Causality:
Explanation versus Prediction

Department of Government
London School of Economics and Political Science
1 Brief Review of MT Material
2 Causality
3 Fundamental Problem of Causal Inference
4 Randomized Experiments
1 Brief Review of MT Material

2 Causality

3 Fundamental Problem of Causal Inference

4 Randomized Experiments
What did we learn about during MT?
New territory...

By the end of today you should be able to:

- Identify what makes for a causal relationship
- Distinguish causation from correlation/association
- Begin to analyse research problems using counterfactual thinking
The broad story arc for LT

- Causal inference!
  - Generating causal theories and expectations
  - Making comparisons
  - Statistical methods useful for causal inference
  - (Quasi-)Experimentation
The broad story arc for LT

- Causal inference!
  - Generating causal theories and expectations
  - Making comparisons
  - Statistical methods useful for causal inference
  - (Quasi-)Experimentation

- Developing your research proposals
  - One-on-ones w/ Thomas
  - Literature review (Reading Week)
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Our intuition about causation relies too heavily on simple comparisons of *pre-post change* in outcomes before and after something happens:

- No change: no causation
- Increase in outcome: positive effect
- Decrease in outcome: negative effect

Several reasons why this is inadequate!
Flaws in causal inference from pre-post comparisons

1. Maturation or trends
2. Regression to the mean
3. Selection
4. Simultaneous historical changes
5. Instrumentation changes
6. Monitoring changes behaviour
Directed Acyclic Graphs

- Causal graphs (DAGs) provide a visual representation of (possible) causal relationships.
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- Causality flows between variables, which are represented as “nodes.”
  - Variables are causally linked by arrows.
  - Causality only flows forward in time.
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- Causality flows between variables, which are represented as “nodes.”
  - Variables are causally linked by arrows.
  - Causality only flows *forward* in time.

- Nodes opening a “backdoor path” from $X \rightarrow Y$ are confounds.
  - “Selection bias” or “Confounding”
Smoking → Cancer
Age → Smoking → Cancer

Parental Smoking → Smoking

Genetic Predisposition → Cancer

Environment → Cancer
Age

Coin Flip

Smoking

Parental Smoking

Genetic Predisposition

Environment

Cancer

Randomized Experiments

Counterfactuals

Causality

MT
The 3 or 4 or 5 principles
The 3 or 4 or 5 principles

1 Correlation
Age

Smoking

Parental Smoking

Environment

Genetic Predisposition

Cancer
The 3 or 4 or 5 principles

1 Correlation
The 3 or 4 or 5 principles

1. Correlation

2. Nonconfounding
The 3 or 4 or 5 principles

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3. Direction ("temporal precedence")
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4. Mechanism
The 3 or 4 or 5 principles

1. Correlation
2. Nonconfounding
3. Direction ("temporal precedence")
4. Mechanism
5. (Appropriate level of analysis)
Brexit vote compared to proportion of those aged over 65; each point representing a local area

Questions?
1. Brief Review of MT Material
2. Causality
3. Fundamental Problem of Causal Inference
4. Randomized Experiments
Causal Inference

Causal inference (typically) involves gathering data in a systematic fashion in order to assess the size and form of correlation between nodes $X$ and $Y$ in such a way that there are no backdoor paths between $X$ and $Y$ by controlling for (i.e., conditioning on, holding constant) any confounding variables, $Z$. 
In essence, this means finding or creating counterfactuals.
Counterfactual Thinking

- Causal inference involves inferring *what would have happened* in a counterfactual reality *where the potential cause took on a different value*

- *Counterfactual*: relating to what has not happened or is not the case
“A Christmas Carol”

- 1843 novel by Charles Dickens
- Ebenezer Scrooge is shown his own future by the “Ghost of Christmas Yet to Come”
- Has the choice to either:
  1. stay on current path (one counterfactual), or
  2. change his ways (take a different counterfactual)
Dickensian Causal Inference

- **Causal effect**: The difference between two “potential outcomes”
  - The outcome that occurs if $X = x_1$
  - The outcome that occurs if $X = x_2$

- The causal effect of Scrooge’s lifestyle is seen in the *difference(s)* between two potential futures
Other Counterfactuals in TV & Film

- Groundhog Day
- Run Lola Run
- Minority Report
- Source Code
- X-Men: Days of Future Past
Fundamental problem of causal inference!

We can only observe any given unit in one reality! So any counterfactual for a given unit is unobservable!!!
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OH NO!
Two solutions!

1 “Scientific” Solution

- (Assume) units are all identical
- Each can provide a perfect counterfactual
- Common in, e.g., agriculture, biology

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1 From Holland
Two solutions!

1. "Scientific" Solution
   - (Assume) units are all identical
   - Each can provide a perfect counterfactual
   - Common in, e.g., agriculture, biology

2. "Statistical" Solution
   - Units are not identical
   - Random exposure to a potential cause
   - Effects measured on average across units
   - Known as the "Experimental ideal"

\(^1\) From Holland
Mill’s methods$^2$

- Agreement
- Difference
- Agreement and Difference
- Residue
- Concomitant variations

$^2$Discussed in Holland
Mill’s Method of Difference

“If an instance in which the phenomenon under investigation occurs, and an instance in which it does not occur, have every circumstance save one in common, that one occurring only in the former; the circumstance in which alone the two instances differ, is the effect, or cause, or an necessary part of the cause, of the phenomenon.”
“Rerum cognoscere causas”

- Causal inference is meant to help “explain” the social world
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  - Other notions of *explain*
    - Concept generation and labelling
    - Descriptive typologies
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- Causation is deterministic at the unit level!
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- Counterfactual approaches to causal inference are “forward” in nature
Prediction is not causation.
Causation is not prediction.
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Why are these distinct?
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The Experimental Ideal

A randomized experiment, or randomized control trial is:

*The observation of units after, and possibly before, a randomly assigned intervention in a controlled setting, which tests one or more precise causal expectations*

This is Holland’s “statistical solution” to the fundamental problem of causal inference
Random Assignment

- A physical process of randomization
  - Breaks the “selection process”
  - Units only take value of $X = x$ because of assignment

This means:

- Treatment groups, on average, provide insight into counterfactual “potential” outcomes
- Randomization means potential outcomes are balanced between groups, so no confounding
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Experimental Inference I

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A causal effect is the difference between these (e.g., \( y_{x=1} - y_{x=0} \)), all else constant.
We cannot see individual-level causal effects

- We want to know: \( TE_i = y_{1i} - y_{0i} \)
Experimental Inference II

- We cannot see individual-level causal effects
  - We want to know: $TE_i = y_{1i} - y_{0i}$
- We can see average causal effects
  - Ex.: Average difference in cancer between those who do and do not smoke
  - $ATE_{naive} = E[y_{1i}|x_i = 1] - E[y_{0i}|x_i = 0]$
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  - Yes, if $X$ randomized
  - Yes, if all confounds controlled
| MT | Causality | Counterfactuals | Randomized Experiments |
|----|-----------|-----------------|------------------------|------------------------|

Preview of next week

- What is a “scientific literature”?
- How do we accumulate scientific evidence?
Mill’s Methods
Agreement

If two or more instances of the phenomenon under investigation have only one circumstance in common, the circumstance in which alone all the instances agree, is the cause (or effect) of the given phenomenon.
Difference

If an instance in which the phenomenon under investigation occurs, and an instance in which it does not occur, have every circumstance save one in common, that one occurring only in the former; the circumstance in which alone the two instances differ, is the effect, or cause, or an necessary part of the cause, of the phenomenon.
Agreement and Difference

If two or more instances in which the phenomenon occurs have only one circumstance in common, while two or more instances in which it does not occur have nothing in common save the absence of that circumstance; the circumstance in which alone the two sets of instances differ, is the effect, or cause, or a necessary part of the cause, of the phenomenon.
Residue

Subduct from any phenomenon such part as is known by previous inductions to be the effect of certain antecedents, and the residue of the phenomenon is the effect of the remaining antecedents.
Concomitant variations

Whatever phenomenon varies in any manner whenever another phenomenon varies in some particular manner, is either a cause or an effect of that phenomenon, or is connected with it through some fact of causation.