

# Complex Networks

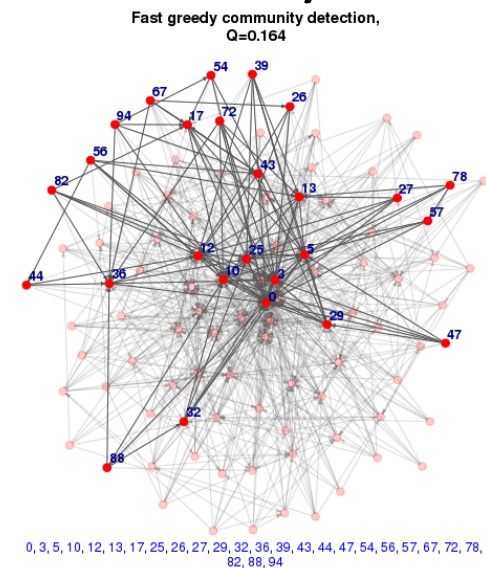
## tools for analyzing networks (igraph)

2018.11.29(Thu)

# igraph

- igraph is a free software package for creating and manipulating undirected and directed graphs. It includes implementations for classic graph theory problems like minimum spanning trees and network flow, and also implements algorithms for some recent network analysis methods, like community structure search.
- The following three are available:
  - igraph R package
  - python-igraph
  - igraph C library

<http://igraph.org>



# tutorials

- tutorial of python-igraph
  - <http://igraph.org/python/doc/tutorial/tutorial.html>
- tutorials of R
  - <http://cran.r-project.org/other-docs.html> (many tutorials in English and other languages)

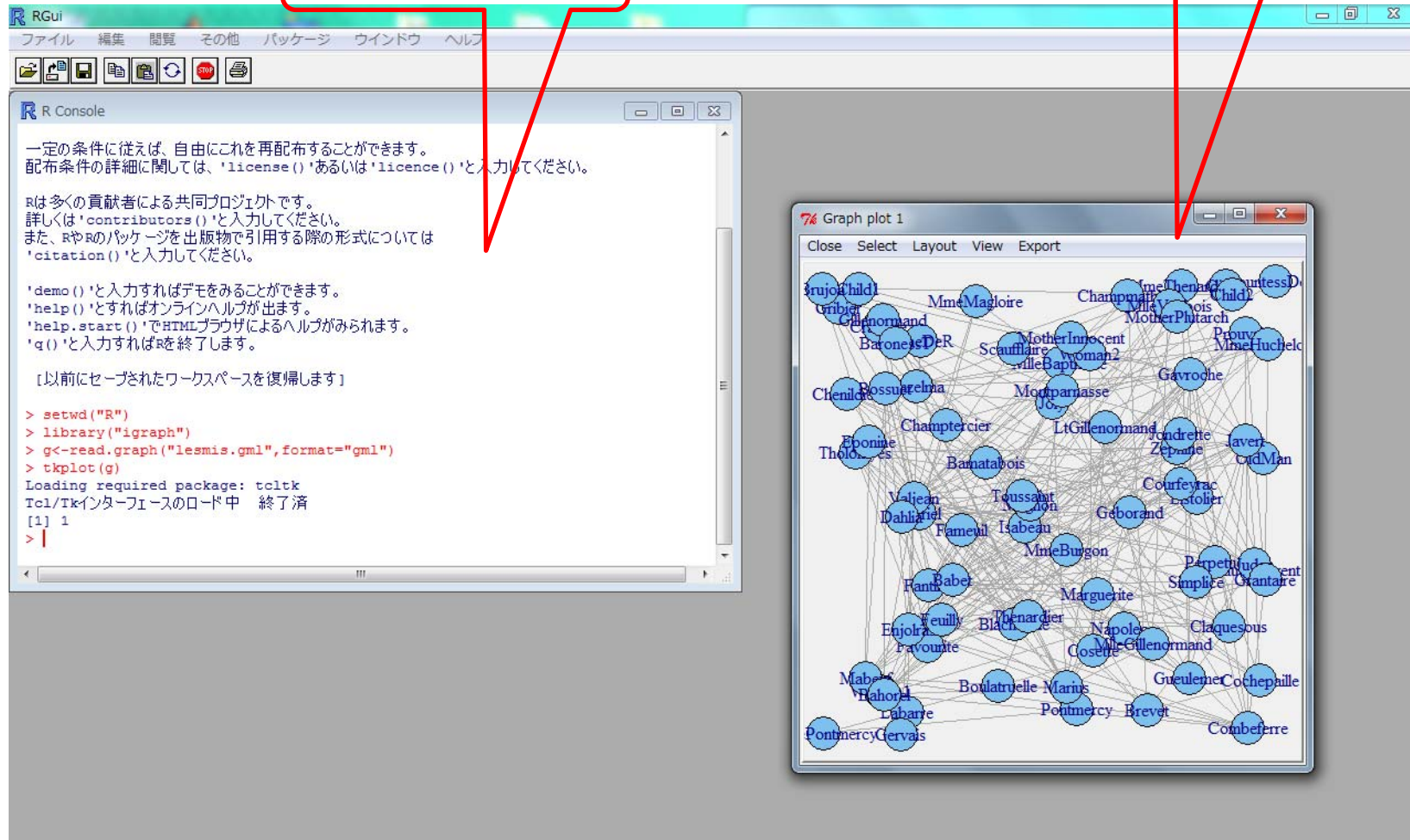
# procedure for analyzing network

1. create graph object
2. layout the network
3. ranking 找到重要的node
4. metrics
5. community detection  
social networks-> group of friends -> community
6. export

# 0. starting igraph

main

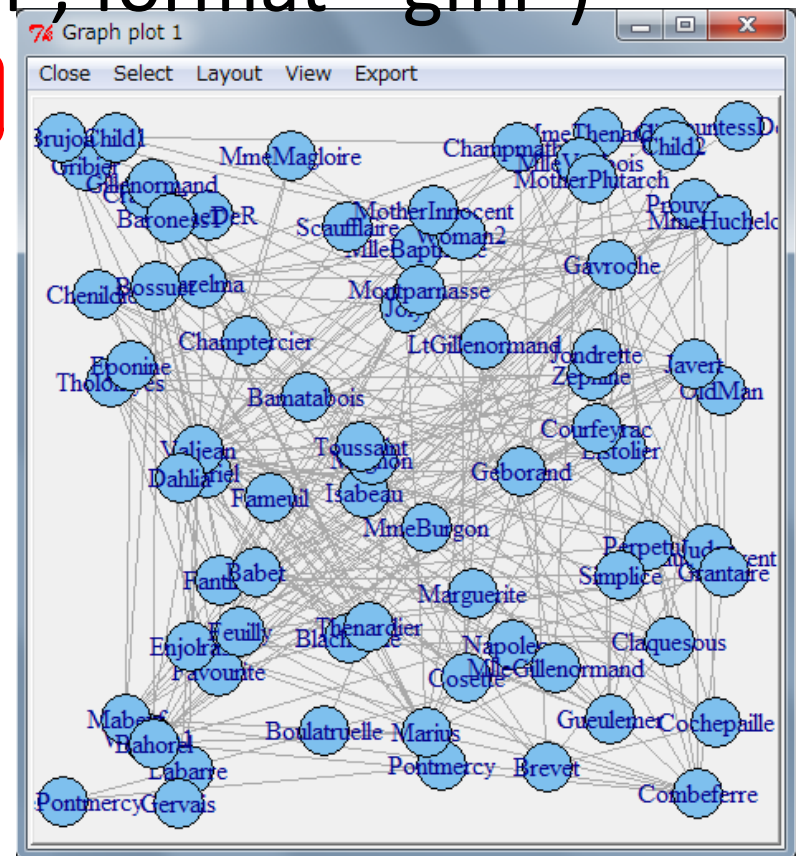
graph layout



# 1. create graph object

- `library("igraph")` start igraph
- `setwd("R")` set directory
- `g<-read.graph("lesmis.gml", format="gml")` create graph
- `tkplot(g)` open graph window

lesmis.gml is available at  
Mark Newman's Website

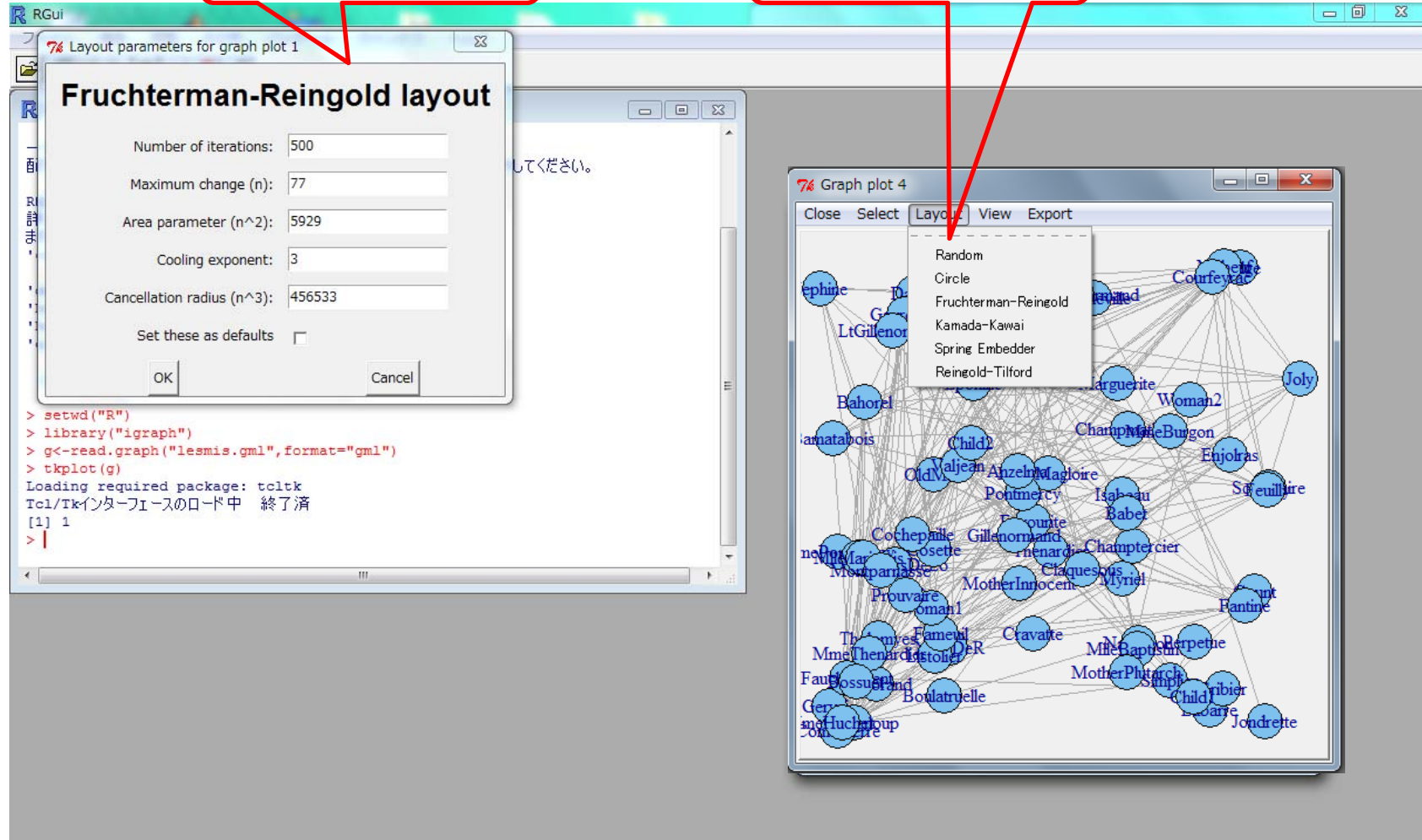


## 2. layout the network

set parameters

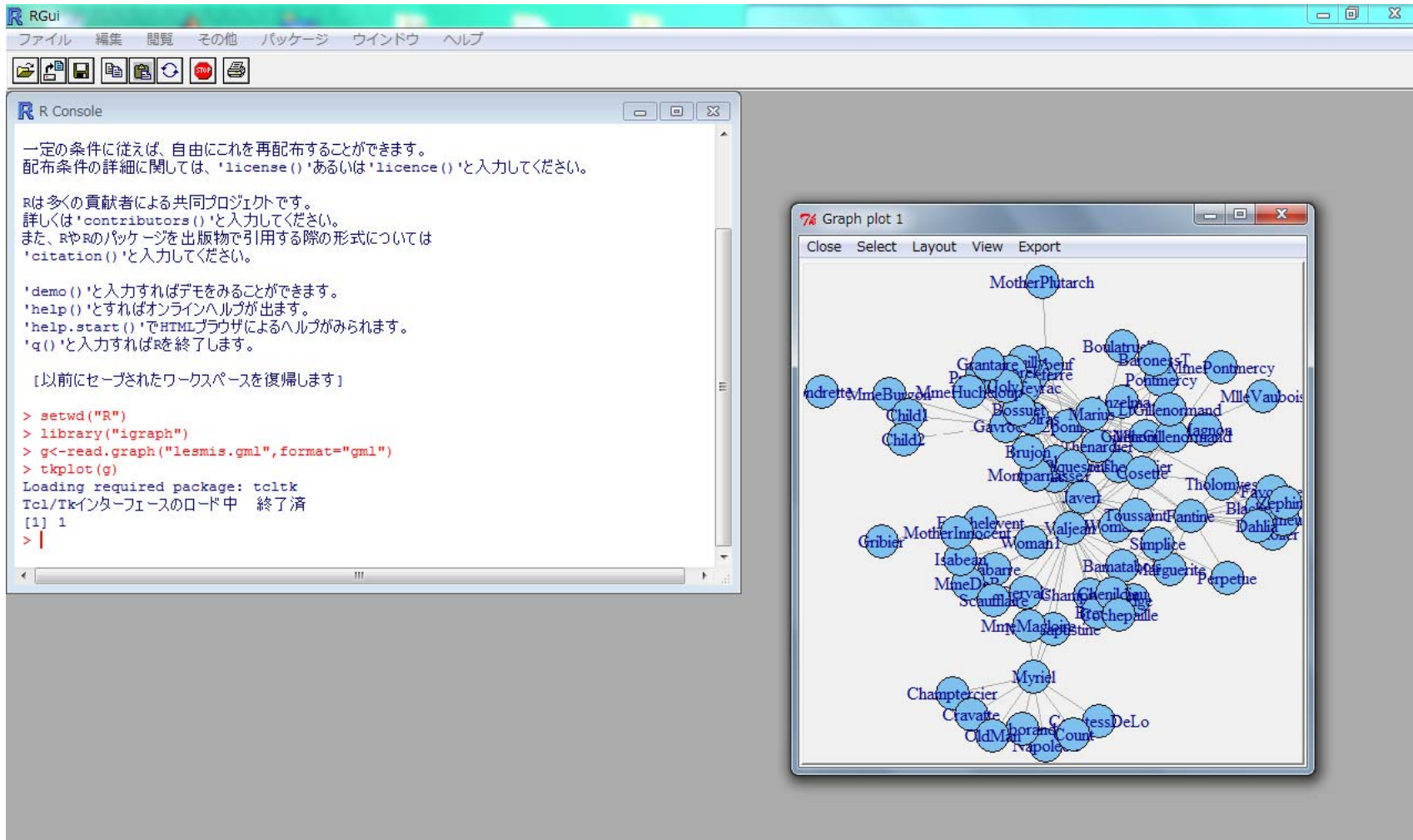
排版

choose layout



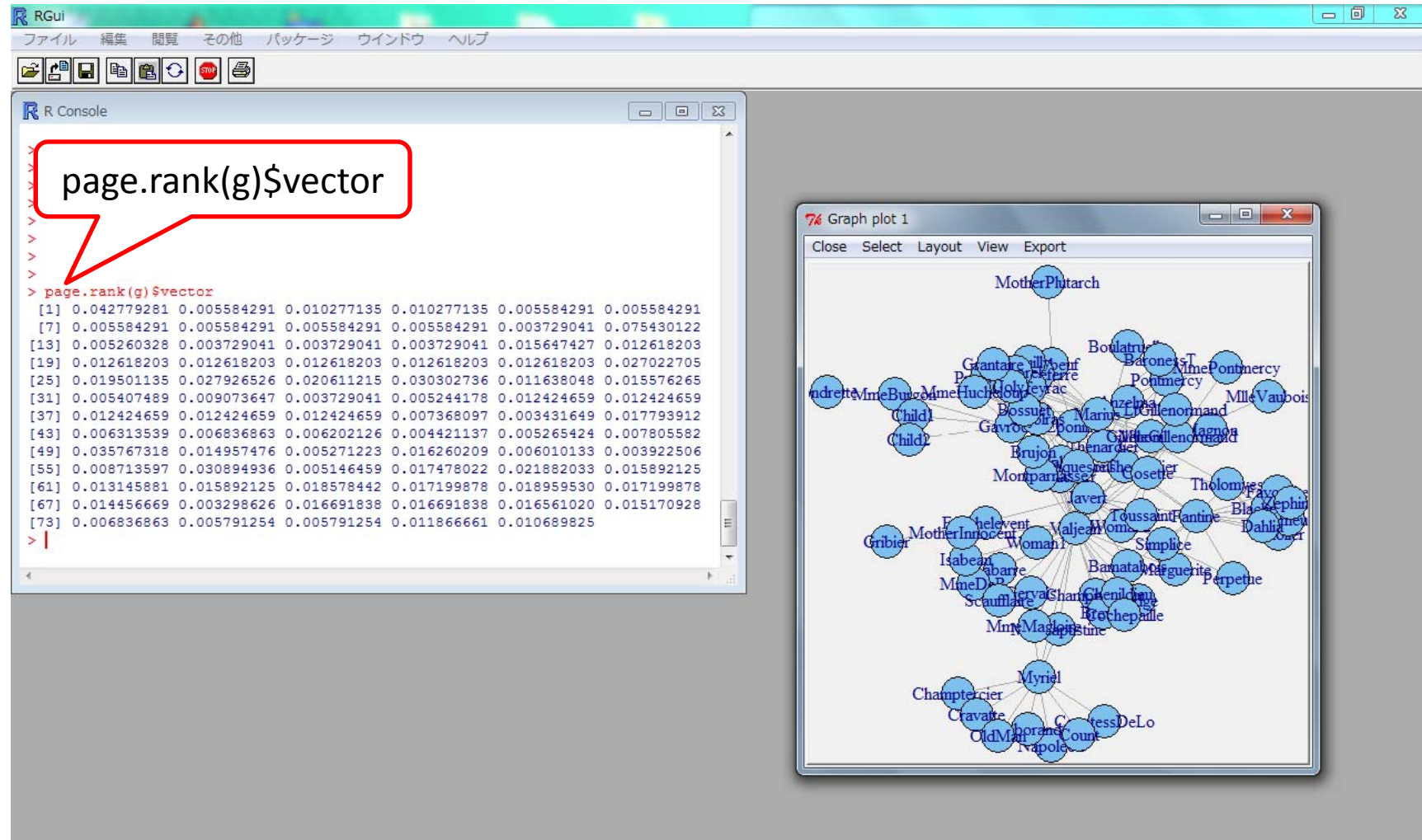


## 2. layout the network





# 3. ranking



- original gml file contain labels

- original gml file contain labels

The screenshot shows two windows from an R environment. The left window, titled 'RGui', displays the R Console with the output of the `page.rank(g)$vector` command. The output is a vector of 73 values, representing the PageRank scores for the nodes in the graph. The right window, titled 'lesmis.gml', shows the GML code for the graph. The code defines a directed graph with 6 nodes (id 0 to id 5) and their labels: 'Myriel', 'Napoleon', 'MlleBaptistine', 'MmeMagloire', 'CountessDeLo', and 'Geborand'. The status bar at the bottom indicates the current file is 'lesmis.gml' and the graph has 1 node and 0 edges.

**R Console Output:**

```
> page.rank(g)$vector
[1] 0.042779281 0.005584291 0.010277135 0.010277135 0.005584291 0.005584291
[7] 0.005584291 0.005584291 0.005584291 0.005584291 0.003729041 0.075430122
[13] 0.005260328 0.003729041 0.003729041 0.003729041 0.015647427 0.012618203
[19] 0.012618203 0.012618203 0.012618203 0.012618203 0.012618203 0.027022705
[25] 0.019501135 0.027926526 0.020611215 0.030302736 0.011638048 0.015576265
[31] 0.005407489 0.009073647 0.003729041 0.005244178 0.012424659 0.012424659
[37] 0.012424659 0.012424659 0.012424659 0.007368097 0.003431649 0.017793912
[43] 0.006313539 0.006836863 0.006202126 0.004421137 0.005265424 0.007805582
[49] 0.035767318 0.014957476 0.005271223 0.016260209 0.006010133 0.003922506
[55] 0.008713597 0.030894936 0.005146459 0.017478022 0.021882033 0.015892125
[61] 0.013145881 0.015892125 0.018578442 0.017199878 0.018959530 0.017199878
[67] 0.014456669 0.003298626 0.016691838 0.016691838 0.016561020 0.015170928
[73] 0.006836863 0.005791254 0.005791254 0.011866661 0.010689825
> |
```

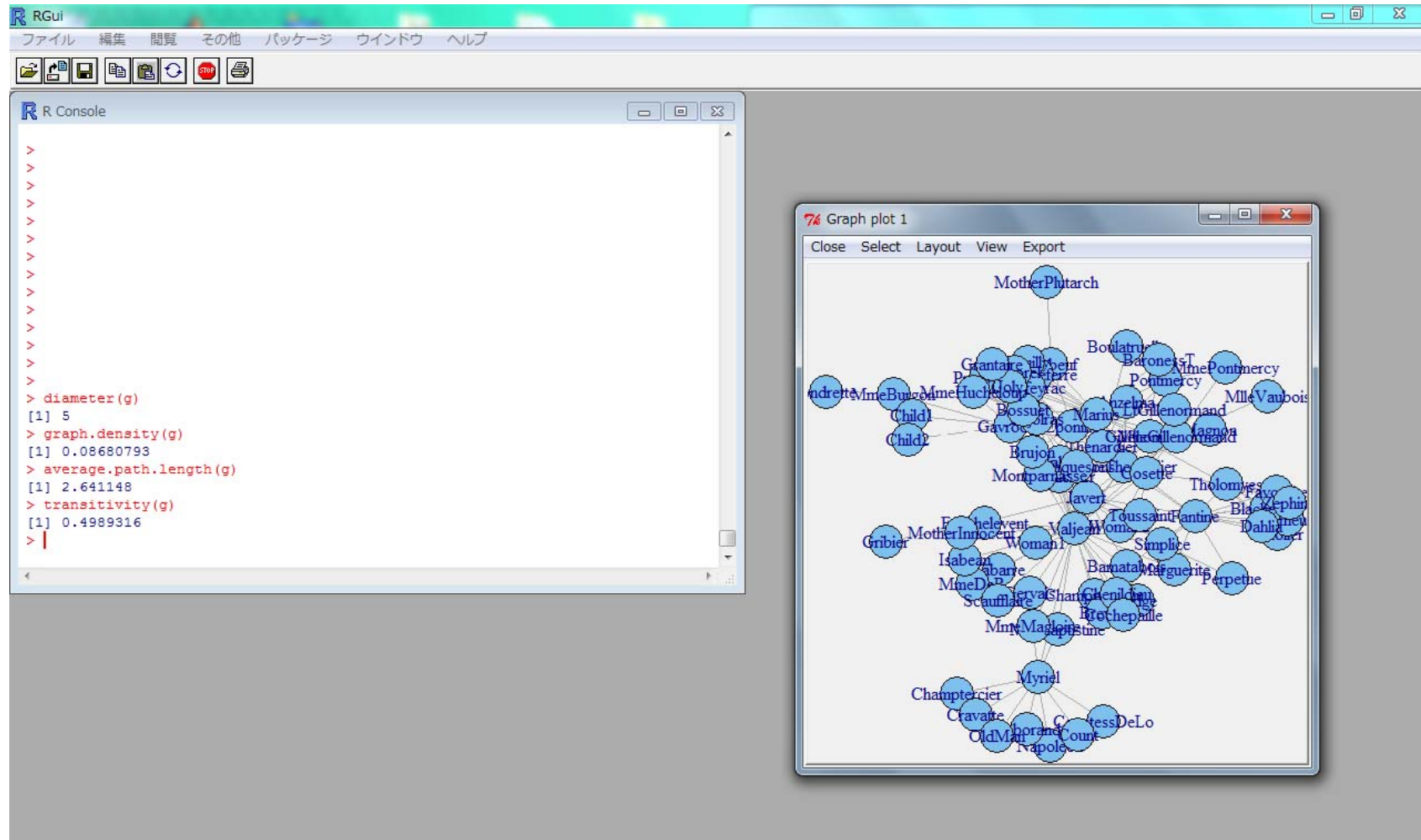
**lesmis.gml Code:**

```
graph
[
  node
  [
    id 0
    label "Myriel"
  ]
  node
  [
    id 1
    label "Napoleon"
  ]
  node
  [
    id 2
    label "MlleBaptistine"
  ]
  node
  [
    id 3
    label "MmeMagloire"
  ]
  node
  [
    id 4
    label "CountessDeLo"
  ]
  node
  [
    id 5
    label "Geborand"
  ]
]
```

## 4. metrics

- `diameter(g)`
- `graph.density(g)`
- `average.path.length(g)`
- `transitivity(g)` percentage two are friends, 然后我们三个就是个三角  
clustering coefficient
- `help`
  - `??rank`
  - `help("page.rank")`

## 4. metrics



# 5. community detection

modularity optimization

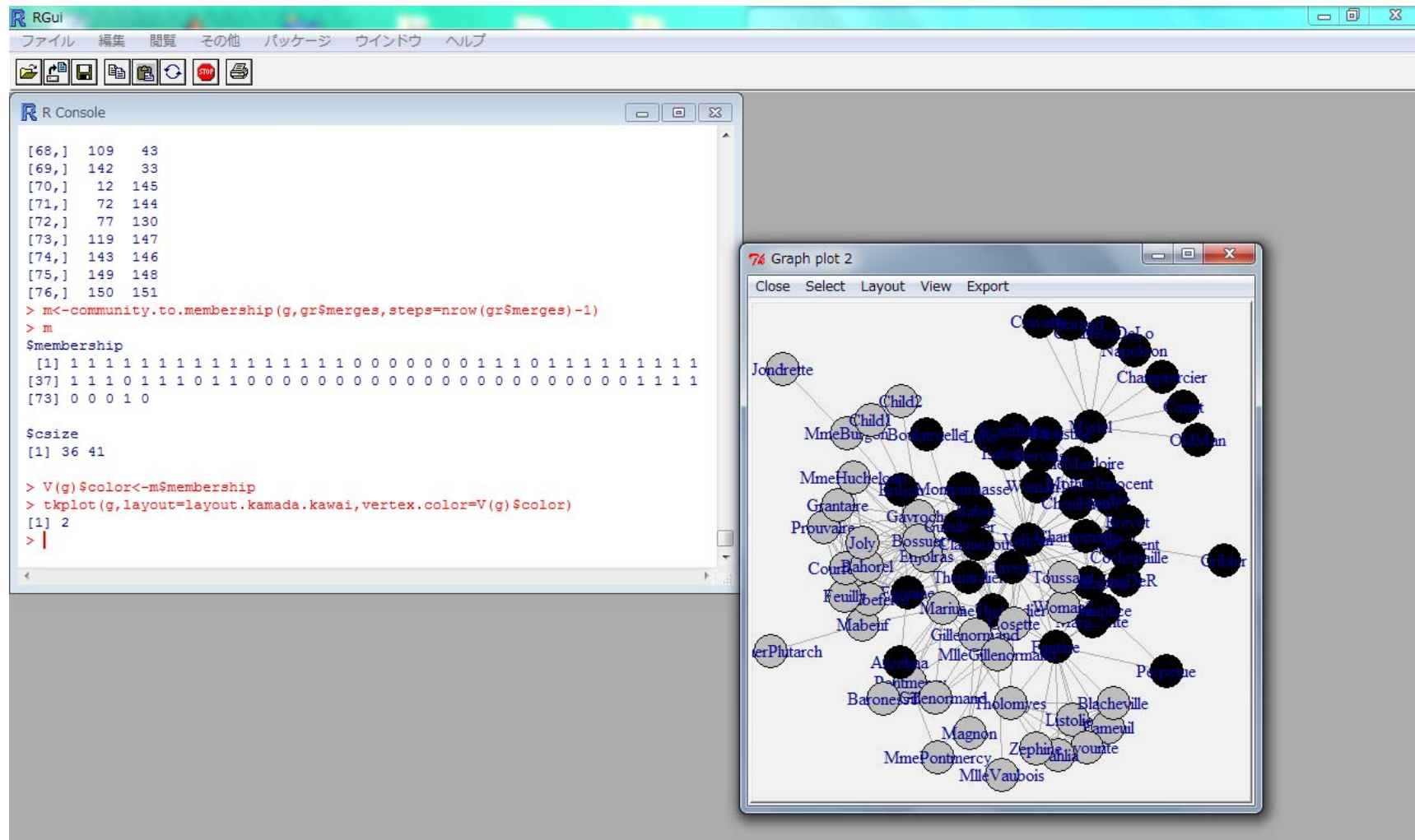
store membership and size

```
> gr<-fastgreedy.community(g)
> m<-community.to.membership(g,gr$merges,steps=nrow(gr$merges)-1)
> m
$membership
[1] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 1 0 0 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1
$size
[1] 17 17
> V(g)$color<-m$membership
> V(g)$color
[1] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 1 0 0 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1
> tkplot(g,layout=layout.kamada.kawai,vertex.color=V(g)$color)
[1] 2
>
```

store membership

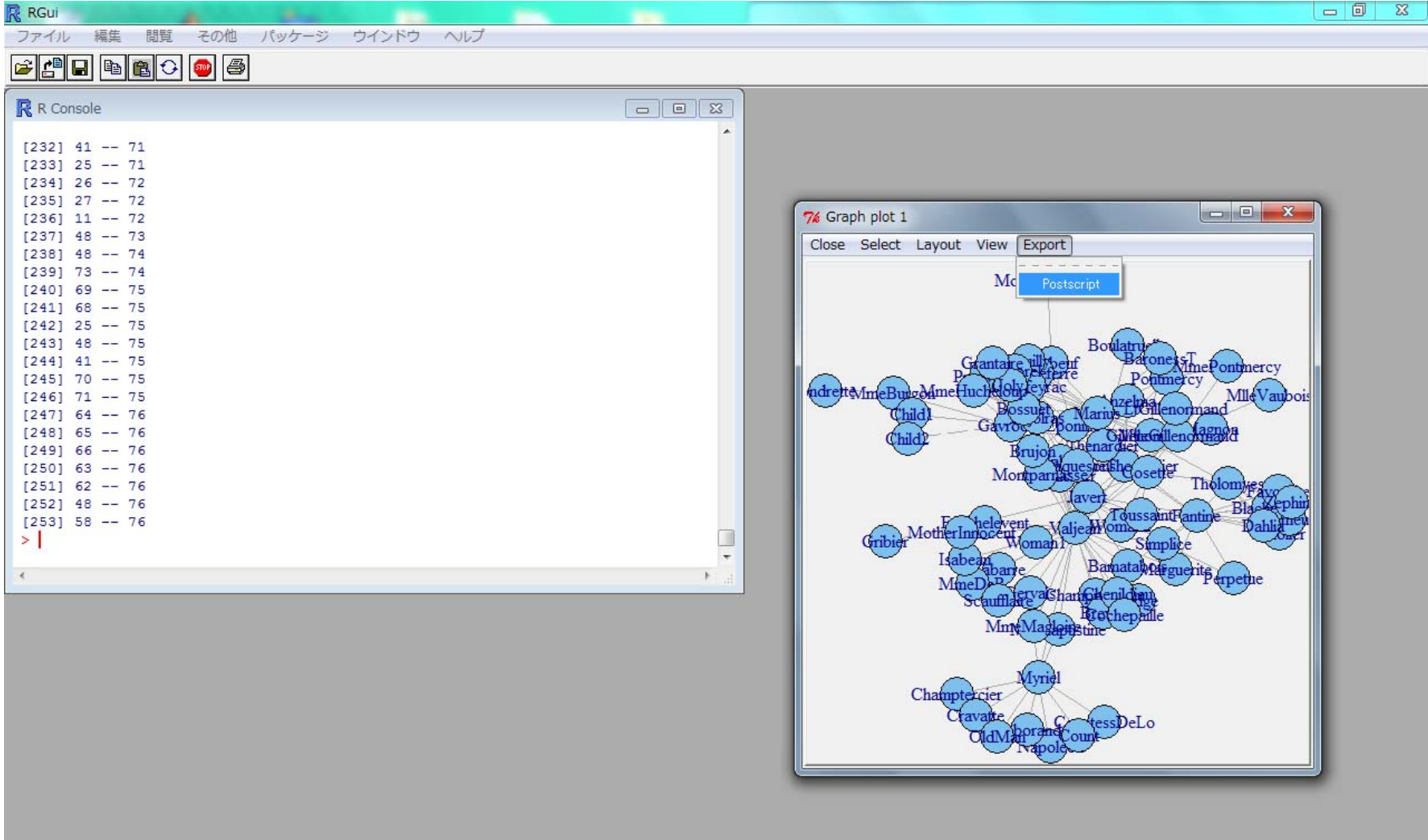
visualize network

# 5. community detection





## 6. export



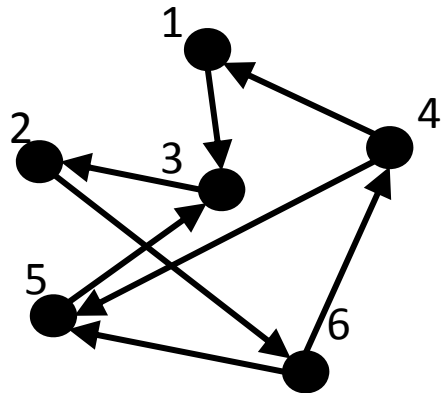




# create from adjacency matrix(1)

- from adjacency matrix

```
> a <- matrix(c(0,0,0,1,0,0,  
                0,0,1,0,0,0,  
                1,0,0,0,1,0,  
                0,0,0,0,0,1,  
                0,0,0,1,0,1,  
                0,1,0,0,0,0),nrow=6,byrow=TRUE)
```



$$A = \begin{matrix} & & & \textcolor{red}{j} & & \\ & & & 1 & 0 & 0 \\ & & & 0 & 0 & 0 \\ \textcolor{red}{1} \rightarrow \textcolor{red}{3} & \textcolor{red}{i} & 1 & 0 & 0 & 1 & 0 \\ & & 0 & 0 & 0 & 0 & 1 \\ & & 0 & 0 & 0 & 1 & 0 & 1 \\ & & 0 & 1 & 0 & 0 & 0 & 0 \end{matrix}$$

# create from adjacency matrix(2)

```
> ga <- graph.adjacency(t(a))
```

```
> ga
```

Vertices: 6

Edges: 8

Directed: TRUE

Edges:

[0] 0 -> 2

[1] 1 -> 5

[2] 2 -> 1

[3] 3 -> 0

[4] 3 -> 4

[5] 4 -> 2

[6] 5 -> 3

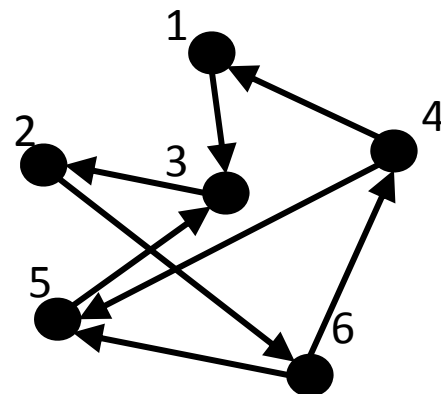
[7] 5 -> 4

transposition

In igraph,

ID starts from 0 &

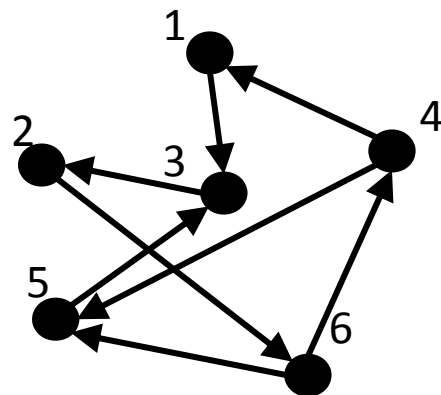
direction is from i to j



# create from edge list

```
> el <-  
  matrix(c(0,2,1,5,2,1,3,0,3,4,4,2,5,  
          3,5,4),nc=2,byrow=TRUE)
```

```
> el  
  [,1] [,2]  
[1,]  0  2  
[2,]  1  5  
[3,]  2  1  
[4,]  3  0  
[5,]  4  2  
[6,]  5  3  
[7,]  5  4
```



```
> gb<-graph.edgelist(el)
```

```
> gb
```

Vertices: 6

Edges: 8

Directed: TRUE

Edges:

[0] 0 -> 2

[1] 1 -> 5

[2] 2 -> 1

[3] 3 -> 0

[4] 3 -> 4

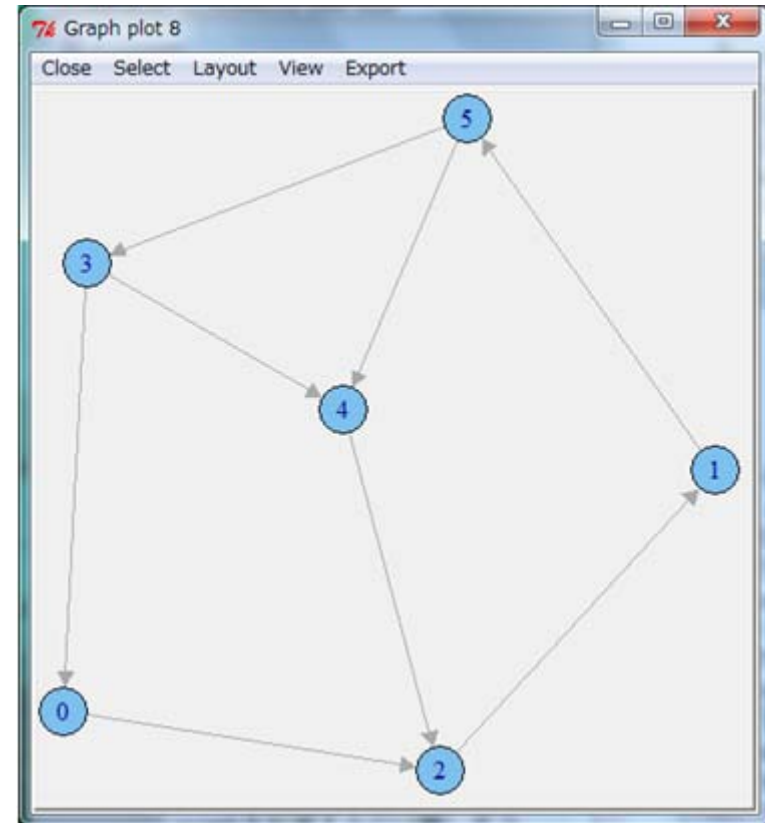
[5] 4 -> 2

[6] 5 -> 3

[7] 5 -> 4

# layout the network

- > `tkplot(ga,layout=layout.kamada.kawai)`
  - choose layout (random, circle, Fruchterman-Reingold, Kamada-Kawai)
  - deform graph
  - export (Postscript)

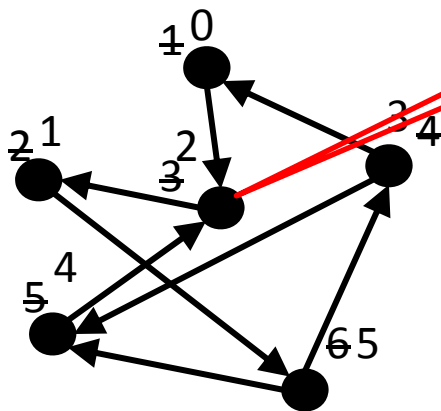


# ranking

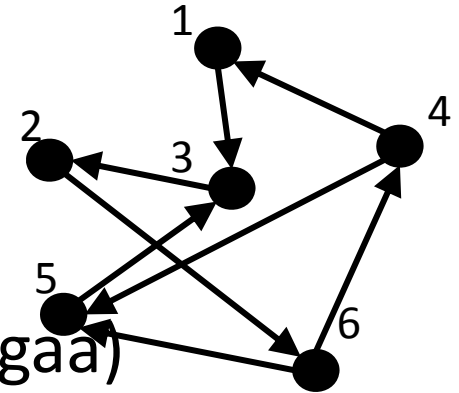
- PageRank: importance of vertices
  - the probability that a random walker will visit

```
> page.rank(ga)$vector
```

```
[1] 0.07337065 0.21643820 0.22522142  
0.11381330 0.16218395 0.20897247
```



# metrics (1)



```
> cocitation(gaa)
```

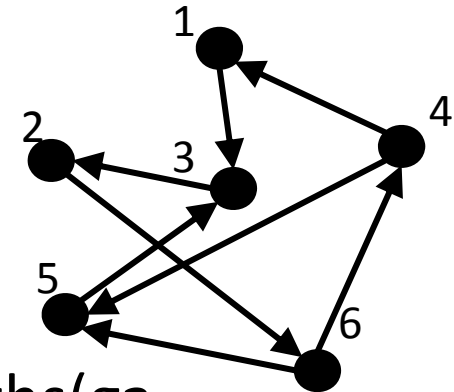
	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]
[1,]	0	0	0	0	1	0
[2,]	0	0	0	0	0	0
[3,]	0	0	0	0	0	0
[4,]	0	0	0	0	1	0
[5,]	1	0	0	1	0	0
[6,]	0	0	0	0	0	0

```
> bibcoupling(gaa)
```

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]
[1,]	0	0	0	0	1	0
[2,]	0	0	0	0	0	0
[3,]	0	0	0	0	0	0
[4,]	0	0	0	0	0	1
[5,]	1	0	0	0	0	0
[6,]	0	0	0	1	0	0



# metrics (2)



- undirected

```
> shortest.paths(ga)
```

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]
[1,]	0	2	1	1	2	2
[2,]	2	0	1	2	2	1
[3,]	1	1	0	2	1	2
[4,]	1	2	2	0	1	1
[5,]	2	2	1	1	0	1
[6,]	2	1	2	1	1	0

- directed

```
> shortest.paths(ga,
  mode="out")
```

	[,1]	[,2]	[,3]	to [,4]	[,5]	[,6]
[1,]	0	2	1	4	4	3
from [2,]	3	0	3	2	2	1
[3,]	4	1	0	3	3	2
[4,]	1	3	2	0	1	4
[5,]	5	2	1	4	0	3
[6,]	2	3	2	1	1	0

# metrics (3)

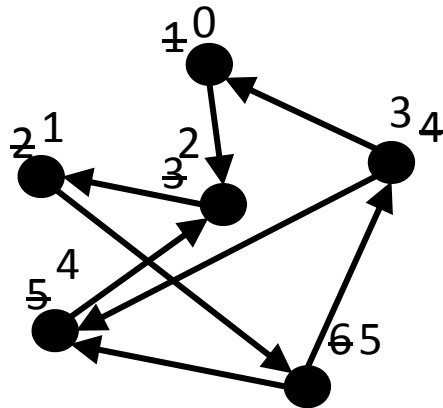
```
> average.path.length(ga)
```

```
[1] 2.433333
```

```
> average.path.length(ga,directed=FALSE)
```

```
[1] 1.466667
```

directed



```
> get.all.shortest.paths(ga,0)
```

```
[[1]]
```

```
[1] 0
```

```
[[2]]
```

```
[1] 0 2 1
```

```
[[3]]
```

```
[1] 0 2
```

```
[[4]]
```

```
[1] 0 3
```

```
[[5]]
```

```
[1] 0 3 4
```

```
[[6]]
```

```
[1] 0 2 4
```

```
[[7]]
```

```
[1] 0 3 5
```

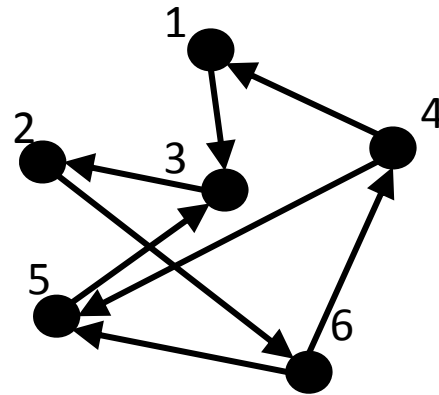
shortest  
paths from 0

# metrics (4)

```
> is.connected(ga)
[1] TRUE
```

```
> no.clusters(ga)
[1] 1
```

```
> clusters(ga)
$membership
[1] 0 0 0 0 0 0
$csizs
[1] 6
$no
[1] 1
```



## metrics (5)

```
> graph.density(ga)
```

```
[1] 0.2666667
```

$$\rho = \frac{m}{n(n-1)} = \frac{8}{6 \cdot 5}$$

