Automatic Detection of Dipolarization Fronts in the Earth's Magnetotail With Supervised Machine Learning

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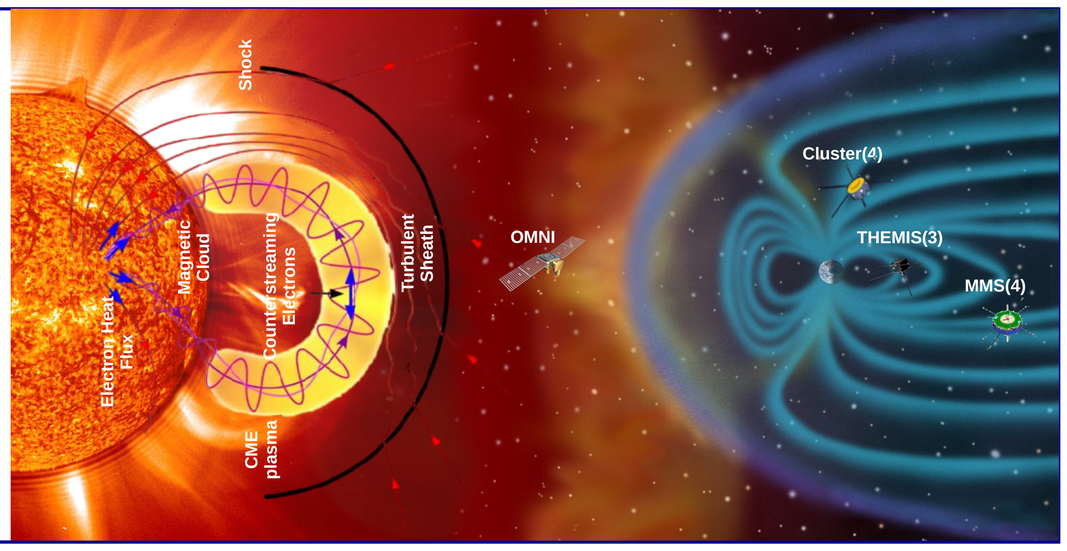
Motivations

- The **Multiscale Magnetospheric Mission (MMS)** provides unprecedented resolution of in-situ plasma environments, offering a unique opportunity to improve space plasma classification.
- Significant developments in deep learning, particularly fully **convolutional neural networks** (FCNs), offer powerful tools for analyzing complex spatiotemporal data like plasma measurements.
- There is a need for robust, **automated methods to classify and interpret dynamic plasma regions** across large volumes of spacecraft data.
- Demonstrating the transferability of machine learning models across missions (e.g., **Cluster, THEMIS**) is essential for building generalizable tools for heliophysics.
- In this study, we apply **Hugo Breuillard**'s et al. (2020) fully convolutional neural network (FCN) algorithm to data from three major space missions: **MMS, Cluster, and THEMIS.**

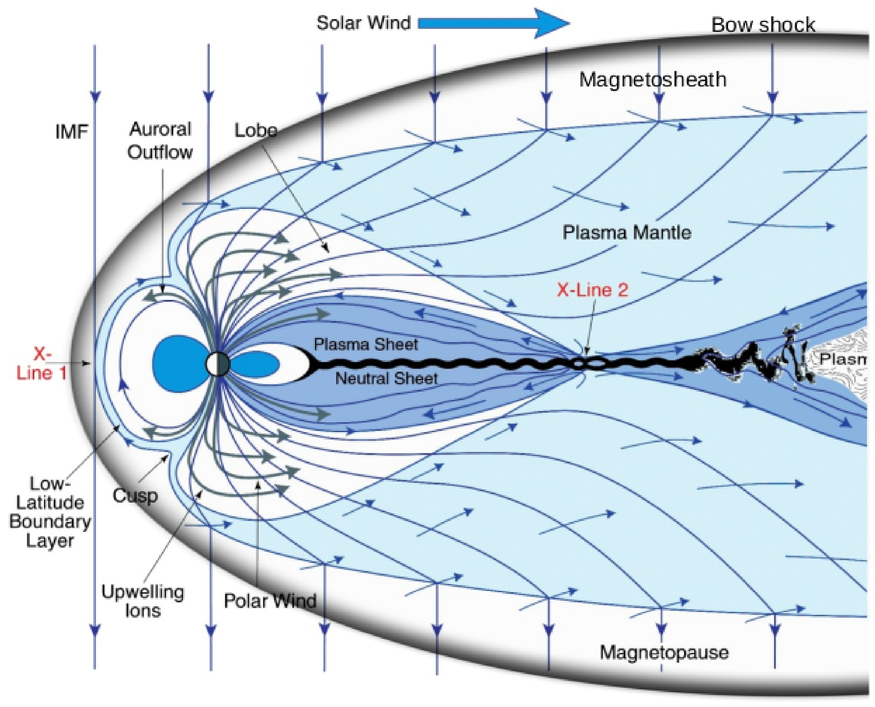


Research Questions

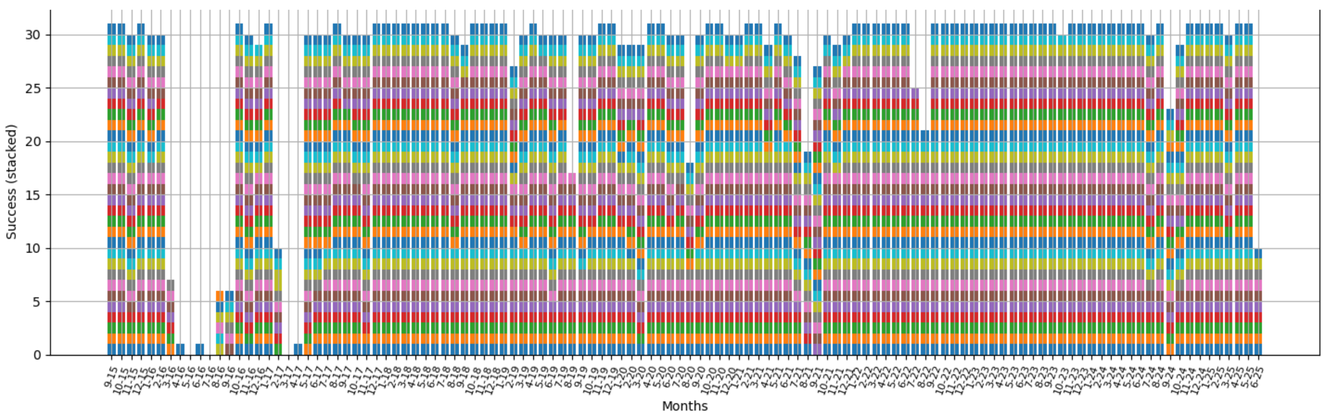
- How accurately can an FCN model classify major plasma regions using MMS data from 2015 to 2025?
- Which plasma region characteristics are most critical for effective classification by deep learning algorithms?
- Can the FCN model maintain high performance when applied to previously unlabeled or unseen MMS data?
- How well does the FCN model generalize to other missions, such as Cluster and THEMIS, with different instrumentation and sampling rates?
- What are the limitations and challenges in using FCNs for real-time or onboard plasma classification in future space missions?

Labels for the 10 different near-Earth regions in our model

Regions	Labels
Solar wind	SW
Ion foreshock	FS
Bow shock	BS
Magnetosheath	MSH
Magnetopause	MP
Boundary layer	BL
Magnetosphere	MSP
Plasma sheet	PS
Plasma sheet boundary layer	PSBL
Lobe	LOBE

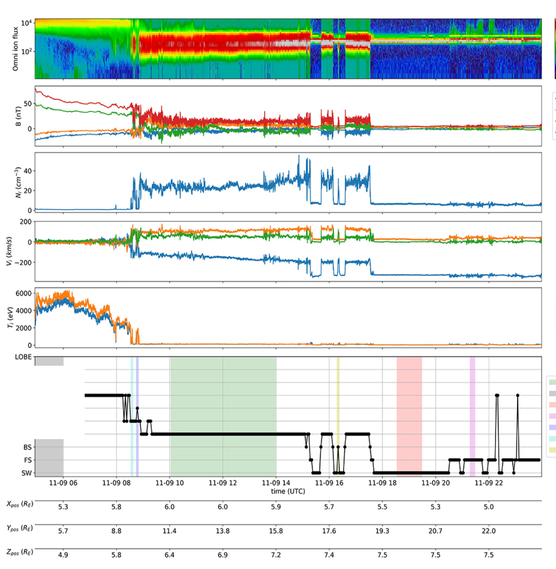


Representation of MMS data days that the model successfully worked on between 2015 and 2025

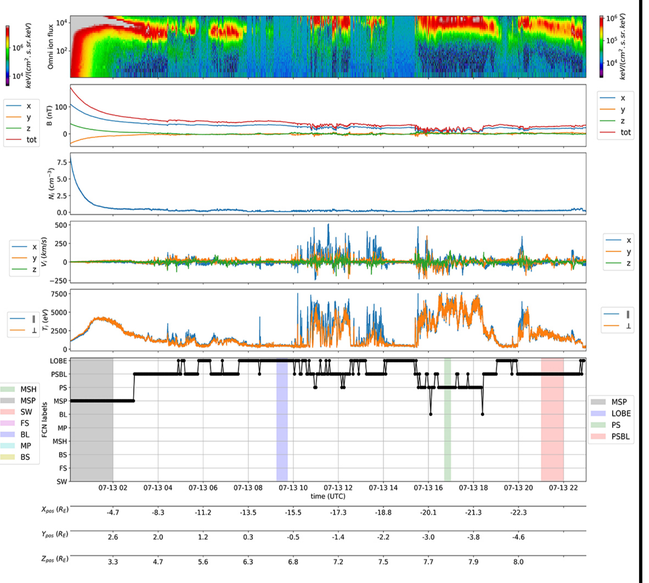


We show that MMS data availability from 2015 to 2025 varies over time, highlighting how data completeness depends on both technical and organizational factors, while data processing for Cluster and THEMIS is still in progress.

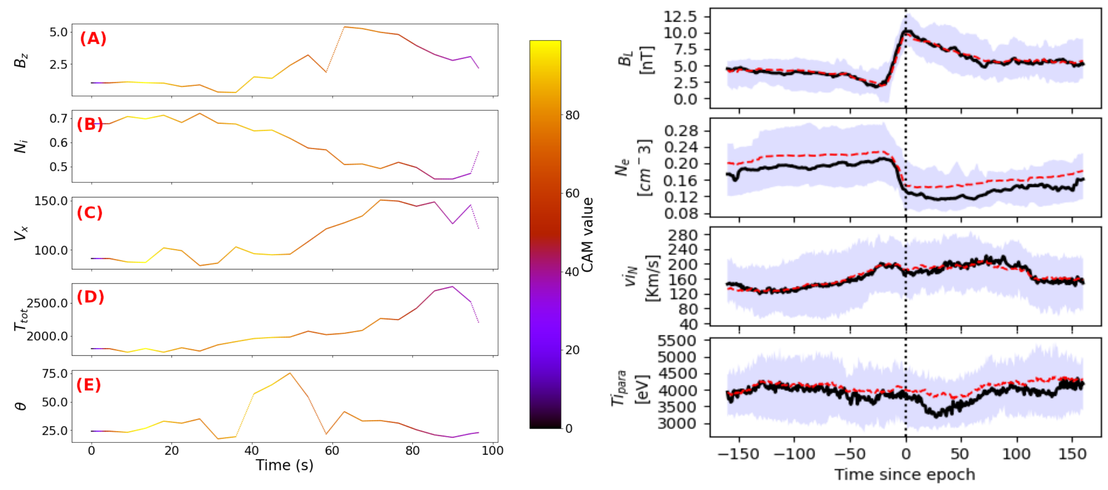
Example of MMS dayside classification



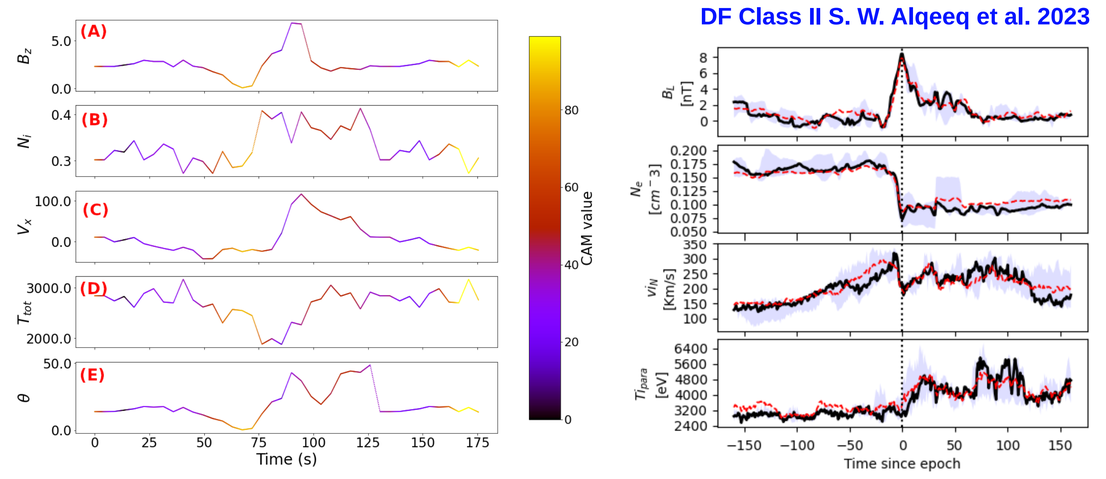
Example of MMS nightside classification



DF Class I S. W. Alqeeq et al. 2023



DF Class II S. W. Alqeeq et al. 2023



A good agreement was found between the results obtained using the FCN model developed by H. Breuillard et al. (2020), originally designed to detect 10 different near-Earth regions, for the detection of Dipolarization Fronts (DFs) in the Earth's magnetotail, and the statistical study of DFs using MMS observations by S. W. Alqeeq et al. (2023).

Conclusion

- We demonstrate the effectiveness of a **fully convolutional neural network (FCN)** in **automatically classifying 10 key plasma regions near Earth** using over **10 years of labeled MMS data**. The model showed high accuracy.
- We will extend to other missions (e.g., **Cluster, THEMIS**) using transfer learning, aiding scientific data selection and onboard event detection.
- **Some parameters appear well suited for detecting plasma jets in the Earth's magnetosphere.** We began extending the algorithm to enable automatic detection of these jets, but only preliminary tests were conducted due to time and technical limitations.
- This exploratory work represents a first step toward adapting the model for identifying such transient events. We also concluded that ML is not essential for MMS data, based on specific criteria are likely sufficient. However, if similar analyses are to be conducted using THEMIS, Cluster, or other space missions, an ML model trained on MMS data could be valuable to complement and enhance the classical detection approach.