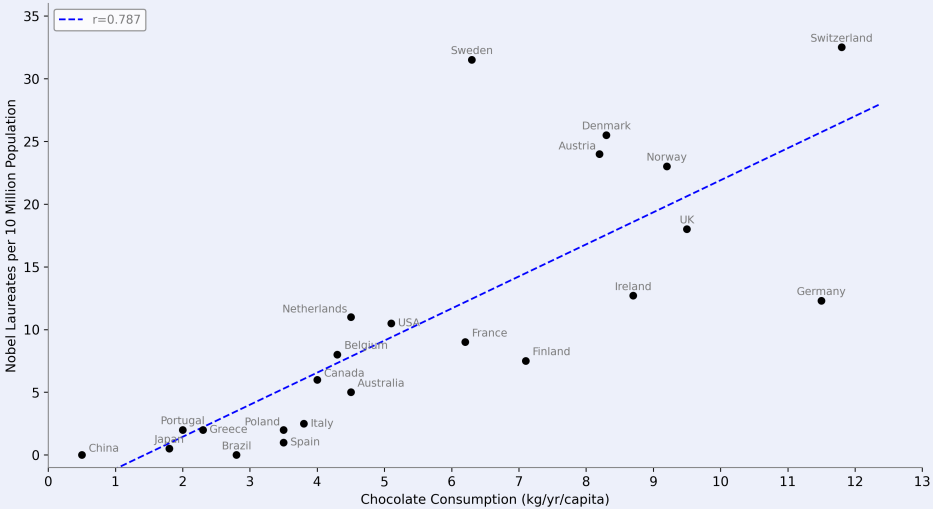
Revisiting the Big Three

- Sufficiency: All common causes are **measured**. (No doubts about parents!)
- Faithfulness: Graph reflects **all** data independencies. (WYSIWYG!)
- Markov: Data reflects **all** independencies in graph. (Graph predicts data!)

Is Chocolate the Secret Ingredient for Genius?

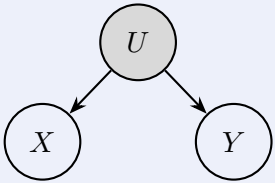


Messerli (2012): Chocolate Consumption, Cognitive Function, and Nobel Laureates

Three Causes of Scientific Sadness

Hidden Confounding

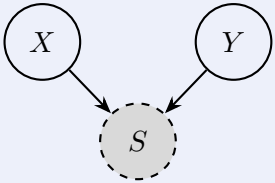
(Sufficiency Sabotage)



Illusory causation

Selection Bias

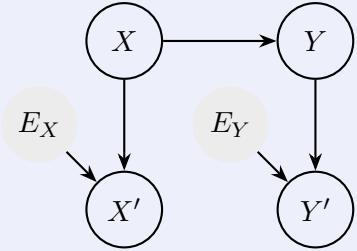
(Faithfulness Fail)



Sample $\neq$ Population

Measurement Error

(Markov Mayhem)



Fuzzy data, fuzzy truths

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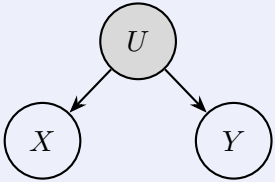

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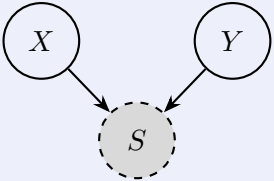

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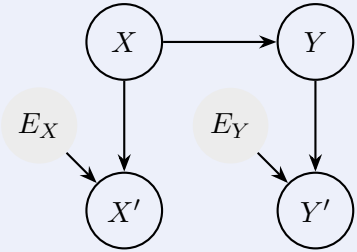
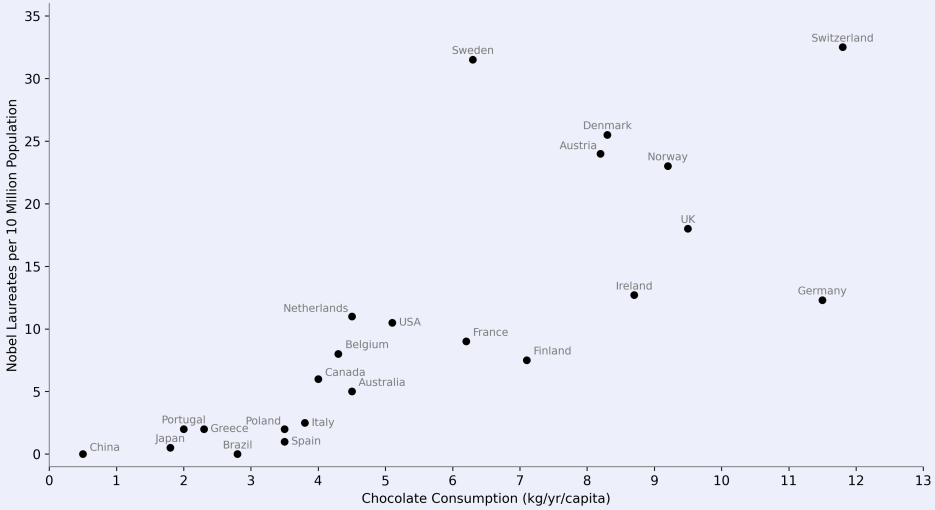


Fuzzy data, fuzzy truths

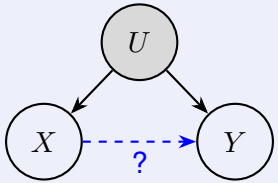
Hidden Confounding

Is Wealth the Hidden Hand?

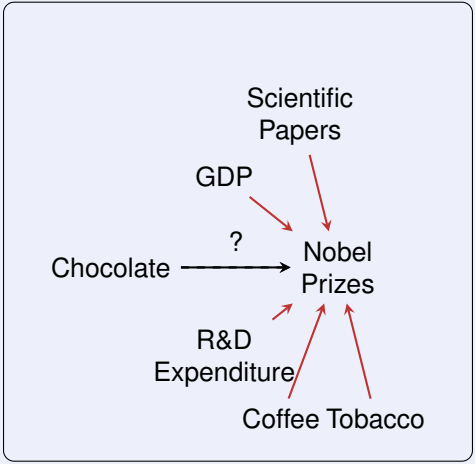


Hidden Confounding: The Unseen Puppeteer

- Unmeasured common cause (U).
- Violated **Causal Sufficiency**.
- "Correlation is not causation".
- Spurious associations found.
- Real associations masked.
- **Wrong** conclusions, **bad** policies.



The Obvious Fix: Just Control For Confounders

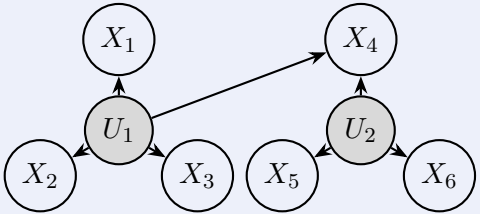


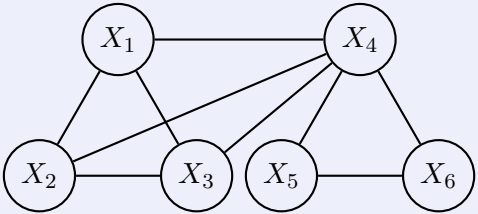
Simply Controlling Does Not Cut It

"Nobel laureates per capita is regressed on chocolate consumption per capita, as well as the number of published scientific papers, R&D expenditures per capita and GDP per capita. In addition, coffee and tobacco consumption per capita are also included. In contrast to the expectation, it is found that a positive correlation between chocolate consumption per capita and the stock of Nobel laureates per capita persists." (emphasis added)

Prinz (2020): Chocolate consumption and Nobel laureates

Graphical Patterns of Confounding





Parametric Patterns of Confounding

If X is generated by

$$X = b^\top U + \epsilon\,,$$

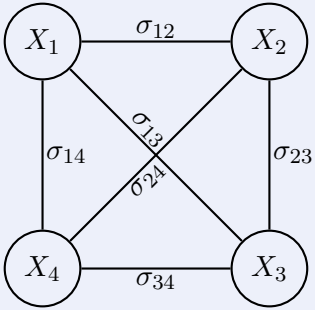
then the **six** covariances

$$\sigma_{ij} = b_i b_j\,,$$

lie on a **four**-dimensional manifold:

$$\sigma_{ij}\sigma_{uv} = \sigma_{iu}\sigma_{jv} = \sigma_{iv}\sigma_{ju} = b_i b_j b_u b_v\,.$$

I.e., the covariance matrix Σ is rank one.



Some Methods for Confounding

- **Compression Discovers Confounding**
  Causal Discovery with Hidden Confounders using the Algorithmic Markov Condition
- **Linear Non-Gaussians, ICA, and Confounding**
  A Versatile Causal Discovery Framework to Allow Causally-Related Hidden Variables
- **Hierarchical Confounding in Linear Non-Gaussians**
  Identification of Linear Non-Gaussian Latent Hierarchical Structure
- **Confounding in Nonlinear Models**
  Nonlinear Causal Discovery with Latent Confounders

RCTs: Not All That Glitters is a Gold Standard

Wait, but why didn't we just do a Randomized Controlled Trial (RCT?)

- **Feasible** RCT? Unlikely.
- **Sample**? Oompa-Loompas or representative humans?
- **Treatment**? What kind of chocolate? Administered how?

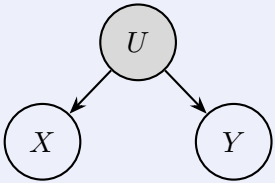
Precise estimate for one kind of chocolate, in one group, in one context.[1]

[1] In behavioral sciences: replication crisis. In CS: "Works on my machine."

Three Causes of Scientific Sadness

Hidden Confounding

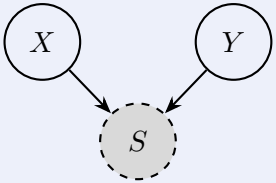
(Sufficiency Sabotage)



Illusory causation

Selection Bias

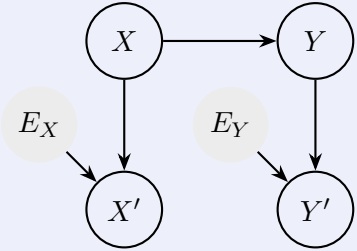
(Faithfulness Fail)



Sample $\neq$ Population

Measurement Error

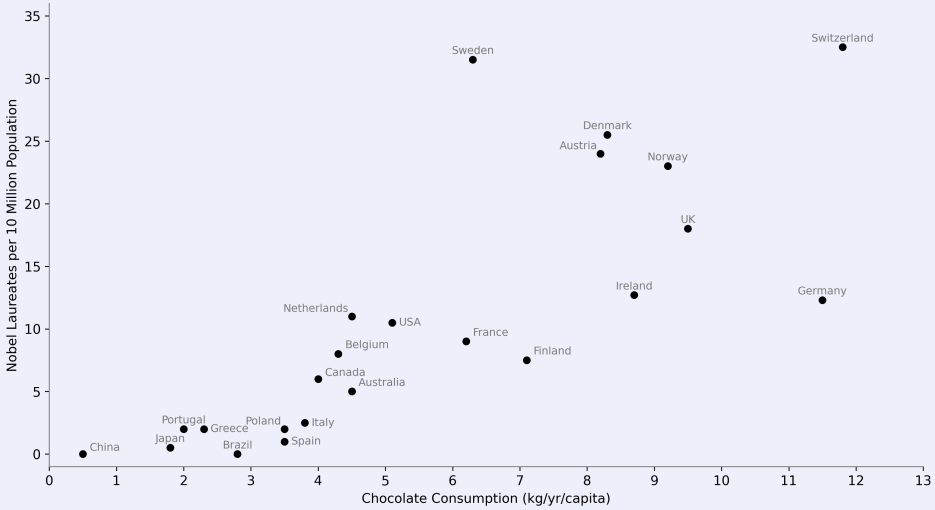
(Markov Mayhem)



Fuzzy data, fuzzy truths

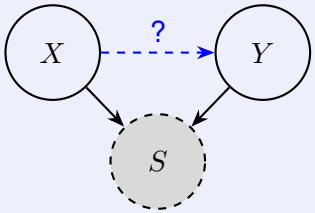
Selection Bias

How Did We Choose These Countries?

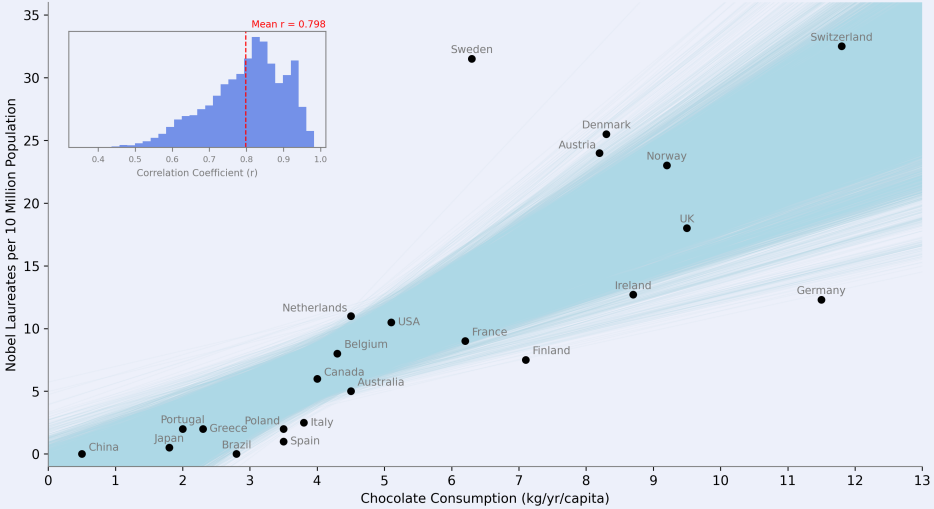


Selection Bias: The VIP Room Problem

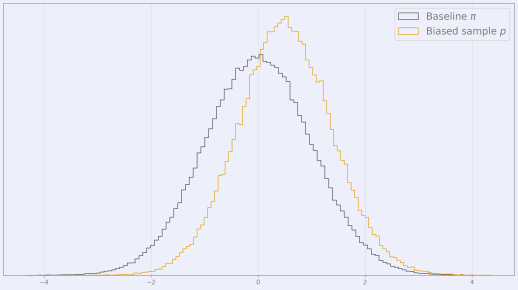
- Conditioning on collider S
- Violated **Faithfulness**
- "Absence of evidence is not evidence of absence".
- Mistaking sample quirks for causal laws.
- Spurious associations found.
- Real associations masked.
- Famous example: **Berkson's Paradox**.

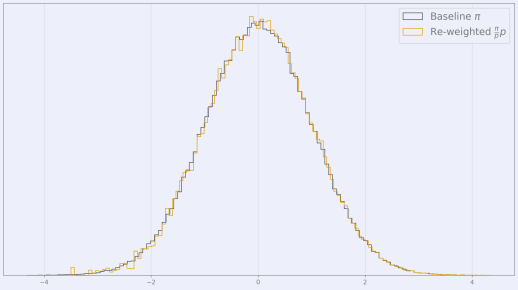


What if We Subsample Some Countries?



Propensity Weights

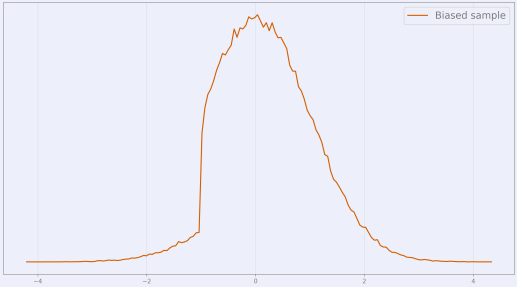


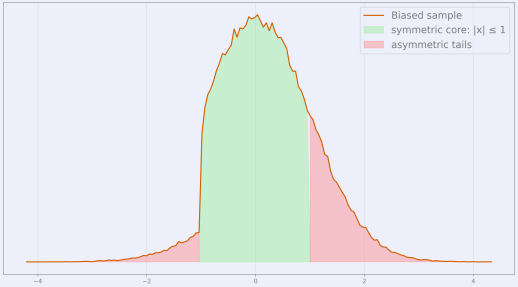


If we know the true distribution, we can use **propensity weights** to adjust models

$$\int h(x)\,\pi(x)\,dx \;=\; \int h(x)\,\frac{\pi(x)}{p(x)}\,p(x)\,dx$$

Boulevard of Broken Symmetries





If we don't know the distribution, we can still notice broken symmetries to adjust

$$\pi \approx p_{\text{sym}} = p(x) \cdot 1_{\{x>-1\}} + p(-x)1_{\{x\leq -1\}}$$

Selection Bias Methods

- **Kernel Mean Matching**
  Correcting Sample Selection Bias by Unlabeled Data
- **Importance Reweighting**
  Covariate Shift Adaptation by Importance Weighted Cross Validation
- **Selection Bias as Class of Distributions**
  A Review on Theory and Applications of Distributionally Robust Optimization
- **Bounding Causal Estimates**
  Nonparametric Bounds on Treatment Effects
- **Parametric and non-Parametric Single-Sample Detection**
  Identifying Selection Bias from Observational Data

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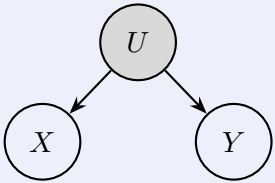

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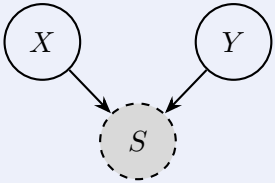

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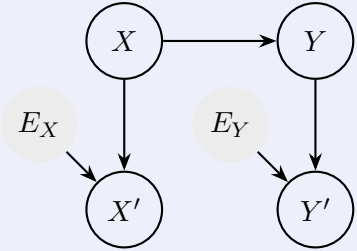
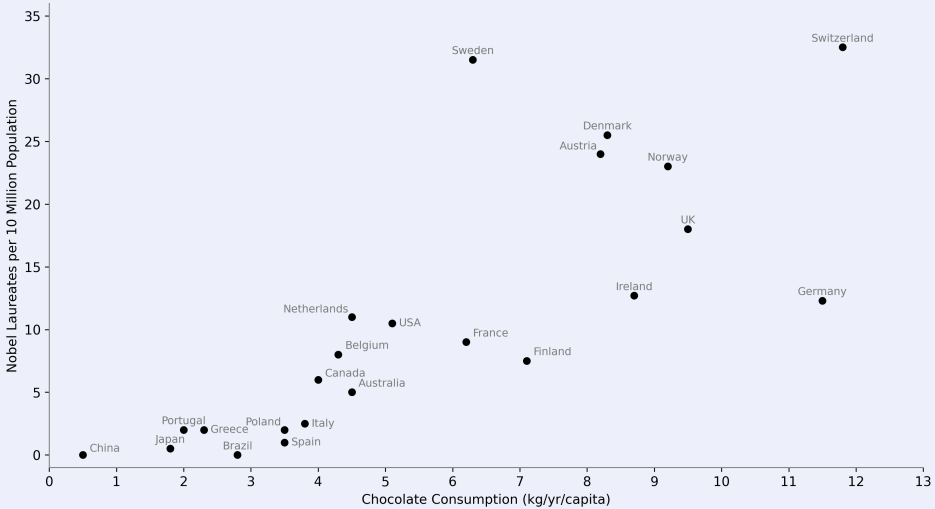


Fuzzy data, fuzzy truths

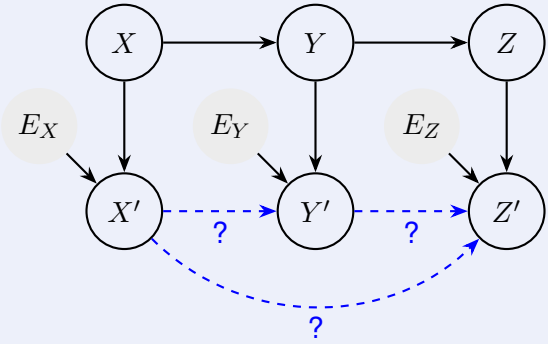
Measurement Error

How Much Can We Trust Those Measurements?

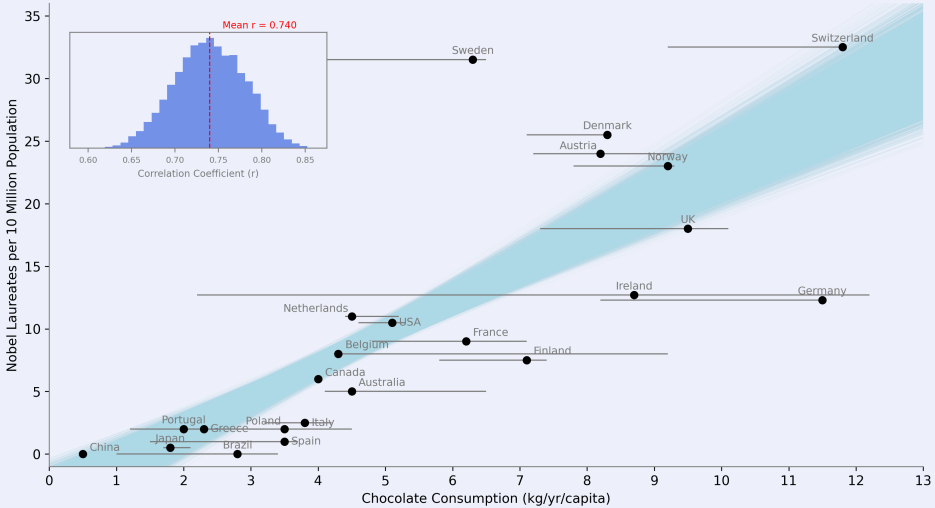


Measurement Error: The Funhouse Mirror

- Observe noisy $X' = f(X, E_X)$.
- Violated **Faithfulness** and **Markov Condition**.
- "The map is not the territory".
- Spurious links found.
- True effects masked.



Measurement Errors and Regression



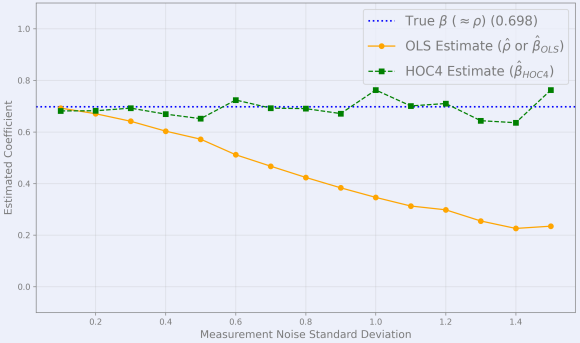
Higher Order Cumulants to the Rescue

If measurement error is Gaussian,

$$\hat{\beta}_{HOC4} = \frac{(n+1)m_{31} - 3(n-1)m_{20}m_{11}}{(n+1)m_{40} - 3(n-1)m_{20}^2}$$

$$m_{pq} = \frac{1}{n}\sum_{k=1}^{n}(x'_k - \bar{x}')^p(y'_k - \bar{y}')^q$$

is still consistent for the true β.



Measurement Error Methods

- **Adding Even More Noise**
  Simulation-Extrapolation Estimation in Parametric Measurement Error Models
- **Correcting Scores for Measurement Error**
  Conditional Scores and Optimal Scores for Generalized Linear Measurement-Error Models
- **Changing the Objective: Total Least Squares**
  Overview of total least squares methods
- **Independence Tests for Linear Non-Gaussian Models**
  Independence Testing-Based Approach to Causal Discovery under Measurement Error and Linear Non-Gaussian Models
- **Regression Calibration and Higher Order Cumulants**
  A comparison of regression calibration, moment reconstruction and imputation for adjusting for covariate measurement error in regression

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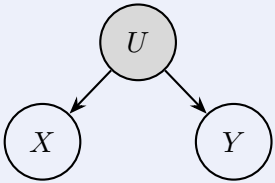

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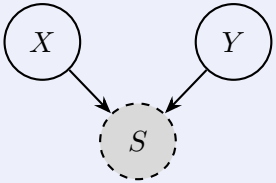

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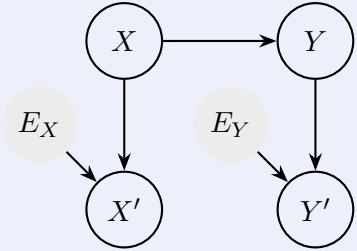
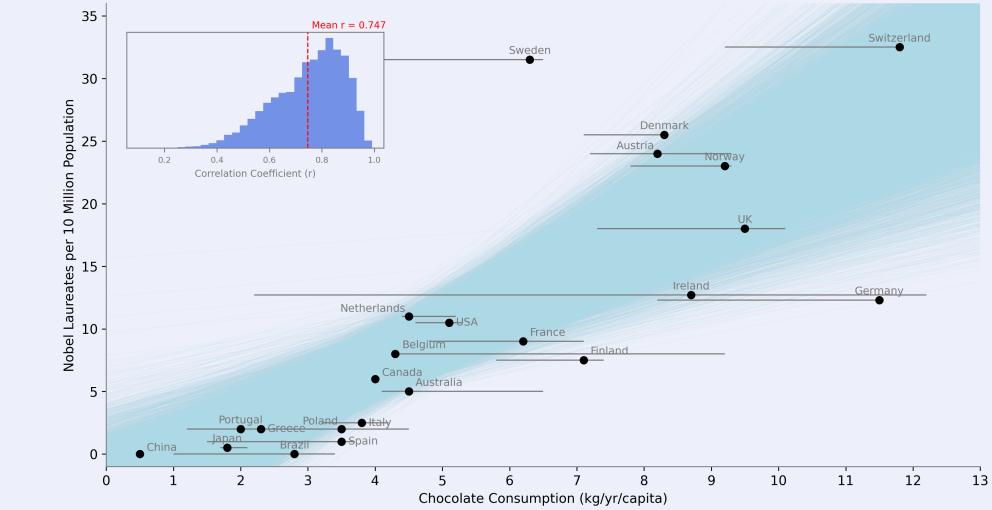
(Markov Mayhem)



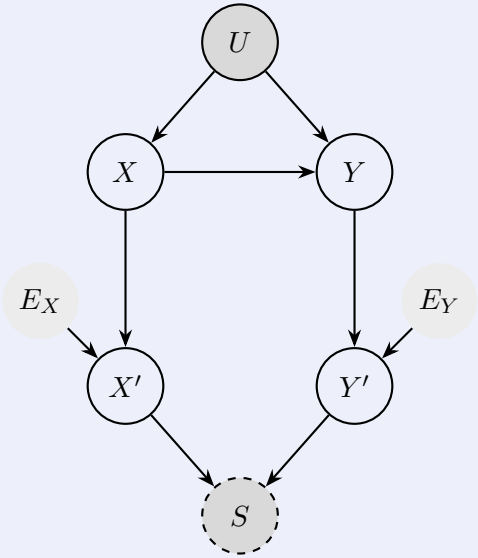
Fuzzy data, fuzzy truths

Cursed Combinations

Selection Meets Measurement Error



Lasciate ogne speranza, voi ch'intrate



What can we do when multiple biases are simultaneously present?

- Denial: Just ignore them.
- Anger: Blame the data.
- Bargain: Make a lot of assumptions.
- Depression: Abandon all hope.[a]
- Acceptance: Get better data.

[a] Most research on causality is here.

Towards Acceptance

Why did we run into problems in the first place?

- RCTs: costly, narrow, unethical, potential selection.
- Observational data: cheap, confounded, biased, unreliable.

What would it take to get better data?

- Naturally existing shifts emulate randomized interventions.
- Leverage existing heterogeneity: no new trials.
- No selection through admission criteria.
- Invariance filters spurious correlations.