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Due May 11 11:59pm   Available from May 5   45 points possible

33 Replies, 15 Unread

Unit 8: Discussion

Directions

Watch the [Causal Inference - EXPLAINED!](https://www.youtube.com/watch?v=Od6oAz1Op2k) (https://www.youtube.com/watch?v=Od6oAz1Op2k)

Discuss the three most striking takeaways from the video.

Note: Once you have posted your initial response, please respond to the postings of **two of your classmates'** initial postings. Subsequent postings can be in whatever format you prefer. To earn full credit, be sure to ask questions or additional information that furthers discussion. Comments that are the equivalent of, "Great response, that's what I think" will not earn full credit.

Criteria for Success

Initial Post (DUE: Thursday 11:59 p.m. CT)

- In the initial post you will do the following:
    - Uses the weekly materials to construct an academic argument that addresses the discussion question in a thorough and logical manner.
    - Correctly uses key terms and concepts. Thoroughly addresses all components of the prompt. Ideas are clear and on-topic.
    - Follows grammar conventions. The writing is concise and easy to read.
    - Writes approximately 200 words.

Response to Two Peers (DUE: Sunday, 11:59 CT)

- Respond to at least two classmates with your takes on their post. Answer the following questions in your response. 1) What did you agree with in their post? 2) What did you see differently? 3) What did you learn from their post?

Please review the rubric for this assignment before beginning to ensure that you earn full credit. Contact me if you have any questions.

Reply

Akhil Muvva (https://canvas.park.edu/courses/85581/users/125122)

May 10 10:07pm

Hi All

Causal Inference – Three Striking Takeaways

One of the most striking insights from the video was how crucial counterfactuals are for causal inference. Counterfactuals are what would have occurred had a given individual had a different treatment than what they did experience. Because we can't see both worlds at once, methods that allow for matching and machine learning attempt to mimic the unobserved world. This allows for estimates of individual treatment effects and helps to get past simple relative comparisons of averages.

Another important realization was the problem of confounders and selection bias when dealing with observational evidence. The video made it clear that neglecting to control for factors such as age distorts results. A treatment may seem effective only because younger people were likely to be treated and would likely get better on their own. This strengthened the importance of randomization for optimal experiments and strict control when analyzing retrospective data.

Finally, I appreciated the topic of heterogeneity of treatment, and especially the metric of Conditional Average Treatment Effect (CATE). You don't treat everyone equally, and it is only by recognizing those differences within a group that you truly make informed policy recommendations. It is a cautionary tale that "one-size-fits-all" outcomes in data science are dangerous without disaggregation.

In general, the video stressed that causal inference is not a statistical exercise per se, but rather making responsible, well-informed choices based on evidence.

Reference

CodeEmporium. (2022). Causal Inference - EXPLAINED!Www.youtube.com. https://www.youtube.com/watch?v=Od6oAz1Op2k

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PN **Pravalika Naathi** (https://canvas.park.edu/courses/85581/users/110436)

May 10 1:28pm

Hello class,

Randomized Controlled Tests (RCTs) as the Gold Standard:

Randomized Controlled Tests are most genuine method to identifying causal relationships because RCTs will apply randomization to remove the confounding variables and the Researchers may be confident that treatments is definitely responsible for variations in outcomes when individuals are equally placed into treatment or control groups.

Challenges in Causal Inference:

The main problem of causal inference that never examine both possible outcomes for a specific individual (what did happen and what would have happened)was important topics raised. Due to this, it is mainly challenging to gauge a treatment's real impact. the film topics like

Confounding variables, selection bias, and reverse causality are other issues the film discusses. If it may ignored, these problems will affect our understanding of cause and effect.

Causal Graphs and Assumptions:

This is very interesting elements in the video was causal graphs, sometimes It may referred to as DAGs (Directed Acyclic Graphs). By deeply mapping out the relationships between variables using these diagrams, researchers may identify which variables need to be managed. These graphs, however, depend on assumptions, and if the assumptions are incorrect, the results problematic. The film providing clear evident that causal inference involves more than simply math.

References:

https://www.youtube.com/watch?v=Od6oAz1Op2k

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Pearl, J. (2009). *Causality: Models, Reasoning, and Inference* (2nd ed.). Cambridge University Press.

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JM **Joseph Maina (https://canvas.park.edu/courses/85581/users/118606)**

May 8 11:47pm | Last reply May 9 12:38pm

Hey Class

The video shared talks about Causal Inference and what we need to learn about it. For effective causal inference, there are factors that need to be taken into account. I have found three interesting things to be about causal inference: why we cannot always perform Randomized Controlled Tests, the Challenges of having confounders leading to selection bias, which requires counterfactuals, and the Assumptions required to make causal inference from past data viable.

Randomized Controlled Tests

Causal inference using past data is crucial when randomized controlled trials (RCTs) are not feasible due to cost, ethics, or logistics. In the case of billboard advertisements across cities, it can be costly and challenging. Historical data eliminates the need for setting up an experiment or waiting for results, as the data already exists. This offers strong evidence.

Confounders and Selection Bias Challenges

The challenges of having confounders have been explained as selection bias, which requires counterfactuals. Confounders for age in the Elixir case and selection bias of a non-representative sample size complicate the causal inference, which distorts the relationship between cause and effect. Age is a confounding variable because younger people may recover from the flu naturally, which distorts the results, which suggest that Elixir is effective when, in the real sense, it is age, not Elixir. Potential confounders in the regression may decrease the bias of the treatment effect; however, adding more variables can decrease statistical power in small samples because it increases the variance (spread) around the regression estimate by decreasing the number of degrees of freedom. (Starks et al., 2009)

Assumptions

Causal inference is said to have requirements with are assumptions about the past data to be viable. These assumptions are critical for ensuring that observational data can approximate the conditions of an RCT, but their viability depends on theoretical justification, empirical validation, and careful study design, such as the Elixir's efficacy across age groups. Igelström et al. (2022) advise specifying a target trial to clarify the causal estimand, such as average treatment effect, and ensure assumptions align with the research goal. Non-interference assumes no spillover effects on the projected goal (Igelström et al., 2022).

Reference

Starks, H., Diehr, P., & Curtis, J. R. (2009). The challenge of selection bias and confounding in palliative care research. *Journal of Palliative Medicine*, *12*(2), 181–187. **https://doi.org/10.1089/jpm.2009.9672** (https://doi.org/10.1089/jpm.2009.9672)

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Battulga Bolormaa (https://canvas.park.edu/courses/85581/users/68062)

May 8 11:45pm

Basically the video consists of three main topics, as follows:

1. Randomized Controlled Tests (RCTs): My simple example to explain this RCT would be, if you want to know if a new medicine works, you randomly give some people the medicine and others a fake pill. Then you compare what happens. Because the groups are random, any difference you see is probably because of the medicine and not something else.

2. Challenges to Causal Inferencing

Causal inference means figuring out what causes what, but it's not always easy. Here are a few reasons why:

- Confounding variables: These are outside factors that can affect... For example, if kids who eat more ice cream get better grades, it doesn't mean ice cream helps studying—it could just be that wealthier families buy more ice cream *and* have better education.
- Selection bias: Sometimes, the groups that are being compared aren't actually equal to start with. If people choose whether they take a treatment, maybe the healthier ones always pick it, so it looks like the treatment works better than it really does.
- Measurement errors: If the data is wrong or unclear, it's hard to trust the results.

3. Causal Graphs and Assumptions

Causal graphs are simple diagrams that help us understand cause-and-effect relationships. They use arrows to show which things might cause other things. For example: Magnesium -> Sleeps, Magnesium -> Relaxation. This means taking magnesium can help with sleep as well as relaxation. So, Magnesium is the cause, and sleep and relaxation are the effects.

`Tulga

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Avinash Bunga (https://canvas.park.edu/courses/85581/users/111811)

May 8 11:19pm | Last edited May 8 11:22pm | Last reply May 9 3:19pm

View History

Avinash Bunga

Information Systems and Business Analytics, Park University

CIS625HOS2P2025 Machine Learning for Business

Professor: Abdelmonaem Jornaz

May 8, 2025

Unit 8: Discussion

Hello Class,

The video on causal inference explained important ideas about causality.

Table 1

Three Takeaways

Takeaway	**Explanation**

Correlation vs. Causation (RCTs)	Randomized tests help clearly identify if something truly causes another thing to happen.
Managing Confounders	Missing important factors can lead to incorrect conclusions.
Importance of Counterfactuals	Thinking about "What if" situations helps us make better decisions.

To make it easier to understand, let us look at some practical car related examples:

To start with, consider how crucial it is to know if one factor truly causes another outcome. Imagine a car company wants to test if their new automatic braking system genuinely reduces accidents. They randomly assign cars into two groups; one group has the new braking system and the other does not. If the group with the braking system experiences fewer accidents, the company can confidently conclude the system actually reduces crashes (Bhandari, 2023).

Another key point is handling factors that can distort your results. Suppose you are testing whether premium gasoline improves car performance. If premium gasoline is tested mostly on newer cars and regular gasoline on older cars, you might wrongly conclude that premium gas is better. In reality, newer cars typically perform better anyway. Testing fuel types evenly across similar car ages ensures accurate conclusions (Frost, n.d.).

Finally, it is important to think about what might have happened under different circumstances. Imagine evaluating whether synthetic oil increases engine life. To understand this, you would estimate how long engines using regular oil would last if they had used synthetic oil instead. This comparison is done by selecting similar cars differing only by the type of oil used (Kallas, Al Sabek, & Saoud, 2024).

Here is an example:

Car Owner	Oil Type	Actual Engine Life (miles)	Estimated Life with Other Oil Type	Difference

Alex	Synthetic Oil	220,000	200,000	+20,000
Jamie	Regular Oil	180,000	205,000	-25,000

In this case, using synthetic oil helped Alex's engine, while using synthetic oil might have given Jamie's engine a longer lifespan. These simple examples show how useful causal inference is in decision making.

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KK **Kouame Hermann Kouame (https://canvas.park.edu/courses/85581/users/123444)**

May 8 11:10pm | Last reply May 10 8:11am

Hello Class, here is my post for this last week!

This video, as its title suggests, focuses on the concept of causal interference, which sheds light on understanding cause-and-effect relationships in data. It clearly addresses the differences between correlation and causation, paying particular attention to randomized controlled trials (RCTs) to establish causality.
My three main takeaways are:
The clear distinction between correlation and causation. The author indicates here that correlation does not necessarily lead to causation. He also draws on the example of summer ice, so ably demonstrated by the professor in last Tuesday's session. This distinction is essential, as the coincidences observed through the correlation and causation link suggest that one necessarily leads to the other. My main takeaway from this section is that causal inference requires careful consideration of external factors and study design to avoid misleading conclusions. Importance of Randomized Controlled Trials (RCTs):
RCTs are presented as the gold standard for establishing causality. By randomly assigning subjects to treatment and control groups, RCTs minimize bias and balance confounding variables. The video explains how this randomization ensures that the only systematic difference between groups is the treatment itself, allowing researchers to confidently attribute outcomes to that treatment. This point underscores why RCTs are widely used in fields such as medicine and their importance for robust causal inferences.
Role of Counterfactuals and Potential Outcomes:
The concept of the counterfactual. The video introduces the potential outcomes framework, where each subject has an outcome for each possible treatment, but only one is observed. Estimating the unobserved counterfactual is the challenge, and methods such as RCTs or propensity score matching aim to approximate it. This framework is remarkable because it formalizes the intuitive idea of "what if," which symbolizes uncertainty, into a rigorous statistical approach.

It was great having this class and I learned a lot .Thanks to professor Abdelmonaem et you guys!

Enjoy your summer !!!

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(https://youtu.be/Od6oAz1Op2k?si=8k8jnP2GcB_UUq4S)
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AA

Atit Adhikari (https://canvas.park.edu/courses/85581/users/126504)

May 8 10:49pm | Last reply May 10 12am

Hi everyone! From the causal inference video, one of the takeaways is how essential Randomized Control Test (RCTs) are. RCTs are the most reliable method of establishing causal relationships because they utilize random allocation to reduce bias (Zabor, Kaizer, & Hobbs, 2020). By assigning participants randomly to treatment and control groups, researchers can be sure that other factors such as age, lifestyle, or underlying health conditions are balanced, so that it is more likely that any difference in outcome is due to the treatment itself.

Another key takeaway is the difficulty of working with RCT. In many real-life situations, conducting an RCT may not be practical due to longer completion time and difficulty in setting up the experiment. Instead, researchers must rely on observational data, which comes with significant challenges as well. The video also talks about challenges with casual inference such as confounders, selection bias, and the inability to observe what would have happened if the treatment had not been applied, also known as the counterfactual. These issues make it harder to confidently draw causal conclusions.

The third takeaways are the assumptions required when using causal models with observational data. These include the Causal Markov Condition, Ignorability, and the Stable Unit Treatment Value Assumption (SUTVA). These assumptions allow researchers to use tools like Directed Acyclic Graphs (DAGs) to model relationships, but they are often untestable. This shows that while causal inference is a powerful tool, it also requires careful judgment and a clear understanding of its limitations (Rafalski, 2025). These insights are essential for anyone working with data to make sound, evidence-based decisions.

Reference

Rafalski, K. (2025, April 1). *Causal inference methods: Understanding cause and effect relationships in data analysis*. Netguru. https://www.netguru.com/blog/causal-inference (https://www.netguru.com/blog/causal-inference)

Zabor, E. C., Kaizer, A. M., & Hobbs, B. P. (2020). Randomized controlled trials. *Chest, 158*(1 Suppl), S79–S87. https://doi.org/10.1016/j.chest.2020.03.013

2 Replies, 2 Unread | Reply | Mark as Unread

George Kumi (https://canvas.park.edu/courses/85581/users/117082)

May 8 10:22pm | Last reply May 10 11:02am

Hello Class,

Kindly find below my discussion post for week 8

The video on causal inferencing presents several critical insights into the complexities of establishing causality in various contexts. Three striking takeaways emerge from the discussion: the significance of randomized control tests (RCTs), the challenges posed by confounding variables, and the necessity of counterfactual reasoning.

Firstly, RCTs are highlighted as the gold standard for causal inference, allowing researchers to isolate the effects of an intervention by randomly assigning participants to treatment and control groups. This method minimizes bias and enhances the validity of conclusions drawn from the data. However, the video emphasizes that RCTs are not always feasible due to practical constraints, such as ethical considerations or logistical challenges, necessitating alternative approaches to causal analysis (Sontag, 2019).

Secondly, the video addresses the issue of confounding variables, which can obscure the true relationship between treatment and outcome. For instance, age may influence recovery rates in a medical trial, leading to misleading conclusions if not adequately controlled. This highlights the importance of careful study design and the need for statistical techniques to account for these confounders (Sontag, 2019).

Lastly, the concept of counterfactuals is crucial in causal inference. Researchers must estimate what would have happened in the absence of the treatment to make valid comparisons. This involves complex modeling techniques, such as matching or machine learning, to approximate these counterfactual scenarios (Molak & Jaokar, 2023). By understanding these elements, practitioners can better navigate the challenges of causal inference and make informed decisions based on observational data.

In conclusion, the video effectively illustrates the intricacies of causal inferencing, emphasizing the importance of RCTs, the challenges of confounding variables, and the necessity of counterfactual reasoning. These insights are essential for researchers and practitioners aiming to draw valid conclusions from data in various fields, including healthcare and marketing.

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(https://www.youtube.com/watch?v=Od6oAz1Op2k)

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KF

Kwame Frempong (https://canvas.park.edu/courses/85581/users/118427)

May 8 5:55pm | Last edited May 8 5:57pm

Hello class,

According to the video, randomized controlled trials (RCTs) have limitations even if they are an effective way to demonstrate cause and effect. Although RCTs perform best in controlled environments, they could not accurately represent the actual world, where a variety of variables interact in intricate ways. Because outcomes can be influenced by hidden factors, it can be challenging to identify genuine causes, even using RCTs. To better understand why something occurs, the video suggests combining RCTs with other techniques such as theory, observation, and systems thinking. It serves as a reminder that true comprehension requires more than simply experiments. It also requires the integration of evidence with more complex reasoning.

Also, the video points out that valid causal claims rely on several key assumptions. These include the notion that all relevant confounding variables have been considered and that every subject has an equal opportunity to receive any treatment option. Additionally, it is assumed that one person's outcome is not affected by the treatment received by another individual. If these assumptions are not met, even carefully designed analyses may lead to inaccurate conclusions. A heightened awareness of these assumptions is essential for rigorous and responsible interpretation.

My final takeaway is confounding variables. These are those that affect both the cause and the outcome, complicating the effort to pinpoint the actual relationship between them. For example, if research indicates that more physically active individuals are generally healthier, a confounding variable could be their diet, since people who exercise regularly often follow healthier eating habits. If we disregard these confounders, we might mistakenly attribute better health solely to exercise. This highlights the importance of controlling for confounders, whether through randomization in experiments or statistical corrections in observational studies. Neglecting this step can result in erroneous or potentially harmful conclusions regarding causal relationships.

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Ashish Thapa (https://canvas.park.edu/courses/85581/users/79401)

May 8 4:56pm | Last reply May 10 7:42am

Hello Everyone,

The three main things that stood out for me after watching the video is that first of all Randomized Controlled Tests (RCTs) are the best way to find out if something truly causes an effect. As randomly putting participants into groups, we make sure that other factors do not confuse the results, which is what I have liked about the RCTs. Another thing that I liked was how the video explained confounding variables and selection bias, which caused problems while studying old data. When these hidden factors are not controlled, it leads us to think that one thing causes another when it actually doesn't. This is where ideas like counterfactuals help in imagining what would have happened without the treatment. Another important factor from the video is the treatment heterogeneity which means that treatment can work differently for different groups of people, to give an example, a certain medication might help older people more than the younger people, which teaches us not only to look at average results but also study different groups separately to make better decisions. The video showed us that good causal analysis needs careful thinking, not only looking at the numbers.

Thanks

Reference:

CodeEmporium. (2022, January 3). *Causal inference - EXPLAINED!* [Video]. YouTube. https://www.youtube.com/watch?v=Od6oAz1Op2k

Michael Oduro (https://canvas.park.edu/courses/85581/users/112167)

May 8 12:34pm

Hello Class,

Unit 8 Discussion.

Three Most Striking Takeaways from the Video on Causal Inference

Because randomization helps account for confounding variables, the video highlights that Randomized Controlled tests are the gold standard for proving causation. But it also emphasizes how logistical, ethical, or temporal limitations sometimes make RCTs problematic or impossible in real-world situations. This lays the groundwork for determining causation from observational data in situations where doing experiments is not feasible.

When concluding causality from data observation, there are significant obstacles. In a medical trial, uncontrolled factors like age can skew outcomes if they are not appropriately taken into consideration. Findings could be deceptive if the treatment and control groups are not typical of the general population. The requirement to guess, using techniques like matching or machine learning, what would have occurred to each individual if they had received the opposite treatment, which is, by nature, unobservable.

To enable causal inference from observational data, the video explains several assumptions, including the Stable Unit Treatment Value Assumption (SUTVA), ignorability (no unmeasured confounders), and the construction of causal graphs. Additionally, it presents the idea of heterogeneous treatment effects, demonstrating that the average impact of a therapy might vary depending on subgroups like age. This is important for making data-driven, nuanced decisions rather than implementing drastic policy changes.

These insights collectively underscore that while causal inference is essential for data-driven decision-making in fields like AI and analytics, it requires careful consideration of methodology, data quality, and underlying assumptions.

Reference

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(https://www.youtube.com/watch?v=Od6oAz1Op2k)

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IK **Ian Koskei (https://canvas.park.edu/courses/85581/users/122159)**

May 8 10:41am | Last reply May 8 10:39pm

UNIT 8 DISCUSSION

One of the most significant challenges in causal inference is the presence of confounding variables which are hidden factors that can influence both the treatment and the outcome. These confounders can mislead researchers into thinking a treatment is effective when the observed effect may be due to an unaccounted third variable. In randomized controlled trials (RCTs), efforts are made to control for these, but in observational studies, especially those using historical data, identifying and adjusting for confounders becomes much more complex (Thomas, 2023).

The video highlights the difficulty of using historical data for causal analysis (CodeEmporium, 2022). Without the structure of an RCT, researchers face three main obstacles: the presence of confounders, selection bias where the treatment group is not representative of the general population and the challenge of defining counterfactuals, or what would have occurred had the treatment not been applied. These limitations make it dangerous to draw causal conclusions purely from patterns in past data.

The video also highlights that causal inference based on historical or observational data depends on **strong assumptions**. Assumptions like the Causal Markov Condition, SUTVA, and Ignorability are essential to constructing valid models. However, these assumptions are often untestable, making it crucial to approach causal claims from non-experimental data with caution and critical thinking.

References

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RN **Robert Nyabiti** (https://canvas.park.edu/courses/85581/users/93498)

May 7 9:18pm | Last reply May 8 10:59am

In this YouTube video https://www.youtube.com/watch?v=Od6oAz1Op2k (https://www.youtube.com/watch?v=Od6oAz1Op2k) [(https://www.youtube.com/watch?v=Od6oAz1Op2k)](https://www.youtube.com/watch?v=Od6oAz1Op2k)

(CodeEmporium, n.d.), the three striking takeaway things that emerged were:

- Randomized Control Tests (RCTs) are widely used for "inferring causality." The test involves selecting two groups randomly that include a control group and a treatment group to remove any causal effect (Krauss, 2021). Despite the benefits, RCTs can be challenging to set and take longer than anticipated (CodeEmporium, n.d.).

- Casual inference provides an understanding of cause-and-effect relationships. A change in a variable helps to determine the influence on the variables. Casual inference challenges include confounders, selection bias, and counterfactuals. In the case of confounding, age was the factor. The age differences provided a clear picture that the outcomes could not be accurate. In the case of selection bias, Walker et al. (2024) suggested that researchers employ quantitative bias analysis and E-values when dealing with observational data to avoid bias. In addition, machine learning and marching can be utilized to project the effects of counterfactuals

- Different types of assumptions can be used for causal inferences. In our case, the assumptions included the causal Markov condition, SUTVA (Stable Unit-Treatment Value Assumption), and ignorability. For example, the causal Markov condition (CMC) can be employed as "a postulate that links observations to causality" (Steudel et al., para.1, 2010).

It's important to distinguish between correlation and causation. Correlation refers to changes occurring simultaneously in two variables, while causation implies that a change in one variable directly influences the other variable. Therefore, it is right to note that correlation does not imply causation (Gershman & Ullman, 2023).

References

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JK **Jagadeesh Korukonda** (https://canvas.park.edu/courses/85581/users/116942)

May 7 8:51pm | Last reply May 8 4:51pm

Hello everyone,

Just watched the Code Emporium video on Causal Inference, and wow, it packed a lot into a short time! Here are the three things that stood out most to me:

Randomized Controlled Tests (RCTs): The video did a solid job explaining Randomized Controlled Tests (RCTs) – basically the gold standard (like A/B testing) for proving cause-and-effect. By randomly assigning people to a treatment or control group (like getting an email vs. not), you wash out other differences and can be pretty sure the treatment caused any change you see. But the reality check was crucial: running RCTs is often impossible (like randomly assigning billboard locations across cities) or just takes way too long. This really highlights why we need these other causal inference methods for digging into the messy, real-world observational data we usually have. It's about finding the best possible answer when the perfect experiment isn't an option.

Beware the Sneaky Confounders and Selection Bias: This was a big one. The example of the flu elixir showing great results until you realize the age difference between the groups (the confounder) was super illustrative. It drove home how easily we can be fooled by correlations in observational data. A hidden factor (like age) can be linked to both who gets the "treatment" (maybe younger people were more likely to seek the elixir or were selected differently) and the outcome (younger people might recover faster anyway). This makes it look like the treatment works when it might not, or not as well as we think. Selection bias feels like a close cousin here – if the group getting the treatment isn't representative, our conclusions are shaky. It seems like identifying and controlling for these confounders is maybe the central challenge when working with past data.

Causal Requires Assumptions & Leads to Smarter Decisions (ATE vs. CATE): The idea that we need to make strong assumptions to even attempt causal claims from observational data was striking. It's not just about running a model; it's about carefully setting up the problem based on domain knowledge (often using those Causal Graphs). But what really blew my mind was the shift from just the Average Treatment Effect (ATE – does the elixir work overall?) to the Conditional Average Treatment Effect (CATE – for whom does it work?). Seeing that the elixir might actually harm younger people but help older people (treatment heterogeneity) shows the real power here. It's not just a yes/no answer; it allows for much more nuanced, targeted decisions based on subgroups. That feels incredibly valuable in practice.

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SS **Selorm Kwaku Soga (https://canvas.park.edu/courses/85581/users/73415)**

May 7 4:54pm | Last reply May 9 10:44pm

Hello Everyone,

The video "Causal Inference - EXPLAINED!" provides a clear and practical introduction to the fundamentals of causal inference, with several key takeaways. Here are three of the most striking takeaways from the video.

Randomized Controlled Trials (RCTs) as the Gold Standard

The video states that RCTs (or A/B testing) seem the best for establishing causality. Since subjects are randomly assigned to treatment-control groups, possible confounders are eliminated, and only effects that are caused by the intervention itself are observed. For instance, in an e-commerce e-mail campaign test, randomization ensures age, prior age, or behavior does not bias results, allowing the photos to assert that changes in purchase conversion are attributed to emails and nothing else. So, with such methodological rigor, it would be the closest thing to proving cases in clinical trials, yet limitations set forth by life will most probably deny such perfection.

Challenges of Observational Data and Confounders

Suppose it is impossible to randomly assign subjects to treatment groups, as in the case of testing billboard ads. In that case, causal inference must be made based on observational data, thus incurring risks such as confounders and selection biases. The video uses a medical example to illustrate this situation, whereby if the people who are diagnosed and treated for the flu are on average younger compared to the control group, they may appear to benefit from it more due to their age, a confounder, but it is not actually due to the treatment. Selection bias would also occur if the treatment group was not representative-i.e., if only healthier people received the drug. One has to address these with methods such as matching or machine learning that attempt to infer counterfactuals (what would have happened without treatment).

Conditional Average Treatment Effects (CATE) for Personalized Insights

It also points out that the treatment impacts tend to be heterogeneous across subgroups. By estimating CATE (e.g., how a flu elixir is effective for patients over 35 and younger patients), the choices can be tailored to groups. For instance, the elixir showed a +0.4 impact in older patients but merely +0.2 in younger patients, favoring targeted prescriptions. This is more than average treatment effects (ATE) and talks about the heterogeneity of treatment so that the resources are allocated where they will have the greatest effect.

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Licurgo Silveira Teixeira (https://canvas.park.edu/courses/85581/users/119244)

May 5 11:19am | Last reply May 10 6:49pm

Discussion Post: Three Striking Takeaways from "Causal Inference - EXPLAINED!"

The YouTube video "Causal Inference - EXPLAINED!" provides a clear explanation to causal inference, emphasizing statistical techniques to distinguish correlation from causation. Below, I discuss three striking takeaways, focusing on technical and statistical aspects, with applications to real-world scenarios like the U.S. economic context (rising interest rates, welfare expansion, inflation, and unsustainable stock market growth) and the Brazilian case of interest rates and investment levels the suppression of economic growth.

- **Randomized Controlled Trials (RCTs) as the Gold Standard**: The video underscores RCTs' ability to eliminate confounding variables through randomization, ensuring treatment and control groups are comparable. This isolates the causal effect, as seen in the average treatment effect (ATE), calculated as the difference in means between groups. For instance, testing whether U.S. interest rate hikes (Federal Reserve rates at 5.25%-5.5% in 2023) was caused by inflation (peaking at 9.1% in 2022) could ideally use RCTs, but macroeconomic constraints make this impractical. Instead, quasi-experimental methods like difference-in-differences are used, controlling for confounders like welfare spending or global supply shocks.
- **Confounding Variables and Bias**: The video highlights how confounders (e.g., corruption, industrial production) distort causal estimates in observational studies. In the Brazilian context, corruption reduces infrastructure investment, confounding the relationship between high Selic (interest) rates (13.75% in 2024) and reduced private investment. Statistically, propensity score matching or regression adjustments can control confounders. In the U.S., welfare expansion (e.g., stimulus checks) and supply chain disruptions confounded the link between interest rates and inflation, requiring instrumental variables (e.g., commodity price shocks) to isolate causality.
- **Counterfactuals and Causal Graphs**: The video explains that causal inference relies on estimating counterfactuals, what would have happened without the treatment. Causal graphs (e.g., DAGs) help map relationships, identifying confounders and mediators. In the U.S., despite stock market gains (S&P 500 up 20% in 2023), high interest rates and inflation eroded purchasing power, suggesting unsustainable growth. Directed acyclic graphs could model how welfare spending mediates inflation, guiding econometric models like Granger causality tests to assess sustainability.

These takeaways highlight the rigor of causal inference, applicable to complex economic questions in Brazil and the U.S., though observational data challenges require advanced statistical tools.

Thank you!

Licurgo Silveira Teixeira.

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(https://www.youtube.com/watch?v=Od6oAz1Op2k)

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