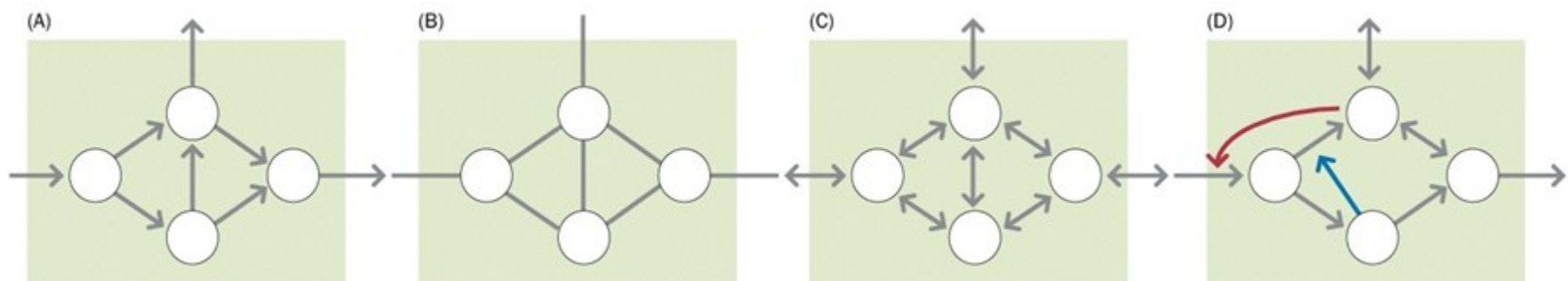


Eberhard O. Voit

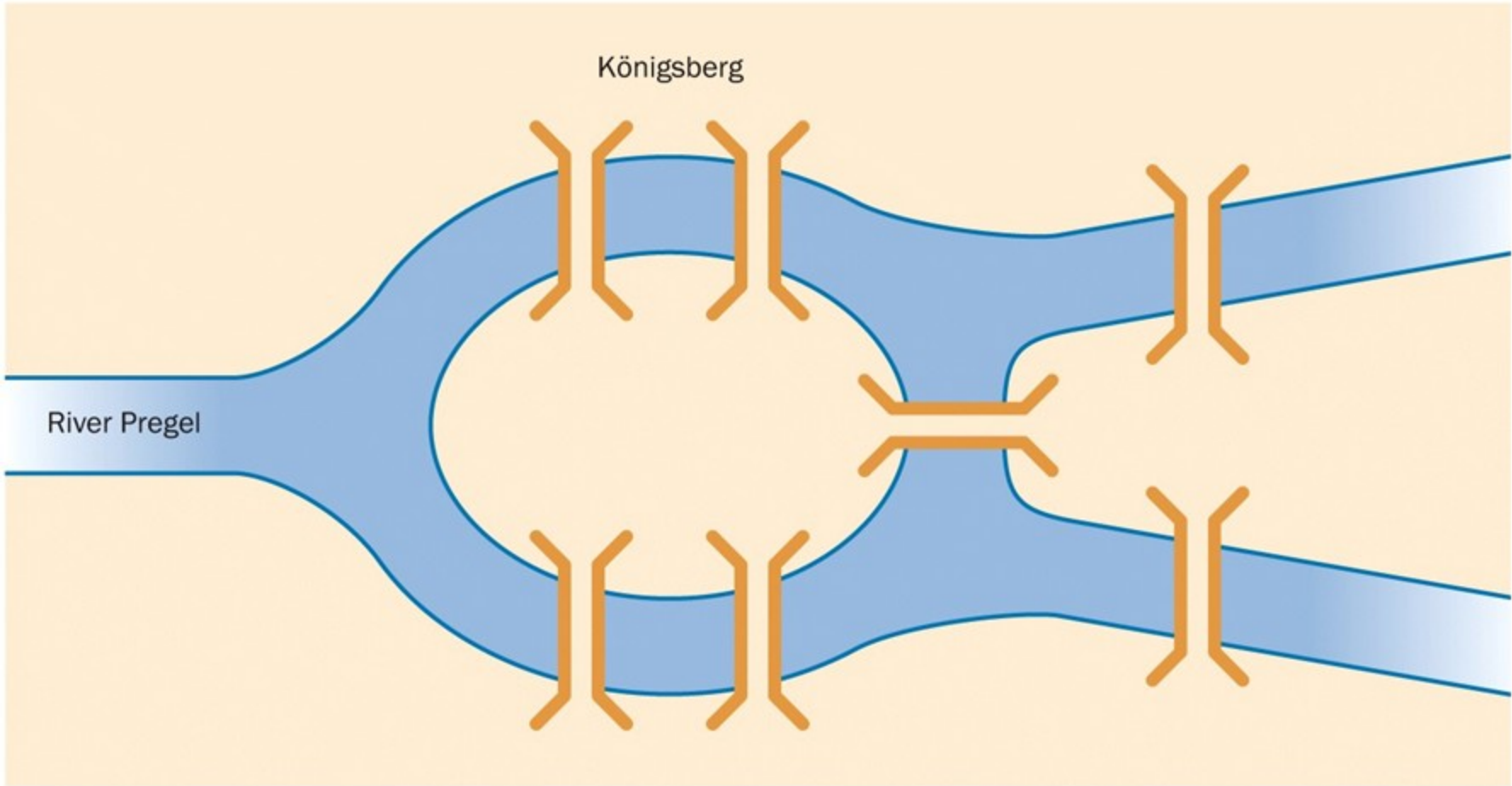
**A First Course in  
Systems Biology**

Chapter 3  
Static Network Models

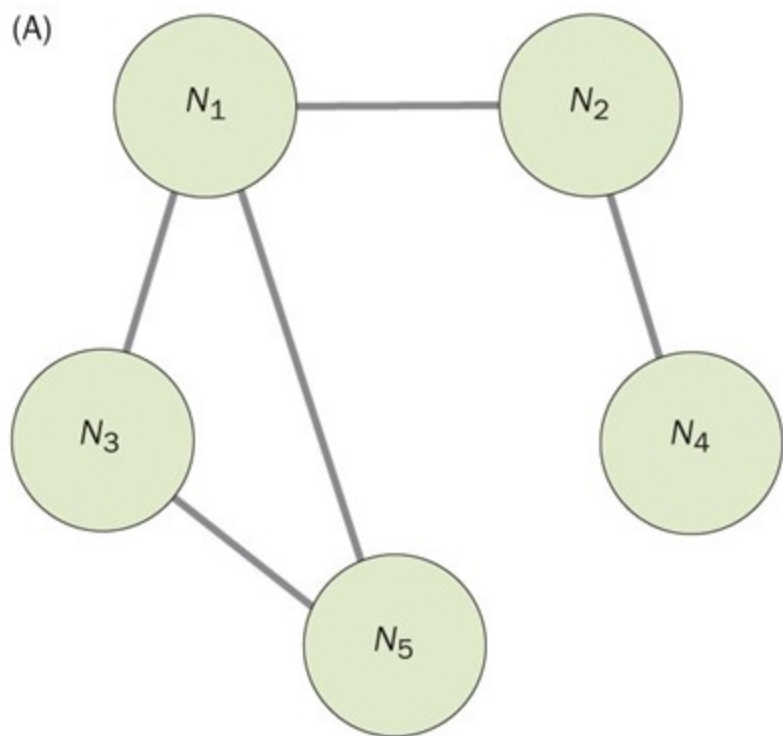


Königsberg

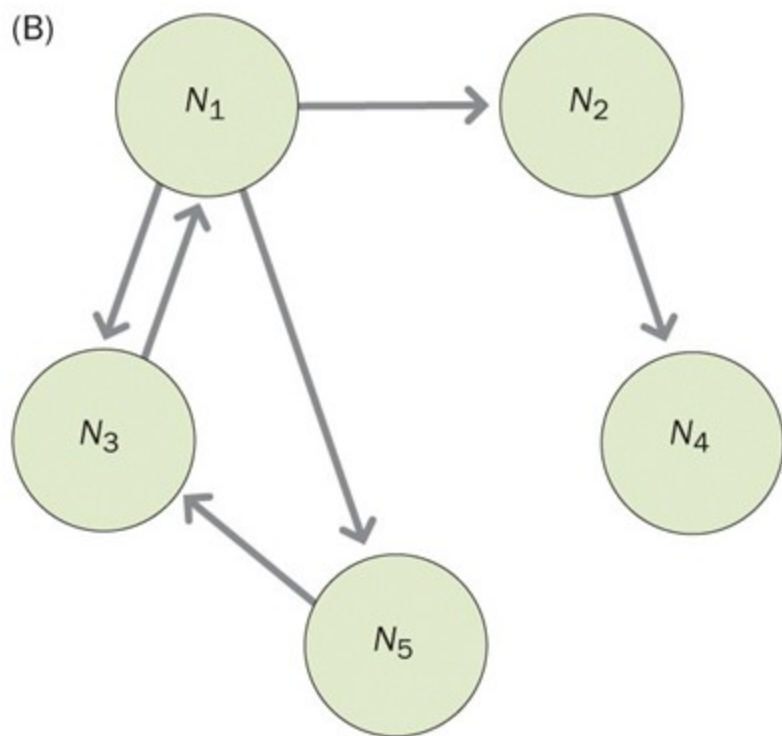
River Pregel

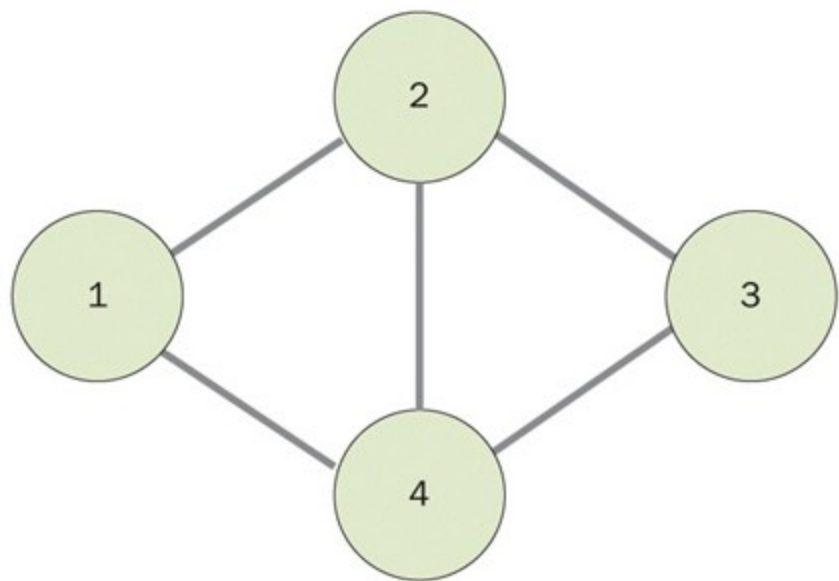


(A)

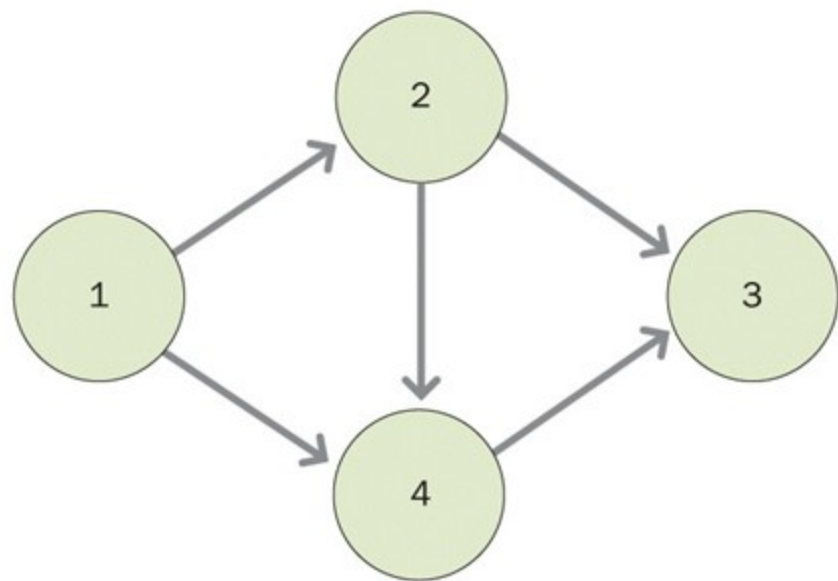


(B)



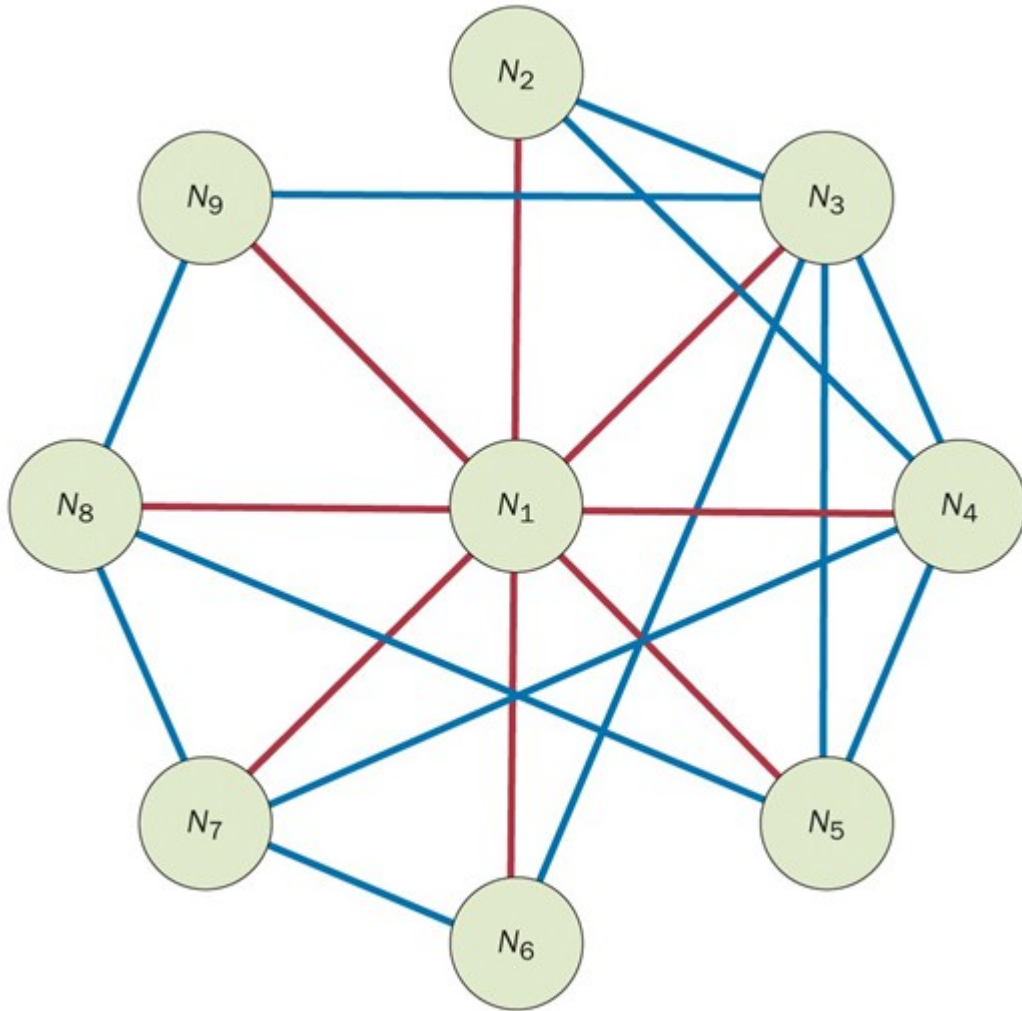


$$A = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix}$$



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

# Clustering coefficient: Characterizing density of edges associated with a node

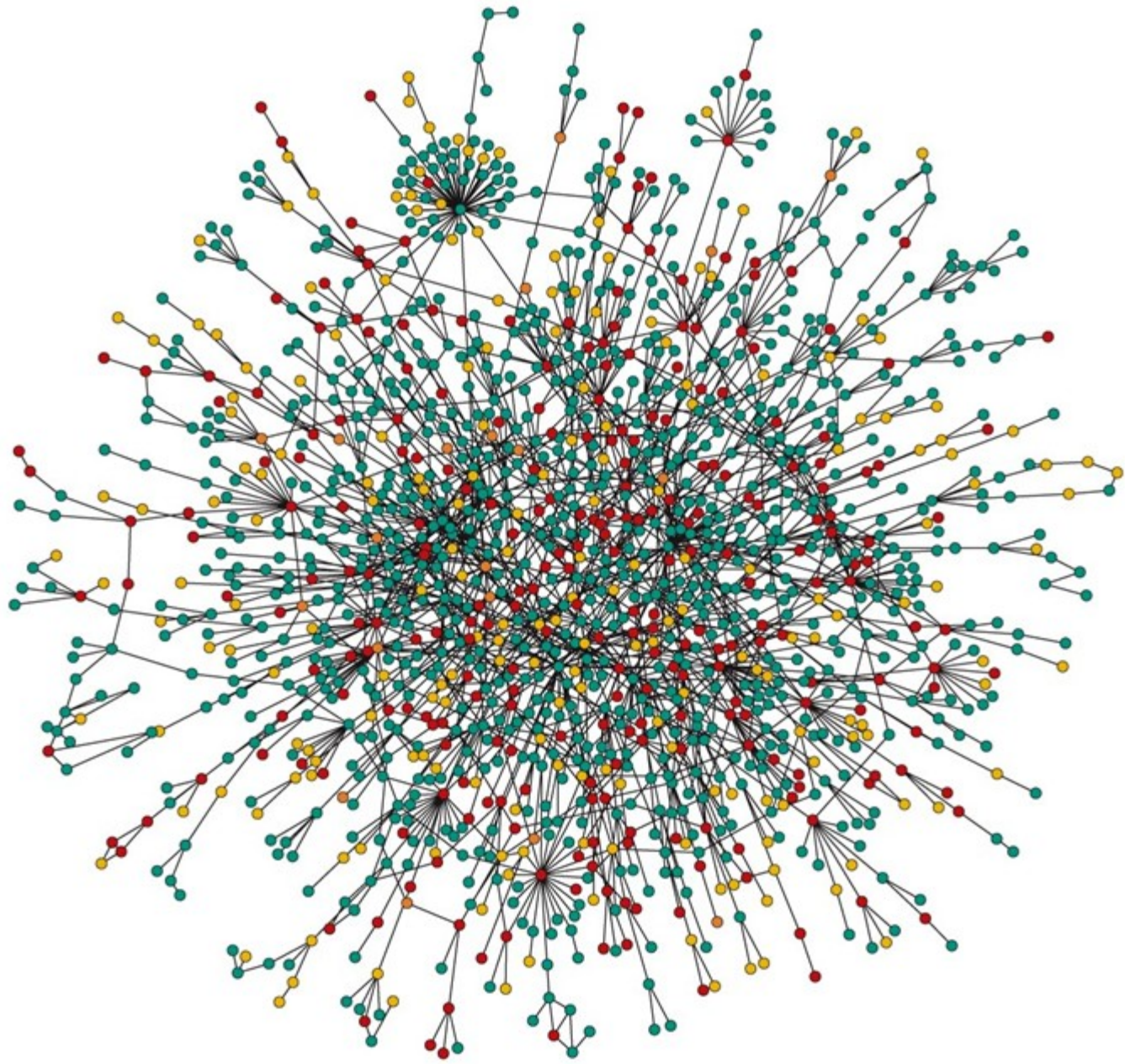


$$\text{UG: } C_N = 2e/k(k-1)$$

$$\text{DG: } C_N = e/k(k-1)$$

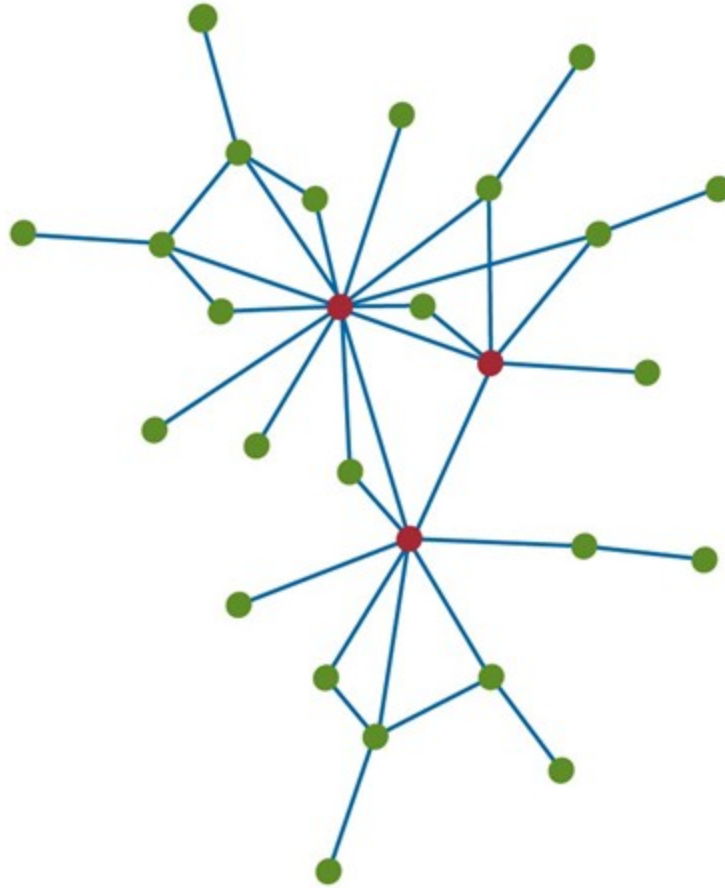
( $k$  is degree)

$$C_G = \frac{1}{m} \sum_{N=1}^m C_N$$

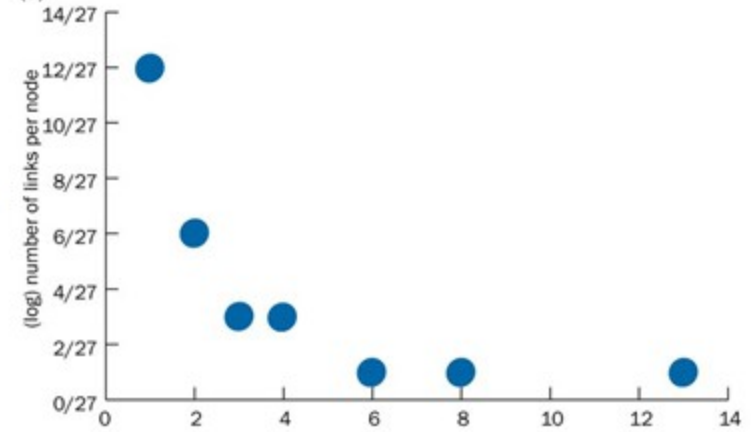


# Power-law and degree distribution: $P(k) \propto k^{-\gamma}$

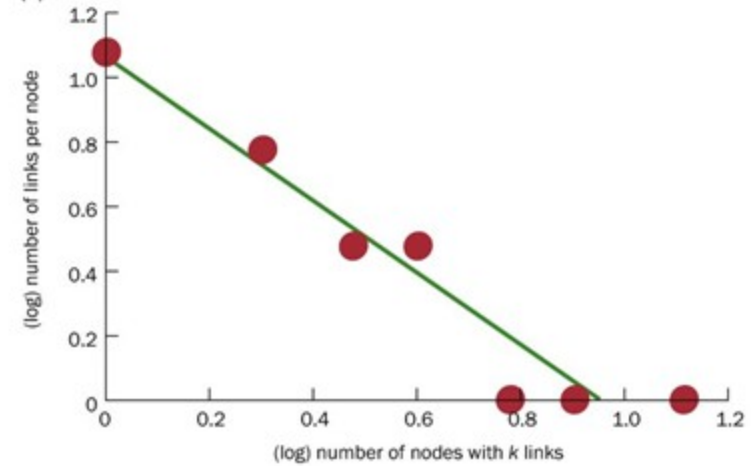
(A)



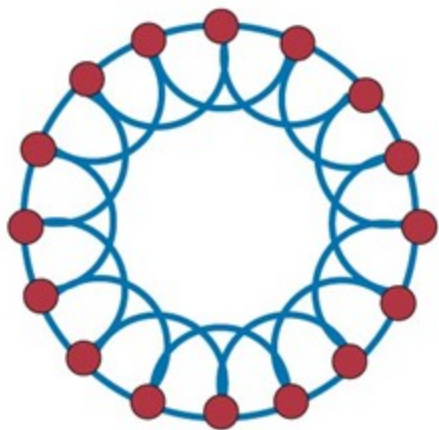
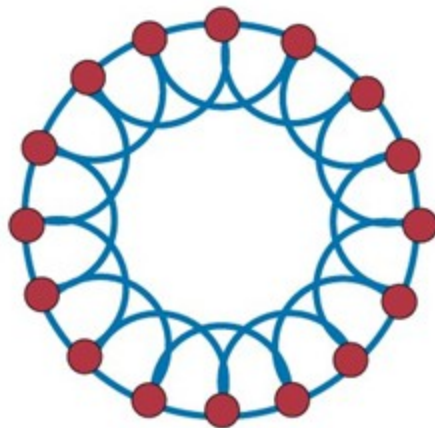
(B)



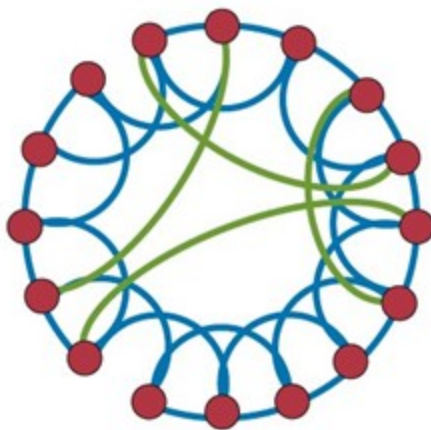
(C)



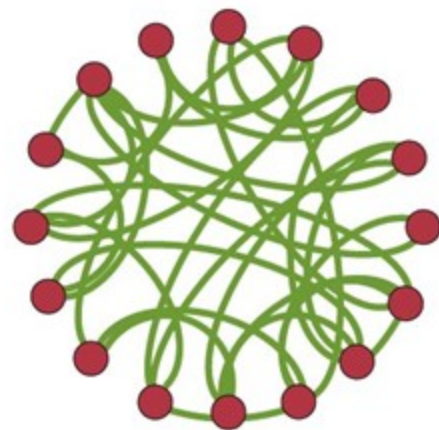




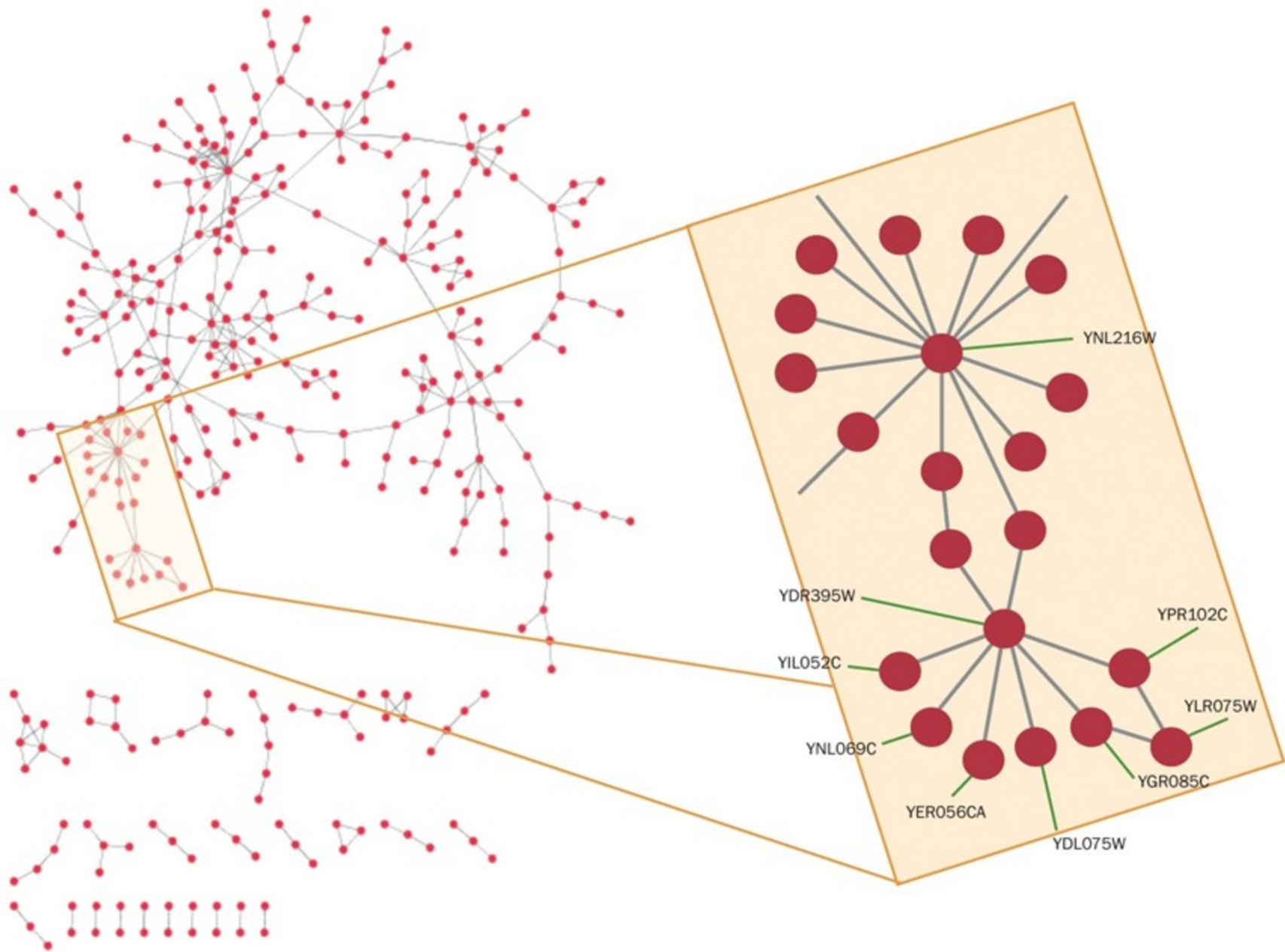
$p = 0$   
regular

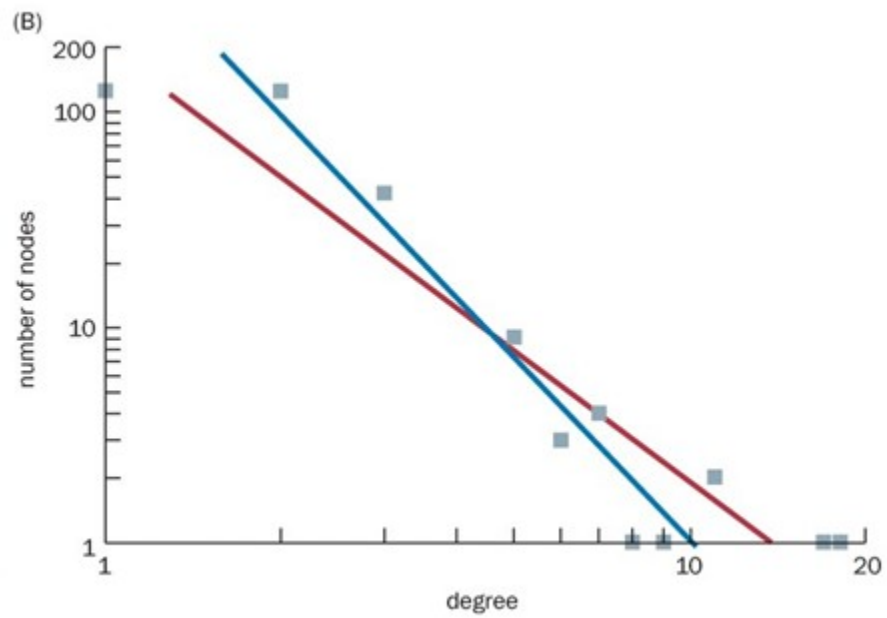
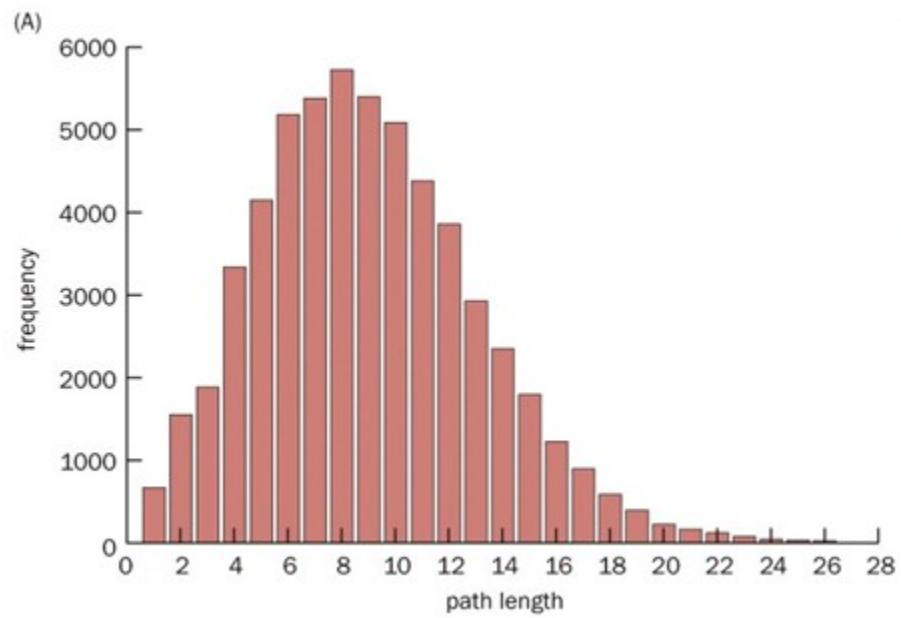


$0 < p < 1$   
small-world

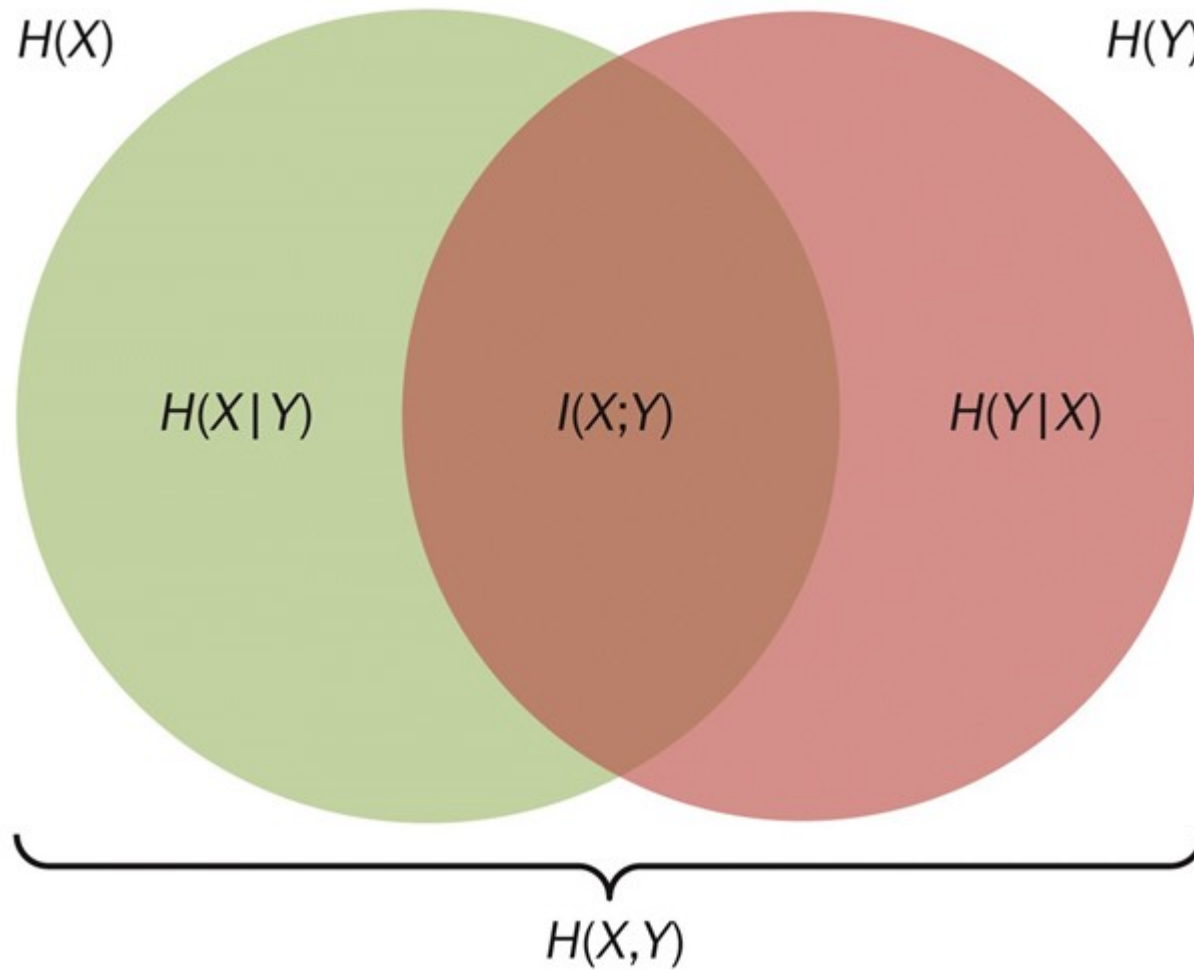


$p = 1$   
random





Mutual information  $I(X;Y)$  in terms of entropies  $H(X)$ ,  $H(Y)$  and conditional entropies  $H(X|Y)$  and  $H(Y|X)$



# Bayes' theorem

(Also called Bayes' law/formula/rule)

When prior knowledge is available, Bayes' theorem allows computation of probability of an event.

$$P(A | B) = \frac{P(B | A)P(A)}{P(B)}$$

Note: P(B) is non-zero.

Where:

- P(A) and P(B) are (independent probabilities of observing events A and B,
- P(A|B) is the 'conditional probability' (ie, prob. of observing A when B happens), and
- P(B|A) is the 'conditional probability' (ie, prob. of observing B when A happens).

$$P(B | A) = \frac{P(B \text{ and } A)}{P(A)}$$

$$P(B | A)P(A) = P(B \text{ and } A) = P(A \text{ and } B) = P(A | B)P(B)$$

$$P(A | B) = \frac{P(A \text{ and } B)}{P(B)} = \frac{P(B | A)P(A)}{P(B)}$$

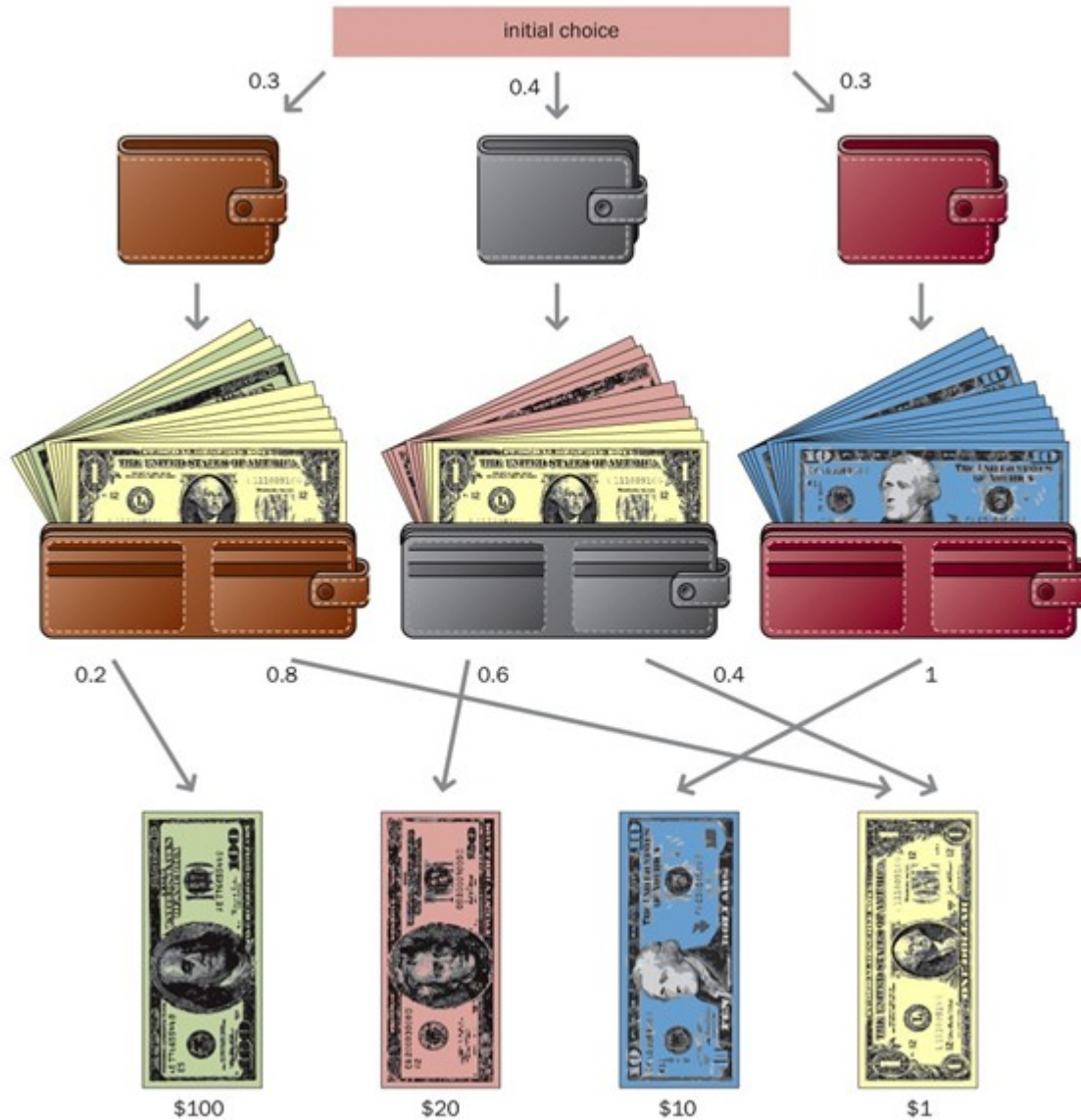
$$P(A | B) = \frac{P(B | A)P(A)}{P(B)}$$

**Prior probability:**  $P(A)$ , the initial belief in A

**Posterior probability:**  $P(A|B)$ , is the probability of A given evidence B

**Support B provides for A:**  $P(B|A)/P(B)$

# Bayesian reconstruction of interaction networks



Probabilities:

$$P(\$100) = 0.06$$

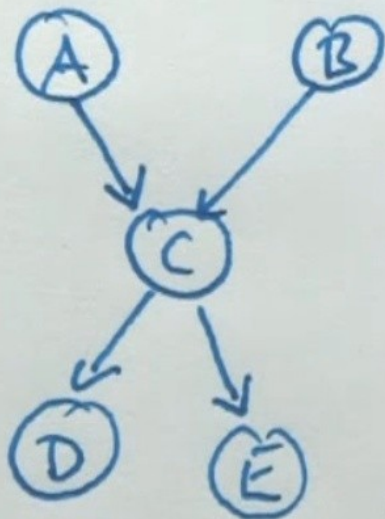
$$P(\$20) = 0.24$$

$$P(\$10) = 0.3$$

$$P(\$1) = 0.4$$



# BAYES NETWORKS



$$2^5 - 1 = 31$$

$$P(A), P(B)$$

$$P(C|A, B)$$

$$P(D|C) P(E|C)$$

$$P(A, B, C, D, E) =$$

$$P(A) \cdot P(B) \cdot P(C|A, B) \cdot P(D|C) \cdot P(E|C)$$

1

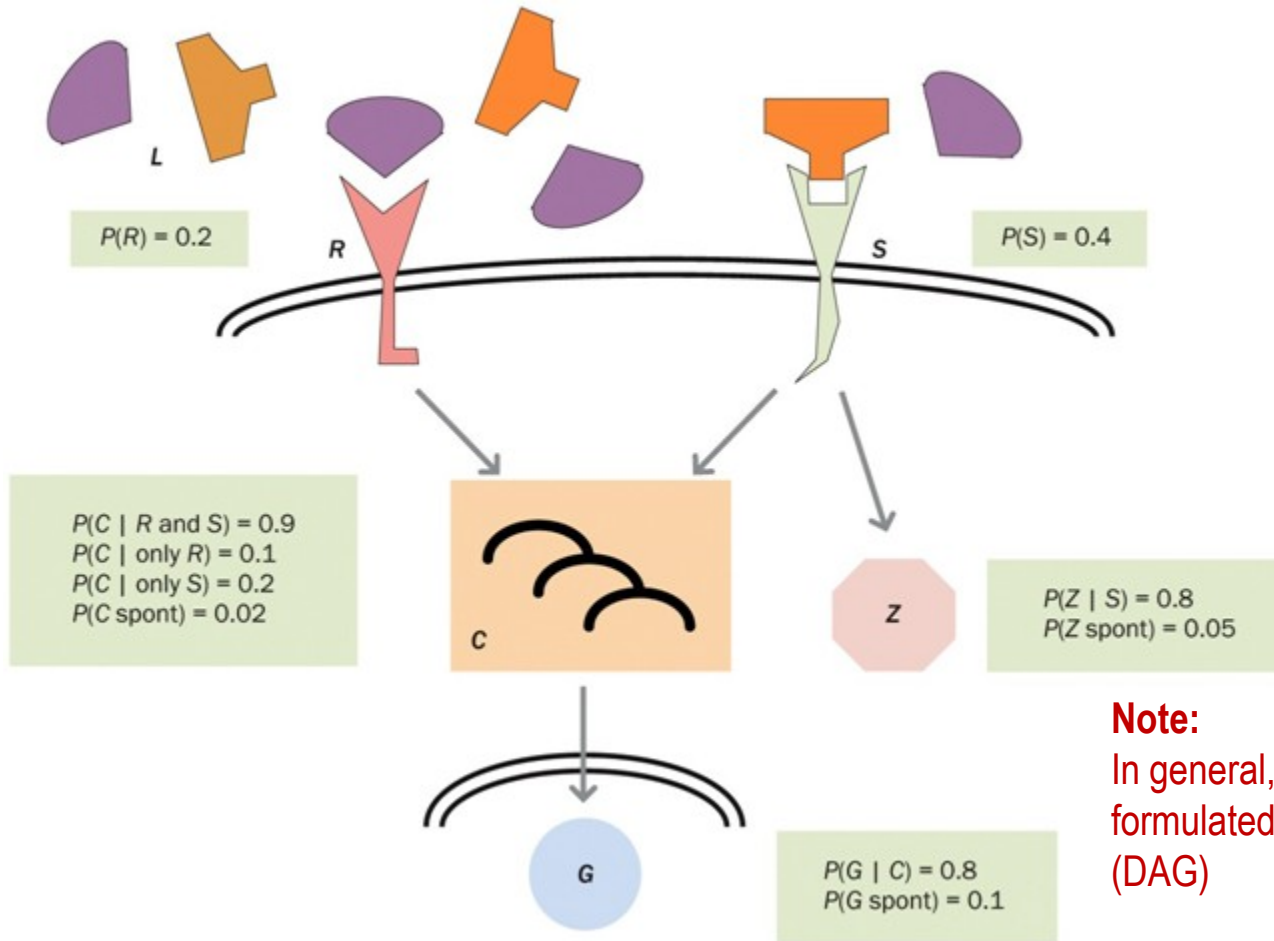
4

2

2

10

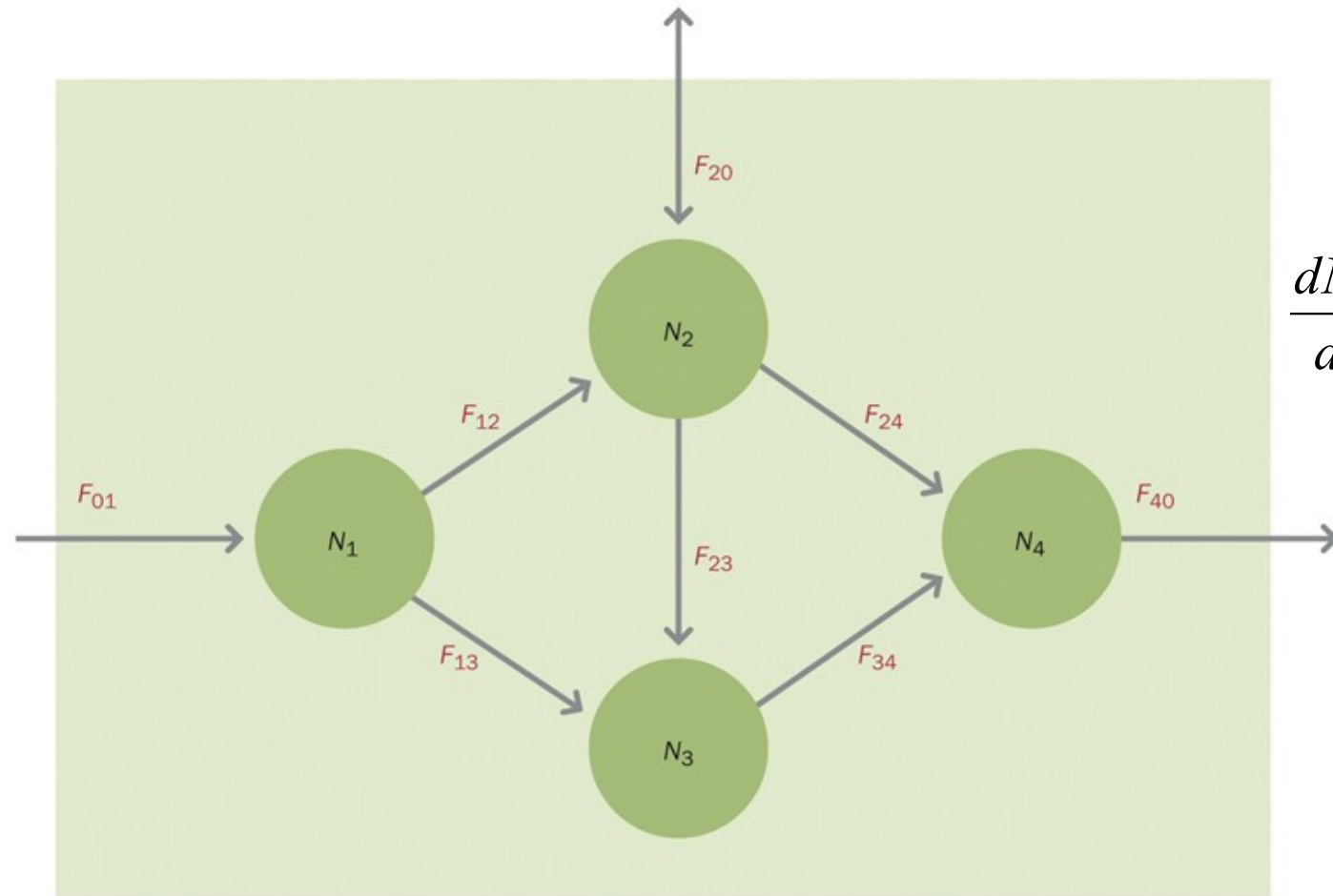
# Signaling networks



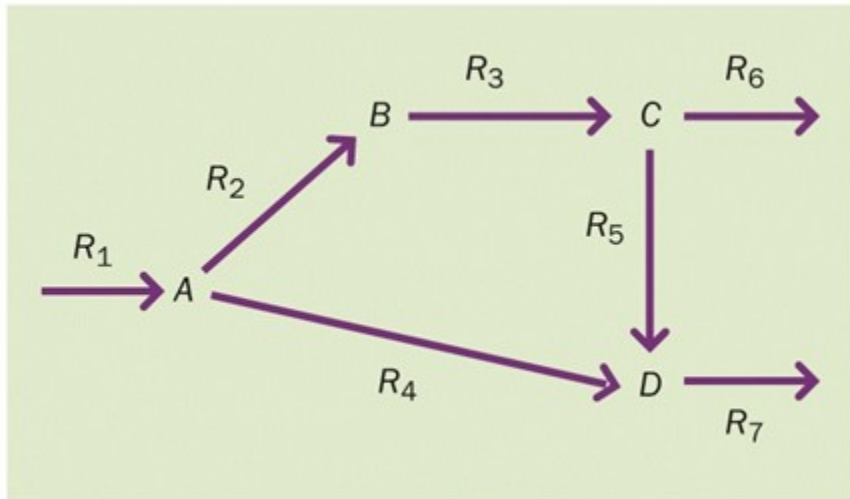
**Note:**  
In general, Bayesian network is formulated as a directed acyclic graph (DAG)

$$\begin{aligned}
 P(G, C, R, S \text{ are "on"}) &= P(G | C) \cdot P(C | R \text{ and } S) \cdot P(R) \cdot P(S) \\
 &= 0.8 * 0.8 * 0.2 * 0.4 \\
 &= 0.0576
 \end{aligned}$$

# Stoichiometric networks



$$\frac{dN_3}{dt} = F_{13} + F_{23} - F_{34} = 0,$$
$$\Rightarrow F_{13} + F_{23} = F_{34}$$



$$\mathbf{N} = \begin{matrix} & \begin{matrix} R_1 & R_2 & R_3 & R_4 & R_5 & R_6 & R_7 \end{matrix} \\ \begin{bmatrix} 1 & -1 & 0 & -1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & -1 & -1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & -1 \end{bmatrix} & \begin{matrix} A \\ B \\ C \\ D \end{matrix} \end{matrix}$$

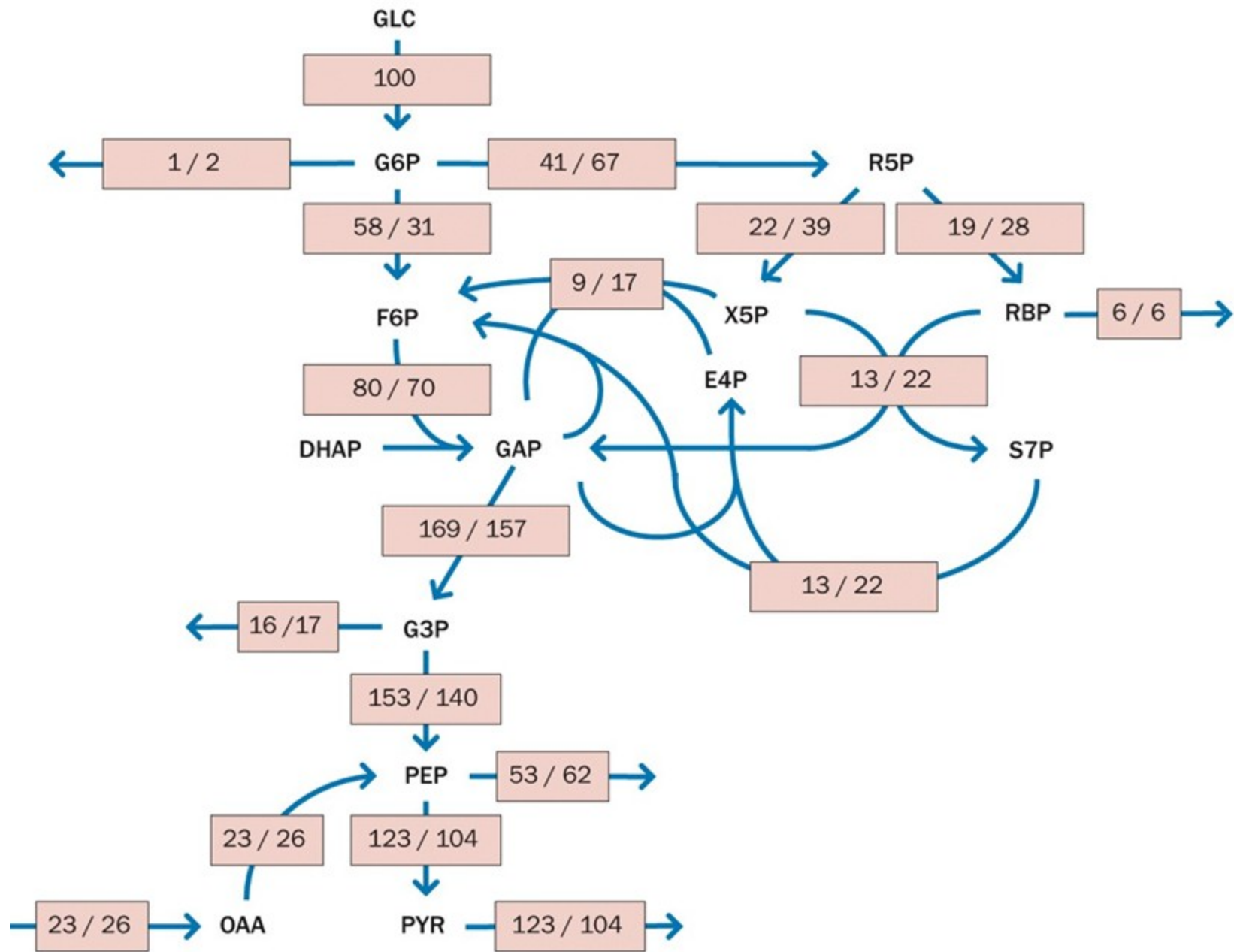
$$\dot{\mathbf{S}} = \mathbf{NR}$$

### Stoichiometric Analysis:

*Flux Balance Analysis* is widely used with biologically motivated constraints using *constrained optimization*.

**N**: Stoichiometric matrix of generic flux matrix

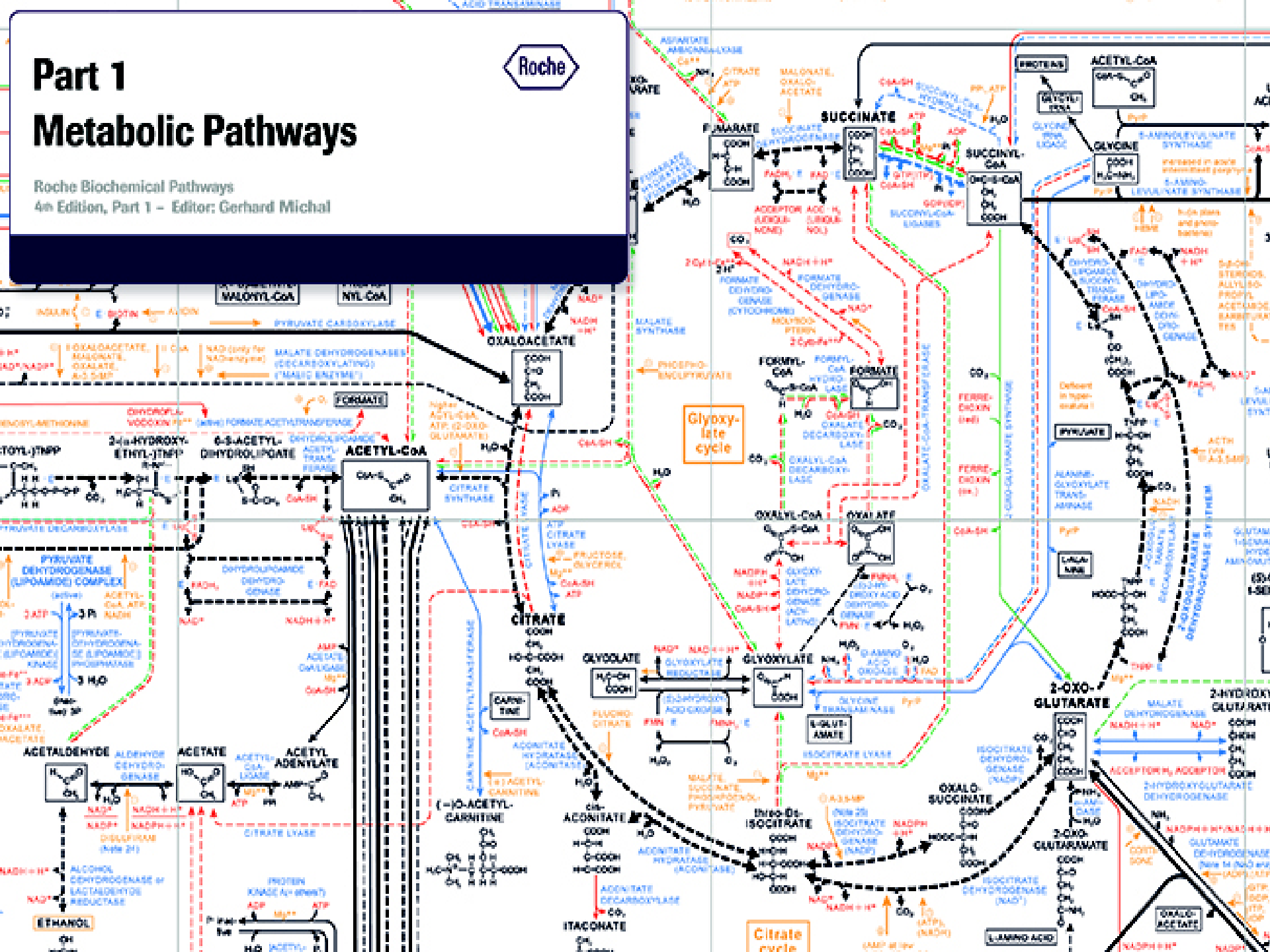
**R**: Fluxes between pools



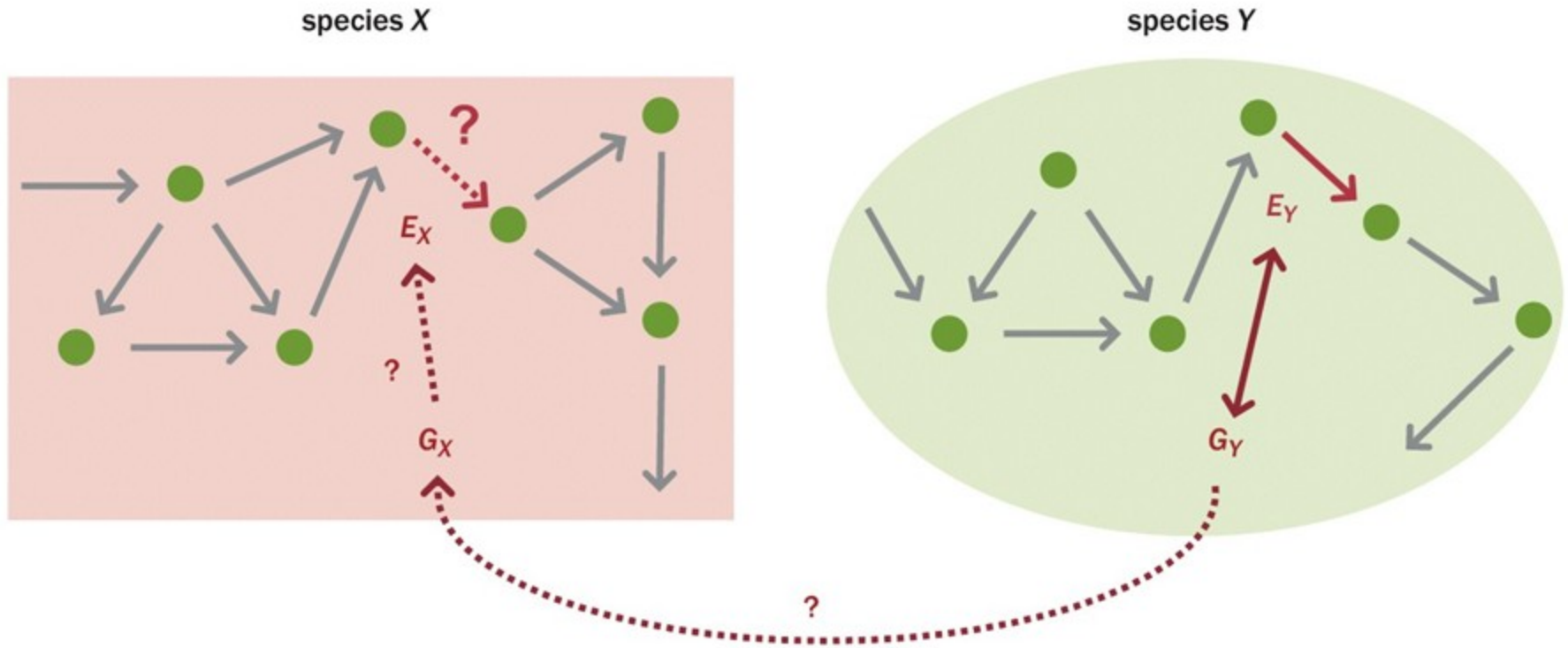
# Part 1 Metabolic Pathways

Roche Biochemical Pathways  
4th Edition, Part 1 – Editor: Gerhard Michal

Roche



# Metabolic network reconstruction



**Note:**  
KEGG and MetaCyc databases are useful

# Metabolic Control Analysis

Characterizes small perturbations in a metabolic pathway that operates at steady state.

It uses:

- **Elasticities**
- **Control coefficients**
  - Pathway flux
  - Concentration

Note: Flux control coefficients sum to 1 and concentration control coefficients sum to 0.





