

3.4 Machine Learning meets Biostatistics II

Qingyuan Zaho

<http://www.statslab.cam.ac.uk/~qz280/teaching/>

<http://www.dagitty.net/>

<http://www.statslab.cam.ac.uk/~qz280/talk/ccaim-summer-school-2022/>.

The 16-hour course is given to Part III mathematicians/statisticians and the course webpage is <http://www.statslab.cam.ac.uk/~qz280/teaching/causal-2021/>.

Randomization and potential outcomes

- Motivating examples: Vitamin studies
 - 1990s, several studies found strong inverse association
 - Conducted RCT showed that supplementation with antioxidants does not protect against these diseases
 - [https://www.thelancet.com/journals/lancet/article/PIIS0140-6736\(04\)16260-0/fulltext](https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(04)16260-0/fulltext)
- What went wrong?
 - Confounder = Common cause of treatment and effect
 - Cannot be removed completely. Always potential issue with unmeasured confounders
 - How can we balance observed confounders? Better design (e.g. blocking)
 - Randomisation
- Randomisation as a basis of inference
 - Randomisation now regarded as gold standard for causal inference – was difficult to accept
 - Example:
 - Physician allowed to administer a promising new drug to 5/10 patients
 - Physician thinks the best way to prove effectiveness of the drug is to give it to the 5 patients that they think are the most ill
 - Flaw
 - Randomization introduces an objective basis of inference which anyone else can use

DAG models:

- Conditional independence
 - Two ways of testing:
 - Conversion to undirected graph
 - Moralisation
 - D-separation on directed graphs
 - Both criteria are mathematically equivalent
 - Factorisation according to DAG

Causal DAGs

- Correlation is not causation

- Model may not generalise to other settings

Readings

The following books/articles are optional. I am providing a short (personal) verdict to help you navigate the literature.

- [Causal Inference for Statistics, Social, and Biomedical Sciences](#) by Guido Imbens and Donald Rubin [IR]. This book provides a gentle introduction to potential outcomes and statistical methods for simple randomised experiments and observational studies with no unmeasured confounders.
- [Causal Inference: What If](#) by Miguel Hernán and James Robins [HR]. This book provides a comprehensive treatment for causal inference without and with models.
- [Causality: Models, Reasoning, and Inference](#) by Judea Pearl [Pearl]. A great book if you are interested in the philosophical debates in causal inference.
- [Statistical Models: Theory and Practice](#) by David Freedman. A less technical textbook is well suited for someone who wants to learn the basic ideas in causal inference through practical examples.
- [Graphical Models](#) by Steffen Lauritzen. A good reference for probabilistic graphical models.
- [Observational Studies](#) by Paul Rosenbaum. A good book for randomisation inference and sensitivity analysis.
- [Mostly Harmless Econometrics: An Empiricist's Companion](#) by Joshua Angrist and Jörn-Steffen Pischke. Very clearly written book from an applied econometrics point of view, with a lot of useful intuitions.