A Generalized Magnetospheric Disturbance Index: Initial Application to Mars Using MAVEN Observations

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MAVEN

Mars Atmosphere and Volatile Evolution Mission

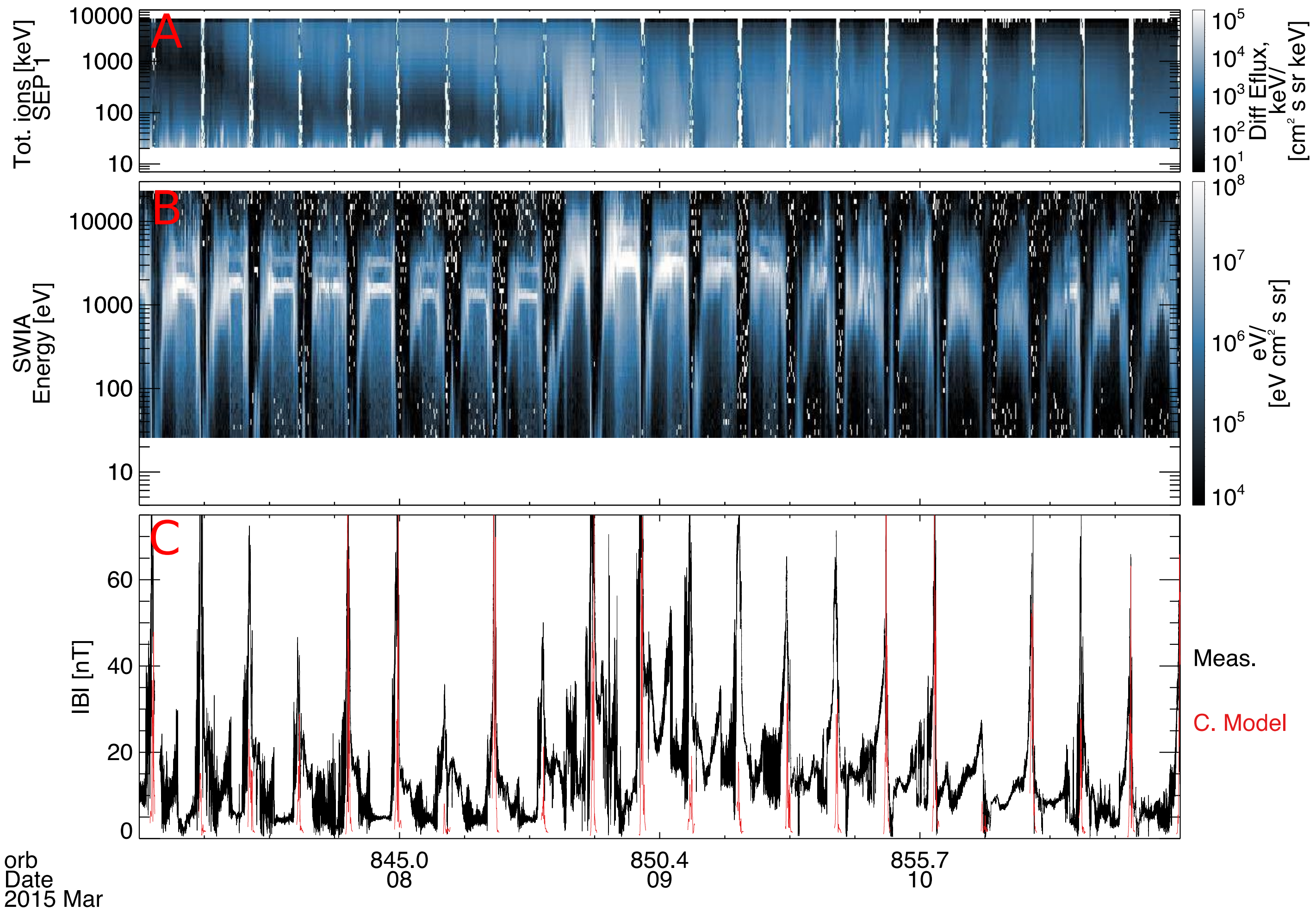
CU/LASP • GSFC • UCB/SSL • LM • JPL

Background and Motivation

- MAVEN's primary mission goal of addressing atmospheric loss
  - Can look at individual case studies of the effects of space weather events
  - Correlating strength of disturbance to loss tends to use qualitative descriptions
- Mars' hybrid magnetosphere causes a unique problem
  - To say something about how disturbed a magnetosphere is requires a statement of what a quiet period looks like
  - At Mars, the baseline is constantly moving
- We have developed a magnetospheric disturbance index
  - Computation by hand is time consuming - machine learning can greatly increase speed

March 8, 2015 ICME

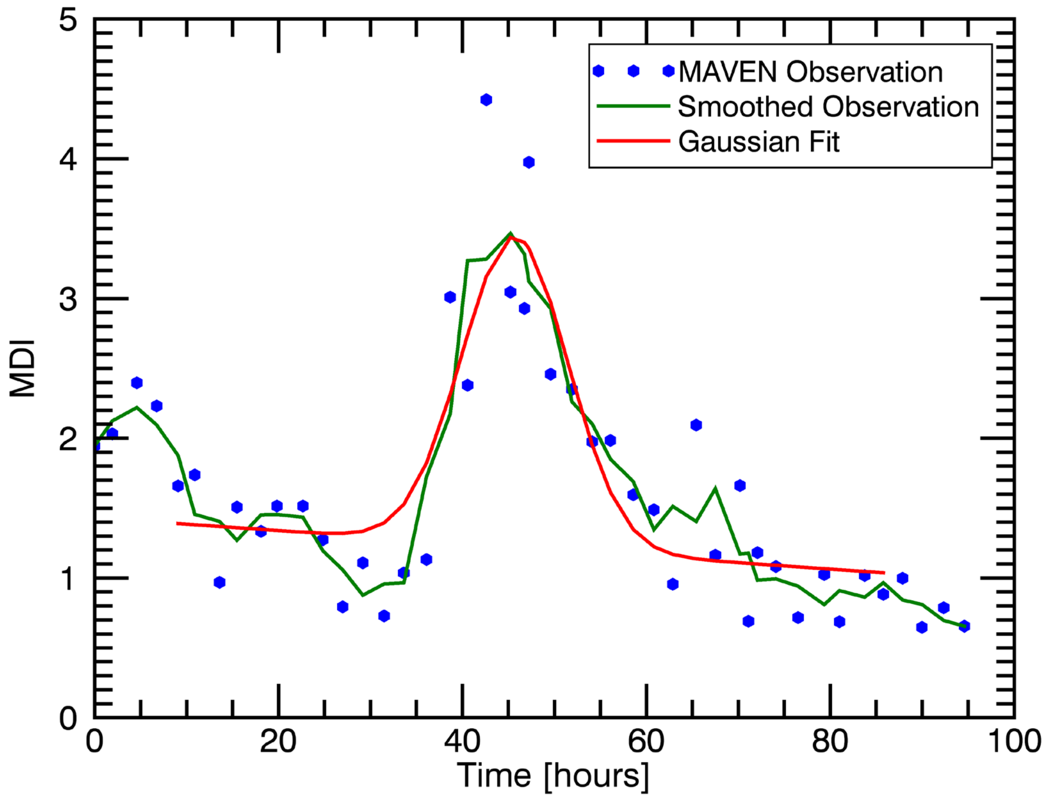
- Panel A – Solar Energetic Particle (SEP) observations
- Panel B – Solar Wind Ion Analyzer (SWIA) observations
- Panel C – Magnetometer (MAG) observations with Morchhauser crustal field model
  - MAG shows a common behavior during space weather impacts at the planet



Magnetospheric Disturbance Index (MDI)

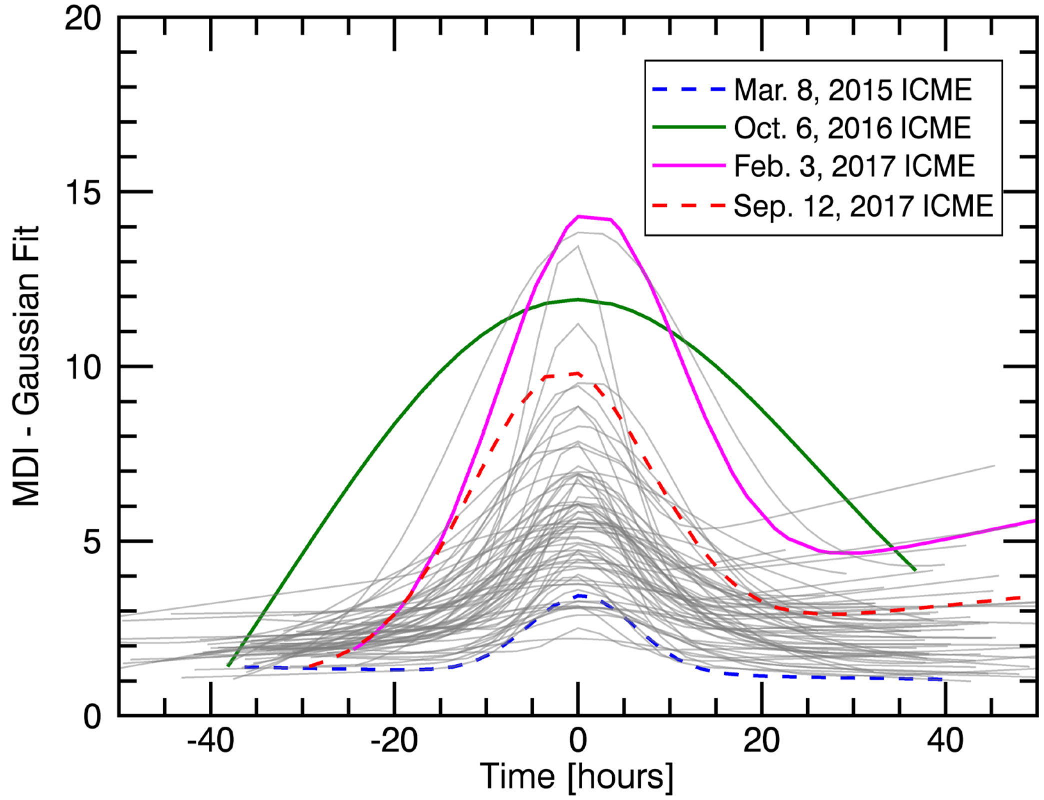
- We start with two parameters that are most evident in all event periods
  - Enhancement of |B|
  - B variability – quantified as the integrated power from an FFT around the proton cyclotron frequency
- Normalize the sheath observation of these two quantities by observations prior to the event
- Compute MDI by the summation of the two enhancements

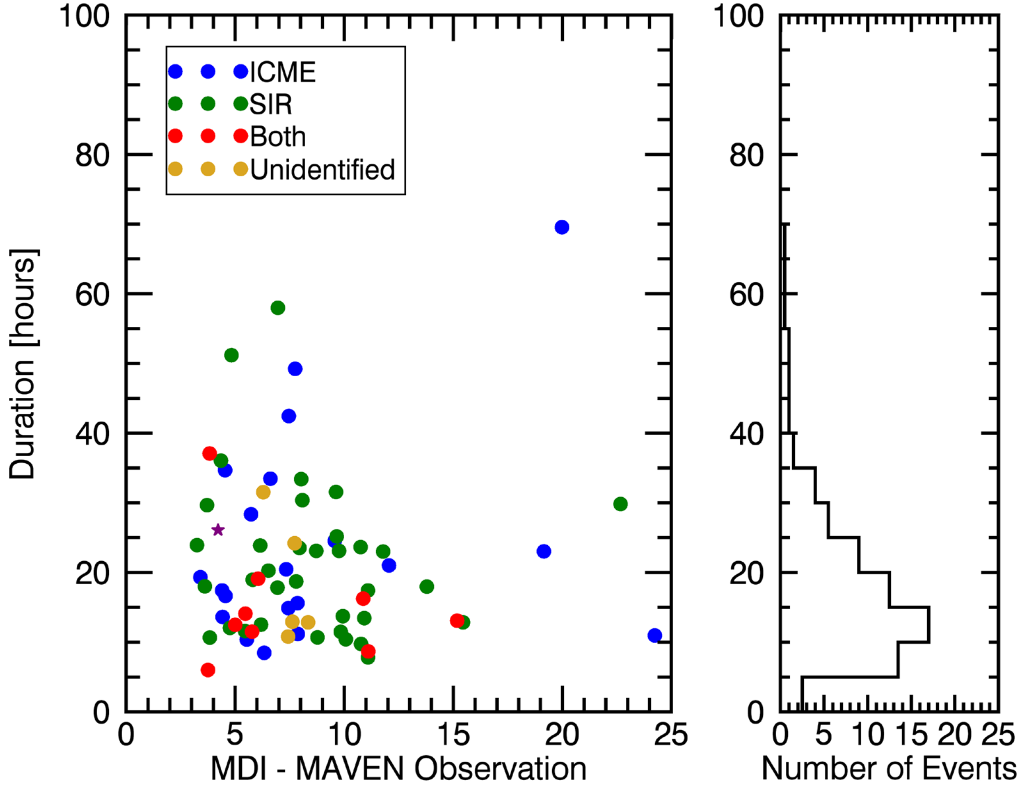
March 8, 2015 ICME



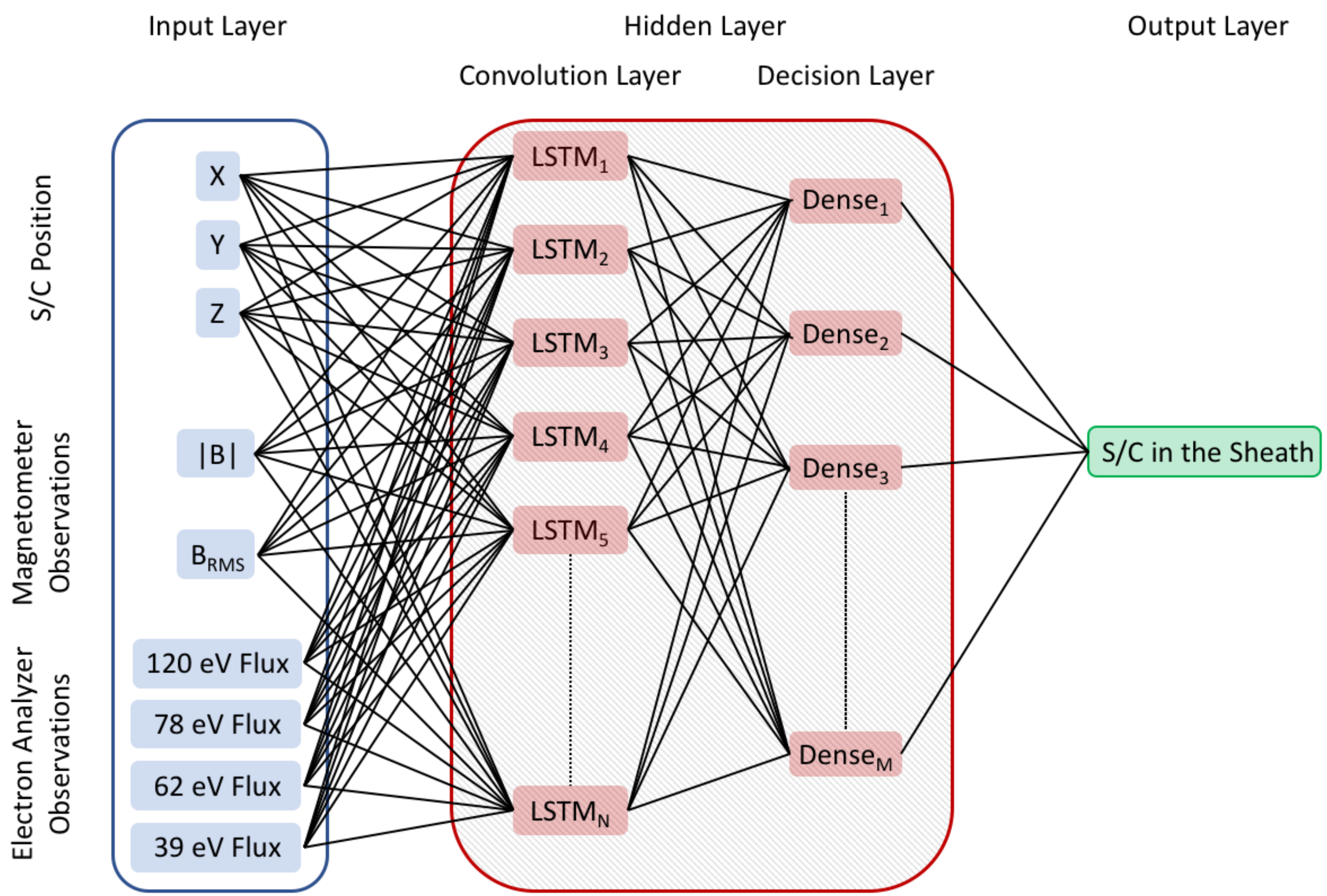
- MDI calculated for 4 days around event
- MDI calculation smoothed to illustrate time history of disturbance
  - An ICME that impacted the planet on March 5th is still evident
- A Gaussian fit is made to quantify the width of disturbance

MDI – Initial Results on 70+ events





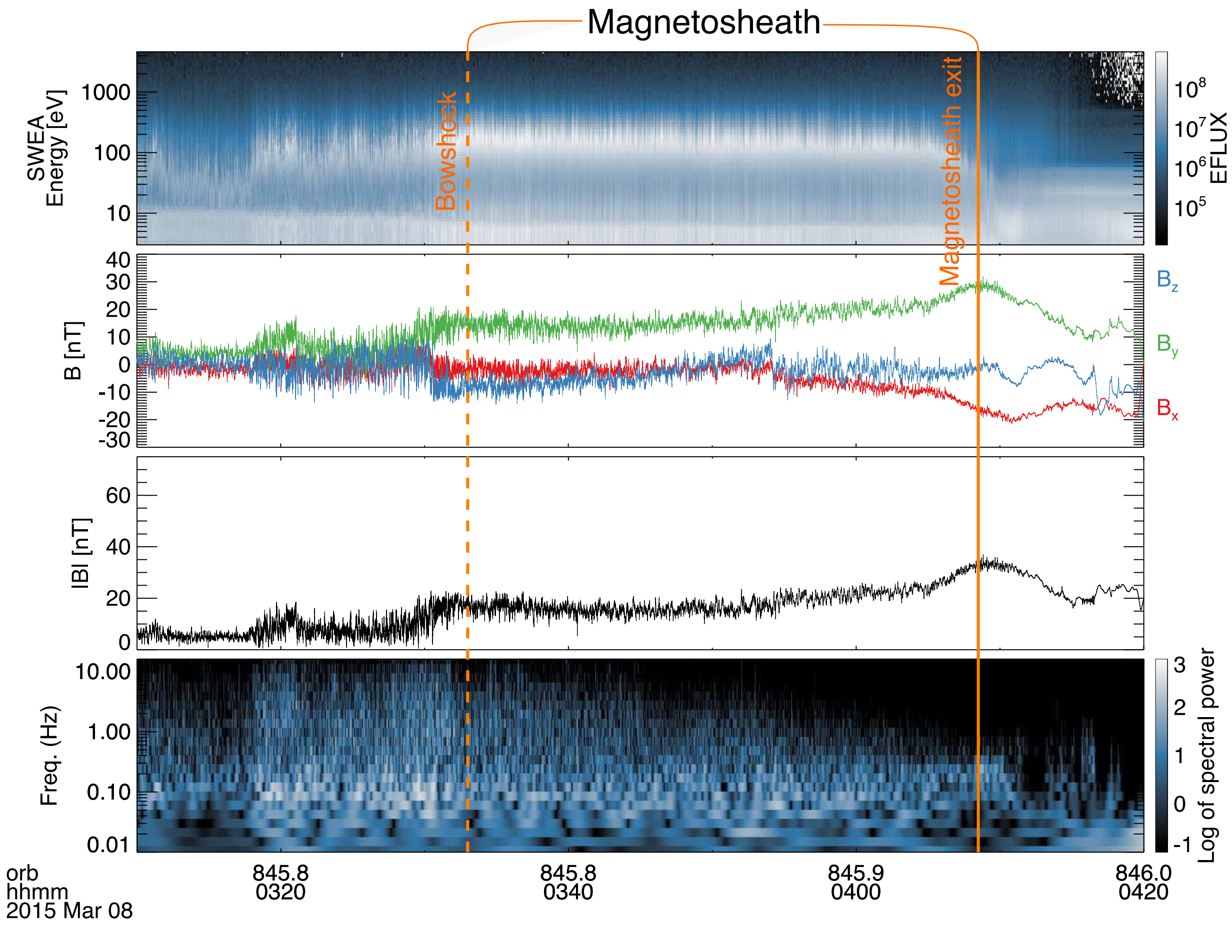
Developing an Artificial Neural Network



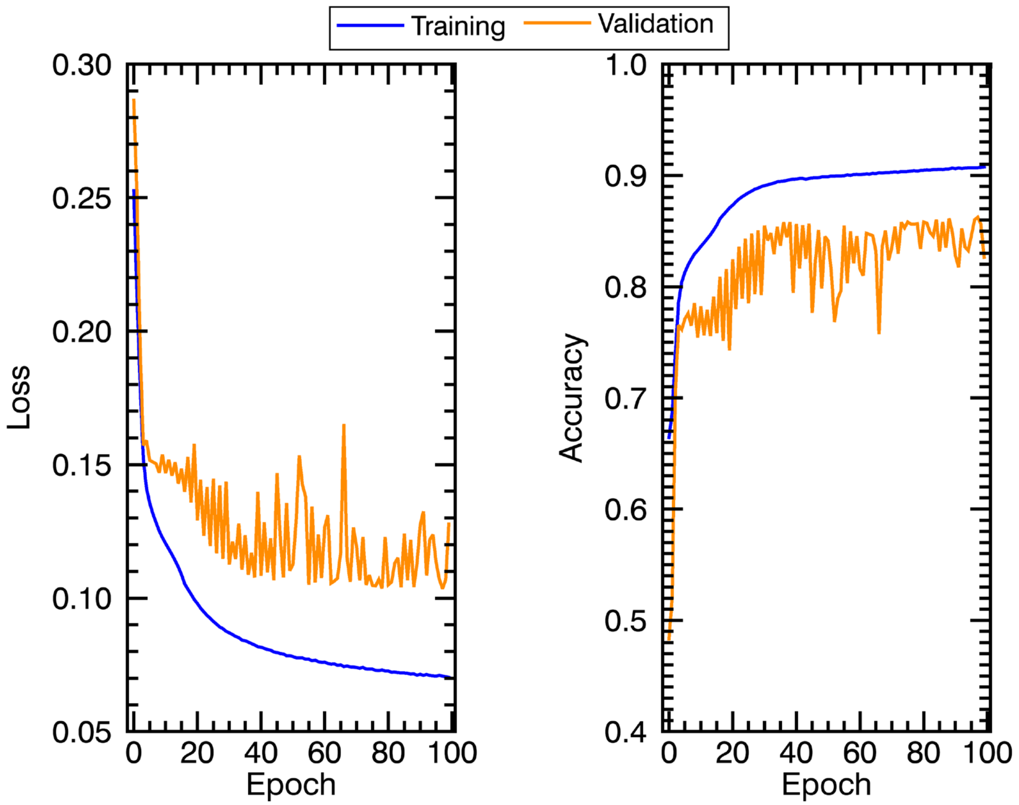
- Current ANN framework consists of 2 hidden layers
- Long Short-Term Memory Layer – To determine patterns in time series data
  - Currently considers pervious 30 timesteps
- Dense Layer – acts as a decision layer as whether data looks like sheath observations

The training data set

- Initial training data set contains 138 days from 2015
- Each day is separated into 2 second observation slices, B measurements are down-sampled to match SWEA cadence
- Magnetosheath is hand-identified for each orbit
- In total, ~3.8 million observations points

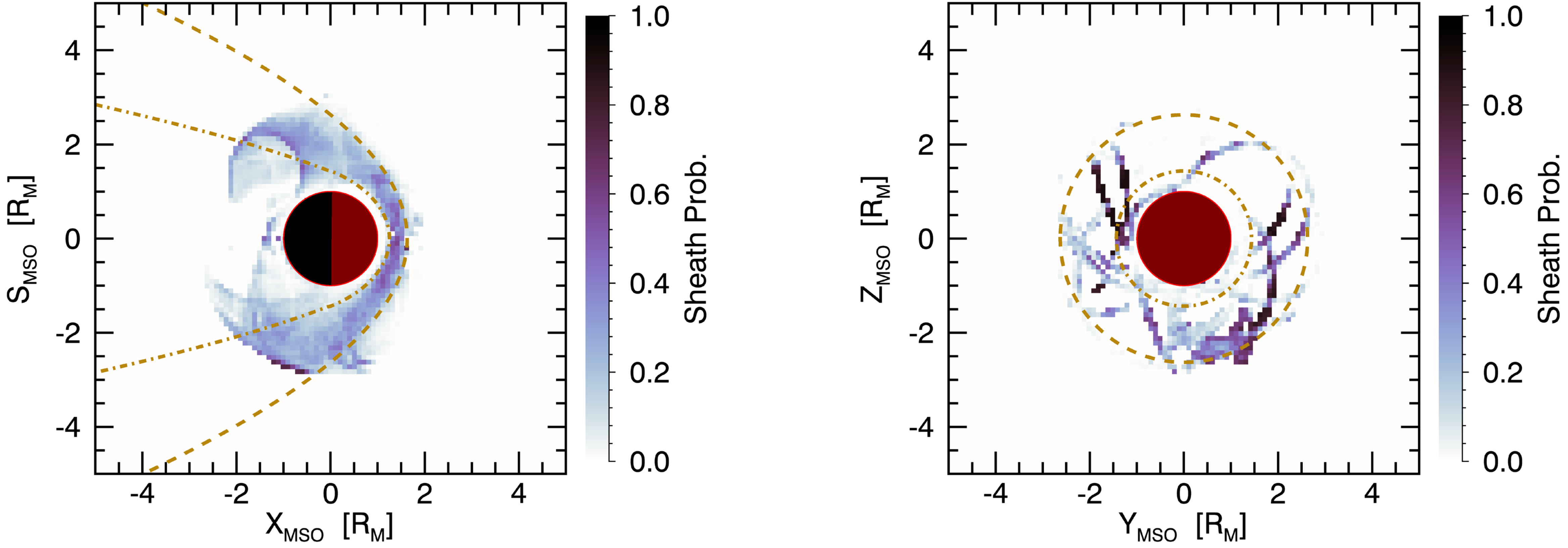


Training the Neural Network



- Dataset is split into 70% Training set and 30% Validation set
- ANN is trained over 100 epochs
- Each epoch the training set is used to determine weights and loss which is minimized. Validation set monitors how well the ANN is doing
- Current ANN achieves ~90% total accuracy, combining both training and validation sets
  - Still different knobs to turn and possible improvements to model

Sheath Prediction



- Predictions cover data from November 2014-November 2018
- Includes predictions of sheath > 0.5
- Bowshock and IMB from Trotignon et al. 2006

Very Early Application of MDI over the Mission

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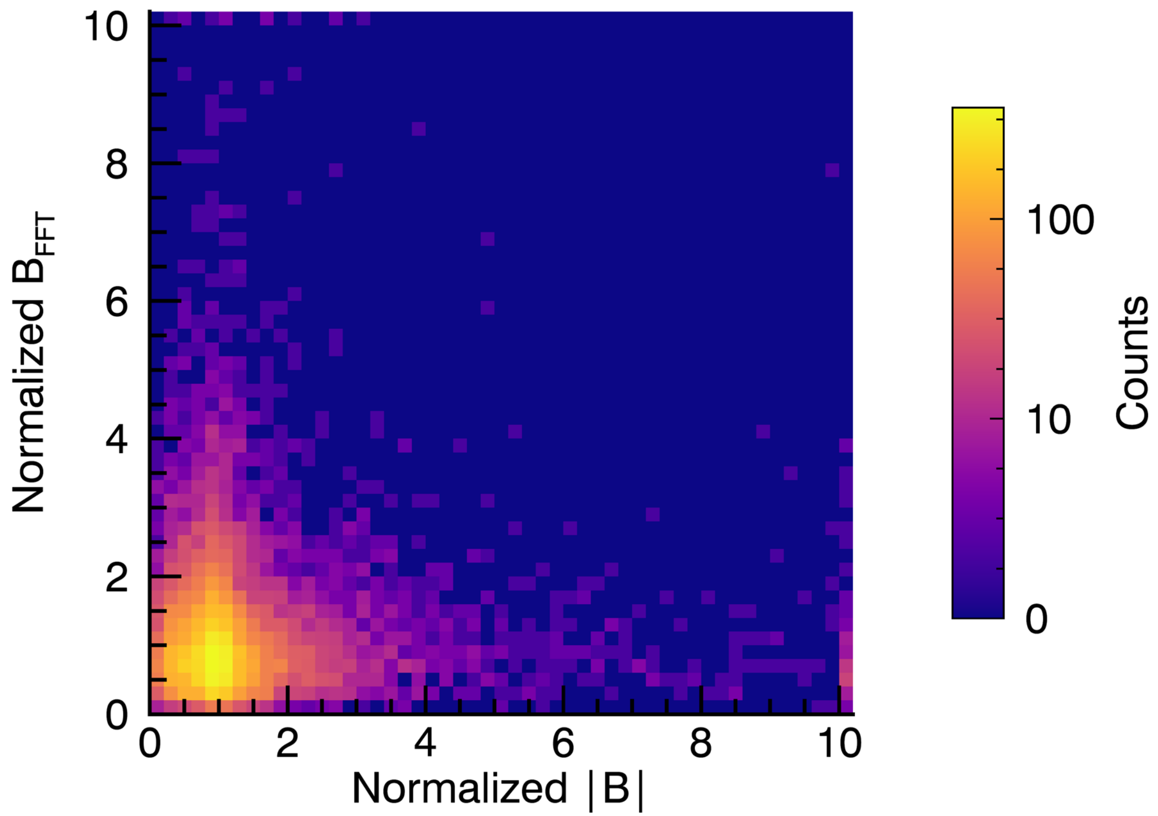
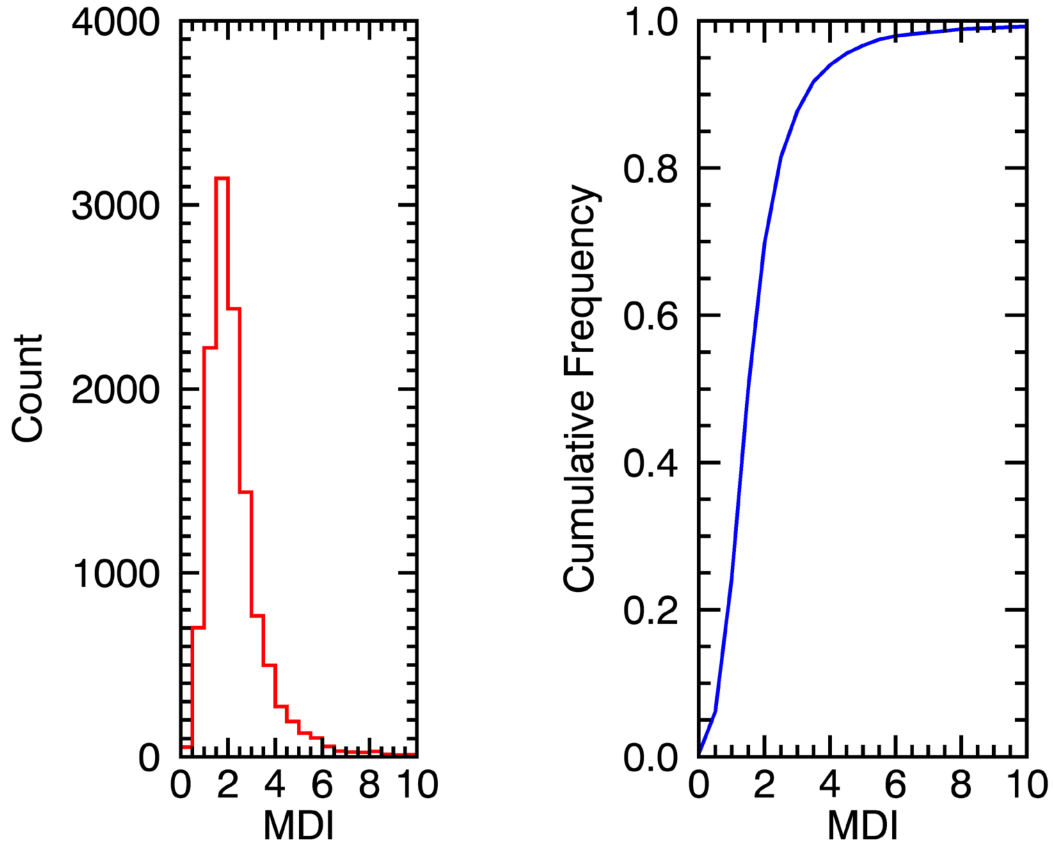
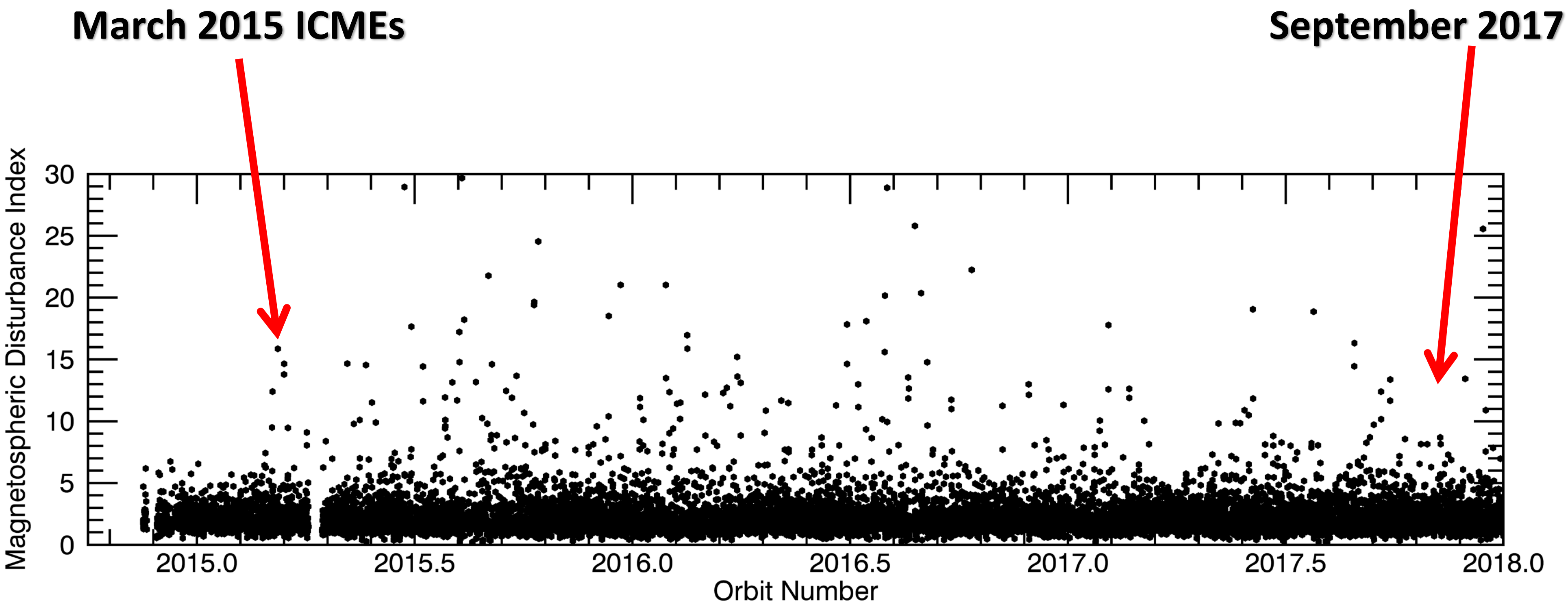
Ingredients of MDI



Distribution of MDI



MDI during 2014 - 2018



Going Forward

- The ANN framework currently achieves ~90% accuracy.
  - Visual inspection shows it does fairly well so far, but could be better
- Only trained on 2015 data, future training should include days throughout the mission covering more solar drivers conditions, seasons, and orbits
- May include other data to help identify the sheath
- Initial application of MDI over a portion of the dataset was shown, but refinement to the normalization
- Repeat process on other bodies
  - Venus is an obvious next step, very similar to Mars, does space weather impact the planet similarly?