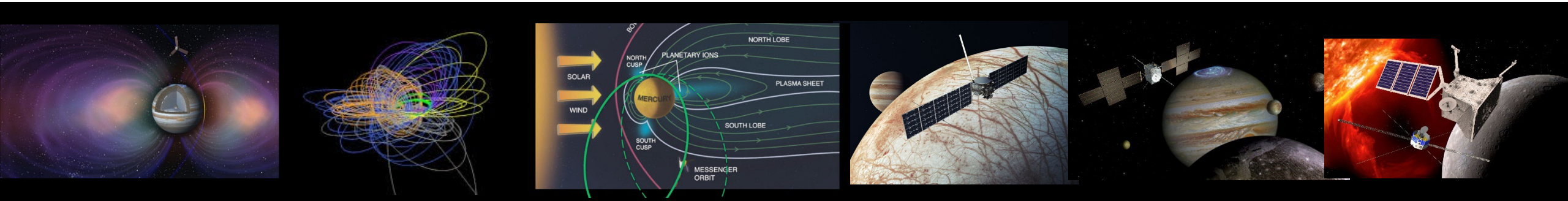
Tools for supervised machine learning in Planetary Space Plasma Physics



1. Domain Introduction – 2. Labelling – 3. Machine Learning approaches

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https://dias.ie/planetary_magnetospheres

DIAS
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1. Machine learning for magnetospheric physics

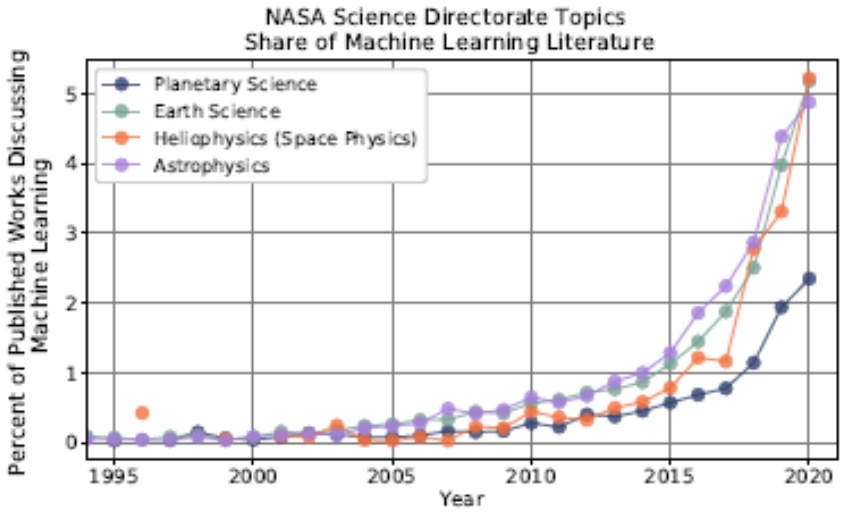
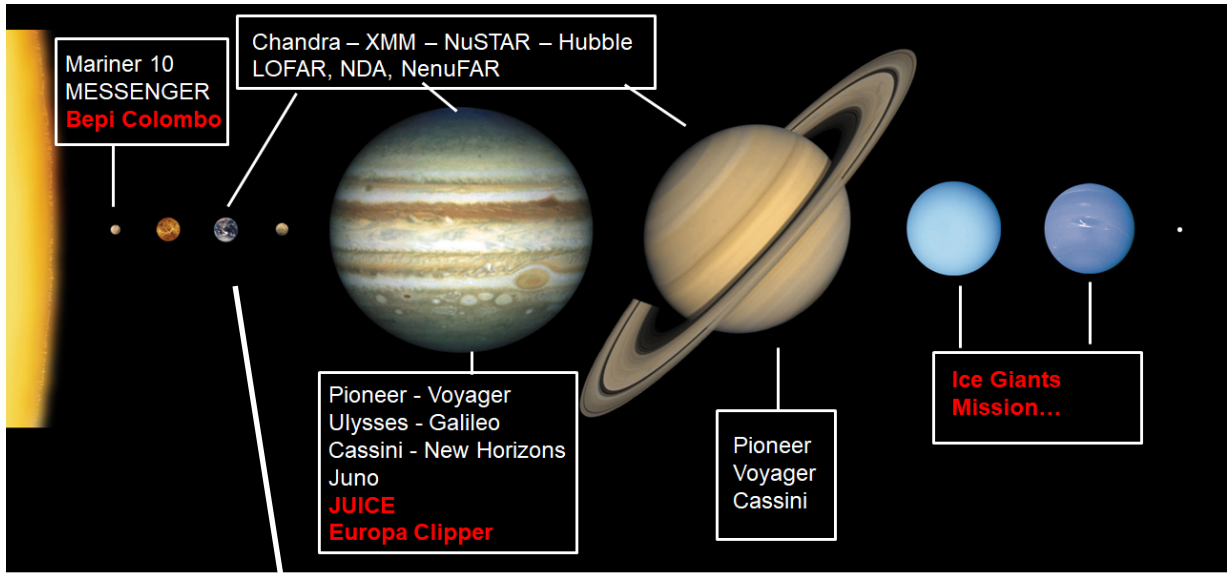
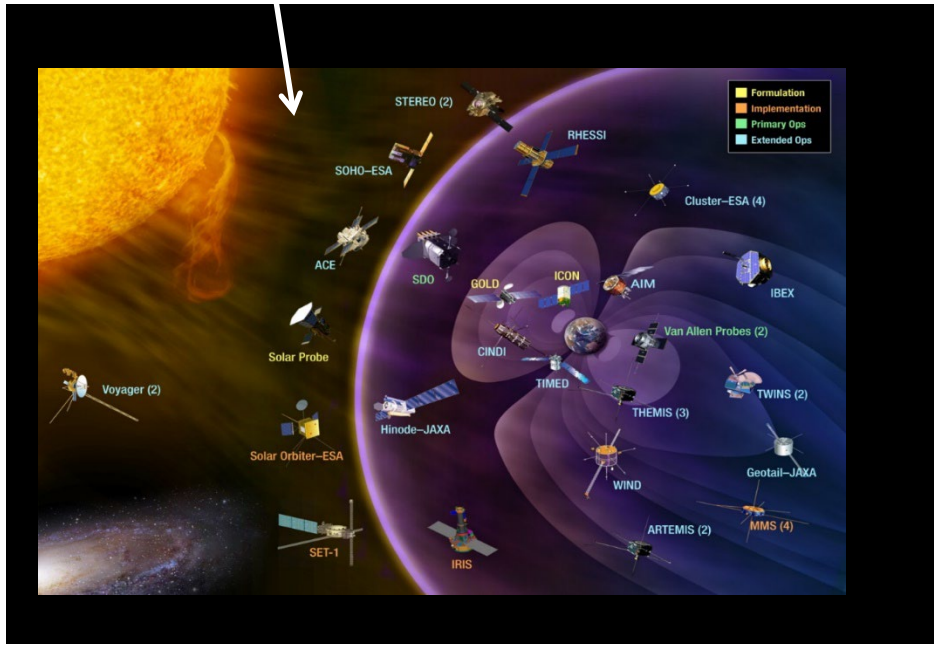


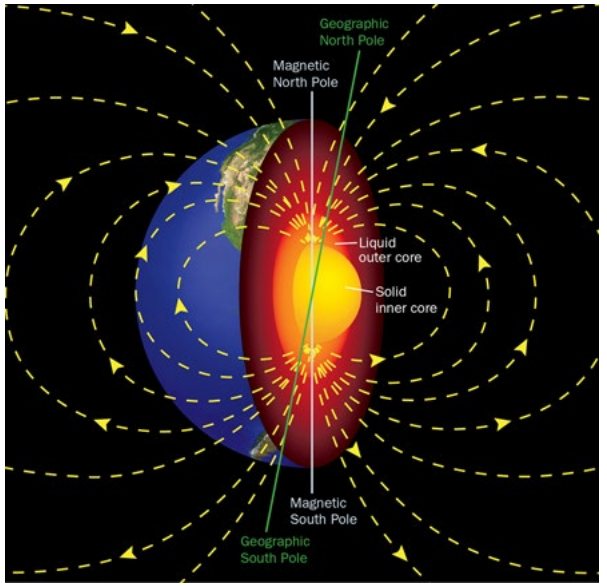
Figure 1: Yearly trends of machine learning across NASA SMD topics as a percentage of published literature. For comparison, in 2019 the term 'modeling' had near identical occurrence rates within publications in both planetary science and Earth science (>50%). Data from Elsevier's Scopus publication database.

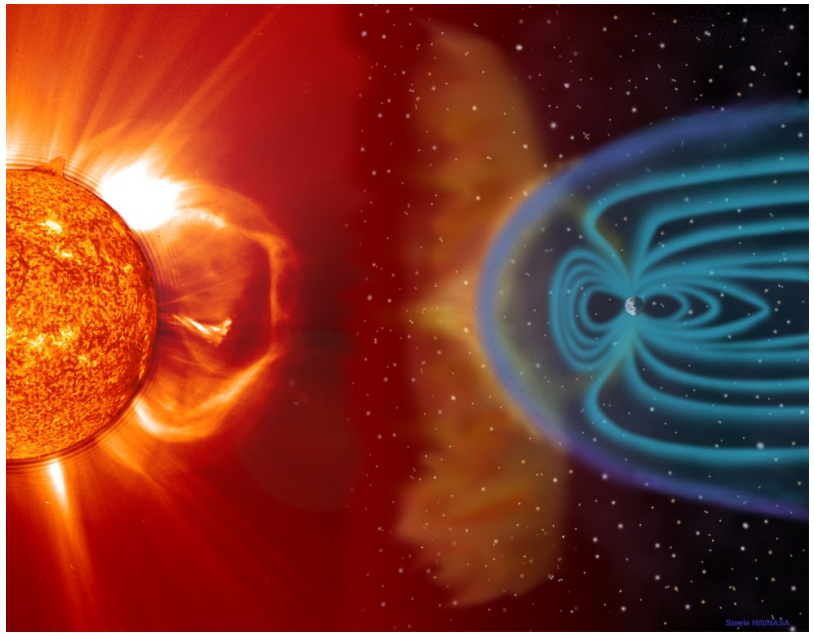
Azari et al., [White Paper, 2020]



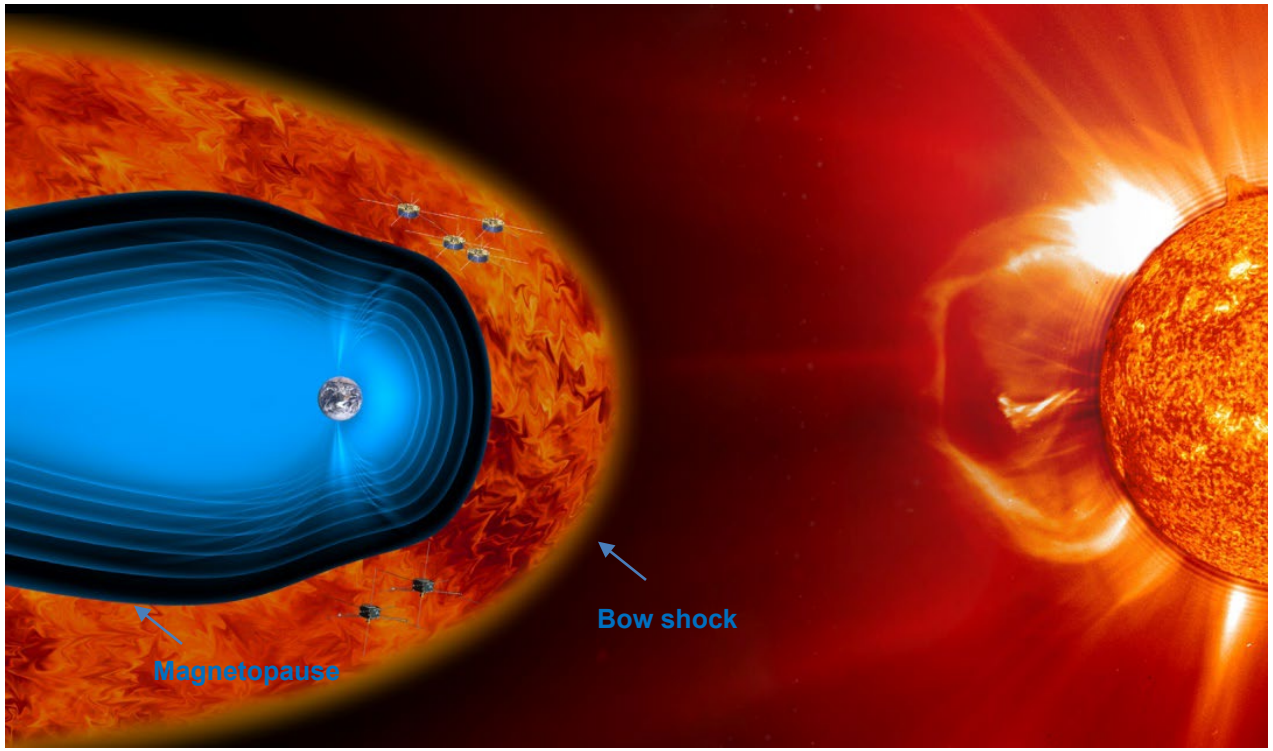


1. Magnetospheres

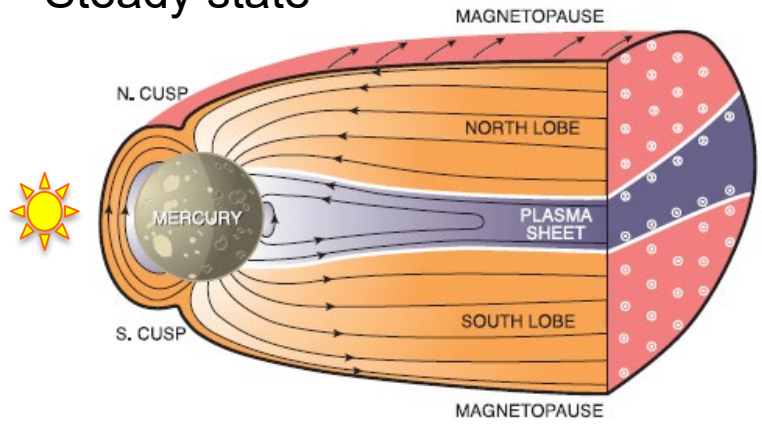




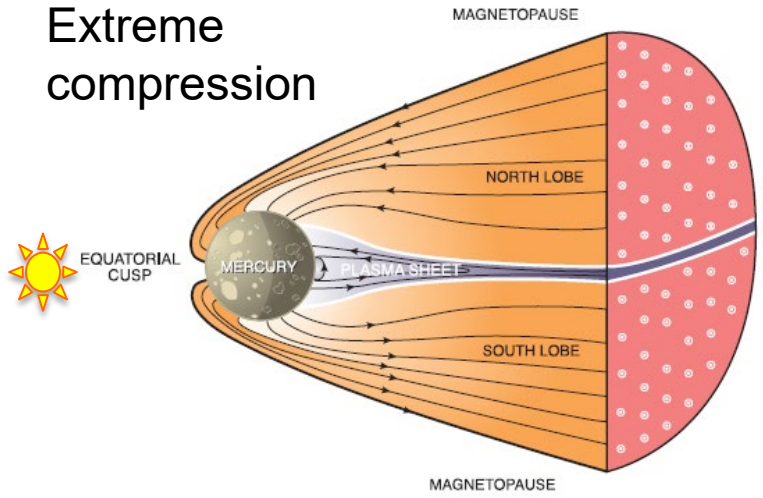
1. Boundary Motion – Reconnection - Auroral Response



Steady state



Extreme compression

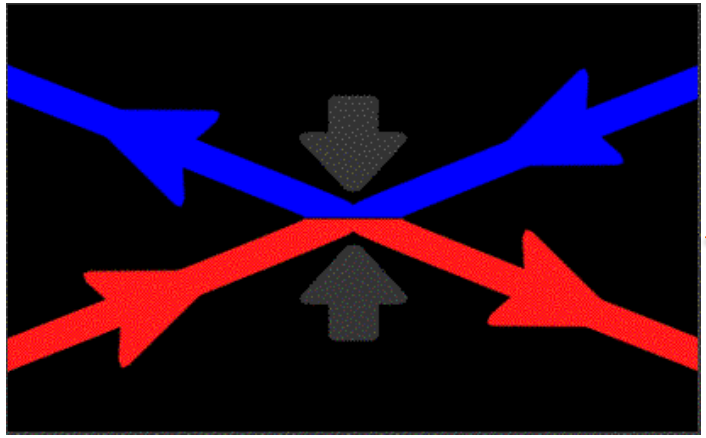


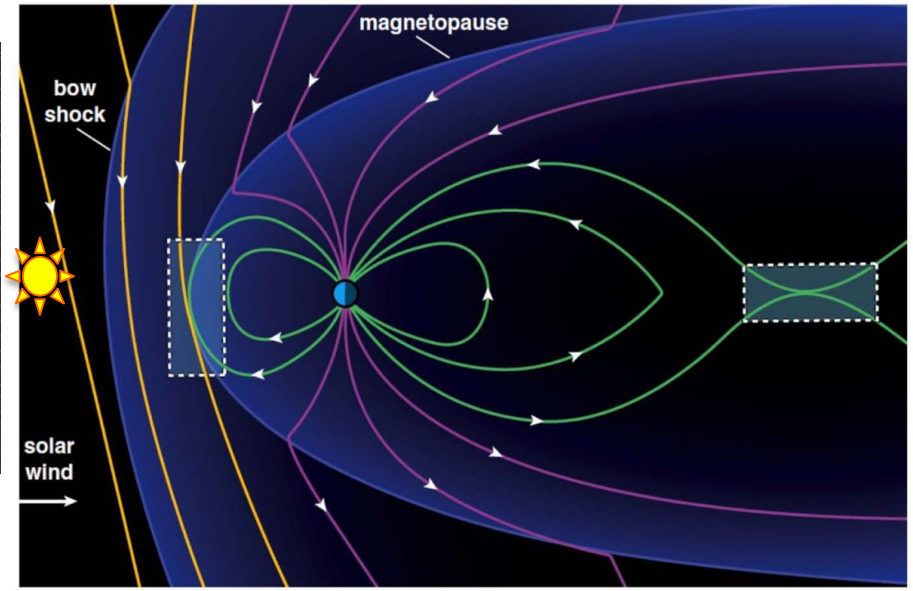
- Position of magnetospheric boundaries reveals nature of solar wind-magnetosphere coupling.

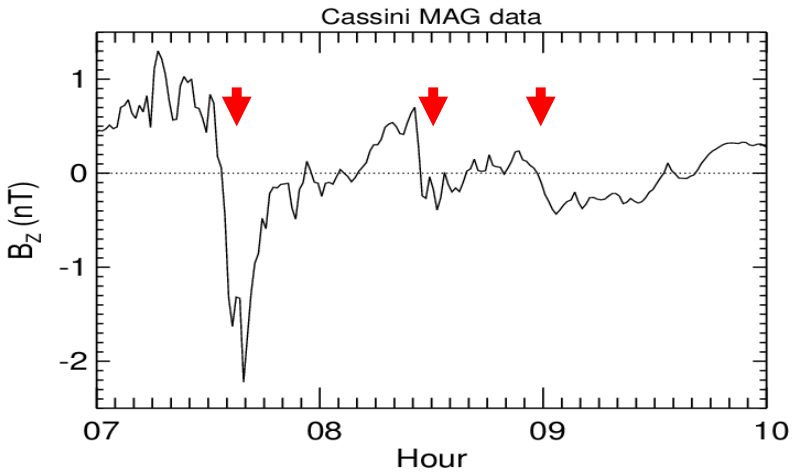
- Characteristic signatures when boundaries crossed in different (magnetic field/plasma/energetic particle/radio) in situ data.

Slavin et al., [Science, 2010]

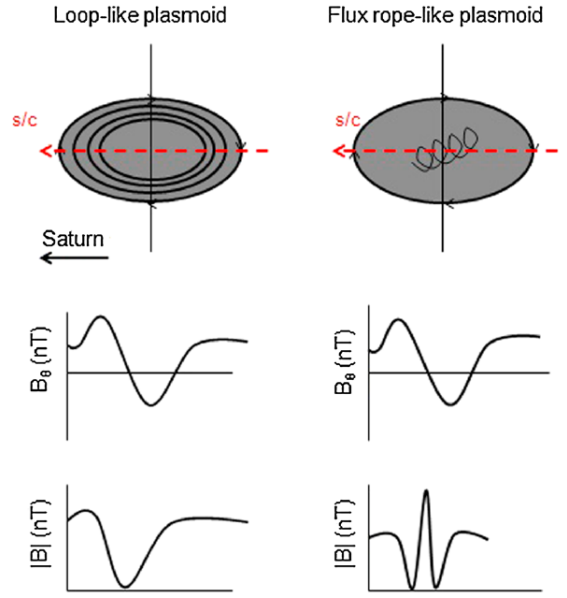
1. Boundary Motion - **Reconnection** - Auroral Response







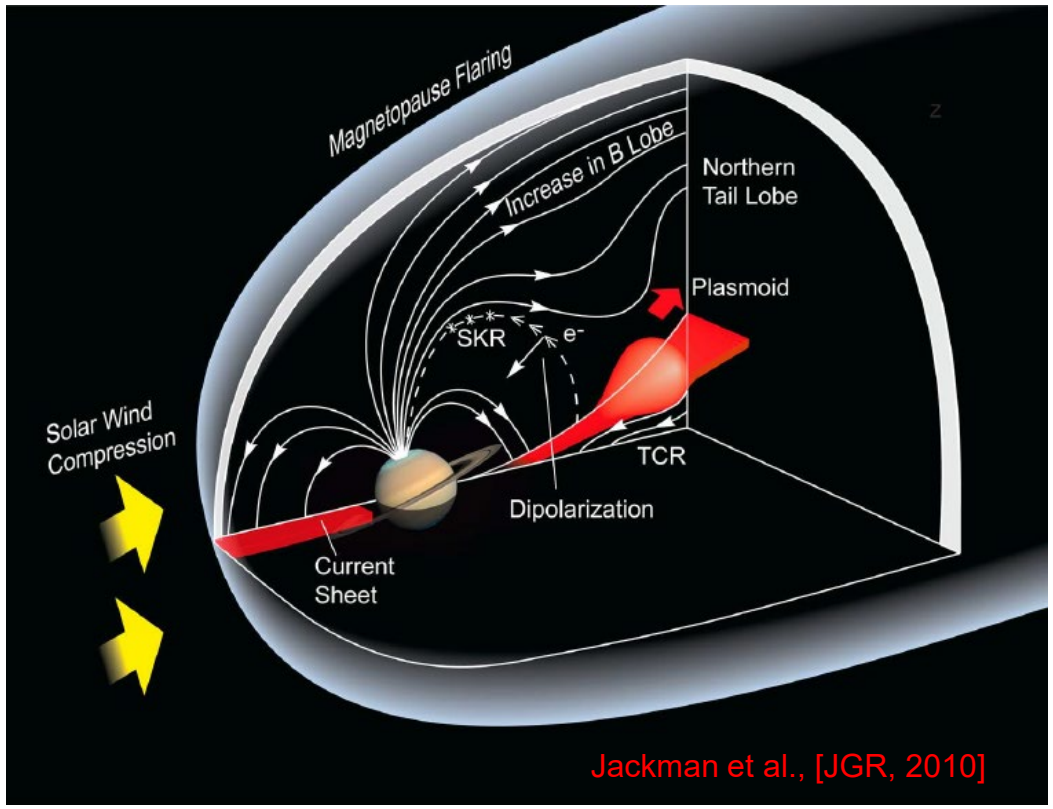
Jackman et al., [2007, 2014]

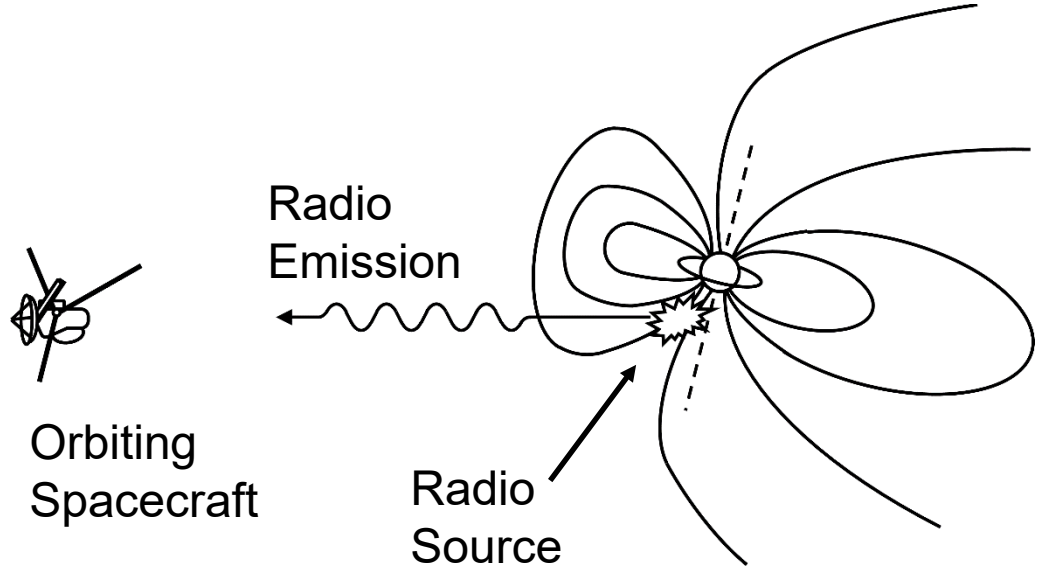


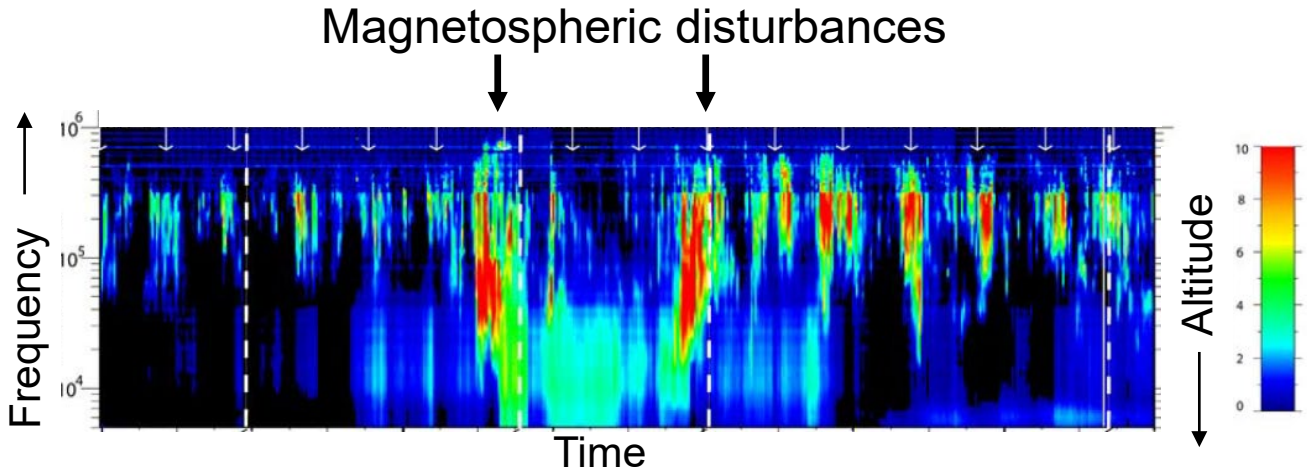
- Products of reconnection can be seen by in situ spacecraft

- Signatures include:
  Field deflections, plasma heating, rapid plasma flows

1. Boundary Motion - Reconnection - **Auroral Response**

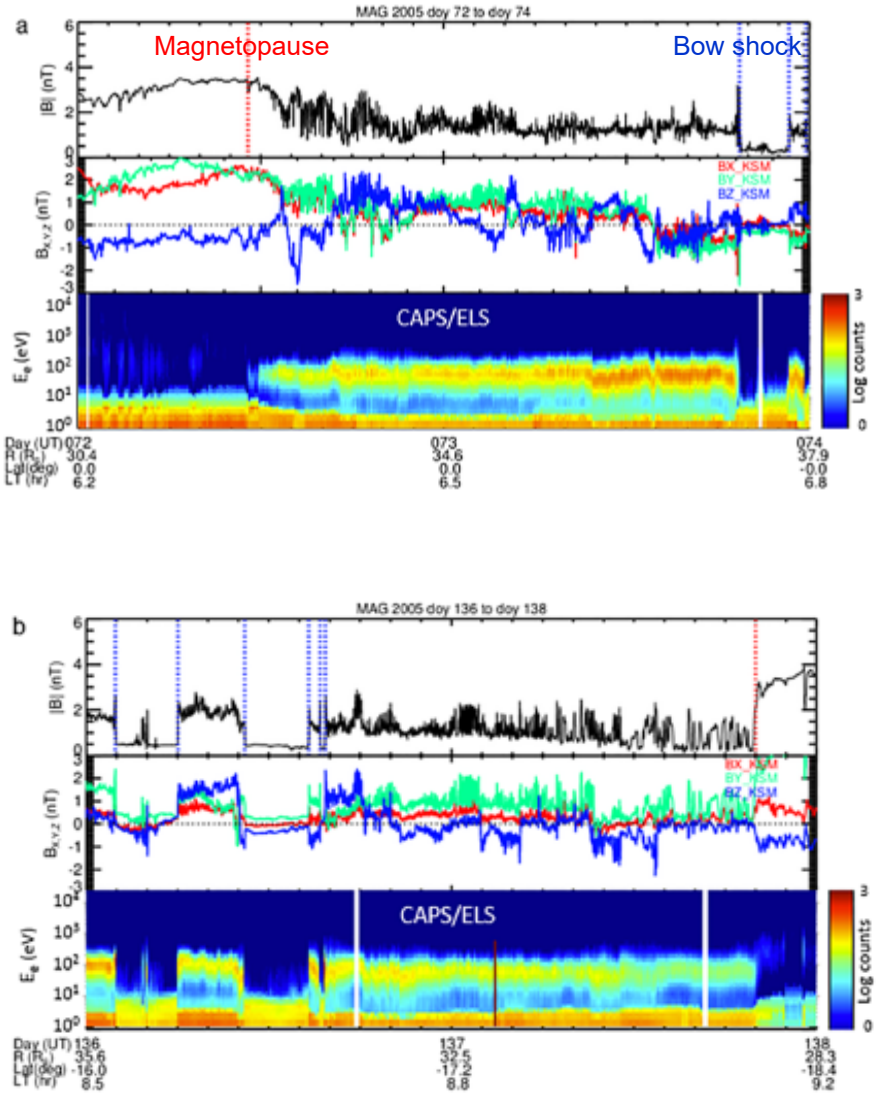




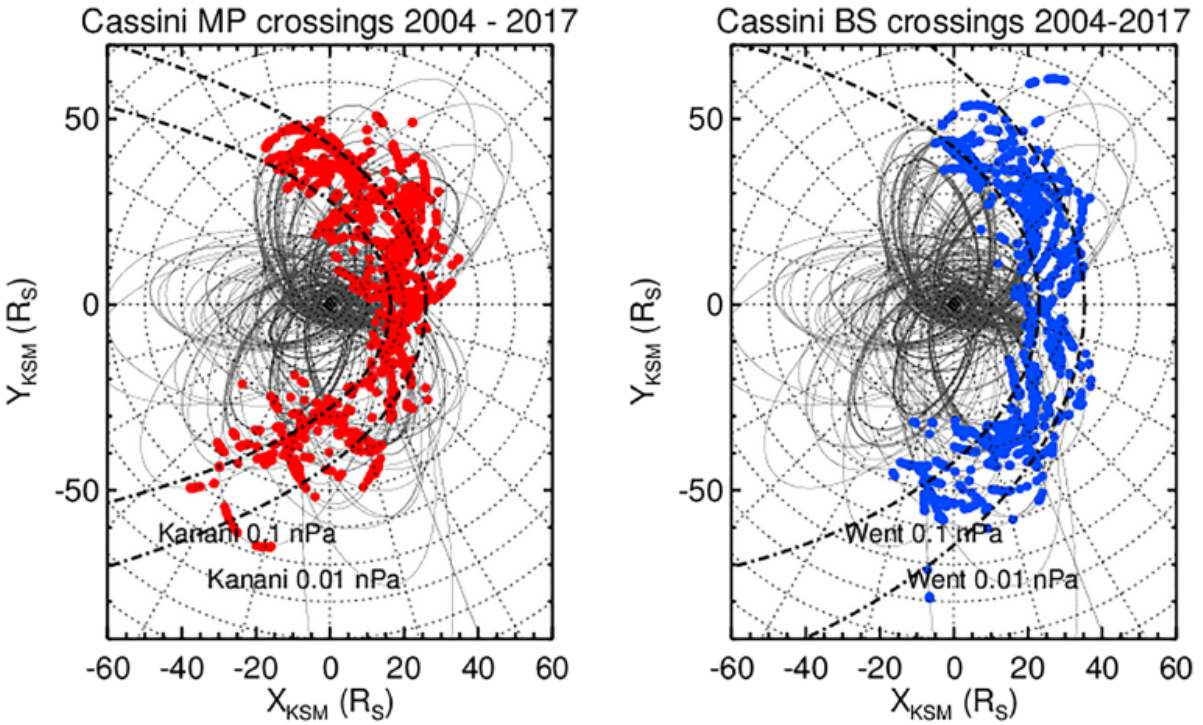


- Magnetospheric dynamics reflected in multi-wavelength auroral emissions
- Focus on labelling radio spectrograms for ML

2. Labelling: Magnetospheric boundaries (Saturn)



Jackman et al. [JGR, 2019]



- Example of manual boundary identification with Cassini at Saturn (magnetic field and plasma)
- Pros and cons to manual selection (build domain knowledge vs. time consuming and biased)
- Different datasets put boundaries at different locations (e.g. magnetic field vs. plasma vs. radio)

2. Labelling: Magnetospheric boundaries (Jupiter radio)

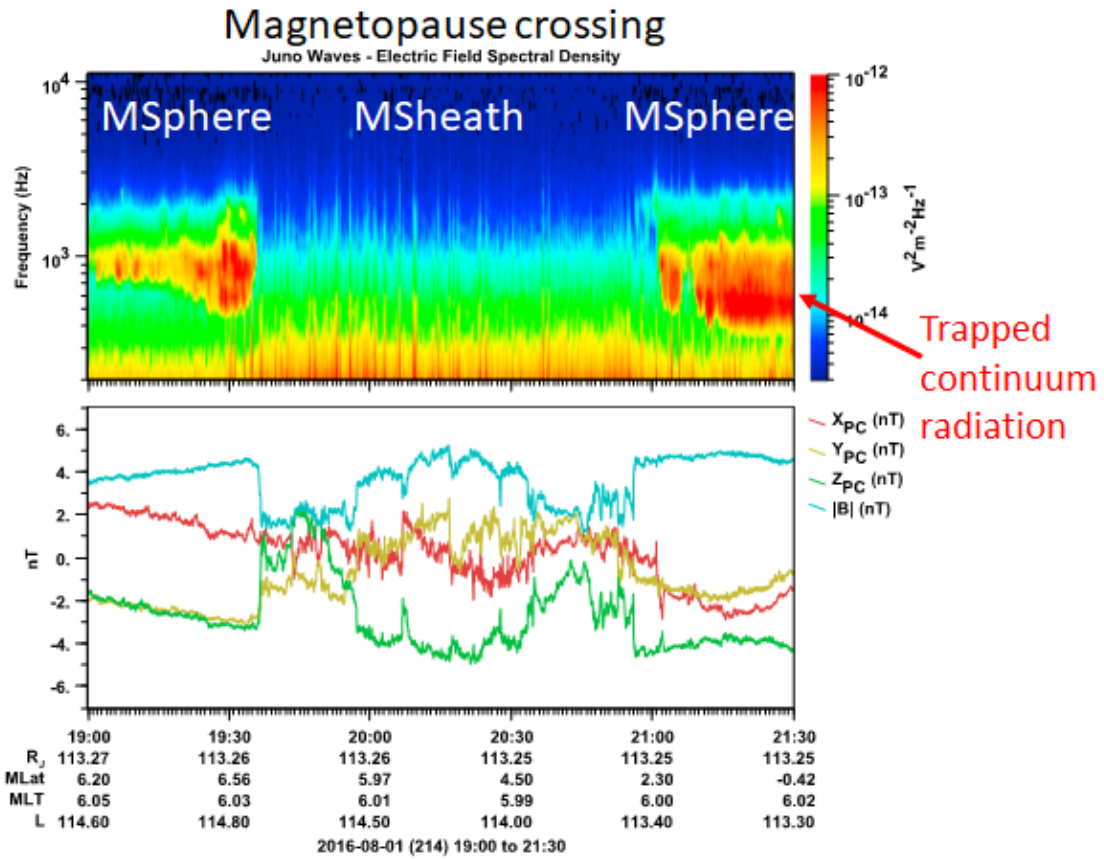


Figure 3. The Juno Waves and MAG data for two magnetopause crossings on 1 August 2016. At about 19:36 UTC, Juno crosses from the magnetosphere to the magnetosheath, and at about 20:57 UTC crosses back into the magnetosphere. These transitions are easily seen in the disappearance and appearance of the nonthermal radio emission in the Waves data from ~500 Hz to 2 kHz and the change of the magnetic field from reasonably steady components in the magnetosphere to more chaotic variation in the magnetosheath.

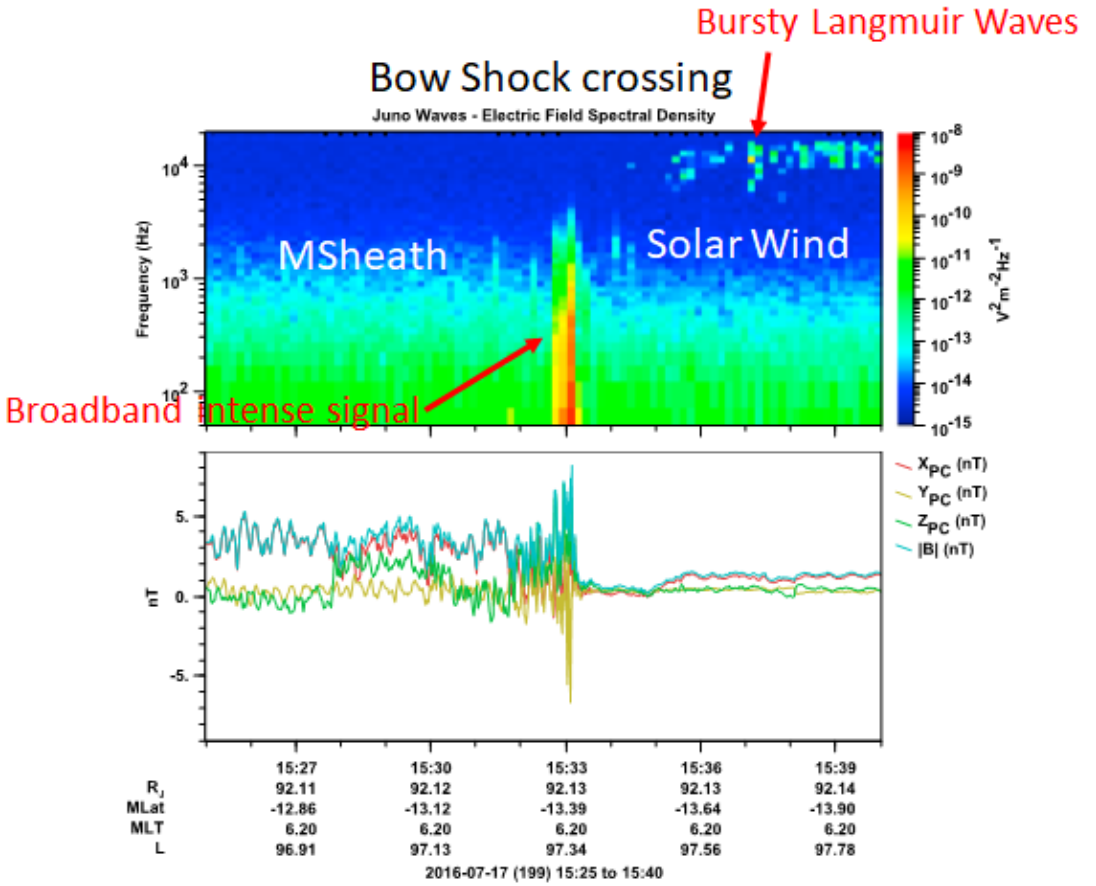


Figure 2. (top and bottom) A typical bow shock crossing observed on 17 July 2016 during the outbound part of the orbit 0. The shock was encountered at ~15:33 UTC as demonstrated by the decrease in magnitude and the quasiperiodic nonlinear wave activity in the magnetic field data (Figure 2, bottom), the broadband, intense signal from ~50 Hz to 2 kHz in the Wave data, and the appearance of the bursty Langmuir waves at about 11.8 kHz (Figure 2, top). The magnetic field components are plotted in the planetocentric (pc) coordinate system. In this system, *Z* is taken to lie along the rotation axis of Jupiter and is positive in the direction of positive angular momentum. The *X* axis is defined to lie in the equatorial plane, perpendicular to *Z*, and in the direction of the prime meridian as defined by the IAU. The *Y* axis completes the right-handed set.

Hospodarsky et al. [GRL, 2017]

2. Labelling: Magnetospheric boundaries (Jupiter locations)

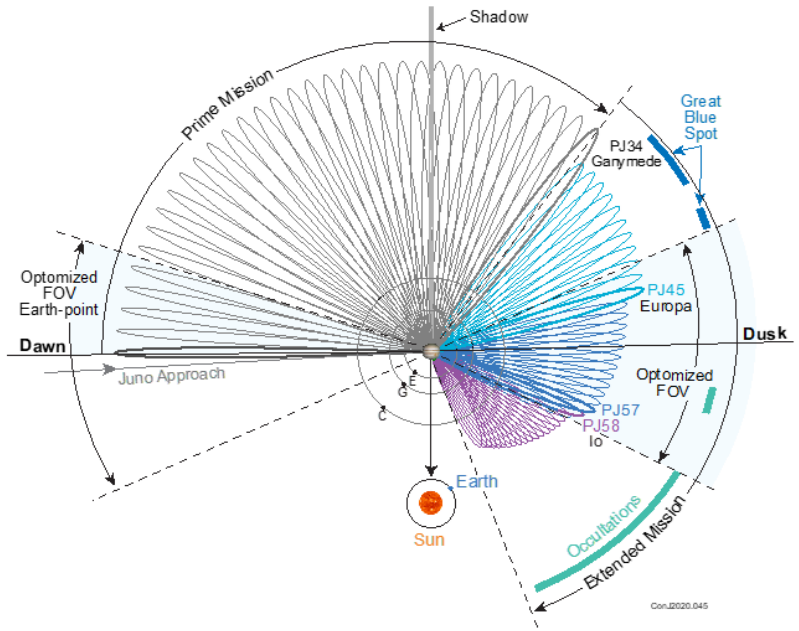
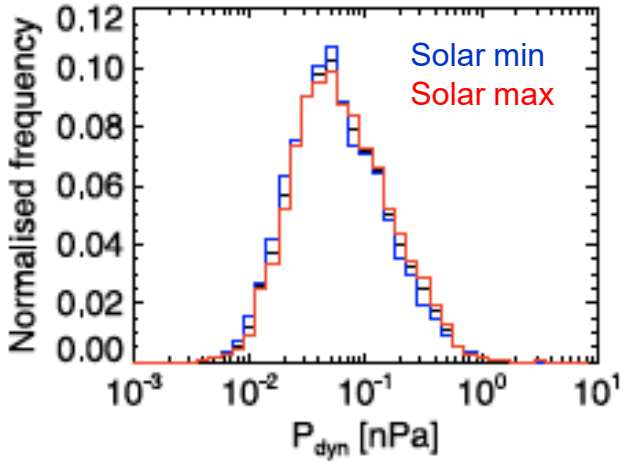


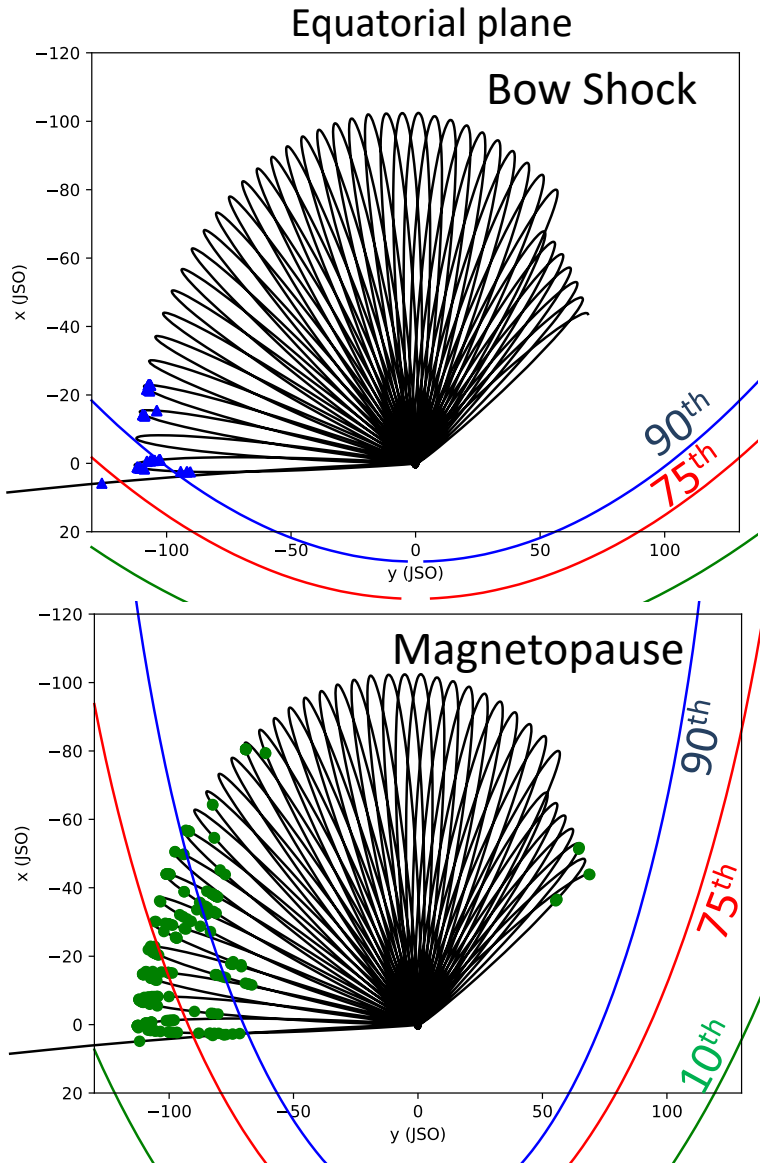
Figure 1. Progression of Juno's orbit. The evolution of orbits in local time during the Prime and Extended Missions orbits as viewed from above Jupiter's north pole.

Bolton et al. Juno mission extension



Distribution of solar wind dynamic pressure at Jupiter

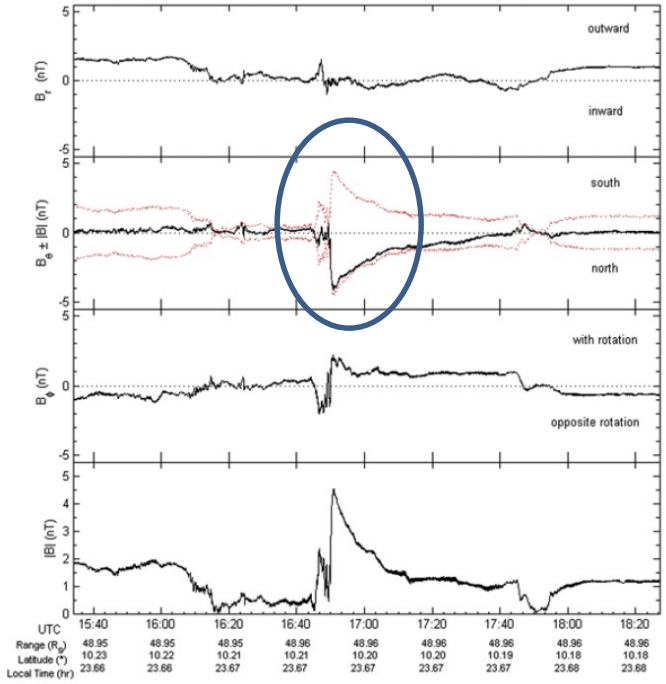
Jackman & Arridge [Sol. Phys. 2011]



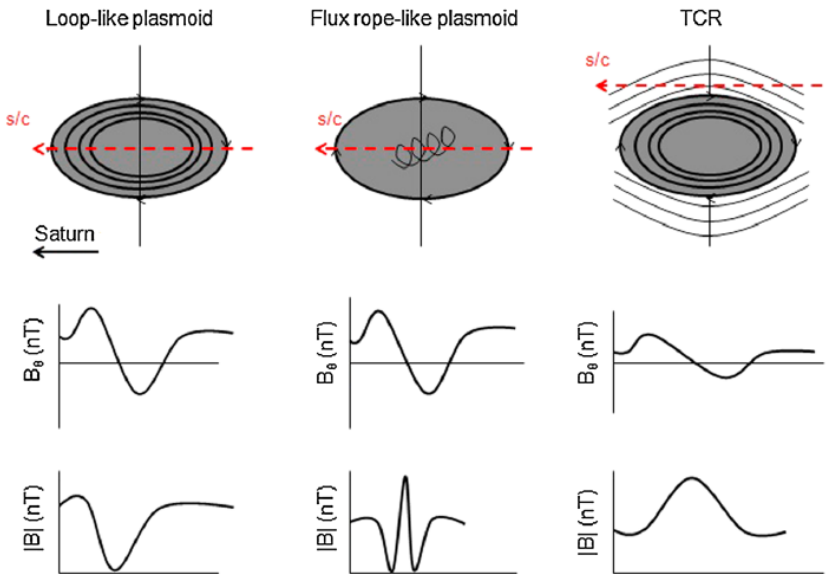
Louis et al. [in prep., 2022]

- Opportunity to sample boundary crossings during Juno exploration of Jupiter under a range of upstream conditions
- MAG, Waves and other instruments enable boundary identification

2. Labelling: Magnetic Reconnection Events (Saturn)

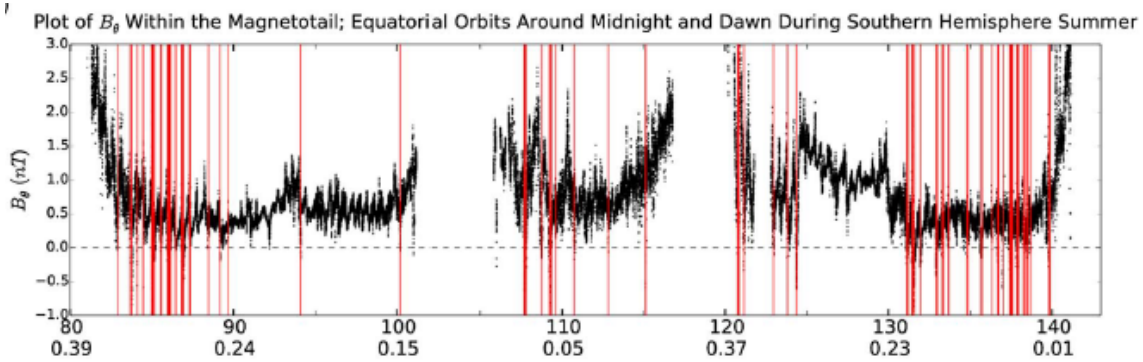


Jackman et al. [GRL, 2007]



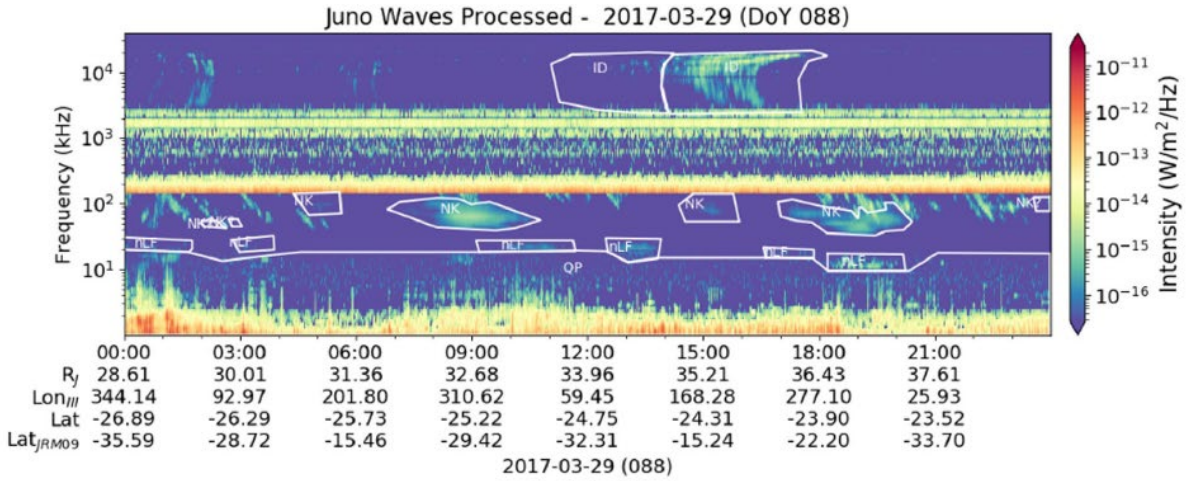
Jackman et al. [JGR, 2014]

- Example of plasmoid, travelling compression region (TCR), dipolarization identification with Cassini at Saturn
- Natural bias to largest/clearest events on low, steady background
- Magnetic field deflections not always accompanied by plasma signatures

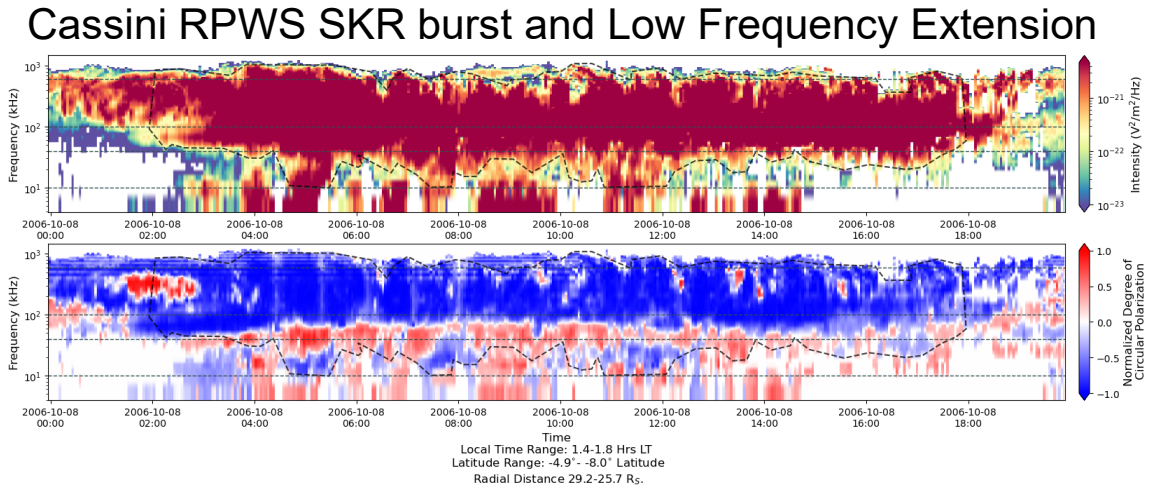


Smith et al. [JGR, 2016]

2. Labelling: Magnetospheric radio events



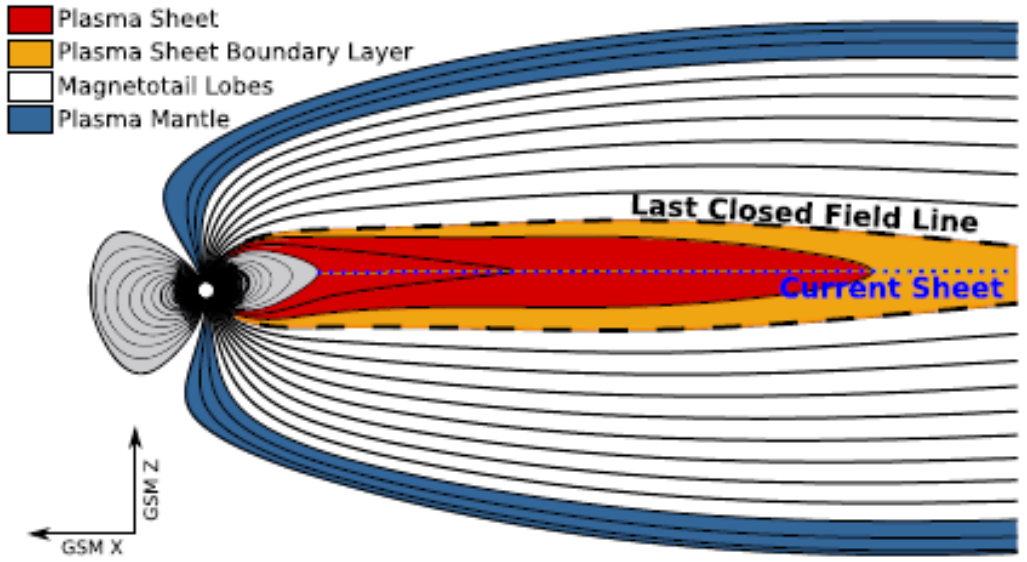
Louis et al. [2021]



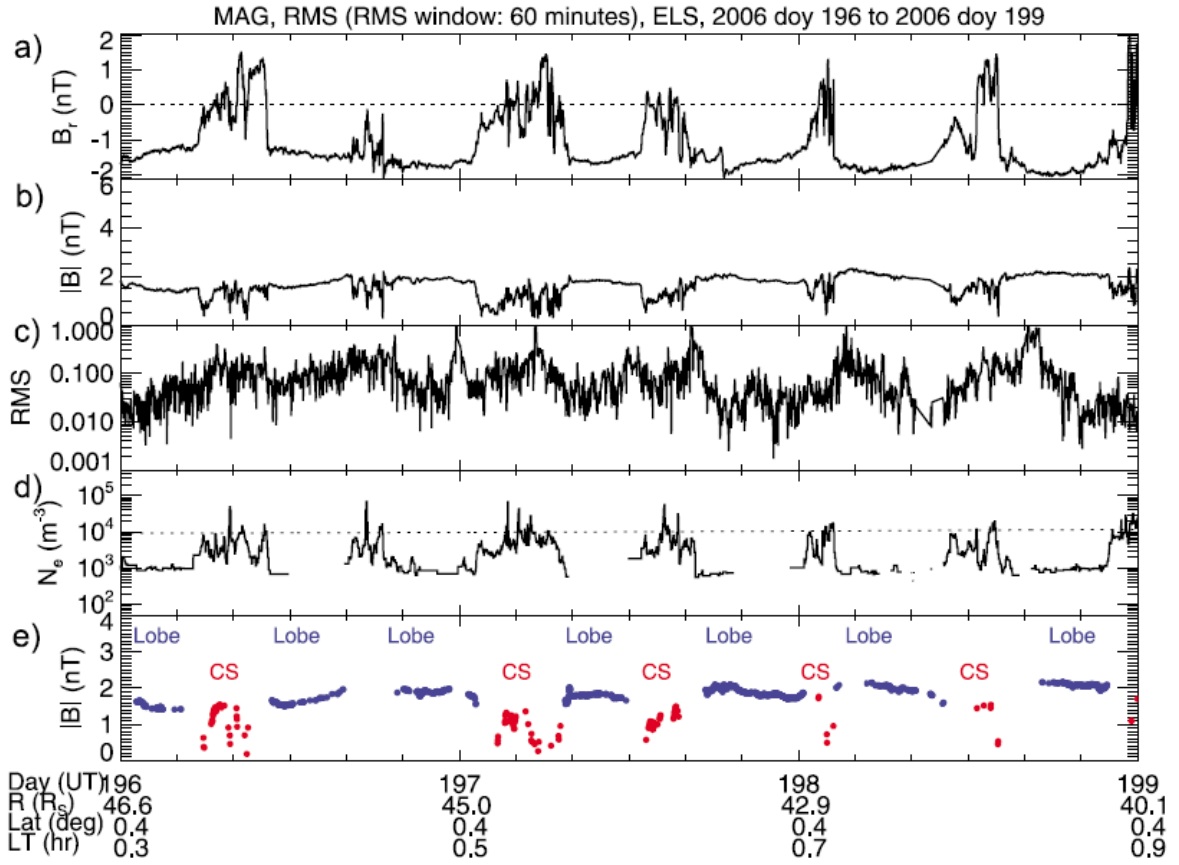
O'Dwyer et al. [in prep., 2022] and SPACE Labelling tool [2021]

- IDL (and now Python) user-friendly labelling tools available to draw polygons around features on radio spectrograms [https://github.com/CorentinLouis/SPACE_labelling_tool]
- 3 years (and growing) of Juno labelled Waves data
- 1000+ Saturn radio Low Frequency Extensions (LFEs) labelled from Cassini RPWS dataset
- Labels form the basis for supervised learning approaches

2. Labelling: Magnetospheric regions



Jackman et al. [SSR, 2014]

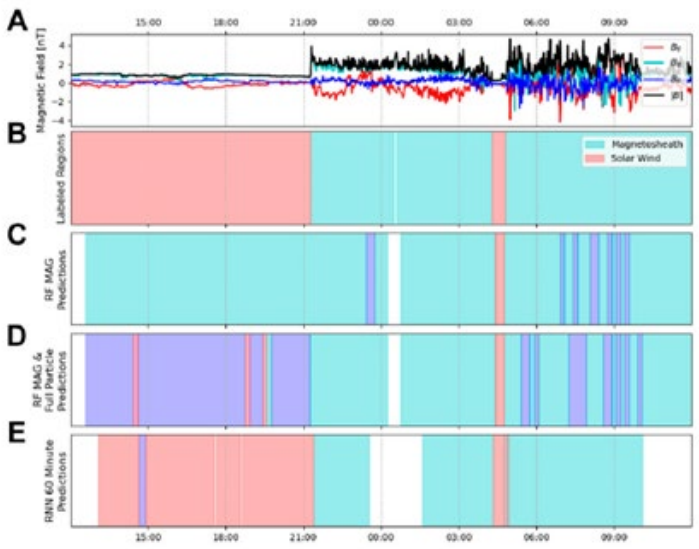


Jackman & Arridge [JGR, 2011]

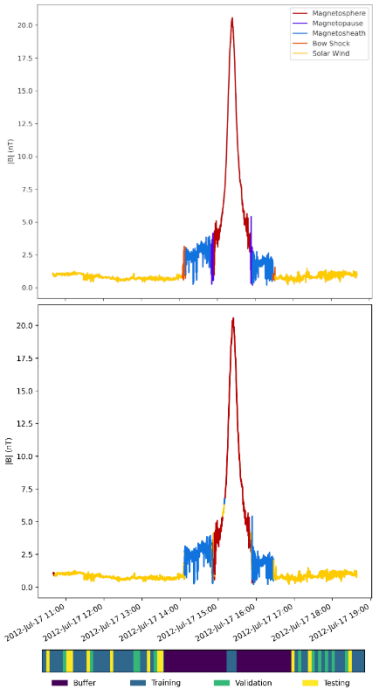
- Manual and semi-automated approaches to label key magnetospheric regions: Lobe, plasma sheet, current sheet, boundary layers…

- Catalogues enable statistical analyses of magnetospheric modes

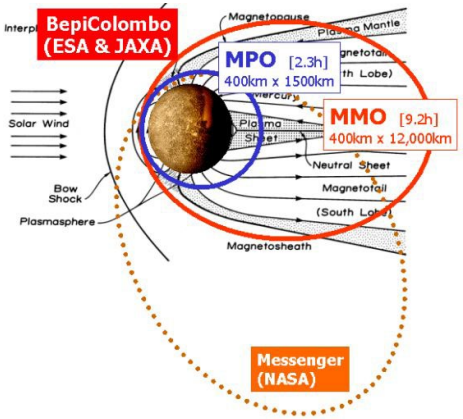
3. Machine Learning: Magnetospheric Region Classifiers

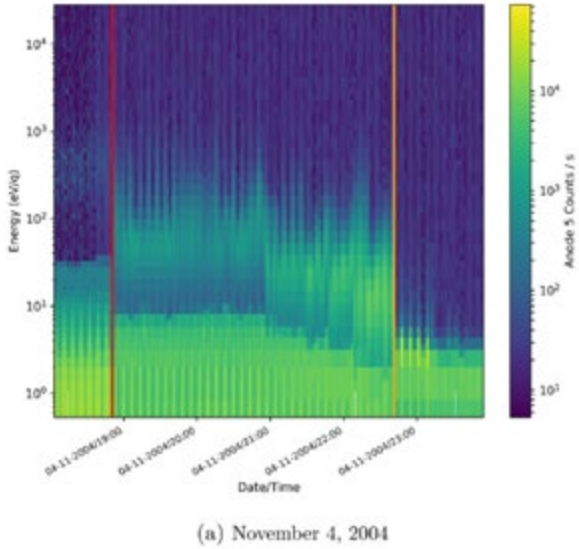


Yeakel et al. [2022]: Supervised learning approach (60-minute window RNN) to classify regions at Saturn: solar wind, magnetosheath, magnetosphere.



Smith et al. [in prep., 2022]: Supervised learning approach to classify regions at Mercury: solar wind, magnetosheath, magnetosphere.





(a) November 4, 2004

Daigavane et al. [2022]: Unsupervised learning approach (non-Bayesian Hidden Markov Model) to classify Saturn regions from plasma spectrometer data.

Careful preparation needed to ensure **diversity** of training data

3. Machine Learning: Event Classifiers (Saturn)

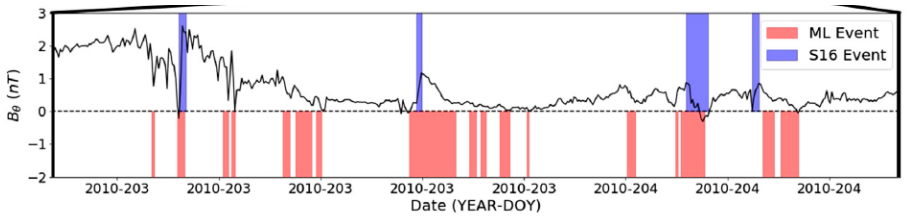
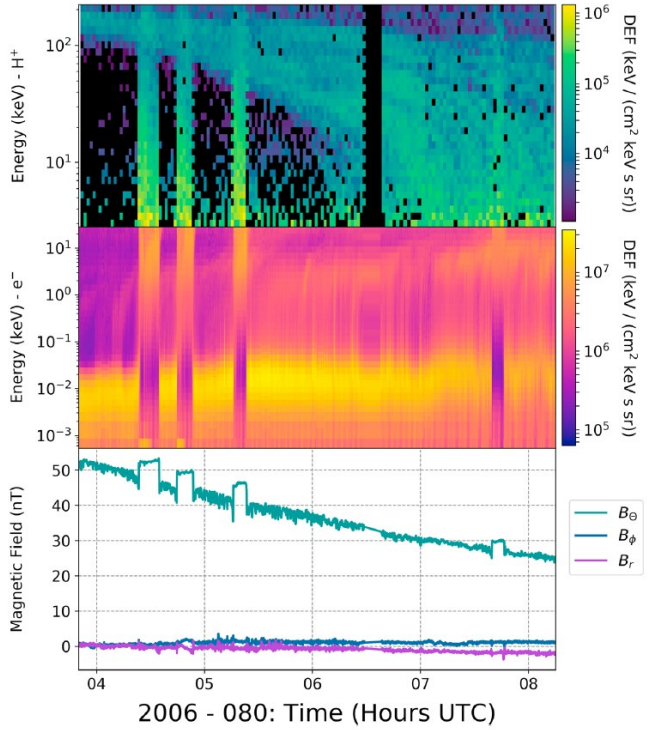
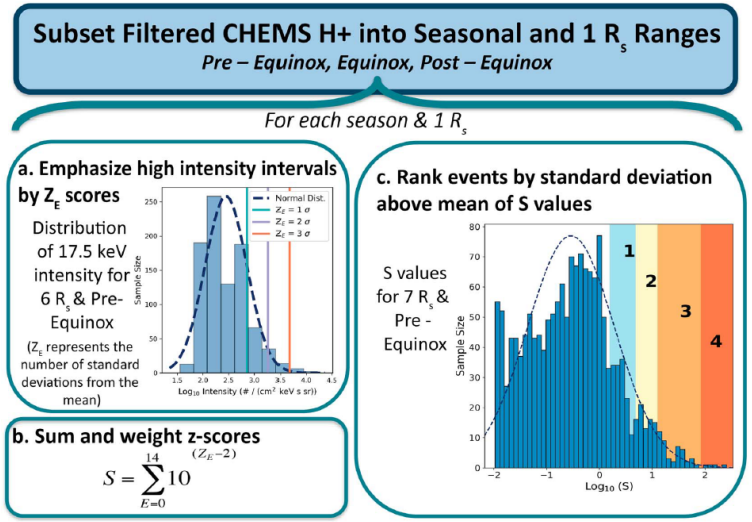


TABLE 3 | Confusion matrices of neural network classification considering only events that the Smith et al. catalog could have identified.

	2010	
	Pred. Null	*Pred. Event*
Obs. Null	1008 (0.82)	208 (0.17)
Obs. Event	58 (0.07)	741 (0.93)



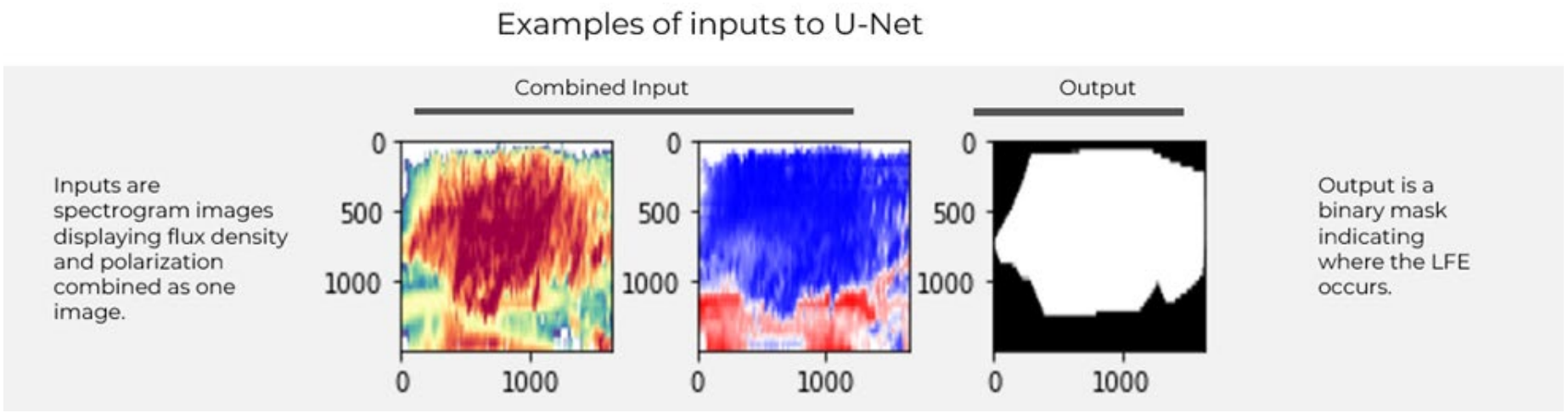


Garton et al. [2021]: Supervised learning approach (FFNN) to classify reconnection events at Saturn.

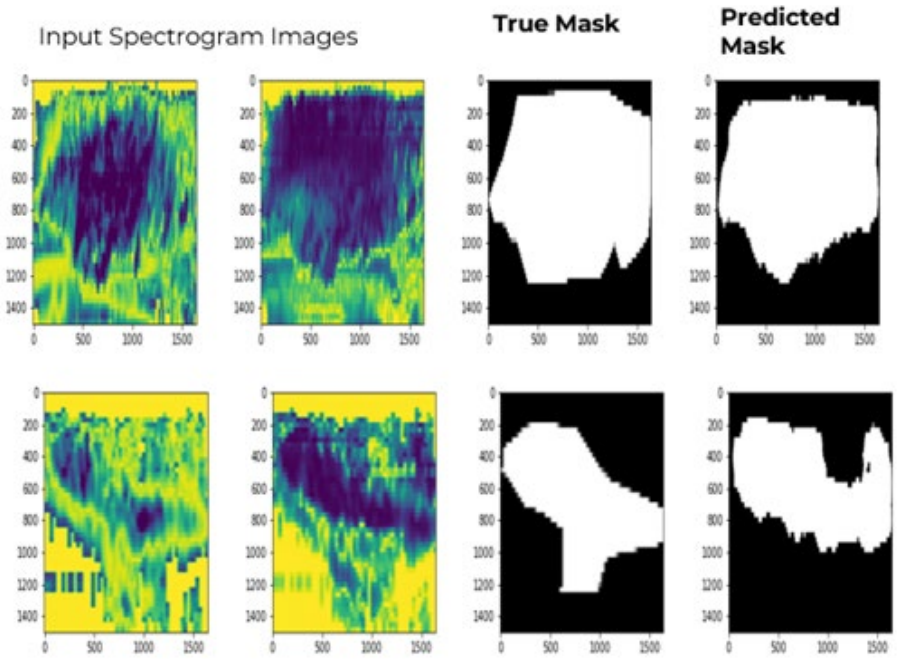
2093 labels (input), 46,000 events (output)

Azari et al. [JGR, 2018]: Automated identification of interchange events from ion intensity data

3. Machine Learning: Radio Features Classifier (Saturn)



O'Dwyer et al. [in prep. 2022]



- Supervised learning approach (U-Net Semantic Segmentation), assigning a label to every pixel in the image
- 1000+ LFEs manually labelled.
- Image-based machine learning approach to extract all LFEs from 13 years of Cassini at Saturn

Summary

Labelling

- Large labelled catalogues of:
  - Magnetospheric boundaries (bow shock/magnetopause)
  - Magnetospheric regions (lobe/current sheet/plasma sheet)
  - Reconnection events (plasmoids/TCRs/dipolarizations)
  - Radio features (e.g. SKR bursts, LFEs)

Machine Learning approaches

- Supervised learning at Saturn (boundaries, reconnection events, radio features), and Mercury (boundaries).

Future Perspectives

- Transfer learning between planets
- Utility for on-board adaptive mode switching and post-downlink processing

We are hiring! https://dias.ie/planetary_magnetospheres @cm_jackman cjackman@cp.dias.ie