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

LMAG Workshop, 24/09/2020. 16:00 CET

Energy exchange and particle energization in turbulent outflows from reconnection

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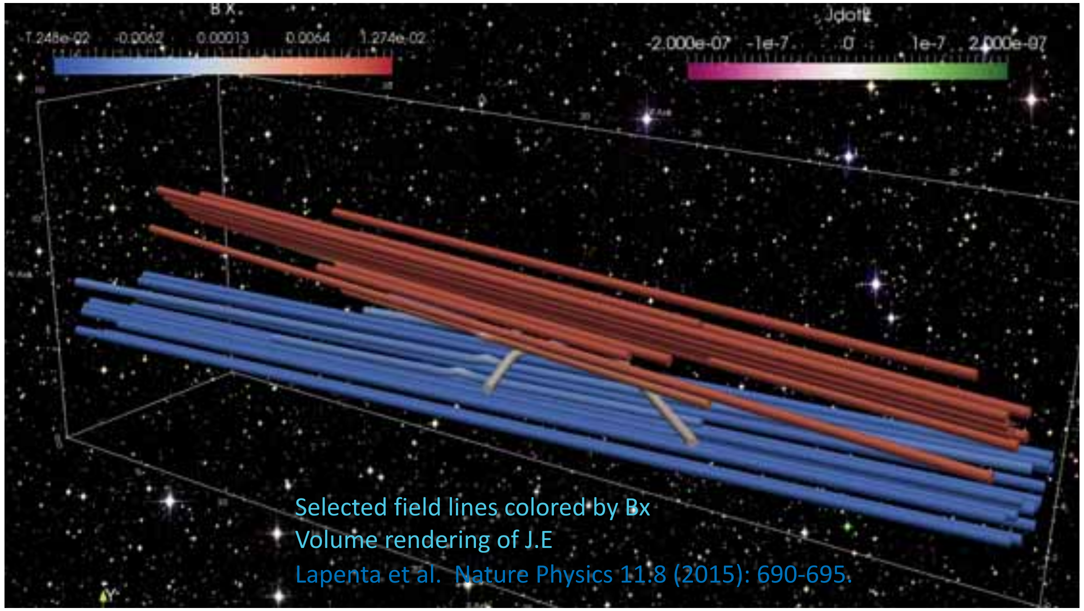
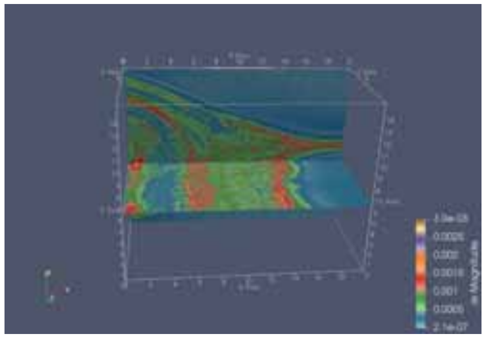
Overview

- Reconnection in 3D
- Reconnection causes turbulence
- Turbulence and reconnection cause energzation of the particles
- But what type of energization? Is it heating or acceleration?
- Effect on velcity distribution functions (VDF)
- Analysis of VDF with machine learning within the AIDA project.

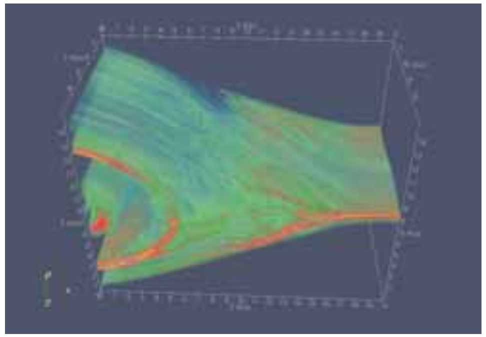


How 3D reconnection really is

Mi/me=256
B_g=1/10
Grid:1200x450x300
Resolution $\Delta x = d_e/2$
Resolution $\omega_{ce} \Delta t = 1/30$



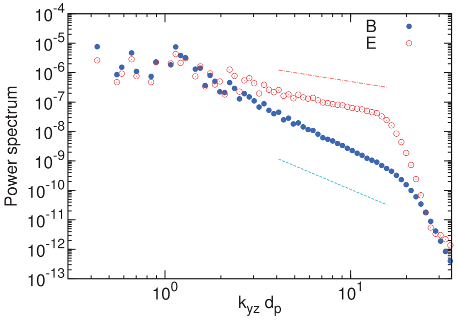
Electron Current Density – Magnitude - Cuts



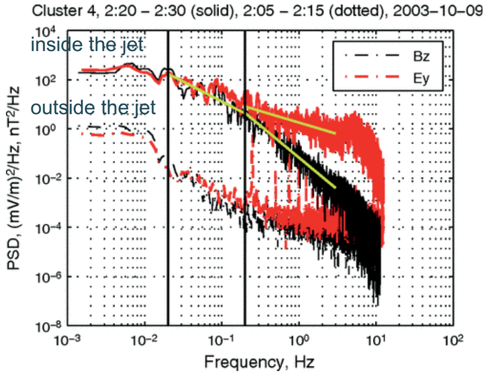
Electron Current Density – Magnitude –Volume rendering

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

Turbulence in the outflow

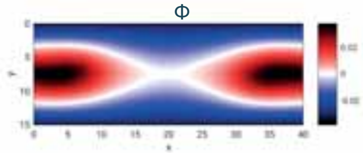


Pucci et al, ApJ, **841**:60 (2017)



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

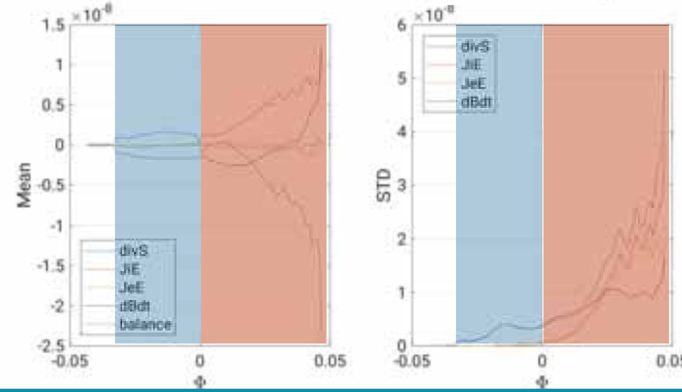
Mean and Standard Deviation of the energy terms



$$\frac{1}{2}\frac{\partial}{\partial t}\left(\epsilon_0 E^2 + \frac{1}{\mu_0}B^2\right) = -\sum_s \boxed{\mathbf{E}\cdot\mathbf{J}_s} - \nabla\cdot\mathbf{S}$$

Blue: fluctuations limited to the electromagnetic fields

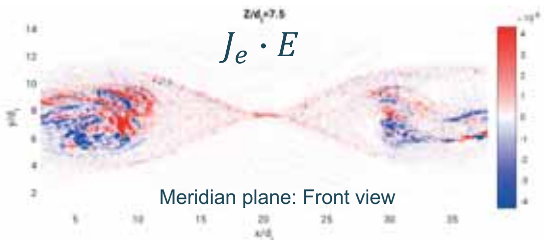
Red: fluctuations include both fields and particles



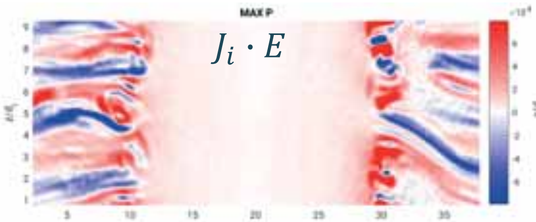
Lapenta, G., et al. "Local regimes of turbulence in 3D magnetic reconnection." *The Astrophysical Journal* 888.2 (2020): 104.

Scales of the electron current

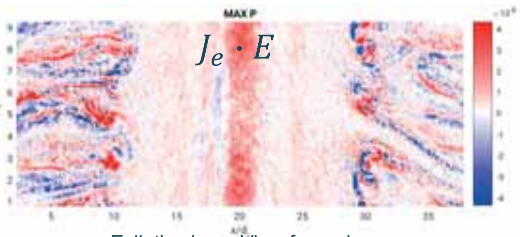
- The reconnection outflows drives the formation of electron currents down to the electron scales (electron gyroradius and electrons skin depth
- Reconnection there happens via electron processes leaving ions largely unaffected



Meridian plane: Front view



Ecliptic plane: View from above

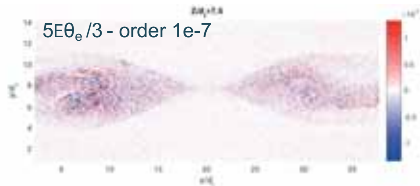


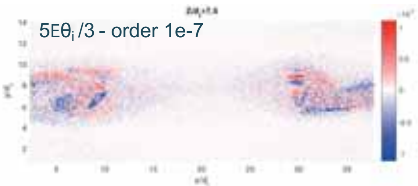
Ecliptic plane: View from above

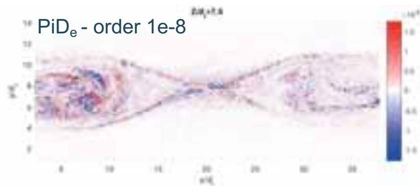
Energy dissipation via the pressure tensor

electrons

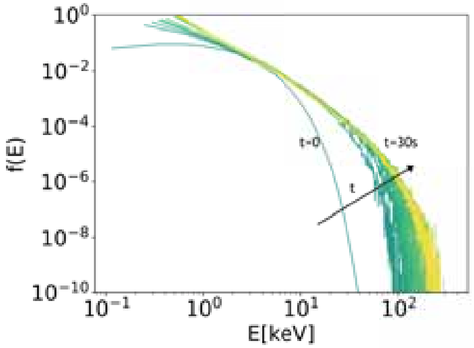
ions







Particle enegization – Importance Sampling

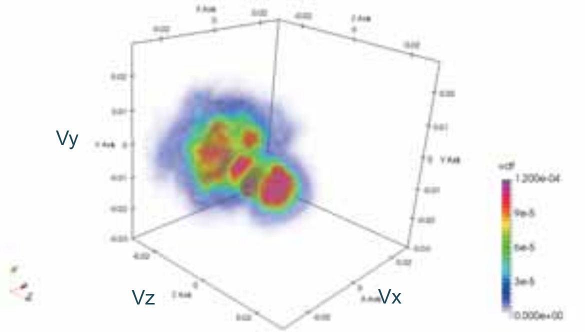


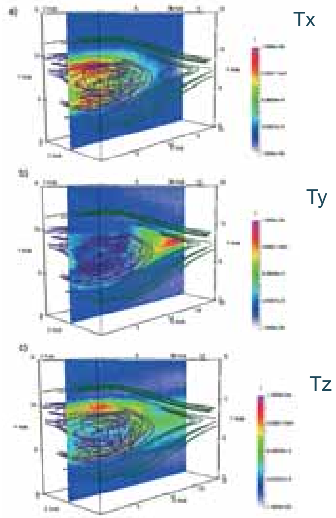
- Formation of **power law tail**
- Observation made possible by **importance sampling**: a way to generate more partilces in the tail to describe the high energy component more accurately.
- **Energization due to the turbulence cascade.**

Lapenta. Walker, El Alaoui, Berchem, PRL, submitted.

Ion energization

Ion Velocity Distribution

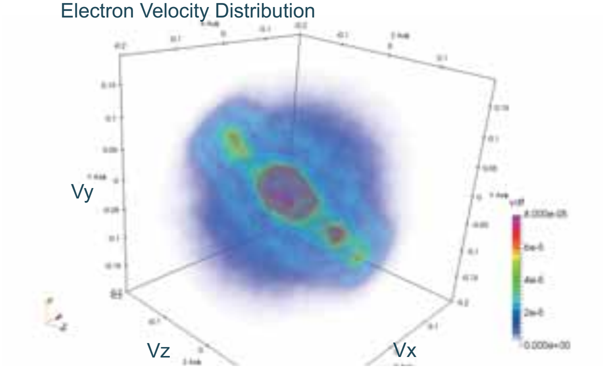


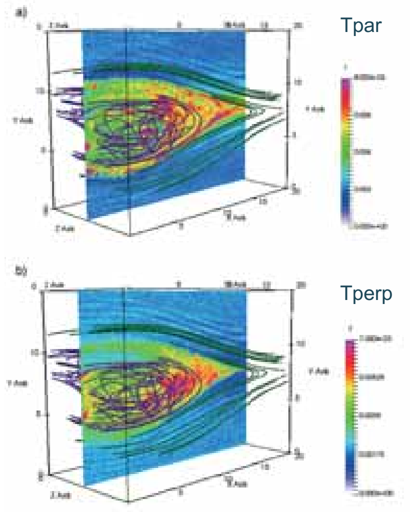


Lapenta, G., Pucci, F., Olshevsky, V., Servidio, S., Sorriso-Valvo, L., Newman, D., & Goldman, M. (2018). *Journal of Plasma Physics, 84*(1), 715840103.

Electron energization

Electron Velocity Distribution





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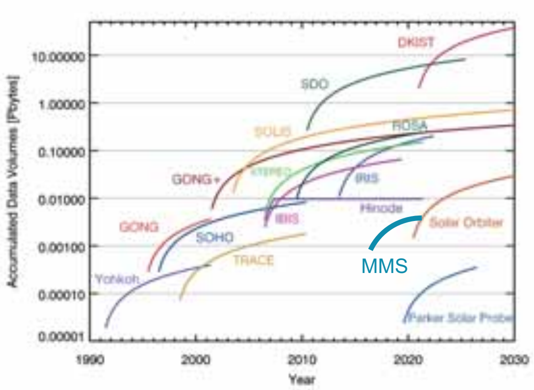
AIDA: Artificial Intelligence Data Analysis

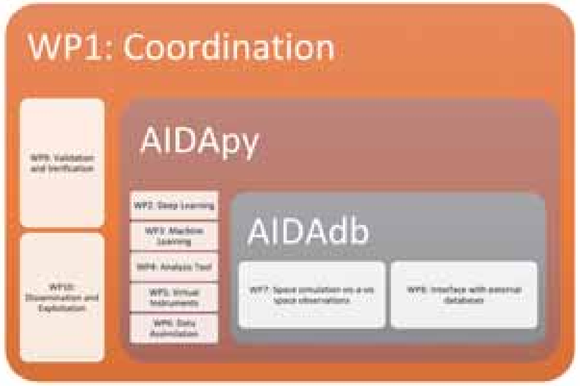
www.aida-space.eu

AIDA Consortium

Space Science - Growth in data



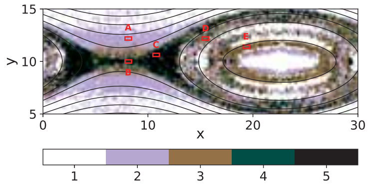
Overview of AIDA



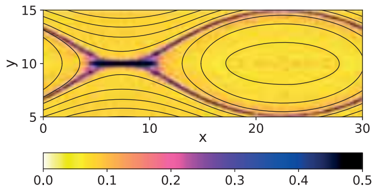
- Development of AIDApy (WP3, WP4, WP5, WP6, with software quality in WP10)
- Machine Learning applied to Heliospheric data (WP3)
- Deep Learning applied to Heliospheric data (WP2)
- Inclusion of advanced heliospheric Data Analysis tools (WP3, WP4, WP6)
- Extensively coupling with real data sources (WP8)
- Coupling with synthetic data sources (WP5)
- Generation of data-base of high level heliospheric data, AIDAdb (WP7)

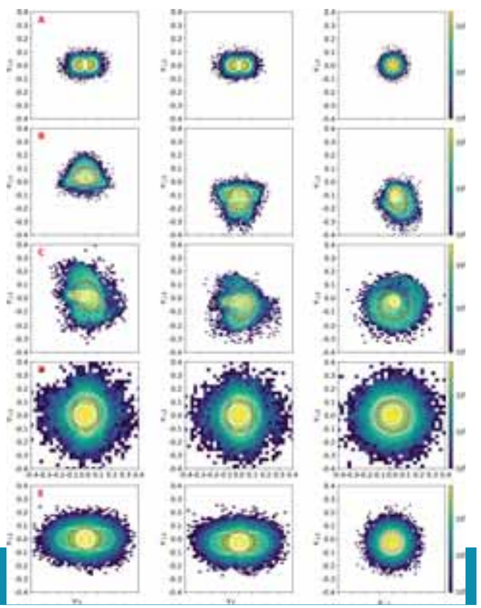
Using particle distributions

Types of distrubutions(GMM)



Agyrotropy

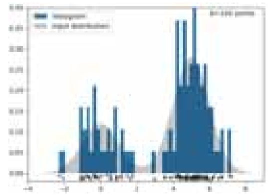


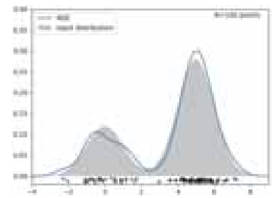


 Dupuis, R., et al(2020). ApJ, *889*(1), 22.

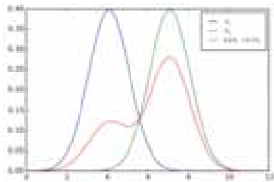
Analyzing distributions

- **Building an estimate of the probability density function**
- **Non-parametric methods**
  - Histogram
  - Kernel Density Estimation
  - K-means
  - DBscan
- **Parametric methods**
  - Fitting given distributions
  - Gaussian Mixture Models (GMM)





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



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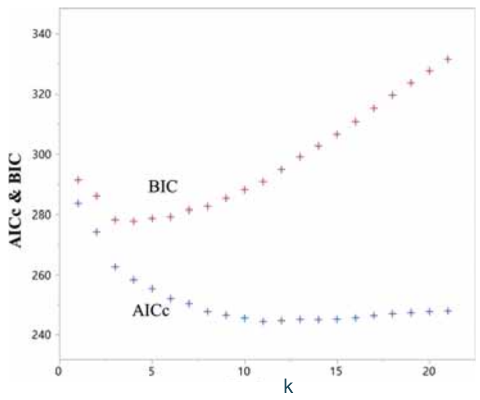
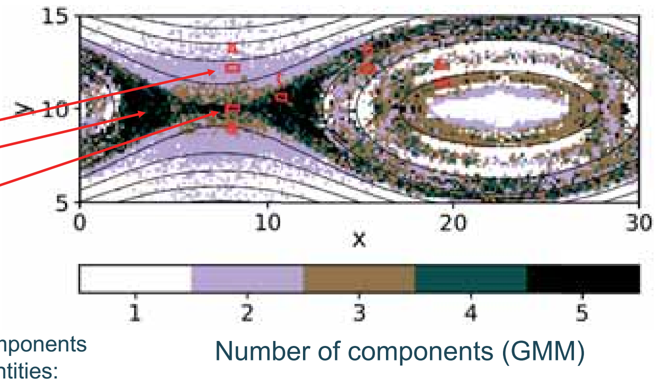
Automatic selection of the number of gaussian beams

- 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

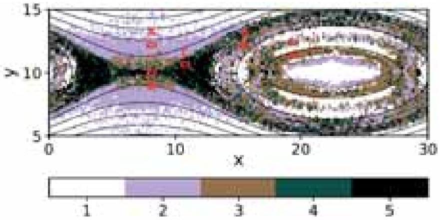


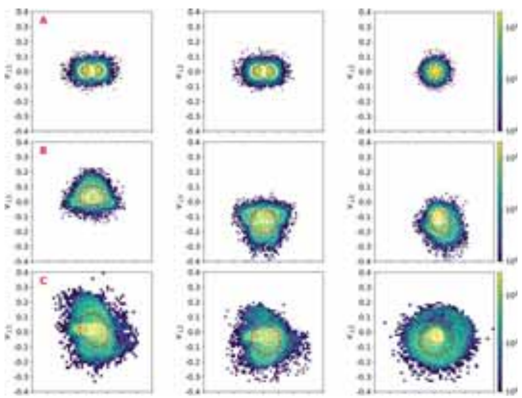
Particle-in-cell simulation

- **Apply on simulations**
  - 2.5D particle in cells
  - applied on each simulation cell
- **Various regions are characterized**
  - Inflow
  - Outflow
  - Electron diffusion region, etc
- **Specific analysis**
  - Qualitative with the number of components
  - Derivation of two quantitative quantities:
    - Measuring change in thermal energy
    - Measuring the spread of the distribution

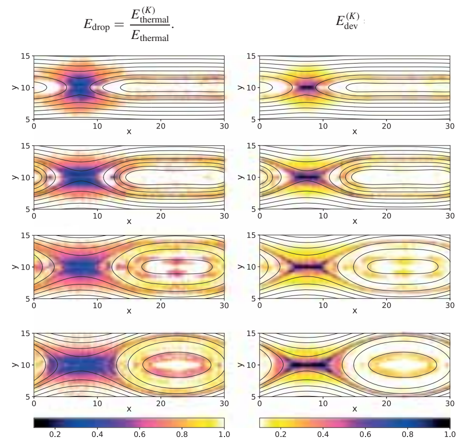


Different distributions



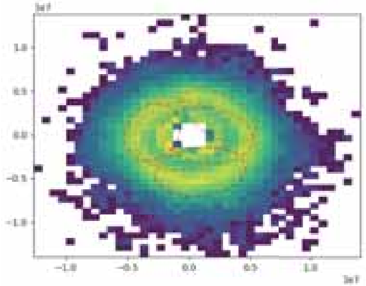


Effect on the definition of thermal energy

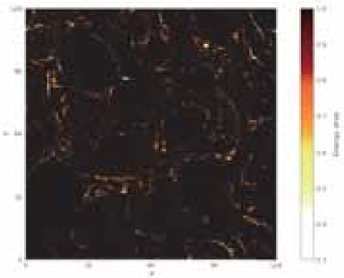


- Fluid thermal energy:
  $$E_{\rm thermal} = \frac{1}{N_p}\sum_{i=1}^{3}\left[\sum_p (V_p - \langle V_p\rangle)^2\right]_i, \text{ with } \langle V_p\rangle = \sum_p \frac{V_p}{N_p}.$$
- Multibeam thermal energy
  $$E^{(K)}_{\rm thermal} = \frac{1}{2}\sum_{i=1}^{3}\sum_{k=1}^{K} w_k^2 [\sigma_k^2]_i.$$
- Drop in thermal energy
  $$E_{\rm drop} = \frac{E^{(K)}_{\rm thermal}}{E_{\rm thermal}}.$$
- False thermal energy
  $$E^{(K)}_{\rm dev} = \sum_{i=1}^{3}\left[\sum_{k=1}^{K} w_k(\mu_k)^2 - \left(\sum_{k=1}^{K} w_k(\mu_k)\right)^2\right]_i.$$

Extension to MMS observations and turbulence simulations



Reconnection event: 16 October 2015-13:07:02.235



Regions of interest from turbulent simulations

Currently working on more modern methods, such as 3D Auto Encoder to deal with a lot of different particle distributions.

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

Conclcusions

- Reconnection in 3D causes turbulence and together they transfer magnetic energy to the particles
- Energization leads to complex velcity distribution functions (VDF)
- VDF include power law tails and multiple bemas
- Interpretation as a single fluid model is very partial
- ML can analyse VDF to indentify the subpopulations automatically
- Multi-cluster energy measures can help identify the ongoing physics

To know more about AIDA:

- Web site: http://www.aida-space.eu
- Talks and Publications: http://www.aida-space.eu/talks
- AIDApy and AIDApy: https://gitlab.com/aidaspace