Lecture 8

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Causal inference

Introduction

Source and thanks

Much of this material comes from Larry Wasserman's lecture in "Statistical Machine Learning 10-702" at CMU.

Some additions come from Cosma Shalizi's textbook Advanced Data Analysis from an Elementary Point of View.

Prediction vs. causation

These two are very different.

- Prediction: Predict Y after observing X = x
- Causation: Predict Y after setting X = x

Example:

- Prediction: Predict health given that a person eats beets.
- Causation: Predict health if I give someone beets.

The first case is simply observational while the second relies on an intervention.

Analysis requires different techniques, and often strong assumptions.

Two types of causal questions

Type I:

Do cell phones cause brain cancer?

In mathematical terms, there are variables X and Y and we want to determine the causal effect of X on Y.

Procedure: find a parameter θ that measures this effect and try to estimate it.

Called causal inference

Type II:

I have a pile of variables and I want to discern their causal relationships.

Called causal discovery

Larry argues that solving this problem is statistically impossible.

Lots of people work on this problem however.

Two types of data

Type I:

Data from randomized, controlled experiments.

The inference problem is straightforward (well-defined).

Type II:

Data from observational studies.

The inference problem is difficult, requires making assumptions and using domain knowledge.

Three languages

- 1. Counterfactuals
- 2. Causal graphs
- 3. Structural equation models

These are essentially equivalent up to minor details.

Motivation for different notation

- Height and reading ability are associated.
- Stretching a child will not improve reading ability.
- Height does not cause improved reading skill.
- Smoking causes cancer.
- Society is pretty confident that giving people cigarettes will give them cancer.

$$P(Y \mid X = x)$$
 v.s. $P(Y \mid set(X = x))$