

A Primer on Causal Diagram Learning

— *Interpreting Causation from the **Causal Discovery** Perspective*

Xuanzhi Chen March 10, 2024

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“As X-rays are to the surgeon, causal diagrams are for causation.” — Judea Pearl

因果图学习入门

A Primer on Causal Diagram Learning

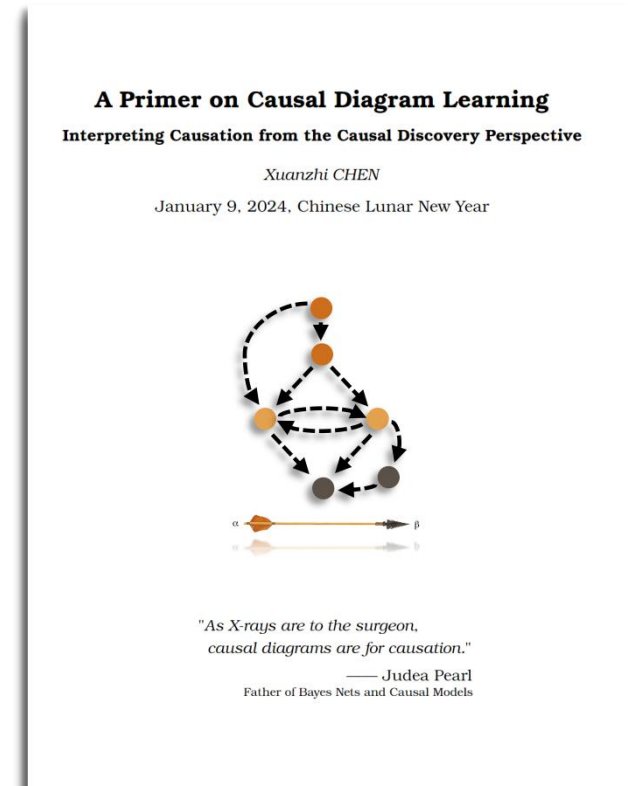
— 基于因果发现的视角阐述因果关系

陈炫志 March 10, 2024

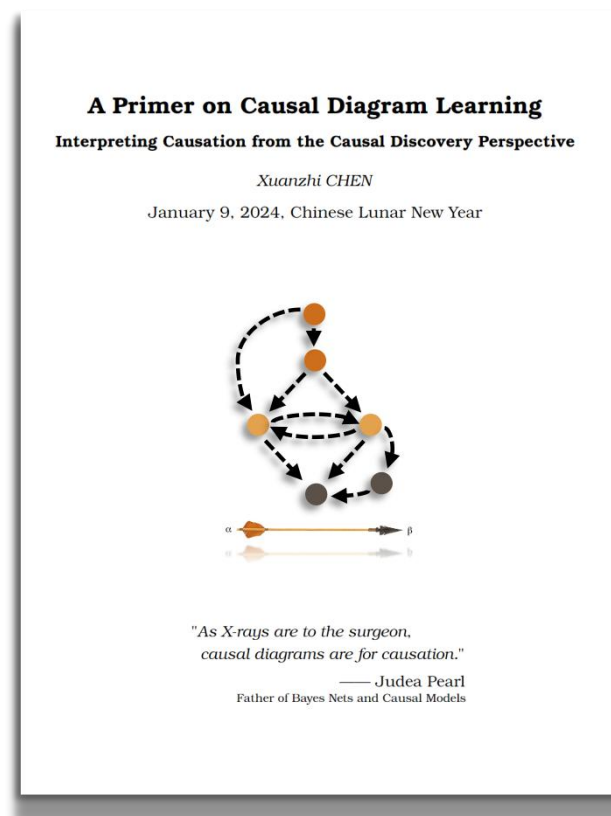
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“因果图之于因果关系，就犹如X-射线之于外科医生” — Judea Pearl （因果模型之父）

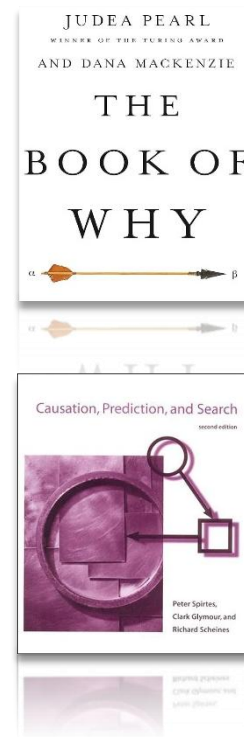
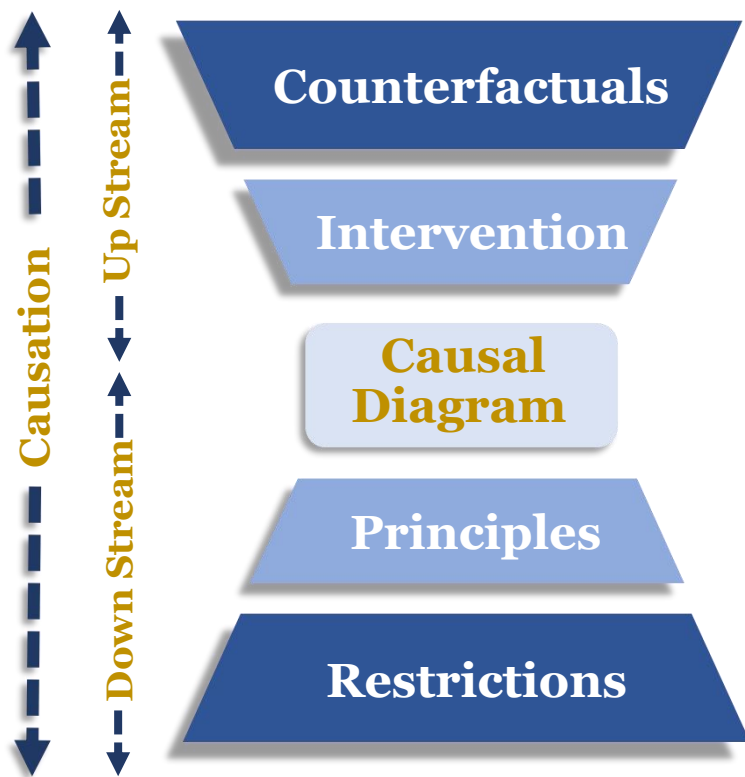
- **Acknowledgements: DMIR Lab, China**
 - **Data Mining and Information Retrieval Laboratory**
 - **Causal Discovery and Causality-Related Learning**
 - **Director: Prof. Cai (Ruichu Cai)**
- **My Undergraduate Mentor: Wei Chen**
 - *“I would not have completed this article during my busy graduation season but for remembering the encouragement from her.”*



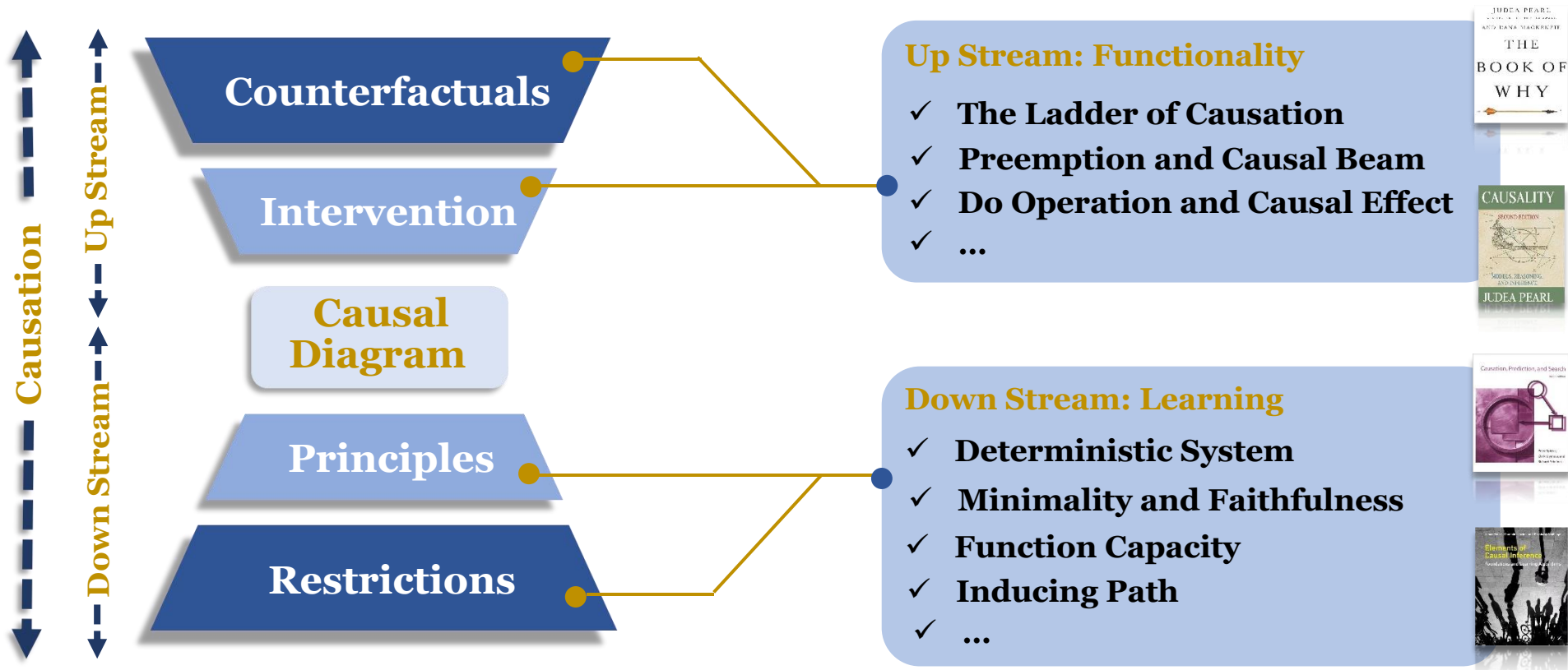
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 - **Director: Prof. Cai (蔡瑞初)**
- **My Undergraduate Mentor: 陈薇**
 - “在繁忙的毕业季里，我本很可能无法坚持完成关于这段因果发现入门手册的写作——但我一直记着两年前当我最开始跟着她研究因果关系时她对我的鼓励”。



Clue to Celebrated Books as for **Causal Diagram Learning**



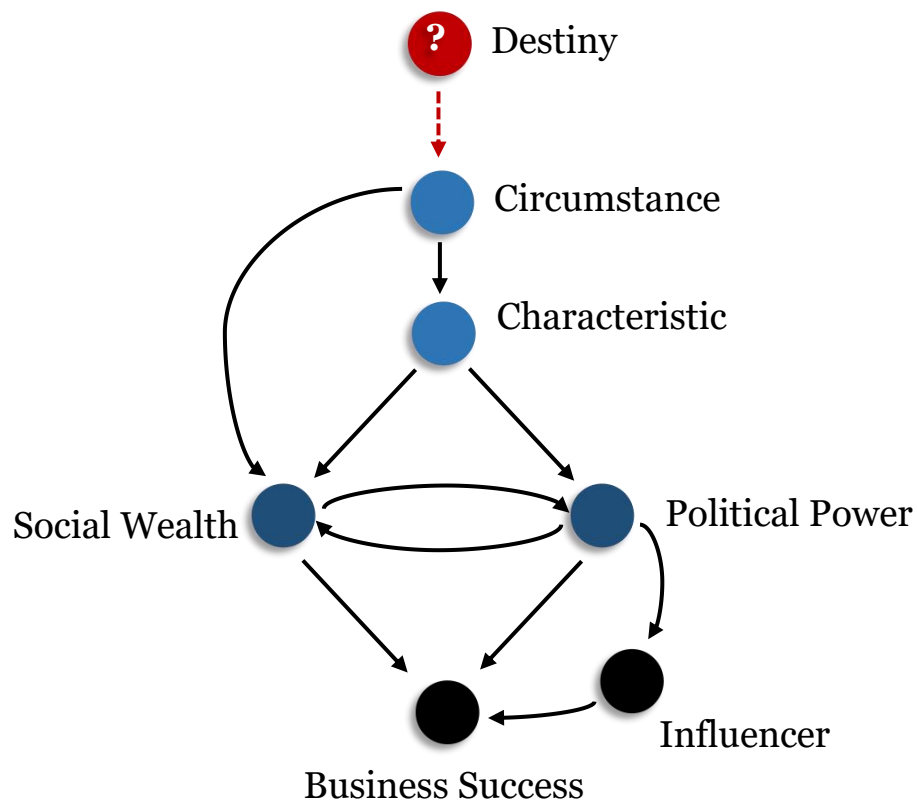
Clue to Celebrated Books as for **Causal Diagram Learning**



CONTENT

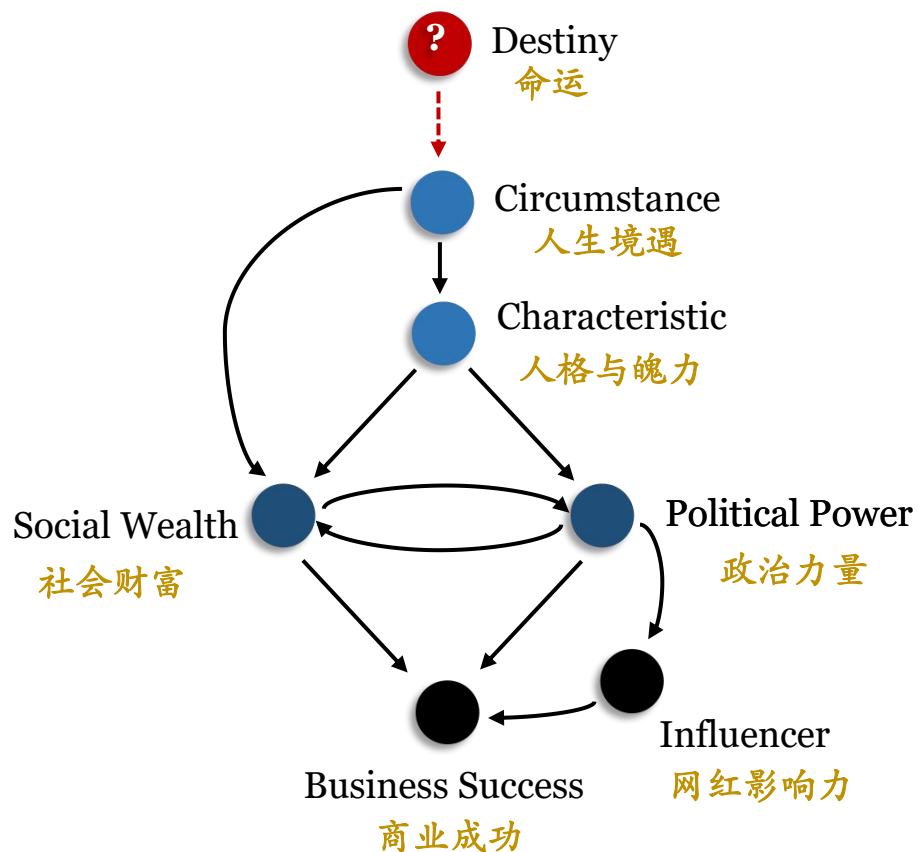
- Acknowledgements
- Introduction
 - Why Did I Write the Primer
 - **An Overview of Causal Diagrams**
 - Structure of This Series
- Source

Over the Causal Diagram: **Causal Model**



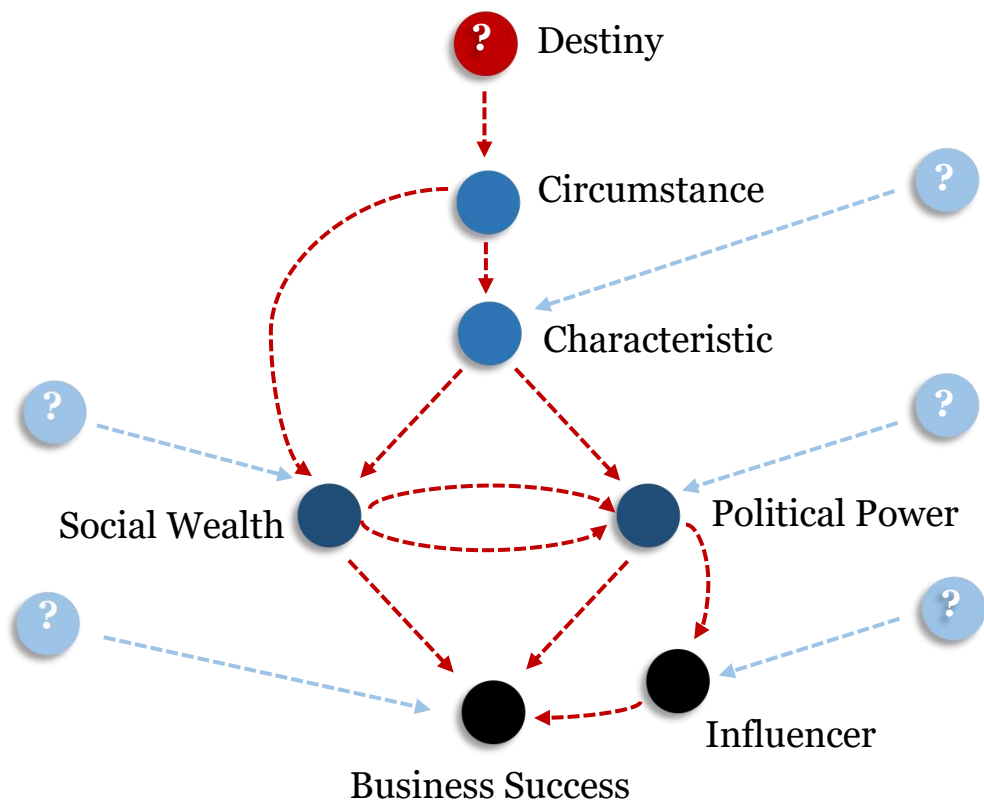
“Does God Play Dice and Conquer the Causation over Our Destiny ?”

Over the Causal Diagram: **Causal Model**

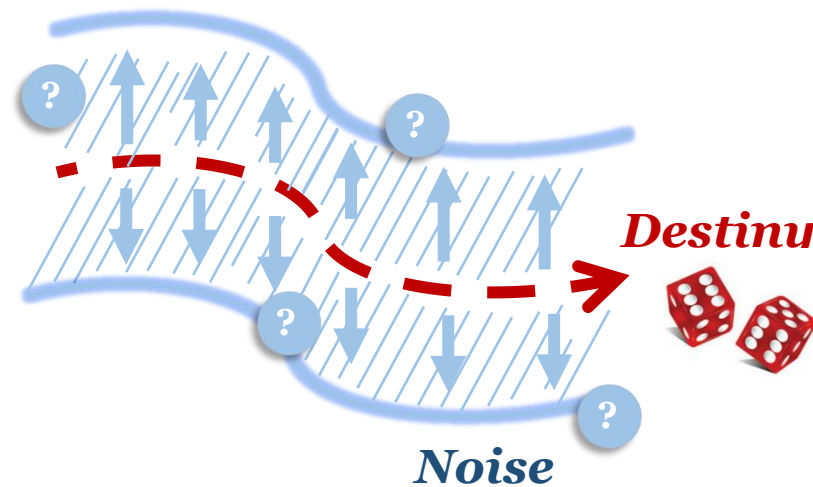


“是上帝掷了一颗骰子并掌握着我们一生中的因果关系吗？”

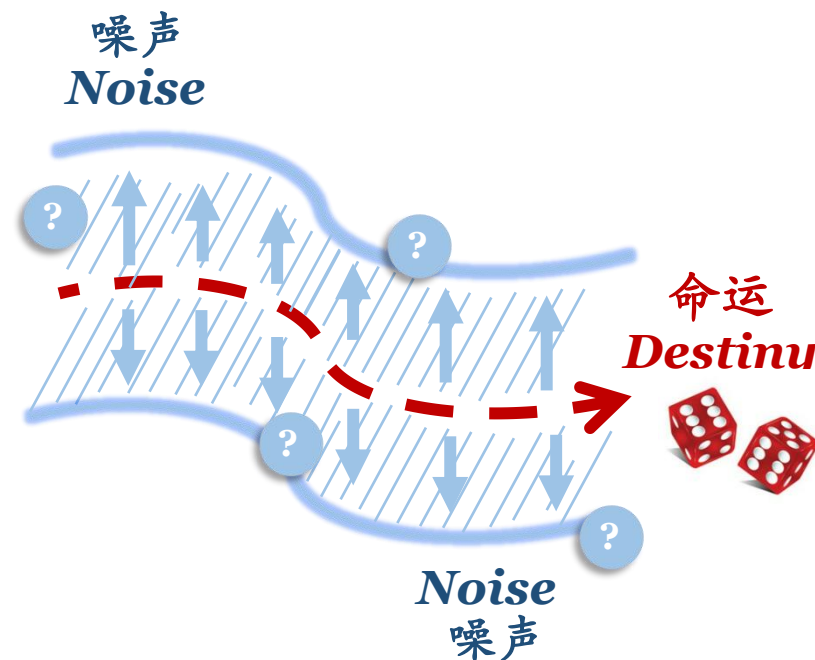
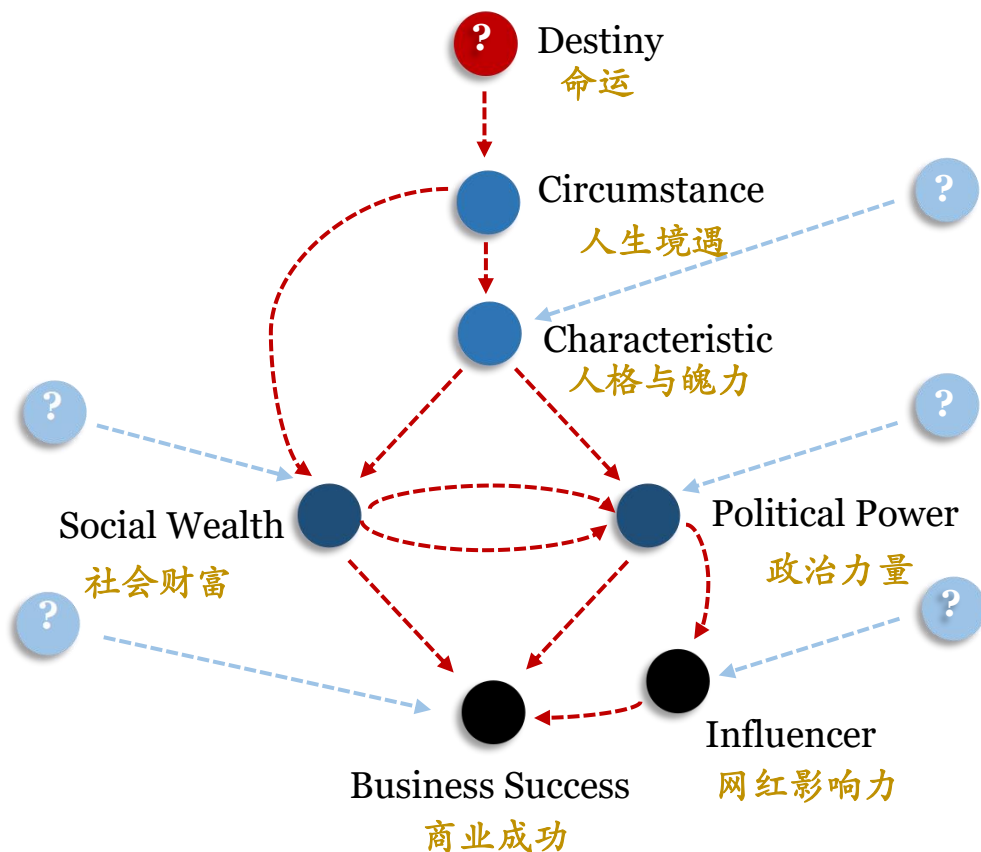
Over the Causal Diagram: **Causal Model**



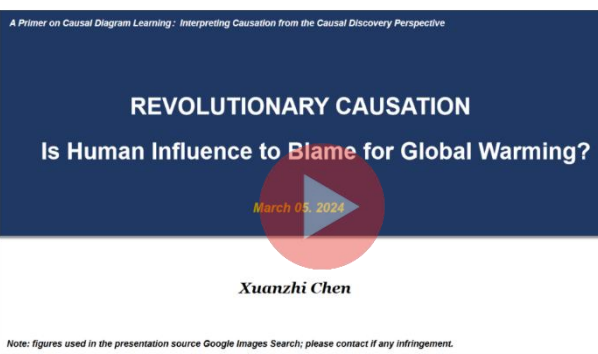
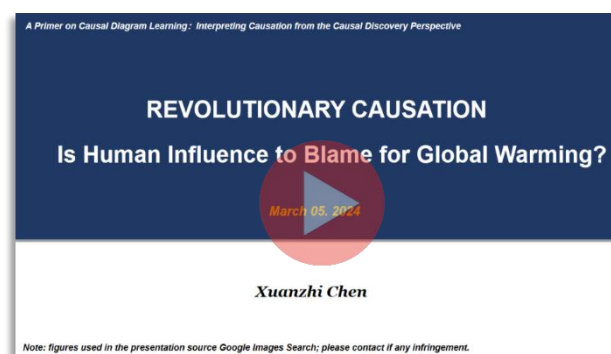
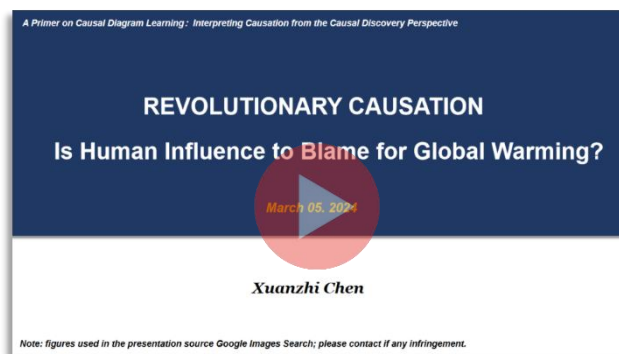
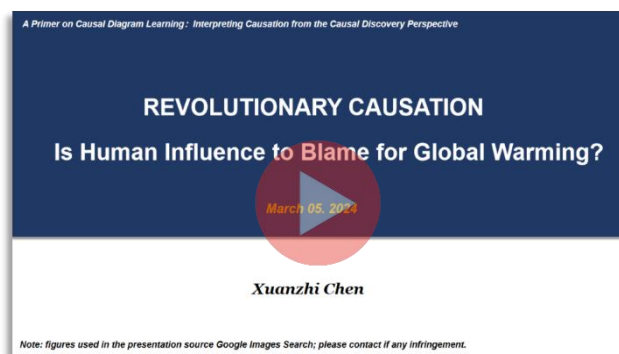
Noise



Over the Causal Diagram: Causal Model



Short Four-Episodes



@Xuanzhi Chen



@Xuanzhi Chen



@__小志__

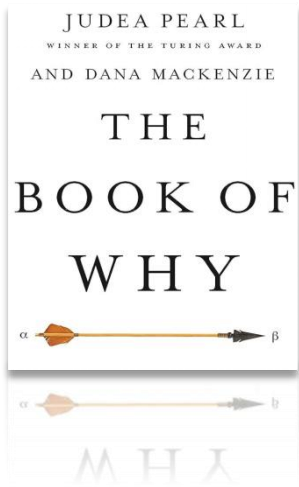
REVOLUTIONARY CAUSATION

Is Human Influence to Blame for Global Warming?

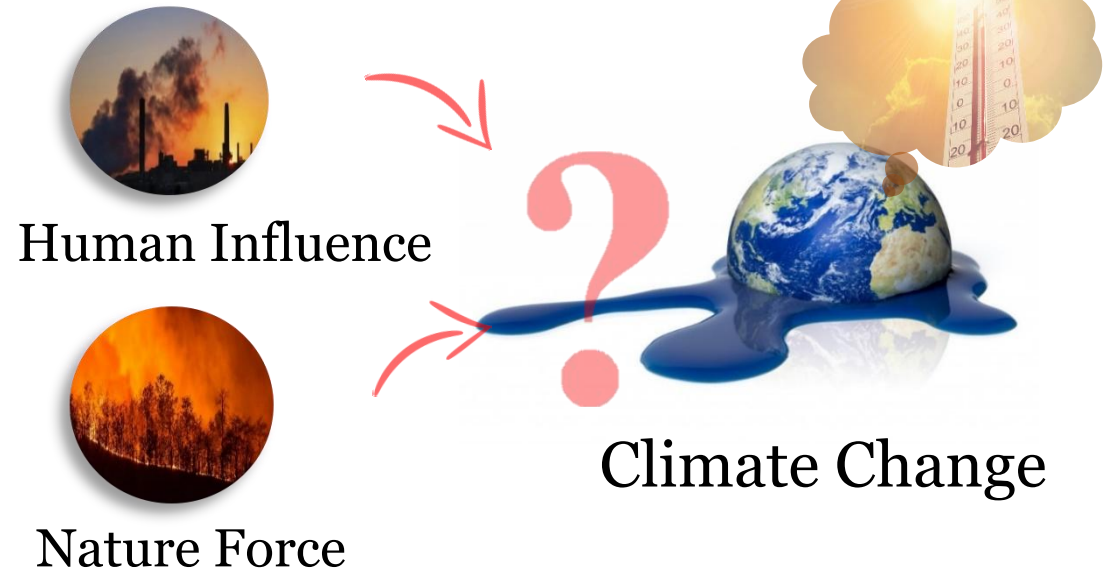
March 05. 2024

Xuanzhi Chen

Why Does Focusing on a Statement is Important?



The July 2003
mega heat wave
killed **70,000**
people.



*“It is **very likely** that **over half** the FAR (Fraction of Attribution Risk) of European summer temperature anomalies is attributable to **human influence**.”*

—Dr. Allen

A Language for Analysis of Causes?

Conceptual Causation: Application of Counterfactuals

Graphical Causation: Use Diagram to Unravel Causation Scenarios

Envision the **(counterfactual)** worlds where...

Probability of **Necessity** (PN):Probability of **Sufficiency** (PS):

“It is **very likely** that **over half** the FAR (Fraction of Attribution Risk) of European summer temperature anomalies is **attributable to human influence**.”

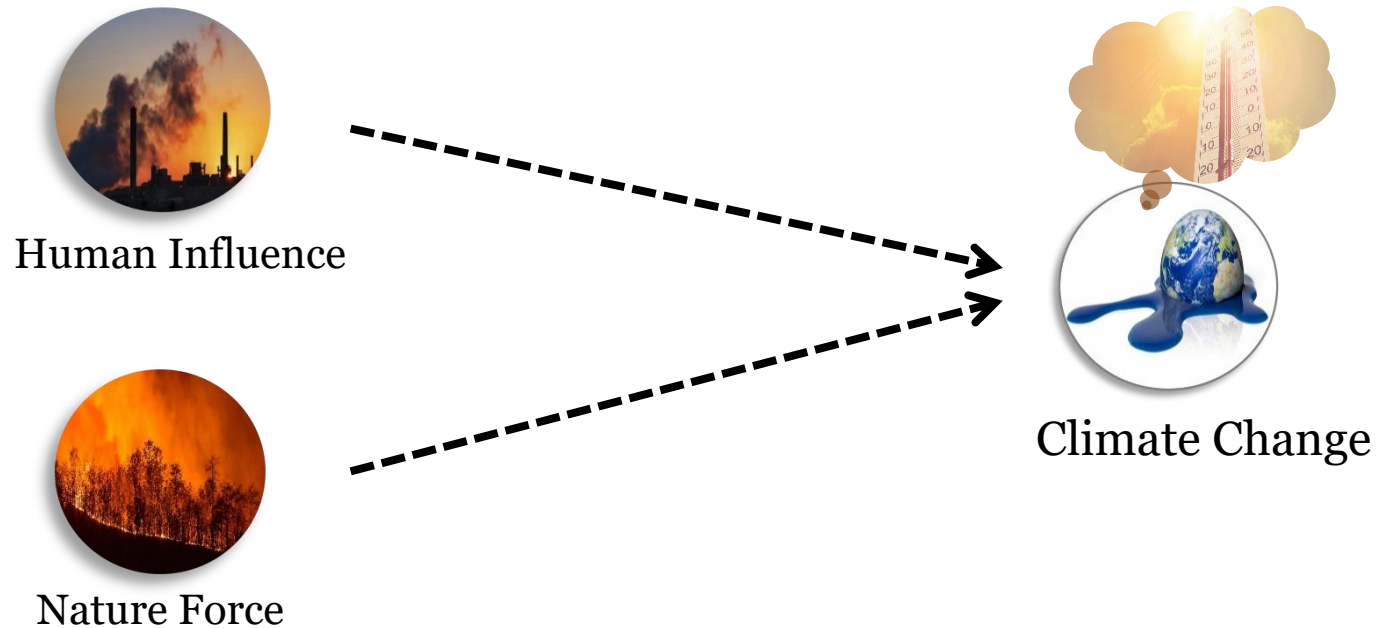
—Dr. Allen

*“It is **very likely** that **over half** the FAR (Fraction of Attribution Risk) of European summer temperature anomalies is **attributable to human influence**.”*

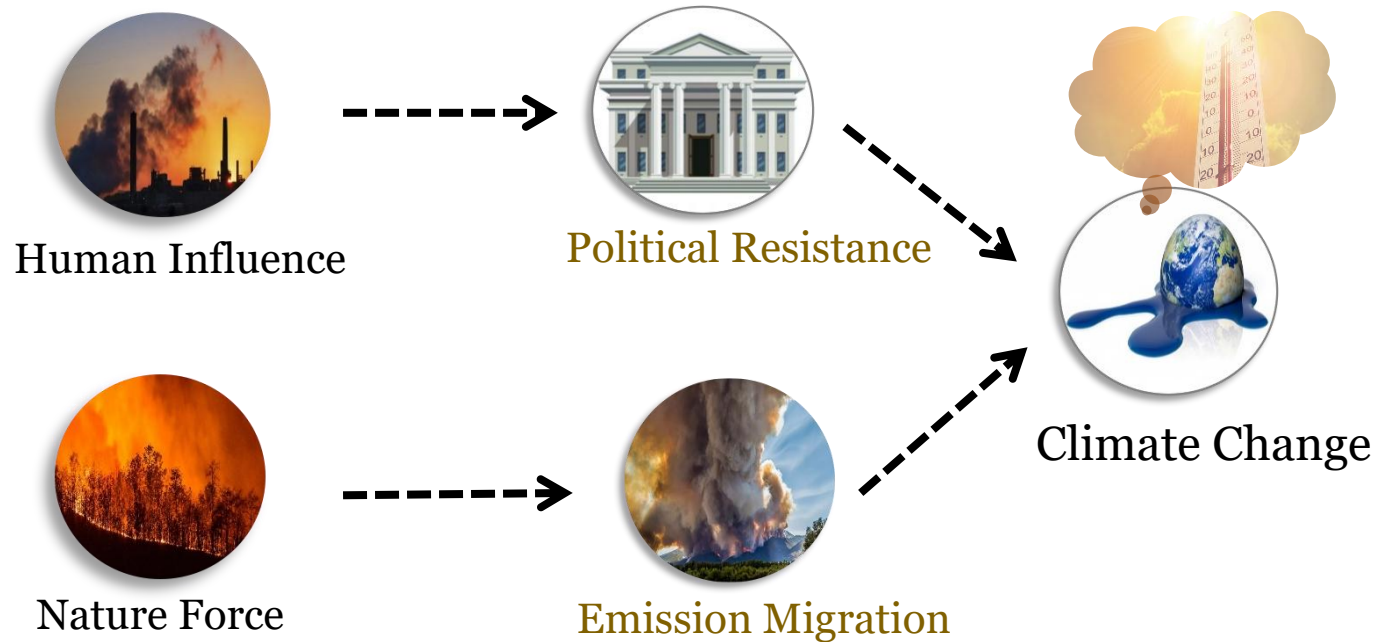
—Dr. Allen

Insufficiency in Analysis of Causes ?

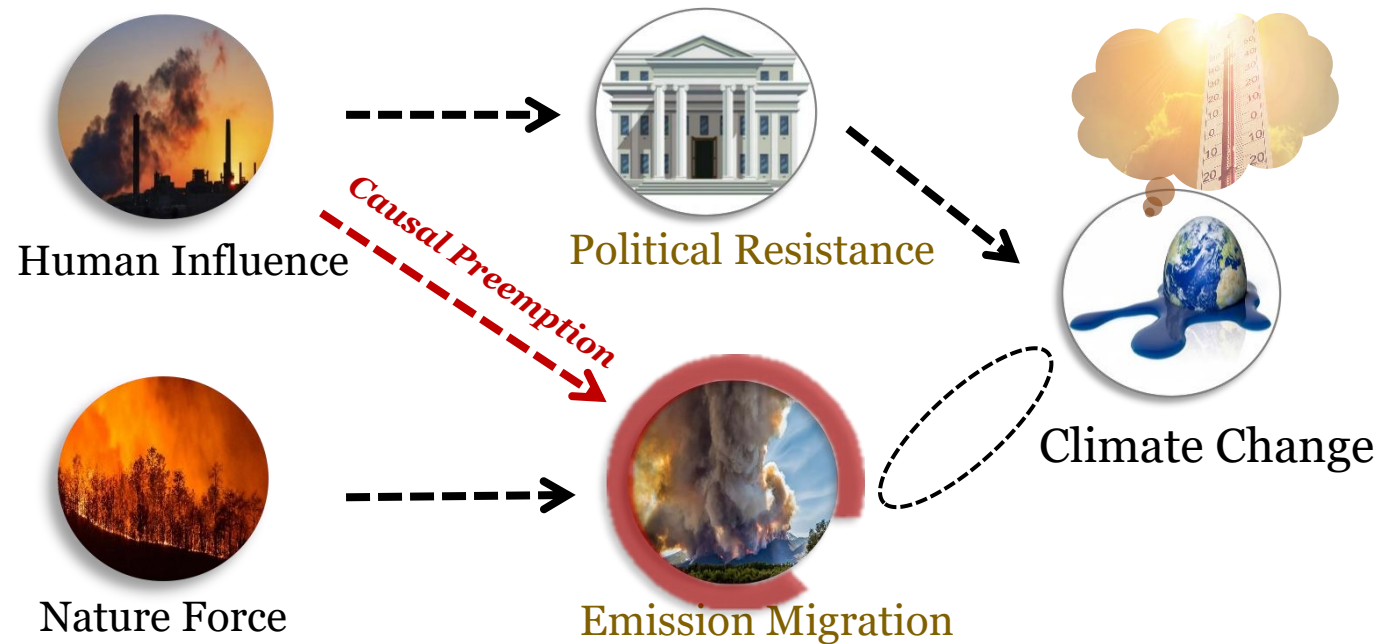
A Causal Diagram Describing Causal Insufficiency



A Causal Diagram Describing Causal Insufficiency



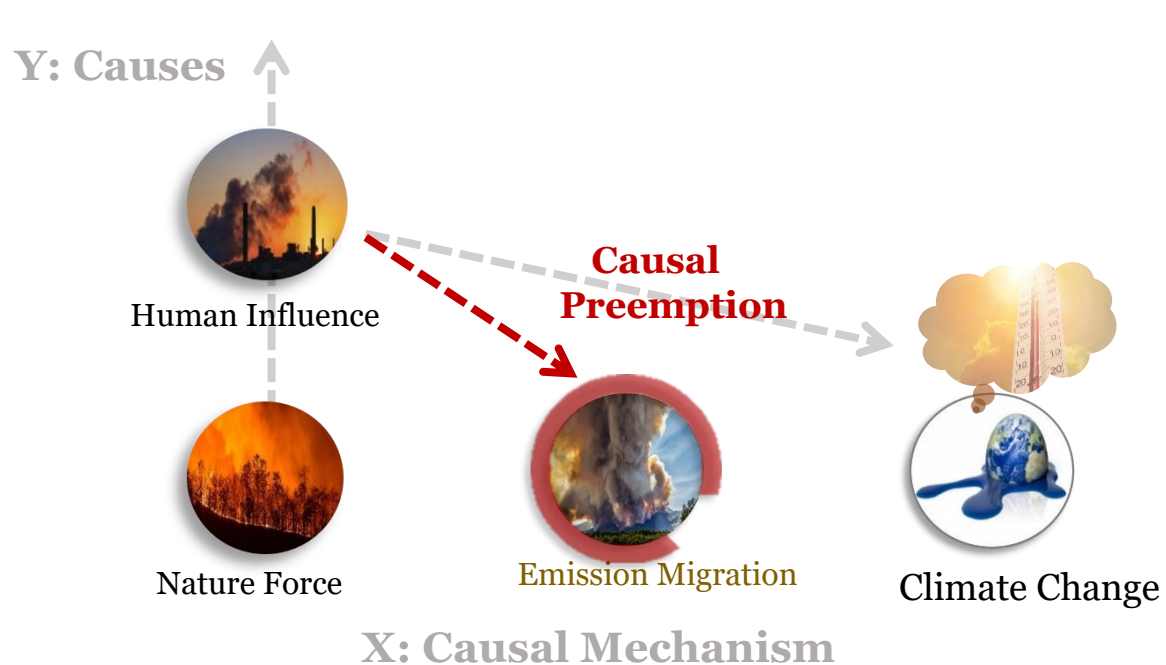
A Causal Diagram Describing Causal Insufficiency



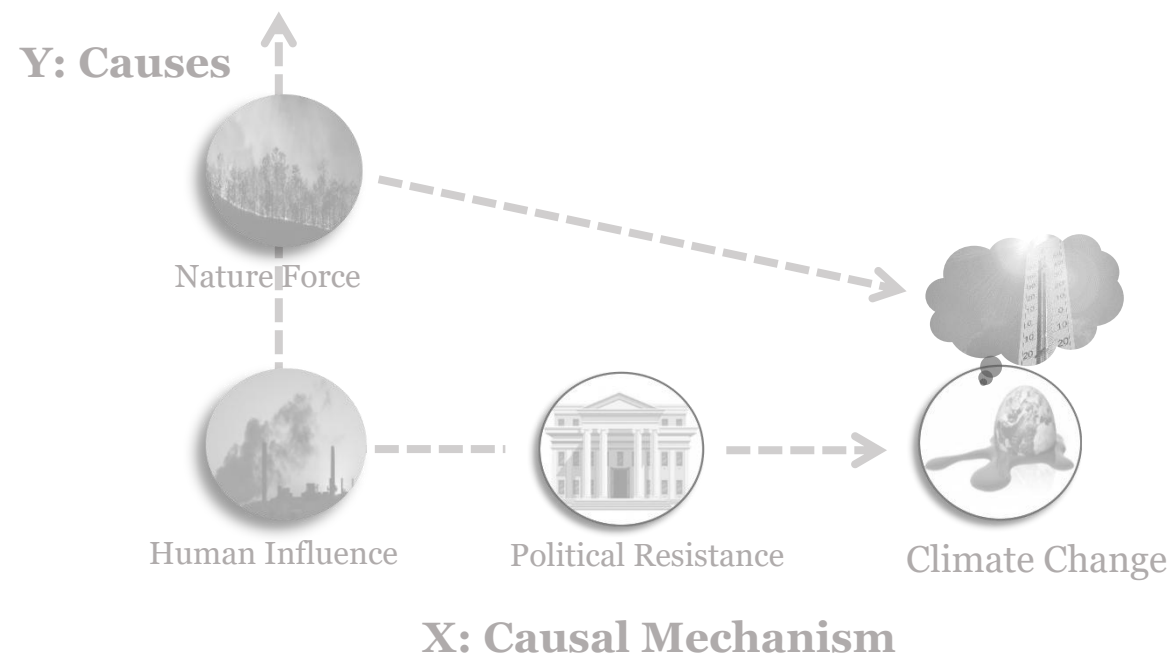
*“Techniques such as **drones** and satellites manufactured by the industries can also **protect** our climate.”*

A **Causal Preemption** happened!

Whether the Cause Can Sufficiently Sustain its Effect?



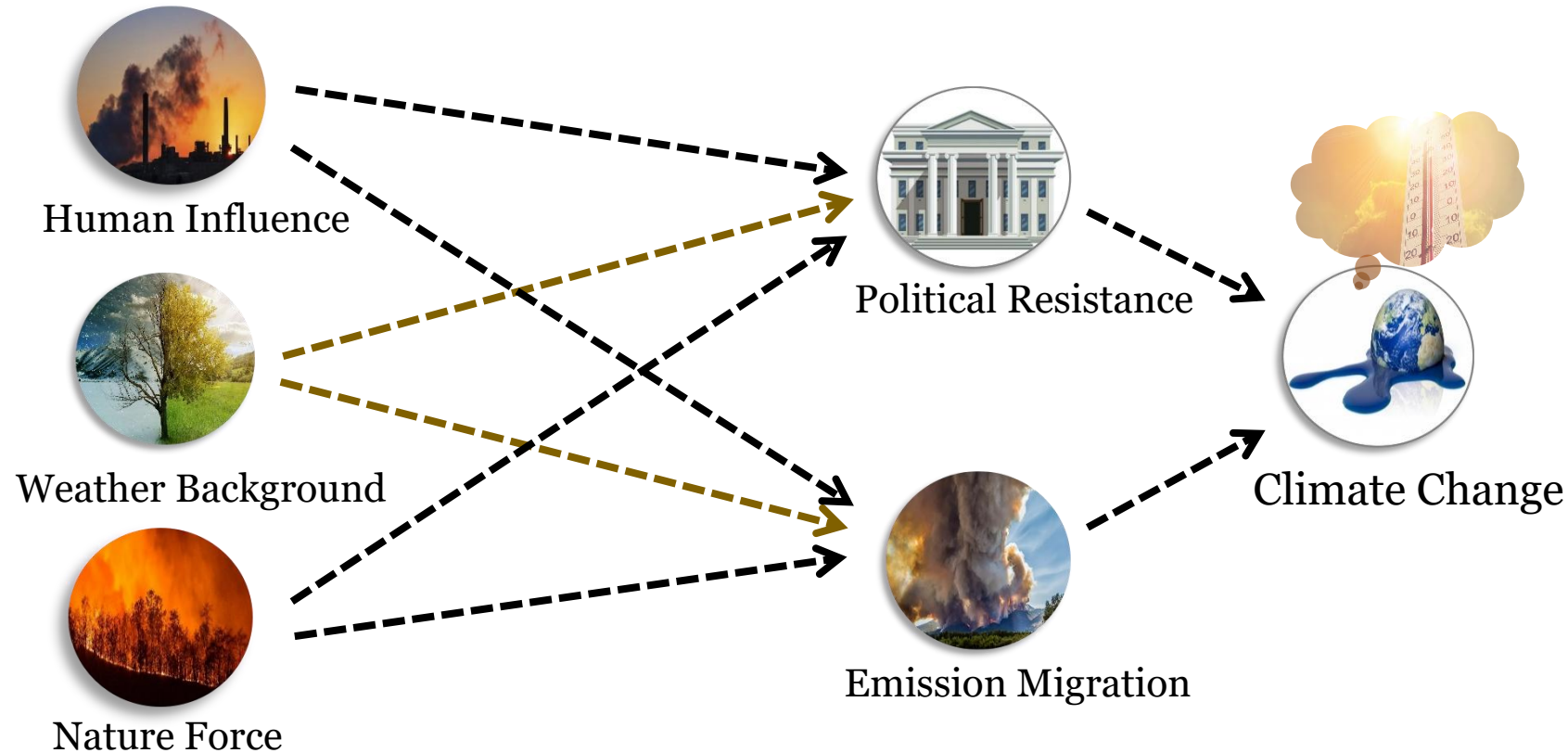
✗ Sustainable



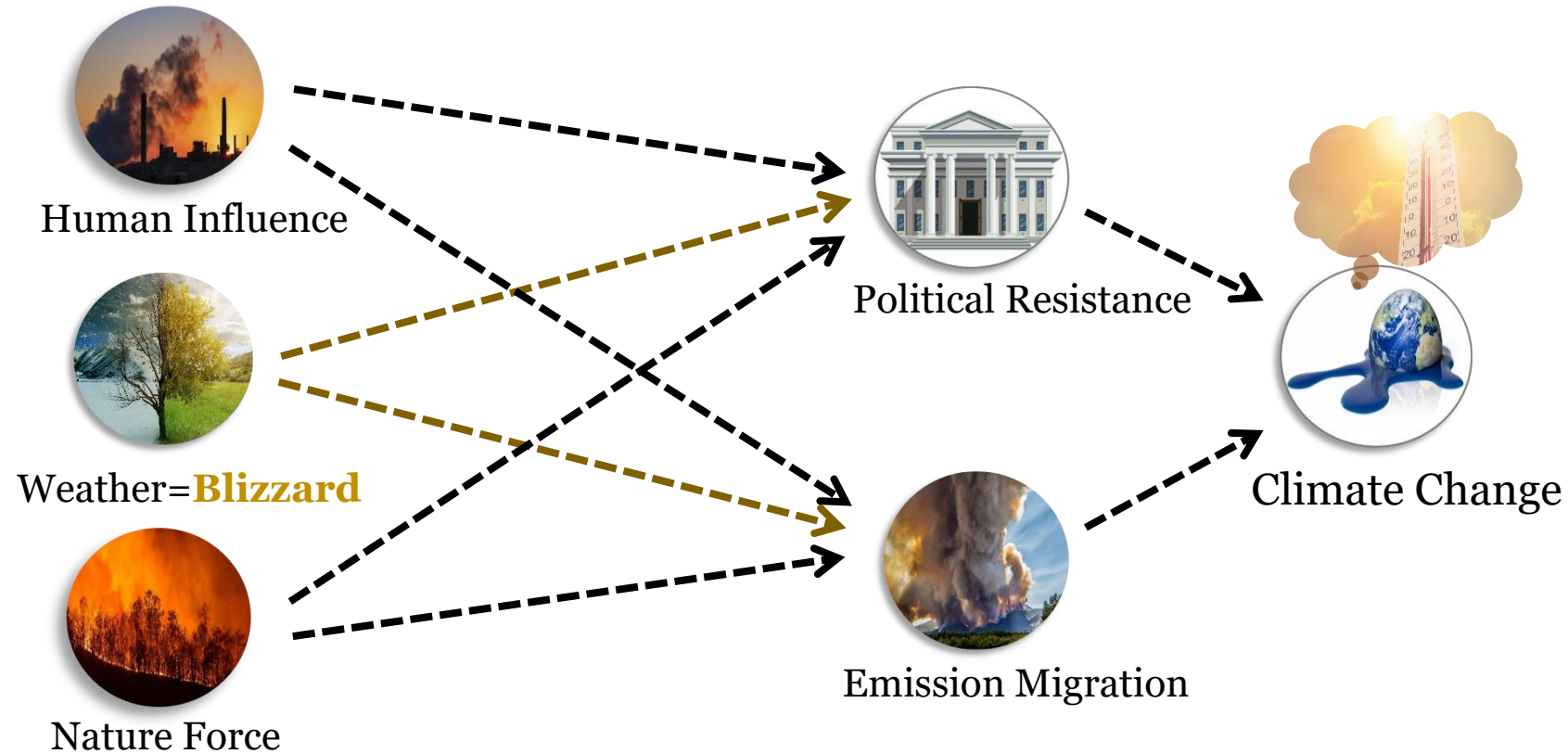
✓ Sustainable

Rule out some mechanisms in a causal diagram
To “slim down ” the causal diagram

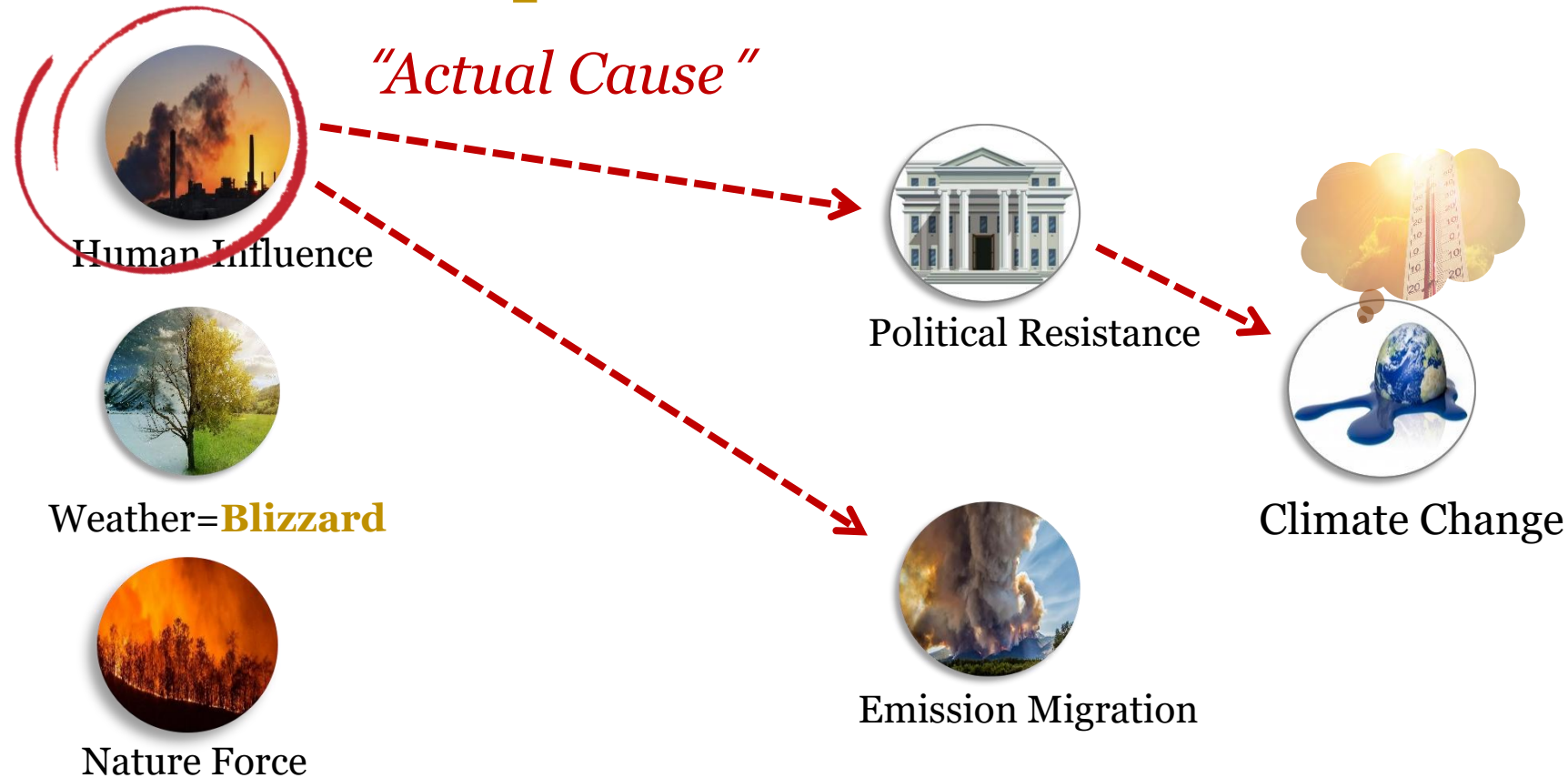
A Causal Diagram of a **General** Scenario



A Causal Diagram of a **General** Scenario



A Causal Beam of a Specific Scenario



*“It is **very likely** that **over half** the FAR (Fraction of Attribution Risk) of European summer temperature anomalies is **attributable to human influence**.”*

—Dr. Allen

“Sufficiency and Necessary Analysis”

Insufficiency of Analysis of Causes ?

*from Causal Diagrams to the **Causal Beam***

Sustenance-Based Causation

—Causality, Judea Pearl

REVOLUTIONARY CAUSATION

Can Vaccinal Treatments Save Lives of Loved Ones?

March 10. 2024

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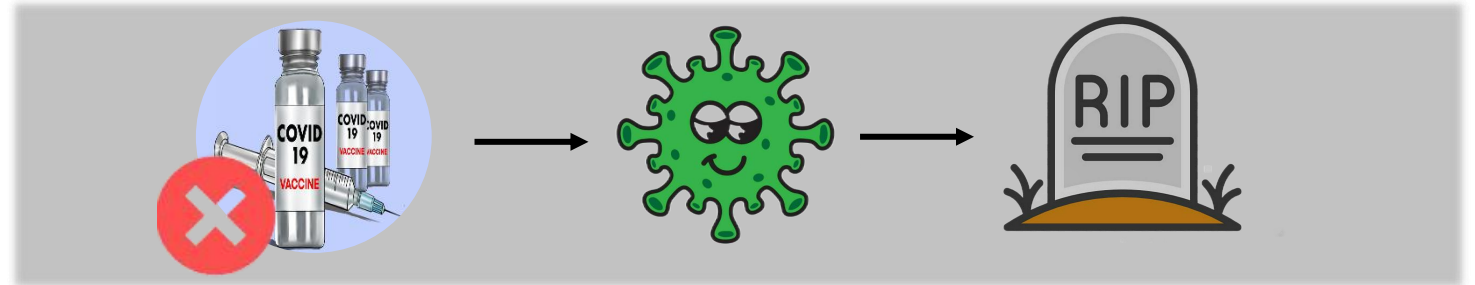
COVID-19 Has Taken away the Life of My Grandfather



My dear grandpa

Analysis of Causes:

Why? How could my grandpa had gotten an infection?



*The **First Version** of the question “Why?”*

COVID-19 Has Taken away the Life of My Grandfather



My dear grandpa

Inquiry About Causal Effect:

Why? What is the mechanism by which vaccine prevent infection?



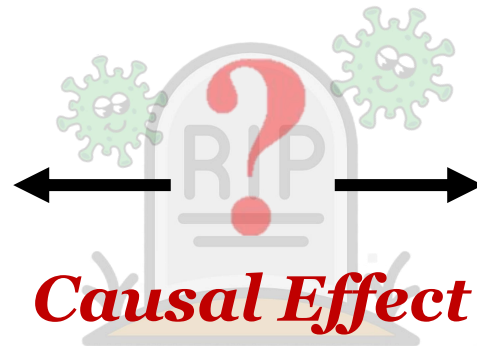
The **Second Version** of the question “Why?”

Can Vaccinal Treatments Save Lives of Loved Ones?

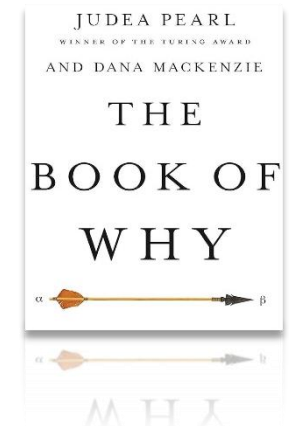
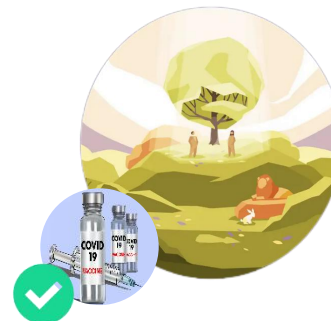
*“There is a **Second Version** of the ‘WHY?’ question, which we ask when we want to better understand the **connection** between a known cause and a known effect.”*

—The Book of WHY, Judea Pearl

The current world



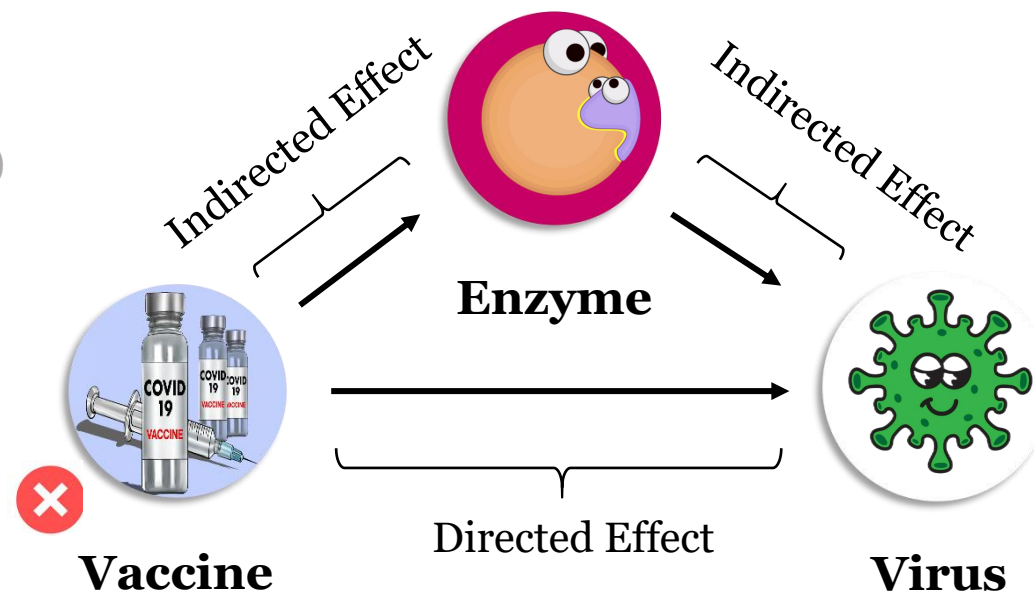
The “parallel” world



Conceptual Causation: Application of Intervention

Graphical Causation: Use Causal Diagrams to Deduce Causal Inquiry

- Break Down the (Total) Causal Effect:
 - Directed Causal Effect (the first version of WHY)
 - Indirected Causal Effect (the second version of WHY)
- **Directed Causal Effect (DE):**
 - Controlled Directed Effect (CDE)

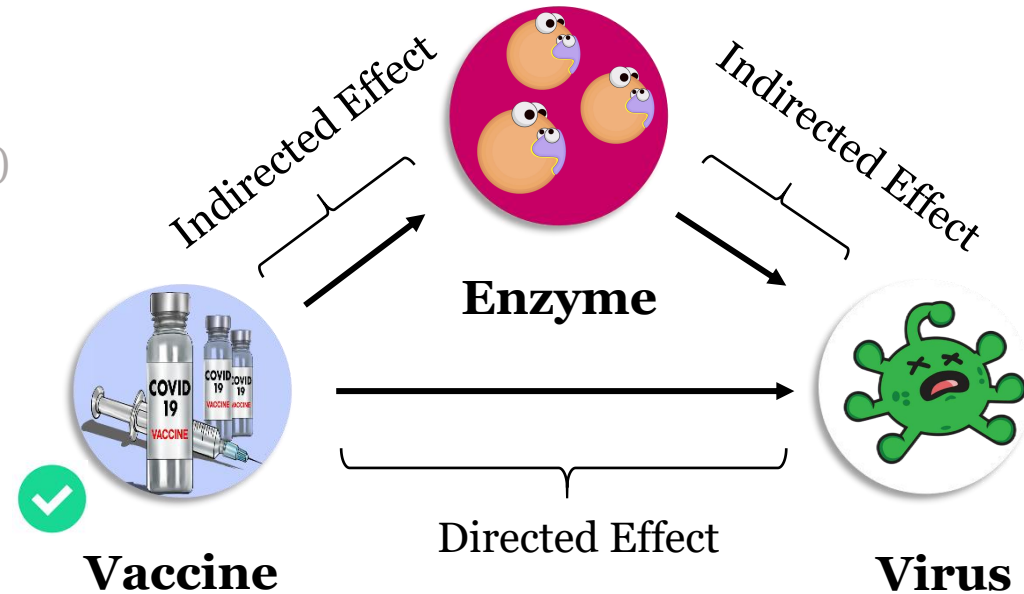


*A plethora of **control** could sometimes lead to pitfalls!*

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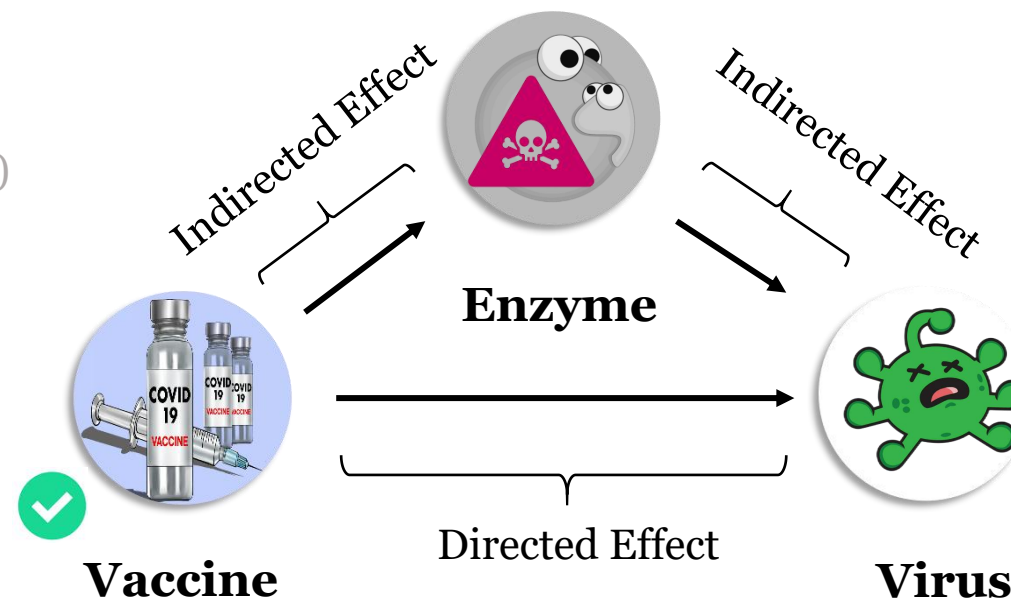


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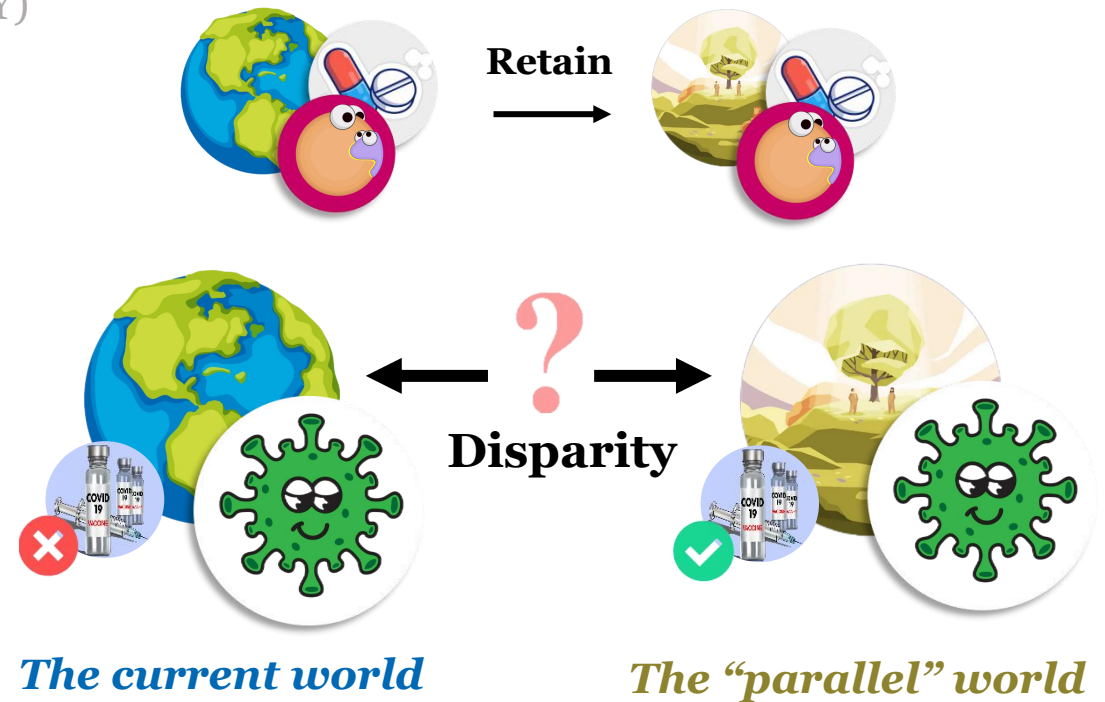
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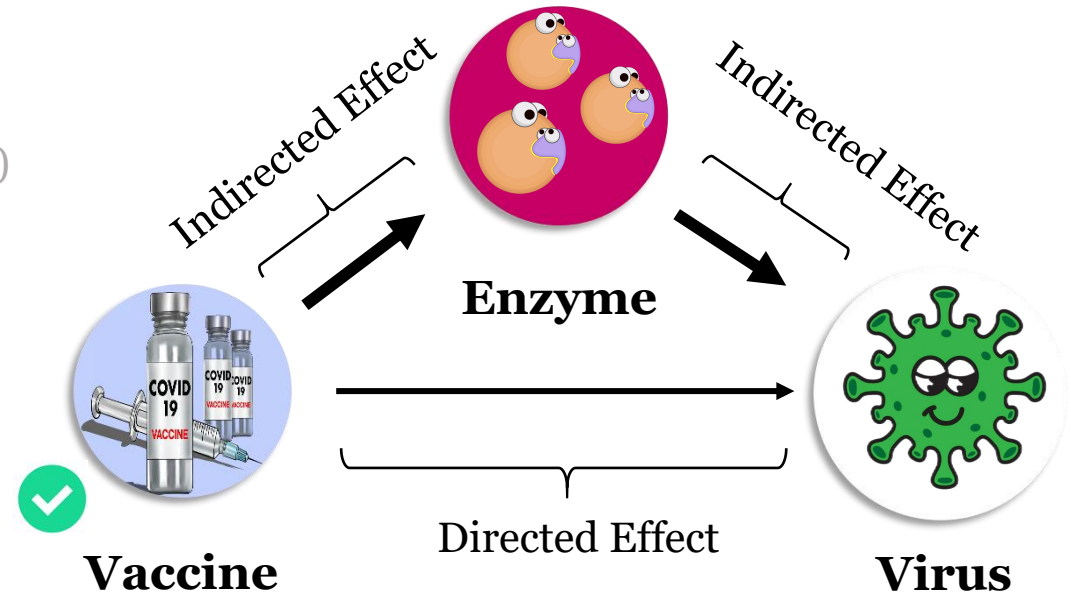
Control: *Hold constant the “preference”:*



Conceptual Causation: Application of Intervention

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The (Natural) Directed Effect can be actually **insignificant** !

$$NDE = 0$$

Conceptual Causation: Application of Intervention

Graphical Causation: Use Causal Diagrams to Deduce Causal Inquiry

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 - Natural Directed Effect (NDE)
- Indirected Causal Effect (IE):
 - ~~Controlled Indirected Effect (CIE)~~



There is **No** Controlled Indirected Effect

Conceptual Causation: Application of Intervention

Graphical Causation: Use Causal Diagrams to Deduce Causal Inquiry

➤ Break Down the (Total) Causal Effect:

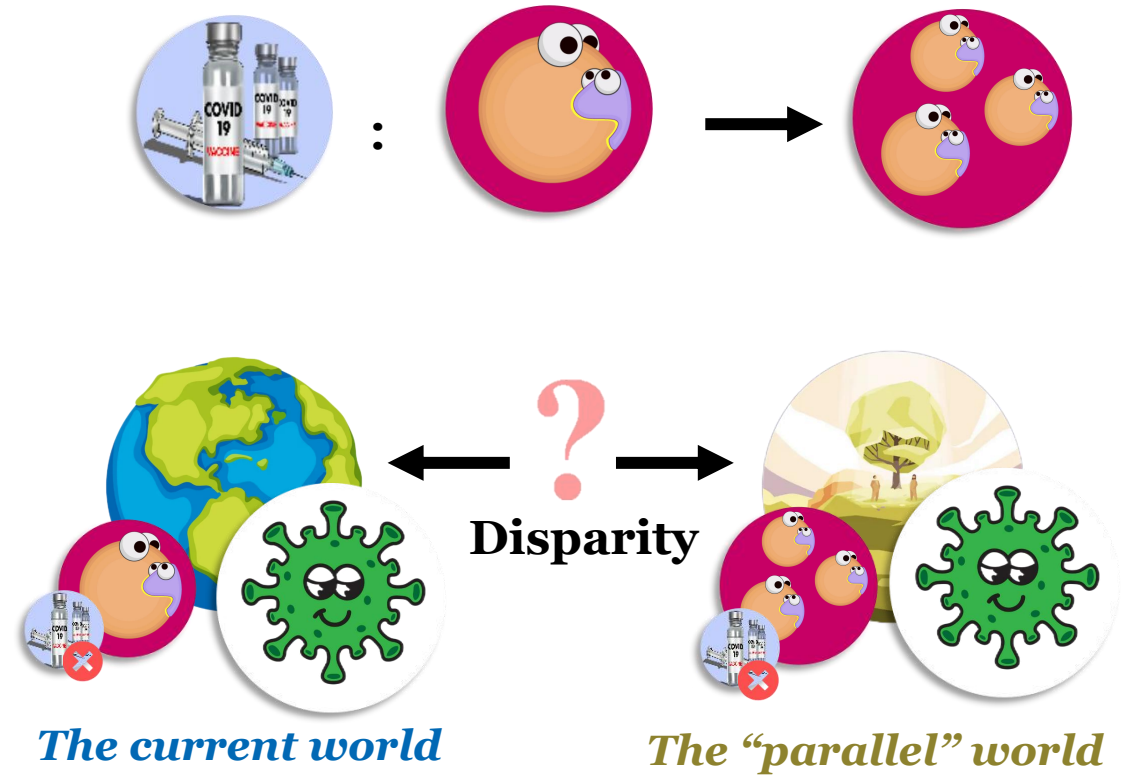
- Directed Causal Effect (the first version of WHY)
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➤ Directed Causal Effect (DE):

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- Natural Directed Effect (NDE)

➤ Indirected Causal Effect (IE):

- ~~Controlled Indirected Effect (CIE)~~
- Natural Indirected Effect (NIE)



Conceptual Causation: Application of Intervention

Graphical Causation: Use Causal Diagrams to Deduce Causal Inquiry

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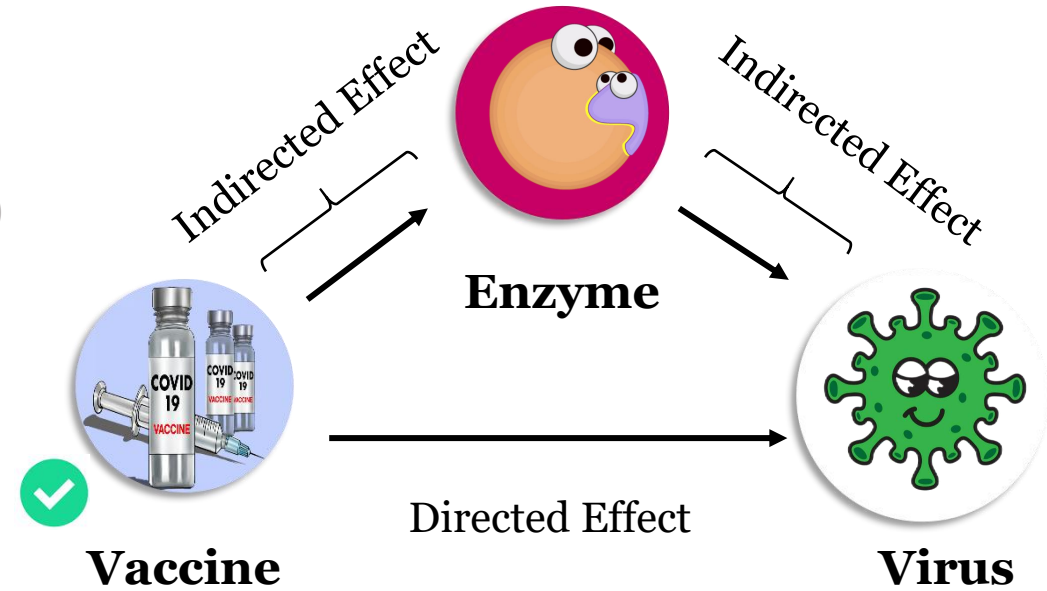
*“When I managed to strip the formula for the **Natural Causal Effect** from all of its **Counterfactual Representation**, it was the greatest thrills in my life.”*

—The Book of WHY, Judea Pearl

Conceptual Causation: Application of Intervention

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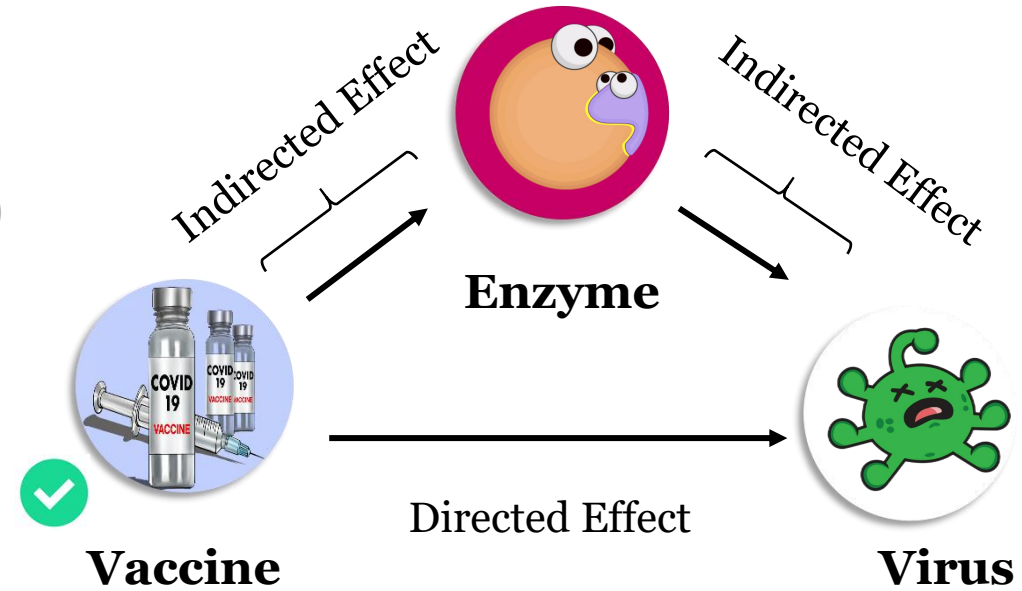


*The (Natural) Indirected Effect can also be **insignificant** !*

Conceptual Causation: Application of Intervention

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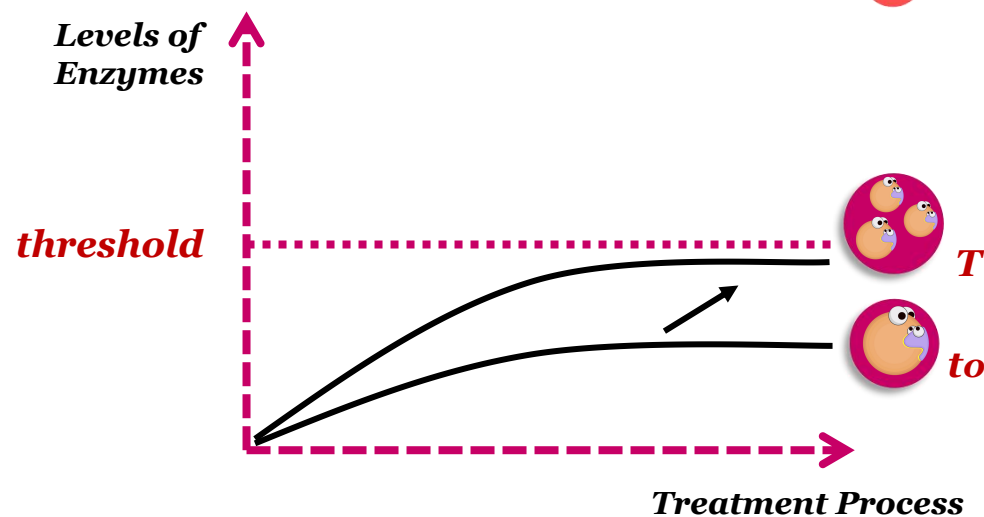
The (Natural) Indirected Effect can also be **insignificant** !

$$NDE = 0, NIE = 0$$

$$TCE = NDE + NIE = 0?$$

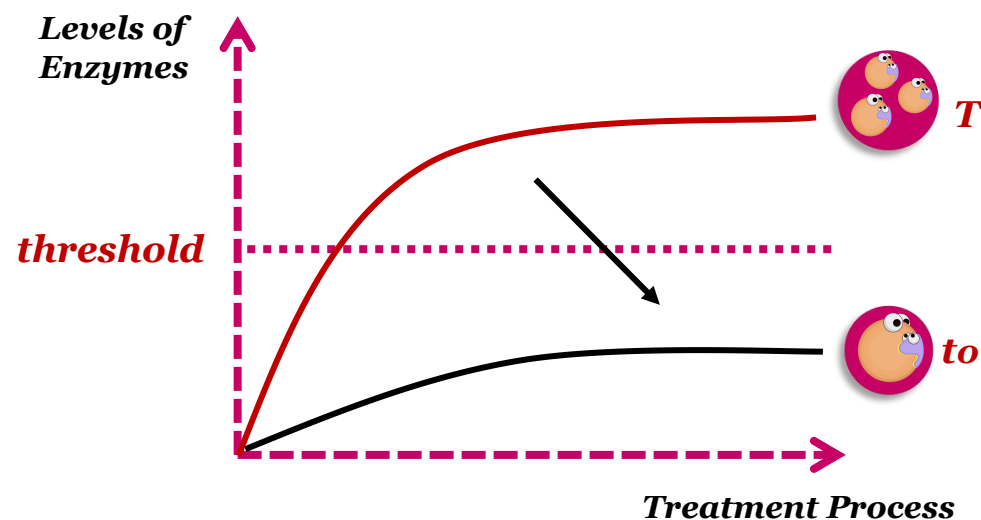
Fix the Non-linearity Issue in Indirected Effects

Current Setting:



$$NIE = Y(T) - Y(to) = 0$$

Counterfactual Setting:

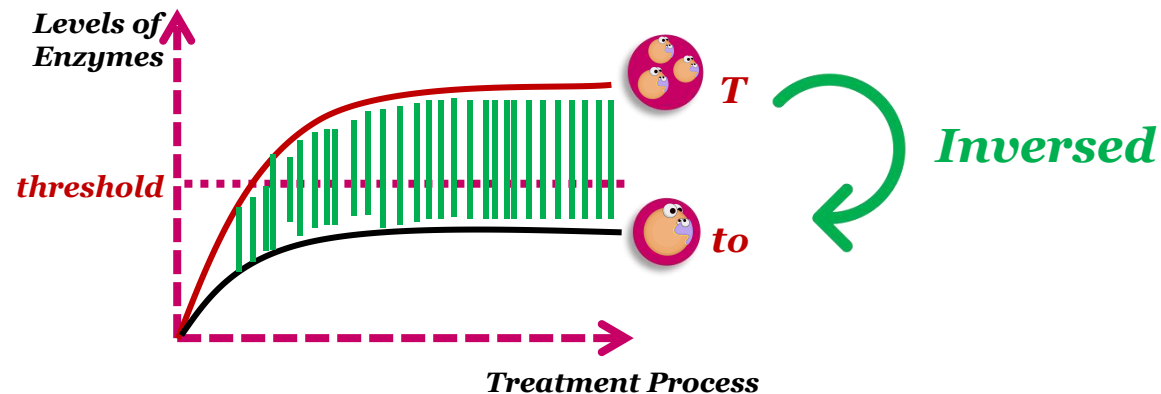


$$\text{"Inversed"} NIE = Y(to) - Y(T) = -1$$

Revelation of “Inversed” NIE (Natural Indirected Effect)

Total Causal Effect = Directed Effect + Indirected Effect. (Advantages)

Inversed Indirected Effect: Potential Loss



Revelation of “Inversed” NIE (Natural Indirected Effect)

Total Causal Effect = Directed Effect + Indirected Effect. (Positive Contribution)

Inversed Indirected Effect: Potential Loss

Total Causal Effect = Directed Effect - (Inversed Indirected Effect).

How to “Naturally” Calculate the Total Causal Effect?

“Envisioning-Parallel-World”



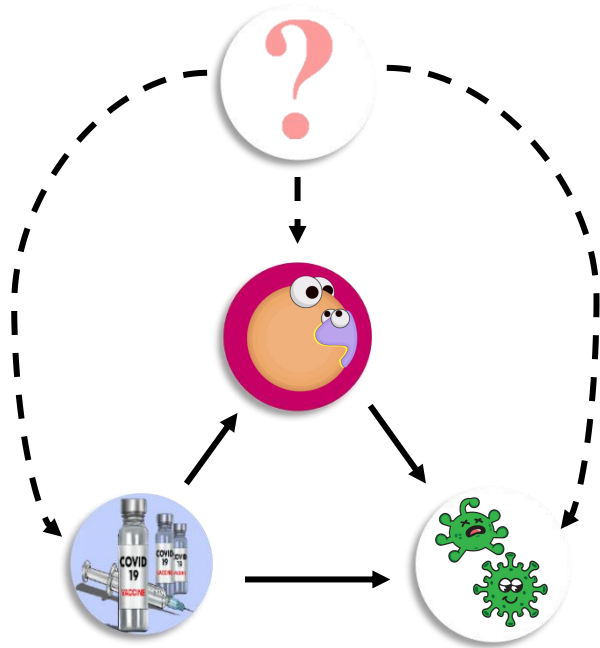
*Total Causal Effect = Directed Effect - (**Inversed Indirected Effect**).*

*“I was extremely thrilled to see this **subtraction principle** emerging from the analysis of **Total Causal Effect** (TCE), despite the **nonlinearity** of the equations.”*

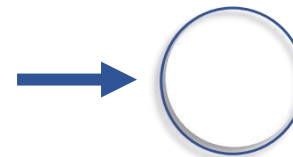
—The Book of WHY, Judea Pearl

*The magic as to the **subtraction principle** lies in: **Intervention** based on **Counterfactuals ideas***

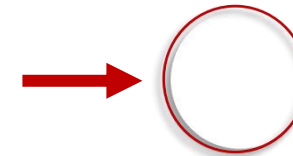
Execute Different Types of “Surgery” for Causal Diagrams



: ***Do Operation***

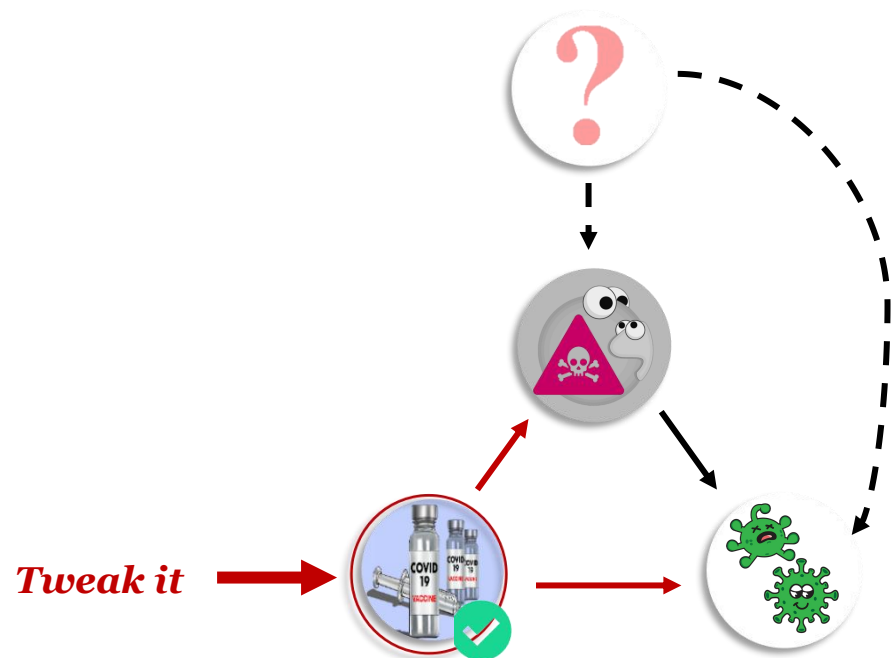


: ***Hold it Constant***

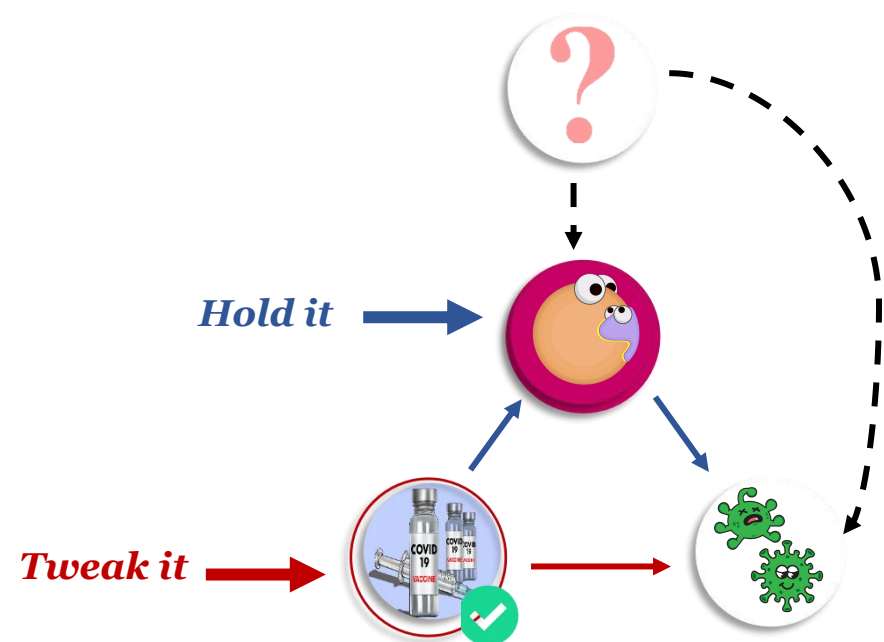


: ***Tweak it On Compulsion***

Execute Different Types of “Surgery” for Causal Diagrams

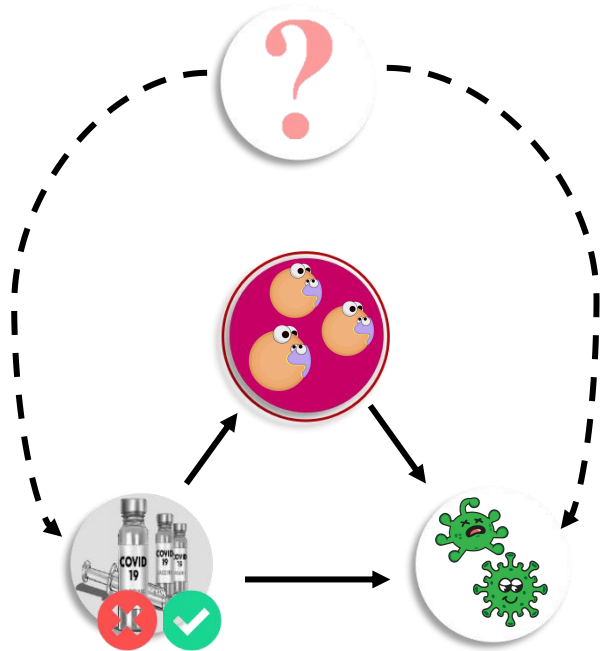


Controlled Directed Effect (CDE)

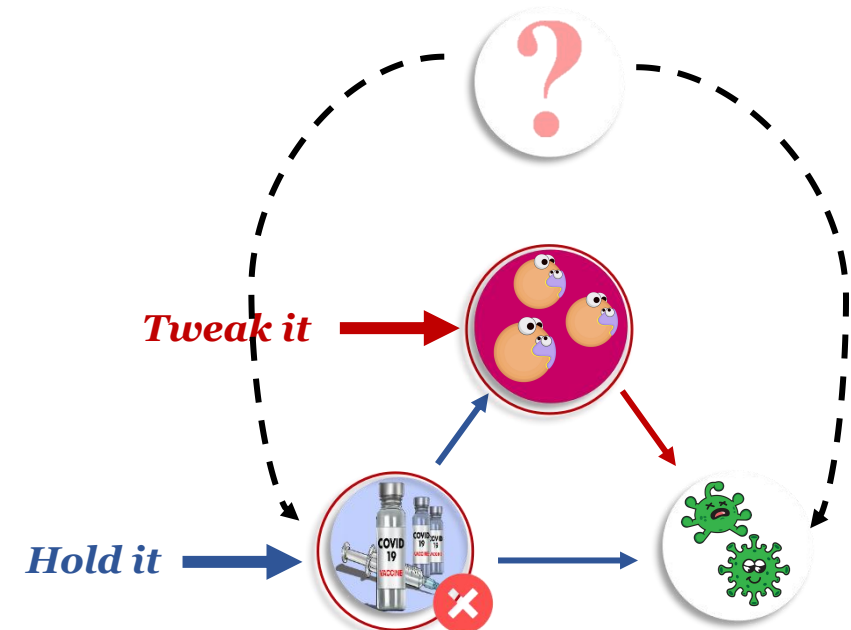


Natural Directed Effect (NDE)

Execute Different Types of “Surgery” for Causal Diagrams



Controlled Indirect Effect (CIE)



Natural Indirect Effect (NIE)



*May my dear grandfather rest in peace in his **Heaven World**.*

愿我亲爱的爷爷（陈超伦）在他的天堂世界安息

INFERRED CAUSATION

Causal Diagram Learning = Data + Restriction

March 10. 2024

Xuanzhi Chen

➤ **Causal Diagrams Entailed by Statistical Data**

- Data-driven methods
- Unstable probability distribution
- Example: Newton's laws of motion

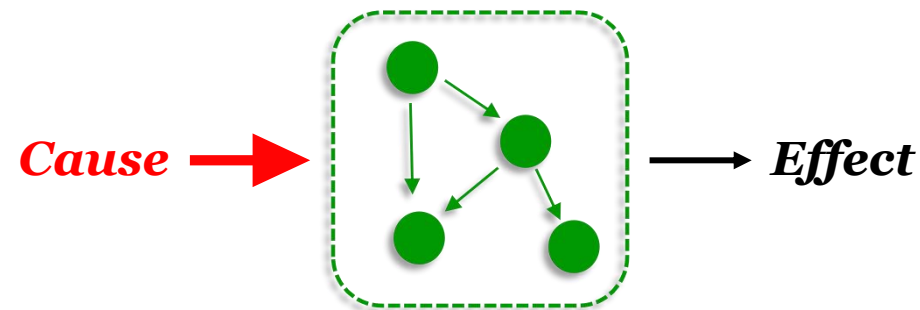


INVARIANT: $F=ma$

Causal Mechanism and Structure Causal Models (SCMs)

Causal Markov Framework

- Causal Diagrams Entailed by Statistical Data
 - Data-driven methods
 - Unstable probability distribution
 - Example: Newton's laws of motion
- **An Invariant Mechanism for Data Generation?**
 - Akin to the “Law of Causality”
 - The cause is irrelevant to the causal mechanism

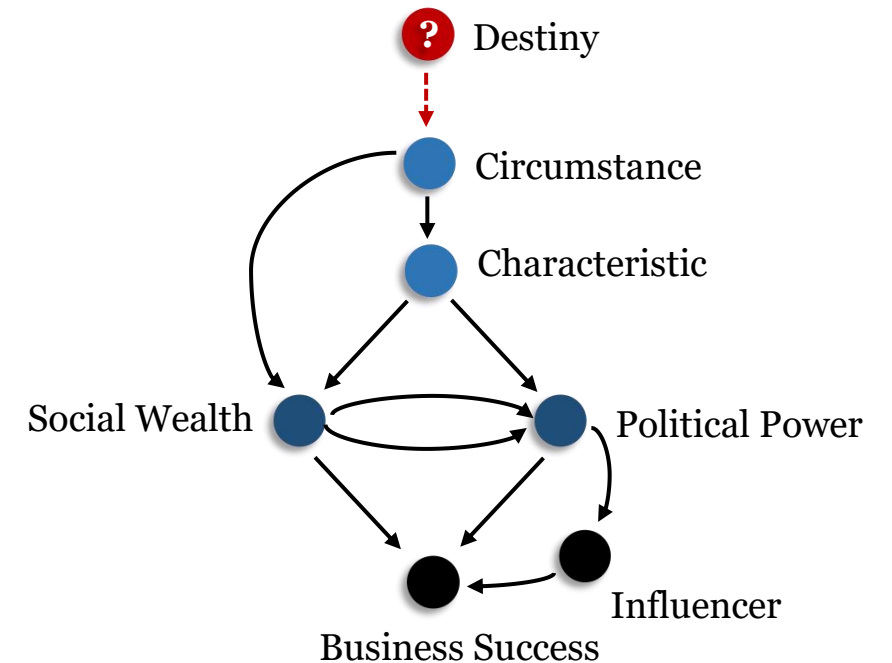


INVARIANT:
“Law of Causality”

Causal Mechanism and Structure Causal Models (SCMs)

- **Causal Diagrams Entailed by Statistical Data**
 - Data-driven methods
 - Unstable probability distribution
 - Example: Newton's laws of motion
- **An Invariant Mechanism for Data Generation?**
 - Akin to the "Law of Causality"
 - The cause is irrelevant to the causal mechanism
- **Invariant Mechanisms Embedded in Causal Structures**
 - Recall the Example: a Diagram of our Lifetime Events
 - Moral of an arrow: "Autonomous" mechanism

Causal Markov Framework

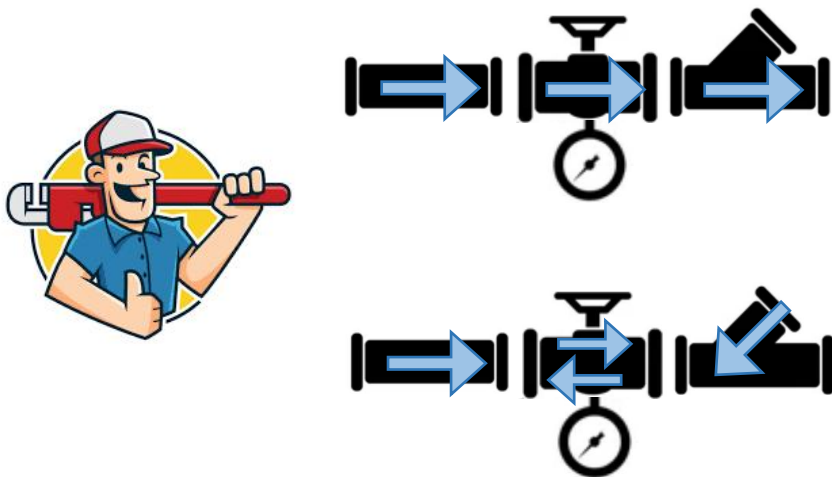


*"If we accept that causation **cannot** be inferred from **statistics** alone,
then the **Markovian** equivalent models is inevitable"*

—Judea Pearl, Causality

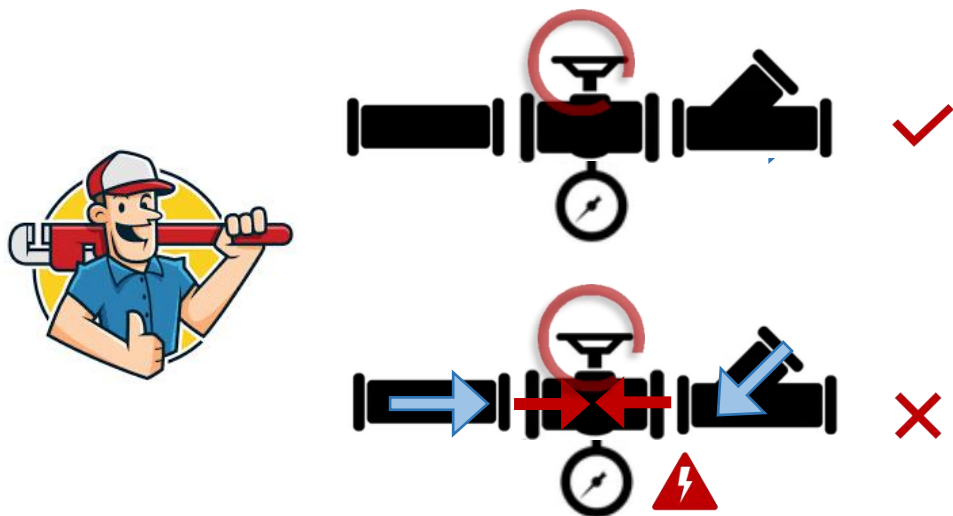
Markovian Property: Conditional Independence

“Conditional independence is the heart in causal modelling” – Judea Pearl



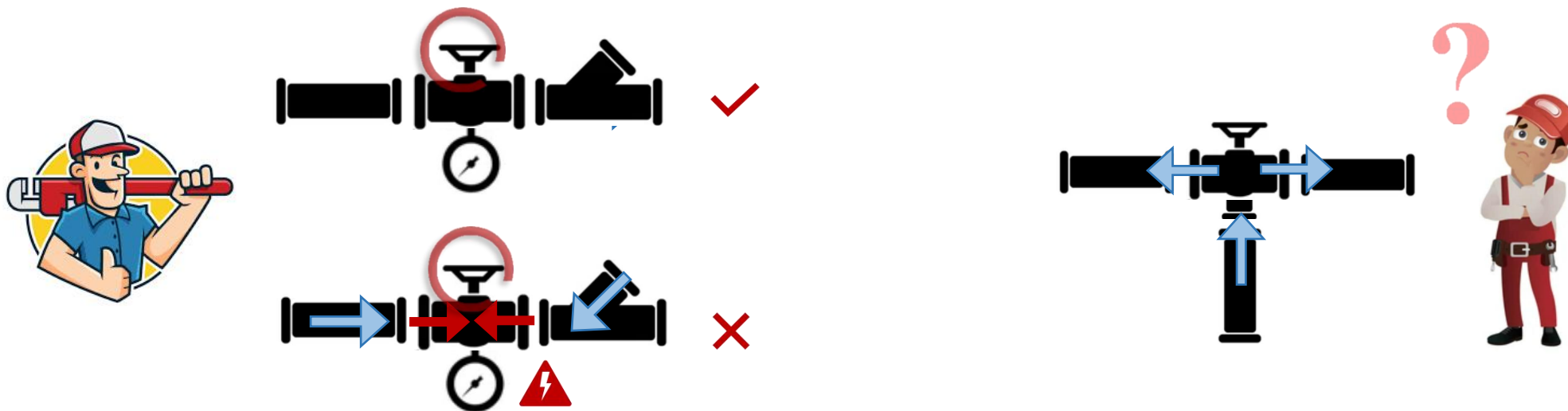
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Markovian Property: Conditional Independence

“Conditional independence is the heart in causal modelling” – Judea Pearl



Think of the **flow of water** carried by a pipe as:
the **flow of causal-dependence** carried by an arrow

Markovian Property: “Deterministic” Systems

➤ Working States of Computer, Keyboard, and Mouse:

- ① The keyboard and mouse work when the **button on** ✓
- ② The keyboard and mouse are stilled when the **button off** ✓
- ③ The keyboard and mouse are (keeping) stilled when the **button on** ✗



Markovian Property: “Deterministic” Systems

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- “Causal Markov ” Doesn’t Hold in “Indeterministic Systems”



Markovian Property: “Deterministic” Systems

- Working States of Laptop, Keyboard, and Mouse:
 - ① The keyboard and mouse work when the button on ✓
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 - ③ The keyboard and mouse are (keeping) stilled when the button on ✕
- “Causal Markov ” Doesn’t Hold in “Indeterministic Systems”
- **Good News: It Will Hold Again in a “Microscopic” System**



Restrict the Trait About Causal Dependence

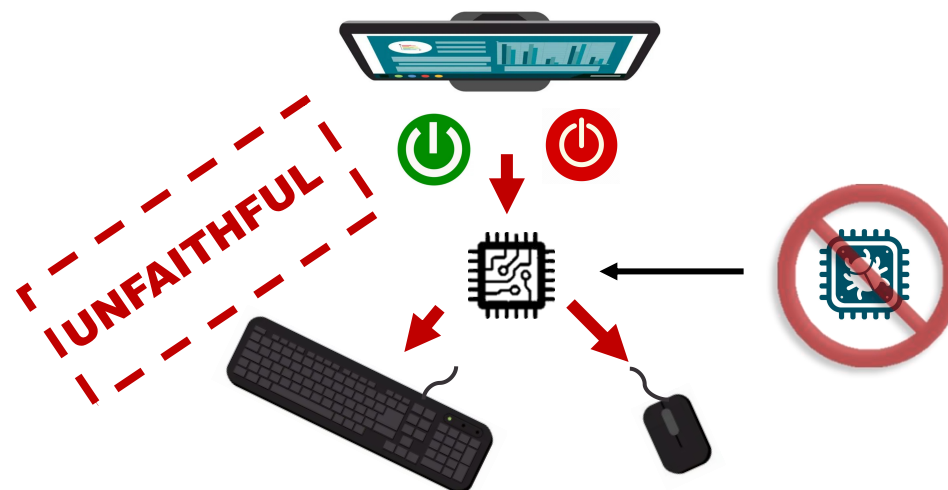
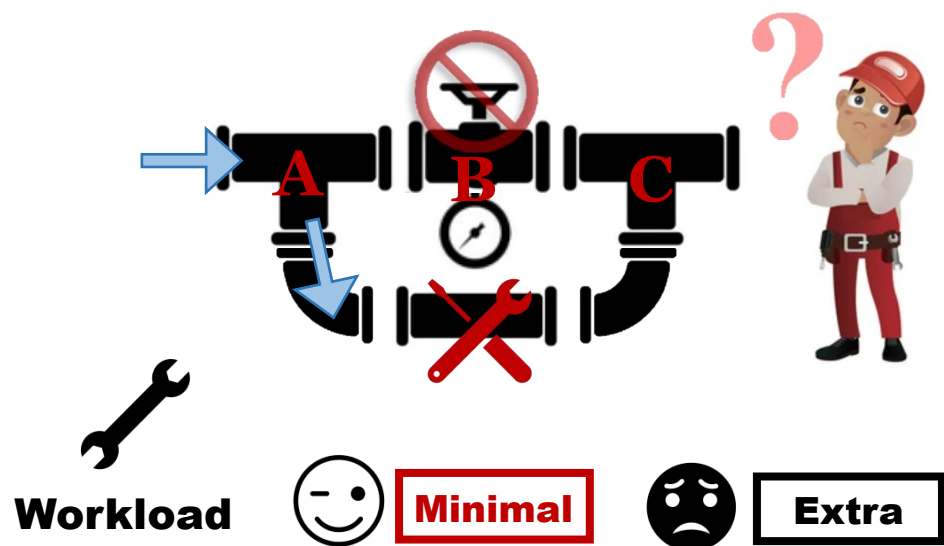
Restrict the Complexity About Causal Mechanisms

Causal Minimality and Causal Faithfulness

“Aside from independence, what about dependence?”

“Restriction **prohibiting** the dependence of **causal insignificance**”

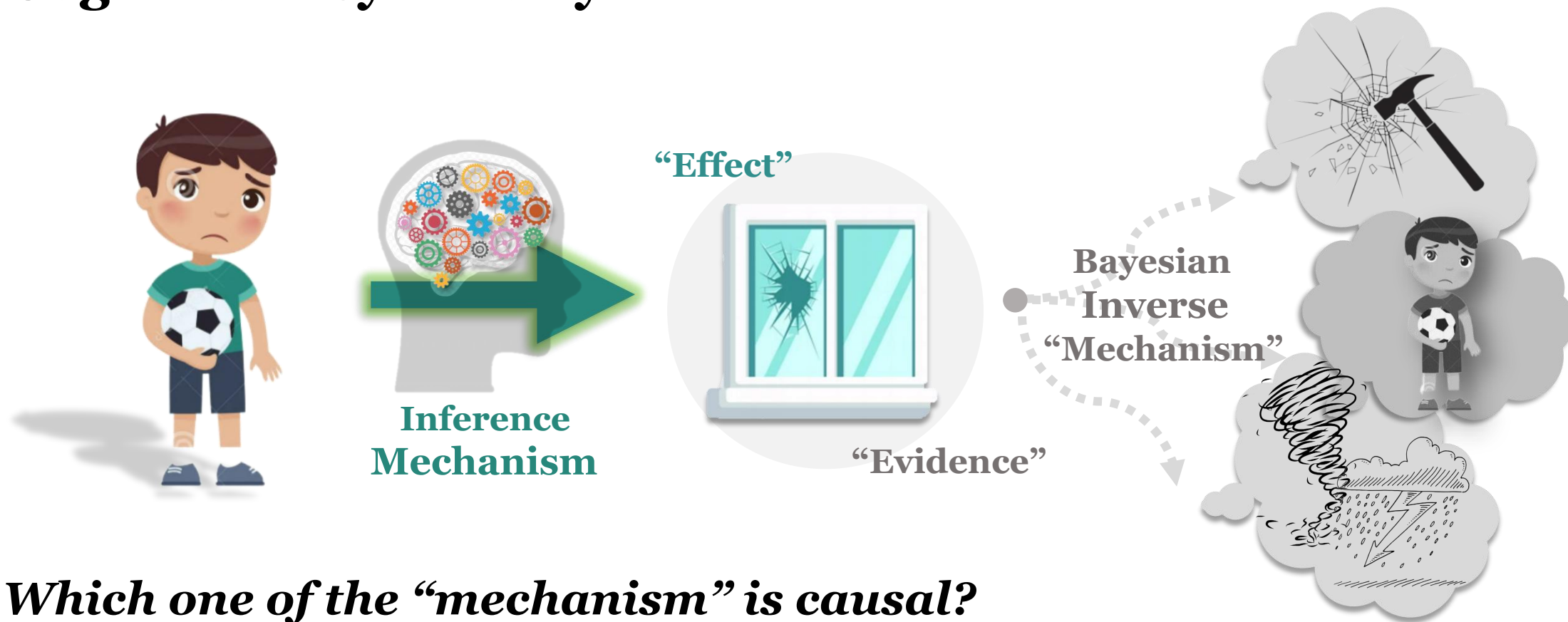
*“to work **normally**”*



Restrict the Trait About Causal Dependence

Restrict the Complexity About Causal Mechanisms

Cognition Asymmetry



Restrict the Trait About Causal Dependence

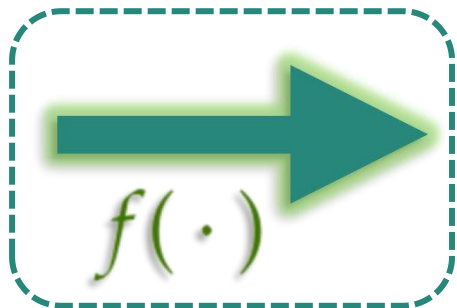
Restrict the Complexity About Causal Mechanisms

Mechanism Complexity

Restrict function capacities from ML perspectives



“Function Capacity”



Forward Direction
(Causal Direction)

“Function Capacity”



Backward Direction



INFERRED CAUSATION

Challenges: Unmeasured Common Cause

March 10. 2024

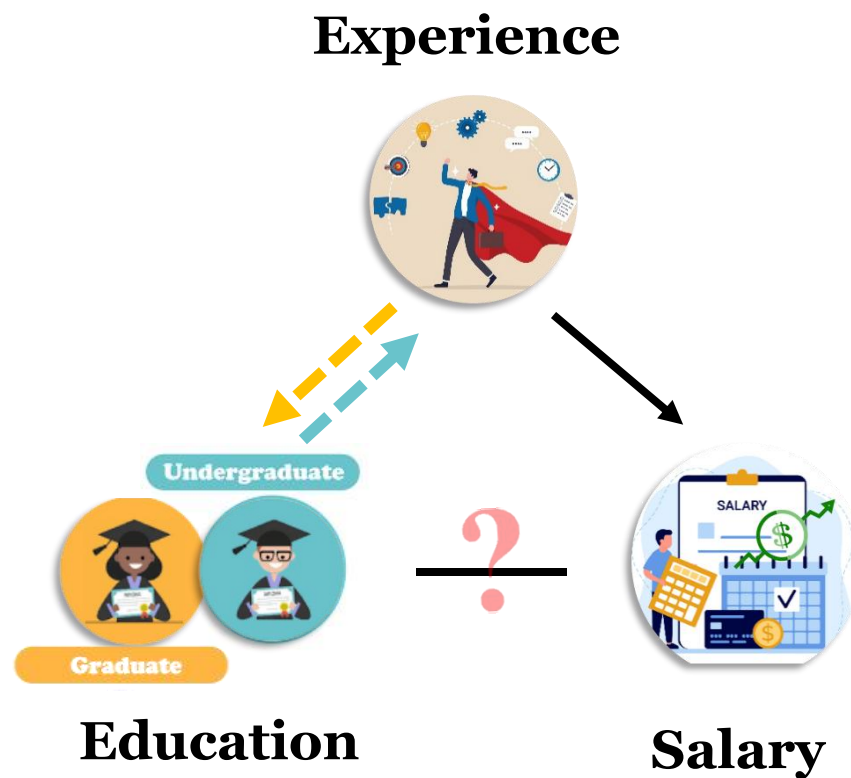
Xuanzhi Chen

Horizontal: Perception is Important than Operation

Vertical: Elaboration of High-Level Causal Semantics

➤ **Example from The Book of WHY**

- Education, salary, experience
- Controlled experiments
- Be care of the possible mechanism



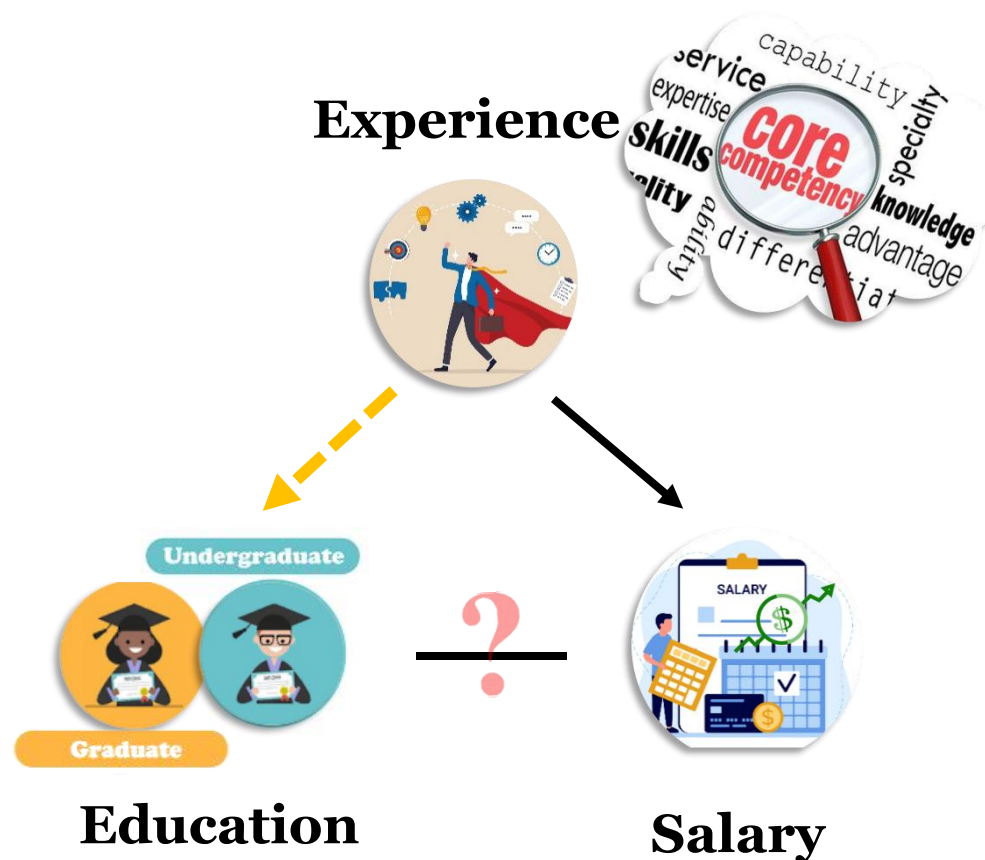
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➤ Experience -> Education



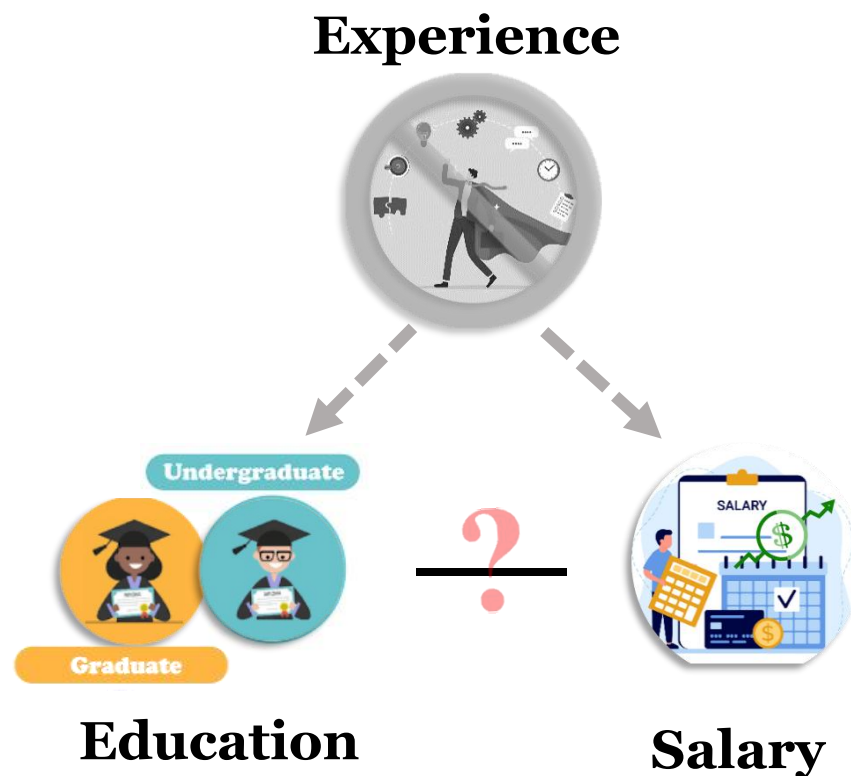
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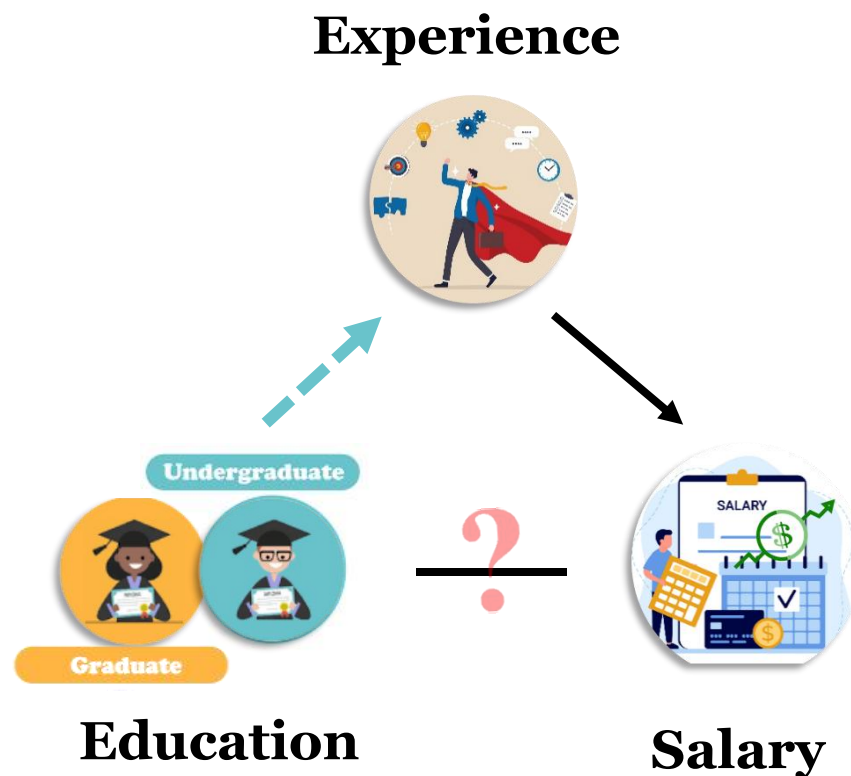
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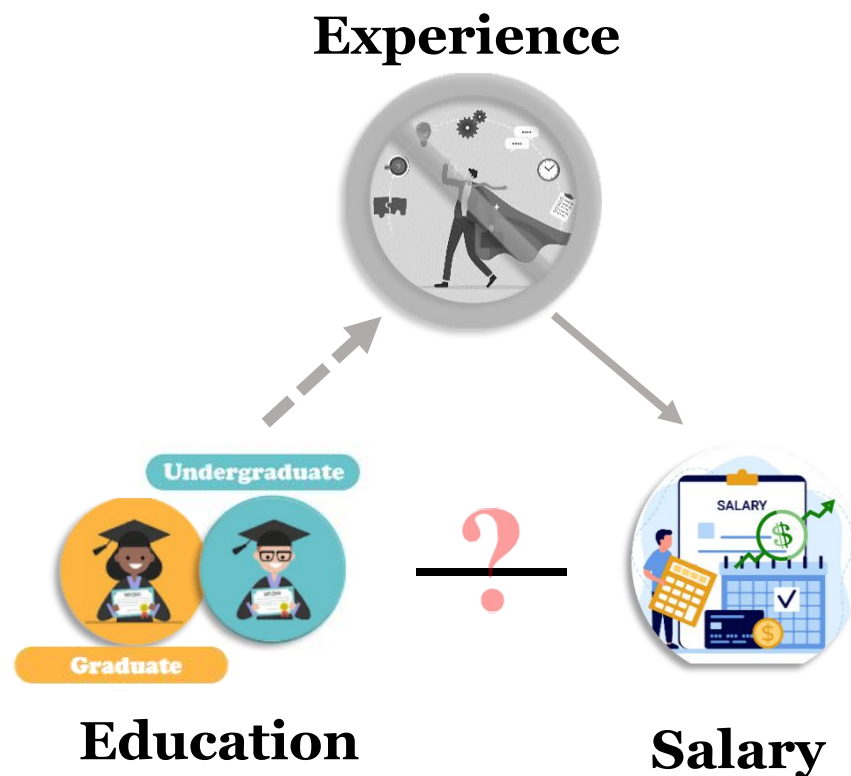
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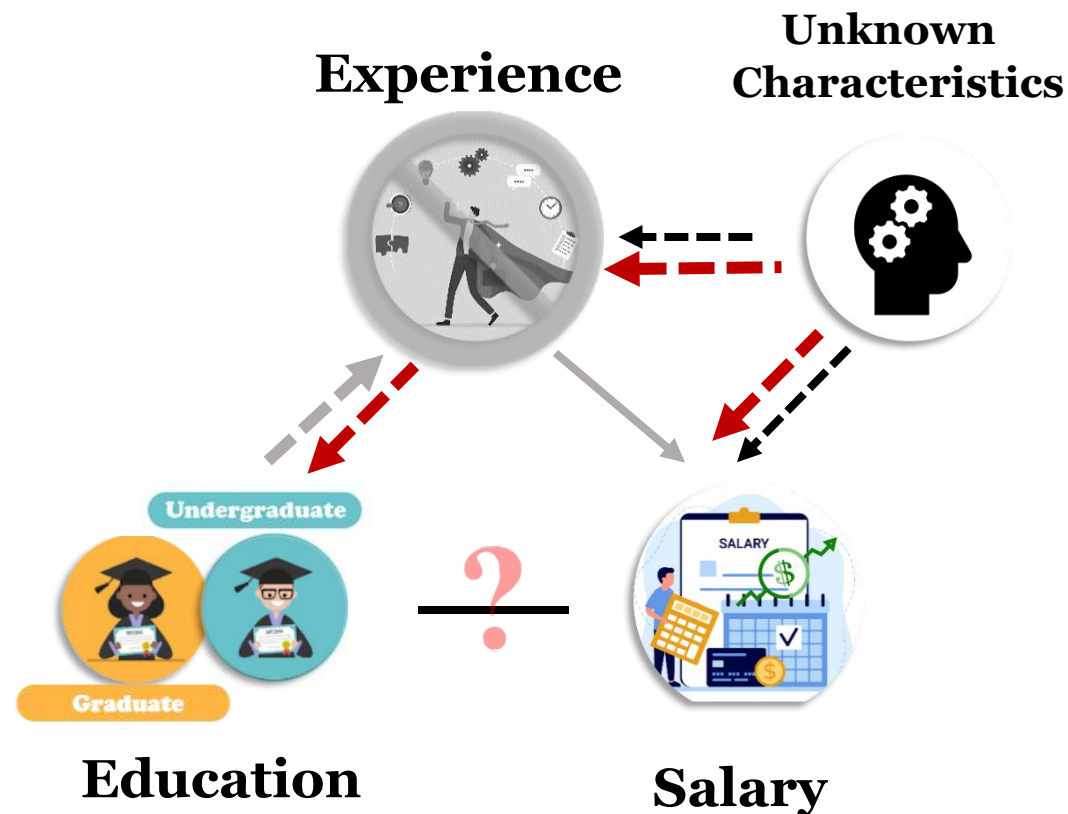
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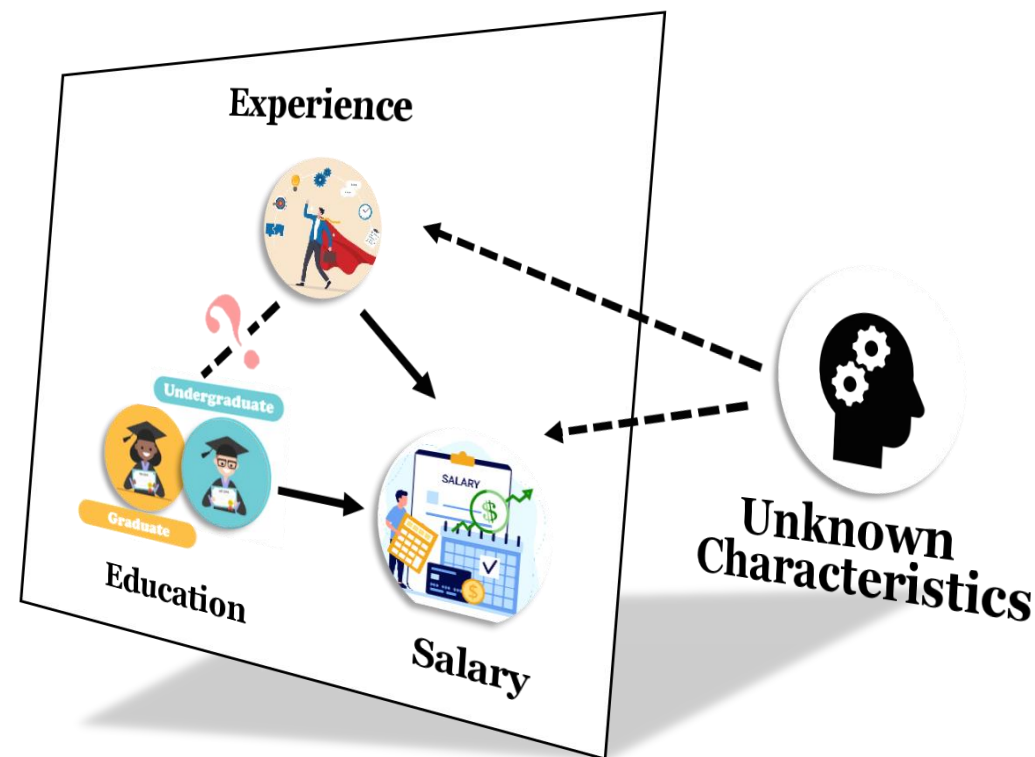
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Horizontal: Perception is Important than Operation

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- Education -> Experience
- **Control it or Keep Unmeasured?**

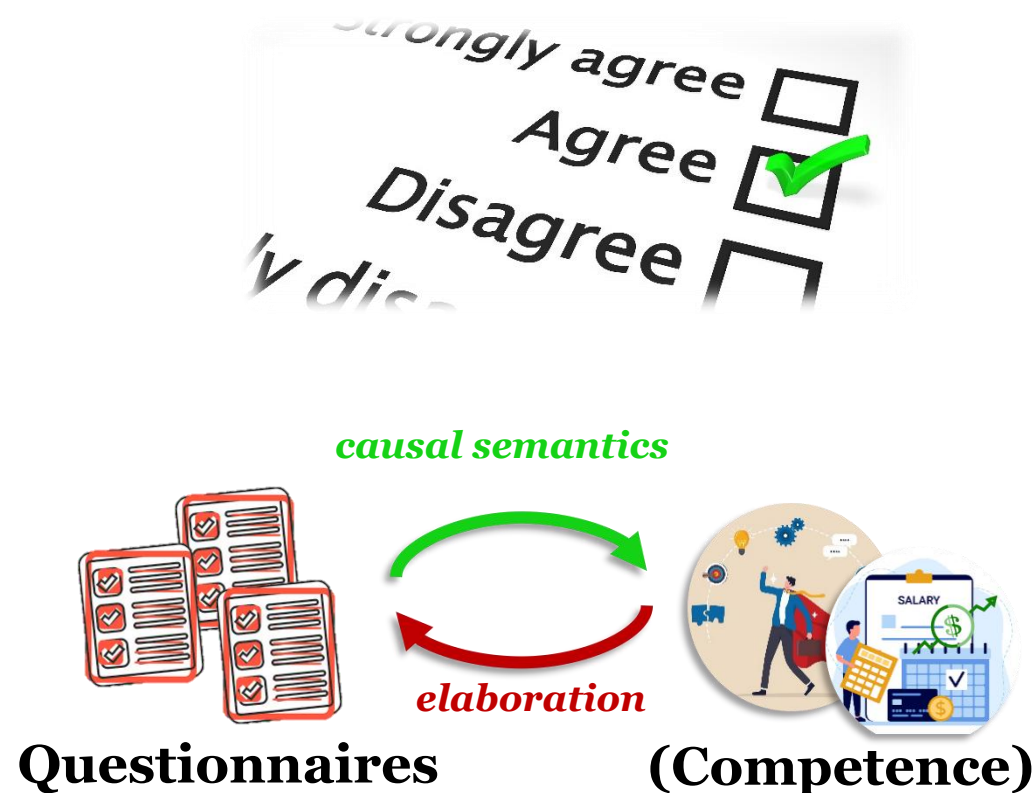
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- **Questionnaires to Characterize the Factors**
 - Superior factors for causal semantics
 - **Elaboration**: measurement model

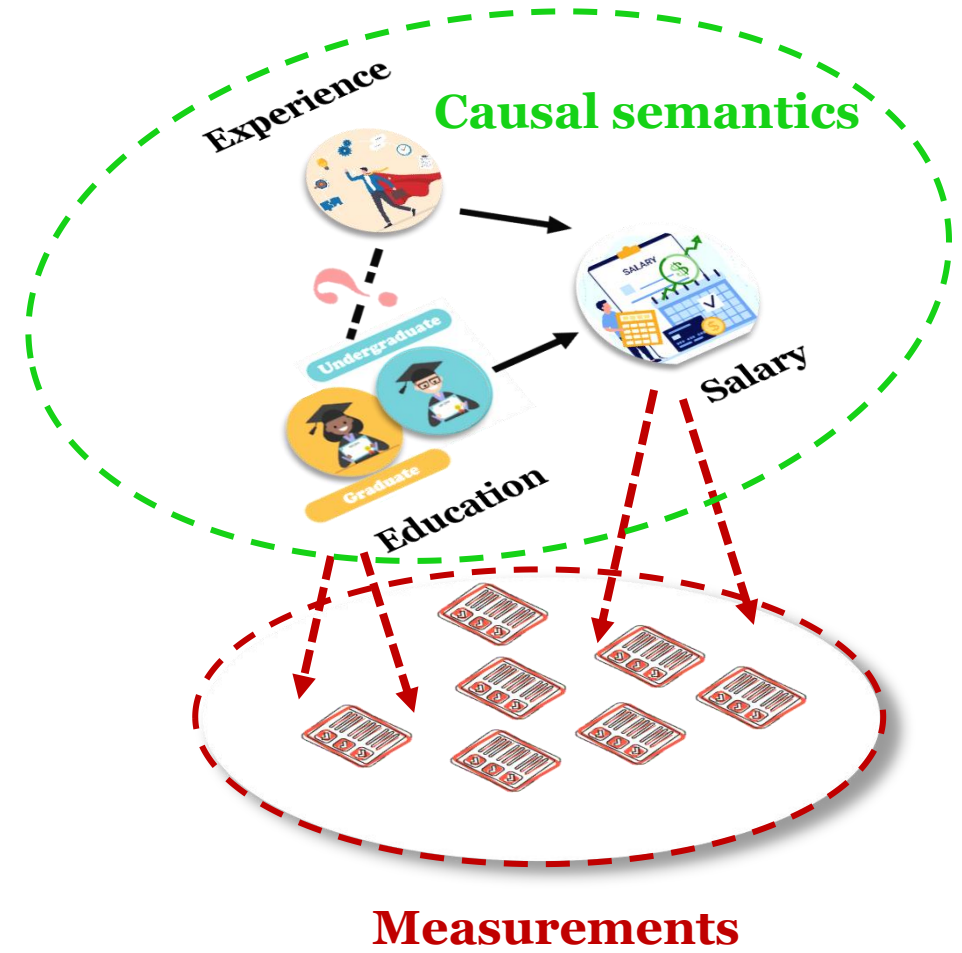
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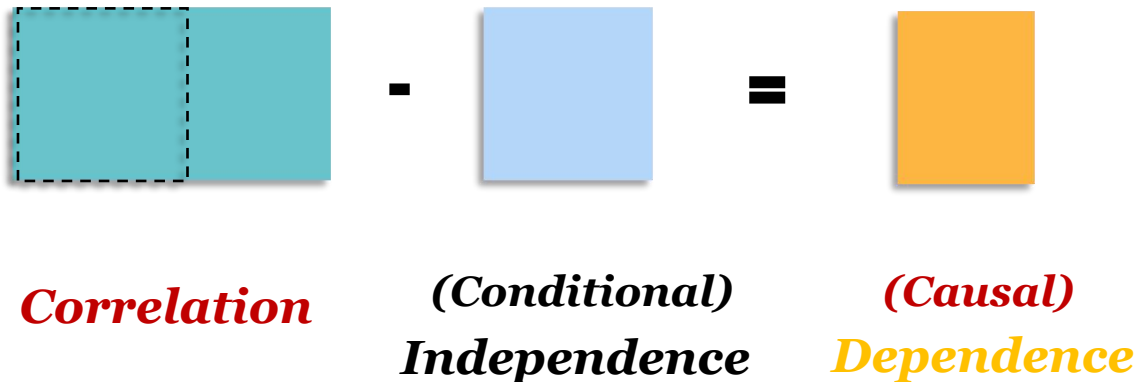


From the Causal Path to the Inducing Path

From Conditional Independence Constraints to Tetrad Constraints

Concept of Inducing Path

"Correlation is not causation."



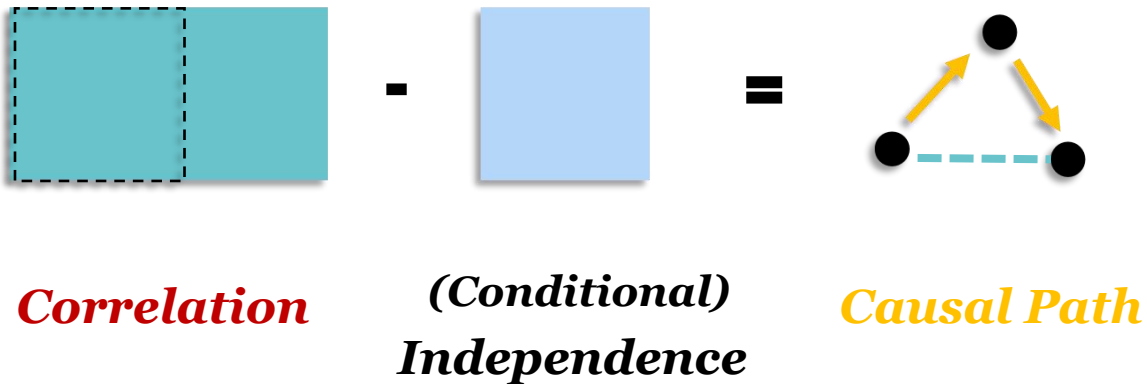
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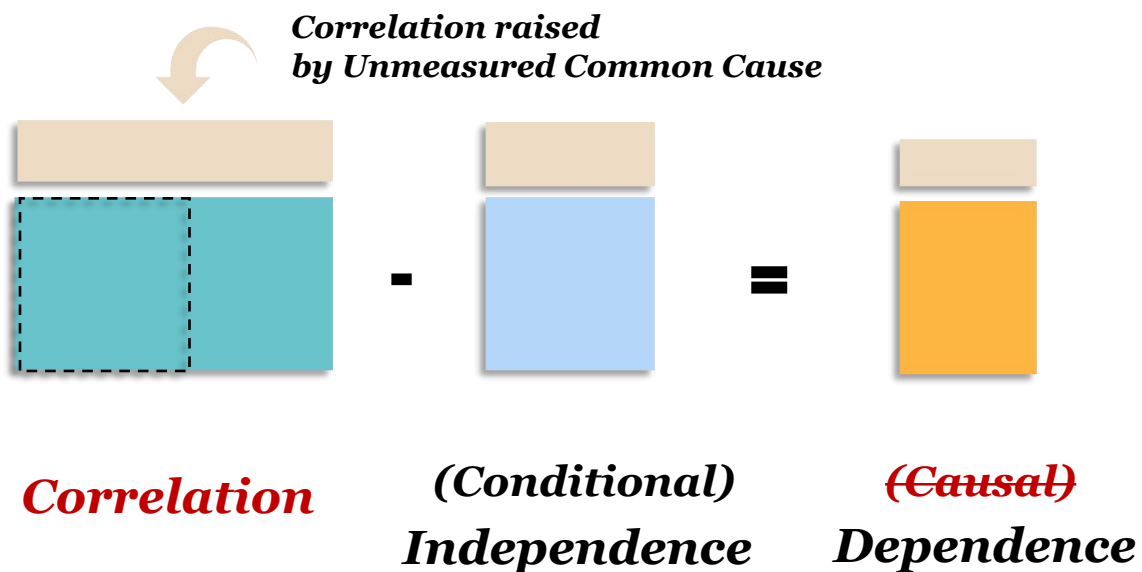
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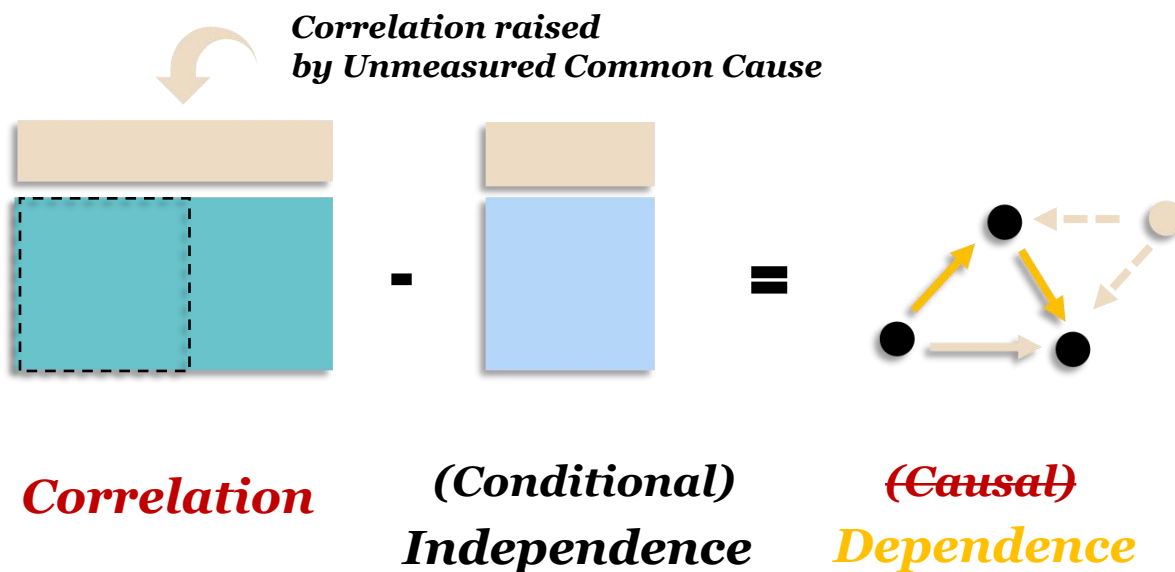
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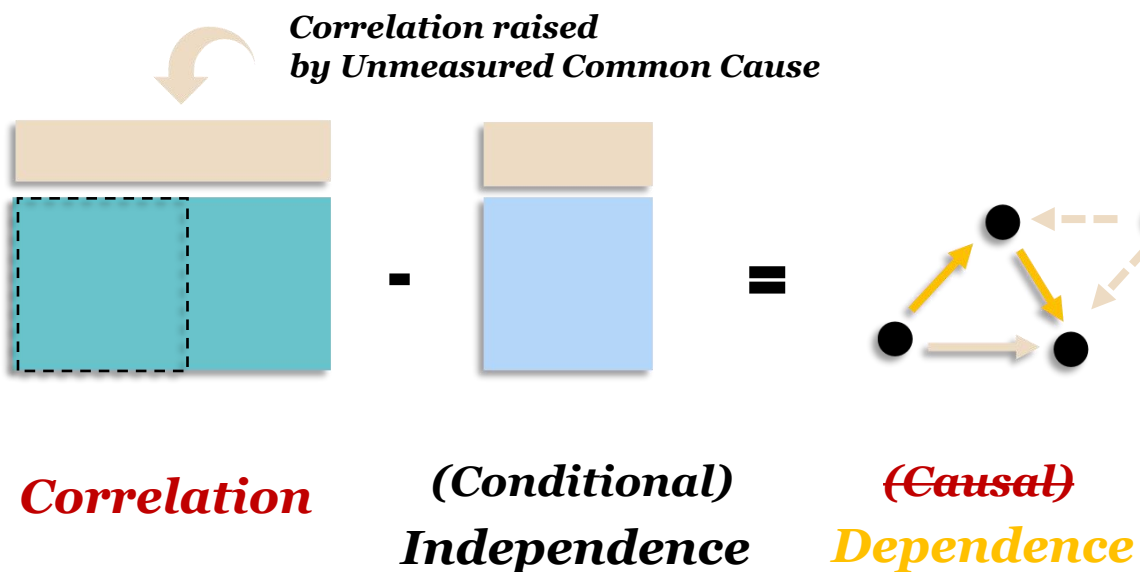
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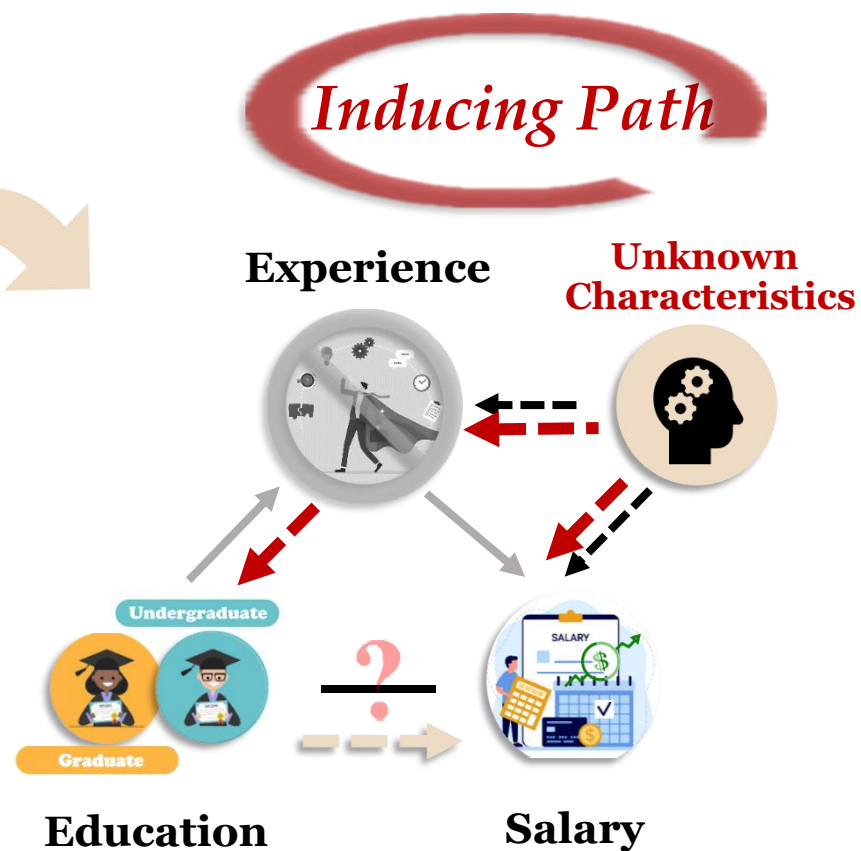
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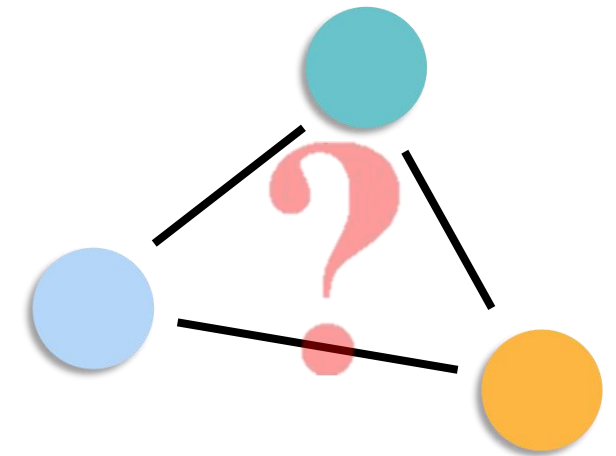
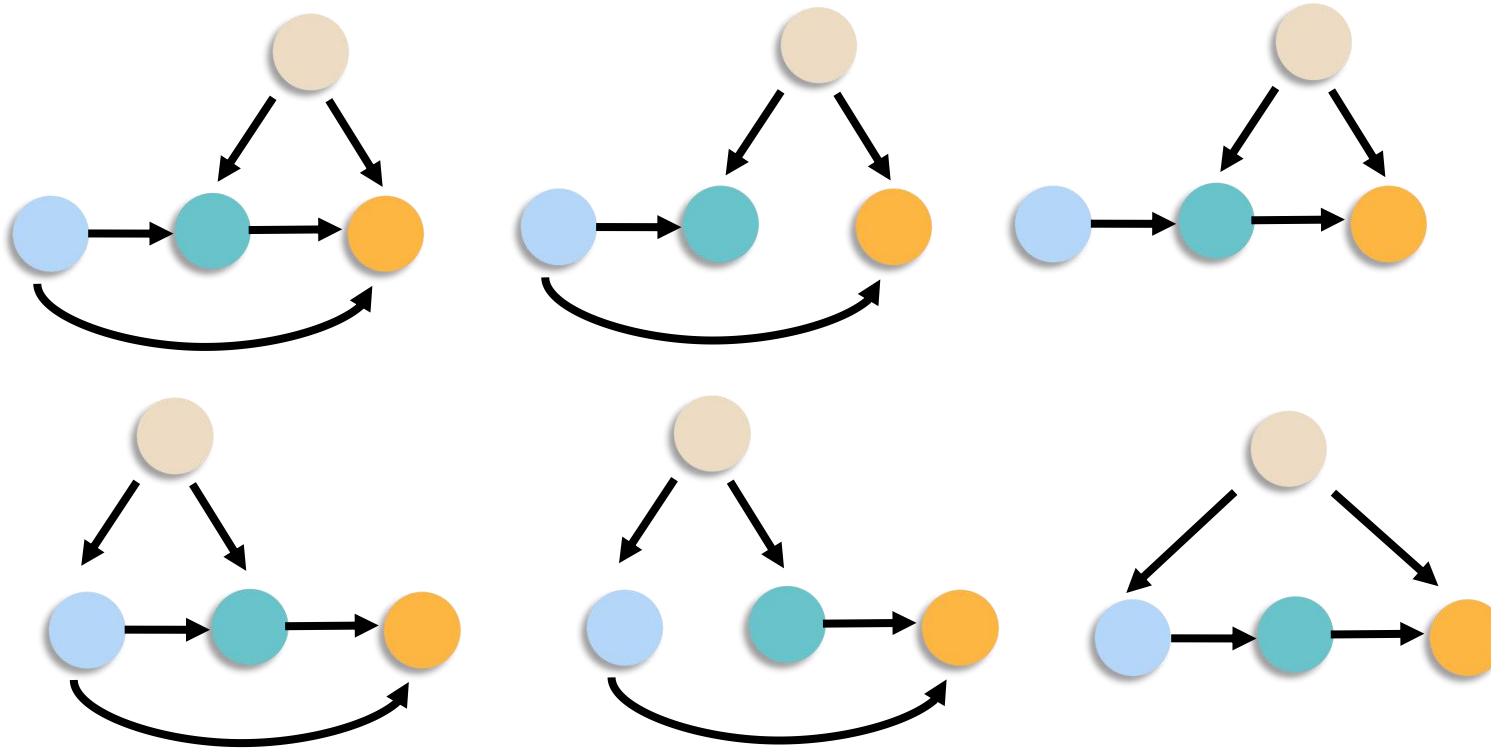
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From the Causal Path to the Inducing Path

From Conditional Independence Constraints to Tetrad Constraints

Matching Diversity and Complexity

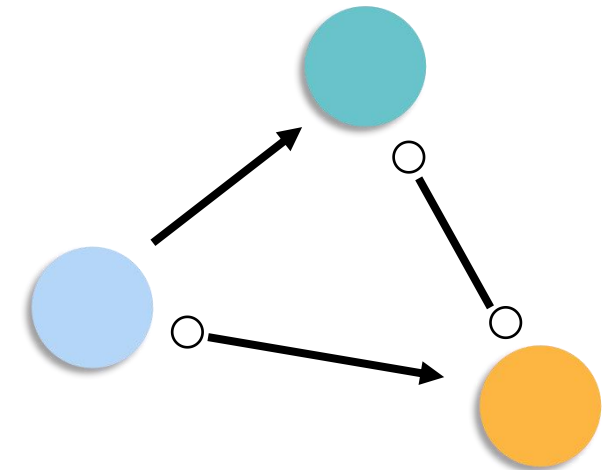
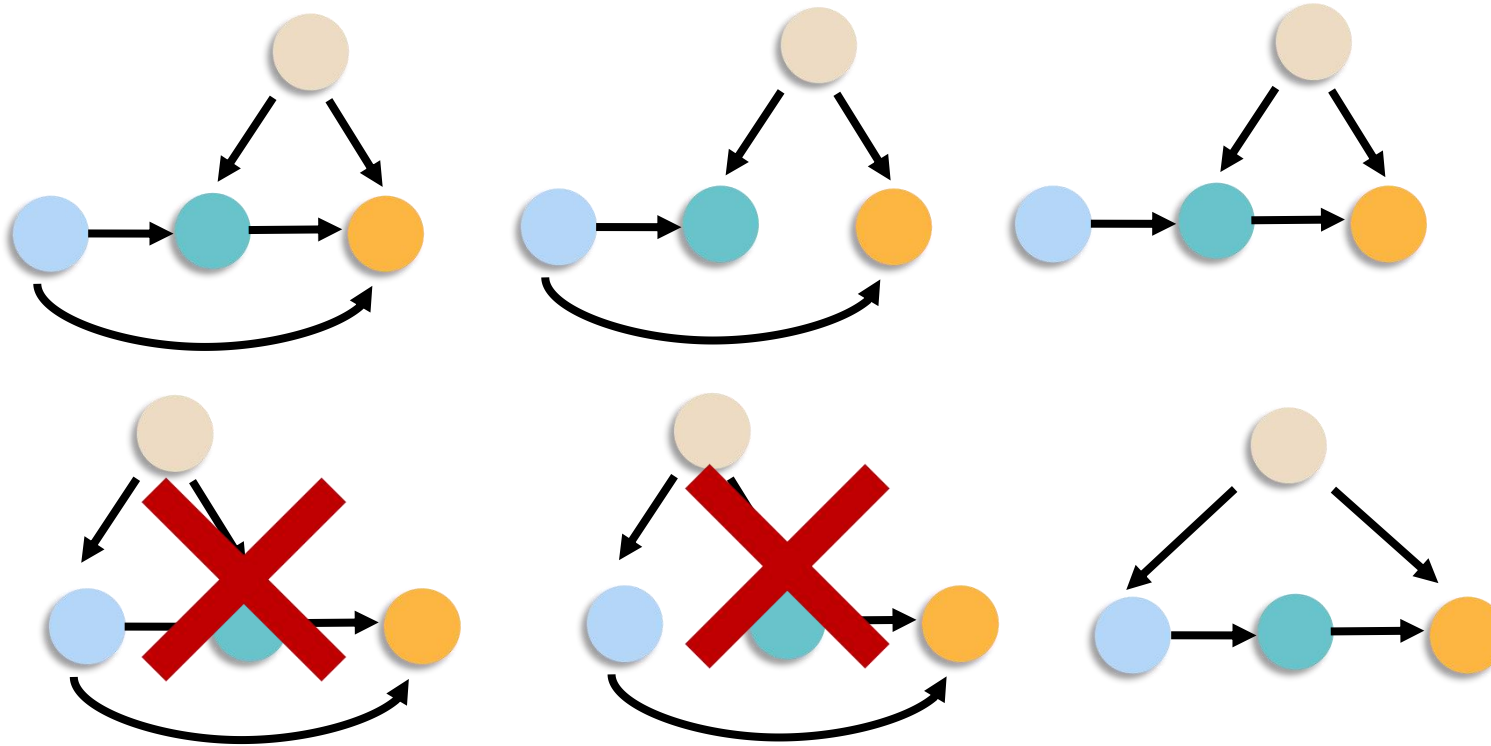


**Markovian
Equivalents**

From the Causal Path to the Inducing Path

From Conditional Independence Constraints to Tetrad Constraints

Matching Diversity and Complexity



**Induce Path
Equivalents**

Developments of Causal Discovery Algorithms

**Markovian
Equivalents**



**Induce Path
Equivalents**

Spites-Glymour-Scheines
The SGS algorithm



Verma, Pearl
The causal inference
(CI) algorithm

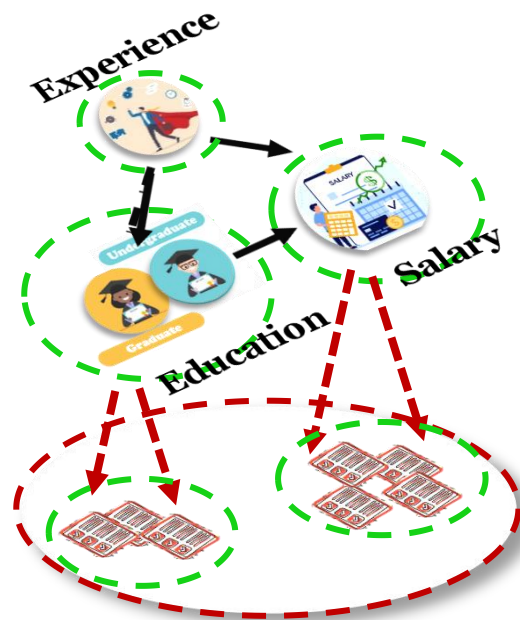


Peter-Clark
The PC algorithm

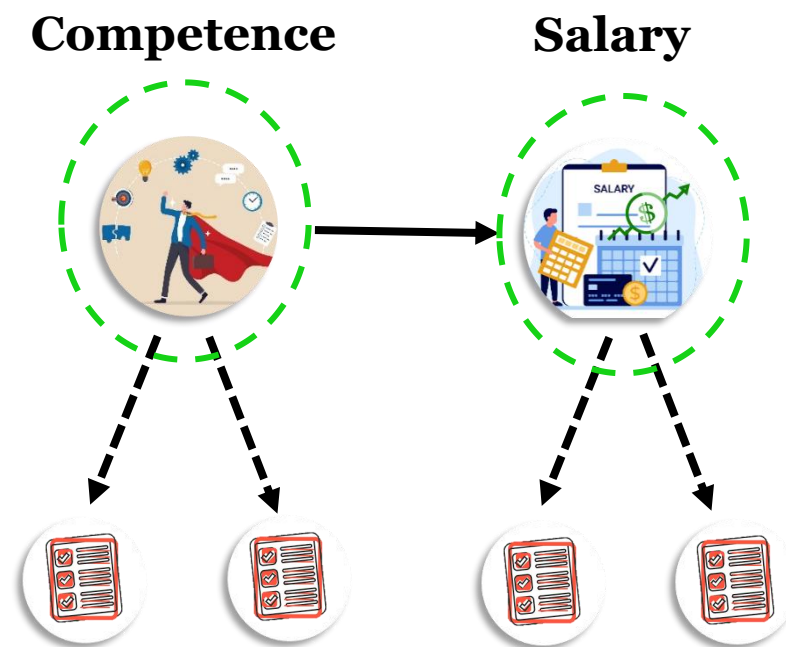


Glymour Clark
The fast causal inference
(FCI) algorithm

Back to the Education-Salary Example



Find out clusters



Intuition of **Tetrad Constraints**