Machine Learning techniques applied to cosmological problems.

Martín de los Rios

Director: Dr. Mariano Domínguez

Resumen

1. Introduction to Machine Learning techniques.

2. The `MeSsI` (Merging Systems Identification) Algorithm.

3. Derived Results.
   - A2029/2033.
   - A1204.
   - A267.
   - Statistical analysis of the magnetic fields in merging clusters.

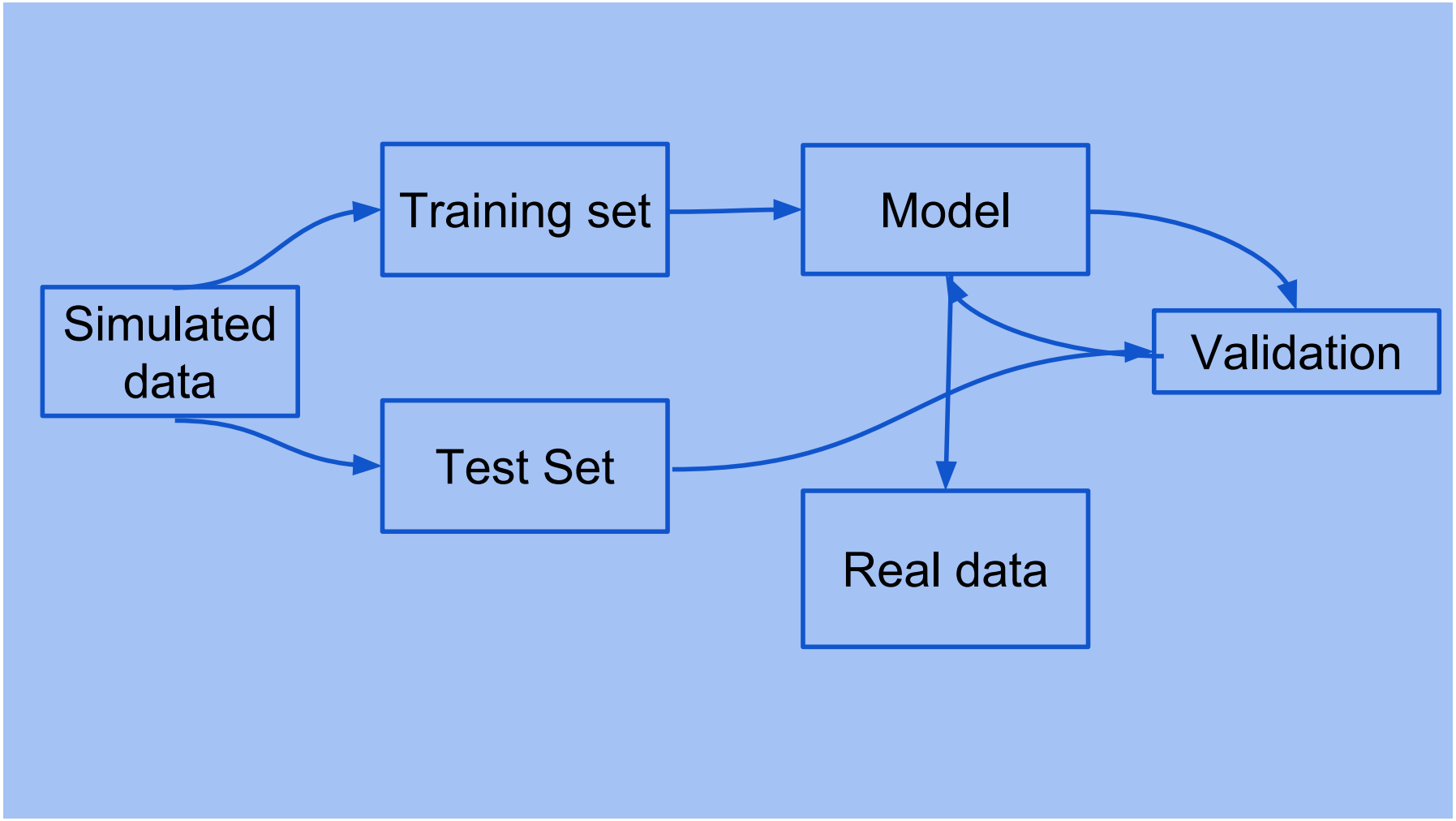
4. DM-γ interactions.

5. `CosmoMl`:Machine Learning techniques applied to the CMB.
   - Construction of the data set.
   - Supervised methods.
   - Cosmological parameters Angular distributions.

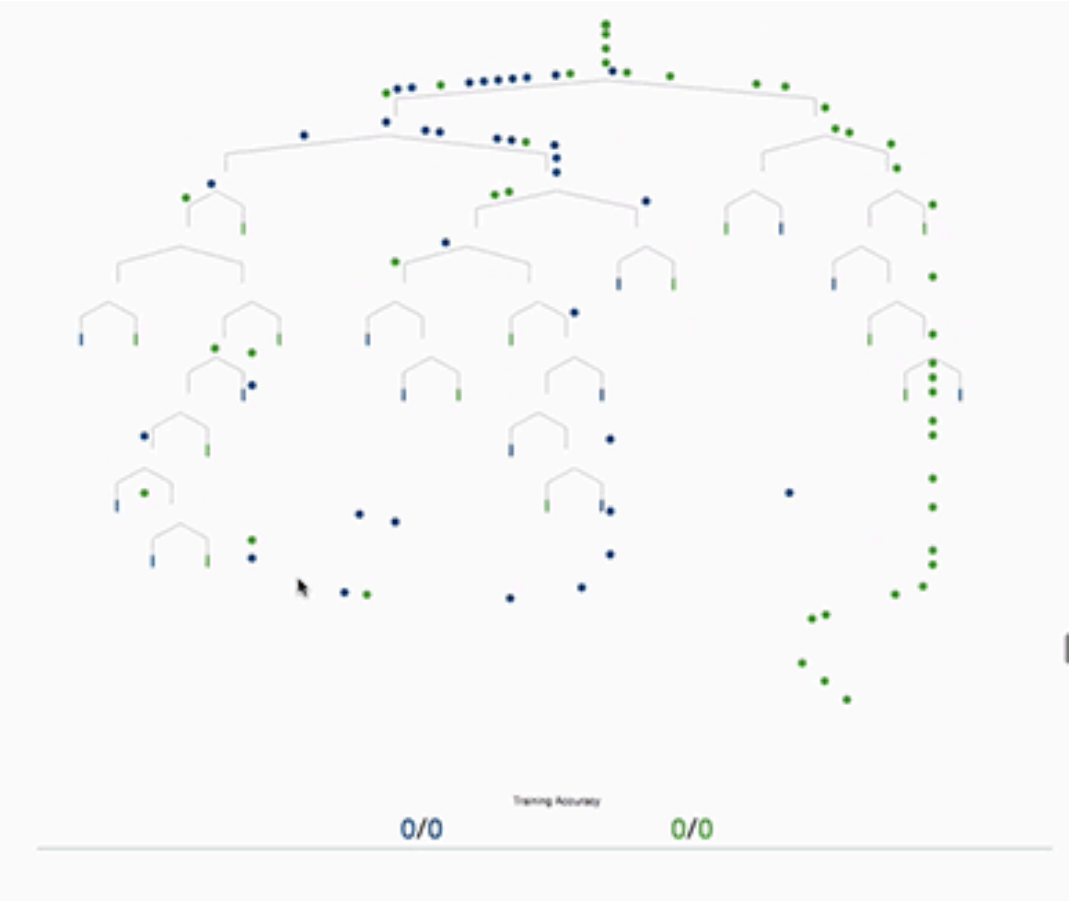
6. Conclusions and Final remarks.

A computer program learns to perform a task T , based on a training E and taking into account a measure P of its performance, if this measure P when making T improves with the training E.

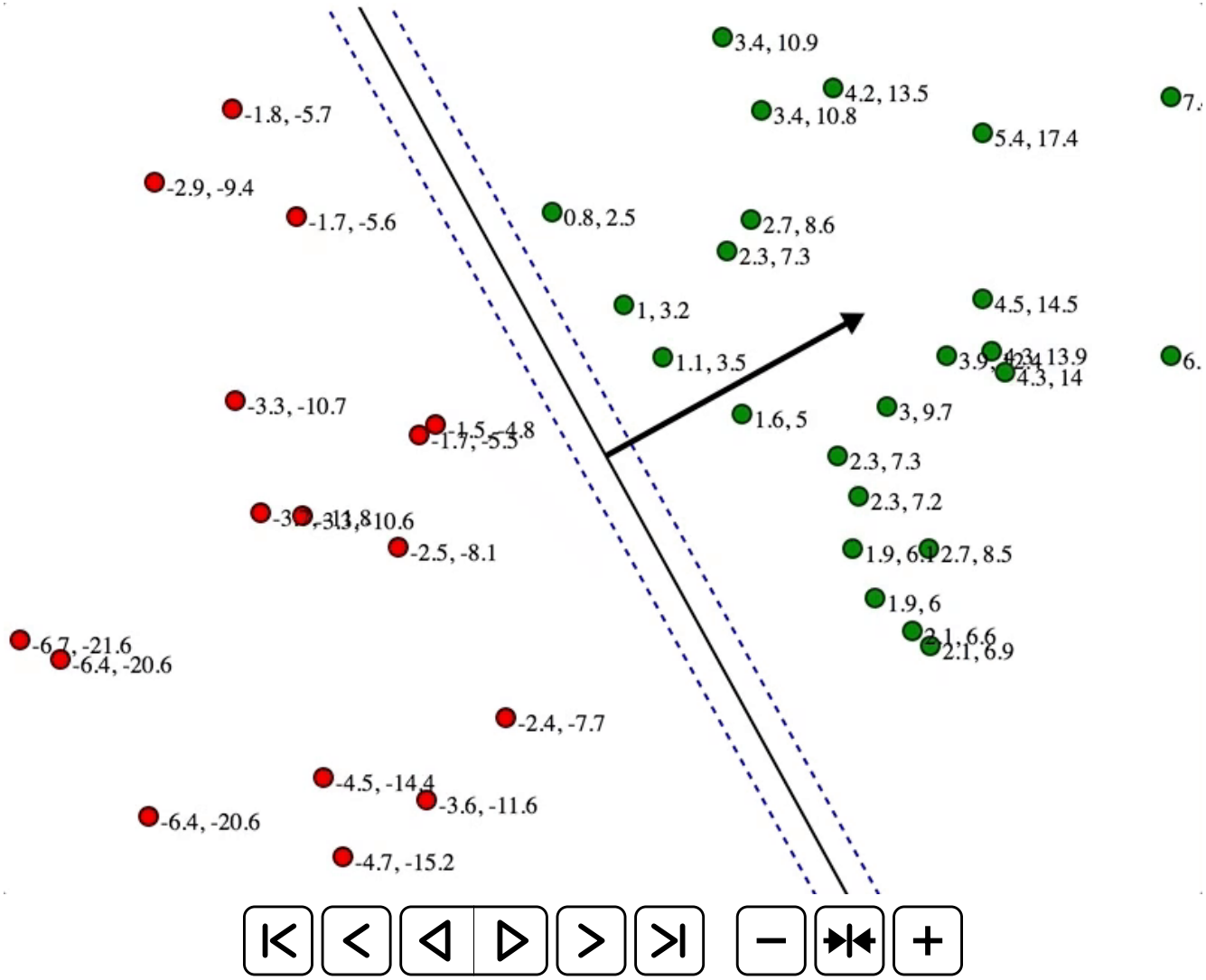
Supervised Learning.



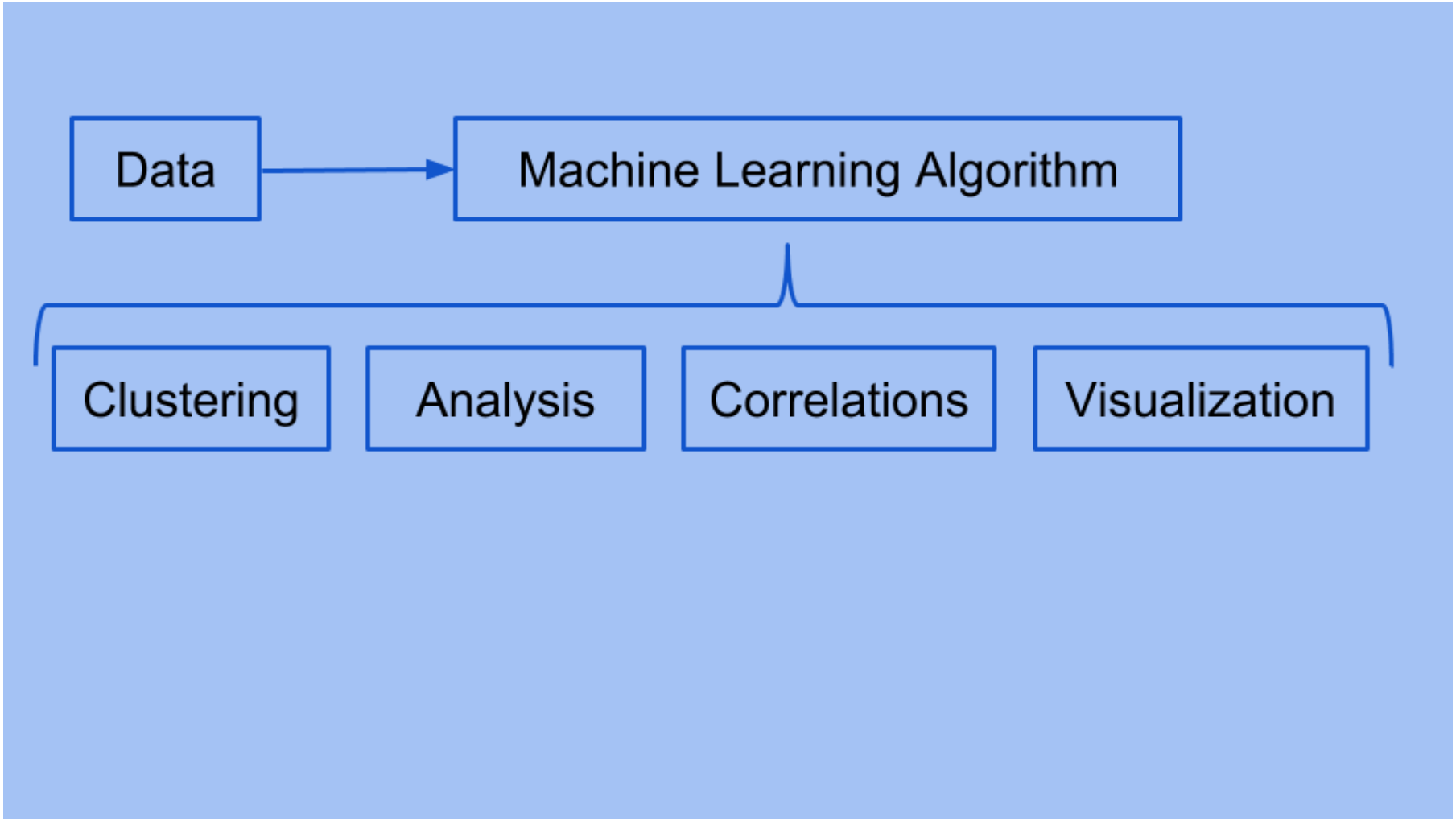
Random Forest



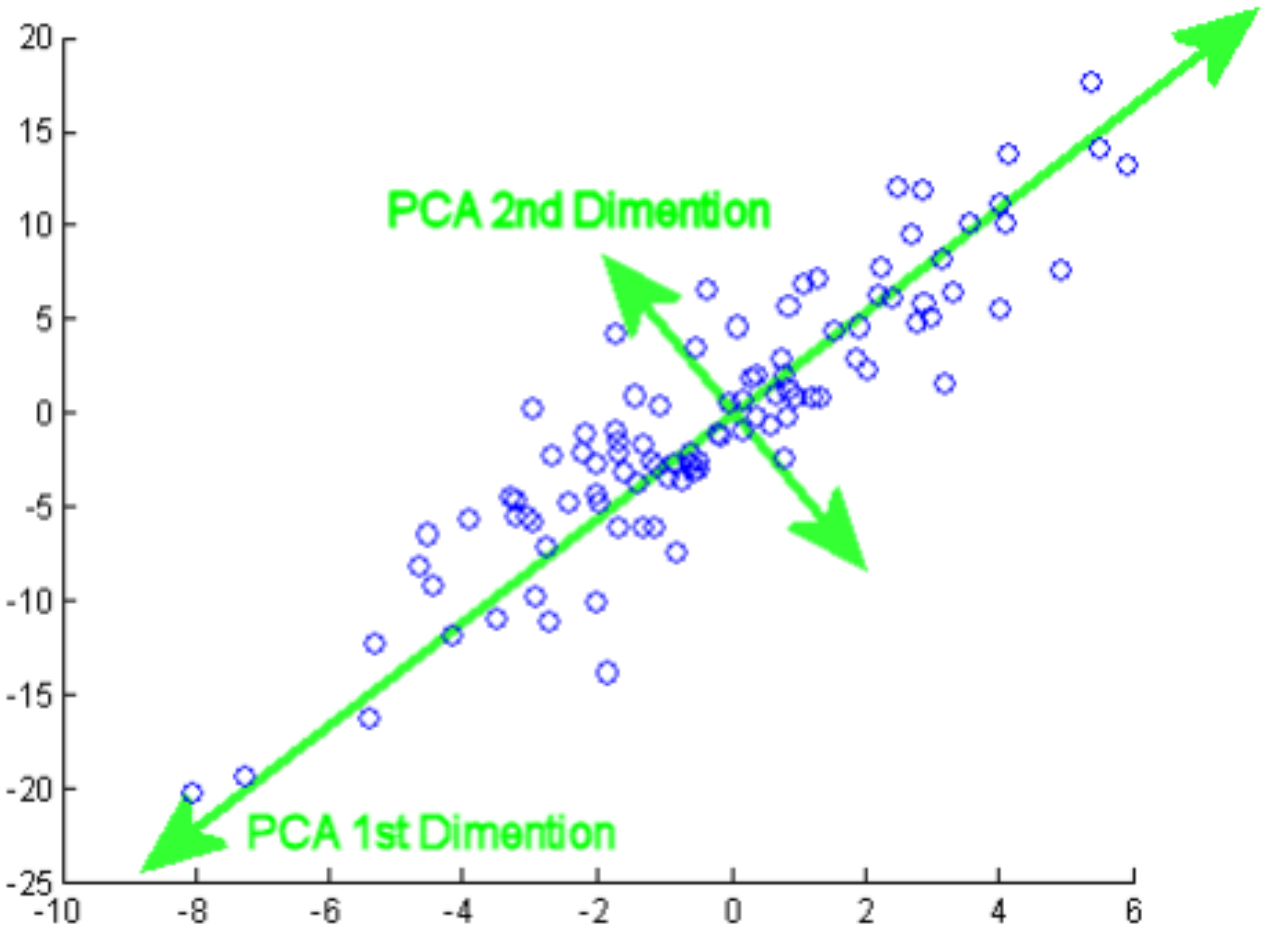
Support Vector Machines



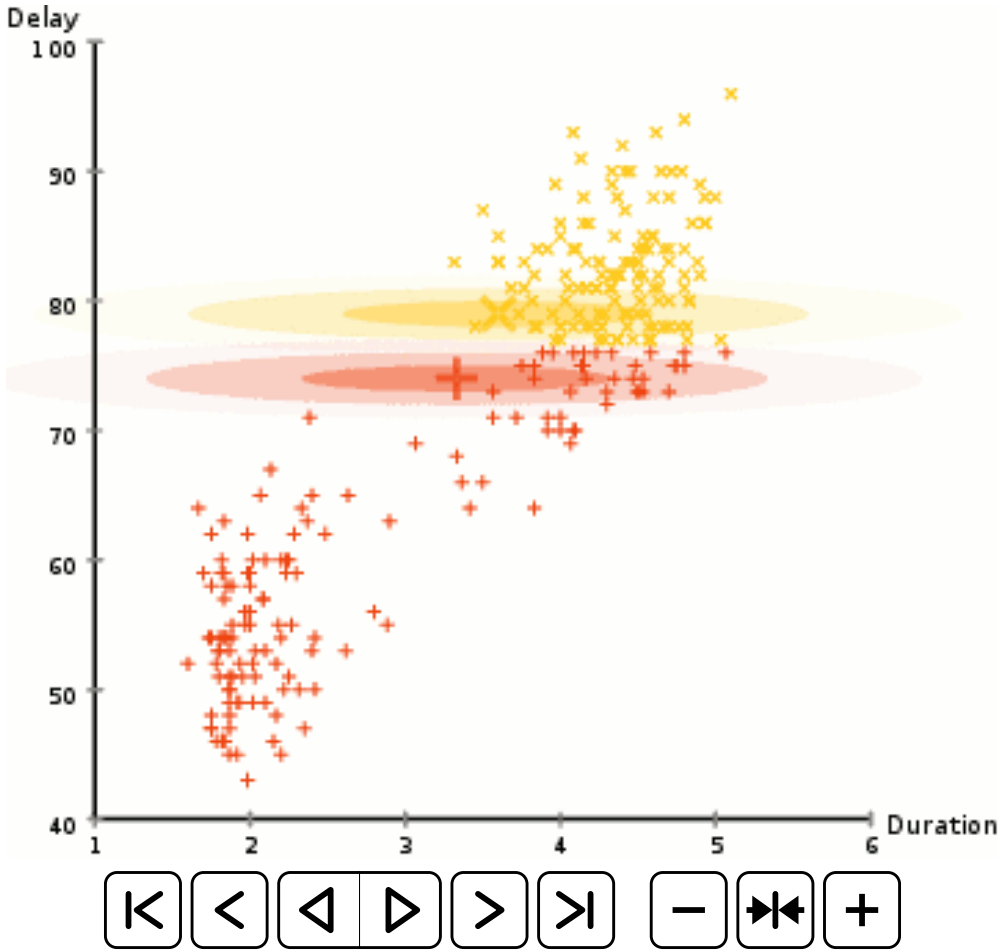
Unsupervised Learning.



Principal Components Analysis.



Mixture of Gaussians

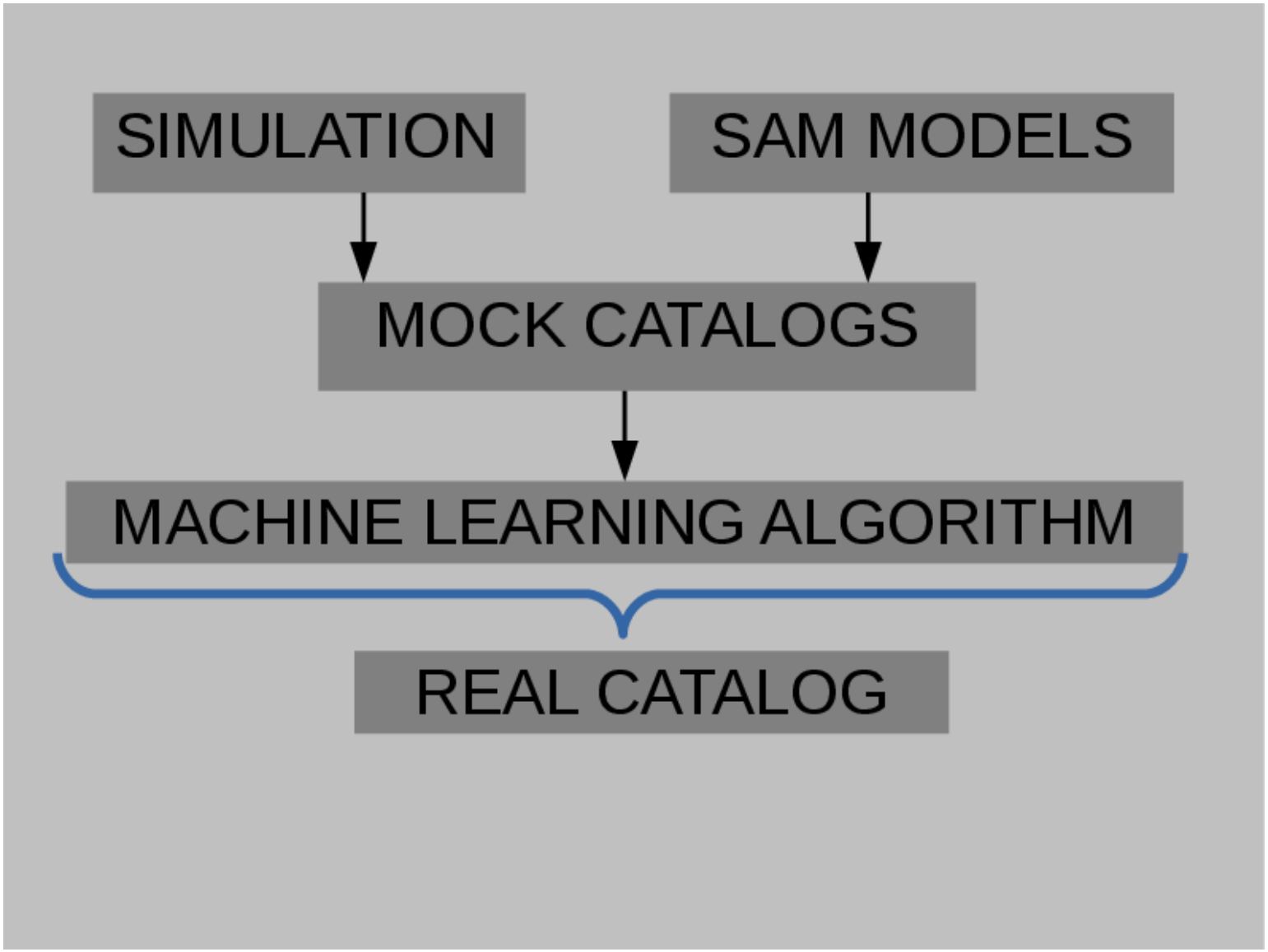


Mon. Not. R. Astron. Soc. **000**, 1–7 (2015) Printed 17 December 2015 (MN LATEX style file v2.2)

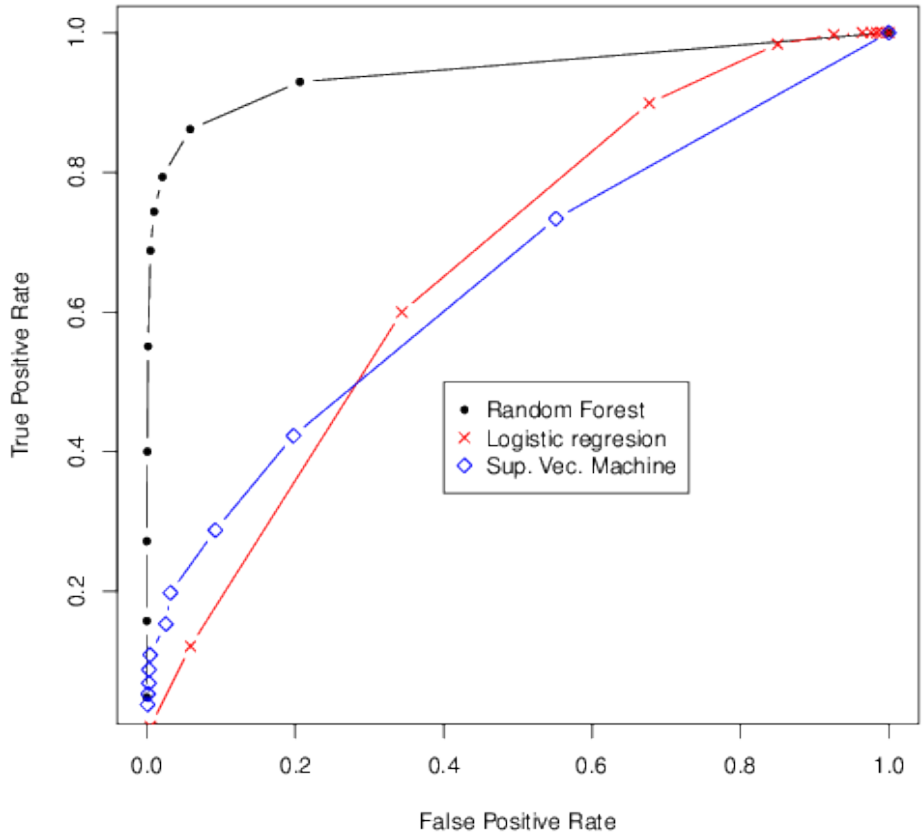
The MeSsI (Merging Systems Identification) Algorithm & Catalogue.

Martín de los Rios⋆, Mariano J. Domínguez R.⋆, Dante Paz, Manuel Merchán [1,2,3].
[1] *Instituto de Astronomía Teórica y Experimental (CCT Córdoba, CON ICET, UNC), Laprida 854, X5000BGR, Córdoba, Argentina.*
[2] *Observatorio Astronómico de Córdoba, Universidad Nacional de Córdoba, Laprida 854, X5000BGR, Córdoba, Argentina.*
[3] *Consejo Nacional de Investigaciones Científicas y Técnicas, Rivadavia 1917, C1033AAJ Buenos Aires, Argentina.*

$\frac{\sigma}{m} < 0.47 m/s^2$ (Harvey et al. 2015)


SIMULATION
SAM MODELS
MOCK CATALOGS
MACHINE LEARNING ALGORITHM
REAL CATALOG

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



- We found 61 candidates to merging clusters.
- In 32 of these we were able to identify the colliding substructures.
- 21 of these were previously classified as merging clusters by other authors.

1. Introduction to Machine Learning techniques.
2. The MeSsI (Merging Systems Identification) Algorithm.
3. Derived Results.
   - A2029/2033.
   - A1204.
   - A267.
   - Statistical analysis of the magnetic fields in merging clusters.
4. DM-γ interactions.
5. CosmoML:Machine Learning techniques applied to the CMB.
   - Construction of the data set.
   - Supervised methods.
   - Cosmological parameters Angular distributions.
6. Conclusions and Final remarks.

Astronomy & Astrophysics manuscript no. merger1_v3
December 4, 2017

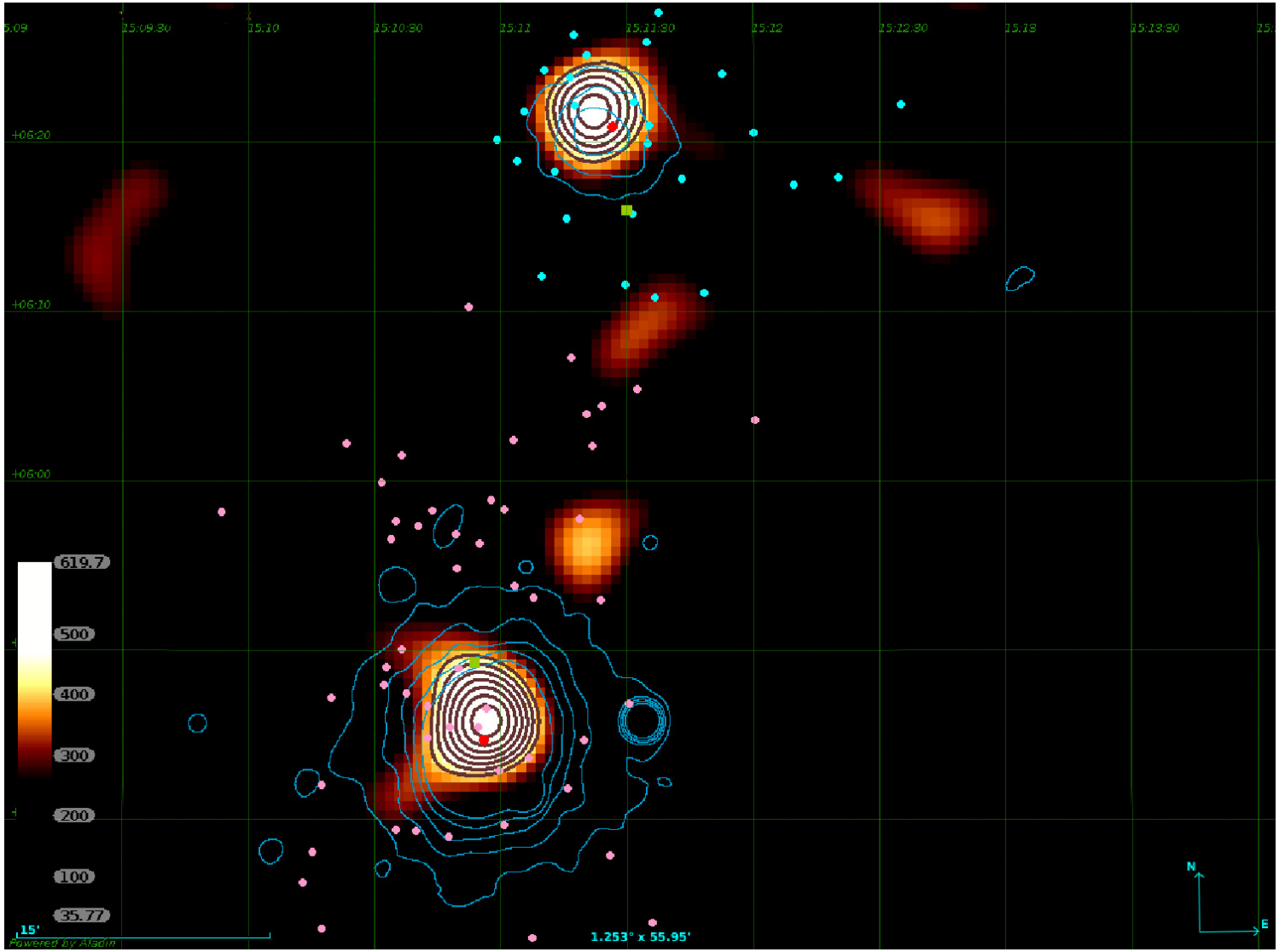
I. Analysis of candidates for interacting galaxy clusters

A1204 and A2029/A2033

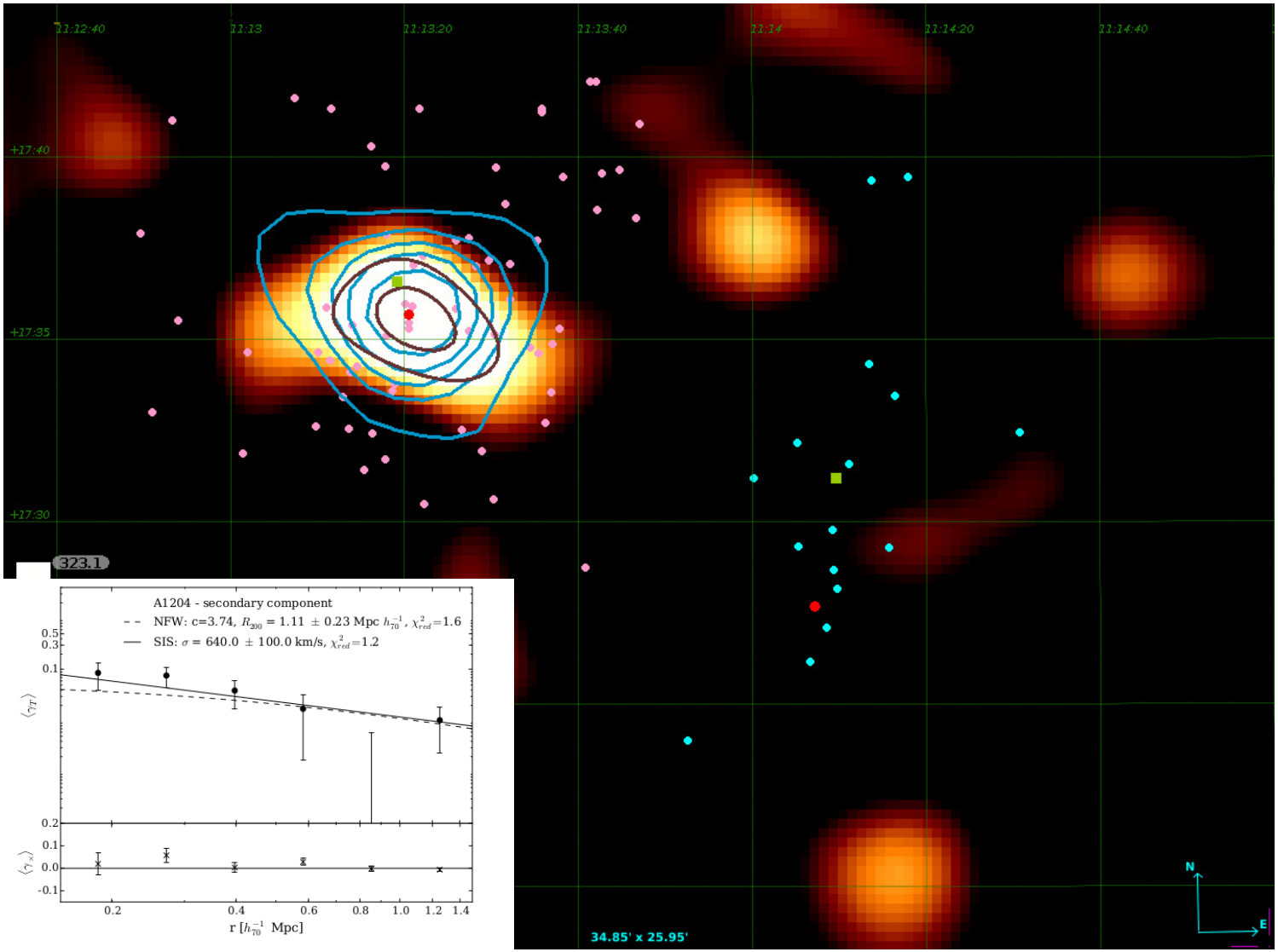
Elizabeth Johana Gonzalez ⋆[1,2], Martín de los Rios[1,2], Gabriel A. Oio[1,2], Daniel Hernández Lang[4], Tania Paez Tagliaferro[1,2], Mariano J. Domínguez R.[1,2], José Luis Nilo Castellón[3,4], Héctor Cuevas L.[4], and Carlos A. Valotto[1,2]

[1] Instituto de Astronomía Teórica y Experimental, (IATE-CONICET), Laprida 854, X5000BGR, Córdoba, Argentina.
[2] Observatorio Astronómico de Córdoba, Universidad Nacional de Córdoba, Laprida 854, X5000BGR, Córdoba, Argentina.
[3] Instituto de Investigación Multidisciplinario en Ciencia y Tecnología, Universidad de La Serena. Benavente 980, La Serena, Chile.
[4] Departamento de Física y Astronomía, Facultad de Ciencias, Universidad de La Serena. Av. Juan Cisternas 1200, La Serena, Chile.

A2029/2033


15:09:30
15:10
15:10:30
15:11
15:11:30
15:12
15:12:30
15:13
+06:20
+06:10
+06:00
619.7
500
400
300
200
100
35.77
15'
Powered by Aladin
1.253° x 55.95'
N
E

A1204


11:12:40
11:13
11:13:20
11:13:40
11:14
11:14:20
11:14:40
+17:40
+17:35
+17:30
323.1
34.85' x 25.95'
N
E

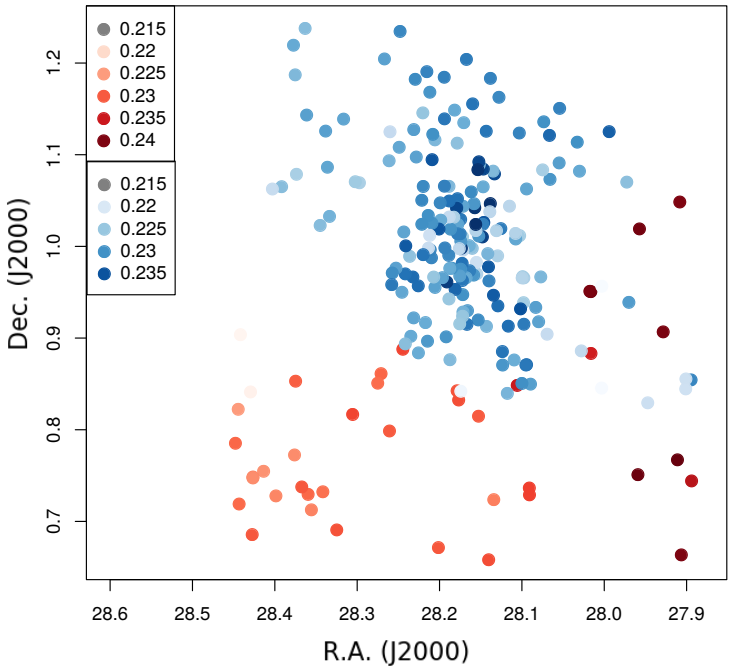
A1204 - secondary component
NFW: c=3.74, R_{200} = 1.11 ± 0.23 Mpc h_{70}^{-1}, χ^2_{red}=1.6
SIS: σ = 640.0 ± 100.0 km/s, χ^2_{red}=1.2
$\langle\gamma_T\rangle$
$\langle\gamma_\times\rangle$
r [h_{70}^{-1} Mpc]

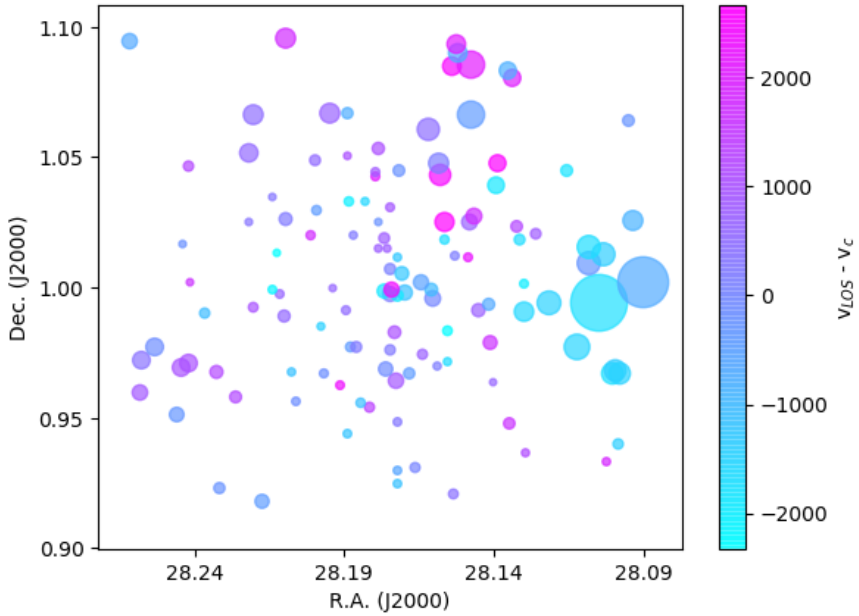
II. Analysis of candidates for interacting galaxy clusters:

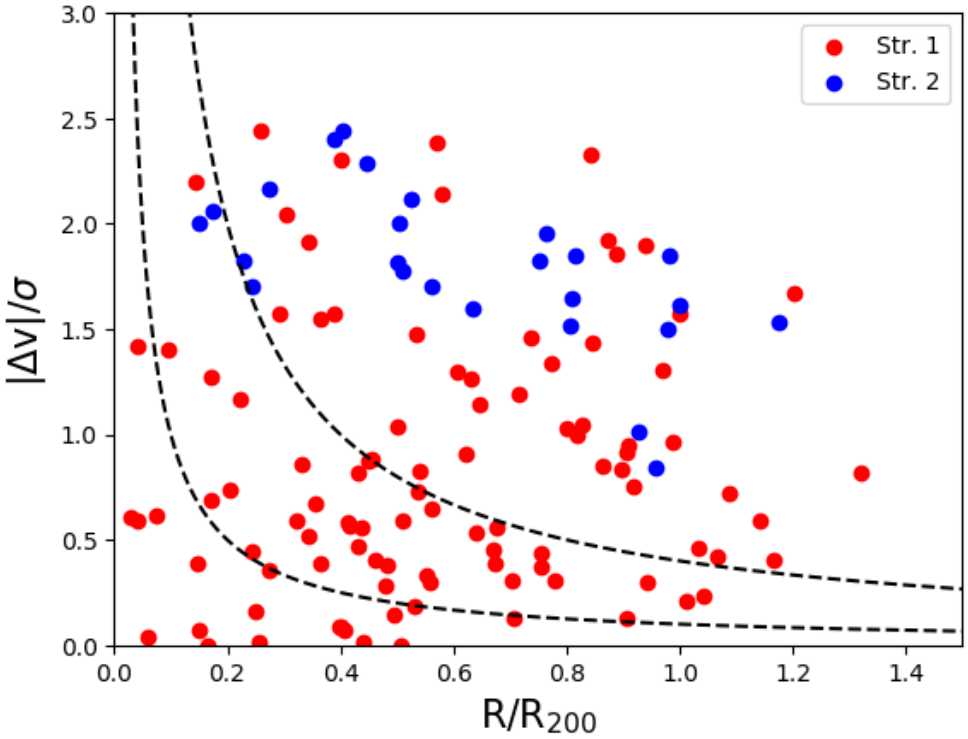
A267, a merging fossil group.

Elizabeth Johana Gonzalez ⋆[1,2], María Jose Kanagusuku[1,2], Martín de los Rios[1,2], Gabriel A. Oio[1,2], Daniel Hernández Lang[4], Tania Aguirre Tagliaferro[1,2], Mariano J. Domínguez R.[1,2], José Luis Nilo Castellón[3,4], Héctor Cuevas L.[4], and Carlos A. Valotto[1,2]

[1] Instituto de Astronomía Teórica y Experimental, (IATE-CONICET), Laprida 854, X5000BGR, Córdoba, Argentina.
[2] Observatorio Astronómico de Córdoba, Universidad Nacional de Córdoba, Laprida 854, X5000BGR, Córdoba, Argentina.
[3] Instituto de Investigación Multidisciplinario en Ciencia y Tecnología, Universidad de La Serena. Benavente 980, La Serena, Chile.
[4] Departamento de Física y Astronomía, Facultad de Ciencias, Universidad de La Serena. Av. Juan Cisternas 1200, La Serena, Chile.


0.215
0.22
0.225
0.23
0.235
0.24
0.215
0.22
0.225
0.23
0.235
Dec. (J2000)
R.A. (J2000)
28.6
28.5
28.4
28.3
28.2
28.1
28.0
27.9
0.7
0.8
0.9
1.0
1.1
1.2


Dec. (J2000)
R.A. (J2000)
1.10
1.05
1.00
0.95
0.90
28.24
28.19
28.14
28.09
2000
1000
0
−1000
−2000
v_{LOS} - v_c

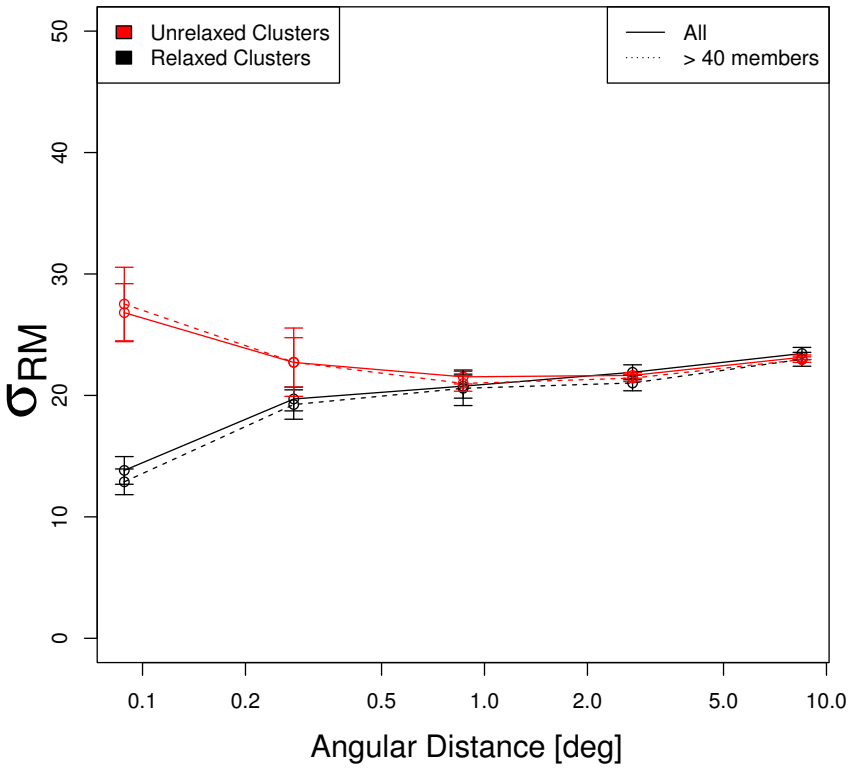


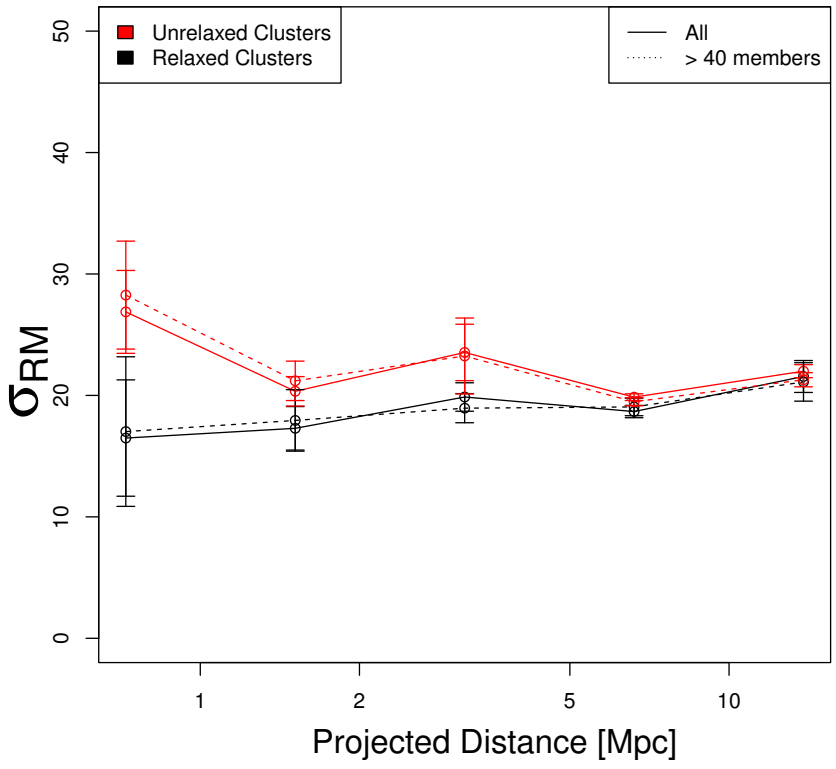
- $\approx$ 40% Fossil groups have a major merger $z < 0.8$.
- $\approx 15 - 25\%$ Fossil groups have a major merger $z < 0.3$.

Noble et al. 2013

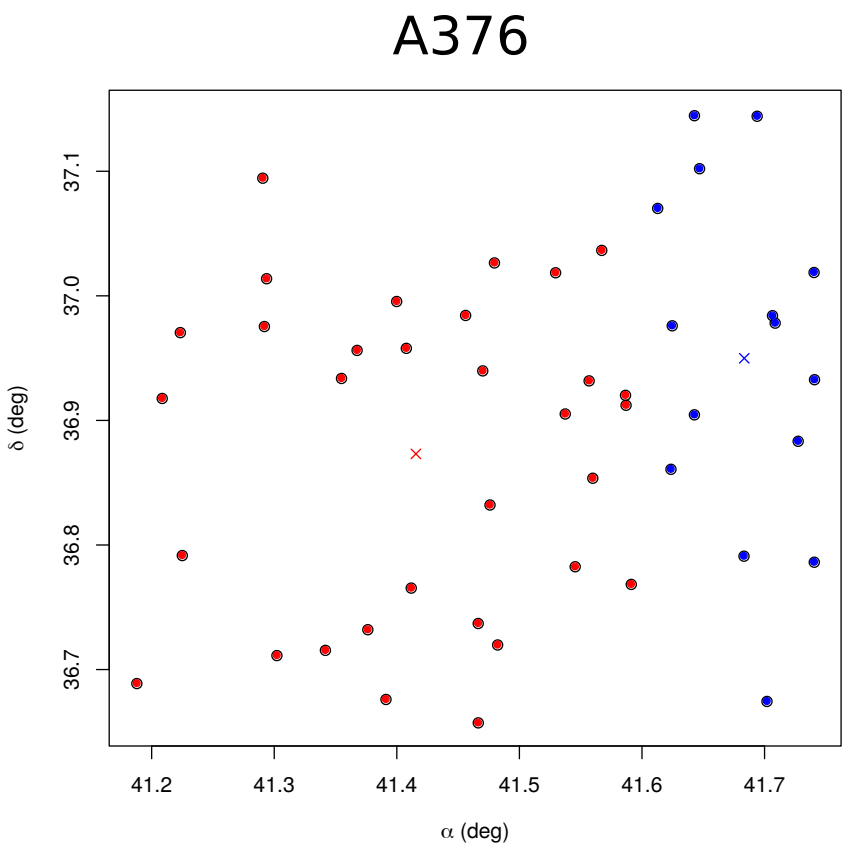
Faraday Rotation Measure dependence with galaxy clusters dynamics

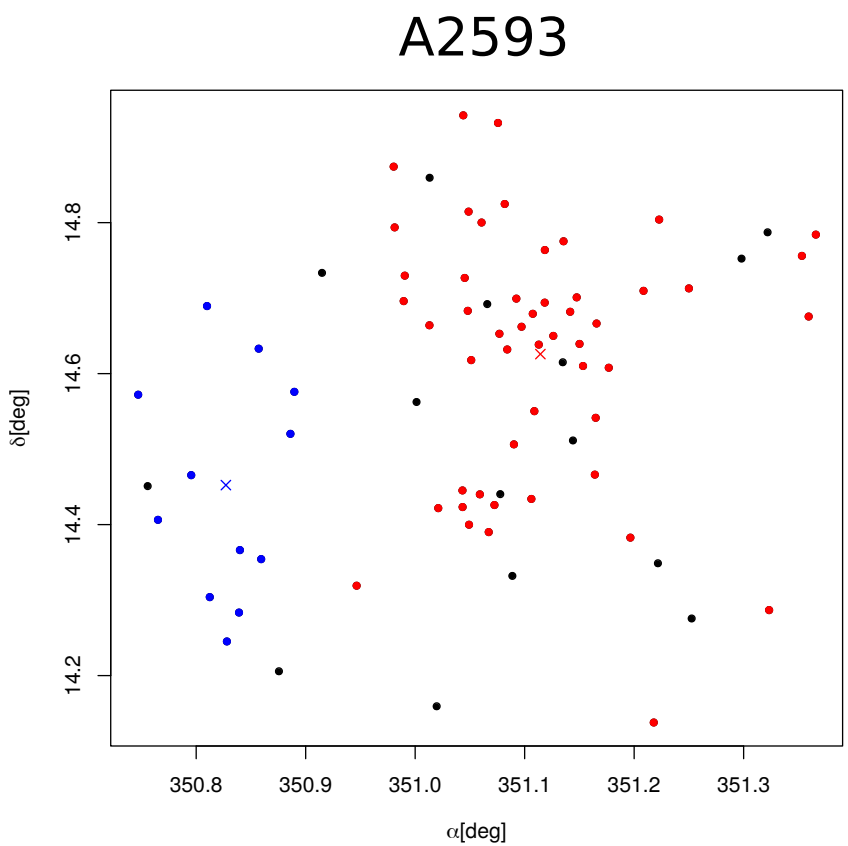
F.A. Stasyszyn[1,2⋆] & M. de los Rios[1,2,3]
[1] *Instituto de Astrofísica Teórica y Experimental (IATE), Laprida 854, Córdoba, Argentina*
[2] *Observatorio Astronómico de Córdoba, Universidad Nacional de Córdoba, Laprida 854, X5000BGR, Córdoba, Argentina.*
[3] *Consejo Nacional de Investigaciones Científicas y Técnicas, Rivadavia 1917, C1033AAJ Buenos Aires, Argentina.*


Unrelaxed Clusters
Relaxed Clusters
All
> 40 members
σRM
0
10
20
30
40
50
0.1
0.2
0.5
1.0
2.0
5.0
10.0
Angular Distance [deg]


Unrelaxed Clusters
Relaxed Clusters
All
> 40 members
σRM
0
10
20
30
40
50
1
2
5
10
Projected Distance [Mpc]

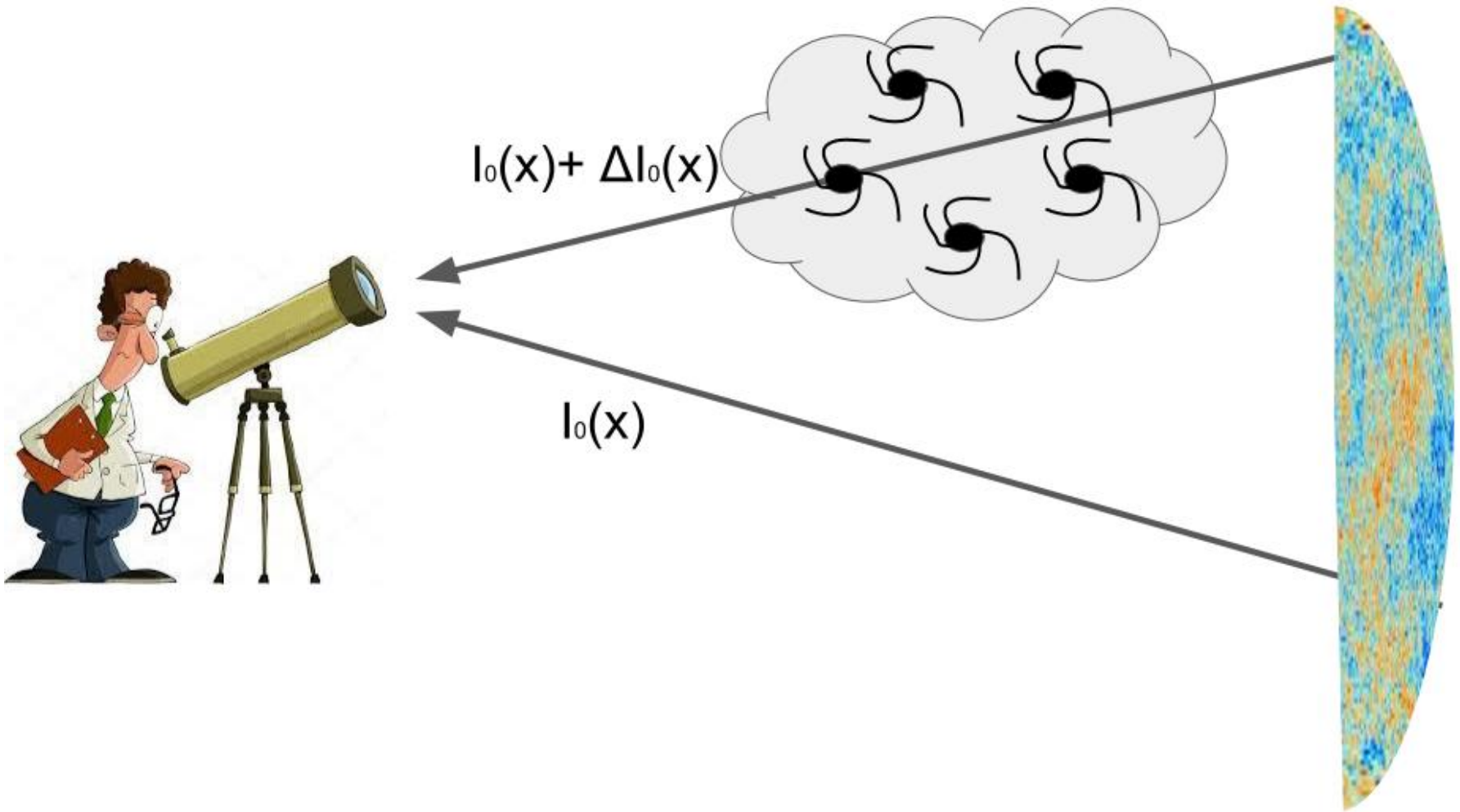
Future work


A376
δ (deg)
37.1
37.0
36.9
36.8
36.7
41.2
41.3
41.4
41.5
41.6
41.7
α (deg)


A2593
δ[deg]
14.8
14.6
14.4
14.2
350.8
350.9
351.0
351.1
351.2
351.3
α[deg]

DM-γ interactions (work in progress)

In collaboration with Dra. Celine Bœhm




CMB
?
SZ
?

1. Introduction to Machine Learning techniques.
2. The `MeSsI` (Merging Systems Identification) Algorithm.
3. Derived Results.
   - A2029/2033.
   - A1204.
   - A267.
   - Statistical analysis of the magnetic fields in merging clusters.
4. DM-γ interactions.
5. `CosmoMl`:Machine Learning techniques applied to the CMB.
   - Construction of the data set.
   - Supervised methods.
   - Cosmological parameters Angular distributions.
6. Conclusions and Final remarks.

CosmoML: Machine Learning techniques applied to the Cosmic Microwave Background.

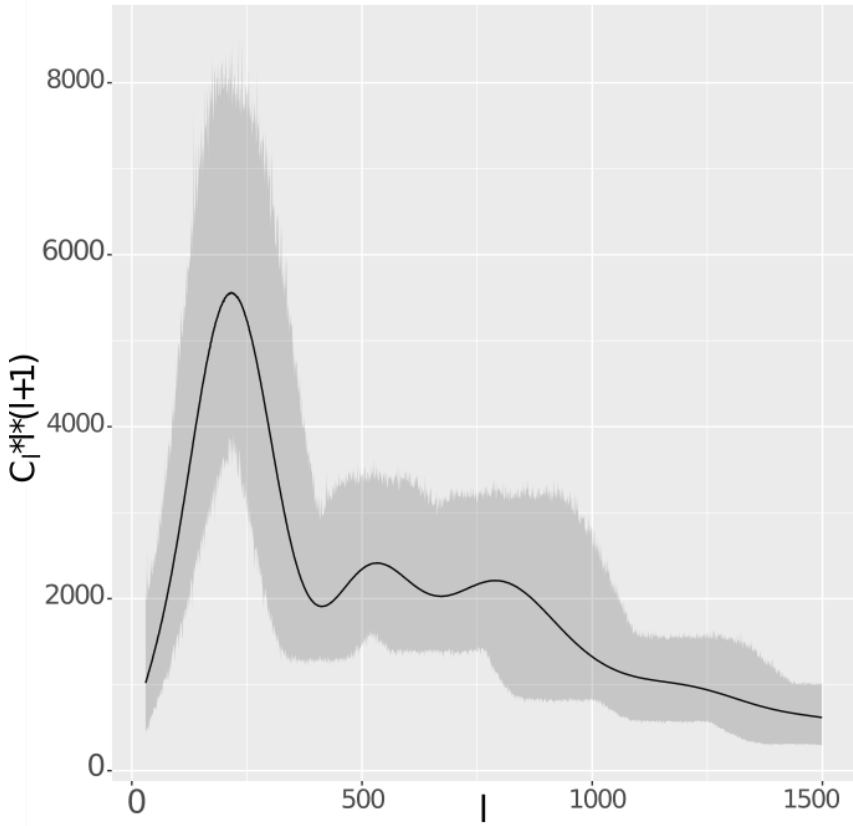
Martín de los Rios*, Mariano J. Domínguez R.* [1,2,3].

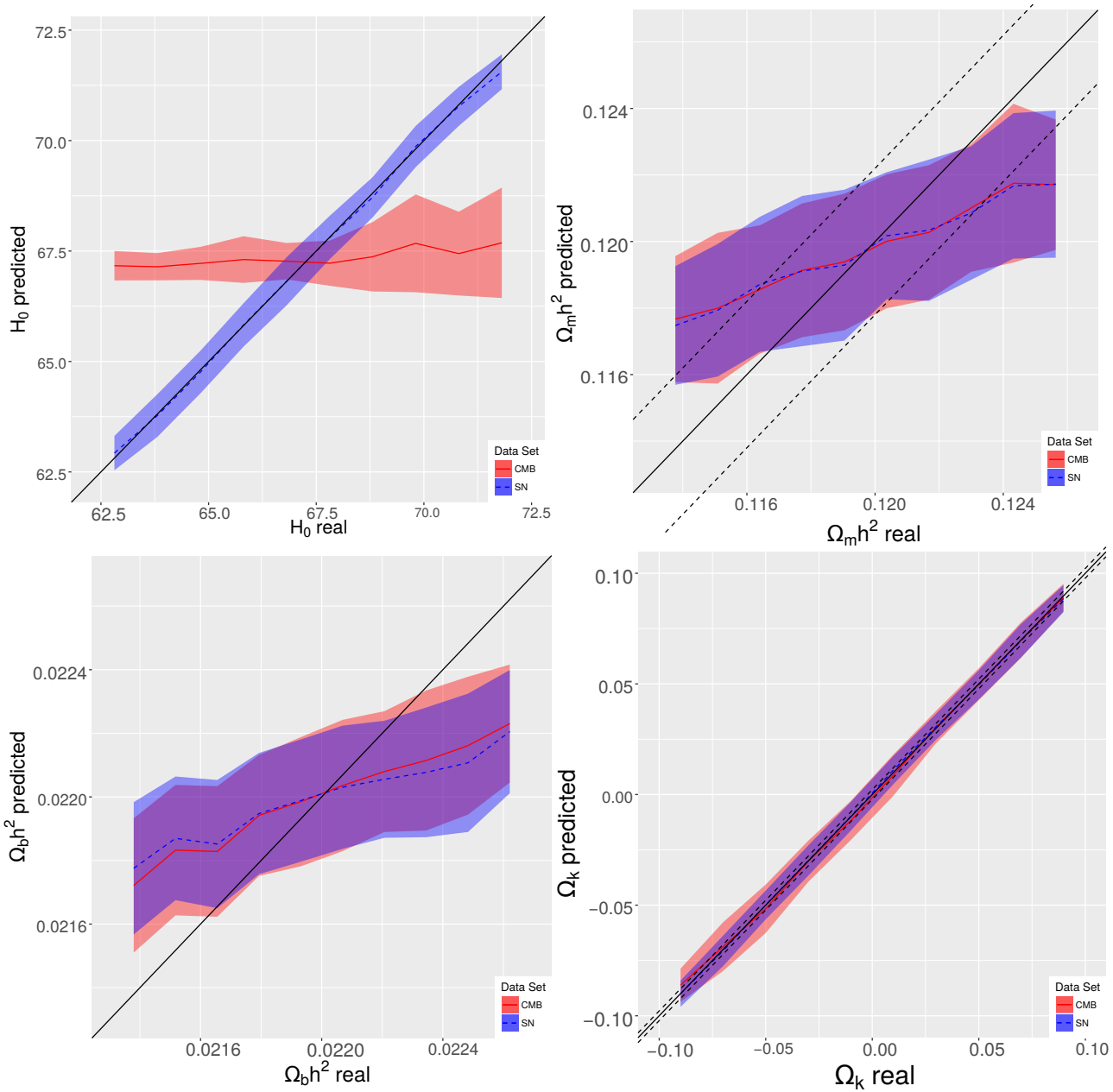
[1] *Instituto de Astronomía Teórica y Experimental (CCT Córdoba, CON ICET, UNC), Laprida 854, X5000BGR, Córdoba, Argentina.*

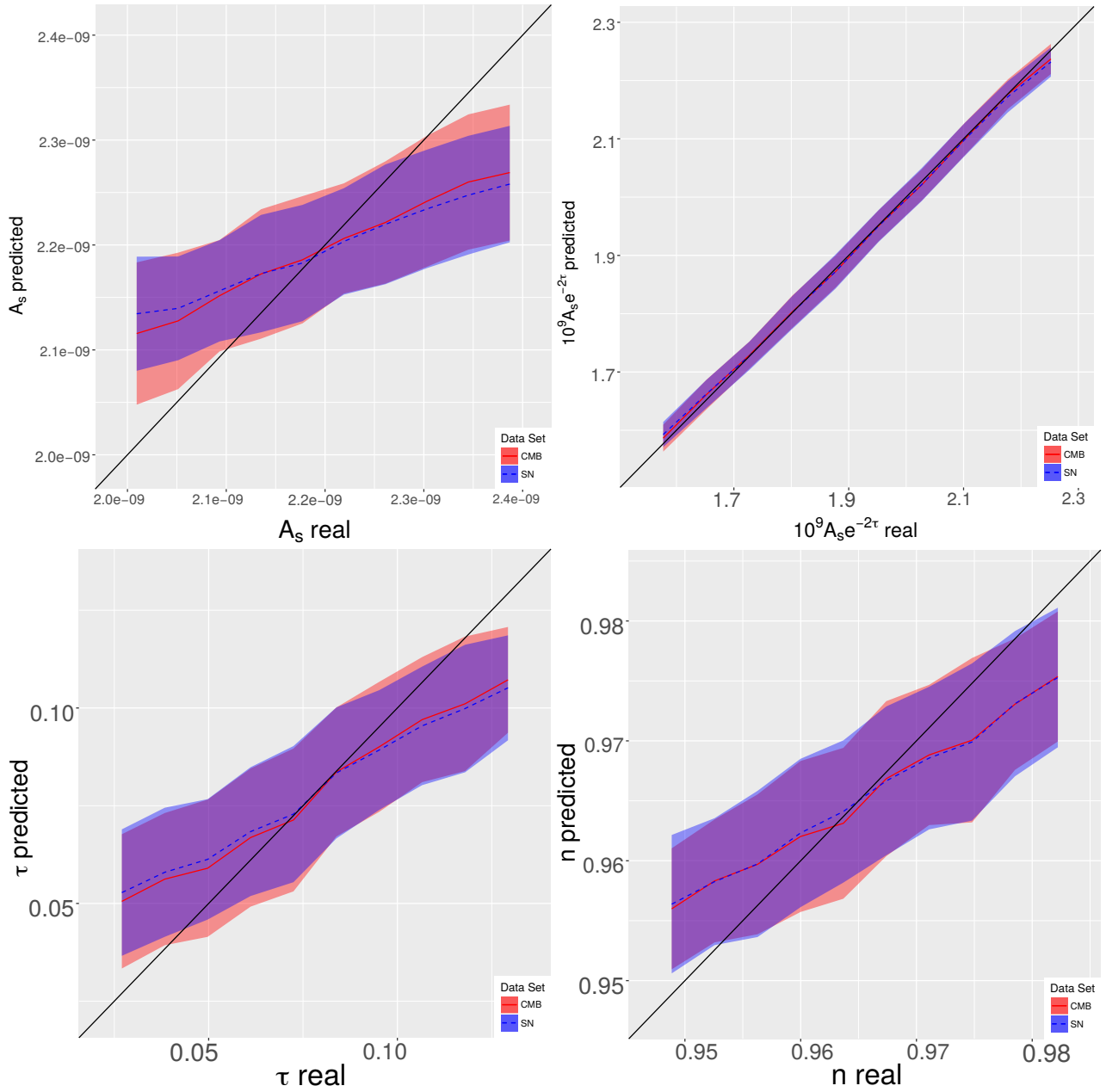
[2] *Observatorio Astronómico de Córdoba, Universidad Nacional de Córdoba, Laprida 854, X5000BGR, Córdoba, Argentina.*

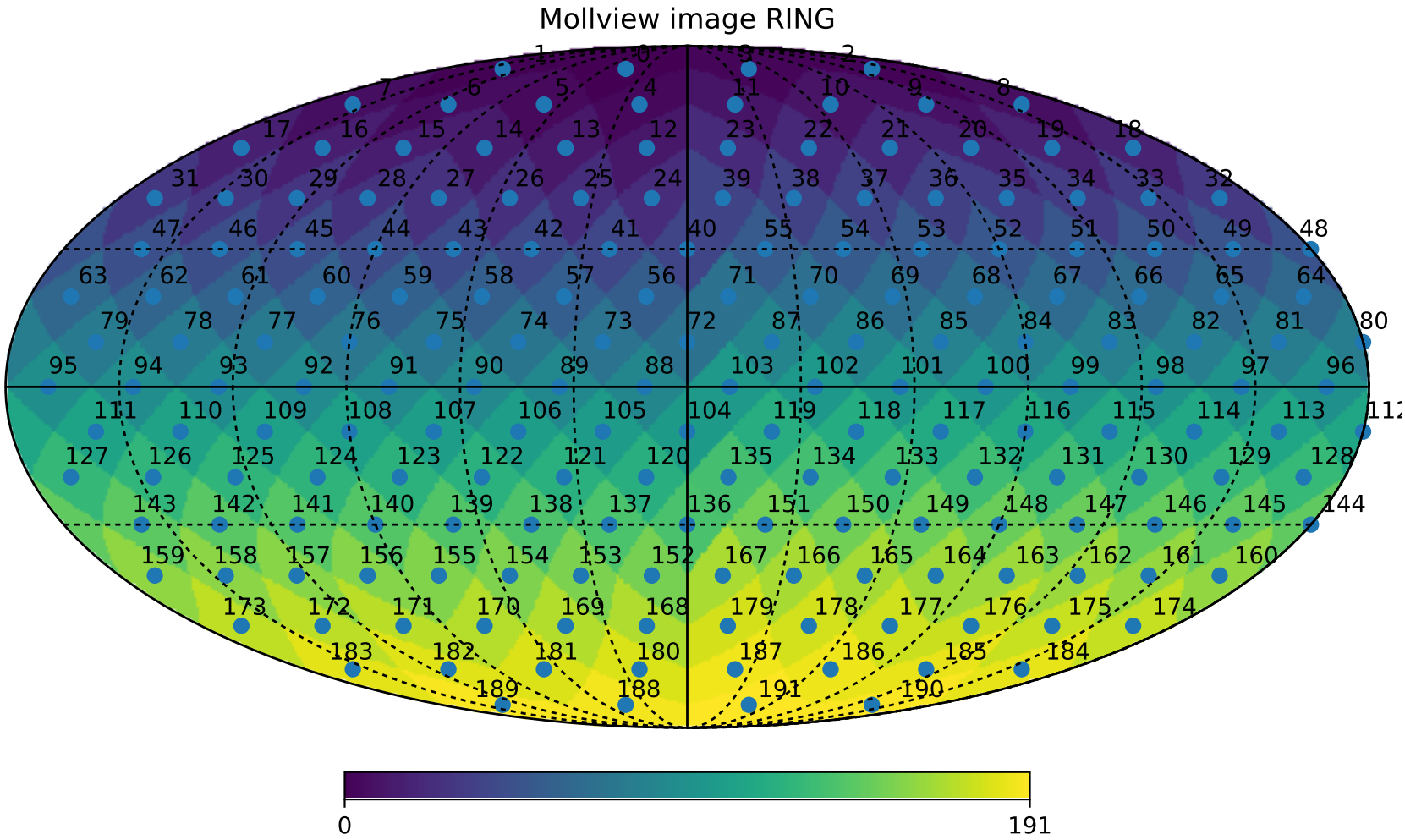
[3] *Consejo Nacional de Investigaciones Científicas y Técnicas, Rivadavia 1917, C1033AAJ Buenos Aires, Argentina.*

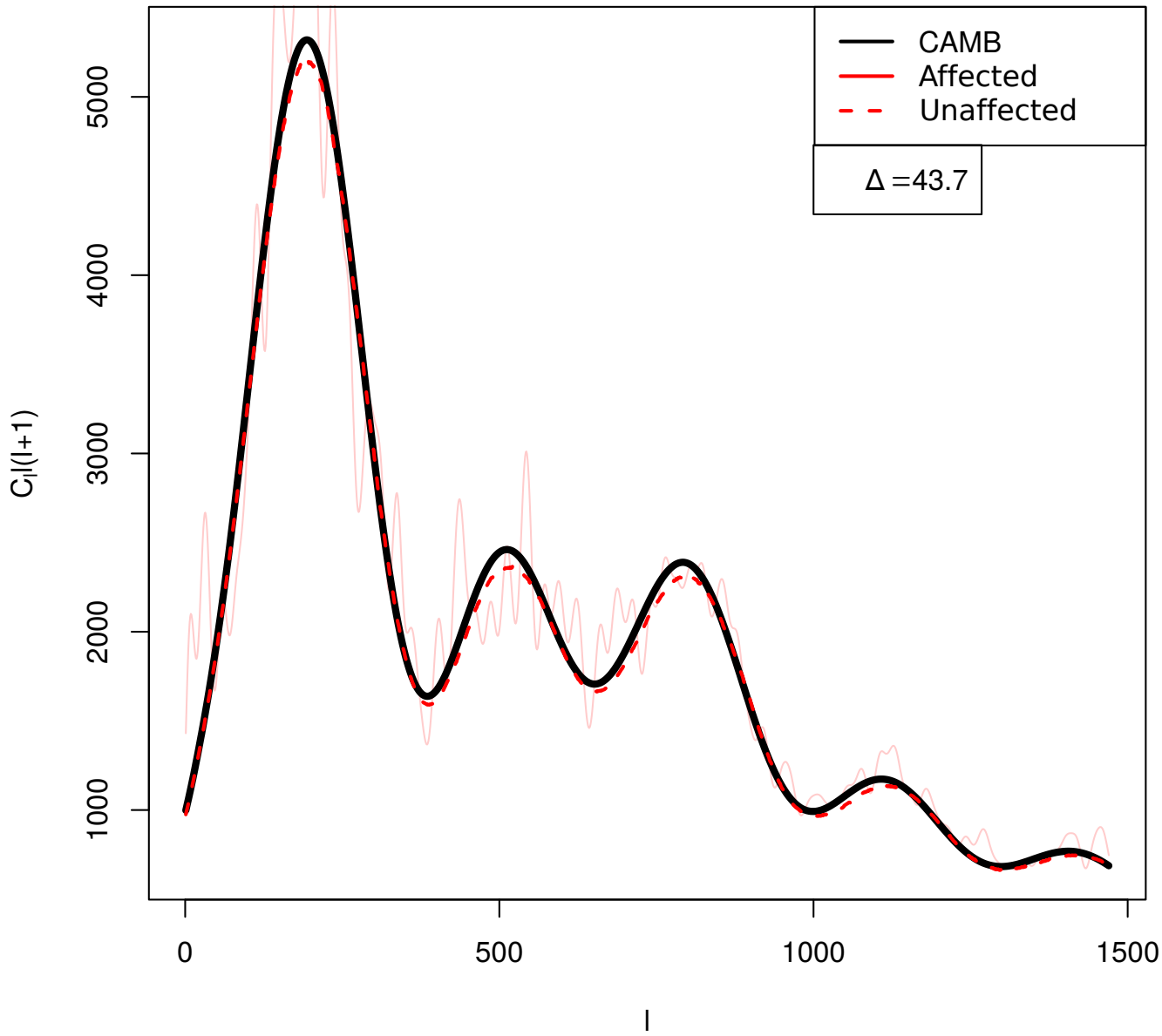
Parameter	Minimum	Maximum	Planck
$\Omega_m h^2$	0.1131	0.1263	0.1197
$\Omega_b h^2$	0.02131	0.02269	0.022
Ω_k	–0.1	0.1	0
H_0	62.31	72.31	67.31
n	0.9469	0.9841	0.9655
A_s	$1.988 * 10^{-9}$	$2.408 * 10^{-9}$	$2.198 * 10^{-9}$
τ	0.021	0.1349	0.078

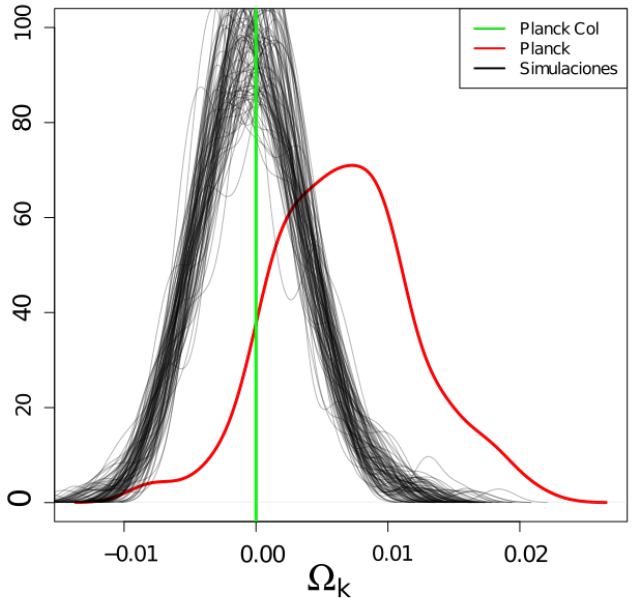


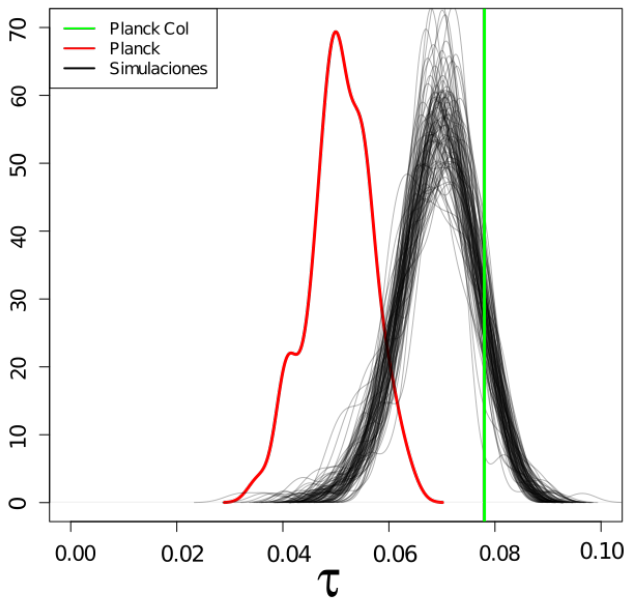

72.5
70.0
67.5
65.0
62.5
H_0 predicted
62.5
65.0
67.5
70.0
72.5
H_0 real
Data Set
CMB
SN
0.124
0.120
0.116
$\Omega_m h^2$ predicted
0.116
0.120
0.124
$\Omega_m h^2$ real
Data Set
CMB
SN
0.0224
0.0220
0.0216
$\Omega_b h^2$ predicted
0.0216
0.0220
0.0224
$\Omega_b h^2$ real
Data Set
CMB
SN
0.10
0.05
0.00
−0.05
−0.10
Ω_k predicted
−0.10
−0.05
0.00
0.05
0.10
Ω_k real
Data Set
CMB
SN

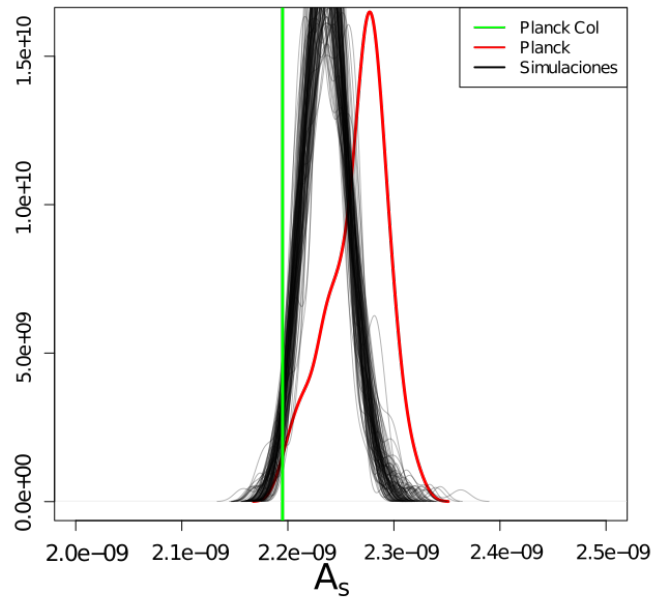

2.4e−09
2.3e−09
2.2e−09
2.1e−09
2.0e−09
A_s predicted
2.0e−09
2.1e−09
2.2e−09
2.3e−09
2.4e−09
A_s real
Data Set
CMB
SN
2.3
2.1
1.9
1.7
$10^9 A_s e^{-2\tau}$ predicted
1.7
1.9
2.1
2.3
$10^9 A_s e^{-2\tau}$ real
Data Set
CMB
SN
0.10
0.05
τ predicted
0.05
0.10
τ real
Data Set
CMB
SN
0.98
0.97
0.96
0.95
n predicted
0.95
0.96
0.97
0.98
n real
Data Set
CMB
SN

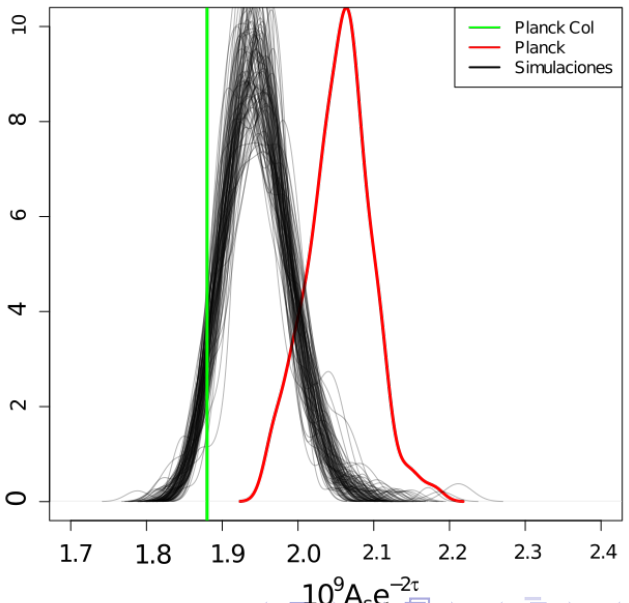

Mollview image RING
0
191


CAMB
Affected
Unaffected
Δ =43.7
$C_l(l+1)$
1000
2000
3000
4000
5000
0
500
1000
1500
l


Planck Col
Planck
Simulaciones
0
20
40
60
80
100
−0.01
0.00
0.01
0.02
Ω_k


Planck Col
Planck
Simulaciones
0
10
20
30
40
50
60
70
0.00
0.02
0.04
0.06
0.08
0.10
τ


Planck Col
Planck
Simulaciones
0.0e+00
5.0e+09
1.0e+10
1.5e+10
2.0e−09
2.1e−09
2.2e−09
2.3e−09
2.4e−09
2.5e−09
A_s


Planck Col
Planck
Simulaciones
0
2
4
6
8
10
1.7
1.8
1.9
2.0
2.1
2.2
2.3
2.4
$10^9 A_s e^{-2\tau}$

1. Introduction to Machine Learning techniques.
2. The MeSsI (Merging Systems Identification) Algorithm.
3. Derived Results.
   - A2029/2033.
   - A1204.
   - A267.
   - Statistical analysis of the magnetic fields in merging clusters.
4. DM-γ interactions.
5. CosmoMl:Machine Learning techniques applied to the CMB.
   - Construction of the data set.
   - Supervised methods.
   - Cosmological parameters Angular distributions.
6. Conclusions and Final remarks.

- We developed a method for the automatic classification of galaxy clusters dynamical state.

- We developed a method for the automatic classification of galaxy clusters dynamical state.
- Using this technique we build a catalogue of merging clusters candidates.

- We developed a method for the automatic classification of galaxy clusters dynamical state.
- Using this technique we build a catalogue of merging clusters candidates.
- We performed individual analysis of 3 of this clusters.

- We developed a method for the automatic classification of galaxy clusters dynamical state.
- Using this technique we build a catalogue of merging clusters candidates.
- We performed individual analysis of 3 of this clusters.
- We performed an Statistical analysis comparing the magnetic fields in relaxed and unrelaxed clusters.

- We developed a method for the automatic classification of galaxy clusters dynamical state.
- Using this technique we build a catalogue of merging clusters candidates.
- We performed individual analysis of 3 of this clusters.
- We performed an Statistical analysis comparing the magnetic fields in relaxed and unrelaxed clusters.
- We studied the effect that a possible interaction between CMB photons and DM haloes may produce in the CMB spectral distribution.

- We developed a method for the automatic classification of galaxy clusters dynamical state.
- Using this technique we build a catalogue of merging clusters candidates.
- We performed individual analysis of 3 of this clusters.
- We performed an Statistical analysis comparing the magnetic fields in relaxed and unrelaxed clusters.
- We studied the effect that a possible interaction between CMB photons and DM haloes may produce in the CMB spectral distribution.
- We studied the cosmic microwave background using Machine Learning techniques.

- We developed a method for the automatic classification of galaxy clusters dynamical state.
- Using this technique we build a catalogue of merging clusters candidates.
- We performed individual analysis of 3 of this clusters.
- We performed an Statistical analysis comparing the magnetic fields in relaxed and unrelaxed clusters.
- We studied the effect that a possible interaction between CMB photons and DM haloes may produce in the CMB spectral distribution.
- We studied the cosmic microwave background using Machine Learning techniques.
- We studied the angular distributions of the cosmological parameters without finding anything unexpected in the standard cosmological model, with the possible exception of the parameter $10^9 A_s e^{-2\tau}$.

- Machine Learning techniques are very powerful tools to study in an independent and agnostic way any data set.

- Machine Learning techniques are very powerful tools to study in an independent and agnostic way any data set.
- They can be very useful for classification and regression problems, achieving, in most of the problems, better results than the traditional methods in lower computational time.

- Machine Learning techniques are very powerful tools to study in an independent and agnostic way any data set.
- They can be very useful for classification and regression problems, achieving, in most of the problems, better results than the traditional methods in lower computational time.
- Taking into account the large amount of data that will be recorded by the future surveys, this technique will be essential for their analysis.


THANK YOU