# The Merging Systems Identification (MeSsI) Algorithm.

Martín de los Rios, Mariano Domínguez, Dante Paz

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   - Study dark matter particle properties.
   - Test cosmological models.
   - Study Intra-Clusters Medium properties.
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   - Machine learning algorithm applied for identification of substructures.
   - Application of the MeSsI Algorithm to spectroscopy catalogues
3. Future Work

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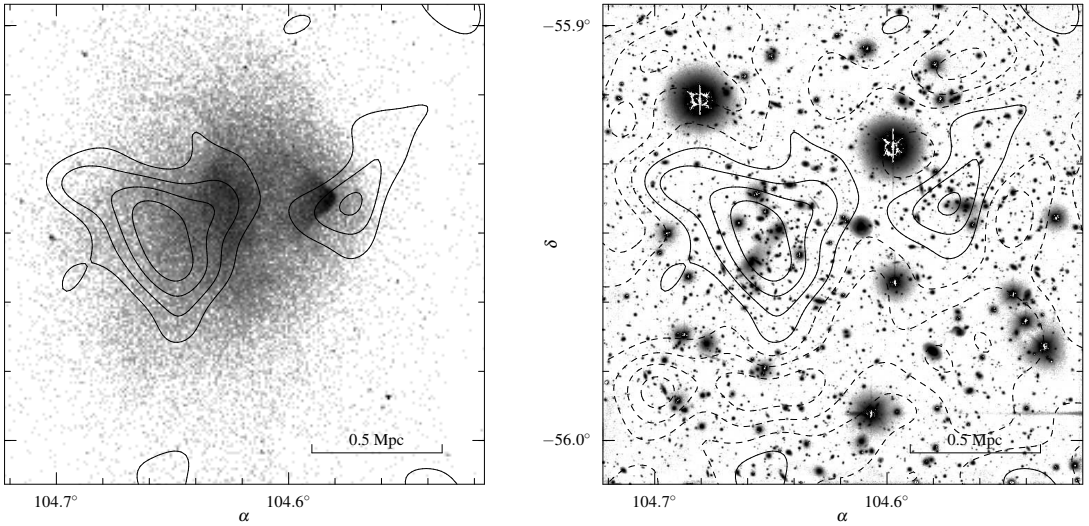
# You can study dark matter particle properties



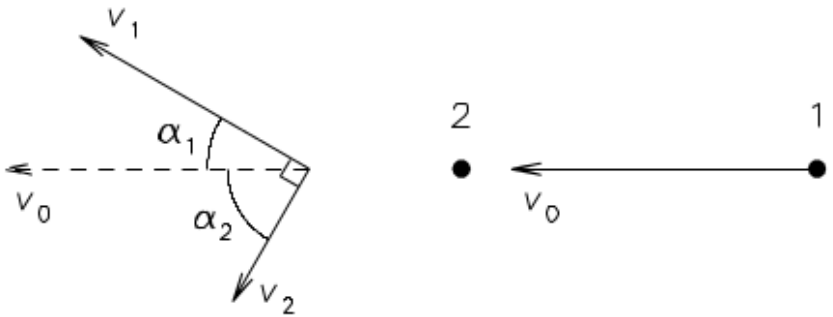
# Markevitch et al. 2004

- Desfasaje entre la materia oscura y el gas:

$\tau_s = \frac{\sigma}{m}\Sigma_s$ donde $\sigma$ es la sección eficaz, $m$ es la masa de la partícula y $\Sigma_s$ es la densidad superficial de DM. La densidad superficial promediada dentro de $r = r_{tr}$ es $\Sigma \approx 0.2 g cm^{-2}$, entonces, asumiendo simetría esférica y pidiendo que $\tau_s < 1$ tenemos: $\frac{\sigma}{m} < 5 cm^2 g^{-1}$.

| Cúmulo | $\frac{\sigma}{m}$ |
|---|---|
| Bullet Cluster | $< 5 cm^2/g$ |
| Musket Ball | $< 7 cm^2/g$ |
| Baby Bullet | $< 4 cm^2/g$ |

- La gran velocidad del cúmulo secundario:




$$\bar{p} = mv_s \left[ 1 - 4 \int_{sen\alpha_c}^{1} x^2 \left( x^2 - \frac{V^2}{v^2}(1 - x^2) \right)^{1/2} dx \right] \approx 0.1 mv_s \quad (1)$$

$$\frac{d(v - v_{ff})}{dt} = \frac{\bar{p}n}{M_s} = \frac{\bar{p}}{m}\frac{\sigma}{m}\rho_m v \quad (2)$$

$$v - v_{ff} = \frac{\bar{p}}{m}\frac{\sigma}{m}\Sigma_m \quad (3)$$

$$v - v_{ff} < 1000 km/s \quad (4)$$

$$\frac{\sigma}{m} < 7 cm^2/g \quad (5)$$

- La supervivencia del cúmulo secundario.

$$\chi = 1 - 2\frac{v_{esc}^2}{v_0^2} \quad (6)$$

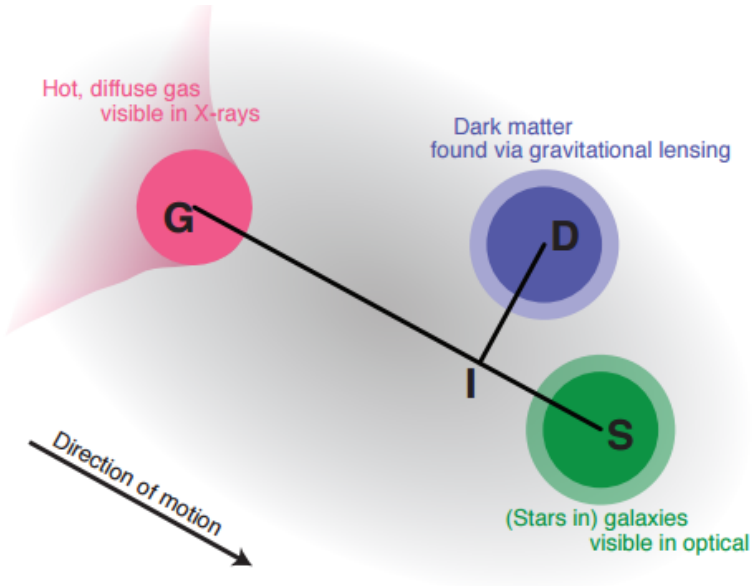
$$\tau_m = \frac{\sigma}{m}\Sigma_m \quad (7)$$

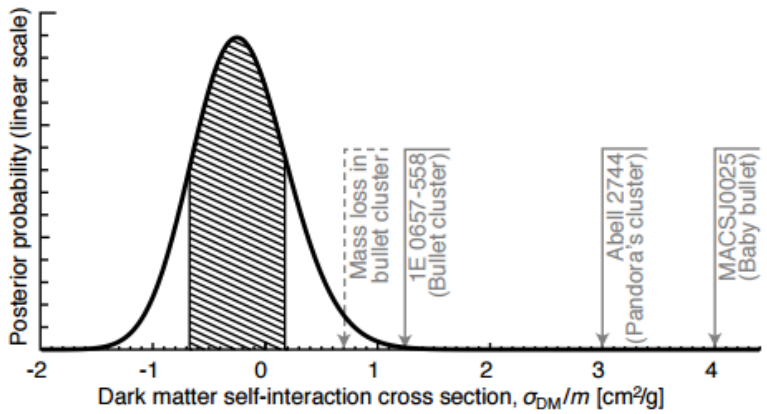
$$\chi\tau_m = \frac{\sigma}{m}\Sigma_m\left[1 - 2\frac{v_{esc}^2}{v_0^2}\right] \quad (8)$$

$$\chi\tau_m < 0.3 \quad (9)$$

$$\frac{\sigma}{m} < 1 cm^2/g \quad (10)$$

# Harvey et al. 2015




$$\frac{\sigma}{m} \leq 0.47 cm^2/g$$

# You can test your favourite cosmological model.

- Estudio de la probabilidad de que un cúmulo tenga una velocidad similar a la del bullet cluster.
  - Hayashi et al. 2006
  - Farrar y Rosen 2007
  - Lee y Komatsu 2010
  - Forero-Romero et al. 2010
  - Thompson y Nagamine 2011
  - Watson et al. 2013
- Estudios con simulaciones hidrodinámicas
  - Springel & Farrar. 2005
  - Milosavljevic et al. 2007
  - Mastropietro & Burket. 2008
  - Lage & Farrar 2014

# The Rise and Fall of a challenger by Thompson (2014).

- They investigate the probability of finding such a high-velocity pair in large-volume N-body simulations, particularly focusing on differences between halo finding algorithms.
- When employing the Rockstart (Behroozi et al 1013) halo finder that considers particle velocities, they find numerous Bullet-like pair candidates that closely match not only the high pairwise velocity, but also the mass, mass ratio, separation distance, and collision angle that have been shown to produce the Bullet Cluster.
- The probability of finding a massive, high pairwise velocity pair among halos with $M_{\rm halo} \geq 10^{14} M_{\odot}$ is $4.6 \times 10^{-4}$ using RS, while it is $\approx 45\times$ lower using a friends-of-friends (FOF) based approach as in previous studies.

# High velocity tail of Bullet like pairs.

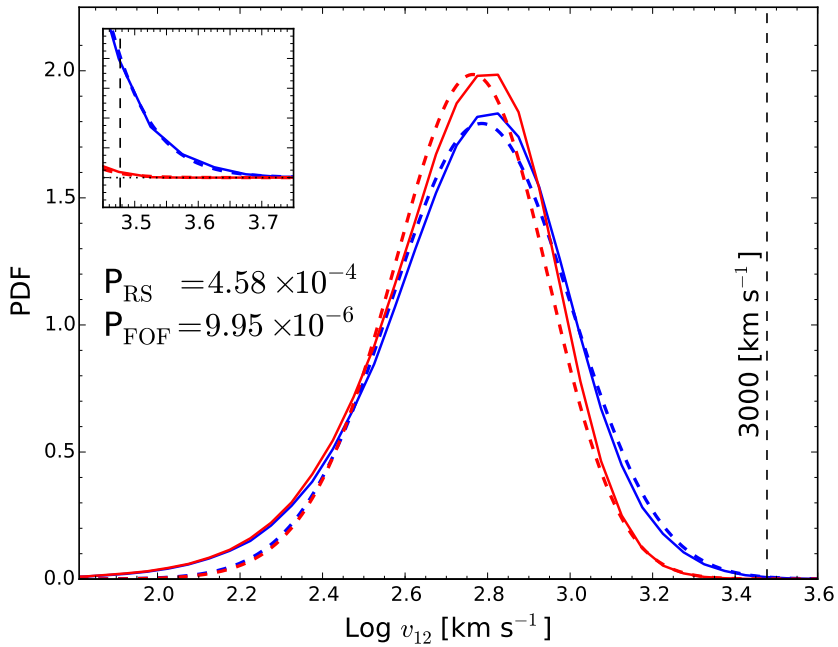



Figure : Probability distribution function of massive halo pairs in largest simulation (L4500) identified by FOF (Red solid line) and RS (Blue solid line).

# You can study the ICM properties.

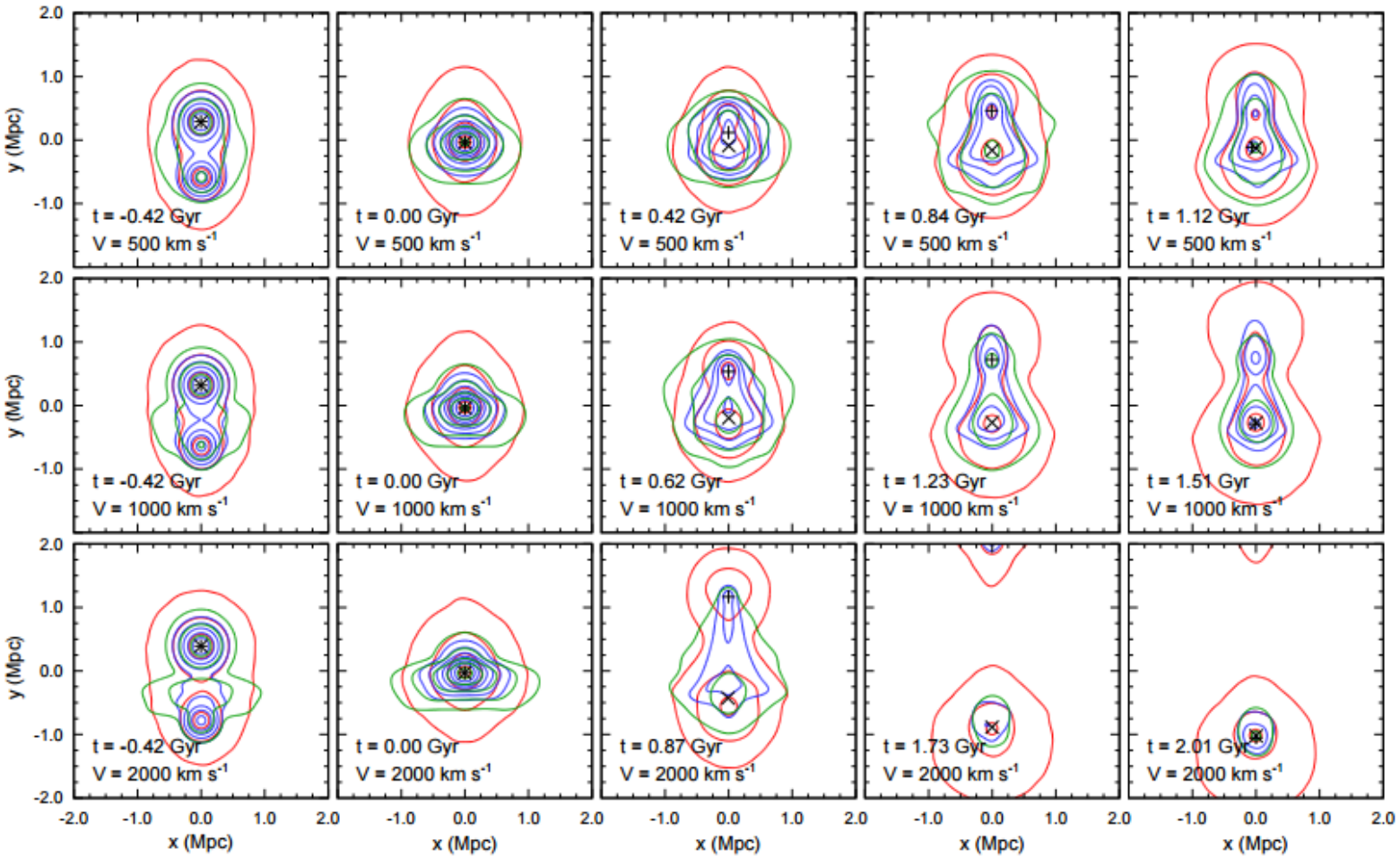



Figure : Zhang et al. 2014

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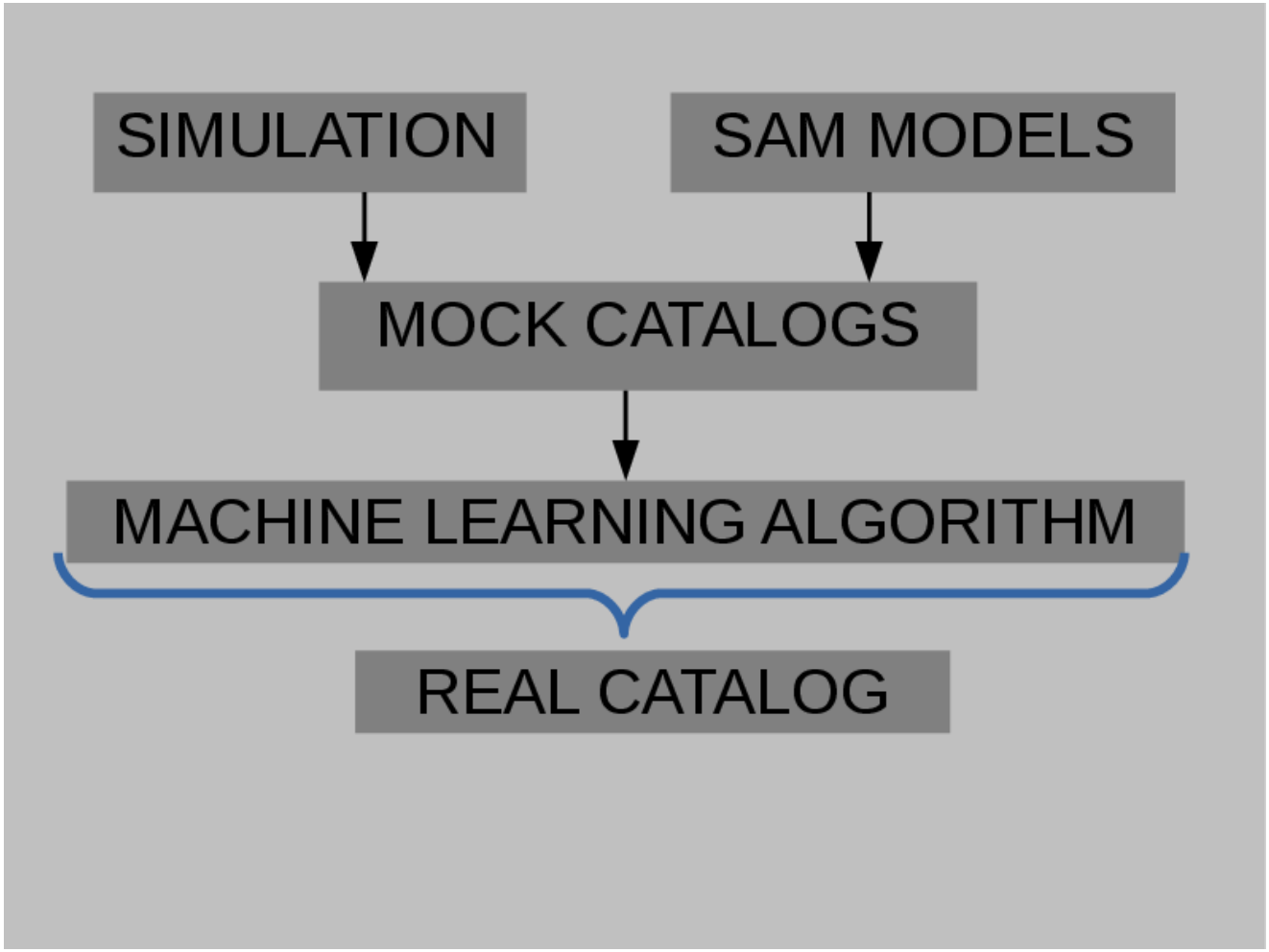
SIMULATION
SAM MODELS
MOCK CATALOGS
MACHINE LEARNING ALGORITHM
REAL CATALOG

# Clusters identification.

- We construct a mock catalogue based on the results of the application of the SAM Model of Guo et al. 2010 to the Millenium simulation.

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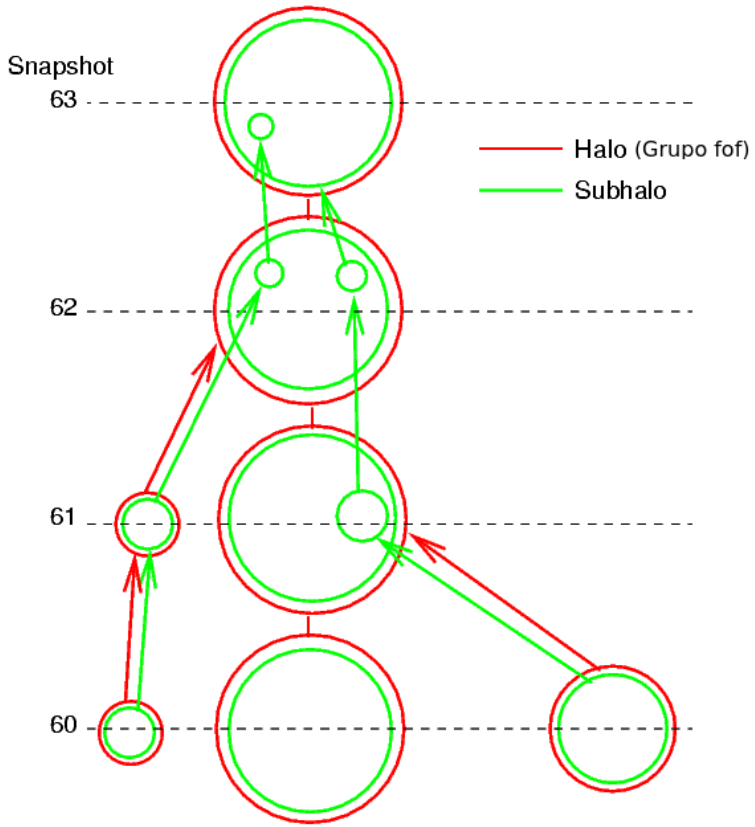
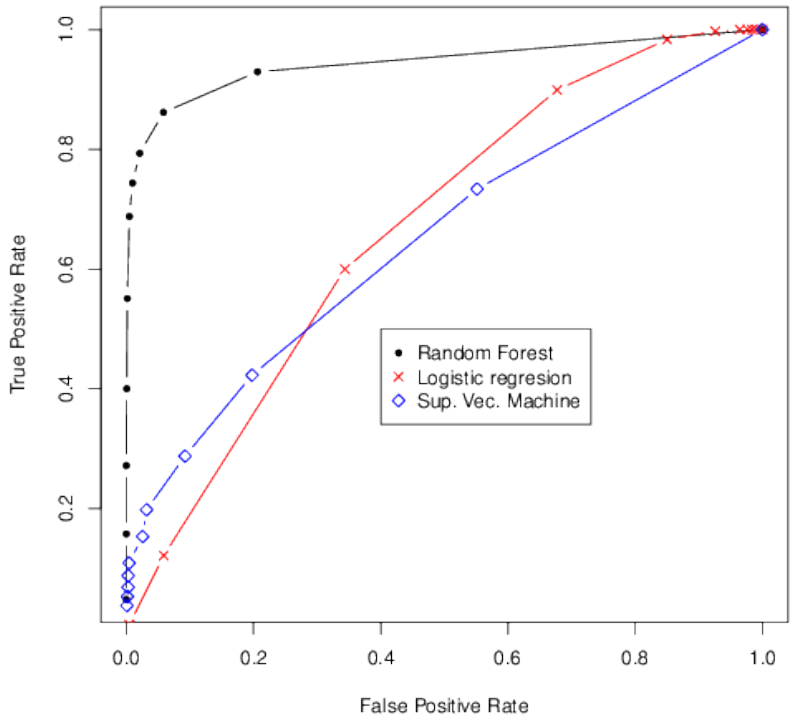
- We Perform a friend-of-friend algorithm (*Merchan & Zandivares 2002* ) to the mock catalog in order to identify the clusters.
- We assign each identified cluster with a fof-group in the simulation.

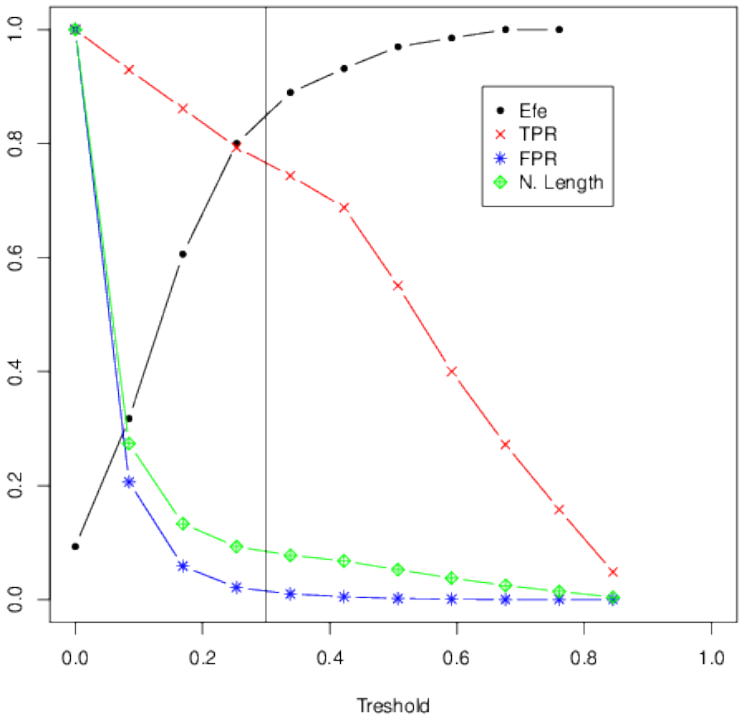
# Study of the merger trees.

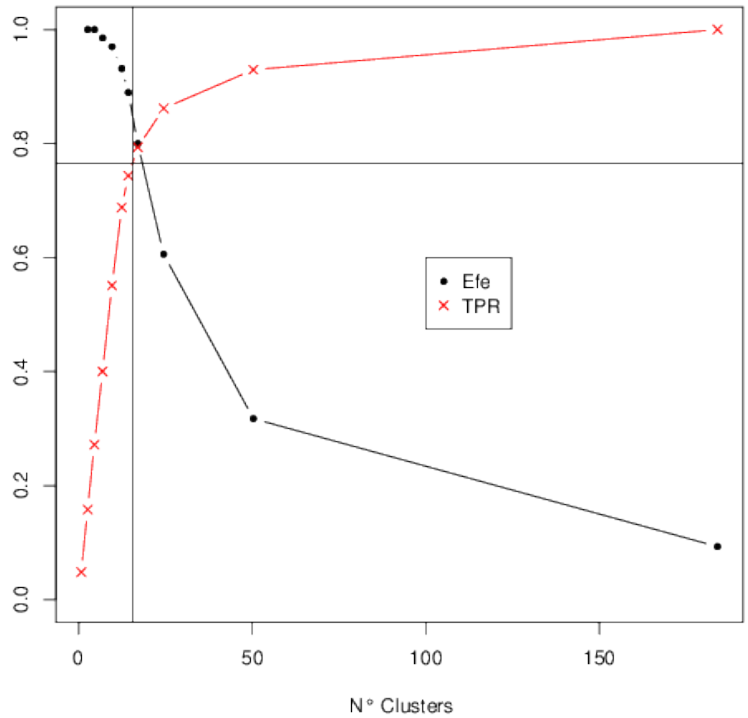
- Based on the subhalos merger trees, we construct the merger tree for every fof group in the simulation.



- Dressler-Shectman test.
- Non gaussianity test.
- Color.
- Number of galaxies.




Efe
TPR
FPR
N. Length
Treshold
0.0
0.2
0.4
0.6
0.8
1.0


Efe
TPR
N° Clusters
0
50
100
150
0.0
0.2
0.4
0.6
0.8
1.0

# Study of the identified substructures.

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- After that, we estimate the velocity dispersion and the virial radius.

$$\begin{aligned} R_{vir} &= \frac{\pi}{2} \frac{ngal(ngal-1)}{\sum_{i>j}^{ngal} R_{ij}^{-1}} \\ \sigma &= \frac{\sqrt{\pi}}{ngal(ngal-1)} \sum_{i=1}^{ngal-1} \omega_i g_i \\ \omega_i &= i(ngal-i) \\ g_i &= v_{i+1} - v_i \end{aligned} \tag{11}$$

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- We compare the virial radius of the identified substructures with the virial radius of the subhalos, finding that we are overestimating the real values.
- We compare the velocity dispersion of the identified substructures with the velocity dispersion of the associated subhalos, finding that our values are in good concordance with the real values.

With this association between substructure and subhalos in the mock, we find 3 cases:

1. Clusters where we identify the type 0 subhalo (the principal subhalo of the fof group) and a type 1 subhalo.

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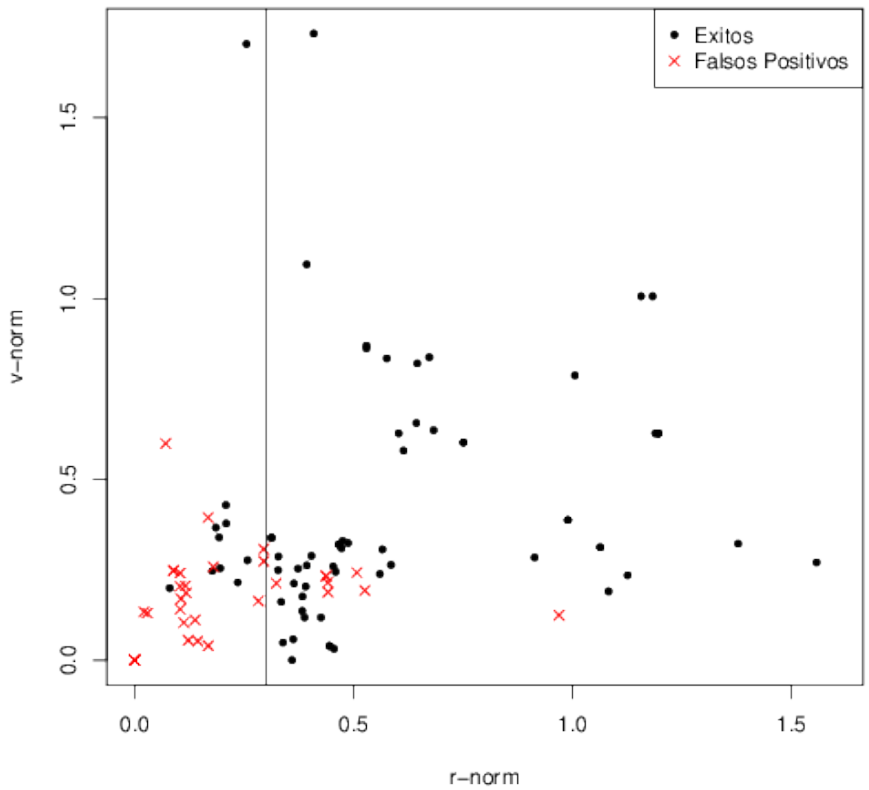
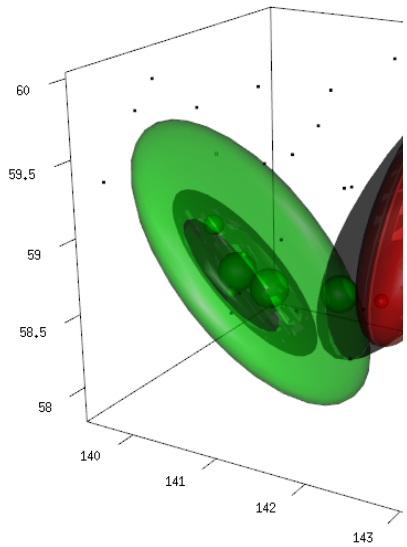
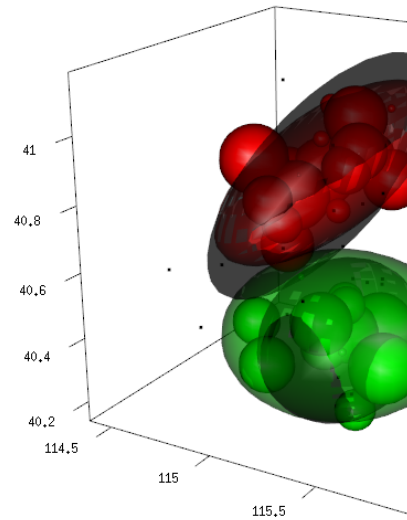


# Mock Clusters

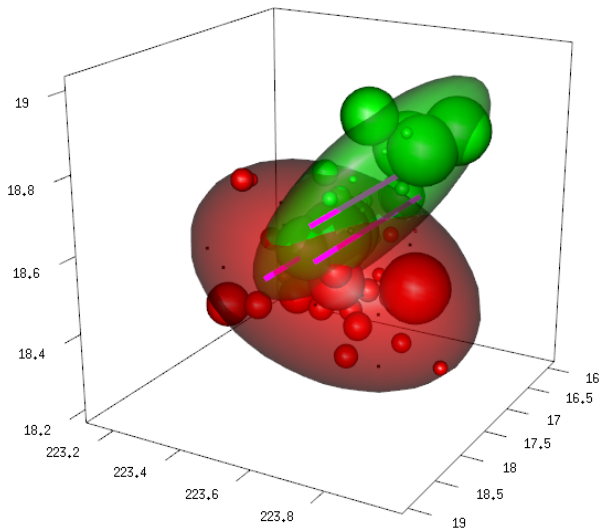


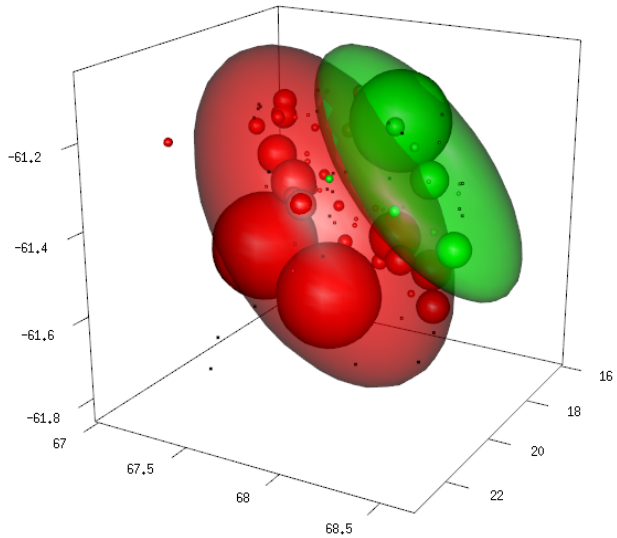
# Application of the MeSsI Algorithm to spectroscopy catalogues

- We find 12 Clusters with high probability of been in a merger in the SDSS DR7.

Abell 1991

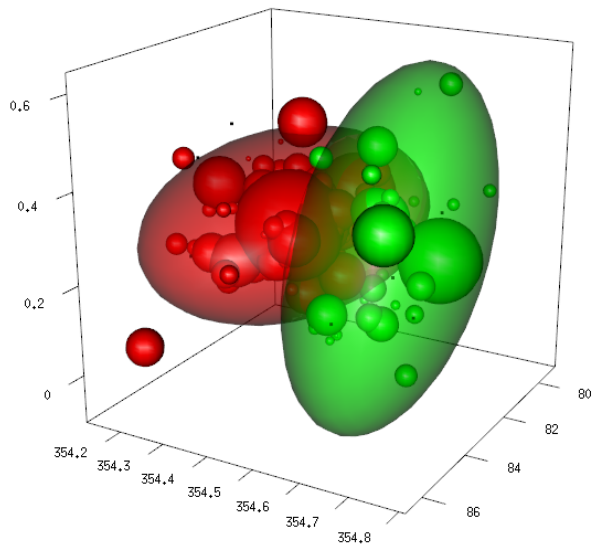


- We find 7 Clusters with high probability of been in a merger in the WINGS Clusters.



- We find 15 Clusters with high probability of been in a merger in the HECs Clusters.

Abell 2631



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# Future Work

- Perform astrophysical test over our sample of colliding cluster candidates of the catalog looking for impose some constraints on dark matter particle properties.

# Future work.

- Apply the detection method to more deep real catalogs.

We will make a ligth-cone mock (Merson et al. 2012) and re-calibrate our machine learning algorithm for high-redshift clusters in order to study the dynamics status of deep real catalogs like the EDISc and the Morphs Clusters.

# Future Work

Reconstruct the 3d merger with the Bayesian techniques presented by *Dawson et al. 2012*.

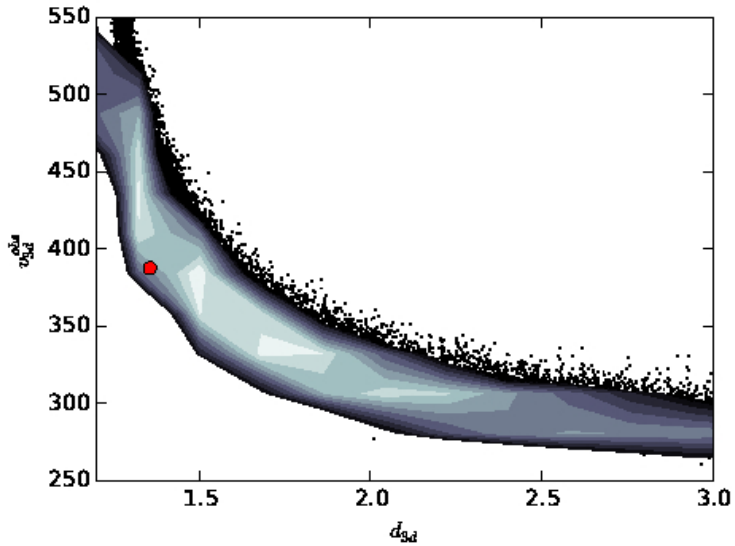


Figure : Distribution of posterior probability in the 3D distance (Mpc) and 3D velocity (Km/s) space for a simulated merging cluster, red dot indicates the real current values. Others kinematical parameters like Time since Collision or velocity at the merger time are also well recovered.

# Future Work

Study the physics properties of the galaxies that belong to the identified substructures, ordering them in a temporal line by the merger state.

# Future Work

Construct a catalog of relaxed clusters in order to study the dark matter equation of state (Serra & Dominguez 2011).

THANK YOU