

時間序列分析中的因果推斷：
概述、學界和業界概況、發展策略（個人觀點）

Causal Inference in Time Series Analysis: Overview, Academic and Industry Landscape, Development Strategies (Personal Perspective)

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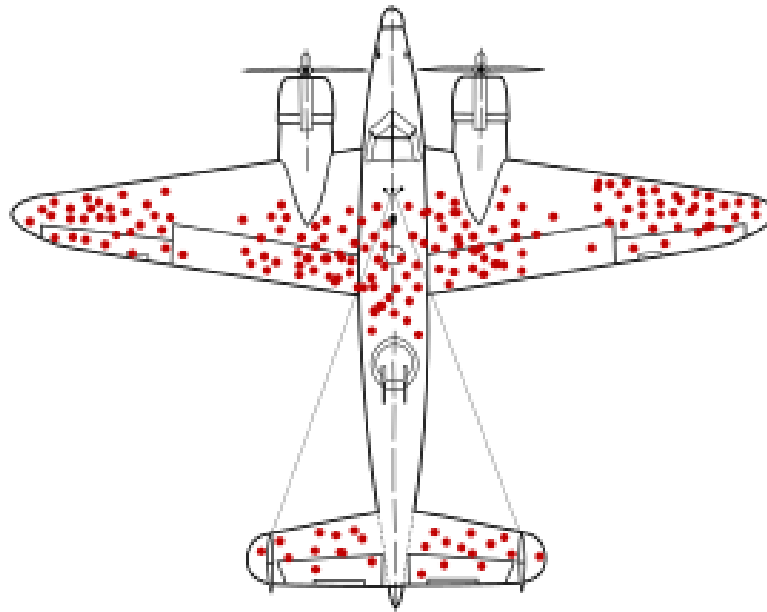


Outline

- 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.



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.

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 ($\text{Corr}(x_1, x_2) \simeq 1$), 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)
```

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](#))

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](#))

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

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)

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

Case Study: causaLens

(leading company specializing in causal AI)

- **Causal AI Platform:**
designed to help enterprises optimize decision-making by using causal inference techniques
- **Key Features:**
 - **Comprehensive Causal Inference Tools:**
providing a wide range of tools for identifying and quantifying causal relationships
 - **Automated Causal Discovery:**
offering automated tools that help users uncover causal structures from their data without manual intervention
 - **Real-Time Causal Analysis:**
supporting real-time causal analysis, allowing for dynamic decision-making and immediate feedback
 - **Industry Applications:**
versatile and applicable across various industries, including finance, healthcare, manufacturing, and retail

Vizuro's Strategy for Developing Causal AI

(i) Implement the functions outlined in the [causaLens product roadmap \(2024\)](#).

(ii) Our technology is temporarily behind, so we need to establish an advantage through our customers.

- This might be related to the characteristics of the customer datasets.
- Continue with (i) and integrate customers into our platform, offering after-sales services to enhance user retention.

Vizuro's Strategy for Developing Causal AI (Cont'd)

(iii) Market Forecast:

- I believe the causal AI field is similar to the markets for mathematical or statistical softwares, where multiple companies can coexist.
- While R can perform functions of multiple statistical software packages, SAS, SPSS, and STATA all have their markets.
- Causal AI is far more complex than these statistical software packages, leading to greater reliance on bundled services.
- To build loyal customers, a robust platform is essential.

Vizuro's Strategy for Developing Causal AI (Cont'd)

(iv) Generative AI: Threats, Opportunities, and Challenges

- Vizuro must focus on the latest developments and choose promising technologies to invest in.
- Companies like H2O and causaLens are working to integrate LLMs into their products.
- There is no need to worry about the sudden emergence of large-scale causal AI, as that would signify a level of general artificial intelligence (AGI) that would bring societal changes beyond our concerns.

Q&A Session

- Questions welcome
- Thank you for listening