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# FIT5047: Intelligent Systems

## Bayesian Networks II: Inference, decision networks, knowledge engineering case studies

Lecturer: Prof. Ann Nicholson

Readings: Russell & Norvig 16.1-2, 16.5

Korb & Nicholson, 2011: 3.1-3.6, 4.1-4.4, Ch 10 plus papers (see end)

Some slides are adapted from those of Stuart Russell, Andrew Moore, Dan Klein, Kevin Korb, Yue Wu and Steven Mascaro

# Bayesian Reasoning I: Learning Objectives

Be able to:

- Do BN inference “by hand” using enumeration for a simple example
- Compare the main approaches to BN inference (at a high level)
- Reason with the 3 types of evidence in Netica (specific, negative and likelihood)
- Extend a BN with a virtual node to do reasoning with uncertain evidence
- Compute the expected utility for a simple decision problem
- Describe the additional nodes and links in Bayesian decision networks (compared to ordinary BNs)

# Bayesian Reasoning I: Learning Objectives

(cont.)

- Construct a syntactically correct Bayesian decision network that plausibly presents a simple problem given via an English language description: nodes, links, parameters (CPTs and utilities)
- Use the Netica BN software to build a Bayesian decision network and reasoning using that BDN (Lab 10)
- Have some understanding of how BNs can be engineered for real-world decision makings as well as the challenges involved



# FIT5047 – Intelligent Systems

## Inference in Bayesian Networks

Korb & Nicholson, 2011: Chapter 3

# RECAP: BN inference task

- Basic task for any probabilistic inference system:  
Compute the posterior probability distribution for a set of *query variables*, given new information about some *evidence variables*
- Also called *conditioning* or *belief updating* or *inference*

# Inference in BNs: Overview

- **Exact inference**
  - Enumeration
  - Message passing
  - Variable elimination
  - Junction-tree algorithms (Netica “compilation”)
- **Approximate inference**
  - Stochastic simulation
    - > Logic sampling
    - > Likelihood weighting
- **Uncertain (“virtual”) evidence**

# Inference

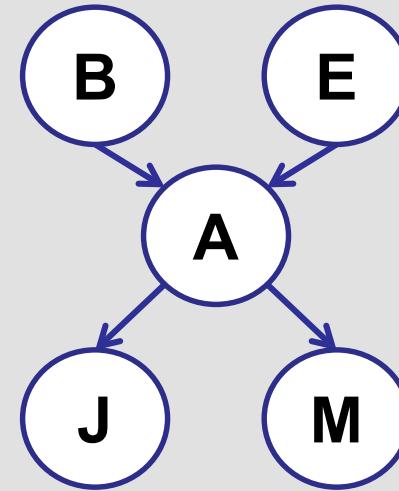
- Calculating some useful quantity from a joint probability distribution

- Posterior probability of a query variable  $Q$

$$\Pr(Q | E_1 = e_1, \dots, E_k = e_k)$$

- Most likely explanation of evidence

$$\operatorname{argmax}_q \Pr(Q = q | E_1 = e_1, \dots, E_k = e_k)$$



# Inference by Enumeration

- Given unlimited time, inference in BNs is easy
- Recipe:

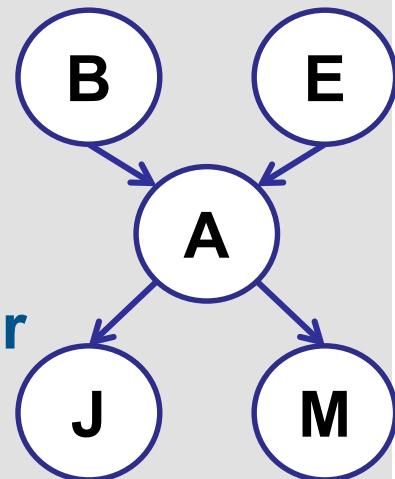
- State the **marginal** probabilities you need
- Figure out ALL the **joint** probabilities you need
- Calculate and combine them

- Example:

$$\Pr(+b | +j, +m) = \frac{\Pr(+b, +j, +m)}{\Pr(+j, +m)}$$

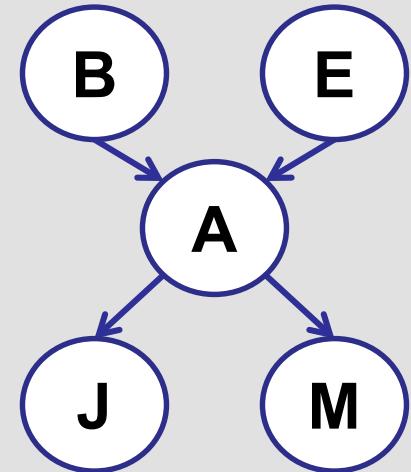
- There is no need to calculate the denominator

- Compute the numerator for  $\Pr(\neg b | +j, +m)$
- Replace the denominator with  $\alpha$  in both equations
- $\Pr(+b | +j, +m) + \Pr(\neg b | +j, +m) =$   
 $\alpha \Pr(+b, +j, +m) + \alpha \Pr(\neg b, +j, +m) = 1$



# Enumeration – Example (I)

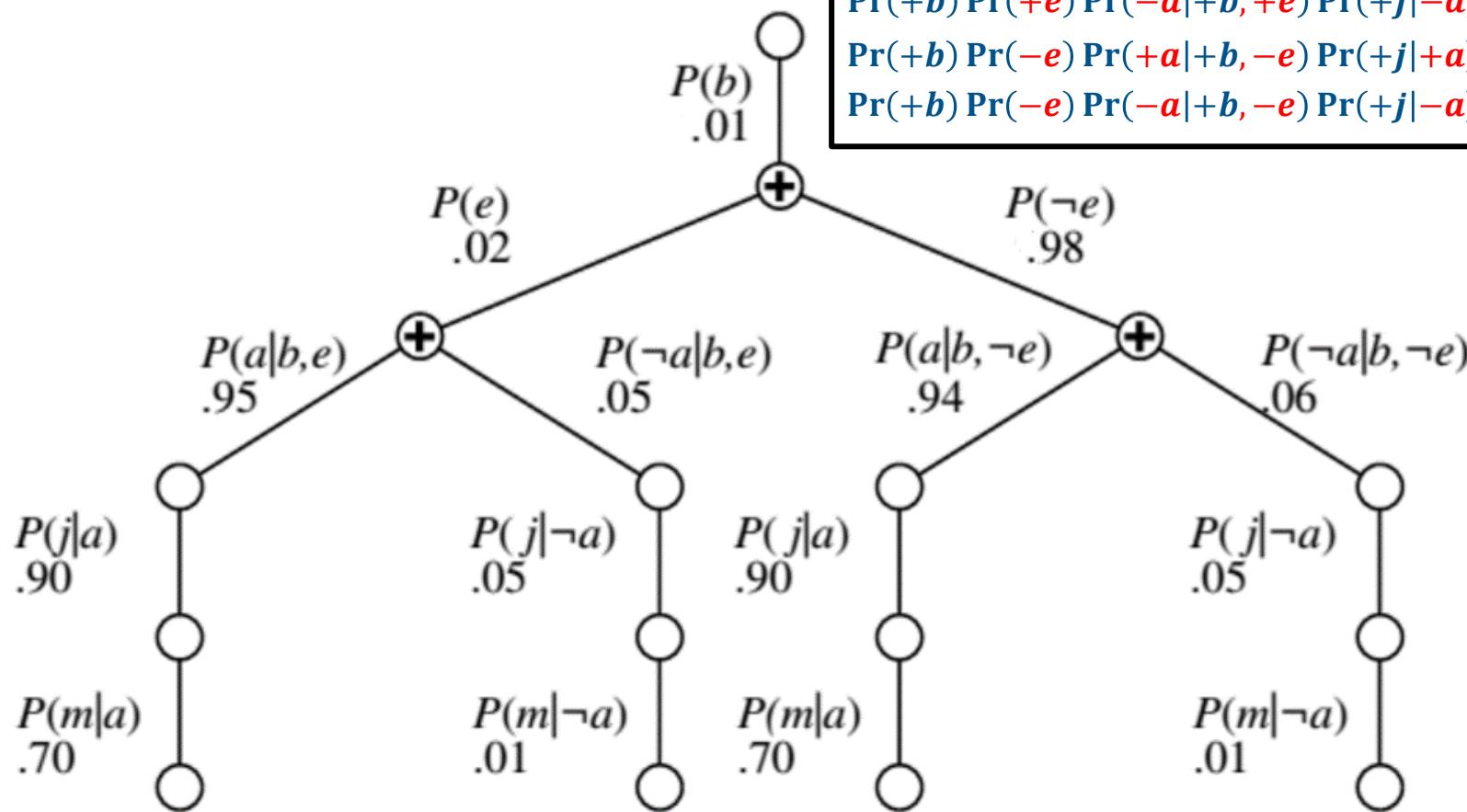
- In this simple method, we only need the BN to synthesize the joint entries from the CPTs



$$\Pr(+b, +j, +m) =$$

$$\begin{aligned} & \Pr(+b) \Pr(+e) \Pr(+a|+b, +e) \Pr(+j|+a) \Pr(+m|+a) + \\ & \Pr(+b) \Pr(+e) \Pr(-a|+b, +e) \Pr(+j|-a) \Pr(+m|-a) + \\ & \Pr(+b) \Pr(-e) \Pr(+a|+b, -e) \Pr(+j|+a) \Pr(+m|+a) + \\ & \Pr(+b) \Pr(-e) \Pr(-a|+b, -e) \Pr(+j|-a) \Pr(+m|-a) \end{aligned}$$

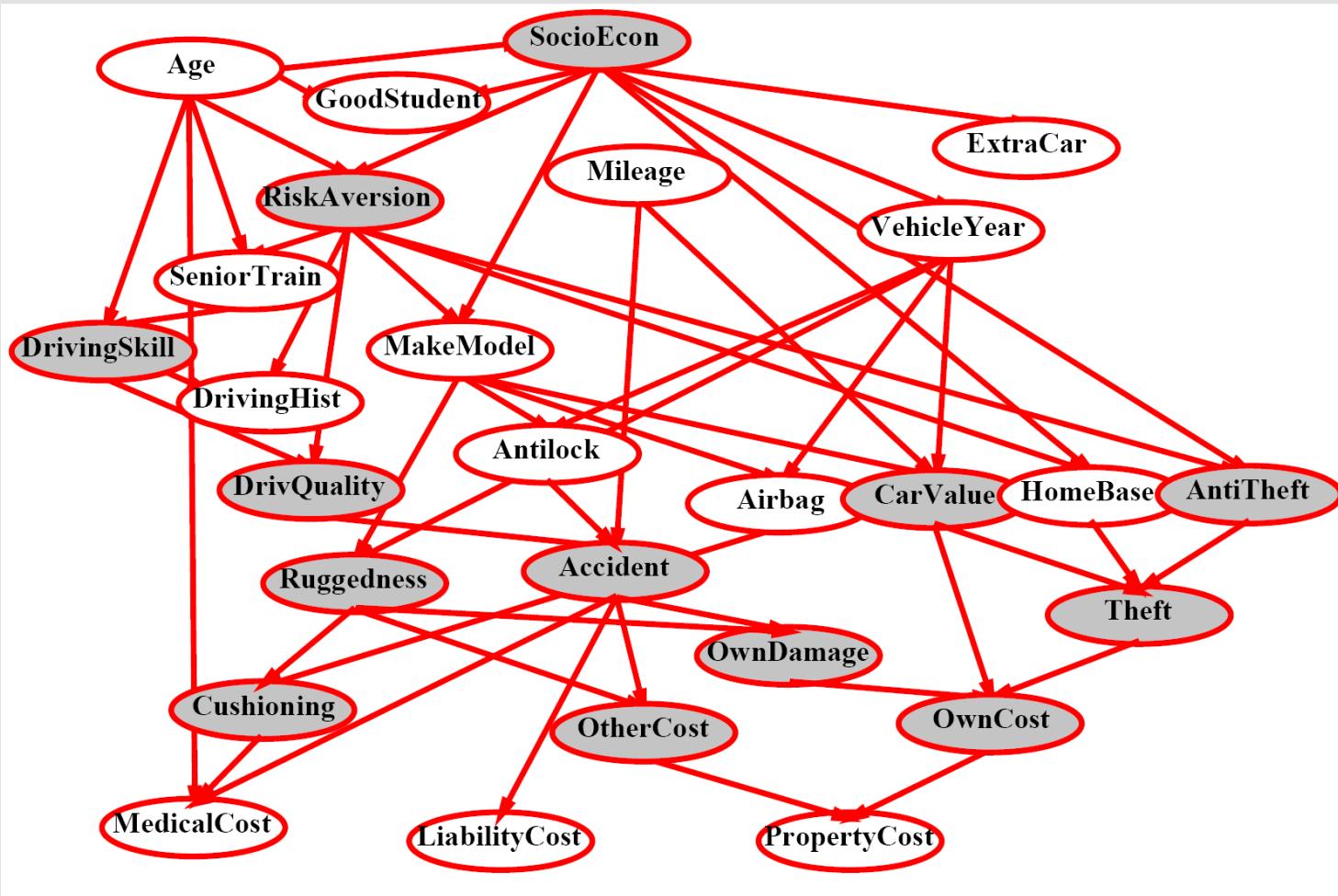
# Enumeration – Example (II)



$$\Pr(+b, +j, +m) =$$
$$\Pr(+b) \Pr(+e) \Pr(+a|+b, +e) \Pr(+j|+a) \Pr(+m|+a) +$$
$$\Pr(+b) \Pr(+e) \Pr(-a|+b, +e) \Pr(+j|-a) \Pr(+m|-a) +$$
$$\Pr(+b) \Pr(-e) \Pr(+a|+b, -e) \Pr(+j|+a) \Pr(+m|+a) +$$
$$\Pr(+b) \Pr(-e) \Pr(-a|+b, -e) \Pr(+j|-a) \Pr(+m|-a)$$



# Inference by Enumeration?



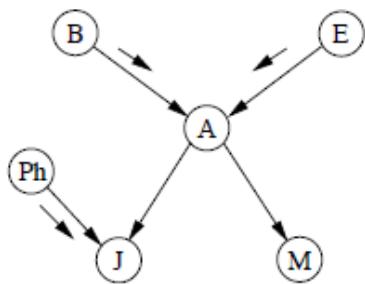
# Variable Elimination (VE)

- **Why is inference by enumeration so slow?**
  - You join up the whole joint distribution before you sum out the hidden variables
  - You end up repeating a lot of work!
- **Idea: do the calculation once and save the results for later use**
  - Called “Variable Elimination”
  - Interleave joining and marginalizing
  - Still NP-hard, but usually much faster than inference by enumeration

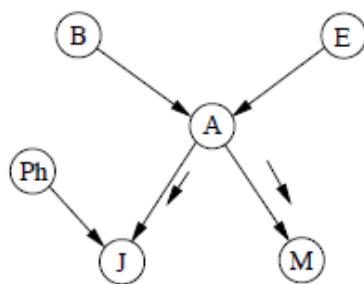
# Message Passing

## PROPAGATION, NO EVIDENCE

PHASE 1

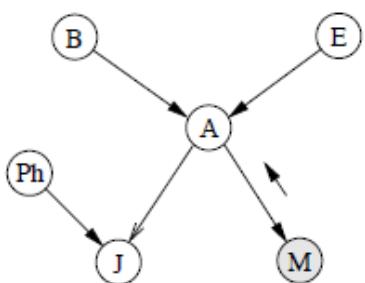


PHASE 2

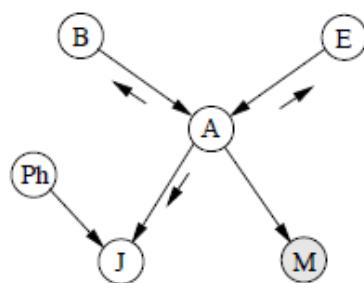


## PROPAGATION, EVIDENCE for node M

PHASE 1



PHASE 2



PHASE 3

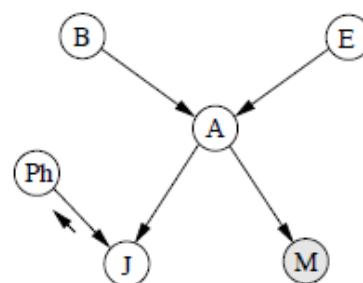


FIGURE 3.4: Message passing algorithm propagation stages for without evidence (above) and with evidence for node  $M$  (below).

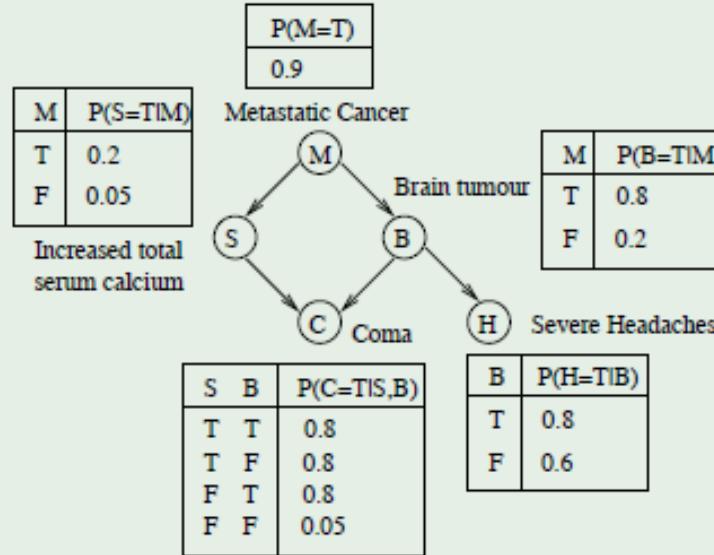


# Message passing

- All computations are local => efficient
- Requires summation over all joint instantiations of parent nodes => exponential in no. of parents.
- No. of propagation steps depends on length of longest path
- Doesn't work for networks where two nodes are connected by more than one path
  - Two or more possible causes which share a common ancestor
  - One variable can influence another through more than one causal mechanism

# Inference in multiply-connected networks

## Example (Metastatic Cancer BN)



- Message passing doesn't work: evidence gets “counted twice”
- Example: evidence for C(coma) gets passed to M(meta-static cancer) via S and B

# Exact algorithms for multiply-connected networks

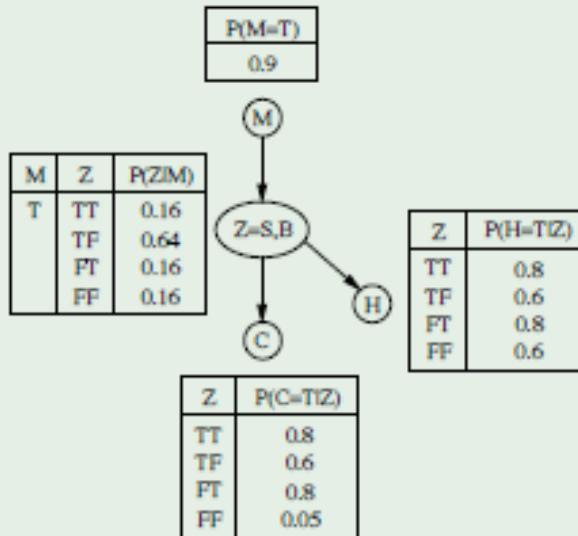
- Clustering: transform network into a probabilistically equivalent polytree by merging offending nodes (Netica method)
- Conditioning: transformation by instantiating variables to definite values, then evaluating a polytree for each possible instantiation [not covered in this unit]

# Clustering method

- Transform network into a probabilistically equivalent polytree (i.e. no undirected loops) by merging (clustering) offending node

## Example (Transformed Metastatic Cancer)

New node Z combines B and C



$$P(z|a) = P(b, c|a) = P(b|a)P(c|a)$$

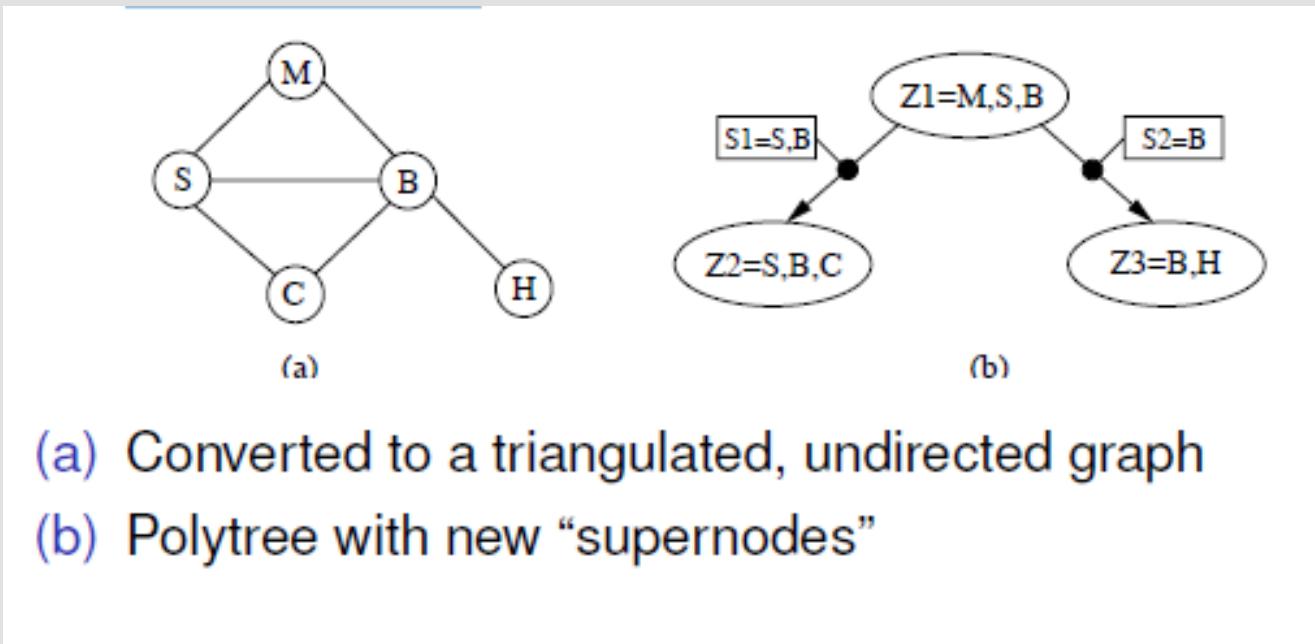
$$P(e|z) = P(e|b, c) = P(e|c)$$

$$P(d|z) = P(d|b, c)$$



# Clustering: Jensen Join-tree method

- Jensen Join-tree (Jensen, 1996) version the current most efficient algorithm in this class (e.g. used in Hugin, Netica). (Also called “junction-tree”)



- (a) Converted to a triangulated, undirected graph
- (b) Polytree with new “supernodes”



# Clustering: Jensen Join-tree method

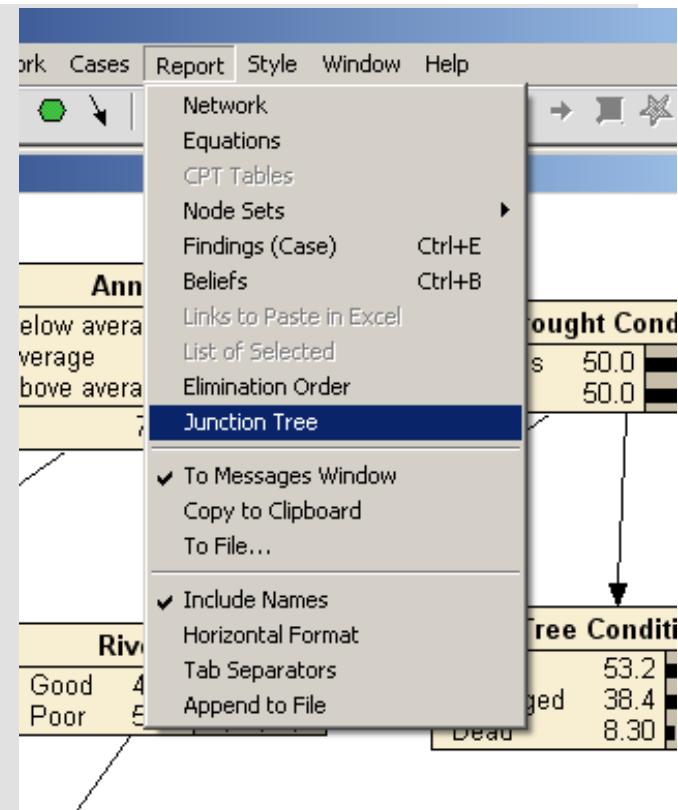
Network evaluation done in two stages

## 1. Compile into join-tree

- May be slow
- May require too much memory if original network is highly connected (CPTs for supernode too big)

## 2. Do belief updating in join-tree (usually fast)

Caveat: clustered nodes have increased complexity; updates may be computationally complex



```
Messages
Clique [Joined To] Size Member nodes (* means home)
0 [1 2 3] 12 (*Rainfall, PesticideConc, Flow)
1 [0] 12 (PesticideConc, Flow, *NativeFish)
2 [0] 12 (*PesticideUse, Rainfall, *PesticideConc)
3 [0 4] 12 (*Drought, Rainfall, *Flow)
4 [3] 18 (*TreeCond, Drought, Rainfall)
Sum of clique sizes = 66 (with sepsets = 88)
```



# Approximate inference

- **Necessary if the network is large and highly connected**
- **Available in various BN software packages (e.g. Hugin, GeNle) but not Netica**
- **Based on stochastic simulation**
  - Starting from the root node, generate a value for each variable (from the prior, or from the CPT)
  - Do this a lot of times (e.g. 1 million), and count up how many times each state was generated

[Approximate inference not used/examined in FIT5047]

# Types of Evidence

(Called "Findings" in Netica)

## Specific evidence:

- A definite finding that a node  $X$  has a particular value,  $x$ .
- Example:  $PesticideUse = High$

## Negative evidence:

- A finding that node  $Y$  is not in state  $y_1$  (but may take any other values)
- Example:  $TreeCondition \neq Dead$



# Types of evidence

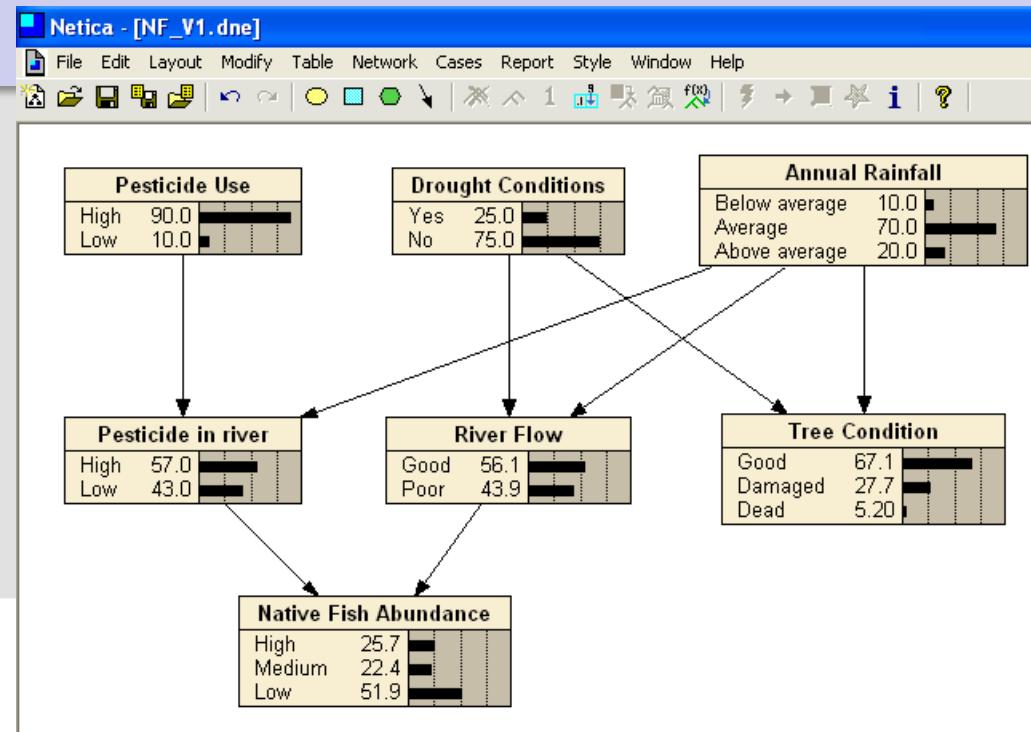
## Uncertain evidence:

- Source of information is not sure about it.
- Example: Environment officers are 80% sure that *Pesticide Concentration in River=High.*
- Also called
  - “virtual evidence” by Pearl
  - “likelihood evidence” in Netica

# Netica: likelihood evidence

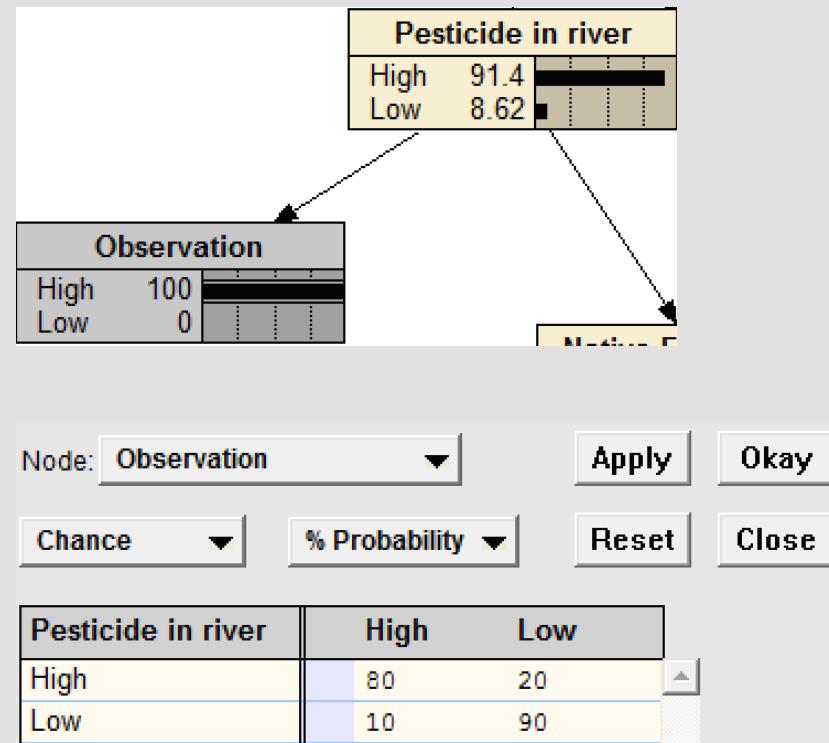
## Example (Ver. 2)

The river managers perform a test on the *Pesticide Concentration in River* which returns *High*. The test is known to report *High* when Pesticide Concentration is *High* 80% of the time, and report *High* when Pesticide Concentration is *Low* 10% of the time.



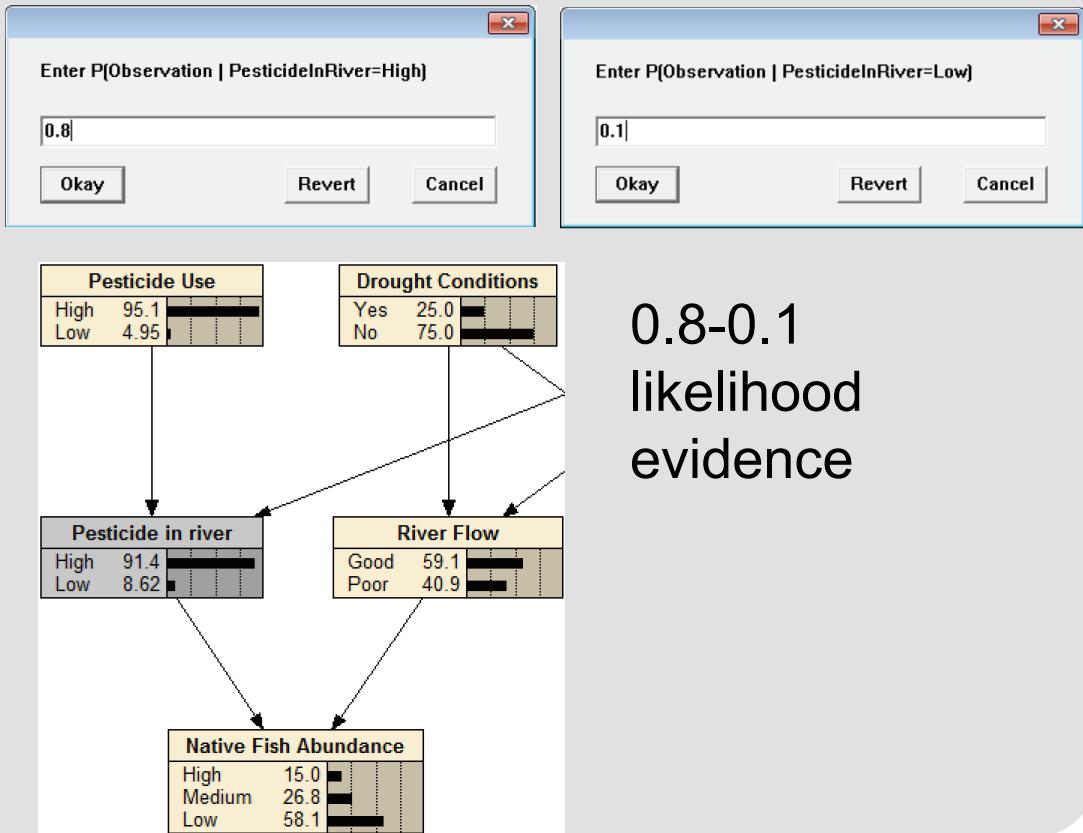
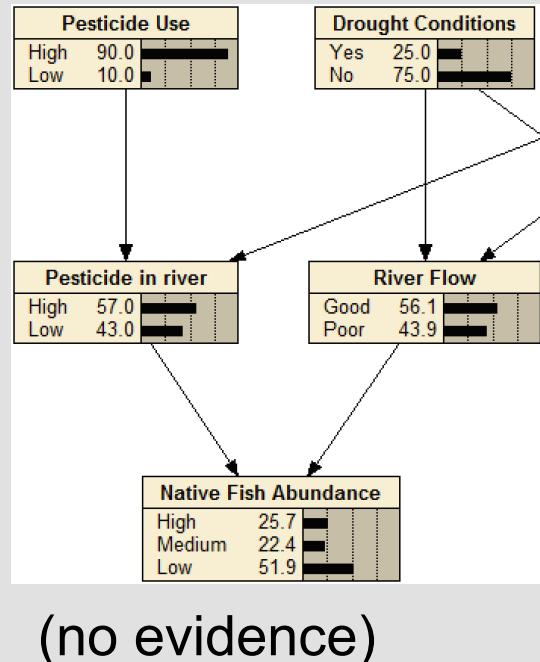
# Using a “virtual node”

- One option is to add a new “virtual” node Observation, with states *High* and *Low* (week 9 tutorial exercise)



# Using Netica's “likelihood evidence”

- Another option is to use Netica's likelihood evidence feature (*Week 9 tutorial exercise*)



# Types of Evidence

**Netica Demo**



# FIT5047 – Intelligent Systems

## Decision Networks

Russell & Norvig Ch 16.1-2, 16.5

Korb & Nicholson, 2011: Ch 4.1-4.4

# How do people make decisions?

**Decision making under uncertainty is ubiquitous.**

- **Shall I take my raincoat today?**
  - Will it rain?
- **Shall I try the prawns?**
  - Will they be safe?
  - Would I prefer them to steak?

→ ***Two very different kinds of uncertainty. . .***

# Bayesian decisions

Most problems have *both* kinds of uncertainty.

- What is the probability SARS-Cov2 coronavirus will be a highly toxic virus during 2020?
- What is the probability it will lose its apparent infectiousness? That it will increase its infectiousness
- What is the disvalue of losing a life to COVID-19?
- How much are we willing to pay or sacrifice to avoid COVID deaths?

# Decision Networks

- Extension of BNs to support making decisions
- Utility theory represents preferences between different outcomes of various plans
- Decision theory =  
Utility theory + Probability theory

# Bayesian Decision Theory (recall from Part 1)

- Frank Ramsey (1926)
- Decision making under uncertainty – what action to take when the state of the world is unknown
- Bayesian answer –  
Find the utility of each possible outcome (action-state pair), and take the action that maximizes the *expected utility*

# Expected Utility

$$EU(A \mid E) = \sum_i \Pr(O_i \mid E, A)U(O_i \mid A)$$

- $E$  = available evidence
- $A$  = a non-deterministic action
- $O_i$  = a possible outcome state
- $U$  = utility



# Bayesian Decision Theory – Example (from part 1/video)

Action	Rain ( $p=0.4$ )	Shine ( $1-p=0.6$ )
Take umbrella	60	-10
Leave umbrella	-100	50

$$EU(A | E) = \sum_i \Pr(O_i | E, A)U(O_i | A)$$

Expected utilities:

- $E(\text{Take umbrella}) = 60 \times 0.4 + (-10) \times 0.6 = 18$
- $E(\text{Leave umbrella}) = -100 \times 0.4 + 50 \times 0.6 = -10$

# Bayesian decision theory - example

$$EU(A | E) = \sum_i \Pr(O_i | E, A)U(O_i | A)$$

## Example (Global Warming)

Action	GWH(p)	$\neg$ GWH (1-p)
Do Nothing	$u_1$	$u_2$
Curtail CO <sub>2</sub>	$u_3$	$u_4$

*Expected utilities:*

$$EU(\text{Do Nothing}) = p \times u_1 + (1 - p) \times u_2$$

$$EU(\text{Curtail CO}_2) = p \times u_3 + (1 - p) \times u_4$$

When people disagree on Global Warming, they may be disagreeing on p (probability that it is true) or on one or more of  $u_1, u_2, u_3, u_4$ .

# Bayesian decision theory: class ACTIVITY

You are considering whether to buy contents insurance. Your things are valued at \$2000, and the insurance will cost \$100. If you get insurance, and there is a burglary, you will have to pay \$200 excess. The probability of a burglary in your neighbourhood is 0.02. Should you buy insurance?

$$EU(A | E) = \sum_i \Pr(O_i | E, A)U(O_i | A)$$

# Decision Networks

**A Decision network represents information about**

- the agent's current state
- its possible actions
- the state that will result from the agent's action
- the utility of that state

**Also called, *Influence Diagrams* (Howard & Matheson, 1981)**

# Types of Nodes

- **Chance nodes – (ovals) random variables**
  - Have an associated CPT
  - Parents can be decision nodes and other chance nodes
- **Decision nodes – (rectangles) points where the decision maker has a choice of actions**
  - The table is the decision with the highest computed EU for each combination of evidence in the *information link* parents
- **Utility nodes (Value nodes) – (diamonds) the agent's utility function**
  - The table represents a multi-attribute utility function
  - Parents are variables describing the outcome states that directly affect utility

# Types of Links

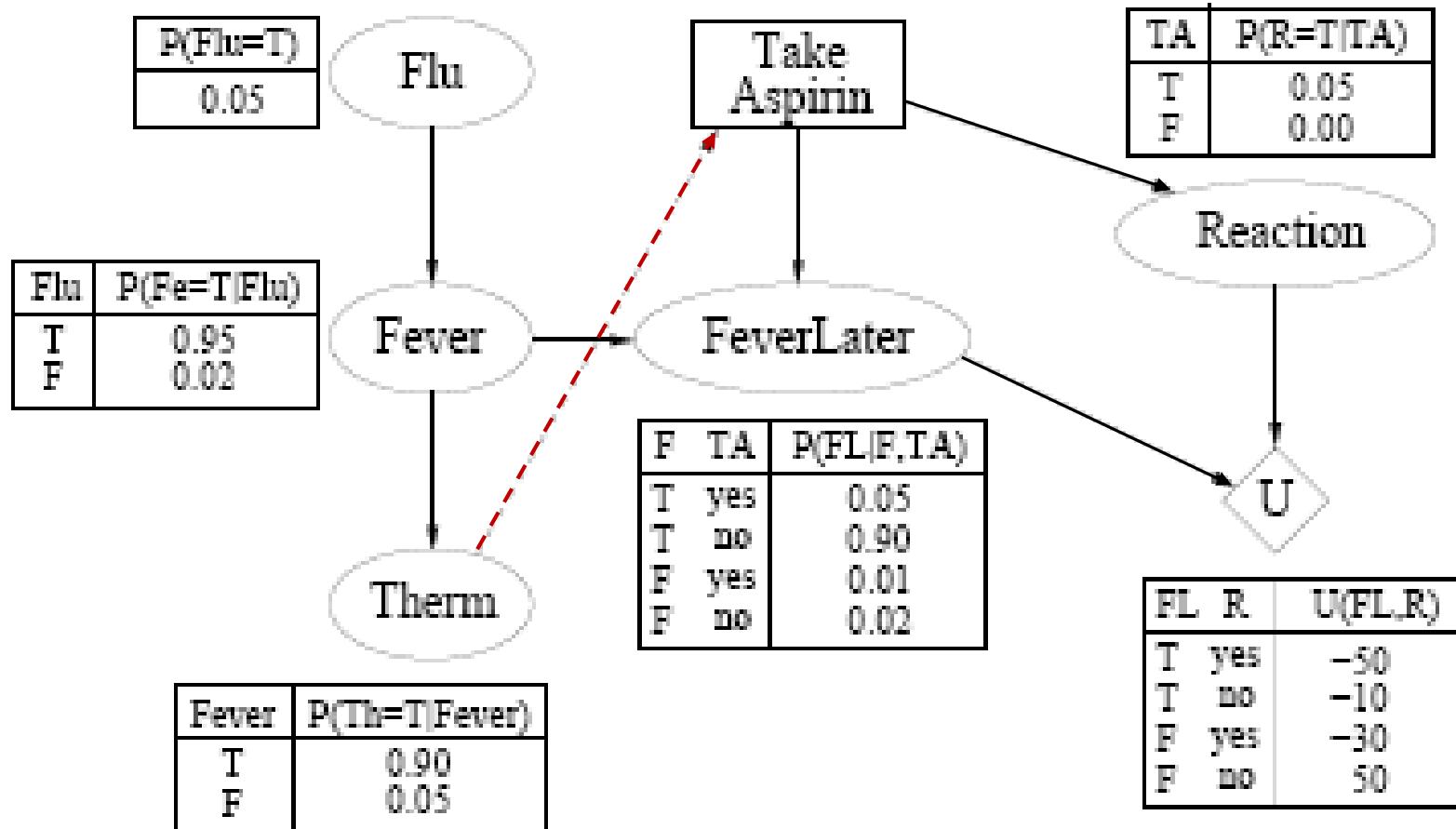
- ***Informational Links*** – indicate when a chance node needs to be observed before a decision is made
  - Any link entering a decision node is an informational link
- ***Conditioning links*** – indicate the variables on which the probability assignment to a chance node will be conditioned

# Fever Problem Description (video)

*Suppose that you know that a fever can be caused by the flu. You can use a thermometer, which is fairly reliable, to test whether or not you have a fever.*

*Suppose you also know that if you take aspirin it will almost certainly lower a fever to normal. Some people (about 5% of the population) have a negative reaction to aspirin. You'll be happy to get rid of your fever, so long as you don't suffer an adverse reaction if you take aspirin.*

# Fever Decision Network



K&N Figure 4.5



# Fever Decision Network

## Netica Demo

# Fever Decision Table

Evidence	$Bel(Flu=T)$	$EU(TA=yes)$	$EU(TA=no)$	Decision
None	0.046	45.27	45.29	no
$Th=F$	0.018	45.40	48.41	no
$Th=T$	0.273	44.12	19.13	yes
$Th=T \ \& \ Re=T$	0.033	-30.32	0	no





# FIT5047 – Intelligent Systems

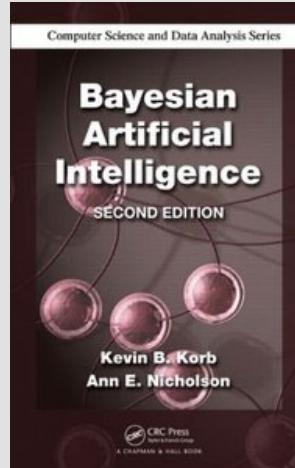
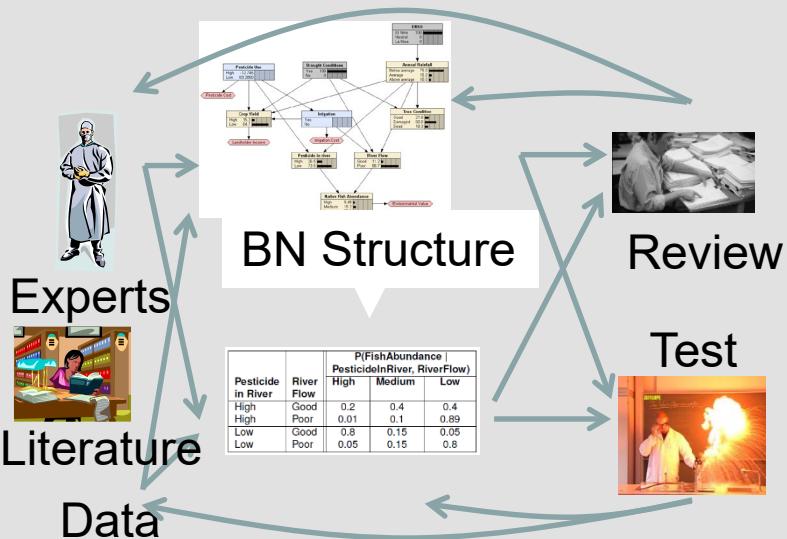
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## Knowledge Engineering BNs

# Knowledge engineering BNs

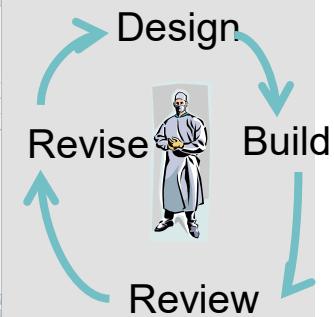
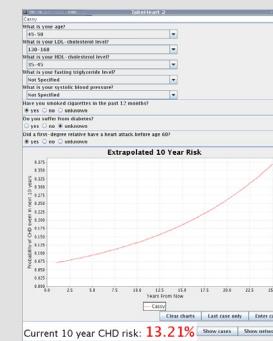
## 1: Build a model

- E.g. Variables: patient's details, diseases, symptoms, interventions
- Costs/benefits: eg. \$, QALY



## 2: Embed model in decision support tool

- Diagnosis
- Prognosis
- Treatment
- Risk assessment
- Prevention

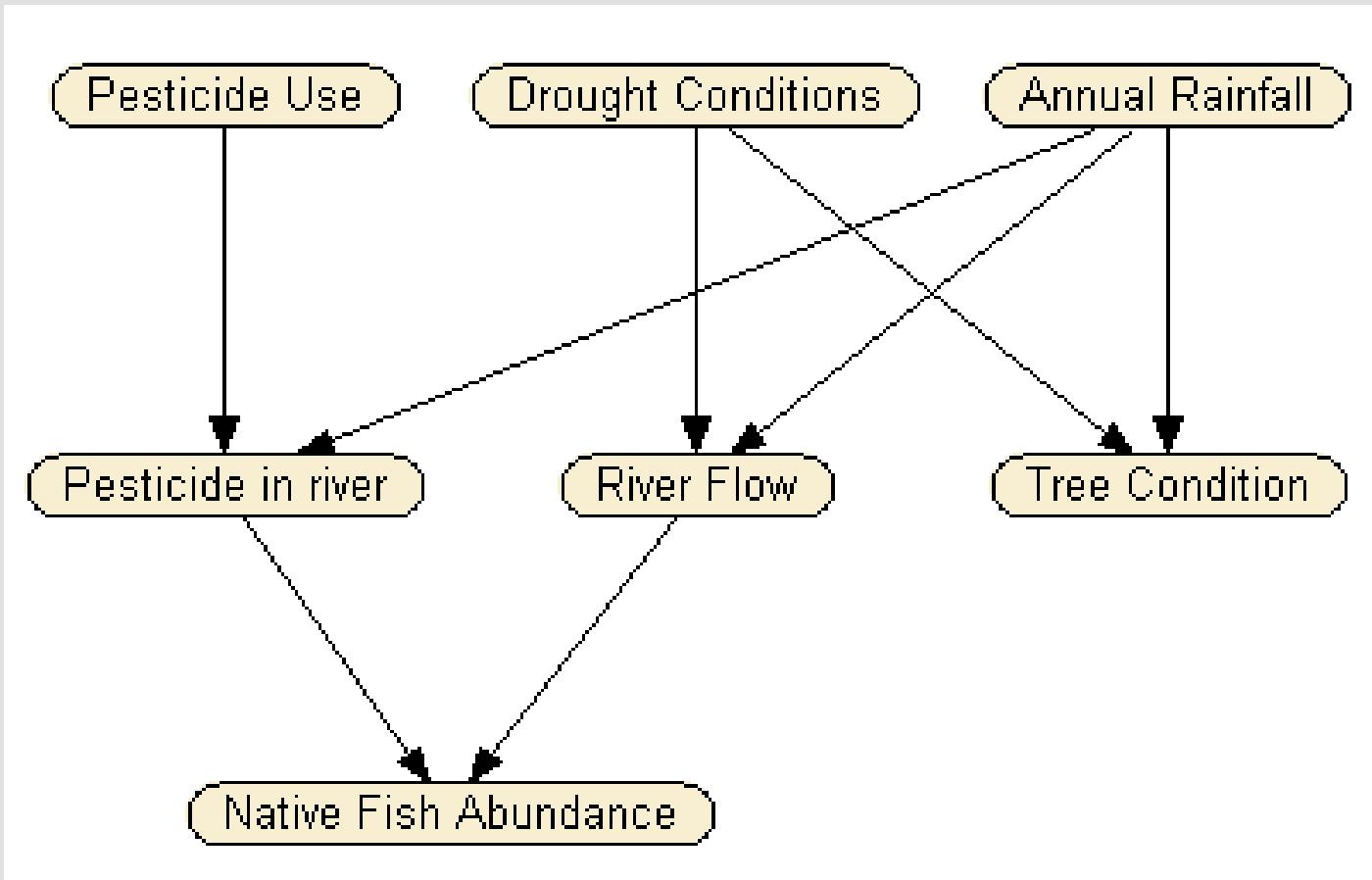


# Example: Native Fish (recall)

## Example (Ver. 1)

A local river with tree-lined banks is known to contain native fish populations, which need to be conserved. Parts of the river pass through croplands, and parts are susceptible to drought conditions. Pesticides are known to be used on the crops. Rainfall helps native fish populations by maintaining water flow, which increases habitat suitability as well as connectivity between different habitat areas. However rain can also wash pesticides that are dangerous to fish from the croplands into the river. There is concern that the trees and native fish will be affected by drought conditions and crop pesticides. (Nicholson et al., 2010) (See [http://bayesianintelligence.com/publications/TR2010\\_3\\_NativeFish.pdf](http://bayesianintelligence.com/publications/TR2010_3_NativeFish.pdf))

# Example: Native Fish (v1) (recall)



# Example: Native Fish (v2)

## Example (Ver. 2)

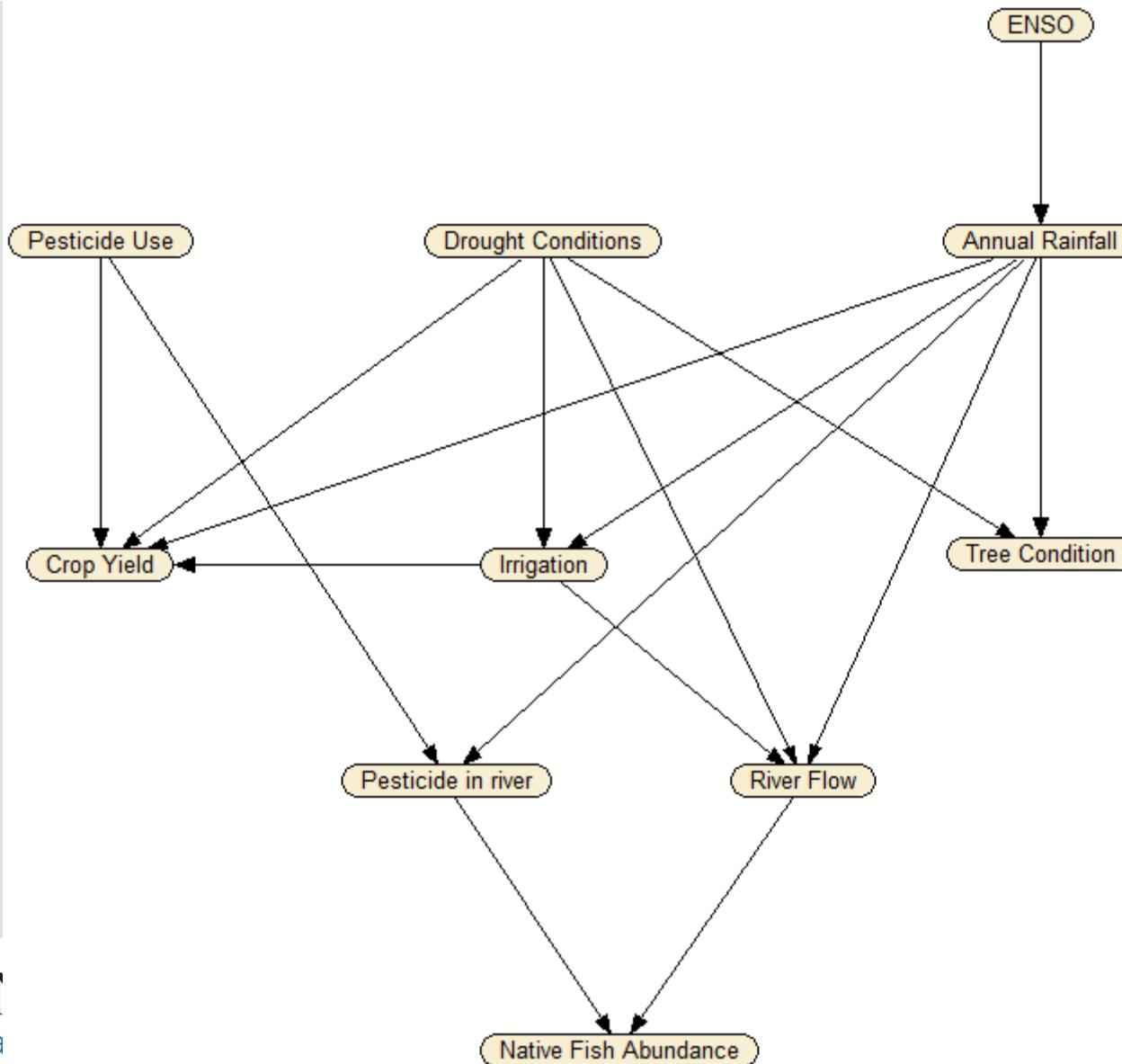
Extending the model:

The El Nino Southern Oscillation (ENSO) is known to influence rainfall patterns. Also, landholders are concerned about how changes to pesticide application regimes (e.g. to protect native fish) might affect crop yields.

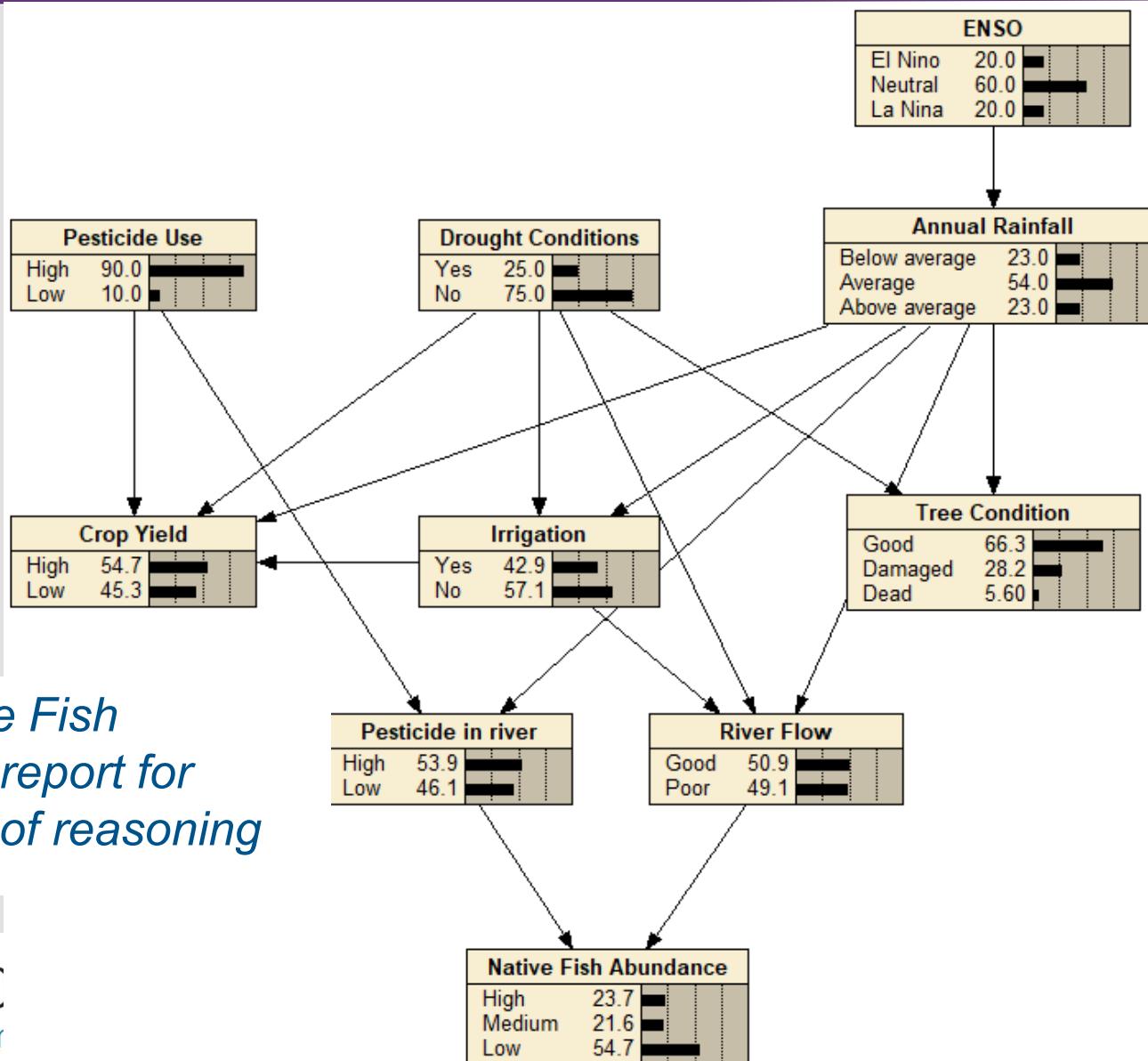
## New Nodes?

- ENSO (El Nino, neutral, La Nina)
- Crop Yield

# Example: Native Fish (v2)



# Example: Native Fish (v2)



See Native Fish  
Technical report for  
examples of reasoning

# Example: Native Fish (v3)

## Using continuous variables

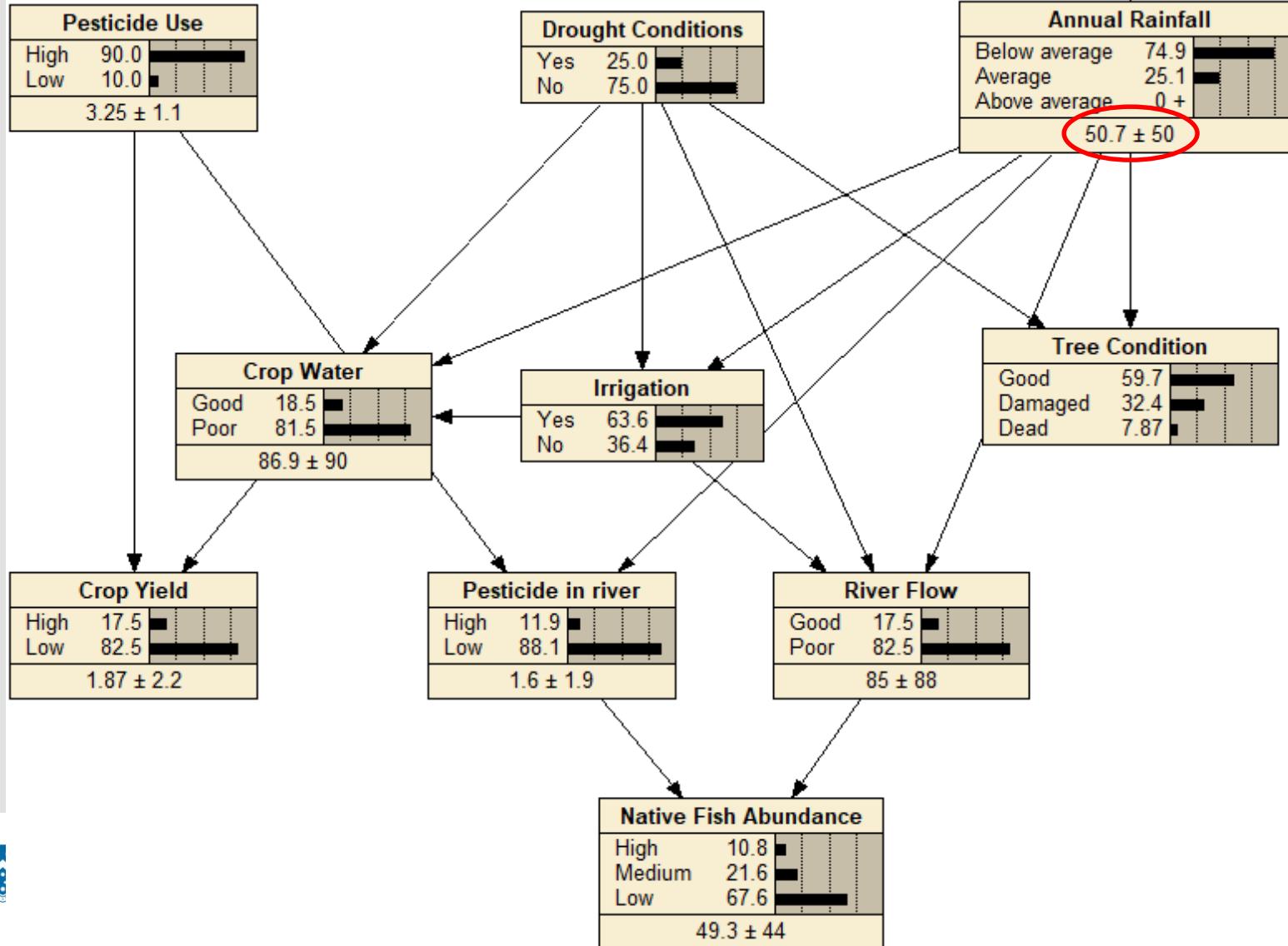
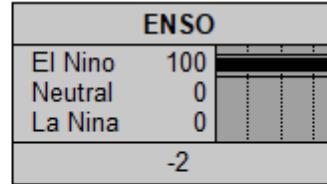
Netica (and other BN software) have functionality to represent continuous variables in a discretised way and use equations to generate the CPTs

The screenshot shows the 'Rainfall (node of NF\_V3)' configuration dialog in Netica. The 'Nature' dropdown is set to 'Continuous'. The 'Title' field contains 'Annual Rainfall'. Below this, there are fields for 'State' (set to 'Below\_average') and 'Interval' (set to 0 - 51). A 'New' button is available for creating new states. On the right side of the dialog are buttons for 'OK', 'Apply', 'Reset', 'Close', 'Table', and 'Help'. A preview window at the top right shows the equation:  $P(\text{Rainfall} \mid \text{ENSO}) = \text{NormalDist}(\text{Rainfall}, 126 + 50 * \text{ENSO}, 30)$ .

*Instead of entering CPTs by hand, use the “Equation to Table” function (under Table menu)*

*NOT required for this unit, but important for real-world modelling*

# Example: Native Fish (v3)



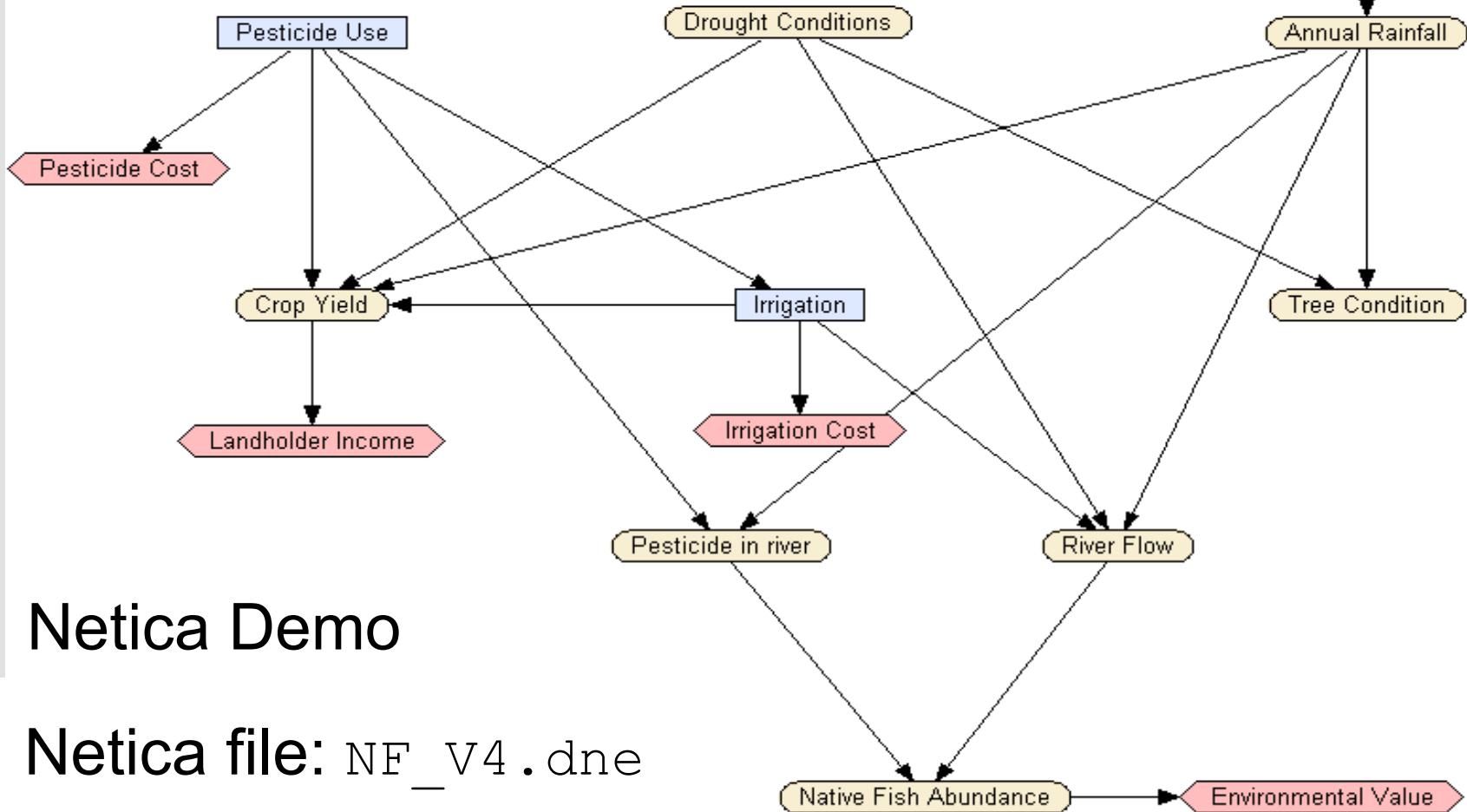
# Decision network: Native Fish (v4)

## Example (Ver. 4)

There is a proposal to allow farmers to take water from the river system to irrigate their crops, but this will affect the provision of flows for fish habitat, as well as the amount of pesticides that could reach the river. River managers are looking at the trade-offs in varying the use of fertilisers in the area, and releasing water for farming irrigation.

# Decision network: Native Fish (v4)

*Example of a sequential decision: first – use pesticide? Second irrigate?*



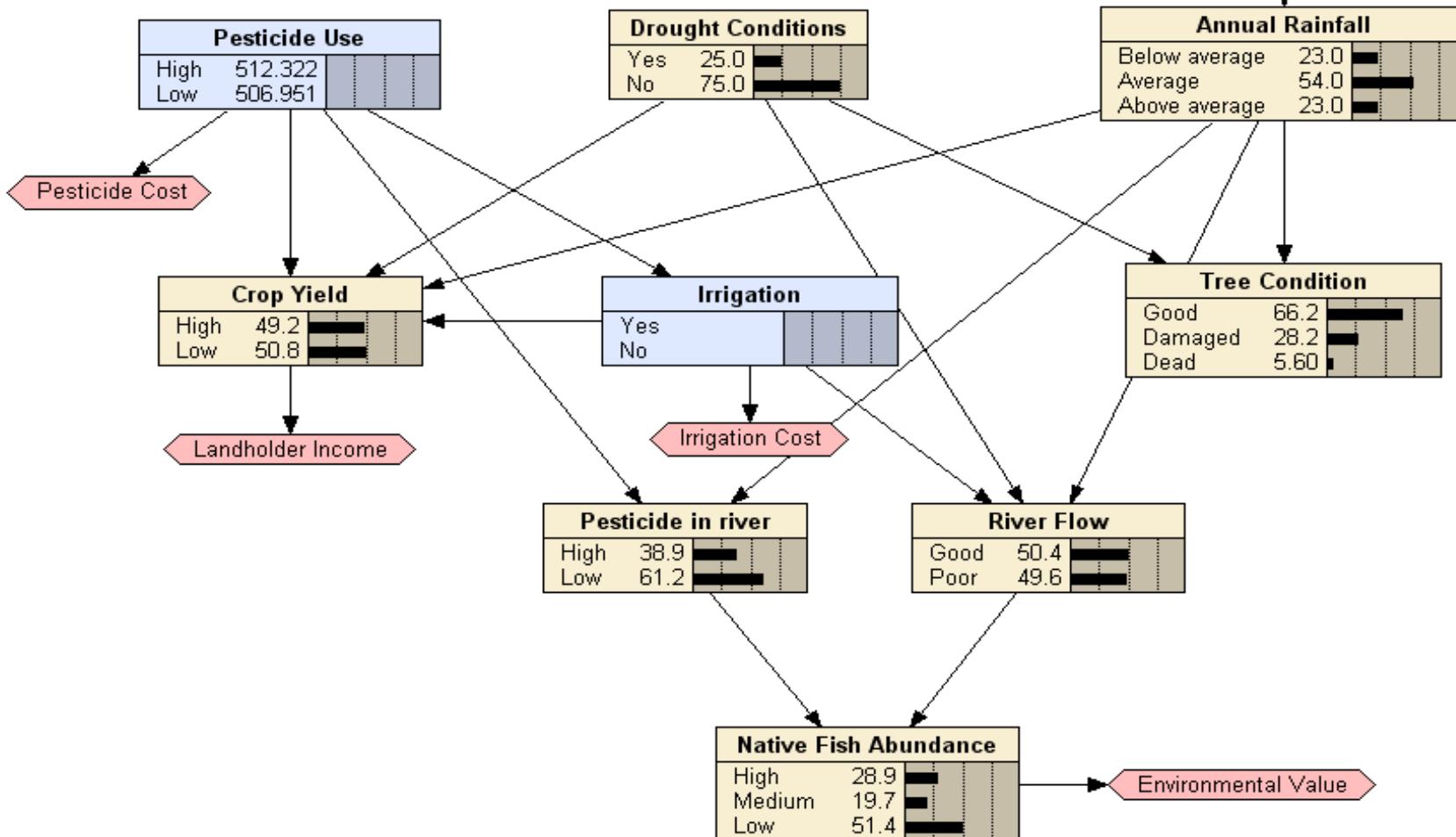
Netica Demo

Netica file: NF\_V4.dne

# Decision network: Native Fish (v4)

First decision:

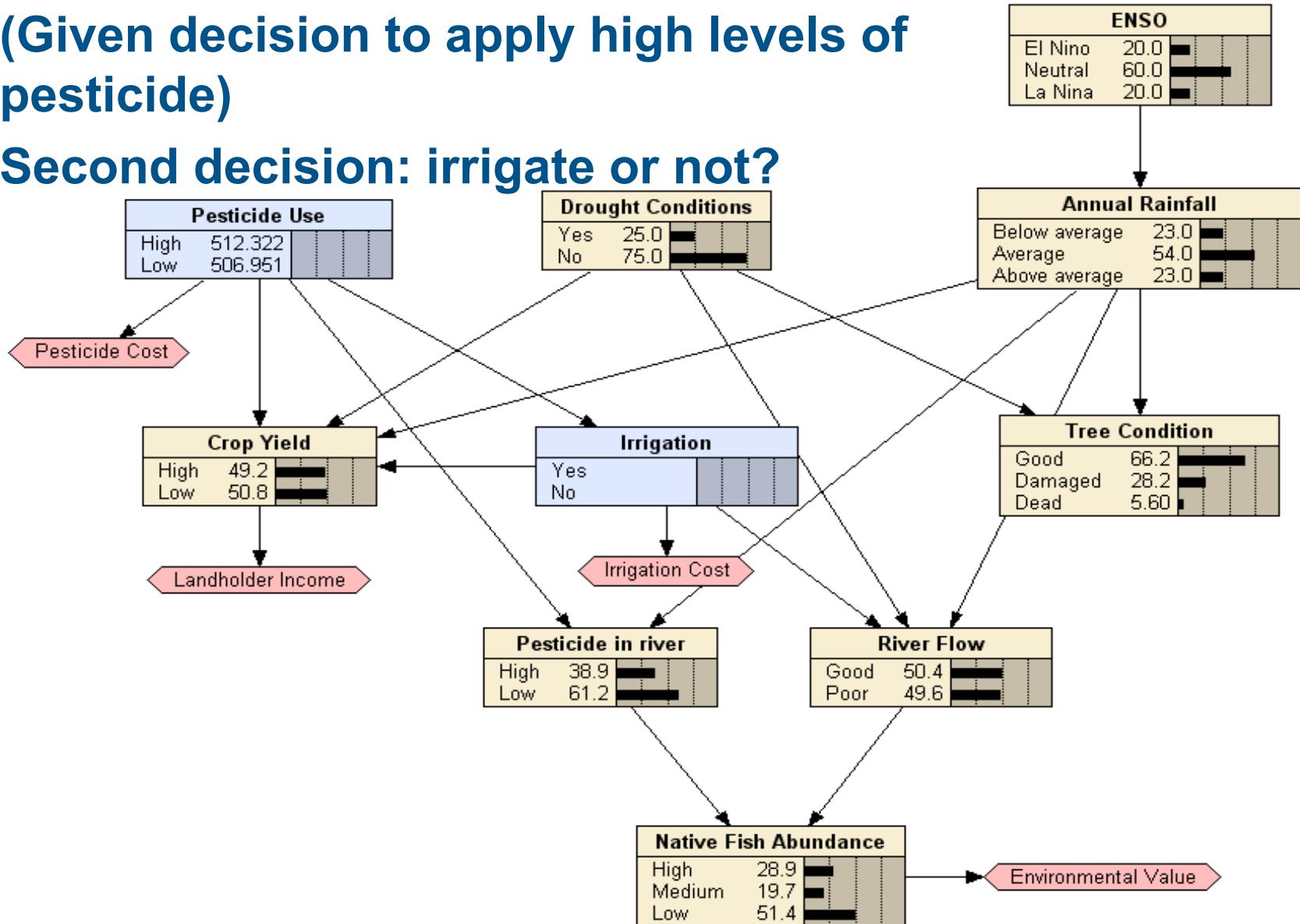
How much pesticide to use?



# Decision network: Native Fish (v4)

(Given decision to apply high levels of pesticide)

Second decision: irrigate or not?



# A BN for Covid-19 testing

Wu, Y., Foley, D., Ramsay, J., Woodberry, O., Mascaro, S., Nicholson, A., & Snelling, T. (2021). Bridging the gaps in test interpretation of SARS-CoV-2 through Bayesian network modelling. *Epidemiology and Infection*, 149, E166.  
doi:10.1017/S0950268821001357 (link to paper on Moodle)

Thanks to Yue Wu for providing her slides for this case study for FIT5047, 2022  
(note – copyright stays with her)

# Bridging the gaps in test interpretation of SARS-CoV-2 through Bayesian network modelling

Yue Wu, David Foley, Jessica Ramsay, Owen Woodberry, Steven Mascaro,  
Tom Snelling, Ann E Nicholson

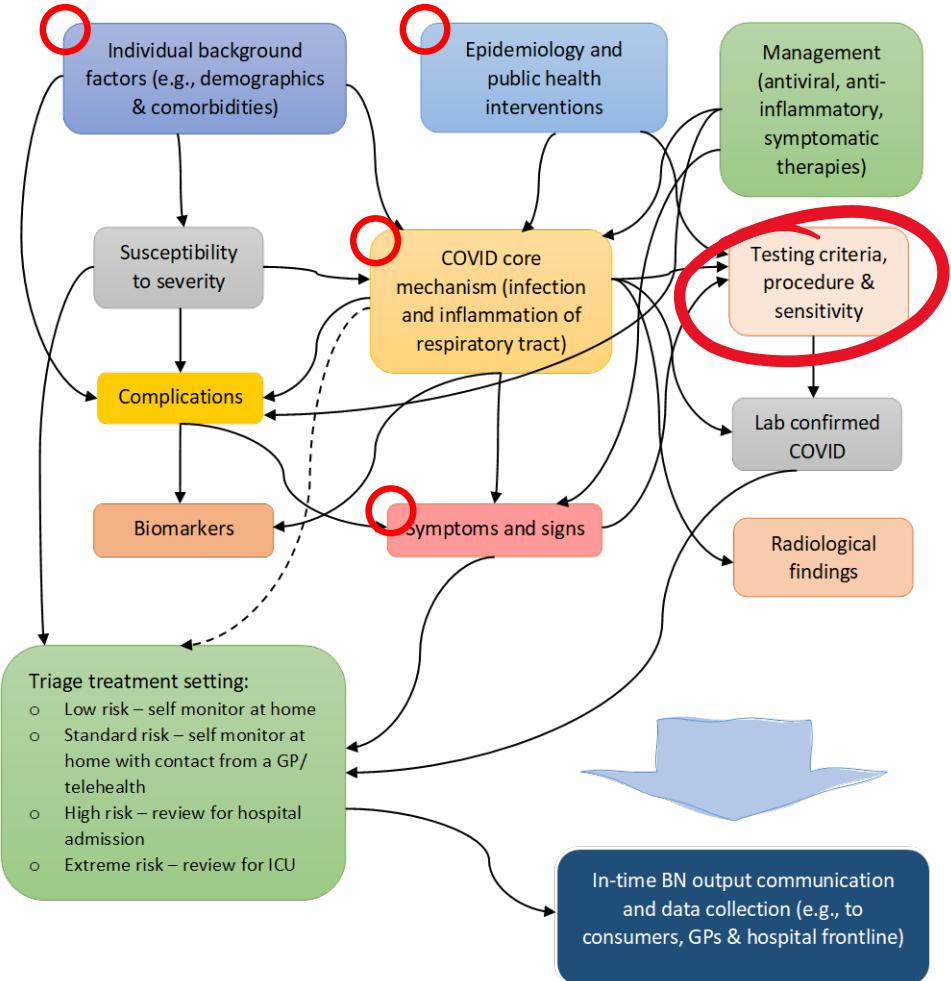
The COVID Intelligence team **with thanks to many experts!**



# High level model framework

## Modelling purpose

how COVID-19 can be diagnosed based on its causal connections with background factors and symptoms, signs and tests.

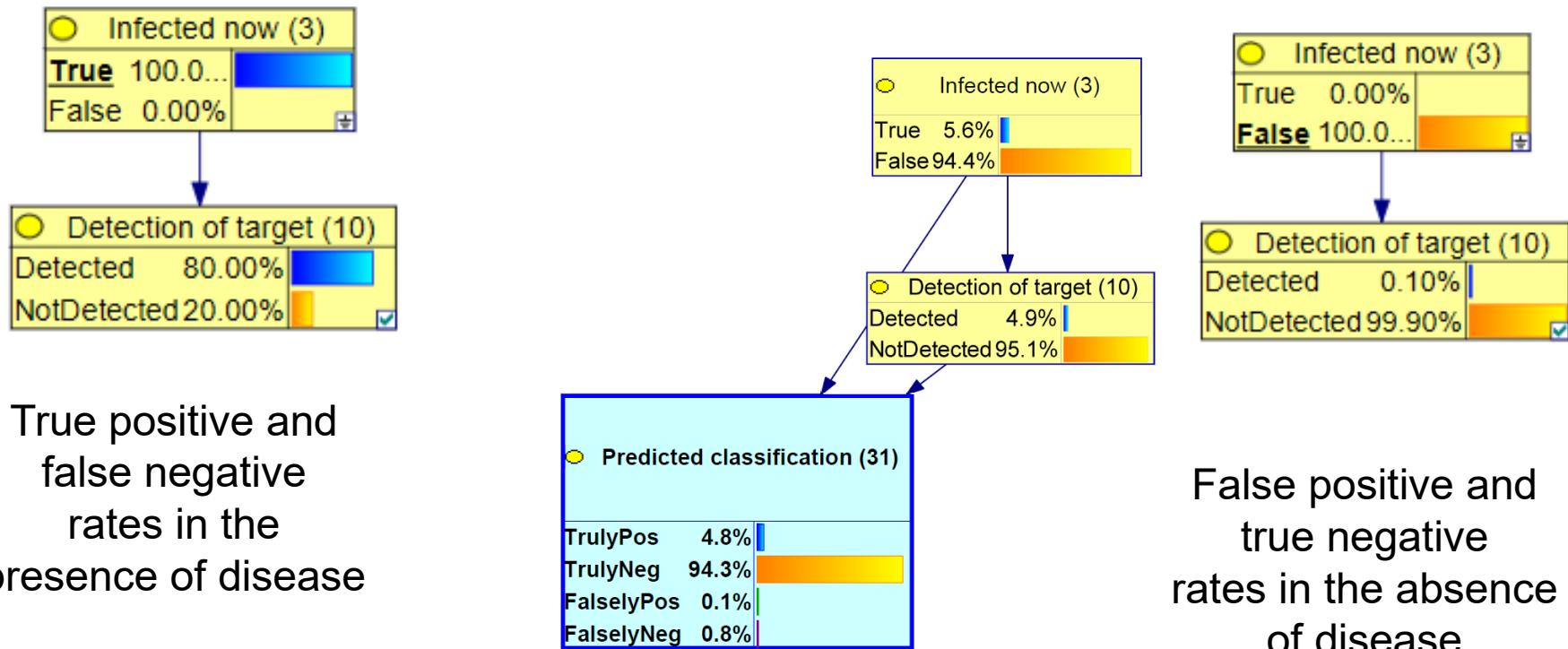


# The model

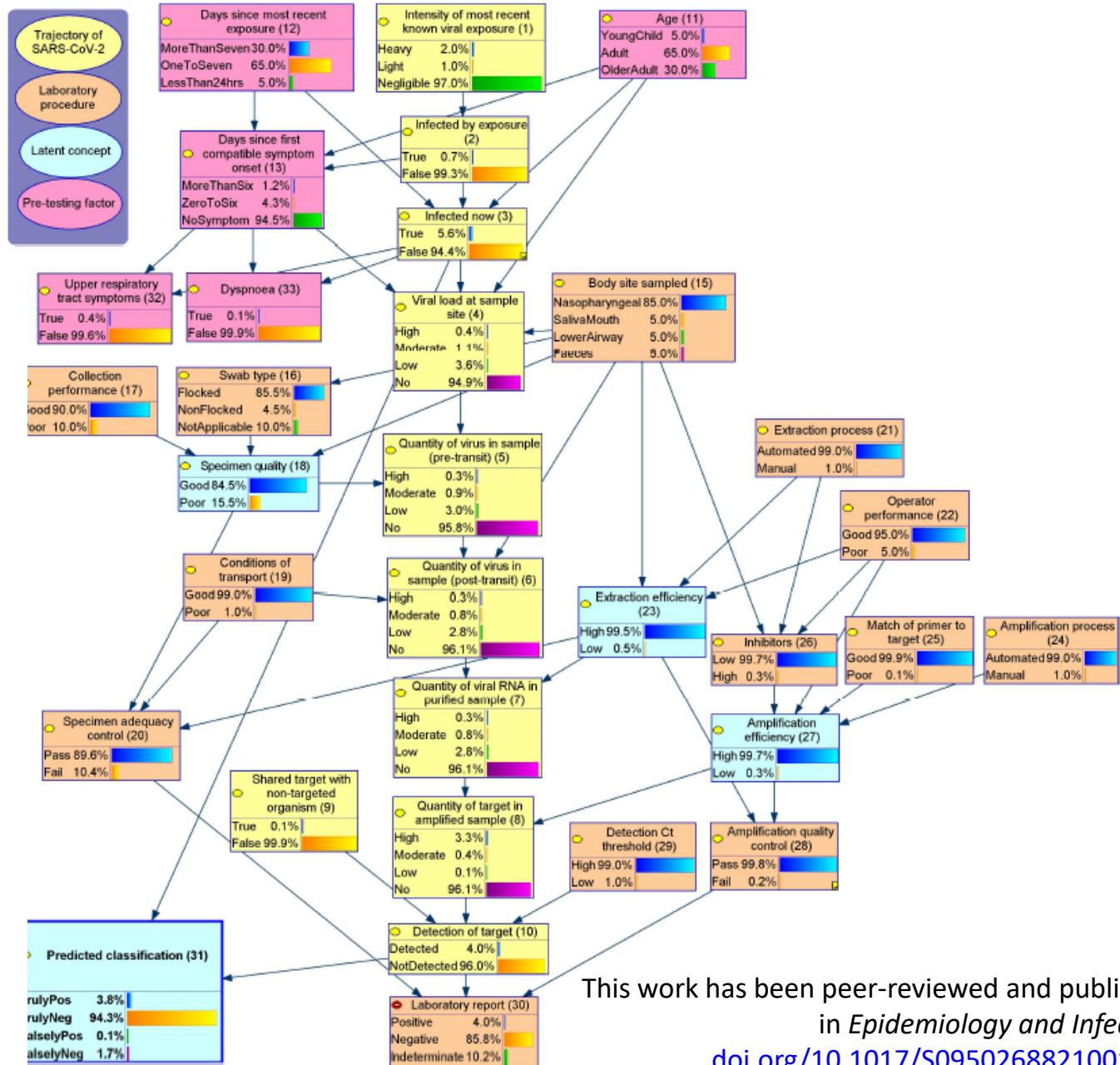
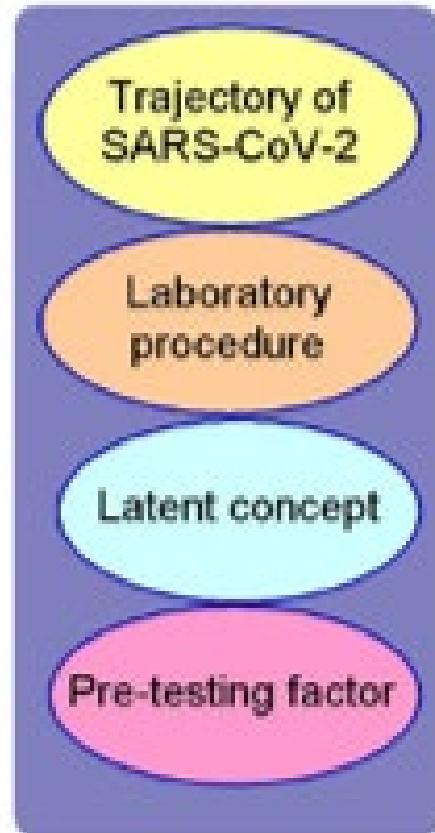
A wide variation in rates of false negatives has been reported for SARS-CoV-2, ranging from 1.8 to 58%.

Arevalo-Rodriguez et al. PLoS One 2020

Kucirka LM et al. Annals of Internal Medicine, 2020

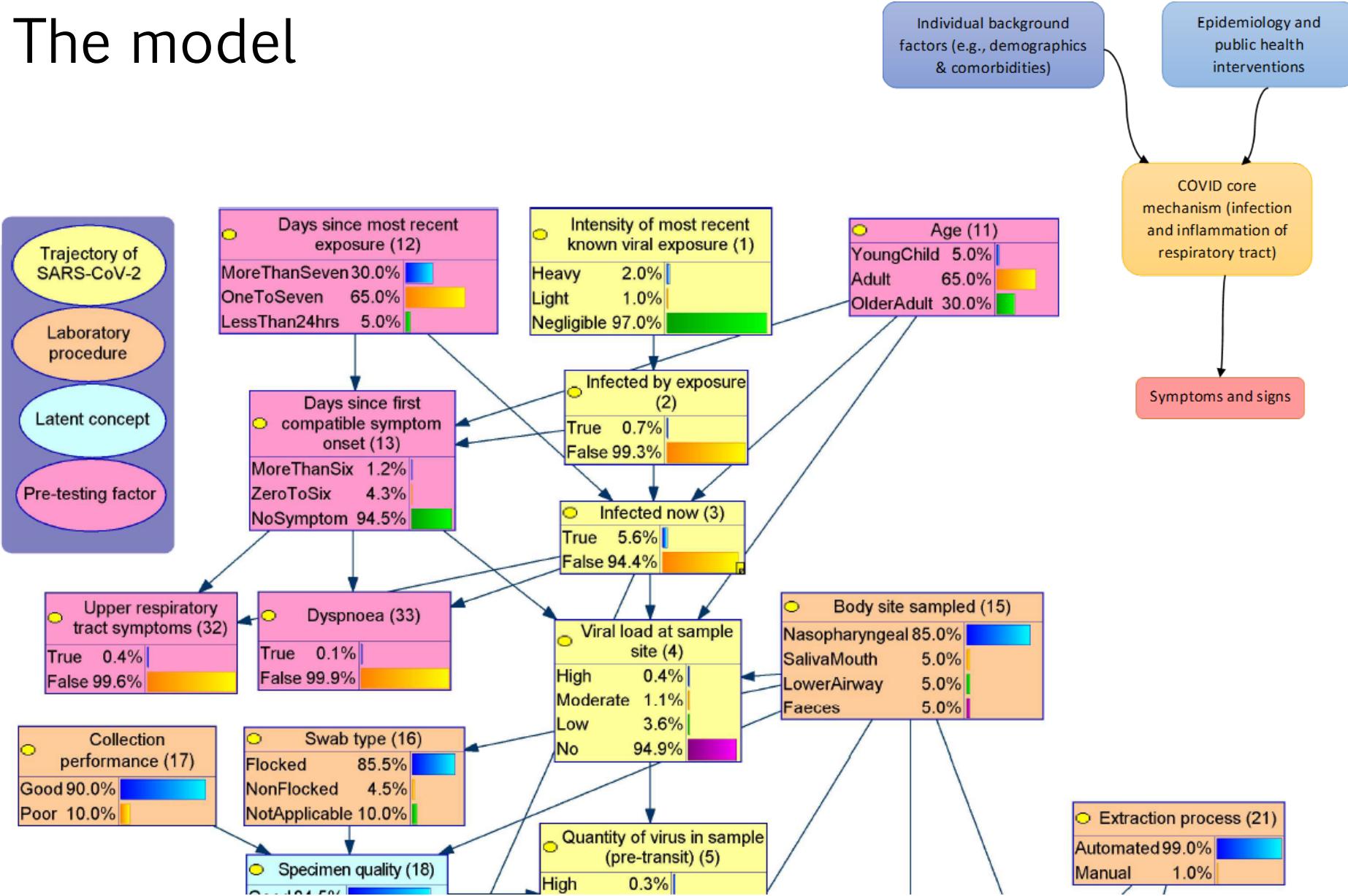


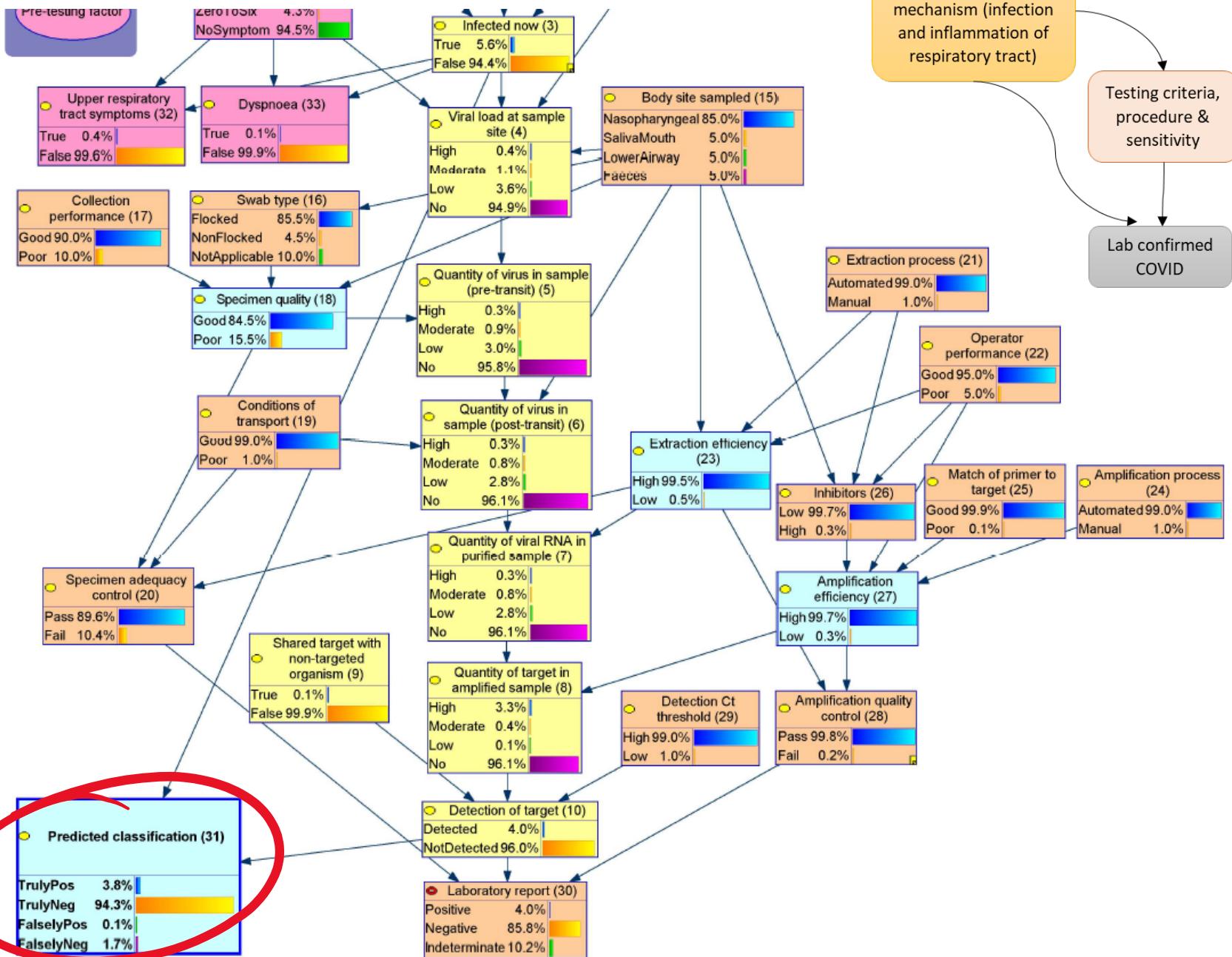
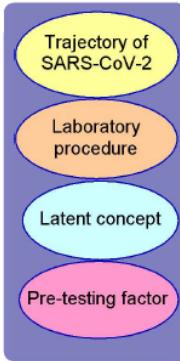
# The model



This work has been peer-reviewed and published  
in *Epidemiology and Infection*  
[doi.org/10.1017/S0950268821001357](https://doi.org/10.1017/S0950268821001357)  
All models and parameters are openly available  
via [osf.io/t834y/](https://osf.io/t834y/)

# The model





# Demonstrative use in simulated scenarios

## Scenario A

Significant impact of baseline prevalence of disease on false-negative rates.

## Scenario B

Influence of exposure intensity and presence of symptoms on the test result and predicted probability of infection.

## Scenario C

Influence of specimen quality on the probability of a positive test result in those who are infected.

This work has been peer-reviewed and published in

*Epidemiology and Infection*

[doi.org/10.1017/S0950268821001357](https://doi.org/10.1017/S0950268821001357)

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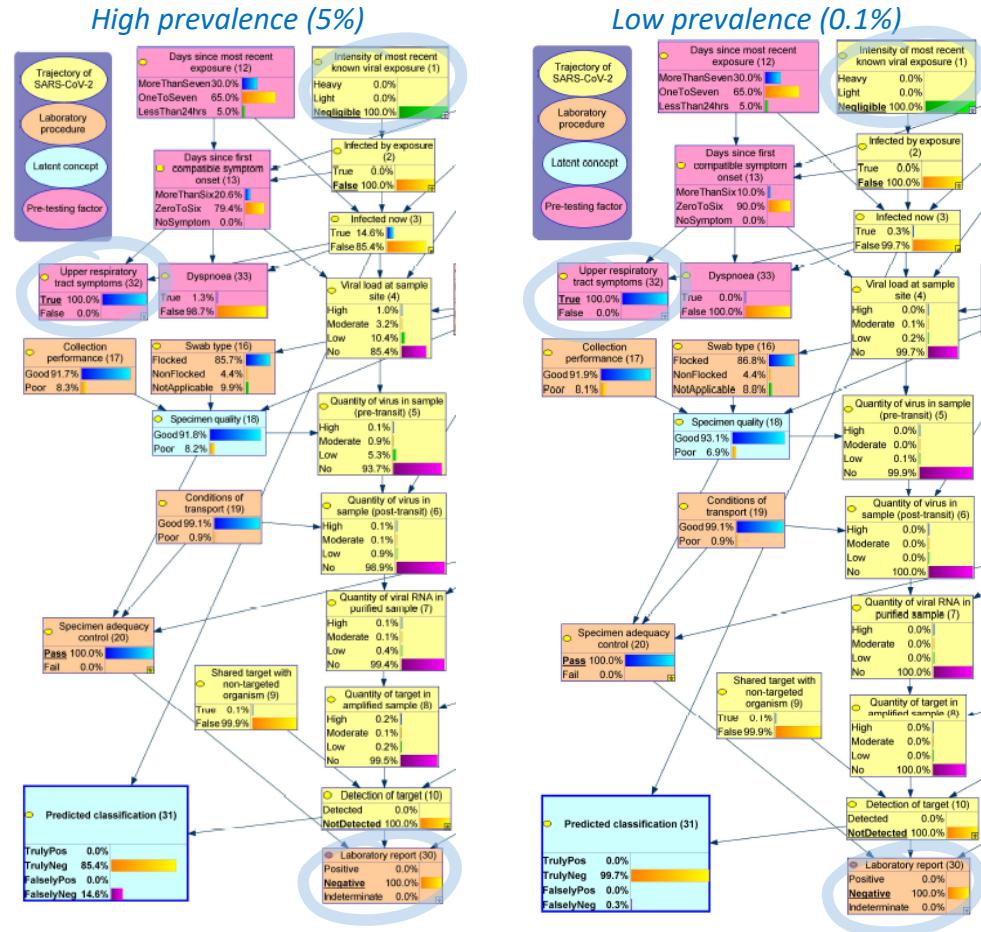
[osf.io/t834y/](https://osf.io/t834y/)

# Demonstrative use

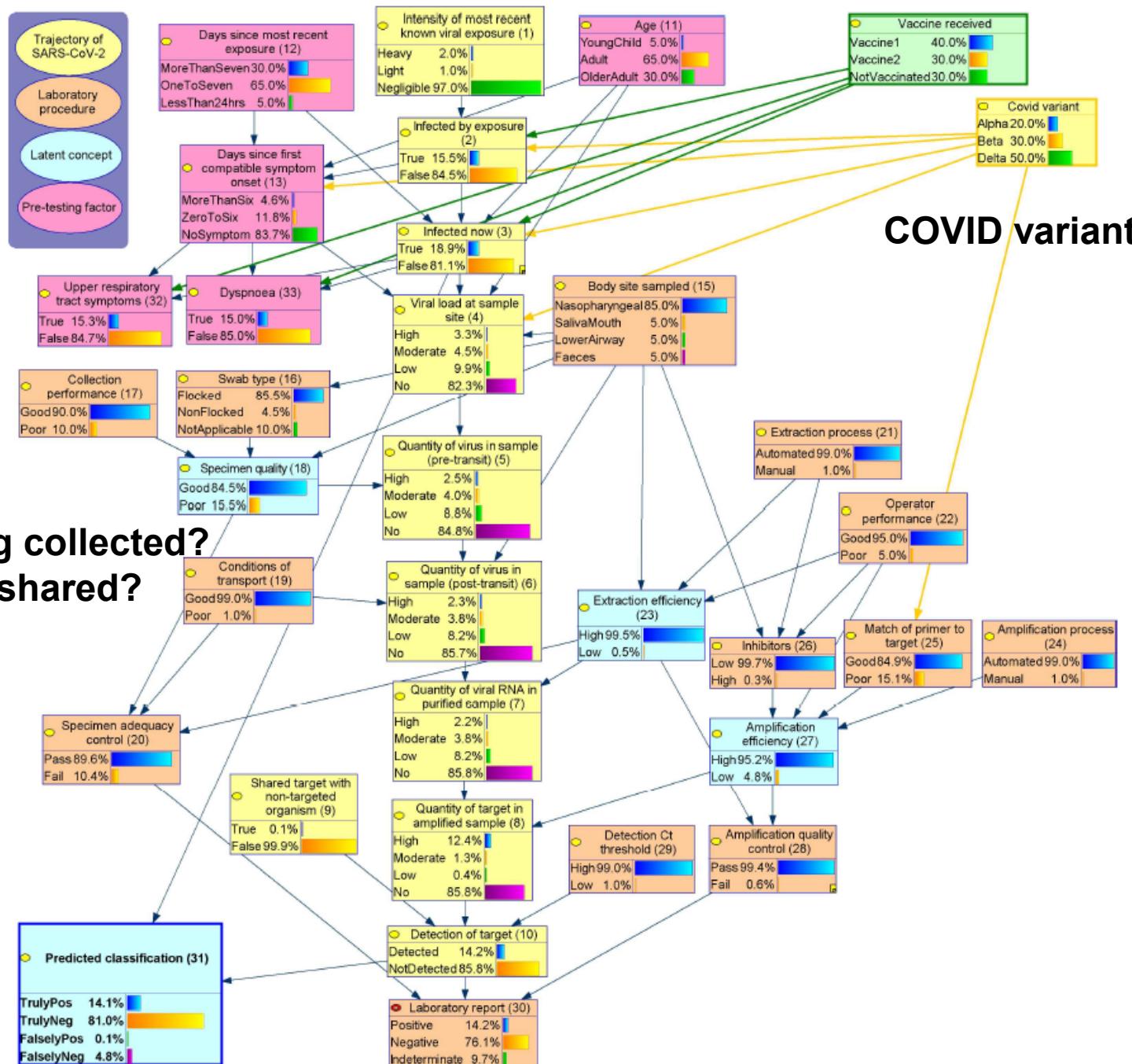
## Scenario A

Significant impact of baseline prevalence of disease on false-negative rates.

Comparing high and low prevalence (5% vs. 0.1% underlying incidence of the virus), for an individual who has **negligible known recent viral exposure (1)** and experiences **upper respiratory symptoms (32)** but **tested negative (30)**, the probability of a falsely negative result is **14.6%** and **0.3%**, respectively.



# Next steps

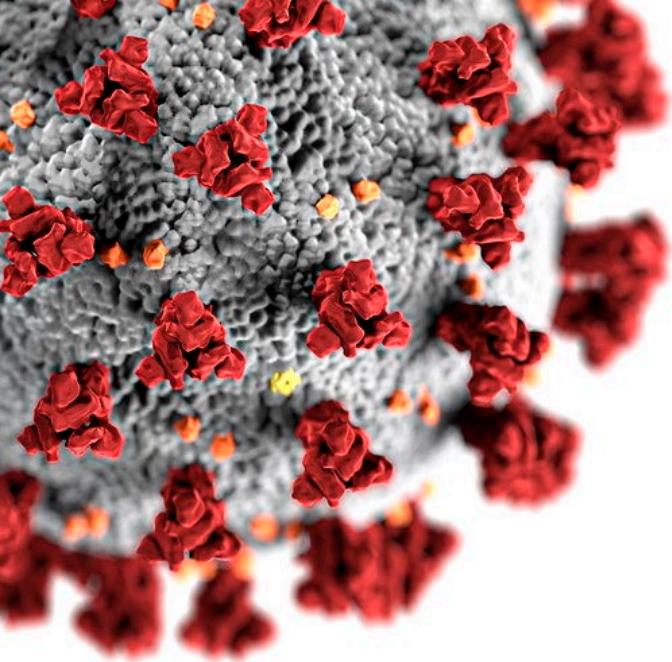


# Model elicitation process

1. Gather information
  - 15-min initial briefing, clarifying purpose of the workshop
  - Experts sent through any useful resource for the diagnosis story
  - Draft model describing modeller's initial understanding
2. Two-hour group workshop (10 experts): develop structure
3. Revisions  $\leftrightarrow$  qualitative parameterisation  $\leftrightarrow$  expert validation
  - Four 1-on-1 sessions (6 experts)
4. Data validation (in plan)

# KEBN Case Study: COVID-19

- A causal BN for COVID-19 Prognosis for individual patient clinical decision support



# Modelling COVID-19 with Bayesian networks for Clinical Decision Support

The COVID Intelligence team



Tom Snelling



Ann Nicholson



Steven Mascaro



Yue Wu



Owen Woodberry



Jessica Ramsay



Ross Pearson

with thanks to many experts!



THE UNIVERSITY OF  
SYDNEY

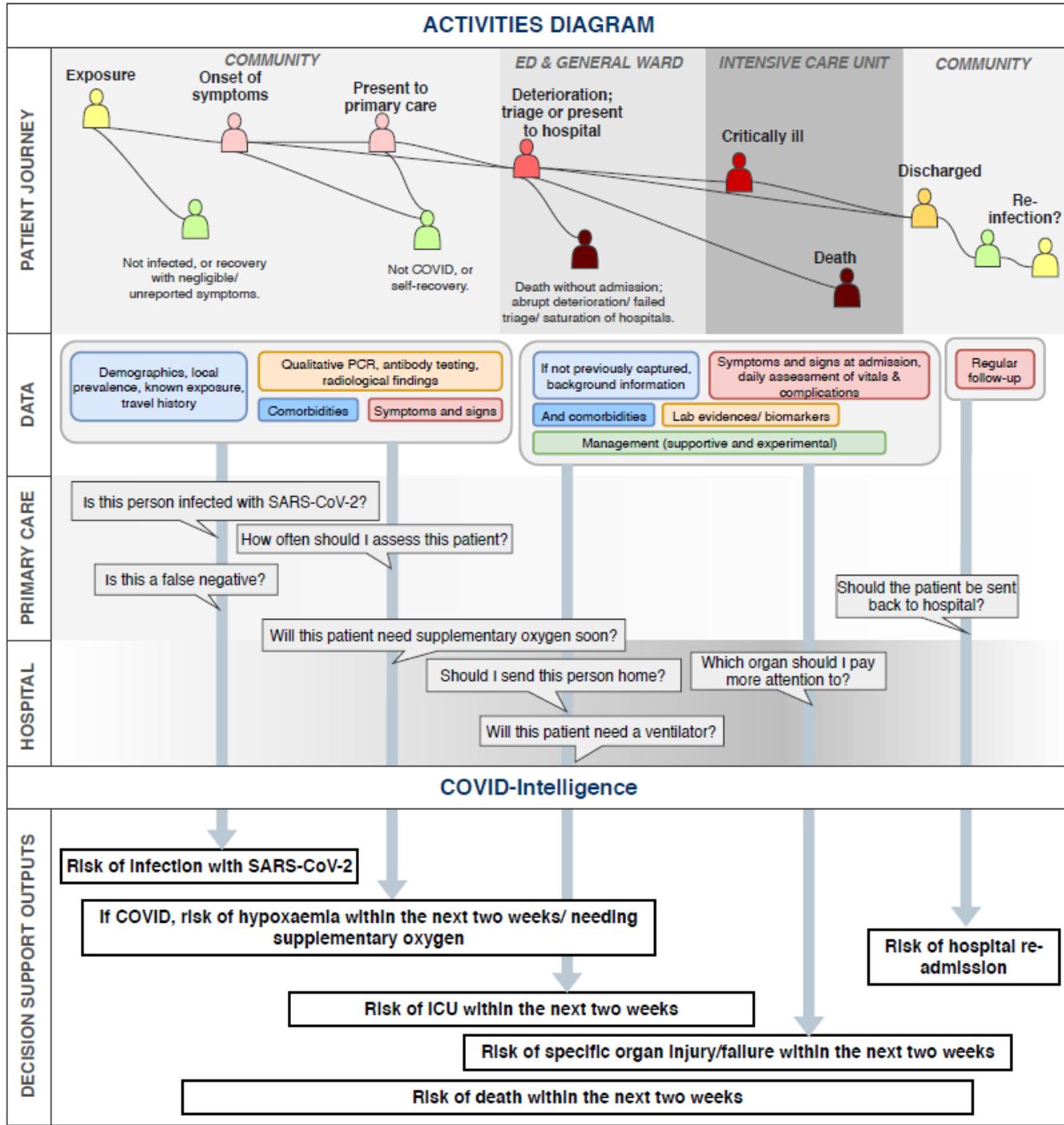


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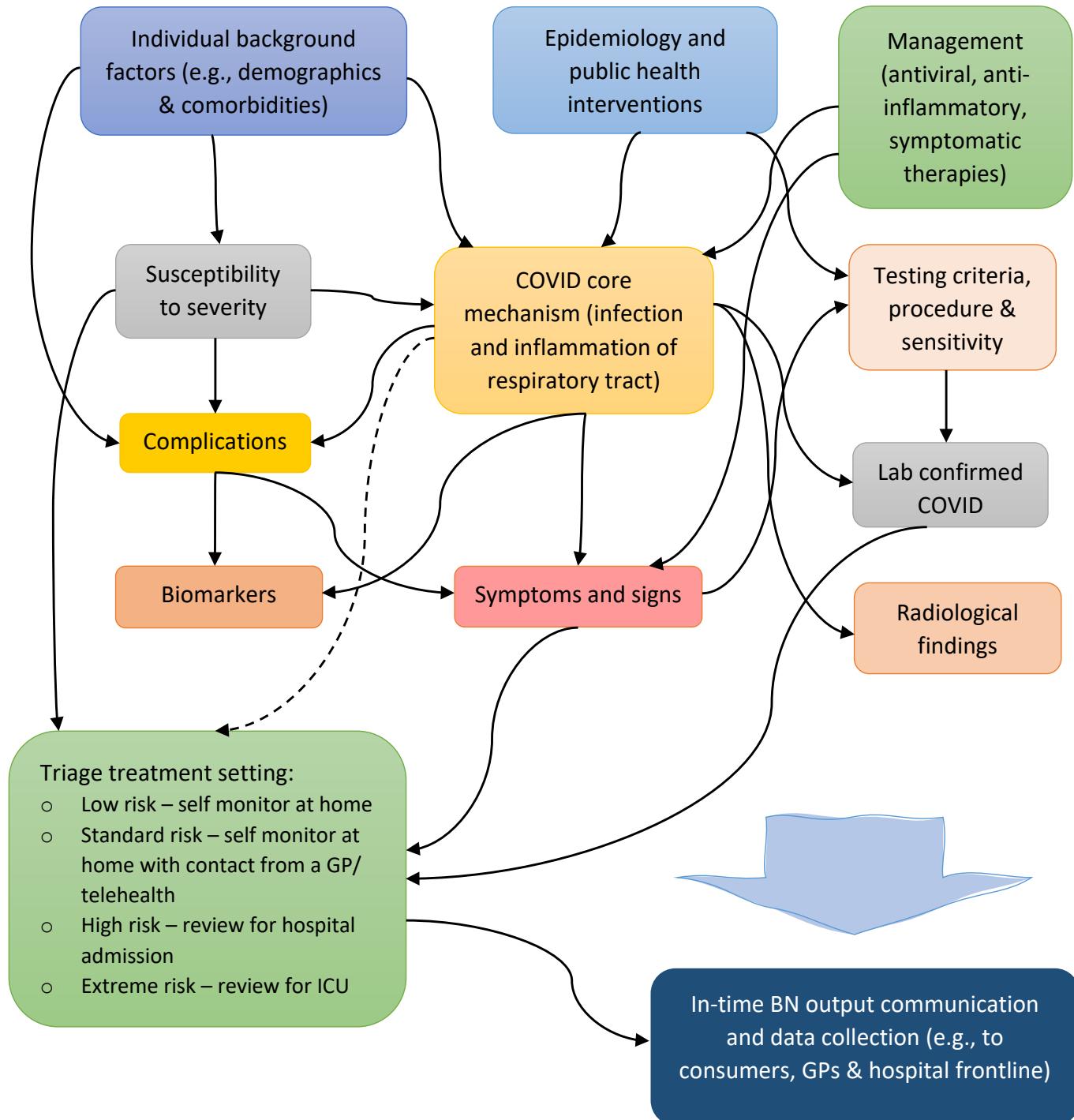
TELETHON  
**KIDS**  
INSTITUTE

COVID-19 | CLINICAL DATA  
ANALYTICS  
PLATFORM  
<https://www.covidcdap.org/>

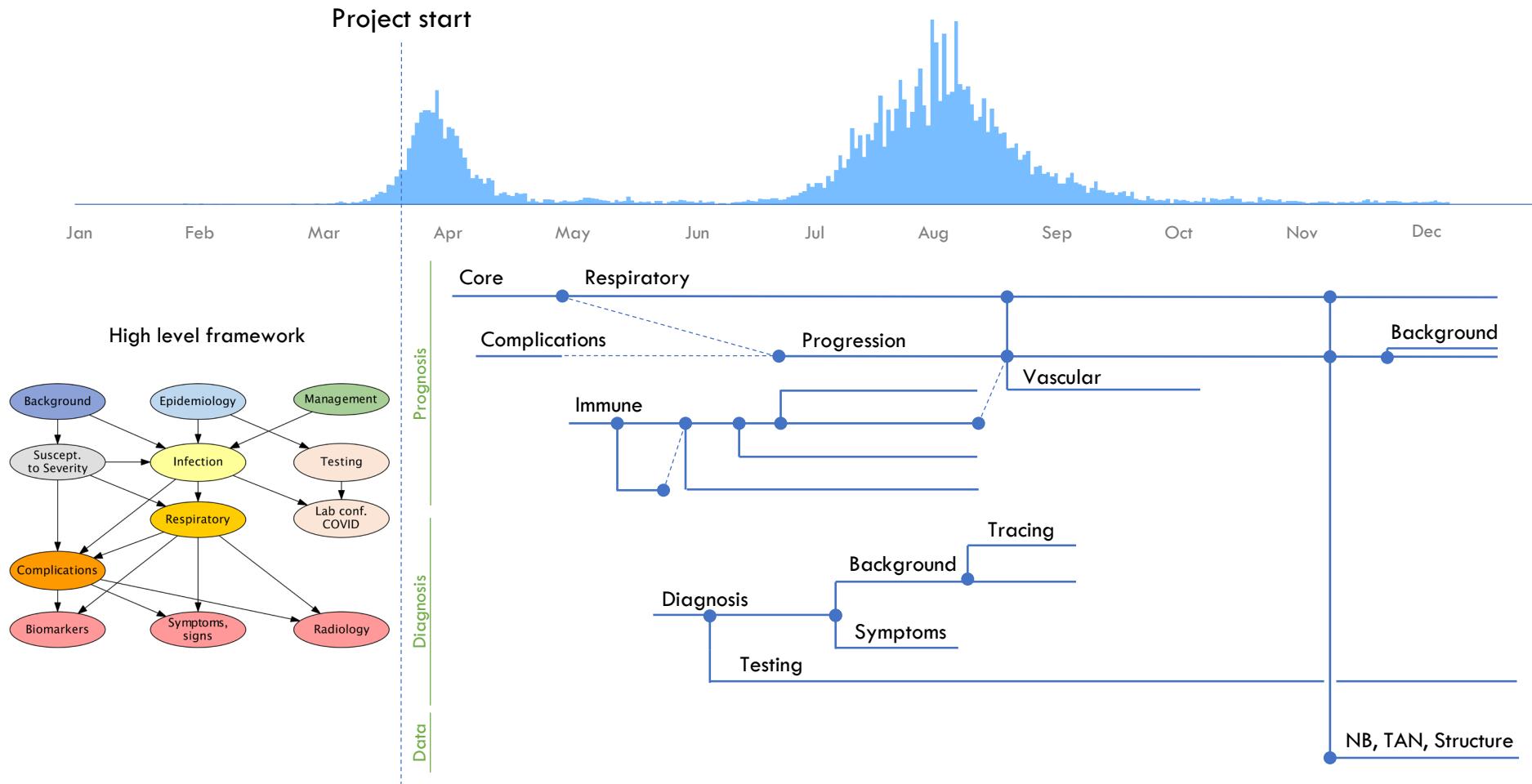
## ACTIVITIES DIAGRAM



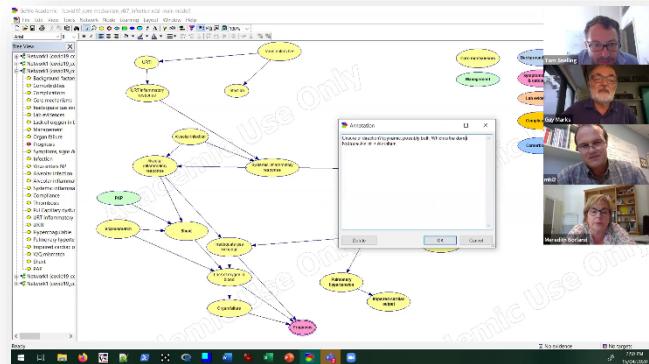
# Modelling Framework



# Model development tree (2020 only)



# Expert elicitation



This screenshot shows a COVID-19 expert elicitation survey interface. It includes sections for understanding the COVID-19 causal process, systemic inflammatory responses, and a risk assessment for severe disease. Participants can rate statements on a scale from impossible to a certainty.

**Understanding the COVID-19 causal process**  
Systemic inflammatory responses to SARS-CoV-2 infection  
Consider that a SARS-CoV-2 infection is present at a given anatomical site. How will the site of infection and background risk factors affect the risk and extent of systemic inflammatory response?

Consider an infection involving the **upper respiratory tract** in a person at **typical/ standard risk** (no important risk factors) for severe disease.

How likely is this to cause a **systemic inflammatory response**?  
How likely is any such systemic inflammatory response to be **severe**?

Now consider infection of the **upper respiratory tract** in a person at **high risk** for severe disease.

How likely is this to cause a **systemic inflammatory response**?  
How likely is any such systemic inflammatory response to be **severe**?

Any other comments?

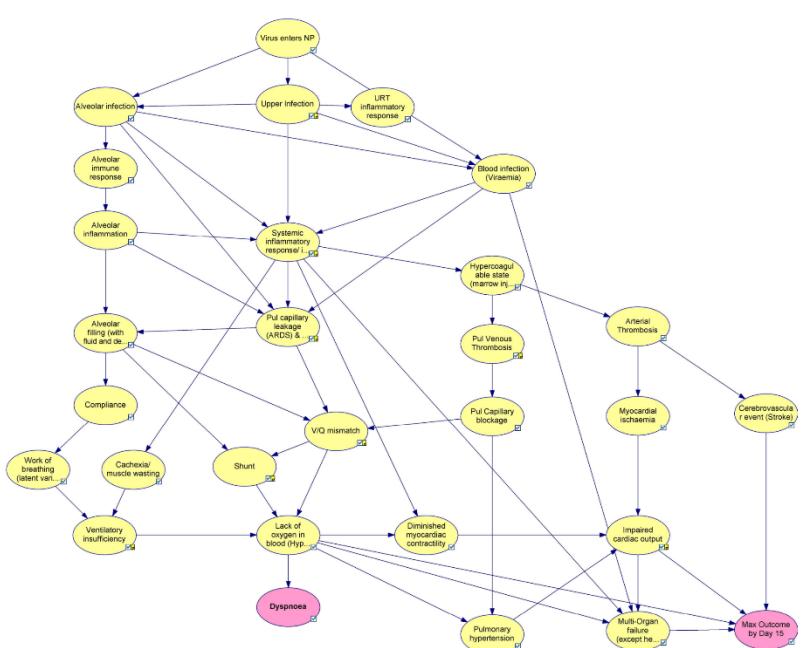
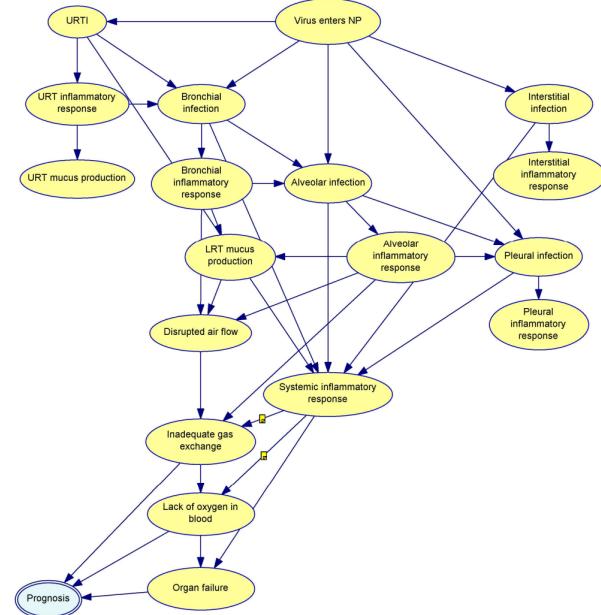
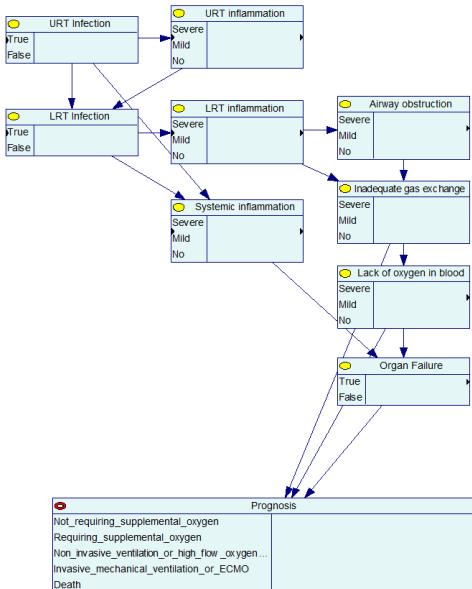
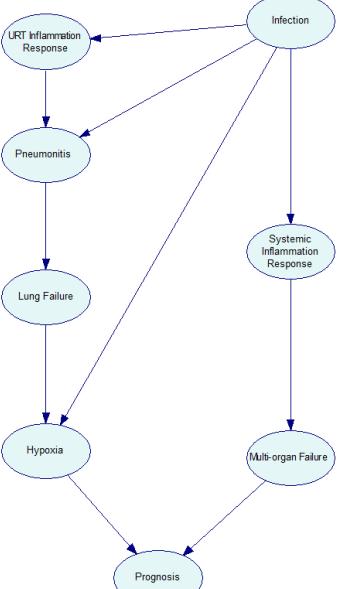
Workshops  
Online

1-on-1s  
Online

Surveys  
Online

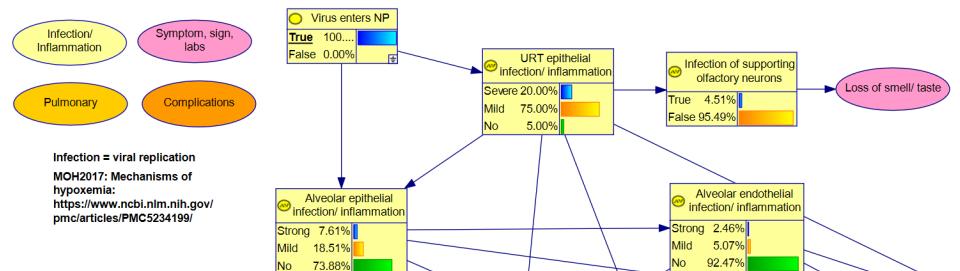
... and literature  
Online

# The Respiratory Model – the evolution



# The Respiratory Model

## Infection



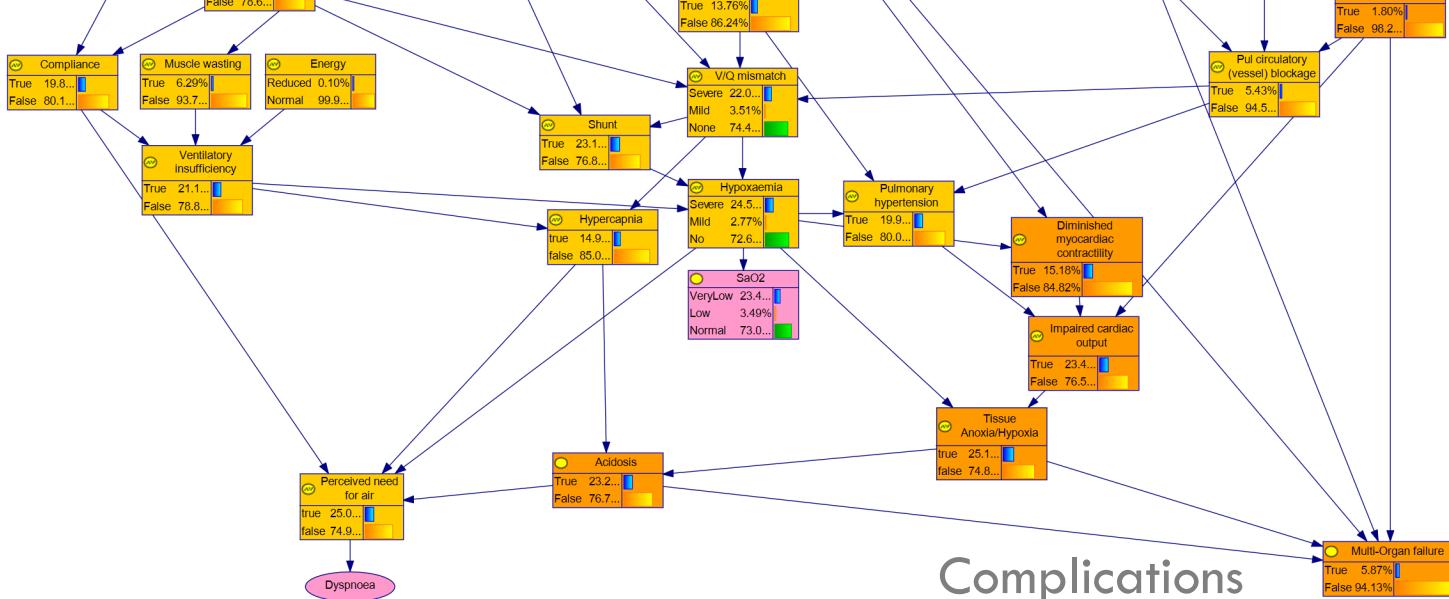
Authors: COVID Intelligence (see respiratory model description\_v1 for expert contributors and further model details)

Affiliated institutions: Monash University, University of Sydney, Telethon Kids Institute

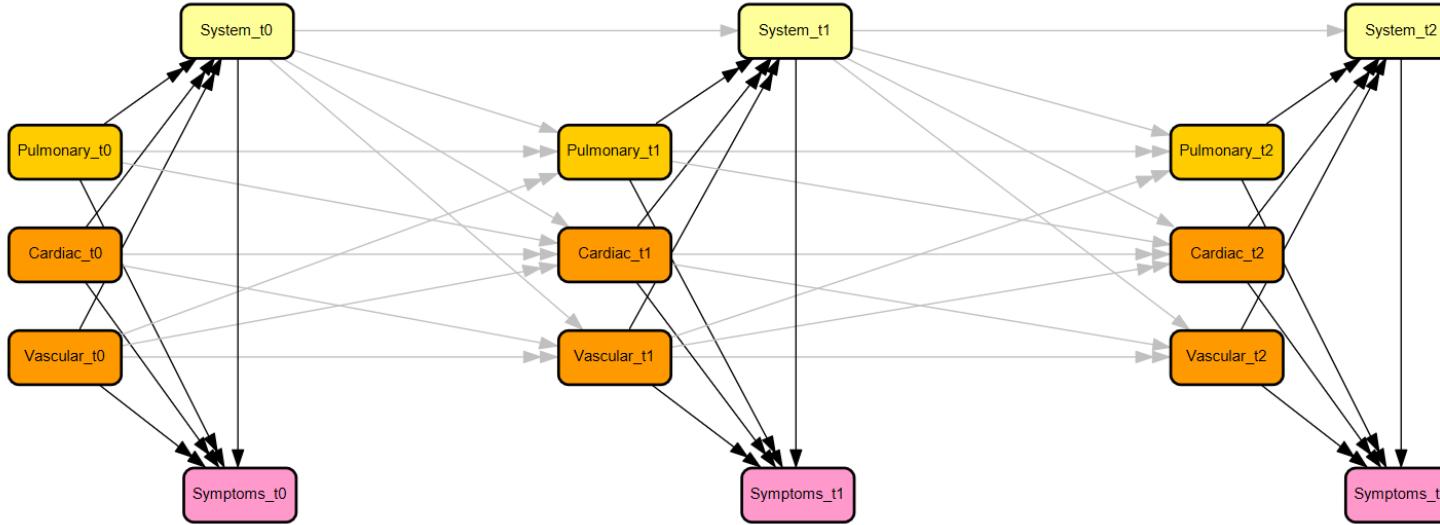
Last update: 10 November 2020

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## Mechanical



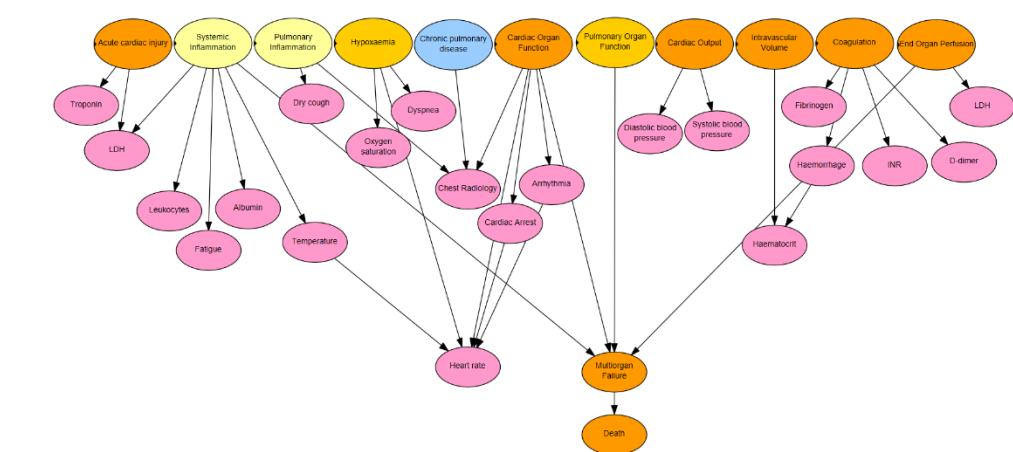
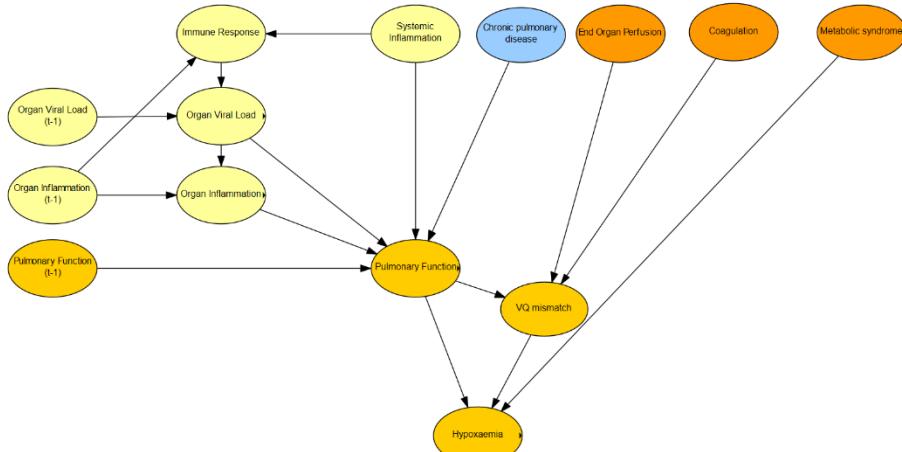
# The Progression Model



Pulmonary

Example of a “Dynamic BN”, where time is represented explicitly [not covered in FIT5047]

Symptoms, etc.



# COVID-BN “Calculator”

- We have developed a web-based interface to the COVID causal BN, for use by clinicians

## DEMO

- <http://covid1.org:3000/home>

# Reading and Software

- **Reading**

- Russell, S. and Norvig, P. (2010) Sections 14.4-5, 16.1-2, 16.5
- Korb, K. and Nicholson, A. (2010) Sections 3.1-3.6, 4.1-4.4, 10.1-10.2
- Papers:

Nicholson, Ann & Woodberry, Owen & Twardy, Charles. (2010). The “Native Fish” Bayesian networks. Bayesian Intelligence Technical Report 2010/3. [http://bayesian-intelligence.com/publications/TR2010\\_3\\_NativeFish.pdf](http://bayesian-intelligence.com/publications/TR2010_3_NativeFish.pdf)

[http://bayesian-intelligence.com/publications/NativeFish\\_BNs.zip](http://bayesian-intelligence.com/publications/NativeFish_BNs.zip)

Wu, Y., Foley, D., Ramsay, J., Woodberry, O., Mascaro, S., Nicholson, A., & Snelling, T. (2021). Bridging the gaps in test interpretation of SARS-CoV-2 through Bayesian network modelling. *Epidemiology and Infection*, 149, E166. doi:10.1017/S0950268821001357

Steven Mascaro et al., (2022, preprint). Modeling COVID-19 disease processes by remote elicitation of causal Bayesian networks from medical experts.

medRxiv 2022.02.14.22270925; doi: <https://doi.org/10.1101/2022.02.14.22270925>

- **Software**

- Netica – <http://www.norsys.com/>

# Next Lecture Topic

- **Lecture Topic 7 (Week 10)**
  - Machine Learning