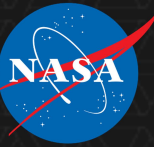




# Neural Data Compression of Plasma Distributions for Space Weather



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## Introduction

Physics has long history of theory-driven dimensionality reduction (Fourier Transform, Spherical Harmonics)

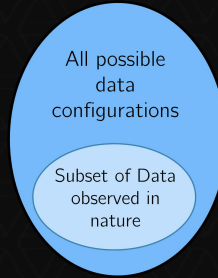
We present a technique for data-driven dimensionality reduction on ion counts distributions (detections as a function of velocity).

Relevance to:

- Feeding other ML algorithms
- Data compression for instruments

The algorithm presented here is lossy, and we present a novel validation technique:

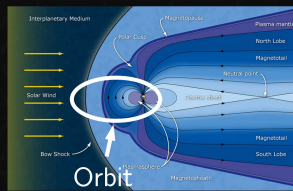
- Calculate and compare macroscopic fluid variables between original/reconstructed data
- **Argument:** Preserving fluid moments would in turn preserve fluid-level physics, and in turn a degree of scientific validity



## Data

Direct Measurements of Space Plasmas near Earth

- Magnetospheric Multiscale Mission (MMS) from NASA
- Studies plasmas within the context of Earth's magnetic field and solar wind
- High-Earth Orbit (up to 11 Earth Radii away in data used)



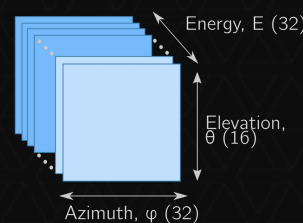
Instrument Measures Ion Particles

- **Ion Count Detection Rate**

$$C(\phi, \theta, E)$$

- $\phi$  – Azimuth
- $\theta$  – Elevation
- $E$  – Energy

- 3D array: shape = (32, 16, 32)



Training Set

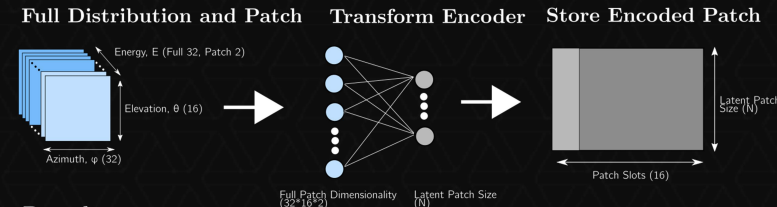
- 90/10 Test/Train Split
- Data from Phase 4B of mission: 11/29/2018 – 4/13/2019

Data Available under Creative Commons at:

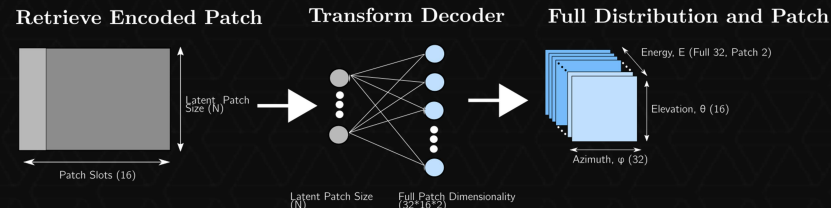
<https://lasp.colorado.edu/mms/sdc/public/>

## AutoEncoder Network Architecture

### Encoding



### Decoding

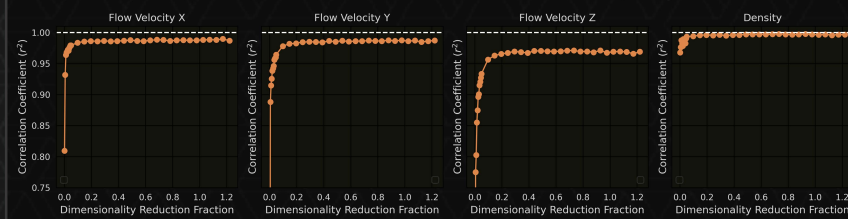


- Separate MLPs encode each patches of two energies (da Silva et al., 2020)
- Loss: RMS in Counts between Original/Reconstructed Patches:
- Covers all azimuths/elevations and two energies
- Mean of Energy Shell forced equal after decoding

$$\tilde{C}_{recon,adjusted}^E = \tilde{C}_{recon}^E \left( \frac{\bar{C}_{orig}^E}{\bar{C}_{recon}^E} \right)$$

## Validation and Fluid Variable Information Bottleneck

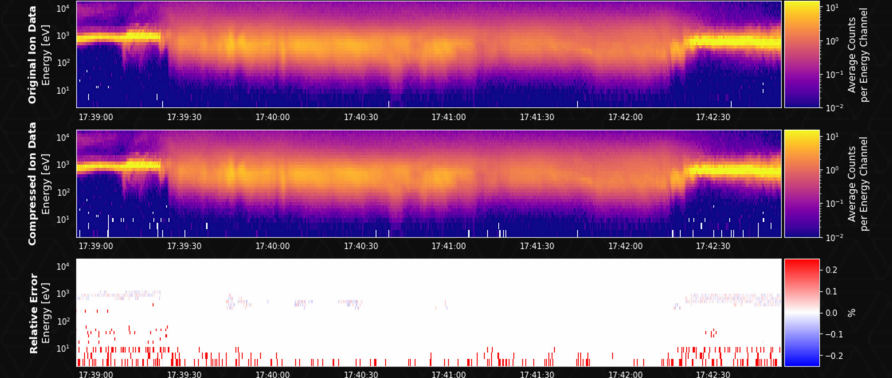
### Neural Network Fluid Parameter Reconstruction Quality



- Correlation coefficient  $r^2$  between the original and reconstructed plasma data as a function of the dimensionality reduction fraction (DRF)
- DRF: defined as the size of the latent representation relative to the original dimensionality (1.0  $\rightarrow$  no dimensional reduction)
- We observe that an information bottleneck, which prevents accurate reconstructions, occurs for dimensional reductions between 10-20x (DRF  $\approx$  0.05-0.10).

## Applications to Data Compression

### Demonstration of Compression (Compression Ratio: 30.2X)



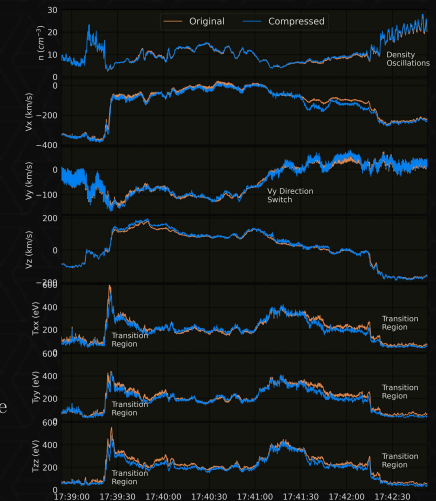
Potential use case for reducing satellite transmission budget for observed data, in turn (i) reducing spaceflight costs and (ii) relieving over-congested telemetry networks.

### Compression Specifications

- Auto-encoder is main transform method
- Quantizer is trimming 6 bits off fractional part of IEEE 16-bit floating point
- Entropy Coding is GZIP/DEFLATE
- Packaged in custom data format

### Qualitative Overview

- Observe figure shows strong ability to capture
  - Energy Spread (bimodal, skewed)
  - Transition Regions (cold to hot plasma)
  - Plasma Waves



## Acknowledgements

We thank the NASA/GSFC Center for HelioAnalytics for seed funding and community support, as well as the AWS Heliocloud resources provided by the NASA/GSFC Heliophysics Sciences Division.

## Source Code

Source code available at: <https://github.com/ddasilva/mms-compression-neurips-2022>

