

Causal inference in the latent space of convergent cross-mapping

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The principle of causal inference for latent spaces

Methods of causal inference and Structural Causal Models assume that there exist

- 1) explainable, labeled measurements represented as variables,
- 2) a computational graph in which each vertex corresponds to a single variable.

In AI, data have excessively high dimensionality. Causality can be re only in a low-dimensional latent space. The model that maps the data into this space is non-interpretable. The problem is therefore to identify causality in the latent space. This causality

- 1) learns the relationship between source and target variables in a reduced-dimensional space,
- 2) explains the observable variables by back-propagation for the source and by forward-propagation for the target.

Significance of this principle: it introduces a new method to dimensionality reduction.

The problem of causal inference for latent spaces

A set of time series x_t and y_t is given, generated by a single observable dynamical system. They are represented as time-delay matrices X and Y . The problem is to forecast the vector y_{t+1} .

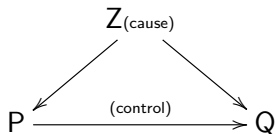
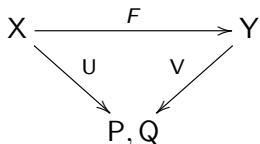
The forecasting model $f : t \mapsto y \ni Y$ assumes that X and Y are mapped by orthogonal operators U and V into low-dimensional manifolds. The components of the resulting vectors are independent. The goal is to find the elements of the linear alignment Λ that express causality in some components of the time series x_t and y_t .

Denote by $\hat{Y} = F(X)$ the forecast \hat{Y} obtained via the linear operator F . To approximate the target Y , make the singular value decomposition of the operator

$$F = U\Lambda V^T$$

and select the components of the diagonal matrix Λ that express the causality.

Causal Inference for Canonical Correlation Analysis



The Canonical Correlation Analysis¹ reduce the dimensionality of the source data. It projects observed data into low-dimensional space and uses it as new model features. It maps the source and the target X, Y onto joint latent space P, Q and maximizes the covariance between the projections

$$\text{cov}(P, Q) \rightarrow \max.$$

The latent variables P, Q approximate hidden dependencies in joint space using linear models U, V .

¹The Partial Least Squares regression comprises.

The plan of action

The background research

- 1) Write Bayesian Inference for CCA
- 2) Generalize for CCM and Transformer
- 3) Propose Causality Propagation model
- 4) Propose Generative Causality Search

The code

- 1) Make a simplest demo for latent spaces
- 2) Compare with Operator Learning for time series
- 3) Include Transformer and other models for text data
- 4) Make computational experiment for available models