

Autoregressive Variational Auto-Encoder for Causal Modeling

Tom Marty

Setting

Generated by a Structural Causal Model (SCM)

Input: multi-intervention dataset

$$\mathcal{D} = \{D_0, D_{I_1}, \dots, D_{I_N}\}$$

$$f_i(\text{Pa}(X_i), \epsilon_i) \rightarrow f_i^I(\text{Pa}(X_i), \epsilon_i) \quad \forall i \in \mathcal{F}_I$$

Unknown regime and unknown target

Known DAG, but the problem remains hard

Goal:

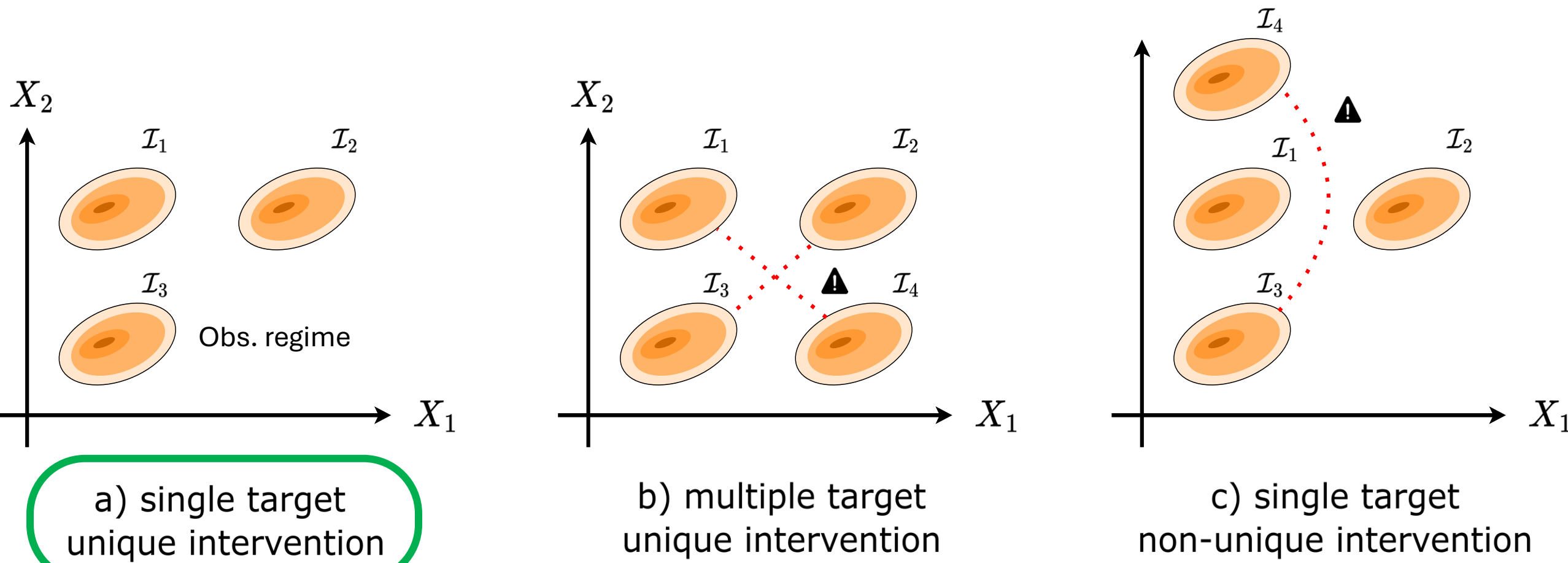
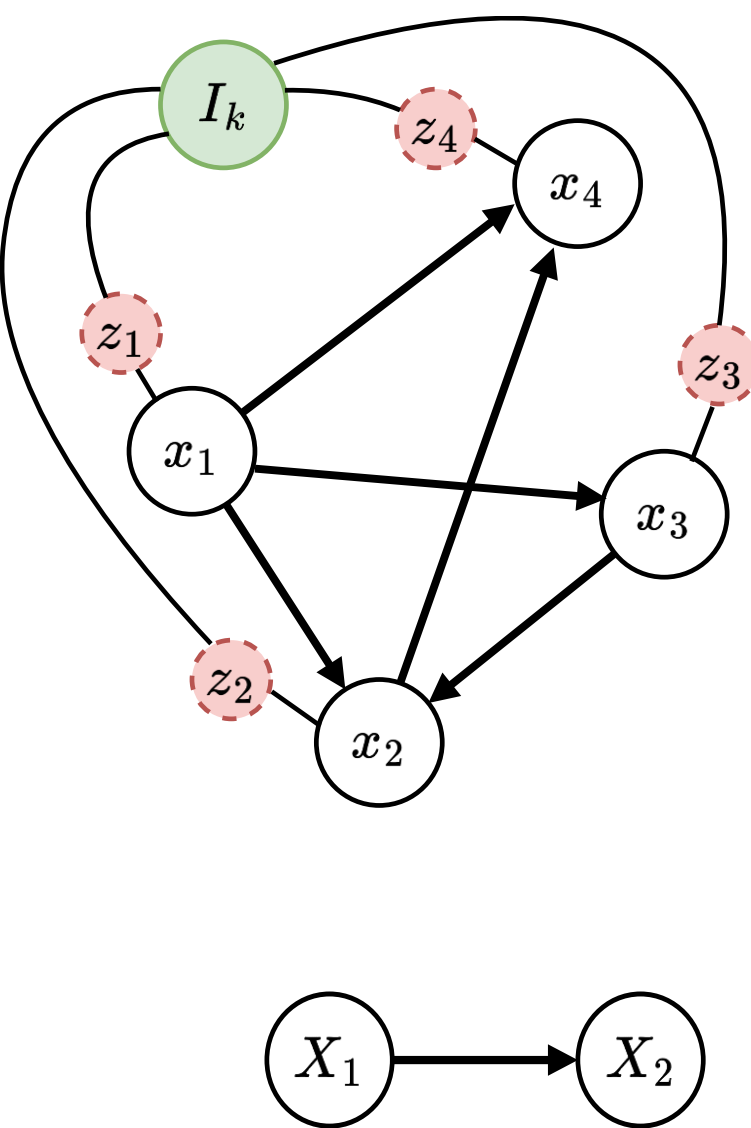
- Model the mechanisms f_i under any regime:

$$X_i = f_i(\text{Pa}(X_i), \epsilon_i) \quad \epsilon_i \sim \mathbb{P}_{\epsilon_i}$$

- Identify the observation regime

Identification requires additional assumptions:

- Interventional-faithfulness / Strong enough interventions



Experiments

SCM: linear additive noise model

- Autoregressive discrete VAE are hard to train... (*Fu et al.)
- ...but not impossible : latent encoding encodes the right regime on 60% of the dataset (no KL vanishing)
- As soon as the regime is identified, **VAE achieves perfect reconstruction of the conditional expectation.**



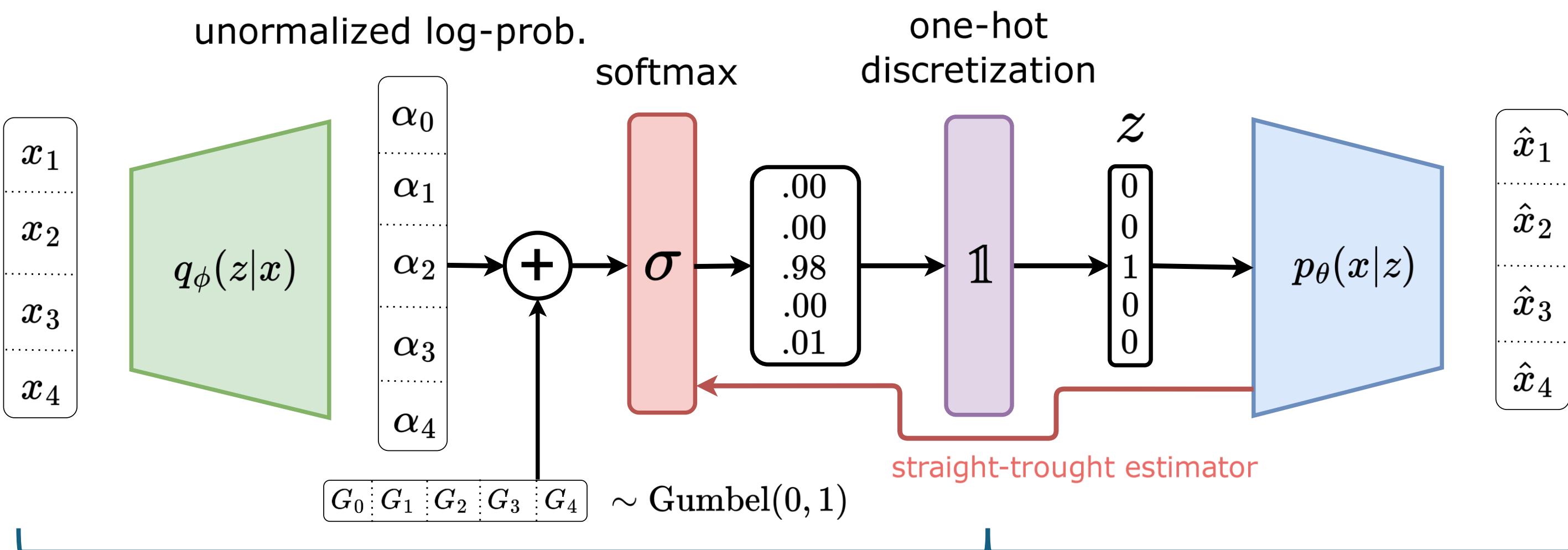
code
report

For the full set of results [→ Please read the report](#)

Method

Idea: formulate this problem as a discrete latent variable problem where the latent variables are the unknown regimes.

Architecture: Variational Auto-Encoder (VAE)



Regime learning
(Categorical encoder)

mechanisms learning
(Autoregressive decoder)

Objective : maximise data log-likelihood

$$\log p_\theta(x) \geq -\text{KL}(q_\phi(z|x) \parallel p_\theta(z)) + \mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x|z)]$$

softmax(α) uniform prior $\mathcal{N}(f_\theta(\text{Pa}(x_i), z), 1)$

Regularization term :

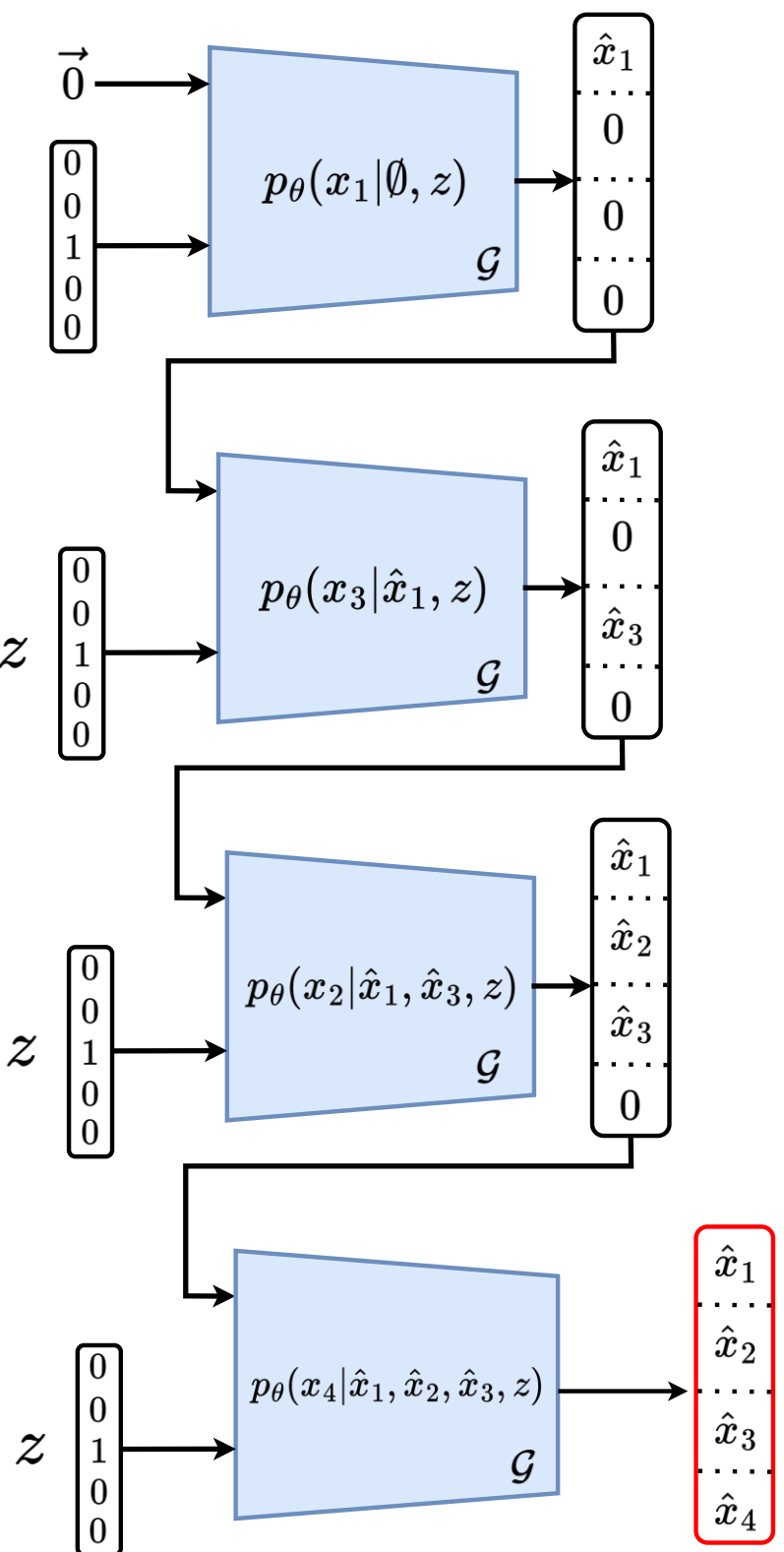
- Maximise entropy of the posterior

Reconstruction term :

- Predict the full sample $\hat{x}$
- Can't learn to perfectly achieve reconstruction because of exogenous noise

Why not Expectation-Maximization ?

Closed form update does not always exist for realistic SCM



PyTorch Lightning