Machine Learning Algorithms for Detection of Plasmoids in Multiple-X-Line Collisionless Reconnection Regions

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Motivations

Goals

- Understanding the role the plasmoid instability plays in reconnection in Earth's magnetotail is key to understanding the connection between the microscale and macroscale physics
- Available in-situ data of magnetotail reconnection has fundamental limitations to its interpretation
- We are developing an algorithm to aid plasmoid detection in magnetotail reconnection data
- The algorithm is currently low-precision due to class imbalance, so we are currently working on improving performance

Near/mid magnetotail reconnection

- Near/mid-tail (10-40 Re) reconnection tends to be bursty and associated with dipolarizations during substorms
- Can have finite guide field
- Internal magnetosphere dynamics are thought to play a large part in the onset and progression
- Not simple driven reconnection like the slow far-tail reconnection

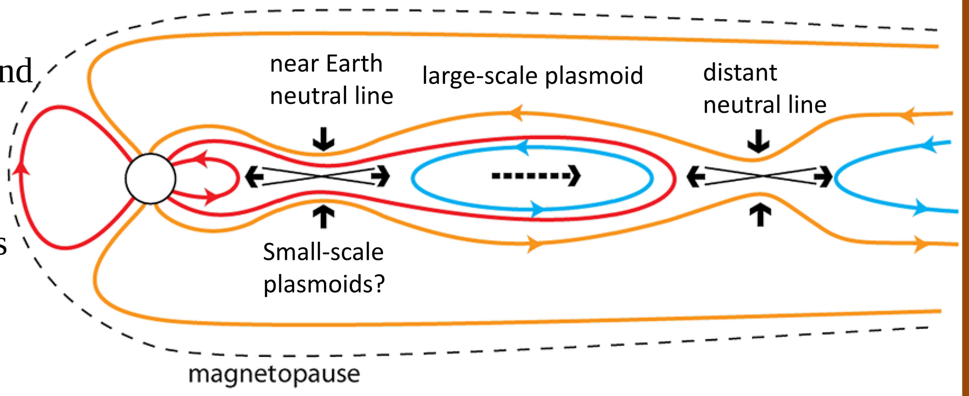
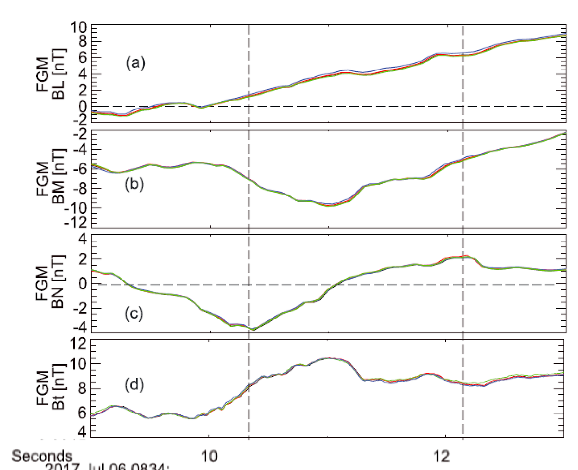


Figure adapted from Eastwood et al. 2017 "The Scientific Foundations of Forecasting Magnetospheric Space Weather"

Small-scale plasmoids in near-tail reconnection

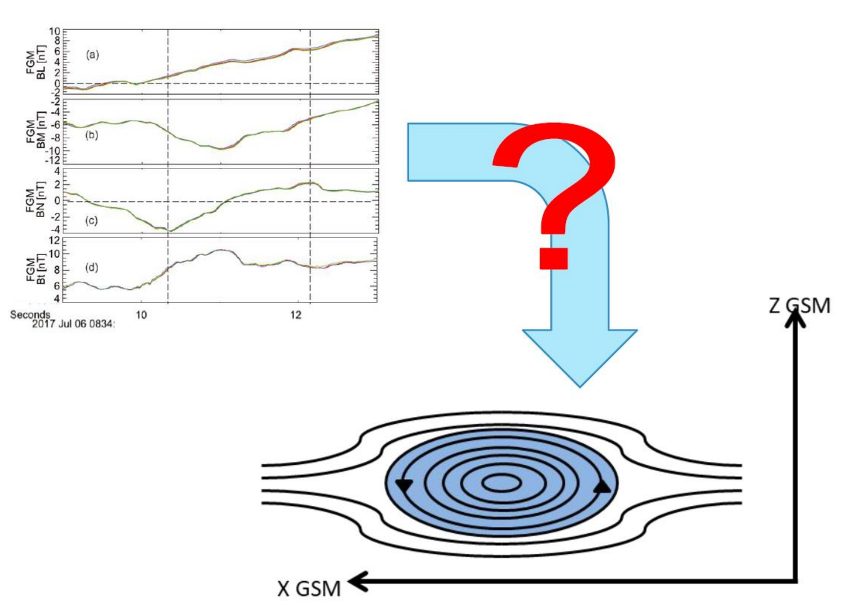
- The development of many plasmoids would significantly impact reconnection dynamics and energization efficiency
- Multiple observations of small-scale near-tail plasmoids have been made (e.g. Chen et al. 2008, Sun et al. 2019)
- Understanding the role of plasmoids requres a comprehensive understanding of the entire near-tail reconnection region



Example magnetotail plasmoid magnetic signature with characteristic bipolar signature in BN (B component normal to current sheet) from Sun et al. 2019

The challenge of in-situ spacecraft data

- Spacecraft is effectively one point in space
- Spacecraft moving through evolving 3D structure gets a 1D picture of the 4D spacetime
- Special techniques must be used to draw robust physics conclusions from this limited data



Methods

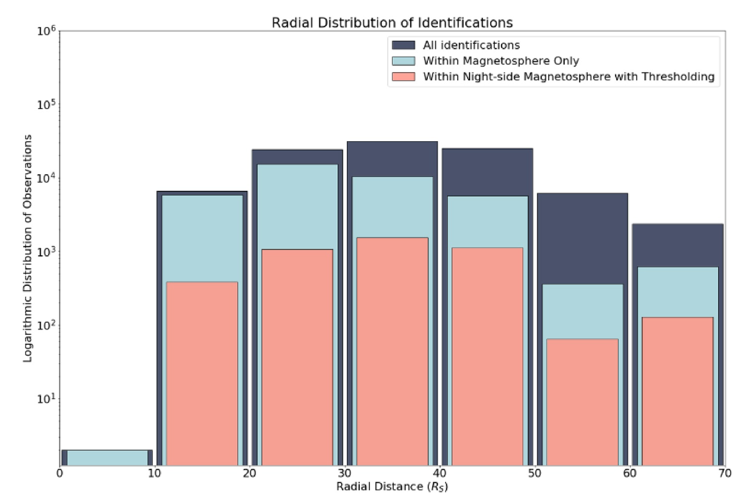
Machine Learning (ML) for nuanced physics conclusions

A ML algorithm can:

- Be nuanced like identifying by eye
- Be quick like other algorithms
- Learn to detect non-ideal plasmoids

Proof of concept, existing similar work:

- classification of reconnection in Saturn's magnetotail using Cassini magnetometer data (Garton et al. 2021)
- Effective statistical survey of many reconnection regions
- Model had good performance even with just magnetometer data



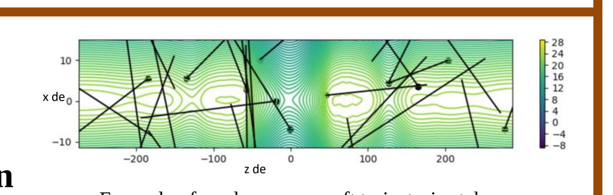
Distribution of reconnection events detected by Garton et al. (2021) using an Artificial Neural Network https://doi.org/10.1029/2021JA029361

Rationale and concerns

How to train a model to detect structures in space data which we cannot already detect?

Idea: use faux spacecraft trajectories through a simulation to train a Convolutional Neural Network-based model to detect plasmoids in the magnetotail

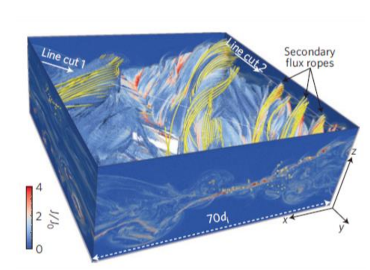
- CNNs are often used for object detection and classification problems
- Simulations (especially 2D) are inexpensive and the state of the entire plasma is known, establishing a rigorous ground truth
- Parameters and initial conditions can be changed to create examples of reconnection in varying tail conditions



Example of random spacecraft trajectories taken through a 2D reconnection simulation plotted over magnetic flux contours

Simulation details:
Code : VPIC
Size : 2000 x 250 de (400 x 50 di)
Resolution : 8880 x 1110
Mass ratio : 25
Upstream beta : 0.01
Initial conditions : antiparallel collisionless harris current sheet (no tail configuration)

Contact kbergste@pppl.gov with methodology questions

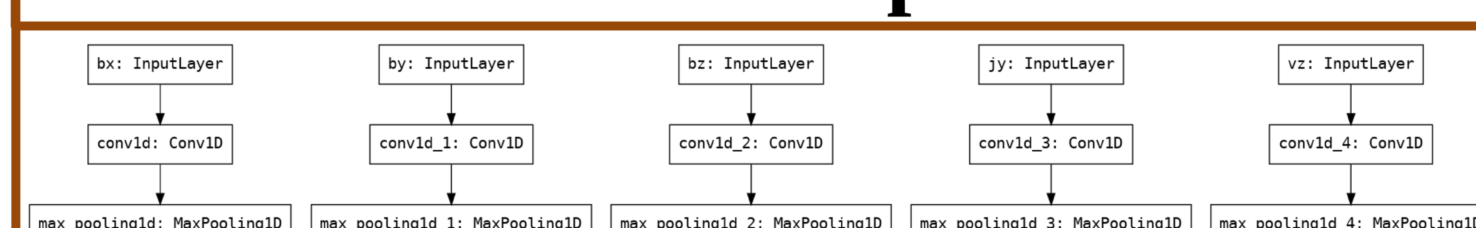


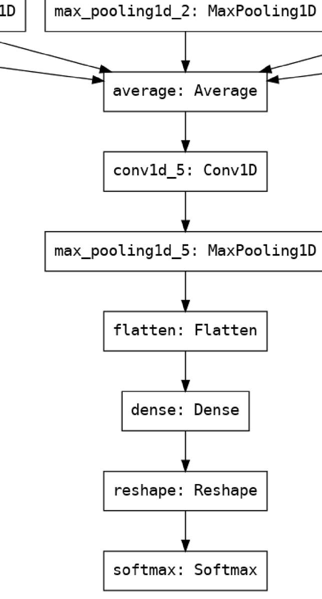
Example of 3D turbulent reconnection from Daughton et al. (2011)
Would an algorithm trained on 2D cases be able to detect those secondary flux ropes?

Potential concern: the concept of "garbage in, garbage out"

- The quality of results is directly dependent on quality of the training data sample
- Good performance requires a lot of training data
- Are 2D simulations sufficient for a 3D reality? We plan to find out.

Model design- typical CNN-based classifier for each datapoint





- 1D CNN
- Binary classifier- point is within a plasmoid or it isn't
- Model inputs are 1d segments of magnetic field, velocity, and current data
  - The prediction is done for a central fraction of each segment
- Convolution and pooling is done to each input separately and then together
- Cross-entropy loss

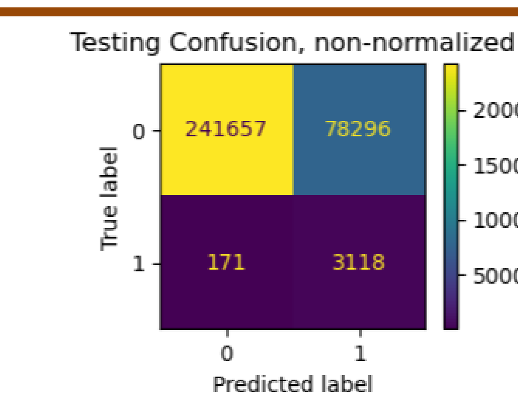
Model details:
Learning rate : ~0.009
convolutional filters : 16
Convolutional kernel size : 3
Pooling size : 2
epochs : 10
Samples per category after undersampling: [96112, 10140]
Contact kbergste@pppl.gov with methodology questions

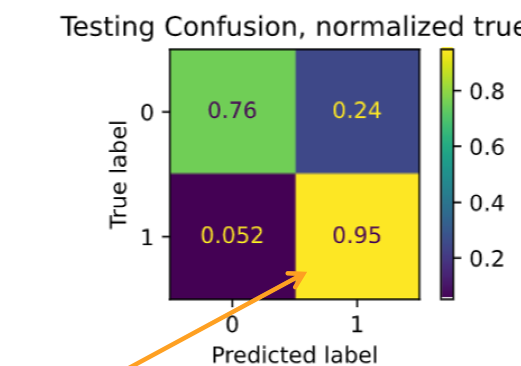
Preliminary Results

Results- Class imbalance affects precision

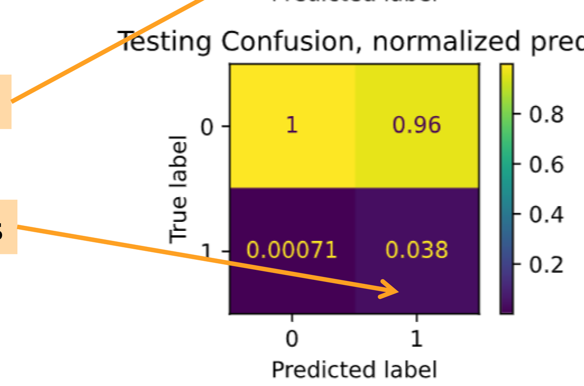
Accuracy: the fraction of all predictions which were correct
Precision: fraction of the predicted positives which are truly positive
Recall: fraction of the true positives which were predicted positive

- Binary confusion matrices report the populations of **true negatives (0,0), false positives (0,1) , false negatives (1,0), and true positives (1,1)**, and can be normalized by the predicted or true population
- Recall is fairly good for both positives and negatives, but **the overwhelming population of negatives means false positives overwhelm true positives**





recall, plasmoids



precision, plasmoids

Conclusions and Next steps

- Interpretation of in-situ data of magnetotail reconnection is a methodological challenge
- We are developing CNN-based algorithms to aid plasmoid detection in magnetotail reconnection data
- Current algorithm has quantifiably low precision, which we need to improve before using the algorithm for physics

Next steps to improve precision

- Additional methods to combat class imbalance, e.g Synthetic Minority Oversampling TEchnique (SMOTE)
- Changes to model structure such as hyperparameter optimization with Optuna
  - More or fewer convolutional layers, different learning rate (step size when minimizing the loss function), different convolutional kernel size, etc.
- Development of a model using more data that would be available from a spacecraft (other components of v and j, density, electron distribution functions)
- Multispacecraft-like implementation to make use of the four-point measurements from Cluster and MMS which provide estimates of spatial gradients

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