4th URSI AT-RASC, Gran Canaria, 19-24 May 2024

Natural Language Processing for an AI-driven Ionosphere Forecast by Historical Analogy

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Given the growing interest in knowing the upcoming ionospheric weather for a multitude of operational systems that rely on ionosphere-transversing radio signals, academia has been called for help in forecasting the ionospheric conditions and mitigating the trans-ionospheric propagation anomaly artifacts. Correspondingly, academia is keen on adopting novel machine learning (ML) techniques that have recently demonstrated astonishing progress in replicating various intelligent reasoning functions.

Time series forecast is one of the dominant ML applications that might be useful in space weather applications. The early brute-force *connectionist* attempts to issue AI-driven weather reports were based on the conventional approach: "learning" the ionospheric timelines *directly*, relying on the possibility of replicating the plasma variability (labels) in the time and heliospace context (features). These attempts were quickly recognized as the "black boxes" and ruled out as insufficient for success, leading to another AI Winter episode in the XXI century geophysics. The next generation of techniques involved so-called Physics-Informed ML reasoning (PI-ML), in which a variety of neural architectures and algorithms were instructed to learn adjustable drivers of an underlying geosystem model that captured the behavioral knowledge in various scenarios. Often regarded as the "gray-box" forecasters, PI-ML techniques have earned recognition as the best performers. Yet, these approaches still come short when the system of interest exhibits remarkable dynamics and rapid response to the forces that act upon it. We argue that capturing the ionosphere response to the wide variety of concurrent external forcings from above and below falls into the challenging category that even modern PI-ML is unable to represent and predict optimally.

The AI community arrived at a similar conclusion in the mid-2020s, suggesting that data analytics leaders should go beyond the conventional ML toolbox [1]. In our concept study, we refer to the Natural Language Processing (NLP) realm that features a set of useful intelligent system techniques that can be leveraged in forecasting anomalous ionospheric responses to various Sun-Earth system events. Using a smart voice assistant as the example application, we first note that the assistant trigger phrase is a useful representation of the anomaly trigger in the ionosphere, such as the geostorm onset that modern space weather assets can identify promptly and reliably. With this consideration, the daunting problem of skewed learning against the imbalanced datasets that hold mostly quiet ionosphere behavior is eliminated. Instead, a library of historical records of the storm-time dynamics is built, similar to the language dictionary. The forecaster's task is, once the anomaly onset is detected, to find the best match among the library-stored timelines, given the current context of the Sun-Earth system conditions. Such a "typical anomalous behavior" concept has been criticized in the past, noting that ionospheric storms are not alike. However, the NLP-enabled capability of noting the *context* of the ionospheric storm storylines is instrumental here; the same capability allows voice assistants to interpret the right meaning of the words in the given sentence. The anomaly library will also benefit from the Dynamic Time Warping (DTW) approach that detects similarities in the various timings of the same storyline. The DTW algorithm will replicate NLP's ability to handle speech and voice variability in natural speakers. Other concepts for building the uniform ionosphere anomaly library will be presented.

[1] Yan, B., et al. (2024), Go beyond Machine Learning and leverage other AI approaches, Gartner Report G00762946, available at https://www.gartner.com/doc/reprints?id=1-2F720M6N&ct=231003&st=sb