Estimation of Treatment Effects in Extreme and Unobserved Data

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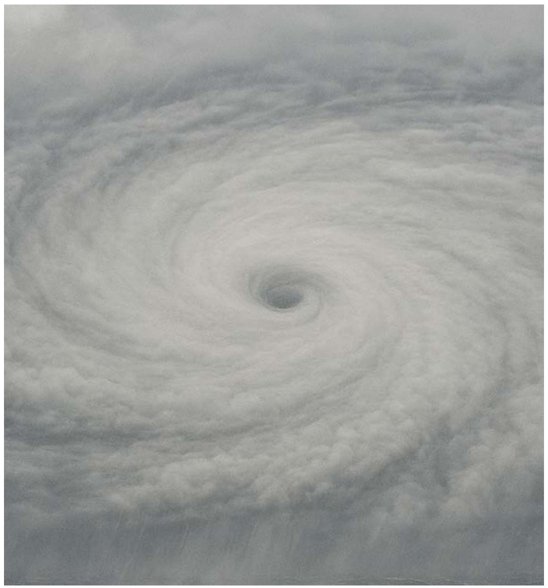
Motivation: Effect of Policies on Extreme Events



Images generated by OpenAI, 8 June 2025. Image created via ChatGPT.

Motivation: characteristics of extreme events

- Rarity
  - Hurricane Harvey (Texas 2017):The return period of inland flood losses of Harvey's severity or greater in Texas is estimated at 250–350 years
  - 2011 Tōhoku Earthquake and Tsunami: the most powerful earthquake ever recorded in Japan
  - …
- Huge impact
  - The National Oceanic and Atmospheric Administration estimated total damage of Hurricane Harvey at $125 billion.
  - The estimated economic loss of 2011 Japan earthquake amounted to over $300 billion.
  - Total property and capital losses of 2025 southern California wildfire could range between $95 billion and $164 billion.

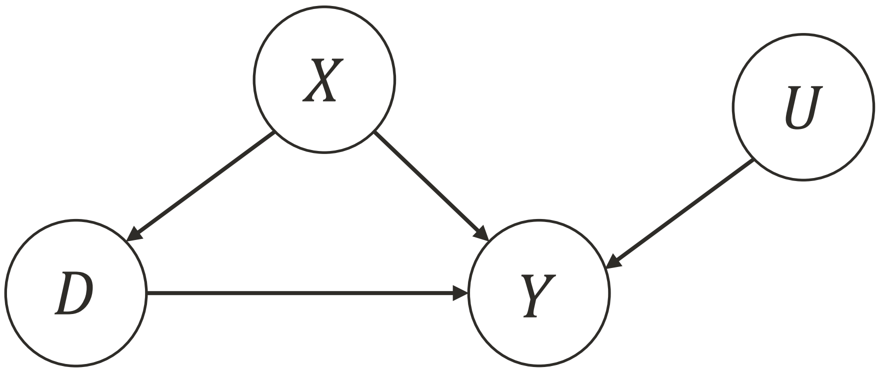
Motivation: Challenges

- Lack of a quantitative measure of policy effect on rare events.
  - Classical measure such as the ATE only care about the overall effects, including non-extreme and extreme events.
  - The measure should characterize the effect of a policy when extreme events happen.
- Small sample size for inference.
  - The number of extreme events is small. We only have scarce data from historical dataset.

How should we measure the effect of a policy on extreme events?

Problem Formulation

- Observation data: D, X, Y, U, where U is a multivariate regularly varying variable, measuring the extremity of a rare event. Suppose the Extreme Value Index (EVI) of U is γ.



Normalized Extreme Treatment Effect

- A natural generalization of ATE is $\lim_{t\to\infty} E[Y(1) - Y(0) \mid ||U||_1 > t]$
  - Drawback: the outcome can explode as norm of U grows to infinity.
- **Assumption 4** (Homogeneity): Assume that $f(x,d,u) = E[Y \mid X = x, D = d, U = u]$ satifies

$$\left|\frac{f(x,d,tu)}{t^{\alpha}} - g(x,d,u)\right| \leq e(t), \forall ||x|| \leq R, u \in S^{d-1},$$

for some continuous function $g(x,d,u)$, $\alpha \geq 0$ and position function $e(t) \to 0$.

Normalized Extreme Treatment Effect II

- Normalized Extreme Treatment Effect (NETE):

$$\theta^{NETE} = \lim_{t \to \infty} E[\frac{Y(1) - Y(0)}{t^{\alpha}} \mid ||U||_1 > t].$$

- NETE measures growth rate of outcome:

$$E\left[Y(1) - Y(0) \mid ||U||_1 > t\right] \approx t^{\alpha}\theta^{NETE}.$$

  - A negative NETE means the policy can make outcome less sensitive to extreme events.

How to estimate NETE?

Summary

- We propose a measure for the treatment effect on rare events named Normalized Extreme Treatment Effect (NETE), which measures the magnitude of treatment on tailed events.
- We develop two consistent estimators for NETE—a doubly robust (DR) estimator and an inverse propensity weighting (IPW) estimator.
- Synthetic and semi-synthetic experiments demonstrate a good empirical performance compared to baseline estimators adapted from standard causal inference literature.

Thank You