Análise de rede: uma introdução e aplicações na psicologia

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PPG Psicologia PUC-Campinas – Avaliação Psicológica do Potencial Humano

ABP+ & Criabrasilis

Avaliação em Psicologia Positiva e Criatividade (ANPEPP)

Resumo

- O curso tem por objetivo fazer uma breve introdução à análise de rede. Serão abordados seus fundamentos e aplicações na psicologia, em especial na psicometria. Apesar de seu uso recente na psicologia a análise de rede (ou de grafos) é uma técnica muito utilizada em outras áreas do conhecimento como, por exemplo, ecologia, genética, medicina (oncologia, epidemiologia) e tecnologia de informação. A análise de rede combina a teoria de grafos com algoritmos robustos para estimação da estrutura e dinâmica de sistemas complexos. Alguns exemplos de aplicações na psicologia são: modelos estruturais indutivos, estudo de agrupamentos ou comunidades de variáveis, modelos de mediação, estudo de comorbidade e comparações entre grupos.

Roteiro

- Introdução e exemplos
- Representação de dados psicométricos em rede
- Redes gaussianas
- Estatísticas de centralidade
- Redes de dados dicotômicos
- Redes de dados misturados (mixed)
- Análise de comunidades
- Comparação de redes
- Estabilidade da rede
- Predição de variáveis
- Modelos de rede de variáveis latentes

Materiais

- Software estatístico R
- R Studio – interface amigável e interativa do R
- Lista de pacotes (email)
- https://github.com/wagnerLM/networkIBAP
- Bancos e o script (lista de comandos) do curso

Introdução e exemplos

- Paradigma de rede
- Paradoxo da era da informação (proporcionalmente, cada vez sabe-se menos, apensar de se ter mais informação disponível)
- Complexidade enquanto prática (não só discurso)

- “Reductionism, as a paradigm, is expired, and complexity, as a field, is tired. Data-based mathematical models of complex systems are offering a fresh perspective, rapidly developing into a new discipline: network science.”

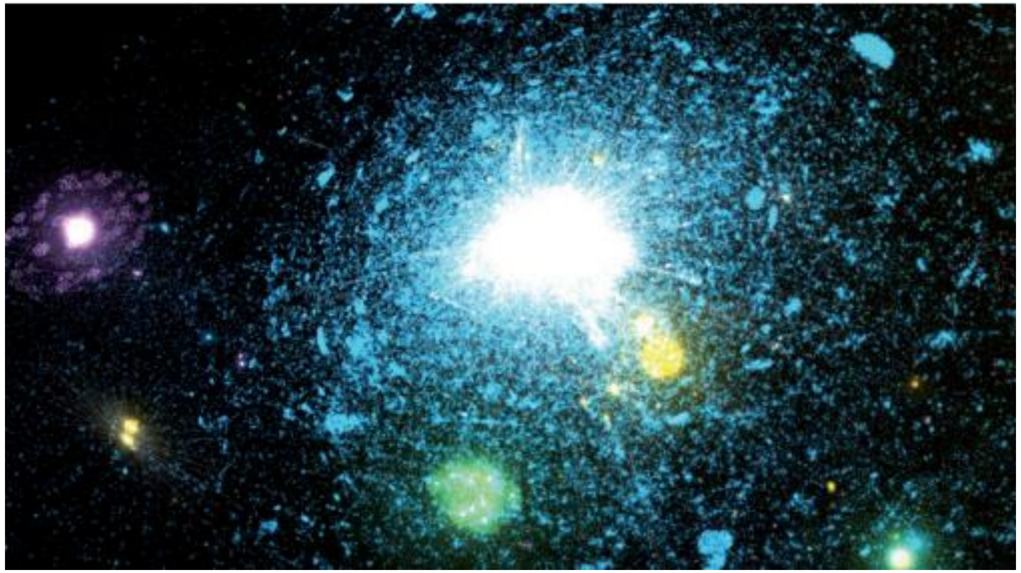
NATURE PHYSICS | COMMENTARY

The network takeover

Albert-László Barabási

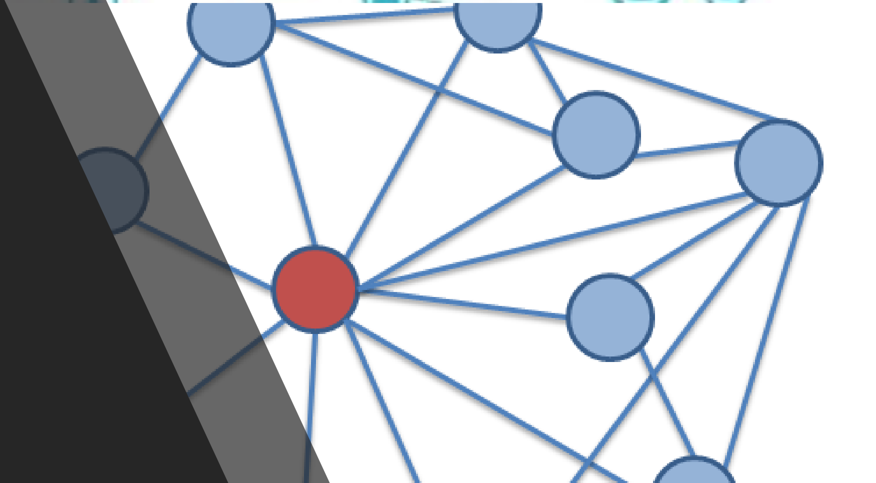
Nature Physics **8**, 14–16 (2012) | doi:10.1038/nphys2188

Published online 22 December 2011



O que é uma rede?

- Vértices (nodos) e arestas (linhas)
- Nodos representam variáveis
- As linhas representam a relação entre os nodos



Social network analysis

- Medicina
- Ecologia

Healthc Inform Res. 2012 Mar; 18(1): 44–56.
Published online 2012 Mar 31. doi: 10.4258/hir.2012.18.1.44

PMCID: PMC3324755

Application of Social Network Analysis to Health Care Sectors

Hae Lan Jang, PhD,[1] Young Sung Lee, MD, PhD,[1] and Ji-Young An, PhD[2]

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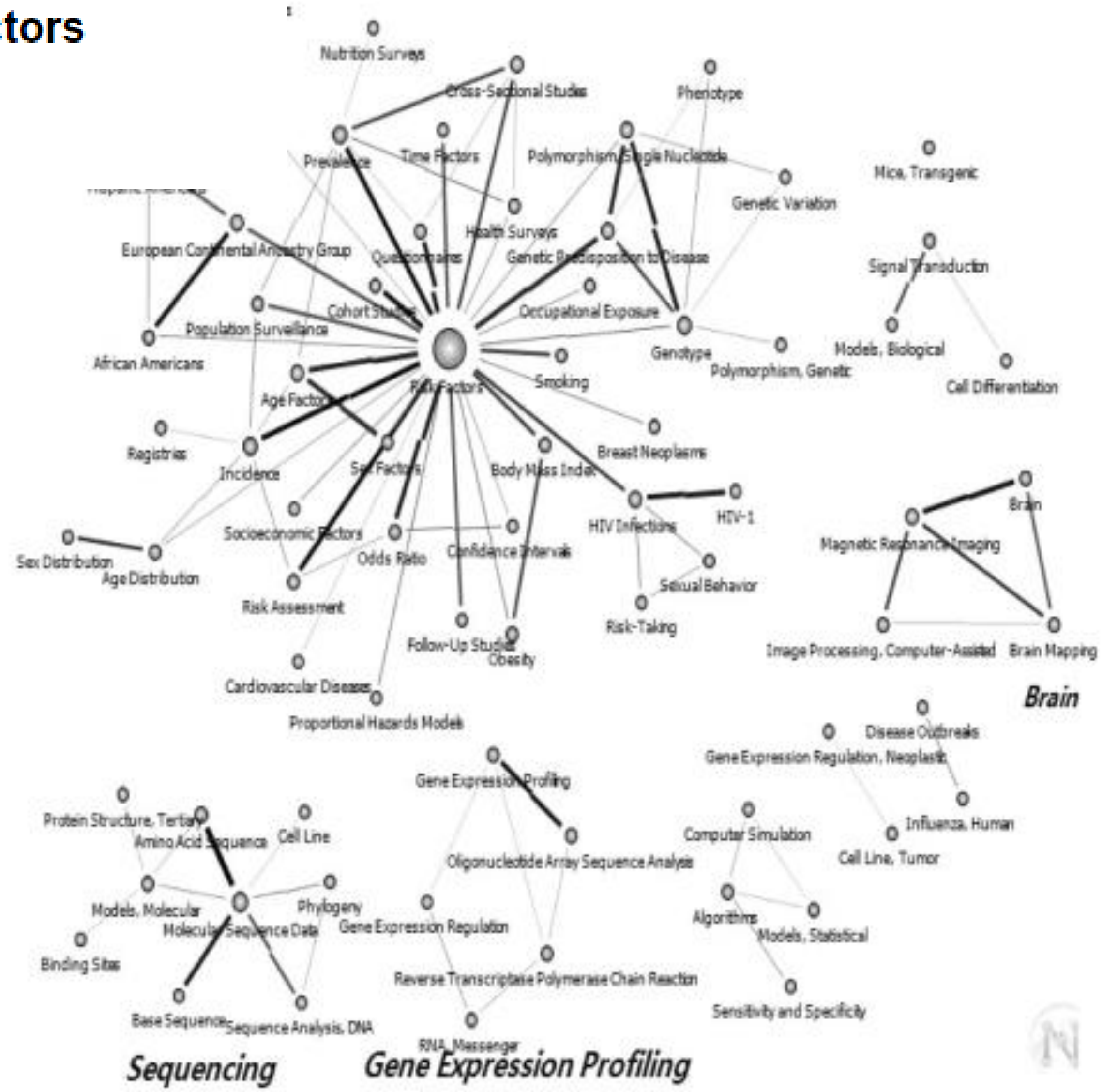


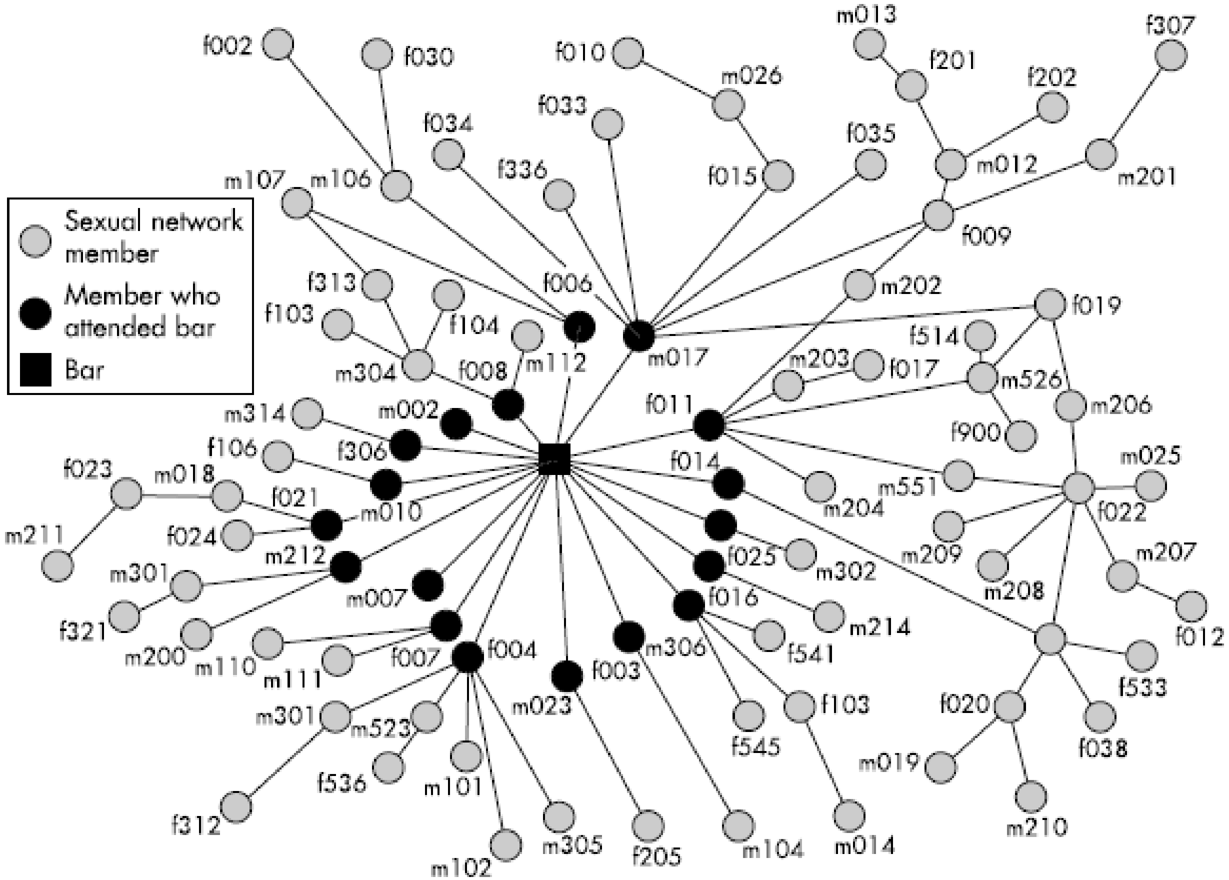


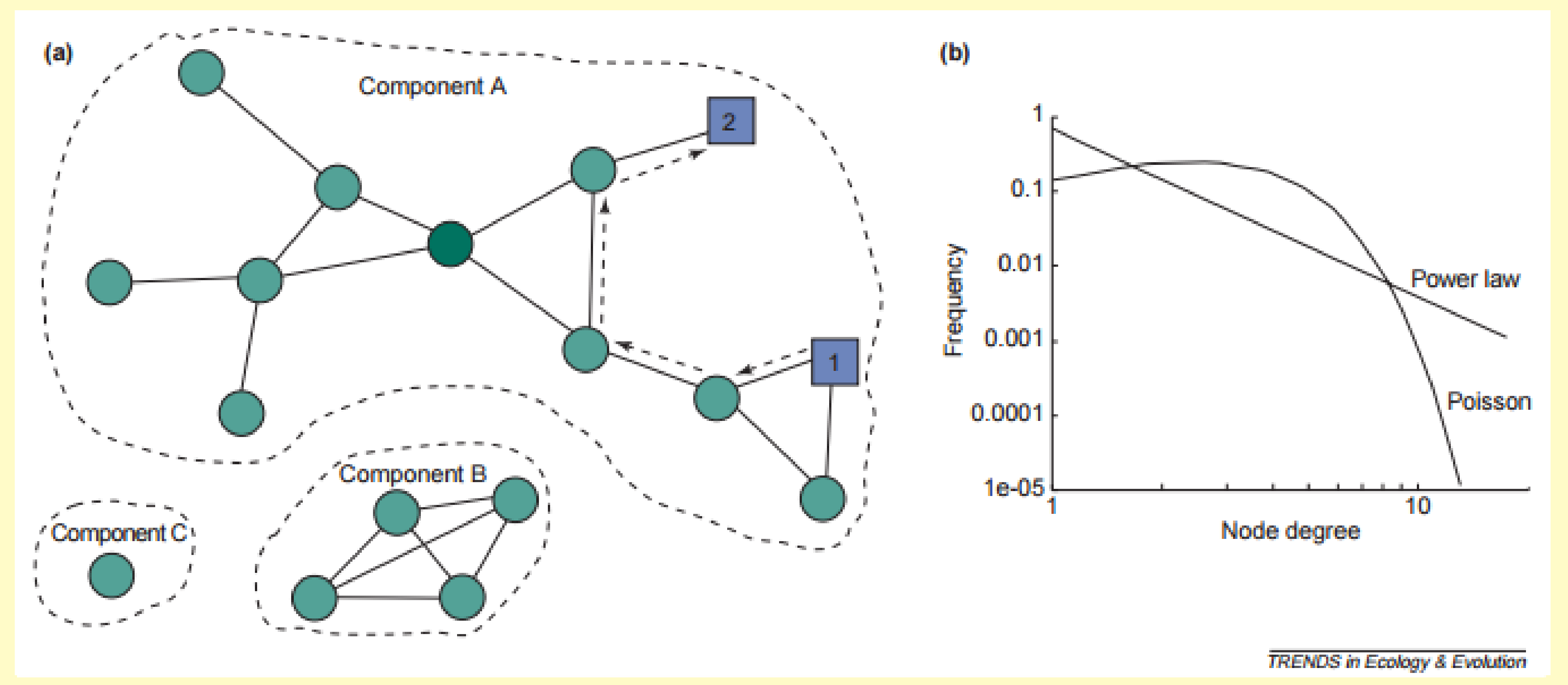
Figure 2 Network members (n = 89) viewed by their connection through a bar associated with gonorrhoea acquisition. A prefix to the unique identifier of "m" designates a male and "f" indicates a female sexual partner. Bar patrons possessed significantly higher information centrality measures compared to non-patrons (table 3).

ORIGINAL ARTICLE

Sexual network analysis of a gonorrhoea outbreak

P De, A E Singh, T Wong, W Yacoub, A M Jolly

Sex Transm Infect 2004;**80**:280–285. doi: 10.1136/sti.2003.007187



Review
TRENDS in Ecology and Evolution Vol.20 No.6 June 2005
Full text provided by www.sciencedirect.com
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Network thinking in ecology and evolution

Stephen R. Proulx[1], Daniel E.L. Promislow[2] and Patrick C. Phillips[1]

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nature neuroscience

ARTICLE PREVIEW

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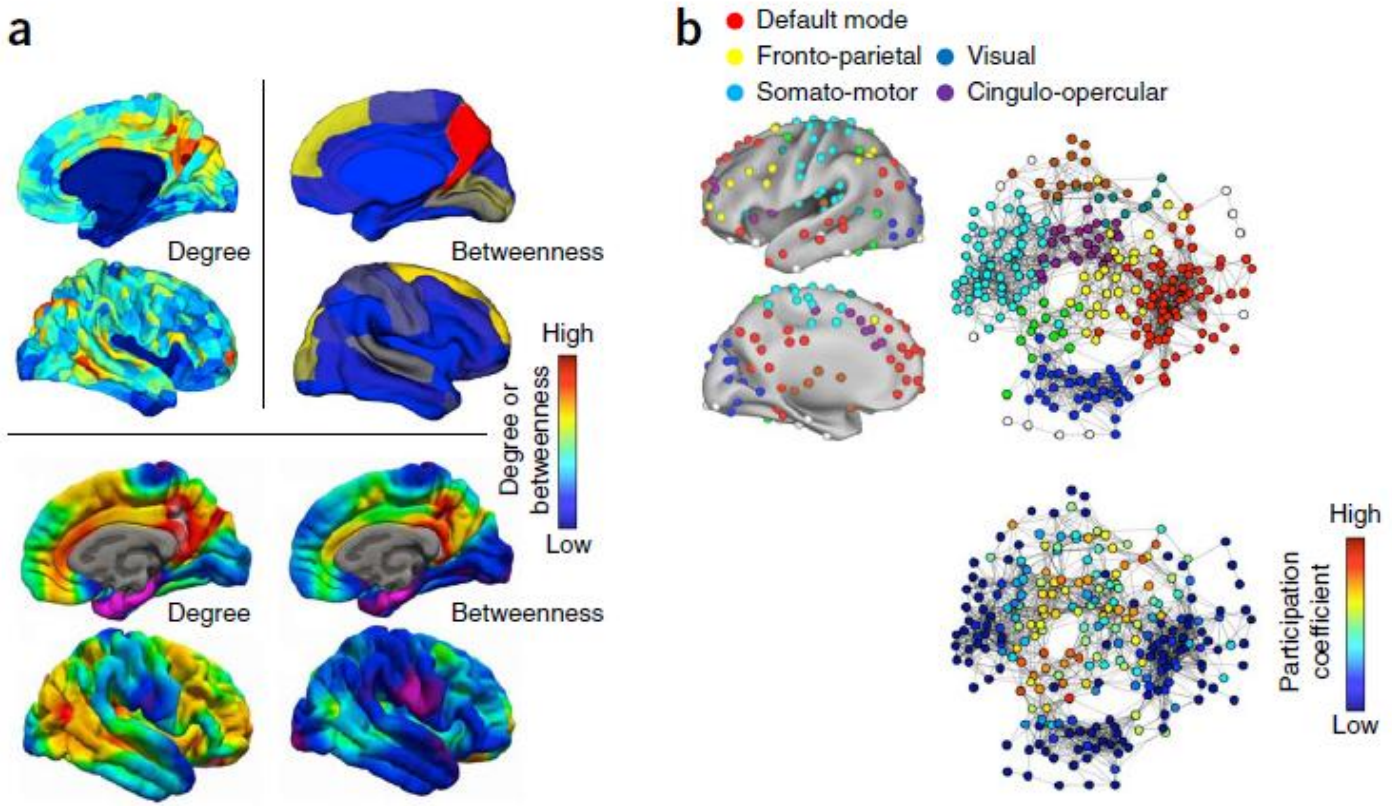
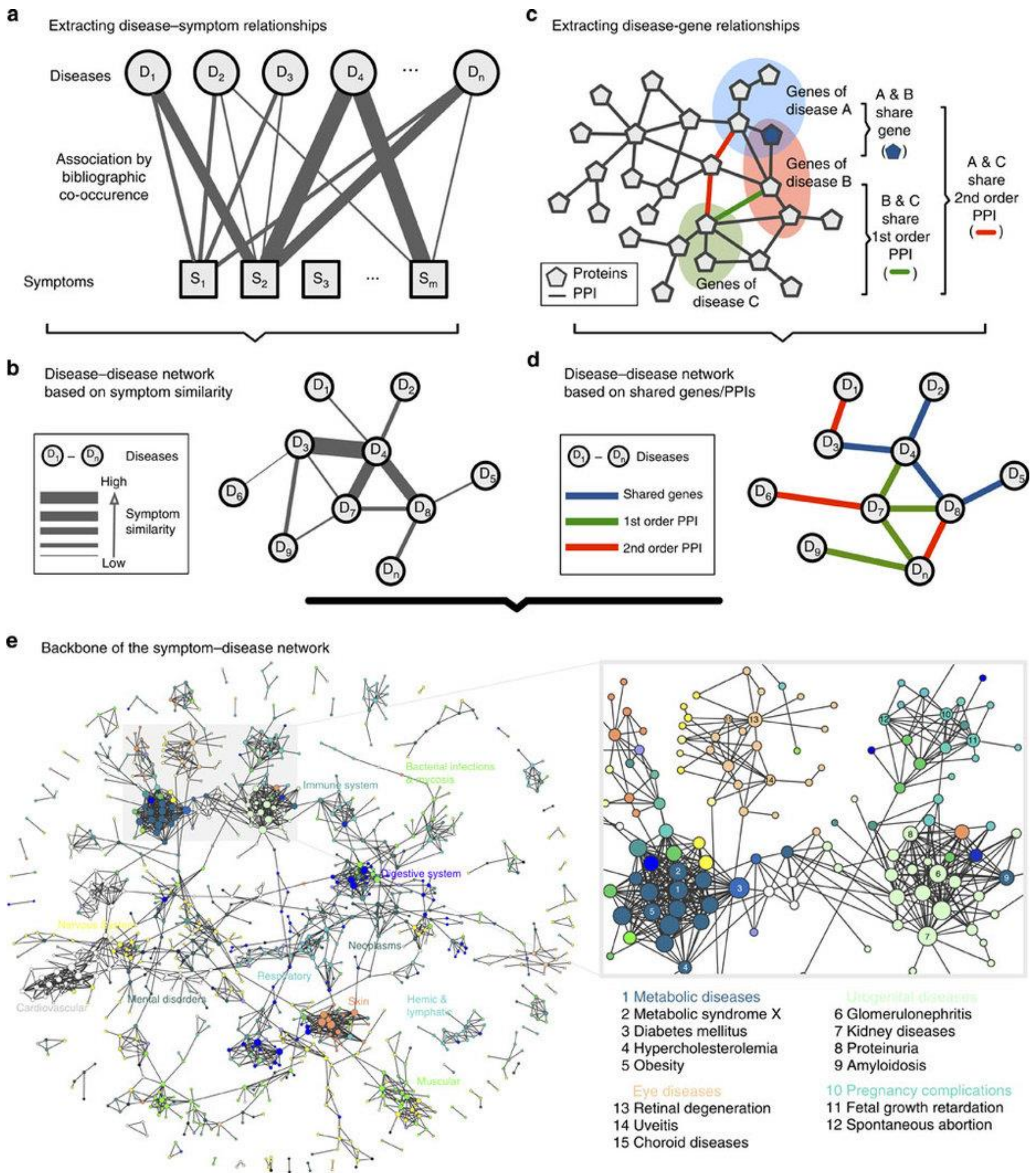
NATURE NEUROSCIENCE | REVIEW

Contributions and challenges for network models in cognitive neuroscience

Olaf Sporns

Nature Neuroscience **17**, 652–660 (2014) | doi:10.1038/nn.3690
Received 06 October 2013 | Accepted 03 March 2014 | Published online 30 March 2014





nature COMMUNICATIONS

Article

Human symptoms–disease network

XueZhong Zhou, Jörg Menche, Albert-László Barabási & Amitabh Sharma

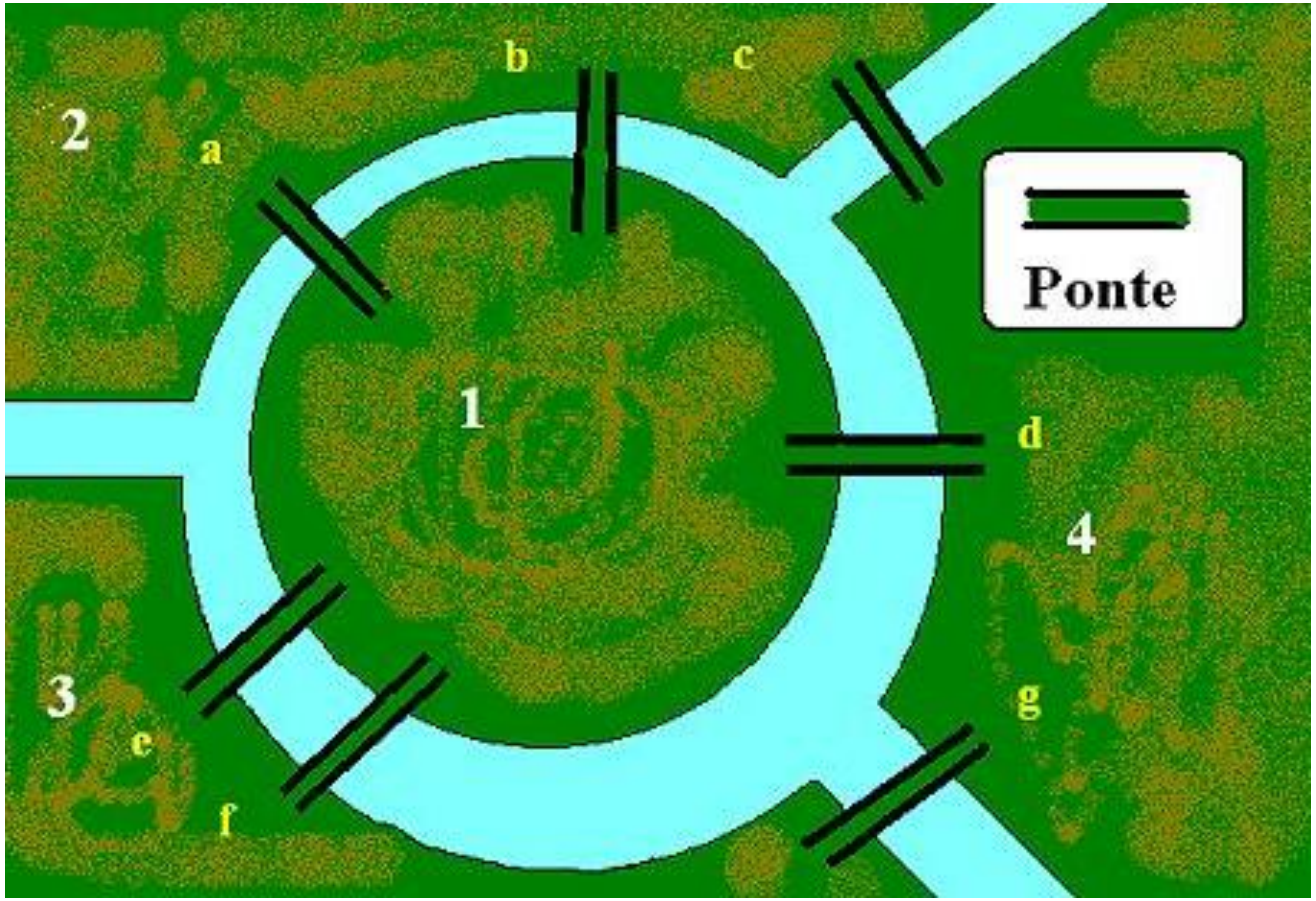
Nature Communications **5**, Article number: 4212 (2014)
doi:10.1038/ncomms5212

Received: 07 November 2013
Accepted: 27 May 2014
Published online: 26 June 2014

We extracted 7,109,429 (about 35.5% in over twenty million records) PubMed bibliographic records with one or more disease/symptom terms in the MeSH metadata field (see Methods), yielding a total of 4,442 disease terms and 322 symptom terms

Teoria dos grafos

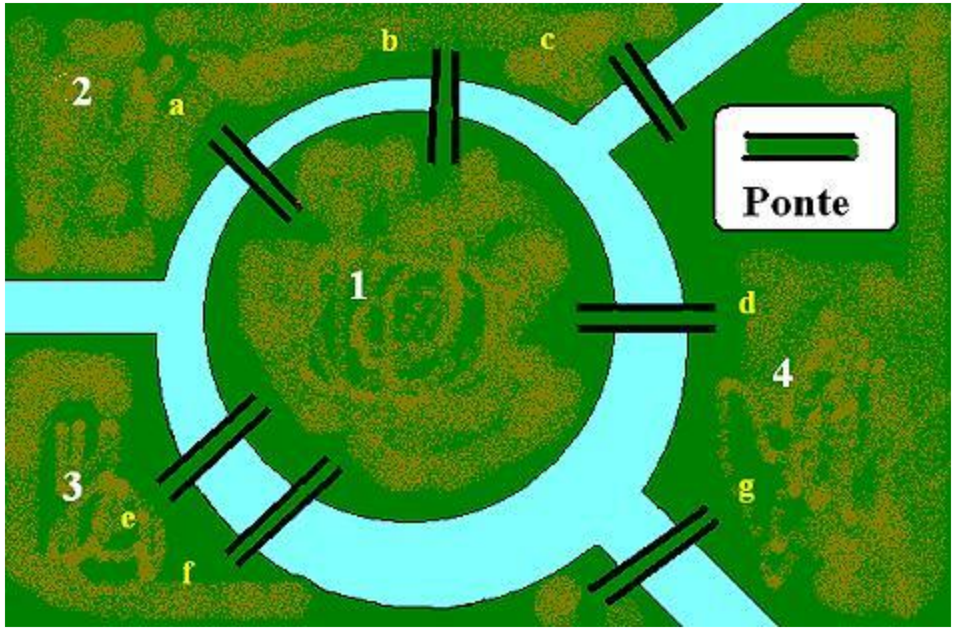
- O problema das pontes de Königsberg
- Discutia-se nas ruas da cidade a possibilidade de atravessar todas as pontes sem repetir nenhuma

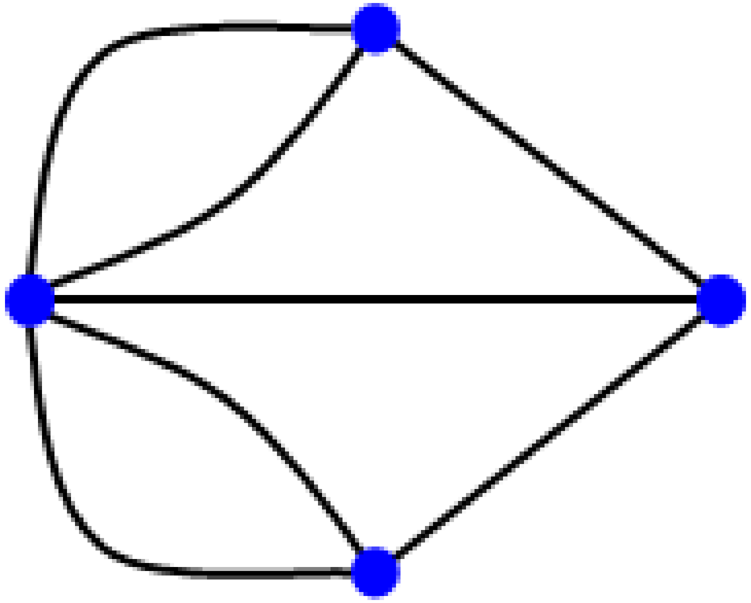


https://pt.wikipedia.org/wiki/Sete_pontes_de_K%C3%B6nigsberg

Teoria dos grafos

- Havia-se tornado uma lenda popular a possibilidade da façanha quando Leonhard Euler , em 1736, provou que não existia caminho que possibilitasse tais restrições.



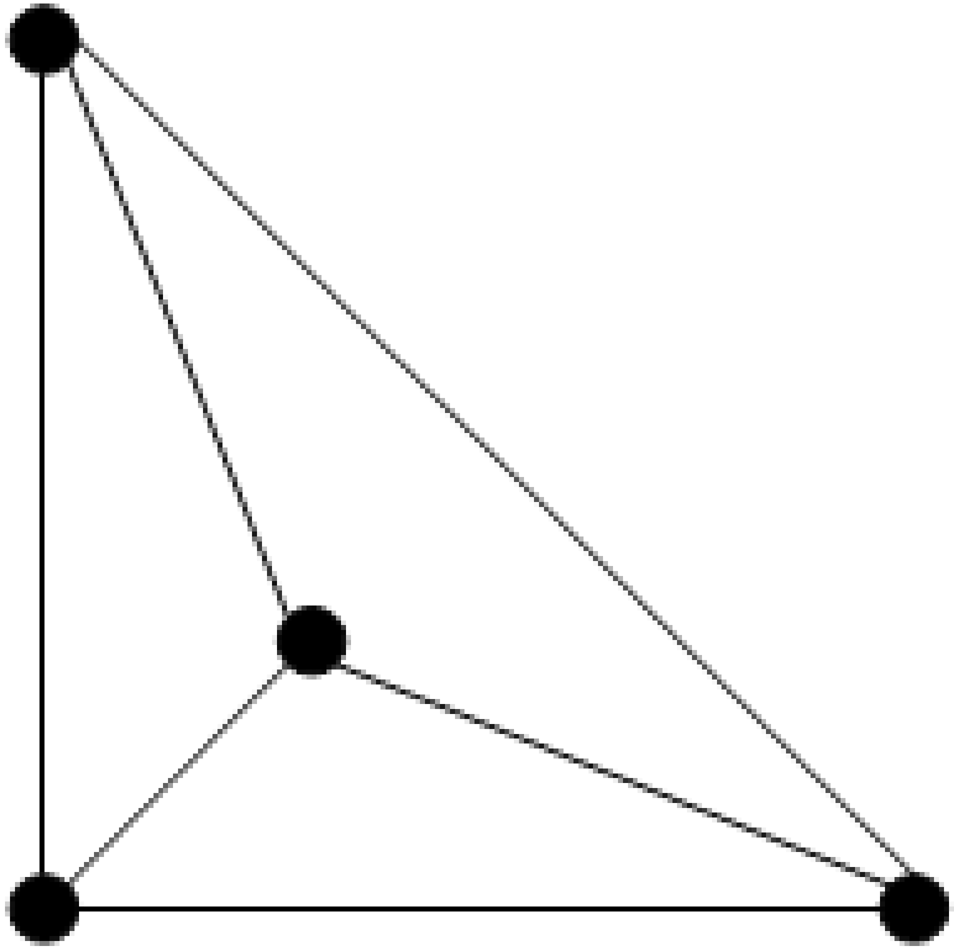


- Topologia

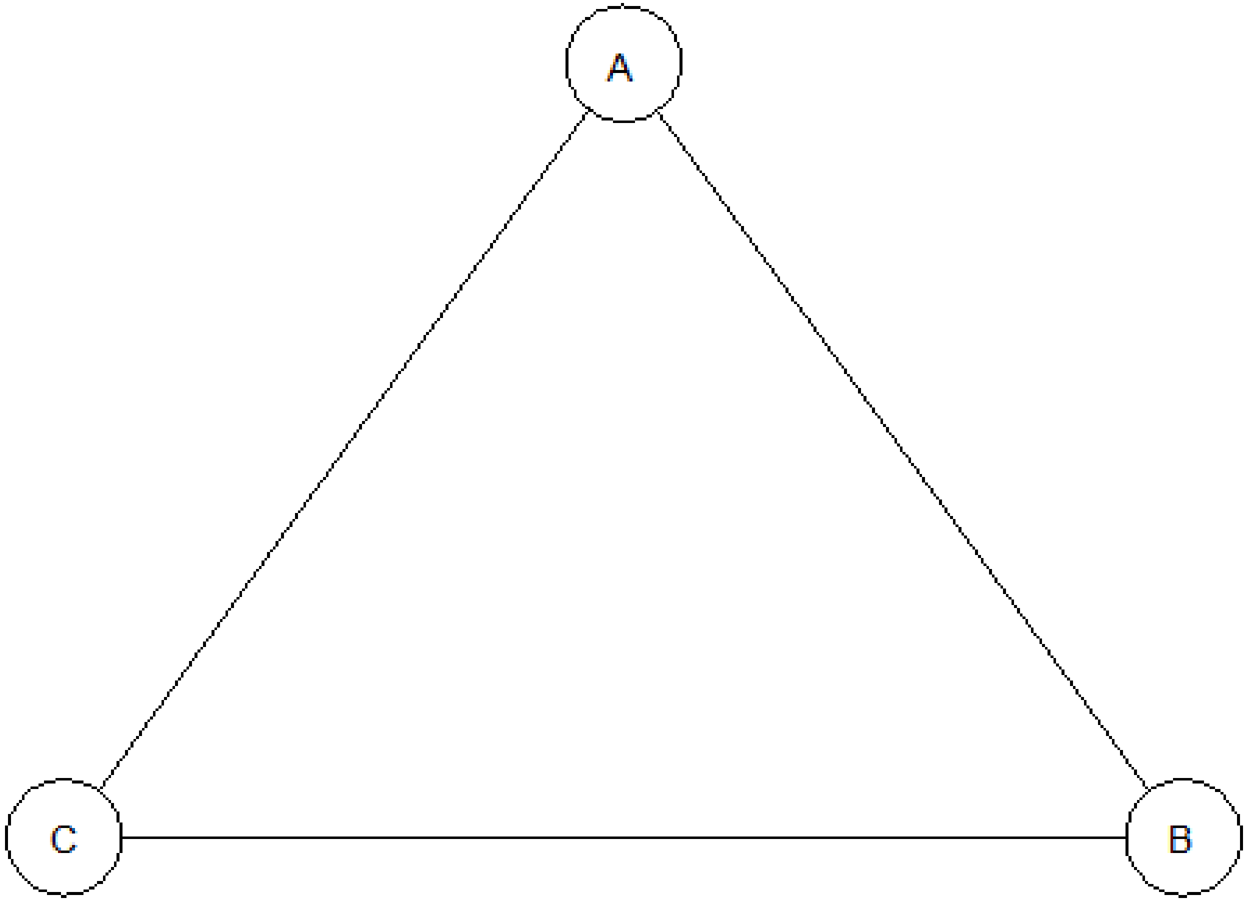
Rede – representação gráfica

- Vértices (nodos, pontos)
  - Variáveis ou observações
- Arestas (linhas, conectores)

Ponderada	Direcional
Não ponderada	Não direcional



https://upload.wikimedia.org/wikipedia/commons/0/02/Grafo_k4_plano.PNG



- Aresta (linha)

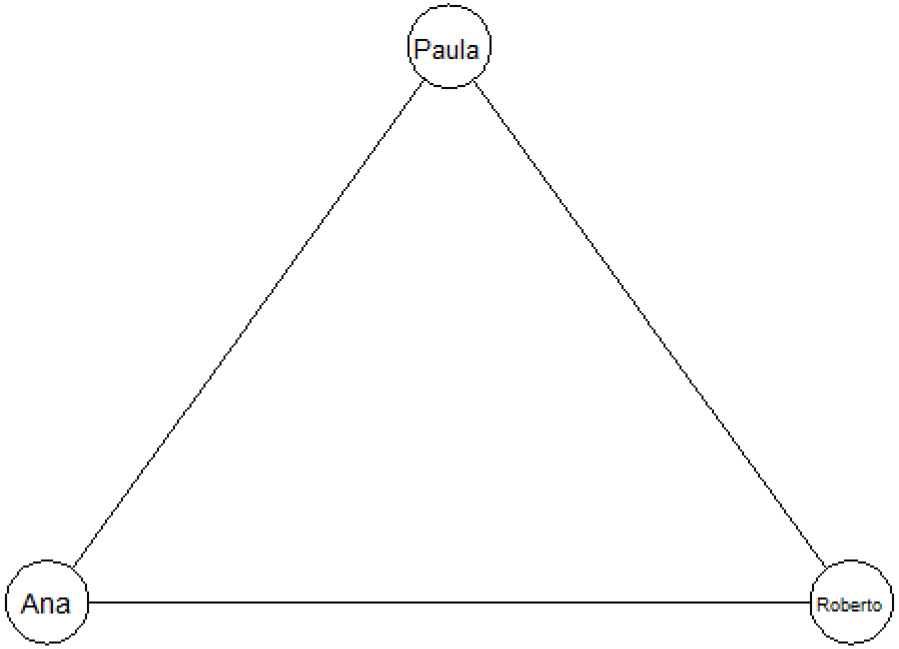
Quais tipo de dados representar?

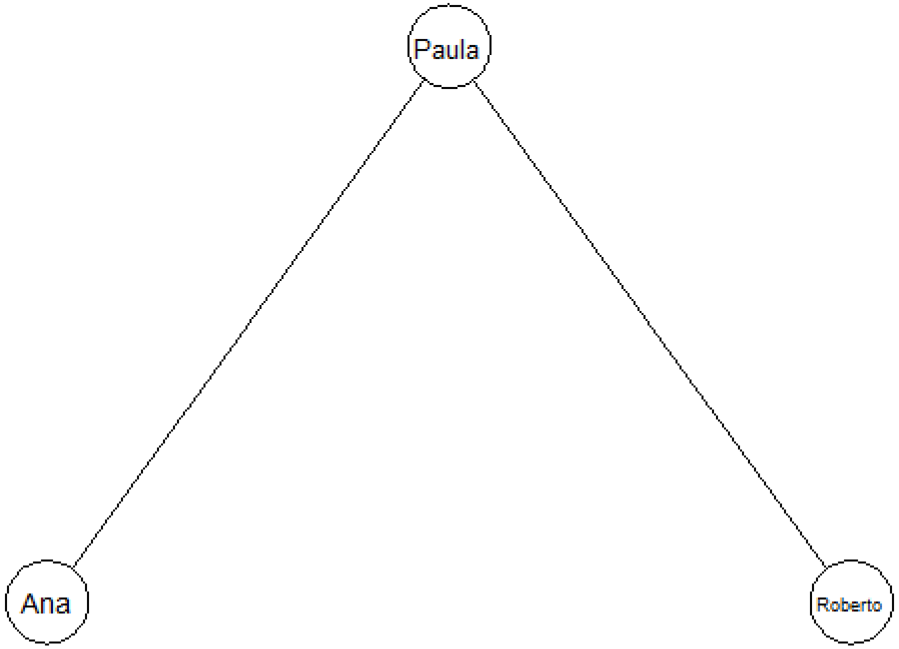
Amizades

	Paula	Roberto	Ana
Paula	0	1	1
Roberto	1	0	0
Ana	1	0	0

Cenário 1: Paula, Ana e Roberto são amigos

Cenário 2: Paula é amiga de Ana, Paula é amiga de Roberto, Ana e Roberto não são amigos

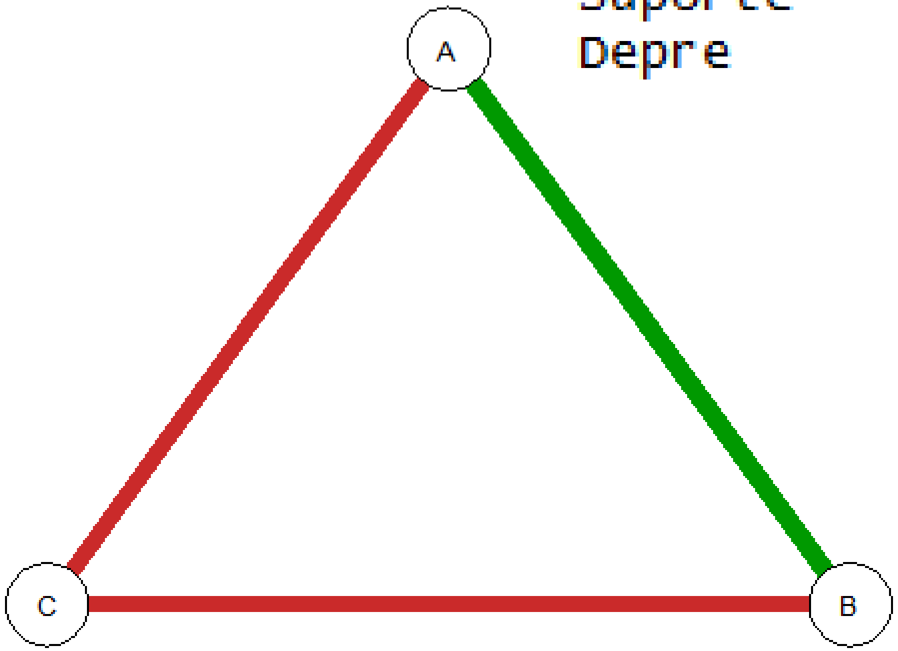


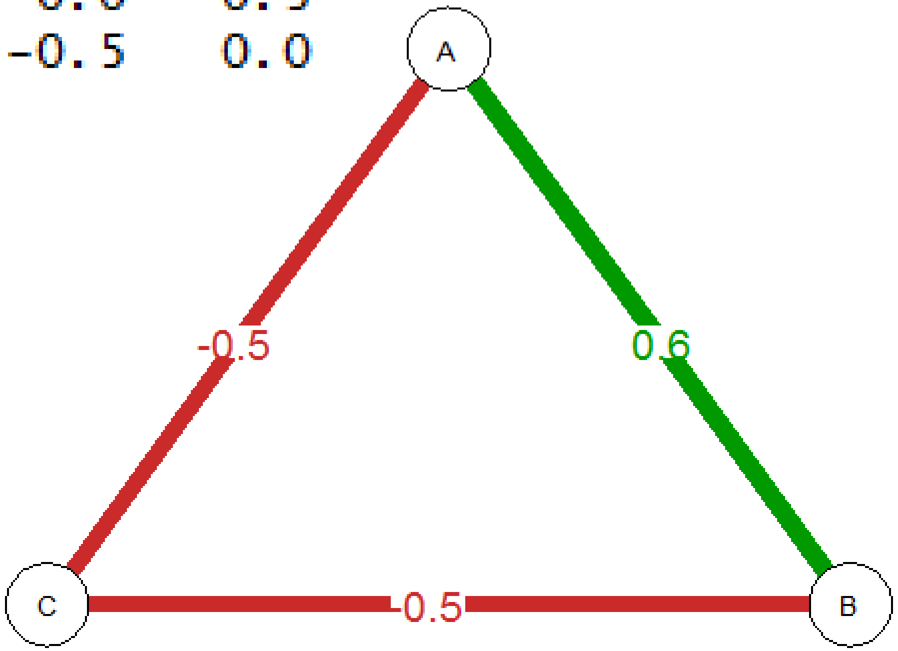


Medidas de associação entre variáveis

- Relação entre bem-estar (A), suporte social (B) e depressão (C)

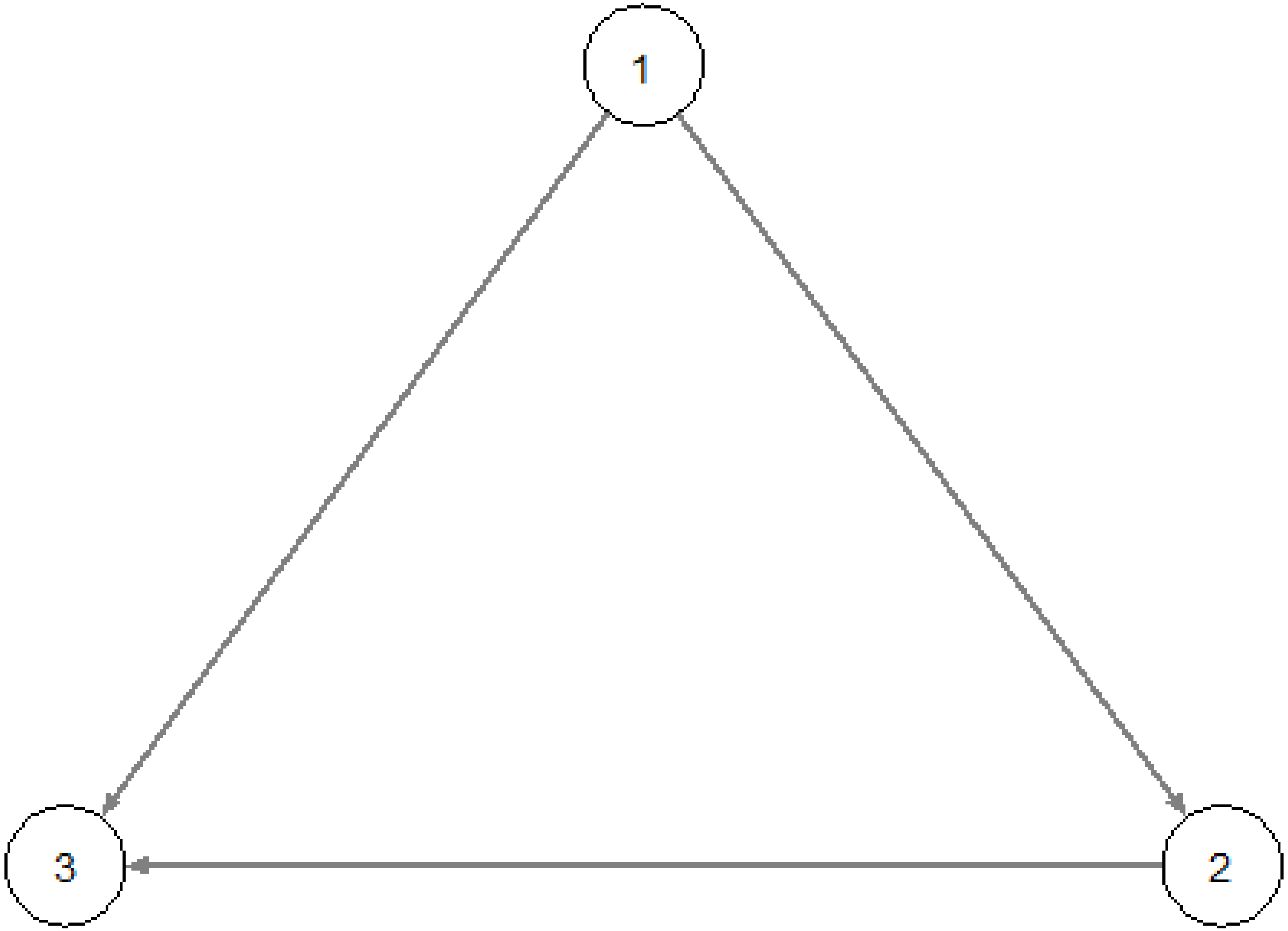
	Bem-estar	Suporte	Depre
Bem-estar	0.0	0.6	-0.5
Suporte	0.6	0.0	-0.5
Depre	-0.5	-0.5	0.0

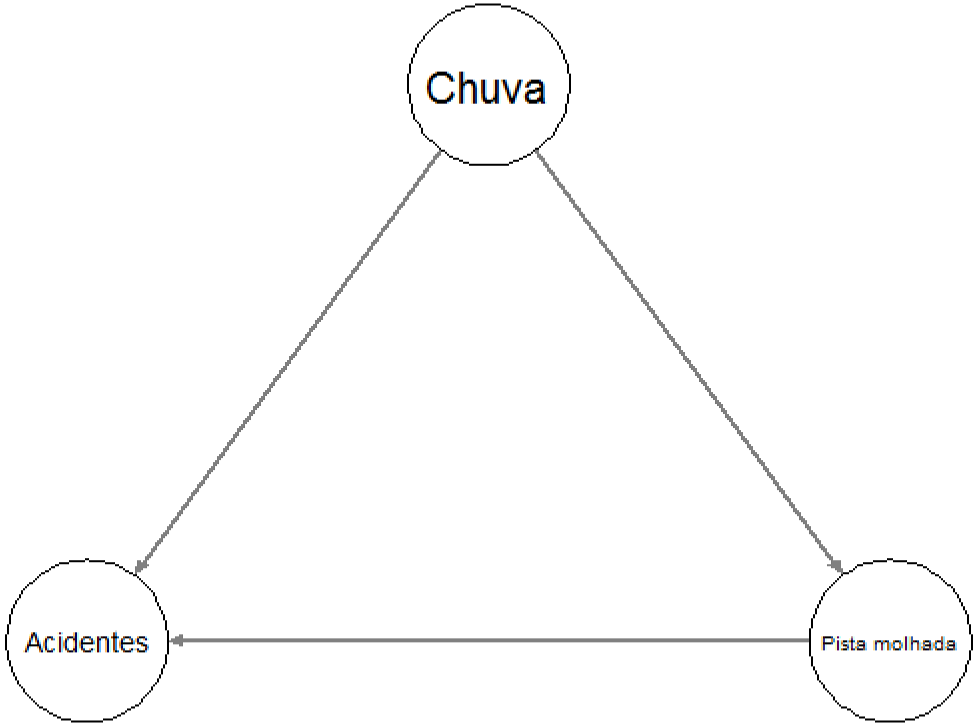


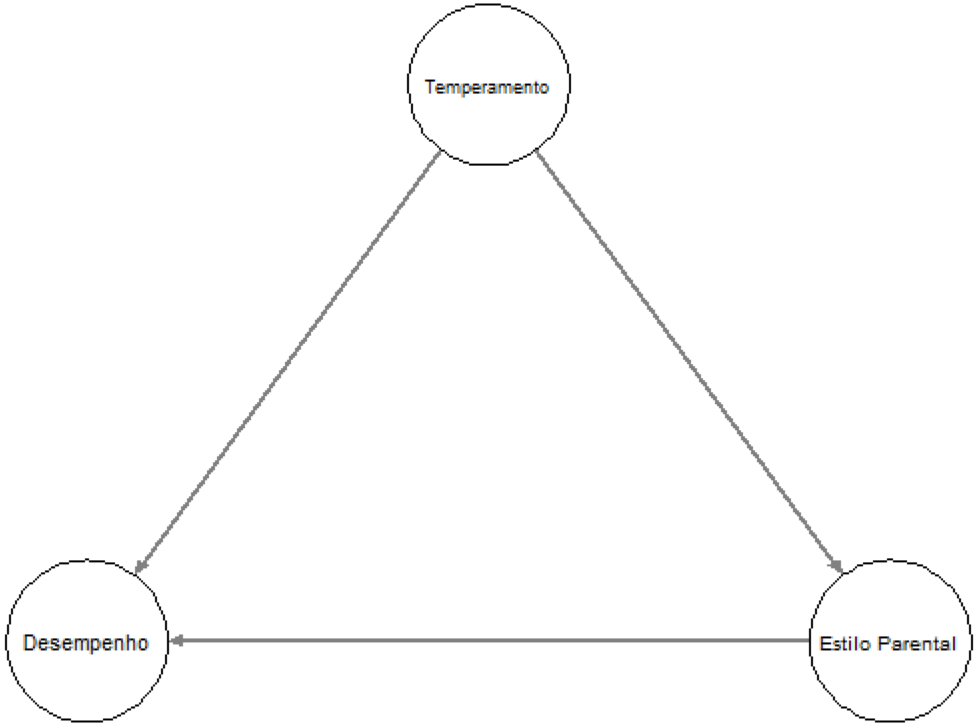


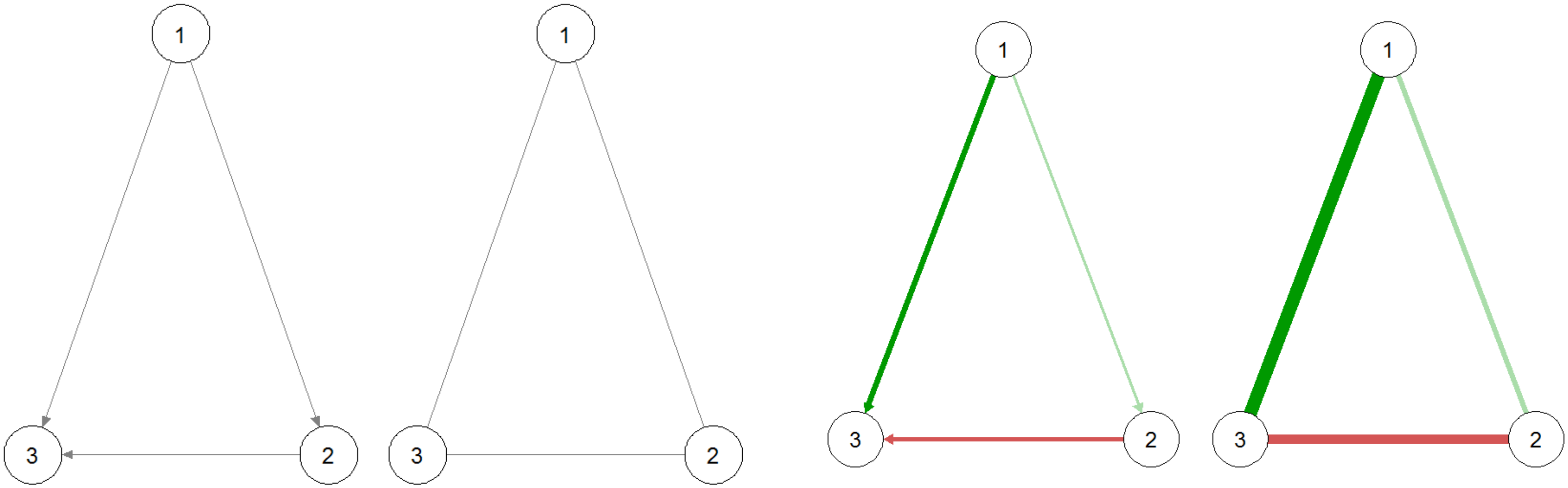
Lista de arestas

	from	to
1	1	2
2	1	3
3	2	3



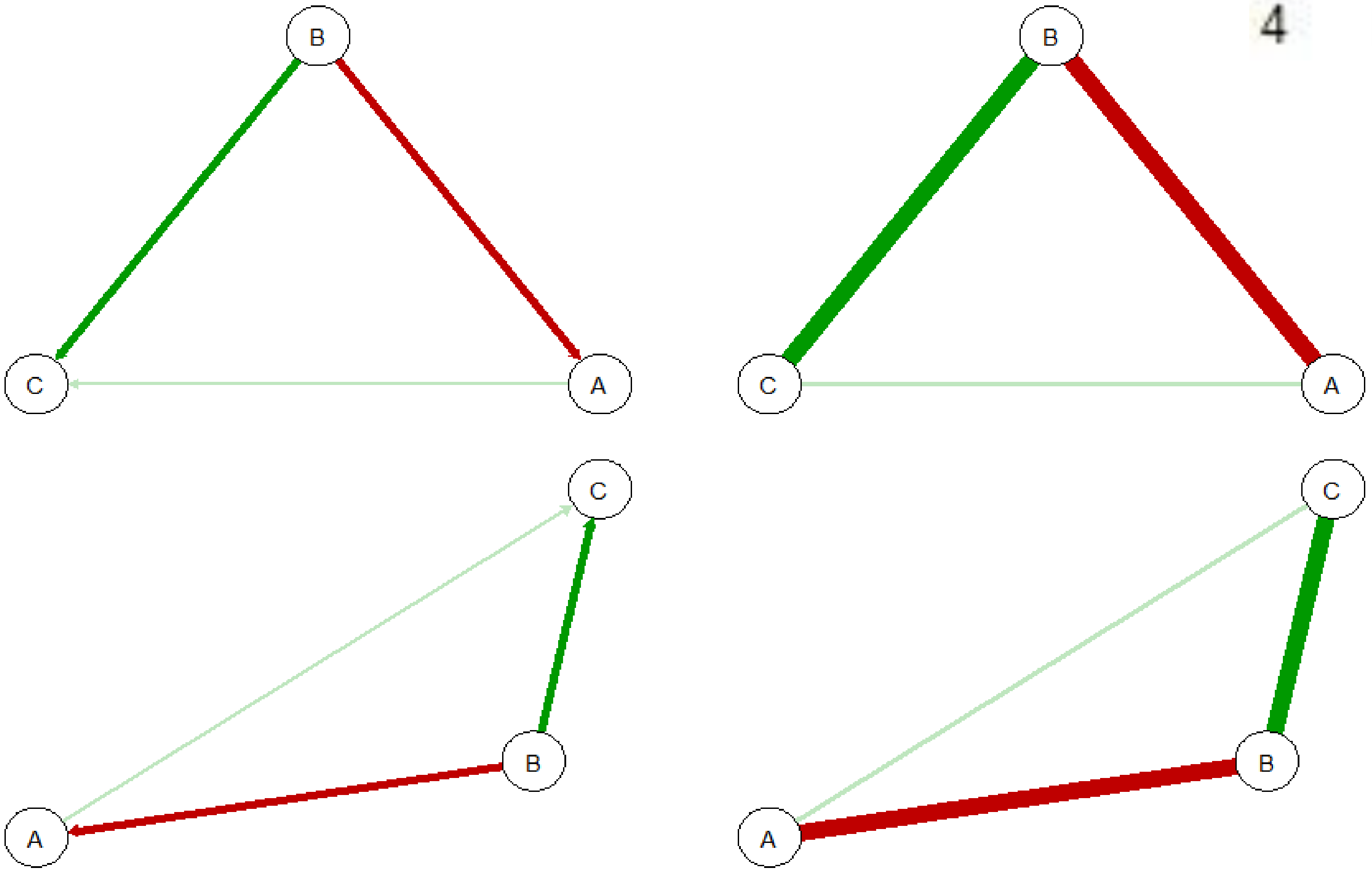

Chuva
Acidentes
Pista molhada


Temperamento
Desempenho
Estilo Parental


1
3
2
1
3
2
1
3
2
1
3
2

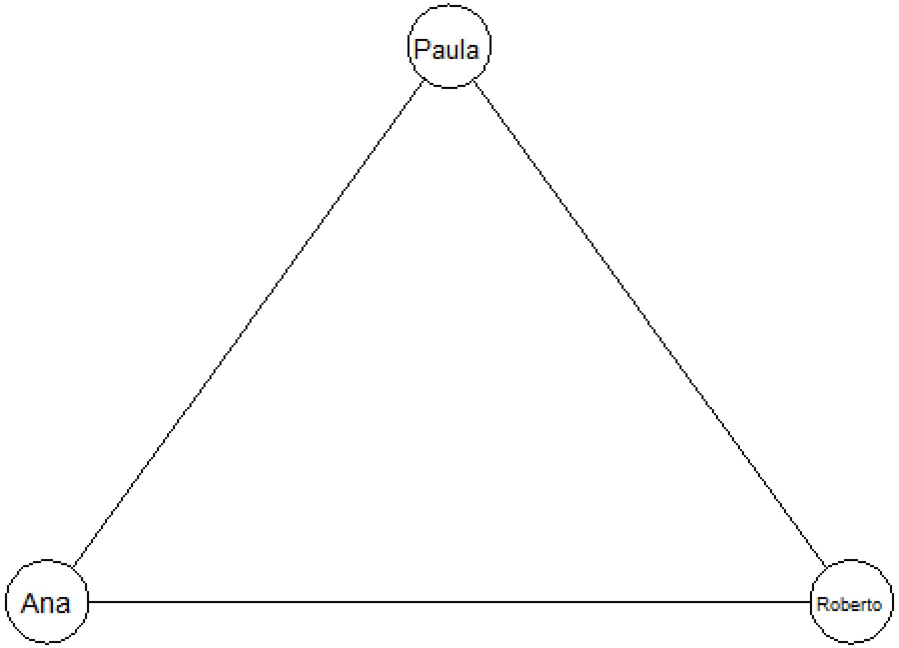
Fruchterman & Reingold, 1991

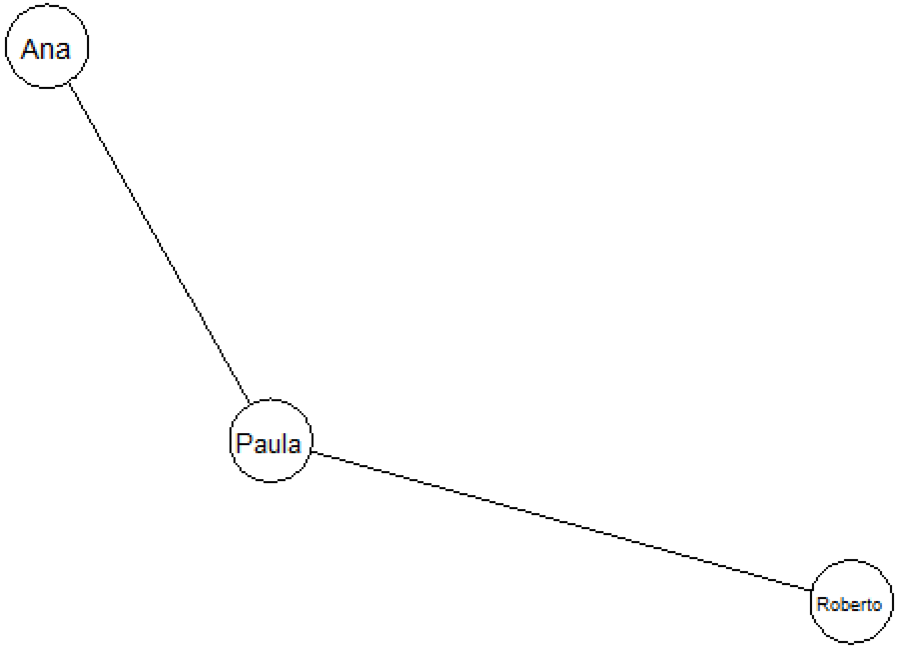
	from	to	weight
1	B	A	-2.0
2	A	C	0.5
3	B	C	2.0
4	A	A	0.0



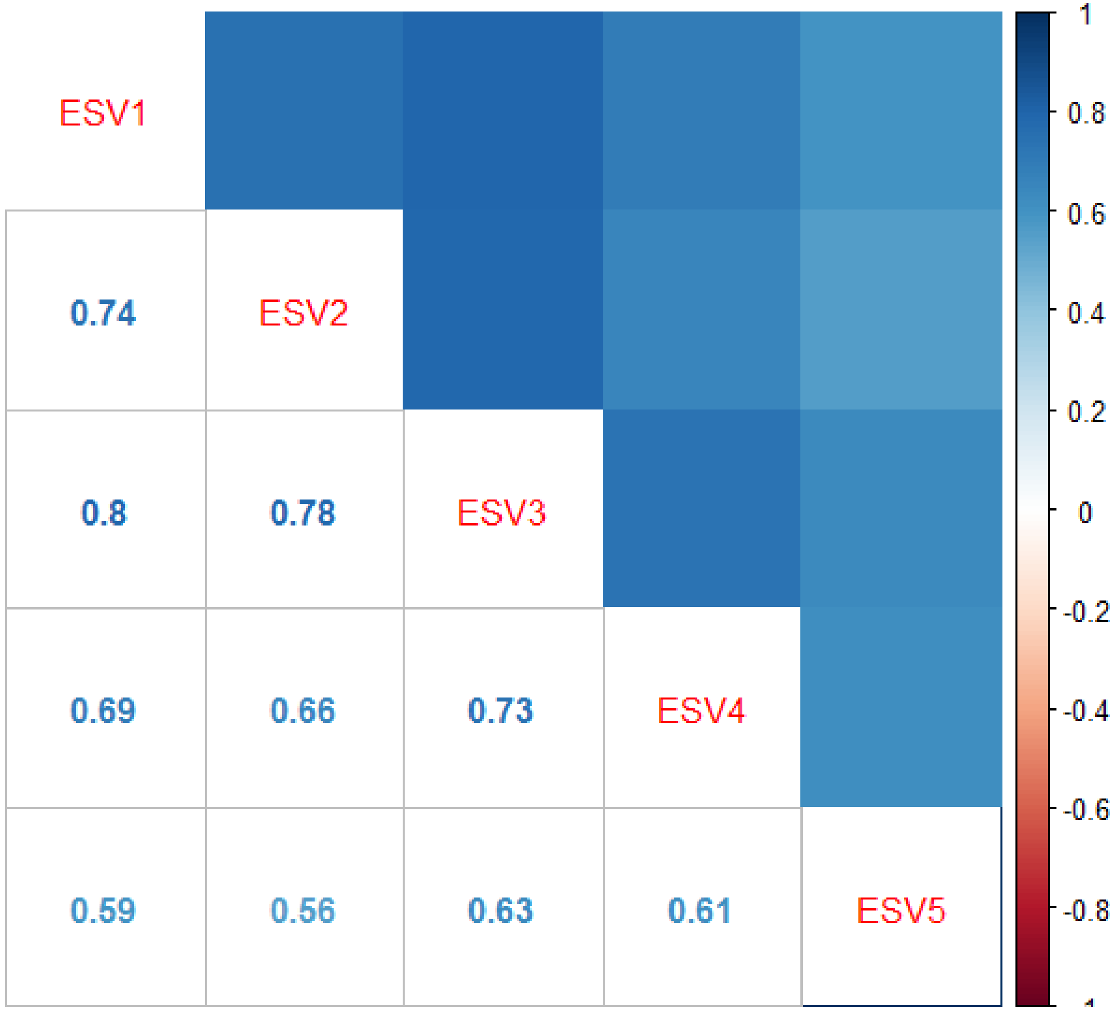
Amizades

	Paula	Roberto	Ana
Paula	0	1	1
Roberto	1	0	0
Ana	1	0	0

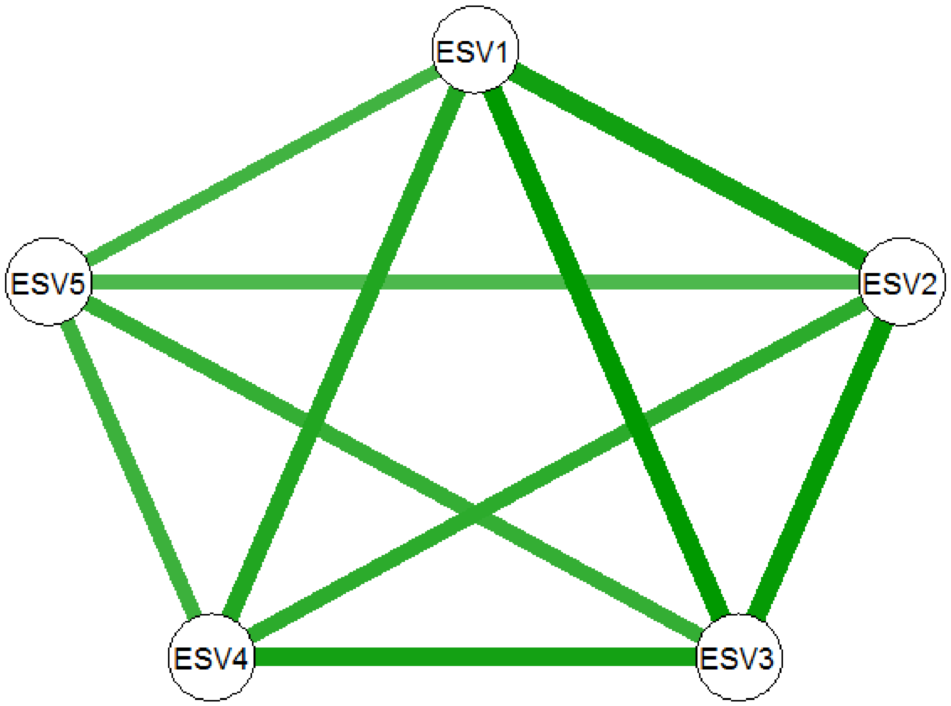


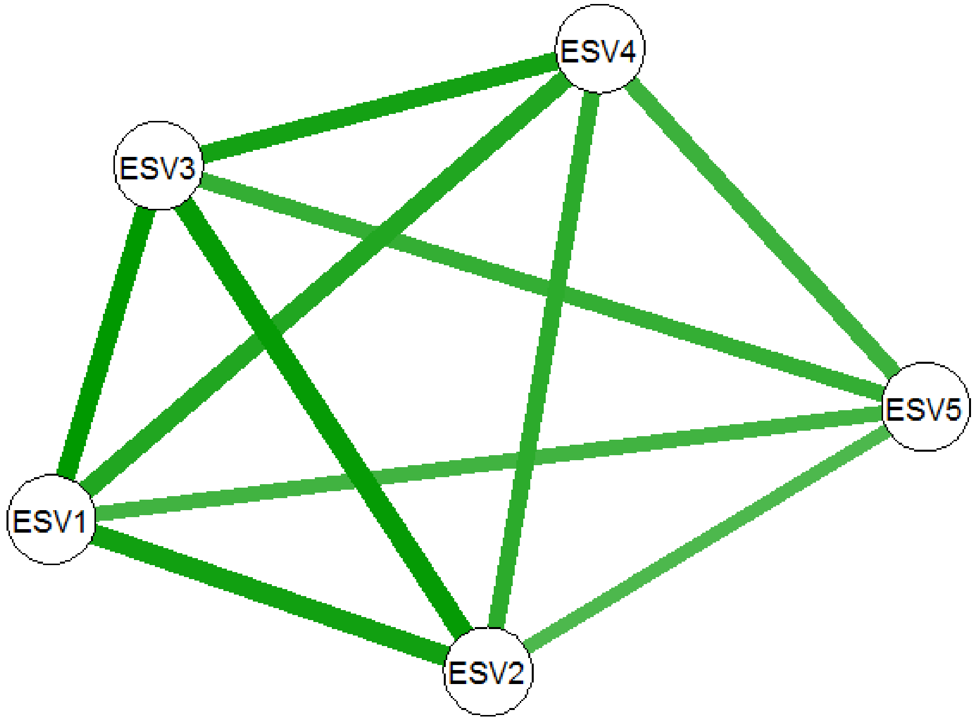


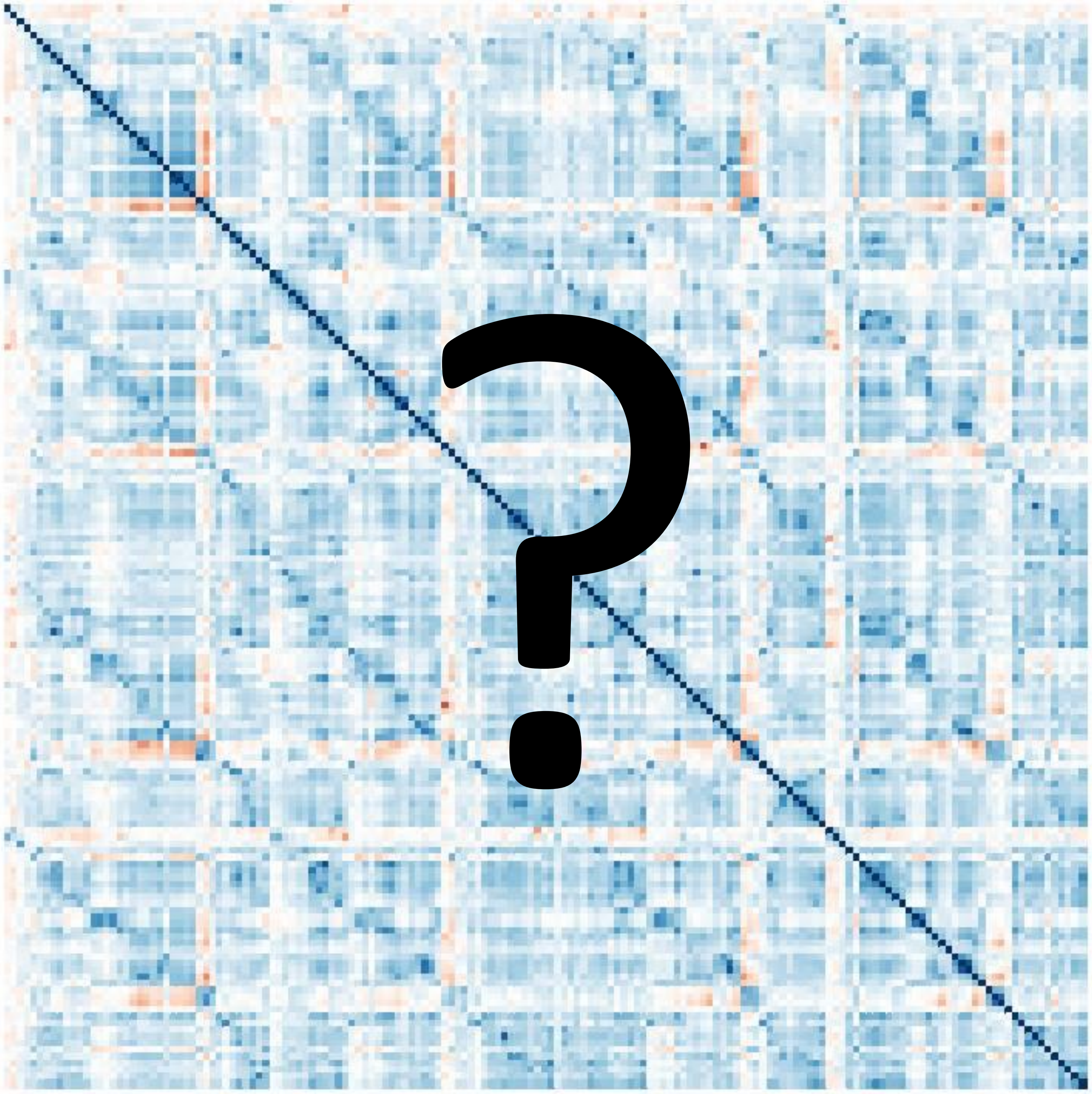
Escala de Satisfação com a Vida (Diener, Emmons, Larsen, & Griffin, 1985)



Escala de Satisfação com a Vida (Diener, Emmons, Larsen, & Griffin, 1985)







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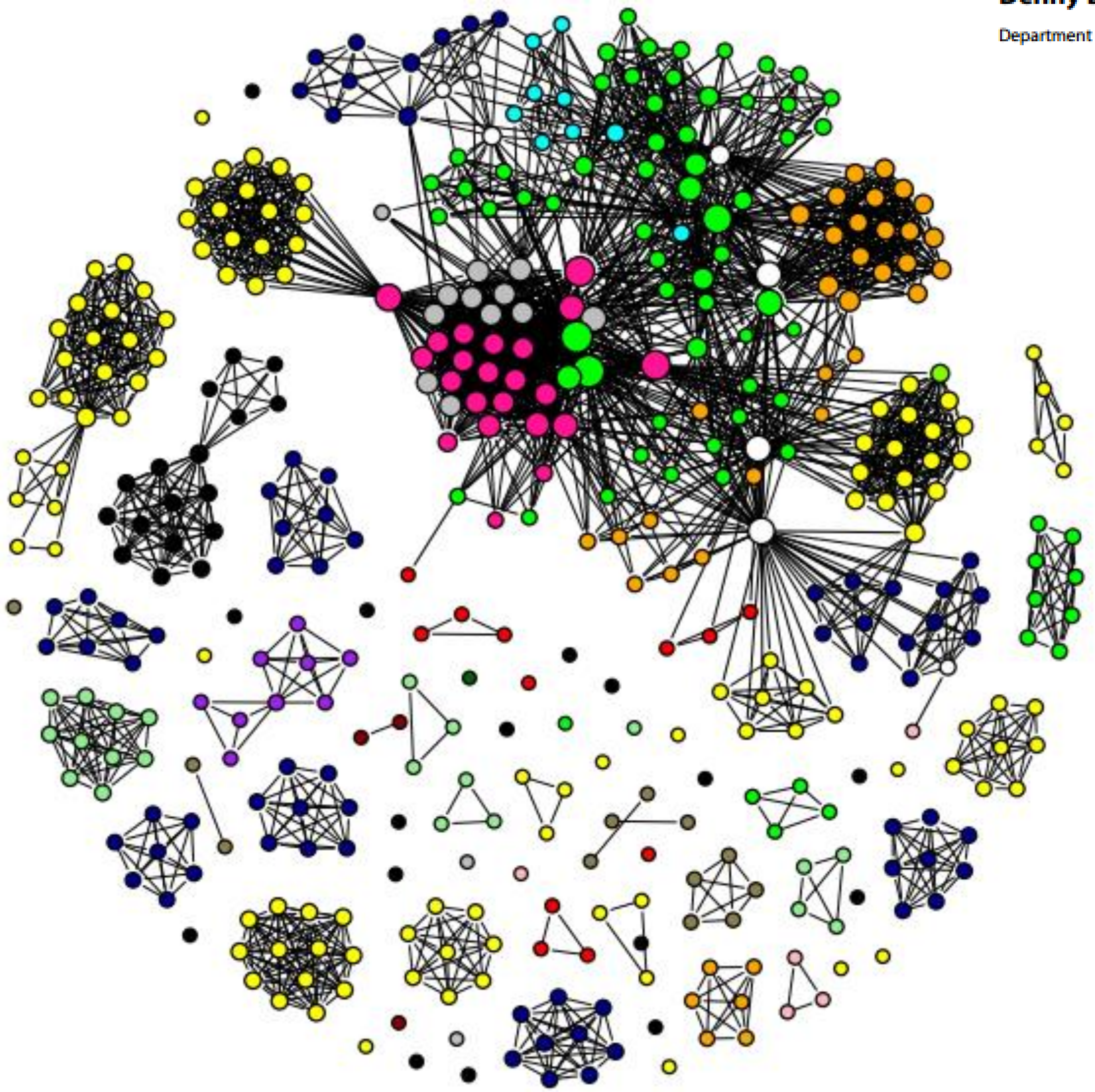
PLoS one

The Small World of Psychopathology

Denny Borsboom*, Angélique O. J. Cramer, Verena D. Schmittmann, Sacha Epskamp, Lourens J. Waldorp

Department of Psychology, University of Amsterdam, Amsterdam, The Netherlands



Chapter of the DSM that feature the symptom the most

- Disorders usually first diagnosed in infancy, childhood or adolescence
- Delirium, dementia, and amnesia and other cognitive disorders
- Mental disorders due to a general medical condition
- Substance−related disorders
- Schizophrenia and other psychotic disorders
- Mood disorders
- Anxiety disorders
- Somatoform disorders
- Facitious disorders
- Dissociative disorders
- Sexual and gender identity disorders
- Eating disorders
- Sleep disorders
- Impulse control disorders not elsewhere classified
- Adjustment disorders
- Personality disorders
- Symptom is featured equally in multiple chapters

Aplicações da análise de rede na Psicologia

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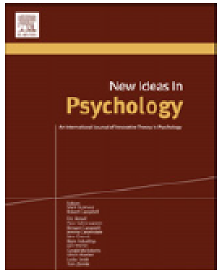
New Ideas in Psychology

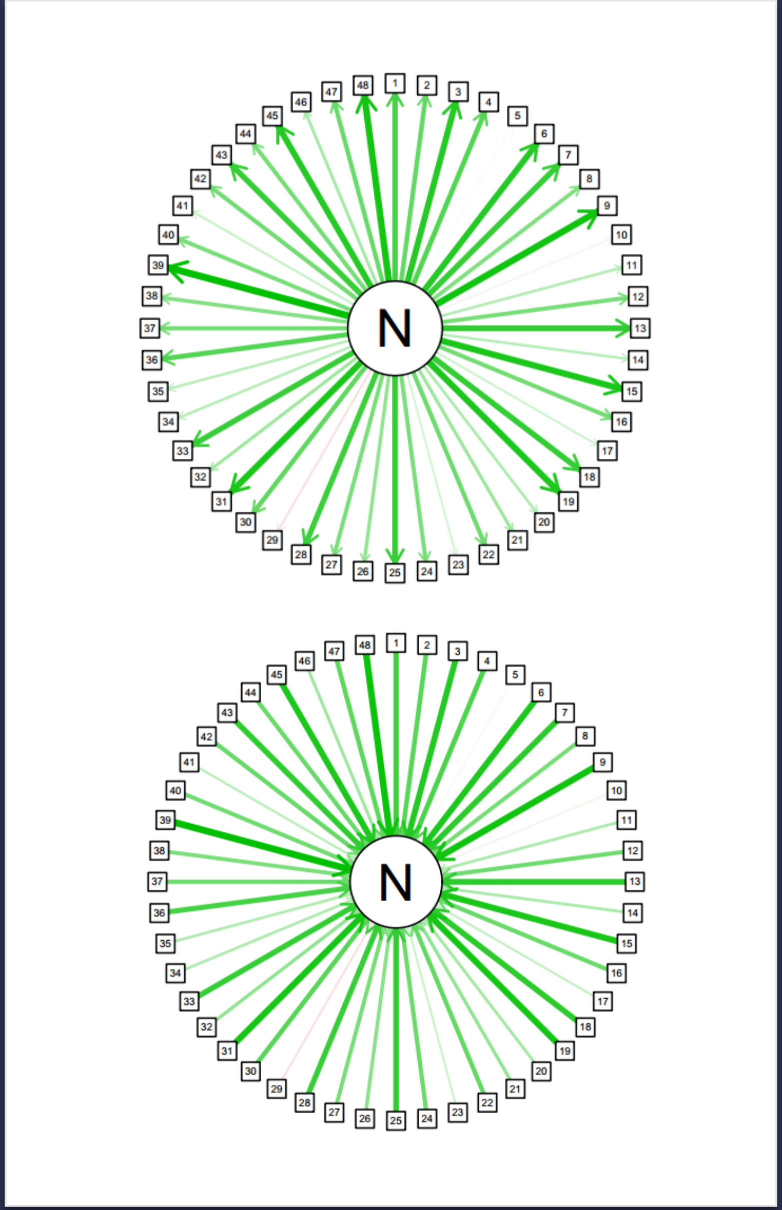
journal homepage: www.elsevier.com/locate/newideapsych



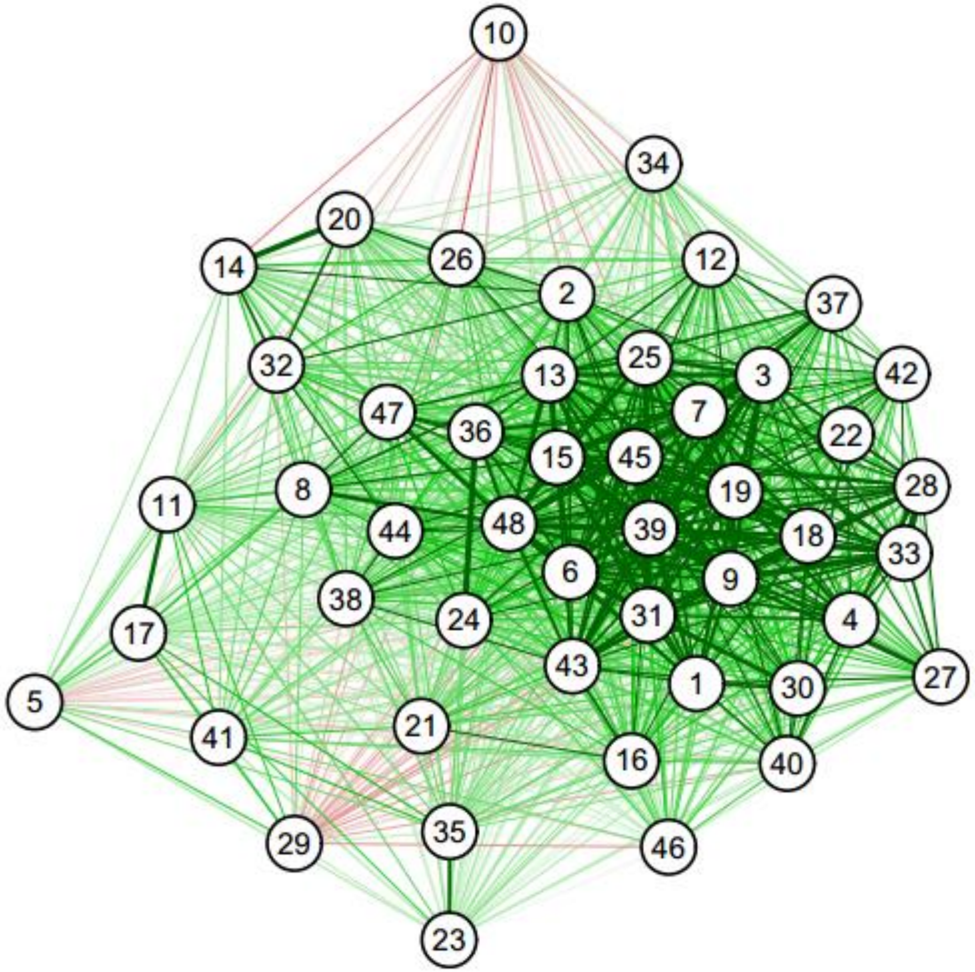
Deconstructing the construct: A network perspective on psychological phenomena

Verena D. Schmittmann, Angélique O.J. Cramer, Lourens J. Waldorp, Sacha Epskamp, Rogier A. Kievit, Denny Borsboom*

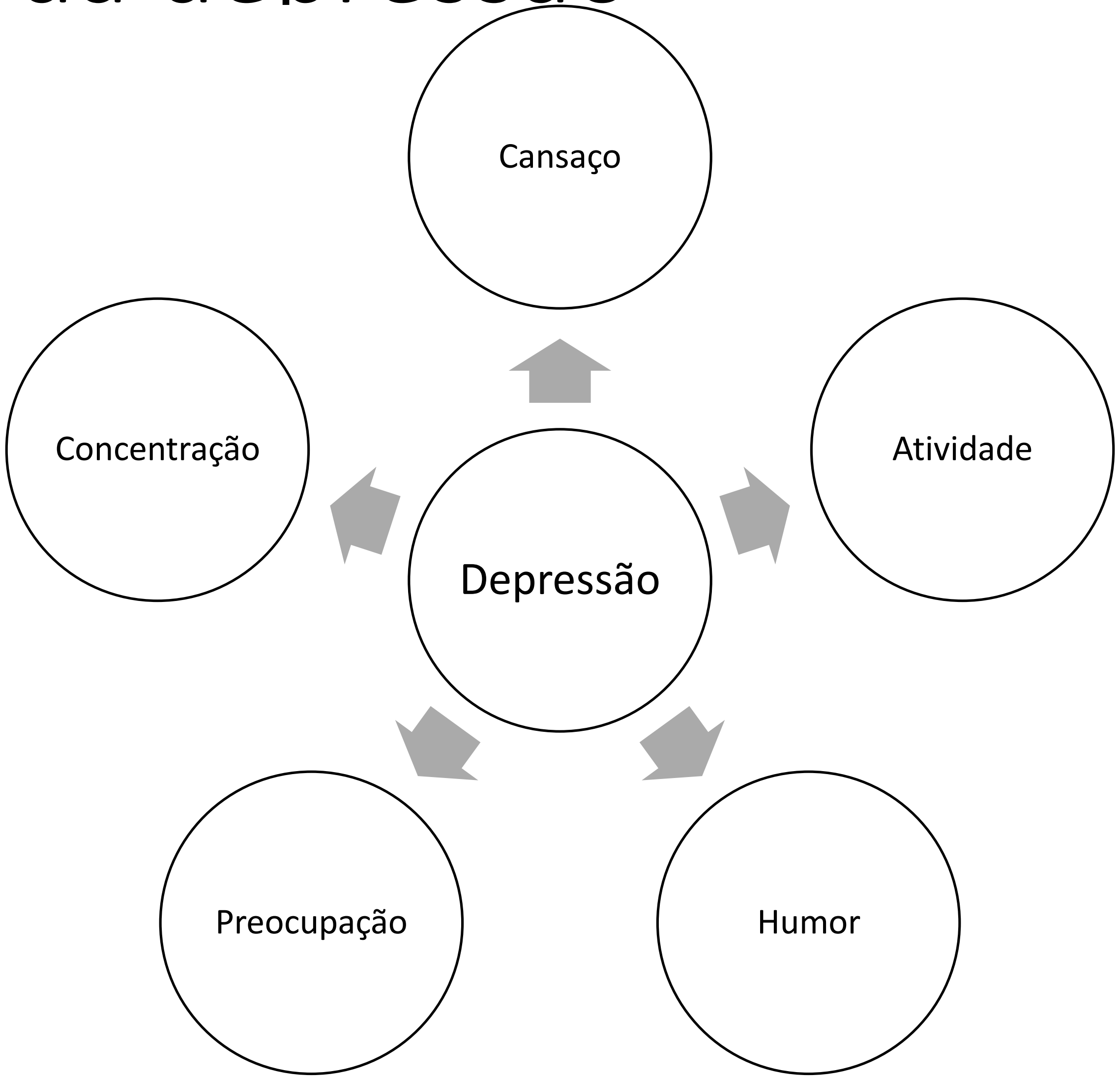
Department of Psychology, University of Amsterdam, Roetersstraat 15, 1018 WB Amsterdam, The Netherlands



Modelos reflexivo, formativo e de rede do traço neuroticismo



Modelo atual da depressão



Modelo alternativo da depressão

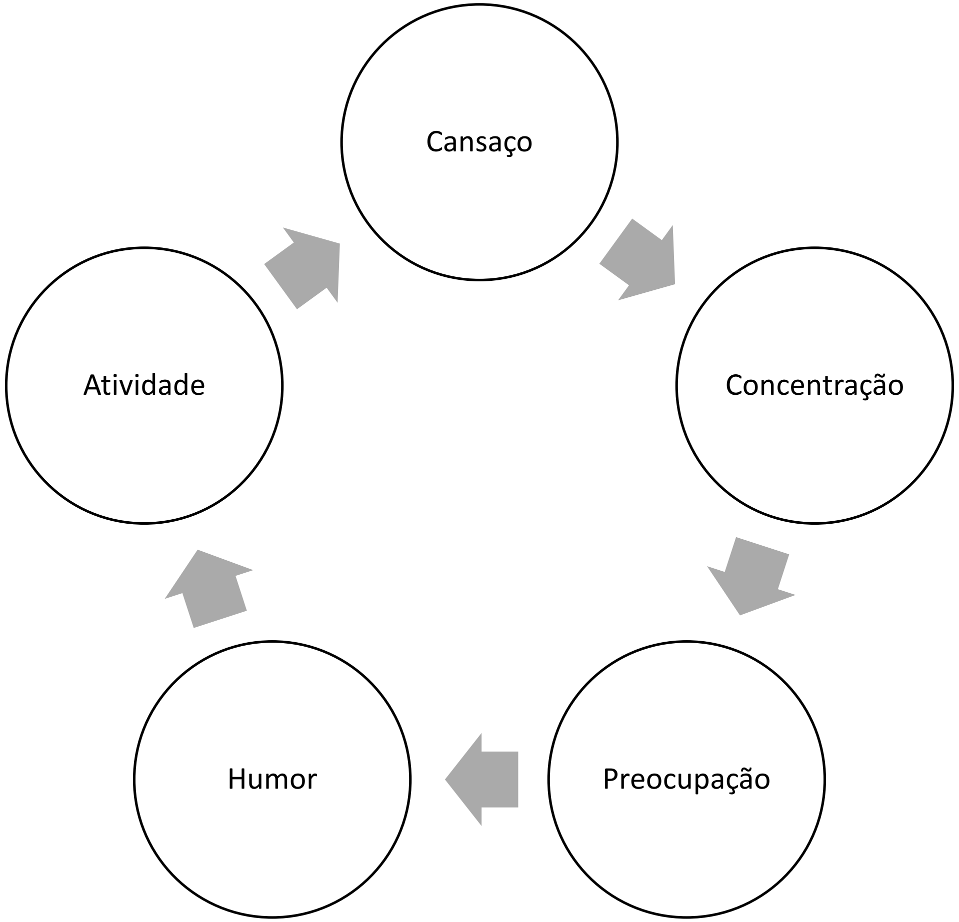


Fig. 6. The best fitting confirmative time series model of the following five constituents of depression: tiredness; concentration difficulties (*concentration*); self-content; sad mood; pleasure in current activity (*activity*).

BEHAVIORAL AND BRAIN SCIENCES (2010) **33**, 137–193
doi:10.1017/S0140525X09991567

Comorbidity: A network perspective

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Han L. J. van der Maas

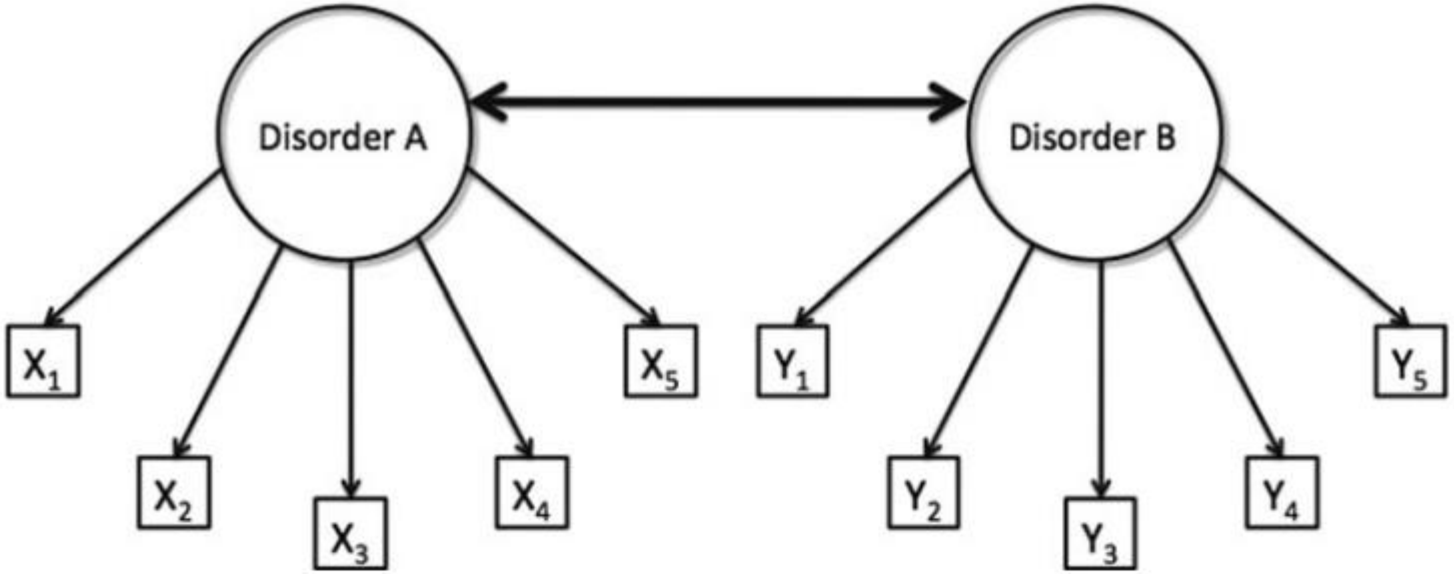

Figure 1. A model of comorbidity between disorders A and B, under the standard assumptions of latent variable modeling. The *circles* represent the disorders (i.e., latent variables) and the *rectangles* represent the observable core symptoms of those disorders (i.e., $X_1 - X_5$ for disorder A, and $Y_1 - Y_5$ for disorder B). In this model, comorbidity is viewed as a correlation between the latent variables, visualized by the *thick bidirectional edge* between disorders A and B.

BEHAVIORAL AND BRAIN SCIENCES (2010) **33**, 137–193
doi:10.1017/S0140525X09991567

Comorbidity: A network perspective

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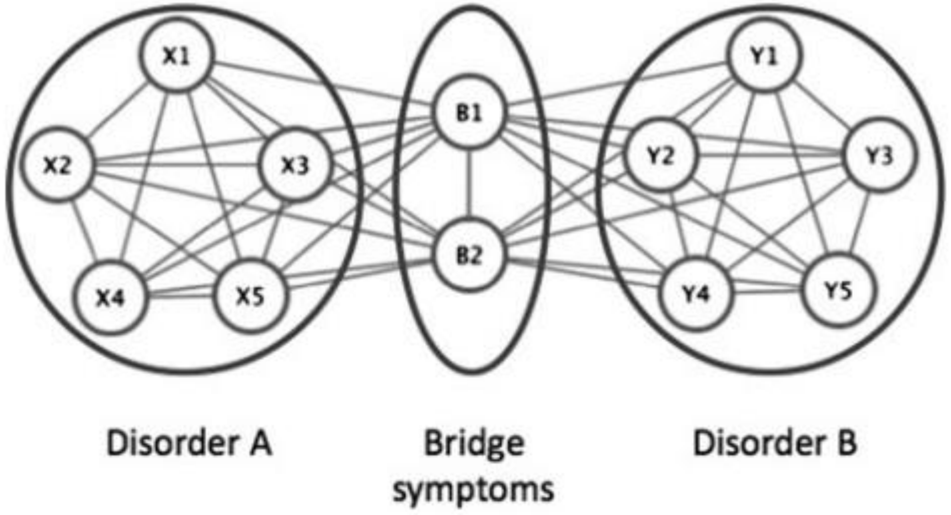

Figure 2. Comorbidity under a network approach. Disorder A consists of bidirectionally related symptoms $X_1 - X_5$, and disorder B consists of symptoms $Y_1 - Y_5$. Symptoms B_1 and B_2 are *bridge symptoms* that overlap between disorders A and B. In this model, comorbidity arises as a result of direct relations between the bridge symptoms of two disorders.

Network Analysis: An Integrative Approach to the Structure of Psychopathology

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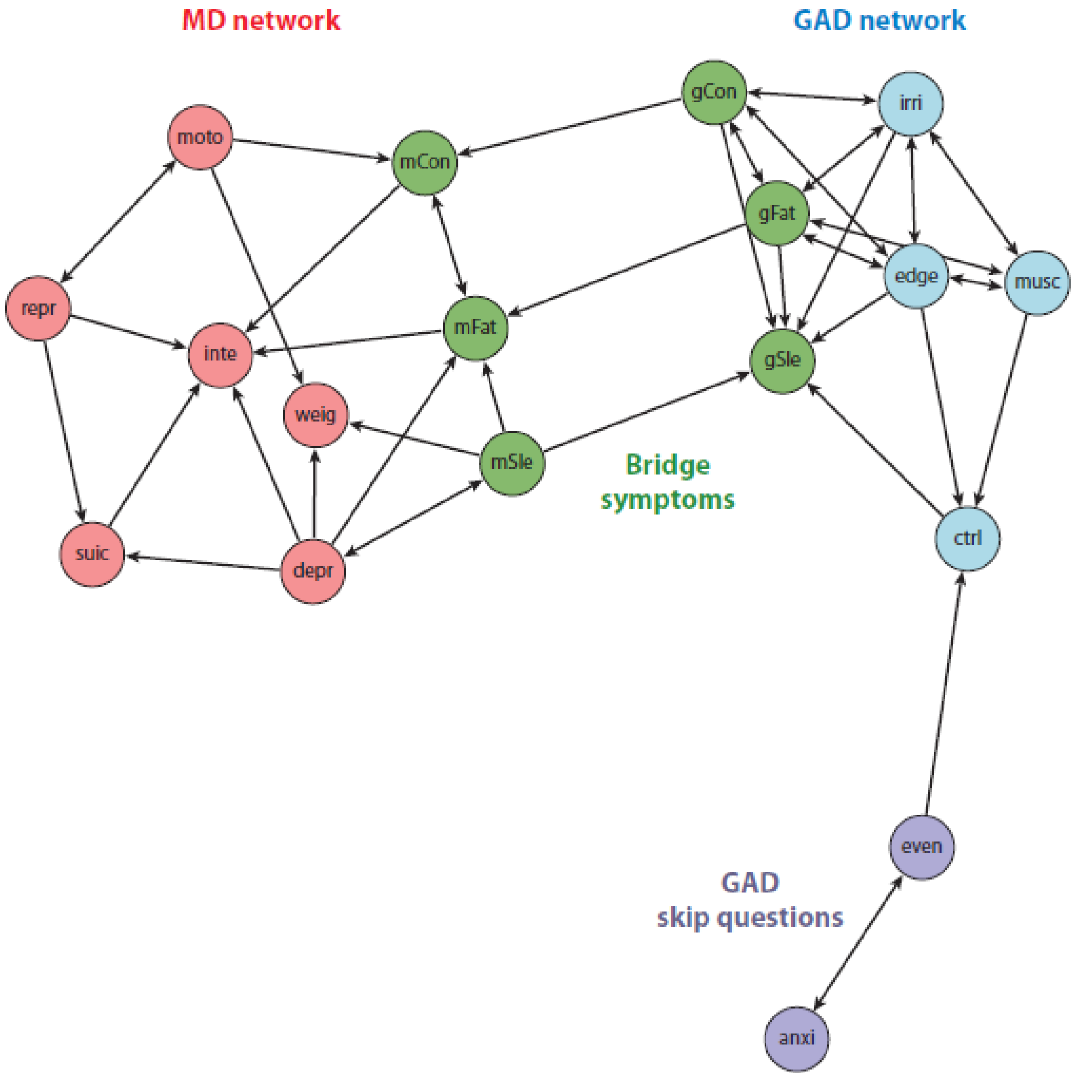

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The Small World of Psychopathology

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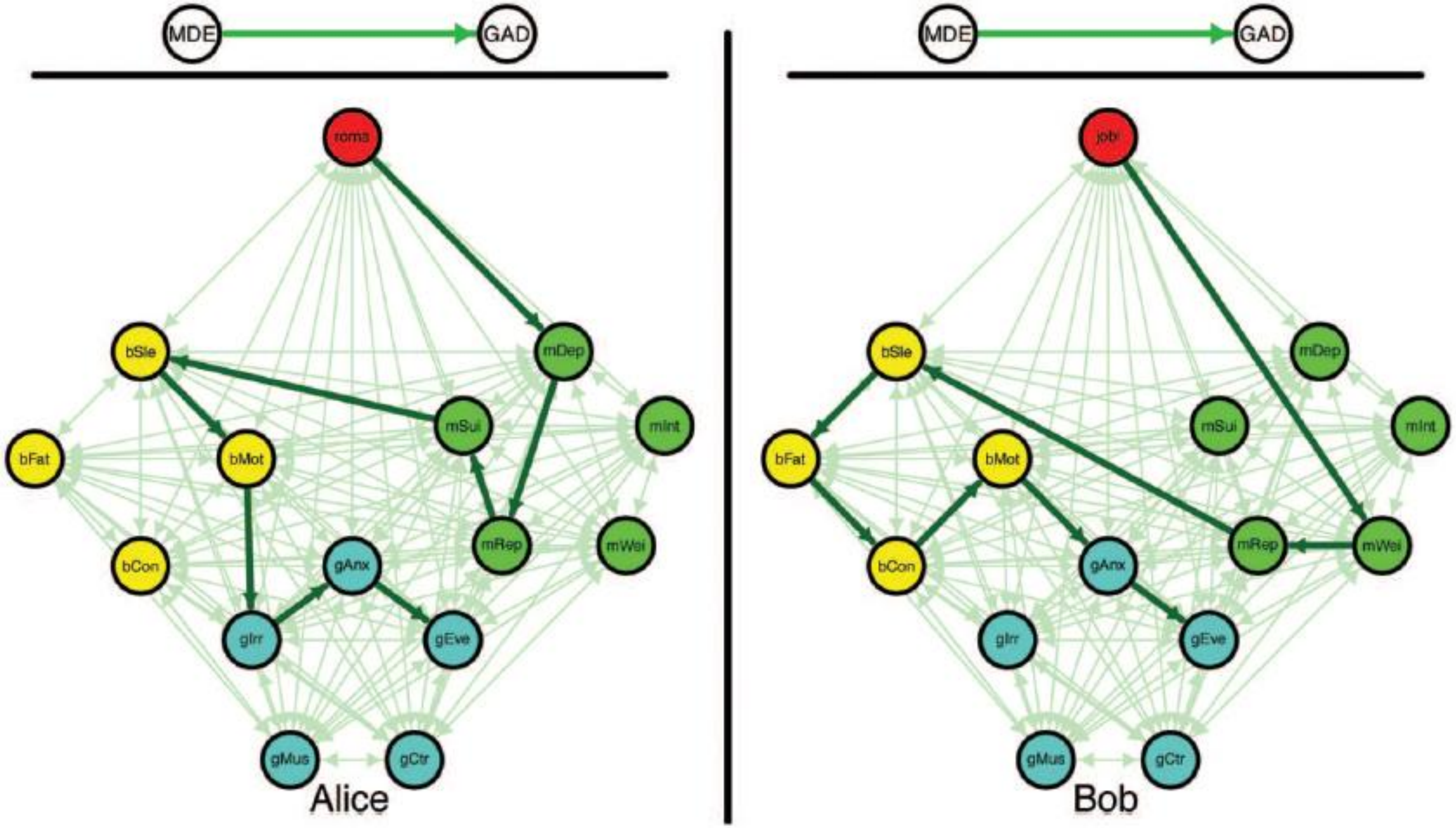

International Journal of Methods in Psychiatric Research
Int. J. Methods Psychiatr. Res. (2016)
Published online in Wiley Online Library
(wileyonlinelibrary.com) **DOI:** 10.1002/mpr.1503

Mapping the manuals of madness: Comparing the ICD-10 and DSM-IV-TR using a network approach

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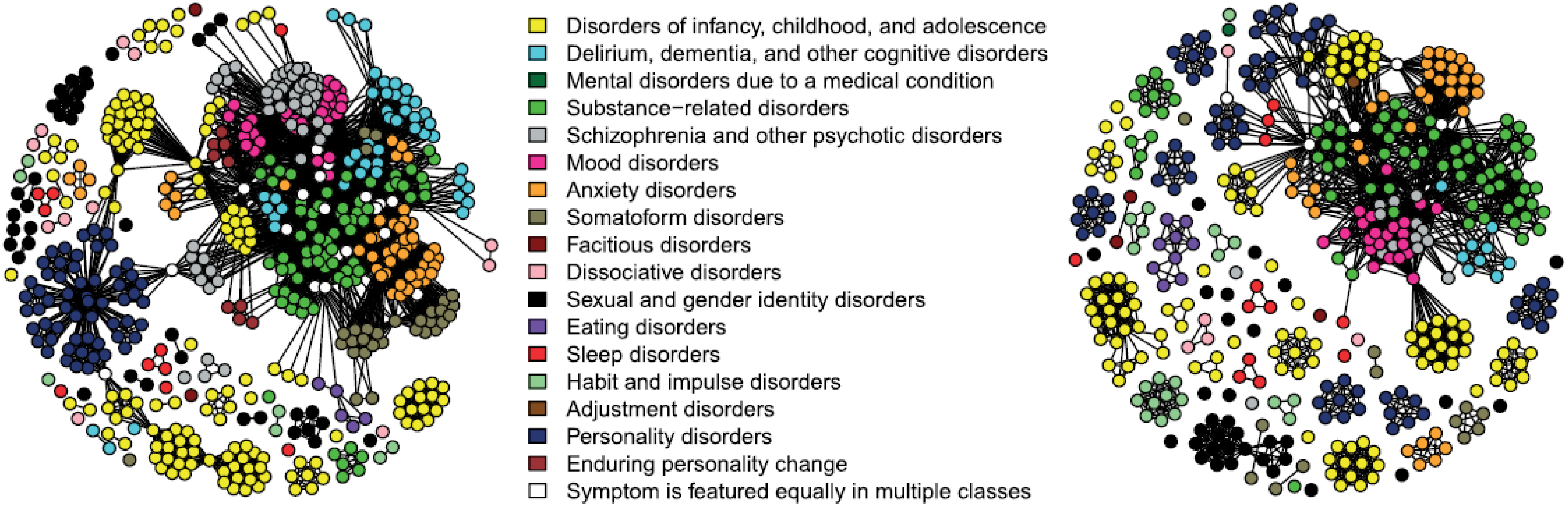

Table 2. Top 10 criteria with the highest degree for ICD-10 and DSM-IV-TR network

	ICD-10	DSM-IV-TR
1	Insomnia[1]	Insomnia[1]
2	Irritability[1]	Psychomotor agitation
3	Apathy	Psychomotor retardation[1]
4	Difficulty in concentrating[1]	Depressed
5	Nausea	Accelerated heart rate
6	Emotional liability	Distractibility
7	Sweating[1]	Irritability[1]
8	Chest pain	Anxiety and Hypersomnia
9	Restless sleep	Sweating[1] and Weight loss
10	Psychomotor retardation[1]	Difficulty in concentrating[1] and Hallucinations/illusions

[1]Criteria that occur in the top 10 of both networks. Places 8 through 10 in the DSM-IV-TR hold multiple symptoms.

Behav Genet (2014) 44:591–604
DOI 10.1007/s10519-013-9625-7

ORIGINAL RESEARCH

The Big Five Personality Traits: Psychological Entities or Statistical Constructs?

Sanja Franić · Denny Borsboom · Conor V. Dolan · Dorret I. Boomsma

European Journal of Personality, Eur. J. Pers. 26: 414–431 (2012)
Published online in Wiley Online Library (wileyonlinelibrary.com) DOI: 10.1002/per.1866

Dimensions of Normal Personality as Networks in Search of Equilibrium: You Can't Like Parties if You Don't Like People

ANGÉLIQUE O. J. CRAMER[1]*, SOPHIE VAN DER SLUIS[1,2], ARJEN NOORDHOF[1], MARIEKE WICHERS[3], NICOLE GESCHWIND[3,4], STEVEN H. AGGEN[5,6], KENNETH S. KENDLER[5,6] and DENNY BORSBOOM[1]

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[3]European Graduate School for Neuroscience, SEARCH, Department of Psychiatry and Psychology, Maastricht University Medical Centre, The Netherlands
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[6]Department of Psychiatry, Virginia Commonwealth University, USA

European Journal of Personality, Eur. J. Pers. 26: 451–459 (2012)
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Author's Response

Measurable Like Temperature or Mereological Like Flocking? On the Nature of Personality Traits

ANGÉLIQUE O. J. CRAMER[1]*, SOPHIE VAN DER SLUIS[1,2], ARJEN NOORDHOF[1], MARIEKE WICHERS[3], NICOLE GESCHWIND[3,4], STEVEN H. AGGEN[5,6], KENNETH S. KENDLER[5,6] and DENNY BORSBOOM[1]

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[3]European Graduate School for Neuroscience, SEARCH, Department of Psychiatry and Psychology, Maastricht University Medical Centre, The Netherlands
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Journal of Research in Personality
journal homepage: www.elsevier.com/locate/jrp
JOURNAL OF RESEARCH IN PERSONALITY

State of the aRt personality research: A tutorial on network analysis of personality data in R

Giulio Costantini[a,*,1], Sacha Epskamp[b,1], Denny Borsboom[b], Marco Perugini[a], René Mõttus[c,d], Lourens J. Waldorp[b], Angélique O.J. Cramer[b]

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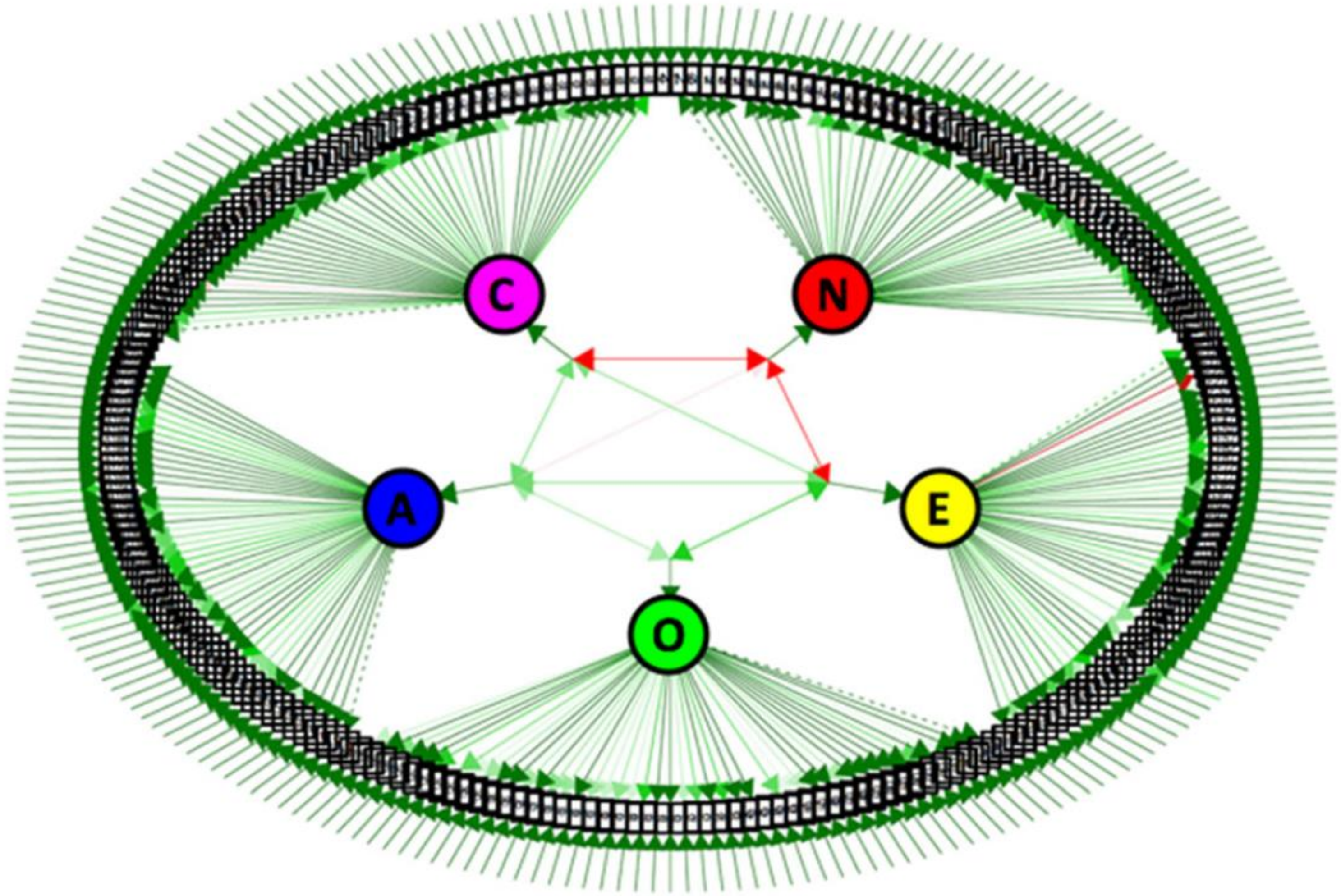
C
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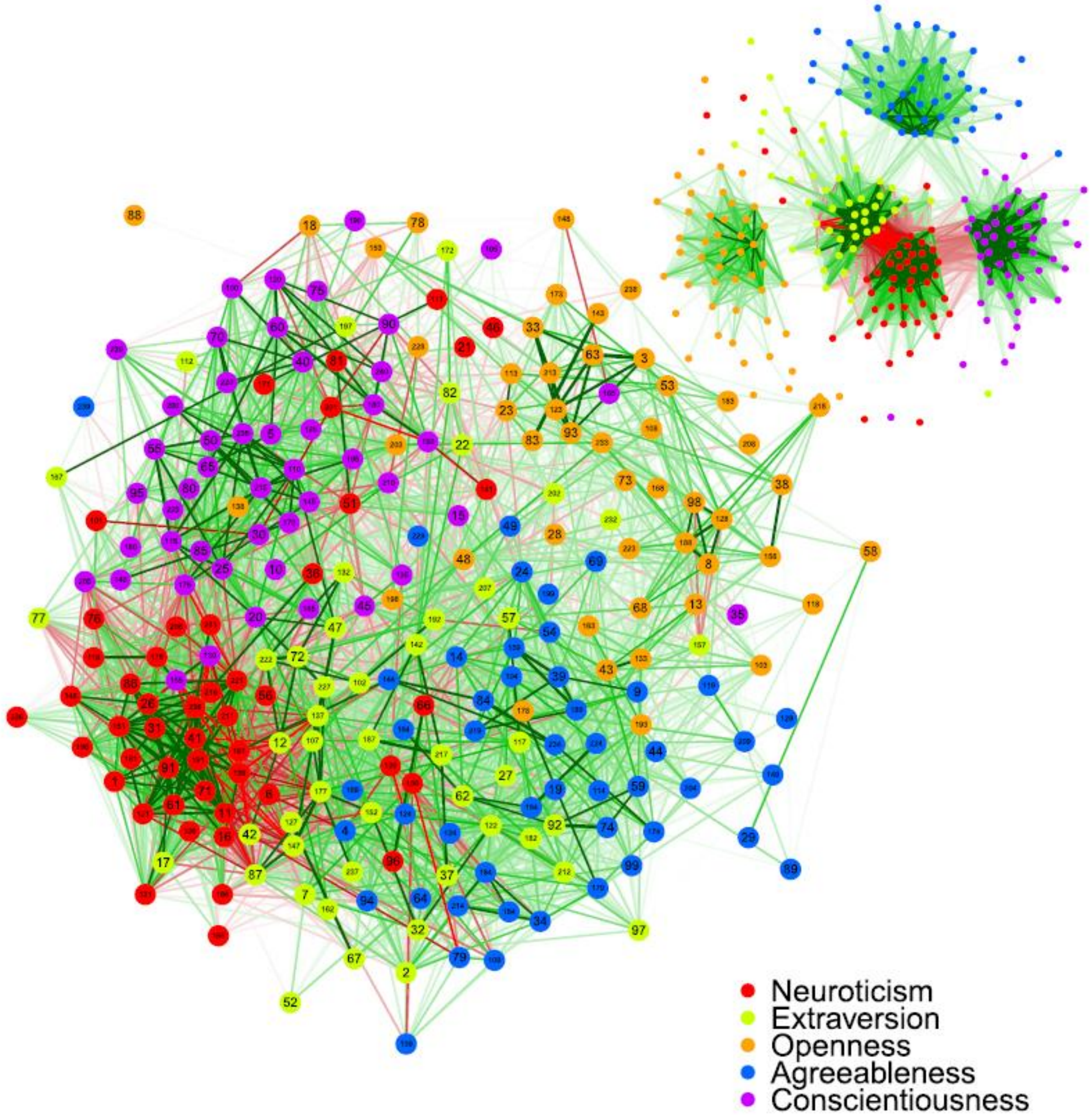
O


Neuroticism
Extraversion
Openness
Agreeableness
Conscientiousness

Psychological Review
2006, Vol. 113, No. 4, 842–861

0033-295X/06/$12.00 DOI: 10.1037/0033-295X.113.4.842

A Dynamical Model of General Intelligence: The Positive Manifold of Intelligence by Mutualism

Han L. J. van der Maas, Conor V. Dolan, Raoul P. P. P. Grasman, Jelte M. Wicherts,
Hilde M. Huizenga, and Maartje E. J. Raijmakers
University of Amsterdam

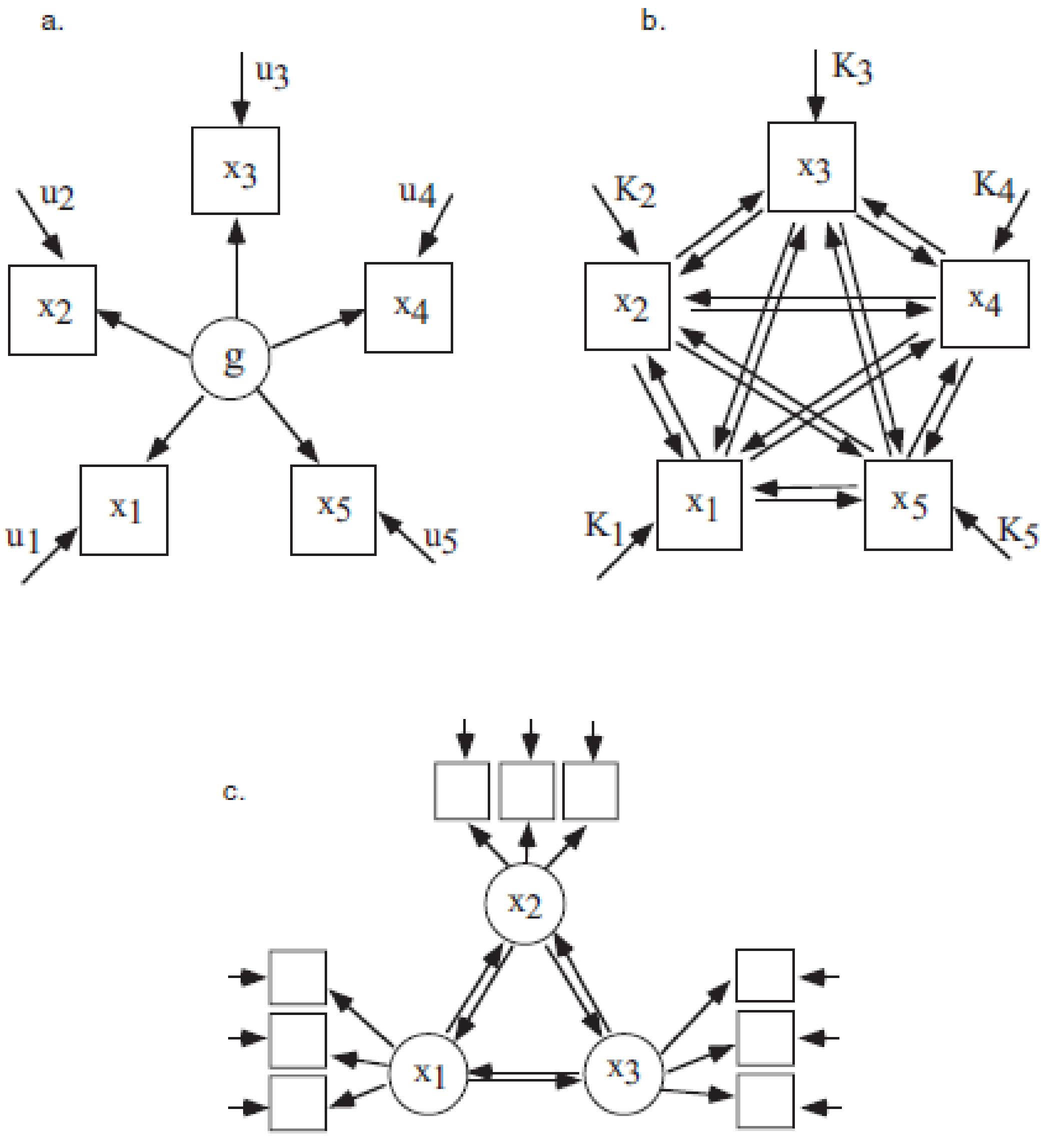


Figure 1. Three models of the positive manifold: (a) the standard g model, (b) the mutualism model, and (c) the extended mutualism model. Squares and circles denote manifest and latent variables, respectively. Symbols *x* denote processes, *u* unique variances, and *K* resources (see text).

Measurement, 6: 25–53, 2008

ISSN 1536-6367 print / 1536-6359 online
DOI: 10.1080/15366360802035497

Psychology Press
Taylor & Francis Group

Latent Variable Theory

Denny Borsboom
University of Amsterdam

Psychological Review
2004, Vol. 111, No. 4, 1061–1071

0033-295X/04/$12.00 DOI: 10.1037/0033-295X.111.4.1061

The Concept of Validity

Denny Borsboom and Gideon J. Mellenbergh
University of Amsterdam

Jaap van Heerden
Maastricht University

Psychological Review
2003, Vol. 110, No. 2, 203–219

0033-295X/03/$12.00 DOI: 10.1037/0033-295X.110.2.203

The Theoretical Status of Latent Variables

Denny Borsboom, Gideon J. Mellenbergh, and Jaap van Heerden
University of Amsterdam

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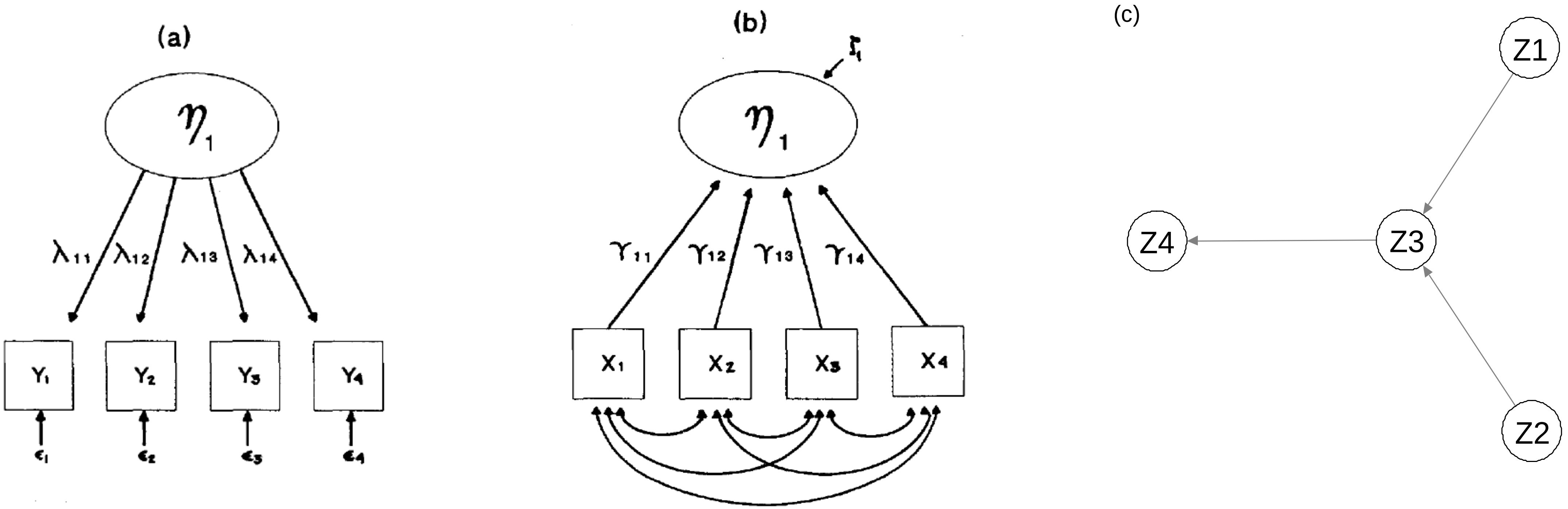
New Ideas in Psychology

journal homepage: www.elsevier.com/locate/newideapsych

Deconstructing the construct: A network perspective on psychological phenomena

Verena D. Schmittmann, Angélique O.J. Cramer, Lourens J. Waldorp, Sacha Epskamp, Rogier A. Kievit, Denny Borsboom*

Department of Psychology, University of Amsterdam, Roetersstraat 15, 1018 WB Amsterdam, The Netherlands


(a)
η1
λ11
λ12
λ13
λ14
Y1
Y2
Y3
Y4
ε1
ε2
ε3
ε4
(b)
ζ1
η1
γ11
γ12
γ13
γ14
X1
X2
X3
X4
(c)
Z1
Z3
Z4
Z2

Psychological Medicine, Page 1 of 11.
doi:10.1017/S0033291714001809

ORIGINAL ARTICLE

Revealing the dynamic network structure of the Beck Depression Inventory-II

L. F. Bringmann[1]*, L. H. J. M. Lemmens[2], M. J. H. Huibers[2,3], D. Borsboom[4] and F. Tuerlinckx[1]

[1] *Faculty of Psychology and Educational Sciences, University of Leuven, Leuven, Belgium*
[2] *Department of Clinical Psychological Science, Maastricht University, Maastricht, The Netherlands*
[3] *Department of Clinical Psychology, VU University of Amsterdam, Amsterdam, The Netherlands*
[4] *Department of Psychology, University of Amsterdam, Amsterdam, The Netherlands*

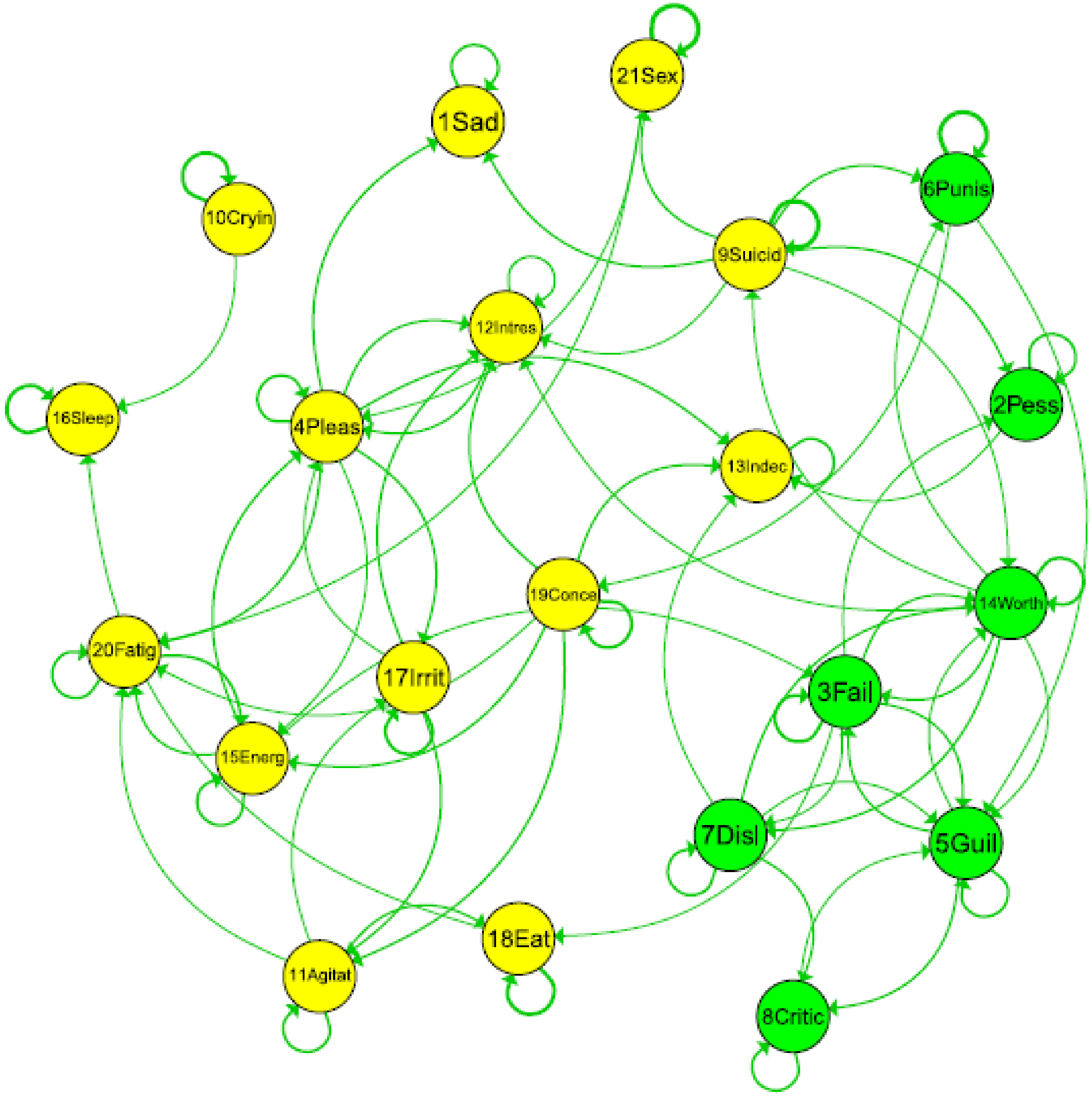


Fig. 3. Community structure of the BDI-II network with the two clusters indicated by two different colours.

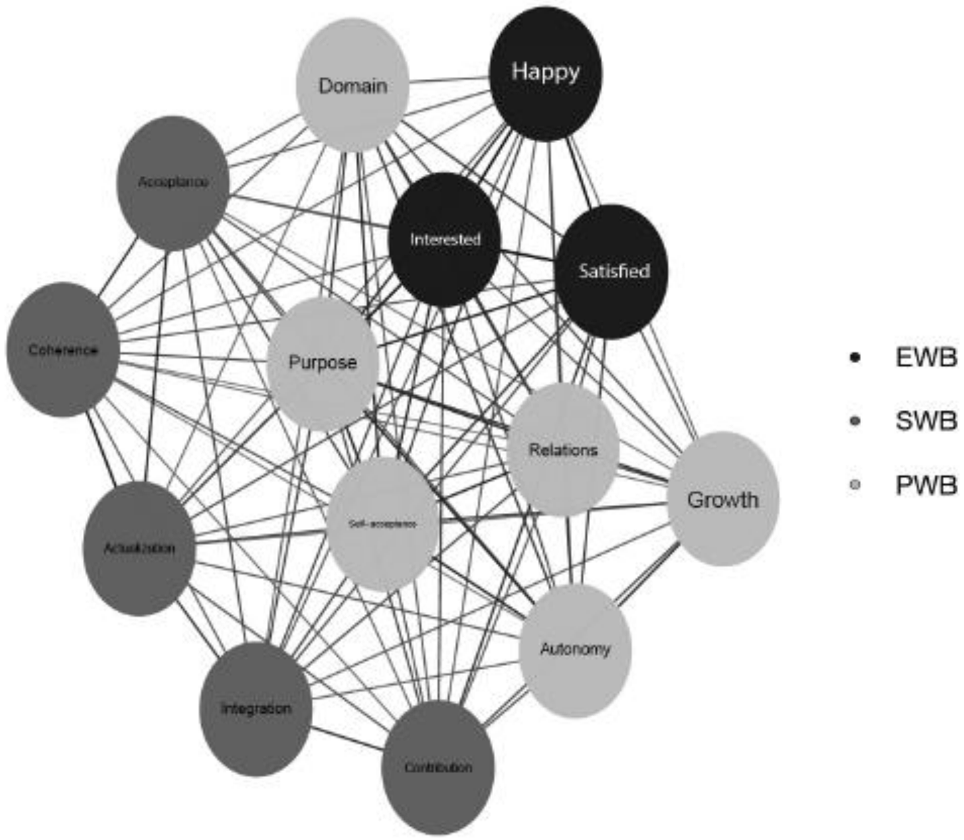


Table 4
Centrality Indexes and Thresholds of the Network Elements

Item (summarized content)	Centrality eigenvector*	τ
1 – Happy	.90	-.77
2 – Interested	.96	-1.12
3 – Satisfied	.97	-.57
4 – Contribute to society	.84	-.24
5 – Belong to community	.85	-.26
6 – Society is becoming a better place	.85	.31
7 – People are good	.83	-.08
8 – Way society works makes sense	.79	.53
9 – Likes own personality	.97	-.54
10 – Manages responsibility well	.87	-.59
11 – Relationships with others	.90	-.81
12 – Grow and become a better person	.82	-.74
13 – Confident to express own ideas	.89	-.67
14 – Life has direction or meaning	1.00	-.80

Note. *The unit represents the central node and follows a decreasing order until the most peripheral node.

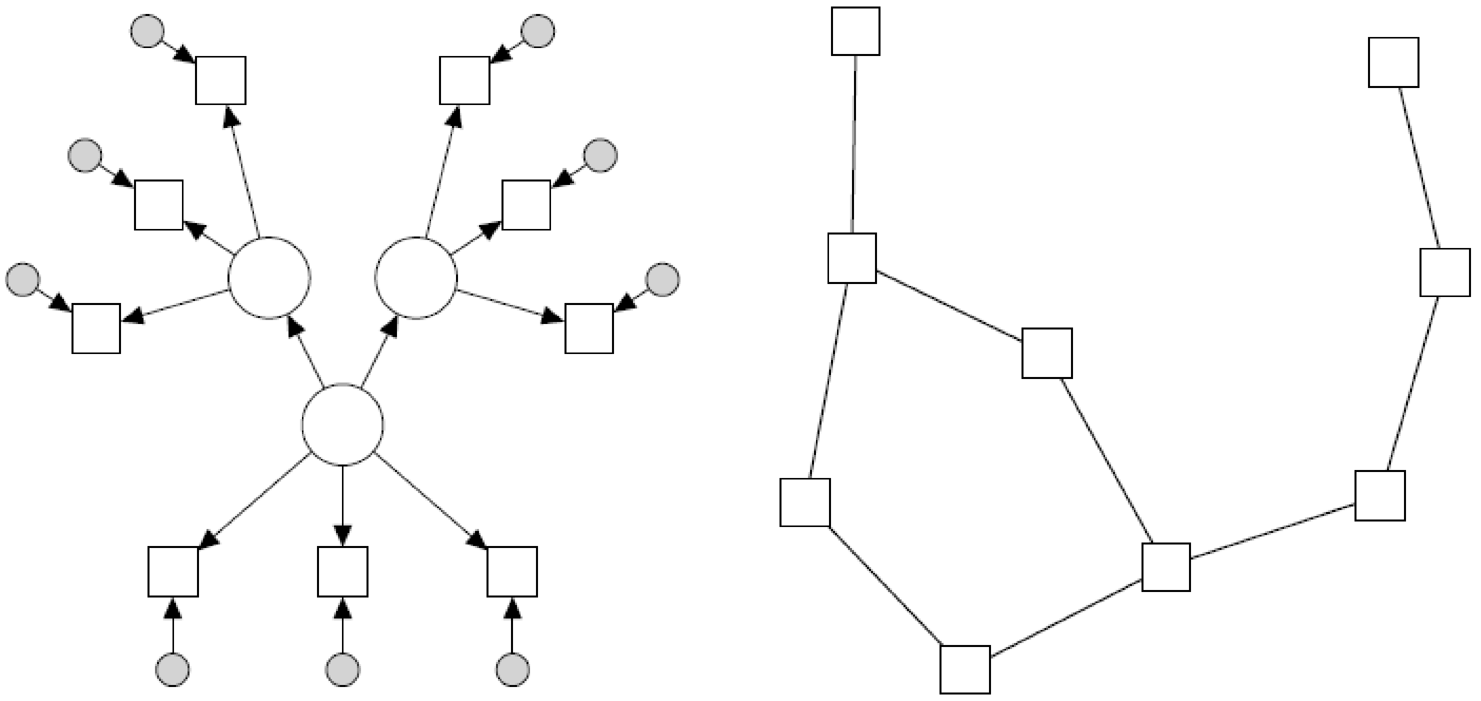
[ealth Scale: Validation of the *Mental Health Continuum – Short Form*

Machado – Pontifícia Universidade Católica de Campinas, Campinas, São Paulo, Brasil
chel Bandeira – Universidade Federal do Rio Grande do Sul, Porto Alegre, Brasil

GENERALIZED NETWORK PSYCHOMETRICS: COMBINING NETWORK AND LATENT VARIABLE MODELS

SACHA EPSKAMP, MIJKE RHEMTULLA & DENNY BORSBOOM

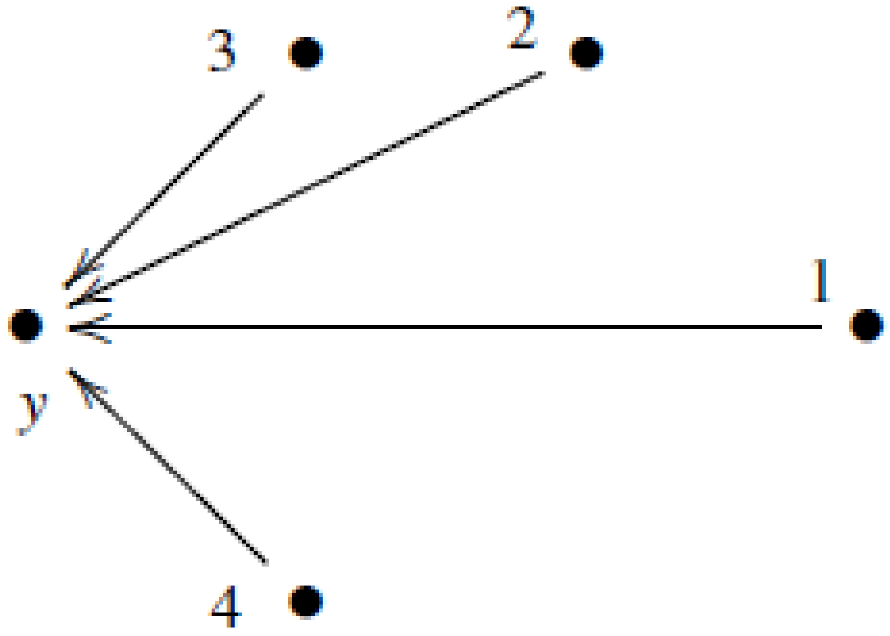
UNIVERSITY OF AMSTERDAM



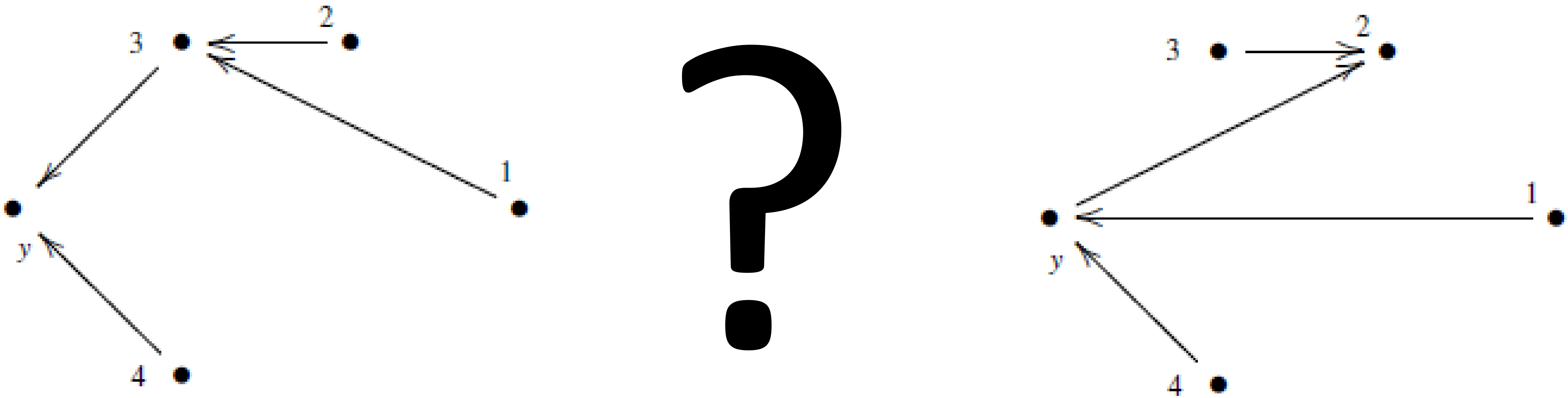
(a) Structural Equation Modeling (b) Network Modeling

Modelos preditivos

- Modelo de regressão comum



(Epskamp, 2013)


3
2
1
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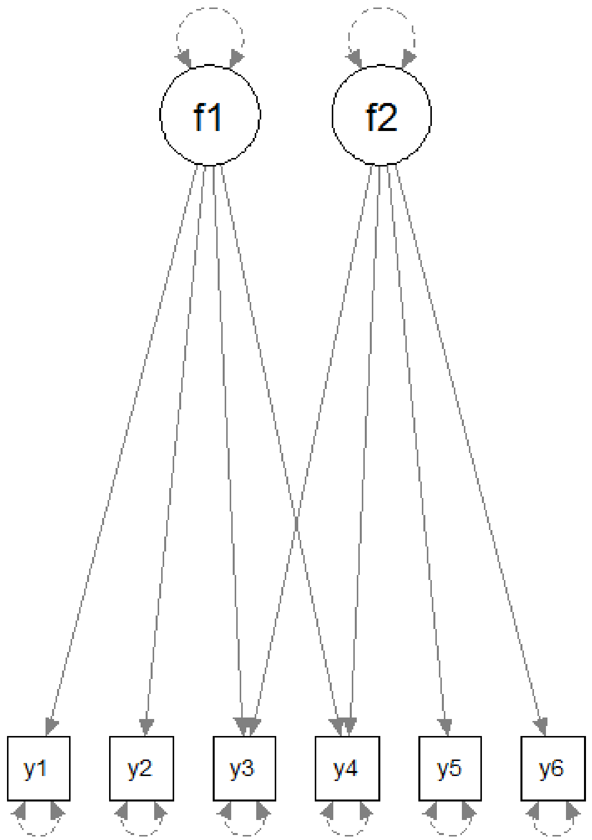
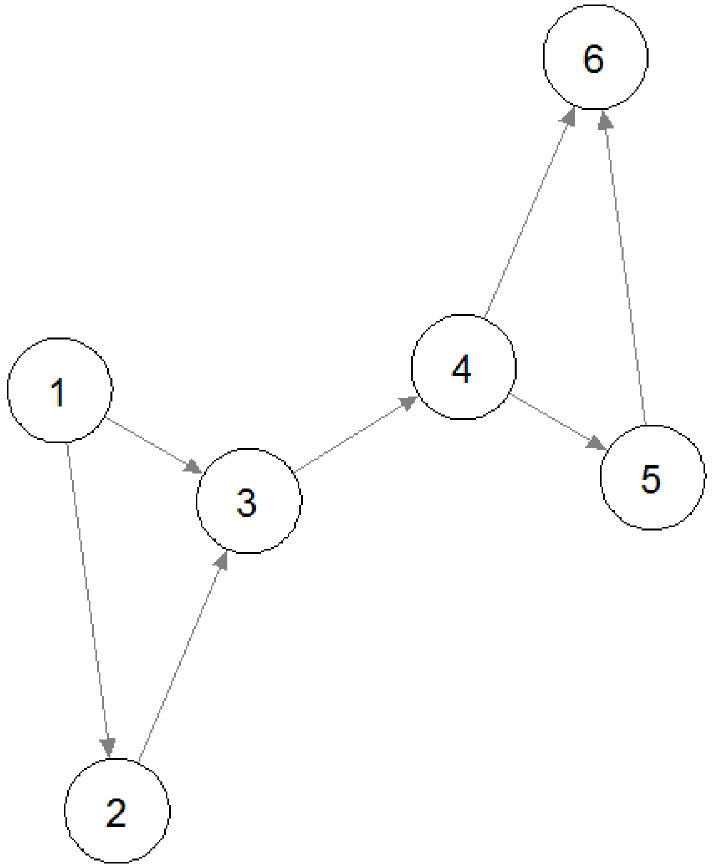
3
2
1
y
4

Representação de dados psicométricos em rede





Exemplos com dados de personalidade

Journal of Statistical Software

May 2012, Volume 48, Issue 4. http://www.jstatsoft.org/

qgraph: Network Visualizations of Relationships in Psychometric Data

Sacha Epskamp
University of Amsterdam

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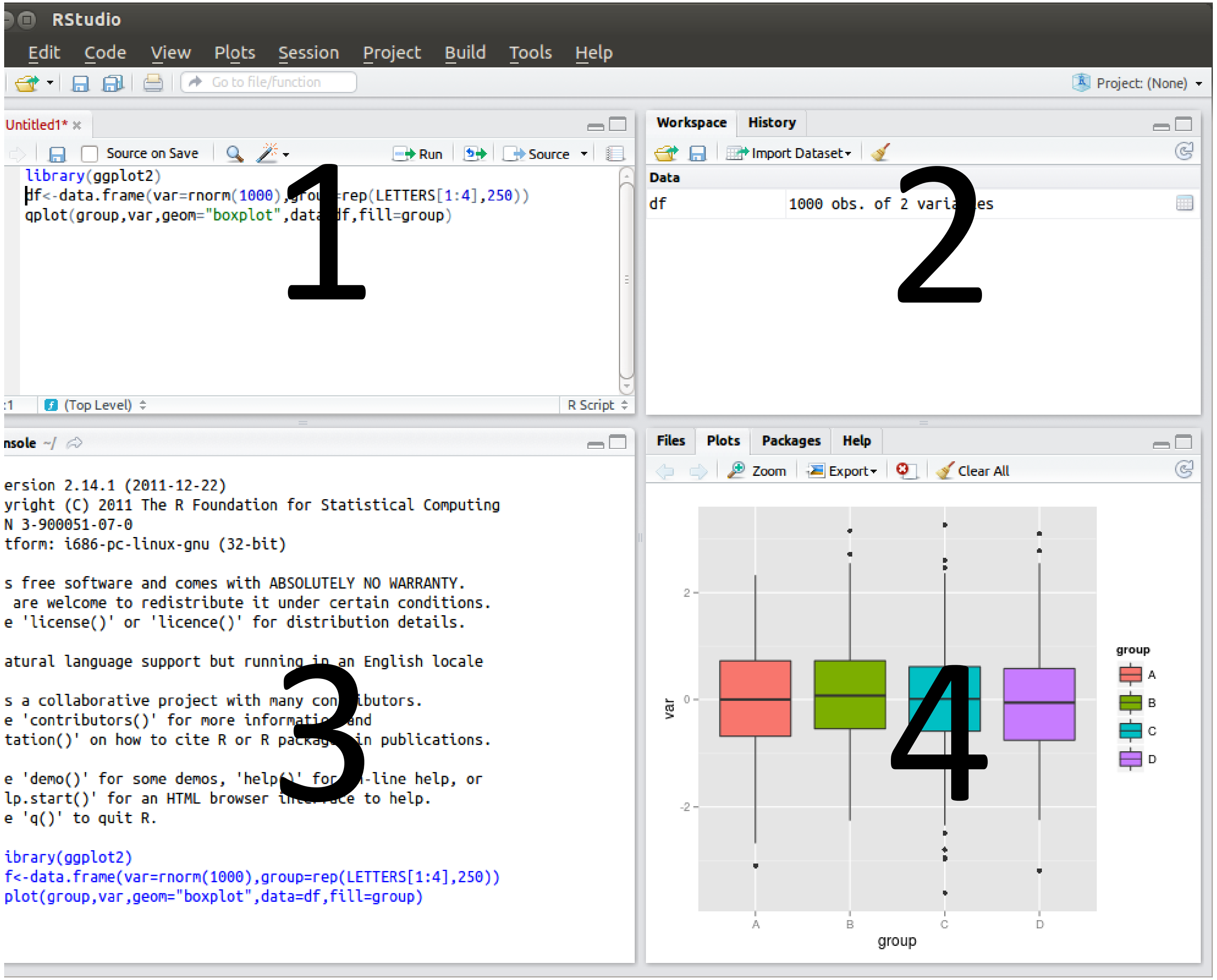
University of Amsterdam

Lourens J. Waldorp
University of Amsterdam

Verena D. Schmittmann
University of Amsterdam

Denny Borsboom
University of Amsterdam

RStudio



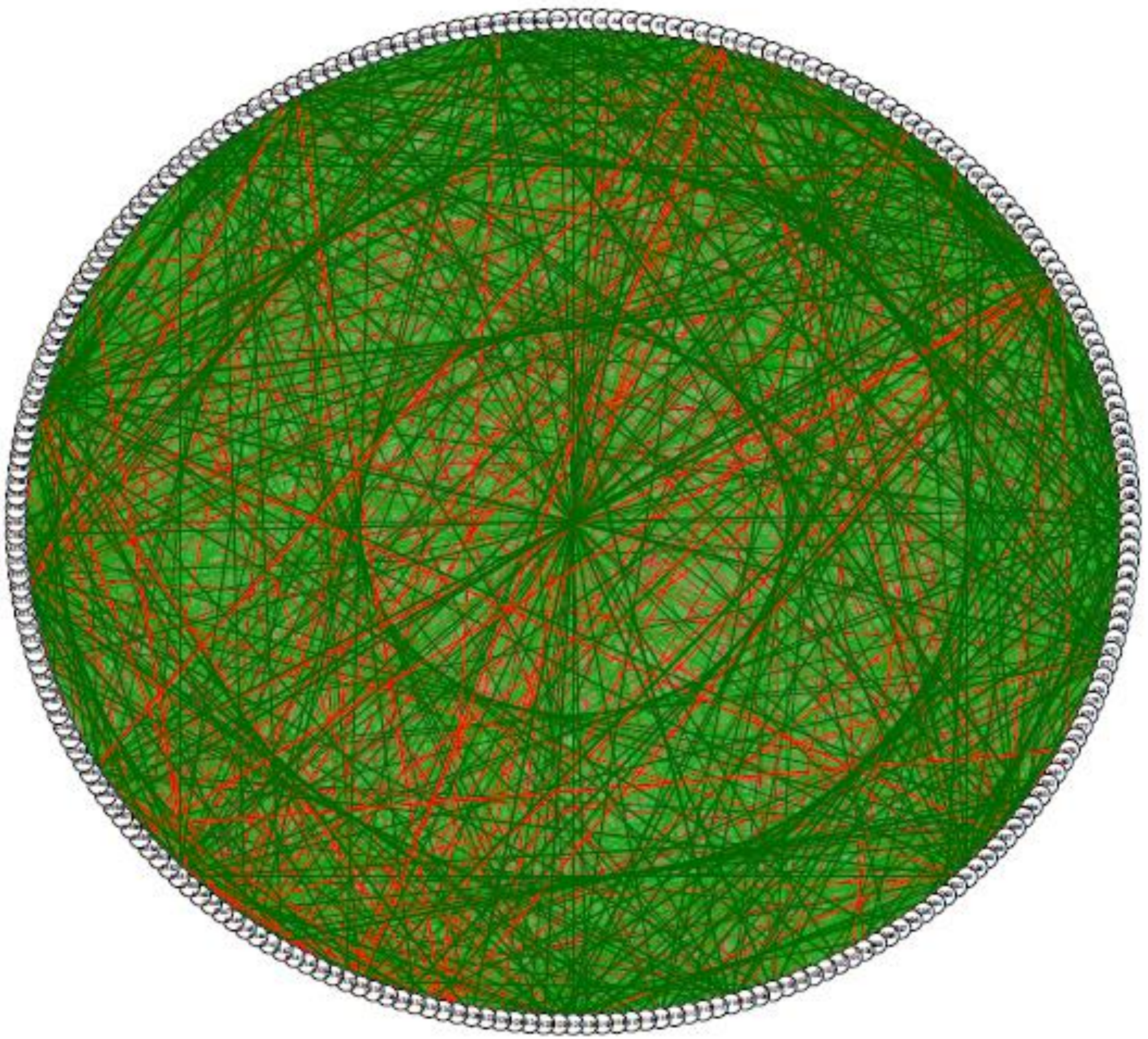
1 – script ou comandos; visualização de bancos de dados ou texto

2 – repositório de objetos e funções

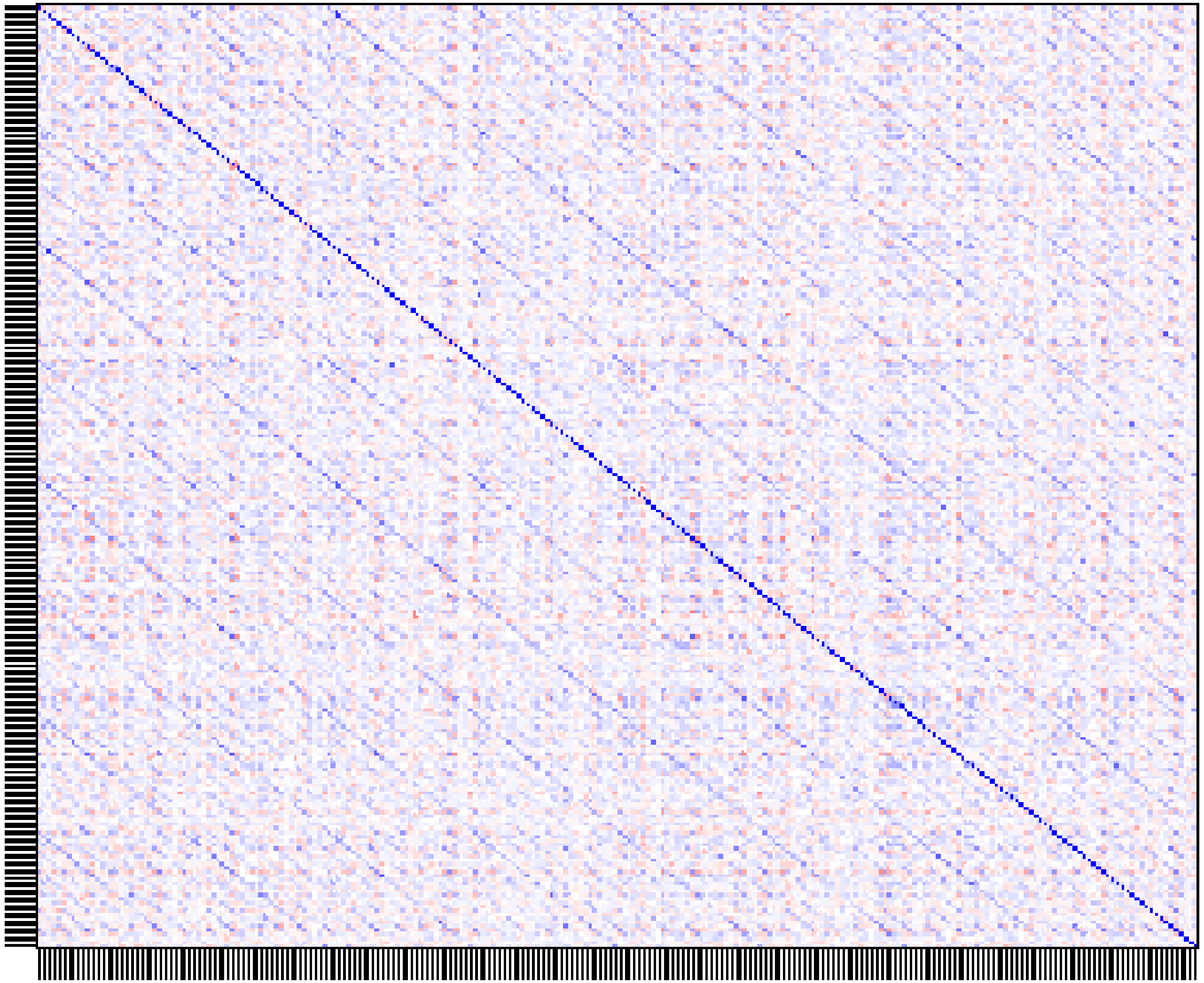
3 – log de atividade

4 – gráficos e documentação

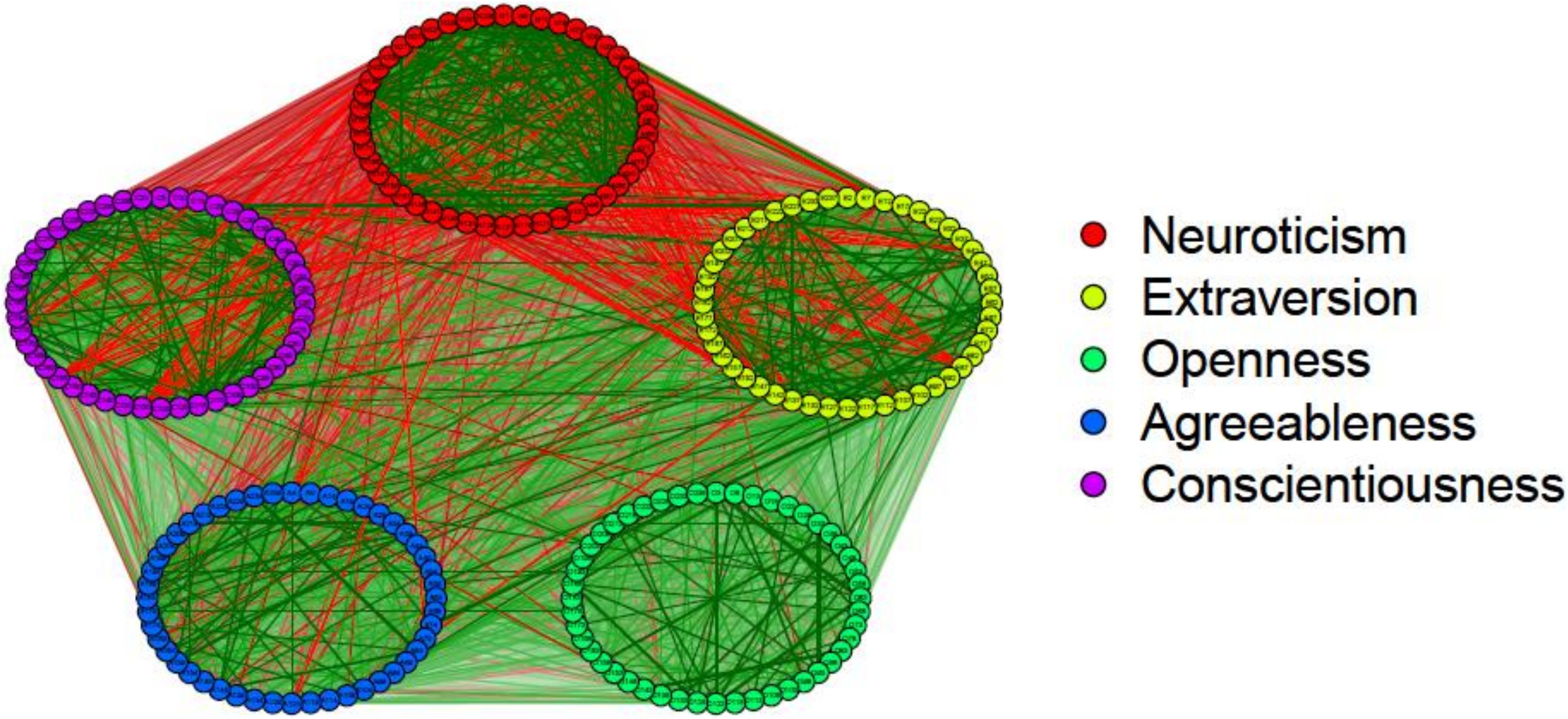
```
#preparação
data("big5")
View(big5)
qgraph(cor(big5))
data("big5groups")
```



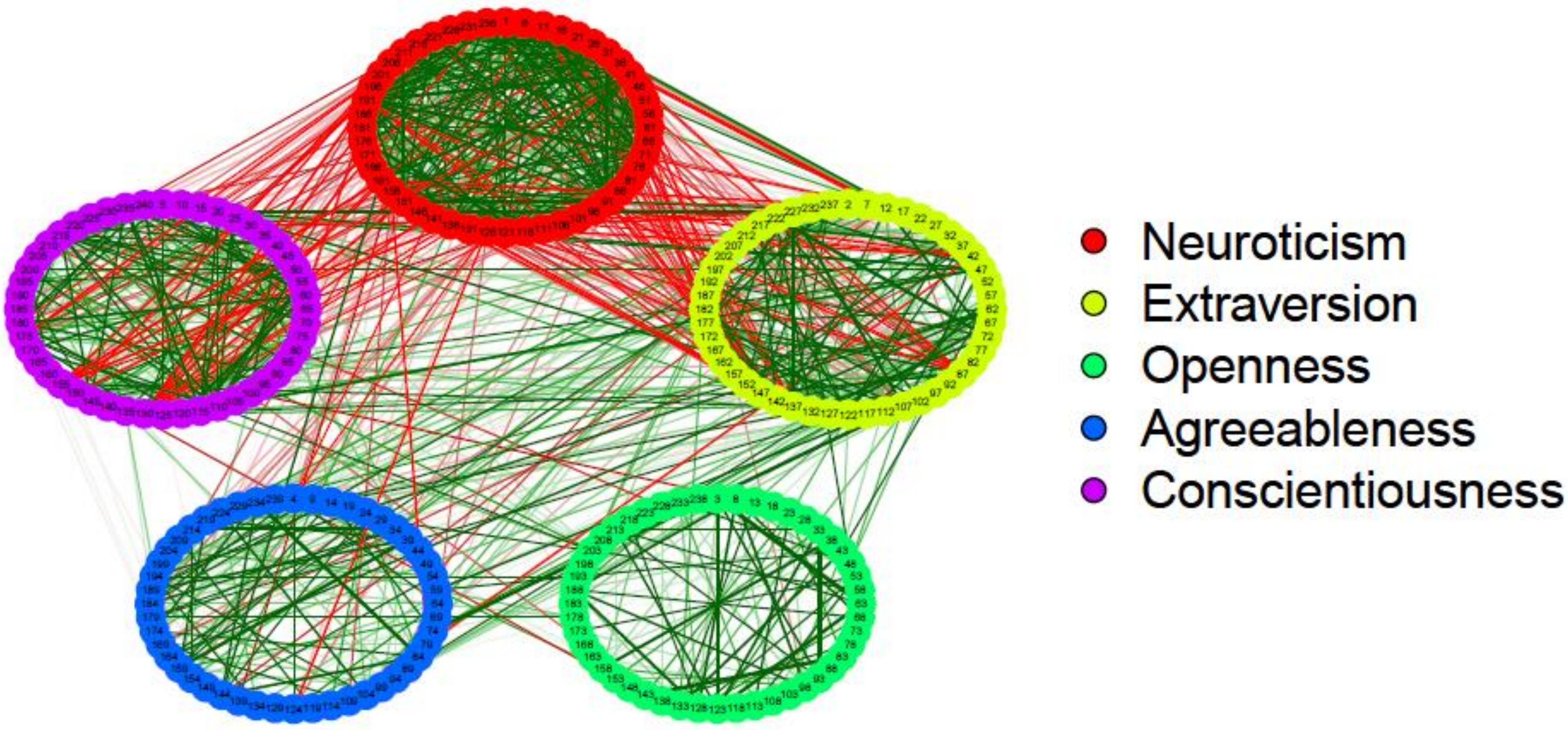
cor.plot(cor(big5))



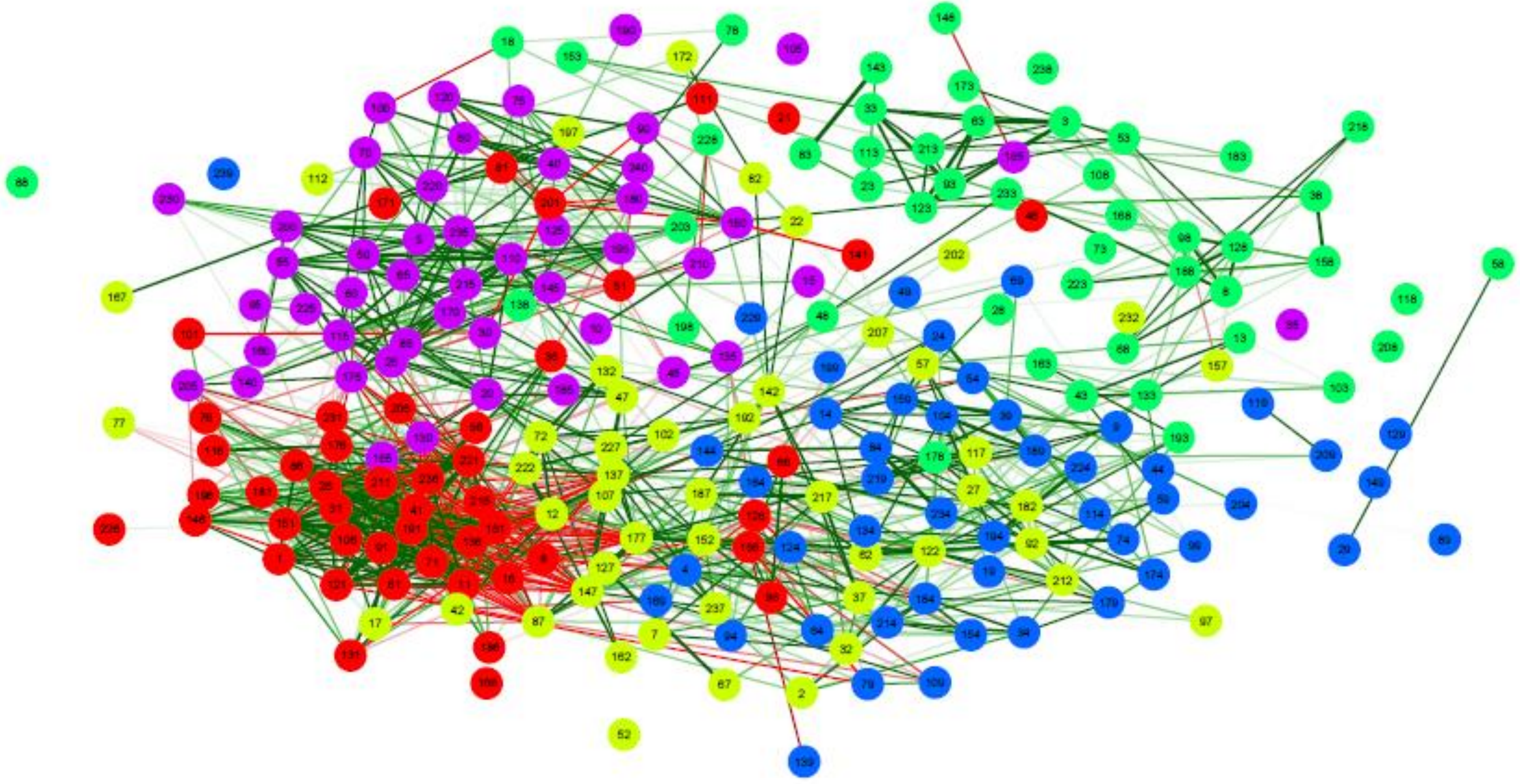
Q<-qgraph(cor(big5),groups=big5groups)



Q<-qgraph(Q,minimum=0.25,borders=F,vsize=2)



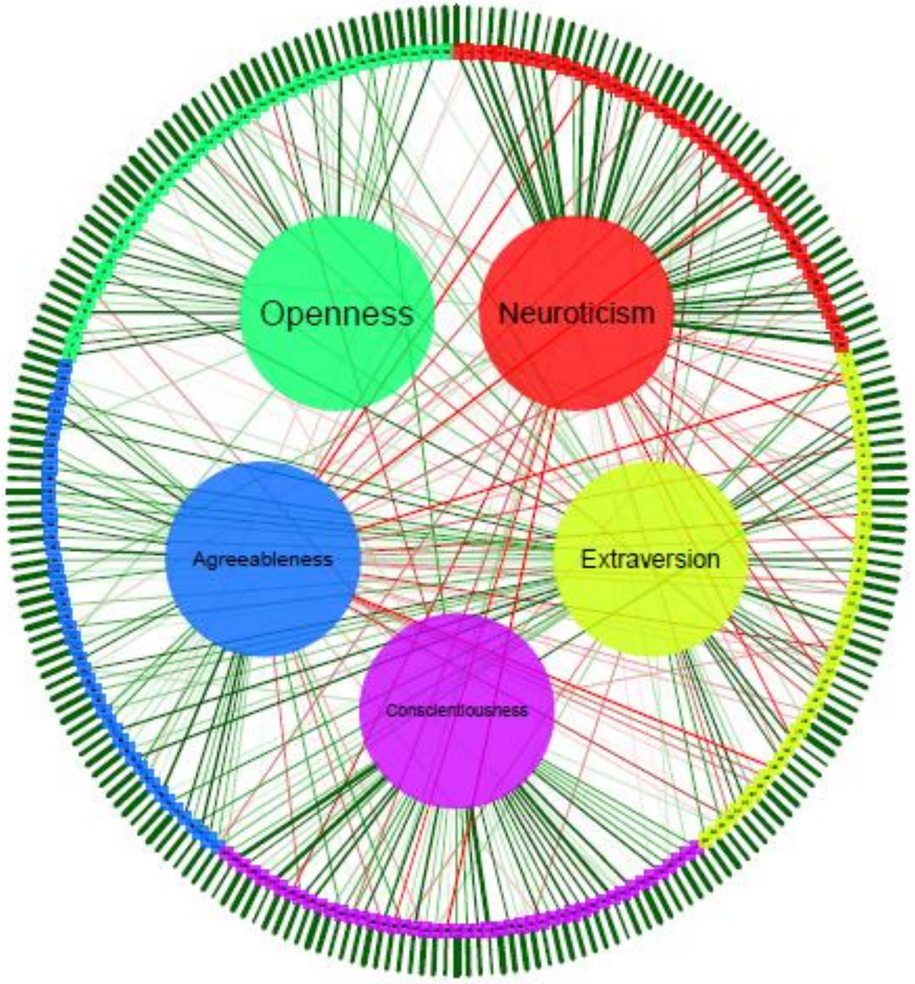
qgraph(Q,layout="spring",legend=F)

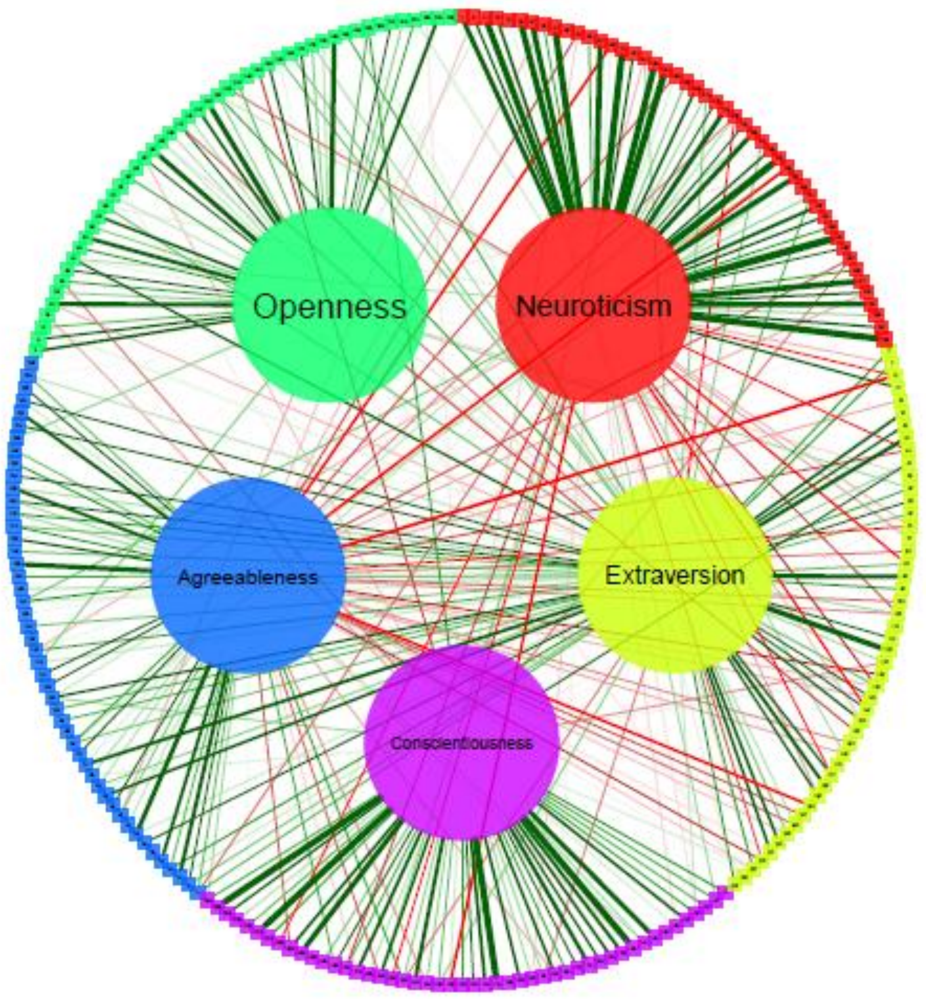


AFE, componentes principais e AFC

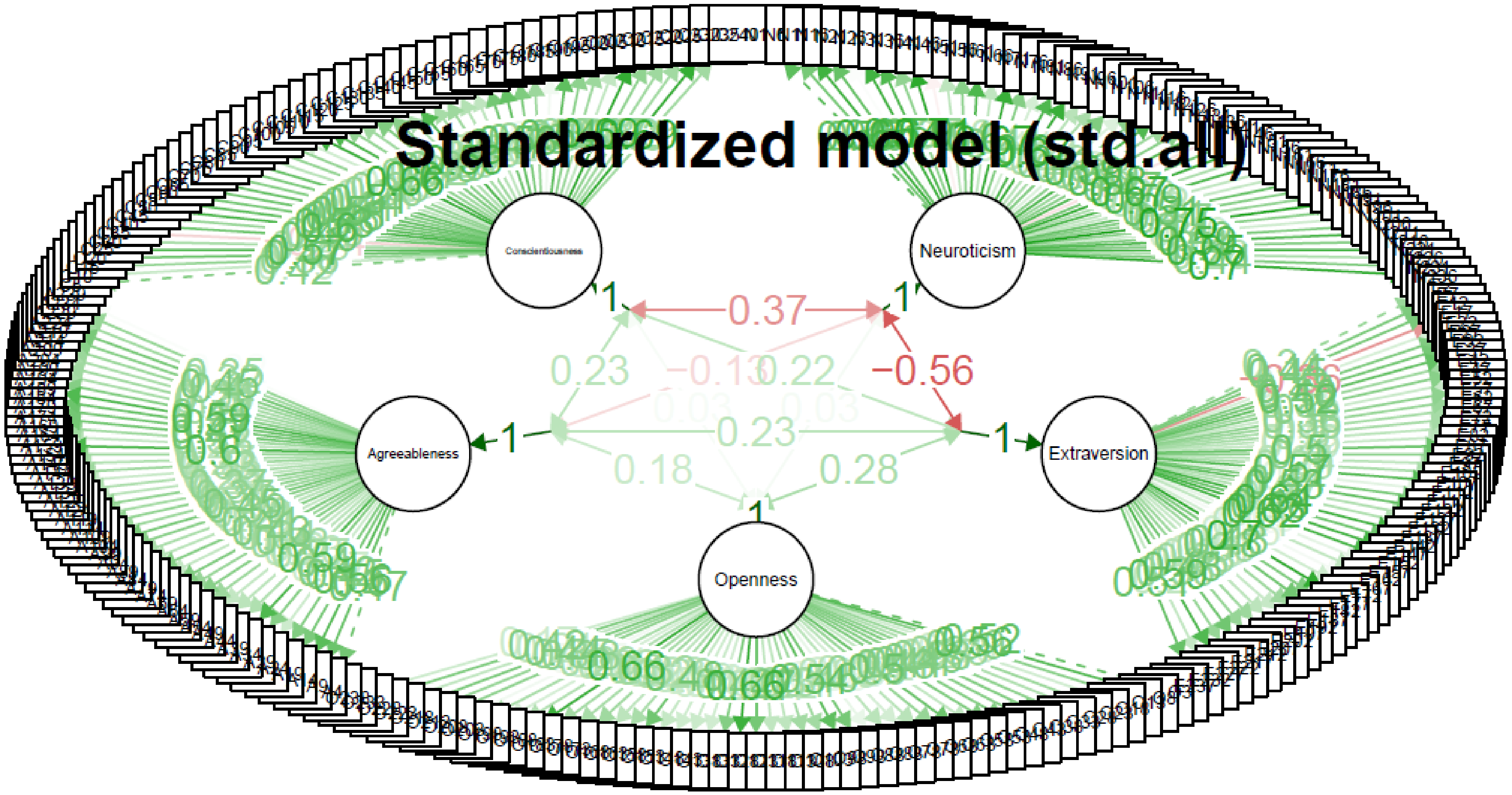
qgraph.efa(big5,5,groups=big5groups,rotation="promax",minimum=0.2,cut=0.4,vsize=c(1,15),borders=F,asize=0.07,esize=4,vTrans=200)

qgraph.pca(big5,5,groups=big5groups,rotation="promax",minimum=0.2,cut=0.4,vsize=c(1,15),borders=F,asize=0.07,esize=4,vTrans=200)





```
big5_fit<-qgraph.cfa(cov(big5), N = nrow(big5), groups = big5groups,pkg="lavaan",opts=list(se="none"),fun=print)
qgraph(big5_fit)
```



Redes gaussianas

3 Oct 2016

A Tutorial on Regularized Partial Correlation Networks

Sacha Epskamp and Eiko I. Fried

University of Amsterdam: Department of Psychological Methods

Regularized Gaussian Psychological Networks: Brief Report on the Performance of Extended BIC Model Selection

Sacha Epskamp
University of Amsterdam: Department of Psychological Methods

In recent literature, the Gaussian Graphical model (GGM; Lauritzen, 1996), a network of partial correlation coefficients, has been used to capture potential dynamic relationships between psychological variables. The GGM can be estimated using regularization in combination with model selection using the extended Bayesian Information Criterion (Foygel and Drton, 2010). I term this methodology *GeLasso*, and asses its performance using a plausible psychological network structure with both continuous and ordinal datasets. Simulation results indicate that GeLasso works well as an out-of-the-box method to estimate a psychological network structure.

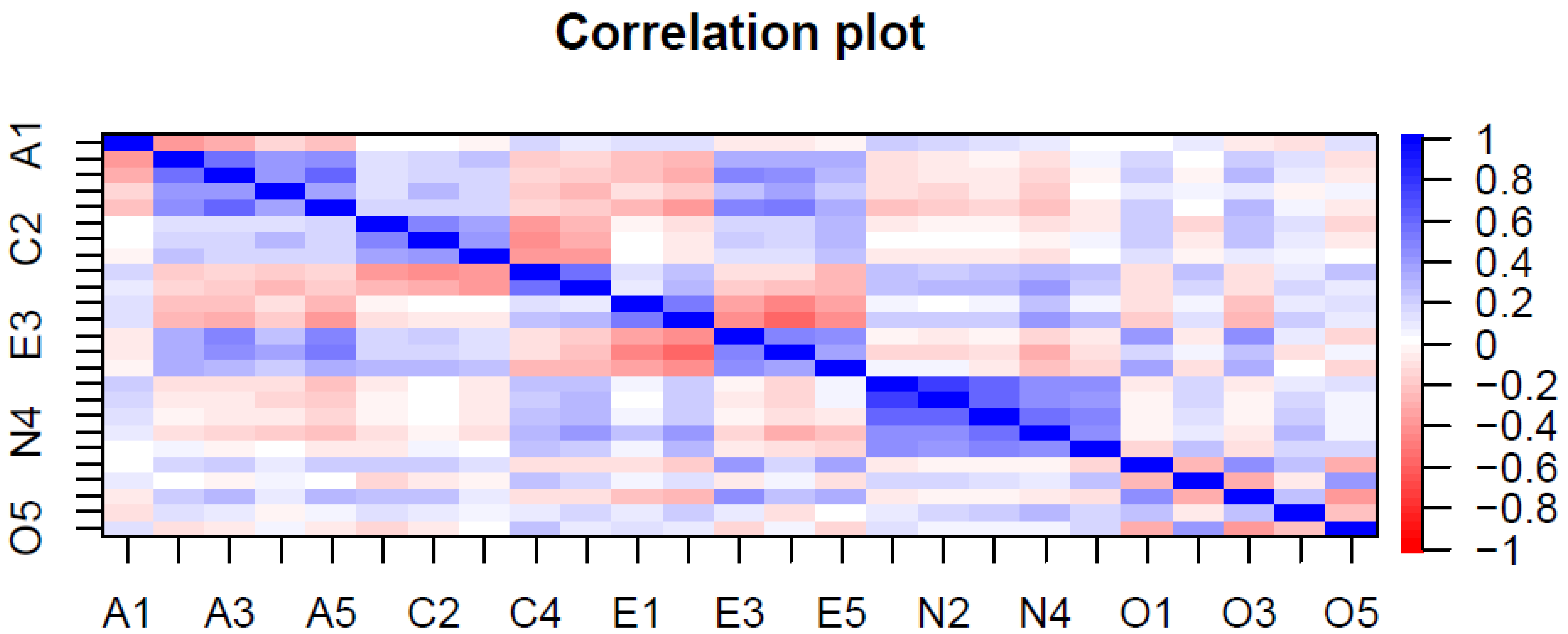
n 2016

Recent years have seen a emergance of the network conceptualisation of psychology, in which relationships between

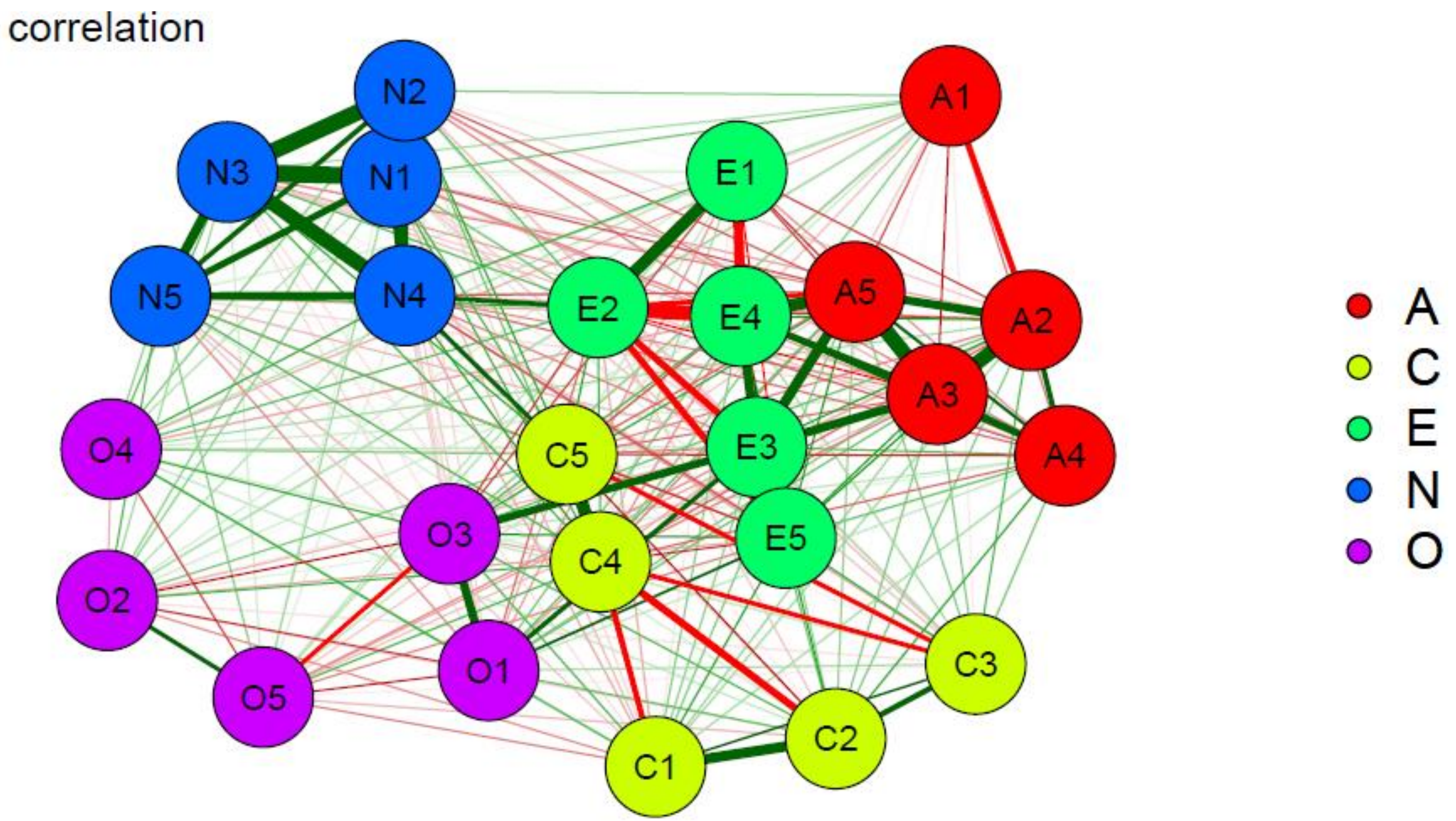
of networks is estimated under different values of λ (Zhao & Yu, 2006). The value for λ under which no edges are retained

Preparação

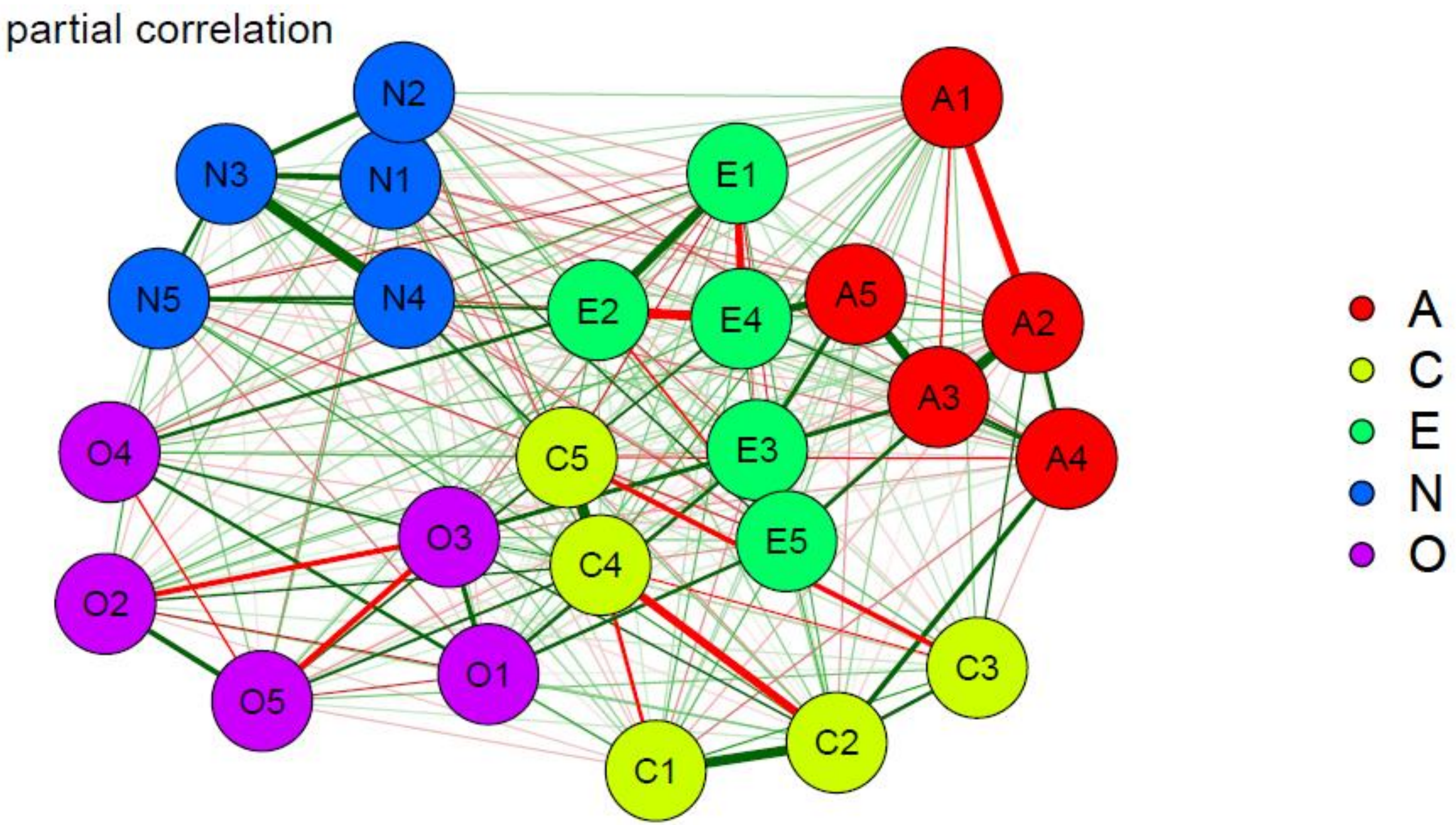
```
#exemplo BFI (banco do pacote psych)

bfi2<-getURL("https://raw.githubusercontent.com/wagnerLM/networkIBAP/master/bfi.csv")

bfi2<-read.csv(text = bfi2,sep=";")

View(bfi2)

#nomes e agrupamentos das variáveis

bfi2_names<-list("Am indifferent to the feelings of others","Inquire about others' well-being","Know how to comfort others","Love children","Make people feel at ease","Am exacting in my work","Continue until everything is perfect","Do things according to a plan","Do things in a half-way manner","Waste my time","Don't talk a lot","Find it difficult to approach others","Know how to captivate people","Make friends easily","Take charge","Get angry easily","Get irritated easily","Have frequent mood swings","Often feel blue","Panic easily","Am full of ideas","Avoid difficult reading material","Carry the conversation to a higher level","Spend time reflecting on things","Will not probe deeply into a subject","Gender(1=M,2=F)","education","age(years)")

bfi2_groups<-rep(c("A","C","E","N","O"),each=5)

#gerando a matriz de correlações

bfi2_cors<-cor_auto(bfi2[1:25])

#visualizando a matriz de correlações

cor.plot(bfi2_cors)
```


Correlation plot
A1
C2
E3
N4
O5
A1
A3
A5
C2
C4
E1
E3
E5
N2
N4
O1
O3
O5
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
−0.8
−1

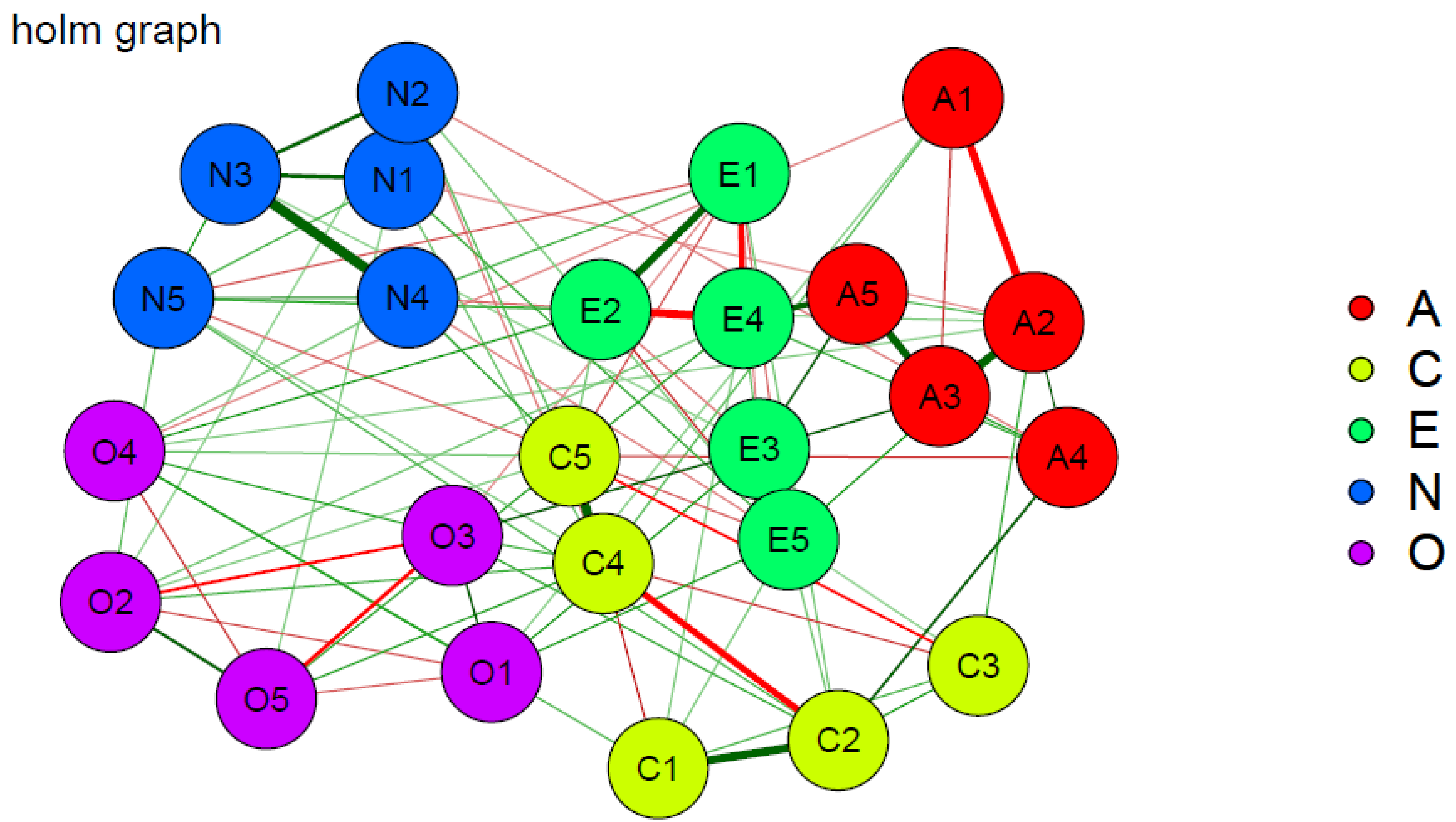
```
bfi2_corG<-qgraph(bfi2_cors,layout="spring",groups=bfi2_groups,title="correlation")
```



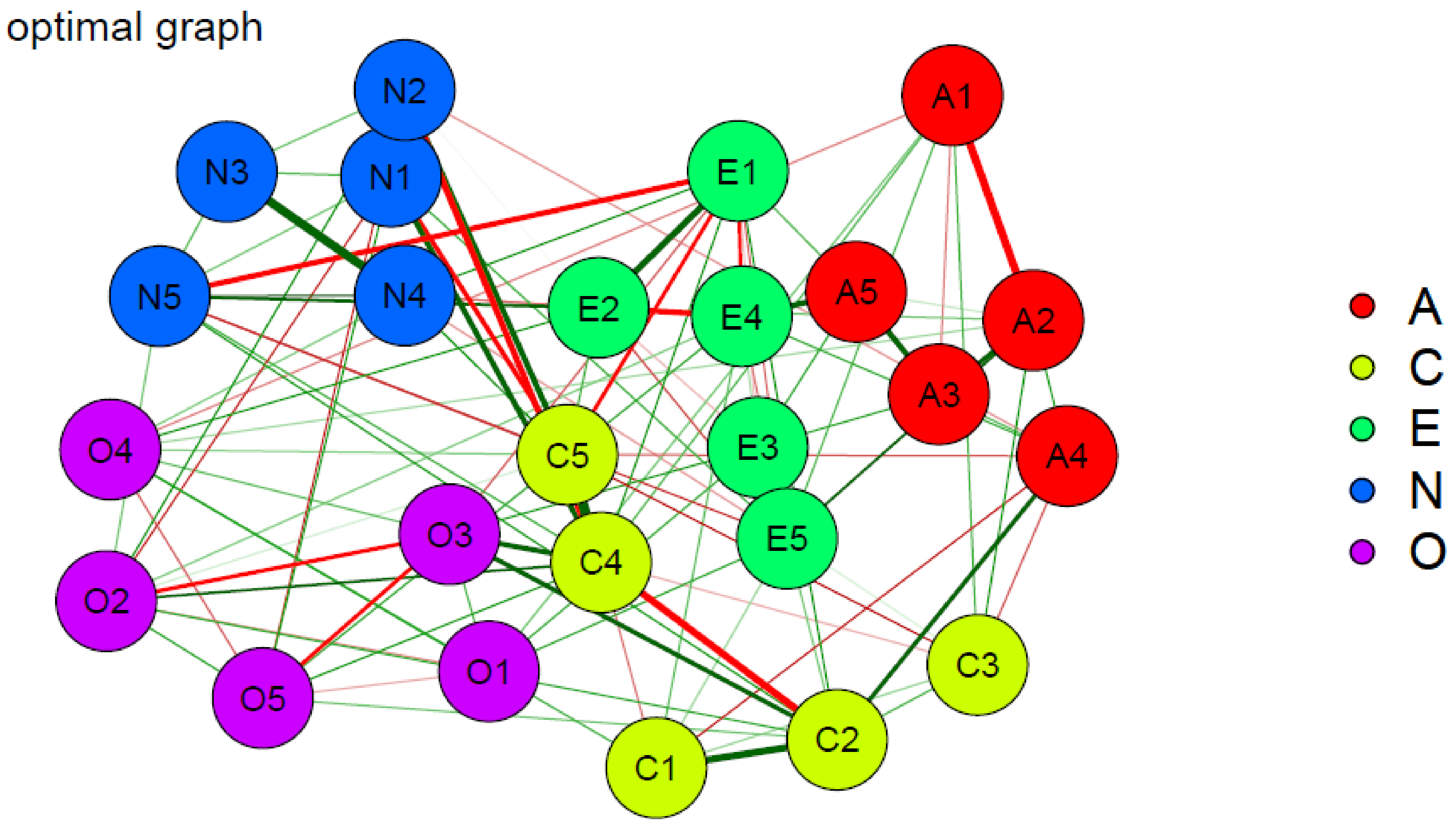
```
bfi2_pcorG<-qgraph(bfi2_cors,layout=bfi2_corG$layout,groups=bfi2_groups,graph="pcor",title="partial correlation")
```

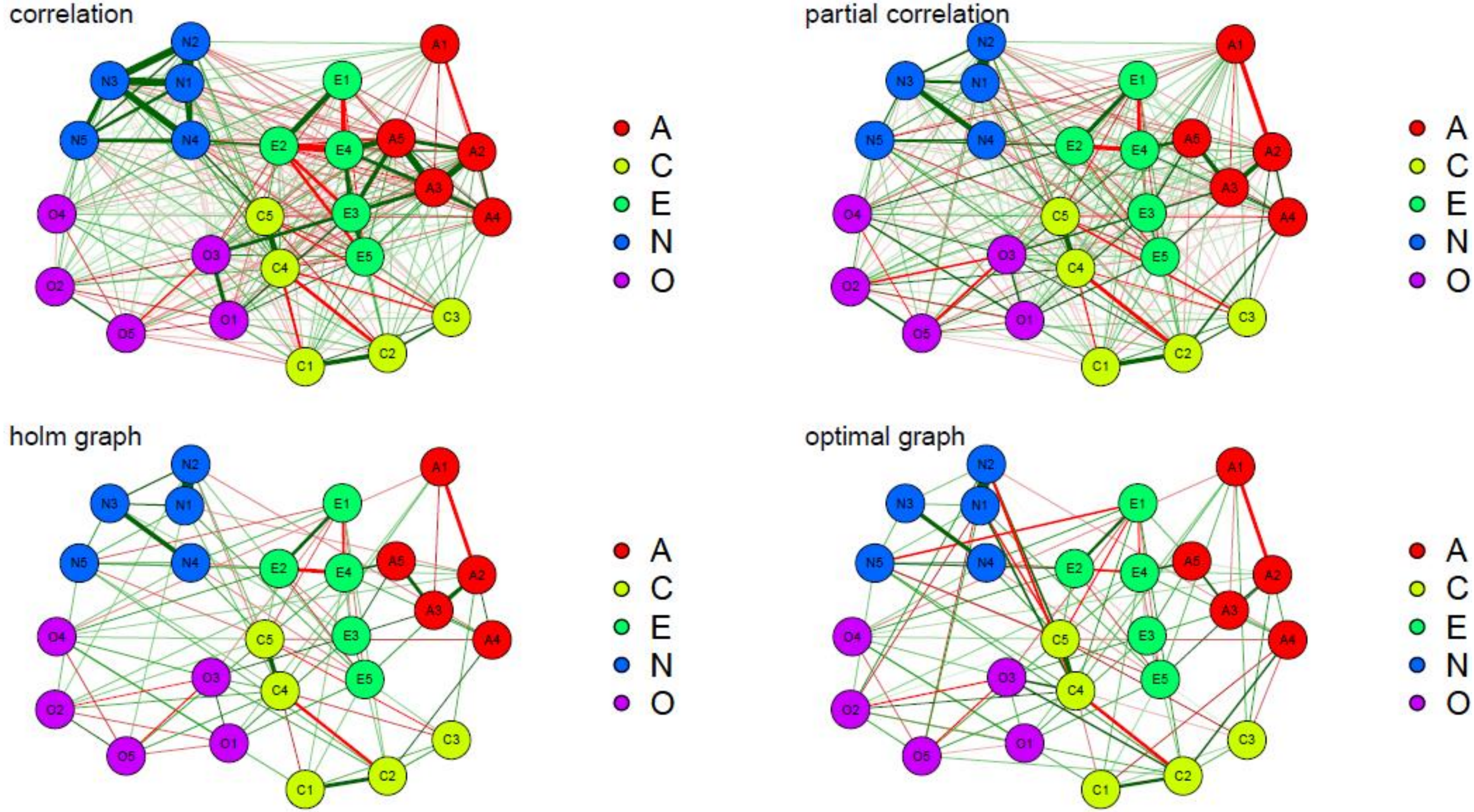


```
bfi2_holmG<-qgraph(bfi2_cors,layout=bfi2_corG$layout,groups=bfi2_groups,graph="pcor",threshold="holm",sampleSize=nrow(bfi),title="holm graph")
```



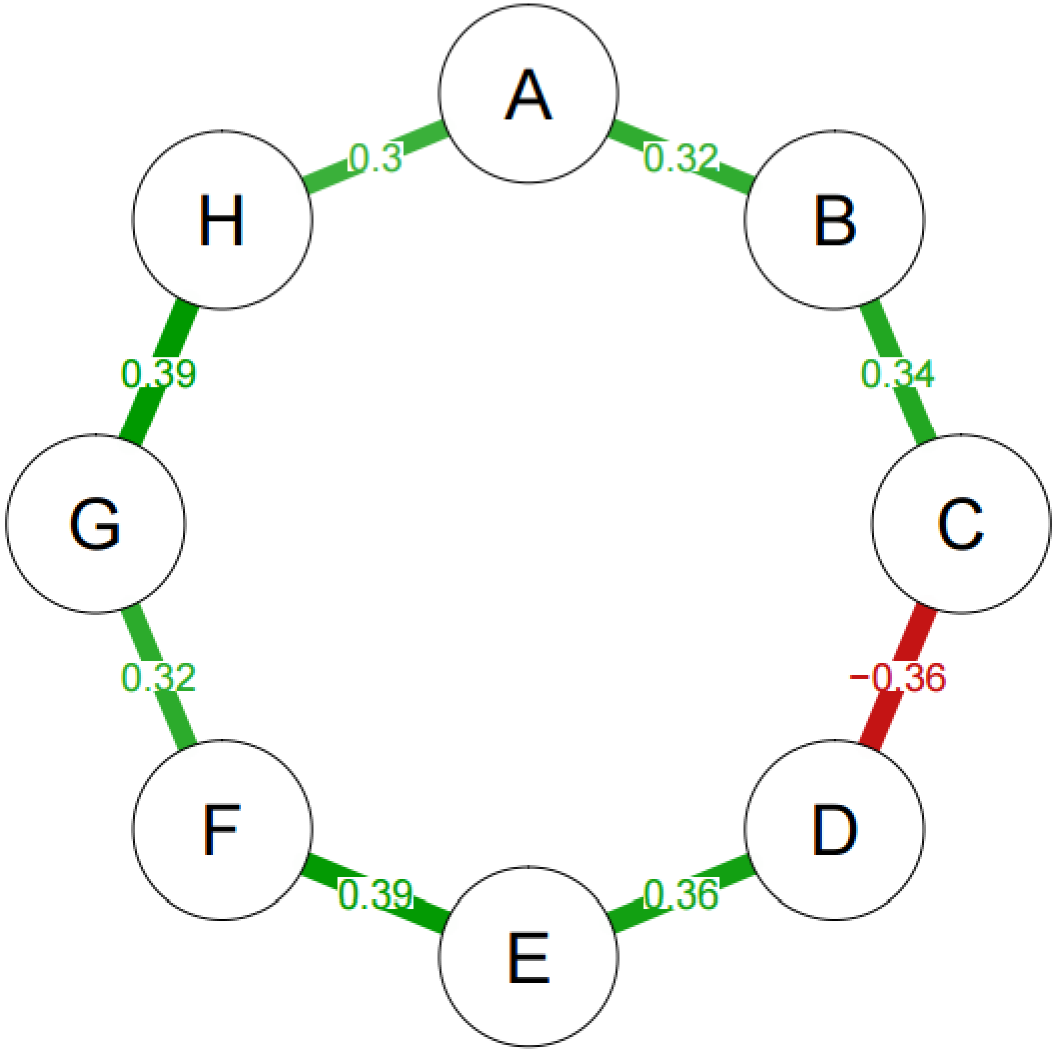
```
bfi2_optmG<-findGraph(bfi2_cors,nrow(bfi),type="pcor")
bfi2_optimalG<-qgraph(bfi2_optmG,layout=bfi2_corG$layout,groups=bfi2_groups,labels=colnames(bfi2_cors),title="optimal graph")
```



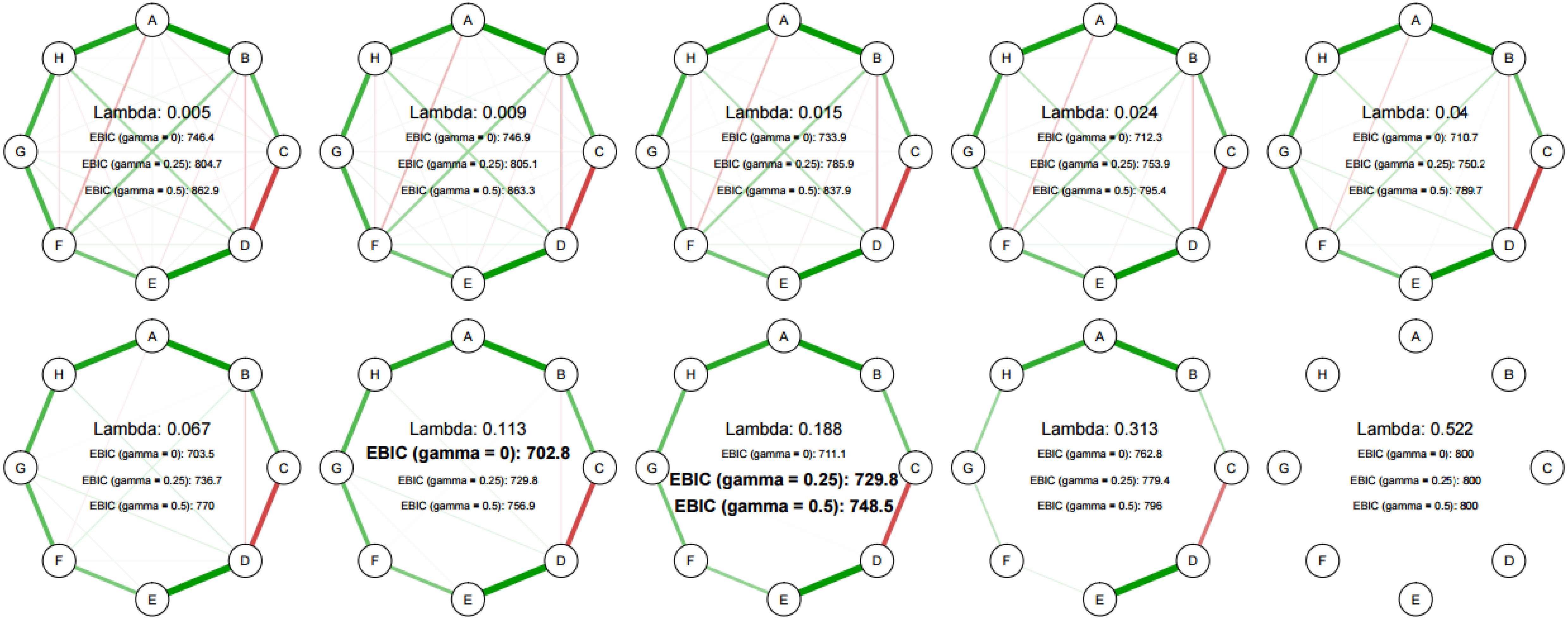

correlation
partial correlation
holm graph
optimal graph
N1 N2 N3 N4 N5
E1 E2 E3 E4 E5
A1 A2 A3 A4 A5
C1 C2 C3 C4 C5
O1 O2 O3 O4 O5
A
C
E
N
O

GeLasso estimation

- Graphical LASSO – (least absolute shrinkage and selection operator)
- Parâmetro de ajuste para o controle da esparcialidade (fixa em zero as arestas com pesos muito pequenos, próximos à zero), chamado λ
- São testados, por default, 100 valores de λ
- A seleção do modelo com menor resíduo é feita por meio do Extended Bayesian Criteria (EBIC), que penaliza modelos complexos (muitas arestas), chamado hiperparâmetro γ. Se $\gamma = 0$, o método é o BIC.
- Correlação parcial – regressões múltiplas “nodewise”

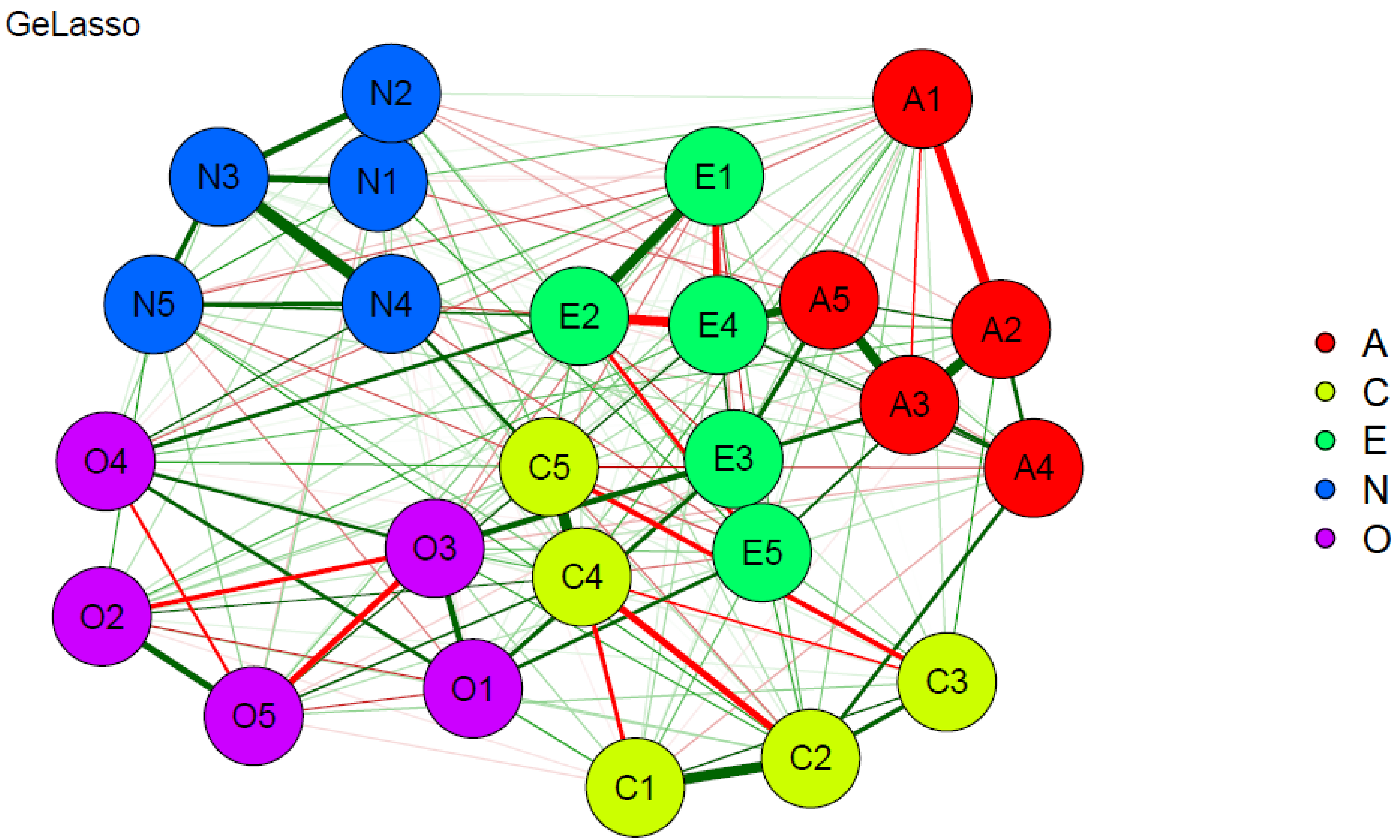


(Epskamp & Fried, 2006)



(Epskamp & Fried, 2006)

```
bfi2_glassoG<-qgraph(bfi2_cors,layout=bfi2_corG$layout,groups=bfi2_groups,graph="glasso",sampleSize=nrow(bfi),tuning=0.25,title="GeLasso")
```



Índices de ajuste, semelhante à SEM

```
bfi2_cov<-cov(bfi2,use = "pairwise.complete.obs")
bfi2_fit<-ggmFit(bfi2_glassoG,bfi2_cov,nrow(bfi2))
bfi2_fit$fitMeasures
```

Chi-squared = 92

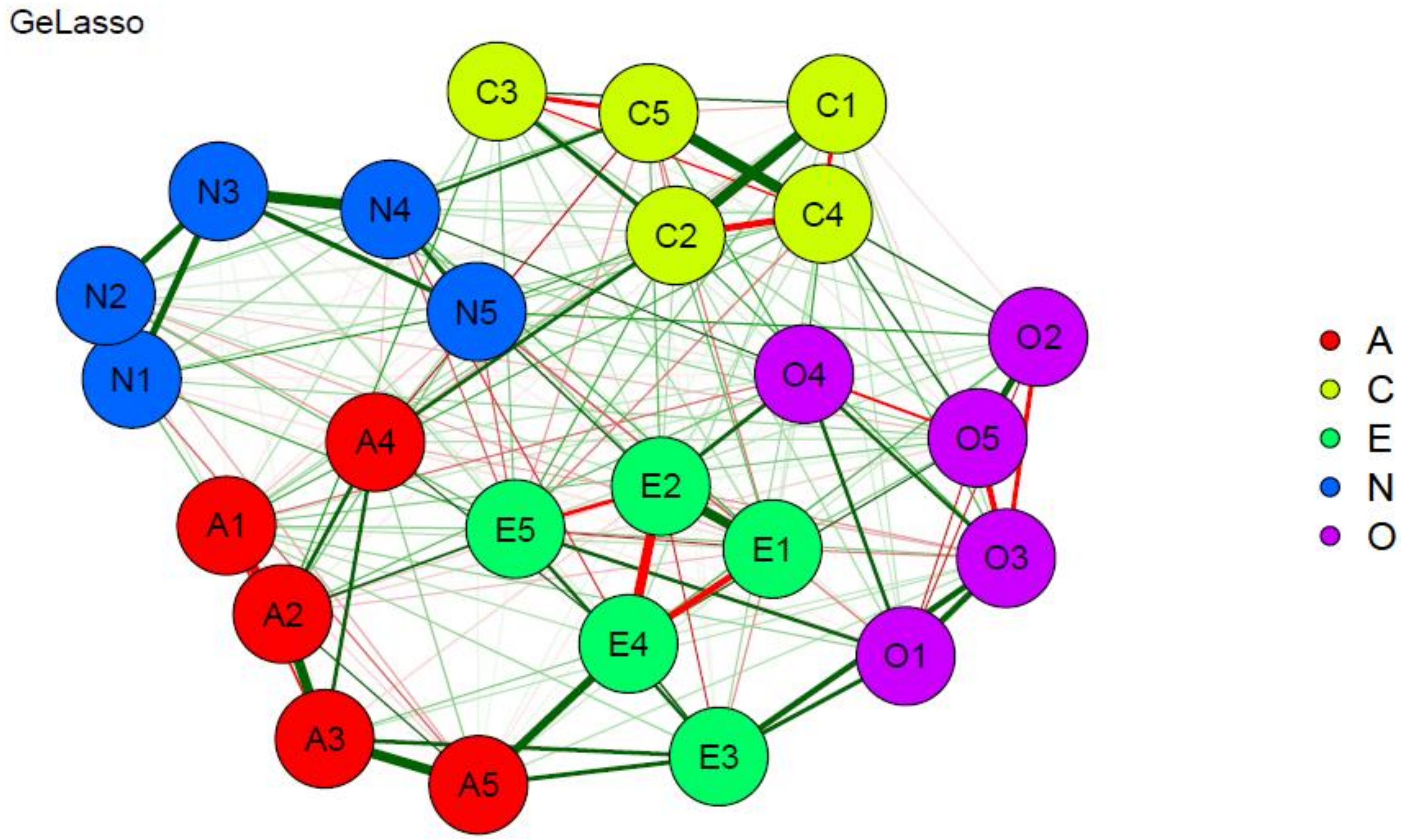
DF = 118

p = 0,96

TLI = 1

RMSEA = 0

```
bfi2_glassoG<-qgraph(bfi2_cors,layout="spring",groups=bfi2_groups,graph="glasso",sampleSize=nrow(bfi),tuning=0.25,title="GeLasso")
```

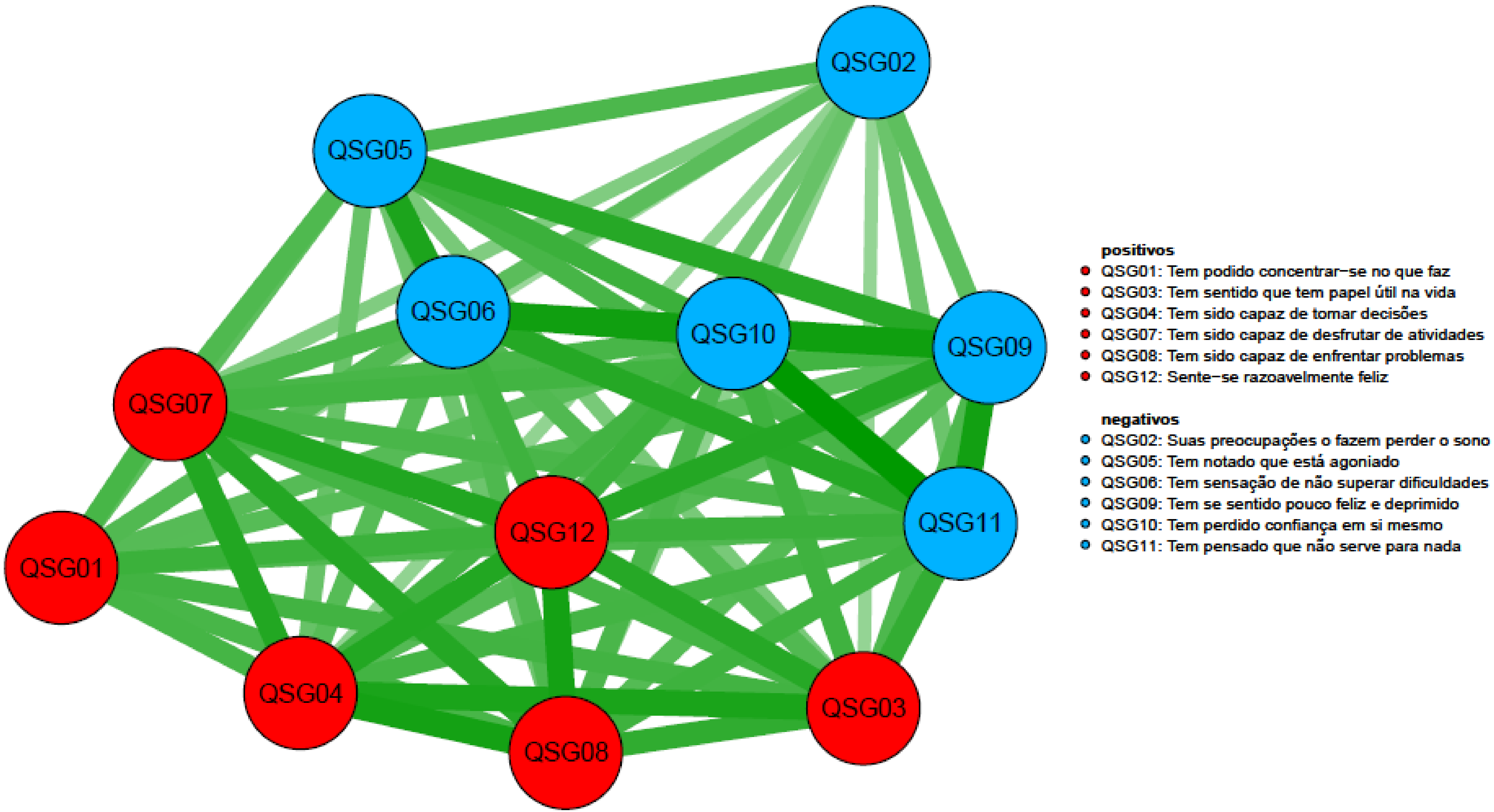


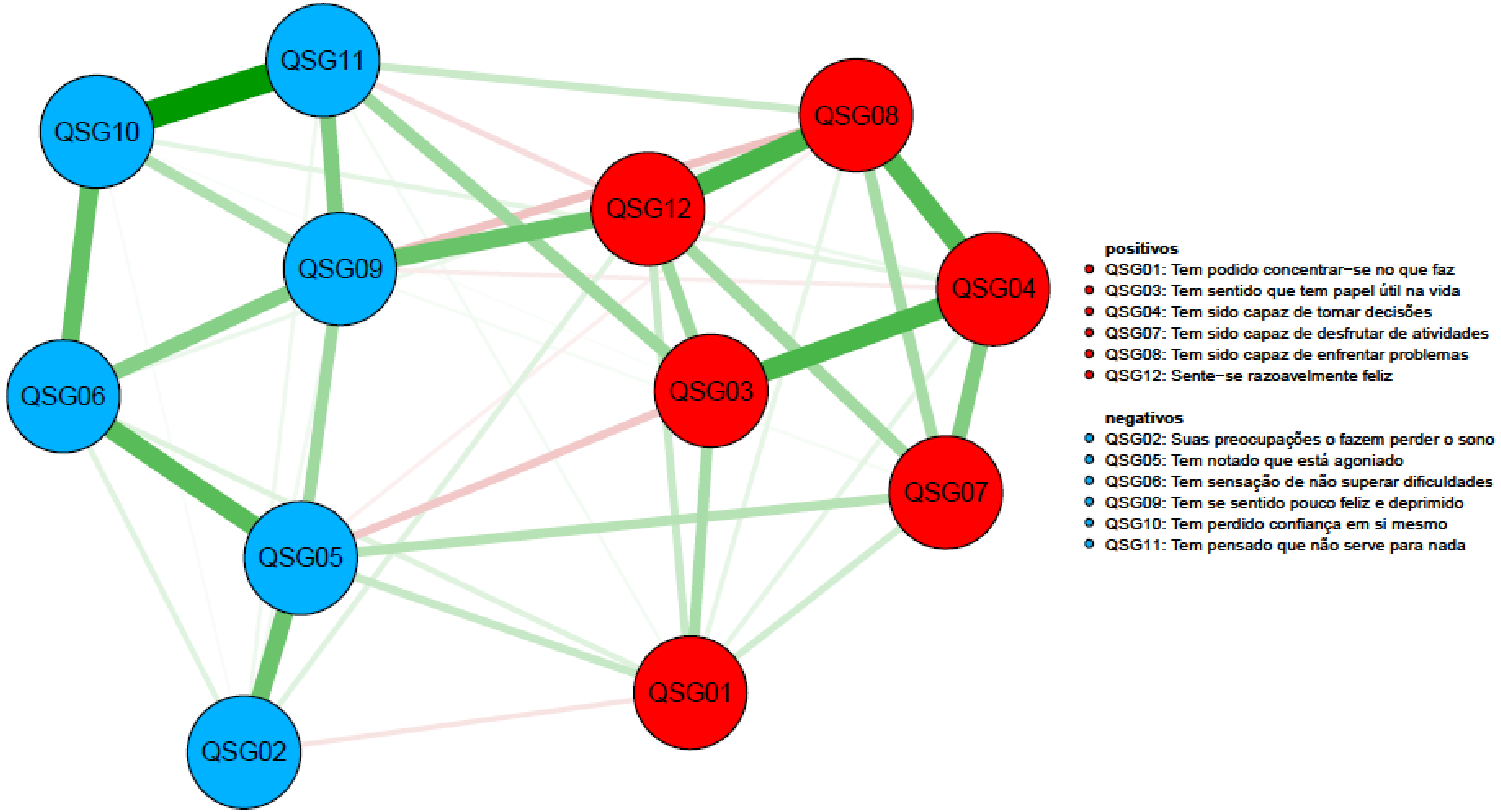
Redes gaussianas

- É possível fazer uma aproximação não paramétrica de variáveis gaussianas (cor_auto)
- Por exemplo, nas correlações tetra e polycóricas se assume que as variáveis latentes são gaussianas e suas realizações amostrais são categóricas

Questionário de Saúde Geral (Goldberg)

- Incerteza na literatura sobre sua estrutura fatorial (1 ou 2 fatores)

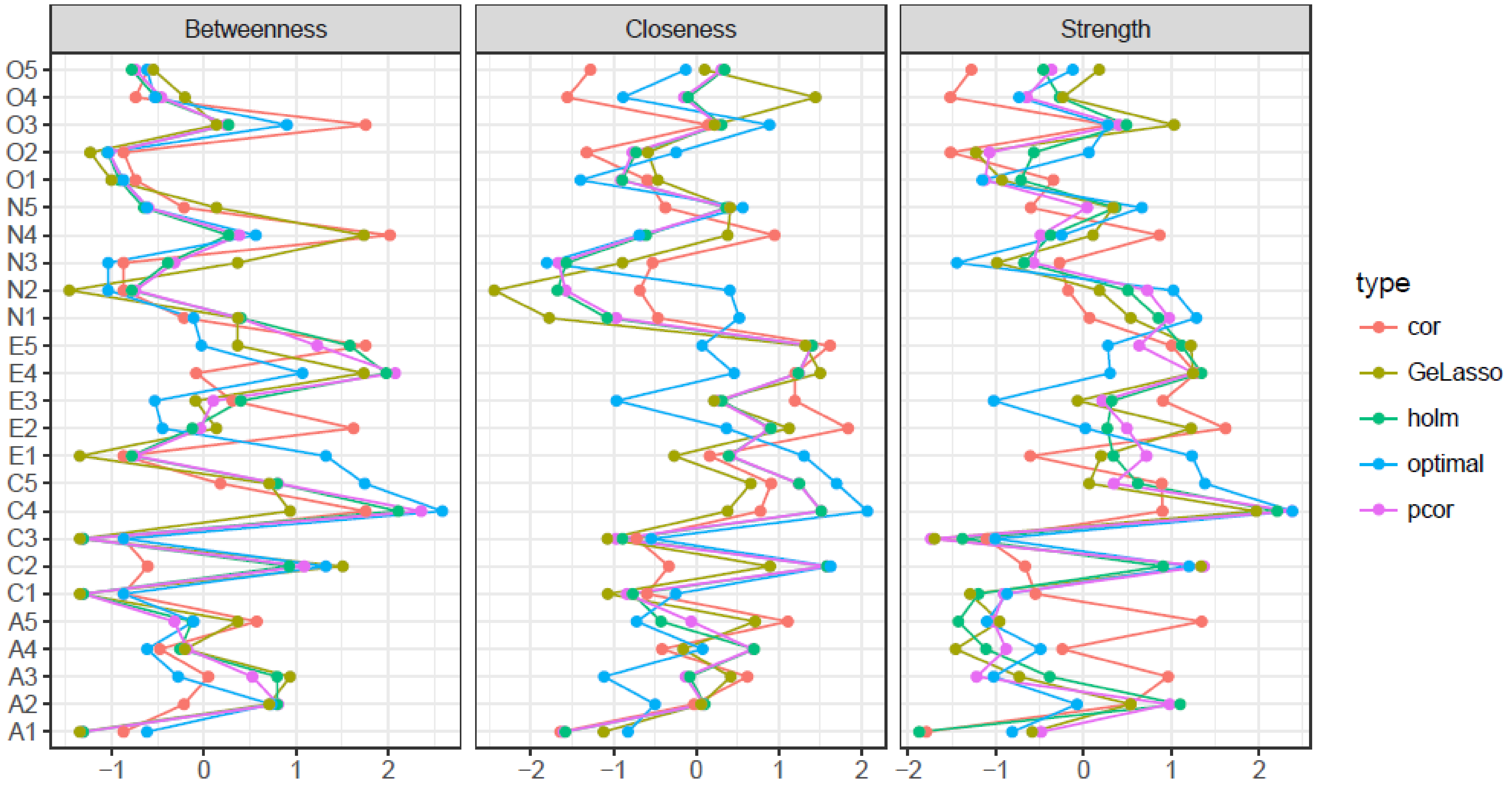

QSG02
QSG05
QSG06
QSG10
QSG09
QSG07
QSG12
QSG11
QSG01
QSG04
QSG08
QSG03
positivos
QSG01: Tem podido concentrar-se no que faz
QSG03: Tem sentido que tem papel útil na vida
QSG04: Tem sido capaz de tomar decisões
QSG07: Tem sido capaz de desfrutar de atividades
QSG08: Tem sido capaz de enfrentar problemas
QSG12: Sente-se razoavelmente feliz
negativos
QSG02: Suas preocupações o fazem perder o sono
QSG05: Tem notado que está agoniado
QSG06: Tem sensação de não superar dificuldades
QSG09: Tem se sentido pouco feliz e deprimido
QSG10: Tem perdido confiança em si mesmo
QSG11: Tem pensado que não serve para nada

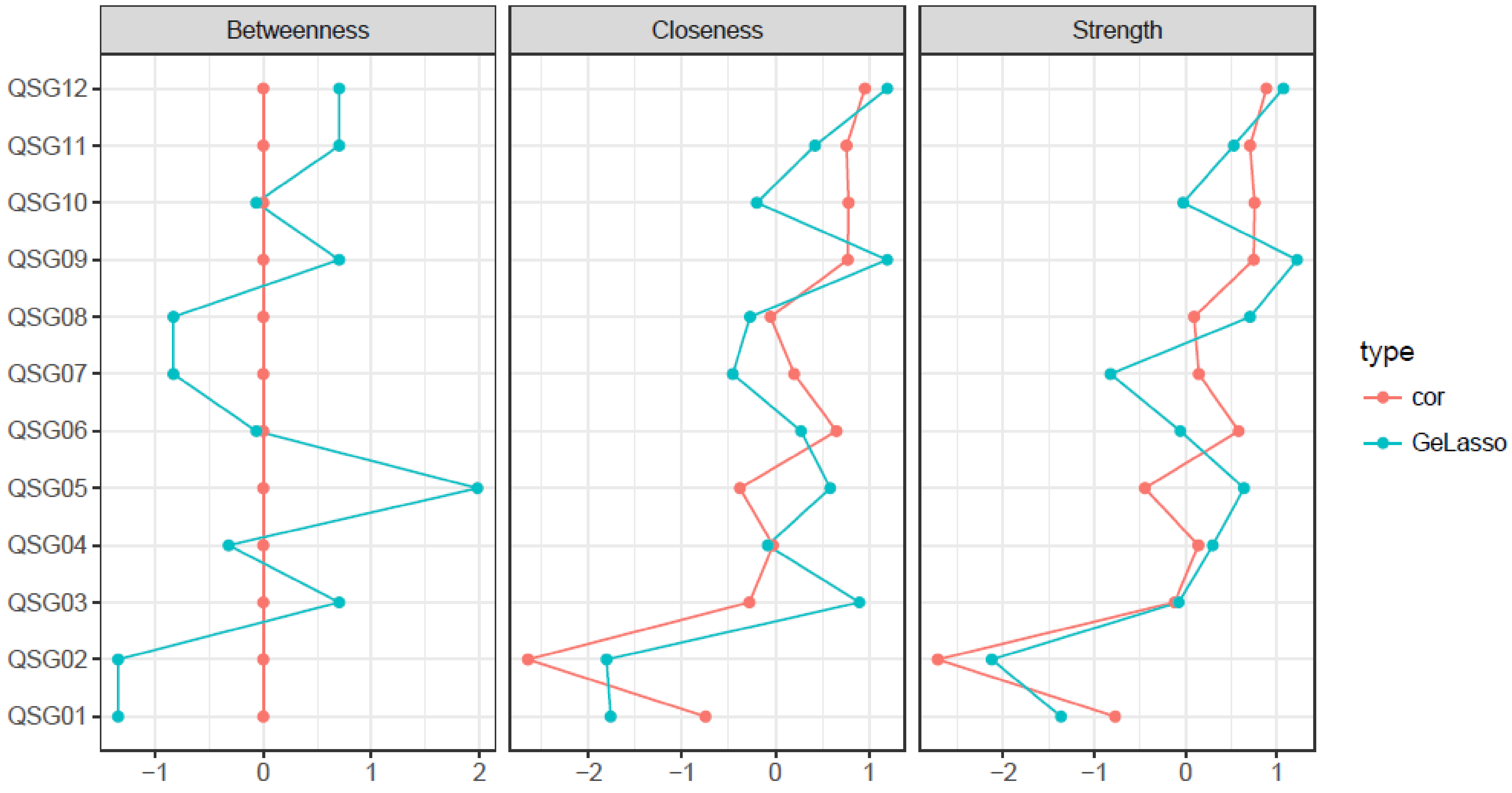

QSG11
QSG10
QSG08
QSG12
QSG09
QSG04
QSG06
QSG03
QSG07
QSG05
QSG01
QSG02
positivos
QSG01: Tem podido concentrar−se no que faz
QSG03: Tem sentido que tem papel útil na vida
QSG04: Tem sido capaz de tomar decisões
QSG07: Tem sido capaz de desfrutar de atividades
QSG08: Tem sido capaz de enfrentar problemas
QSG12: Sente−se razoavelmente feliz
negativos
QSG02: Suas preocupações o fazem perder o sono
QSG05: Tem notado que está agoniado
QSG06: Tem sensação de não superar dificuldades
QSG09: Tem se sentido pouco feliz e deprimido
QSG10: Tem perdido confiança em si mesmo
QSG11: Tem pensado que não serve para nada

Estatísticas descritivas da rede

- Centralidade (centrality) – conjunto de medidas descritivas e estatísticas de uma rede
- Betweeness (conectividade) – considerando os menores caminhos entre todos os pares de variáveis na rede, quantas vezes a variável faz parte deste caminho (ponderado pelo número máximo possível)
- Closeness (proximidade) – é a soma do inverso da distância (path length) de todas as suas conexões (nos grafos não ponderados é chamado degree)
- Strength (força) – soma modular do peso de todas as suas conexões
- Shortest path – menor caminho considerando o número ou o peso das arestas
- Shortest path length – soma dos pesos do caminho menos caminho entre os pares conectados

Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks*, *23*, 245-251.


Betweenness
Closeness
Strength
O5
O4
O3
O2
O1
N5
N4
N3
N2
N1
E5
E4
E3
E2
E1
C5
C4
C3
C2
C1
A5
A4
A3
A2
A1
−1
0
1
2
−2
−1
0
1
2
−2
−1
0
1
2
type
cor
GeLasso
holm
optimal
pcor


Betweenness
Closeness
Strength
QSG12
QSG11
QSG10
QSG09
QSG08
QSG07
QSG06
QSG05
QSG04
QSG03
QSG02
QSG01
−1
0
1
2
−2
−1
0
1
−2
−1
0
1
type
cor
GeLasso

Shortest path length – quanto menor, mais eficiente é o “caminho” e transmissão de infomação

aicarede | dsin | y | qsg_cent$ShortestPathLengths | qsg_cen

Filter

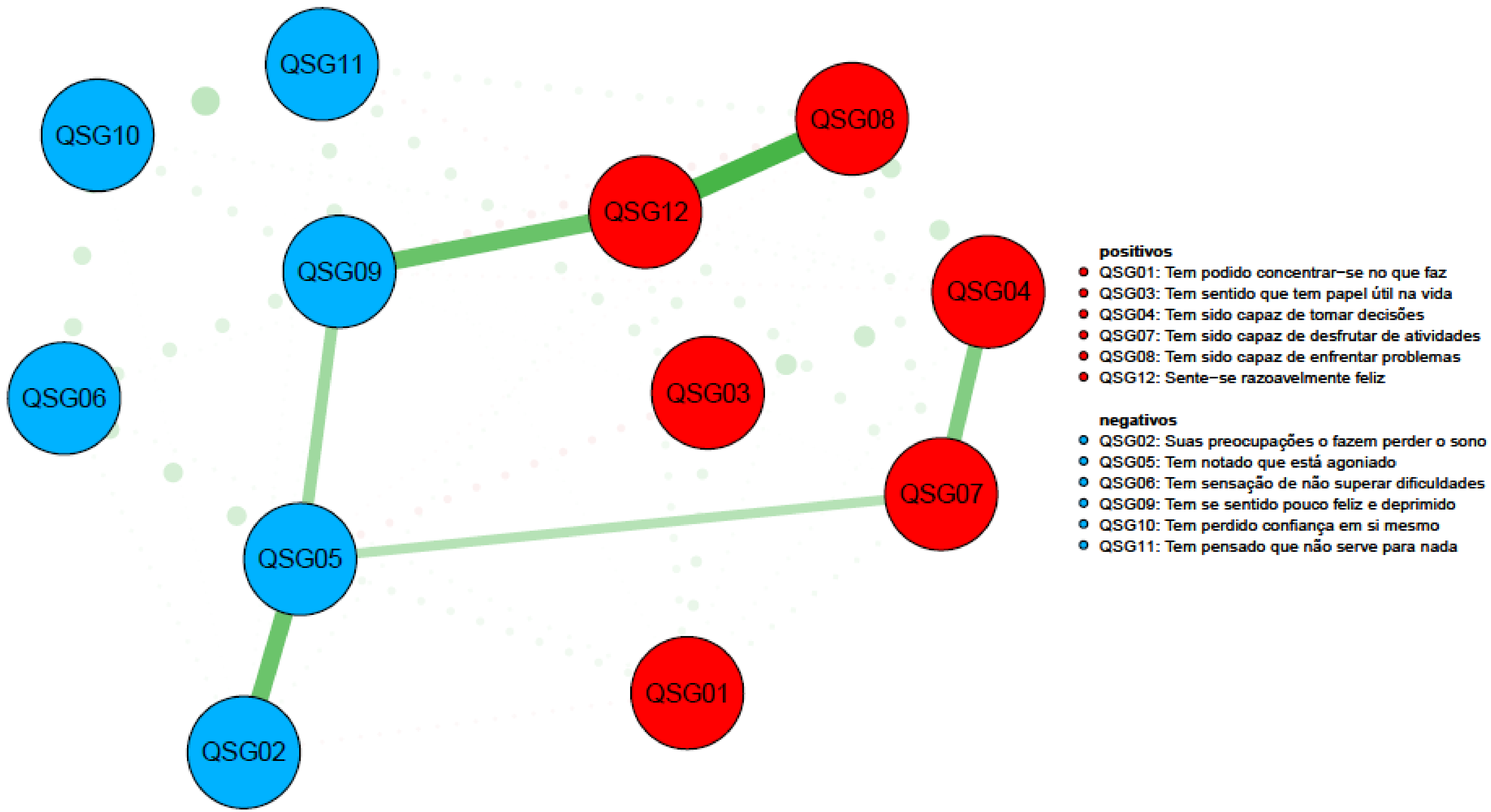
	QSG01	QSG02	QSG03	QSG04	QSG05	QSG06	QSG07
QSG01	0.000000	12.244544	5.738064	8.479290	8.860945	11.855189	10.90518
QSG02	12.244544	0.000000	12.263885	14.244783	3.383599	6.377842	10.21295
QSG03	5.738064	12.263885	0.000000	2.741226	8.880287	10.309503	6.77305
QSG04	8.479290	14.244783	2.741226	0.000000	10.861185	13.050729	4.03182
QSG05	8.860945	3.383599	8.880287	10.861185	0.000000	2.994244	6.82935
QSG06	11.855189	6.377842	10.309503	13.050729	2.994244	0.000000	9.82359
QSG07	10.905180	10.212954	6.773055	4.031829	6.829356	9.823599	0.00000
QSG08	11.394571	14.684558	5.656507	2.915281	11.300960	10.177917	5.68237

Shortest path – o menor caminho é direto ou mediado? Redes regularizadas de correlação parcial (GeLasso) são redes de mediação!

qsg_cent$ShortestPathLengths | qsg_cent$ShortestPaths | getWma

Filter

	QSG01	QSG02	QSG03	QSG04	QSG05
QSG01	list()	list(c(1, 5, 2))	list(c(1, 3))	list(c(1, 3, 4))	list(
QSG02	list(c(2, 5, 1))	list()	list(c(2, 5, 3))	list(c(2, 5, 7, 4))	list(
QSG03	list(c(3, 1))	list(c(3, 5, 2))	list()	list(c(3, 4))	list(
QSG04	list(c(4, 3, 1))	list(c(4, 7, 5, 2))	list(c(4, 3))	list()	list(
QSG05	list(c(5, 1))	list(c(5, 2))	list(c(5, 3))	list(c(5, 7, 4))	list(
QSG06	list(c(6, 5, 1))	list(c(6, 5, 2))	list(c(6, 10, 11, 3))	list(c(6, 10, 11, 3, 4))	list(
QSG07	list(c(7, 1))	list(c(7, 5, 2))	list(c(7, 4, 3))	list(c(7, 4))	list(
QSG08	list(c(8, 4, 3, 1))	list(c(8, 12, 9, 5, 2))	list(c(8, 4, 3))	list(c(8, 4))	list(


QSG11
QSG10
QSG08
QSG12
QSG09
QSG04
QSG03
QSG06
QSG07
QSG05
QSG01
QSG02
positivos
QSG01: Tem podido concentrar−se no que faz
QSG03: Tem sentido que tem papel útil na vida
QSG04: Tem sido capaz de tomar decisões
QSG07: Tem sido capaz de desfrutar de atividades
QSG08: Tem sido capaz de enfrentar problemas
QSG12: Sente−se razoavelmente feliz
negativos
QSG02: Suas preocupações o fazem perder o sono
QSG05: Tem notado que está agoniado
QSG06: Tem sensação de não superar dificuldades
QSG09: Tem se sentido pouco feliz e deprimido
QSG10: Tem perdido confiança em si mesmo
QSG11: Tem pensado que não serve para nada

Matriz adjacente (GeLasso) – betas de regressão linear múltipla!

:PathLengths | qsg_cent$ShortestPaths | getWmat(qsg_G2) | dass_sul

Filter

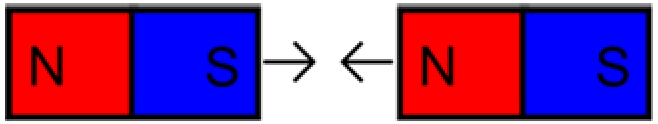
	QSG01	QSG02	QSG03	QSG04	QSG05	QSG06
QSG01	0.00000000	-0.05503783	0.17427480	0.05202109	0.11285478	0.06677430
QSG02	-0.05503783	0.00000000	0.00000000	0.00000000	0.29554334	0.06167212
QSG03	0.17427480	0.00000000	0.00000000	0.36480023	-0.11260898	0.00000000
QSG04	0.05202109	0.00000000	0.36480023	0.00000000	0.00000000	0.00000000
QSG05	0.11285478	0.29554334	-0.11260898	0.00000000	0.00000000	0.33397413
QSG06	0.06677431	0.06167213	0.00000000	0.00000000	0.33397414	0.00000000
QSG07	0.09169954	0.00000000	0.00000000	0.24802639	0.14642670	0.00051071
QSG08	0.05006202	0.00000000	0.00000000	0.34302016	-0.03119161	0.03899027

Dados dicotômicos?

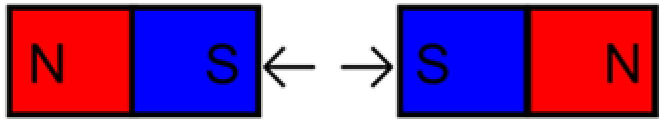
- Na Psicologia, Saúde e Educação não são raros os instrumentos que resultam em dados dicotômicos (presença/ausência, acerto/erro, etc.)
- Se para os dados Gaussianos utiliza-se regressões lineares múltiplas regularizadas, então...
- Regressão logística! Yes!

Ising model

- Estudo do ferromagnetismo



Opposite poles **attract**



Same poles **repel**

SCIENTIFIC REPORTS

OPEN

SUBJECT AREAS:
PSYCHOLOGY
SIGNS AND SYMPTOMS

A new method for constructing networks from binary data

Claudia D. van Borkulo[1,2], Denny Borsboom[2], Sacha Epskamp[2], Tessa F. Blanken[2], Lynn Boschloo[1], Robert A. Schoevers[1] & Lourens J. Waldorp[2]

$$\mathbb{P}_{\Theta}\left(x_j \middle| x_{\setminus j}\right) = \frac{\exp\left[\tau_j x_j + x_j \sum_{k \in V_{\setminus j}} \beta_{jk} x_k\right]}{1 + \exp\left[\tau_j + \sum_{k \in V_{\setminus j}} \beta_{jk} x_k\right]}, \qquad (1)$$

where τ_j and β_{jk} are the node parameter (or threshold) and the pairwise interaction parameter respectively.

Network Psychometrics

Sacha Epskamp, Gunter K. J. Maris, Lourens J. Waldorp and Denny Borsboom
University of Amsterdam, Department of Psychological Methods

Abstract

This chapter provides a general introduction of network modeling in psychometrics. The chapter starts with an introduction to the statistical model formulation of pairwise Markov random fields (PMRF), followed by an introduction of the PMRF suitable for binary data: the *Ising model*. The Ising model is a model used in ferromagnetism to explain phase transitions in a

The Relation Between the Ising Model and Item Response Theory

In this section we will show that the Ising model is a closely related modeling framework of Item Response Theory (IRT), which is of central importance to psychometrics. In fact, we will show that the Ising model is equivalent to a special case of the multivariate 2-parameter logistic model (MIRT). However, instead of being hypothesized common causes of the item responses, in our representation the latent variables in the model are *generated* by cliques in the network.

DASS

Nome: *Data:*

Por favor, leia cada afirmativa e marque um dos números (0, 1, 2 ou 3) que indique quanto a afirmativa se aplica a você. Não há respostas certas ou erradas. Não gaste muito tempo em nenhuma das afirmativas.

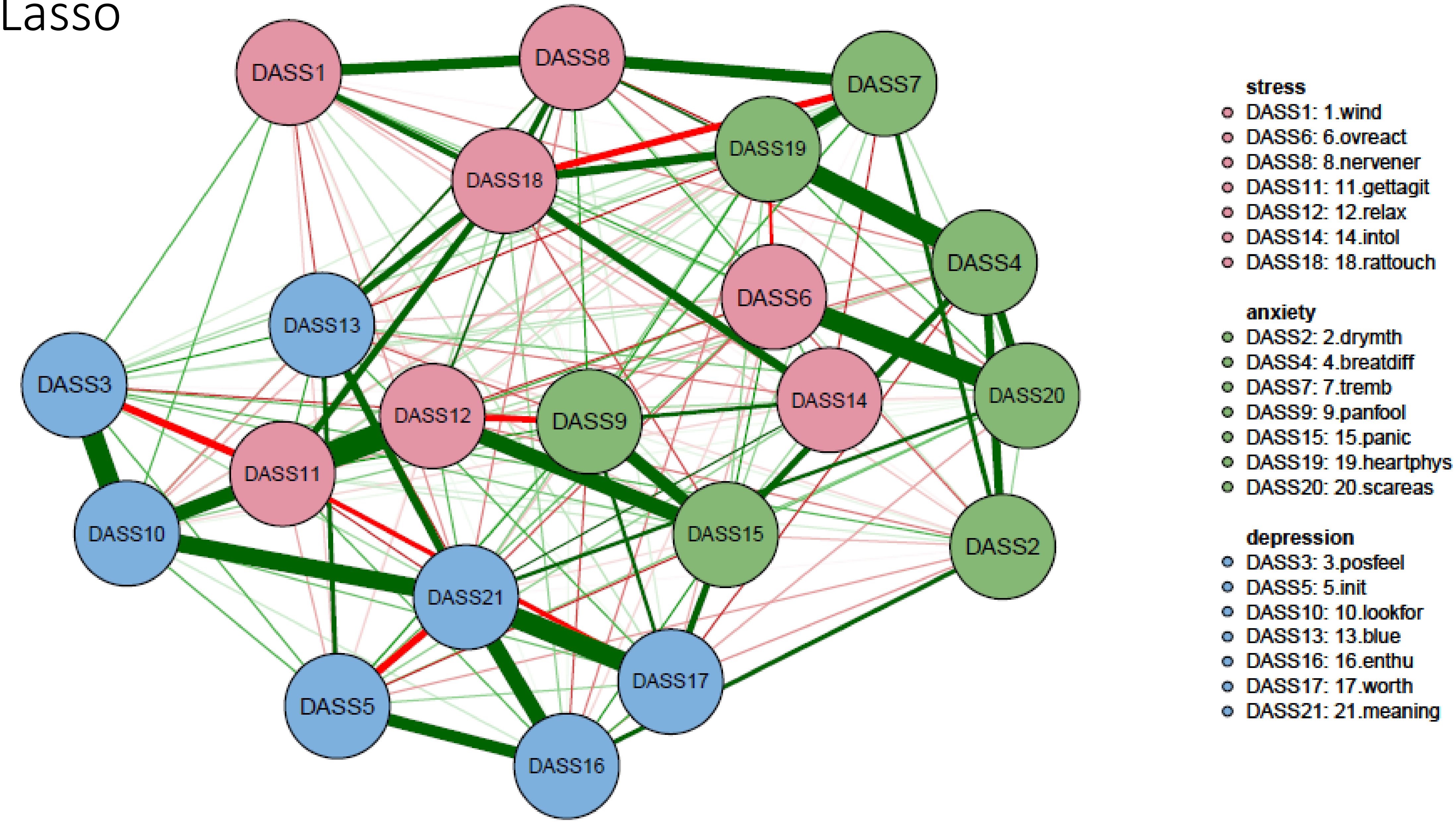
0. Não se aplicou a mim de forma alguma
1. Aplicou-se a mim de alguma forma ou em algumas vezes
2. Aplicou-se a mim de forma considerável ou em boa parte do tempo
3. Aplicou-se muito a mim ou na maior parte do tempo

1	Eu tive dificuldade para me acalmar	0	1	2	3
2	Eu percebi que estava com a boca seca	0	1	2	3

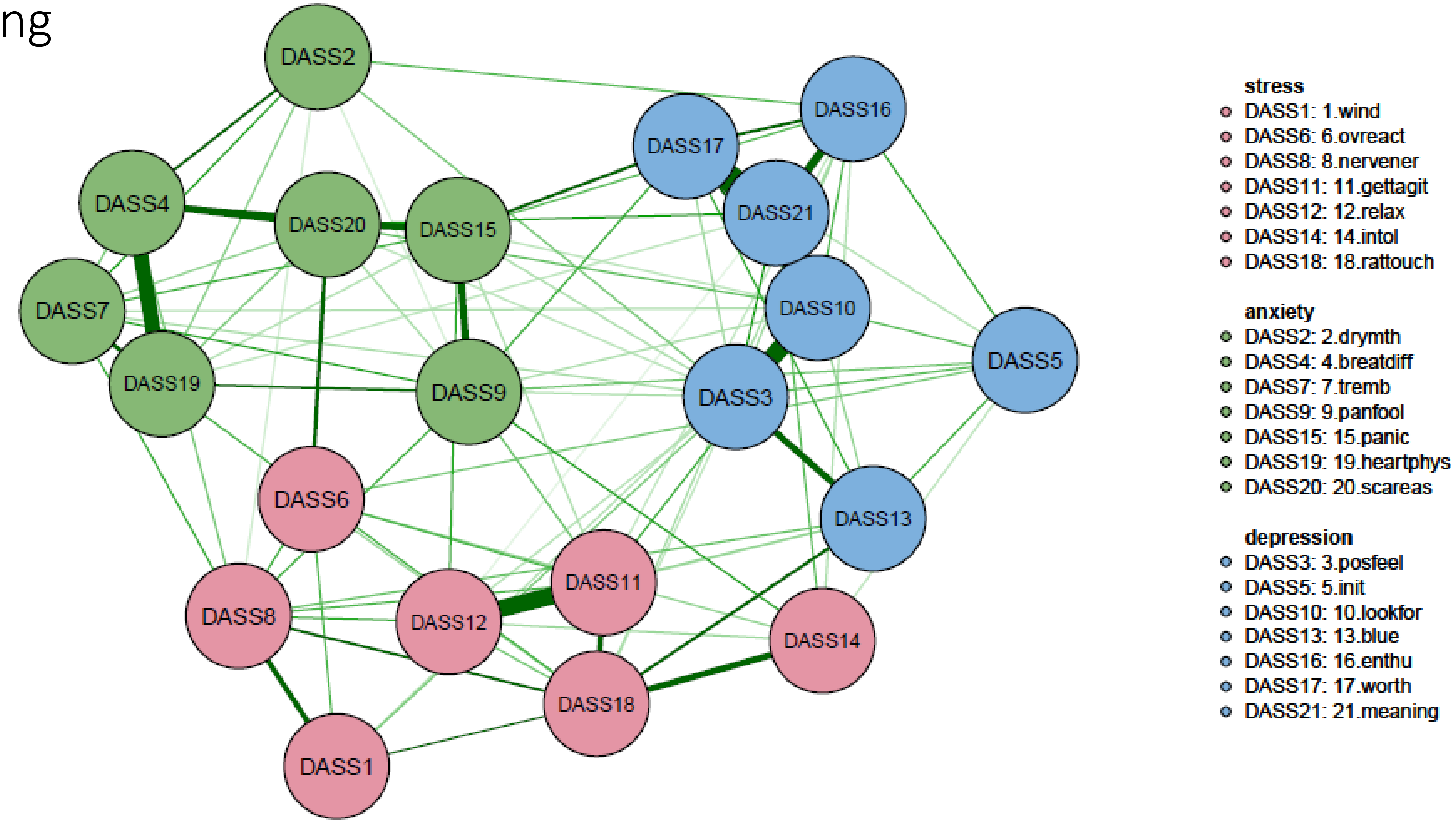
Preparação

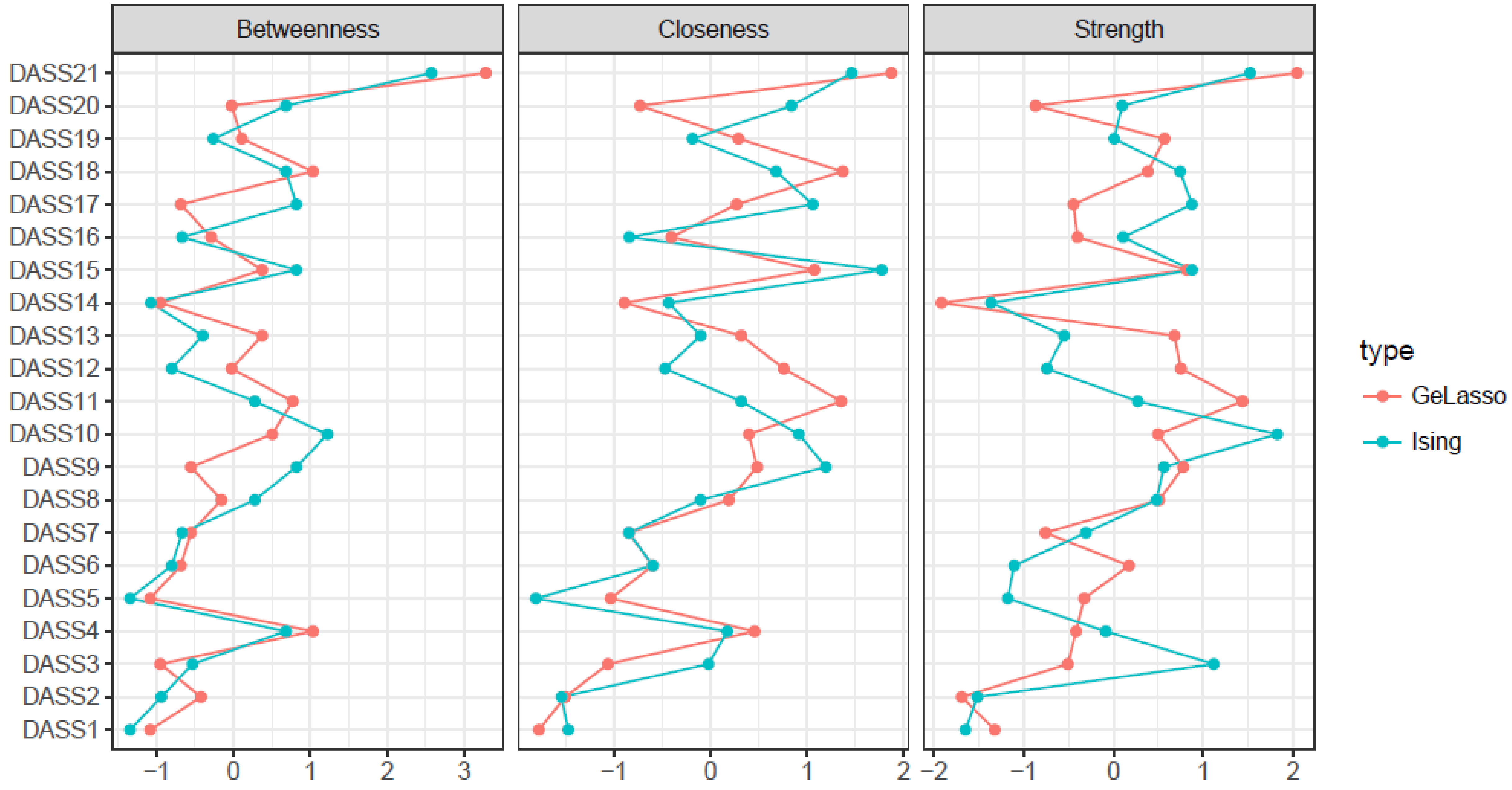
```
dass_sub<-dass[2:22]
View(dass_sub)
namesdass<-list("1.wind","2.drymth","3.posfeel","4.breatdiff","5.init","6.ovreact","7.tremb","8.nervener","9.panfool","10.lookfor","11.gettagit","12.relax","13.blue","14.intol","15.panic","16.enthu","17.worth","18.rattouch","19.heartphys","20.scareas","21.meaning")
dass_groups<-list("stress"=c(1,6,8,11,12,14,18),"anxiety"=c(2,4,7,9,15,19,20),"depression"=c(3,5,10,13,16,17,21))
```

GeLasso


DASS1
DASS8
DASS7
DASS19
DASS18
DASS4
DASS6
DASS13
DASS20
DASS14
DASS3
DASS12
DASS9
DASS11
DASS15
DASS2
DASS10
DASS21
DASS17
DASS5
DASS16
stress
DASS1: 1.wind
DASS6: 6.ovreact
DASS8: 8.nervener
DASS11: 11.gettagit
DASS12: 12.relax
DASS14: 14.intol
DASS18: 18.rattouch
anxiety
DASS2: 2.drymth
DASS4: 4.breatdiff
DASS7: 7.tremb
DASS9: 9.panfool
DASS15: 15.panic
DASS19: 19.heartphys
DASS20: 20.scareas
depression
DASS3: 3.posfeel
DASS5: 5.init
DASS10: 10.lookfor
DASS13: 13.blue
DASS16: 16.enthu
DASS17: 17.worth
DASS21: 21.meaning

Ising

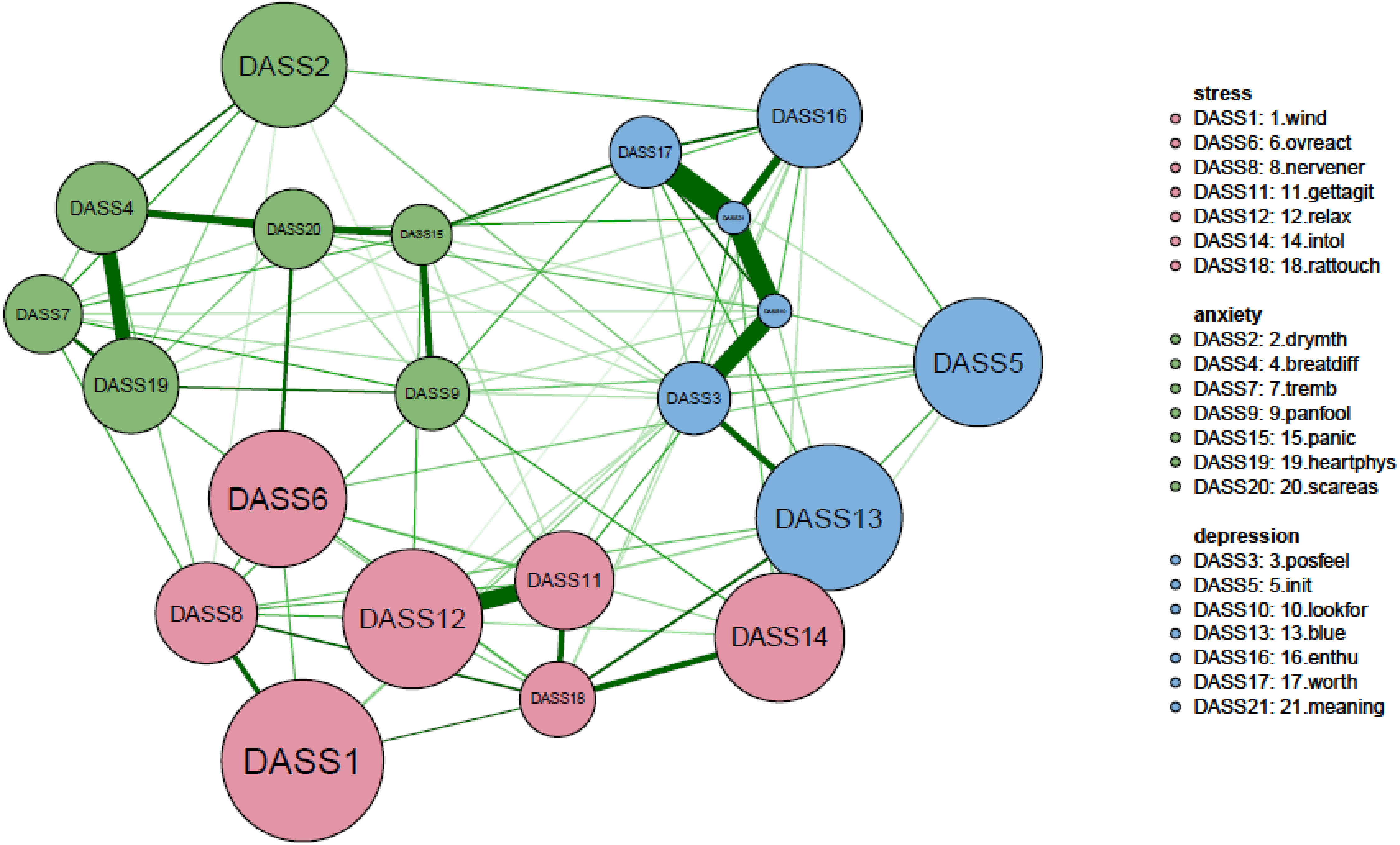

DASS2
DASS4
DASS20
DASS15
DASS7
DASS19
DASS9
DASS17
DASS16
DASS21
DASS10
DASS5
DASS3
DASS13
DASS6
DASS11
DASS8
DASS12
DASS14
DASS18
DASS1
stress
DASS1: 1.wind
DASS6: 6.ovreact
DASS8: 8.nervener
DASS11: 11.gettagit
DASS12: 12.relax
DASS14: 14.intol
DASS18: 18.rattouch
anxiety
DASS2: 2.drymth
DASS4: 4.breatdiff
DASS7: 7.tremb
DASS9: 9.panfool
DASS15: 15.panic
DASS19: 19.heartphys
DASS20: 20.scareas
depression
DASS3: 3.posfeel
DASS5: 5.init
DASS10: 10.lookfor
DASS13: 13.blue
DASS16: 16.enthu
DASS17: 17.worth
DASS21: 21.meaning



Betweenness
Closeness
Strength
DASS21
DASS20
DASS19
DASS18
DASS17
DASS16
DASS15
DASS14
DASS13
DASS12
DASS11
DASS10
DASS9
DASS8
DASS7
DASS6
DASS5
DASS4
DASS3
DASS2
DASS1
−1 0 1 2 3
−1 0 1 2
−2 −1 0 1 2
type
GeLasso
Ising

dass_ising$thresholds

```
> dass_ising$thresholds
     DASS1      DASS2      DASS3      DASS4      DASS5 
-0.1179269 -1.2356752 -2.8089300 -2.2411057 -1.1422524 
     DASS6      DASS7      DASS8      DASS9     DASS10 
-0.8712178 -2.6446057 -1.9478597 -2.7809815 -3.9904660 
    DASS11     DASS12     DASS13     DASS14     DASS15 
-2.0258820 -0.7975360 -0.6003909 -1.1090307 -3.1695024 
    DASS16     DASS17     DASS18     DASS19     DASS20 
-1.8677412 -2.8432269 -2.7238942 -2.1216984 -2.5878984 
    DASS21 
-4.0047676 
```


DASS2
DASS16
DASS17
DASS4
DASS20
DASS15
DASS7
DASS19
DASS9
DASS3
DASS5
DASS6
DASS13
DASS11
DASS8
DASS12
DASS14
DASS18
DASS1
stress
DASS1: 1.wind
DASS6: 6.ovreact
DASS8: 8.nervener
DASS11: 11.gettagit
DASS12: 12.relax
DASS14: 14.intol
DASS18: 18.rattouch
anxiety
DASS2: 2.drymth
DASS4: 4.breatdiff
DASS7: 7.tremb
DASS9: 9.panfool
DASS15: 15.panic
DASS19: 19.heartphys
DASS20: 20.scareas
depression
DASS3: 3.posfeel
DASS5: 5.init
DASS10: 10.lookfor
DASS13: 13.blue
DASS16: 16.enthu
DASS17: 17.worth
DASS21: 21.meaning

View(dass_cent$ShortestPaths)

Filter

	DASS1	DASS2	DASS3	DASS4
DASS1	list()	list(c(1, 8, 7, 2))	list(c(1, 3))	list(c(1, 8, 4))
DASS2	list(c(2, 7, 8, 1))	list()	list(c(2, 3))	list(c(2, 4))
DASS3	list(c(3, 1))	list(c(3, 2))	list()	list(c(3, 10, 21,
DASS4	list(c(4, 8, 1))	list(c(4, 2))	list(c(4, 20, 21, 10, 3))	list()
DASS5	list(c(5, 13, 18, 1))	list(c(5, 16, 2))	list(c(5, 3))	list(c(5, 9, 19,
DASS6	list(c(6, 1))	list(c(6, 20, 4, 2))	list(c(6, 20, 21, 10, 3))	list(c(6, 20, 4))
DASS7	list(c(7, 8, 1))	list(c(7, 2))	list(c(7, 3))	list(c(7, 19, 4))
DASS8	list(c(8, 1))	list(c(8, 7, 2))	list(c(8, 13, 3))	list(c(8, 4))

View(dass_ising$weiadj)

Filter

	DASS1	DASS2	DASS3	DASS4	DASS5	DASS6	DASS7
DASS4	0.0000000	0.7249200	0.0000000	0.0000000	0.0000000	0.0000000	0.36604
DASS5	0.0000000	0.0000000	0.4543805	0.0000000	0.0000000	0.3668149	0.00000
DASS6	0.4966041	0.0000000	0.0000000	0.0000000	0.3668149	0.0000000	0.00000
DASS7	0.0000000	0.6237433	0.2356706	0.3660434	0.0000000	0.0000000	0.00000
DASS8	0.8391341	0.1259954	0.0000000	0.3755290	0.0000000	0.5420260	0.55125
DASS9	0.0000000	0.1108908	0.0000000	0.0000000	0.3972706	0.0000000	0.61023
DASS10	0.2001959	0.0000000	1.4777947	0.0000000	0.4479508	0.0000000	0.21298

Redes de dados misturados (mixed)

- É comum ter dados de diferentes níveis de mensuração
- Gaussianos, contagens (discretas e positivas, dicotômicas, etc.)
- Número de vezes que procurou serviço de saúde
- Score em uma escala de qualidade de vida
- Gênero
- É preciso utilizar o modelo linear
- Método: generalized covariance matrices of mixed joint distributions

Journal of Statistical Software

MMMMMM YYYY, Volume VV, Issue II. http://www.jstatsoft.org/

mgm: Structure Estimation for time-varying Mixed Graphical Models in high-dimensional Data

Jonas M. B. Haslbeck   Lourens J. Waldorp

Submitted to the Annals of Applied Statistics

STRUCTURE ESTIMATION FOR MIXED GRAPHICAL MODELS IN HIGH-DIMENSIONAL DATA

By Jonas M. B. Haslbeck

Utrecht University

and

By Lourens J. Waldorp

View(smmix)

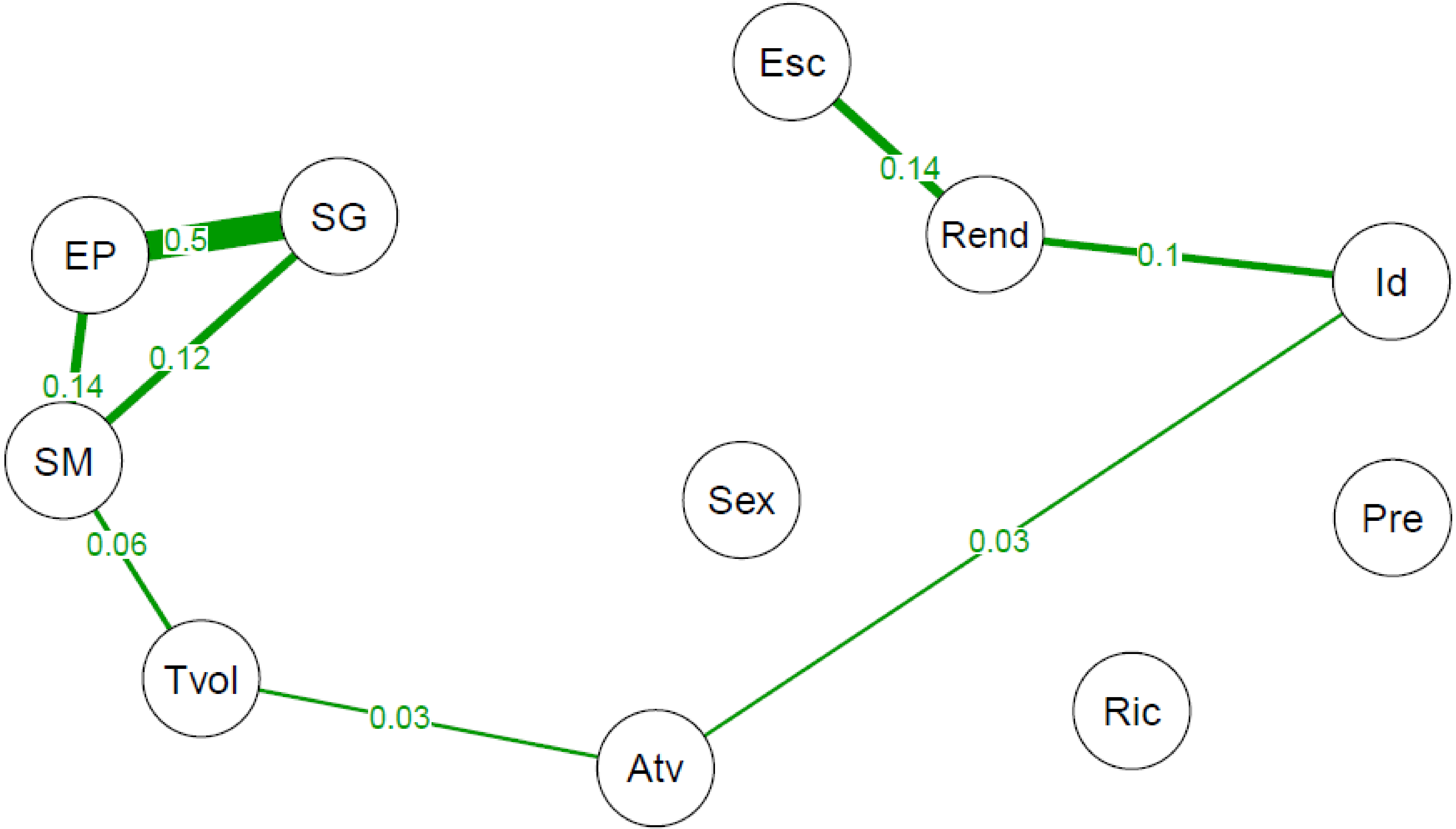
	Id	Sex	Esc	Atv	Ric	Rend	Tvol	Pre	SG	EP	SM
46	35	1	2	3	1	10000	2	2	-0.11863235	-0.56906658	0.2132730
48	32	1	2	1	1	2000	2	1	0.53416597	-0.16147631	-0.0509919
49	39	1	2	2	1	8000	2	1	-0.03733537	-0.28882954	0.5303768
53	23	1	2	2	1	2500	1	2	0.64731763	0.37319223	-0.1245692
57	26	1	0	3	1	730	2	1	0.06208173	-0.27076626	0.7565538
58	26	1	2	1	1	2000	2	1	0.01113756	0.35633705	0.3300596
61	30	1	2	1	1	2000	2	1	-1.16311943	-1.40868239	1.0479772
64	40	1	1	2	2	3500	1	1	0.39791164	1.04496906	-1.1893725

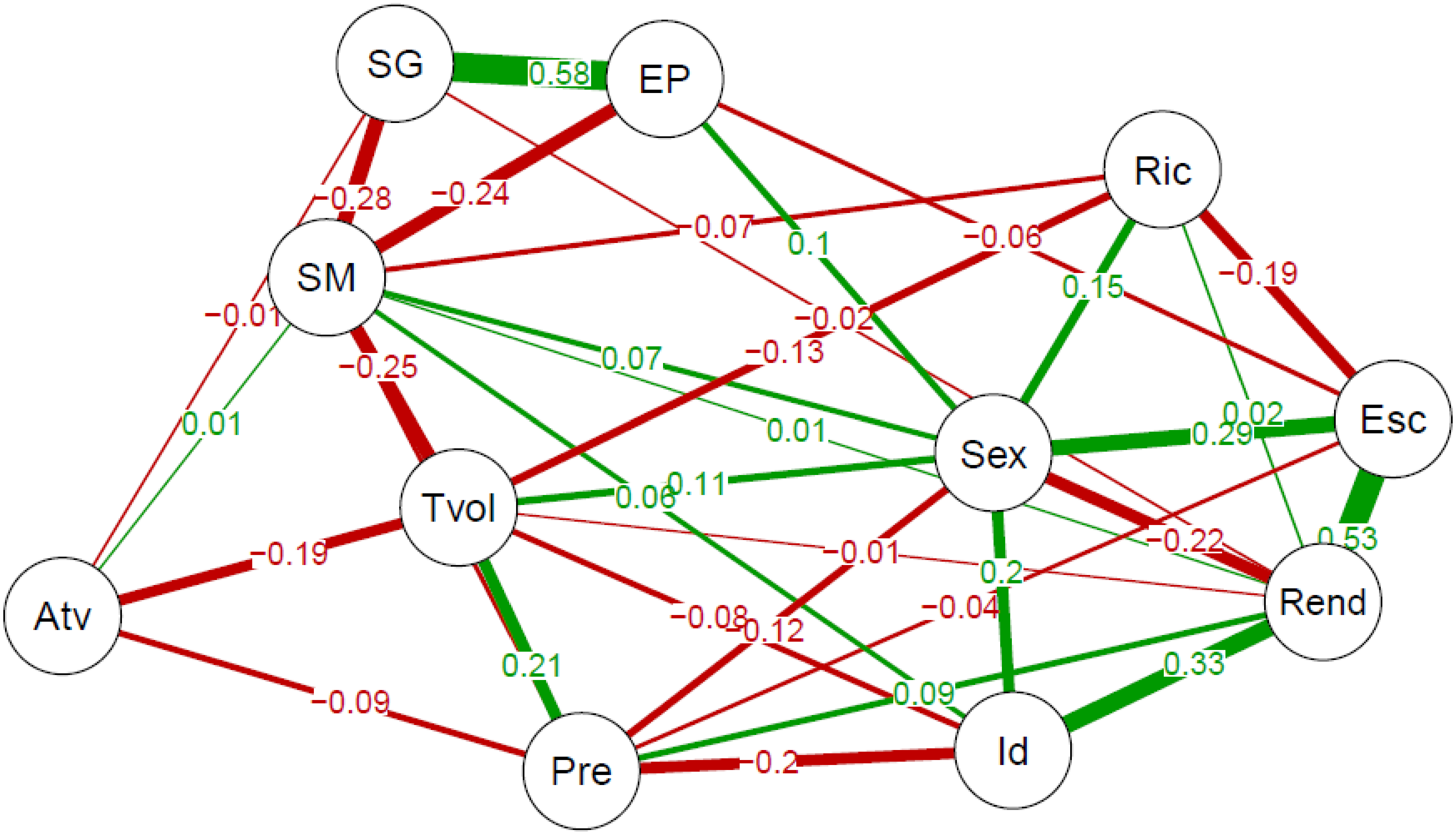
lm(formula = smmix$SM ~ smmix$Id + smmix$Sex + smmix$Esc + smmix$Atv + smmix$Ric + smmix$Rend + smmix$Tvol + smmix$Pre + smmix$SG + smmix$EP, data = smmix)

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.393e-01  3.440e-01   0.986 0.324800
smmix$Id     7.799e-03  4.248e-03   1.836 0.067320 .
smmix$Sex    1.722e-01  9.108e-02   1.890 0.059679 .
smmix$Esc   -2.056e-02  5.850e-02  -0.352 0.725448
smmix$Atv    4.492e-02  5.654e-02   0.794 0.427578
smmix$Ric   -1.376e-01  8.815e-02  -1.561 0.119619
smmix$Rend   5.535e-06  1.548e-05   0.358 0.720833
smmix$Tvol  -3.256e-01  8.939e-02  -3.642 0.000317 ***
smmix$Pre   -1.407e-01  8.989e-02  -1.565 0.118669
smmix$SG    -3.386e-01  6.120e-02  -5.533 6.72e-08 ***
smmix$EP    -2.657e-01  6.030e-02  -4.406 1.45e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6796 on 310 degrees of freedom
Multiple R-squared:  0.4617,    Adjusted R-squared:  0.4443
F-statistic: 26.59 on 10 and 310 DF,  p-value: < 2.2e-16
```

stepwise

```
Stepwise Model Path
Analysis of Deviance Table

Initial Model:
smmix$SM ~ smmix$Id + smmix$Sex + smmix$Esc + smmix$Atv + smmix$
Ric +
    smmix$Rend + smmix$Tvol + smmix$Pre + smmix$SG + smmix$EP

Final Model:
smmix$SM ~ smmix$Id + smmix$Sex + smmix$Ric + smmix$Tvol + smmix
$Pre +
    smmix$SG + smmix$EP


          Step Df   Deviance Resid. Df Resid. Dev       AIC
1                                  310   143.1766 -237.1633
2   - smmix$Esc  1 0.05706563      311   143.2337 -239.0354
3 - smmix$Rend  1 0.02766346      312   143.2613 -240.9734
4   - smmix$Atv  1 0.29391817      313   143.5552 -242.3155
```


Esc
0.14
Rend
0.1
Id
SG
EP
0.5
0.12
0.14
SM
Sex
Pre
0.06
0.03
Tvol
0.03
Ric
Atv


SG
EP
Ric
SM
Esc
Sex
Tvol
Rend
Atv
Pre
Id
0.58
−0.28
−0.24
−0.07
0.1
−0.06
−0.19
0.15
−0.01
−0.02
0.07
−0.13
−0.25
0.01
0.01
0.02
0.29
0.11
0.06
−0.22
0.53
−0.19
−0.01
0.2
−0.08
−0.12
−0.04
0.21
0.33
−0.09
0.09
−0.2

Exemplo banco autismo

sm_sub | smmix$Pre | smmix$Sex | autism_data | autism_

Filter

.of.Housing	data.Workinghours	data.Satisfaction..Treatment	type	lev	colnames
1	0	3.000000	c	2	Gender
1	0	2.000000	g	1	IQ
1	0	4.000000	c	3	Integratio
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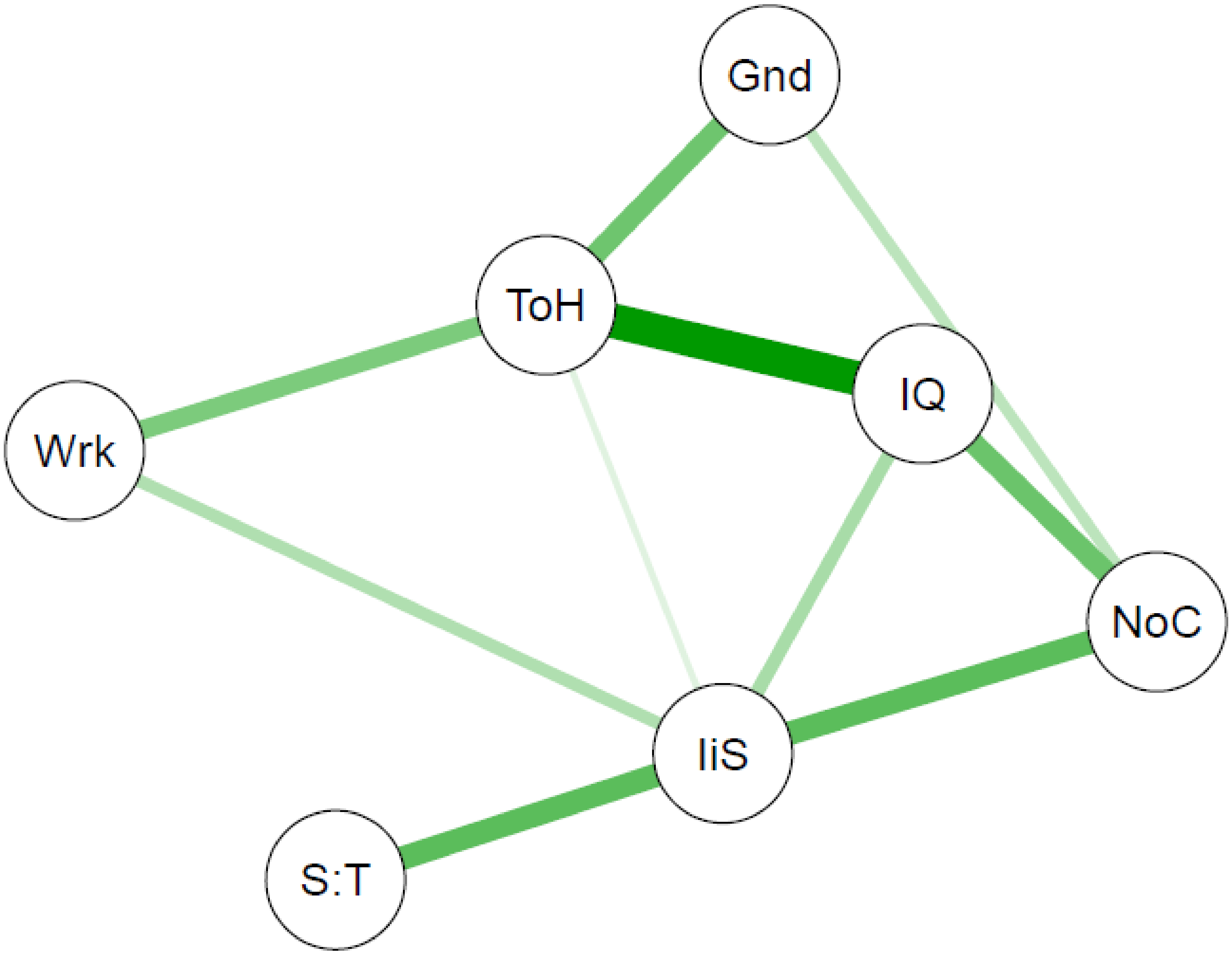
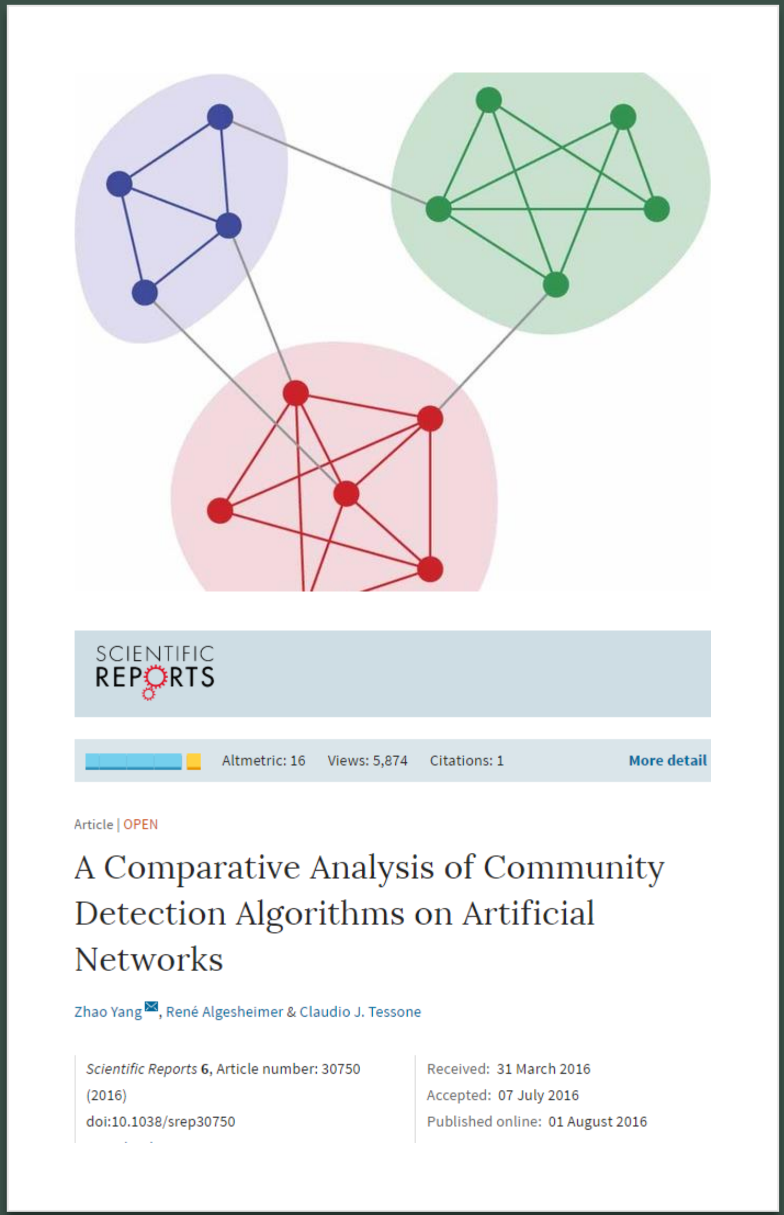


Gnd: Gender
IQ: IQ
IiS: Integration in Society
NoC: No of Comorbidities
ToH: Type of Housing
Wrk: Workinghours
S:T: Satisfaction: Treatment



SCIENTIFIC REPORTS

Article | OPEN

A Comparative Analysis of Community Detection Algorithms on Artificial Networks

Zhao Yang, René Algesheimer & Claudio J. Tessone

Scientific Reports 6, Article number: 30750 (2016)
doi:10.1038/srep30750

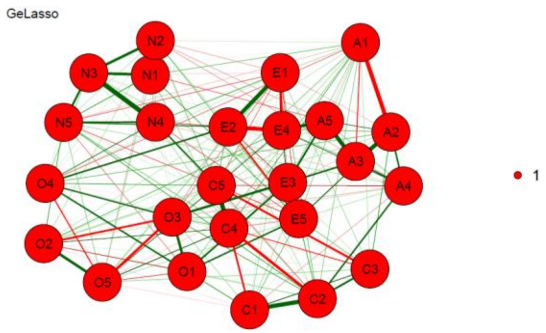
Received: 31 March 2016
Accepted: 07 July 2016
Published online: 01 August 2016

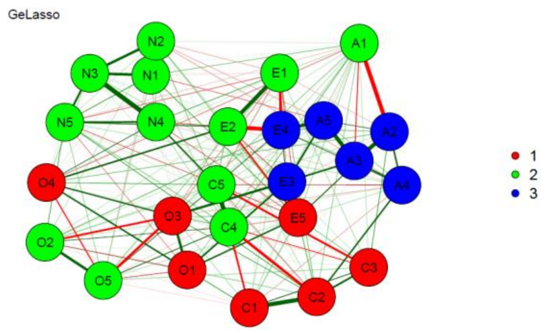
Análise de comunidades

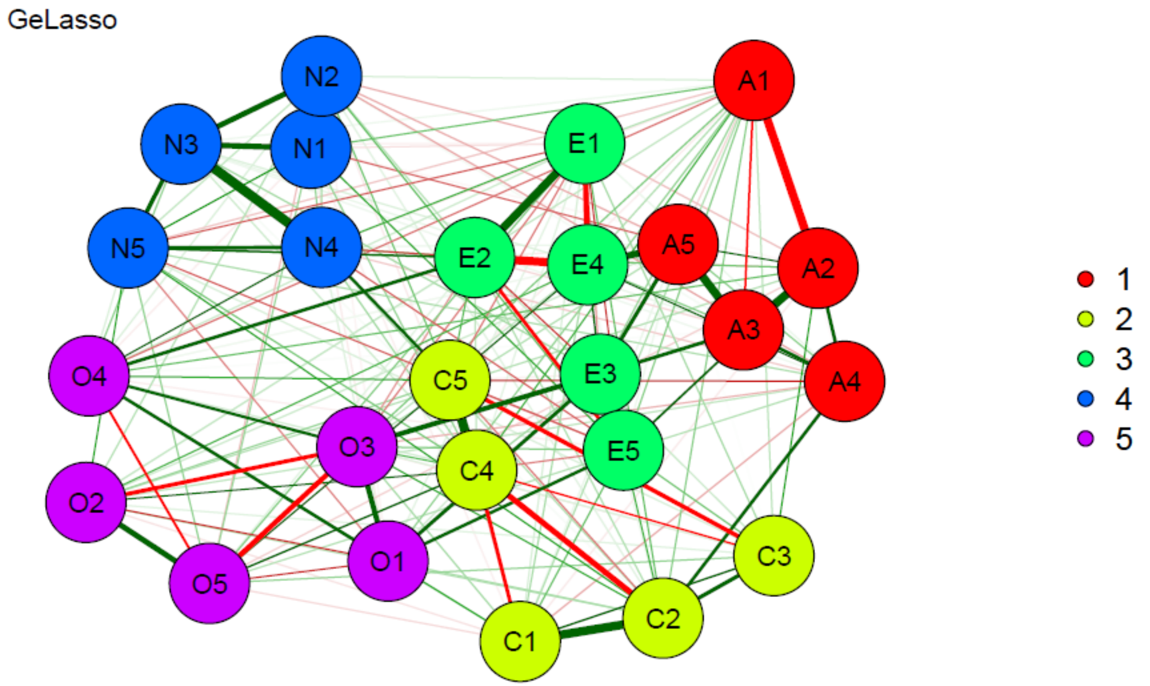
- Existem subgrupos de variáveis ou observações na rede?
- Três métodos mais populares:
- Waltrap – parte de passos aleatórios e vai decompondo o conjunto em N-1 comunidades, calculando a distância das arestas entre e dentre comunidades
- Spinglass – baseado também em um modelo do ferromagnetismo (Potts), baseado na ideia de “spin state” e fluxo de energia
- **Multinível** – decomposição e permutação dos vértices até encontrar a solução que otimiza a modularidade (divisão em módulos ou grupos)

Desempenho

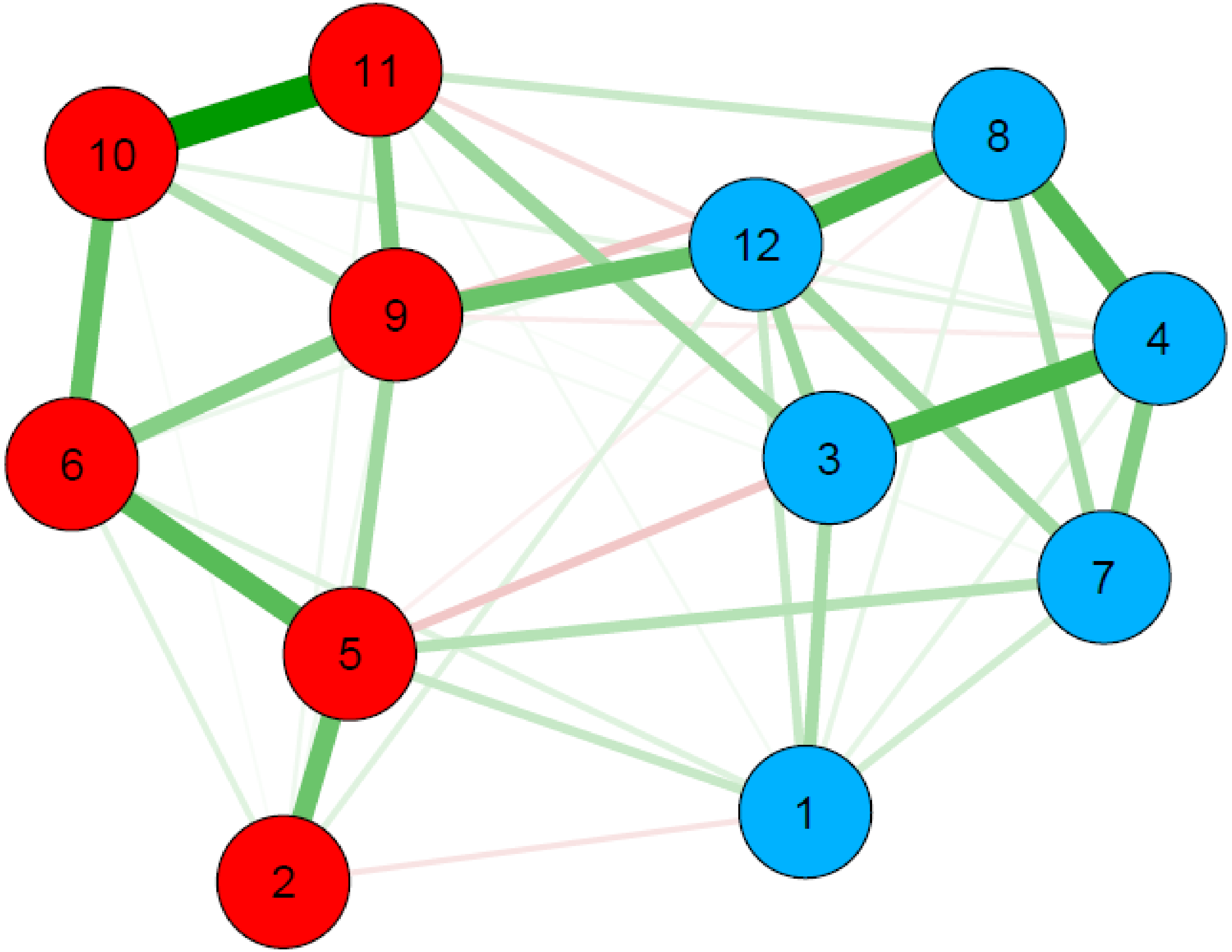
- Walktrap = 1 comunidade
- Spinglass = 3 comunidades
- Louvain = 5 comunidades*





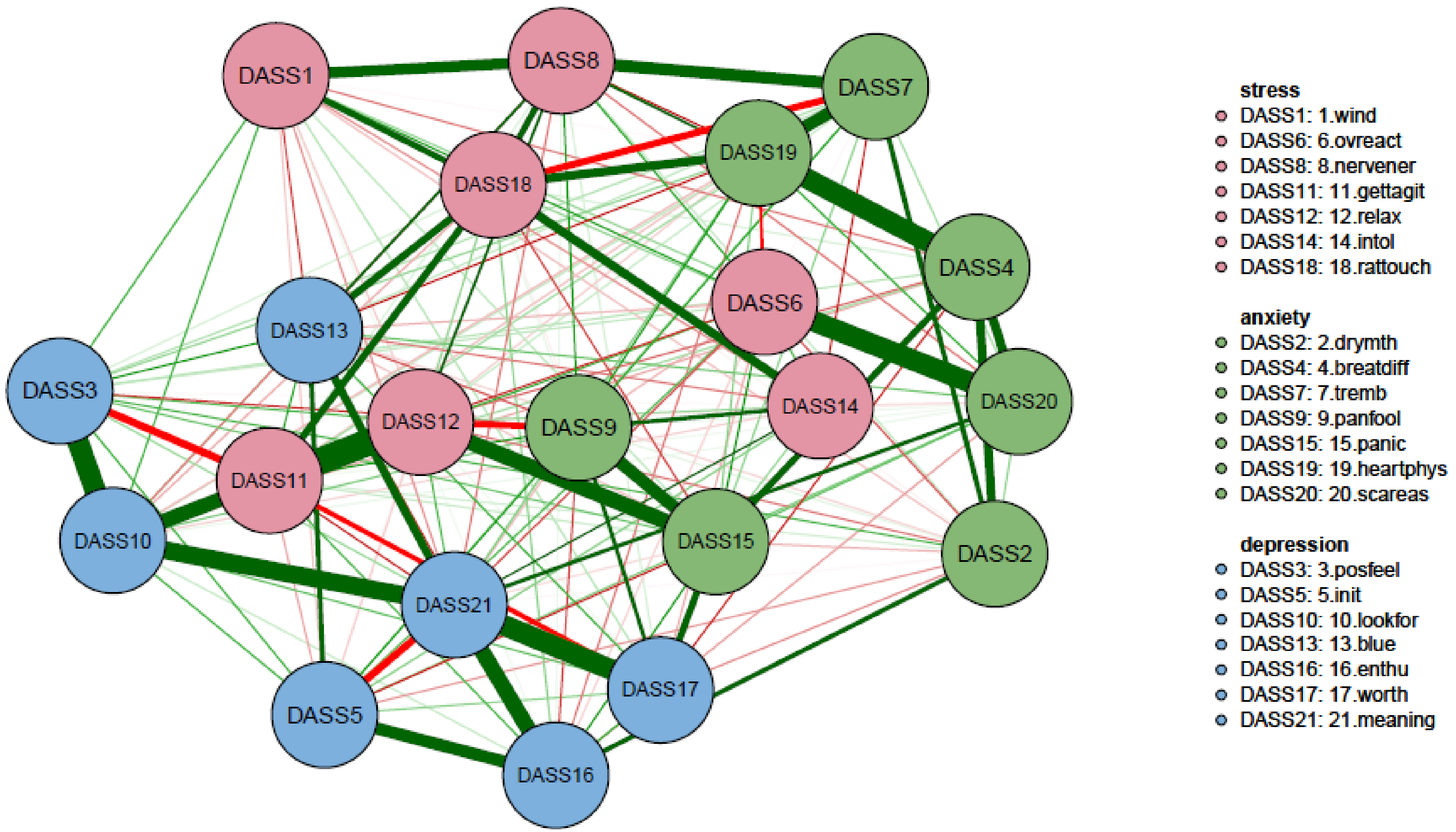


QSG – 1 ou 2 “clusters”



1
- 2: Suas preocupações o fazem perder o sono
- 5: Tem notado que está agoniado
- 6: Tem sensação de não superar dificuldades
- 9: Tem se sentido pouco feliz e deprimido
- 10: Tem perdido confiança em si mesmo
- 11: Tem pensado que não serve para nada

2
- 1: Tem podido concentrar−se no que faz
- 3: Tem sentido que tem papel útil na vida
- 4: Tem sido capaz de tomar decisões
- 7: Tem sido capaz de desfrutar de atividades
- 8: Tem sido capaz de enfrentar problemas
- 12: Sente−se razoavelmente feliz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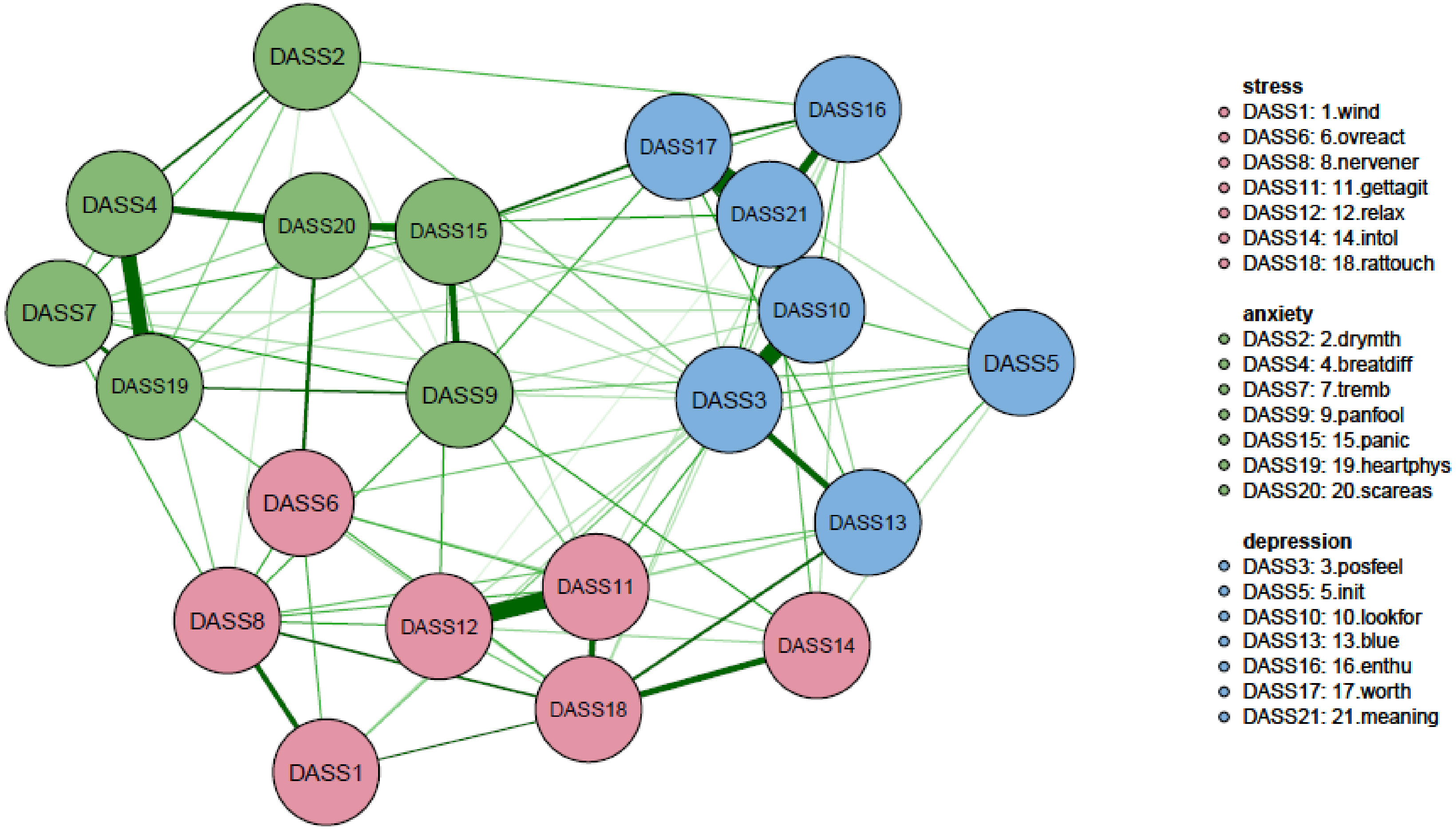
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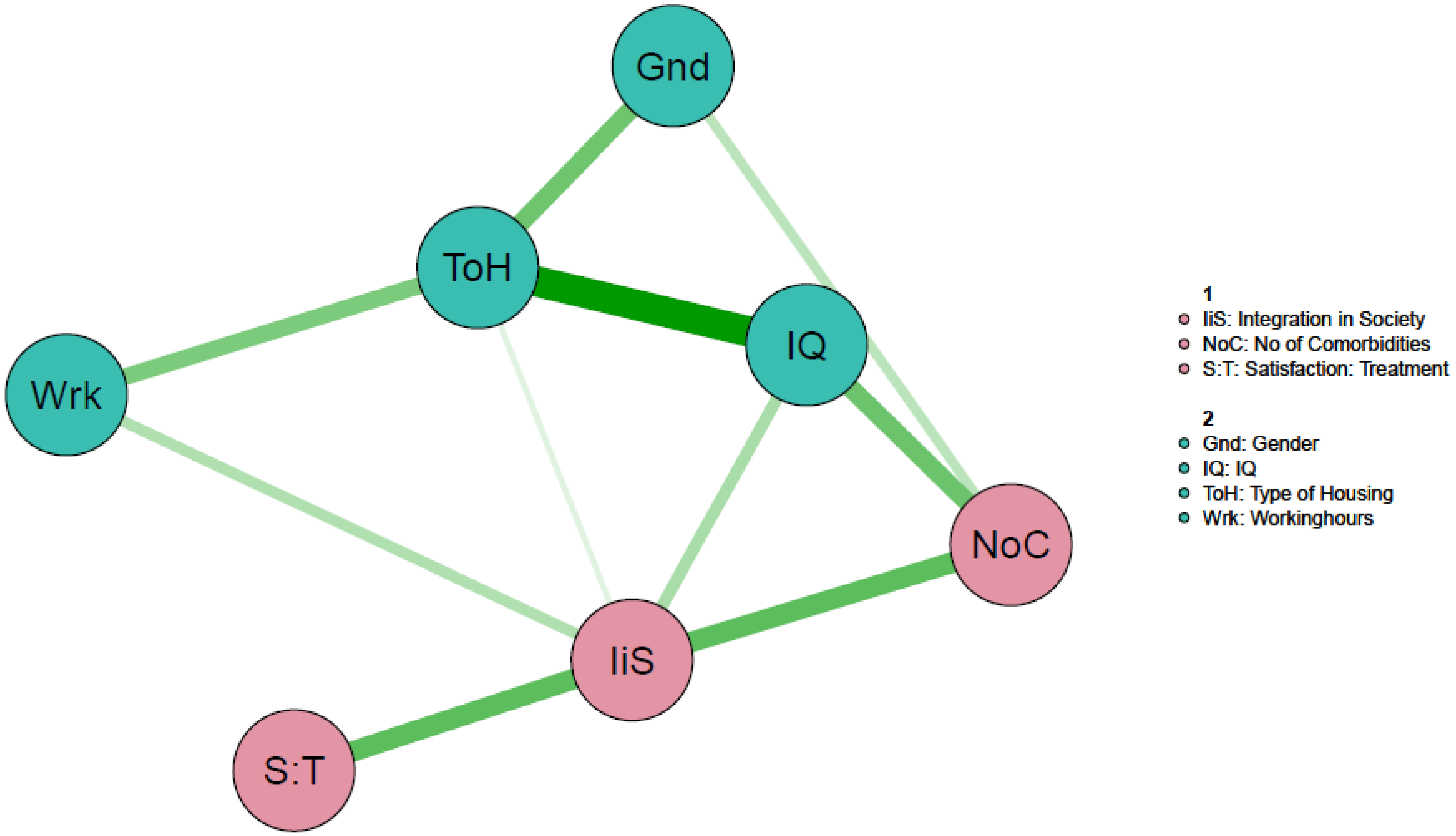
DASS21: 21.meaning

Satisfação tratamento - autismo



Comparação de redes

Comparing network structures on three aspects: A permutation test

Working Paper · March 2017

DOI: 10.13140/RG.2.2.29455.38569

7 authors, including:

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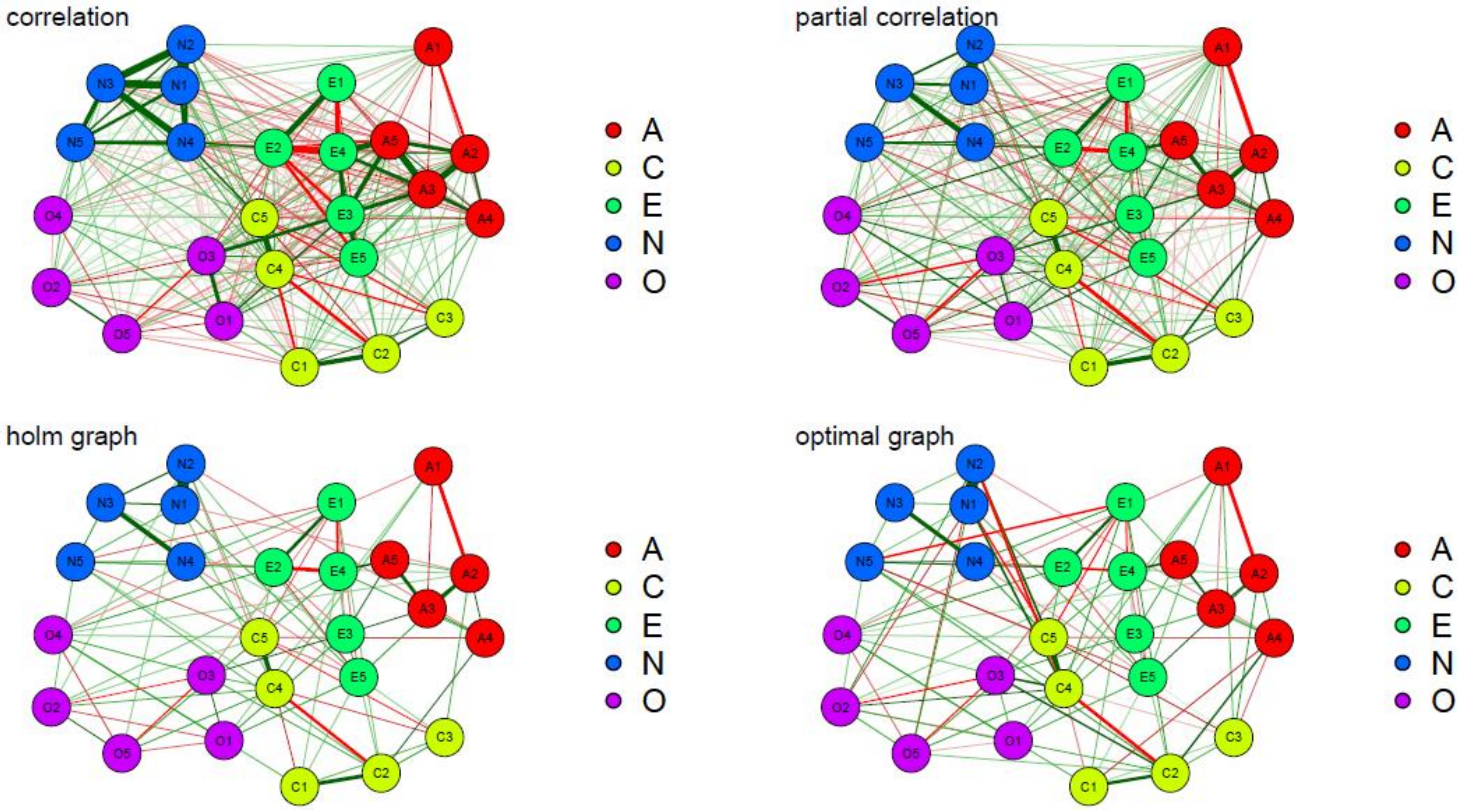
Denny Borsboom
University of Amsterdam


correlation
partial correlation
holm graph
optimal graph
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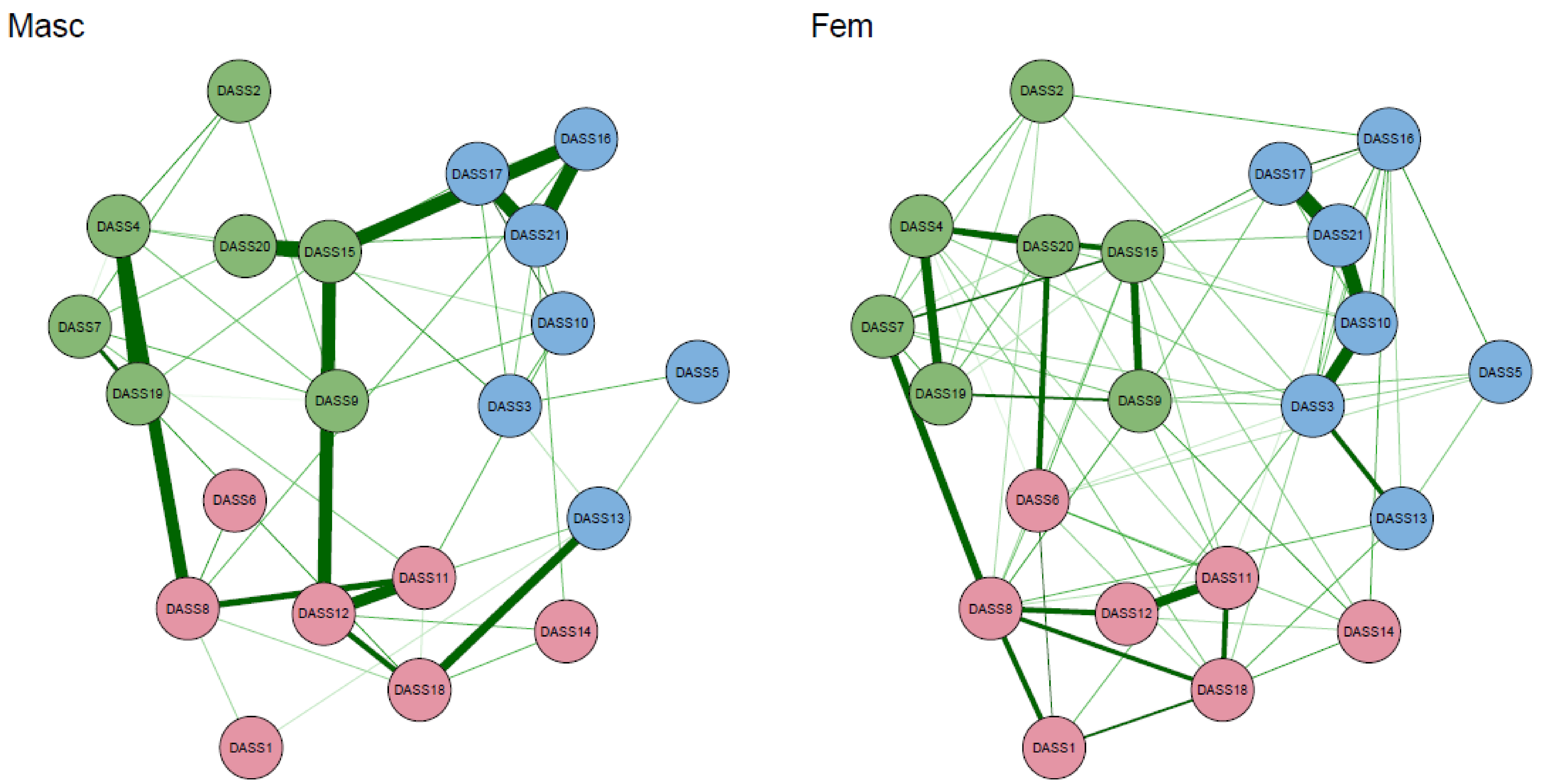
- 175 homens
- 466 mulheres

- Variância estrutural
- Variância da força global
- Variância de arestas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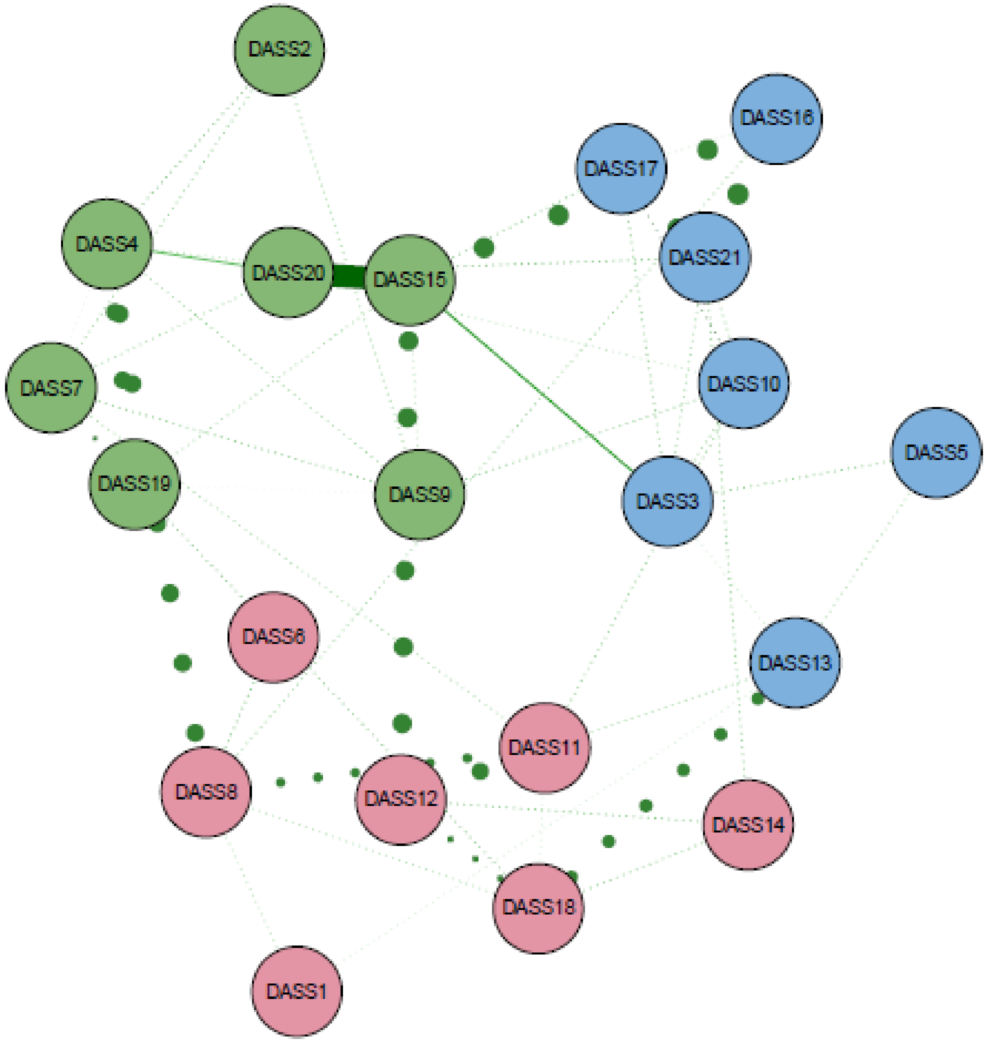
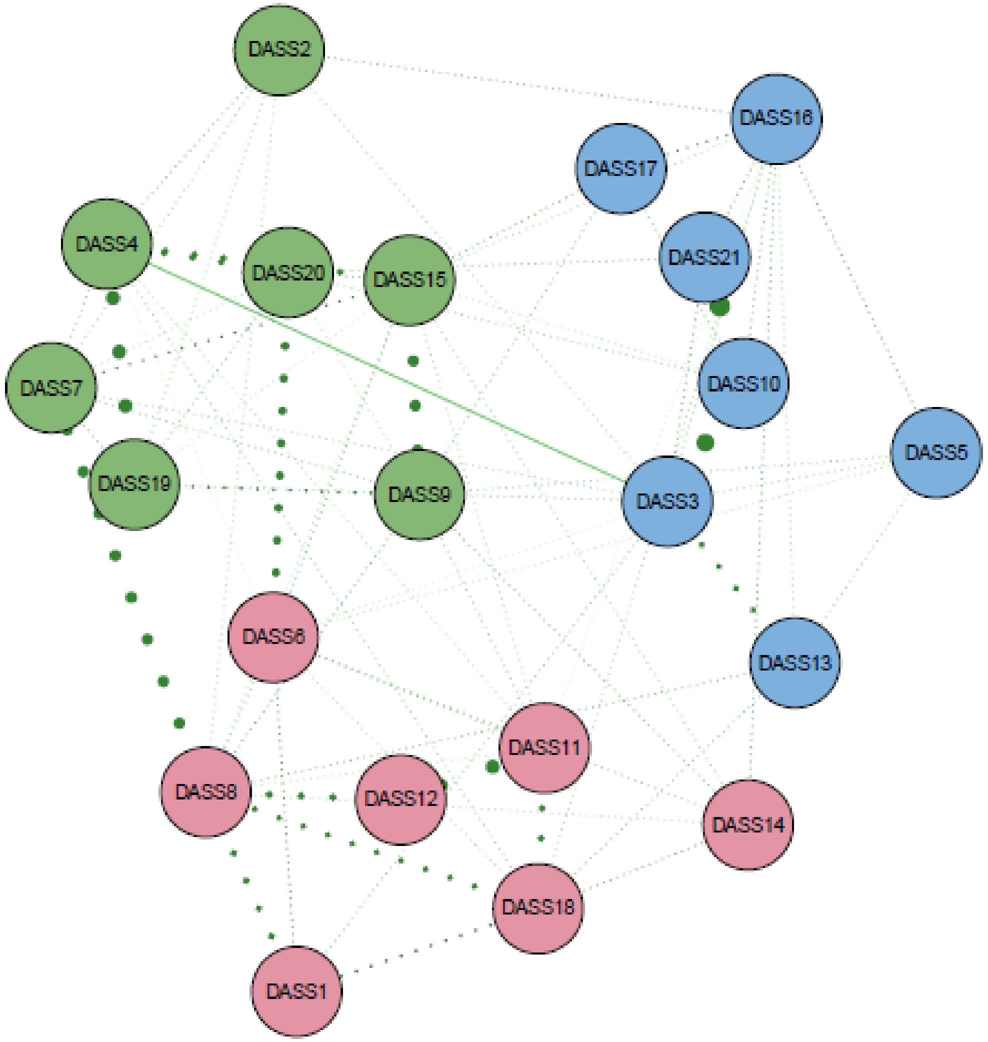
```
> dass_nct$nwinv.real
[1] 1.413075
> dass_nct$nwinv.perm
 [1]  1.750312  1.052788  1.591741 81.859487  1.089525
 [6]  1.578179  1.334670  1.237239  1.487468  1.357517
> dass_nct$nwinv.pval
[1] 0.5
> dass_nct$glstrinv.sep
[1] 45.50014 37.04170
> dass_nct$glstrinv.real
[1] 8.45844
> dass_nct$glstrinv.perm
 [1]  11.266876  19.126481  15.865341 323.624139  17.840545
 [6]   4.235305  13.926695  23.694099   4.963055  15.847453
> dass_nct$glstrinv.pval
[1] 0.8
```

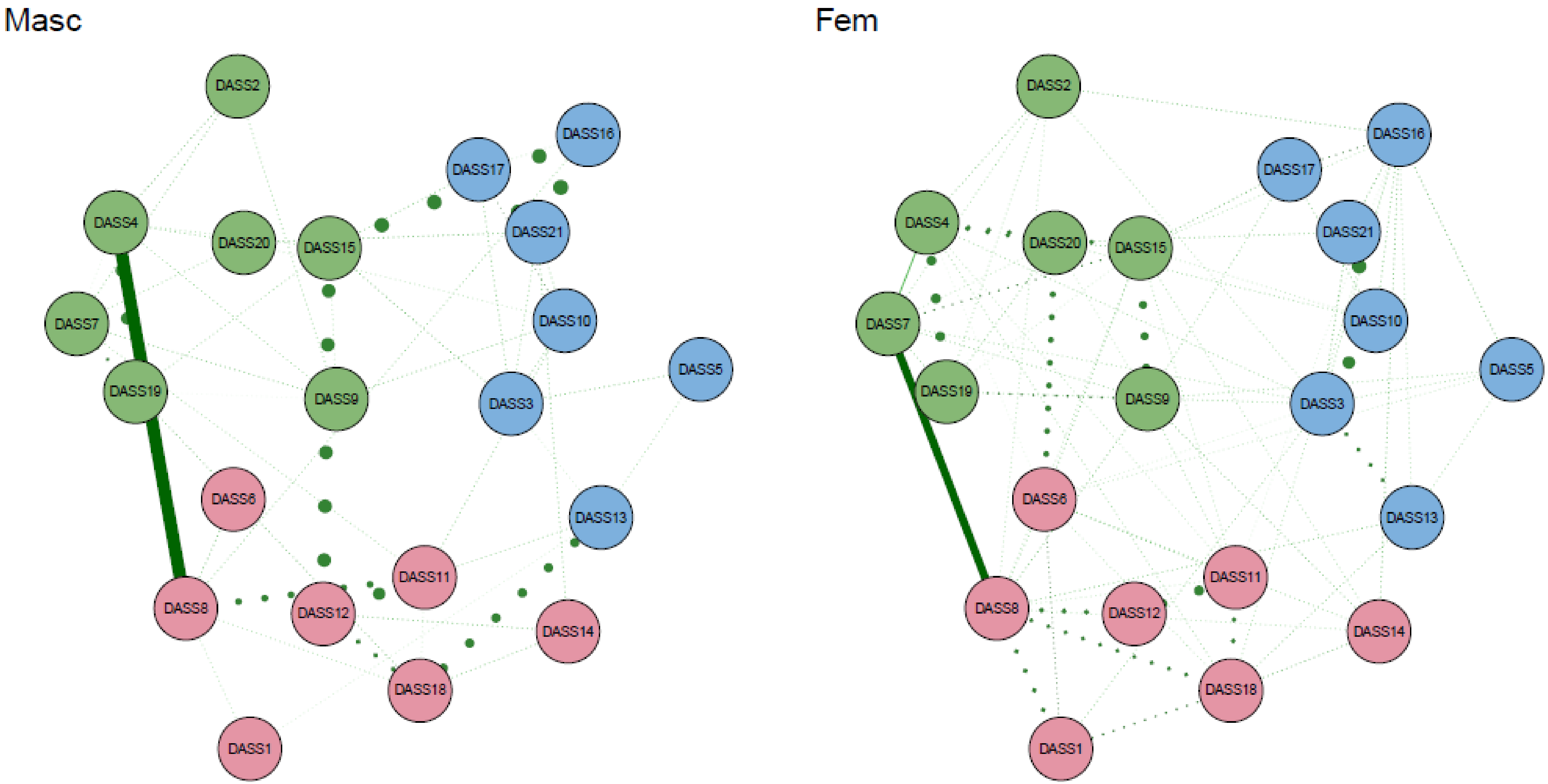
Aretas testadas – 3 e 4, 4 e 8

Masc



Fem

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Estabilidade da rede

Jan 2017

Estimating Psychological Networks and their Accuracy: A Tutorial Paper

Sacha Epskamp, Denny Borsboom and Eiko I. Fried
Department of Psychology, University of Amsterdam

Abstract

The usage of *psychological networks* that conceptualize behaviour as a complex interplay of psychological and other components has gained increasing popularity in various research fields. While prior publications have tackled

Predição de vértices em uma rede

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Predictability in Network Models

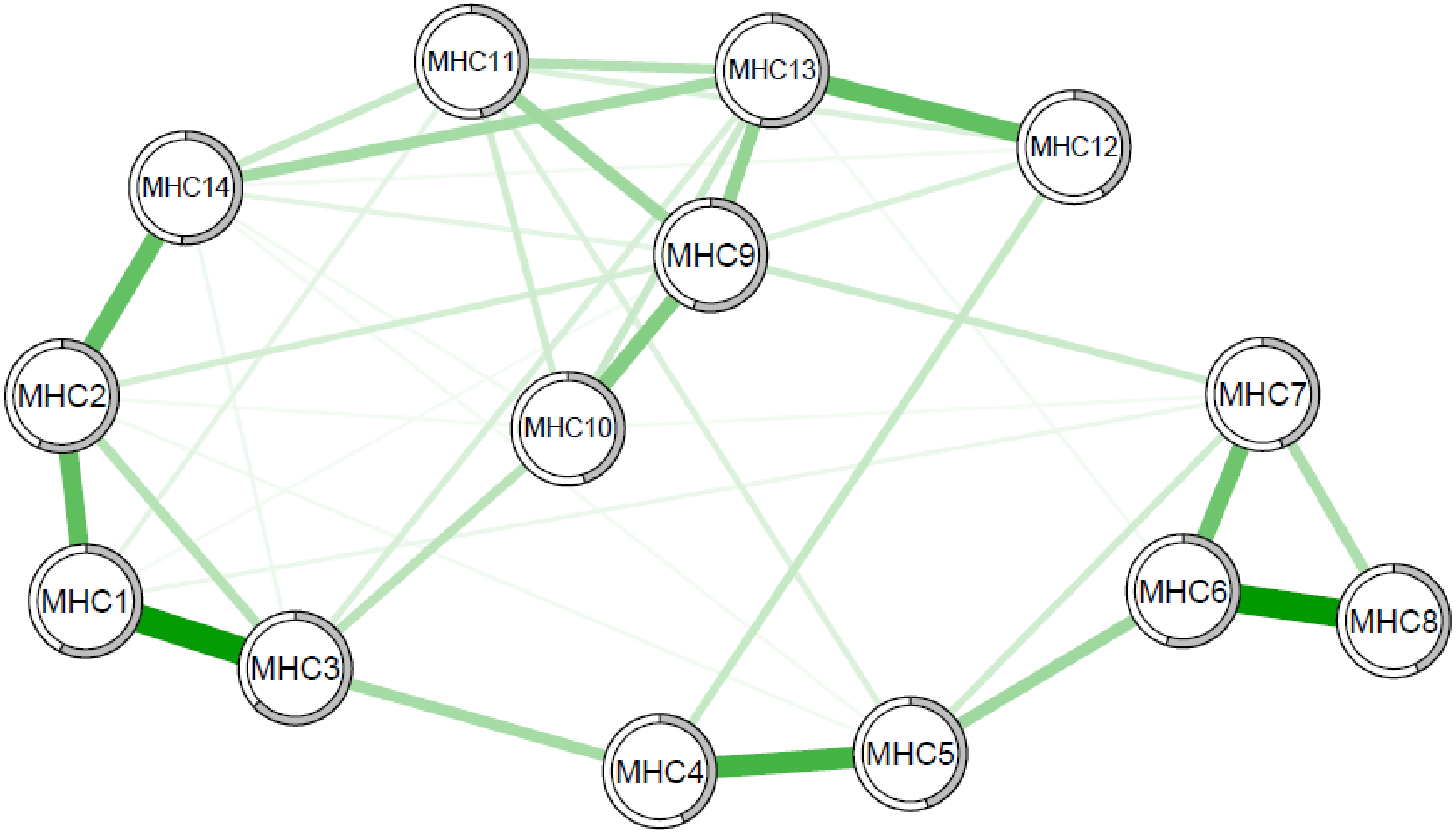
October 31, 2016

By Jonas Haslbeck - r

(This article was first published on Jonas Haslbeck - r, and kindly contributed to R-bloggers)

```
> pred_mhc<-predict(fit_mhc,mhc,error.continuous = "VarExpl")
> pred_mhc$error
   Variable Error ErrorType
1      MHC1 0.577   VarExpl
2      MHC2 0.570   VarExpl
3      MHC3 0.631   VarExpl
4      MHC4 0.428   VarExpl
5      MHC5 0.448   VarExpl
6      MHC6 0.548   VarExpl
7      MHC7 0.441   VarExpl
8      MHC8 0.428   VarExpl
9      MHC9 0.551   VarExpl
10    MHC10 0.451   VarExpl
11    MHC11 0.468   VarExpl
12    MHC12 0.408   VarExpl
13    MHC13 0.534   VarExpl
14    MHC14 0.511   VarExpl
```

mean(pred_mhc$error$Error) [1] 0.4995714



Modelos de rede de variáveis latentes

Psychometrika
pp 1–24

Generalized Network Psychometrics: Combining Network and Latent Variable Models

Authors
Authors and affiliations

Sacha Epskamp, Mijke Rhemtulla, Denny Borsboom

Article

First Online: 13 March 2017

DOI: 10.1007/s11336-017-9557-x

Cite this article as:
Epskamp, S., Rhemtulla, M. & Borsboom, D. Psychometrika (2017). doi:10.1007/s11336-017-9557-x

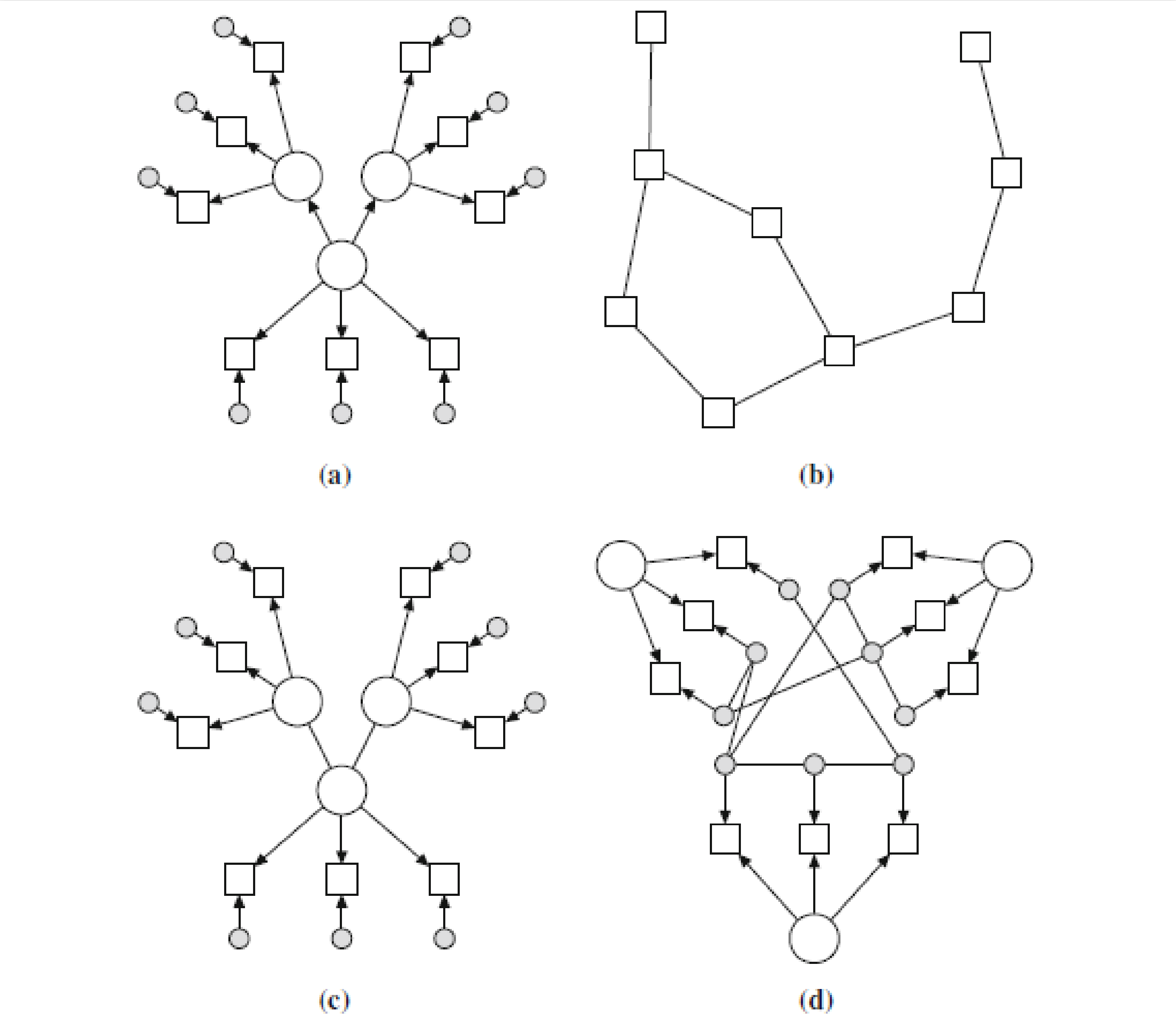
PSYCHOMETRIKA
DOI: 10.1007/s11336-017-9557-x

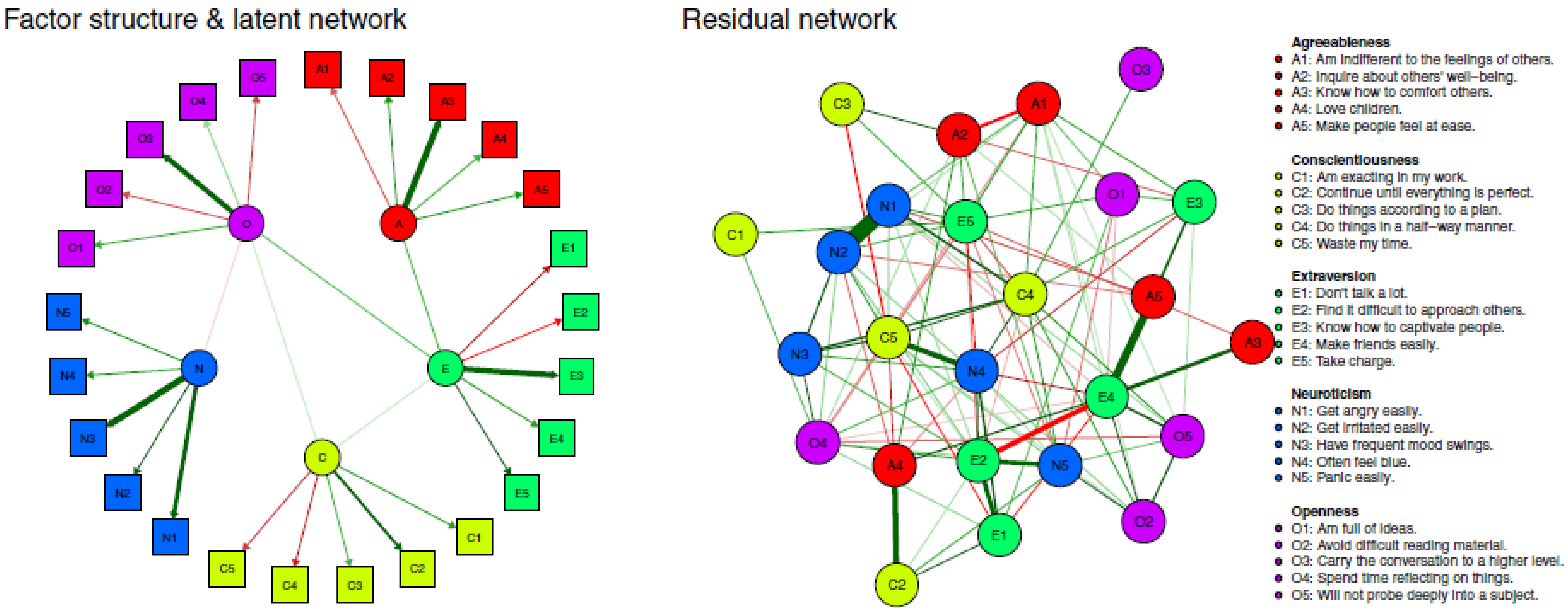
GENERALIZED NETWORK PSYCHOMETRICS: COMBINING NETWORK AND LATENT VARIABLE MODELS

SACHA EPSKAMP, MIJKE RHEMTULLA AND DENNY BORSBOOM
UNIVERSITY OF AMSTERDAM

Casos especiais de SEM

- a) SEM
- b) Netowrk
- c) Latent Network
- d) Residual Network




Factor structure & latent network
Residual network
Agreeableness
A1: Am indifferent to the feelings of others.
A2: Inquire about others' well–being.
A3: Know how to comfort others.
A4: Love children.
A5: Make people feel at ease.
Conscientiousness
C1: Am exacting in my work.
C2: Continue until everything is perfect.
C3: Do things according to a plan.
C4: Do things in a half–way manner.
C5: Waste my time.
Extraversion
E1: Don't talk a lot.
E2: Find it difficult to approach others.
E3: Know how to captivate people.
E4: Make friends easily.
E5: Take charge.
Neuroticism
N1: Get angry easily.
N2: Get irritated easily.
N3: Have frequent mood swings.
N4: Often feel blue.
N5: Panic easily.
Openness
O1: Am full of ideas.
O2: Avoid difficult reading material.
O3: Carry the conversation to a higher level.
O4: Spend time reflecting on things.
O5: Will not probe deeply into a subject.