





The Cosmostatistics Initiative

MAESTRO, June/2017

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Contribute to the establishment of Astrostatistics and Astroinformatics as full fledged scientific disciplines

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Astrostatistics and Astroinformatics as full

fledged scientific disciplines **ASAP!**

Short term:

Make astronomers, statisticians, computer scientists and data experts understand each other ...

WHILE doing science!

COIN's activities cannot be merely pedagogical

Contribute to the establishment of

Astrostatistics and Astroinformatics as full

fledged scientific disciplines **ASAP!**

Short term:

Make astronomers, statisticians, computer scientists and data experts understand each other ...

WHILE doing science!

Directive:

Significantly contribute to the CV of our members

Contribute to the establishment of Astrostatistics and Astroinformatics as full

fledged scientific disciplines **ASAP!**

Short term:

Make astronomers, statisticians, computer scientists and data experts understand each other ...

WHILE doing science!

Try to remember: they might work as robots, but they are not!



Annual meetings

Conference

Workshop

Hackathon

Annual meetings



Workshop

Hackathon

Annual meetings





Hackathon

Annual meetings







The COIN Residence Program - CRP Annual meetings



John Johnson/HBO



https://www.theroadtosiliconvalley.com/moving/comparing-sydney-silicon-valley/

The COIN Residence Program - CRP A non-profit start-up?

Annual meetings

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CRP #2, UK, 2015

CRP #2, UK, 2015

Choosing the participants









Choosing the projects

Questions posed by the organizers

- 1. What do you know how to do?
- 2. What do you like to do?
- 3. What would you like to learn?

Participants can propose projects. Everyone votes to which project will be selected

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From CRP #2, UK - 2015

Proj. Name: HBM SNe host galaxies Method: <u>Hierarchical Bayesian Models</u> Object: SNe/GRB Data: TBD Manager : TBD	Project type: application Method: <u>Spatial Statistics - INLA</u> Object: TBD Data: Spatio-Temporal evolution of chemical abundances in primordial galaxies	Proj. Name: Galaxy AGN connection Method: <u>Bayesian Logistic Regression</u> Objects: Galaxy bars, rings, AGNs Data: TBD Manager: TBD
Scientific Question: Can HBM improve our understanding of the bias between type la SN hubble residuals and their host galaxy properties?	Scientific Question: Explore Spatial Statistics (spatstat, INLA) capabilities for astronomical research Participants: Marina, Mariana, Sandro,	Scientific Question: How do the properties of the galaxy influence its probability to host an AGN? Participants: Marina, Rafael, Alberto, Joseph,
Participants: Heather, Rafael, Emille, Joseph, Mohammad, Paniez, Miguel, Madhura	Alberto, Rafael, Ewan, Joseph, Miguel, Mohammad, Eric?	Mohammad, Arlindo, Malu, Paula
Proj. Name: Review on Variable selection Method: <u>different variable selection algorithms</u> Object: Data: Manager: Scientific Question: What is the state of art methodology to subset the best predictors for multivariate regression in astronomical datasets?	Proj. Name: MAchine learning in SNe spectra Method: <u>Dim. Reduction + unsupervised</u> <u>learning</u> Object: Sne Data: SN spectral series Manager: Michele Scientific Question: Use unsupervised/ semi-supervised learning to identify subtypes of SNe	6
Participants: Alberto, Rafael, Zoe, Luke, Paniez, Miguel, Arlindo, Bruce, Alan, Yabebal, Malu	Participants: Michele, Emille, Rafael, Ricardo, Paolo, Fabian, Arlindo, Paniez	

Does it work?

COIN products



)egustazior Alberto Krone-Martins astrometry



60 researchers from **15** countries

ntica mozic

Scientific outcomes

		In 3 years				
	Paper	Citation				
1	GLM I	de Souza <i>et al.</i> , 2015				
2	GLM II	Elliott et al., 2015				
3	GLM III	de Souza <i>et al.</i> , 2015				
4	AMADA	de Souza & Ciardi, 2015				
5	CosmoABC	Ishida et al., 2015				
6	DRACULA	Sasdelli et al., 2016				
7	AGNlogit	de Souza <i>et al.</i> , 2016				
8	PhotoZ	Beck <i>et al.</i> , 2017				
9	AGNgmm	de Souza <i>et al.</i> , 2017				

- CosmoPhotoZ de Souza *et al.*, 2014,
 - AMADA de Souza & Ciardi, 2015
 - CosmoABC Ishida et al., 2015
- DRACULA
- Aguena et al., 2015

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+ 1 galaxy catalog
+ 1 GMM tutorial
  2 photoz catalogs
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COIN products are open source!

Infographic by Rafael S. de Souza

Example from CRP #4, Budapest 2016

The problem with text-book ML: Representativeness



Spec \rightarrow training/validation Photo \rightarrow test What if you wish to try a method which address the realistic situation?



COIN Residence Program #3

http://iaacoin.wixsite.com/crp2016



Teddy catalogue The effect of color coverage

A /B follow SDSS spec distribution

B is completely representative of A

- C has the same coverage but slightly different shape
- D has a wider domain in r-mag and color (no coverage)





Beck, Lin, Ishida et al., astro-ph:1701.08748, MNRAS (2017), 468, issue 4, pp. 4323-4339 – from CRP #3

Happy catalogue The effect of coverage + photometric errors

Photometry from SDSS

Spec-z from many different surveys leads to larger photometric errors and consequently wide domain in r-band and color

- A /B follow SDSS spec distribution
- B is completely representative of A
- C was constructed performing a nearest neighbor between the SDSS-DR12 photo sample and the extended spec sample but with a cut on photometric errors
- D is the same of C but without the photometric error cut.
- Consequently, D follows exactly the SDSS-DR12 photo sample distribution





Beck, Lin, Ishida et al., astro-ph:1701.08748, MNRAS (2017), 468, issue 4, pp. 4323-4339 – from CRP #3



Happy catalogue The effect of coverage + photometric errors

Empirical methods



		Diagnostics				
Method	Set	$_{(\times 10^{-2})}^{\rm Mean}$	$ ext{Std}$ $(imes 10^{-2})$	$_{(\times 10^{-2})}^{\rm MAD}$	Outlier rate (%)	
ANNz	В	0.04	2.87	1.49	0.99	
	\mathbf{C}	0.16	5.41	3.60	5.59	
	D	-0.52	6.53	5.44	14.01	
	В	0.09	3.50	1.95	1.36	
GAM	\mathbf{C}	0.86	6.34	4.84	7.37	
	D	-0.51	7.21	6.70	16.38	
LLR	В	0.13	2.81	1.39	1.11	
	\mathbf{C}	0.52	5.45	3.59	6.07	
	D	-0.79	6.62	5.62	14.52	
Random Forest	В	0.05	2.82	1.41	1.02	
	\mathbf{C}	0.34	5.39	3.51	5.58	
	D	-0.28	6.51	5.36	14.2	

Beck et al., astro-ph:1701.08748, MNRAS in press

https://github.com/COINtoolbox/photoz_catalogues



Happy is maintained by Robert Beck (ELTE, Hungary).

Potential solution: Active Learning

SAMSI & COIN, in prep



The future of COIN

https://iaacoin.wixsite.com/crp2017








solve bureaucracy





solve bureaucracy







Solve bureaucracy









Solve bureaucracy









IAA facebook page



COIN on twitter



IAA-COIN @iaa_coin_FOLLOWS YOU

COIN promotes the development of novel statistical tools for astronomy. #rstats #astrostatistics #cosmology #python #datascience #astronomy #bigdata

Vorldwide

S goo.gl/alvZYA

Tweet to Dessage

Registrations will open July 7th!



Do we need to rethink the academic model?





Attempted solutions: Domain Adaptation







Photometric redshifts for the SDSS Data Release 12

Róbert Beck 🖾, László Dobos 🖾, Tamás Budavári, Alexander S. Szalay, István Csabai 🖾

Mon Not R Astron Soc (2016) 460 (2): 1371-1381.

Attempted solution: Domain Adaptation

supervised regression



Attempted solutions: **Domain Adaptation**

supervised regression



Estimating the redshift distribution of photometric galaxy samples

Marcos Lima,^{1,2*} Carlos E. Cunha,^{2,3} Hiroaki Oyaizu,^{2,3} Joshua Frieman,^{2,3,4} Huan Lin⁴ and Erin S. Sheldon⁵

Mon. Not. R. Astron. Soc. 390, 118-130 (2008)

Works well when data is not sparse, and there is coverage!

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If there is no coverage, identify problematic areas and discard!

Happy catalogue The effect of coverage + photometric errors

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Error distributions correlate with features



Beck, Lin, Ishida et al., astro-ph:1701.08748, MNRAS (2017), 468, issue 4, pp. 4323-4339, from CRP #3



Happy catalogue The effect of coverage + photometric errors



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Beck, Lin, Ishida et al., astro-ph:1701.08748, MNRAS (2017), 468, issue 4, pp. 4323-4339 – from CRP #3

Potential solution: Active Learning

SAMSI & COIN, in prep



Background: Active Learning in Astronomy

ACTIVE LEARNING TO OVERCOME SAMPLE SELECTION BIAS: APPLICATION TO PHOTOMETRIC VARIABLE STAR CLASSIFICATION

Joseph W. Richards^{1,2}, Dan L. Starr¹, Henrik Brink³, Adam A. Miller¹, Joshua S. Bloom¹, Nathaniel R. Butler¹, J. Berian James^{1,3}, James P. Long², and John Rice²

supervised classification

THE ASTROPHYSICAL JOURNAL, 744:192 (19pp), 2012 January 10

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Background: Active Learning in Astronomy Automated Supernova Ia Classification Using Adaptive Learning Techniques

Kinjal Dhar Gupta*, Renuka Pampana*, Ricardo Vilalta*, Emille E. O. Ishida[†], Rafael S. de Souza[‡]

supervised classification

How are spectroscopic sets constructed?





How are spectroscopic sets constructed?

Take spectra for learning and determine everything else





















Alternative approach Landmark selection + Active Learning





Alternative approach Landmark selection + Active Learning





Background: Active Learning in Astronomy Automated Supernova Ia Classification Using Adaptive Learning Techniques

Kinjal Dhar Gupta*, Renuka Pampana*, Ricardo Vilalta*, Emille E. O. Ishida[†], Rafael S. de Souza[‡]



Dhar Gupta et al. (incl. Ishida), 2016 IEEE Symposium in Computational Intelligence, Athens

Active Learning for supervised regression? Active Learning for supervised regression?

Main tasks:

Supervised Learning





Regression:

- photometric redshift
- stellar parameters determination

Classification:

- detection
- star/galaxy separation
- galaxy morphology
- variable stars
- supernova

Clustering:

. . .

- SN Ia spectra characterization
- galaxy spectral classification

Anomaly/Novelty detection:

- unforeseen new objects
- detection error analysis
- identification of predicted objects

• • •

What about the future?

urgent: Build a support community



urgent: Build a support community





urgent: Build a support community





solve bureaucracy


urgent: Build a support community





solve bureaucracy

The REAL goal is HUMAN learning



