Exploration of a Statistical Approach for the Calibration of the NOAA CrIS Sensors Using Machine Learning

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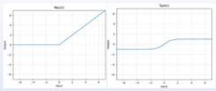
Objective

Assess the capability of a statistical approach with Artificial Intelligence (AI) to perform the calibration of infrared sounder data and weigh the benefits and the challenges of the process. This includes quantifying the volume of data and the sampling of the data in time and space required to capture changes associated to the sounder as part of the calibration process.

Models



Base model

Inputs: (partially calibrated radiances, zenith angle)

1. Flatten:
(nInputs x nUncalibrated) to
(1 x nInputs*nUncalibrated)

2. FC layer with tanh activation:
(1 x nInputs*nUncalibrated) to (1 x nUncalibrated)

3. FC layer with tanh activation:
(1 x nUncalibrated) to
(1 x nUncalibrated)

4. FC layer, no activation
(1 x nUncalibrated) to
(1 x nCalibrated)

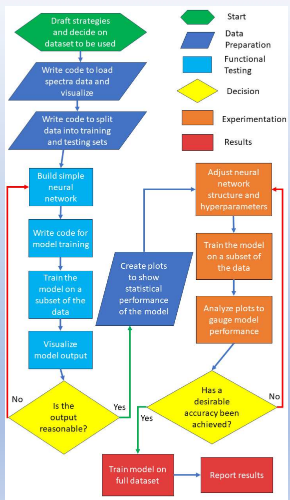
Model Layers

- Fully-connected (**FC**) layer
  - $Outputs = Inputs * Weights^T + Bias$
  - Learns many linear patterns in the data
- Activation functions (pictured left, top)
  - Used after FC layers to transform the data
  - Learn nonlinear pattens in the data
- Flatten layer
  - Combines data from two dimensions into one
- Dropout layer
  - Zero a given percentage of input data
  - Helps improve model generalization

Experiments

1. Base model (pictured left, bottom)
2. Adding dropout
   - 20% Dropout layer after first FC layer
3. Dropout and latitude as an input
   - 20% Dropout layer after first FC layer
   - Uses |latitude| as third input

Methodology



Correction Matrix Operator (CMO) for the AI to Perform

The model in intended to perform the CMO operator, which corrects for biases arising from the instrument shape, resamples the frequency scale, and truncates anomalous data points to achieve the calibrated data.

CMO Input

(Input) $L_{es} = T_b L_{ict}[n'] * \mathrm{Real}(\Delta S_{1;b,p}/\Delta S_{2;b,p})|$.

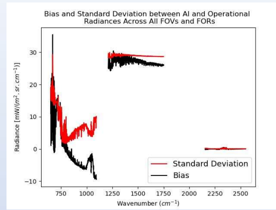
- For band 'b' and FOV 'p'
- Consequently, we train a separate model for each band and FOV.

Feature Normalization

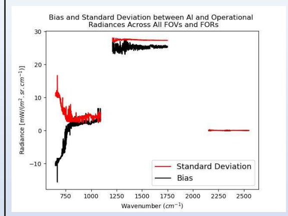
Initial results showed the AI was giving the same output across a channel regardless of geolocation, showing a lack of data variation. This was partially resolved by normalizing the input and target data of the model during training.

Results

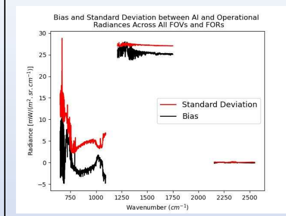
1. Base model – 50 scan files



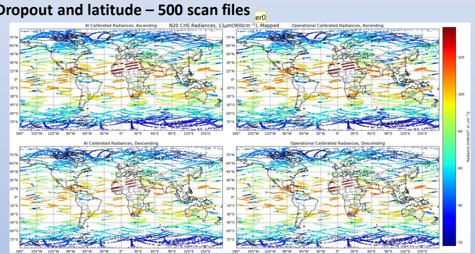
2. Dropout – 50 scan files

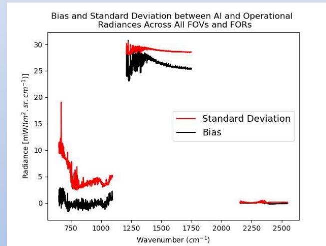


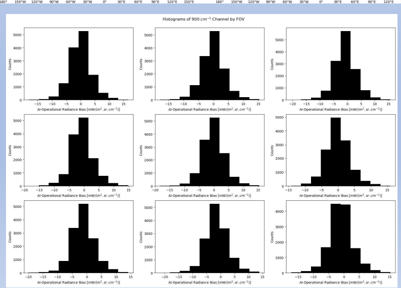
3. Dropout and latitude – 50 scan files

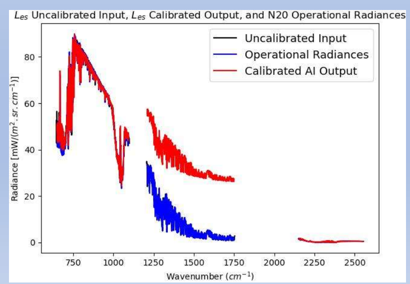


4. Dropout and latitude – 500 scan files



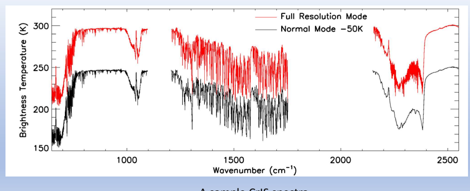






The CrIS Observations

- The Cross-Track Infrared Sounder (CrIS) is a Fourier Transform Spectrometer that measures radiance values across three IR spectral bands, LWIR (650-1095 cm^{-1}), MWIR (1210-1750 cm^{-1}), and SWIR (2155-2550 cm^{-1}).
- **Mission:** Provide High spectral resolution Infrared Radiance Spectra for High vertical resolution Temperature and Water Vapor profiles. Coarse profile and total column of trace gases (CO_2, CH_4, CO).

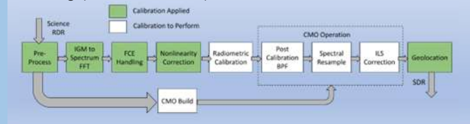


A sample CrIS spectra

Datasets

Full-days from 04/01/2023 and 04/02/2023

- Corresponding calibrated (target model output) and uncalibrated (model input) radiances.
- 70%/30% Split of data for *training* (model improvement) and *testing* (model evaluation).



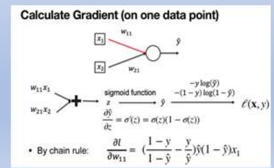
CrIS calibration process, showing the steps for the AI model to perform

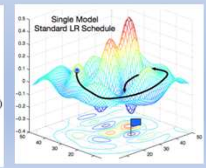
Neural Networks

General idea:

1. Pass inputs through a series of linear operations and nonlinear activation functions.
2. Compare output to desired values and calculate loss.
3. Improve the model to reduce the loss

A process called *backpropagation* uses loss gradients (left) to update the weights of each neuron to minimize the loss between nodes. This is part of the optimization algorithm *gradient descent* (right).





Project Conclusions

- From an initial test, the prospect of using AI to perform the CMO on partially calibrated CrIS data appears promising.
- Significant efforts are needed in the definition of the training dataset to capture the variability of Earth scenes over different sky conditions, surface types and seasons.
- An AI model must be trained on much more data than done in this work to gain a desirable accuracy.

Future Work

1. Constrain the network by using (operational-input) difference as the model output.
2. Modify the inputs to the neural network, specifically to capture variability over different sky conditions, surface types, and season.
3. Further optimize network hyperparameters, such as implementing adaptive learning rates.
4. Train the model on a much larger dataset.

Acknowledgments

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References

Hanna, J. (2023). Machine Learning: Neural Network II (Calc review and Training). Retrieved from https://pages.cs.wisc.edu/~jphanna/teaching/2023spring_cs540/schedule.html

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Slide 1

er0 starfeldt@wisc.edu - Looking at the section "4. Dropout and latitude - 500 scan files" I'm wondering if the AI calibration algorithm is producing a single value (possibly with a small variation) at all locations. That behavior can usually be tied to a lack of input feature/output feature normalization(or standardization).

I'd suggest trying feature-wise normalization of the inputs and outputs to see if the results can be improved.

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