



**UNIVERSITÀ
DEGLI STUDI
DI TRIESTE**

Causal Effect Variational Autoencoder

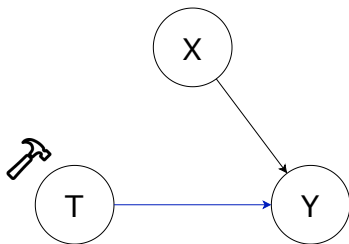
Final Exam Project

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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.

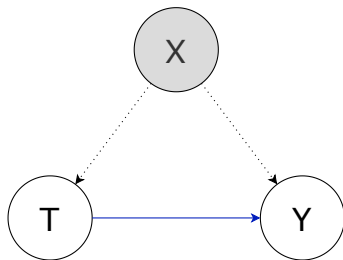


$$P(Y|\text{do}(T = t)) = P(Y|T = t)$$

Confounder

In an 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 .

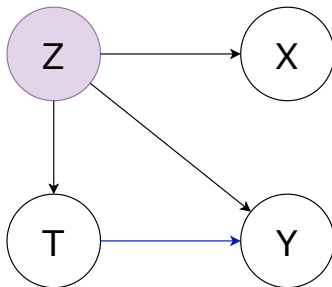


$$P(Y|\text{do}(T = t)) = \sum_x P(Y|T = t, X = x)P(X = x)$$

Latent confounder

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

Experiment: noise in the proxies

Experiment: latent distribution misspecified

Experiment: changing latent dimension

Experiment: increasing the treatment effect

Conclusions

Thank You!