An Adaptive Kernel Approach to Federated Learning of Heterogeneous Causal Effects

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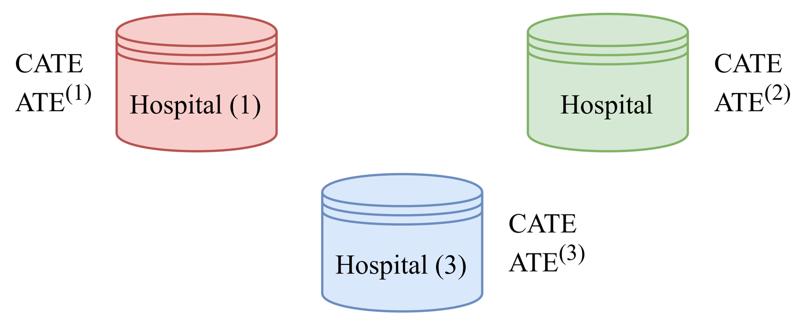
Contributions

- We propose CausalRFF that learns causal effects from multiple data sources while maintaining the sources at their local sites.
- CausalRFF minimizes information transmitted among the sources, thus enabling privacy-preserving causal inference.
- CausalRFF adaptively learn similarity of data distributions among the sources and hence reduce negative transfer.
- The performance of CausalRFF is competitive to the baselines trained on combined data whose sources are dissimilar.

Motivation

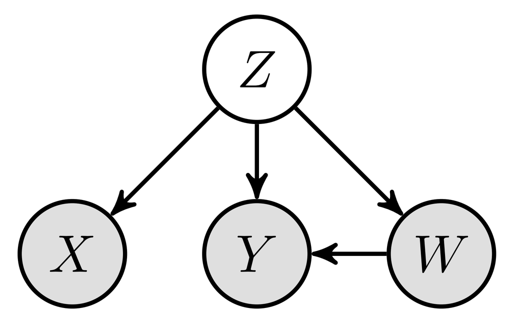
- Multiple data sources cannot be combined or shared due to privacy concern.
- Different data sources might have different data distributions.
- Some sources with sufficient data observations might dominate the ones with fewer data observations.



- For example: Patient data are private and confidential, and they are maintained in multiple hospitals.
- How to estimate causal effects from multiple sources without combining them?

Assumptions & Causal Quantities of Interest

The causal graph



- Z: latent confounder
- Y: the outcome
- W: the treatment
- X: covariate/proxy variable

(1). *Consistency*: $W = w \Longrightarrow Y(w) = Y$.

(2). *No interference* + *Positivity*.

(3). Individuals in all sources have the same set of *common* covariates.

(4). Any individual can be uniquely identified across different sources.

We estimate the following quantities:

- **Conditional average treatment effect (CATE):**

$$\tau(\boldsymbol{x}) := E\Big[Y|\text{do}(W{=}1), X{=}\boldsymbol{x}\Big] - E\Big[Y|\text{do}(W{=}0), X{=}\boldsymbol{x}\Big].$$

- **Average treatment effect (ATE):**

$$\tau := E[\tau(X)].$$

The Proposed Method

Expectation of the outcome given intervention on the treatment

$E[y_i^{\mathsf{s}}|\text{do}(w_i^{\mathsf{s}}), \mathbf{x}_i^{\mathsf{s}}]$

The interventional distribution of the outcome

$p(y_i^{\mathsf{s}}|\text{do}(w_i^{\mathsf{s}}), \mathbf{x}_i^{\mathsf{s}}) = \int p(y_i^{\mathsf{s}}|w_i^{\mathsf{s}}, \mathbf{z}_i^{\mathsf{s}})\, p(\mathbf{z}_i^{\mathsf{s}}|\mathbf{x}_i^{\mathsf{s}})\, d\mathbf{z}_i^{\mathsf{s}}$

The conditional distributions to be estimated

$p(\mathbf{z}_i^{\mathsf{s}}|\mathbf{x}_i^{\mathsf{s}}, y_i^{\mathsf{s}}, w_i^{\mathsf{s}})$, $p(y_i^{\mathsf{s}}|w_i^{\mathsf{s}}, \mathbf{z}_i^{\mathsf{s}})$, $p(w_i^{\mathsf{s}}|\mathbf{x}_i^{\mathsf{s}})$ & $p(y_i^{\mathsf{s}}|\mathbf{x}_i^{\mathsf{s}}, w_i^{\mathsf{s}})$

Augmented representer theorem estimator

Transfer kernel function

Allow dissimilar data distributions among the sources.

Random Fourier feature: enable federated training

$k(\boldsymbol{u}, \boldsymbol{u}') \simeq \phi(\boldsymbol{u})^\top \phi(\boldsymbol{u}')$,

$\phi(\boldsymbol{u}) = B^{-\frac{1}{2}}[\cos(\boldsymbol{\omega}_1^\top \boldsymbol{u}),\ldots, \cos(\boldsymbol{\omega}_B^\top \boldsymbol{u}), \sin(\boldsymbol{\omega}_1^\top \boldsymbol{u}),\ldots, \sin(\boldsymbol{\omega}_B^\top \boldsymbol{u})]^\top$,

where $\boldsymbol{\omega}_b\}_{b=1}^B$ are drawn i.i.d from spectral distribution of the kernels.

Federated inference:

Repeat the following steps until convergence:

(1). Compute gradients using local data and send to a server.

(2). The sever collects all *local* gradients and updates the model.

(3). The server sends the new model to all sources.

Minimax lower bound: for learning distributions with latent confounders

$$\inf_{\hat{\theta}} \sup_{P\in\mathcal{P}} \mathbb{E}_P\left[\|\hat{\theta} - \theta(P)\|_2\right] \geq \frac{\sqrt{m(d_x+3)}\log(2\sqrt{m})}{64\sqrt{B}\sum_{\mathsf{s}\in\mathcal{S}} n_{\mathsf{s}}\left(1 + \sum_{\mathsf{v}\in\mathcal{S}_{\setminus\mathsf{s}}}\lambda^{\mathsf{s},\mathsf{v}}\right)^2}.$$

Lower bound for the worst case of the best estimator. The bound shows how the sources are incorporated through the transfer factors $\lambda^{\mathsf{s},\mathsf{v}}$.

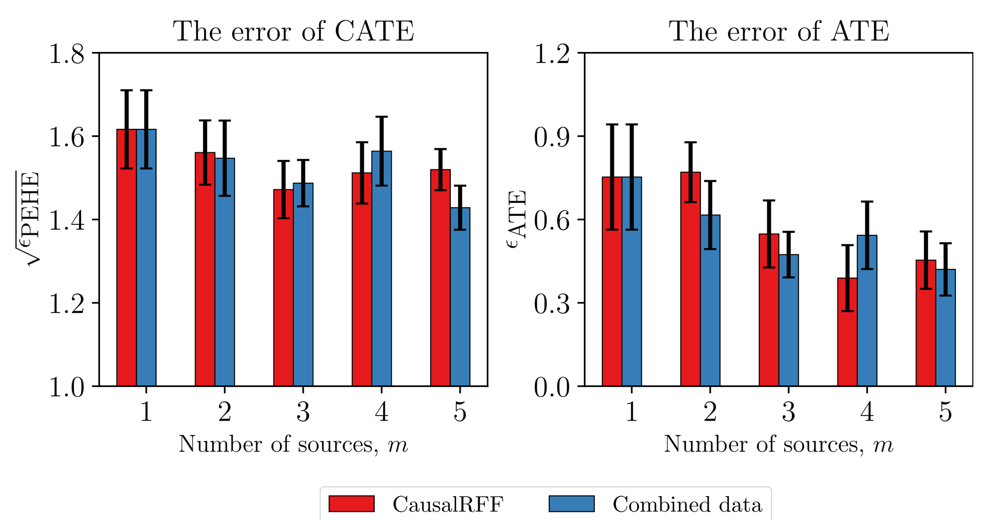
Experiments

Synthetic data

- The data are simulated with a ground truth causal model.
- We use a factor Δ to control for dissimilar data distributions.

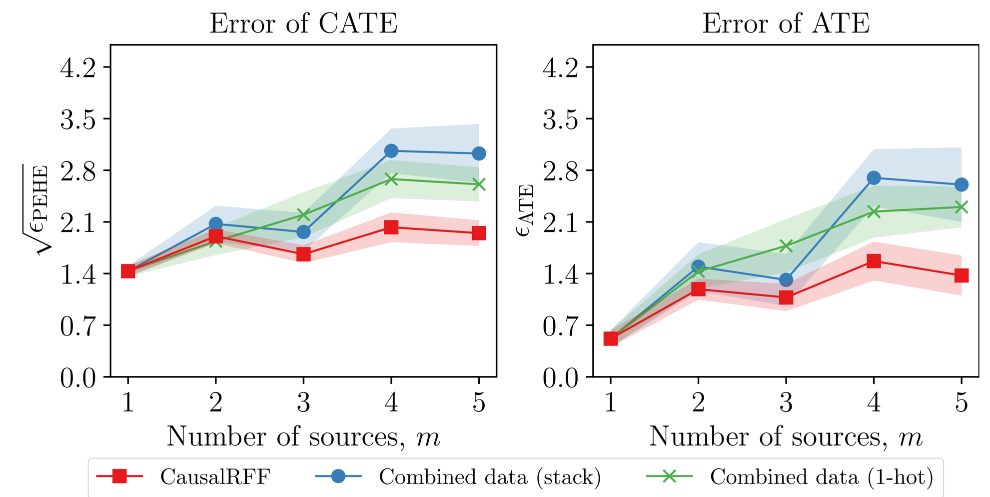
Analysis 1: The sources have the same data distribution ($\Delta = 0$).

Result: The errors of CausalRFF are as low as those of training on combined data. This result verifies the efficacy of CausalRFF for federated learning.



Analysis 2: The sources have different data distributions ($\Delta \neq 0$).

Result: The errors of CausalRFF are lower than those of training on combined data. This verifies the importance of CausalRFF when the sources have different data distributions.



IHDP dataset

- This dataset is from a study on the impact of specialist visits on the cognitive development of children.
- Treatment/control group are children with/without specialist visit.
- The dataset has 747 entries with 25 covariates, it is divided to 3 sources.

We compare with the recent baselines trained on combined data (cb)

Method	The error of CATE ($\sqrt{\epsilon_{\text{PEHE}}}$)			The error of ATE (ϵ_{ATE})		
	1 source	2 sources	3 sources	1 source	2 sources	3 sources
BART_{cb}	2.2±.22	2.1±.26	2.1±.25	1.0±.16	0.8±.20	0.7±.17
$\text{X-Learner}_{\text{cb}}$	1.9±.21	1.9±.21	1.8±.18	**0.5±.21**	**0.5±.18**	**0.4±.11**
$\text{R-Learner}_{\text{cb}}$	2.8±.31	2.6±.23	2.6±.17	1.6±.25	1.6±.26	1.6±.19
$\text{OthoRF}_{\text{cb}}$	2.8±.16	2.1±.14	1.9±.14	**0.8±.15**	**0.6±.10**	**0.6±.10**
$\text{TARNet}_{\text{cb}}$	3.5±.59	2.7±.12	2.5±.15	1.6±.61	**0.7±.12**	**0.6±.17**
$\text{CFR-wass}_{\text{cb}}$	2.2±.15	2.1±.22	2.1±.23	**0.7±.23**	**0.6±.18**	**0.6±.16**
$\text{CFR-mmd}_{\text{cb}}$	2.7±.19	2.3±.26	2.2±.10	0.9±.30	**0.7±.17**	**0.5±.17**
CEVAE_{cb}	**1.8±.22**	2.0±.11	**1.7±.12**	**0.5±.14**	1.4±.07	0.9±.07
FedCI	**1.6±.10**	**1.6±.12**	**1.7±.09**	**0.5±.10**	**0.5±.24**	**0.5±.09**
CausalRFF	**1.7±.34**	**1.4±.33**	**1.2±.18**	**0.7±.14**	**0.7±.17**	**0.5±.16**

Result: CausalRFF is among top-3 performance. Importantly, it preserves privacy under federated setting while the other baselines violate this constraint.

Conclusion & Future Work

- We proposed CausalRFF that learns causal effects without sharing raw data.
- CausalRFF is an important step towards a privacy-preserving causal learning model.
- Future research direction: Combining CausalRFF with differential privacy to give a stronger privacy guarantee.

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This work was conducted while YL was at Harvard University and the views expressed here do not necessarily reflect the position of Roche AG.