PREDICTIVE MODELS OF IONOSPHERIC CONVECTION PATTERNS DURING SUBSTORMS RELATED TO STEVE

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AGU FALL MEETING

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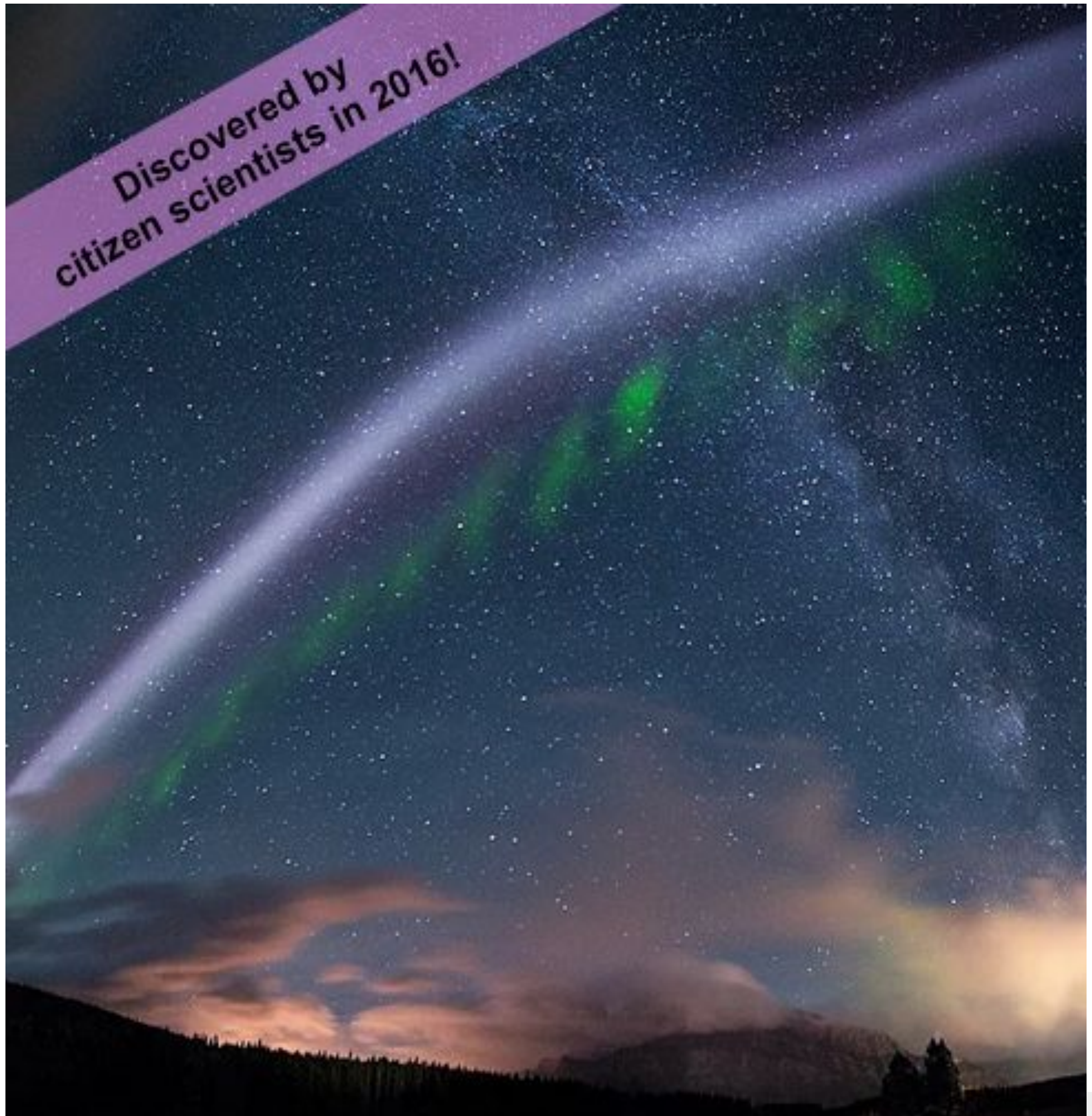
STEVE INTRODUCTION AND GEOPHYSICAL MOTIVATION

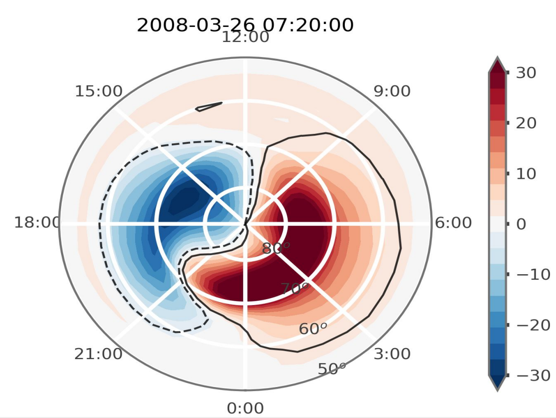


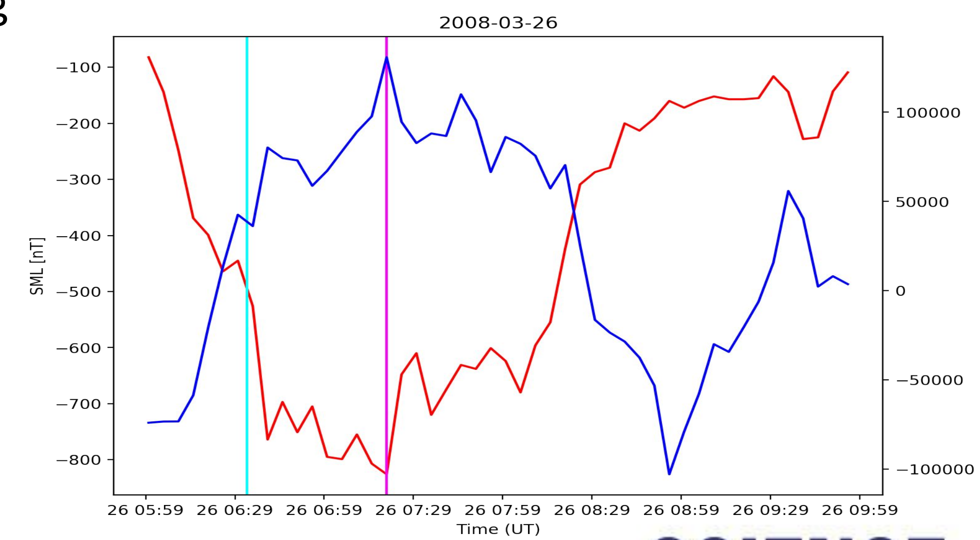
Meet STEVE
"Strong Thermal Emission Velocity Enhancement"

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





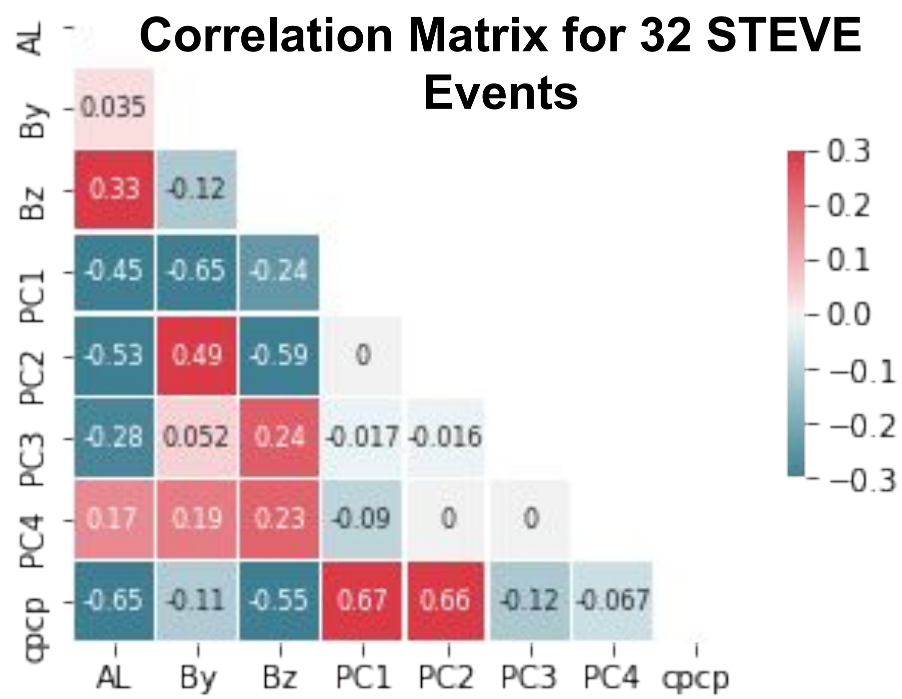
See SM11B-05 High Latitude Ionospheric Electrodynamics during STEVE and Non-STEVE Substorm Events [Svaldi et al., 2021] for more information on this study

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



- 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

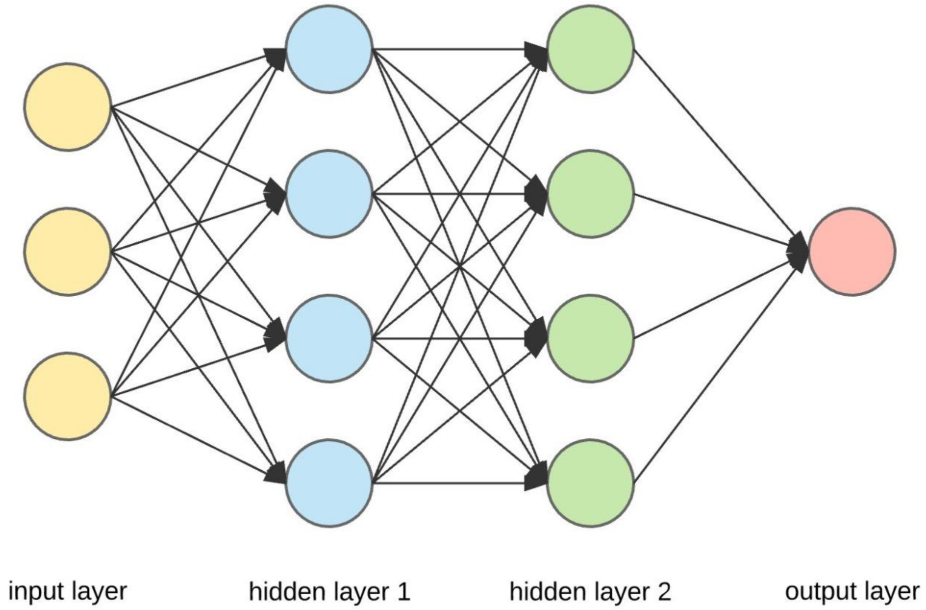
PREDICTIVE MODEL DESIGN

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?



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

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

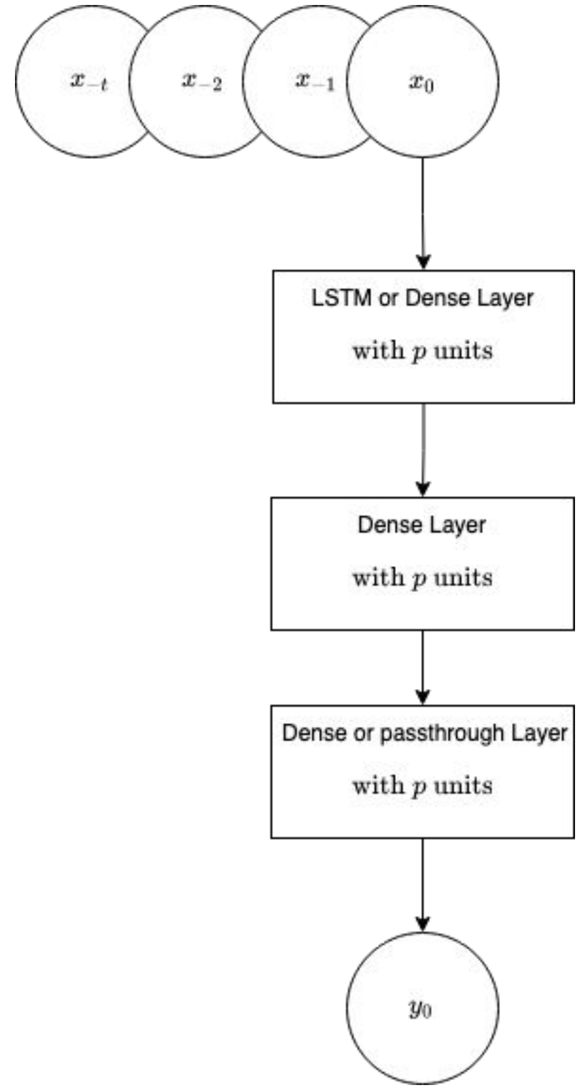
- set of all hyperparameters to choose from: Λ, $\lambda \in \Lambda$
  Ex: $\lambda = 32$ units in a first dense layer, 16 units in next dense layer
- validation data: S_v
- model given set of hyperparameters and trained on S_t: $f^\lambda_{S_t}$
- loss function given a model trained on S_v: $l(f_{S_t}(x), y)$

IMPLEMENTATION OF MODEL

- 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

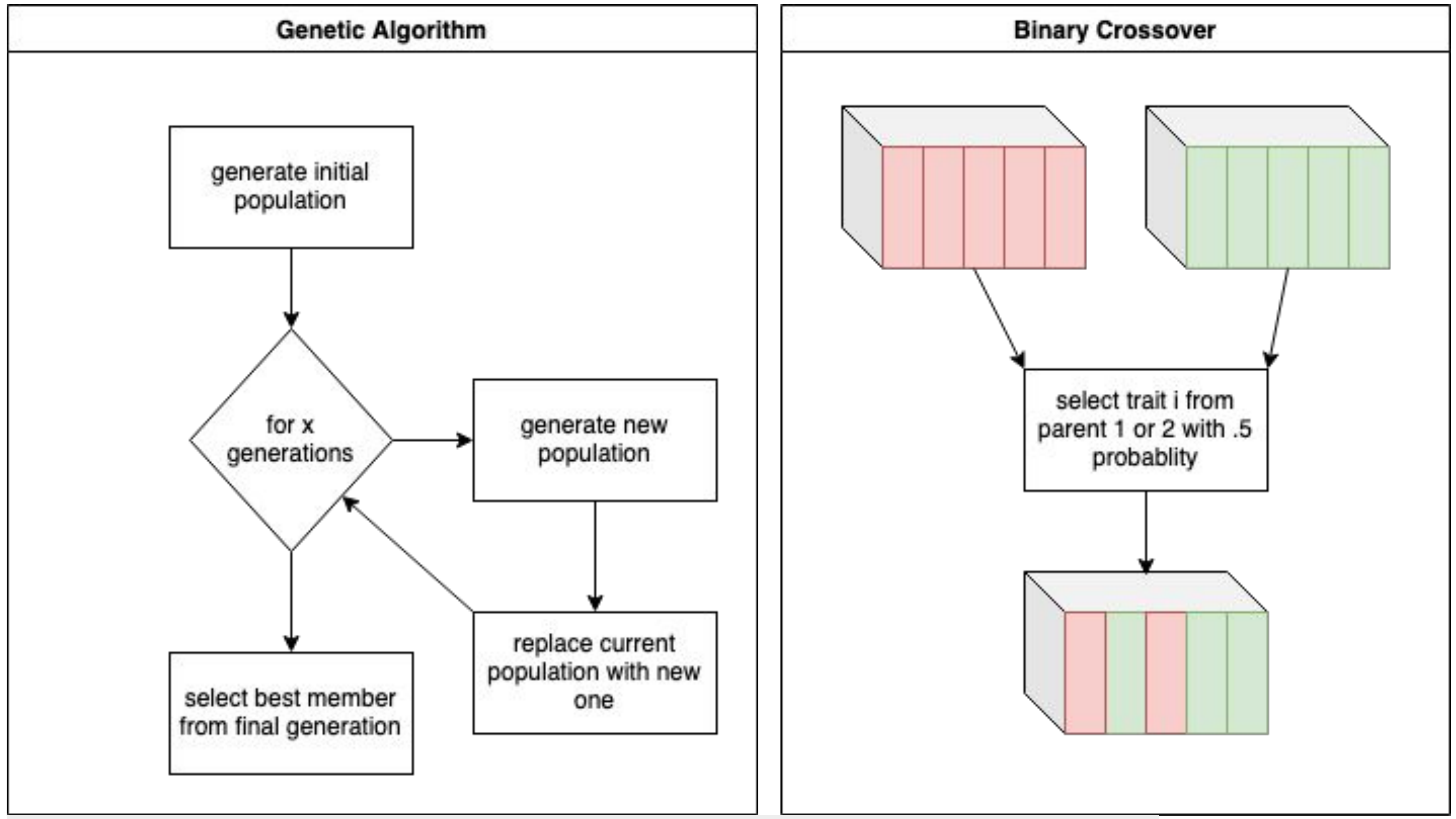
Question: How are we going to automate the selection of our hyperparameters/features for this model architecture?

Neural Network Architecture



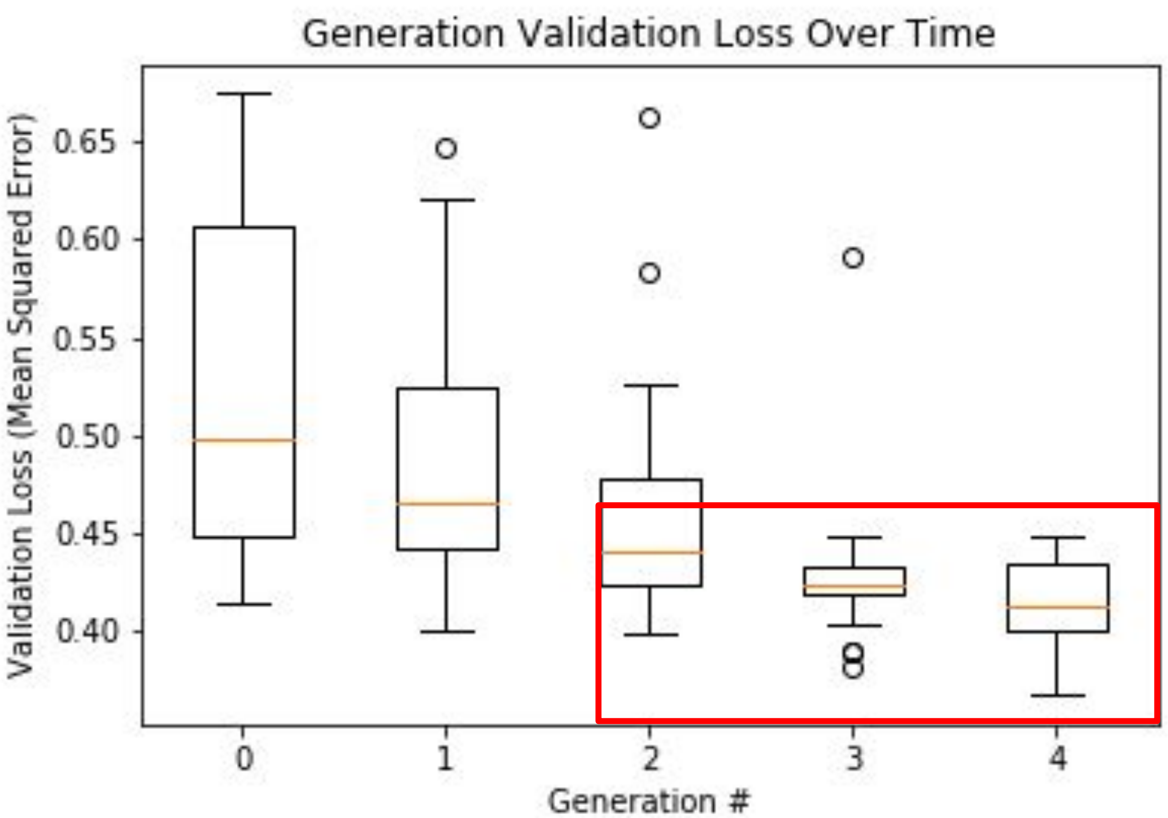
IMPLEMENTATION OF AUTOMATED APPROACH: GENETIC ALGORITHM

- 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



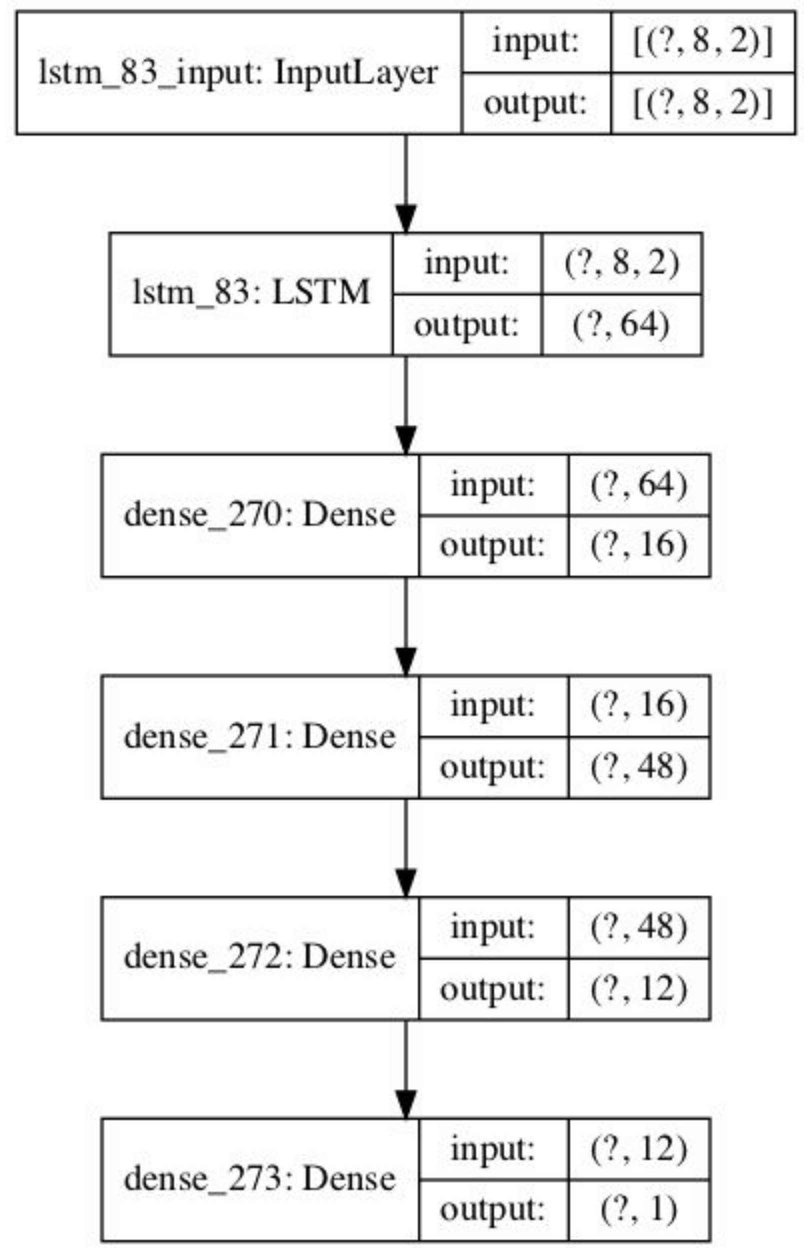
Best member after 4 generations

- 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}
```

Tensorflow model image



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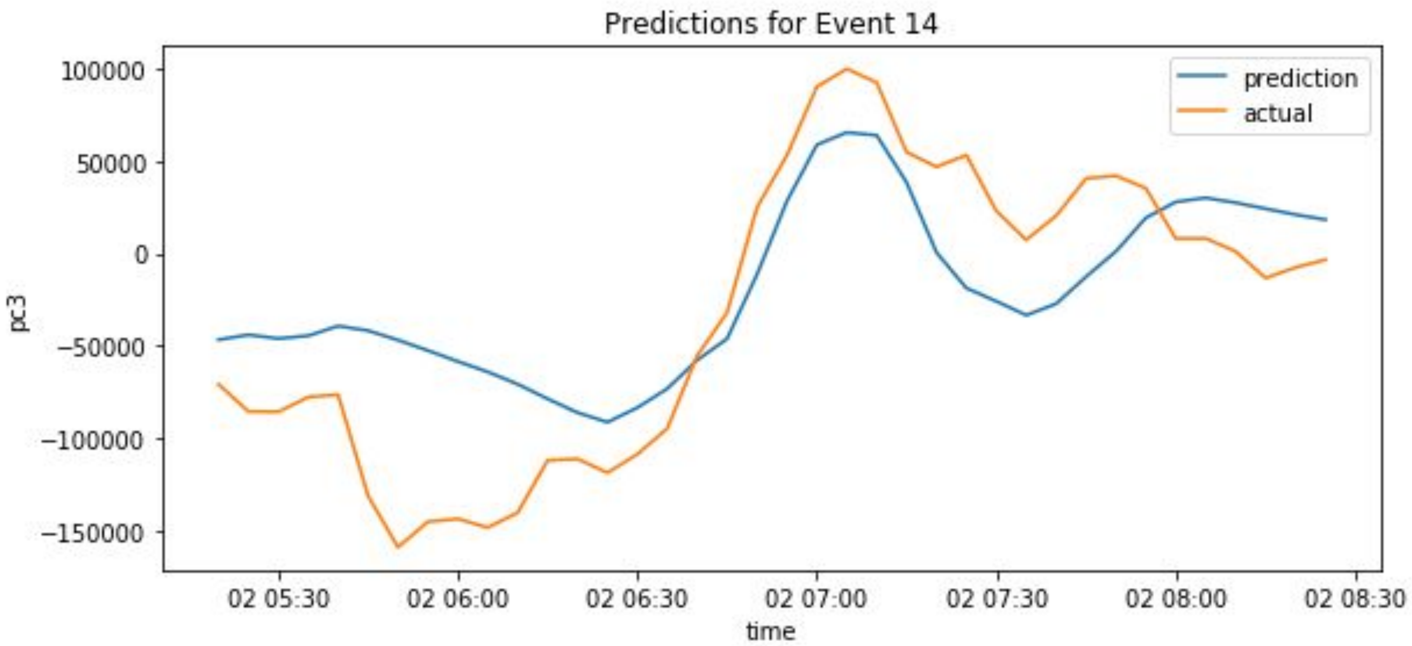
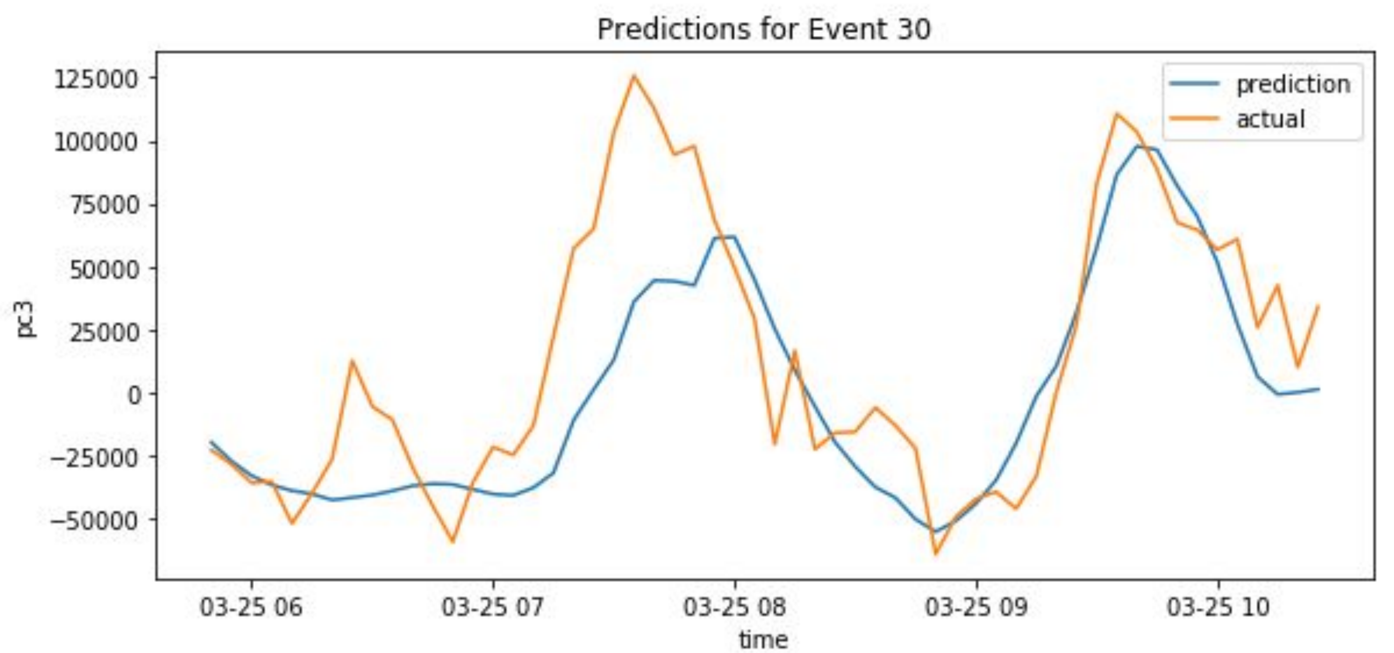
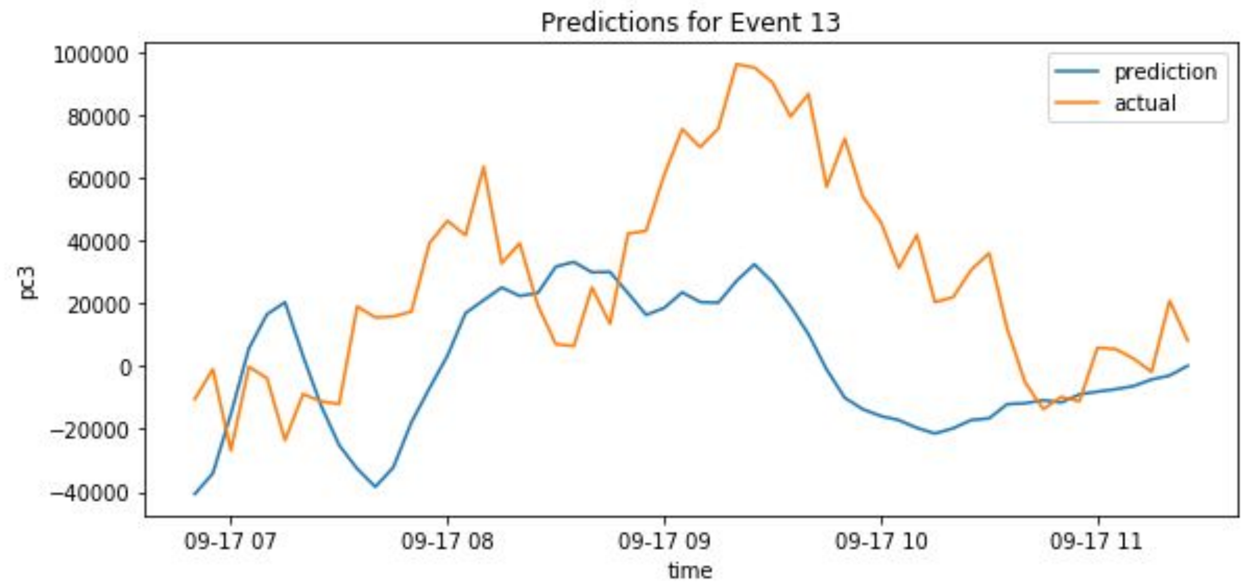
PREDICTIVE MODEL RESULTS

Classic STEVE Event Predictions





Outlier STEVE Event Predictions



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CONCLUSIONS & LINKS

- With no domain experience, able to construct a predictive model using automated approach to domain specific problem
- Based on model generated, able to make good time series predictions for PC3 (our target variable for STEVE Events)
- Reproducible method for selecting features/hyperparameters for a given problem if dataset exists
- 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

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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.