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

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

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- Causal inference!
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  - Statistical methods useful for causal inference
  - (Quasi-)Experimentation
- Developing your research proposals
  - One-on-ones w/ Thomas
  - Literature review (Reading Week)

Directed Acyclic Graphs

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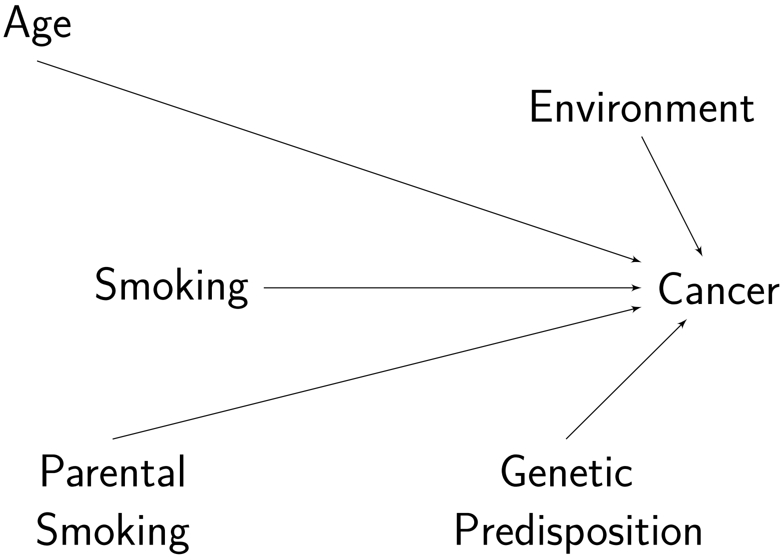
  - Variables are causally linked by arrows
  - Causality only flows *forward* in time
- Nodes opening a “backdoor path” from $X \rightarrow Y$ are confounds
  - “Selection bias” or “Confounding”

Smoking $\longrightarrow$ Cancer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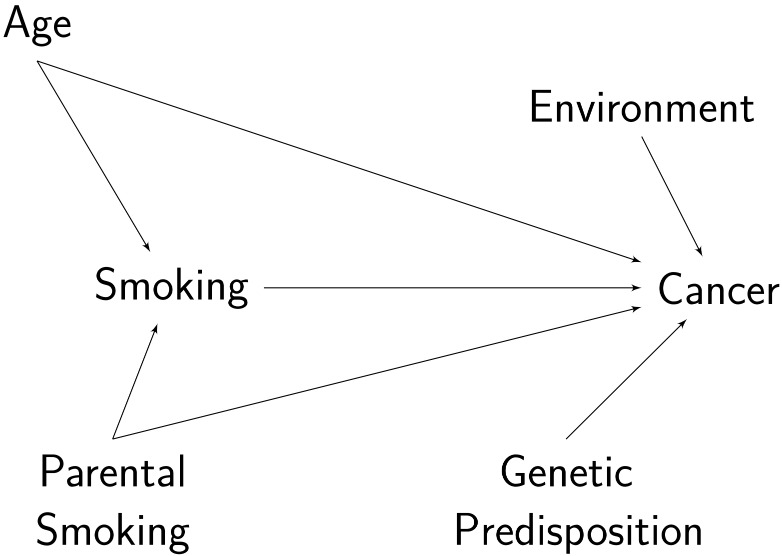
Smoking
Cancer
Parental Smoking
Genetic Predisposition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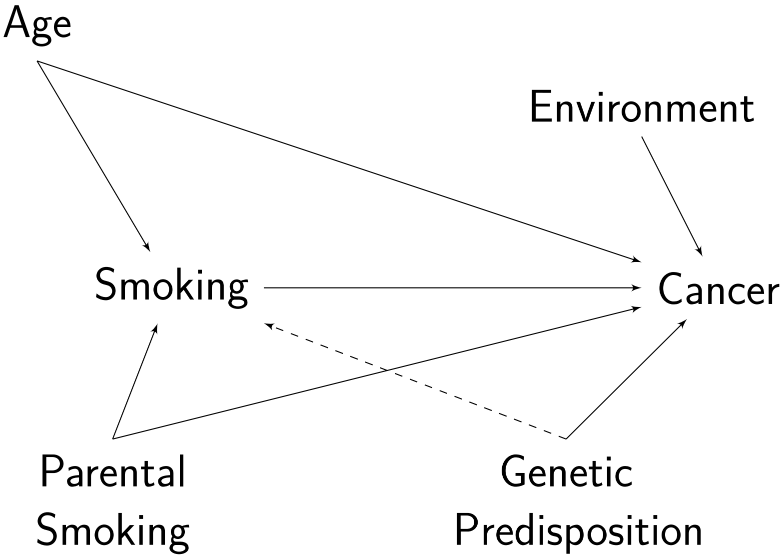
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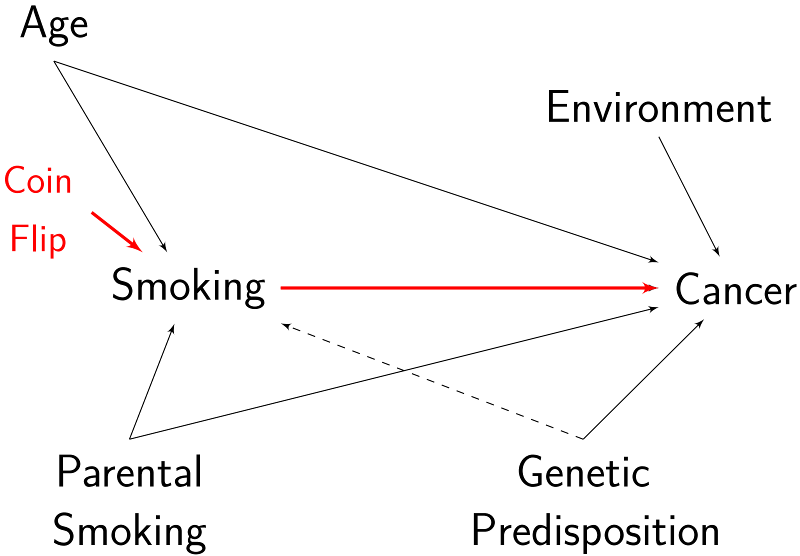
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The 3 or 4 or 5 principles

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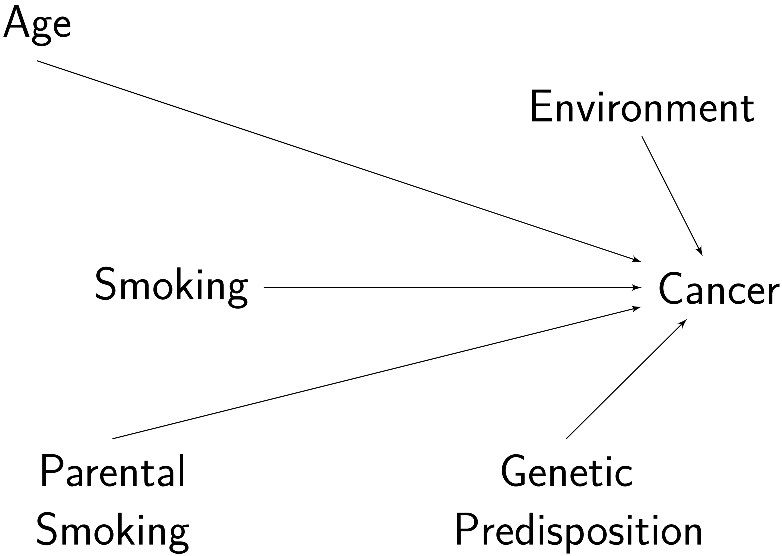
1. Correlation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The 3 or 4 or 5 principles

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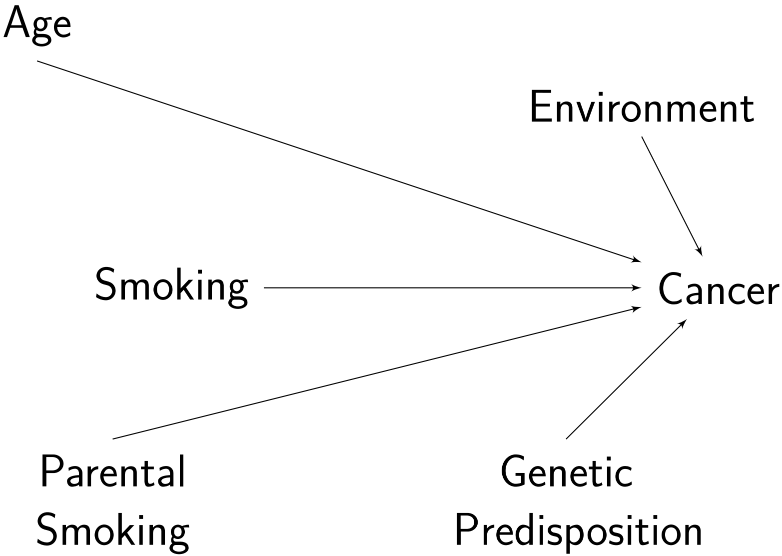
2. Nonconfounding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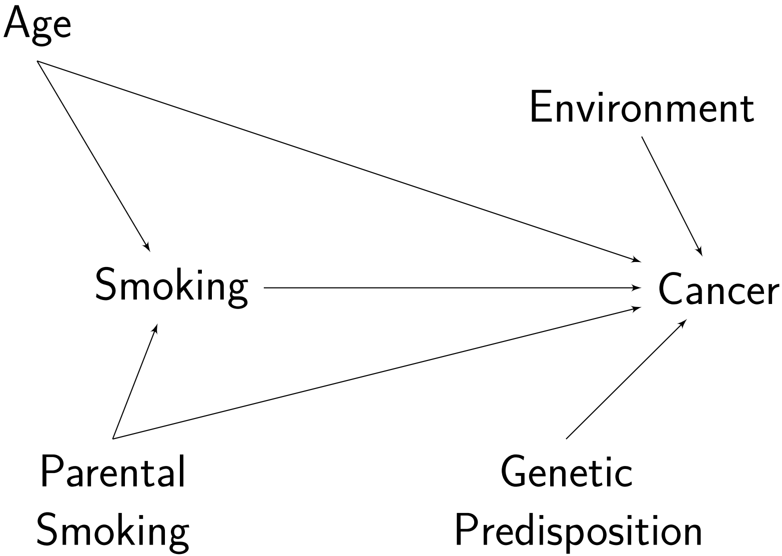
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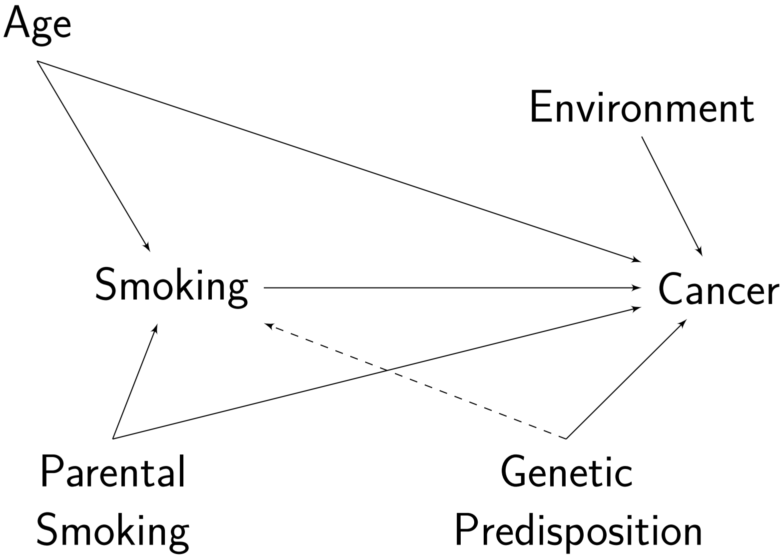
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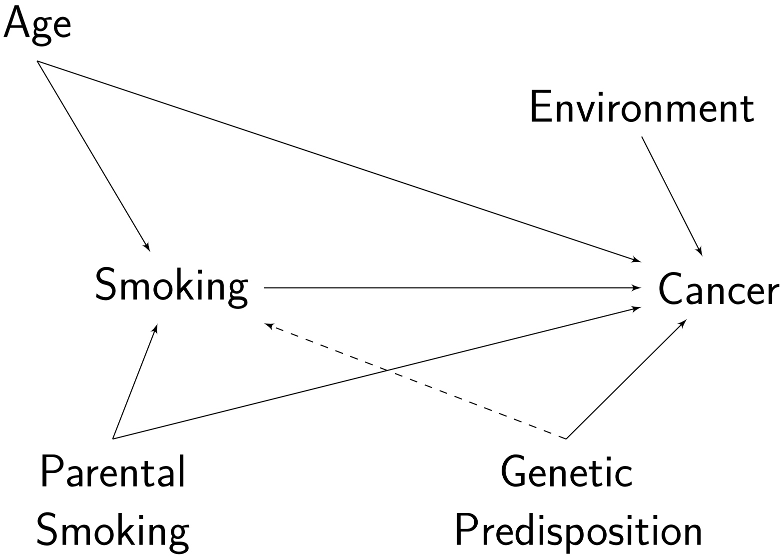
3. Direction ("temporal precedence")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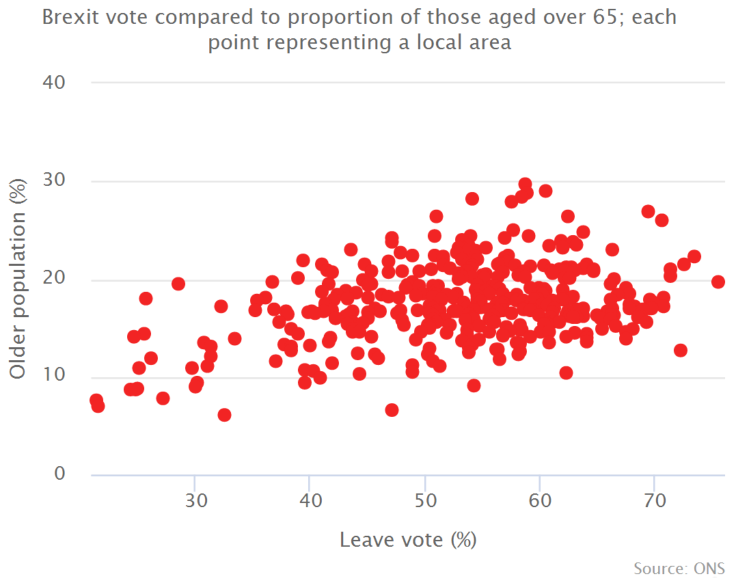
5. (Appropriate level of analysis)



Source: *The Telegraph*. 27 June 2016. `http://www.telegraph.co.uk/news/2016/06/24/eu-referendum-how-the-results-compare-to-the-uks-educated-old-an/`

Questions?

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, $\mathbf{Z}$.

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:
  - stay on current path (one counterfactual), or
  - 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

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OH NO!

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1. Scientific Solution
   - (Assume) units are all identical
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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."

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- Causal inference is meant to help "explain" the world
  - Other notions of explain (e.g., description)
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- Causation is deterministic at the unit level!
- Counterfactual approaches to causal inference are "forward" in nature

Prediction is not causation.
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Why are these distinct?

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

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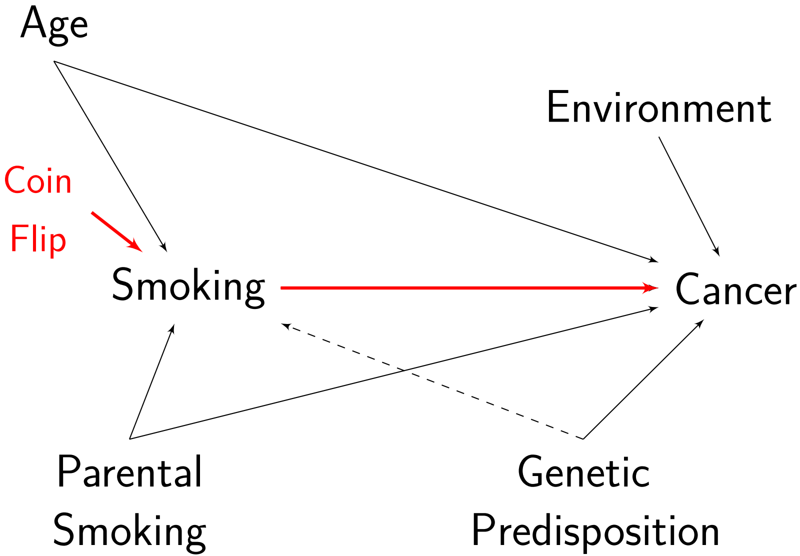
- This means:
  - Treatment groups, on average, provide in sight into counterfactual “potential” outcomes
  - Randomization means potential outcomes are balanced between groups, so no confounding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- A *causal effect* is the difference between these (e.g., $y_{x=1} - y_{x=0}$), all else constant

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- Is this what we want to know?
  - Yes, if X randomized
  - Yes, if all confounds controlled

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.