Causal Effect Variational Autoencoder

Final Exam Project

Valeria De Stasio, Christian Faccio, Giovanni Lucarelli

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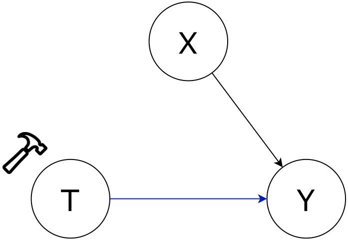
Objective: estimating causal effects

To estimate how a treatment T affects an outcome Y, we would like to intervene on T for *random* subjects and observe the effect on Y. This corresponds to a Randomized Clinic Trial.

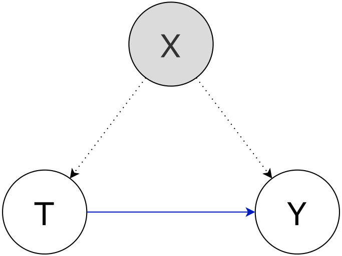


$$P(Y|\text{do}(T = t)) = P(Y|T = t)$$

Confounder

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

If we observe all confounders X, then we can block the backdoor path and compute the causal effect of T on Y.

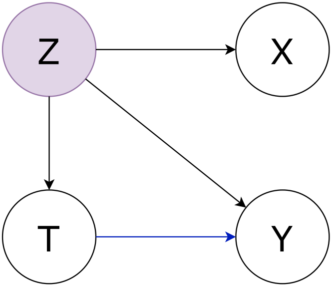


$$P(Y|\mathrm{do}(T=t)) = \sum_x P(Y|T=t, X=x)P(X=x)$$

Latent confounder

But what if there is a confounder Z that is **not** observed? This is the most likely scenario in which X is only a proxy for Z.

This time the back-door criterion is not satisfied: we cannot compute the causal effect of T on Y.



Synthetic dataset

../images/synthetic_data.pdf

- T is a binary treatment
- Y is a continuous outcome
- X is a proxy for the latent confounder Z
- Z is a continuous latent variable

Experiment: noise in the proxies

Experiment: latent distribution misspecified

Experiment: changing latent dimension

Experiment: increasing the treatment effect

Conclusions

Thank You!