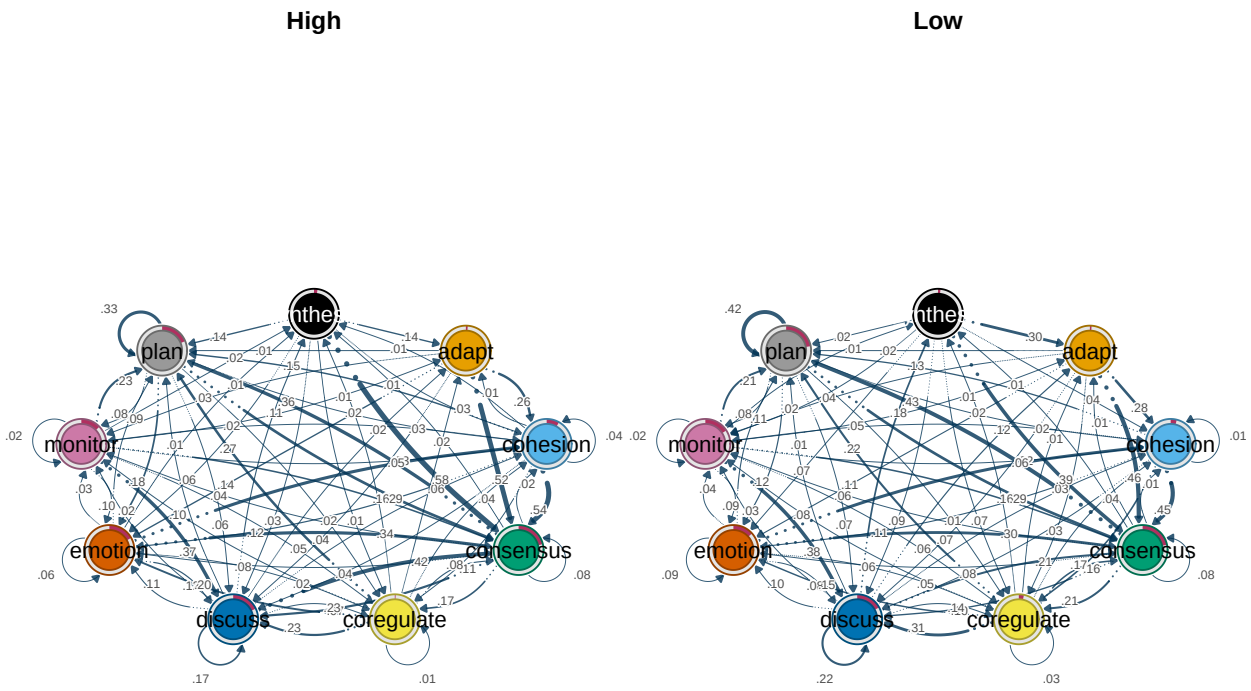
Group networks

`group =` estimates one network per value of a covariate and returns a group of networks (López-Pernas, Tikka, & Saqr, 2025). `splot()` draws the groups side by side on a common scale, so edge widths can be compared across panels.

```
group_net <- build_network(group_regulation_long, action = "Action",
                           actor = "Actor", time = "Time",
                           method = "relative", group = "Achiever")
group_net
```

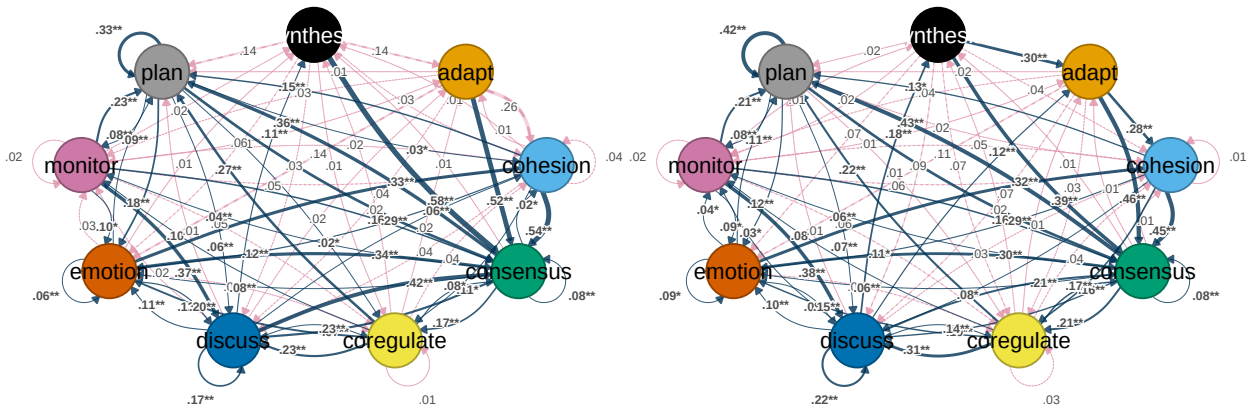
```
## Group Networks (2 groups, group_col: Achiever)
##
##   Group  Nodes  Edges  Weights
##   High   9      76     [0.001, 0.576]
##   Low    9      75     [0.000, 0.462]
```

```
splot(group_net)
```



`bootstrap_network()` on the group resamples each group.

```
set.seed(265)
group_boot <- bootstrap_network(group_net, iter = 500)
splot(group_boot)
```



Comparing groups

`permutation()` compares the networks of the groups edge by edge: it shuffles the group labels of the sequences, recomputes the difference of every edge, and compares the observed difference with the shuffled ones (Saqr et al., 2025). On a group of networks it compares every pair of groups.

```
set.seed(265)
group_perm <- permutation(group_net, iter = 1000)
group_perm
```

```
## Grouped Permutation Test
## Groups: High vs Low
##
## -- High vs Low --
## Permutation Test: Transition Network (relative probabilities) [directed]
##   Iterations: 1000  |  Alpha: 0.05
##   Nodes: 9  |  Edges tested: 78  |  Significant: 42
##  Global test (networks differ overall?): M = 2.612 (p = 0.000999)  |  S = 0.210 (p = 0.000999)
```

The networks of high and low achievers differ: 42 of the 78 transitions differ at the 5% level, and the global statistic M, the sum of the absolute edge differences, is 2.61 (p = 0.001).

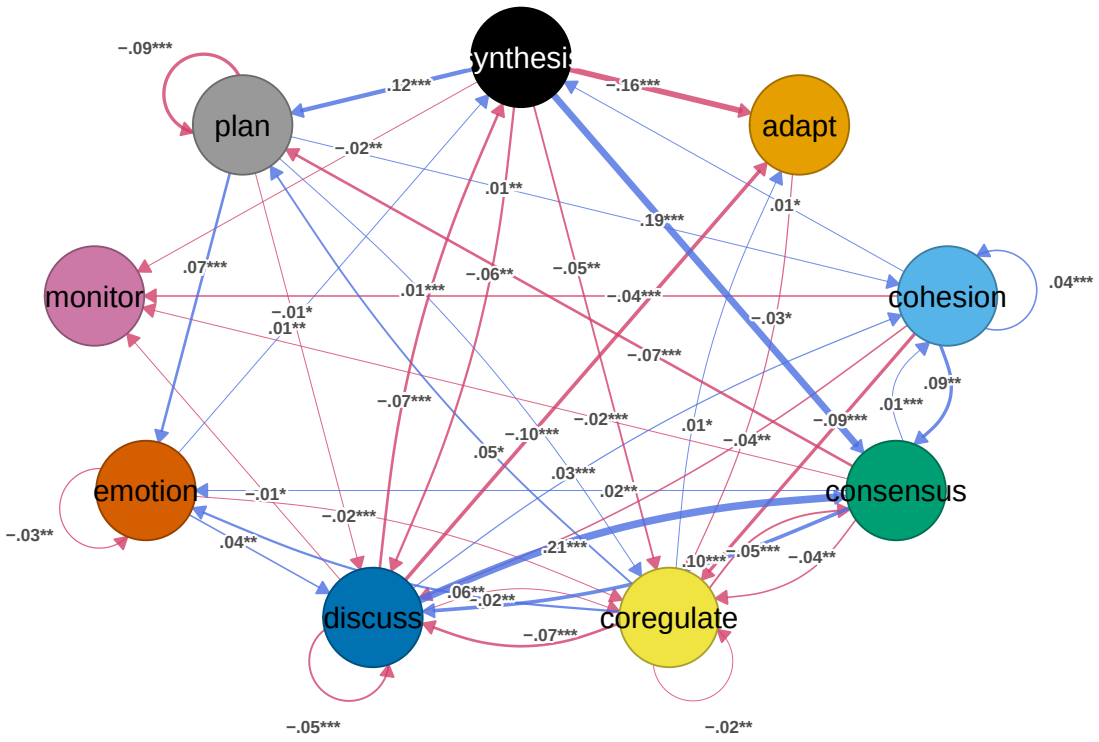
```r
head(summary(group_perm), 10)
```

```
##          group     from         to   weight_x   weight_y         diff
## 1  High vs Low    adapt   cohesion 0.26241135 0.27717391 -0.014762566
## 2  High vs Low    adapt  consensus 0.51773050 0.46195652  0.055773975
## 3  High vs Low    adapt coregulate 0.00000000 0.02989130 -0.029891304
## 4  High vs Low    adapt    discuss 0.03546099 0.06793478 -0.032473790
## 5  High vs Low    adapt    emotion 0.14184397 0.11141304  0.030430928
## 6  High vs Low    adapt    monitor 0.02836879 0.03532609 -0.006957293
## 7  High vs Low    adapt       plan 0.01418440 0.01630435 -0.002119951
## 8  High vs Low cohesion      adapt 0.00533049 0.00000000  0.005330490
## 9  High vs Low cohesion   cohesion 0.04371002 0.00660502  0.037105002
## 10 High vs Low cohesion  consensus 0.53624733 0.45046235  0.085784983
##    effect_size     p_value   sig
## 1   -0.3922188 0.712287712 FALSE
## 2    1.2669055 0.201798202 FALSE
## 3   -2.4196843 0.011988012  TRUE
## 4   -1.6142325 0.103896104 FALSE
## 5    1.0508991 0.300699301 FALSE
## 6   -0.4479287 0.665334665 FALSE
## 7   -0.1965672 0.751248751 FALSE
## 8    2.0799910 0.054945055 FALSE
## 9    4.4791305 0.000999001  TRUE
## 10   3.5701213 0.001998002  TRUE
```

`weight_x` and `weight_y` are the transition probabilities of high and low achievers, `diff` their difference, and `effect_size` the difference in standard deviations of the permuted differences. For example, low achievers move from `cohesion` to `coregulate` more often (0.17 against 0.08), and high achievers from `cohesion` to `consensus` (0.54 against 0.45).

`splot()` draws the edges that differ, coloured by the group in which they are stronger.

```r
splot(group_perm, edge_positive_color = "#4A6FE3",
      edge_negative_color = "#D33F6A")
```



Blue edges are stronger among high achievers and red edges among low achievers; `show_nonsig = TRUE` adds the edges that do not differ, and `show_stars = TRUE` the significance stars.

Clusters of states

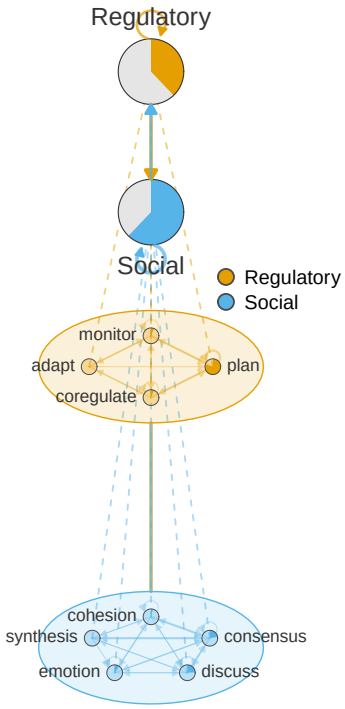
The nine actions fall into two groups of behaviour: regulation of the task (`monitor`, `plan`, `coregulate`, `adapt`) and social interaction (`cohesion`, `consensus`, `discuss`, `emotion`, `synthesis`). `build_mcml()` estimates a multi-cluster, multi-level network: a network of the clusters, and a network of the actions within each cluster (Zhang et al., 2026).

```
clusters <- list(
  Regulatory = c("monitor", "plan", "coregulate", "adapt"),
  Social     = c("cohesion", "consensus", "discuss", "emotion", "synthesis")
)
cluster_net <- build_mcml(net, clusters = clusters)
cluster_net
```

```
## MCML Network
## ============
## Type: tna  | Method: sum
## Nodes: 9  | Clusters: 2
## Transitions: 25533
##   Macro: 11997  | Per-cluster: 13536
```

```
##
## Clusters:
##   Regulatory (4): monitor, plan, coregulate, adapt
##   Social (5): cohesion, consensus, discuss, emotion, synthesis
##
## Macro (cluster-level) weights:
##            Regulatory Social
## Regulatory     0.4042 0.5958
## Social         0.3879 0.6121
```

```
splot(cluster_net)
```

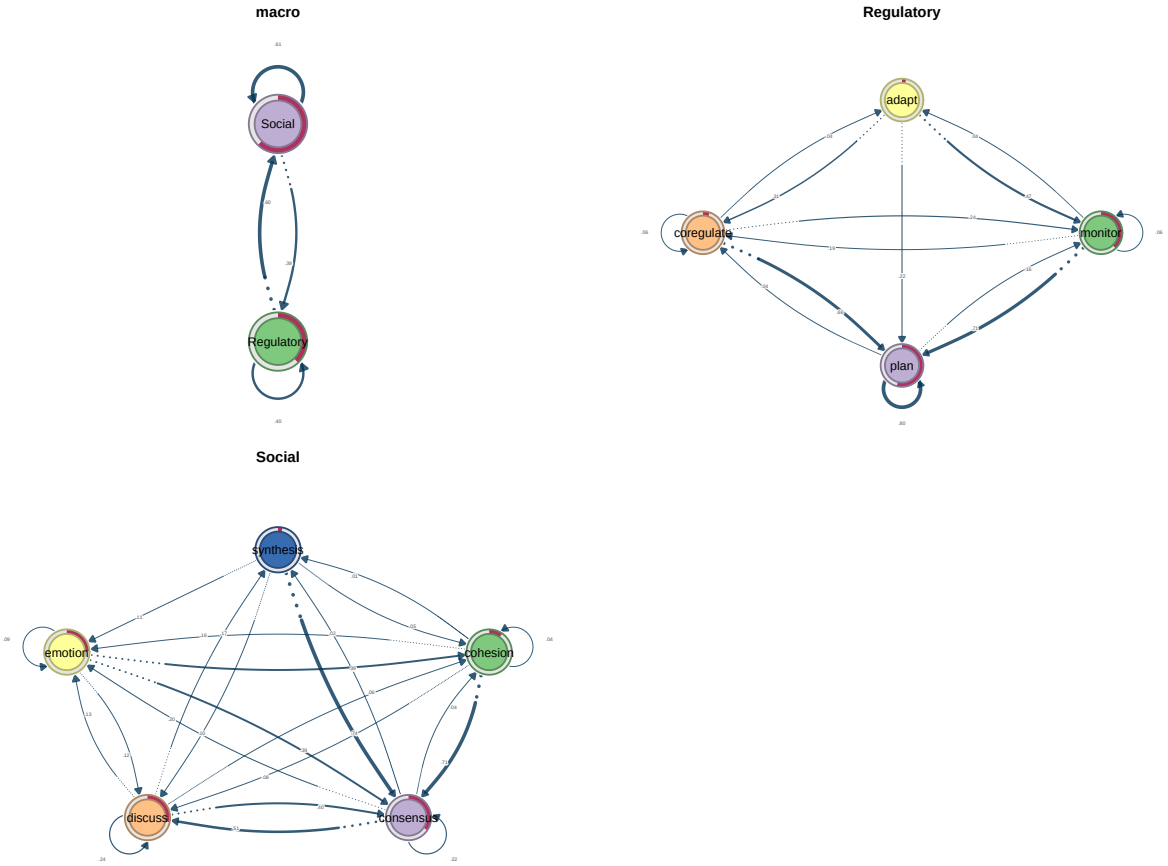


At the level of the clusters, both kinds of action are followed more often by a social action: a regulatory action by a social one with probability 0.60, and a social action by another social action with probability 0.61. `as_tna()` converts the levels into transition networks, one for the clusters and one for the actions within each cluster.

```
cluster_levels <- as_tna(cluster_net)
```

```
## Registered S3 method overwritten by 'tna':
##   method             from
##   plot.tna_bootstrap cograph
```

```
splot(cluster_levels)
```



How to cite this article

Saqr, M., López-Pernas, S., & Misiejuk, K. (2026). *Network estimation and visualization with Nestimate + cograph*. Nestimate. https://doi.org/10.5281/zenodo.24528512 · HTML · PDF

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