Practical statistical network analysis (with R and igraph)

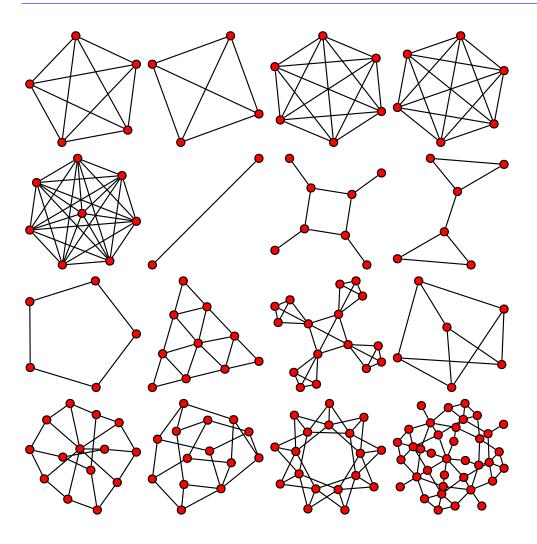
Gábor Csárdi csardi@rmki.kfki.hu

Department of Biophysics, KFKI Research Institute for Nuclear and Particle Physics of the Hungarian Academy of Sciences, Budapest, Hungary

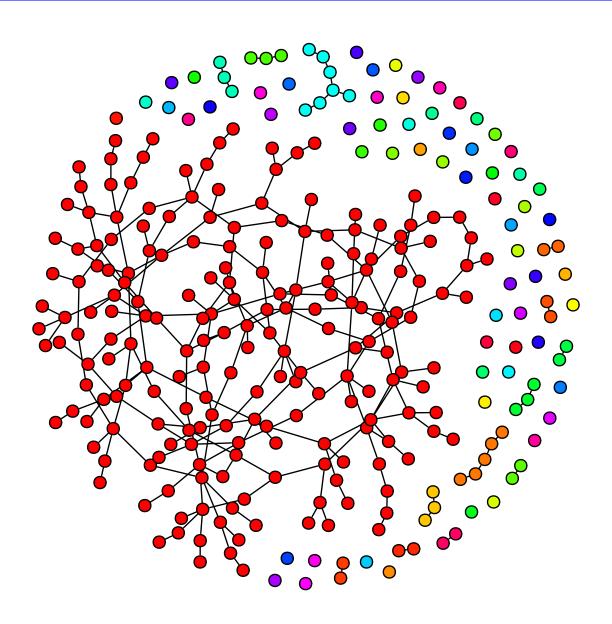
Currently at

Department of Medical Genetics,
University of Lausanne, Lausanne, Switzerland

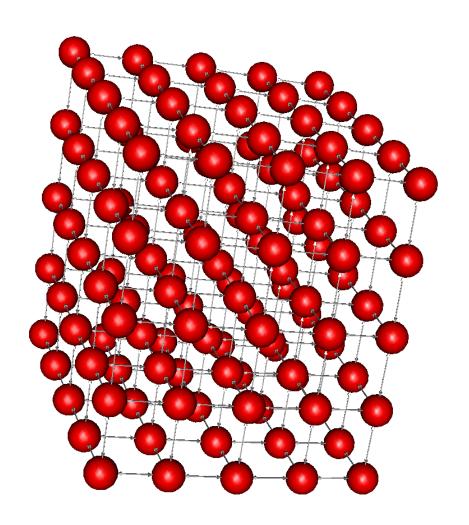
What is a network (or graph)?



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• Binary relation (=edges) between elements of a set (=vertices).

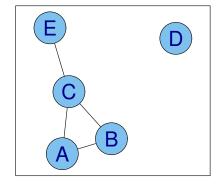
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- E.g.

$$\begin{aligned} \text{vertices} &= \{A,B,C,D,E\} \\ \text{edges} &= (\{A,B\},\{A,C\},\{B,C\},\{C,E\}). \end{aligned}$$

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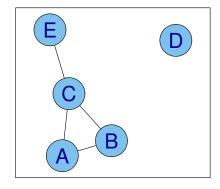
• It is "better" to draw it:

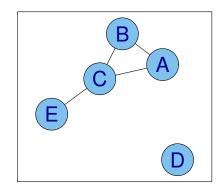


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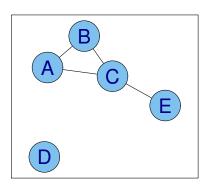




Undirected and directed graphs

• If the pairs are unordered, then the graph is undirected:

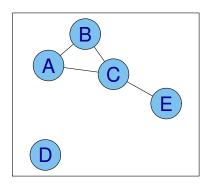
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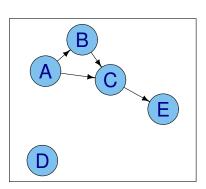
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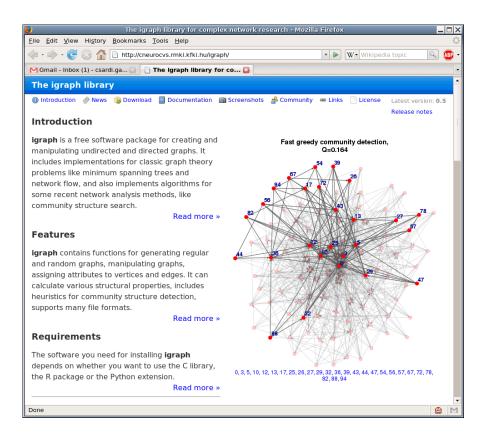
• Otherwise it is directed:

$$\begin{aligned} \text{vertices} &= \{A, B, C, D, E\} \\ &= \text{edges} &= ((A, B), (A, C), (B, C), (C, E)). \end{aligned}$$



The igraph "package"

- For classic graph theory and network science.
- Core functionality is implemented as a C library.
- High level interfaces from R and Python.
- GNU GPL.
- http://igraph.sf.net



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$$E = ((A, B), (A, C), (B, C), (C, E)).$$

$$A = 0, B = 1, C = 2, D = 3, E = 4.$$

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$$> g <- graph(c(0,1, 0,2, 1,2, 2,4), n=5)$$

Creating igraph graphs

• igraph objects

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- print(), summary(), is.igraph()

Creating igraph graphs

```
• igraph objects
  • print(), summary(), is.igraph()
  • is.directed(), vcount(), ecount()
1 > g \leftarrow graph(c(0,1, 0,2, 1,2, 2,4), n=5)
2 > g
3 Vertices: 5
4 Edges: 4
5 Directed: TRUE
6 Edges:
8 [0] 0 -> 1
 [1] 0 \rightarrow 2
 [2] 1 \rightarrow 2
```

11 [3] 2 -> 4

```
1 > g <- graph.tree(40, 4)
2 > plot(g)
3 > plot(g, layout=layout.circle)
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```
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1 # Force directed layouts
2 > plot(g, layout=layout.fruchterman.reingold)
3 > plot(g, layout=layout.graphopt)
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1 # Interactive
2 > tkplot(g, layout=layout.kamada.kawai(g)
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1 # 3D
2 > rglplot(g, layout=1)
```

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1 # Interactive
2 > tkplot(g, layout=layout.kamada.kawai)
3 > 1 <- layout=layout.kamada.kawai(g)</pre>
1 # 3D
2 > rglplot(g, layout=1)
1 # Visual properties
2 > plot(g, layout=1, vertex.color="cyan")
```

Simple graphs

• igraph can handle multi-graphs:

```
V = \{A, B, C, D, E\}

E = ((AB), (AB), (AC), (BC), (CE)).
```

```
1 > g <- graph( c(0,1,0,1, 0,2, 1,2, 3,4), n=5 )
2 > g
3 Vertices: 5
4 Edges: 5
5 Directed: TRUE
6 Edges:
7
8 [0] 0 -> 1
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12 [4] 3 -> 4
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Simple graphs

• igraph can handle loop-edges:

```
V = \{A, B, C, D, E\}

E = ((AA), (AB), (AC), (BC), (CE)).
```

```
1 > g <- graph( c(0,0,0,1, 0,2, 1,2, 3,4), n=5 )
2 > g
3 Vertices: 5
4 Edges: 5
5 Directed: TRUE
6 Edges:
7
8 [0] 0 -> 0
9 [1] 0 -> 1
10 [2] 0 -> 2
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```

```
el <- scan("lesmis.txt")
el <- matrix(el, byrow=TRUE, nc=2)
gmis <- graph.edgelist(el, dir=FALSE)
summary(gmis)
```

Naming vertices

```
V(gmis)$name
g <- graph.ring(10)
V(g)$name <- sample(letters, vcount(g))</pre>
```

```
# A simple undirected graph
2 > g <- graph.formula( Alice-Bob-Cecil-Alice,
3 Daniel-Cecil-Eugene, Cecil-Gordon )</pre>
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1 # Another undirected graph, ":" notation
2 > g2 <- graph.formula( Alice-Bob:Cecil:Daniel,</pre>
      Cecil:Daniel-Eugene:Gordon )
1 # A directed graph
2 > g3 <- graph.formula( Alice +-+ Bob --+ Cecil
      +-- Daniel, Eugene --+ Gordon: Helen )
1 # A graph with isolate vertices
2 > g4 <- graph.formula( Alice -- Bob -- Daniel,
      Cecil:Gordon, Helen )
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1 # A graph with isolate vertices
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      Cecil:Gordon, Helen )
1 # "Arrows" can be arbitrarily long
2 > g5 <- graph.formula( Alice +----+ Bob )</pre>
```

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- V(g) and E(g).
- Smart indexing, e.g.V(g) [color=="white"]
- Easy access of attributes:

Creating (even) more graphs

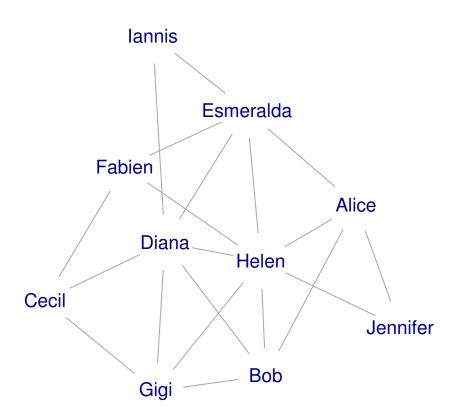
• E.g. from .csv files.

```
1 > traits <- read.csv("traits.csv", head=F)
2 > relations <- read.csv("relations.csv", head=F)
3 > orgnet <- graph.data.frame(relations)
4
5 > traits[,1] <- sapply(strsplit(as.character
6    (traits[,1]), split=" "), "[[", 1)
7 > idx <- match(V(orgnet)$name, traits[,1])
8 > V(orgnet)$gender <- as.character(traits[,3][idx])
9 > V(orgnet)$age <- traits[,2][idx]
10
11 > igraph.par("print.vertex.attributes", TRUE)
12 > orgnet
```

Creating (even) more graphs

• From the web, e.g. Pajek files.

• There is no best format, everything depends on what kind of questions one wants to ask.



 Adjacency matrix. Good for questions like: is 'Alice' connected to 'Bob'?

	Alice	Bob	Cecil	Diana	Esmeralda	Fabien	Gigi	Helen	lannis	Jennifer
Alice	0	1	0	0	1	0	0	1	0	1
Bob	1	0	0	1	0	0	1	1	0	0
Cecil	0	0	0	1	0	1	1	0	0	0
Diana	0	1	1	0	1	0	1	1	1	0
Esmeralda	1	0	0	1	0	1	0	1	1	0
Fabien	0	0	1	0	1	0	0	1	0	0
Gigi	0	1	1	1	0	0	0	1	0	0
Helen	1	1	0	1	1	1	1	0	0	1
lannis	0	0	0	1	1	0	0	0	0	0
Jennifer	1	0	0	0	0	0	0	1	0	0

• Edge list. Not really good for anything.

Alice Bob Bob Diana Cecil Diana Alice Esmeralda Esmeralda Diana Cecil Fabien Esmeralda Fabien Bob Gigi Cecil Gigi Diana Gigi Helen Alice Bob Helen Diana Helen Esmeralda Helen Fabien Helen Gigi Helen Diana **Iannis** Esmeralda Iannis Alice Jennifer Helen Jennifer

 Adjacency lists. GQ: who are the neighbors of 'Alice'?

Alice Bob, Esmeralda, Helen, Jennifer

Bob Alice, Diana, Gigi, Helen

Cecil Diana, Fabien, Gigi

Diana Bob, Cecil, Esmeralda, Gigi, Helen, Iannis

Esmeralda Alice, Diana, Fabien, Helen, lannis

Fabien Cecil, Esmeralda, Helen

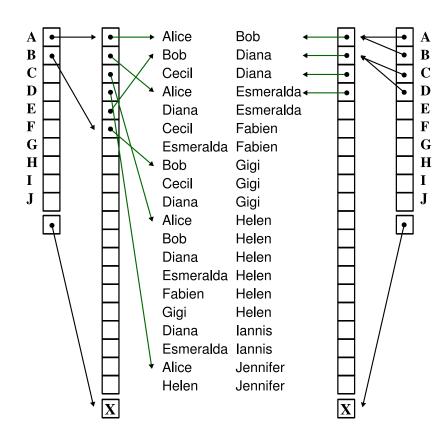
Gigi Bob, Cecil, Diana, Helen

Helen Alice, Bob, Diana, Esmeralda, Fabien, Gigi, Jennifer

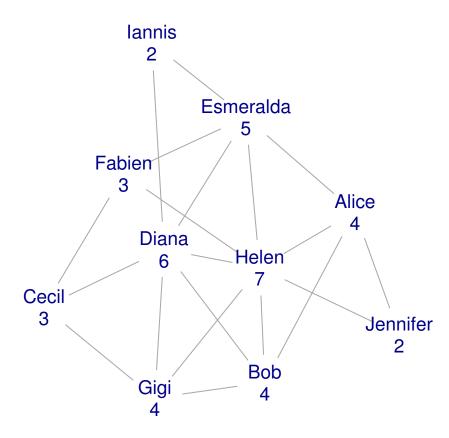
Iannis Diana, Esmeralda

Jennifer Alice, Helen

• igraph. Flat data structures, indexed edge lists. Easy to handle, good for many kind of questions.

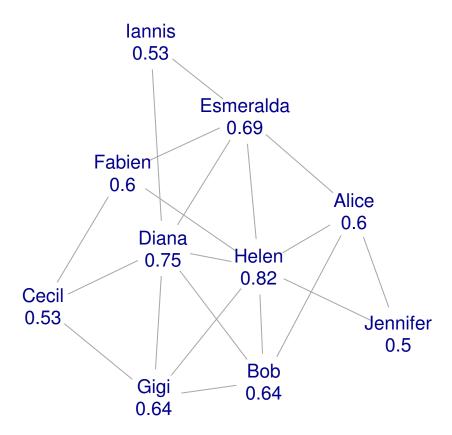


degree



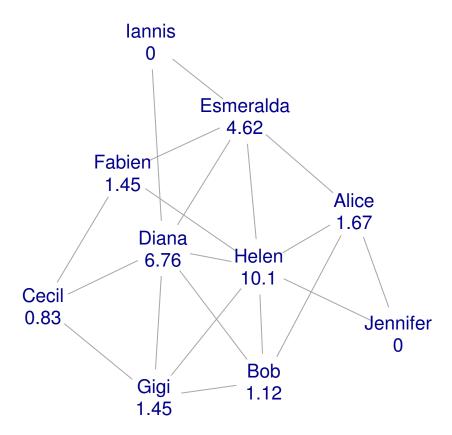
closeness

$$C_v = \frac{|V| - 1}{\sum_{i \neq v} d_{vi}}$$



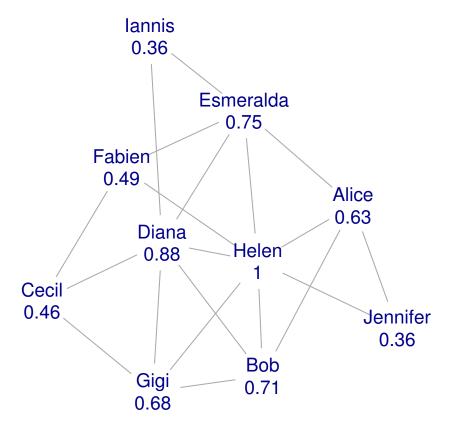
betweenness

$$B_v = \sum_{i \neq j, i \neq v, j \neq v} g_{ivj} / g_{ij}$$



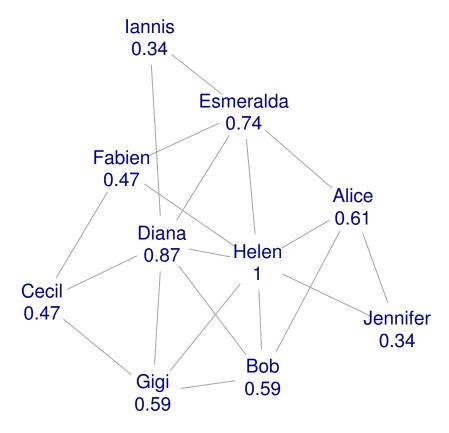
eigenvector centrality

$$E_v = \frac{1}{\lambda} \sum_{i=1}^{|V|} A_{iv} E_i, \quad Ax = \lambda x$$

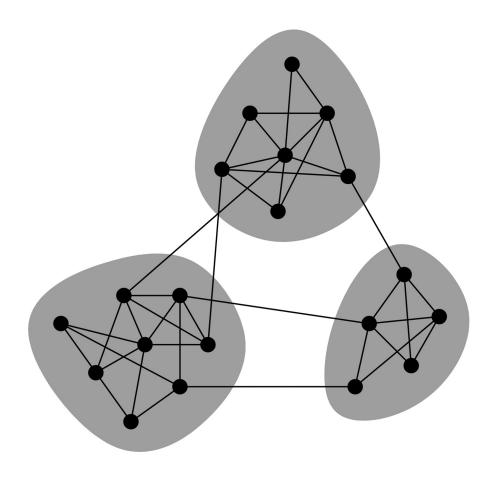


page rank

$$E_v = \frac{1 - d}{|V|} + d\sum_{i=1}^{|V|} A_{iv} E_i$$



• Organizing things, clustering items to see the structure.



M. E. J. Newman, PNAS, 103, 8577-8582

 How to define what is modular?
 Many proposed definitions, here is a popular one:

$$Q = \frac{1}{2|E|} \sum_{vw} [A_{vw} - p_{vw}] \delta(c_v, c_w).$$

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• Degree sequence based null model:

$$p_{vw} = \frac{k_v k_w}{2|E|}$$

(Based on 'Structural Cohesion and Embeddedness: a Hierarchical Concept of Social Groups' by J.Moody and D.White, Americal Sociological Review, 68, 103–127, 2003)

Definition 1: A collectivity is structurally cohesive to the extent that the social relations of its members hold it together.

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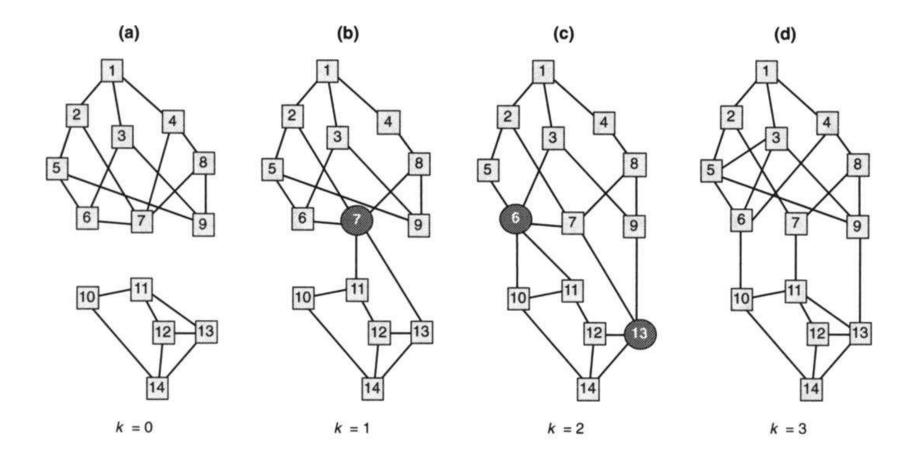
Vertex-independent paths and vertex connectivity.

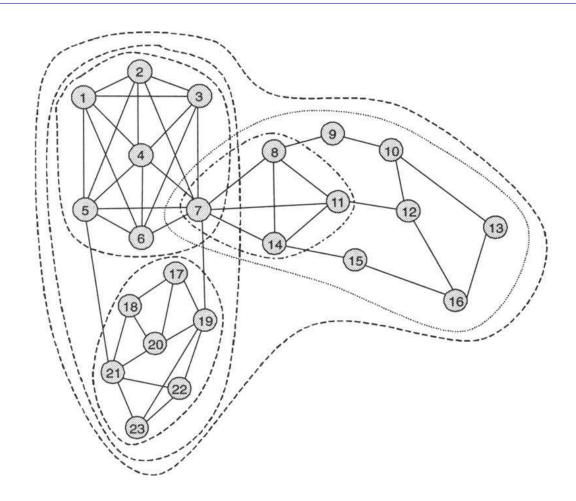
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- Vertex-independent paths and vertex connectivity.
- Vertex connectivity and network flows.





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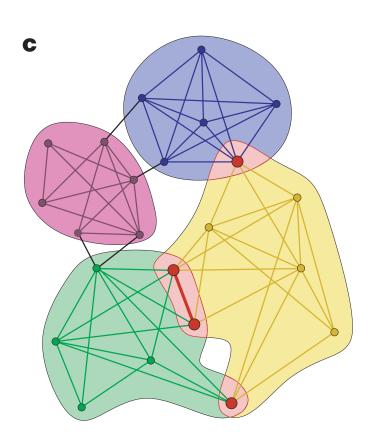
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```
wtrans <- function(g) {
    W <- get.adjacency(g, attr="weight")
    WM <- matrix(max(W), nrow(W), ncol(W))
    diag(WM) <- 0
    diag( W %*% W %*% W ) /
        diag( W %*% WM %*% W)
}</pre>
```

Clique percolation (Palla et al., Nature 435, 814, 2005)



...and the rest

- Cliques and independent vertex sets.
- Network flows.
- Motifs, i.e. dyad and triad census.
- Random graph generators.
- Graph isomorphism.
- Vertex similarity measures, topological sorting, spanning trees, graph components, K-cores, transitivity or clustering coefficient.
- etc.
- C-level: rich data type library.

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Tamás Nepusz

All the people who contributed code, sent bug reports, suggestions

The R project

Hungarian Academy of Sciences

The OSS community in general