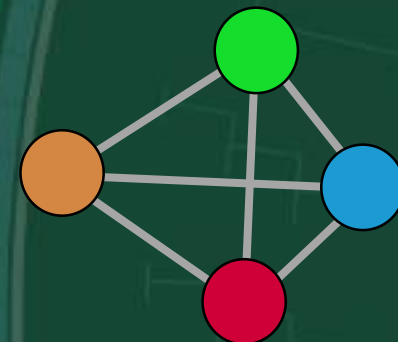
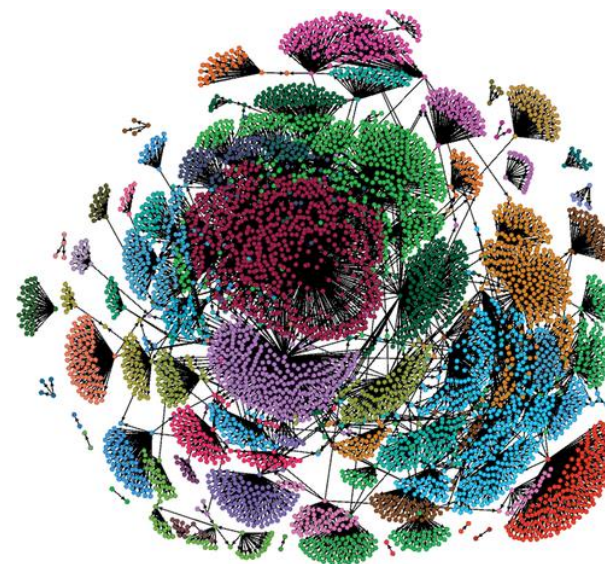


Social network analysis

Hector Marina

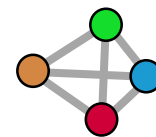


- A **social network** can be constructed from relational data and can be defined as a set of social entities, such as people, groups, and organizations, with some relationships or interactions between them. These networks are usually modelled by graphs, where vertices represent the social entities and edges represent the relationships established between them

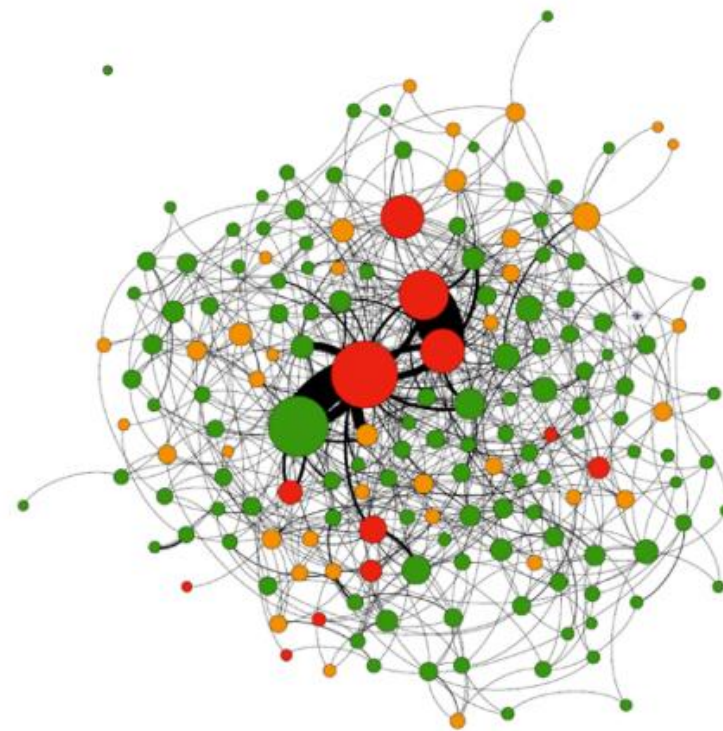


(Tabassum et al., 2018)

What is SNA?

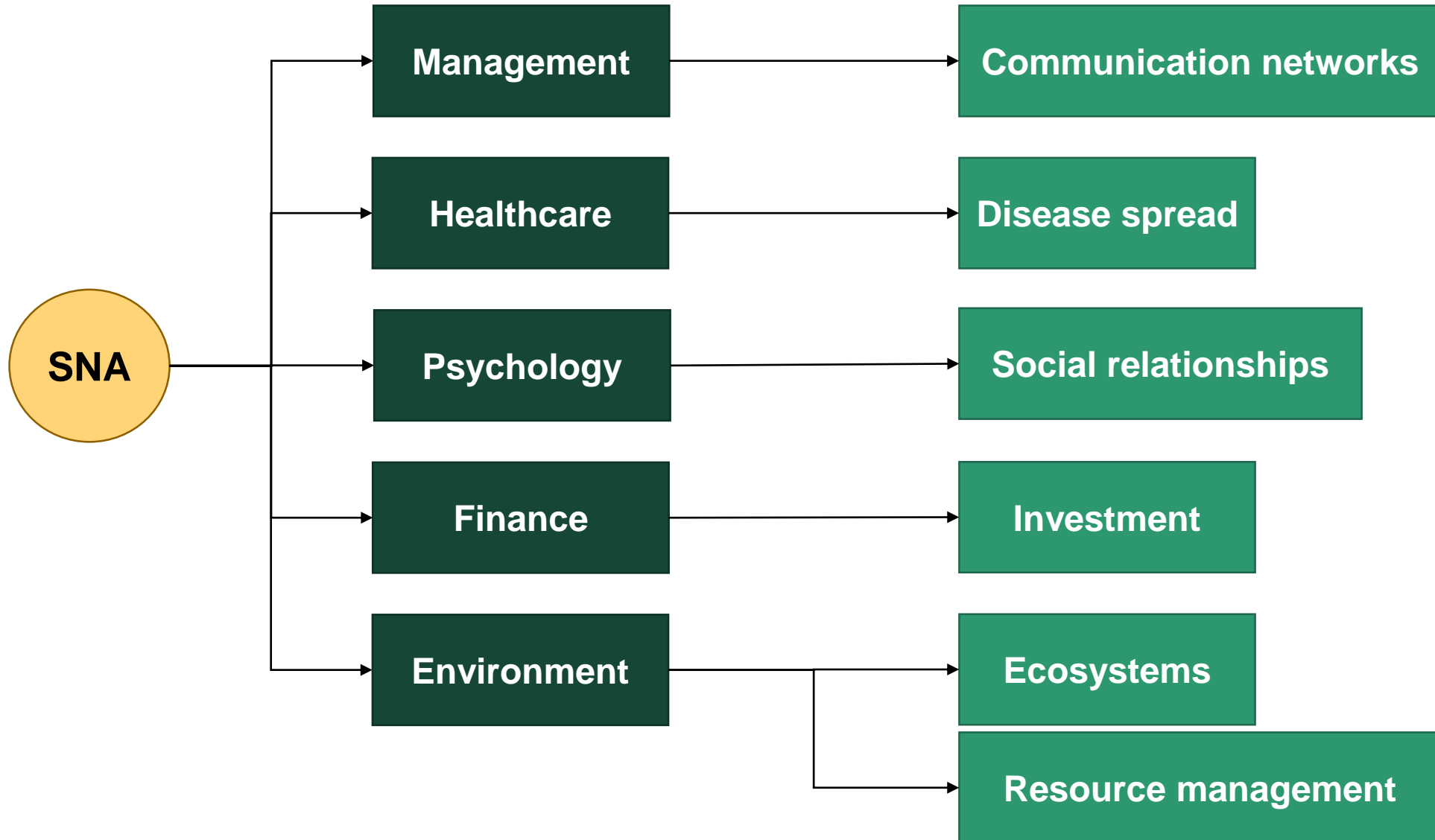


- **Social network analysis** studies structures of relationships linking individuals and interdependencies in behaviour or attitudes related to configurations of social relations

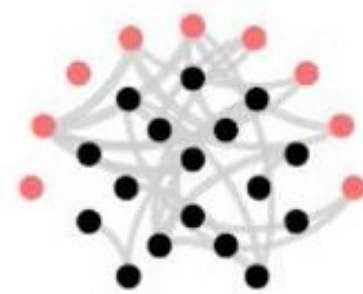
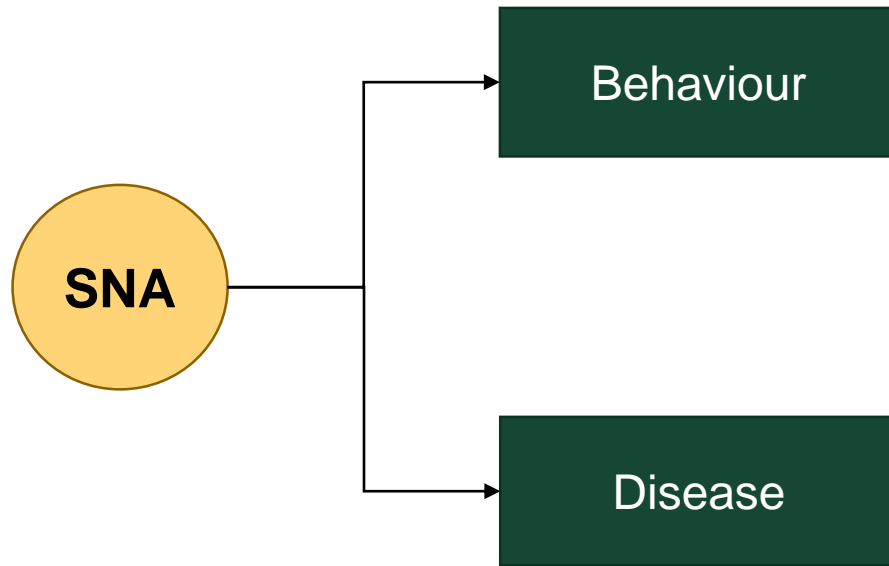


(Freslon et al., 2019)

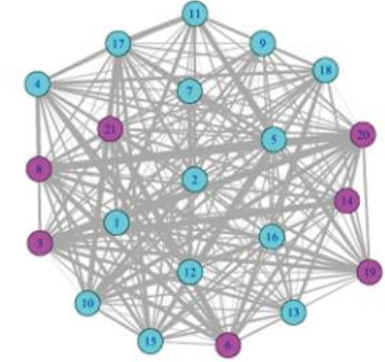
SNA applications



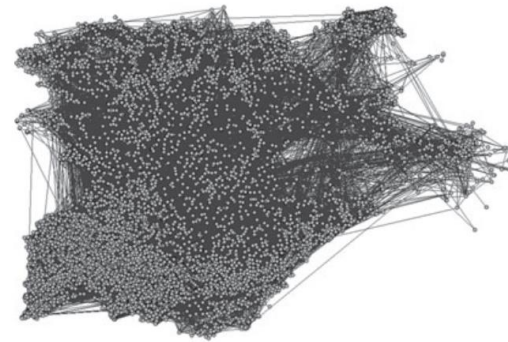
SNA applications in animals



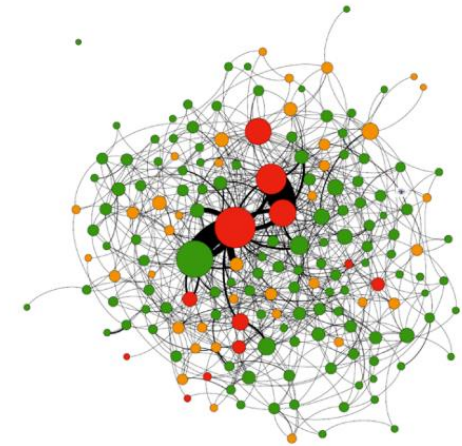
(Rocha et al., 2020)



(Chen et al., 2015)



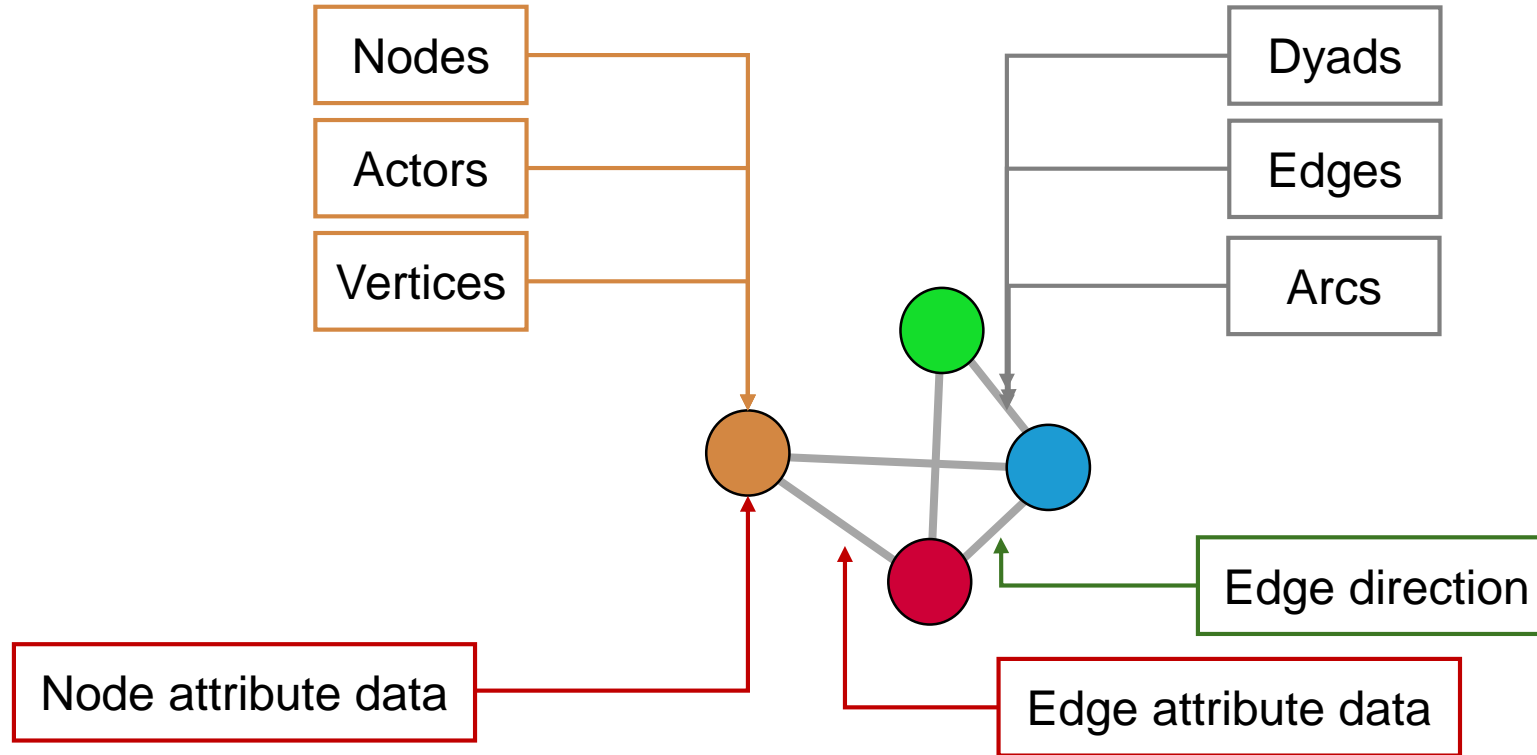
(Martínez-López et al., 2009)



(Freslon et al., 2019)



Part of the networks

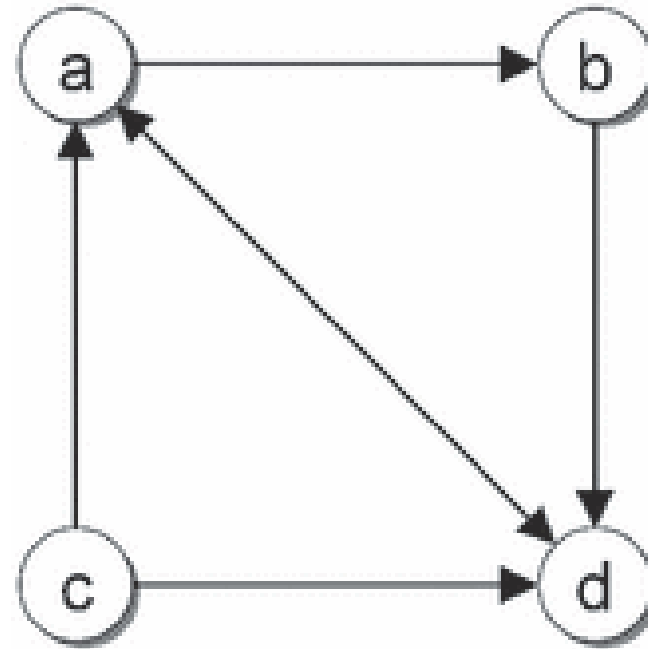


Ways to represent networks

Adjacency matrix

| | a | b | c | d |
|---|---|---|---|---|
| a | 0 | 1 | 0 | 1 |
| b | 0 | 0 | 0 | 1 |
| c | 1 | 0 | 0 | 1 |
| d | 1 | 0 | 0 | 0 |

Graph

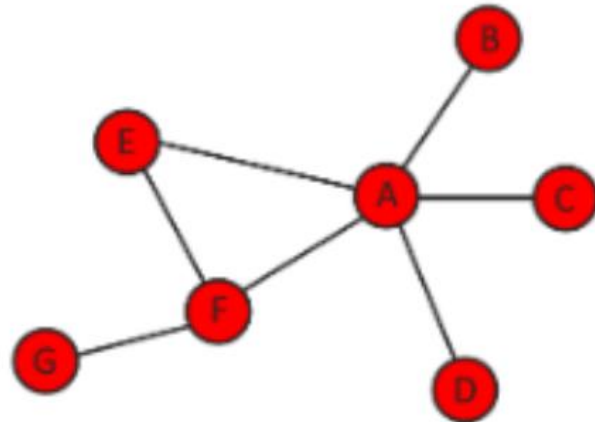


Notation

$$G = \{(a, b), (a, d), (b, d), (c, a), (c, d), (d, a)\}$$

Ways to represent networks

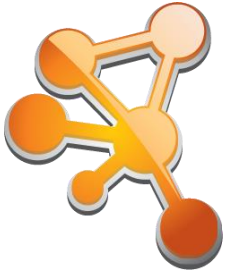
| | |
|---|---|
| A | B |
| A | C |
| A | D |
| A | E |
| A | F |
| E | F |
| F | G |



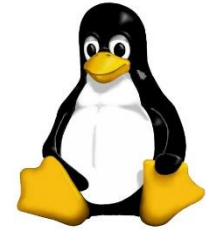
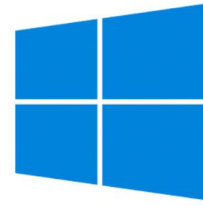
| | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| A | 0 | 1 | 1 | 1 | 1 | 1 | 0 |
| B | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| C | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| D | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| E | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| F | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| G | 0 | 0 | 0 | 0 | 0 | 1 | 0 |



Network analysis software



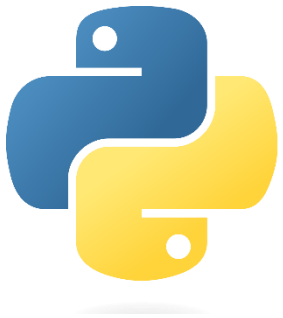
Cytoscape



sna

igraph

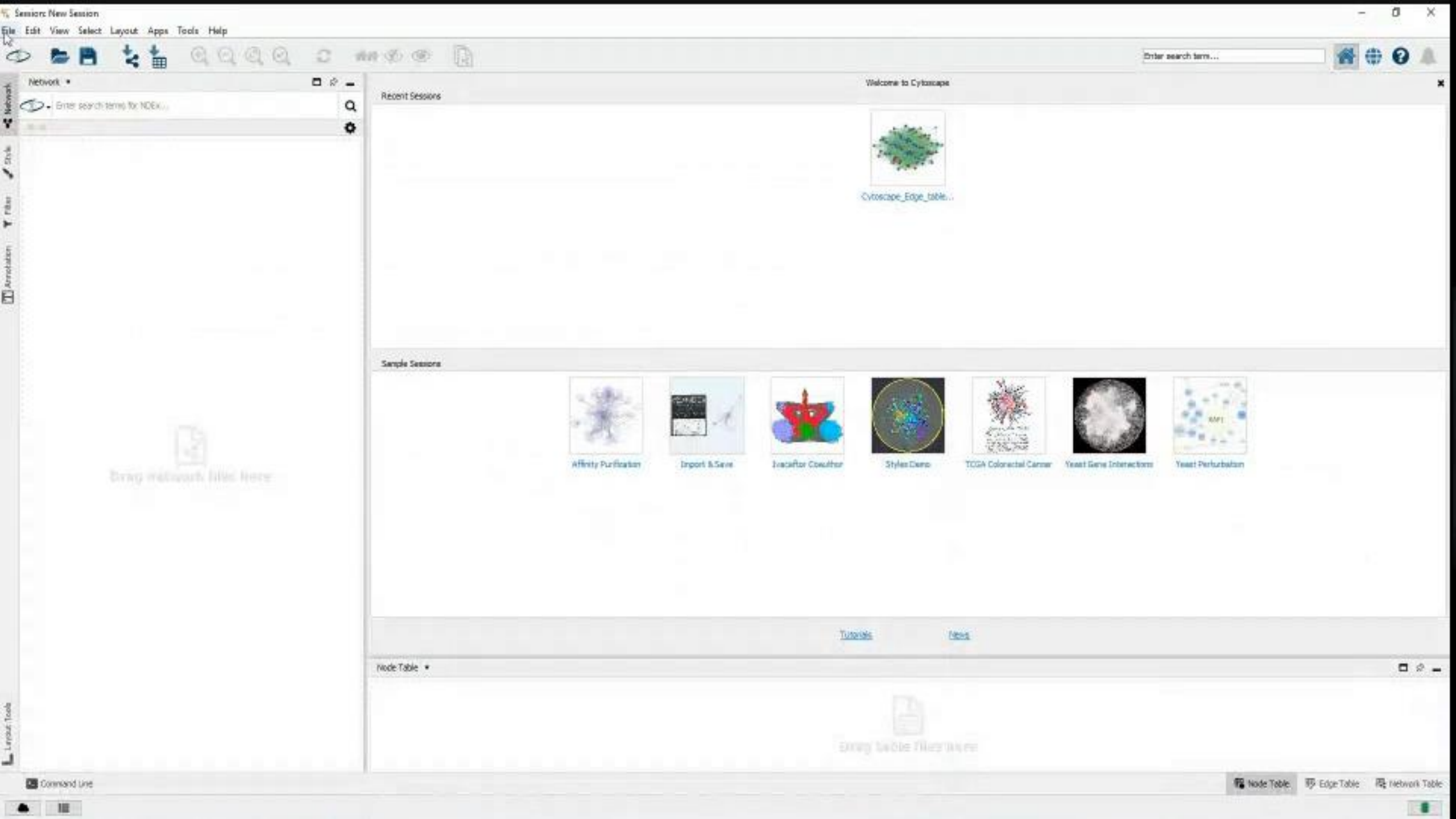
network



networkX

igraph

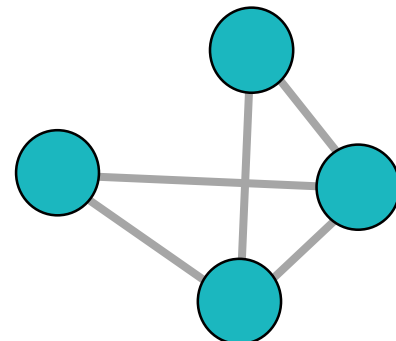




Ways to analyze the information

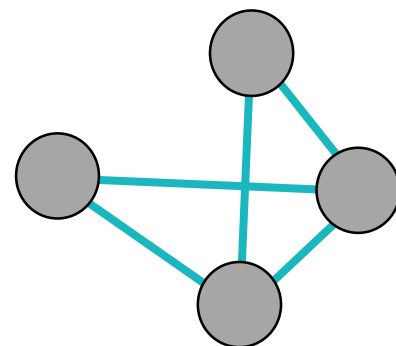
individual- level models

focuses on an **individual-level outcome**, network data are used to define explanatory variables



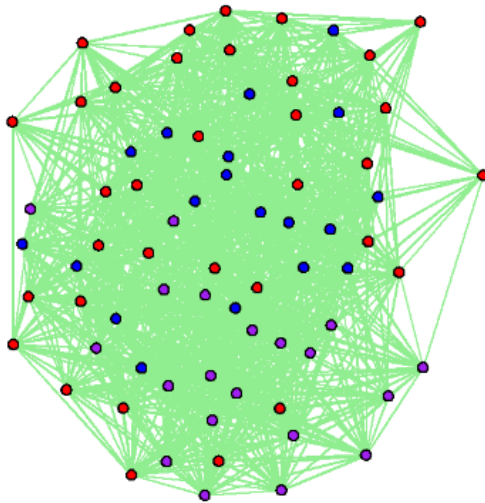
relational-level models

focuses on an **dyad-level**, analyse the **relationship** rather than a characteristic of particular individuals

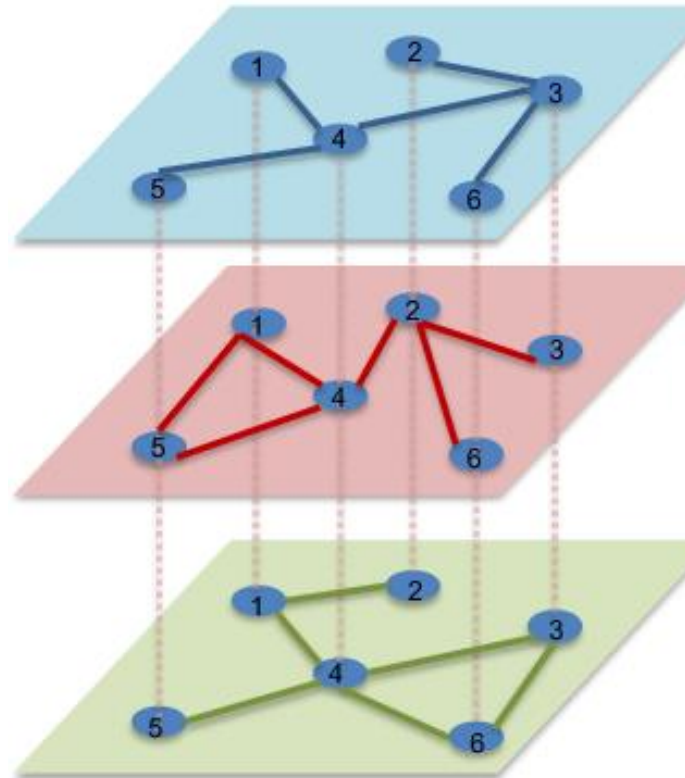


Network dimensions

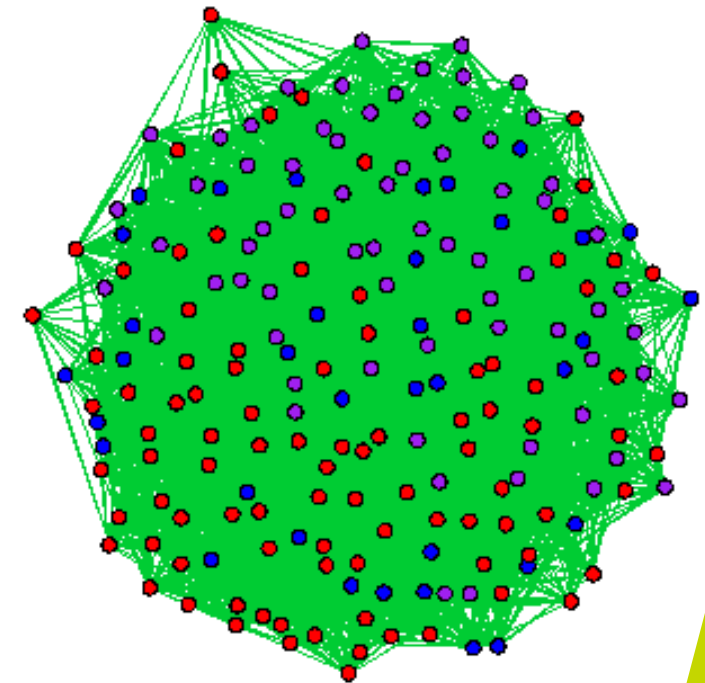
Unidimensional
data



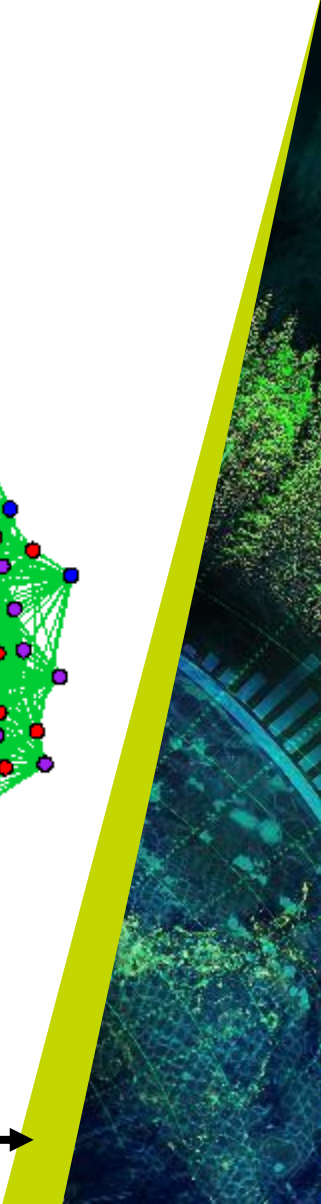
Multidimensional
data



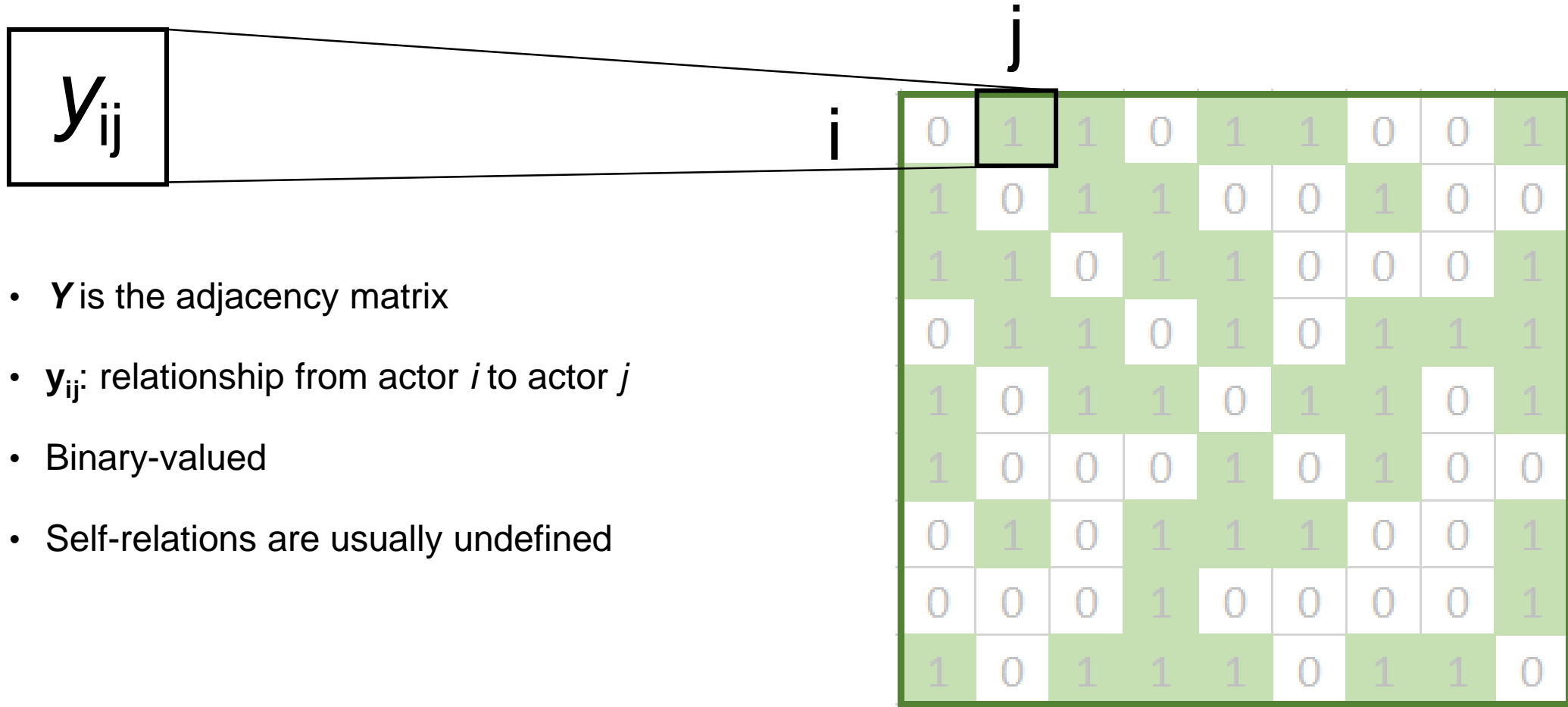
Longitudinal data



Time

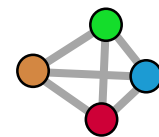


Descriptive properties of networks



- Y is the adjacency matrix
- y_{ij} : relationship from actor i to actor j
- Binary-valued
- Self-relations are usually undefined

Descriptive properties of networks

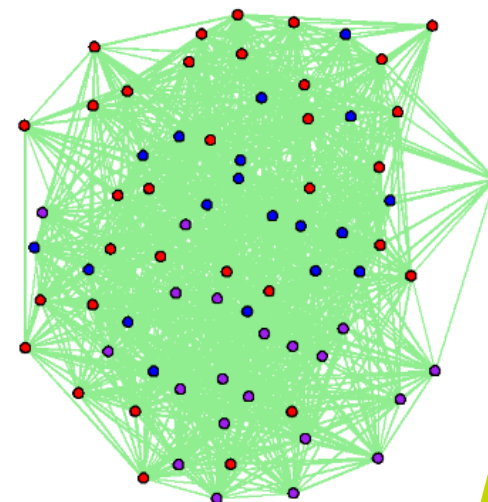


1) Size and density of the network

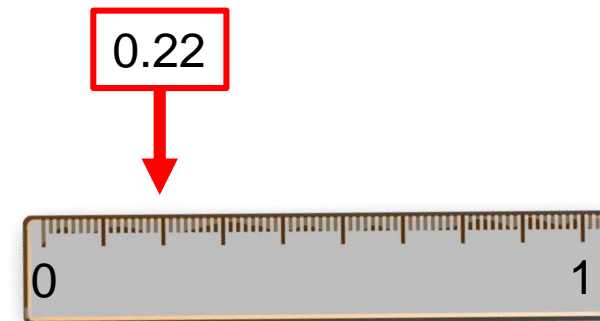
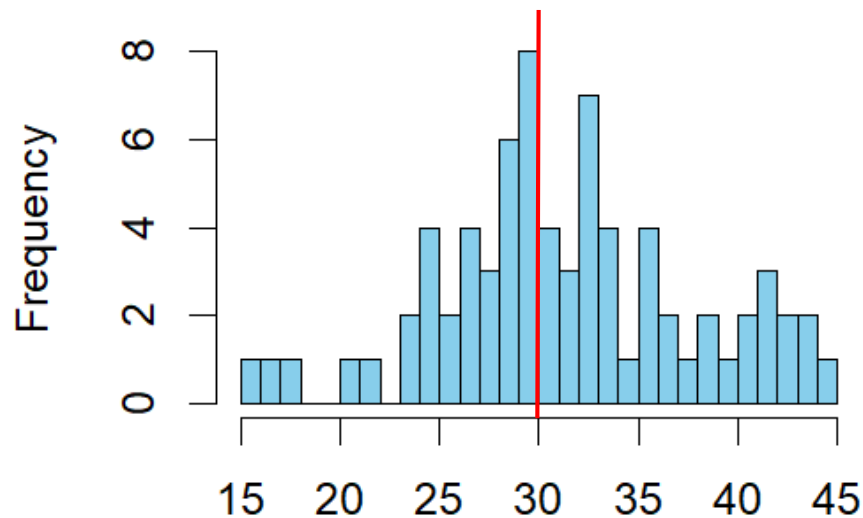
$$(L = \sum_{i,j} y_{ij})$$

$$L/(N(N - 1))$$

Feeding area

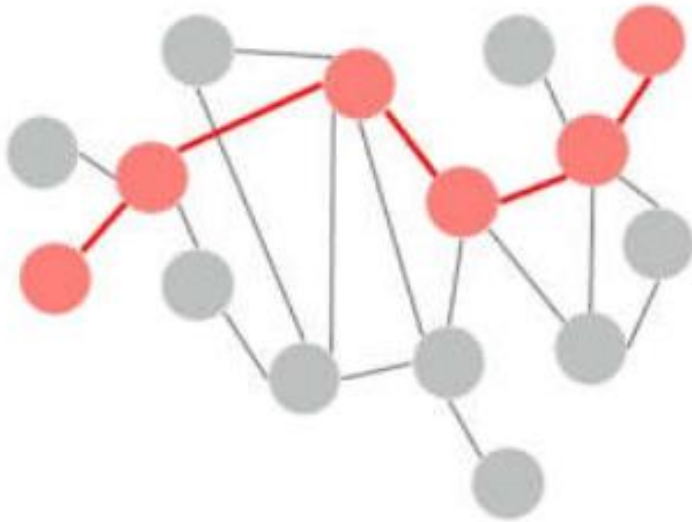


2) Degree and the degree distribution



Descriptive properties of networks

3) Geodesic distance:



Diameter

2

1.5

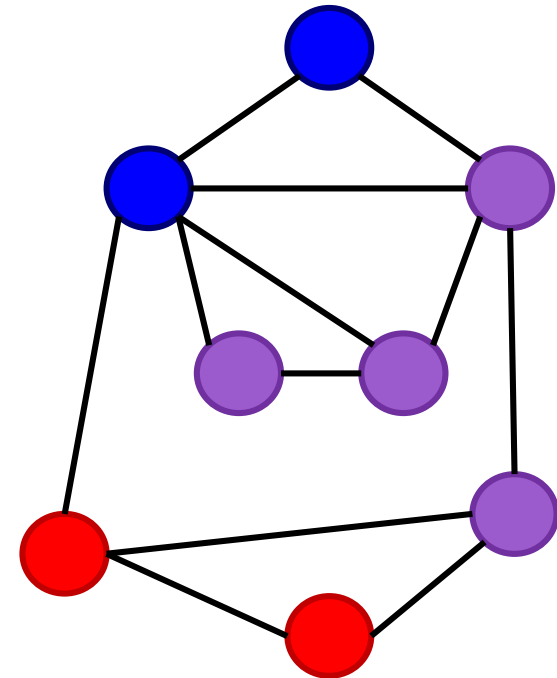


Descriptive properties of networks

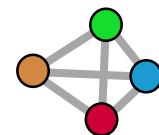
4) Centrality parameters:

Degree:

- The simplest is based on an actor's degree
- Reflects an actor's level of network activity or involvement



Descriptive properties of networks



4) Centrality parameters:

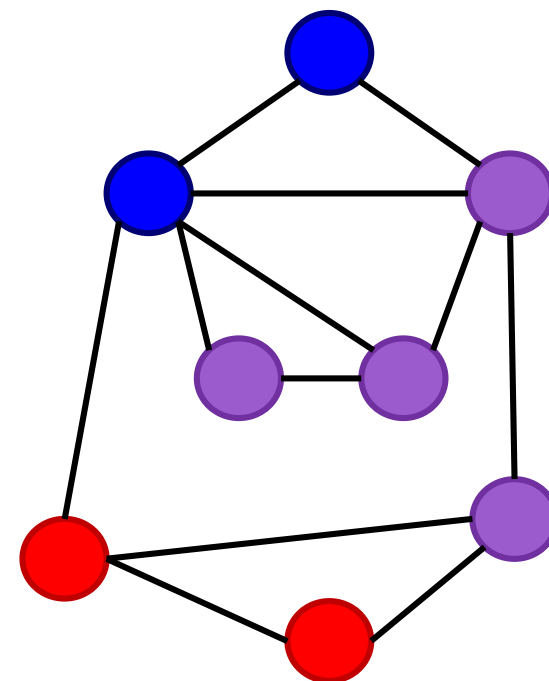
Betweenness:

- Number of times a node acts as a bridge along the shortest path between two other nodes

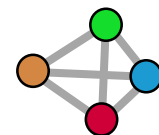
Shortest path from s->t
that cross through v

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Shortest path from s->t



Descriptive properties of networks



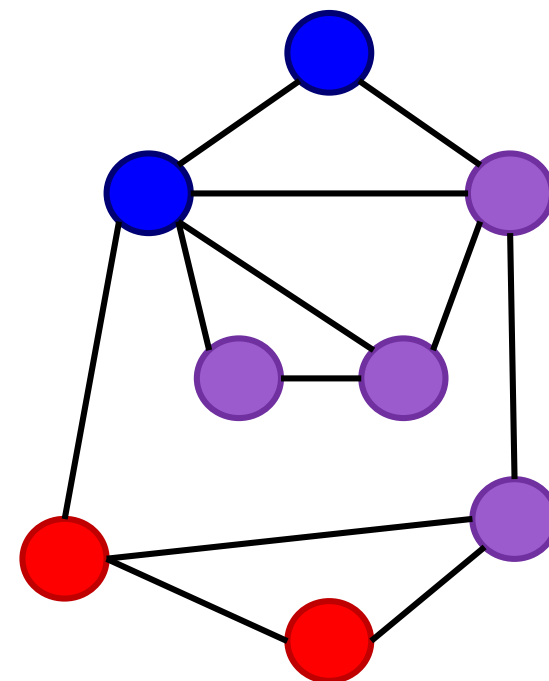
4) Centrality parameters:

Closeness:

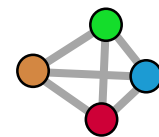
- Sum of the length of the shortest paths between the node and all other nodes in the graph

$$C(v) = \frac{N - 1}{\sum_u d(u, v)}$$

← Number of nodes in the graph
 ← Distance between vertices u and v



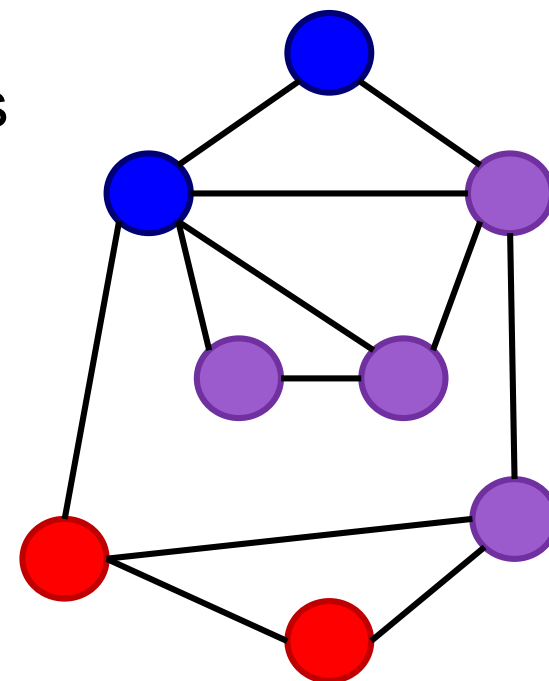
Descriptive properties of networks



4) Centrality parameters:

Eigenvector:

- Principal eigenvector using the adjacency matrix
- Measures a node's importance while giving consideration to the importance of its neighbors

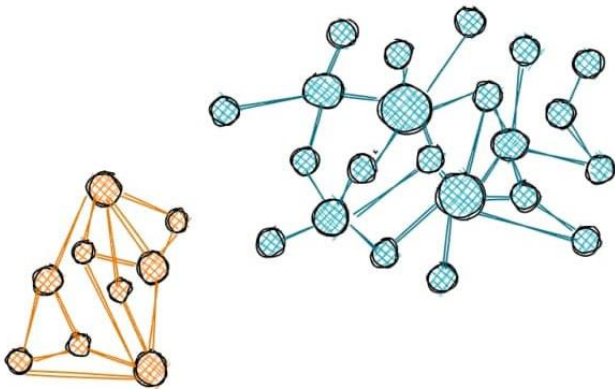


Descriptive properties of networks

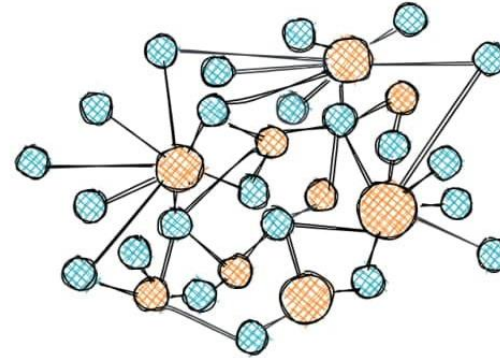
5) Homophily:

- Represents the propensity of individuals to interact with others of similar characteristics

Homophily

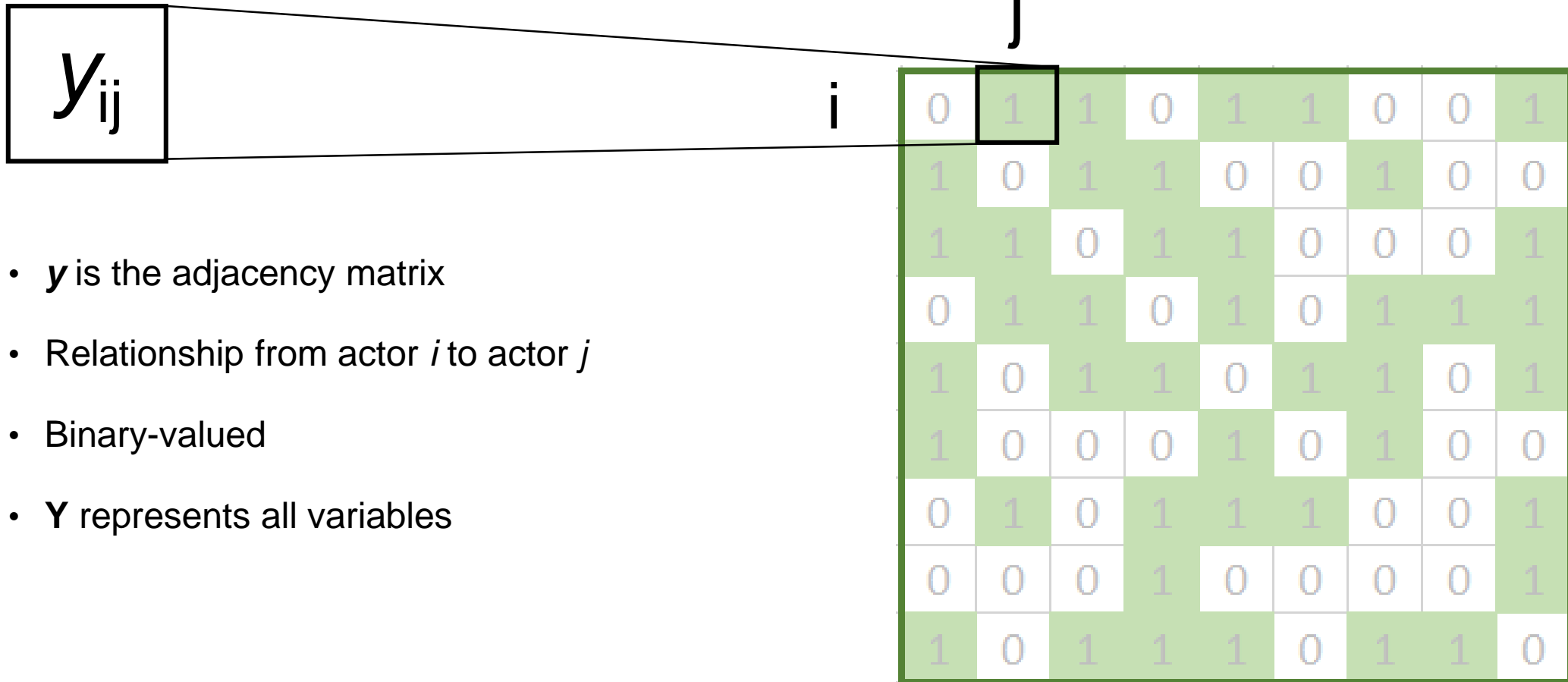


Heterophily



Relational or dyad-level models

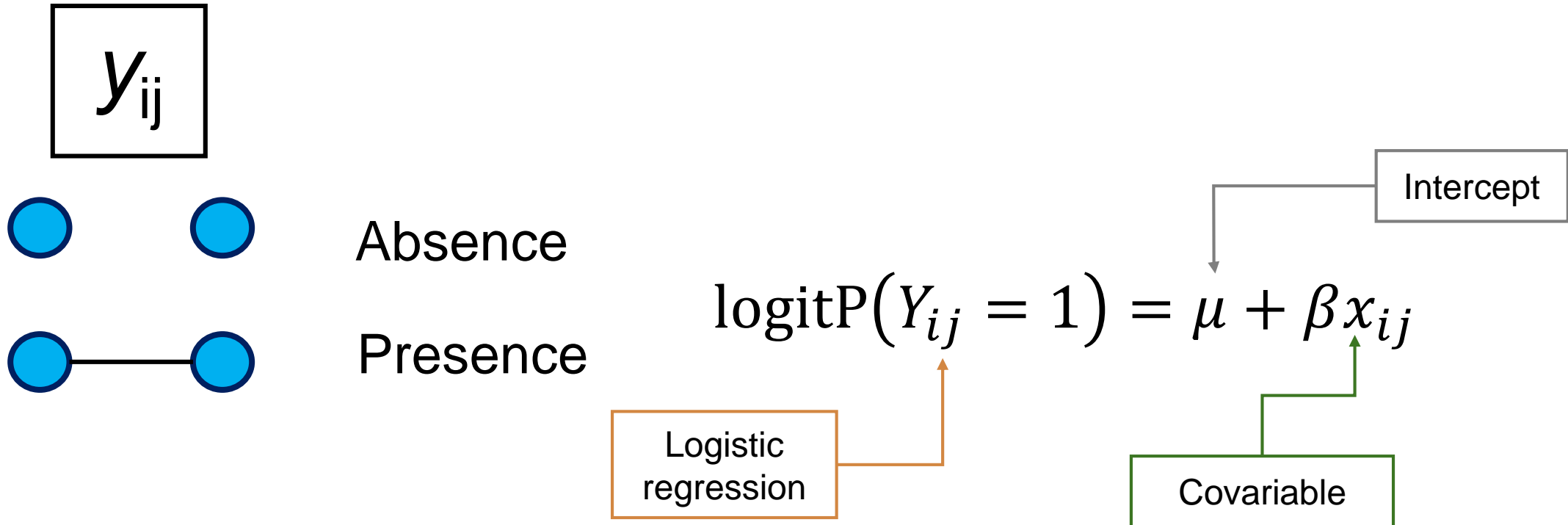
- Exponential random graph models (ERGMs):



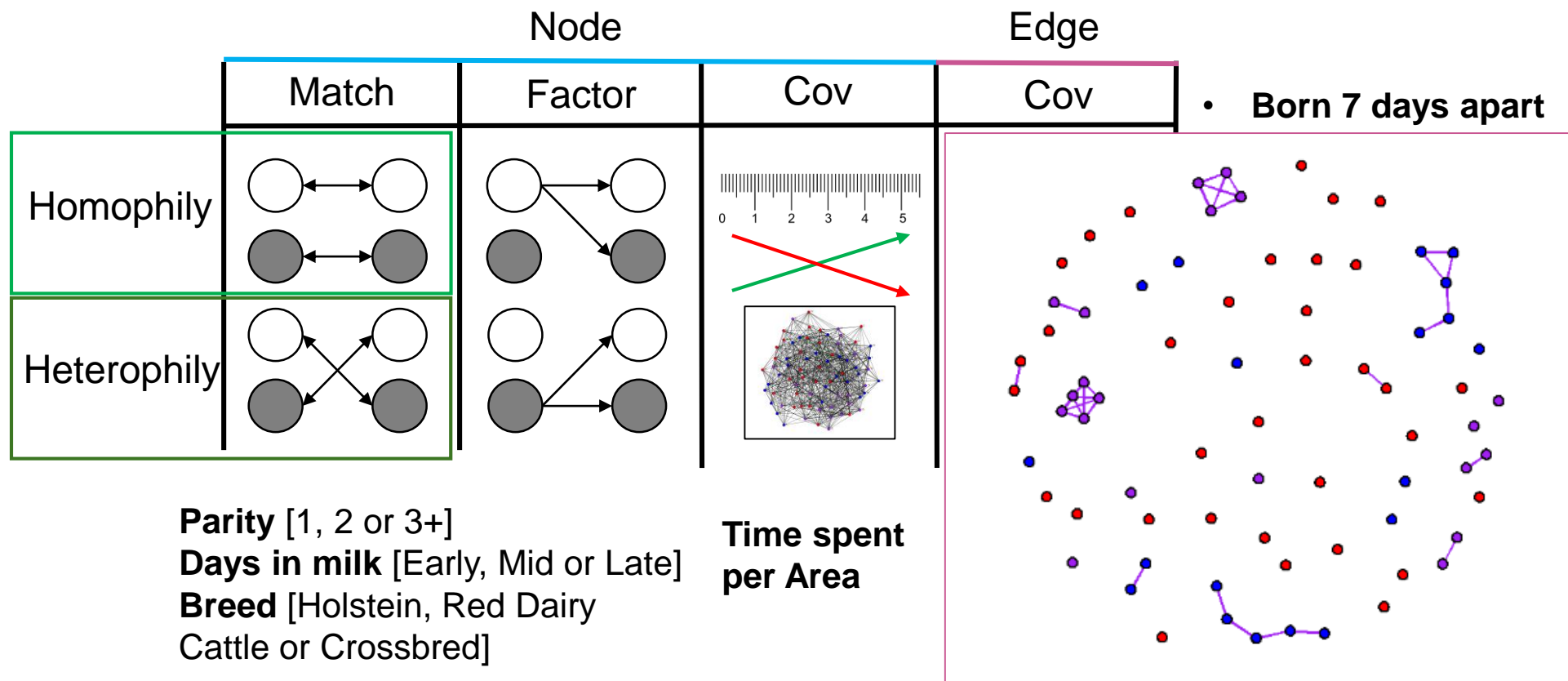
- y is the adjacency matrix
- Relationship from actor i to actor j
- Binary-valued
- Y represents all variables

Relational or dyad-level models

- Exponential random graph models (ERGMs):











Relational or dyad-level models






Relational or dyad-level models

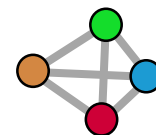
- Exponential random graph models (ERGMs):

| | | | Parity | | TimeInArea | AGEnet |
|---|---|--------------|--------|--------|------------|--------|
| | | | Match | Factor | Cov | Cov |
|  |  | $Y_{ij} = 0$ | 1 | 0 | 0.22+0.43 | 1 |
|  |  | $Y_{ik} = 0$ | 0 | 2 | 0.22+0.33 | 0 |
|  |  | $Y_{jk} = 1$ | 0 | 3 | 0.56+0.33 | 0 |
|  |  | $Y_{im} = 1$ | 1 | 0 | 0.22+0.13 | 0 |

Parity

-  1
-  2
-  3+

Social interactions



Essential feature of
cattle behavior

Meaningful social
relationships

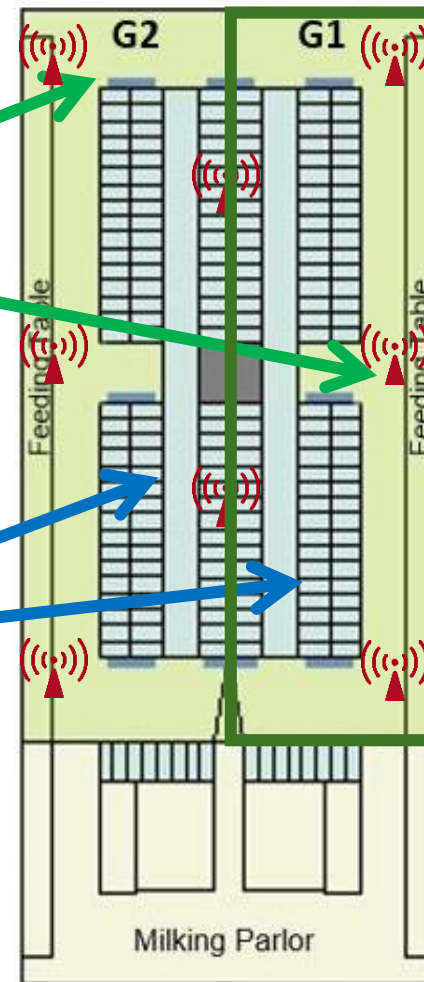
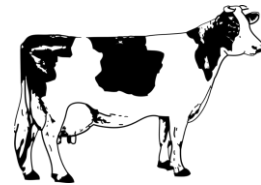
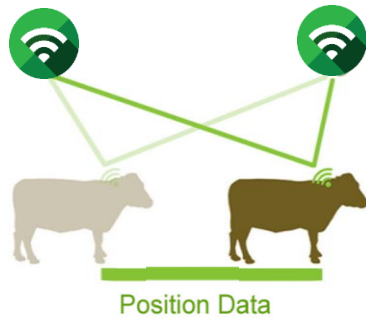
Ultra-Wide Band technology



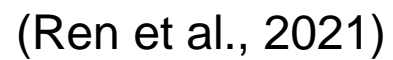
- Collecting positions of all cows every second
- Spatial interactions
- Real time information

Spatial interactions

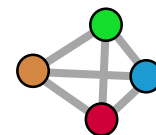
Real-time Location System






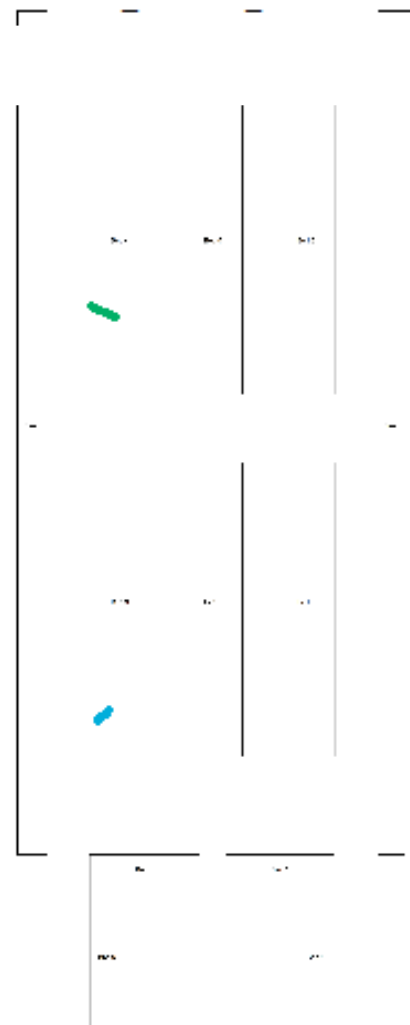
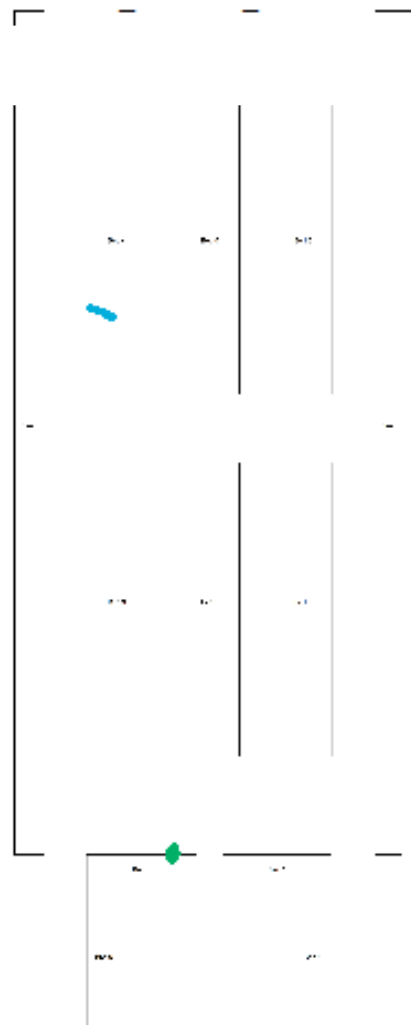
-  Feeding Area
-  Resting Area
-  Water trough
-  Feed boxes (not in use)



Spatial contacts

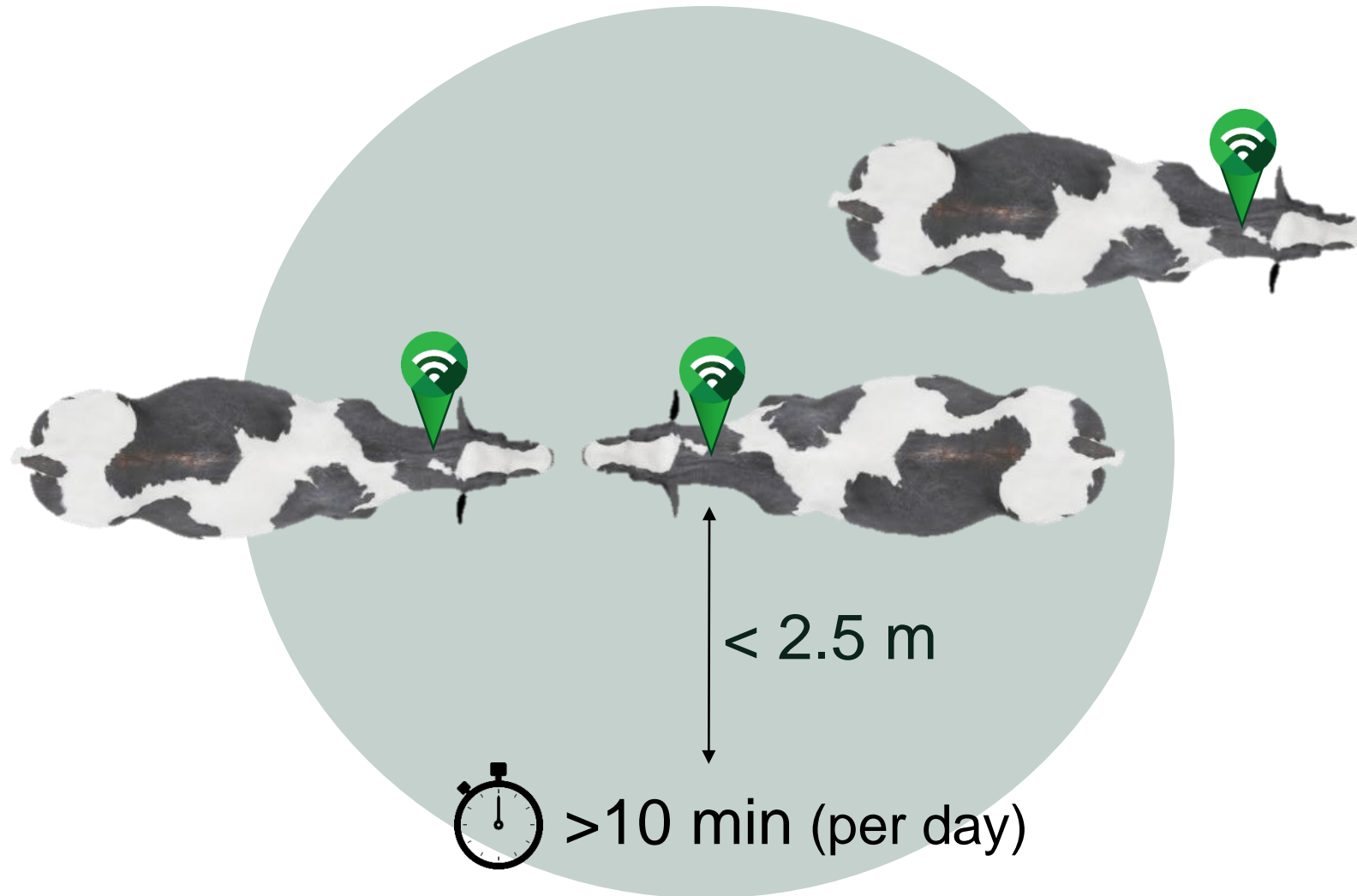


-  Cow: 1
-  Cow: 2
-  Spatial interaction

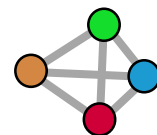





Spatial contacts

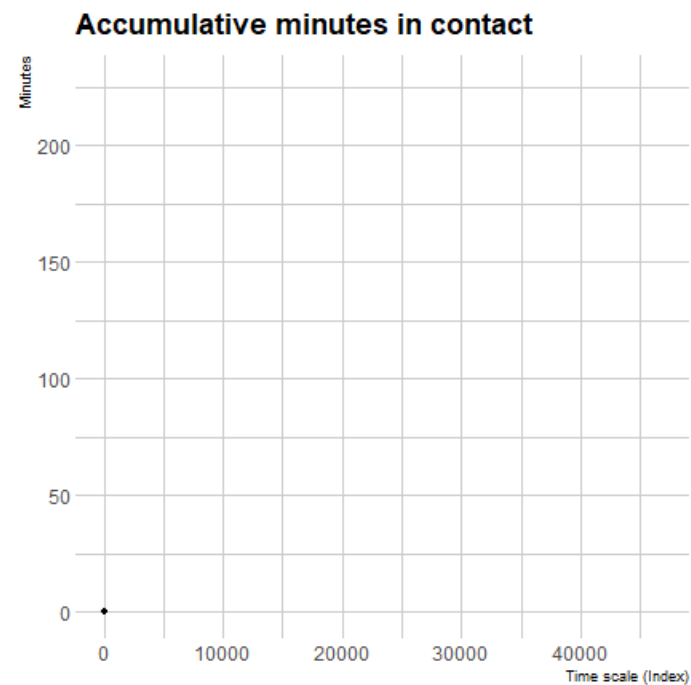
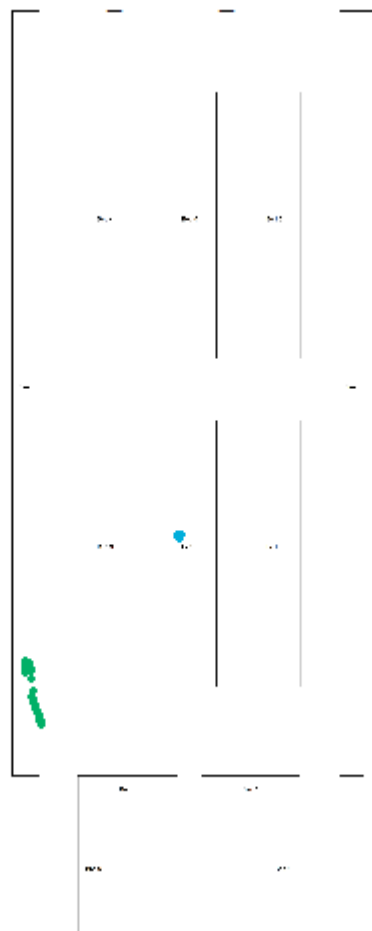
What was consider as social contact?



Spatial contacts



-  Cow: 1
-  Cow: 2
-  Spatial interaction



Spatial contacts

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 |
| 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 |
| 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 |
| 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 |
| 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 |
| 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 |
| 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 |
| 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 |
| 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 |
| 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 |

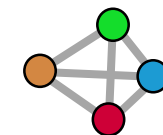
Absence

Presence



hands
on





1. O'Malley, A.J., and P. V. Marsden. 2008. The Analysis of Social Networks. Health Serv. Outcomes Res. Methodol. 8:222. doi: <https://doi.org/10.1007/S10742-008-0041-Z>
2. de Freslon, I., Martínez-López, B., Belkhiria, J., Strappini, A., Monti, G., 2019. Use of social network analysis to improve the understanding of social behaviour in dairy cattle and its impact on disease transmission. Appl. Anim. Behav. Sci. 213, 47–54. <https://doi.org/10.1016/J.APPLANIM.2019.01.006>
3. Tabassum, S, Pereira, FSF, Fernandes, S, Gama, J. Social network analysis: An overview. WIREs Data Mining Knowl Discov. 2018; 8:e1256. <https://doi.org/10.1002/widm.1256>
4. Martínez-López, B., Perez, A.M. and Sánchez-Vizcaíno, J.M. (2009), Social Network Analysis. Review of General Concepts and Use in Preventive Veterinary Medicine. Transboundary and Emerging Diseases, 56: 109-120. <https://doi.org/10.1111/j.1865-1682.2009.01073.x>
5. Chen, S., Ilany, A., White, B.J., Sanderson, M.W., Lanzas, C., 2015. Spatial-Temporal Dynamics of High-Resolution Animal Networks: What Can We Learn from Domestic Animals? PLoS One 10, e0129253. <https://doi.org/10.1371/JOURNAL.PONE.0129253>
6. Rocha, L.E.C., Terenius, O., Veissier, I., Meunier, B., Nielsen, P.P., 2020. Persistence of sociality in group dynamics of dairy cattle. Appl. Anim. Behav. Sci. 223, 104921. <https://doi.org/10.1016/J.APPLANIM.2019.104921>



SCIENCE AND
EDUCATION **FOR**
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