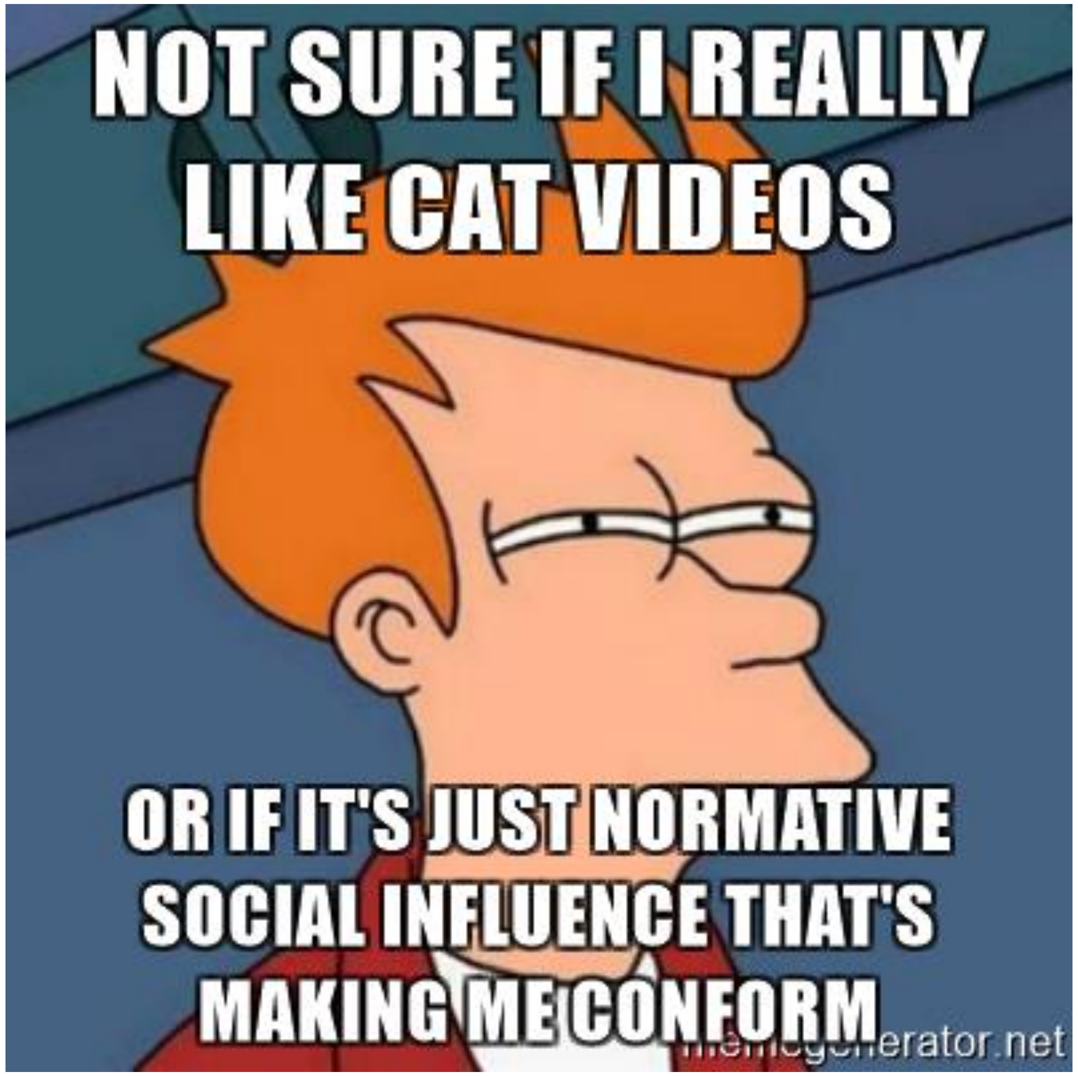
MAS and Social Influence

MARIJA SLAVKOVIK & TRULS PEDERSEN

AAMAS-2018 TUTORIAL

Why social networks & influence



Overview

- Social networks models and measures
- Symptoms of social influence: diffusion and convergence
- Macro level effects of micro level actions: cascades, fake majorities and pluralistic ignorance

Class and Committees in a Norwegian Island Parish

J. A. Barnes

First Published February 1, 1954 | Other

Article information

CLASS AND COMMITTEES IN A NORWEGIAN ISLAND PARISH[1]

J. A. BARNES

I

Representing and measuring networks

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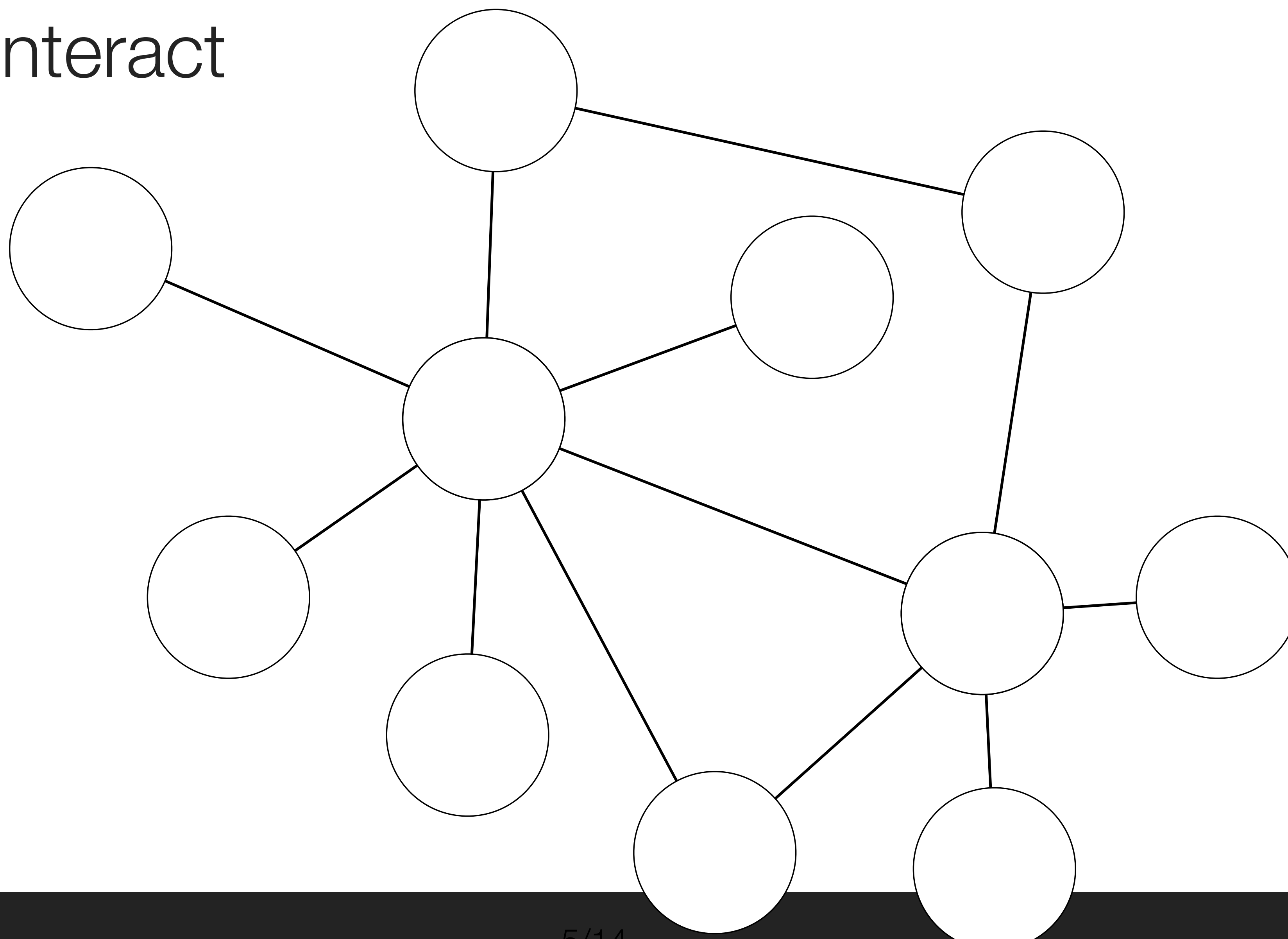

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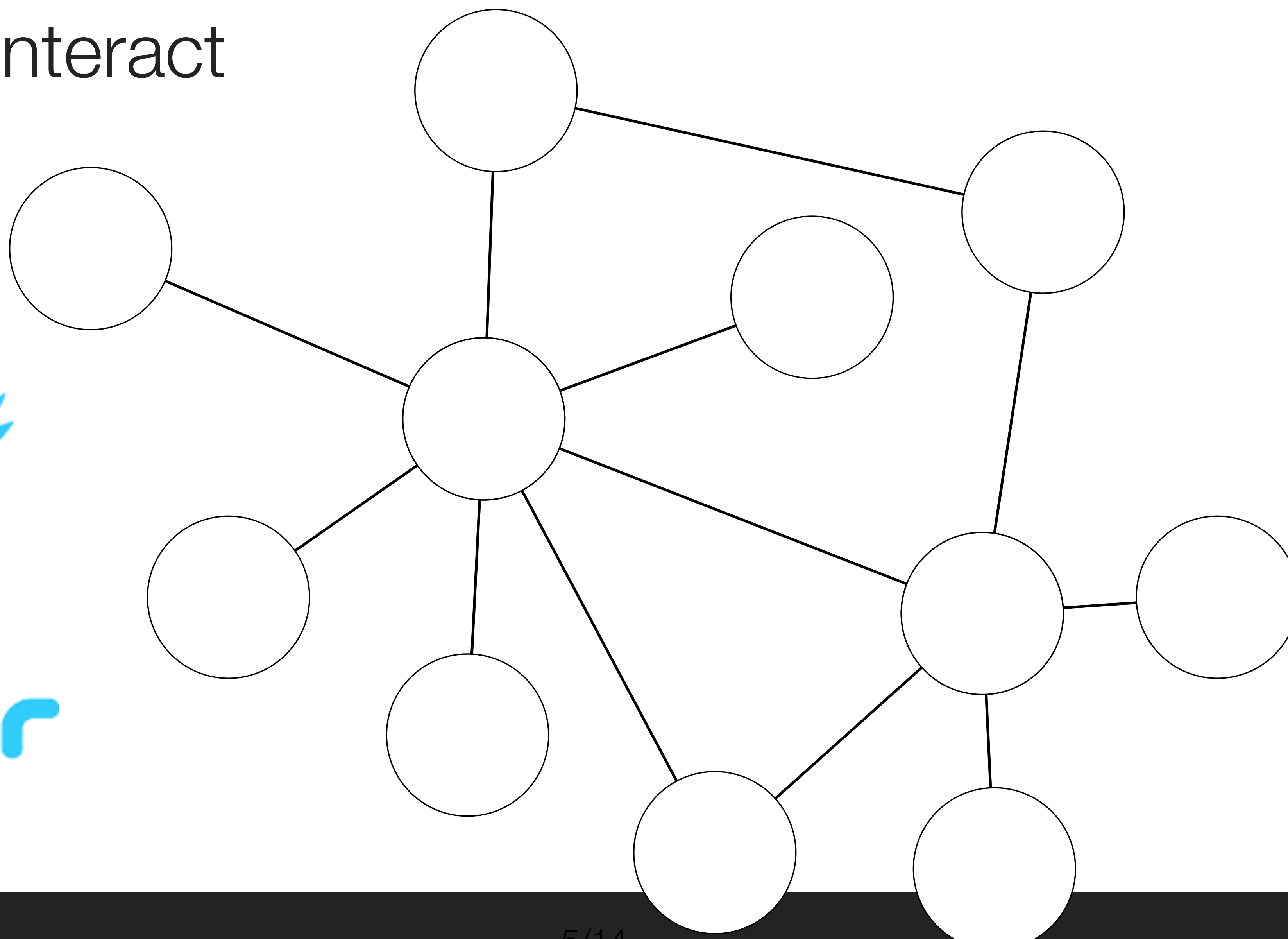

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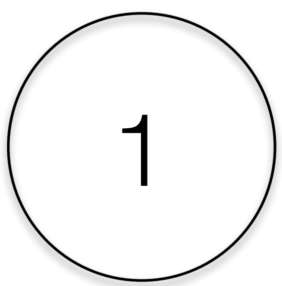

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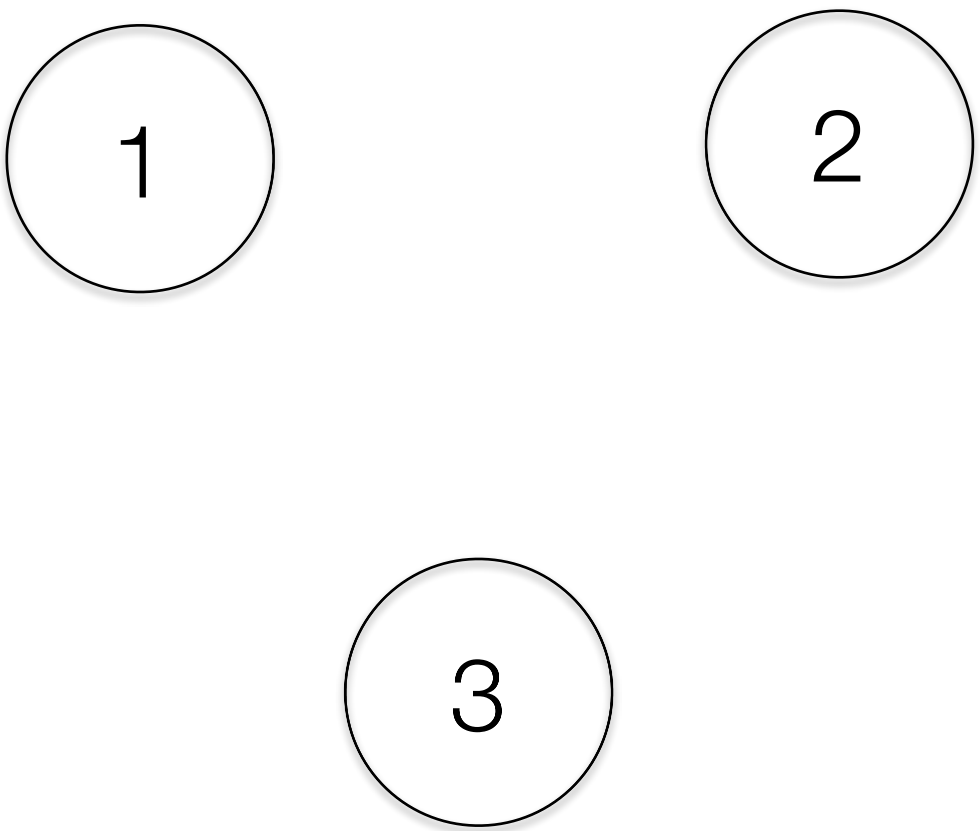

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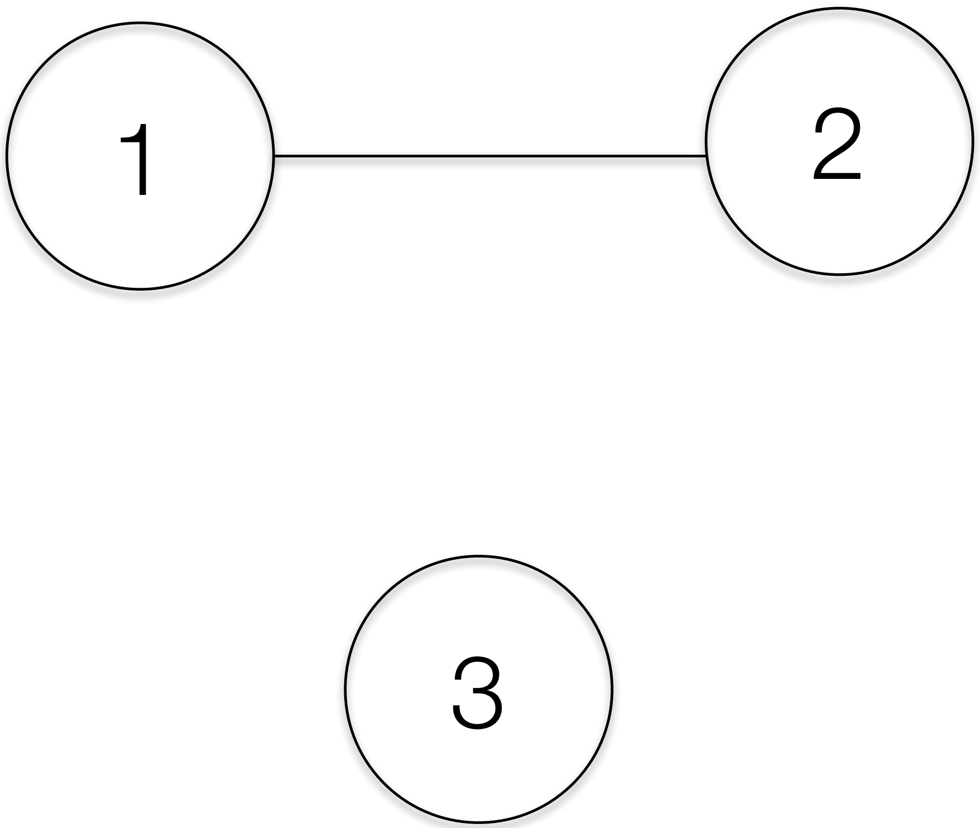

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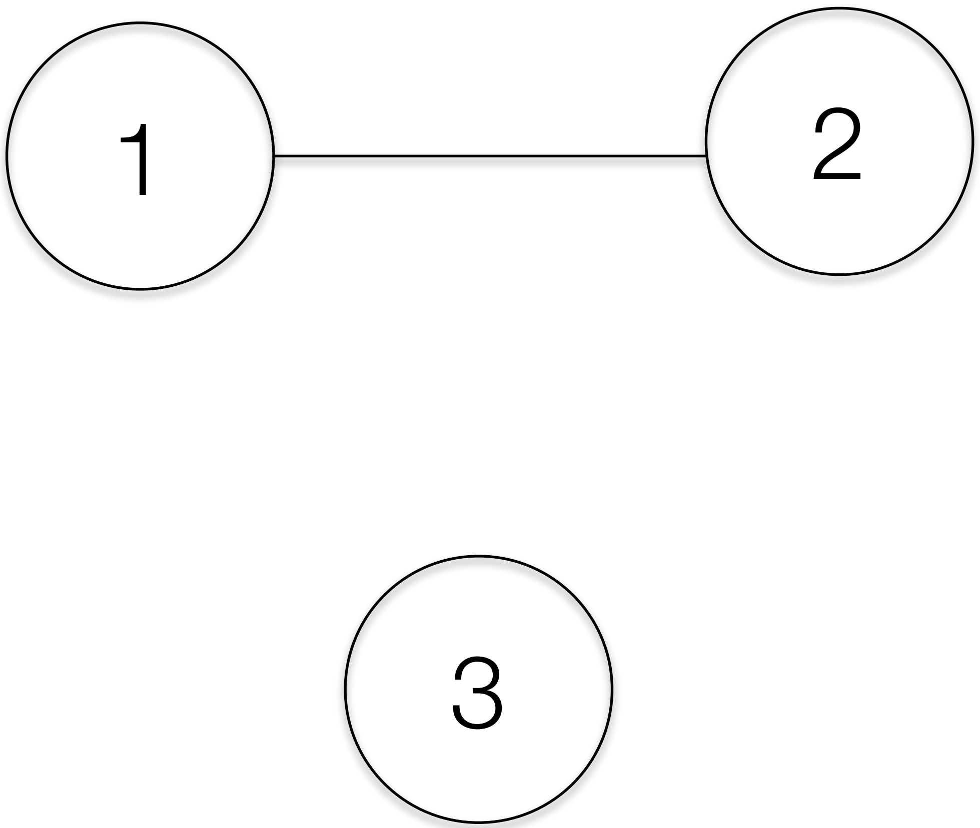

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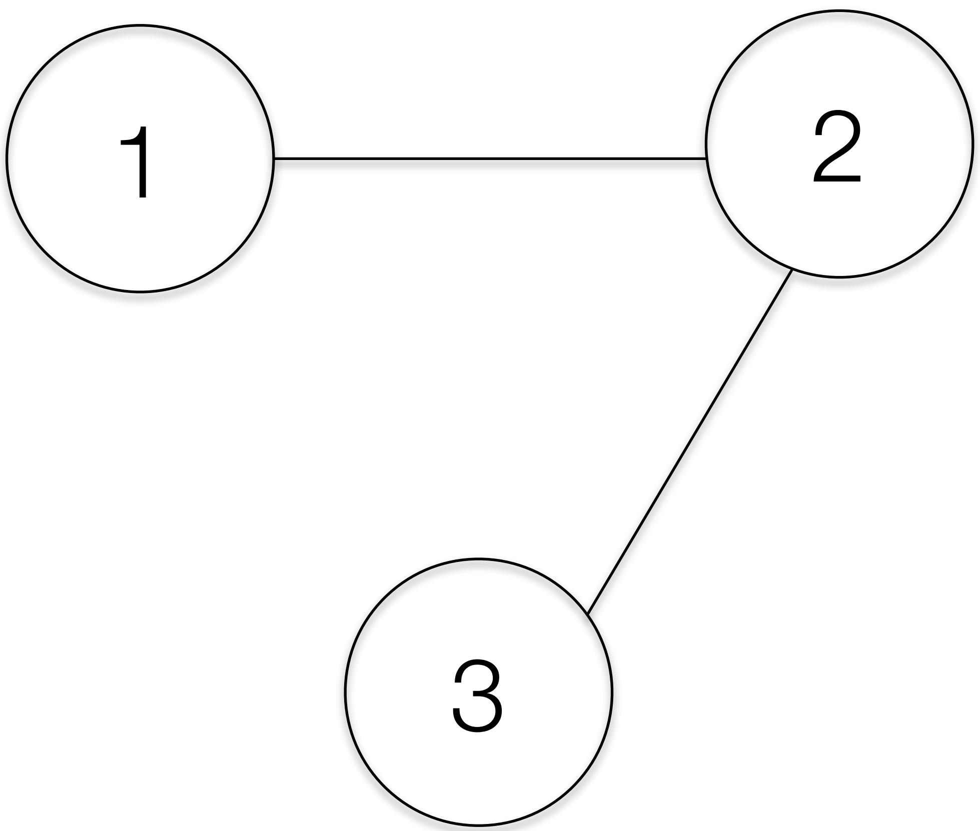

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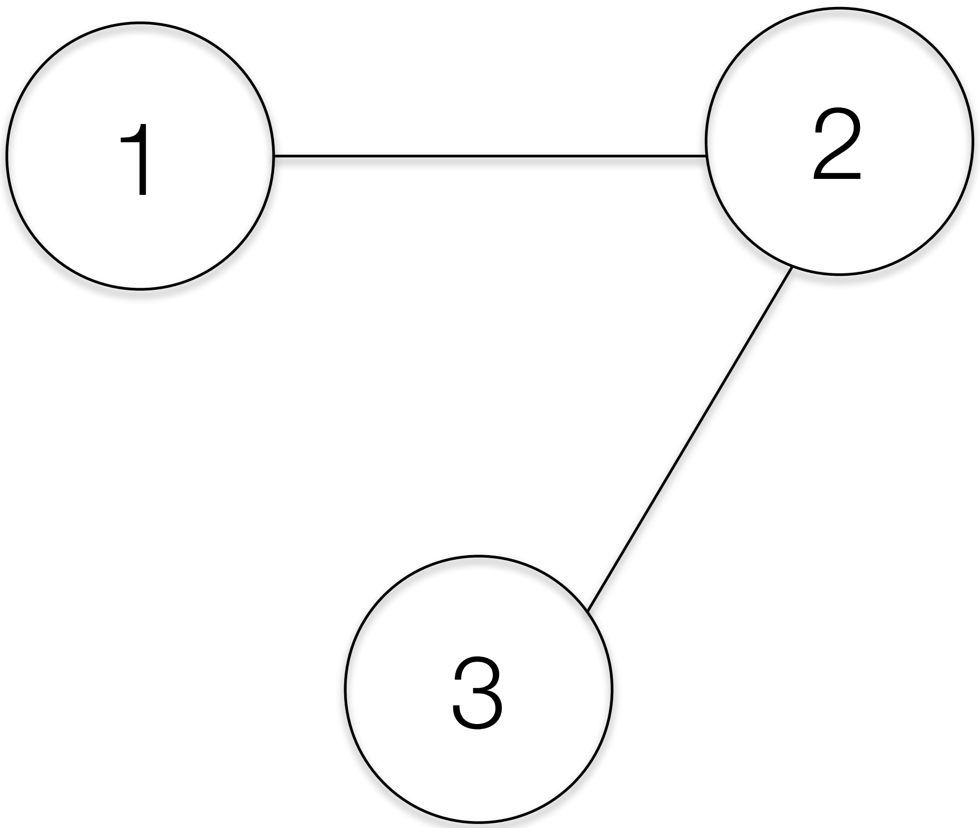

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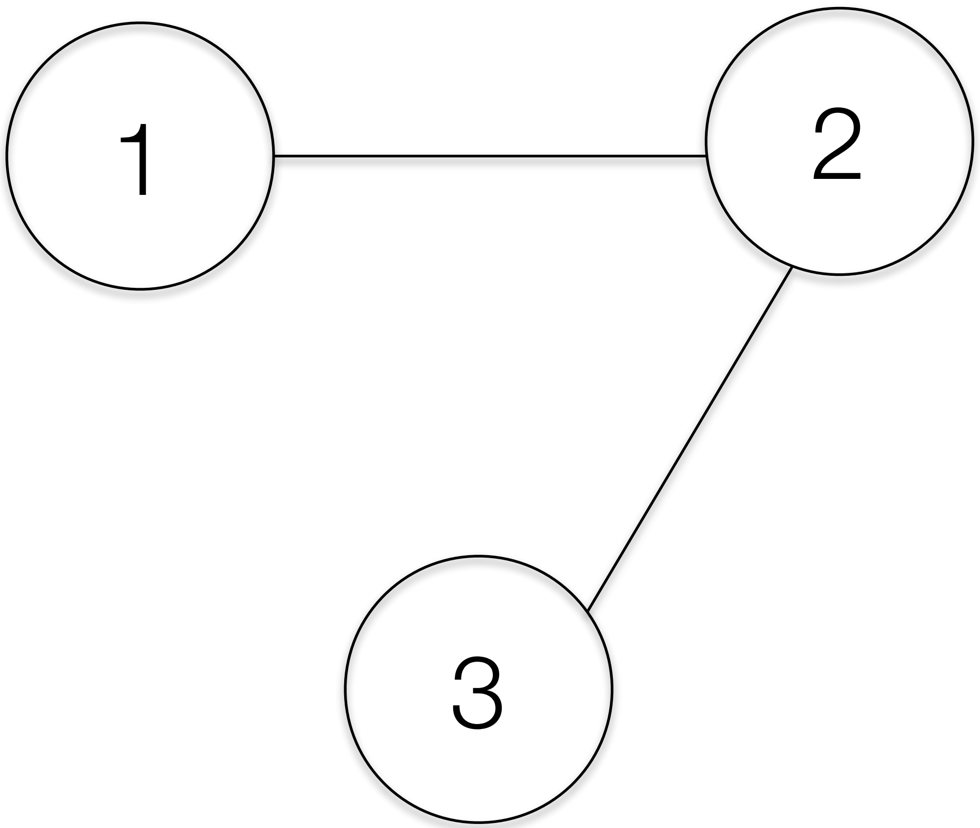

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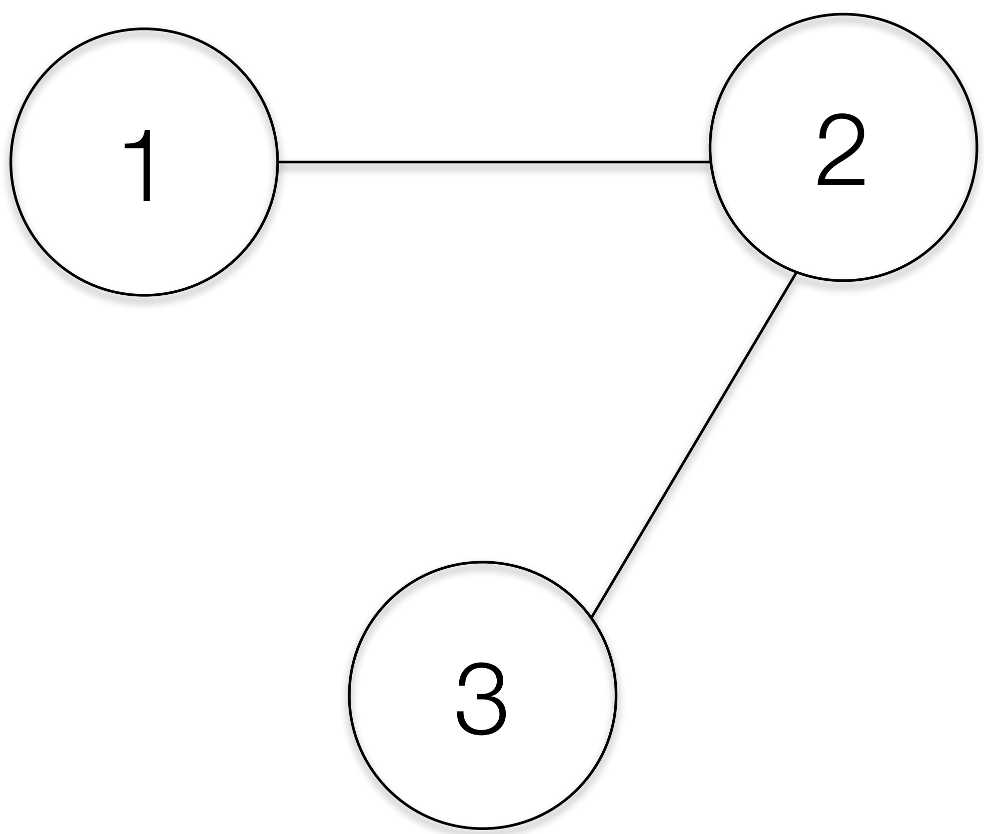

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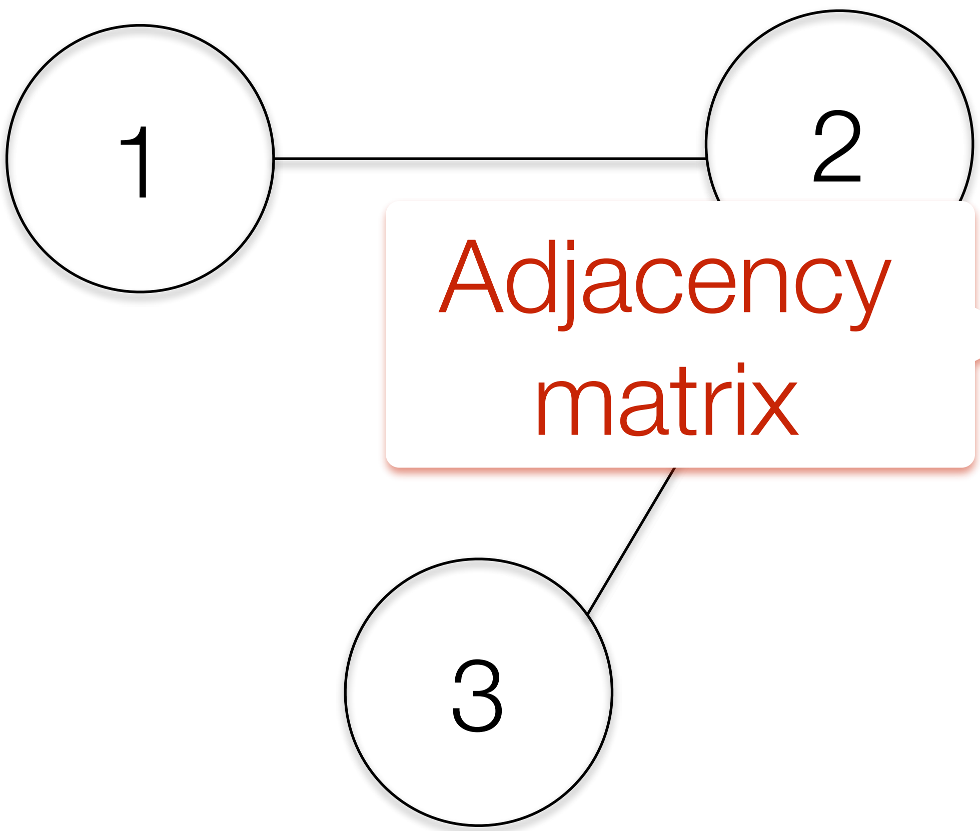

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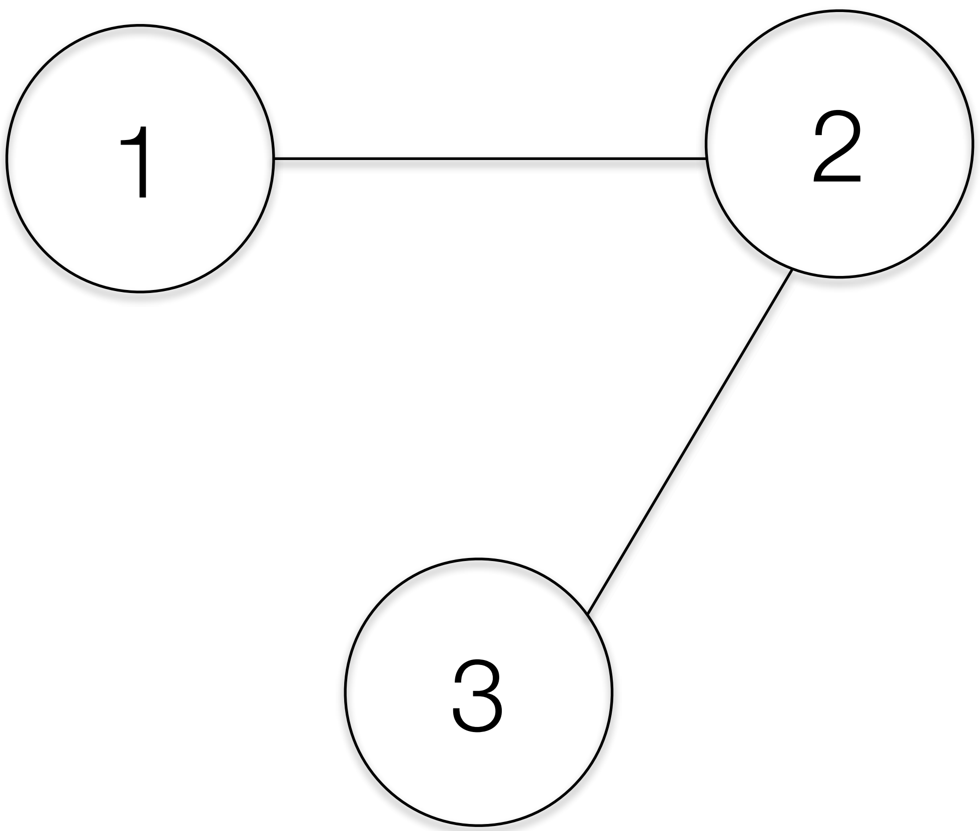

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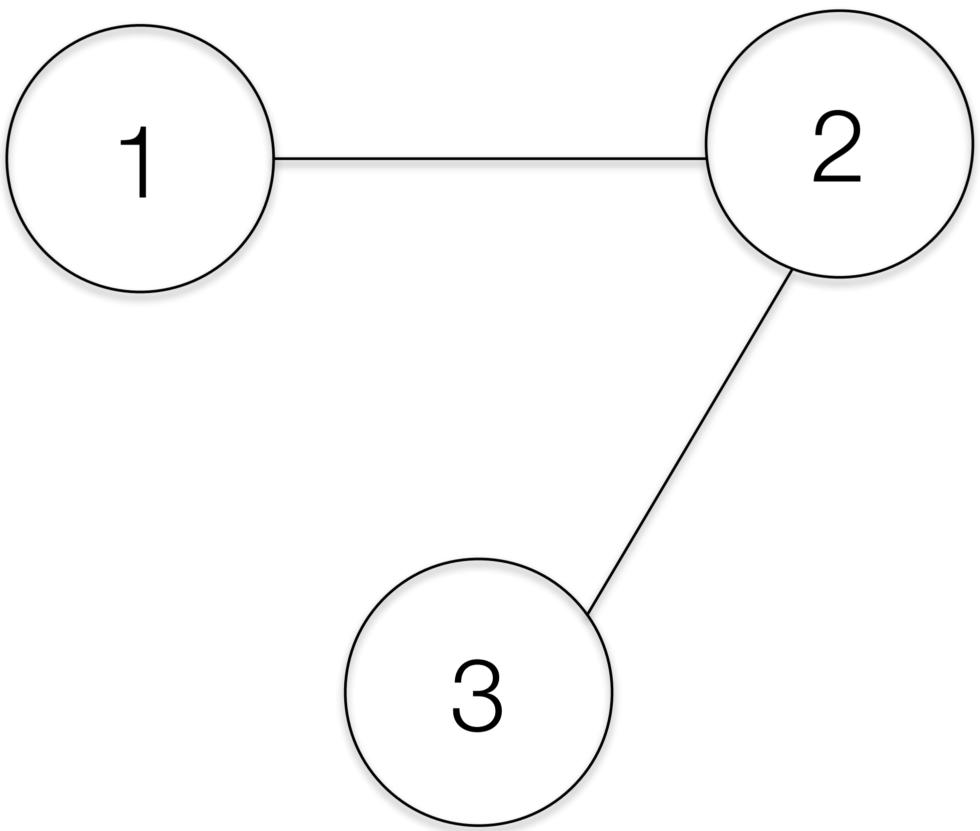

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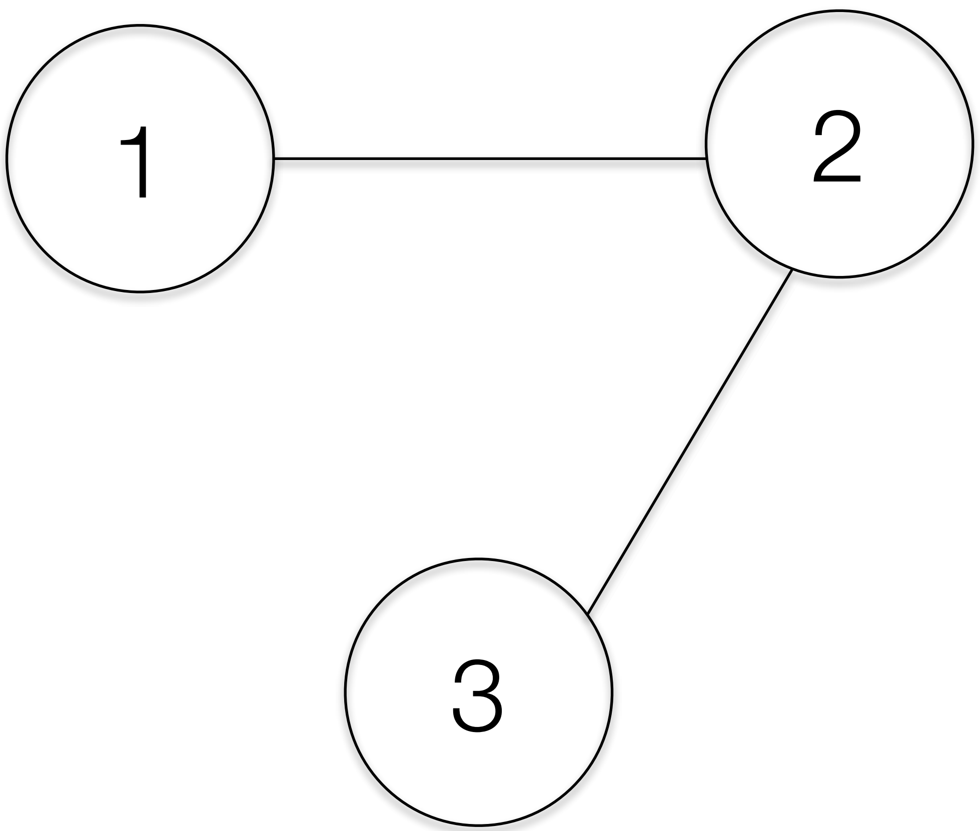

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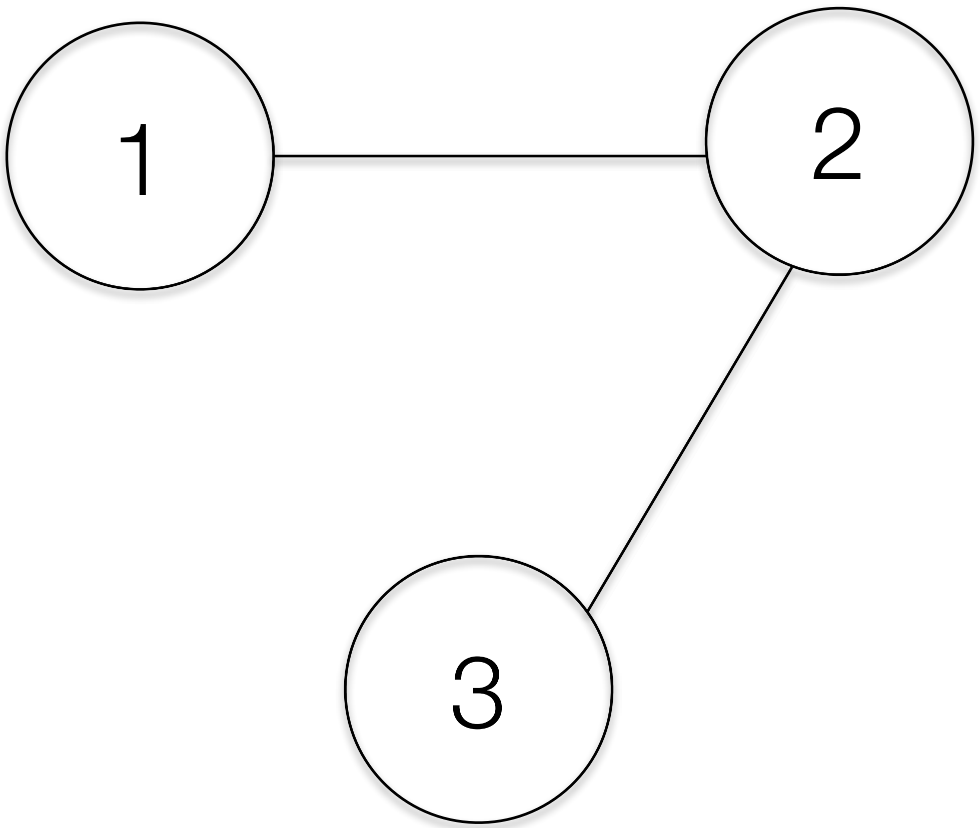

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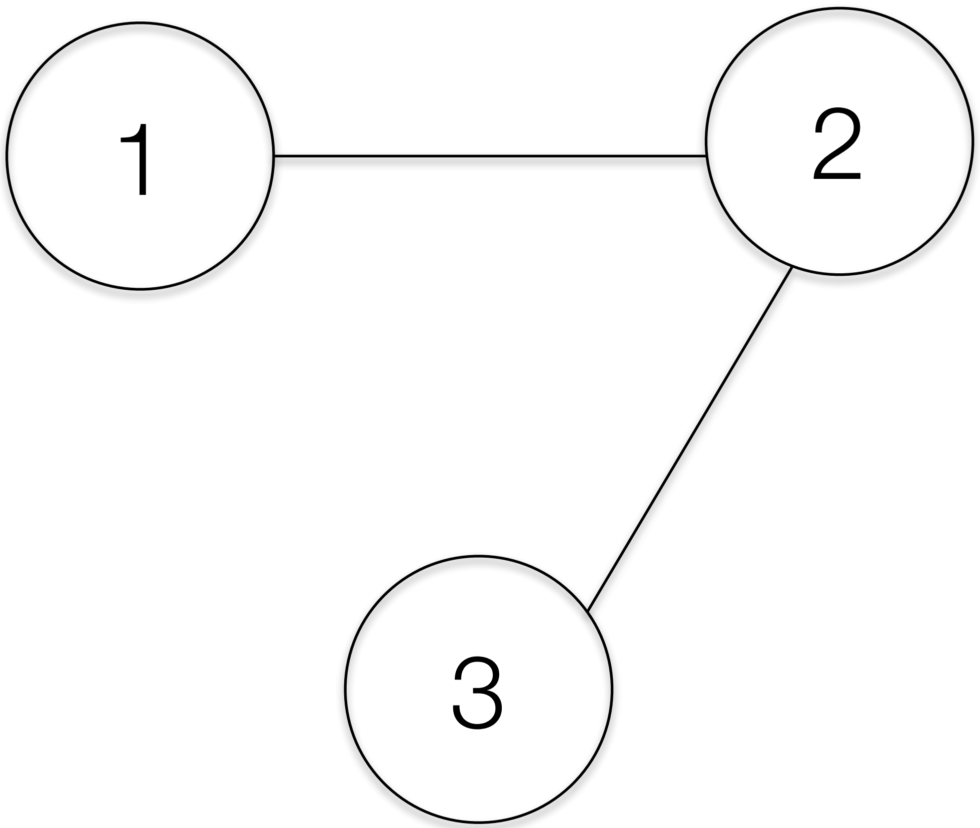

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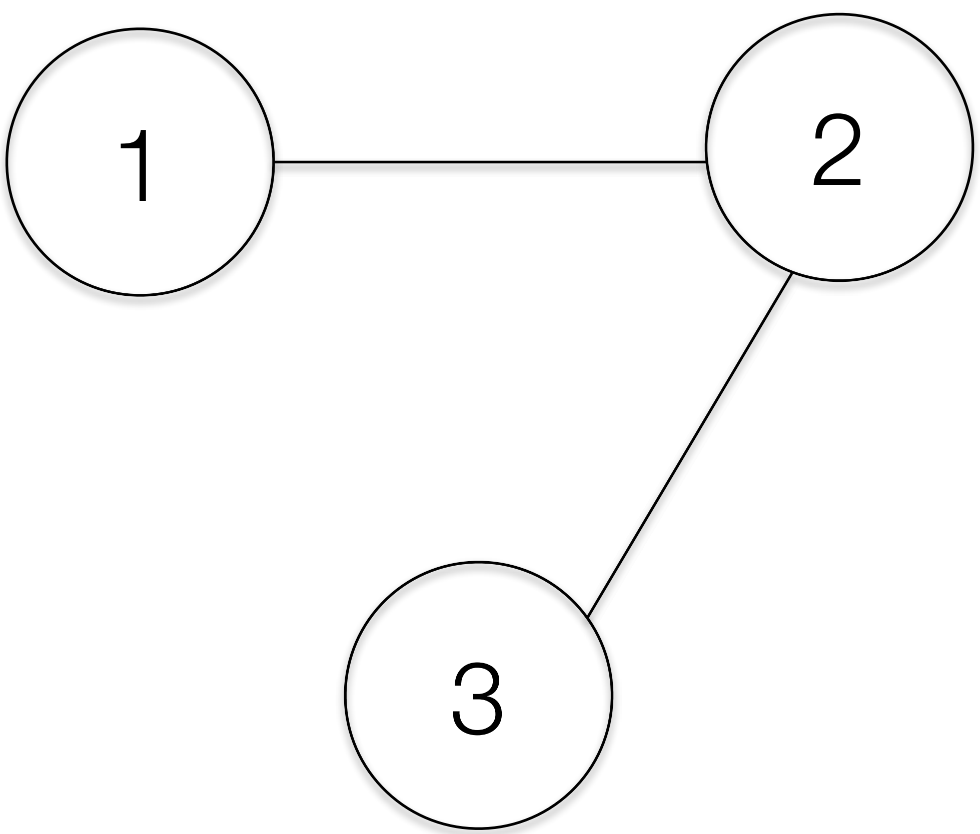

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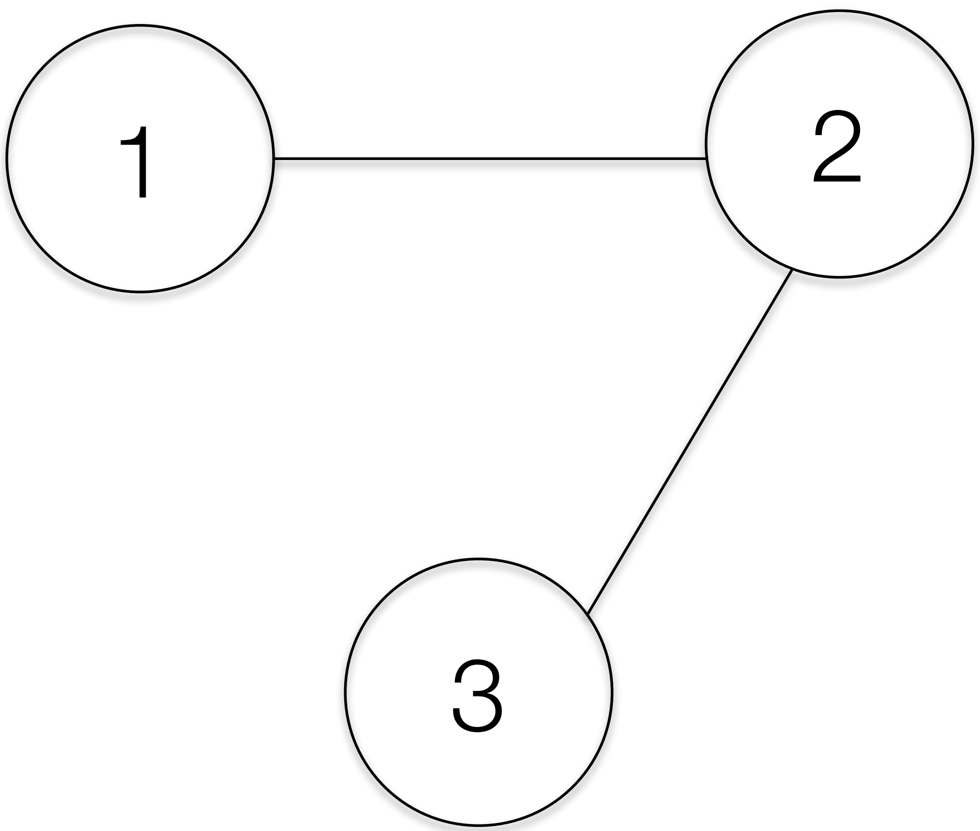

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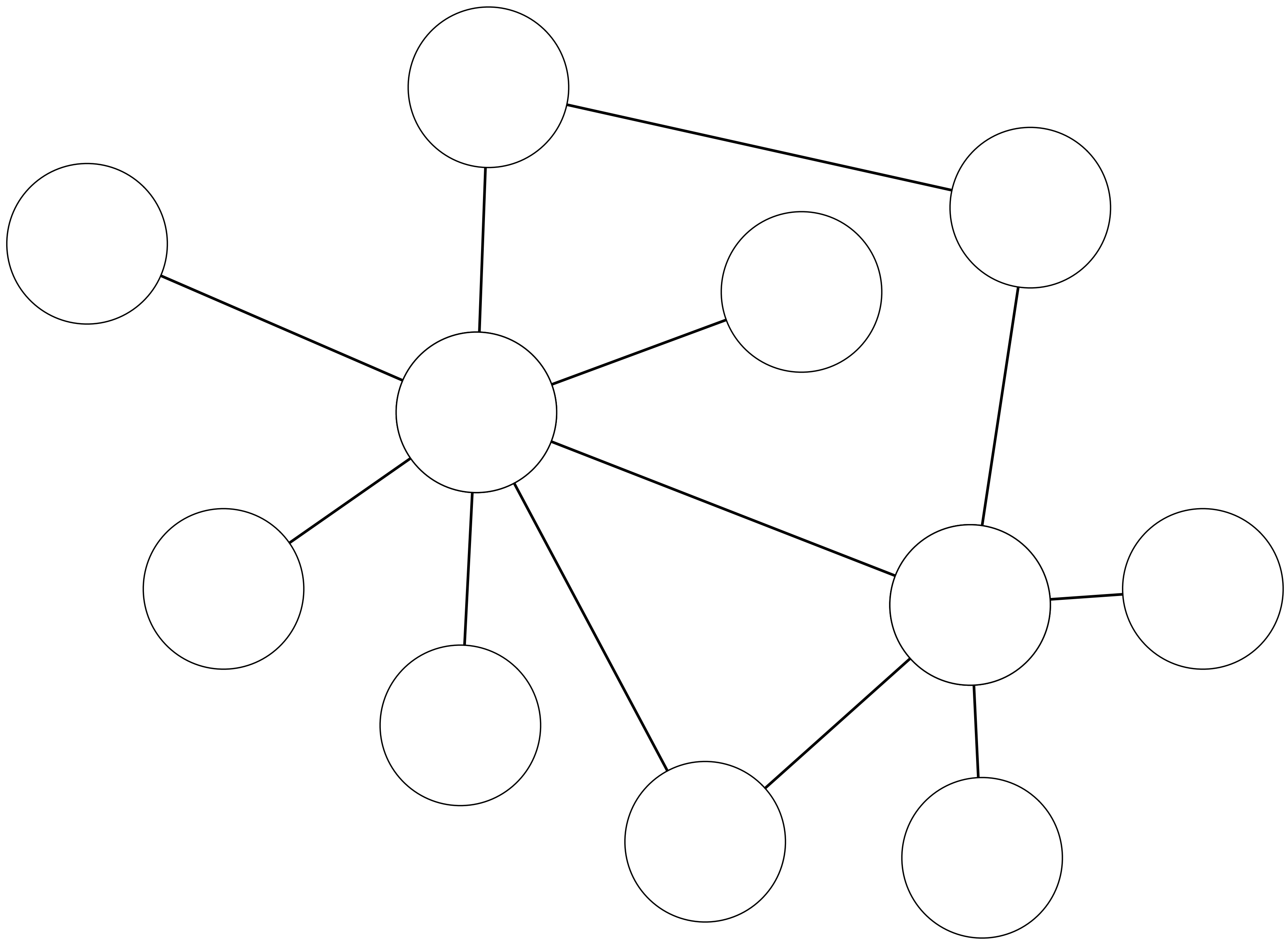
Path, cycle, distance



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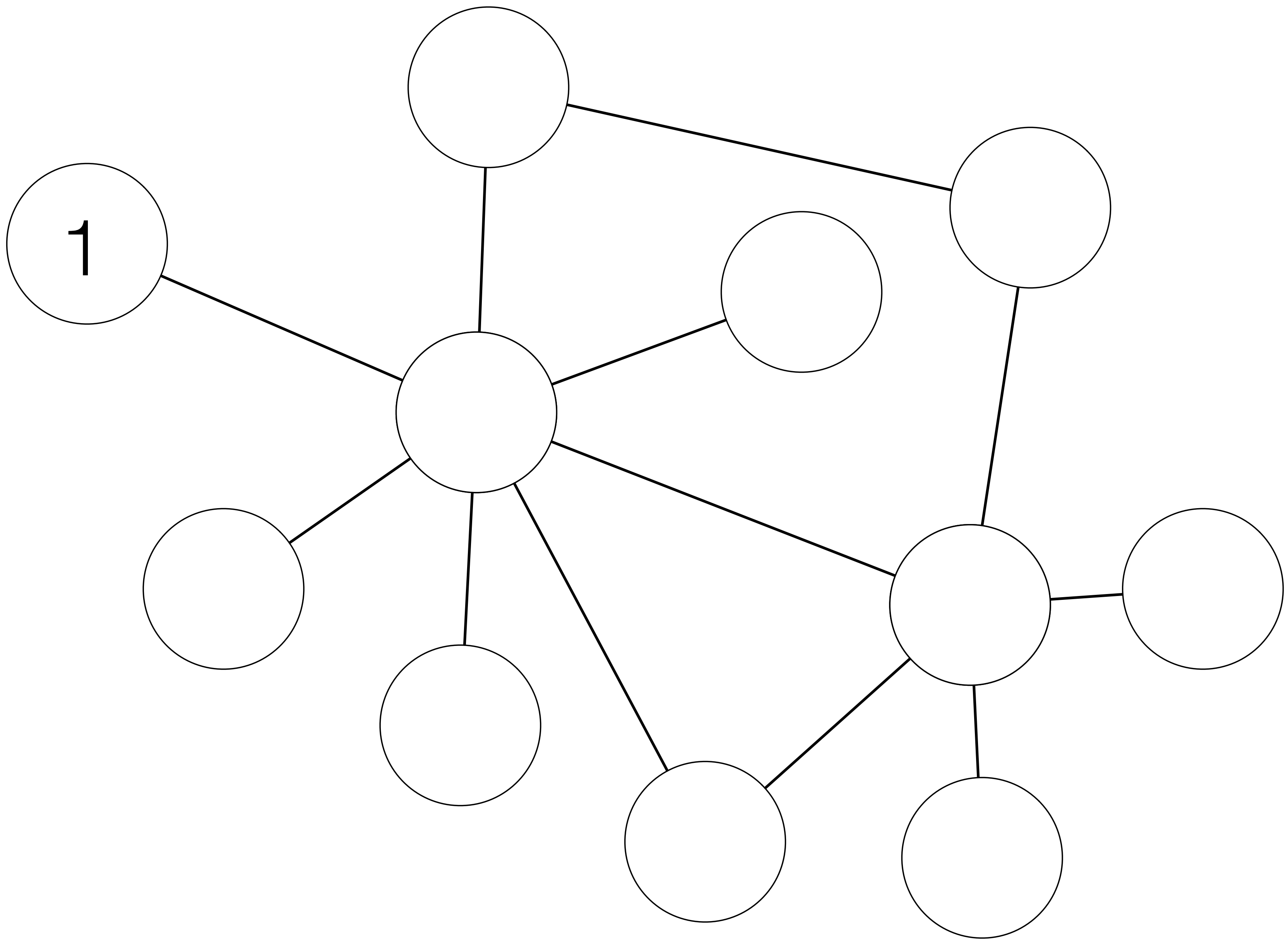

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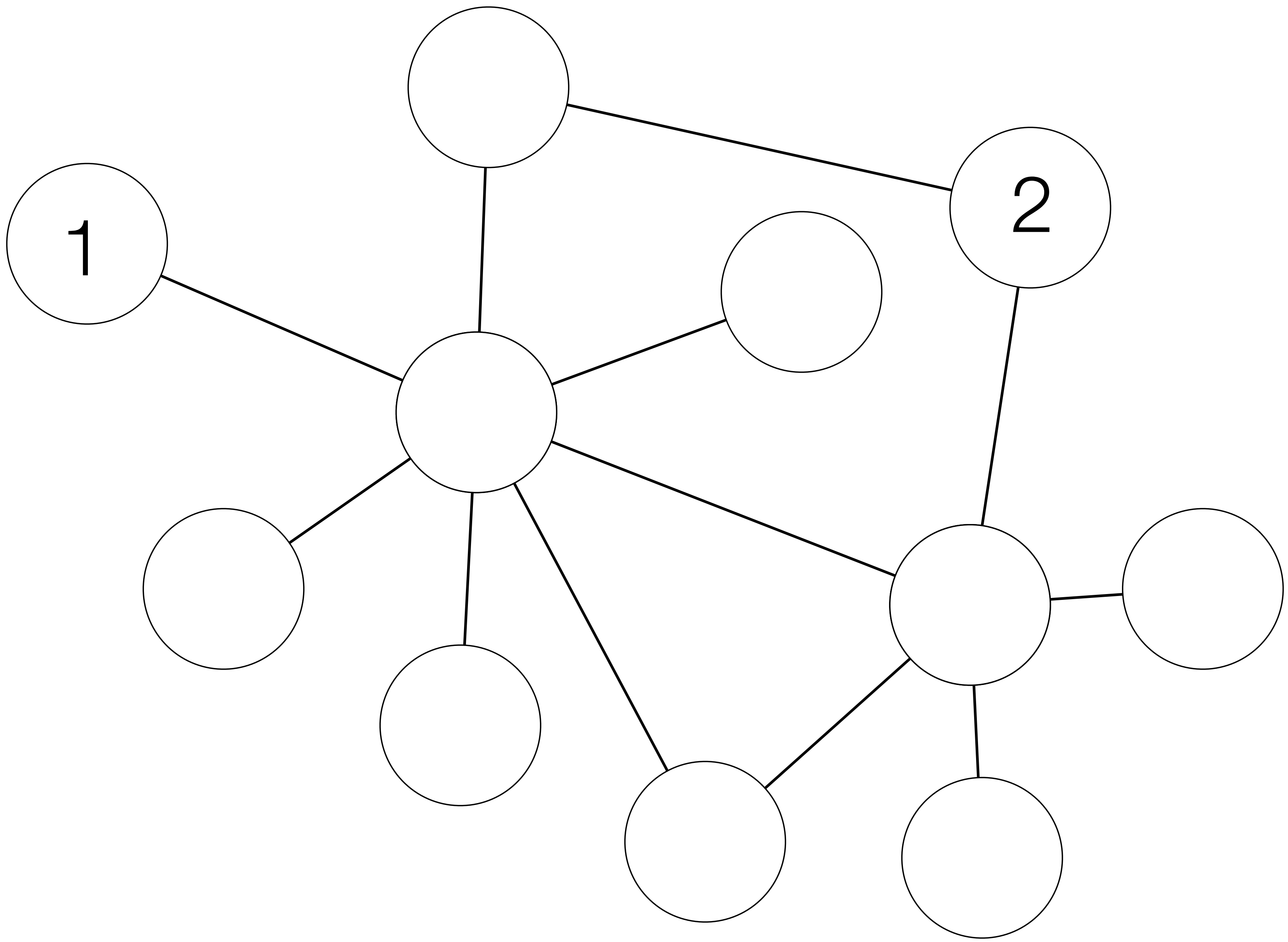

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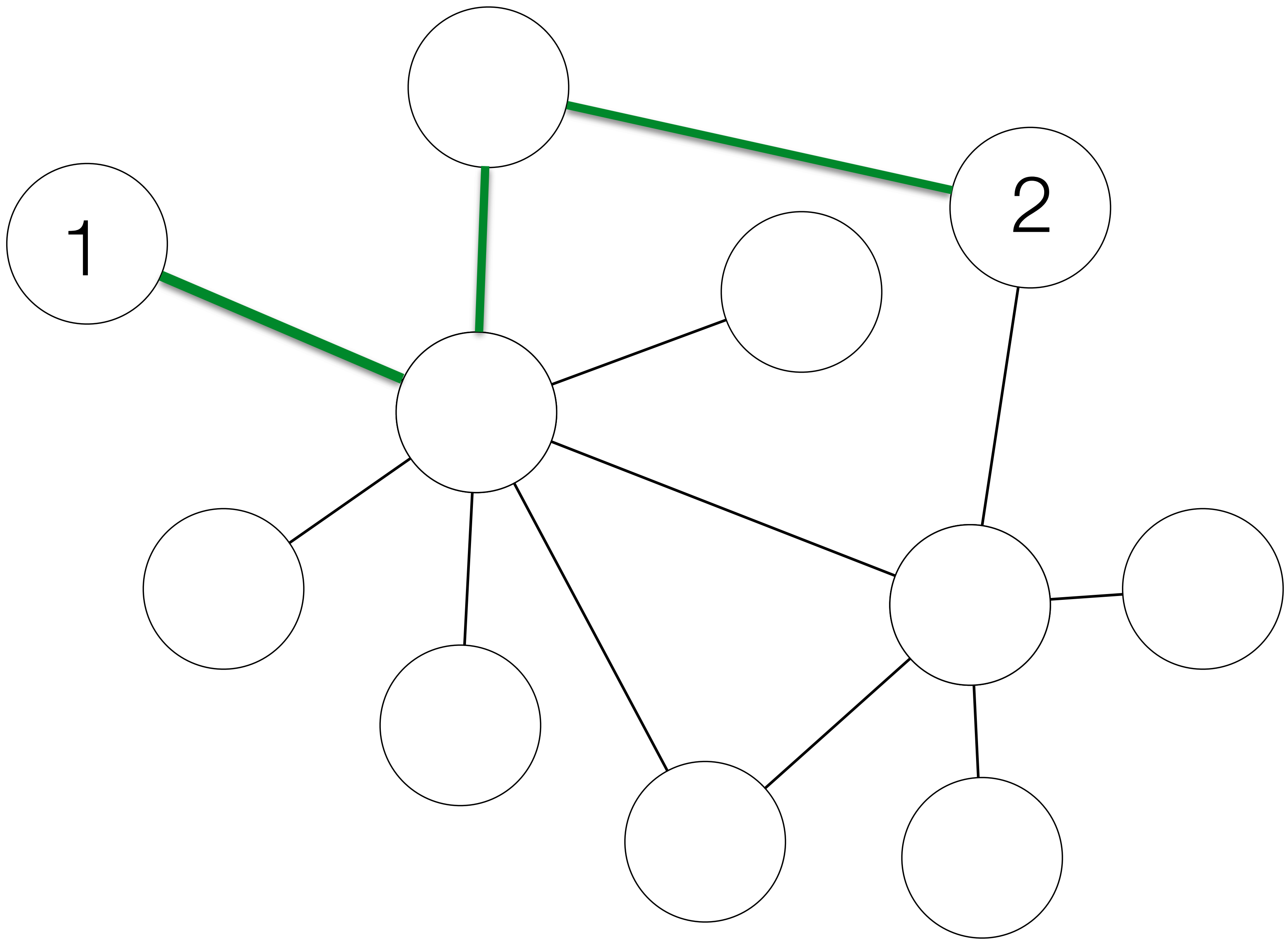

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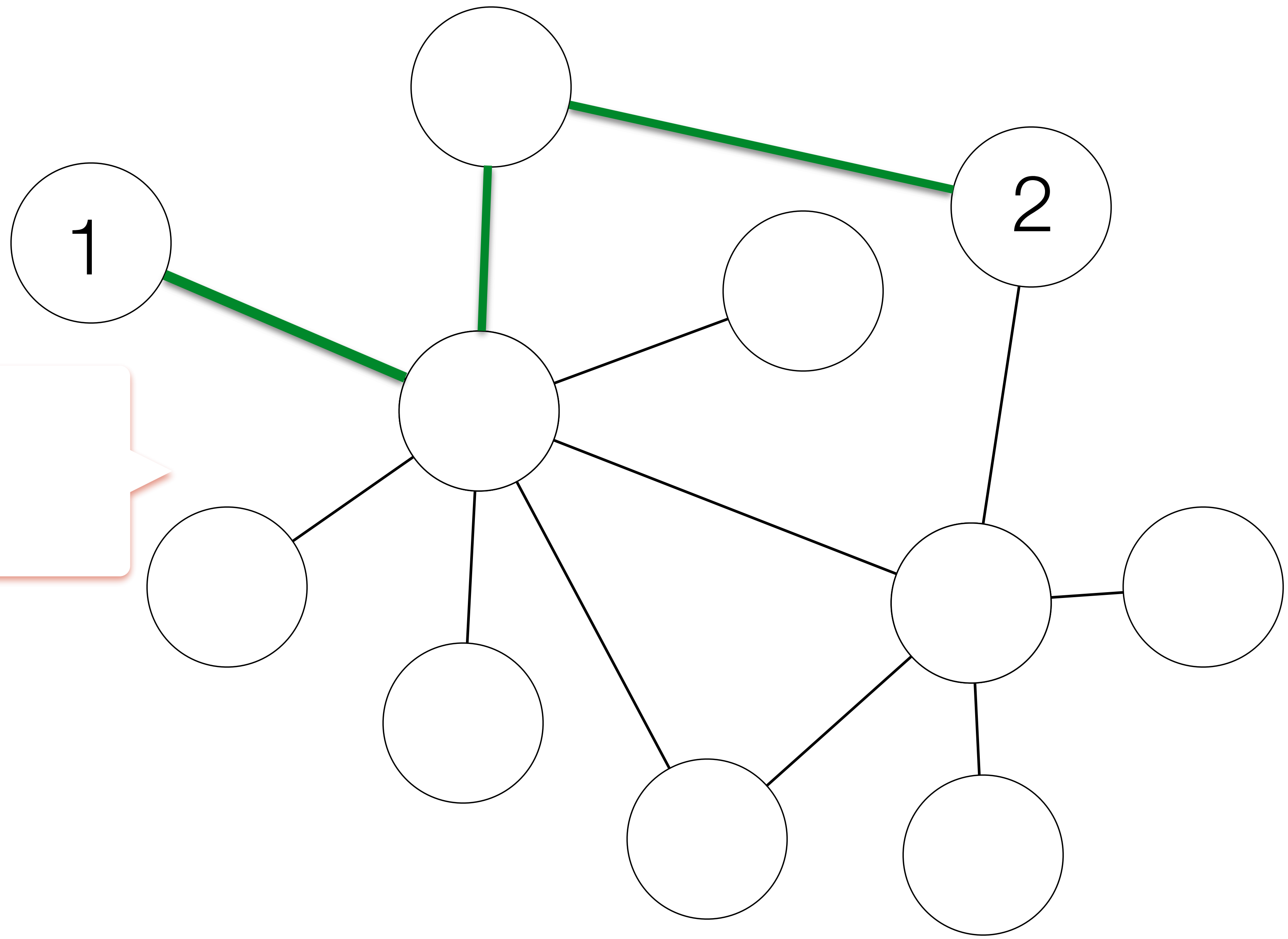

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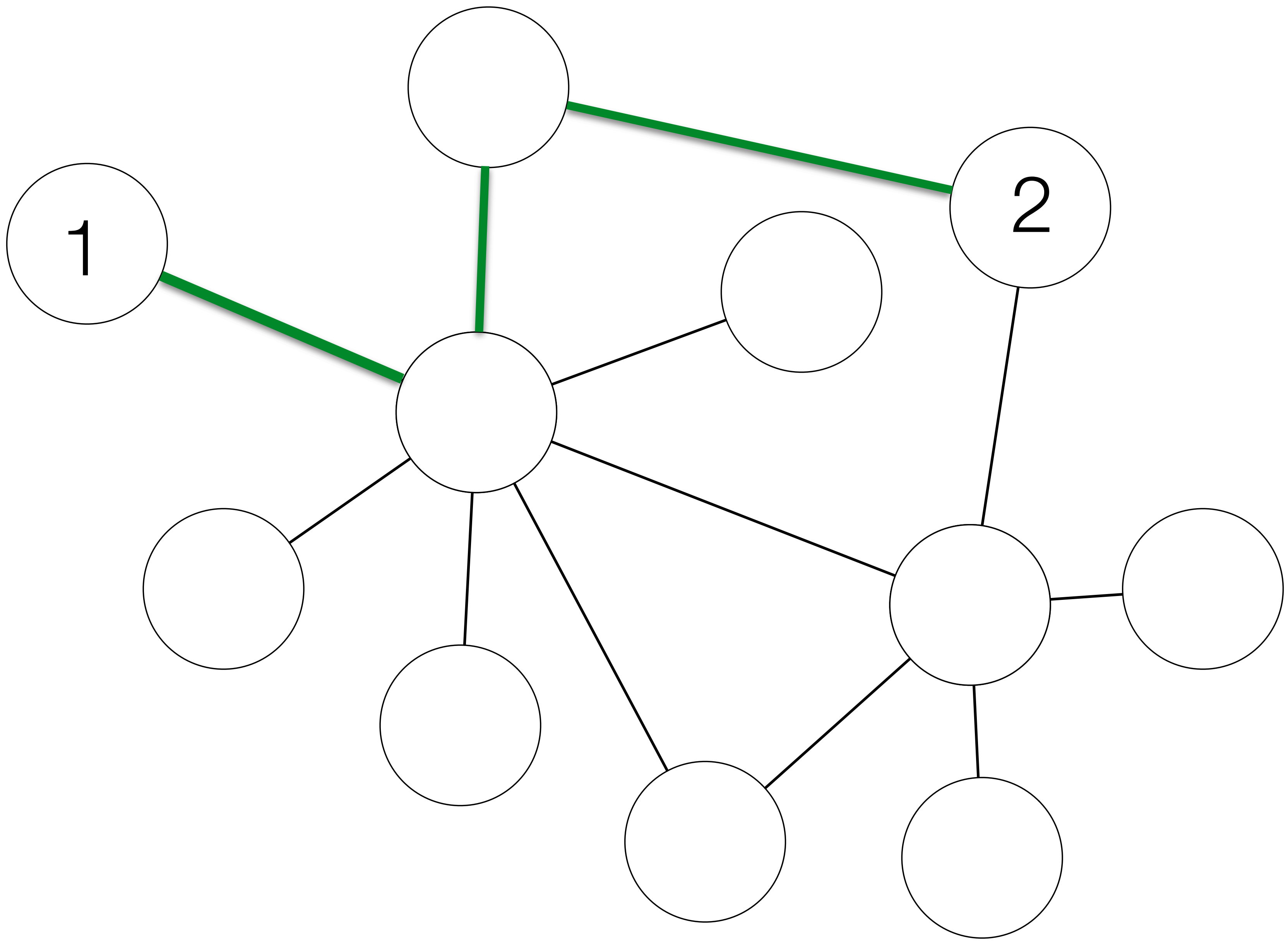

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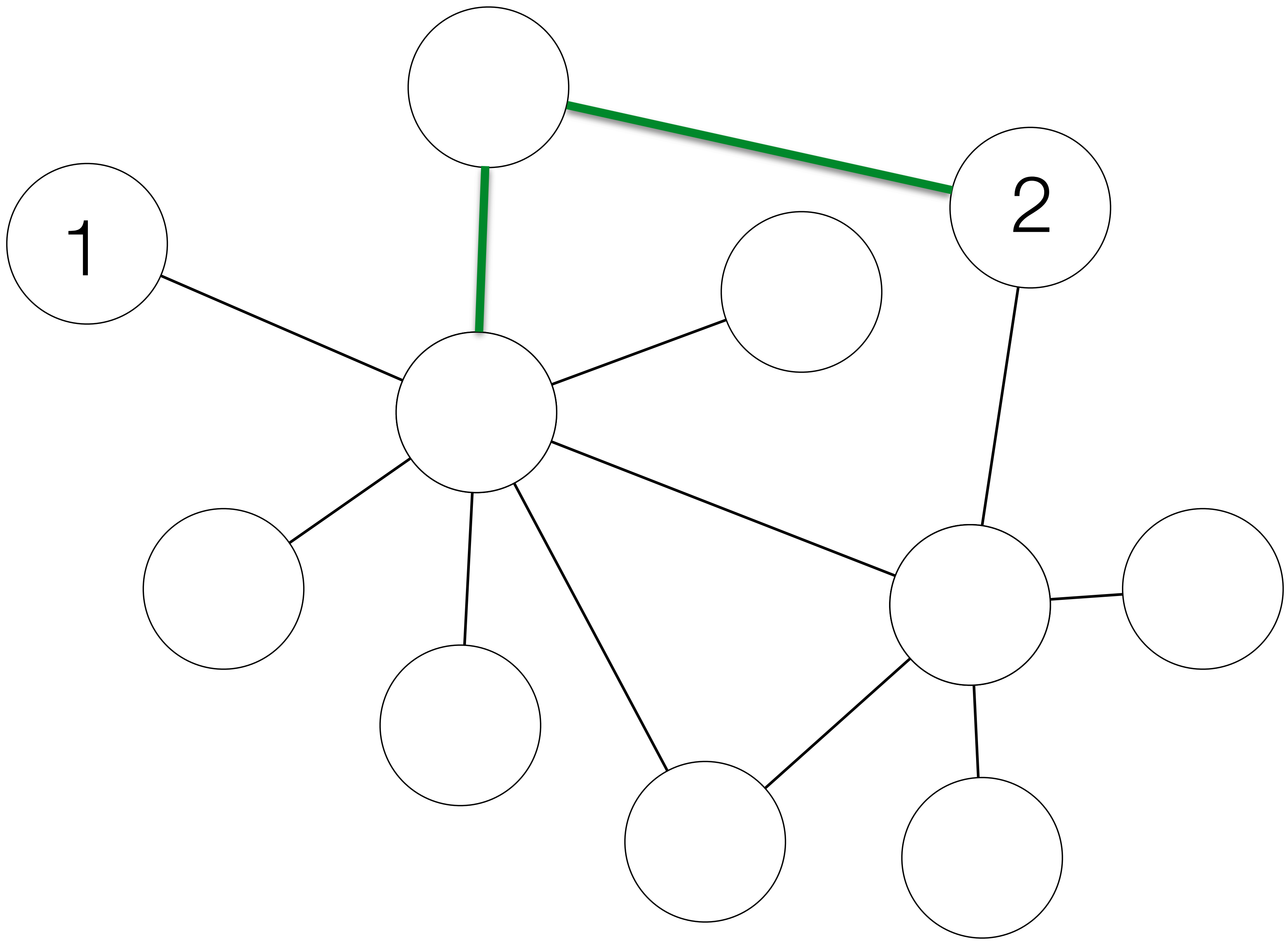

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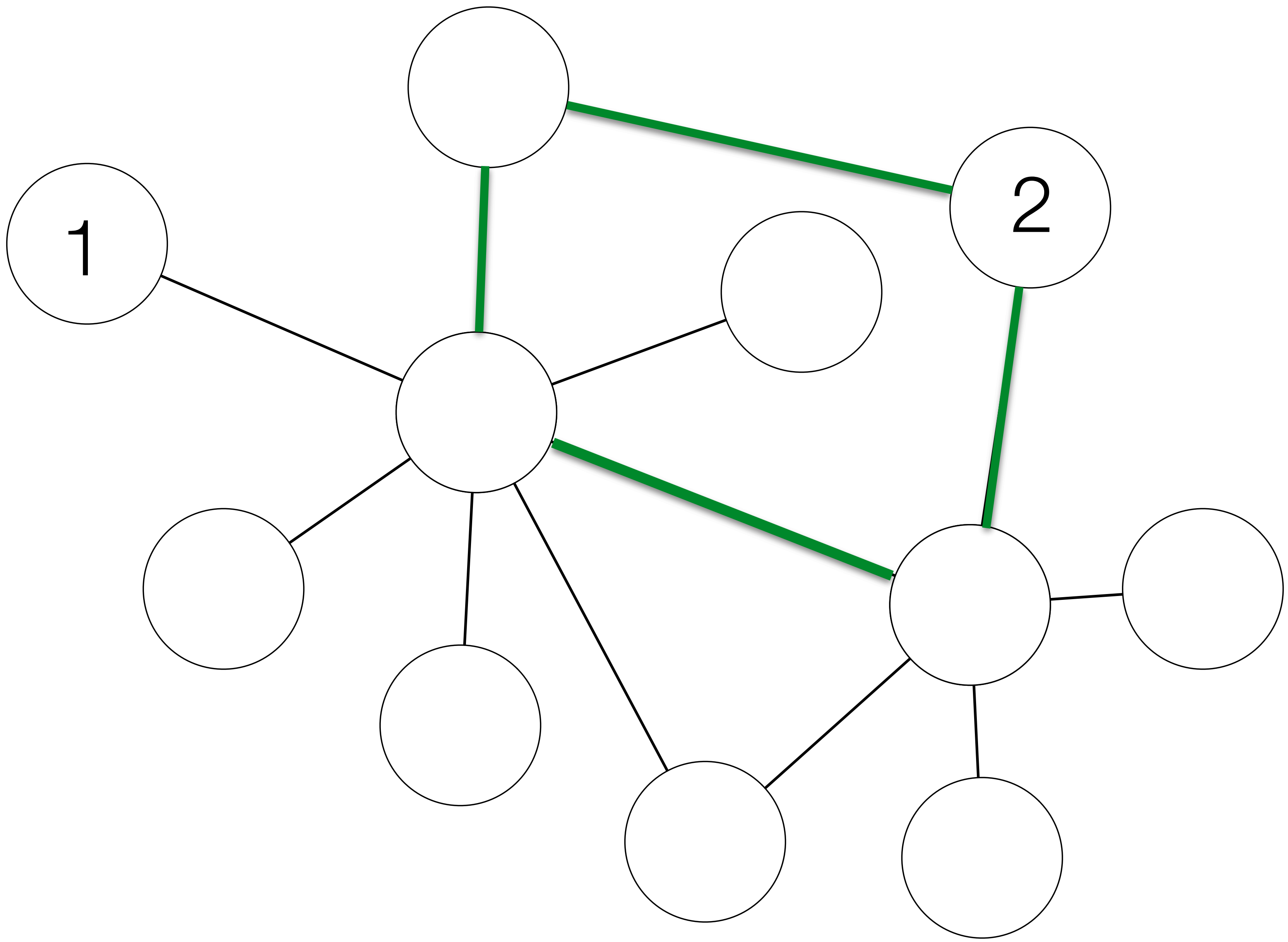

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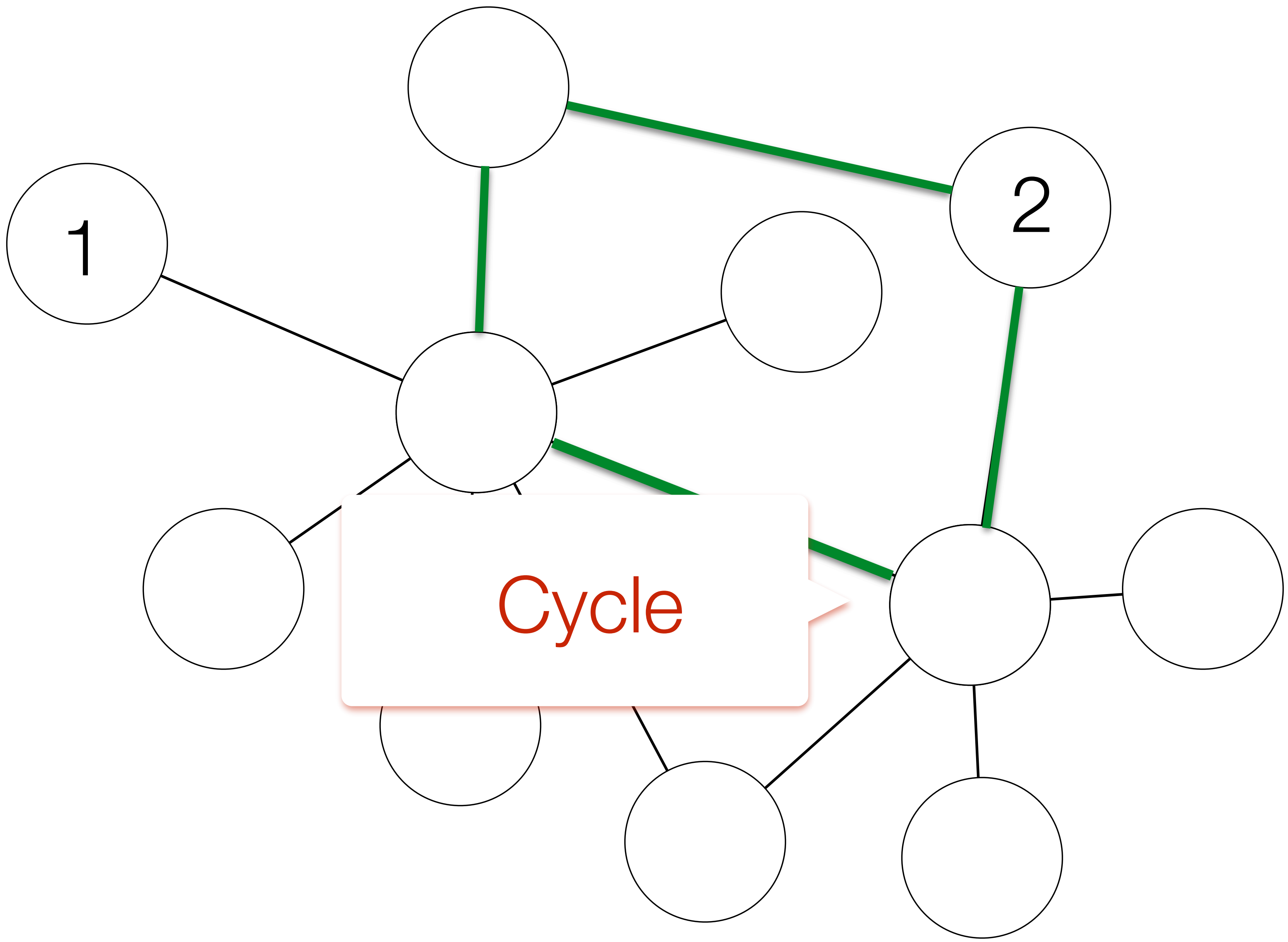

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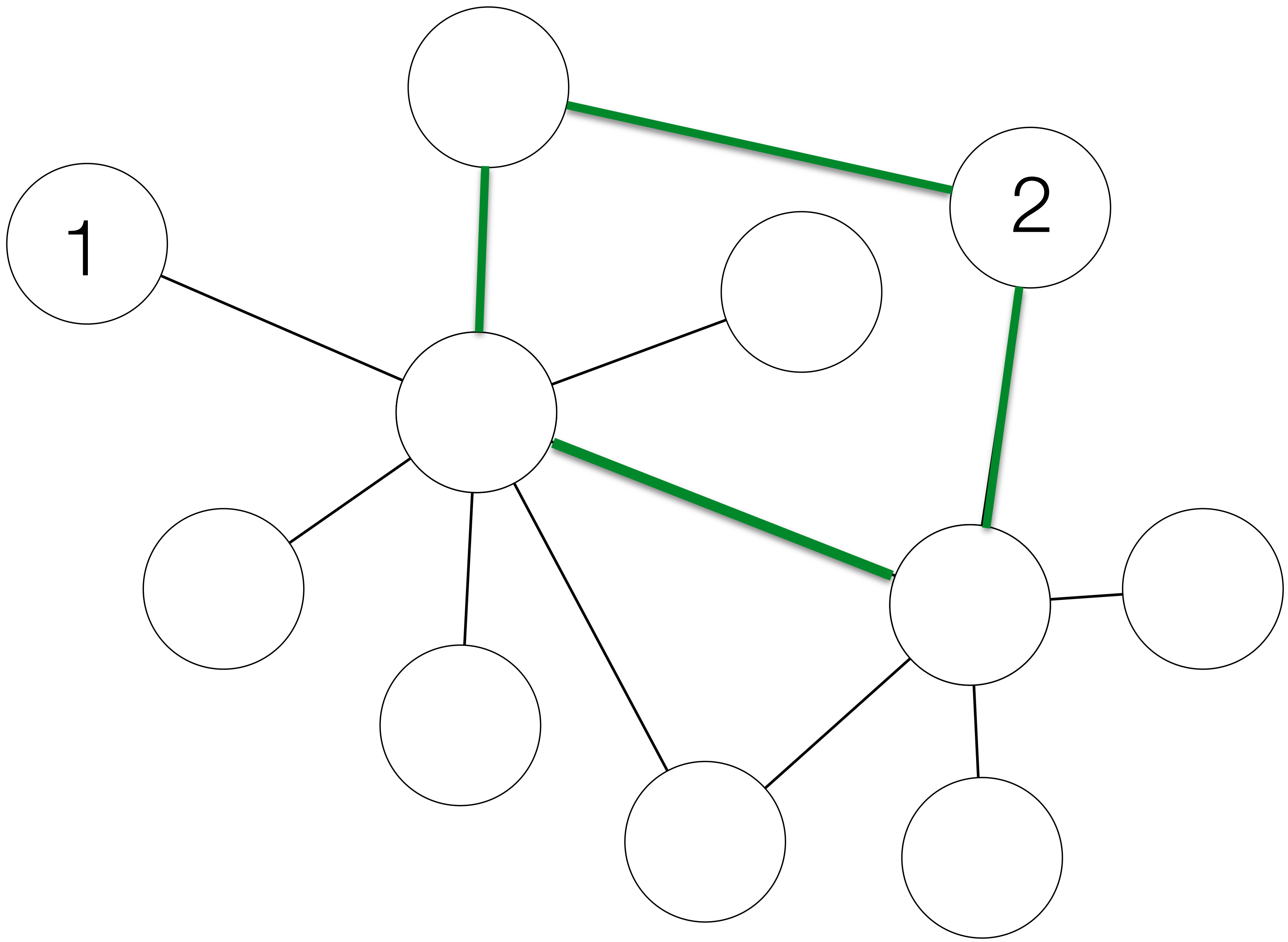

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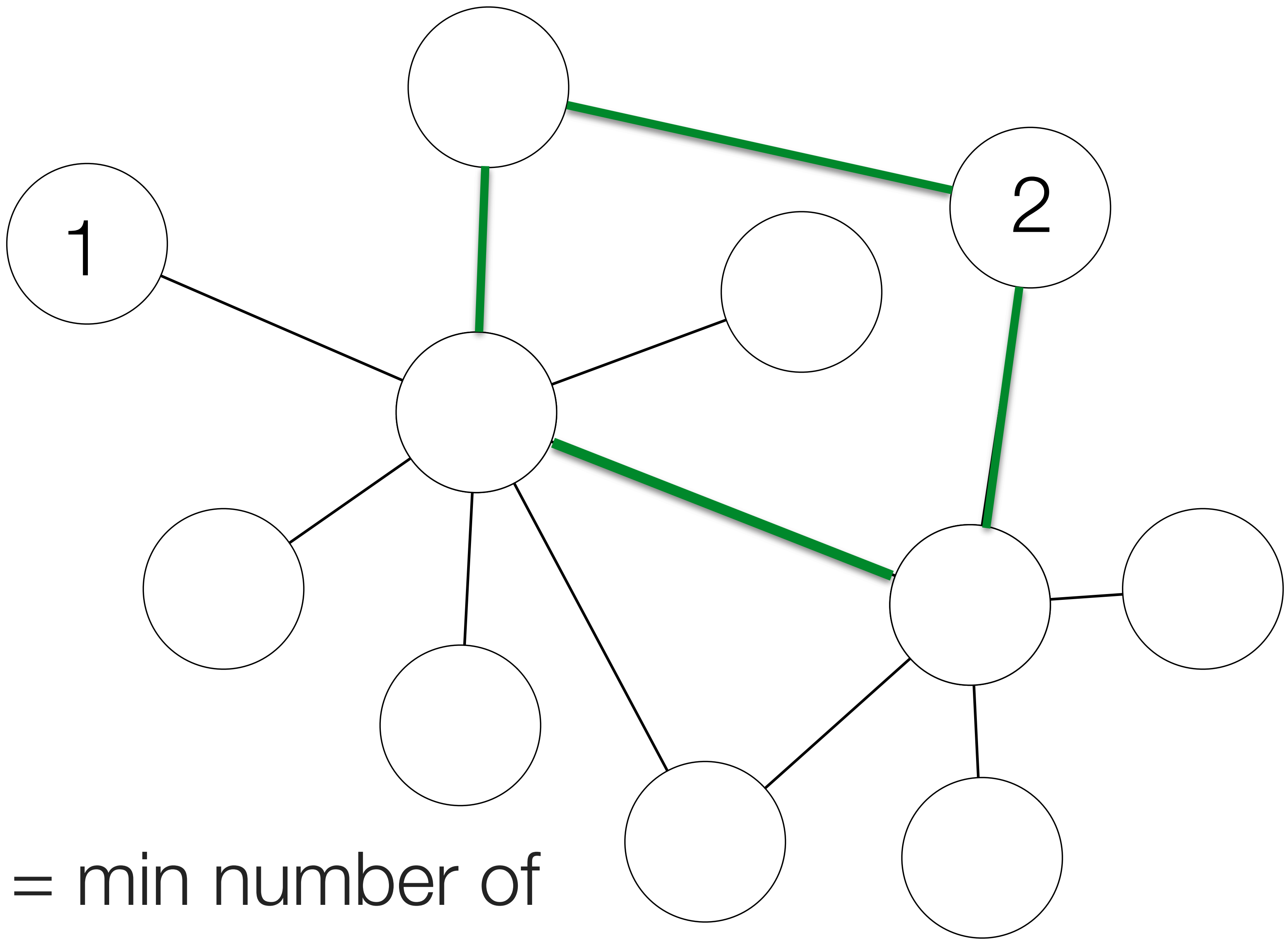

Distance = min number of edges between two nodes

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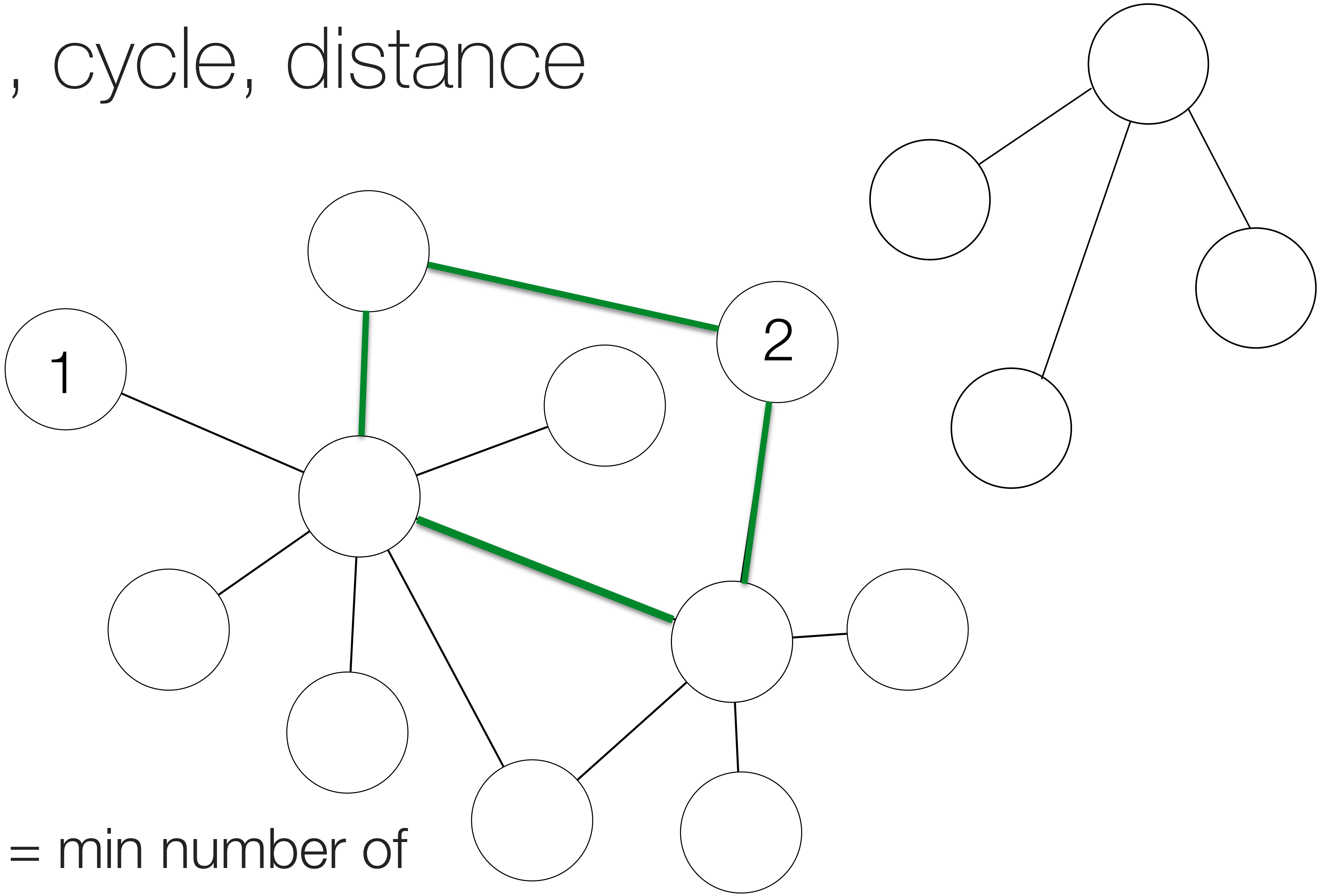

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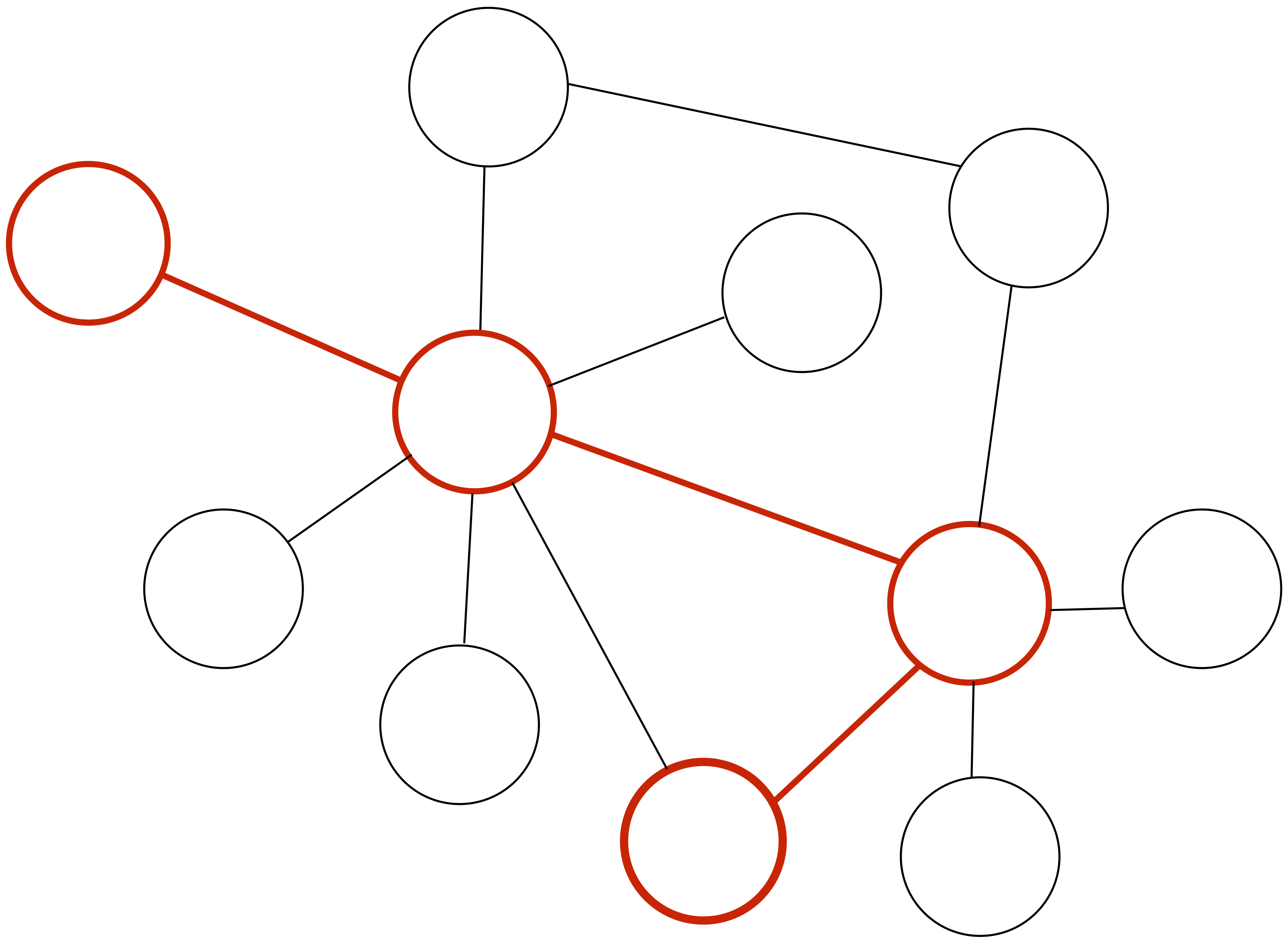
Subgraph



Components

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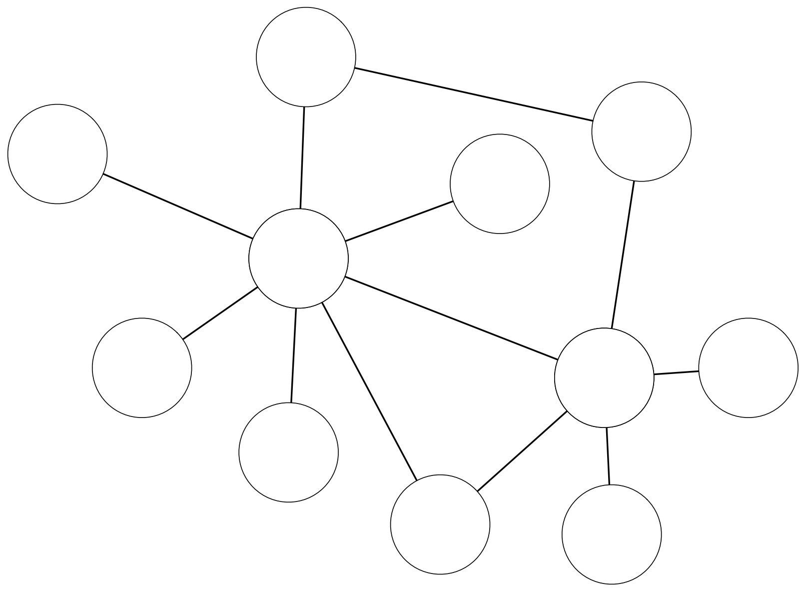

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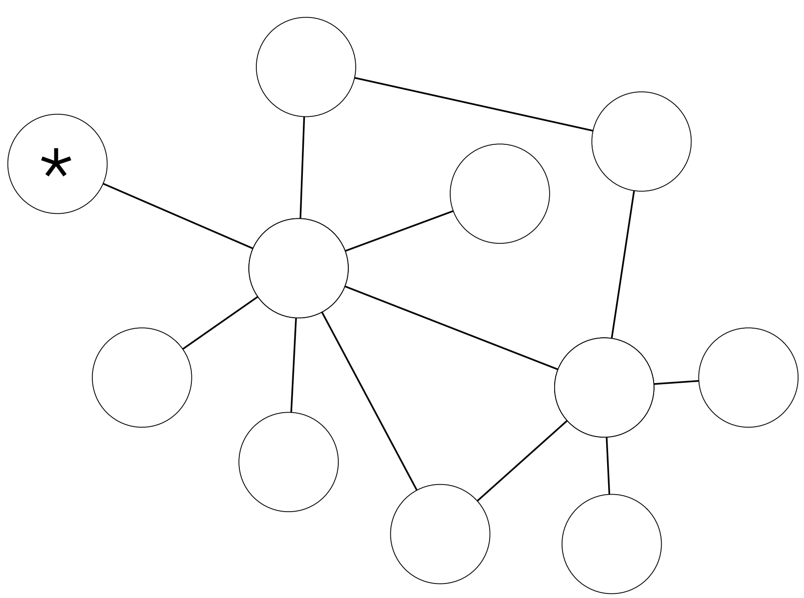

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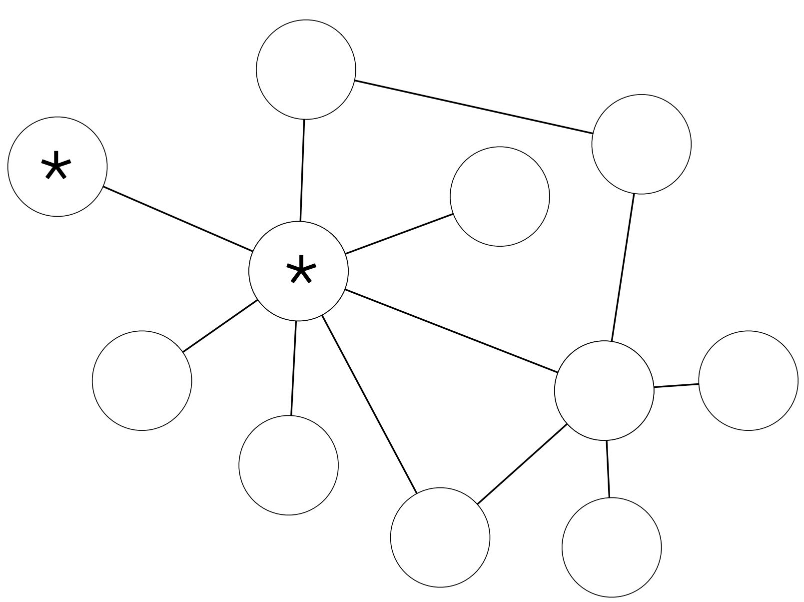

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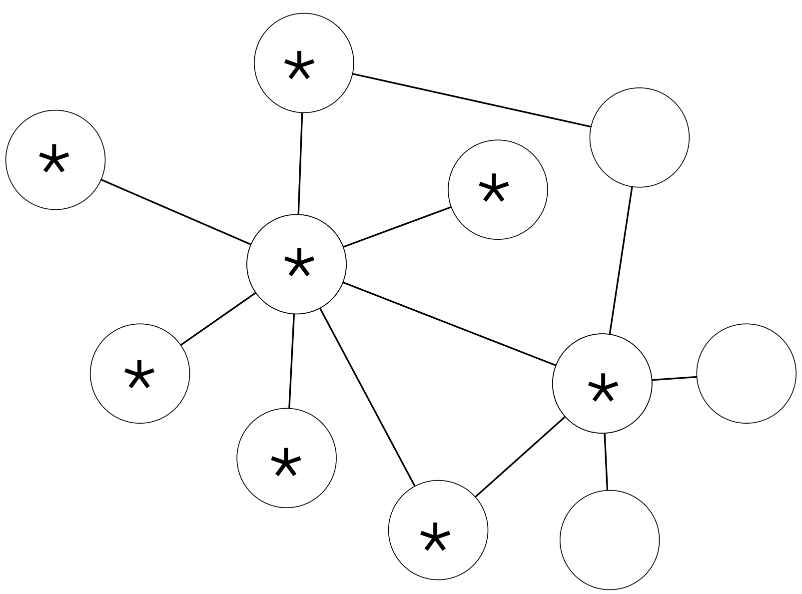

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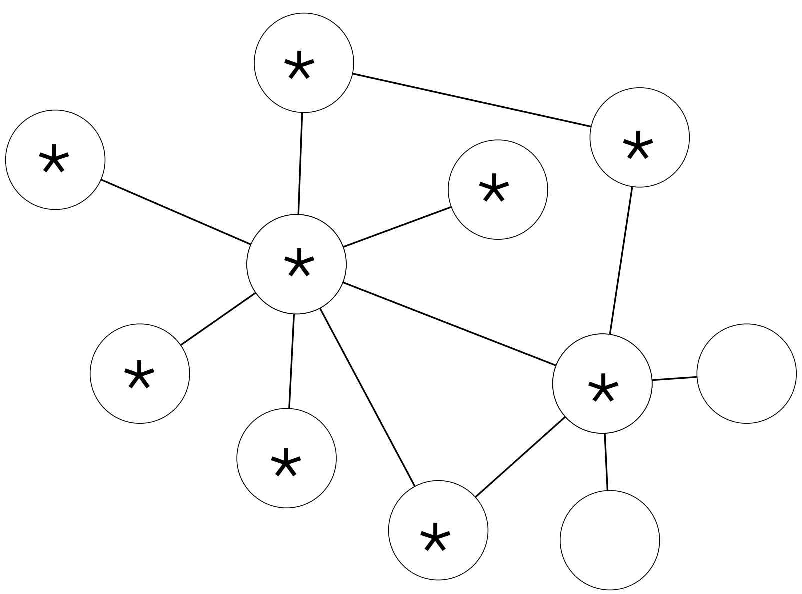

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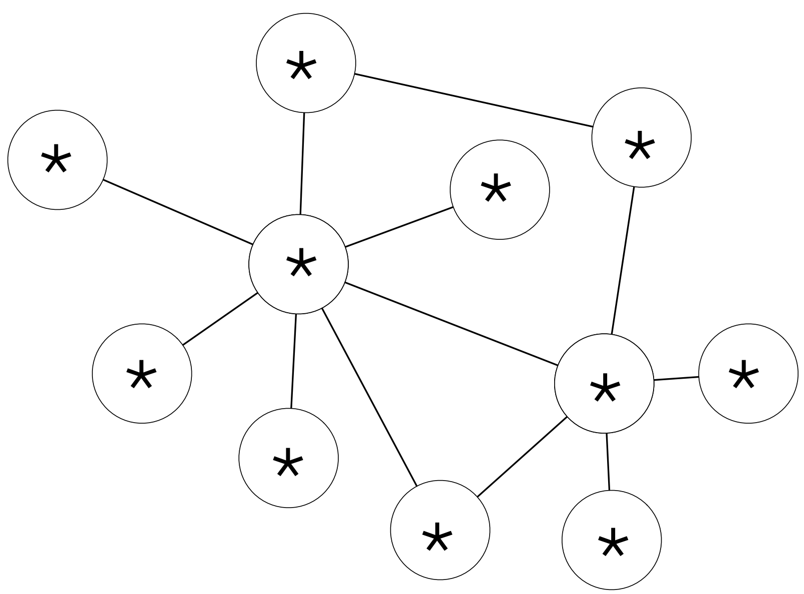

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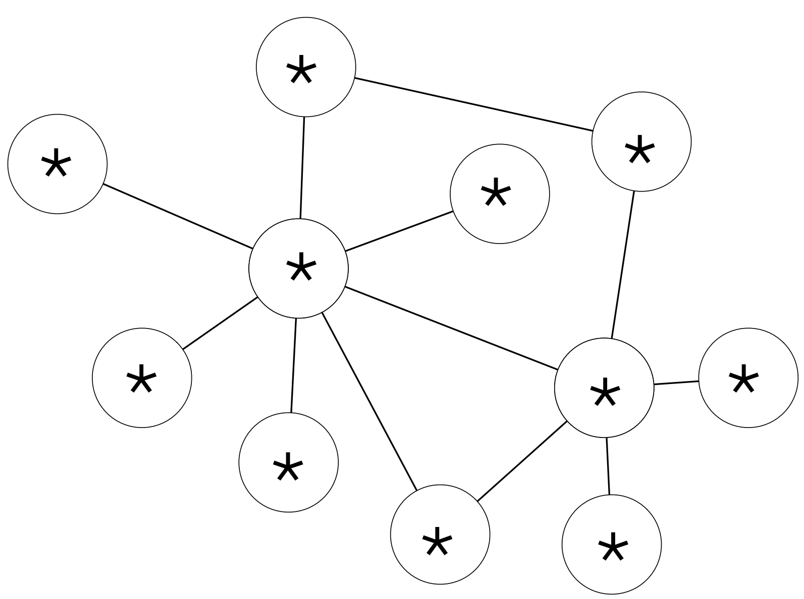
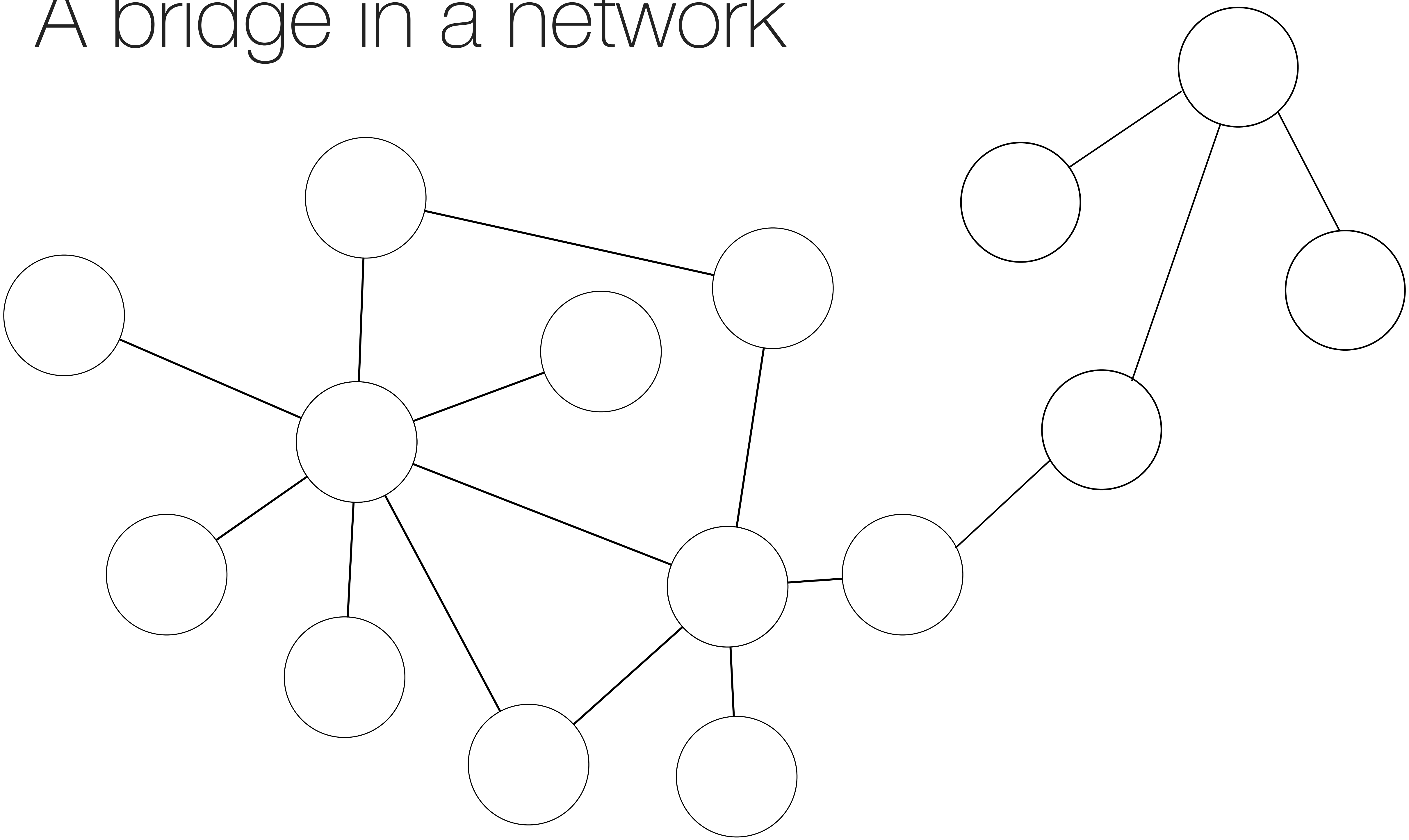


A network is connected iff it has one single component

A bridge in a network



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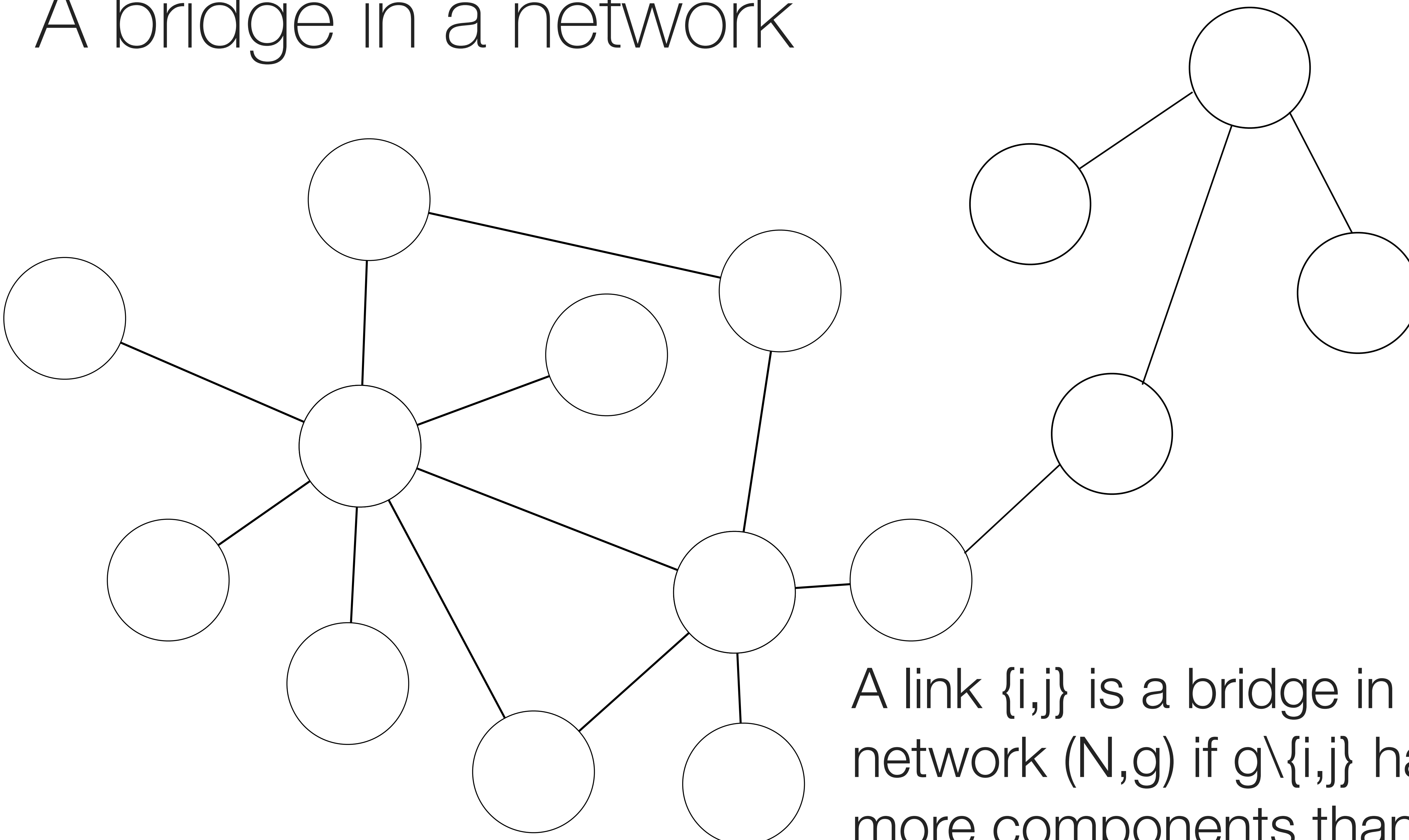
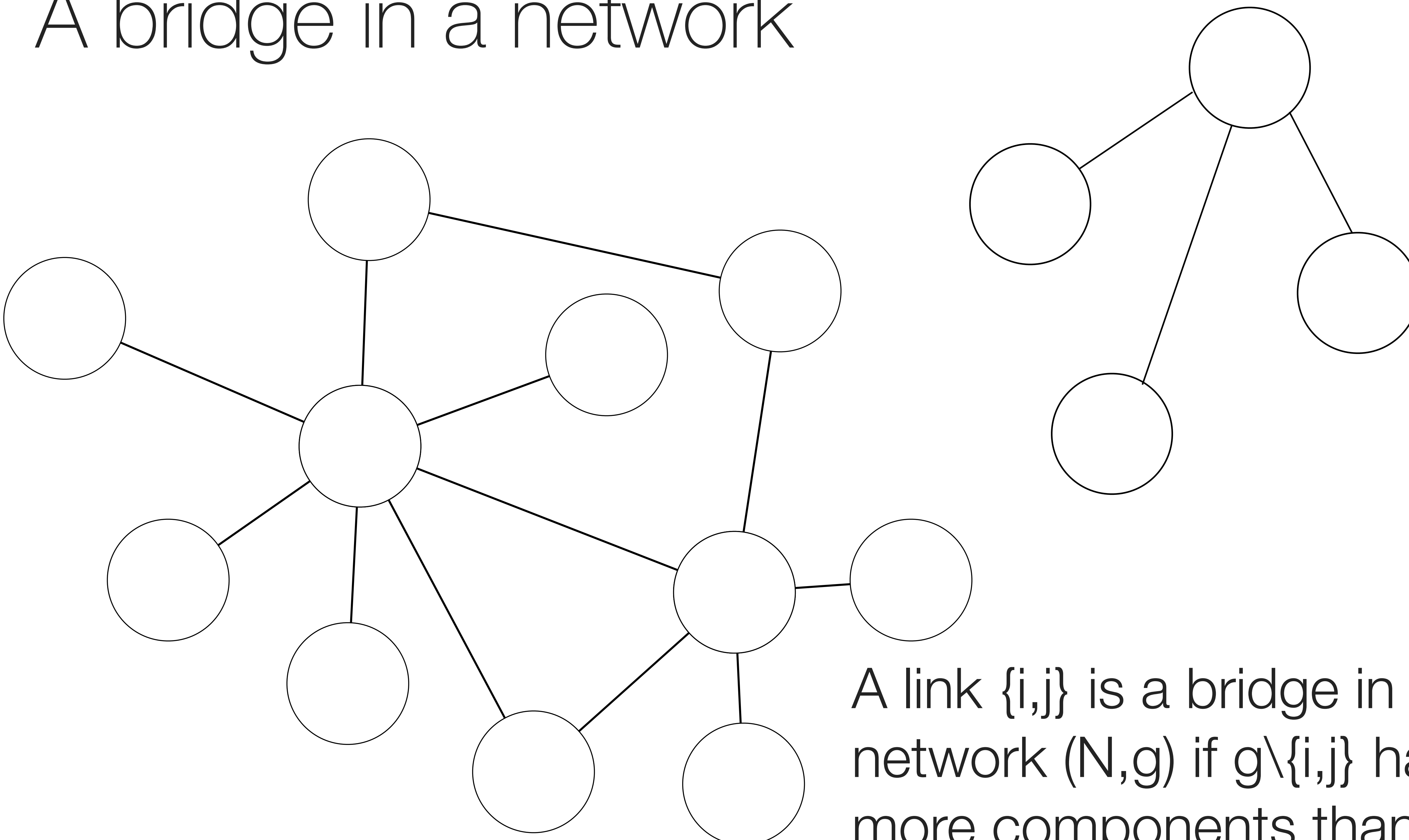


A link {i,j} is a bridge in the network (N,g) if g\{i,j} has more components than (N,g)

A bridge in a network



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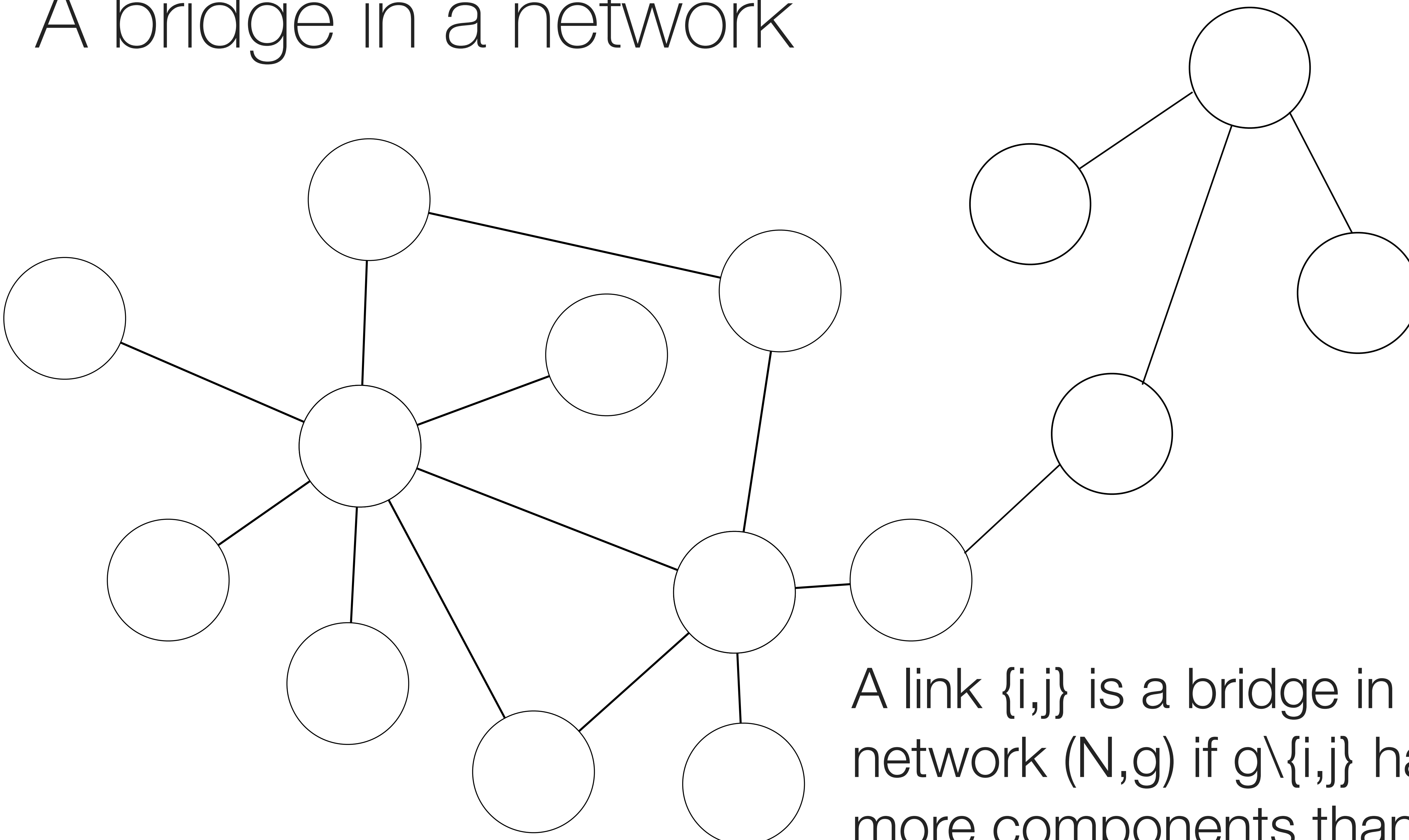

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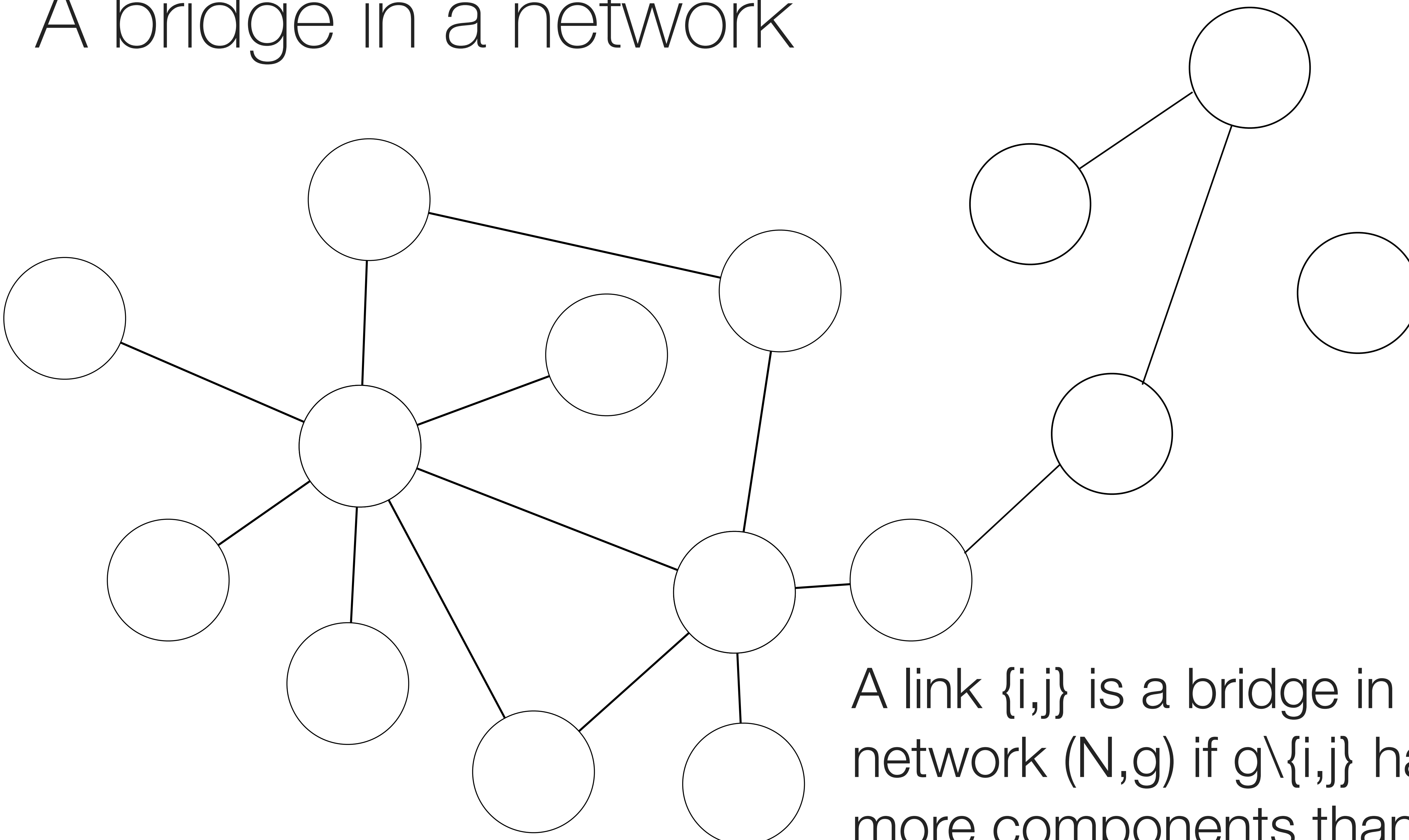

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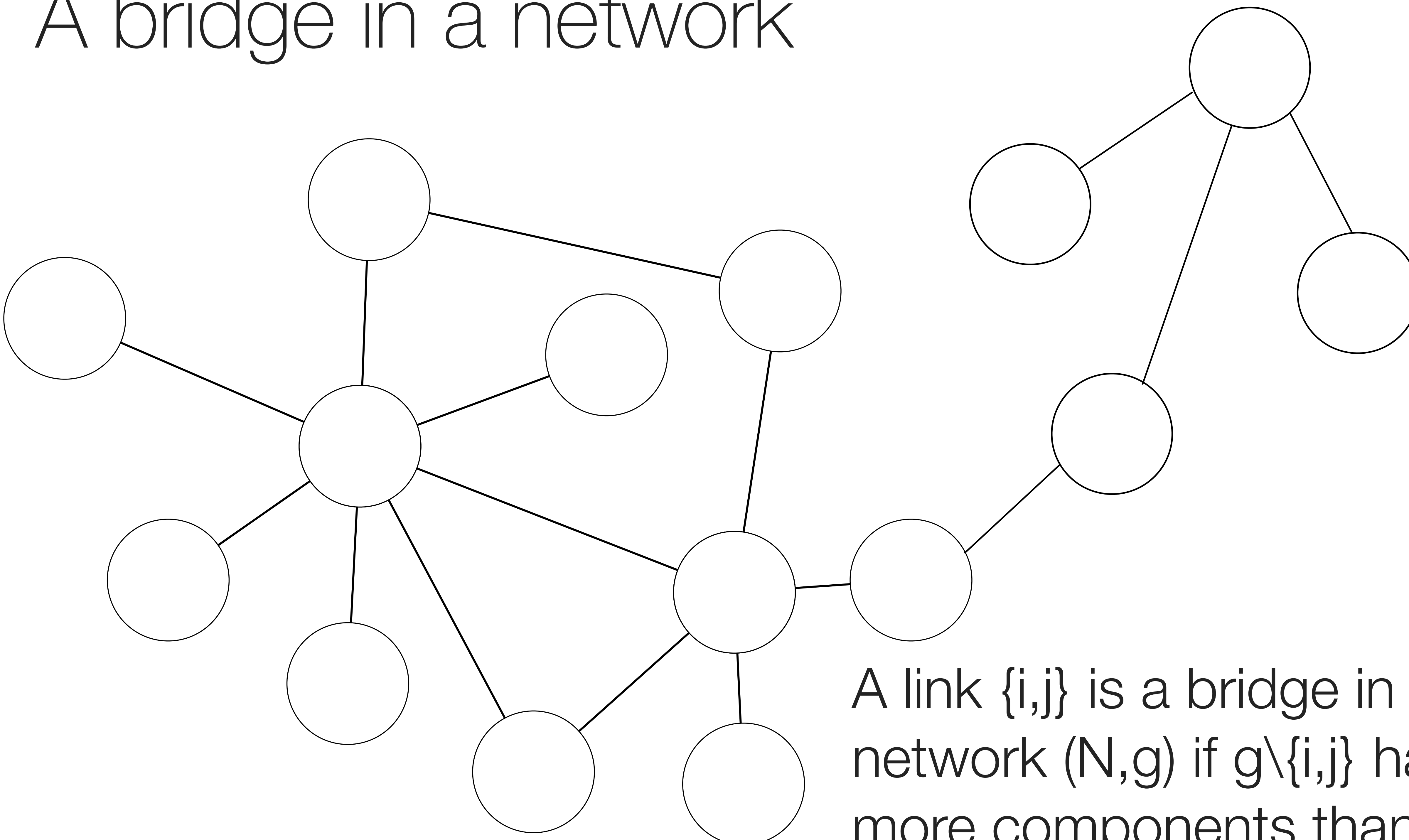

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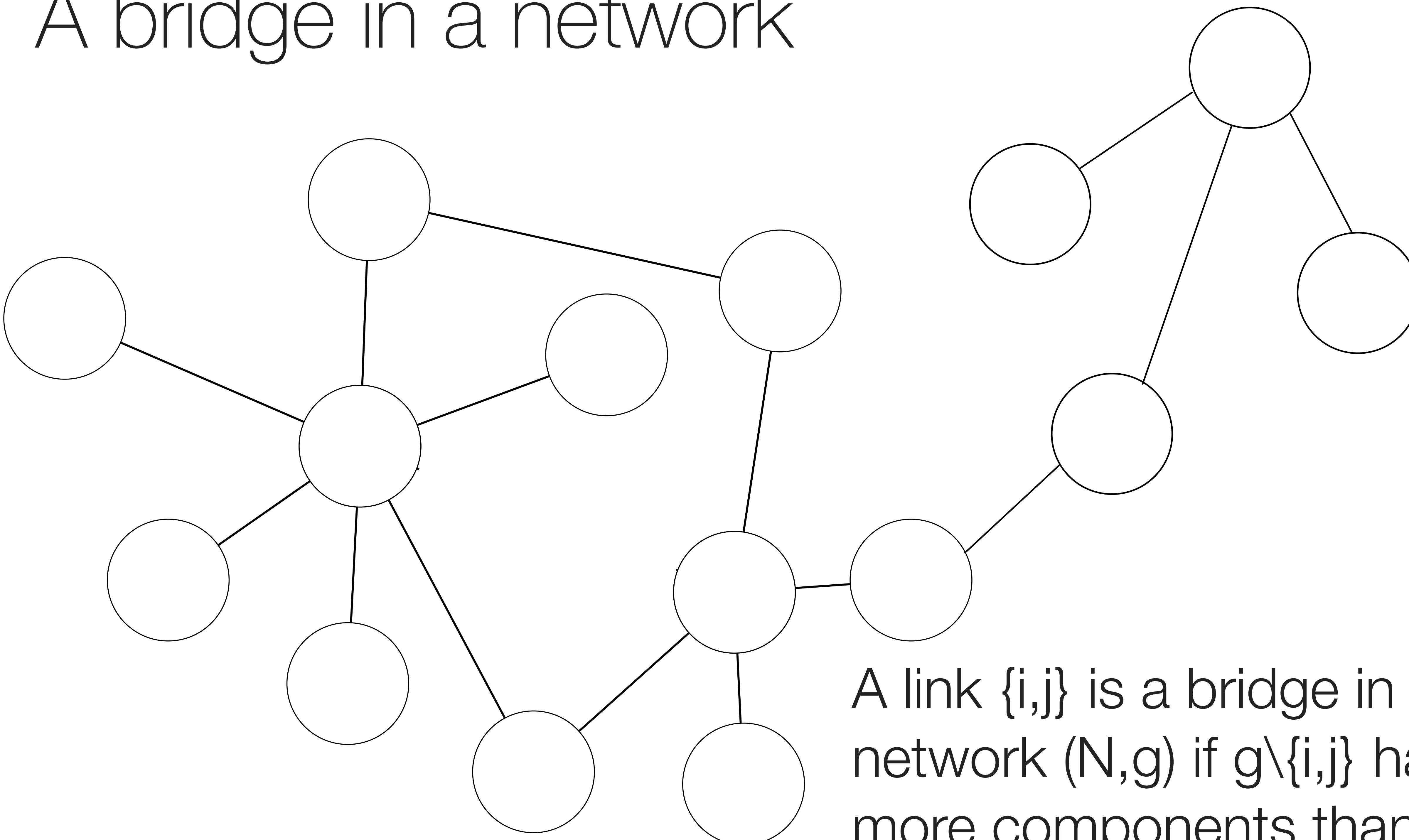

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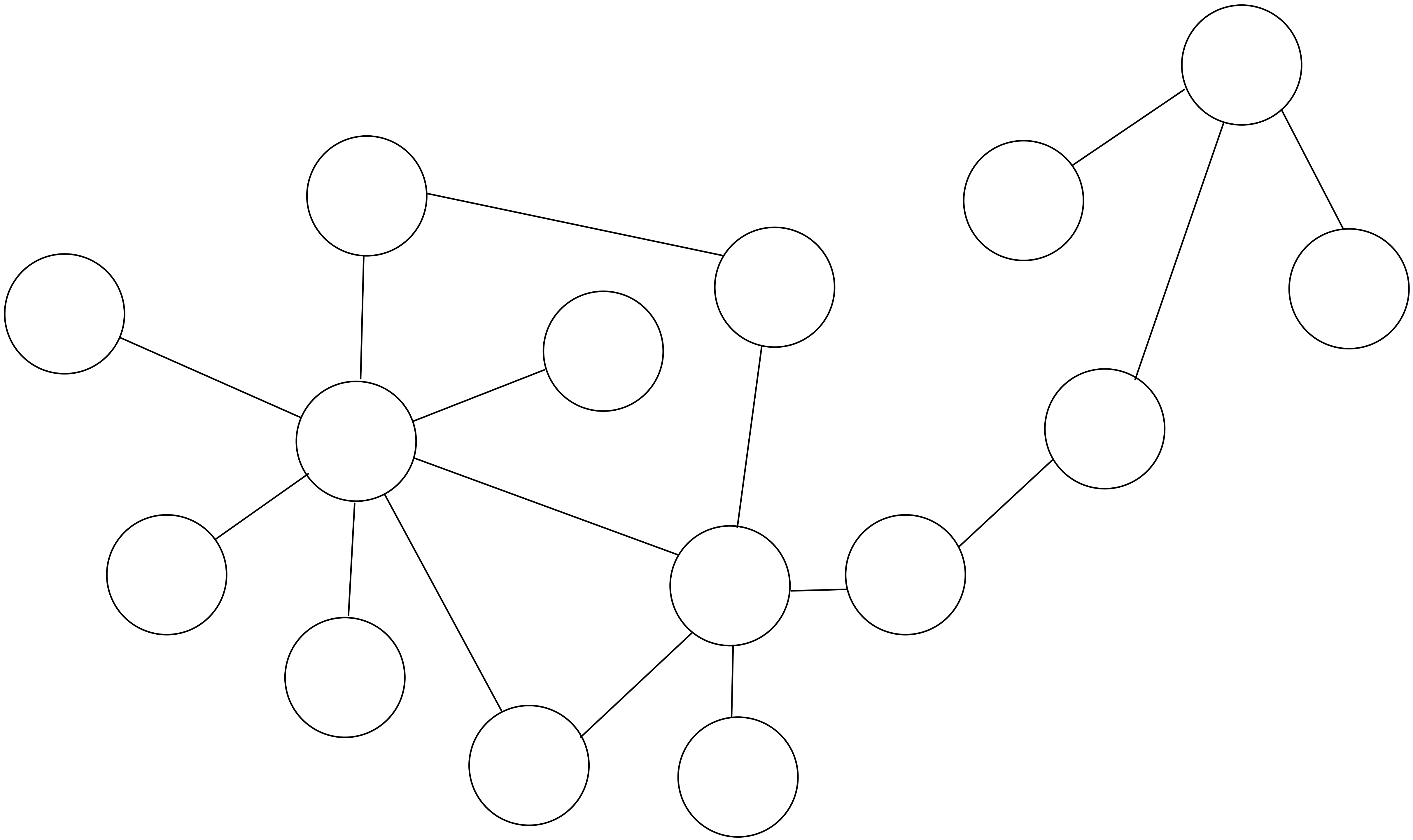
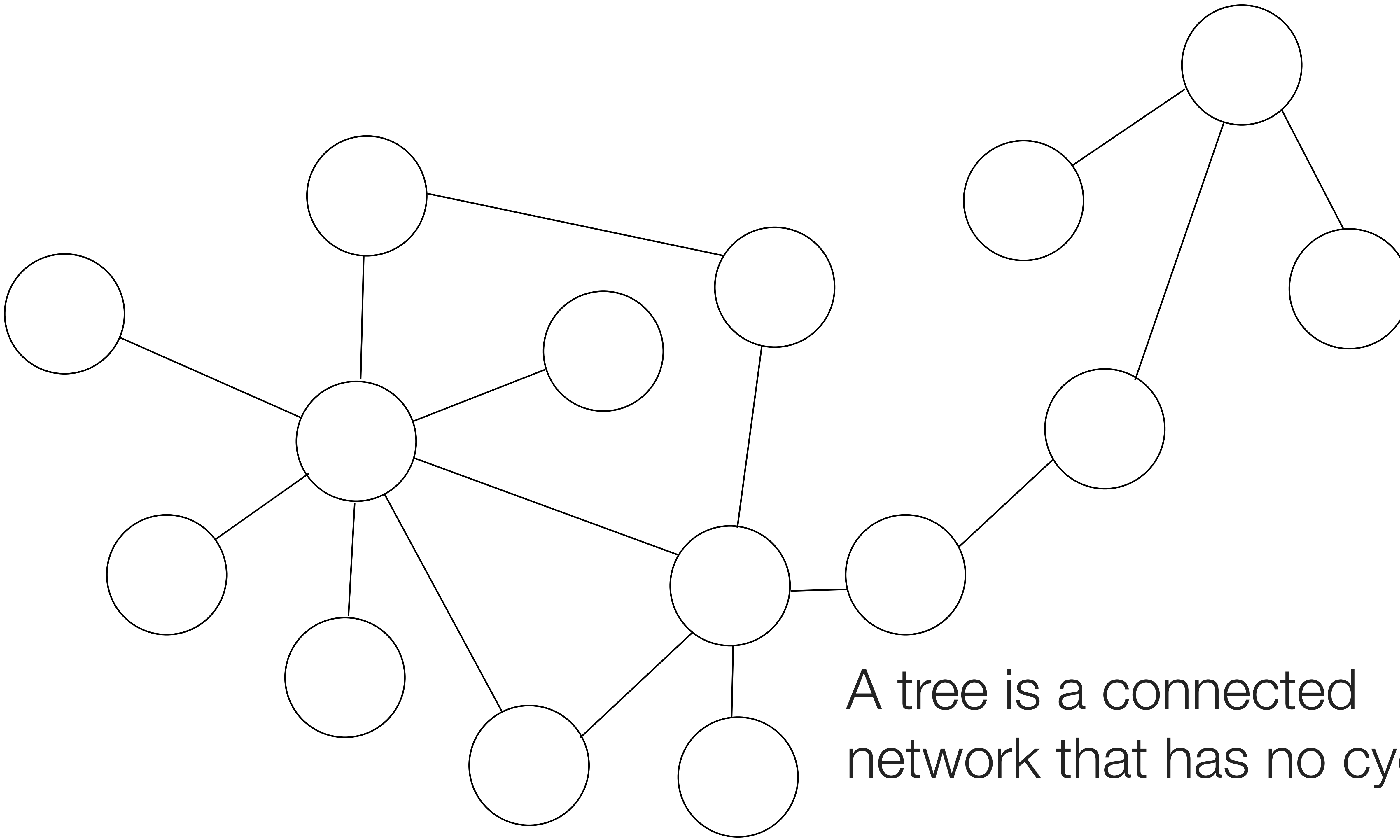
Trees, stars, circles, complete networks



Trees, stars, circles, complete networks



A tree is a connected network that has no cycles

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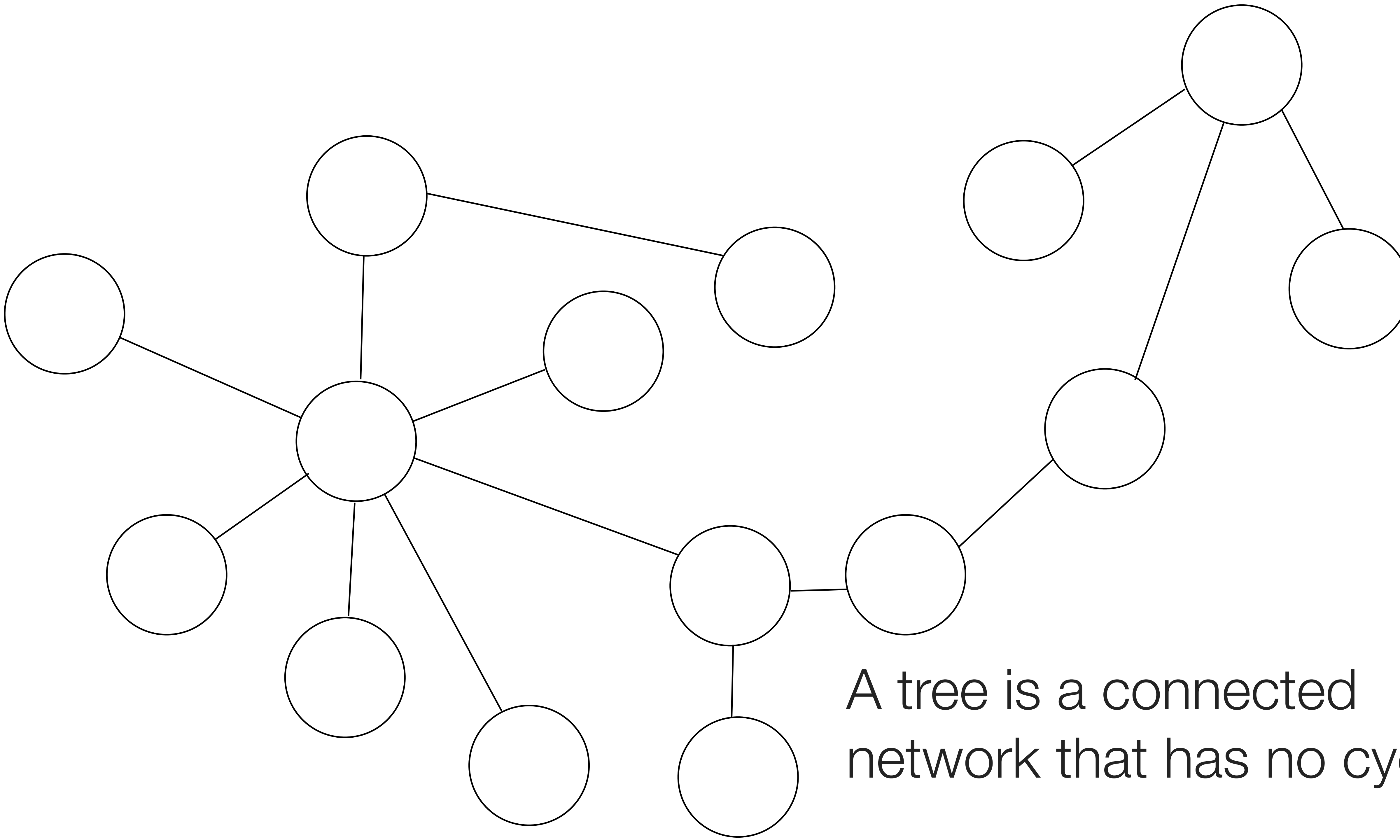

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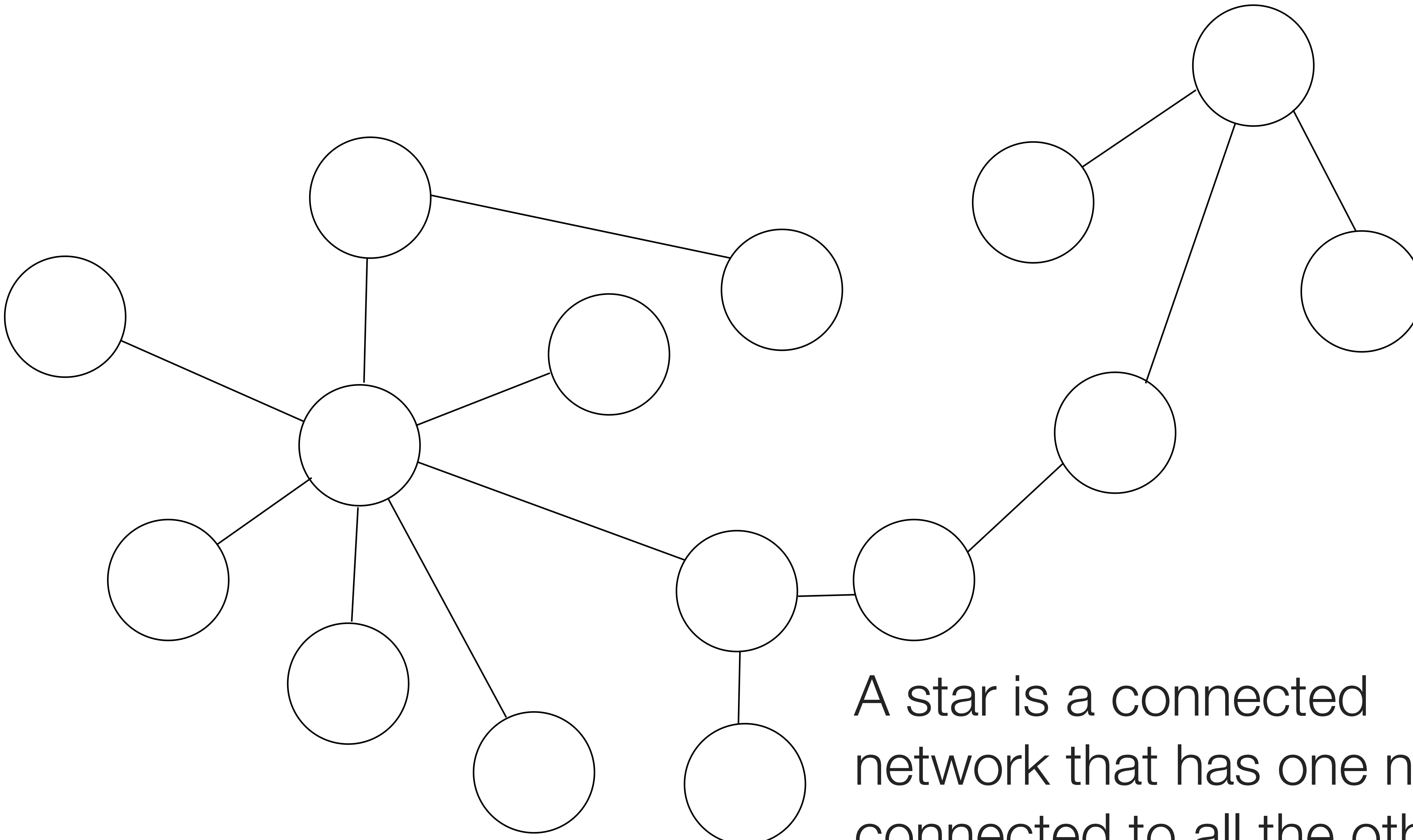
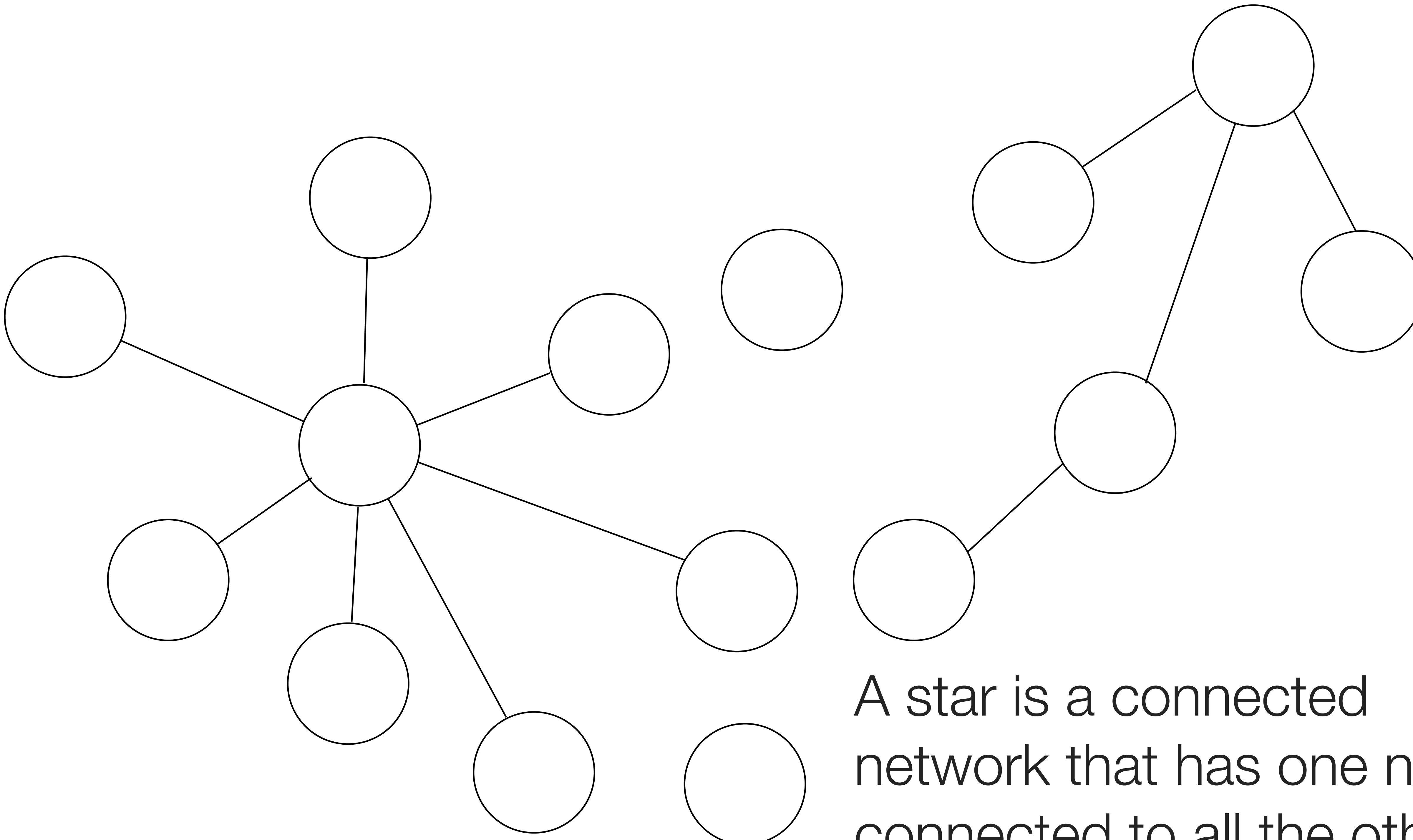


A star is a connected network that has one node connected to all the other nodes

Trees, stars, circles, complete networks



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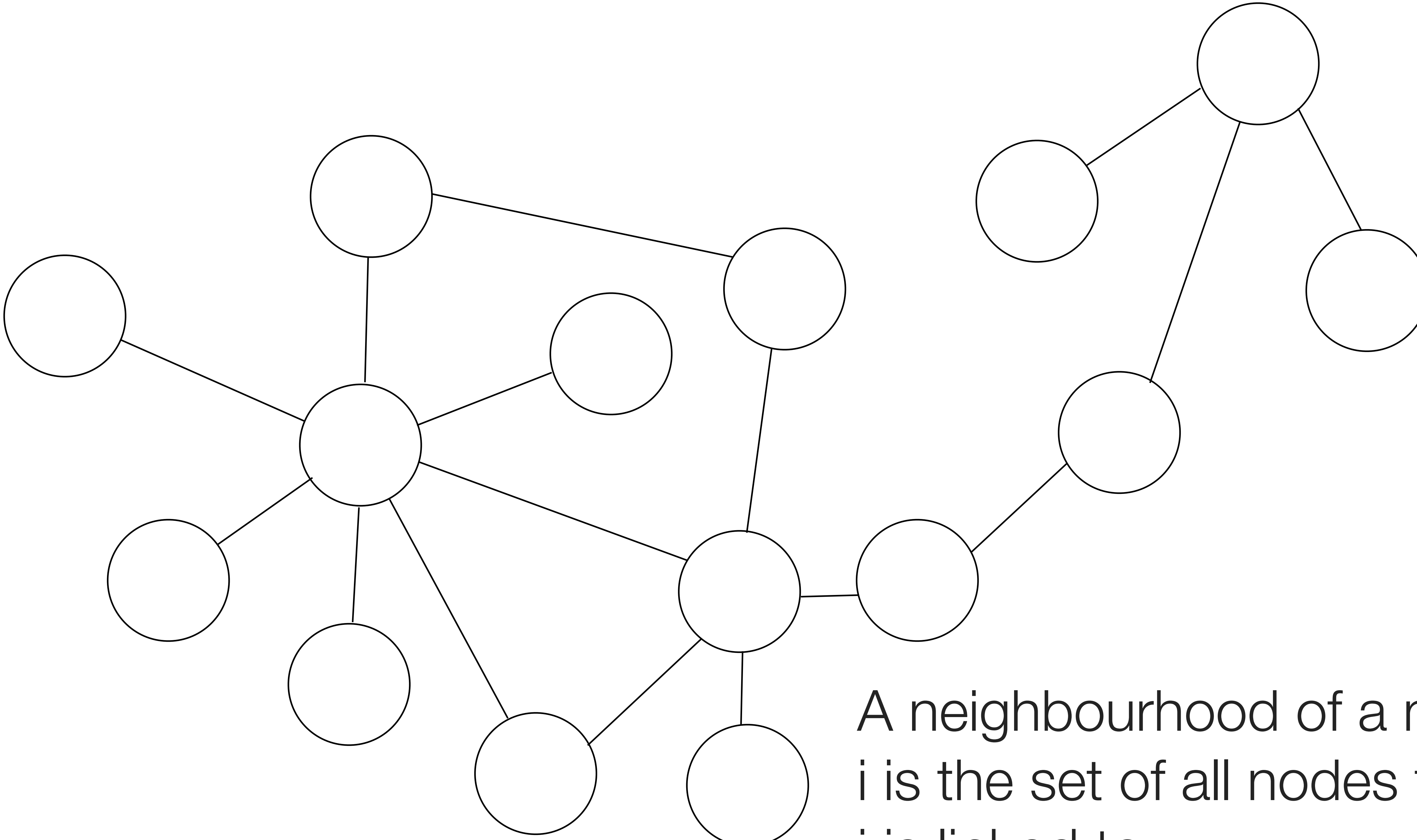
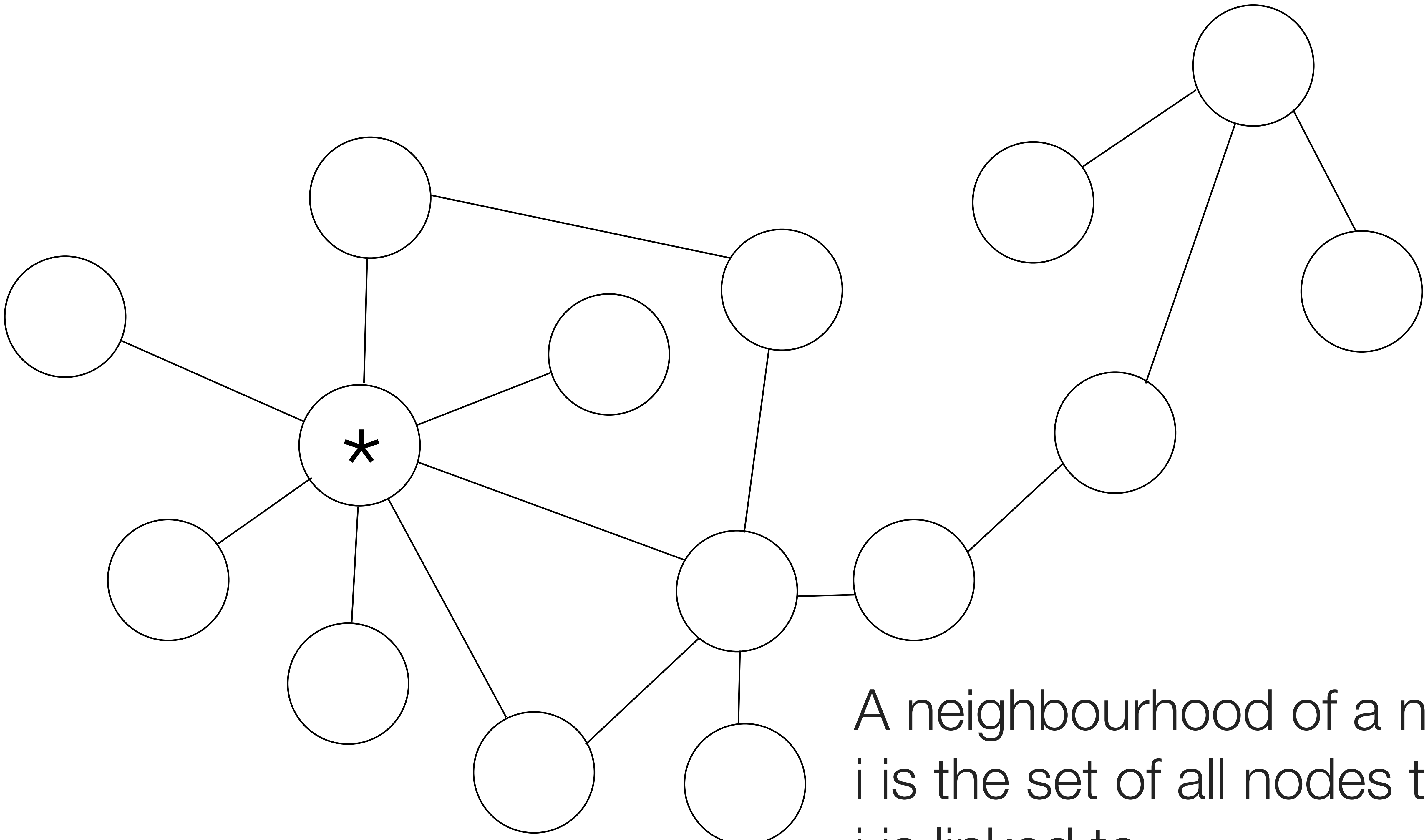
Neighbourhood



A neighbourhood of a node i is the set of all nodes that i is linked to

Neighbourhood



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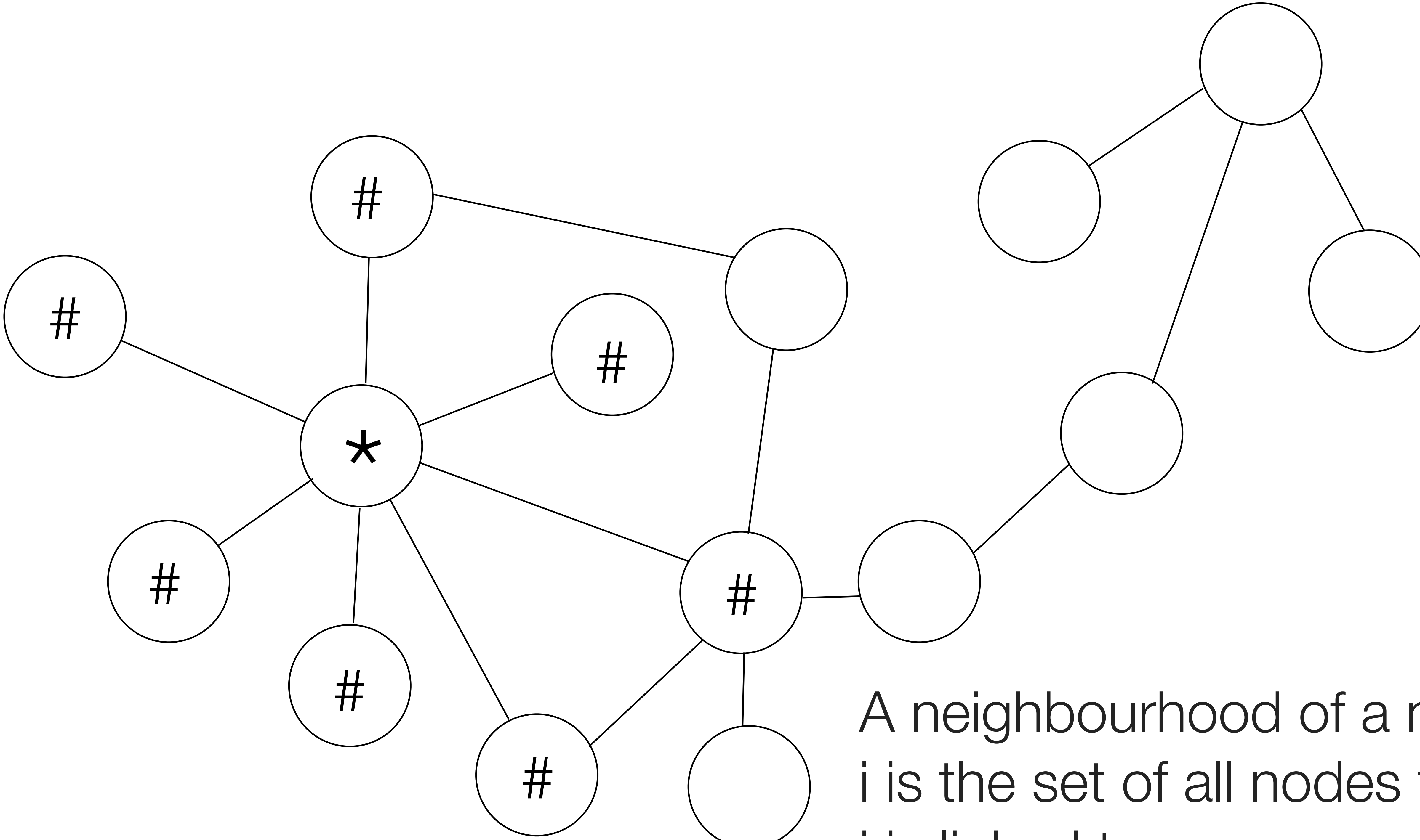

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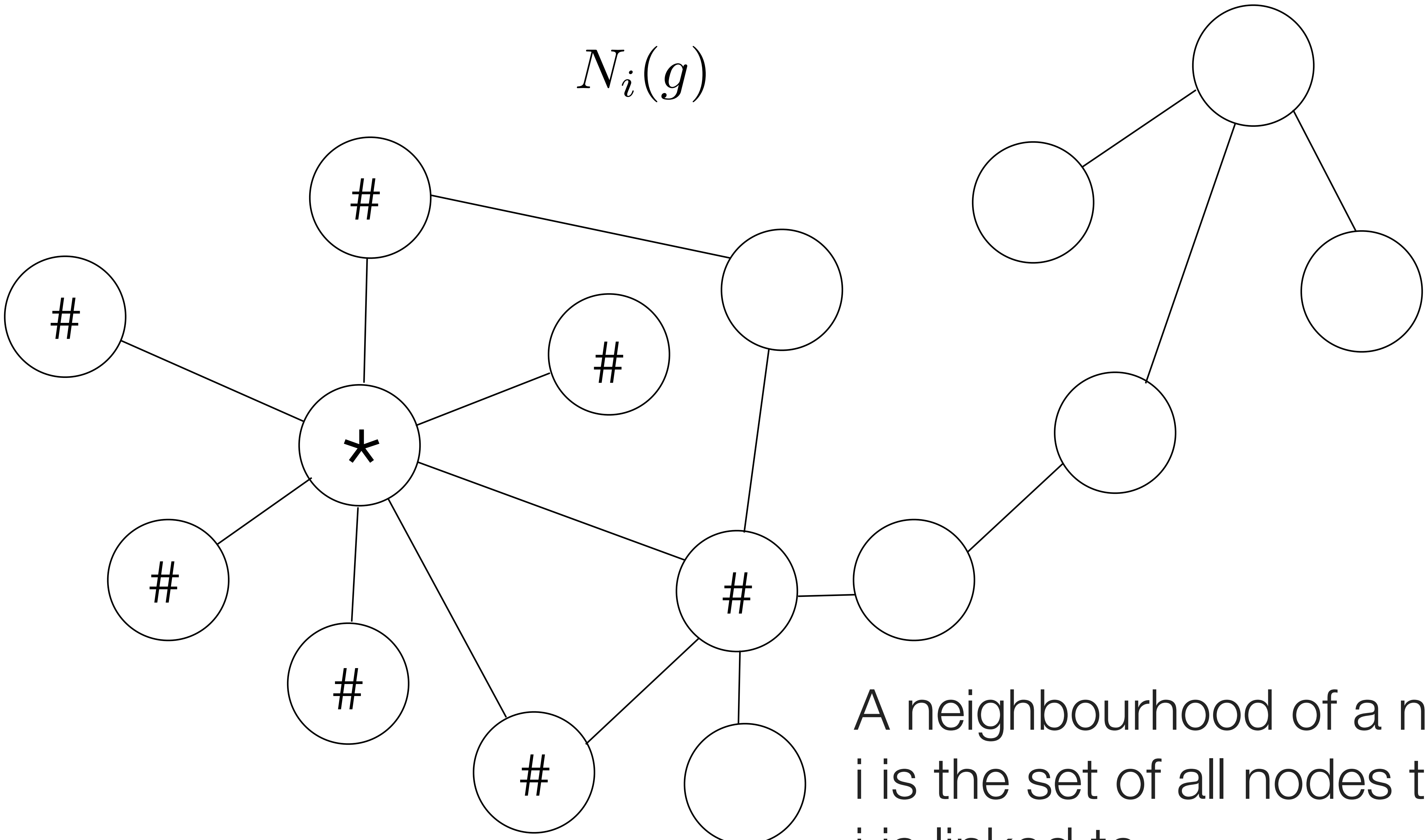
Neighbourhood

$N_i(g)$



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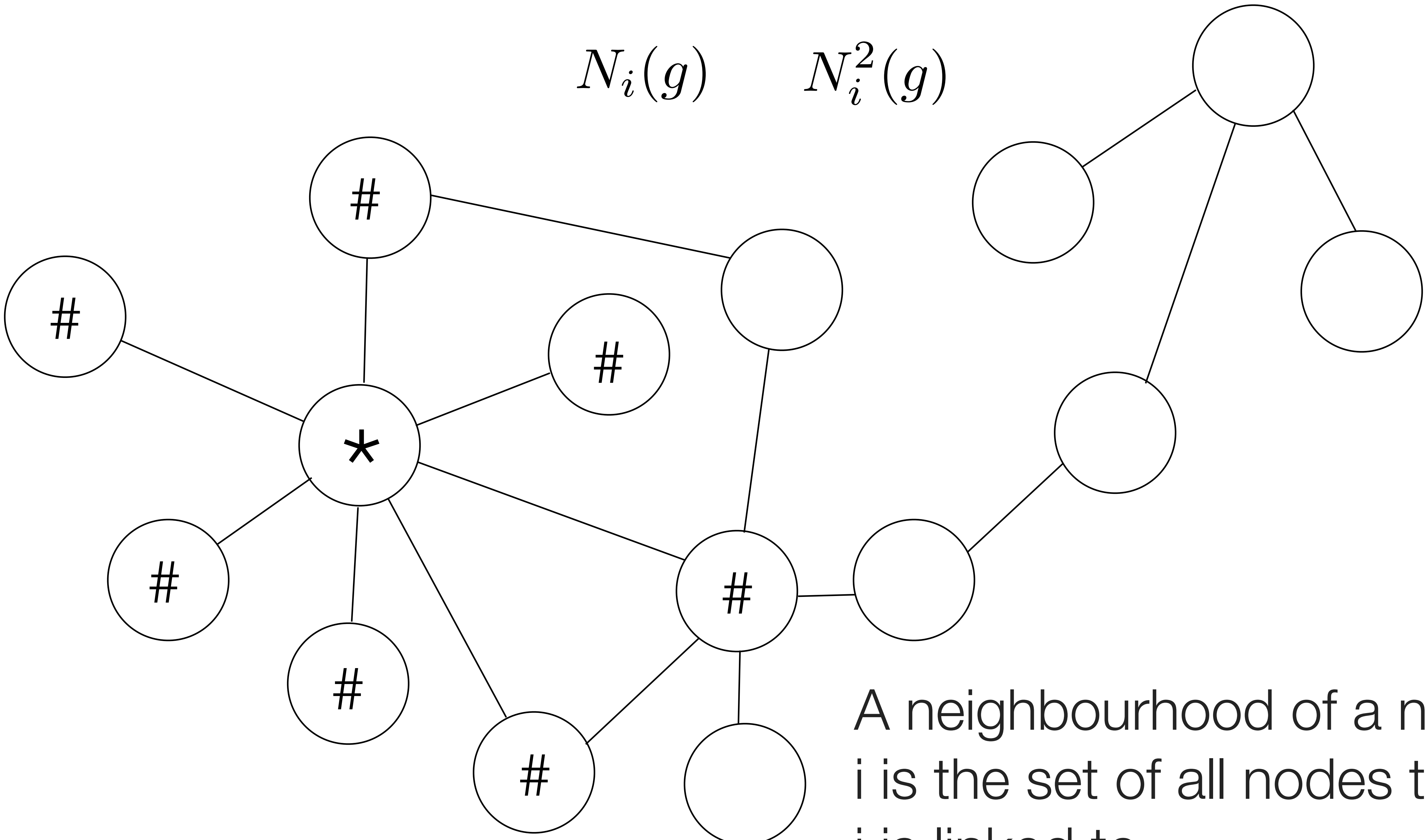
Neighbourhood

$N_i(g)$ $N_i^2(g)$



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Neighbourhood

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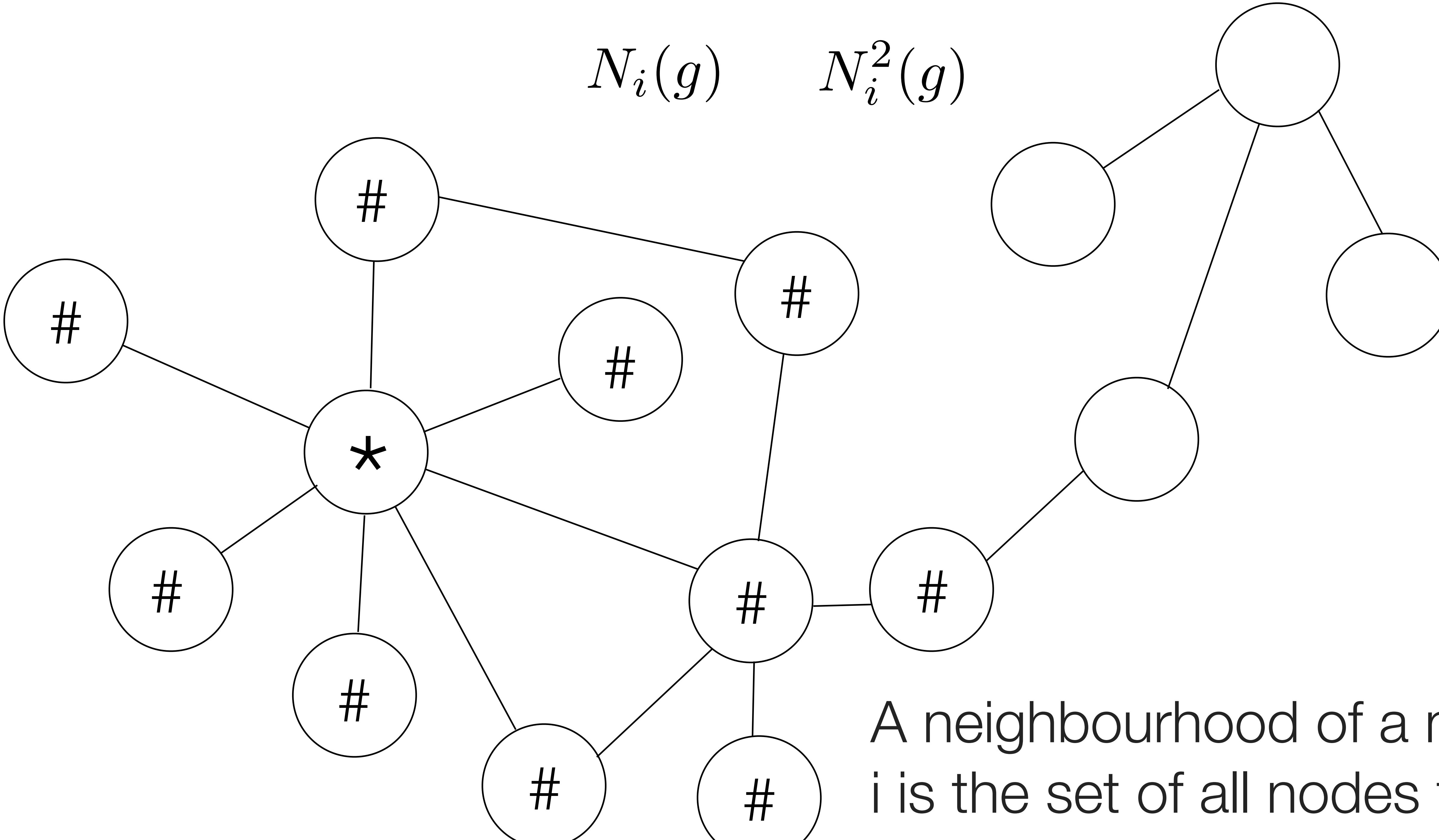

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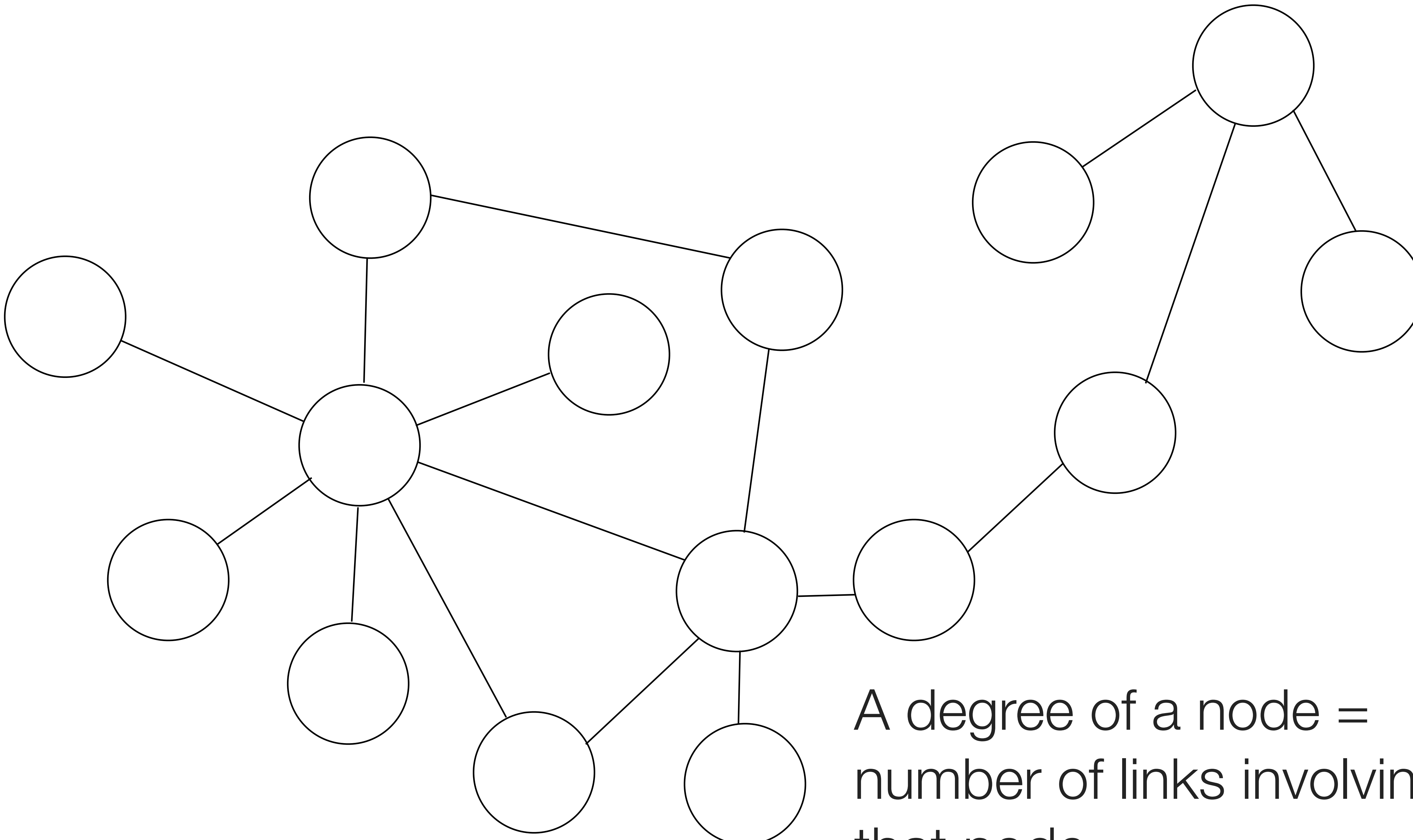
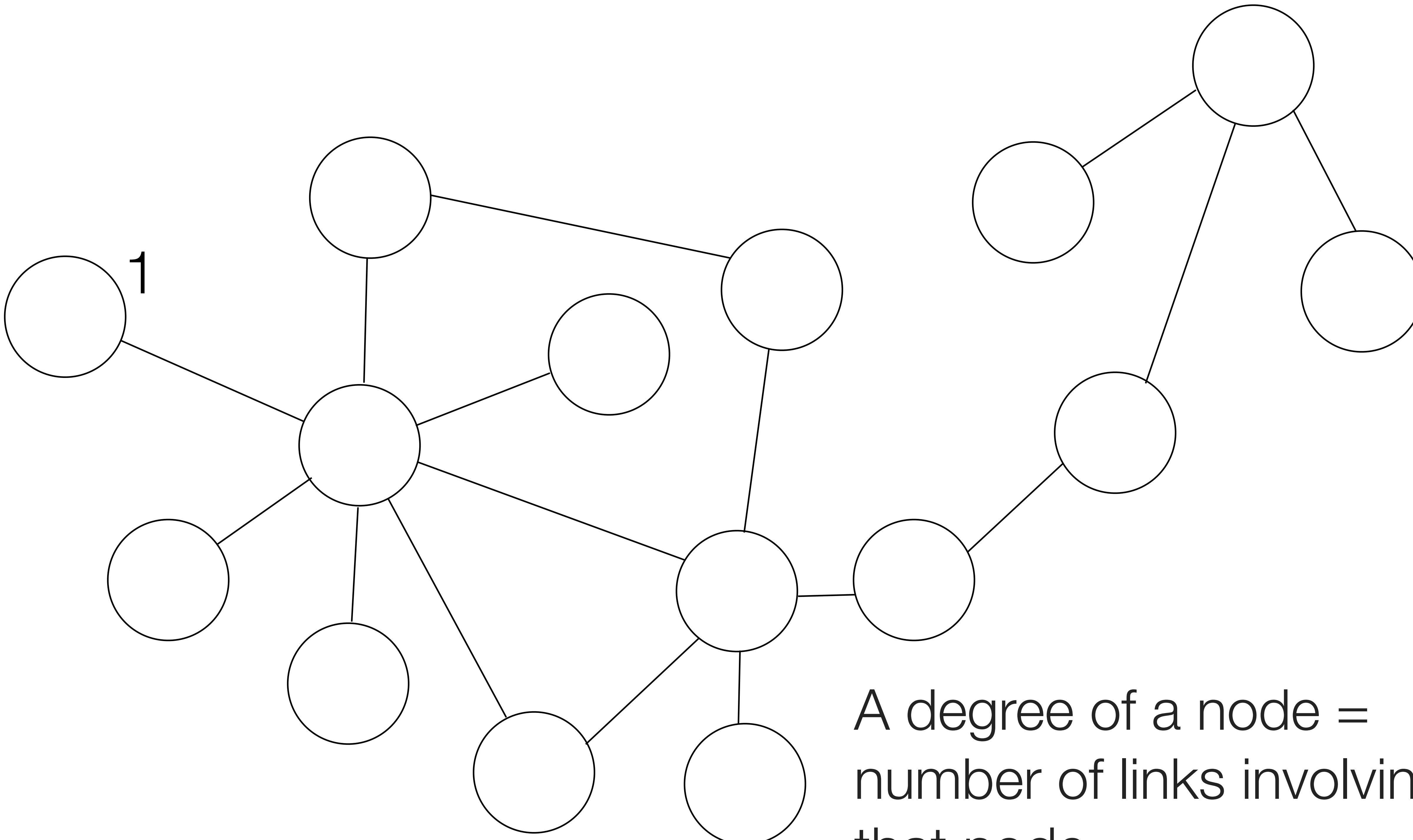
Degree, network density



A degree of a node = number of links involving that node

Degree, network density



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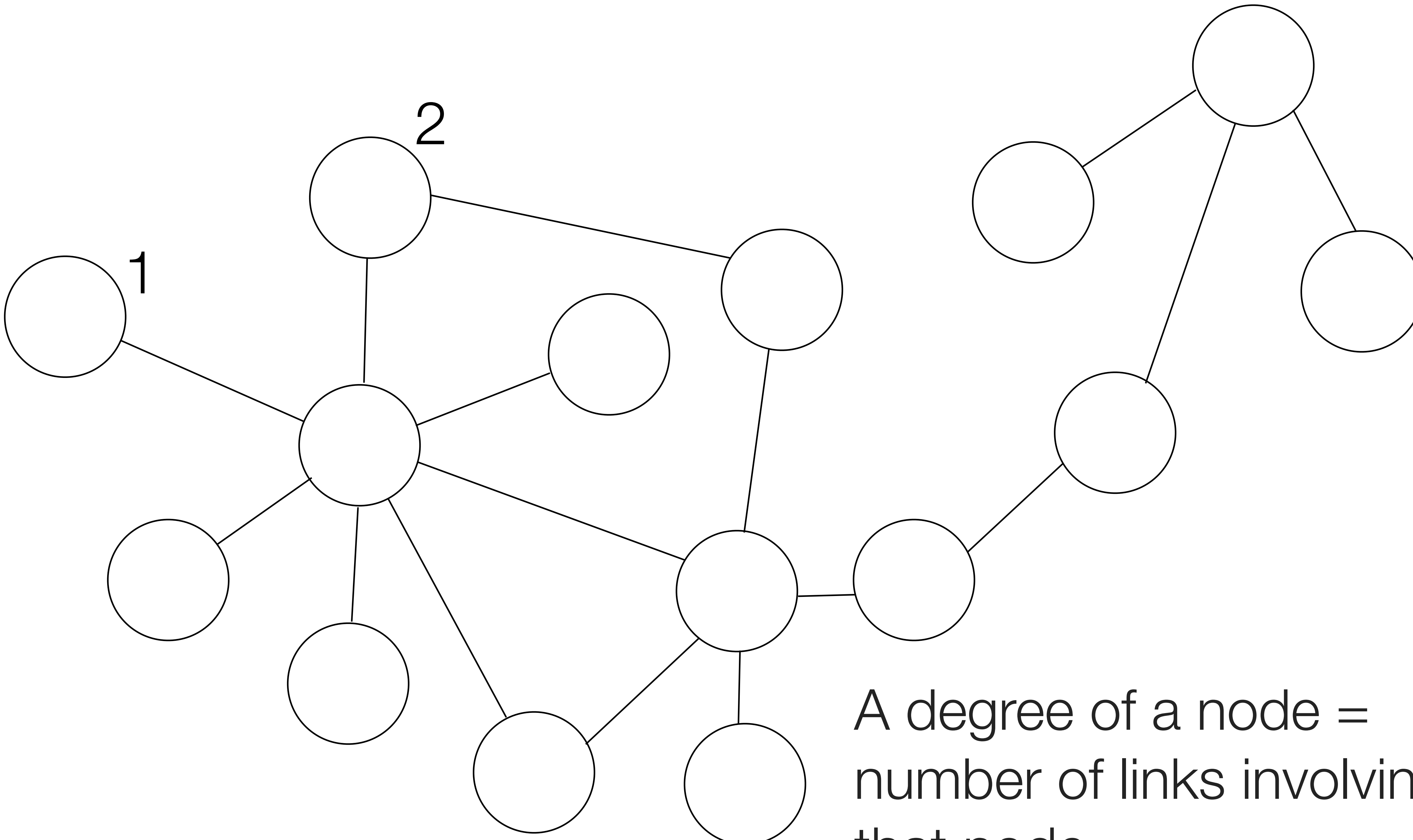

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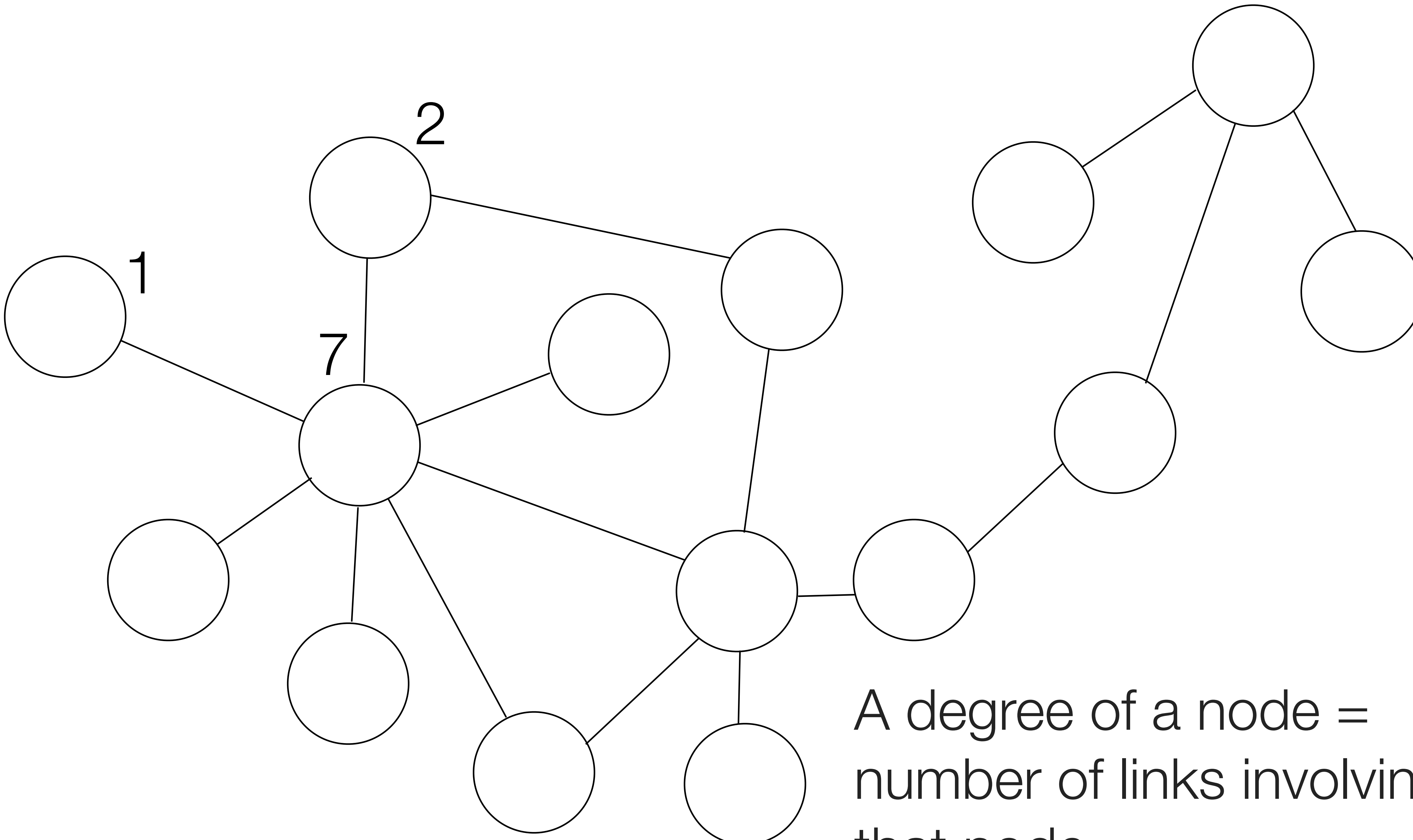

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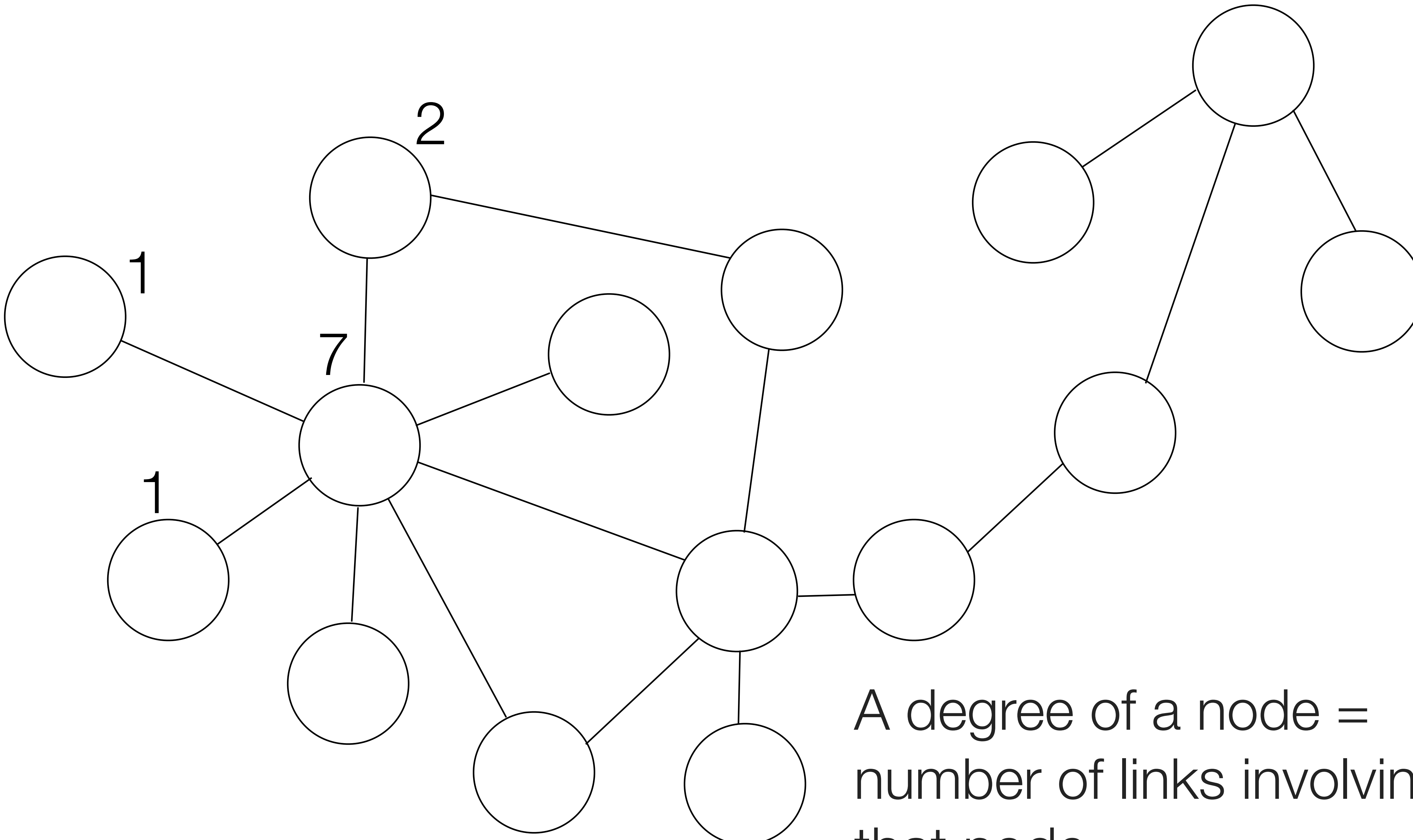

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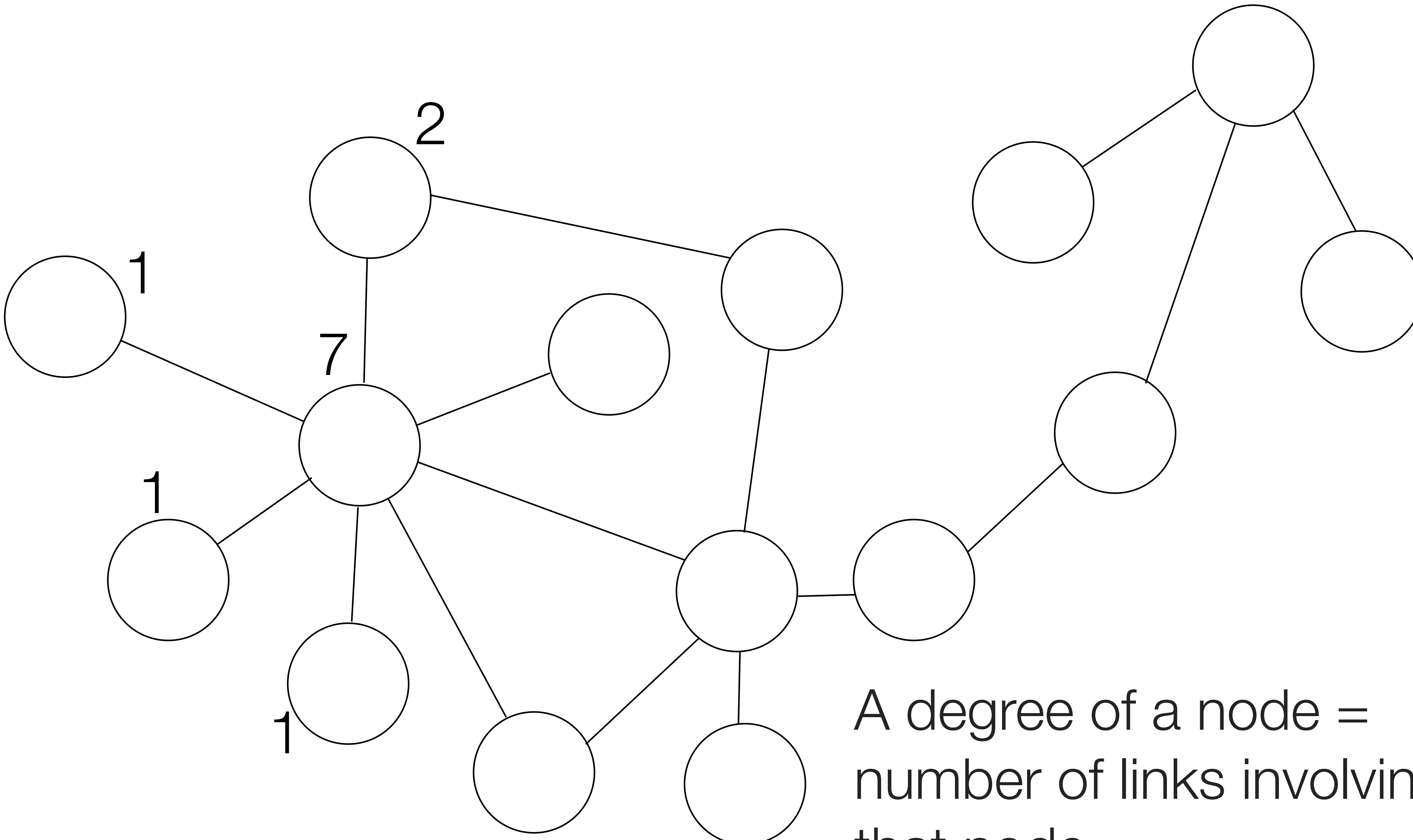

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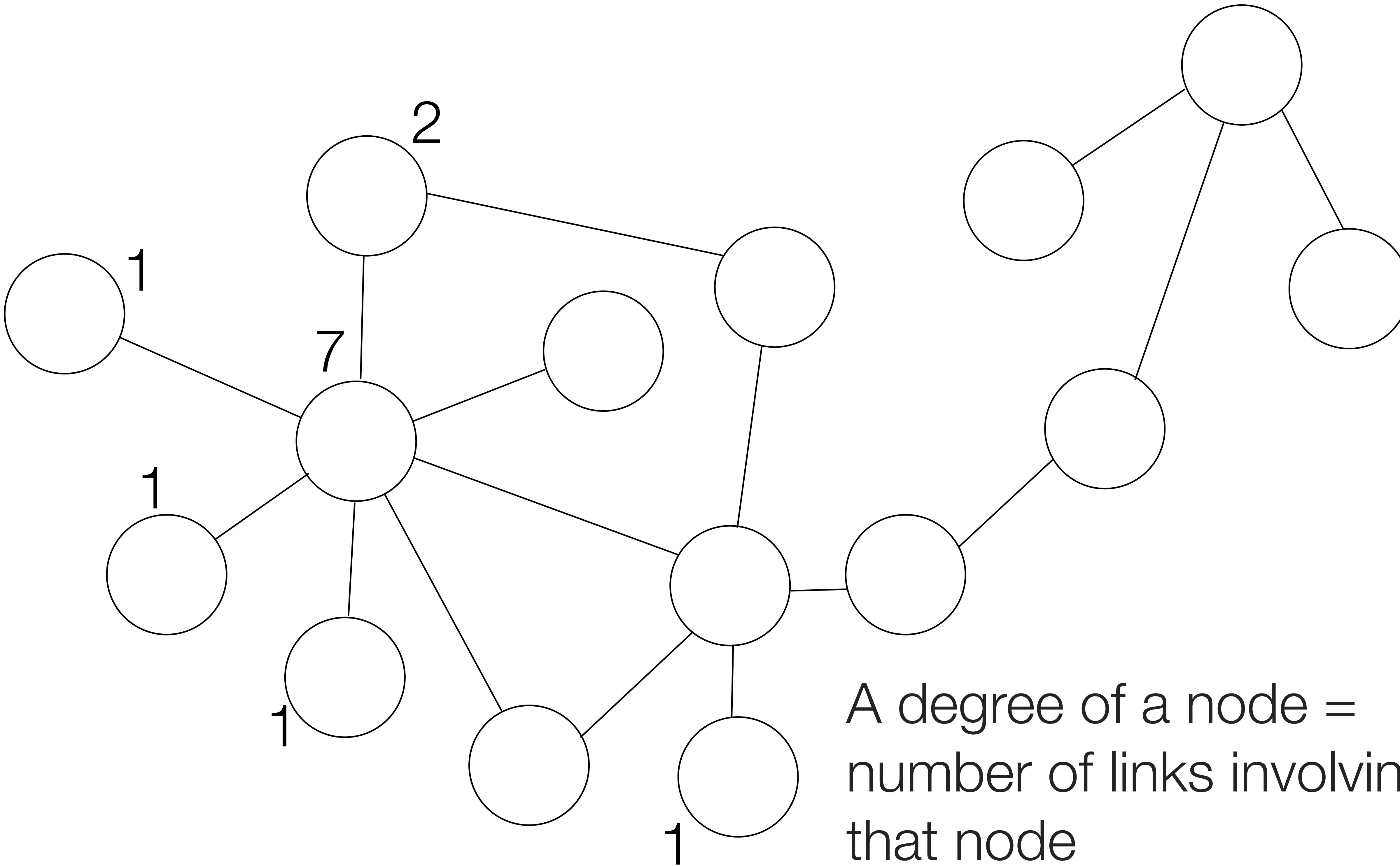

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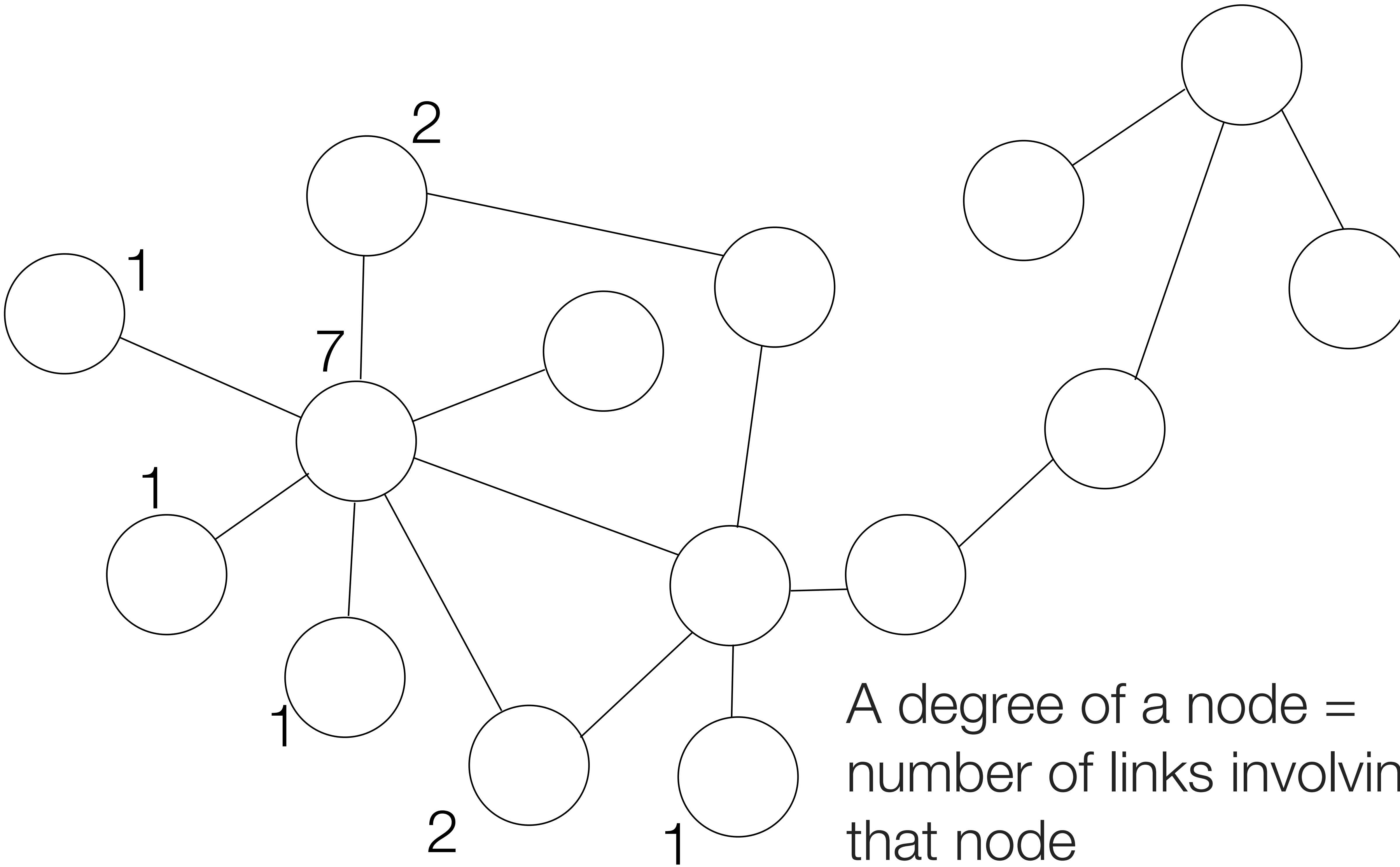

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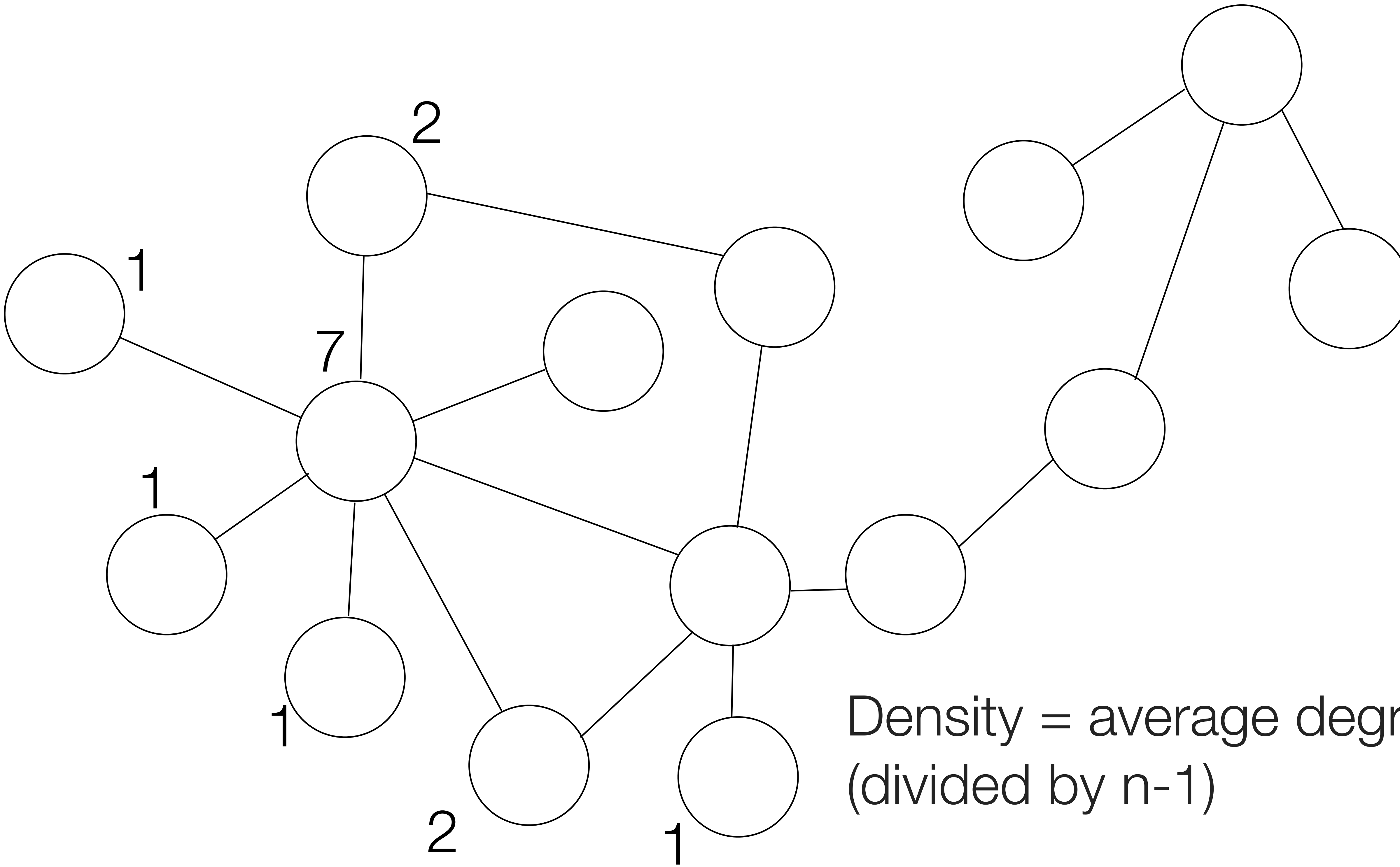

Density = average degree
(divided by n-1)

Degree distribution

The degree distribution of a network is a description of the relative frequency of nodes that have different degrees.

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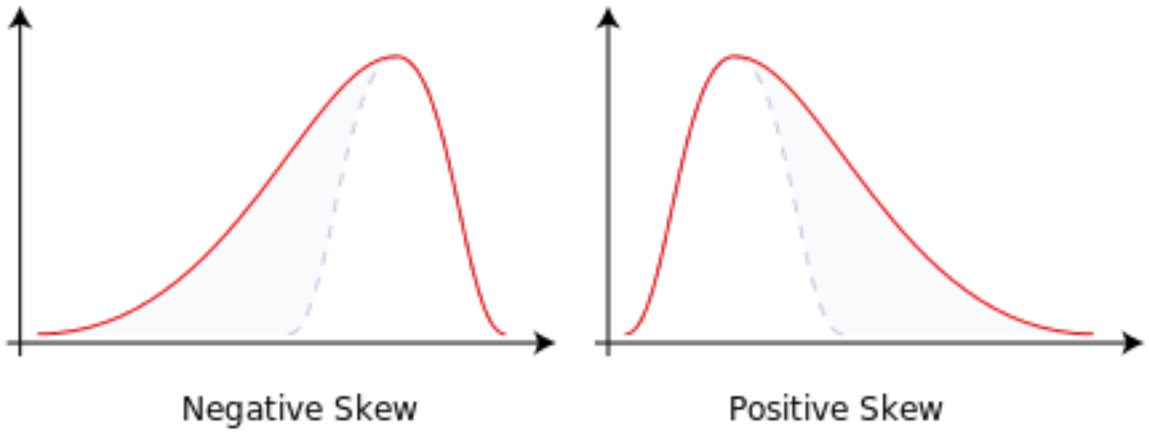
Regular network = all nodes have the same degree

Degree distribution



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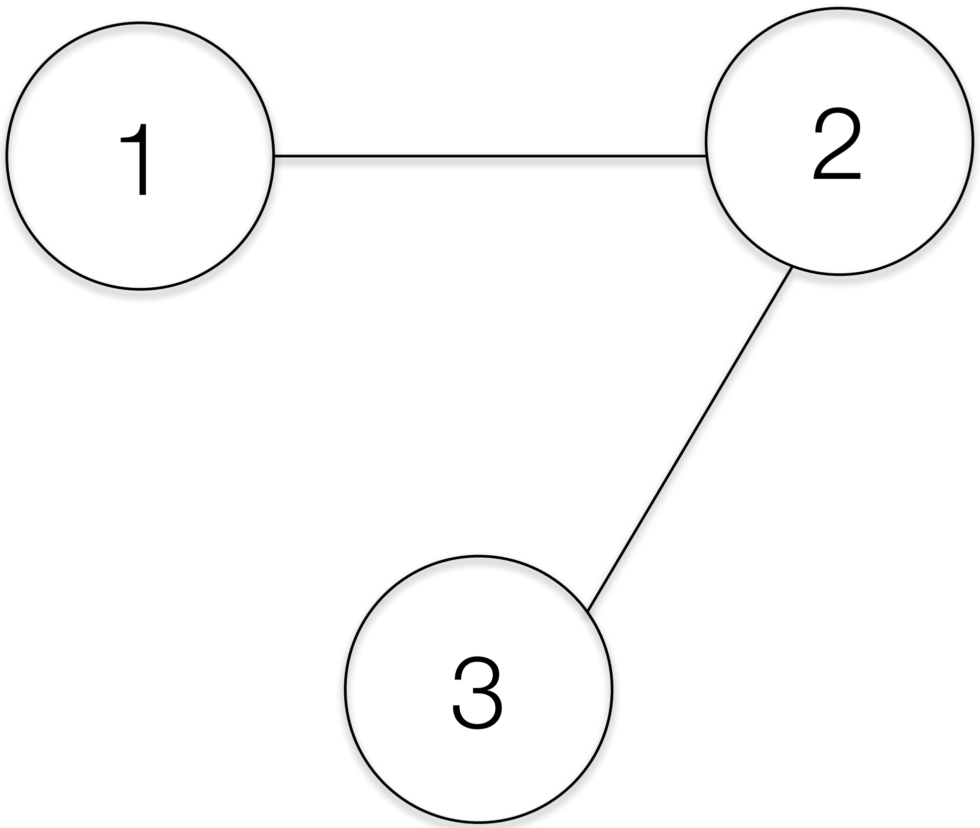
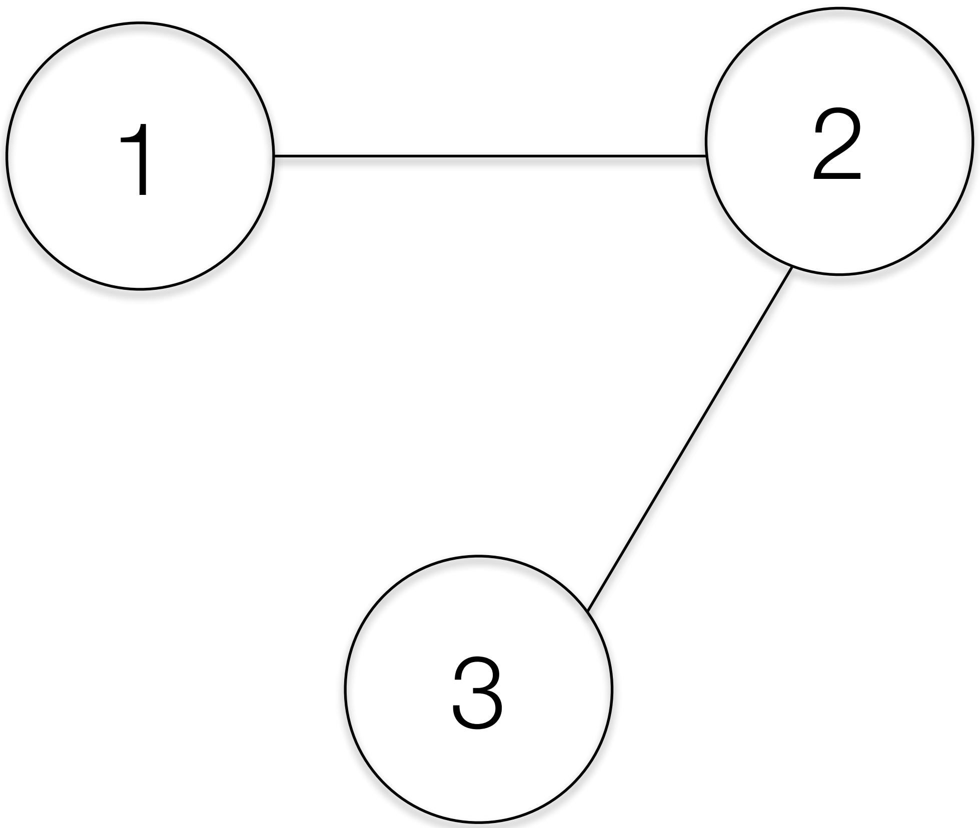
Random graphs



$$g = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Random graphs



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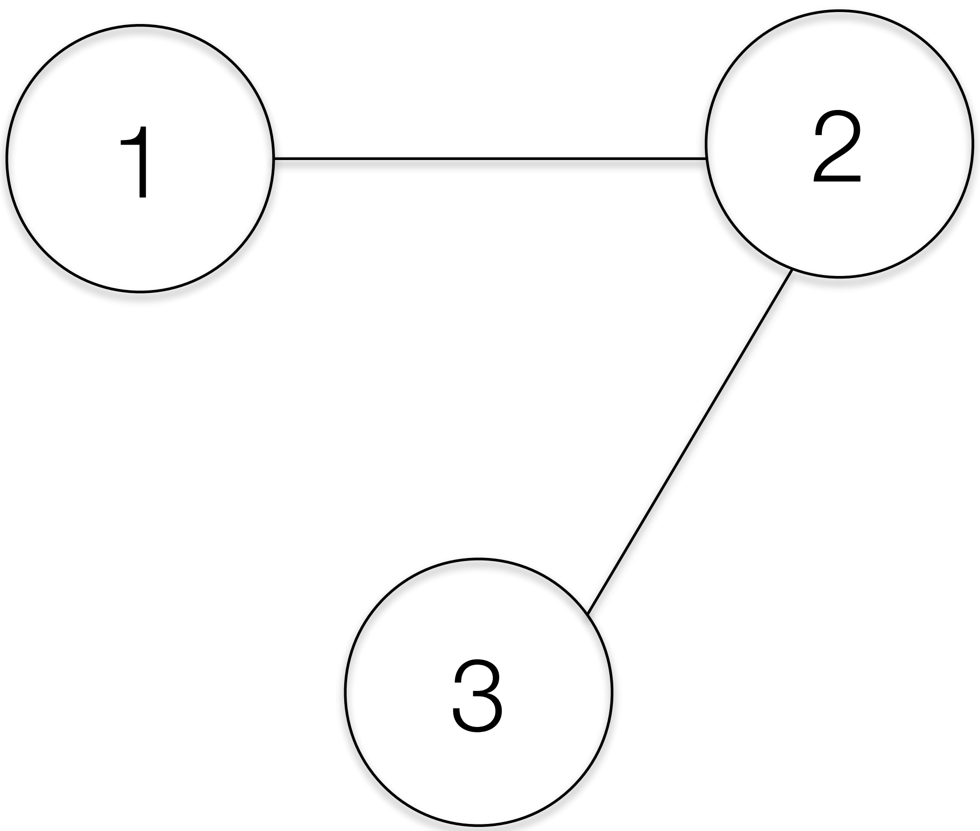

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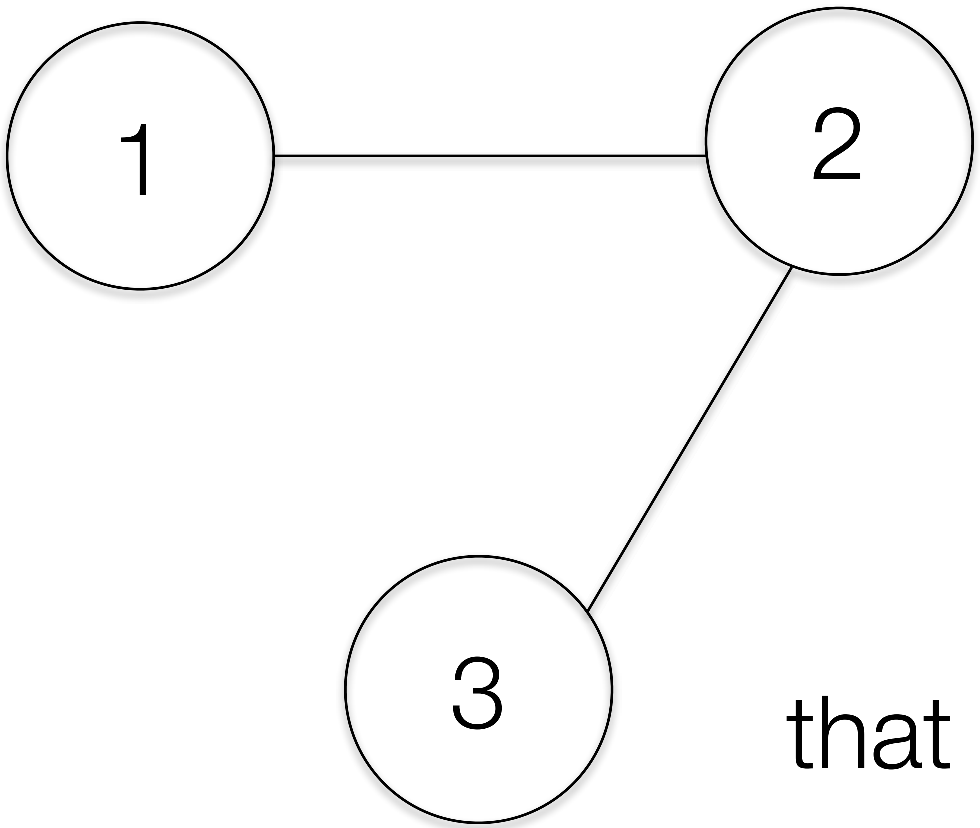

$$g = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

g_{ij} is now the probability
that an edge exists between i and j

Properties of social networks

Colloquium

Random graph models of social networks

M. E. J. Newman*†, D. J. Watts‡, and S. H. Strogatz§

*Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, NM 87501; ‡Department of Sociology, Columbia University, 1180 Amsterdam Avenue, New York, NY 10027; and §Department of Theoretical and Applied Mechanics, Cornell University, Ithaca, NY 14853-1503

We describe some new exactly solvable models of the structure of social networks, based on random graphs with arbitrary degree distributions. We give models both for simple unipartite networks, such as acquaintance networks, and bipartite networks, such as affiliation networks. We compare the predictions of our models to data for a number of real-world social networks and find that in some cases, the models are in remarkable agreement with the data, whereas in others the agreement is poorer, perhaps indicating the presence of additional social structure in the network that is not captured by the random graph.

A social network is a set of people or groups of people, "actors" in the jargon of the field, with some pattern of interactions or "ties" between them (1, 2). Friendships among a group of individuals, business relationships between companies, and intermarriages between families are all examples of networks that have been studied in the past. Network analysis has

actually connected by a very short chain of intermediate acquaintances. He found this chain to be of typical length of only about six, a result which has passed into folklore by means of John Guare's 1990 play *Six Degrees of Separation* (10). It has since been shown that many networks have a similar small-world property (11–14).

It is worth noting that the phrase "small world" has been used to mean a number of different things. Early on, sociologists used the phrase both in the conversational sense of two strangers who discover that they have a mutual friend—i.e., that they are separated by a path of length two—and to refer to any short path between individuals (8, 9). Milgram talked about the "small-world problem," meaning the question of how two people can have a short connecting path of acquaintances in a network that has other social structure such as insular communities or geographical and cultural barriers. In more recent work, D.J.W. and S.H.S. (11) have used the phrase "small-world network" to mean

Properties of social networks

Properties of social networks

- “small-world” property - maximal degree of separation is low (6)

Proper

An Experimental Study of the Small World Problem
Author(s): Jeffrey Travers and Stanley Milgram
Source: *Sociometry*, Vol. 32, No. 4 (Dec., 1969), pp. 425-443
Published by: American Sociological Association
Stable URL: http://www.jstor.org/stable/2786545
Accessed: 23/09/2010 13:05

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Letter | Published: 04 June 1998

Collective dynamics of ‘small-world’ networks

Duncan J. Watts & Steven H. Strogatz

Nature **393**, 440–442 (04 June 1998) | Download Citation

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Statistical mechanics of complex networks

Réka Albert and Albert-László Barabási
Rev. Mod. Phys. **74**, 47 – Published 30 January 2002

Properties of social networks

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information

MDPI

Review

A Survey on Information Diffusion in Online Social Networks: Models and Methods

Mei Li *, Xiang Wang, Kai Gao and Shanshan Zhang

School of Information Science and Engineering, Hebei University of Science and Technology, Shijiazhuang 050018, China; wangxiang@hebust.edu.cn (X.W.); gaokai@hebust.edu.cn (K.G.); zshanshanmiss@gmail.com (S.Z.)

* Correspondence: limei@hebust.edu.cn; Tel.: +86-139-3317-5921

Received: 16 August 2017; Accepted: 22 September 2017; Published: 29 September 2017

Diffusion as infection

Phys Rev Lett. 2001 Apr 2;86(14):3200-3.

Epidemic spreading in scale-free networks.

Pastor-Satorras R[1], Vespignani A.

Author information

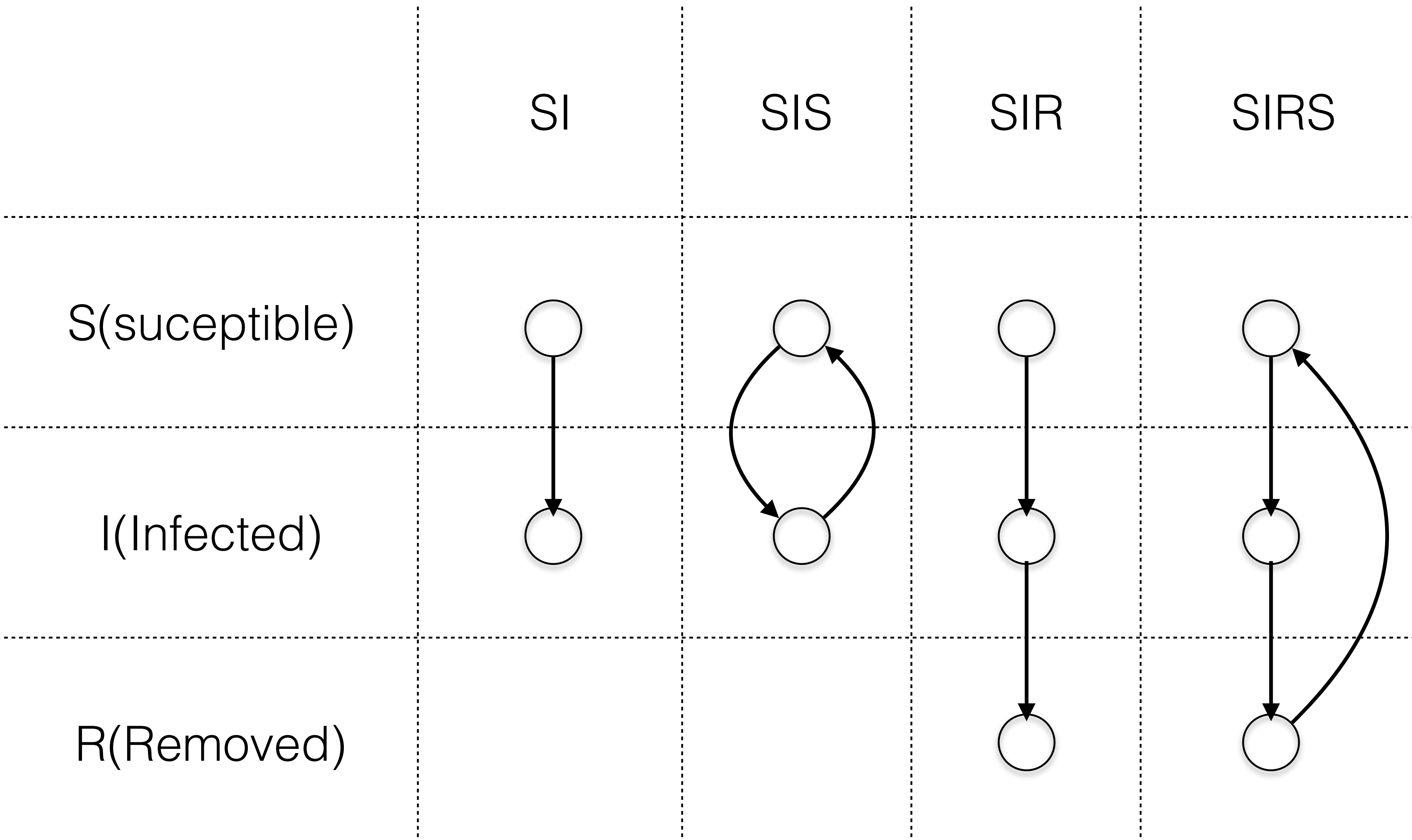
Abstract

The Internet has a very complex connectivity recently modeled by the class of scale-free networks. This feature, which appears to be very efficient for a communications network, favors at the same time the spreading of computer viruses. We analyze real data from computer virus infections and find the average lifetime and persistence of viral strains on the Internet. We define a dynamical model for the spreading of infections on scale-free networks, finding the absence of an epidemic threshold and its associated critical behavior. This new epidemiological framework rationalizes data of computer viruses and could help in the understanding of other spreading phenomena on communication and social networks.

PMID: 11290142 DOI: 10.1103/PhysRevLett.86.3200

[Indexed for MEDLINE]

Diffusion as infection - basic models



Centrality measures - micro view

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Centrality measures - micro view

- degree - how connected a node is
- closeness - how easily a node can reach other nodes
- betweenness - how important a node is in terms of connecting other nodes
- neighbours' characteristics - how important, central, or influential a node's neighbours are

American Journal of Sociology

Volume 78, Number 6 | May, 1973

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The Strength of Weak Ties

Mark S. Granovetter

Abstract Cited by PDF

The strength of weak ties

The strength of weak ties

- The stronger the tie (edge) between A and B, the larger the proportion of nodes that are linked to both A and to B

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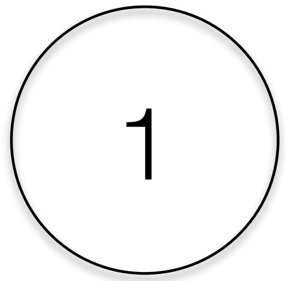

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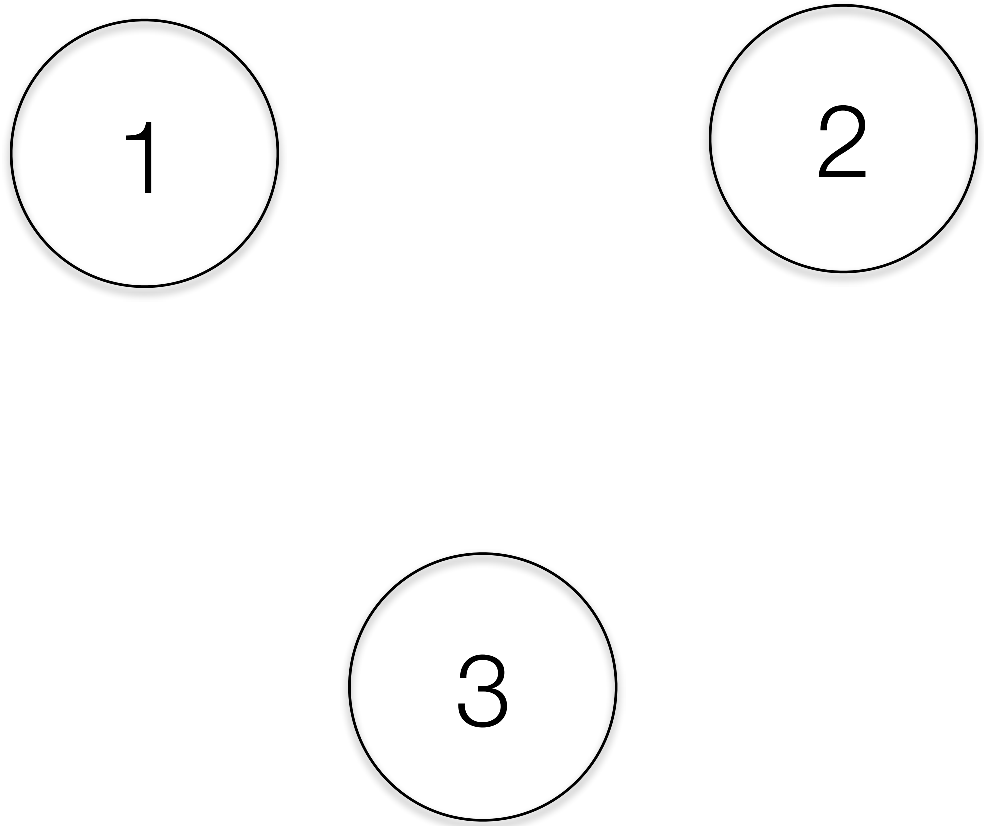

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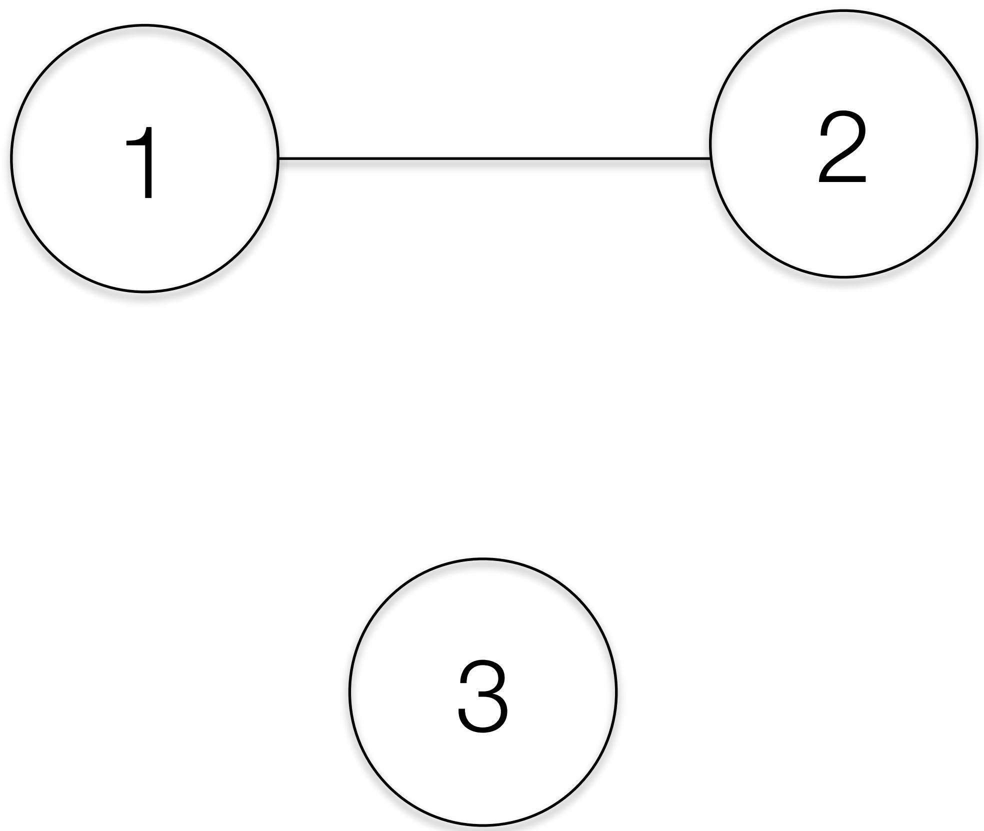

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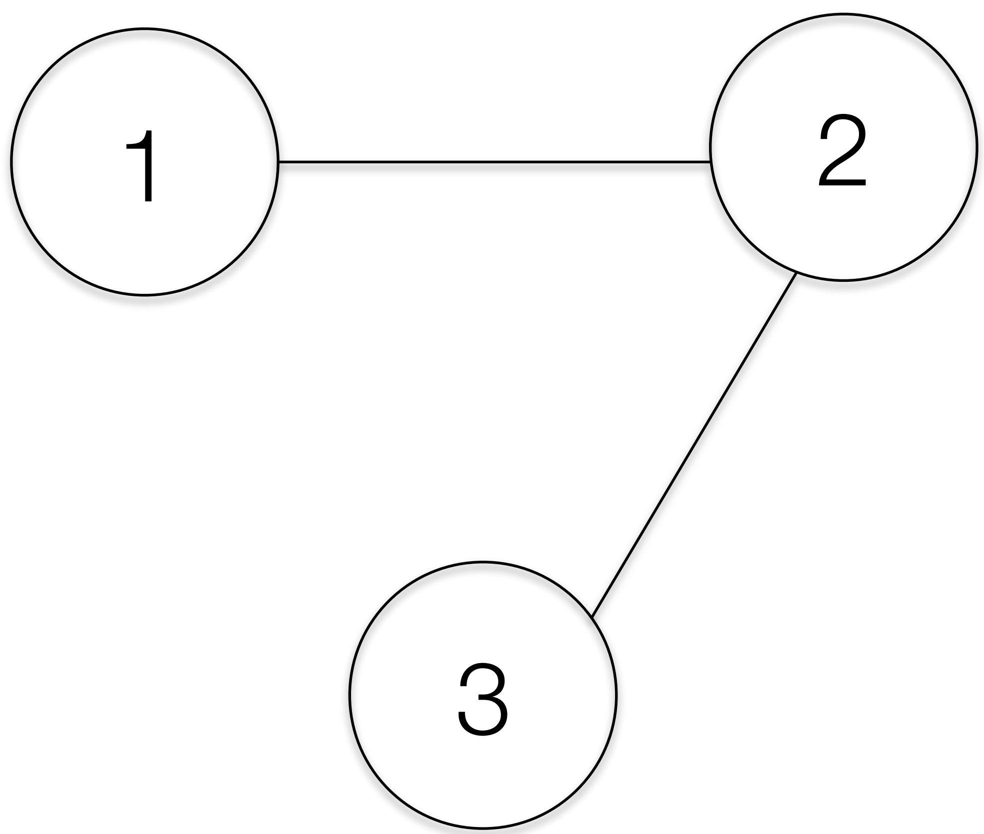

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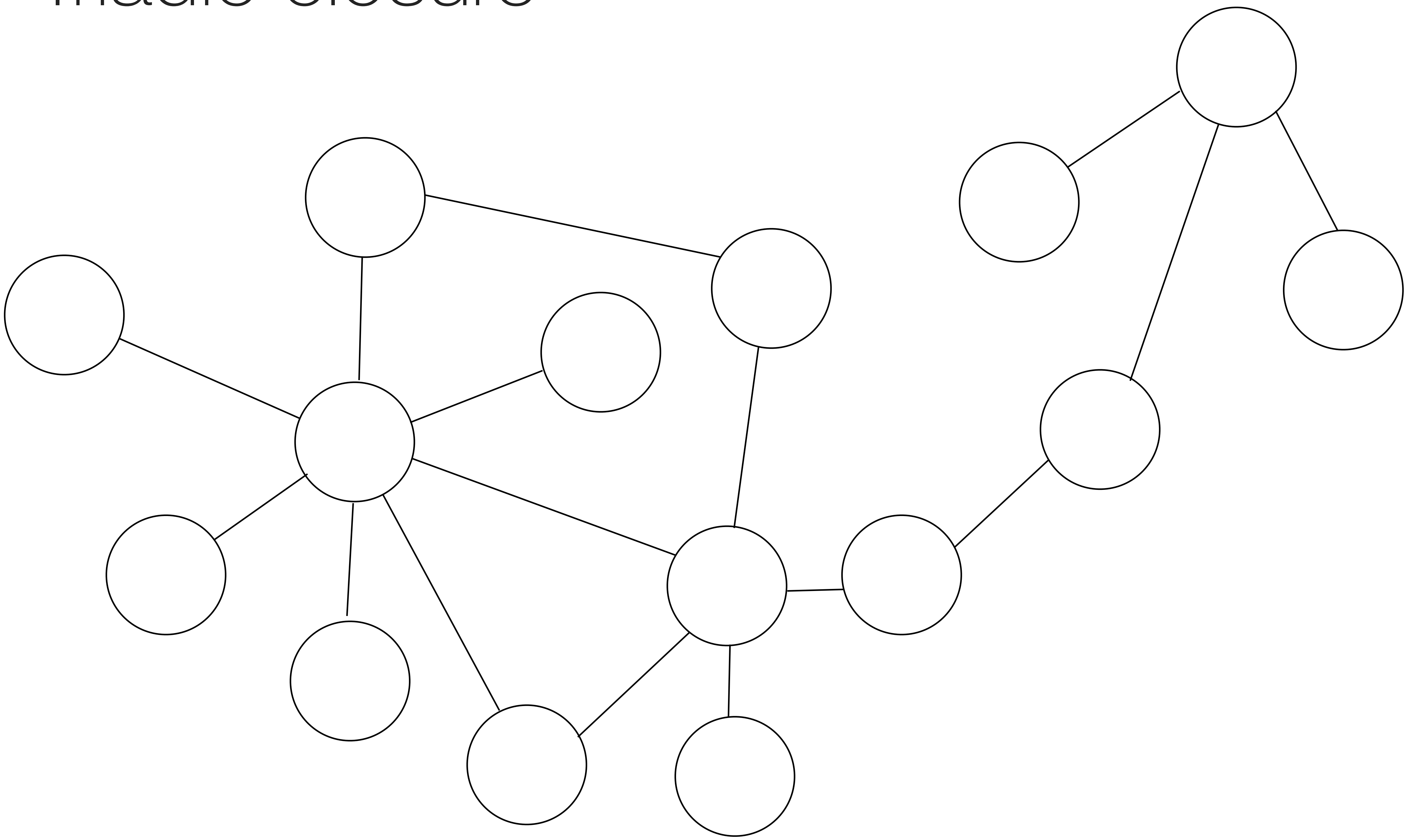

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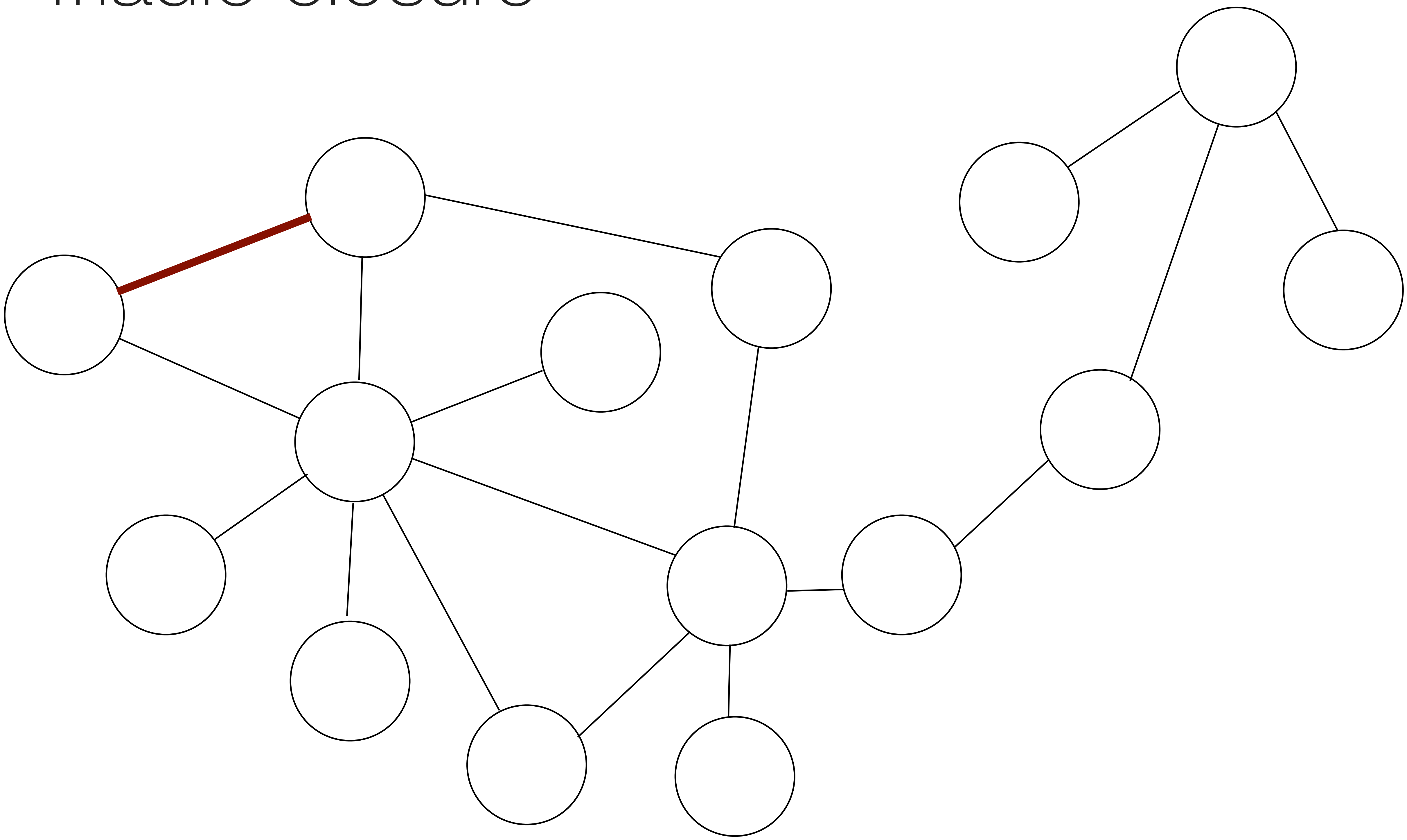

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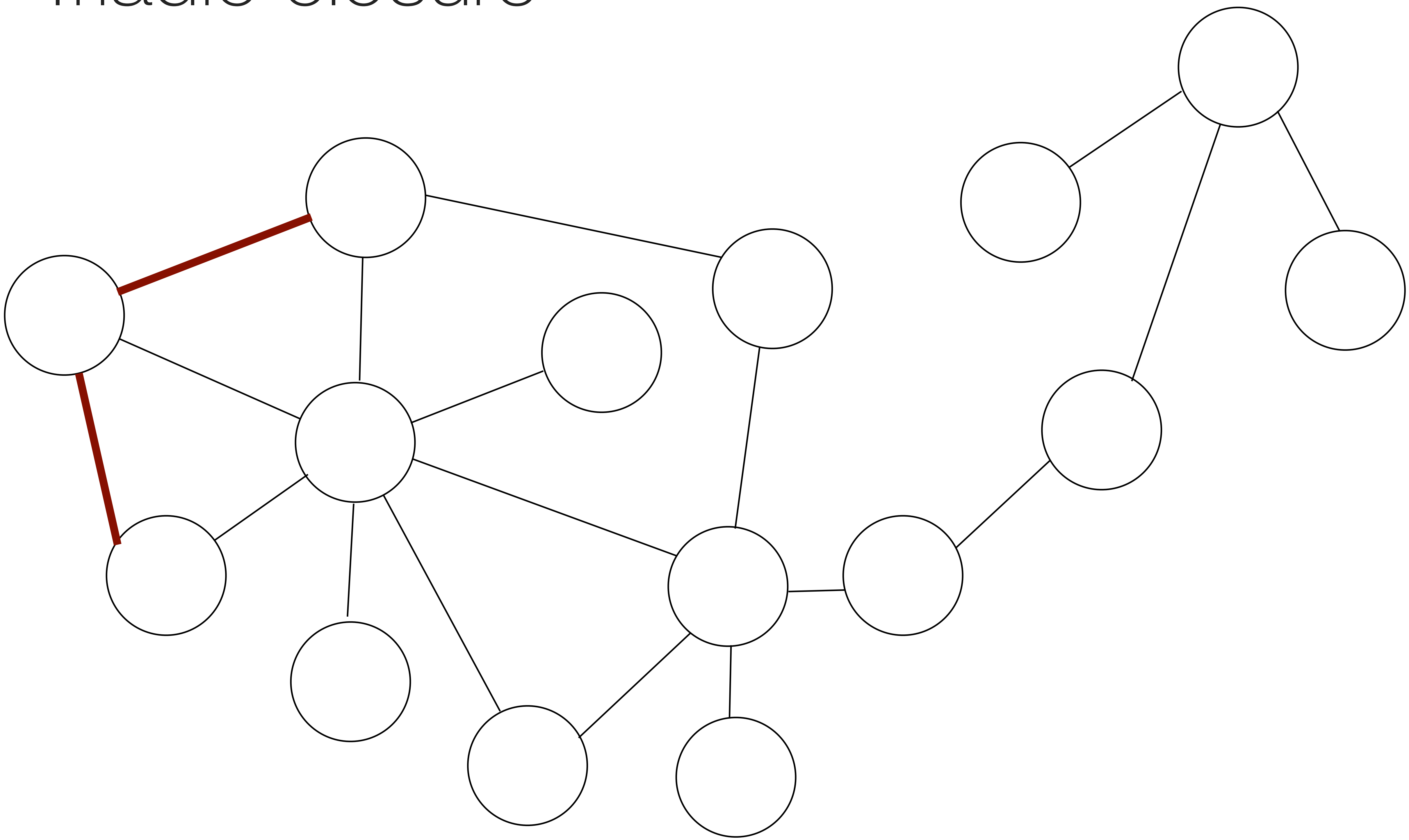

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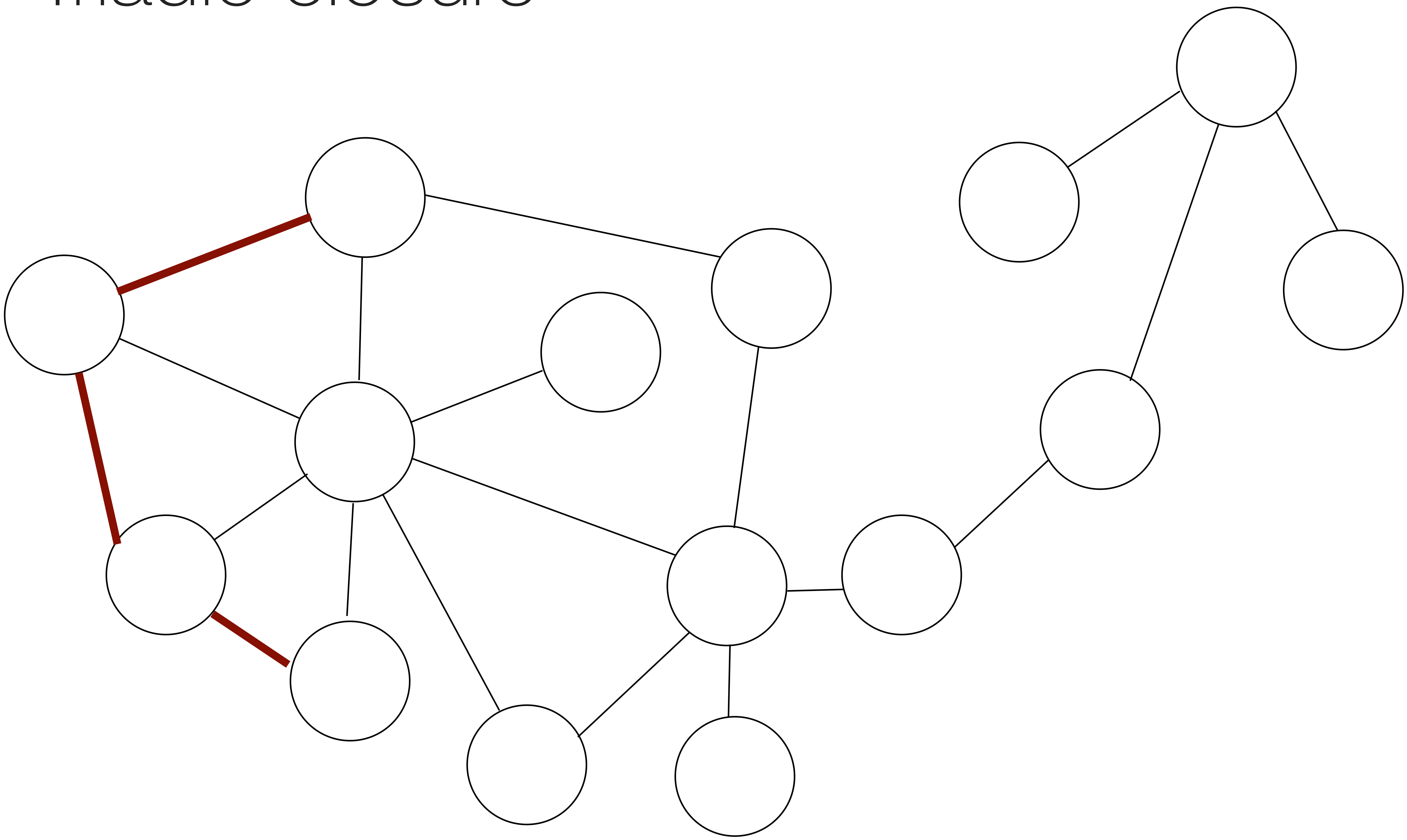

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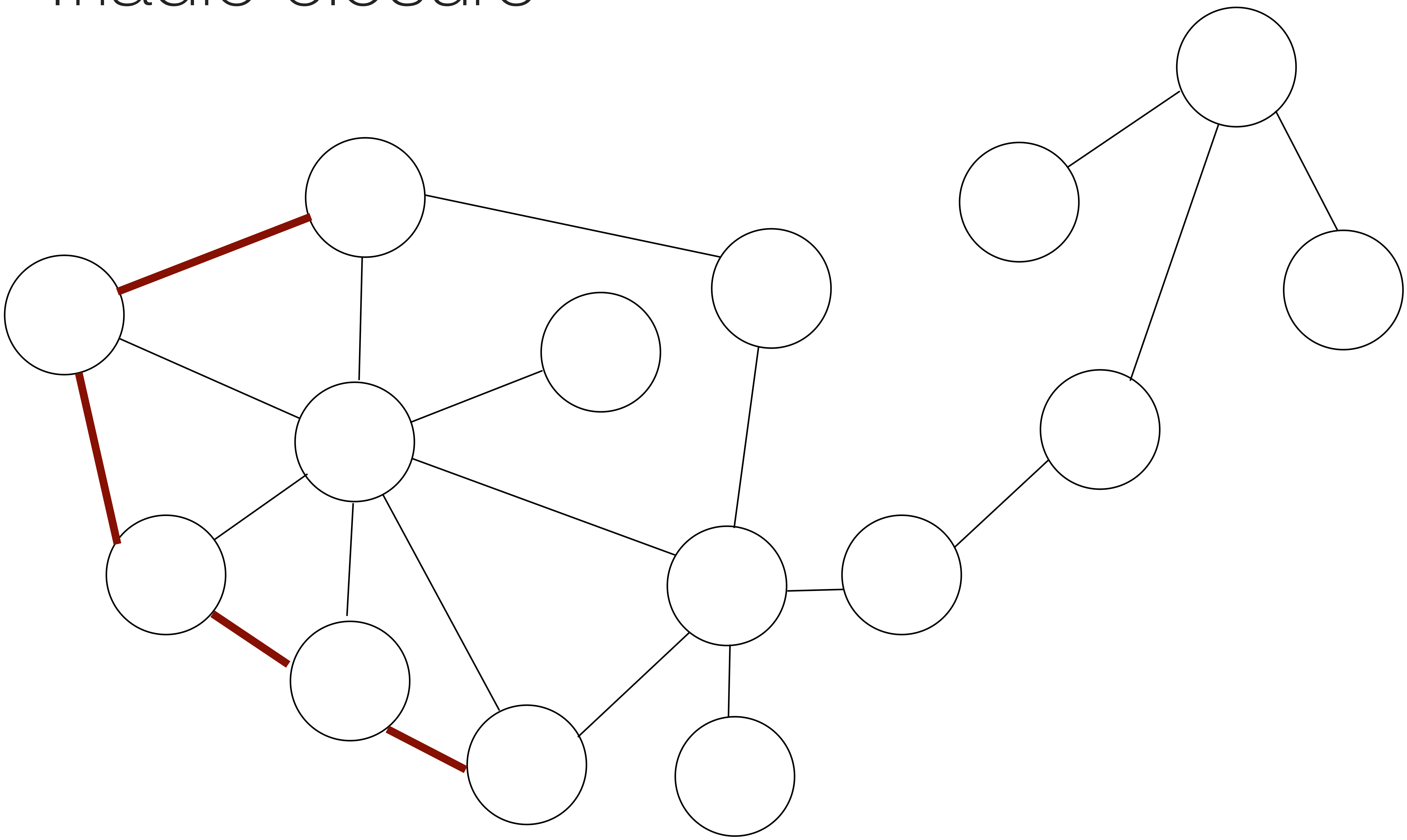

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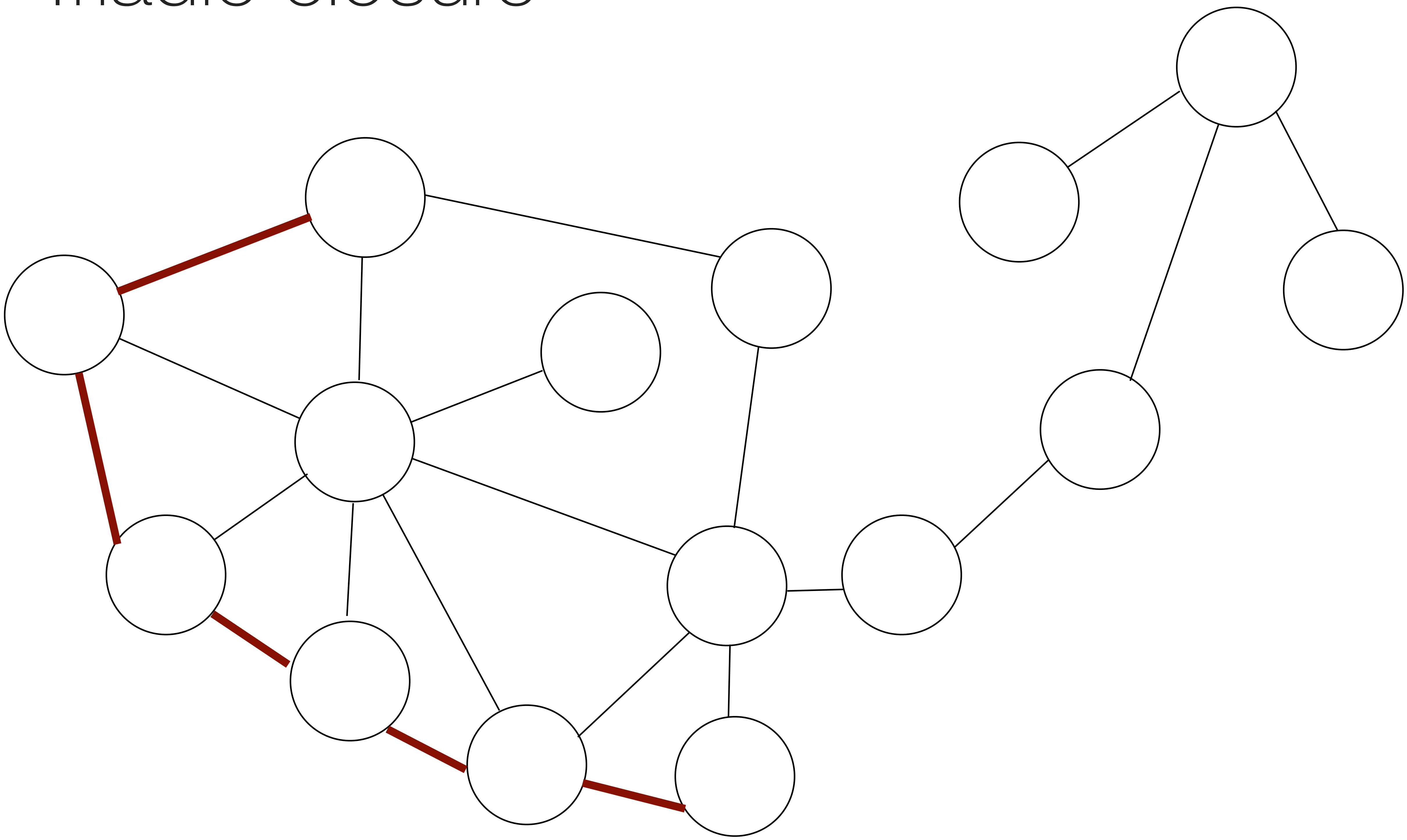

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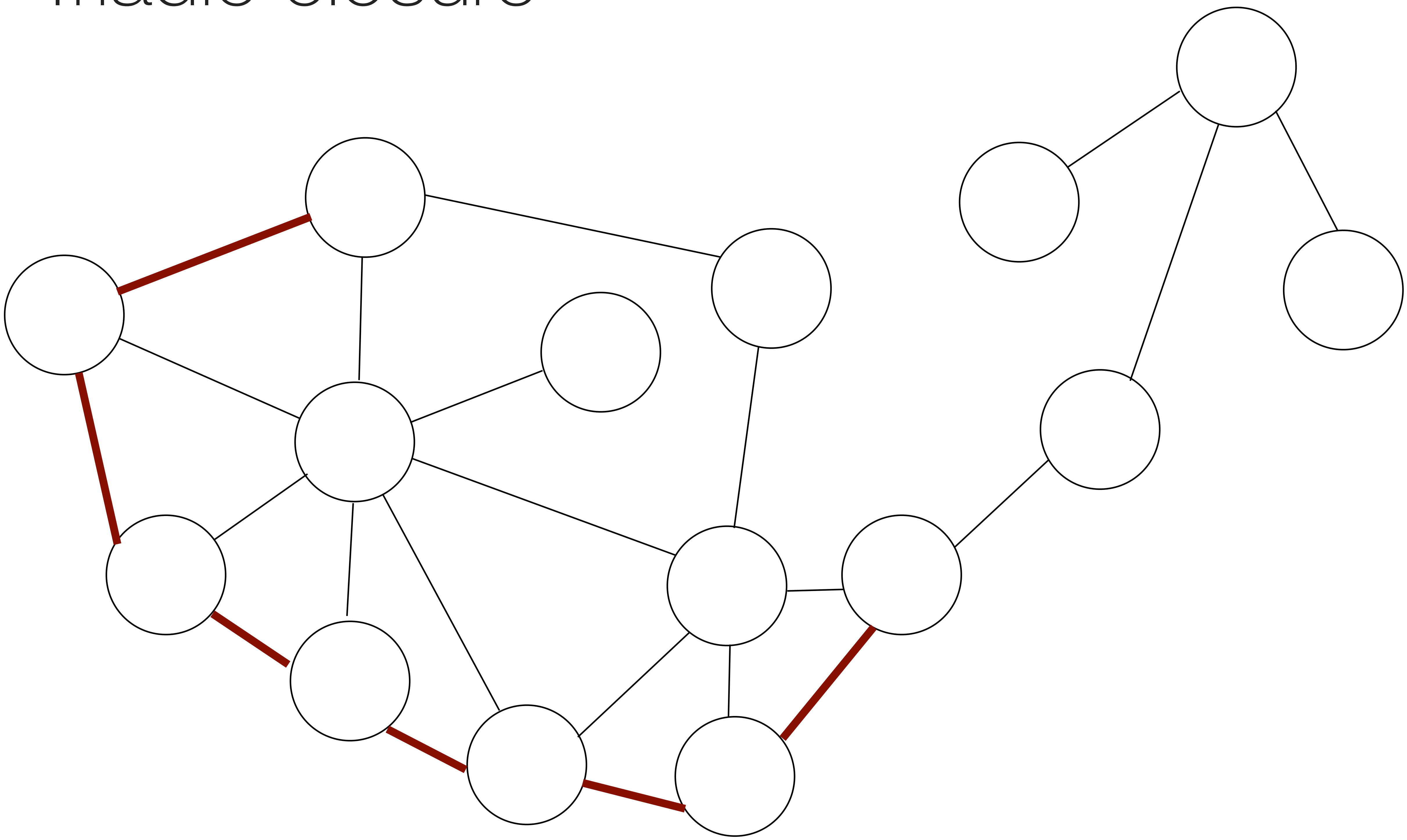

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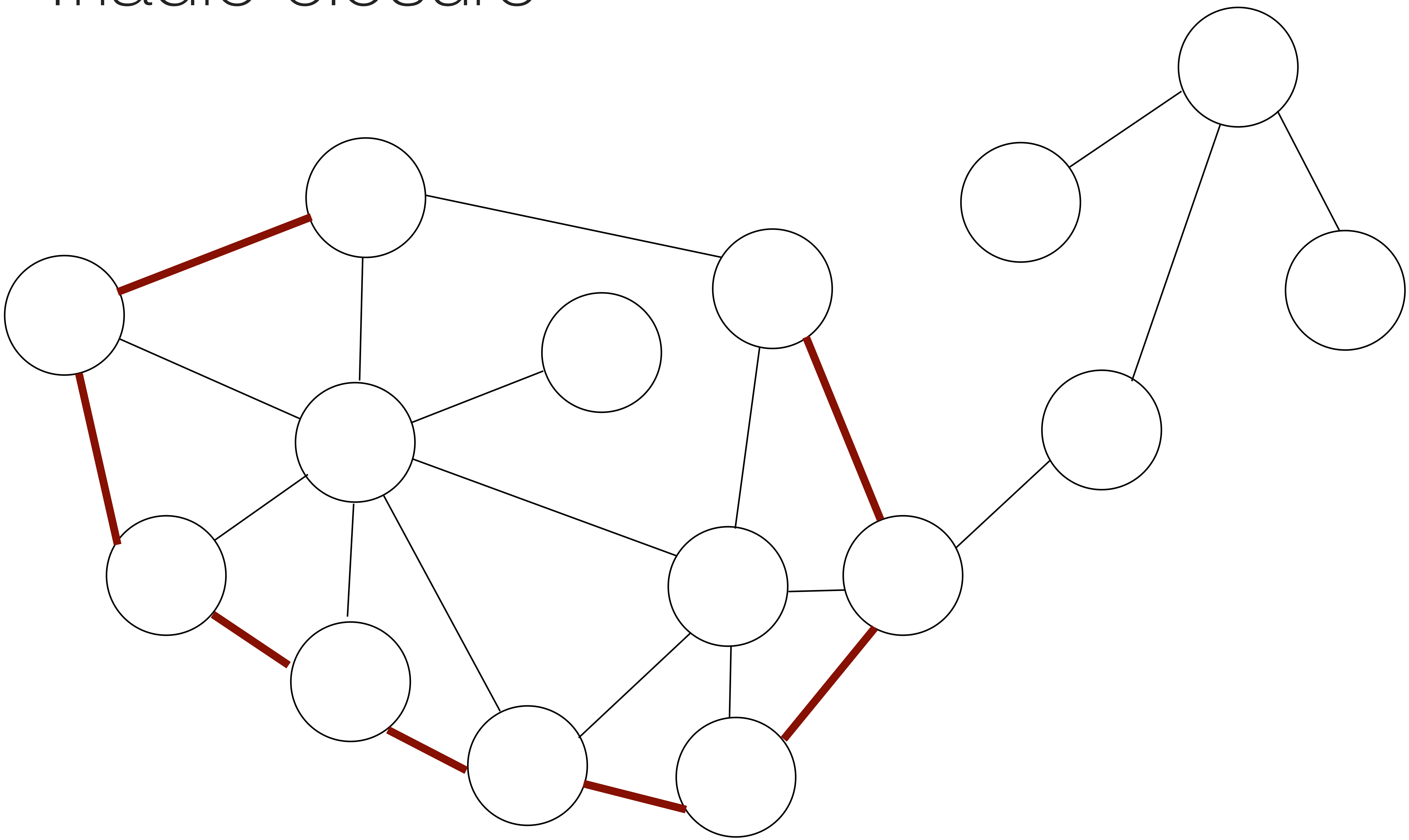

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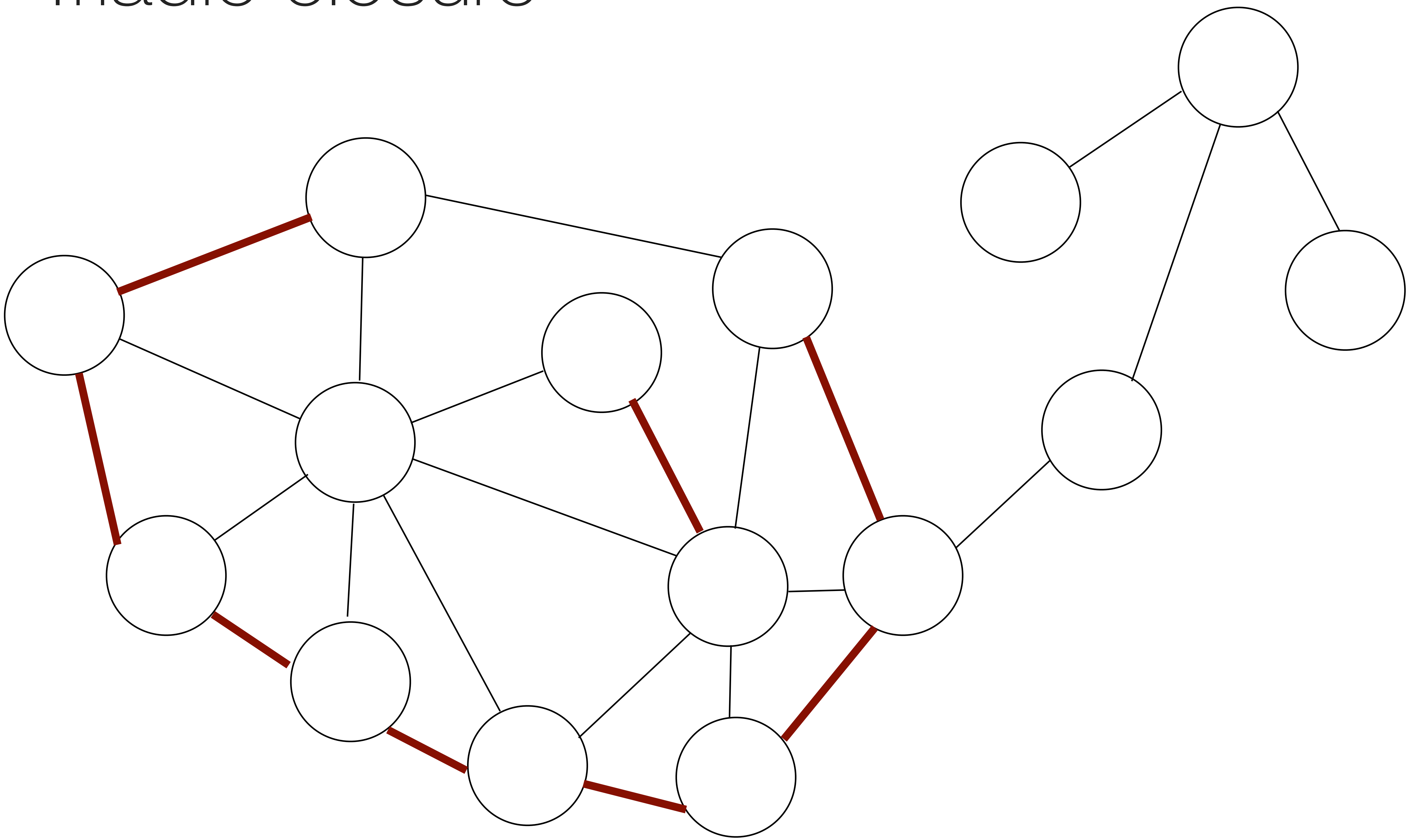

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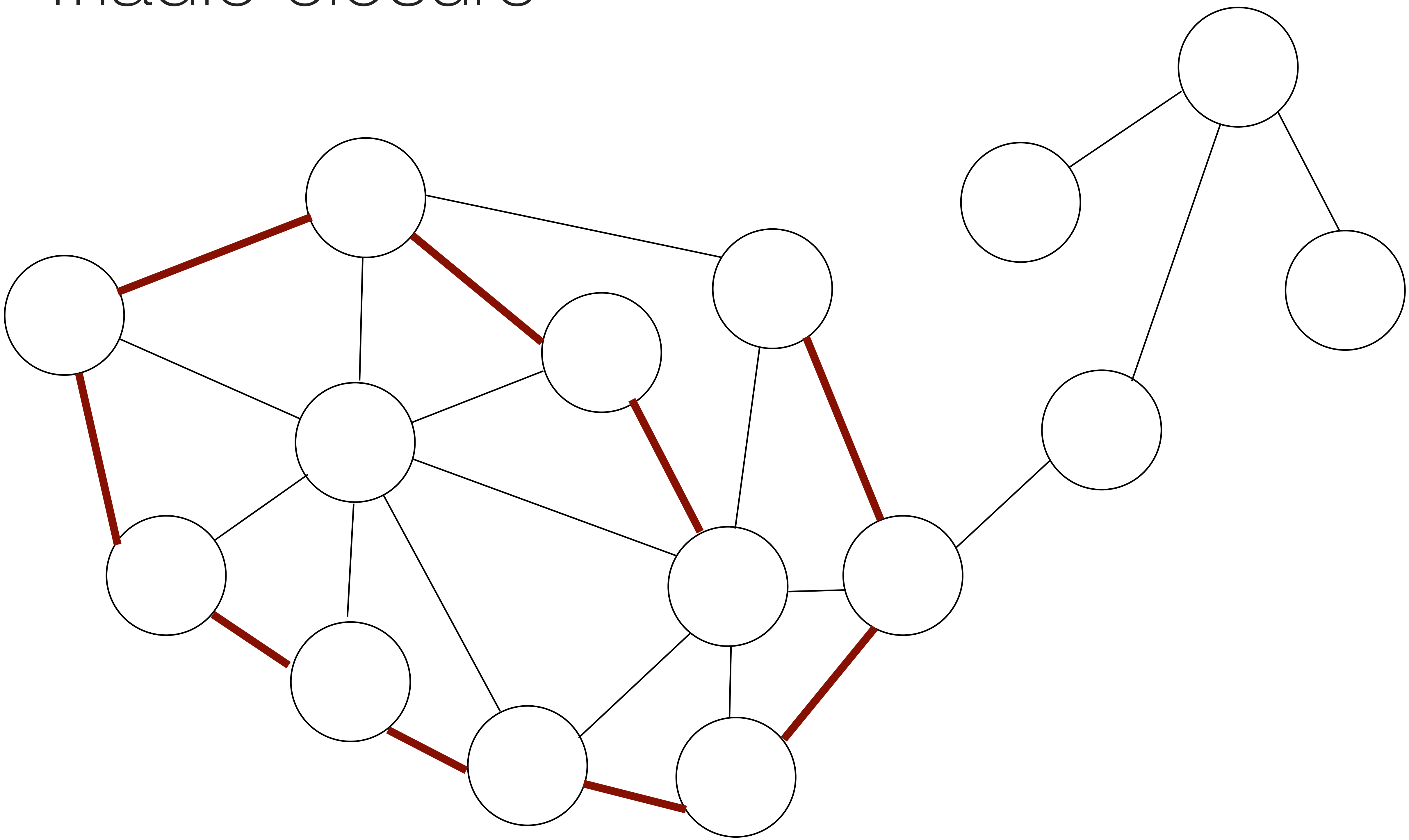

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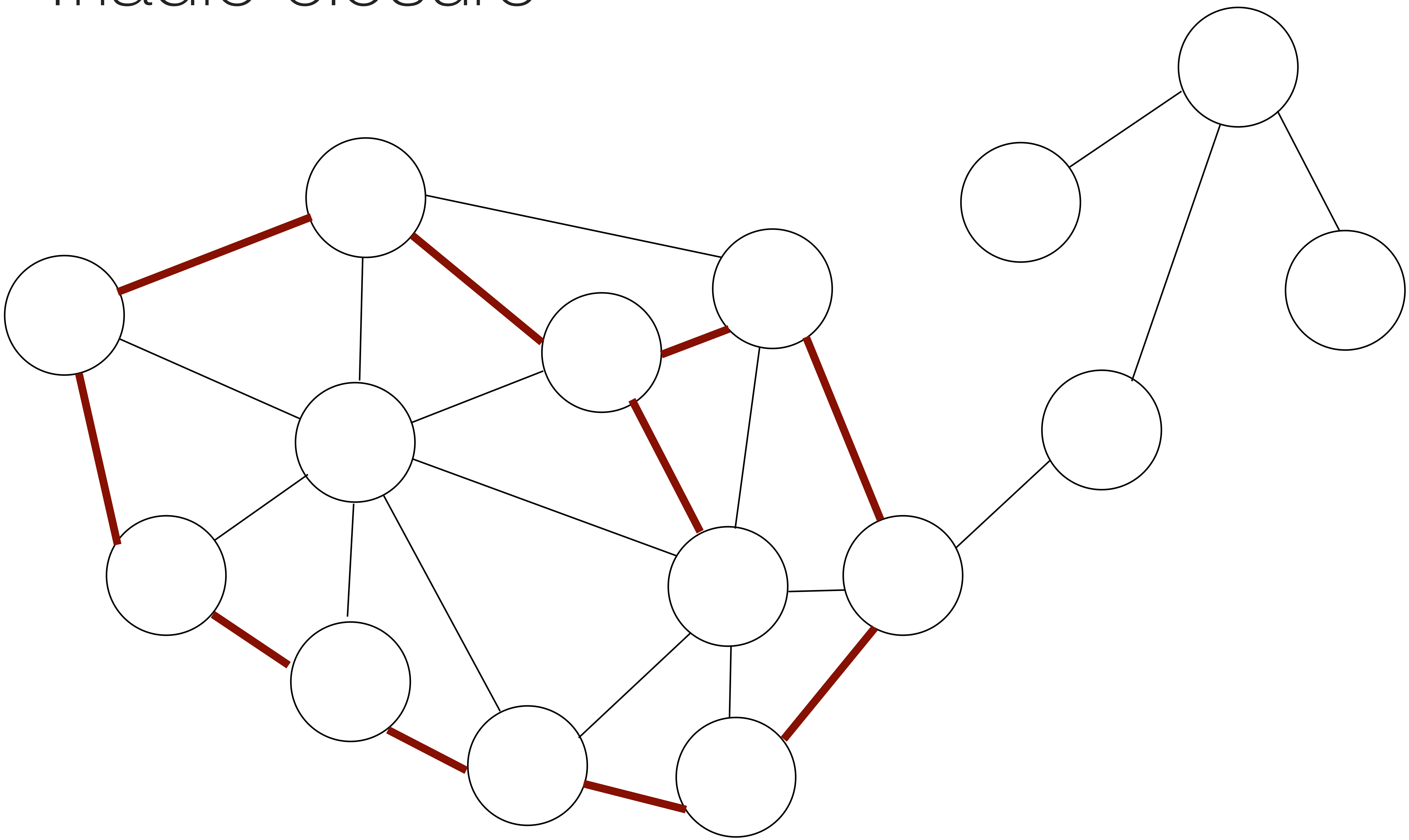

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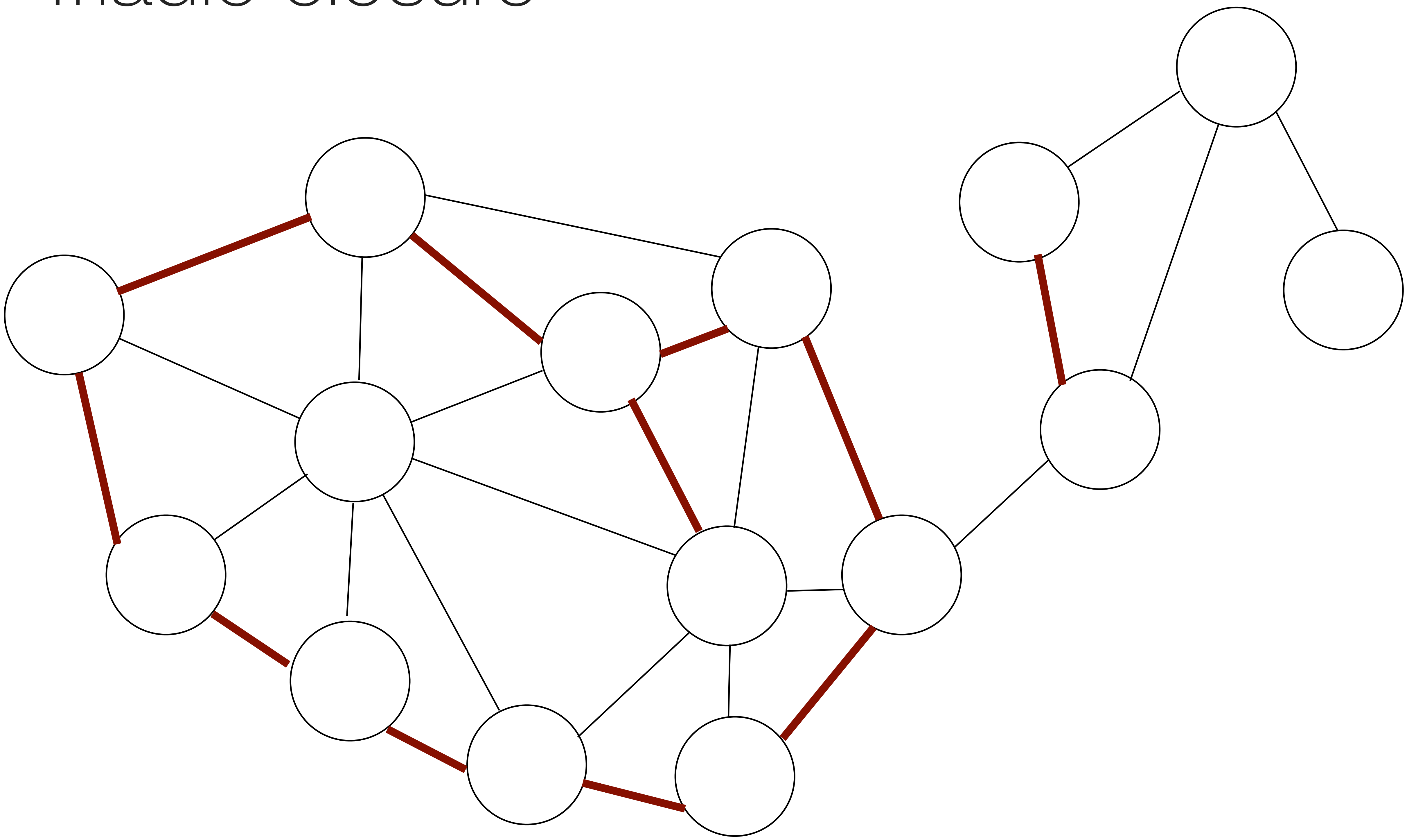

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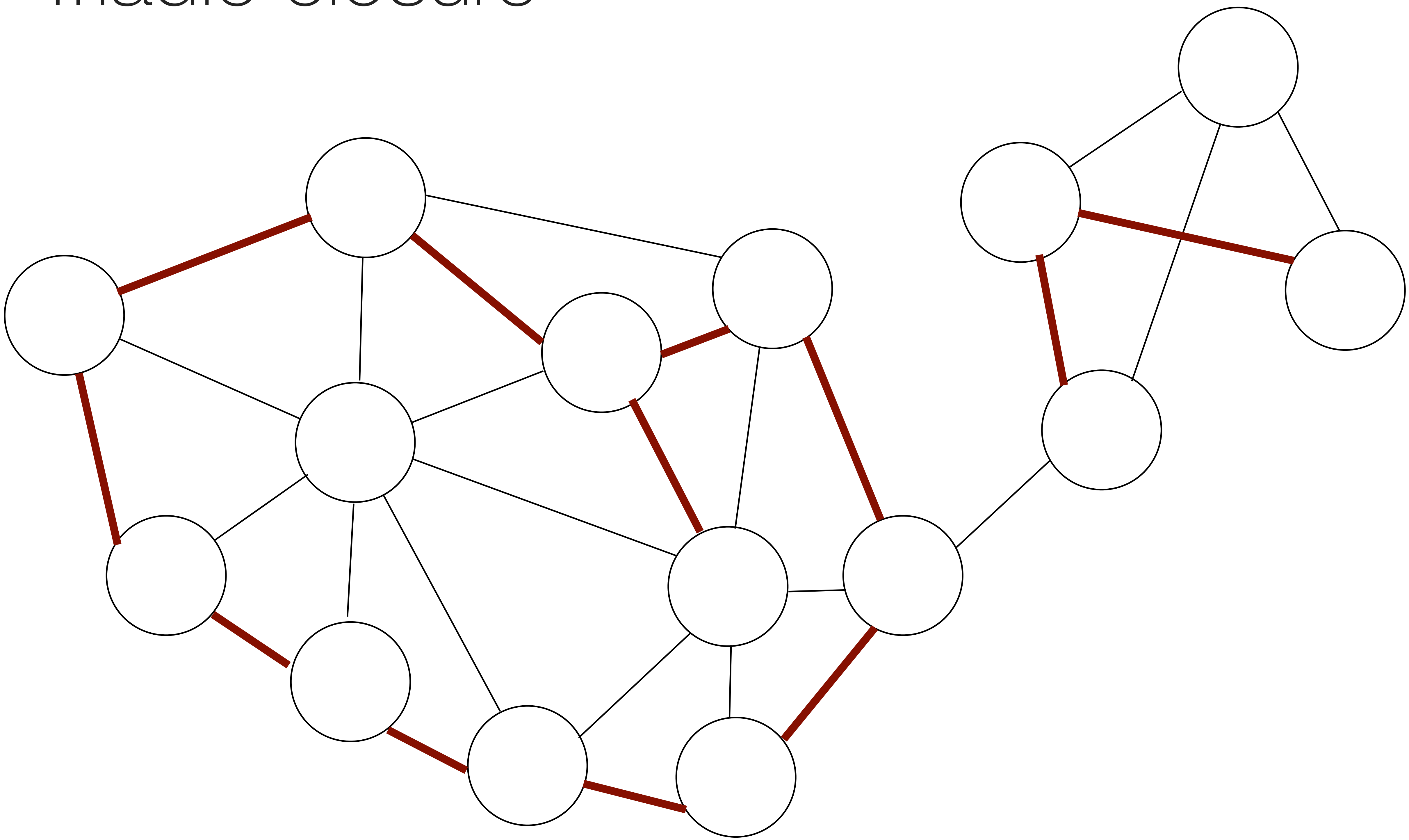

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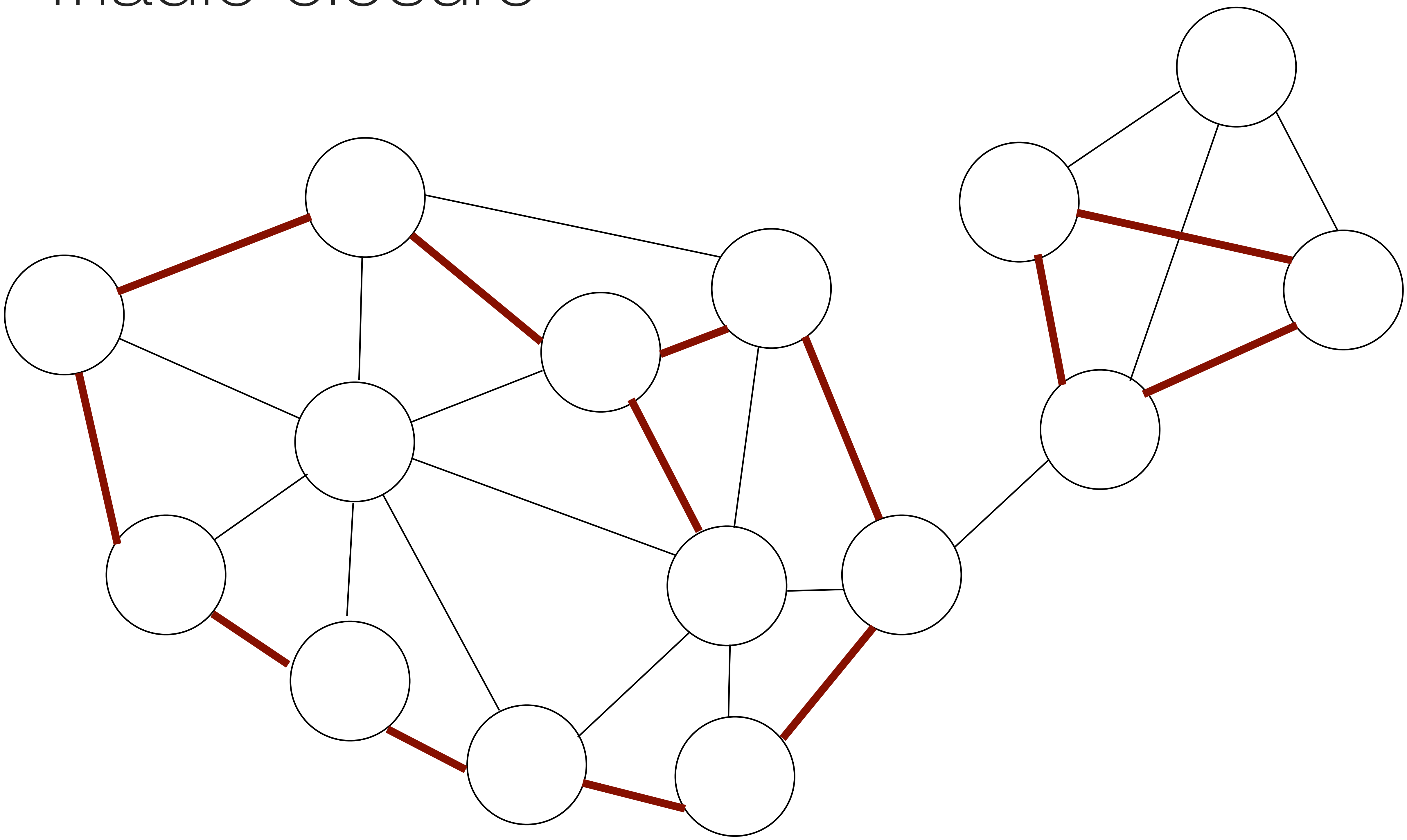
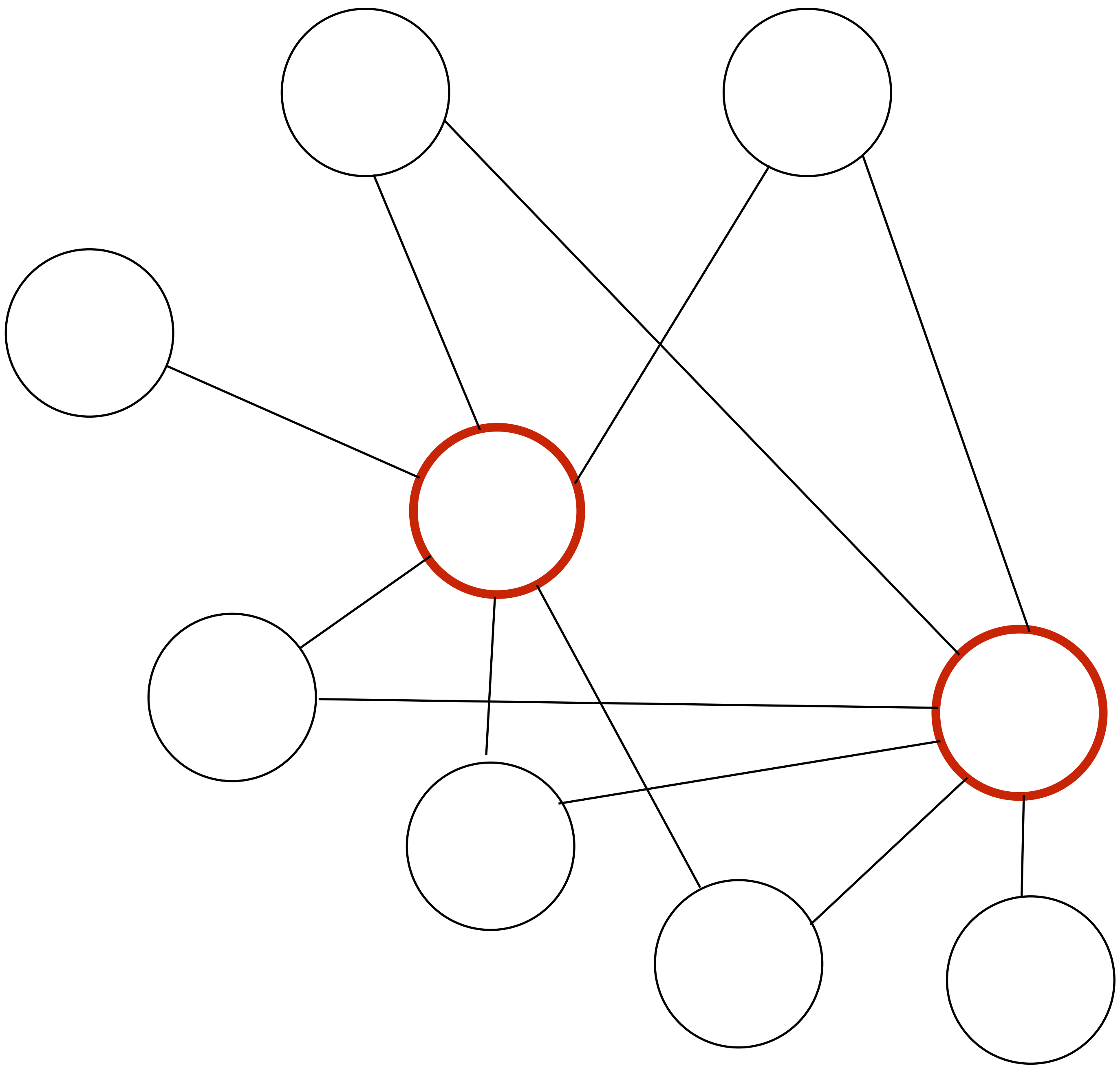


Triadic closure + homophyly



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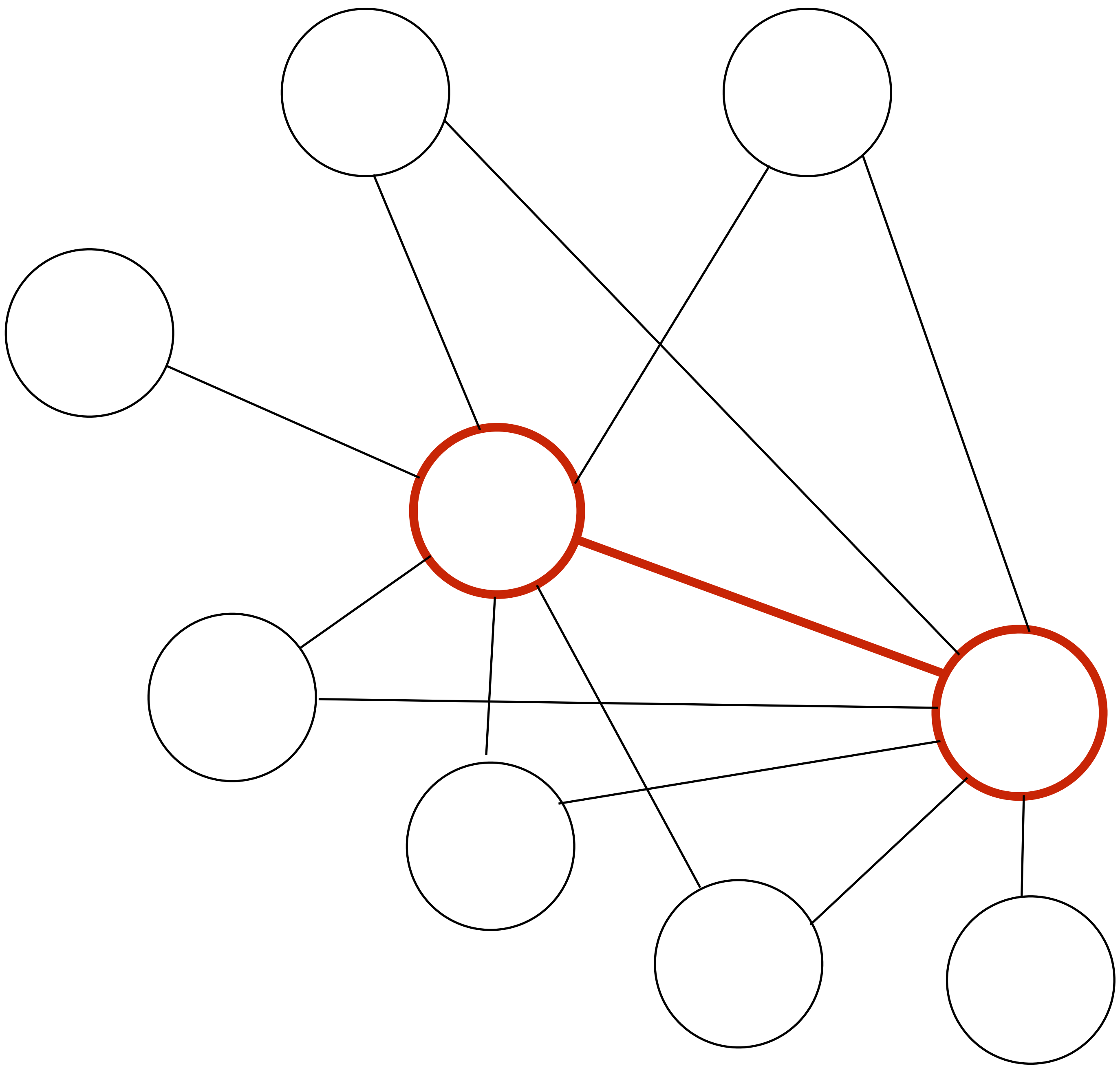
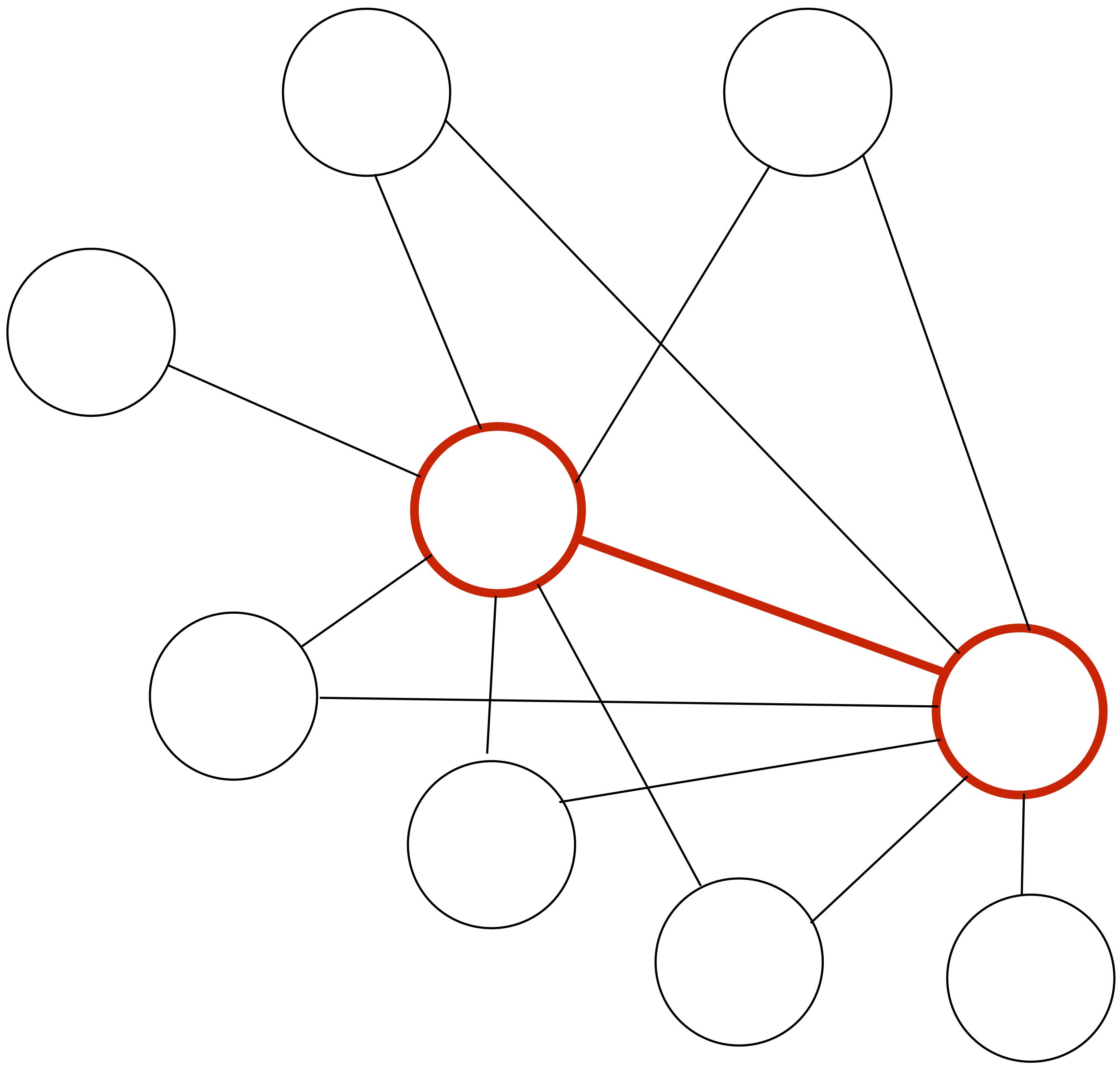
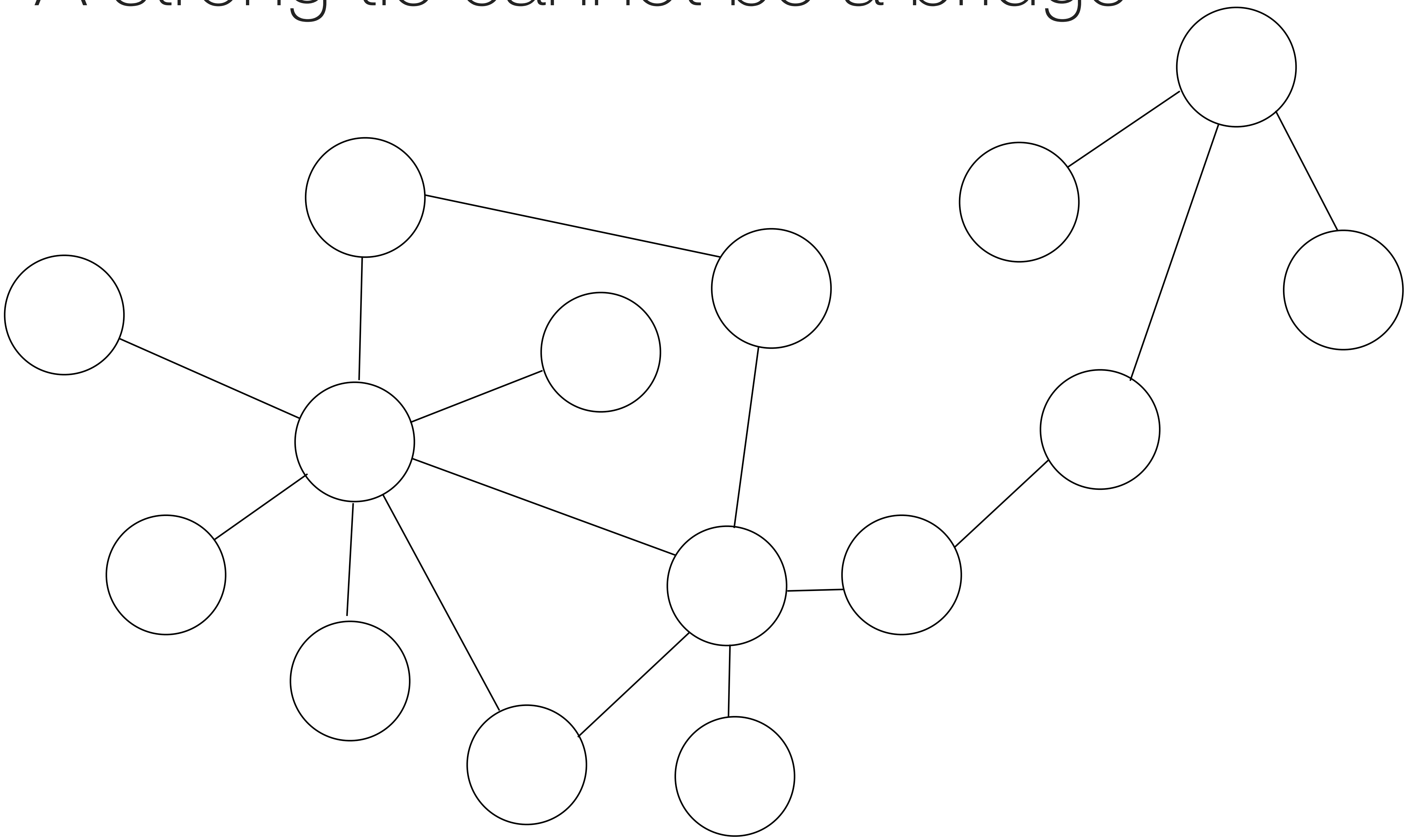


Triadic closure + homophyly

- Influence spreads wider if it spread via weak ties



A strong tie cannot be a bridge



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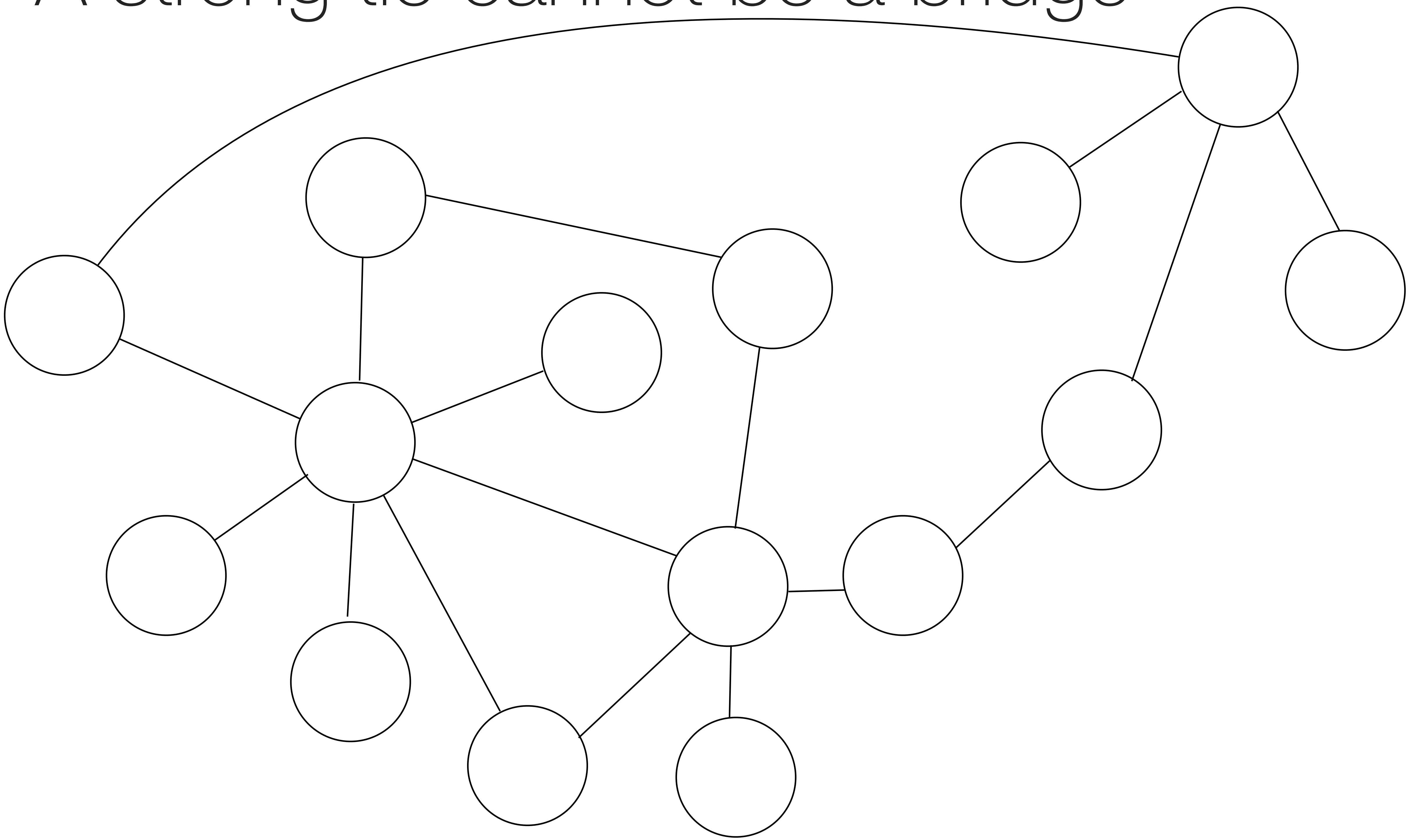

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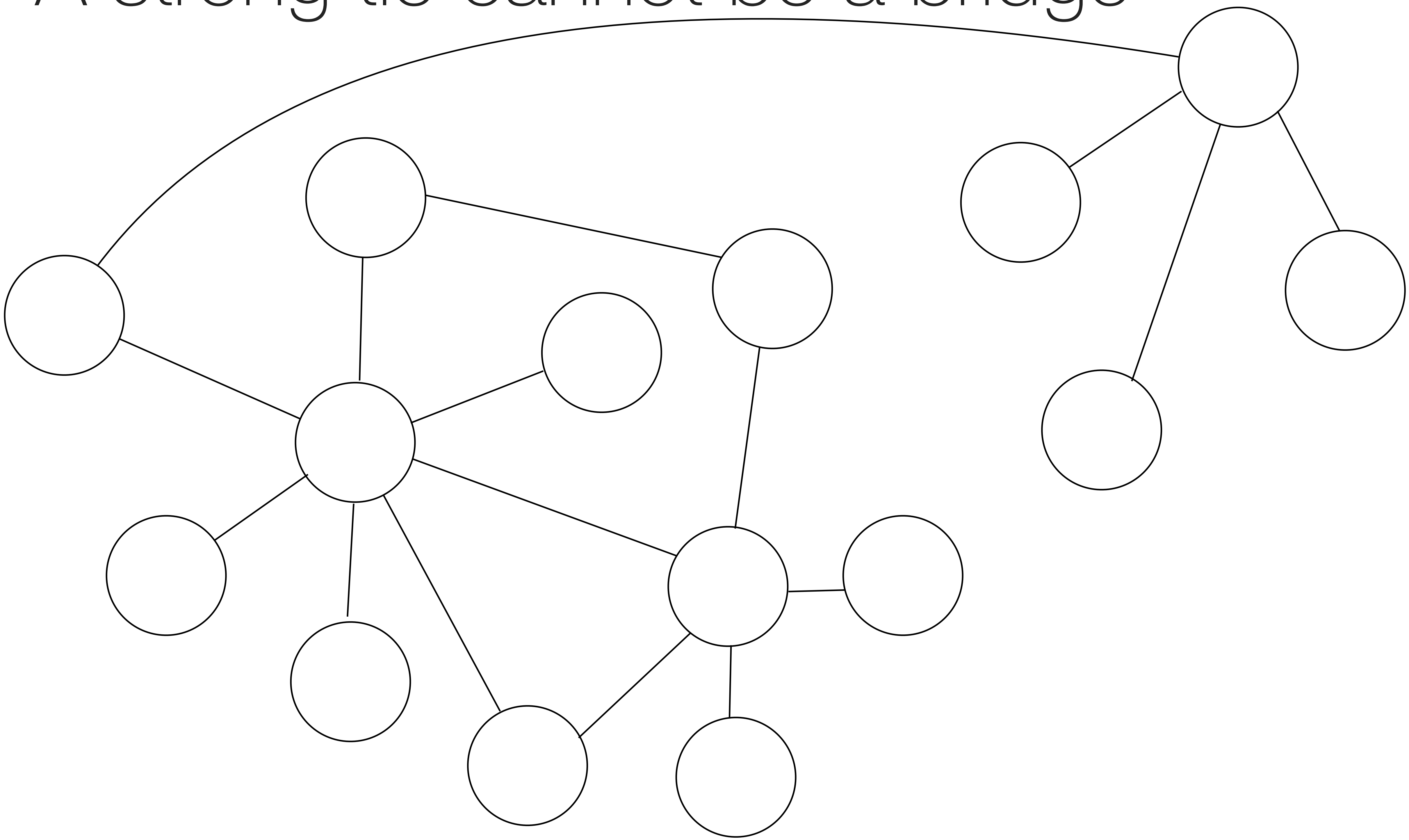

Simmelian ties

Simmelian ties

THE TIES THAT TORTURE:

SIMMELIAN TIE ANALYSIS IN ORGANIZATIONS

David Krackhardt

Simmelian ties

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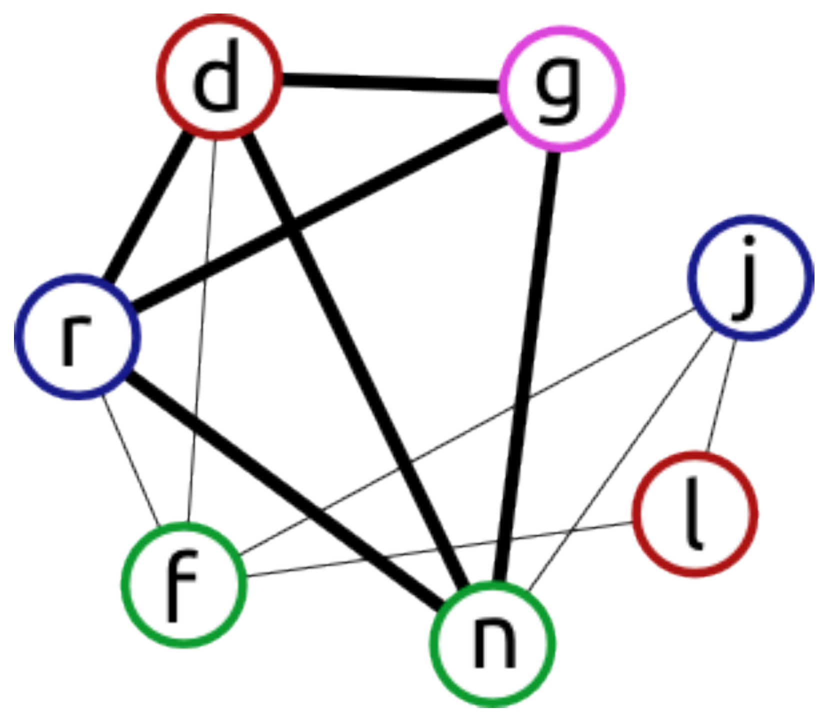

Theory of social power

A formal theory of social power.

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French Jr., John R. P.

Citation

French, J. R. P., Jr. (1956). A formal theory of social power. *Psychological Review, 63*(3), 181-194. http://dx.doi.org/10.1037/h0046123

Abstract

"This theory illustrates a way by which many complex phenomena about groups can be deduced from a few simple postulates about interpersonal relations. By the application of digraph theory we are able to treat in detail the *patterns of relations* whose importance has long been noted by the field theorists." Three major postulates are presented as well as a variety of theorems dealing with the effects of the power structure of the group, the effects of communication patterns, the effects of patterns of opinion, and leadership. 32 references. (PsycINFO Database Record (c) 2016 APA, all rights reserved)

DeGroot's Consensus

Morris Herman DeGroot	
Born	June 8, 1931 Scranton, Pennsylvania
Died	November 2, 1989 (aged 58) Pittsburgh, Pennsylvania
Alma mater	Roosevelt University University of Chicago
Awards	ASA Fellow (1966) [1] IMS Fellow [2] AAAS Fellow [3]
Scientific career	
Fields	Statistics
Institutions	Carnegie Mellon University
Doctoral advisor	Leonard Jimmie Savage
Doctoral students	Kathryn Chaloner

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Reaching a Consensus

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Journal of the American Statistical Association, Volume 69, Issue 345 (Mar., 1974), 118-121.

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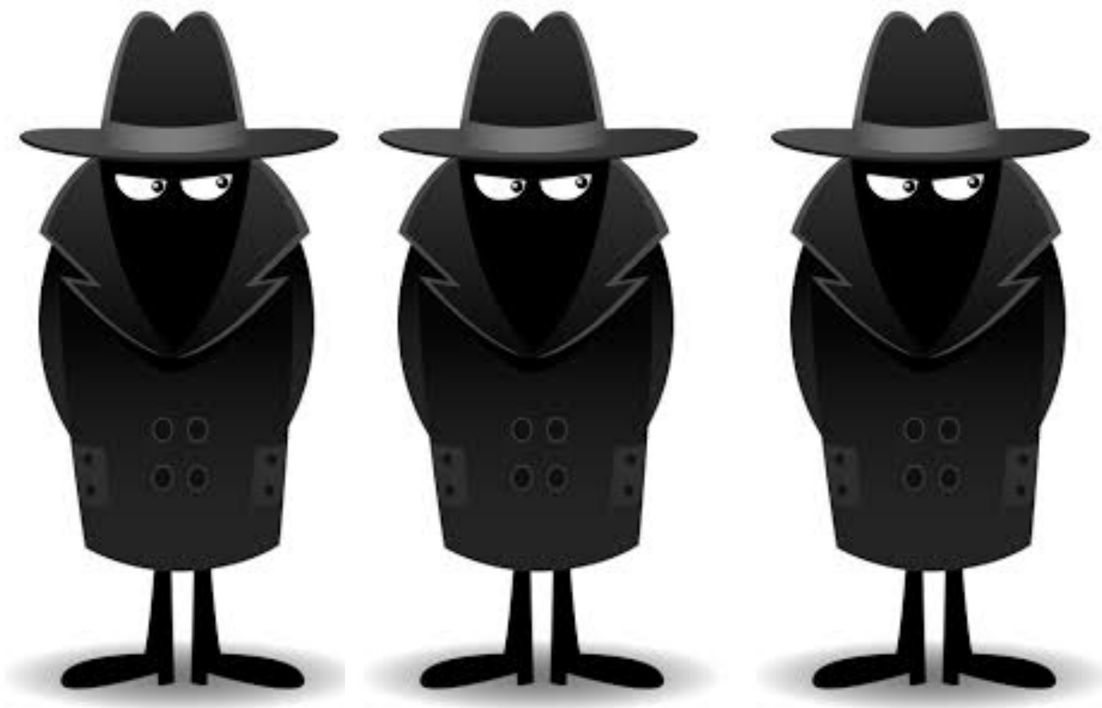

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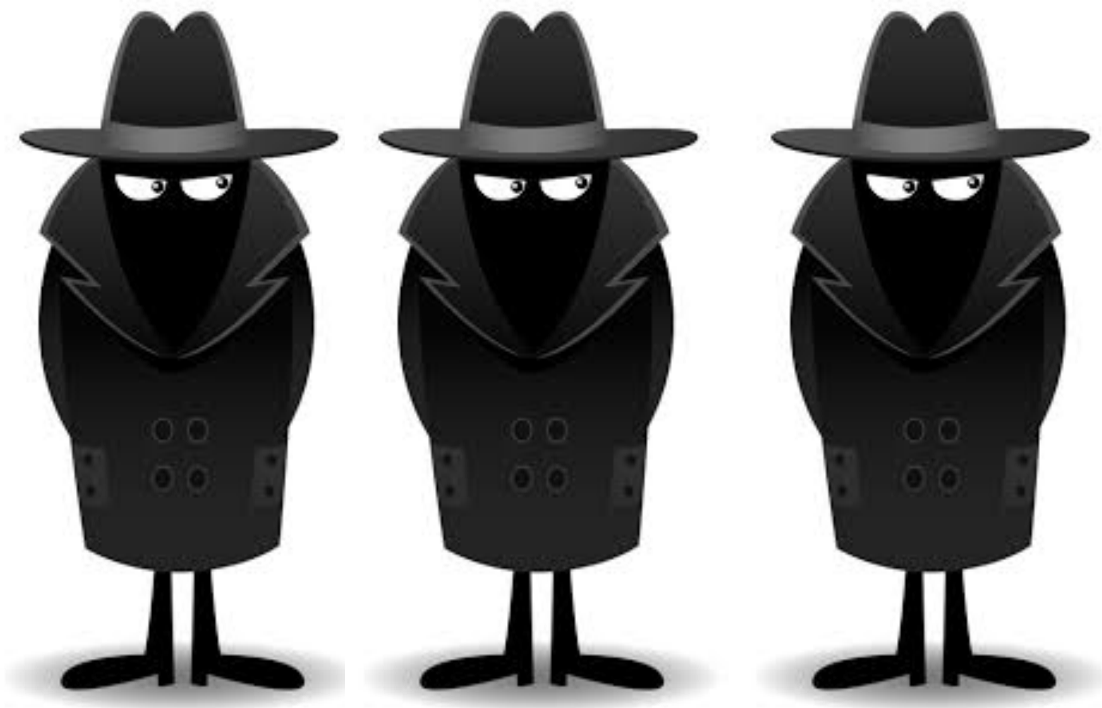

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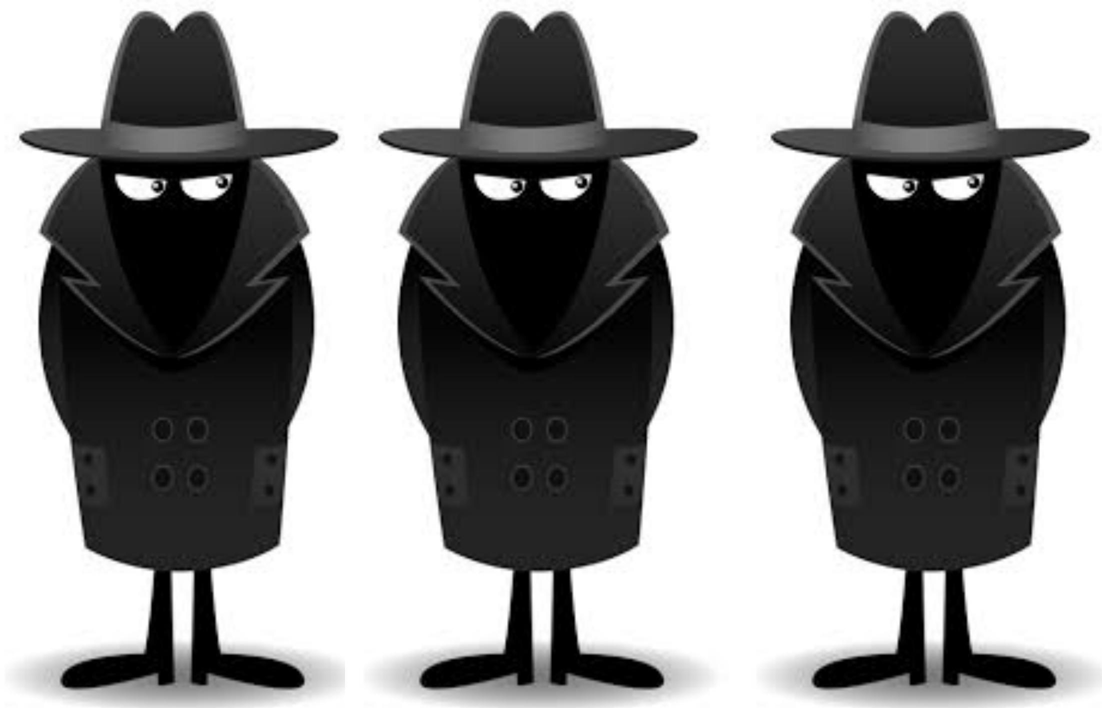

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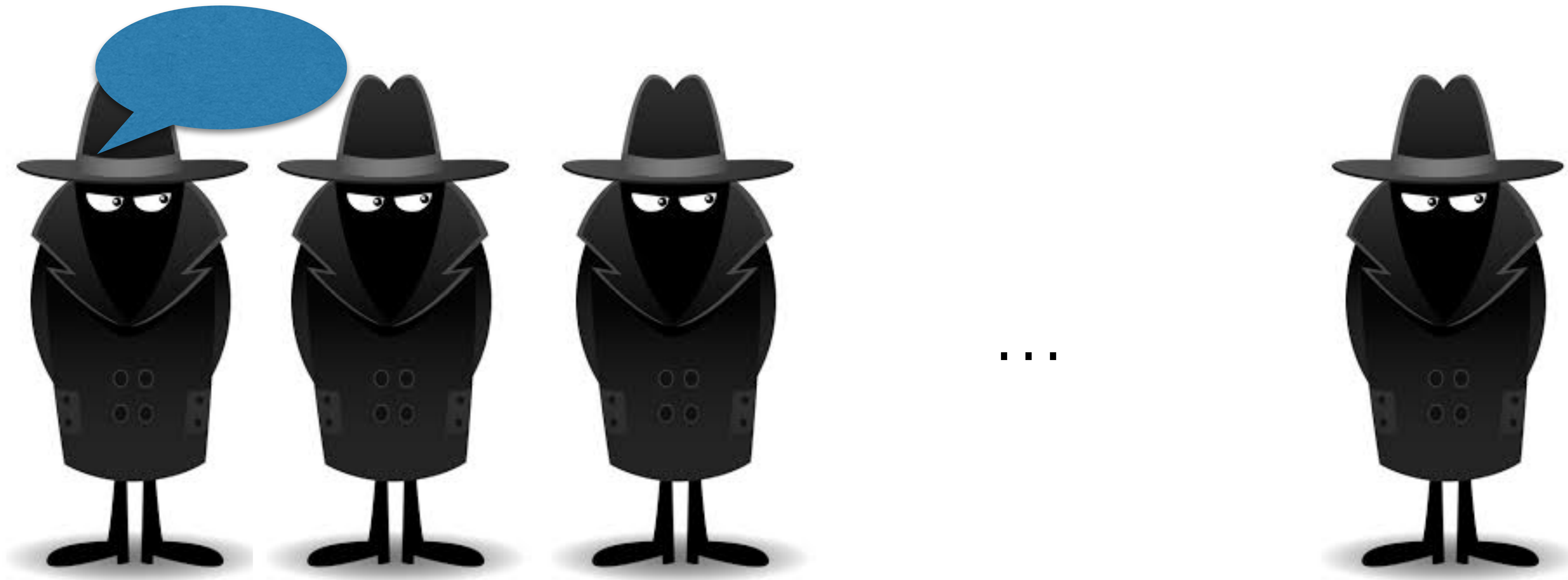

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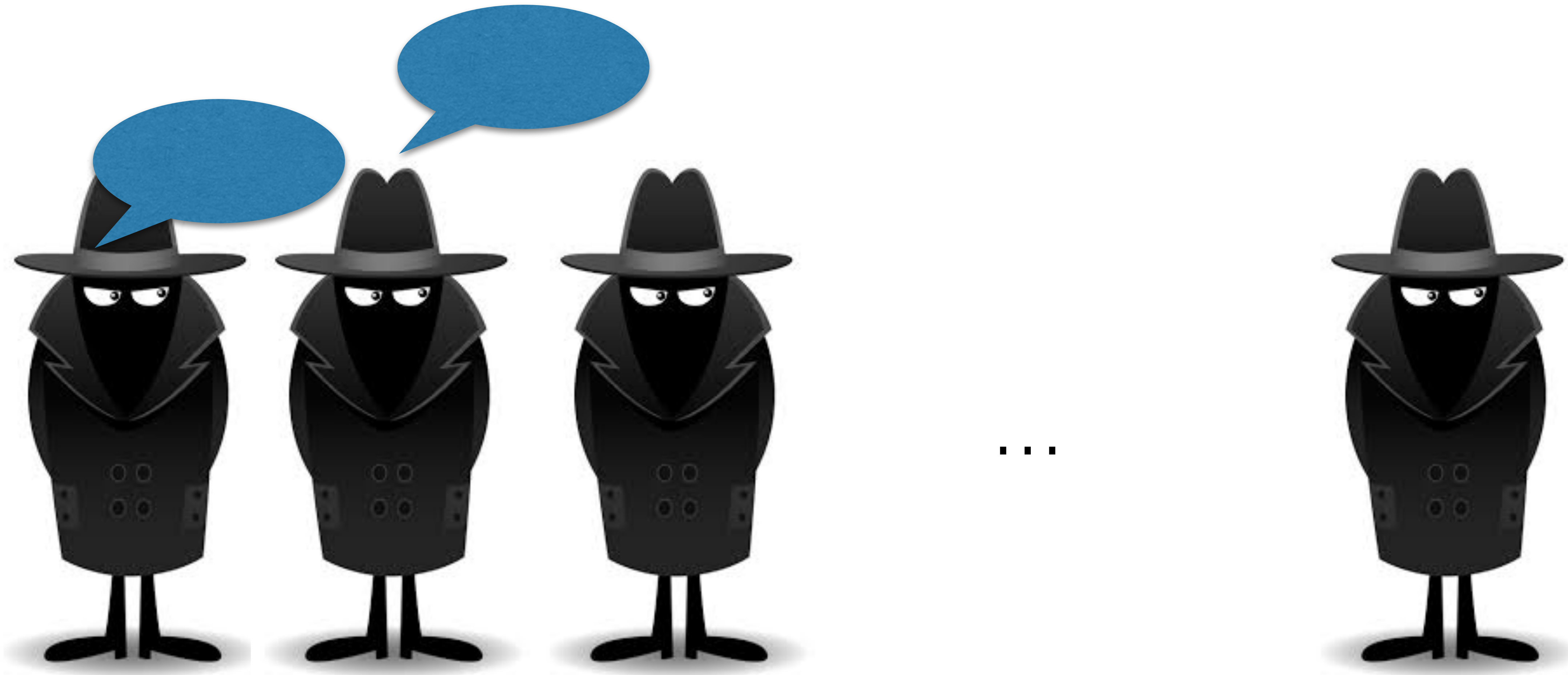

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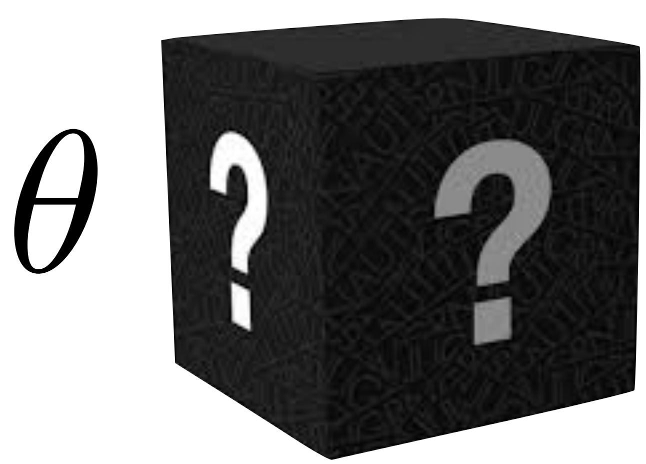

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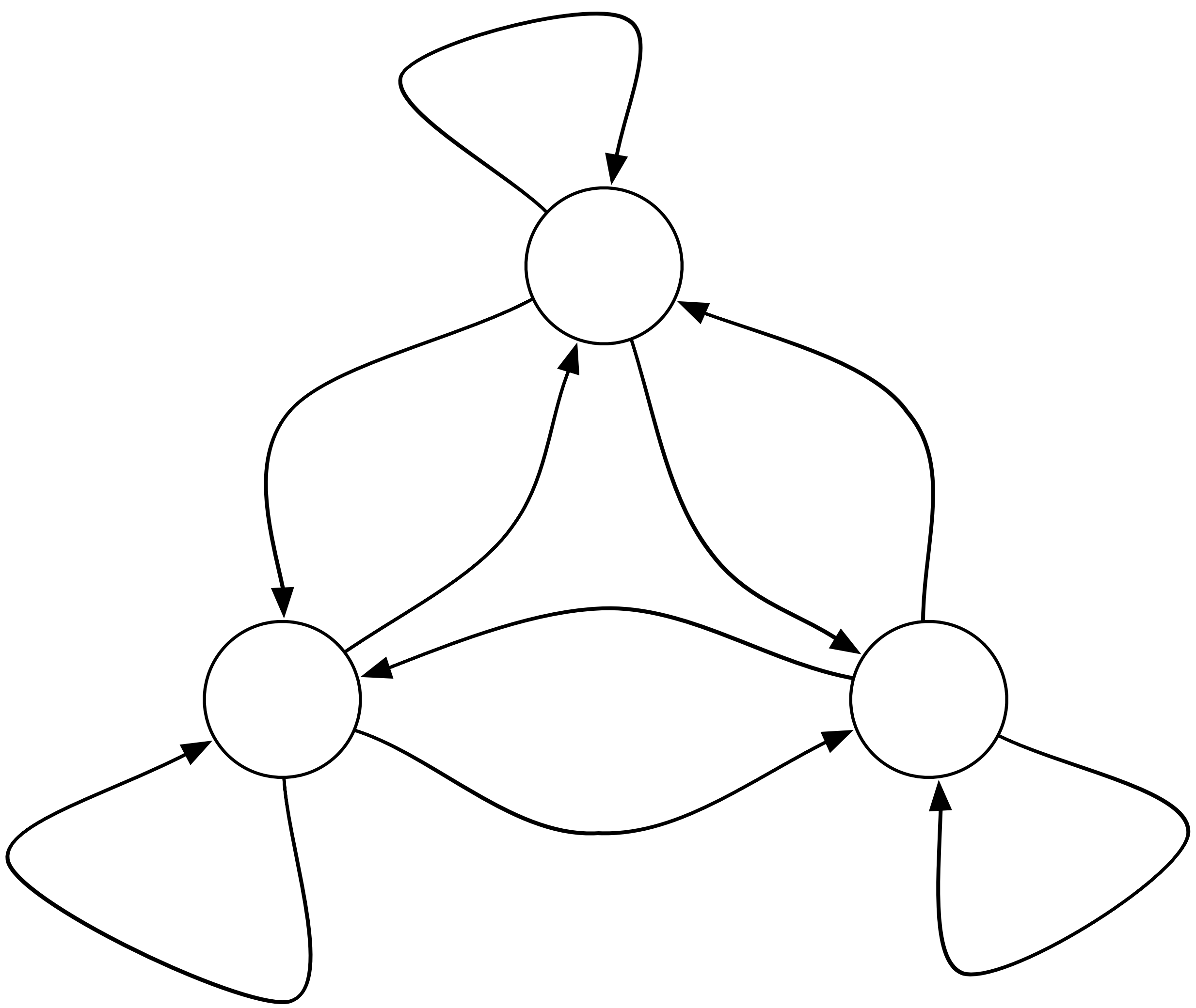

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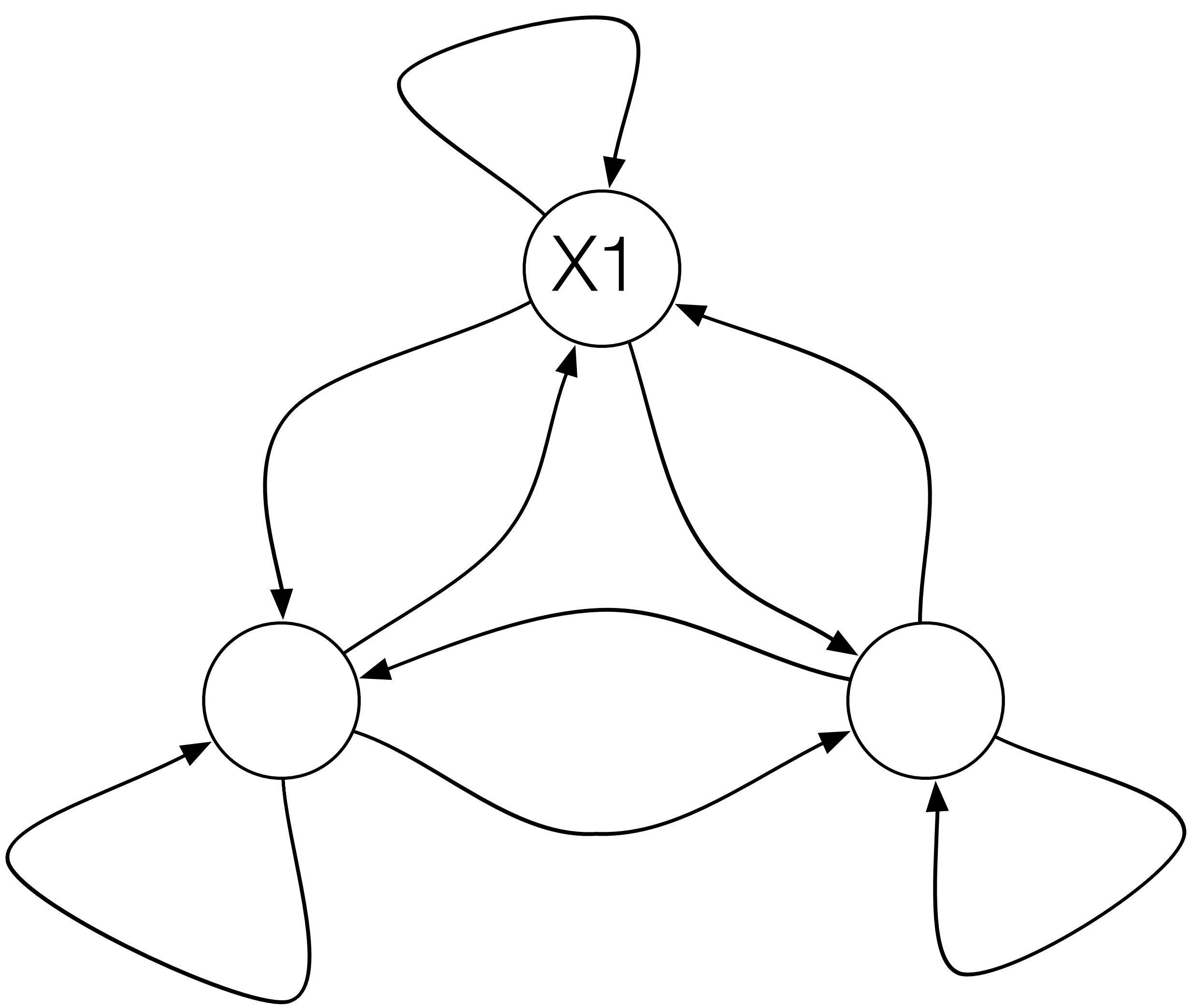

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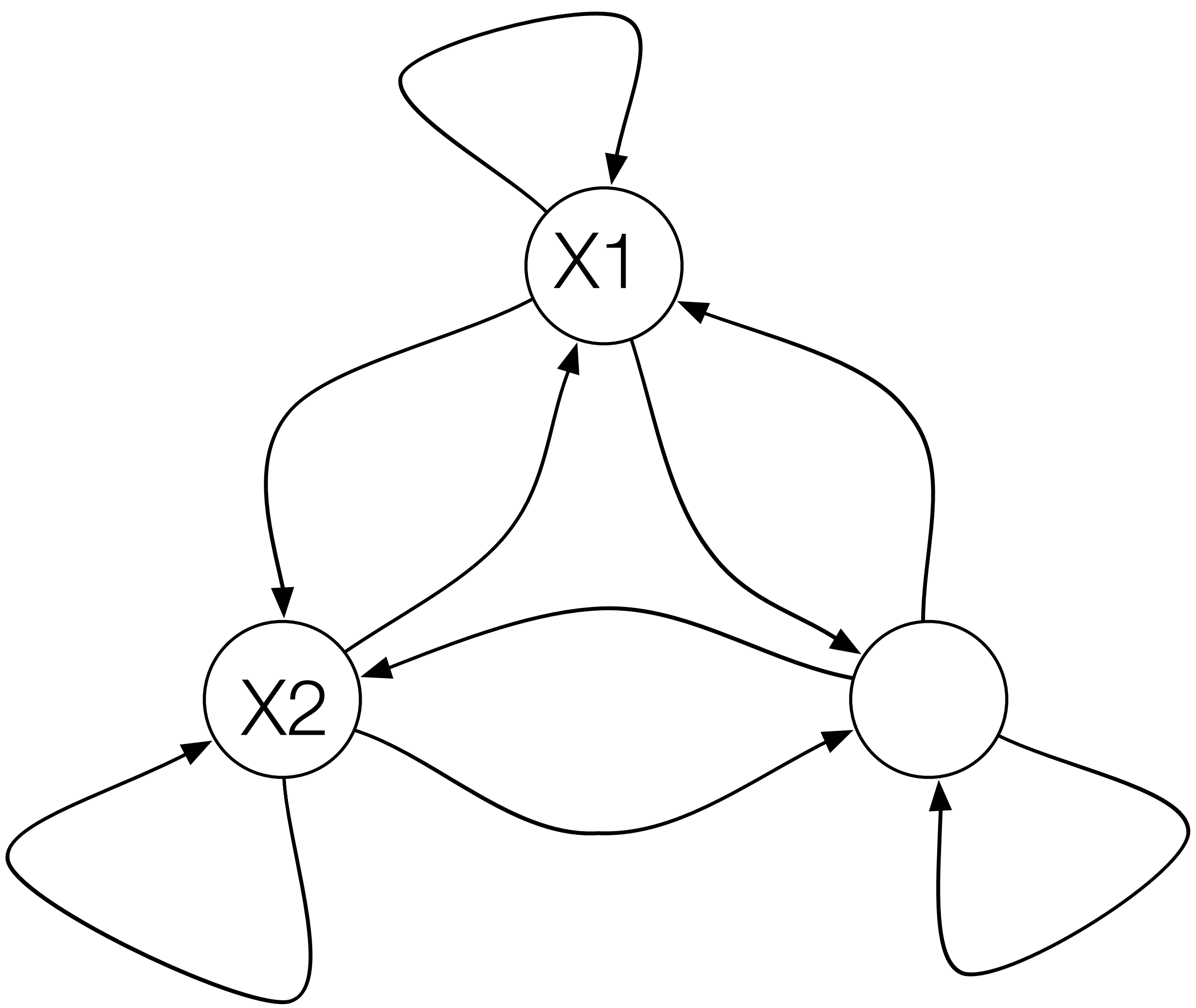

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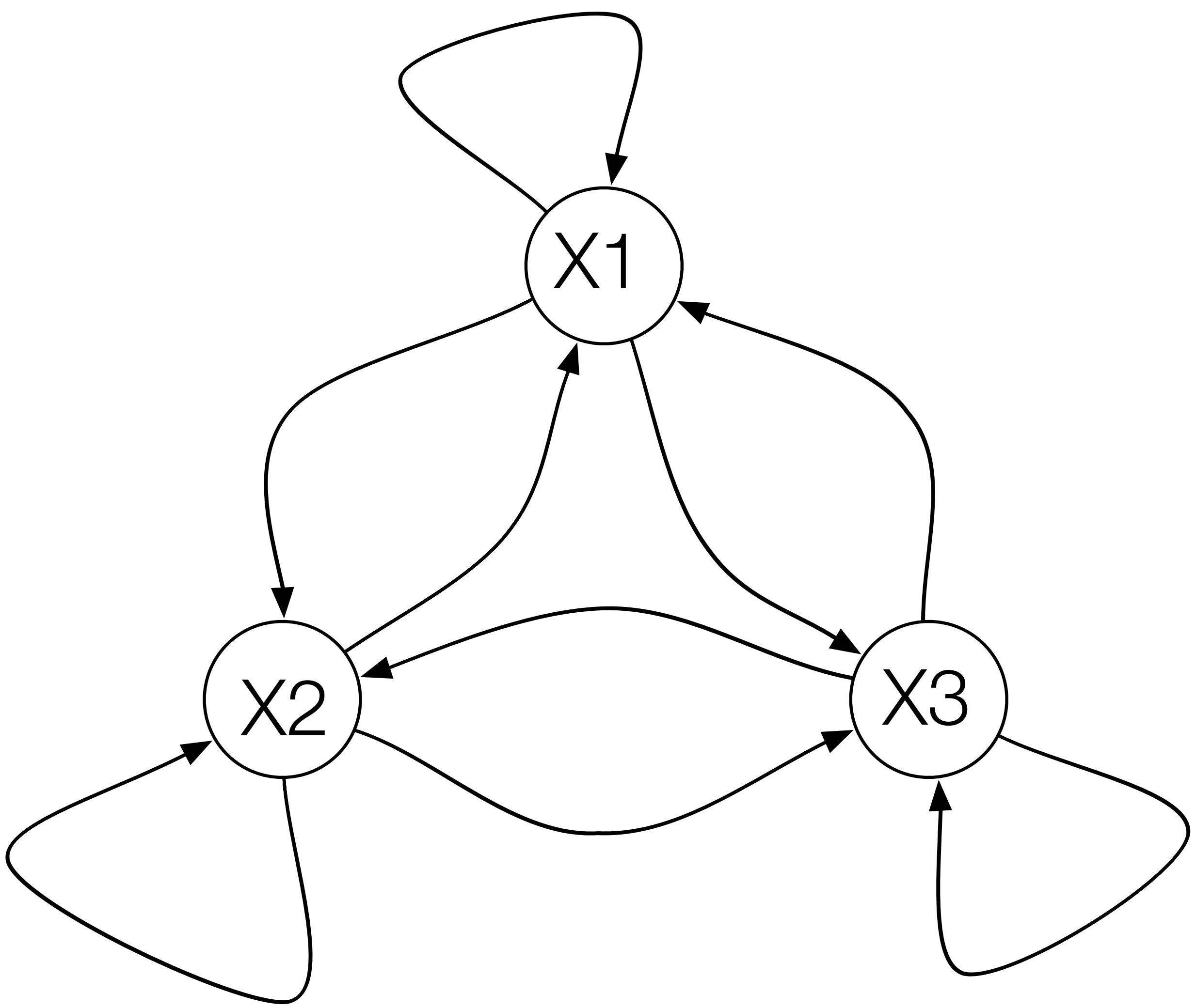

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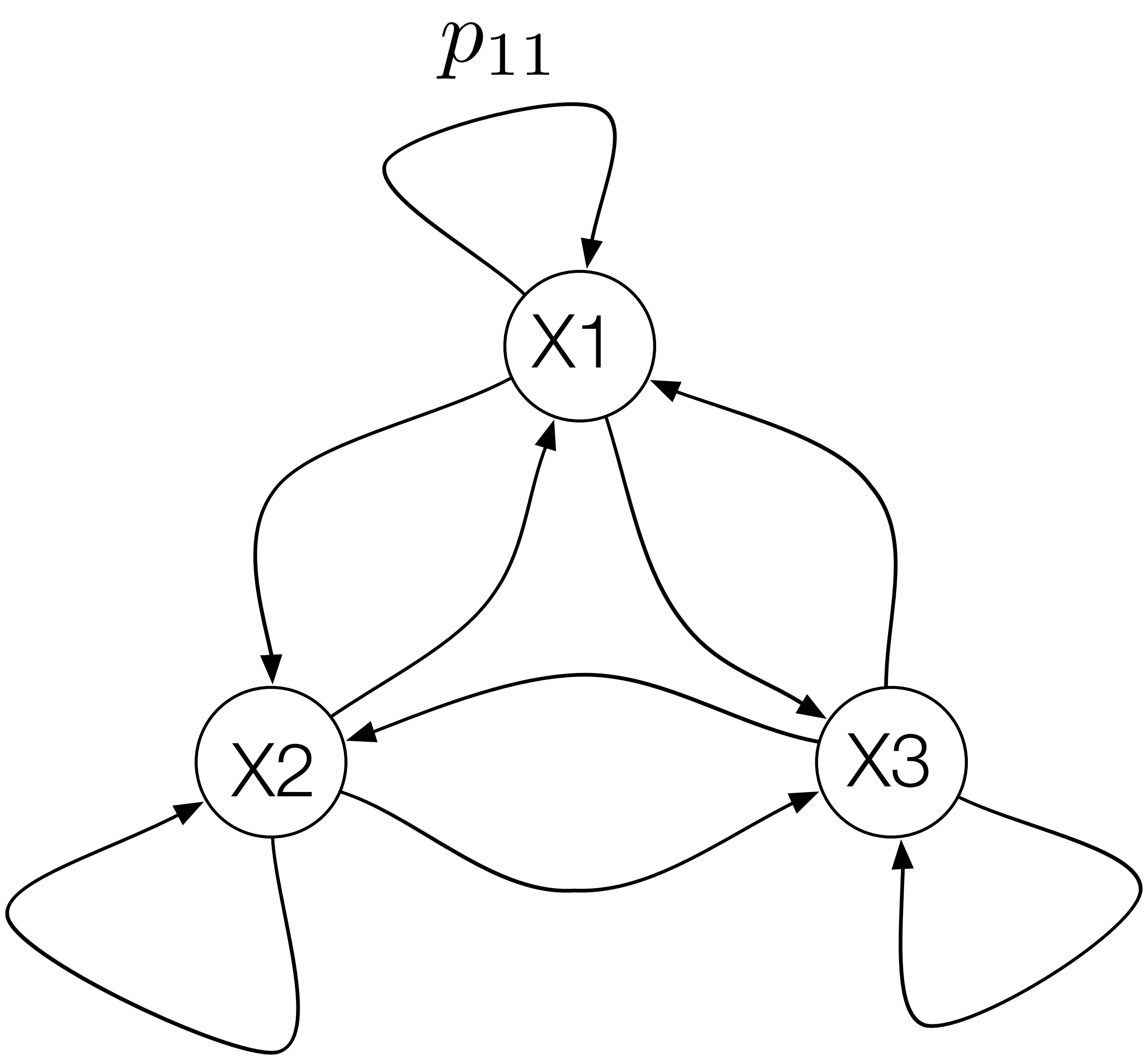

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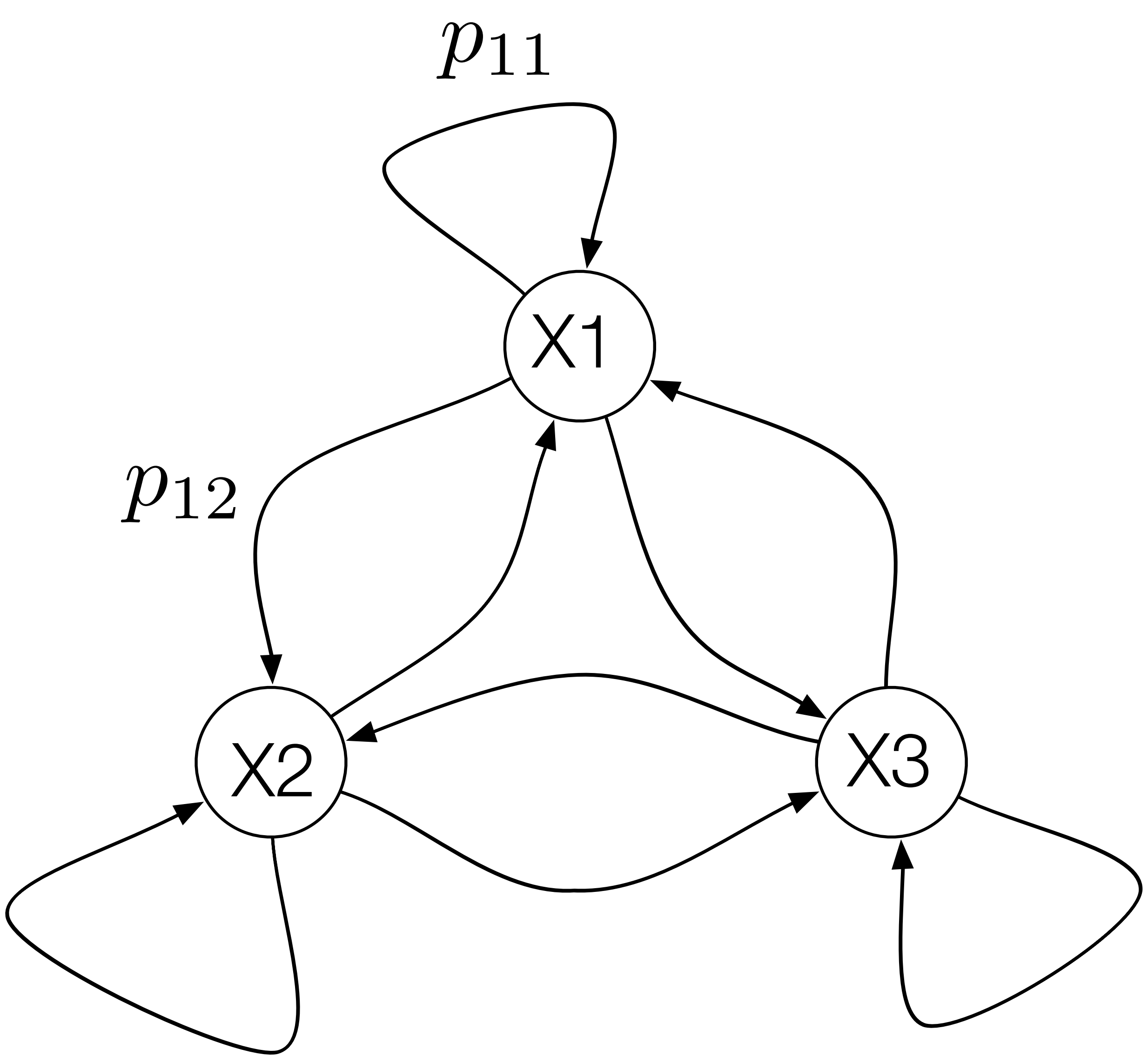

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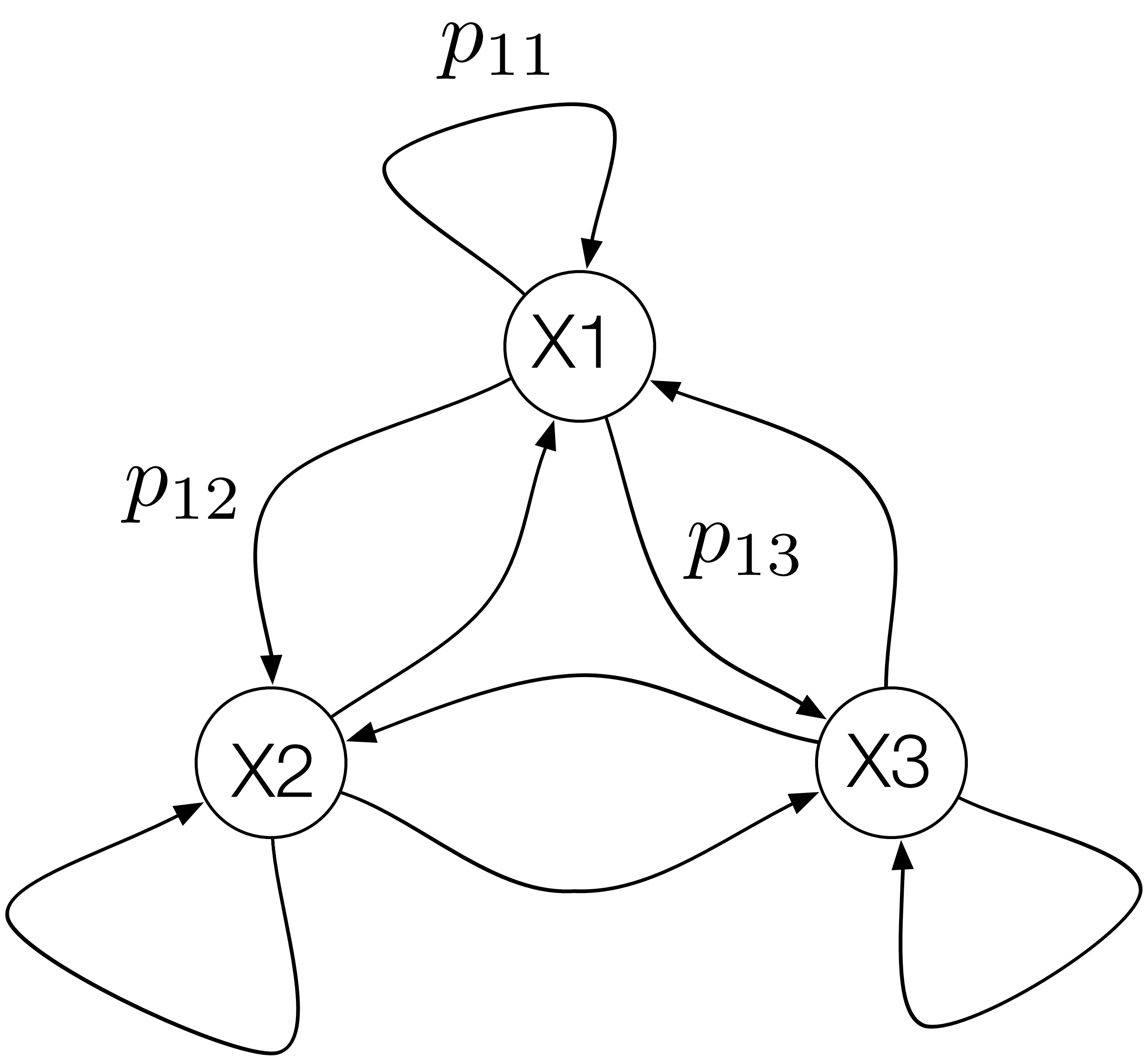

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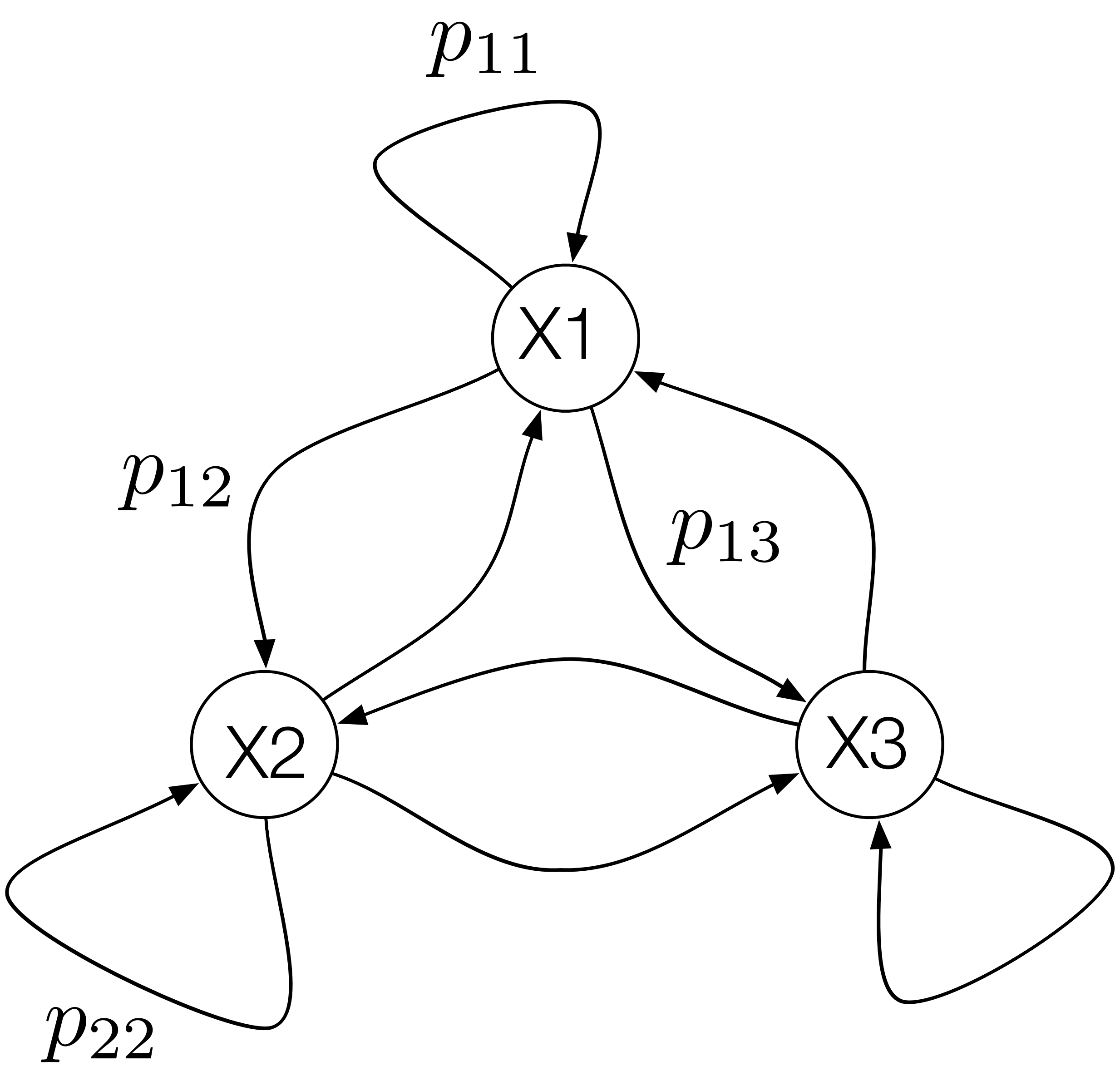

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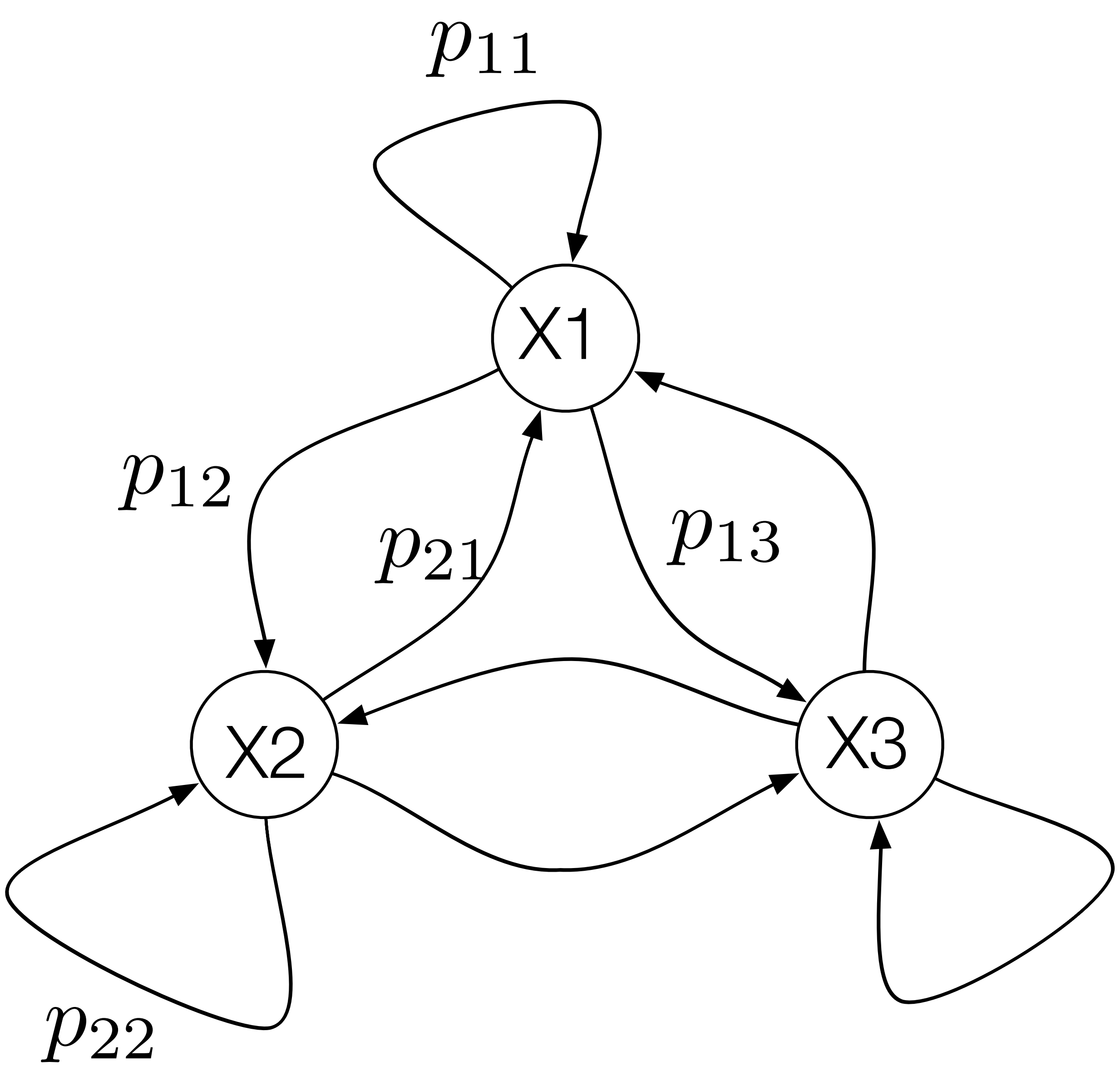

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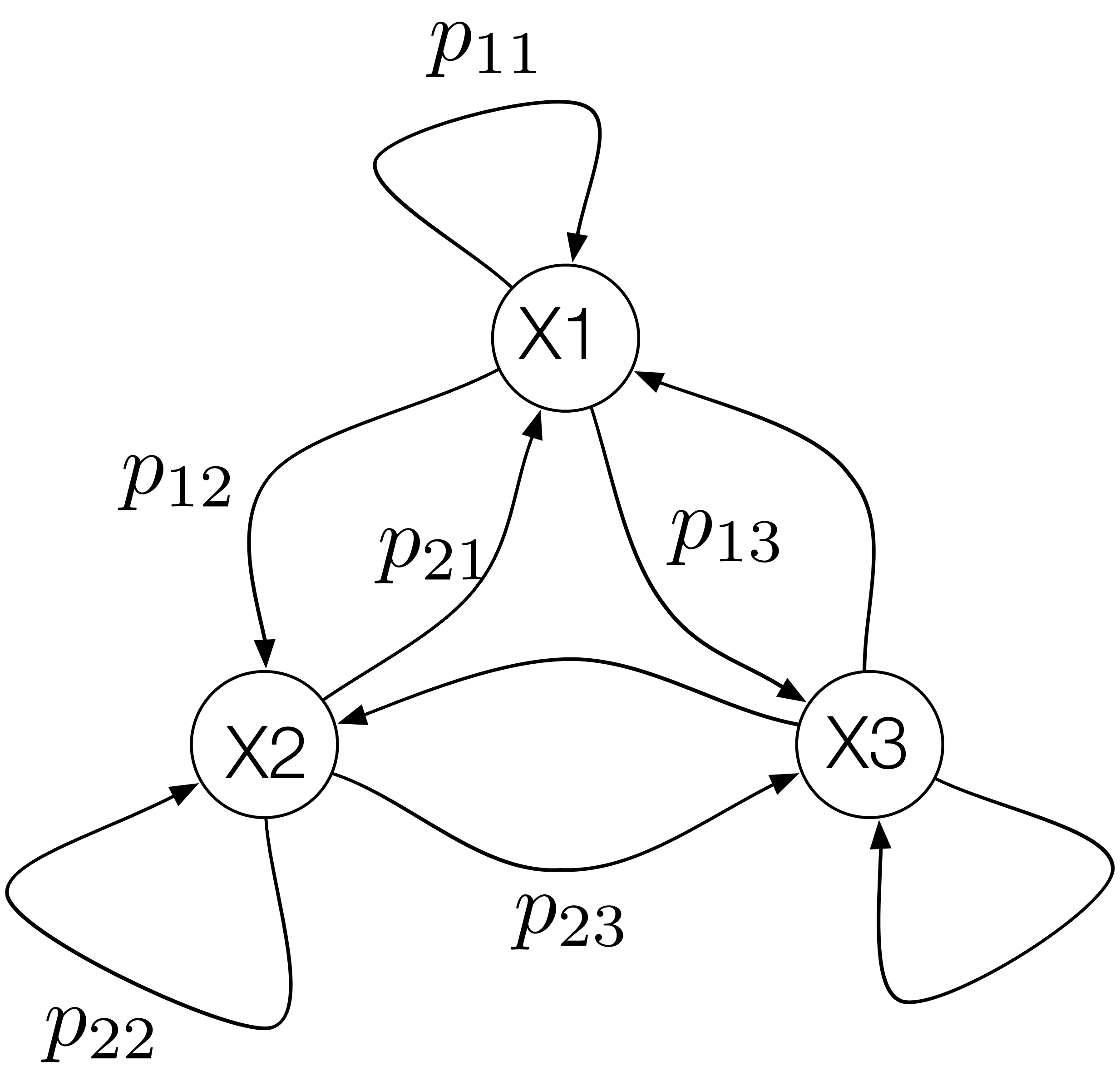

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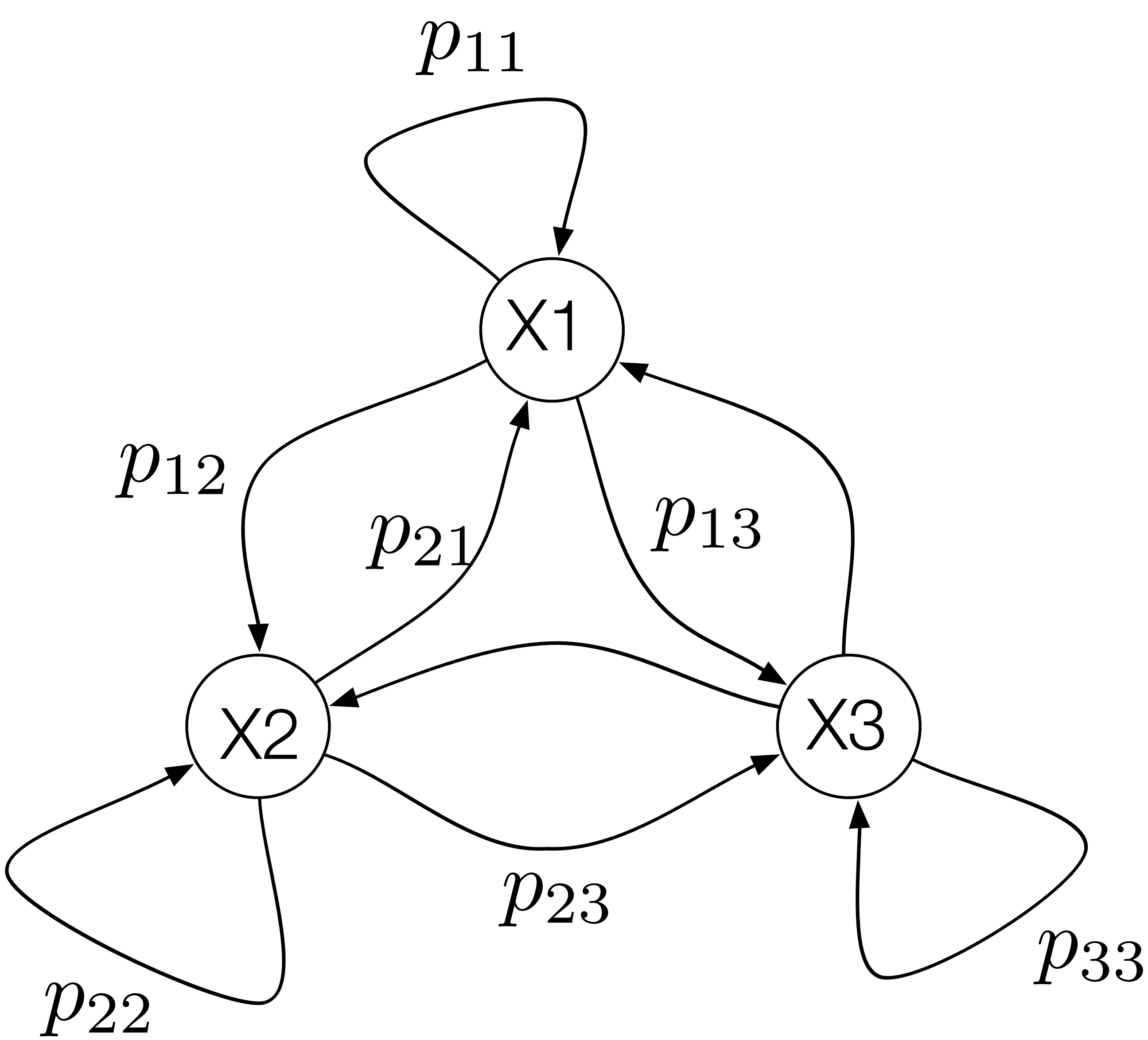

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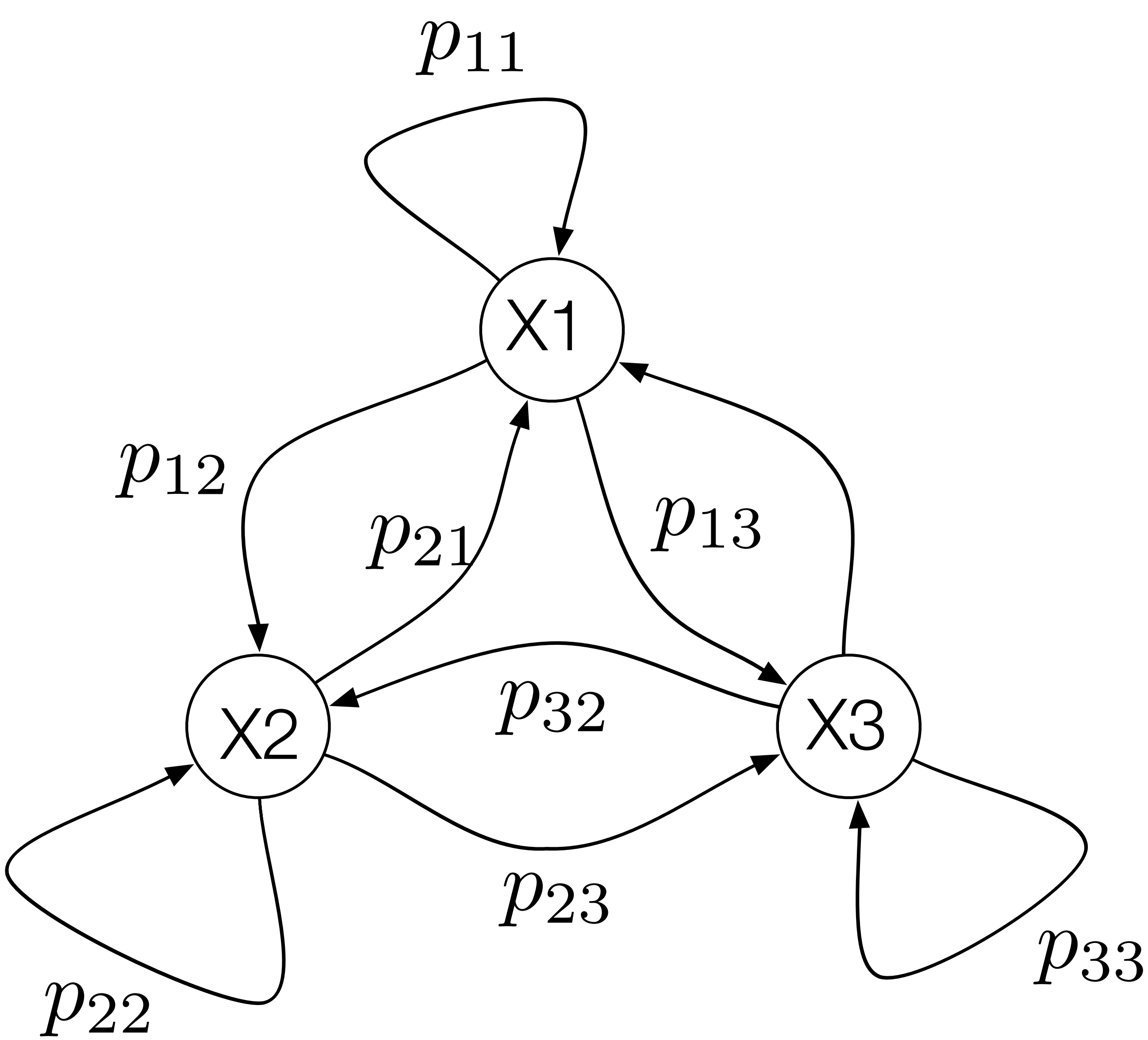

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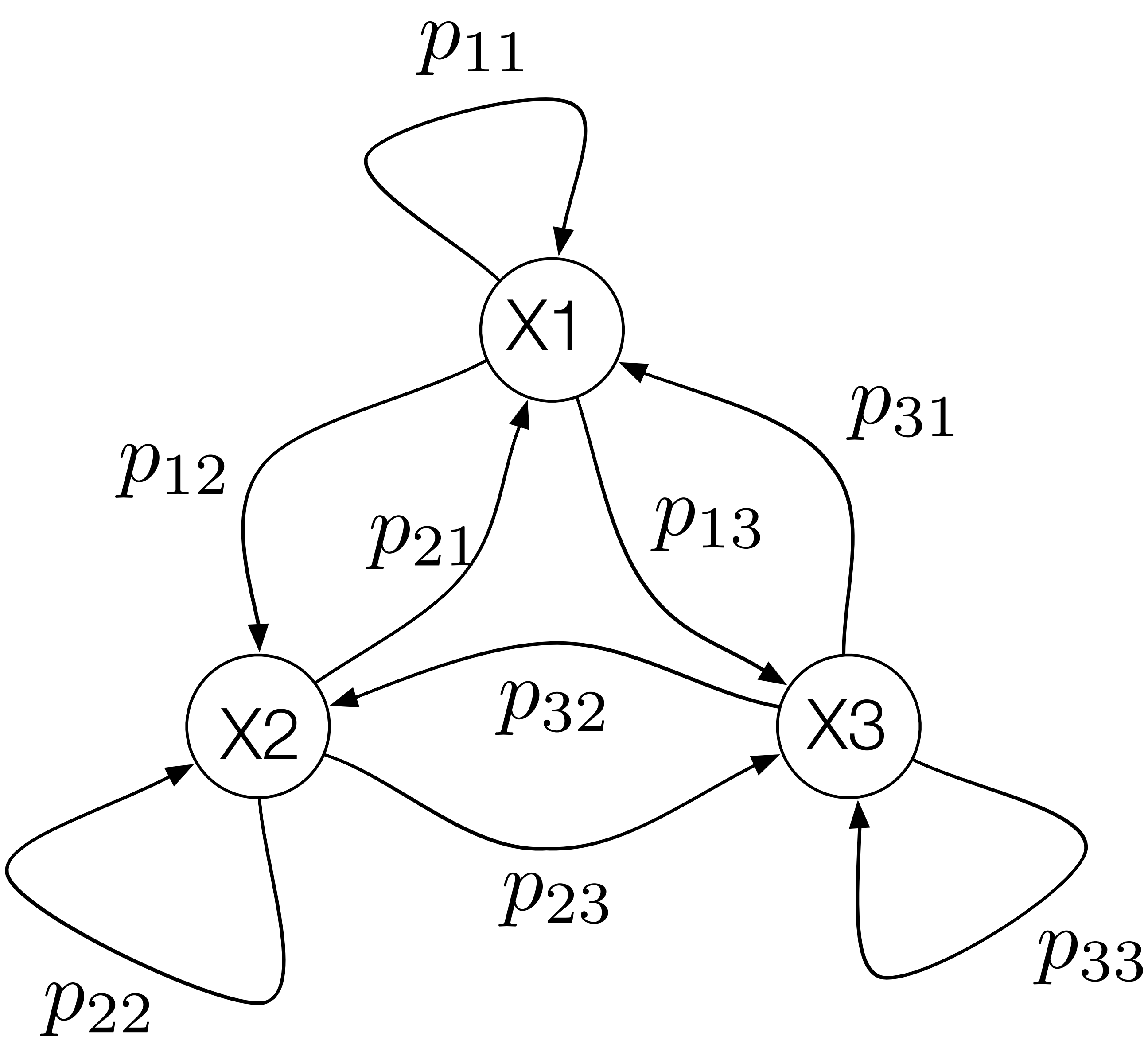

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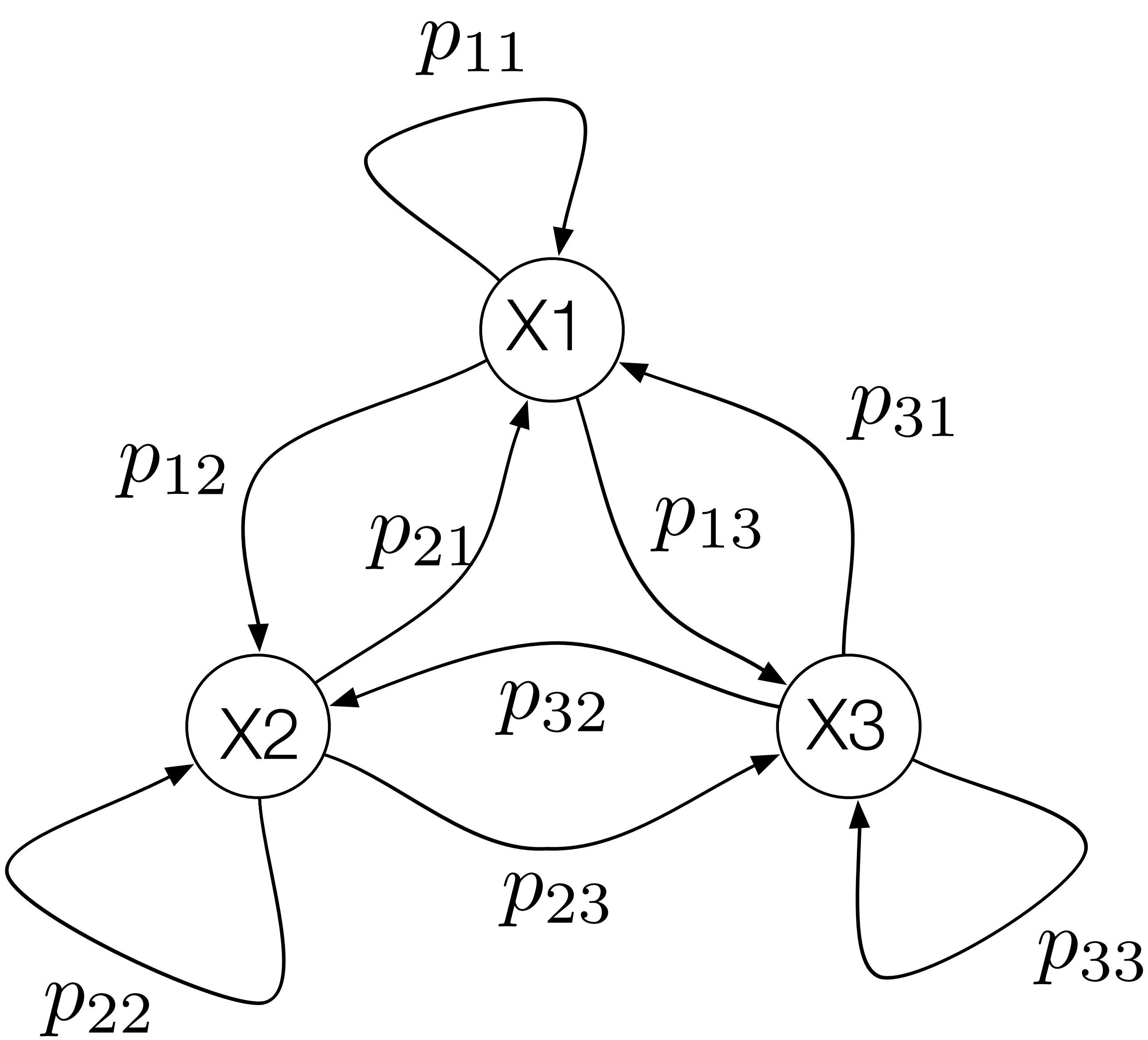

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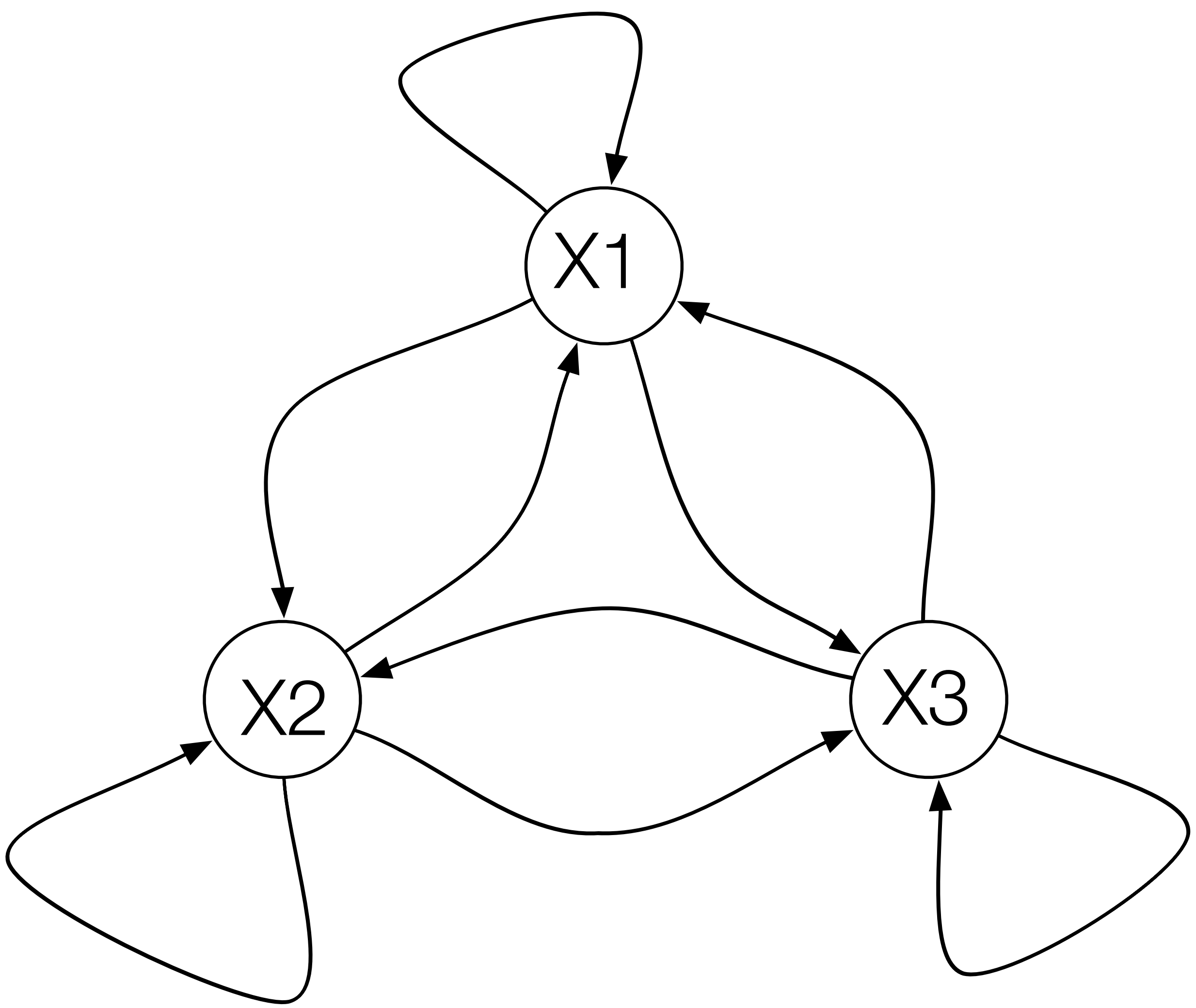

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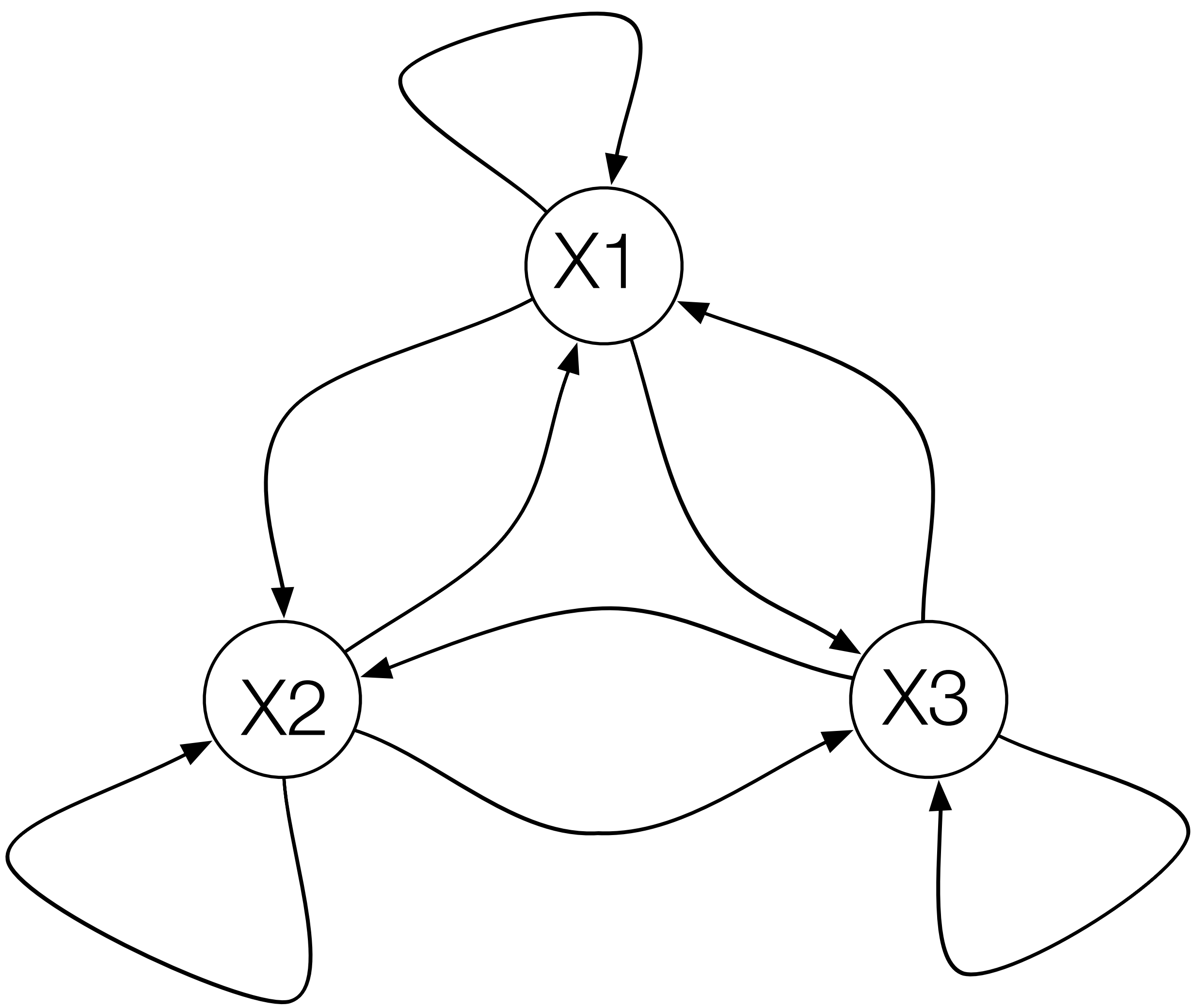

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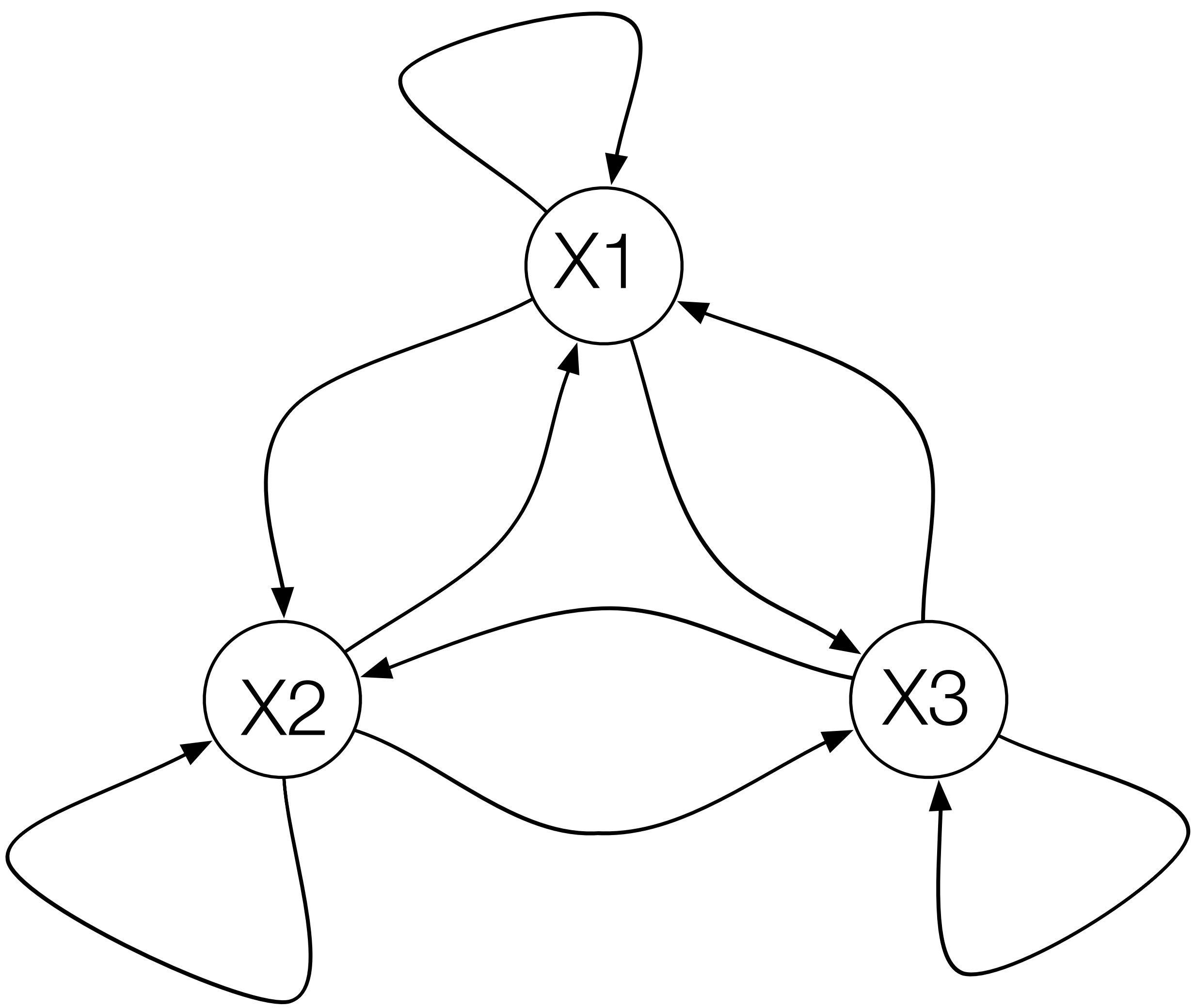

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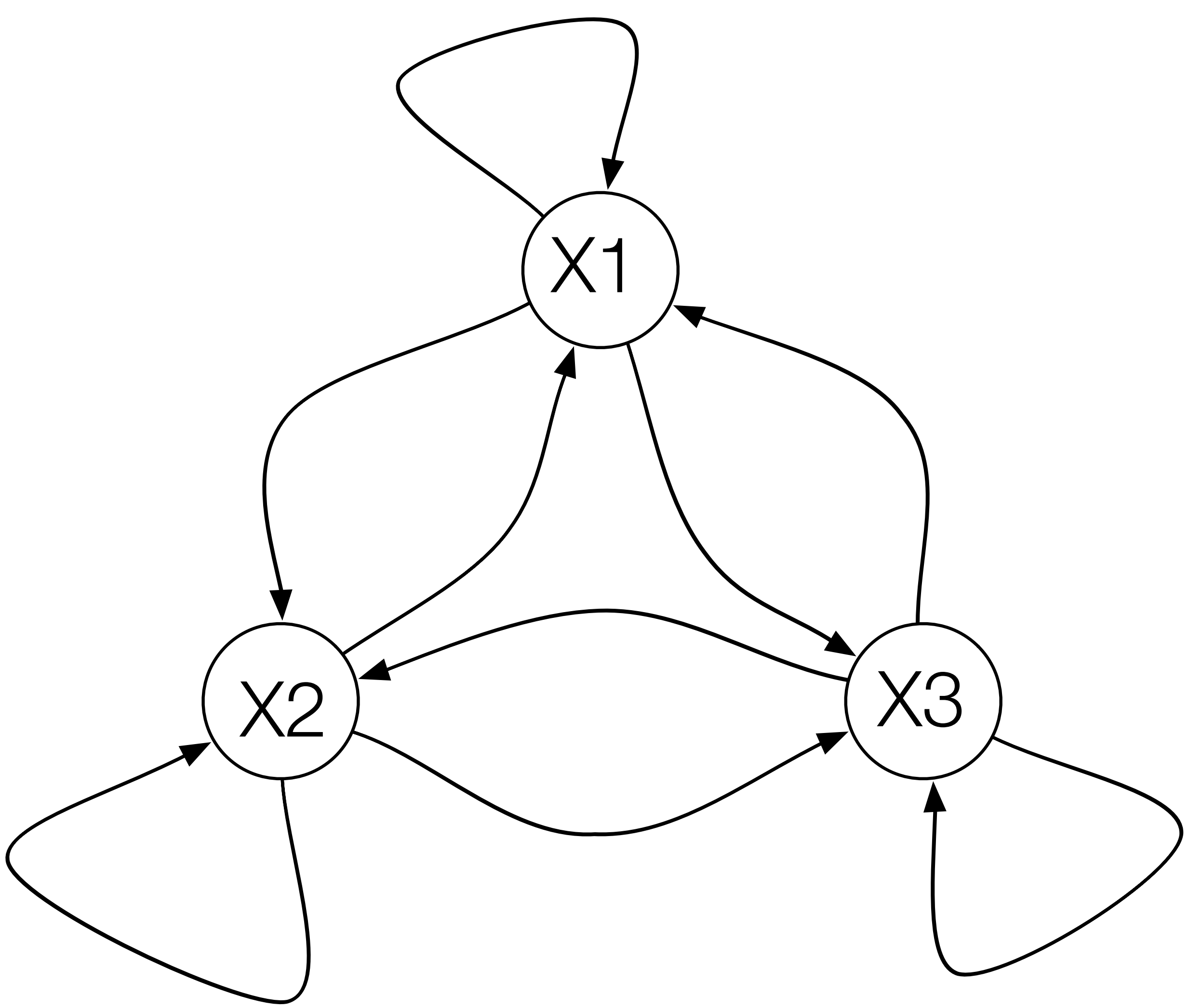

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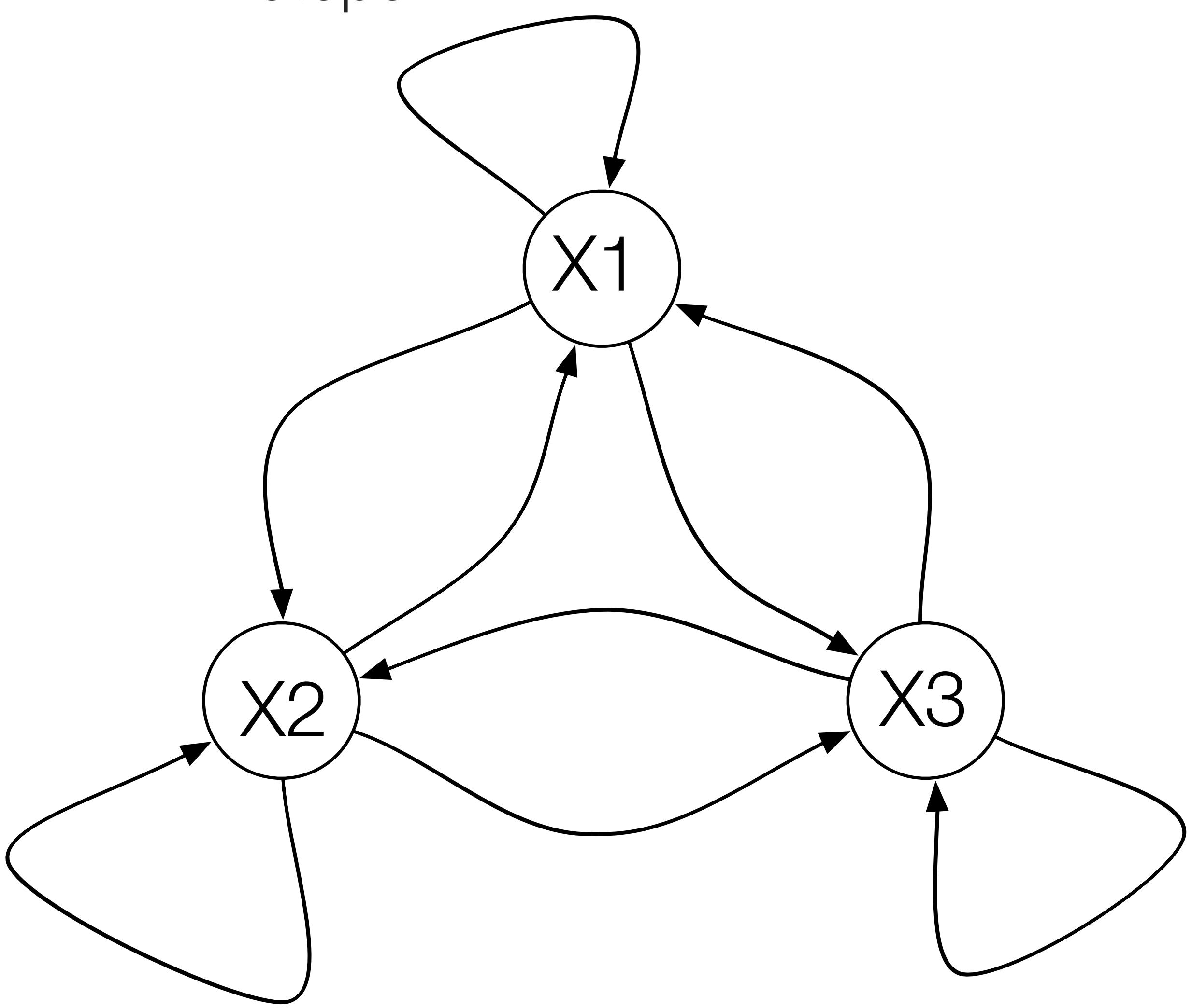

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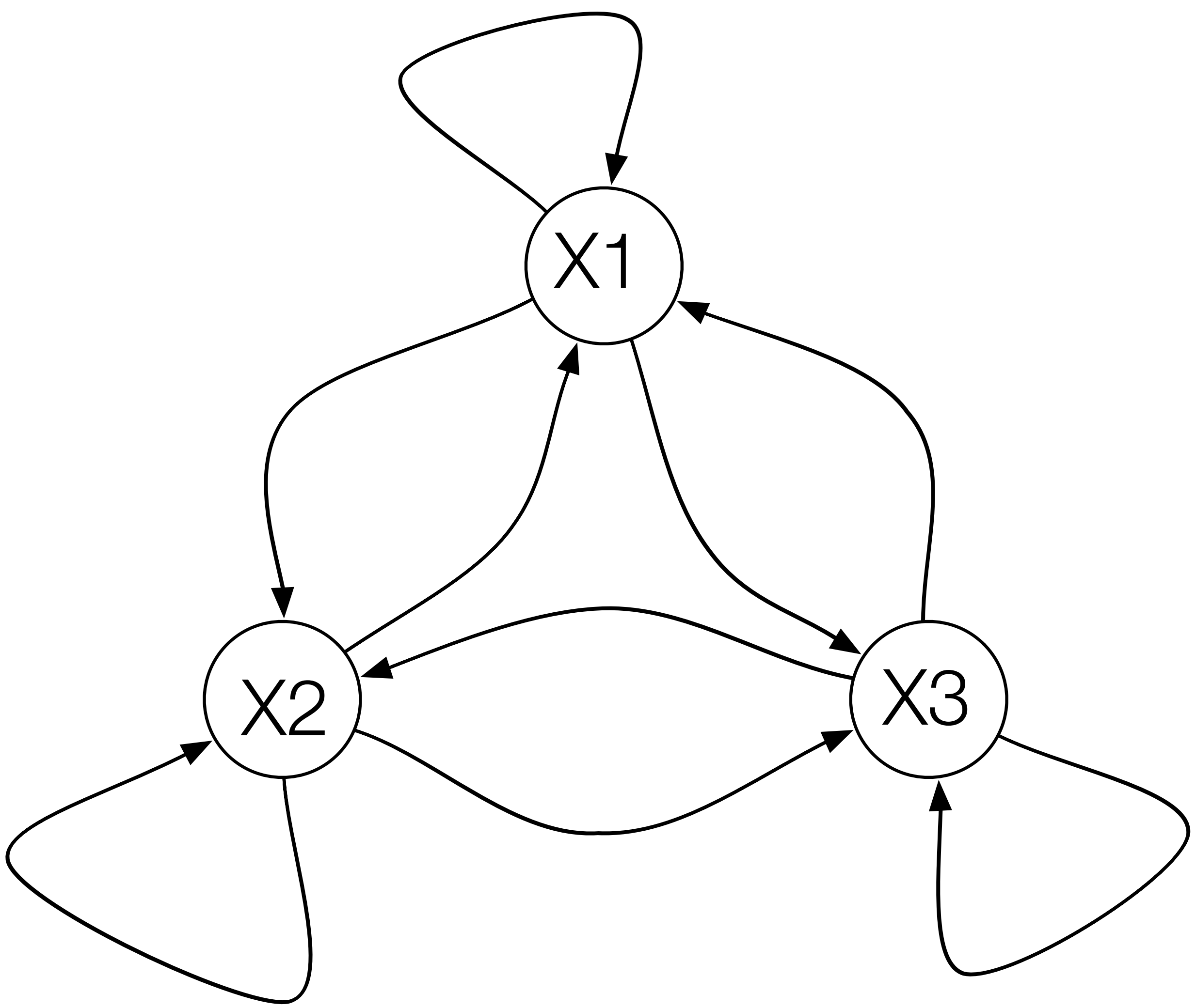

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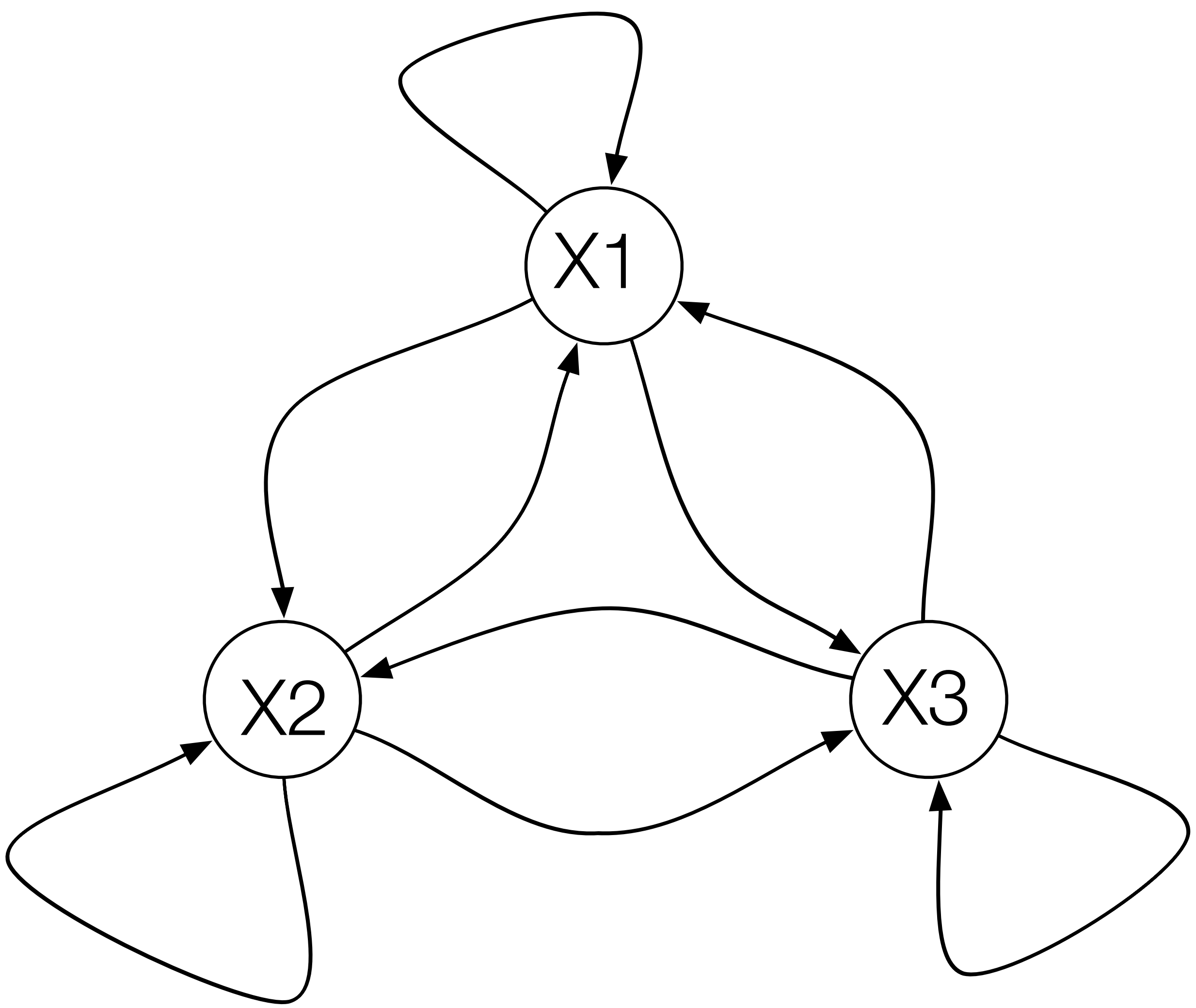

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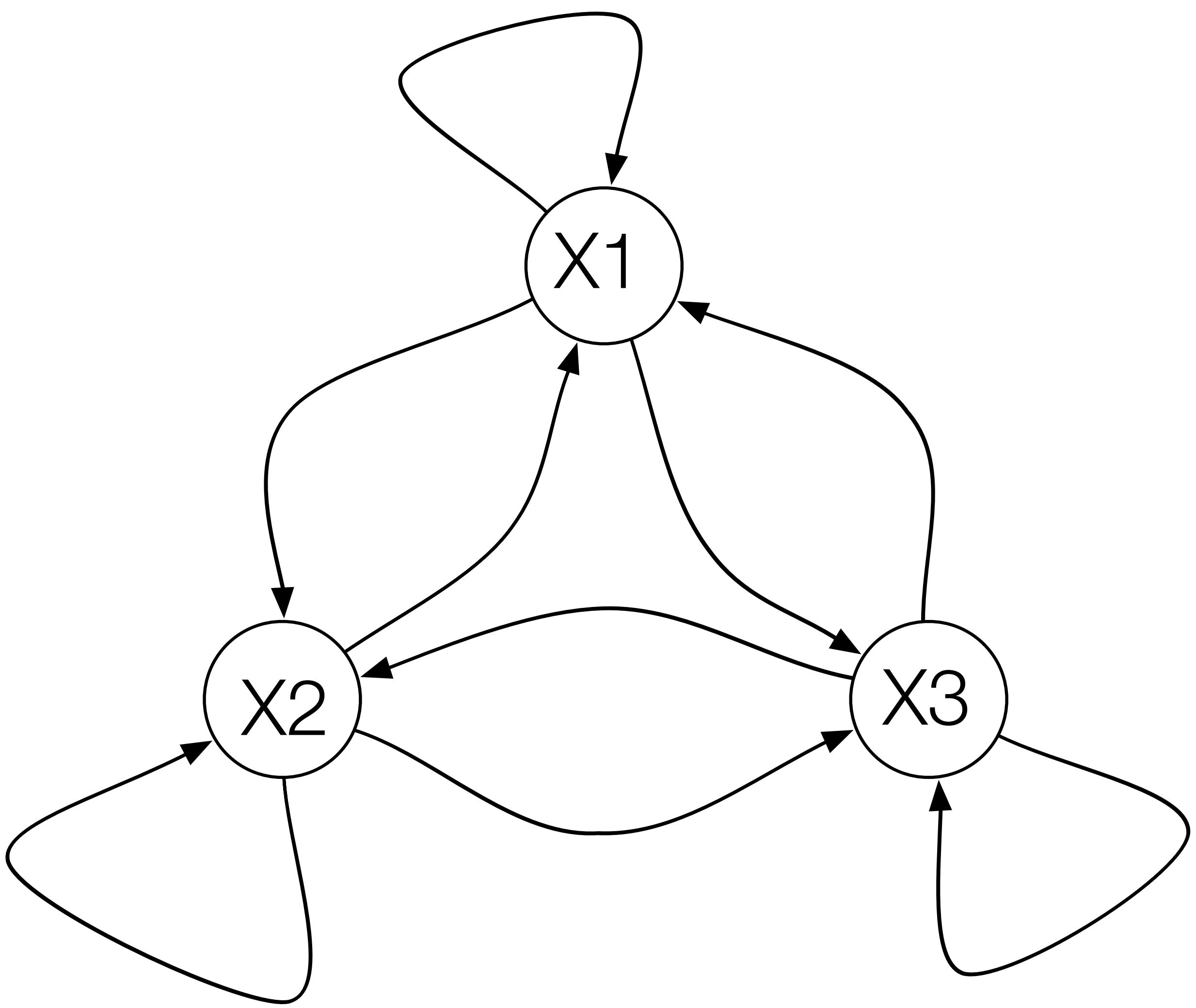

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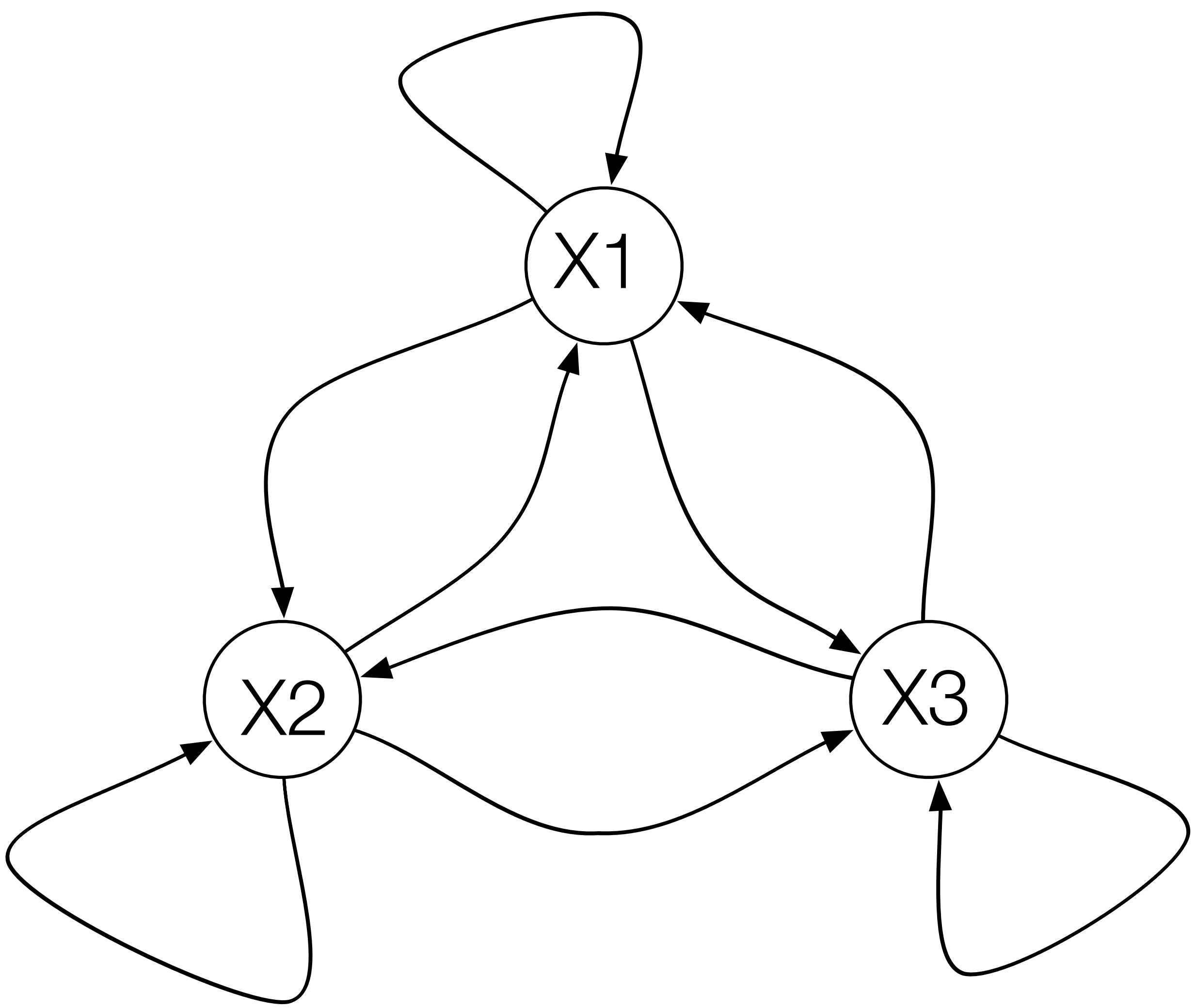

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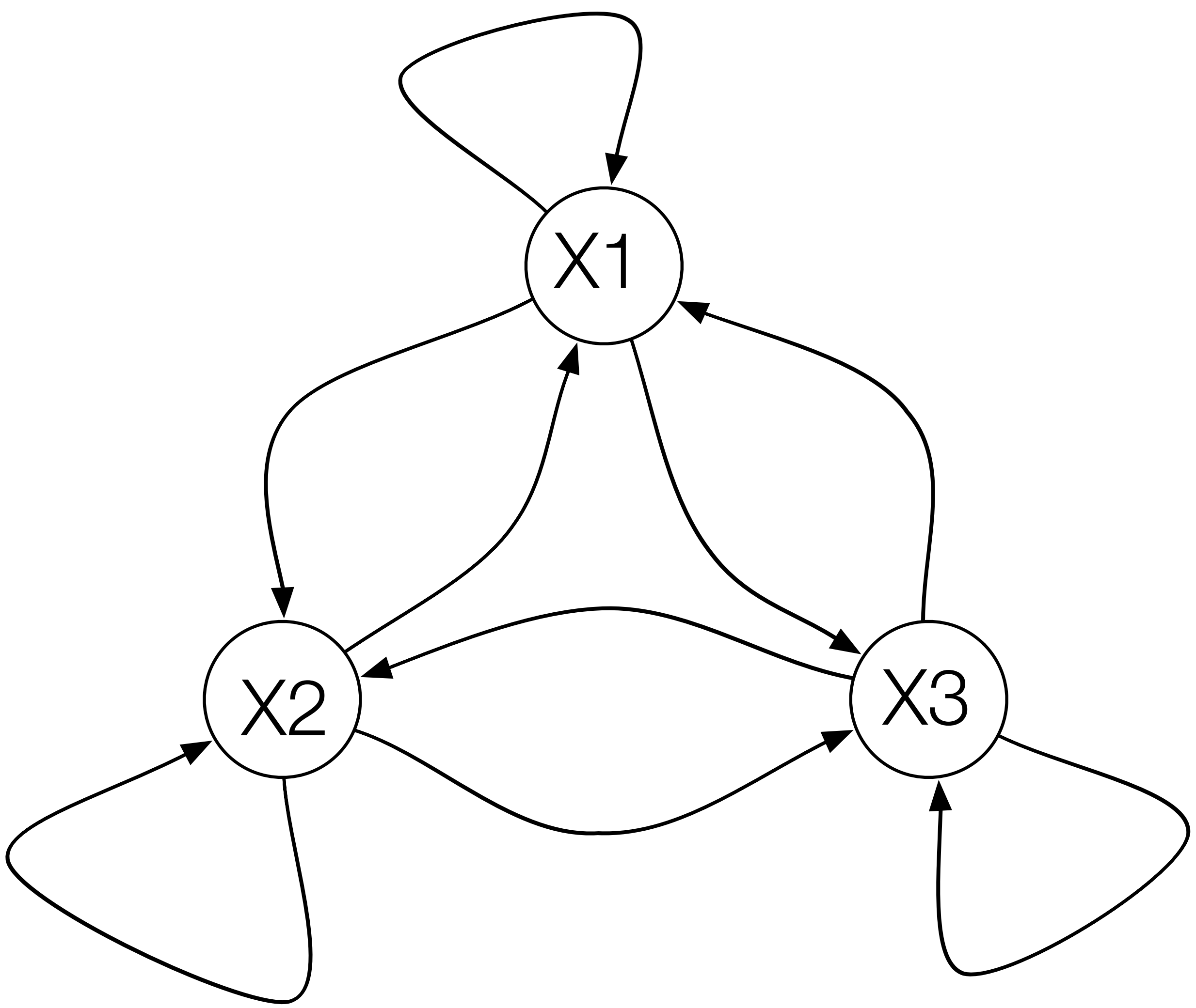

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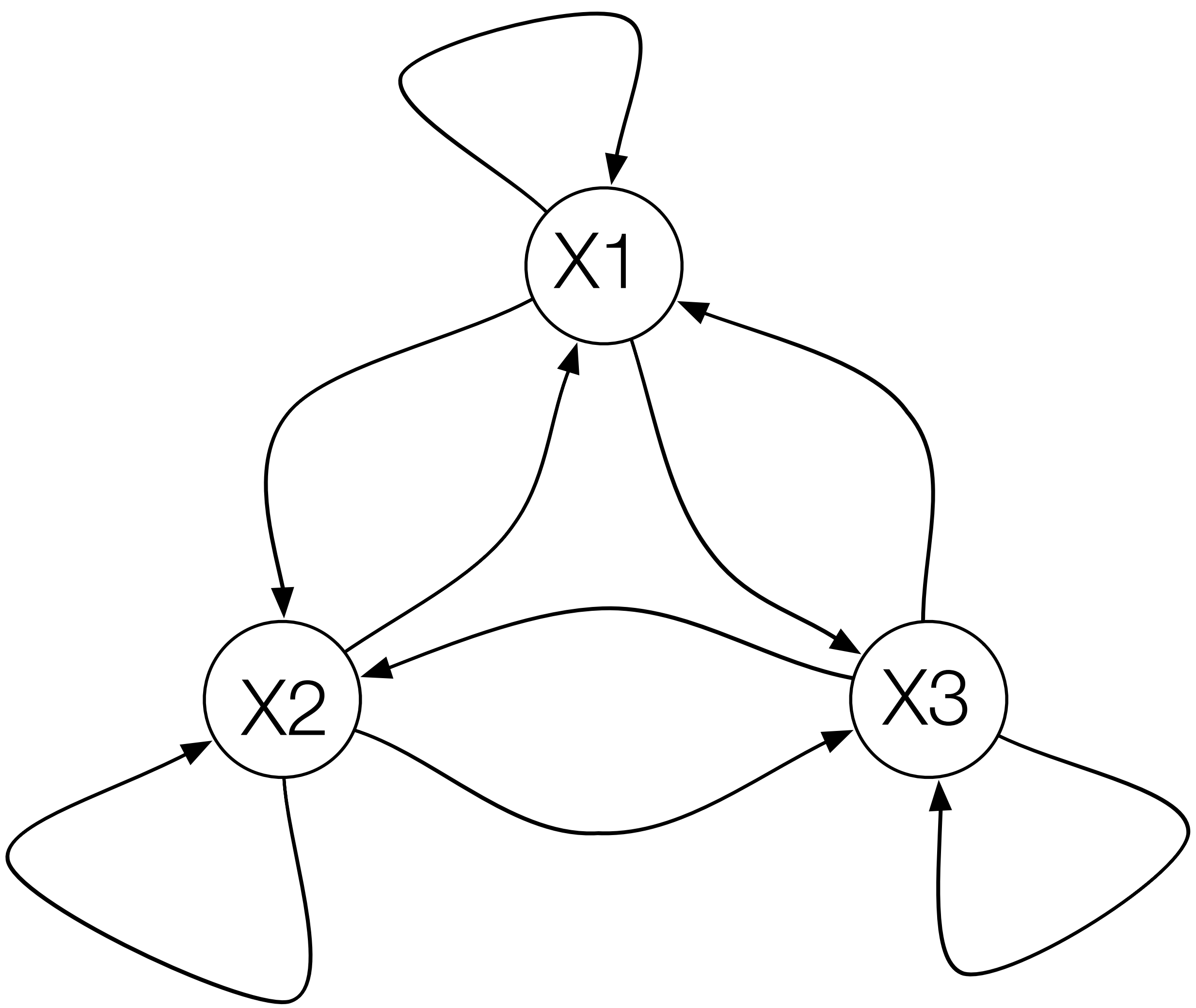

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- An analogous result: If all the recurrent states of the Markov chain **communicate** with each other and are aperiodic, then a consensus is reached.

DeGroot's Consensus convergens

- Because matrix **P** is a **k** x **k** stochastic matrix, it can be regarded as the one step transition probability matrix of a Markov chain with k states and stationary transition probabilities
- => standard theorems of theory of Markov chains hold

- Theorem (Doob 1953): If there exists a positive integer **n** s.t. every element in at least one column of the matrix $\mathbf{P}^n$ is positive, then a consensus is reached.
- An analogous result: If all the recurrent states of the Markov chain **communicate** with each other and are aperiodic, then a consensus is reached.
- If a consensus is reached, then it is unique!

Example

Example

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \\ \frac{1}{4} & \frac{3}{4} \end{bmatrix}$$

Example

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & \frac{3}{4} \end{bmatrix} \qquad \frac{1}{3}F_1 + \frac{2}{3}F_2$$

Example

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$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 \\ \frac{1}{4} & \frac{3}{4} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix}$$

Example

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & \frac{3}{4} \end{bmatrix} \qquad \frac{1}{3}F_1 + \frac{2}{3}F_2$$

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 \\ \frac{1}{4} & \frac{3}{4} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \qquad \frac{1}{3}F_1 + \frac{2}{3}F_2$$

Example

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & \frac{3}{4} \end{bmatrix} \qquad \frac{1}{3}F_1 + \frac{2}{3}F_2 \qquad P = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 \\ \frac{1}{4} & \frac{3}{4} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \qquad \frac{1}{3}F_1 + \frac{2}{3}F_2$$

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$$P = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$ no consensus

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 \\ \frac{1}{4} & \frac{3}{4} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \qquad \frac{1}{3}F_1 + \frac{2}{3}F_2$$

Example

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & \frac{3}{4} \end{bmatrix}$$

$$\frac{1}{3}F_1 + \frac{2}{3}F_2$$

$$P = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

no consensus

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 \\ \frac{1}{4} & \frac{3}{4} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix}$$

$$\frac{1}{3}F_1 + \frac{2}{3}F_2$$

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} \end{bmatrix}$$

Example

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & \frac{3}{4} \end{bmatrix}$$

$$\frac{1}{3}F_1 + \frac{2}{3}F_2$$

$$P = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

no consensus

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 \\ \frac{1}{4} & \frac{3}{4} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix}$$

$$\frac{1}{3}F_1 + \frac{2}{3}F_2$$

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} \end{bmatrix}$$

no consensus

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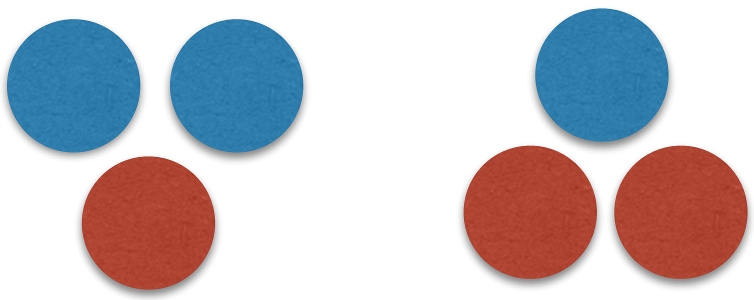

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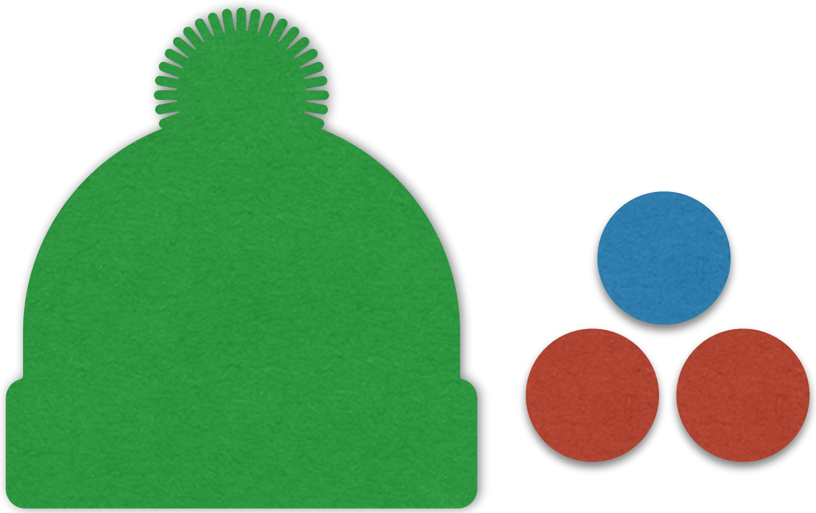

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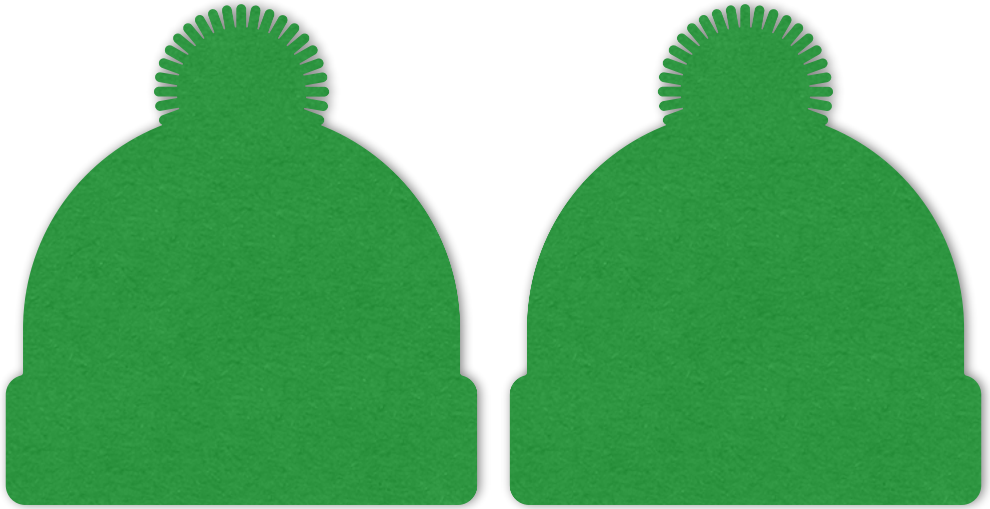

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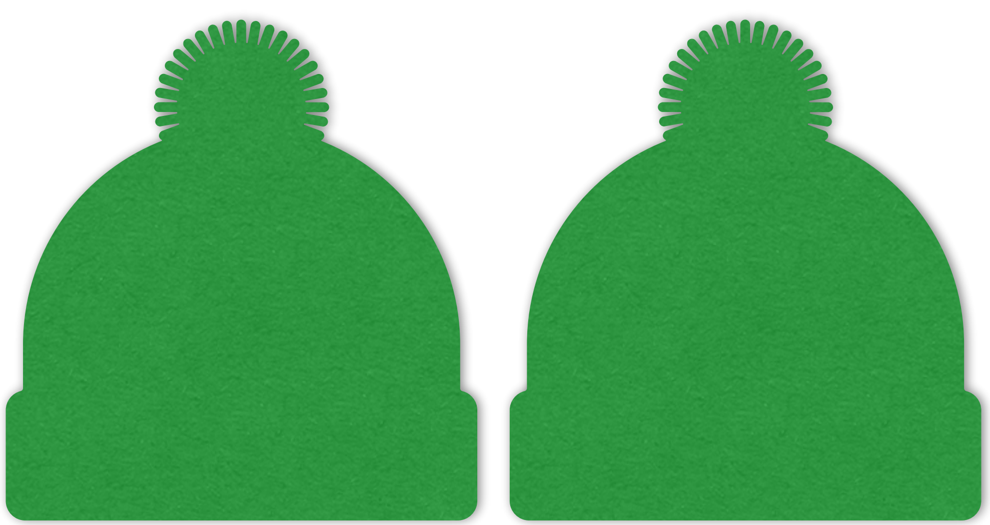

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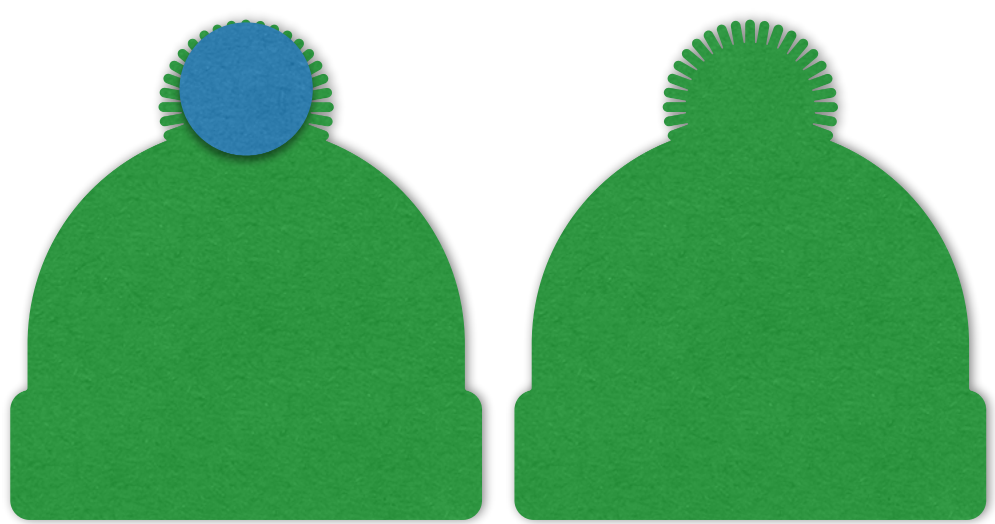

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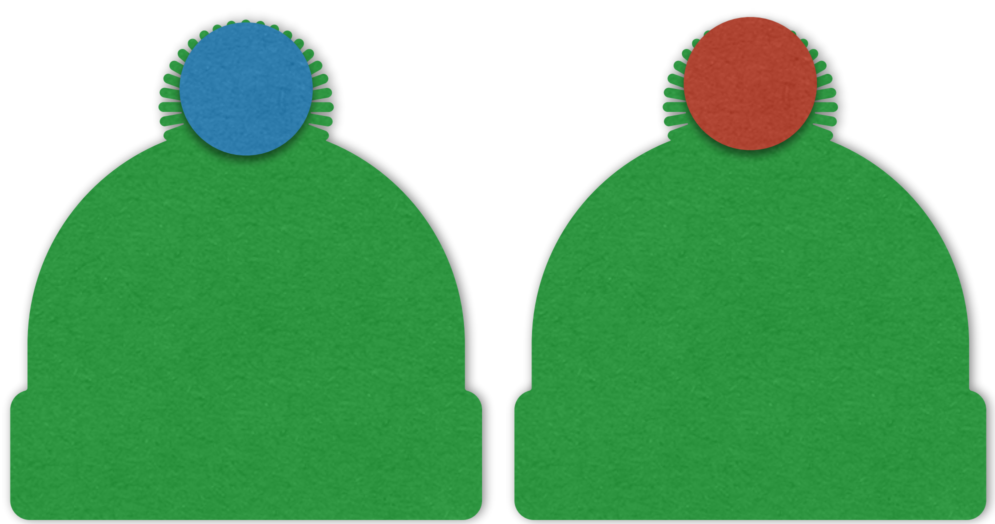

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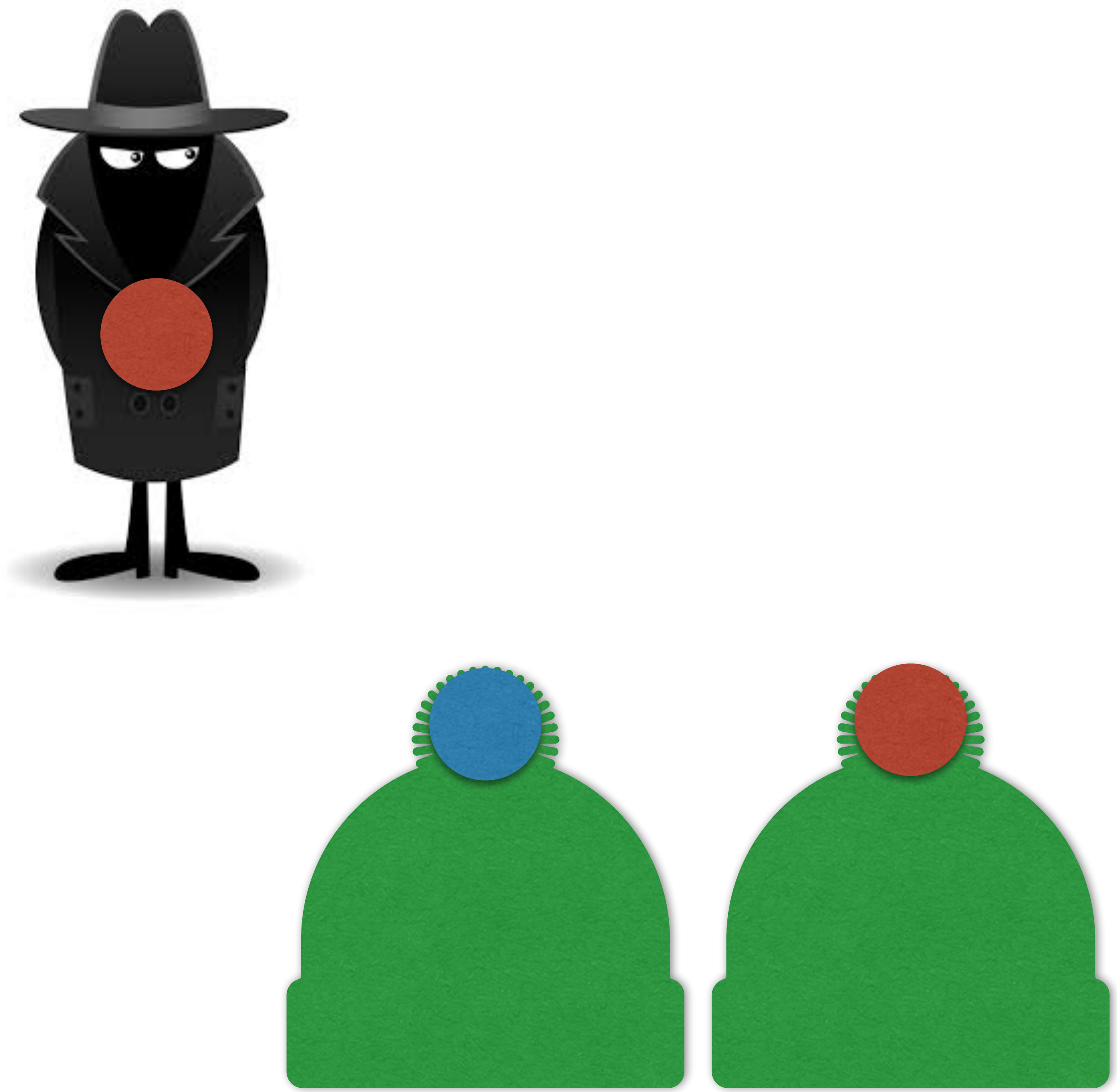

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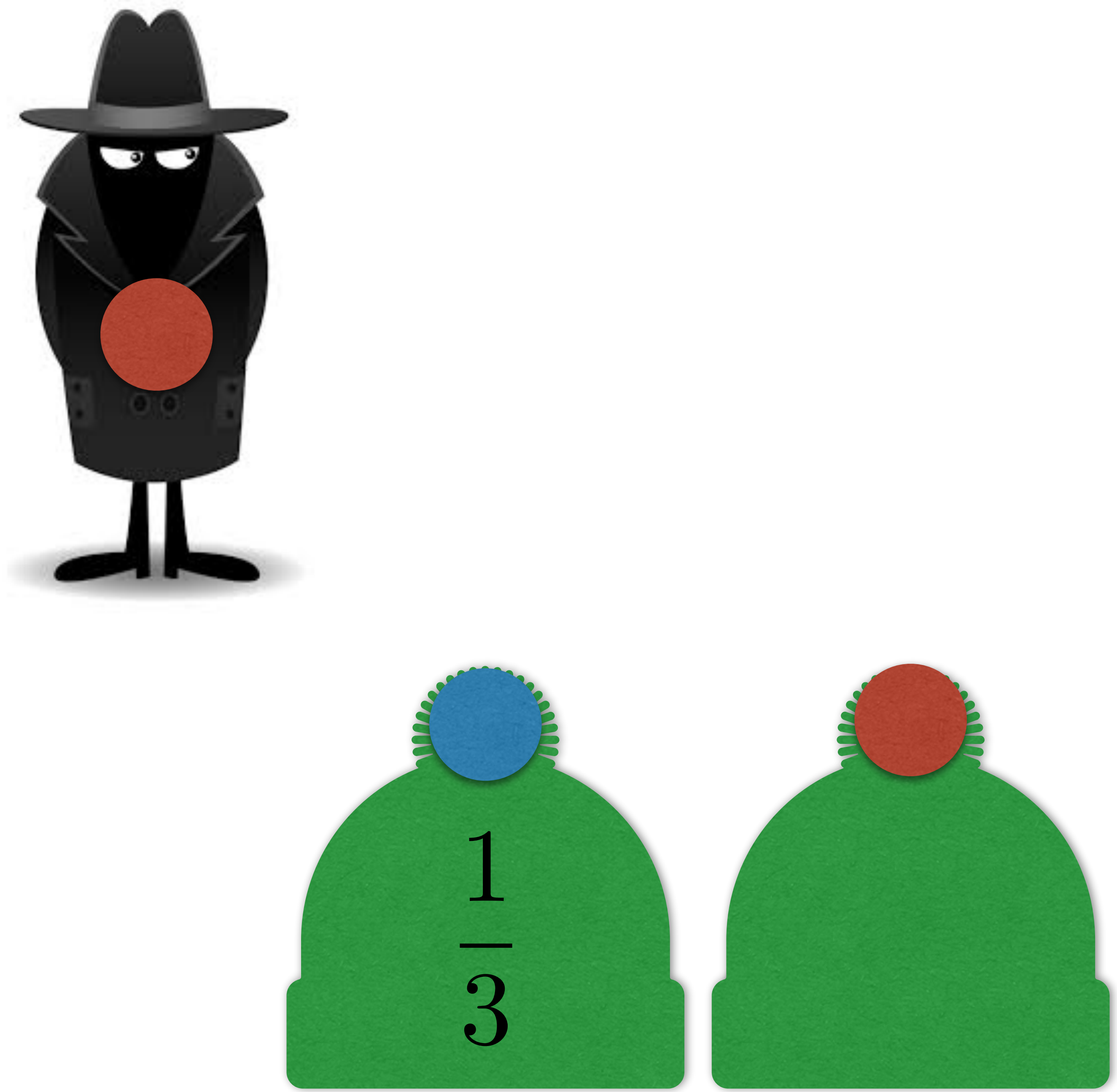

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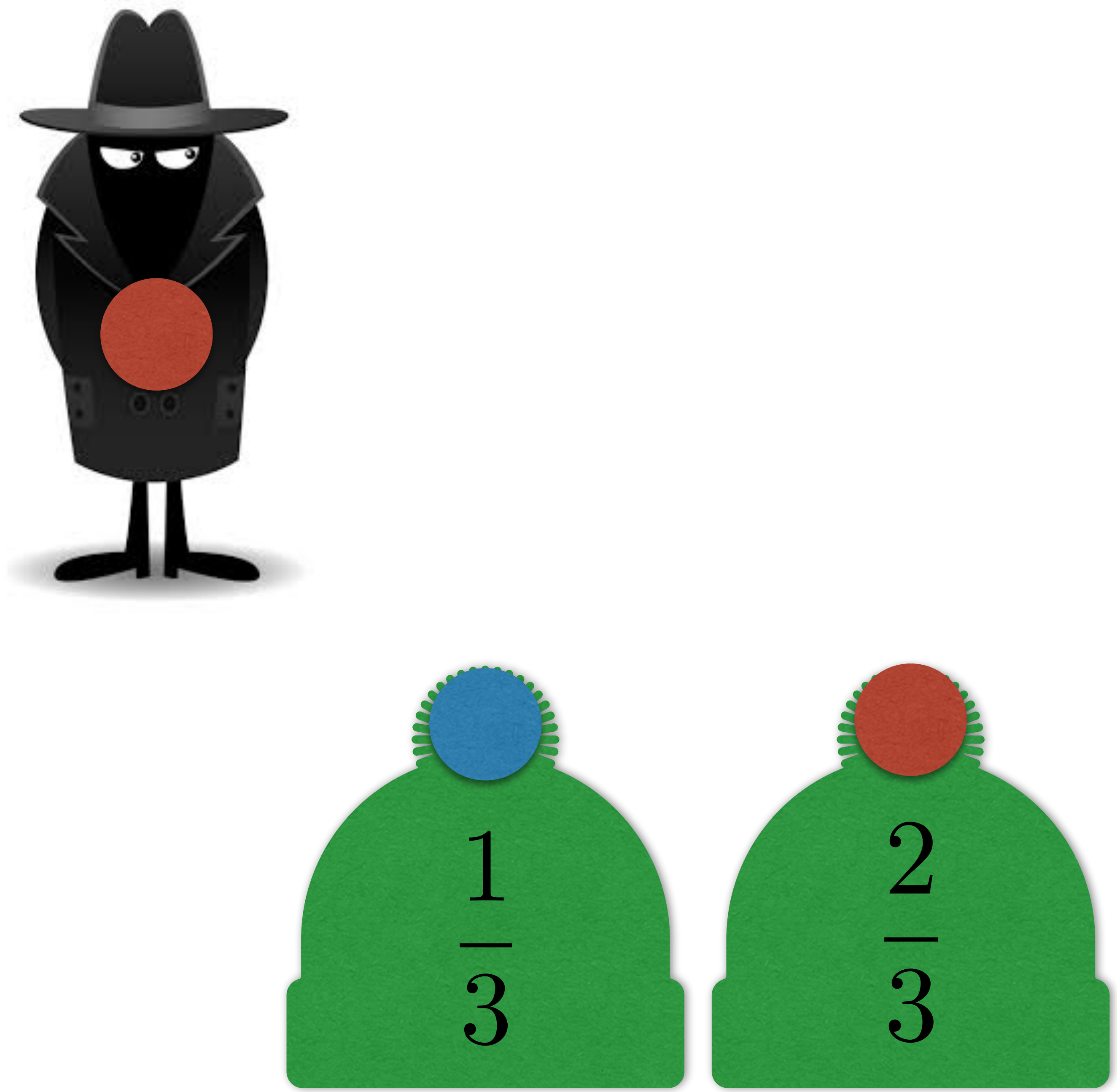

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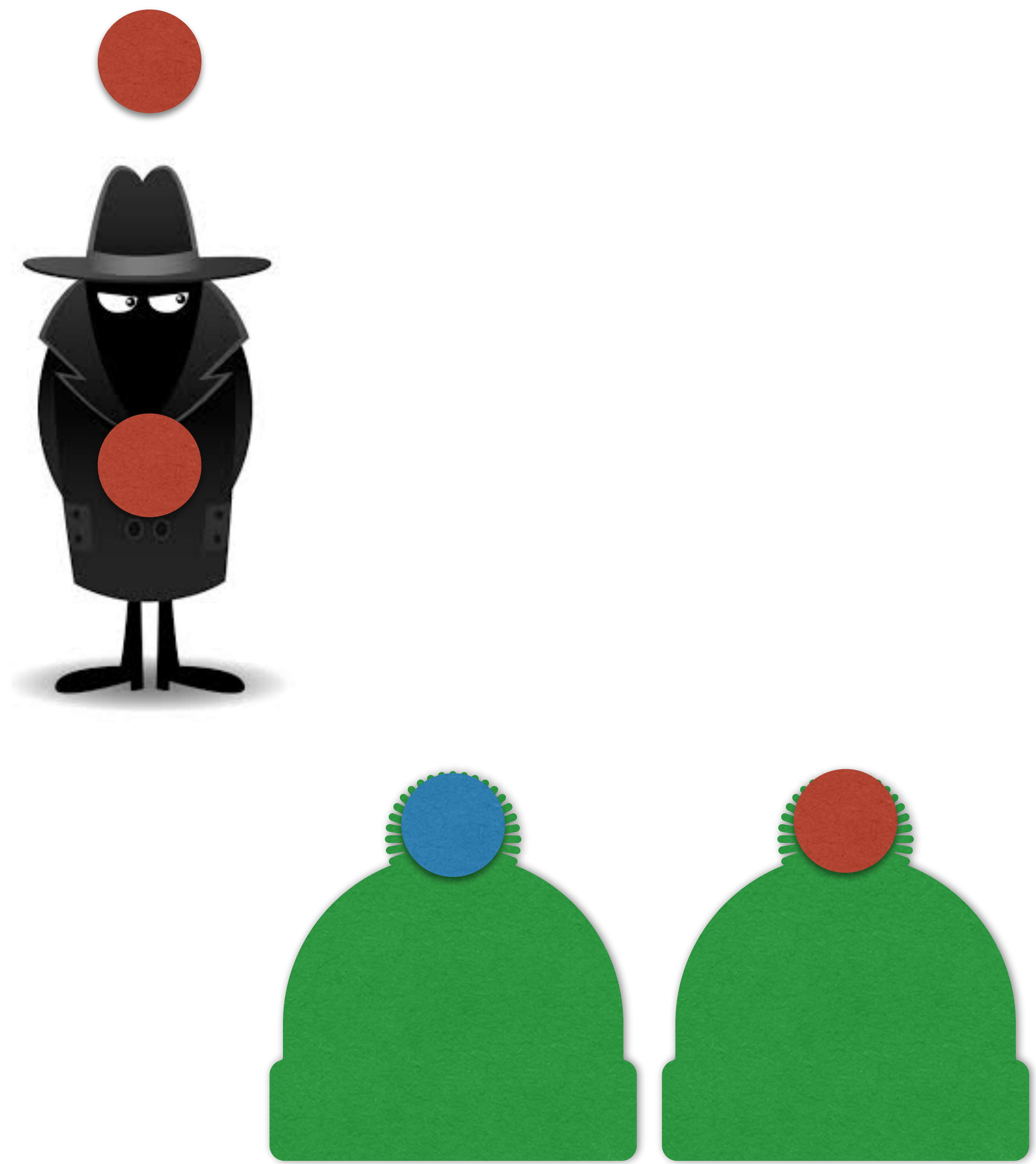

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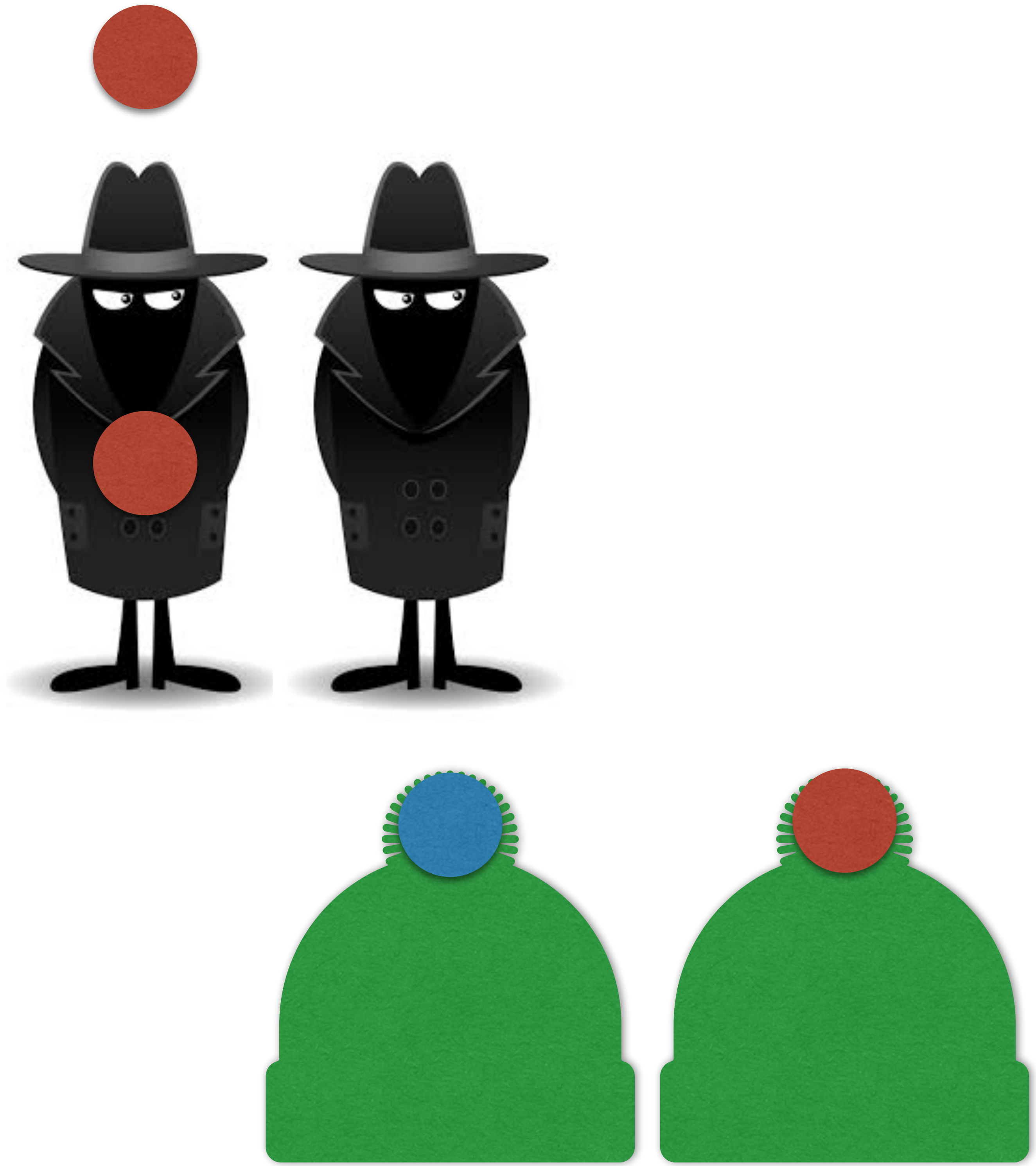

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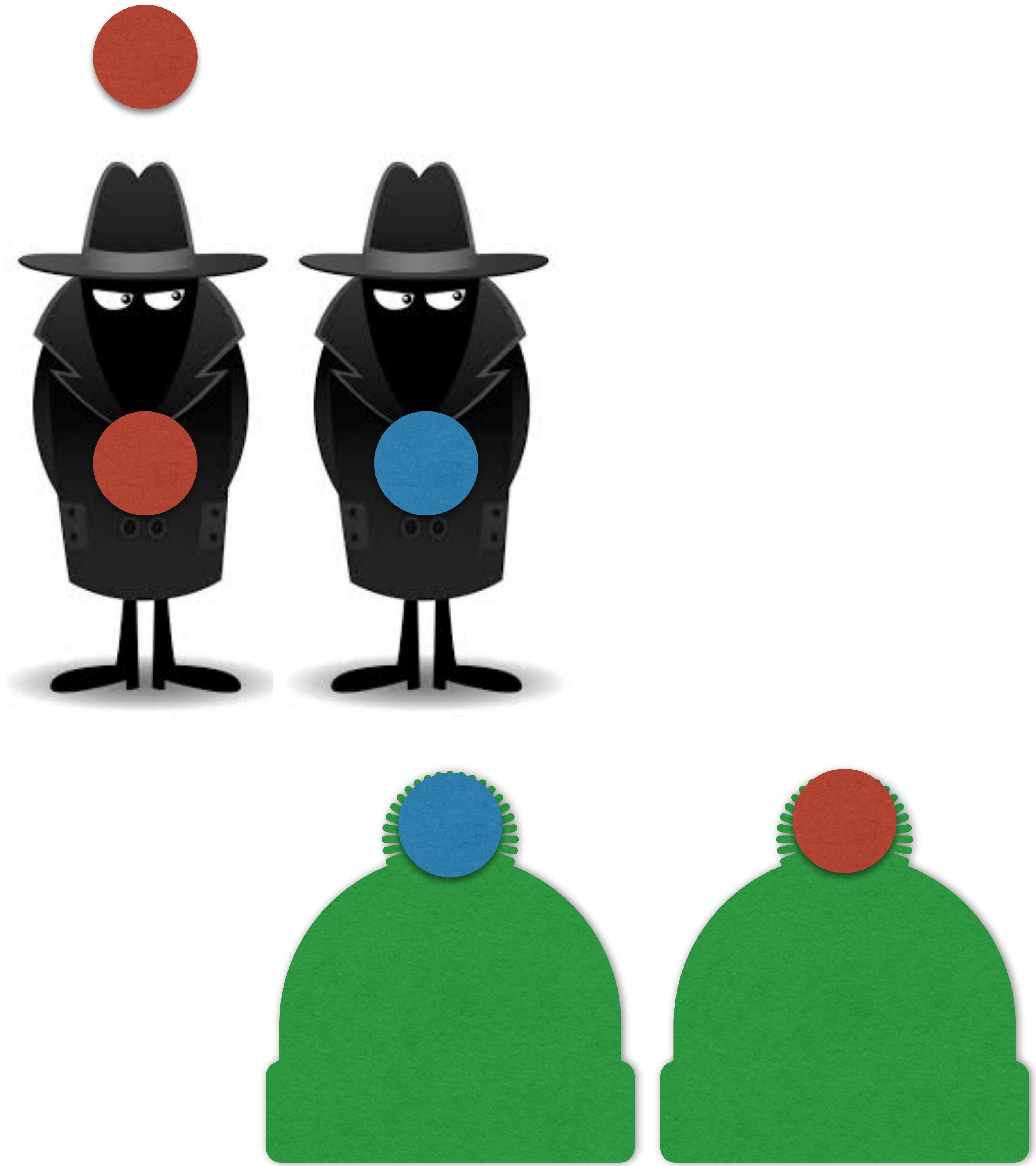

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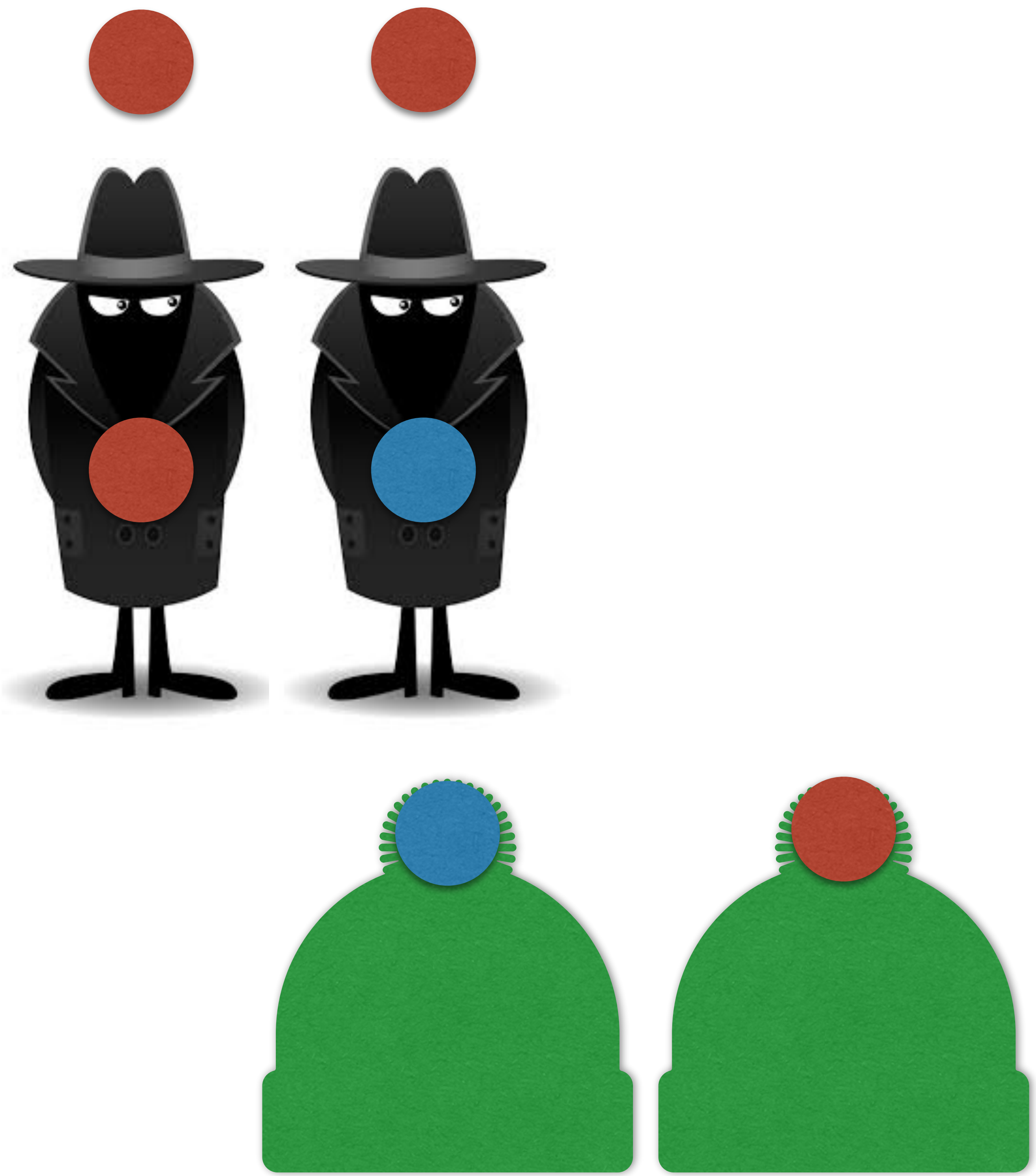

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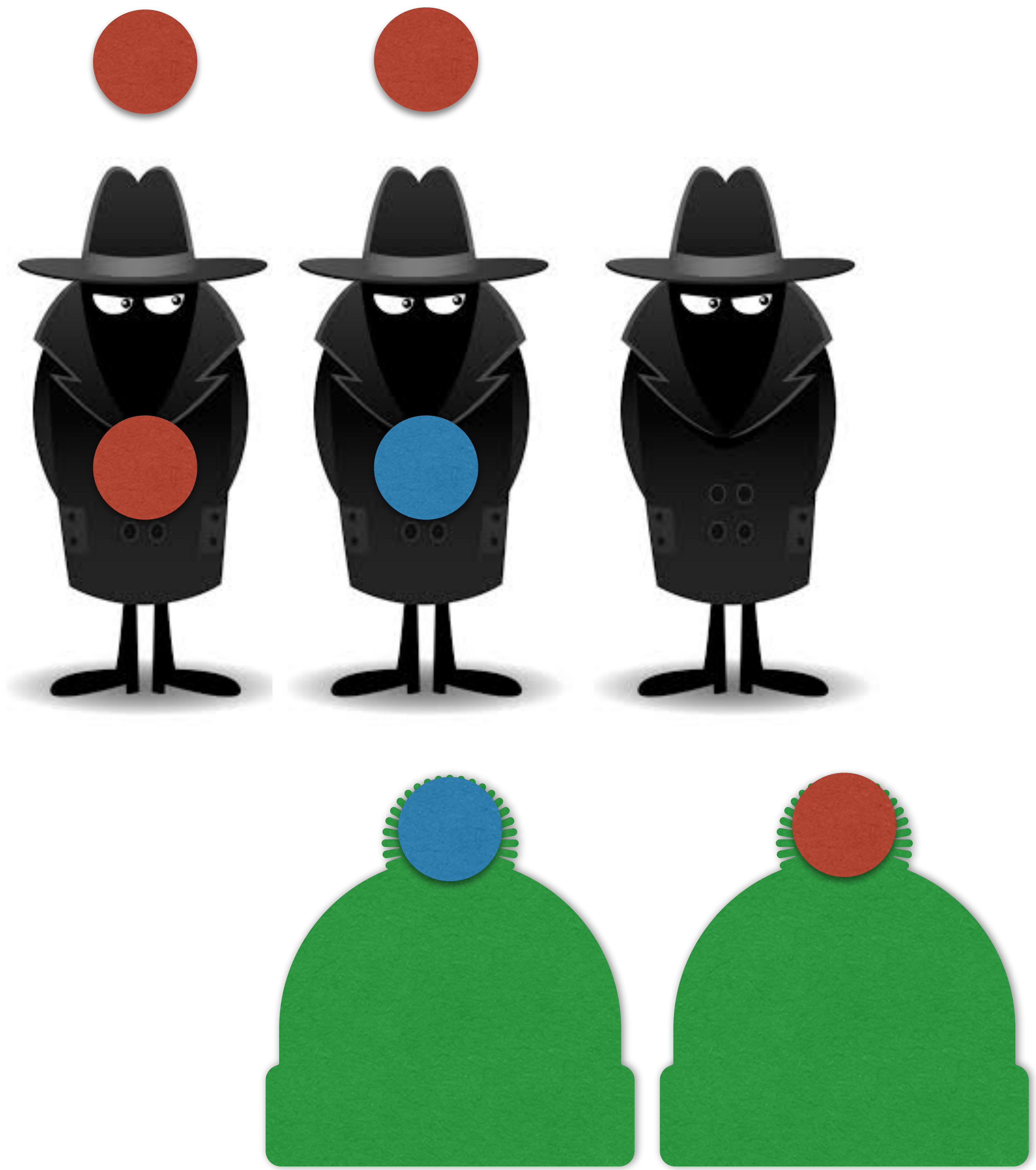

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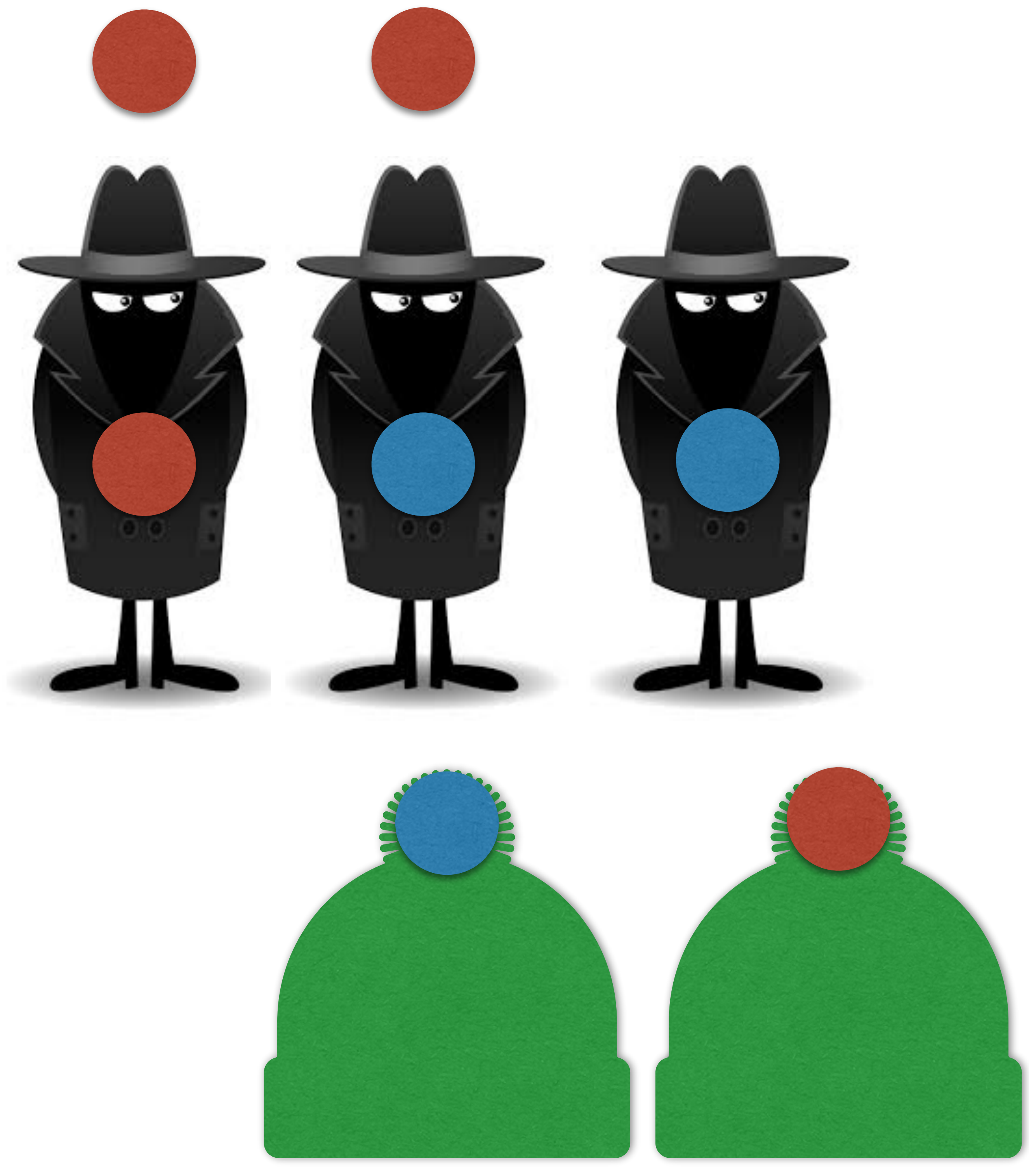

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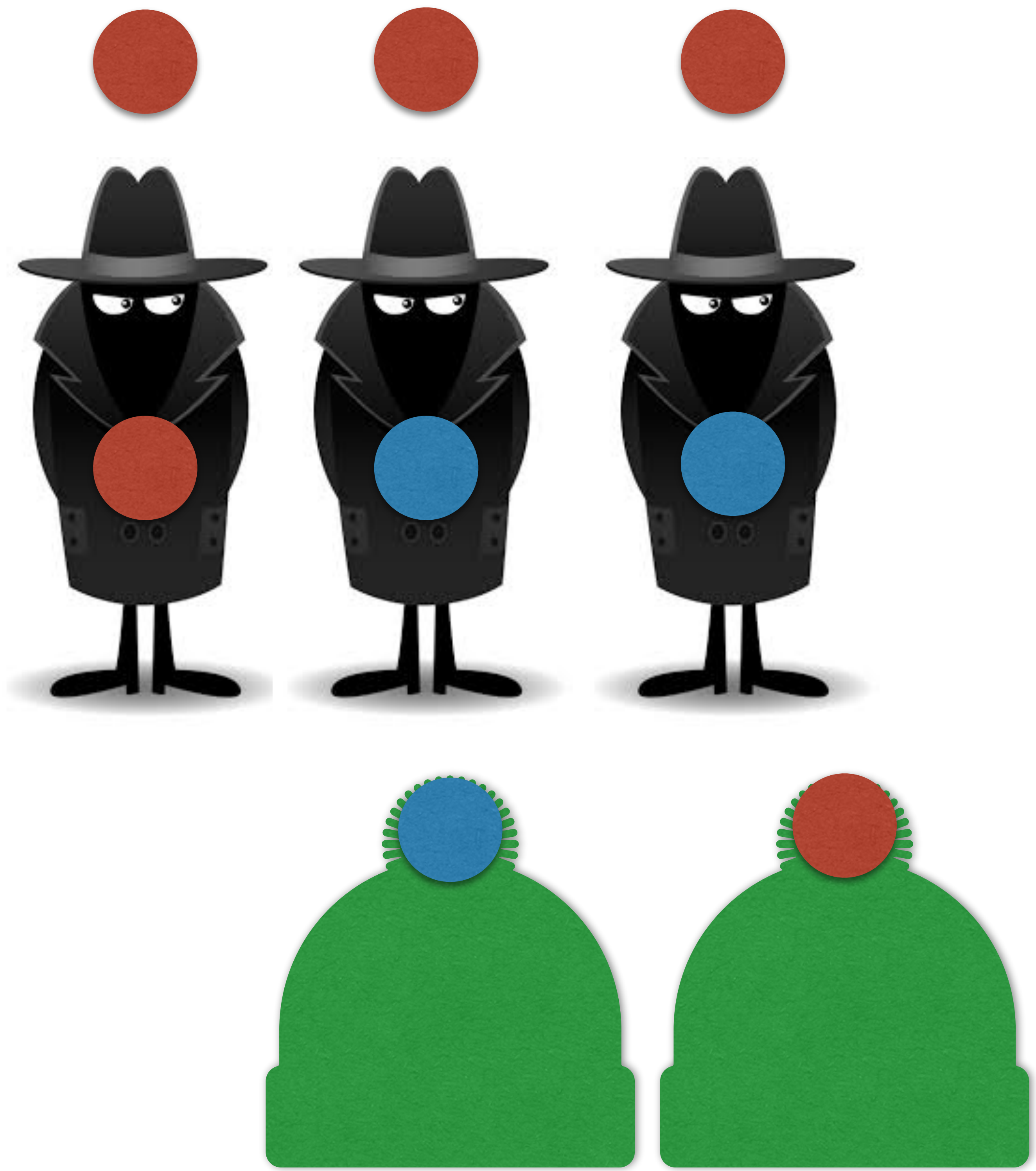

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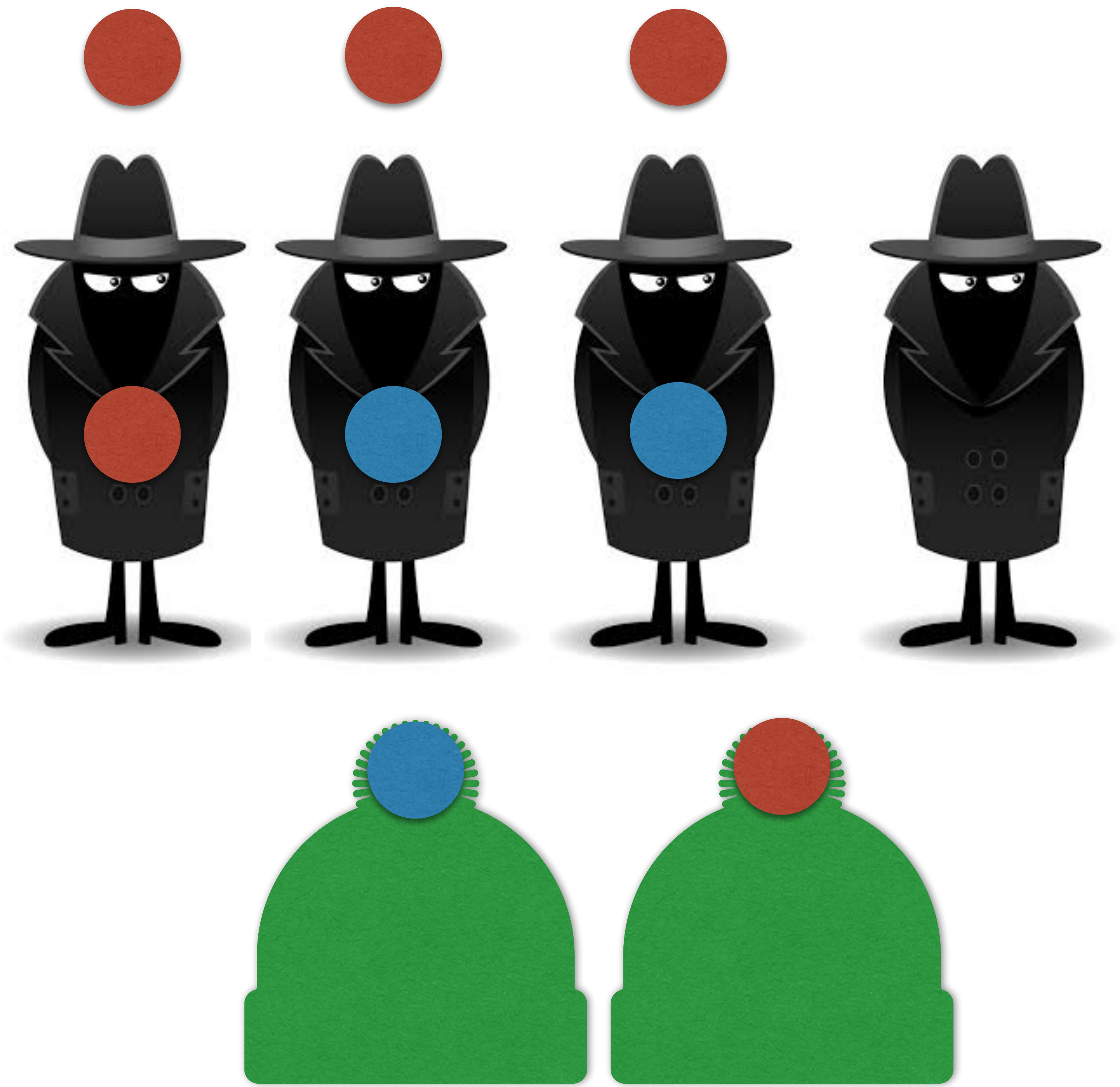

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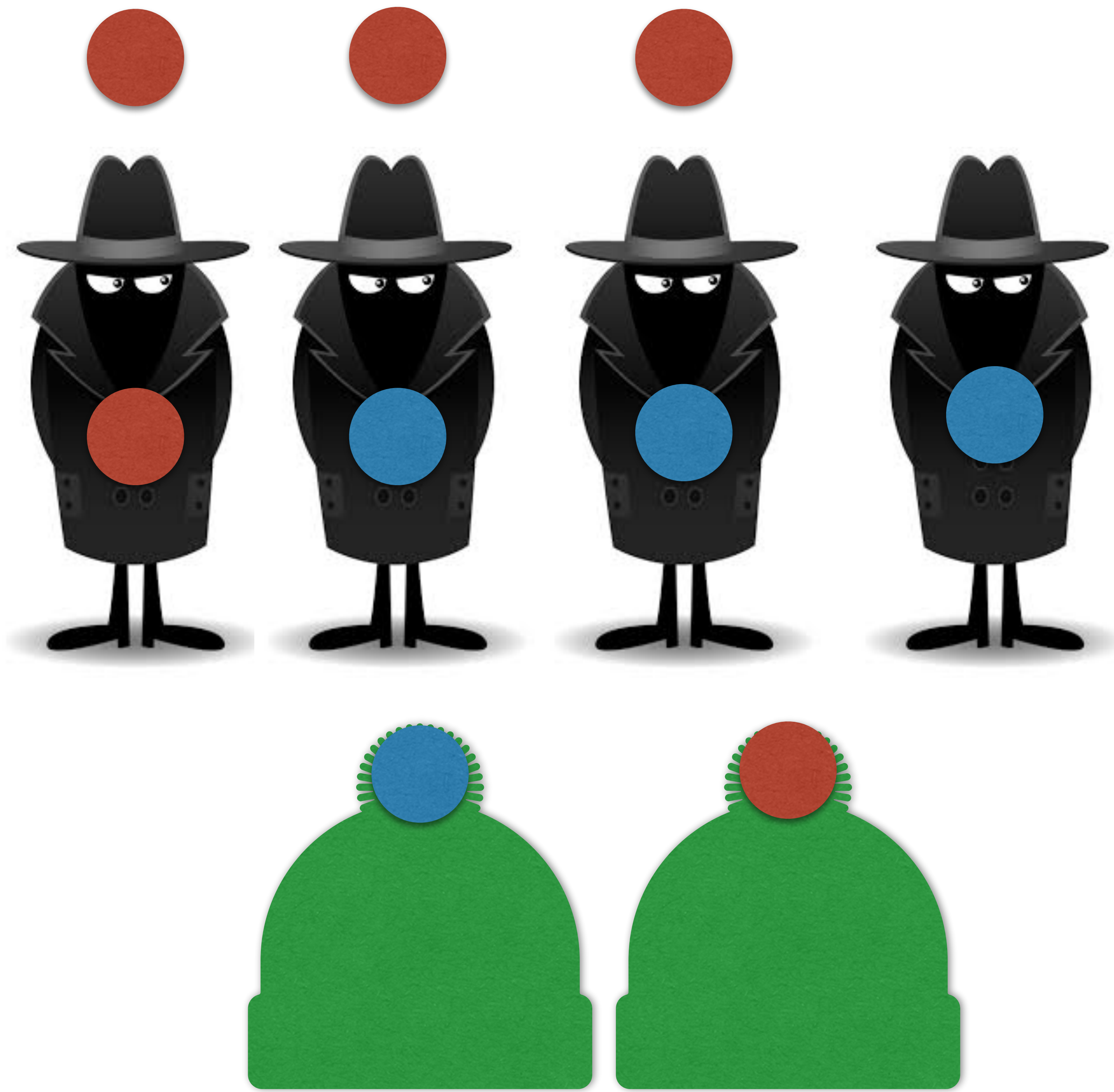

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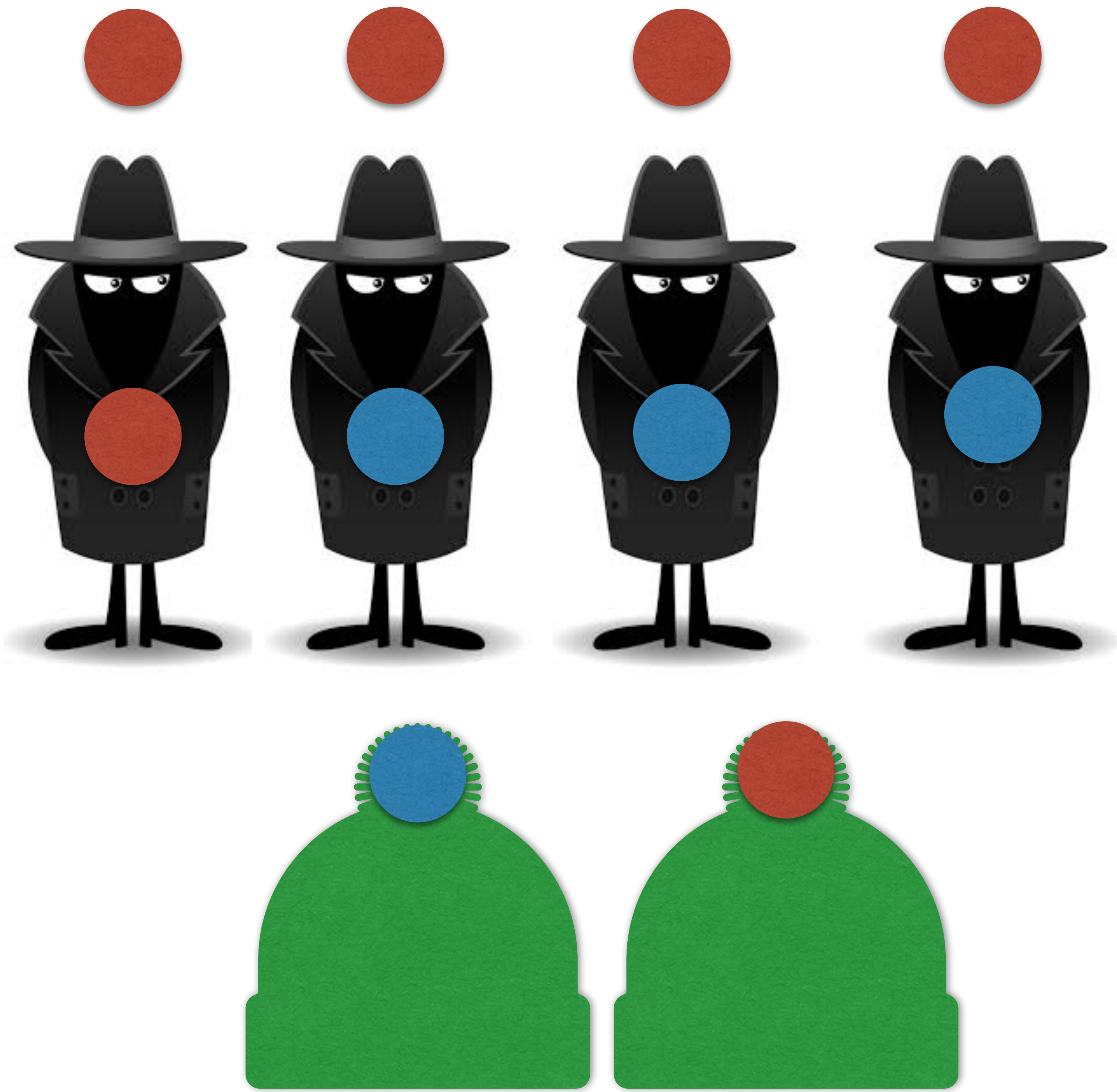

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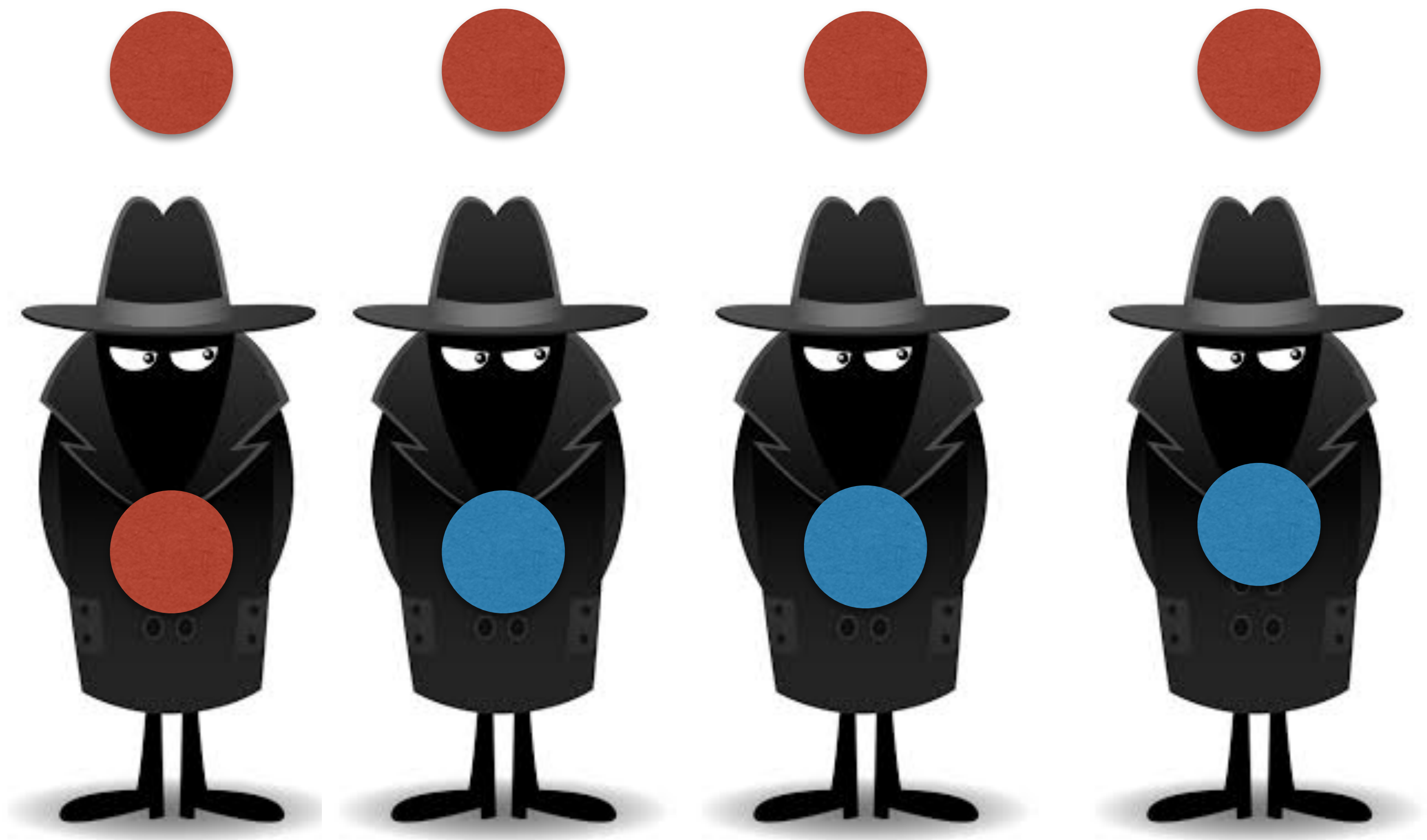

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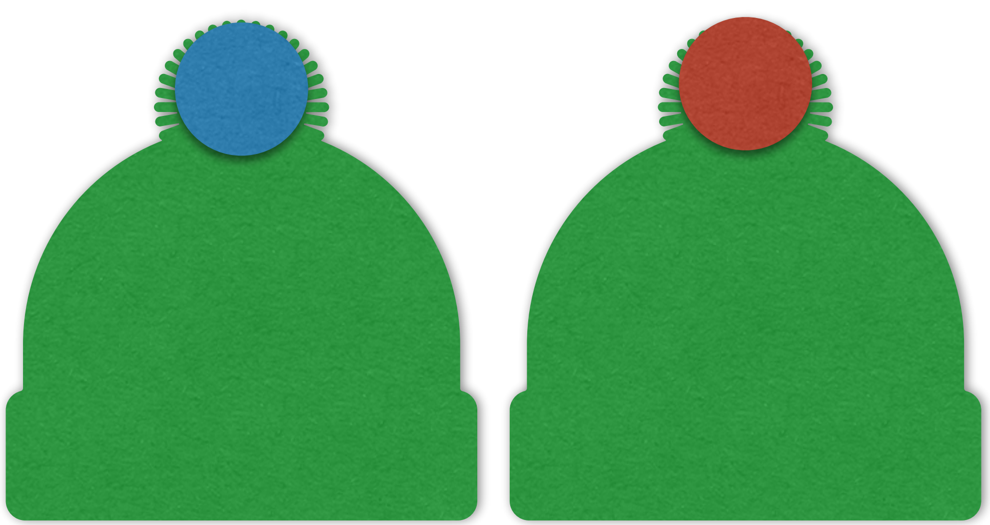

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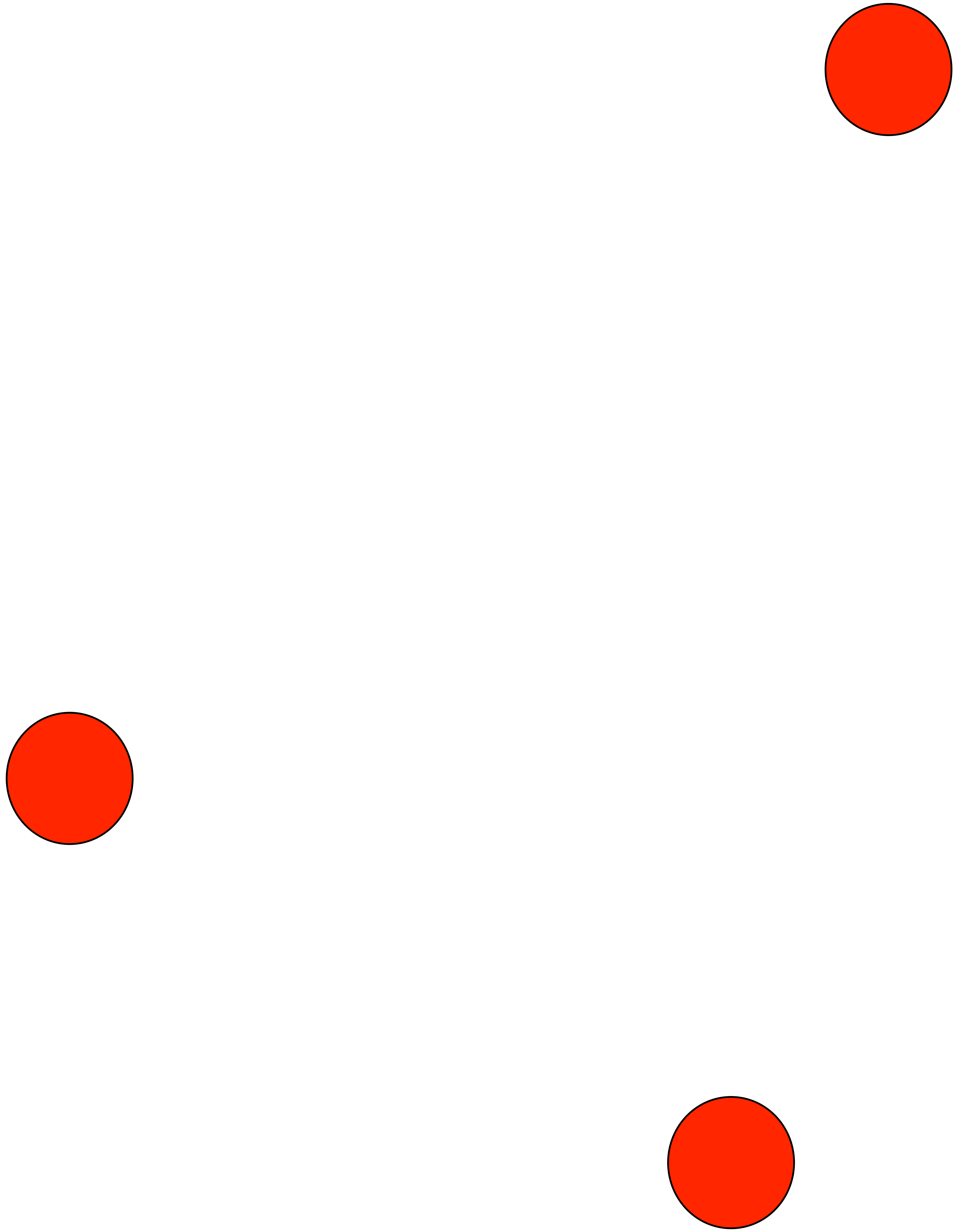

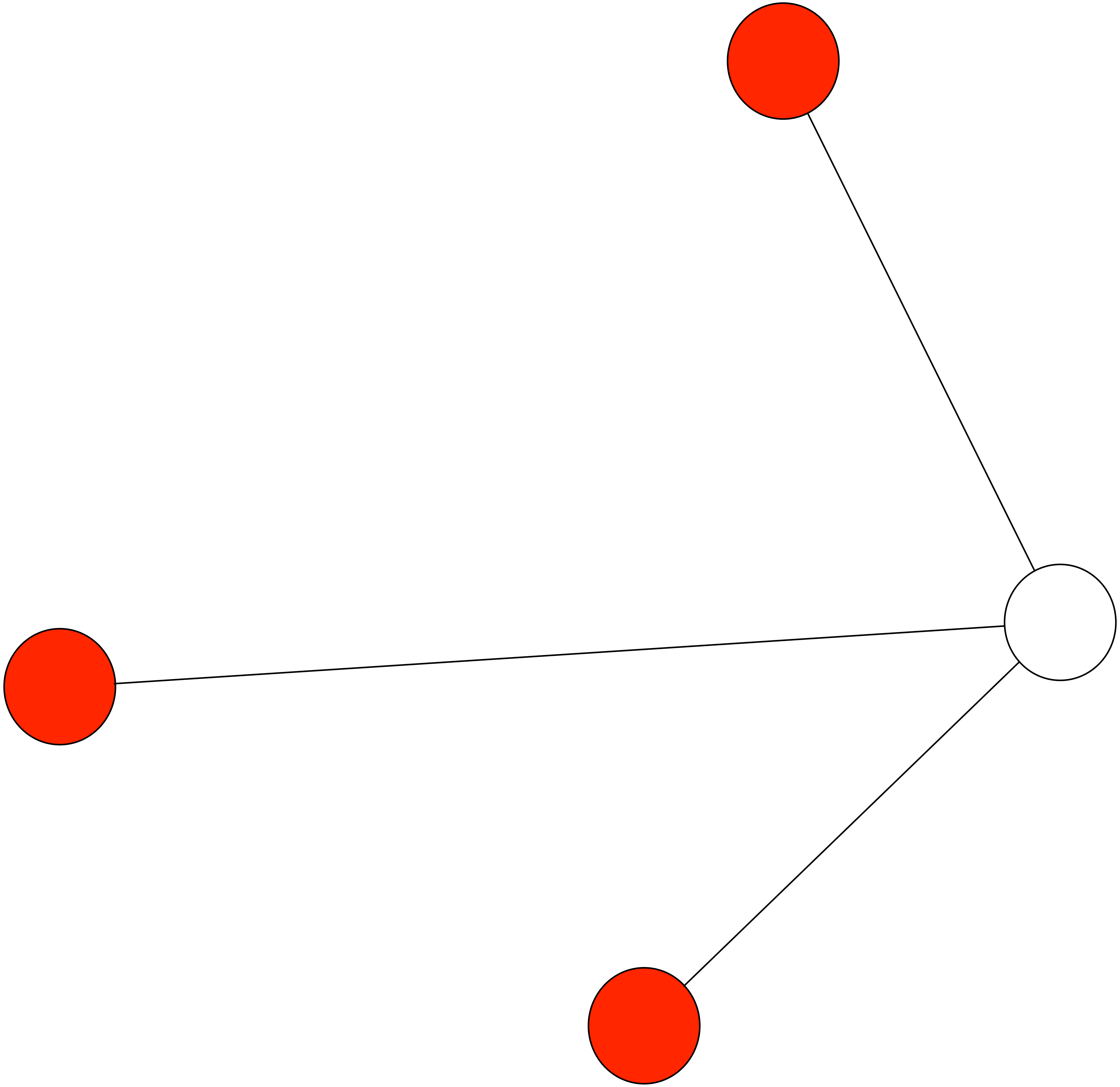

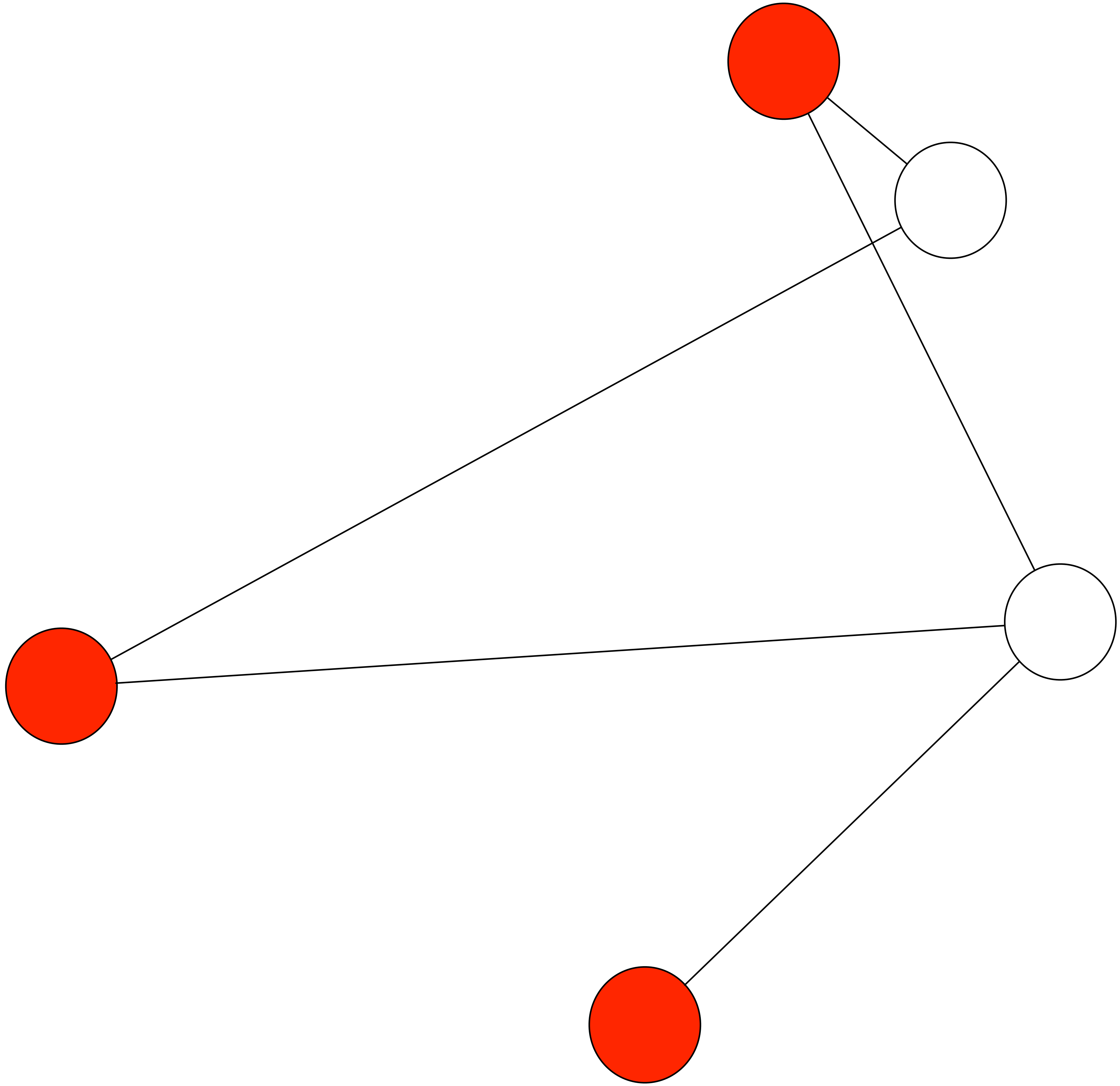

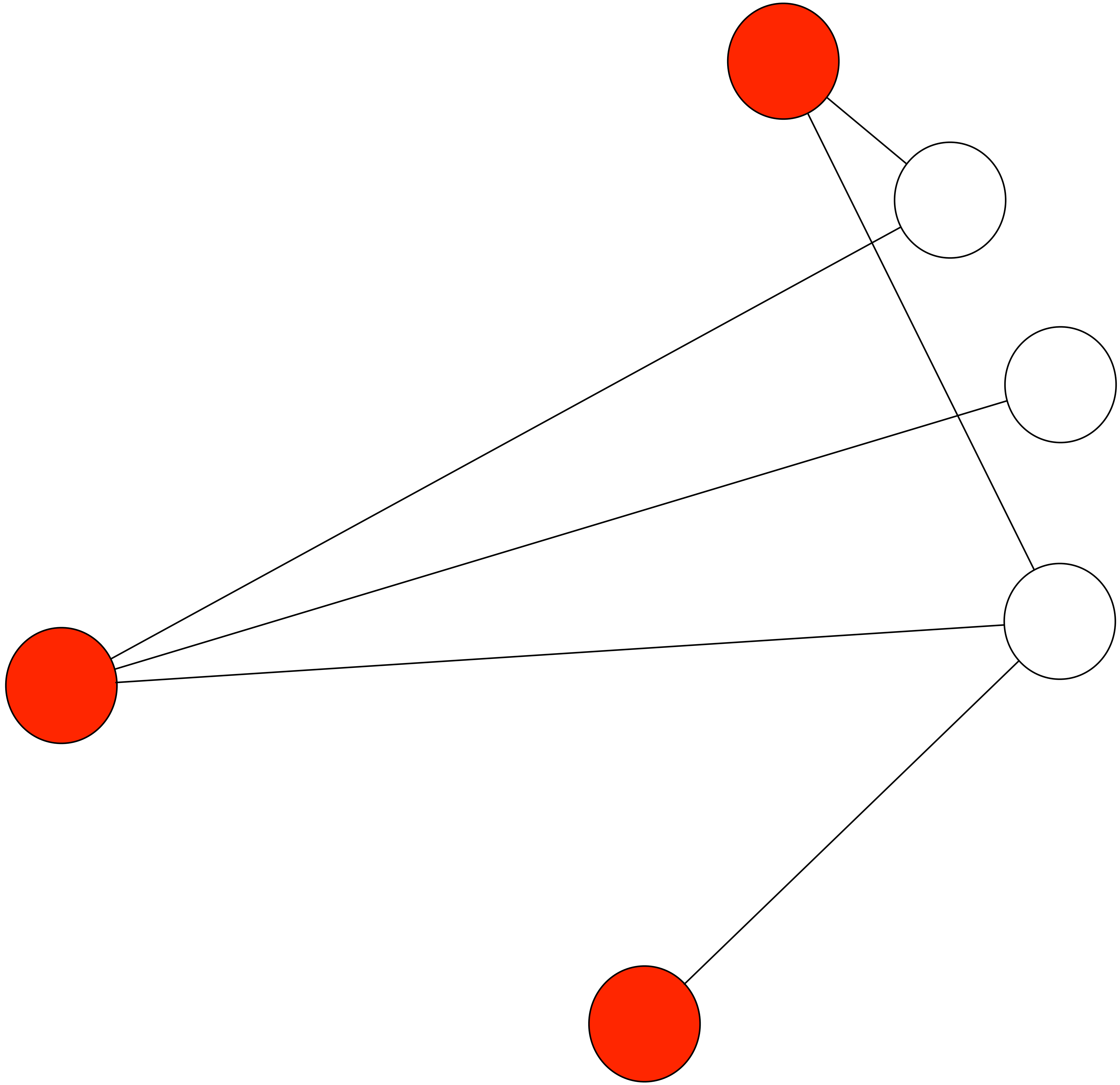

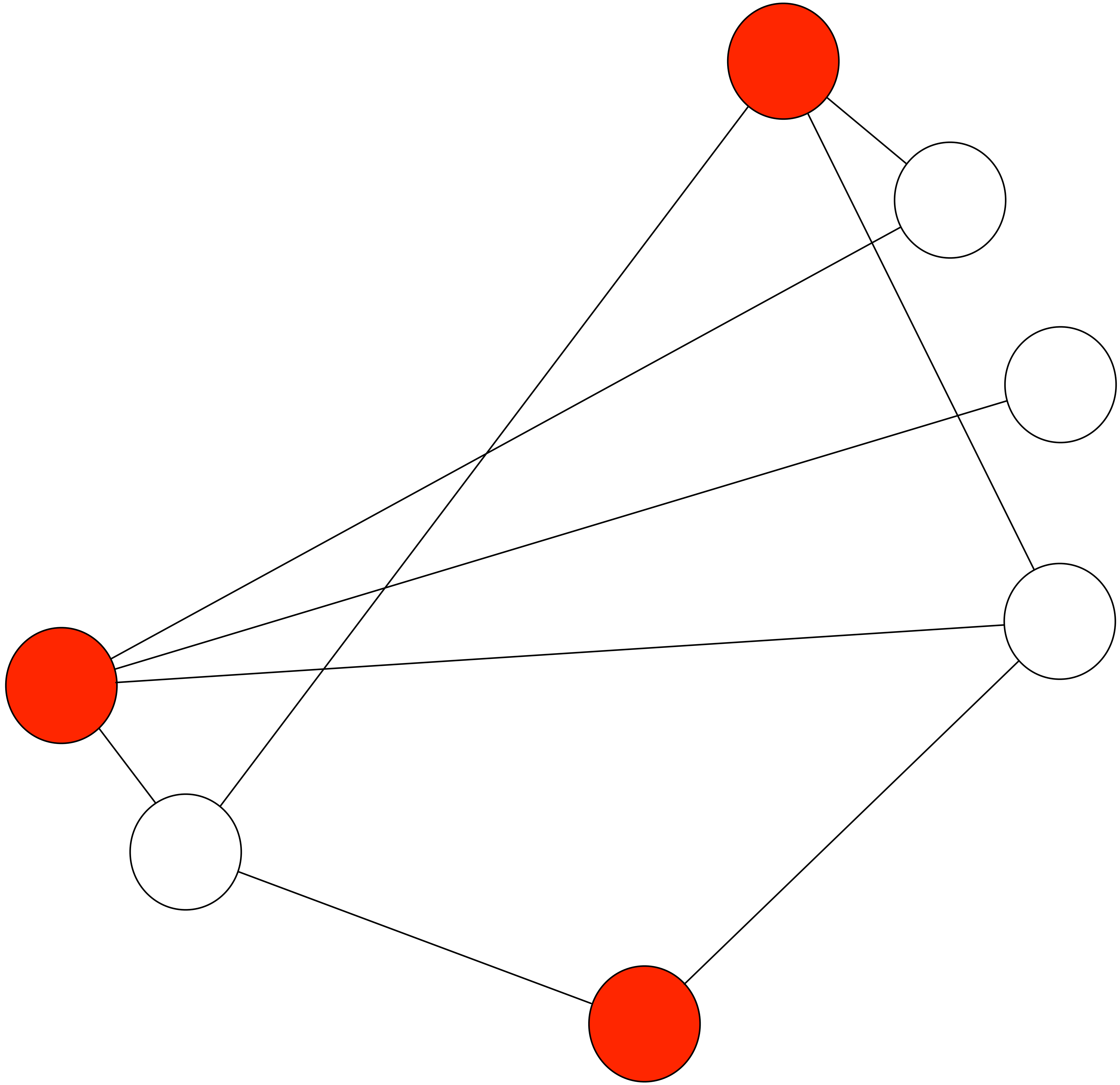

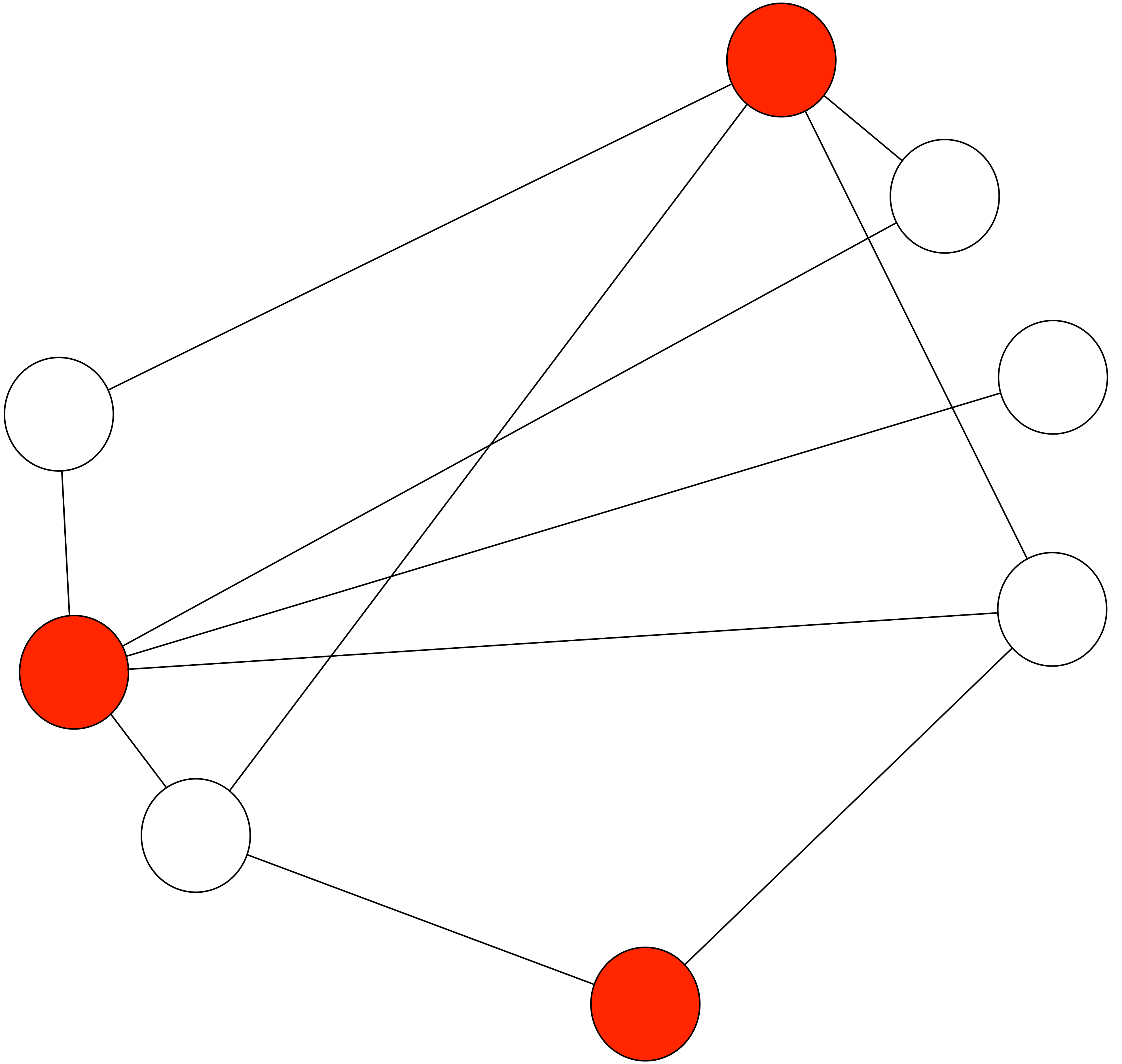

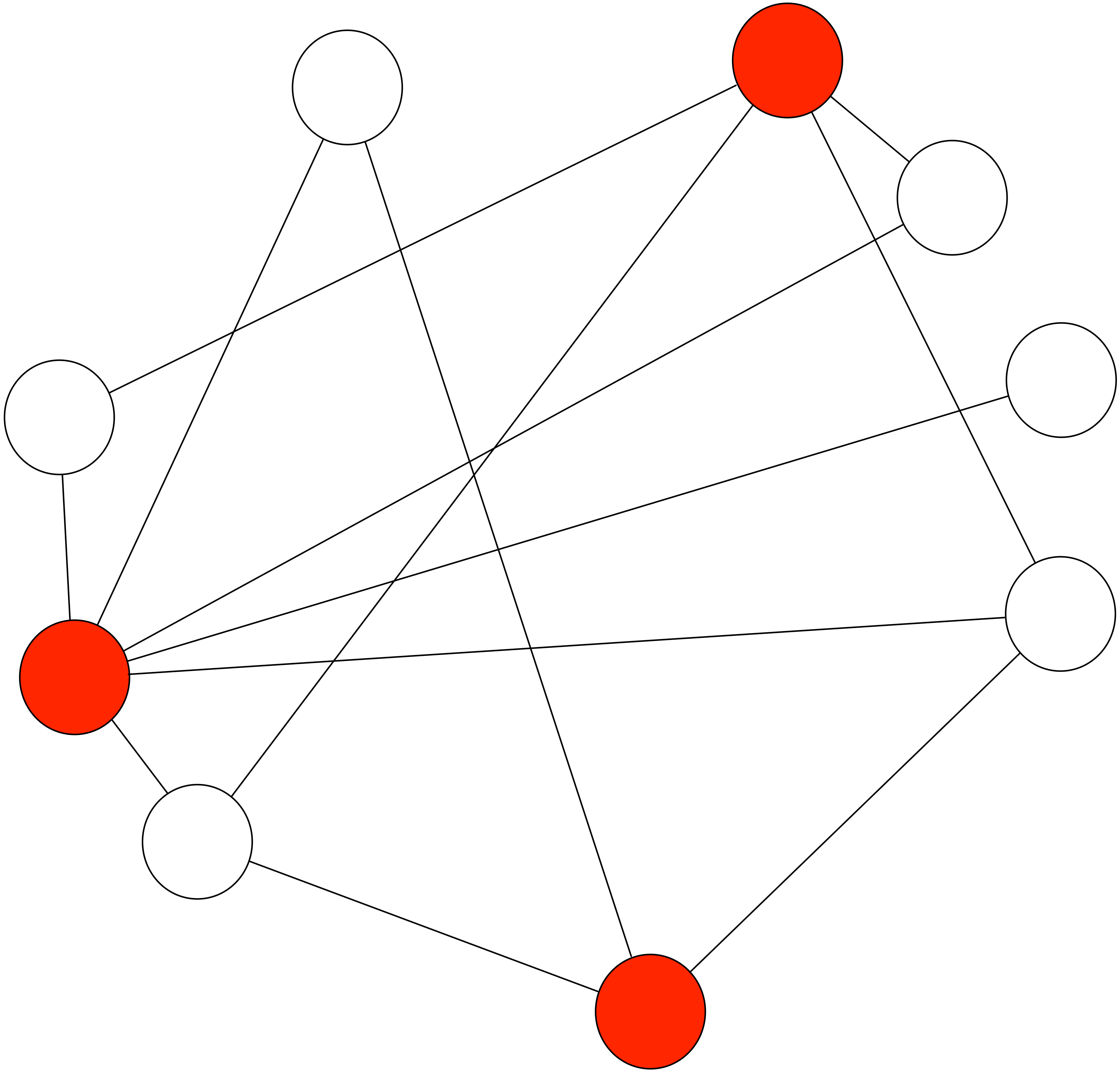

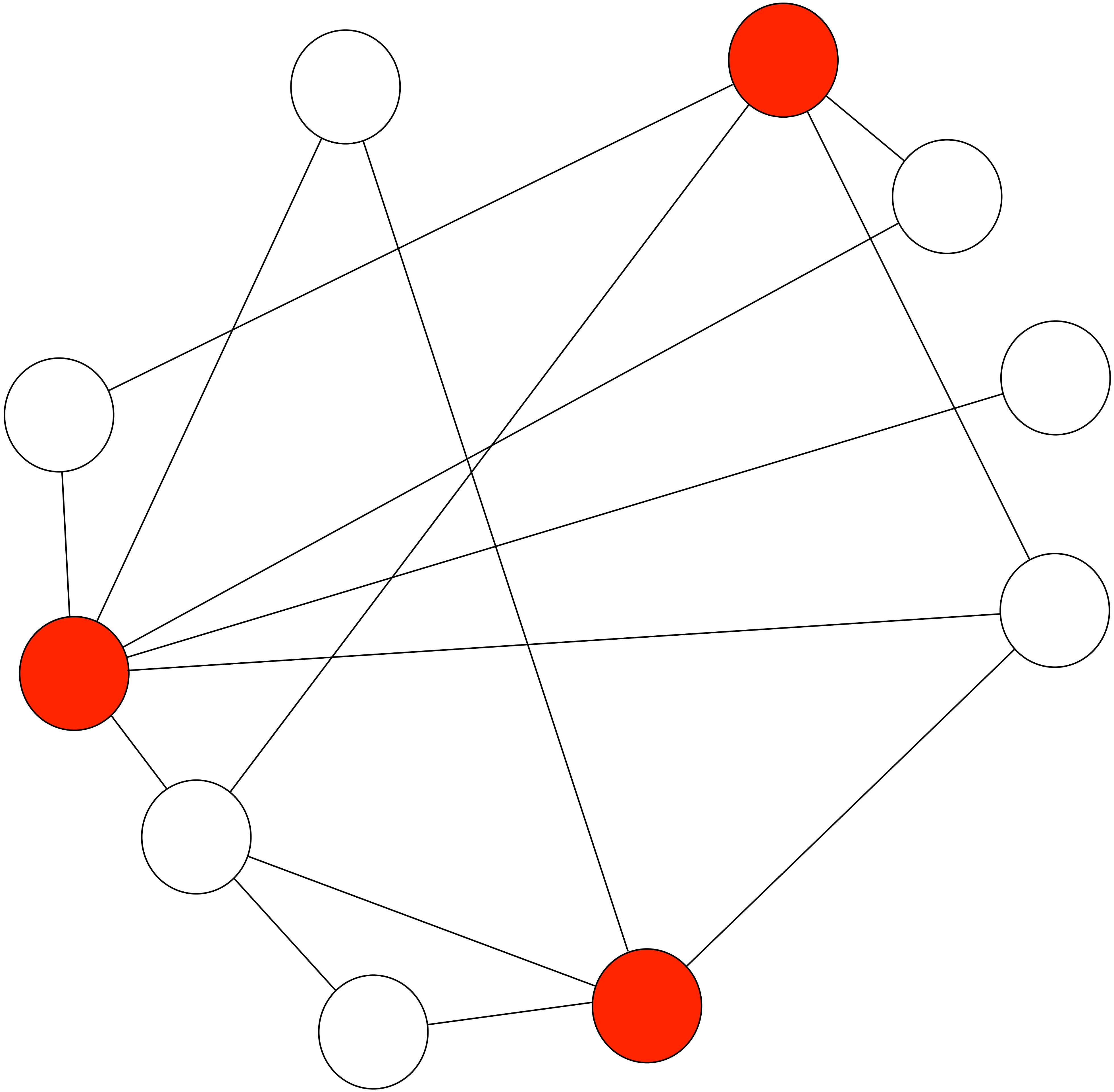

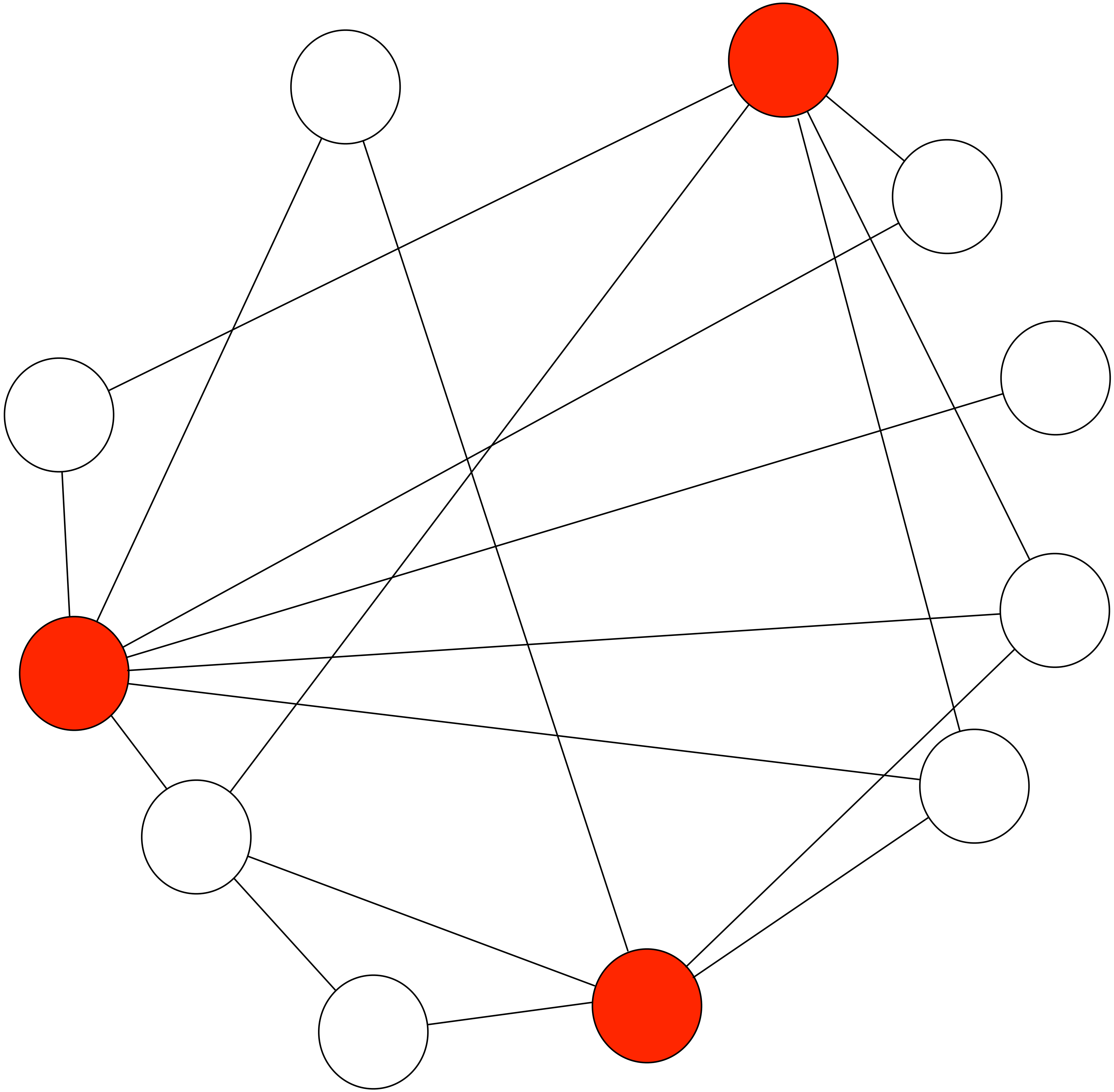

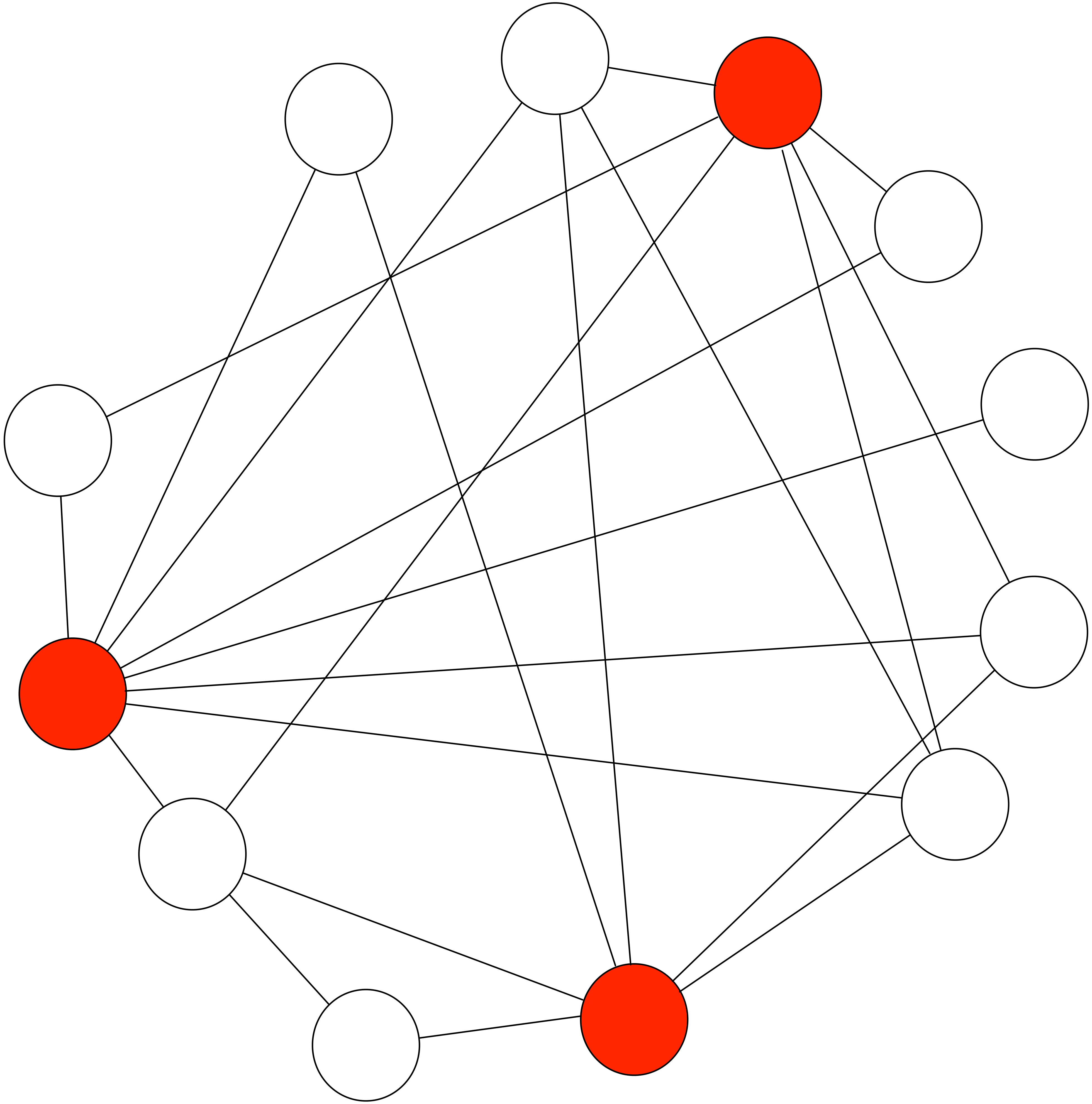

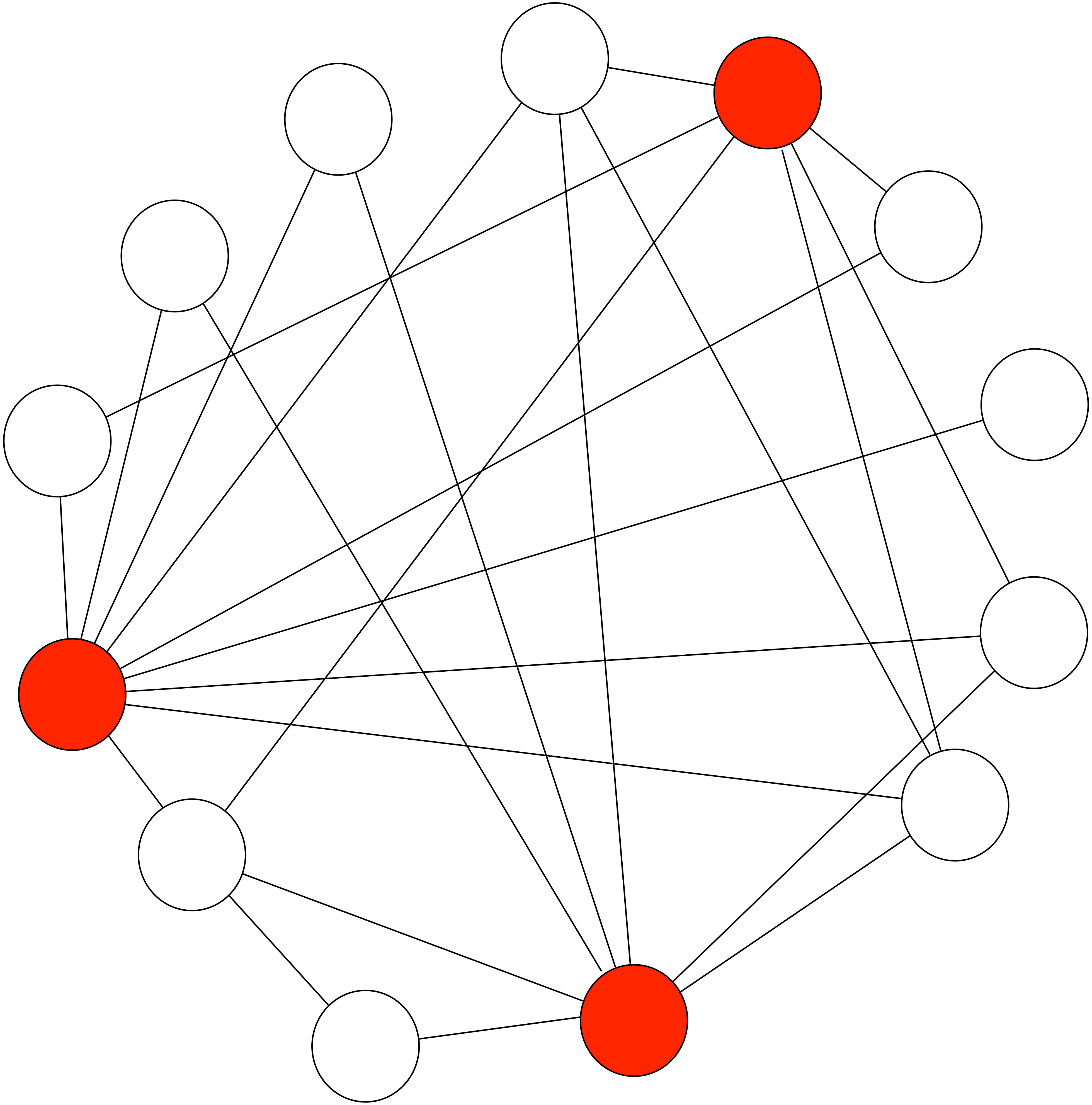

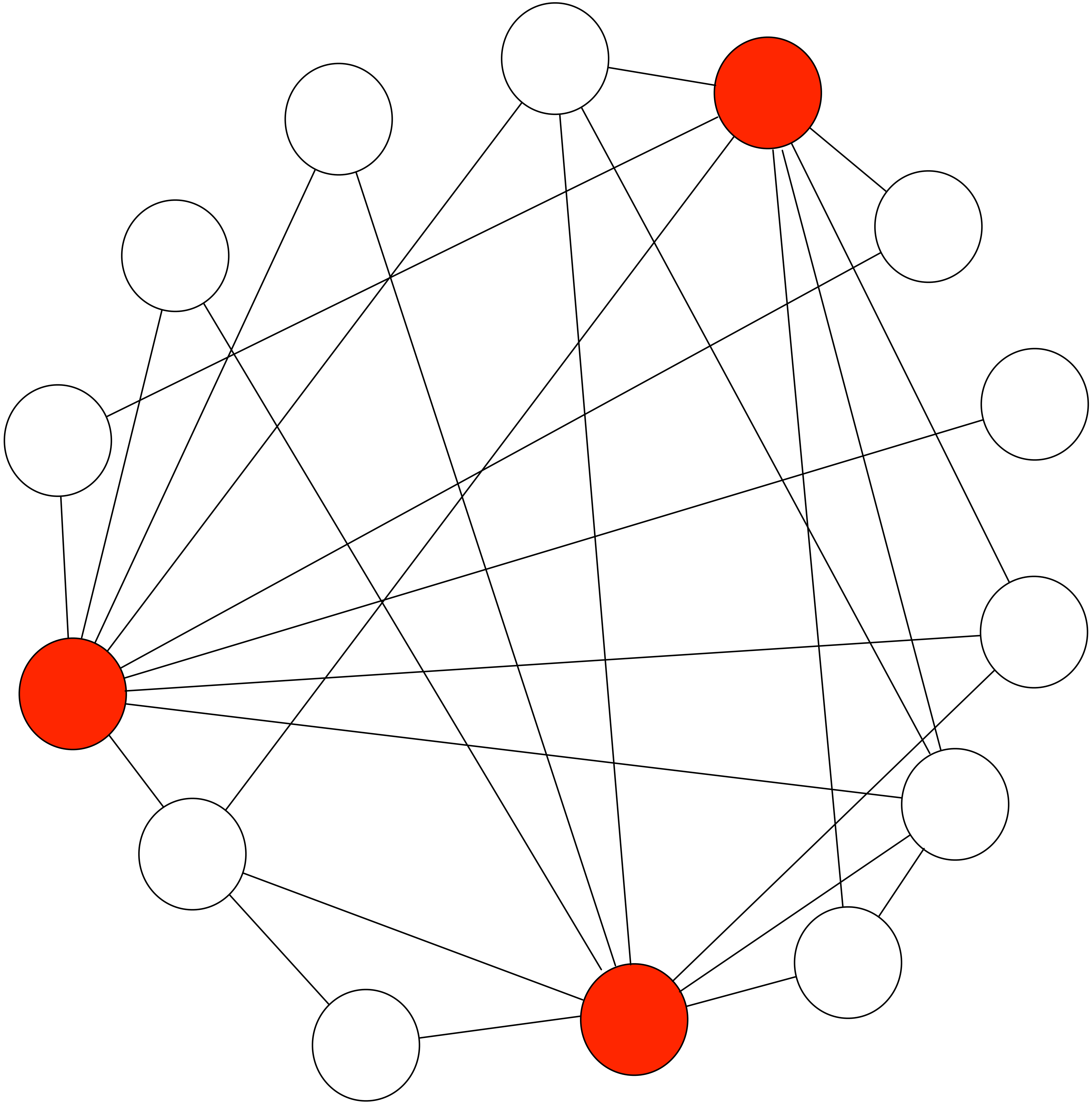

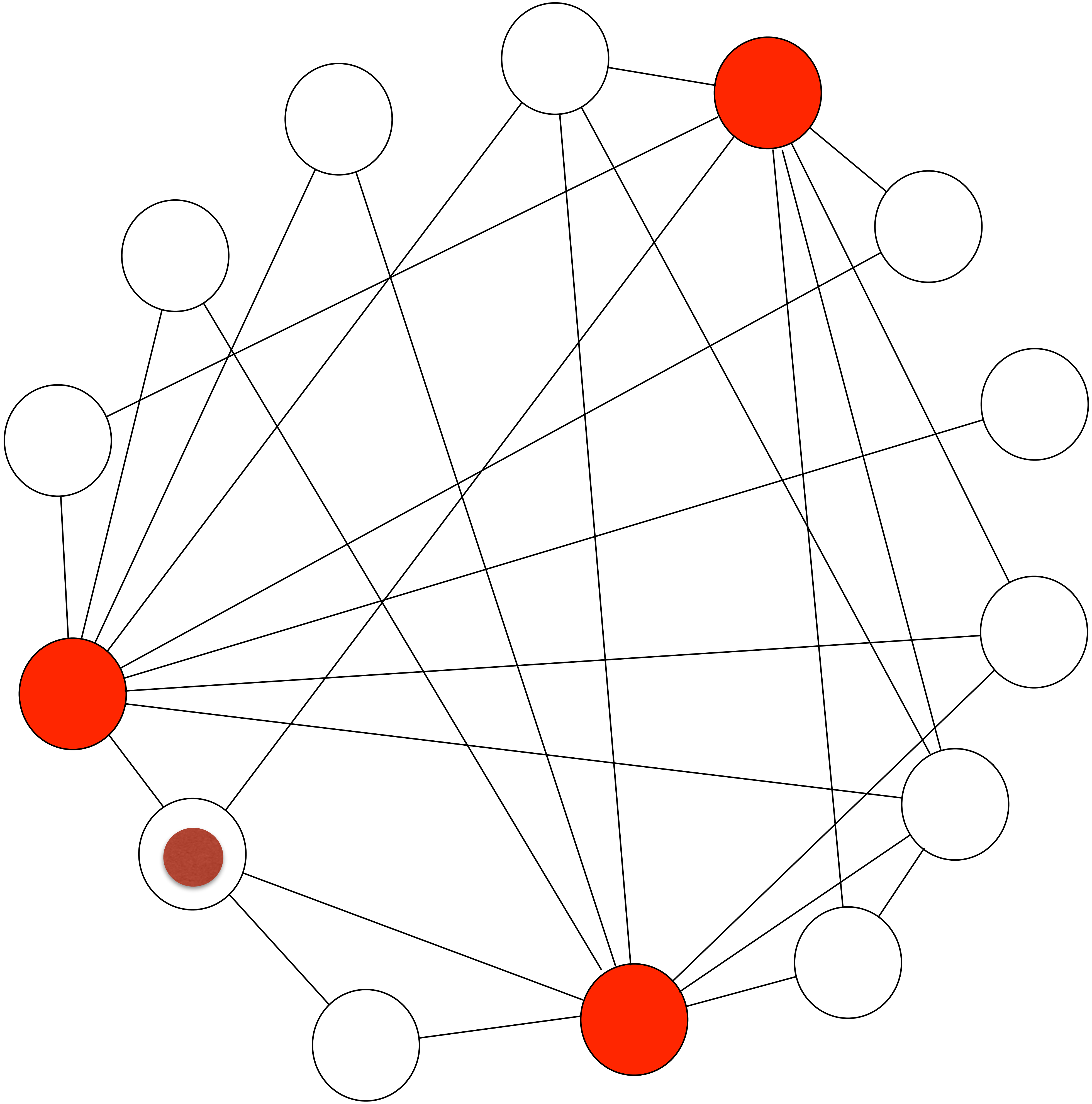

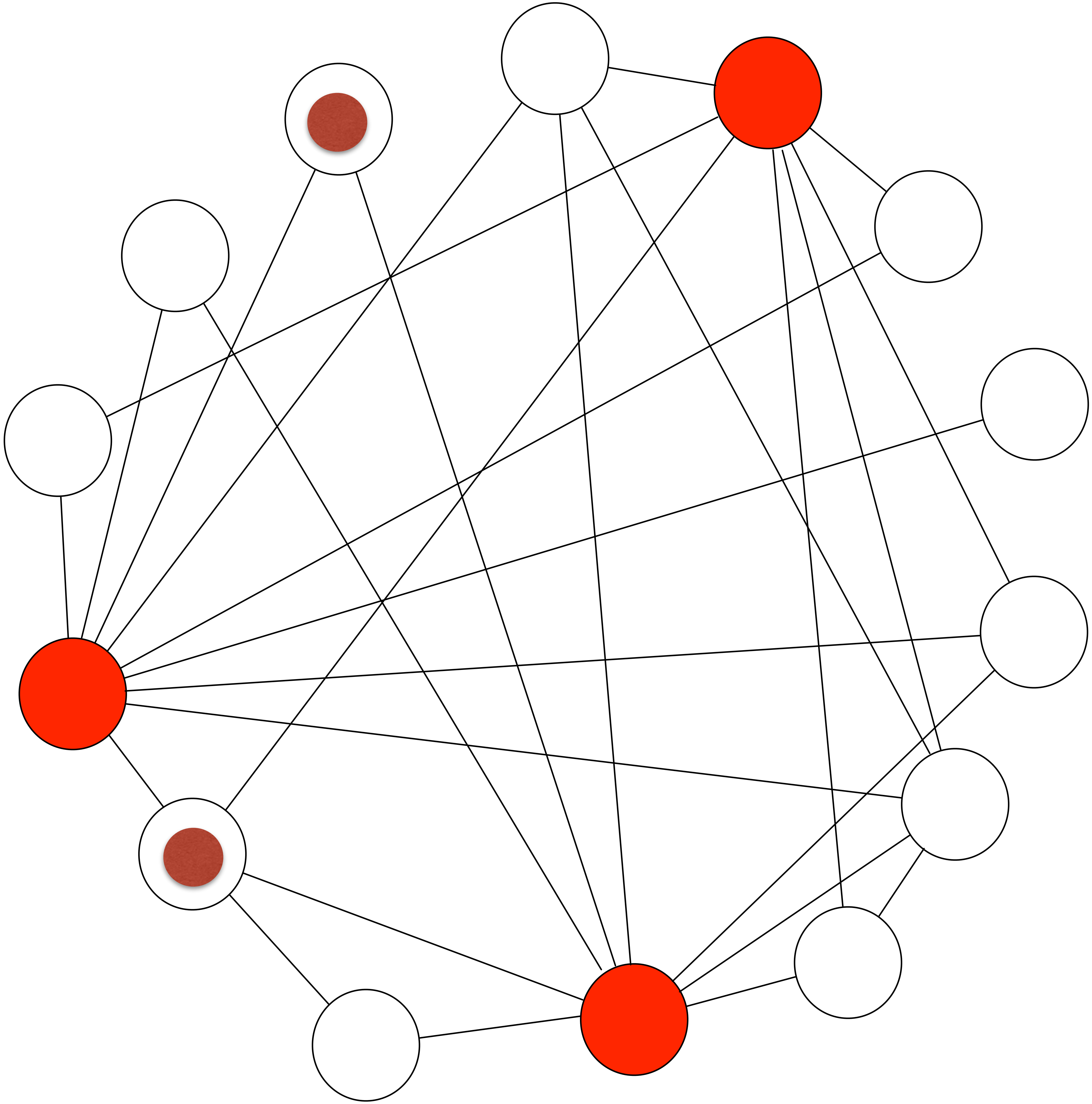

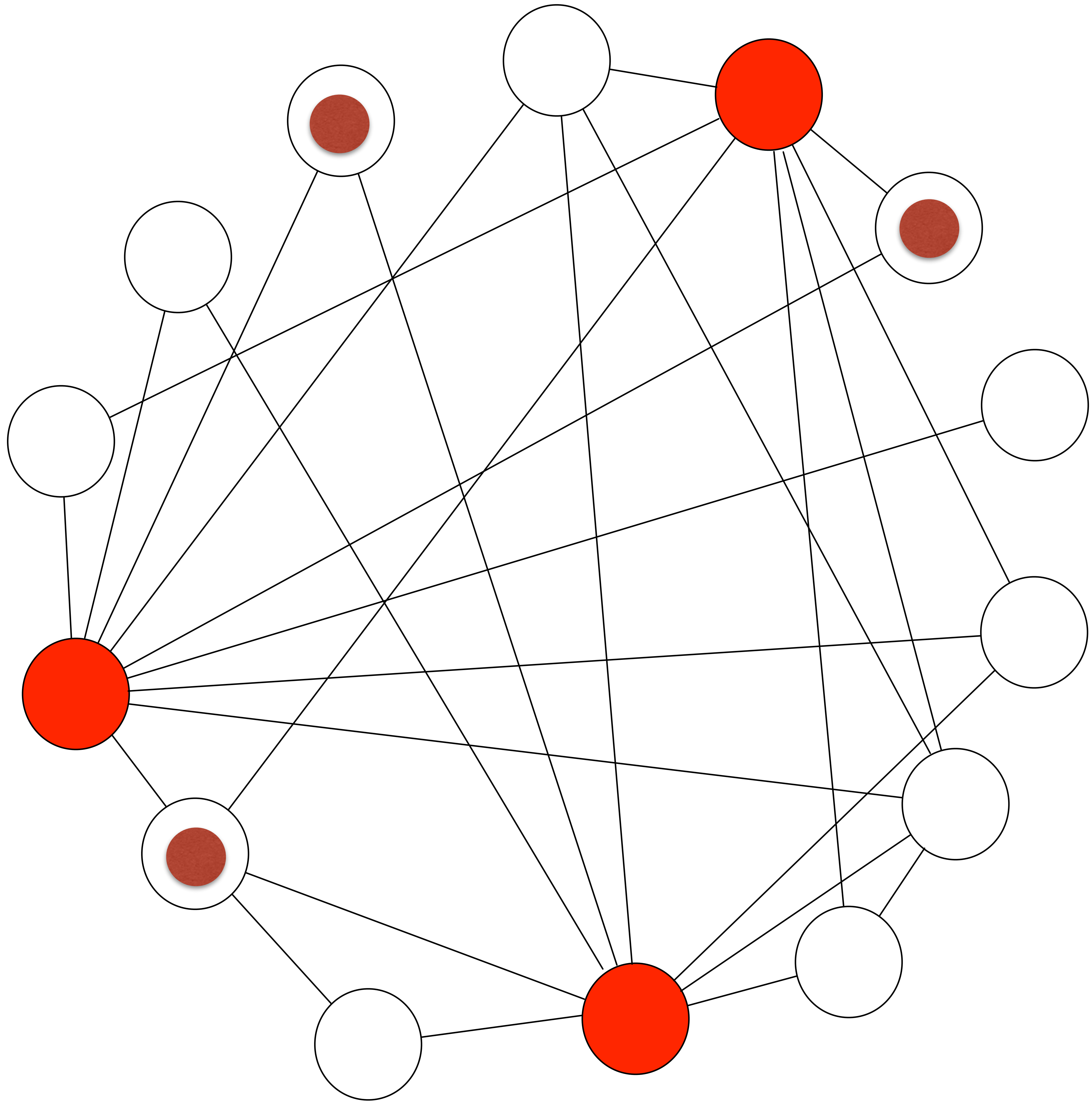

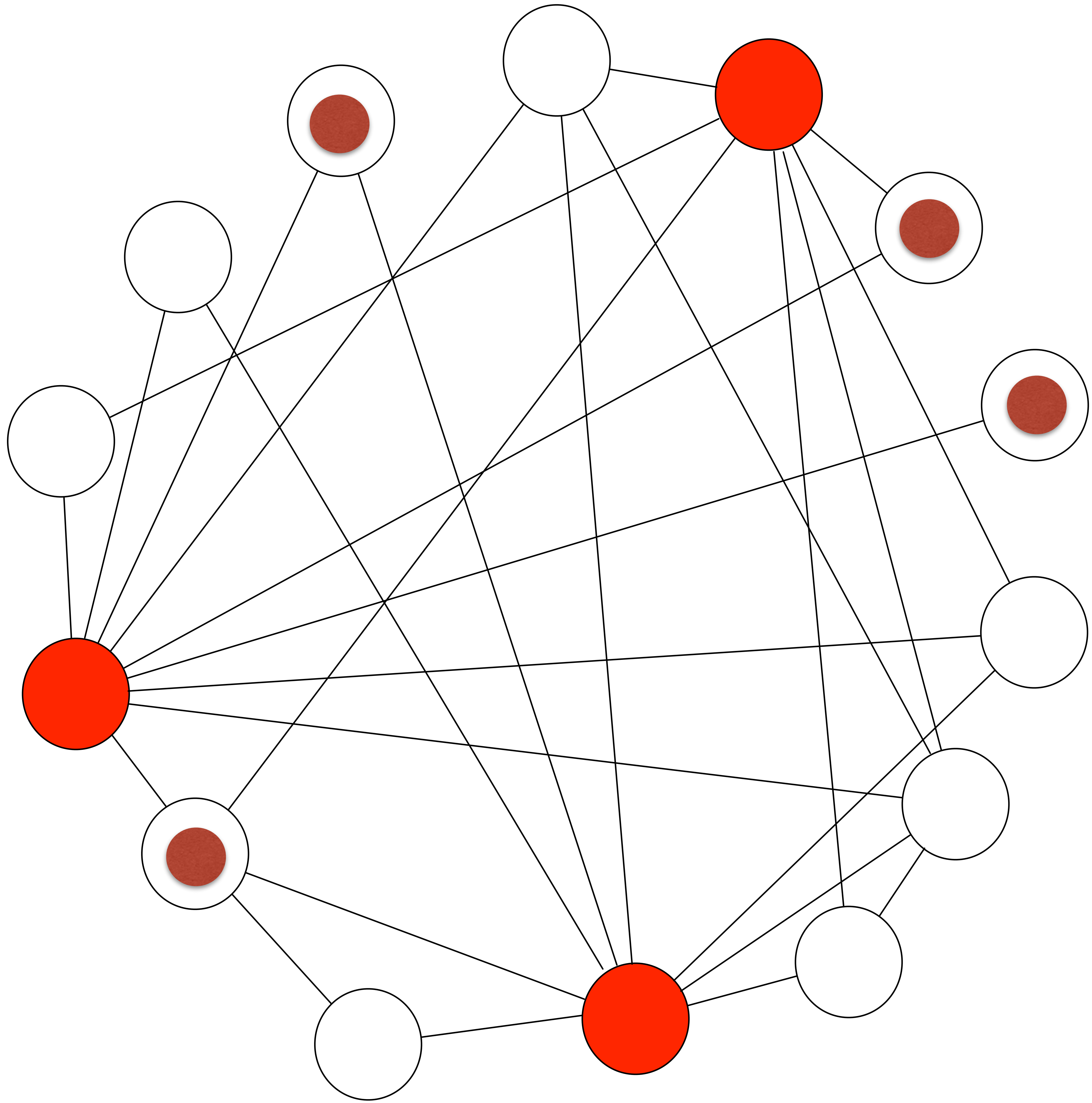

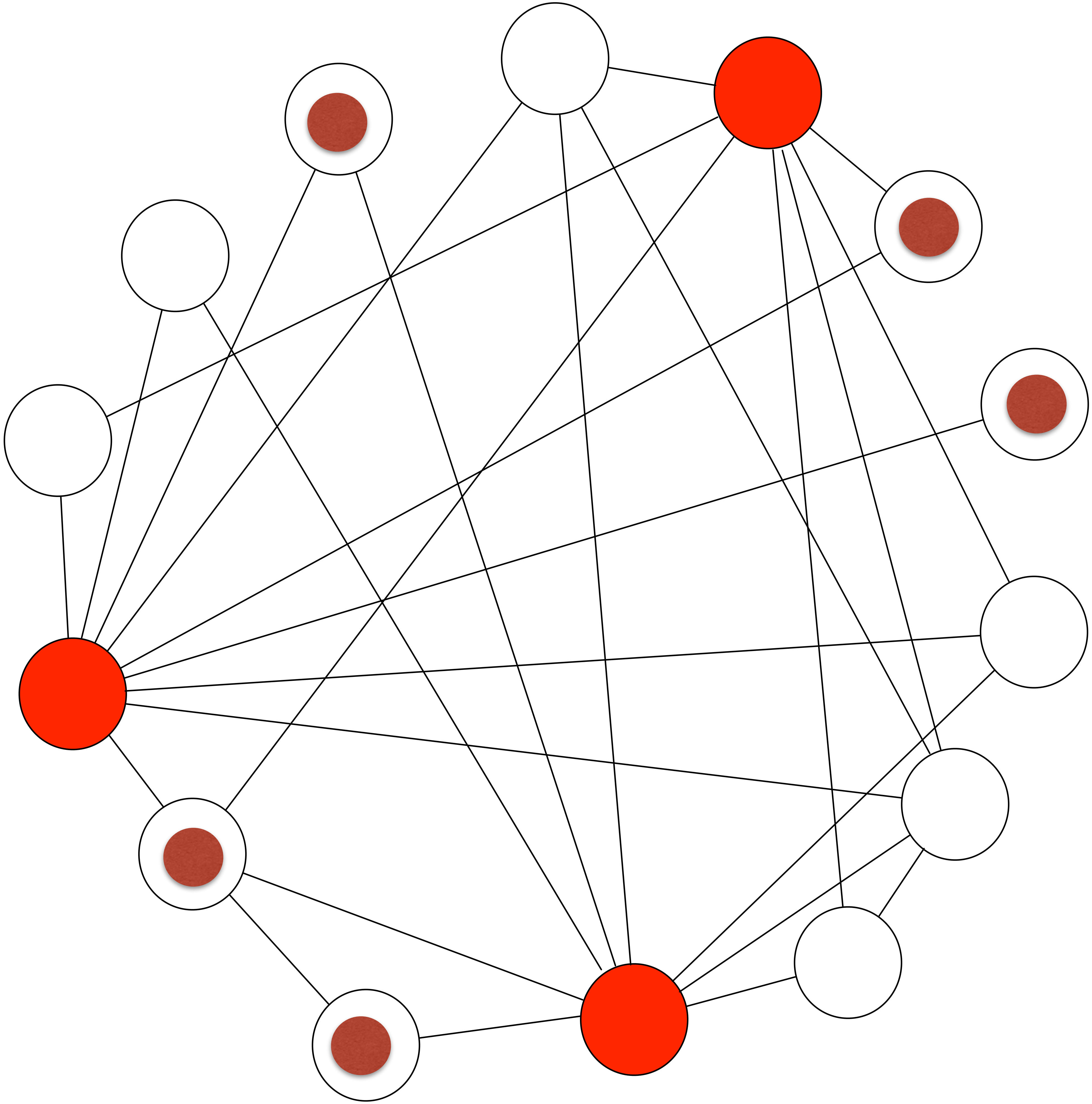

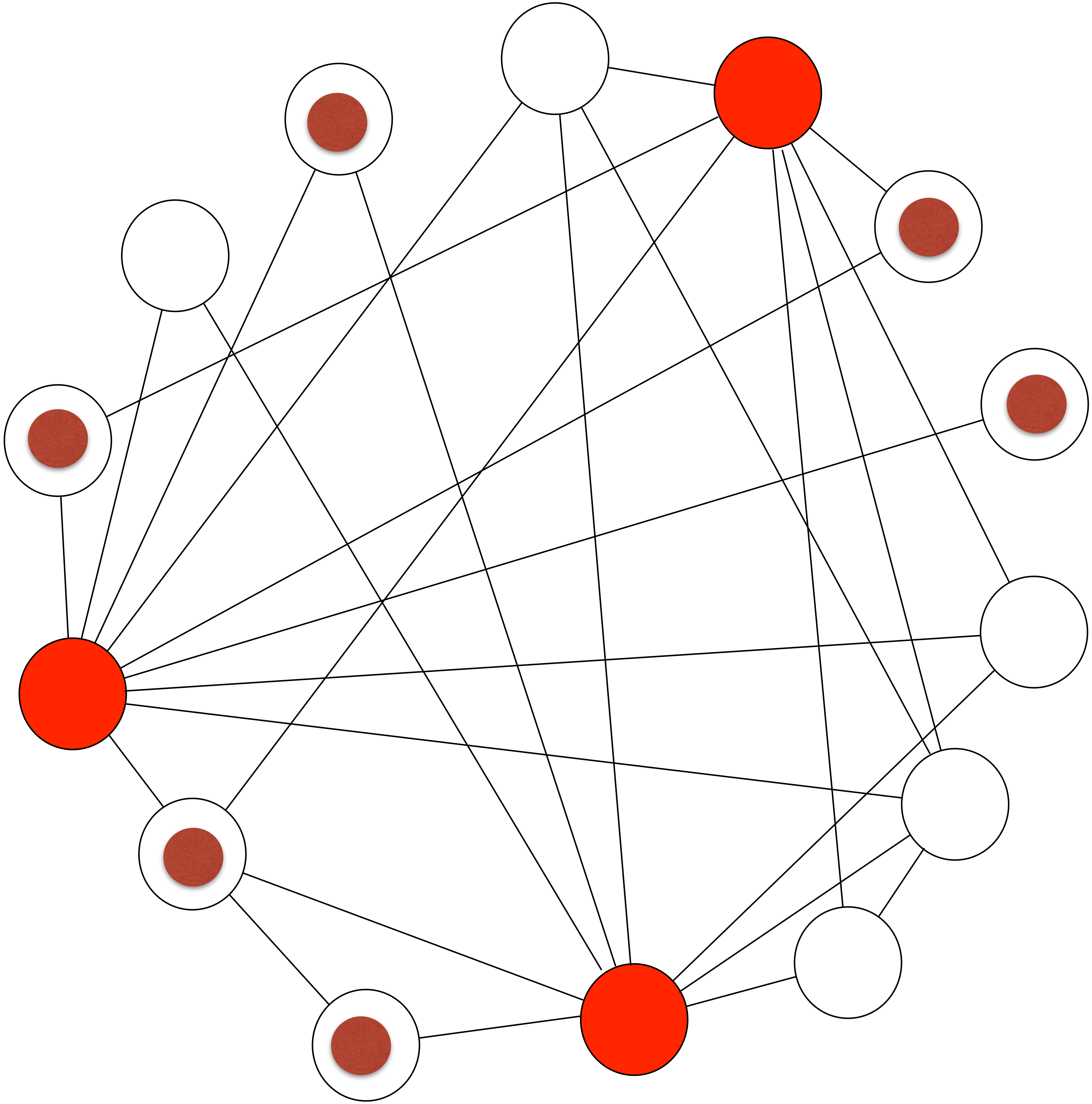

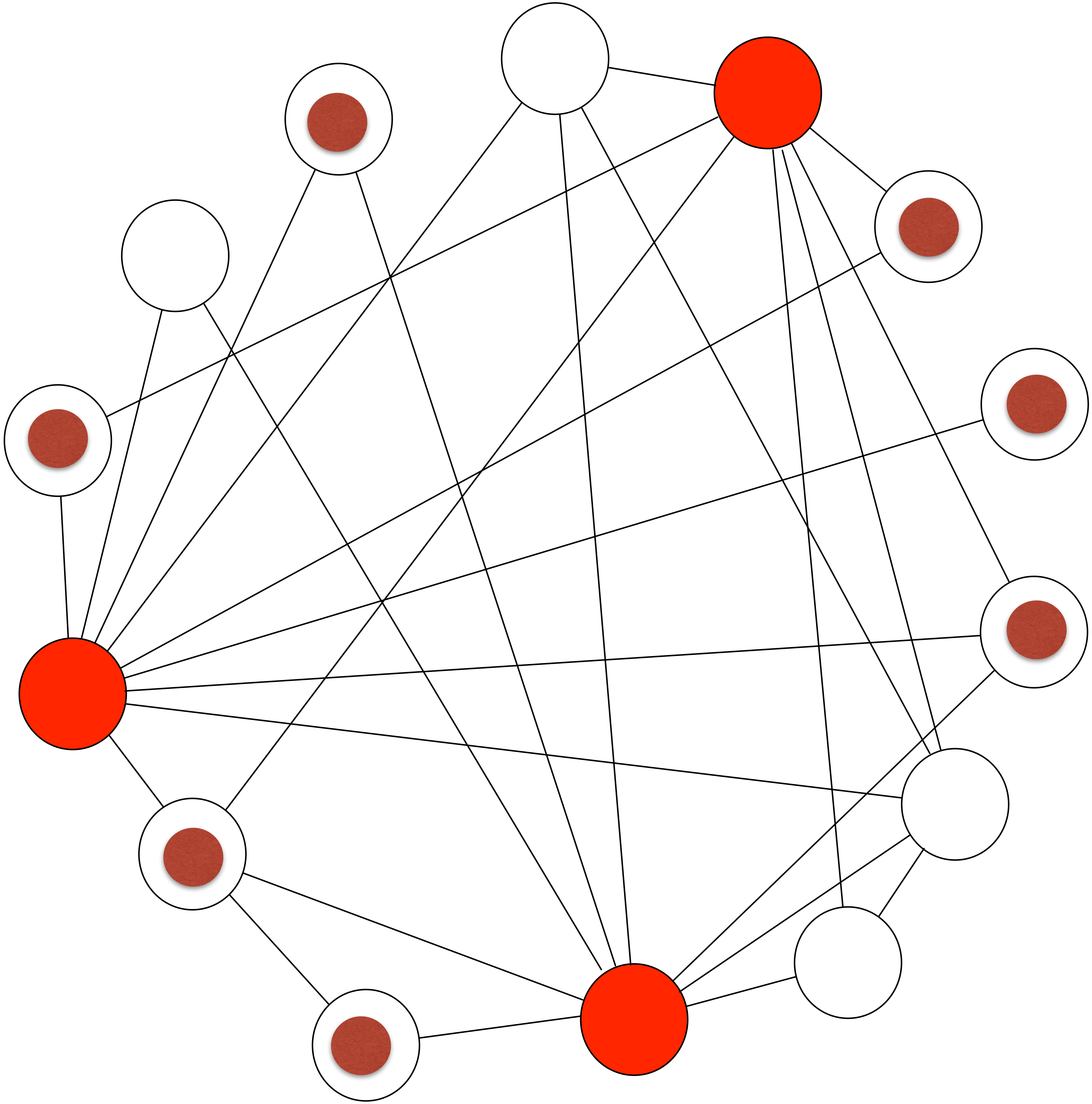

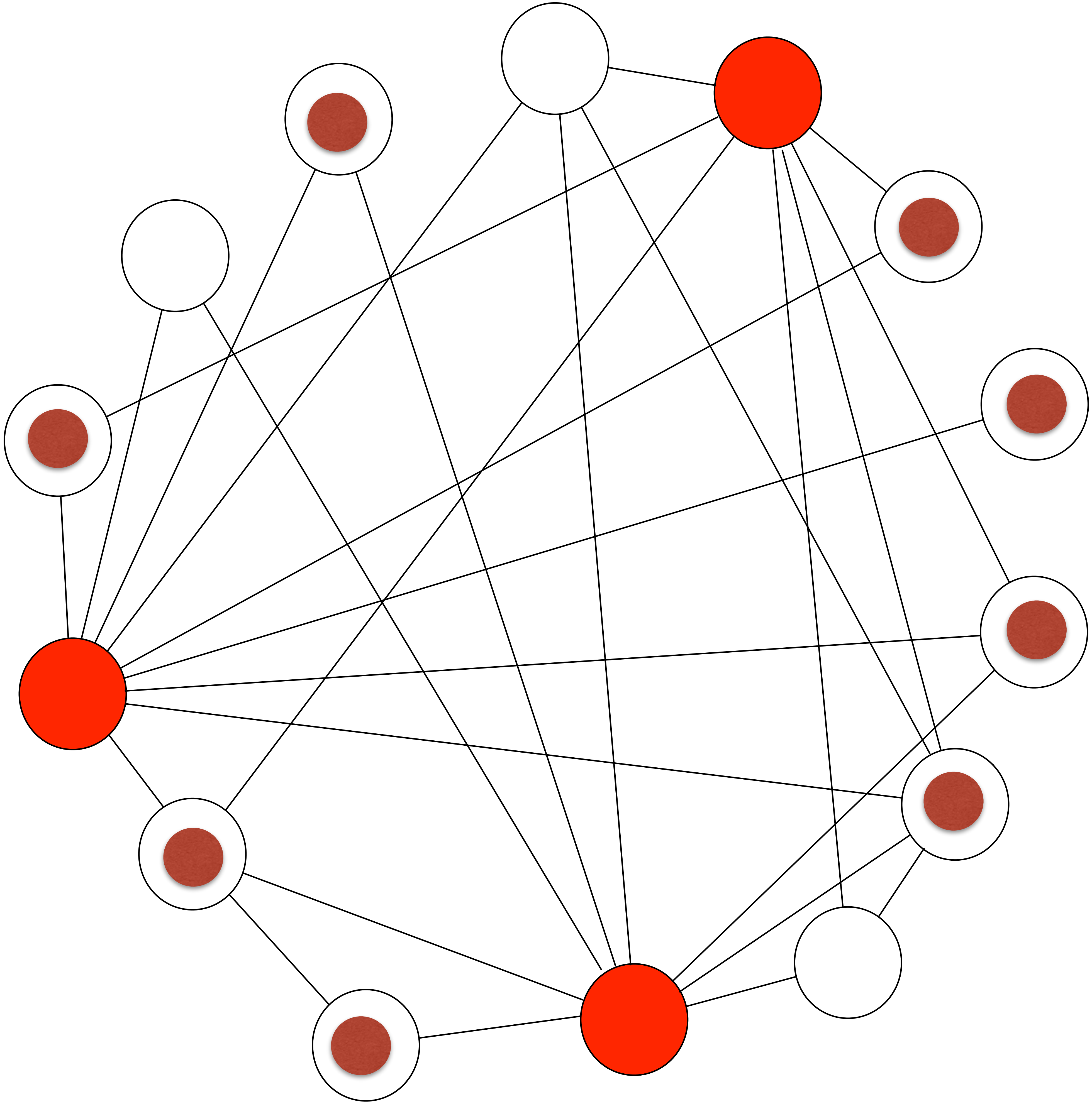

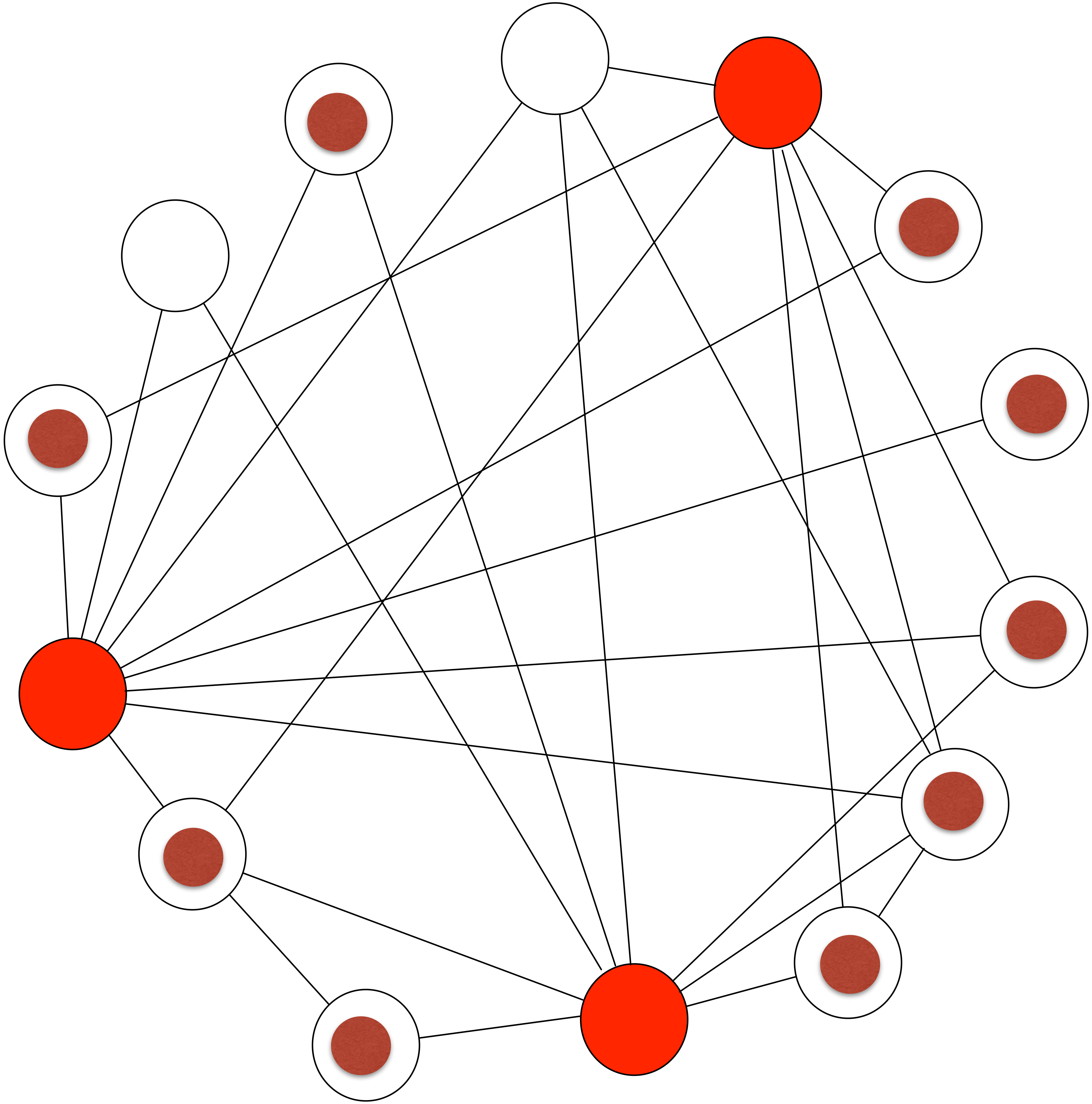

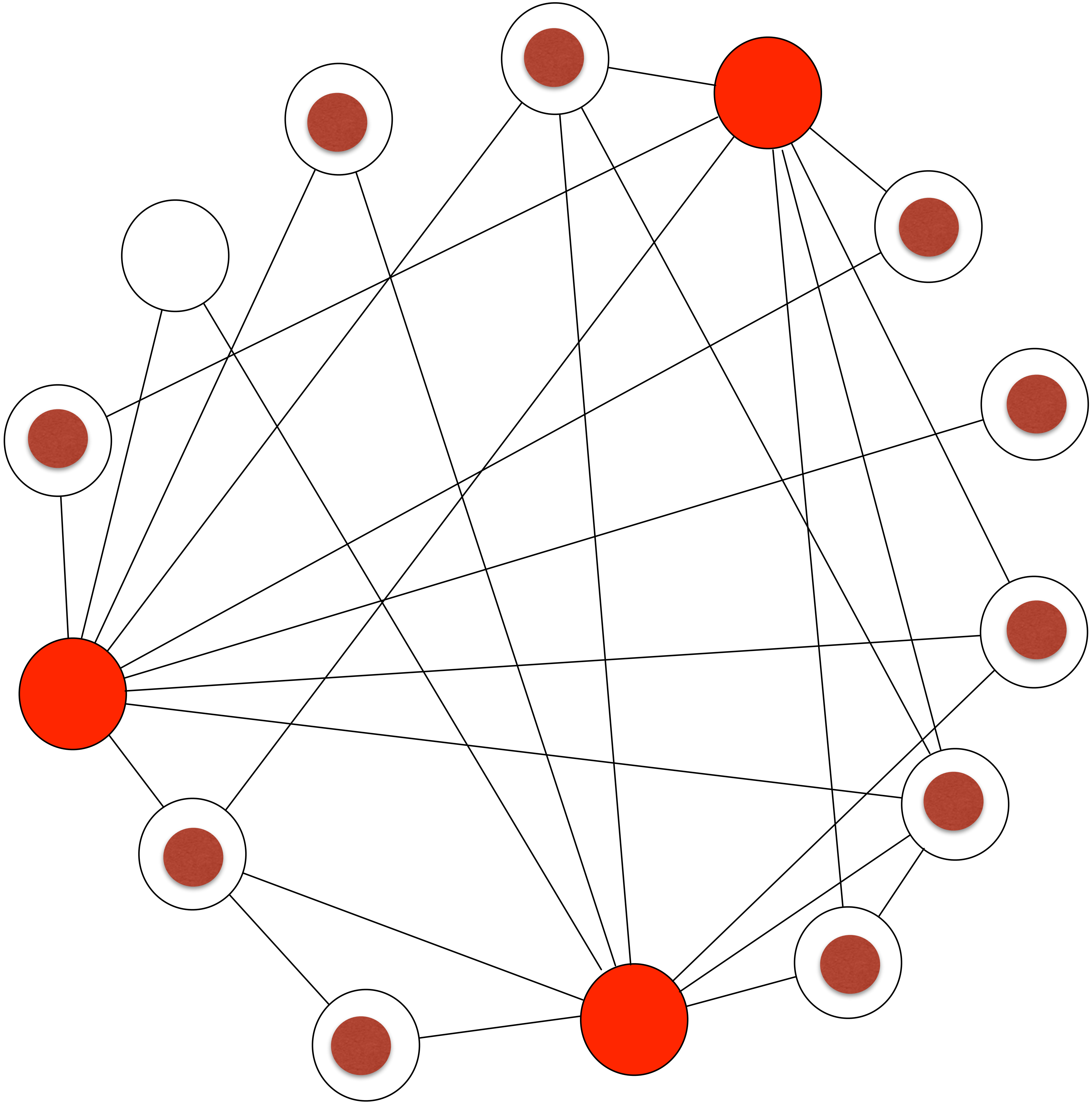

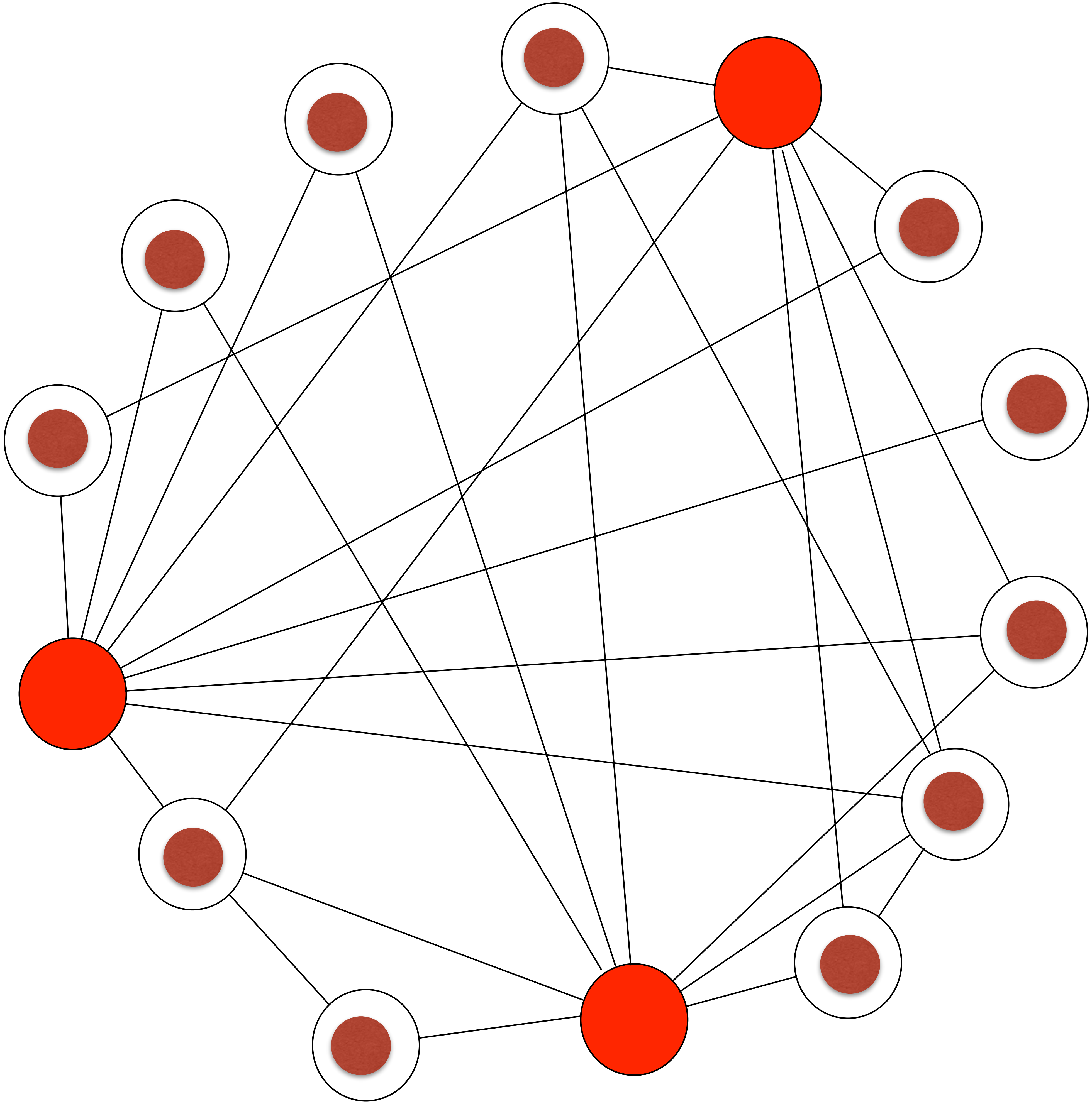

Pluralistic ignorance

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Hubert J. O'Gorman

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Pluralistic ignorance

Pluralistic ignorance

"All those in favour say 'Aye'."

"Aye." "Aye." "Aye." "Aye." "Aye."

Pluralistic ignorance

So far…

only symptoms of influence… but no models of social influence