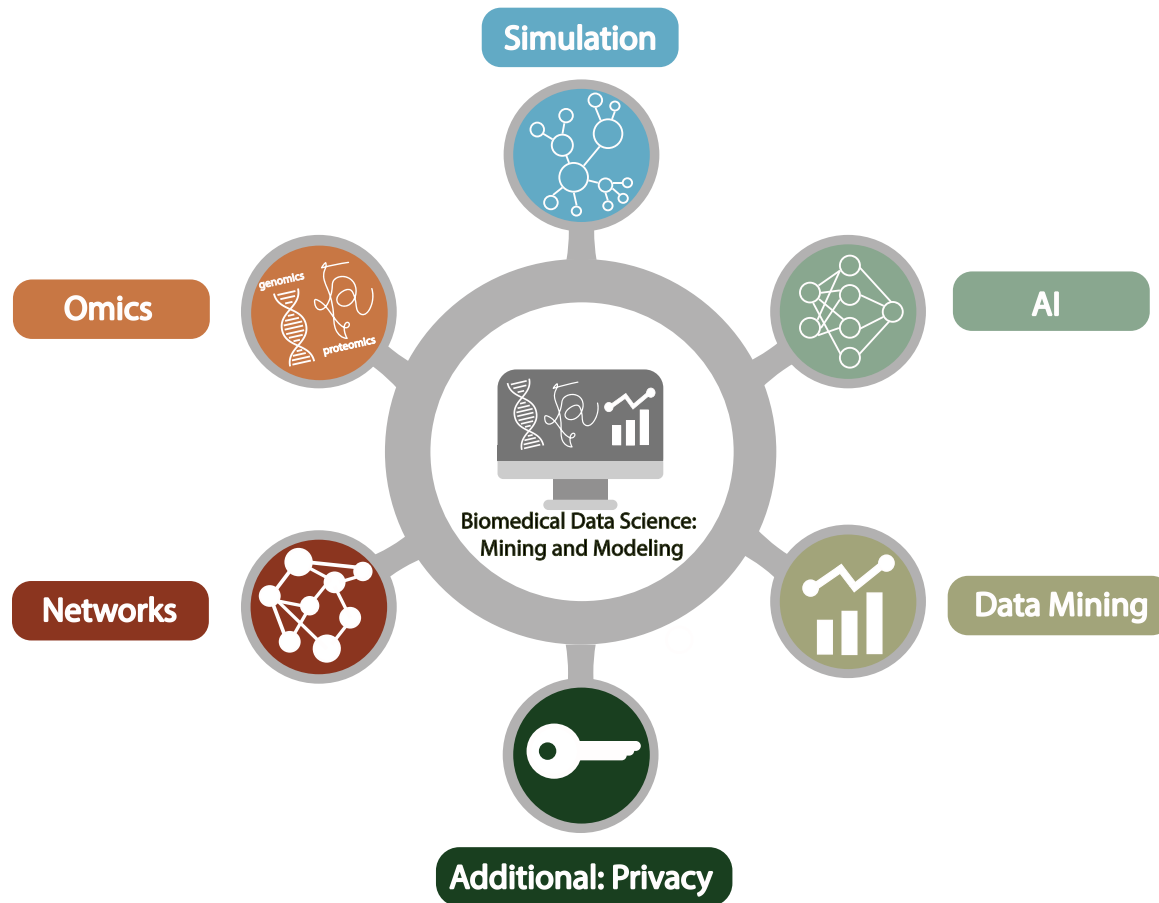


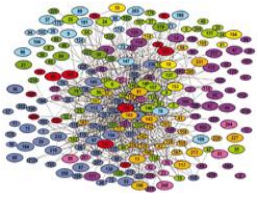
Biomedical Data Science (GersteinLab.org/courses/452)

Network Prediction (25m10e)



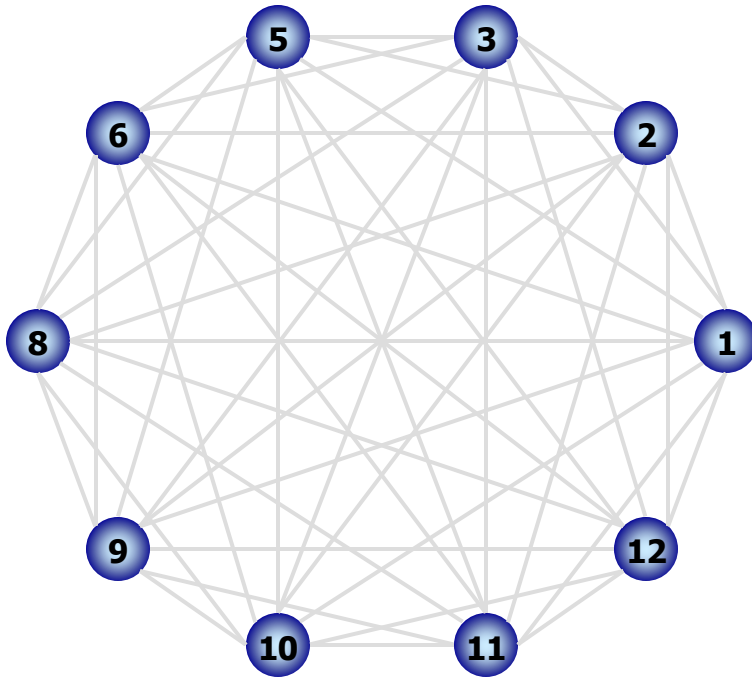
Predicting Networks
via Bayesian Integration

Problem Motivation



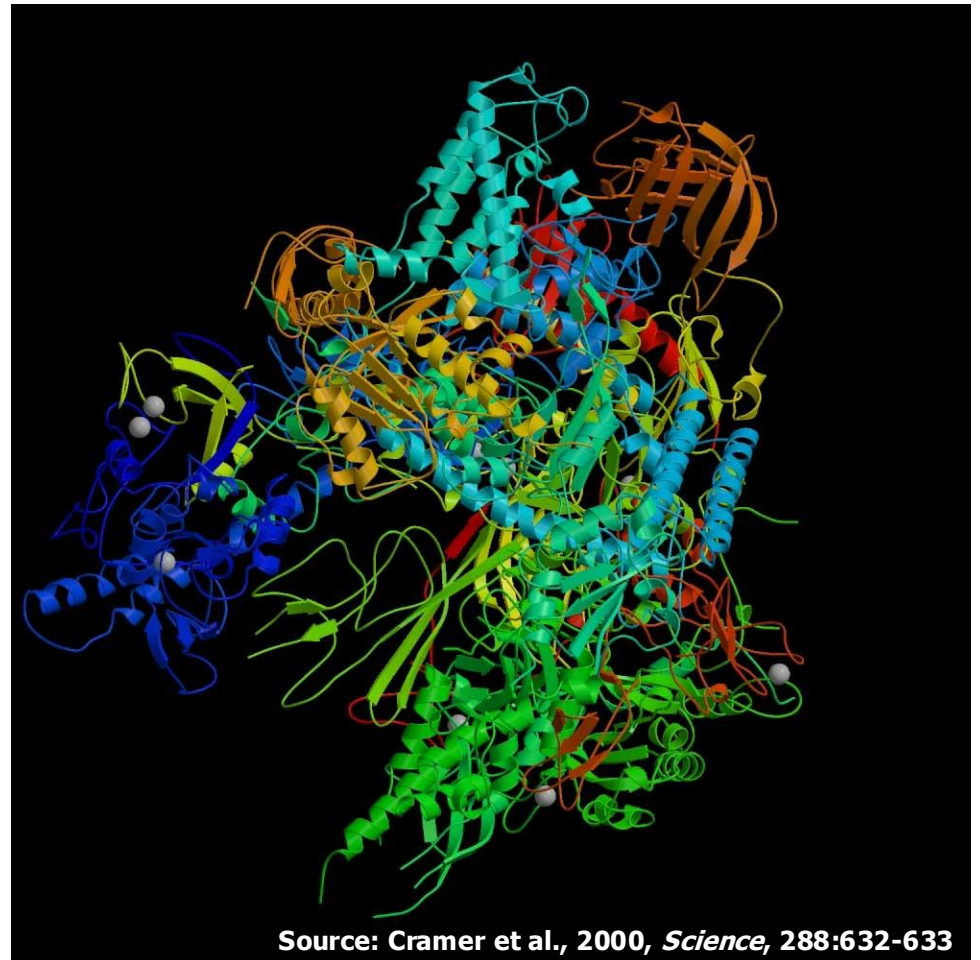
RNA polymerase II: Structure

Which subunits interact?
Based on Binding
experiments

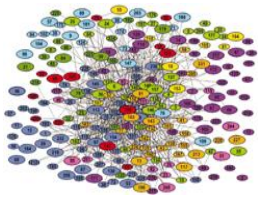


Source: Edwards et al., 2002, *Trends in Genetics*

Compare with Gold Std. Structure



Source: Cramer et al., 2000, *Science*, 288:632-633



Binding Experiments on Subunit Pairs

Subunits
Subunits

1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3 5 5 5 5 5 5 6 6 6 6 6 8 8 8 8 9 9 9 10 10 12
2 3 5 6 8 9 10 11 12 3 5 6 8 9 10 11 12 5 6 8 9 10 11 12 6 8 9 10 11 12 8 9 10 11 12 9 10 11 12 10 11 12 11 11 12

Pull-down 1

1 1 0 1 0 1 0 1 1 0 1 0 1 0 1 1 1 0 1 1 1 1 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0

Pull-down 2

1 1 1 1 0 1 0 1 1 0 1 0 1 0 1 1 1 0 1 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0

Pull-down 3

1 1 0 1 0 0 1 0

Cross-linking

1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 0 1

Far Western 1

1 1 1 0 0 0 0 0 0 1 0 0 0

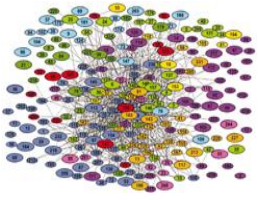
Far Western 2

1 1 1 1 1 1 1 1 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

Far Western 3

1 0 0 0 1 0

Interaction experiments
before structure was known

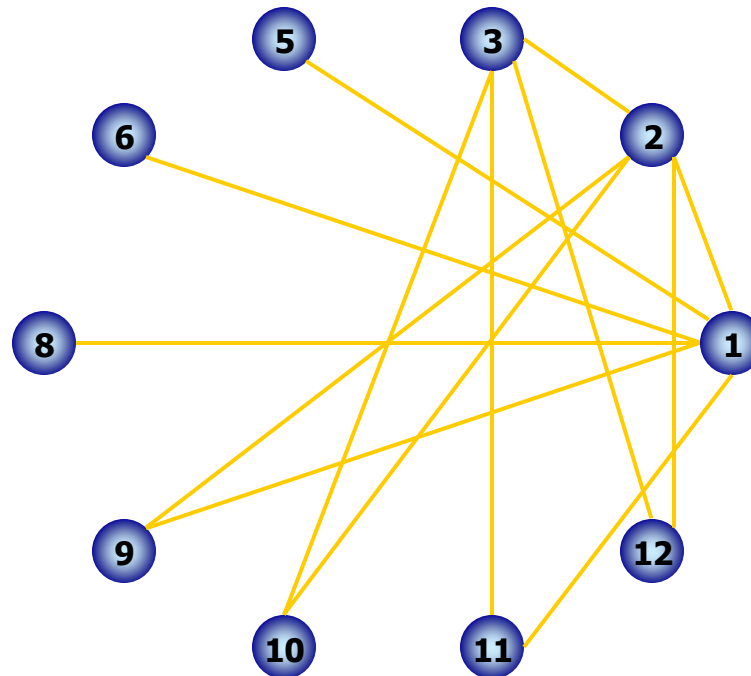


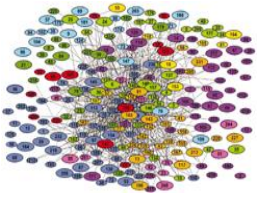
Gold-Standard Positives

Subunits
Subunits

1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	3	3	3	3	3	3	3	5	5	5	5	5	5	6	6	6	6	6	8	8	8	8	9	9	9	10	10	12	
2	3	5	6	8	9	10	11	12	3	5	6	8	9	10	11	12	5	6	8	9	10	11	12	6	8	9	10	11	12	8	9	10	11	12	9	10	11	12	10	11	12	11	11	12

Gold-Standard Positive (GSTD+): 13



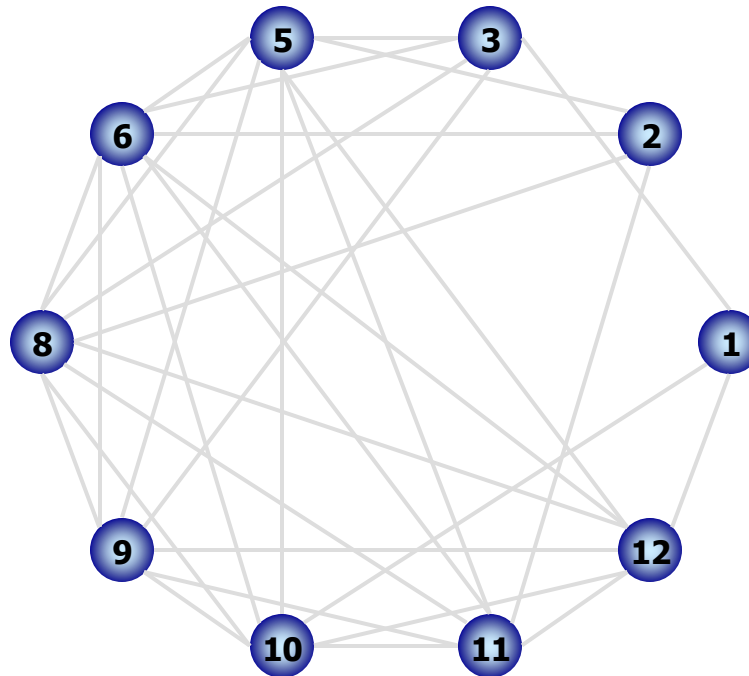


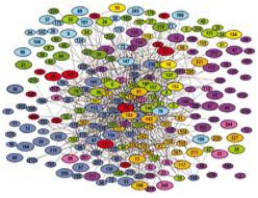
Gold-Standard Negatives

Subunits
Subunits

1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	5	5	5	5	5	5	6	6	6	6	6	8	8	8	8	9	9	9	10	10	12
2	3	5	6	8	9	10	11	12	3	5	6	8	9	10	11	12	5	6	8	9	10	11	12	6	8	9	10	11	12	8	9	10	11	12	9	10	11	12	10	11	12	11	11	12	

Gold-Standard Negative (GSTD-): 32





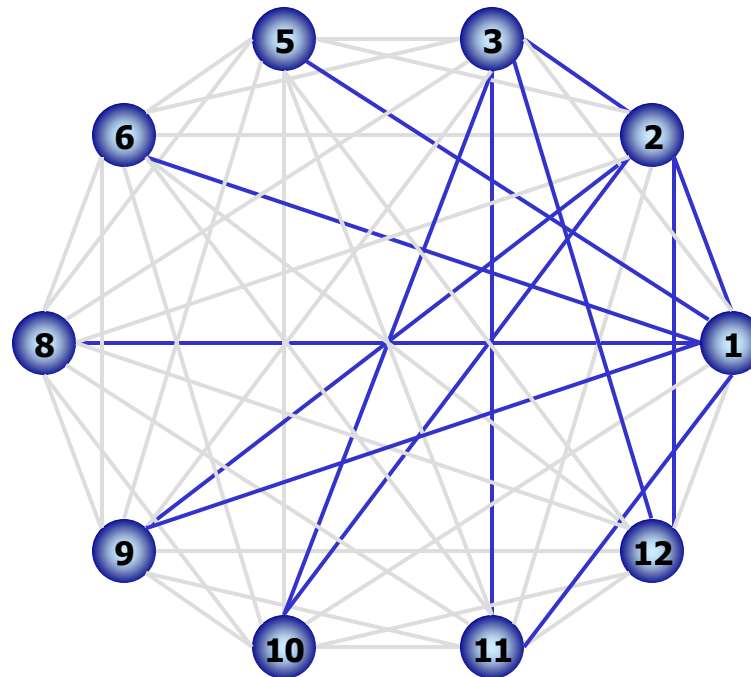
RNA Polymerase II: Gold-Standards

Subunits
Subunits

1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	5	5	5	5	5	5	6	6	6	6	6	8	8	8	8	9	9	9	10	10	12
2	3	5	6	8	9	10	11	12	3	5	6	8	9	10	11	12	5	6	8	9	10	11	12	6	8	9	10	11	12	8	9	10	11	12	9	10	11	12	10	11	12	11	11	12

Gold-Standard Positive (GSTD+): 13

Gold-Standard Negative (GSTD-): 32





1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	5	5	5	5	5	5	6	6	6	6	6	8	8	8	8	9	9	9	10	10	12
2	3	5	6	8	9	10	11	12	3	5	6	8	9	10	11	12	5	6	8	9	10	11	12	6	8	9	10	11	12	8	9	10	11	12	9	10	11	12	10	11	12	11	11	12

1 1 0 1 0 1 0 1 1 0 1 0 1 0 1 1 1 0 1 1 1 1 0 1 0 0 0 0 0 0 1 0 0 0 0

1 1 1 1 0 1 0 1 1 0 1 0 1 0 1 1 1 0 1 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0

[illegible]

1	1	1	1	1	0	1	1	1	1	1	0	1	1	1					1	1		1	0						1
----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	--	--	--	--	----------	----------	--	----------	----------	--	--	--	--	--	----------

1 **1** **1** **1** **1** **0** **0** **0** **0** **0** **0** **1** **0** **0** **0**

1	1	1	1	1	1	1	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------	----------

1 0 0 0 1 0

Lectures.gersteinlab.org

Re-drawn in a different color scheme

Subunit A

Subunit B

structural contact

Far western

Cross-linking

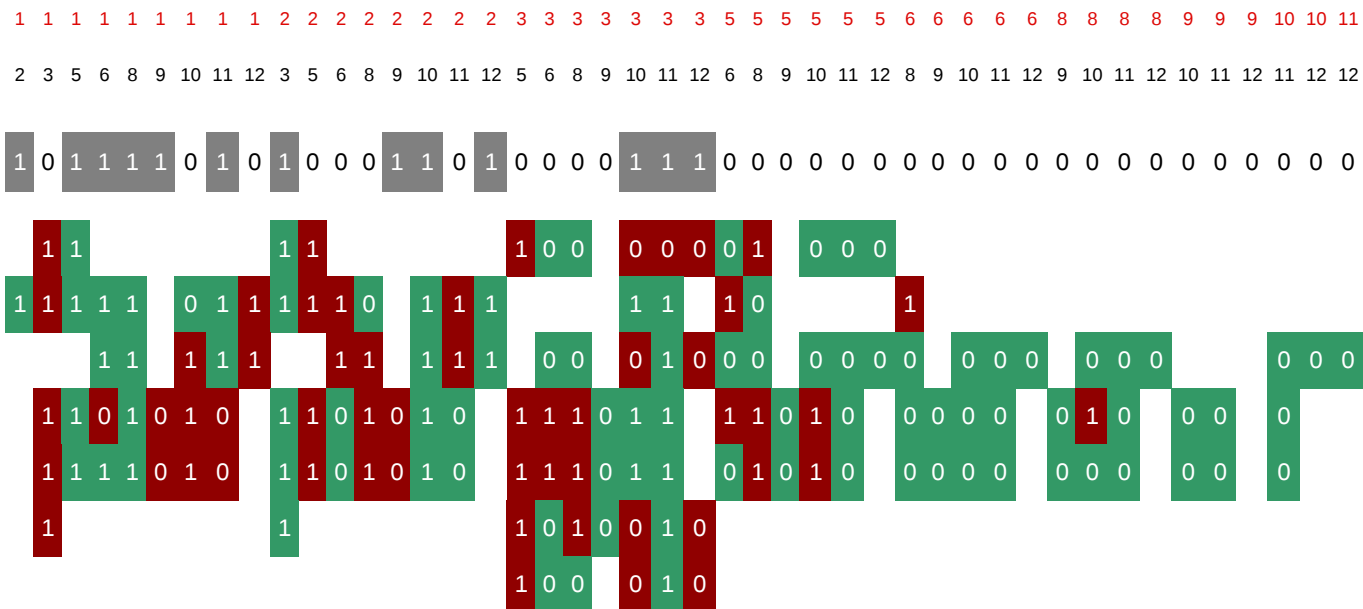
Far western

Pull-down

Pull-down

Pull-down

Far western



■ = false

☒ = true

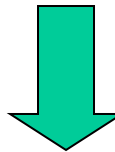
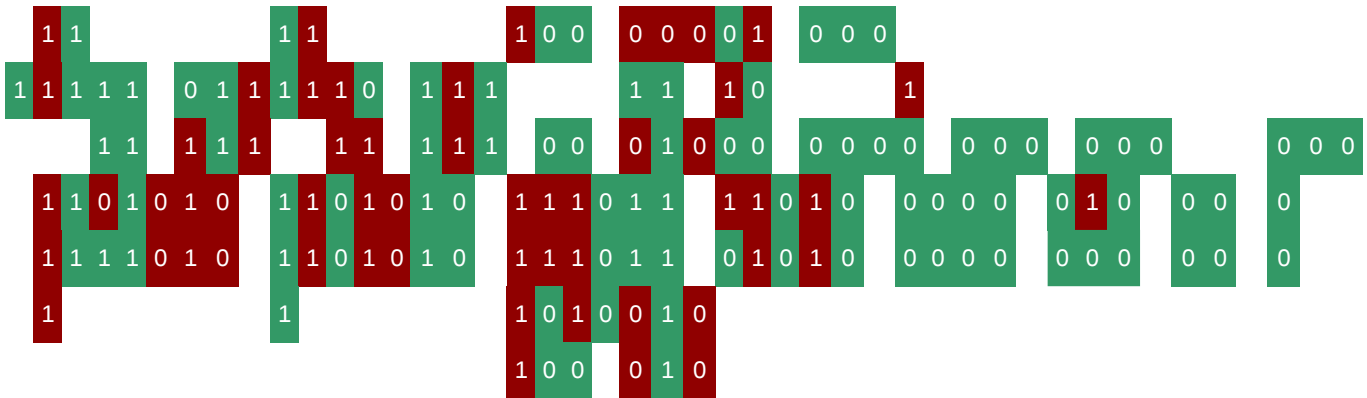
Subunit A
Subunit B

2 3 5 6 8 9 10 11 12 3 5 6 8 9 10 11 12 5 6 8 9 10 11 12 6 8 9 10 11 12 8 9 10 11 12 9 10 11 12 10 11 12 11 12 12

structural contact

1 0 1 1 1 1 0 1 0 1 0 0 0 1 1 0 1 0 0 0 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

Far western
Cross-linking
Far western
Pull-down
Pull-down
Pull-down
Far western



■ = false

☒ = true

Union

1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

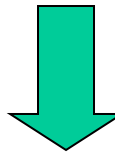
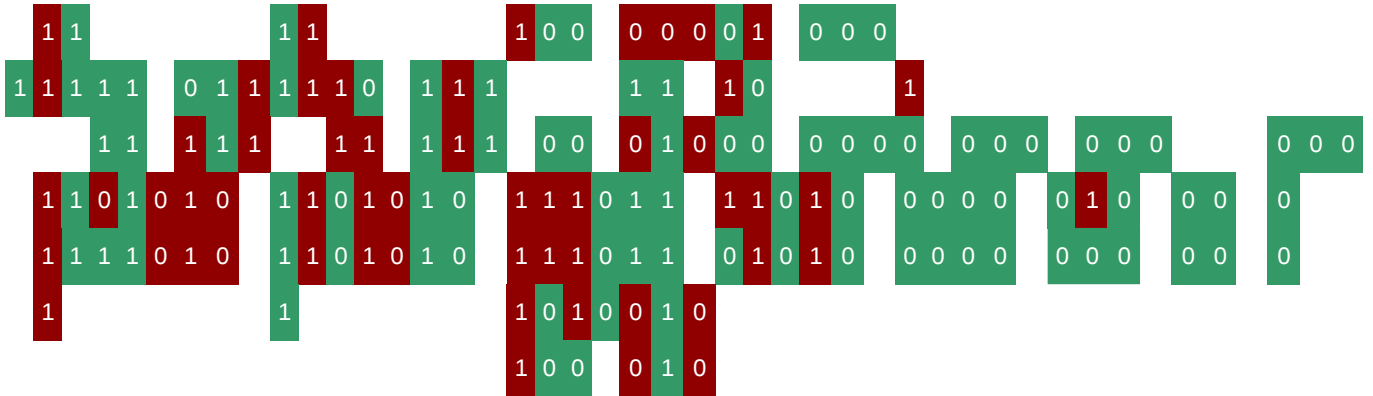
Subunit A
Subunit B

2 3 5 6 8 9 10 11 12 3 5 6 8 9 10 11 12 5 6 8 9 10 11 12 6 8 9 10 11 12 8 9 10 11 12 9 10 11 12 10 11 12 11 12 12

structural contact

10**1**1**1**1**0**1**0**1**0**00**1**1**0**1**0**000**1**1**1**000000000000000000000000000000

Far western
Cross-linking
Far western
Pull-down
Pull-down
Pull-down
Far western

[illegible]

Subunit A
Subunit B

structural contact

Far western
Cross-linking
Far western
Pull-down
Pull-down
Pull-down
Far western

(Cross validate)

Integrate using naive Bayes classifier

[illegible]

Weighted Voting: the Likelihood Ratio

structural contact

1 0 1 1 1 1 0 1 0 1 0 0 0 1 1 0 1 0 0 0 0 1 1 1 0 0 0 0

Far western

Far western (dup)

Cross-linking

Far western

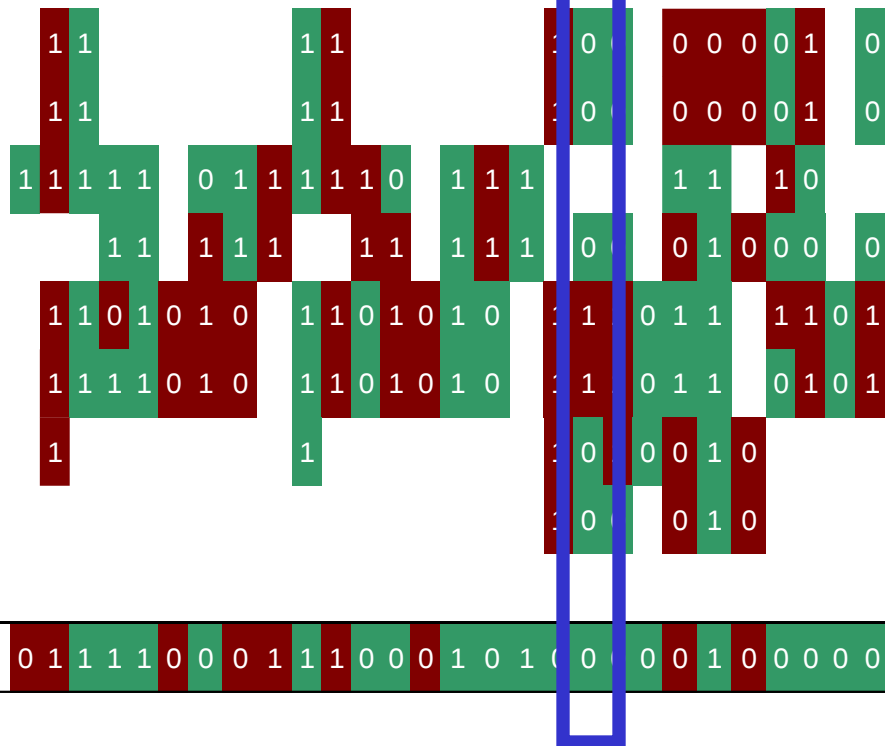
Pull-down

Pull-down

Pull-down

Far western

Combined



Maj. Vote: 0 = $\text{round}(\text{avg}(0 + 0 + 0 + 1 + 1 + 0 + 0))$

With weights: likelihood ratio $L = L_1 + L_2 + L_3 \dots$

Predicting Networks
via Bayesian Integration

Formalism

Supervised Classification by Weighted Voting

Similar form to many
other classifiers – e.g.
SVC, LDA, logistic
(see ISLR for
comparison)

Simple Vote: $R = f_1 + f_2 + f_3 + \dots + f_n$ With $f = 1$ or -1

If $\begin{cases} R > 0; & I \text{ Interact} \\ R < 0; & \sim I \text{ No interaction} \end{cases}$

Modify with feature weight:

$$R = w_1 f_1 + w_2 f_2 + w_3 f_3 + \dots + w_n f_n = \vec{w} \cdot \vec{f}$$

If has prior knowledge w_0

$$R = \vec{w} \cdot \vec{f} + w_0$$

Bayes Rule

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)}$$

Which is shorthand for:

$$P(Y = y_i|X = x_j) = \frac{P(X = x_j|Y = y_i)P(Y = y_i)}{P(X = x_j)}$$

More Bayes Rule

$$P(I \mid f_1, f_2, f_3, \dots) = \frac{P(f_1, f_2, f_3, \dots \mid I)P(I)}{P(f_1, f_2, f_3, \dots)}$$

Assume
independent
(Naïve Bayes)

$$= \frac{P(f_1 \mid I)P(f_2 \mid I)P(f_3 \mid I) \dots P(I)}{P(f_1, f_2, f_3, \dots)}$$

$$P(\sim I \mid f_1, f_2, f_3, \dots) = \frac{P(f_1, f_2, f_3, \dots \mid \sim I)P(\sim I)}{P(f_1, f_2, f_3, \dots)}$$

$$= \frac{P(f_1 \mid \sim I)P(f_2 \mid \sim I)P(f_3 \mid \sim I) \dots P(\sim I)}{P(f_1, f_2, f_3, \dots)}$$

$$\log\left(\frac{P(I \mid f_1, f_2, f_3, \dots)}{P(\sim I \mid f_1, f_2, f_3, \dots)}\right) = \log\left(\frac{P(f_1 \mid I)}{P(f_1 \mid \sim I)} \frac{P(f_2 \mid I)}{P(f_2 \mid \sim I)} \frac{P(f_3 \mid I)}{P(f_3 \mid \sim I)} \dots \frac{P(I)}{P(\sim I)}\right)$$

$$= \log \frac{TPR_1}{FPR_1} + \log \frac{TPR_2}{FPR_2} + \log \frac{TPR_3}{FPR_3} + \dots + \log \frac{P}{N}$$

$$w_1 = \log \frac{P(f_1 = 1 \mid I)}{P(f_1 = 1 \mid \sim I)}$$

$$= \log \frac{TP / P}{FP / N}$$

$$w_0 = \log \frac{P}{N}$$

Update form of Bayes Rule

Updating our **prior odds** (w_0) by successively adding **likelihood ratio terms** (w_1, w_2, w_3) for each feature to get a final **posterior odds**

$$\log\left(\frac{P(I \mid f_1, f_2, f_3, \dots)}{P(\sim I \mid f_1, f_2, f_3, \dots)}\right) = \log \frac{TPR_1}{FPR_1} + \log \frac{TPR_2}{FPR_2} + \log \frac{TPR_3}{FPR_3} + \dots + \log \frac{P}{N}$$

$\uparrow$
 w_1

$\uparrow$
 w_2

$\uparrow$
 w_3

$\uparrow$
 w_0

This simple additive update form supposedly,
secretly invented by A Turing during WWII
[Spiegelhalter & Brooks, The Art of Uncertainty ('25)]

- We have so far estimated $P(X=x | Y=y)$ by the fraction $n_{x|y}/n_y$,

where n_y is the number of instances for which $Y=y$ and $n_{x|y}$ is the number of these for which $X=x$

- This is a problem when n_x is small
 - ◇ E.g., assume $P(X=x | Y=y)=0.05$ and the training set is s.t. that $n_y=5$. Then it is highly probable that $n_{x|y}=0$
 - ◇ The fraction is thus an underestimate of the actual probability
 - ◇ It will dominate the Bayes classifier for all new queries with $X=x$

$$\frac{\text{\# count with feature } i \text{ in GS+}}{\text{\# count with feature } i \text{ in GS-}} = \frac{TPR_i}{FPR_i}$$

- Replace $n_{x|y}/n_y$ by:

$$\frac{n_{x|y} + mp}{n_y + m}$$

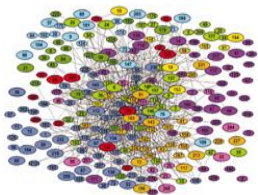
Dummy
Counts

- Where p is our prior estimate of the probability we wish to determine and m is a constant
 - ◇ Typically, $p = 1/k$ (where k is the number of possible values of X)
 - ◇ m acts as a weight (similar to adding m virtual instances distributed according to p)

Estimating Probabilities & Dummy Counts

Predicting Networks
via Bayesian Integration

**Worked Example
(for reference)**



Likelihood Ratios

Subunits
Subunits

1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	5	5	5	5	5	5	6	6	6	6	6	8	8	8	8	9	9	9	10	10	12
2	3	5	6	8	9	10	11	12	3	5	6	8	9	10	11	12	5	6	8	9	10	11	12	6	8	9	10	11	12	8	9	10	11	12	9	10	11	12	10	11	12	11	11	12

Pull-down 1

1	1	0	1	0	1	0	1	1	0	1	0	1	0	1	1	1	1	0	1	1	1	0	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

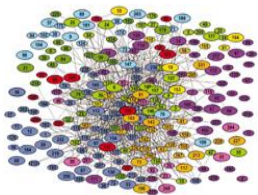
$$L_1 = \frac{p(x_1 | GSTD+)}{p(x_1 | GSTD-)}$$

$$L_0 = \frac{p(x_0 | GSTD+)}{p(x_0 | GSTD-)}$$

Likelihood Ratio
for Feature f :

$$L_f \equiv \frac{p(x_f | GSTD+)}{p(x_f | GSTD-)}$$

■ GSTD+
■ GSTD-
■ True
■ False



Calculating Likelihood Ratios

Subunits
Subunits

1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	3	3	3	3	3	3	3	5	5	5	5	5	5	6	6	6	6	6	8	8	8	8	9	9	9	10	10	12	
2	3	5	6	8	9	10	11	12	3	5	6	8	9	10	11	12	5	6	8	9	10	11	12	6	8	9	10	11	12	8	9	10	11	12	9	10	11	12	10	11	12	11	11	12

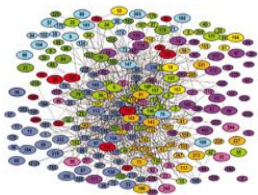
Pull-down 1

1	0	1	0	0	1	0	1	1	1
---	---	---	---	---	---	---	---	---	---

$$L_1 = \frac{p(x_1 | GSTD+)}{p(x_1 | GSTD-)} = \frac{6/13}{1/13} = 6$$

$$L_0 = \frac{p(x_0 | GSTD+)}{p(x_0 | GSTD-)} = \frac{4/13}{1/13} = 4$$

Blue	GSTD+
Grey	GSTD-
Green	True
Red	False



Calculating Likelihood Ratios

Subunits
Subunits

1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	5	5	5	5	5	5	6	6	6	6	6	8	8	8	8	9	9	9	10	10	12
2	3	5	6	8	9	10	11	12	3	5	6	8	9	10	11	12	5	6	8	9	10	11	12	6	8	9	10	11	12	8	9	10	11	12	9	10	11	12	10	11	12	11	11	12

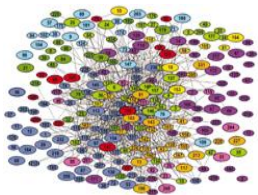
Pull-down 1

1	1	0	1	0	1	0	1	1	0	1	0	1	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

$$L_1 = \frac{p(x_1 | GSTD+)}{p(x_1 | GSTD-)} = \frac{6/13}{11/32} = 1.34$$

$$L_0 = \frac{p(x_0 | GSTD+)}{p(x_0 | GSTD-)} = \frac{4/13}{14/32} = 0.70$$

Blue	GSTD+
Grey	GSTD-
Green	True
Red	False



Calculating Likelihood Ratios

Subunits
Subunits

1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	5	5	5	5	5	5	6	6	6	6	6	8	8	8	8	9	9	9	10	10	12
2	3	5	6	8	9	10	11	12	3	5	6	8	9	10	11	12	5	6	8	9	10	11	12	6	8	9	10	11	12	8	9	10	11	12	9	10	11	12	10	11	12	11	11	12

Pull-down 1

Pull-down 2

Pull-down 3

Cross-linking

Far Western 1

Far Western 2

Far Western 3

1	1	0	1	0	1	0	1	1	1	0	1	0	1	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	
1	1	1	1	0	1	0	1	0	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
1																																							
1	1	1	1	1	0	1	1	1	1	0	1	1	1	0	1	1	1	1	0	1	1	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	
1	1																																						
		1	1		1	1	1		1	1		1	1	1		0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
																1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
																1	0	0	0	1	0																		
																1	0	0	0	0	1	0																	

Pull-down 1

Pull-down 2

Pull-down 3

Cross-linking

Far Western 1

Far Western 2

Far Western 3

$L1 = (6/13) / (11/32) = 1.34$	$L0 = (4/13) / (14/32) = 0.70$
$L1 = (7/13) / (9/32) = 1.91$	$L0 = (2/13) / (16/32) = 0.31$
$L1 = (2/13) / (3/32) = 1.64$	$L0 = (2/13) / (2/32) = 2.46$
$L1 = (10/13) / (7/32) = 3.52$	$L0 = (0/13) / (3/32) = 0$
$L1 = (2/13) / (4/32) = 1.23$	$L0 = (3/13) / (6/32) = 1.23$
$L1 = (6/13) / (5/32) = 2.95$	$L0 = (2/13) / (17/32) = 0.29$
$L1 = (1/13) / (1/32) = 2.46$	$L0 = (2/13) / (2/32) = 2.46$

Blue	GSTD+
Grey	GSTD-
Green	True
Red	False



1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	5	5	5	5	5	5	6	6	6	6	6	8	8	8	8	9	9	9	10	10	12
2	3	5	6	8	9	10	11	12	3	5	6	8	9	10	11	12	5	6	8	9	10	11	12	6	8	9	10	11	12	8	9	10	11	12	9	10	11	12	10	11	12	11	11	12

1 1 0 1 0 1 0 1 1 0 1 0 1 0 1 1 1 0 1 1 1 1 0 1 0 0 0 0 0 0 1 0 0 0 0

1	1	1	1	0	1	0	1	1	0	1	0	1	0	1	1	1	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

1 1 1 0 1 0 0 1 0

1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	0	1
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

1 1 1 1 1 0 0 0 0 0 0 1 0 0 0

1	1	1	1	1		1	1	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
---	---	---	---	---	--	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

1 0 0 0 1 0

[illegible]

$$\uparrow$$

$$L(f_1, \dots, f_n) = L(f_1) \dots L(f_n)$$

“Weighted Voting”



1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	3	3	3	3	3	3	3	5	5	5	5	5	5	6	6	6	6	6	8	8	8	8	9	9	9	10	10	12	
2	3	5	6	8	9	10	11	12	3	5	6	8	9	10	11	12	5	6	8	9	10	11	12	6	8	9	10	11	12	8	9	10	11	12	9	10	11	12	10	11	12	11	11	12

[illegible][illegible]

Predicting Networks
via Bayesian Integration

Feature Correlation

Correlations between similar features

structural contact

1 0 1 1 1 1 0 1 0 1 0 0 0 1 1 0 1 0 0 0 0 1 1 1 0 0 0 0

Far western

1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 1 0

Far western (dup)

1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 1 0

Cross-linking

1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1 0

Far western

1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0

Pull-down

1 1 0 1 0 1 0 1 1 0 1 0 1 0 1 1 1 1

Pull-down

1 1 1 1 0 1 0 1 1 0 1 0 1 0 1 1 0 1

Pull-down

1 1 1 1 0 1 0 1 1 0 1 0 1 0 1 1 0 1

Far western

1 1 1 1 0 1 0 1 1 0 1 0 1 0 1 1 0 1

Combined

0 1 1 1 1 0 0 0 1 1 1 0 0 0 1 0 1 0 0 0 0 0

GS	1	0	0	1	1	1	...
F1	1	0	0	1	0	0	...
F2	1	0	0	1	0	0	...
F3	0	0	1	0	1	0	...
F4	0	1	0	0	1	0	...
F5	0	1	0	0	1	0	...
F6	1	0	1	1	0	0	...

Feature Correlation and Fully Connected Bayes

$$w_{4,5} = \log \frac{P(f_4 = 1, f_5 = 1 | I)}{P(f_4 = 1, f_5 = 1 | \sim I)}$$

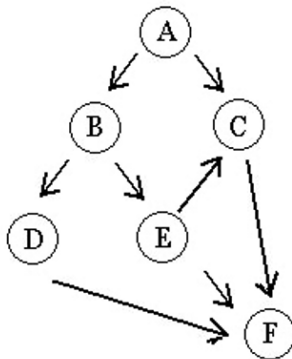
Predicting Networks
via Bayesian Integration

Bayesian Networks

Bayesian network is a model that represent the relationship between variables

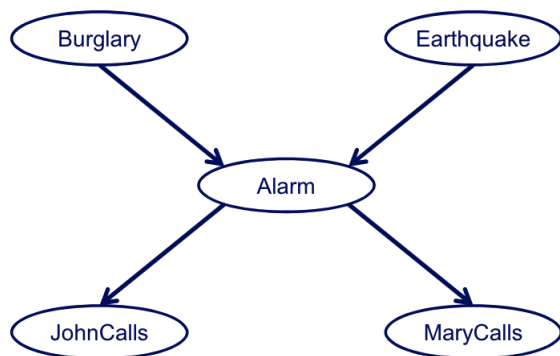
A **Bayesian network** is a directed acyclic graph (DAG) that specifies a **joint distribution** over X as a product of **local conditional distributions**, one for each node:

$$\mathbb{P}(X_1 = x_1, \dots, X_n = x_n) \stackrel{\text{def}}{=} \prod_{i=1}^n p(x_i \mid x_{\text{Parents}(i)})$$



$$\begin{aligned} P(A,B,C,D,E,F) &= P(F|C,D,E)P(A,B,C,D,E) \\ &= P(F|C,D,E)P(C|A,E)P(D|B)P(E|B)P(B,A) \\ &= P(F|C,D,E)P(C|A,E)P(D|B)P(E|B)P(B|A)P(A) \end{aligned}$$

With the network structure (local conditional probabilities), the model describes the joint probability in a more compact manner



Number of parameters (assuming all variables are binary):

Chain rule:

$$P(B, E, A, J, M) = P(B)P(E|B)P(A|B, E)P(J|B, E, A)P(M|B, E, A, J)$$

1 2 4 8 16

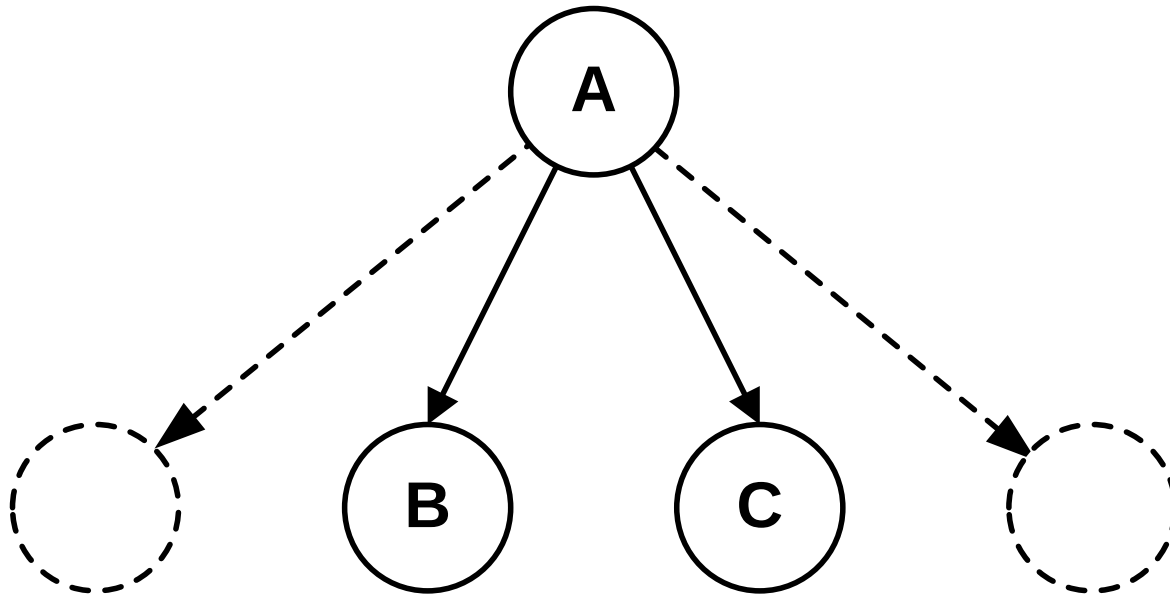
BN:

$$P(B, E, A, J, M) = P(B)P(E)P(A|B, E)P(J|A)P(M|A)$$

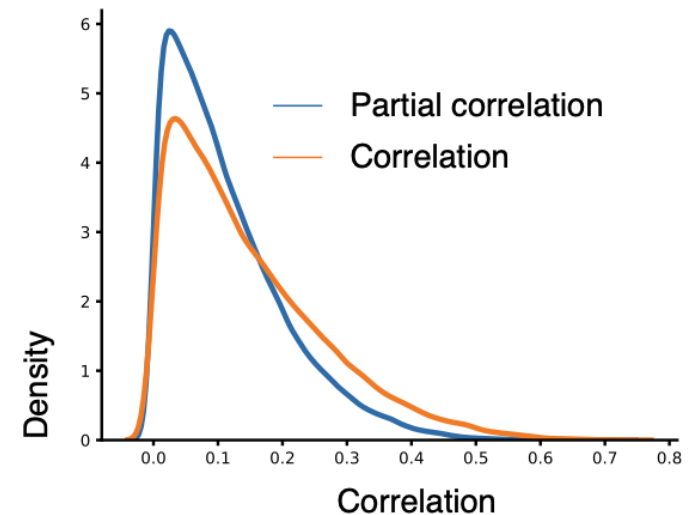
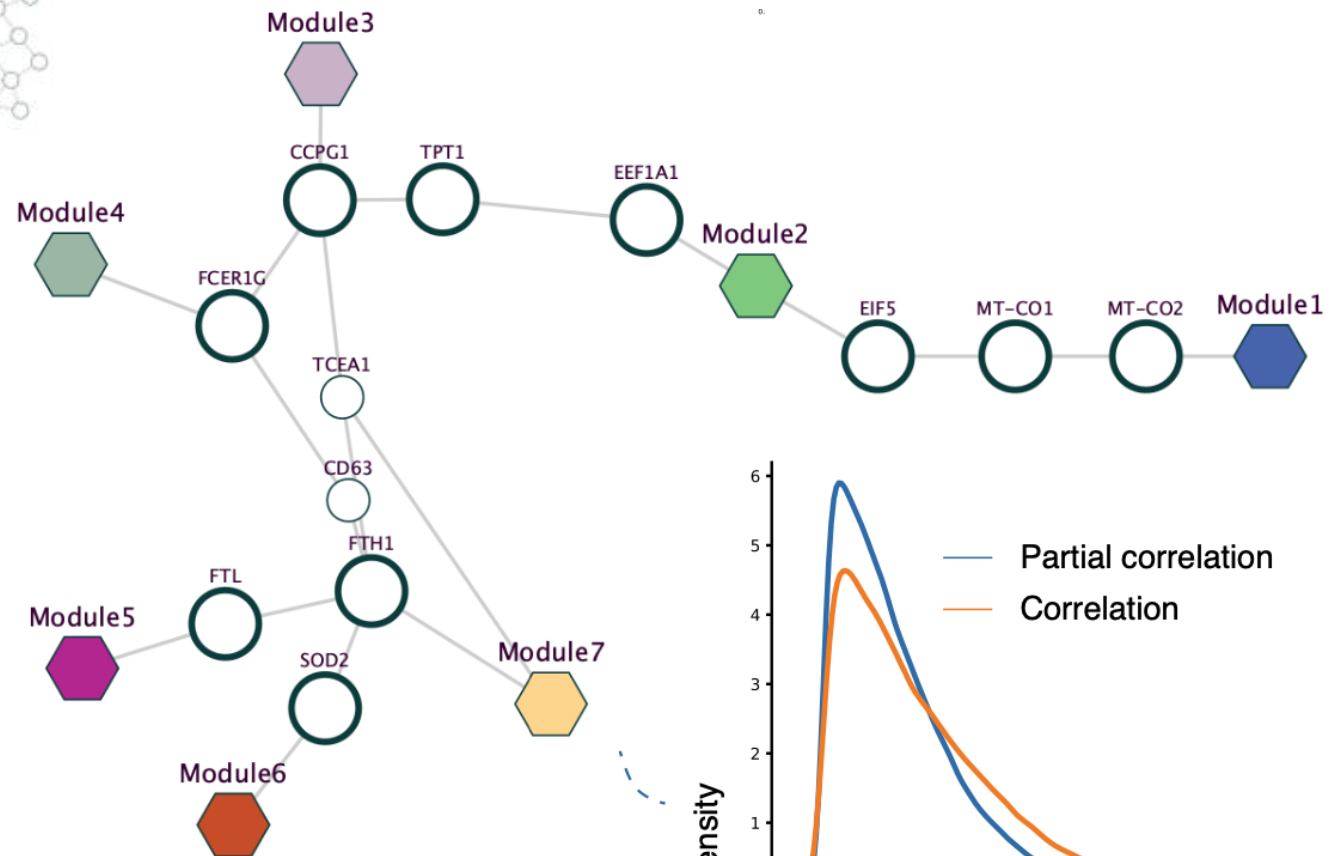
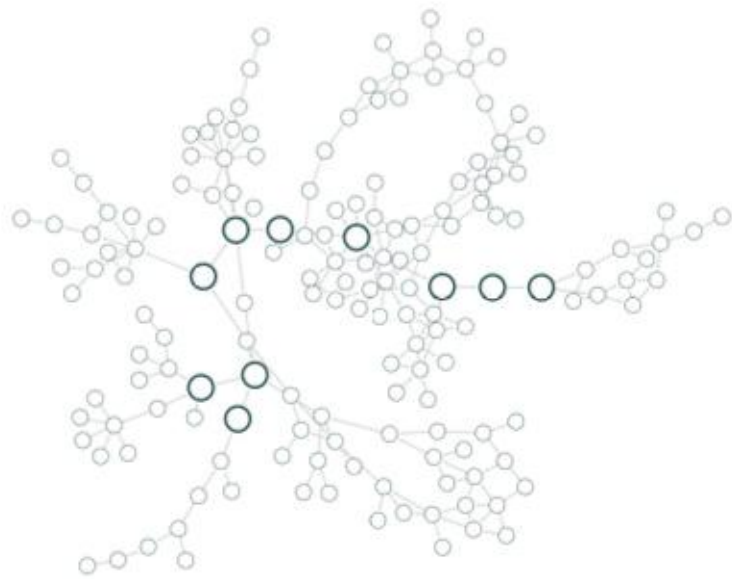
1 1 4 2 2

Naive Bayes

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



Relatively independent gene modules, after fixing the “connector” genes (“Markov Blanket”)



References

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(Relates to the worked example.)