**Reading Notes: Praveen Kumar and Hoshin V. Gupta (2020), Debates—Does Information Theory Provide a New Paradigm for Earth Science? Water Resources Research, 56,**

**e2019WR026398.**

**Uwe Ehret**

**Summary**

This is a wrapper paper for a WRR debates series "Does Information theory provide a new paradigm for earth science?". The main statement of the authors is that it indeed does, and that both philosophical and methodological advances are best achieved by combining the various perspectives that information theory offers on earth science and the scientific process in general. The authors start by a historical account on how information and entropy (through thermodynamics) have a physical interpretation, and how (through probability theory) they have a dual interpretation as a measure of certainty/uncertainty, and how the principle of maximum entropy, a general guideline for inference, provides a link between both. They continue by stating several key questions, by which information theory can foster progress in the earth sciences:

* Can information‐based approaches better inform the development of Earth system models that are intended to be isomorphic representations of natural processes?
* Can we characterize the information content of models themselves, and can this characterization be used for model improvement?
* Can natural system dynamics be represented and predicted using information‐theoretic frameworks, in forms that are independent and/or complementary to physics‐based modeling approaches?
* Does information have a role in the deterministic characterization of natural processes?

The authors then summarize the four papers of the debate series, and highlight the particular role of information theory in each. The first describes how information theory can be used for causality detection, going beyond correlation-based approaches due to their time-asymmetrical approach. The second paper explores how quantifying the information content in data and models could replace standard model identification/falsification approaches, and how ML-based models trained on available data could serve as a upper benchmark for what physics-based models can learn from limited data. Also, it is proposed that there are two complementary types of model performance - predictive accuracy and functional accuracy – and that both should be taken into account when building models. The third paper discusses the connections of entropy as a physical and statistical quantity, and that for dynamical systems, more can be learned from the system's time trajectory rather than from its statistical distribution of states only. The fourth paper states that the key objective of science is optimal compression, suggesting Algorithmic Information Theory as a useful framework for the scientific process. More practical, the authors suggest that model-building can be guided by Occams razor via the dual objective of maximal predictive accuracy and minimal model size (complexity), both measured in bit, which is applicable for both physics-based and data-based modeling approaches.

**How this might be useful**

* There are two complementary types of model performance: predictive accuracy and functional accuracy. Both should be taken into account when building models
* Model building can, in the framework and language of Algorithmic Information Theory, be guided by the dual objective of maximal predictive accuracy and minimal model size

 **Open questions**

* How to overcome the curse of dimensionality when trying to learn general high-dimensional patterns from limited data?
* Can ML-based models really serve as an upper benchmark for what can be learned by physics-based models from limited data (how about the curse of dimensionality)?
* How to make Occam's razor as proposed by Weijs and Ruddell (2020) work in practice?