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## Learning ENSO-related Principal Modes of Vegetation via a Granger-Causal Variational Autoencoder

**Gherardo Varando**, Miguel-Ángel Fernández-Torres, and Gustau Camps-Valls

Universitat de València, Image Processing Laboratory, Image and Signal Processing Group, Paterna (València), Spain

Tackling climate change needs to understand the complex phenomena occurring on the Planet. Discovering teleconnection patterns is an essential part of the endeavor. Events like El Niño Southern Oscillation (ENSO) impact essential climate variables at large distances, and influence the underlying Earth system dynamics. However, their automatic identification from the wealth of observational data is still unresolved. Nonlinearities, nonstationarities and the (ab)use of correlation analyses hamper the discovery of true causal patterns. Classical approaches proceed by first, extracting principal modes of variability and second, by performing lag-correlations or Granger causal analysis to identify possible teleconnections. While the principal modes are an effective representation of the data, they could be causally not meaningful.

To address this, we here introduce a deep learning methodology that extracts nonlinear latent representations from spatio-temporal Earth data that are Granger causal with the index altogether. The proposed algorithm consists of a variational autoencoder trained with an additional causal penalization that enforces the latent representation to be (partially) Granger-causally related to the considered signal. The causal loss term is obtained by training two additional autoregressive models to forecast some of the latent signals, one of them including the target signal as predictor. The causal penalization is finally computed by comparing the log variances of the two autoregressive models, similarly to the standard Granger causality approach.

The major drawback of deep autoencoders with respect to the classical linear principal component approaches is the lack of a straightforward interpretability of the representations learned.

To address this point we perform synthetic interventions in the latent space and analyse the differences in the recovered NDVI signal.

We illustrate the feasibility of the approach described to study the impact of ENSO on vegetation, which allows for a more rigorous study of impacts on ecosystems globally. The output maps show NDVI patterns which are consistent with the known phenomena induced by El Niño event.