PREDICTIVE MODELS OF IONOSPHERIC CONVECTION PATTERNS DURING SUBSTORMS RELATED TO STEVE

WILLEM MIRKOVICH, (1)
TOMOKO MATSUO, (1)
VALERIE SVALDI, (2)
12-11-21

AGU FALL MEETING

1. ANN AND H.J. SMEAD AEROSPACE ENGINEERING SCIENCES UNIVERSITY OF COLORADO BOULDER
2. COLORADO SCHOOL OF MINES

SCIENCE is SOCIETY

WILLEM MIRKOVICH

SOFTWARE ENGINEER AND PROFESSIONAL RESEARCH ASSISTANT

- Github
- Wjmirkovich.com
- LinkedIn

SCIENCE *is* SOCIETY

STEVE INTRODUCTION AND GEOPHYSICAL MOTIVATION

Discovered by citizen scientists in 2016!

Meet STEVE
"Strong Thermal Emission Velocity Enhancement"

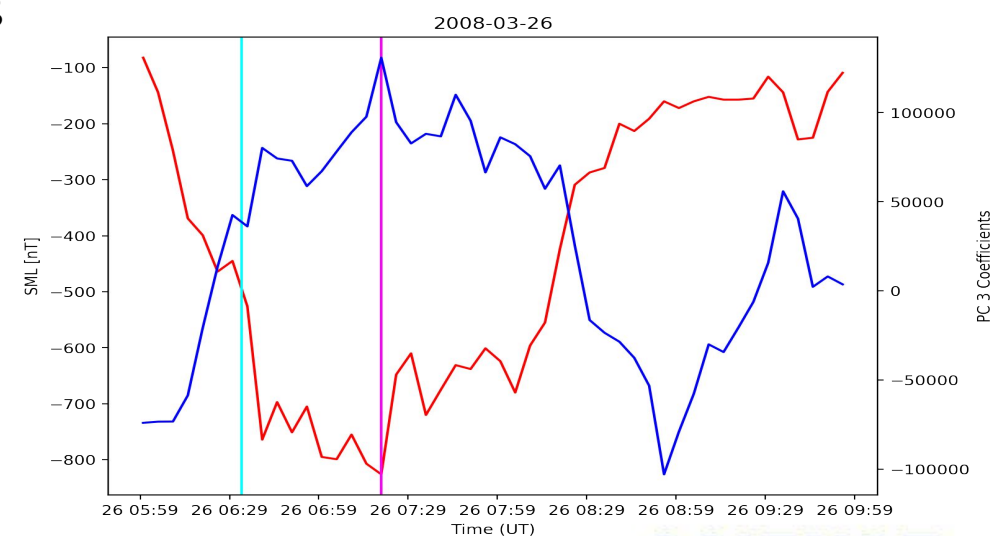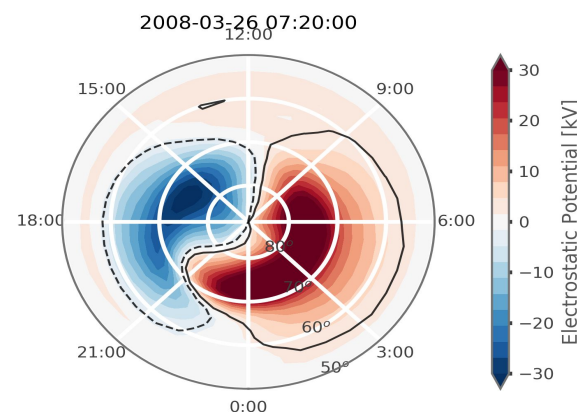Photo Credit: Paul Zika

- Assimilative Mapping of Geospace Observations (AMGeO) has enabled further analysis of STEVE events by providing global maps of high-latitude electrodynamic features for 32 STEVE and 32 non-STEVE substorm events.
- Global modes of ionospheric convection variability analysis identified using principal component analysis
- Difference discovered between STEVE and Non-STEVE substorms manifests as the Principal Component 3 (PC3)
  - Amplitude of PC3 coefficients appears to anti-correlate the AL- index with some time lag

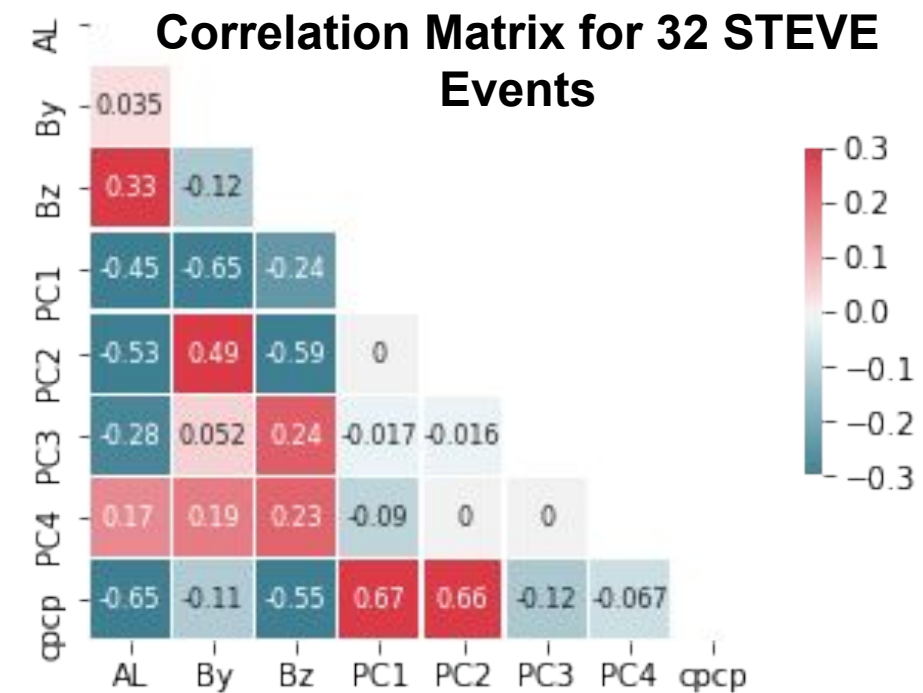**STEVE Event**
March 3, 2008

See SM11B-05 High Latitude Ionospheric Electrodynamics during STEVE and Non-STEVE Substorm Events [Svaldi et al., 2021] for more information on this study

OBJECTIVE: BUILD A MODEL TO PREDICT PC3

STEVE Event Data Set:

Classic events	17
Outliers events	5

Event #	Date	STEVE Onset (UT)	Event #	Date	STEVE Onset (UT)
1	2008-02-11	9:30	17	2012-02-20	8:40
2	2008-03-26	7:20	18	2013-09-13	8:30
3	2008-03-27	3:00	19	2014-08-21	9:20
4	2008-03-28	2:14	20	2015-09-07	5:35
5	2008-03-28	7:22	21	2015-09-11	5:20
6	2008-04-12	8:20	22	2016-02-08	6:30
7	2008-05-04	8:14	23	2016-04-17	5:10
8	2008-07-12	3:40	24	2016-07-25	6:00
9	2010-03-11	6:00	25	2016-07-29	5:20
10	2010-04-04	7:20	26	2017-08-22	3:08
11	2010-04-05	5:30	27	2017-08-24	6:11
12	2010-08-03	5:40	28	2017-09-18	6:35
13	2010-09-17	8:22	29	2017-09-27	6:41
14	2011-04-02	6:47	30	2018-03-25	7:46
15	2011-04-20	8:38	31	2018-04-10	5:10
16	2011-06-23	7:15	32	20018-07-17	6:30

Correlation Matrix for 32 STEVE Events

	AL	By	Bz	PC1	PC2	PC3	PC4	cpcp
By	0.035							
Bz	0.33	-0.12						
PC1	-0.45	-0.65	-0.24					
PC2	-0.53	0.49	-0.59	0				
PC3	-0.28	0.052	0.24	-0.017	-0.016			
PC4	0.17	0.19	0.23	-0.09	0	0		
cpcp	-0.65	-0.11	-0.55	0.67	0.66	-0.12	-0.067	

- y: Principal Component 3 Coefficient
- μ: Some subset of possible features from M (AL index, By, Bz, ...)
- x^μ: Input data using μ features
- x_{-t}: Input data from t time steps back

PREDICTIVE MODEL DESIGN

GOAL: Principal Component 3 Coefficient Predictive Model

$$f(x_0^\mu, x_{-1}^\mu, ..., x_{-t}^\mu) = \hat{y}$$

- some time steps back t

- some set of features μ selected from all combinations of features M (AL index, By, Bz, ...)

- estimated value of PC3 $\rightarrow \hat{y}$

Central Question: Can this be done algorithmically without domain knowledge?

input layer   hidden layer 1   hidden layer 2   output layer

SCIENCE *is* SOCIETY
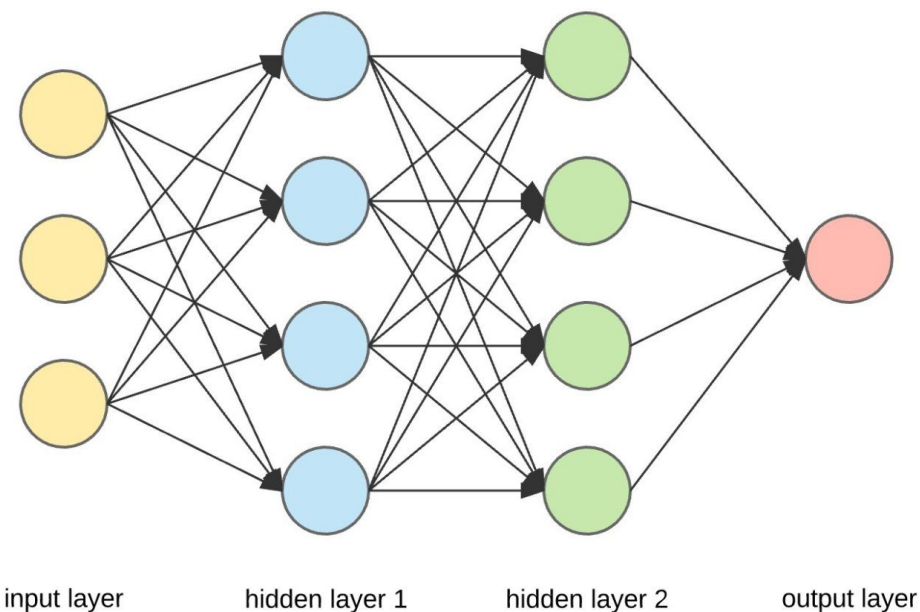
AUTOMATE SELECTION OF HYPERPARAMETERS/FEATURES

Goal: Develop a model based on algorithm able to find the best hyperparameters/features based on training and validation data

Equation took influence from Reference (3)

hyperparameter/fearure optimization problem

$$\min_{\lambda \in \Lambda, \mu \in M} \sum_{(x^\mu, y) \in S_v} l(f_{S_t}^\lambda(x^\mu), y)$$

- set of all hyperparameters to choose from: Λ, $\lambda \in \Lambda$
  Ex: $\lambda = 32$ units in a first dense layer, 16 units in next dense layer

- validation data: S_v

- model given set of hyperparameters and trained on S_t: $f_{S_t}^\lambda$

- loss function given a model trained on S_v: $l(f_{S_t}(x), y)$

SCIENCE is SOCIETY

IMPLEMENTATION OF MODEL

Neural Network Architecture

- Neural Network Library: TensorFlow
- Loss function: Mean Squared Error
- Possible layers: LSTM (Long Short Term Memory) and Dense
- Train/Validation/Test Split
  - 22 events (~70%) Train
 - 7 events (~20%) Validation
  - 3 events (~10%) Test

Question: How are we going to automate the selection of our hyperparameters/features for this model architecture?

SCIENCE is SOCIETY
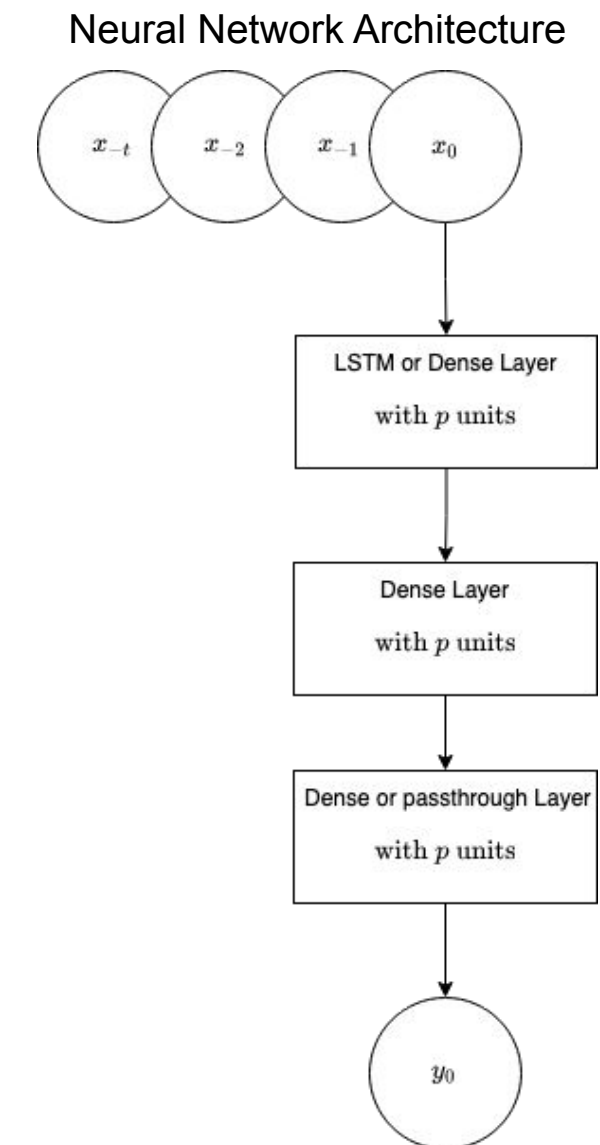
IMPLEMENTATION OF AUTOMATED APPROACH: GENETIC ALGORITHM

- Run for *n* generations

- Fitness function: Rank of validation loss compared to others in population

- Generating new members in a population: Binary Crossover of weighted probability of selection based on rank
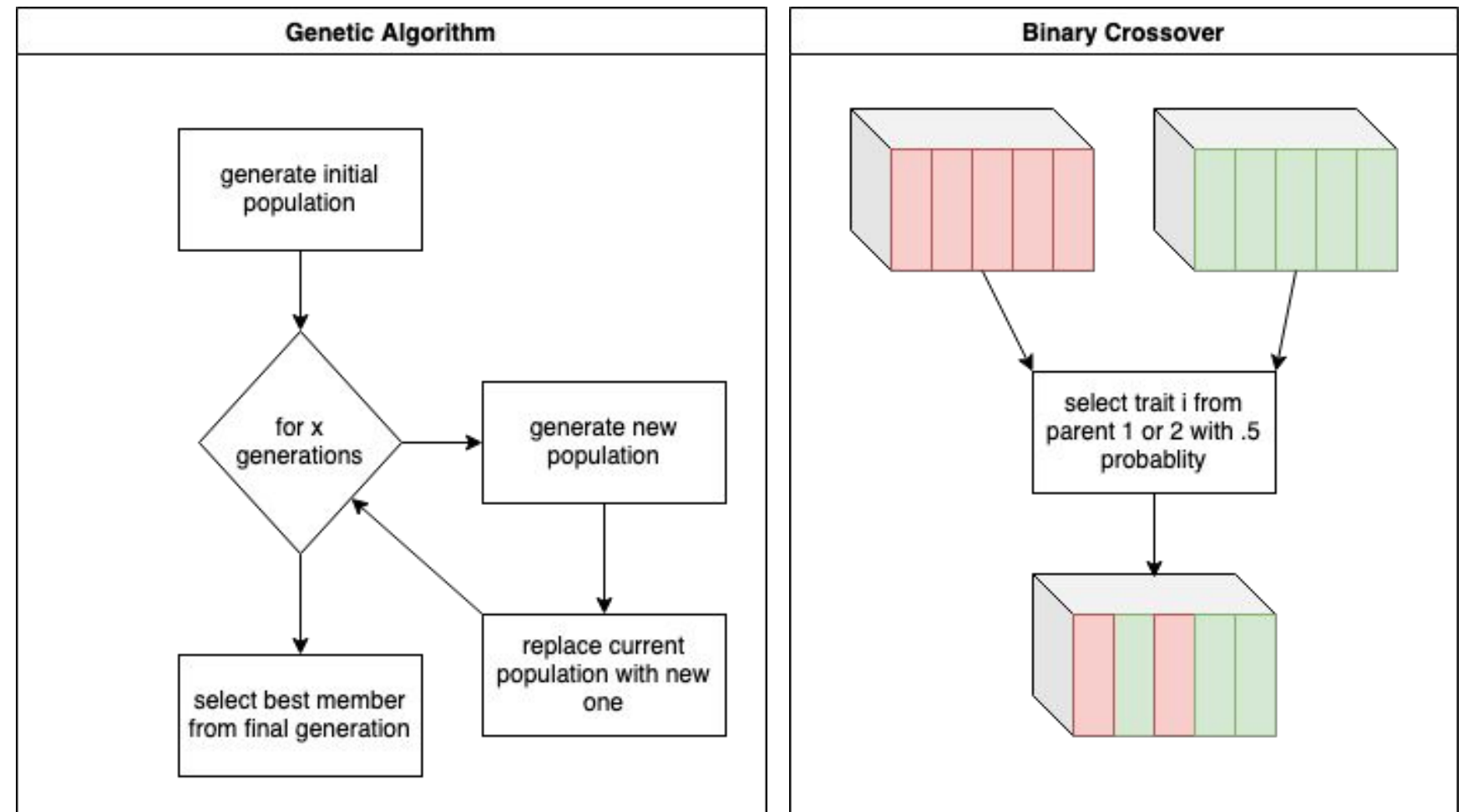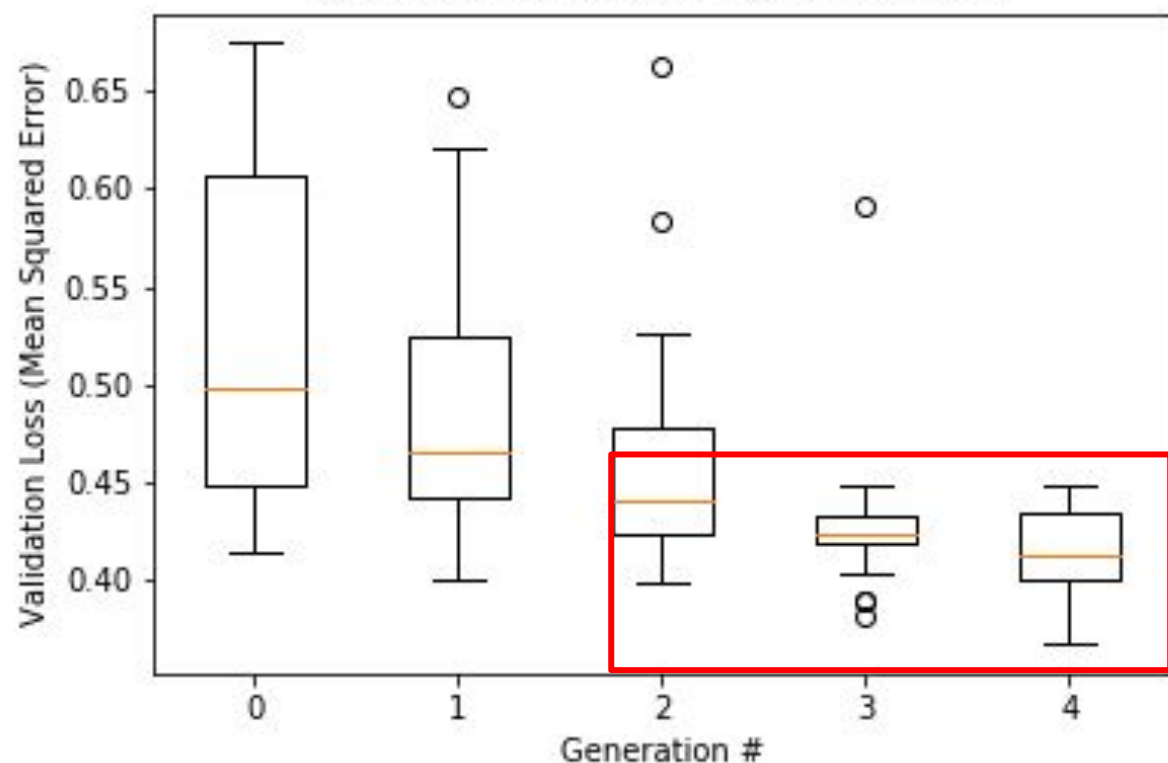

Approach borrowed from some parts of Genetic Algorithm from Reference (3)

AUTOMATED SELECTION RESULTS

Generation Validation Loss Over Time

Tensorflow model image
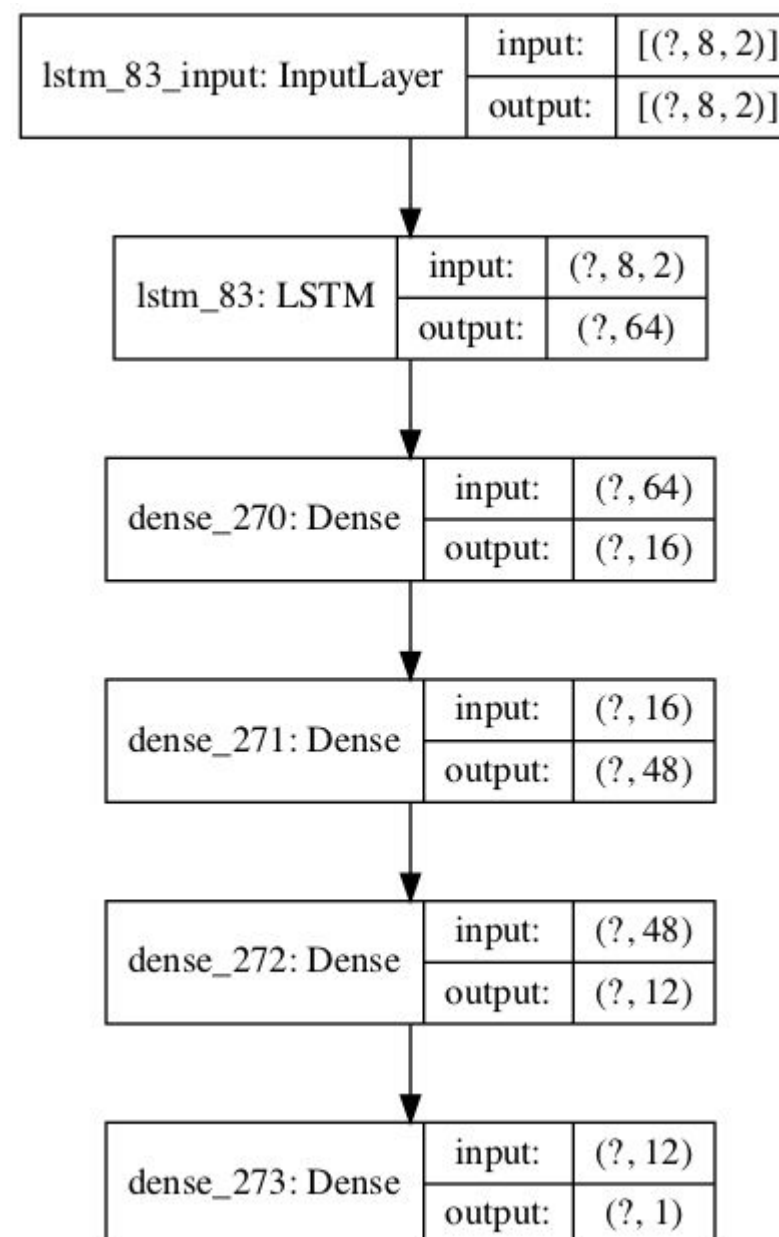

Best member after 4 generations
- Features: AL index, Bz
- Validation Loss (MSE): .3676
- Test Loss (MSE): .2227
- Time steps: 7

Best member hyperparameters

```
'layer_1_units': 64,
'layer_2_units': 16,
'layer_3_units': 48,
'layer_4_units': 12}
```

PREDICTIVE MODEL RESULTS
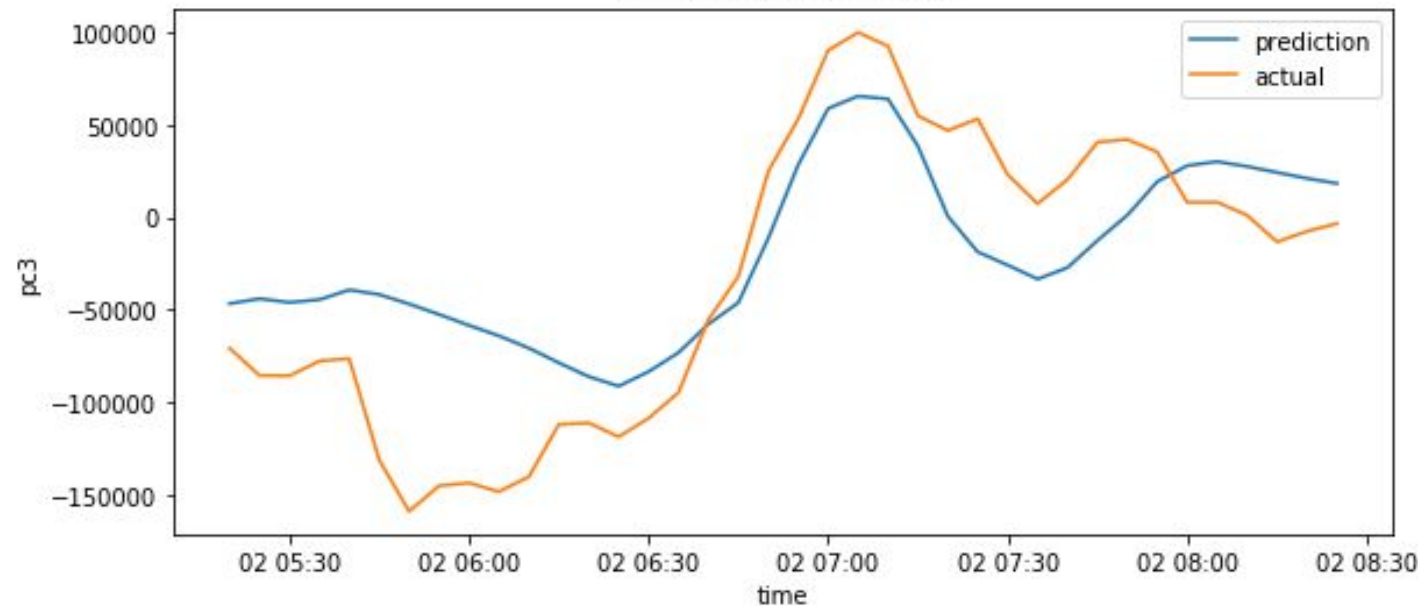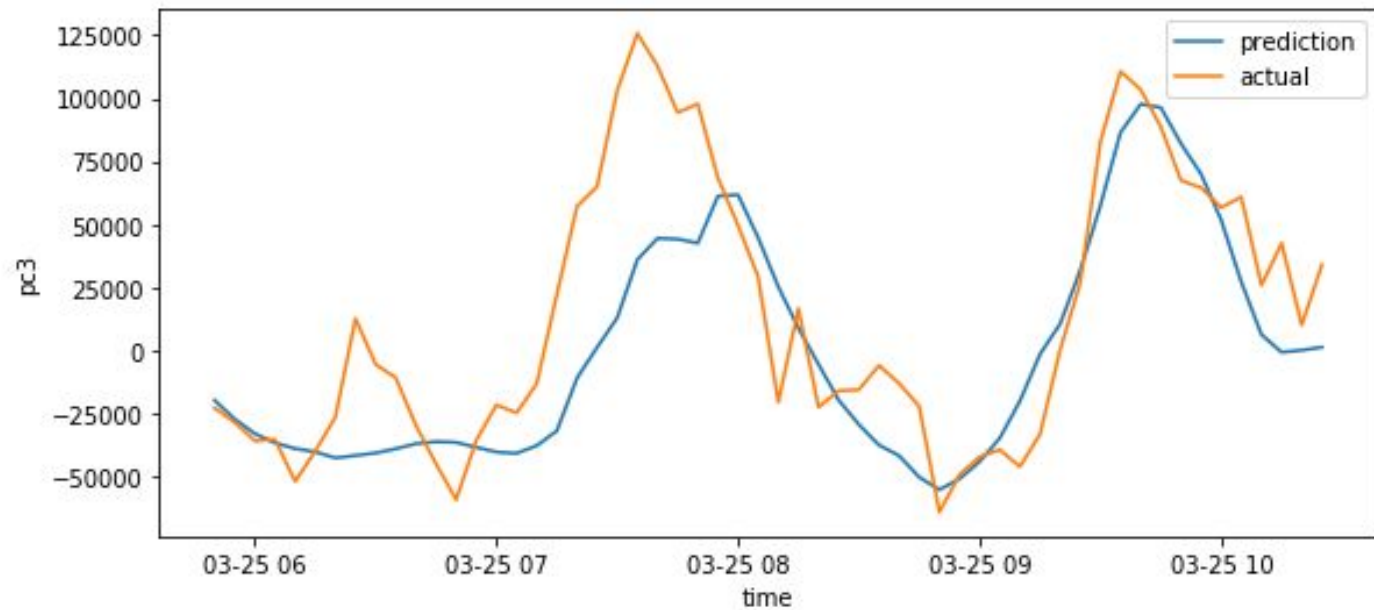
Classic STEVE Event Predictions

Outlier STEVE Event Predictions
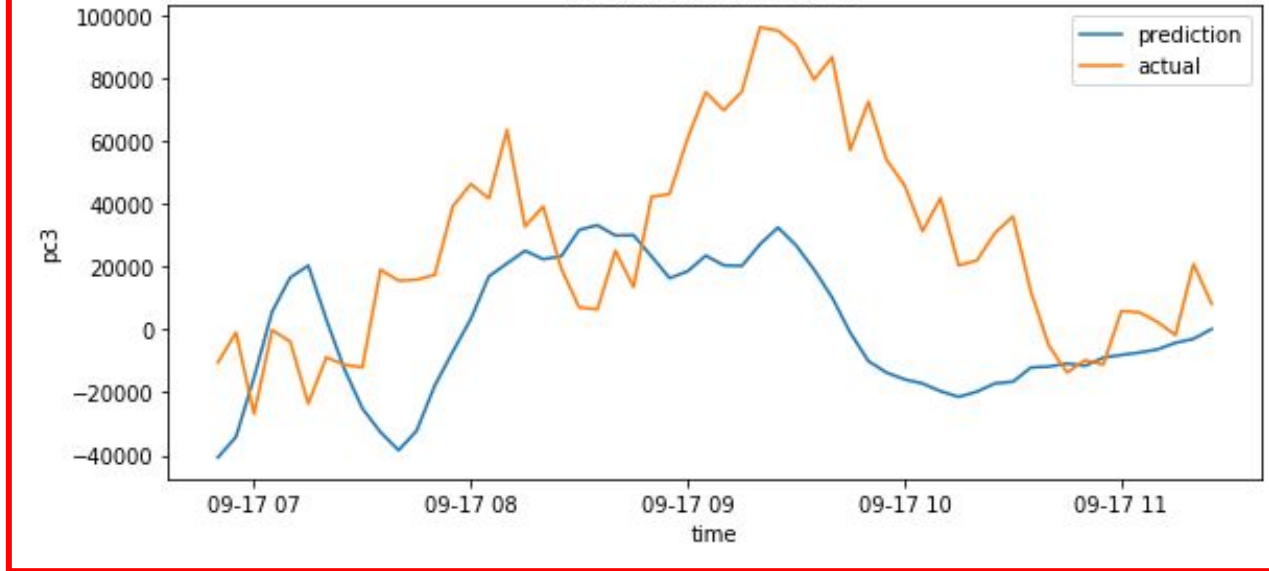
CONCLUSIONS & LINKS

- With no domain experience, constructed a predictive model of ionospheric convections using the combination of LSTM NN and genetic algorithms

- Demonstrated the approach's reproducibility for selecting features/hyperparameters for neural network training, eliminating the need of domain experience

- Aim to continue searching for other methods of automating this process

- Please checkout my colleagues poster, who this work is based on:
  SM11B-05 - High Latitude Ionospheric Electrodynamics during STEVE and Non-STEVE Substorm Events

- See the source: https://github.com/willemmirkovich/AGU-2021

THANK YOU

WILLEM MIRKOVICH

WILLEMMIRKOVICH@GMAIL.COM
WJMRIKOVICH.COM

REFERENCES

1. Valerie Svaldi's work inspired and generated data for this project: https://agu.confex.com/agu/fm21/meetingapp.cgi/Paper/900392

2. The assimilative mapping analysis (which was used to create the data) is produced with the use of the AMGeO open source software (doi:10.5281/zenodo.3564915) available upon registration at https://amgeo.colorado.edu/

3. F. Johnson, A. Valderrama, C. Valle, B. Crawford, R. Soto and R. Ñanculef, "Automating Configuration of Convolutional Neural Network Hyperparameters Using Genetic Algorithm," in IEEE Access, vol. 8, pp. 156139-156152, 2020, doi: 10.1109/ACCESS.2020.3019245.

SCIENCE
is SOCIETY