NOAA ROSES Semi-Annual Report

Reporting Period: September 2021 – February 2022 (3rd report)

PI: Kyle Hilburn
Co-PI(s): Yoonjin Lee, Milija Zupanski

Project Title: Assimilating GOES-R Latent Heating in FV3 using Machine Learning

Executive Summary (1 paragraph max)

The main objective of this project is to use the high-resolution information from GOES-R Advanced Baseline Imager (ABI) and Geostationary Lightning Mapper (GLM) to improve short-term forecasts of high-impact weather hazards. This will be accomplished through using machine learning (ML) to derive three-dimensional fields of latent heating to spin-up convection in the Rapid Refresh Forecast System. The secondary goal of this project is to provide new data assimilation capabilities for the new generation of FV3 dynamical core models at NOAA, utilizing the Joint Effort for Data Assimilation Integration (JEDI) framework.

Progress toward FY21 Milestones and Relevant Findings (with any Figs)

- Kyle Hilburn made a breakthrough (**Figure 1**) in understanding how the GREMLIN convolutional neural network makes skillful predictions of radar reflectivity. Previously, I used “Explainable AI (XAI)”, which is where an XAI technique (such as Layerwise Relevance Propagation) is applied to a trained “black box” model. XAI provides insights into how a model makes predictions, but it does not provide guarantees for how the model will behave in the future. My latest approach, called Interpretable GREMLIN, uses “Interpretable AI (IAI)”, which is where the explainability is built in right from the start, so that the outcome is an understandable model. The key insight, coming from my PhD research, is that any convolutional neural network (CNN) can be decomposed into the combination of an image pyramid and a filter bank. The image pyramid provides a multi-resolution representation of the data, and the filter bank provides image kernels to represent gradients and patterns in the imagery. In a CNN, this work is done “under the hood”, and so Interpretable GREMLIN brings this out into the data pre-processing, so that each pixel has the number of inputs given by the product of the number of channels, the number of pyramid levels, and the number of image kernels. For GREMLIN, only four image kernels were needed to reproduce the skill of the CNN. A regression framework is still needed to associate the inputs with the output, and I started with using a dense neural network (DNN) as a nonlinear function approximator to prove the concept. After that, I replaced the DNN with an interpretable linear model

$$y = \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{j \le i} w_{i,j} x_i x_j = \sum_{i=1}^{N} w_i x_i$$

where n is the number of inputs (4*4*4=64). The model includes linear functions of each input, two-way interaction terms, and quadratic functions of each input, with a total number of terms given by $N = n + n(n+1)/2 = 2144$. This can be solved using the linear minimum mean squared error (MMSE) estimator

$$w^T = C_x^{-1} C_{yx}$$

where C_x is the autocovariance matrix and C_{yx} is the cross-covariance matrix. This approach was found to produce ML predictions with better temporal consistency than the CNN, and the work on temporal consistency reported in the last period has been folded into these current efforts. This approach provides much more information about the nature of the “spatial context” used by CNNs to make skillful predictions. It also separates-out the contribution to prediction skill coming from nonlinearity. A paper to AMS AIES on Interpretable GREMLIN is in preparation. The understanding provided by IAI will be important for validation of Full Disk GREMLIN, which we are beginning in the next period.

- A “toy” version of the GREMLIN model and dataset were provided to Jamin Rader (CSU ATS) to use for a course project in Machine Learning for the Atmospheric Sciences. The course is also making use of our GREMLIN paper (Hilburn et al., 2021) and XAI paper (Ebert-Uphoff and Hilburn, 2020), with very positive feedback from several students that these papers are helping them to develop their own ML applications.

- Yoonjin Lee made a significant advance in the application of ML to extracting spatio-temporal information from satellite image sequences. This was based on an old idea (advocated by Jim Purdom) of putting satellite images in a storm-relative reference frame, which allows the ML to better learn the spatio-temporal patterns by minimizing the confusion that arises from storm motion. The input GOES images are warped to remove storm motion using Jason Apke’s Optical flow Code for Tracking, Atmospheric motion vector, and Nowcasting Experiments (OCTANE) during preprocessing. In addition, she found that the resulting ML predictions have the highest correlation with radar images 10 minutes *in the future*. She hypothesizes that this time lag is due to the time scale of precipitation processes because GOES is viewing the cloud top and it takes about 10 minutes for the corresponding radar echoes to develop deep within the cloud. Preliminary results show that using warped images provides higher skill compared to using un-warped images (CSI of 0.69 vs 0.64). More investigation will be conducted to explain these results, which will be presented at the AMS Madison Collective Meeting in August.

- Yoonjin Lee attended the 7th JEDI Academy via Zoom in October 4-8 and completed all the exercises. In addition to learning how to use JEDI, which is a big step forward from the GSI software, this course demystified use of software containers that allow moving applications quickly and reliably from one computing environment to another.

- Publications:
  - Lee, Y., C. D. Kummerow, M. Zupanski, 2022: Latent heating profiles from GOES-16 and its impacts in precipitation forecast. Atmospheric Measurement Techniques, *submitted*.
  - Hilburn, K., 2022: Understanding spatial context in convolutional neural networks using interpretable GREMLIN. Artificial Intelligence for the Earth Systems. *in preparation*.

- Presentations:
  - Hilburn, K., Y. Lee, and I. Ebert-Uphoff, 2021: Improving GREMLIN: A Case Study in AI Application Development, 3rd NOAA Workshop on Leveraging AI in Environmental Sciences, 15-Sep.
  - Lee, Y., K. Hilburn, and I. Ebert-Uphoff, 2021: Exploring Ways to Effectively Use Temporal Satellite Images in Detecting Convection from GOES-16, 3rd NOAA Workshop on Leveraging AI in Environmental Sciences, 14-Sep.
  - Hilburn, K., Y. Lee, and I. Ebert-Uphoff, 2021: GREMLIN: GOES Radar Estimation via Machine Learning to Inform NWP. Fall AGU Meeting, A047.
  - Lee, Y., C. D. Kummerow, and I. Ebert-Uphoff, 2021: Applying Machine Learning Methods to Detect Convection Using GOES-16 ABI Data. Fall AGU Meeting, A086.
  - Back, A., S. Weygandt, C. Alexander, S. Benjamin, M. Hu, G. Ge, E. James, A. Kliewer, J. R. Mecikalski, D. Dowell, E. C. Bruning, K. Hilburn, and A. Sebok, 2021: Convection-indicating GOES-R products assimilating in the experimental UFS Rapid Refresh System. AGU Fall Meeting.
  - Ebert-Uphoff, I., R. Lagerquist, K. Hilburn, Y. Lee, K. Haynes, J. Stock, C. Kumler, and J. Q. Stewart, 2022: How to Develop Custom Loss Functions for Neural Networks in Meteorology. AMS Annual, 21AI.
  - Back, A., A. Kliewer, J. R. Mecikalski, K. Hilburn, Y. Lee, E. Sebok, D. Dowell, E. C. Bruning, M. Xue, R. Kong, S. Benjamin, E. P. James, C. R. Alexander, G. Ge, K. Pederson, and S. Weygandt, 2022: Novel Convection-Indicating Satellite Products Assimilated in Experimental Rapid Refresh Systems, AMS Annual, 26IOAS.
  - Hilburn, K., 2021: Machine Learning in Atmospheric Science, CIRA Jamboree, 9-Sep.
  - Hilburn, K., 2022: Understanding spatial context in convolutional neural networks. CIRA ML Core, 09-Feb.

Plans for Next Reporting Period

- Kyle Hilburn and Steve Miller will attend the NOAA ESRL GSL Retreat (May 10-11)

- Complete and submit Interpretable GREMLIN manuscript to AIES

- Complete review process for Latent Heating Profiles manuscript to AMT

- Begin development and validation of Full Disk GREMLIN product

- Begin creating a lookup table for latent heating profiles over the ocean

- Presentations scheduled during the next reporting period:
  - Hilburn, K., 2022: GOES radar estimation via machine learning to inform NWP (GREMLIN). Seminar to the Korean Meteorological Agency, 12 May.
  - Hilburn, K., 2022: Using machine learning to assimilate GOES observations in precipitating scenes. International Data Assimilation Symposium, 6-10 June.
  - Lee, Y. C. Kummerow, M. Zupanski, 2022: Latent heating profiles from GOES-16 and its impacts in precipitation forecast, International Precipitation Working Group Meeting (IPWG), 13-17 June.
  - Hilburn, K., 2022: Interpretable GREMLIN. American Meteorological Society Collective Madison Meeting, 16th Conference on Cloud Physics, Remote Sensing of Clouds Session, 8-12 August.

- Lee, Y., J. Apke, I. Ebert-Uphoff, and K. Hilburn, 2022: Using optical flow to preprocess GOES-16 image sequences for a machine learning model to detect convection. American Meteorological Society Collective Madison Meeting, 16th Conference on Cloud Physics, Remote Sensing of Clouds Session, 8-12 August.
- Hilburn, K., 2022: GOES radar estimation via machine learning to inform NWP (GREMLIN). GLM Science Team Meeting, 13-15 September.

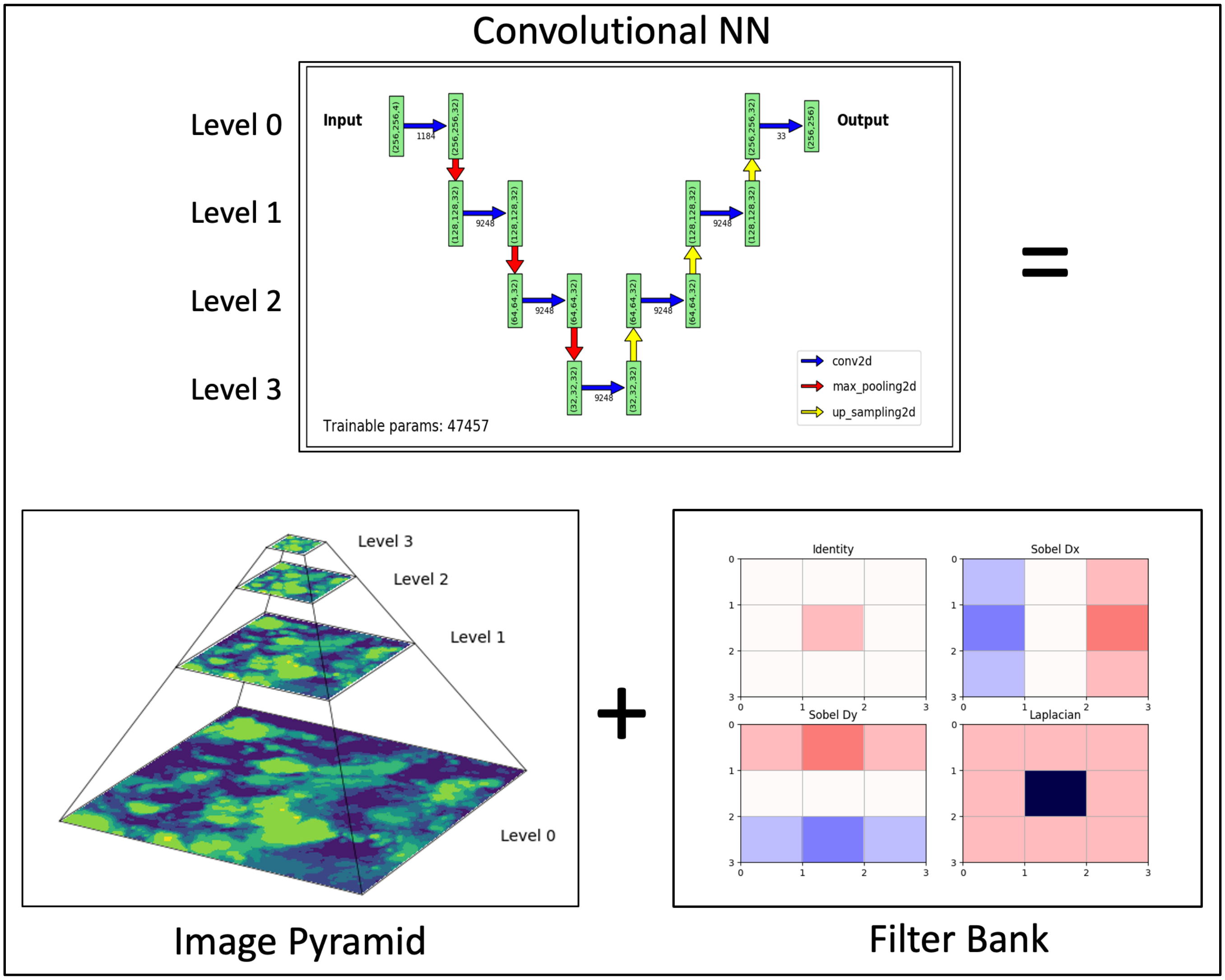

Figure 1. The GREMLIN convolutional neural network (top) can be represented as a combination of an image pyramid (lower left) and a filter bank of image kernels (lower right) with no loss in skill but far better interpretability than what is provided using Layerwise Relevance Propagation.