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Forecasting Ionosphere by Deep Learning of Historic Analogies

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The forecasting capability of neural architectures for time series analysis was first noted in the 1980s. After an initial enthusiasm, however, the interest in forecasting with artificial neural networks (NN) faded and soon replaced with another round of the dreadful "AI winter" of disappointment. Although the superior inductive bias of the feed-forward NN was recognized and universally complimented, the "blackbox" outcome of their back-propagation-of-error training kept leaving scientists in the dark about the underlying principles and meaningful findings about the predicted system behavior. It was not until the next generation recurrent Deep Learning architectures that the interest in neural architectures for the times series forecast rejuvenated, driven by success stories in several neighboring domains of computer science. We will concern ourselves with one potential application of the modern day machine learning (ML) solutions to a particular kind of modeling the ionospheric plasma dynamics, *analog forecast* [1], or forecast by historic analogy. The primary concept behind analog models is their presumed capability to retrieve the forecast timeline of the modeled geosystem from an intelligent memory of previous events. Such retrieval is guided by an algorithm that locates the *context* (combination of the system drivers) that resembles current conditions most closely. Such approach corresponds to a statistical view of the geosystem dynamics, which makes it an easy target for criticism in the space weather domain. Indeed, even though many constituent mechanisms that impact the ionosphere may now be well understood individually, their intricate interplay during each storm still defies specification in sufficient detail to permit high quality theoretical forecast. The analog modeling approach would use (1) associative memories to first specify entire timelines of the multiple ionosphere drivers from the observed initial fragments of the current storm and then (2) context-aware recurrent neural network architectures to retrieve the closest ionospheric response observed previously during such context. Initial design concepts of the model with Deep Learning of the historic analogies will be discussed.

1. McNamara, L. F., Bishop, G. J., and Welsh, J. A. (2011), Analog ionospheric forecasts: Space weather forecasts by analogy with previous events, *Radio Sci., 46*, RS1002, doi:10.1029/2010RS004399.