Machine Learning for econometrics

Reminders of potential outcomes and Directed Acyclic Graphs

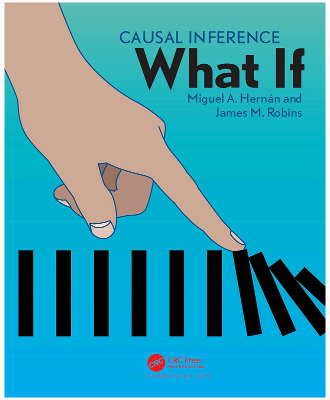
Matthieu Doutreligne

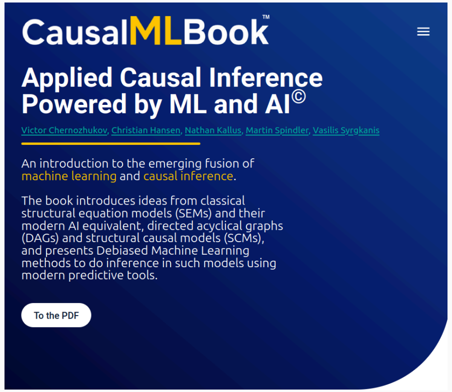
Thanks to Judith Abecassis for the slides on DAGs

Contents

Contents

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





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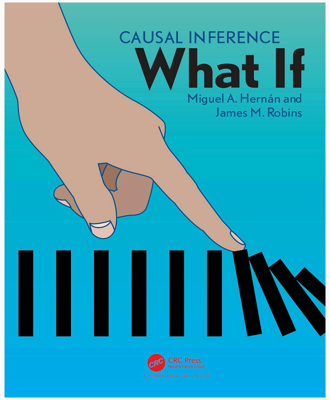

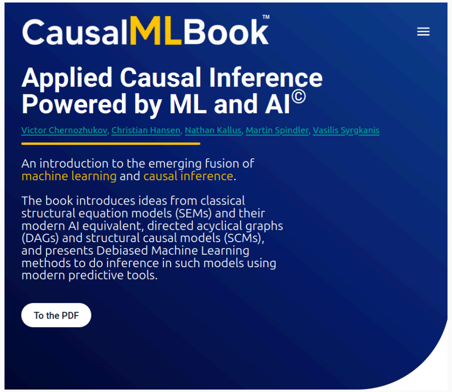

At the center of epidemiology (Hernan & Robins, 2020), econometrics (Chernozhukov et al., 2024), social sciences, machine learning...

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

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Economics: How does supply and demand (causally) depend on price?

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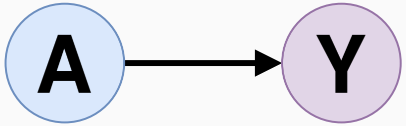
Sociology: What is the effect of social media on political opinions?

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



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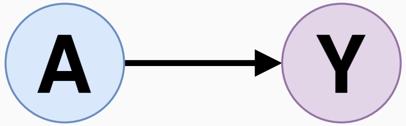

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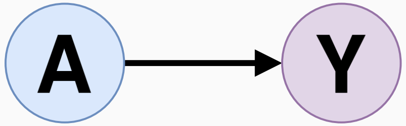

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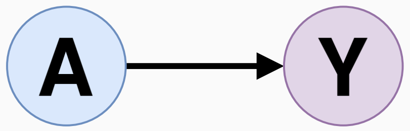

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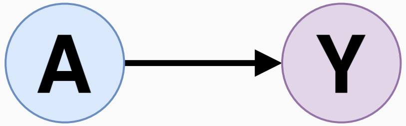

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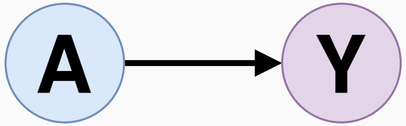

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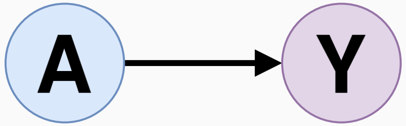

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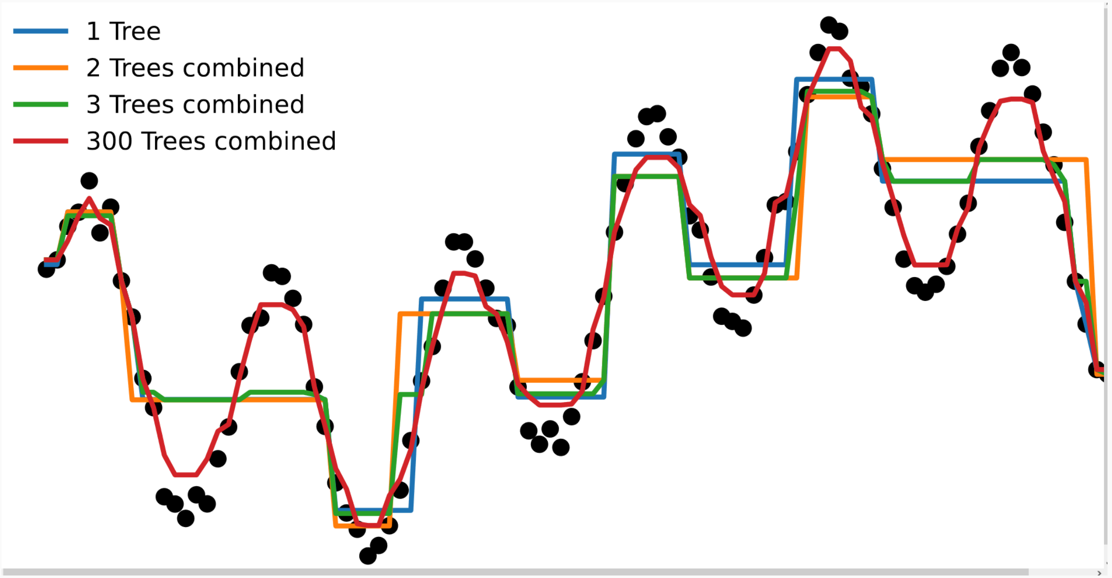
Assumption Train and test data are drawn from the same distribution.

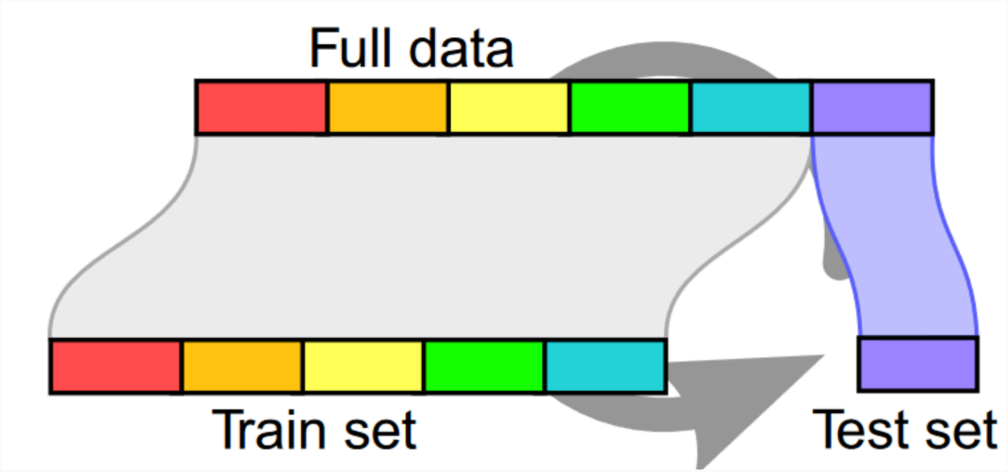
Machine learning is pattern matching

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



Boosted trees : iterative ensemble of decision trees

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)

Machine learning is great for prediction on complex data

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

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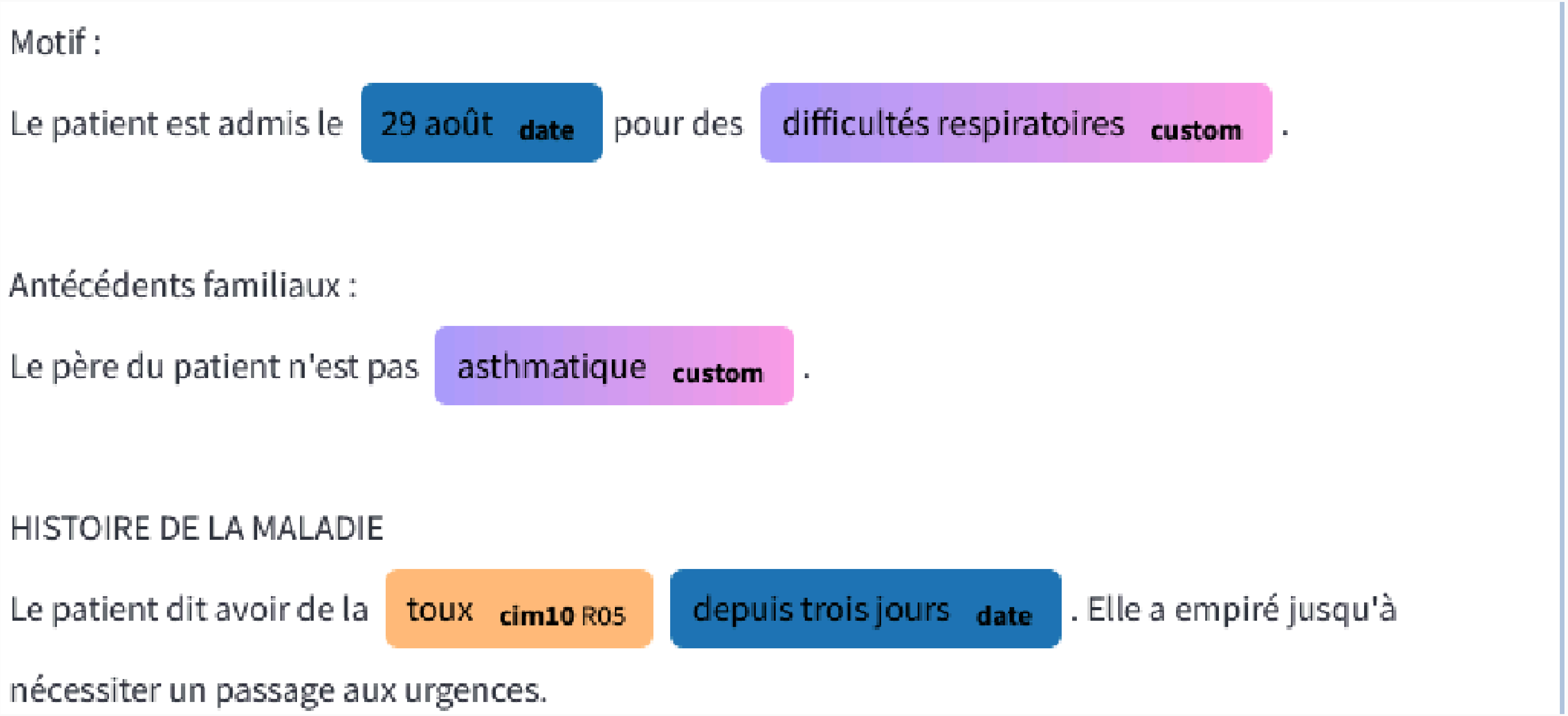
Text: Attention is all you need (Vaswani, 2017)

ImageNet 1K: 1.5 million images, 1000 classes



Named entity recognition

Machine learning might be less successful for what if questions

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.

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

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- 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.

Definition

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?

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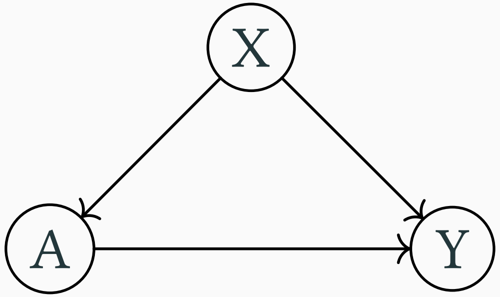

Causal inference models $(X, A, Y(A=1), Y(A=0))$
ie. the covariate shift between treated and control units.

Assumption

No unmeasured variables influencing both treatment and outcome
ie. no confounders.

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Population: patients experiencing a stroke

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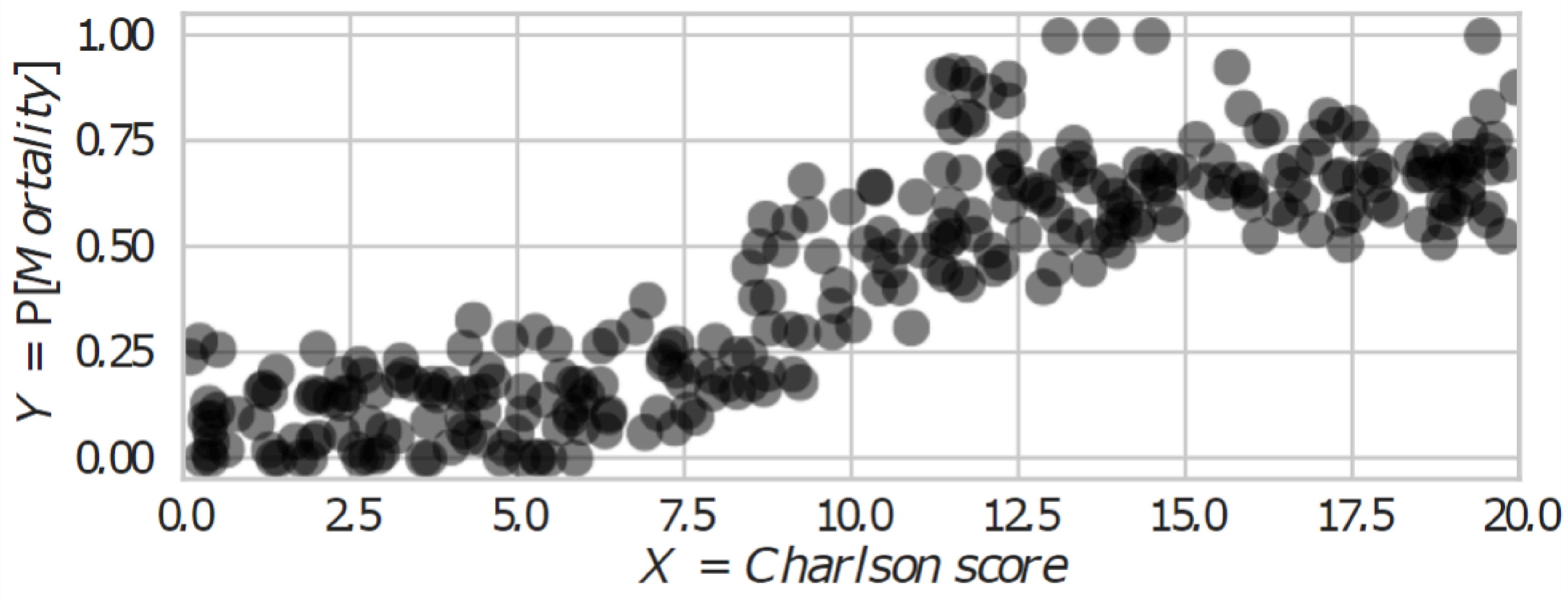
❓ What is the effect of early access to MRI on the mortality at 7 days for stroke patients?

Draw a population sample without treatment status



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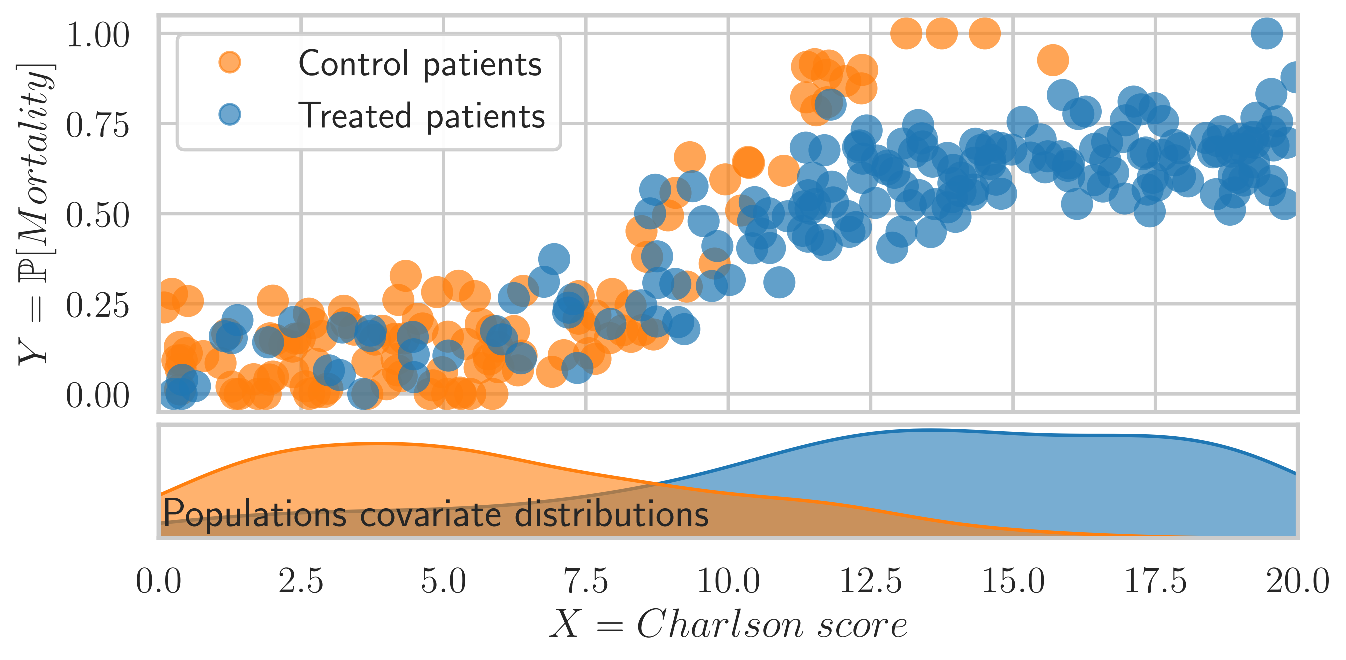

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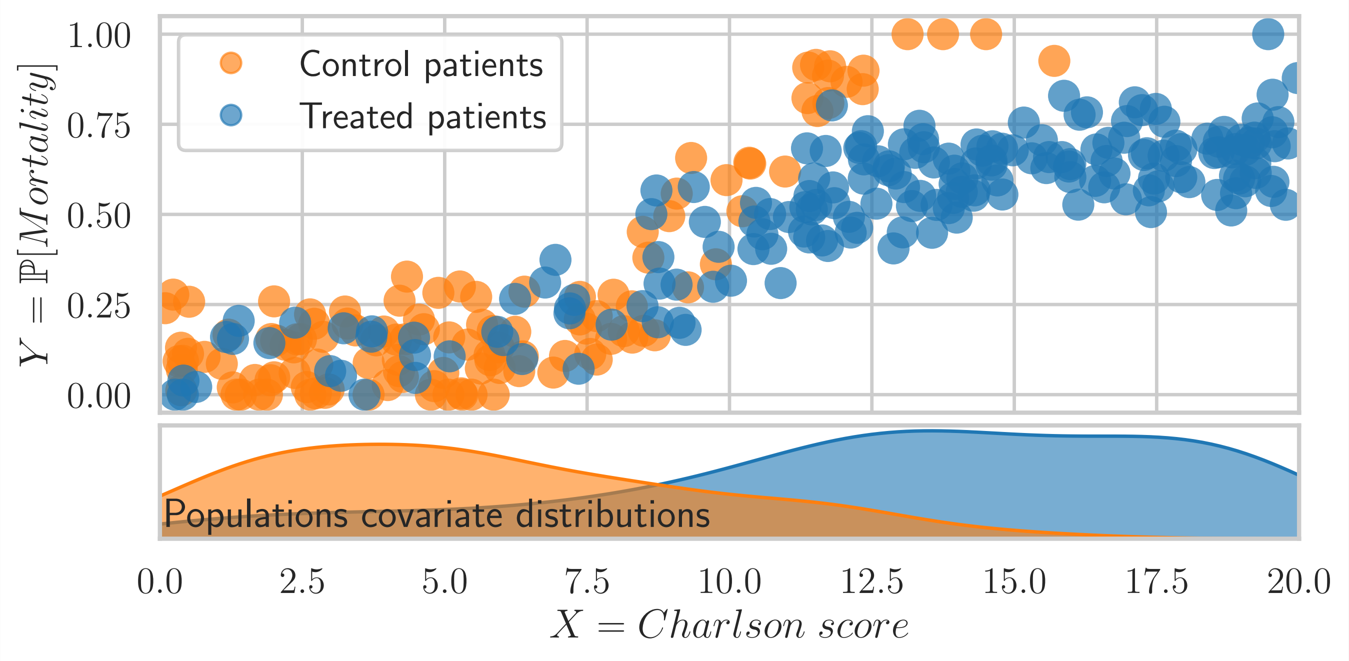

👀 Patient with higher risks have early access to MRI.

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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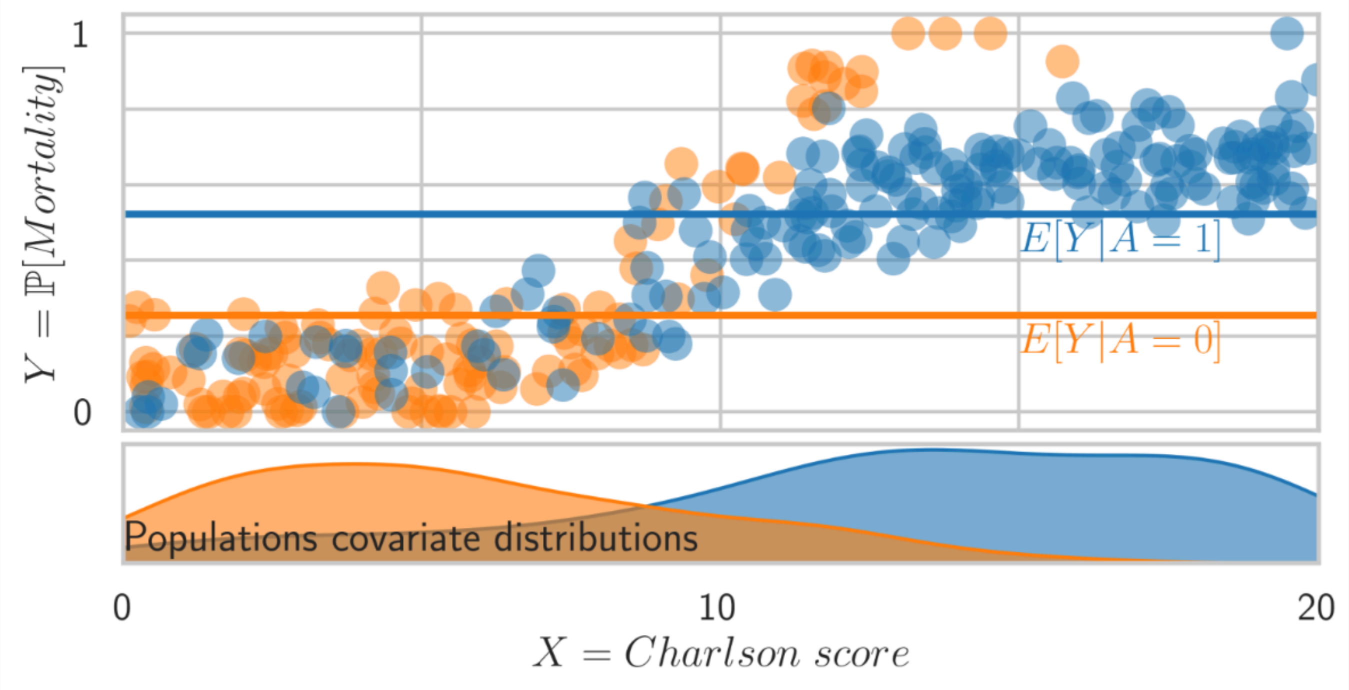

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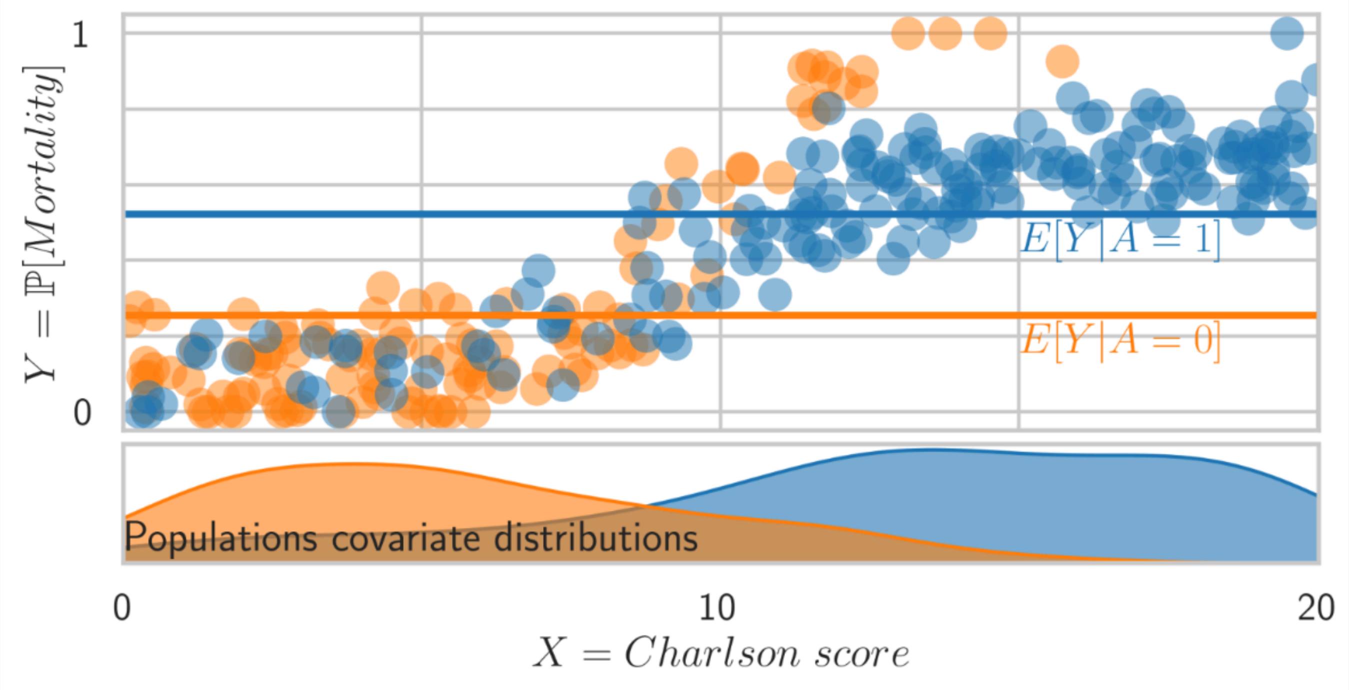
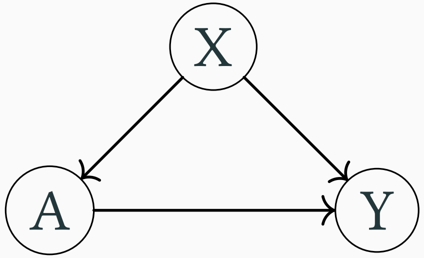


(False) conclusion: early access to MRI is associated with a higher mortality at 7 days.

RCT case: No problem of confounding

Observational data

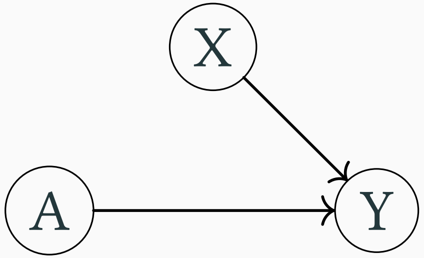


$$Y(1), Y(0) \not\perp\!\!\!\perp A$$

Intervention is not random

(with respect to the confounders)

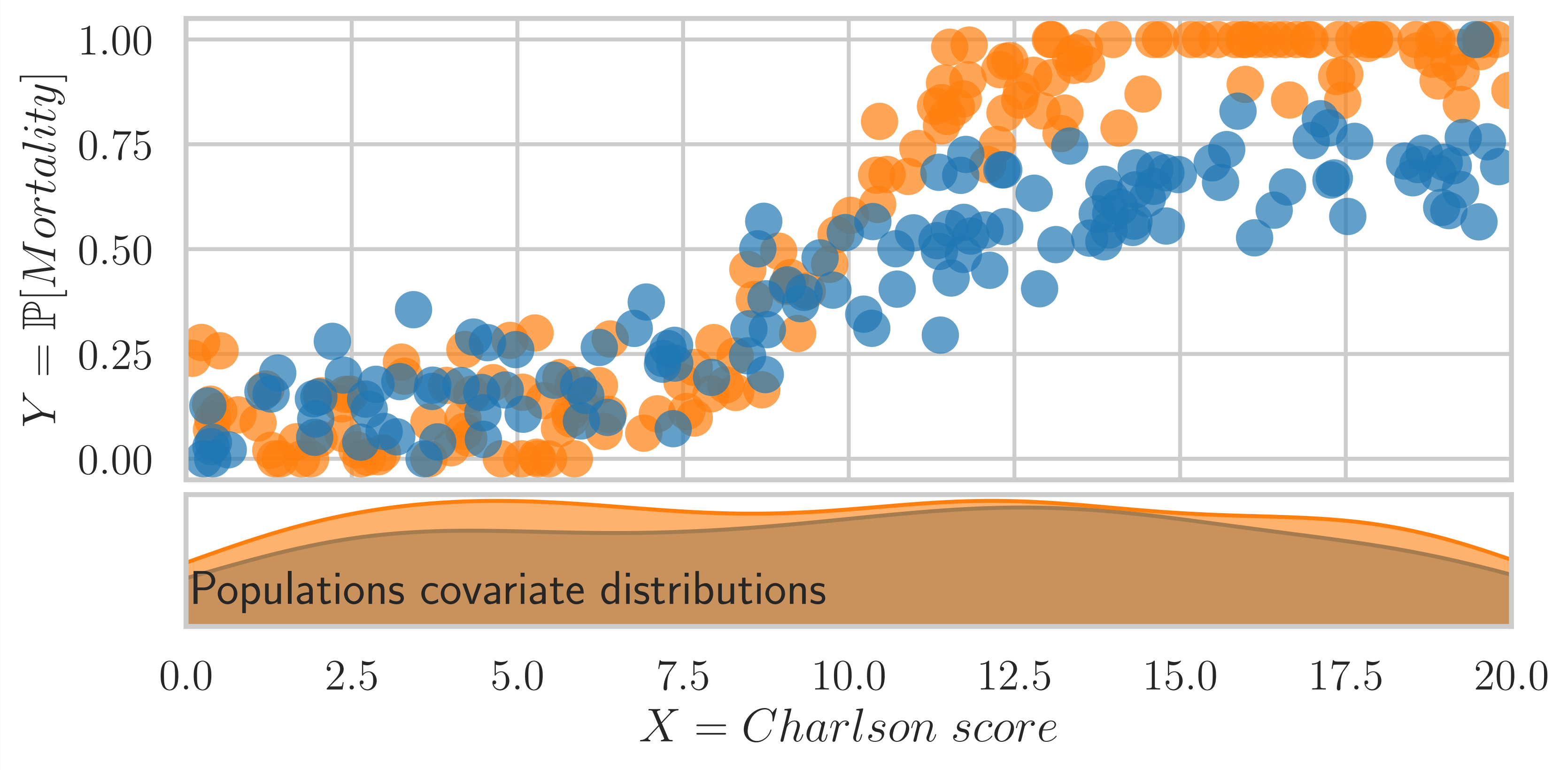
RCT data



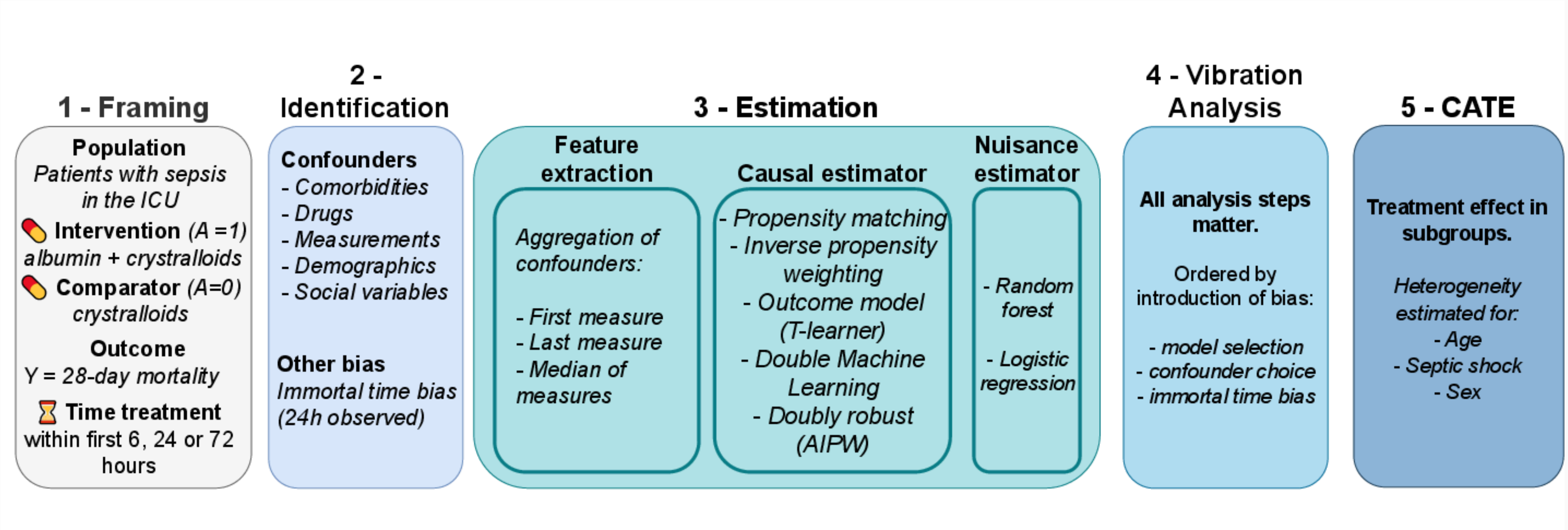
$$Y(1), Y(0) \perp\!\!\!\perp A$$

Force random assignment of the intervention

Illustration: RCT data



Full pipeline



Focus: studying the effect of incomplete DAGs

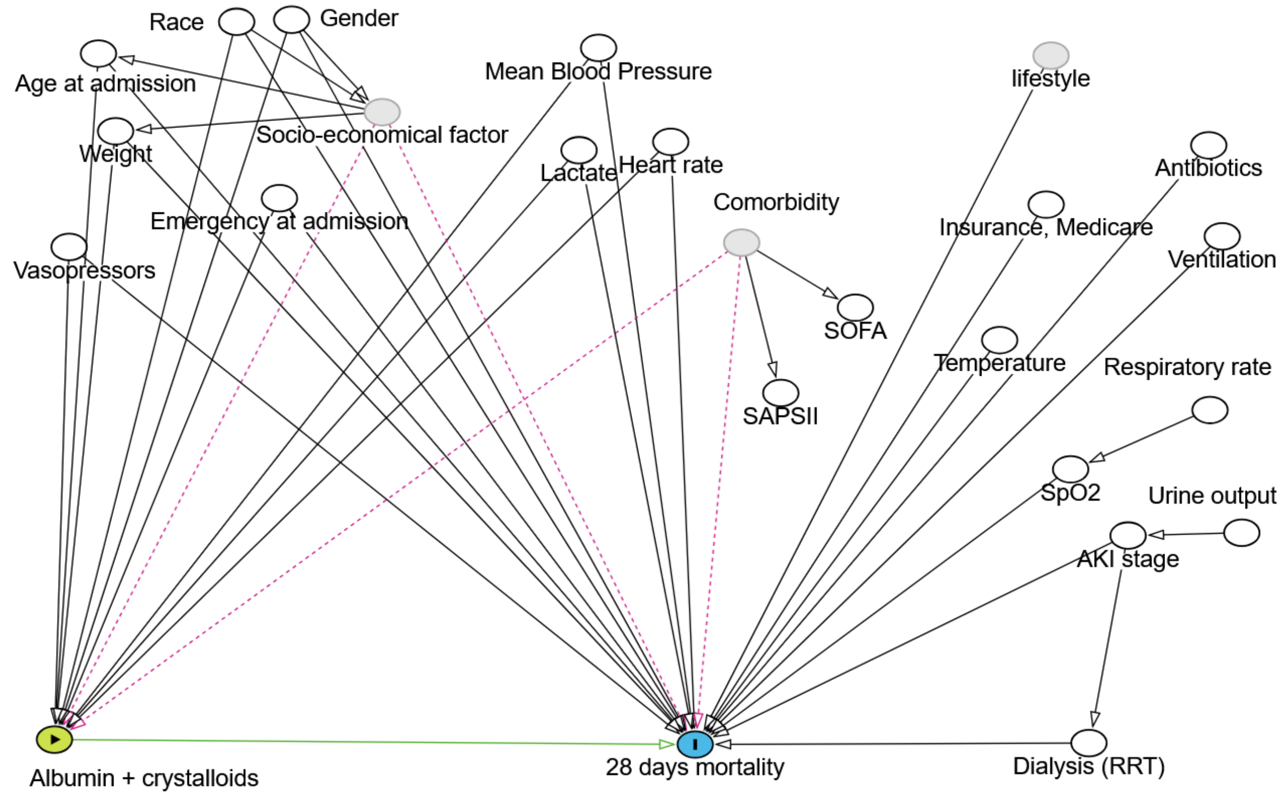
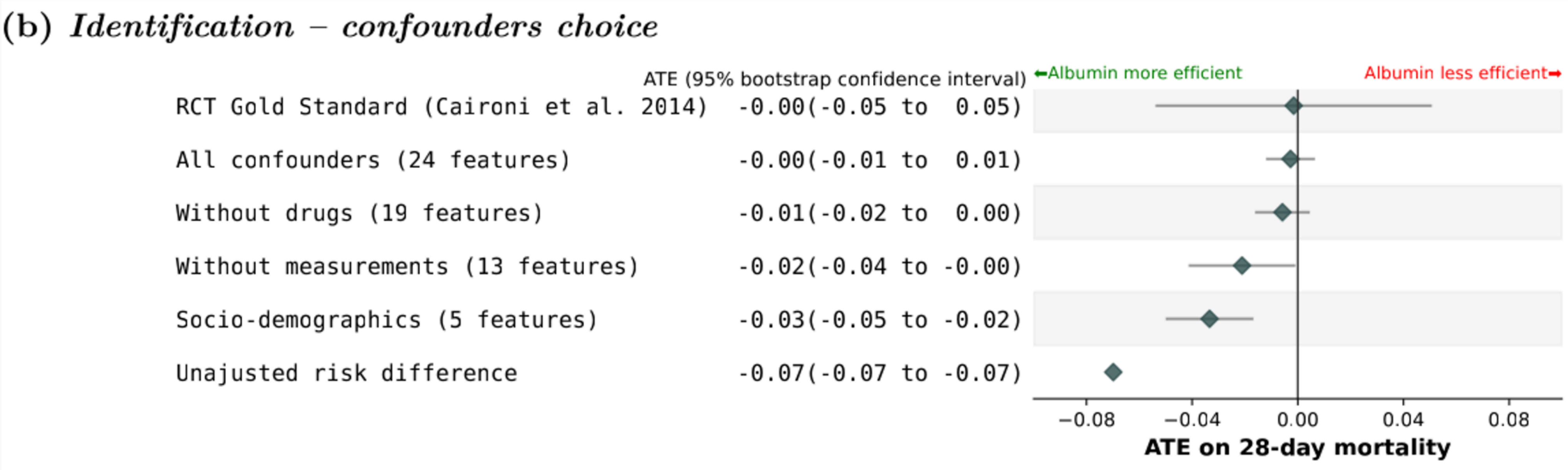


Fig 1. *Causal graph for the Albumin vs crystalloids emulated trial*

Results of an increasingly complete confounder set



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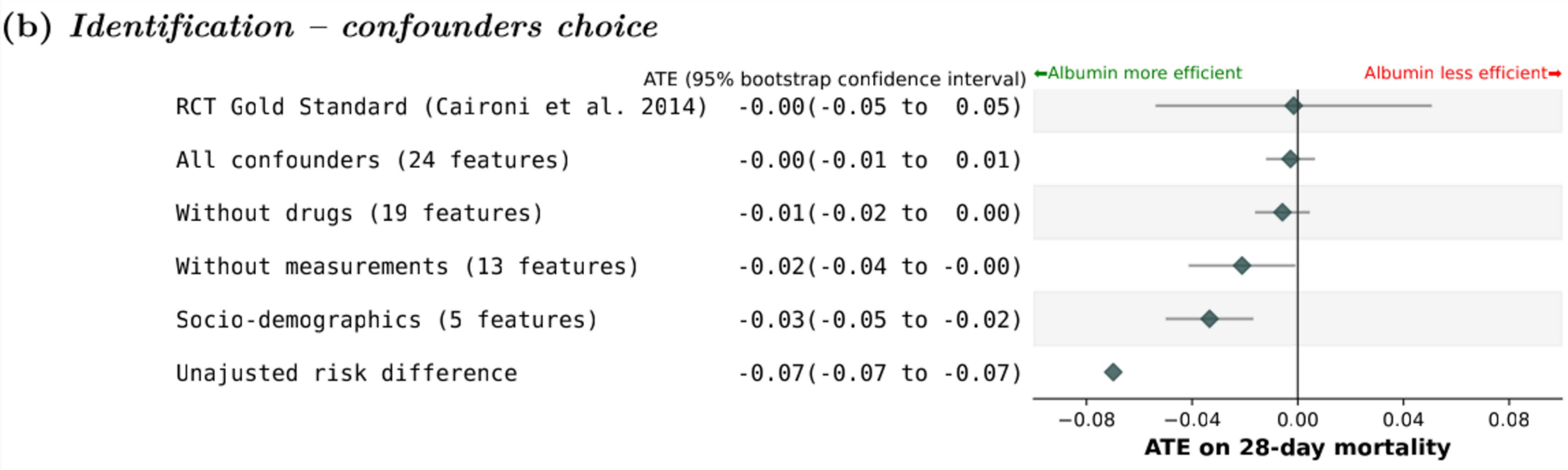
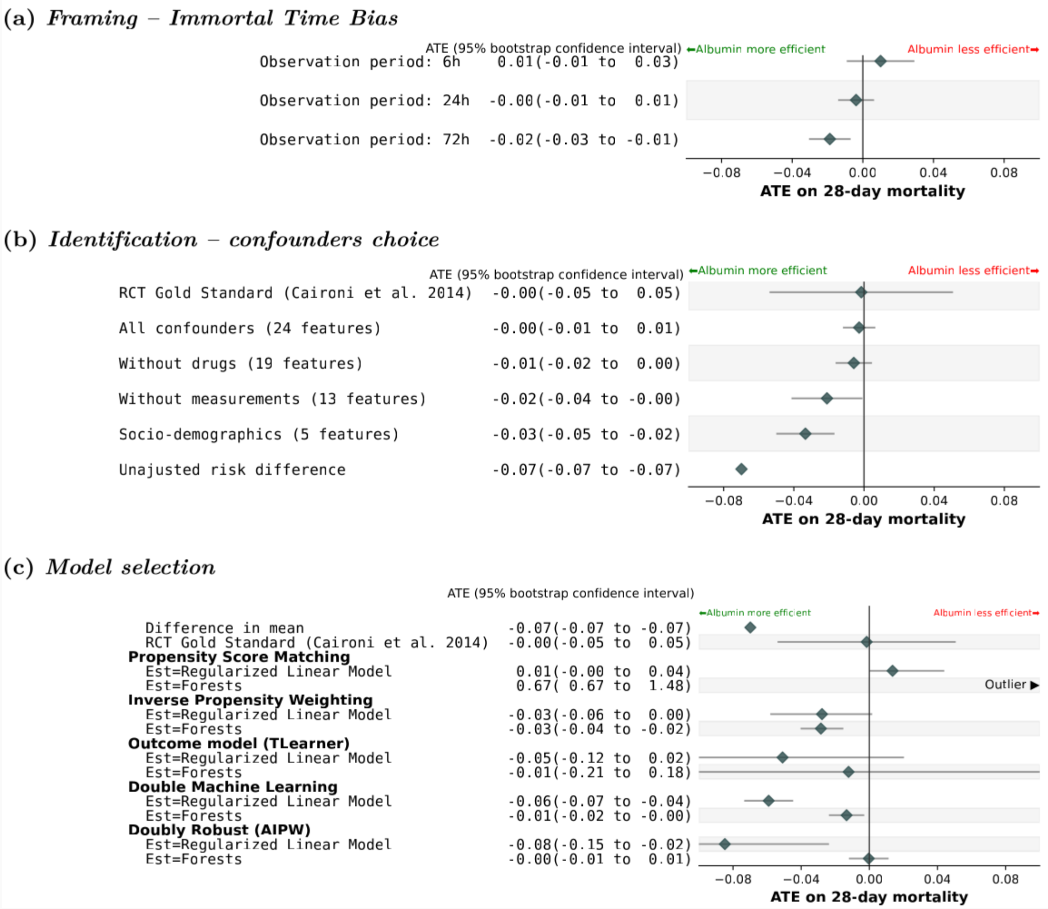


- Missing imortant confounders lead to bias estimates.
- Missing less important confounders lead to less precise estimates: a perfect DAG might not be needed.

Full results of the sensitivity analysis



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

Practical session

To your notebooks! 👩‍💻

- url: https://straymat.github.io/causal-ml-course/practical_sessions.html

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Bibliography

Supplementary material

DAG: Effect modifier

Effect modifier: influences the treatment effect on the outcome.