Causal Effect Estimation with Context and Confounders

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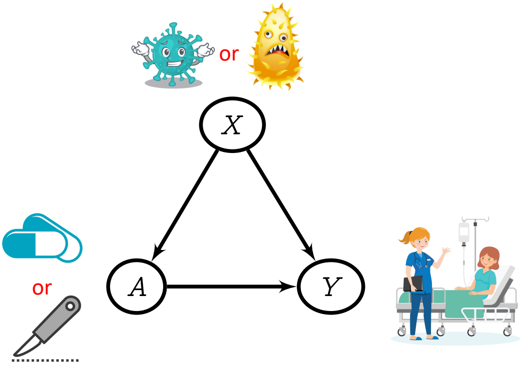
Observation vs intervention

Conditioning from observation: $\mathbb{E}[Y|A=a] = \sum_x \mathbb{E}[Y|a,x]p(x|a)$

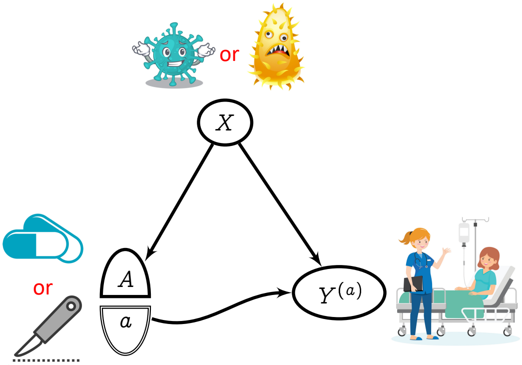


From our *observations* of historical hospital data:

- $P(Y = \text{cured}|A = \text{pills}) = 0.85$
- $P(Y = \text{cured}|A = \text{surgery}) = 0.72$

Observation vs intervention

Average causal effect (intervention): $\mathbb{E}[Y^{(a)}] = \sum_x \mathbb{E}[Y \mid a, x]\, p(x)$

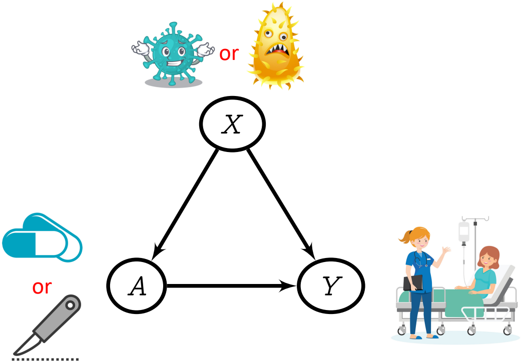


From our *intervention* (making all patients take a treatment):

- $P(Y^{(\text{pills})} = \text{cured}) = 0.64$
- $P(Y^{(\text{surgery})} = \text{cured}) = 0.75$

Richardson, Robins (2013), Single World Intervention Graphs (SWIGs): A Unification of the Counterfactual and Graphical Approaches to Causality

Some core assumptions



Assume:

- Stable Unit Treatment Value Assumption (aka "no interference"),
- Conditional exchangeability $Y^{(a)} \perp\!\!\!\perp A | X$.
- Overlap.

One model: linear functions of features

All learned functions will take the form:

$$\gamma(x) = \gamma^\top \varphi_\theta(x)$$

NN approach: Finite dictionaries of learned neural net features $\varphi_\theta(x)$ (linear final layer γ)

Xu, G., A Neural mean embedding approach for back-door and front-door adjustment. (ICLR 23)

Xu, Chen, Srinivasan, de Freitas, Doucet, G. Learning Deep Features in Instrumental Variable Regression. (ICLR 21)

Xu, Kanagawa, G. "Deep Proxy Causal Learning and its Application to Confounded Bandit Policy Evaluation". (NeurIPS 21)

Model fitting: *neural* ridge regression

Learn $\gamma_0(x) := \mathbb{E}[Y|X = x]$ from features $\varphi_\theta(x_i)$ with outcomes y_i:

$$\hat{\gamma} \quad = \quad \arg\min_{\gamma \in \mathcal{H}} \left(\sum_{i=1}^{n} \left(y_i - \gamma^\top \varphi_\theta(x_i) \right)^2 + \lambda \|\gamma\|_{\mathcal{H}}^2 \right) \tag{1}$$

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Solution for linear final layer γ:

$$\hat{\gamma} = C_{YX}^{(\theta)} (C_{XX}^{(\theta)} + \lambda)^{-1}$$

$$C_{YX}^{(\theta)} = \frac{1}{n} \sum_{i=1}^{n} [y_i \, \varphi_\theta(x_i)^\top]$$

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How to solve for θ:

Substitute $\hat{\gamma}$ into (1), backprop through Cholesky for θ.

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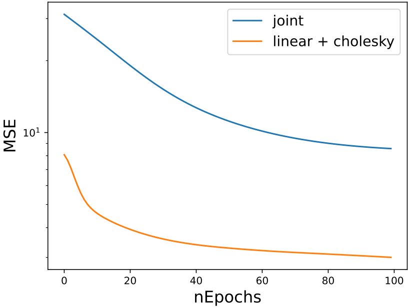

MNIST, 4 layer FF, sigmoid, fully connected

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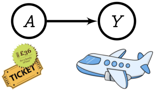
Instrumental variable regression

Illustration: ticket prices for air travel

Ticket price A, seats sold Y.



What is the effect on seats sold $Y^{(a)}$ of intervening on price a?

Simplification of example from Hartford, Lewis, Leyton-Brown, Taddy (2017): Deep IV: A Flexible Approach for Counterfactual Prediction.

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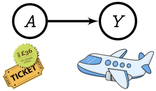

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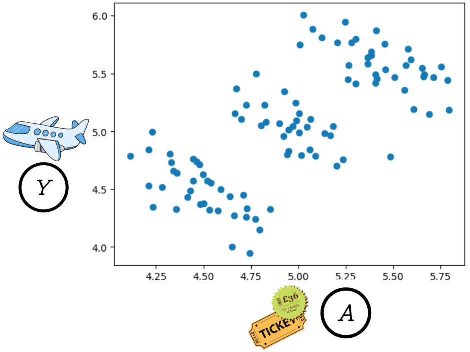

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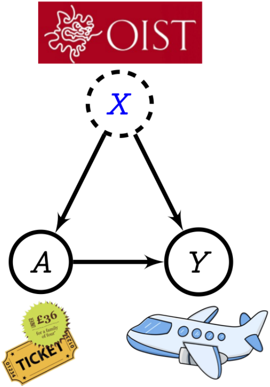
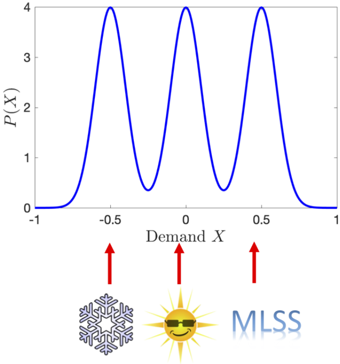
Unobserved variable X =desire for travel, affects *both* price (via airline algorithms) *and* seats sold.

- Desire for travel:
  $X \sim \mathcal{N}(\mu, 0.1)$
  $\mu \sim \mathcal{U}\left\{-\frac{1}{2}, 0, \frac{1}{2}\right\}$





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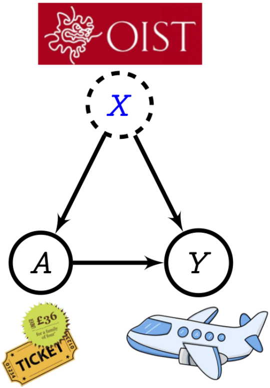

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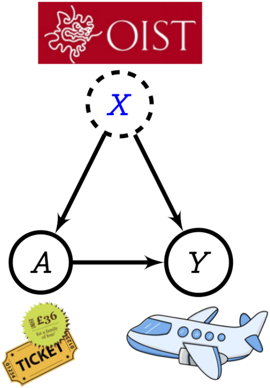

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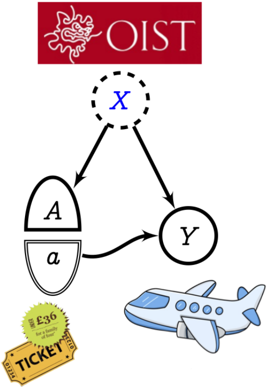

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Average treatment effect:

$$\mathrm{ATE}(a) = \mathbb{E}[Y^{(a)}] = \int (10 - a + 2X)\, dp(X) = 10 - a$$

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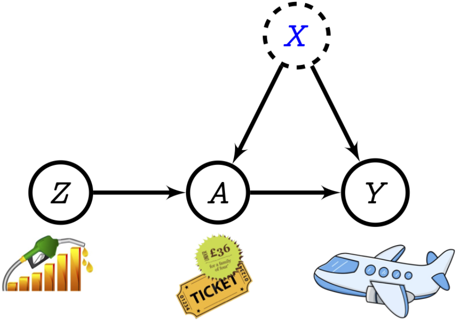

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Z is an instrument (cost of fuel). Condition on Z,

$$\mathbb{E}[Y|Z] = 10 - \mathbb{E}[A|Z] + 2\underbrace{\mathbb{E}[X|Z]}_{=0}$$

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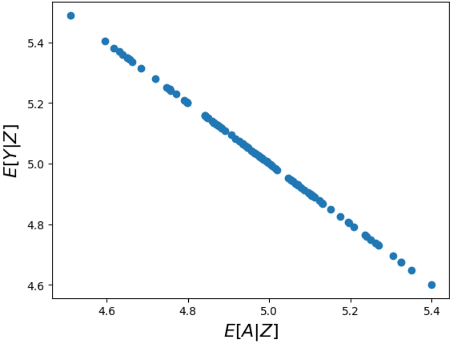

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Regressing from $\mathbb{E}[A|Z]$ to $\mathbb{E}[Y|Z]$ recovers causal relation!

Plain linear regression: what goes wrong?

Output $y \in \mathbb{R}$, noise $X \in \mathbb{R}$, input A with NN features $\varphi_\theta(a)$.

Crucially, $X \not\perp A$ and

$$C_{ax} := \mathbb{E}[\varphi_\theta(A) X] \neq 0$$

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Average treatment effect:

$$y = {\gamma_0}^\top \varphi_\theta(a) + X \qquad \mathbb{E}(X) = 0$$

$$ATE := \mathbb{E}(Y^{(a)}) = \int ({\gamma_0}^\top \varphi_\theta(a) + X) dP(X) = {\gamma_0}^\top \varphi_\theta(a).$$

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Least-squares loss for γ:

$$\mathcal{L}(\gamma, \theta) = \mathbb{E} \left\| Y - \gamma^\top \varphi_\theta(A) - X \right\|^2$$

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Minimizing for γ,

$$\gamma_0 = C_{aa}^{-1}(C_{ay} - C_{ax}) \qquad C_{aa} = \mathbb{E}[\varphi_\theta(A)\varphi_\theta(A)^\top]$$

$$C_{ay} = \mathbb{E}[\varphi_\theta(A)Y]$$

...but we don't have C_{ax}.

Instrumental variable regression

The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2021

© Nobel Prize Outreach. Photo: Paul Kennedy

David Card

Prize share: 1/2

© Nobel Prize Outreach. Photo: Risdon Photography

Joshua D. Angrist

Prize share: 1/4

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Guido W. Imbens

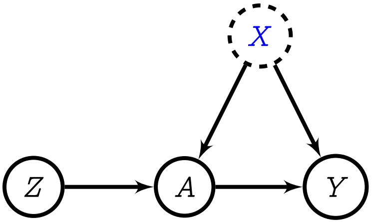
Prize share: 1/4

The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2021 was divided, one half awarded to David Card "for his empirical contributions to labour economics", the other half jointly to Joshua D. Angrist and Guido W. Imbens "for their methodological contributions to the analysis of causal relationships"

Instrumental variable regression with NN features

Definitions:

- X: unobserved confounder.
- A: treatment
- Y: outcome
- Z: instrument



Assumptions

$$\mathbb{E}[X] = 0, \quad \mathbb{E}[X|Z] = 0$$

$$Z \not\perp\!\!\!\perp A$$

$$(Y \perp\!\!\!\perp Z|A)_{G_{\bar{A}}}$$

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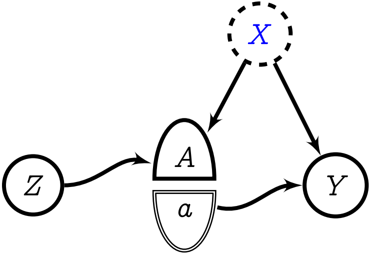

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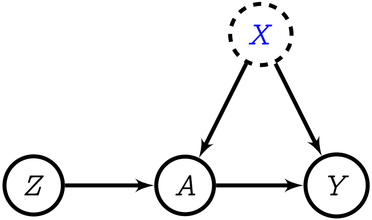

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IV regression: Condition both sides on Z,

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Two-stage least squares for IV regression

Kernel features (NeurIPS 2019):

arXiv.org > cs > arXiv:1906.00232

Computer Science > Machine Learning

[Submitted on 1 Jun 2019 (v1), last revised 15 Jul 2020 (this version, v6)]

Kernel Instrumental Variable Regression

Rahul Singh, Maneesh Sahani, Arthur Gretton

NN features (ICLR 2021):

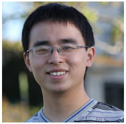
arXiv > cs > arXiv:2010.07154

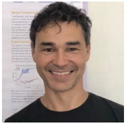
Computer Science > Machine Learning

[Submitted on 14 Oct 2020 (v1), last revised 1 Nov 2020 (this version, v3)]

Learning Deep Features in Instrumental Variable Regression

Liyuan Xu, Yutian Chen, Siddarth Srinivasan, Nando de Freitas, Arnaud Doucet, Arthur Gretton





Code for NN and kernel IV methods:

https://github.com/liyuan9988/DeepFeatureIV/

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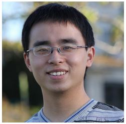

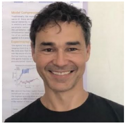

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IV using neural net features

Stage 2 regression (IV): learn NN features $\varphi_\theta(A)$ and linear layer γ to obtain Y with RR loss:

$$\mathbb{E}_{YZ}\left[(Y - \gamma^\top \mathbb{E}[\varphi_\theta(A)|Z])^2\right] + \lambda_2 \|\gamma\|^2$$

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$$\mathbb{E}[\varphi_\theta(A)|Z] \approx F\varphi_\zeta(Z)$$

with RR loss

$$\mathbb{E}\|\varphi_\theta(A) - F\varphi_\zeta(Z)\|^2 + \lambda_1 \|F\|_{HS}^2$$

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...which requires $\mathbb{E}[\varphi_\theta(A)|Z]$ from Stage 1 regression

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...which requires $\mathbb{E}[\varphi_\theta(A)|Z]$ from Stage 1 regression

...which requires $\varphi_\theta(A)$... which requires θ...

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$$\mathbb{E}[\varphi_\theta(A)|Z] \approx F\varphi_\zeta(Z)$$

with RR loss

$$\mathbb{E}\|\varphi_\theta(A) - F\varphi_\zeta(Z)\|^2 + \lambda_1\|F\|^2_{HS}$$

Challenge: how to learn θ?

From Stage 2 regression?

...which requires $\mathbb{E}[\varphi_\theta(A)|Z]$ from Stage 1 regression

...which requires $\varphi_\theta(A)$... which requires θ...

Use the linear final layers! (i.e. γ and F)

Xu, Chen, Srinivasan, De Freitas, Doucet, G. (2021) Learning Deep Features in Instrumental Variable Regresion

IV using neural net features

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$\hat{F}_{\theta,\zeta}$ in closed form wrt $\varphi_\theta, \varphi_\zeta$:

$$\hat{F}_{\theta,\zeta} = C_{AZ}(C_{ZZ} + \lambda_1 I)^{-1} \qquad C_{AZ} = \mathbb{E}[\varphi_\theta(A)\varphi_\zeta^\top(Z)]$$

$$C_{ZZ} = \mathbb{E}[\varphi_\zeta(Z)\varphi_\zeta^\top(Z)]$$

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$$C_{ZZ} = \mathbb{E}[\varphi_\zeta(Z)\varphi_\zeta^\top(Z)]$$

Plug $\hat{F}_{\theta,\zeta}$ into S1 loss, bp through Cholesky for ζ (...but not θ...)

Xu, Chen, Srinivasan, De Freitas, Doucet, G. (2021) Learning Deep Features in Instrumental Variable Regresion

Stage 2: IV regression

Stage 2 regression (IV): learn NN features $\varphi_\theta(A)$ and linear layer γ to obtain Y with RR loss:

$$\mathcal{L}_2(\gamma, \theta) = \mathbb{E}_{YZ}\left[(Y - \gamma^\top \mathbb{E}[\varphi_\theta(A)|Z])^2\right] + \lambda_2\|\gamma\|^2$$

Xu, Chen, Srinivasan, De Freitas, Doucet, G. (2021)

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$\hat{\gamma}_\theta$ in closed form wrt φ_θ:

$$\hat{\gamma}_\theta := \widetilde{C}_{YA|Z}(\widetilde{C}_{AA|Z} + \lambda_2 I)^{-1} \qquad \widetilde{C}_{YA|Z} = \mathbb{E}\left[Y\ [\hat{F}_{\theta,\zeta}\varphi_\zeta(Z)]^\top\right]$$
$$\widetilde{C}_{AA|Z} = \mathbb{E}\left[[\hat{F}_{\theta,\zeta}\varphi_\zeta(Z)]\ [\hat{F}_{\theta,\zeta}\varphi_\zeta(Z)]^\top\right]$$

Xu, Chen, Srinivasan, De Freitas, Doucet, G. (2021)

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$$\widetilde{C}_{AA|Z} = \mathbb{E}\left[[\hat{F}_{\theta,\zeta}\varphi_\zeta(Z)]\,[\hat{F}_{\theta,\zeta}\varphi_\zeta(Z)]^\top\right]$$

From linear final layers in Stages 1,2:

Learn $\varphi_\theta(A)$ by plugging $\hat{\gamma}_\theta$ into S2, bp through Cholesky for θ

Xu, Chen, Srinivasan, De Freitas, Doucet, G. (2021)

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From linear final layers in Stages 1,2:

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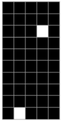
....but ζ changes with θ

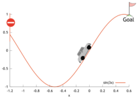
...so alternate first and second stages until convergence.

Xu, Chen, Srinivasan, De Freitas, Doucet, G. (2021)

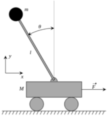
Neural IV in reinforcement learning



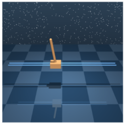
(a) Catch



(b) Mountain Car



(c) Cartpole



(a) Cartpole Swingup

(b) Cheetah Run

(c) Humanoid Run

(d) Walker Walk

Policy evaluation: want Q-value:

$$Q^{\pi}(s, a) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^{t} R_{t} \middle| S_0 = s, A_0 = a\right]$$

for policy $\pi(A|S = s)$.

Osband et al (2019). Behaviour suite for reinforcement learning.https://github.com/deepmind/bsuite
Tassa et al. (2020). dm_control:Software and tasks for continuous control. https://github.com/deepmind/dm_control

Application of IV: reinforcement learning

Q value is a minimizer of Bellman loss

$$\mathcal{L}_{\text{Bellman}} = \mathbb{E}_{SAR}\left[\left(R + \gamma[\mathbb{E}\left[Q^\pi(S', A')\middle|S, A\right] - Q^\pi(S, A)\right)^2\right].$$

Corresponds to "IV-like" problem

$$\mathcal{L}_{\text{Bellman}} = \mathbb{E}_{YZ}\left[\left(Y - \mathbb{E}[f(X)|Z]\right)^2\right]$$

with

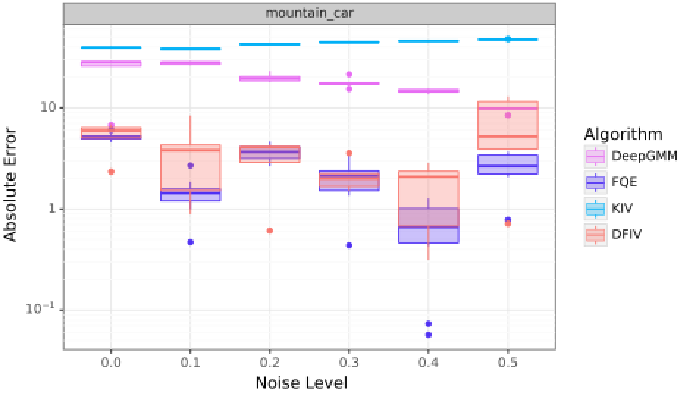
$$\begin{aligned} Y &= R, \\ X &= (S', A', S, A) \\ Z &= (S, A), \\ f_0(X) &= Q^\pi(s, a) - \gamma Q^\pi(s', a') \end{aligned}$$

RL experiments and data:

https://github.com/liyuan9988/IVOPEwithACME

Bradtke and Barto (1996). Linear least-squares algorithms for temporal difference learning.
Xu, Chen, Srinivasan, De Freitas, Doucet, G. (2021)
Chen, Xu, Gulcehre, Le Paine, G, De Freitas, Doucet (2022). On Instrumental Variable Regression for Deep Offline Policy Evaluation.

Results on mountain car problem



Good performance compared with FQE.

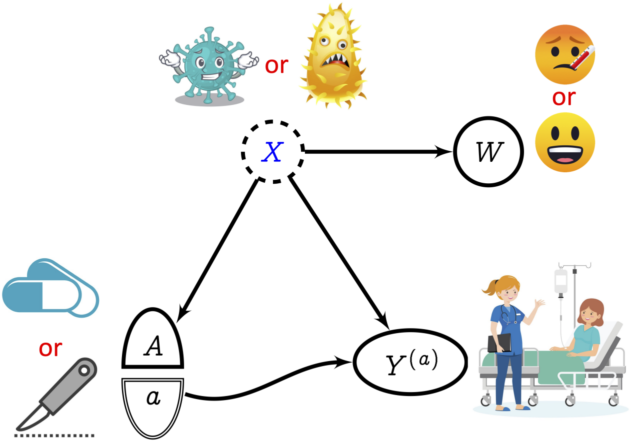
Warning: IV assumption can fail when regression underfits. See papers for details.

Xu, Chen, Srinivasan, De Freitas, Doucet, G. (2021)

Chen, Xu, Gulcehre, Le Paine, G, De Freitas, Doucet (2022). On Instrumental Variable Regression for Deep Offline Policy Evaluation.

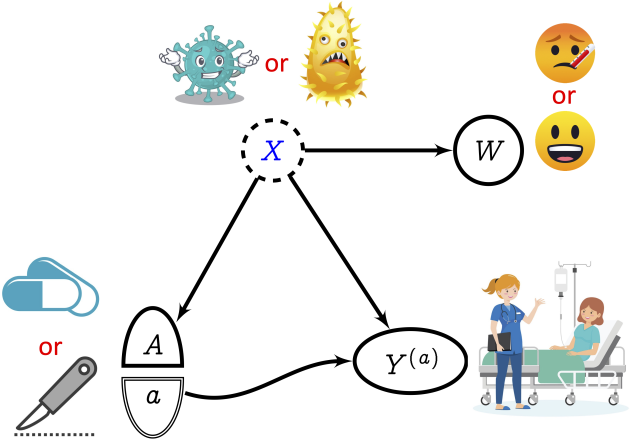
Proxy causal learning

We record symptom W, not disease X



- $P(W = \text{fever} | X = \text{mild}) = 0.2$
- $P(W = \text{fever} | X = \text{severe}) = 0.8$

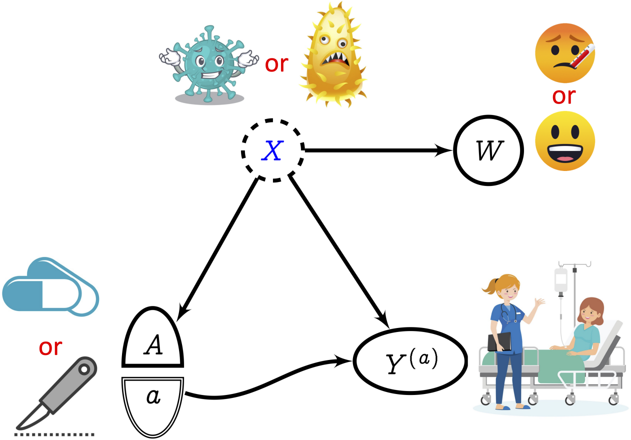
We record symptom W, not disease X



- $P(W = \text{fever} | X = \text{mild}) = 0.2$
- $P(W = \text{fever} | X = \text{severe}) = 0.8$

Could we just write: $P(Y^{(a)}) \overset{?}{=} \sum_{w \in \{0,1\}} \mathbb{E}[Y | a, w] p(w)$

We record symptom W, not disease X



Wrong recommendation made:

- $\sum_{w\in\{0,1\}} \mathbb{E}[\text{cured}|\text{pills}, w]p(w) = 0.8 \quad (\neq 0.64)$
- $\sum_{w\in\{0,1\}} \mathbb{E}[\text{cured}|\text{surgery}, w]p(w) = 0.73 \quad (\neq 0.75)$

Correct answer impossible without observing X

Pearl (2010), On Measurement Bias in Causal Inference

Outline

Causal effect estimation, with hidden covariates X:

- Use proxy variables (negative controls)

Applications: effect of actions under

- privacy constraints (email, ads, DMA)
- data gathering constraints (edge computing)
- fundamental limitations (preferences, state of mind)

Outline

Causal effect estimation, with hidden covariates X:

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- privacy constraints (email, ads, DMA)
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What's new and why?

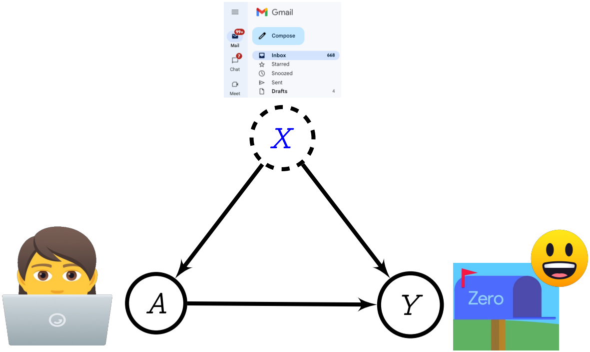
- Treatment A, proxy variables, etc can be multivariate, complicated...
- ...by using adaptive neural net feature representations
- Don't ~~meet your heroes~~ model your hidden variables!

What are proxies, and when are they useful?

Unobserved X with (possibly) complex nonlinear effects on A, Y

In this example:

- X: email inbox
- A: prioritize important
- Y: outcome (efficiency)



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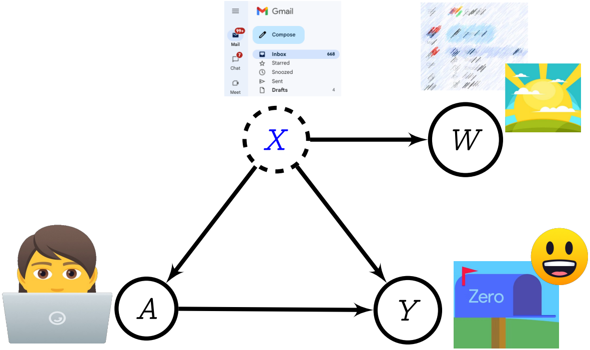

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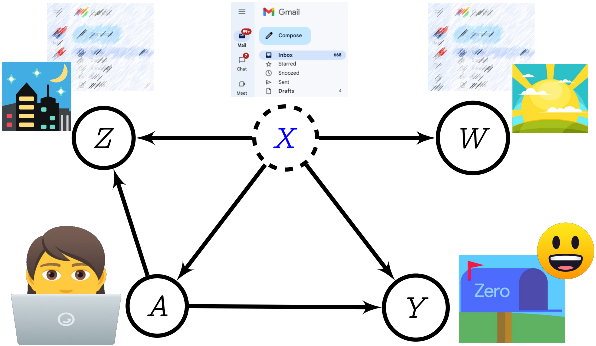

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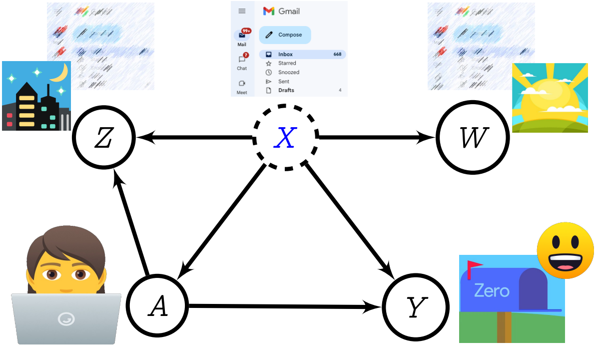

$\Longrightarrow$ Can recover $\mathbb{E}(Y^{(a)})$ from observational data

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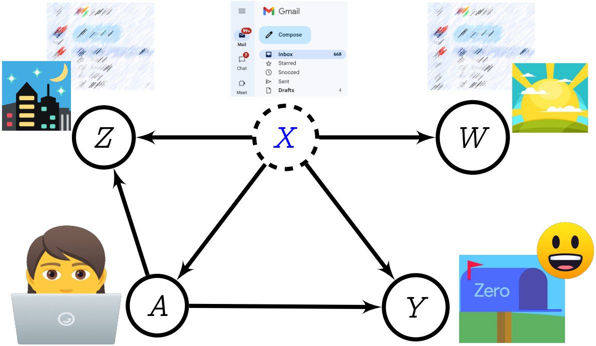


$\Longrightarrow$ Can recover $\mathbb{E}(Y^{(a)})$ from observational data

$\Longrightarrow$ More usefully: evaluate novel, on-device policy:

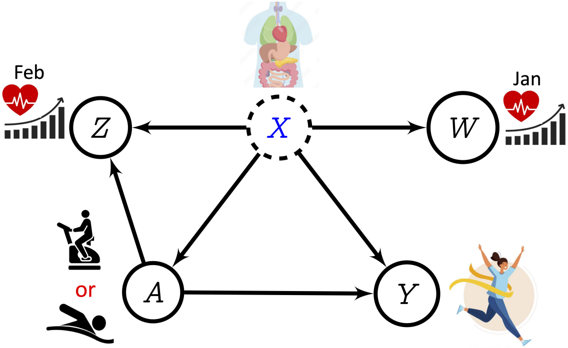
$$\mathbb{E}(Y^{(\pi(A|X))})$$

What are proxies, and when are they useful (2)?

Unobserved X with (possibly) complex nonlinear effects on A, Y

In this example:

- X: true physical status
- A: exercise regimes
- Y: fitness goal
- W: health readings before A
- Z: health readings after A

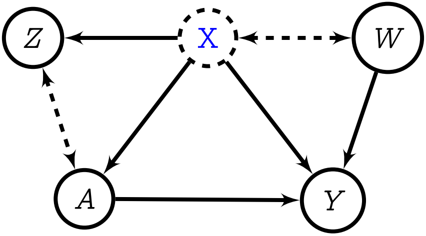


Proxy variables: general setting

Unobserved X with (possibly) complex nonlinear effects on A, Y

The definitions are:

- X: unobserved confounder.
- A: treatment
- Y: outcome
- Z: treatment proxy
- W outcome proxy



Miao, Geng, Tchetgen Tchetgen (2018): Identifying causal effects with proxy variables of an unmeasured confounder.

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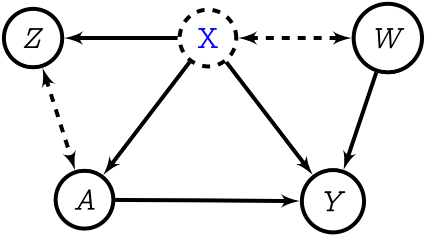

Structural assumptions:

$$W \perp\!\!\!\perp (Z, A) | X$$
$$Y \perp\!\!\!\perp Z | (A, X)$$

Miao, Geng, Tchetgen Tchetgen (2018): Identifying causal effects with proxy variables of an unmeasured confounder.

Why proxy variables? A simple proof

The definitions are:

- X: unobserved confounder.
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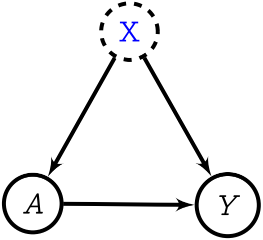

If X were observed,

$$\underbrace{P(Y^{(a)})}_{d_y \times 1} := \sum_{i=1}^{d_x} P(Y|x_i, a)P(x_i)$$

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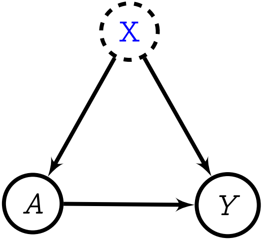

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$$\underbrace{P(Y^{(a)})}_{d_y \times 1} := \sum_{i=1}^{d_x} P(Y|x_i, a) P(x_i) = \underbrace{P(Y|X, a)}_{d_y \times d_x} \underbrace{P(X)}_{d_x \times 1}$$

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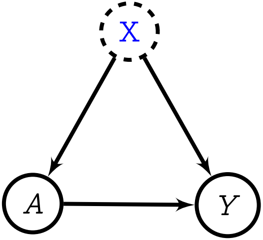

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Goal: "get rid of the blue" X

...add the outcome proxy W

The definitions are:

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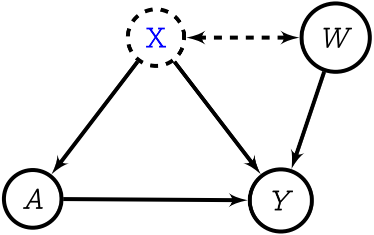

For each a, if we could solve:

$$\underbrace{P(Y|X,a)}_{d_y \times d_x} = \underbrace{H_{w,a}}_{d_y \times d_w} \underbrace{P(W|X)}_{d_w \times d_x}$$

...add the outcome proxy W

The definitions are:

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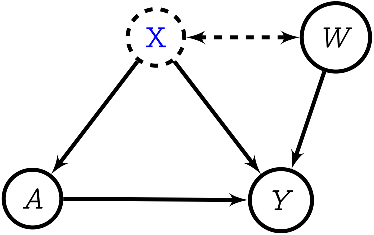

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.....then

$$P(Y^{(a)}) = P(Y|X,a)P(X)$$

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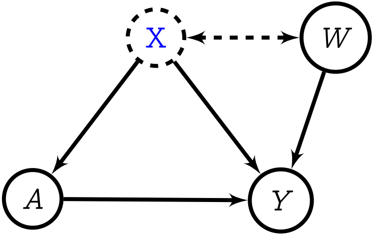

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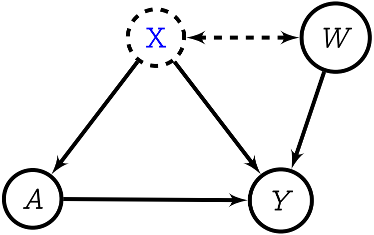

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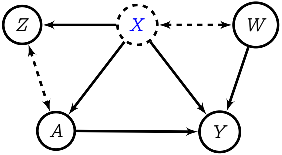
.....then

$$\begin{aligned} P(Y^{(a)}) &= P(Y|X,a)P(X) \\ &= H_{w,a}P(W|X)P(X) \\ &= H_{w,a}P(W) \end{aligned}$$

...now project onto $p(X|Z,a)$

From last slide,

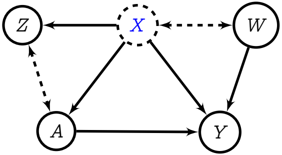
$$P(Y|X,a) \quad = H_{w,a} P(W|X)$$



...now project onto $p(X|Z,a)$

From last slide,

$$P(Y|X,a)\underbrace{p(X|Z,a)}_{d_x \times d_z} = H_{w,a} P(W|X) \underbrace{p(X|Z,a)}_{d_x \times d_z}$$



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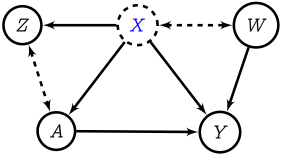


From last slide,

$$P(Y|X,a)\underbrace{p(X|Z,a)}_{d_x \times d_z} = H_{w,a} P(W|X)\underbrace{p(X|Z,a)}_{d_x \times d_z}$$

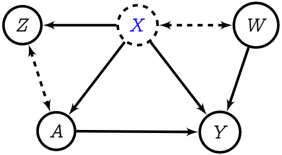
Because $W \perp\!\!\!\perp (Z,A)|X$,

$$P(W|X)p(X|Z,a) = P(W|Z,a)$$

...now project onto $p(X|Z,a)$

From last slide,

$$P(Y|X,a)\underbrace{p(X|Z,a)}_{d_x \times d_z} = H_{w,a} P(W|X)\underbrace{p(X|Z,a)}_{d_x \times d_z}$$



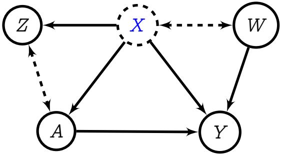
Because $W \perp\!\!\!\perp (Z,A)|X$,

$$P(W|X)p(X|Z,a) = P(W|Z,a)$$

Because $Y \perp\!\!\!\perp Z|(A,X)$,

$$P(Y|X,a)p(X|Z,a) = P(Y|Z,a)$$

...now project onto $p(X|Z,a)$



From last slide,

$$P(Y|X,a)\underbrace{p(X|Z,a)}_{d_x \times d_z} = H_{w,a} P(W|X) \underbrace{p(X|Z,a)}_{d_x \times d_z}$$

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Solve for $H_{w,a}$:

$$P(Y|Z,a) = H_{w,a} P(W|Z,a)$$

Everything observed!

Proxy/Negative Control Methods in the Real World

Unobserved confounders: proxy methods

Kernel features (ICML 2021):

arXiv.org > cs > arXiv:2105.04544

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Computer Science > Machine Learning

[Submitted on 10 May 2021 (v1), last revised 9 Oct 2021 (this version, v4)]

Proximal Causal Learning with Kernels: Two-Stage Estimation and Moment Restriction

Afsaneh Mastouri, Yuchen Zhu, Limor Gultchin, Anna Korba, Ricardo Silva, Matt J. Kusner, Arthur Gretton, Krikamol Muandet







NN features (NeurIPS 2021):

arXiv.org > cs > arXiv:2106.03907

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Code for NN and kernel proxy methods:

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Road map: NN proxy learning

We'll proceed as follows:

- Proxy relation for continuous variables
- Loss function for deep proxy learning
- Define primary (ridge) regression with this loss
- Define secondary (ridge) regression as input to primary

Proxy relation, general domains

If X were observed, we would write (average treatment effect)

$$\mathbb{E}(Y^{(a)}) = \int_x \mathbb{E}(Y|a, x)p(x)dx.$$

....but we do not observe X.

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....but we do not observe X.

Main theorem: Assume we solved for link function:

$$\mathbb{E}(Y|a,z) = \mathbb{E}_{W|a,z} h_y(W,a)$$

- "Primary" $\mathbb{E}(Y|a,z)$, "secondary" $\mathbb{E}_{W|a,z}$ linked by h_y
- All variables observed, X not seen *or modeled.*

(Fredholm equation of first kind: existence of solution requires identifiability conditions)

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Average treatment effect via $p(w)$:

$$\mathbb{E}(Y^{(a)}) = \int_w h_y(a, w)p(w)dw$$

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Average treatment effect via $p(w)$:

$$\mathbb{E}(Y^{(a)}) = \int_w h_y(a,w)p(w)dw$$

Challenge: need a loss function for h_y

(Fredholm equation of first kind: existence of solution requires identifiability conditions)

Primary loss function for $h_y(w, a)$

Goal:

$$\mathbb{E}(Y|a,z) = \mathbb{E}_{W|a,z} h_y(W, a)$$

Primary loss function:

$$\hat{h}_y = \arg\min_{h_y} \mathbb{E}_{Y,A,Z} \left(Y - \mathbb{E}_{W|A,Z} h_y(W, A) \right)^2$$

Why?

Deaner (2021).
Mastouri, Zhu, Gultchin, Korba, Silva, Kusner, G., Muandet (2021).
Xu, Kanagawa, G. (2021).

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Why?

$f^*(a, z) = \mathbb{E}(Y|a, z)$ solves

$$\operatorname*{argmin}_f \mathbb{E}_{Y,A,Z} (Y - f(A, Z))^2$$

Deaner (2021).
Mastouri, Zhu, Gultchin, Korba, Silva, Kusner, G., Muandet (2021).
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Why?

$f^*(a, z) = \mathbb{E}(Y|a, z)$ solves

$$\underset{f}{\operatorname{argmin}} \, \mathbb{E}_{Y,A,Z} (Y - f(A, Z))^2$$

...and by the proxy model above,

$$\mathbb{E}(Y|a, z) = \mathbb{E}_{W|a,z} h_y(W, a)$$

Deaner (2021).
Mastouri, Zhu, Gultchin, Korba, Silva, Kusner, G., Muandet (2021).
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NN for link $h_y(a, w)$

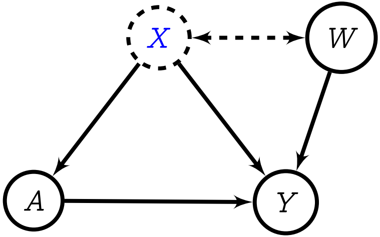
The link function is a function of two arguments

$$h_y(a, w) = \gamma^\top [\varphi_\theta(w) \otimes \varphi_\xi(a)] = \gamma^\top \begin{bmatrix} \varphi_{\theta,1}(w)\varphi_{\xi,1}(a) \\ \varphi_{\theta,1}(w)\varphi_{\xi,2}(a) \\ \vdots \\ \varphi_{\theta,2}(w)\varphi_{\xi,1}(a) \\ \vdots \end{bmatrix}$$

Assume we have:

- output proxy NN features $\varphi_\theta(w)$
- treatment NN features $\varphi_\xi(a)$
- linear final layer γ

(argument of feature map indicates feature space)



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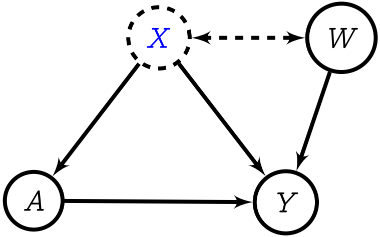

Questions:

- Why feature map $\varphi_\theta(w) \otimes \varphi_\xi(a)$?
- Why final linear layer γ?

Both are necessary (next slide)!

NN ridge regression for $h_y(w, a)$

Goal:

$$\mathbb{E}(Y|a, z) = \mathbb{E}_{W|a,z} h_y(W, a)$$

Primary regression:

$$\hat{h}_y = \arg\min_{h_y} \mathbb{E}_{Y,A,Z} \left(Y - \mathbb{E}_{W|A,Z} h_y(W, A) \right)^2 + \lambda_2 \|\gamma\|^2$$

Deaner (2021).
Mastouri, Zhu, Gultchin, Korba, Silva, Kusner, G., Muandet (2021).
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How to get conditional expectation $\mathbb{E}_{W|a,z} h_y(W, a)$?

Density estimation for $p(W|a,z)$? Sample from $p(W|a,z)$?

Deaner (2021).

Mastouri, Zhu, Gultchin, Korba, Silva, Kusner, G., Muandet (2021).

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Recall link function

$$h_y(W,a) = \left[\gamma^\top (\varphi_\theta(W) \otimes \varphi_\xi(a))\right]$$

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Deaner (2021).
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$$\begin{aligned} \mathbb{E}_{W|a,z}\, h_y(W, a) &= \mathbb{E}_{W|a,z} \left[\gamma^\top (\varphi_\theta(W) \otimes \varphi_\xi(a)) \right] \\ &= \gamma^\top \Big(\underbrace{\mathbb{E}_{W|a,z} [\varphi_\theta(W)]}_{\text{cond. feat. mean}} \otimes \varphi_\xi(a) \Big) \end{aligned}$$

(this is why linear γ and feature map $\varphi_\theta(w) \otimes \varphi_\xi(a)$)

Deaner (2021).
Mastouri, Zhu, Gultchin, Korba, Silva, Kusner, G., Muandet (2021).
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Ridge regression (again!)

$$\mathbb{E}_{W|a,z} \varphi_\theta(W) = \hat{F}_{\theta,\zeta} \varphi_\zeta(a, z)$$

Deaner (2021).
Mastouri, Zhu, Gultchin, Korba, Silva, Kusner, G., Muandet (2021).
Xu, Kanagawa, G. (2021).

NN ridge regression for $\mathbb{E}_{W|a,z}\varphi_\theta(W)$

Secondary regression: learn NN features $\varphi_\zeta(Z)$ and linear layer F:

$$\mathbb{E}_{W|a,z}\varphi_\theta(W) = \hat{F}_{\theta,\zeta}\varphi_\zeta(a,z)$$

with RR loss

$$\mathbb{E}_{W,A,Z}\|\varphi_\theta(W) - F\varphi_\zeta(A,Z)\|^2 + \lambda_1\|F\|^2$$

$\hat{F}_{\theta,\zeta}$ in closed form wrt $\varphi_\theta, \varphi_\zeta$.

Xu, Kanagawa, G. (2021).

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$\hat{F}_{\theta,\zeta}$ in closed form wrt $\varphi_\theta, \varphi_\zeta$.

Plug $\hat{F}_{\theta,\zeta}$ into S1 loss, backprop through Cholesky for ζ
(...not θ...why not?)

Xu, Kanagawa, G. (2021).

Final algorithm

Solve for θ, ξ, ζ:

Repeat until convergence:

- Secondary: Solve for $\hat{F}_{\theta,\zeta}$, then gradient steps on ζ (backprop through Cholesky)

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Xu, Kanagawa, G. (2021).

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- Primary: Gradient steps on θ, ξ (backprop through Cholesky)
    - $\hat{F}_{\theta,\zeta}$ remains optimal wrt current φ_{θ}.

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Iterate between updates of θ, ξ and ζ

Xu, Kanagawa, G. (2021).

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Key point: features $\varphi_\theta(W)$ learned specially for:

$$\mathbb{E}(Y|a, z) = \mathbb{E}_{W|a,z} h_y(W, a)$$

Contrast with autoencoders/sampling: must reconstruct/sample all of W.

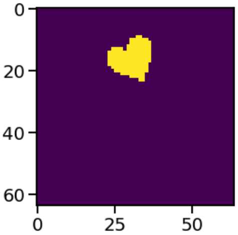
Xu, Kanagawa, G. (2021).

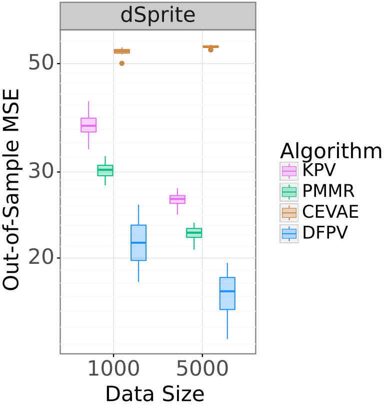
Experiments

Synthetic experiment, adaptive neural net features

dSprite example:

- $X = \{\texttt{scale}, \texttt{rotation}, \texttt{posX}, \texttt{posY}\}$
- Treatment A is the image generated (with Gaussian noise)
- Outcome Y is quadratic function of A with multiplicative confounding by posY.
- $Z = \{\texttt{scale}, \texttt{rotation}, \texttt{posX}\}$, W = noisy image sharing posY
- Comparison with CEVAE (Louzios et al. 2017)



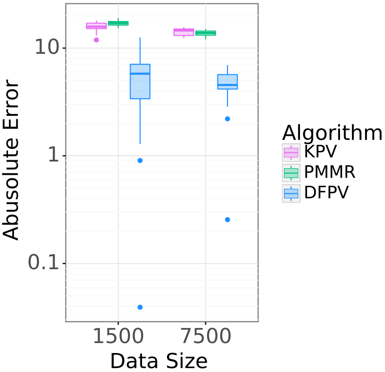


Louizos, Shalit, Mooij, Sontag, Zemel, Welling, Causal Effect Inference with Deep Latent-Variable Models (2017)

Confounded offline policy evaluation

Synthetic dataset, demand prediction for flight purchase.

- Treatment A is ticket price.
- Policy $A \sim \pi(Z)$ depends on fuel price.

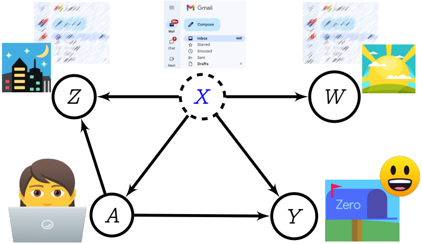


Conclusion

Causal effect estimation with unobserved X, (possibly) complex nonlinear effects on A, Y

We need to observe:

- Treatment proxy Z (interacts with A, but not directly with Y)
- Outcome proxy W (no direct interaction with A, can affect Y)



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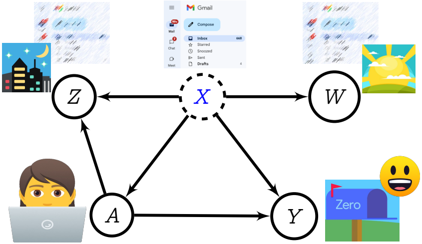

Key messages:

- Don't ~~meet your heroes~~ model/sample latents X
- Don't model all of W, only relevant features for Y
- "Ridge regression is all you need"

Code available:

https://github.com/liyuan9988/DeepFeatureProxyVariable/

Research support

Work supported by:

The Gatsby Charitable Foundation

Google Deepmind

Questions?


THE KERNEL
BREWERY LONDON
BALTIC PORTER
7.3% ABV
THE KERNEL
EXPORT STOUT

A failure of identifiability assumptions

Failure 2: "exploitable invariance" of $p(X|z)$

$$X \sim \mathcal{N}(0,1),$$
$$Z = |X| + \mathcal{N}(0,1),$$

where $p(x|z) \propto p(z|x)p(x)$ symmetric in x. Consider square integrable *antisymmetric* function $g(x) = -g(-x)$. Then

$$\begin{aligned}
&\int_{-\infty}^{\infty} g(x)p(x|z)dx \\
&= \int_{-\infty}^{0} g(x)p(x|z)dx + \int_{0}^{\infty} g(x)p(x|z)dx \\
&= 0.
\end{aligned}$$

If distribution of $X|Z$ retains the same "symmetry class" over a set of Z with nonzero measure, then the assumption is violated by $g(x)$ with zero mean on this class.