MLMI

The 4th International Conference on
Machine Learning and Machine Intelligence

CAUSAL INFERENCE IN OBSERVATIONAL STUDIES

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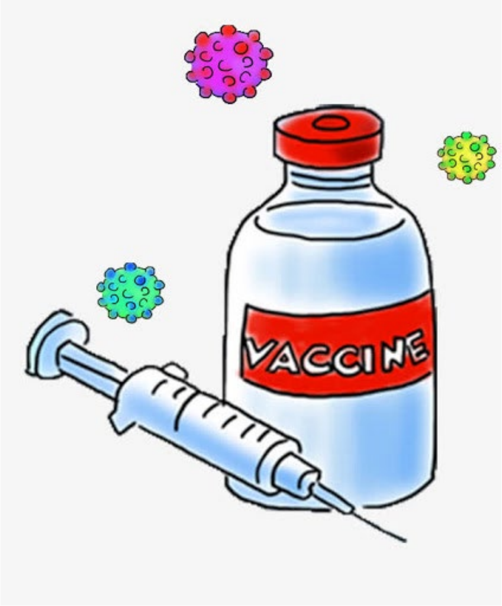
Decision Making with Causality

- Causal Effect Estimation is necessary for decision making!



Causal effect estimation plays an important role on decision making!

A practical definition

Definition: T causes Y if and only if

changing T leads to a change in Y,

keep everything else constant.

Causal effect is defined as the magnitude by which Y is changed by a unit change in T.

Two key points: changing T, keeping everything else constant

**Interventionist* definition [http://plato.stanford.edu/entries/causation-mani/]

Treatment Effect Estimation

- Treatment Variable: $T = 1$ or $T = 0$
- Potential Outcome: $Y(T = 1)$ and $Y(T = 0)$
- Individual Treatment Effect (ITE)

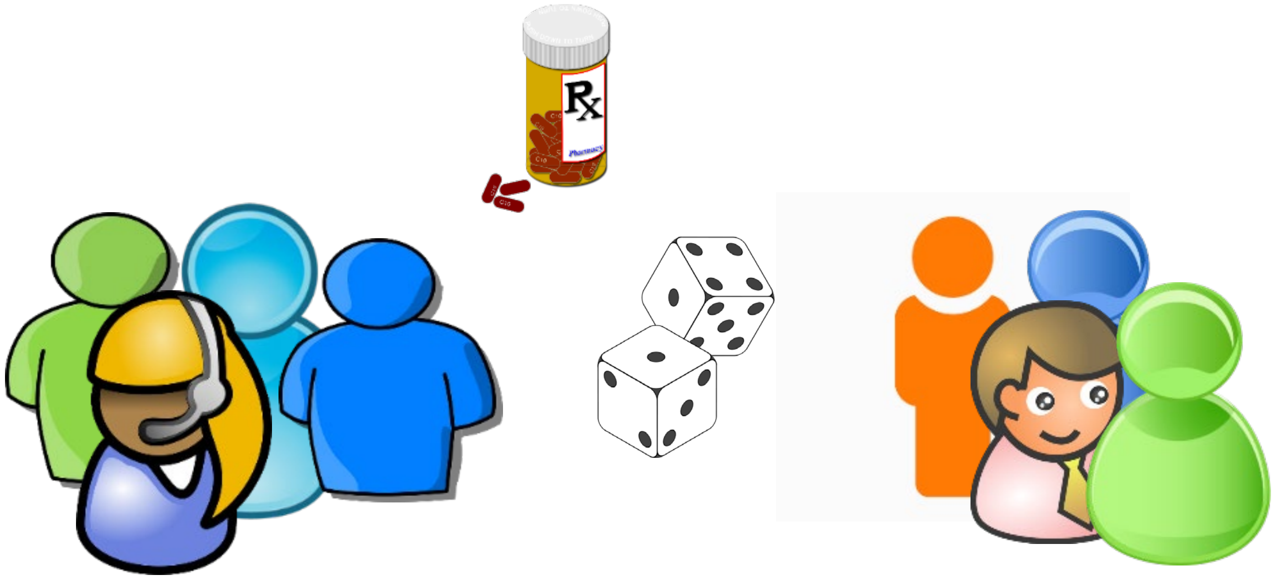
$$ITE(i) = Y_i(T_i = 1) - Y_i(T_i = 0)$$

- Average Treatment Effect (ATE):

$$ATE = E[Y(T = 1) - Y(T = 0)]$$

Two key points: changing T, keeping everything else constant

Randomized Experiments are the “Gold Standard”



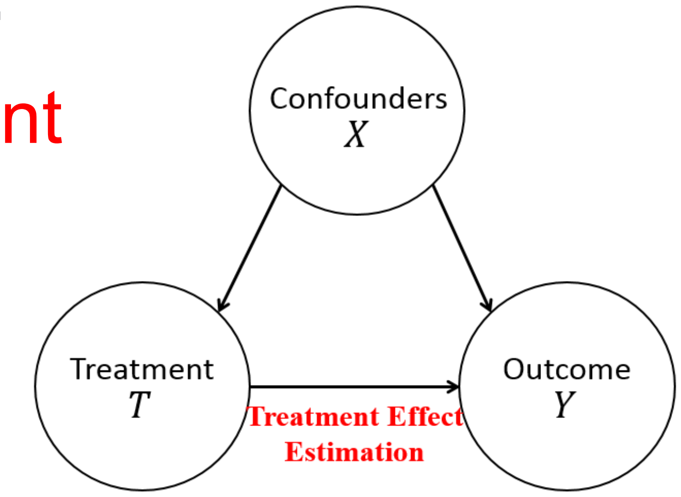
- Drawbacks of randomized experiments:
  - Cost
  - Unethical

Causal Inference with Observational Data

- Counterfactual problem: $Y(T=1)$ or $Y(T=0)$
- In observational data, we have units with different T:

$$E[Y(T=1)] \text{ or } E[Y(T=0)]$$

- Can we estimate ATE by directly comparing the average outcome between groups with T=1 and T=0?
  - No, because confounders X might not be constant



- Two key points:
  - Changing T (T=1 and T=0)
  - Keeping everything else (Confounder X) constant

Causal Inference with Observational Data

- Counterfactual problem: $Y(T=1)$ or $Y(T=0)$
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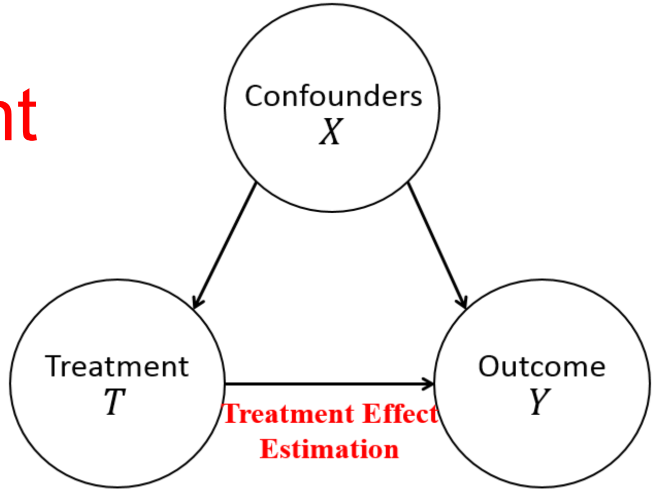
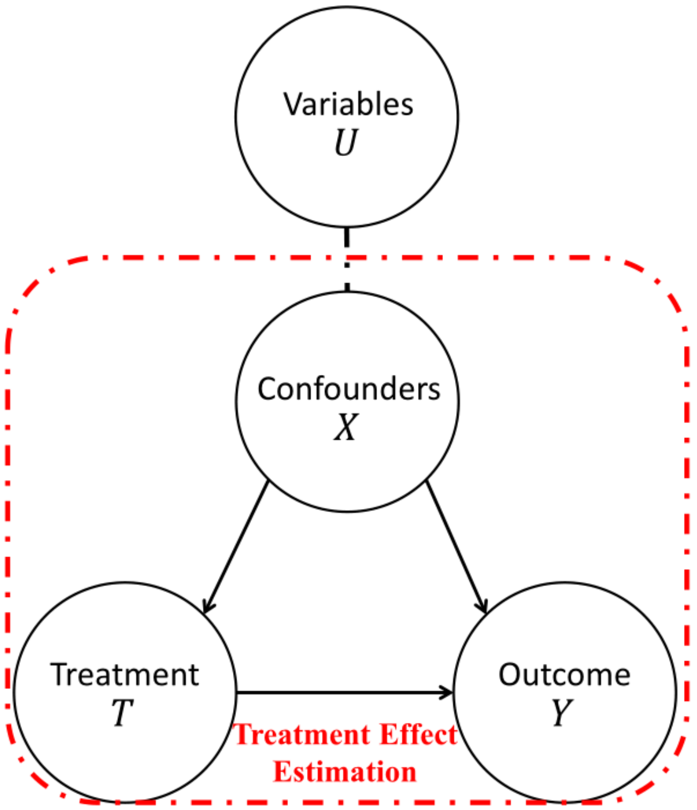


- Two key points:

Balancing Confounders' Distribution

Related Work

- Matching Methods
  - *Exactly Matching, Coarse Matching*
  - Poor performance in high dimensional settings
- Propensity Score based Methods
  - Propensity score $e(\mathbf{X}) = p(T = 1|\mathbf{X})$
  - *Matching, Weighting, Doubly Robust*
  - Treat all observed variables as confounders, and ignore the non-confounders
  - Mainly designed for binary treatment



(a) Previous Causal Framework.

New challenges in Big Data era

- Automatically separate confounders
  - Not all observed variables are confounders
  - Data-Driven Variables Decomposition (D^2VD)
- Remove unobserved confounding bias
  - Not all confounders are observed
  - Automatic Instrumental Variable Decomposition (AutoIV)
- Continuous treatment effect estimation
  - Treatment variables are not always binary
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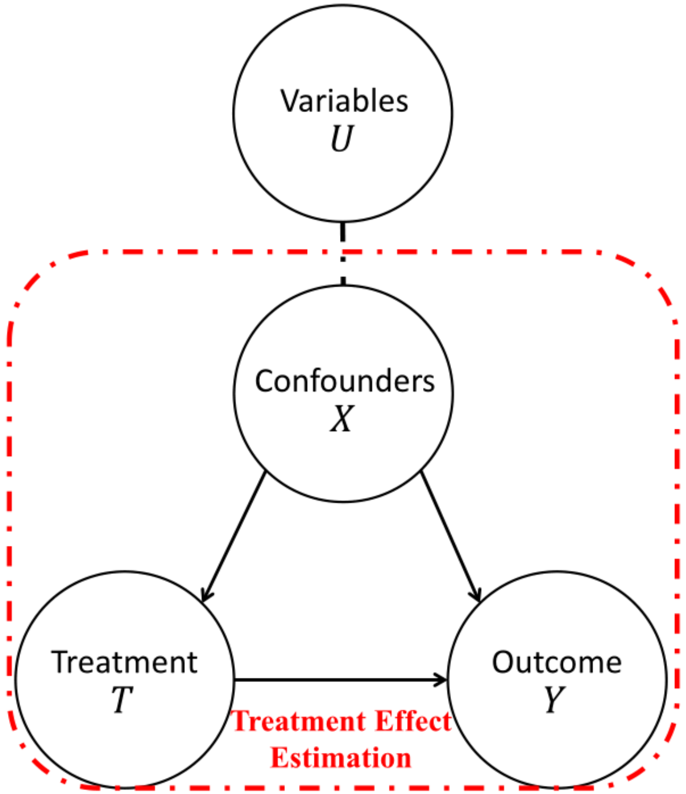
Previous Causal Framework



(a) Previous Causal Framework.

- Treat all observed variables **U** as confounders **X**
- Propensity Score Estimation:

$$e(\mathbf{U}) = p(T = 1|\mathbf{U}) = p(T = 1|\mathbf{X}) = e(\mathbf{X})$$

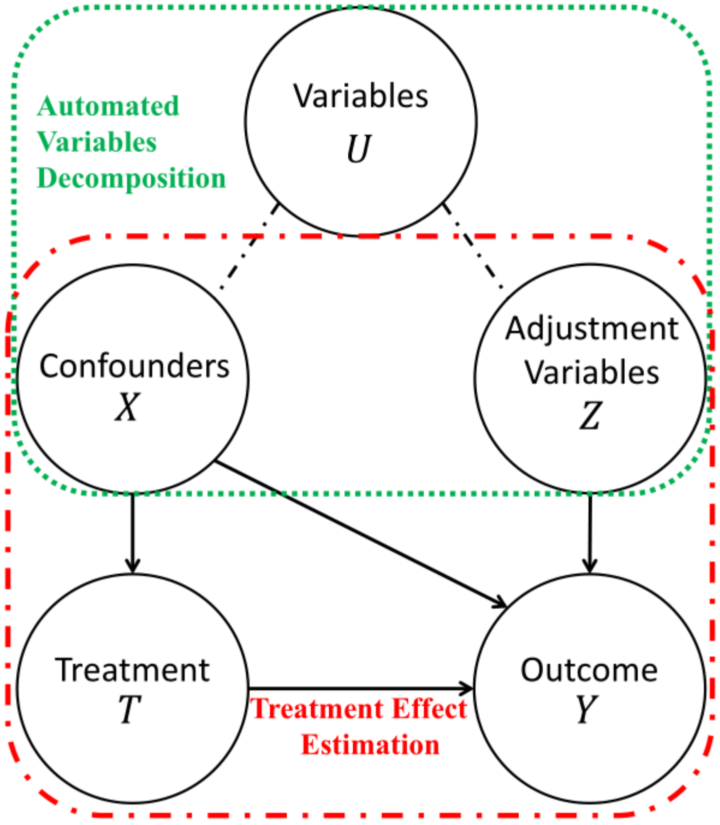
- Adjusted Outcome:

$$Y^{\star} = Y^{obs} \cdot \frac{T - e(\mathbf{U})}{e(\mathbf{U}) \cdot (1 - e(\mathbf{U}))} = Y^{obs} \cdot \frac{T - e(\mathbf{X})}{e(\mathbf{X}) \cdot (1 - e(\mathbf{X}))}$$

- IPW ATE Estimator:

$$\widehat{ATE}_{IPW} = \hat{E}(Y^{\star})$$

Our Causal Framework



(b) Our Causal Framework.

- Separateness Assumption:
  - All observed variables U can be decomposed into two sets: Confounders **X**, and Adjustment Variables **Z**
- Propensity Score Estimation:

$$e(\mathbf{X}) = p(T = 1|\mathbf{X})$$

- Adjusted Outcome:

$$Y^{+} = \left(Y^{obs} - \phi(\mathbf{Z})\right) \cdot \frac{T - e(\mathbf{X})}{e(\mathbf{X}) \cdot (1 - e(\mathbf{X}))}$$

- Our D²VD ATE Estimator:

$$\widehat{ATE}_{D^2VD} = \hat{E}(Y^{+})$$

Kuang K, Cui P, Li B, et al. Treatment effect estimation with data-driven variable decomposition [C]//AAAI, 2017 (and extended to TKDE 2020)

Data-Driven Variable Decomposition (D²VD)

$$minimize \quad \|Y^+ - h(\mathbf{U})\|^2 \quad \text{where} \quad Y^+ = \left(Y^{obs} - \phi(\mathbf{Z})\right) \cdot \frac{T - e(\mathbf{X})}{e(\mathbf{X}) \cdot (1 - e(\mathbf{X}))}$$

$$\boxed{e(\mathbf{X}) = \frac{1}{1 + \exp(-\mathbf{X}\beta)} \qquad \phi(\mathbf{Z}) = \mathbf{Z}\alpha,}$$

Replace X, Z with U $\quad h(\mathbf{U}) = \mathbf{U}\gamma,$

$$minimize \quad \|(Y^{obs} - \mathbf{U}\alpha) \odot W(\beta) - \mathbf{U}\gamma\|_2^2, \quad \text{where} \quad W(\beta) := \frac{T - e(\mathbf{U})}{e(\mathbf{U}) \cdot (1 - e(\mathbf{U}))}$$

$$s.t. \quad \sum_{i=1}^{m} \log(1 + \exp((1 - 2T_i) \cdot U_i\beta)) < \tau,$$

$$\|\alpha\|_1 \leq \lambda, \ \|\beta\|_1 \leq \delta, \ \|\gamma\|_1 \leq \eta, \ \boxed{\|\alpha \odot \beta\|_2^2 = 0.}$$

α, β, γ

- Adjustment variables: $\mathbf{Z} = \{\mathbf{U}_i : \hat{\alpha}_i \neq 0\}$
- Confounders: $\mathbf{X} = \{\mathbf{U}_i : \hat{\beta}_i \neq 0\}$
- Treatment Effect: $\widehat{ATE}_{D^2VD} = E(\mathbf{U}\hat{\gamma})$

Data-Driven Variable Decomposition (D^2VD)

Bias Analysis:

Our D^2VD algorithm is unbiased to estimate causal effect

THEOREM 1. *Under assumptions 1-4, we have*

$$E(Y^+|X, Z) = E(Y(1) - Y(0)|X, Z).$$

Variance Analysis:

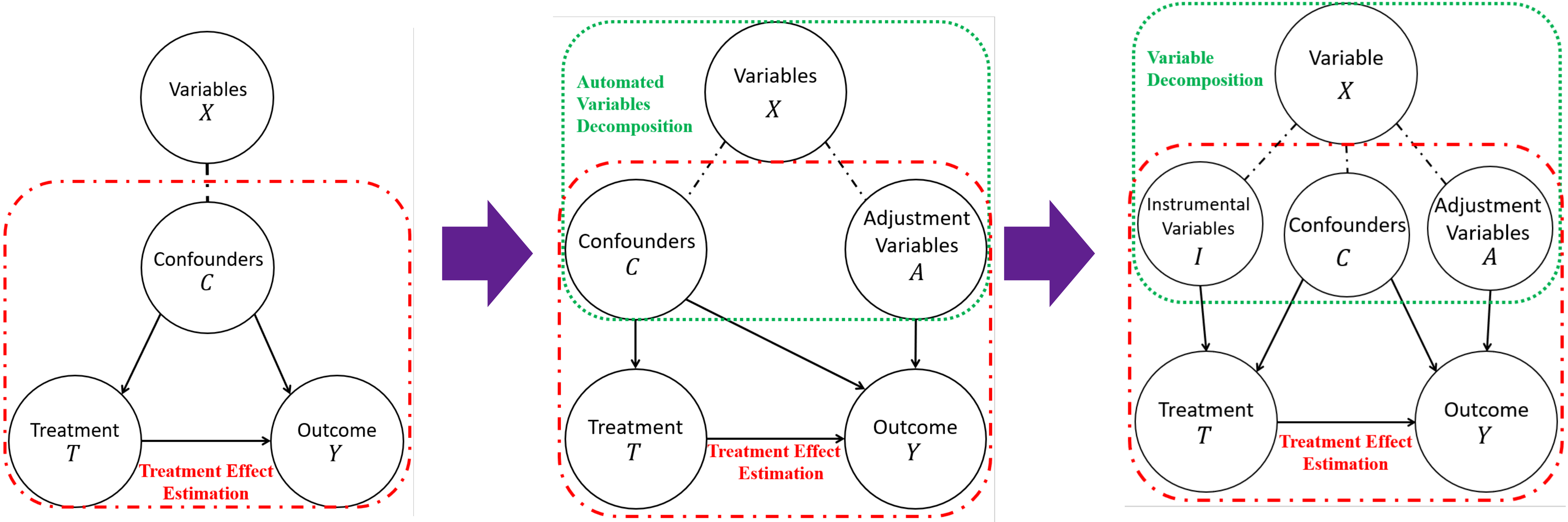
The asymptotic variance of Our D^2VD algorithm is smaller

THEOREM 2. *The asymptotic variance of our adjusted estimator $\widehat{ATE}_{adj}$ is no greater than IPW estimator $\widehat{ATE}_{IPW}$:*

$$\sigma^2_{adj} \leq \sigma^2_{IPW}.$$

Kun Kuang, Peng Cui, Hao Zou, Bo Li, Jianrong Tao, Fei Wu, and Shiqiang Yang. Data-Driven Variable Decomposition for Treatment Effect Estimation, TKDE, 2020

Learning Decomposed Representation for Counterfactual Inference

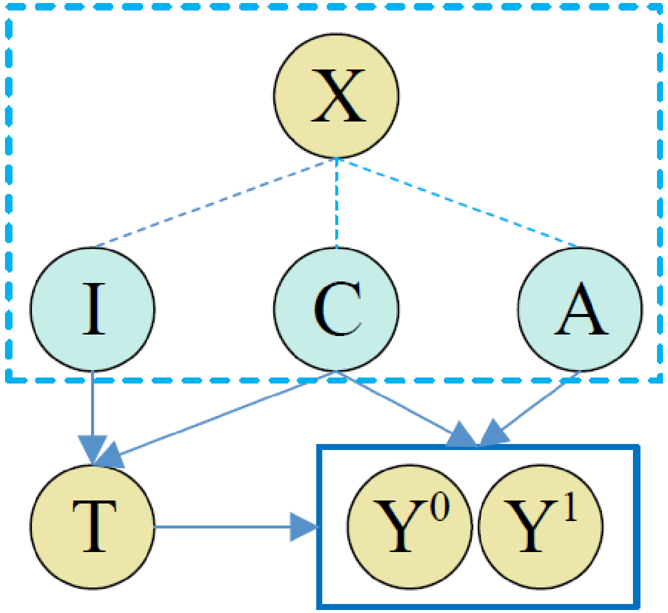


Wu A, Kuang K, Yuan J, et al. Learning Decomposed Representation for Counterfactual Inference[J]. arXiv preprint arXiv:2006.07040, 2020.

Learning Decomposed Representation for Counterfactual Inference

- Three decomposed representation networks
  - $I(X),\ C(X),\ A(X)$
- Three decomposition and balancing regularizers
  - Confounder identification: $A(X) \perp T, I(X) \perp Y \mid T$
  - Confounder balancing: $w \cdot C(X) \perp T$
- Two regression networks
  - $Y(T=1),\ Y(T=0)$
- Orthogonal Regularizer for Decomposition

$$\mathcal{L}_O = \bar{I}_W^T \cdot \bar{C}_W + \bar{C}_W^T \cdot \bar{A}_W + \bar{A}_W^T \cdot \bar{I}_W$$



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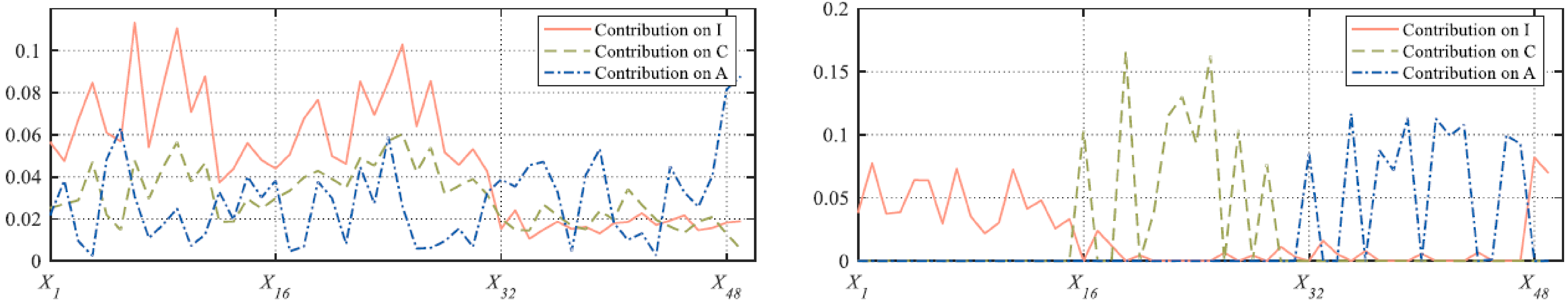

(a) DR-CFR in Syn_16_16_16_3000

(b) DeR-CFR in Syn_16_16_16_3000

Wu A, Kuang K, Yuan J, et al. Learning Decomposed Representation for Counterfactual Inference[J]. arXiv preprint arXiv:2006.07040, 2020.

Learning Decomposed Representation for Counterfactual Inference

Table 1: The results on IHDP.

IHDP				
Mean +/- Std	**Within-sample**		**Out-of-sample**	
Methods	PEHE	ϵ_{ATE}	PEHE	ϵ_{ATE}
CFR-MMD	0.702 +/- 0.037	0.284 +/- 0.036	0.795 +/- 0.078	0.309 +/- 0.039
CFR-WASS	0.702 +/- 0.034	0.306 +/- 0.040	0.798 +/- 0.088	0.325 +/- 0.045
CFR-ISW	0.598 +/- 0.028	0.210 +/- 0.028	0.715 +/- 0.102	0.218 +/- 0.031
SITE	0.609 +/- 0.061	0.259 +/- 0.091	1.335 +/- 0.698	0.341 +/- 0.116
DR-CFR	0.657 +/- 0.028	0.240 +/- 0.032	0.789 +/- 0.091	0.261 +/- 0.036
DeR-CFR	**0.444 +/- 0.020**	**0.130 +/- 0.020**	**0.529 +/- 0.068**	**0.147 +/- 0.022**

Table 2: Ablation studies of DeR-CFR.

$\mathcal{L}_A$	$\mathcal{L}_I$	$\mathcal{L}_{C\_B}$	$\mathcal{L}_O$	PEHE	
				Within-sample	Out-of-sample
✓	✓	✓	✓	**0.444 +/- 0.020**	**0.529 +/- 0.068**
✓	✓	✓		0.478 +/- 0.033	0.542 +/- 0.053
✓	✓		✓	0.482 +/- 0.039	0.565 +/- 0.075
✓		✓	✓	0.479 +/- 0.030	0.560 +/- 0.071
	✓	✓	✓	0.635 +/- 0.035	0.858 +/- 0.133

Wu A, Kuang K, Yuan J, et al. Learning Decomposed Representation for Counterfactual Inference[J]. arXiv preprint arXiv:2006.07040, 2020.

New challenges in Big Data era

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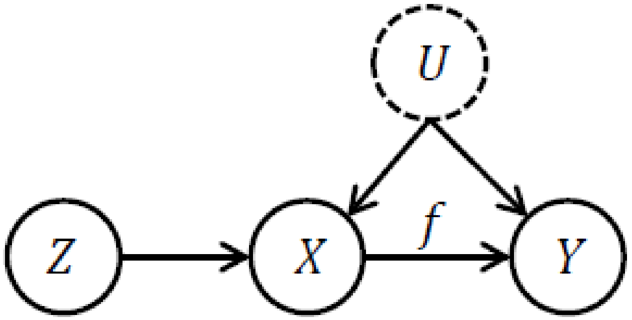
AutoIV: Counterfactual Learning with Unobserved Confounders via Automatically generating IVs



Conditions of IV (instrumental variable)

- Relevance: $P(X|Z) \neq P(X)$
- Exclusion: $P(Y|Z,X,U) \neq P(Y|X,U)$
- Unconfounded: $Z \perp U$

2SLS:

First Stage: regressing X on Z $\quad \hat{X} = \hat{g}(Z)$

Second Stage: regressing Y on $\hat{X}$ $\quad \hat{Y} = \hat{f}(\hat{X})$

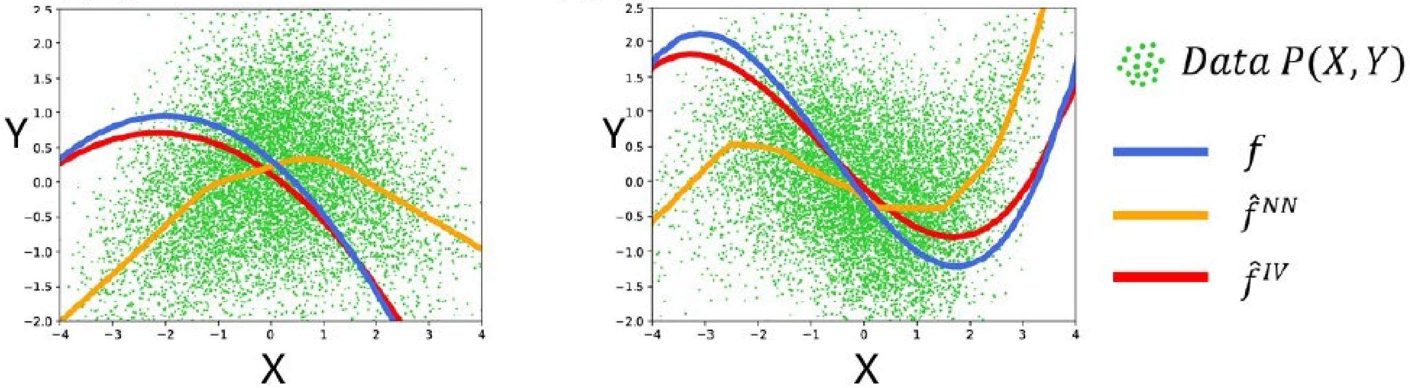
$Z \sim \mathcal{N}(0,1)$

$U \sim \mathcal{N}(0,1)$

$X = Z + U$

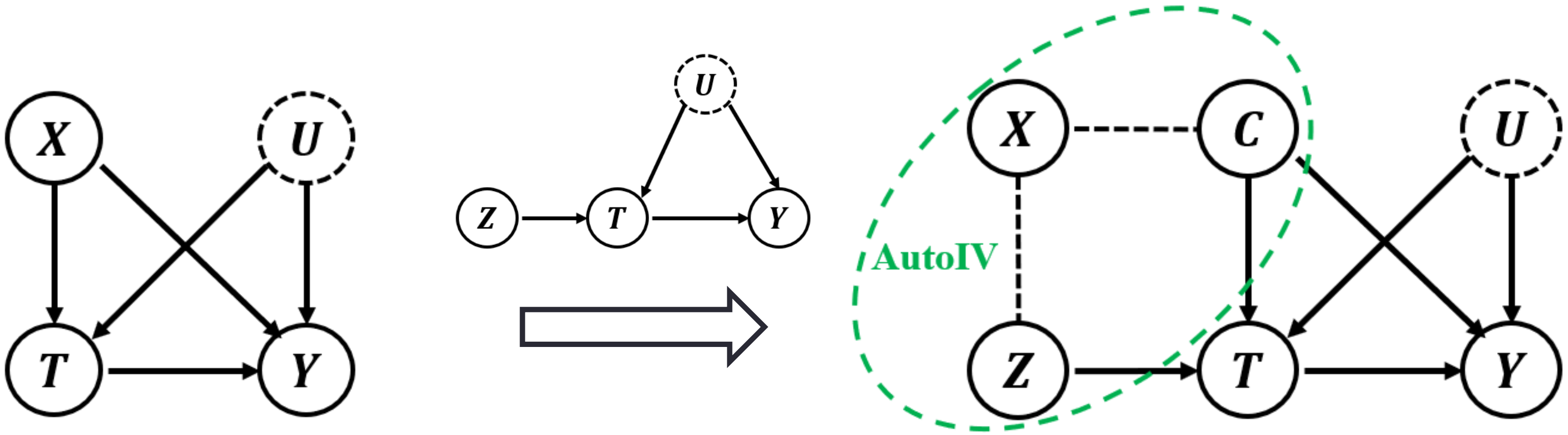
$Y = f(X) + U$

$f(X) = -0.1 \cdot X^2 - 0.4 \cdot X$ $\qquad$ $f(X) = 0.05 \cdot X^3 + 0.1 \cdot X^2 - 0.8 \cdot X$



But these methods require a pre-defined IV and find a valid IV is very hard.

AutoIV: Counterfactual Learning with Unobserved Confounders via Automatically generating IVs



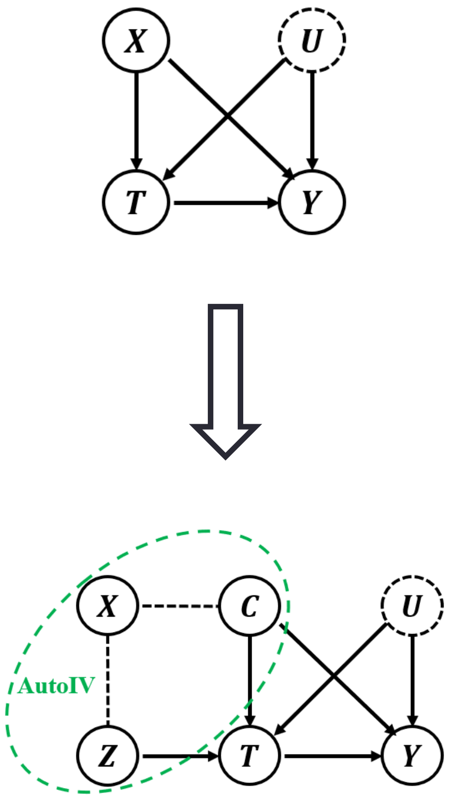
Conditions of IV

- Relevance: $P(T|Z) \neq P(T)$
- Exclusion: $P(Y|Z,T,C) \neq P(Y|T,C)$
- Unconfounded: $Z \perp C$

Mutual Information Representation Learning

Yuan J, Wu A, Kuang K, et al. Auto IV: Counterfactual Prediction via Automatic Instrumental Variable Decomposition[J]. arXiv preprint arXiv:2107.05884, 2021.

AutoIV: Counterfactual Learning with Unobserved Confounders via Automatically generating IVs



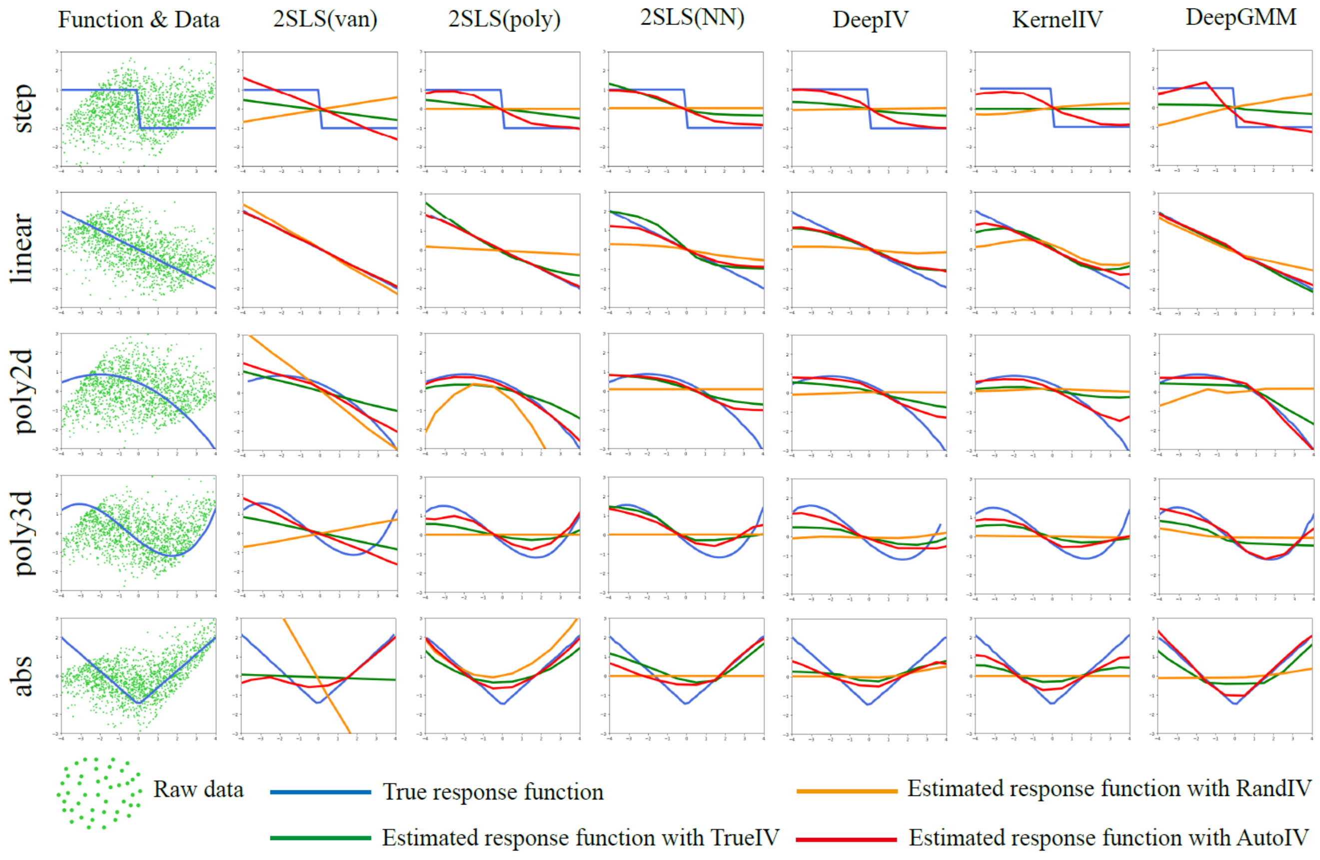


Figure 2: Response function prediction in low-dimensional scenarios.

Yuan J, Wu A, Kuang K, et al. Auto IV: Counterfactual Prediction via Automatic Instrumental Variable Decomposition[J]. arXiv preprint arXiv:2107.05884, 2021.

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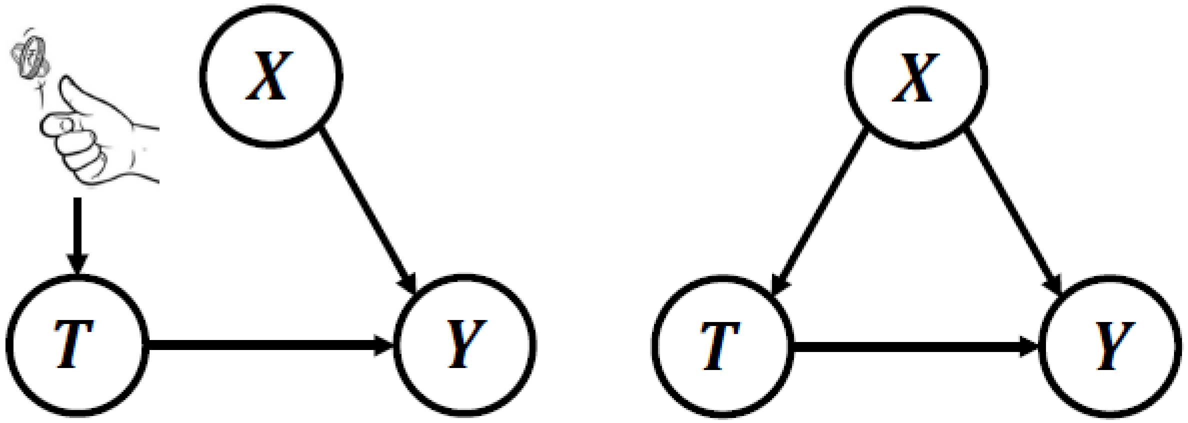
Continuous Treatment Effect Estimation



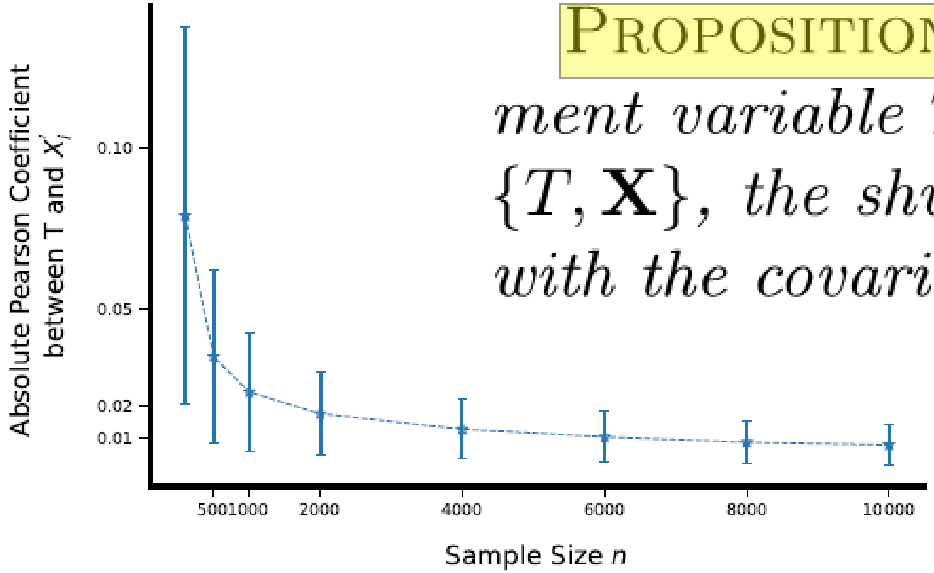
(a) Randomized Controlled Trial (RCT) (b) Observational Studies

- Binary Treatment
  - T=0 or T=1
  - $T \perp X$: confounder balancing
- Multi-valued Treatment
  - T=0,1,2,…
  - $T \perp X$: confounder balancing
- Continuous Treatment
  - How to make $T \perp X$?

Kuang K, Li Y, Li B, et al. Continuous Treatment Effect Estimation via Generative Adversarial De-confounding[J]//DMKD 2021.

Continuous Treatment Effect Estimation

- Our goal: $T \perp X$
- Variable randomly shuffle to achieve independence



PROPOSITION 1. *By randomly shuffle the value of the treatment variable T over all samples in observed data $\mathbf{D}_{obs} = \{T, \mathbf{X}\}$, the shuffled treatment T' would become independent with the covariates $\mathbf{X}$ if sample size $n \rightarrow \infty$.*

Kuang K, Li Y, Li B, et al. Continuous Treatment Effect Estimation via Generative Adversarial De-confounding[J]//DMKD 2021.

Continuous Treatment Effect Estimation

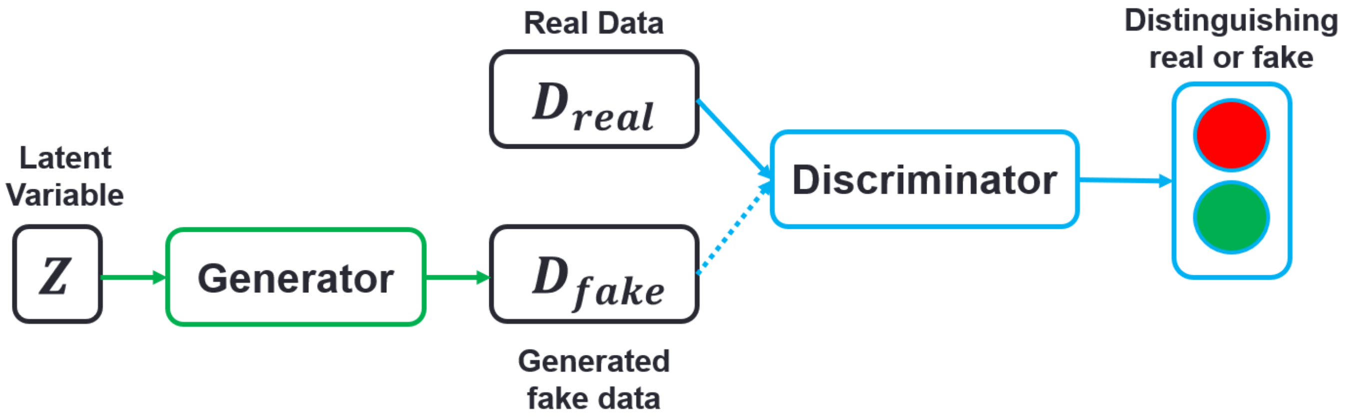
- Our goal: $T \perp X$
- "calibration" distribution generation
  - $\mathbf{D}_{cal} = \{T', \mathbf{X}\}$ on "calibration", we have $T' \perp X$
- "calibration" distribution approximation
  - Observed distribution: $\mathbf{D}_{obs} = \{T, \mathbf{X}\}$
  - Learning sample weights for distribution approximation

$$\mathbf{D}_{obs} = \{T, \mathbf{X}\} \xrightarrow{\text{sample weights } W} \mathbf{D}_{cal} = \{T', \mathbf{X}\}$$

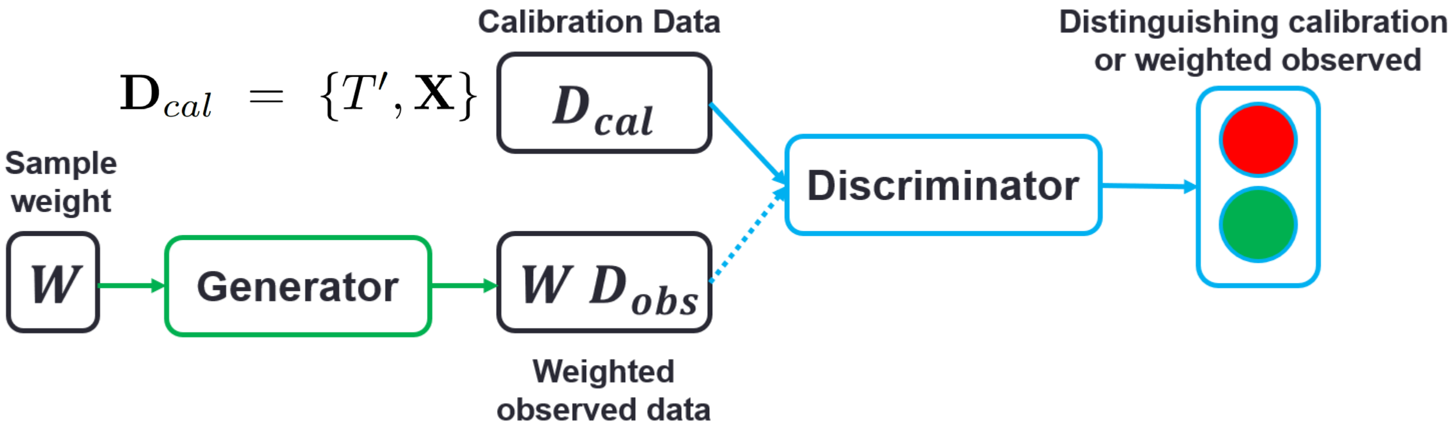
  - Such that: $W\ T \perp W\ X$

Idea from GAN mechanism

- Generative Adversarial Networks (GAN)



- Generative Adversarial De-confounding (GAD)



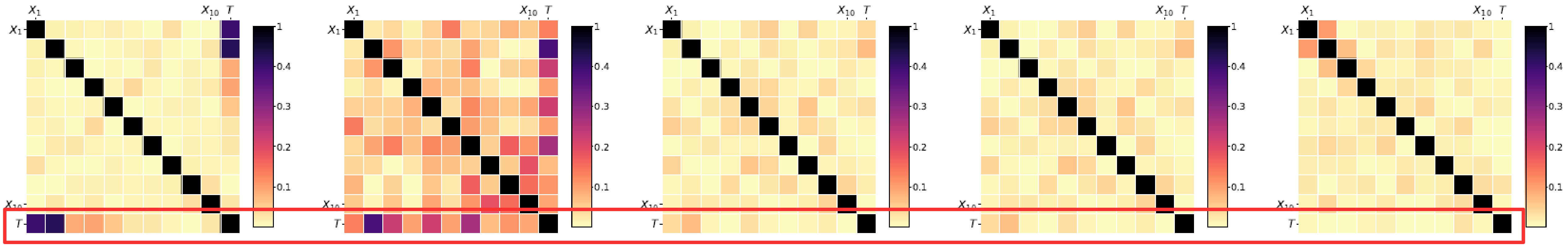
Generative Adversarial De-confounding (**GAD**)

- "Calibration" distribution: $\mathbf{D}_{cal} = \{T', \mathbf{X}\}$
- Observed distribution: $\mathbf{D}_{obs} = \{T, \mathbf{X}\}$
- Sample weights learning with GAD

$$
\begin{aligned}
L(\mathbf{w}, d) = & \mathbb{E}_{(t,x)\sim\mathbf{D}_{cal}}[l(d(t,x),\boxed{1})] \\
& + \mathbb{E}_{(t,x)\sim\mathbf{D}_{obs}}[\boxed{w_{(t,x)}} \cdot l(d(t,x),\boxed{0})], \\
s.t. \quad & \mathbb{E}_{(t,x)\sim\mathbf{D}_{obs}}[w_{(t,x)}] = 1, \mathbf{w} \succeq 0,
\end{aligned}
$$

Kuang K, Li Y, Li B, et al. Continuous Treatment Effect Estimation via Generative Adversarial De-confounding[J]//DMKD 2021.

Continuous Treatment Effect Estimation



(a) Raw Data (b) $\text{IPW}_{unstable}$ (c) IPW_{stable} (d) CBGPS (e) GAD

Method	*TWINS*		
	BIAS_{MTEF}	RMSE_{MTEF}	RMSE_{ADRF}
OLS	0.208(0.079)	0.236(0.089)	0.686(0.350)
$\text{IPW}_{unstable}$	1.385(0.757)	1.532(0.890)	5.506(2.061)
IPW_{stable}	1.693(1.599)	1.878(1.849)	6.982(4.453)
ISMW	0.165(0.062)	0.181(0.069)	0.962(0.214)
CBGPS	0.187(0.137)	0.216(0.158)	0.683(0.380)
GAD	**0.127(0.039)**	**0.144(0.046)**	**0.383(0.091)**

Summary: New challenges in Big Data era

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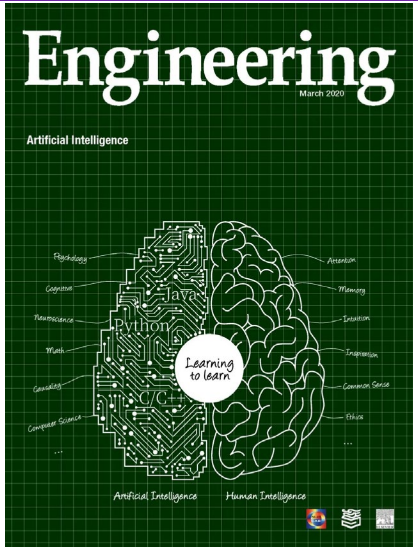
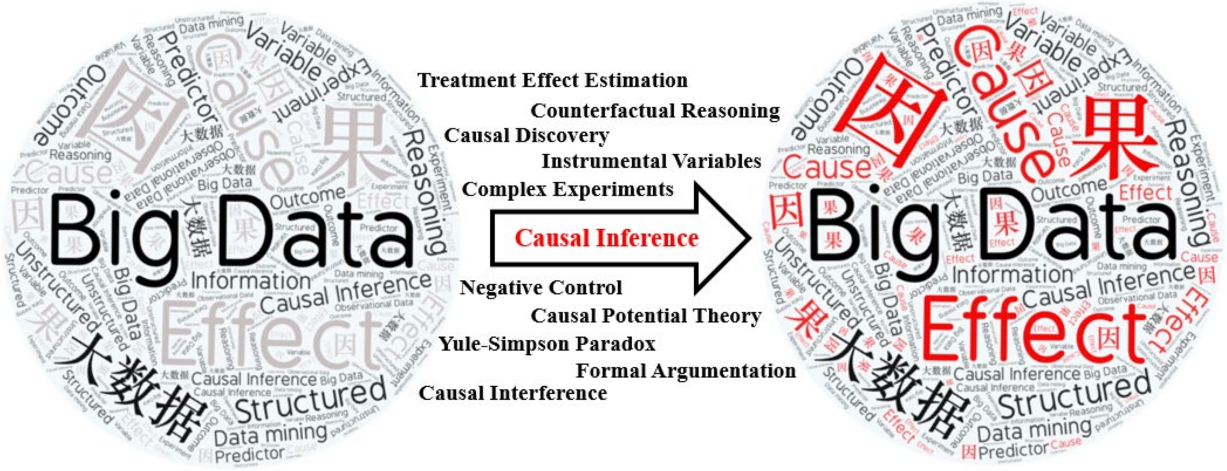


Survey Paper：
Causal Inference（因果推理）



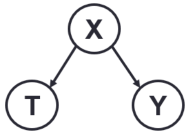
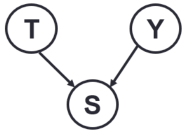
Kuang, K., Li, L., Geng, Z., Xu, L., Zhang, K., Liao, B., Huang, H., Ding, P., Miao, W., Jiang, Z. (2020). Causal Inference. *Engineering*. http://www.engineering.org.cn/ch/10.1016/j.eng.2019.08.016

Content

- Kun Kuang: Estimating average treatment effect: A brief review and beyond
- Lian Li: Attribution problems in counterfactual inference
- Zhi Geng: The Yule–Simpson paradox and the surrogate paradox
- Lei Xu: Causal potential theory
- Kun Zhang: Discovering causal information from observational data
- Beishui Liao and Huaxin Huang: Formal argumentation in causal reasoning and explanation
- Peng Ding: Causal inference with complex experiments
- Wang Miao: Instrumental variables and negative controls for observational studies
- Zhichao Jiang: Causal inference with interference

Kuang, K., Li, L., Geng, Z., Xu, L., Zhang, K., Liao, B., Huang, H., Ding, P., Miao, W., Jiang, Z. (2020). Causal Inference. *Engineering*. http://www.engineering.org.cn/ch/10.1016/j.eng.2019.08.016

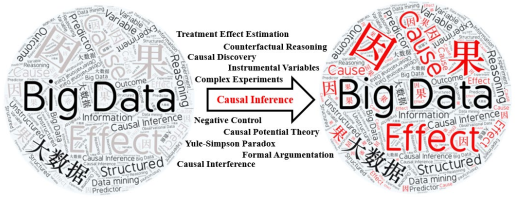
Sources of Correlation

Causation	Confounding	Sample Selection
		
Stable Actionable Explainable	Spurious Correlation: T is correlated with Y ignoring X	Spurious Correlation: T is correlated with Y given S

Causal Inference

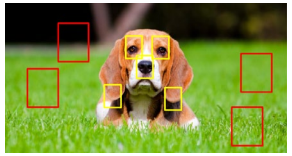
Causality Regularized Machine Learning

Draw Causation from Big Data



Causal Representation/Learning

Stable & Explainable



Fair & Actionable

Thank You!

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Homepage: https://kunkuang.github.io/