

BAYESIAN NETWORK MODELS

WHAT ARE BAYESIAN NETWORK MODELS?

A Bayesian network (BN) is probabilistic graph model that describes how a system operates with uncertainties. It comprises two parts:

- 1) a graphical structure that uses *nodes* to describe the variables relevant to the system and *arrows* to identify the direct statistical (and in some cases, causal) dependencies between them; and
- 2) a joint probability distribution over those variables, which specifies the strength of dependencies.

Clinical researchers have built BNs to describe and understand the natural history of disease, predict the probability of a disease based on outcomes of diagnostic tests, evaluate the effectiveness of potential health interventions, and inform personalised treatment recommendations for individual patients.

HOW DO WE BUILD THE MODEL?

Existing data and knowledge (complex thinking by those experts in the field) are used, alone or in conjunction, to create the network of variable dependencies, as well as to quantify those dependencies.

The contribution of expert knowledge can be significant in many clinical domains because of the inherent complexity of specific disease processes. Software packages used in our projects include [Netica](#), [GeNIe](#) or [R](#), which are all freely available online. The figure to the right is a schematic of an example workflow.

HOW DO BAYESIAN NETWORK MODELS WORK?

BNs can calculate the probability of an outcome (e.g. infection with a specific pathogen) based on the information available for other related variables (e.g. patient age, culture results). By making use of Bayes' rule, BNs can propagate new information across a network while taking into account important prior information (for example, the base rate of disease).

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Concept Map

- Brainstorm everything relevant to the problem

Identify high-level model structure

- Background factors
- Treatment regimen
- Disease progress
- Patient outcomes

Identify key factors within sub-models

- Elicitation with experts via a Delphi-like process

Model structure development

- Revise structure
- Revise factors
- Validate
- Iterate

Parameterise model & further validation

- Elicitation of parameters
- Iteration of all above

How do BNs work? (continued from previous page)

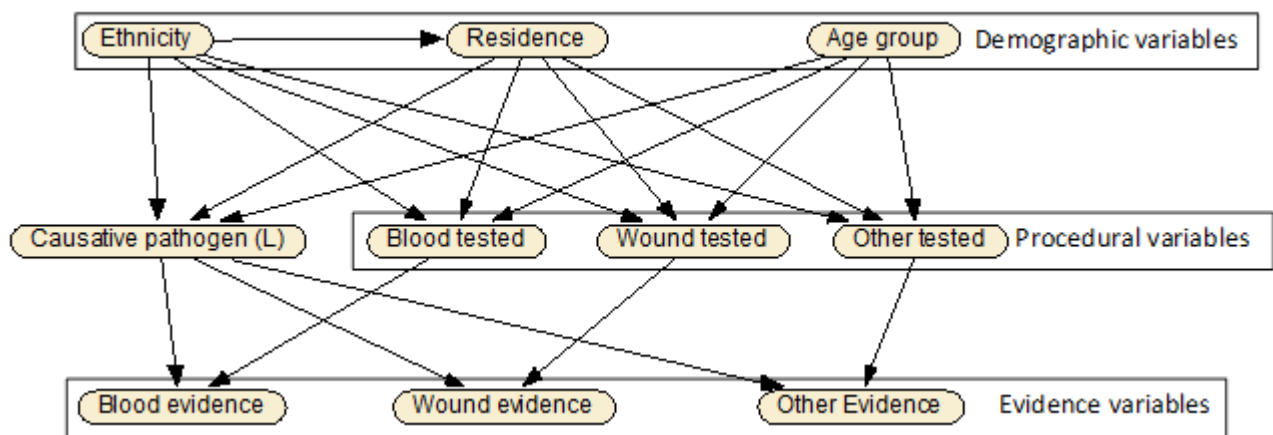
New evidence for any variable can be used to produce updated predictions for any other variable, and providing more evidence to the BN generally produces more certain predictions.

BNs that are causal apply a causal interpretation to the arrows in a BN. It requires extra work to develop and validate a causal BN, but the reward is a particularly powerful model. Causal BNs are generally intuitive to understand and easier to communicate than non-causal models. They can perform forward prediction from cause to effect, backward (or diagnostic) inference from effect to cause, or mixed inference using available evidence about both causes and effects.

Importantly, they can be used to assess and handle issues such as confounding and selection bias and they can properly model the consequences of interventions, an ability unique to causal models.

Predictions produced by these models can be used to assist clinicians with decision-making during clinical practice. How the BN's predictions are presented can be important, and consideration needs to be given to what information is most valuable. Ultimately, modelling tools can be implemented with consumer and clinician-friendly interfaces. These take advantage of the insights that BNs can provide about the key disease processes, treatments and possible outcomes, allowing clear and useful guidance to be provided to the clinician.

EXAMPLE BAYESIAN NETWORK MODEL: BONE INFECTION MODEL



Model provided by Dr Yue Wu & Dr Steven Mascaro

WHAT DO WE OFFER?

- Develop qualitative conceptual models via knowledge elicitation for clinical problems
- Decision support tools using clinical data, elicited knowledge or both; including localisation of developed models
- Introductory seminars on demo projects