時間序列分析中的因果推斷：
概述、學界和業界概況

Causal Inference in Time Series Analysis:
Overview, Academic and Industry Landscape

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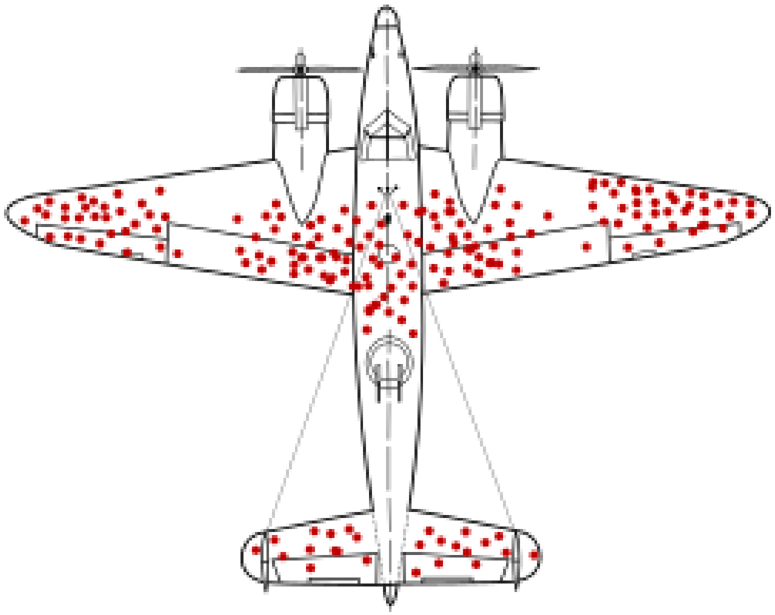
Outline

- Why Causal Inference
- Causal Inference in Academia
- Causal Inference in Industry
- Case Study: causaLens
- Vizuro’s Strategy for Developing Causal AI
- Q&A

Why Causal Inference

- Everyone knows, “Correlation does not imply causation.”
- Without a **model**, it's easy to make erroneous judgments. Example: survivorship bias.



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Why Causal Inference (Cont'd)

In traditional econometrics:

- central theme:
  understanding the causes of bias in estimated coefficients
- various methods to obtain (asymptotically) unbiased-estimators for coefficients

In traditional machine learning:

- We essentially do not see these discussions how to obtain unbiased-estimators.

Why?

Why Causal Inference (Cont'd)

My personal view:

- If the data is *sufficient* and *representative*, and no policy decisions are involved, but only *predictions* based on the data, causal analysis may not be crucial.

- predictions vs explanation (+ policy recommendations):
  When it comes to *explanation* and *policy recommendations*, causal analysis is essential.
- reduce reliance on data representativeness and lower costs:
  Additionally, when data is *insufficient* or *unrepresentative*, a correct causal model can save substantial costs from erroneous inferences.

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Why Causal Inference: An Example

A numerical example:

- True Model:

$$y = \beta_1 x_1 + \beta_2 x_2 + \epsilon, \quad (\beta_1, \beta_2) = (0.9, 0.1).$$

- If multicollinearity occurs ($\mathrm{Corr}(x_1, x_2) \simeq 1$), the estimated coefficients by OLS could be highly inaccurate.

e.g. (R-code)

```
set.seed(121)
mu <- c(0, 0)
Sigma <- matrix(c(1, 0.98, 0.98, 1), ncol=2)
data <- mvrnorm(n, mu, Sigma)
x1 <- data[, 1]
x2 <- data[, 2]
epsilon <- rnorm(n, mean = 0, sd = 1)
y <- 0.9 * x1 + 0.1 * x2 + epsilon
model <- lm(y ~ x1 + x2)
summary(model)
```

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Why Causal Inference: An Example (Cont'd)

A numerical example (cont'd):

- Result:

```
 Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.03597    0.03239   1.111   0.2670
x1           1.38972    0.16651   8.346 2.33e-16 ***
x2          -0.35426    0.16692  -2.122   0.0341 *
```

- The estimators are biased, leading to errors in *explanation*.
- From a *prediction* standpoint, these biased estimators are acceptable because $\hat{\beta}_1 + \hat{\beta}_2 \simeq 1$. Given the high correlation (0.98) between x_1 and x_2, $\hat{y}$ closely matches actual y.

Causal Inference in Academia: Overview

1980s: Foundations and Early Developments

- Key Figures:
- Donald Rubin, Paul Rosenbaum
- Methods:
  Potential Outcomes Framework, Propensity Score Matching
- Characteristics:
  - Emphasis on **randomized controlled trials** (RCTs)
  - Introduction of propensity score matching to handle confounding in observational studies (ar5iv) (Harvard Scholars)

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Causal Inference in Academia: Overview (Cont'd)

1980-2000s: Expansion and Formalization

- Key Figures: **Judea Pearl**
- Methods: **Causal Diagrams, Structural Causal Models (SCM)**
- Characteristics:
  - Use of **graphical models** to represent causal relationships
  - Development of **do-calculus** for formal causal inference
  - Increased focus on **counterfactual reasoning** and **interventions** (ar5iv)

Causal Inference in Academia: Overview (Cont'd)

1990-2000s: Applied Methods and Policy Impact

- Key Figures: **James Heckman, Guido Imbens**
- Methods: **Instrumental Variables, Natural Experiments, Difference-in-Differences** (mainly in Economics)
- Characteristics:
  – Addressing **endogeneity** and **selection bias**
  – Emphasis on **quasi-experimental designs** for policy evaluation and impact assessment
  – Expansion of econometric techniques for causal inference (ar5iv) (Harvard Scholars)

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Causal Inference in Academia: Overview (Cont'd)

2010s: **Integration with Big Data and Machine Learning**

- Key Figures: **Susan Athey, Stefan Wager**
- Methods: **Causal Trees, Double Machine Learning, Synthetic Control Methods**
- Characteristics:
  - Integration of ML techniques to **enhance causal inference accuracy**
  - Development of scalable methods for high-dimensional data, such as **causal forests** and **ensemble learning**
  - Emphasis on **robustness** and **generalizability** of causal estimates (Oxford University Press) (ar5iv)

Causal Inference in Academia: Overview (Cont'd)

2020s: **Current Trends and Future Directions**

- Methods: **Deep Learning for Causal Inference, Causal Discovery Algorithms**
- Characteristics:
  - Cross-disciplinary approaches integrating AI and causal inference
  - Advanced techniques for causal discovery in complex systems
  - Focus on improving **transparency** and **interpretability** of causal models

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Causal Inference in Academia: GitHub Projects

Institution	Project Name	Description
PyWhy (Carnegie Mellon University)	causal-learn	A Python package for causal discovery implementing various causal discovery algorithms. **(Discovery)**
University of Hamburg	DoubleML	An R and Python package for double machine learning for causal inference. **(Inference)**
Stanford University	GRF	A package for generalized random forests for estimating heterogeneous treatment effects. **(Inference)**

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Causal Inference in Industry: Overview (2010s to now)

- **Marketing and Customer Analytics**:
  Analysis of the impact of marketing strategies on customer behavior and sales
- **Healthcare**:
  Analysis of treatment effects and healthcare policies
- **Finance**:
  Risk assessment and investment strategy optimization
- **Real-Time Personalization:**
  Personalized recommendations and advertisements in real-time
- **Supply Chain Optimization:**
  Improving supply chain efficiency by understanding the causal impact of various factors on logistics and inventory management

Causal Inference in Industry: GitHub Projects

Company	Project Name	Description
Google	CausalImpact	An R package for causal inference using Bayesian structural time-series models. **(Inference)**
	TFP CausalImpact	Python version of above **(Inference)**
Uber	CausalML	A Python package for uplift modeling and causal inference with ML. **(Inference)**
Microsoft	DoWhy	A Python library supports explicit modeling and validation of causal assumptions, combining causal graphical models and the potential outcomes framework. **(Discovery)**
	EconML	A Python package for interpretable machine learning methods to estimate heterogeneous treatment effects. **(Inference)**

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