KU LEUVEN

TerraVirtualE

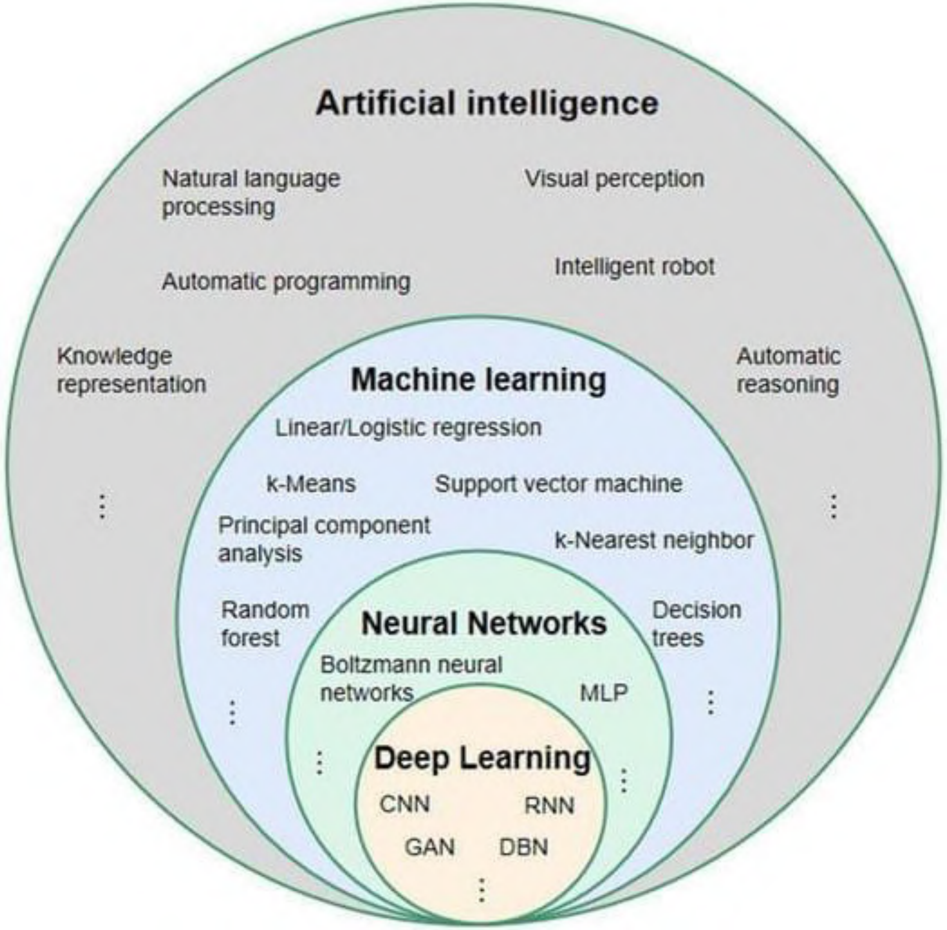
Work funded by the **ERC Advanced Grant TerraVirtualE**, by **EC-Horizon Europe DEEP-SEA** and **ASAP**, **EuroHPC CoE SPACE**, **Belspo-BrainBE**, **KULueven**, **FWO**, **Belgian Defense**, **NASA** and the **USA Air Force**.

The role of Machine Learning in space science

Giovanni Lapenta

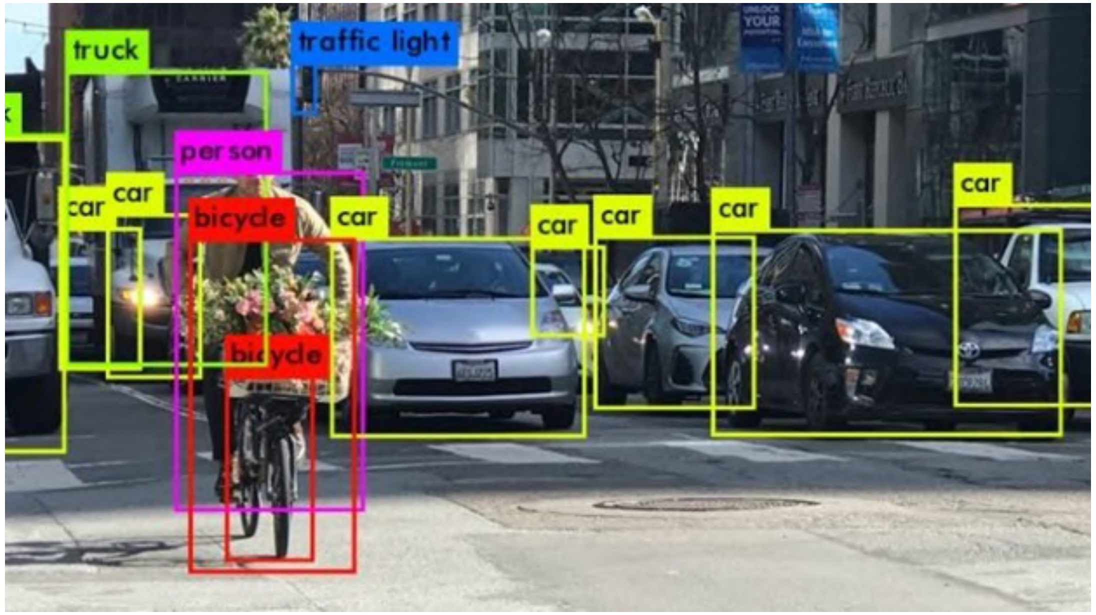
PITHA-T-FORS School, Leuven 6 Feb 2024, 11:00

What has AI in store for plasma physics?



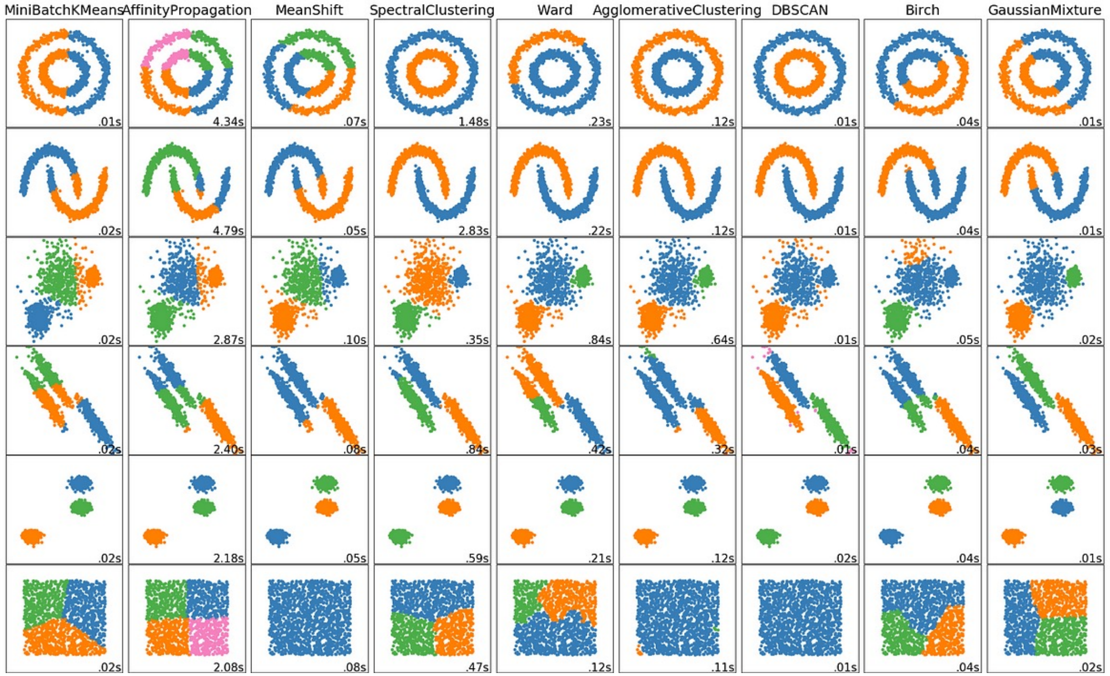
Supervised vs Unsupervised

Supervised: It replaces and improves on what humans can do



Since 2016 AI is better than humans at recognizing images

Unsupervised: It takes independent direction but needs human post facto interpretation



Generative Neural Networks

- Chat GPT, Bard
- Image generation
- Replacing physics-based simulations with trained neural Networks
- Surrogate models
- Graph Neural Networks
- Generative Adversarial Networks

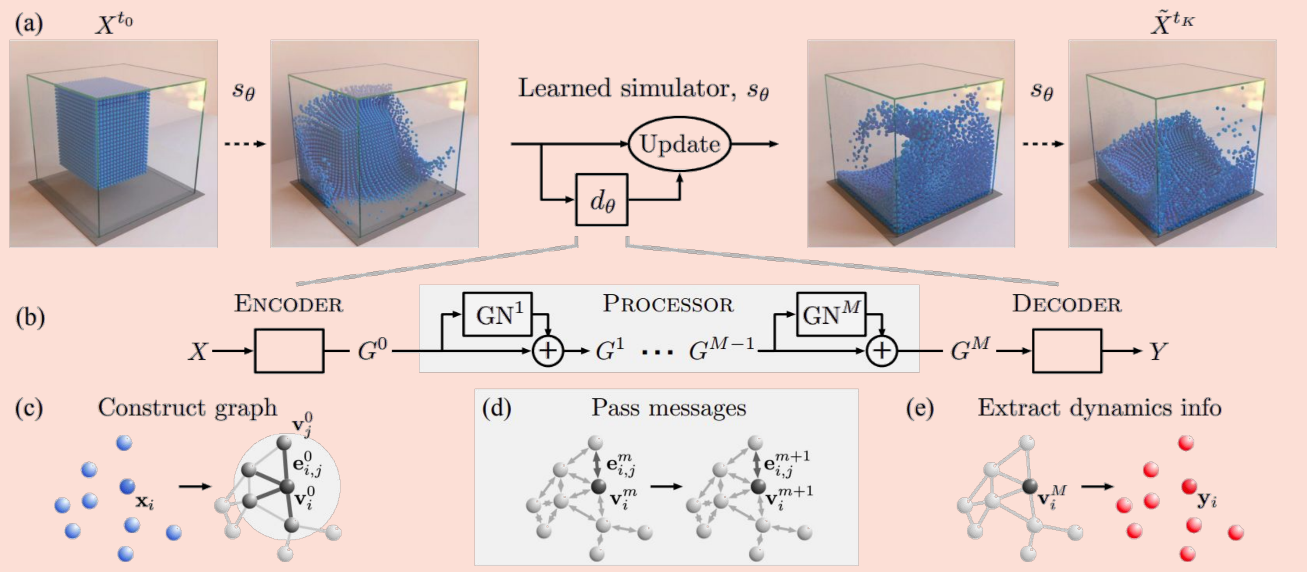
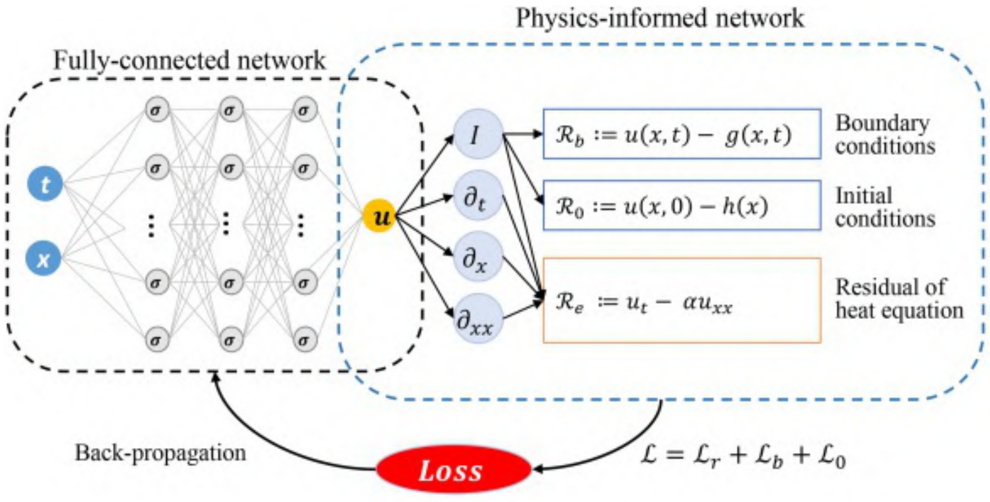


Figure 1 : (a) The GNN predicts future states represented as particles using a learned simulator, s_θ. (b) s_θ uses an "encode-process-decode" scheme to compute dynamics information, Y, from input state, X, with (c) the encoder, (d) the processor and (e) the decoder. Figure from Sanchez et al. (2020).

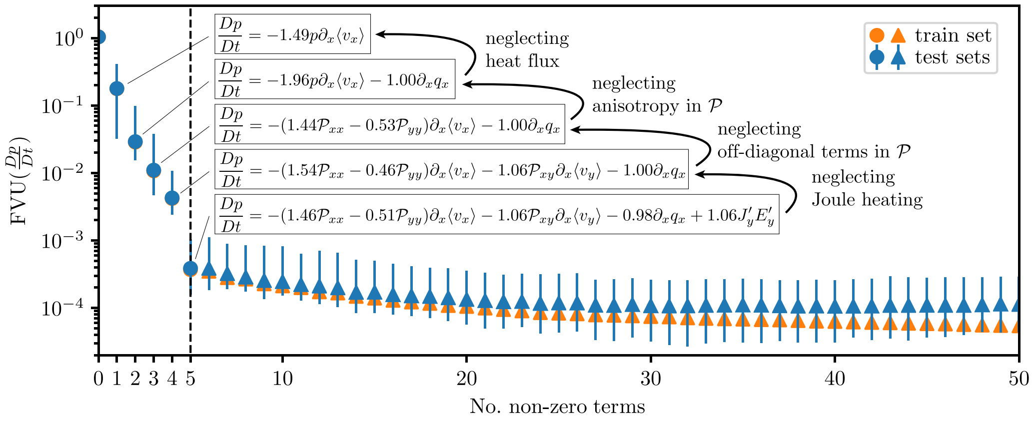
Physics informed NN

Inserting physics into the NN workings



Copyright © ASME. Cai et al., DOI: 10.1115/1.4050542

Discovering physics with ML: equation



Alves, E. P., & Fiuza, F. (2022). *Physical Review Research*, *4*(3), 033192.

What can we hope

Replacing humans for tedious tasks	• well established. • social risks (jobs lost). • probably unstoppable
Helping with data discovery with tasks not humanly feasible	• well established. • sheer brute power • great opportunity
Replacing physics-based models with NN	• seen as an alternative numerical method • great opportunity on new heterogeneous architectures • need for numerical analysis (stability, accuracy)
Making forecasts (long term, with human supervision)	• opportunity for large data ingestion • human revision in final decision • example: major geomagnetic storm (3 days since solar origin)
Making rapid decisions (no human supervision)	• can we trust decision not based on physics? • need for uncertainty quantification and explainable AI • need for societal adjustments
Finding patterns/correlations we never thought of	• this will still rely on human post facto interpretation • an additional tool of theoretical investigation • possibly the most exciting opportunity
Discovering equations	• surrogate models to allow more efficient modelling • it's very new but potentially it gives a satisfying answer • it can be validated and verified in the usual manner

Courtesy of Glen Wurden (LANL)

If anything ML can be fun.

I asked Adobe AI to generate a picture of a "stellarator nuclear fusion rocket".... and this is what I got (Glan Wurden)

KU LEUVEN

The project AIDA receives funding from the European Union's Horizon 2020 Research and Innovation programme under grant agreement No 776262.

The project ASAP receives funding from the European Union's Horizon Europe Research and Innovation programme under grant agreement No 101082633.

AIDA:
Artificial **I**ntelligence **D**ata **A**nalysis

aida-space.eu

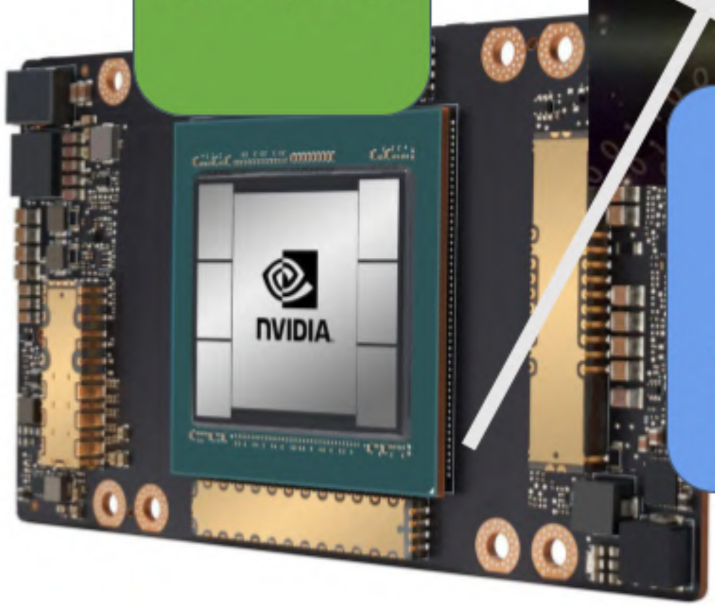
ASAP
Automatics in Space Exploration

ASAP: **A**utomatics in **S**p**A**ce ex**P**loration

asap-space.eu

Coordinator: Giovanni Lapenta

ASAP
Automatics in Space Exploration



WP2

Algorithms Selection and Development

WP3

Testbed hardware design and production

WP4

Testbed software interface and validation tests

WP5

Flight Simulator validation. Validation with past mission data

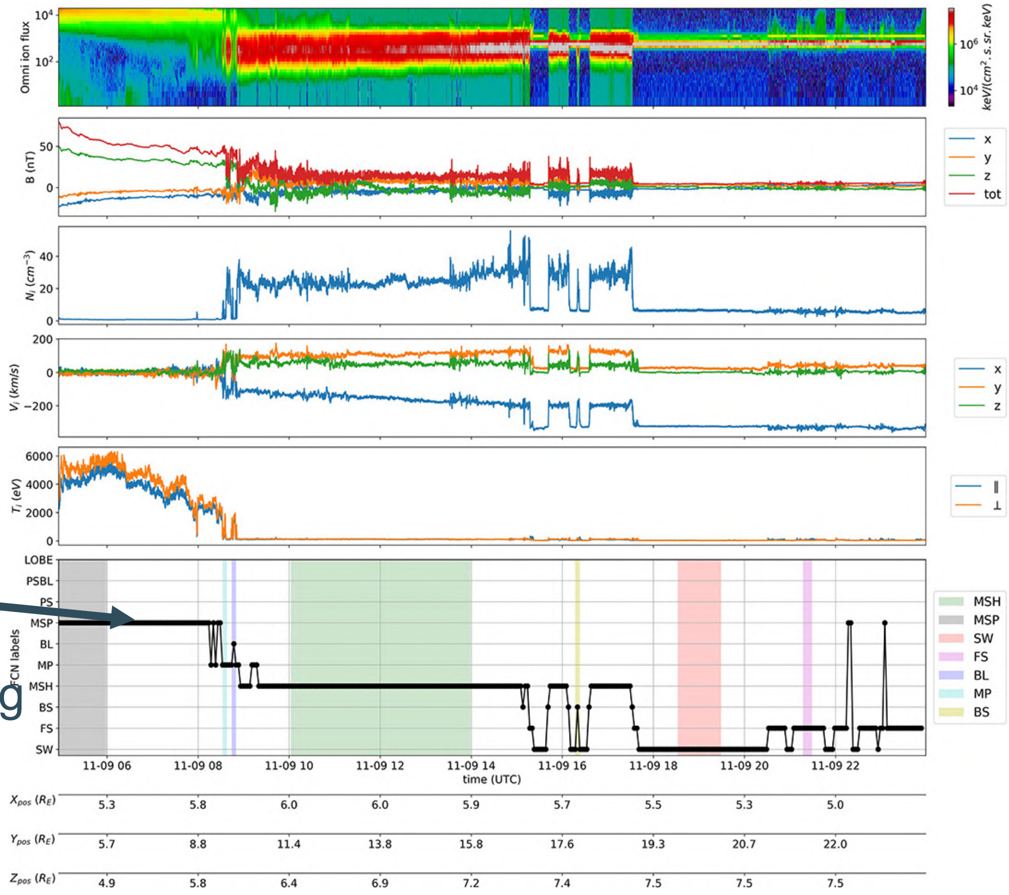
AI services for space missions

Supervised classification of MMS data

H. Breuillard et al.
Front. Astron. Space Sci.,
03 September 2020
https://doi.org/10.3389/fspas.2020.00055

- *Data retrieval tools:* **avoiding any replica**tion with other python tools, e.g. pySPEDAS, Heliopy.
- *Link with ongoing missions:* **SDO**,**MMS** and **PSP.**
- *Link with upcoming data:* strong initiative to provide AidaPy services to **SolO**
- *Virtual Mission Tool:* to create **synthetic data** from simulation as if it were created by a missiong under design
- *Linking simulation and observation:* so that the **same analysis can be applied** to both
- *ML tools to identify extreme events:* e.g. shock, **reconnection**.
- *ML-driven creation of lists of events*

ML labelling



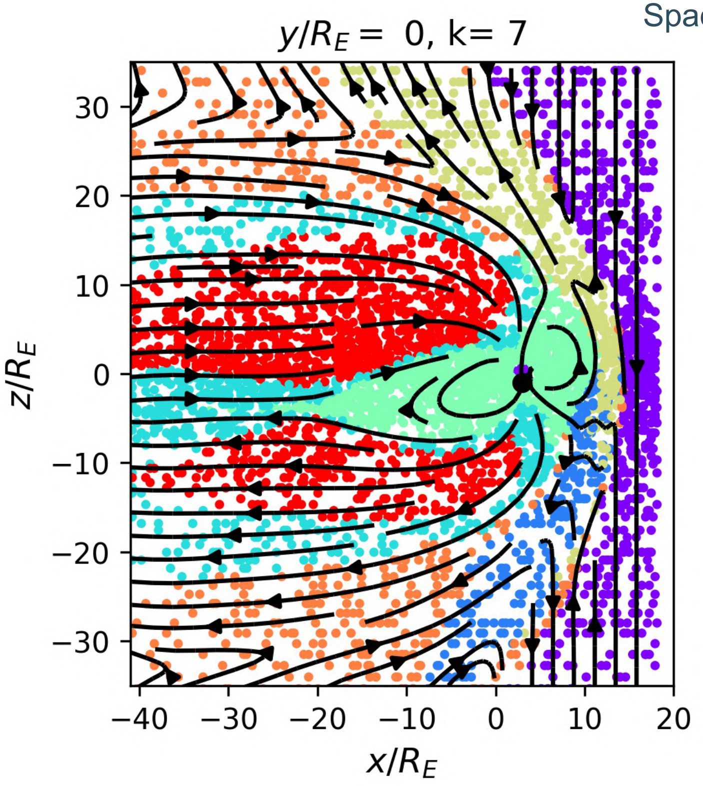
SITL labelling

AI services for scientific discovery via data analysis

- *AidaPy statistical tools package:* to **standardise operations** typically done in C, IDL.
- *Identification of Reconnection:* **different methods** using simulation and observation together and using **supervised ML** trained on human-labelled events and using **unsupervised methods**.
- *Analysis of Turbulenct structure:* using **unsupervised ML** (DBSCAN)
- *Explainable ML tool for classification of in situ data:* applied to **solar wind classification**
- *ML tools to analysis with the same approach simulation and observational data*

SOM classification of OpnGGM data

Innocenti et al., Front. Astron. Space Sci, 2021



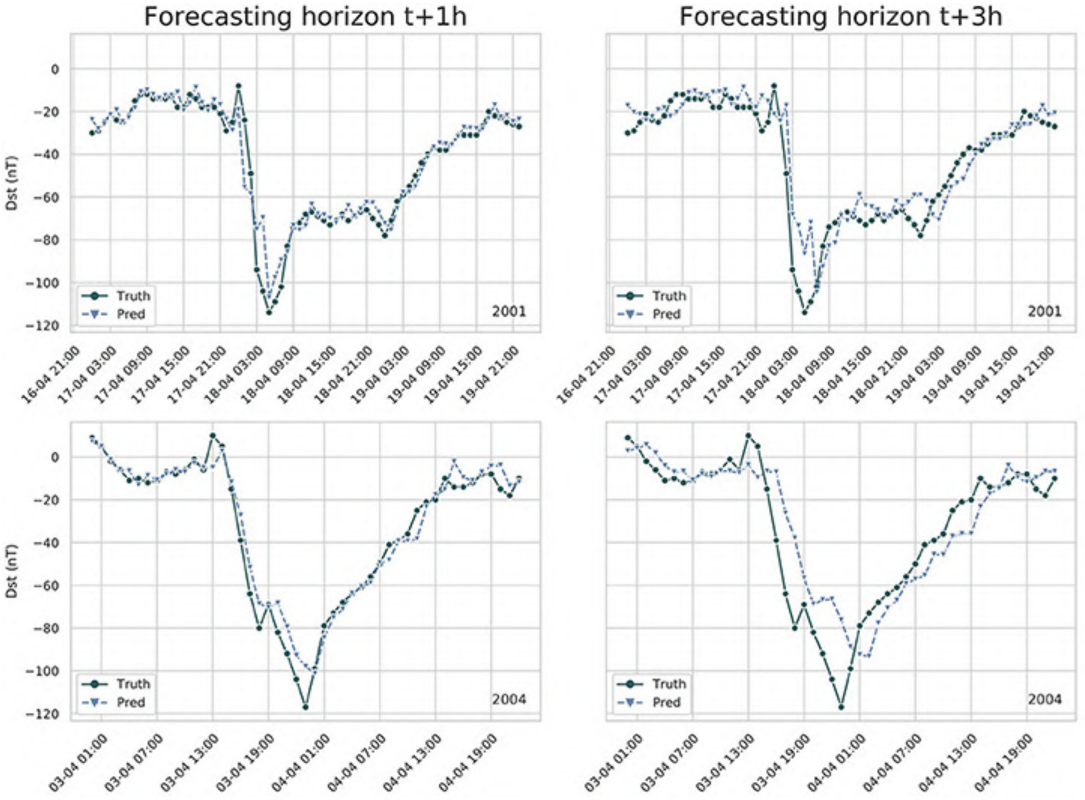
Class	Region
0	Pristine solar wind
1	Magnetosheath (DS BS)
2	Boundary layer
3	Plasmasphere
4	Magnetosheath (DS BS)
5	Magnetosheath
6	Lobes

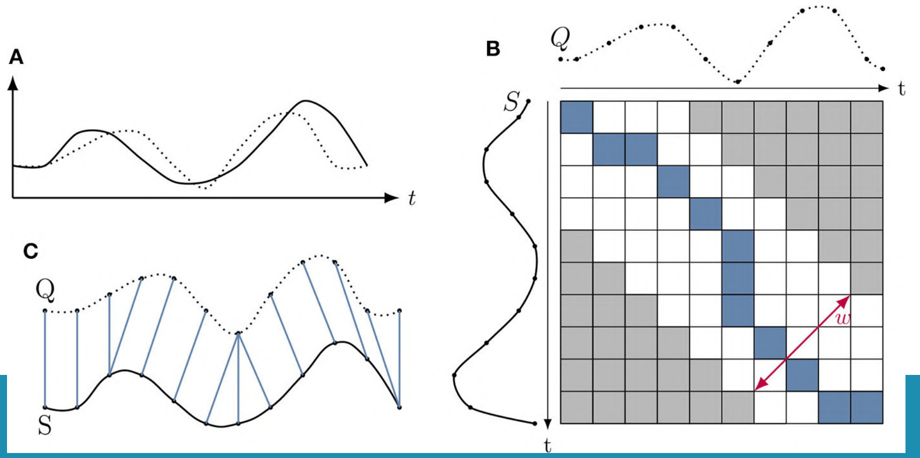
Sisti, M, et al. "Detecting Reconnection Events in Kinetic Vlasov Hybrid Simulations Using Clustering Techniques." *ApJ,* 908.1 (2021): 107.

AI services for space weather

- *Supervised Classification* of Plasma Regions in **Near-Earth Space**: applied to **MMS data** using CNN
- *Unsupervised Classification* of **incoming solar wind using Dimensionality reduction** and **Self Organizing maps (SOM)**
- *Unsupervised Classification* of Plasma Regions in **Near-Earth Space**: applied to **OpenGGCM** simulations using SOM
- *Prediction of DST index* and **time-warping methods** to establish the accuracy of **predicting storm times.**
- *Data Assimilation* methods based on Kalman filters: application of **representer technique to OpenGGCM and EUHFORIA**
- *Solar image segmentation with NN:* identification of **coronal holes** for space weather prediction

DST Iundex Prediction and Time Warping



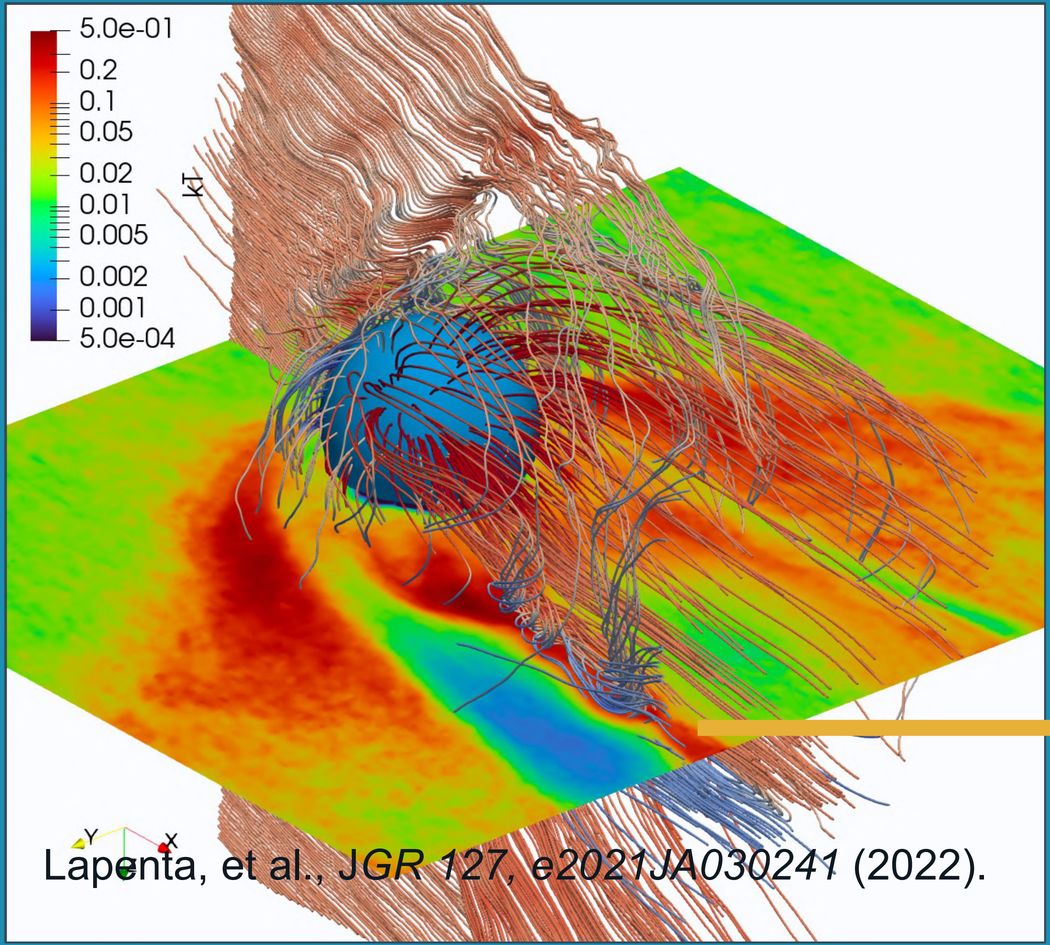


Laperre et al., Front. Astron. Space Sci., 22 July 2020 https://doi.org/10.3389/fspas.2020.00039

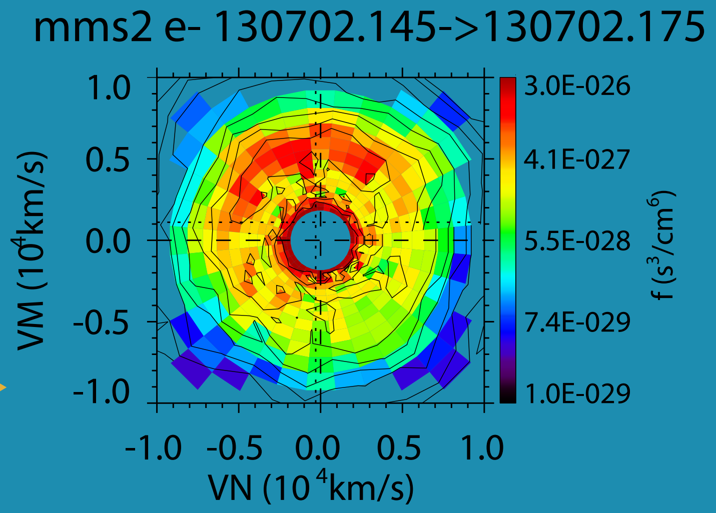
TerraVirtualE

ECSim simulation at KULeuven

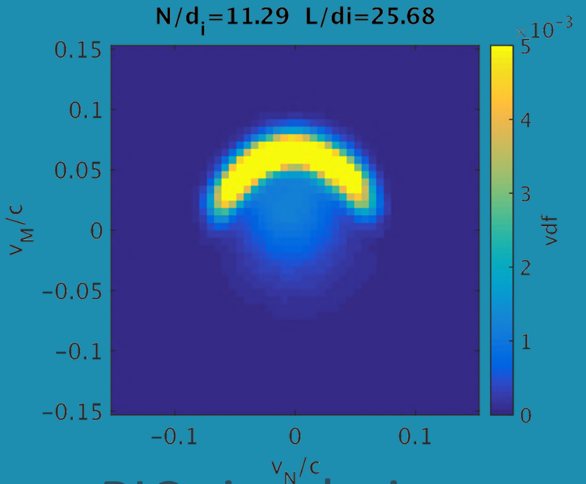
Challenges in planetary modelling



Burch et al, Science, 2016



Lapenta et al, JGR, 2017.



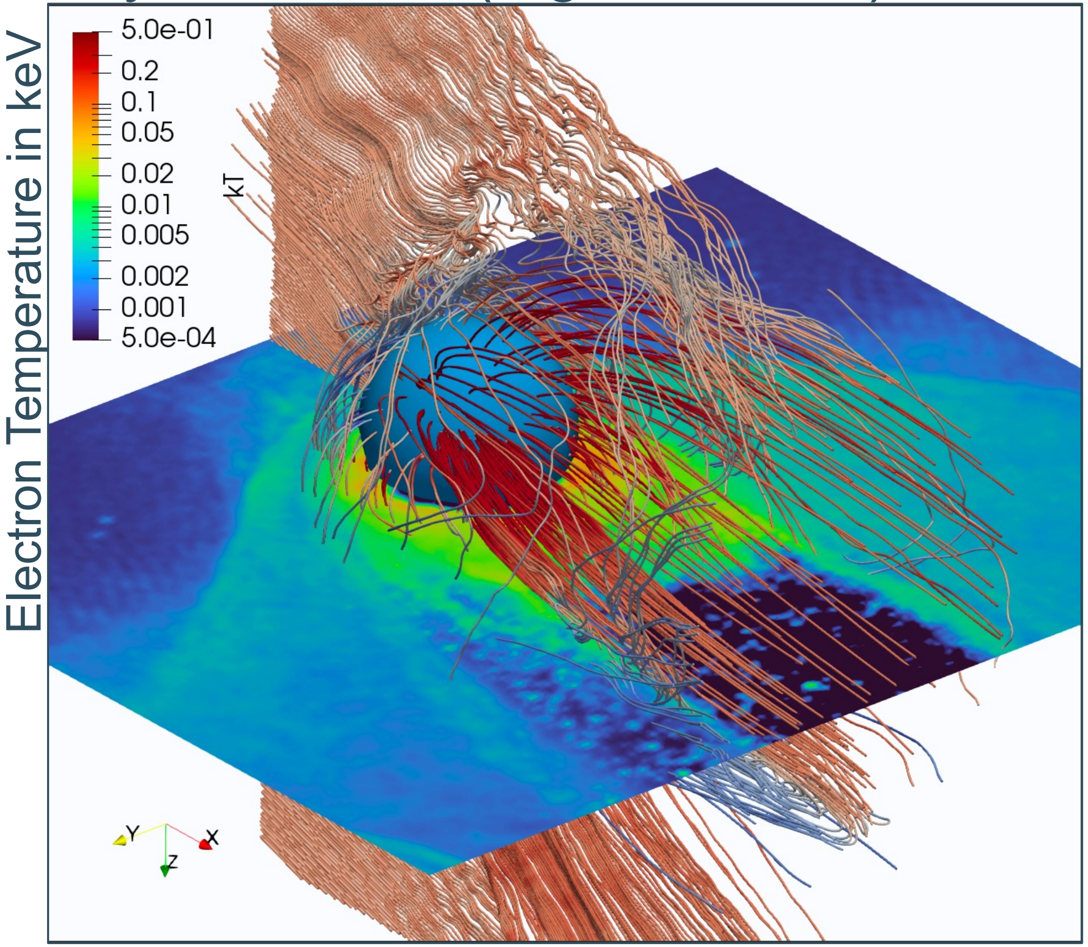
PIC simulation

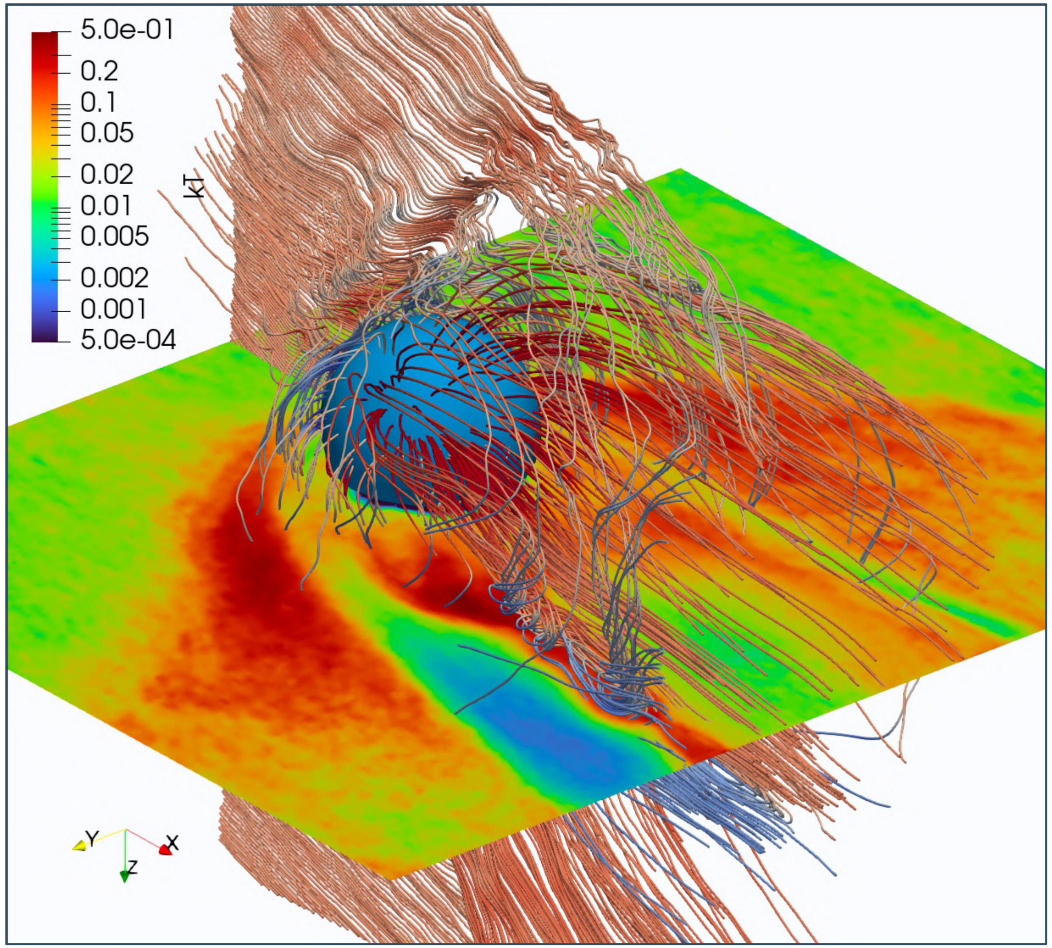
Work funded by the **ERC Advanced Grant TerraVirtualE**

Do we need to bother with kinetic electrons?

Hybrid model (e.g. Vlasiator)

Full PIC

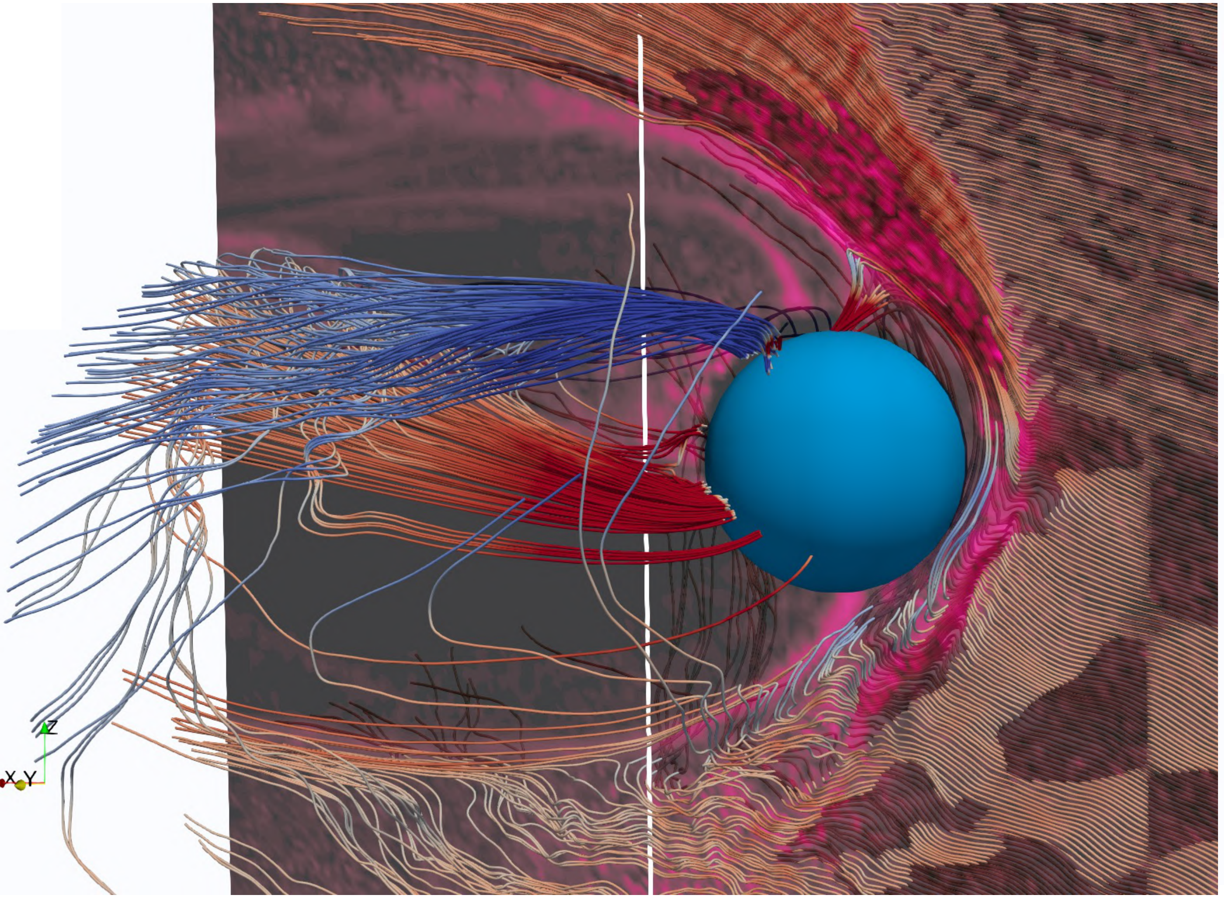


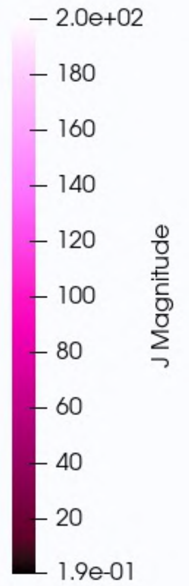


Lapenta, et al., J*GR 127, e2021JA030241* (2022).

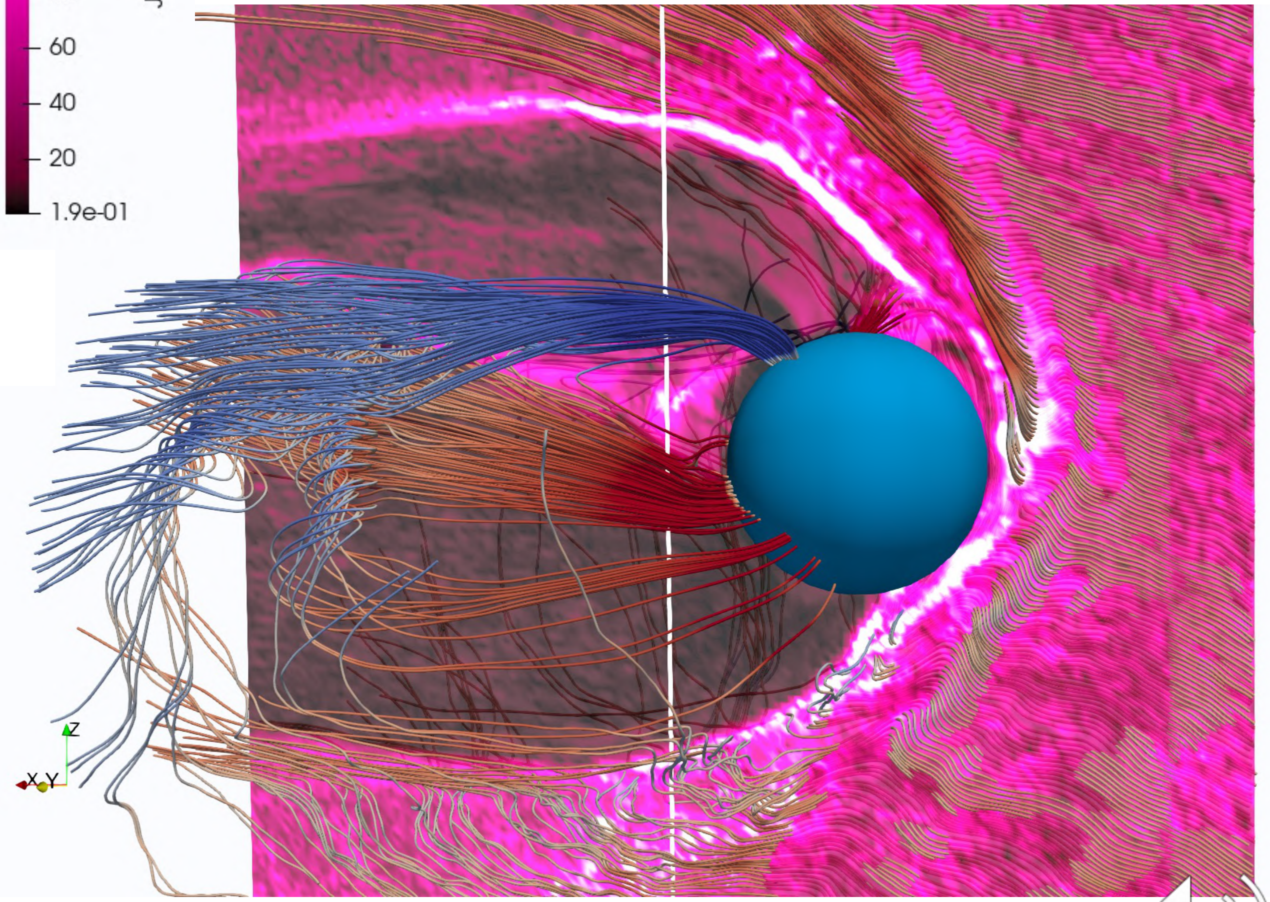
Electron Current

Hybrid model (fluid electrons)

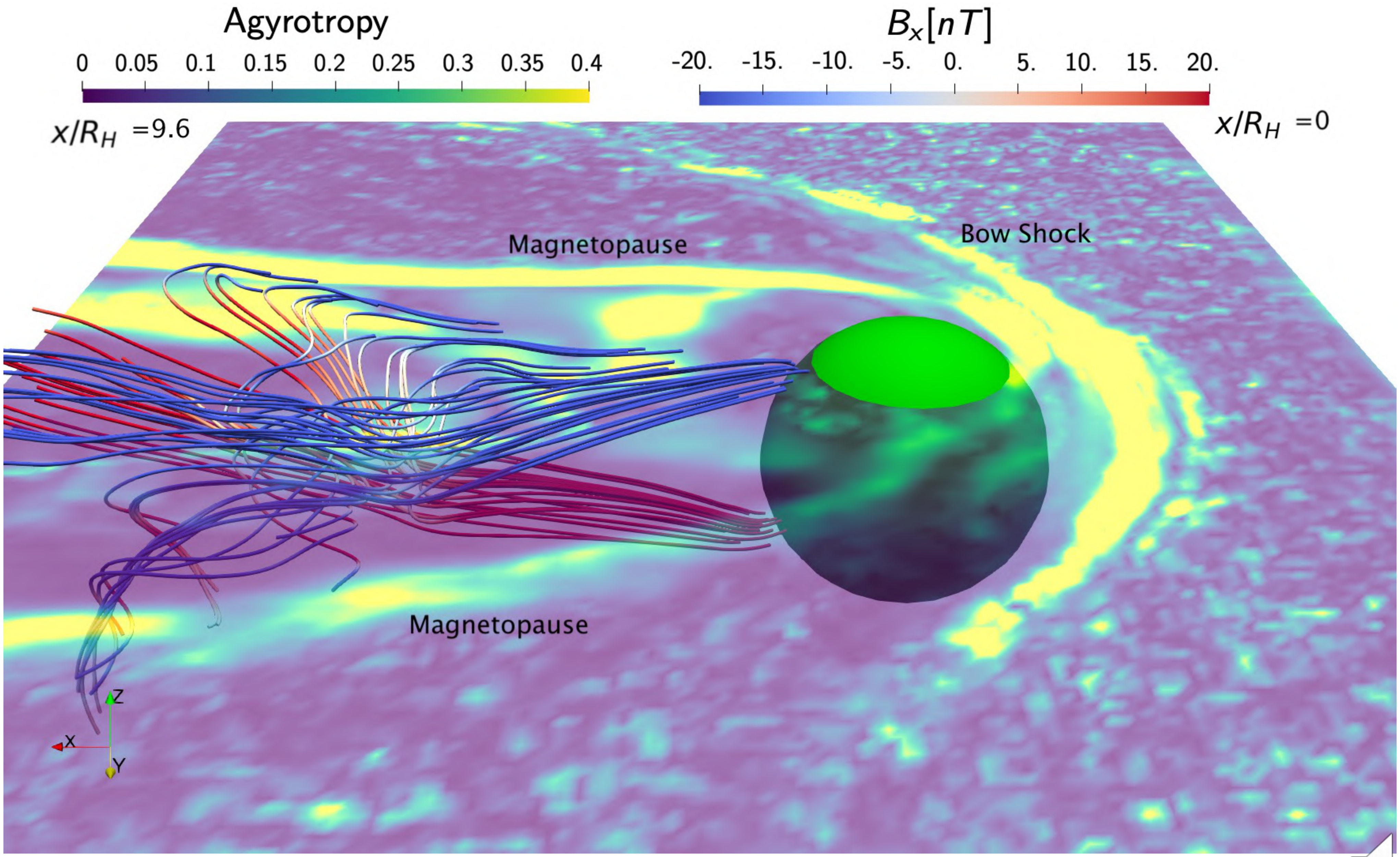




Full PIC (kinetic electrons)

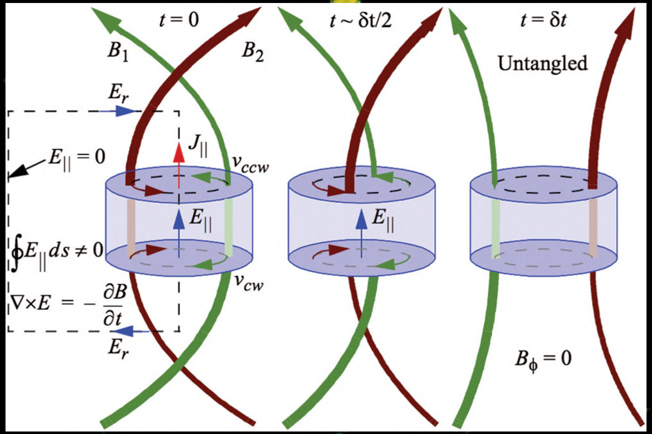


Reconnection regions



Lapenta, et al., JGR 127, e2021JA030241 (2022).

We use a precise reconnection identifier that is capable of including more complex 3D reconnection topologies, like tangling magnetic filed lines



Ergun, R. E., et al. PRL (2016): 235102.

Lorentz Reconnection indicator
[Lapenta, ApJ 911.2 (2021): 147].

iPic3D

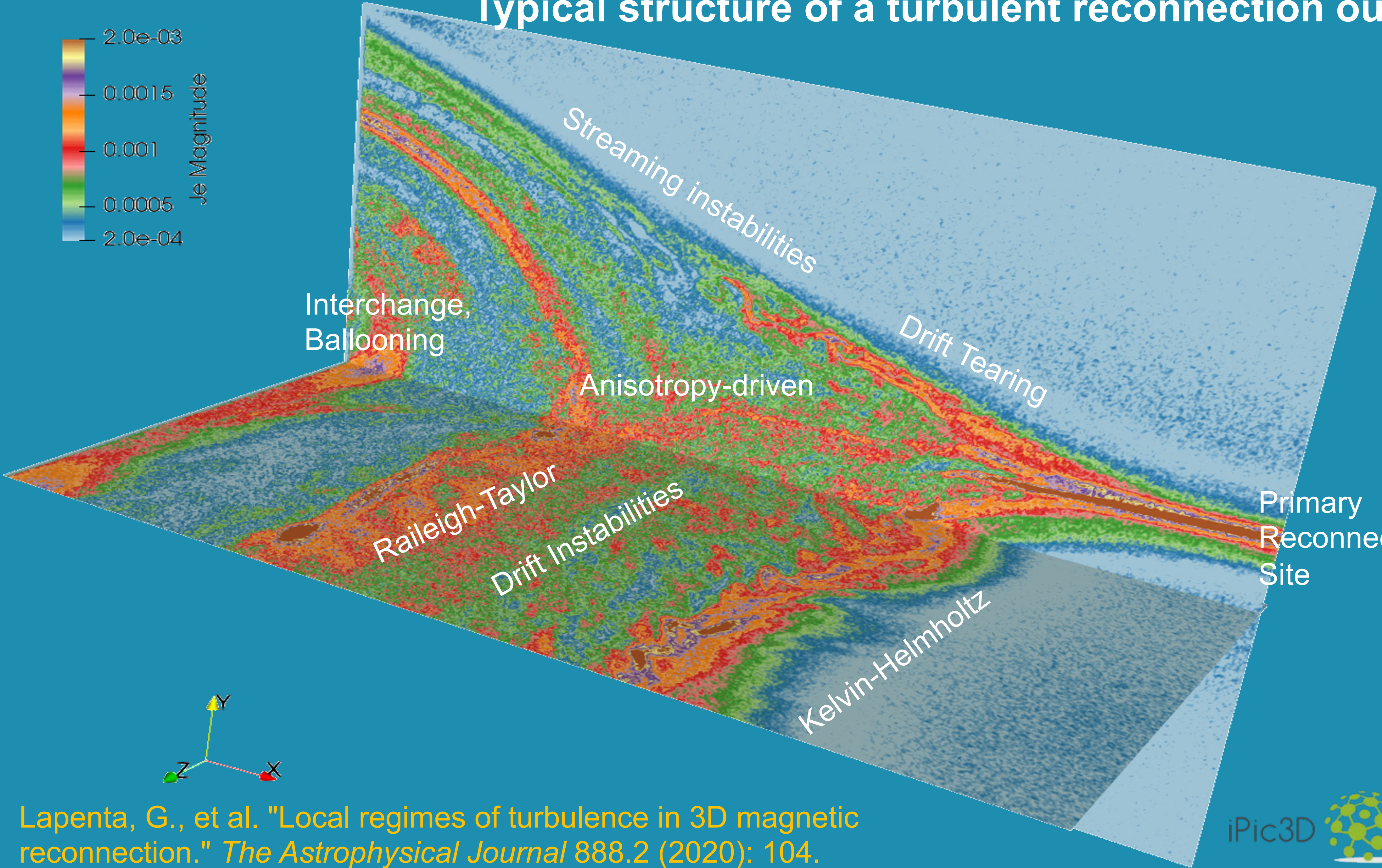
Vicinity of one 3D reconnection site

Lapenta, Nature Physics, January 2023.

ML Tools for clustering features: DBSCAN

Lapenta, Nature Physics, January 2023.

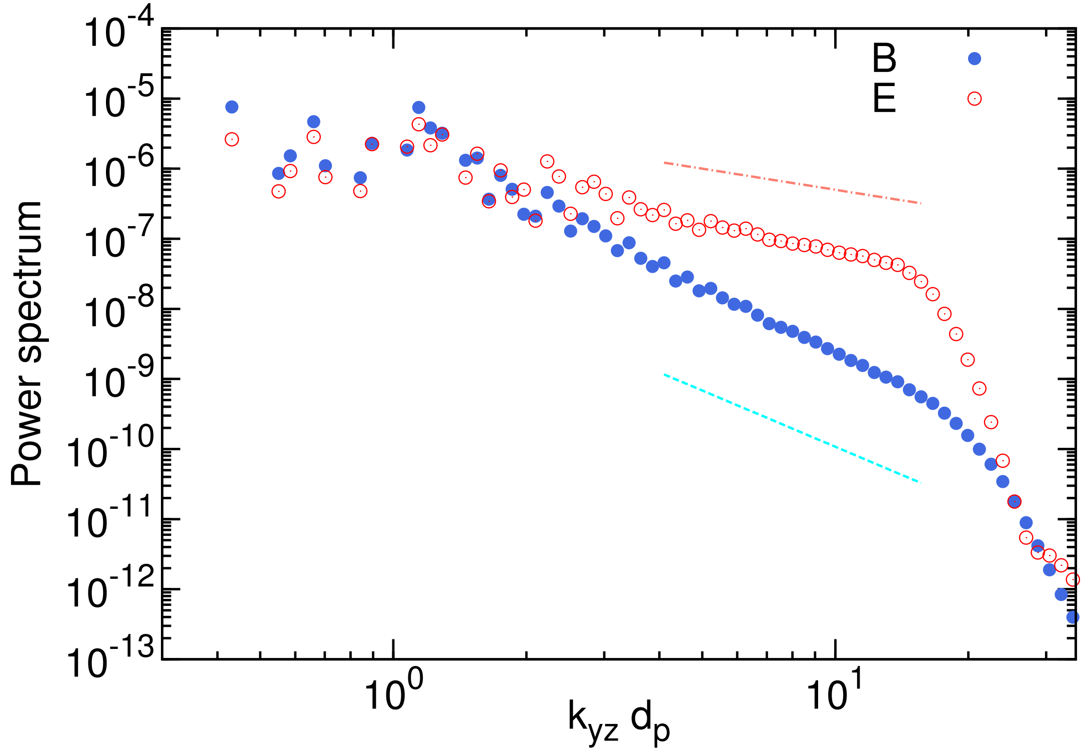
Typical structure of a turbulent reconnection outflow



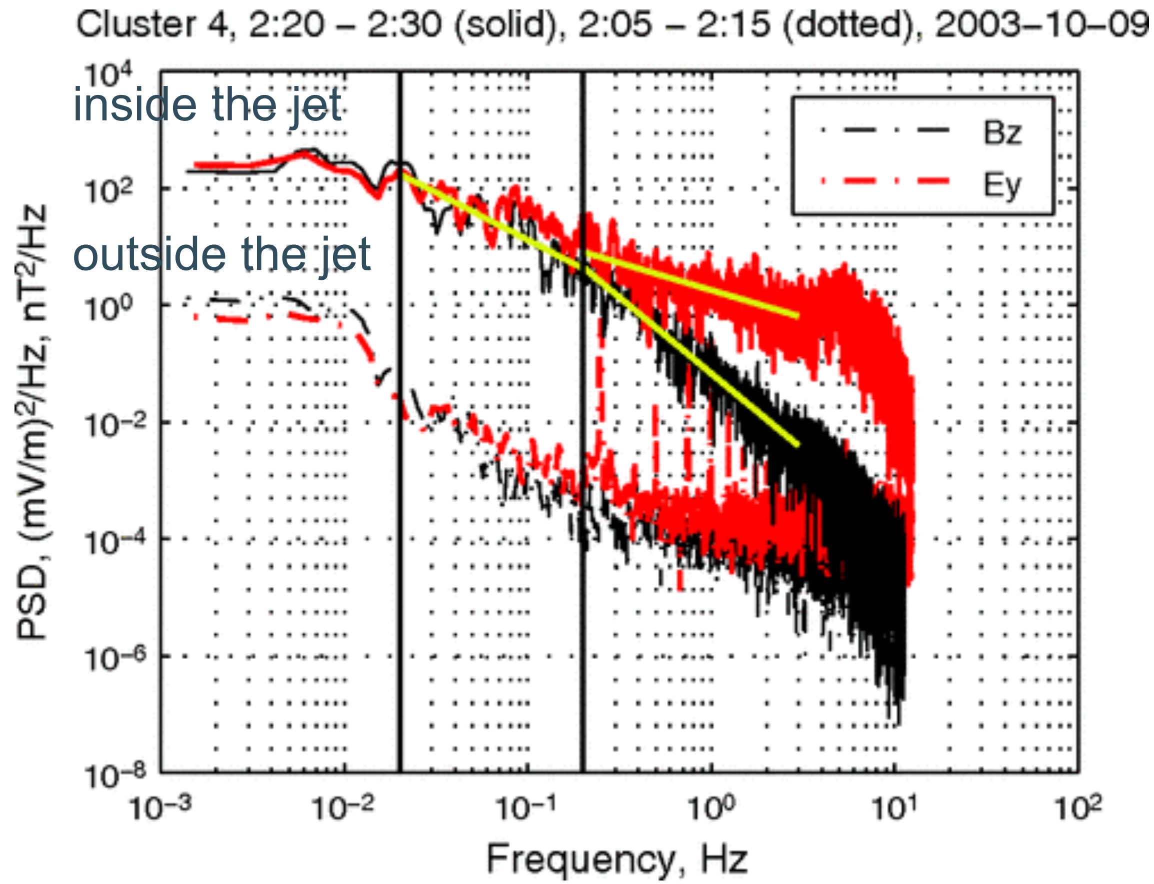
Lapenta, G., et al. "Local regimes of turbulence in 3D magnetic reconnection." *The Astrophysical Journal* 888.2 (2020): 104.

iPic3D

Traditional methods: Fourier modes, structure functions, correlations

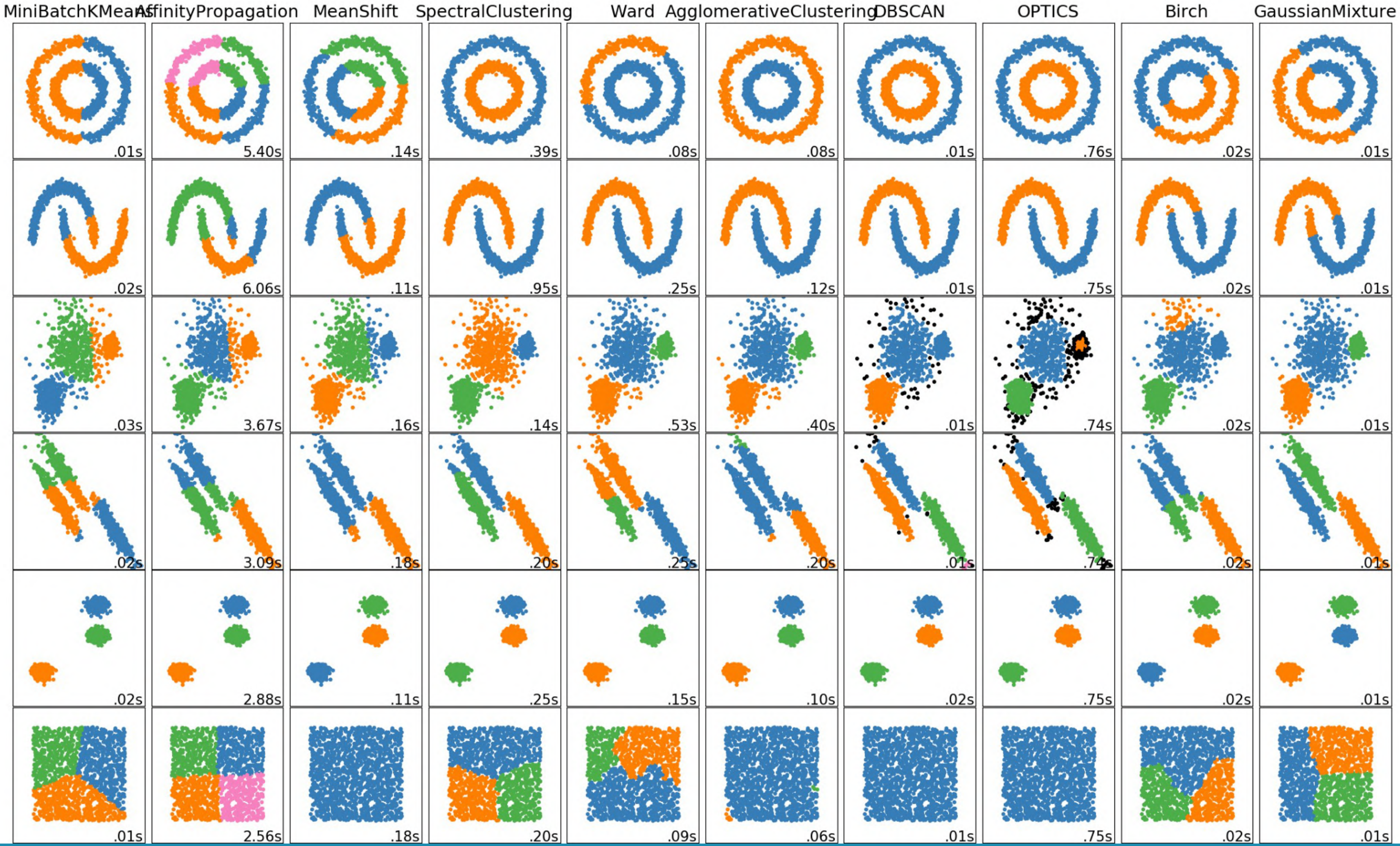


Pucci, Lapenta et al, ApJ, **841**:60 (2017)

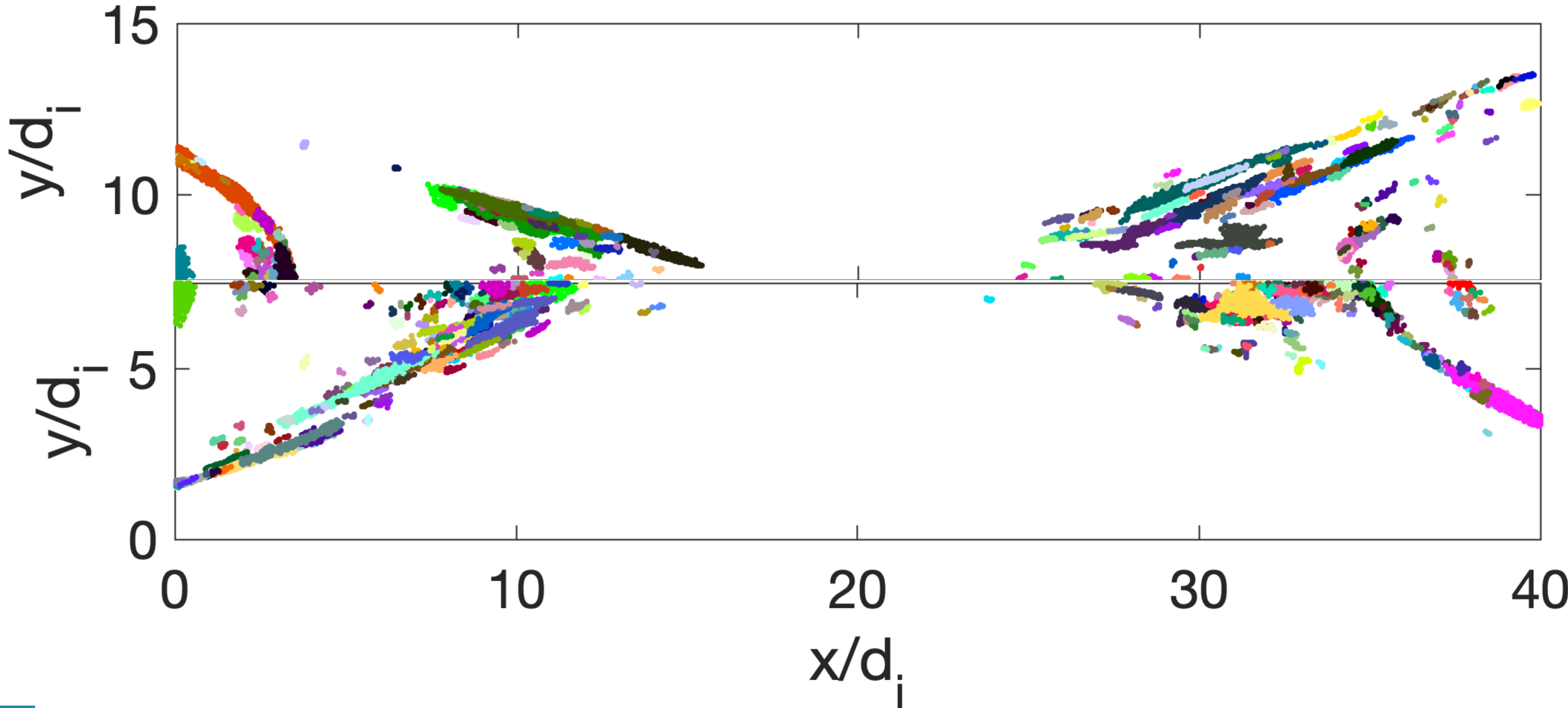


J. P. Eastwood, et al. , PRL **102**, 035001 (2009)

ML Tools: Clustering methods

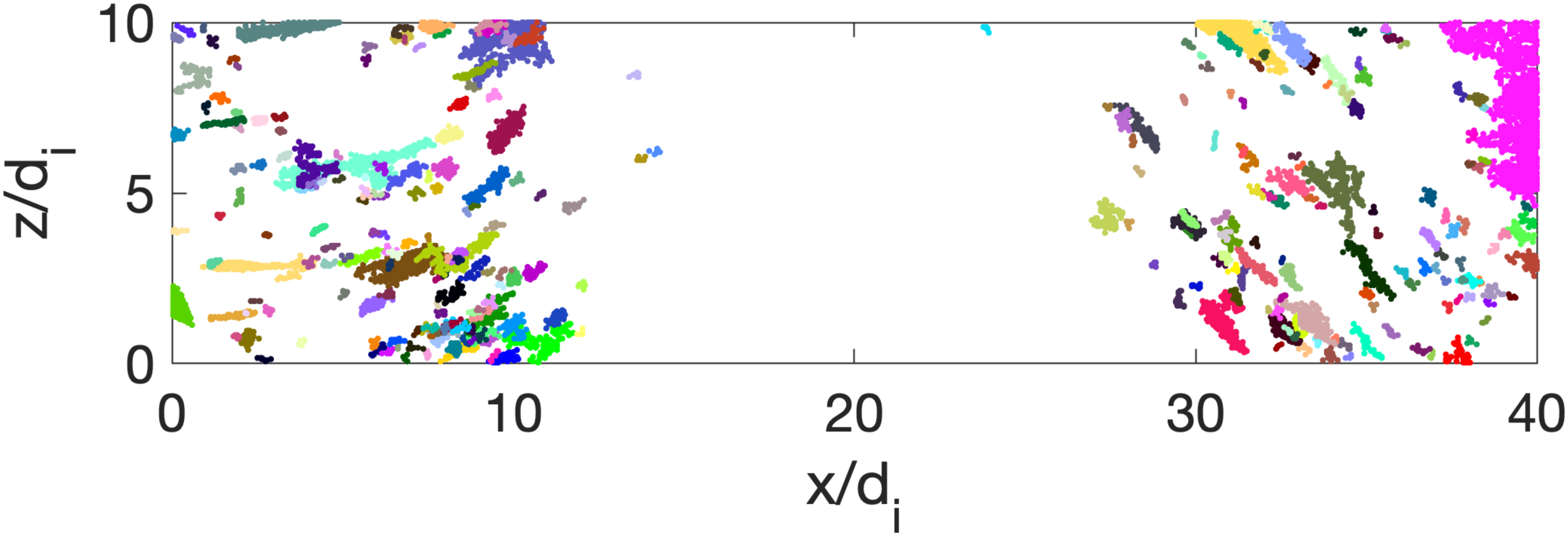


ML scientific discovery via data analysis



G. Lapenta et al. Formation and reconnection of electron scale current layers in the turbulent outflows of a primary reconnection site, ApJ, 940:187 (2022). https://doi.org/10.3847/1538-4357/ac98bc

Clusters of current identified by DBSCAN: 290

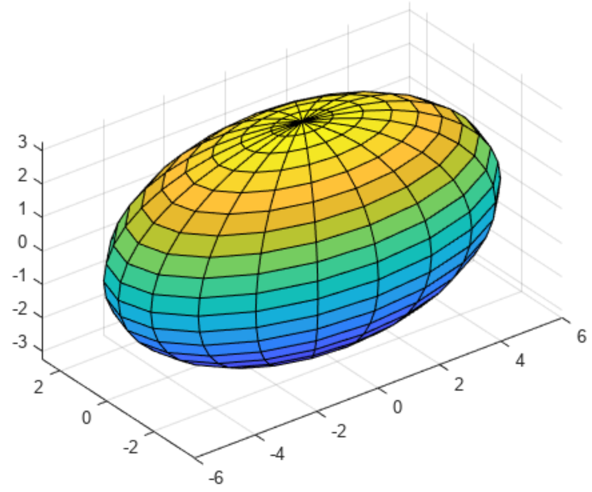


G. Lapenta et al. Formation and reconnection of electron scale current layers in the turbulent outflows of a primary reconnection site, ApJ, 940:187 (2022). https://doi.org/10.3847/1538-4357/ac98bc

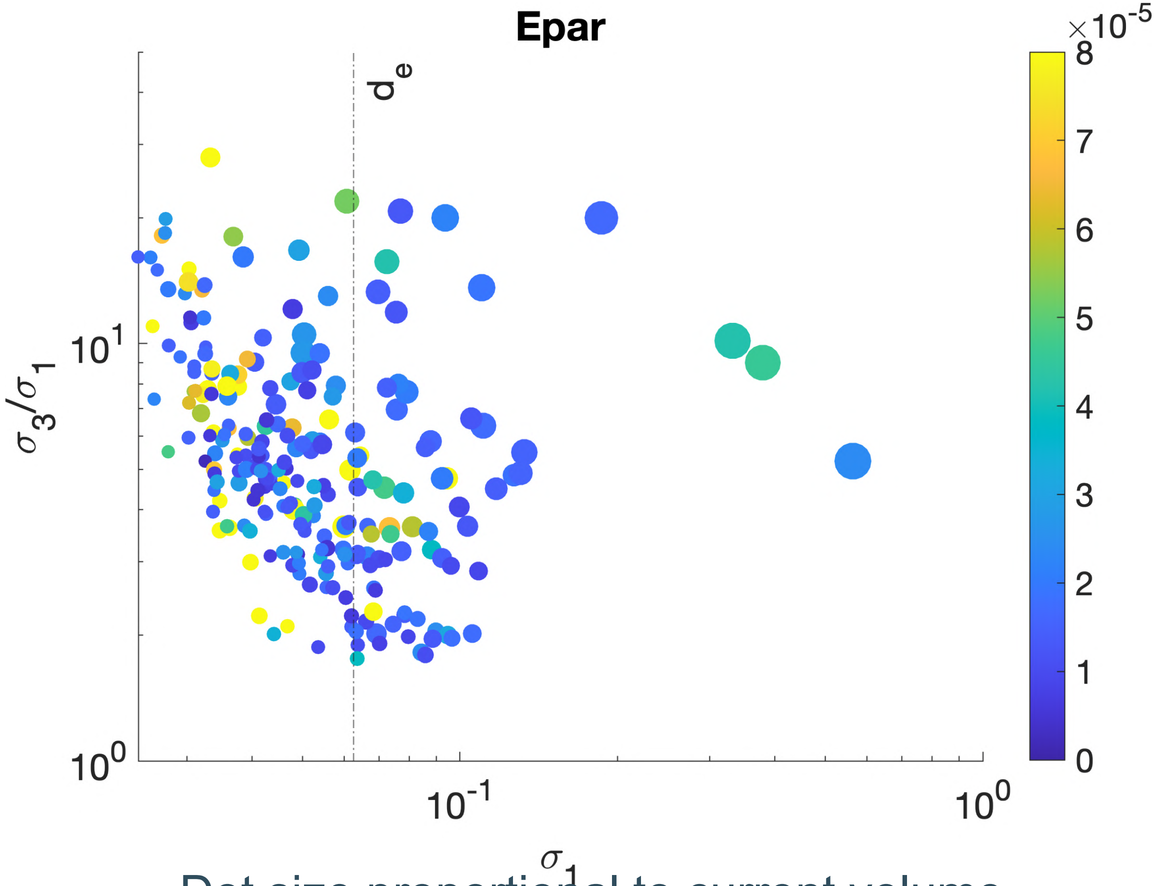
The smallest most elongated reconnect more

Most reconnection is at sub electron scale

Each current cluster is modelled as an ellipsoid



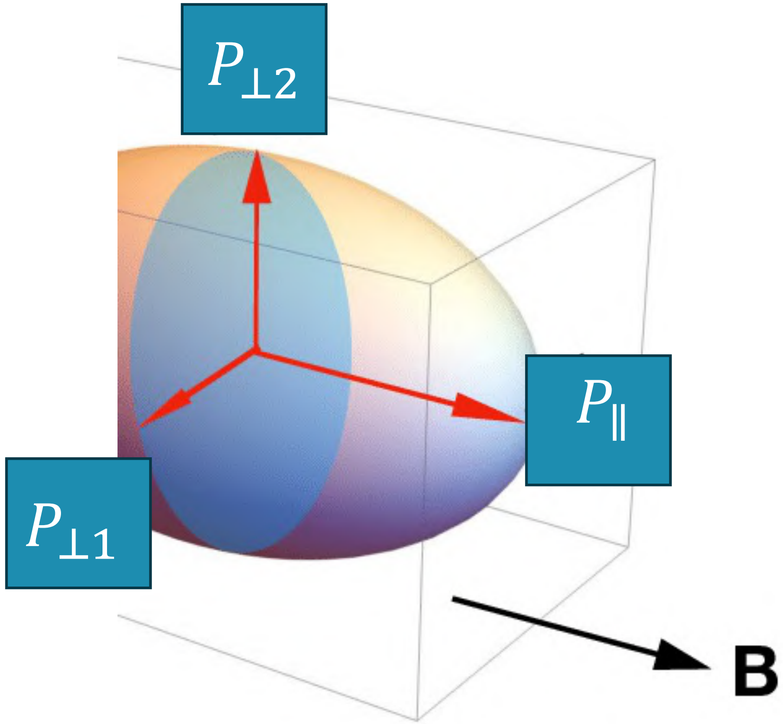
Axes in order of size: $\boldsymbol{\sigma}_1\ \boldsymbol{\sigma}_{2.}\ \boldsymbol{\sigma}_3$



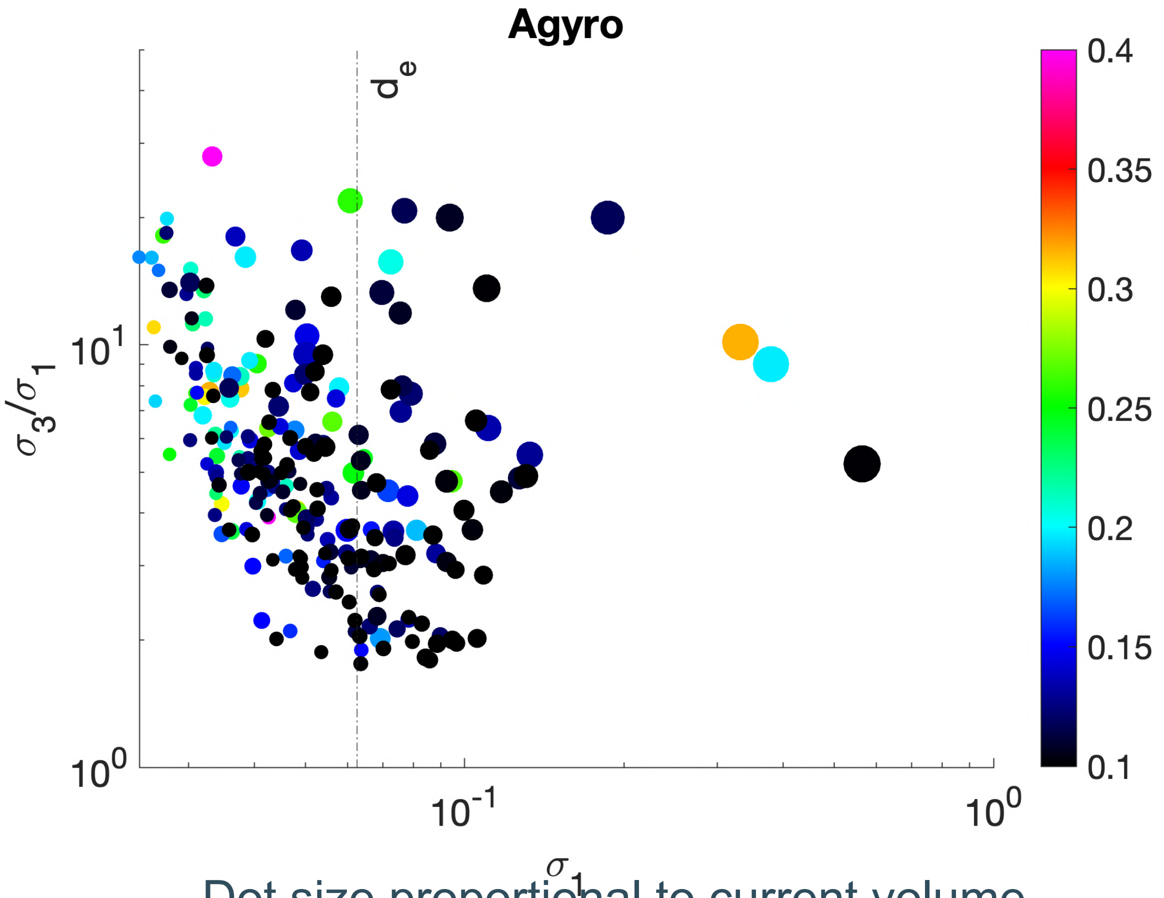
Dot size proportional to current volume

G. Lapenta et al. Formation and reconnection of electron scale current layers in the turbulent outflows of a primary reconnection site, ApJ, 940:187 (2022). https://doi.org/10.3847/1538-4357/ac98bc

The smallest most elongated reconnect more



Most reconnection is at sub electron scale



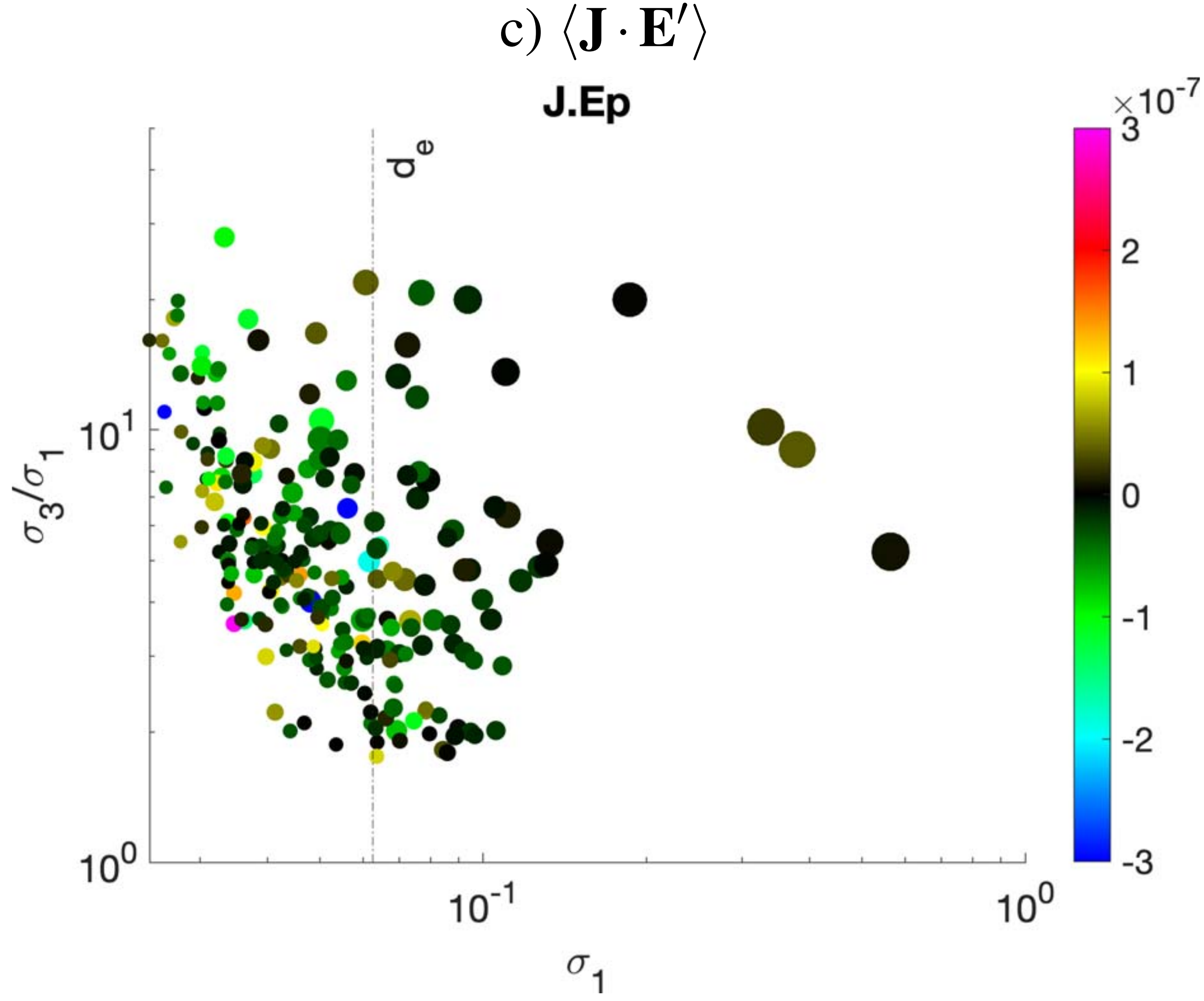
Dot size proportional to current volume

G. Lapenta et al. Formation and reconnection of electron scale current layers in the turbulent outflows of a primary reconnection site, ApJ, 940:187 (2022). https://doi.org/10.3847/1538-4357/ac98bc

Energy exchanges

- E' is the electric field in the electron frame

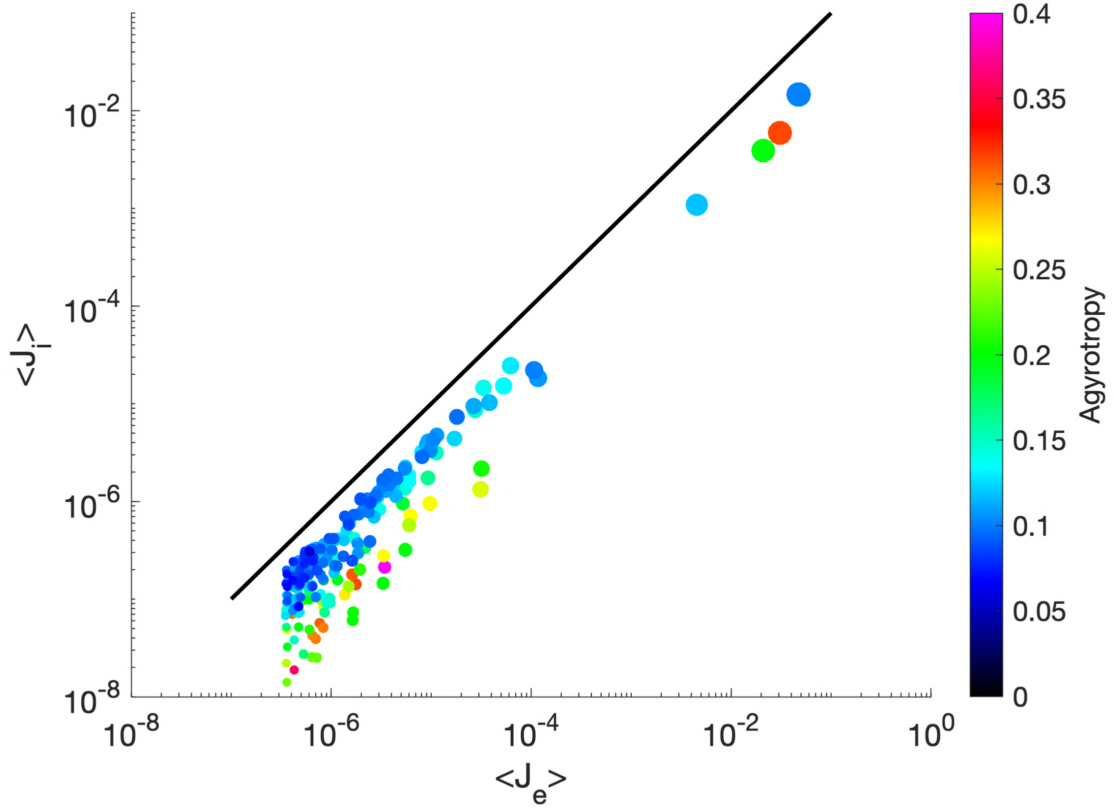
- The smallest current structures have the most intense energy exchanges in the electron frame



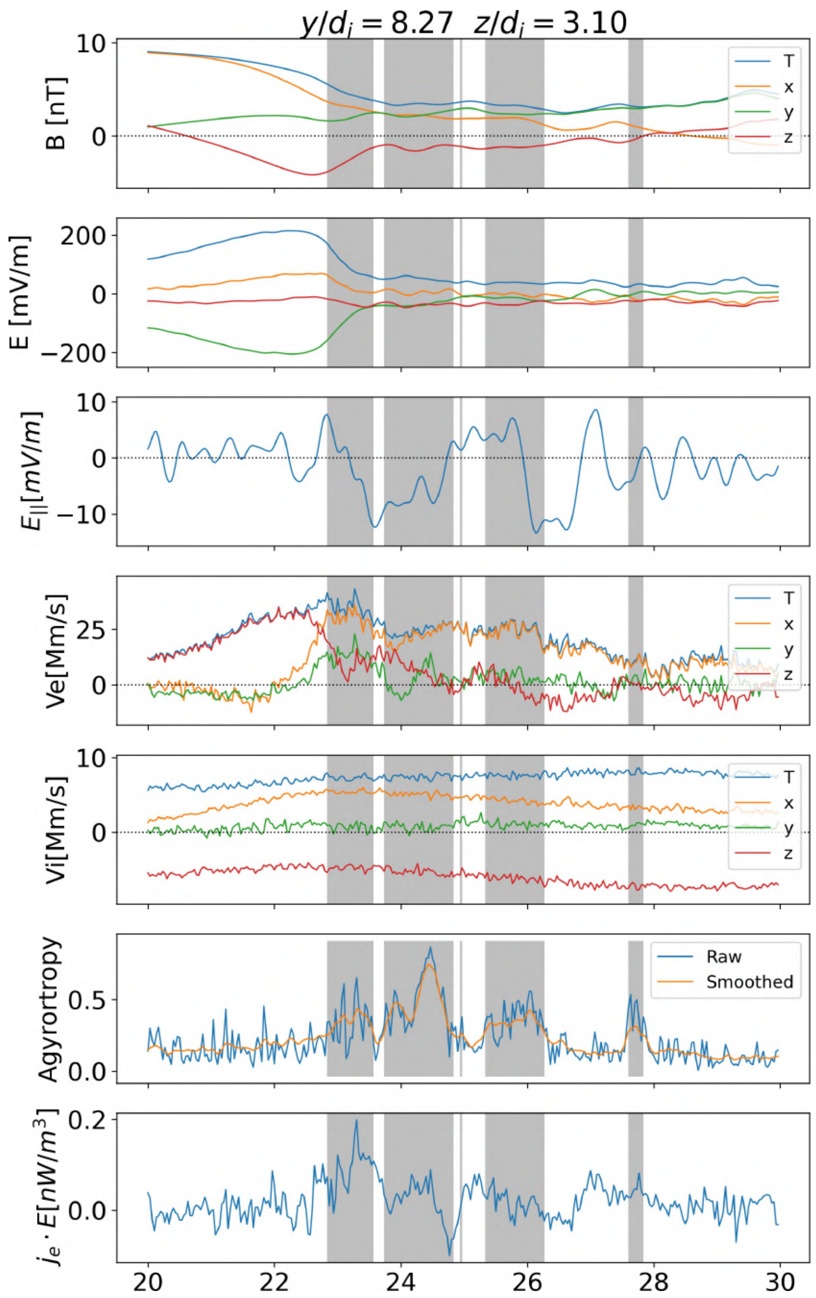
G. Lapenta et al. Formation and reconnection of electron scale current layers in the turbulent outflows of a primary reconnection site, ApJ, 940:187 (2022). https://doi.org/10.3847/1538-4357/ac98bc

Reconnection is mostly electron-only reconnection

The electron current dominates in the high agyrotropy layers

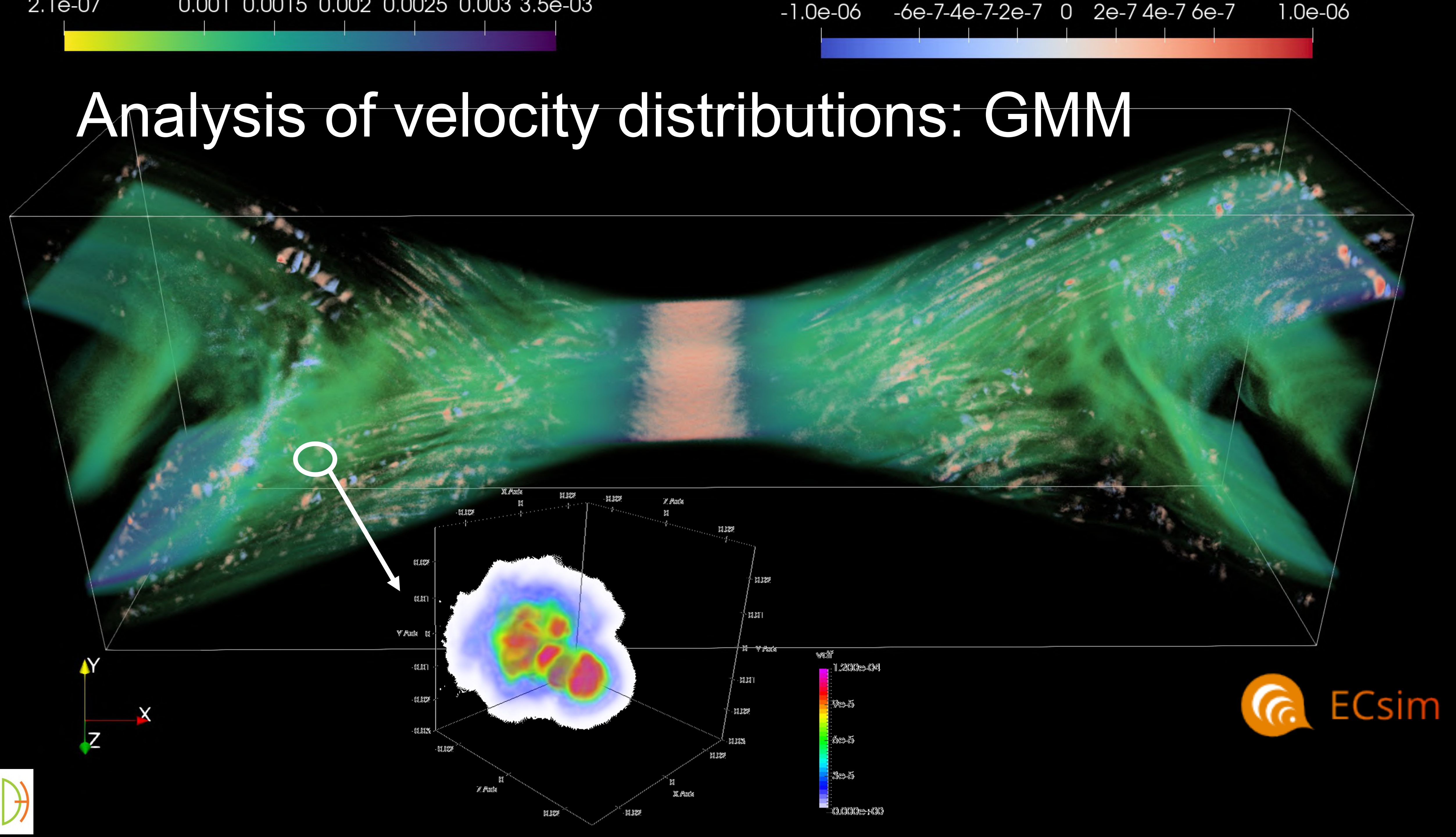


Dot size proportional to current volume



G. Lapenta et al. Formation and reconnection of electron scale current layers in the turbulent outflows of a primary reconnection site, ApJ, 940:187 (2022). https://doi.org/10.3847/1538-4357/ac98bc

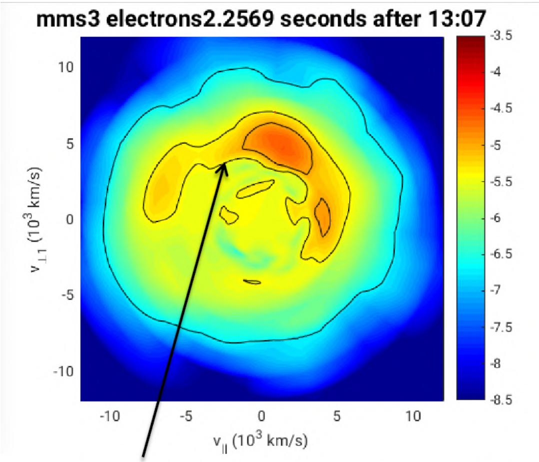
Analysis of velocity distributions: GMM



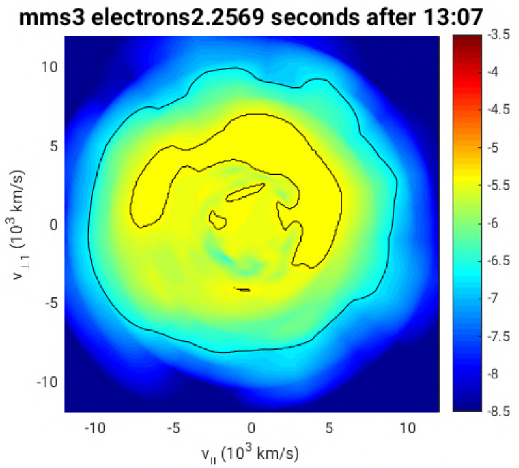
ML Tools for different type of data-sets

Velocity or energy distributions, $f(v_1, v_2, v_3)$

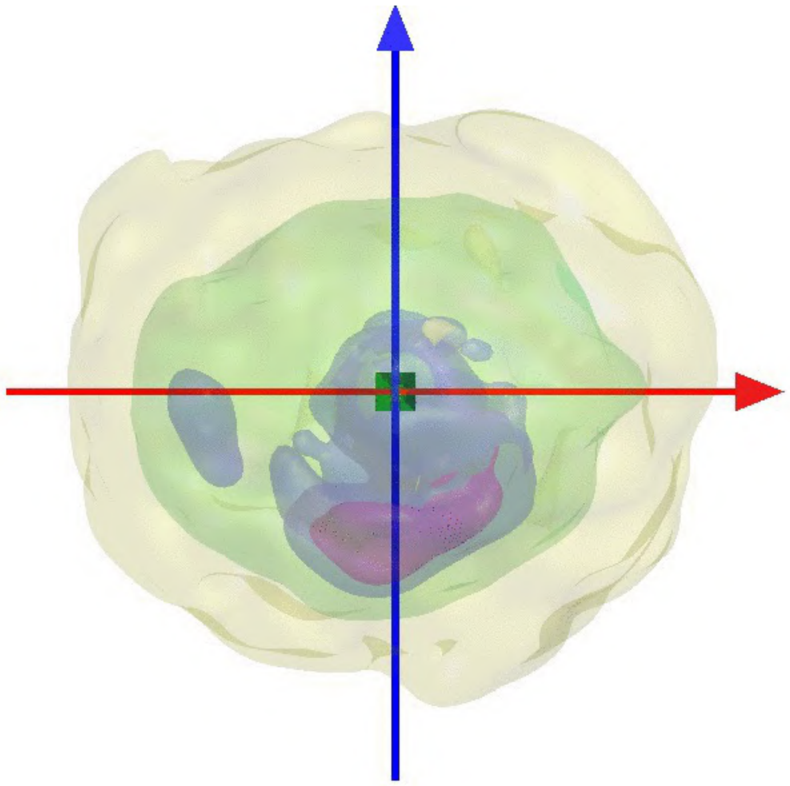
- Identifying reconnection from its impact on the distribution functions
- This is a new rarely tried approach, spurred by the discovery of crescents and the role of electron agyrotropy.



Crescent plus background



Background alone



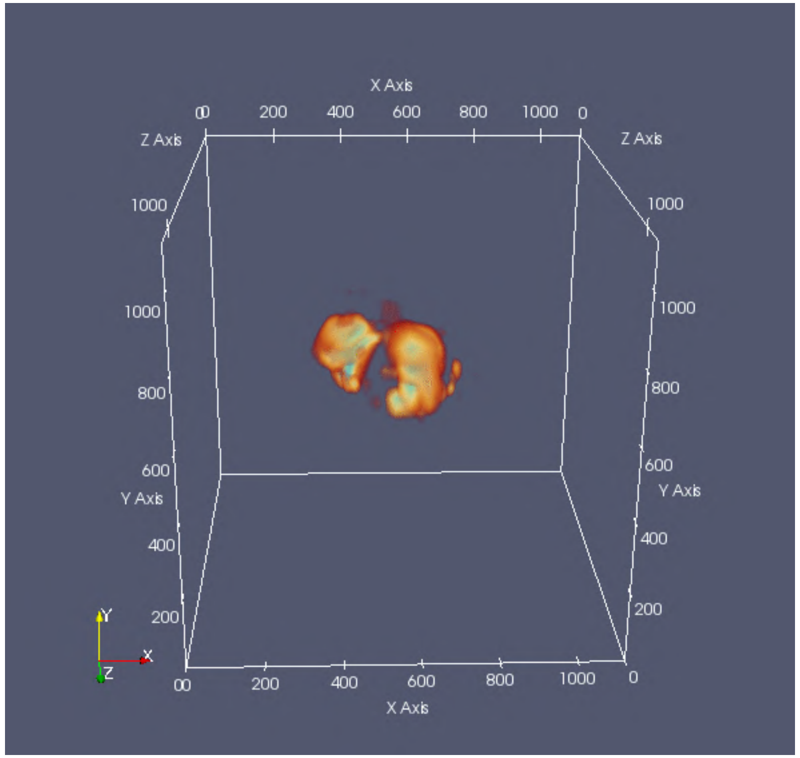
Courtesy of David Newman

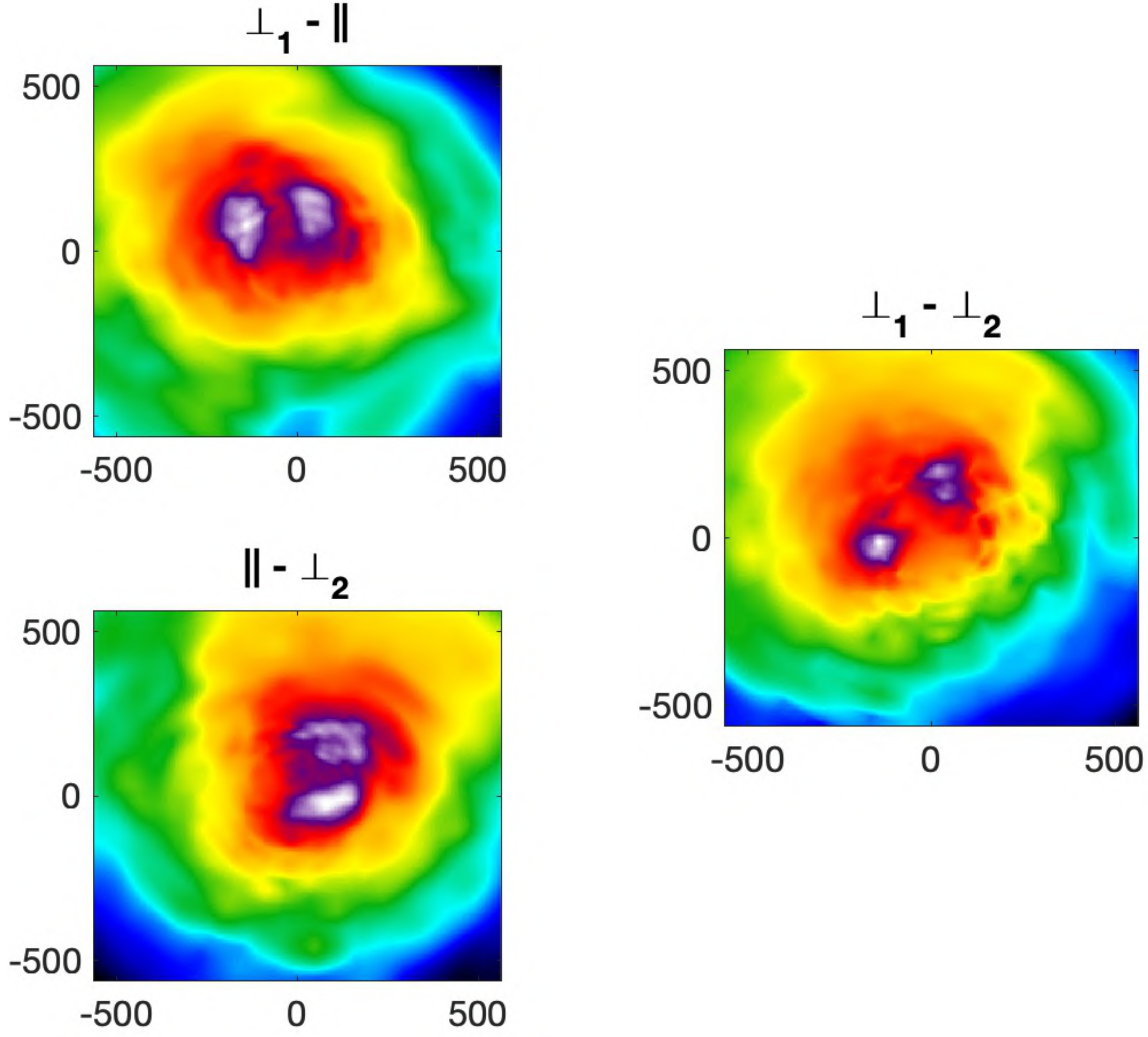
Why is data from the velocity distribution rarely used?

Typical simulation:

- 200x200x200 grid with 1000 particles per cell per species
- **The grid is about 2GB** of data per time step (considering all cells and all fields: B, E, n, p, V per species)
- **The particles instead are about 1TB** of data for each time step.
- Discerning patterns in the particle data is a tremendous challenge
- ML tools can be a game changer.

FPI instrument on MMS

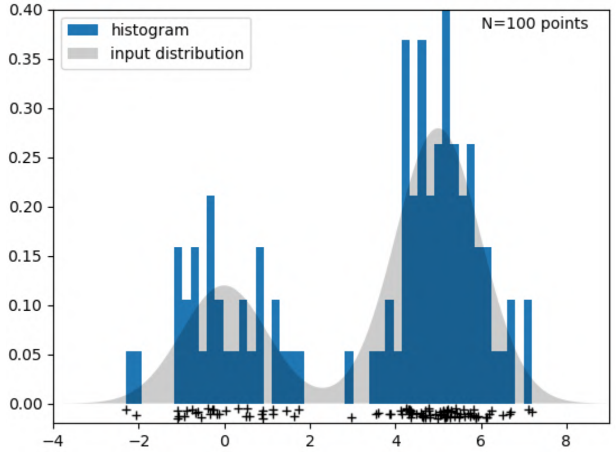


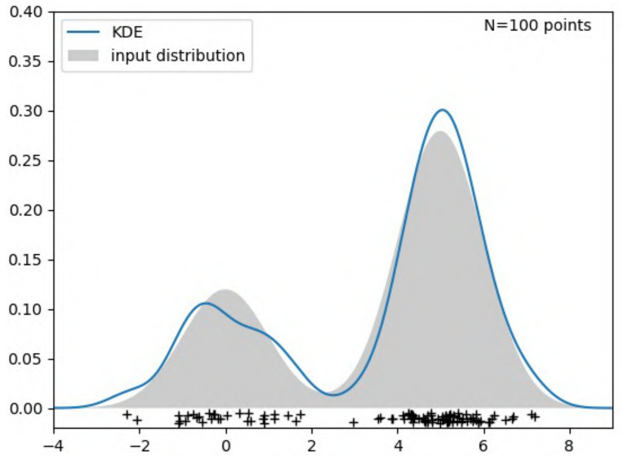


Goldman, M. V., et al. *JGR* 125.12 (2020): e2020JA028340.

Analyzing distributions

- **Building an estimate of the probability density function**

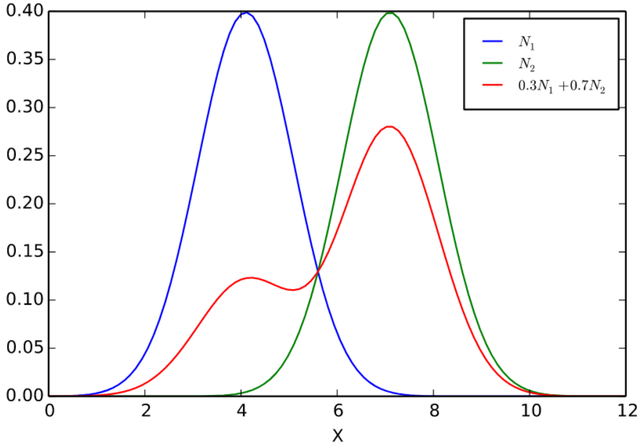




- **Non-parametric methods**
  - Histogram
  - Kernel Density Estimation
  - K-means
  - Fuzzy C-means
  - DBscan

- **Parametric methods**
  - Fitting given distributions
  - Gaussian Mixture Models (GMM)

$$p(\boldsymbol{x}|\boldsymbol{\Phi}) = \sum_{k=1}^{K} w_k \mathcal{N}(\boldsymbol{x}|\boldsymbol{\theta_k})$$



Dupuis, R., et al(2020). ApJ, *889*(1), 22.

GMM: Automatic selection of the number of gaussian beams

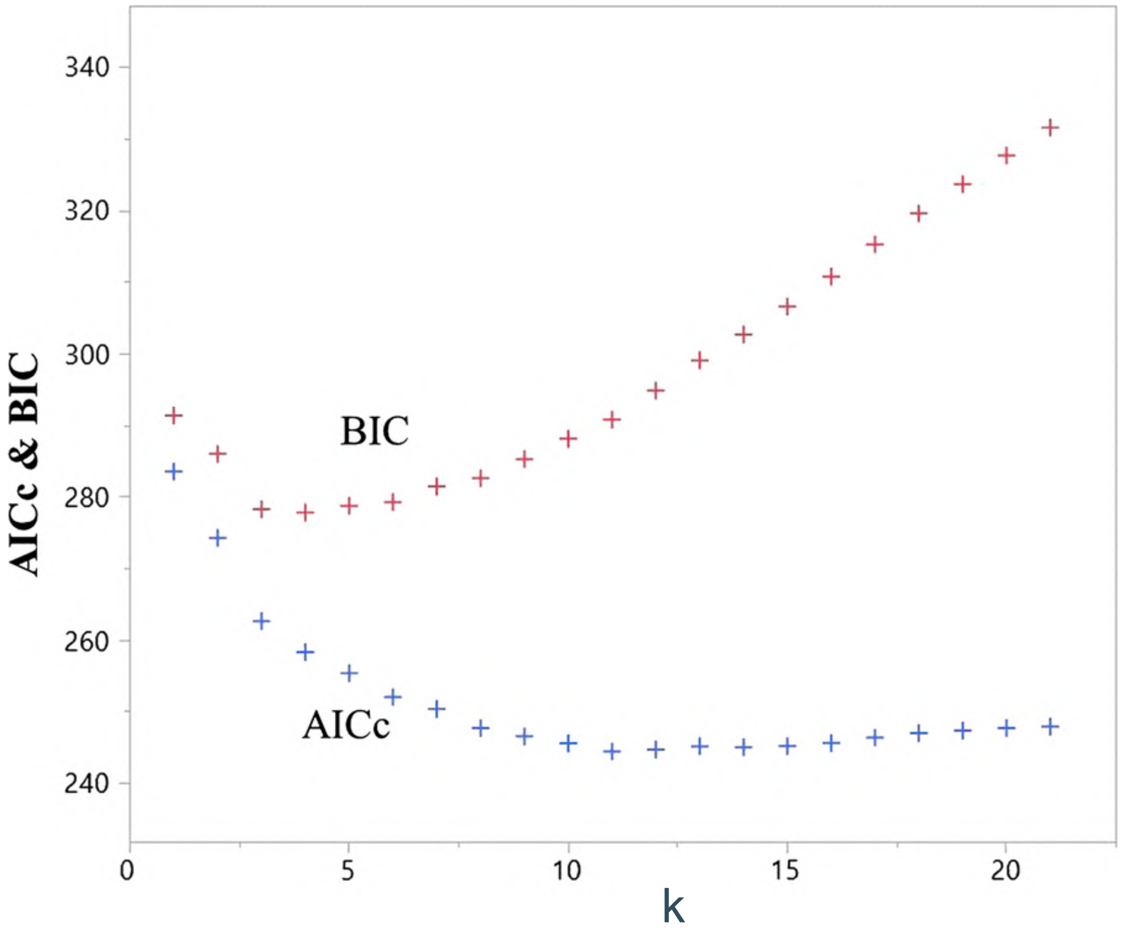
- Akaike information criterion (AIC):

  $AIC = 2k - 2\ln(L)$

- Bayesian information criterion

  $BIC = \ln(n)k - 2\ln(L)$,

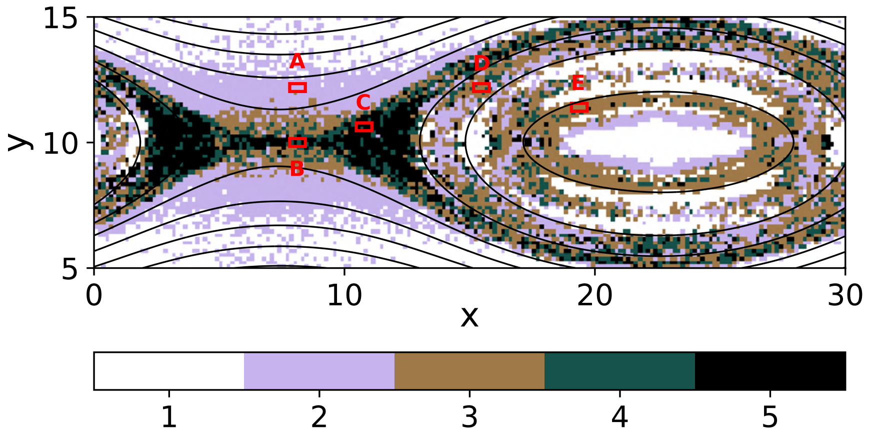
- k is the number of parameters to estimate in the model
- L the likelihood



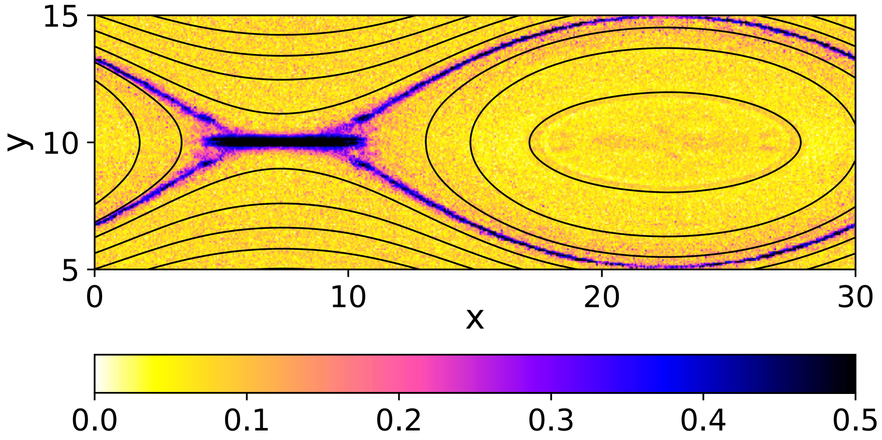
Dupuis, R., et al(2020). ApJ, *889*(1), 22.

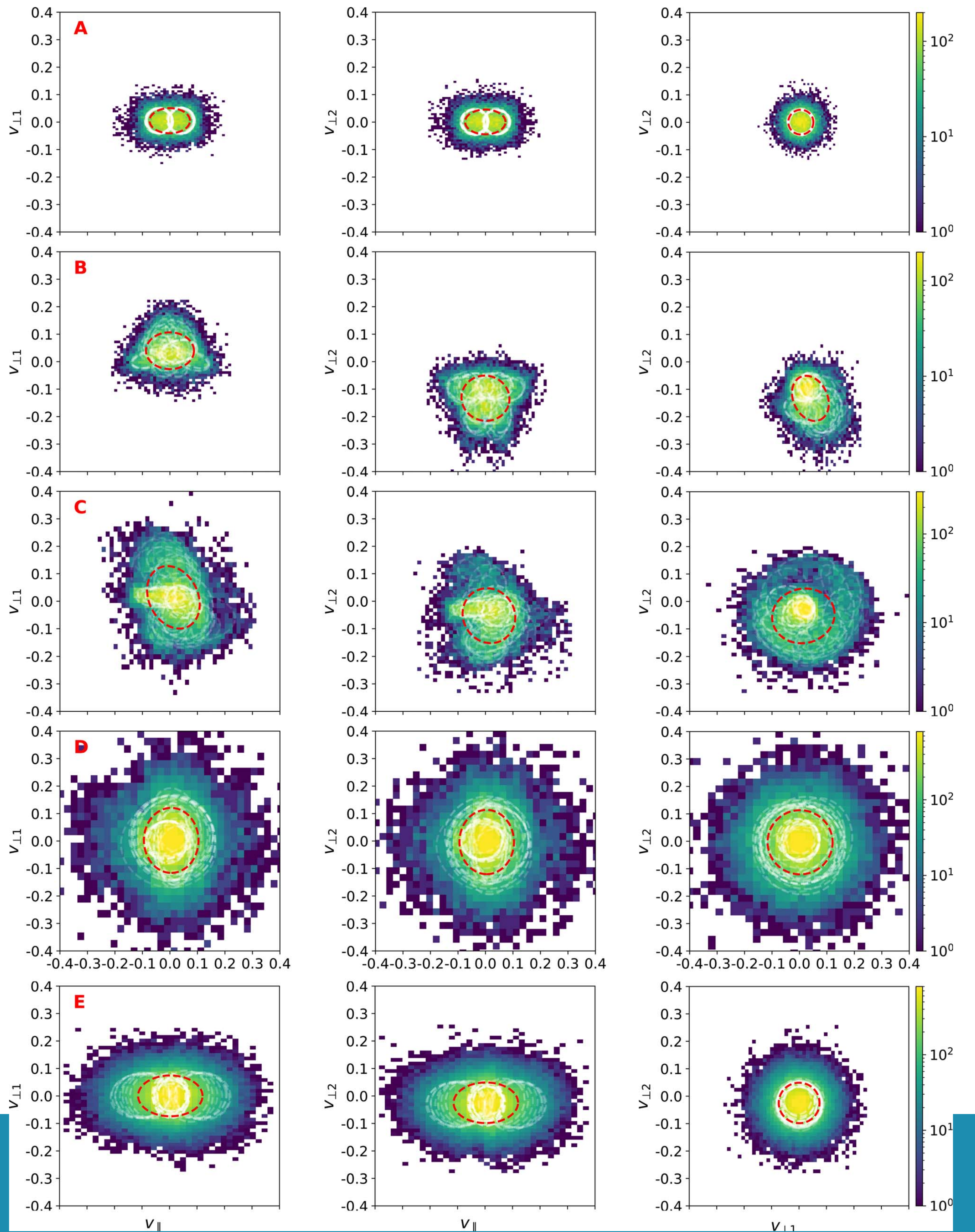
Using ML based on particle distributions

Types of distrubutions(GMM)



Agyrotropy



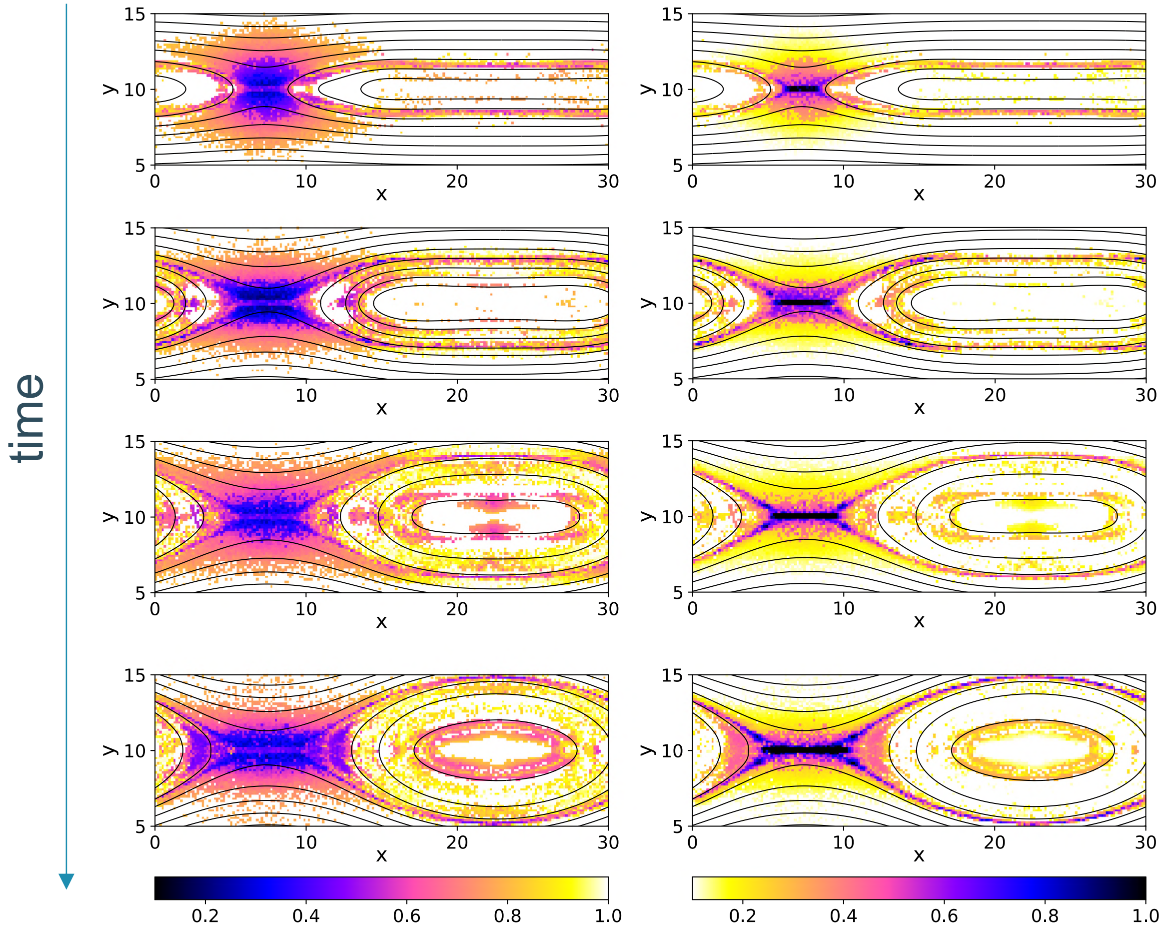


Dupuis, R., et al(2020). ApJ, *889*(1), 22.

Effect on the definition of thermal energy

$$E_{\rm drop} = \frac{E^{(K)}_{\rm thermal}}{E_{\rm thermal}}.$$

$$E^{(K)}_{\rm dev}$$



- Fluid thermal energy:

$$E_{\rm thermal} = \frac{1}{N_p}\sum_{i=1}^{3}\left[\sum_p (\boldsymbol{V_p} - \langle \boldsymbol{V_p}\rangle)^2\right]_i, \text{ with } \langle \boldsymbol{V_p}\rangle = \sum_p \frac{\boldsymbol{V_p}}{N_p}.$$

- Multibeam thermal energy

$$E^{(K)}_{\rm thermal} = \frac{1}{2}\sum_{i=1}^{3}\sum_{k=1}^{K} w_k^2 [\boldsymbol{\sigma}_{\boldsymbol{k}}^2]_i.$$

- Drop in thermal energy

$$E_{\rm drop} = \frac{E^{(K)}_{\rm thermal}}{E_{\rm thermal}}.$$

- Pseudo (False) thermal energy

$$E^{(K)}_{\rm dev} = \sum_{i=1}^{3}\left[\sum_{k=1}^{K} w_k (\boldsymbol{\mu_k})^2 - \left(\sum_{k=1}^{K} w_k(\boldsymbol{\mu_k})\right)^2\right]_i.$$

Dupuis, R., et al.(2020). ApJ, *889*(1), 22.
Goldman, M. V., et al. *JGR* 125.12 (2020): e2020JA028340.

To know more

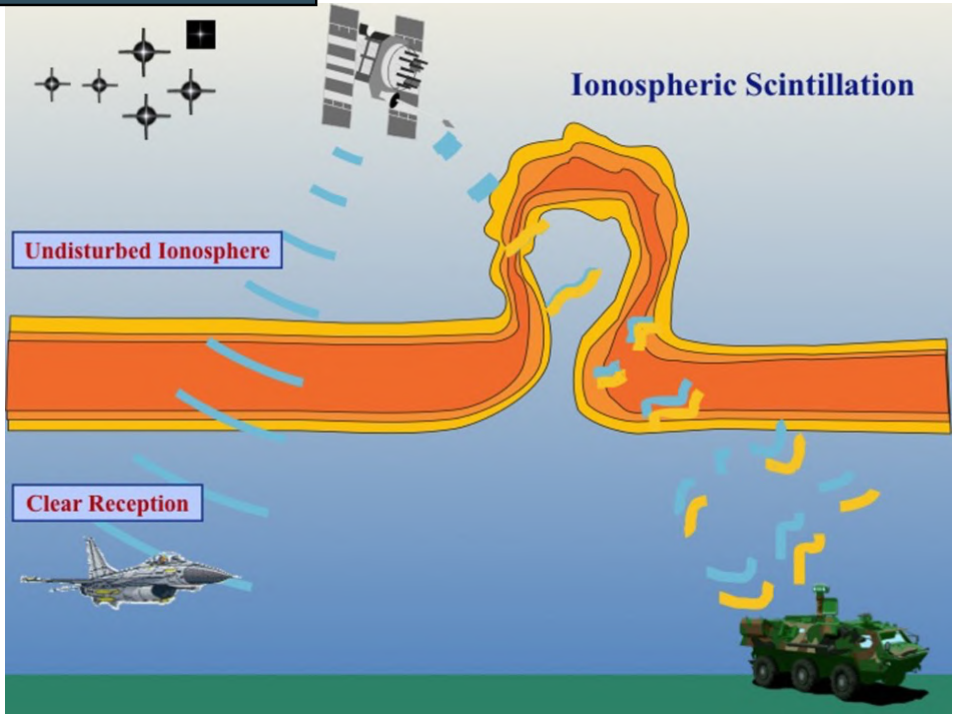
- ✓AIDA: http://www.aida-space.eu
- ✓ASAP: http://www.asap-space.eu

AIDefSpace:

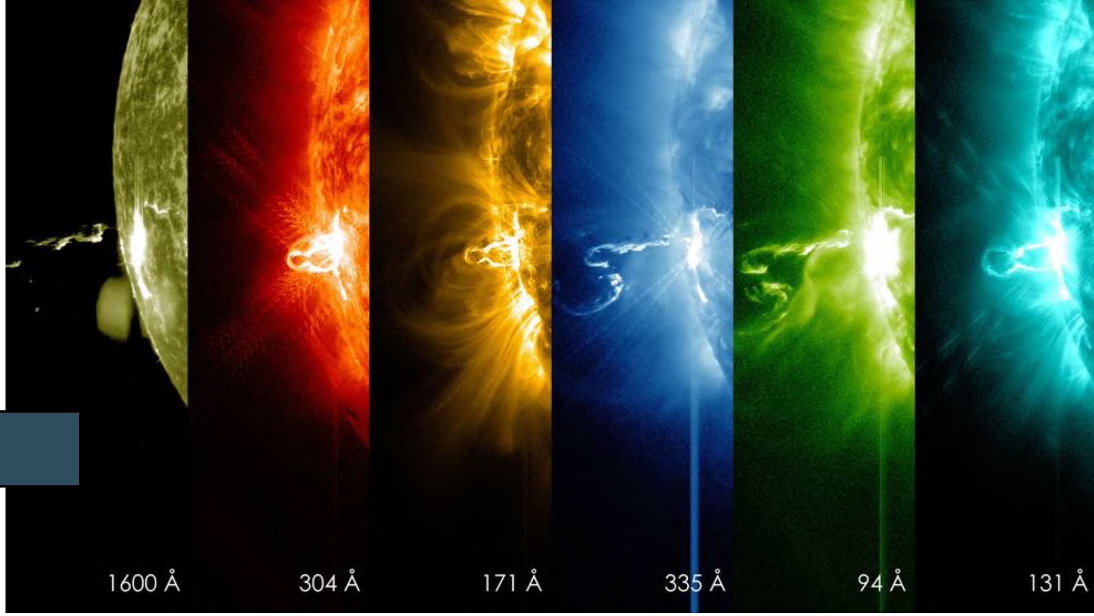
Using Artificial Intelligence to defend telecommunications and satellite positioning systems from the interference of space weather events

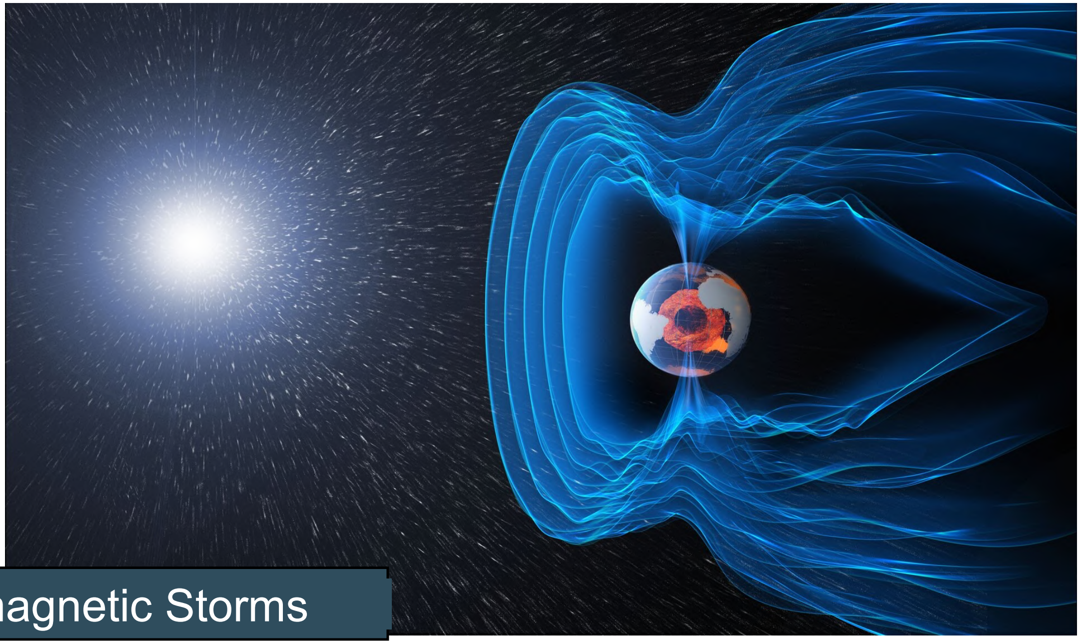
Goals of this project:
Space Weather Phenomena

Scintillation



Solar Flares





Geomagnetic Storms

Images Courtesy ESA, NASA, US AirForce