

Bayesian Graphical Modeling

Theory

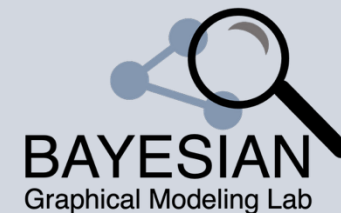
Summer School on Network Psychometrics
August 2025

m.marsman@uva.nl

bayesiangraphicalmodeling.com



UvA



Psych  Systems

Session setup



Part I: Theory



Part II: Tutorial



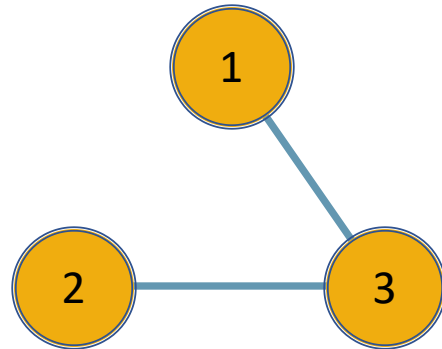
Part III: Practical

Session setup



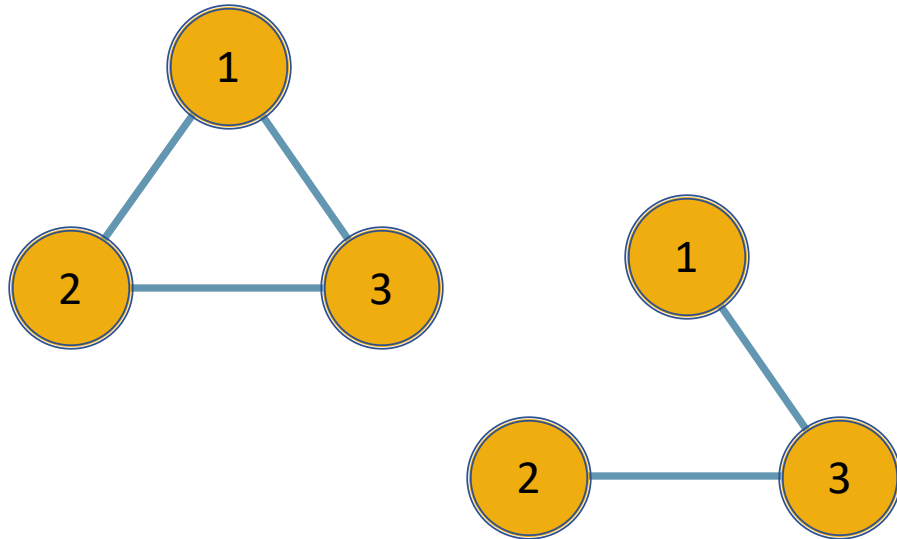
Part I: Theory

Two fundamental questions in network analysis



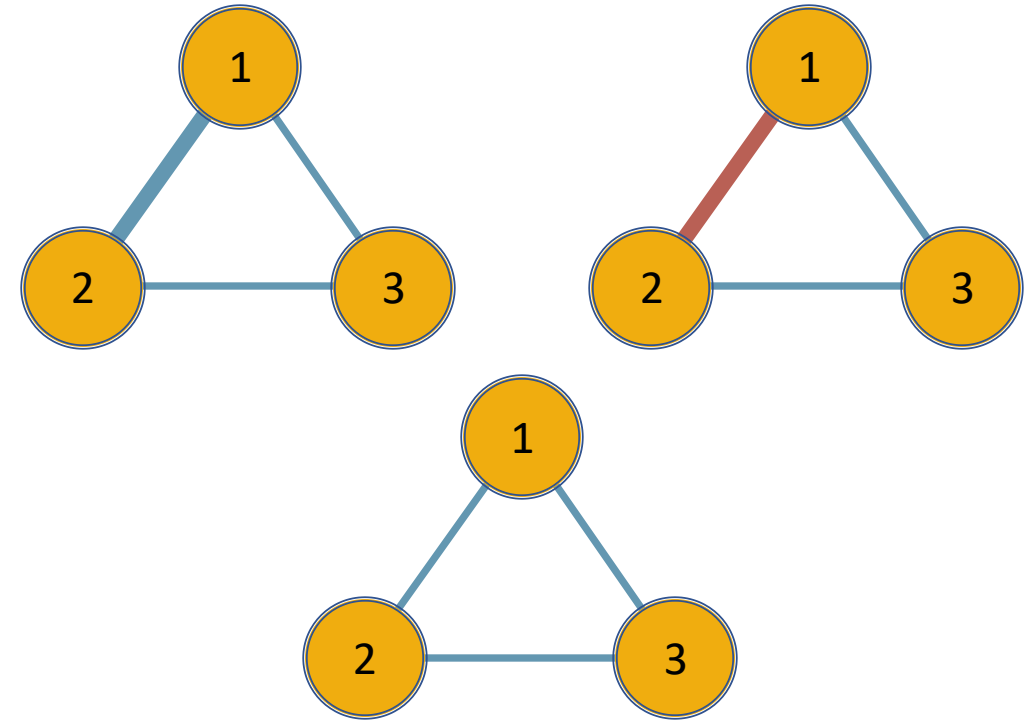
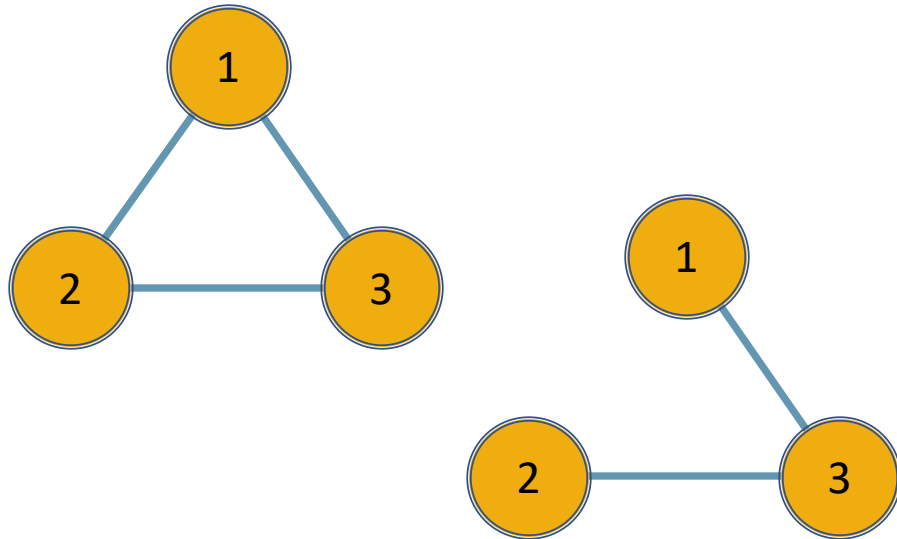
Two fundamental questions in network analysis

Is there an effect?



Two fundamental questions in network analysis

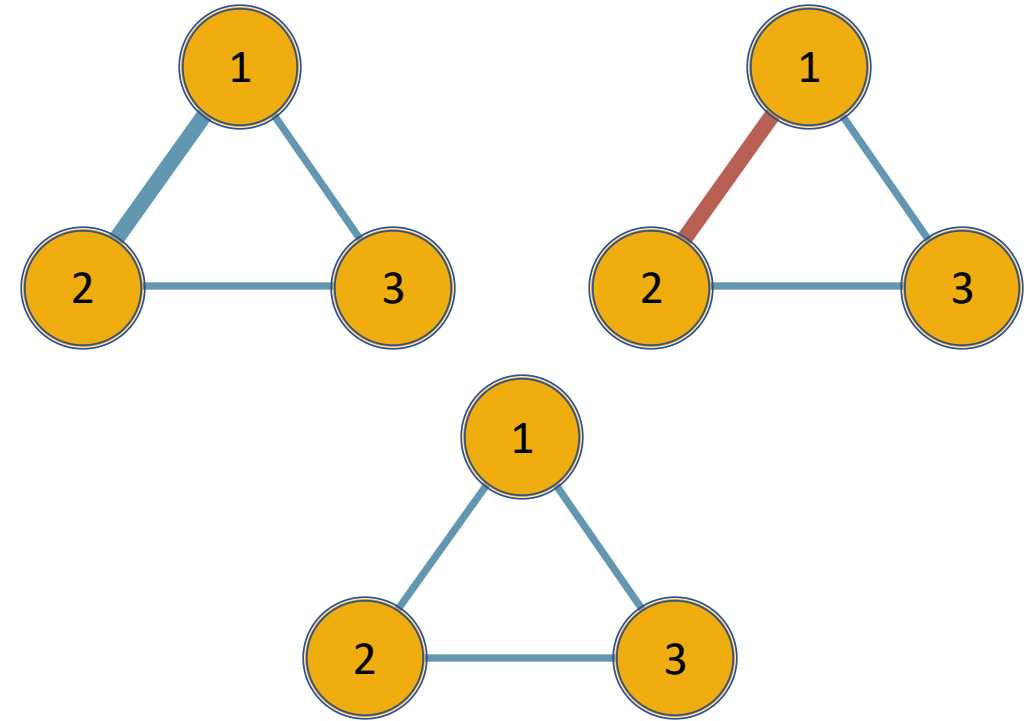
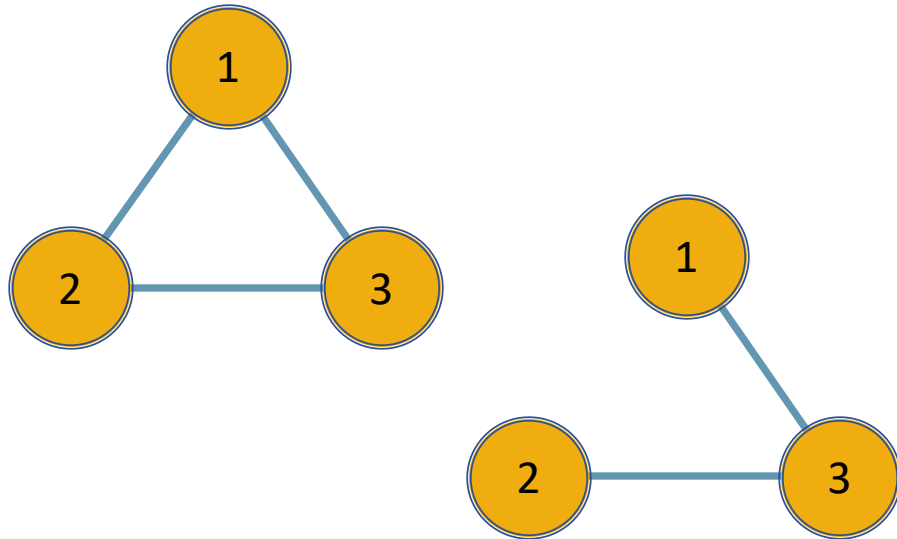
Is there an effect?



What is the effect?

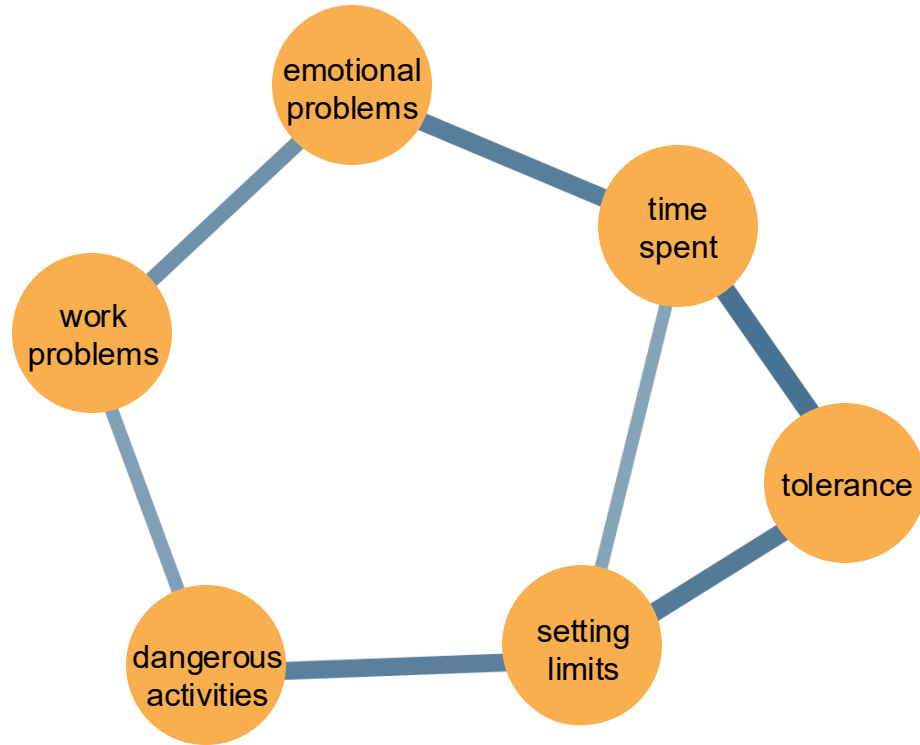
Two fundamental questions in network analysis

Is there an effect?

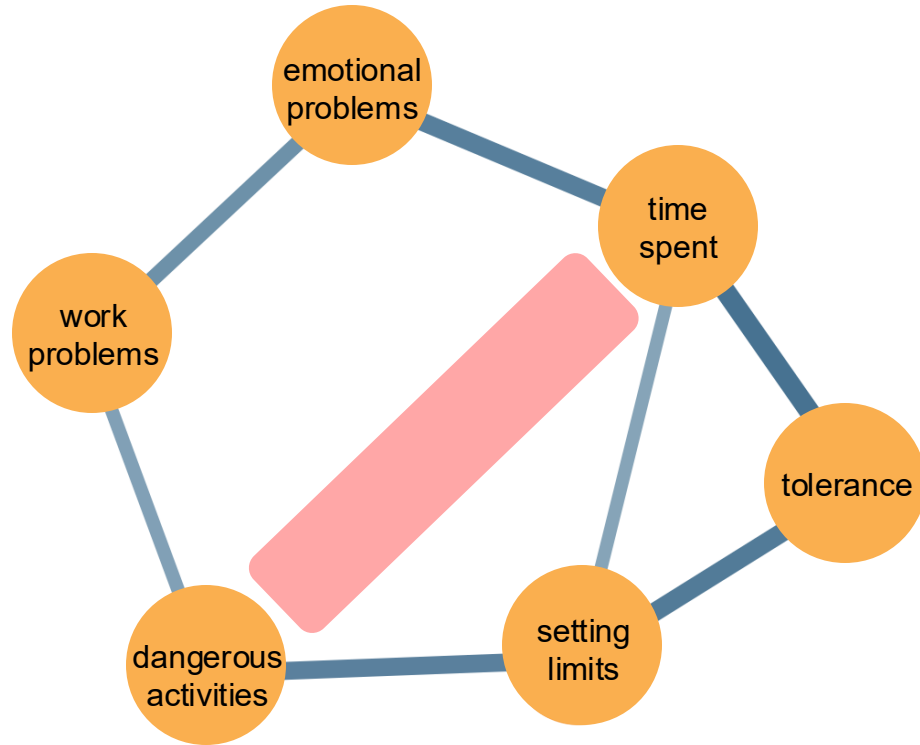


What is the effect?

A network of alcohol disorder symptoms

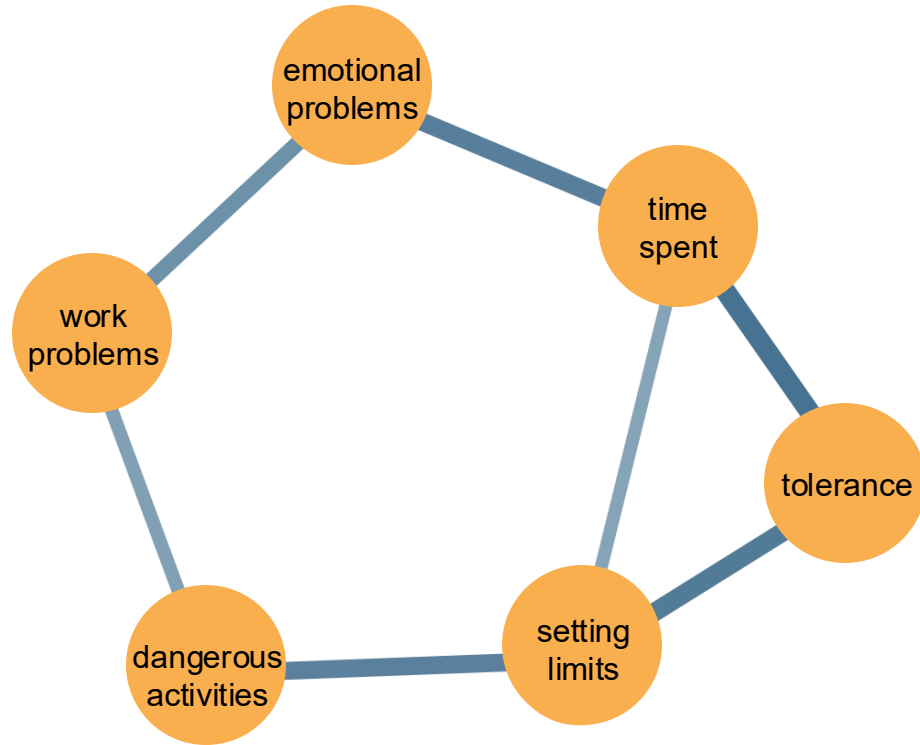


A network of alcohol disorder symptoms



Why is the edge missing?

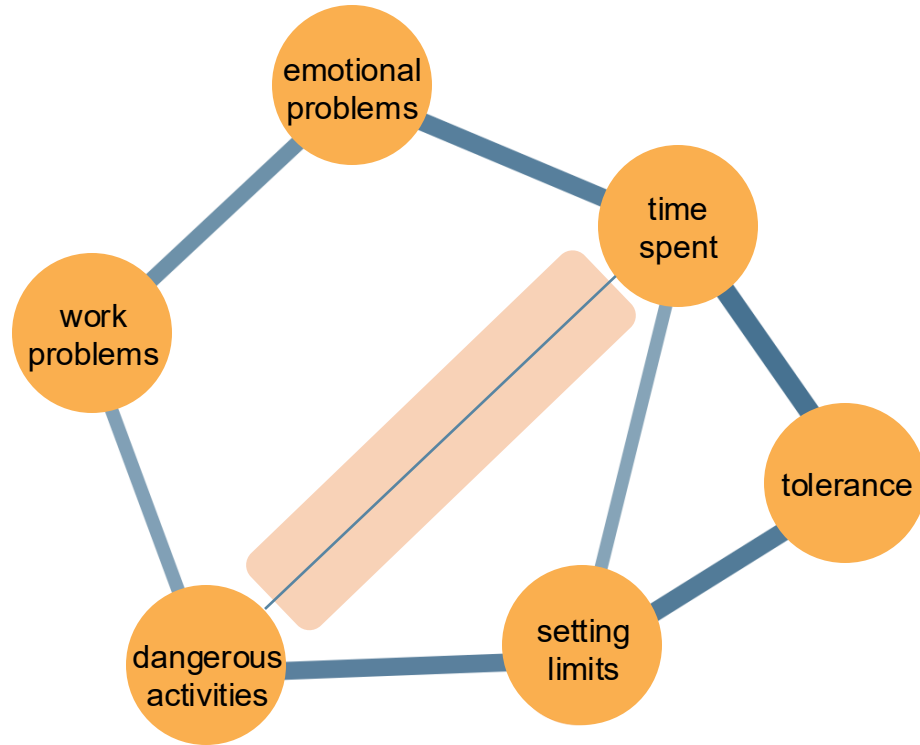
A network of alcohol disorder symptoms



Why is the edge missing?

Two possible explanations:

A network of alcohol disorder symptoms

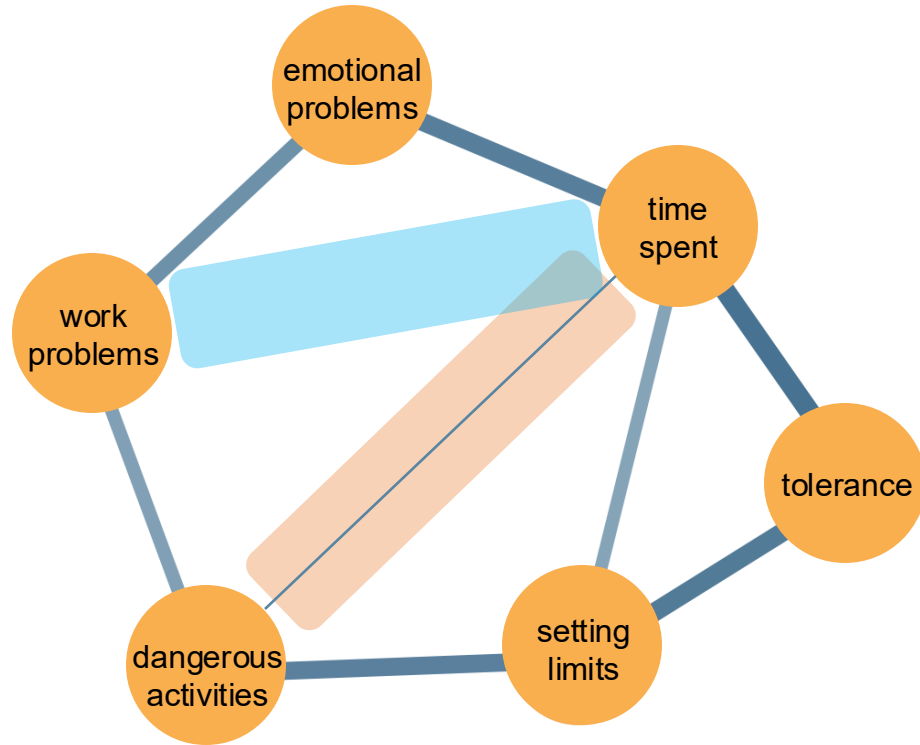


Why is the edge missing?

Two possible explanations:

1. Too little information.

A network of alcohol disorder symptoms

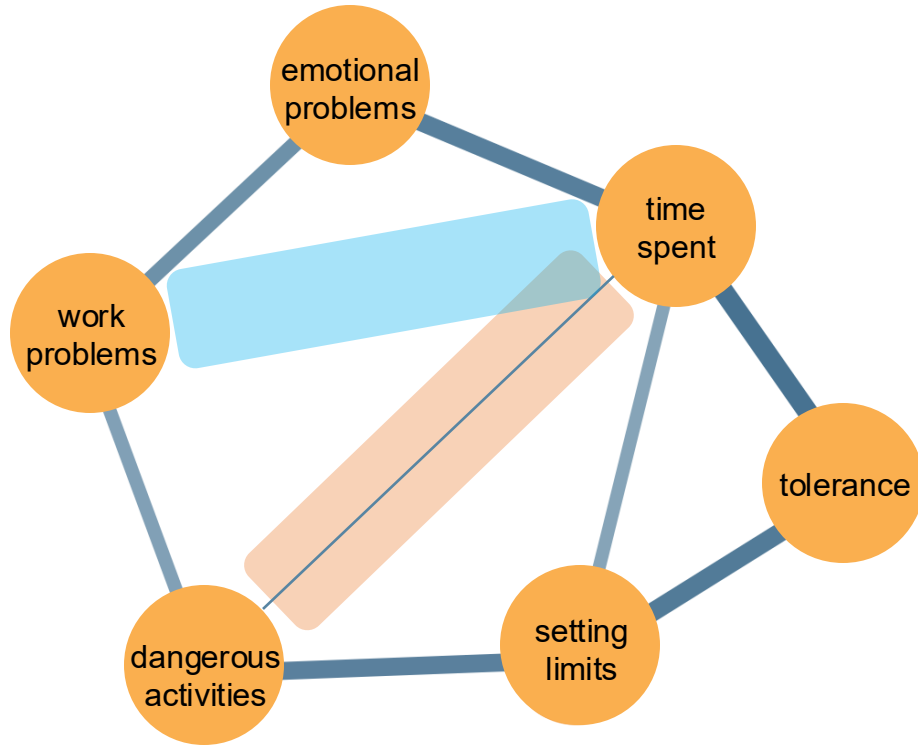


Why is the edge missing?

Two possible explanations:

1. Too little information.
2. True absence.

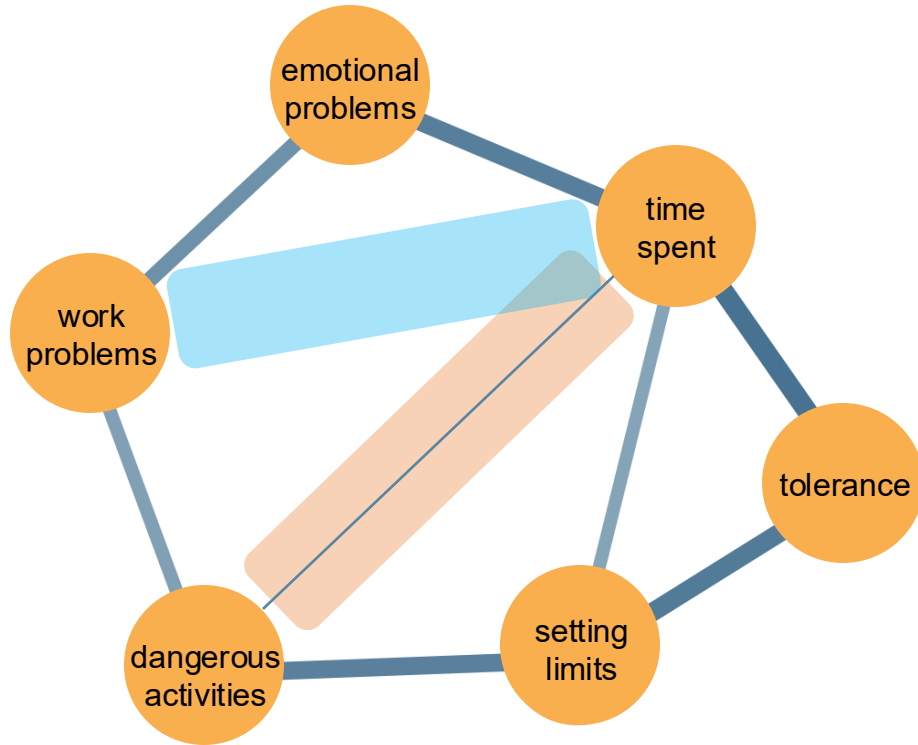
Two take-home messages



Network estimation is insufficient to determine whether an edge should be included or excluded.

Inclusion tests need to distinguish between **evidence of absence** and **absence of evidence**.

Two take-home messages



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Inclusion tests need to distinguish between **evidence of absence** and **absence of evidence**.

The Bayesian analysis of network structures

Evaluate the predictive success of the network structure.

$$P(\text{data} \mid \text{structure})$$

The Bayesian analysis of network structures

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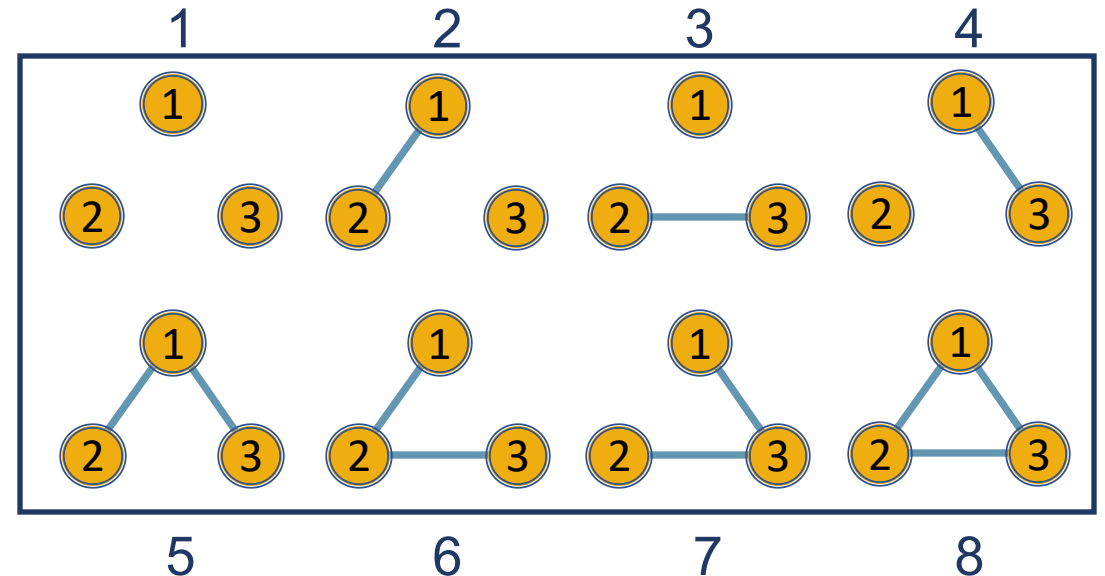
But which structure?

The Bayesian analysis of network structures

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But which structure?

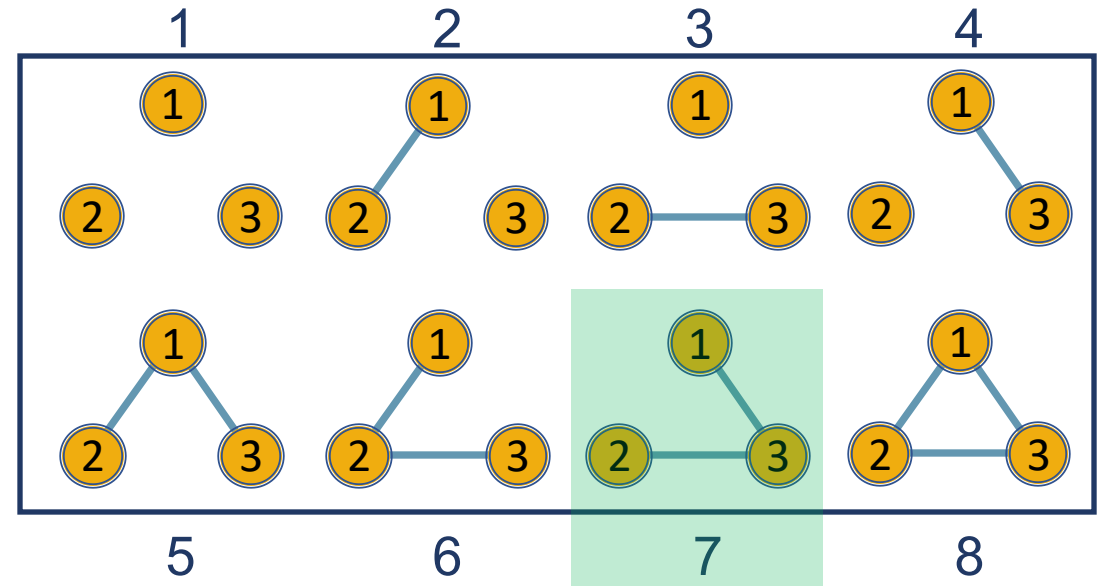


The Bayesian analysis of network structures

Evaluate the predictive success of the network structure.

$$P(\text{data} \mid \text{structure } 7)$$

But which structure?

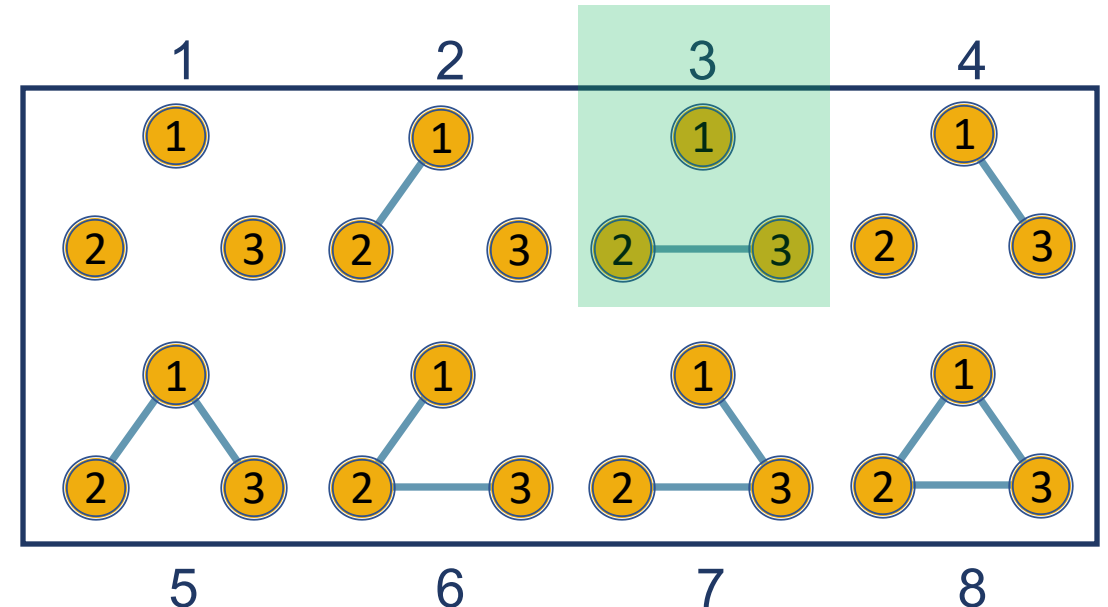


The Bayesian analysis of network structures

Evaluate the predictive success of the network structure.

$$P(\text{data} \mid \text{structure } 3)$$

But which structure?



The Bayesian analysis of network structures

Evaluate the predictive success of the network structure.

$$P(\text{data} \mid \text{structure } s)$$

We assign **prior** weights (probabilities) to the possible structures to reflect our uncertainty about the true structure.

$$P(\text{structure } s)$$

The Bayesian analysis of network structures

We use data to update our **prior** probabilities to **posterior** probabilities – what we know after having seen the data

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$$P(\text{structure 3} \mid \text{data}) = \frac{P(\text{data} \mid \text{structure 3}) P(\text{structure 3})}{P(\text{data})}$$

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Predictive Updating Factor

The Bayesian analysis of network structures

We use data to update our **prior** probabilities to **posterior** probabilities – what we know after having seen the data



$$P(\text{structure } 3 \mid \text{data}) = \frac{P(\text{data} \mid \text{structure } 3)P(\text{structure } 3)}{\sum_{s=1}^8 P(\text{data} \mid \text{structure } s)P(\text{structure } s)}$$

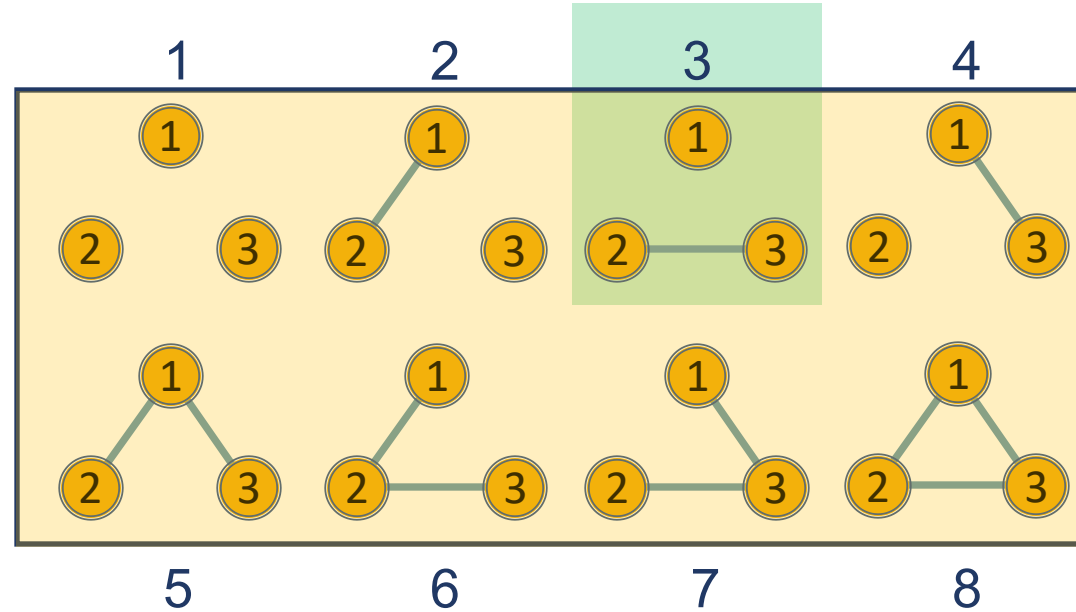
The Bayesian analysis of network structures

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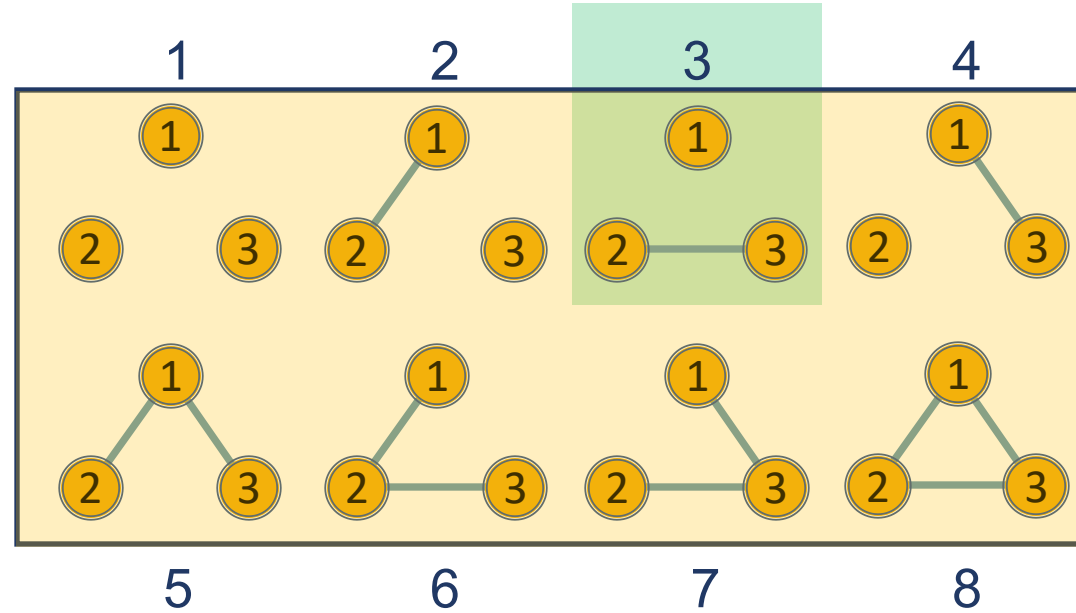
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The **prior** structure probabilities



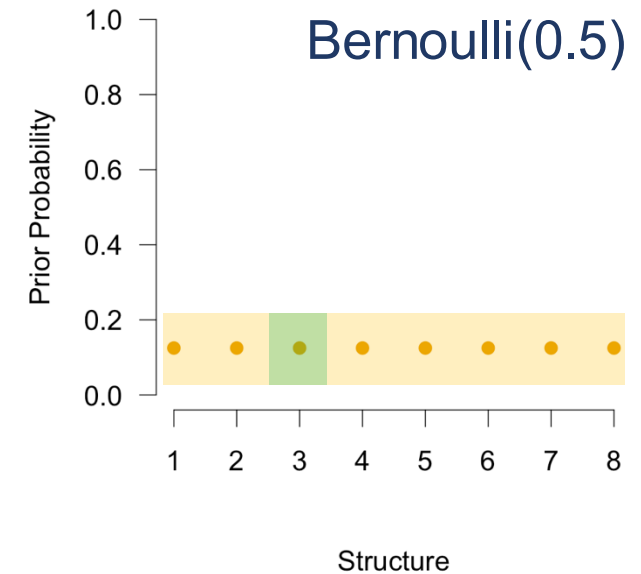
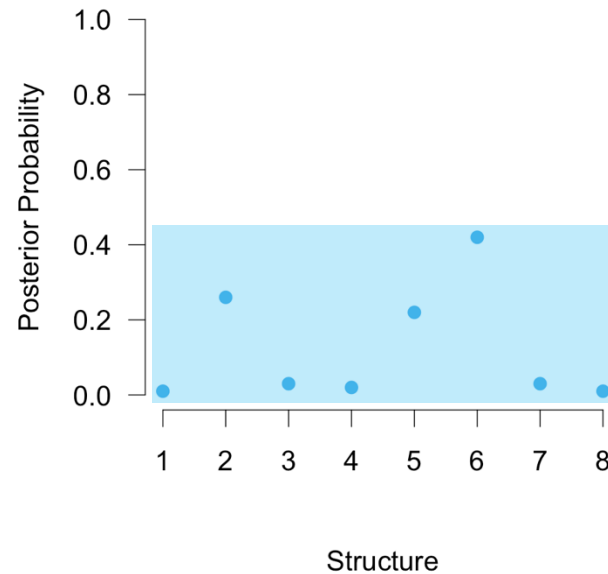
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The **prior** structure probabilities



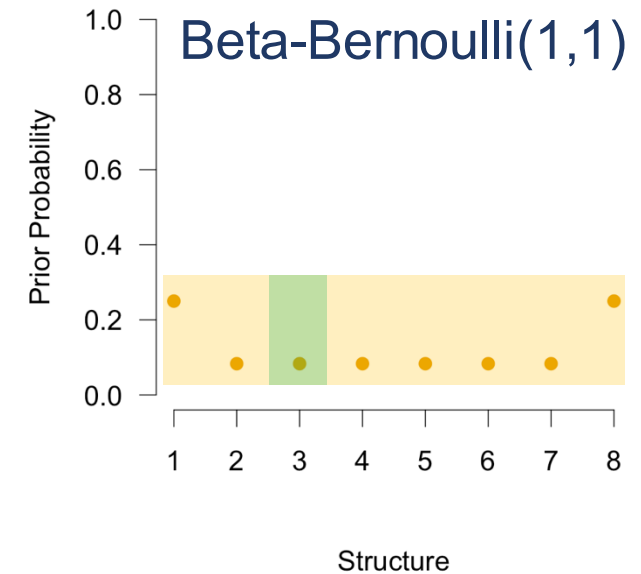
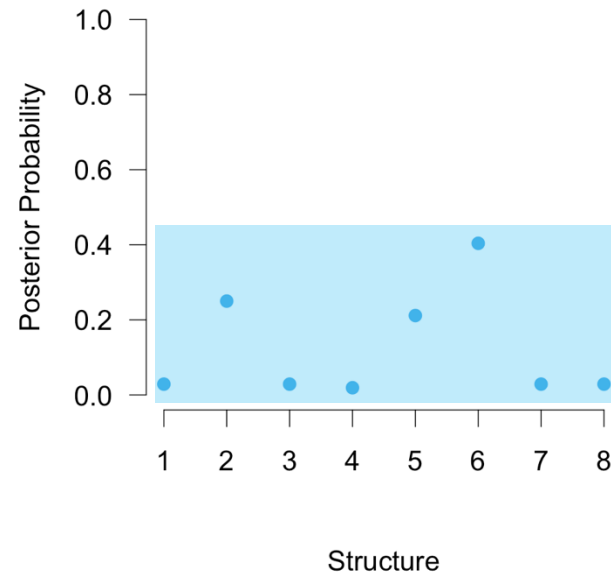
$$P(\text{structure 3} \mid \text{data}) = \frac{P(\text{data} \mid \text{structure 3}) \frac{1}{8}}{\sum_{s=1}^8 P(\text{data} \mid \text{structure } s) \frac{1}{8}}$$

The **prior** structure probabilities



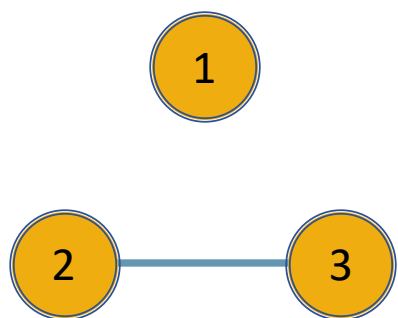
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The **prior** structure probabilities



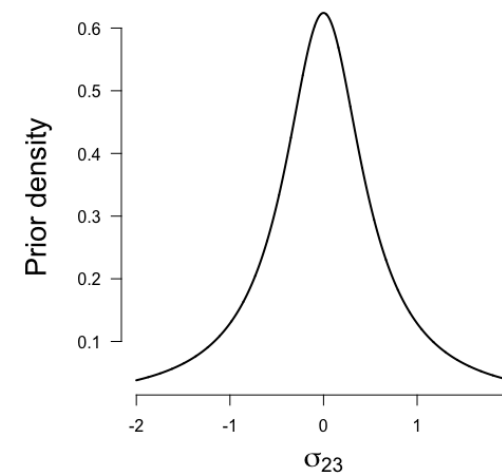
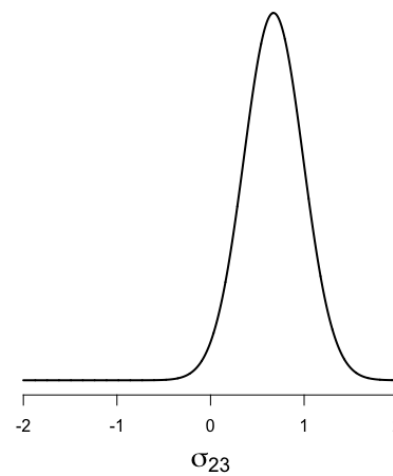
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The marginal likelihood



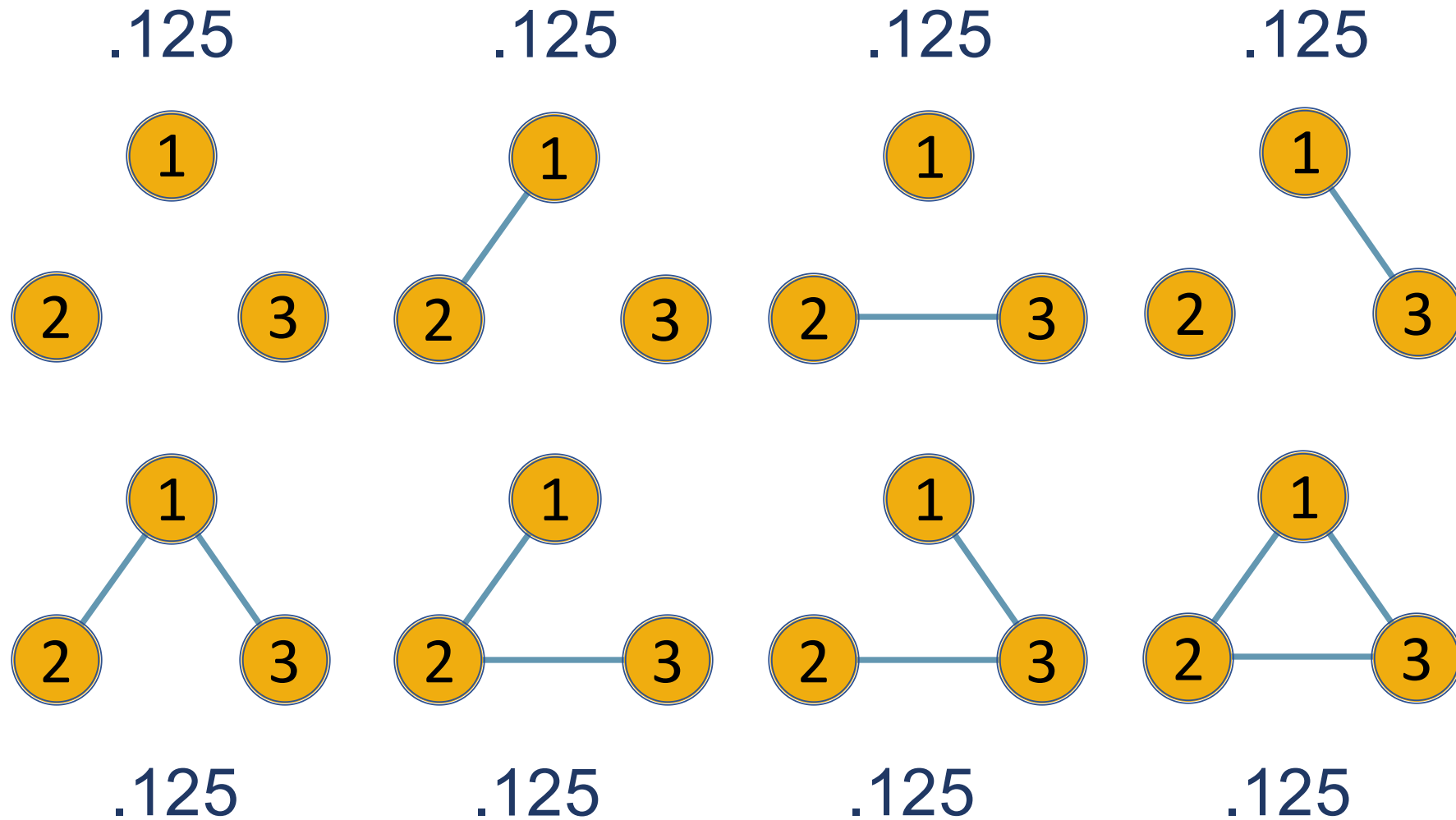
$$P(\text{data} \mid \text{structure 3}) = \int_{\mathbb{R}} p(\text{data} \mid \sigma_{23}) p(\sigma_{23}) d\sigma_{23}$$

Predictive updating factor

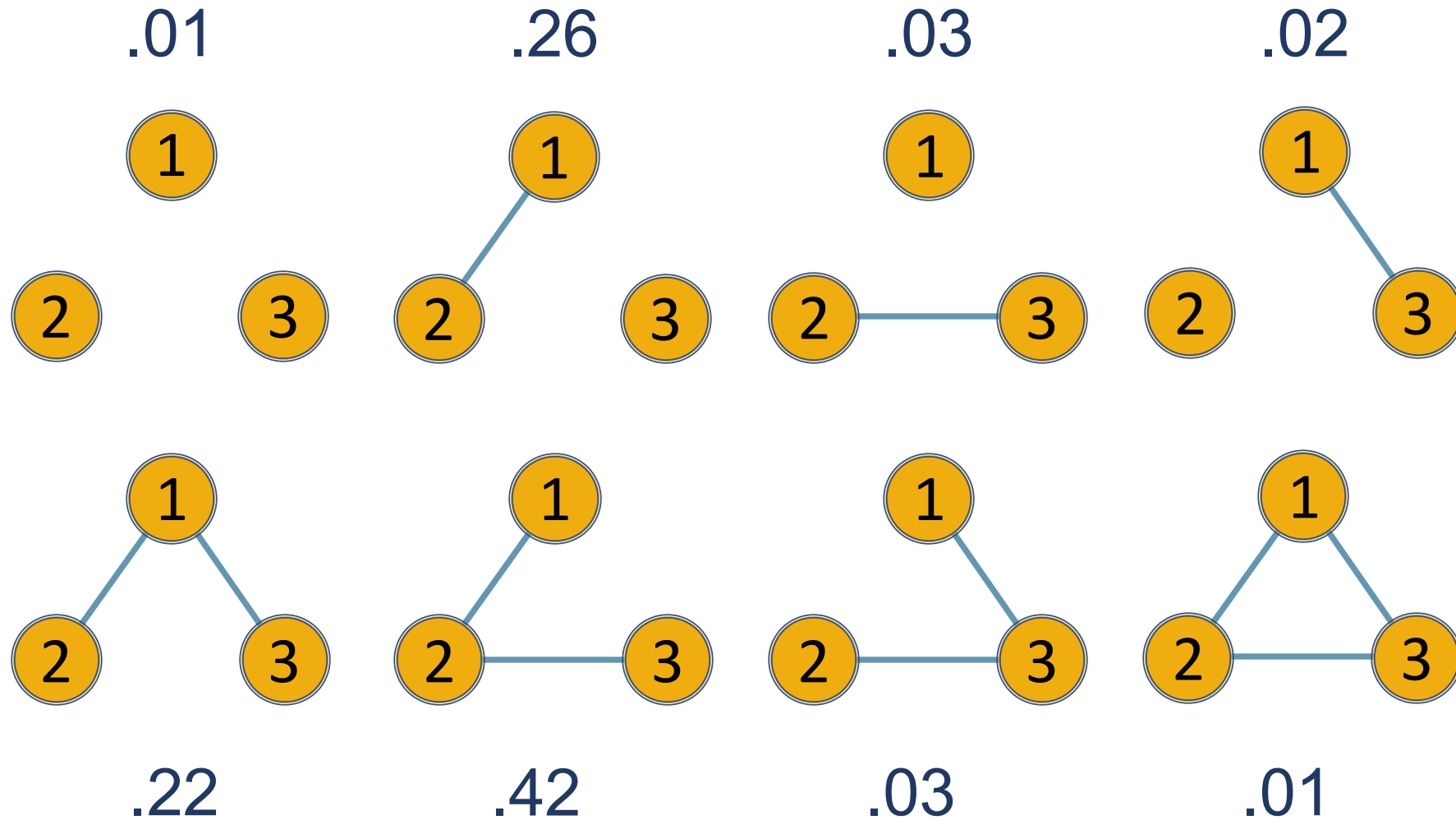


$$P(\text{structure 3} \mid \text{data}) = \frac{P(\text{data} \mid \text{structure 3})^{\frac{1}{8}}}{\sum_{s=1}^8 P(\text{data} \mid \text{structure } s)^{\frac{1}{8}}}$$

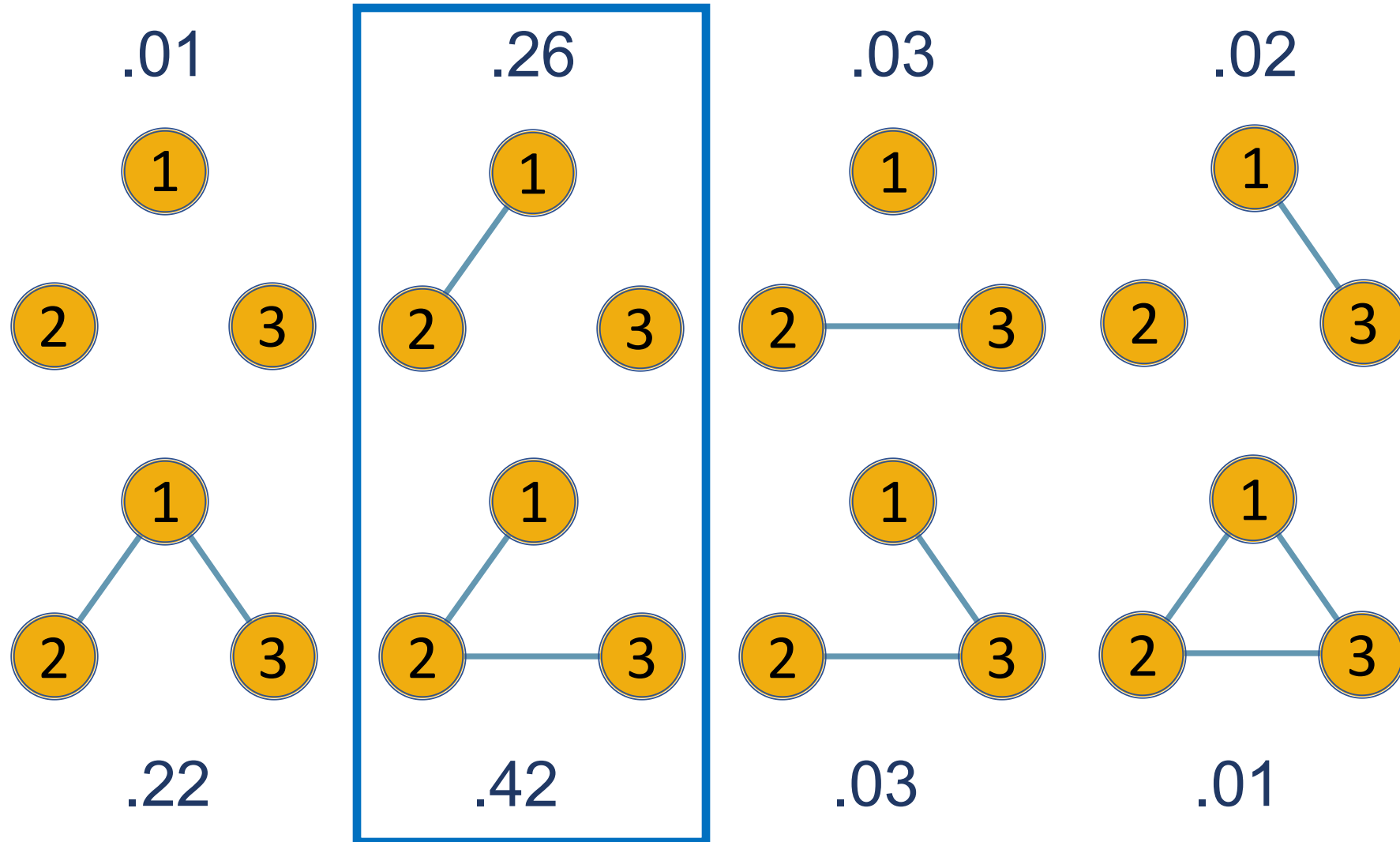
Bayesian estimation: **prior** probabilities



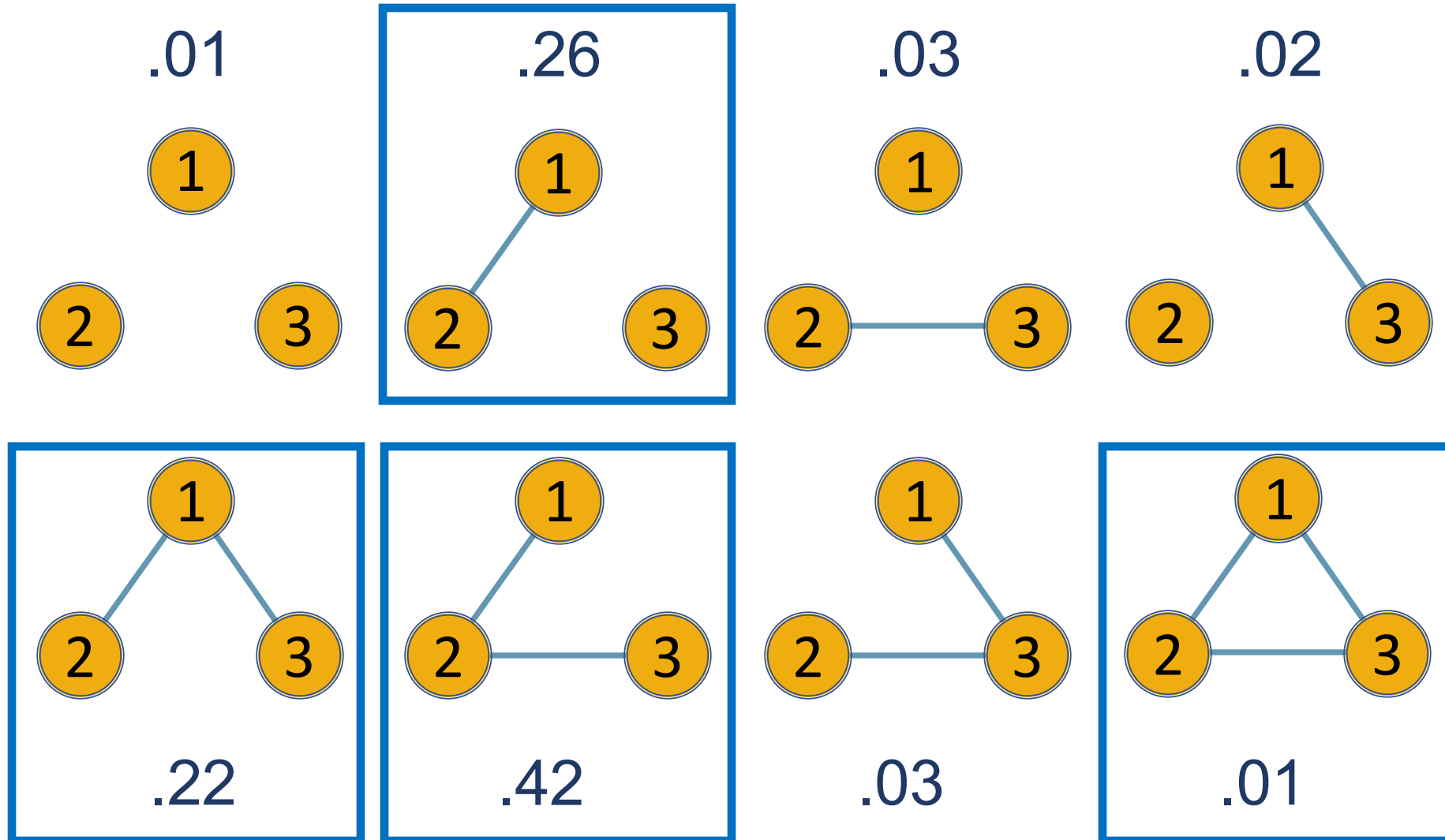
Bayesian estimation: **posterior** probabilities



Bayesian estimation: **posterior** probabilities



Bayesian estimation: **posterior** probabilities



Bayesian hypothesis testing

\mathcal{H}_0 : There is no edge between variables 1 and 2

\mathcal{H}_1 : There is an edge between variables 1 and 2

Bayesian hypothesis testing

\mathcal{H}_0 : There is no edge between variables 1 and 2

\mathcal{H}_1 : There is an edge between variables 1 and 2

$$\underbrace{\frac{P(\mathcal{H}_1 \mid \text{data})}{P(\mathcal{H}_0 \mid \text{data})}}_{\text{Posterior odds}} = \underbrace{\text{BF}_{10}}_{\text{Bayes factor}} \times \underbrace{\frac{P(\mathcal{H}_1)}{P(\mathcal{H}_0)}}_{\text{Prior odds}}$$

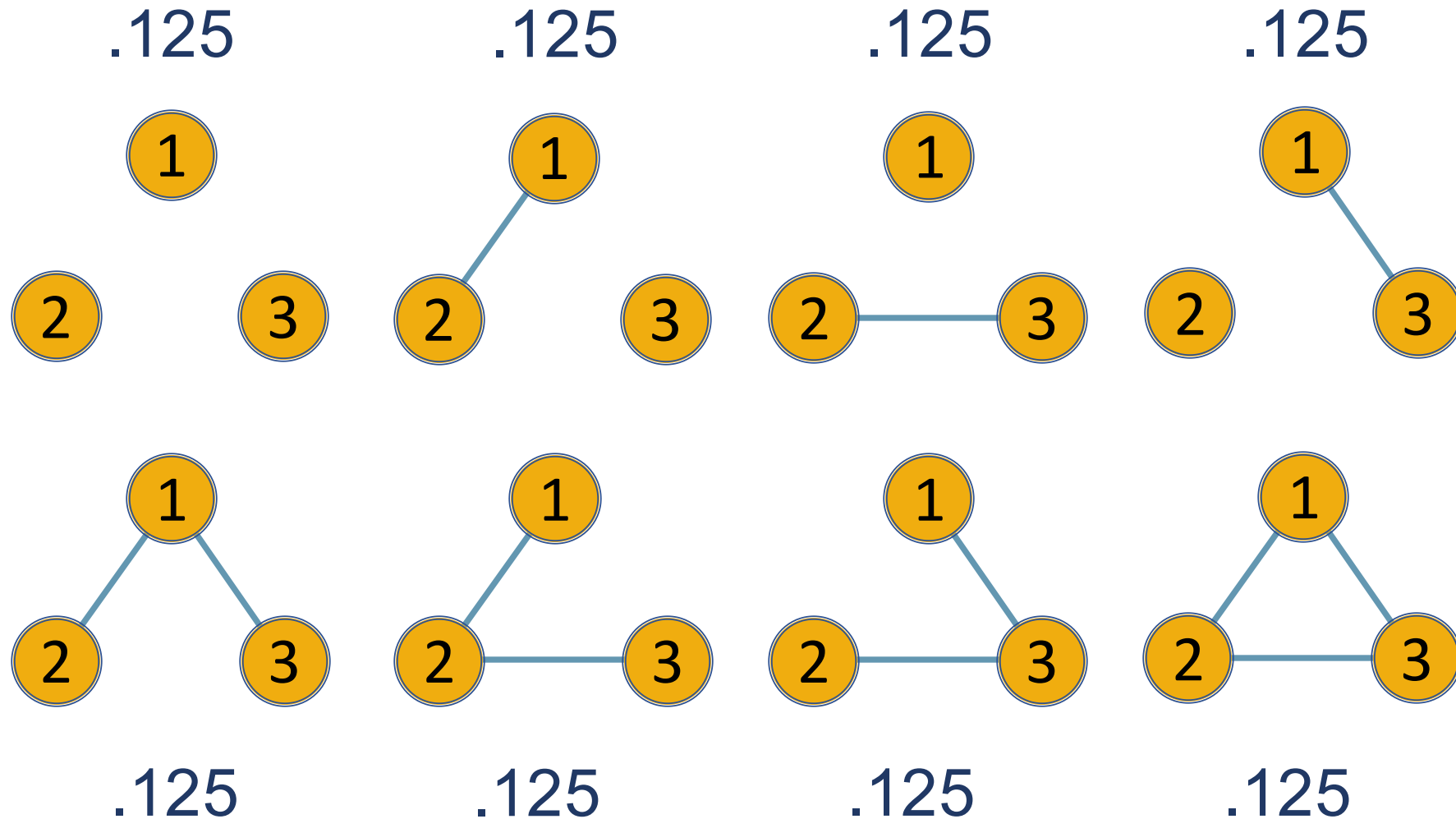
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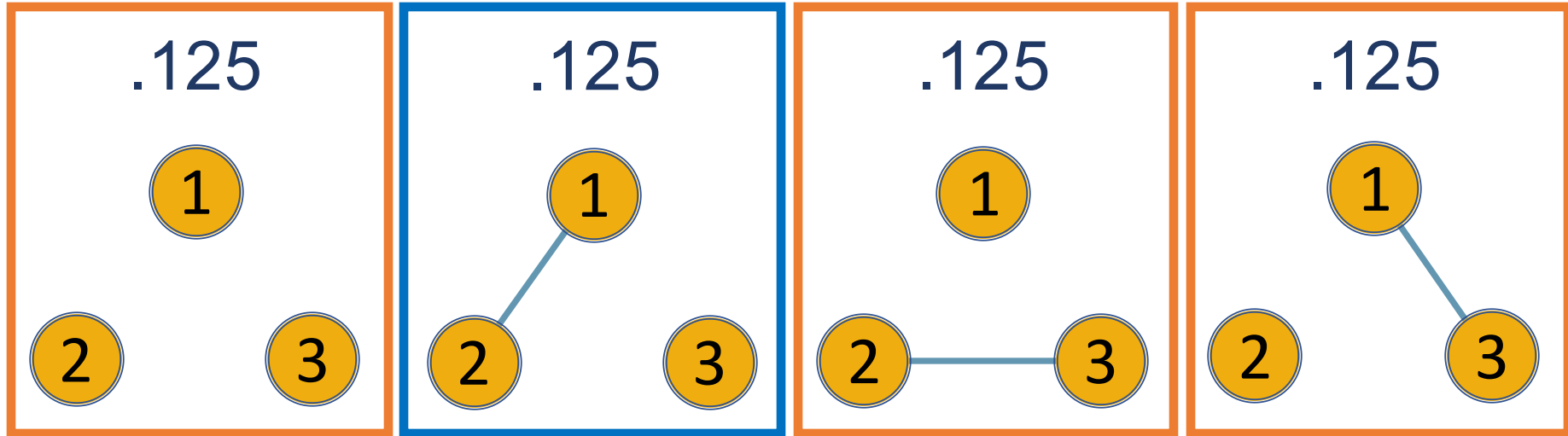
$$\underbrace{\text{BF}_{10}}_{\text{Bayes factor}} = \frac{P(\mathcal{H}_1 \mid \text{data})}{\underbrace{P(\mathcal{H}_0 \mid \text{data})}_{\text{Posterior odds}}} \bigg/ \frac{P(\mathcal{H}_1)}{\underbrace{P(\mathcal{H}_0)}_{\text{Prior odds}}}$$

Bayesian hypothesis testing: **prior odds**

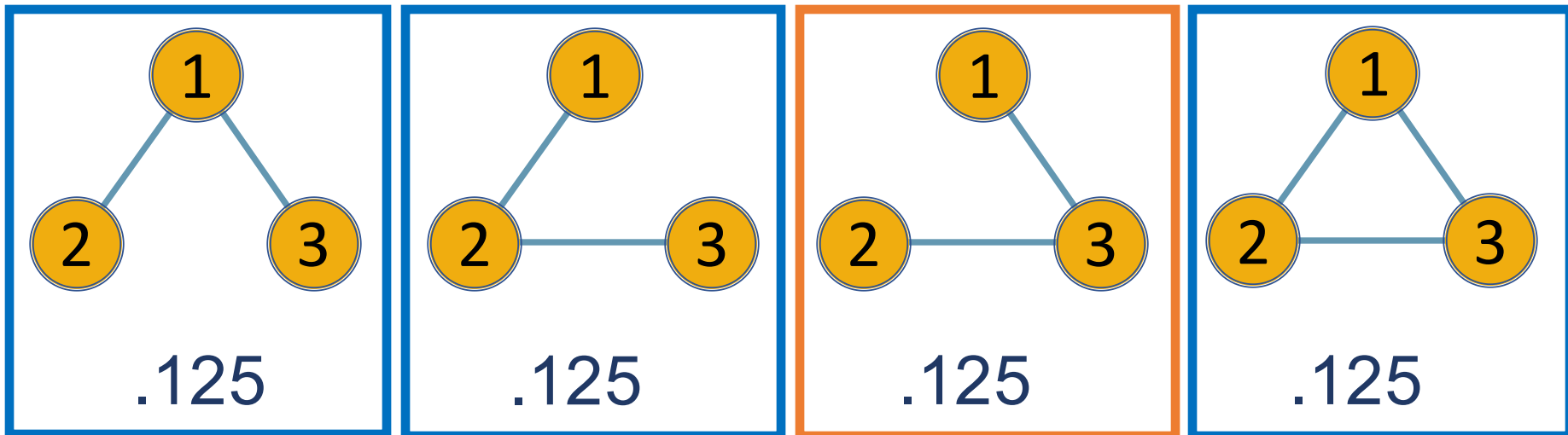


Bayesian hypothesis testing: **prior odds**

\mathcal{H}_0



\mathcal{H}_1



Bayesian hypothesis testing: **prior odds**

.125

.125

.125

.125

$$p(\mathcal{H}_0) = .125 + .125 + .125 + .125 = .5$$

$$p(\mathcal{H}_1) = .125 + .125 + .125 + .125 = .5$$

.125

.125

.125

.125

Bayesian hypothesis testing: **prior odds**

.125

.125

.125

.125

$$P(\mathcal{H}_0) = .5$$

$$P(\mathcal{H}_1) = .5$$

$$\frac{P(\mathcal{H}_1)}{P(\mathcal{H}_0)} = 1$$

.125

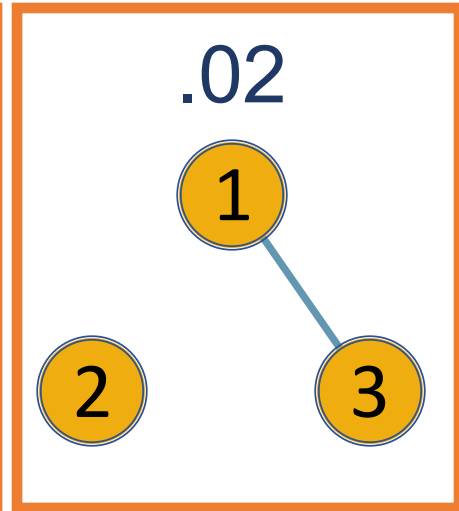
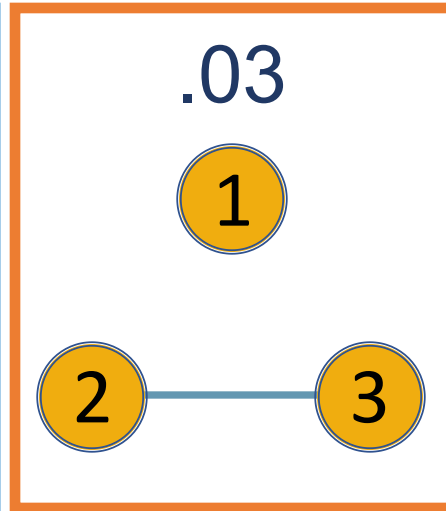
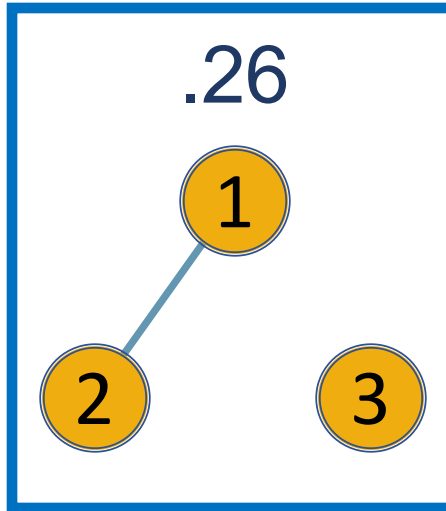
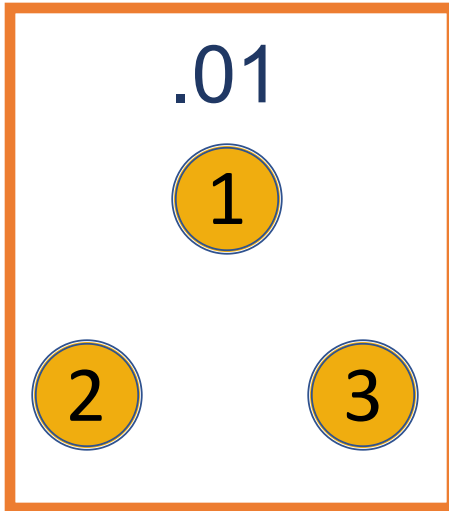
.125

.125

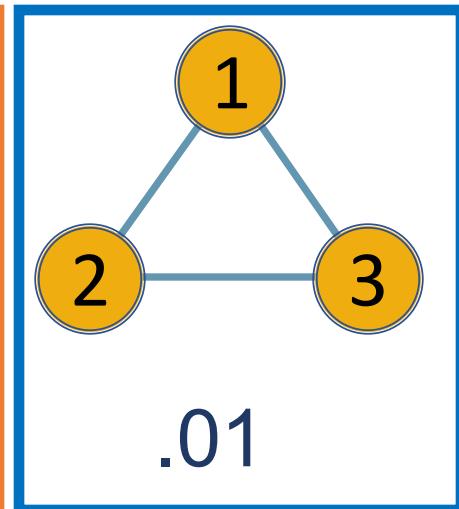
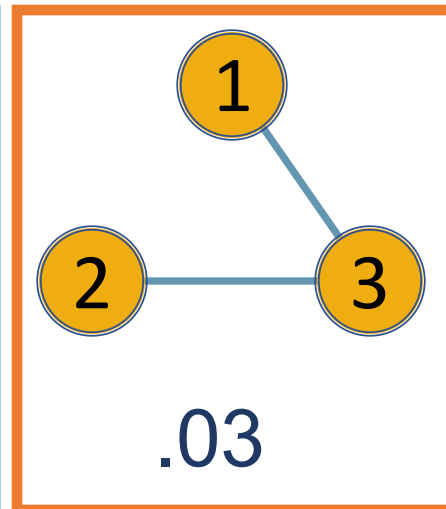
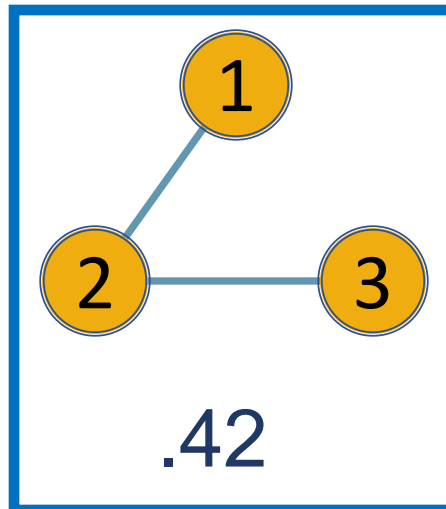
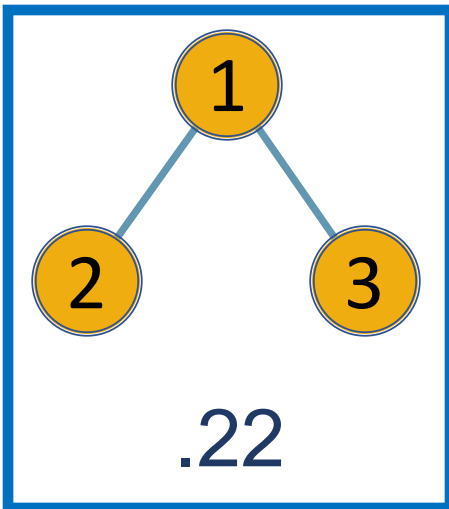
.125

Bayesian hypothesis testing: **posterior odds**

\mathcal{H}_0



\mathcal{H}_1



Bayesian hypothesis testing: **posterior odds**

.01

.26

.03

.02

\mathcal{H}_0

$$P(\mathcal{H}_0 \mid \text{data}) = .01 + .03 + .02 + .03 = .09$$

\mathcal{H}_1

$$P(\mathcal{H}_1 \mid \text{data}) = .26 + .22 + .42 + .01 = .91$$

.22

.42

.03

.01

Bayesian hypothesis testing: **posterior odds**

.01

.26

.03

.02

$$P(\mathcal{H}_0 \mid \text{data}) = .09$$

$$P(\mathcal{H}_1 \mid \text{data}) = .91$$

$$\frac{P(\mathcal{H}_1 \mid \text{data})}{P(\mathcal{H}_0 \mid \text{data})} = \frac{.91}{.09} = 10.11$$

.22

.42

.03

.01

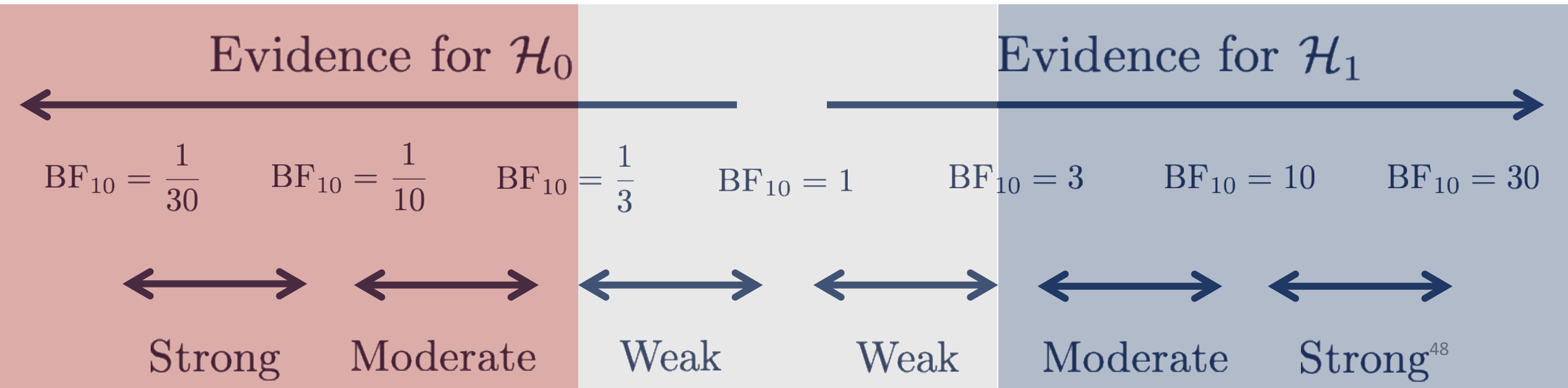
Bayesian hypothesis testing: **Bayes factor**

$$\text{BF}_{10} = \frac{P(\mathcal{H}_1 \mid \text{data})}{P(\mathcal{H}_0 \mid \text{data})} \bigg/ \frac{P(\mathcal{H}_1)}{P(\mathcal{H}_0)} = 10.11$$

The data are 4.6 times more likely under structures that include an edge between variables 1 and 2!

Bayesian hypothesis testing: **Bayes factor**

$$\text{BF}_{10} = \frac{P(\mathcal{H}_1 \mid \text{data})}{P(\mathcal{H}_0 \mid \text{data})} \bigg/ \frac{P(\mathcal{H}_1)}{P(\mathcal{H}_0)} = 10.11$$

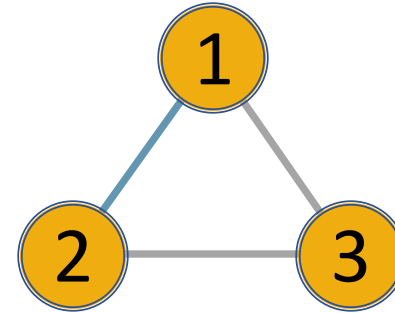


Bayesian hypothesis testing: Bayes factor

$$BF_{10}(1 - 2) = 10.11$$

$$BF_{10}(1 - 3) = 0.39$$

$$BF_{10}(2 - 3) = 0.96$$



Evidence for \mathcal{H}_0

Evidence for \mathcal{H}_1

$$BF_{10} = \frac{1}{30}$$

$$BF_{10} = \frac{1}{10}$$

$$BF_{10} = \frac{1}{3}$$

$$BF_{10} = 1$$

$$BF_{10} = 3$$

$$BF_{10} = 10$$

$$BF_{10} = 30$$



Strong

Moderate

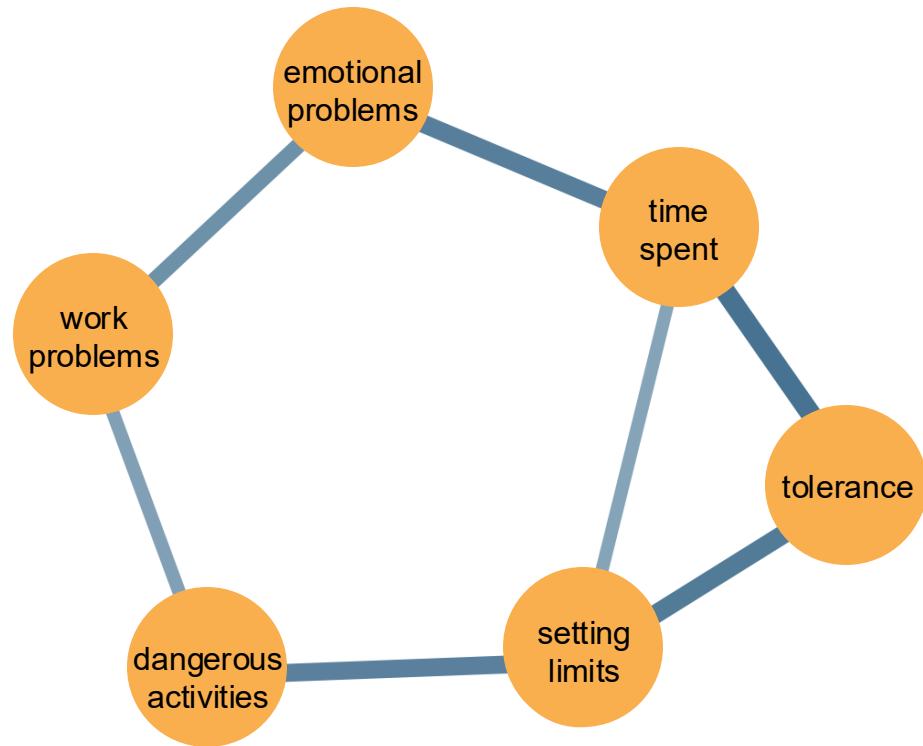
Weak

Weak

Moderate

Strong⁴⁹

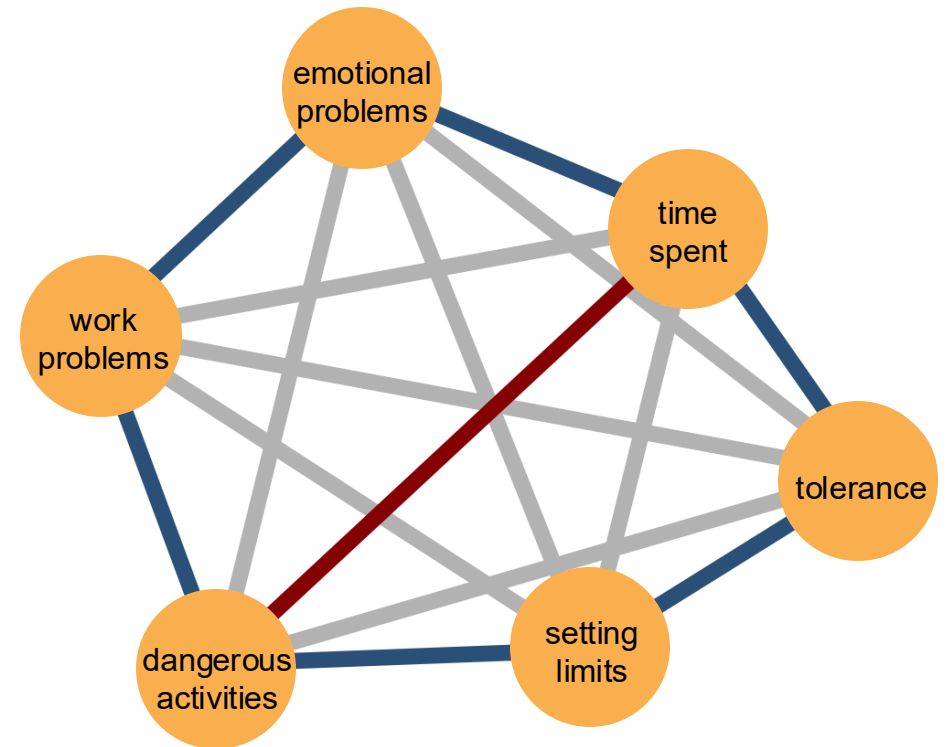
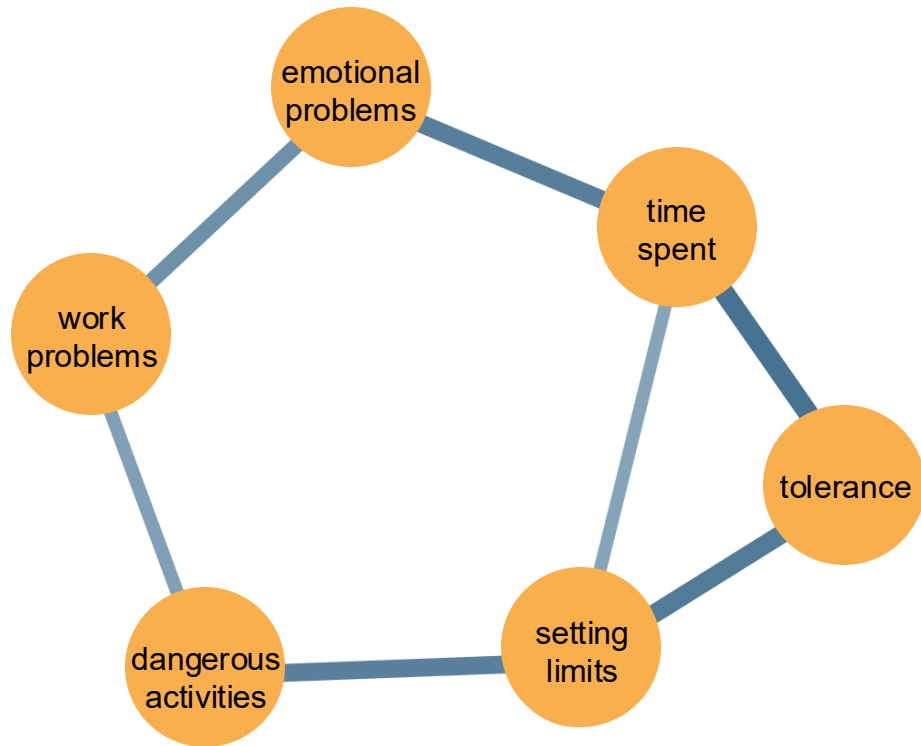
Quiz: Why are edges missing?



Solution: Evidence plot

Absence of evidence

Evidence of absence



End of Part I



Part I: Theory

Part II: Tutorial

Before we take a break:

```
install.packages("easybgm")
```

```
https://jasp-stats.org/download/
```