CSE458 Bayesian Networks Lecture 5

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Text: *Bayesian Artificial Intelligence*, Kevin B. Korb and Ann E. Nicholson, Chapman & Hall/CRC, 2004.

KEBN: Overview

- The BN Knowledge Engineering Process
- Model construction
  - Variables and values
  - Graph Structure
  - Probabilities
  - Preferences
- Evaluation

Knowledge Engineering with Bayesian Networks (KEBN)

(Laskey, 1999).

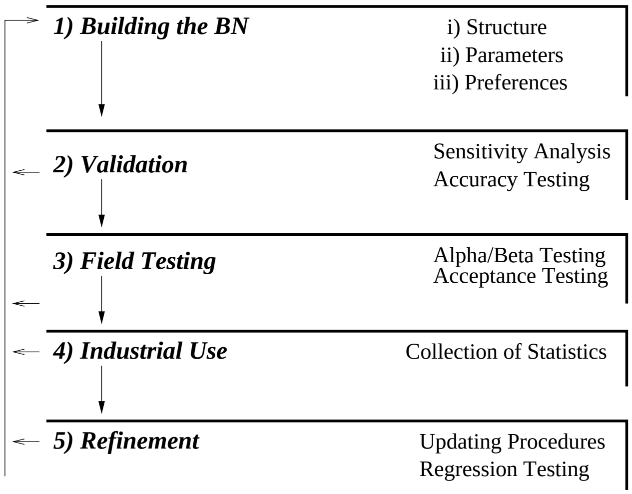
- Objective: Construct a model to perform a defined task
- Participants: Collaboration between domain expert(s) and BN modelling expert(s), including use of automated methods.
- Process: iterate until "done"
  - Define task objective
  - Construct model
  - Evaluate model

KEBN

Production of Bayesian/decision nets for

- **Decision making:** Which policy carries the least risk of failure?
- **Forward Prediction:** Hypothetical or factual. Who will win the election?
- **Retrodiction/Diagnosis:** Which illness do these symptoms indicate?
- **Monitoring/control:** Do containment rods needs to be inserted here at Chernobal?
- **Explanation:** Why did the patient die? Which cause exerts the greater influence?
- **Sensitivity Analysis:** What range of probs/utilities make no difference to X?
- **Information value:** What's the differential utility for changing precision of X to ϵ?

KEBN Lifecycle Model



Notes on Lifecycle Model

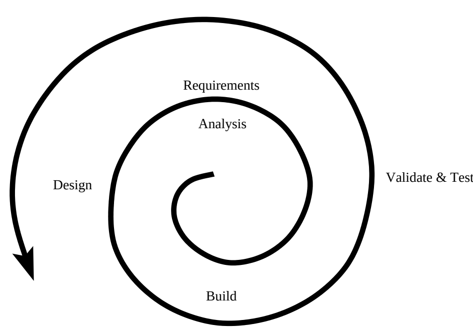
- Phase 1: Building Bayesian Networks.
  - Major network components: structure, parameters and utilities.
  - Elicitation: from experts, learned with data mining methods, or some combination of the two.
- Phase 2: Evaluation.
  - Networks need to be validated for: predictive accuracy, respecting known temporal order of the variables and respecting known causal structure.
  - Use statistical data (if available) or expert judgement.
- Phase 3: Field Testing.
  - Domain expert use BN to test usability, performance, etc.

Notes on Lifecycle Model (cont.)

- Phase 4: Industrial Use.
  - Requires a statistics collection regime for on-going validation and/or refinement of the networks.
- Phase 5: Refinement.
  - Requires a process for receiving and incorporating change i requests
  - Includes regression testing to verify that changes do not undermine established performance.

KEBN Spiral Model

From Laskey & Mahoney (2000)
Idea (from Boehm, Brooks): prototype-test cycle



KEBN Tasks

For Bayesian Networks, identifying:

1. What are the variables? What are their values/states?
2. What is the graph structure? What are the direct causal relationships?
3. What are the parameters (probabilities)? Is there local model structure?

When building decision nets, identifying:

4. What are the available actions/decisions?
5. What are the utility nodes & their dependencies?
6. What are the preferences (utilities)?

The major methods are:

- Expert elicitation (1-6)
- Automated learning from data (1-3, 5-6?)
- Adapting from data (1-3, 5-6?)

Which are the most important variables?

- "Focus" or "query" variables
  - variables of interest
- "Evidence" or "observation" variables
  - What sources of evidence are available?
- "Context" variables
  - Sensing conditions, background causal conditions
- "Controllable" variables
  - variables that can be "set", by intervention

Start with query variables and spread out to related variables.

NB: Roles of variables may change.

Variable values/states

- Variable values must be exclusive and exhaustive
  - Naive modelers sometimes create separate (often Boolean) variables for different states of the same variable
- Types of variables
  - Binary (2-valued, including Boolean)
  - Qualitative
  - Numeric discrete
  - Numeric continuous
- Dealing with infinite and continuous variable domains
  - Some BN software (e.g. Netica) requires that continuous variables be discretized
  - Discretization should be based on differences in effect on related variables (i.e. not just be even sized chunks)

Graphical structure

Goals in specifying graph structure

- Minimize probability elicitation: fewer nodes, fewer arcs, smaller state spaces
- Maximize fidelity of model
  - Sometimes requires more nodes, arcs, states
  - Tradeoff between more accurate model and cost of additional modelling
  - Too much detail can decrease accuracy
- Drawing arcs in causal direction is not "required" BUT
  - Increases conditional independence
  - Results in more compact model
  - Improves ease of probability elicitation
- If mixing continuous and discrete variables
  - Exact inference algorithms only for the case where discrete variables are ancestors, not descendants of continous variables

Relationships between variables

Types of qualitative understanding can help determine local/global structure

- Causal relationships
  - Variables that could cause a variable to take a particular state
  - Variables that could prevent a variable taking a particular state
- Enabling variables
  - Conditions that permit, enhance or inhibit operation of a cause
- Effects of a variable
- Associated variables
  - When does knowing a value provide information about another variable?

variables (cont.)

- Dependent and independent variables
  - D-separation tests
  - Which pairs are directly connected? Probabilities dependent regardless of all other variables?

  Matilda - software tool for visual exploration of dependencies (Boneh, 2002)
- Temporal ordering of variables
- Explaining away/undermining
- Causal non-interaction/additivity
- Causal interaction
  - Positive/negative Synergy
  - Preemption
  - Interference/XOR
- Screening off: causal proximity
- Explanatory value
- Predictive value

Probabilities

- The parameters for a BN are a set of conditional probability distributions of child values given values of parents
- One distribution for each combination of values of parent variables
- Assessment is exponential in the number of parent variables
- The number of parameters can be reduced by taking advantage of additional structure in the domain (called **local model structure**)

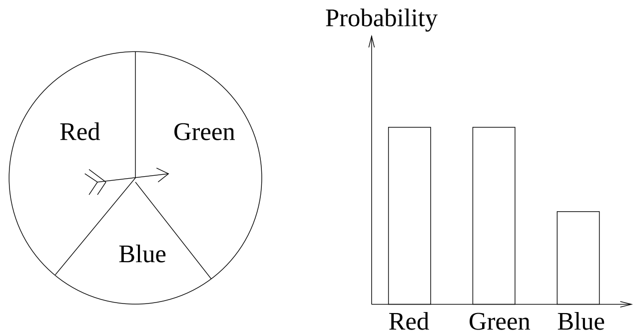
Probability Elicitation

- Discrete variables
  - Direct elicitation: “p=0.7”
  - Odds (esp. for very small probs): “1 in 10,000”
  - Qualitative assessment: “very high probability”
    - Use scale with numerical and verbal anchors (van der Gaag et al., 1999)
    - Do mapping separately from qualitative assessment
- Continuous variables
  - bi-section method
    - Elicit median: equally likely to be above and below
    - Elicty 25th percentile: bisects interval below median
    - Continue with other percentiles till fine enough discriminations
  - Often useful to fit standard functional form to expert’s judgements
  - Need to discreteize for most BN software

Probability Elicitation

Graphical aids are known to be helpful

- pie charts
- histograms



(a) (b)

Probability Elicitation (cont.)

- Combination of qualitative and quantitative assessment
- Automated correction of incoherent probabilities (Hope, Korb & Nicholson, 2002)
  - Minimizing squared deviations from original estimates
- Automated maxentropy fill of CPTs (Hope, Korb & Nicholson, 2002)
- Automated normalization of CPTs (Hope, Korb & Nicholson, 2002)
- Use of lotteries to force estimates (also useful for utility elicitation)

Local model structure

Not every cell in CPT is independent from every other cell. Examples:

- Deterministic nodes
  - It is possible to have nodes where the value of a child is exactly specified (logically or numerically) by its parents
- Linear relationships:

$$X_i = a_0 X_0 + \ldots a_n X_n + \epsilon_i$$

- Logit model (binary, 2 parents):

$$\log \frac{P(X_2|X_0, X_1)}{P(\neg X_2|X_0, X_1)} = a + bX_0 + cX_1 + dX_1 X_2$$

- Partitions of parent state space
- Independence of causal influence
- Contingent substructures

Elicitation by Partition

(See Heckerman, 1991)

- Partition state set of parents into subsets
  - set of subsets is called a partition
  - each subset is a partition element
- Elicit one probability distribution per partition element
- Child is independent of parent given partition element
- Examples
  - P(reportedLoc|loc, sensor-type,weather) independent of sensor type given weather = sunny
  - P(fever=high|disease) is the same for disease $\in$ {flu,measles}.

Independence of Causal Influence (ICI)

- Assumption: causal influences operate independently of each other in producing effect
  - Probability that C1 causes effect does not depend on whether C2 is operating
  - Excludes synergy or inhibition
- Examples
  - Noisy logic gates (Noisy-OR, Noisy-AND, Noisy-XOR)
  - Noisy adder
  - Noisy max
  - General noisy deterministic function

Noisy-OR nodes

- Adds some uncertainty to logical OR.

  Example: $Fever$ is true if and only if $Cold$, Flu or $Malaria$ is true.

  Assumptions:
  - each cause has an independent chance of causing the effect.
  - all possible causes are listed
  - inhibitors are independent

    E.g.: whatever inhibits $Cold$ from causing $Fever$ is independent of whatever inhibits Flu from causing a $Fever$.
- Inhibitors summarised as “noise parameters”.

Noisy-OR parameters

E.g. if $P(Fever|Cold) = 0.4$, $P(Fever|Flu) = 0.8$, and $P(Fever|Malaria) = 0.9$, then noise parameters are 0.6, 0.2 and 0.1 respectively.

Probability that output node is $False$ is the product of the noise parameters for all the input nodes that are true.

$Cold$	Flu	Mal	$P(Fev)$	$P(\neg Fev)$
F	F	F	0.0	1.0
F	F	T	0.9	0.1
F	T	F	0.8	0.2
F	T	T	0.98	0.02 = 0.2 × 0.1
T	F	F	0.4	0.6
T	F	T	0.94	0.06 = 0.6 × 0.1
T	T	F	0.88	0.12 = 0.6 × 0.2
T	T	T	0.988	0.012 = 0.6 × 0.2 × 0.1

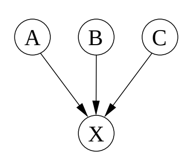
Savings: for binary noisy-OR

CPT requires $2^{10} = 1024$ parameters; noisy-OR requires 11 parameters

Classification Tree Repn

(Boutillier et al. 1996).

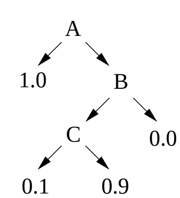
Example: Suppose node X has 3 parents, A, B and C (all nodes Boolean).



(a)

A	B	C	P(X|A,B,C)
T	T	T	1.0
T	T	F	1.0
T	T	T	1.0
T	F	F	1.0
F	T	T	0.1
F	T	F	0.9
F	F	T	0.0
F	F	F	0.0

(b)



(c)

Savings: CPT = 8, tree rep = 4 parameters.

Object-oriented BNs

- Facilitate network construction wrt both structure and probabilities
- Allow representation of commonalities across variables
- Inheritance of priors and CPTs

OOBNs are not supported by the Netica BN software package at all; a version recently in Hugin.

As yet, not widely used.

Decision Analysis

Since 1970s there have been nice software packages for decision analysis:

- Eliciting actions
- Eliciting utilities
- Eliciting probabilities
- Building decision trees
- Sensitivity analysis, etc.

See: Raiffa's *Intro to Decision Analysis* (an excellent book!)

Main differences from KEBN:

- *Scale:* tens vs thousands of parms!!
- *Structure:* trees reflect state-action combinations, not causal structure, prediction, intervention

Eliciting Decision Networks

- Action nodes: What actions can be taken in domain?
- Utility node(s):
  - What unit(s) will "utile" be measured in?
  - Are there difference aspects to the utility that should each be represented in a separate utility node?
- Graph structure:
  - Which variables can decision/actions affects?
  - Does the action/decision affect the utility?
  - What are the outcome variables that there are preferences about?

Model Evaluation

- Elicitation review
  - Review variable and value definition
    - clarity test, agreement on definitions, consistency
  - Review graph and local model structure
  - Review probabilities
    - compare probabilities with each other
- Sensitivity analysis (Laskey, 1993)
  - Measures effect of one variable on another
- Case-based evaluation
  - Run model on test of test cases
  - Compare with expert judgement or "ground truth"
- Validation methods using data (if available)
  - Predictive Accuracy
  - Expected value
  - Kullback-Leibler divergence
  - (Bayesian) Information reward

The need to prototype!

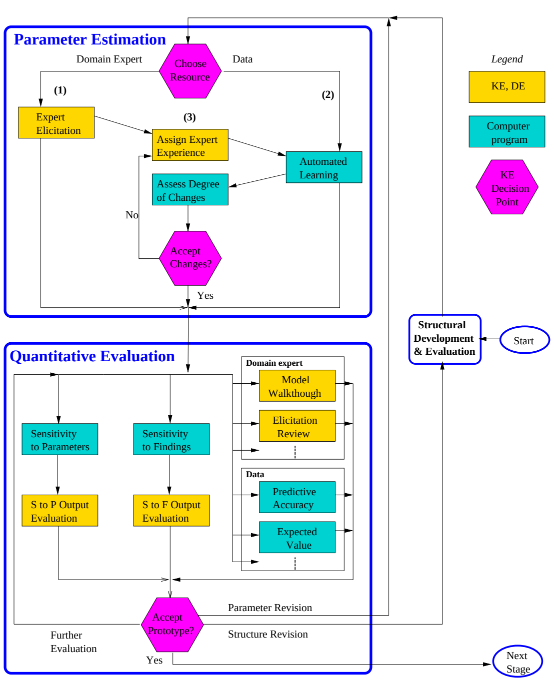
Why prototype?

- It's just the best software development process overall (Brooks). Organic growth of software:
  - tracks the specs
  - has manageable size (at least initially)
- Attacks the comprehensiveness vs. intelligibility trade-off from the right starting point.
- Few off-the-shelf models; prototyping helps us fill in the gaps, helps write the specs

Prototypes

- Initial prototypes minimize risk
  - Don't oversell result
  - Employ available capabilities
  - Simplify variables, structure, questions answered
  - Provide working product for assessment
- Incremental prototypes
  - Simple, quick extension to last
  - Attacks high priority subset of difficult issues
  - Helps refine understanding of requirements/approach

More recent KEBN methodologies



KEBN Summary

- Various BN structures are available to compactly and accurately represent certain types of domain features.
- There is an interplay between elements of the KE process: variable choice, graph structure and parameters.
- No standard knowledge engineering process exists as yet.
- Integration of expert elicitation and automated methods still in early stages.
- There are few existing tools for supporting the BN KE process.
  - We at Monash are developing some! (e.g. VerbalBN, Matilda)