Validating Causal Inference Methods

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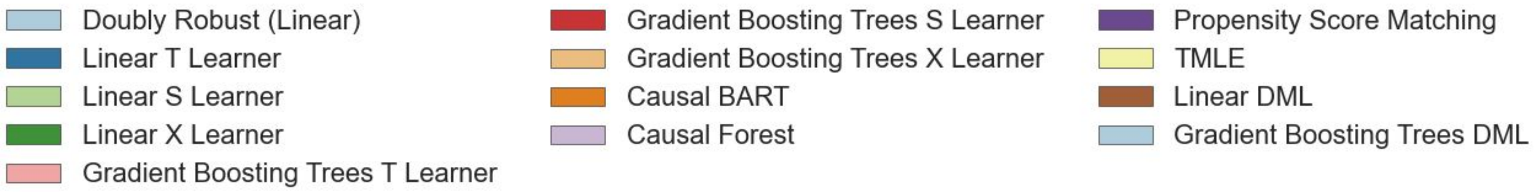
The Zoo of Causal Methods

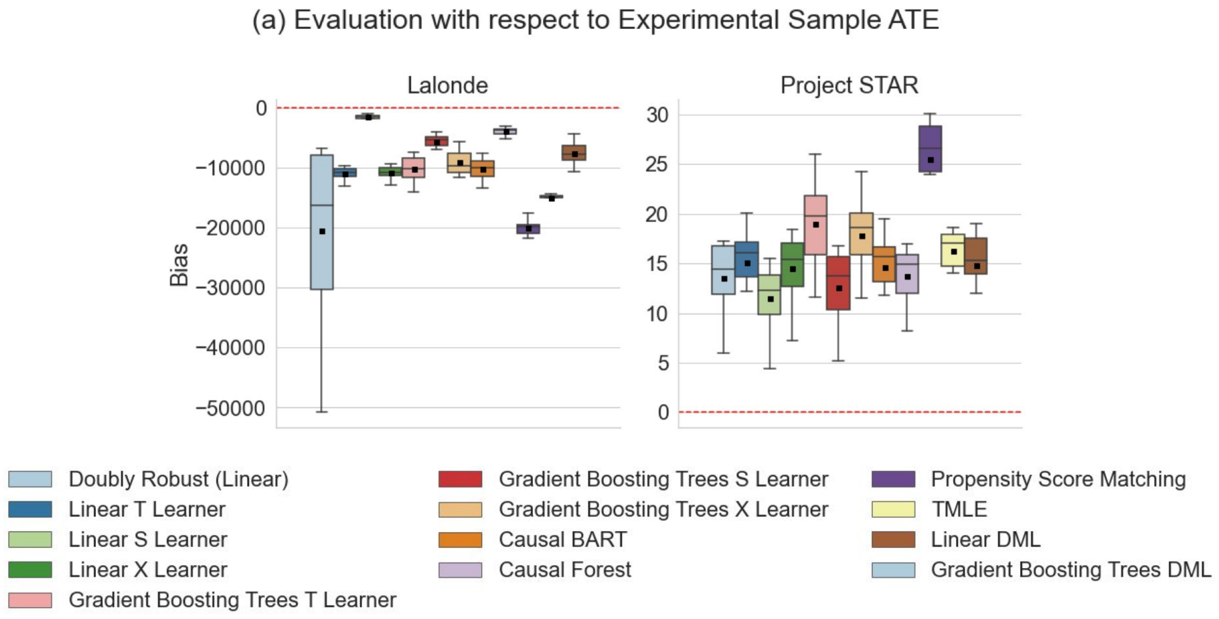
Many statistical methods have emerged for causal inference under unconfoundedness conditions given pre-treatment covariates, including:

- propensity score-based methods,
- prognostic score-based methods,
- doubly robust methods.



No ‘One-Size Fits All’ Method

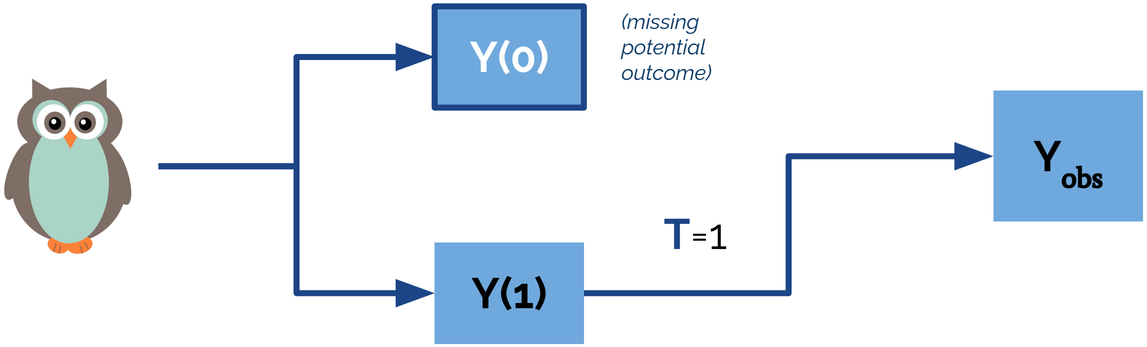
Unfortunately for applied researchers, there is *no ‘one-size-fits-all’* causal method that can perform optimally universally



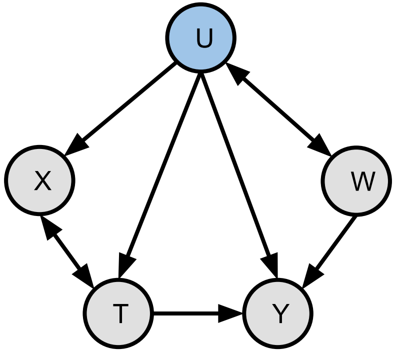
The Difficulty on Estimating and Validating Causal Effects

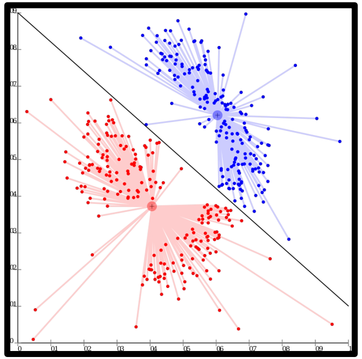
The fundamental challenge of drawing causal inference is that

- The counterfactual outcomes are not fully observed for any unit.
- Furthermore, in observational studies, treatment assignment is likely to be confounded.
- Thus, almost all causal inference methods depend on some untestable assumption(s).



Existing Approaches





Face-Validity Test

Placebo/Negative Control Tests

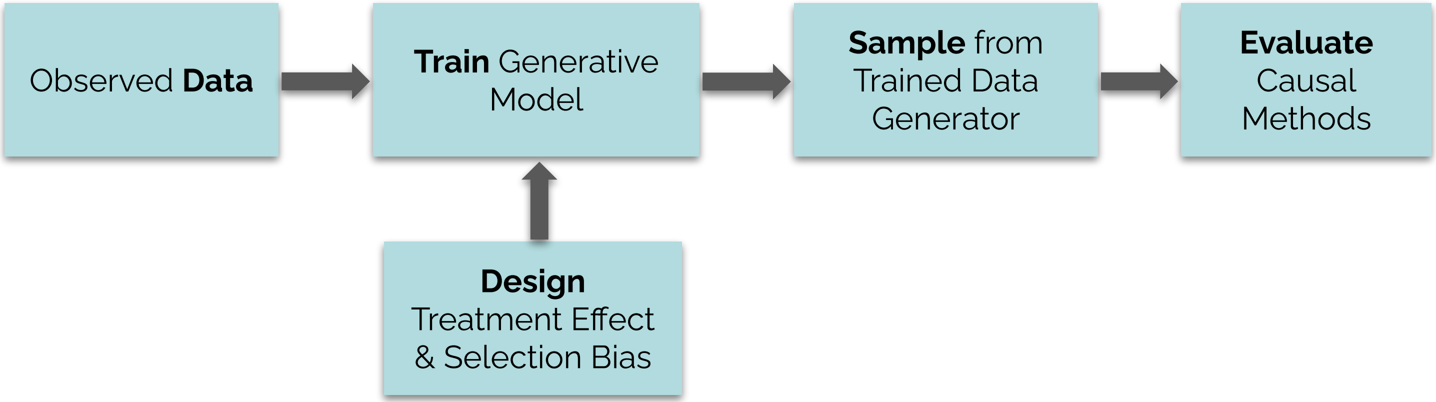
Handcrafted Synthetic Data Tests

Credence Framework

Our approach to generate synthetic data satisfies two salient properties sought out in simulation studies:

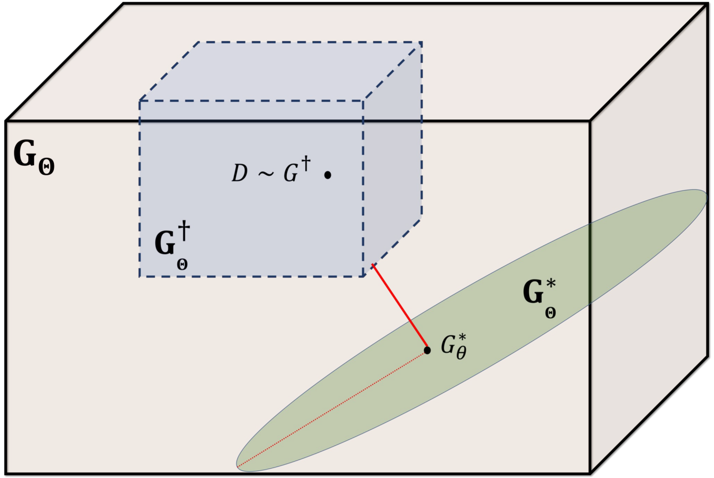
(i) user-specified causal treatment effects, heterogeneity, and endogeneity;

(ii) simulated samples that are stochastically indistinguishable from the observed data sample of interest.



Learning a Candidate Data Generator under Constraints

$$\min_\theta \left(\begin{array}{c} \mathbf{E}\left[d((X,Y,Z),(X',Y',Z'))\right] \\ +\alpha \left\|\mathbf{E}[Y'(1)-Y'(0)|X'=x'] - f(x')\right\| \\ +\beta \left\|\mathbf{E}[Y'(z')|X'=x',Z'=z'] - \mathbf{E}[Y'(z')|X'=x',Z'=1-z'] - g(x',z')\right\| \end{array} \right)$$



Validate and evaluate the performance using learned DGP anchored at

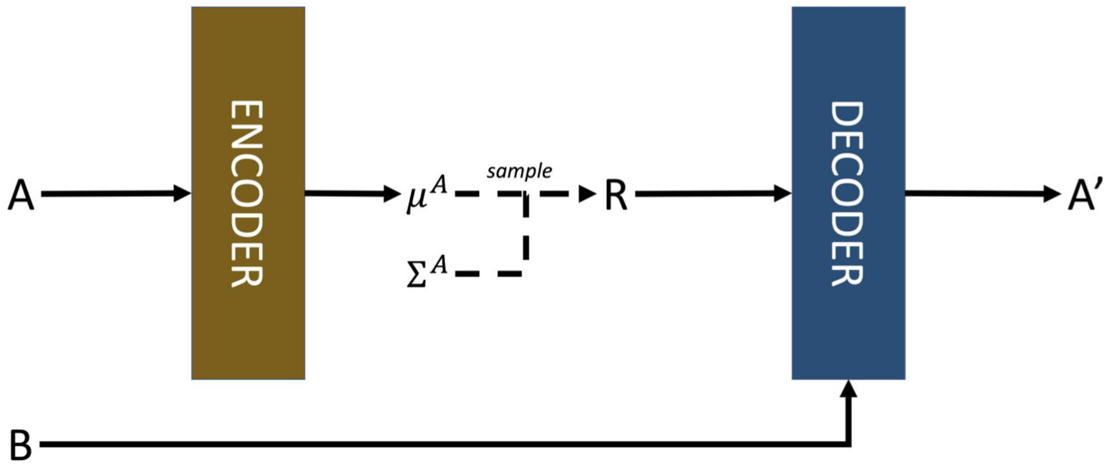
(i) the empirical distribution of a given data set of interest

(ii) user defined treatment effect/selection bias functions

Conditional Variational Autoencoders

We leverage deep generative model trained on the data set of primary interest, which is the basis to operationalize the proposed framework.

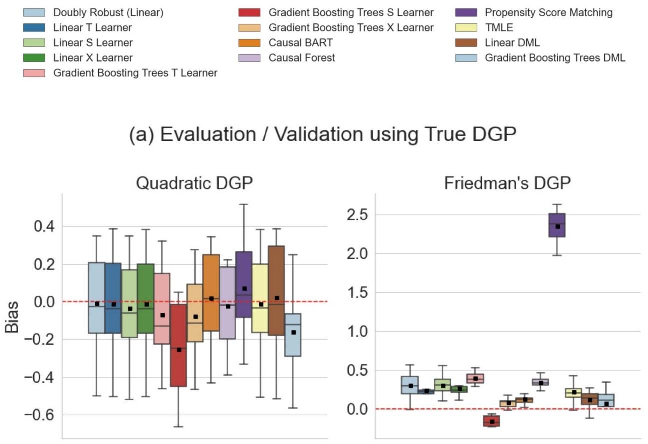
Learning P(A|B)

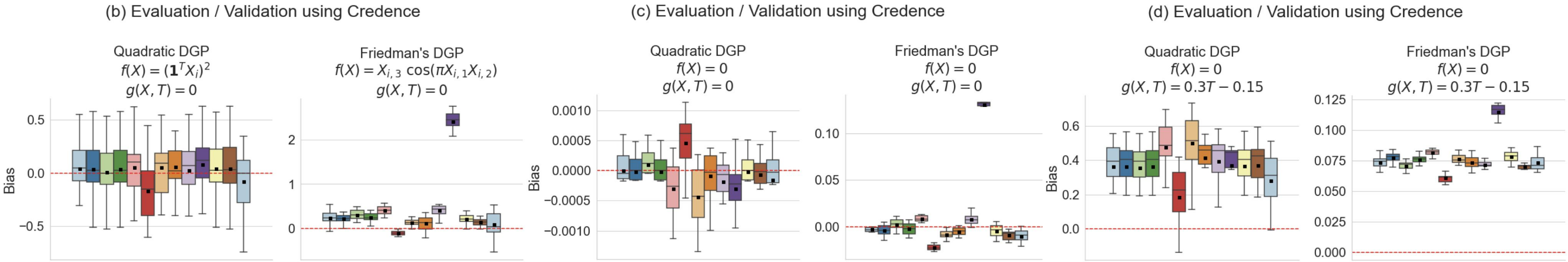


True DGP* vs Credence learned DGP?

* only possible for synthetic data

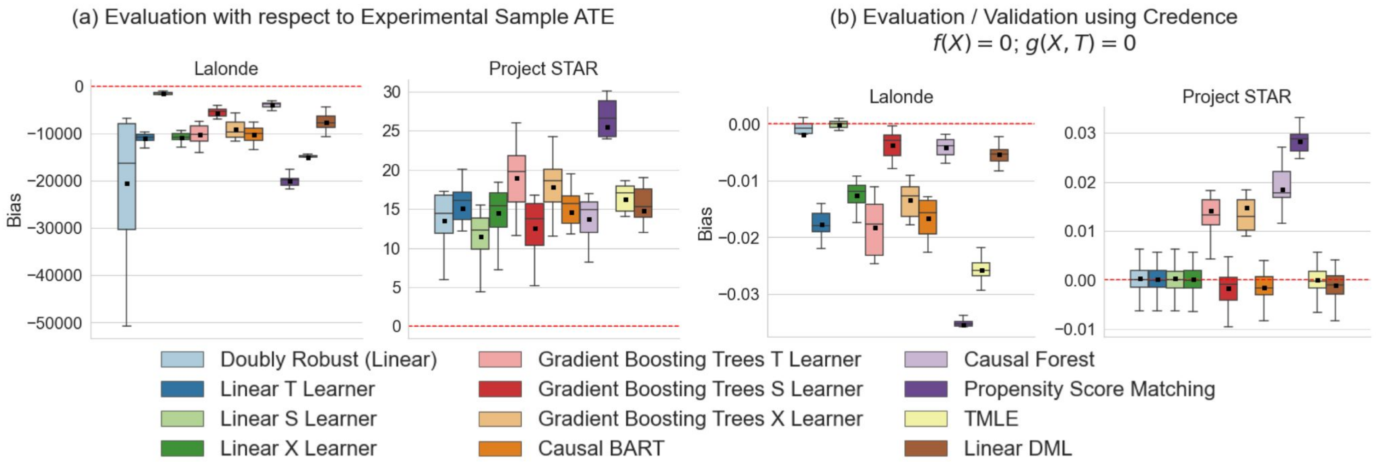
- The *main takeaway* from this analysis is that Credence is able to **reproduce rankings** obtained by an oracle with access to the true DGP in cases where the constraints broadly align with the structure of true DGP.
- This highlights that the performances **evaluated using Credence can provide reliable inferences** in such a setting.





Experimental ATE* vs Credence learned DGP?

* only possible for where we have access to both experimental as well as observational data



- For *Lalonde's data*, rankings based on comparing observational ATE with experimental ATE are largely similar to rankings produced using Credence learned DGP except with respect to estimated variance of estimators.
- For *Project STAR data*, the estimated treatment effect based on observational data is significantly different from experimental data which possibly indicates that the experimental sample lacks external validity [von Hippel and Wagner (2018); Justman (2018)].
    - Acknowledging this caveat, most methods perform similarly except GBT T-learner, GBT X-learner, Causal Forest and PSM

Limitations

- Generative models are sensitive to hyper-parameters
- Evaluations as good as the assumptions user makes

Future Directions

- Use Credence as a deep-bootstrap for *inference*
- Extension to scenarios with interference/homophily
- Theoretical guarantees on Credence based ranking

Thank you so much!

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