Bayesian Networks for Judges

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Agenda

PART I: What Are Bayesian Networks?

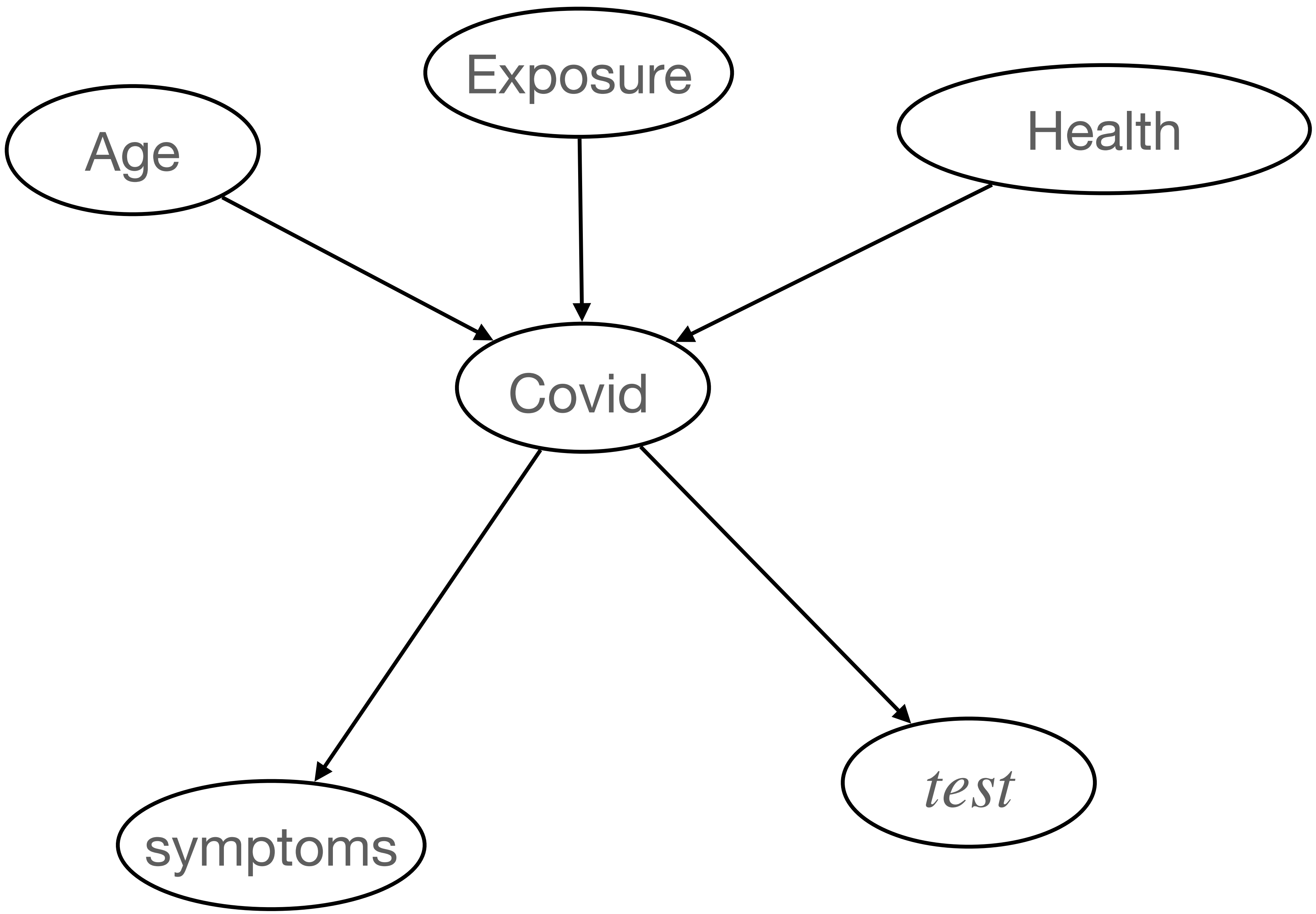
PART II: Group Exercise and Discussion

PART III: Analyzing a Legal Case Using Bayesian Networks

PART I

What Are Bayesian Networks?

Example: Bayes Nets for Covid Diagnosis



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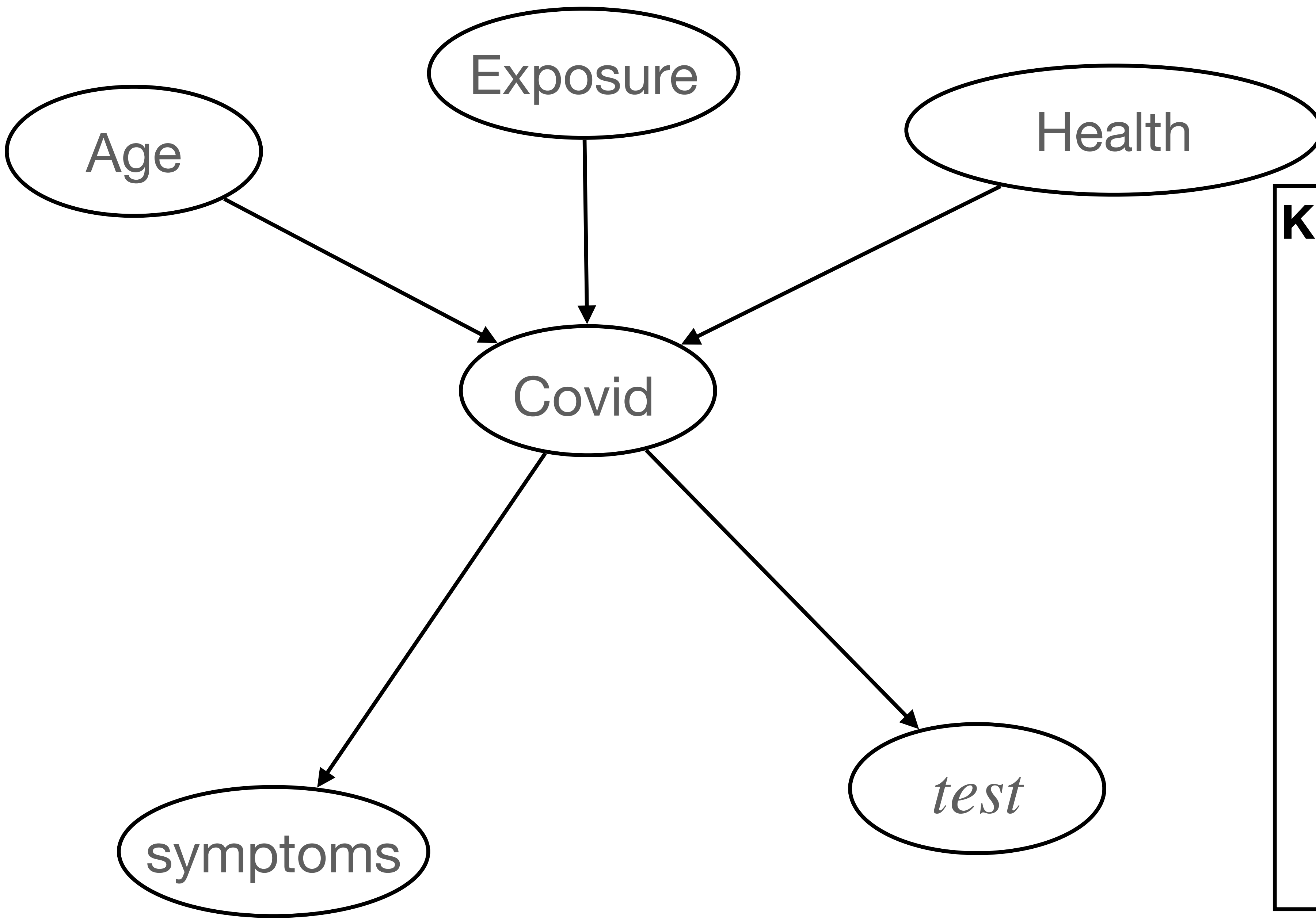

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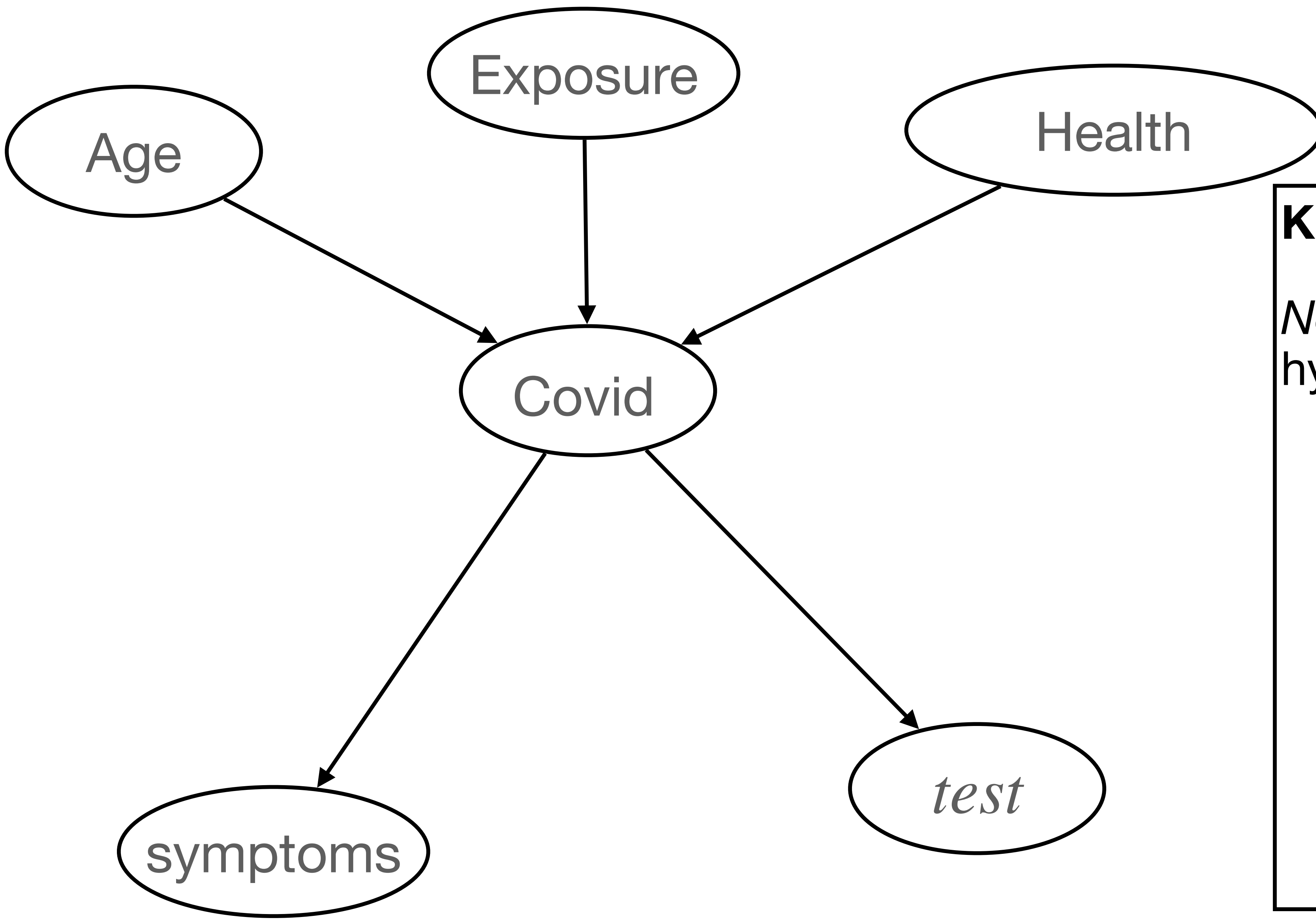

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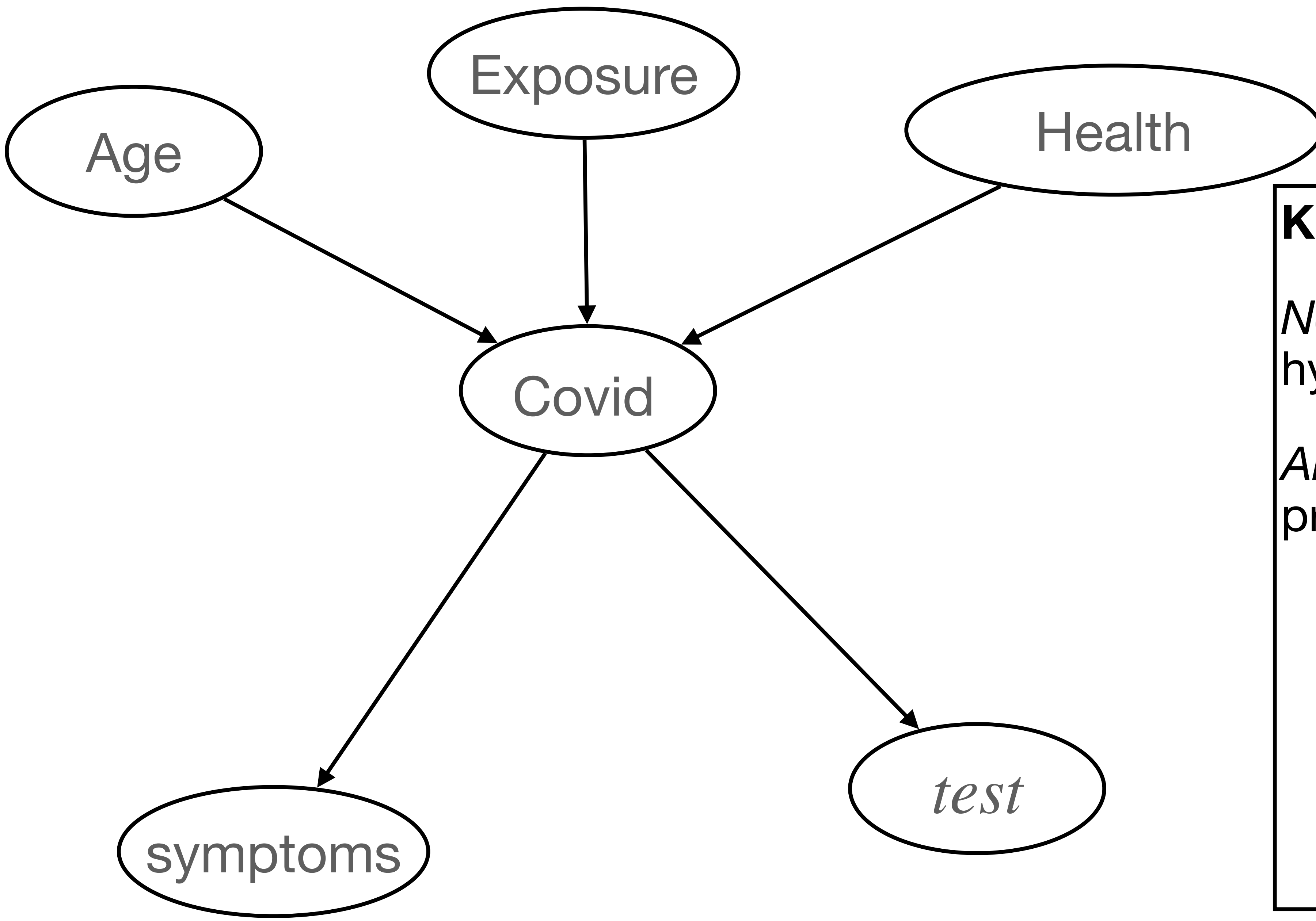

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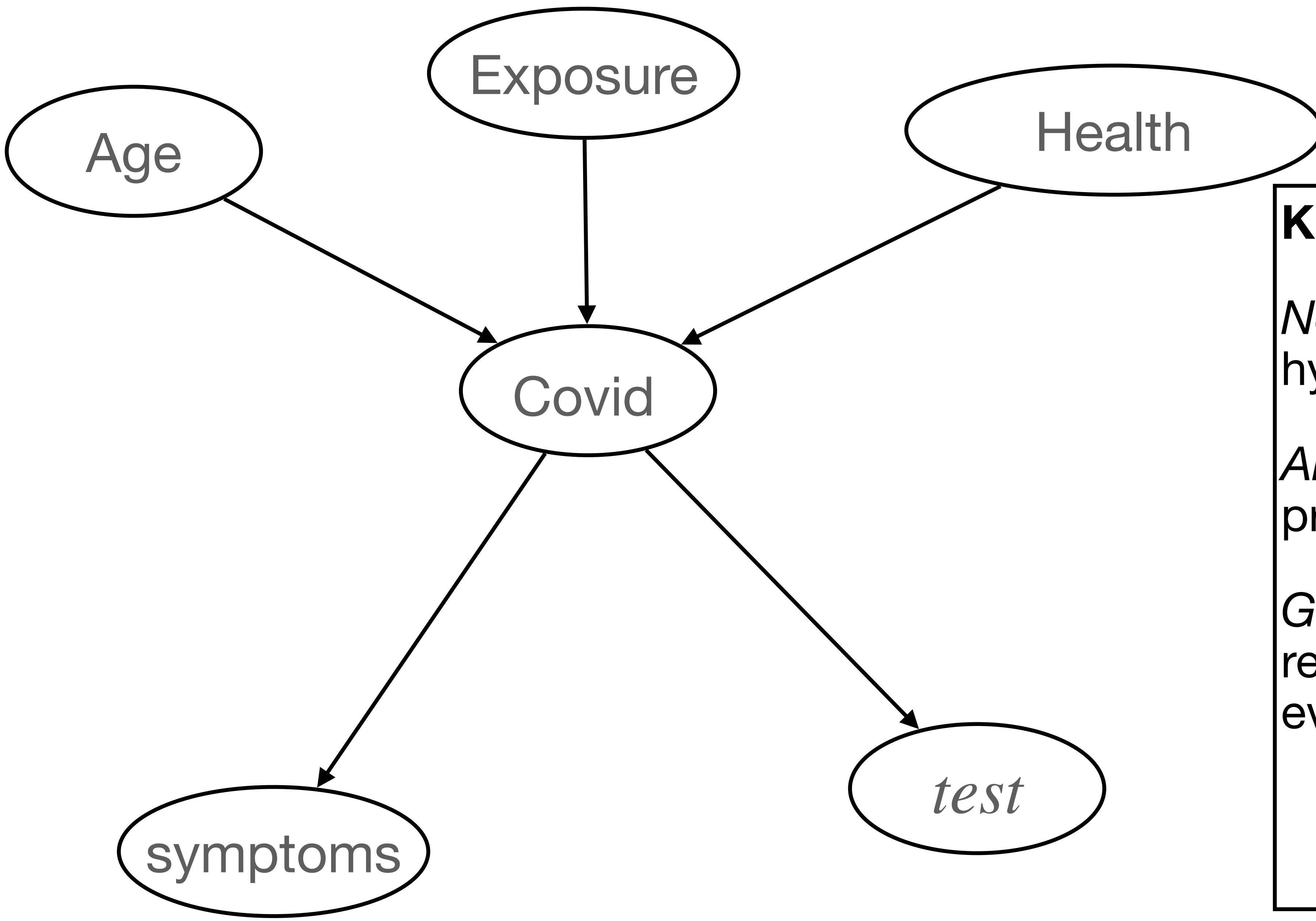

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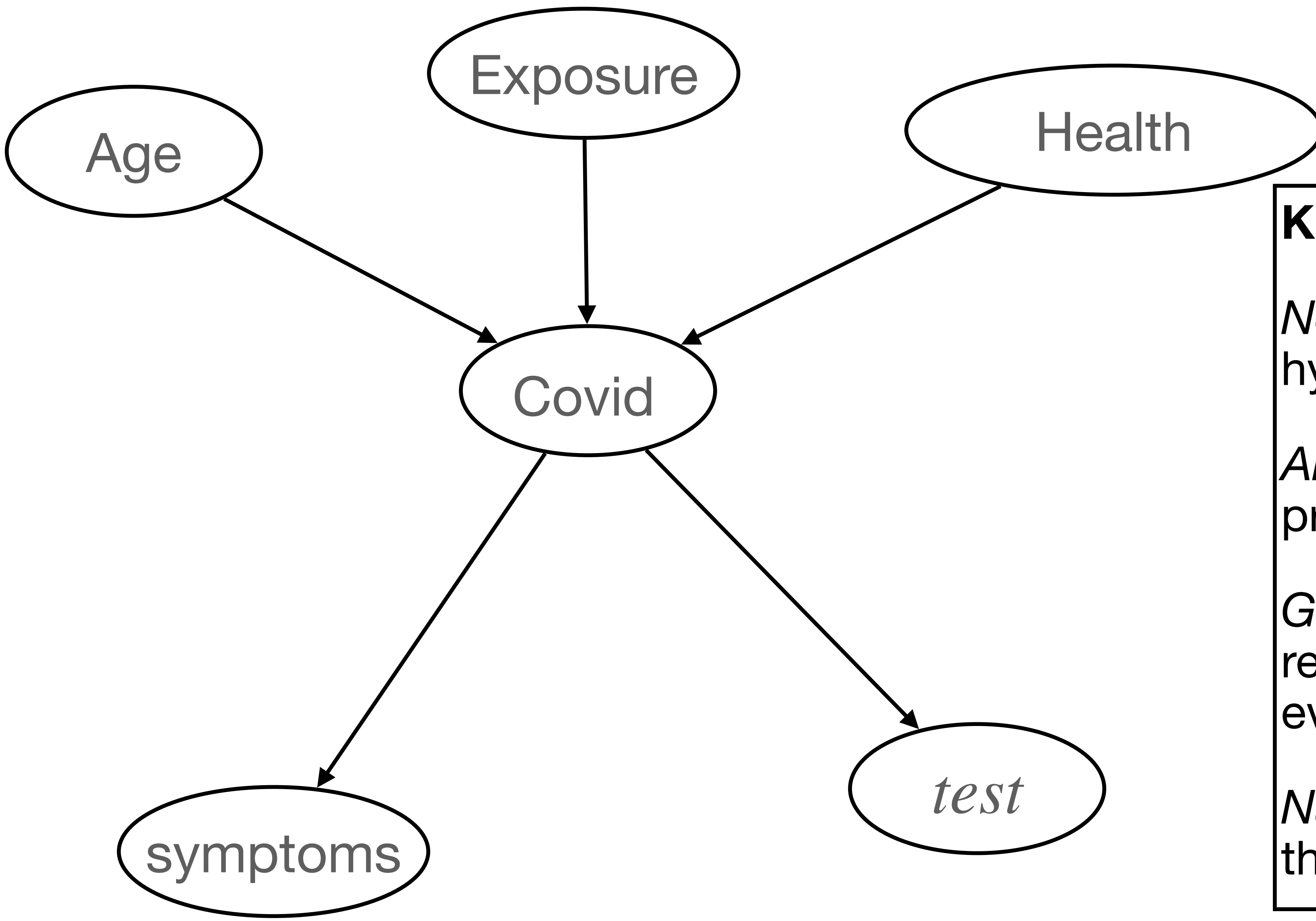

Key ideas:

Nodes: evidence v. hypothesis

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Graphical part: qualitative relations between evidence and hypothesis

Numerical part: strength of these relations (*more later*)

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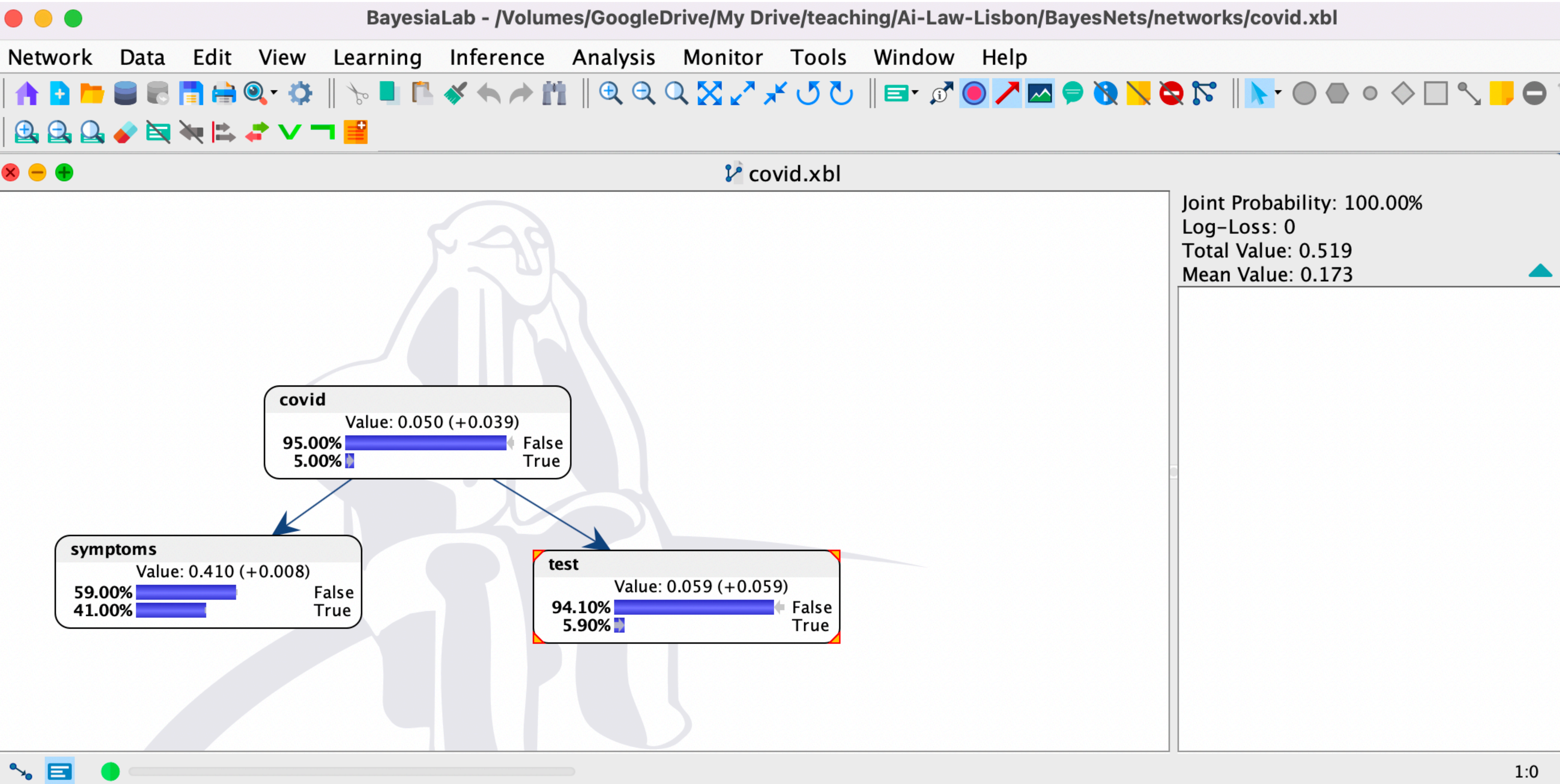
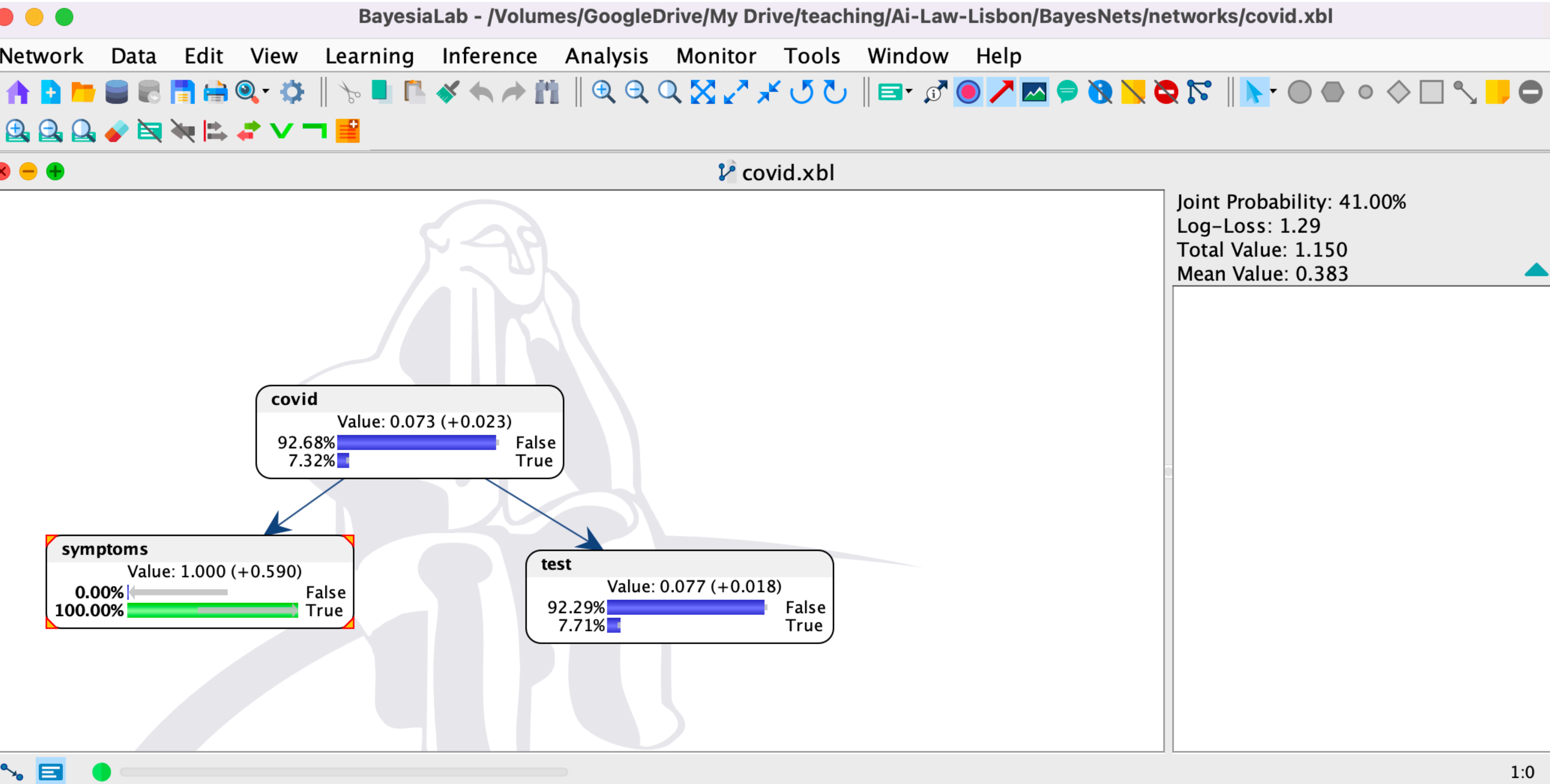
(1) Bayesian Network with BayesiaLab



(2) Bayesian Network with BayesiaLab



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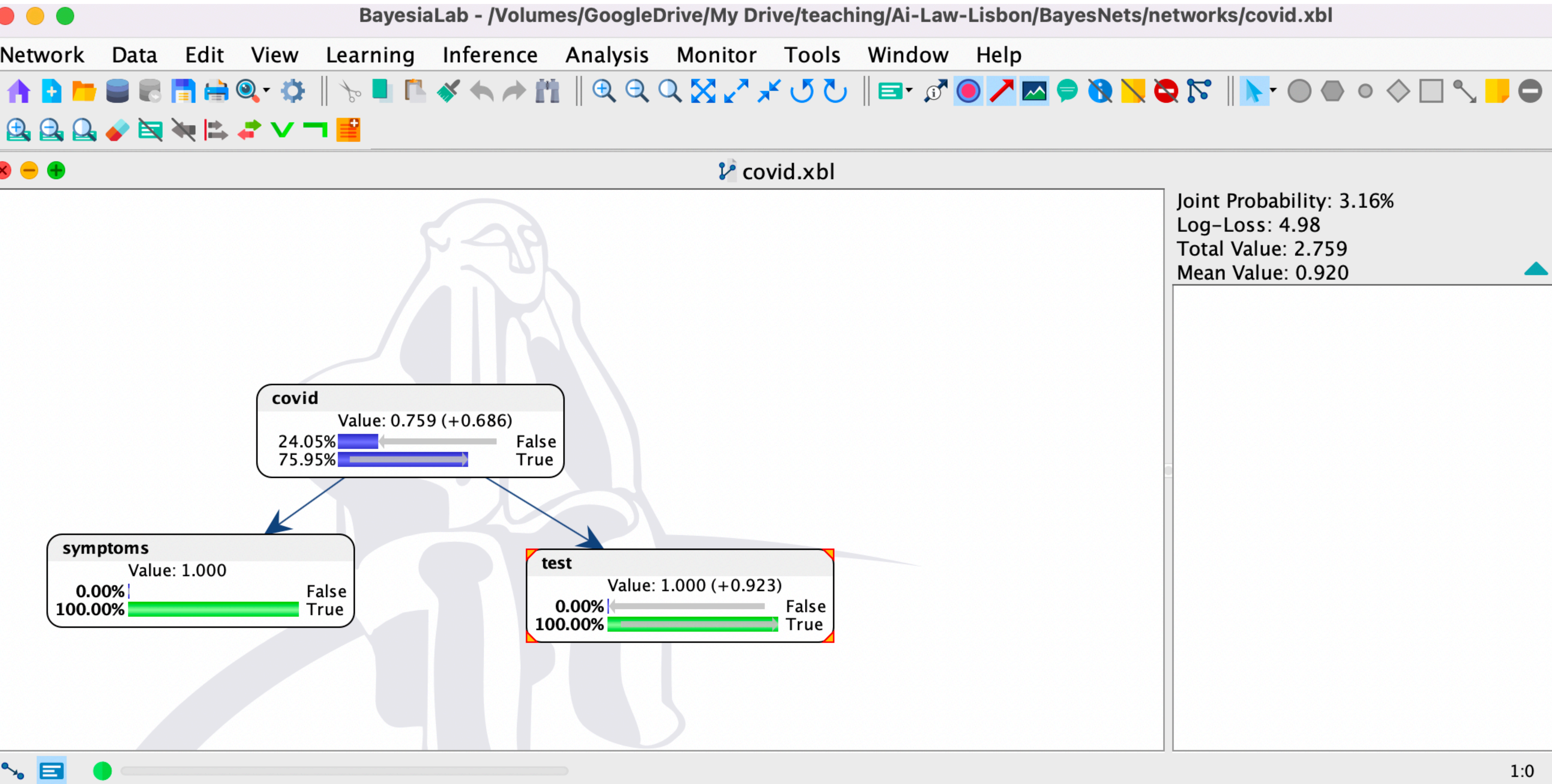


Graphical Components:
Nodes, Arrows and Idioms

(1) Graphical Components of a Bayesian Network

Nodes

Each **node** represents *possible states of the world*

"defendant killed victim" // "defendant did not kill victim"

"defendant had a motive" // "defendant did not have a motive"

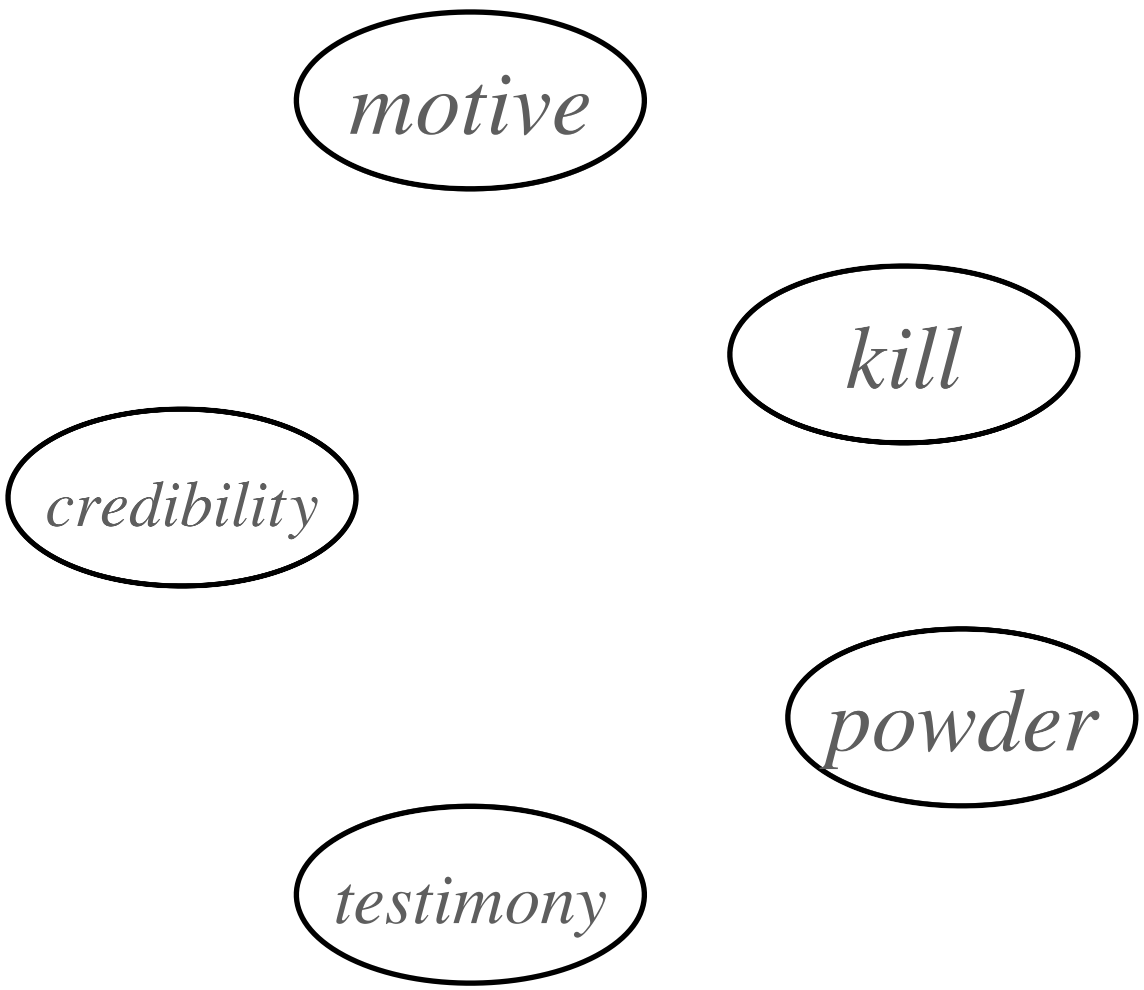
"gun powder found on defendant" // "gun powder not found on defendant"

"witness testifies they saw defendant near crime scene" // "witness testifies they did not see defendant near crime scene"

"witness is credible" // "witness is not credible"

(1) Graphical Components of a Bayesian Network

Nodes



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“defendant killed victim” // “defendant did not kill victim”

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“gun powder found on defendant” // “gun powder not found on defendant”

“witness testifies they saw defendant near crime scene” // “witness testifies they did not see defendant near crime scene”

“witness is credible” // “witness is not credible”

(2) Graphical Components of a Bayesian Network

Arrows

As a first approximation, think of **arrows** as *directions of causal influence* (though this interpretation is debated):

Whether or not the defendant had a motive to kill influences whether or not the defendant killed the victim

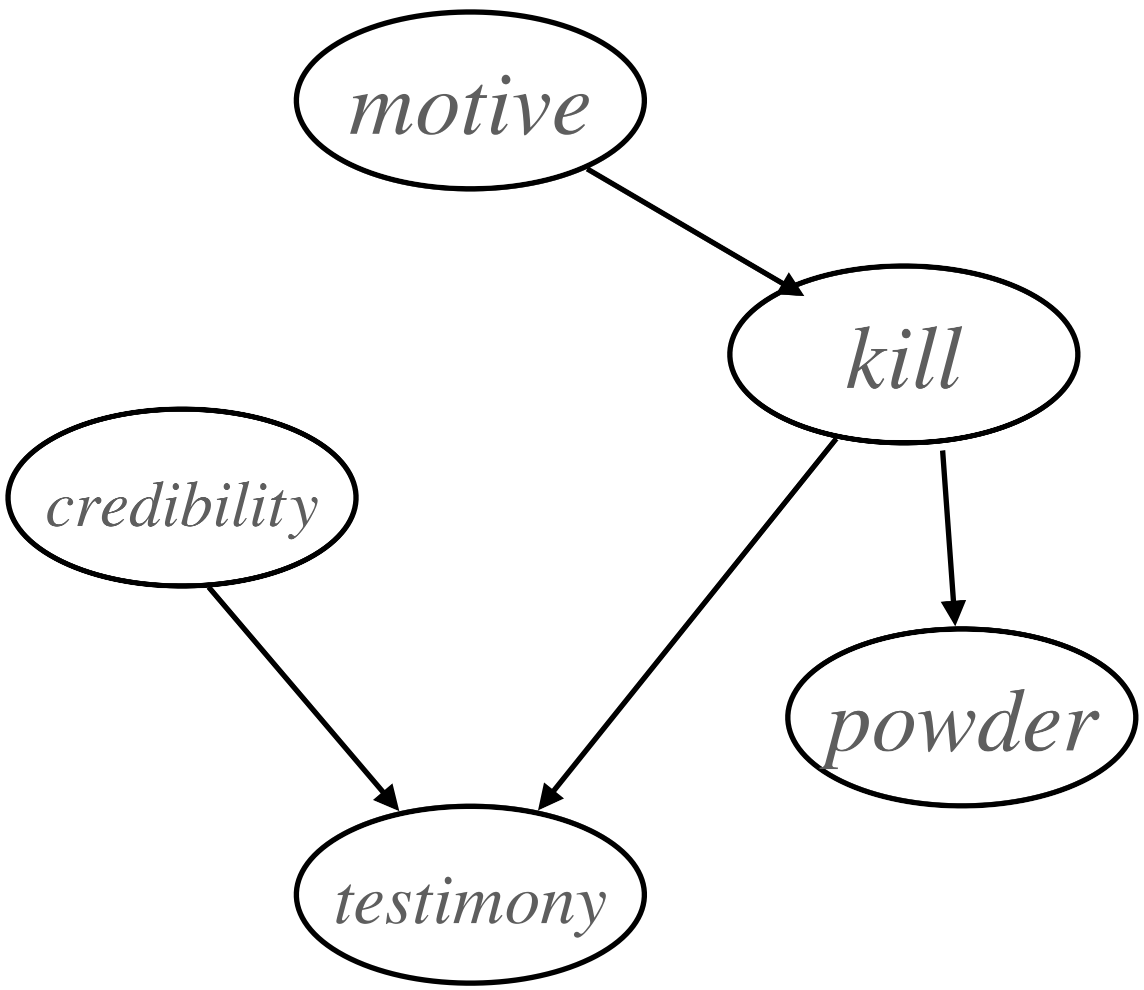
Whether or not the defendant killed the victim influences whether or not gunpowder was found on defendant

Whether or not the defendant killed the victim influences what the witness saw

Whether or not the witness is credible influences what the witness says

(2) Graphical Components of a Bayesian Network

Arrows



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Whether or not the witness is credible influences what the witness says

(3a) Graphical *Components of a Bayesian Network*

Idioms (=basic graphical structures)

Hypothesis / one
piece of evidence

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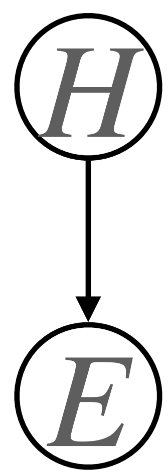
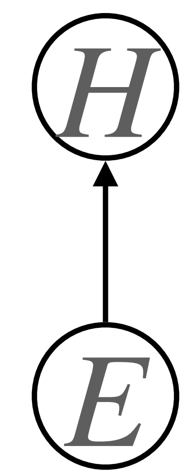


Hypothesis / one piece of evidence



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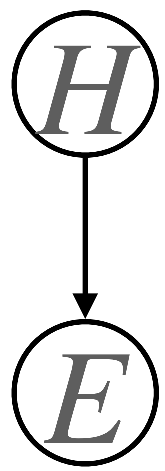

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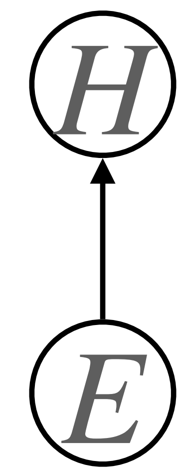
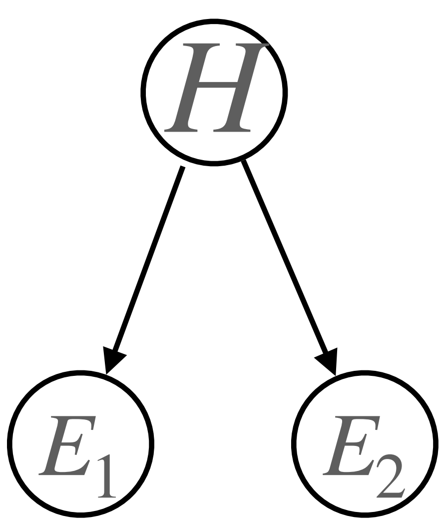
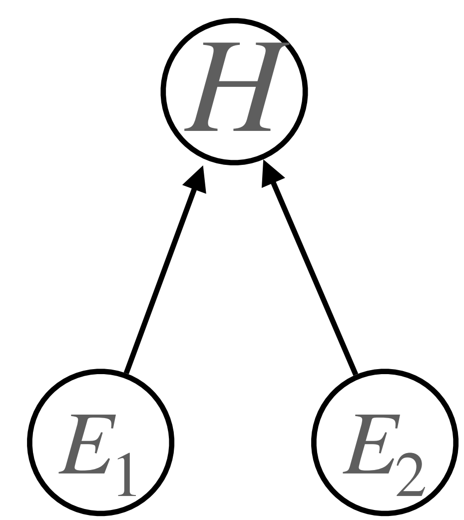




Hypothesis / two
piece of evidence



(3b) Graphical *Components of a Bayesian Network*

Idioms (=basic graphical structures)

Evidence /
Hypothesis *plus*
Credibility

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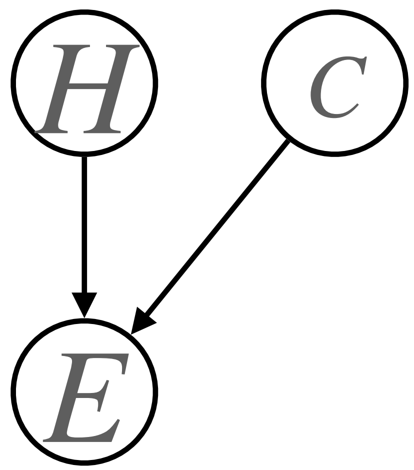

Evidence /
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Credibility

(3b) Graphical *Components of a Bayesian Network*

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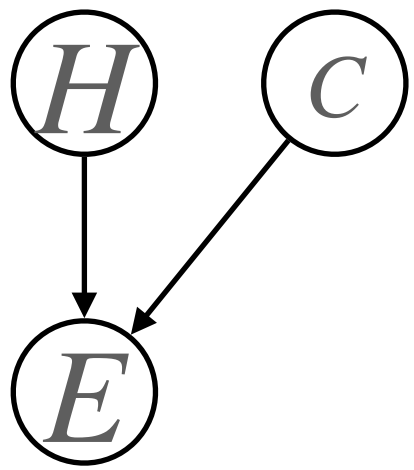

Evidence /
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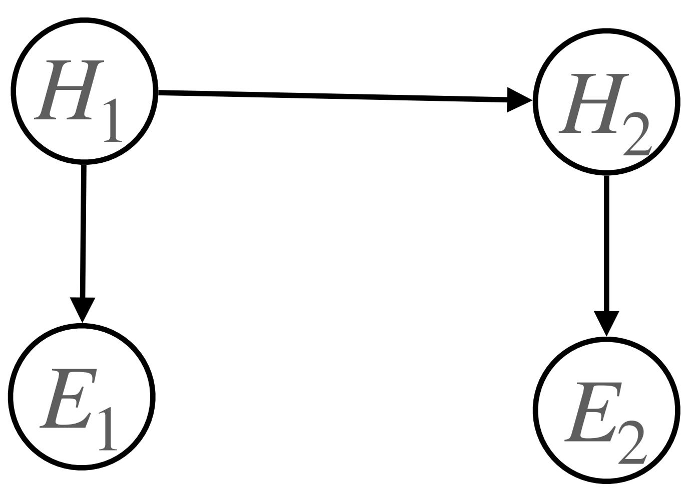
Credibility



Rebuttal:
hypotheses H1 and
H2 are incompatible

Basic Idioms Can Be Combined and Form More Complex Graphs

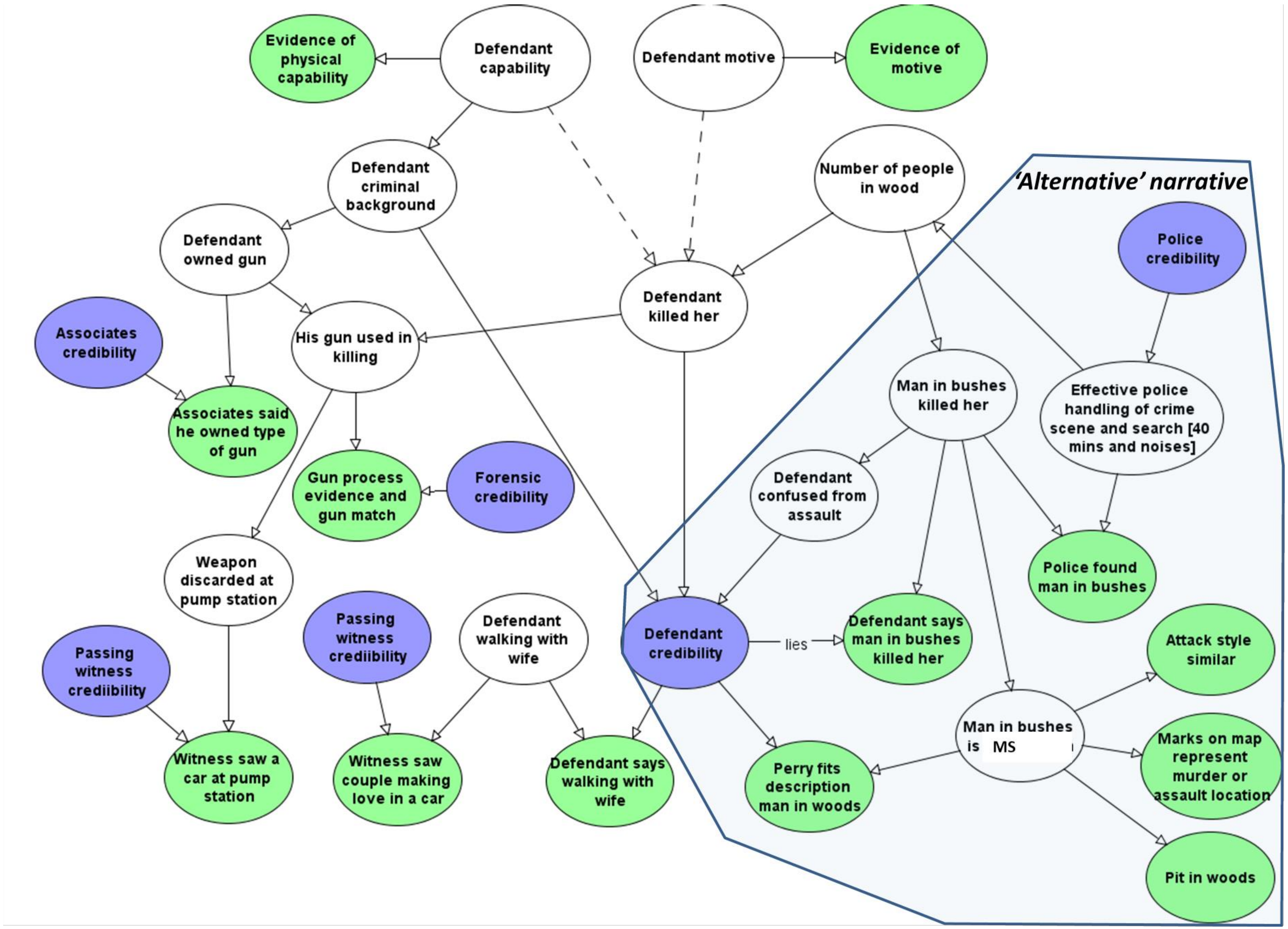


Figure 8 Full Simonshaven model, subdivided into the prosecution and alternative narratives

Numerical Component: Probability Tables

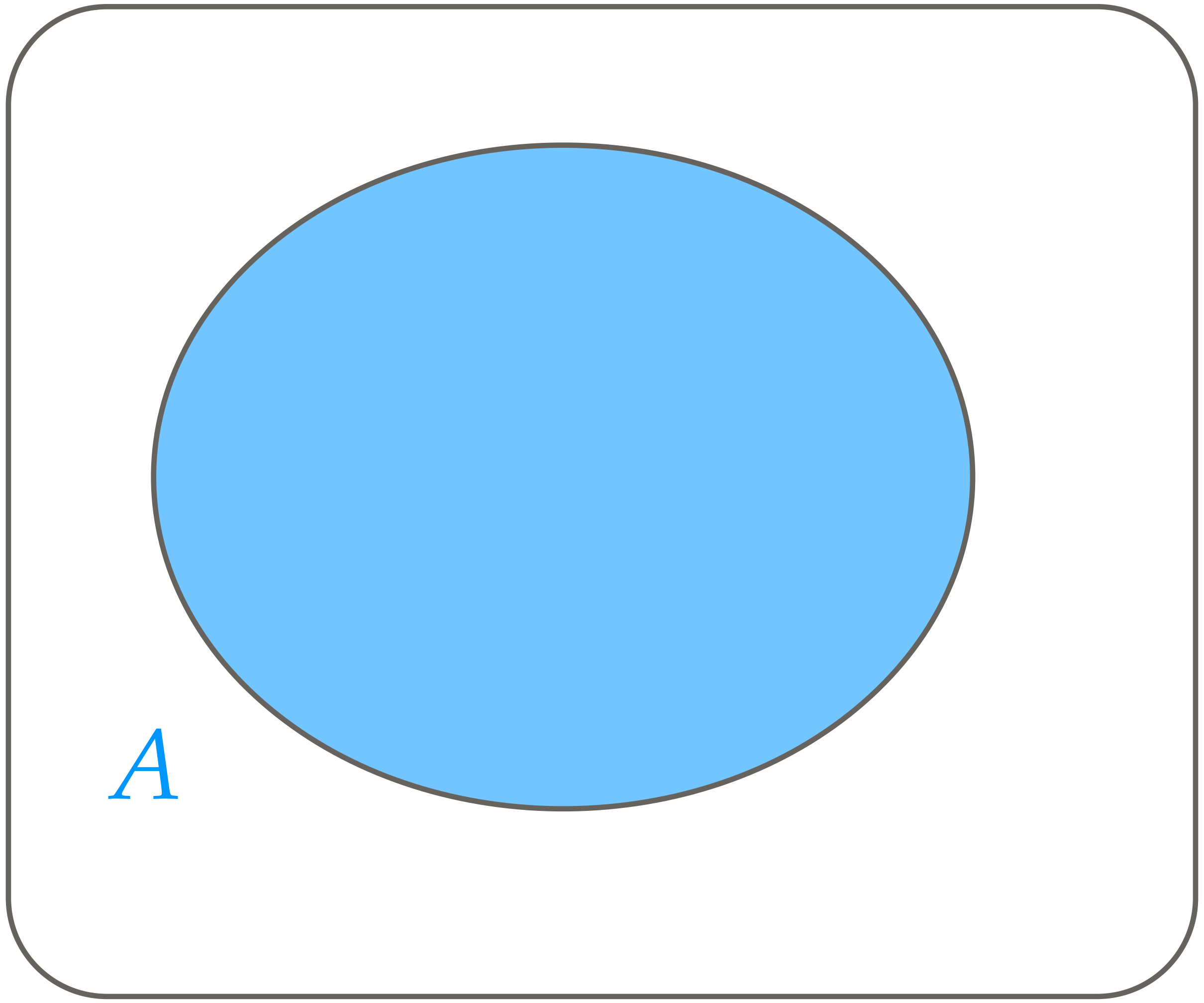
Before we get into that…

Two preliminary topics:

- Conditional probability
- Bayes' theorem (see also handout)

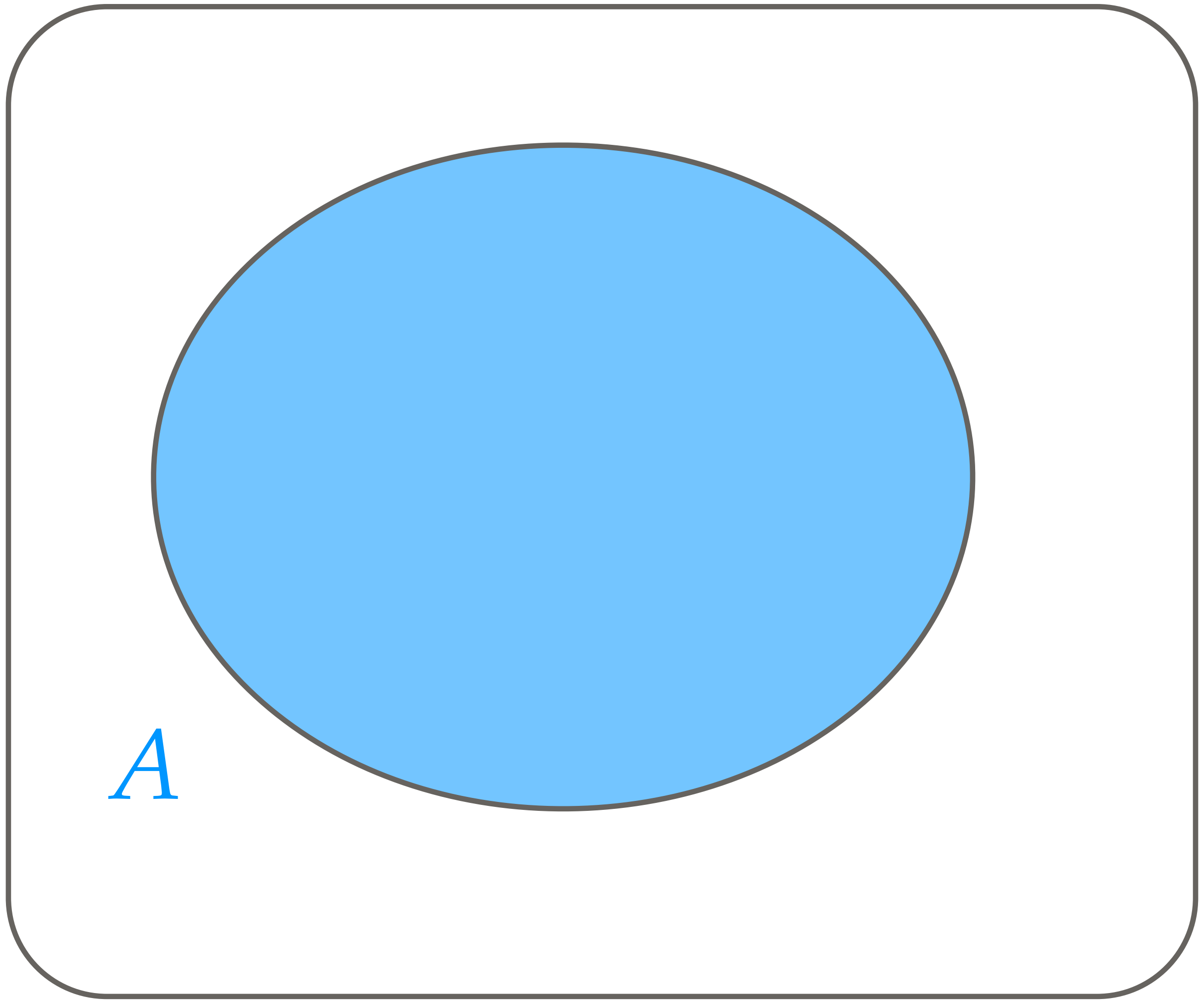
Probability as Area

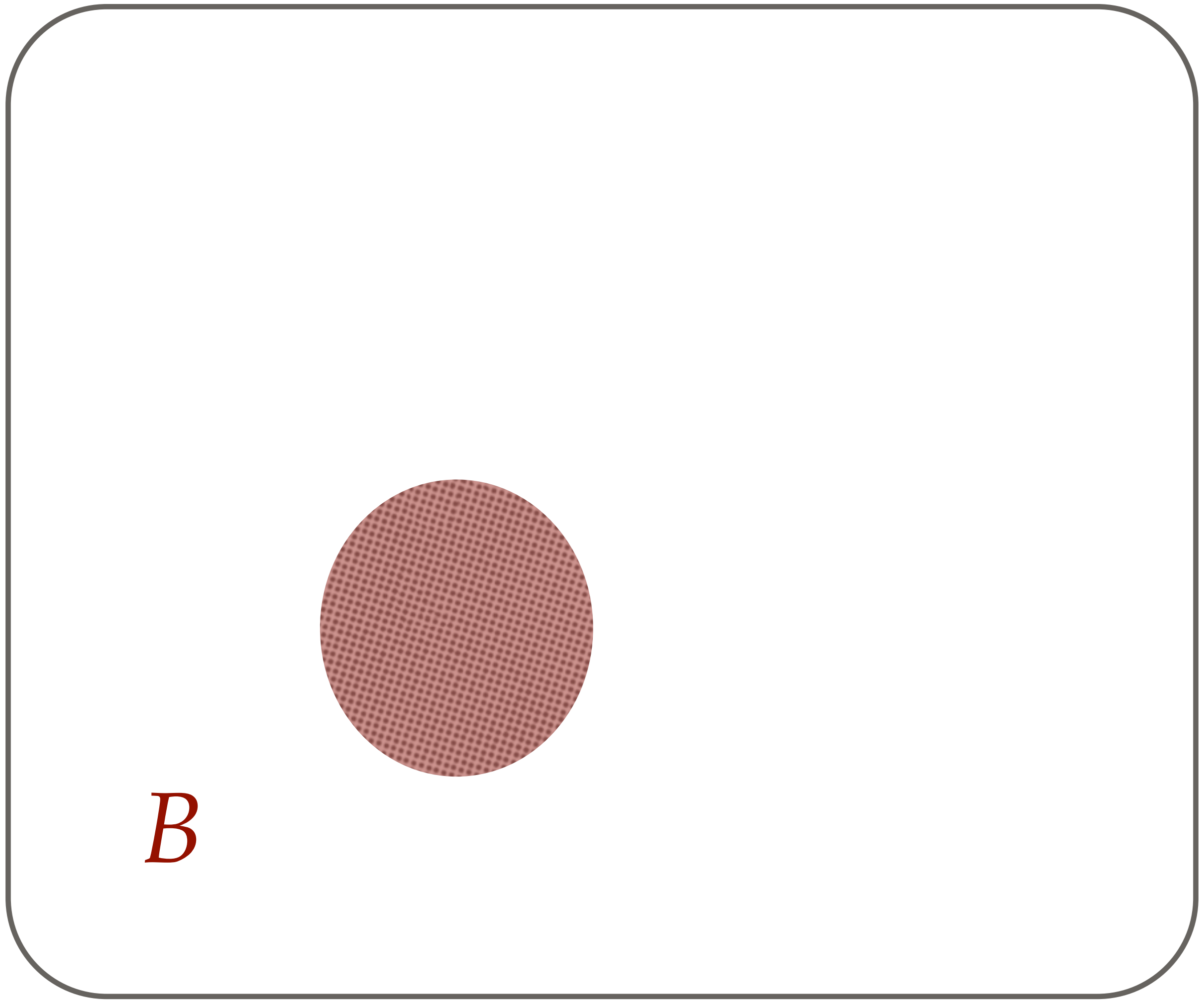
Probability as Area



$Pr(A)$

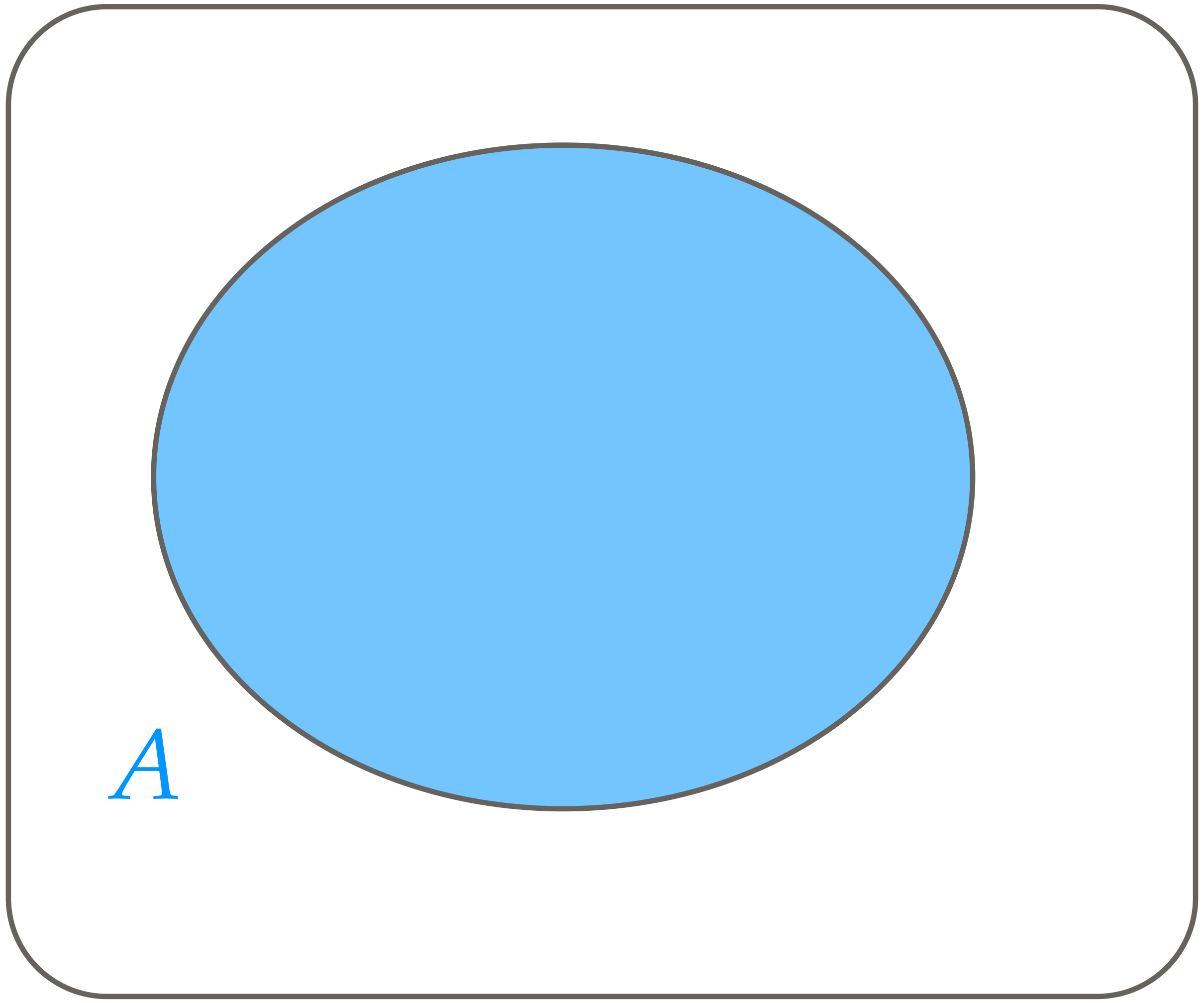
Probability as Area

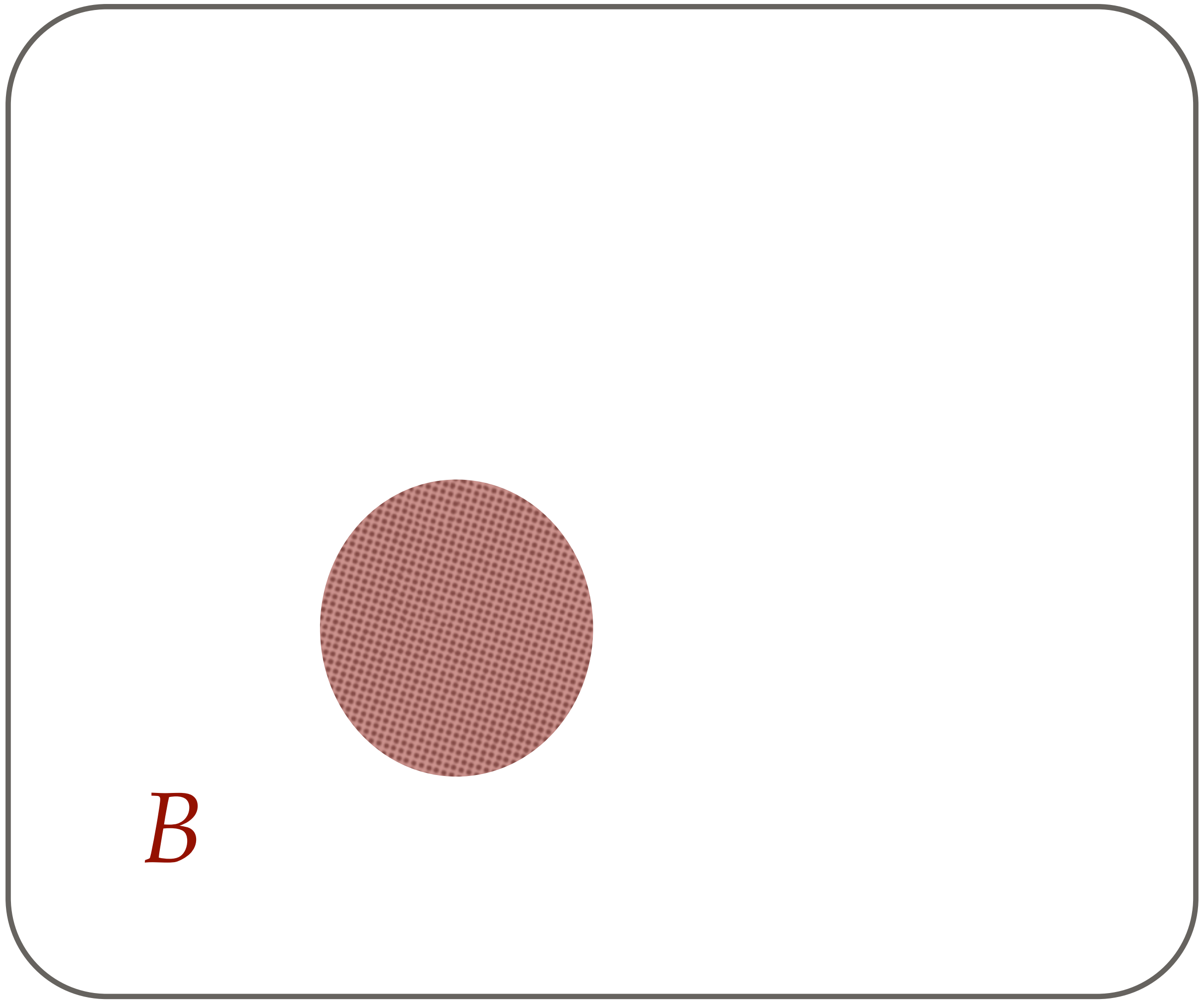




$Pr(A)$ $Pr(B)$

Probability as Area





$$Pr(A) > Pr(B)$$

(1) Conditional Probability

Pr(B|A)= proportion of area A that is also B =

Pr(B & A) / Pr(A)

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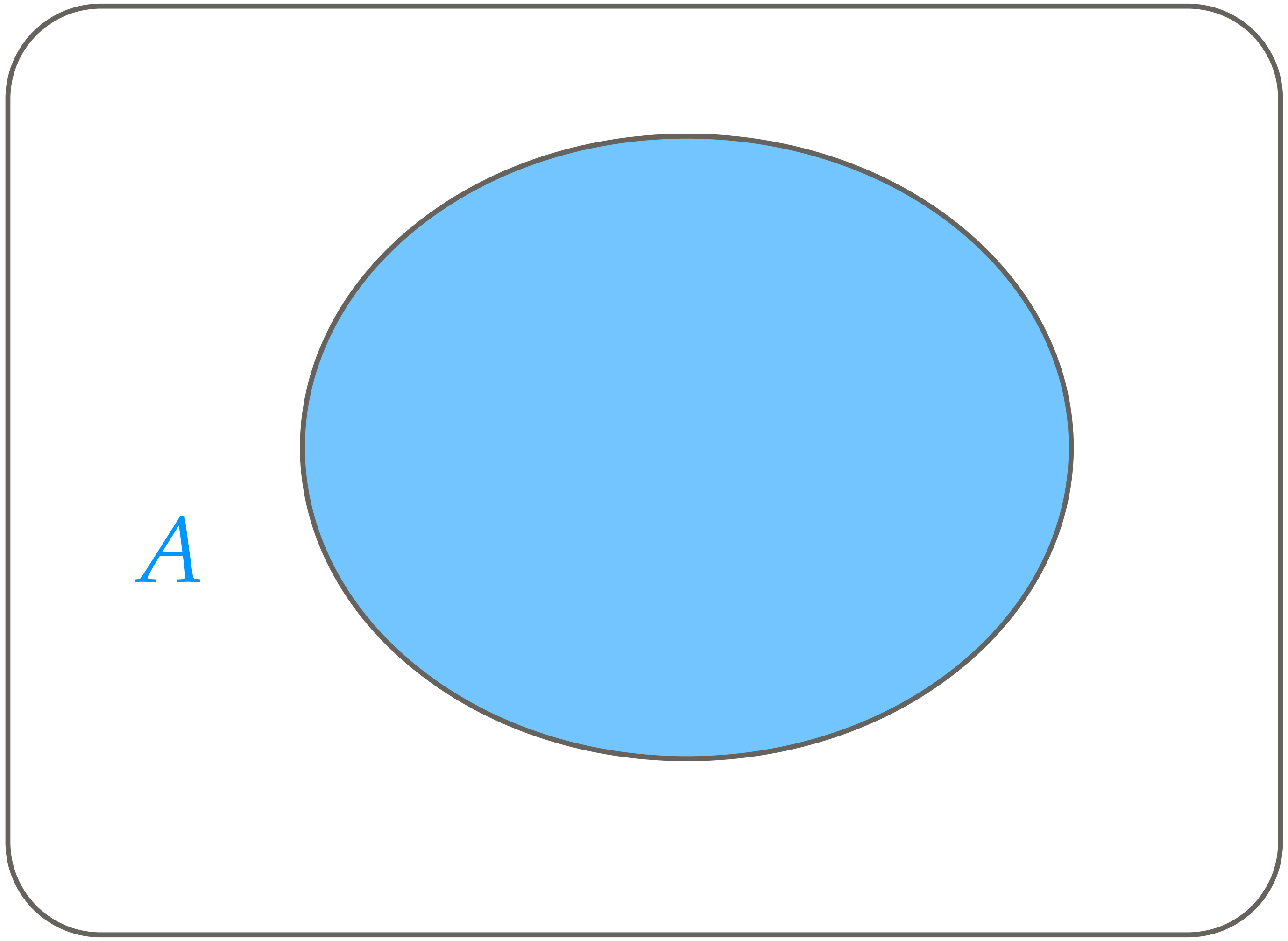
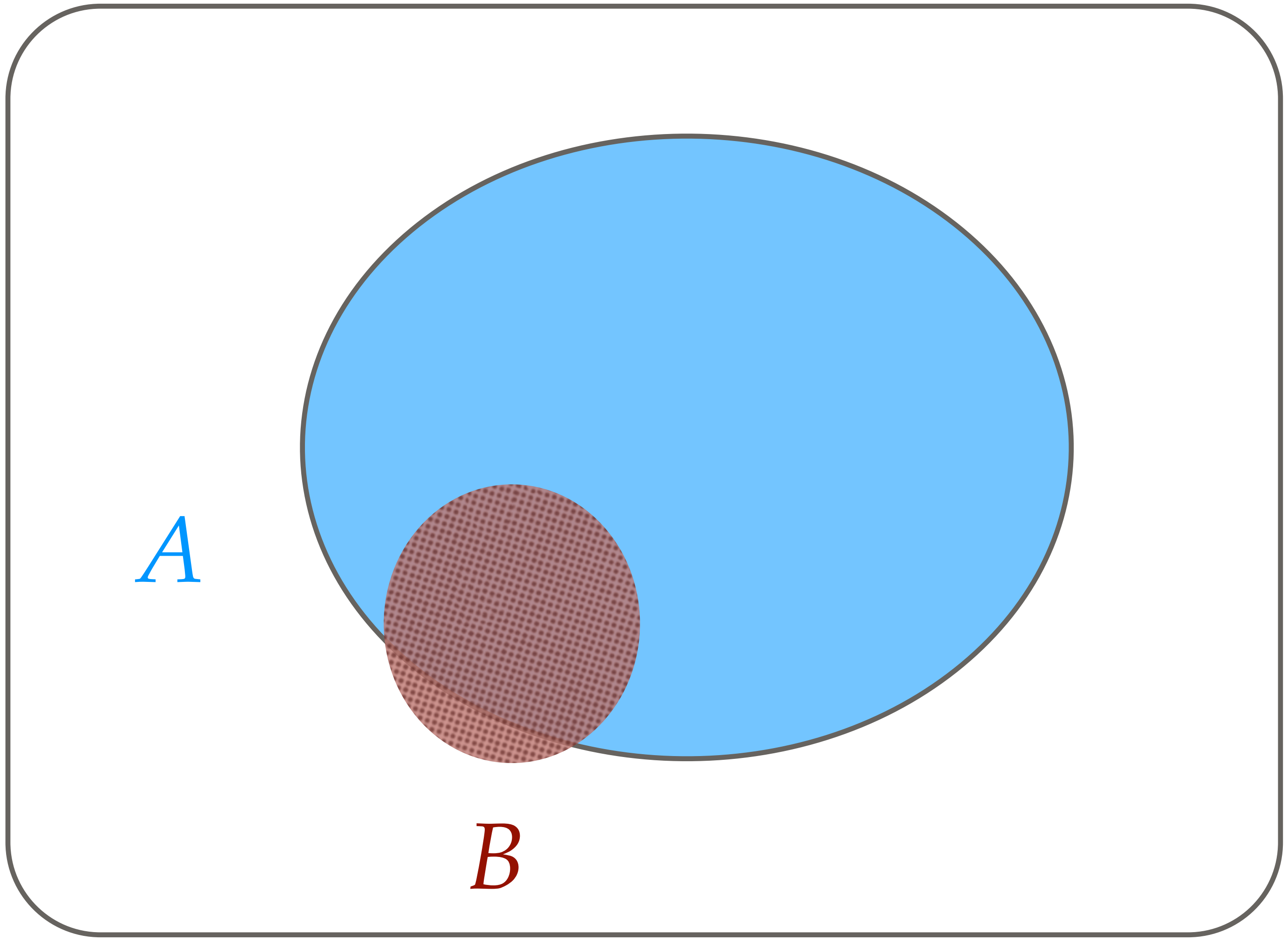


(1) Conditional Probability

Pr(B|A)= *proportion of area A that is also B =*

Pr(B & A) / Pr(A)



(2) Conditional Probability

$Pr(A|B)$= proportion of area B that is also A =

$Pr(A \,\&\, B) \,/\, Pr(B)$

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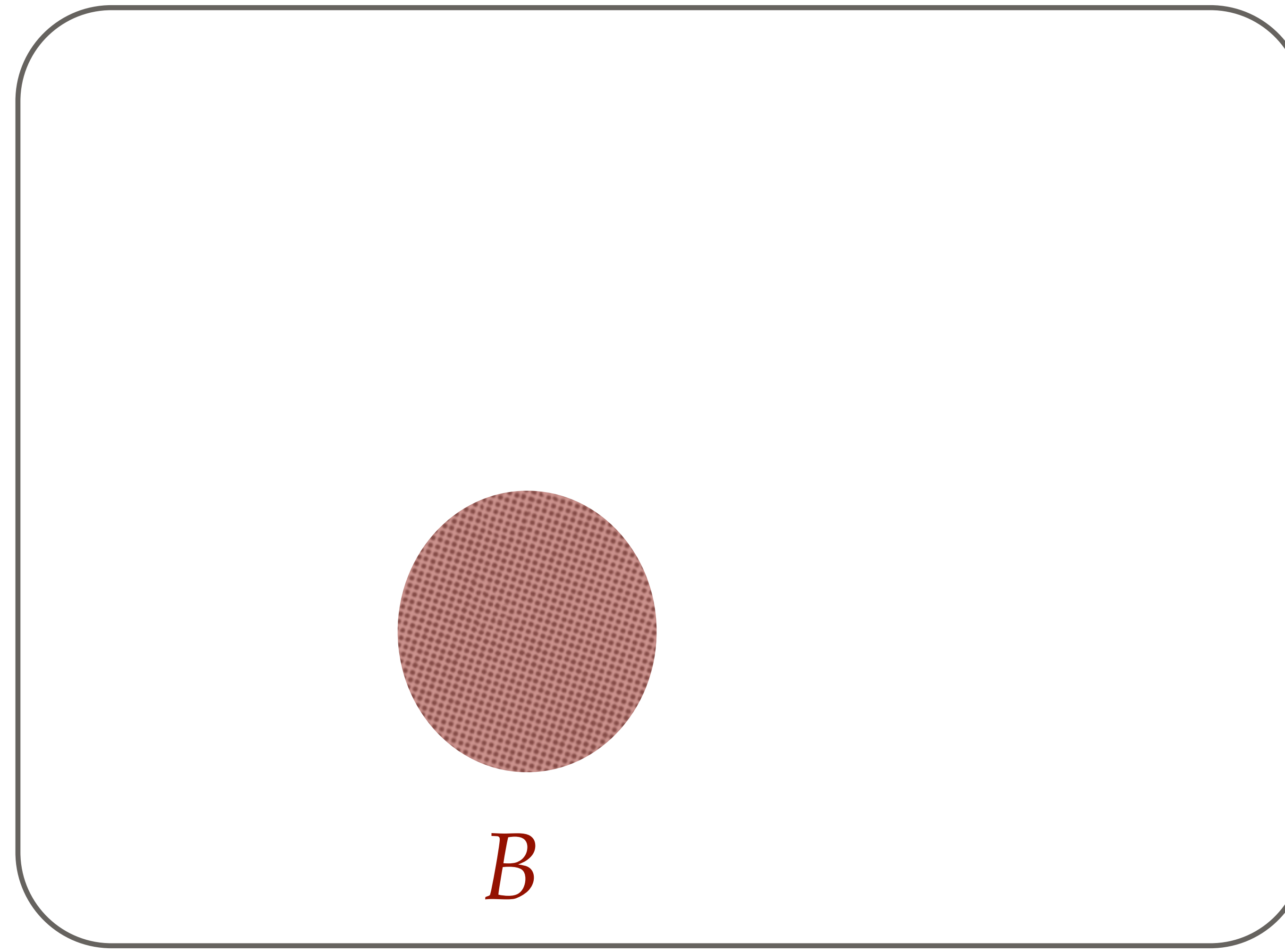

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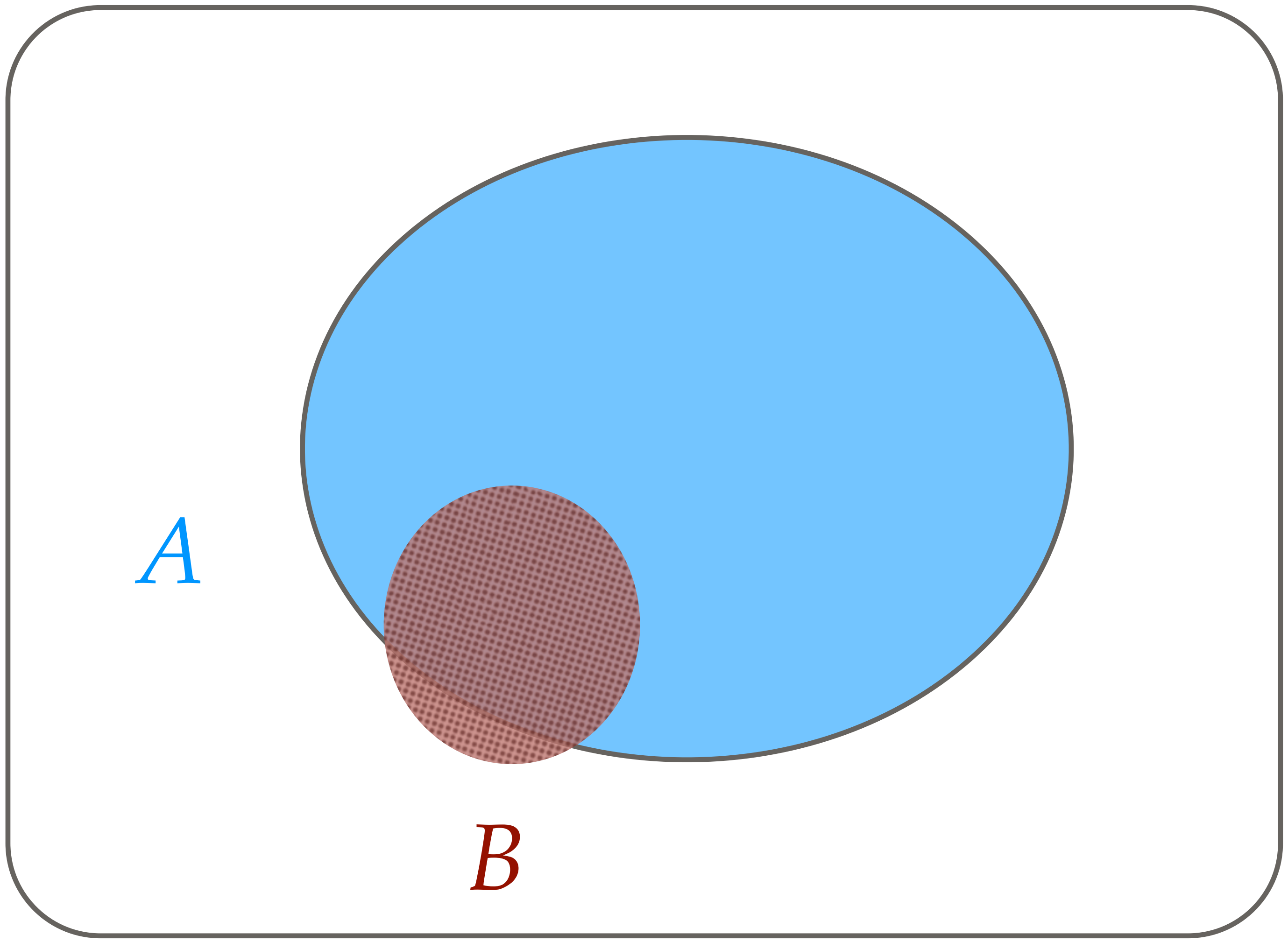
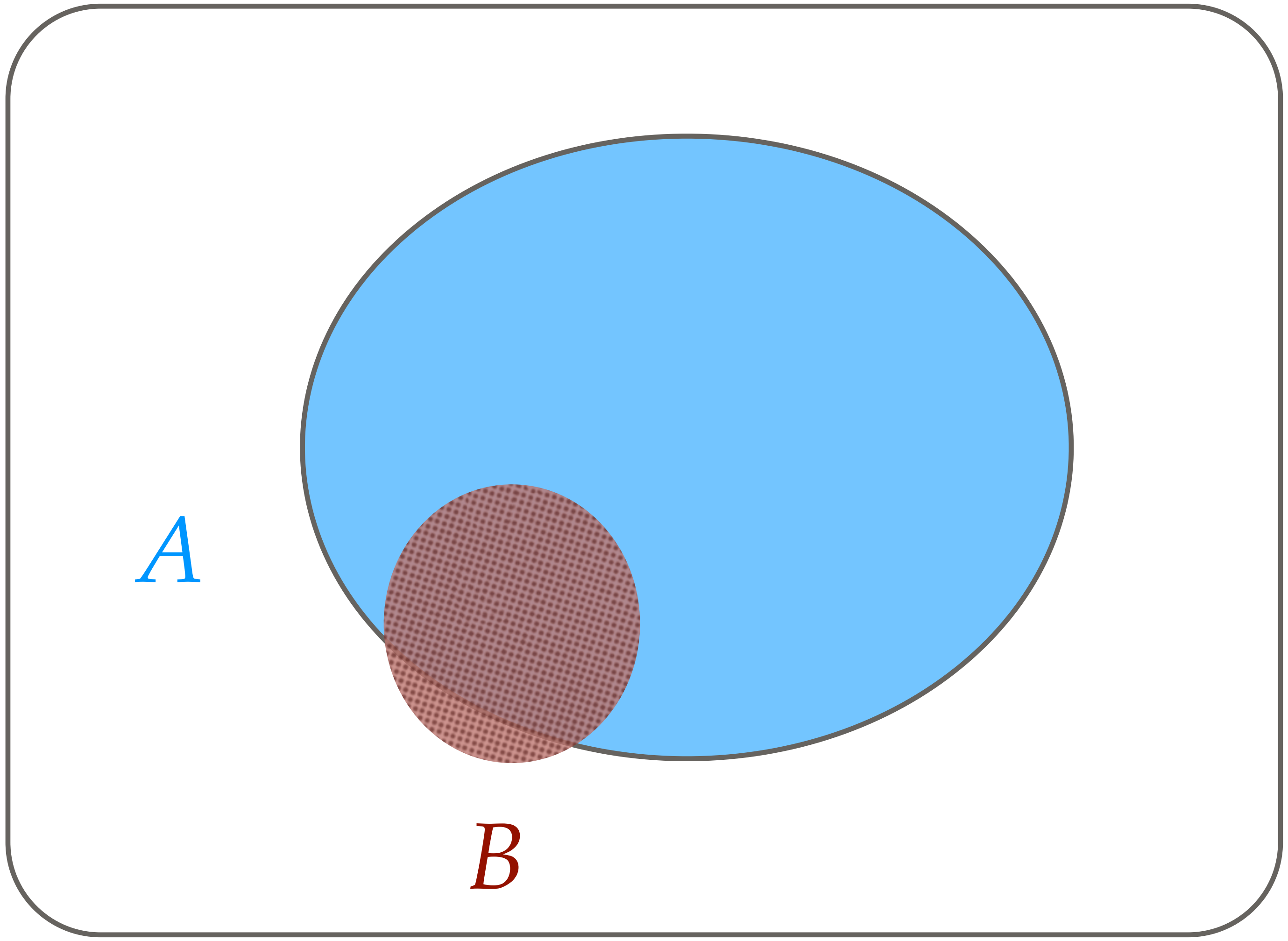


A Difference to Keep in Mind

$Pr(B|A)$

versus

$Pr(A|B)$



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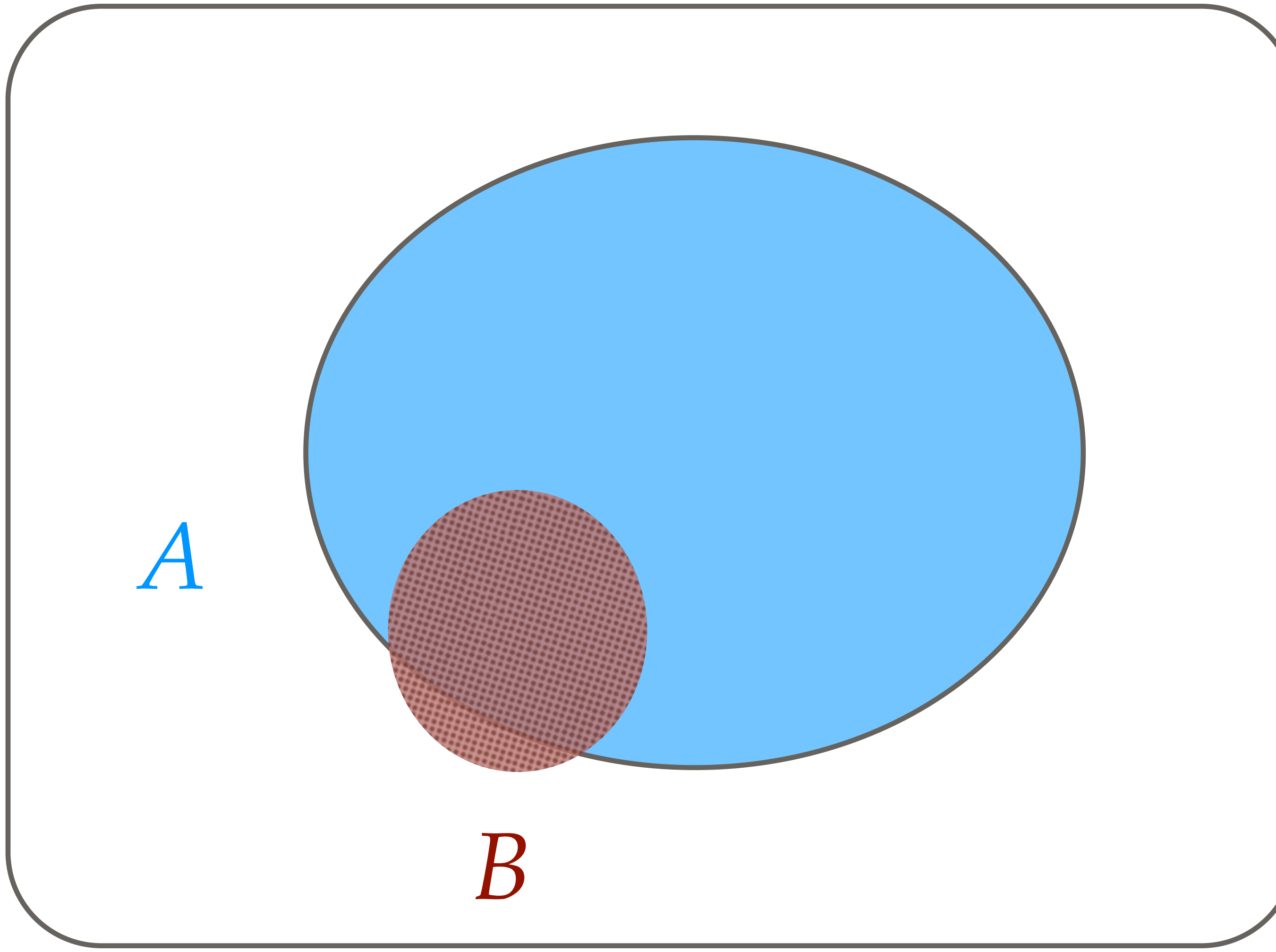

$Pr(A|B)$ can be **HIGH**

A Difference to Keep in Mind

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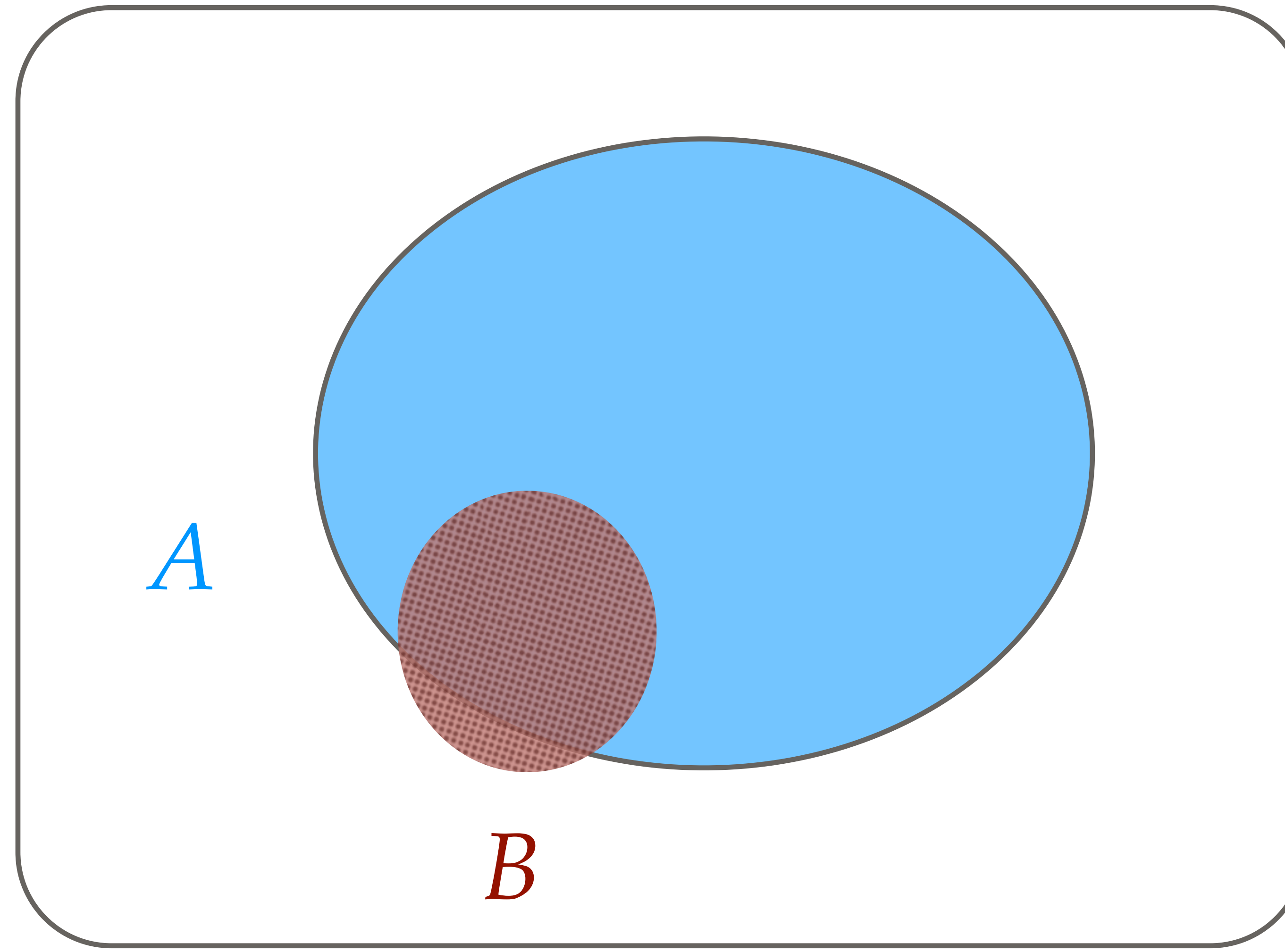
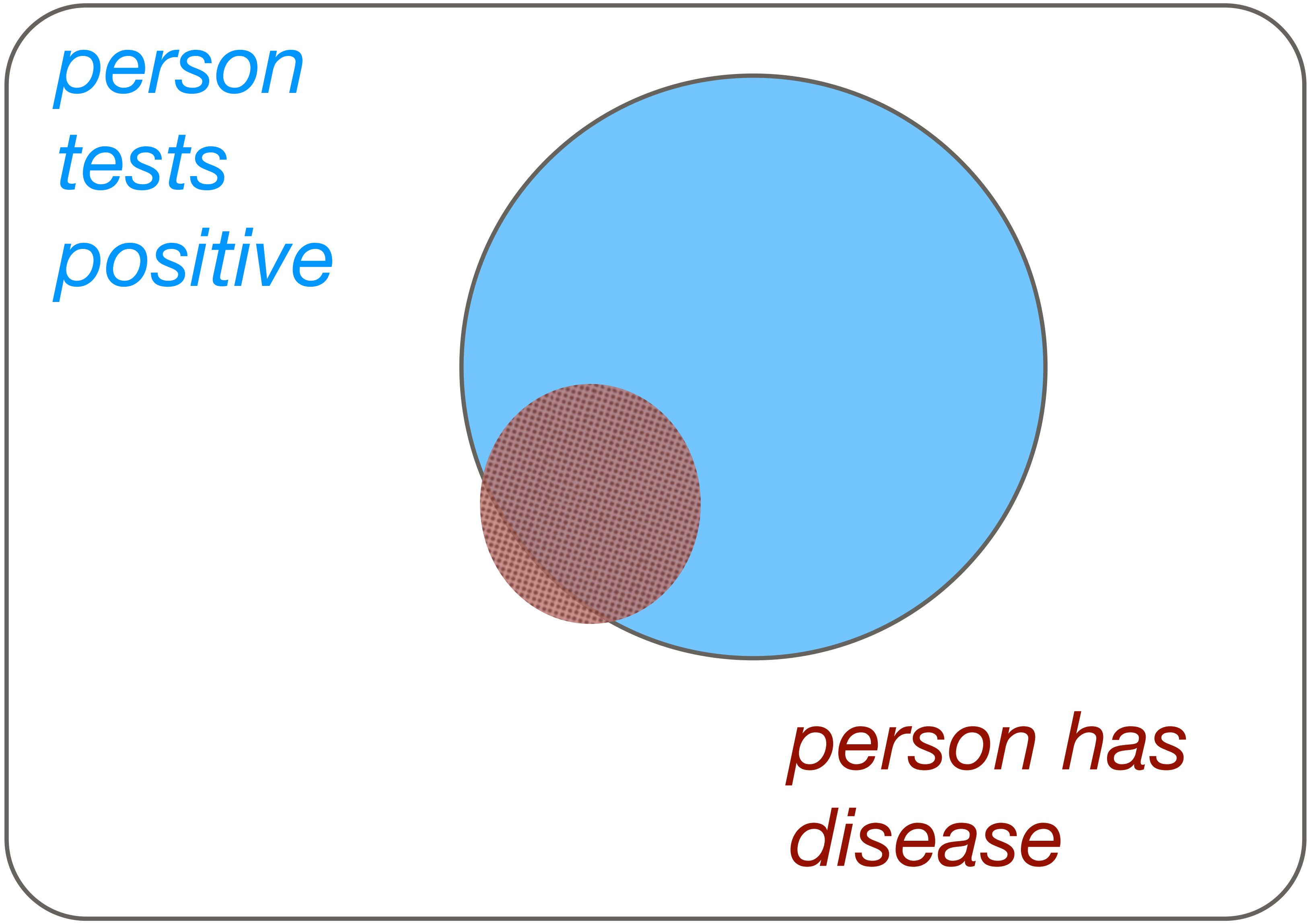


$Pr(A|B)$ can be **HIGH**

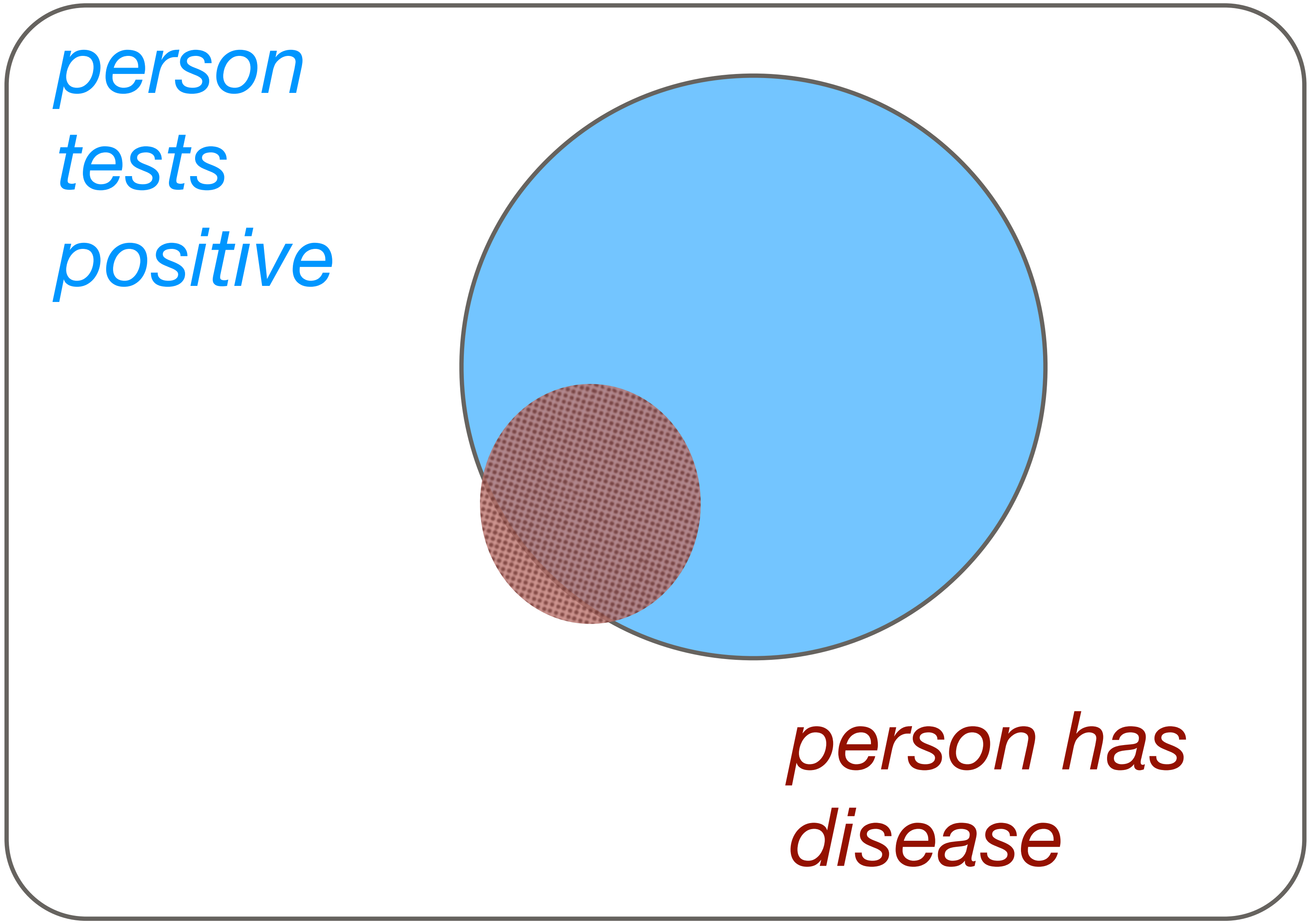
$Pr(B|A)$ while is **LOW**

Example



Example

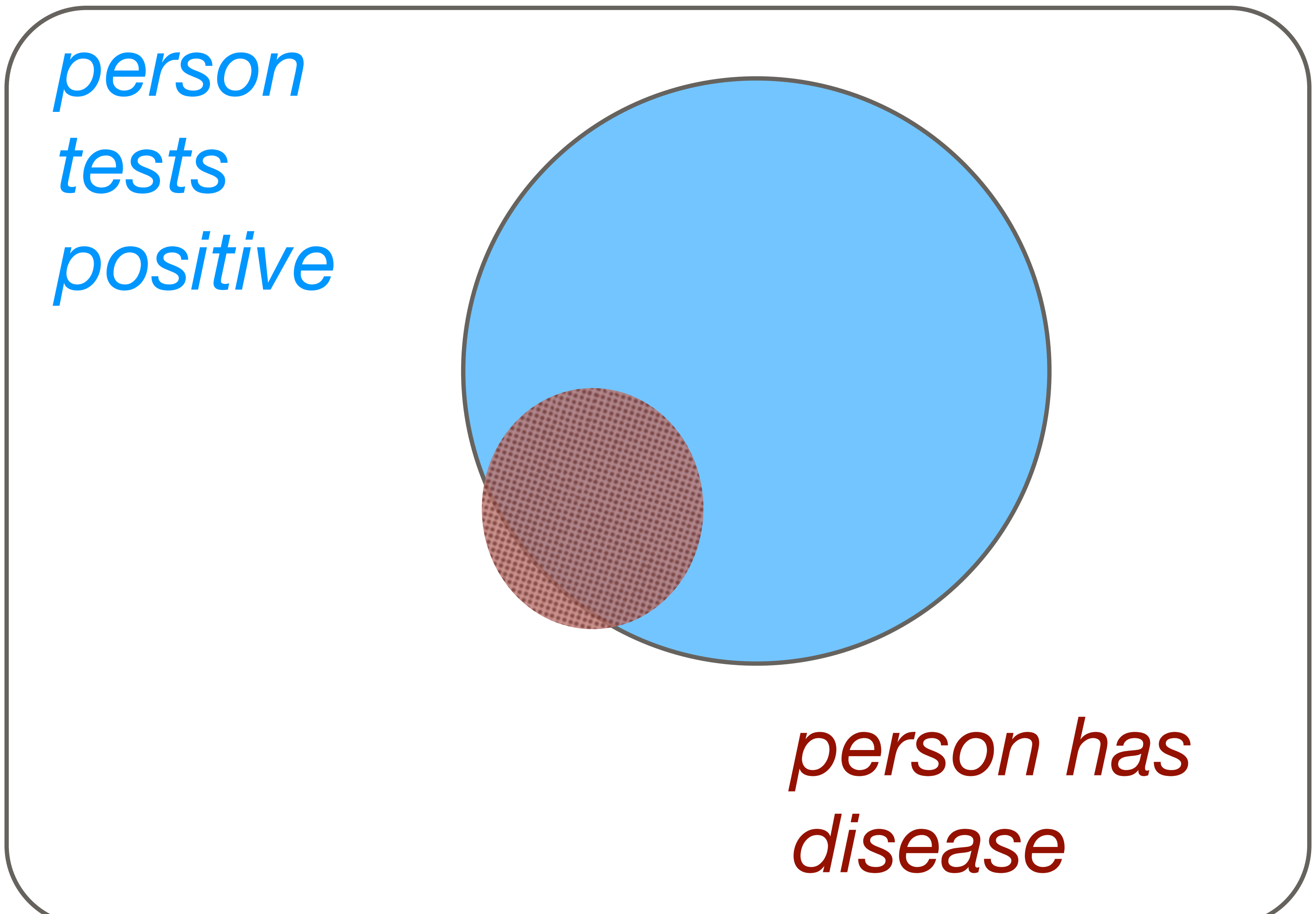
Pr(test positive|disease) is **HIGH**

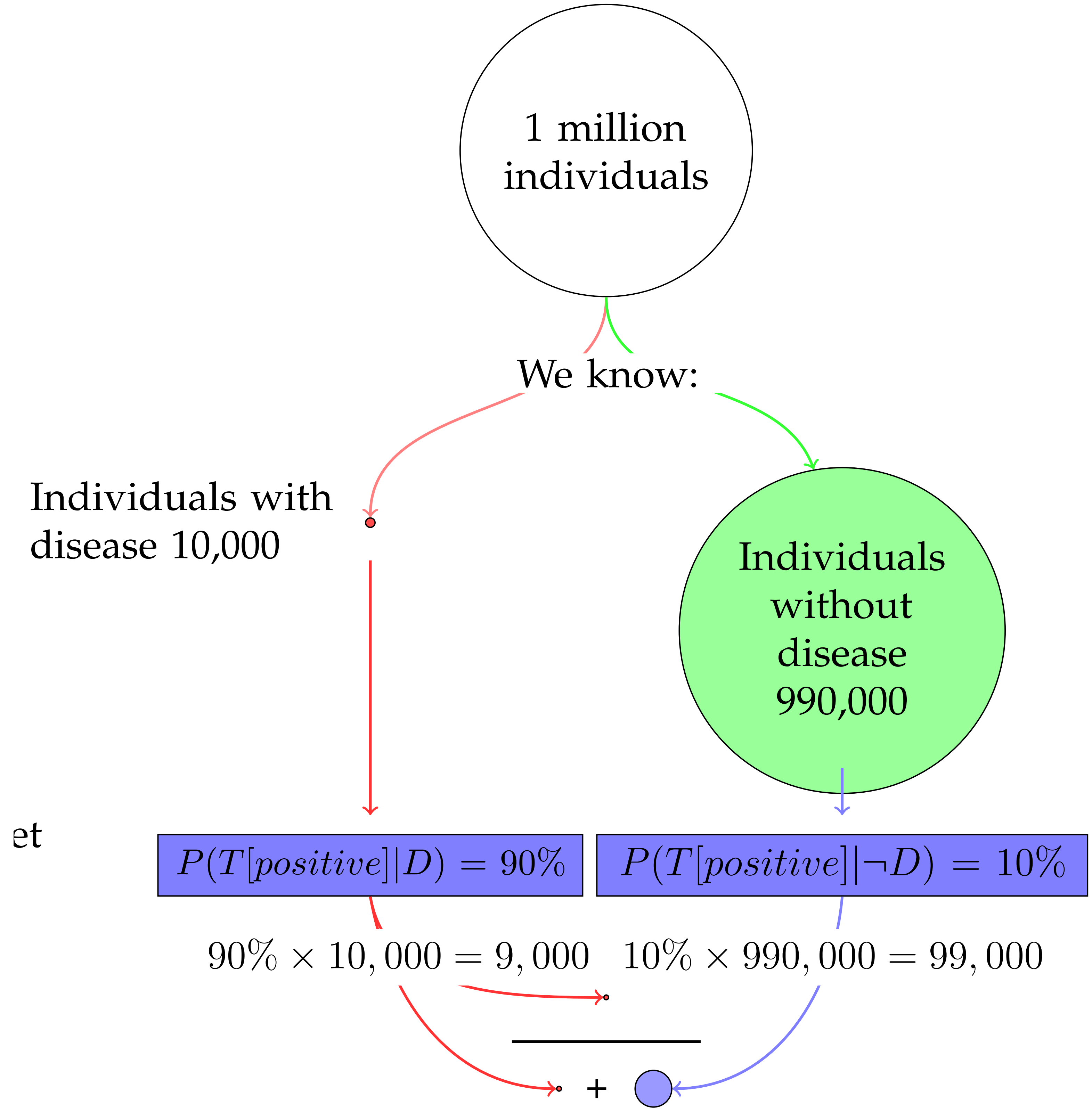


Example

Pr(*test positive*|*disease*) is **HIGH**

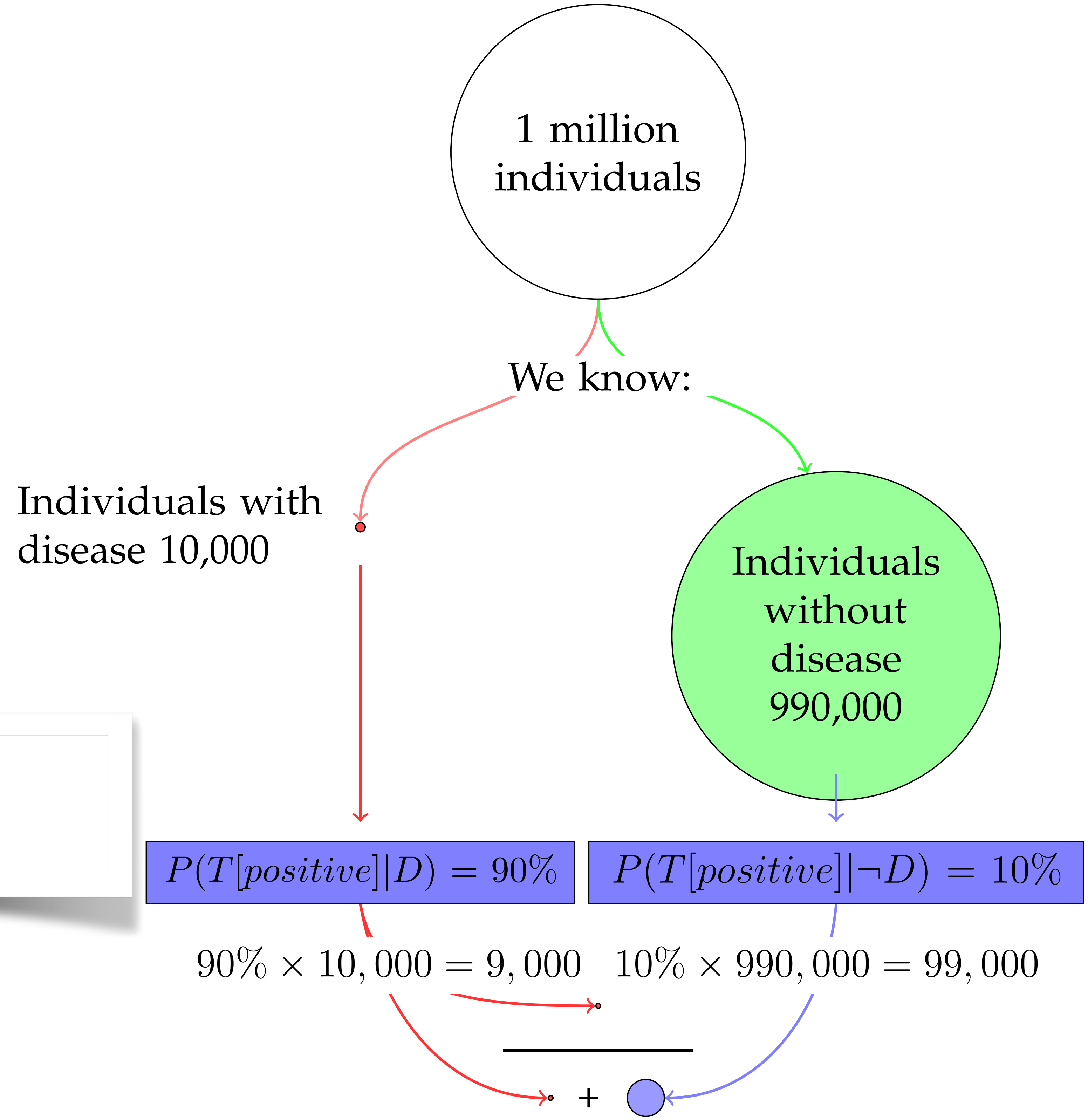
Pr(*disease*|*test positive*) is **LOW**





$$\frac{9,000}{9,000 + 99,000} \approx 8.3\%$$

Pr(test positive|disease) = **90%**



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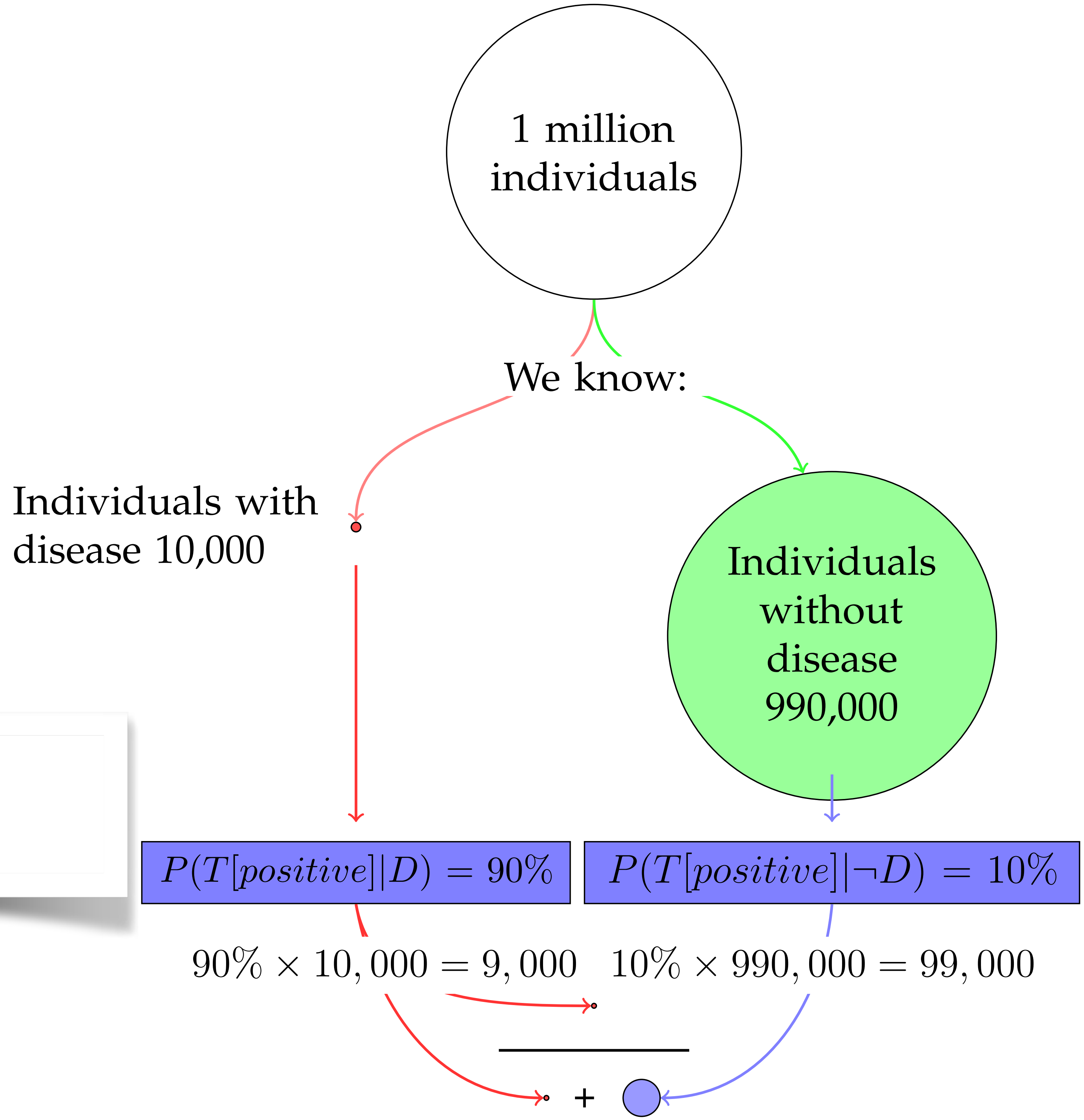


Pr(test positive|disease) = **90%**

Pr(disease|test positive) = **8.3%**

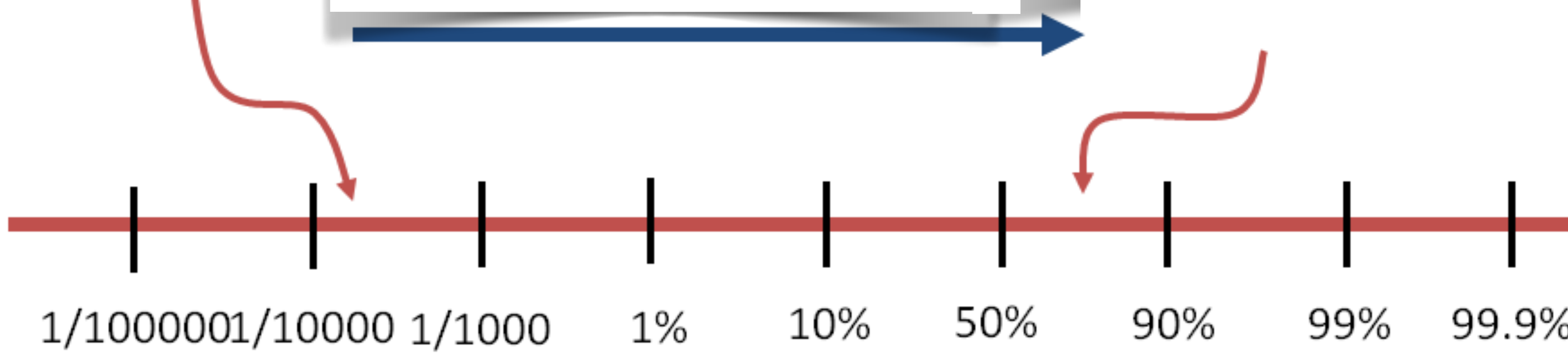
$$\frac{9,000}{9,000 + 99,000} \approx 8.3\%$$

Bayes' Theorem (graphical representation)

Prior *probability — i.e. Pr(disease)*

Strength *of evidence — depends on Pr(test positive|disease) and Pr(test positive|not-disease)*

Posterior *probability — i.e. Pr(disease|test positive)*



Prior x Strength of evidence = Posterior

Bayes’ Theorem

Upshot: even if the test is good, the posterior probability of having the disease given a positive test result, could still be low if the priors are low

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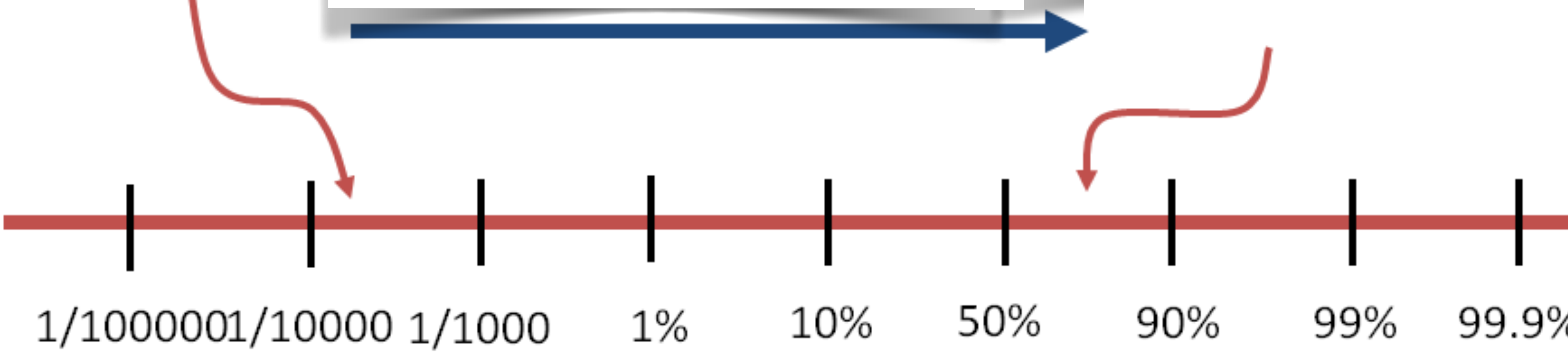

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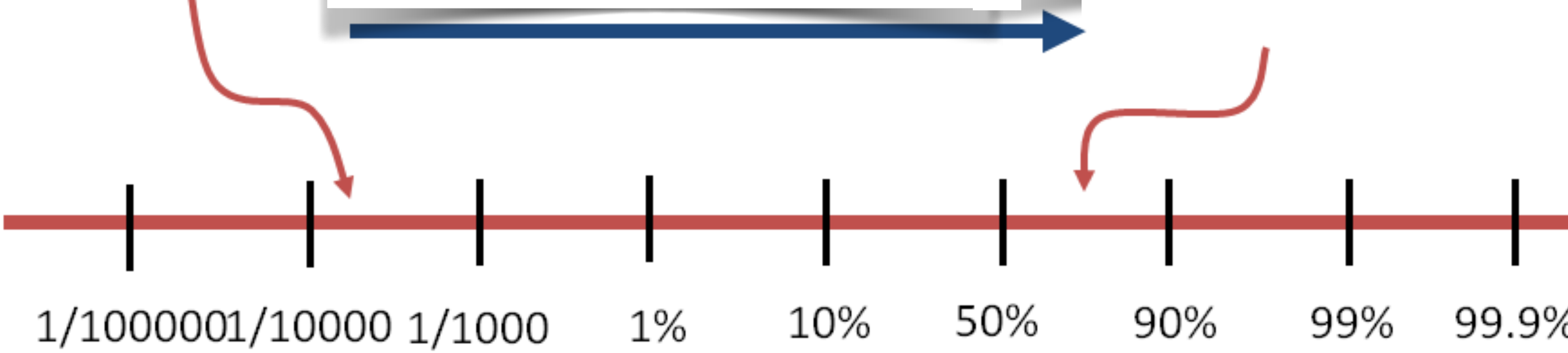

Prior x Strength of evidence = Posterior

Back to Bayesian Networks

Examples of Bayesian Networks for Assessing DNA Evidence and Eyewitness Evidence

Example 1: DNA Match Evidence (M) Source Hypothesis (S)

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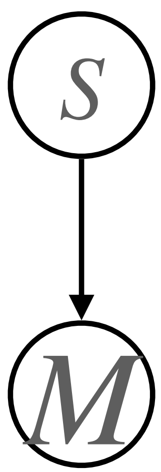
Graph



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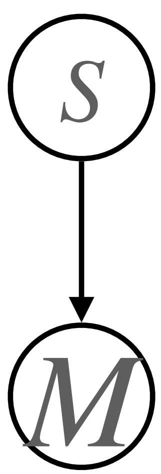


Probabilities

$P(S = yes) =$ prior

$P_0(M = yes \,|\, S = yes) = 1$
$P(M = yes \,|\, S = no) = RMP$

Random Match Probability

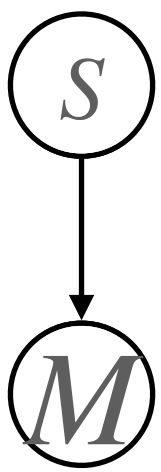
Probability Tables

S=yes	Prior
S=no	1-prior

	S=yes	**S=no**
M=yes	100%	RMP
M=no	0%	1-RMP

Example 1: DNA Match Evidence (M) Source Hypothesis (S)

Graph



Probabilities

$P(S = yes)$ = prior

$P_0(M = yes \mid S = yes) = 1$

$P(M = yes \mid S = no) = RMP$

Random Match Probability

Probability Tables

S=yes	Prior
S=no	1-prior

	S=yes	**S=no**
M=yes	100%	RMP
M=no	0%	1-RMP

Bayes' theorem needed to calculate P(S = yes | M = yes), as follows:

$$P_0(S = yes \mid M = yes) = \frac{P(M = yes \mid S = yes)}{P(M = yes)} P(S = yes)$$

$$= \frac{P(M = yes \mid S = yes)}{P(M = yes \mid S = yes)P(S = yes) + P(M = yes \mid S = no)P(S = no)} P(S = yes)$$

Aside
How Are Random Match Probabilities Calculated?

See Charles H. Brenner's "Forensic mathematics of DNA matching" available at https://dna-view.com/profile.htm

DNA Profile		Allele frequency from database				Genotype frequency for locus	
Locus	Alleles	times allele observed	size of database	Frequency		formula	number
CSF1PO	10	109	432	$p=$	0.25	$2pq$	0.16
	11	134		$q=$	0.31		
TPOX	8	229	432	$p=$	0.53	p^2	0.28
	8						
THO1	6	102	428	$p=$	0.24	$2pq$	0.07
	7	64		$q=$	0.15		
vWA	16	91	428	$p=$	0.21	p^2	0.05
	16						
						profile frequency=	**0.00014**

Example 2: DNA Match + Test Reliability

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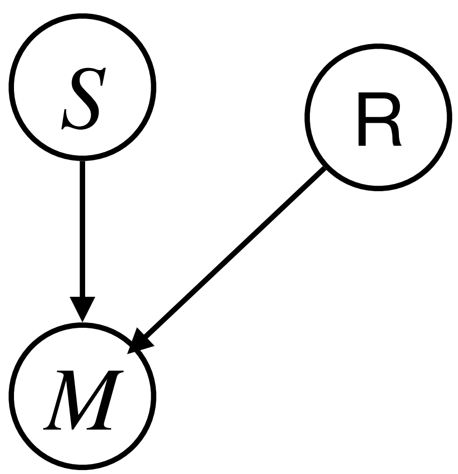
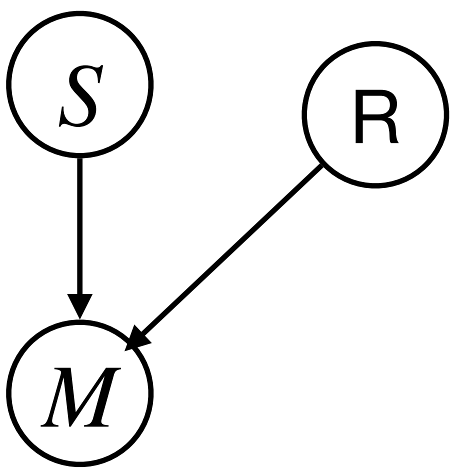
$\boxed{\text{Graph}}$



Example 2: DNA Match + Test Reliability

Graph

Probabilities



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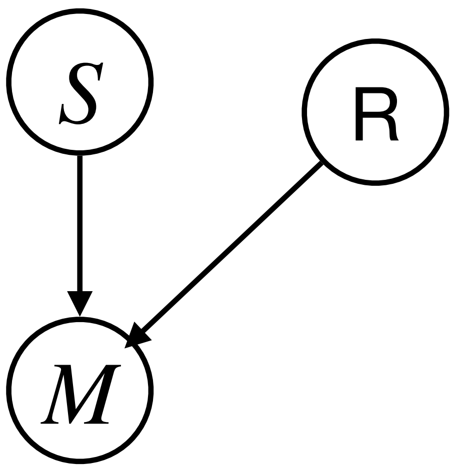
Example 2: DNA Match + Test Reliability

Graph



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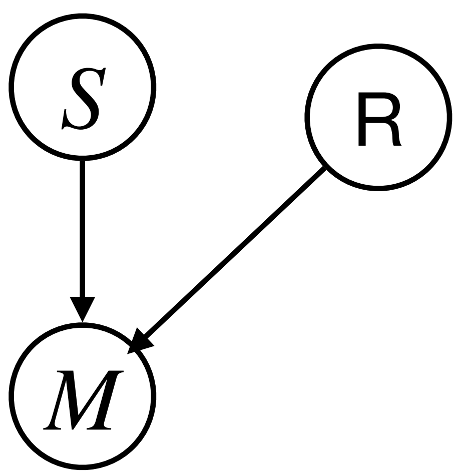

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$$P_0(M = yes \,|\, S = yes \;\&\; R = yes) = 1$$

$$P(M = yes \,|\, S = no \;\&\; R = yes) = RMP$$

Random Match Probability

$$P_0(M = yes \,|\, S = yes \;\&\; R = no) = 0.5$$

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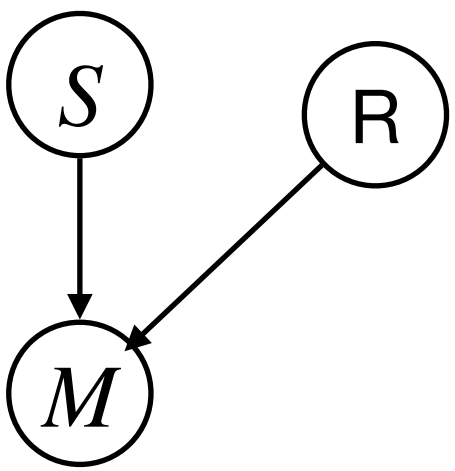

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M=yes	100%	RMP	50%	50%
M=no	0%	1-RMP	50%	50%

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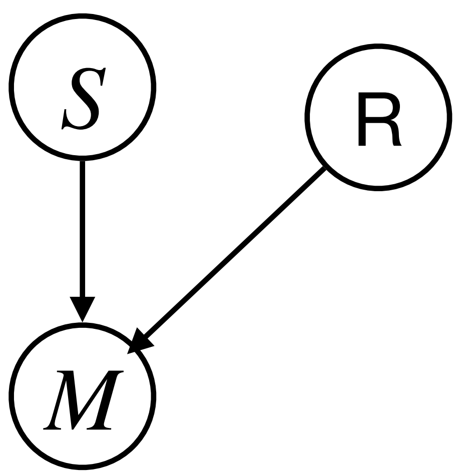

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Bayes' theorem needed to calculate P(S = yes | M = yes).
But manual calculations quickly become unmanageable!

Example 3: Eyewitness and Distance

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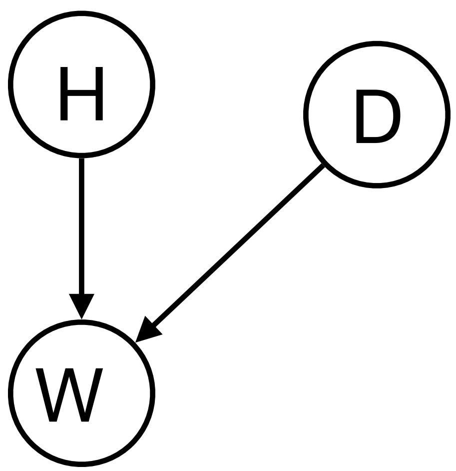
Graph



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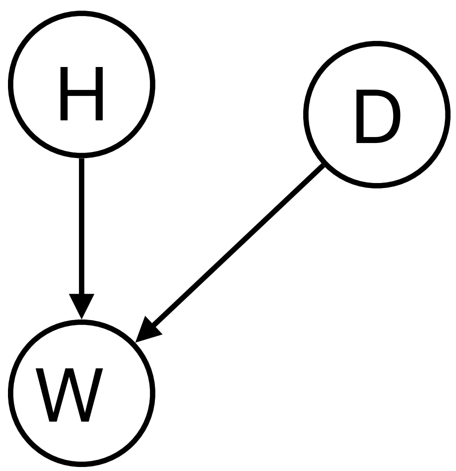

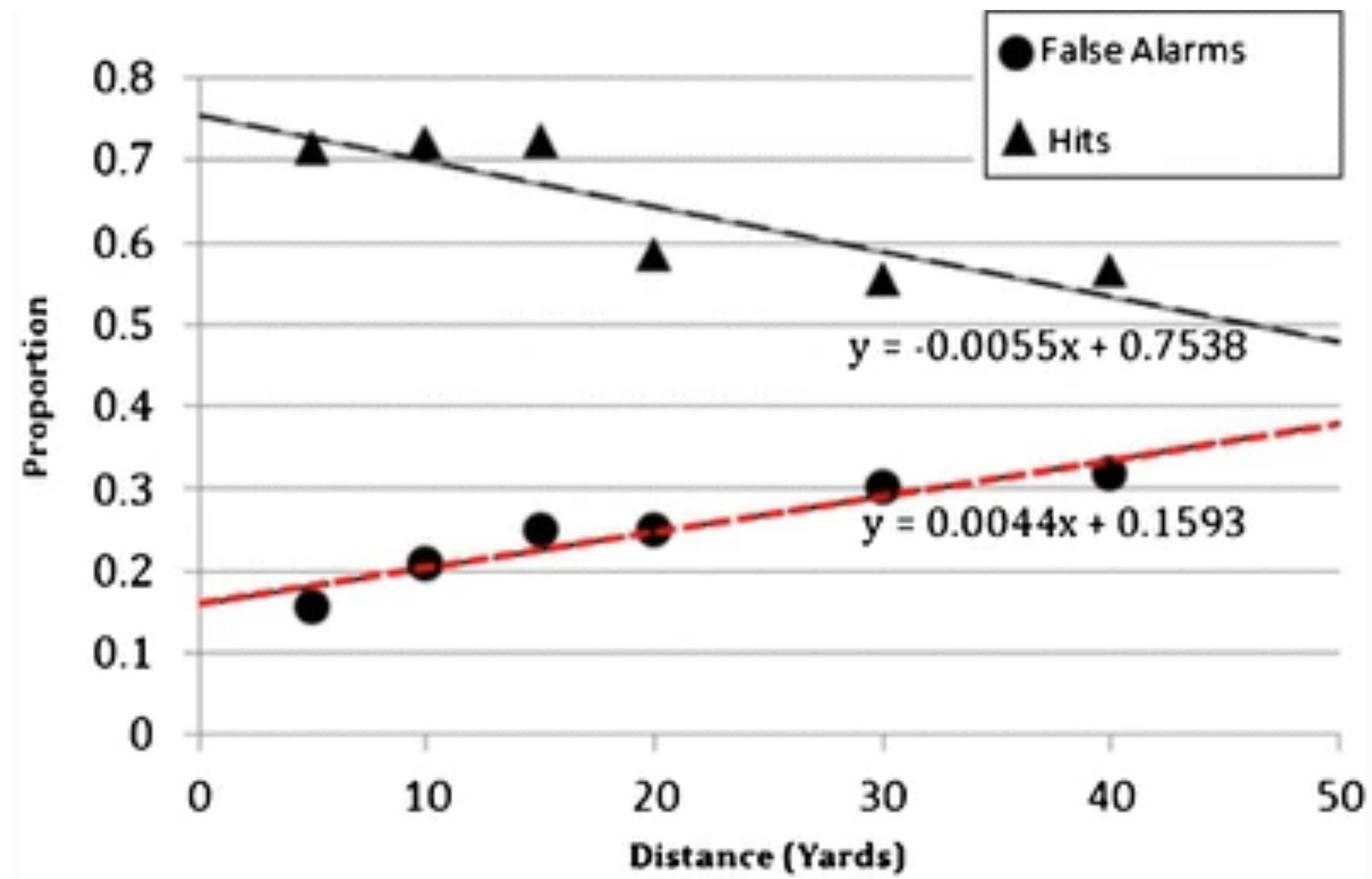

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Lampinen, James Michael, Erickson, William Blake, Moore, Kara N., & Hittson, Aaron (2014), “Effects of distance on face recognition: implications for eyewitness identification”, *Psychonomic Bulletin & Review*, 21.

Bayesian Networks Summary

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(2) **Numerical:** The *strength of these relationships is expressed numerically with probabilities tables*

(3) **Reasoning**: *Able to calculate probabilities of hypotheses based on evidence using Bayes' theorem (or dedicated software)*

PART II
Group Exercise and Discussion

Consider this Stylized Legal Case

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What is the probability that Fred shot Chris?

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- Sketch how a **graph of a Bayesian network** (nodes and arrows) could look like. Is there only one possible graph or multiple graphs seem appropriate here?

- Fill in the **probability tables** with the right numbers. Do you have all the numbers you need or are some numbers missing?

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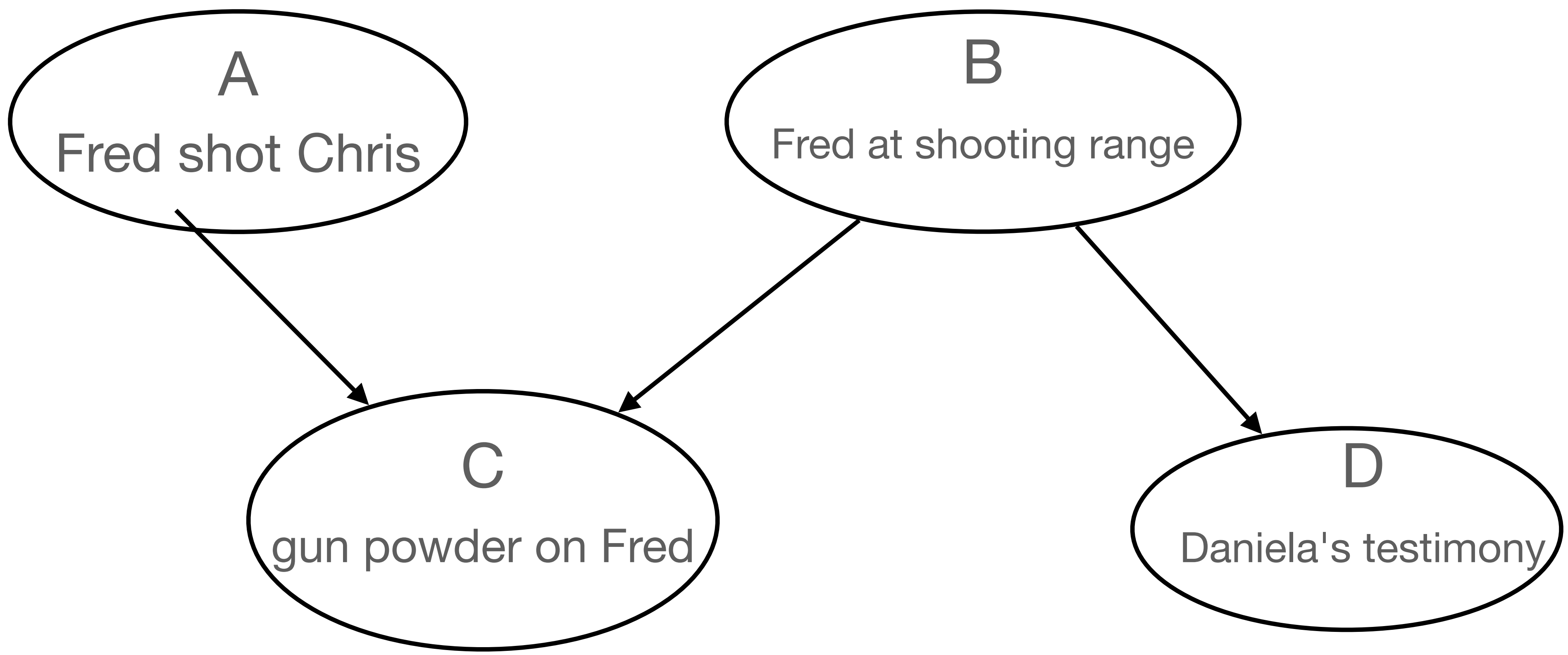
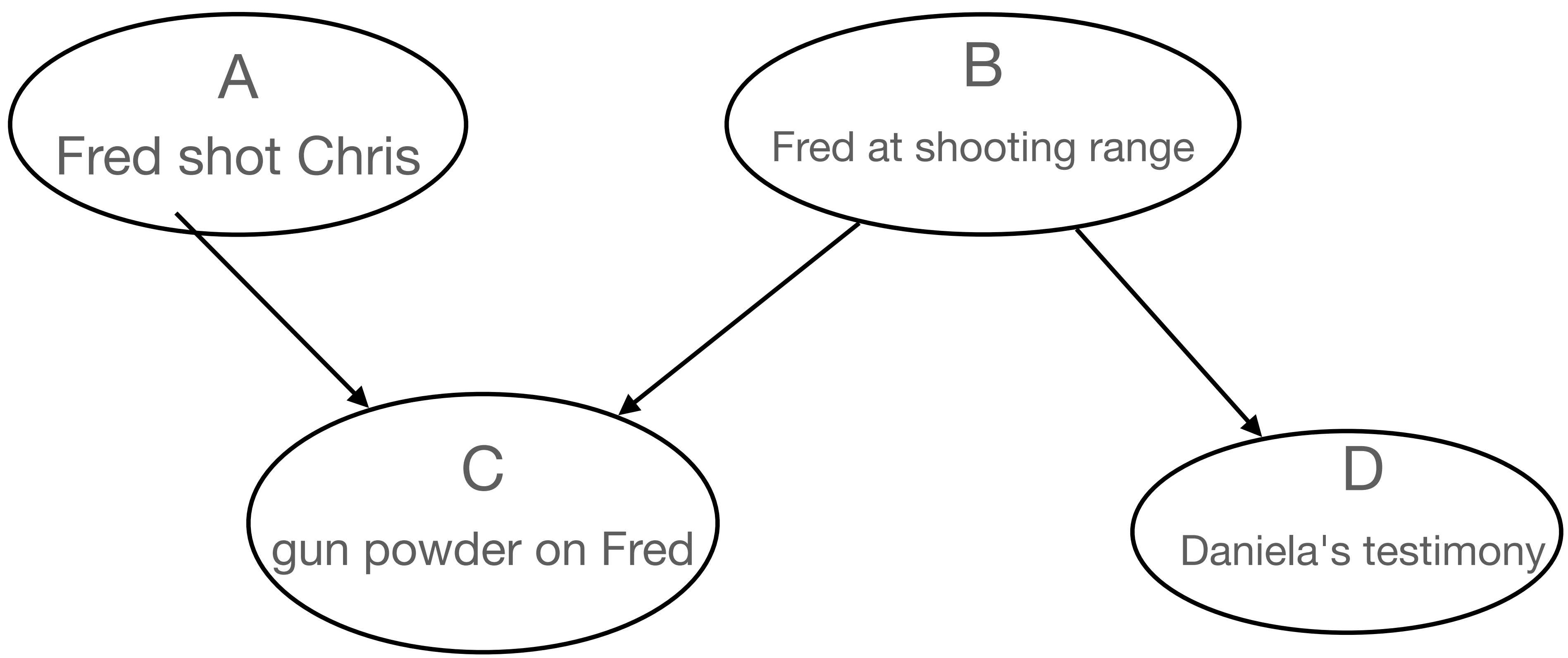
Daniela's testimony changes things. She is highly reliable (99%). If the hypothesis that Fred was at the shooting range that day is ruled out, the most likely explanation is that Fred did indeed shot Chris.

Bayesian Network Approach

Bayesian Network - Graph

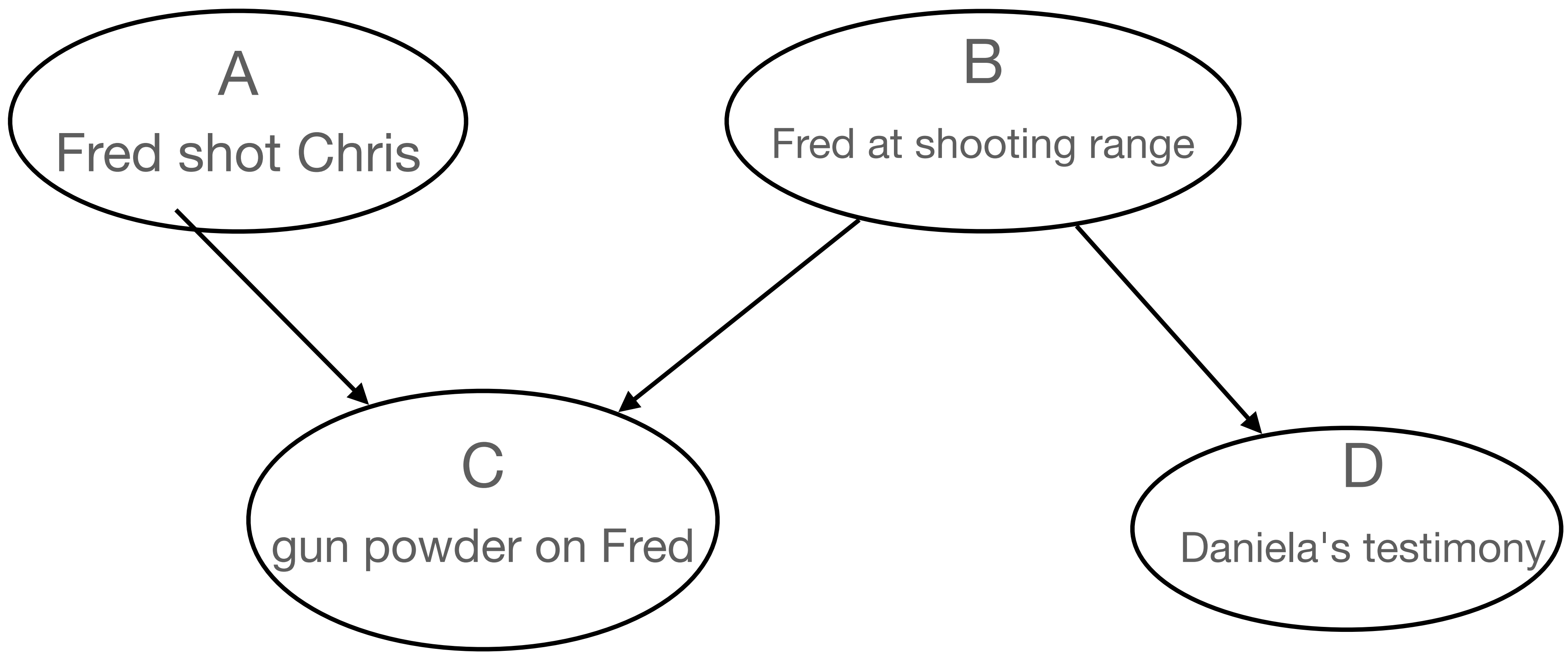


Bayesian Network - Probability Tables



Bayesian Network - Probability Tables

A=yes	1/100=1%
A=no	99%



Bayesian Network - Probability Tables

A=yes	1/100=1%
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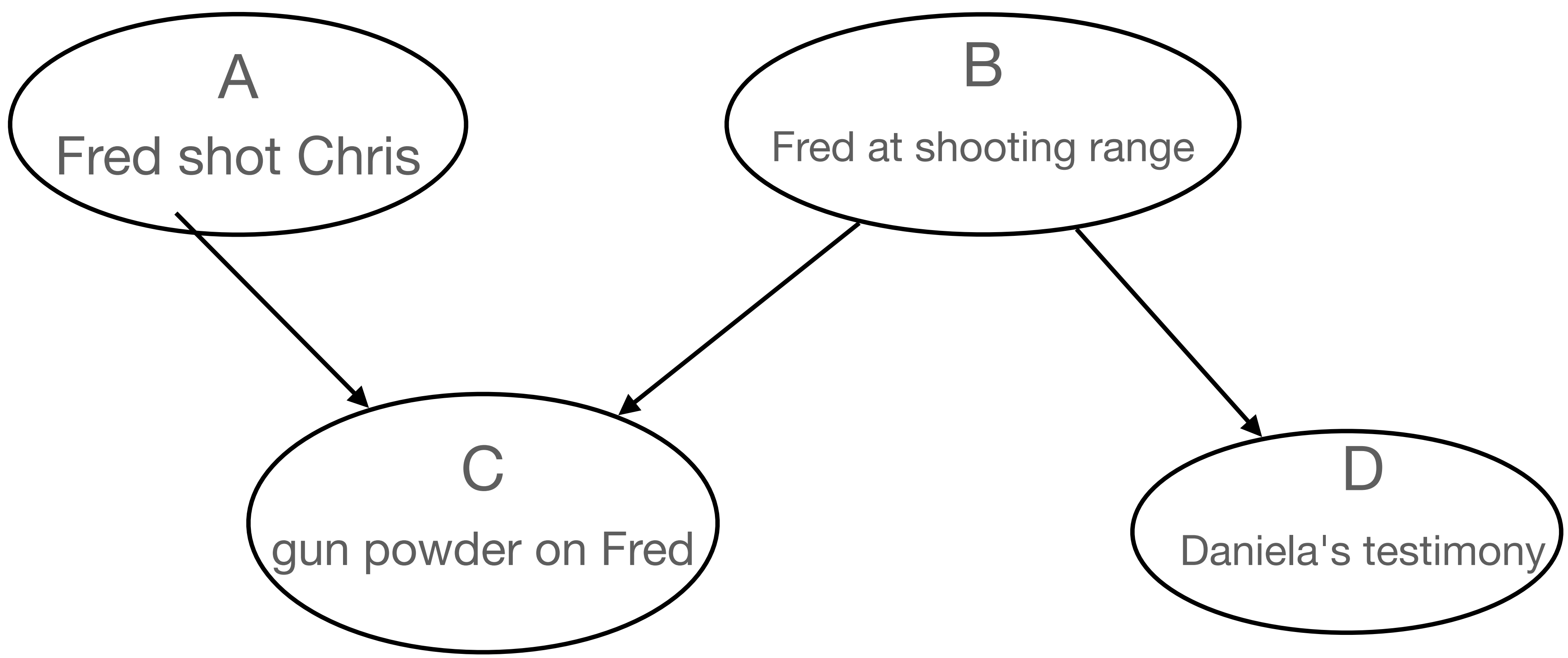
B=yes	4/7=57%
B=no	3/7=43%



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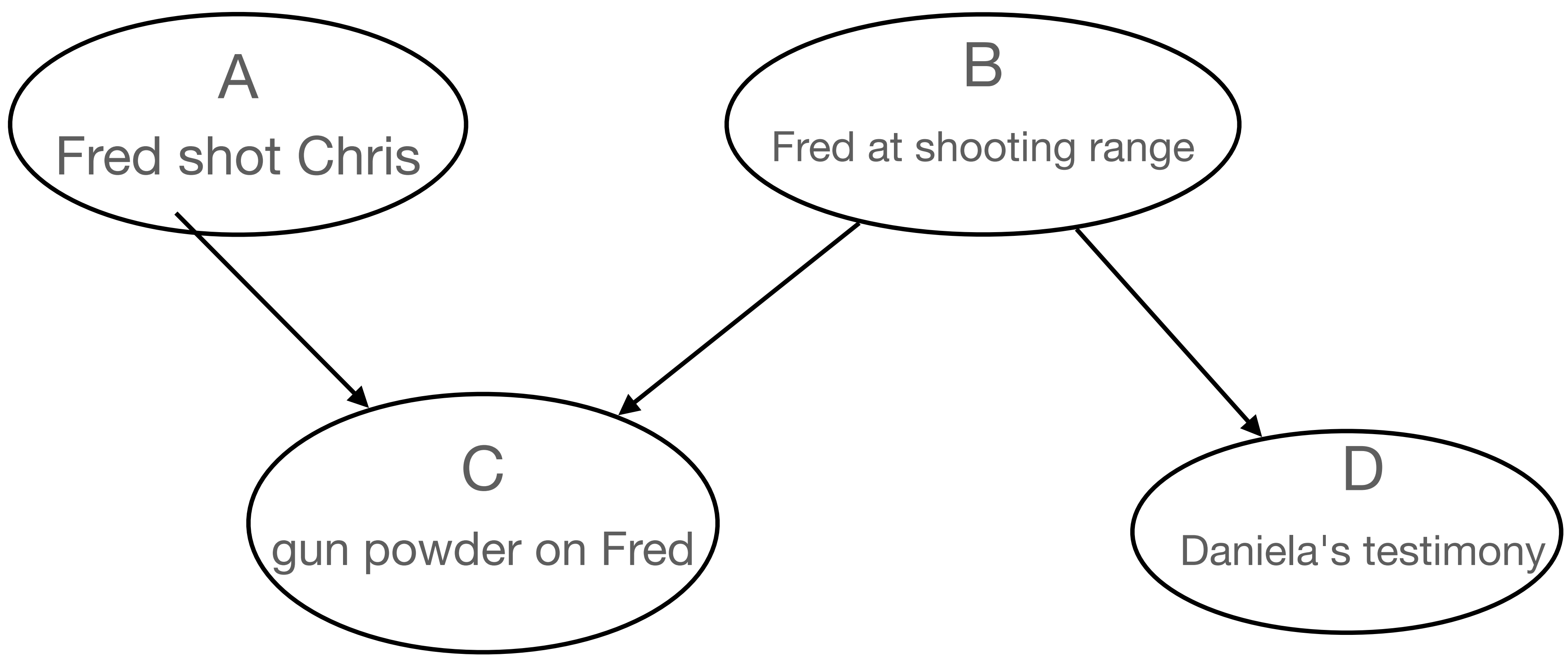

	B=yes	**B=no**
D=yes	99%	1%
D=no	1%	99%

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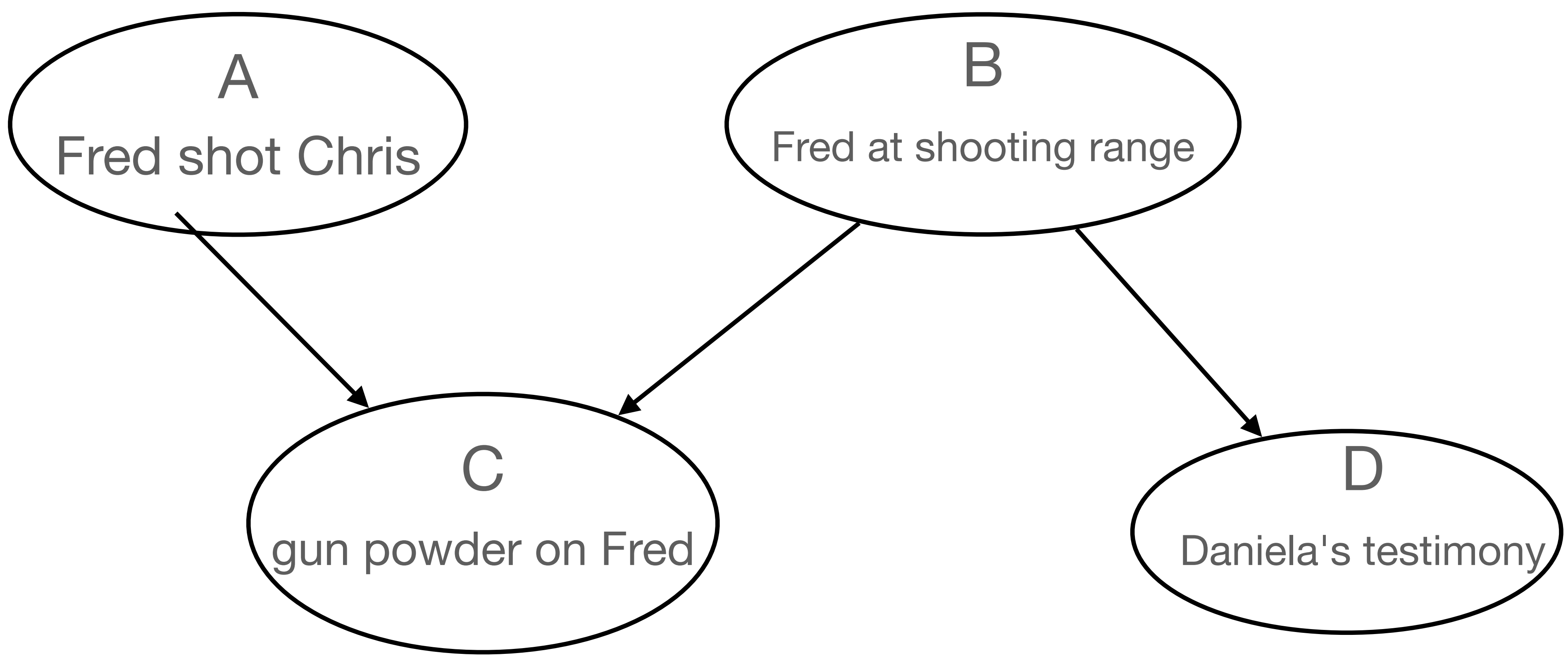
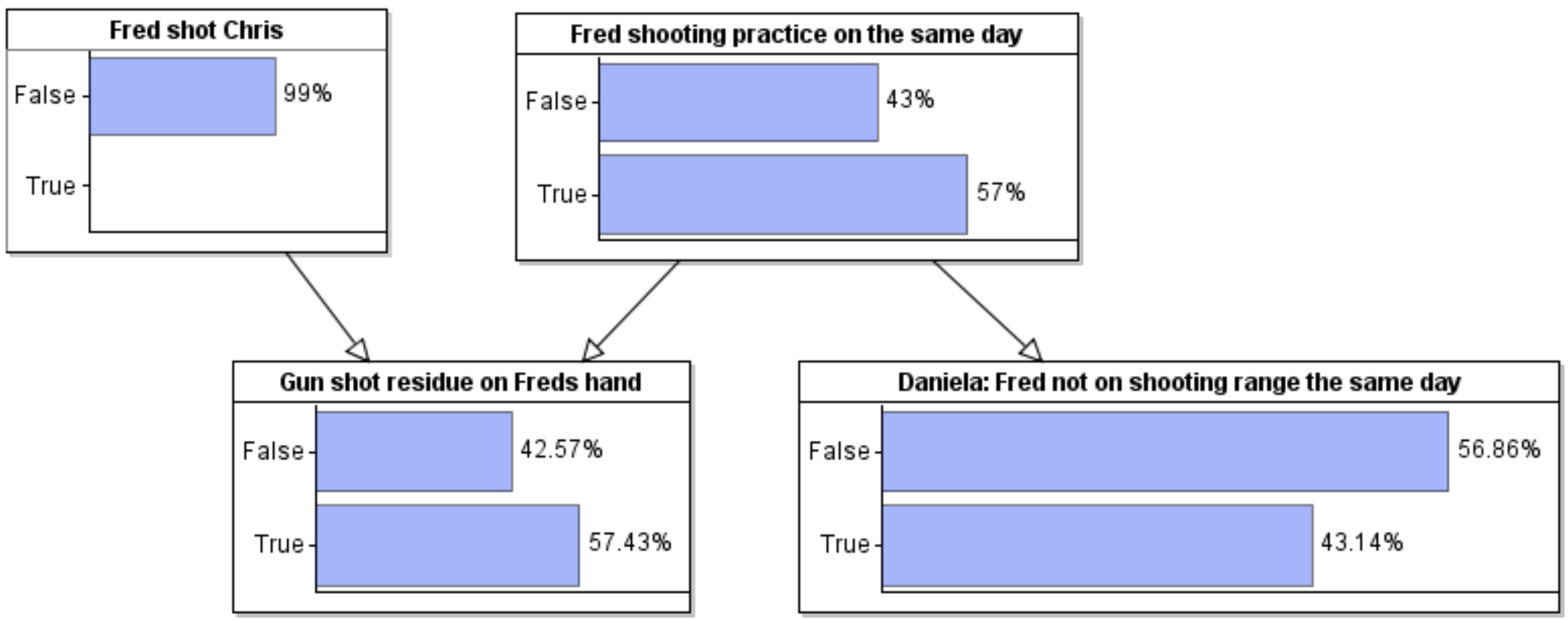


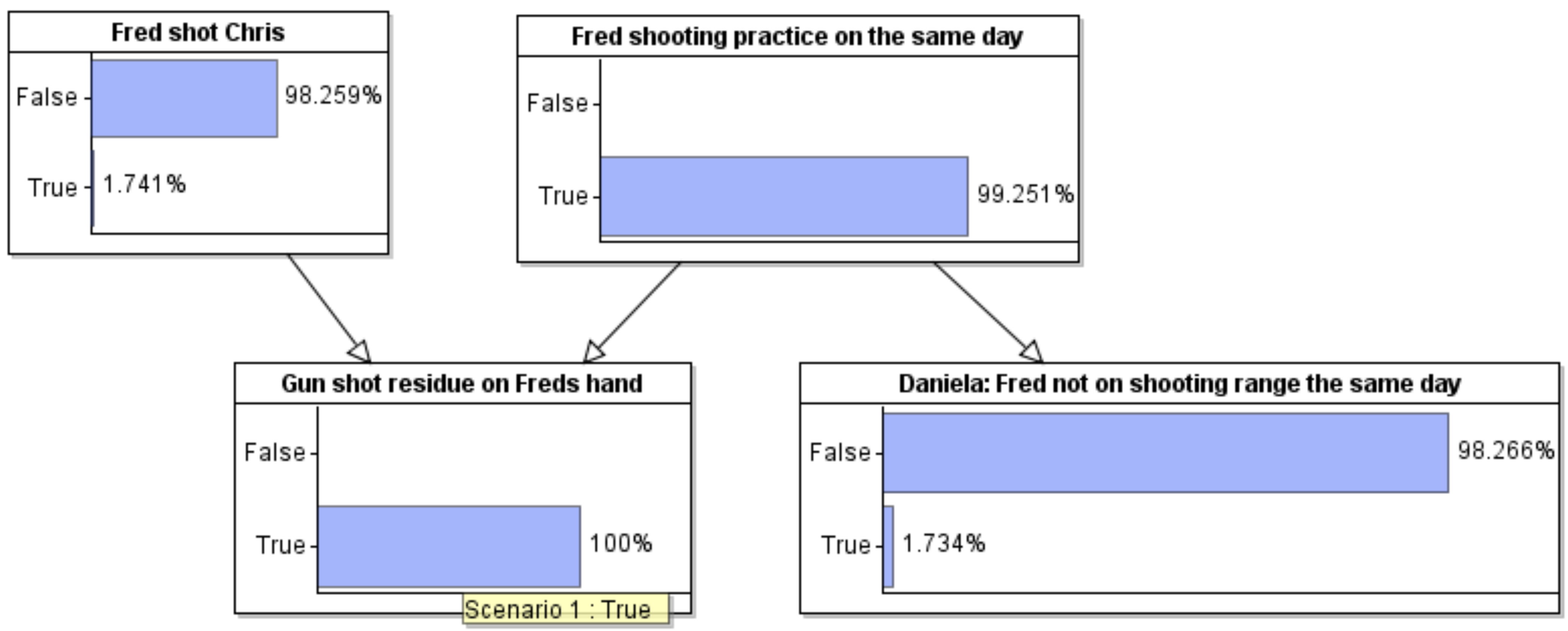
	A=yes & B=yes	**A=no & B=yes**	**A=yes & B=no**	**A=no & B=no**
C=yes	100%	100%	100%	0%
C=no	0%	0%	0%	100%

	B=yes	**B=no**
D=yes	99%	1%
D=no	1%	99%

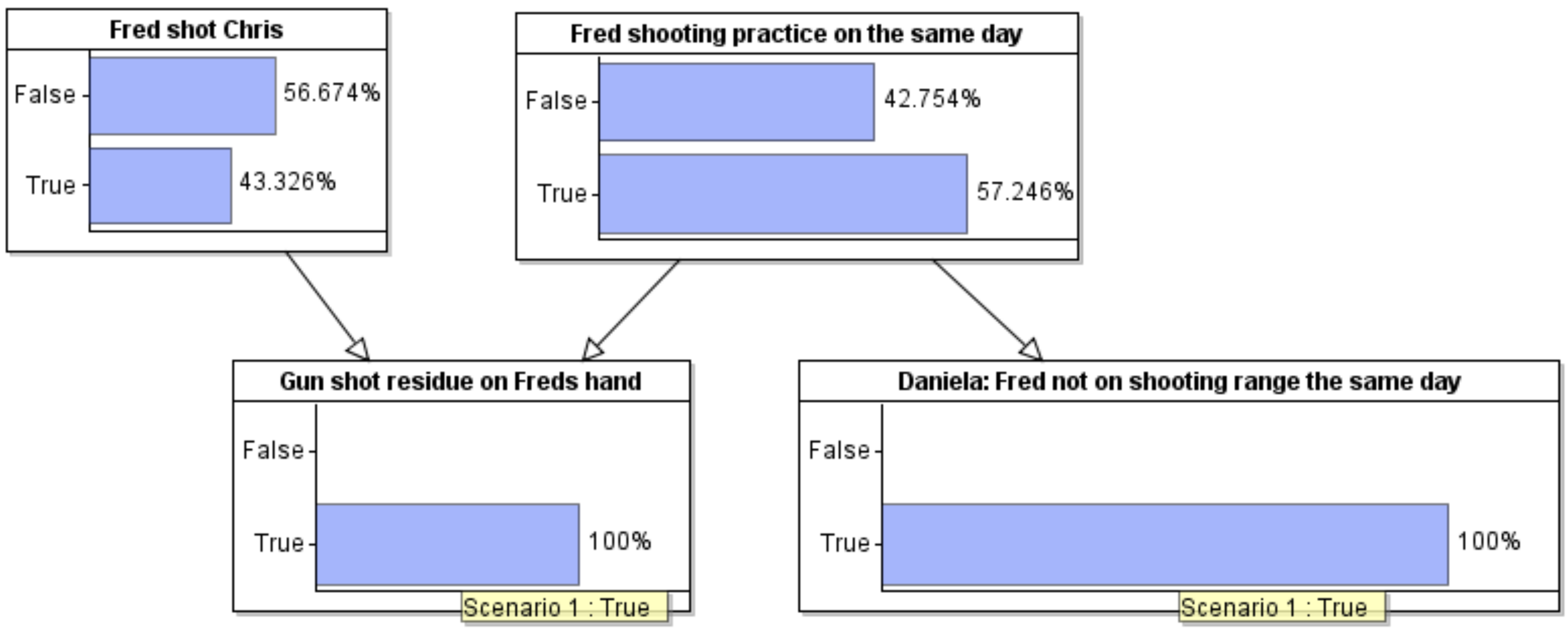
No Evidence:
Unlikely Fred Shot Chris



Gun Powder on Fred:
Still *Unlikely Fred Shot Chris*



Gun Powder on Fred *plus* Daniela's Testimony: Still *Unlikely Fred Shot Chris*



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2. Will different people come up with different graphs for a Bayesian networks?

   If yes, wouldn't such subjectivity be a problem?

3. Where do the numbers needed to fill the probability tables come from?

PART III

Analysis of a Legal Case Using Bayesian Networks

Tasks of a Judge

(1) *Gatekeeping:* apply exclusionary rules about relevance, hearsay, character evidence, privileges, etc.

(2) *Assess* the evidence for and against the defendant, and then finally decide

(2) Seek evidence and asks questions

(4) Write down a written opinion that lays down in detail the reasoning that supports to the decision

Simonshaven case

If You Were a Judge Writing the Opinion, How Would You Organize Your Analysis?

Informal Analysis of the Case

(NB: *Matters of fact only*)

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(1) Identify factual propositions (=hypotheses) under dispute.

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(1) Identify factual propositions (=hypotheses) under dispute.

These can be ultimate *probanda* or intermediate propositions.

(2) Identify key pieces of evidence which favor or oppose the factual propositions under dispute

(3) Make an assessment of the case as a whole, all things considered.

This can can require an assessment of the balance of the evidence for/against the accused or an assessment of whether a reasonable doubt about guilt exists.

The Analysis That Follows Is Taken From this Paper

Analyzing the Simonshaven Case using Bayesian Networks

Norman Fenton*, School of Electronic Engineering and Computer Science, Queen Mary University of London

Martin Neil, School of Electronic Engineering and Computer Science, Queen Mary University of London

Barbaros Yet, Department of Industrial Engineering, Hacettepe Universitesi,Turkey

David Lagnado, Department of Experimental Psychology, University College London

Full Bayesian Network

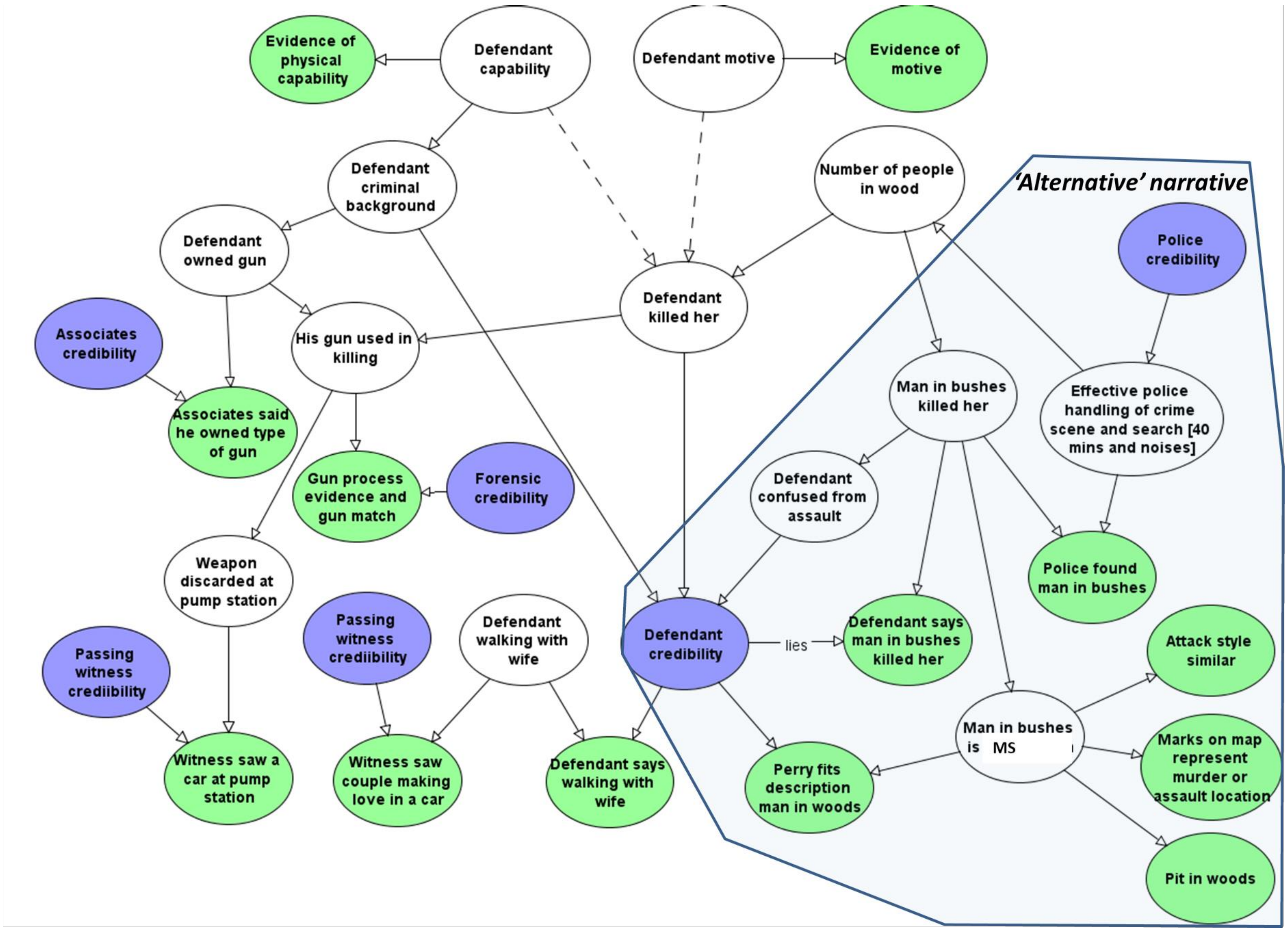
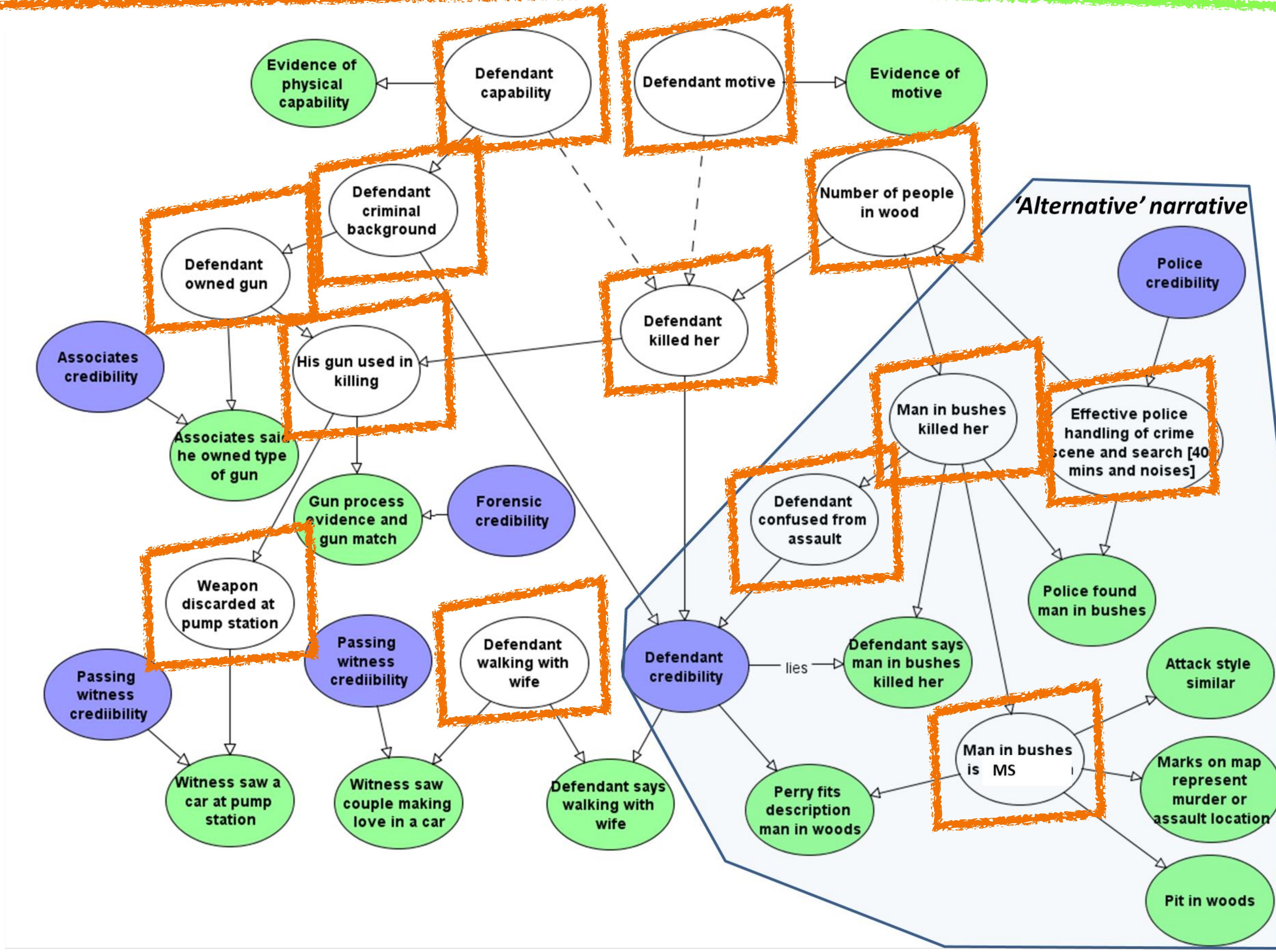


Figure 8 Full Simonshaven model, subdivided into the prosecution and alternative narratives

Hypothesis Nodes v. *Evidence* Nodes



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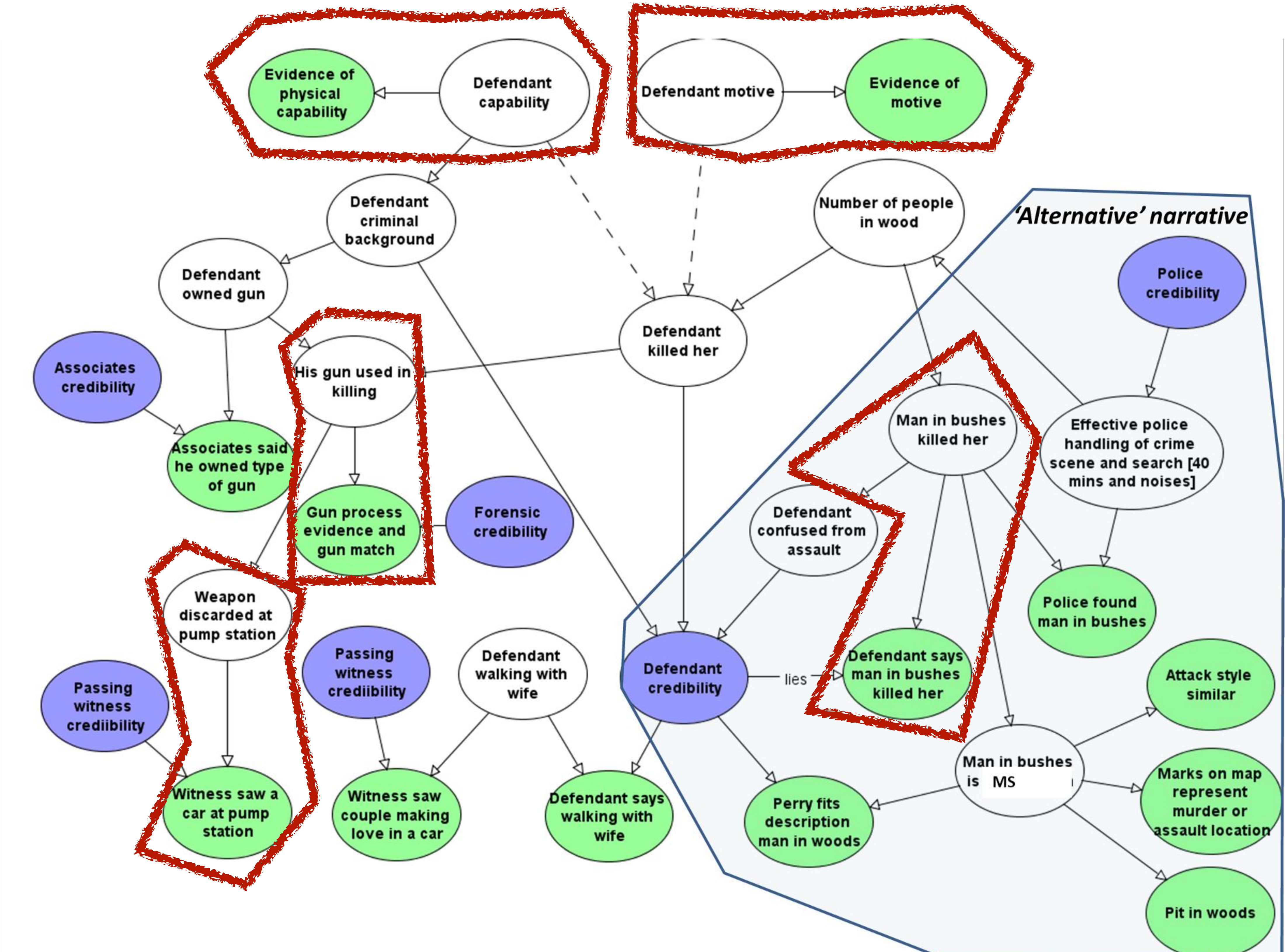
Examples: Evidence/Hypothesis Idioms



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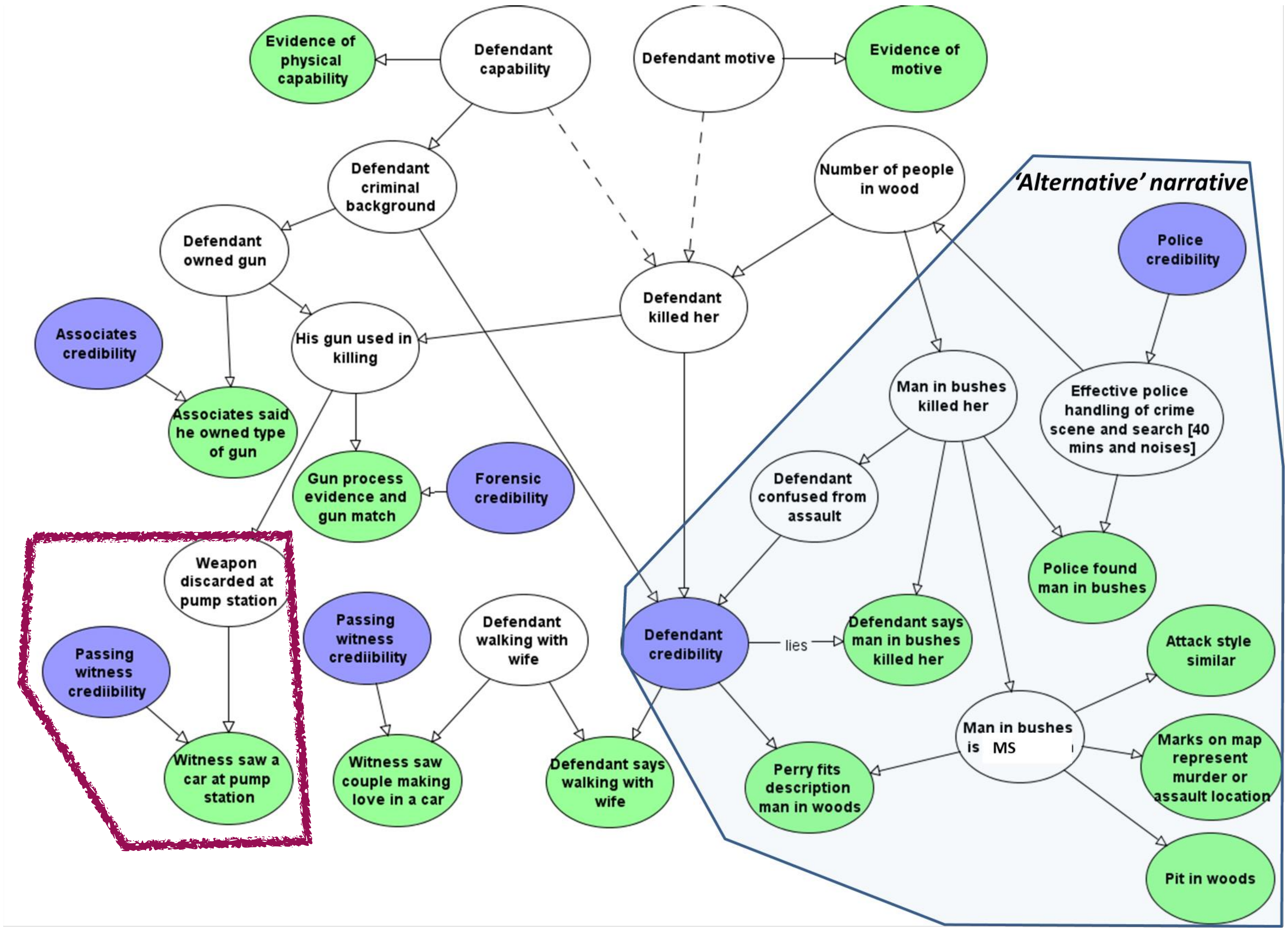
Examples: Evidence Credibility Idiom



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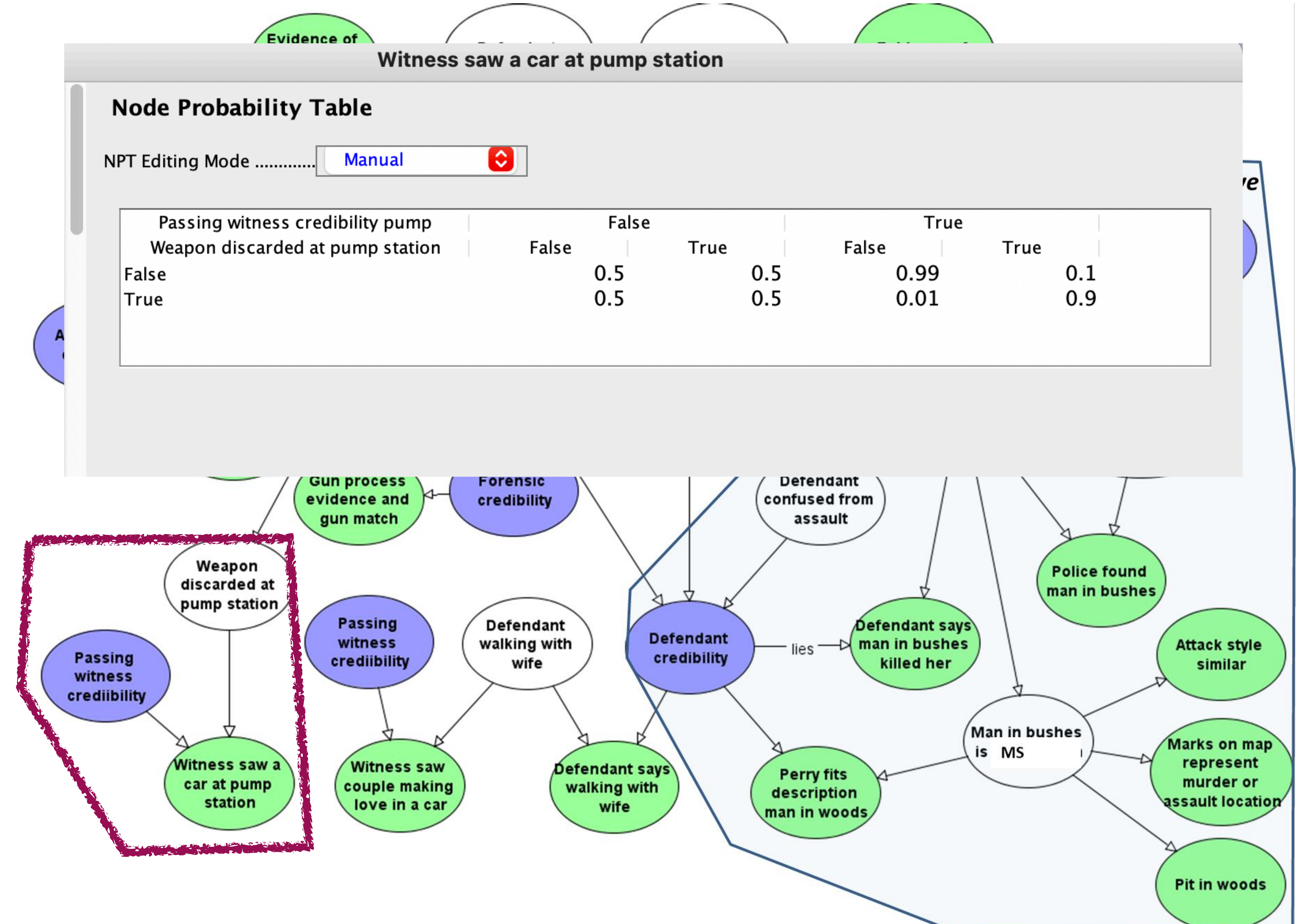
Examples of Probability Tables

Weapon Discarded at Pump Station?


Witness saw a car at pump station

Node Probability Table

NPT Editing Mode .... Manual

Passing witness credibility pump	False		True	
Weapon discarded at pump station	False	True	False	True
False	0.5	0.5	0.99	0.1
True	0.5	0.5	0.01	0.9

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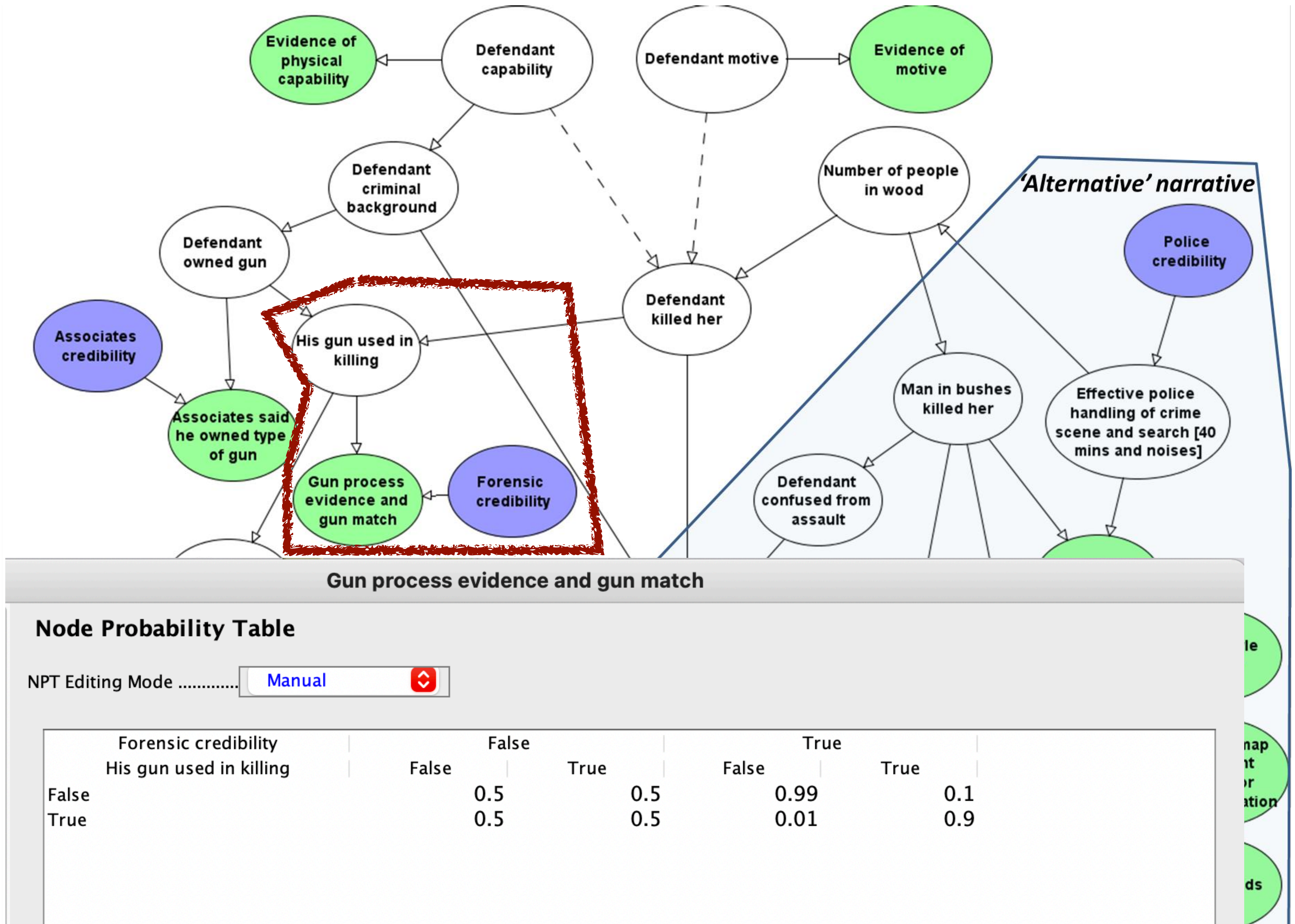
Gun Match Evidence



Gun process evidence and gun match

Node Probability Table

NPT Editing Mode .... Manual

Forensic credibility	False		True	
His gun used in killing	False	True	False	True
False	0.5	0.5	0.99	0.1
True	0.5	0.5	0.01	0.9

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Did the Defendant Kill the Victim?

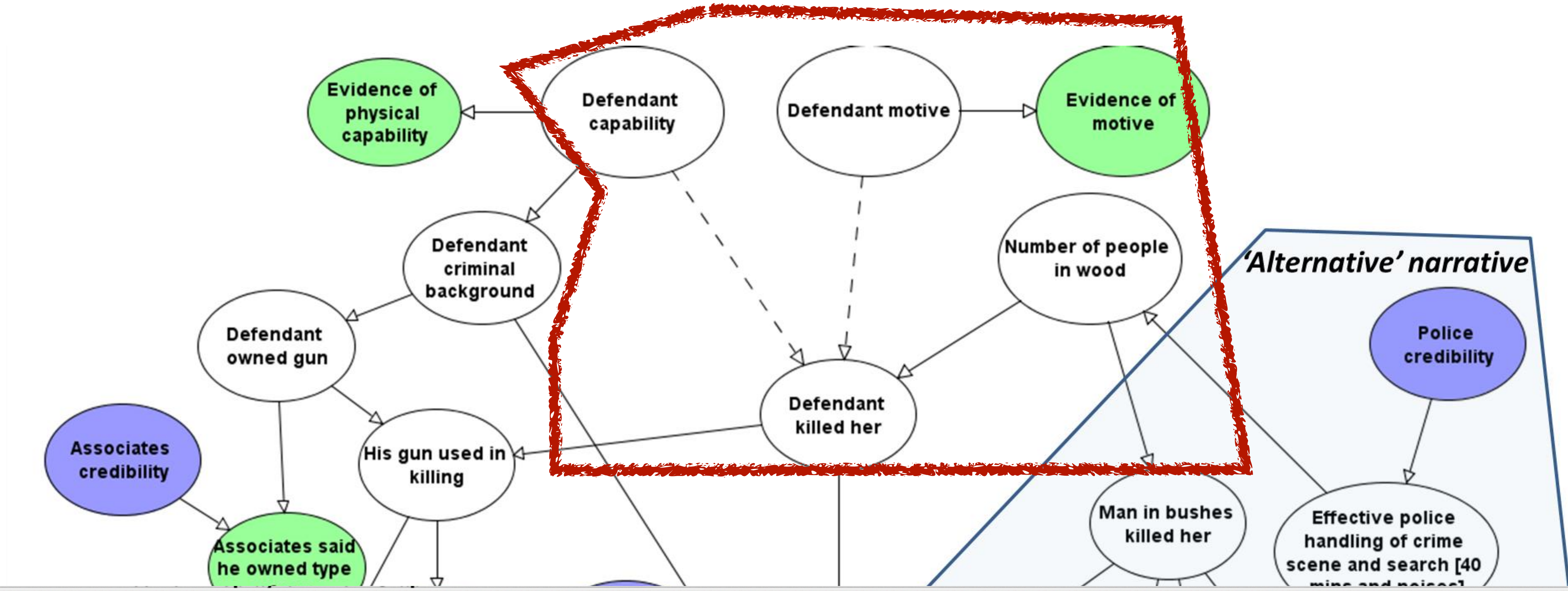


Figure 8 Full Simonshaven model, subdivided into the prosecution and alternative narratives

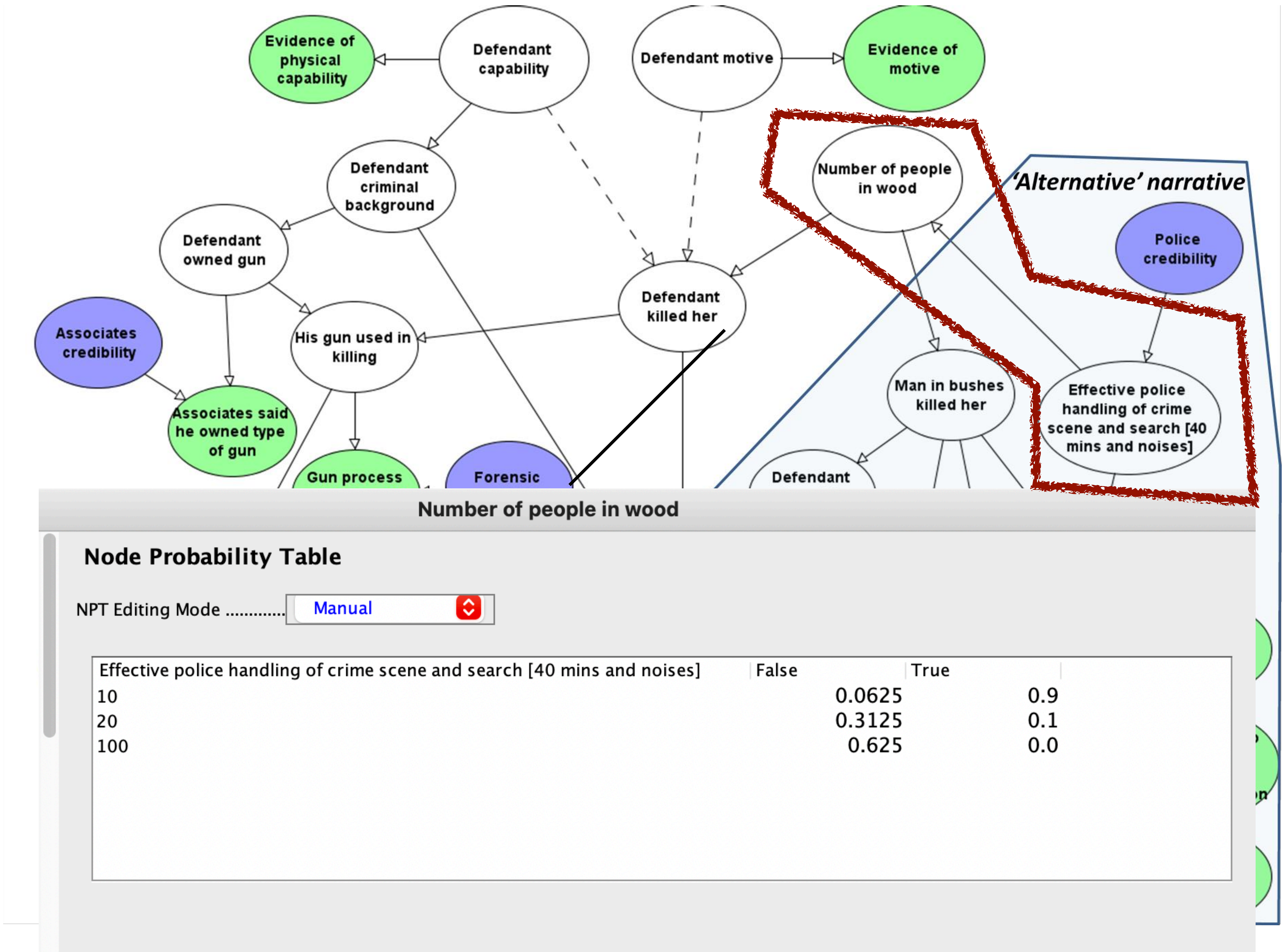
Defendant killed her

Node Probability Table

NPT Editing Mode .... Manual

Defendant motive and capability	False			True		
Number of people in wood	10	20	100	10	20	100
False	0.9	0.95	0.99	0.1	0.2	0.5
True	0.1	0.05	0.01	0.9	0.8	0.5

How Many People Were in the Woods?



Effective police handling of crime scene and search [40 mins and noises]	False	True
10	0.0625	0.9
20	0.3125	0.1
100	0.625	0.0

Figure 8 Full Simonshaven model, subdivided into the prosecution and alternative narratives

Did The Man in the Bushes Kill the Victim?

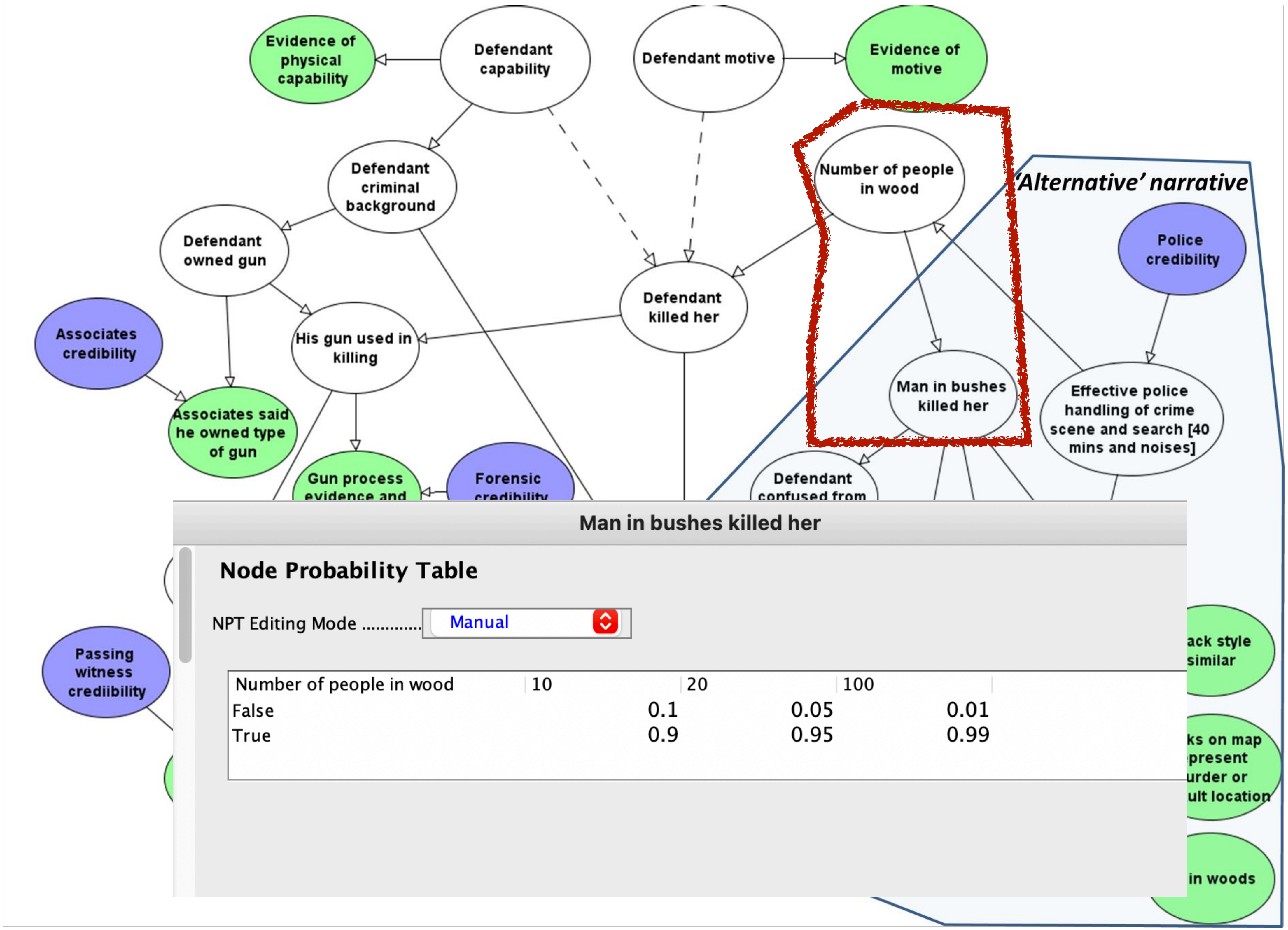
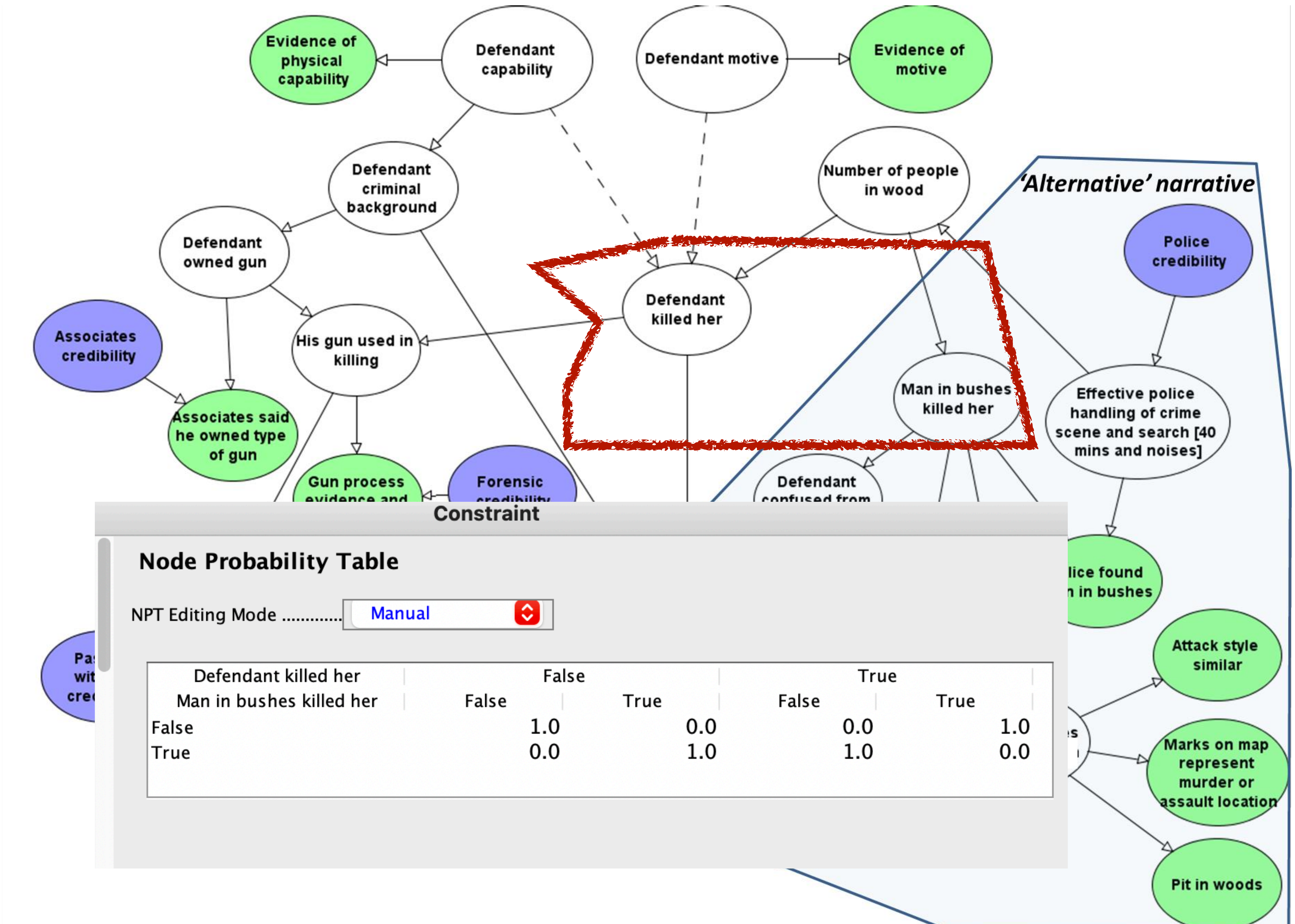


Figure 8 Full Simonshaven model, subdivided into the prosecution and alternative narratives

Incompatible Hypotheses



Defendant killed her	False		True	
Man in bushes killed her	False	True	False	True
False	1.0	0.0	0.0	1.0
True	0.0	1.0	1.0	0.0

Figure 8 Full Simonshaven model, subdivided into the prosecution and alternative narratives

Was *Perry Sultan* in the Woods?

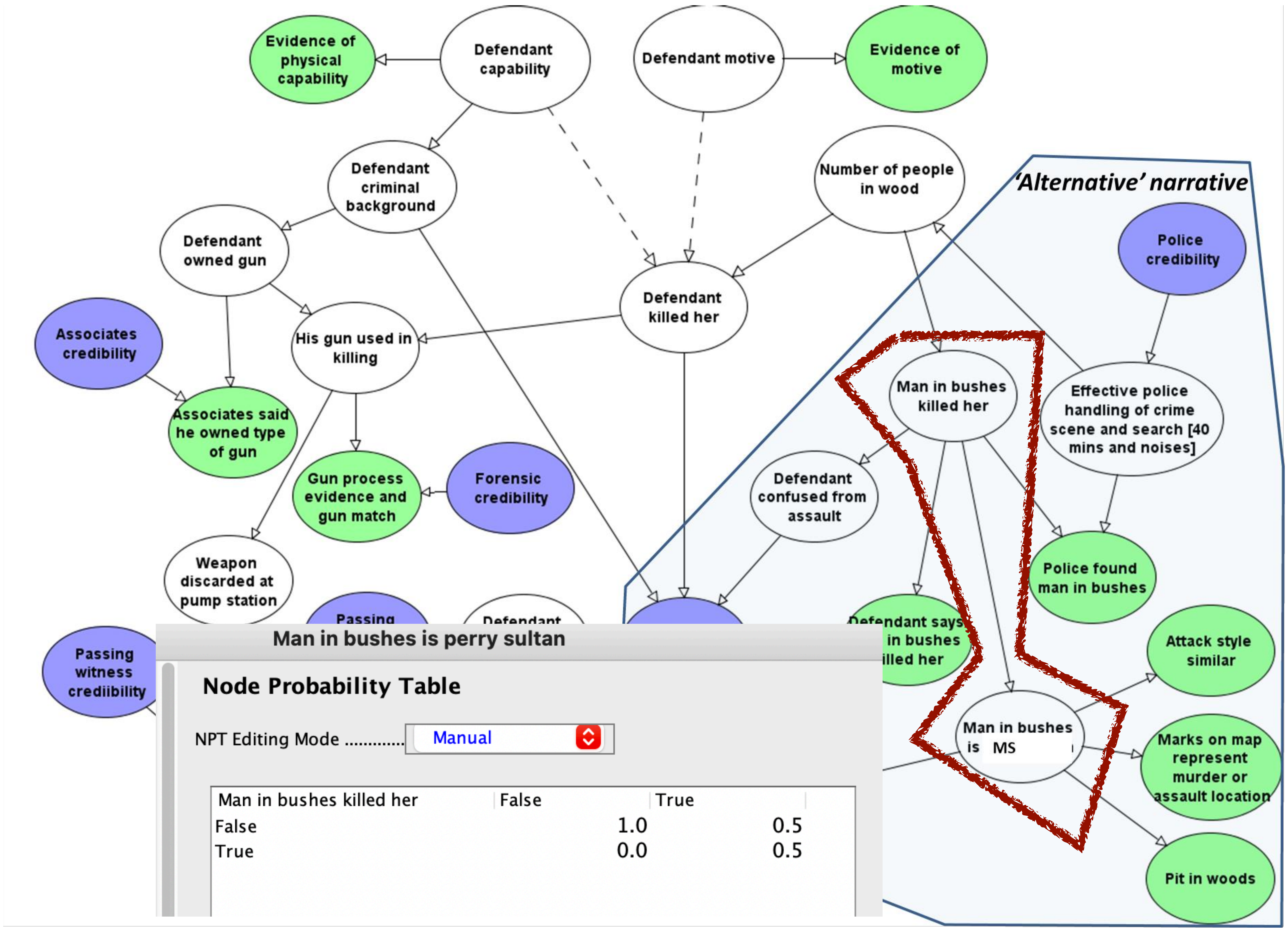


Figure 8 Full Simonshaven model, subdivided into the prosecution and alternative narratives

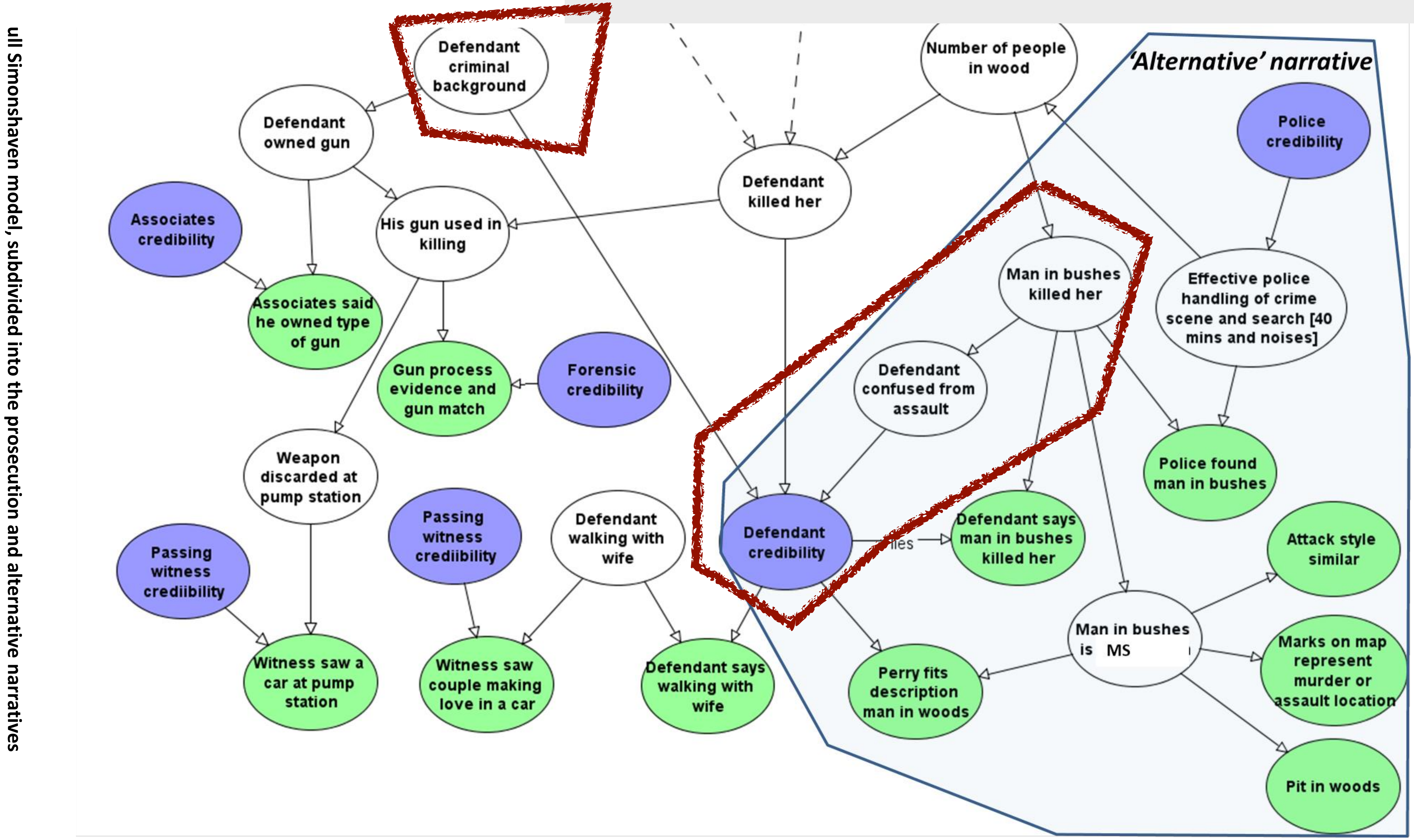
Defendant's credibility

Defendant credibility

Node Probability Table

NPT Editing Mode .... Manual

Defendant killed her	False				True			
Defendant criminal background	False		True		False		True	
Defendant confused from assault	False	True	False	True	False	True	False	True
False	0.1	0.5	0.1	0.6	0.9	0.9	0.99	0.99
True	0.9	0.5	0.9	0.4	0.1	0.1	0.01	0.01



Credibility in General

ull Simonshaven model, subdivided into the prosecution and alternative narratives

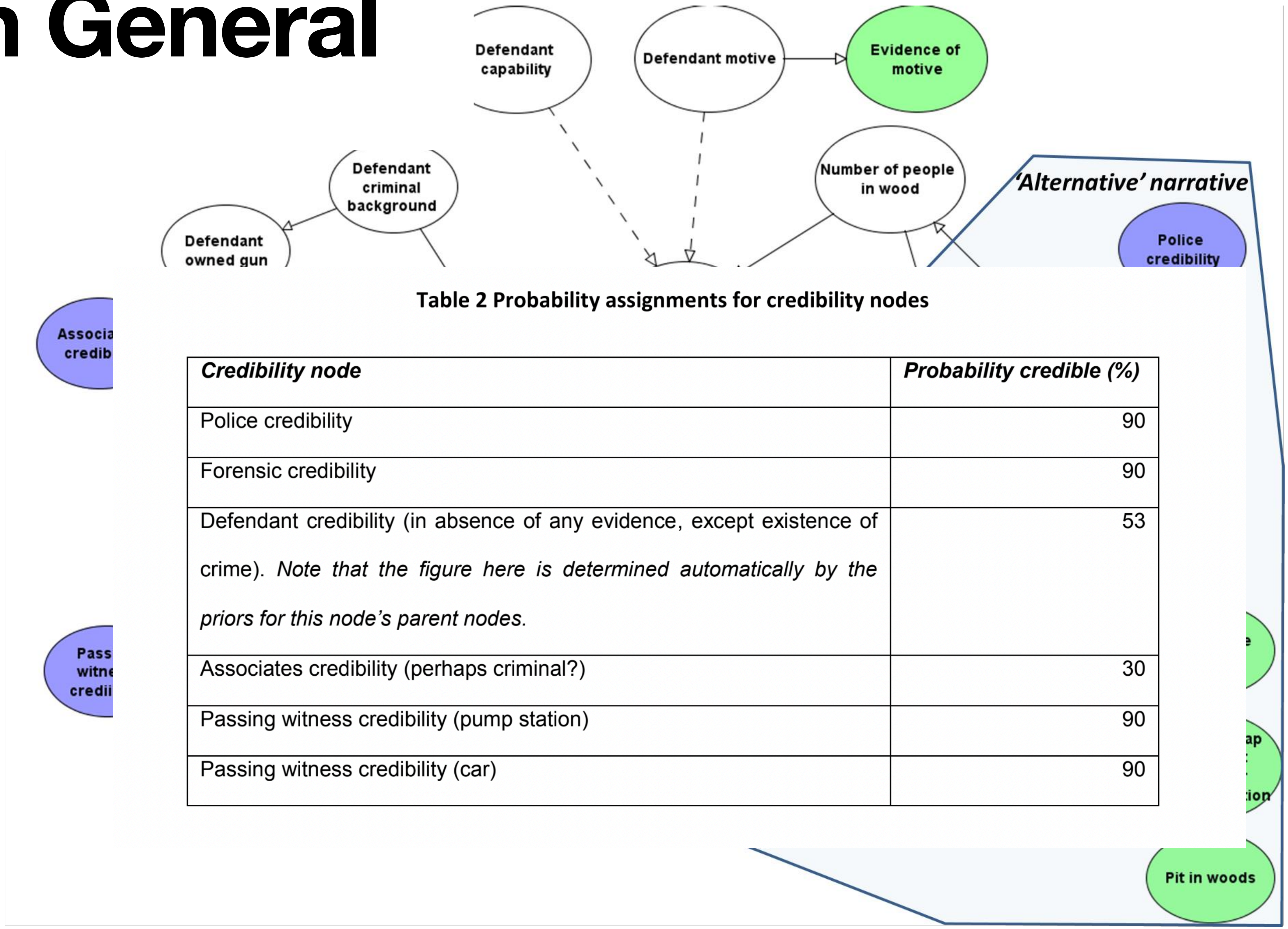


Table 2 Probability assignments for credibility nodes

Credibility node	***Probability credible (%)***
Police credibility	90
Forensic credibility	90
Defendant credibility (in absence of any evidence, except existence of crime). *Note that the figure here is determined automatically by the priors for this node's parent nodes.*	53
Associates credibility (perhaps criminal?)	30
Passing witness credibility (pump station)	90
Passing witness credibility (car)	90

Changes in Probability as Evidence is Added

Table 3 Changes to probability of guilt, and defendant credibility, as evidence is entered in model (P refers to prosecution evidence and D to defence evidence)

Evidence (cumulative)	***Probability defendant guilty (%)*** *[rounded down]*	***Probability defendant credible*** *[rounded down]*
None	1	55
Evidence physical capability and Evidence of motive (P)	21	41
Associates said he owned type of gun + witness saw car at pump station (P)	53	25
Gun process evidence and gun match (P)	93	5
Witness saw couple making love on car (P) but defendant says walking with wife at time (D)	96	< 1
Police failed to find man in bushes and poor handling of crime scene (D)	80	2
Various bits of MS evidence {attack style, marks on map, pit in woods} and fact that defendant says man in bushes killed her (D)	46	6
MS does not fit suspect's description of the man in the woods (P)	74	4

Sensitivity Analysis: What If We Had Assigned Different Numbers?