Ph.D. Defense Announcement
Kyle Hilburn
August 2, 2023, at 10:00am

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Wednesday, August 2, 2023
10:00am

Defense
CIRA Commons or Teams

Post Defense Meeting
Riehl Conference Room (211 ACRC)

Committee:
Steven Miller (Adviser)
Christian Kummerow
Elizabeth Barnes
Imme Ebert-Uphoff (CIRA/Electrical and Computer Engineering)
Curtis Alexander (NOAA GSL)

GREMLIN: GOES Radar Estimation via Machine Learning to Inform NWP

Imagery from the Geostationary Operational Environmental Satellite (GOES) has been a key element of U.S. operational weather forecasting since 1975. The latest generation, the GOES-R Series, offers new capabilities to support the need for high-resolution rapidly refreshing imagery for situational awareness. Despite the well demonstrated value to human forecasters, usage of GOES imagery in data assimilation (DA) for initializing numerical weather prediction (NWP) has been limited, particularly in cloudy and precipitating scenes. By providing a rich and powerful library of nonlinear statistical tools, artificial intelligence (AI) / machine learning (ML) enables new approaches to connecting models and observations. The objective of this research is to develop techniques for assimilating GOES-R Series observations in precipitating scenes for the purpose of improving short-term convective-scale forecasts of high-impact weather hazards. The hypothesis of this dissertation is that by harnessing the power of ML, the new GOES-R capabilities can be used to create “radar everywhere” for initializing convection in high-resolution NWP models.

Part 1 will present a proof-of-concept that ML can be used as an observation operator for GOES-R to initialize convection in NOAA’s Rapid Refresh Forecast System (RRFS). Development of the GREMLIN (GOES Radar Estimation via Machine Learning to Inform NWP) convolutional neural network (CNN) will be described. This includes the creation of a hierarchy of open-source datasets, and will emphasize the importance of the neural network loss function in focusing the attention of the network on the most important meteorological features. Explainable AI (XAI) tools are applied to GREMLIN to discover three primary strategies employed by the network in making predictions, highlighting the unique ability of CNNs to utilize spatial context in satellite imagery. The results of retrospective RRFS forecasts will be described, which show that GREMLIN can produce more accurate short-term forecasts than using real radar data over areas of the U.S. with poor radar coverage.

In Part 2, the Interpretable GREMLIN model is developed to elucidate the nature of the spatial context utilized by CNNs to make accurate predictions. This clarity is accomplished by moving the inner workings of the CNN out into a feature engineering step and replacing the neural network with a linear regression model. This exposes the effective input space of the CNN and establishes well defined relationships between inputs and outputs, which provides guarantees on how the model will respond to novel inputs. Despite a 24x reduction in the number of trainable parameters, the interpretable model has similar accuracy as the original CNN. Using the interpretable model, five additional physical strategies missed by XAI are discovered. The pros and cons of interpretable model development and implications for generalizability, consistency, and trustworthy AI will be discussed.

Finally, Part 3 will extend this research for the development of Global GREMLIN, discussing the challenges and opportunities. GREMLIN is validated for regimes outside of the training dataset, and regime dependence is quantified in terms of temperature and moisture. The impacts of additional predictors and advanced ML architectures are assessed. Uncertainty estimates that will be needed for new DA approaches in RRFS will be discussed. Current efforts to implement GREMLIN on NOAA’s GeoCloud, which will make GREMLIN available to a broader base of users, will be described.