

# GENERAL CONSIDERATIONS FOR MODELING WITH PROBABILITY NETWORKS

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Define the purpose of the model:

- prediction (possible future outcomes based on initial conditions)
- forecast (most likely future outcome based on initial conditions)
- projection (possible future outcomes based on changing future conditions)
- scenario planning (peg the corners of the implications of hypothetical situations)
- represent knowledge (synthesize what we think we know)
- identify uncertainties & key data gaps (identify factors or interactions with the greatest influence on outcomes; sensitivity analysis)
- diagnosis (determine potential causes of a known or specified condition or outcome)
- mitigation (identify alternative conditions that could lead to a desired outcome)
- aid individual or collaborative decision-making

Provide a simple influence diagram representation of the model:

- just node names without states or probabilities
- show linkages among nodes

Document the influence diagram:

- what data, information sources, publications, or consultations were used to generate the influence diagram structure?
- identify what each arrow represents: simple correlation, direct causation, part of an input to a summary variable, etc.
- have the influence diagram peer reviewed if appropriate

Provide clear definitions of each variable (node) in the model:

- input (usually parentless) nodes
- intermediate nodes (latent variables, summary nodes)
- output nodes (usually childless nodes)

Provide clear definitions and units of measure of all states of each node in the model

- also identify known or expected source of values for the key nodes (i.e., input nodes for prediction, forecast, projection, or scenario models; output nodes for diagnosis or mitigation models)

Provide documentation on the underlying probability values of each node in the model:

- what is the basis, source of information, and methods of identification, for each probability value or at least each unconditional and conditional probability table? (e.g., expert judgment, field data, consultation, etc.)

- what are probability values intended to represent? (e.g., relative influence so that the “corners” of each CPT are pegged at 0 and/or 100%; or absolute frequencies; etc.)

Identify the sensitivity structure of the model

- degree to which an outcome variable is influenced by each input variable set to its default prior probability distribution

Identify the influence structure of the model

- influence on output variables by setting input variables to best- or worst-case values

Calculate metrics of model complexity

- number of variables (nodes), number of links, number of node cliques, number of conditional probabilities

Calculate metrics of prediction performance (for prediction models)

- if data are available (subdivide existing case data sets, procure independent data sets, or develop test data sets from independent expert knowledge elicitation)
- can conduct for model subsets
- as appropriate and deemed useful, can calculate: prediction error rates, confusion tables, ROC and AUC, k-fold cross-validation, spherical payoff, Schwarz’ Bayesian information criterion, true skill statistic, Cohen’s kappa, covariate-weighted confusion error, conditional probability-weighted confusion error

Update portion or all of the model using case data (to beta or gamma model level)

- using convergent log-likelihood approaches such as the expectation maximization (EM) algorithm or gradient algorithm, or just straight incorporation of case data

Calculate metrics of uncertainty in posterior probability (outcome node) distributions

- Bayesian credible intervals
- posterior probability certainty index
- certainty envelope
- inequality of posterior probability distributions (normalized Gini index)

Calculate statistical comparisons of alternative probability distributions, as appropriate and needed

- Mantel’s r correlation test, Kolmogorov-Smirnov test, others

## LITERATURE

MacCracken, M. 2001. Prediction versus projection - forecast versus possibility. WeatherZine 26:<http://sciencepolicy.colorado.edu/zine/archives/1-29/26/guest.html>.

Marcot, B. G. 1987. Testing your knowledge base. AI Expert 2:42-47.

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Marcot, B. G. 2012. Metrics for evaluating performance and uncertainty of Bayesian network models. *Ecological Modelling* 230:50-62.

Marcot, B. G., J. D. Steventon, G. D. Sutherland, and R. K. McCann. 2006. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. *Canadian Journal of Forest Research* 36:3063-3074.