CAUSAL INFERENCE IN OBSERVATIONAL STUDIES

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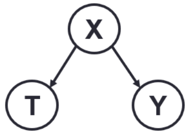
- Associate Professor, Zhejiang University
- Vice Director of AI Department
- Received Ph.D. from Tsinghua University @ 2019
- Visited Stanford @ 2017 (work with Prof. Susan Athey)
- Research: Causal Inference, Explainable AI, and Causality Regularized Machine Learning

Sources of Correlation

Causation

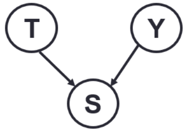
Stable
Actionable
Explainable

Confounding



Spurious Correlation:
T is correlated with Y ignoring X

Sample Selection

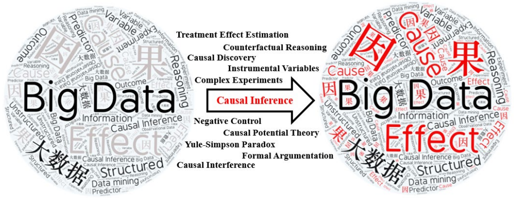


Spurious Correlation:
T is correlated with Y given S

Causal Inference →

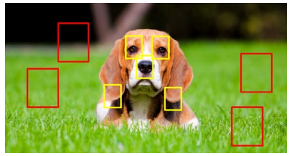
Causality Regularized Machine Learning →

- Draw Causation from Big Data



- Causal Representation/Learning

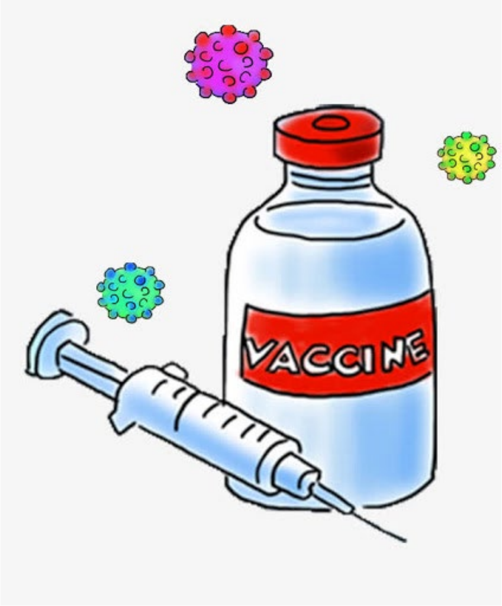
Stable & Explainable



Fair & Actionable

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, 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 $Y(T = 0)$
- Average Treatment Effect (ATE):

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

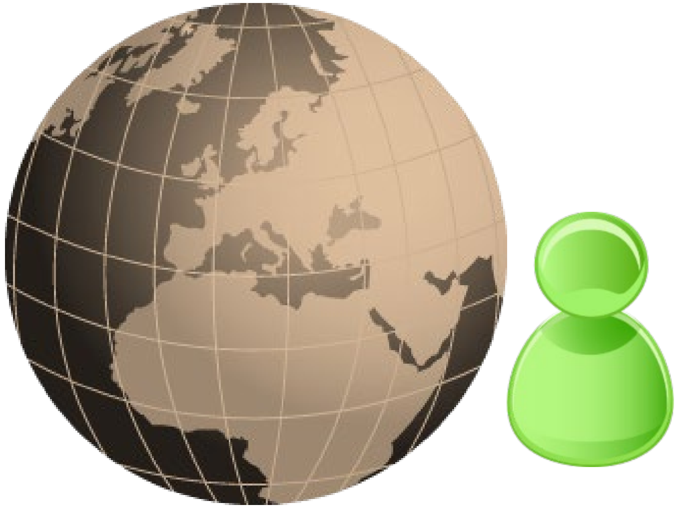
- Counterfactual Problem:

$$Y(T = 1) \quad \text{or} \quad Y(T = 0)$$

Ideal Solution: Counterfactual World

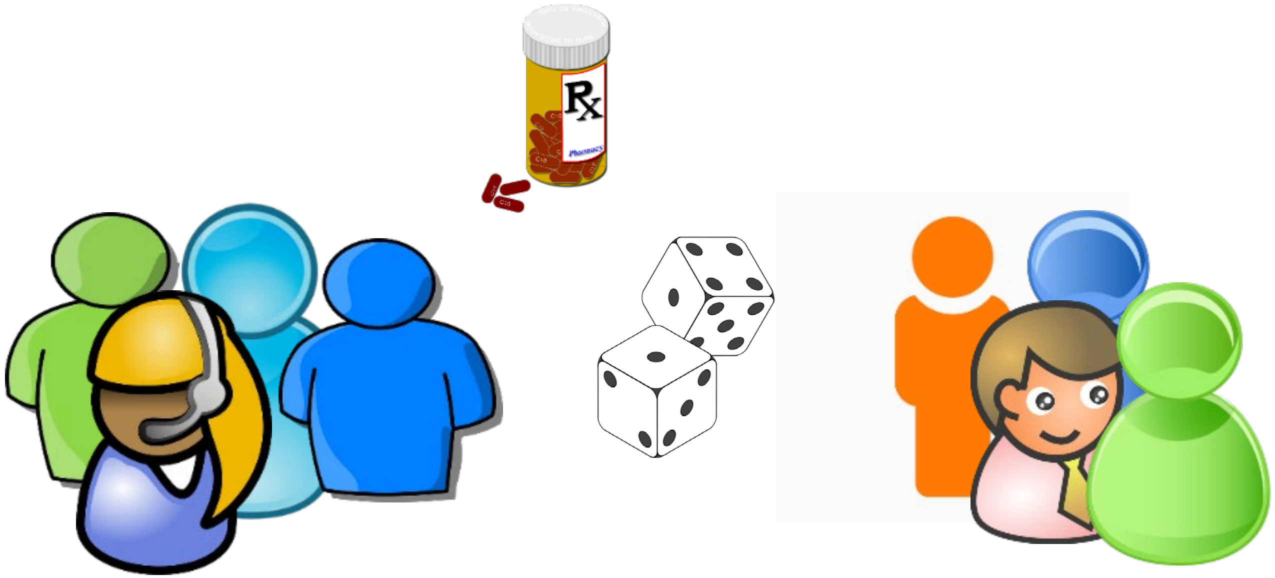
- Reason about a world that does not exist
- Everything is the same on real and counterfactual worlds, but the treatment

$Y(T = 1)$



$Y(T = 0)$

Randomized Experiments are the "Gold Standard"



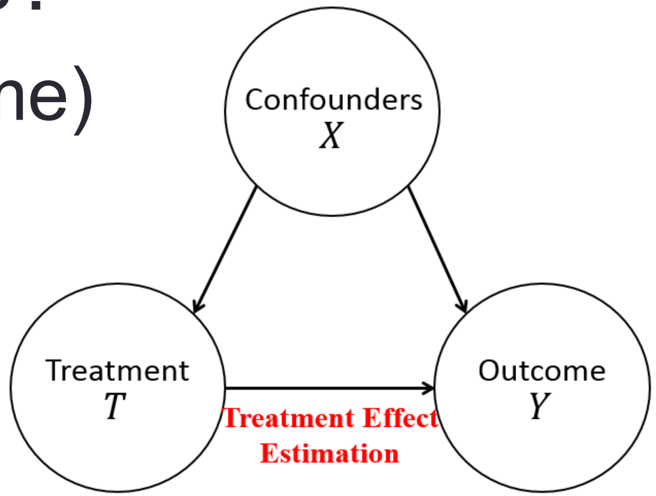
- Drawbacks of randomized experiments:
  - Cost
  - Unethical

Causal Inference with Observational Data

- Counterfactual Problem:

$$Y(T=1) \quad \text{or} \quad Y(T=0)$$

- Can we estimate ATE by directly comparing the average outcome between treated and control groups?
  - Yes, with randomized experiments (X are the same)
  - No with observational data (X might be different)
- Two key points:
  - Changing T (T=1 and T=0)
  - Keeping everything else (Confounder X) constant



Causal Inference with Observational Data

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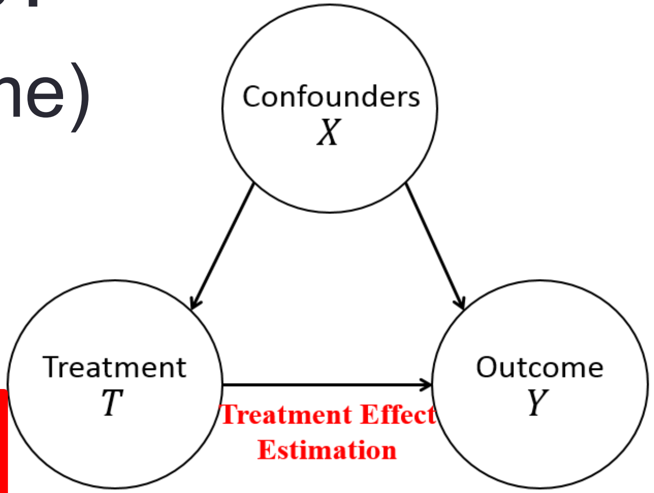
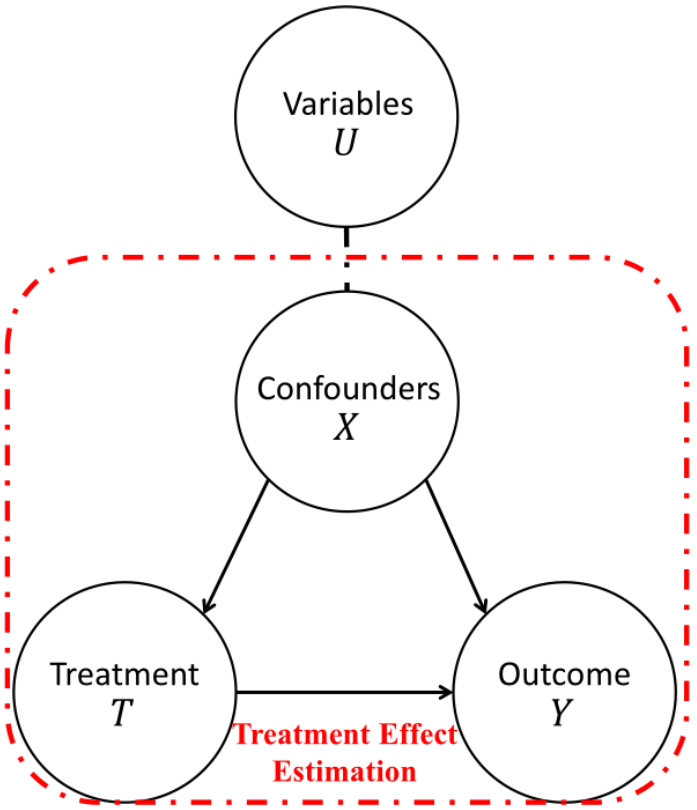


Balancing Confounders' Distribution

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)
- Continuous treatment effect estimation
  - Treatment variables are not always binary
  - Generative Adversarial De-confounding (GAD)

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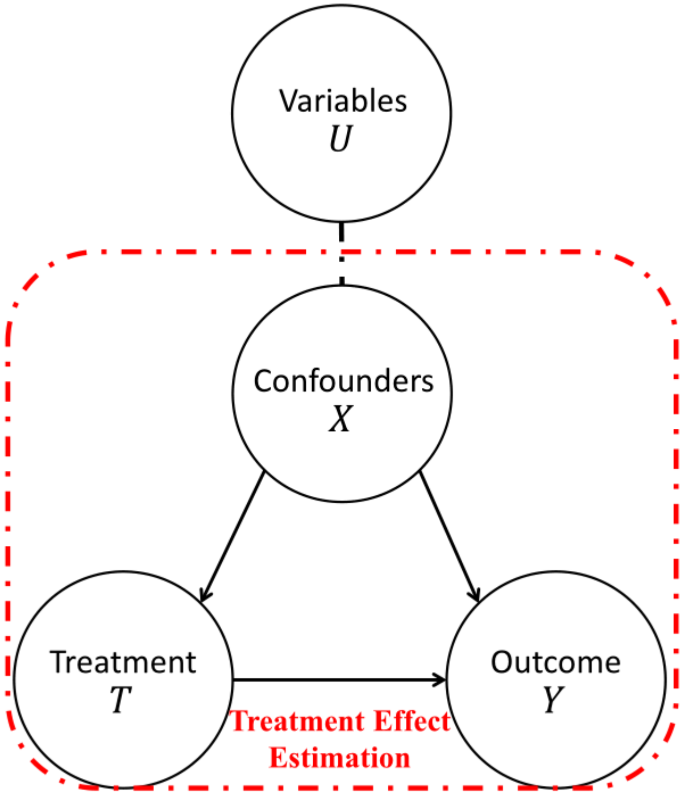
Previous Causal Framework



(a) Previous Causal Framework.

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

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

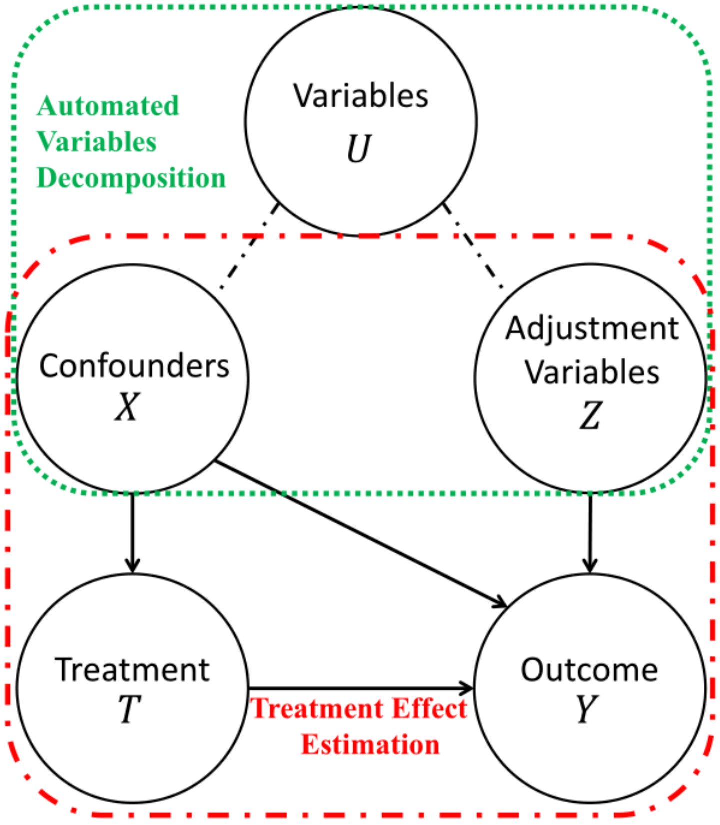
- Adjusted Outcome:

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

- 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 (D^2VD)

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

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

Replace X, Z with U

$$h(\mathbf{U}) = \mathbf{U}\gamma,$$

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

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

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

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:

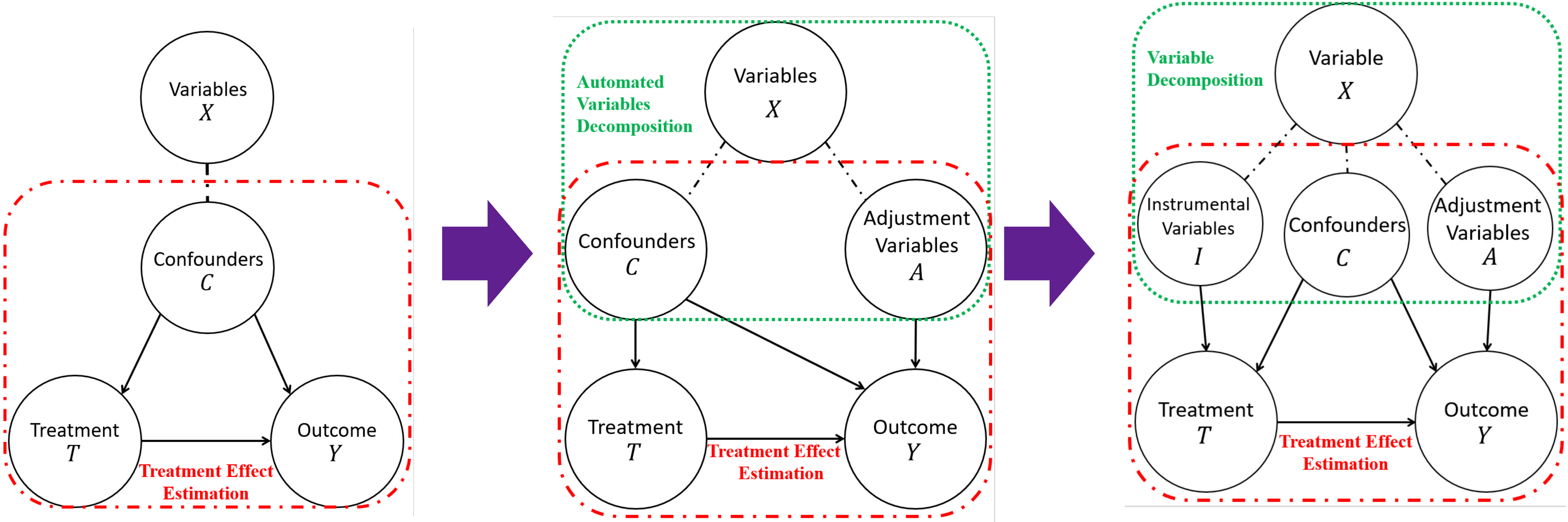
The asymptotic variance of Our D^2VD algorithm is smaller

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

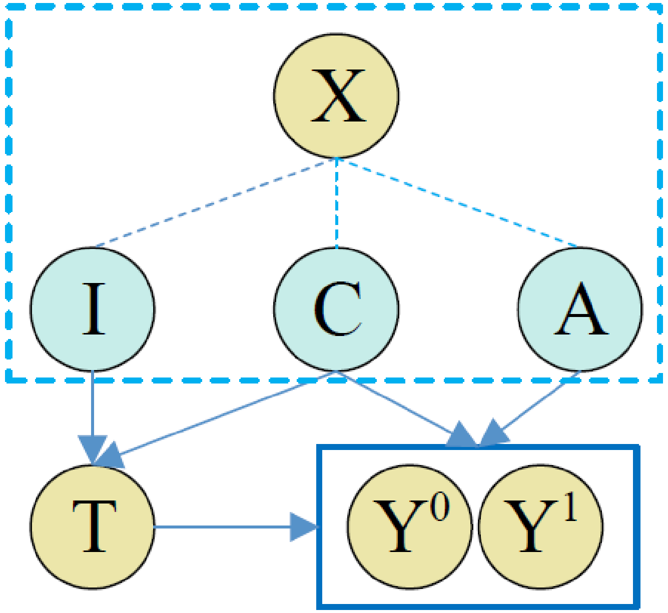


Wu A, Kuang K, Yuan J, et al. Learning Decomposed Representation for Counterfactual Inference[J]. arXiv preprint arXiv:2006.07040, 2020.

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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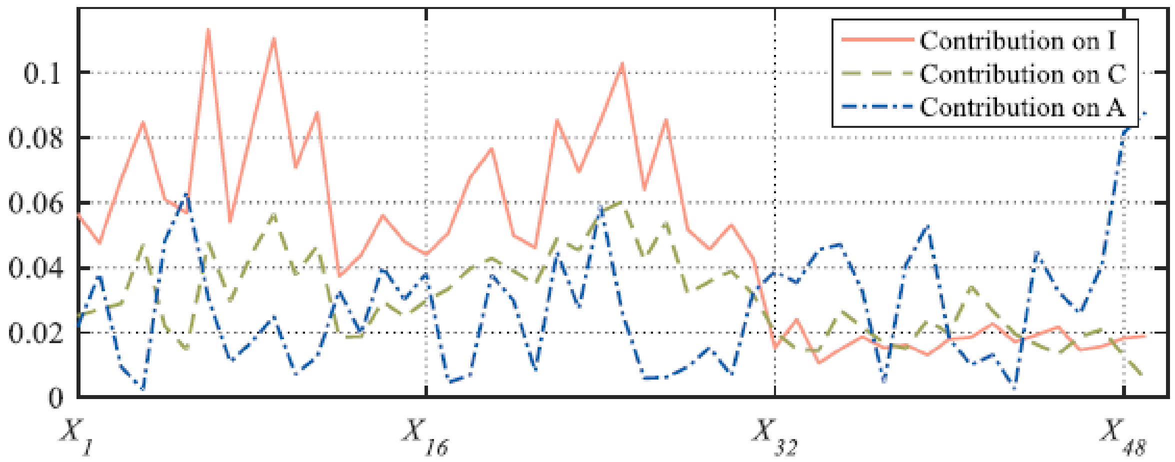
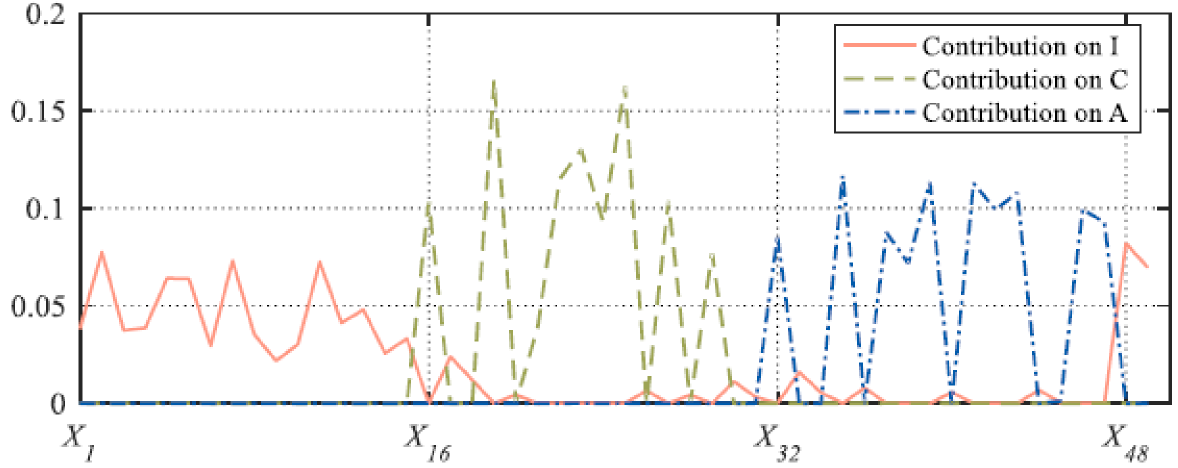


(a) DR-CFR in Syn_16_16_16_3000



(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

- Automatically separate confounders
  - Not all observed variables are confounders
  - Data-Driven Variables Decomposition (D^2VD)
- Continuous treatment effect estimation
  - Treatment variables are not always binary
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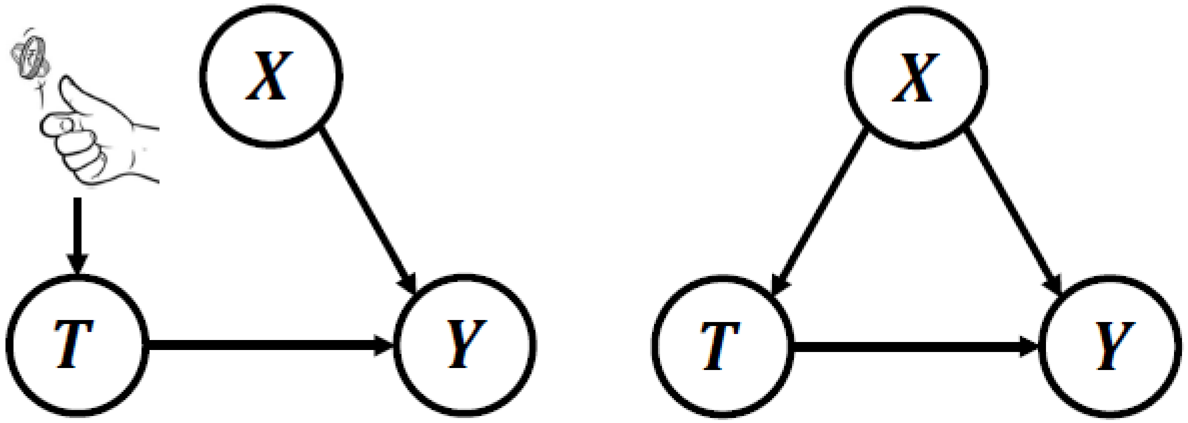
Continuous Treatment Effect Estimation



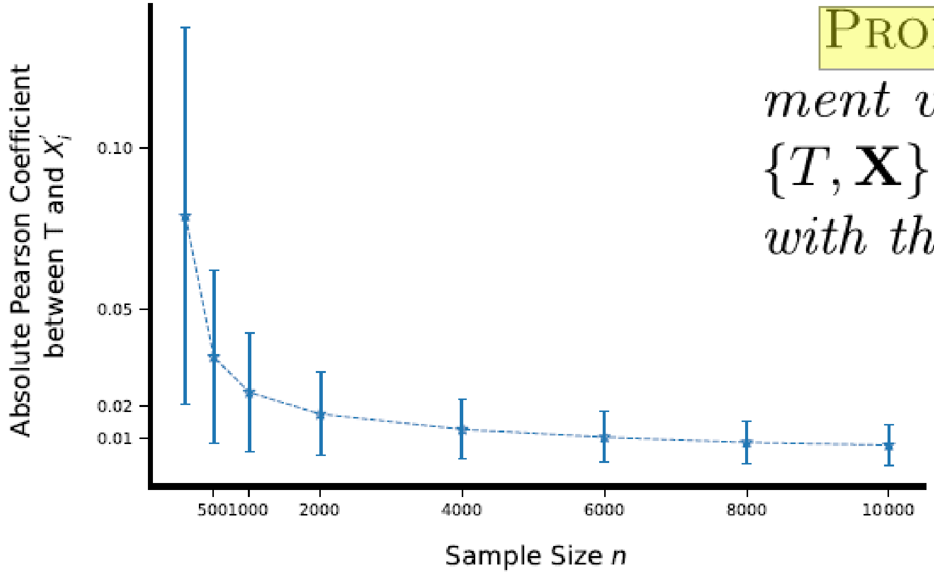
(a) Randomized Controlled Trial (RCT) (b) Observational Studies

- 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 $T \perp X$?

Li Y, Kuang K, Li B, et al. Continuous Treatment Effect Estimation via Generative Adversarial De-confounding[C]//KDD workshop 2020.

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 $n \rightarrow \infty$.*

Li Y, Kuang K, Li B, et al. Continuous Treatment Effect Estimation via Generative Adversarial De-confounding[C]//KDD workshop 2020.

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

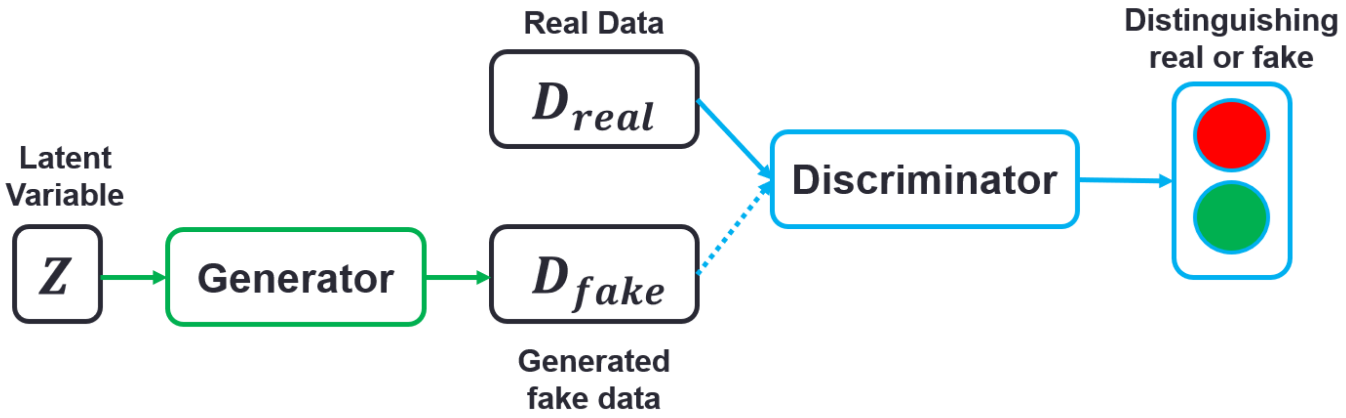
sample weights W

$$\mathbf{D}_{obs} = \{T, \mathbf{X}\} \longrightarrow \mathbf{D}_{cal} = \{T', \mathbf{X}\}$$

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

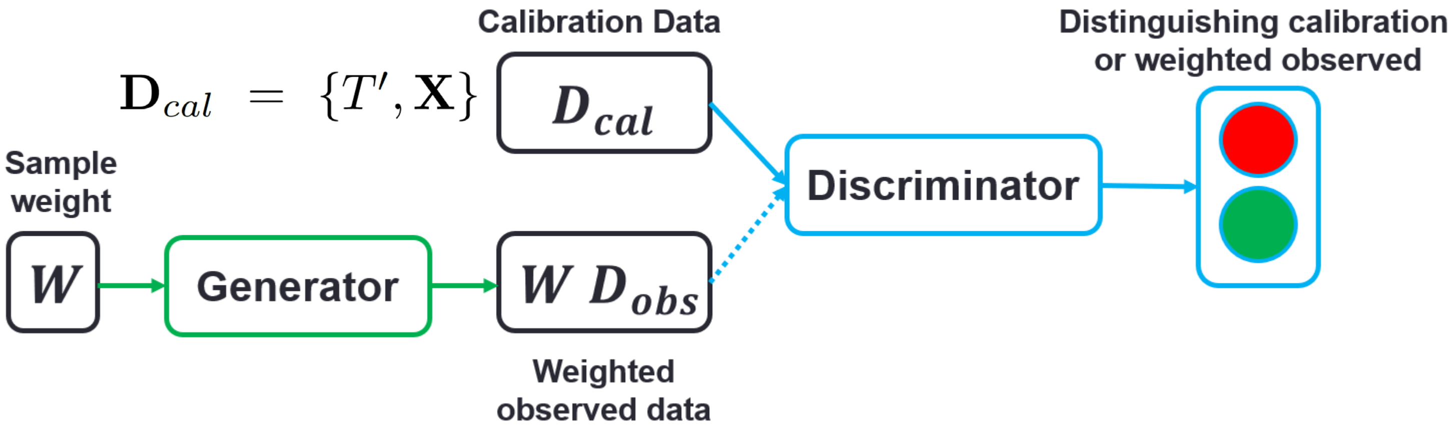
Idea from GAN mechanism

- Generative Adversarial Networks (GAN)



- Generative Adversarial De-confounding (GAD)

$$\mathbf{D}_{cal} = \{T', \mathbf{X}\}$$



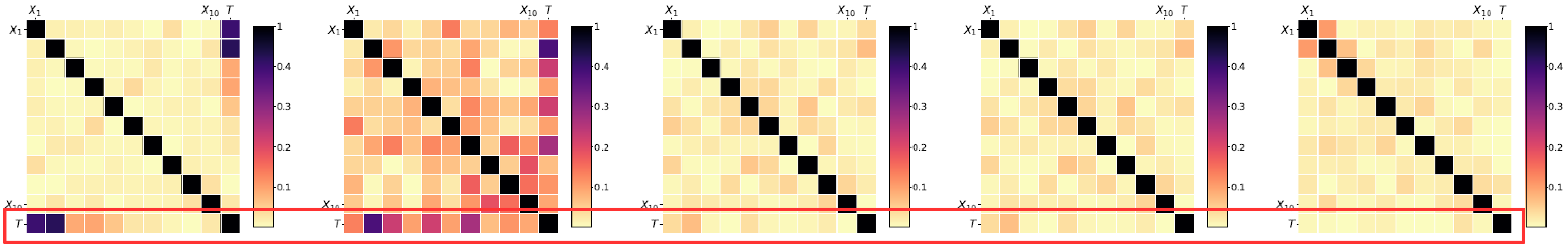
Generative Adversarial De-confounding (**GAD**)

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

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

Li Y, Kuang K, Li B, et al. Continuous Treatment Effect Estimation via Generative Adversarial De-confounding[C]//KDD workshop 2020.

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)**

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De-Biased Court's View Generation with Causality

Yiquan Wu[1], Kun Kuang[1], Yating Zhang[2], Xiaozhong Liu[3], Changlong Sun[2], Jun Xiao[1], Yueting Zhuang[1], Luo Si[2], Fei Wu[1]

Zhejiang University[1], Alibaba Group[2], Indiana University Bloomington[3]

Task Definition - Court's View Generation

PLAINTIFF'S CLAIM	The plaintiff A claimed that the defendant B should return the loan of $29,500 *[Principle Claim]* and the corresponding interest *[Interest Claim]*.
FACT DESCRIPTION	After the hearing, the court held the facts as follows: The defendant B borrowed $29,500 from the plaintiff A, and agreed to return after one month. After the loan expired, the defendant failed to return *[Fact]*.
COURT'S VIEW	The court concluded that the loan relationship between the plaintiff A and the defendant B is valid. The defendant failed to return the money on time *[Rationale]*. Therefore, the plaintiff's claim on principle was supported *[Acceptance]* according to law. The court did not support the plaintiff's claim on interest *[Rejection]* because the evidence was insufficient *[Rationale]*.

Input:

- Plaintiff's claim
- Fact description

Output:

- Court's View, which consists of
  - Rationale
  - Judgment

Court's view generation is a specific text generation task

Challenges

PLAINTIFF'S CLAIM	The plaintiff A claimed that the defendant B should return the loan of $29,500 *Principle Claim* and the corresponding interest *Interest Claim*.
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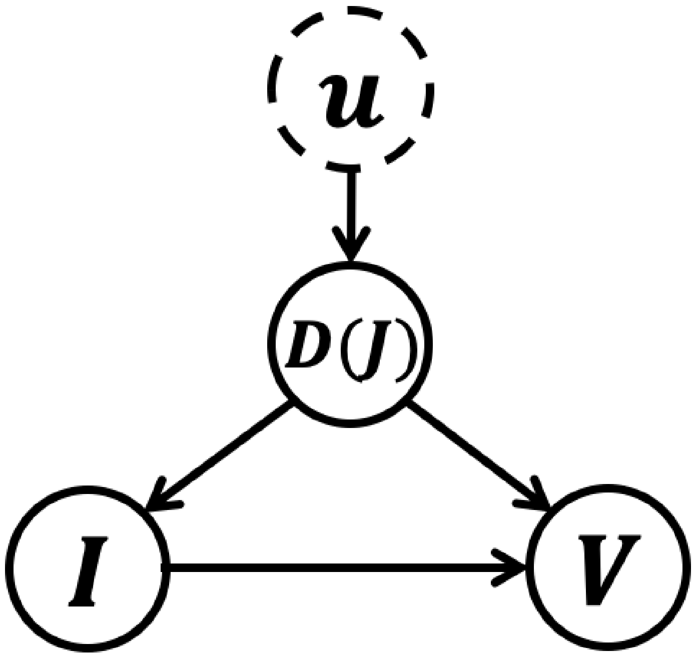
COURT'S VIEW	The court concluded that the loan relationship between the plaintiff A and the defendant B is valid. The defendant failed to return the money on time *Rationale*. Therefore, the plaintiff's claim on principle was supported *Acceptance* according to law. The court did not support the plaintiff's claim on interest *Rejection* because the evidence was insufficient *Rationale*.

- There exists '**no claim, no trial**' principle in civil legal systems
  - court's view should only focus on the facts related to the claims
- The **imbalance** of judgment in civil cases
  - over 76% cases were supported in private lending
  - would blind the training of the model by focusing on the supported cases while ignoring the non-supported cases

Imbalance: Mechanism Confounding Bias

- Imbalance between supported and non-supported cases
  - Lead to confounding bias during model training
- Understanding confounding bias with a causal graph:
  - u: unobserved data generation mechanism
  - D(J): judgment in dataset
  - I: input (i.e., plaintiff's claim and fact description)
  - V: court's view
- Understanding confounding bias mathematically
  - j: judgment (support and non-support):



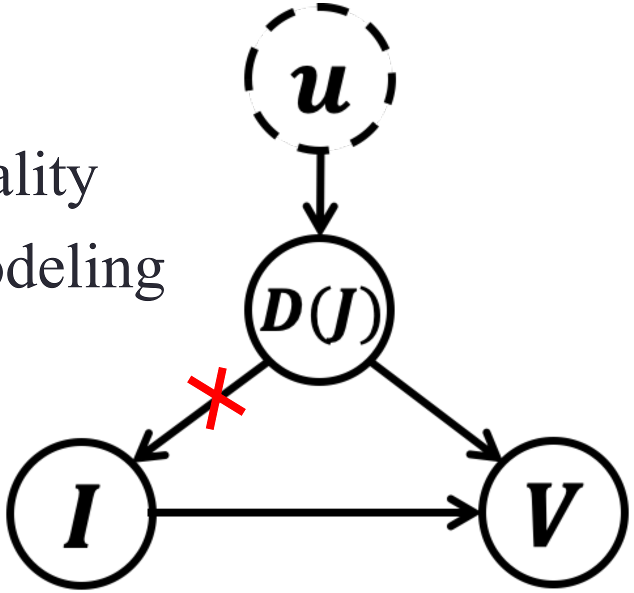
$$P(V|I) = \sum_j P(V|I,j)P(j|I) \xrightarrow{P(j=1|I) \approx 1} P(V|I) \approx P(V|I,j=1)$$

Method

Attentional and Counterfactual based Natural Language Generation

Attentional and Counterfactual based NLG

- There exists ‘**no claim, no trial**’ principle in civil legal systems
  - Attentional encoder: keep the fact that related to the claims
- The **imbalance** of judgment in civil cases
  - Counterfactual decoder:
  - Back-door adjustment: from observation to intervention/causality
  - Cut the dependence between D(J) and I via counterfactual modeling



$$P(V|I) = \sum_j P(V|I,j)P(j|I)$$

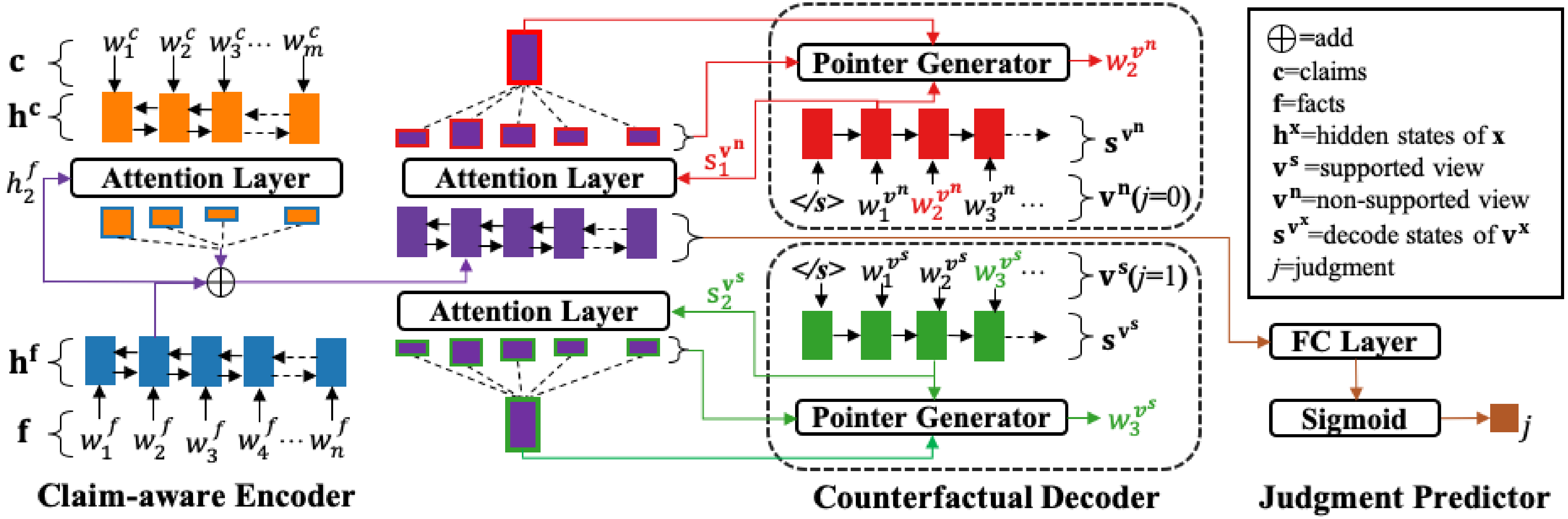
Back-door

$$P(V|do(I)) = \sum_j P(V|I,j)P(j)$$

Binary j

$$P(V|do(I)) = P(V|I,j=0)P(j=0) + P(V|I,j=1)P(j=1)$$

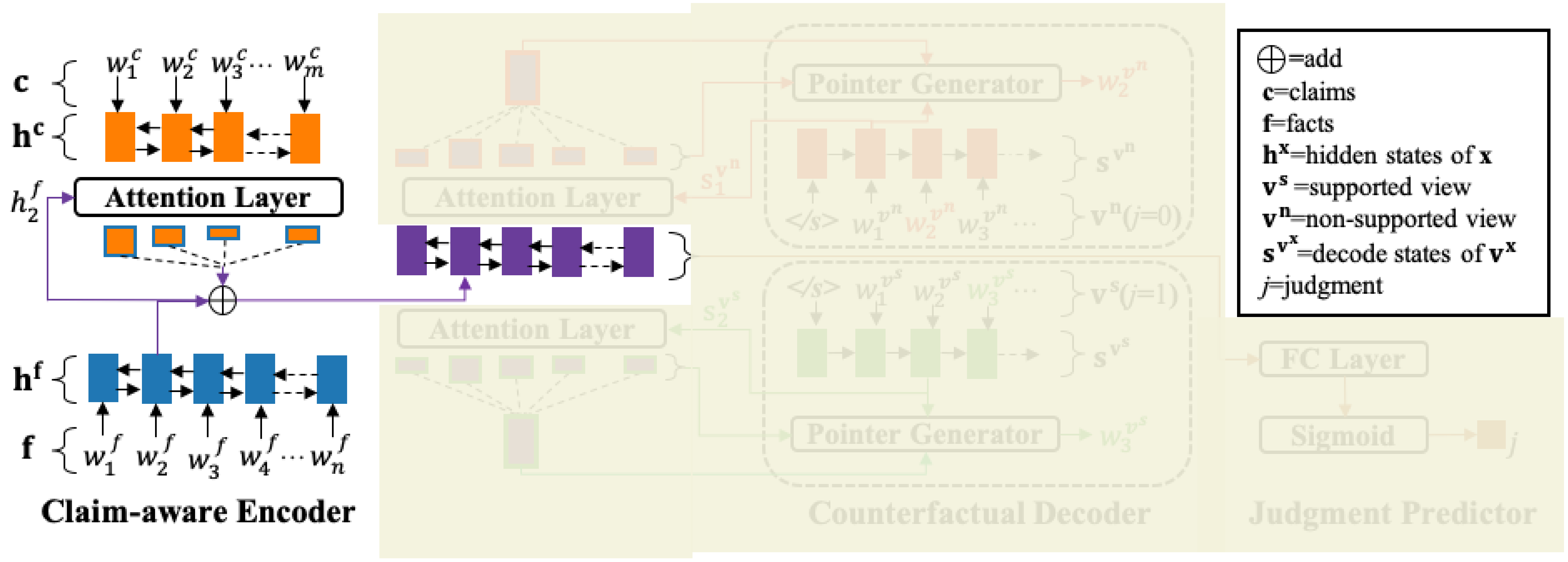
Our Framework



AC-NLG is a multi-task model with:

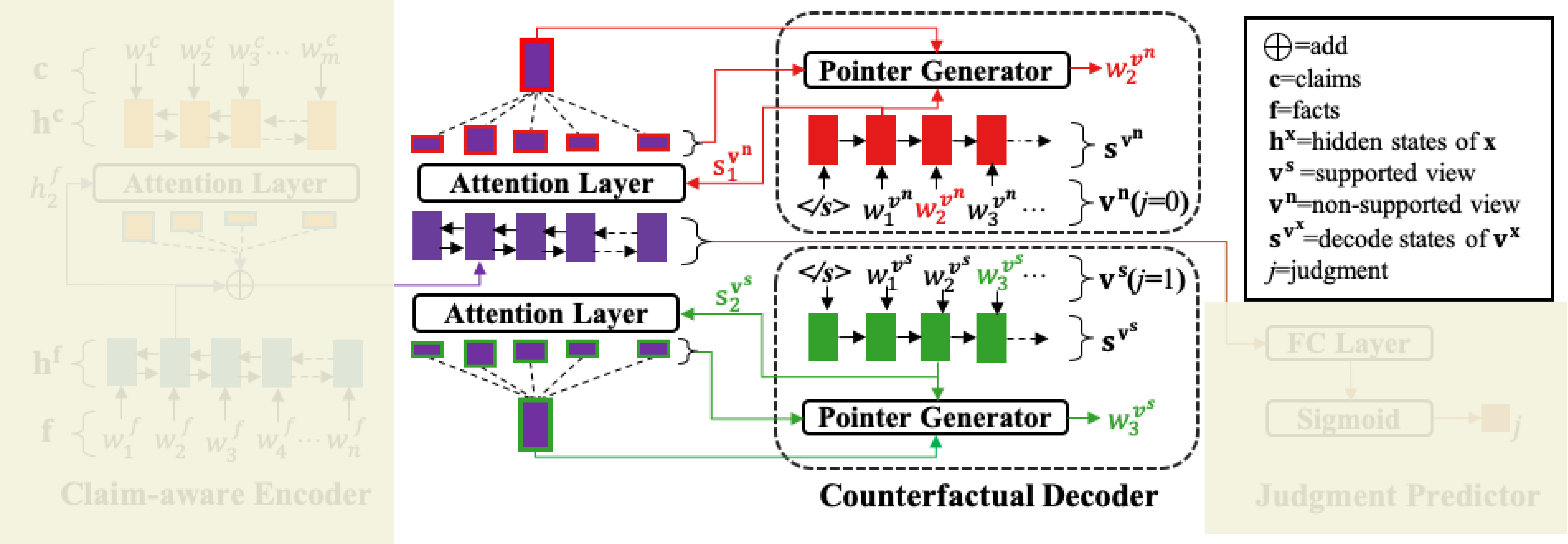
- Claim-aware encoder
  - Claim embedding
  - Fact embedding
  - Claim-Fact attention
- Counterfactual decoders
  - Supportive court's view generation
  - Non-supportive court's view generation
- Judgment predictor

Claim-aware encoder



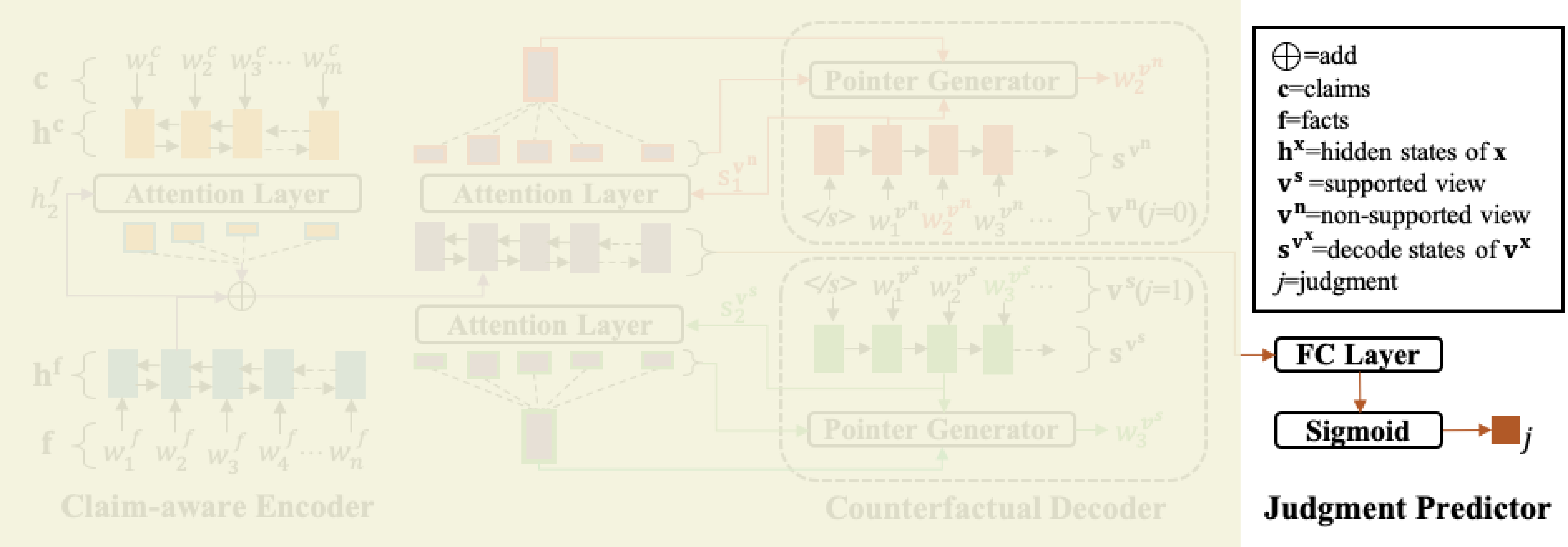
Challenge 1: court's view should only focus on the facts related to the claims

Counterfactual decoders



$$P(V|do(I)) = P(V|I, j = 0)P(j = 0) + P(V|I, j = 1)P(j = 1)$$

Judgment predictor



$$P(V|do(I)) = P(V|I, j=0)P(j=0) + P(V|I, j=1)P(j=1)$$

Result

Results on court's view generation

Method	ROUGE			BLEU			BERT SCORE		
	R-1	R-2	R-L	B-1	B-2	B-N	p	r	f1
S2S	54.0	35.7	48.3	**65.0**	**57.6**	50.5	89.6	89.5	89.6
S2SwS	51.5	32.0	45.0	63.3	55.6	47.9	83.8	88.8	86.2
PGN	53.3	37.1	48.8	62.0	56.1	50.0	94.0	91.2	92.6
PGNwS	53.2	36.0	48.0	63.1	56.7	50.2	95.7	94.0	94.8
AC-NLGw/oBA	54.1	38.1	49.9	61.8	55.9	49.9	93.6	91.9	92.8
AC-NLGw/oCA	53.7	36.7	49.1	62.1	56.0	49.7	94.5	92.6	93.5
AC-NLGwS	53.7	36.4	48.5	62.8	56.5	50.0	94.0	92.1	93.0
AC-NLG	**55.1**	**38.6**	**50.8**	63.2	57.1	**51.0**	**96.5**	**94.6**	**95.5**

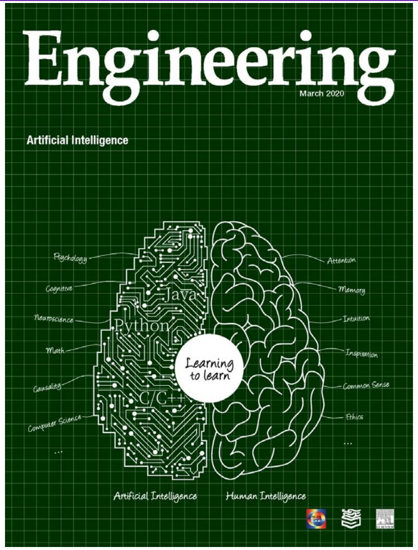
Results on judgment prediction

Method	Prediction Acc.					
	Support			Non-support		
	p	r	f1	p	r	f1
w/oD	72.1	81.0	76.3	56.9	44.3	49.8
w/oCA	92.0	**97.2**	94.5	**85.6**	66.0	74.5
wS	86.0	94.3	90.0	62.8	38.6	47.8
AC-NLG	**93.4**	95.9	**94.6**	81.5	**72.9**	**76.9**

Results of human evaluation

Method	Judgment		Rational	Flu.
	Support	Non-support		
PGN	3.34	1.78	3.11	3.41
AC-NLG	**3.52**	**3.24**	**3.25**	**3.50**

The official journal of the Chinese Academy of Engineering



Engineering Survey Paper：Causal Inference（因果推理）

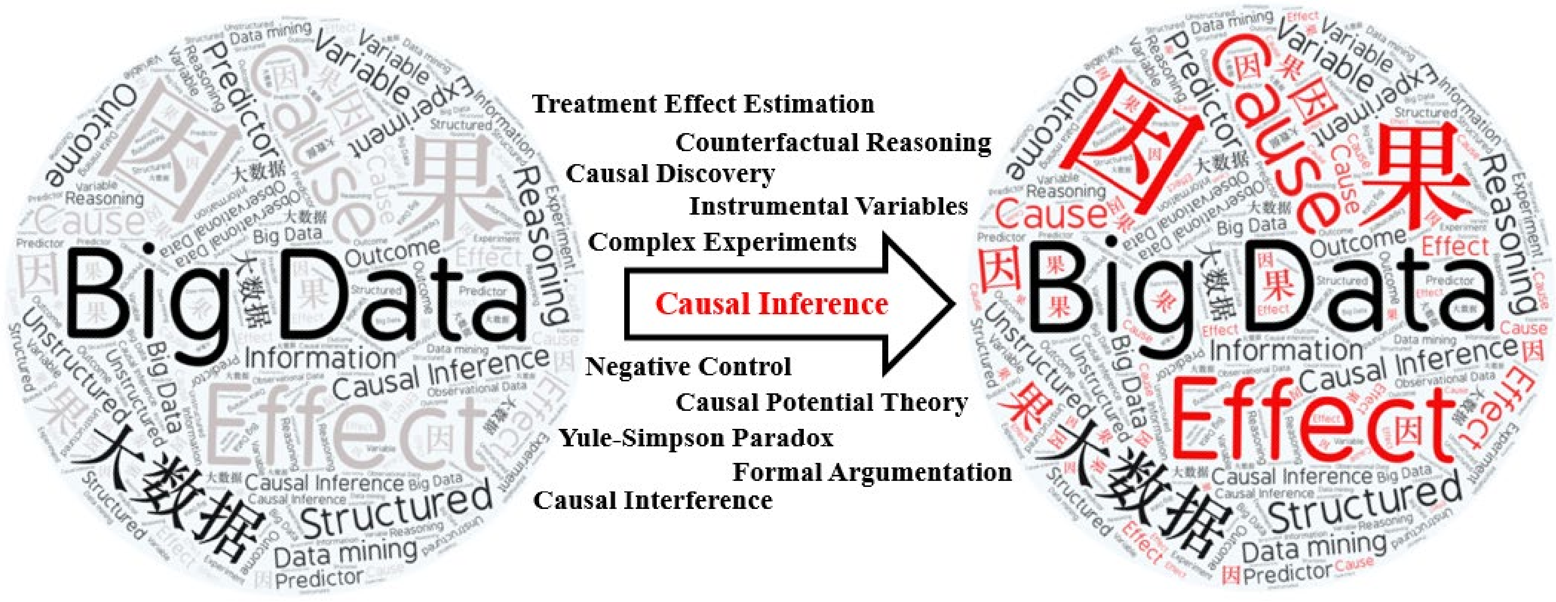
Kun Kuang, Lian Li, Zhi Geng, Lei Xu, Kun Zhang, Beishui Liao, Huaxin Huang, Peng Ding, Wang Miao, Zhichao Jiang

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



Thank You!

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