

Bayes is a practical choice

Also, it's just probability theory...

- Using Bayesian methods is simply easier in real life:
 - Simple models are the same, so why bother?
 - Because complicated models are possible:
 - Real data is messy: missing data, replicates, correlated observations, mark-recapture...
- Models are **generative**, easy to simulate from and easy(er?) to build using scientific knowledge

Probability Theory

The Logic of Science

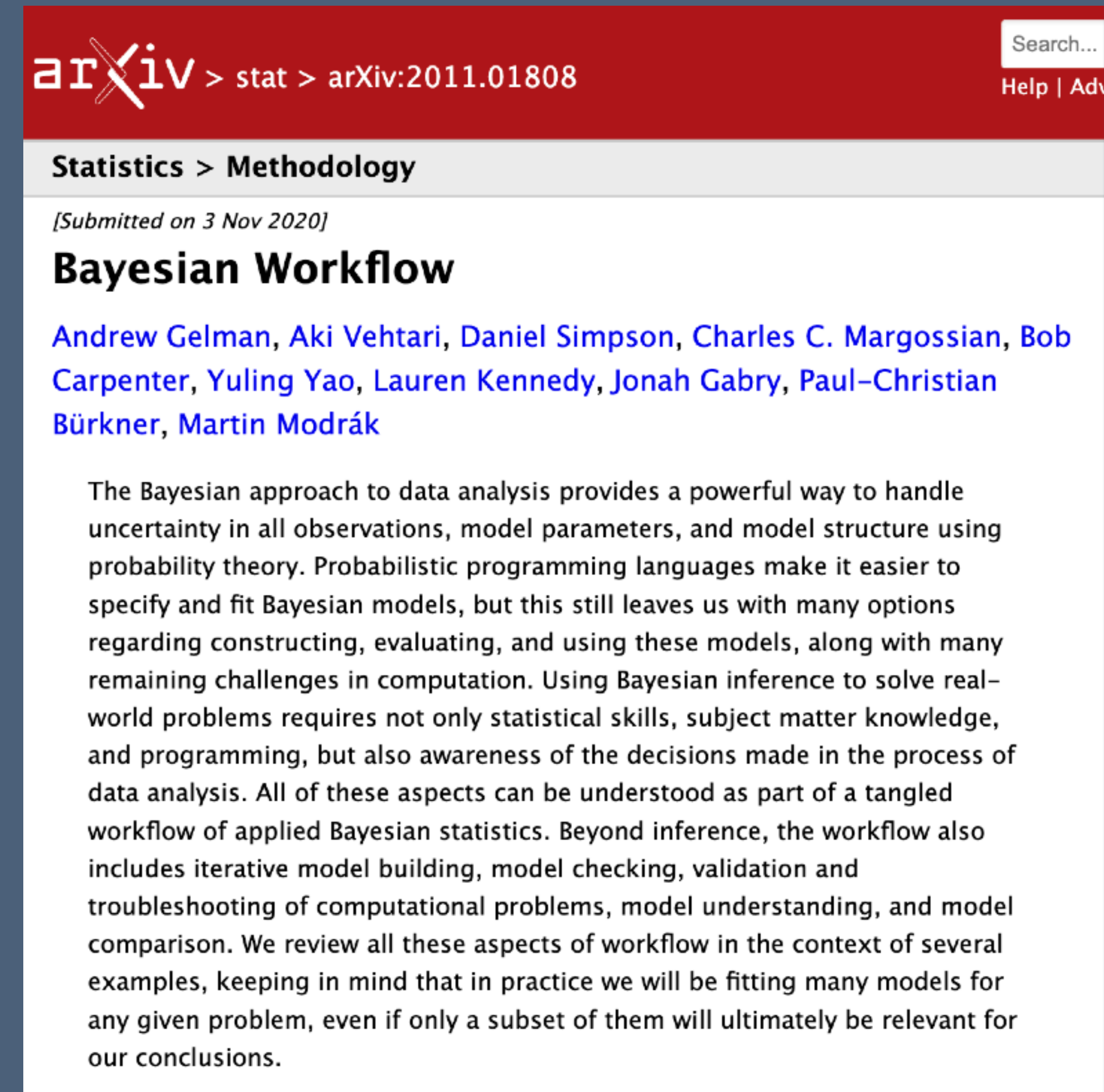
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CAMBRIDGE

Inference and prediction

We are most of the time doing both at the same time!

- Use the tools we have:
 - Build DAGs to understand the causal implication of the assumptions we are making about our system
 - Use cross-validation and WAIC to check model fit and predictive accuracy
 - Plot model predictions and parameter estimates
- Simulate, simulate, **simulate!**
- Start with simple models, gradually make them complex



The screenshot shows the arXiv website interface. At the top, the arXiv logo is followed by the breadcrumb 'stat > arXiv:2011.01808'. A search bar and links for 'Help' and 'Adv' are in the top right. Below the red header, a grey bar indicates the category 'Statistics > Methodology'. The paper's submission date '[Submitted on 3 Nov 2020]' is shown. The title 'Bayesian Workflow' is prominently displayed, followed by the authors' names: Andrew Gelman, Aki Vehtari, Daniel Simpson, Charles C. Margossian, Bob Carpenter, Yuling Yao, Lauren Kennedy, Jonah Gabry, Paul-Christian Bürkner, and Martin Modrák. The abstract text begins with 'The Bayesian approach to data analysis provides a powerful way to handle uncertainty in all observations, model parameters, and model structure using probability theory. Probabilistic programming languages make it easier to specify and fit Bayesian models, but this still leaves us with many options regarding constructing, evaluating, and using these models, along with many remaining challenges in computation. Using Bayesian inference to solve real-world problems requires not only statistical skills, subject matter knowledge, and programming, but also awareness of the decisions made in the process of data analysis. All of these aspects can be understood as part of a tangled workflow of applied Bayesian statistics. Beyond inference, the workflow also includes iterative model building, model checking, validation and troubleshooting of computational problems, model understanding, and model comparison. We review all these aspects of workflow in the context of several examples, keeping in mind that in practice we will be fitting many models for any given problem, even if only a subset of them will ultimately be relevant for our conclusions.'