Better Causal Diagrammes

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A penance

It is a truism that correlation is not causation. Yet in many human sciences it is common practice to report correlations using hedging language. The assumption: correlation is causal-ish. For many years, I adopted this common practice. In many scientific publications I would report correlational data using hedging, causal-ish langauge. This practice is disasterous for science. In contenting myself with causal-ish language, I contributed to what has become a **causal crisis** across many human sciences. I have spent the past several years immersing myself in the literatures on causal inference.

Although causal diagrammes are becomming more commonplace, however, in the areas that stand to benefit most from causal diagrammes confusion still reighs.

My purpose here is share what I have learned about causal diagrammes, and to offer advice. Some of my advice is opinioned.

In any case, this article is a penance.

Purpose

Correlation is not, in itself, the problem. We say a relation between an exposure A and and outcome Y is causal if the corration between A and Y is unbiased.

Causal diagrammes, or directed acyclic graphs (DAGS), are qualitative tools for identifying sources of bias. They are powerful because they translate a mathematical artiface that underpinns causal inference into simple, useable images. We may therefore use the images to understand how we may answer causal questions.

However we must recognise that we never start by answering a causal question. We start by asking a causal question. Many who utilise causal graphs fail to appreciate this fact.

Causal questions

Common Causal Graphs

Graphs of Canonical confounders

Confounding by Common Cause

The problem of confounding by common cause arises when there is an unmeasured or unaccounted-for variable, denoted as "L," that influences both the treatment variable, denoted by A, and the outcome variable, denoted as Y. This confounder, L, creates an association between A and Y that is not solely due to the direct causal effect of A

on Y. Instead, the observed association between A and Y may be partially or entirely driven by the presence of L, making it difficult to isolate and accurately estimate the true causal effect of A on Y.

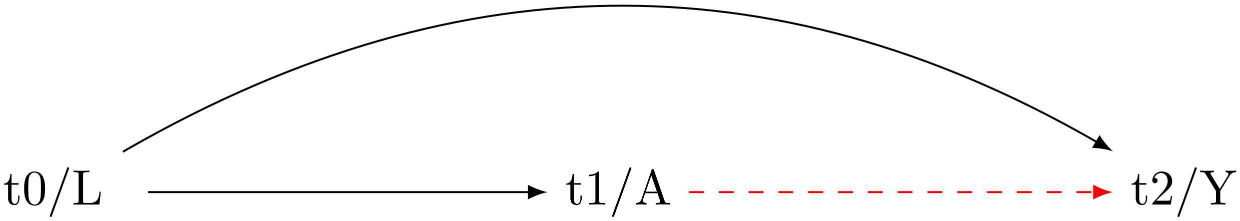

Figure 1: Counfounding by common cause.

Solution: adjust for the pre-exposure confounder

Confounding by common cause can be addressed by adjusting for it. If L is measured before the treatment (or exposure) is assigned, we may adjust for this confounder to account for its influence. Typically we adjust through through statistical techniques such as stratification, regression, matching, or inverse probability of treatment weighting. Sucg adjustment helps to mitigate the bias caused by the confounder, allowing for a more accurate estimation of the true causal relationship.

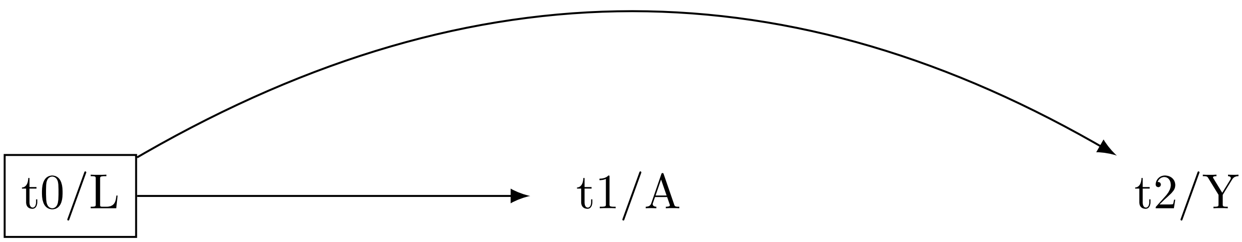

Figure 2: Solution: adjust for pre-exposure confounder.

Second problem: Collider stratification: conditioning on a common effect

Conditioning on a common effect occures when a variable L is affected by both the treatment A and an outcome Y. Conditioning on L creates a spurious association between A and Y, biasing the true causal relationship. This occurs because the relationship between A and Y becomes confounded by the common effect L. The observed association between A and Y may be solely driven by the influence of L.

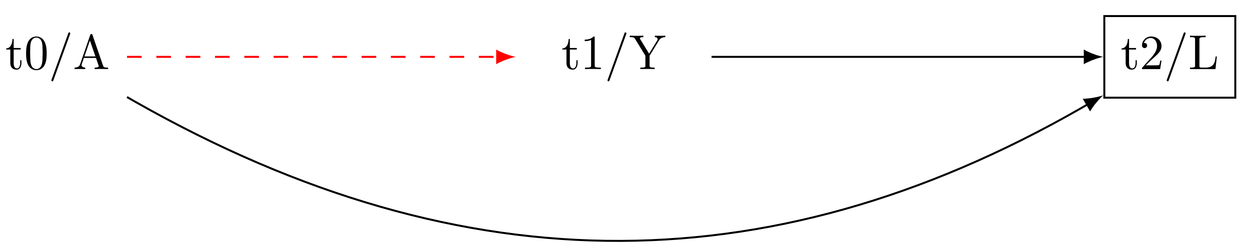

Figure 3: Solution: ensure confounder is measured prior to the exposure.

Solution: ensure all confounders are measured before the exposure

To address the problem of conditioning on a common effect, it is crucial to ensure that every potential confounder L that may affect A is measured before A. If such temporal order is preserved, L cannot be an effect of A, and thus neither of Y. By measuring all relevant confounders in advance, researchers can minimize bias and obtain more reliable estimates of the true causal relationship between A and Y. Note that collider stratification may arise even if L occurs before A, when L does not affect A or Y. This is called M-bias. We describe this case below. Note, however, that if L is not a common cause of A and Y, L should not be included in our model because it is not a source of confounding.

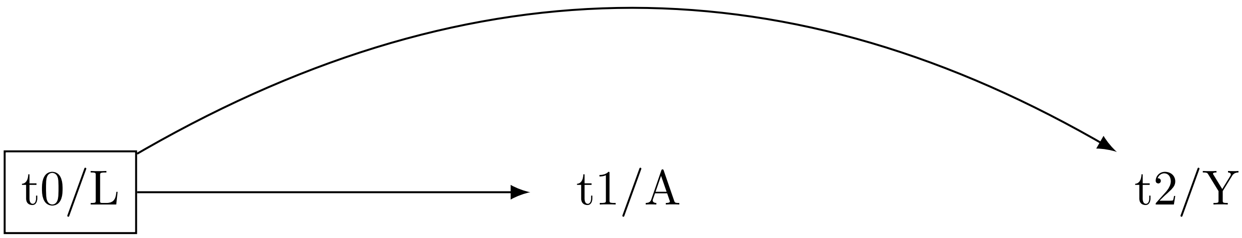

Figure 4: Causal graph reveals bias: solve by stratification

Third problem: conditioning on a mediator

Conditioning on a mediator refers to a situation where L lies on the causal pathway between the treatment A and the outcome Y. Conditioning on L can lead to biased estimates by blocking or distort the true causal pathway between A and Y, obscuring the total effect of A on Y. Where L is a collider between A and an unmeasured confouder U, then including L may increase the strength of association between A and Y. We review this second possibility next. In either case, unless one is interested in mediation analysis (see below), conditioning on a post-treatment variable is nearly always a bad idea. [JB to discuss the exception]

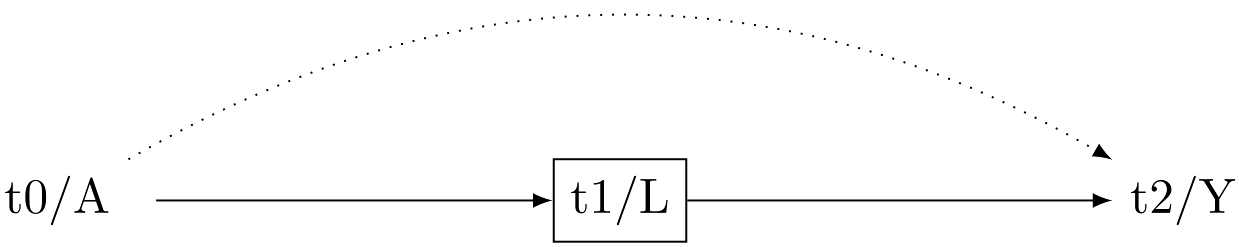

Figure 5: Third problem: conditioning on a mediator.

Solution: ensure confounders are measured before the exposure

To address the problem of mediator bias, when interested in total effects do not condition on a mediator. This can be done by ensuring that L occurs before A (and Y). Again we discover the importance of an explicit temporal ordering for our variables. Although note, if L is associated with Y but is not associated with A conditioning on L will improve the efficiency of the causal effect estimate of A on Y. However, if A might affect L, then L might be a mediator, and including L risks bias. As with some much in causal estimation, we must understand the context.

Fourth problem: conditioning on a descendant

Say A is a cause of $A*$. There is a theorem that proves that when we condition on $A*$ we partially condition on A.

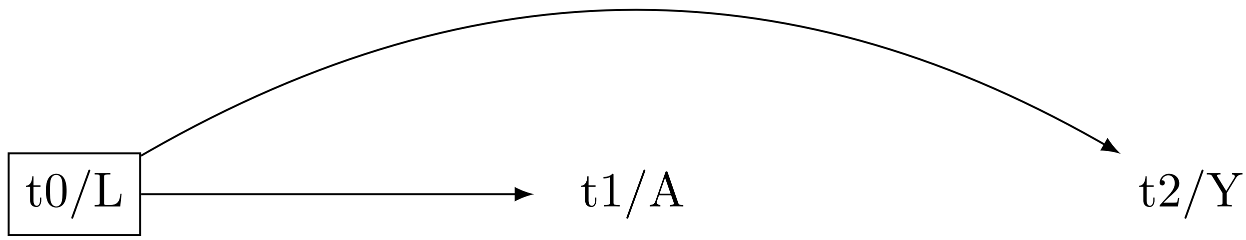

Figure 6: Do not condition on a mediator

There are both negative and positive implications of this theorem for causal estimation in real-world scenarios.

First the negative. Suppose there is a confounder L that is caused by an unobserved variable U, and is affected by the treatment A. Suppose further that U causes the outcome Y. In this scenario, as described in Figure 7, conditioning on L, which is a descendant of A and U, can lead to a spurious association between A and Y through the path $A \to L \to U \to Y$.

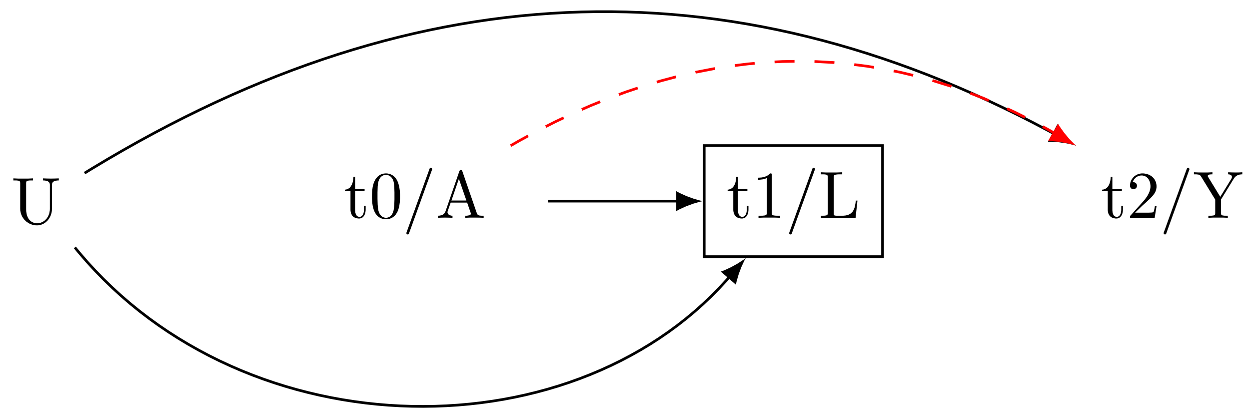

Figure 7: Conditioning on a descendant

Solution: (yet again) ensure that counfounders are measured before the exposure

Ensuring the confounder (L) is measured before the exposure (A) has two beneficial properties. Firstly, if L is a confounder, that is, if L is a variable which if we fail to condition on it will bias the association between treatment and outcome, the strategy of including only pre-treatment indicators of L will eliminate collider bias. Secondly, there is the positive side to the theorem that conditioning on a descendent is equivalent to partially conditioning on its parent: if an unmeasured confounder is associated with both A, Y, and L, then adjusting for L helps to reduce confounding caused by the unmeasured confounder. By obtaining measure of L that occur before A, such advantages can be achieved, allowing for more accurate estimation for the causal effect of A on Y. We use the convention of a blue dotted arrow to indicate that the association between A and Y may still be biased, but that bias is reduced by inluding L

This ends the examples of cannoical casual diagrammes

Examples

Next some worked examples.

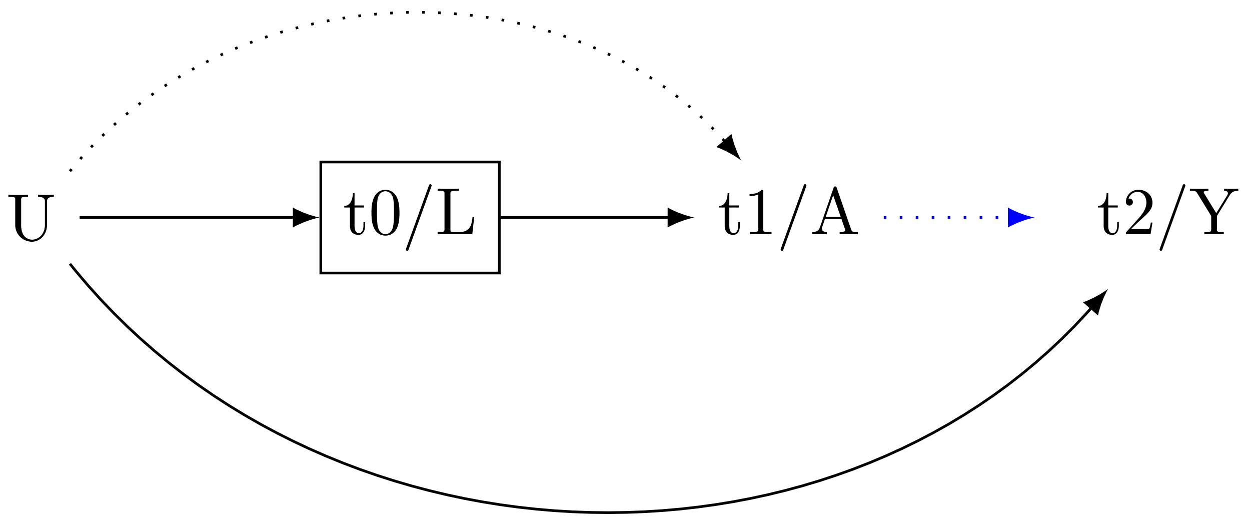

Figure 8: Solution: conditioning on a descendent is part of the solution, not the problem, when baseline confounders are measured before the exposure.

Common cause of exposure and outcome.

Figure 9: Common cause of exposure and outcome: example

Solution: Adjust for Confounder

Figure 10: Solution to this problem.

Figure 11: Causal graph reveals bias from pre-exosure indicator

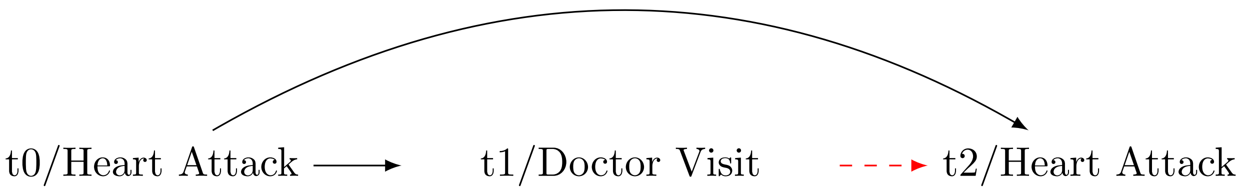

Figure 12: Solution to this problem

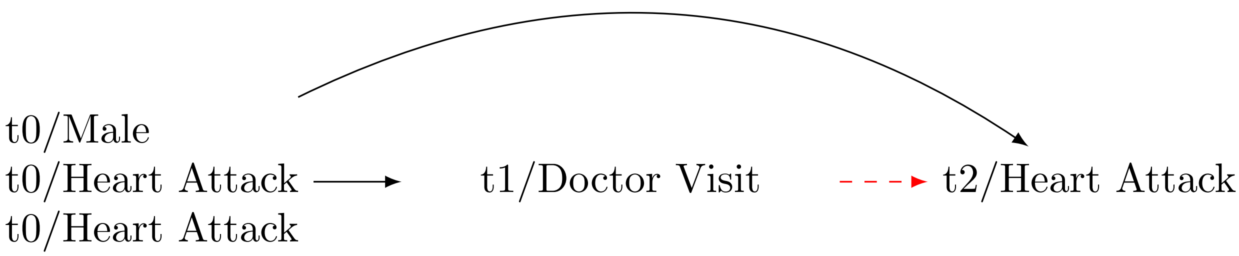

Figure 13: Causal graph:more general panel design

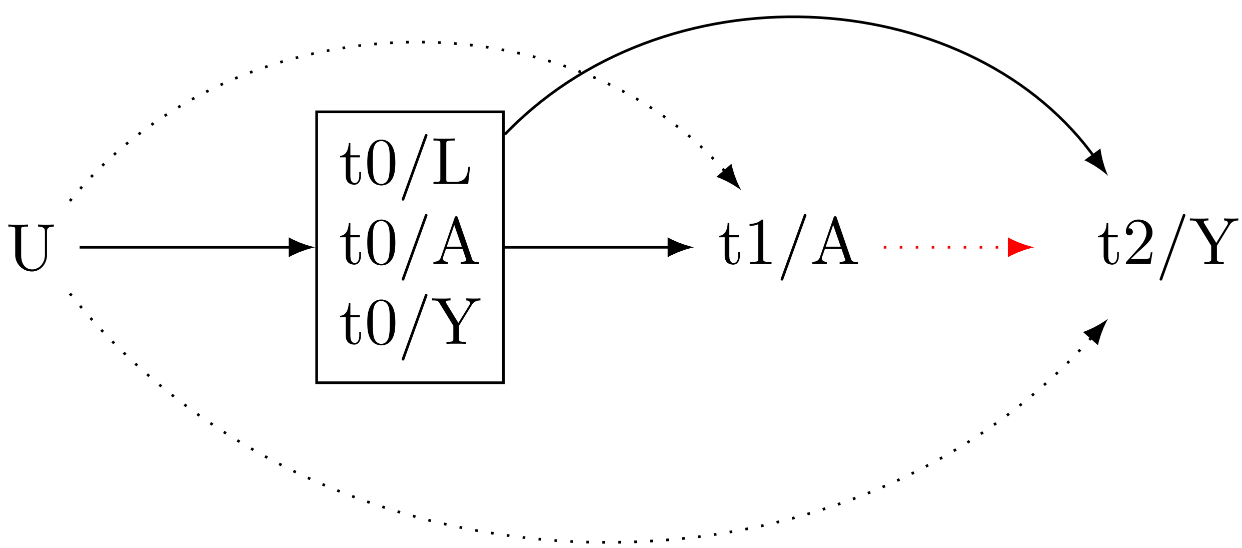

Figure 14: Causal graph: three-wave panel design

Bias: exposure at baseline is a common cause of the exposure at t1 and outcome at t2

Solution: adjust for confounder at baseline

A more thorough confounding control

Generic 3-wave panel design (VanderWeeele 2020)

Selection bias: there are several types

Unmeasured confounder affects selection and the outcome

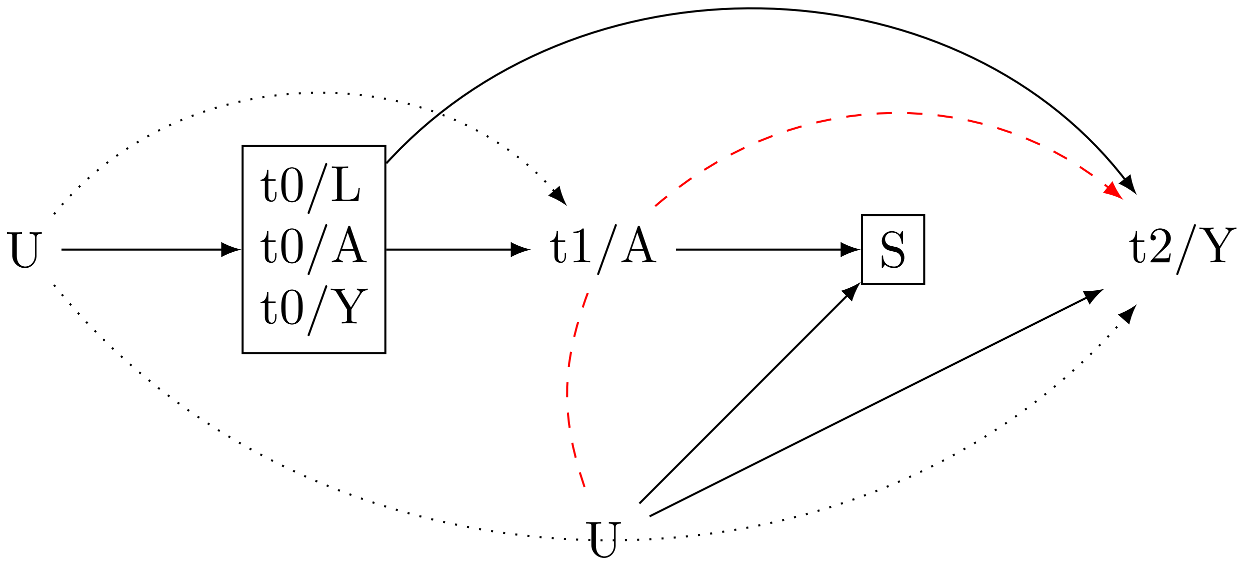

Figure 15: Causal graph: three-wave panel design with selection bias

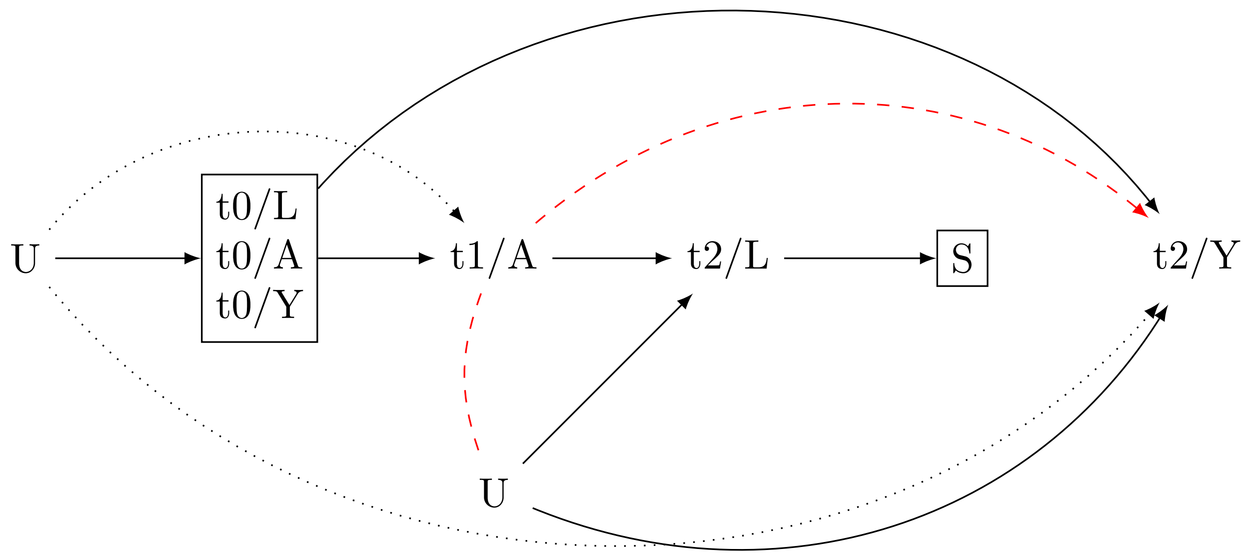

Figure 16: Causal graph: three-wave panel design with selection bias: example 2

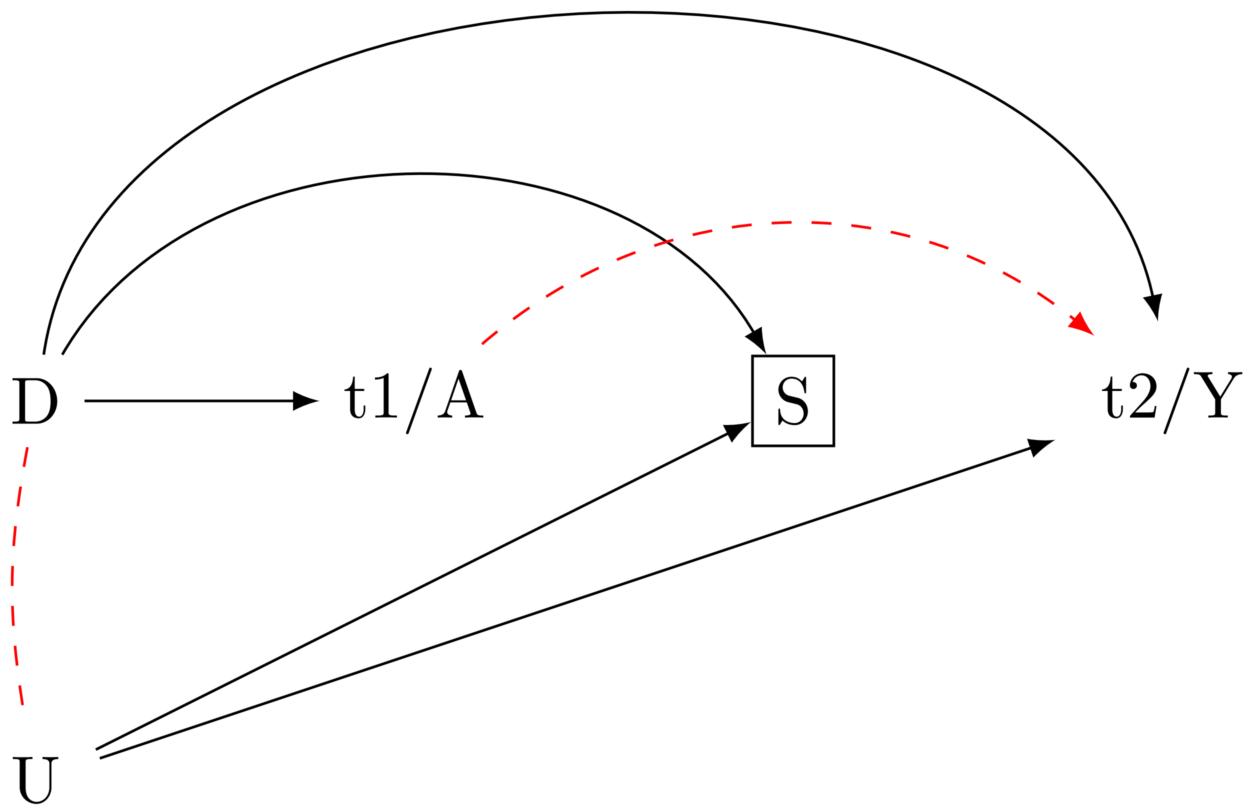

Figure 17: Causal graph: three-wave panel design with selection bias: selection into the study (D) affects attrition

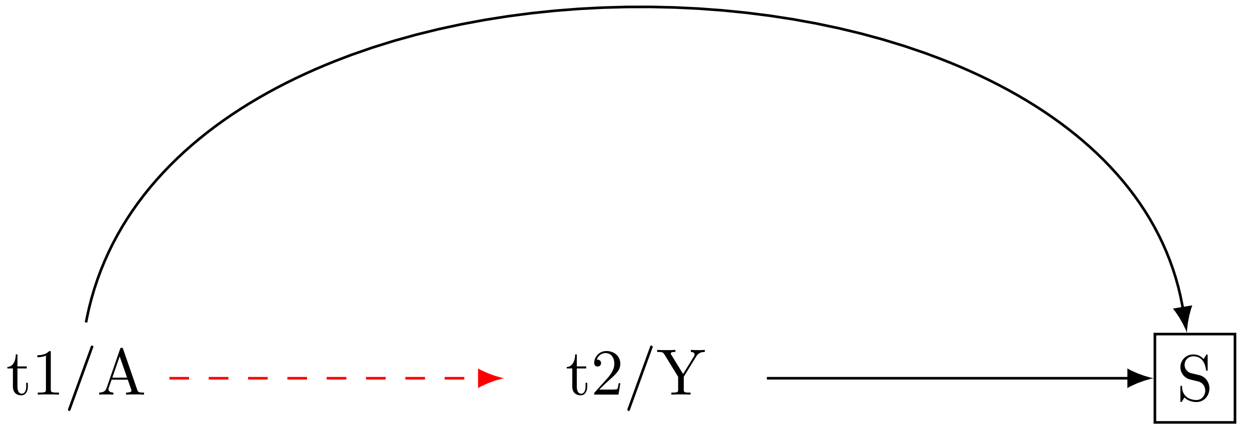

Figure 18: Causal graph:outcome and exposure affect attrition (Y measured with directed measurement error)

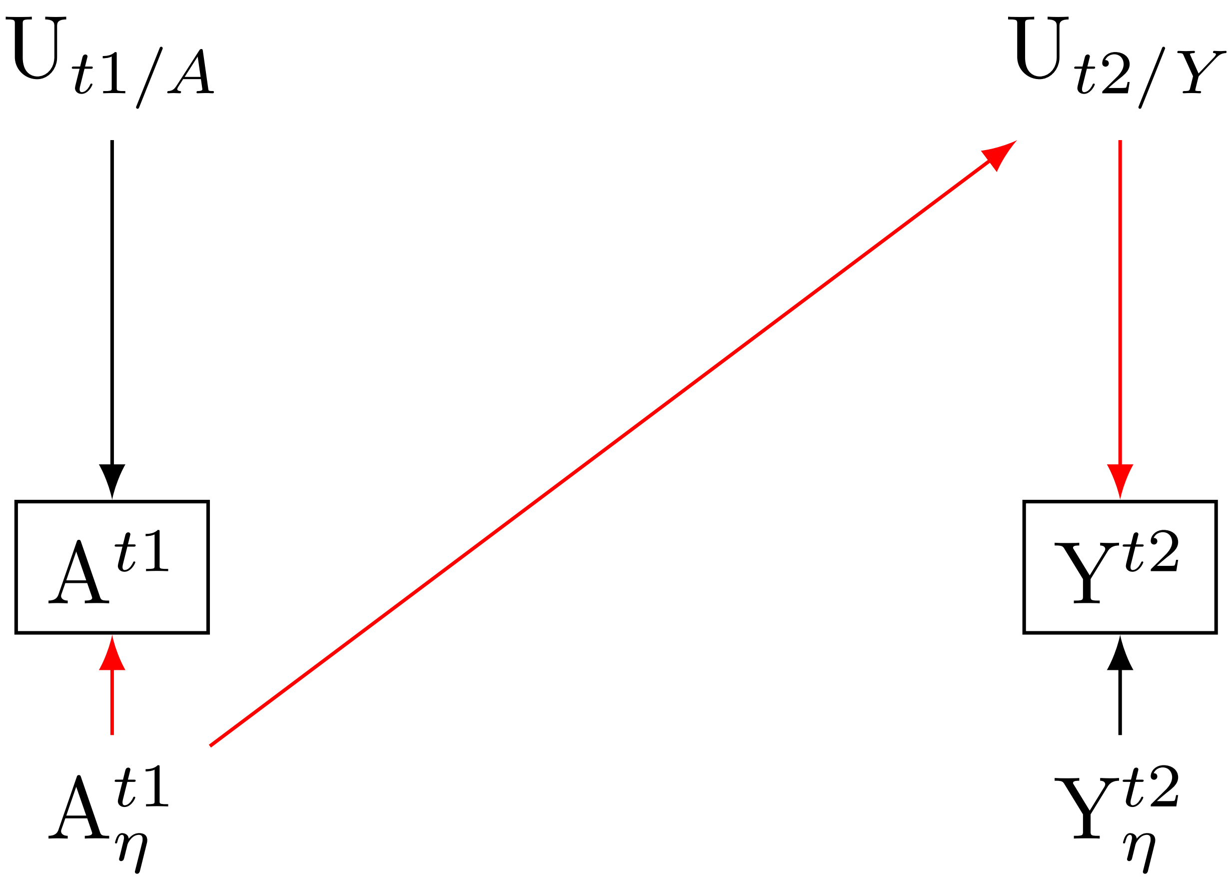

Figure 19: TBA

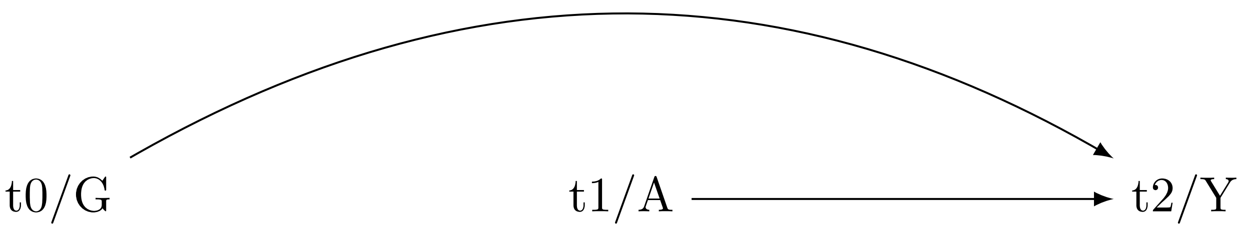

Figure 20: A simple graph for effect-modification.

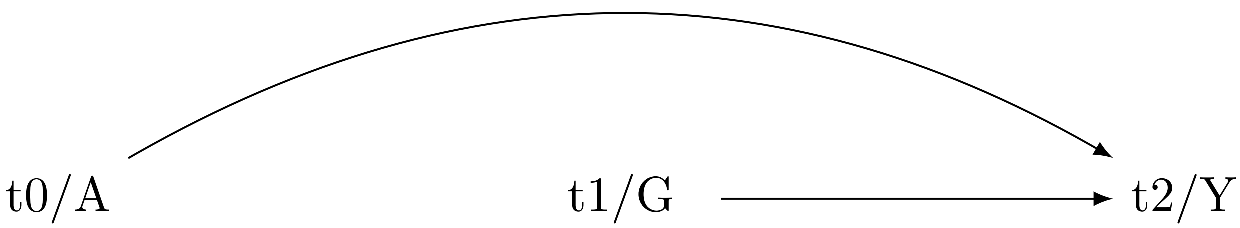

Figure 21: A simple graph for effect-modification.

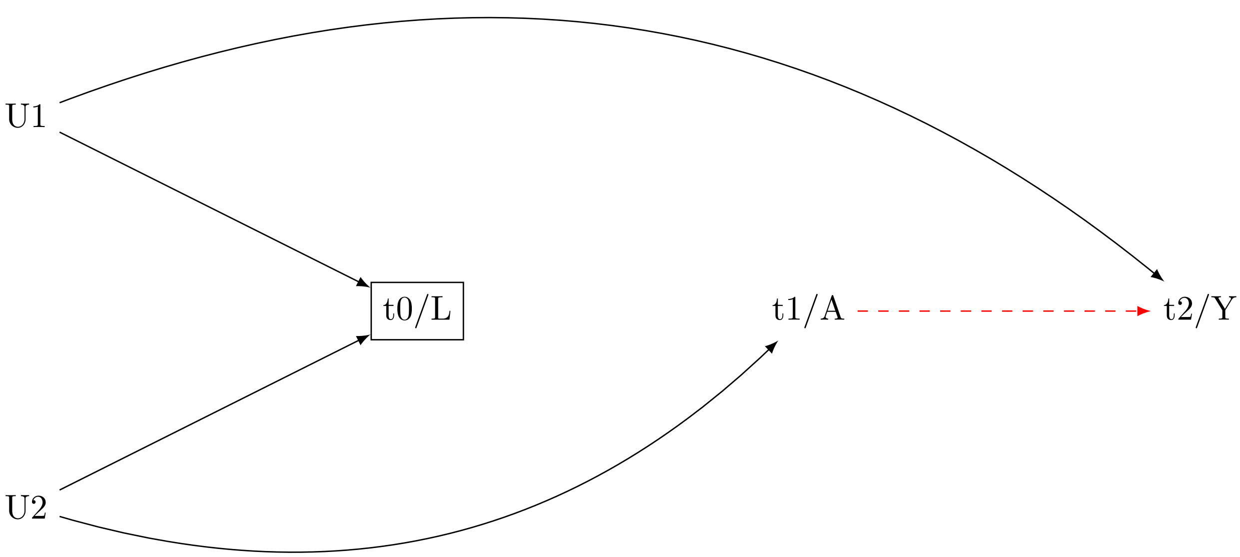

Figure 22: M-bias: confounding control by including previous measures of the outcome

Unmeasured confounder affects a measured confounder of selection and the outcome, and there are unmeasured confourders that affect the measured confounder

Unmeasured confounder affects slection into the study and also attrition

Outcome and exposure affect attrition

Outcome and exposure affect attrition: we may approach this problem as one of directed measurement error.

Important Causal Diagrammes

How do we draw interactions?

Common cause of exposure and outcome.

Another graph for interaction

M-Bias

What if mediation is of interest?

Consider the assumptions required for mediation analysis:

1. No unmeasured exposure-outcome confounders given L

$$Y^{am} \coprod A|L$$

2. No unmeasured meadiator-outcome confounders given L

$$Y^{am} \coprod M|L$$

3. No unmeasured exposure-mediator confounders given L

$$M^{a} \coprod A|L$$

4. No mediator-outcome confounder affected by the exposure (no red arrow)

$$Y^{am} \coprod M^{a*}|L$$

Confounder-Treatment Feedback

Multiple Versions of Treatment

Does the Multiple Versions of Treatments Approach Save Us?

Measurement error remeains a problem if errors are either directed or dependent (correlated) or both. (See: measurement link.)

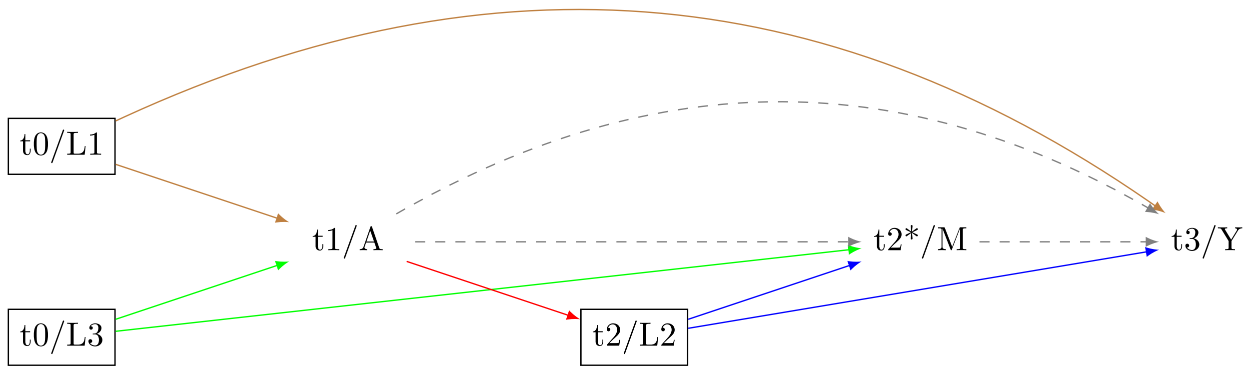

Figure 23: Assumptions for mediation analysis

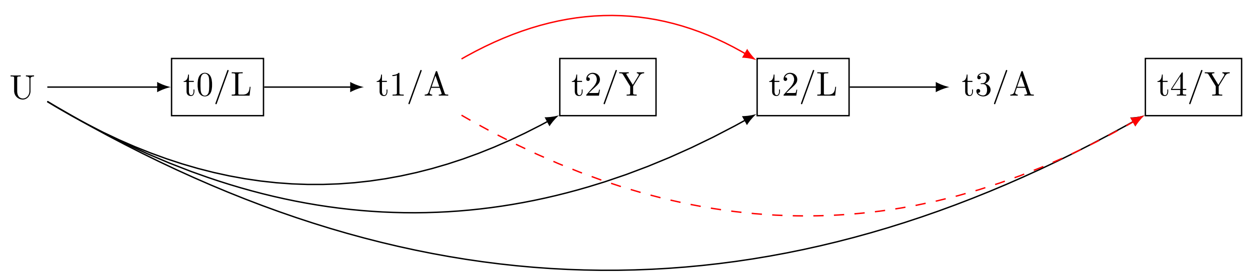

Figure 24: Confounder Treatement Feedback

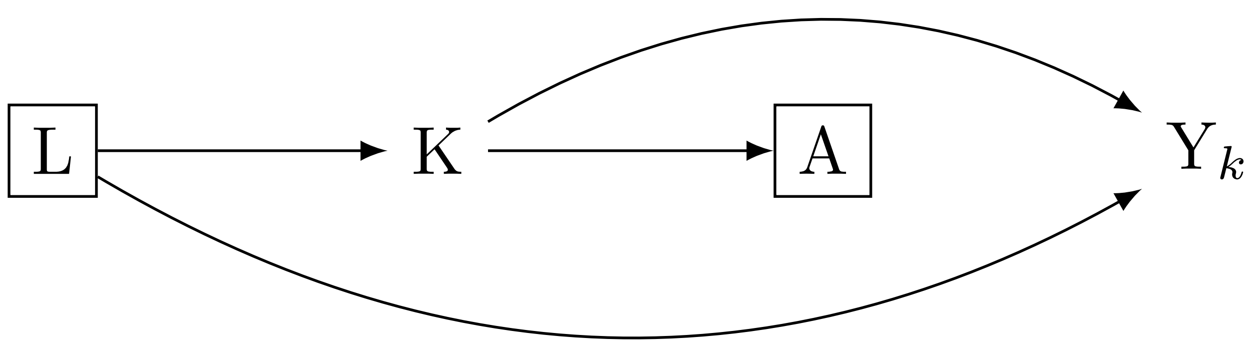

Figure 25: Multiple Versions of treatment. Heae, A is regarded to bbe a coarseneed version of K

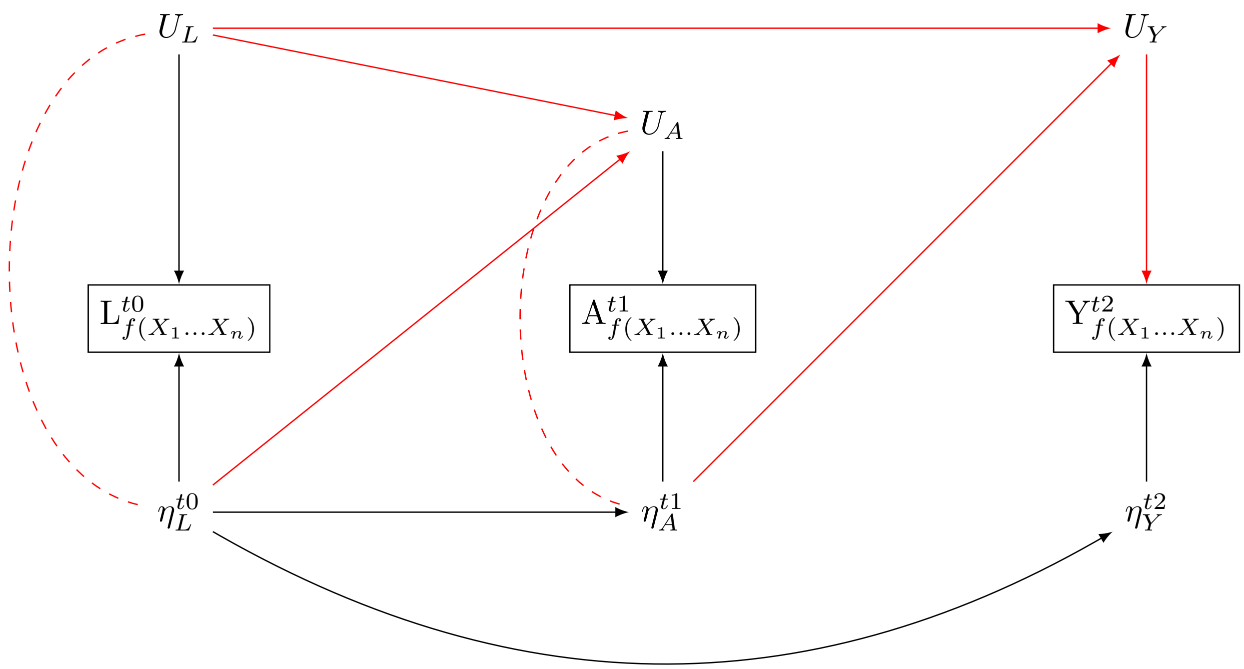

Figure 26: Measurement error opens a pathway to confounding if either there are correlated errors, or a directed effect of the exposure on the errors of measured outcome.

Add Graph on when we might want to condition on a post treatment indicator

Stray points to address

1. Structural equation models are not causal diagrammes
2. Causal diagrammes are non-parametric
3. Causal diagrammes represent interactions A − > Y <— B (two arrows into the outcome)
4. We may distinguish between effect modification and interaction.