From Latent to Deep Latent

Causal Inference with CEVAE

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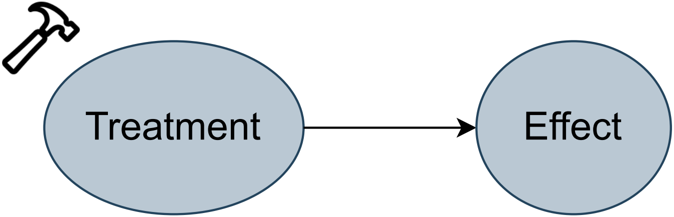
Objective: estimating causal effects

Estimate how a medical treatment T affects the health Y of a *random* patient.



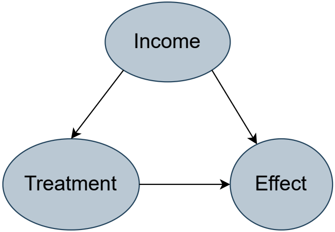
$$P(Y|\mathrm{do}(T=t)) = P(Y|T=t)$$

$$\mathrm{ITE} = \mathbb{E}[(Y|\mathrm{do}(T=1)] - \mathbb{E}[(Y|\mathrm{do}(T=0)]$$

Confounder

In a observational study we do **not** have control over the treatment T: there may be a confounder X that influences both variables!

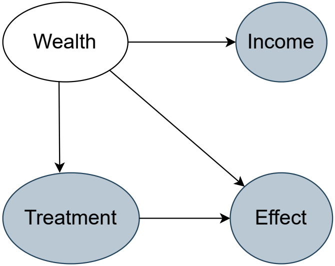
$$P(Y|\text{do}(T = t)) \neq P(Y|T = t)$$



$$P(Y|\text{do}(T = t)) = \sum_{x} P(Y|T = t, X = x)P(X = x)$$

Latent confounder

But what if there is a confounder Z that is **not** observed?



We can use latent models:

- Latent Variable Model
- Deep Latent Variable Model

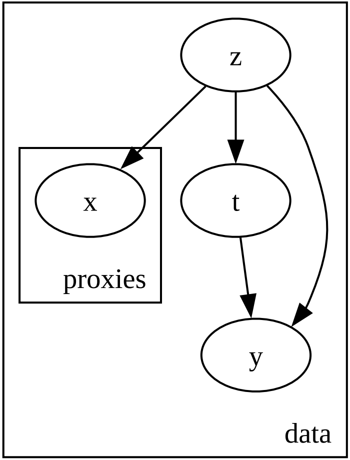
Latent Variable Model

- Assume parametric distributions
- Assume parametric relationships between variables
- Infer parameters using Stochastic Variational Inference (SVI)
- Problem: to infer from new data point x we need to train a new model at test time!

Deep Latent Variable Model

- Assume parametric distributions
- Assume parametric relationships between variables through Neural Networks

Synthetic linear dataset



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

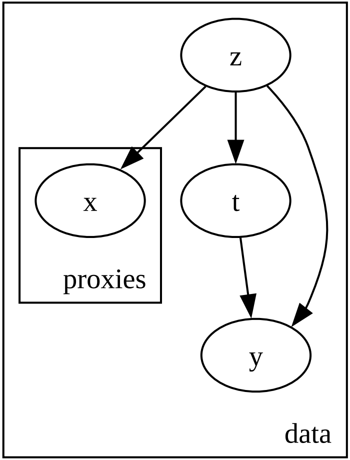
$$a_j \sim \mathcal{U}(-10,10)$$

$$X_j \sim \mathcal{N}(a_j z, \sigma_X^2)$$

$$T|Z \sim \mathrm{Be}(\sigma(\beta z))$$

$$Y|T,Z \sim \mathcal{N}(z+t, \sigma_Y^2)$$

Synthetic non linear dataset



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

$$a \sim \mathcal{U}(-1.5, 1.5)^d$$

$$\Sigma = \sigma_X^2[(1-\rho)\mathbb{I} + \rho J]$$

$$X_1, ..., X_d \sim \mathcal{N}(a \tanh(z), \Sigma)$$

$$T|Z \sim \mathrm{Be}(\sigma(\beta z))$$

$$Y|T, Z \sim \mathcal{N}\left(f_{nonLinear}(z,t), \sigma_Y^2\right)$$

Experiment: latent distribution misspecified

Experiment: changing latent dimension

Experiment: increasing the treatment effect

Conclusions

Thank You!