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Motivation

- Counterfactuals are useful for explainability, interpretability, fairness and data-augmentation;
- For images, deep generative models are essential to estimate mechanisms;
- In the general case, model identifiability is impossible for deep models;
- Many approaches have been proposed for approximate counterfactual inference. Less work has been done on evaluation.

Axiomatic characterisation

 The soundness theorem states that the properties of composition, effectiveness and reversibility are necessary in all causal models. The completeness theorem states that these properties are sufficient.

These properties can be measured for approximate counterfactual models in order to compare and evaluate them.

Measuring axiomatic soundness of counterfactual image models

Defining and measuring soundness:

- 1. Composition: intervening on a variable to have the value it would otherwise have without the intervention will not affect other variables. Implies the existence of a nullintervention. Measured using distance metrics (e.g. 12 distance);
- 2. Effectiveness: intervening on a variable to have a specific value will cause the variable to take that value. Measured using auxiliary classifiers or regressors;
- 3. Reversibility: Informally, it prohibits the existence of feedback loops. Measured using distance metrics.

Example: VAE trained on colour MNSIT

- Digit and colour are confounded in the training set;
- One model is trained using a simulated intervention to de-bias the data, one is not;

Composition

High composition (de-biased model)



do_colour = original colour do_digit = original_digit









