Machine learning classification of Mercury magnetospheric boundary crossings

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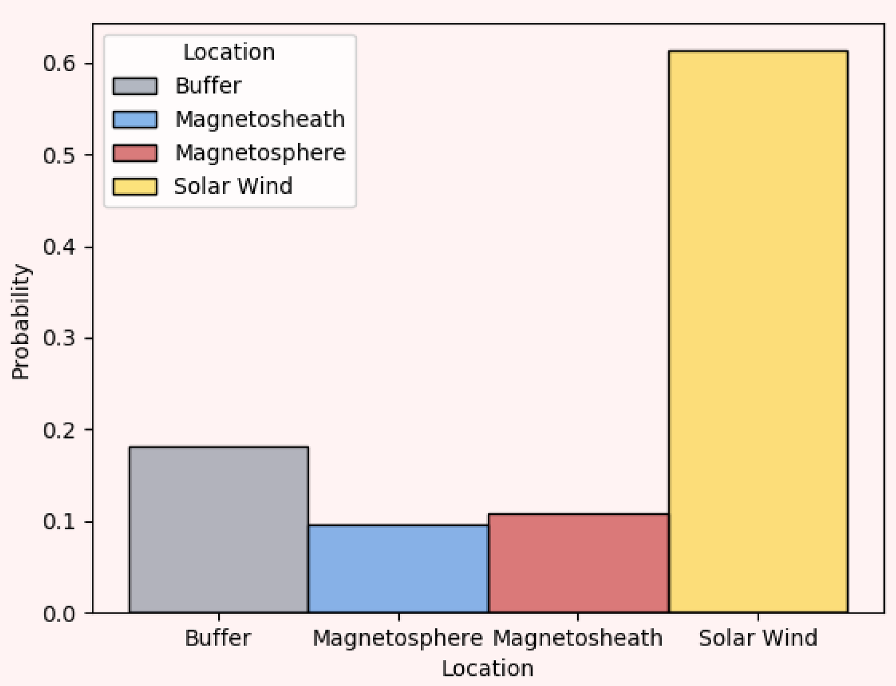
Introduction

Given the astronomical quantities of data generated by astrophysical instruments, machine learning (ML) and artificial intelligence (AI) models maximise our ability to understand and use these data. This project focuses on assessing the viability of automatic detection algorithms for classifying time series data. Specifically, we seek to develop an AI which can classify the regions of Mercury's magnetosphere based on observations made using the MErcury Surface, Space ENvironment, GEochemistry, and Ranging (MESSENGER) spacecraft's magnetometer (MAG) measurements taken between 2011 and 2015.

Dataset

- The target variable is the magnetospheric region MESSENGER is passing through when measurements are taken. The three features used to train the model are the magnetic field components measured by MAG.
- A manually labelled list of magnetopause and bow shock crossings created by [Sun *et al.* 2020] is used to train, test, and validate the model.



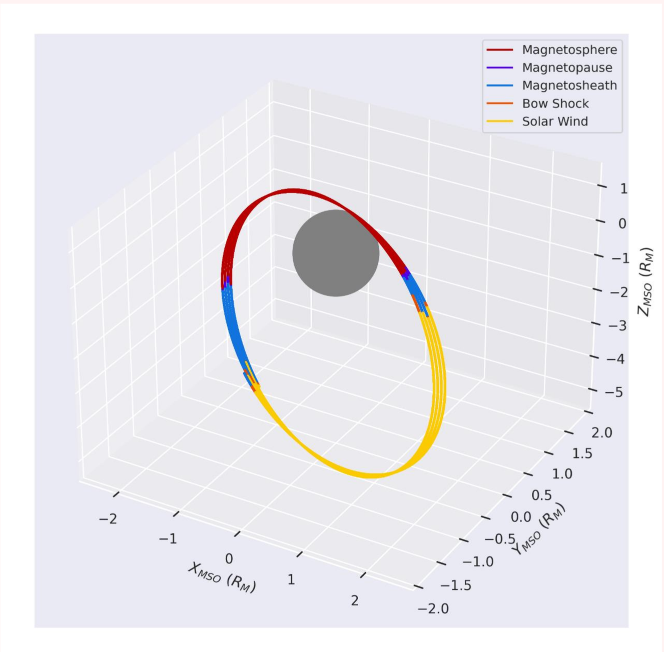


Figure 1
Left: Histogram demonstrating the class imbalance prior to data preparation.
Right: 5 randomly selected orbits of MESSENGER. Colour corresponds to the magnetospheric region as labelled by Sun *et al.* [2020].

Data Preparation and Cleaning

Datapoints were used for training/testing/validation if they were not contained within the transition regions from Sun *et al.* [2020] or inside a 10 minute buffer surrounding these regions. Data were then split into training, testing, and validation subsets by randomly assigning valid 5 minute sequences to a subset. This ensured no time bias was introduced during training.
The data were found to have a significant class imbalance with approximately 80% of measurements being taken in the solar wind with 20% of remaining measurements being evenly split between the other regions. This was resolved by randomly culling solar wind sequences from the testing/training/validation subsets.
The partitioned and class balanced data were also normalised using scikit-learn's RobustScalar module.

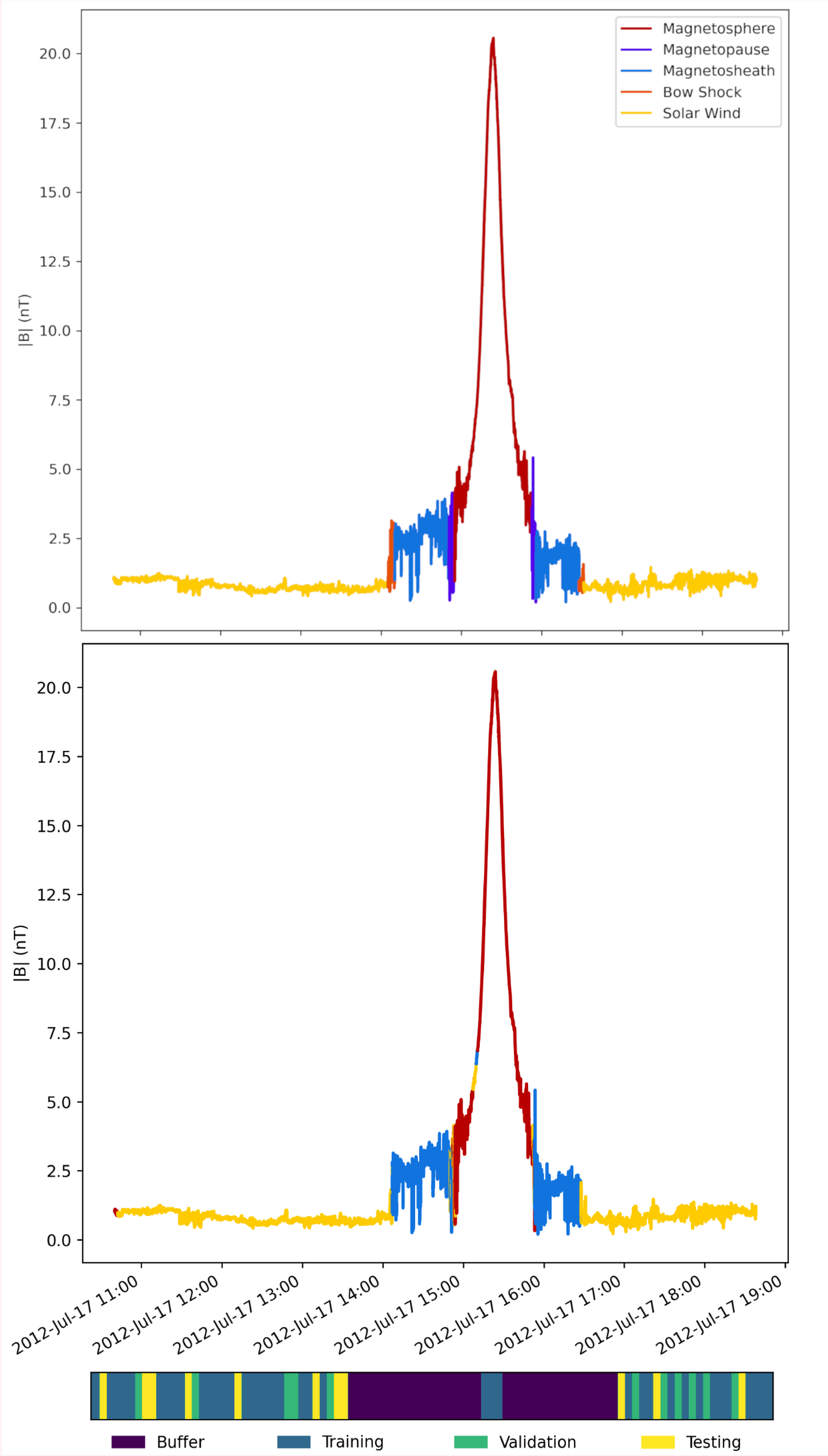


Figure 2
Top: Visualisation of the magnetic field strength vs. time measured by MESSENGER on July 17th 2012 with region labels taken from Sun *et al*. [2020].
Middle: Visualisation of the magnetic field strength vs. time measured by MESSENGER on July 17th 2012 with region labels taken from a prototype Long-short Term Memory (LSTM) Recurrent Neural Network (RNN) trained on data from Sun *et al.* [2020].
Bottom: Visualisation showing which portions of the data was used in testing, training, or validation to train the RNN or discarded as part of the transition region/buffer.

Machine Learning Model

A number of algorithms were evaluated including a feedforward neural network, a gaussian mixture model and random forests. However, the most successful classifier thus far has been a long short-term memory recurrent neural network. The model in Figure 2 consisted of one LSTM cell of size 64 trained with a dropout of 0.2, a learning rate of and a decay of The performance of the model is detailed in the table and confusion matrix below:

	Precision	Recall	F1-Score	Support
Magnetosphere	0.96	0.95	0.96	1841036
Magnetosheath	0.93	0.88	0.90	1836710
Solar Wind	0.84	0.94	0.89	1122062
Accuracy		0.92		4799808

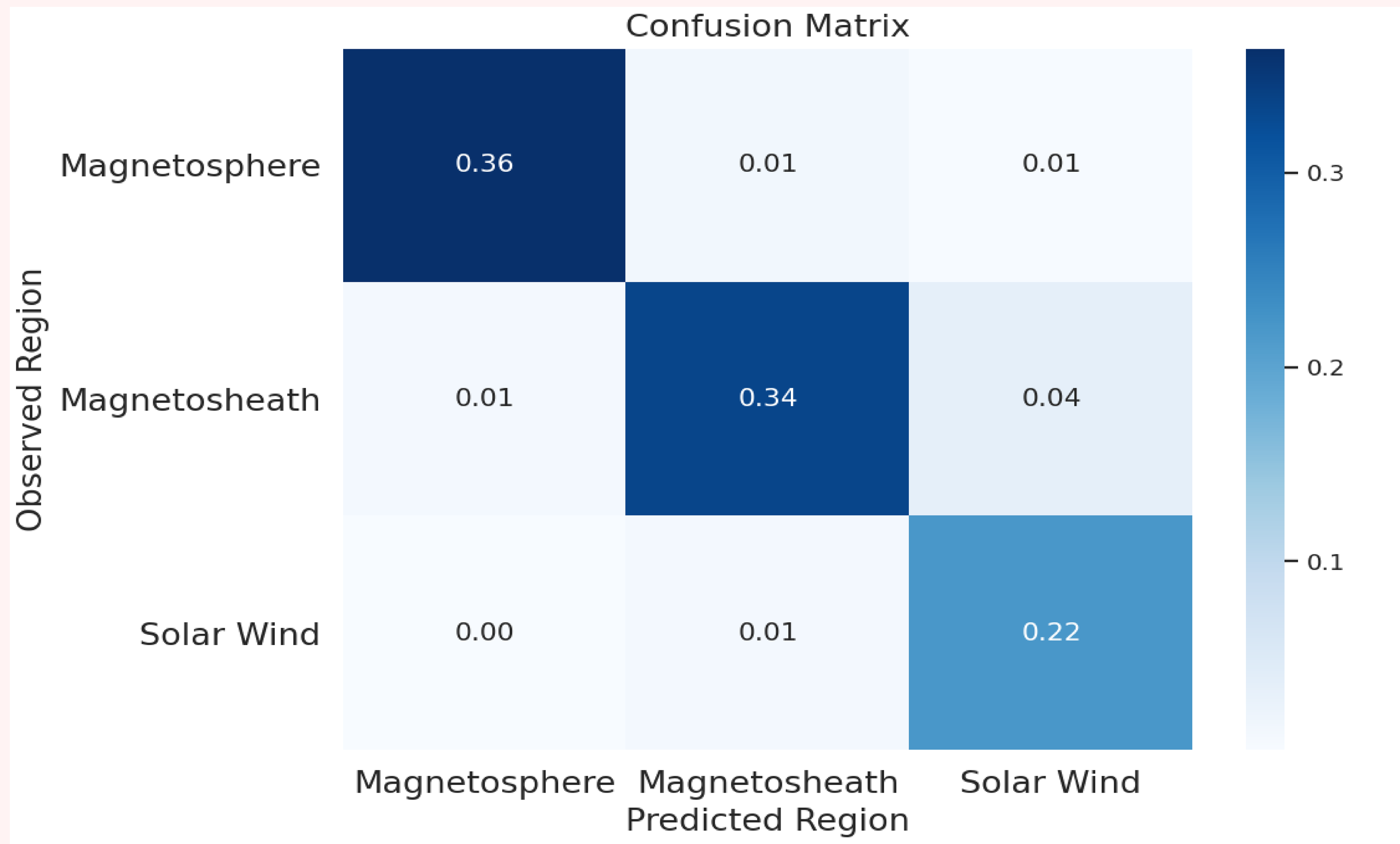


Figure 3
Confusion matrix demonstrating how a prototype FFNN performs in each region of Mercury's Magnetosphere.

Conclusion and Future Work

A LSTM region classifier has been prototyped for this project. Future work will yield improvements to this model *via* parameter tunning and model optimisation procedures. We will also explore the effect shortening the buffer region will have on classification.
Finally, we will produce more detailed analysis of the model performance such as analysing which conditions tend to lead to poorer performance (e.g. seasonal effects, compressions due to CMEs, etc.).
The final, trained LSTM model could be used to quickly classify data for future study, for example to analyse magnetospheric data from the upcoming BepiColumbo mission. The final pipeline could also be generalised for supervised learning for region classification at other planets.

References
Sun, W. J., *et al.*, GRL, 2020

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