

Network Modeling in Systems Biology with R

Tutorial 1

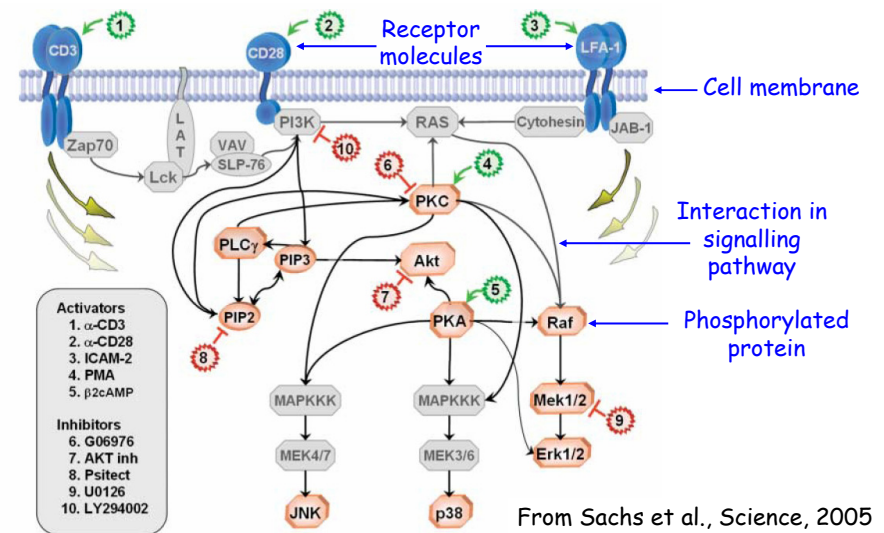
Markov chain Monte Carlo (MCMC) sampling
of Gaussian Bayesian networks
for static (steady-state) data

Statistical Computing 2010, Reimsburg
21-June-2010

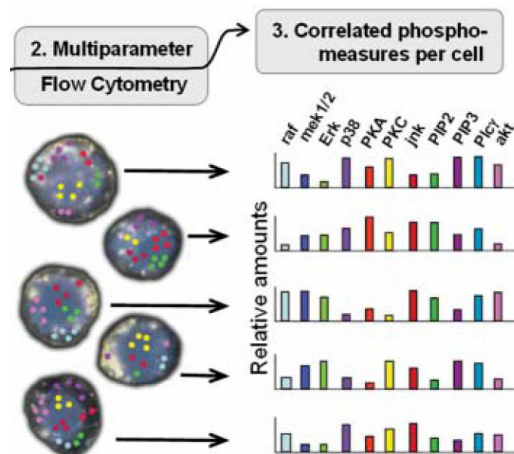
Miriam Lohr and Marco Grzegorzczak
Department of Statistics
TU Dortmund University



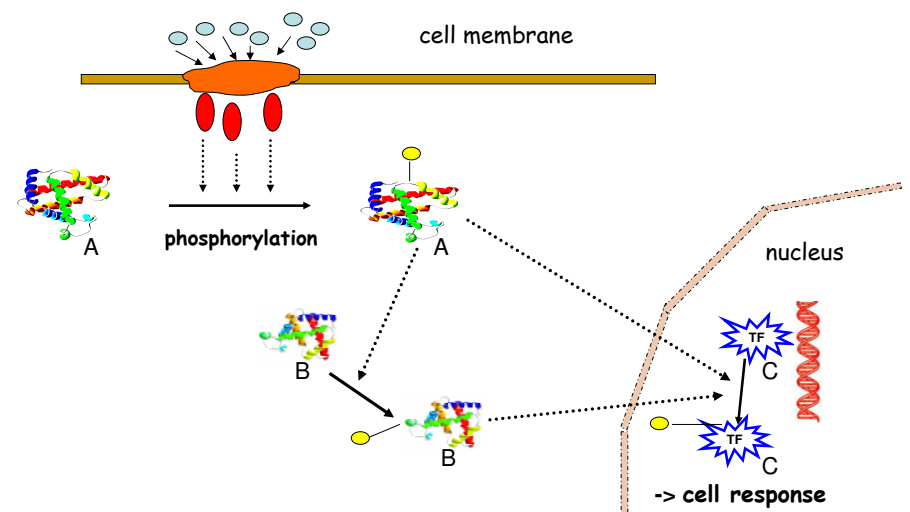
Regulatory networks and protein signalling pathways



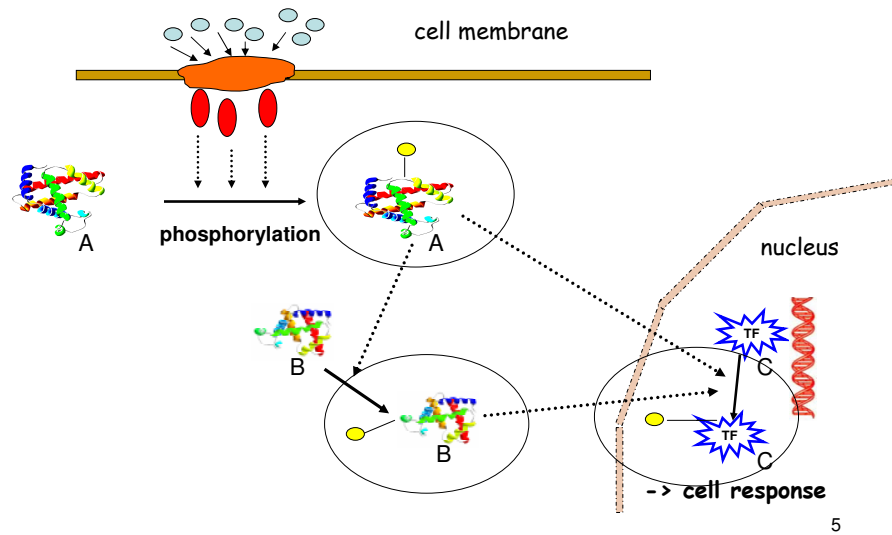
Flow cytometry technology



Protein activation cascade

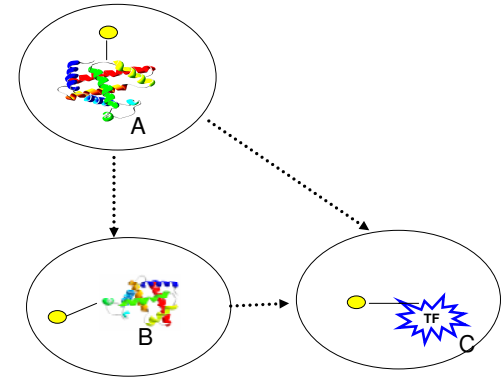


Protein activation cascade



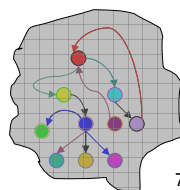
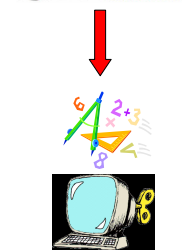
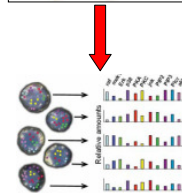
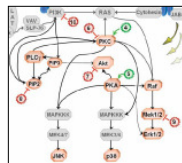
5

Protein activation cascade



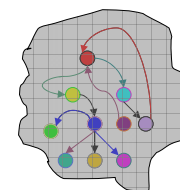
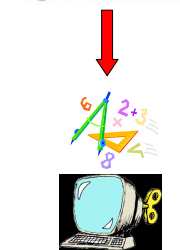
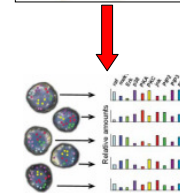
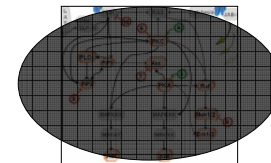
6

True regulatory pathway/network

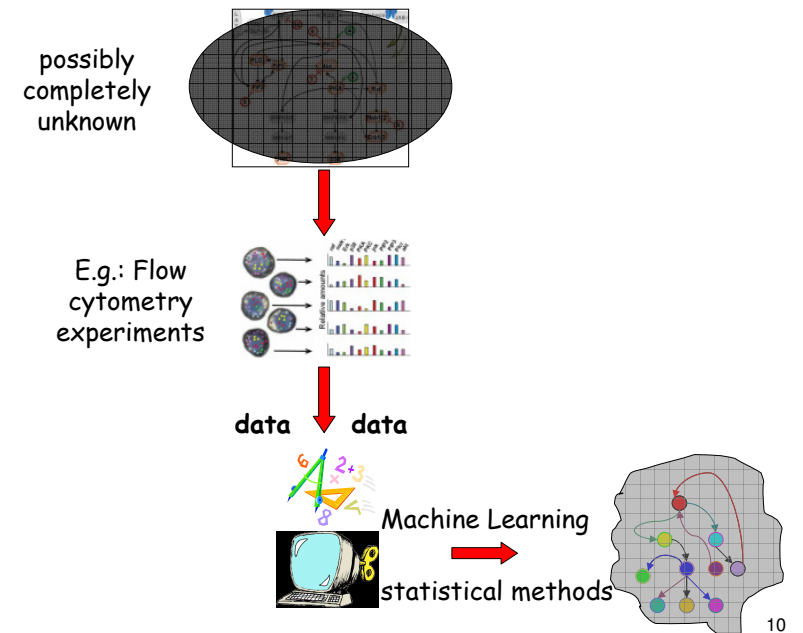
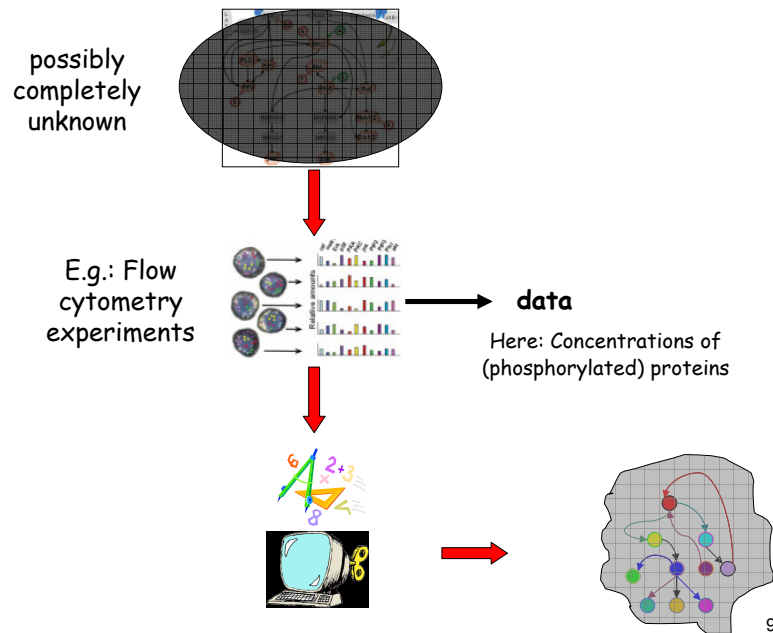


7

possibly completely unknown

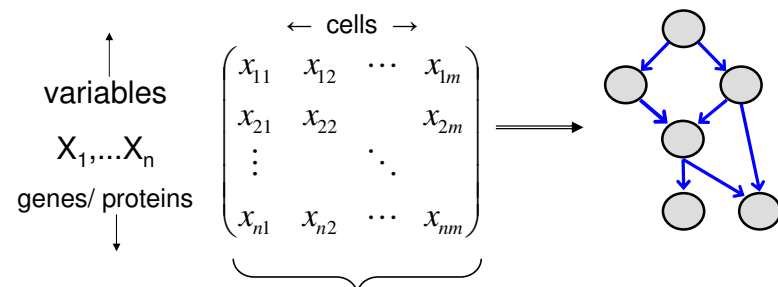


8



Statistical Task

Extract a network from a data matrix

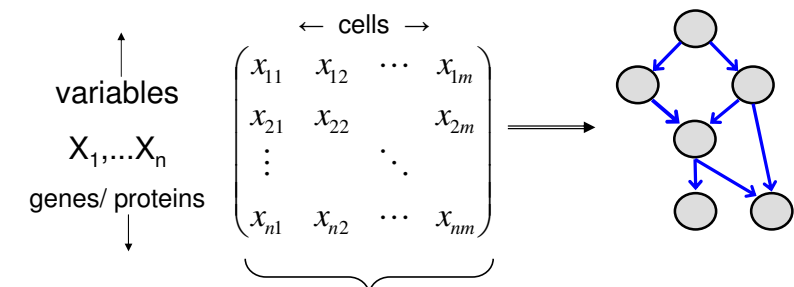


Either m independent (steady-state) observations of the system X_1, \dots, X_n

Or time series of the system of length m : $(X_1, \dots, X_n)_{t=1, \dots, m}$

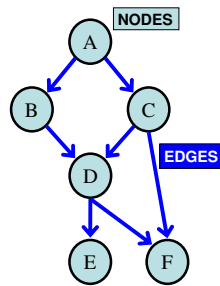
Statistical Task

Extract a network from a data matrix



⇒ m independent (steady-state) observations of the system X_1, \dots, X_n

Static Bayesian networks



• Marriage between **graph theory** and **probability theory**.

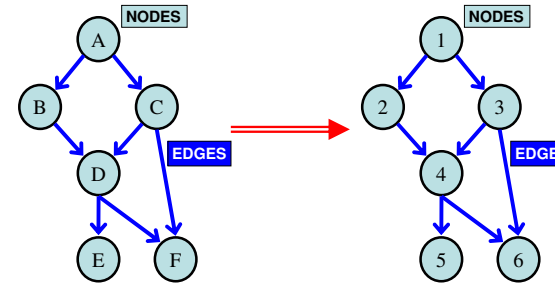
• Directed acyclic graph (DAG) represents conditional independence relations.

• **Markov assumption** leads to a factorization of the joint probability distribution:

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

13

Incidence Matrix of a DAG



Number the variables/nodes
1=A, 2=B, 3=C, etc.

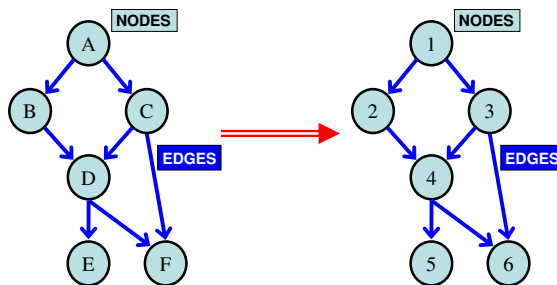
$I(i, j) = 1$ if there is an edge from node i to node j

$I(i, j) = 0$ if there is **no** edge from node i to node j

$$I = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

14

Ancestor Matrix of a DAG



Number the variables/nodes
1=A, 2=B, 3=C, etc.

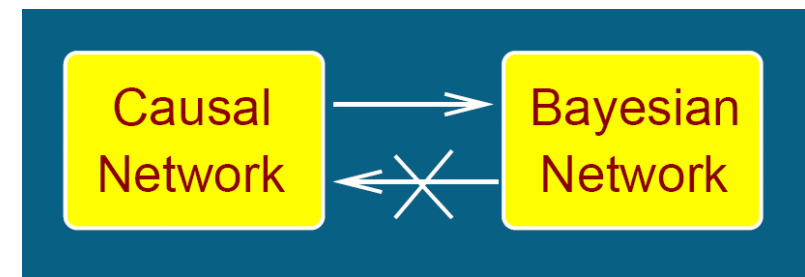
$A(j, i) = 1$ if there is a path from node i to node j

$A(j, i) = 0$ if there is no path from node i to node j

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

15

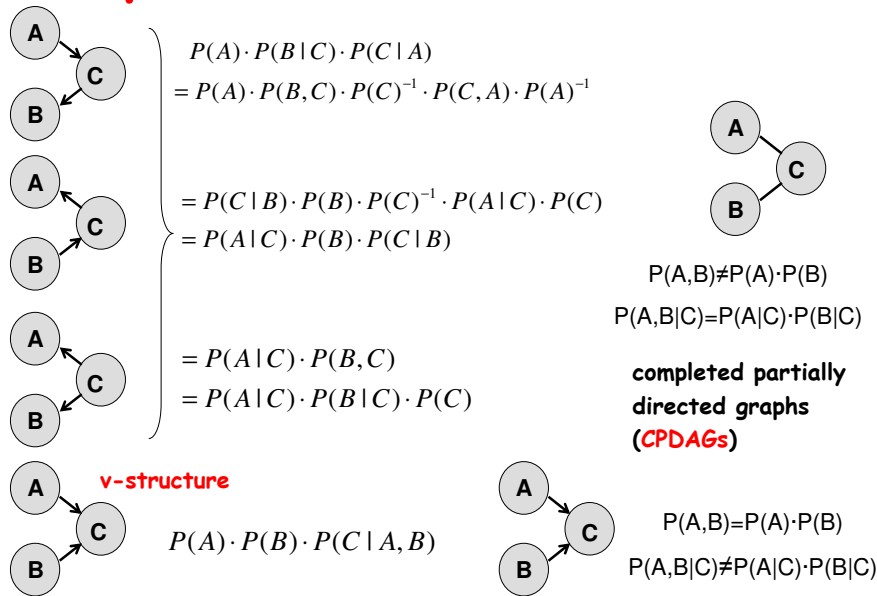
Bayesian networks versus causal networks



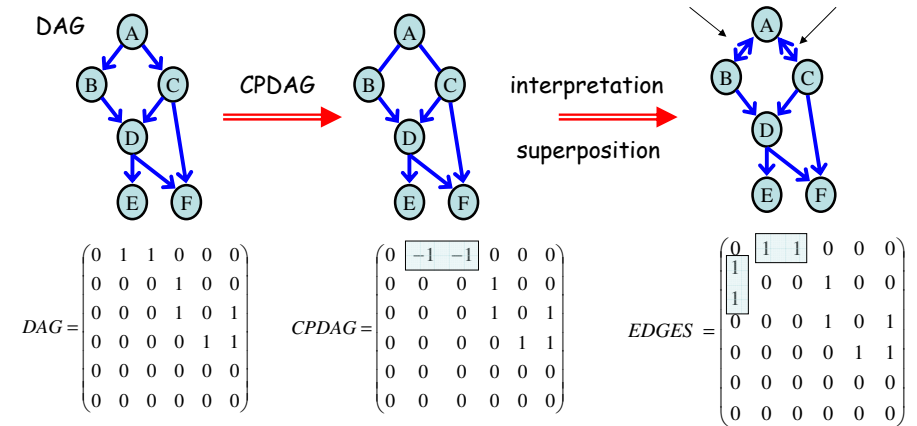
Bayesian networks represent conditional (in)dependency relations - **not** necessarily **causal interactions**.

16

Equivalence classes of BNs



CPDAG representations



18

Static Bayesian networks

$$P(\text{graph} | \text{data}) = \frac{P(\text{data} | \text{graph}) \cdot P(\text{graph})}{P(\text{data})} \propto P(\text{data} | \text{graph}) \cdot P(\text{graph})$$

$$= P(\text{graph}) \cdot \int P(\text{data}, \theta(\text{graph}) | \text{graph}) d\theta(\text{graph})$$

19

Static Bayesian networks

$$P(\text{graph} | \text{data}) = \frac{P(\text{data} | \text{graph}) \cdot P(\text{graph})}{P(\text{data})} \propto P(\text{data} | \text{graph}) \cdot P(\text{graph})$$

$$= P(\text{graph}) \cdot \int P(\text{data}, \theta(\text{graph}) | \text{graph}) d\theta(\text{graph})$$

Parameterisation: Gaussian BGe scoring metric:

$$\text{data} \sim N(\mu, \Sigma)$$

with the (conjugate) normal-Wishart distribution for the parameters

$$\mu \sim N(\mu^*, (vW)^{-1}) \text{ and } W \sim \text{Wishart}(T_0)$$

20

Static Bayesian networks

$$P(\text{graph} | \text{data}) = \frac{P(\text{data} | \text{graph}) \cdot P(\text{graph})}{P(\text{data})} \propto P(\text{data} | \text{graph}) \cdot P(\text{graph})$$

$$= P(\text{graph}) \cdot \underbrace{\int P(\text{data}, \theta(\text{graph}) | \text{graph}) d\theta(\text{graph})}_{\text{BGe metric: closed form solution}}$$

21

Static Bayesian networks

$$P(\text{graph} | \text{data}) = \frac{P(\text{data} | \text{graph}) \cdot P(\text{graph})}{P(\text{data})} \propto P(\text{data} | \text{graph}) \cdot P(\text{graph})$$

$$= \underbrace{P(\text{graph})}_{\text{uniform distribution}} \cdot \underbrace{\int P(\text{data}, \theta(\text{graph}) | \text{graph}) d\theta(\text{graph})}_{\text{BGe metric: closed form solution}}$$

$$= \text{score}_{\text{BGe}}(\text{graph} | \text{data})$$

22

Learning the network/graph structure

graph \rightarrow $\text{score}_{\text{BGe}}(\text{graph})$

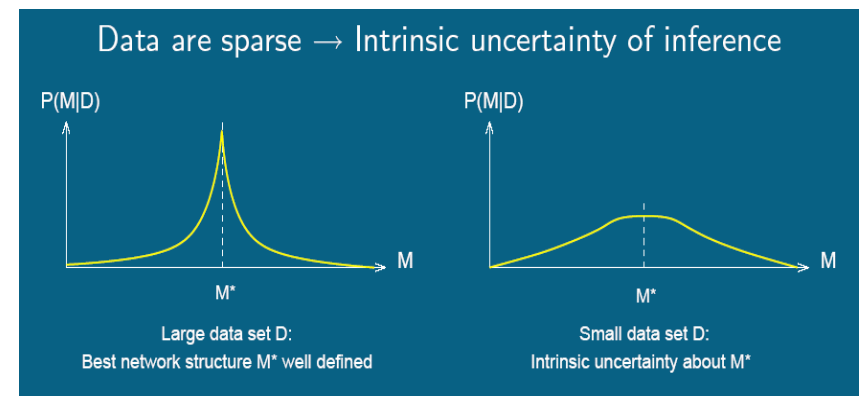
n	4	6	8	10
#DAGs	543	$3,7 \cdot 10^6$	$7,8 \cdot 10^{11}$	$4,2 \cdot 10^{18}$

Idea: Heuristically searching for the graph M^* that is most supported by the data
 $P(M^* | \text{data}) > P(\text{graph} | \text{data})$,
 e.g.: greedy search algorithm

23

Learning the network/graph structure

Distribution of $P(\text{graph} | \text{data})$



24

MCMC sampling of Bayesian networks

Better idea: Bayesian model averaging via **Markov Chain**

Monte Carlo (MCMC) simulations

Construct and simulate a Markov Chain $(M_t)_t$ in the space of DAGs whose distribution converges to the graph posterior distribution as stationary distribution, i.e.:

$$P(M_t = \text{graph} | \text{data}) \rightarrow P(\text{graph} | \text{data})$$

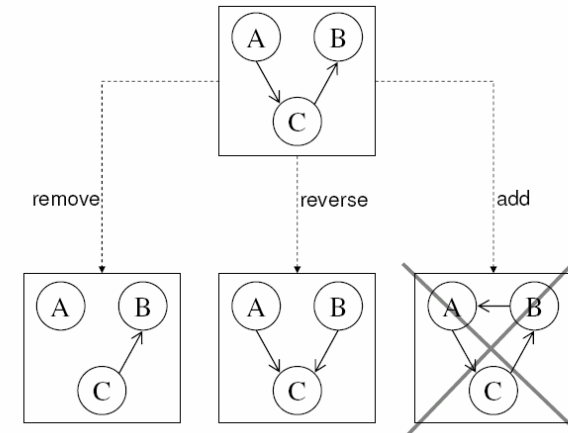
$$t \rightarrow \infty$$

to generate a DAG sample: $G_1, G_2, G_3, \dots, G_T$

25

Structure MCMC sampling scheme

(based on single edge operations)



26

Metropolis Hastings sampler

A Metropolis Hastings MCMC sampling scheme consists of two parts.

- (i) Given a graph G_{old} , a new graph is proposed with a **proposal probability** $Q(G_{new} | G_{old})$.
- (ii) The new graph is accepted with an **acceptance probability** $A(G_{new} | G)$, or rejected otherwise.

In the **structure MCMC sampling scheme** a neighbour graph, that is a graph G_{new} that can be reached from G_{old} by one single edge operation, is randomly drawn from a discrete uniform distribution in the proposal move (i).

And in step (ii) the new graph is accepted with probability:

$$A(G_{new} | G_{old}) = \min \left\{ 1, \frac{P(D | G_{new})}{P(D | G_{old})} \cdot \frac{P(G_{new})}{P(G_{old})} \cdot \frac{Q(G_{old} | G_{new})}{Q(G_{new} | G_{old})} \right\}$$

27

Metropolis Hastings sampler

A Metropolis Hastings MCMC sampling scheme consists of two parts.

- (i) Given a graph G_{old} , a new graph is proposed with a **proposal probability** $Q(G_{new} | G_{old})$.
- (ii) The new graph is accepted with an **acceptance probability** $A(G_{new} | G)$, or rejected otherwise.

In the **structure MCMC sampling scheme** a neighbour graph, that is a graph G_{new} that can be reached from G_{old} by one single edge operation, is randomly drawn from a discrete uniform distribution in the proposal move (i).

And in step (ii) the new graph is accepted with probability:

$$A(G_{new} | G_{old}) = \min \left\{ 1, \underbrace{\frac{P(D | G_{new})}{P(D | G_{old})}}_{\text{Likelihood ratio}} \cdot \underbrace{\frac{P(G_{new})}{P(G_{old})}}_{\text{Prior ratio}} \cdot \underbrace{\frac{Q(G_{old} | G_{new})}{Q(G_{new} | G_{old})}}_{\text{Hastings ratio}} \right\}$$

28

Metropolis Hastings sampler

A Metropolis Hastings MCMC sampling scheme consists of two parts.

- (i) Given a graph G_{old} , a new graph is proposed with a **proposal probability** $Q(G_{new}|G_{old})$.
- (ii) The new graph is accepted with an **acceptance probability** $A(G_{new}|G)$, or rejected otherwise.

In the **structure MCMC sampling scheme** a neighbour graph, that is a graph G_{new} that can be reached from G_{old} by one single edge operation, is randomly drawn from a discrete uniform distribution in the proposal move (i).

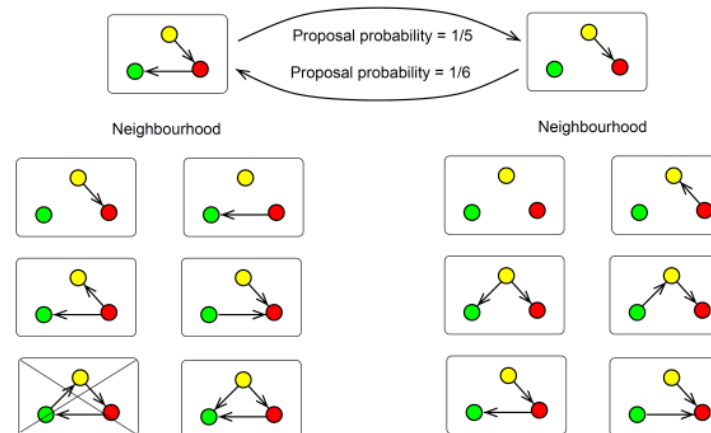
And in step (ii) the new graph is accepted with probability:

$$A(G_{new} | G_{old}) = \min \left\{ 1, \underbrace{\frac{Score_{BGe}(G_{new})}{Score_{BGe}(G_{old})}}_{\text{Ratio of Scores}} \cdot \underbrace{\frac{Q(G_{old} | G_{new})}{Q(G_{new} | G_{old})}}_{\text{Hastings ratio}} \right\}$$

29

Hastings ratio

$Q(G_i|G_{i-1}) \neq Q(G_{i-1}|G_i)$ is possible



30

Metropolis Hastings algorithm structure MCMC for Bayesian networks

Initialisation: Start from an arbitrary initial graph G

(e.g. the empty-seeded graph) and set $G_0=G$.

Iteration: For $i=1, \dots, T$

- Obtain a new graph G_i from the proposal distribution $Q(G_i|G_{i-1})$
- Accept the new graph with probability $A(G_i|G_{i-1})$ where $A(.,.)$ has to be specified as described above; otherwise reject G_{i-1} leave the Markov chain state unchanged; symbolically: $G_i=G_{i-1}$.

END

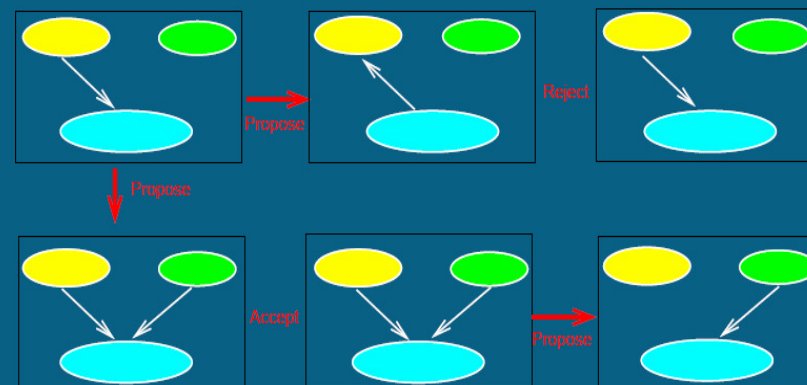
Discard an initial 'burn-in' period to allow the Markov chain to reach stationarity, i.e to converge. For example discard the first $I < T$ MCMC samples.

Output: An MCMC sample from the posterior distribution $P(G|D)$, symbolically:

MCMC sample: G_{I+1}, \dots, G_T

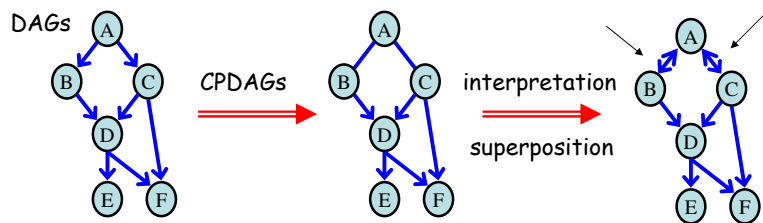
31

Markov chain Monte Carlo (MCMC)



$$\text{Acceptance probability: } \min \left\{ 1, \frac{P(D|M_{new})}{P(D|M_{old})} \times \frac{P(M_{new})}{P(M_{old})} \times \frac{Q(M_{old}|M_{new})}{Q(M_{new}|M_{old})} \right\}$$

Marginal edge posterior probabilities



Use the DAG (CPDAG) sample for estimating the marginal posterior probability of „directed edge relation features“

$$\hat{P}(A \rightarrow B) = \frac{1}{(T-I)} \sum_{i=I+1}^T I(G_i)$$

where $I(G_i)$ is 1 if the CPDAG of G_i contains the directed edge $A \rightarrow B$, and 0 otherwise

33

Convergence of MCMC sampling

The DAG sample $G_1, G_2, G_3, \dots, G_T$ is generated via Markov Chain Monte Carlo (MCMC) simulations so that the Markov Chain $(M_t)_t$ converges to the graph posterior distribution:

$$P(M_t = \text{graph} | \text{data}) \rightarrow P(\text{graph} | \text{data})$$

$$t \rightarrow \infty$$

34

Convergence of MCMC sampling

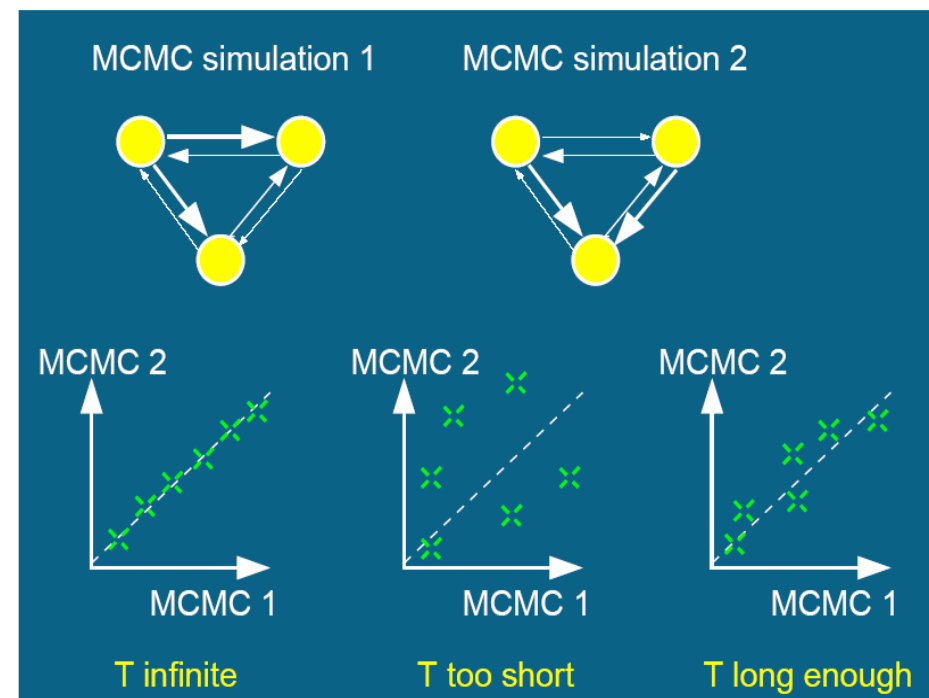
The DAG sample $G_1, G_2, G_3, \dots, G_T$ is generated via Markov Chain Monte Carlo (MCMC) simulations so that the Markov Chain $(M_t)_t$ converges to the graph posterior distribution:

$$P(M_t = \text{graph} | \text{data}) \rightarrow P(\text{graph} | \text{data})$$

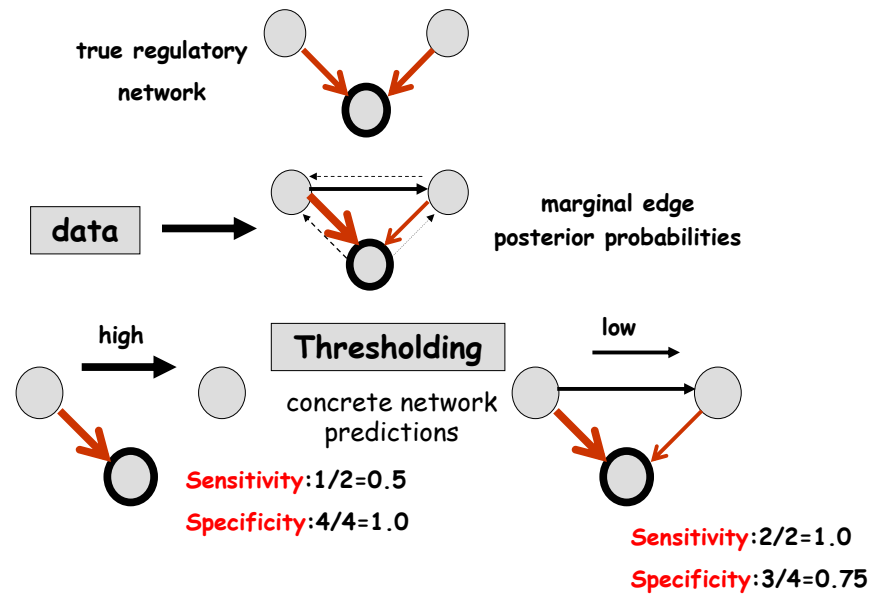
$$t \rightarrow \infty$$

In practice: t is not infinite!!!

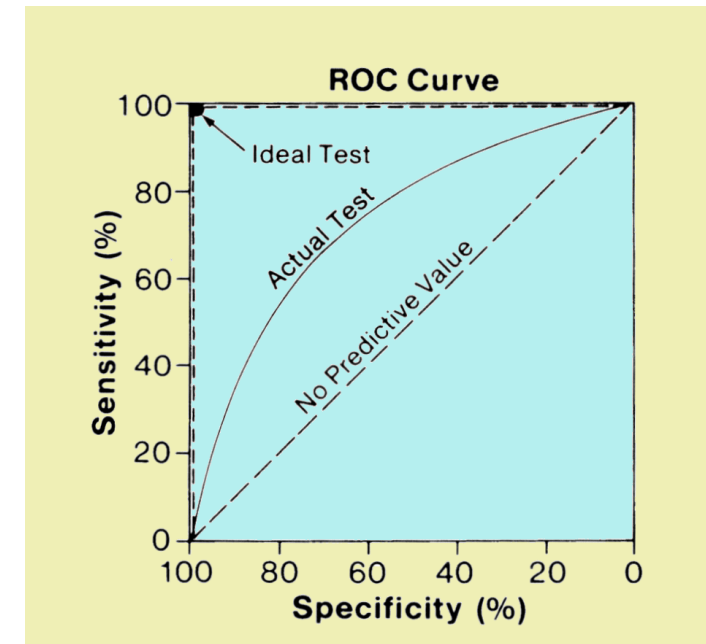
35



Network reconstruction accuracy



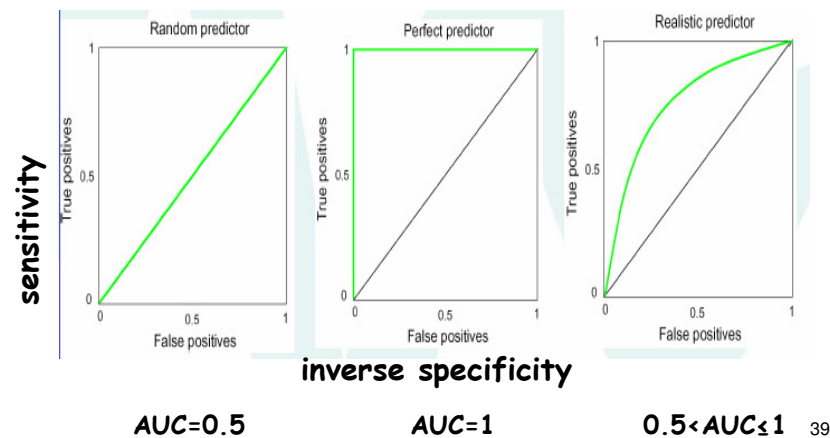
Receiver Operator Characteristic (ROC) curve



38

AUC scores

Area under Receiver Operator Characteristic (ROC) curve

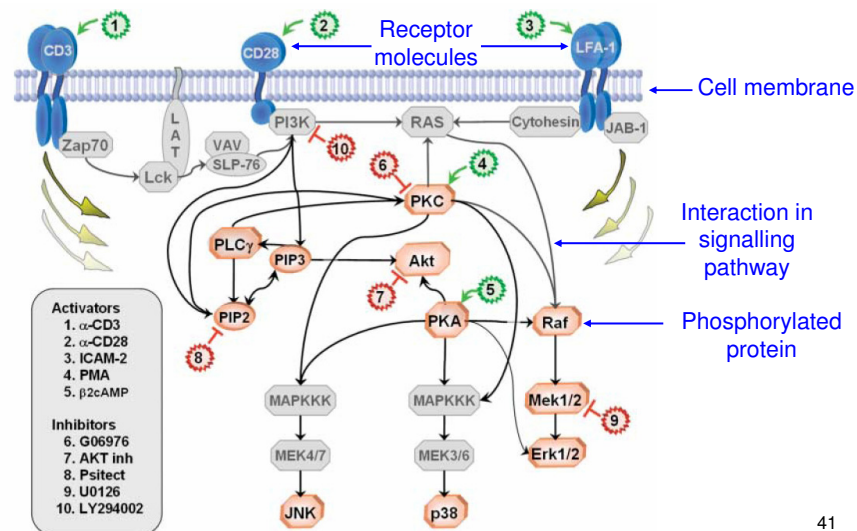


39

Outlook to practical application

40

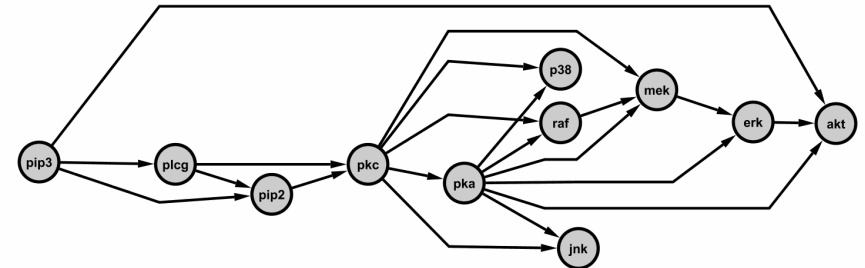
Gold-standard RAF pathway according to Sachs et al. (2004)



41

Outlook

Take the RAF pathway topology

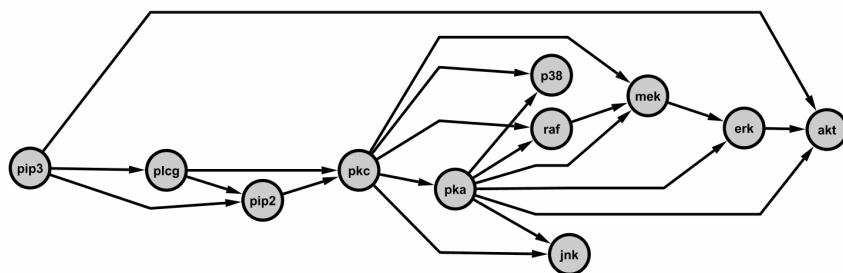


Cellular signalling cascade which consists of 11 phosphorylated proteins and phospholipids in human immune systems cell (true network known from the literature)

42

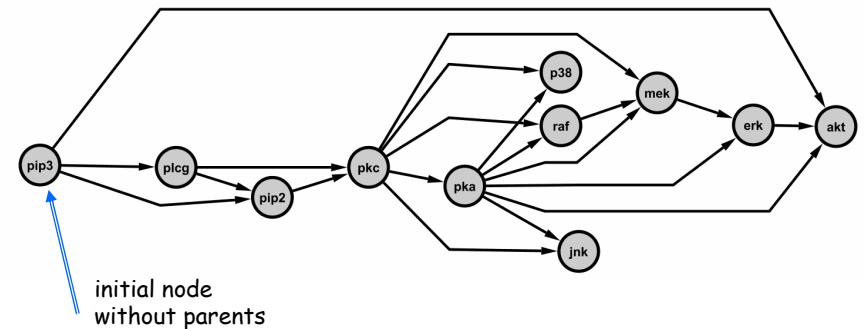
Outlook

Generate synthetic Gaussian network data



43

Generate synthetic Gaussian network data



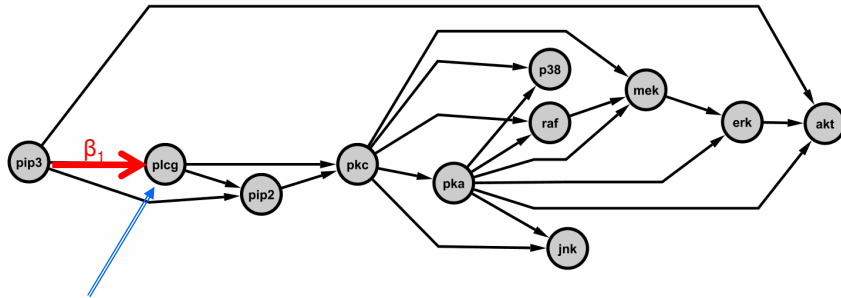
$$pip3 = \varepsilon_{pip3} \quad \text{where } \varepsilon_{pip3} \text{ is a Gaussian with expectation } \mu=0 \text{ and variance } \sigma^2=1$$

We generate m independently and identically distributed (iid) realisations for $pip3$, and we standardise the m observations:

$$pip3 \leftarrow \text{zscore}(pip3) := (pip3 - \text{mean}(pip3)) / \text{std}(pip3)$$

44

Generate synthetic Gaussian network data

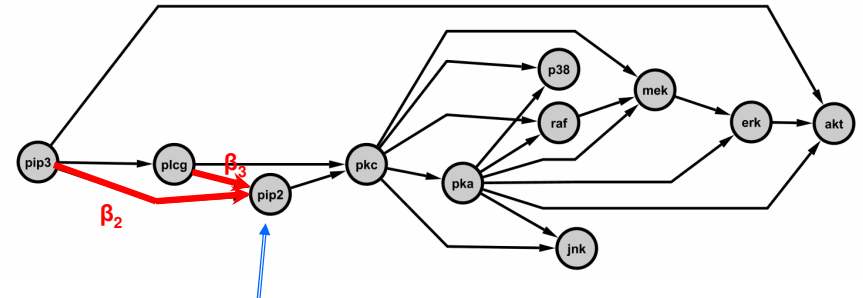


Having sampled m realisations for parent node **pip3**, we sample the regression coefficient β_1 from a uniform distribution on $[0.5, 2]$ with a randomly drawn sign +/-
And we generate m iid realisations for **plcg** as follows :

$$plcg = \beta_1 \cdot pip3 + \epsilon_{plcg} \quad \text{where the noise term } \epsilon_{plcg} \text{ is a Gaussian with expectation } \mu=0 \text{ and variance } \sigma^2$$

Standardise the m values for **plcg** $\leftarrow \text{zscore}(plcg) := (plcg - \text{mean}(plcg)) / \text{std}(plcg)$

Generate synthetic Gaussian network data

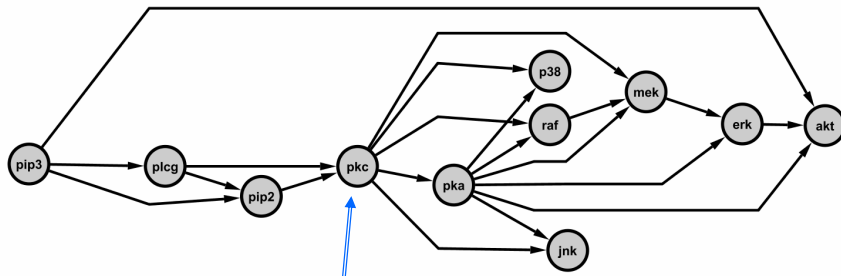


Having sampled m realisations for **pip3** and **plcg**, we sample both regression coefficients β_2 and β_3 from a uniform distribution on $[0.5, 2]$ with randomly drawn signs +/-
And we generate m iid realisations for **pip2** as follows :

$$pip2 = \beta_2 \cdot pip3 + \beta_3 \cdot plcg + \epsilon_{pip2} \quad \text{where the noise term } \epsilon_{pip2} \text{ is a Gaussian with expectation } \mu=0 \text{ and variance } \sigma^2$$

Standardise the m values for **pip2** $\leftarrow \text{zscore}(pip2) := (pip2 - \text{mean}(pip2)) / \text{std}(pip2)$

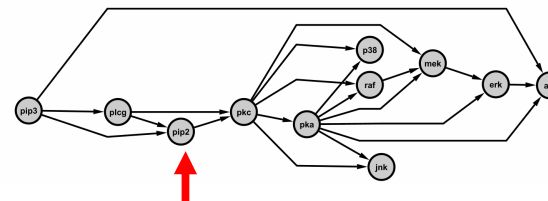
Generate synthetic Gaussian network data



We go to the next node, etc.

Each node is described as a linear combination of its parent nodes. The regression coefficients are randomly sampled, and the noise terms are Gaussian distributed. We standardise the data to avoid that the signals become stronger and stronger. The parameter σ^2 can be used to vary the signal-to-noise (SNR) ratio:

Generate synthetic Gaussian network data

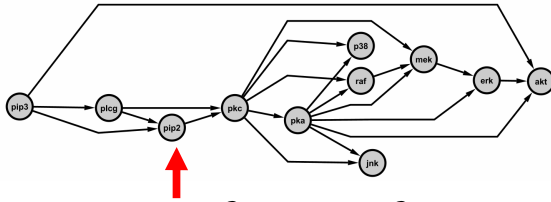


$$\text{E.g.: } pip2 = \beta_2 \cdot pip3 + \beta_3 \cdot plcg + \epsilon_{pip2}$$

signal
from the parents

$$\text{std}(\text{signal}) = \text{std}(\underbrace{\beta_2 \cdot pip3}_{N(0,1)} + \underbrace{\beta_3 \cdot plcg}_{N(0,1)})$$

Generate synthetic Gaussian network data

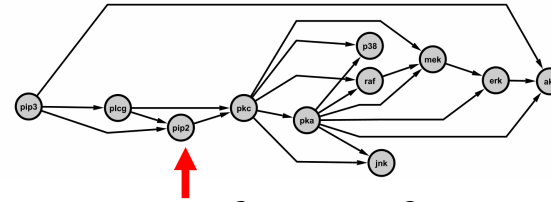


E.g.: $pip2 = \beta_2 \cdot pip3 + \beta_3 \cdot plc\gamma + \underbrace{\epsilon_{pip2}}_{\text{noise}}$

$$std(noise) = std(\epsilon_{pip2}) = \sigma$$

49

Generate synthetic Gaussian network data



E.g.: $pip2 = \underbrace{\beta_2 \cdot pip3 + \beta_3 \cdot plc\gamma}_{\text{signal from the parents}} + \underbrace{\epsilon_{pip2}}_{\text{noise}}$

$$SNR = \frac{std(signal)}{std(noise)} = \frac{std(\beta_2 \cdot pip3 + \beta_3 \cdot plc\gamma)}{\sigma}$$

50

Task: We will try to infer the Raf-pathway graph topology from a synthetically generated data set

51