All That Glitters Is Not Gold

Should We Reconsider or Upgrade Bayesian Networks for Environmental Assessments?

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Introduction

The many claims about the power and usefulness of Bayesian networks [1] leave me with a spark of doubt [2] – it sounds too good to be true!

Bayesian networks have become an icon of flexible modelling and are being adopted in many domains, supported by powerful and user friendly software.

To continue the adoption of Bayesian networks for environmental assessments, it is important that the models are able to integrate scientific knowledge in a sound and reproducible way.

What a Bayesian network can offer must match with **What we want to do in our scientific assessment**.

To avoid the risk that something called a Bayesian network becomes a hammer for every nail, a discussion is needed how Bayesian networks compare to other flexible probabilistic modelling approaches. In this comparison, what is - and what is not - seen as a Bayesian network may become obsolete.

As a way forward, I propose to let the Bayesian network concept include a wide range of modelling approaches, offering different hammers for different of nails.

The aim of this study is to provide support for the question if we should reconsider or upgrade Bayesian networks for environmental assessments.

Method

Meta-modelling of Bayesian networks

Different types of modelling approaches to include as potential Bayesian networks were identified from the field of decision analysis, risk assessment, weight of evidence approaches, statistics and machine learning.

Bayesian networks to query data (or data simulated from a model) [3] were not considered, as they are not the scientific model per se.

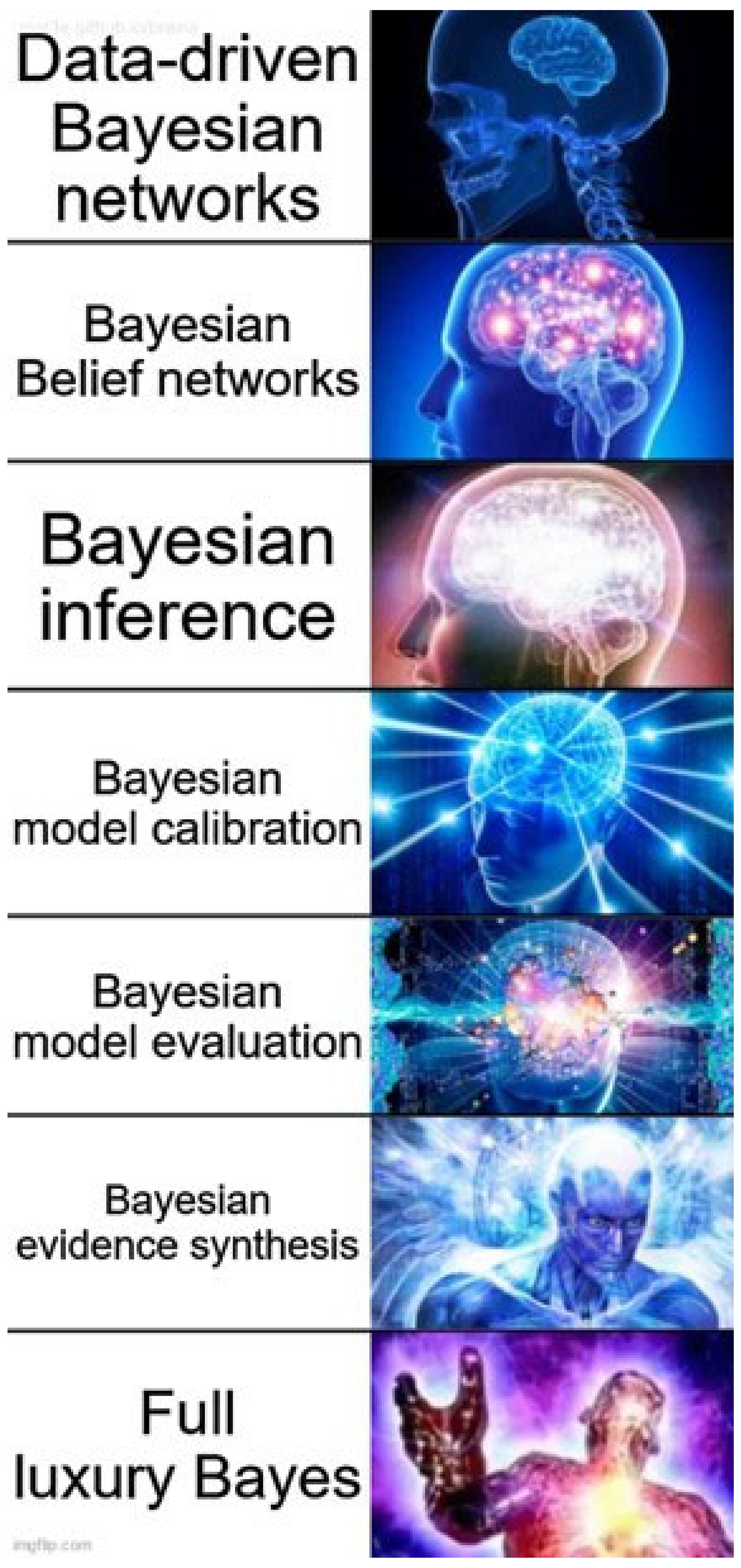
For each model type, I characterised the purpose of the modelling and how the model is informed. To facilitate comparative discussions, each model type was associated with names of contributing researchers.

Bayesian network concept survey

Scientific experts and modellers are invited to a survey about **What is NOT a Bayesian network?** with the purpose to capture the current perception of this concept. You are welcome to take part at this survey bit.ly/bnsetac22

Results

Seven types of modelling approaches



Data-driven Bayesian network à la Koller and Friedman [4] – fully data driven predictive inference with or without learning of network structure. No need for Bayesian inference to train the network. The probabilities express sampling variation in data or predictions.

Bayesian Belief network à la Pearl [5] – expert informed probabilistic model for probabilistic reasoning in light of evidence. Bayesian Belief networks express subjective probability and are usually specified with categorical nodes.

Model for Bayesian inference à la Gelman [6] – statistical model for data to estimate parameters or make predictions of future observations.

Bayesian model calibration à la Kennedy and O'Hagan [7] – inference on parameters in a scientific model, combined with data generating processes, for the purpose of backcasting or forecasting.

Bayesian model evaluation à la Vehtari [8] – Bayesian model calibration on several models with the purpose of model selection or back/forecasting under multi-model inference.

Bayesian evidence synthesis à la Spiegelhalter and Best[9, 10] - Bayesian calibration and evaluation of complex models using multiple sources of evidence for the purpose of assessment and decision or policy analysis.

Bayesian causal modelling using "Full luxury Bayes" à la McElreath [11]– causal analysis to identify variables to include in model for Bayesian inference with the purpose to draw conclusions on causality.

What is not a Bayesian network

Can any of the seven types of models not be classified as a Bayesian network? The results from the survey is continuously being updated and can be viewed on twitter - search for #bnsetac22

Discussion

Scientific assessments are in need of complex and flexible statistical modelling [12] relying on probabilistic graphical modelling and Bayesian inference to quantify uncertainty in parameters and model outputs. With some exceptions, it is only tradition that prevents the seven Bayesian modeling approaches to be referred to as a Bayesian network. It is therefore timely to reconsider the Bayesian network concept.

Upgrading Bayesian networks to include a wide range of modelling approaches that are useful for research and scientific assessment, will allow for flexibility without having to abandon what traditionally have been seen as Bayesian networks.

With more modelling approaches included in the concept of Bayesian network, it becomes necessary to distinguish them from each other and identify strenghts and weaknesses.

Software for Bayesian networks are often for the extremes modelling approaches: purely data driven models (Bayesian networks à la Koller and Friedman) and purely expert informed systems (Bayesian Belief networks à la Pearl). The extreme models are "flat," in the sense that the probabilistic graphical model does not include parameters [2]. Parameters is an essential part of scientific modelling, as it allows for inference combining expert judgement with data, avoids discretisation of continuous variables, and enable quantification of model uncertainty as separate from variability.

Conclusion

To ensure best practice in research and assessment, I recommend to

- always be precise about what we are modelling and how the model has been informed
- upgrade our perception of what a Bayesian network is to include a wider range of probabilistic graphical models able to support scientific modelling
- develop support to find the suitable **hammer** in the upgraded Bayesian network toolbox for each **nail**

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