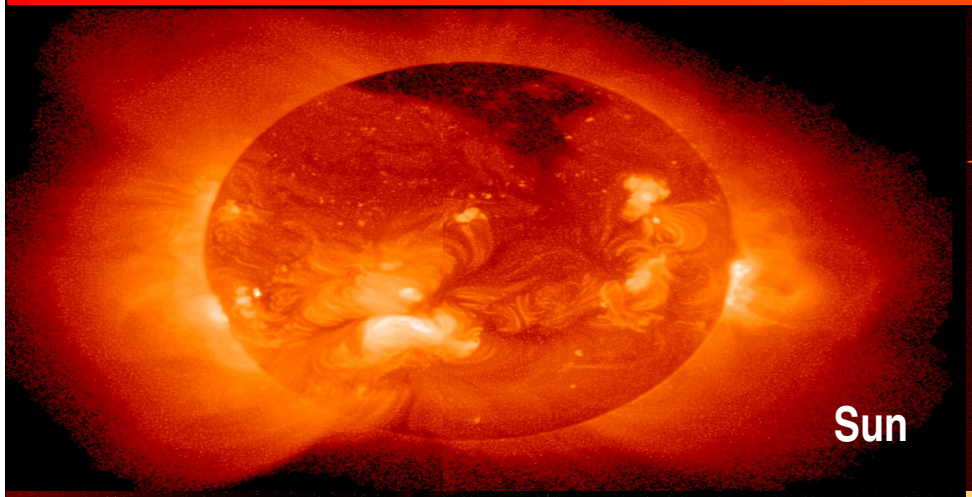
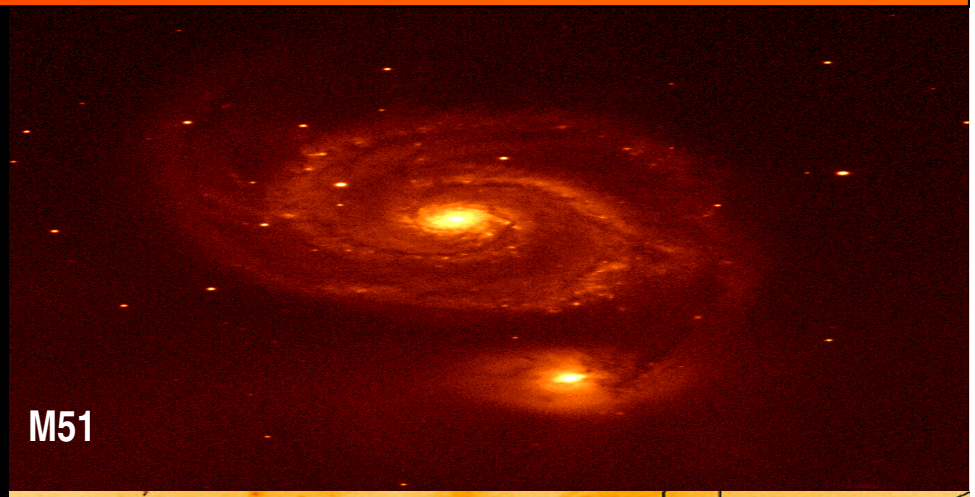
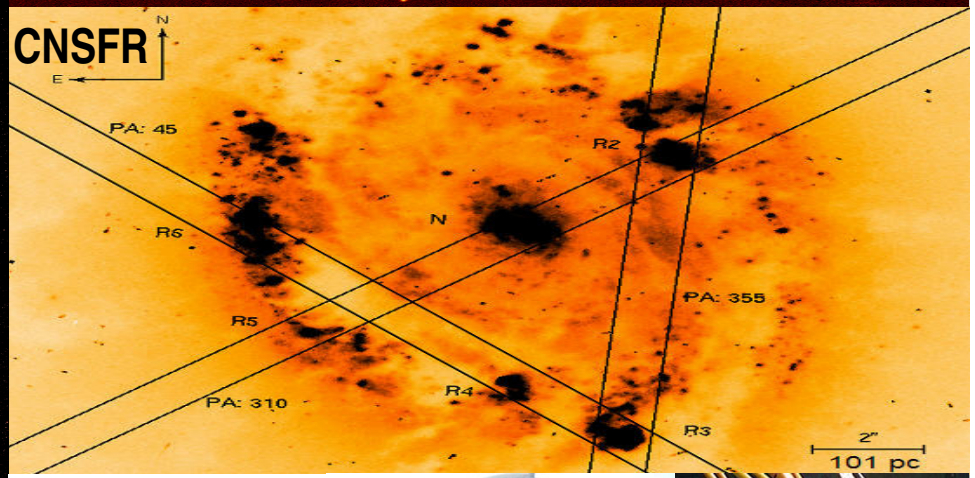
Unravelling the nonlinear physics of high-Z regions with neural networks







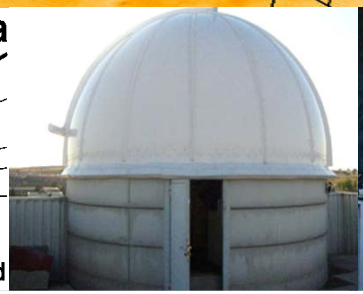


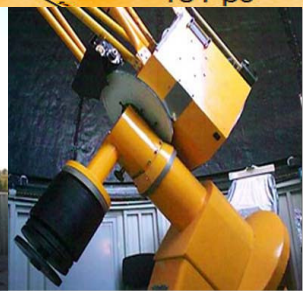
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michael.taylor@uam.es

Grupo de Astrofísica

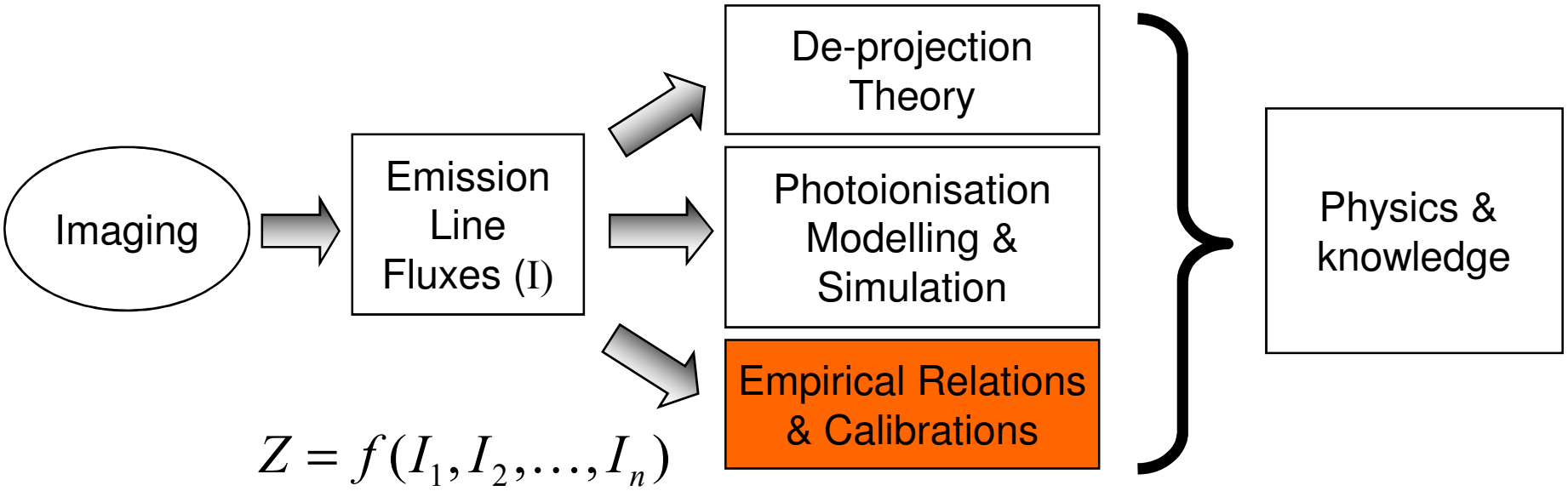
Universidad Autónoma de Madrid

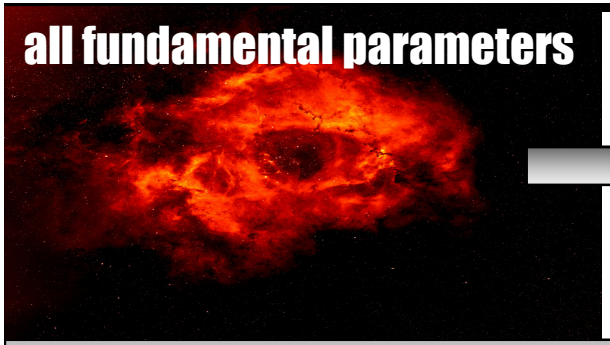




Fundamental → Functional parameters

Abundances
AI - A new opportunity
n-D Calibrations
Ideas for the future





S23 **Abundance indicator**

T* **Effective Temperature**

Z **Metallicity**

eta **Softness parameter**

U **Ionisation parameter**

Unravelling the nonlinear physics of high-Z regions with neural networks

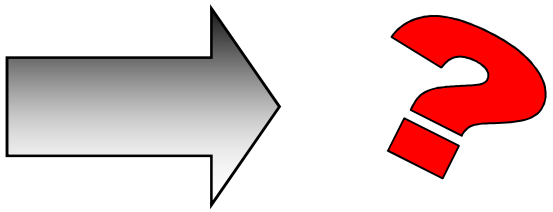
Mike Taylor, Pepe Vilchez & Angeles Diaz

The **IDEAL** Indicator x_n?

- Would be **MONOTONIC** with respect to metallicity **Z**
- Would be observationally **detectable** up to **high Z**
- Would have **low** average **dispersion** (least-square error)
- Would span a **W I D E** range of **Z** when empirically-calibrated using **REAL** galaxy data

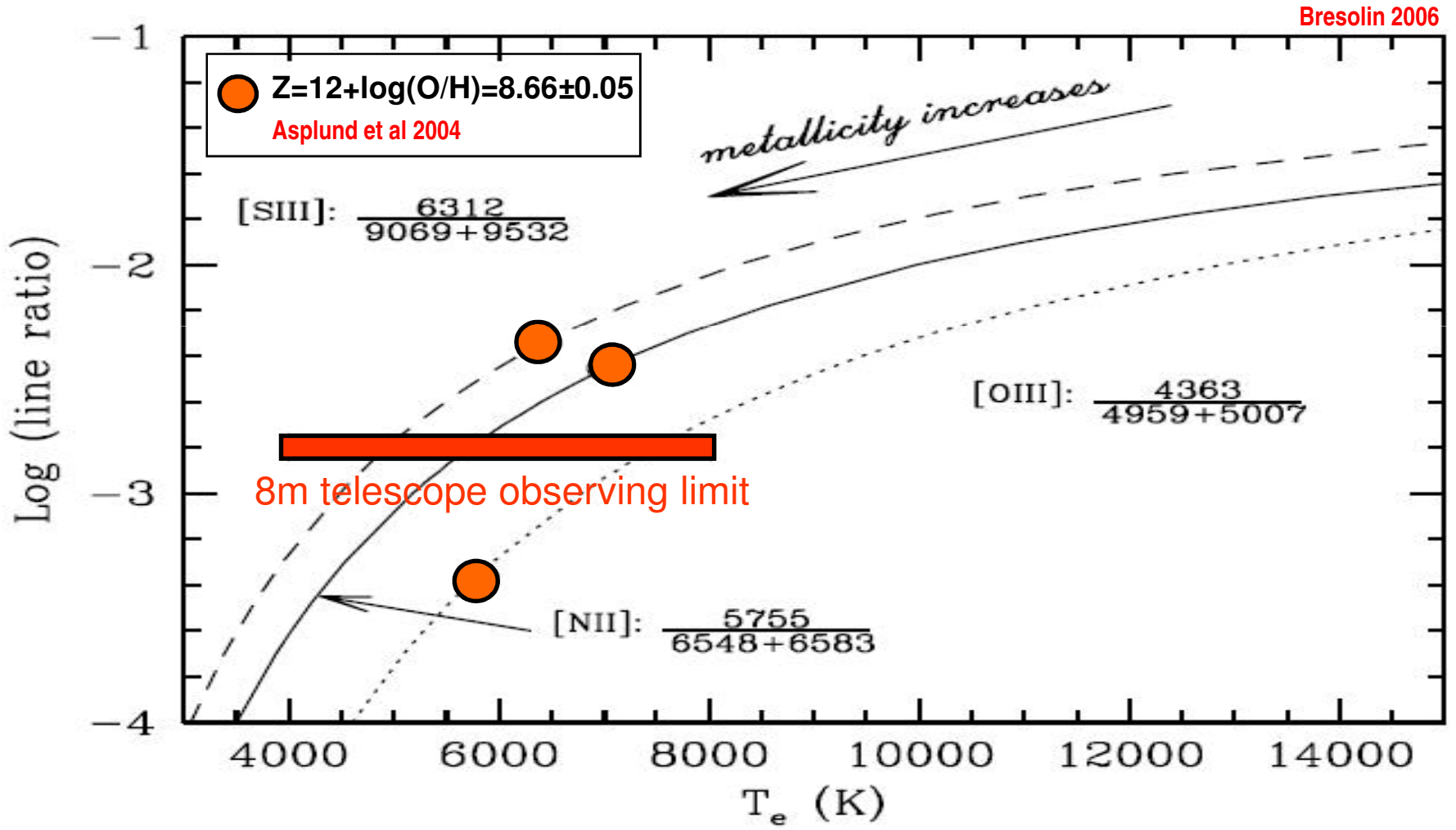
& IF ALL THAT WENT PERFECTLY…

It would also be independent of chemical evolution and have an understandable behaviour with Z



Observational Limits at high Z

Commonly used auroral-to-nebular emission line ratios…



Indicators in HII-like regions

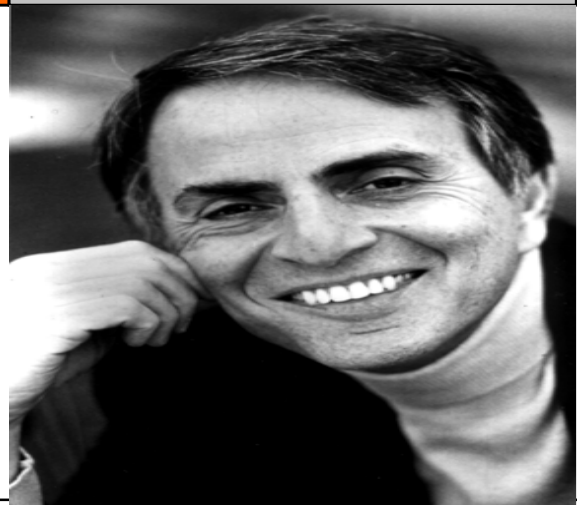
Galactic HII-Regions | Extra-Galactic HII-Regions | HII Galaxies | **CNSFRs?**

Parameter	Validity	Dispersion
↑ O_{23}	$Z < 8.0$	0.12
~ O_{23}	$8.0 \leq Z \leq 8.4$	1.30
↓ O_{23}	$Z > 8.4$	0.20
N2	up to $Z_\odot$	0.24
S_{23}	up to $Z_\odot$	0.16
S_{234}	up to $Z_\odot$	<0.10
S_{23}/O_{23}	all Z	0.27

Perez-Montero 2002

AI: An opportunity

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Scale-invariant And Genetic Algorithm Network (SAGAN)

Dimensional Analysis
Taylor & Diaz 2006

10^3 ERROR REDUCTION
Taylor 2005

Net DNA Ecoding { Architecture, Weights, Node Functions
+ Genetic Operators { Mutation, Cross-over
+ Pruning Algorithm

EQUATIONS
Taylor & Diaz 2006

Multi-Layer Perceptron

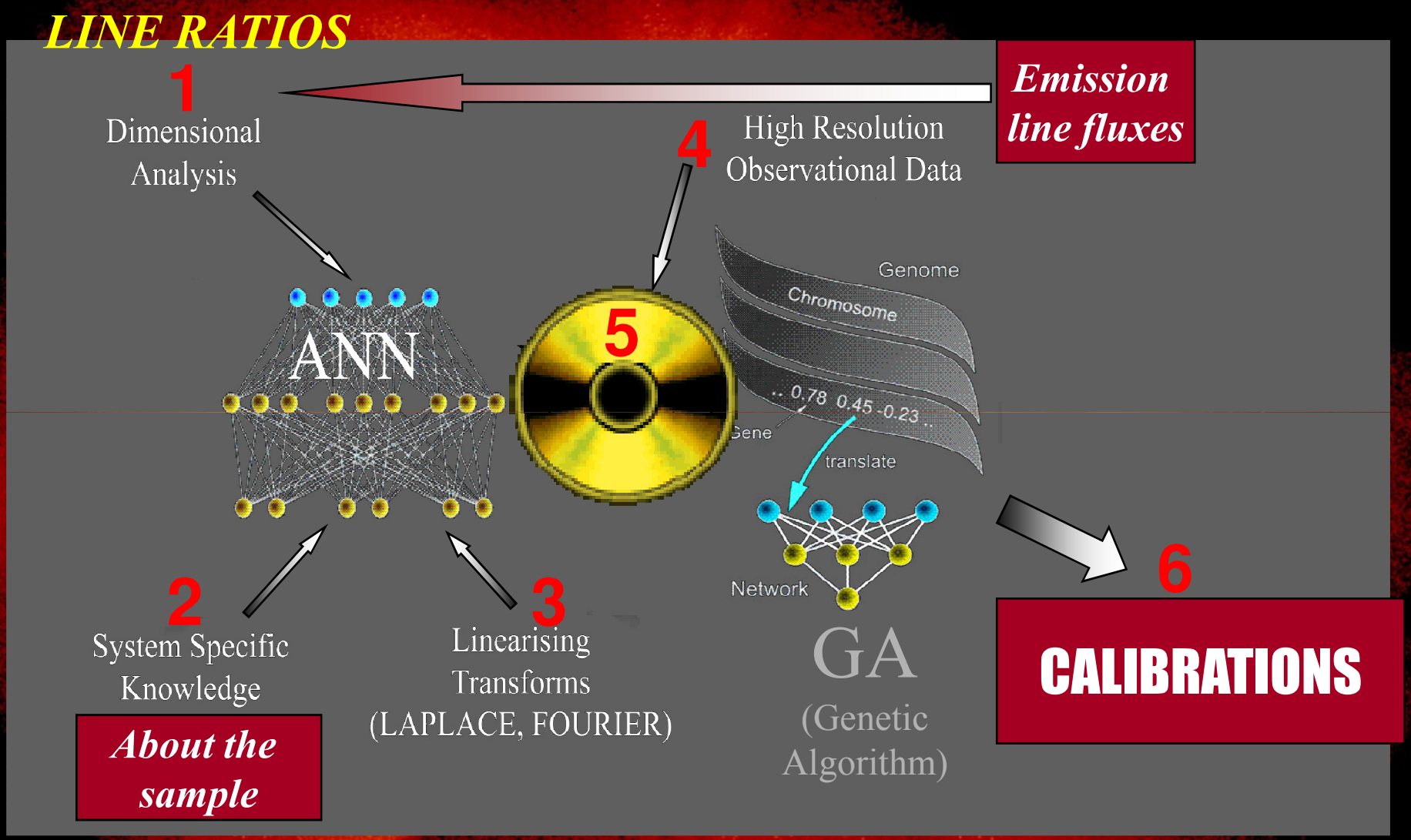
+ Back-Propagation

UNIVERSAL FUNCTION APPROXIMATOR
Taylor 2005

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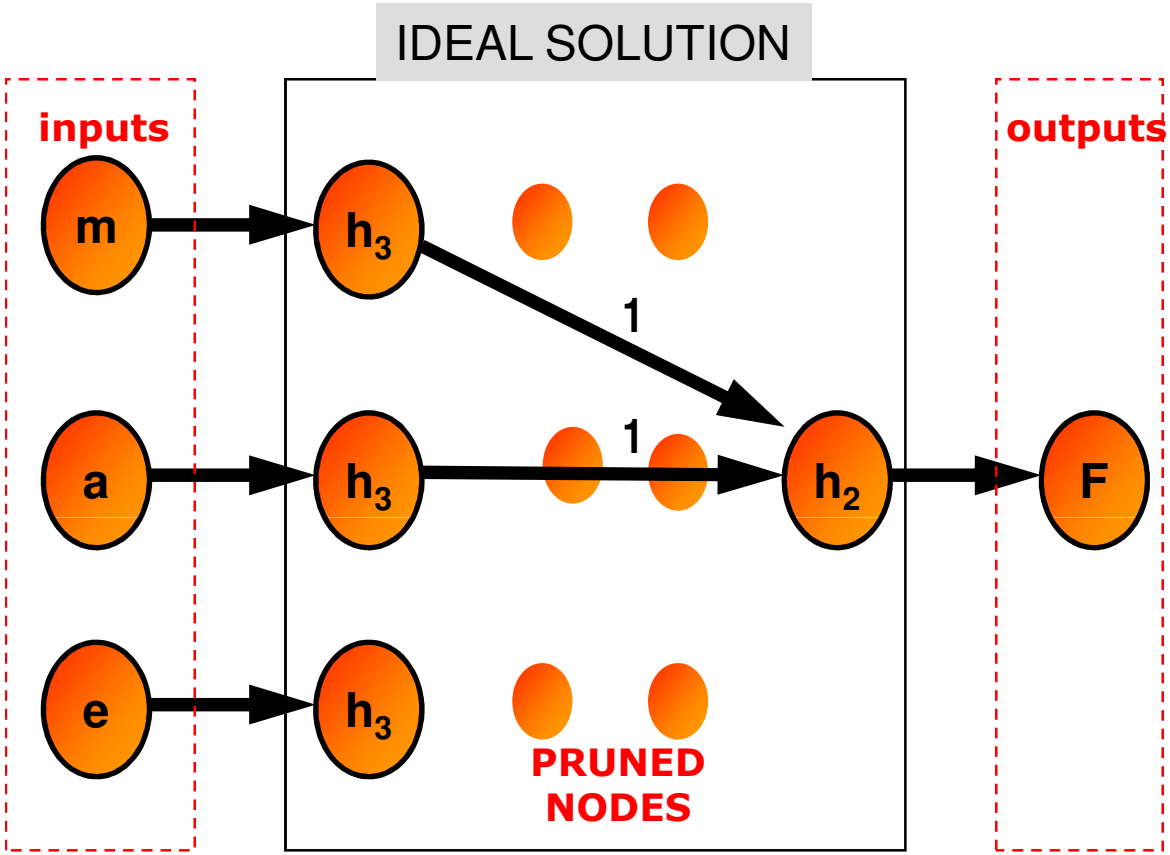
A new strategy



Unravelling the nonlinear physics of high-Z regions with neural networks

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How it Works: e.g. Newton's Law



Neural Node Functions

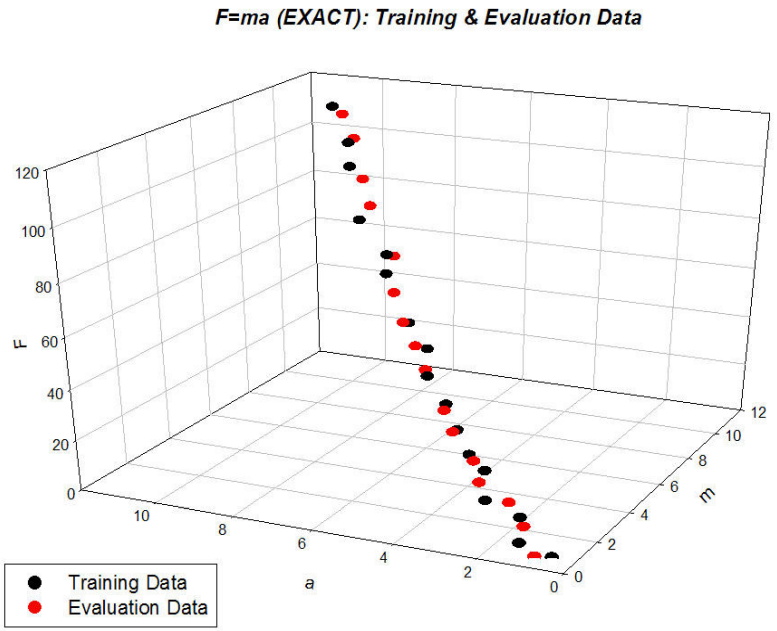
$h(s)_1$	$= s$	Linear	
$h(s)_2$	$= e^s$	Power Laws	
$h(s)_3$	$= \ln \lvert s \rvert$		
$h(s)_4$	$= 1/(1+e^{-s})$	Sigmoids	
$h(s)_5$	$= (1+e^{-s})/2(1+e^{-s})$		
$h(s)_6$	$= \tanh s$	Trig. Functions	
$h(s)_7$	$= \sin s$		
$h(s)_8$	$= \cos s$		
$h(s)_9$	$= e^{-s^2}$	Gaussians	
$h(s)_{10}$	$= 1$	Constants	

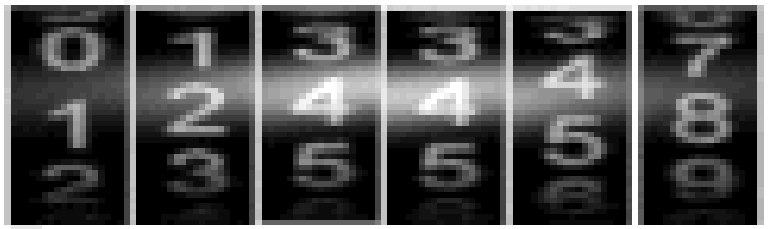
$$F = e^{\{\ln m + \ln a\}} = e^{\ln ma} = ma$$

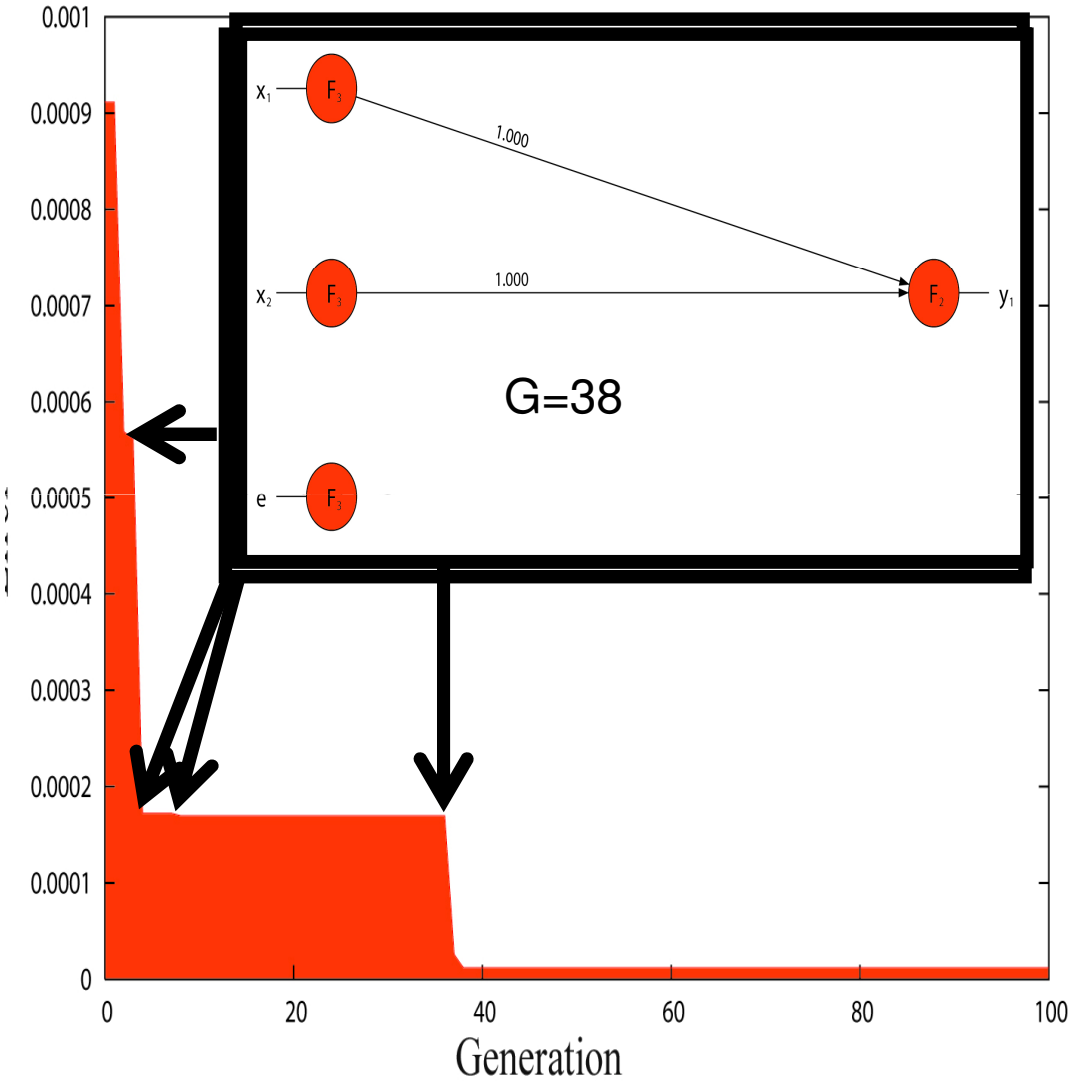
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Newton's Law: F=ma (EXACT)



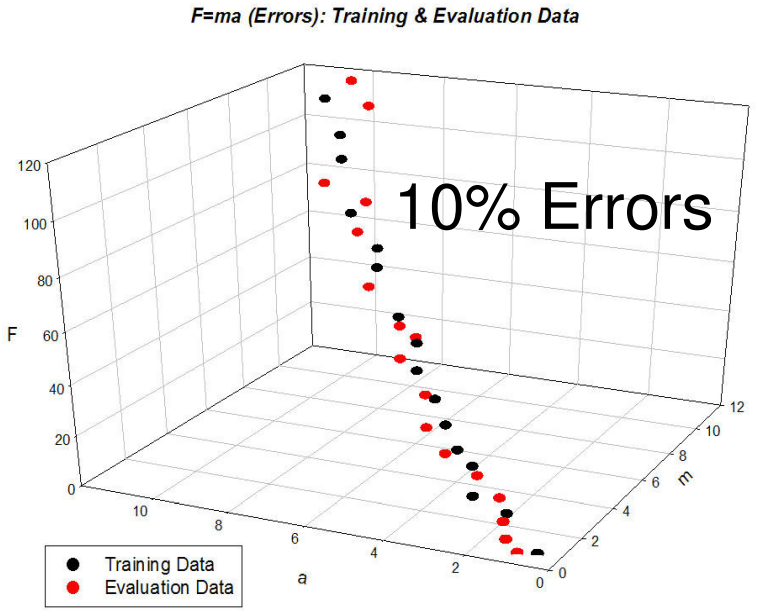


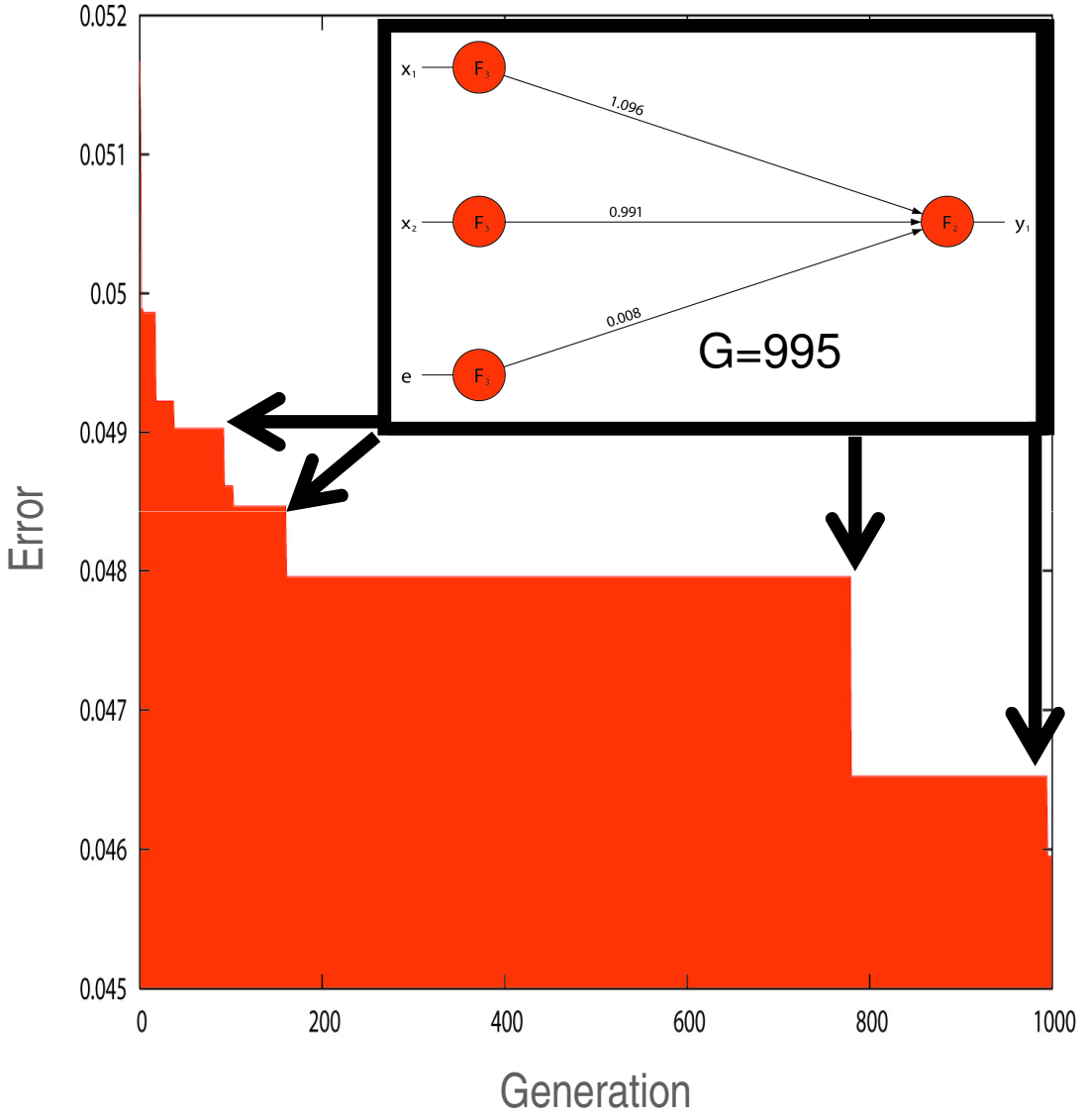


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Newton's Law: F=ma (10% Errors)

Abundances
AI - A new opportunity
n-D Calibrations
Ideas for the future



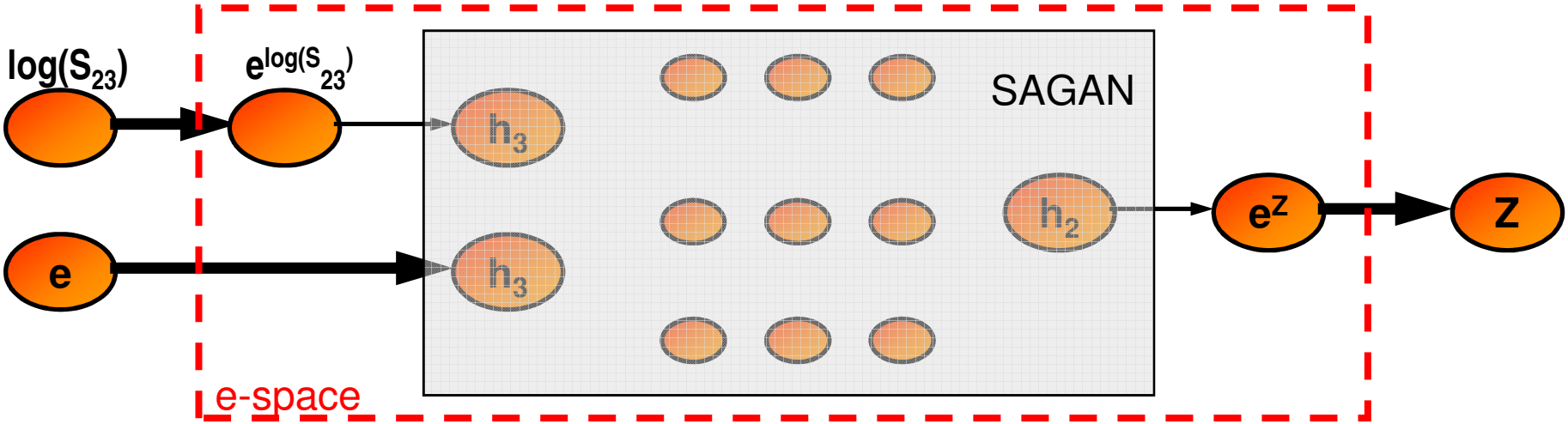


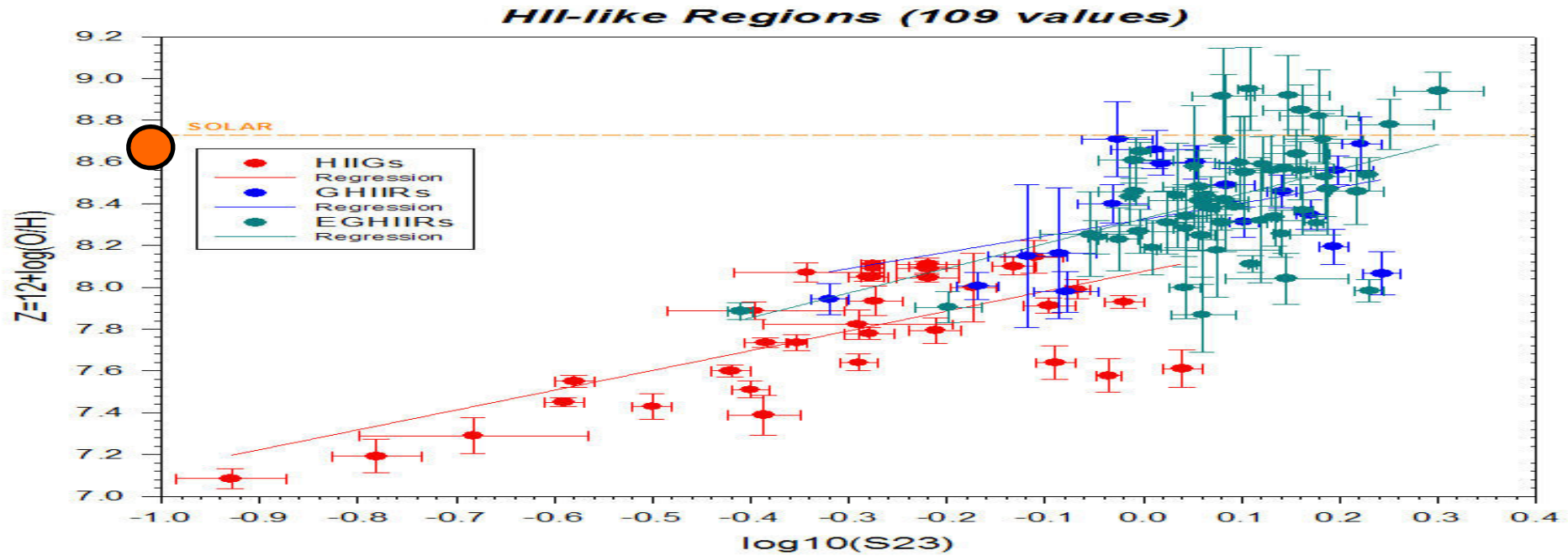
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HII-like regions: HIIGs, GHIIRs & EGHIIRs

Abundances
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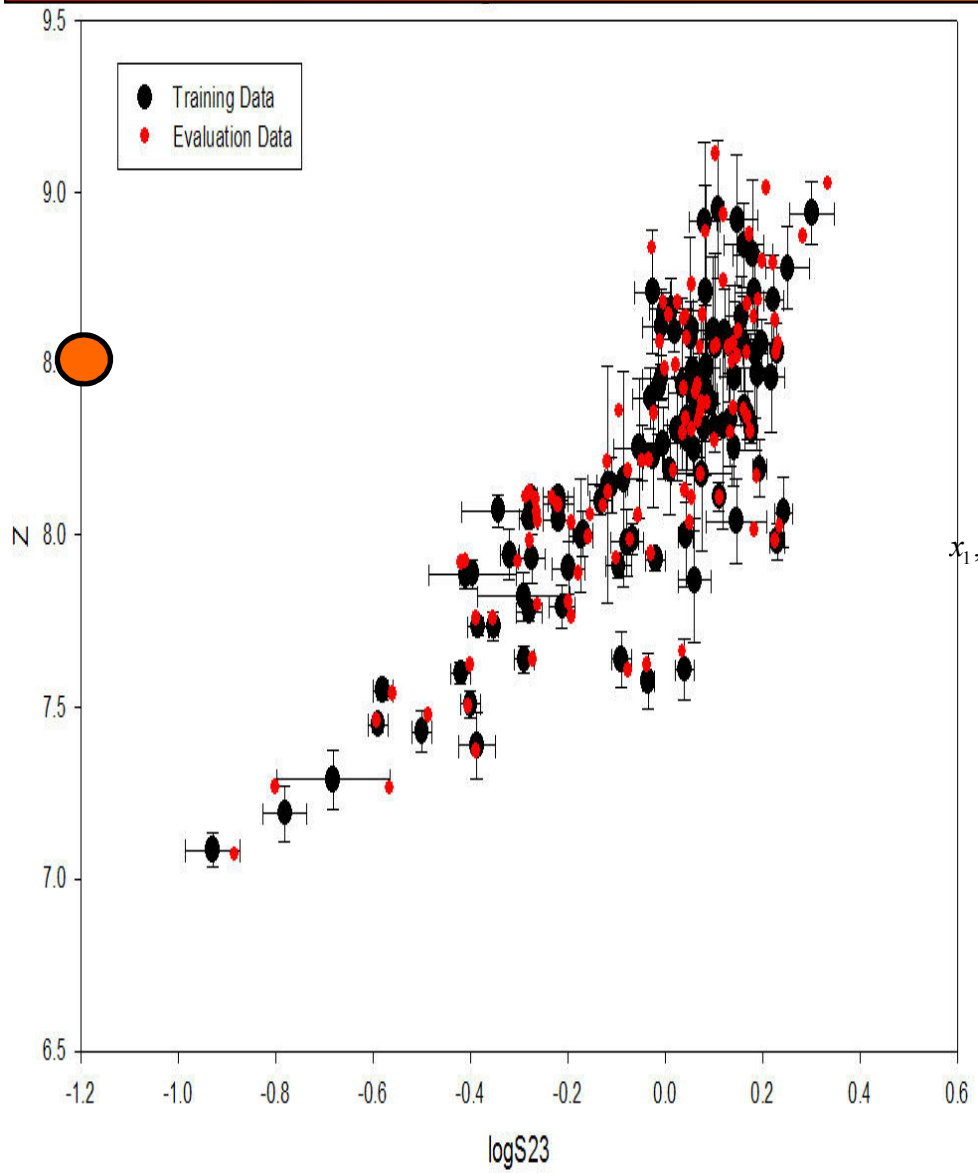


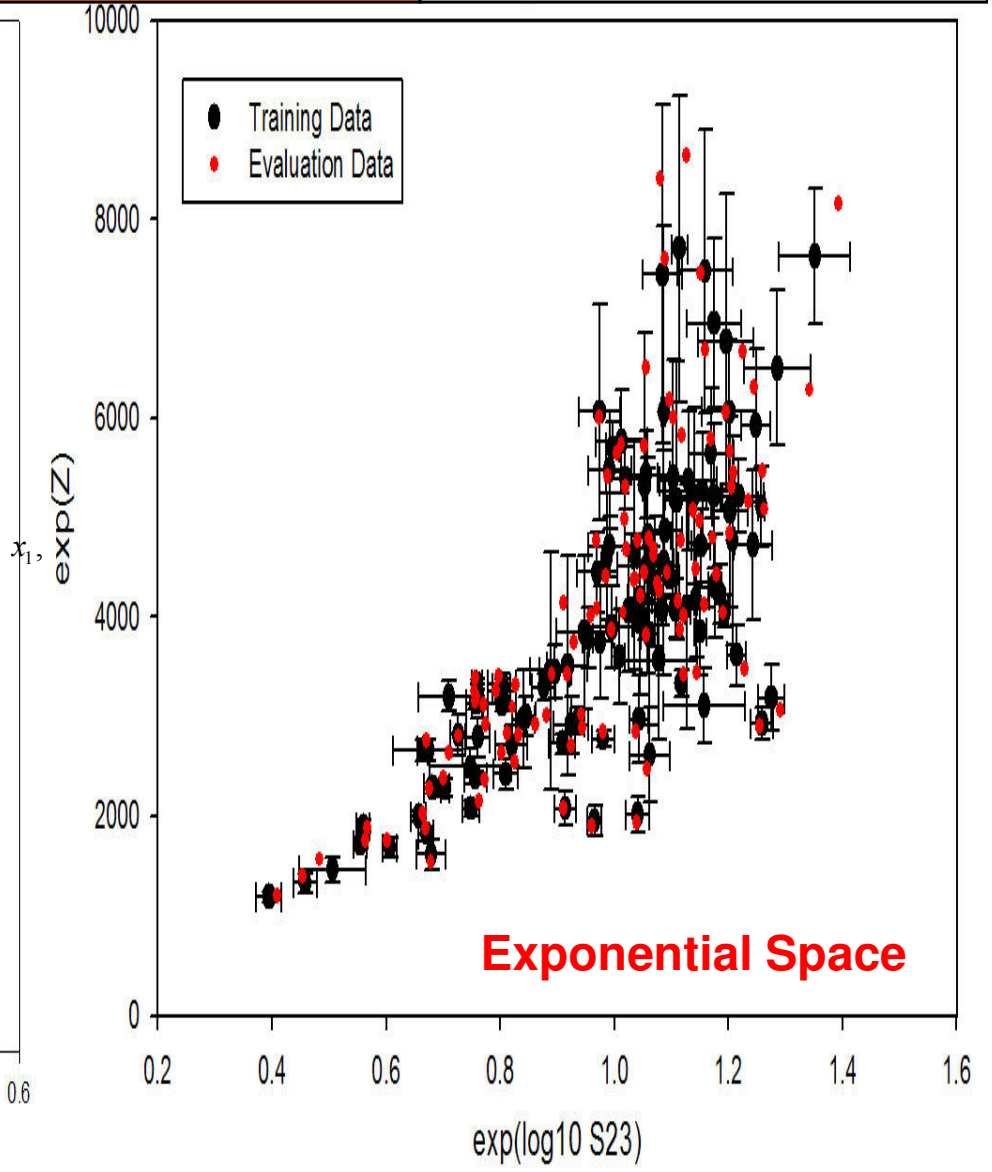


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Training & Evaluation Data

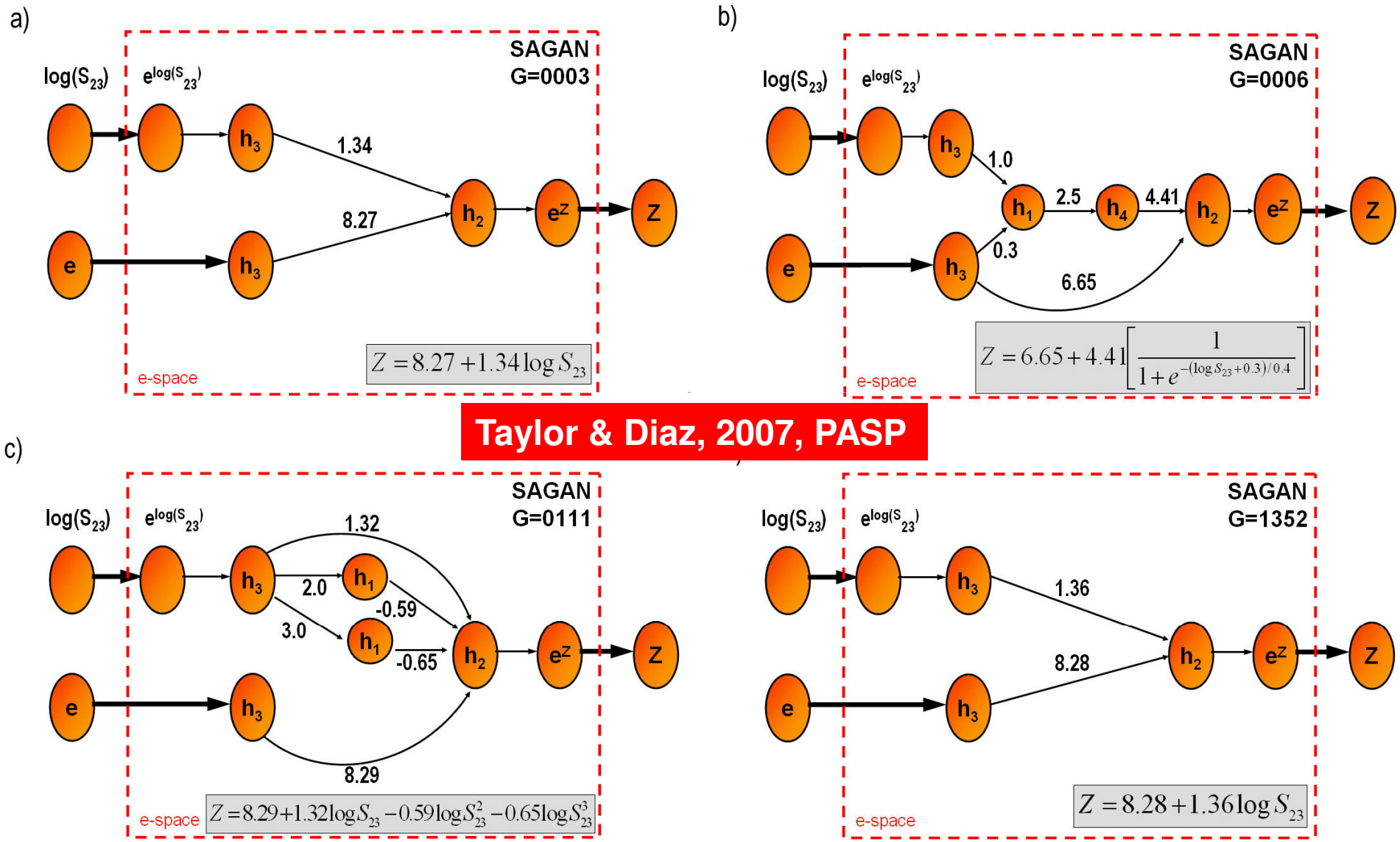




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SAGAN Evolution (2 days on a dual 3Ghz PC)

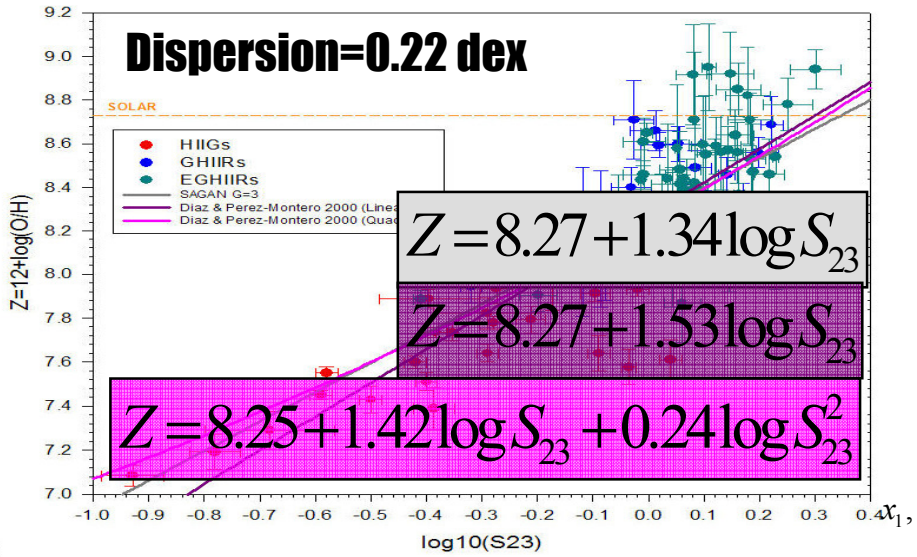


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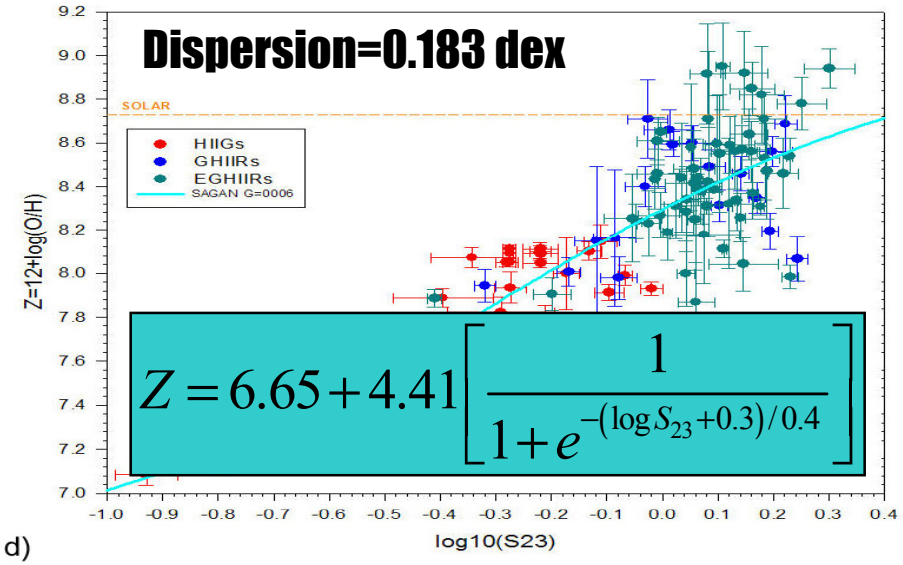
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Evolution of the calibration: Z=f(S23)

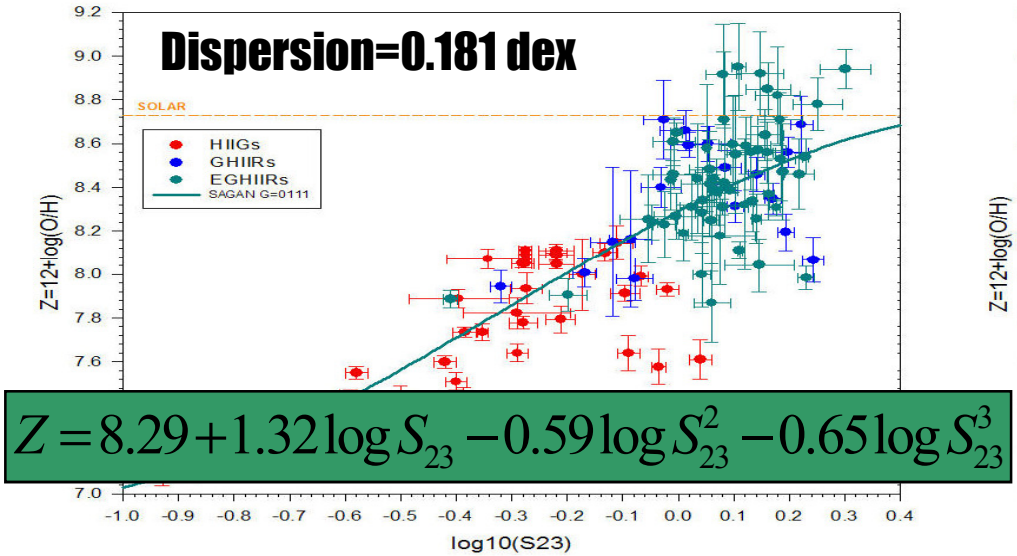
a)



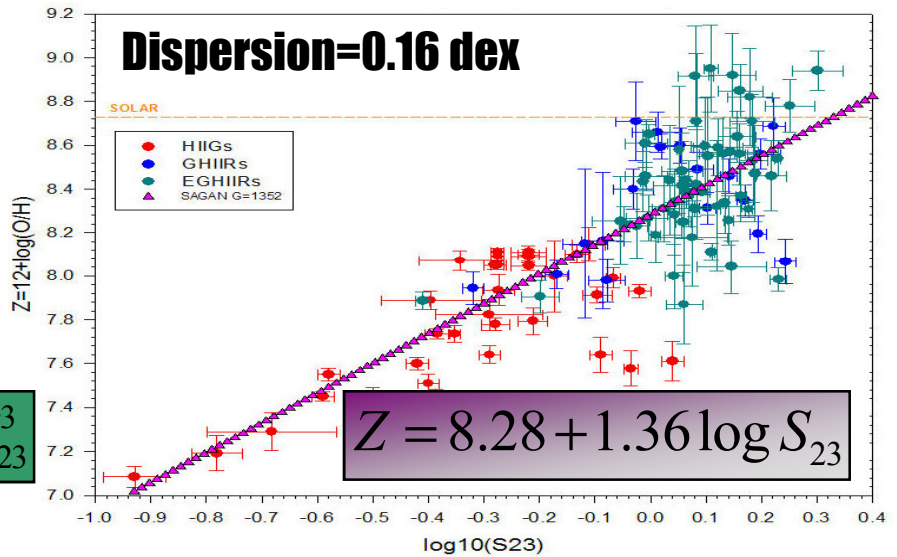
b)



c)



d)



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Fitting & n-D Calibrations

$$Z(O/H) = f(c, x_1, x_2, \ldots, x_n)$$

e.g. Dimensionless Line Ratios

$$x_1 = O_{23} = ([OII]_{\lambda 3727 + \lambda 3739} + [OIII]_{\lambda 4959 + \lambda 5007}) / H_\beta$$

$$x_2 = S_{23} = ([SII]_{\lambda 6717 + \lambda 6731} + [SIII]_{\lambda 9069 + \lambda 9532}) / H_\beta$$

Needs a big and homogeneous data-set

Can potentially reduce subjectivity

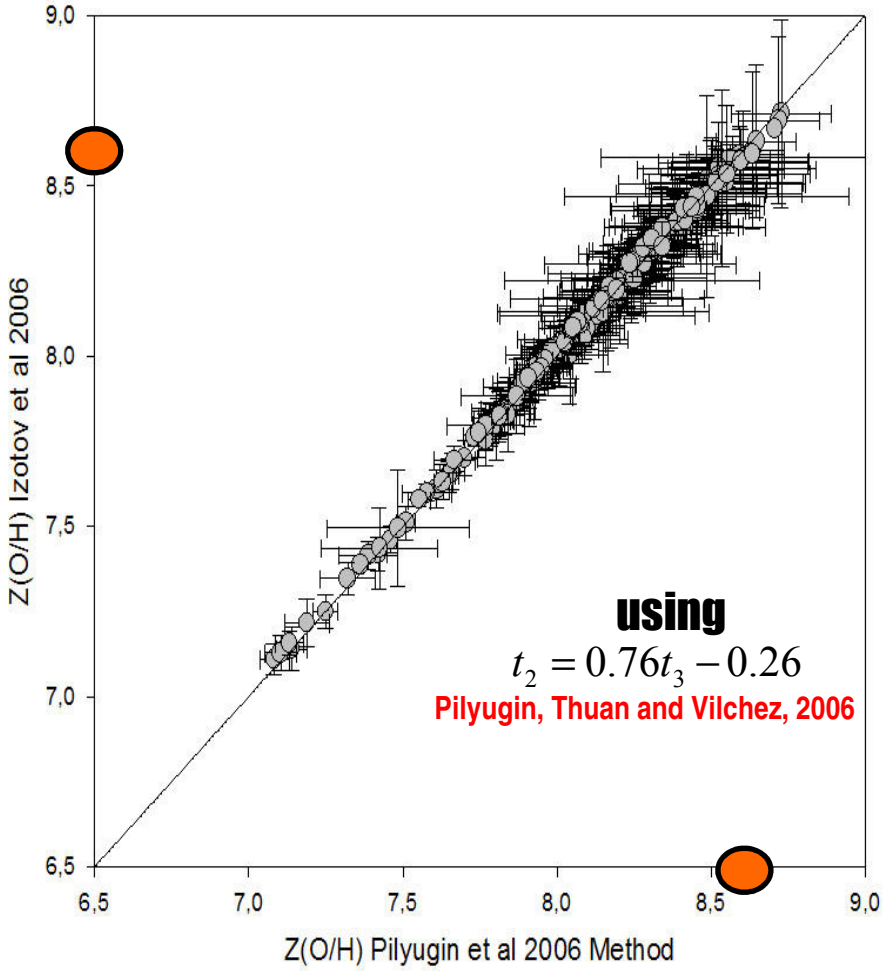
Can potentially identify new indicators

A sample for n-D studies

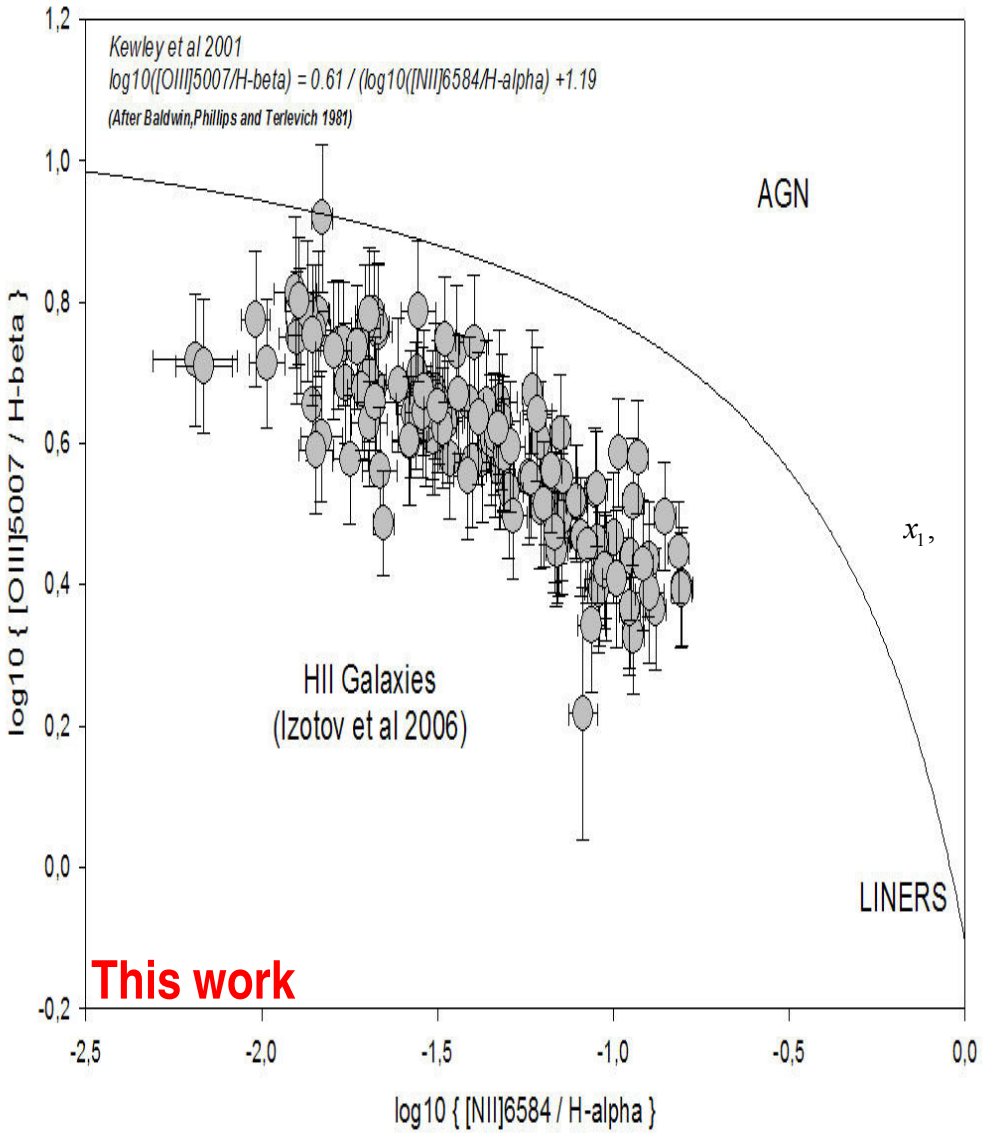
1	Izotov et al. 2006, A&A, 448, 955I.
2	Díaz, Terlevich, Pagel, Vílchez & Edmunds, 1987, MNRAS, 226, 19.
3	Pastoriza, Dottori, Terlevich, Terlevich & Díaz, 1993, MNRAS, 260, 177.
4	González-Delgado et al., 1994, ApJ, 437, 239.
5	Castellanos, Díaz & Terlevich, 2002, MNRAS, 329, 315.
6	Skillman, Terlevich, Kennicutt, Garnett & Terlevich, 1994, ApJ, 431, 172
7	Skillman & Kennicutt, 1993, ApJ, 411, 655
8	González-Delgado et al., 1995, ApJ, 439, 604.
9	Bresolin, Schaerer, González-Delgado & Stasinska, 2005, A&A, 441, 981.
10	Lequeux, Peimbert, Rayo, Serrano & Torres-Peimbert, 1979, A&A, 80, 155.
11	Kunth & Sargent, 1983, ApJ, 273, 81
12	French, 1980, ApJ, 240, 41
13	Izotov & Thuan, 1998, ApJ, 500, 188.
14	Pagel, Simonson, Terlevich & Edmunds, 1992, MNRAS, 255, 325.
15	Dinerstein & Shields, 1986, ApJ, 311, 45.
16	Kennicutt, Bresolin & Garnett, 2003, ApJ, 591, 801.
17	Garnett & Kennicutt, 1994, ApJ, 426, 123.
18	Shields & Searle, 1978, ApJ, 222, 821
19	Vílchez, Pagel, Díaz, Terlevich & Edmunds, 1988, MNRAS, 235, 633
20	Kwitter & Aller, 1981, MNRAS, 195, 939.
21	Vílchez, Pagel, Díaz, Terlevich & Edmunds, 1988, MNRAS, 235, 633
22	Garnett, Kennicutt & Bresolin, 2004, ApJ, 607, L21.
23	Bresolin, Garnett & Kennicutt, 2004, ApJ, 615, 228.
24	Peimbert, Peña & Torres-Peimbert, 1986, A&A, 158, 266
25	Garnett, Shields, Skillman, Sagan & Dufour, 1997, ApJ, 489, 63.
26	Díaz, Terlevich, Pagel, Vílchez & Edmunds, 1987, MNRAS, 226, 19.
27	Vermeij, Damour, van der Hulst & Baluteau, 2002, A&A, 390, 649
28	Vílchez & Esteban, 1996, MNRAS, 280, 720
29	Dennefeld & Stasińska, 1983, A&A, 118, 255
30	Hägele, Pérez-Montero, Díaz, Terlevich & Terlevich, 2006, MNRAS,
31	Kehrig, Vílchez, Telles, Cuisinier & Pérez-Montero, 2006 A&A
32	Izotov, Thuan & Lipovetsky, 1994, ApJ, 435, 647
33	Terlevich, Melnick, Masegosa, Moles & Copetti, 1991, A&ASS, 91, 285
34	Guseva, Izotov & Thuan, 2000, ApJ, 531, 776.
35	Kniazev et al, 2004, ApJS, 153, 429K.

1	H12
2	H11
3	H10
4	H9
5	H-delta
6	H-gamma
7	H-beta
8	H-alpha
9	[He I] 5876
10	[He II] 4686
11	[O II] 3727+ 3739
12	[O III] 4363
13	[O III] 4959
14	[O III] 5007
15	[O I] 6300
16	[O II] 7325
17	[N II] 6548
18	[N II] 6584
19	[S II] 6312
20	[S II] 6717 + 6731
21	[S III] 9069
22	[S III] 9532
23	[Ne III] 3868
24	[Fe III] 4658
25	[Fe III] 4988
26	[Ar IV] 4740
27	[Ar IV] 7136

Izotov et al 2006 → 144 objects
(another 163 from other sources)



Data classification with the BPT plot



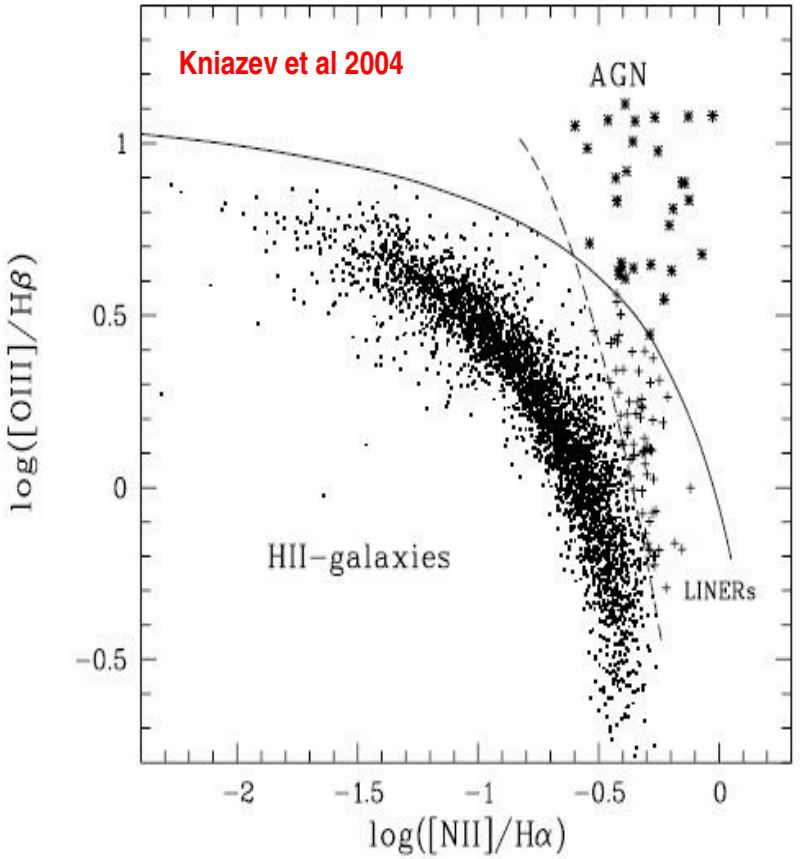
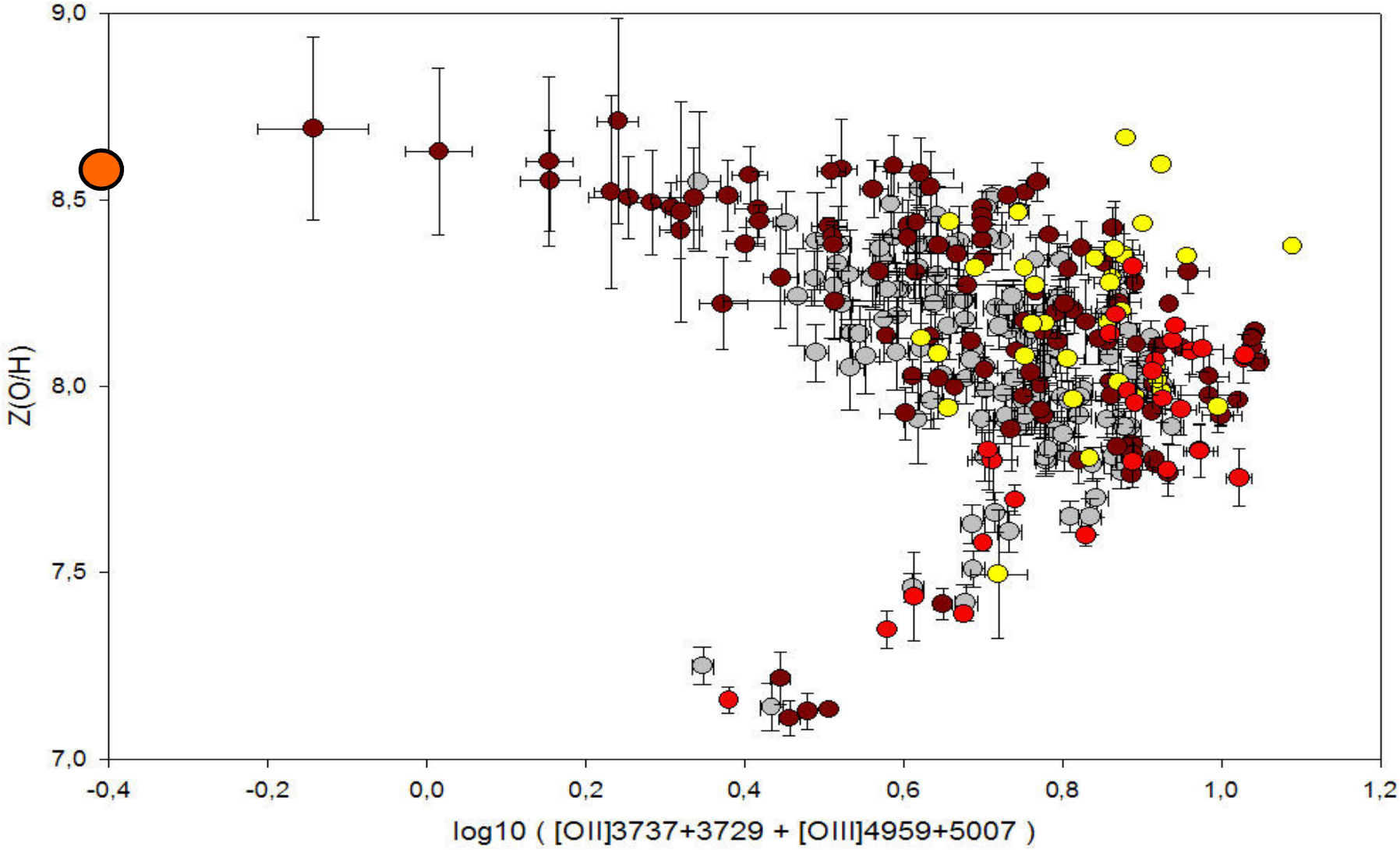


FIG. 2.—Classification diagram for all preselected ELGs (~5000 spectra). Galaxies identified as AGNs are shown as asterisks, and galaxies identified as LINERs are shown as crosses. The other ELGs are plotted as filled circles. The dashed line separates regions of H II-type and AGN/LINER spectra following Veilleux & Osterbrock (1987) and Baldwin et al. (1981). The solid line shows models from Kewley et al. (2001) that were used for AGN/LINER separation.

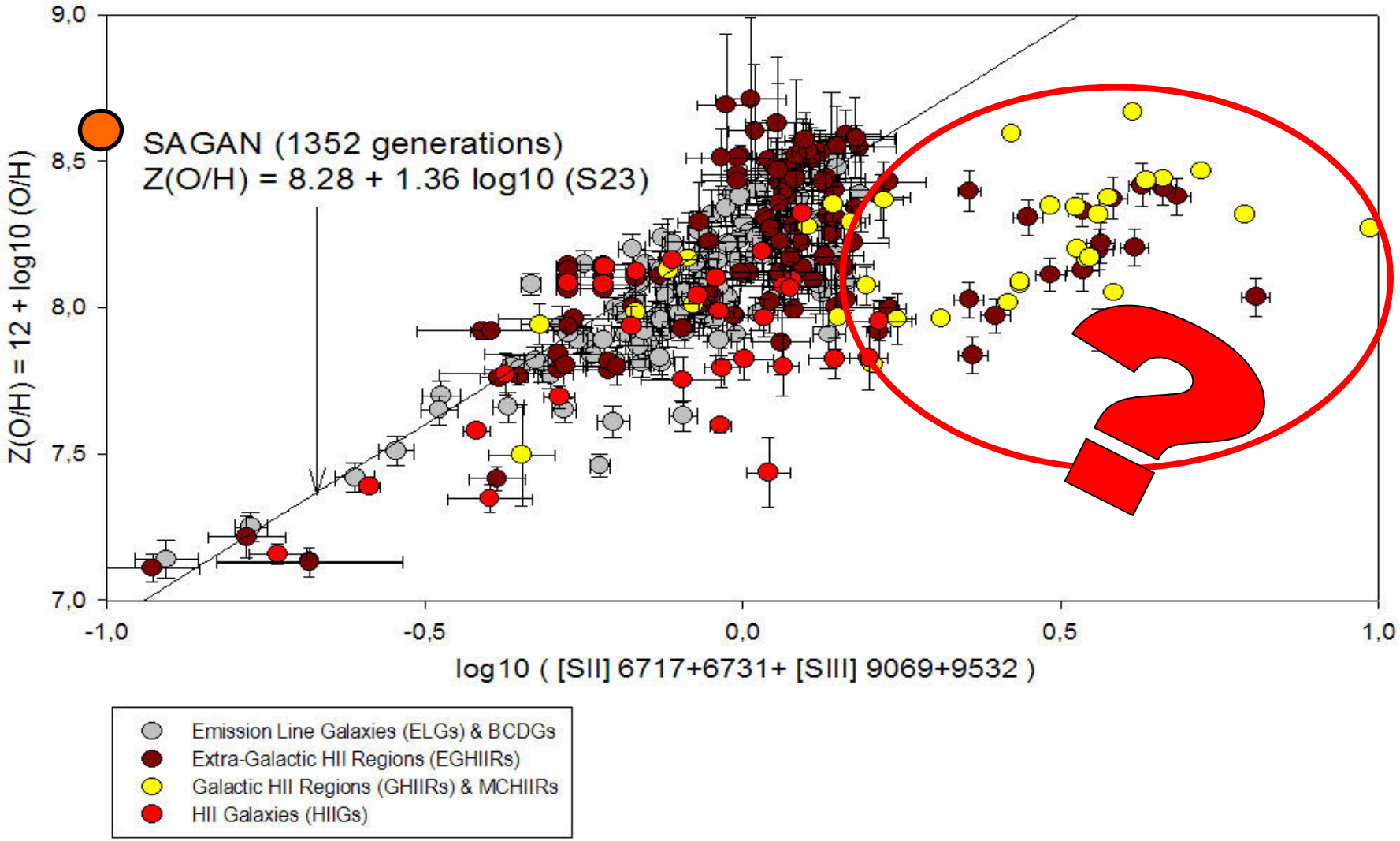
Metallicity and O_{23}



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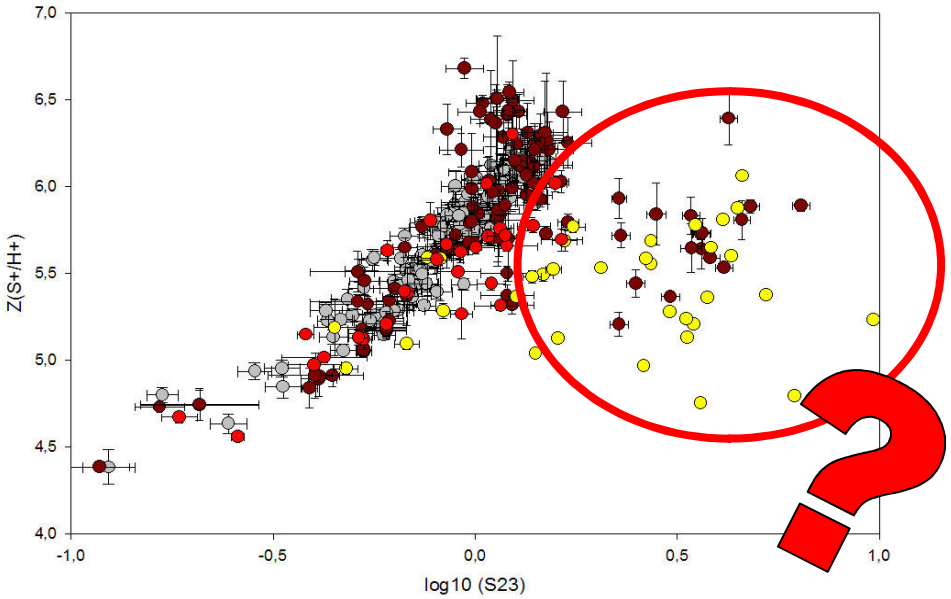
Metallicity and S_{23}

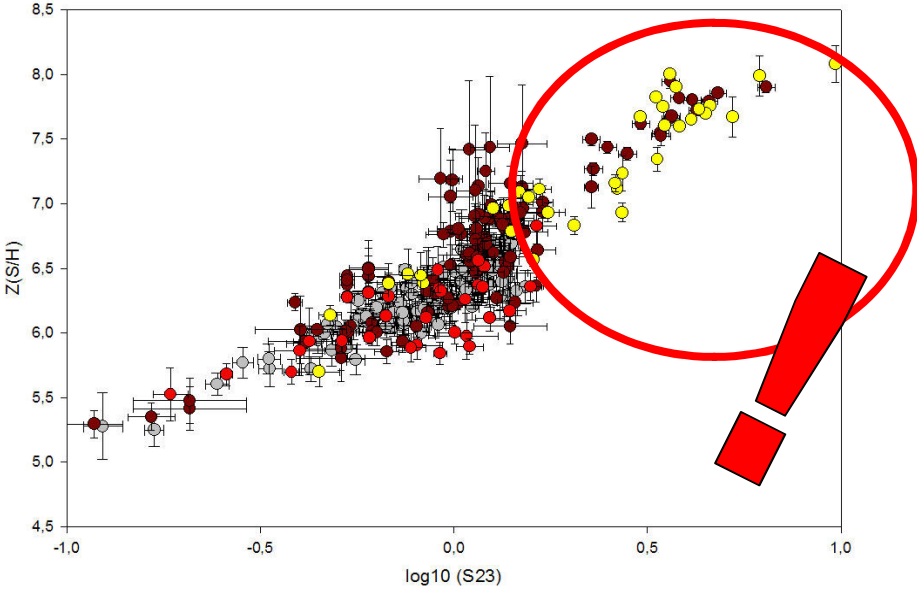


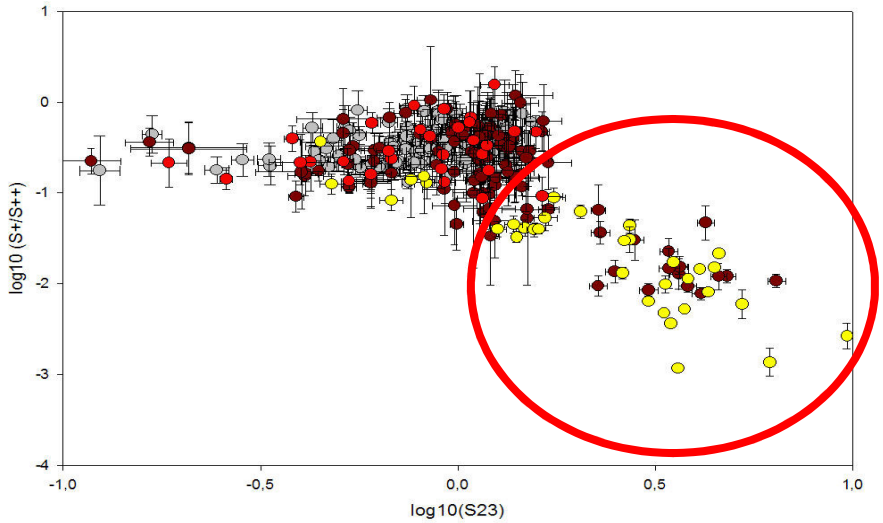
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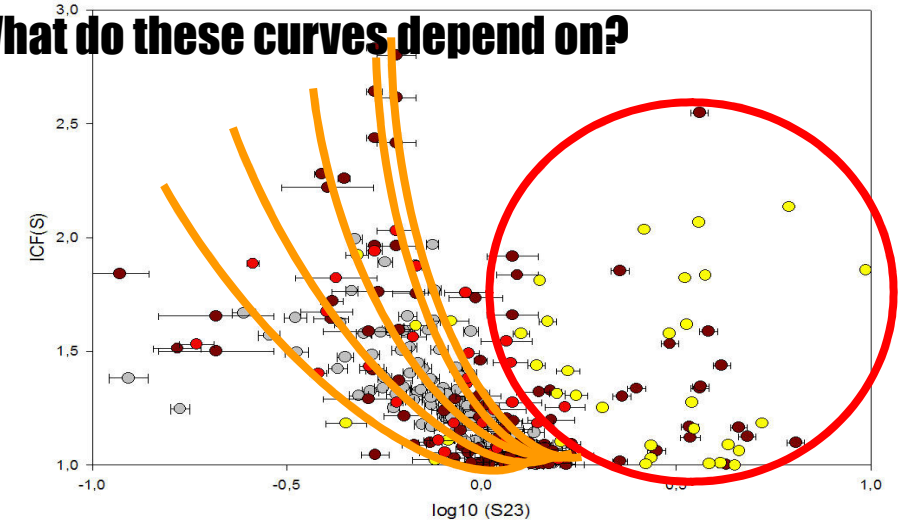
The role of S (S+, S2+, S, ICF)







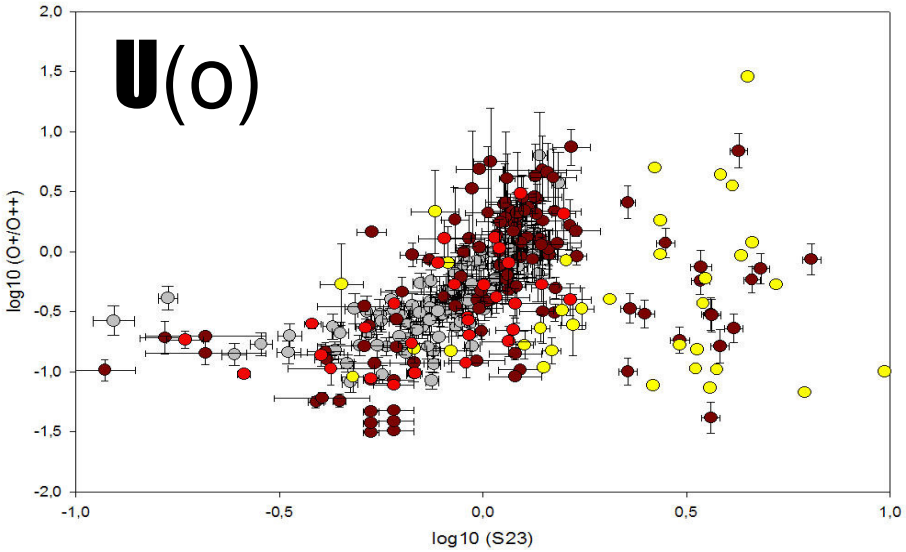
What do these curves depend on?

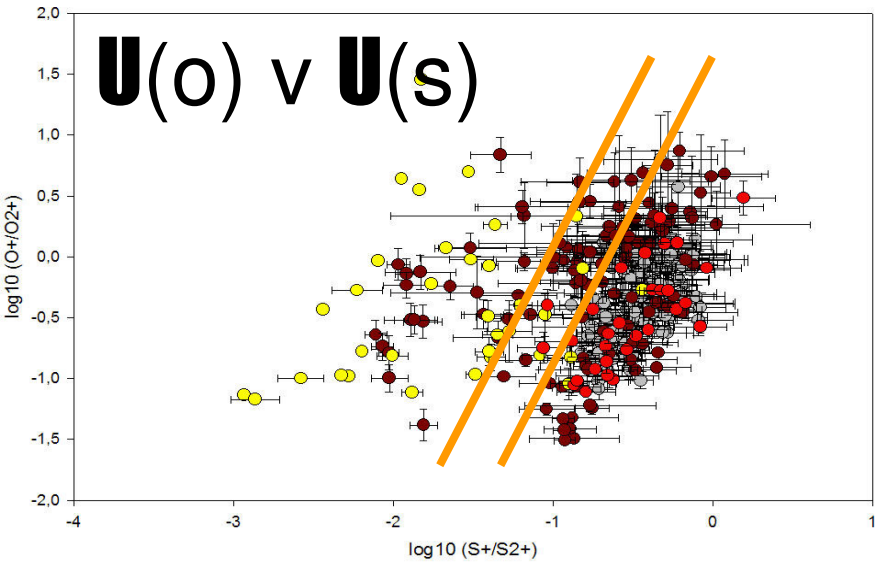


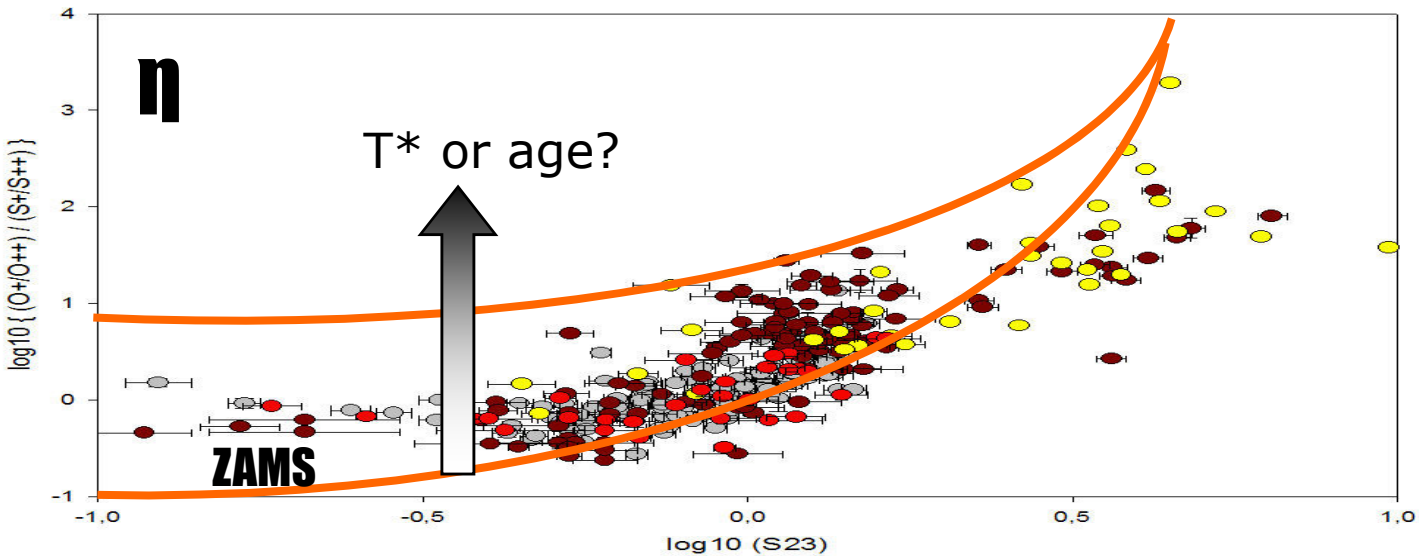
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Trends of U and η with S_{23}





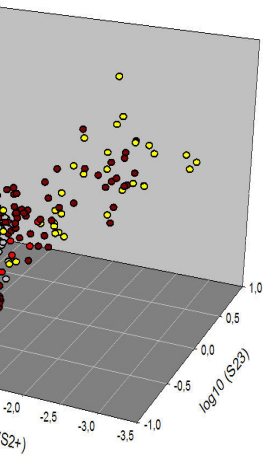


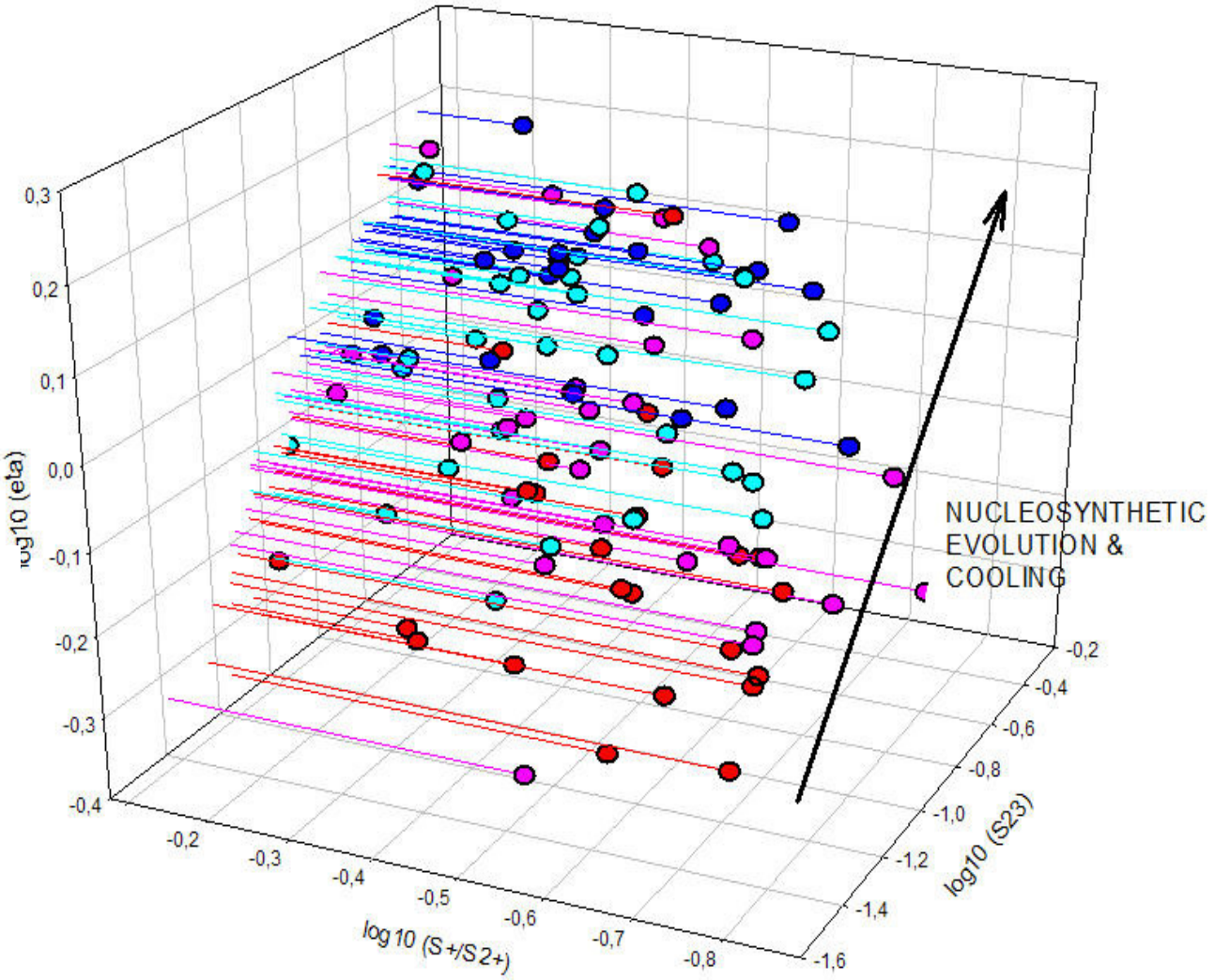
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& Angeles Diaz

Data in the η-U-S_{23} space

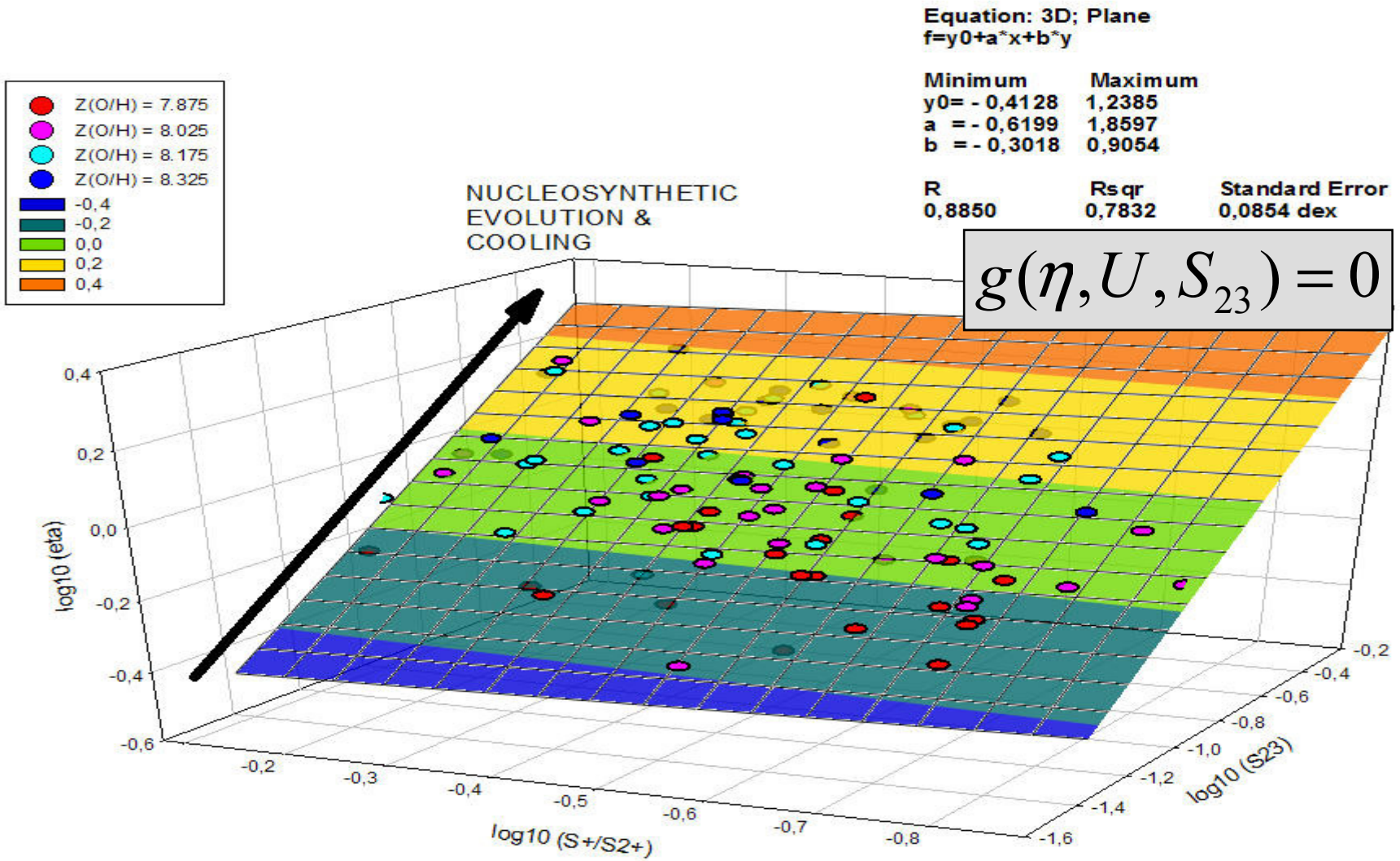
Clustering objects with Z





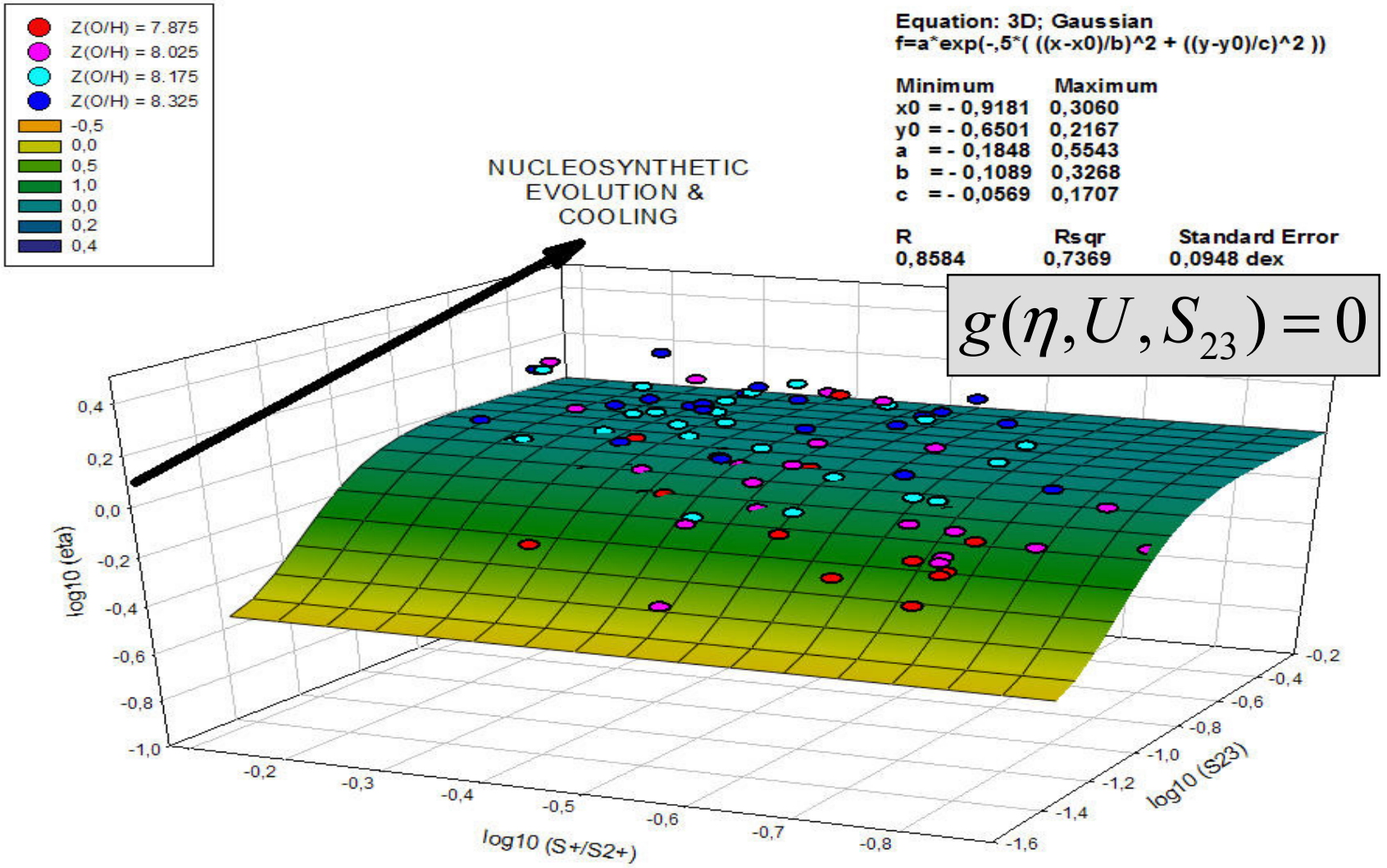
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Fitting with a plane



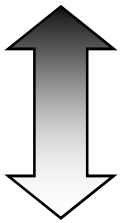
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Fitting with a Gaussian surface



The biggest question...

$$Z(O/H) = f(c, x_1, x_2, \ldots, x_n)$$



$$g(\eta, U, S_{23}) = 0$$

This mapping is possible if we can define a scale of effective temperature T* using empirical measures **ONLY**. But how?

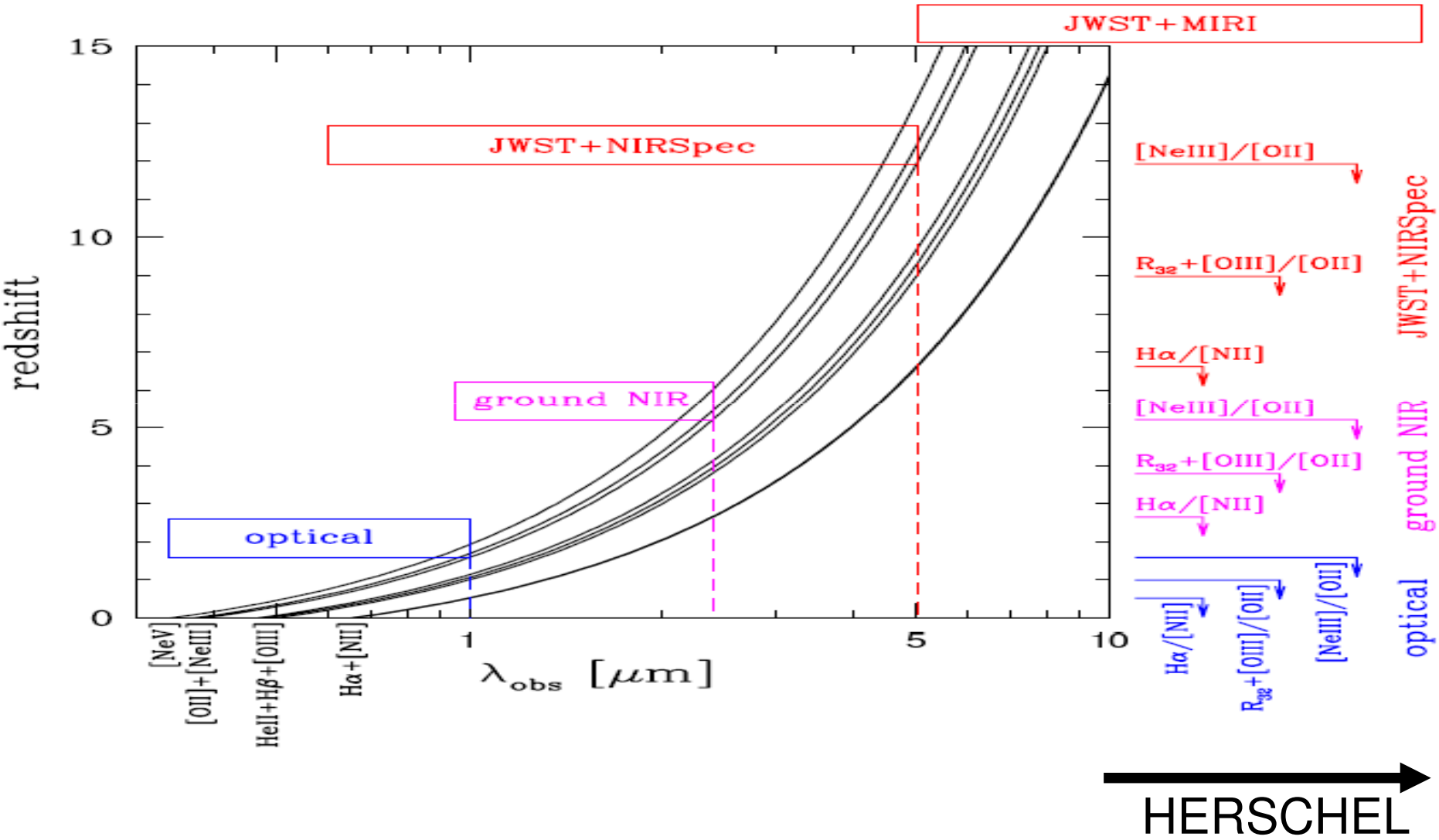
Ideas for the Future

- To find new n-D indicators & improve calibrations of the form: $Z=f(c, x_1, x_2 \ldots x_n)$ for HII-like regions and then for AGNs and PNs
- Find the relation $g(\eta, U, S_{23}) = 0$ and to test its robustness
- To investigate finding an empirical scale for T*

On behalf of myself, Pepe and Angeles, I would like to thank Guille Hägele, Enrique Perez-Montero and Mariluz Martin for kindly making observational data available and to everyone who has patiently and carefully taken accurate images

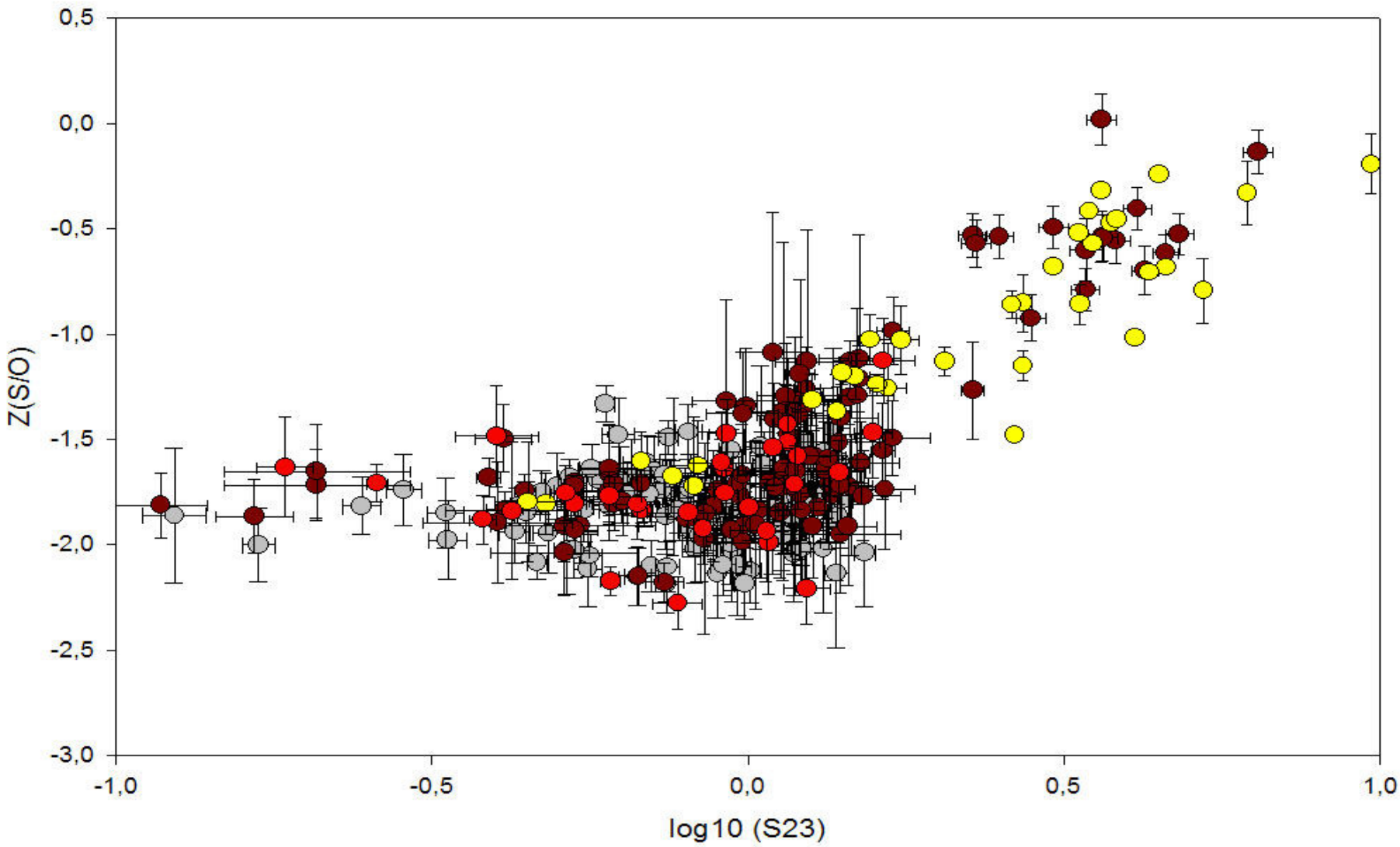
Many thanks

Going INFRA-RED...



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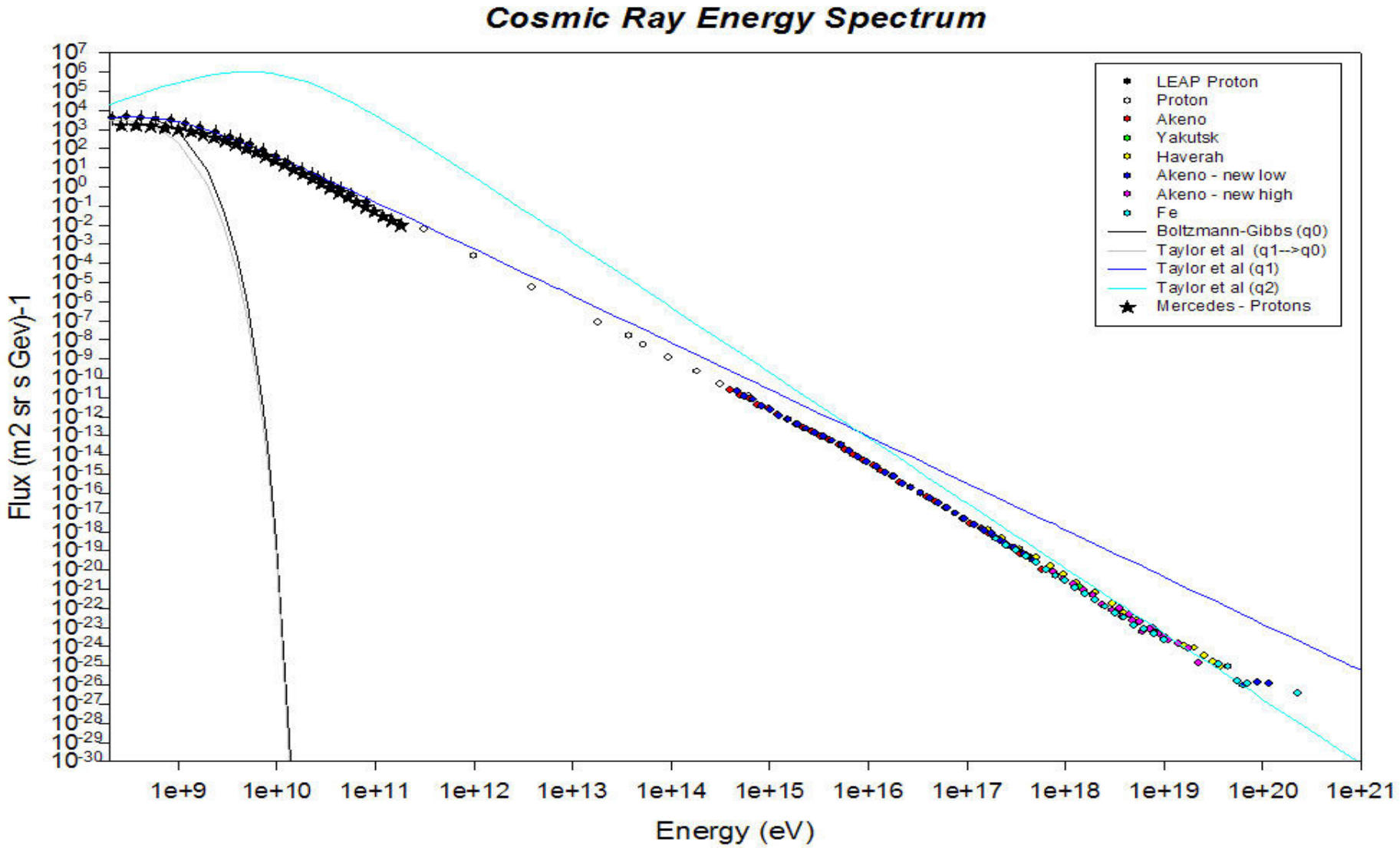
S/O with S23



Unravelling the nonlinear physics of high-Z regions with neural networks

Mike Taylor, Pepe Vilchez
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Applying SAGAN to cosmic rays



Unravelling the nonlinear physics of high-Z regions with neural networks

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