Machine Learning for econometrics

Causal perspective

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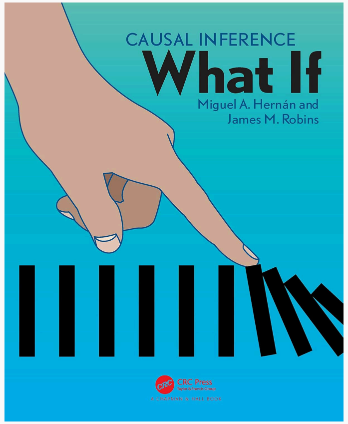
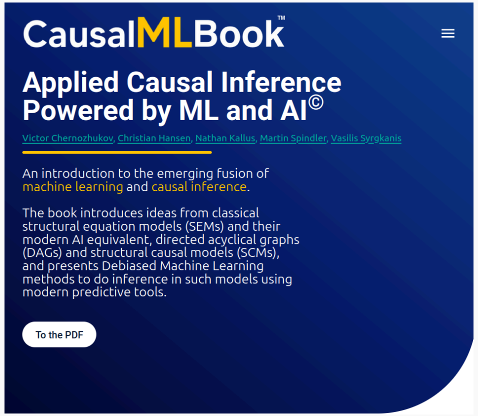
Introduction

Causal inference: subfield of statistics dealing with "why questions"





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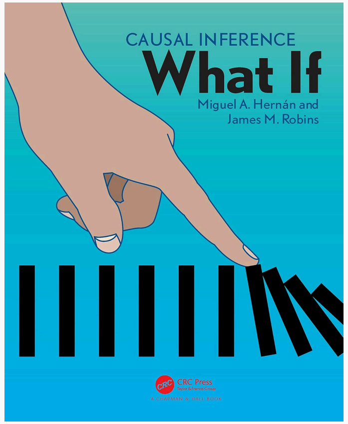
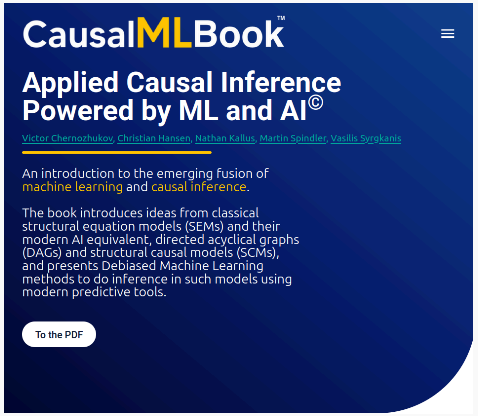
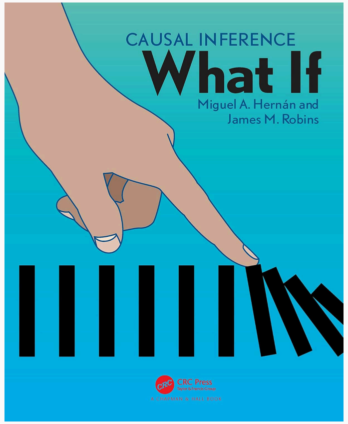


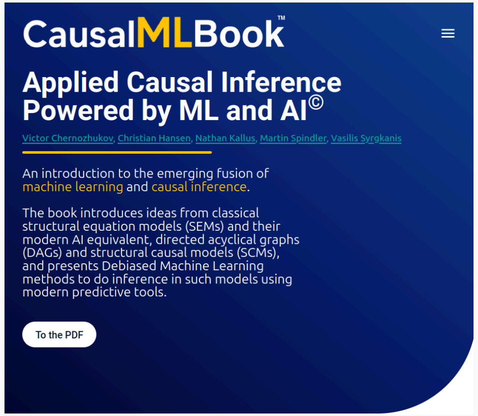


At the center of epidemiology (Hernan & Robins, 2020), econometrics (Chernozhukov, Hansen, Kallus, Spindler, & Syrgkanis, 2024), social sciences, machine learning…

Now, bridging with machine learning (Kaddour et al., 2022) : Fairness, reinforcement learning, causal discovery, causal inference for LLM, causal representations…

Causal inference: subfield of statistics dealing with "why questions"





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This course:

- Basis of causal inference using ML approaches (semi-parametric),
- Inspiration from epidemiology,
- Application in econometrics.

What is a "why question"?

- Economics: How does supply and demand (causally) depend on price?
- Policy: Are job training programmes actually effective?
- Epidemiology: How does this threatment affect the patient's health?
- Public health : Is this prevention campaign effective?
- Psychology: What is the effect of family structure on children's outcome?
- Sociology: What is the effect of social media on political opinions?

This is different from a predictive question

- What will be the weather tomorrow?
- What will be the outcome of the next election?
- How many people will get infected by flue next season?
- What is the cardio-vacular risk of this patient?
- How much will the price of a stock be tomorrow?

Why is prediction different from causation? (1/2)

Prediction (most part of ML): What usually happens in a given situation?

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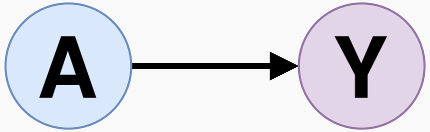
Prediction (most part of ML): What usually happens in a given situation?

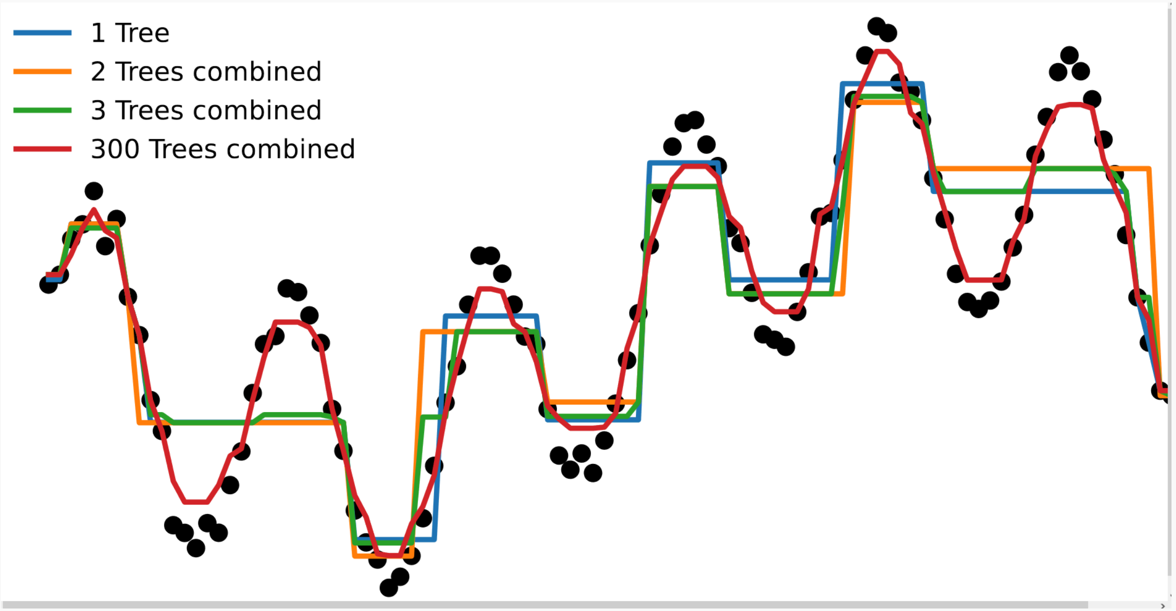
Assumption Train and test data are drawn from the same distribution.



Prediction models (X, Y)

Machine learning is (basically) pattern matching

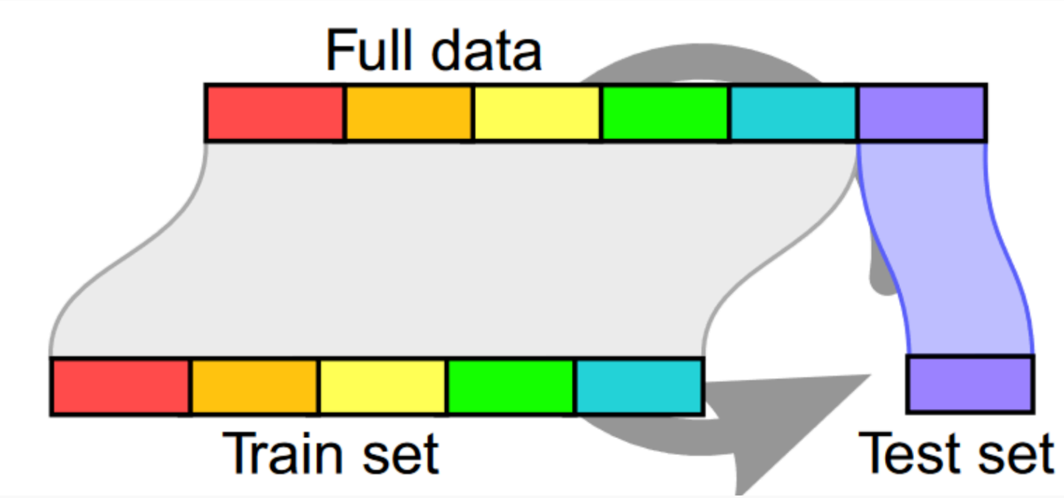
Find an estimator $f : x \to y$ that approximates the true value of y so that $f(x) \approx y$



Boosted trees : iterative ensemble of decision trees

Machine learning is pattern matching that generalizes to new data

Select models based on their ability to generalize to new data : (train, test) splits and cross validation (Stone, 1974).



“Cross validation” (Varoquaux et al., 2017)

Leverages complex data structures

- Images: Image classification with deep convolutional neural networks (Krizhevsky et al., 2012)

Leverages complex data structures

- Speech-to-text: Towards end-to-end speech recognition with recurrent neural networks (Graves & Jaitly, 2014)

Machine learning is great for prediction

Leverages complex data structures

- Text: Attention is all you need (Vaswani, 2017)

Machine learning is not driven by causal mechanisms

- For example people that go to the hospital die more than people who do not[1]:
  - Naive data analysis might conclude that hospitals are bad for health.

  The fallacy is that we are comparing different populations: people who go to the hospital typically have a worse baseline health than people who do not.

This is a confounding factor: a variable that influences both the treatment and the outcome.

[1]Example from https://inria.github.io/scikit-learn-mooc/concluding_remarks.html?highlight=causality

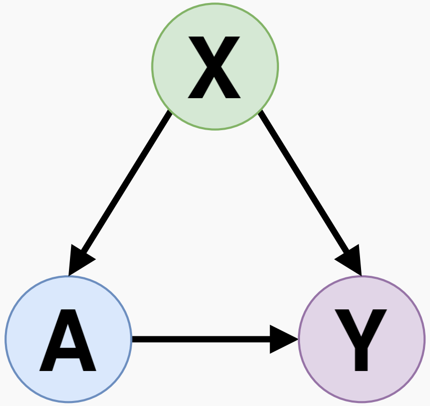
Why is prediction different from causation? (2/2)

Causal inference (most part of economists) : What would happen if we changed the system ie. under an intervention?

Why is prediction different from causation? (2/2)

Causal inference (most part of economists) : What would happen if we changed the system ie. under an intervention?

Assumption: No unmeasured variables influencing both treatment and outcome $\rightarrow$ confounders.



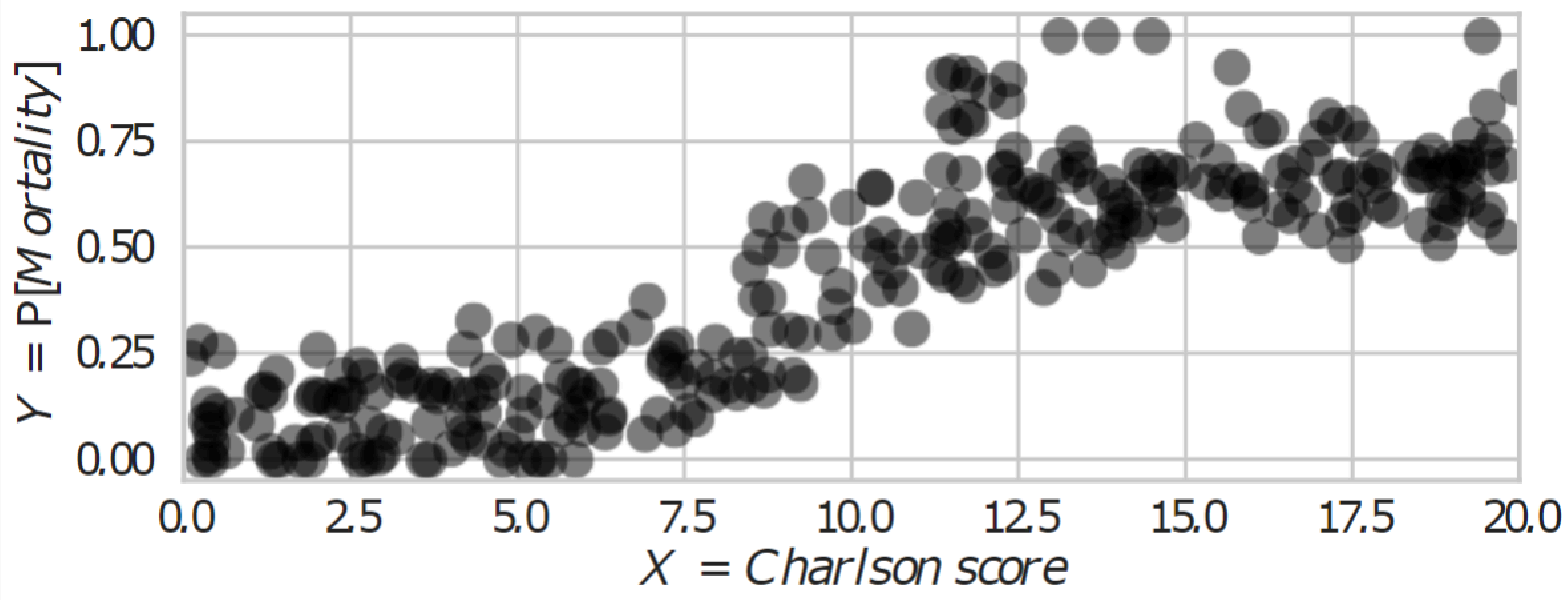
Causal inference models
$(X, A, Y(A=1), Y(A=0))$
the covariate shift between treated and control units.

Illustration of the fundamental problem of causal inference

Consider an example from epidemiology:

- Population: patients experiencing a stroke
- Intervention $A = 1$: patients had access to a MRI scan **in less than 3 hours** after the first symptoms
- Comparator $A = 0$: patients had access to a MRI scan **in more than 3 hours** after the first symptoms
- $Y = \mathbb{P}[\text{Mortality}]$: the mortality at 7 days
- $X = \mathbb{P}[\text{Charlson score}]$: a comorbidity index summarizing the overall health state of the patient. Higher is bad for the patient.

Draw a population sample without treatment status



Draw a population sample with treatment status

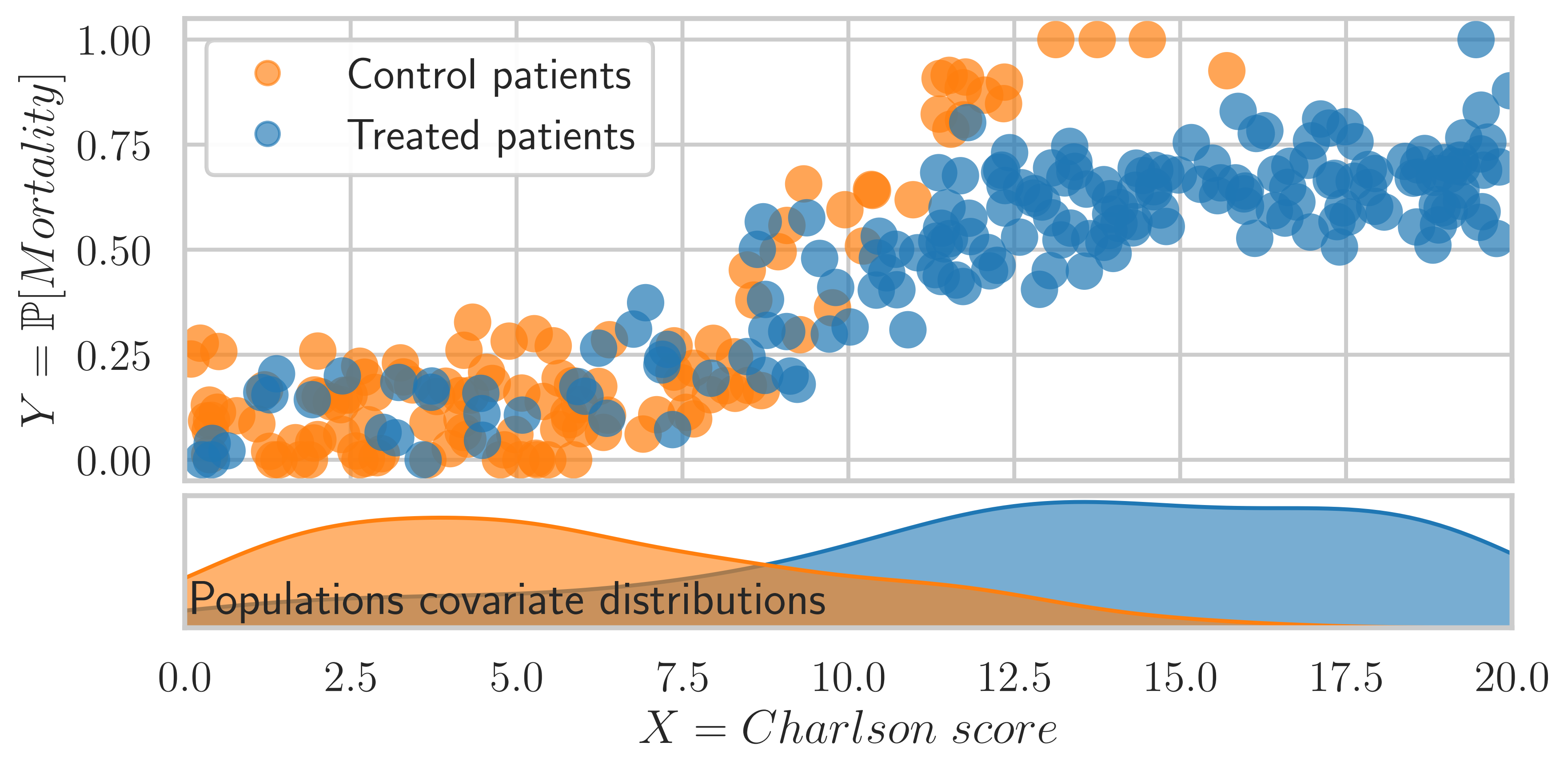


Illustration: observational data, a naive solution

Compute the difference in mean (DM): $\tau_{\mathrm{DM}} = \mathbb{E}[Y(1)]$ - $\mathbb{E}[Y(0)]$

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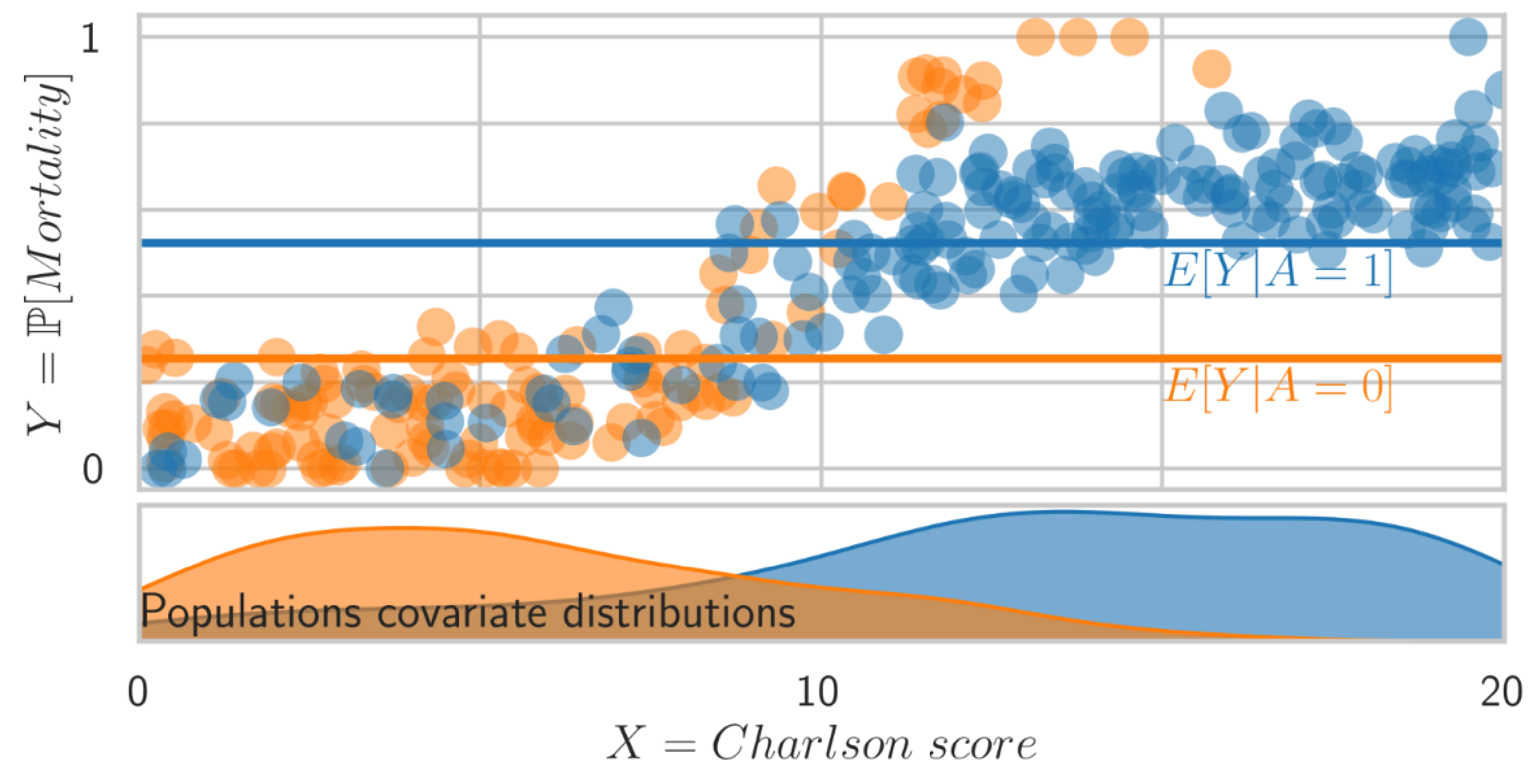
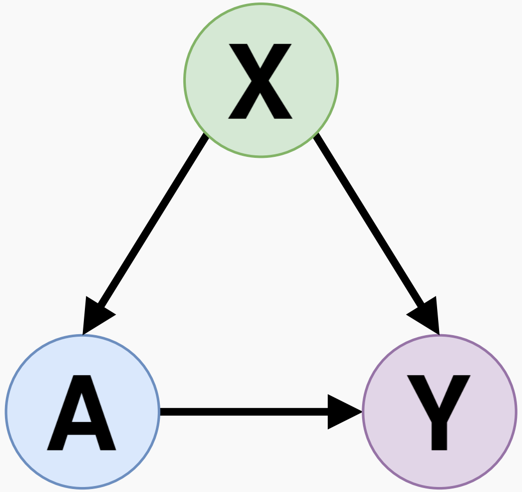


Observational data

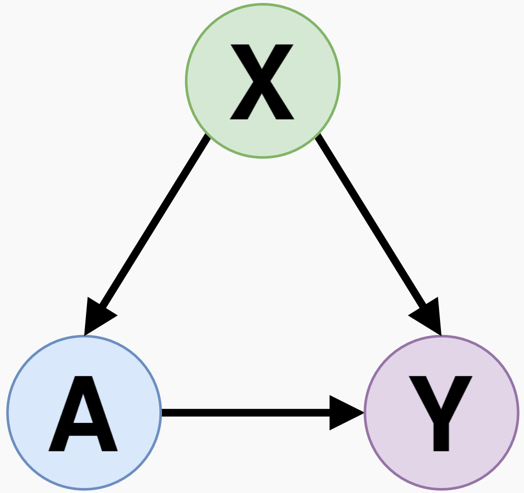


$$Y(1), Y(0) \not\perp\!\!\!\perp A$$

Intervention is not random

(with respect to the confounders)

Observational data



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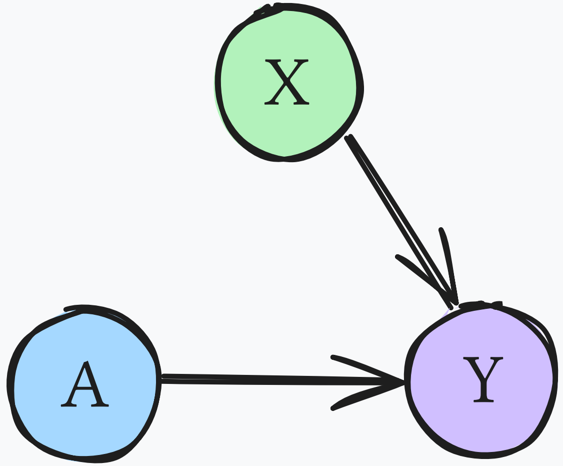
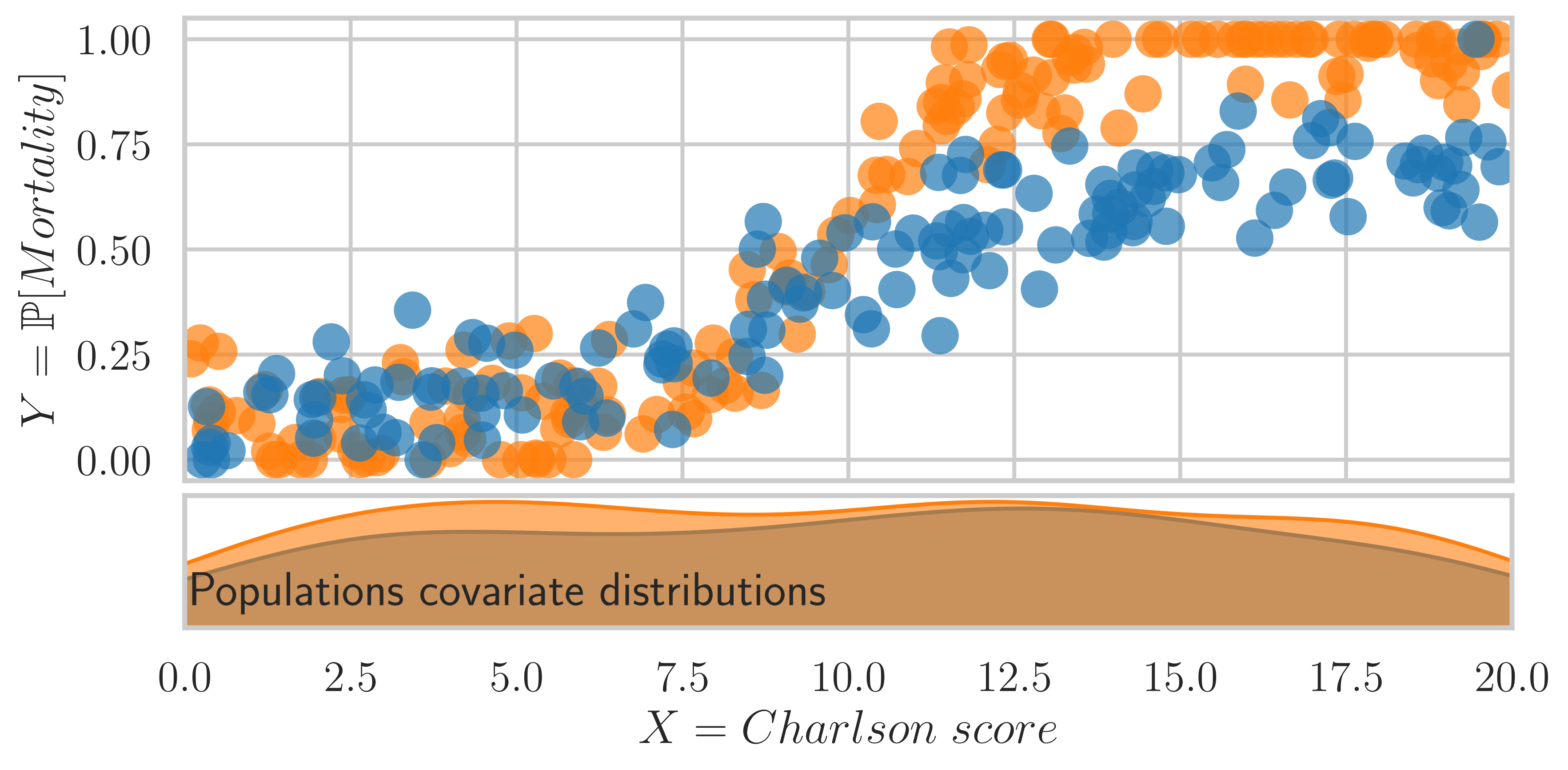
RCT data



$$Y(1), Y(0) \perp\!\!\!\perp A$$

Force random assignment of the intervention

Illustration: RCT data



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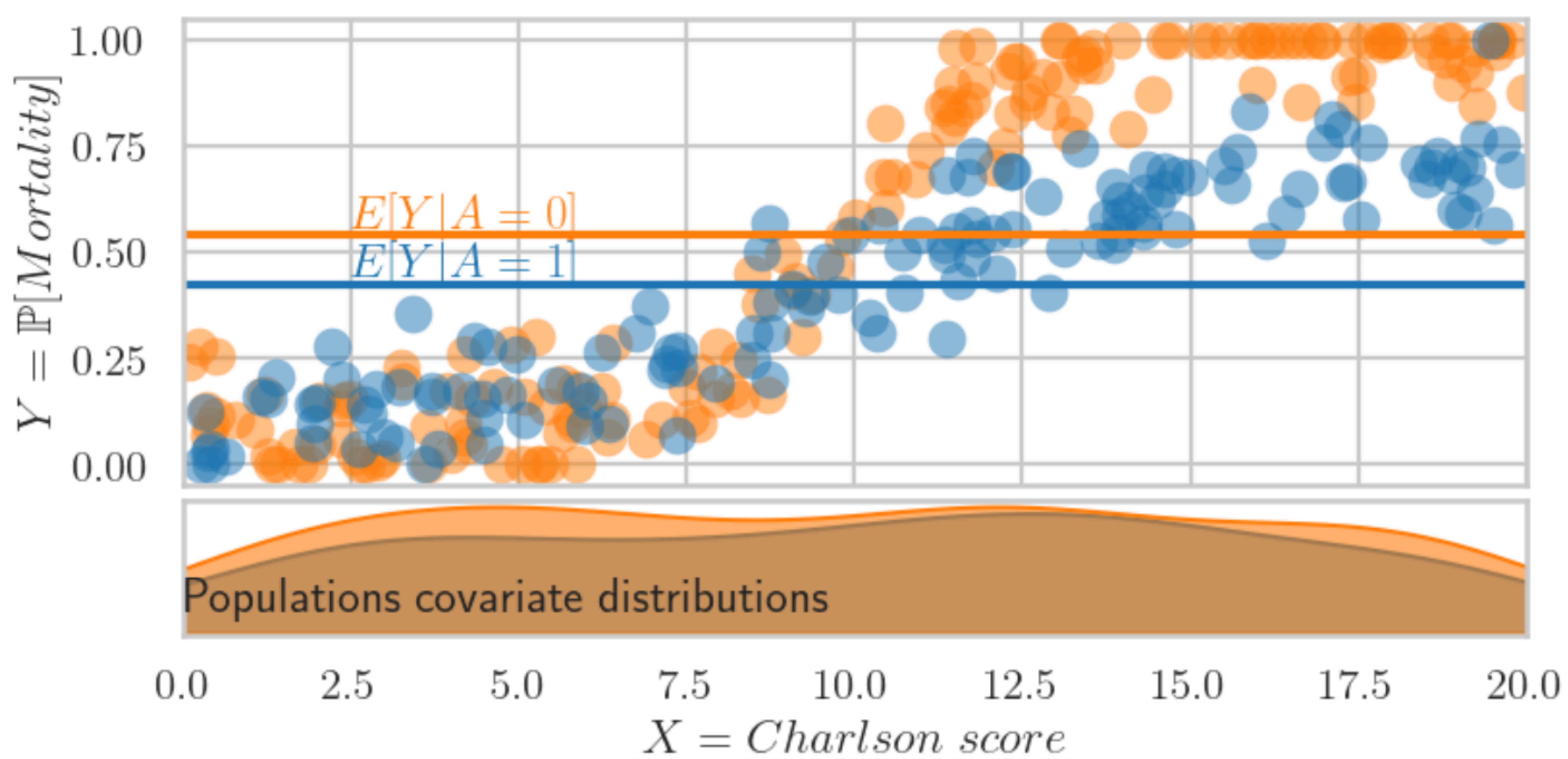
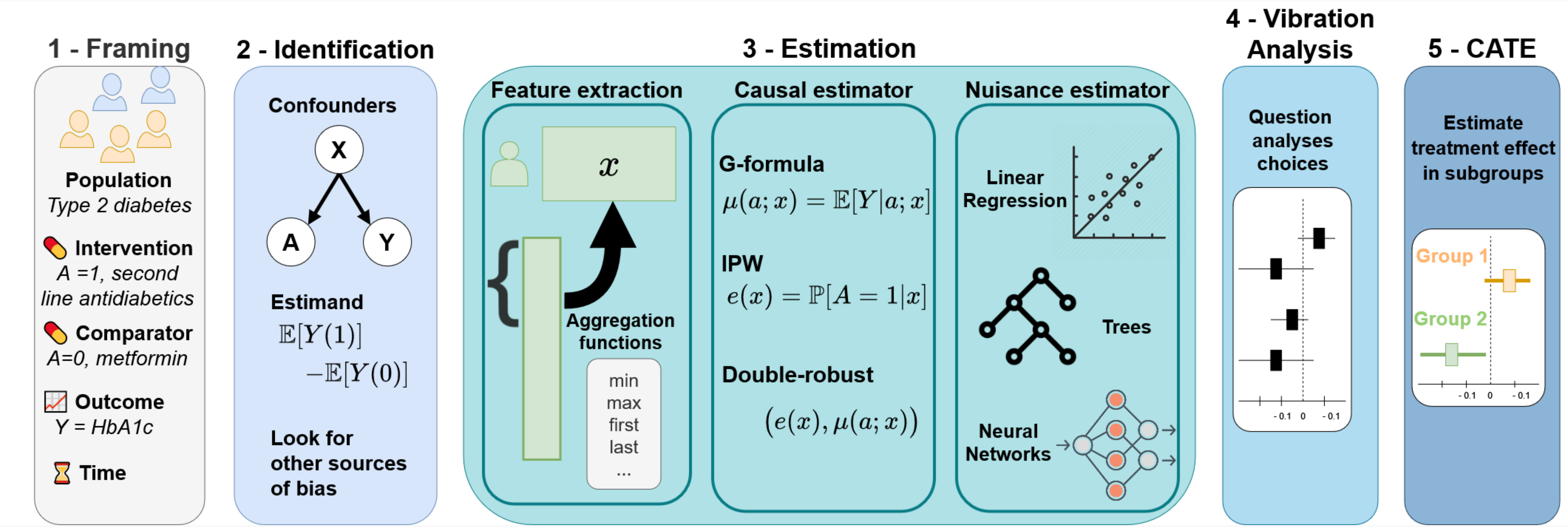


Four steps of causal inference : Framing, identification, statistical inference, vibration analysis

Complete inference flow



Today: Framing and identification

Framing: How to ask a sound causal question

PICO framework (Richardson et al., 1995)

Originally designed for clinical research. It is a structured approach to formulate a research question. Critical for health technology assessment (eg. Haute Autorité de santé).

PICO stands for

- Population : Who are we interested in?
- Intervention : What treatment/intervention do we study?
- Comparison : What are we comparing it to?
- Outcome : What are we interested in?

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Example with the job dataset (LaLonde, 1986)

Built to evaluate the impact of the National Supported Work (NSW) program. The NSW is a transitional, subsidized work experience program targeted towards people with long-standing employment problems.

The PICO framework

Component	Description	Example
Population	What is the target population of interest?	People with longstanding employment problems
Intervention	What is the intervention?	On-the-job training lasting between nine months and a year
Control	What is the relevant comparator?	No training
Outcome	What are the outcomes?	Earnings in 1978
Time	Is the start of follow-up aligned with intervention assignment?	The period of follow-up for the earning is the year after the intervention

PICO: other examples in econometrics

The Oregon Health Insurance Experiment (Finkelstein et al., 2012) : A randomized experiment by lottery assessing the impact of Medicaid on low-income adults in Oregon.

- P: Low-income adults in Oregon
- I: Medicaid
- C: No insurance
- O: Healthcare uses and expenditures, health outcomes

PICO: other examples in econometrics

The economic impact of climate change on US agricultural land. (Deschênes & Greenstone, 2007): difference-in-differences design assessing the impact of climate change on agricultural profits.

- P: US agricultural land
- I: Climate change
- C: No climate change
- O: Agricultural profits

PICO: other examples in econometrics

The impact of class size on test scores. (Angrist & Lavy, 1999): regression discontinuity design.

- P: Fourth and fifth grades school in Israel
- I: Class size increases by one unit
- C: No class size increase
- O: Test scores (math and reading)

Identification: List necessary information to answer the causal question

Build a causal model

The identification step builds a causal model to answer the research question.

Several important steps:

- Potential outcome framework : mathematical tool to reason about causality
- Directed acyclic graphs (DAG) : graphical tool to reason about causality
- Causal estimand : what is the targeted quantity?

Potential outcomes, (Neyman, 1923; Rubin, 1974)

The Neyman-Rubin model, let:

- Y be the outcome,
- A the (binary) treatment

For each individual, we have two potential outcomes: $Y(1)$ and $Y(0)$. But only one is observed, depending on the treatment assignment: $Y(A)$.

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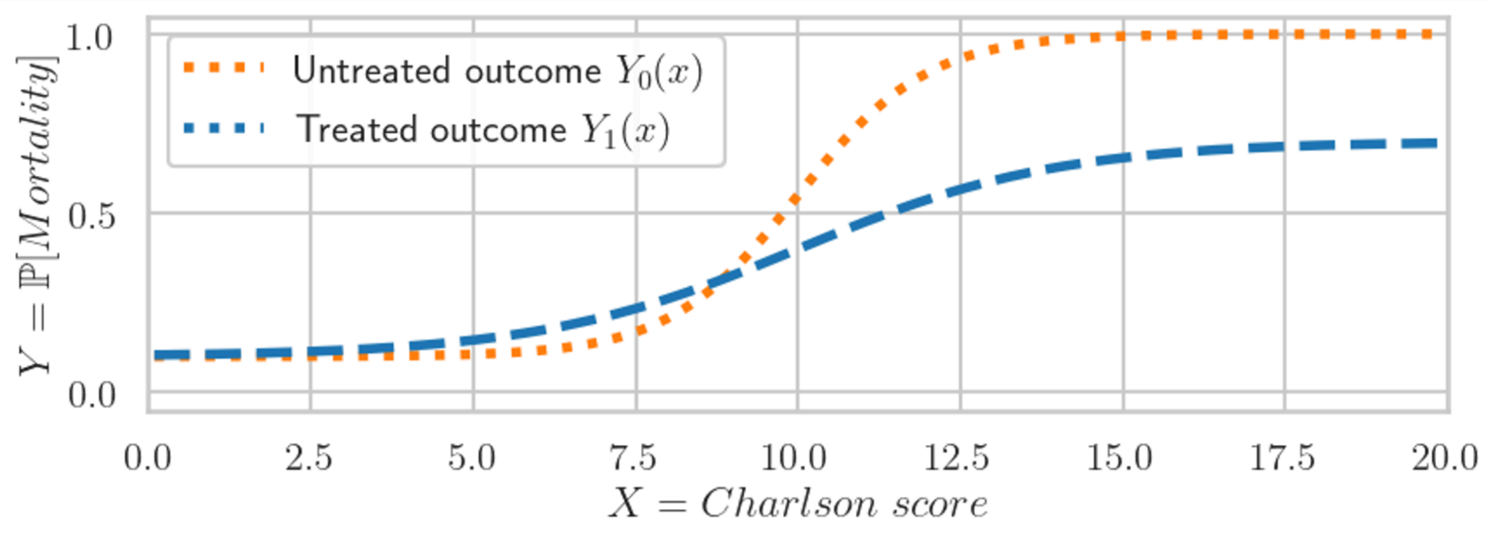

Causal estimand: What is the targeted quantity (with potential outcomes)?

- Average treatment effect (ATE): $\mathbb{E}[Y(1) - Y(0)]$
- Conditional average treatment effect (CATE): $\mathbb{E}[Y(1) - Y(0) \mid X]$

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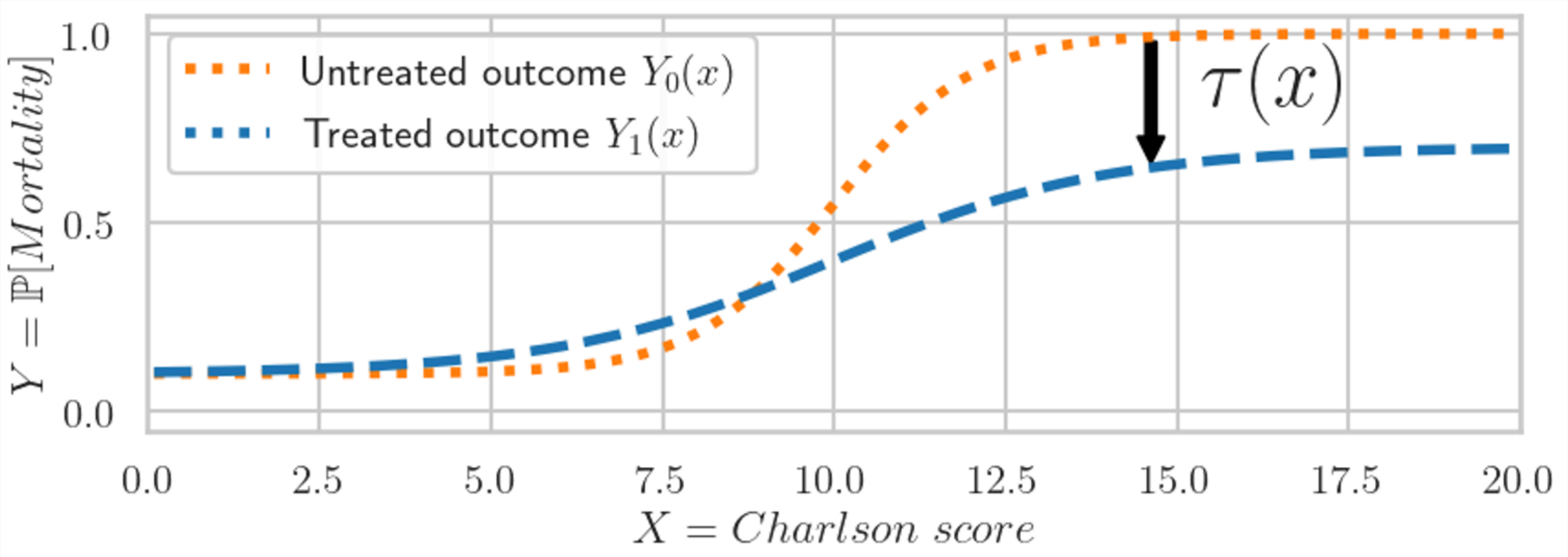

Other estimands

- Average treatment effect on the treated (ATT): $\mathbb{E}[Y(1) - Y(0) \mid A = 1]$
- Conditional average treatment effect on the treated (CATT):

$$\mathbb{E}[Y(1) - Y(0) \mid A = 1, X]$$

Other estimands

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Other estimands more used in epidemiology

- Risk ratio (RR): $\frac{\mathbb{E}[Y(1)]}{\mathbb{E}[Y(0)]}$
- Odd ratio (OR) for binary outcome: $\left(\frac{\mathbb{P}[Y(1)=1]}{\mathbb{P}[Y(1)=0]}\right) / \left(\frac{\mathbb{P}[Y(0)=1]}{\mathbb{P}[Y(0)=0]}\right)$

See (Colnet, Josse, Varoquaux, & Scornet, 2023) for a review of the different estimands and the impact on generalization.

PICO framework, link to the potential outcomes

Component	Description	Notation	Example
Population	What is the target population of interest?	$X \sim P(X)$	People with longstanding employment problems
Intervention	What is the intervention?	$A \sim P(A=1) = p_A$	On-the-job training lasting between nine months and a year
Control	What is the relevant comparator?	$1 - A \sim 1 - p_A$	No training
Outcome	What are the outcomes?	$Y(1), Y(0) \sim P(Y(1), Y(0))$	Earnings in 1978
Time	Is the start of follow-up aligned with intervention assignment?	N/A	The period of follow-up for the earning is the year after the intervention

What can we learn from the data?

- Four assumptions, referred as strong ignorability
- Required to assure identifiability of the causal estimands with observational data (Rubin, 2005)

Assumption 1: Unconfoundedness, also called ignorability

Treatment assignment is as good as random given the covariates X

$$\{Y(1), Y(0)\} \perp\!\!\!\perp A \mid X$$

- Equivalent to the conditional independence on the propensity score $e(X) \mathrel{\hat{=}} \mathbb{P}(A = 1|X)$ (Rosenbaum & Rubin, 1983):

$$\{Y(1), Y(0)\} A \mid e(X)$$

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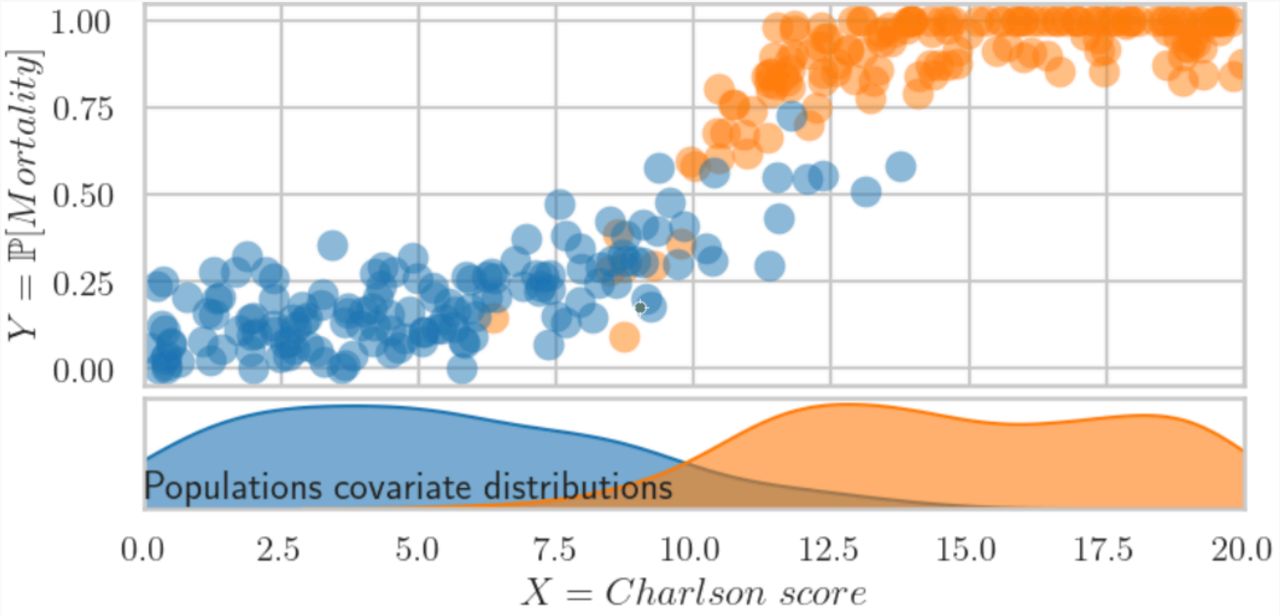
$$\{Y(1), Y(0)\} A \mid e(X)$$

- Knowledge based ie. cannot be validated with data
- Because of possibly unmeasured confounders
- In practice : ask yourself if you have measured all the relevant variables that could influence both the treatment and the outcome.

The treatment is not deterministic given X

$$\eta < e(x) < 1 - \eta \text{ with } e(X) \hat{=} \mathbb{P}(A = 1|X)$$



- NB: The choices of covariates X can be viewed as a trade-off between ignorability and overlap (D'Amour et al., 2021)

Assumption 3 and 4: Consistency and generalization

Consistency, also called Stable Unit Treatment Values (SUTVA)

The observed outcome is the potential outcome of the assigned treatment for each unit i.

$$Y_i = A_i Y_i(1) + (1 - A_i) Y_i(0)$$

- The intervention A is well defined (Hernan & Robins, 2020)
- There is no interfrence ie. network effect

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Generalization, also called no-covariate shift

Training and test data are are drawn from the same distribution

Directed acyclic graphs (DAG)

A tool to reason about causality: What are the causal status of each variable?

The confounder: a variable that influences both the treatment and the outcome.

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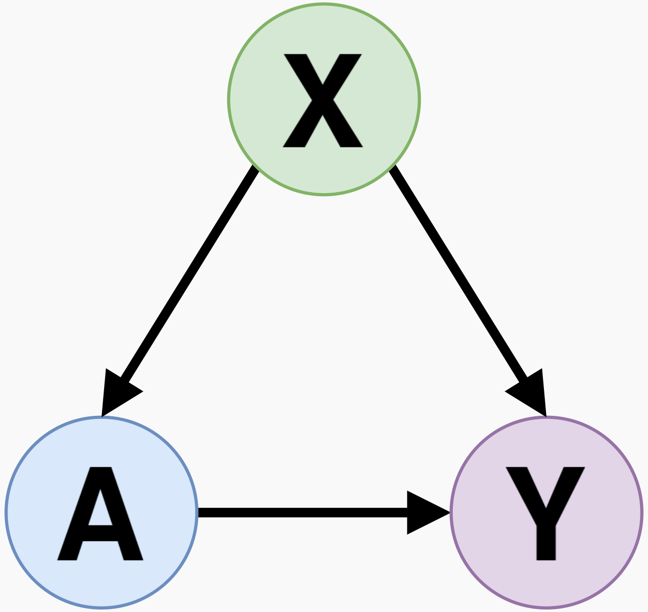

A word on structural equation models

Session summary

Going further

Resources

- https://web.stanford.edu/~swager/stats361.pdf
- https://www.mixtapesessions.io/
- https://alejandroschuler.github.io/mci/
- https://theeffectbook.net/index.html

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