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Predicting Auroral Substorms Using Machine Learning

Problem

As streams of charged particles originating from the Sun in the form of Solar Winds come in contact with the Earth's magnetosphere, the particles in the Earth's atmosphere are energized and ionized and emit bright lights forming the spectacular sights of auroras.

An auroral substorm is the phenomenon of the sudden brightening of these auroral arcs, caused by disturbances in the Earth's magnetosphere due to a sudden release of accumulated energy. Very intense substorms can lead to outages of GPS signals and create intense electric currents that can damage electronic systems in satellites and on the ground.

In order to capture these brief moments when a substorm occurs, the goal of this project was to develop a system that is capable of predicting their onset ahead of time, similar to that of a weather forecasting system. Currently, we only attempt to predict several minutes ahead of time.

Data

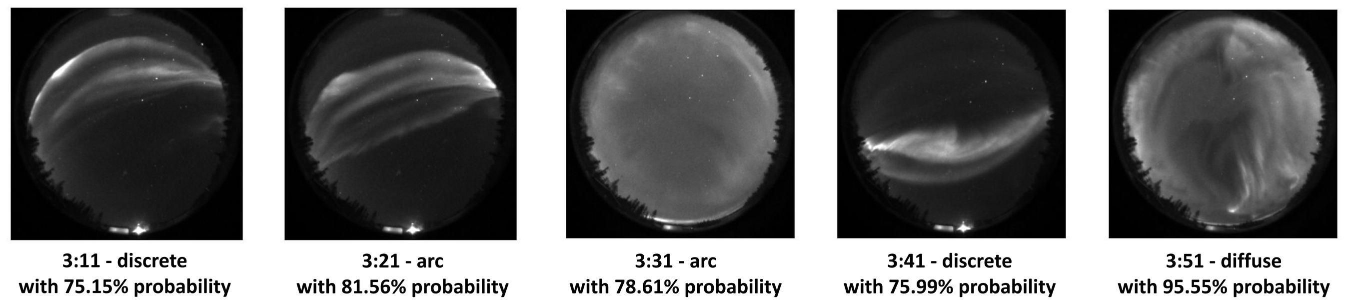
Our data included time series of magnetometer readings and aurora images taken by ground stations of the NASA THEMIS project near the Earth's pole. The raw data was in the form of CDF (Common Data Format) files, which is a library and toolkit that was developed by the National Space Science Data Center (NSSDC) at NASA. We utilized various existing Python libraries to clean and process this data for use in our machine learning models.

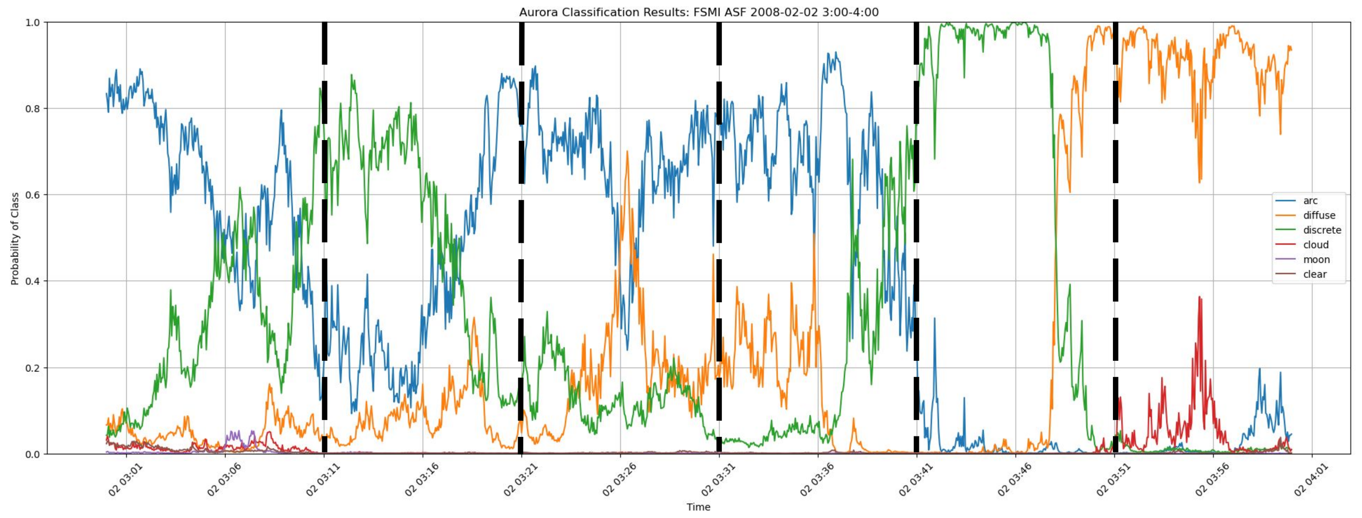
Magnetometer Readings:
Magnetic field measurements of H (north), D (east) and Z (down) components, in units of nanotesla, recorded every half second.

Aurora Images:
Grayscale pixel data of images which are taken every 3 seconds at each station that we converted into PNG files. We also use these images to generate brightness readings.

Solution

Aurora Image Classification:
Our first goal was to classify our aurora image data, and we used an existing transfer learning model to do so. The TAME classifier[1] takes in aurora PNG files as input and classifies them into one of six different classes ("arc," "diffuse," "discrete," "cloud," "moon," and "clear"). The classifier trained the most accurate pre-trained PyTorch neural network on a support vector machine to determine these classes.





Substorm Prediction:
Once we classified the set of images, we combined it with the magnetometer data and total brightness of the image to create our dataset for our predictive model. The magnetometer and brightness readings were normalized by subtracting the background levels. Then, all the processed data was reorganized and aligned into readings starting at every hour from t = 0, 15, 30, 45 mins etc. for 30 min intervals.

Our final input for our neural network model was a 10*600 matrix:
10 rows -> 6 classes, 3 magnetic field components, total brightness
600 columns -> 30 mins = 30 * 60 (seconds) / 3 = 600 seconds

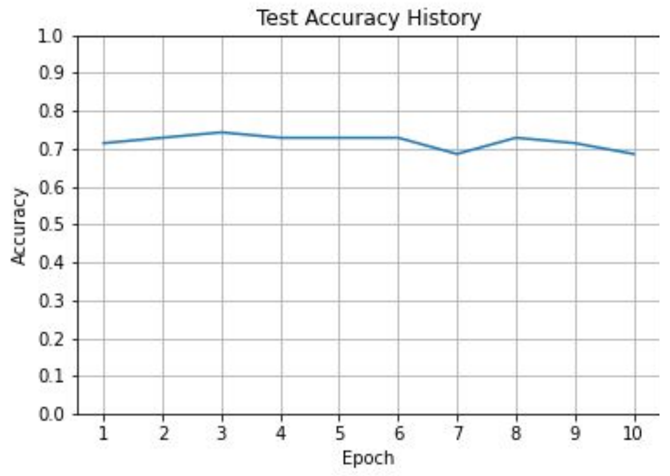
Our model used LSTM (Long short-term memory) modules as a base, as this specific type of model is good for analyzing time series data. LSTM modules have feedback connections between each module (hence the name), allowing subsequent data points that are temporally adjacent to each other have a more meaningful effect on how the model detects overall change between regular activity and a possible substorm onset.

We base our model on an existing ResNet model[2] which could classify time series magnetometer data as a possible substorm onset within a 1 hour prediction period (taking in a 2 hour input period). A ResNet model is a special type of Convolutional Neural Net that adds skip connections within the net to reduce problems with vanishing or exploding gradients that could damage the test accuracy of the model when deeper layers are added to the model.

Although this model had similar goals as our project, we decided to use an LSTM-based approach because our model incorporates multiple sources of input data to get a more holistic view of the environment when making predictions. We also found that the ResNet model took in only 1-dimensional time series data to process, while our project wanted to also incorporate 2-dimensional image time series data to improve model robustness.

Success

Our model achieved about 70% accuracy on our validation set. However, we noticed that the accuracy was fairly stagnant and never really increasing with further training. Due to the lack of labelled data, our model is experiencing overfitting (our model has 3000 learning parameters but currently only using 300 datapoints).



Next Steps

Our model is currently a descriptive sequential model; we eventually want to forecast the probability of the occurrence of a substorm in the near future. That requires more labels of substorms (we only have one month but need tens of years).

To better performance, we also need to work more on feature engineering, especially on auroral images. What one could use is a splitting of images into 4 quadrants and do classification within each quadrant. A substorm starts in a small area and one quadrant could change while the others do not making the system more sensitive.

Once we have a larger database, we can look for small changes that actually precede the substorm onset, like change in one magnetic field component while the others remain steady, fluctuations in aurora brightness, or changes in shape of arcs but not their brightness.

References

1. Sado, P., Clausen, L. B. N., Miloch, W. J., & Nickisch, H. (2022). Transfer learning aurora image classification and magnetic disturbance evaluation. Journal of Geophysical Research: Space Physics, 127, e2021JA029683. https://doi.org/10.1029/2021JA029683
2. Maimaiti, M., Kunduri, B., Ruohoniemi, J. M., Baker, J. B. H., & House, L. L. (2019). A deep learning-based approach to forecast the onset of magnetic substorms. *Space WeatherSpace Weather*, 17, 1534– 1552. https://doi.org/10.1029/2019SW002251