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Learning Disentangled Latent Factors for Individual Treatment Effect Estimation Using Variational Generative Adversarial Nets

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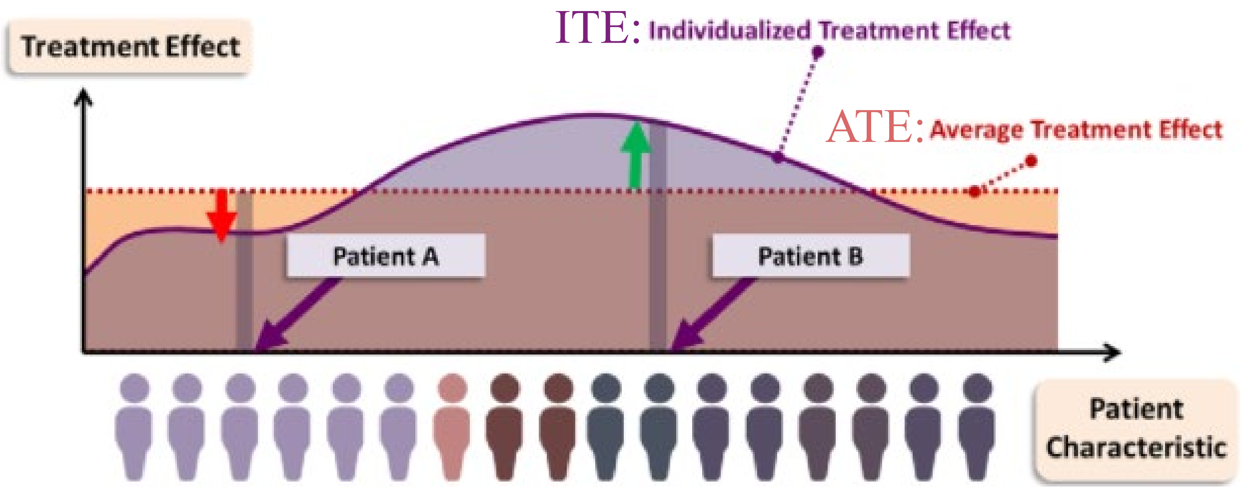
CONTENT

Background and Motivation

Individualized Treatment Effect (ITE)

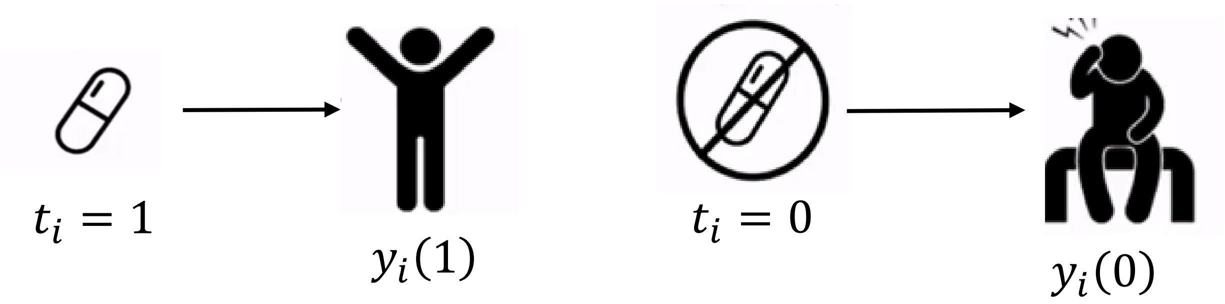


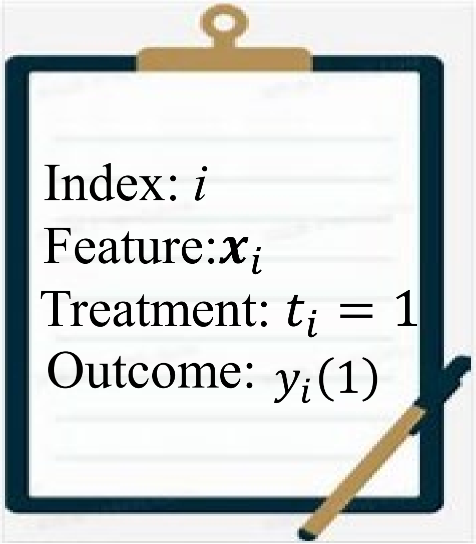
- Doctors choose the most appropriate treatment for individual patient (Precision medicine).
- The gold standard for evaluating treatment effect is randomized controlled trials (RCTs).

Challenges of Estimating ITE from observational data

- Individual's **potential outcomes**

$$\boxed{ITE_i = y_i(1) - y_i(0)}$$





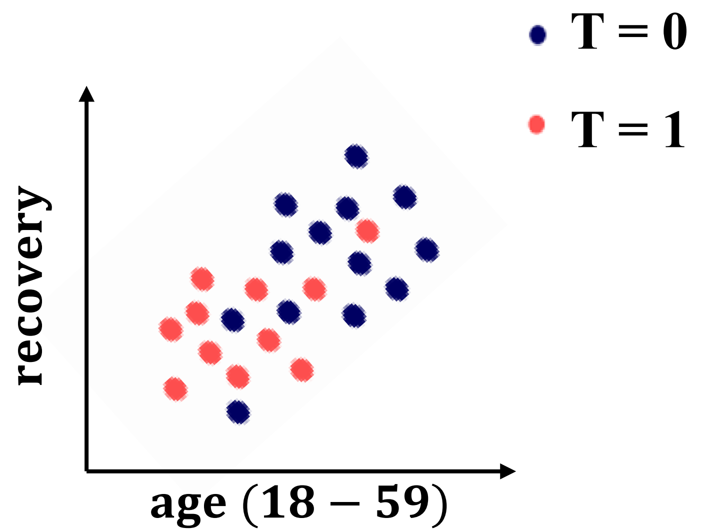
But only one potential outcome (factual outcome) can be observed, others (counterfactual outcomes) cannot be observed.

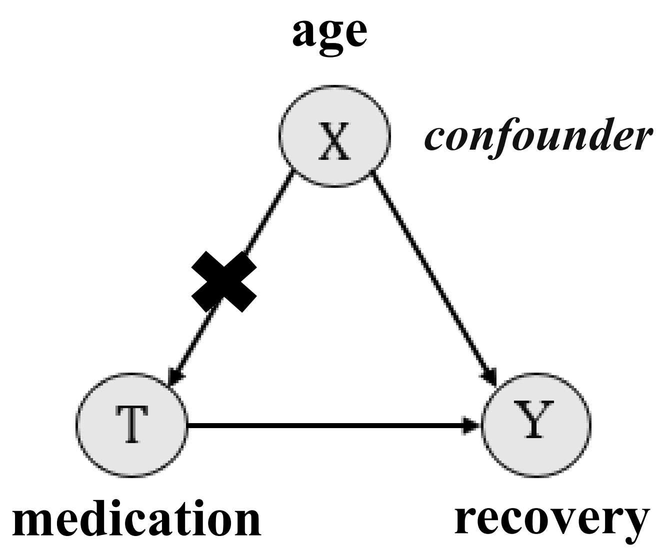
Rubin, Donald B. Causal inference using potential outcomes. *Journal of the American Statistical Association*, 2011.

Challenges of Estimating ITE from observational data

--- Biased data :

The possible distribution shift of *confounders* results in the *selection bias* in observational data.

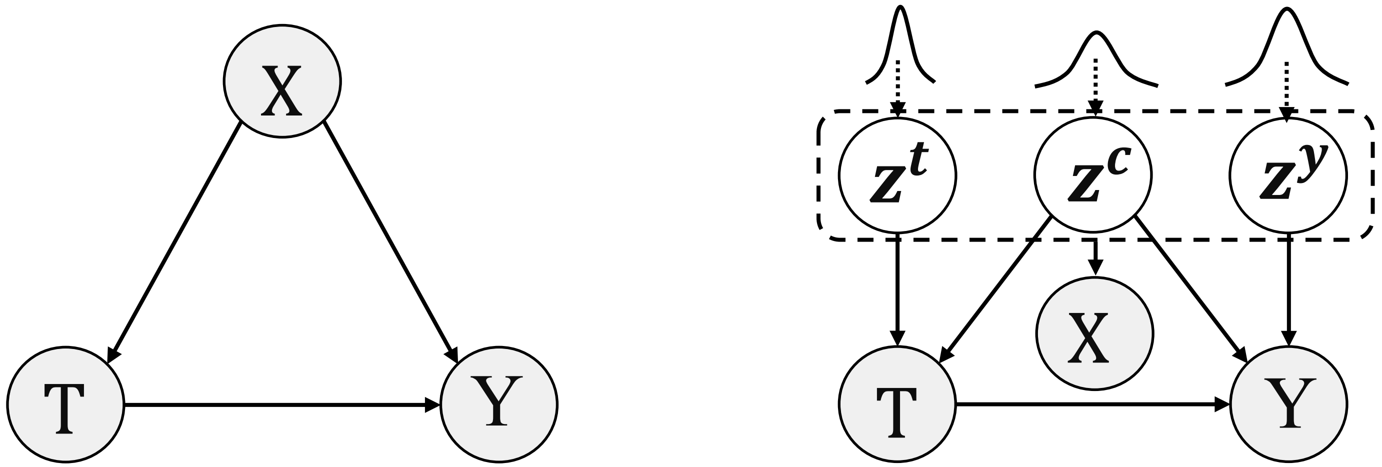




selection bias : $p(T|X) \neq p(T)$, the treatment assignment depends on the individual observed features.

Balancing confounders

Motivation



z^t: Instrumental factors (e.g., **wealth**)
z^c: Confounding factors (e.g., **age**)
z^y: Adjustment factors (e.g., **gene**)

(a) No-disentangled latent factors (b) Disentangled latent factors

- **Previous methods ignore the identification of confounders and non-confounders, and assume that complete confounders are observed.**
- **Balancing the non-confounders(instrumental factors) can reduces the efficiency of treatment effect estimation.**
- **Inferring the distribution of factual and counterfactual outcomes**

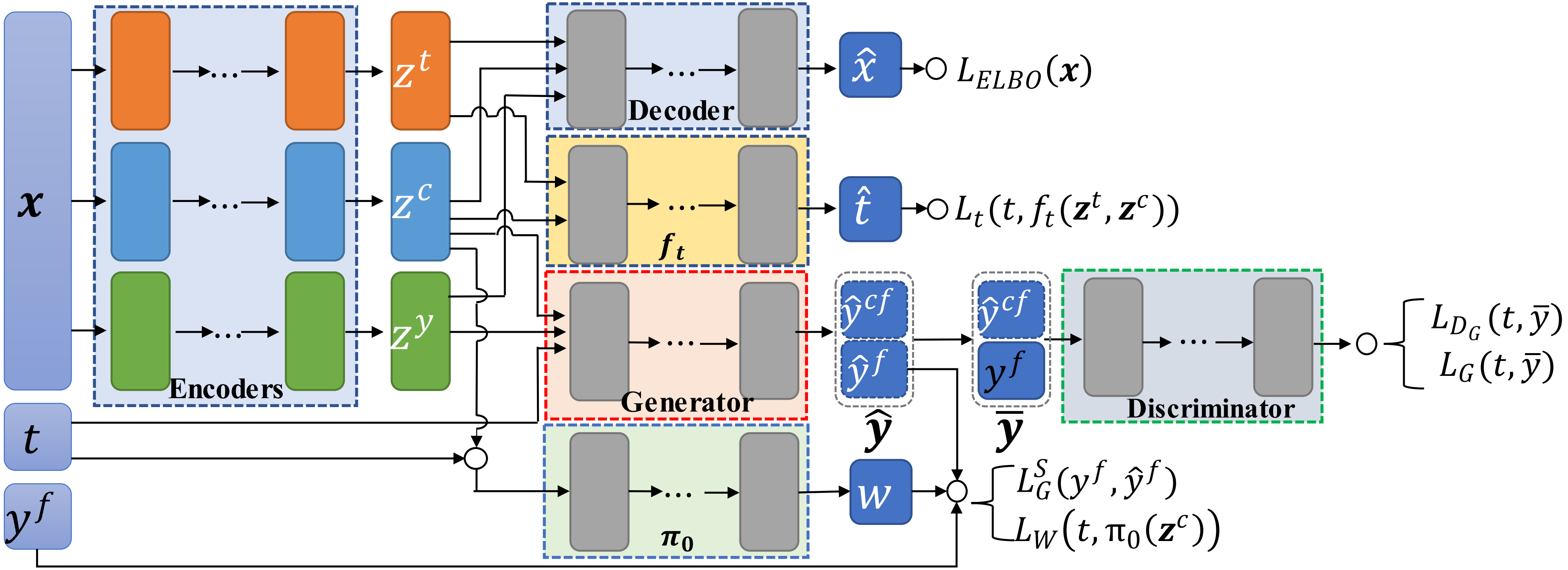
Proposed Method: VGANITE

Method

Variational AutoEncoder(VAE) and Generative Adversarial Nets (GAN).

$$\mathcal{R}_{CF} = \frac{1}{N}\sum_{i=1}^{N}\Big[\underbrace{-L_{ELBO}(\boldsymbol{x}_i)}_{①} + \alpha \cdot \underbrace{L_t\big(t_i, f_t(\boldsymbol{z}_i^t, \boldsymbol{z}_i^c)\big)}_{②} + \beta \cdot \underbrace{\big(L_{D_G}(t_i, \overline{\boldsymbol{y}}_i) + L_G(t_i, \overline{\boldsymbol{y}}_i)\big)}_{③} + w_i \cdot \underbrace{L_G^S(y_i^f, \hat{y}_i^f)}_{④} + \gamma \cdot \underbrace{L_W\big(t_i, \pi_0(\boldsymbol{z}_i^c)\big)}_{⑤}\Big]$$

① Evidence Lower Bound; ②Treatment Loss; ③ Generative Adversarial Loss; ④ Supervised Loss; ⑤ Weights Loss

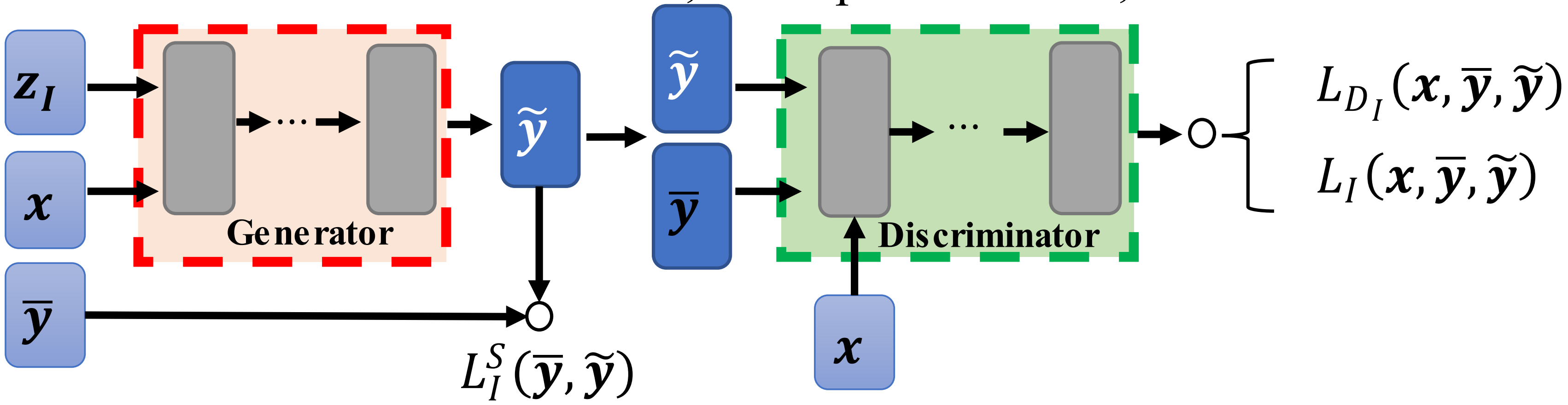


$\boldsymbol{x}$ Feature vector	z^t Latent Instrumental factors	$\hat{x}$ Reconstructed Feature vector	$\hat{y}^f$ Generated Factual outcome
t Treatment	z^c Latent Confounding factors	$\hat{t}$ Reconstructed Treatment	w Learned sample weights
y^f Factual outcome	z^y Latent Adjustment factors	$\hat{y}^{cf}$ Generated Counterfactual outcome	

Method

$$\mathcal{R}_{ITE} = \frac{1}{N}\sum_{i=1}^{N}\left[L_{D_I}(\boldsymbol{x}_i,\bar{\boldsymbol{y}}_i,\tilde{\boldsymbol{y}}_i) + \underbrace{L_I(\boldsymbol{x}_i,\bar{\boldsymbol{y}}_i,\tilde{\boldsymbol{y}}_i)}_{①} + \omega\cdot \underbrace{L_I^S(\bar{\boldsymbol{y}}_i,\tilde{\boldsymbol{y}}_i)}_{②}\right]$$

① Generative Adversarial Loss; ② Supervised Loss;



x Feature vector
z_I Randomness vector
$\bar{y}$ Potential outcomes vector
$\tilde{y}$ Generated Potential outcomes vector

Experiments and Summary

Experiences

TABLE I ITE AND ATE ESTIMATION PERFORMANCE OF VGANITE ON TWO REAL DATASETS

Methods	Datasets							
	IHDP (*PEHE*)		**IHDP** (ϵ_{ATE})		**Twins** (*PEHE*)		**Twins** (ϵ_{ATE})	
	In-sample	Out-sample	In-sample	Out-sample	In-sample	Out-sample	In-sample	Out-sample
BLR	5.82±0.30	5.82±0.30	0.72±0.04	0.93±0.05	0.312±0.001	0.323±0.018	0.0057±0.0025	0.0334±0.0027
CEVAE	2.70±0.12	2.60±0.14	0.34±0.01	0.46±0.01	0.335±0.001	0.344±0.001	0.0411±0.0056	0.0563±0.0070
k-NN	2.11±0.10	4.11±0.20	0.14±0.01	0.9±0.05	0.333±0.009	0.345±0.005	0.0038±0.0039	**0.0051±0.0040**
BART	2.14±0.10	2.32±0.10	0.23±0.01	0.34±0.02	0.347±0.002	0.338±0.003	0.1206±0.0021	0.1265±0.0025
R-Forest	4.25±0.20	6.63±0.30	0.73±0.05	0.96±0.06	**0.306±0.002**	0.321±0.002	0.0049±0.0091	0.0080±0.0056
C-Forest	3.82±0.20	3.84±0.20	0.18±0.01	0.40±0.03	0.366±0.002	0.316±0.018	0.0286±0.0012	0.0335±0.0016
TARNET	0.88±0.02	0.92±0.02	0.26±0.01	0.28±0.01	0.319±0.005	0.315±0.002	0.0108±0.0015	0.0151±0.0025
CFR_WASS	0.71±0.02	0.76±0.02	0.25±0.01	0.27±0.01	0.315±0.007	**0.313±0.004**	0.0112±0.0025	0.0284±0.0046
CFR_MMD	0.71±0.02	0.79±0.02	0.28±0.01	0.30±0.01	0.318±0.005	0.316±0.008	0.0111±0.0010	0.0285±0.0012
DR-CFR	0.65±0.02	0.78±0.03	0.24±0.03	0.26±0.03	0.319±0.002	0.322±0.018	0.0060±0.0010	0.0090±0.0013
TEDVAE	0.65±0.11	0.70±0.14	0.12±0.02	0.16±0.02	0.320±0.002	0.321±0.025	0.0060±0.0012	0.0060±0.0016
GANITE	1.91±0.40	2.41±0.40	0.43±0.05	0.49±0.05	0.330±0.005	0.332±0.016	0.0058±0.0017	0.0089±0.0075
VGANITE	**0.64±0.03**	**0.67±0.03**	**0.11±0.02**	**0.15±0.02**	0.315±0.007	0.318±0.005	**0.0035±0.0013**	0.0062±0.0038

[a] The best results of all methods are highlighted with the bold font and the second with an underscore for each dataset

Experiences

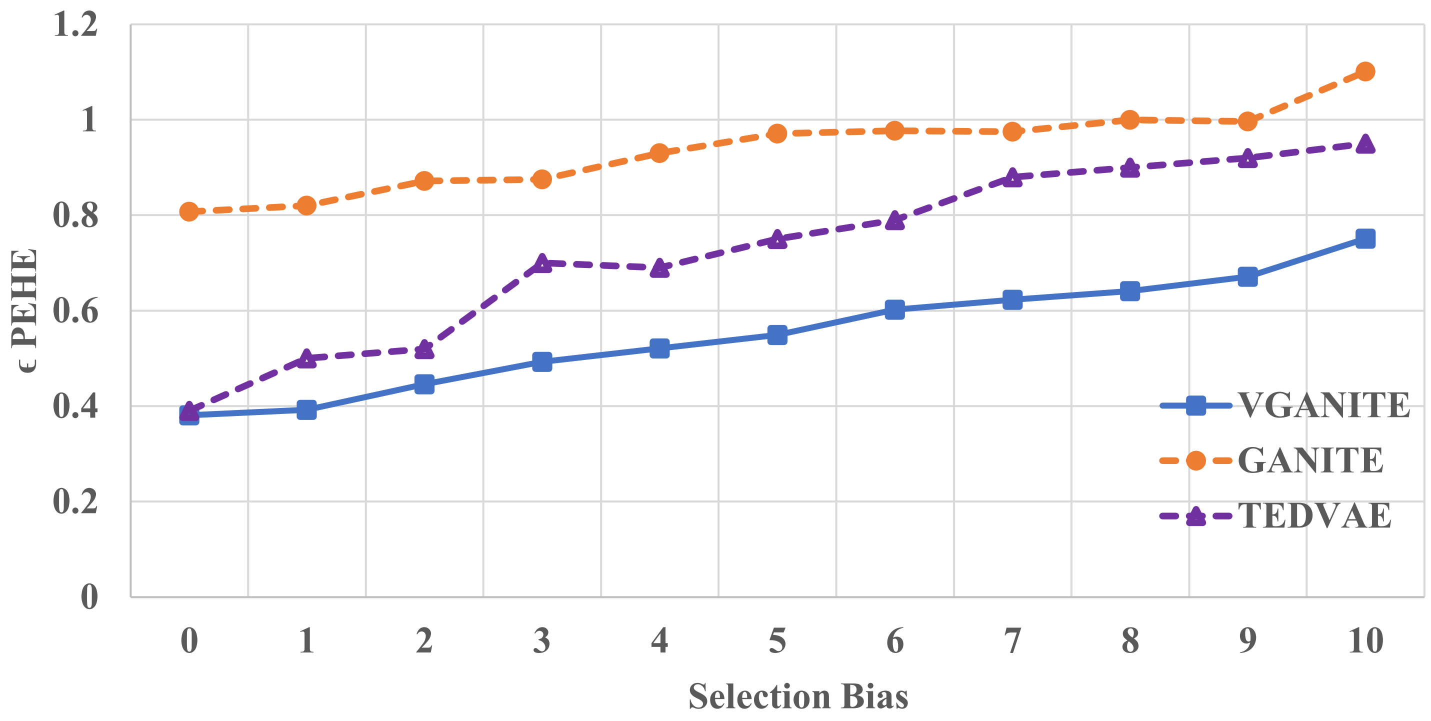


Fig. 4. As the selection bias increases, VGANITE performs better than other models.

Experiences

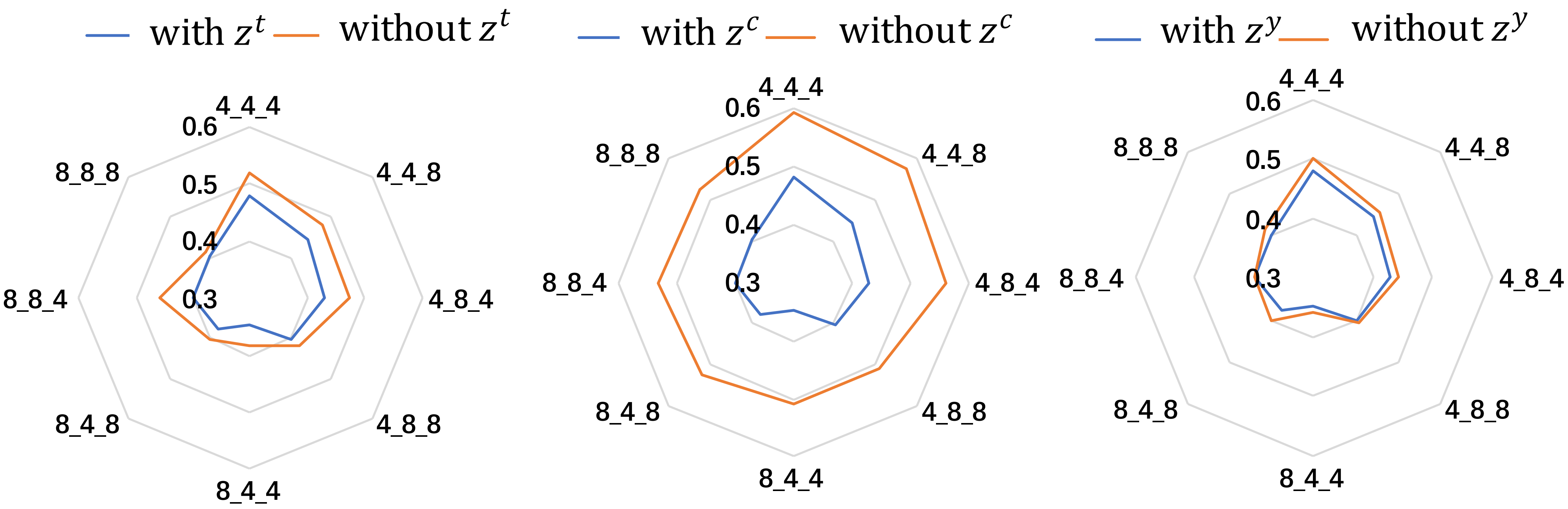


Fig. 5. In the radar charts, each vertex on the polygon is identified using a sequence of latent factor dimensions from the synthetic datasets, with each polygon representing the model's PEHE metric (the small polygon is better).

Summary

- Explicit identification of the latent factors (z^t, z^c, z^y) in observational data can better handle selection bias and achieve better performance in estimating ITE;
- The collaborative learning strategy with VAE and GAN can infer the latent representations of observed variables to access the unobserved confounding factors;
- For future work we try to incorporate trustworthy learning to give predictions with uncertainty estimate, which is important in the medical field.

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Thank you for listening