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## Why all emergent constraints are wrong but some are useful - a machine learning perspective

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Global climate change projections, such as those from the Coupled Model Intercomparison Project phase 6 (CMIP6), are still subject to substantial modelling uncertainties. A variety of Emergent Constraints (ECs) have been suggested to address these uncertainties, but remain heavily debated in the scientific community. Still, the central idea behind ECs to relate future projections to already observable quantities has no real substitute.

Here we discuss machine learning (ML) approaches for new types of controlling factor analyses (CFA) as a promising alternative. The principal idea is to use ML to find climate-invariant relationships in historical data, which also hold approximately under strong climate change scenarios. On the basis of existing big data archives such as those from the CMIPs, these climate-invariant relationships can be validated in perfect-climate-model frameworks.

From a ML perspective, we argue that CFA are promising for three reasons: (a) they can be objectively validated both for present-day data and future data and (b) they provide more direct - by design physically-plausible - links between historical observations and potential future climates compared to ECs and (c) they can take higher dimensional relationships into account that better characterize the still complex nature of large-scale emerging relationships. We highlight these advantages for three examples in the form of constraints on climate feedback mechanisms (clouds [1], stratospheric water vapour [2]) and forcings (aerosol-cloud interactions).

## References:

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