The **qgraph** package for network visualizations of psychometric data in R

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All codes in these slides were run using R version 2.12.1 (2010-12-16) and **qgraph** version 0.4.8 and were made on Windows 7 x64 x86-64 build 7600.

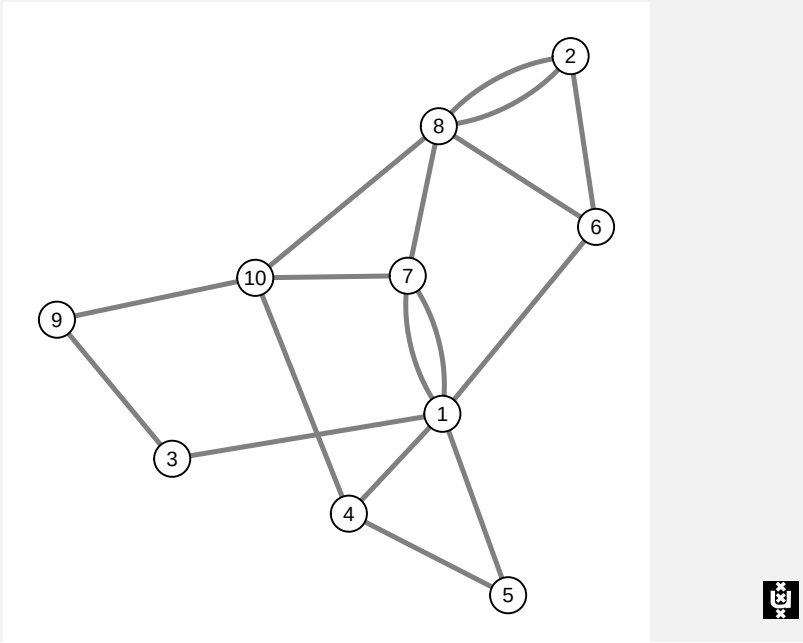
qgraph

- A R package (CRAN link)
- Can be used to plot various types of graphs
- Different from other R packages (e.g. **igraph** Csardi & Nepusz, 2006) in:
  - Focus on *weighted graphs*
  - Intended for visualization of data as graphs
  - Optimized for vector-type image files (e.g. PDF, SVG)
- Aims in **qgraph**
  - Simple input
  - Summarize a large amount of statistics without needing data reduction methods.
  - Visualize *relations between variables*
- Main idea: Show variables as nodes, relationships as edges

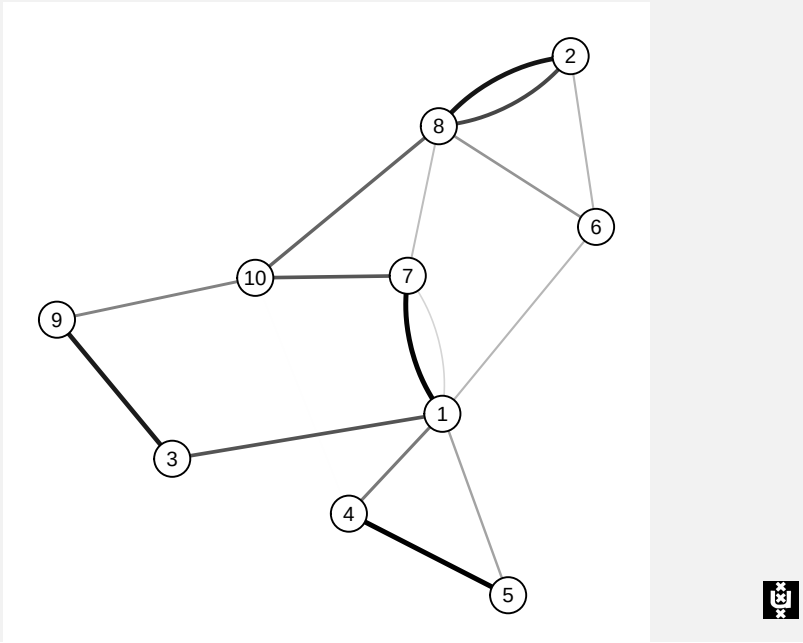
Graphs

- A graph is a *network* that consists of n nodes (or vertices) that are connected with m edges.
- Each edge has a *weight* indicating the strength of that connection
- An edge can be directed (have an arrow) or undirected

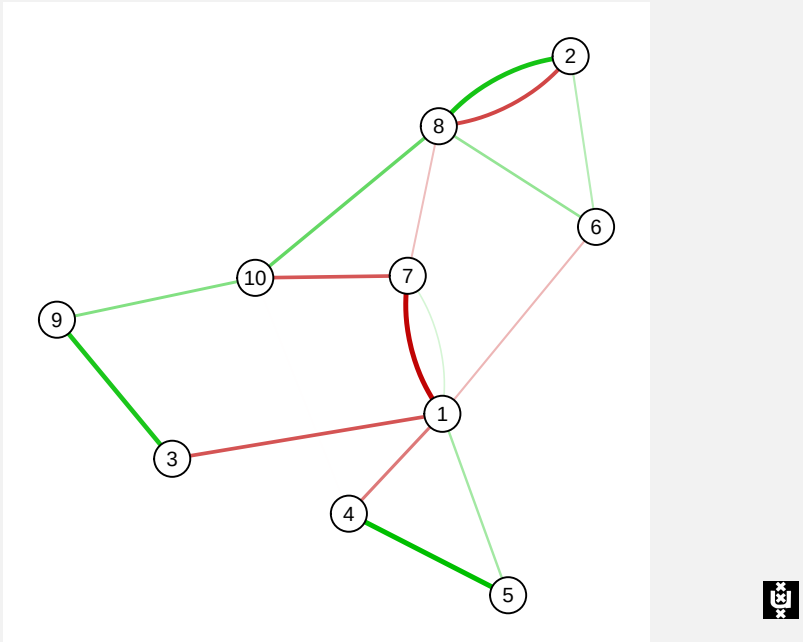
Unweighted graph



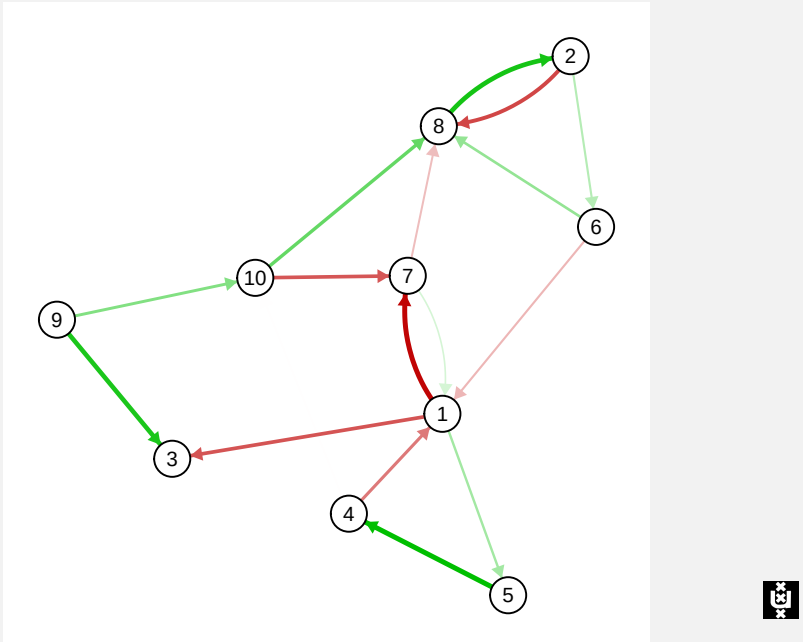
Weighted graph



Weighted graph



Directed graph



The qgraph() function

- The main function in **qgraph** is `qgraph()`
  - Most other functions are either wrapping functions using `qgraph()` or functions used in `qgraph()`
- The `qgraph()` function requires only one argument (`adj`)
- A lot of other arguments can be specified, but these are all optional

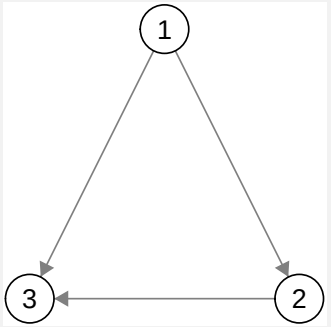
Usage:

```
qgraph( adj, ... )
```

The adjacency matrix

- The `adj` argument is the input. This can be an *adjacency matrix*
- An adjacency matrix is a square *n* by *n* matrix in which each element indicates the relationship between two variables
- Any relationship can be used as long as:
  - A 0 indicates no relationship
  - Absolute negative values are similar in strength to positive values
- Examples:
  - A 1 indicating a connection (unweighted graphs)
  - Correlations
  - Regression parameters
  - Factor loadings
- *Adjacency matrices occur naturally in statistics!*

```
     [,1] [,2] [,3]
[1,]    0    1    1
[2,]    0    0    1
[3,]    0    0    0
```



Weighted graphs

$$\mathbf{Y} = \boldsymbol{\eta}\boldsymbol{\Lambda}^{\mathrm{T}} + \boldsymbol{\Theta}$$

```
> set.seed(2)
> eta <- matrix(rnorm(200 * 5), ncol = 5)
> lam <- matrix(rnorm(50 * 5, 0, 0.15), 50,
+     5)
> lam[apply(diag(5) == 1, 1, rep, each = 10)] <- rnorm(50,
+     0.7, 0.3)
> th <- matrix(rnorm(200 * 50), ncol = 50)
> Y <- eta %*% t(lam) + th
```

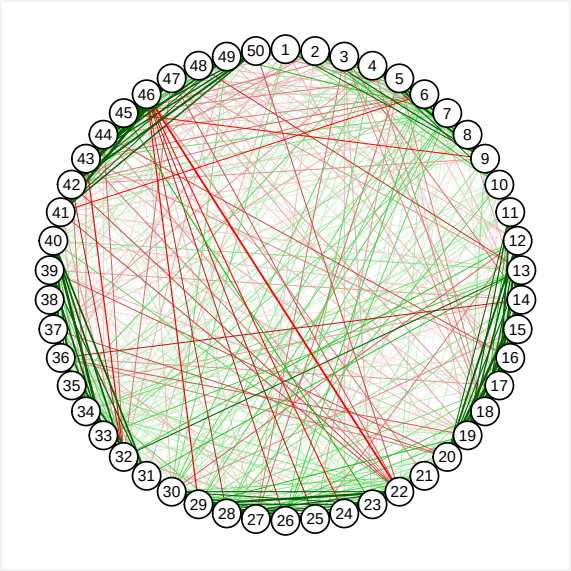
Weighted graphs

```
> cor(Y)[1:15, 1:3]
```

```
              [,1]         [,2]         [,3]
 [1,]  1.000000000  0.218987651  0.197325805
 [2,]  0.218987651  1.000000000  0.231696634
 [3,]  0.197325805  0.231696634  1.000000000
 [4,]  0.464897112  0.346780772  0.279845144
 [5,]  0.295912130  0.275030523  0.209220603
 [6,]  0.235201044  0.272947122  0.197676521
 [7,]  0.157314986 -0.001815960 -0.027551034
 [8,]  0.234392422  0.212721700  0.192401237
 [9,]  0.321680277  0.350685995  0.210808452
[10,]  0.204097076  0.277127339  0.148343574
[11,] -0.072734280 -0.000913891 -0.085440215
[12,]  0.052842181  0.105870583 -0.056247479
[13,]  0.001850306  0.025604291  0.081077133
[14,] -0.083391834 -0.088641129 -0.215127641
[15,] -0.055847218  0.007651554  0.004209916
```

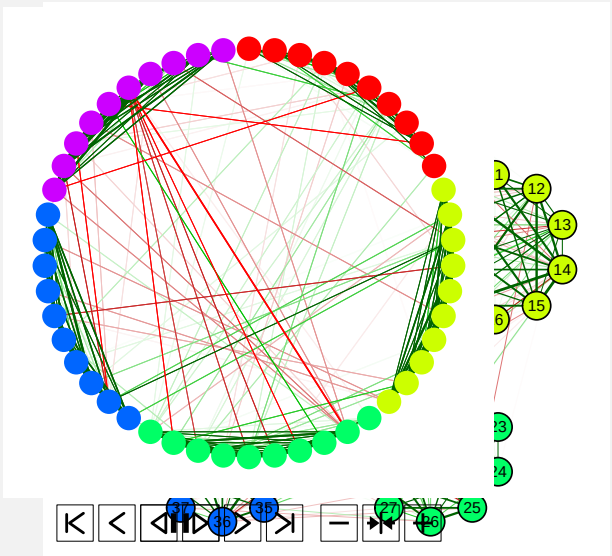
Weighted graphs

```
> qgraph(cor(Y))
```



Weighted graphs

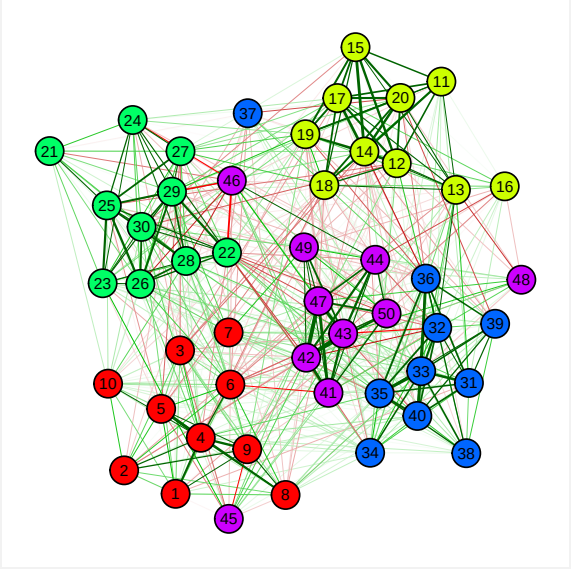
```
> gr <- list(1:10, 11:20, 21:30, 31:40, 41:50)
> qgraph(cor(Y), groups = gr)
```



Fruchterman-Reingold layout (20 iterations)

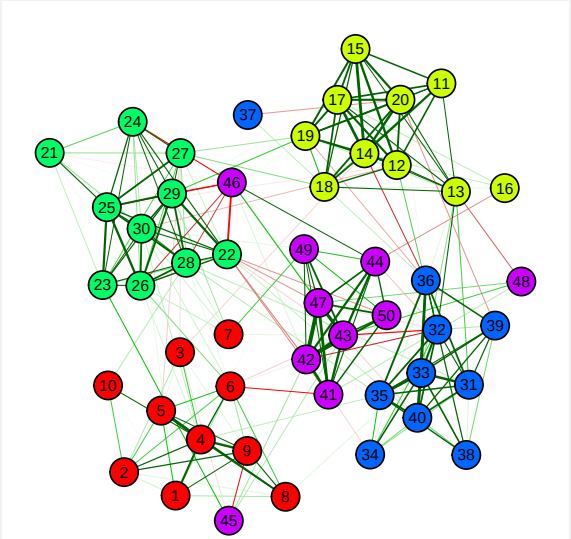
Fruchterman-Reingold layout (500 iterations)

```
> qgraph(cor(Y), groups = gr, layout = "spring")
```



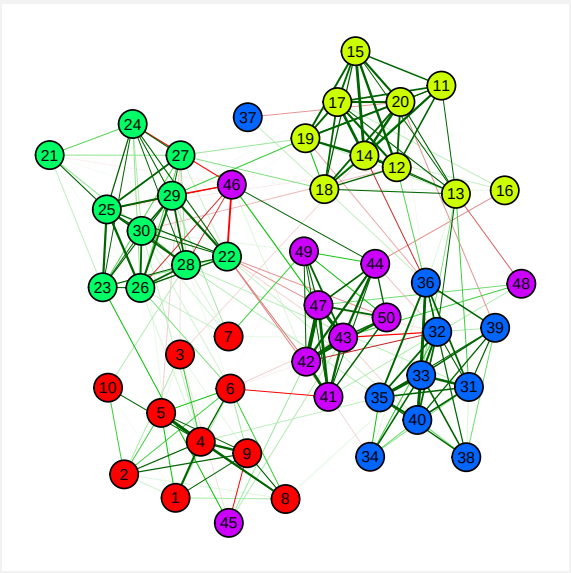
Saving arguments

```
> Q <- qgraph(cor(Y), groups = gr, layout = "spring",
+     minimum = 0.2)
```



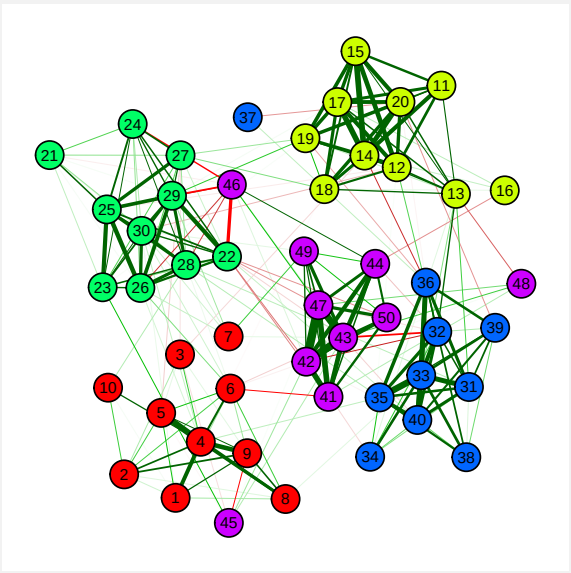
Saving arguments

```
> Q <- qgraph(Q)
```



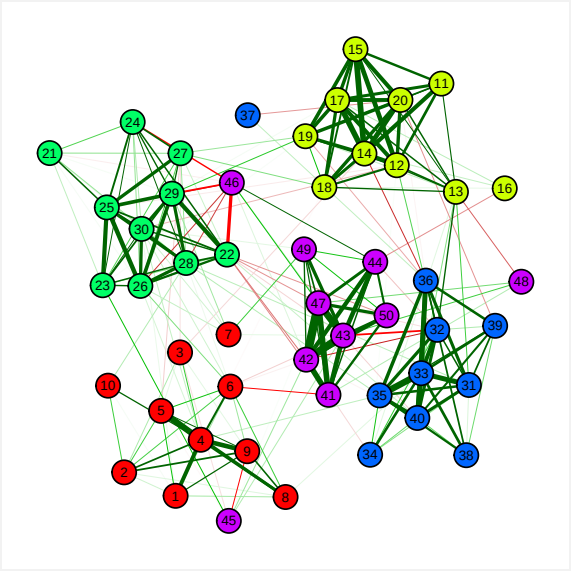
Graphical arguments

```
> Q <- qgraph(Q, esize = 10)
```



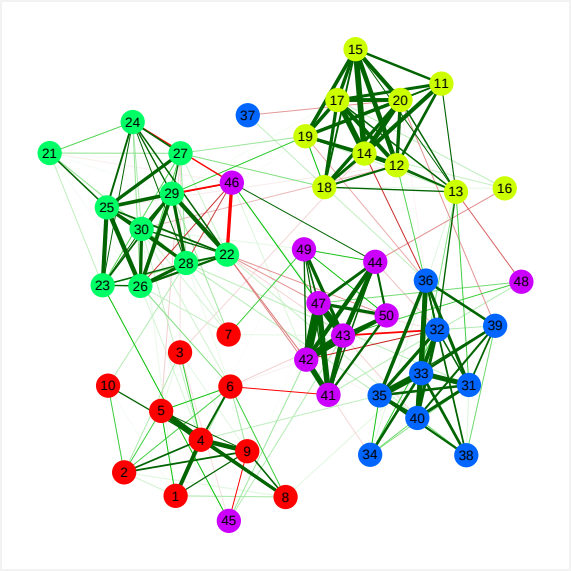
Graphical arguments

```
> Q <- qgraph(Q, vsize = 4)
```



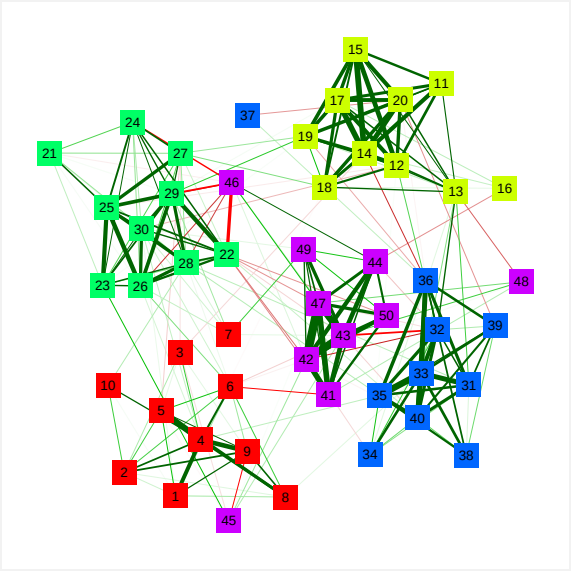
Graphical arguments

```
> Q <- qgraph(Q, borders = FALSE)
```



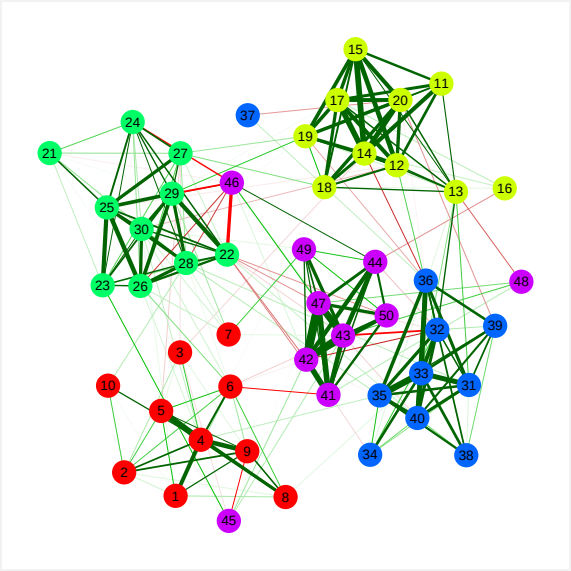
Graphical arguments

```
> Q <- qgraph(Q, shape = "square")
```



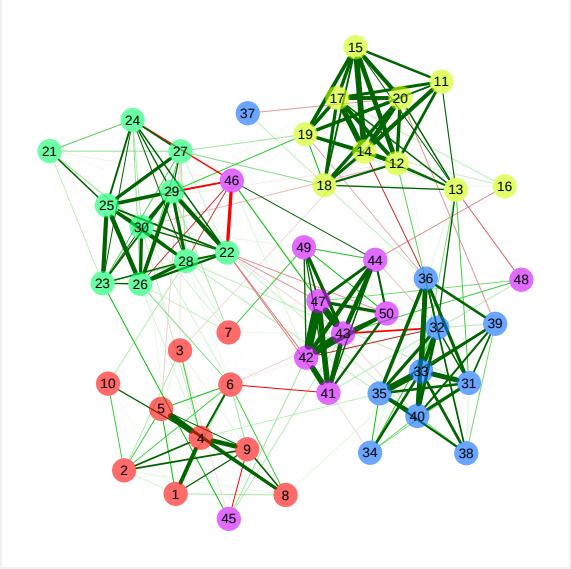
Graphical arguments

```
> Q <- qgraph(Q, shape = "circle")
```



Graphical arguments

```
> Q <- qgraph(Q, vTrans = 150)
```

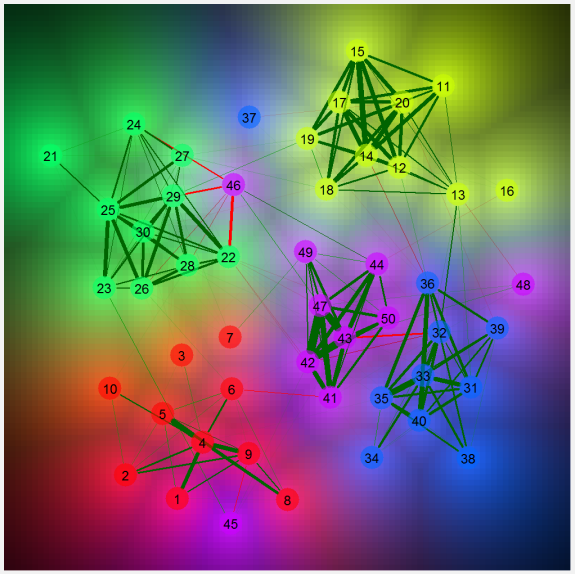


Graphical arguments

```
> qgraph(Q, transparency = T, bg = T, bgcontrol = 5,
+     filetype = "png", filename = "bg", res = 144,
+     width = 7, height = 7)
```

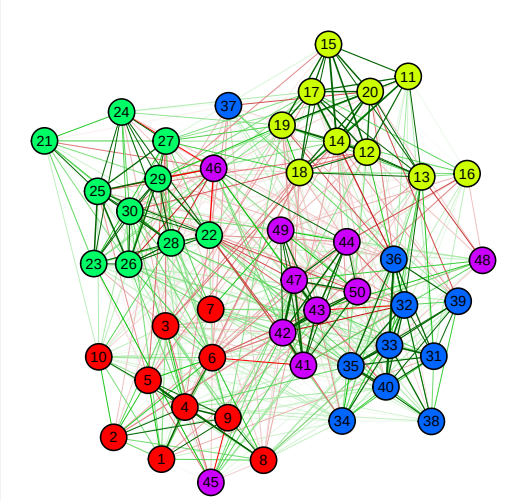
```
[1] "Output stored in C:/Users/Sacha/Documents/Work/qgraph/Psych
```

Graphical arguments



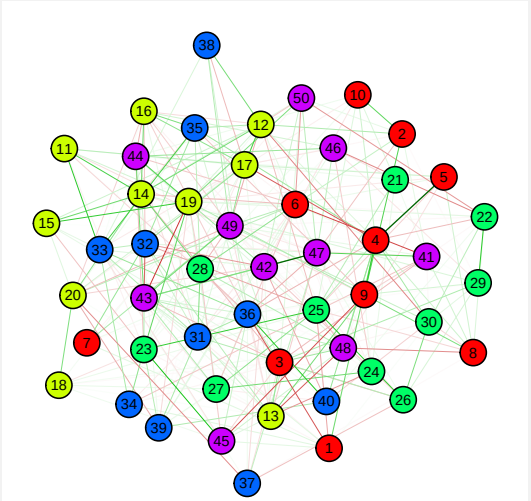
Correlations

```
> qgraph(cor(Y), layout = "spring", groups = gr,
+     cut = 0.3, minimum = 0.1, maximum = 1,
+     graph = "association")
```



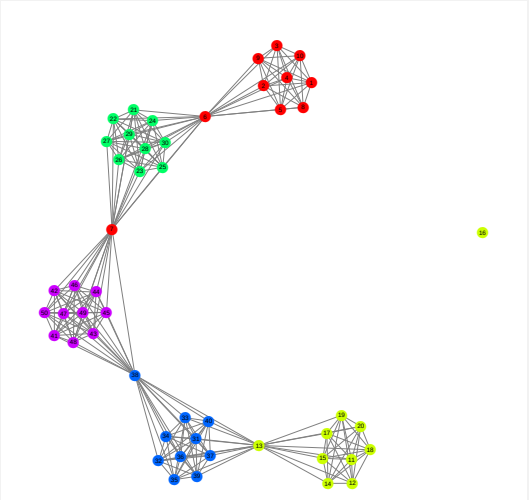
Partial correlations

```
> qgraph(cor(Y), layout = "spring", groups = gr,
+      cut = 0.3, minimum = 0.1, maximum = 1,
+      graph = "concentration")
```



Factorial graph

```
> qgraph(cor(Y), layout = "spring", groups = gr,
+      cut = 0.2, vsize = 2, esize = 1, borders = F,
+      graph = "factorial")
```

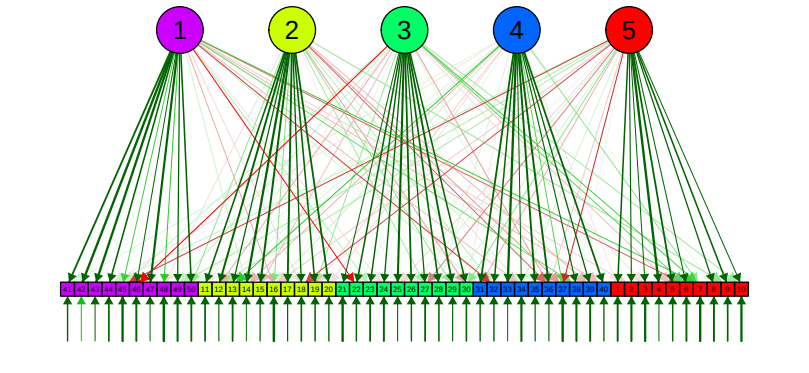


Factor loadings

- A factor loadings matrix can be visualized using `qgraph.loadings()`
- There are two wrapper functions that perform an analysis and send the results to `qgraph.loadings()`:
  - `qgraph.efa()` performs an exploratory factor analysis (EFA) using `stats:::factanal`
  - `qgraph.pca()` performs a principal component analysis (PCA) using `psych:::principal` (Revelle, 2010)
- These functions use a correlation or covariance matrix as input

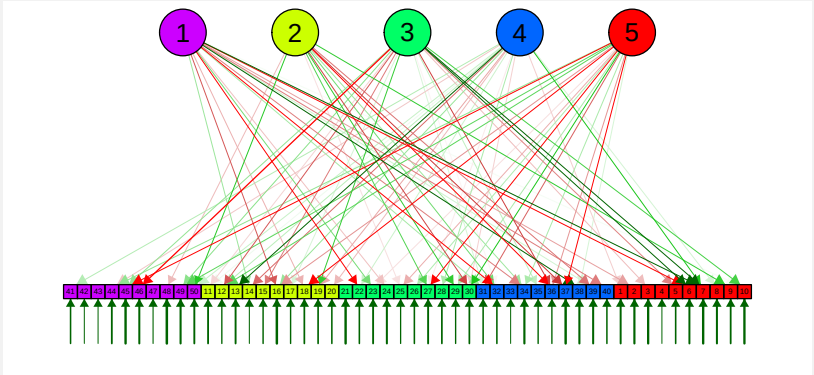
Factor loadings: EFA

```
> qgraph.efa(cor(Y), 5, rotation = "promax",
+      layout = "tree", vsize = c(3, 10), groups = gr)
```



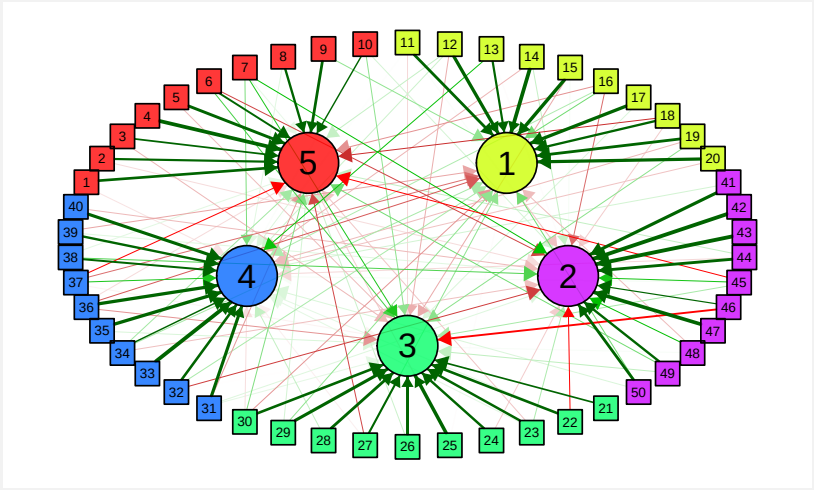
Factor loadings: EFA crossloadings

```
> qgraph.efa(cor(Y), 5, rotation = "promax",
+     layout = "tree", crossloadings = TRUE,
+     vsize = c(3, 10), groups = gr, cut = 0.2)
```



Factor loadings: PCA

```
> qgraph.pca(cor(Y), 5, rotation = "promax",
+     vsize = c(4, 10), groups = gr, vTrans = 200)
```

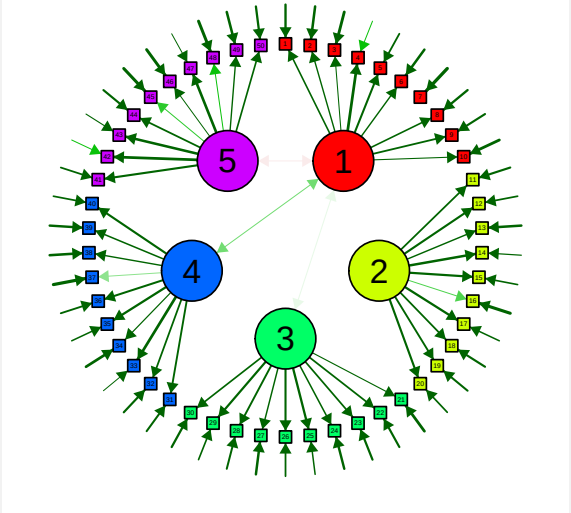


Confirmatory Factor Analysis

- `qgraph.cfa()` can be used to fit a simple confirmatory factor model
  - Each variable loads on only one factor
  - Factors are correlated
  - Scaling by fixing first loading of each factor to 1
- This is done with the **sem** (Fox, 2010) package
- Returns a `"sem"` object
- Results can be send to `qgraph.sem()` for a full report

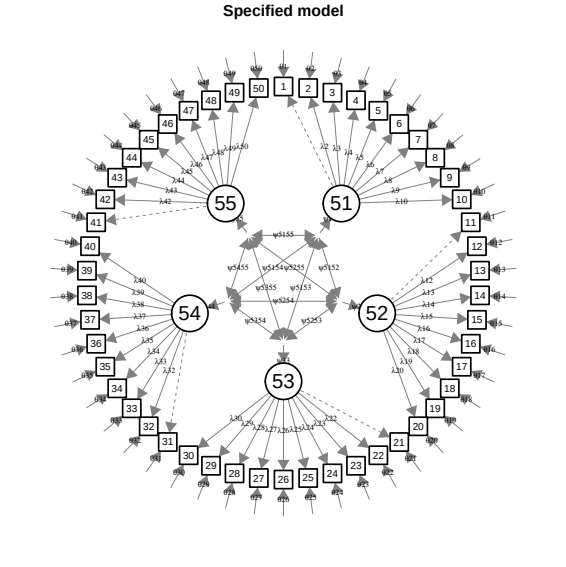
Confirmatory Factor Analysis

```
> res <- qgraph.cfa(cov(Y), N = 200, groups = gr,
+     vsize = c(2, 10))
```



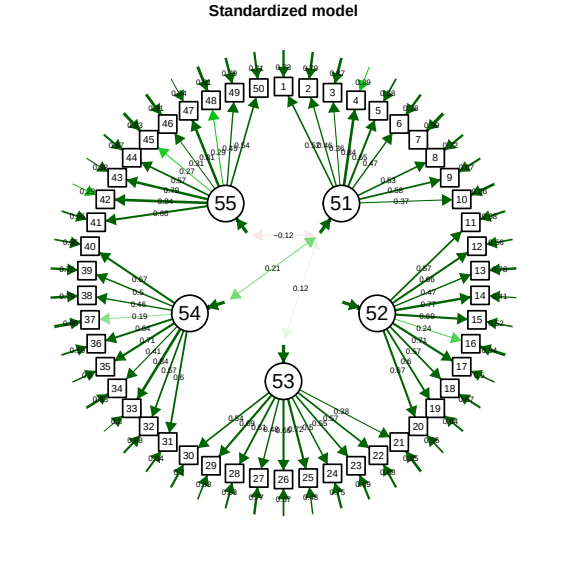
Confirmatory Factor Analysis

```
> qgraph.semModel(res, edge.label.cex = 0.6)
```



Confirmatory Factor Analysis

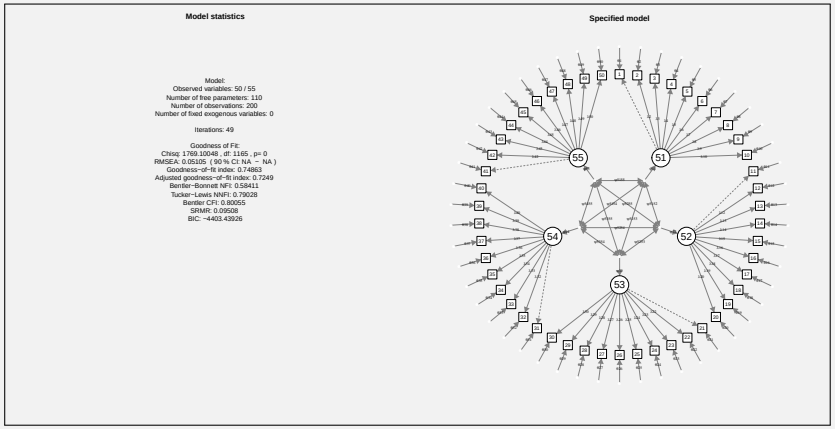
```
> qgraph(res, edge.label.cex = 0.6)
```



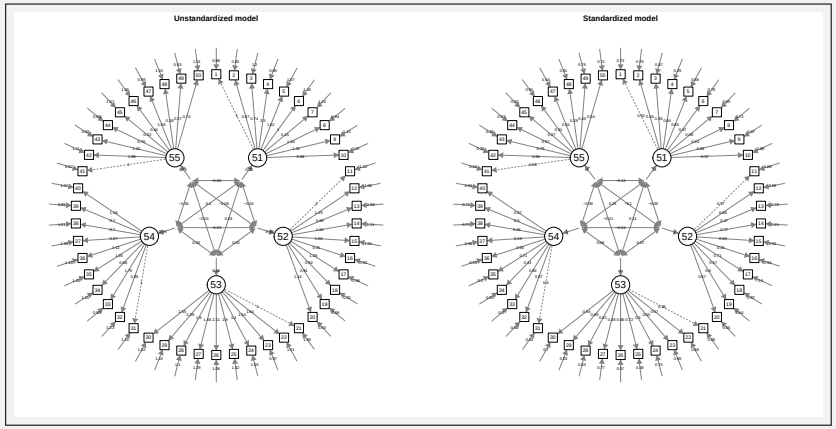
Confirmatory Factor Analysis

```
> qgraph.sem(res, filename = "sem%03d", onefile = F,
+     panels = 2, legend = FALSE, groups = gr,
+     edge.label.cex = 0.6)
```

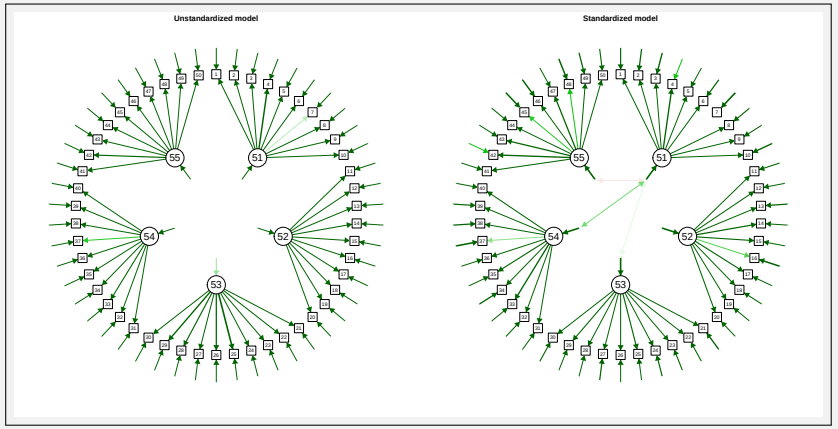
Confirmatory Factor Analysis



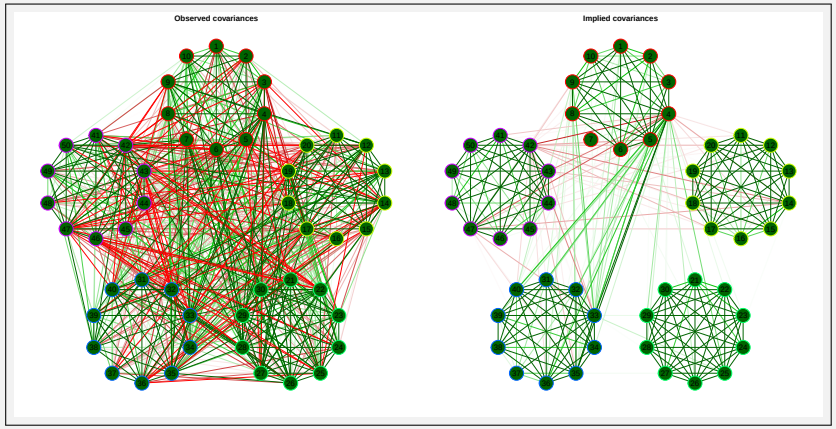
Confirmatory Factor Analysis



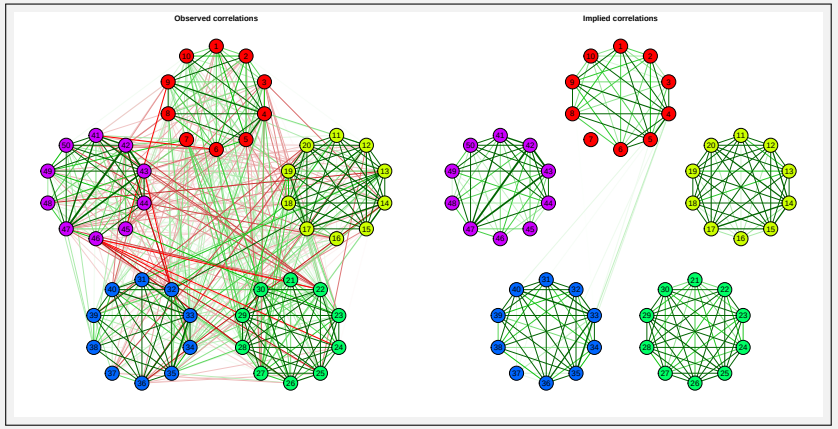
Confirmatory Factor Analysis



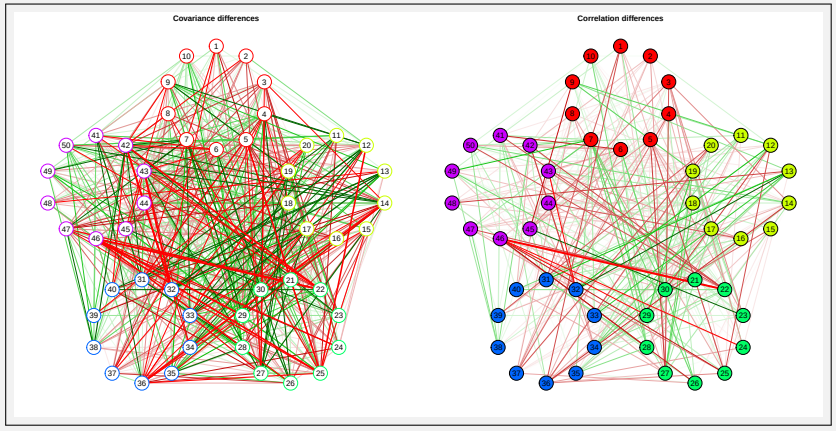
Confirmatory Factor Analysis



Confirmatory Factor Analysis



Confirmatory Factor Analysis



Structural Equation Modelling

- **qgraph** comes with a function that extends output from **sem** (Fox, 2010) with path diagrams and graphs visualizing the parameter estimates
- This is done with the `qgraph.sem()` function
- The output of `qgraph.sem()` is a multi-page pdf file
- We can use **sem** as usual and pass the output to `qgraph.sem()` with only two things to note:
  - It is best to limit variable names in the model to three characters
  - **qgraph** supports Greek letters, by adding an asterisk a label is printed in the symbol font

Structural Equation Modelling

```
> library('sem')
> R.thur <- read.moments(diag=FALSE, names=c('Sen','Voc',
+                   'SC','FL','4LW','Suf','LS','Ped','LG'))
1:     .828
2:     .776   .779
4:     .439   .493    .46
7:     .432   .464    .425   .674
11:    .447   .489    .443   .59    .541
16:    .447   .432    .401   .381   .402   .288
22:    .541   .537    .534   .35    .367   .32    .555
29:    .38    .358    .359   .424   .446   .325   .598   .452
37:
Read 36 items
```

Structural Equation Modelling

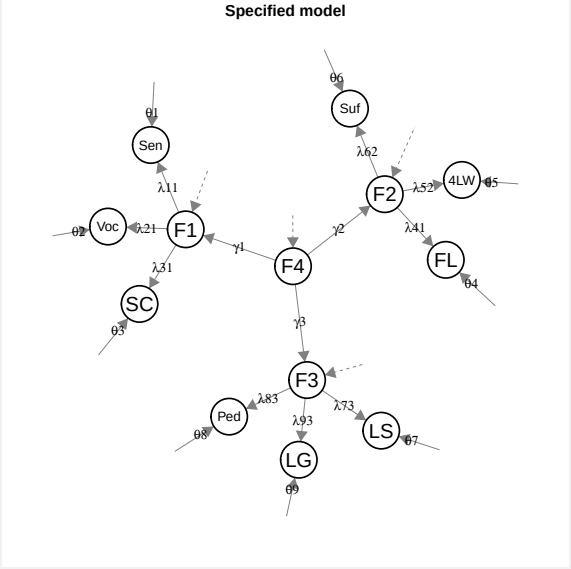
```
> model.thur <- specify.model()
1:     F1 -> Sen,    *l11, NA
2:     F1 -> Voc,    *l21, NA
3:     F1 -> SC,     *l31, NA
4:     F2 -> FL,     *l41, NA
5:     F2 -> 4LW,    *l52, NA
6:     F2 -> Suf,    *l62, NA
7:     F3 -> LS,     *l73, NA
8:     F3 -> Ped,    *l83, NA
9:     F3 -> LG,     *l93, NA
10:    F4 -> F1,     *g1,  NA
11:    F4 -> F2,     *g2,  NA
12:    F4 -> F3,     *g3,  NA
13:    Sen <-> Sen,  q*1,  NA
14:    Voc<-> Voc,   q*2,  NA
15:    SC <-> SC,    q*3,  NA
```

Structural Equation Modelling

```
16:    FL <-> FL,   q*4,  NA
17:    4LW <-> 4LW, q*5,  NA
18:    Suf<-> Suf,  q*6,  NA
19:    LS <-> LS,   q*7,  NA
20:    Ped<-> Ped,  q*8,  NA
21:    LG <-> LG,   q*9,  NA
22:    F1 <-> F1,   NA,    1
23:    F2 <-> F2,   NA,    1
24:    F3 <-> F3,   NA,    1
25:    F4 <-> F4,   NA,    1
26:
Read 25 records
> sem.thur <- sem(model.thur, R.thur, 213)
```

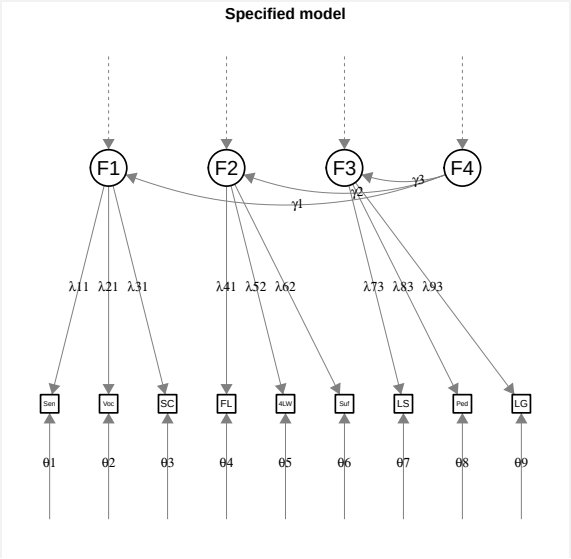
Structural Equation Modelling

```
> qgraph(model.thur)
```



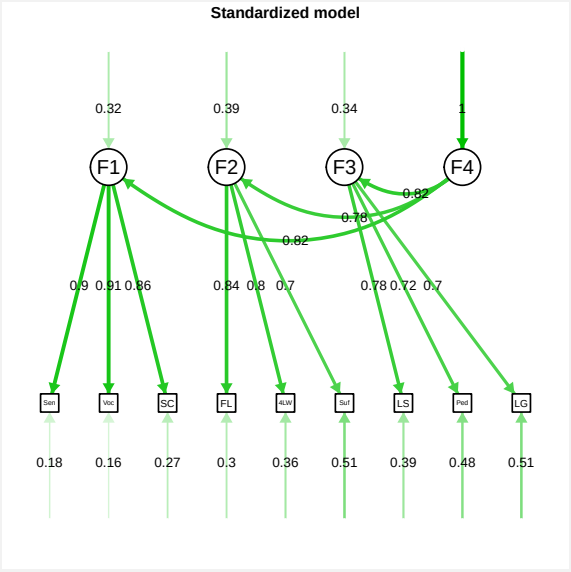
Structural Equation Modelling

```
> qgraph(model.thur, manifest = rownames(R.thur),
+     layout = "tree")
```



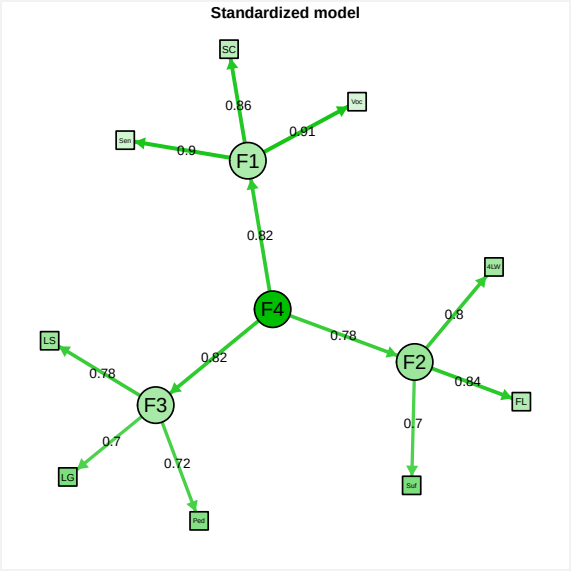
Structural Equation Modelling

```
> qgraph(sem.thur, layout = "tree", curve = 0.4)
```



Structural Equation Modelling

```
> qgraph(sem.thur, layout = "spring", residuals = FALSE)
```



The big 5

```
> library(qgraph)
> data(big5)
> str(big5)
```

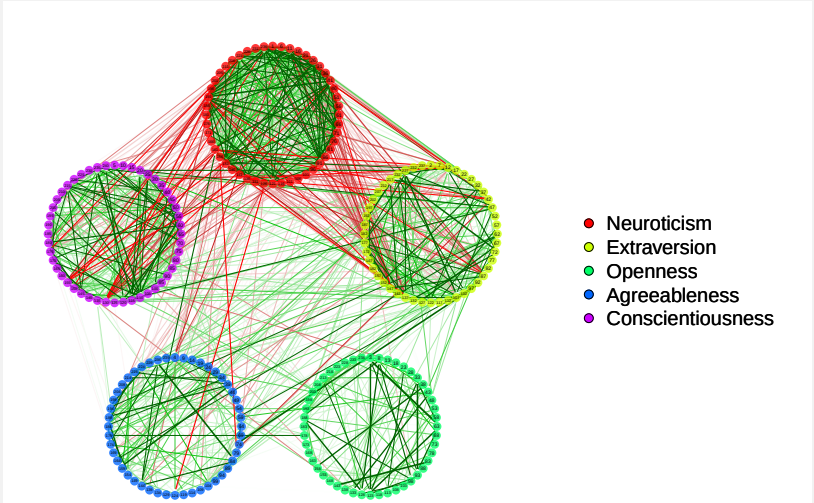
```
 num [1:500, 1:240] 2 3 4 4 5 2 2 1 4 2 ...
 - attr(*, "dimnames")=List of 2
  ..$ : NULL
  ..$ : chr [1:240] "N1" "E2" "O3" "A4" ...
```

```
> data(big5groups)
> str(big5groups)
```

```
List of 5
 $ Neuroticism      : num [1:48] 1 6 11 16 21 26 31 36 41 46 ...
 $ Extraversion     : num [1:48] 2 7 12 17 22 27 32 37 42 47 ...
 $ Openness         : num [1:48] 3 8 13 18 23 28 33 38 43 48 ...
 $ Agreeableness    : num [1:48] 4 9 14 19 24 29 34 39 44 49 ...
 $ Conscientiousness: num [1:48] 5 10 15 20 25 30 35 40 45 50 ..
```

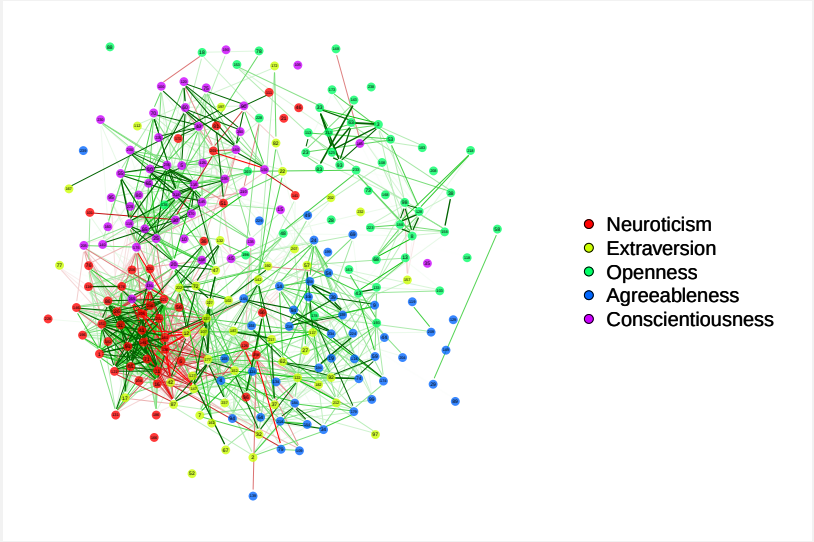
The big 5

```
> Q <- qgraph(cor(big5), minimum = 0.25, cut = 0.4,
+     vsize = 2, groups = big5groups, legend = T,
+     borders = F, vTrans = 200)
```



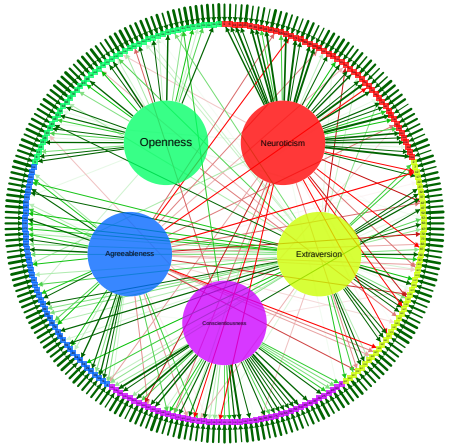
The big 5

```
> qgraph(cor(big5), Q, layout = "spring")
```



EFA

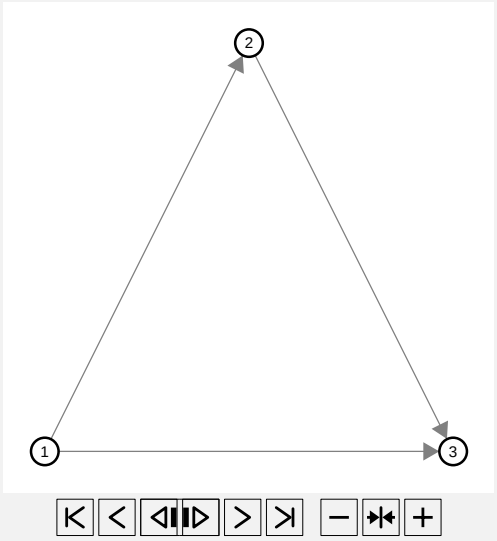
```
> qgraph.efa(cor(big5), factors = 5, Q, layout = "circle",
+     vsize = c(1, 15), borders = F, asize = 0.07,
+     esize = 4, rotation = "promax", residSize = 0.1)
```



Concluding comments

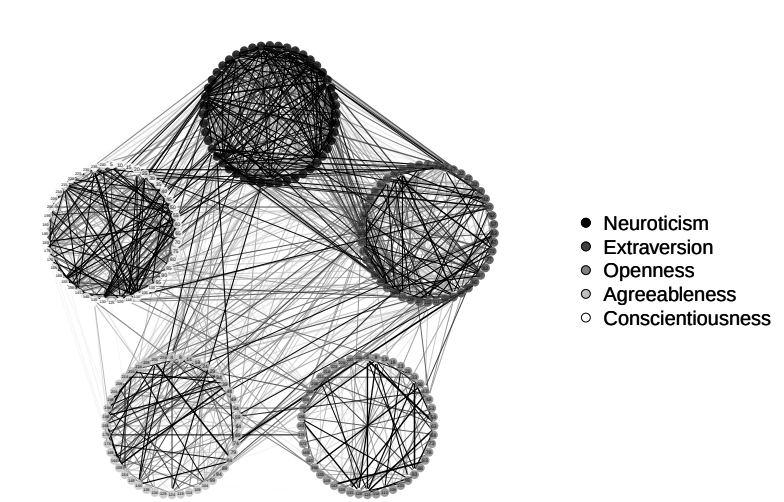
- **qgraph** is still work in progress
- Plans for the future:
  - More wrapper functions for different statistics (e.g. IRT)
  - More layout modes
  - Estimating and fitting causal models
- Some things I couldn't describe...

Layout constraints



Grayscale colors

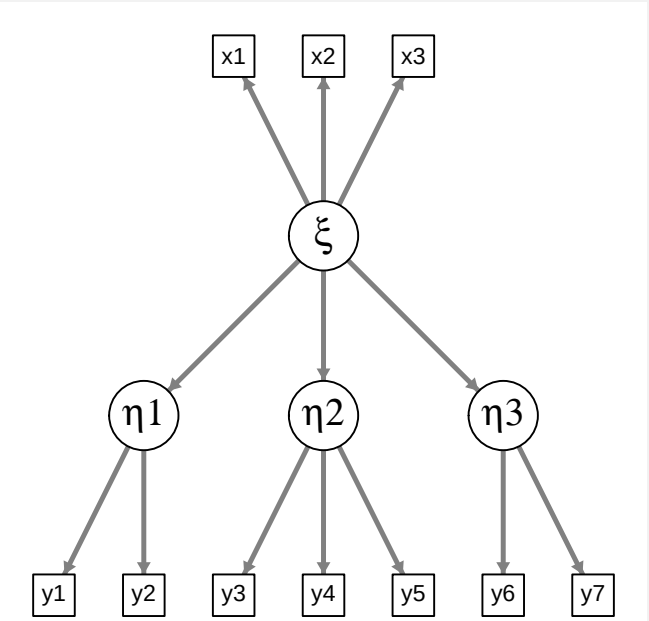
```
> Q <- qgraph(cor(big5), minimum = 0.25, cut = 0.4,
+     vsize = 2, groups = big5groups, legend = T,
+     borders = F, vTrans = 200, gray = TRUE)
```

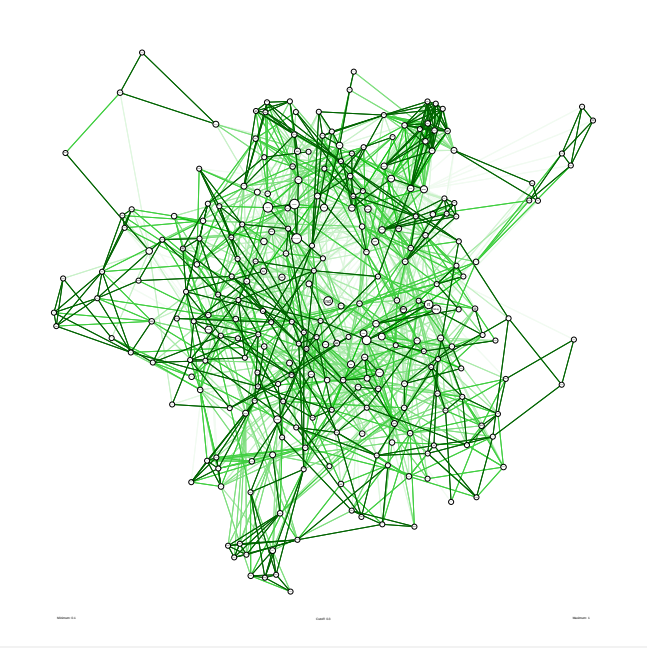


Tooltips

Link

Modelling





Concluding comments

Thank you for your attention!

References

Butts, C. T. (2010). **sna**: Tools for social network analysis [Computer software manual]. Available from `http://CRAN.R-project.org/package=sna` (R package version 2.2-0)

Csardi, G., & Nepusz, T. (2006). The **igraph** software package for complex network research. *InterJournal*, *Complex Systems*, 1695. Available from `http://igraph.sf.net`

Fox, J. (2010). **sem**: Structural equation models [Computer software manual]. Available from `http://CRAN.R-project.org/package=sem` (R package version 0.9-21)

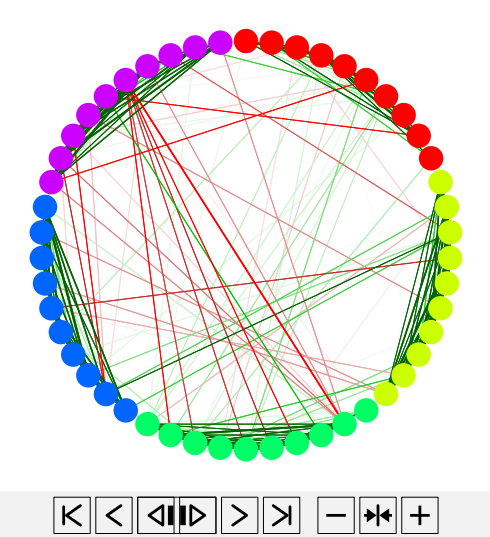
Fruchterman, T., & Reingold, E. (1991). Graph drawing by force-directed placement. *Software: Practice and Experience*, *21*(11), 1129–1164.

Revelle, W. (2010). **psych**: Procedures for psychological, psychometric, and personality research [Computer software manual]. Evanston, Illinois. Available from `http://personality-project.org/r/psych.manual.pdf` (R package version 1.0-93)

Layout modes

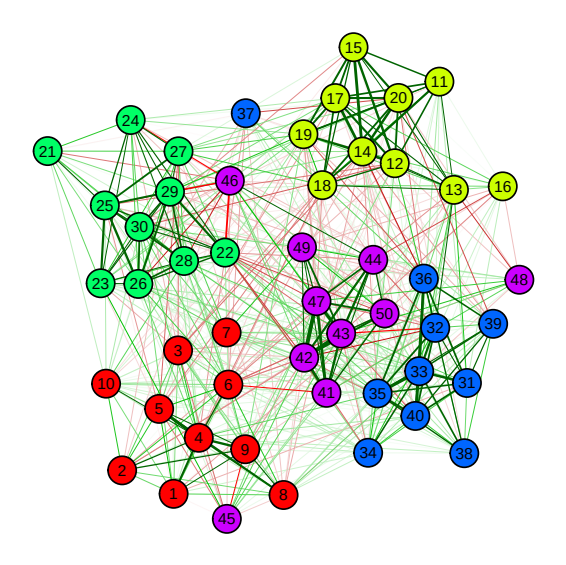
- The placement of the nodes is specified with the `layout` argument in `qgraph()`
- This can be a n by 2 matrix indicating the x and y position of each node
- `layout` can also be given a character indicating one of the two default layouts
- If `layout="circular"` the nodes are placed in circles per group (if the `groups` list is specified)
- If `layout="spring"` a force-embedded algorithm (Fruchterman & Reingold, 1991) is used for the placement
  - This is an iterative algorithm that clusters the nodes so that the length of the edges correspond to the absolute strength of the edges

Fruchterman-Reingold layout (20 iterations)



Fruchterman-Reingold layout (500 iterations)

```
> qgraph(cor(Y), groups = gr, layout = "spring")
```



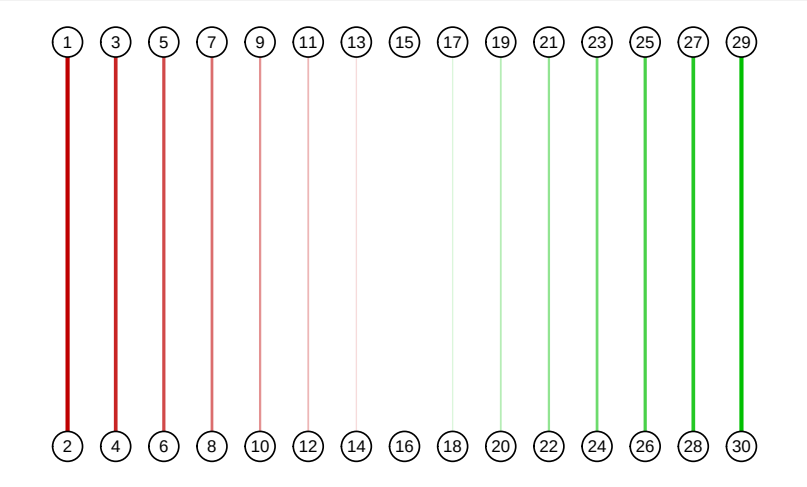
Grid layout

- A final option is to specify a grid as layout
- This can be done by specifying a matrix to `layout` with more than two columns
- This matrix contains zeros and a number for each node

```
> dat.3 <- matrix(c(1:15 * 2 - 1, 1:15 * 2),
+     , 2)
> dat.3 <- cbind(dat.3, round(seq(-0.7, 0.7,
+     length = 15), 1))
> L.3 <- matrix(1:30, nrow = 2)
> L.3
     [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9]
[1,]    1    3    5    7    9   11   13   15   17
[2,]    2    4    6    8   10   12   14   16   18
     [,10] [,11] [,12] [,13] [,14] [,15]
[1,]    19    21    23    25    27    29
[2,]    20    22    24    26    28    30
```

Grid layout

```
> qgraph(dat.3, layout = L.3, directed = FALSE)
```



Fruchterman-Reingold layout

- `layout="spring"` uses a force-embedded algorithm that was proposed by Fruchterman and Reingold (1991)
  - This layout was ported from the **sna** package (Butts, 2010)
  - A solution for weighted graphs was taken from **igraph** (Csardi & Nepusz, 2006)
- This is an iterative algorithm.
- The initial layout is a circle
- Then in each iteration:
  - Each node is repulsed by all other nodes
  - Connected nodes are also attracted to each other
  - The maximum displacement weakens each iteration
- After this process the layout is rescaled to fit the -1 to 1 xy-plane
- The unscaled layout is returned as `layout.orig`

Fruchterman-Reingold layout

- The Fruchterman-Reingold algorithm can be controlled with the `layout.par` argument
- This must be a list containing other arguments:

niter	Number of iterations, default is 500
max.delta	Maximum displacement, default is n
area	The area of the plot, default is n^2
cool.exp	Cooling exponent, default is 1.5
repulse.rad	Repulse radius, default is $n \cdot \text{area}$
init	Matrix indicating initial layout

Constraints in the Fruchterman-Reingold layout

- The Fruchterman-Reingold algorithm behaves like a chaotic system
- A small difference in initial setup can result in a completely different layout
- In **qgraph** the layout can be constrained to compensate this
- Hard constraints
  - Hard constraints can be used to fix the x and y position of certain nodes
  - This can be done with the `constraints` argument in `layout.par`
- Soft constraints
  - Soft constraints can be used to limit the displacement of certain nodes
  - This can be done with the `max.delta` and `init` arguments in `layout.par`

No constraints

```
> dat.3 <- matrix(c(1, 2, 1, 3, 2, 3), 3, 2,
+     byrow = T)
> L <- matrix(c(1:3, 1, 3, 1), 3, 2)
> Q <- qgraph(dat.3, layout = L, vsize = 3,
+     esize = 1)
> par <- list(init = L)
> set.seed(1)
> for (i in 3:20) {
+     dat.3 <- rbind(dat.3, c(sample(c(i, sample(1:i,
+         1)), 1), i + 1))
+     L <- rbind(L, 0)
+     par$init <- L
+     L <- qgraph(dat.3, Q, layout.par = par,
+         layout = "spring")$layout.orig
+ }
```

No constraints

Hard constraints

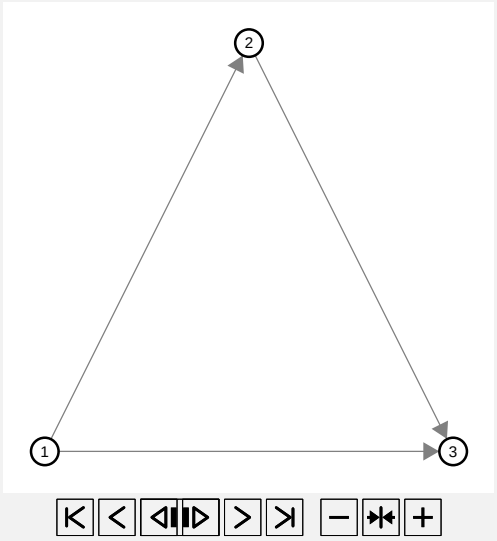
```
> dat.3 <- matrix(c(1, 2, 1, 3, 2, 3), 3, 2,
+     byrow = T)
> L <- matrix(c(1:3, 1, 3, 1), 3, 2)
> par <- list(max.delta = 10, area = 10^2,
+     repulse.rad = 10^3)
> Q <- qgraph(dat.3, layout = L, vsize = 3,
+     esize = 1, layout.par = par)
> set.seed(1)
> for (i in 3:20) {
+     dat.3 <- rbind(dat.3, c(sample(c(i, sample(1:i,
+         1)), 1), i + 1))
+     par$init <- rbind(L, 0)
+     L <- rbind(L, NA)
+     par$constraints <- L
+     L <- qgraph(dat.3, Q, layout.par = par,
+         layout = "spring")$layout.orig
+ }
```

Hard constraints

Soft constraints

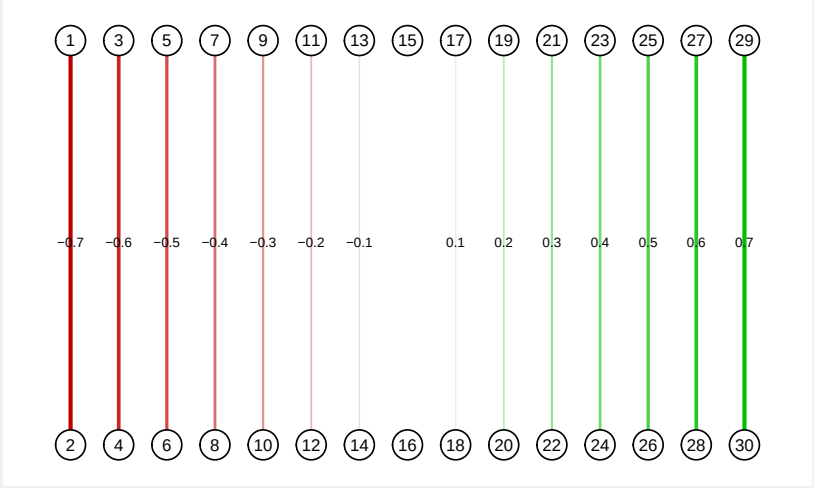
```
> dat.3 <- matrix(c(1, 2, 1, 3, 2, 3), 3, 2,
+     byrow = T)
> L <- matrix(c(1:3, 1, 3, 1), 3, 2)
> par <- list(max.delta = 10, area = 10^2,
+     repulse.rad = 10^3)
> Q <- qgraph(dat.3, layout = L, vsize = 3,
+     esize = 1, layout.par = par)
> set.seed(1)
> for (i in 3:20) {
+     dat.3 <- rbind(dat.3, c(sample(c(i, sample(1:i,
+         1)), 1), i + 1))
+     par$init <- rbind(L, 0)
+     L <- rbind(L, NA)
+     par$max.delta <- 10/(i + 1):1
+     L <- qgraph(dat.3, Q, layout.par = par,
+         layout = "spring")$layout.orig
+ }
```

Soft constraints



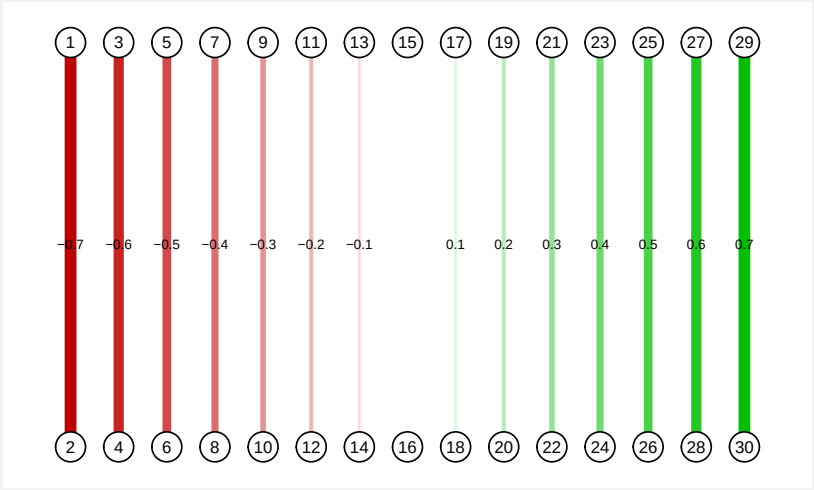
Interpreting weighted graphs

```
> qgraph(dat.3, layout = L.3, directed = FALSE,
+     edge.labels = T)
```



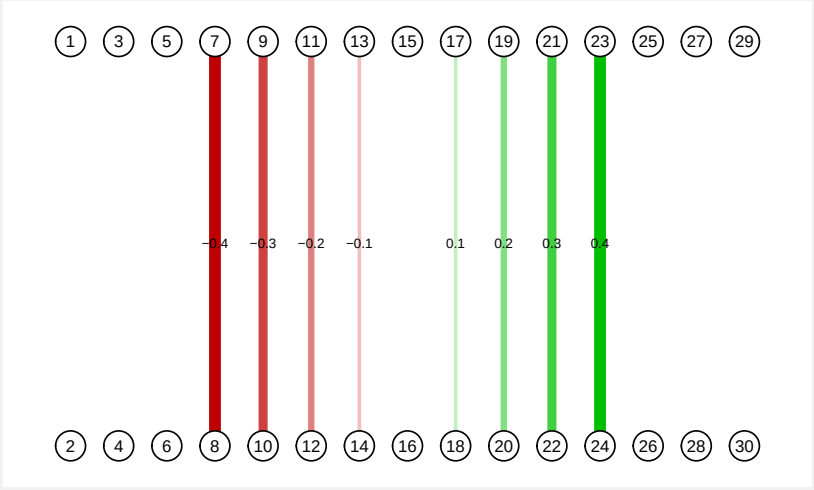
Interpreting weighted graphs

```
> qgraph(dat.3, layout = L.3, directed = FALSE,
+     edge.labels = T, esize = 14)
```



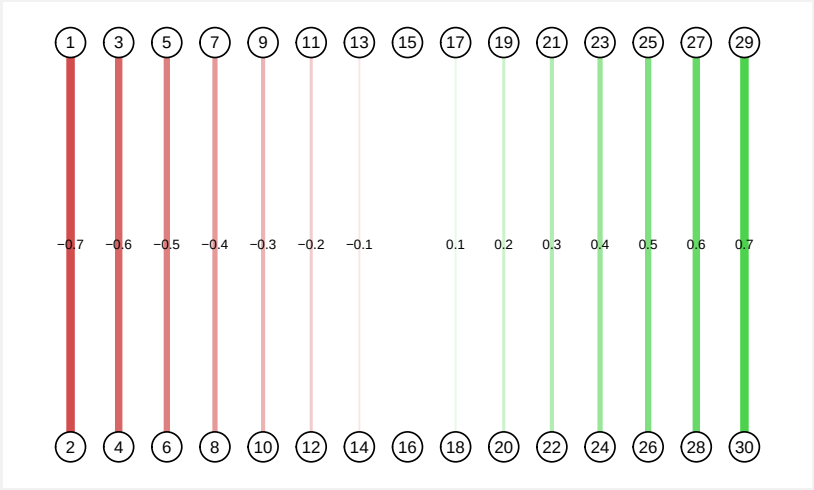
Interpreting weighted graphs

```
> qgraph(dat.3[-c(1:3, 13:15), ], layout = L.3,
+     nNodes = 30, directed = FALSE, edge.labels = T,
+     esize = 14)
```



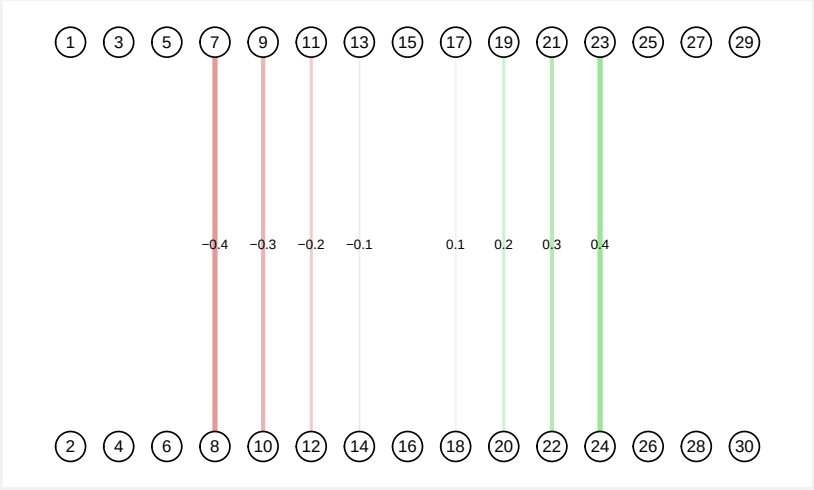
Interpreting weighted graphs

```
> qgraph(dat.3, layout = L.3, directed = FALSE,
+     edge.labels = T, esize = 14, maximum = 1)
```



Interpreting weighted graphs

```
> qgraph(dat.3[-c(1:3, 13:15), ], layout = L.3,
+     nNodes = 30, directed = FALSE, edge.labels = T,
+     esize = 14, maximum = 1)
```

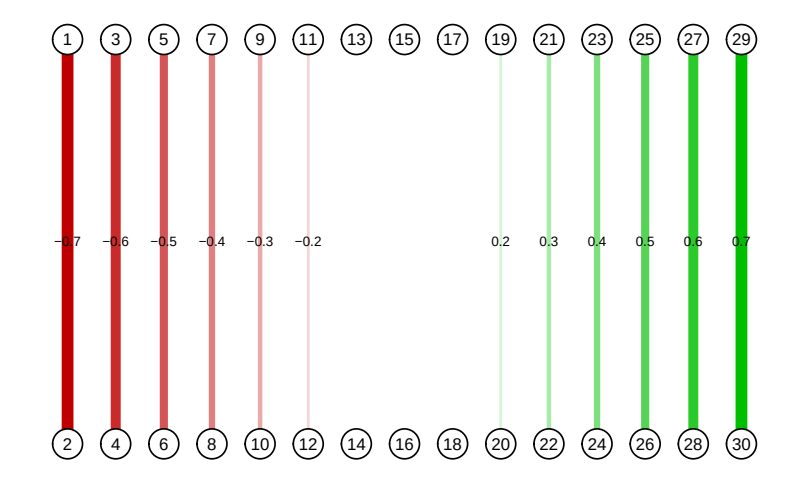


Interpreting weighted graphs

`maximum` **must be set to be able to compare multiple graphs!**

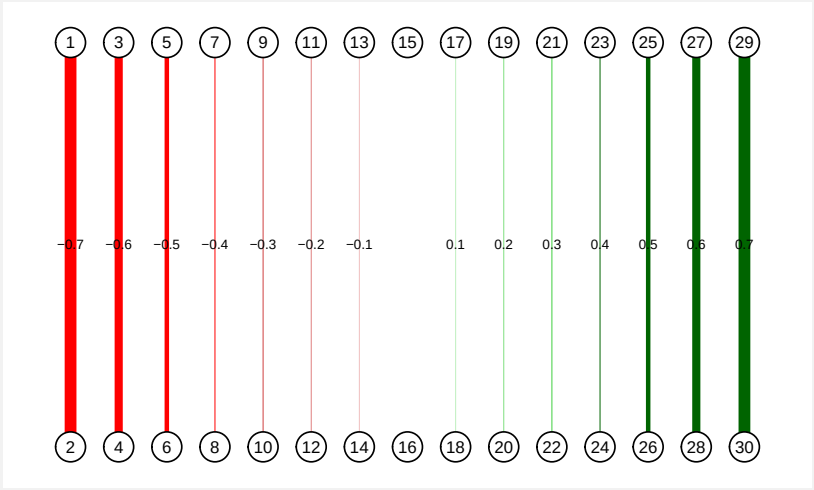
Interpreting weighted graphs

```
> qgraph(dat.3, layout = L.3, directed = FALSE,
+      edge.labels = T, esize = 14, minimum = 0.1)
```



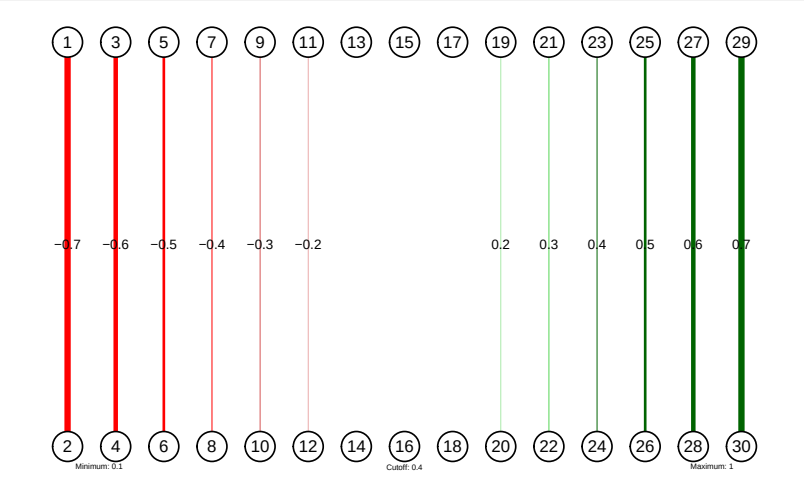
Interpreting weighted graphs

```
> qgraph(dat.3, layout = L.3, directed = FALSE,
+      edge.labels = T, esize = 14, cut = 0.4)
```



Interpreting weighted graphs

```
> qgraph(dat.3, layout = L.3, directed = FALSE,
+      edge.labels = T, esize = 14, minimum = 0.1,
+      maximum = 1, cut = 0.4, details = TRUE)
```



Interpreting weighted graphs

Graphs can not be interpreted without knowing `minimum`, `cut` **and** `maximum`**!**