Overview, Hard Problems, and Open Questions

Causal Inference

- What have we (hopefully) learned?
  - A representation of causal structures
  - Given a causal structure, algorithms for:
    - Predicting patterns of independence
    - Updating probabilities given observations, interventions, or both
  - Given a set of data, algorithms for:
    - Learning causal structures, potentially including:
      - Multiple unobserved common causes
      - Selection bias
      - And so on…

Causal Inference

- What else do we know how to do?
- Short answer: *Quite a lot*, including:
  - Clustering, classification, and causal learning under a range of conditions
  - Text and image classification/processing
  - Information fusion from multiple sources
  - Inference of communication networks
  - Route- or plan-generation

Causal Inference

- What do we know we *cannot* do?
  - Go (significantly) “beyond the data”
  - Learn when there is no variation
  - Learn efficiently in all situations
  - Reliably learn from very small samples
  - Reliably learn complex structure within an individual, given group-level data

Some Hard & Open Problems

- Can un-intervenable features be causes?
  - Not just a philosophical puzzle! Important question for policy-making decisions…
- Learning and prediction w/ definitional vars.
- Large-scale regularity and predictability from small-scale causation
- Problems of aggregation
- Distributed datasets
- Spatiotemporal data
- Feedback systems

Definitional Variables

- What happens to the Markov and Faithfulness Conditions (and thus learning and prediction) when there are definitionally related variables and (un)ambiguous manipulations?
  - Issues independently posed by Hoover and Scheines

- Short answer (Spirtes): Can sometimes learn and predict, but they are *much* harder
  - Theory is complicated and only partially worked-out

Large-scale from Small-scale

- Some seemingly innocuous observations:
  - Big stuff is made of lots of little stuff, and features of big stuff are aggregates of features of little stuff
    - There are regularities among features of little stuff
  - When we manipulate features of big stuff we are manipulating many features of little stuff

Large-scale from Small-scale

- Two questions:
  - How do the regularities among features of big stuff result from aggregation of features of little stuff and their regularities?
  - How can the regularities among features of the big stuff give us information about effects of interventions on the big stuff?

Large-scale from Small-scale

- You might be wondering: who cares?
  - We seem to be able to do prediction and learning with big stuff, so why worry?

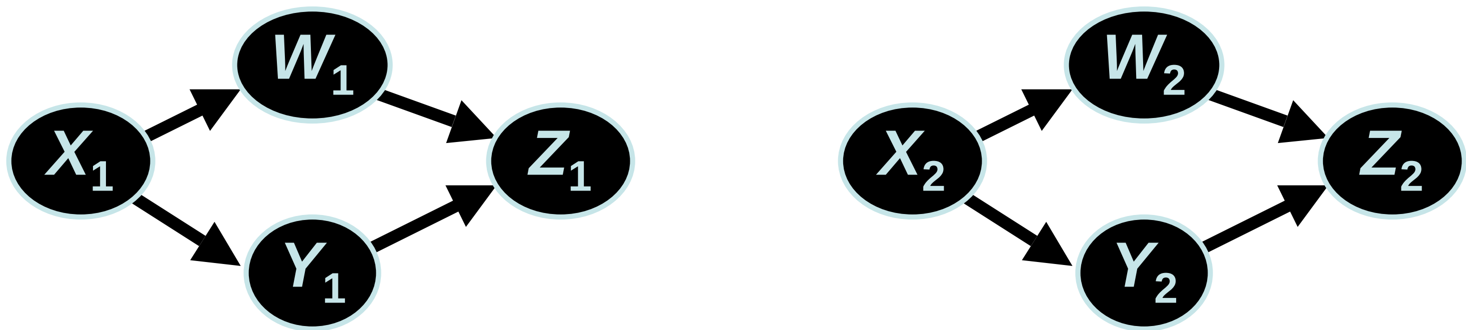
- But we have principled reasons to question whether we really can do prediction and learning with big stuff…

Large-scale from Small-scale

- Take the simplest case:
  - Big-stuff is composed of lots of little-stuff
  - Every little-stuff is exactly the same
  - Every big-stuff feature is a function of the little-stuff features in the components
- The Markov properties of the big-stuff features are not (in general) the Markov properties of the little-stuff features
  - I.e., Markov properties do not necessarily hold when we aggregate lots of individuals

Large-scale from Small-scale

- Two components with the same structure



- For all i, $X_i \perp\!\!\!\perp Z_i \mid W_i, Y_i$
- But $\{X_1+X_2\} \not\perp\!\!\!\perp \{Z_1+Z_2\} \mid \{W_1+W_2\}, \{Y_1+Y_2\}$
  - I.e., Aggregation destroys the independence

Large-scale from Small-scale

- If Markov properties change as we shift scale, then it seems that learning and prediction should only work on one level

- How can we actually do causal inference?
  - Partial answers (e.g., from Reichenbach, Strevens), but no complete theory

Distributed Datasets

- Suppose the relevant data is split into multiple datasets based on variables
  - Dataset #1 contains variables V_1, V_2, …; Dataset #2 contains variables W_1, W_2, …; etc.
  - Assume the variables in the datasets overlap
    - Otherwise, it isn't a very interesting problem…
- Central question: What is the causal structure for *all* variables?

Distributed Datasets

- Sometimes, the datasets can potentially be unified
  - E.g., each datapoint might have a unique ID
- In these cases, there is no principled barrier to learning, since we could (if necessary) determine every datapoint's value for every variable
  - And there has been some work designing efficient data passing algorithms

Distributed Datasets

- More interesting (and much harder) problem arises when there are no IDs
  - E.g., medical databases (from hospitals, insurers, doctors' offices); or financial databases (from credit agencies, banks, credit card companies)
- How much information can we recover about the global causal structure?

Distributed Datasets

- Two traditional responses:
  1. Without global IDs, we can only recover structure in the local datasets, not globally
     - Overly pessimistic!
  2. Statistical Matching
     - Assume a (generic) model underlying the data, and estimate the “missing” datapoints
     - But this process assumes structural knowledge that may not be known, or may not be true

Distributed Datasets

- We can do better than these options
  - Provably correct algorithm for learning close-to-maximal information about global causal structure from multiple overlapping datasets
    - And we can sometimes learn a *lot* about the global structure from limited local information
  - But this algorithm is computationally hopeless
    - And its performance is not well-understood

Spatiotemporal Data

- Numerous methods for spatiotemporal data in econometrics and environmental sciences
  - But most of those methods either explicitly disavow causal interpretations, or make unreasonable assumptions
- Can we find more principled methods?
- What if the underlying generating system changes over time?
  - Can we even detect those changes reliably?

Feedback Systems

- We know how to do causal learning in feedback systems if there are no unobserved common causes
  - But not if there are such latents
- And only if we assume systems settle in equilibrium states (from which it is periodically perturbed)
  - What if that assumption is violated?