Causality and research design: experiments versus observation

Harry Ganzeboom

Research Skills #3

November 10 2008

Experiments

- All scientific questions are implicitly explanatory questions and ask for causal inference.
- Experiments are the Golden Standard for testing causal hypotheses.
- Unfortunately (?), the social world is not very amenable to experimentation. We have to do observational (non-experimental) studies.
- We are not alone in this: meteorology, astronomy, geology etc.
- Even if never used, it is useful to know how experiments work.

Randomized groups experiments

- Randomization.
- Manipulation of one group, the other one is the control.
- Effect is difference in group means (t-test).
- Note (practical) limitations, even if applied:
  - At best two independent variables.
  - Independent variables are almost always qualitative (=categorical).
  - External validity (generalisation) is often quite problematic.

Increasing power – beyond randomization

- Randomization leads to expected inequality between groups – but random fluctuation still occurs.
- We can do better than that by matching: make sure that the two groups are exactly equal with respect to known covariates.
- In fact, we introduce correlated residuals by design.
- Matched samples T-test adjusts for this correlation.
- Note that in matched designs we have more statistical power (we 'see sharper') than in randomized designs.
- To some extent the advantages of matching can be imitated by using post-hoc adjustments ("analysis of covariance").

Ultimate power: pretest/posttest

- The ultimate match (finding a case that is exactly like the test person) is easy to find: it is the same person before the manipulation.
- Pretest / posttest designs have ultimate power.
- However, pretest / posttest designs also have major disadvantages (Campbell & Stanley): maturation, history, mortality, testing.
- Nevertheless pretest/posttest design are often used in program evaluation. In a policy context randomization is often a problem.

Observational designs

- In observational designs, we investigate causal processes by only looking at nature, we do not interfere.
- Nevertheless, we look at nature as if interference takes place (and take experimental designs as our reference).

Causality

- X causes Y:
  - If Y → X can be ruled out
  - If confounding by Z (X ← Z → Y) can be ruled out
  - If X and Y are correlated
- In experiments:
  - Causal order naturally arises
  - Confounders are ruled out by randomization
  - Effect ➔ correlation

Causal order in observational designs

- The most common argument about causal order of X and Y is a reference to time order:
  - By design (panel design, retrospective questions)
  - By assumption (e.g. life cycle)
- Other commonly used arguments:
  - Unchangeable background variables (gender) are cause, not effect
  - General attitudes cause specific attitudes, not the other way around.

Two relationships between three variables

- Confounding: Z causes both X and Y
- Intervening: X causes Z, Z causes Y.
- These are very different situations:
  – With confounding Z, there is no causal relationship X → Y; this is called <u>spurious</u> causation. (Not: spurious correlation!!).
  – With intervening Z, there ***is*** a causal effect X → Y. This is called an <u>indirect</u> effect.
- The difference between the two situations cannot be determined by statistical analysis, it follows from an <u>assumption</u> that you need to bring to the analysis and may be justified by your research design.

Ruling out confounding Z

- If Z can be regarded as a antecedent variable, its confounding effect can be ruled out by controlling it (“holding constant”). We test whether the correlation X → Y still exists within levels of Z.
- Lazarsfeld’s elaboration (‘tabelsplitsing’) is a way to do this using cross-tabulations.
- A regression model is a much more convenient and powerful way of doing it.

Regression and causal analysis

- Regression models only inform about causal effects if we can assume a causal model (causal order) .
- Causal models are always multi-equation systems (“path analysis”). Regression can be used to estimate partial and total effects.
- In practice, this often waters down to blockwise regression (forward steps), with confounders and interveners added in groups.
- Many articles are very sloppy about causal order.