

GGMnonreg: Non-Regularized Gaussian Graphical Models in R

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Summary

Studying complex relations in multivariate datasets is a common task across the sciences. Cognitive neuroscientists model brain connectivity with the goal of unearthing functional and structural associations between cortical regions (Ortiz et al., 2015). In clinical psychology, researchers wish to better understand the intricate web of symptom interrelations that underlie mental health disorders (Borsboom et al., 2011; McNally, 2016). To this end, graphical modeling has emerged as an oft-used tool in the chest of scientific inquiry. The basic idea is to characterize multivariate relations by learning the conditional dependence structure. The cortical regions or symptoms are *nodes* and the featured connections linking nodes are *edges* that graphically represent the conditional dependence structure.

Graphical modeling is quite common in fields with wide data, that is, when there are more variables (p) than observations (n). Accordingly, many regularization-based approaches have been developed for those kinds of data. There are key drawbacks of regularization, including, but not limited to, the fact that obtaining a valid measure of parameter uncertainty is very (very) difficult (Bühlmann et al., 2014) and there can be an inflated false positive rate (see for example, Donald R. Williams et al., 2019).

Statement of Need

More recently, graphical modeling has emerged in psychology (Epskamp et al. 2018), where the data is typically long or low-dimensional ($p < n$; Donald R. Williams et al. (2019), Donald R. Williams & Rast (2019)). The primary purpose of **GGMnonreg** is to provide methods that were specifically designed for low-dimensional data (e.g., those common in the social-behavioral sciences).

Supported Models

- Gaussian graphical model (GGM). The following data types are supported.
 - Gaussian
 - Ordinal
 - Binary
- Ising model (Marsman et al., 2017)
- Mixed graphical model

34 Additional methods

35 The following are also included

- 36 ■ Expected network replicability ([Donald R. Williams, 2020](#))
- 37 ■ Compare Gaussian graphical models
- 38 ■ Measure of parameter uncertainty ([Donald R. Williams et al., 2019](#))
- 39 ■ Edge inclusion “probabilities” (e.g., Figure 6.4 in [Hastie et al., 2015](#))
- 40 ■ Network visualization
- 41 ■ Constrained precision matrix (the network, given an assumed graph, see p. 631 in [Hastie et al., 2009](#))
- 42 ■ Predictability (variance explained for each node, [Haslbeck & Waldorp, 2018](#))

44 Gaussian graphical Model

45 The following estimates a GGM for 5 post-traumatic stress disorder (PTSD) symptoms ([Armour et al., 2017](#)):

```
47 fit <- ggm_inference(Y = ptsd[,1:5],
48                      boot = FALSE)
49
50 fit
51 #>           1           2           3           4           5
52 #> 1 0.0000000 0.2262934 0.0000000 0.3335737 0.1547986
53 #> 2 0.2262934 0.0000000 0.4993419 0.0000000 0.0000000
54 #> 3 0.0000000 0.4993419 0.0000000 0.2205442 0.1841798
55 #> 4 0.3335737 0.0000000 0.2205442 0.0000000 0.3407634
56 #> 5 0.1547986 0.0000000 0.1841798 0.3407634 0.0000000
```

57 Predictability

58 It is common to then estimate “predictability,” which corresponds to R^2 for each node in the network. In **GGMnonreg**, this is implemented with the following code:

```
60 predictability(fit)
61
62 #>   Estimate Est.Error Ci.lb Ci.ub
63 #> 1    0.45      0.05  0.35  0.54
64 #> 2    0.50      0.05  0.41  0.59
65 #> 3    0.55      0.04  0.47  0.64
66 #> 4    0.50      0.05  0.41  0.59
67 #> 5    0.46      0.05  0.37  0.55
```

68 Ising Model

69 An Ising model is for binary data. The PTSD symptoms can be binary, indicating the symptom was either present or absent. This network is estimated with:

```
71 # make binary
72 Y <- ifelse(ptsd[,1:5] == 0, 0, 1)
73
```

```

74 # fit model
75 fit <- ising_search(Y, IC = "BIC",
76                     progress = FALSE)
77
78 fit
79 #>           1           2           3           4           5
80 #> 1 0.000000 1.439583 0.000000 1.273379 0.000000
81 #> 2 1.439583 0.000000 1.616511 0.000000 1.182281
82 #> 3 0.000000 1.616511 0.000000 1.716747 1.077322
83 #> 4 1.273379 0.000000 1.716747 0.000000 1.662550
84 #> 5 0.000000 1.182281 1.077322 1.662550 0.000000

```

85 Network Replicability

86 Recently, the topic of replicability has captivated the network literature. To this end, I developed an analytic solution to estimate network replicability ([Donald R. Williams, 2020](#)).

88 The first step is to define a “true” partial correlation network. As an example, I generate a synthetic partial correlation matrix, and then compute expected network replicability.

```

90 # edges between 0.05 and 0.25
91 main <- gen_net(p = 20,
92                lb = 0.05,
93                ub = 0.25)
94
95 # enr
96 enr(main$pcors,
97      n = 500,
98      replications = 4)
99
100 #> Average Replicability: 0.53
101 #> Average Number of Edges: 30 (SD = 2.12)
102 #>
103 #> ----
104 #>
105 #> Cumulative Probability:
106 #>
107 #> prop.edges edges Pr(R > prop.edges)
108 #>      0.0      0      1.00
109 #>      0.1      6      1.00
110 #>      0.2     11      1.00
111 #>      0.3     17      1.00
112 #>      0.4     23      1.00
113 #>      0.5     28      0.78
114 #>      0.6     34      0.02
115 #>      0.7     40      0.00
116 #>      0.8     46      0.00
117 #>      0.9     51      0.00
118 ----
119 Pr(R > prop.edges):
120 probability of replicating more than the
121 corresponding proportion (and number) of edges

```

122 On average, we see that we can expect to replicate roughly half of the edges in four replication

123 attempts, where replication is defined as detecting a given edge in each attempt. Further, the
124 probability of replicating more than 70% of the edges is zero.

125 Network Visualization

126 A key aspect of graphical modeling is visualizing the conditional dependence structure. To
127 this end, **GGMnonreg** makes network plots with **ggplot2** (Wickham, 2016).

```
128 plot(get_graph(fit),  
129       node_names = colnames(Y),  
130       edge_magnify = 2)
```

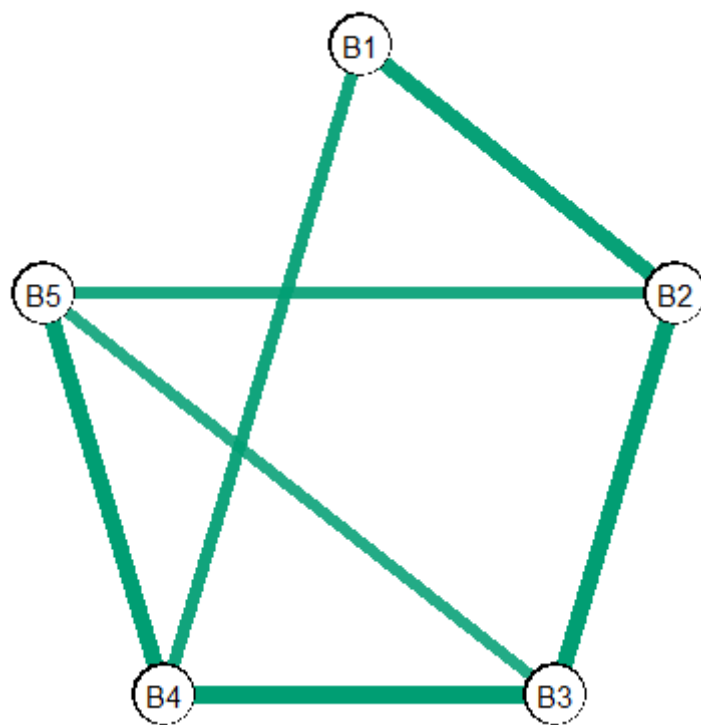


Figure 1: Conditional Dependence Structure

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