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Consensus on Long-Range Prediction by Adaptive Synchronization of Models

G. Duane (1), J. Tribbia (2), and B. Kirtman (3)
(1) Gregory.Duane@Colorado.edu, (2) tribbia@ucar.edu, (3) bkirtman@rsmas.miami.edu

A collection of climate models typically gives divergent results for reasons that are not obvious a priori. The differences seem buried in detailed dynamical choices, none clearly superior, with effects that amplify over the course of a simulation. The chaotic dynamics of the climate system is a well known obstacle to short-term weather prediction and to the validation of forecast models. In predicting long-term climate change, one hopes that different models will produce similar attractors defining overall climate, but the divergent results of different climate models suggest similar difficulties. If one were able to combine the different models - in a way better than by simply averaging their outputs - some advantage might result.

A theoretical paradigm that has been applied to describe order in the climate, and seems appropriate for model fusion, is that of the synchronization of loosely coupled chaotic systems. Two or more chaotic systems, loosely coupled through only a few of many degrees of freedom, fall into synchronized motion along their strange attractors under a surprisingly wide variety of conditons, despite sensitivity to differences in initial conditions. The phenomenon has been used to establish a new theoretical framework for data assimilation as the synchronization of two systems, corresponding to “truth” and “model”, respectively. Here, we suggest that a collection of models, synchronized by limited exchange of information as they run, could form an “intelligent” consensus in regard to long-range predictions, improving on the simple output-averaging procedures that have been used previously.

The synchronous coupling approach succeeds because detailed
coupling coefficients can be chosen adaptively, as an instance of a general scheme for model learning in the synchronization context. That scheme adjusts model parameters so as to reduce synchronization error, with the possible addition of noise to escape local optima. Here, the parameters to be adjusted are weights attached to each of many model variables in each pairwise comparison with a corresponding variable of another model. By training on 20th century data, weights will be selected so that the best features of each model will maximally influence the collective behavior of the entire suite.

We show that a small collection of Lorenz systems with different parameters can be fused in this manner, so as to represent yet another “real” Lorenz system with a different parameter set than that of any in the collection. The error in the representation is much less than the error with any weighted combination of the Lorenz “models”, run independently. Further, the Lorenz fused “model” continues to reproduce the behavior of the real system after the adaptation process is turned off. We explore the limits of this procedure as the parameters of the “real” system are changed after the training period.

Then we show that the procedure can be extended so as to adaptively fuse two quasigeostrophic channel models with different forcing terms so as to represent a third “real” system. Results suggest that the procedure can naturally be extended to large climate models.

The procedure can indeed be extended to form a multi-model of any time series produced by a real physical system. As with the synchronization approach to data assimilation, it is argued that the fusion approach is justified by contemporary theories of the role of synchronization in neurobiological processing.