



USAID
FROM THE AMERICAN PEOPLE

Potential Outcomes

USAID MENA Advanced MEL Workshop

Objectives of Impact Evaluation Sessions

- Understand the need for impact estimation of USAID activities
- Understand how impact estimation fits into the Agency performance management framework
- Gain practical knowledge about impact evaluation to help USAID staff better manage and support IEs

Benchmarks for Success

By the end of this session, participants will be able to:

- Explain the fundamental problem of causal inference
- Explain how impact estimation can be seen as a problem of missing data
- Relive unpleasant schoolhood memories of having to learn algebra

Benchmarks for Success

Bonus content:

- Is causal inference a two-body or three-body problem?
- How has causal inference developed out of traditions from MENA region?

The Fundamental Problem

Measuring Social Benefit

We want to know the causal effect of an activity on its beneficiaries

- Job training on earnings and employment
- Teacher qualifications on student outcomes
- Humanitarian assistance on food security

Identifying a Treatment Assignment

- Consider an indicator for a *potential* beneficiary, D_i
- D tells us whether there is an activity, or a “treatment”
- The subscript i denotes a single individual who is either treated or not treated
 - $D_i = 1$ means participation in an activity
 - $D_i = 0$ means no participation in an activity

Identifying an Outcome

Now consider an indicator for the outcome of a potential beneficiary, Y_i , where i denotes each person or unit under study.

- Y_i^1 is the outcome after activity participation ($D_i = 1$)
- Y_i^0 is the outcome without the activity ($D_i = 0$)
- Note that Y^1 and Y^0 denote possibilities for the same unit, unit i

From Potential to Realized Outcomes

We use what is called a ‘switching equation’ to assign treatment and move from a potential to a realized outcome

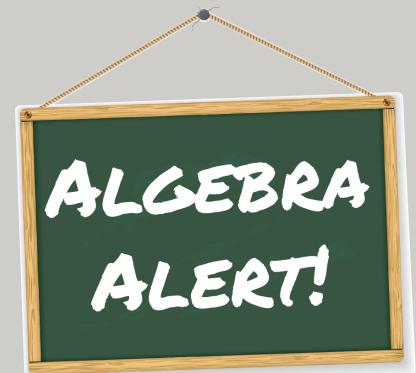
- $Y_i = D_i Y_i^1 + (1 - D_i) Y_i^0$

(Plug in $D_i = 1$ and $D_i = 0$ and see what you end up with)

Treated Outcome

$Y_i = D_i Y_i^1 + (1 - D_i) Y_i^0$ where $D_i = 1$

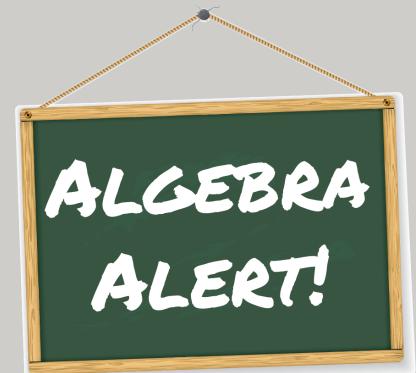
- $Y_i = (1 \times Y_i^1) + (1 \times Y_i^0) - (1 \times Y_i^0)$
- $Y_i = Y_i^1 + Y_i^0 - Y_i^0$
- $Y_i = Y_i^1$



Untreated Outcome

$Y_i = D_i Y_i^1 + (1 - D_i) Y_i^0$ where $D_i = 0$

- $Y_i = (0 \times Y_i^1) + (1 \times Y_i^0) - (0 \times Y_i^0)$
- $Y_i = 0 + Y_i^0 - 0$
- $Y_i = Y_i^0$



Difference Between Assignment and Mechanism

- The switching equation determines where (to whom) treatment is assigned
- We call this the treatment assignment
- The switching equation does **NOT** address **HOW** treatment is assigned
- We call this the treatment assignment *mechanism*

From Assignment to Treatment Effect

We can also write the switching equation this way:

- $Y_i = Y_i^0 + (Y_i^1 - Y_i^0)D_i$
- Notice our treatment effect $Y_i^1 - Y_i^0$, or the difference between the treated and untreated outcome
- We call the difference $Y_i^1 - Y_i^0$ *delta*, or δ_i
- Remember that the treatment effect δ_i refers to a *single* unit or person!

Recap

- The effect of the activity (treatment effect) on unit i is the difference between the two potential outcomes
- $Y_i^1 - Y_i^0$ is the difference in outcomes for the *same unit or person*
- A person participates in an activity, and then goes back in time and does not participate in the activity
- Or, a person participates in an activity, and then we check an alternate universe where she did not participate in the activity

You Ask the Impossible

- But how can one person be both treated and untreated?
- In the real world, person i experiences one of the potential outcomes, but not both
- If $D_i = 1$, the potential outcome of Y_i becomes Y_i^1 in fact and the outcome of Y_i^0 is unknowable
- If $D_i = 0$, the potential outcome of Y_i becomes Y_i^0 in fact and the outcome of Y_i^1 is unknowable

The Fundamental Problem of Causal Inference

- This is the fundamental problem of causal inference
- We observe only one outcome, but we need both outcomes to describe the effect of the activity
- We refer to the outcome that didn't happen as the *counterfactual*, or what would have happened in the absence of the activity

Something is Missing

Group	Y_i^1	Y_i^0
Treatment	Observed	Counterfactual
Control	Counterfactual	Observed

- Researchers sometimes refer to impact evaluation as a “missing data problem”
- We are missing two pieces of information about what happens with or without the treatment

What Do We Do Now?

- How do we estimate the effect of a activity, if we cannot observe both realized outcomes?
- We can't go back in time, and we don't have access to alternate universes
- We must compare what was treated with something that was not treated
- But, what are the differences between the two? How might these differences obscure the true effect of the activity?

Cliffhanger

Tune into next sessions for resolution of the Fundamental Problem of Causal Inference!

- Experimental impact evaluation
- Quasi-experimental impact evaluation

Bonus Content

- Causal inference as a two-body or a three-body problem
- Causal inference from traditions in Middle East and North Africa

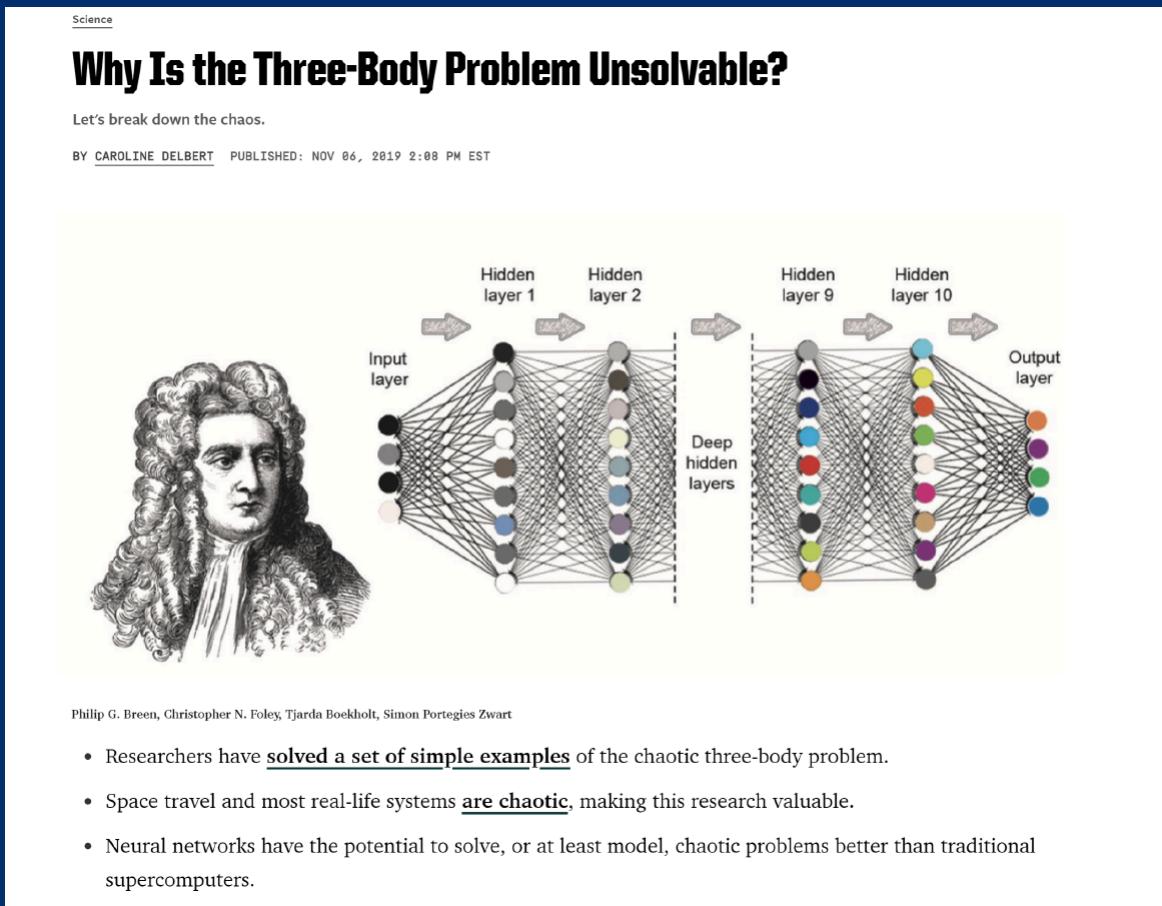
The Three-Body Problem

Science

Why Is the Three-Body Problem Unsolvable?

Let's break down the chaos.

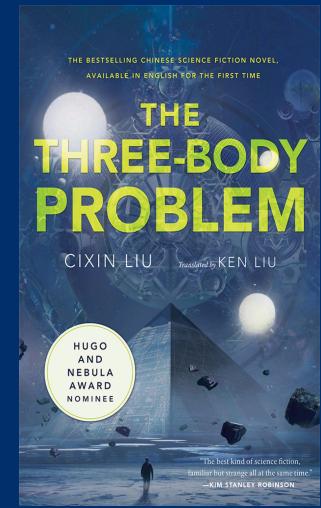
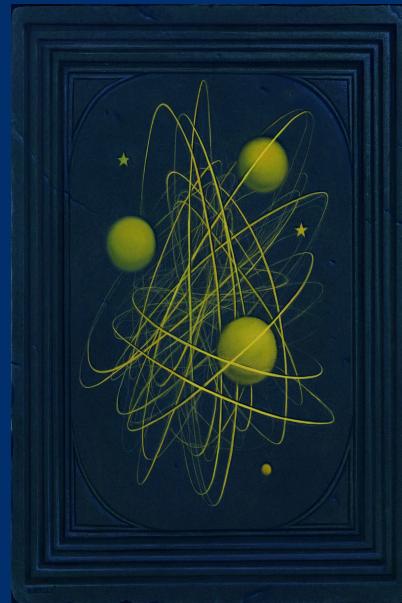
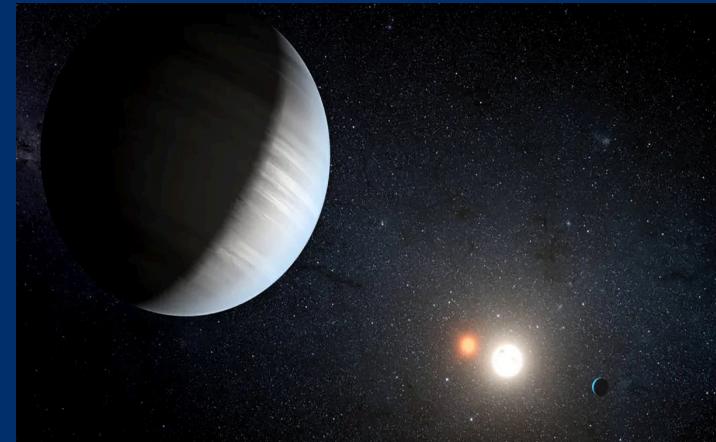
BY CAROLINE DELBERT PUBLISHED: NOV 06, 2019 2:08 PM EST



A diagram illustrating a deep learning model's architecture. On the left, there is a black and white portrait of Isaac Newton. To the right of the portrait is a diagram of a neural network. The network consists of an input layer with 10 nodes, followed by two hidden layers (Hidden layer 1 and Hidden layer 2) each with 10 nodes, and then a deep hidden section containing 9 more hidden layers, each with 10 nodes. The final layer is the output layer with 10 nodes, each colored differently (orange, yellow, green, red, blue, purple, brown, pink, light blue, and grey). Arrows indicate the flow of data from the input layer through the hidden layers to the output layer.

Philip G. Breen, Christopher N. Foley, Tjarda Boekholt, Simon Portegies Zwart

- Researchers have solved a set of simple examples of the chaotic three-body problem.
- Space travel and most real-life systems are chaotic, making this research valuable.
- Neural networks have the potential to solve, or at least model, chaotic problems better than traditional supercomputers.



Causal Inference in the MENA Tradition

- Al-Kindi, Al-Farabi, Ibn Sina: The Philosophers
- Al-Ghazali: The Incoherence of the Philosophers
- Ibn Rushd: The Incoherence of the Incoherence
- Scientific method
 - Al-Biruni (Astronomy)
 - Al-Haythem (Optics)

Who else ..?

Thank you!