

BNLEARN, LEARNING  
BAYESIAN NETWORKS  
15 YEARS LATER

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June 24, 2024



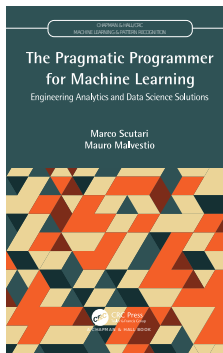
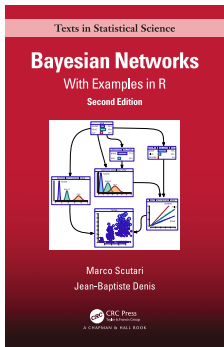
Sonia Shah ✓



Kitty Lo  
Scientist | Data scientist



David Balding



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(Initial) | patch  
  
Initial commit (v 0.1).  
  
author Marco Scutari < >  
Tue, 12 Jun 2007 18:53:43 +0000 (20:53 +0200)  
committer Marco Scutari < >  
Tue, 12 Jun 2007 18:53:43 +0000 (20:53 +0200)  
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man/gs.Rd [new file with mode: 0644] blob  
  
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```

**Machine learning** creates black boxes that use probabilistic associations for prediction, but scientific questions are inherently causal. Causation is central to how we think and how we understand the world.

Article

## Highly accurate protein structure prediction with AlphaFold

Nature | Vol 596 | 26 August 2021 | 583



Science & technology | Generative AI

## Large, creative AI models will transform lives and labour markets

They bring enormous promise and peril. In the first of three special articles we explain how they work

nature  
computational  
science

PERSPECTIVE

## Scaling digital twins from the artisanal to the industrial

Steven A. Niederer, Michael S. Sacks, Mark Girolami and Karen Willcox

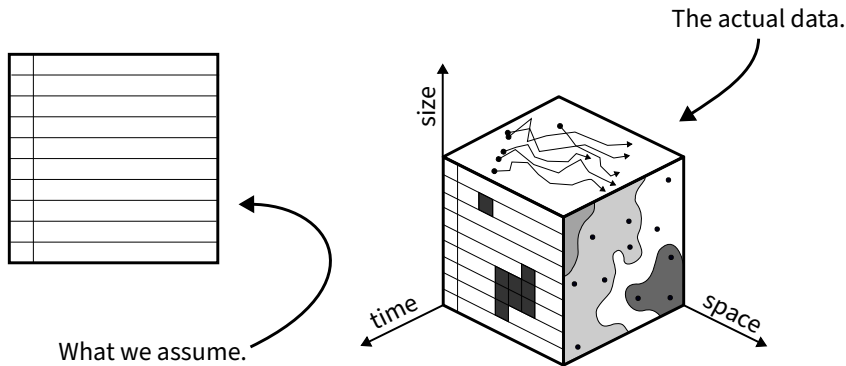
NATURE COMPUTATIONAL SCIENCE | VOL 1 | MAY 2021 | 313-320

**Bayesian networks** are the opposite: they promote **understanding** so that we **act to improve** the world, easily modelling how interventions will impact **outcomes**.

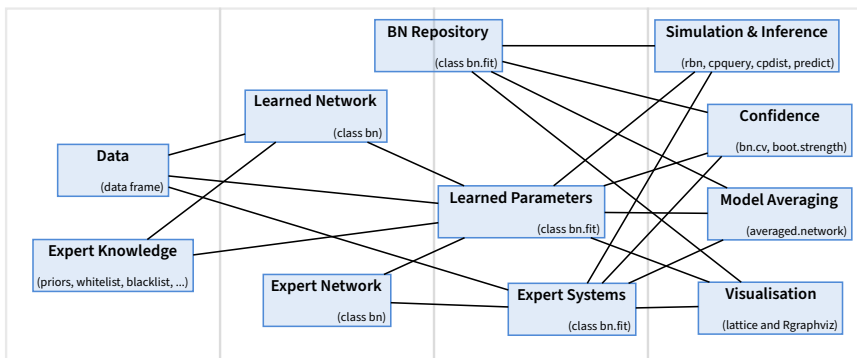
Bayesian networks have come a long way...

... but there is much we do not understand or we cannot do well:

- A **theory of statistical learning** for causal network models.
  - Handling latent confounders?
  - Model identifiability?
  - Relative contributions of parameter and structure learning?
- **Scalable methods and software** to empower applications.
- Model **challenging data with complex structures**.
  - Space-time data?
  - Missing data?
  - Heterogeneous populations?



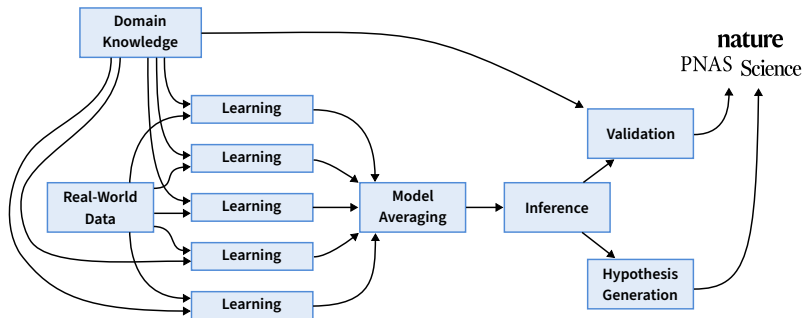
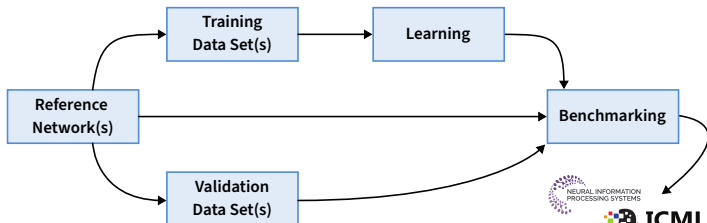
This why I develop **bnlearn**: I want a software developed with the best practices **software engineering** has to offer and that does not crash and burn when fed **real-world data**.



**New and upcoming features:** Don't delay, download today!

- Missing data (EM, PNAL).
- Entropy and KL Divergence.
- Custom tests and scores.
- More C code, for speed.
- Exact inference (DBN, GBN).
- Updating bn.fit objects (soon).

# TWO MAIN WORKFLOWS IN BNLEARN



1. Choose some networks from [www.bnlearn.com/bnrepository](http://www.bnlearn.com/bnrepository).
2. Possibly alter their structure and/or parameters to match the scientific question you want to answer.
3. Generate data sets with `rbn()`, with replicates across  $n/p \in \{0.1, 0.2, 0.5, 1, 2, 5\}$ .
4. Run the learning approach of your choice.
5. Benchmark its outputs.
  - Structural measures: `compare()` and `shd()`.
  - Information theoretic measures: `H()` and `KL()`.
  - Empirical measures, with a validation data set: `predict()` or `logLik()`.
  - Visual analysis: `graphviz.compare()` and `graphviz.chart()`.
6. Profit!



## 1. Preprocess the data.

- Remove highly correlated variables: `dedup()`.
- Possibly discretising variables: `discretize()`.
- Possibly imputing missing values: `impute()`.

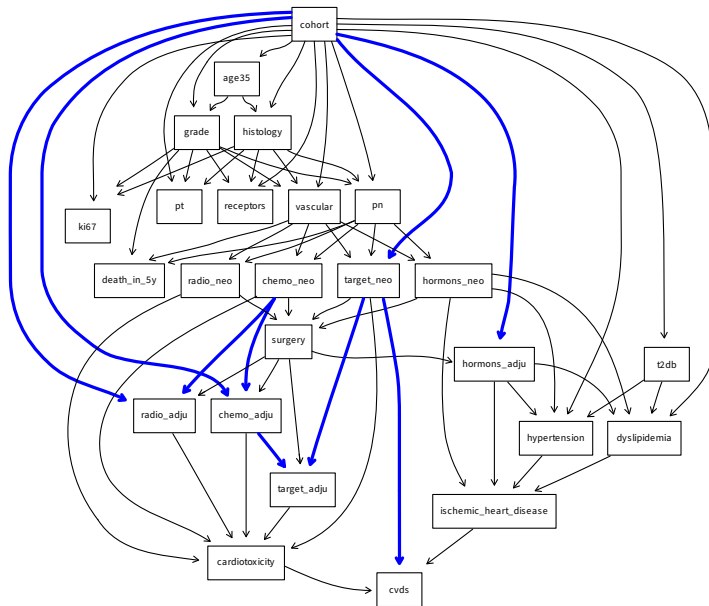
## 2. Structure learning with model averaging.

- Establish a blacklist of arc directions that make no sense.
- Learn multiple structures with `boot.strength()` or `custom.strength()`.
- Average them with `averaged.network()`.

## 3. Parameter learning with `bn.fit()`.

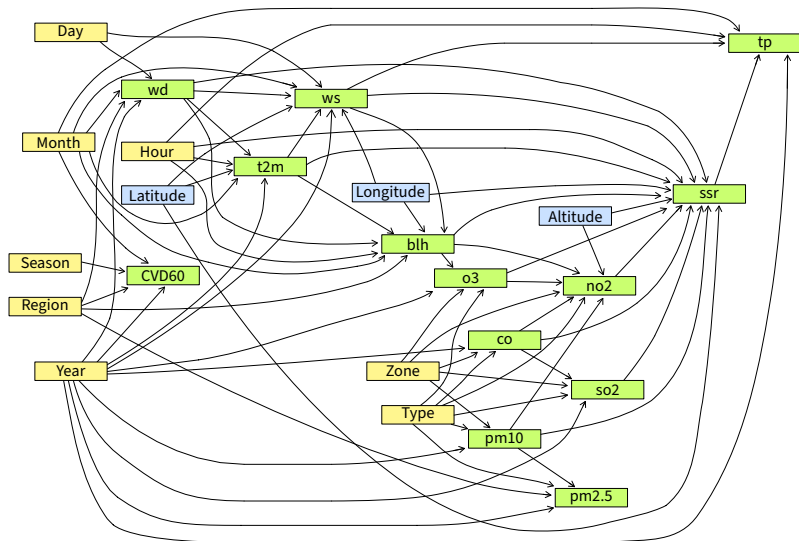
## 4. Model validation and hypothesis generation.

- Can you find literature supporting the existence of arcs and paths?
- Do their answers (through `cpquery()`, `cpdist()`, `mutilated()`, `predict()`) to key questions agree with domain experts?

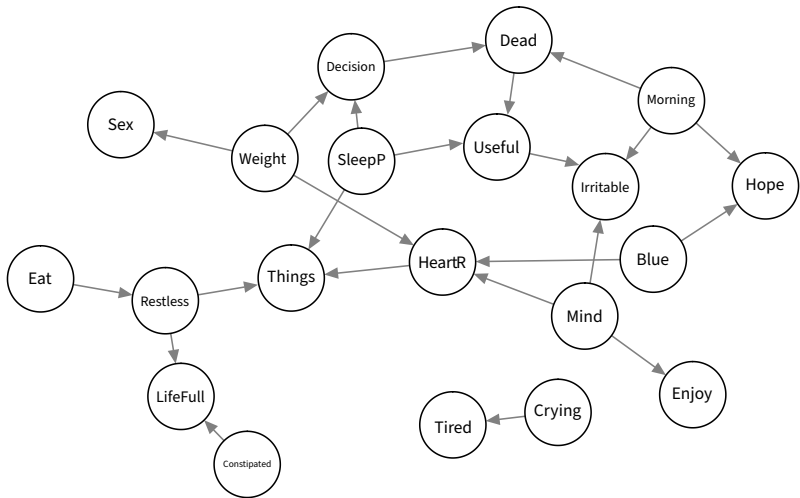


Combining population and clinical trial data for breast cancer survivors [1].

# IN ENVIRONMENTAL SCIENCES AND EPIDEMIOLOGY!



Linking pollution with respiratory and cardiovascular diseases in the UK [5].



Mapping causal paths between depression symptoms[2].

- At least one between **GES** and **LiNGAM**, which have become baselines in much of the causal discovery literature.
- **Exact uniform sampling** over DAGs from Kuipers & Moffa (2012).
- A **query** function that returns a conditional distribution.
- Better **exact inference**, including CGBNs.
- The **Structural Intervention Distance** from Peters & Bühlmann (2015).
- Creating **twin networks** for **counterfactuals**.
- Support for either **state-space** or **stratified data**.
- Better support for **incomplete data**.

THAT'S ALL!

HAPPY TO DISCUSS IN MORE DETAIL.

- ◆ A. Bernasconi, A. Zanga, P. J. F. Lucas, M. Scutari, and F. Stella.  
[Towards a Transportable Causal Network Model Based on Observational Healthcare Data.](#)  
*In Proceedings of the 2nd Workshop on Artificial Intelligence for Healthcare, 22nd International Conference of the Italian Association for Artificial Intelligence (AixIA 2023)*, pages 67–82, 2023.
- ◆ G. Briganti, M. Scutari, and P. Linkowski.  
[Network Structures of Symptoms from the Zung Depression Scale.](#)  
*Psychological Reports*, 124(4):1897–1911, 2021.
- ◆ M. Scutari and J.-B. Denis.  
[Bayesian Networks with Examples in R.](#)  
Chapman & Hall, 2nd edition, 2021.
- ◆ M. Scutari and M. Malvestio.  
[The Pragmatic Programmer for Machine Learning: Engineering Analytics and Data Science Solutions.](#)  
Chapman & Hall, 2023.
- ◆ C. Vitolo, M. Scutari, A. Tucker, and A. Russell.  
[Modelling Air Pollution, Climate and Health Data Using Bayesian Networks: a Case Study of the English Regions.](#)  
*Earth and Space Science*, 5(4):76–88, 2018.