Learning Representations for Counterfactual Inference

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Setting of Causal Inference

Define the following:

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- $\mathcal{T}$ the set of possible actions
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Fundamental problem of causal inference: we can only observe $Y_t(x)$ for one specific value of t.

More setting

We will only look at the case where $\mathcal{T} = \{0, 1\}$.
Two quantities of interest are then

- **Individual Treatment Effect**

$$\mathrm{ITE}(x) = Y_1(x) - Y_0(x)$$

- **Average Treatment Effect**

$$\mathrm{ATE} = \mathbb{E}_{x \sim p(x)}\Big[\mathrm{ITE}(x)\Big]$$

More settings

Finally, we define

- the observed outcome associated with x as the **factual outcome**, denoted $y^F(x)$.
- the unobserved outcome associated with x as the **counterfactual outcome**, denoted $y^{CF}(x)$.

Goal of The Paper

Come up with a framework to train models for factual and counterfactual inference.

A First Supervised Approach

- Given n samples $\{x_i, t_i, y_i^F\}_{i=1}^n$, where $y_i^F = t_i Y_1(x_i) + (1 - t_i) Y_0(x_i)$

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- To compute ITE on training data we could do

$$\hat{\text{ITE}}(x_i) = \begin{cases} y_i^F - h(x_i, t_i - 1) & \text{if } t_i = 1 \\ h(x_i, 1 - t_i) - y_i^F & \text{if } t_i = 0 \end{cases}$$

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What is the problem with this ?

- We are training on the set

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We do not want to make assumptions on the treatment assignment.

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The authors propose a general approach for causal inference

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- Learn a function h from a hypothesis class $\mathcal{H}$, such that $h : \mathbb{R}^d \times \mathcal{T} \to \mathbb{R}$ predicts the outcome.

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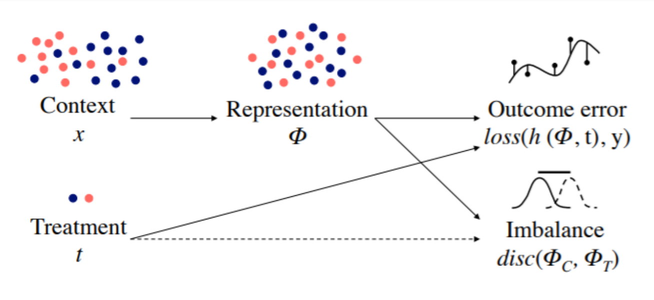

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- Then the error term is

$$\frac{1}{n}\sum_{i=1}^{n} |h(\Phi(x_i), 1 - t_i) - y_{j(i)}^F|$$

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- By controlling the discrepancy between them, namely given our hypothesis class $\mathcal{H}$ and a loss function L, we have

$$\text{disc}_{\mathcal{H}}(\hat{P}_\Phi^F, \hat{P}_\Phi^{CF}) = \max_{\beta,\beta' \in \mathcal{H}} \left[\mathop{\mathbb{E}}_{z \sim \hat{P}_\Phi^F} [L(\beta(z), \beta'(z))] - \mathop{\mathbb{E}}_{z \sim \hat{P}_\Phi^{CF}} [L(\beta(z), \beta'(z))] \right]$$

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- Discrepancy in the case of linear hypotheses class, namely $\mathcal{H} \subset \mathbb{R}^{d+1}$, has a closed form formula.
- From now on we restrict the study to linear hypotheses.

This gives rise to the following objective function

$$
\begin{aligned}
B_{\mathcal{H},\alpha,\gamma}(\Phi, h) = & \frac{1}{n}\sum_{i=1}^{n} |h(\Phi(x_i), t_i) - y_i^F| \\
& + \frac{\gamma}{n}\sum_{i=1}^{n} |h(\Phi(x_i), 1 - t_i) - y_{j(i)}^F| + \\
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Algorithm 1 Balancing counterfactual regression

1: **Input:** $X, T, Y^F; \mathcal{H}, \mathcal{N}; \alpha, \gamma, \lambda$

2: $\Phi^*, g^* = \underset{\Phi\in\mathcal{N}, g\in\mathcal{H}}{\arg\min}\, B_{\mathcal{H},\alpha,\gamma}(\Phi, g)$ (2)

3: $h^* = \arg\min_{h\in\mathcal{H}} \frac{1}{n}\sum_{i=1}^{n}(h(\Phi, t_i) - y_i^F)^2 + \lambda\|h\|_{\mathcal{H}}$

4: **Output:** h^*, Φ^*

Theoretical Motivation behind Algorithm 1

- The former analysis gave an intuition on the form of the objective function $B_{\mathcal{H},\alpha,\gamma}(\Phi, h)$

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- Existence of a theoretical bound

A Theoretical Bound

Theorem 1. *For a sample* $\{(x_i, t_i, y_i^F)\}_{i=1}^n$, $x_i \in \mathcal{X}$, $t_i \in \{0,1\}$ *and* $y_i \in \mathcal{Y}$, *and a given representation function* $\Phi : \mathcal{X} \to \mathbb{R}^d$, *let* $\hat{P}_\Phi^F = (\Phi(x_1), t_1), \ldots, (\Phi(x_n), t_n)$, $\hat{P}_\Phi^{CF} = (\Phi(x_1), 1-t_1), \ldots, (\Phi(x_n), 1-t_n)$. *We assume that* $\mathcal{X}$ *is a metric space with metric* d, *and that the potential outcome functions* $Y_0(x)$ *and* $Y_1(x)$ *are Lipschitz continuous with constants* K_0 *and* K_1 *respectively, such that* $\mathrm{d}(x_a, x_b) \le c \implies |Y_t(x_a) - Y_t(x_b)| \le K_t \cdot c$ *for* $t = 0, 1$.

Let $\mathcal{H}_l \subset \mathbb{R}^{d+1}$ *be the space of linear functions* $\beta : \mathcal{X} \times \{0,1\} \to \mathcal{Y}$, *and for* $\beta \in \mathcal{H}_l$, *let* $\mathcal{L}_P(\beta) = \mathbb{E}_{(x,t,y)\sim P}[L(\beta(x,t), y)]$ *be the expected loss of* β *over distribution* P. *Let* $r = max\left(\mathbb{E}_{(x,t)\sim P^F}[\|[\Phi(x), t]\|_2], \mathbb{E}_{(x,t)\sim P^{CF}}[\|[\Phi(x), t]\|_2]\right)$ *be the maximum expected radius of the distributions. For* $\lambda > 0$, *let* $\hat{\beta}^F(\Phi) = \arg\min_{\beta \in \mathcal{H}_l} \mathcal{L}_{\hat{P}_\Phi^F}(\beta) + \lambda\|\beta\|_2^2$, *and* $\hat{\beta}^{CF}(\Phi)$ *similarly for* $\hat{P}_\Phi^{CF}$, *i.e.* $\hat{\beta}^F(\Phi)$ *and* $\hat{\beta}^{CF}(\Phi)$ *are the ridge regression solutions for the factual and counterfactual empirical distributions, respectively.*

Let $\hat{y}_i^F(\Phi, h) = h^\top[\Phi(x_i), t_i]$ *and* $\hat{y}_i^{CF}(\Phi, h) = h^\top[\Phi(x_i), 1 - t_i]$ *be the outputs of the hypothesis* $h \in \mathcal{H}_l$ *over the representation* $\Phi(x_i)$ *for the factual and counterfactual settings of* t_i, *respectively. Finally, for each* $i, j \in \{1 \ldots n\}$, *let* $\mathrm{d}_{i,j} \equiv \mathrm{d}(x_i, x_j)$ *and* $j(i) \in \arg\min_{j\in\{1\ldots n\} \text{ s.t. } t_j = 1 - t_i} \mathrm{d}(x_j, x_i)$ *be the nearest neighbor in* $\mathcal{X}$ *of* x_i *among the group that received the opposite treatment from unit* i. *Then for* both $Q = P^F$ *and* $Q = P^{CF}$ *we have:*

$$\frac{\lambda}{\mu r}(\mathcal{L}_Q(\hat{\beta}^F(\Phi)) - \mathcal{L}_Q(\hat{\beta}^{CF}(\Phi)))^2 \le$$

$$disc_{\mathcal{H}_l}(\hat{P}_\Phi^F, \hat{P}_\Phi^{CF}) + \tag{3}$$

$$\min_{h\in\mathcal{H}_l} \frac{1}{n}\sum_{i=1}^n \left(|\hat{y}_i^F(\Phi,h) - y_i^F| + |\hat{y}_i^{CF}(\Phi,h) - y_i^{CF}|\right) \le \tag{4}$$

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$$\frac{K_0}{n}\sum_{i:t_i=1} \mathrm{d}_{i,j(i)} + \frac{K_1}{n}\sum_{i:t_i=0} \mathrm{d}_{i,j(i)}. \tag{6}$$

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- Define $\hat{\beta}^{CF}(\Phi)$ similarly
- The theorem then states that for both $Q = P^F$ and $Q = P^{FC}$, we have

$$
\begin{aligned}
& c_1\Big(\mathcal{L}_Q(\hat{\beta}^F(\Phi)) - \mathcal{L}_Q(\hat{\beta}^{CF}(\Phi))\Big) \\
\leq & \min_{h \in \mathcal{H}_\ell} \frac{1}{n} \sum_{i=1}^{n} |h(\Phi(x_i), t_i) - y_i^F| + |h(\Phi(x_i), 1 - t_i) - y_{j(i)}^F| \\
& + \text{disc}_{\mathcal{H}_\ell}(\hat{P}^F_\Phi, \hat{P}^{CF}_\Phi) \\
& + \frac{K_0}{n} \sum_{i:t_i=1} d(x_i, x_{j(i)}) + \frac{K_1}{n} \sum_{i:t_i=0} d(x_i, x_{j(i)})
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$$+\mathrm{disc}_{\mathcal{H}_\ell}(\hat{P}_\Phi^F, \hat{P}_\Phi^{CF})$$

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Which is close to

$$B_{\mathcal{H},\alpha,\gamma}(\Phi, h) = \frac{1}{n}\sum_{i=1}^{n} |h(\Phi(x_i), t_i) - y_i^F|$$

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- Features that differ a lot between treatment groups will receive a smaller weight

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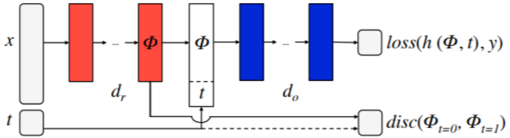

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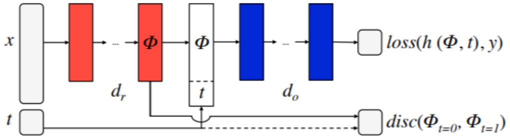

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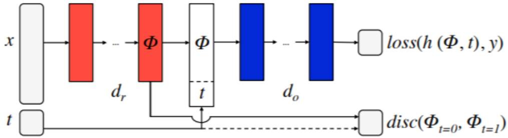

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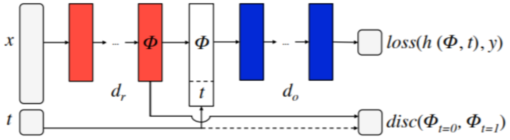

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- The d_o layers learn h given t
- Given Φ, the discrepancy is calculated

Experiments

- We don't have the data !
- Need to simulate

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- the factual outcome $y^F(x_i) \in \mathbb{R}$ is the readers experience of x_i

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$$y(x_i) = C(z(x_i)^T z_0 + t_i z(x_i)^T z_1)$$

- Finally, we assume that the assignment of a news item x_i to a device t_i is biased towards the preferred devices, i.e.

$$p(t_i = 1 \mid x_i) = \frac{e^{\kappa z(x_i)^T z_1}}{e^{\kappa z(x_i)^T z_0} + e^{\kappa z(x_i)^T z_1}}$$

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- A neural network with 4 layers to learn the representation, and a single linear output layer, BNN-4-0.
- A neural network with 2 layers to learn the representation, followed by 2 ReLU layers and a single layer. (BNN-2-2)

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The authors compare

- The balanced linear regression model (BLR), i.e. $\Phi(x) = Wx$.
- A neural network with 4 layers to learn the representation, and a single linear output layer, BNN-4-0.
- A neural network with 2 layers to learn the representation, followed by 2 ReLU layers and a single layer. (BNN-2-2)
- Different classical supervised learning regression algorithms like linear regression, doubly robust linear regression, BART, etc..

Results

The quantities measured to evaluate the models are

- The RMSE of the estimated individual treatment effect

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- The Precision in Estimation of Heterogeneous Effect,

$$\text{PEHE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \Big(\hat{y}_1(x_i) - \hat{y}_0(x_i) - (Y_1(x_i) - Y_0(x_i))\Big)^2}$$

Results

Table 2. News. Results and standard errors for 50 repeated experiments. (Lower is better.) Proposed methods: BLR, BNN-4-0 and BNN-2-2. † (Chipman et al., 2010)

	ϵ_{ITE}	ϵ_{ATE}	PEHE
LINEAR OUTCOME			
OLS	3.1 ± 0.2	0.2 ± 0.0	3.3 ± 0.2
DOUBLY ROBUST	3.1 ± 0.2	0.2 ± 0.0	3.3 ± 0.2
LASSO + RIDGE	2.2 ± 0.1	0.6 ± 0.0	3.4 ± 0.2
BLR	2.2 ± 0.1	0.6 ± 0.0	3.3 ± 0.2
BNN-4-0	2.1 ± 0.0	0.3 ± 0.0	3.4 ± 0.2
NON-LINEAR OUTCOME			
NN-4	2.8 ± 0.0	1.1 ± 0.0	3.8 ± 0.2
BART†	5.8 ± 0.2	0.2 ± 0.0	3.2 ± 0.2
BNN-2-2	$\mathbf{2.0 \pm 0.0}$	0.3 ± 0.0	$\mathbf{2.0 \pm 0.1}$

IDHP Dataset

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	ϵ_{ITE}	ϵ_{ATE}	PEHE
LINEAR OUTCOME			
OLS	4.6 ± 0.2	0.7 ± 0.0	5.8 ± 0.3
DOUBLY ROBUST	3.0 ± 0.1	0.2 ± 0.0	5.7 ± 0.3
LASSO + RIDGE	2.8 ± 0.1	0.2 ± 0.0	5.7 ± 0.2
BLR	2.8 ± 0.1	0.2 ± 0.0	5.7 ± 0.3
BNN-4-0	3.0 ± 0.0	0.3 ± 0.0	5.6 ± 0.3
NON-LINEAR OUTCOME			
NN-4	2.0 ± 0.0	0.5 ± 0.0	1.9 ± 0.1
BART†	2.1 ± 0.2	0.2 ± 0.0	1.7 ± 0.2
BNN-2-2	$\mathbf{1.7 \pm 0.0}$	0.3 ± 0.0	$\mathbf{1.6 \pm 0.1}$

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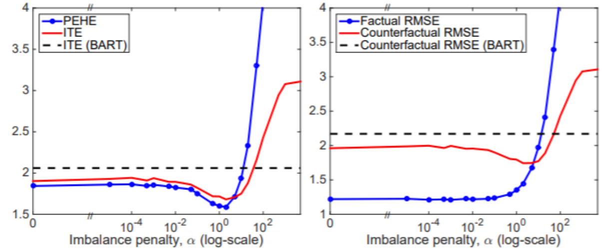

Figure 4. Error in estimated treatment effect (ITE, PEHE) and counterfactual response (RMSE) on the IHDP dataset. Sweep over α for the BNN-2-2 neural network model.

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- generalize this for more than 2 treatments
- allow for other distribution measures
- allow for non-linear hypotheses

Any questions?

Thank you!