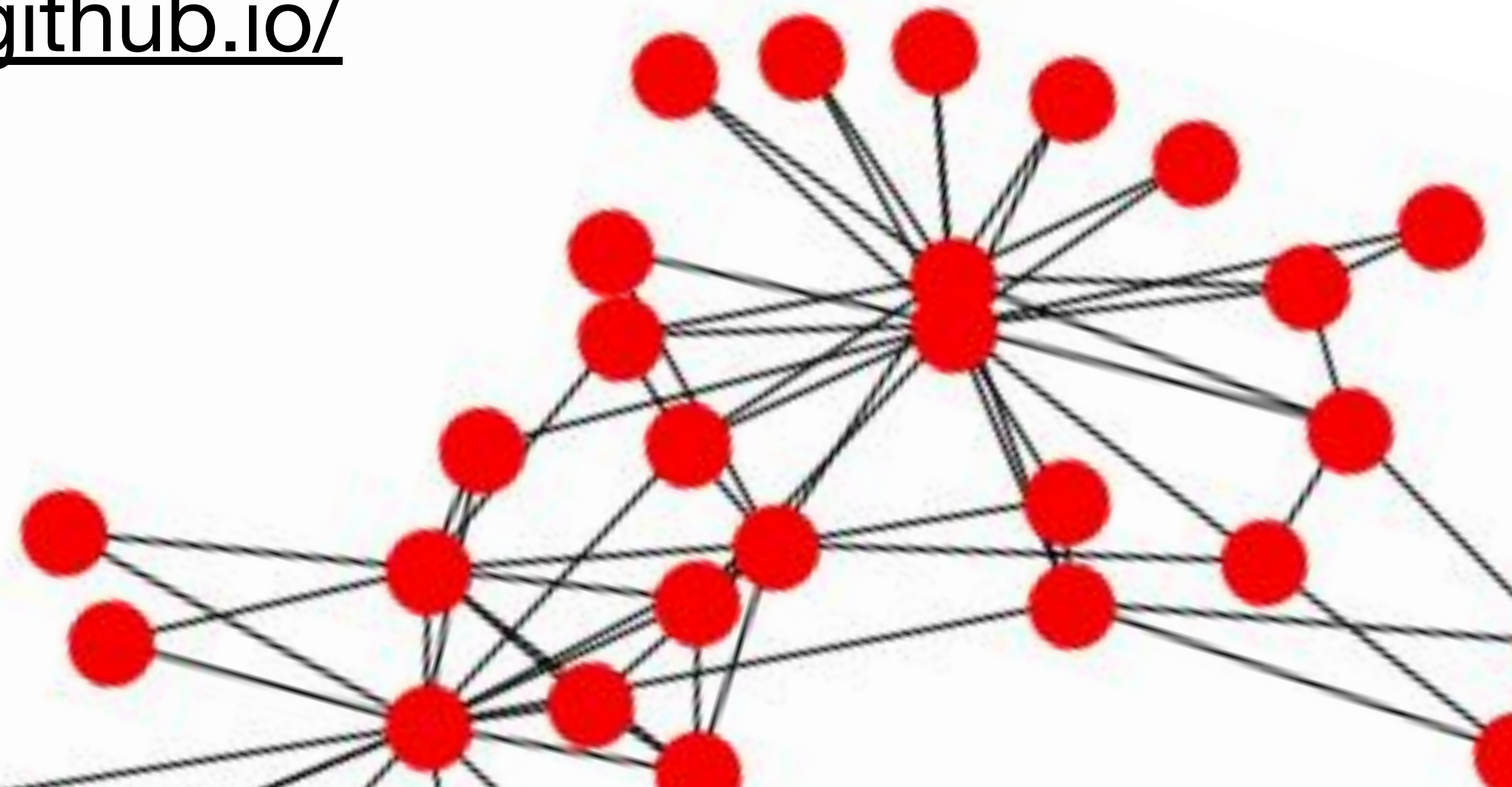


DMSN Tutorial 1: Networks and Random Graphs

Naomi Arnold

<https://narnolddd.github.io/>

Session will start at 9:05,
see you soon! :-)



About me

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Naomi Arnold

PhD Student

📍 Queen Mary University of London

✉ Email

🐦 Twitter

🌐 LinkedIn

📷 Instagram

🐙 Github

Naomi Arnold

I am Naomi Arnold, a PhD student within the [Networks group](#) in the [School of Electronic Engineering and Computer Science](#) at [Queen Mary University of London](#). My supervisors are [Richard Clegg](#) and [Raul Mondragon](#). My research interests are broadly in modelling different types of social and information systems as evolving graphs. Specific areas of interest to me are

- Network growth models: model selection and changepoint detection.
- Tools for temporal networks.

I maintain the [FETA](#) (Framework for Evolving Topology Analysis) codebase with [Richard Clegg](#), which can be used for generating graphs from different growth models, and for model selection (paper describing the background and process [here](#)).

I am also a contributor to the [Raphorty](#) software for the analysis of temporal graphs.

News

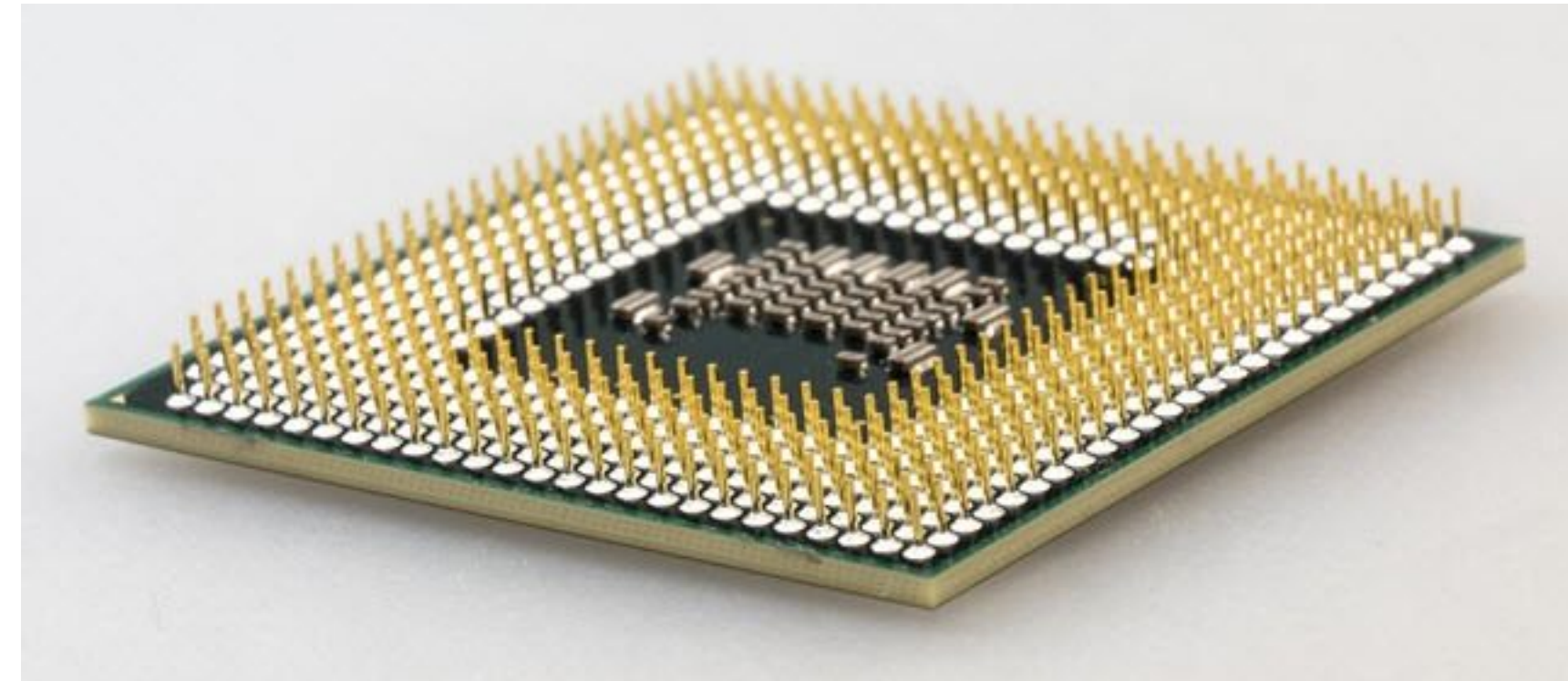
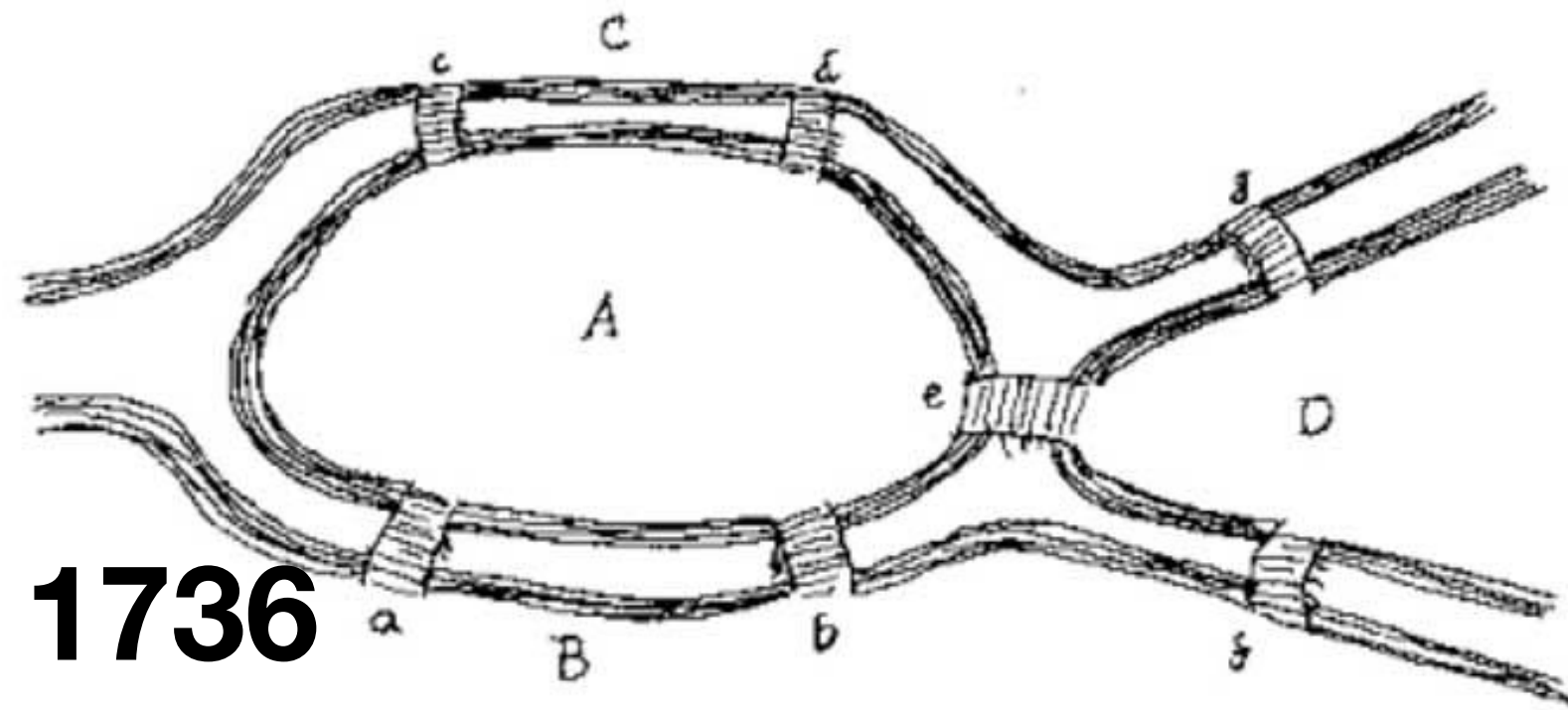
Housekeeping

- Asking questions -- “raise hand” feature
- Chat channels -- bear in mind that moderators can see these
- Session recordings -- each session will be recorded
- Tutorial materials -- will be uploaded after end of each session

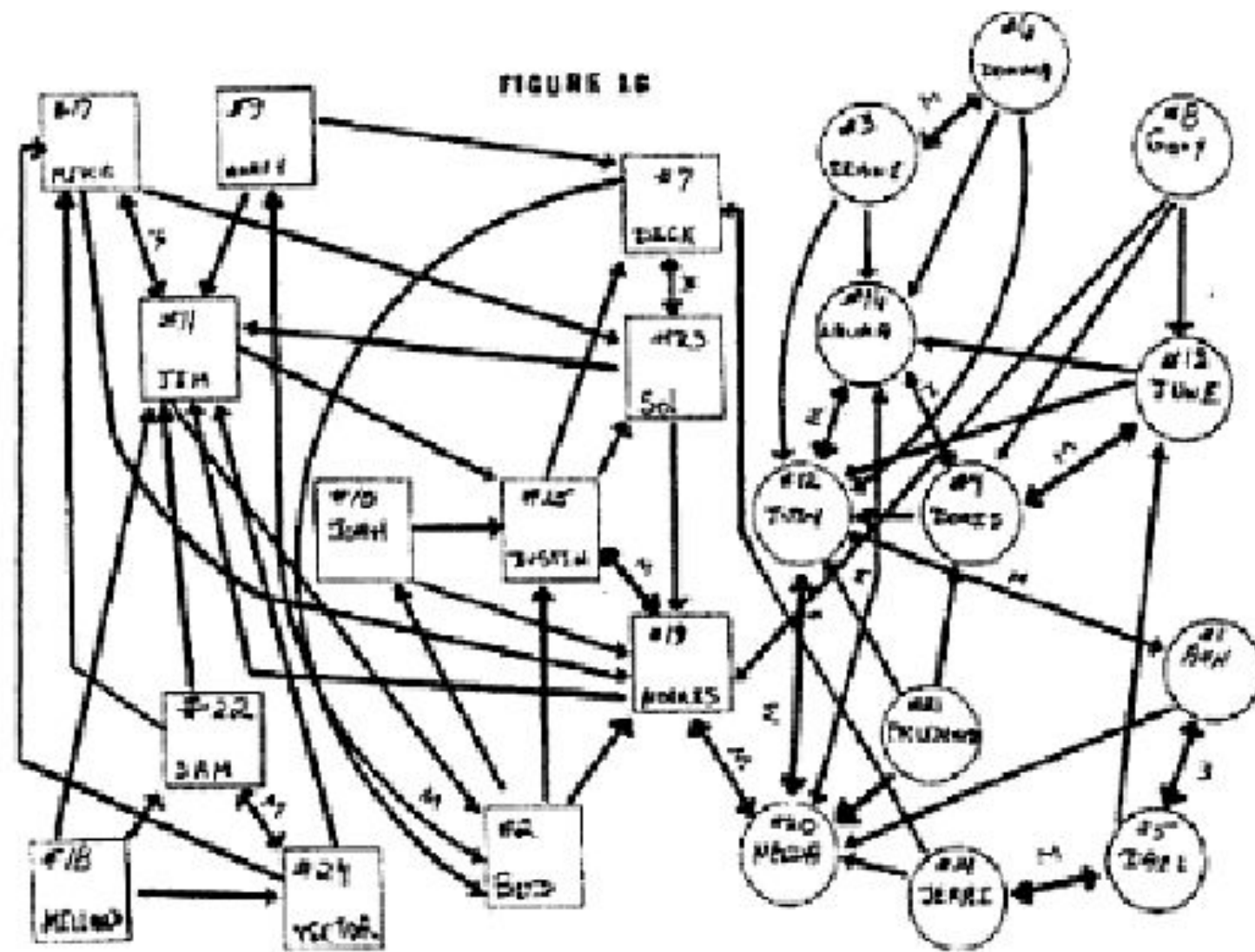
In this tutorial:

- **Recap** on concepts and metrics covered in the lecture
- **Get to grips** with the Erdos-Renyi random graph model
- **See** some of the key similarities and differences between random graphs and real networks

A (very) brief history of network science



Availability of rich datasets
+
Computing power



1933



If you could draw one edge per second and didn't take breaks, it would take **12,600 years** to draw the Facebook graph

Network Science is Interdisciplinary

- **Social sciences:** made first use of ‘sociograms’ as networks, and drive a lot of the motivation for network science
- **Mathematics/Physics:** development of graph theory, models for dynamics on/of networks (often using theory from particle physics!)
- **Computer Science:** developing and implementing algorithms for networks, working with scalability challenges of big data
- **Field specific applications:** epidemiologists studying disease prevention/vaccination, Internet network operators, social network

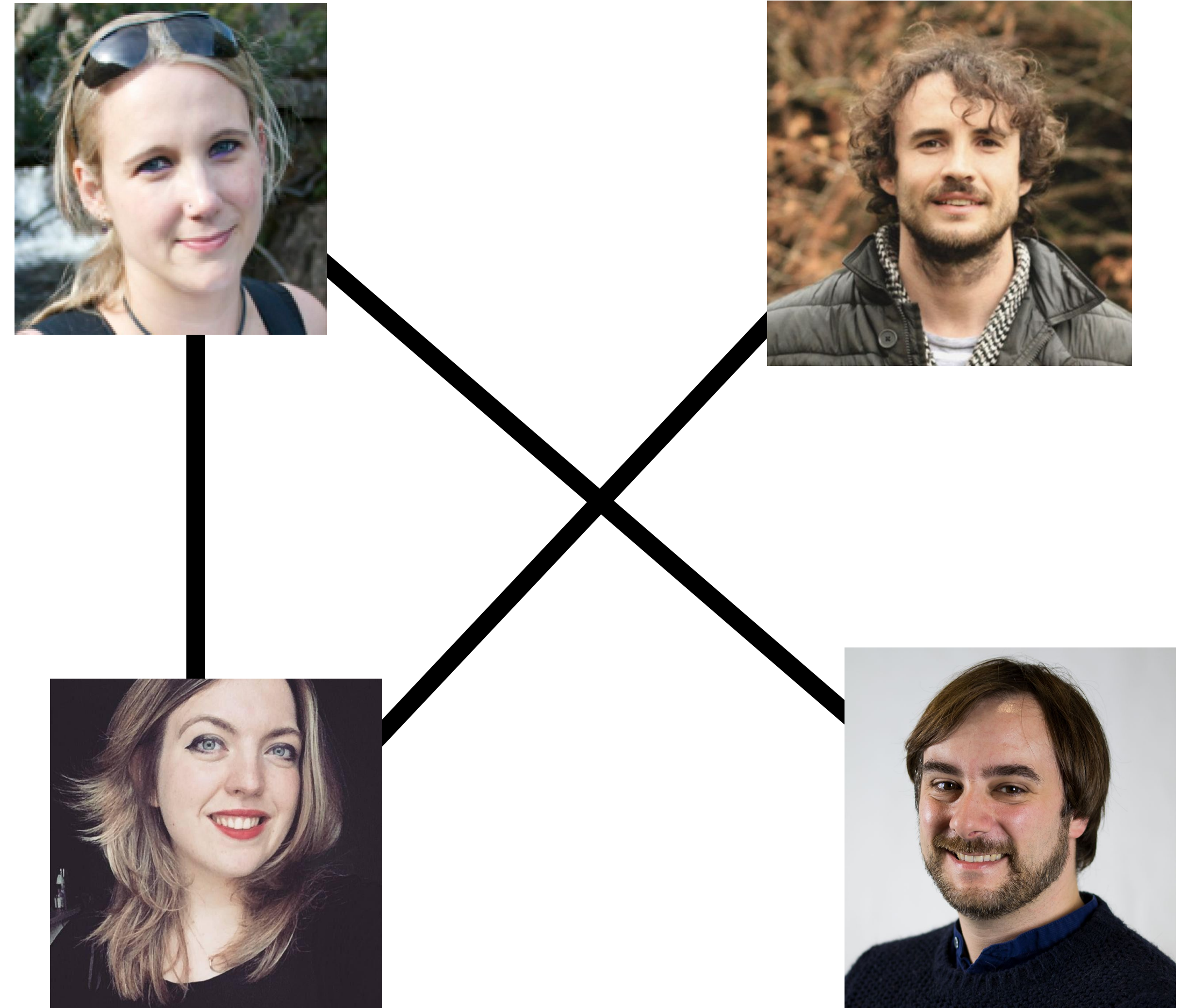
(Undirected) Graph

A **graph** is a tuple (V,E) of a set V of vertices and E of edges

Vertex (node) set: {Laurissa, Teo, Naomi, Mathieu}

Edge (link) set: { (Laurissa, Naomi), (Laurissa, Mathieu), (Naomi, Teo)}

Here, order doesn't matter as graph is **undirected**

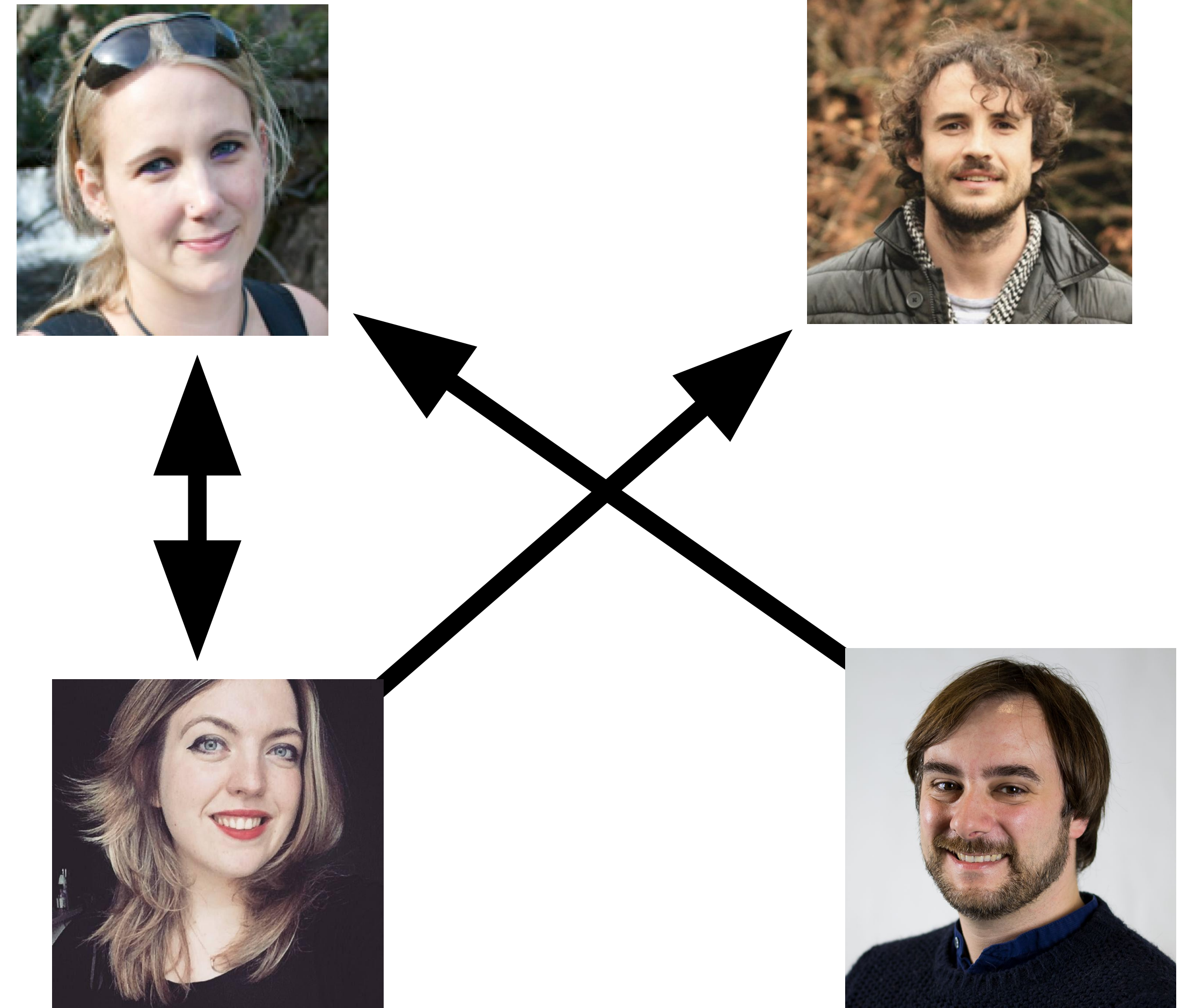


Directed Graph

Vertex (node) set: {Laurissa, Teo, Naomi, Mathieu}

Edge (link) set: { (Laurissa, Naomi),
(Naomi, Laurissa),
(Mathieu, Laurissa),
(Naomi, Teo) }

Here, order **does** matter as
graph is **directed**



How do we measure graphs?
How do we compare them?

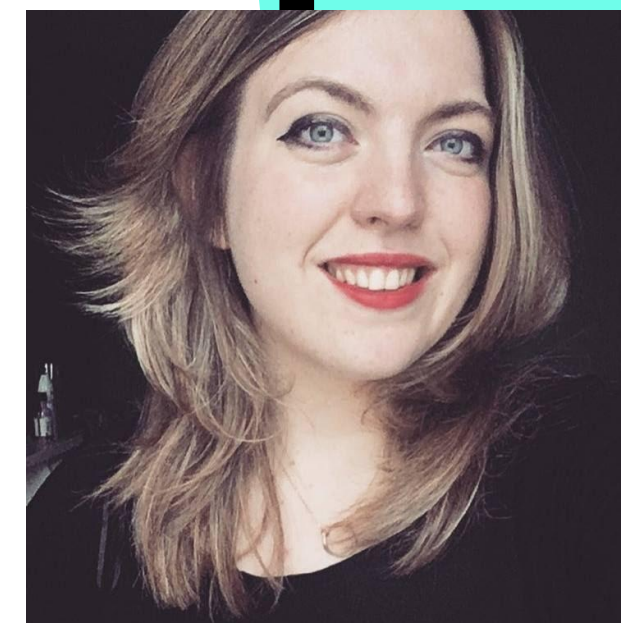
Neighbourhood and Degree

The **neighbourhood** $N(v)$ of a vertex v is the set of vertices adjacent to v

e.g. $N(\text{Naomi}) = \{\text{Laurissa, Teo}\}$

The **degree** $k(v)$ of a vertex v is the size of the neighbourhood: $|N(v)|$

e.g. $k(\text{Naomi}) = 2$



Degree Sequence/Average Degree

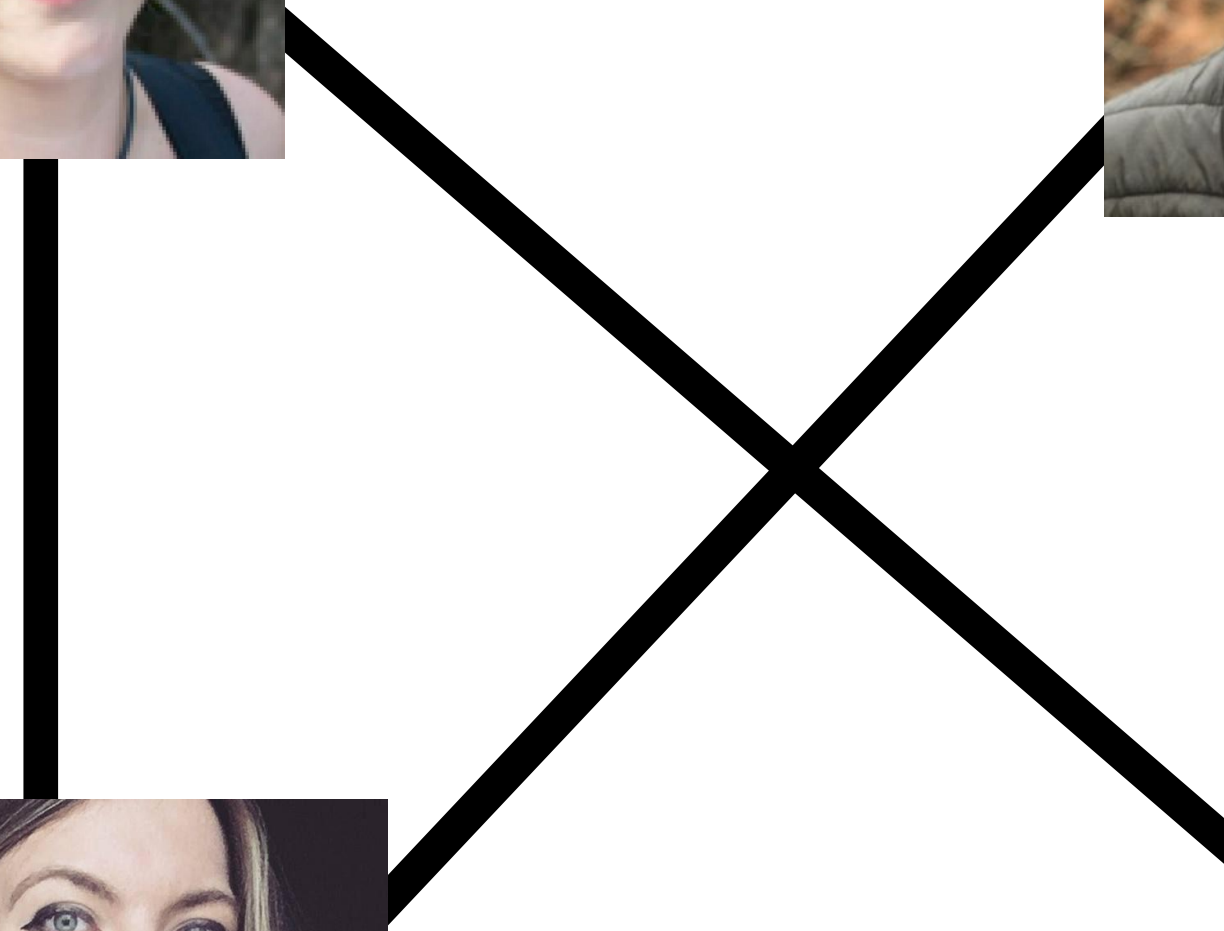
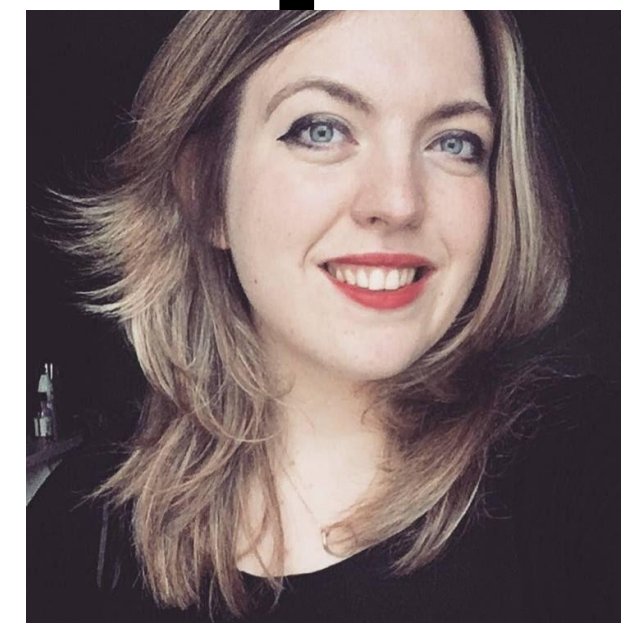
The **degree sequence** of a graph is the list of the vertex degrees for that graph

e.g. 2, 2, 1, 1

The **average degree** of a graph $\langle k \rangle$ is the mean of the node degrees

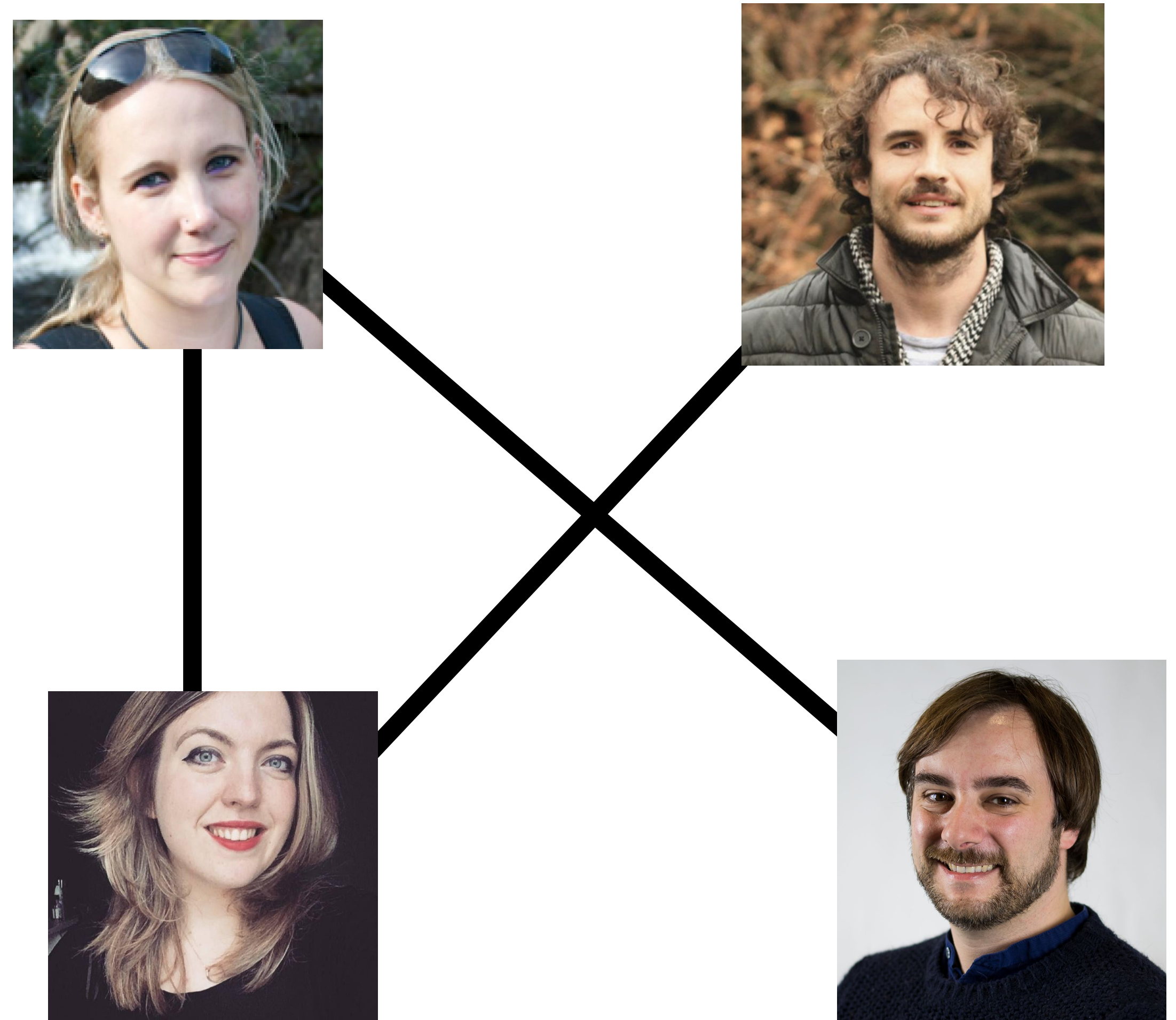
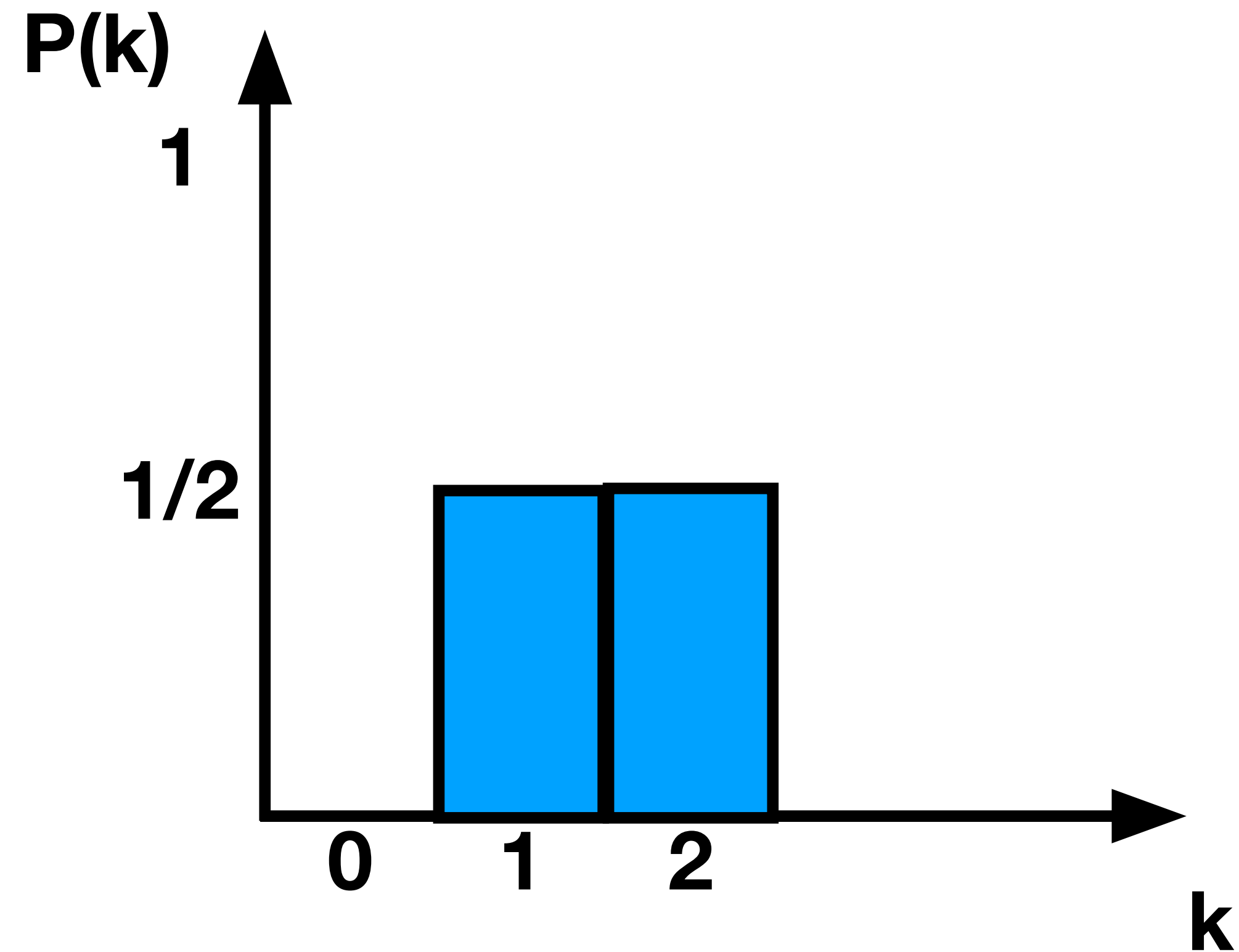
e.g. $\langle k \rangle = (2 + 2 + 1 + 1)/4 = 1.5$

(also equal to $2 * |\text{edges}| / |\text{nodes}| \dots$ why?)



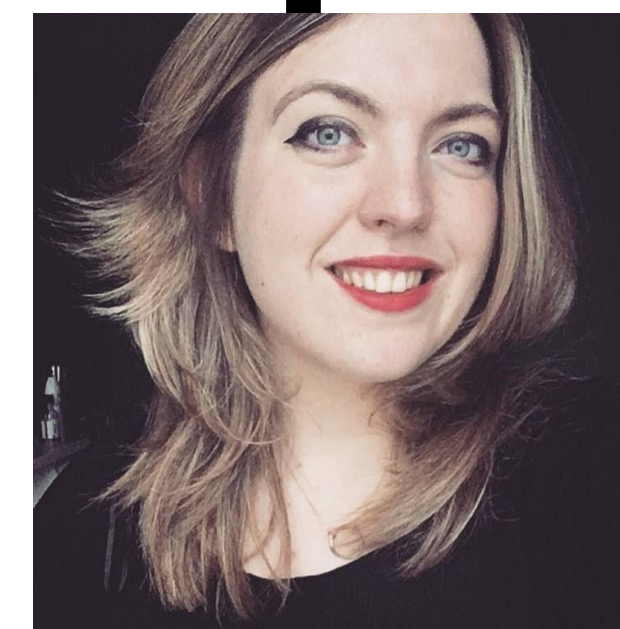
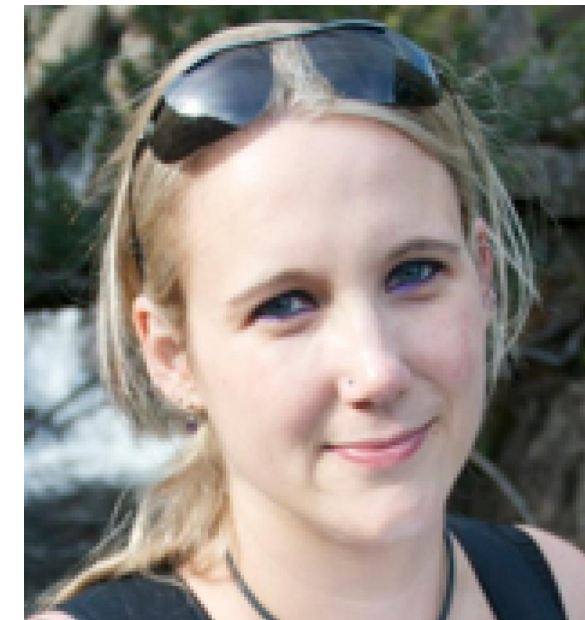
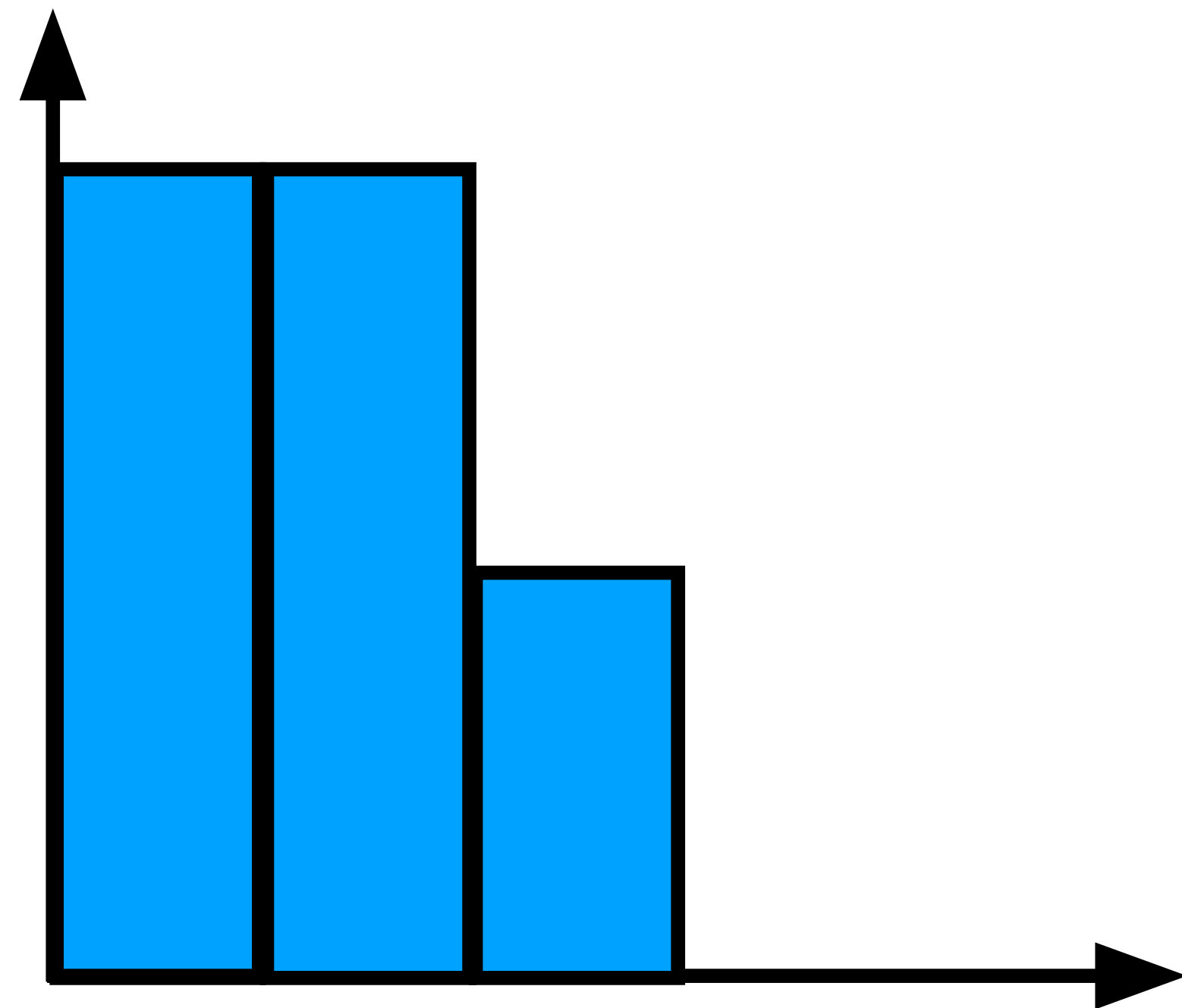
Degree distribution

The degree distribution $P(k)$ is the proportion of nodes with degree equal to k

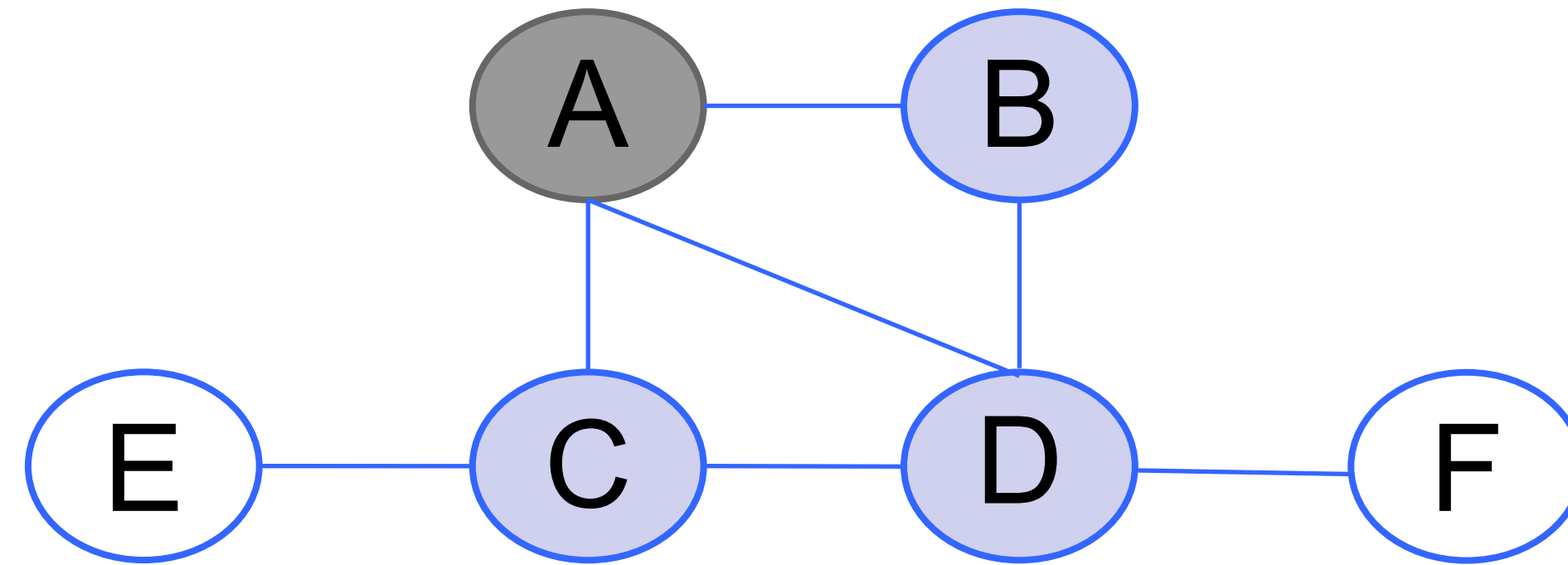


Degree distribution

... but it's common to look at the proportion of nodes with degree **greater than or equal to k**



CLUSTERING COEFFICIENT



The **clustering coefficient** defines the proportion of A's neighbours ($N(A)$) which are connected by an edge (are friends).

The number of triangles in which A is involved wrt to the ones it could be involved in.

FORMALLY: CLUSTERING COEFFICIENT

Local Clustering Coefficient

$$C_i = \frac{2|\{e_{jk}\}|}{k_i(k_i-1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

Proportion of my friends who are also friends with my other friends...

Network Clustering Coefficient

$$CG = \frac{1}{N} \sum_i C_i$$

The average all all the node's local clustering coefficients

FORMALLY: CLUSTERING COEFFICIENT

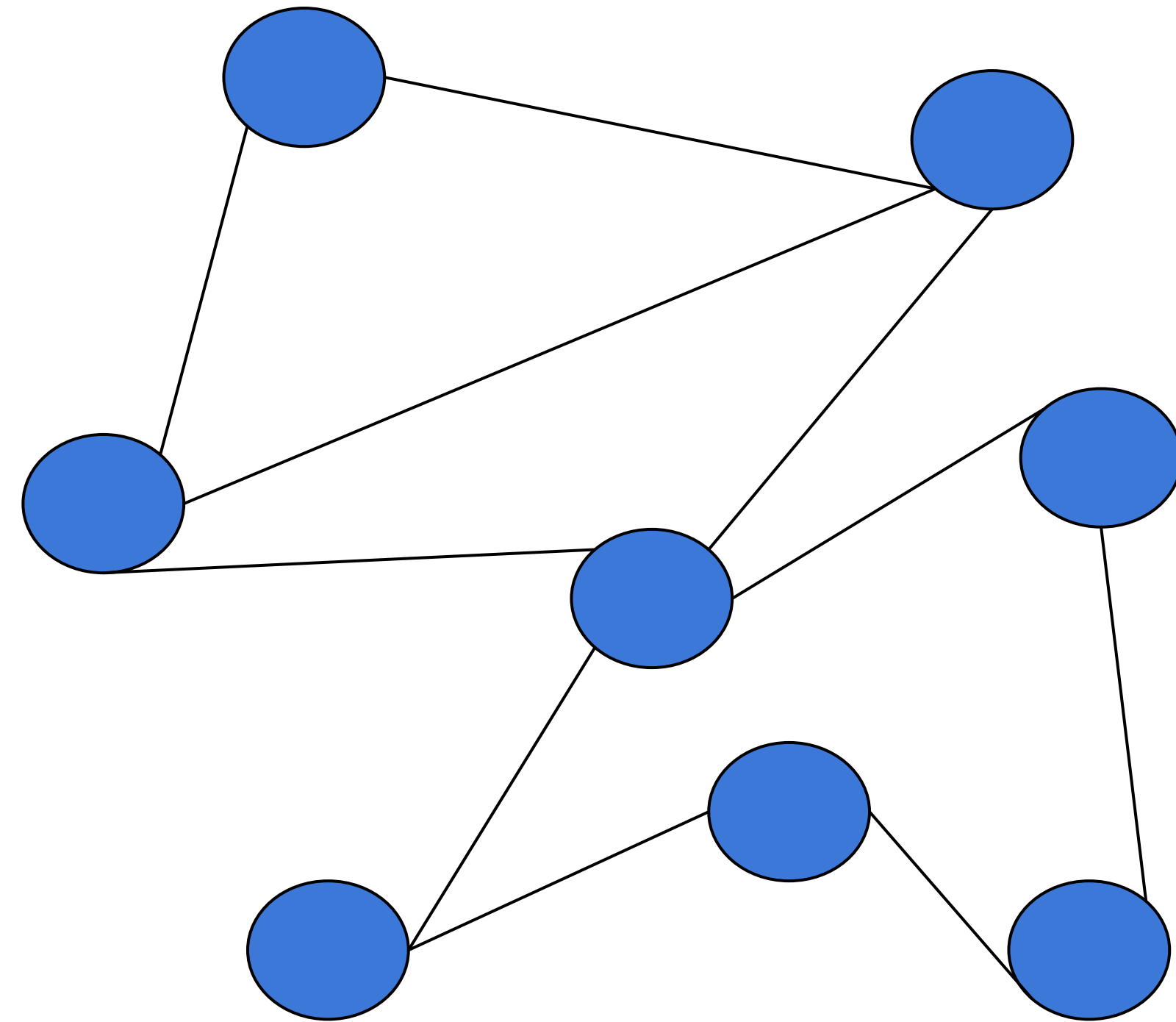
Local Clustering
Coefficient

$$C_i = \frac{2|\{e_{jk}\}|}{k_i(k_i-1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

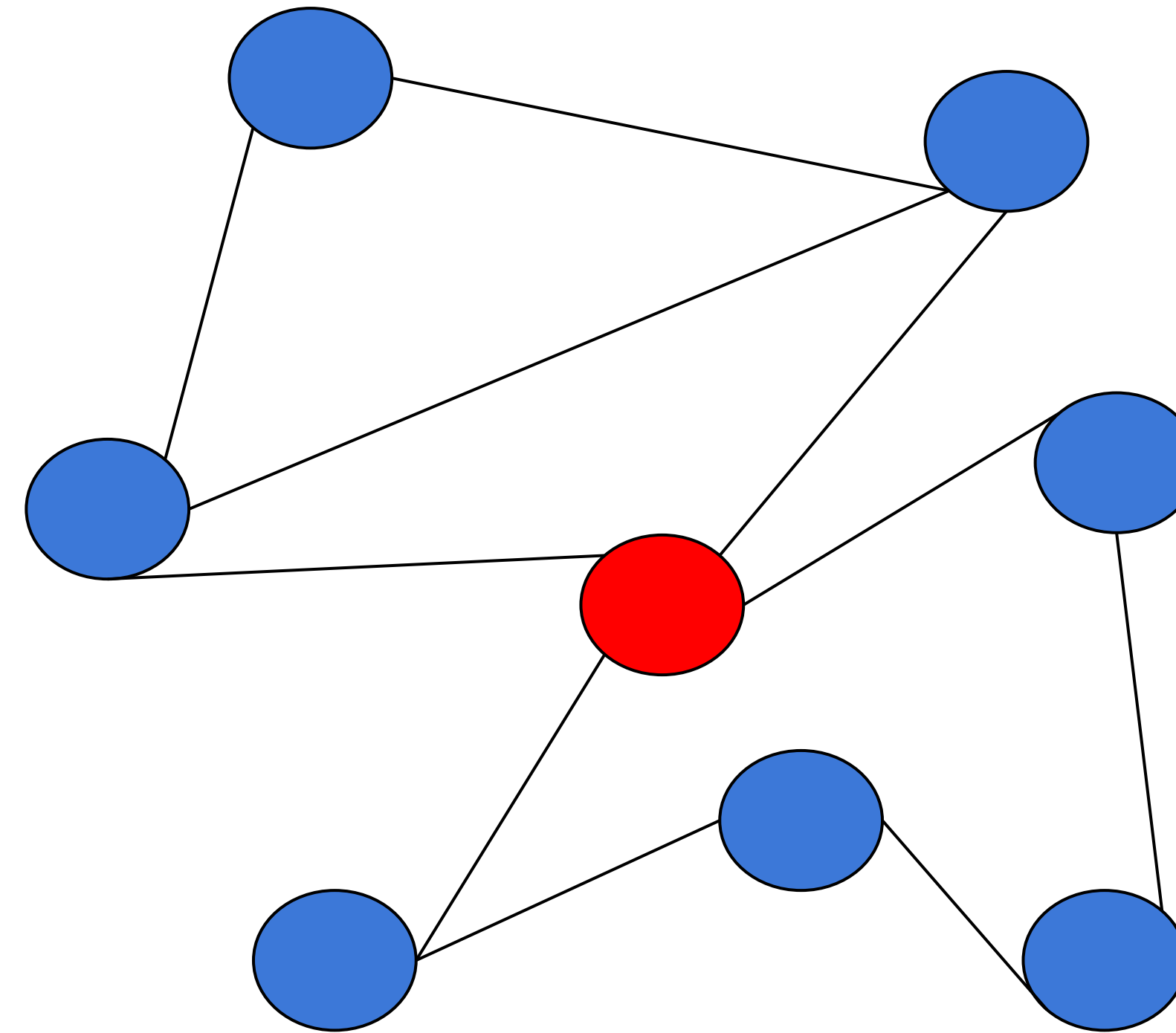
Network Clustering
Coefficient

$$CG = \frac{1}{N} \sum_i C_i$$

CLUSTERING COEFFICIENT: EXAMPLE

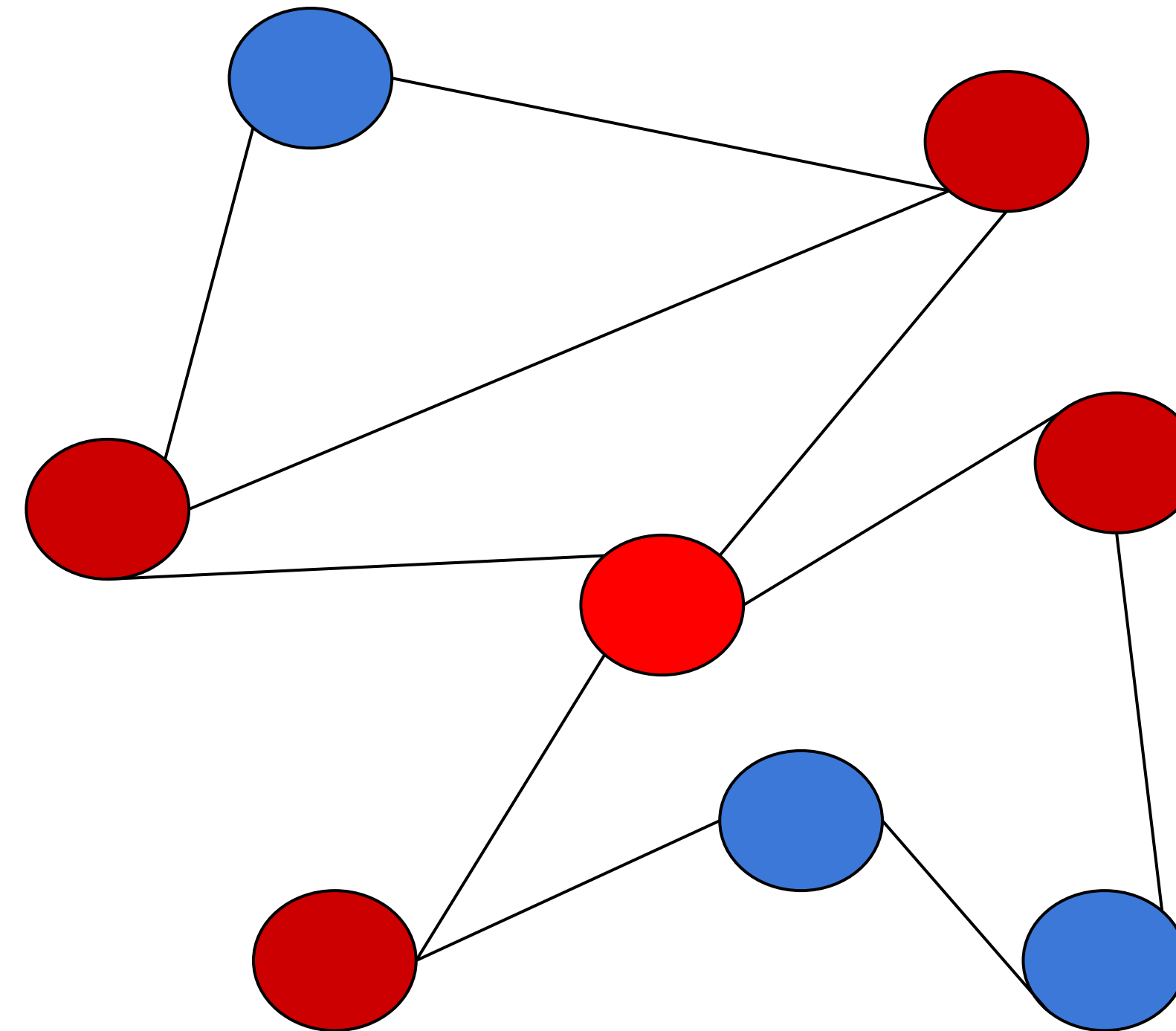


CLUSTERING COEFFICIENT: EXAMPLE



CLUSTERING COEFFICIENT: EXAMPLE

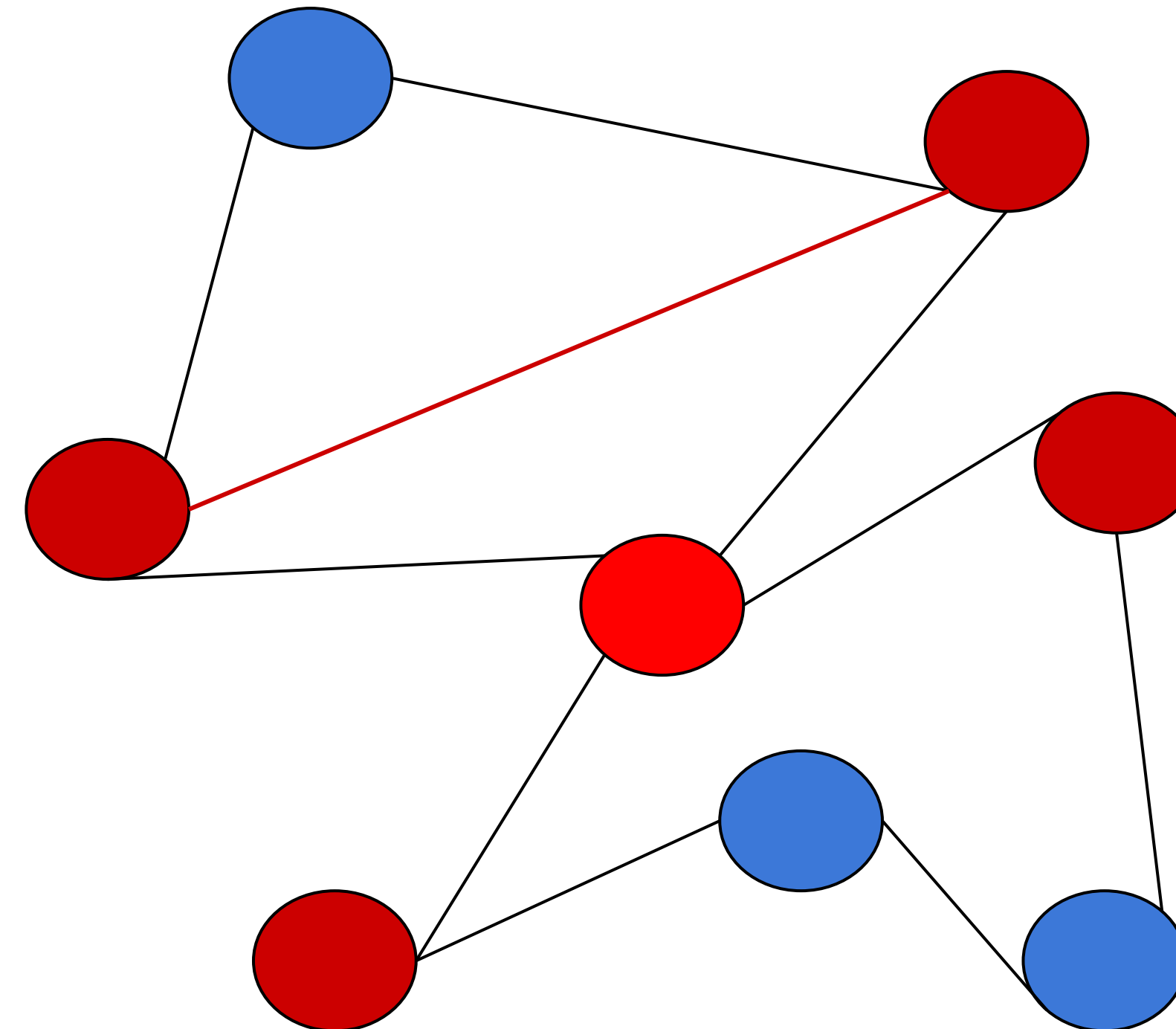
Degree = 4



CLUSTERING COEFFICIENT: EXAMPLE

Degree = 4

Links between
neighbours = 1

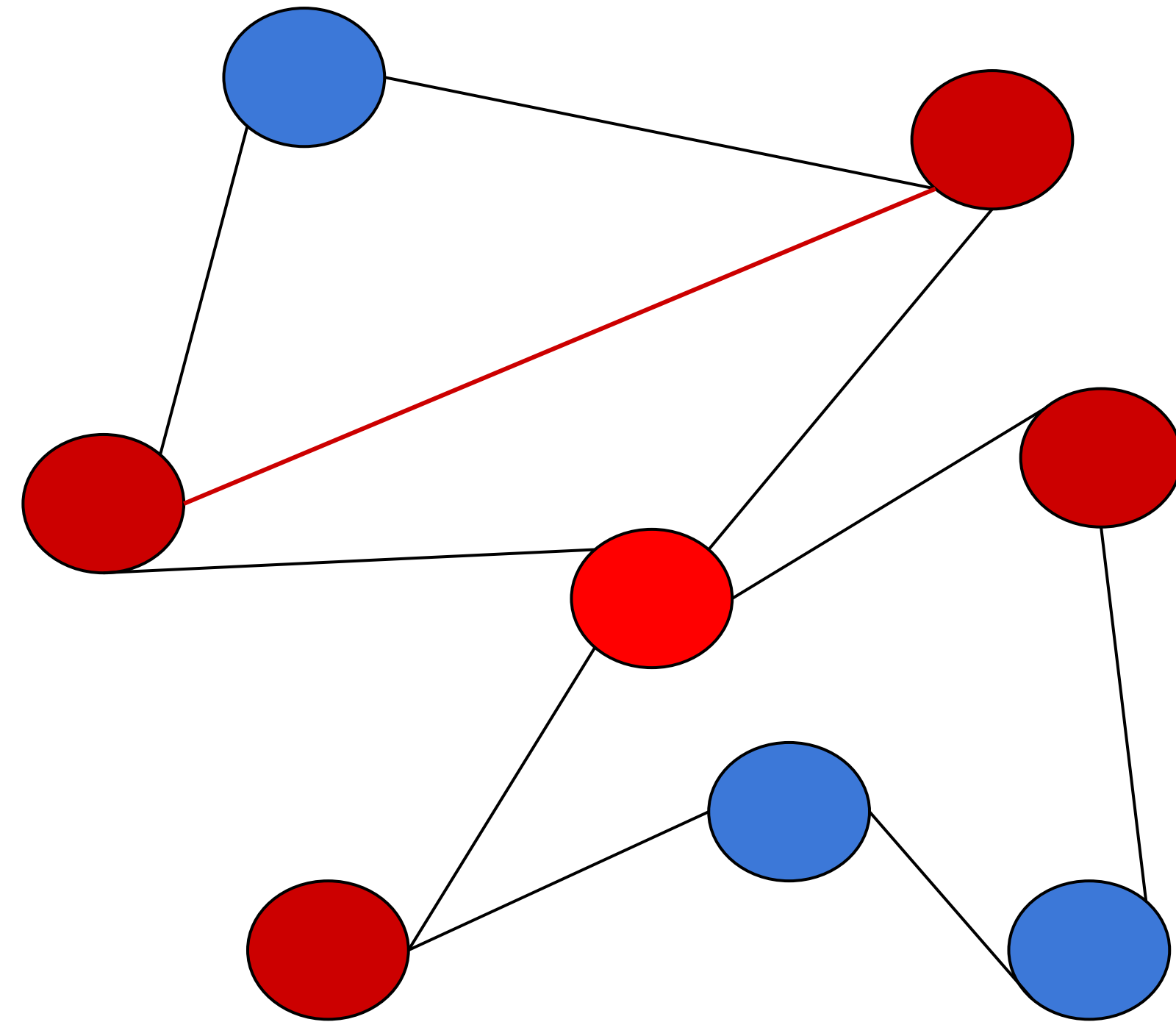


CLUSTERING COEFFICIENT: EXAMPLE

Degree = 4

Links between
neighbours = 1

$$C_i = \frac{2|\{e_{jk}\}|}{k_i(k_i - 1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

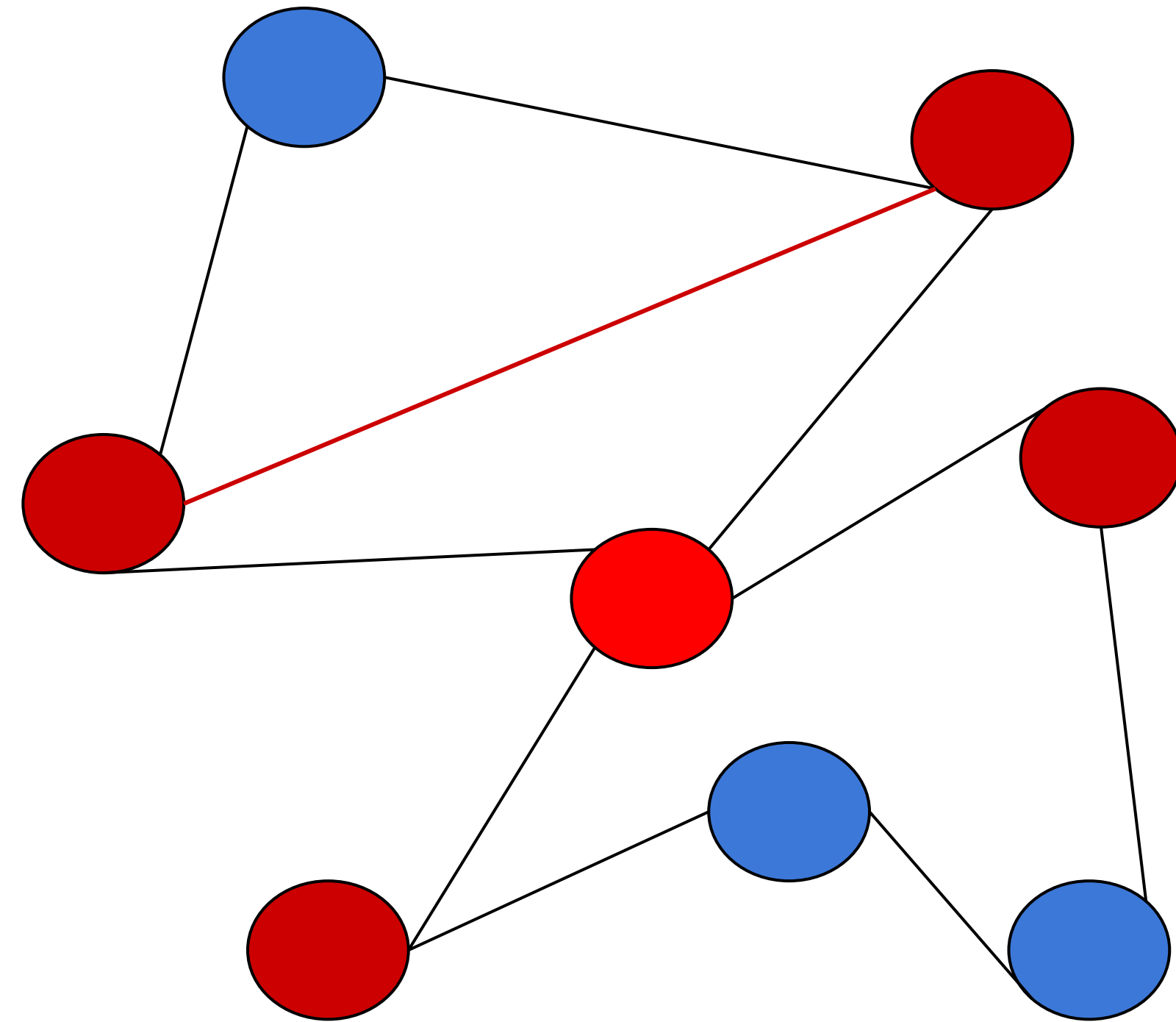


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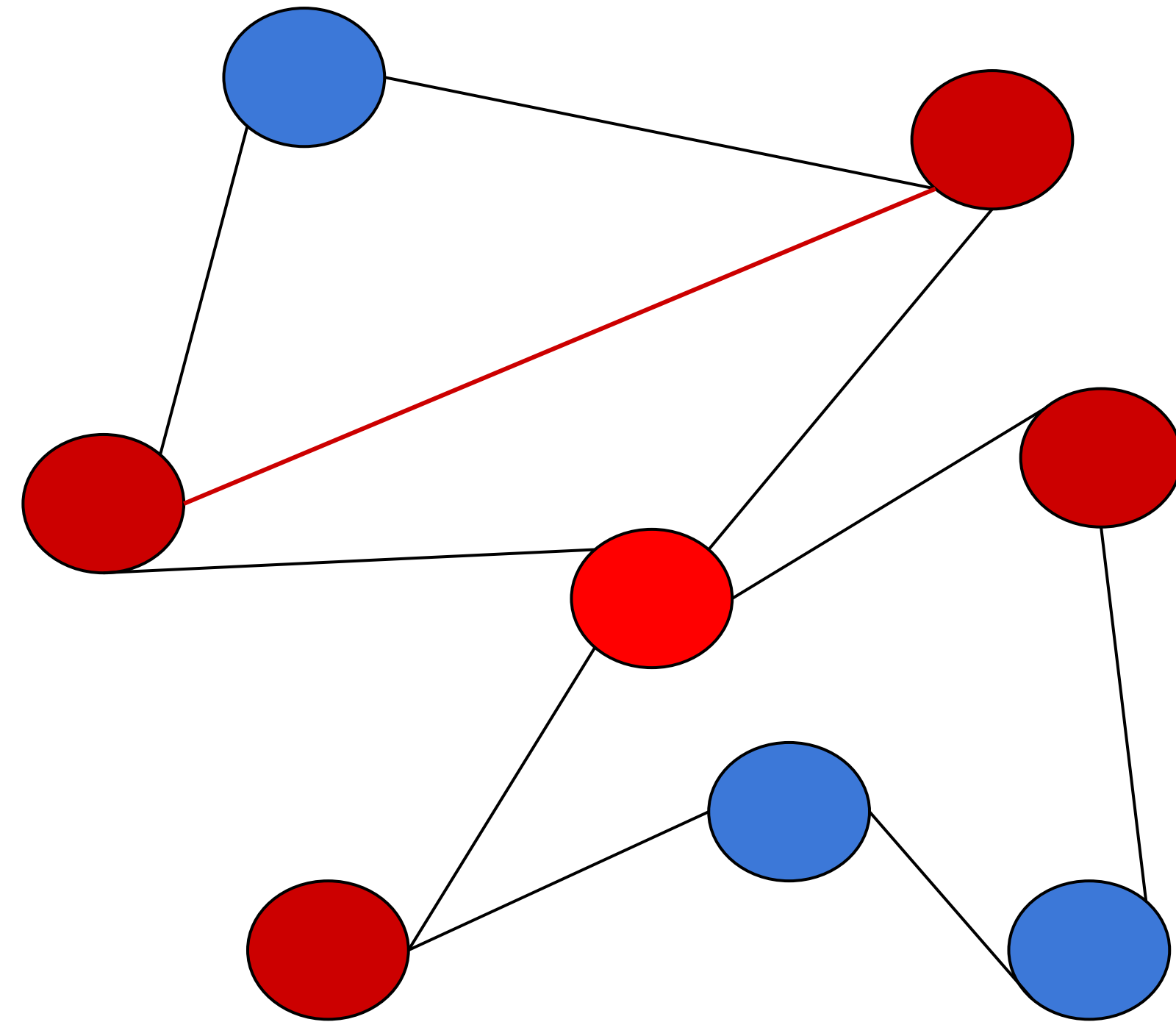


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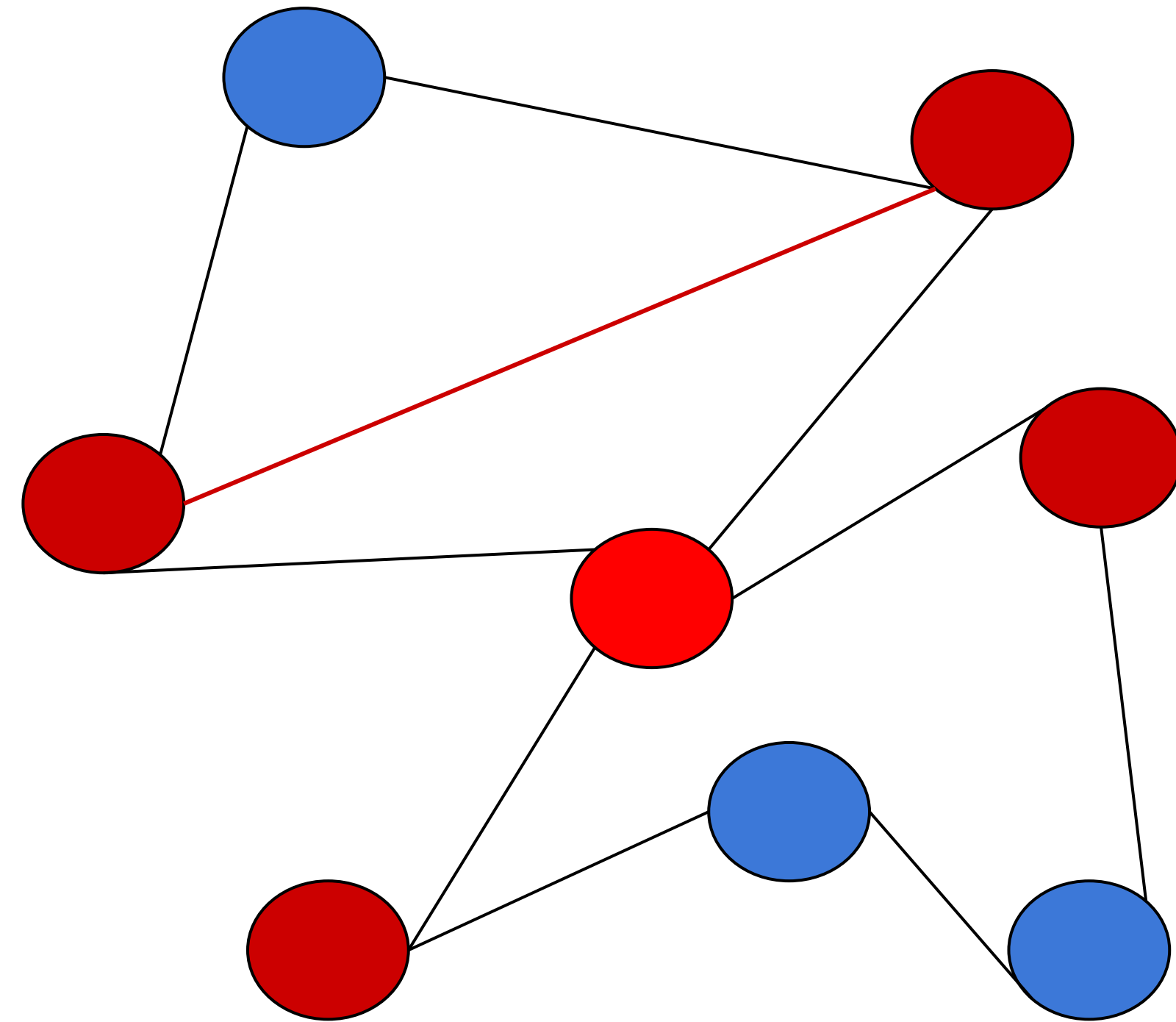
CLUSTERING COEFFICIENT: EXAMPLE

Degree = 4

Links between
neighbours = 1

$$C_i = \frac{2|\{e_{jk}\}|}{k_i(k_i - 1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

$$C_i = \frac{2}{-}$$



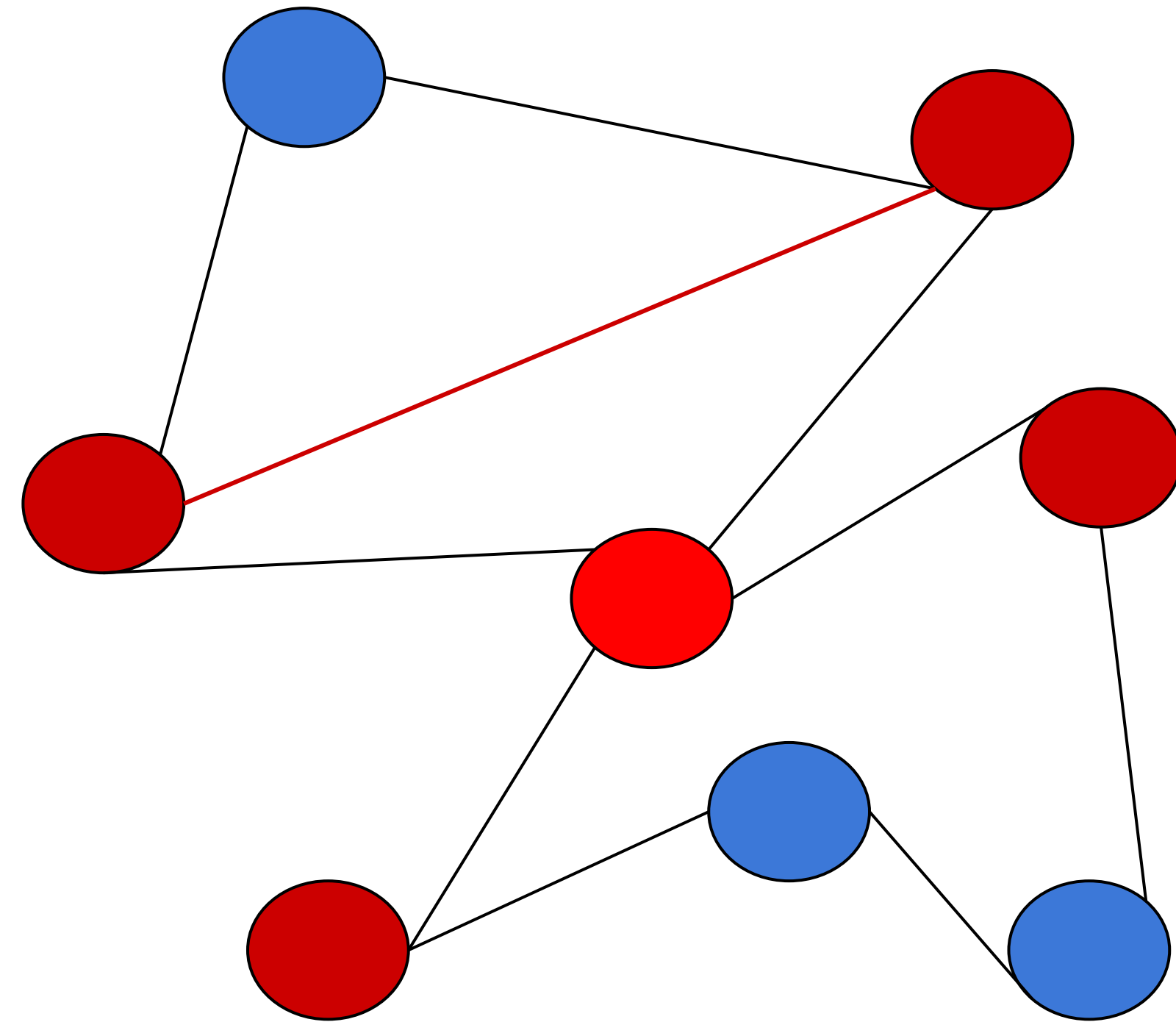
CLUSTERING COEFFICIENT: EXAMPLE

Degree = 4

Links between
neighbours = 1

$$C_i = \frac{2 |\{e_{jk}\}|}{k_i(k_i - 1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

$$C_i = \frac{2 * 1}{4 * 3}$$



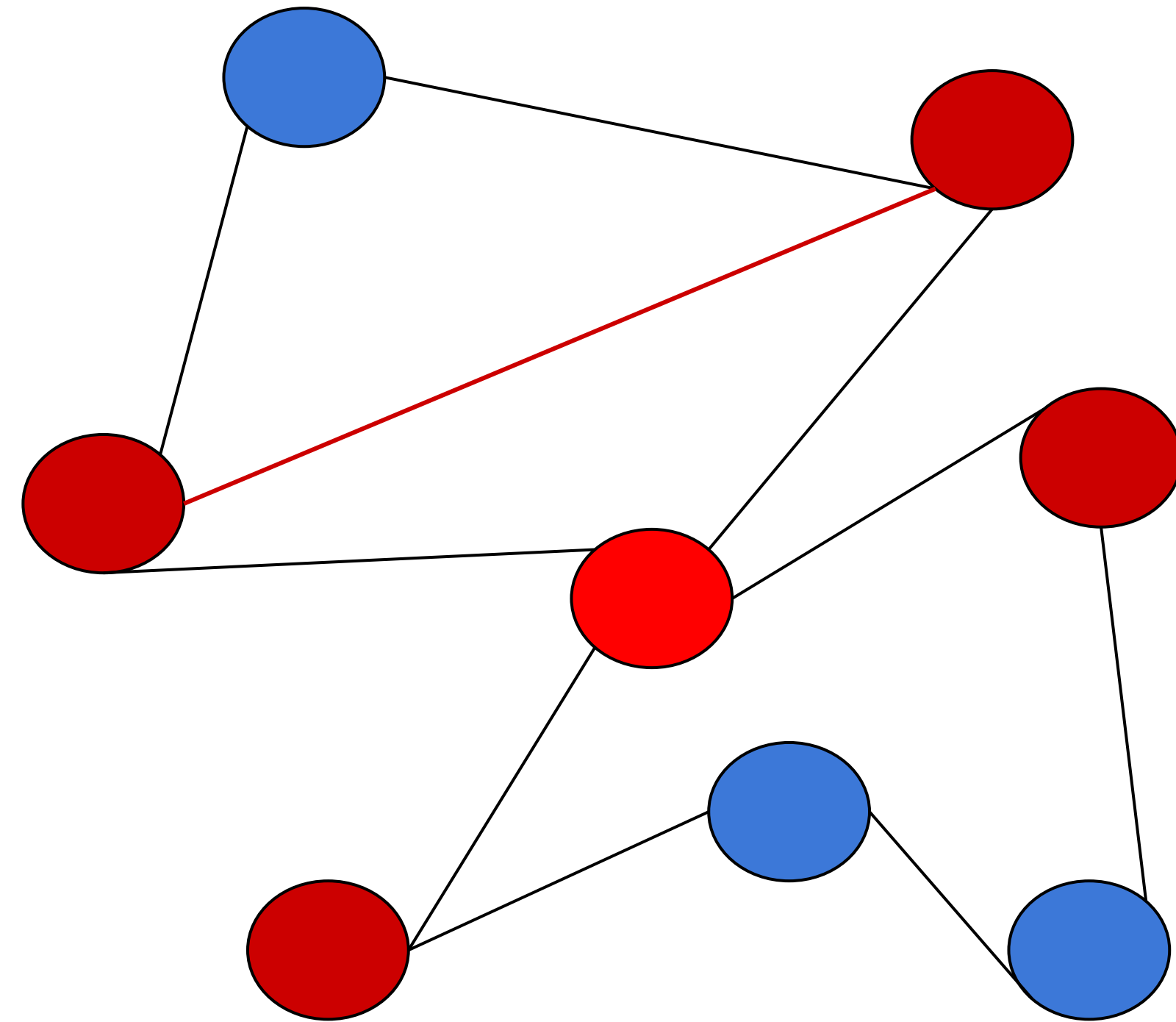
CLUSTERING COEFFICIENT: EXAMPLE

Degree = 4

Links between
neighbours = 1

$$C_i = \frac{2 |\{e_{jk}\}|}{k_i(k_i - 1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

$$C_i = \frac{2 * 1}{4}$$



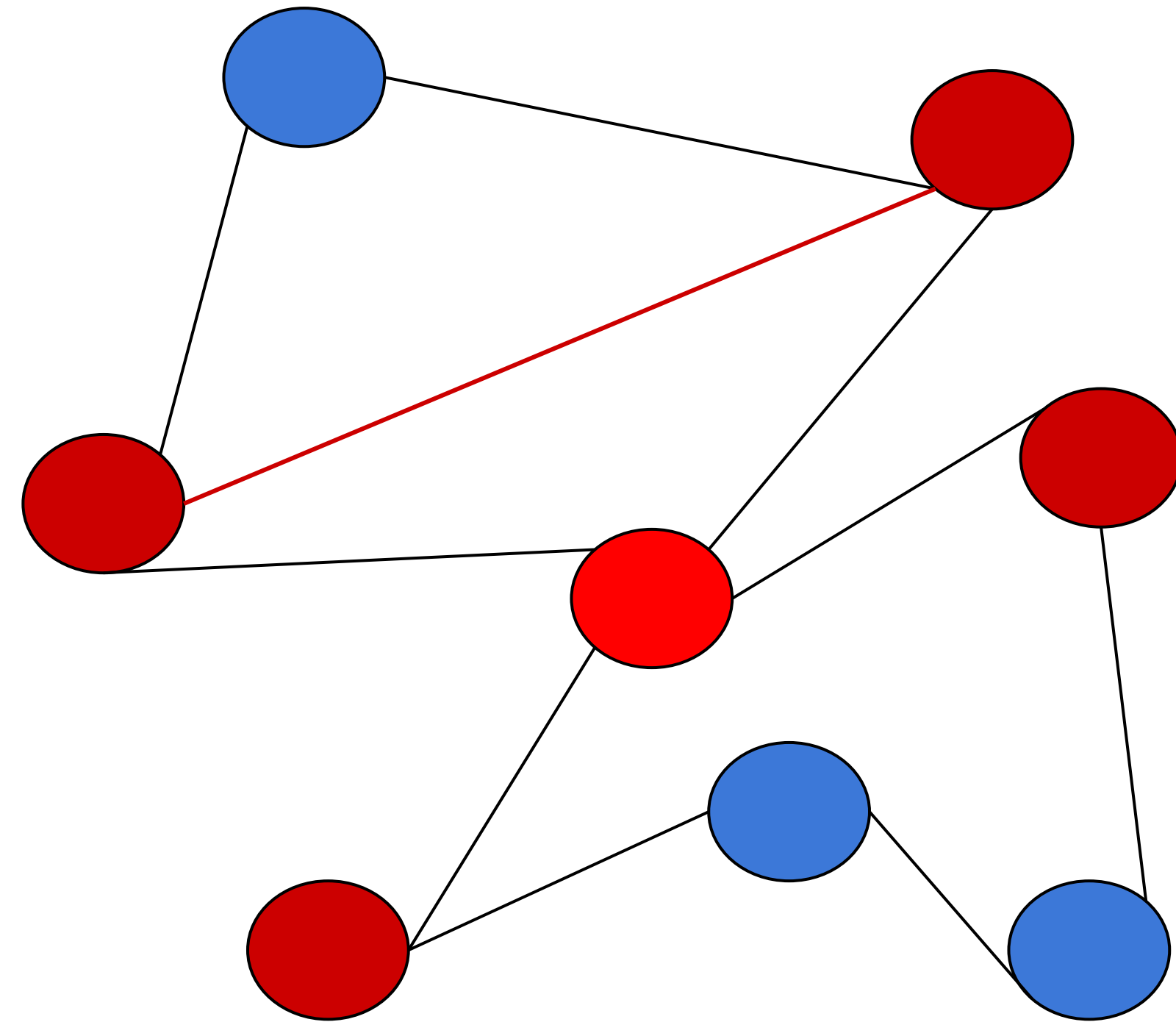
CLUSTERING COEFFICIENT: EXAMPLE

Degree = 4

Links between
neighbours = 1

$$C_i = \frac{2 |\{e_{jk}\}|}{k_i(k_i - 1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

$$C_i = \frac{2 * 1}{4 * 3}$$



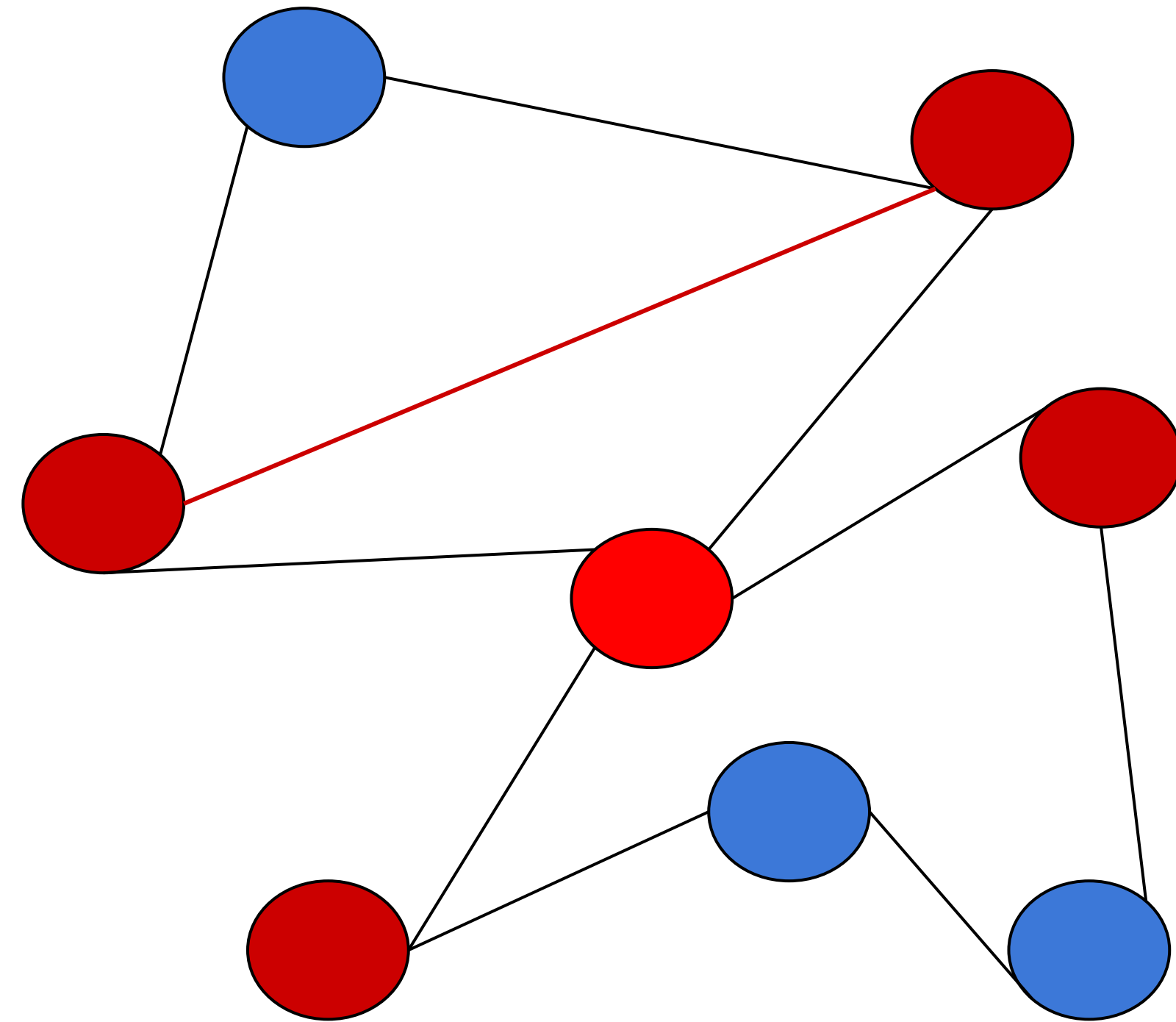
CLUSTERING COEFFICIENT: EXAMPLE

Degree = 4

Links between
neighbours = 1

$$C_i = \frac{2|\{e_{jk}\}|}{k_i(k_i - 1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

$$C_i = \frac{2}{12}$$



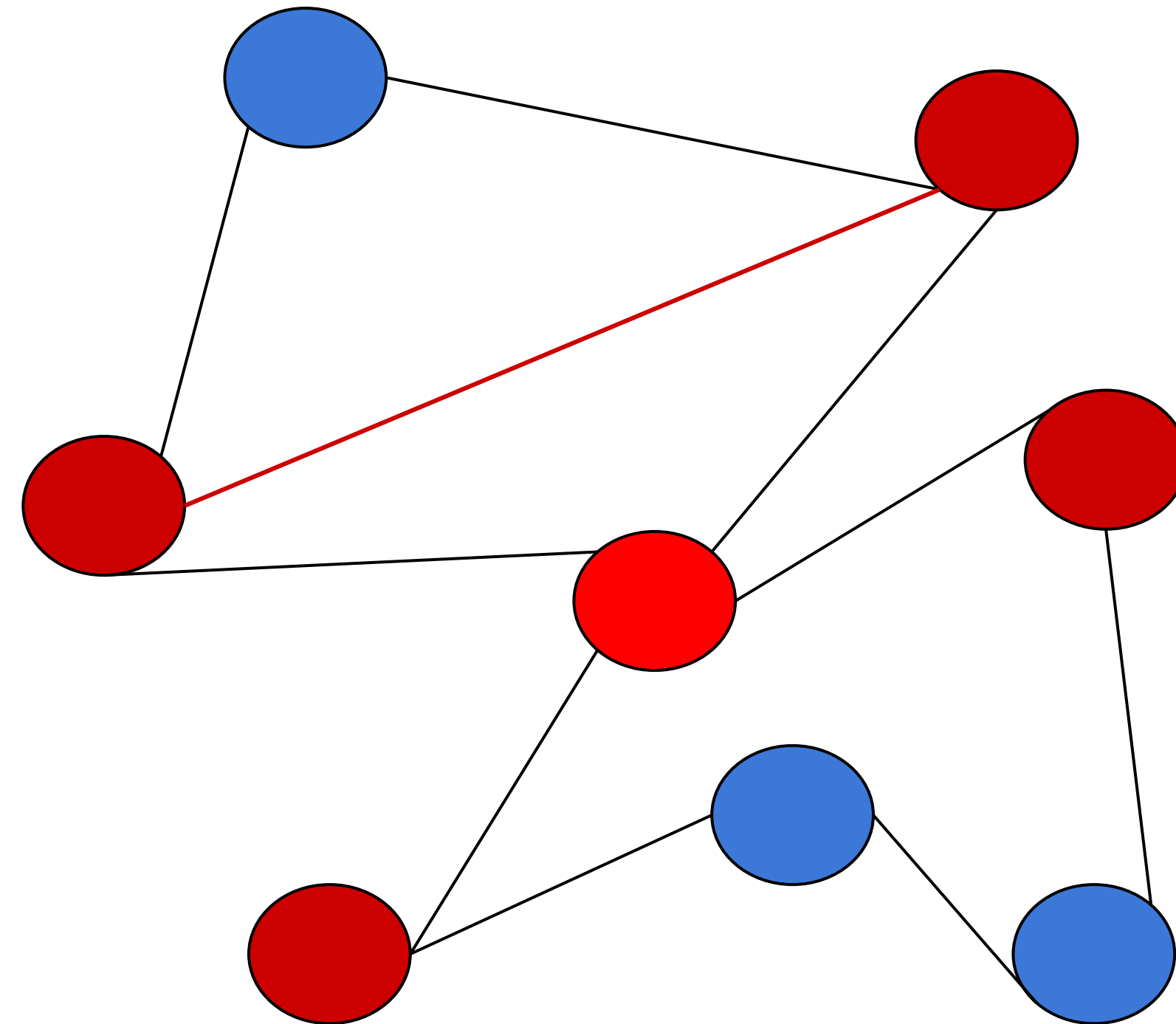
CLUSTERING COEFFICIENT: EXAMPLE

Degree = 4

Links between
neighbours = 1

$$C_i = \frac{2|\{e_{jk}\}|}{k_i(k_i - 1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

$$C_i = \frac{1}{6}$$



CLUSTERING COEFFICIENT: EXAMPLE

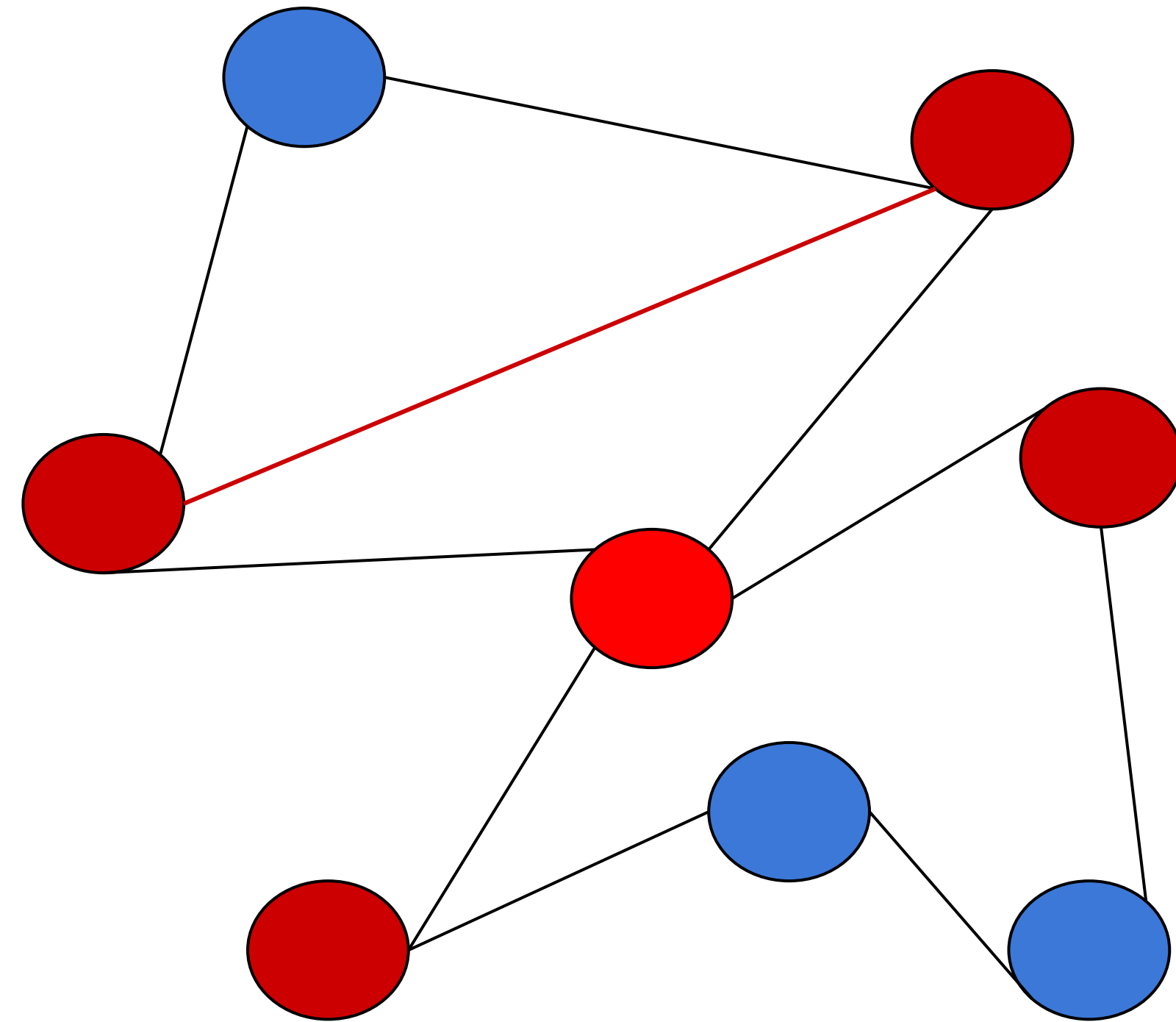
Degree = 4

Links between
neighbours = 1

$$C_i = \frac{2|\{e_{jk}\}|}{k_i(k_i - 1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

$$C_i = \frac{1}{6}$$

Fraction of possible interconnections
between my neighbour!



Clustering Coefficient

Proportion of possible interconnections between neighbours

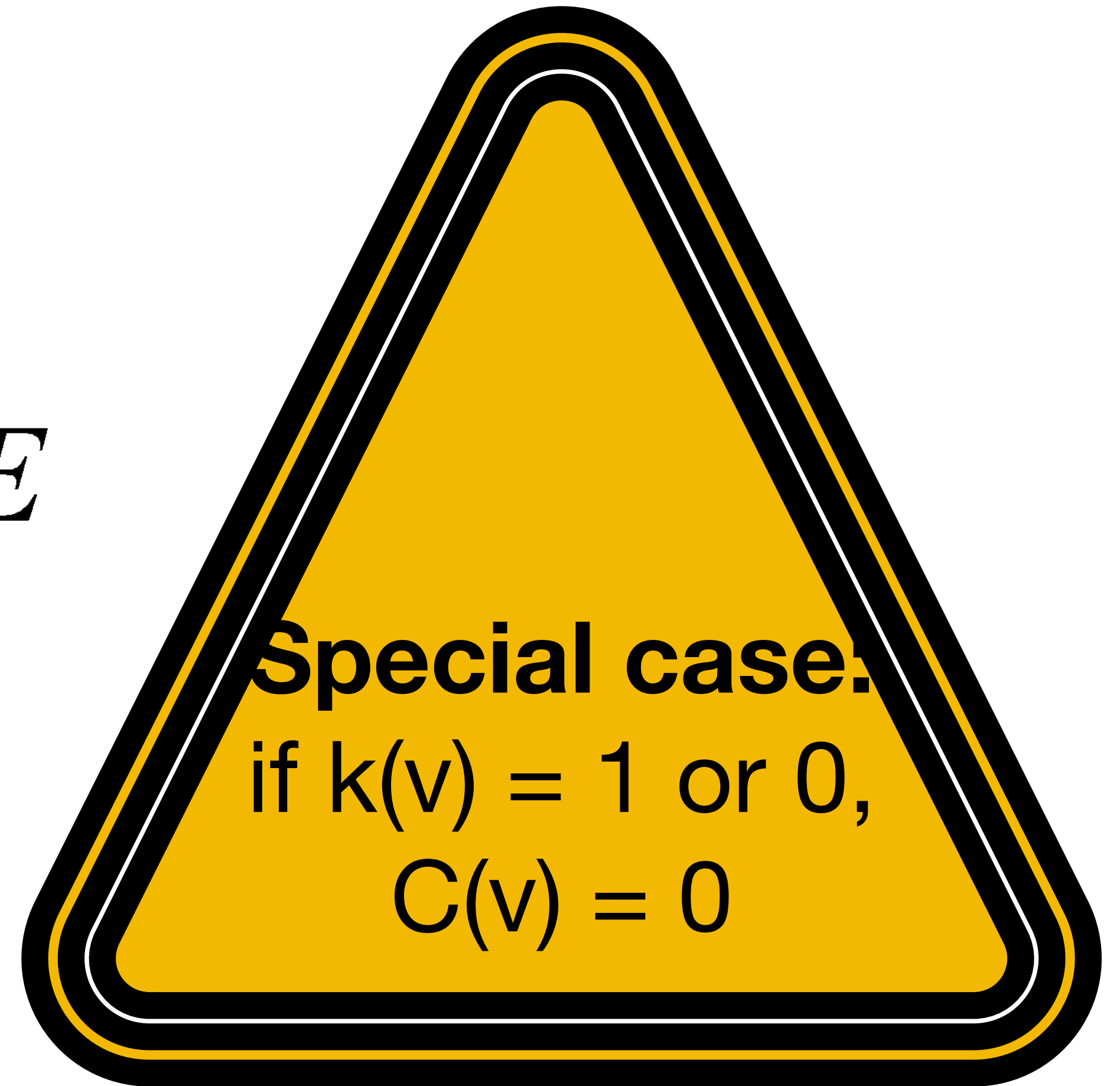
Node clustering coefficient C_i

$$C_i = \frac{2 |\{e_{jk}\}|}{k_i(k_i - 1)} : v_j, v_k \in N_i, e_{j,k} \in E$$

Special case:

if $k(v) = 1$ or 0 ,

$$C(v) = 0$$



Clustering Coefficient

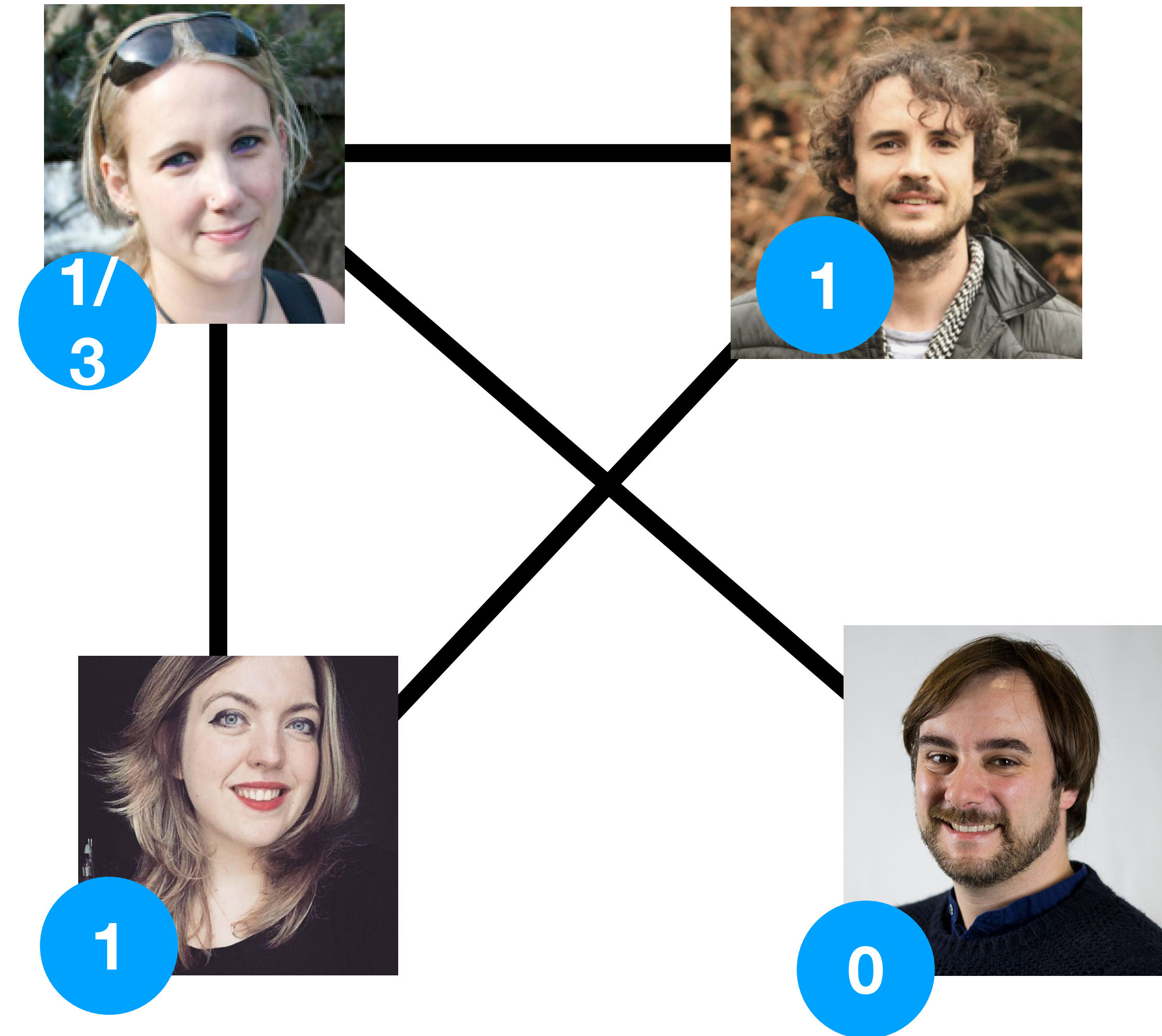
What is Laurissa's clustering coefficient?

Numerator: Only one pair of Laurissa's neighbours are connected (Naomi, Teo), so 2*1

Denominator: Laurissa's degree is 3, so $3*2 = \underline{6}$

So $C(\text{Laurissa}) = \underline{2/6} = \underline{1/3}$

Average clustering $C(G) = 7/12$



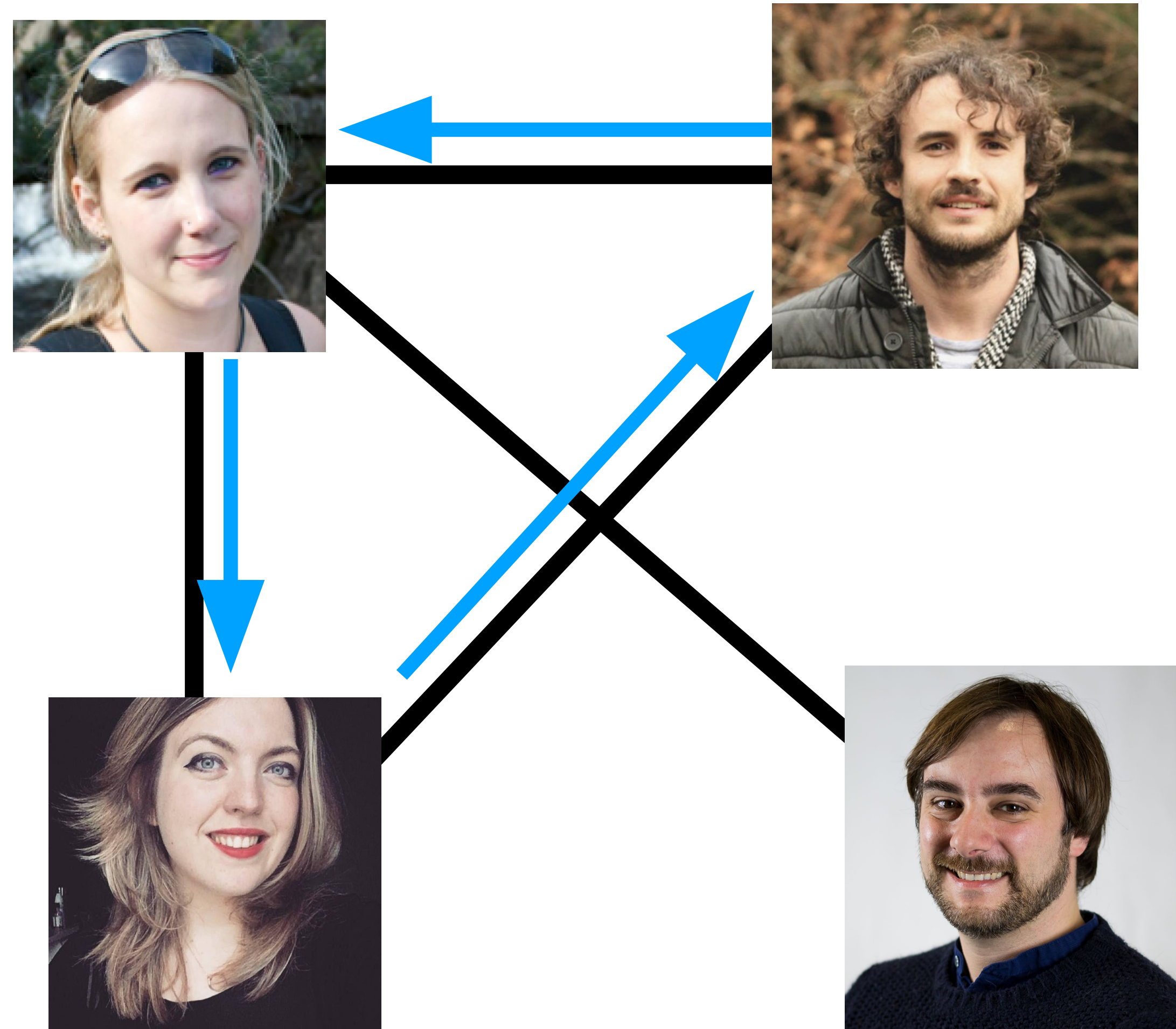
Paths and Cycles

A **path** is a sequence of nodes where each consecutive pair of nodes is linked by an edge

Teo, Laurissa, Naomi

A **cycle** is a path where the start node is also the end node

Teo, Laurissa, Naomi, Teo



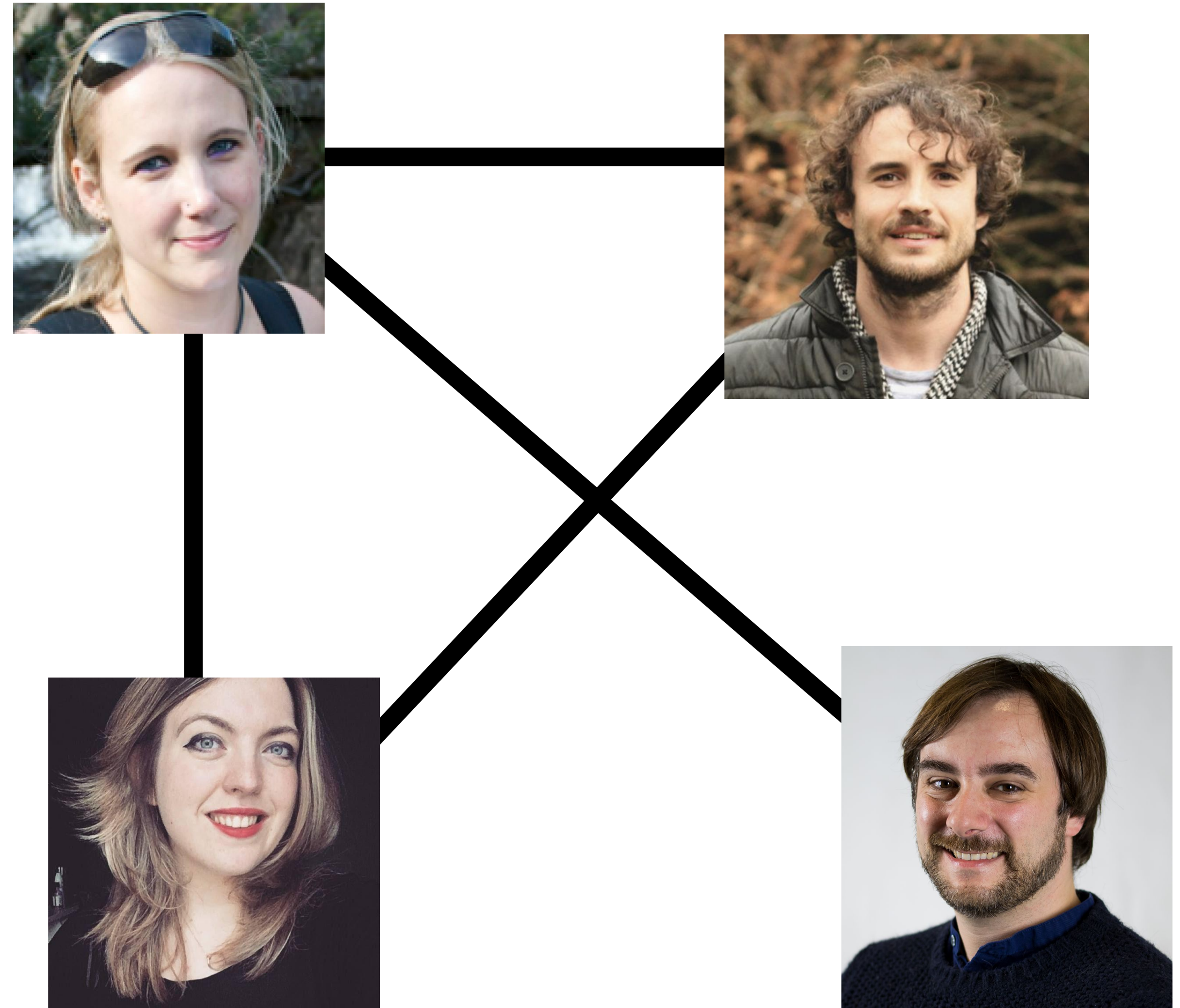
Paths and Cycles

The **distance** $d(u,v)$ between two nodes is the length of the shortest path connecting them

$$d(\text{Teo}, \text{Mathieu}) = 2$$

The **diameter** of a graph is the largest distance between a pair of nodes in the graph

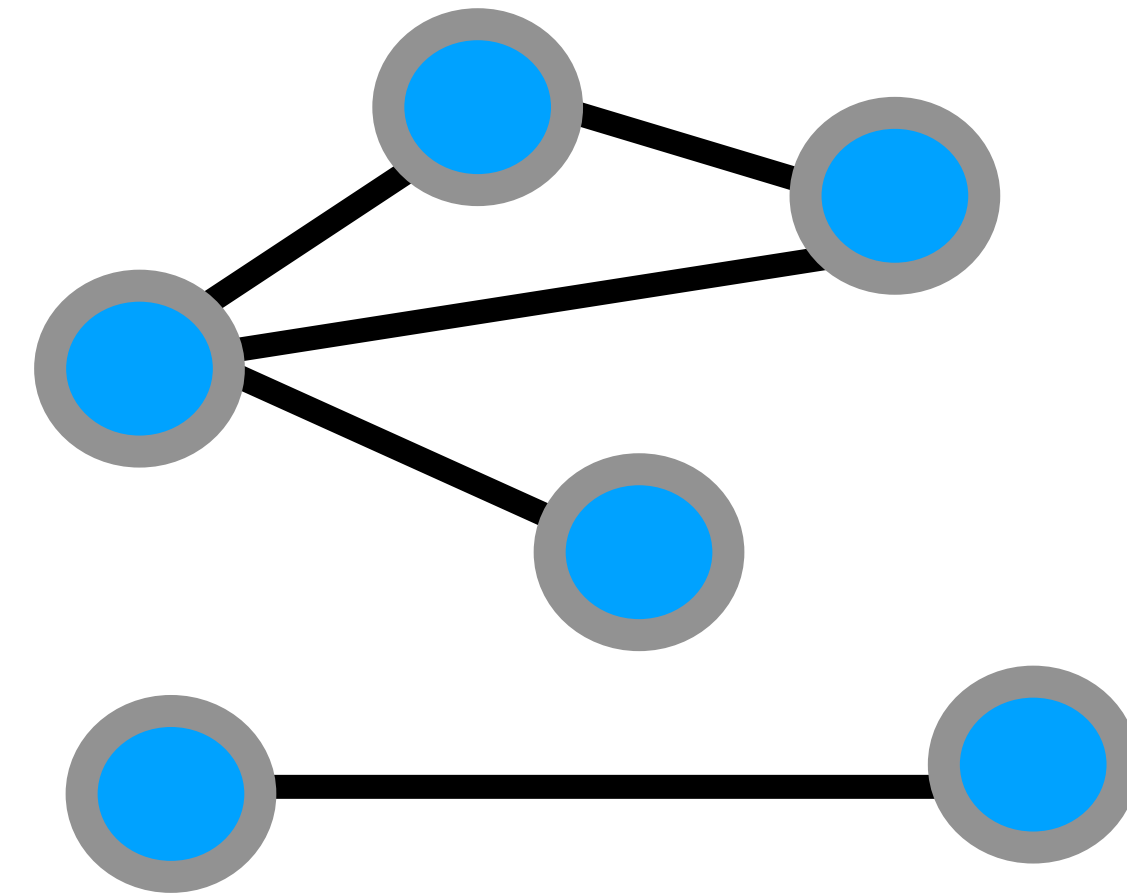
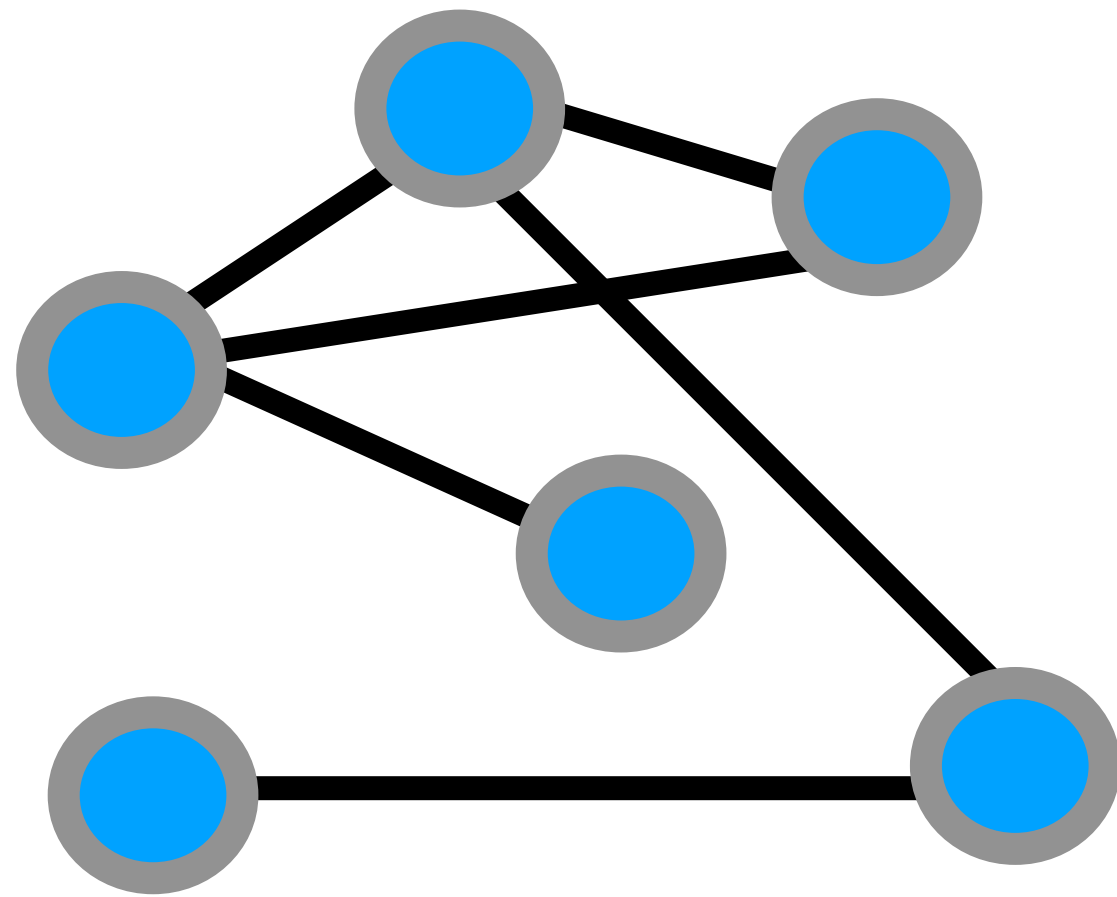
$$d(G) = 2$$



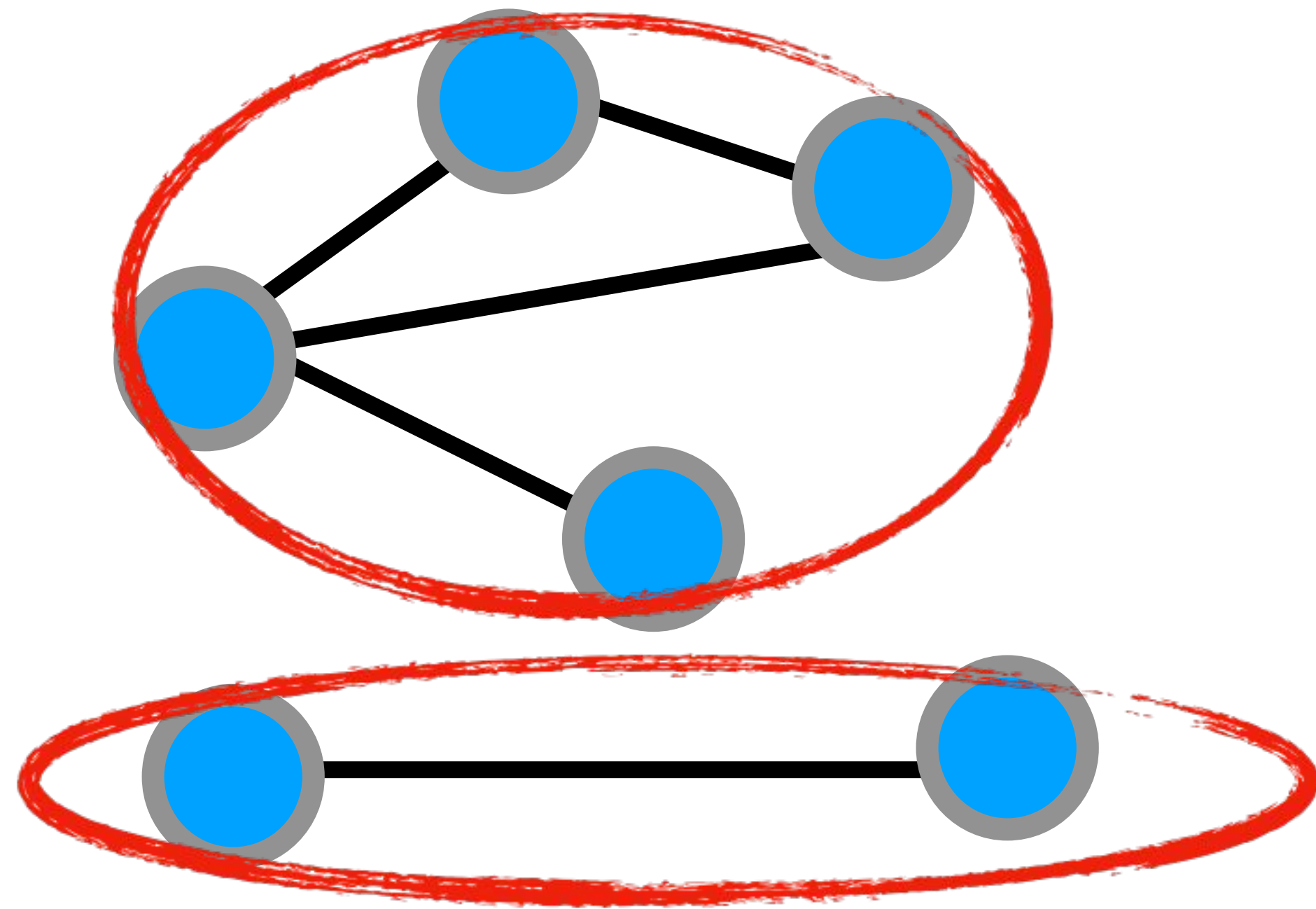
Often more meaningful to look at average path length

Connected Graph

A graph is **connected** if there is a path between every pair of vertices



Connected Components



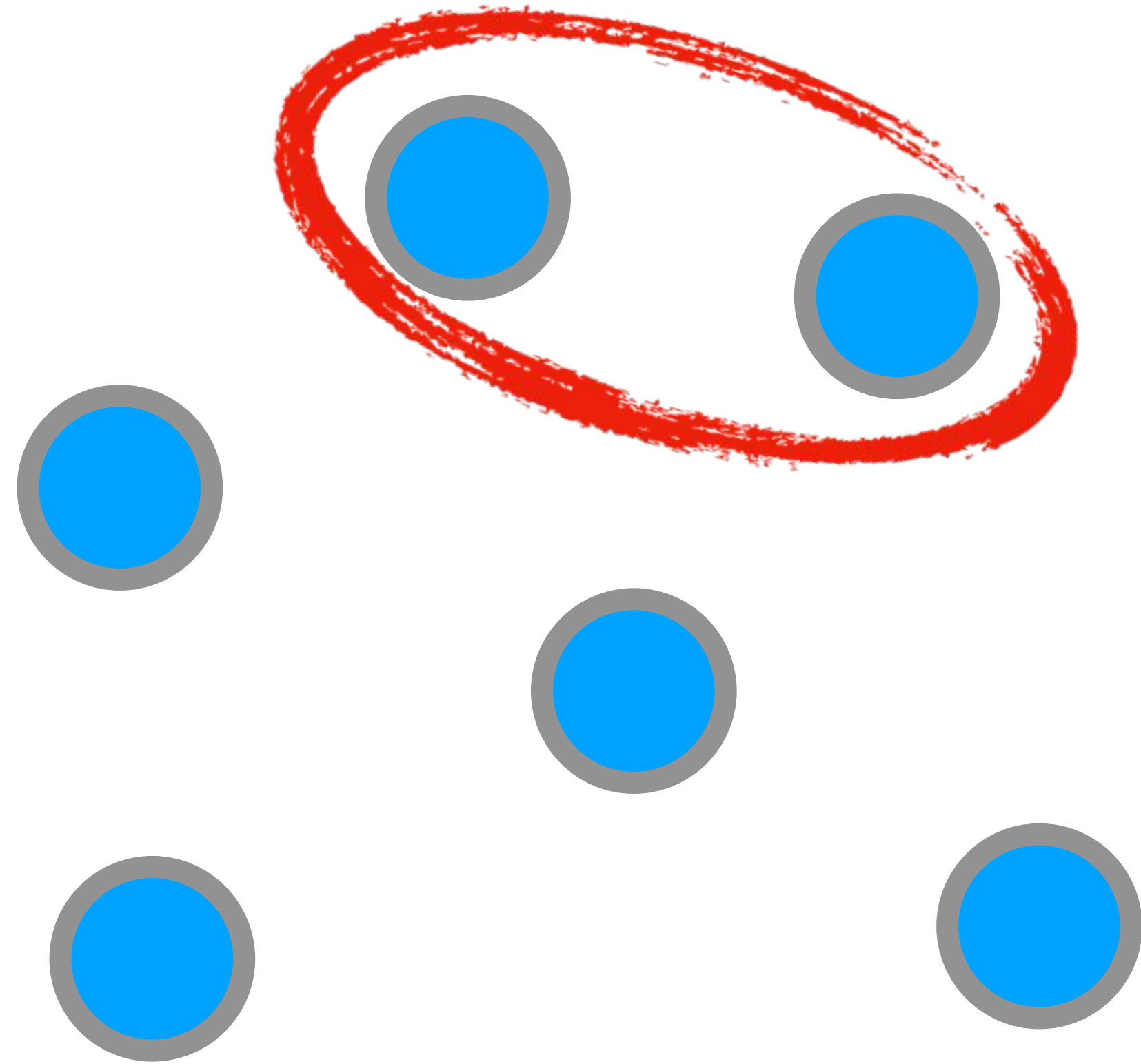
- A **connected component** of a graph G is a subgraph in which:
1. Any two vertices are **connected** by paths
 2. There are **no edges** to other vertices in G .

Questions?

Erdos-Renyi Random Graph Model

- Want to model real networks, have some baseline to compare
- “Is the value of this network metric unusual?”
Want a null model
- What is the very simplest model formulation we can look at?

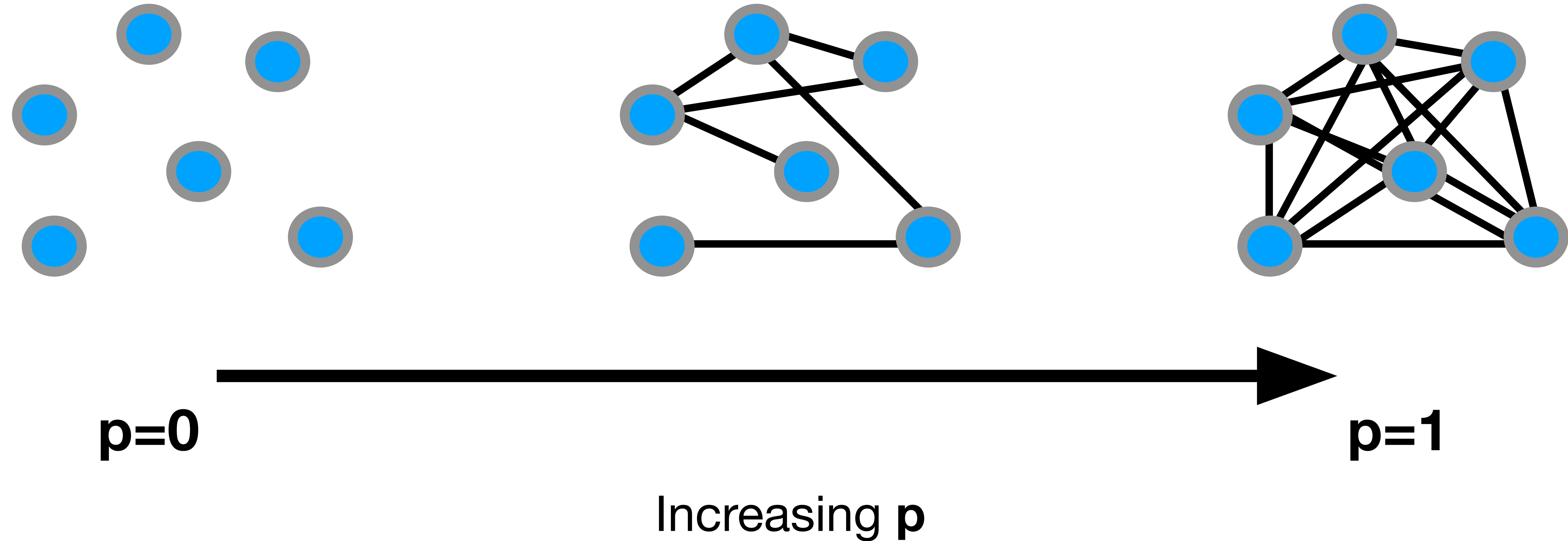
Erdos-Renyi $G(n,p)$ Model



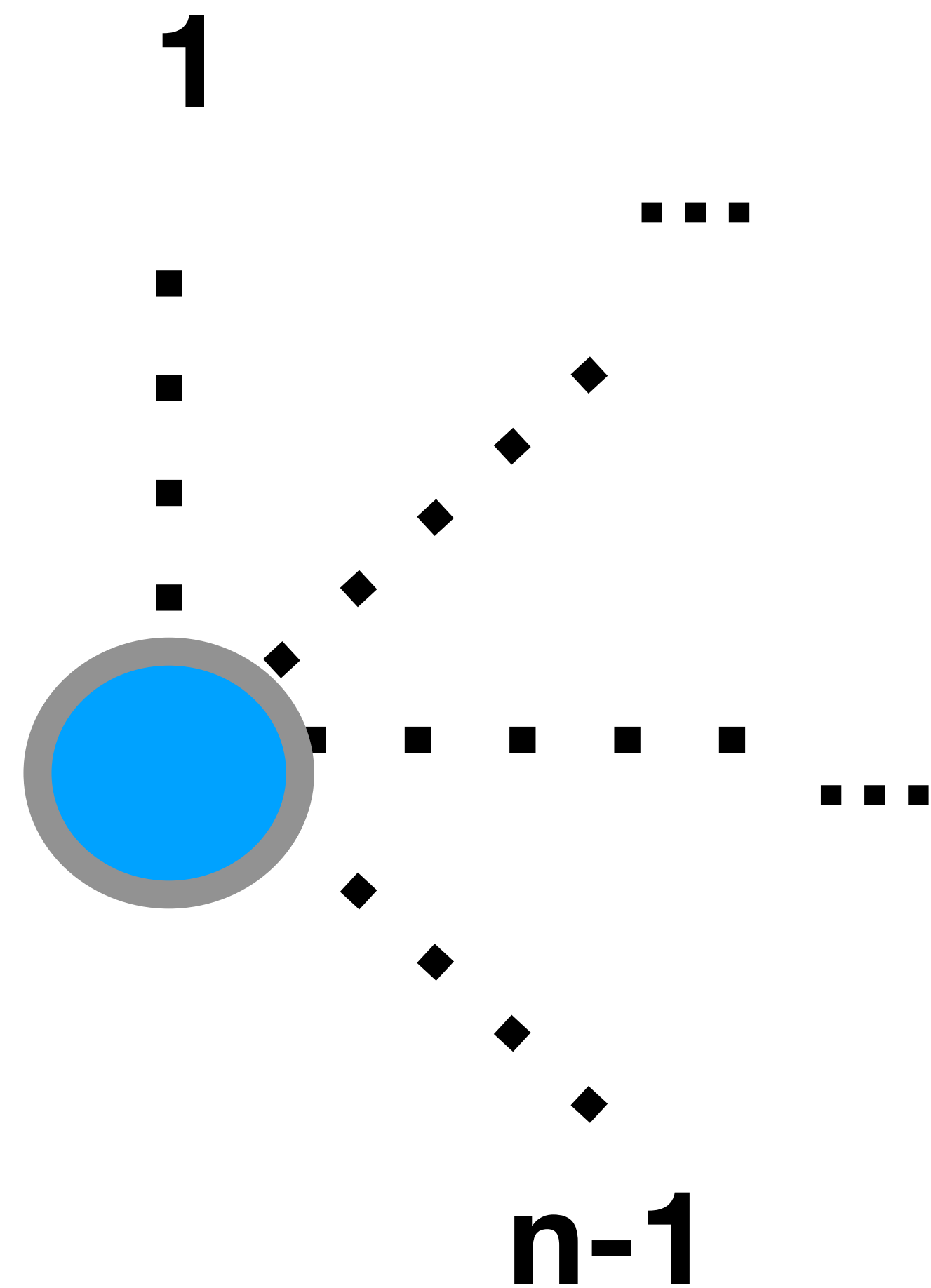
1. Start with an empty graph of n nodes
2. Acquire a biased coin with head probability p
3. For each pair of nodes, do a coin toss. If heads, draw an edge between them. If not, move on.



Erdos-Renyi $G(n,p)$ model



Average degree of ER networks



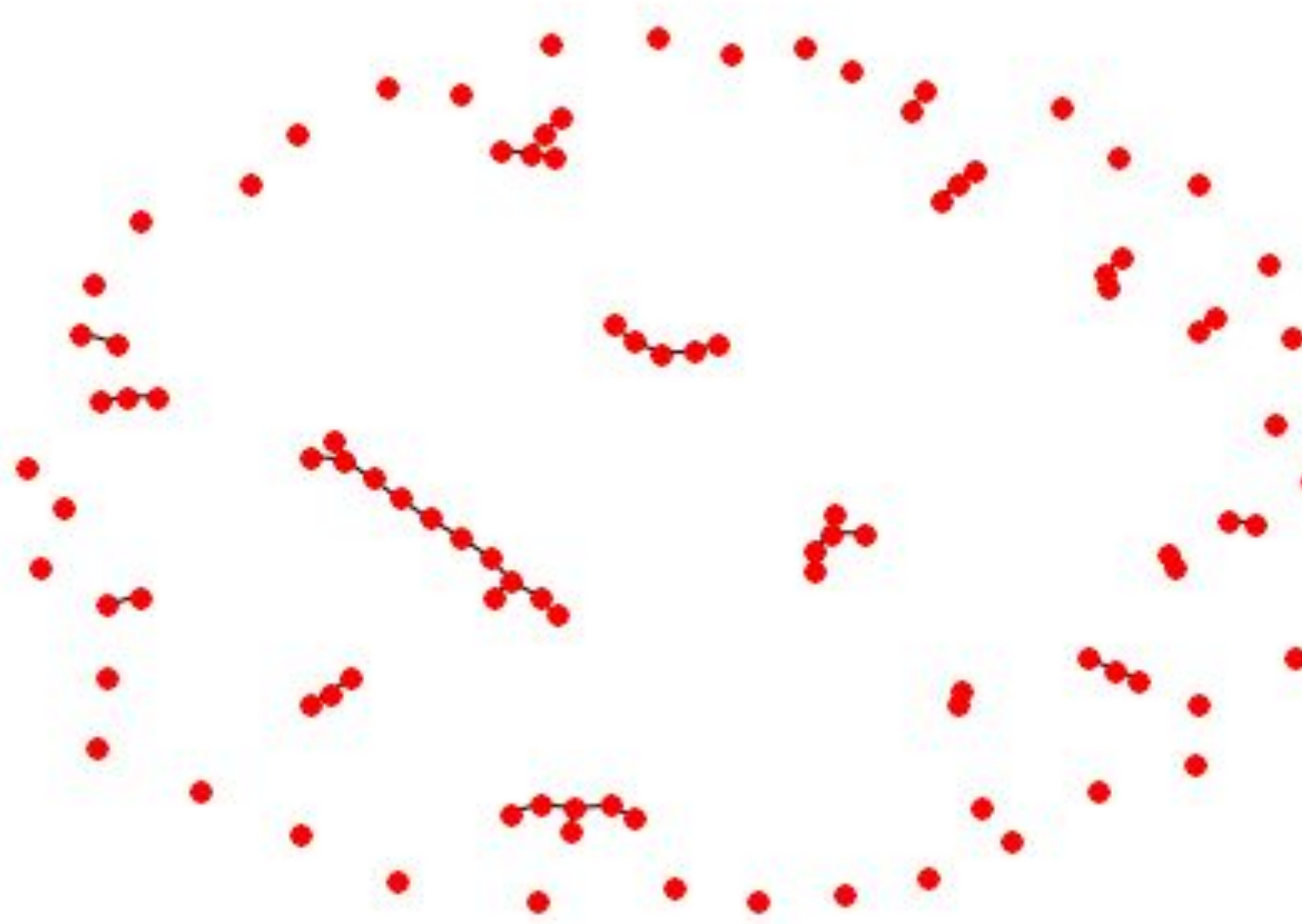
For each node, there are $n-1$ others in the graph it could connect to.

Each of those connections can happen with probability p

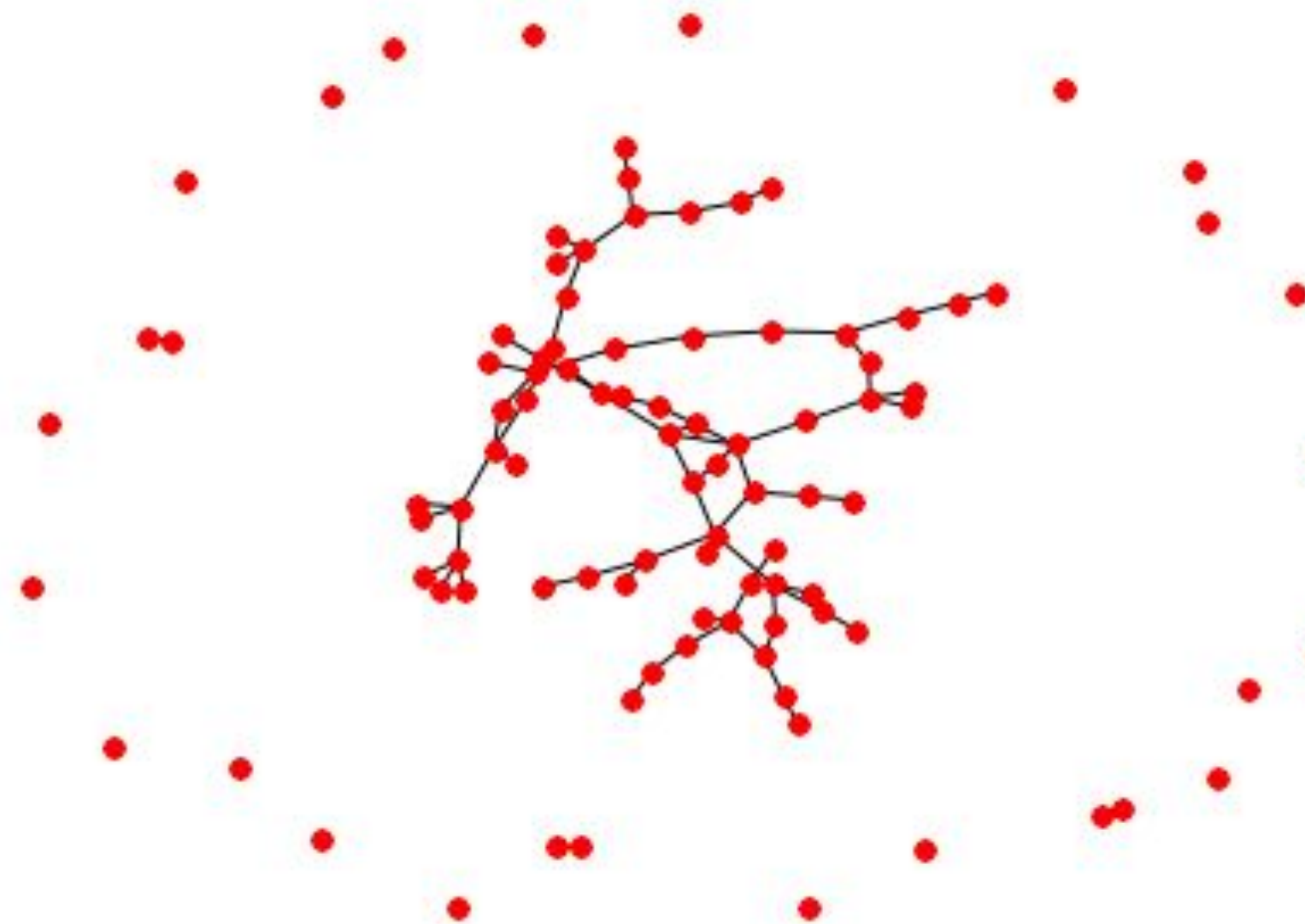
(If you were a fan of Probability and Matrices, this is a binomial with $n-1$ trials and success probability p)

So average degree is $(n-1)p$, or approximately np

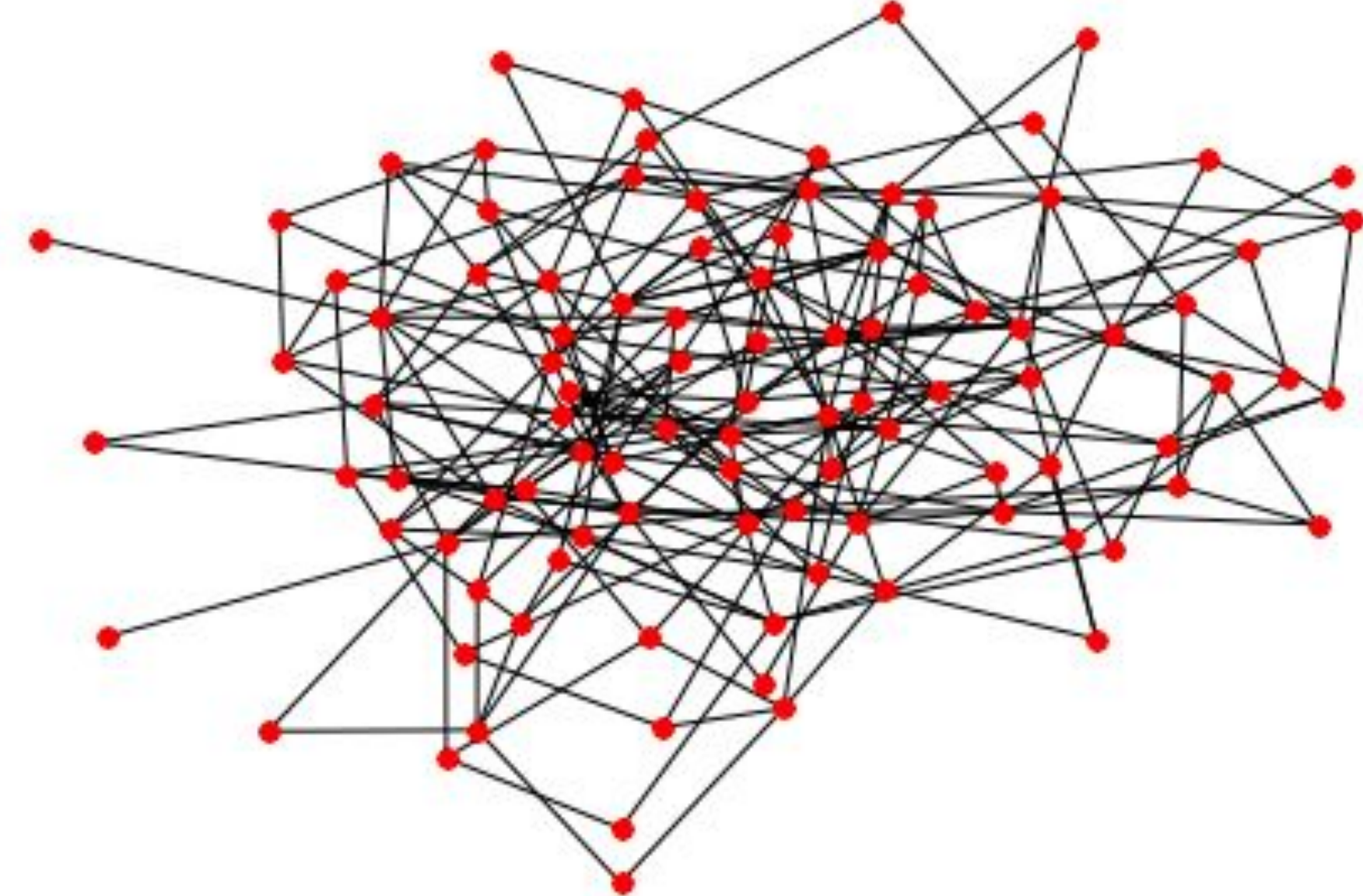
What do ER graphs look like?



Very disconnected graph,
only tiny connected
components

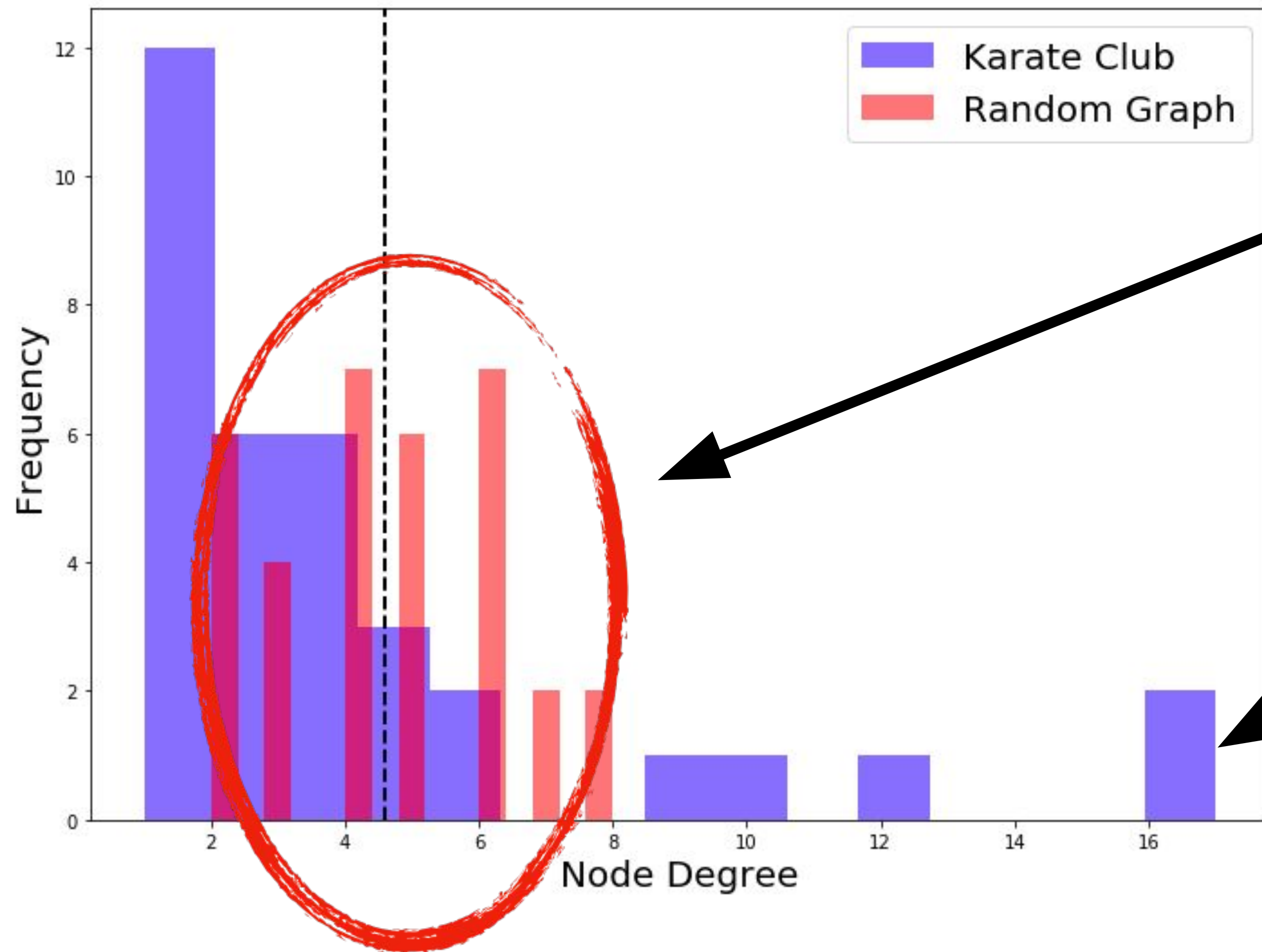


A giant component
appears, no/very few
cycles



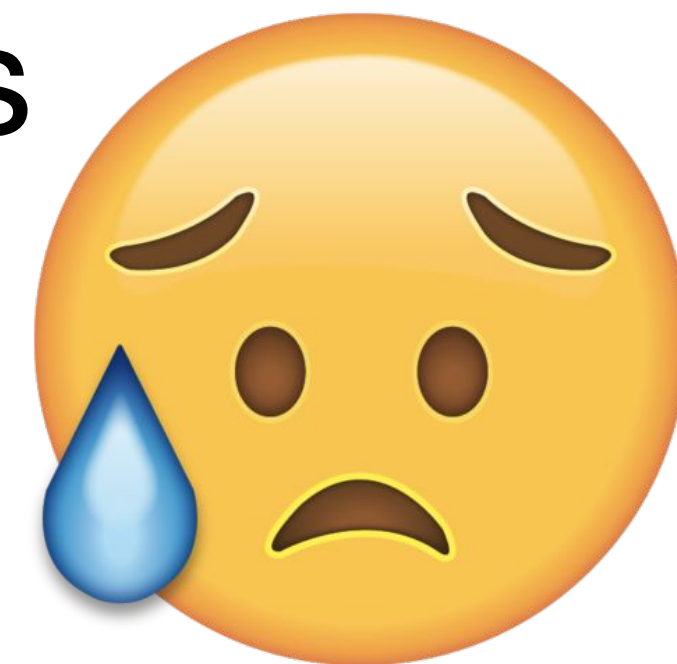
Whole graph is connected,
some cycles present

Random Graphs vs Real Networks

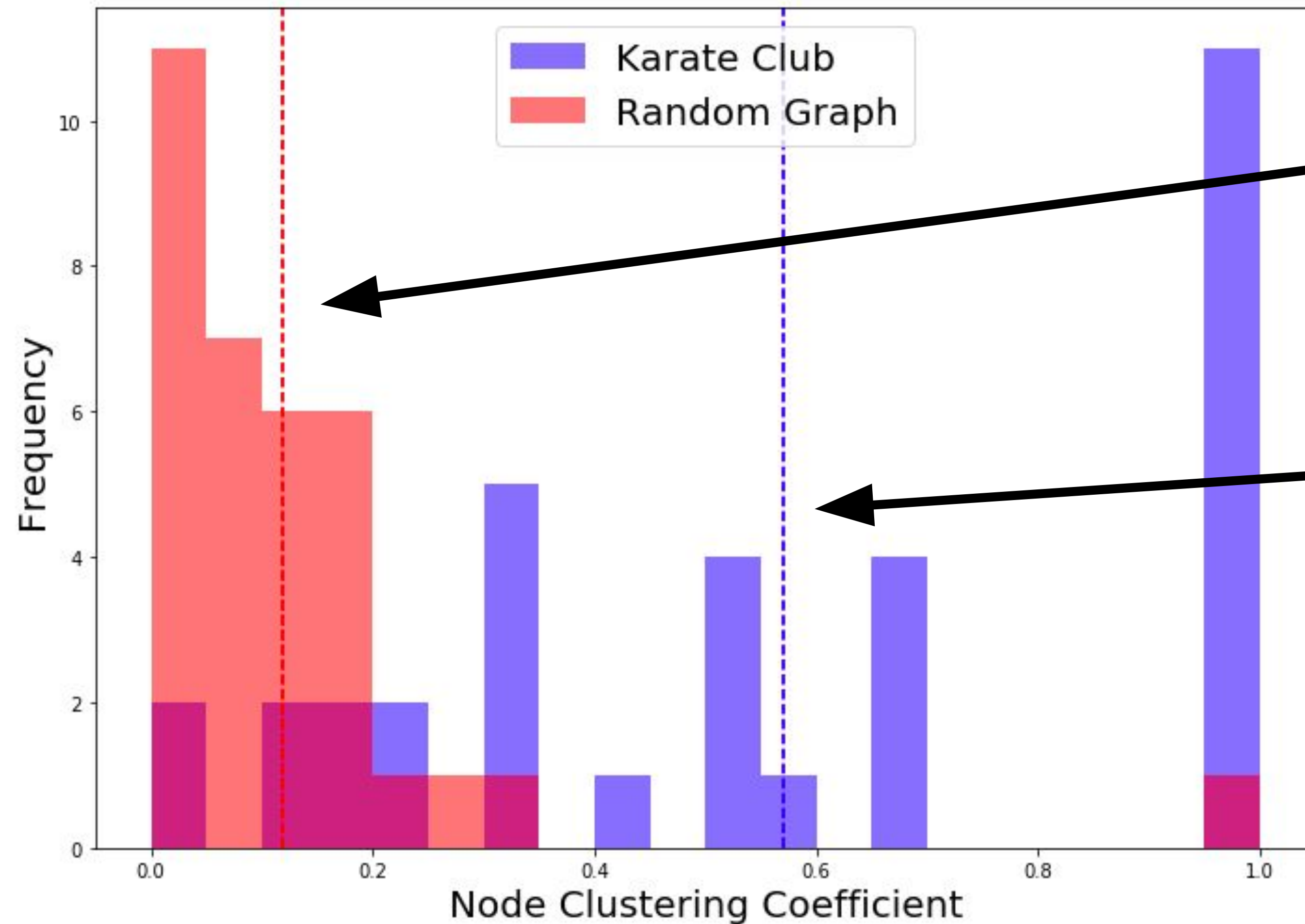


Random: node degrees all clustered round the average value

Real: small number of high degree nodes, large number of low degree nodes



Random Graphs vs Real Networks

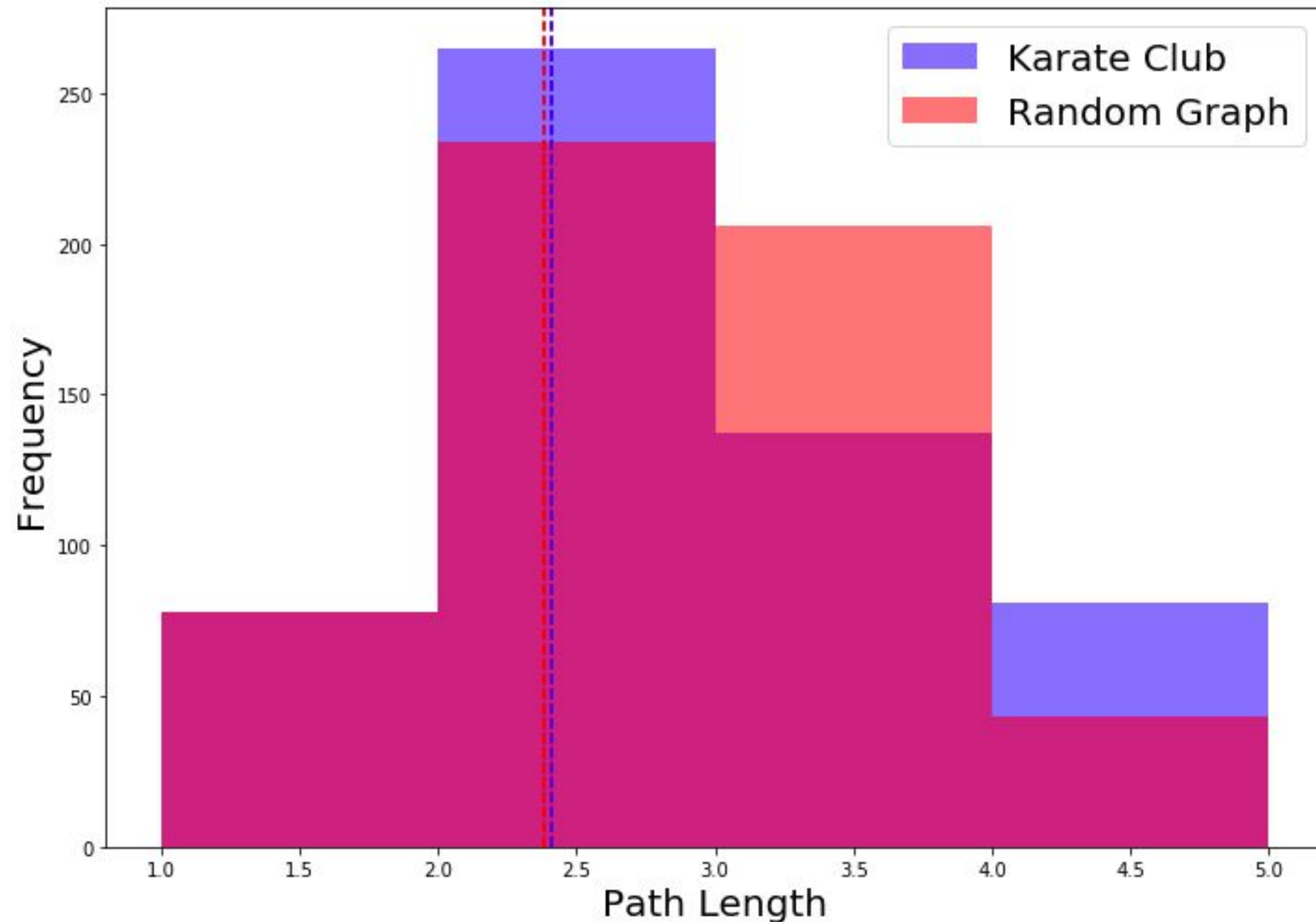


Random: very low average clustering coefficient

Real: much higher average clustering coefficient, with some nodes having very high values



Random Graphs vs Real Networks



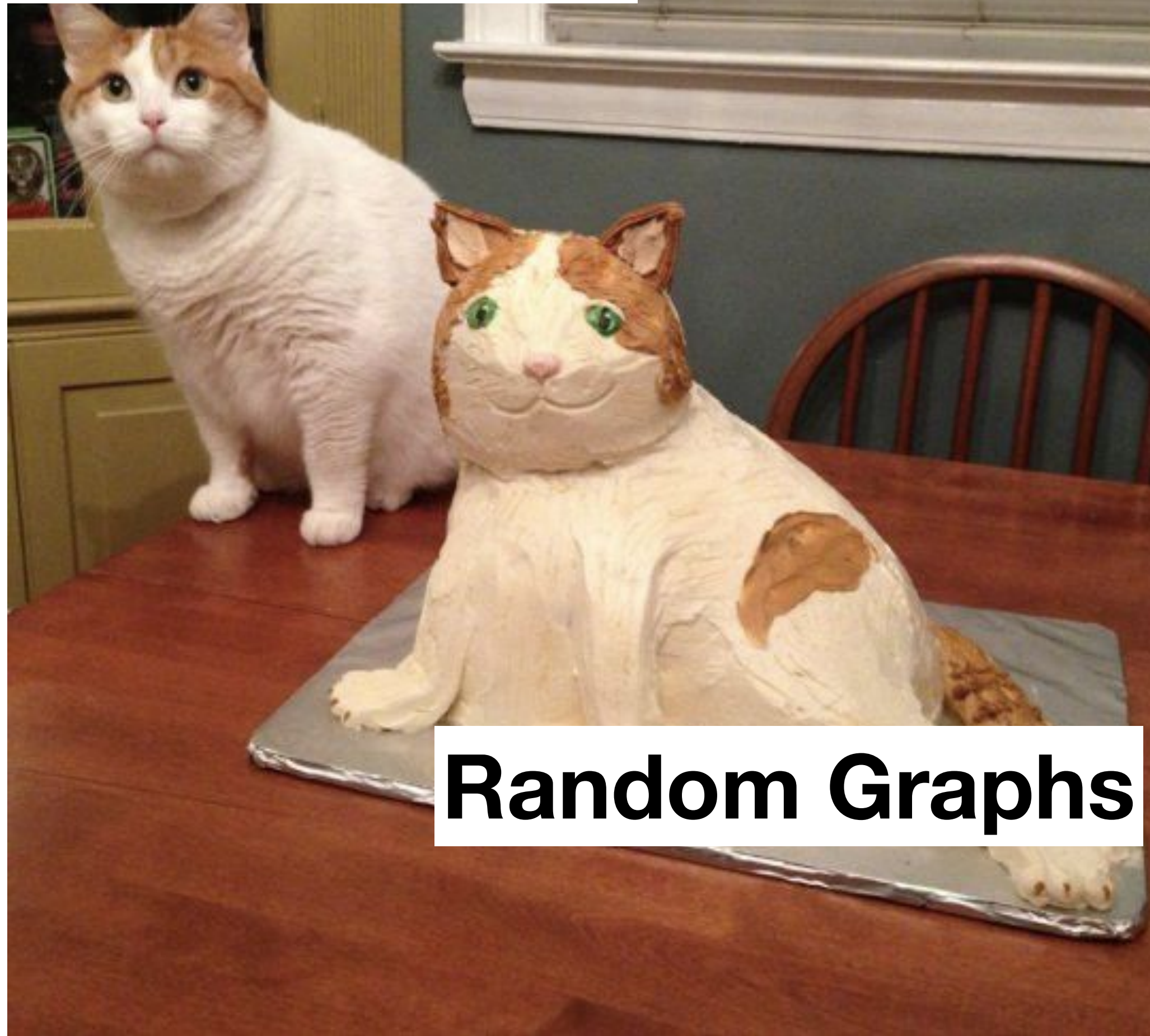
Fairly spot on with **almost the same** average path length for each!



Summary: Random Graphs vs Real Networks

	Real Social Networks	Random Graphs	?
Degree Distribution	Heavy Tailed (most nodes have low degree, small few with high degree)	Light tailed (all nodes have close to the average degree)	?
Clustering Coefficient	High	Low	?
Path Lengths	Low	Low	?
?	?	?	?

Real Networks



Random Graphs

**Thank you for
listening! What are
your questions?**