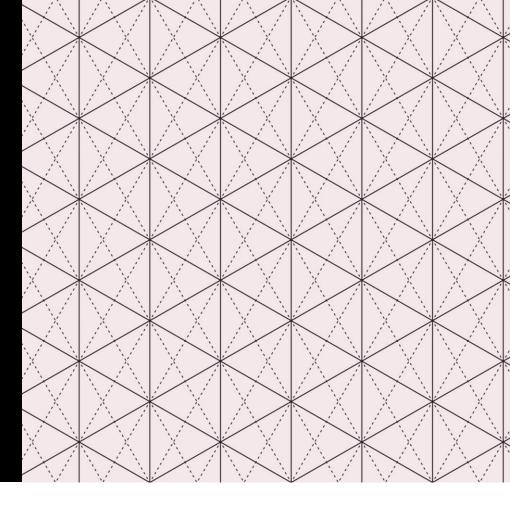
# (L)TI (T)raite de l'(I)nformation

### Participants:

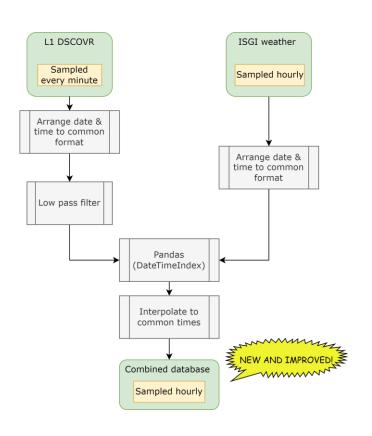
- Alexandre Beaulieu
- Mathieu Bergeron
- Samuel Fortin



DSCOVR DATA: PROCESSING, INTERPRETATION & PREDICTION



# DATA WRANGLING & PREPROCESSING



### **Data sources**

**DSCOVR** dataset (L1 data)

ISGI hourly space weather (aa, am, Kp, Dst, PCN, PCS, AE, AU, AL, AO, SC, SFE)

### **Transformation**

In both databases, datetime is not in the same format. Steps are taken to make them similar.

Since we aim to resample to an hourly rate, low pass filtering of L1 DSCOVR data is applied to reduce the SNR as much as possible.

### Combination

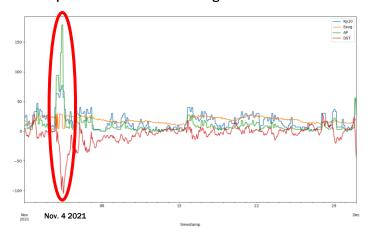
Using DateTimeIndex functionality of the pandas library, both databases are merged.

### Resampling

The merged dataset is then re-sampled to common times at an hourly rate. When the time is not just, are then resampled to the desired rate.

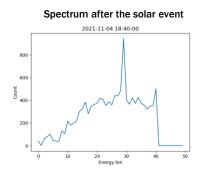
# ANOMALY DETECTION

#### Space weather metrics during November 2012



#### L1 DSCOVR data columns 4 to 54

# Spectrum during solar event 2021-11-04 13:40:00 140 120 100 80 60 40 20 Energy bin 20 5



### **Hypothesis:**

Solar events can cause errors in the sensors of the DSCOVR probe.

### **Example:**

On November 4<sup>th</sup>, 2021, a solar storm caused what we interpret as saturation of the spectrum sensor of the probe in all bands. We observed this as abnormally high variation in the average energy  $(E_{avg})$  and the energy variance of the spectra.

$$E_{avg} = \frac{1}{\sum_{i=0}^{50} N(i)} \sum_{i=0}^{50} (N(i) * (i+0.5))$$

$$E_{var} = \frac{1}{\sum_{i=0}^{50} N(i)} \sum_{i=0}^{50} (N(i) * (i + 0.5 - E_{avg})^{2})$$

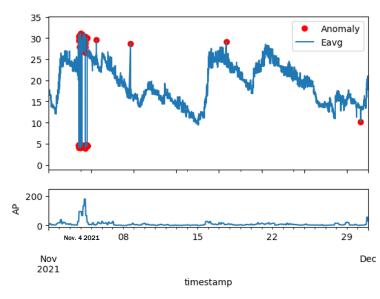
Observing and comparing the energy measurements between the spectra during and outside of the event shows differences in their distributions.

Note: Kp10 in these plots is 10 times Kp. It is the format in which the IGSI saves the metric.

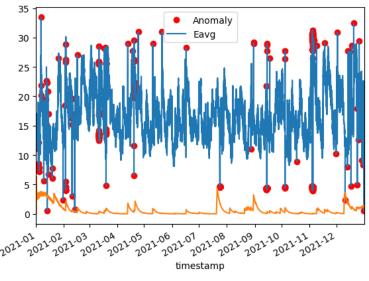
### **Decision:**

Ap seems to be (at a glance) less noisy than Kp. From now, it will be our reference measurement to determine the level of solar activity. A peak high Ap is interpreted as a solar event.

# GENERALISATION



Anomalies shown superimposed on the  $E_{avg}$  signal and aligned in time with the  $A_p$  signal. We see that the number of anomalies is high when there is a high density of peaks.



Results of the anomaly detection algorithm over a year. The orange signal is a proxy for the density of missing data in the spectra. We see that the anomalies in the signal do not always correspond to periods of high missing data.

#### **Anomaly detection**

Assuming the spectrometer signals are unreliable during solar events, there should be a higher density of peaks and anomalous samples in the  $E_{avg}$  and  $E_{var}$  signals for its duration. Another hypothesis was that solar storms yielded a large amount of missing data. The orange time series of the rightmost plot do not support this hypothesis.

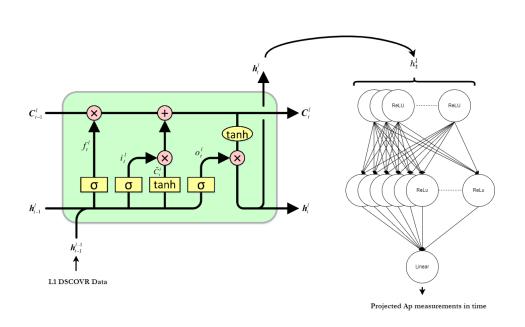
#### Tool

The <u>DBSCAN</u> algorithm is used to detect anomalies in the  $E_{avg}$  &  $E_{var}$  signals.

#### Conclusion

While it is true that the Nov 4<sup>th</sup> solar event produced a large number of anomalies in the data, the anomaly exhibited also tagged a many samples that do not correspond to solar events

# MACHINE LEARNING MODEL



### **Hypothesis:**

A link exists between the present measurements of space weather, their future value and the L1 DSCOVR dataset.

### Goal:

Predict the value of  $A_p$  in the future over a fixed window.

### Means:

### Why a Long Short-term Memory (LSTM)?

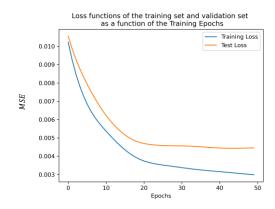
The network topology allows it to make links with its past inputs. For physical system representation, this property is a requirement.

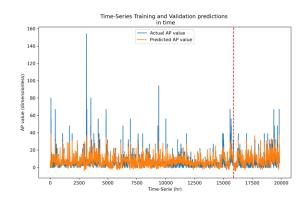
### Why a Feed Forward Neural net (FFNN)?

Adding a FFNN to the LSTM layer allows for added complexity of the output. This is principally because the DSCOVR data is not stable\*.

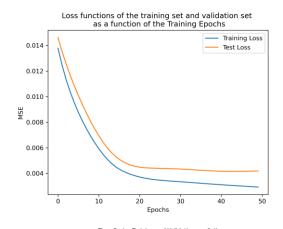
# TRAINING

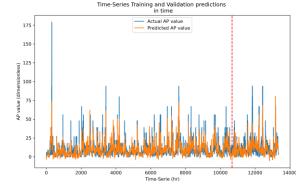
#### **DSCOVR** data only





#### Concatenated DSCOVR & weather data





# **Training & Testing set**

Imported from the pre-processing phase.

# Input

- 1) DSCOVER L1 data.
- 2) Concatenation of existing space weather & DSCOVER L1 data.

[ [L1 DSCOVR ], aa, am, Kp, Dst, PCN, PCS, AE, AU, AL, AO, SC, SFE ]

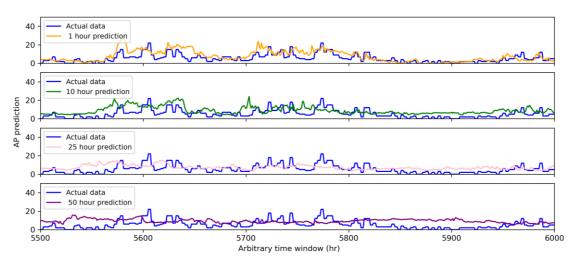
## **Ouput**

Prediction of the Ap over the next 50 hours from the time of the last data point.

# RESULTS

## **Prediction using ONLY the DSCOVR data as input**

Real and prediction of AP for multiple time prediction for an arbitrary Time-step.



# Prediction using the DSCOVR data & past space weather metrics as inputs

Real and prediction of AP for multiple time prediction for an arbitrary Time-step.

