1. Introduction

How can we learn causal models from diverse sources of observational and experimental data?

H1: “Only skill matters”

- Causal Graph
- Observational MiniStan Program
- Encouragement Design

H2: “Belief and skill matter”

- Stochastically generate MiniStan programs to encode a prior distribution over causal model structures and parameters.
- Programmatically edit the generated MiniStan programs to reflect experimental conditions.
- Interpret the MiniStan programs to induce a likelihood given observational and experimental data.

2. Interventions

Experiments can be represented as the composition of MiniStan program transformations.

- Experimental MiniStan Program
- MiniStan Program Prior
- Observational Data

- Experimental maximum likelihood surface
- True causal parameters

3. Generative model over MiniStan Programs

- MiniStan Program Prior
- Observational and Experimental Data Likelihood

4. Experiments and Discussion

- Causal models are represented as code.
- Prior beliefs are represented as code generators.
- Interventions/experiments are represented as code transformations.

Future work: Can more expressive grammars of causal programs [6] help us learn more realistic causal models of the world?

Future work: How can the Bayesian synthesis approach be used to encode more richly structured priors [3, 8] over causal models using probabilistic programs?

Future work: How can the Bayesian synthesis approach be used to model realistic [7] experimental conditions?

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References


