Psychological Network Analysis:
A (gentle) introduction

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Looking at systems as networks
Common language


Looking at systems as networks
Common language
Psychological network models

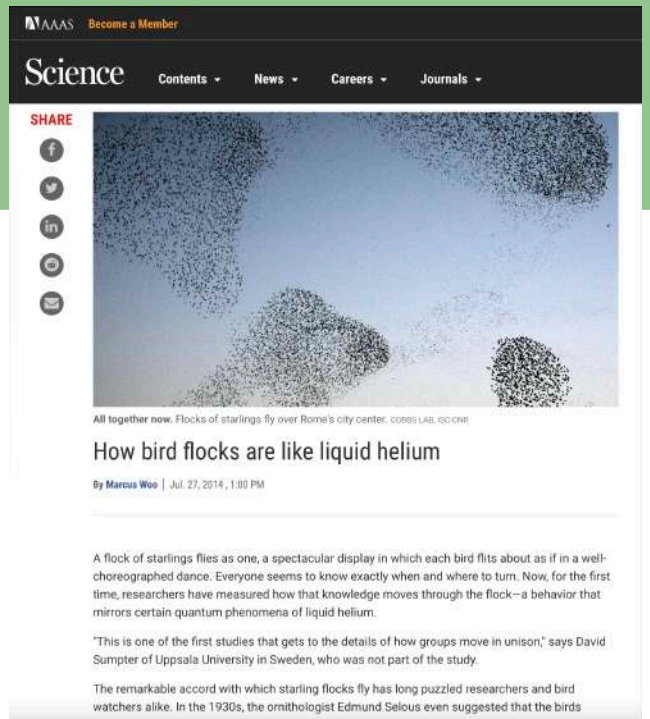

Looking at systems as networks
Common language
Psychological network models
Estimation
Accuracy
Centrality
Tutorial

A Network manifesto

- Understand emergent behavior (decentralized!)
  - No need to know the precise behavior to understand how collective patterns emerge.

A Network manifesto

- It gives you a common language across sciences
- Same properties in across different systems



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All together now. Flocks of starlings fly over Rome's city center. COBBS LAB, ISC-CNR

How bird flocks are like liquid helium

By Marcus Woo | Jul. 27, 2014 , 1:00 PM

A flock of starlings flies as one, a spectacular display in which each bird flits about as if in a well-choreographed dance. Everyone seems to know exactly when and where to turn. Now, for the first time, researchers have measured how that knowledge moves through the flock—a behavior that mirrors certain quantum phenomena of liquid helium.

"This is one of the first studies that gets to the details of how groups move in unison," says David Sumpter of Uppsala University in Sweden, who was not part of the study.

The remarkable accord with which starling flocks fly has long puzzled researchers and bird watchers alike. In the 1930s, the ornithologist Edmund Selous even suggested that the birds

How to study complex systems?

Complex system = many elements interacting with each other

Tools:

- Agent-based modelling
- Dynamic sytems
- Networks

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- **Networks ← today's topic**

How to study complex systems?

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Tools:

- Agent-based modelling
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- **Networks ← today's topic**

With networks you empasize the interacting between elements in the system.

What are networks?

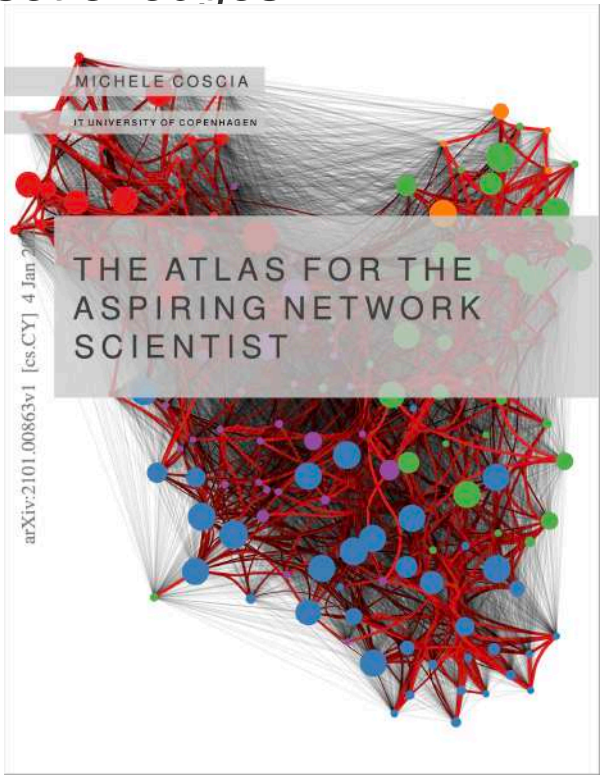
A network is a set of nodes connected by a set of edges

A node represents an entity:

- People
- Cities
- Symptoms
- Train stations

An edge represents a relationship:

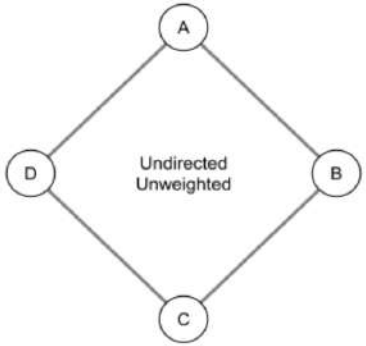
- Distance
- Causality
- Interaction
- Friendship

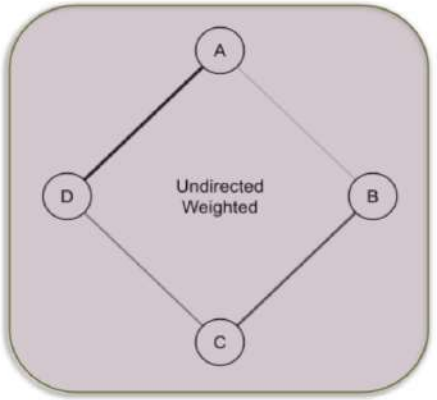


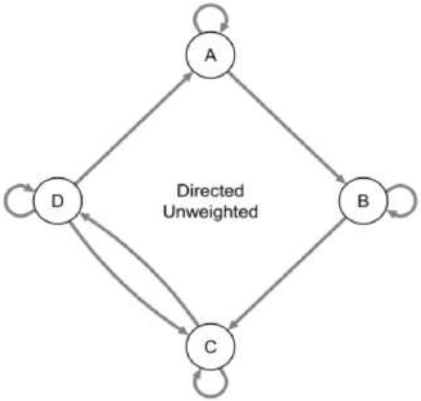
What kind of networks are there?

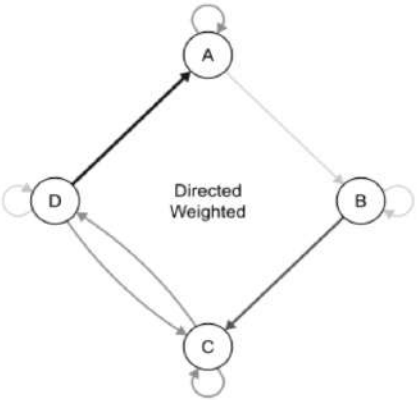
Edges can be..

- Weighted or unweighted
- Directed or undirected





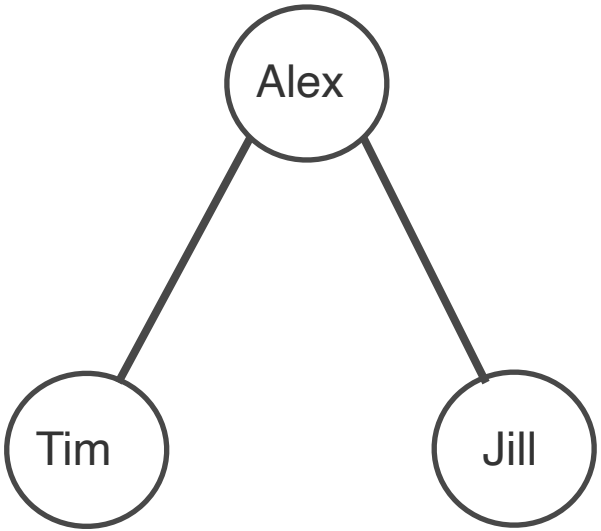




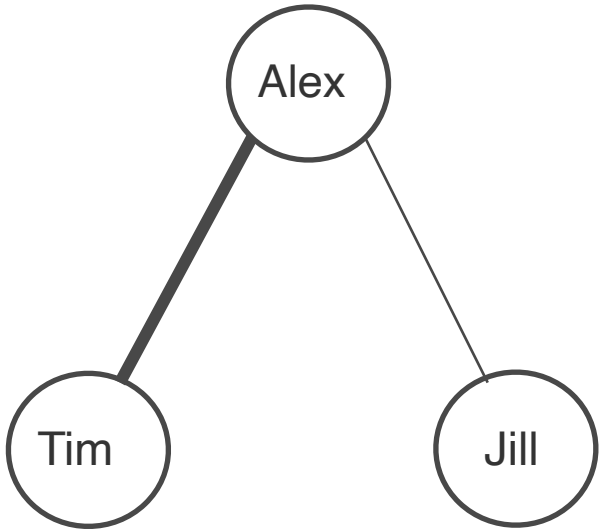
Edge weights

A network can be weighted or unweighted

unweighted

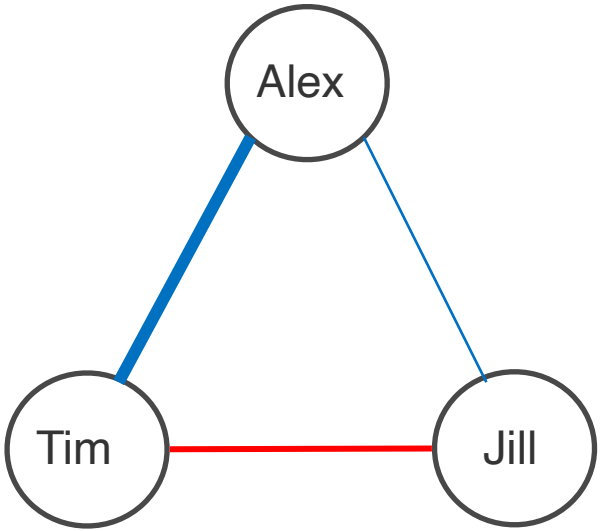


weighted



Edge sign

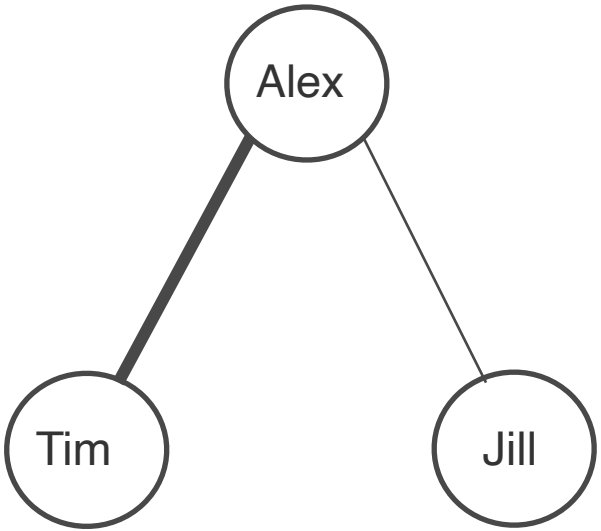
A network can have positive and negative edges



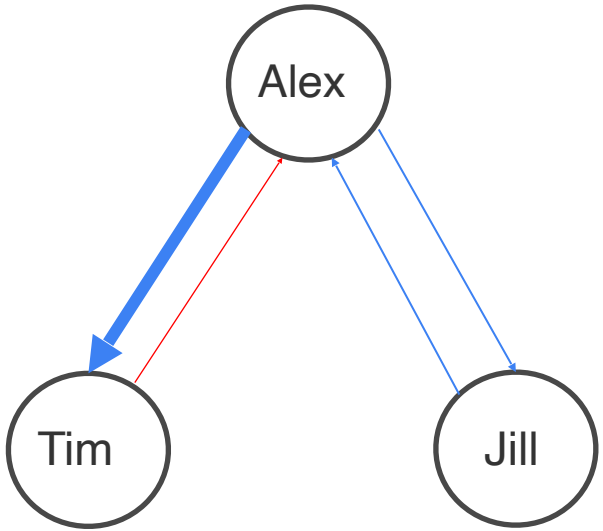
Edge direction

A network can be directed or undirected

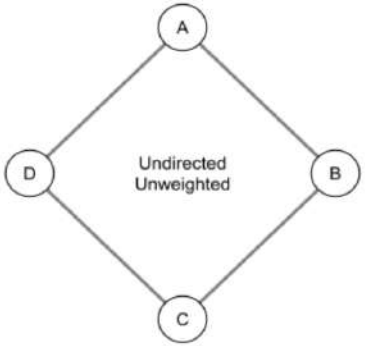
Undirected

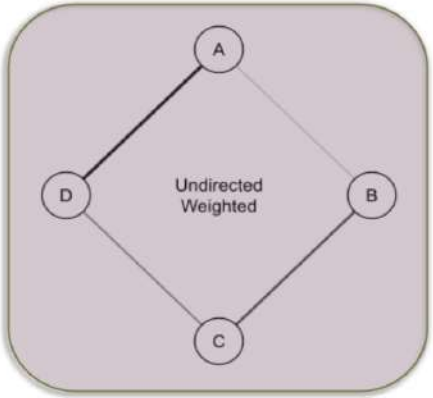


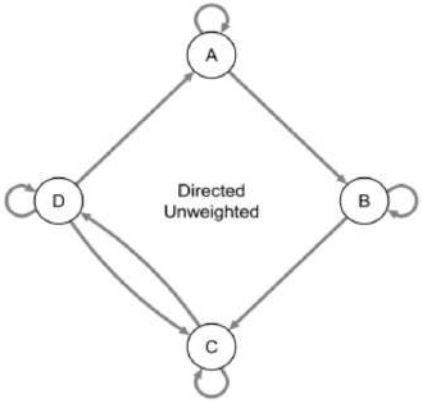
Directed

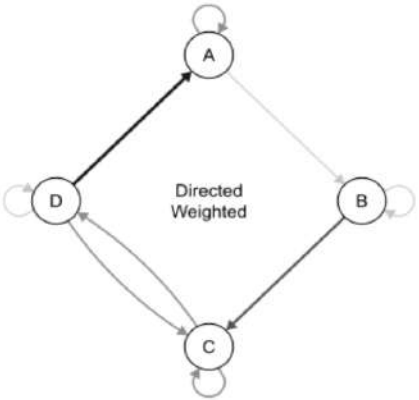


Let’s look at some networks!

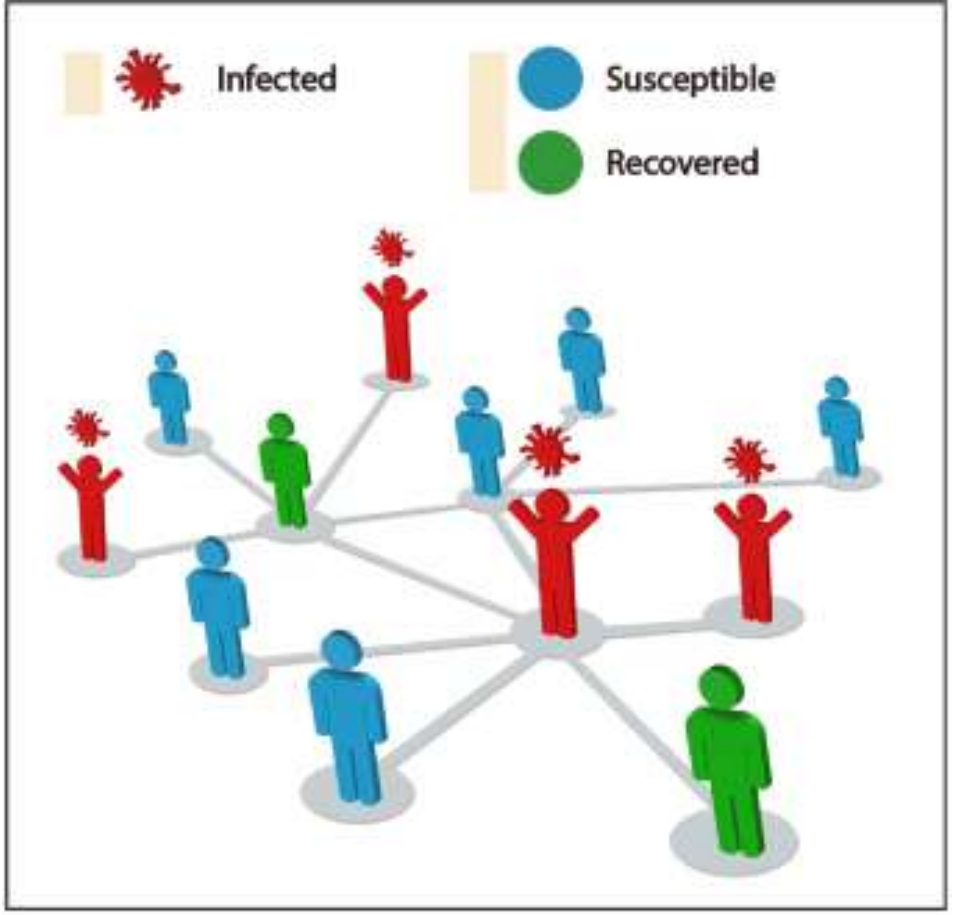




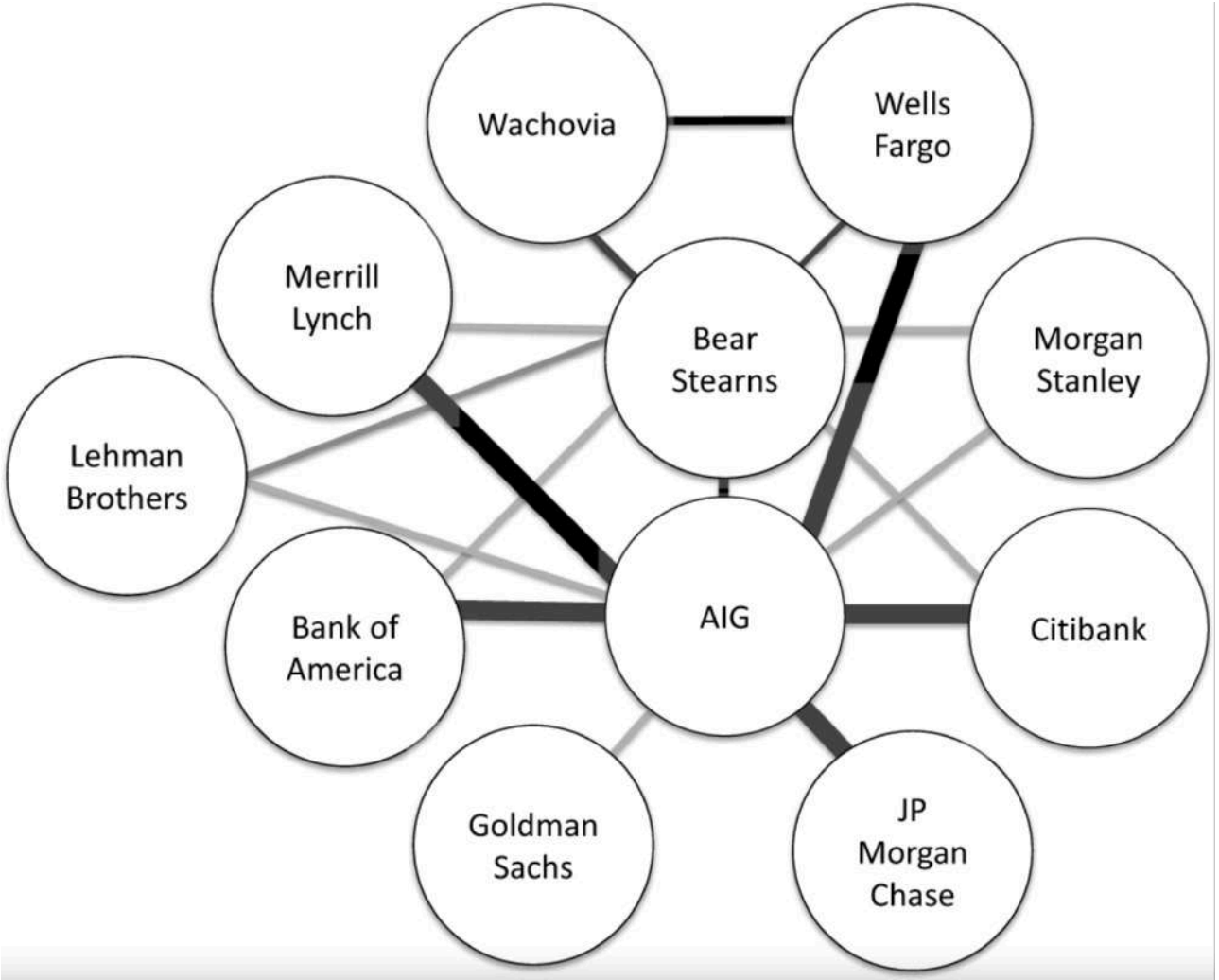





FROM FACEBOOK



(a) An illustrated human contact network with susceptible, infected, and recovered individuals.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AIG
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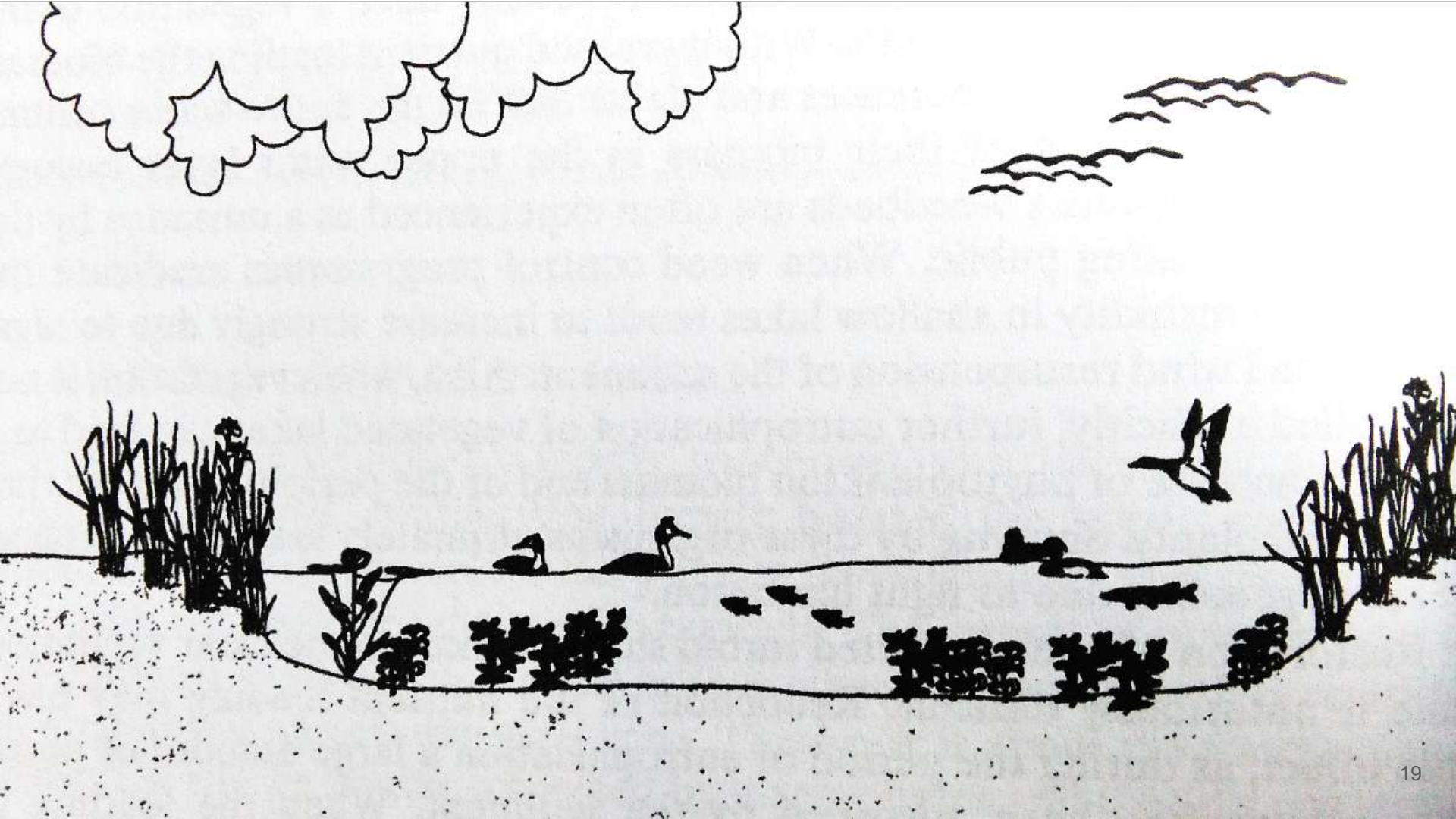
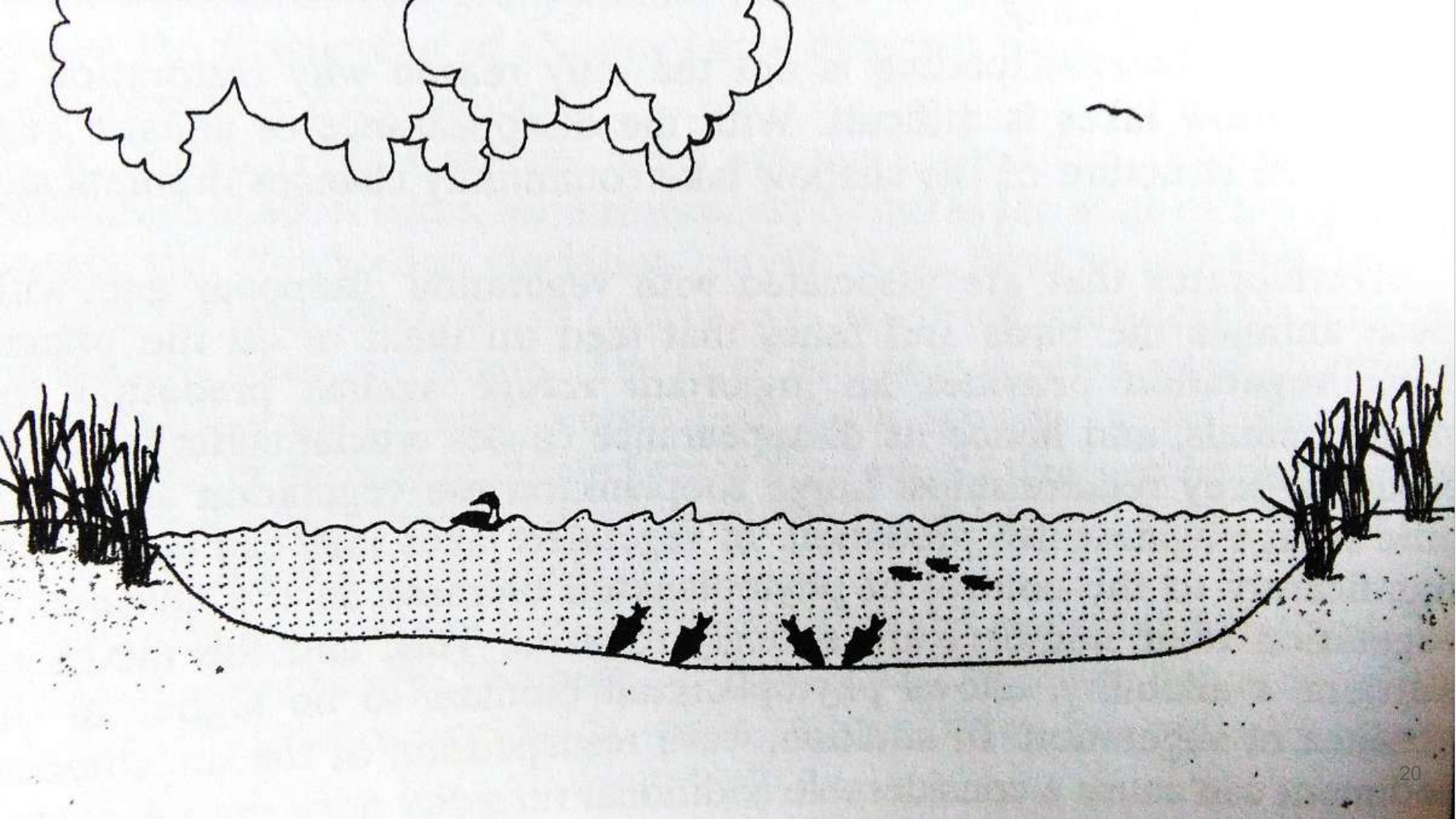
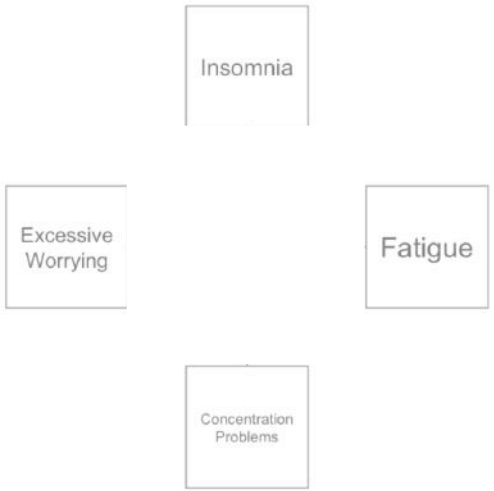
JP Morgan Chase





Psychology as a complex system

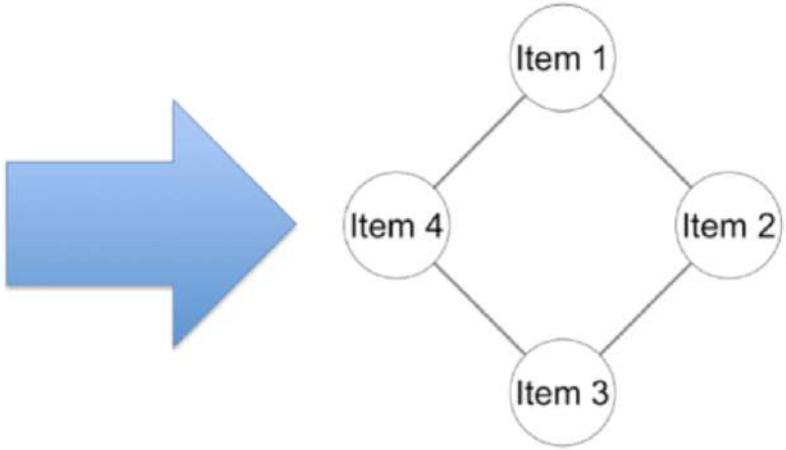


Estimating networks

Psychological networks differ from networks of many other disciplines in one very fundamental aspect

- Edges are not observed but need to be estimated

	Item 1	Item 2	Item 3	Item 4
Subject 1	2	2	1	3
Subject 2	3	2	3	2
Subject 3	2	1	2	4
Subject 4	5	5	5	5
Subject 5	3	3	2	2
Subject 6	5	5	3	3
Subject 7	4	5	5	4
Subject 8	5	5	5	5
Subject 9	2	5	4	4
Subject 10	5	4	5	4



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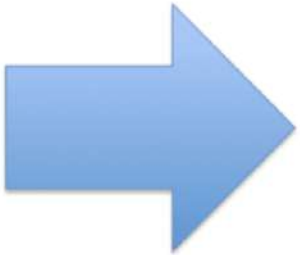
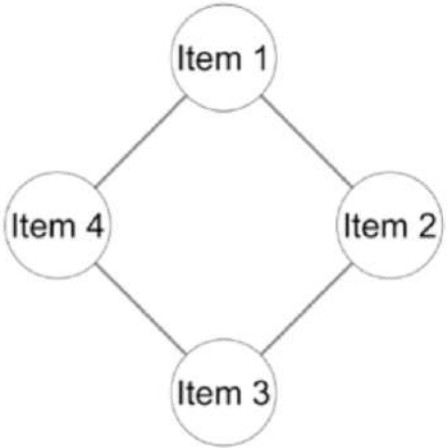
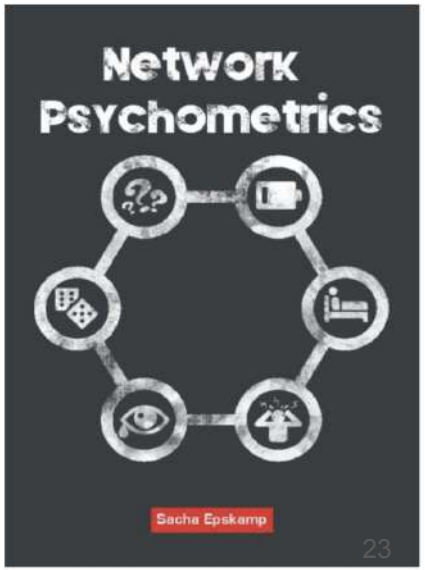
Subject 6	5	5	3	3
Subject 7	4	5	5	4
Subject 8	5	5	5	5
Subject 9	2	5	4	4
Subject 10	5	4	5	4







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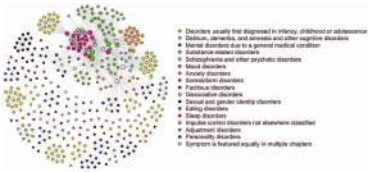
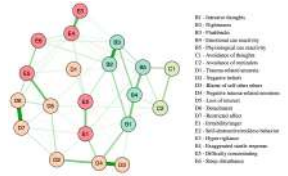
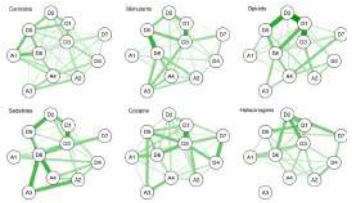
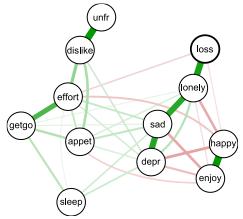
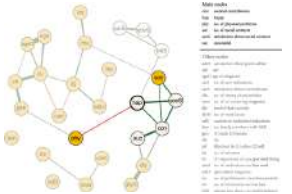
Clinical Applications

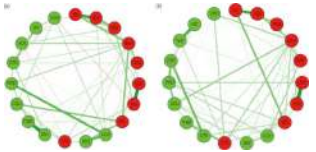


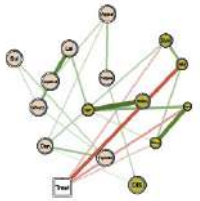


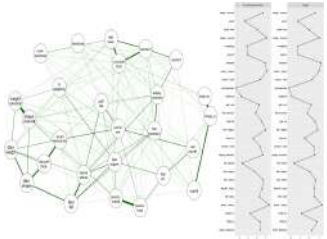


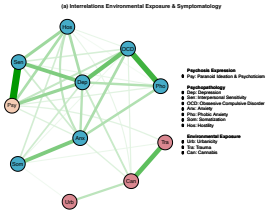












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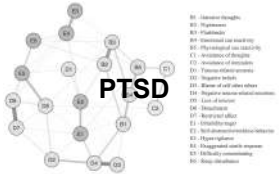
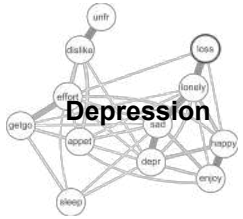
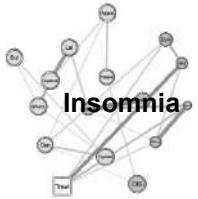
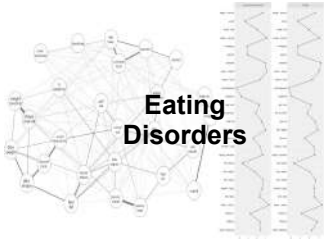
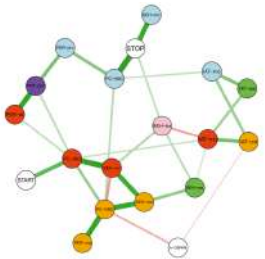








Other Applications



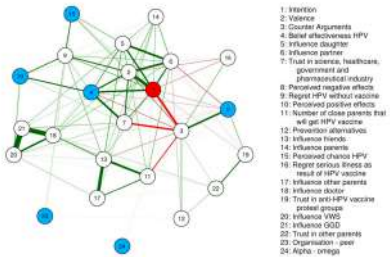
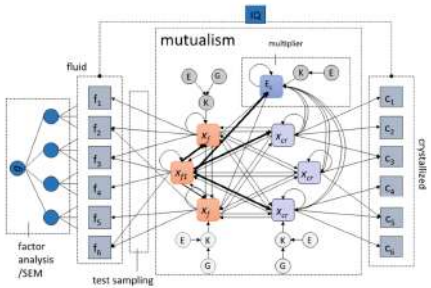
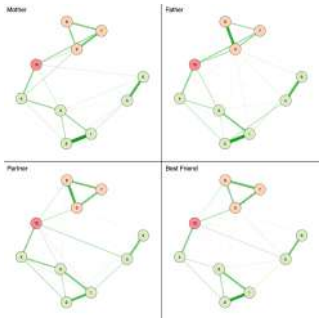


Figure 2. Network Analysis (qgraph) output for the adapted Health Belief Model (HBM), showing partial correlations between constructs. Traditional HBM constructs are shown in blue.





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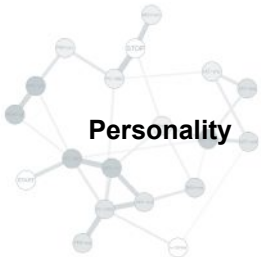
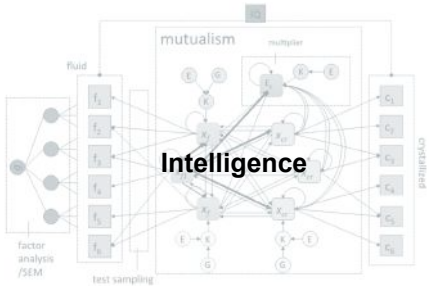
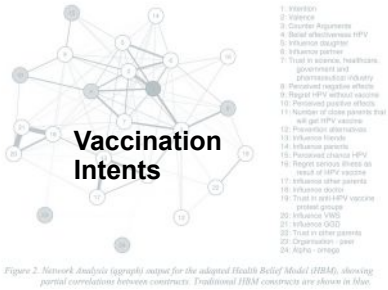


Personality



Intelligence



Vaccination Intents

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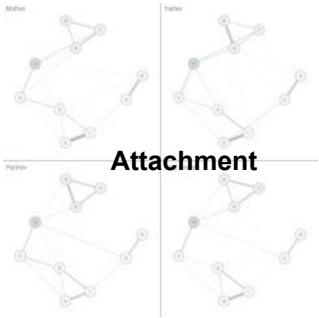
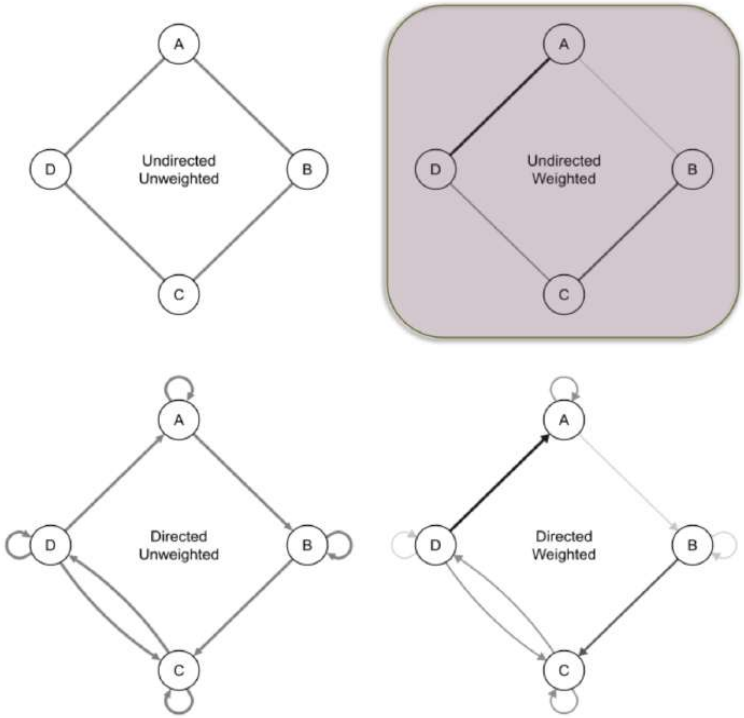


Attachment

Can you think of a system as network in your own field?

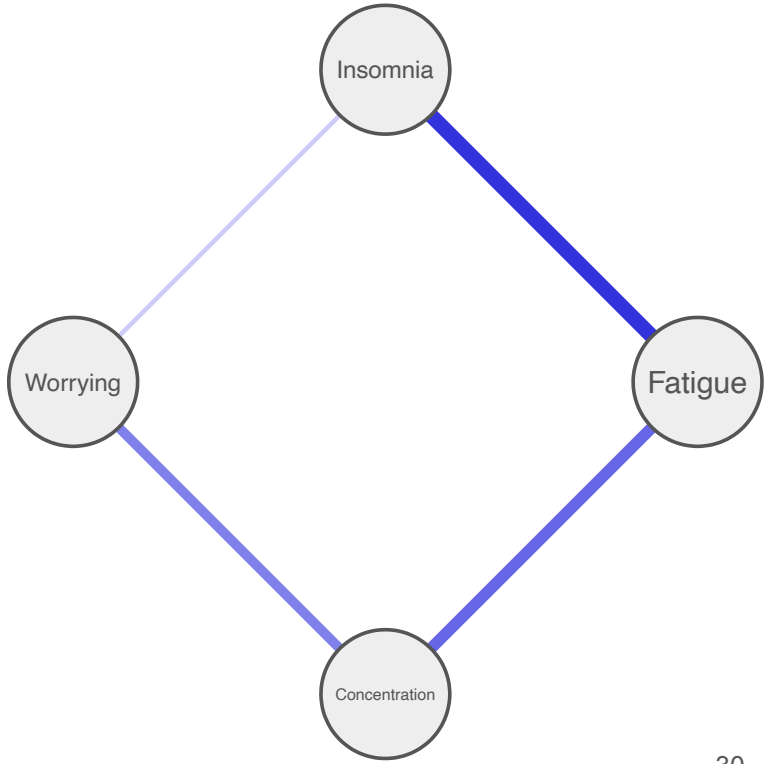
Undirected weighted network models

- We focus on undirected weighted network models
- Estimated on Gaussian / Ordinal data



Undirected weighted network models

- We focus on undirected weighted network models
- Estimated on Gaussian / Ordinal data
- Edges show *conditional dependencies*
  - Partial correlations
  - Blue = positive
  - Red = negative



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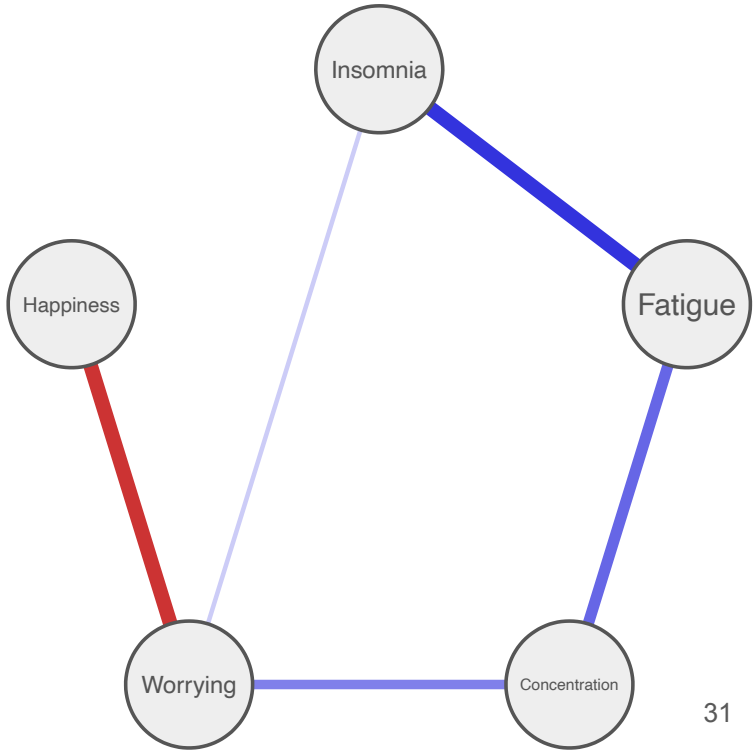
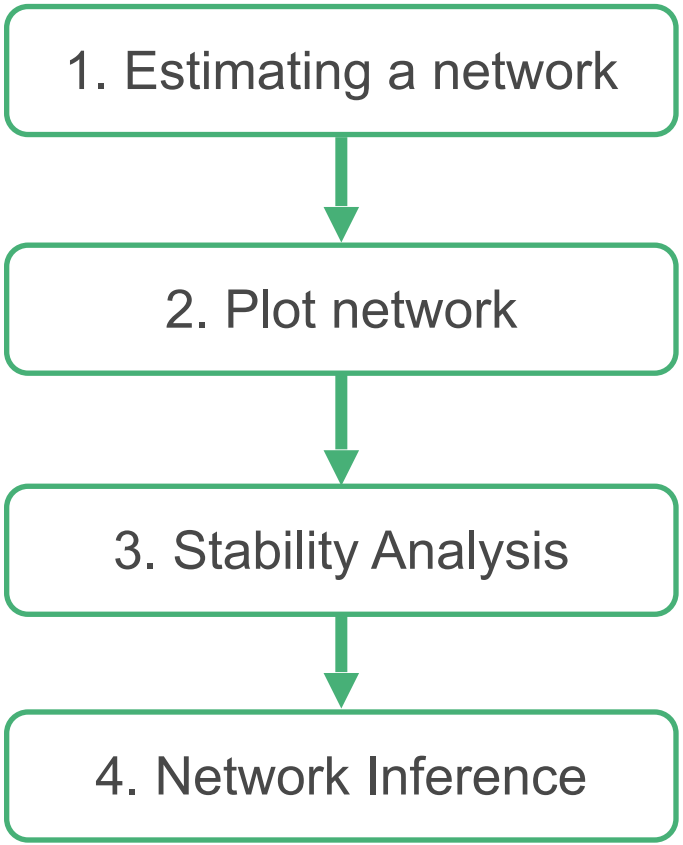


How to do a network analysis?



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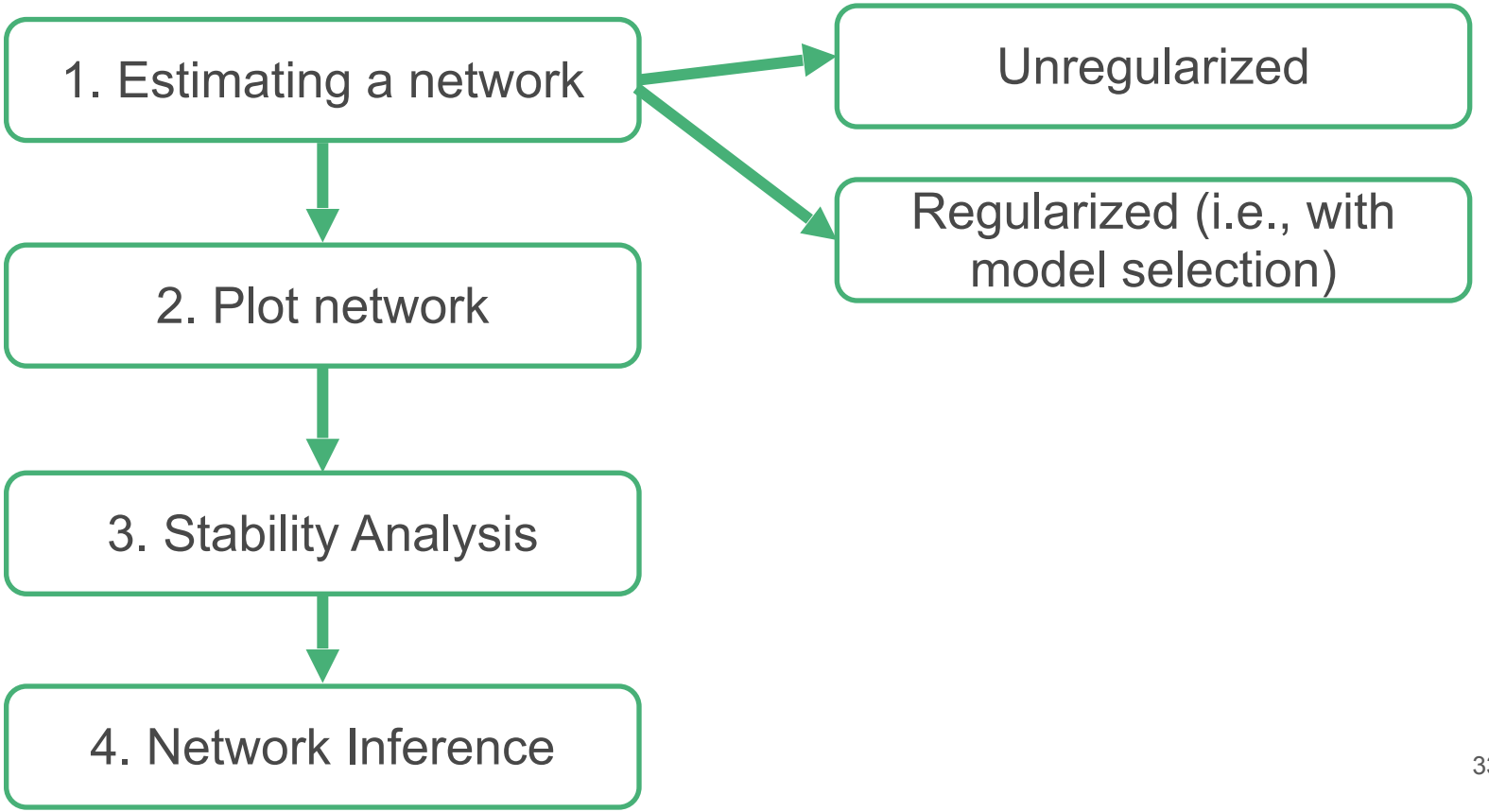


The code is quite easy!

```
# Estimate a network with bootnet:
Network <- estimateNetwork(Data, default = "...")

# Plot network:
qgraph(Network$graph)

# Perform bootstraps (i.e., stability):
Boots1 <- bootnet(Data, default = "..."  nCores = 8)
Boots2 <- bootnet(Data, type = "case", nCores = 8)

# Inspect centrality:
centralityPlot(Network, include = c(”Closeness”, ”Strength”,
“Betweenness”)
```

Tutorial

Big Five personality traits:

- Openness
- Conscientiousness
- Extraversion
- Agreeableness
- Neuroticism

What are (research) questions you could ask?

Tutorial

- How do traits relate to each other?
- Are people who are more extraverted also more open to new experiences?
- Do items of the same personality trait cluster together more than items of other personality traits?

Practical on the BFI data

- 25 personality questions
- 5 items per personality trait: Agreeableness, Conscientiousness, Extraversion, Neuroticism, and Openness
- 6 point response scale
- 2800 subjects

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.

Opennness
- 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.

	A1	A2	A3	A4	A5	C1	C2	C3	C4	C5	E1	E2	E3	E4	E5	N1	N2
61617	2	4	3	4	4	2	3	3	4	4	3	3	3	4	4	3	
61618	2	4	5	2	5	5	4	4	3	4	1	1	6	4	3	3	
61620	5	4	5	4	4	4	5	4	2	5	2	4	4	4	5	4	
61621	4	4	6	5	5	4	4	3	5	5	5	3	4	4	4	2	
61622	2	3	3	4	5	4	4	5	3	2	2	2	5	4	5	2	
61623	6	6	5	6	5	6	6	6	1	3	2	1	6	5	6	3	
61624	2	5	5	3	5	5	4	4	2	3	4	3	4	5	5	1	
61629	4	3	1	5	1	3	2	4	2	4	3	6	4	2	1	6	
61630	4	3	6	3	3	6	6	3	4	5	5	3	*NA*	4	3	5	
61633	2	5	6	6	5	6	5	6	2	1	2	2	4	5	5	5	
61634	4	4	5	6	5	4	3	5	3	2	1	3	2	5	4	3	
61636	2	5	5	5	5	5	4	5	4	5	3	3	4	5	4	4	
61637	5	5	5	6	4	5	4	3	2	2	3	3	3	2	4	1	
61639	5	5	5	6	6	4	4	4	2	1	2	2	4	6	5	1	
61640	4	5	2	2	1	5	5	5	2	2	3	4	3	6	5	2	
61643	4	3	6	6	3	5	5	5	3	5	1	1	6	6	4	4	
61650	4	6	6	2	5	4	4	4	4	4	1	2	5	5	5	4	
61651	5	5	5	4	5	5	5	5	4	3	2	2	4	6	6	6	

Showing 1 to 18 of 2,800 entries, 28 total columns

First some data preparation

Run the code until line 33

```
# Select relevant variables:
bfi <- na.omit(bfi[,1:25])

# Some items need to be recoded:
bfi$A1 <- 7 – bfi$A1
...

# Sum-scores:
bfi_traits <- data.frame(Agreeableness     = rowSums(bfi[,1:5]),
                         Conscientiousness = rowSums(bfi[,6:10]),
                         Extraversion      = rowSums(bfi[,11:15]),
                         Neuroticism       = rowSums(bfi[,16:20]),
                         Openness          = rowSums(bfi[,21:25]))
```

Ex. 1 Estimate a partial correlation network

Estimate a **partial correlation network** by looking at the help page of estimateNetwork with estimator needs to be specified in default = “…”

```
# Estimate a network with bootnet:
??estimateNetwork
Network <- estimateNetwork(Data, default = "...")

# Show edge weights:
Network$graph
```

Ex. 1 Estimating a partial correlation network

The default = “pcor” is used when you want to estimate a partial correlation network.

```
# Estimate a network with bootnet:
Network <- estimateNetwork(Data, default = "pcor")

# Show edge weights:
Network$graph
```

```
> Network$graph
            Agr        Cns        Ext          Nrt          Opn
Agr  0.00000000  0.1326268  0.4100635 -0.066162658  0.022477662
Cns  0.13262685  0.0000000  0.1266902 -0.170390657  0.136110037
Ext  0.41006354  0.1266902  0.0000000 -0.131911896  0.147989189
Nrt -0.06616266 -0.1703907 -0.1319119  0.000000000 -0.004809086
Opn  0.02247766  0.1361100  0.1479892 -0.004809086  0.000000000
```

Ex. 2 Plotting a network model

Using the qgraph package now plot your partial correlation network. Vary the different layout settings of your network:

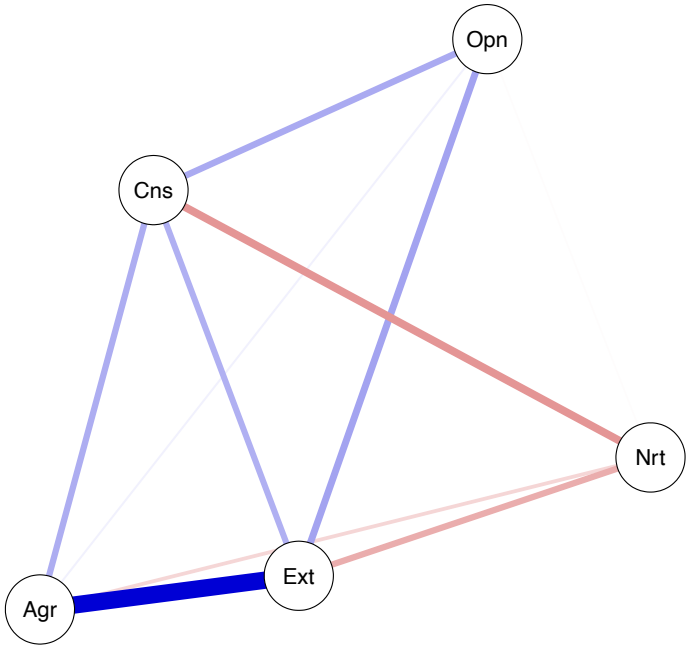
- spring
- circle

Which one do you find the most useful?

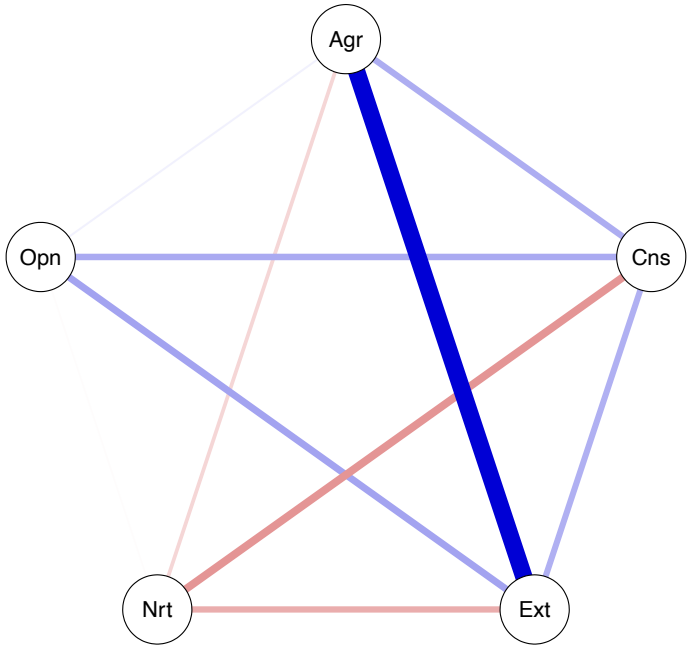
```
# Plotting a network with qgraph:
??qgraph
qgraph(Network$graph, layout = "...", theme = "colorblind")
```

Ex. 2 Plotting a network model

Spring



Circle



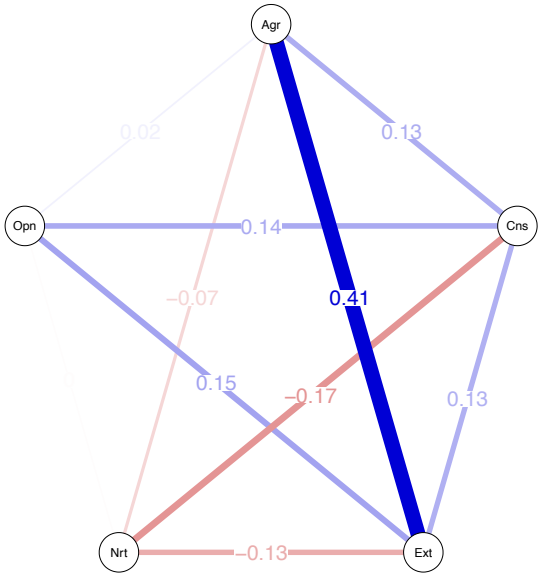
Plotting a network model

When you want to save your network, the pdf() function is recommended

```
# Plotting a network with qgraph:
qgraph(Network$graph, layout = “spring”, theme = “colorblind”)

# Do you want to save your network?
pdf(“network.pdf”)
qgraph(Network$graph)
dev.off()
```

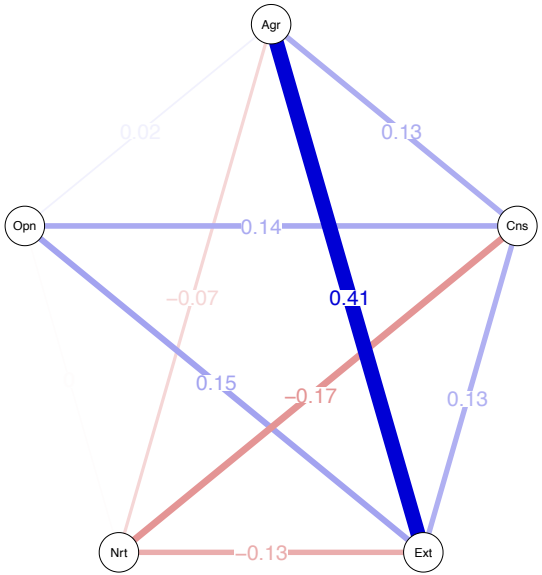
Extra: Plotting a network model

```
edge.labels = TRUE
```

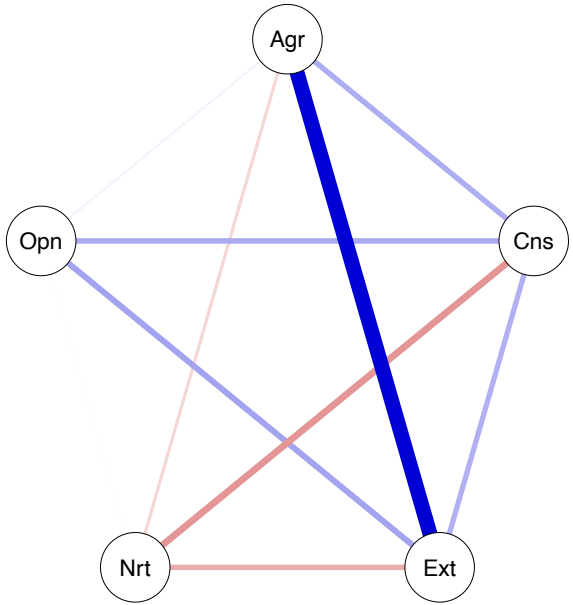


Extra: Plotting a network model

`edge.labels = TRUE`

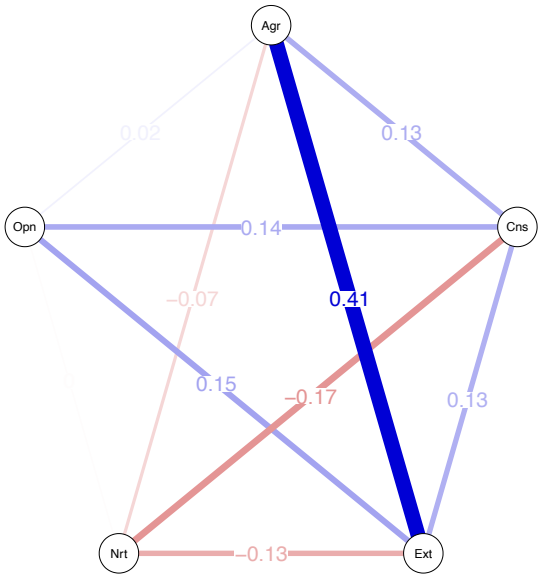


`vsize = 15`

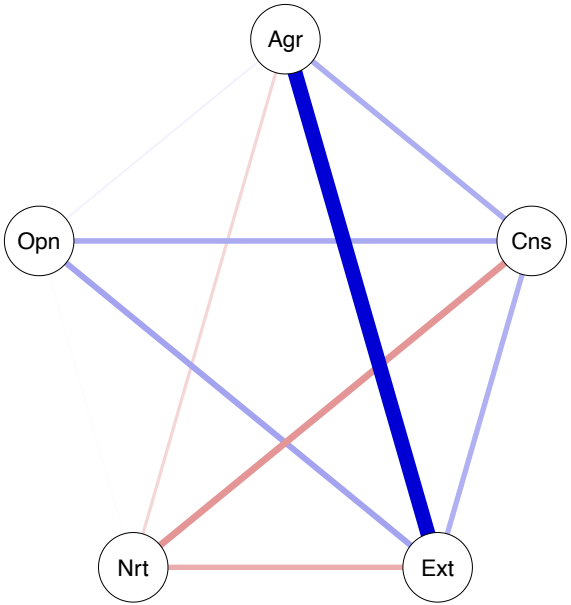


Extra: Plotting a network model

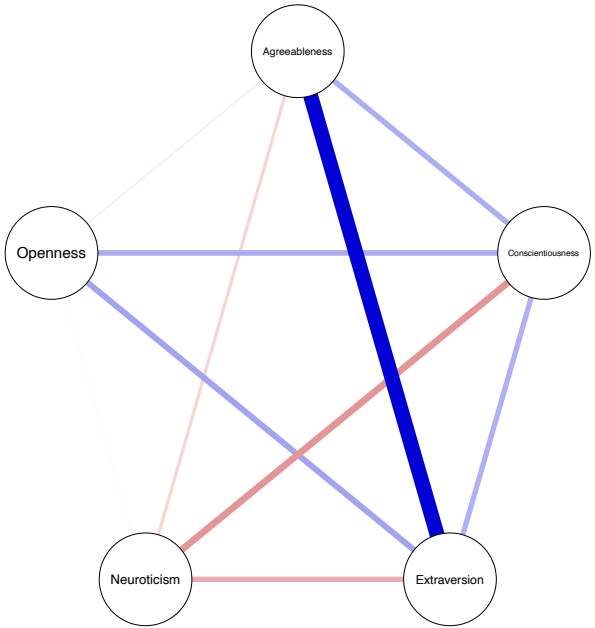
`edge.labels = TRUE`



`vsize = 15`



`labels = names()`



Ex 3. Estimate a partial correlation network

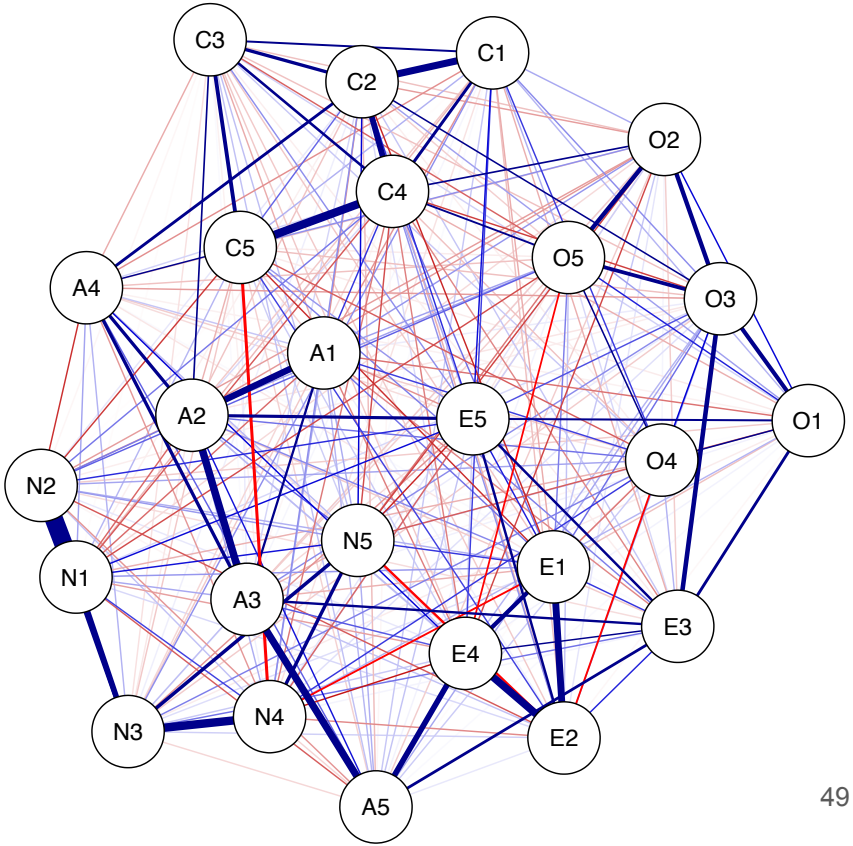
Estimate a **partial correlation network** on all 25 personality items

```
# Estimate a network with bootnet:
??estimateNetwork
Network <- estimateNetwork(Data, default = "...")

qgraph(..., layout = “...”, theme = “colorblind”)
```

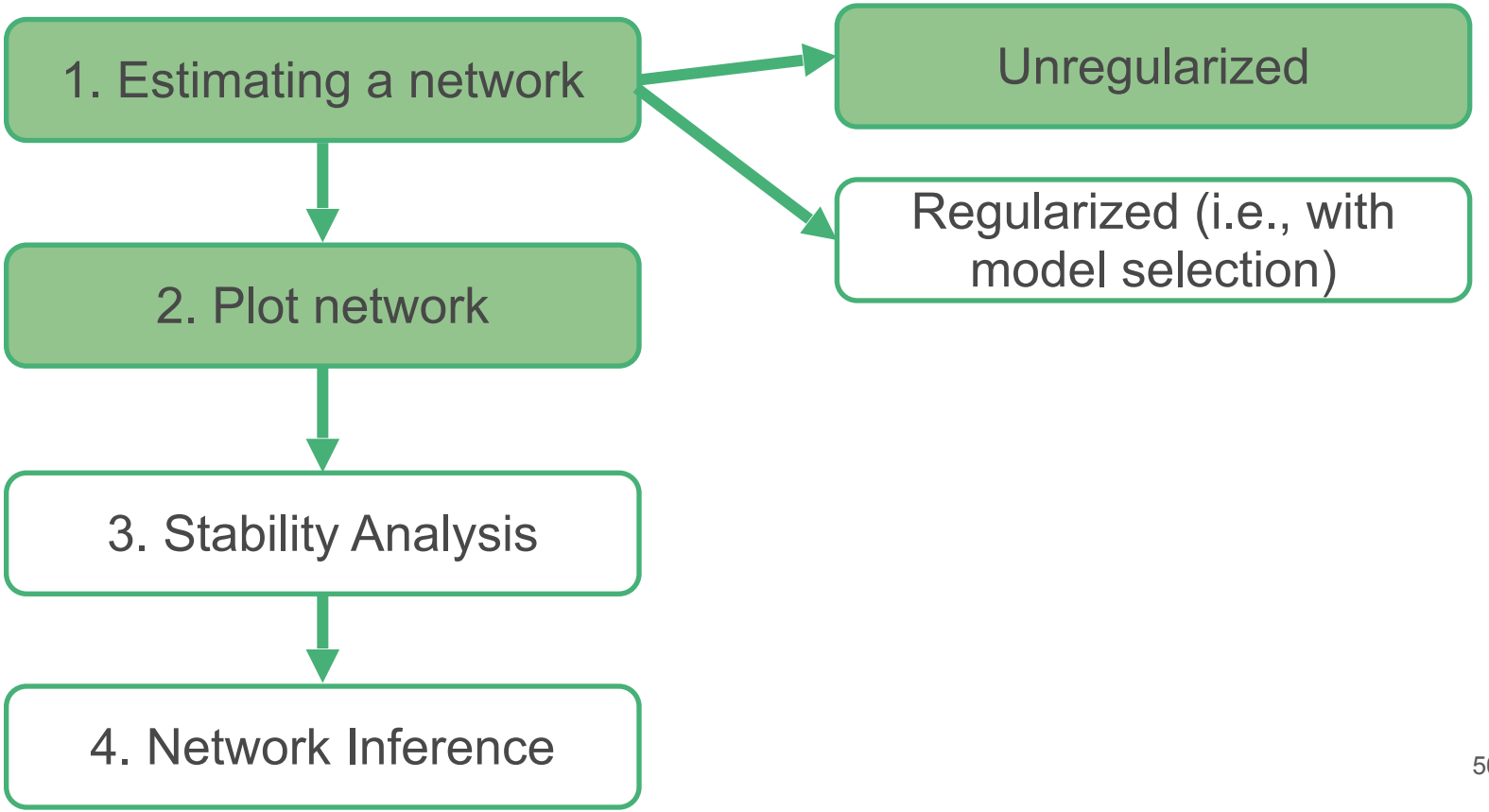
Estimate a partial correlation network

Estimate a partial correlation network on all 25 personality items

```
# Estimate a network with bootnet:
Network <- estimateNetwork(Data,
default = "pcor")

qgraph(Network$graph, layout =
"spring", theme = "colorblind")
```

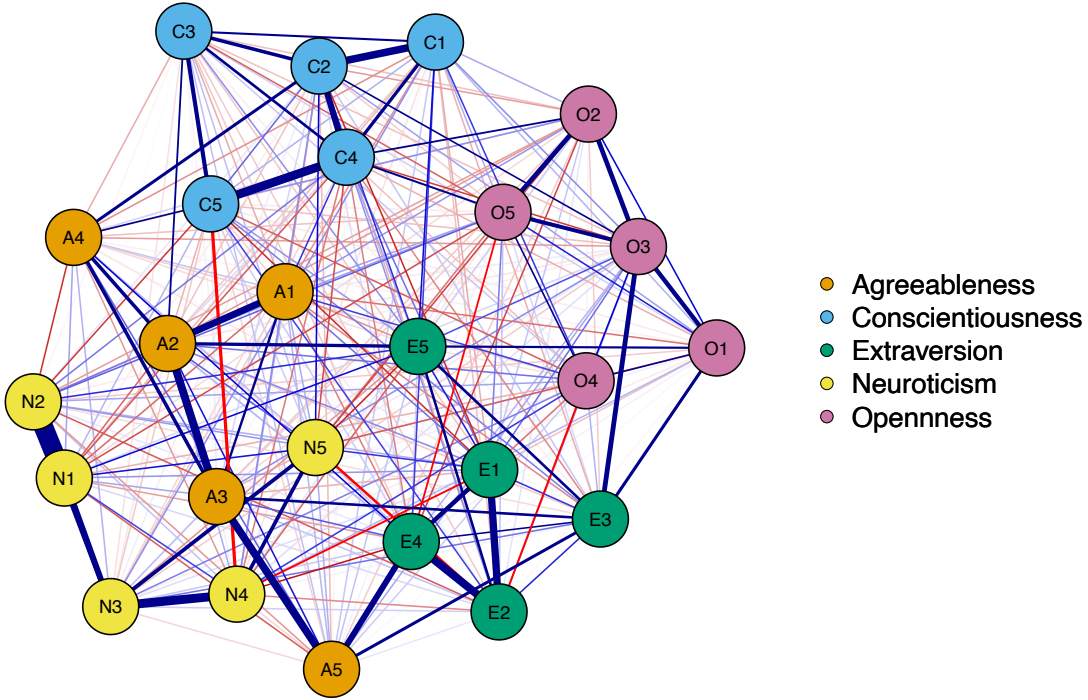


Workflow network models



Extra: Plotting a network model

You also have way more plotting options, see the help page of qgraph

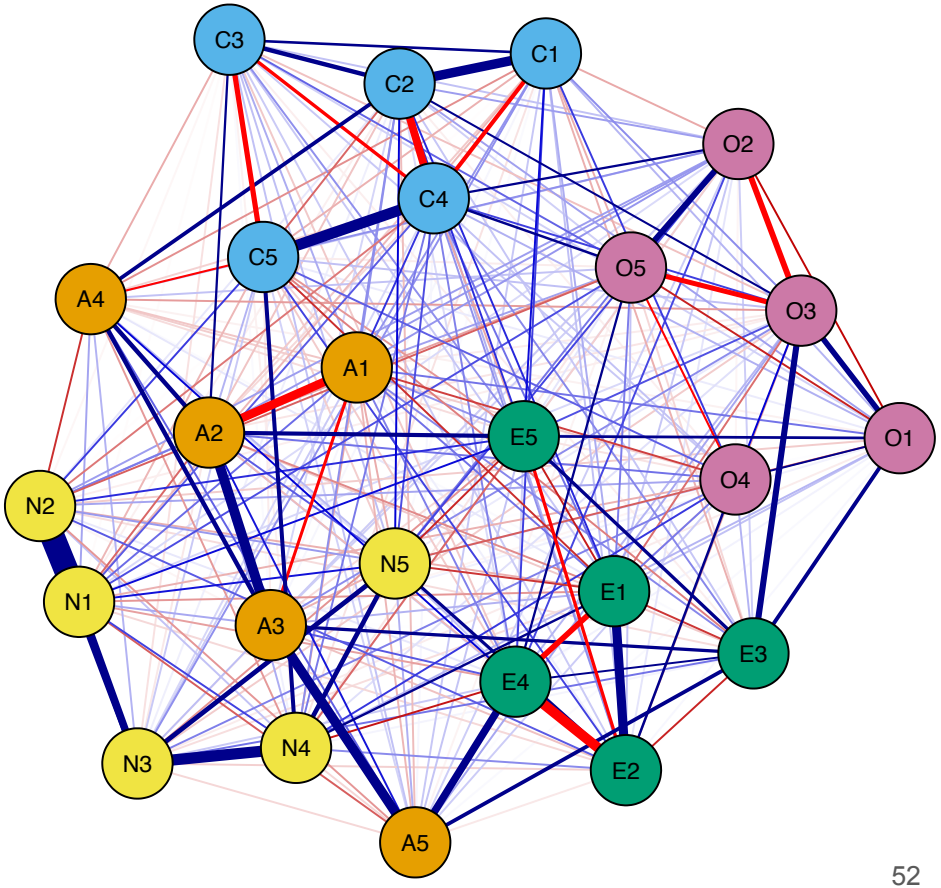


Model selection

How to select the best model?

Options:

1. Tuning
2. Regularization
3. Model search



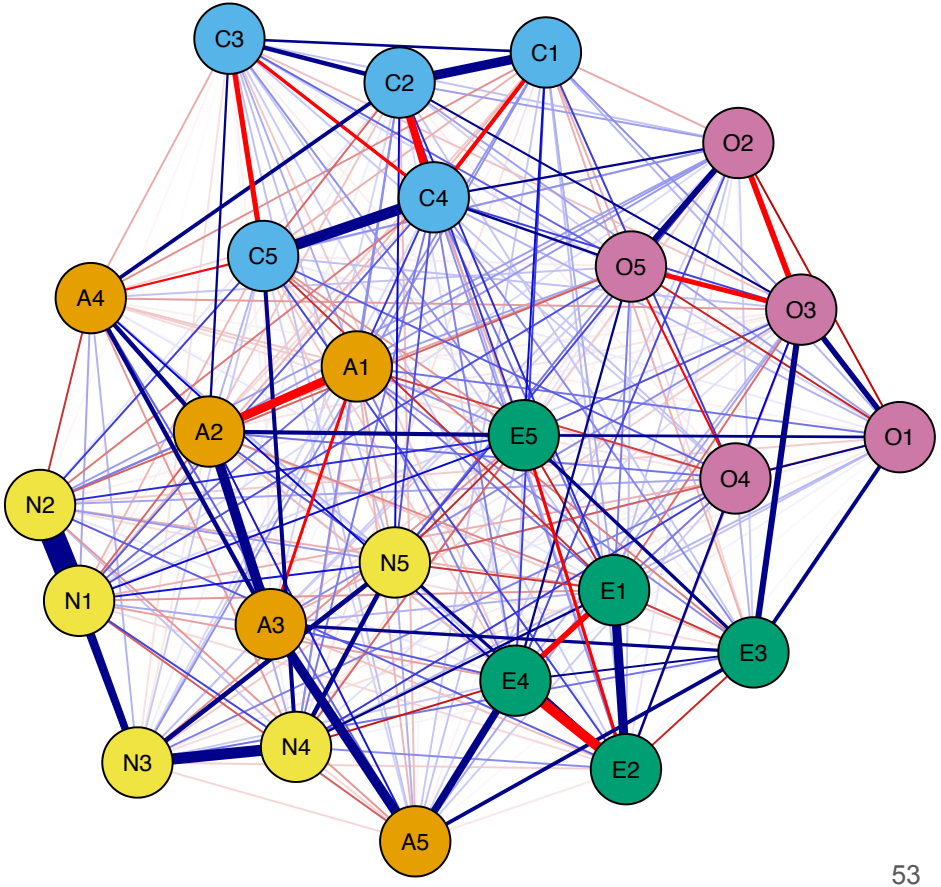
Model selection

How to select the best model?

Options:

1. Tuning
2. Regularization
3. Model search

No one method is the clear winner! See “What estimator to use?” from Isvornau & Epskamp (2021)



Model selection

Tuning: Hides egdes based on some criterion

```
estimateNetwork(Data,
   default = "pcor",
   threshold = "sig",
   alpha = 0.01)
```

Model selection

Tuning: Hides egdes based on some criterion

Regularization: Shrinks (according to some tuning parameter) small edge weights to 0

```
estimateNetwork(Data,
   default = "pcor",
   threshold = "sig",
   alpha = 0.01)
```

```
estimateNetwork(Data,
  default   = ”EBICglasso",
  corMethod = “spearman”,
  tuning = 0.5)
```

Model selection

Tuning: Hides egdes based on some criterion

```
estimateNetwork(Data,
   default = "pcor",
   threshold = "sig",
   alpha = 0.01)
```

Regularization: Shrinks (according to some tuning parameter) small edge weights to 0

```
estimateNetwork(Data,
  default   = ”EBICglasso",
  corMethod = “spearman”,
  tuning = 0.5)
```

Model search: Extensive model search strategies

```
estimateNetwork(Data,
   stepwise = FALSE,
   default   = ”ggmModSelect",
  corMethod = “spearman”)
```

Ex. 4 Estimate regularized network

Use one of the previously discussed methods to estimate a new network.

Tuning

```
estimateNetwork(Data,
   default = "pcor",
   threshold = "sig",
   alpha = 0.01)
```

Regularization

```
estimateNetwork(Data,
  default   = ”EBICglasso",
  corMethod = “spearman”,
  tuning = 0.5)
```

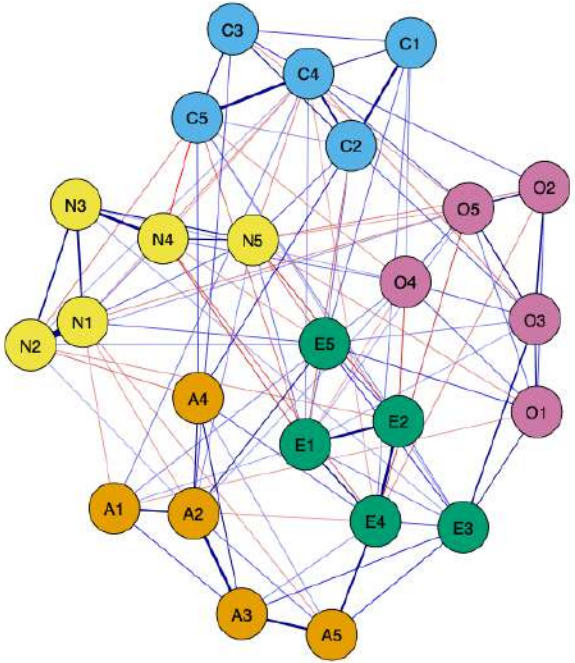
Model search

```
estimateNetwork(Data,
   stepwise = FALSE,
   default   =
   ”ggmModSelect",
  corMethod = “spearma
```

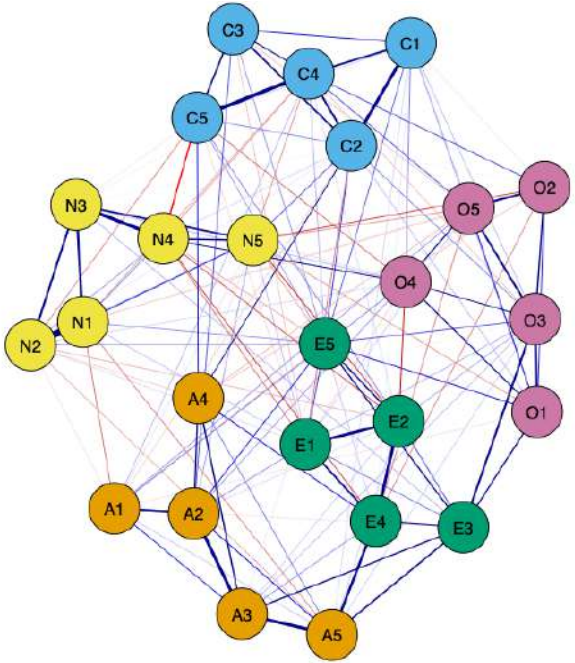
Time left? You can also change parameter setting such as alpha and tuning parameter. What is the difference between using difference parameter setting?

Ex. 4 Estimate regularized network

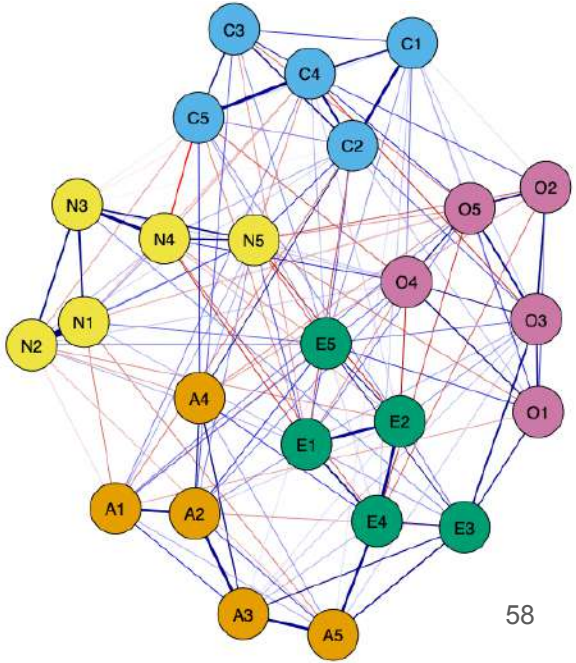
Tuning



Regularization



Model search



Ex. 5 Comparing networks

Compare your regularized network to the previous unregularized network. Are they similar?

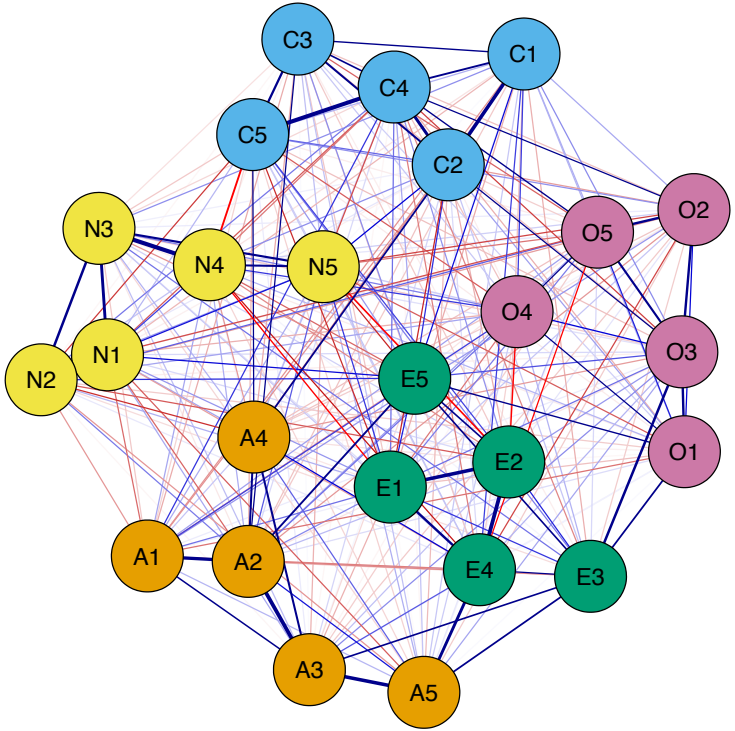
Make sure the layout is the same if you want to compare networks:

```
Layout <- averageLayout(network, network_ggmModSelect)
par(mfrow=c(1,2))
qgraph(network_EBICglasso, layout = Layout, title = ”EBICglasso”)
qgraph(network_ggmModSelect, layout = Layout, title = ”ggmModSelet”)
```

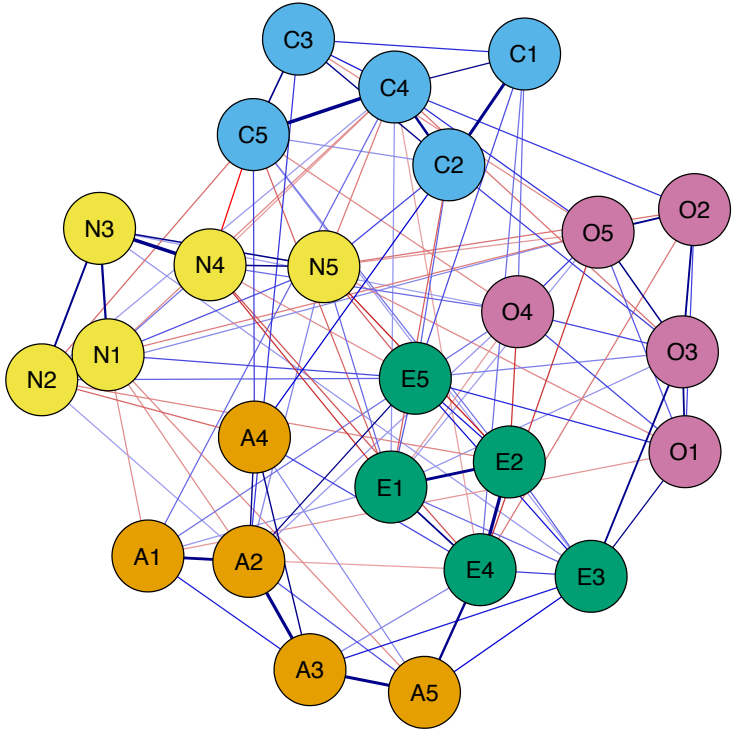
Time left? Pick another estimation method and compare the networks. What is the difference?

Ex. 5 Comparing networks

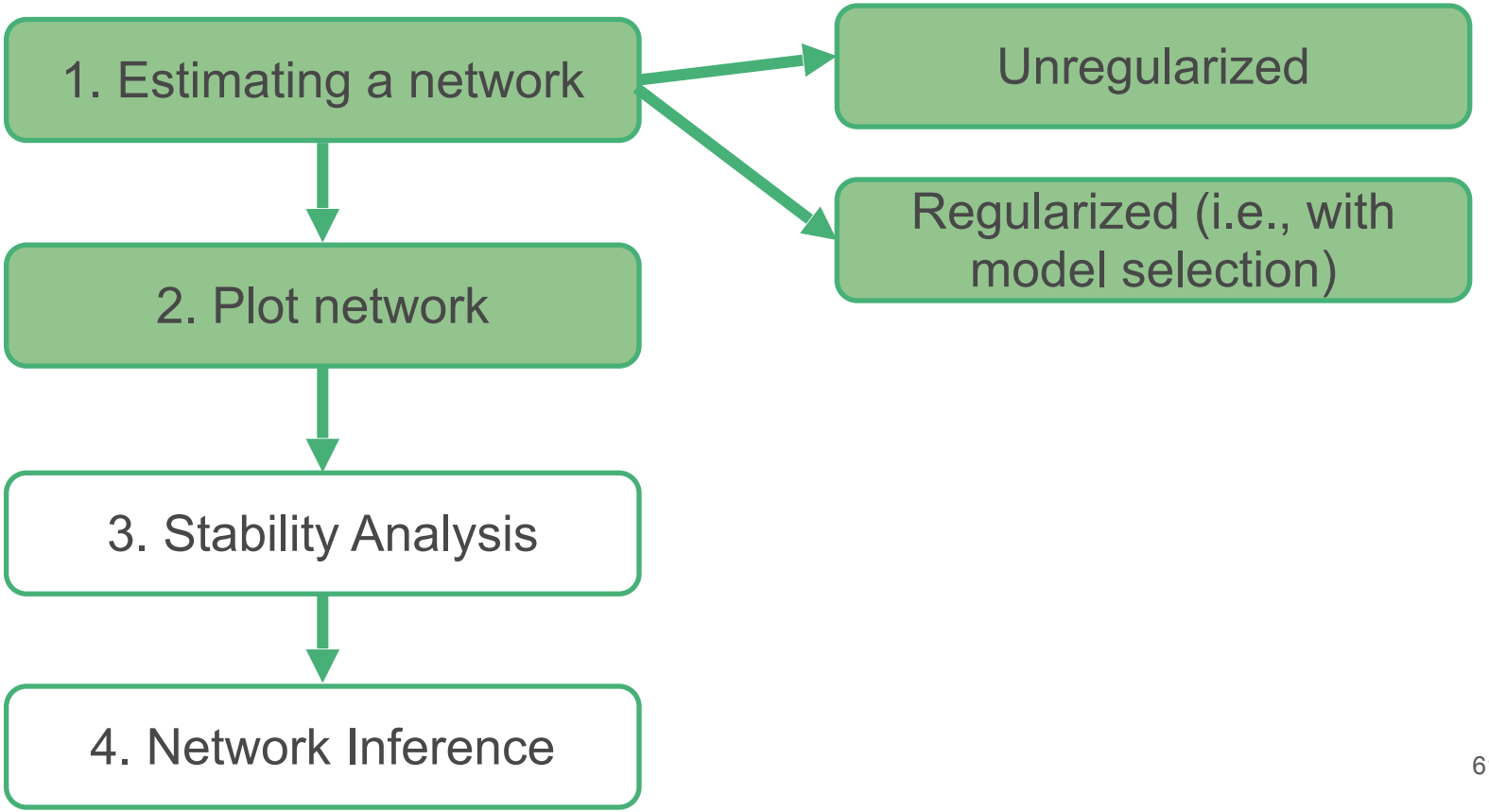
Partial correlation



Model selection

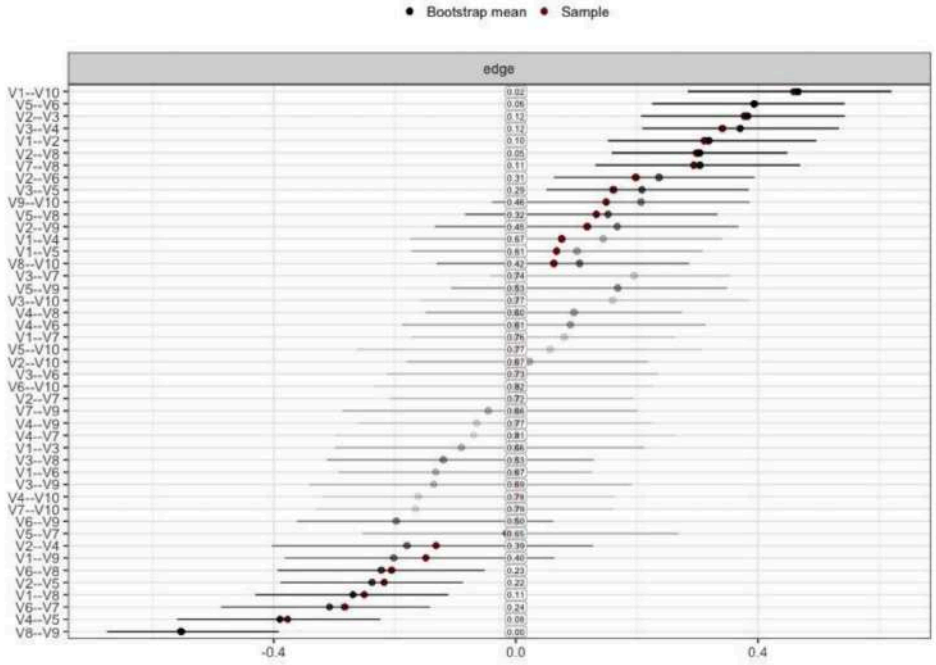


Workflow network models



Stability Analysis

Edges are not observed but need to be estimated

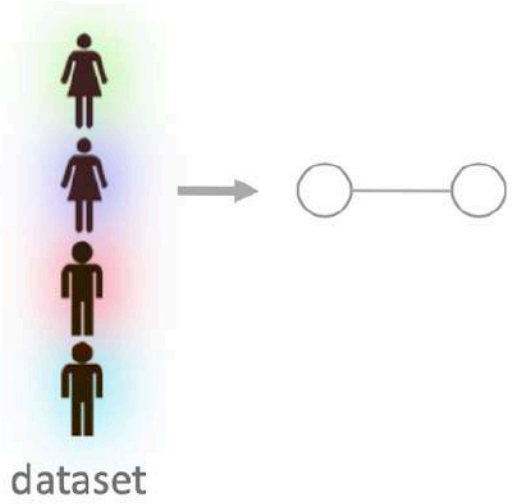


Stability Analysis: Non parametric bootstrap

1. Compute statistic (e.g., edge weight) in original sample

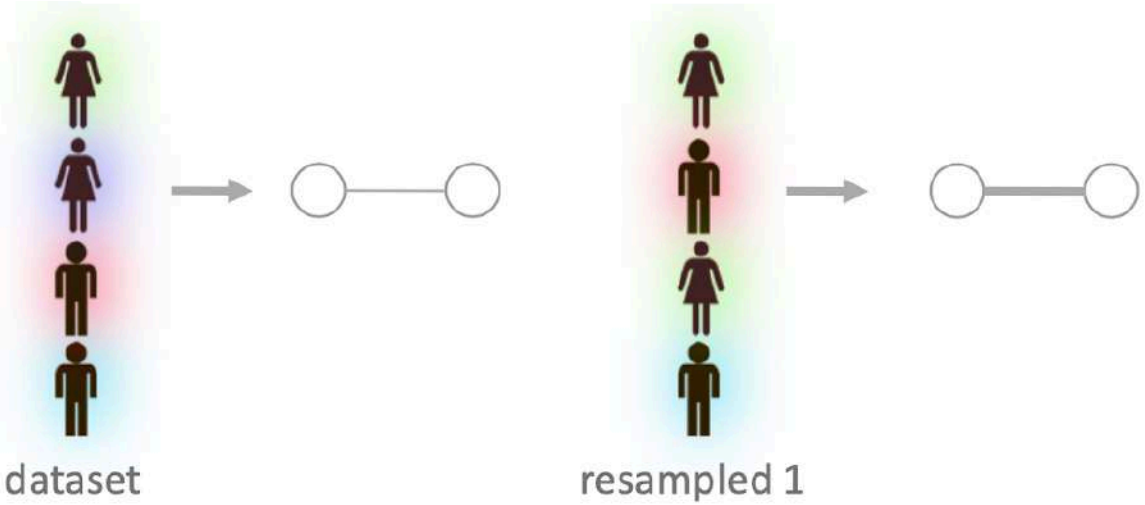
nent

nce



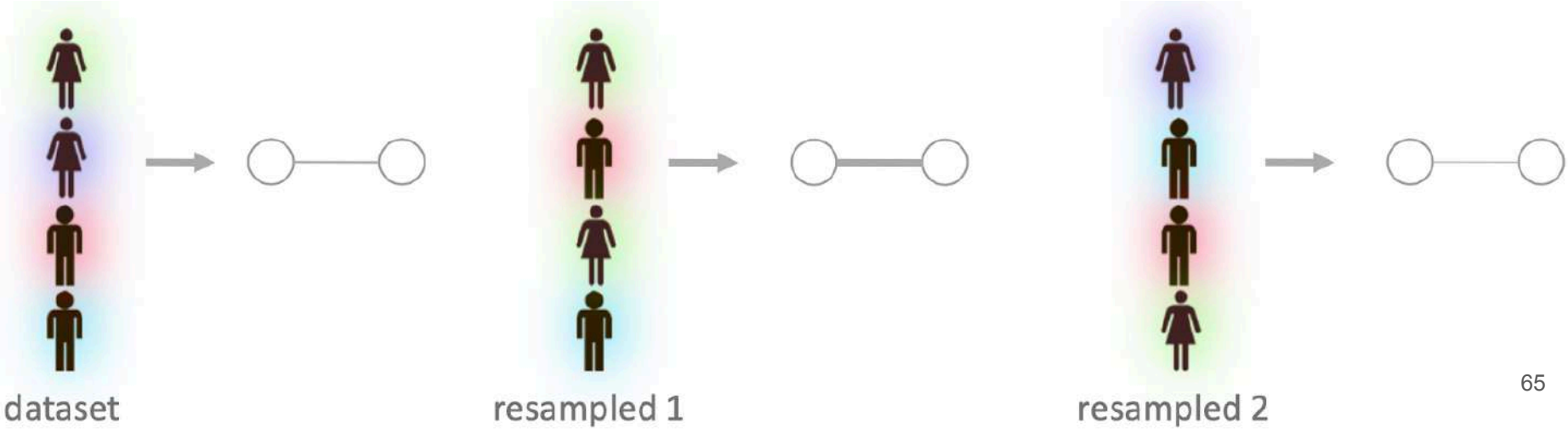
Stability Analysis: Non parametric bootstrap

1. Compute statistic (e.g., edge weight) in original sample
2. Generate a new dataset by sampling from your original data with replacement
3. Compute statistic (e.g., edge weight) in new dataset
4. Repeat steps 2-3 and use the ranges of compute statistic to draw confidence



Stability Analysis: Non parametric bootstrap

1. Compute statistic (e.g., edge weight) in original sample
2. Generate a new dataset by sampling from your original data with replacement
3. Compute statistic (e.g., edge weight) in new dataset
4. Repeat steps 2-3 and use the ranges of compute statistic to draw confidence intervals



Ex. 6 Assess stability

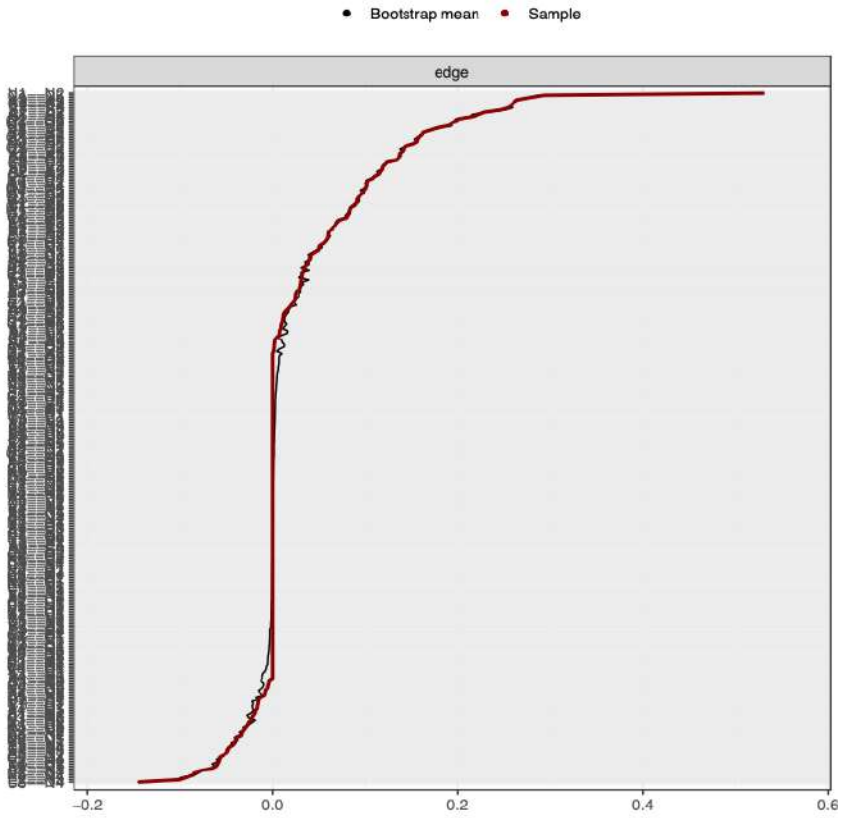
Perform a nonparametric bootstrap on the EBICglasso network. Only do 100 bootstraps at most (you can do less too)

```
# Perform bootstraps:
Stability <- bootnet(Data, default = "...", nBoots = ...)

plot(Stability, order = "sample")
```

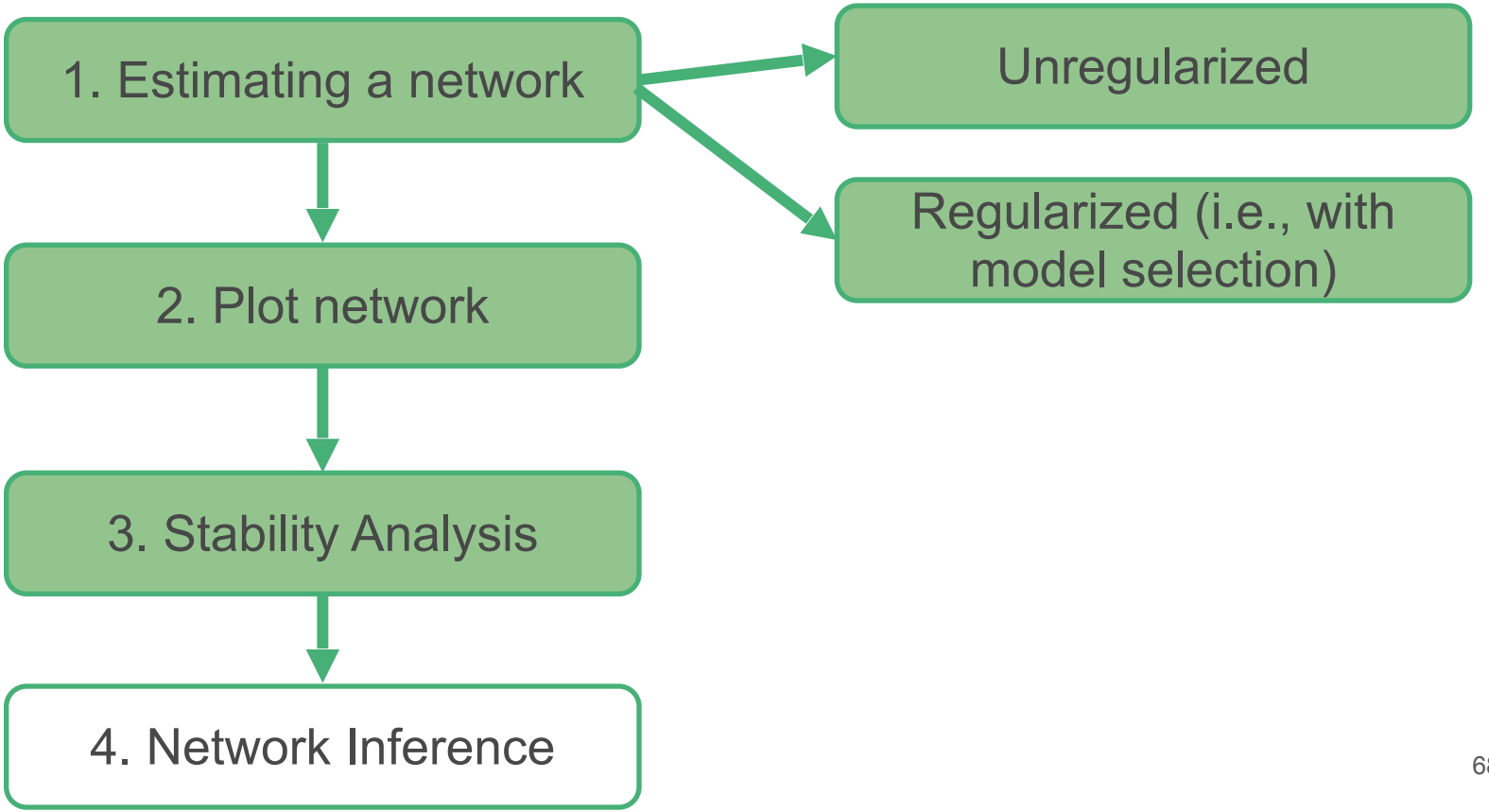
Ex. 6 Assess stability

Would you consider this network stable? Why or why not?

```
# Perform bootstraps:
Accuracy <- bootnet(Data,
default = "EBICglasso",
nBoots = 100)
plot(Accuracy, order =
"sample")
```

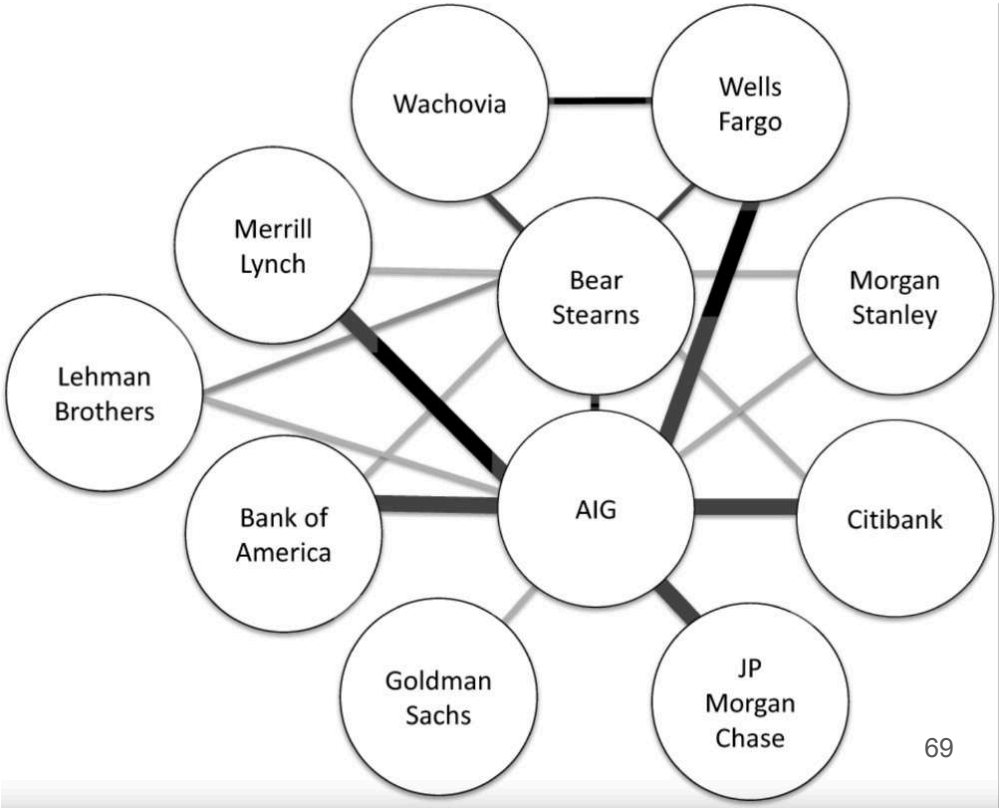


Workflow network models



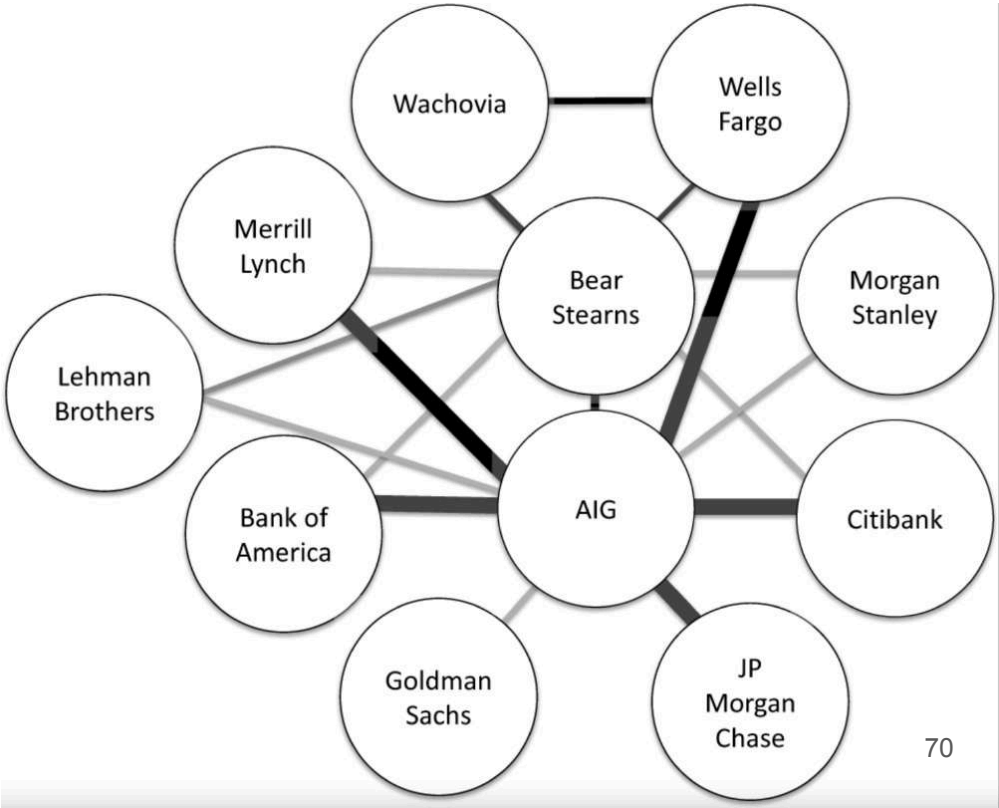
Centrality measures

- Aim to assess the connectedness of a given variable with all other variables in the network
- Give insights in the relative importances of nodes



Centrality measures

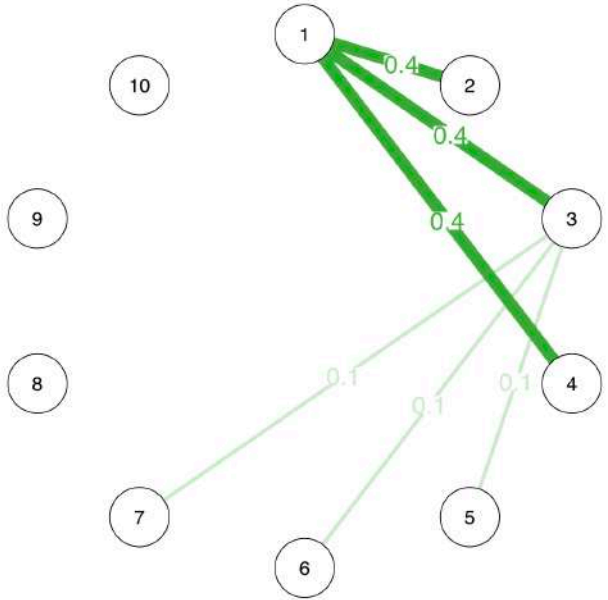
- Aim to assess the connectedness of a given variable with all other variables in the network
- Give insights in the relative importances of nodes
- BUT use centrality measures with caution!
- It is unclear how they perform in undirected, weighted networks



Centrality measures

Mainly three measures:

- **Node strength / degree centrality**: how strongly a node is directly connected



Centrality measures

Mainly three measures:

- **Node strength / degree centrality**: how strongly a node is directly connected
- **Closeness**: how strongly a node is indirectly connected (= the sum of all shortest path lengths from one node to all other nodes)

Centrality measures

Mainly three measures:

- **Node strength / degree centrality**: how strongly a node is directly connected
- **Closeness**: how strongly a node is indirectly connected
- **Betweenness**: how well one node connects to other nodes (= how often a node is in the shortest path between other nodes)

Centrality measures

Centrality measures aim to assess the connectedness of a given variable with all other variables in the network

Mainly three measures:

- **Node strength / degree centrality**: how strongly a node is directly connected
- **Closeness**: how strongly a node is indirectly connected
- **Betweenness**: how well one node connects to other nodes

Often give similar results, but not necessarily

Ex. 7 Estimate the centrality

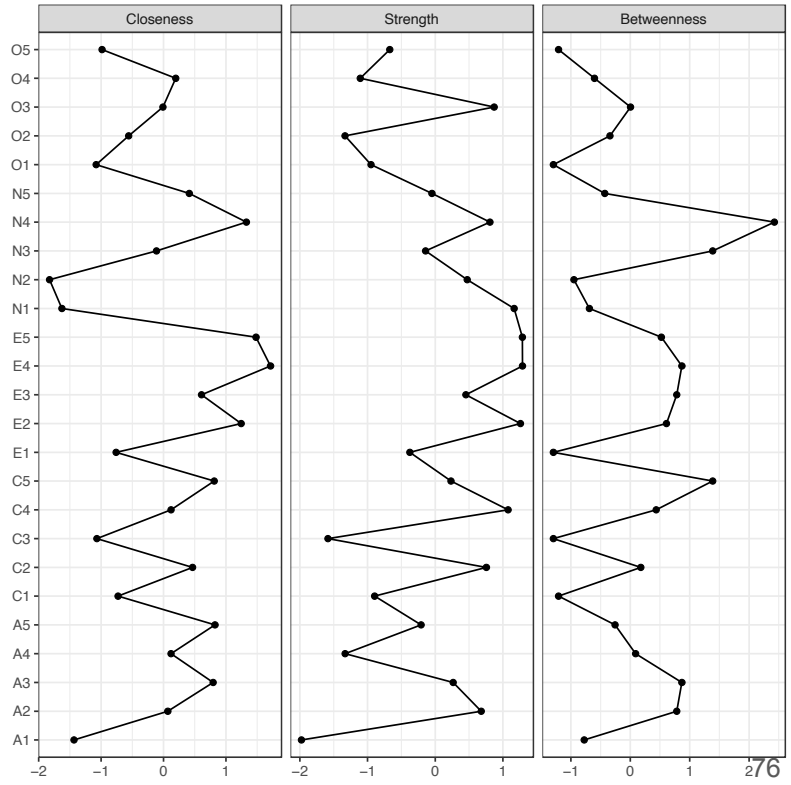
Investigate the node **Strength**, **Closeness**, and **Betweenness** the regularized network using the centralityPlot function

```
# Centrality measures
??centralityPlot
centralityPlot(Network, include = "...")
```

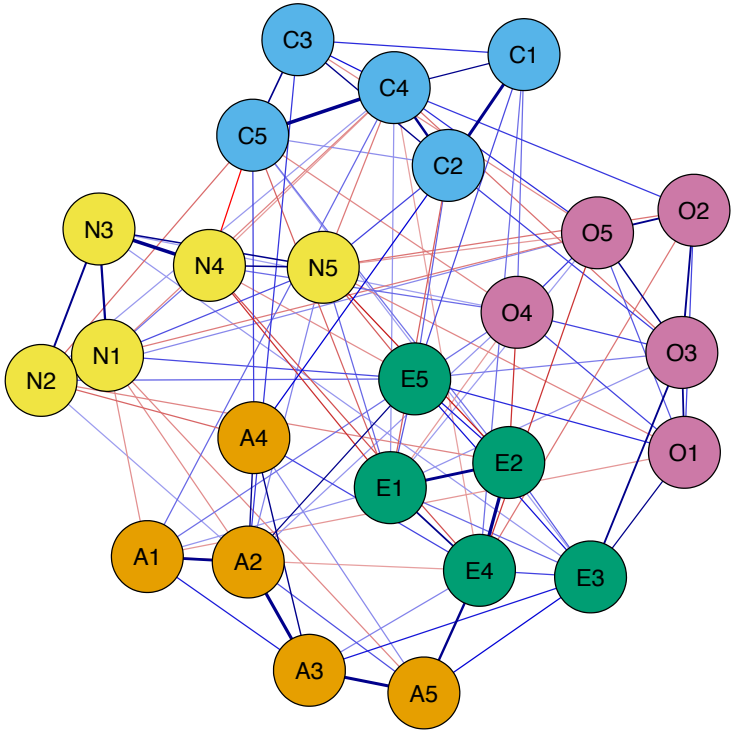
Ex. 7 Estimate the centrality

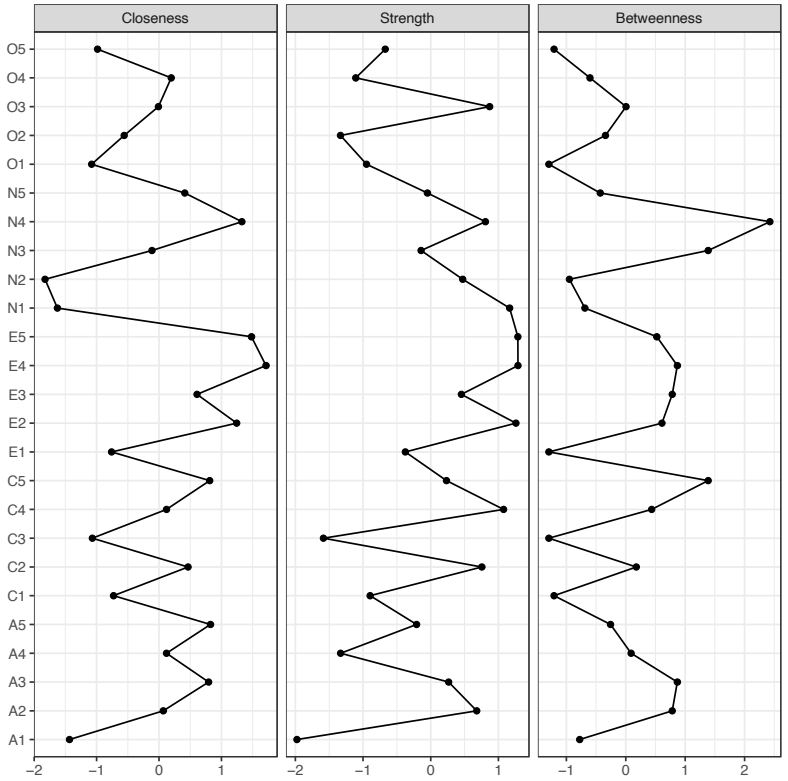
Which personality item is the most central? Which is the least central?

```
# Centrality measures
library(qgraph)
centralityPlot(Network,
include = c("Closeness", "Strength",
"Betweenness"))
```

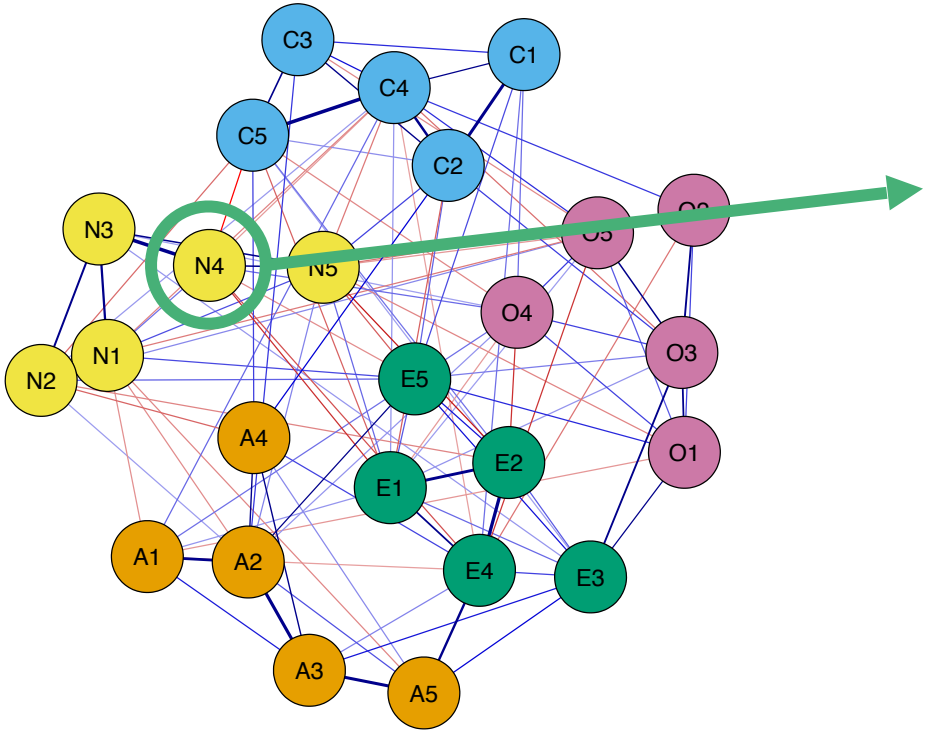


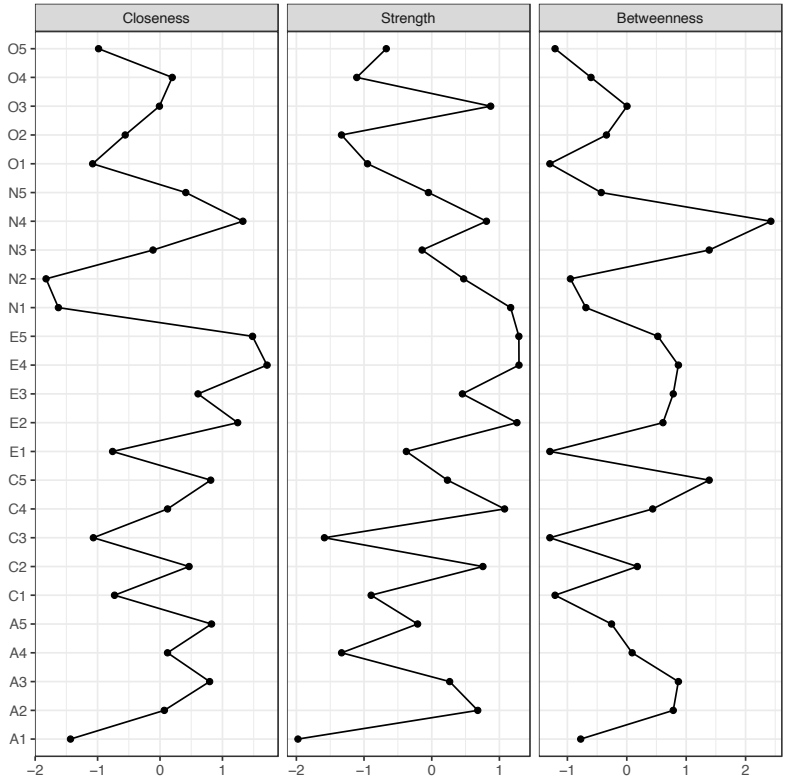
What is the most central node?



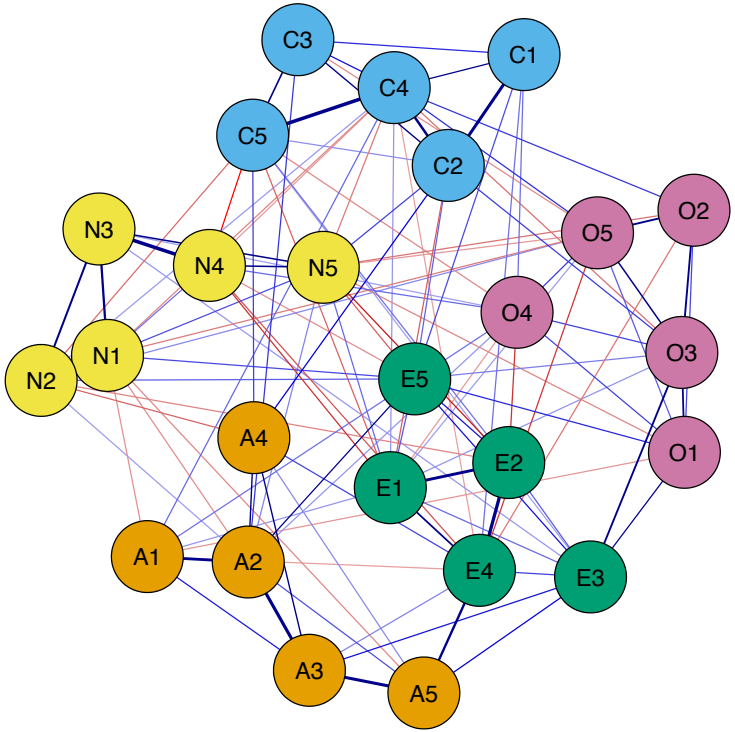


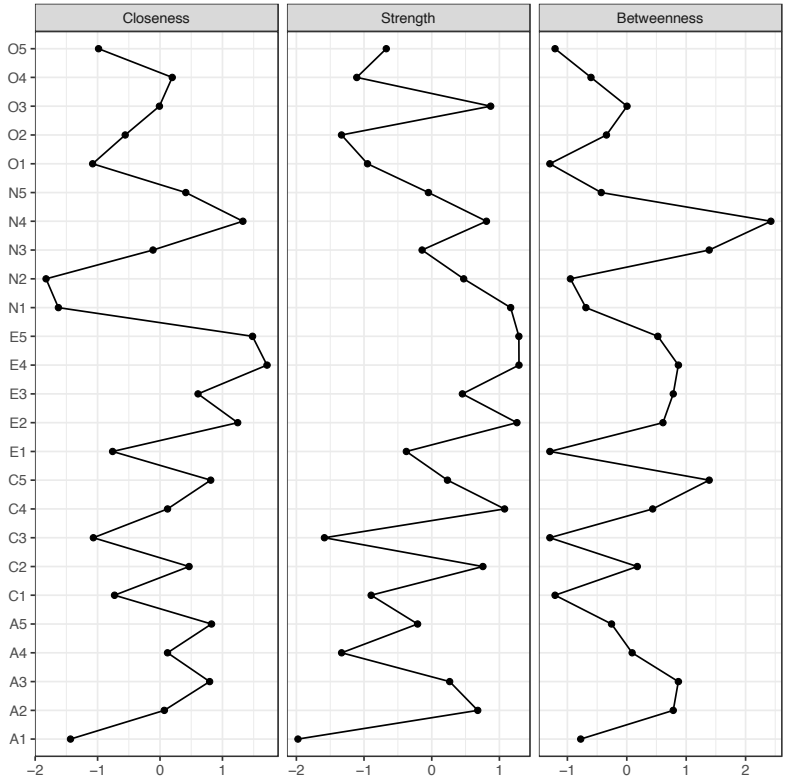
What is the most central node?



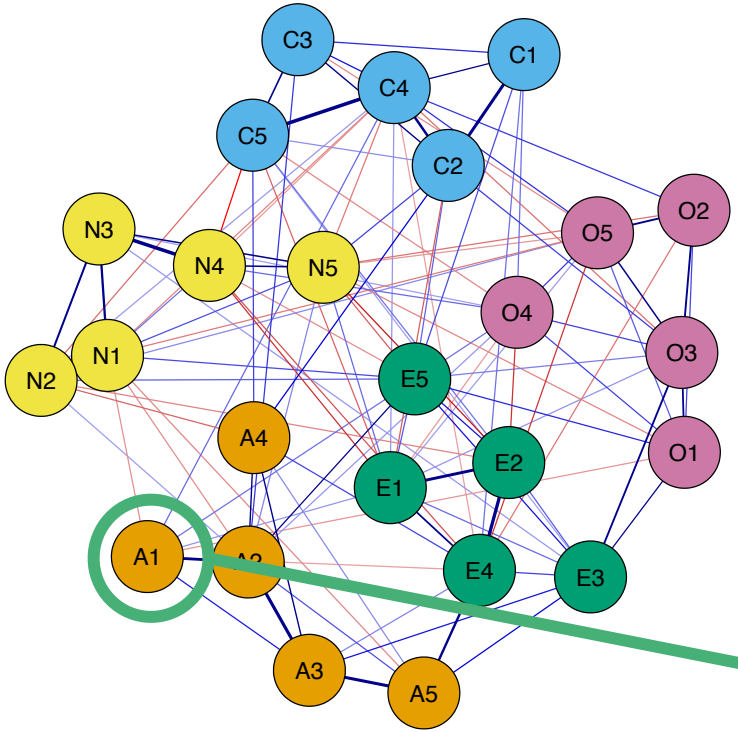


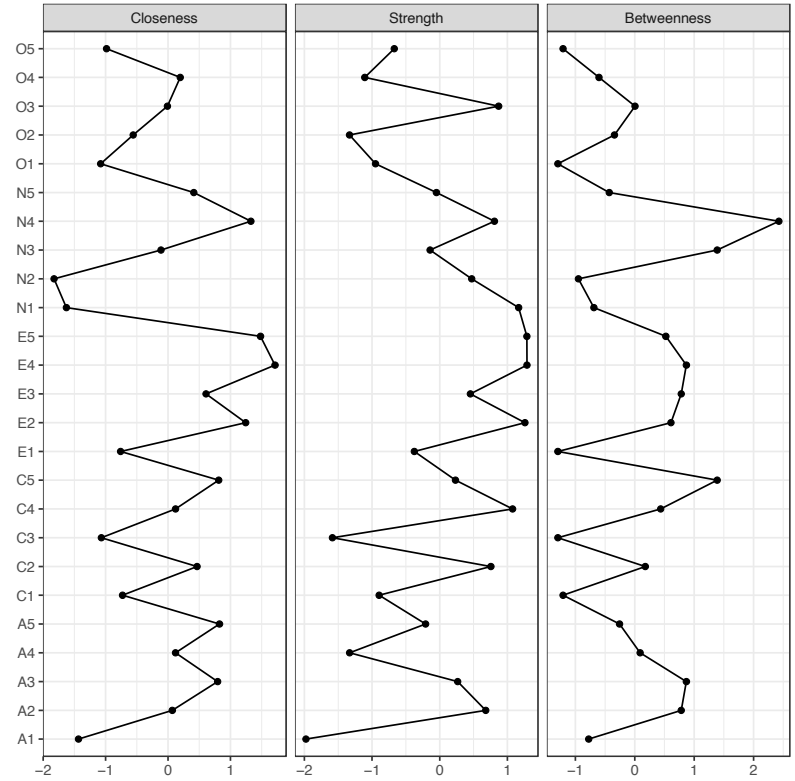
What is the least central node?





What is the least central node?



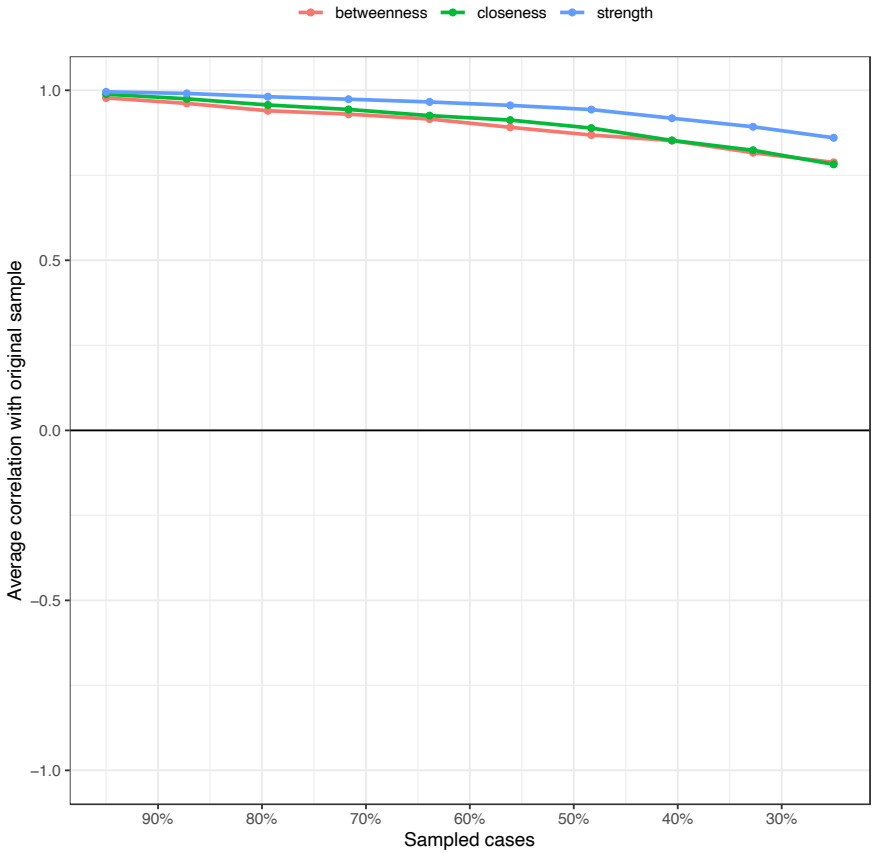


Assess reliability centrality

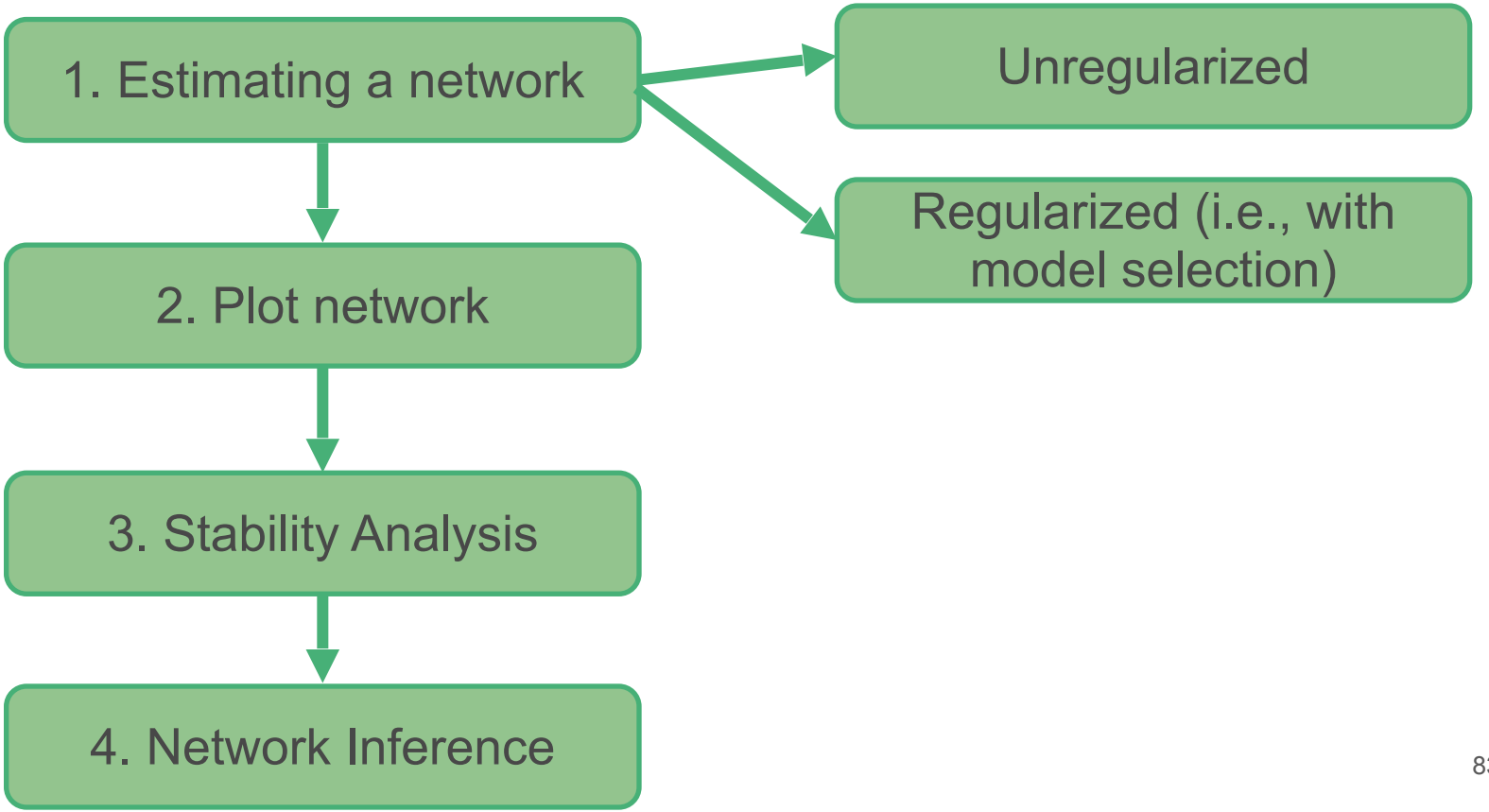
Investigate the node strength, closeness, and betweenness the regularized network using the centralityPlot function

```
# Centrality measures
Boots2 <- bootnet(bfi, default = "EBICglasso", type = "case",
statistics = c("Closeness", "Strength", "Betweenness"))

plot(Boots2, statistics = c("strength","betweenness","closeness"))
```

Assess reliability centrality



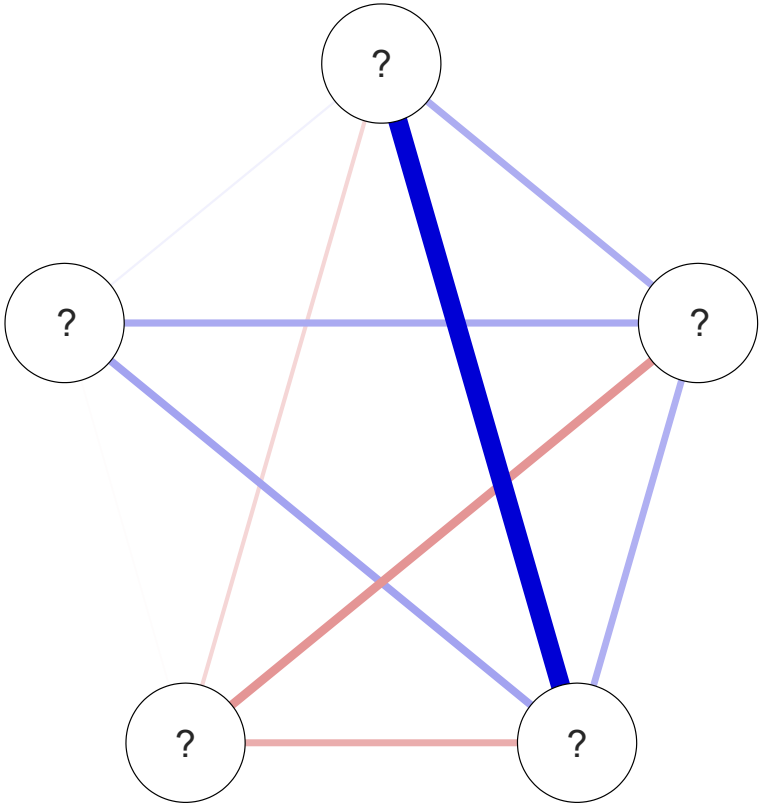
Workflow network models



Summary network analysis

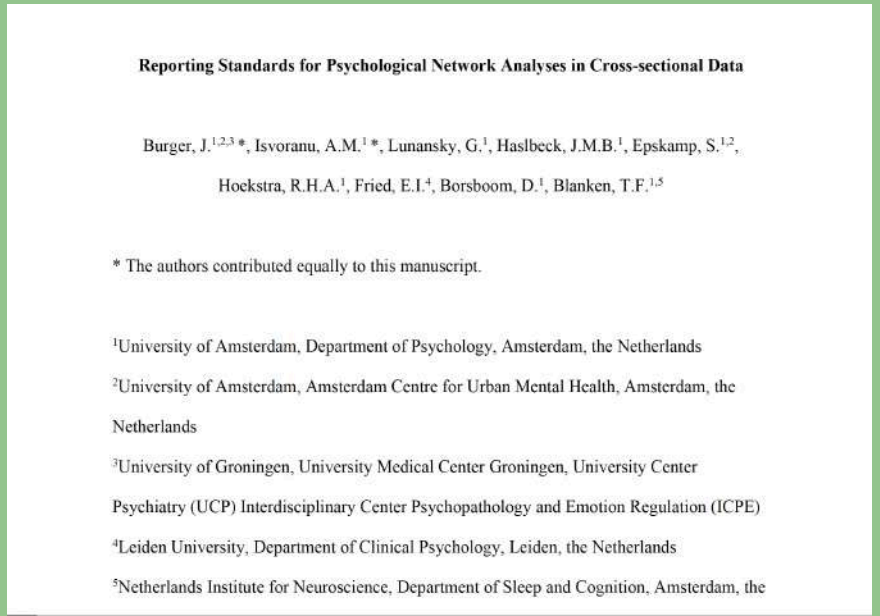
```
# Estimate a network with bootnet:
Network <- estimateNetwork(Data, default = "...")

# Plot network
qgraph(Network$graph)

# Perform bootstraps:
Boots1 <- bootnet(Data, default = "..."  nCores = 8)
Boots2 <- bootnet(Data, type = "case", nCores = 8)

# Inspect centrality:
centralityPlot(Network, include = c(”Closeness”, ”Strength”,
“Betweenness”)
```

I am curious about your networks!



Recommendations

- **Reporting standards**
  Burger, J., Isvoranu, A., Lunansky, G., Haslbeck, J. M. B., Epskamp, S., Hoekstra, R. H. A., … Blanken, T. (2020, November 28). Reporting Standards for Psychological Network Analyses in Cross-sectional Data.



Reporting Standards for Psychological Network Analyses in Cross-sectional Data

Burger, J.[1,2,3] *, Isvoranu, A.M.[1] *, Lunansky, G.[1], Haslbeck, J.M.B.[1], Epskamp, S.[1,2], Hoekstra, R.H.A.[1], Fried, E.I.[4], Borsboom, D.[1], Blanken, T.F.[1,5]

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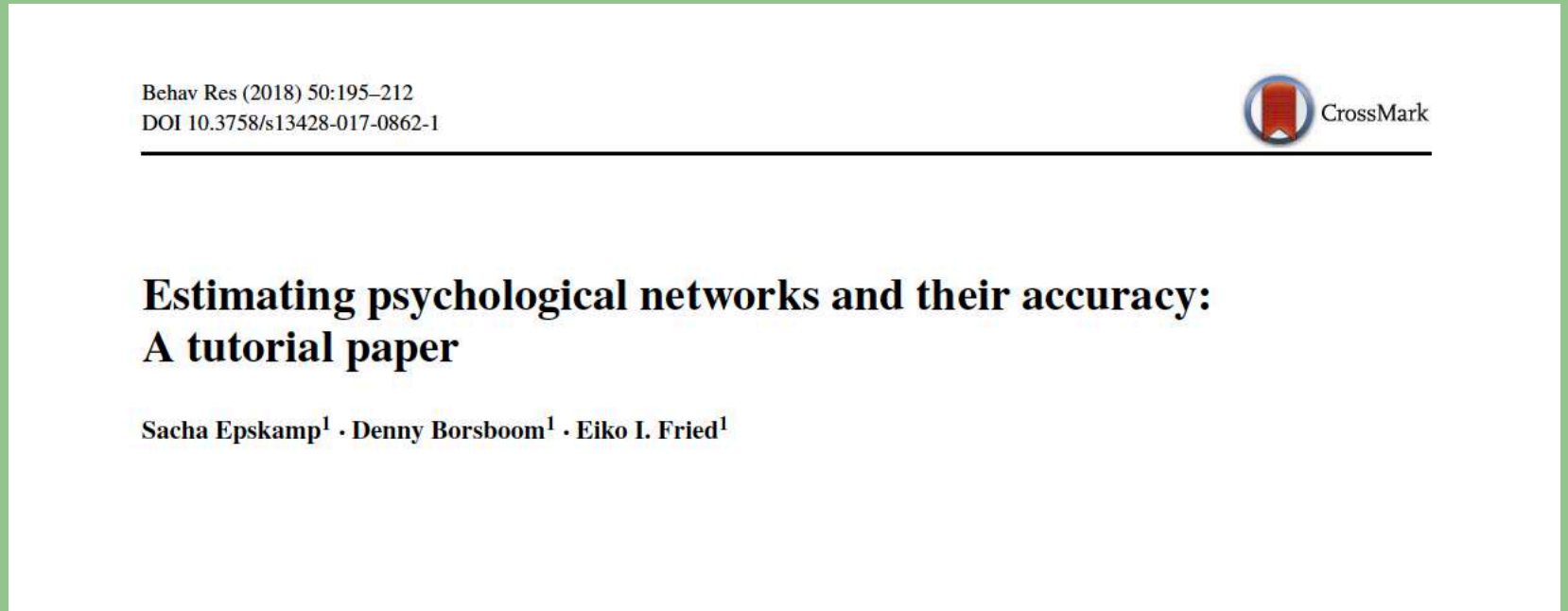
[3]University of Groningen, University Medical Center Groningen, University Center Psychiatry (UCP) Interdisciplinary Center Psychopathology and Emotion Regulation (ICPE)

[4]Leiden University, Department of Clinical Psychology, Leiden, the Netherlands

[5]Netherlands Institute for Neuroscience, Department of Sleep and Cognition, Amsterdam, the

Recommendations

- **Bootnet**
  Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper.



Behav Res (2018) 50:195–212
DOI 10.3758/s13428-017-0862-1

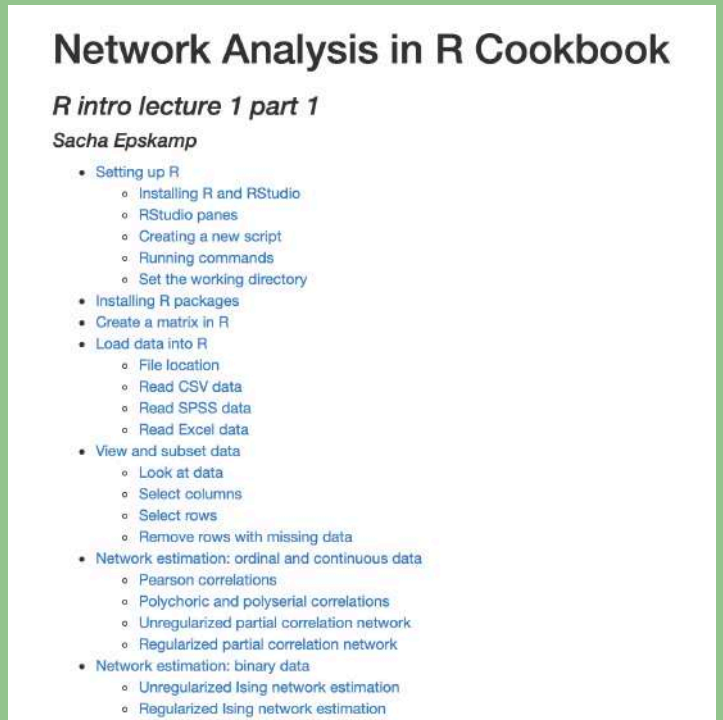
CrossMark

Estimating psychological networks and their accuracy: A tutorial paper

Sacha Epskamp[1] · Denny Borsboom[1] · Eiko I. Fried[1]

Recommendations

- **Network Analyses in R Cookbook**
  By Sacha Epskamp: http://sachaepskamp.com/files/Cookbook.html



Network Analysis in R Cookbook

R intro lecture 1 part 1

Sacha Epskamp

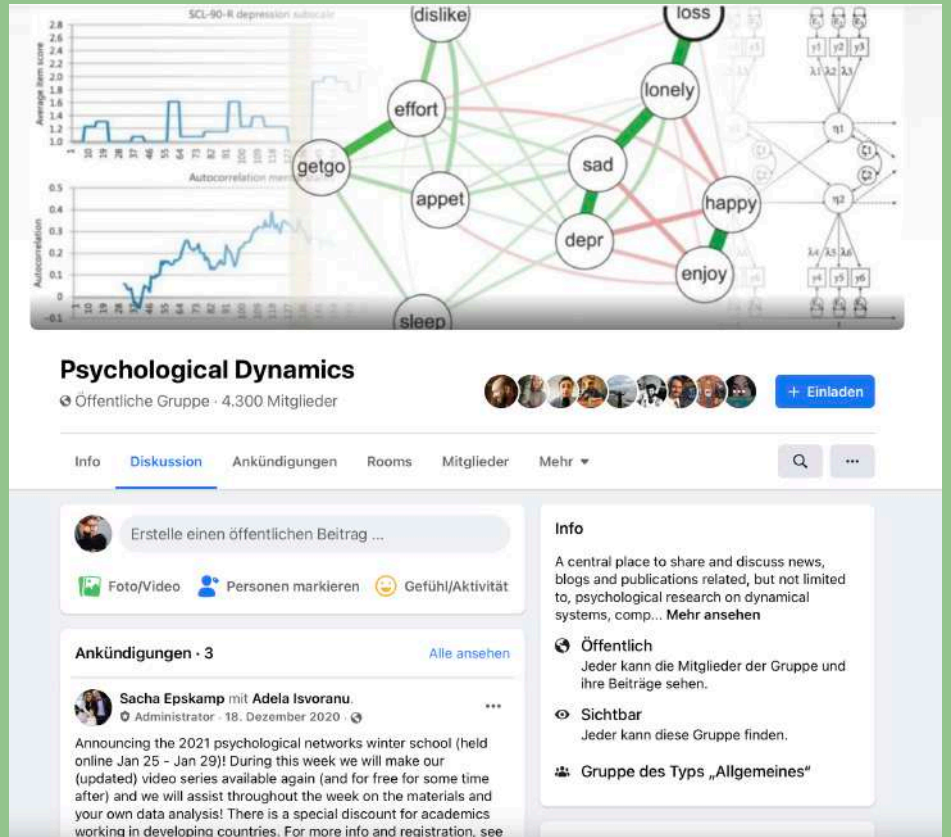
- Setting up R
  - Installing R and RStudio
  - RStudio panes
  - Creating a new script
  - Running commands
  - Set the working directory
- Installing R packages
- Create a matrix in R
- Load data into R
  - File location
  - Read CSV data
  - Read SPSS data
  - Read Excel data
- View and subset data
  - Look at data
  - Select columns
  - Select rows
  - Remove rows with missing data
- Network estimation: ordinal and continuous data
  - Pearson correlations
  - Polychoric and polyserial correlations
  - Unregularized partial correlation network
  - Regularized partial correlation network
- Network estimation: binary data
  - Unregularized Ising network estimation
  - Regularized Ising network estimation

Recommendations

- **Psychological Networks Amsterdam Summer/Winter School** http://psychosystems.org/

Recommendations

- **Our Facebook page**



Resources

- **Slide 5: Flock of birds (https://blogs.sw.siemens.com/solidedge/stuff-to-do-at-seu-birds-of-a-feather/)**
- **Slide 5: Brain (https://s823401281.websitebuilder.online/bc/)**
- **Slide 6: https://www.sciencemag.org/news/2014/07/how-bird-flocks-are-liquid-helium**
- **Slide 7: The atlas for aspiring network scientists (https://arxiv.org/abs/2101.00863)**
- **Slide 12-15: Thanks to https://osf.io/m9yz4/**
- **Slide 16: Facebook network https://blog.revolutionanalytics.com/2010/12/facebooks-social-network-graph.html**
- **Slide 17: human contact network (https://link.springer.com/article/10.1007/s00521-020-05285-9)**

Resources

- **Slide 18: The model thinker (https://www.amazon.nl/Model-Thinker-What-Need-Know/dp/0465094627)**
- **Slide 19+20: Scheffer, M. (2004). Ecology of shallow lakes. Berlin, Germnay: Springer Science & Business Media.**
- **Slide 20-21: Copied from to https://osf.io/m9yz4/**
- **Slide 35-36: https://slidemodel.com/the-big-five-personality-traits-model/**
- **Slide 53: Continuous and Ordered Categorical Data in Network Psychometrics: Which estimation method to choose? Isvornau & Epskamp (2021) https://psyarxiv.com/mbycn/?fbclid=IwAR1ZborIpds4Xh3D2ygxXTAn5IV2NN8YYIxIy5RrAGZm9K__WOTI_N79FvY**
- **Slide 62-65: Copied from to https://osf.io/m9yz4/**