The Cosmostatistics Initiative

Reshaping interdisciplinary science development

Artificial Intelligence and Physics
21 March 2019, LAL, Orsay - France

Emille E. O. Ishida
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Clermont Ferrand, France

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In Astronomy

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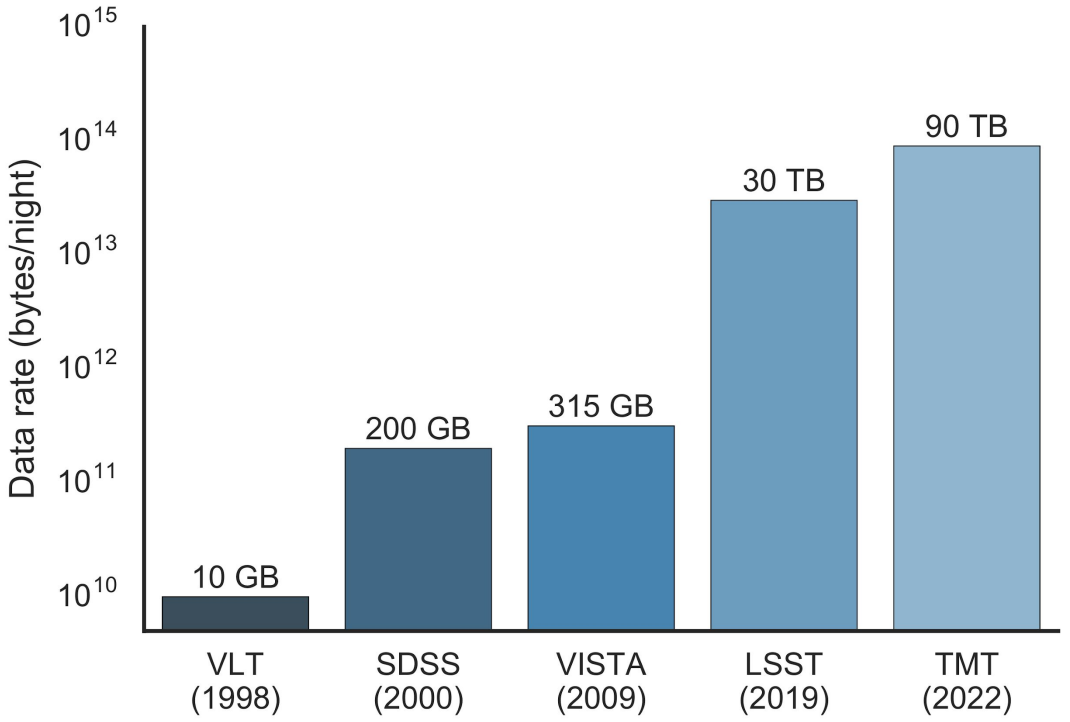
Astronomy has been,
traditionally,
an experience of
solitude

The old astronomer, *by Charlie Bowater*

Big data is slowly arriving…



Kremer et al., 2017

… new methods might take a little longer

The goal of the

Cosmostatistics Initiative

is to speed up this process

while acknowledging

Volatile and competitive job market
Potential contribution of non-astronomers
Diversity of personal and academic background

The COIN Residence Program (CRP)

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Step 1 – Choose the people

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Step 3 - give them good working conditions

Preparation, **comfort,** motivation

CRP #4, 2017, Clermont Ferrand, France

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CRP #4, 2017, Clermont Ferrand, France

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CRP #5, 2018, Chania, Greece

The COIN Residence Program (CRP)

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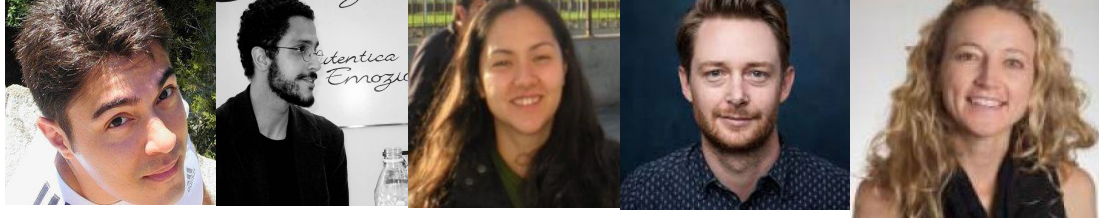
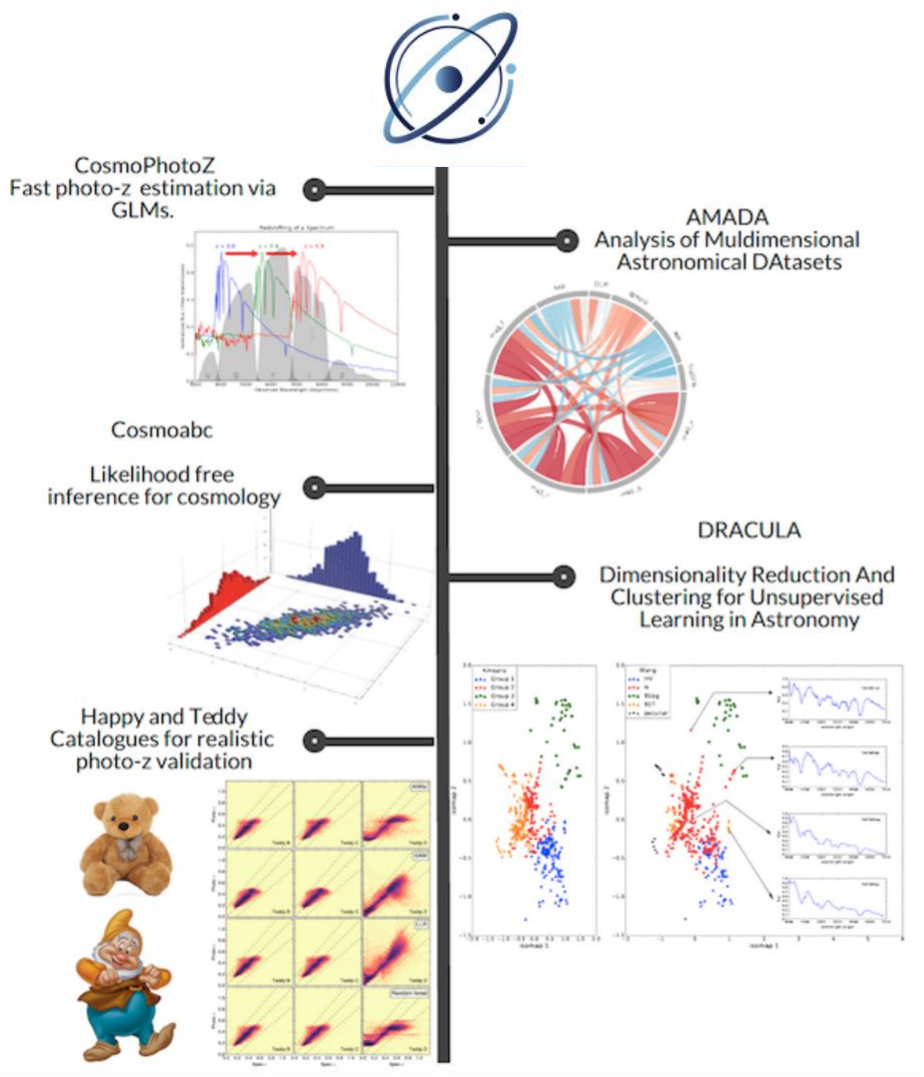
Step 3 - give them good working conditions

Step 4 - make sure they do not diverge

In 5 years,
60 researchers
15 countries





	Paper	Citation
1	GLM I	de Souza *et al.*, 2015
2	GLM II	Elliott *et al.*, 2015
3	GLM III	de Souza *et al.*, 2015
4	AMADA	de Souza & Ciardi, 2015
5	CosmoABC	Ishida *et al.*, 2015
6	DRACULA	Sasdelli *et al.*, 2016
7	AGNlogit	de Souza *et al.*, 2016
8	PhotoZ	Beck *et al.*, 2017
9	AGNgmm	de Souza *et al.*, 2017
10	GalINLA	Gonzalez-Gaitan *et al.*, 2018
11	ActSNclass	Ishida *et al.*, 2018
12	COIN-Gaia	Cantat-Gaudin *et al.*, 2018
13	Hurdle	Hattab *et al.*, 2019
14	SNCosmo	Moews *et al.*, 2018

	Code	Citation
1	CosmoPhotoZ	de Souza *et al.*, 2014,
2	AMADA	de Souza & Ciardi, 2015
3	CosmoABC	Ishida *et al.*, 2015
4	DRACULA	Aguena *et al.*, 2015
5	CoinINLA	Gonzalez-Gaitan *et al.*, 2018

+ 1 galaxy catalog
+ 1 GMM tutorial
+ 2 photoz catalogs
+ 41 open clusters

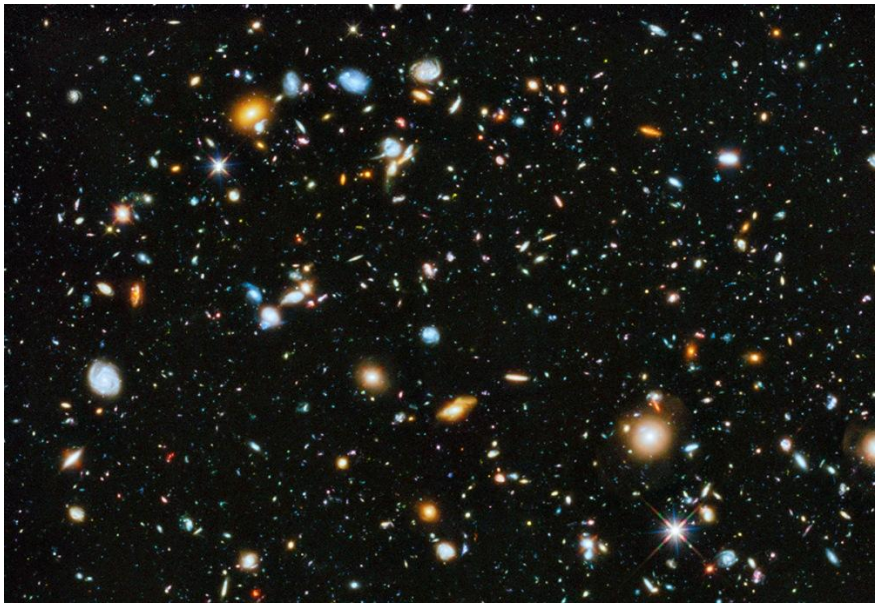
Case study:

Astronomy needs a recommendation system

Types of astronomical data:

Photometry

Features (cheap)

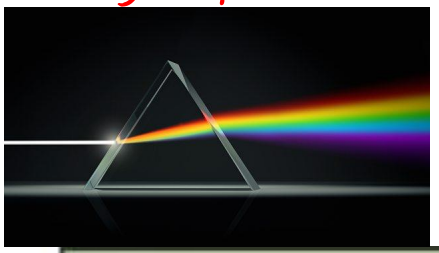


Brightness per object given wavelength range

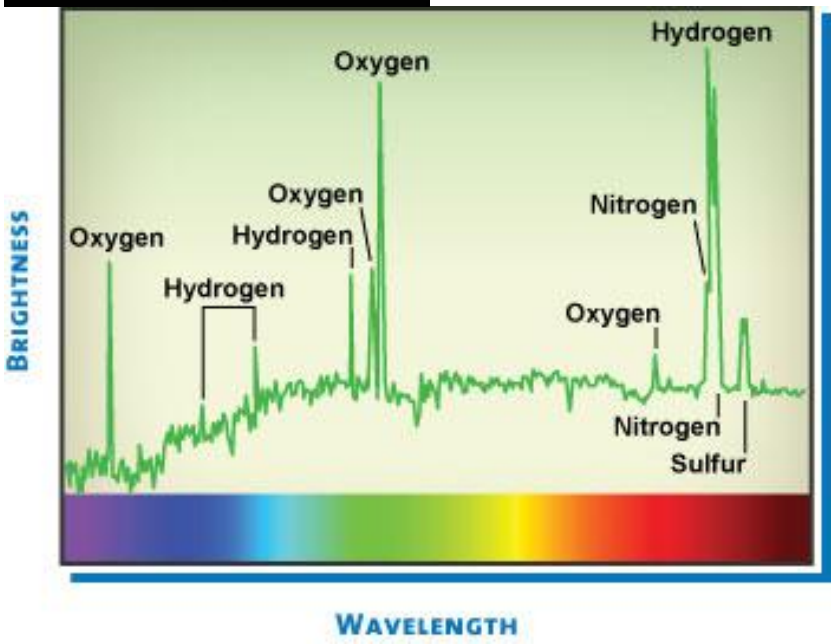
Spectroscopy

Used to derive labels (classes)

Very expensive

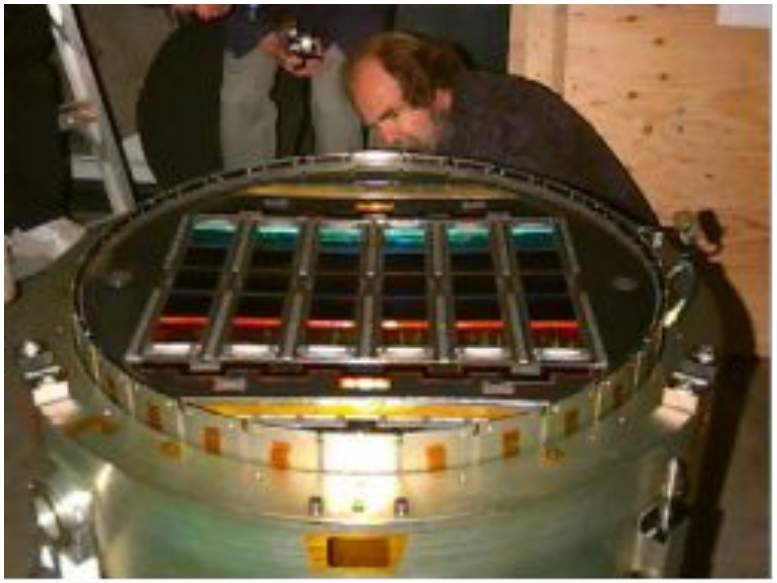


Brightness given wavelength per object



Photometry x Spectroscopy

An example from SDSS



Exposure time 2 x 54s

Integration time of at least

45 minutes

http://www.preposterousuniverse.com/blog/2009/10/06/practicality-and-the-universe/

http://www.stsci.edu/~inr/bdpics/bd5.htm

Astronomers would like spectra of everything

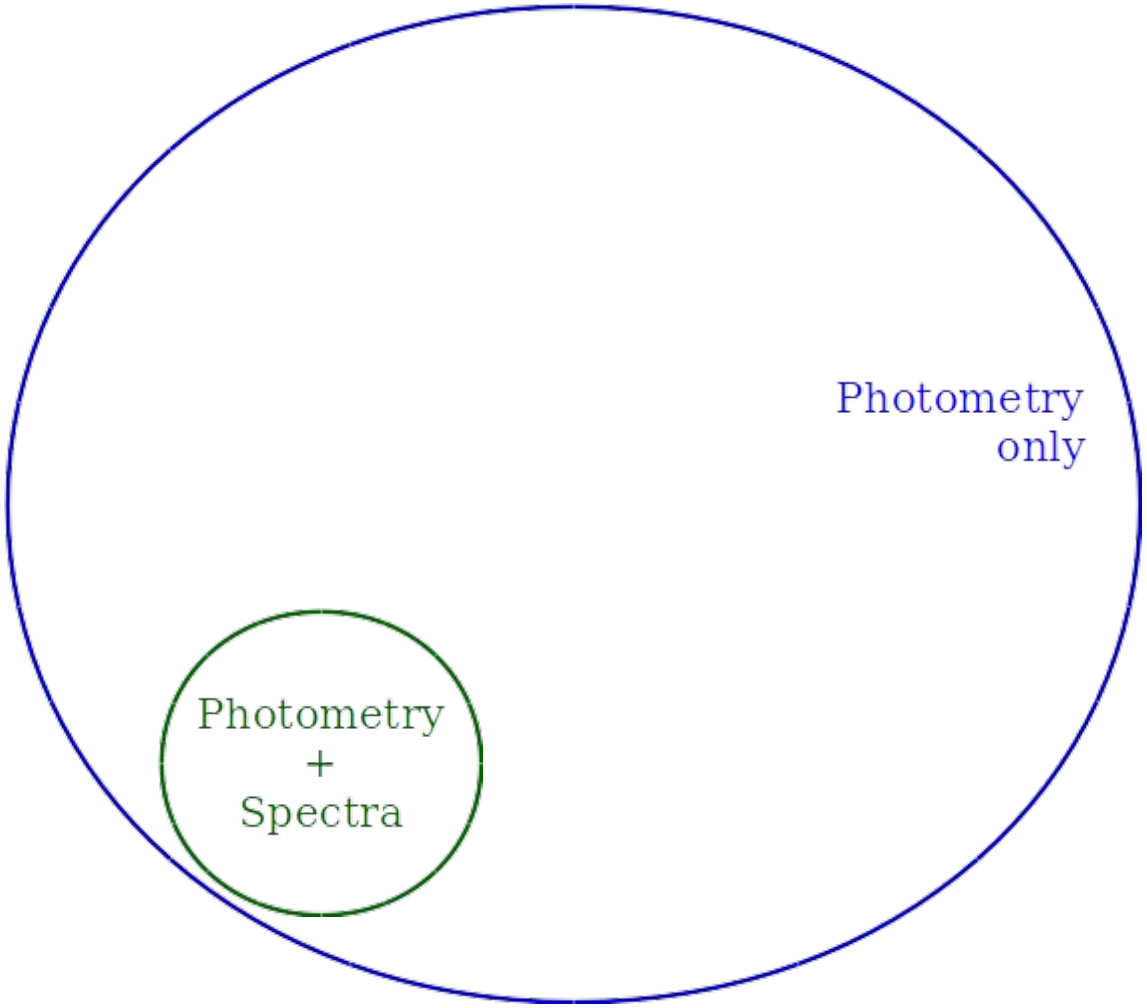
Spectroscopy is the key

… which we will not have

Big Data in astronomy means more photometry!

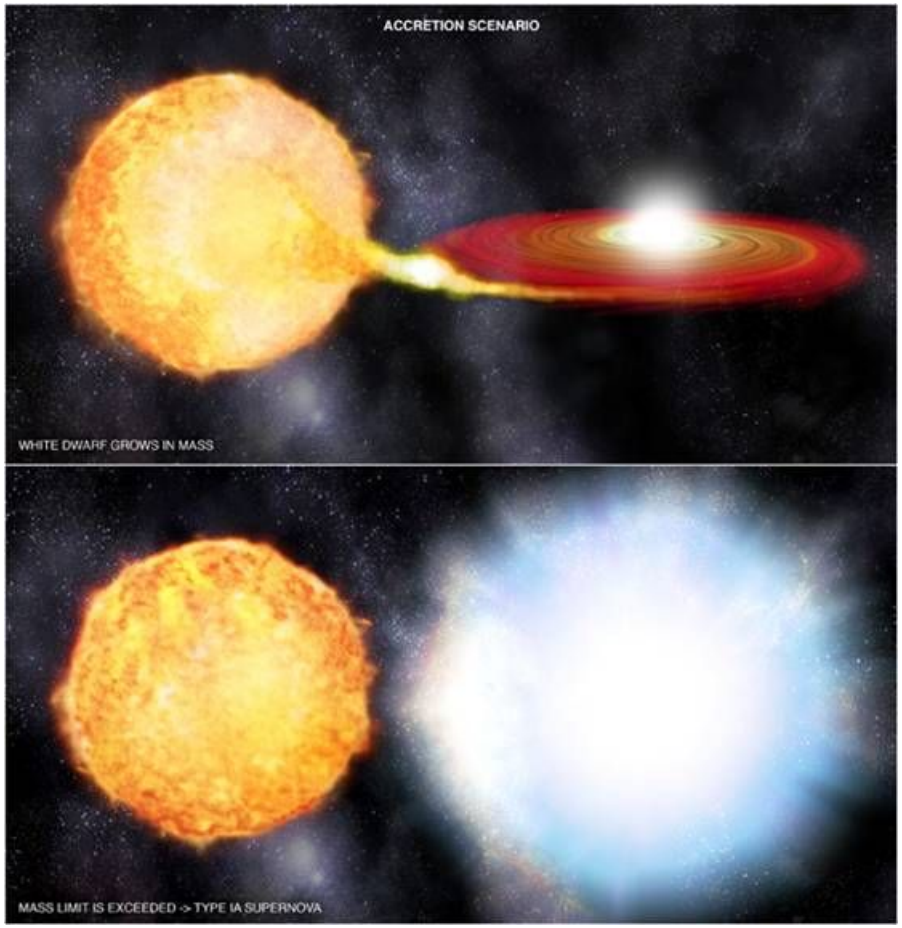
Data situation:

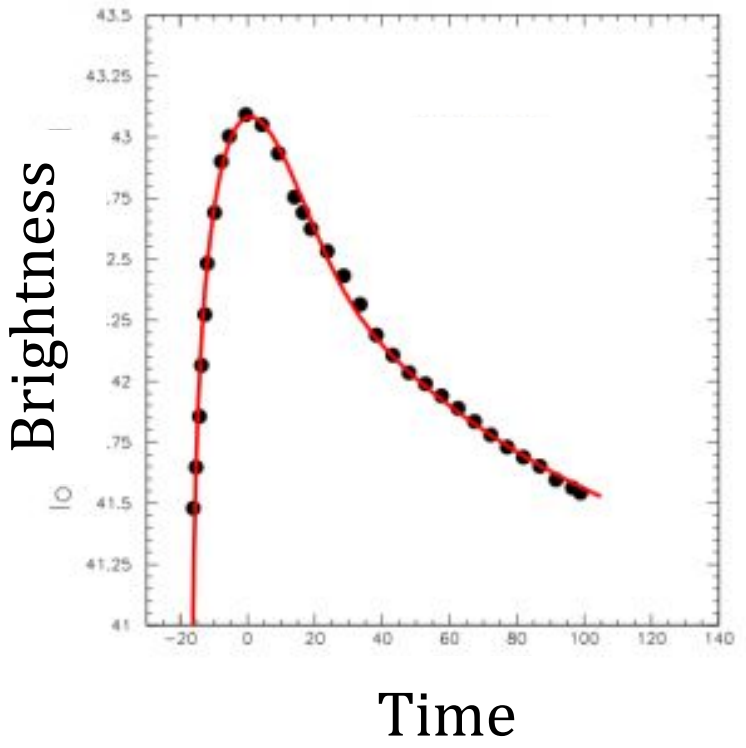
The Problem



Example of things you might want to classify

Supernova Ia





https://phys.org/news/2014-08-ia-supernovae-stem-explosion-white.html

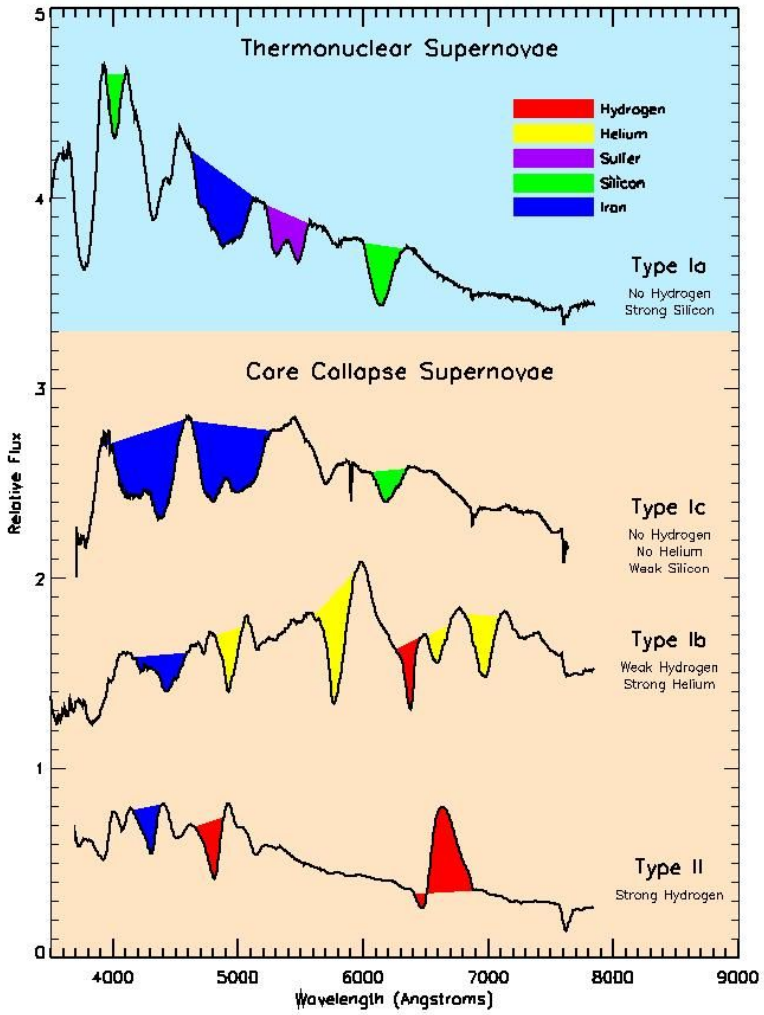
Supernova Ia

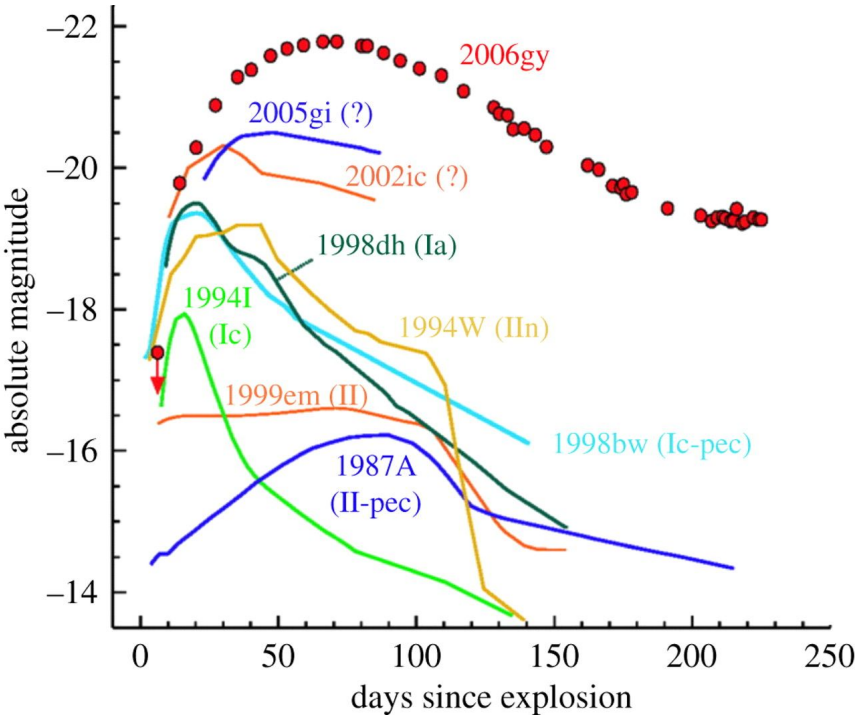
Only Supernova Ia can be used as standard candles

2011

Supernova photometric classification:

It's complicated!

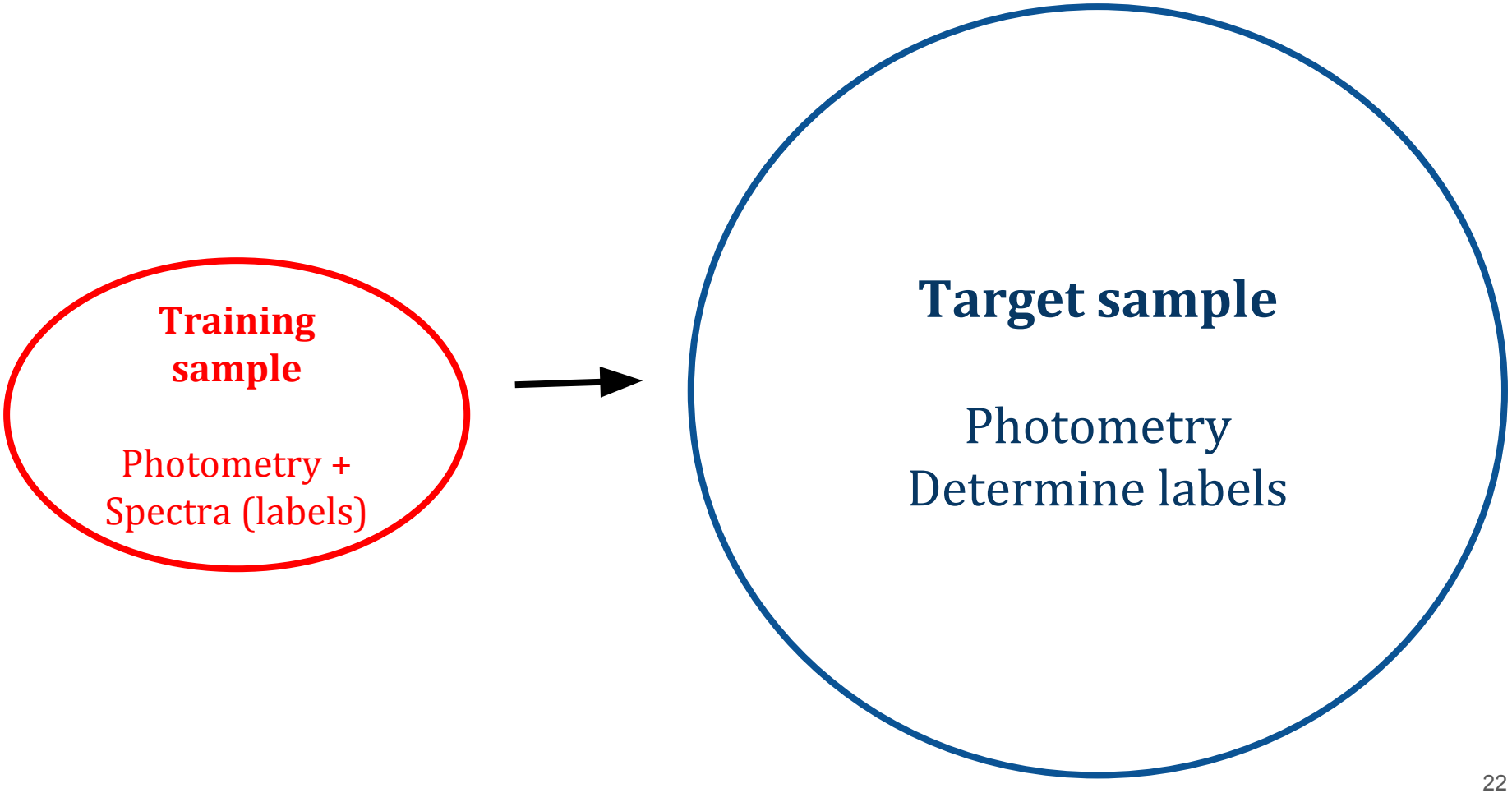




http://rsta.royalsocietypublishing.org/content/370/1960/774

Machine Learning solution

Spectra as labels, photometry as features



Machine Learning solution

Spectra as labels, photometry as features

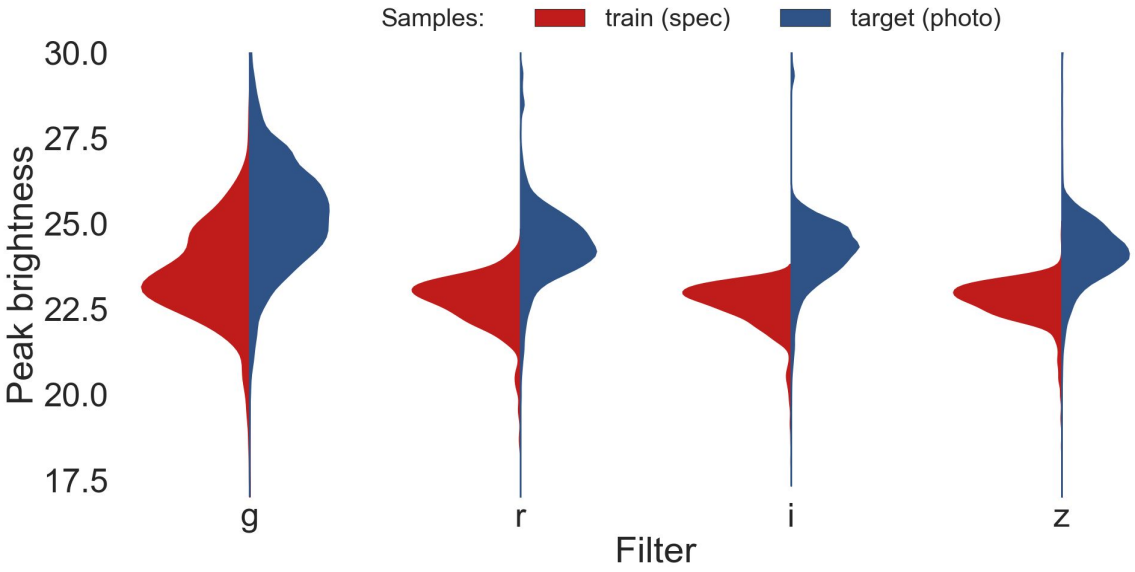
Training sample

Photometry +
Spectra (labels)

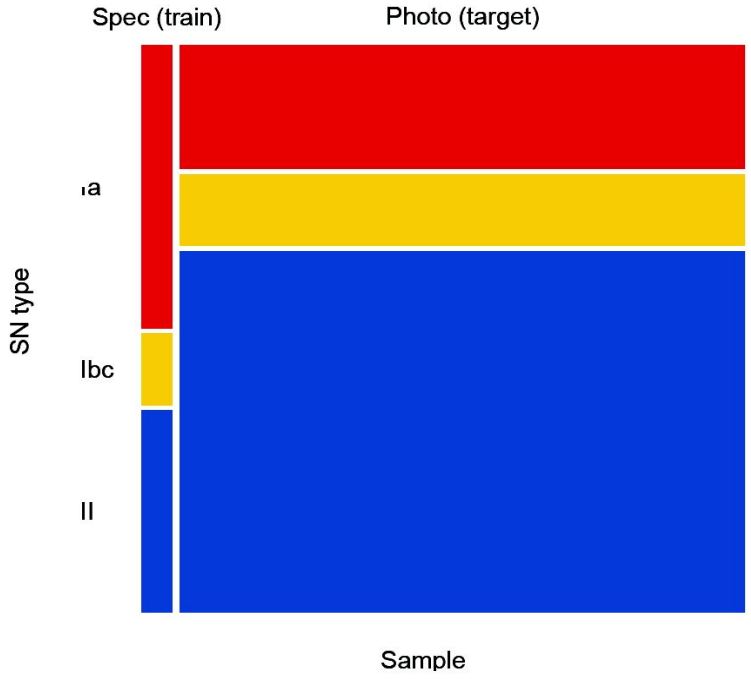
Target sample

Photometry
Determine labels

Representativeness

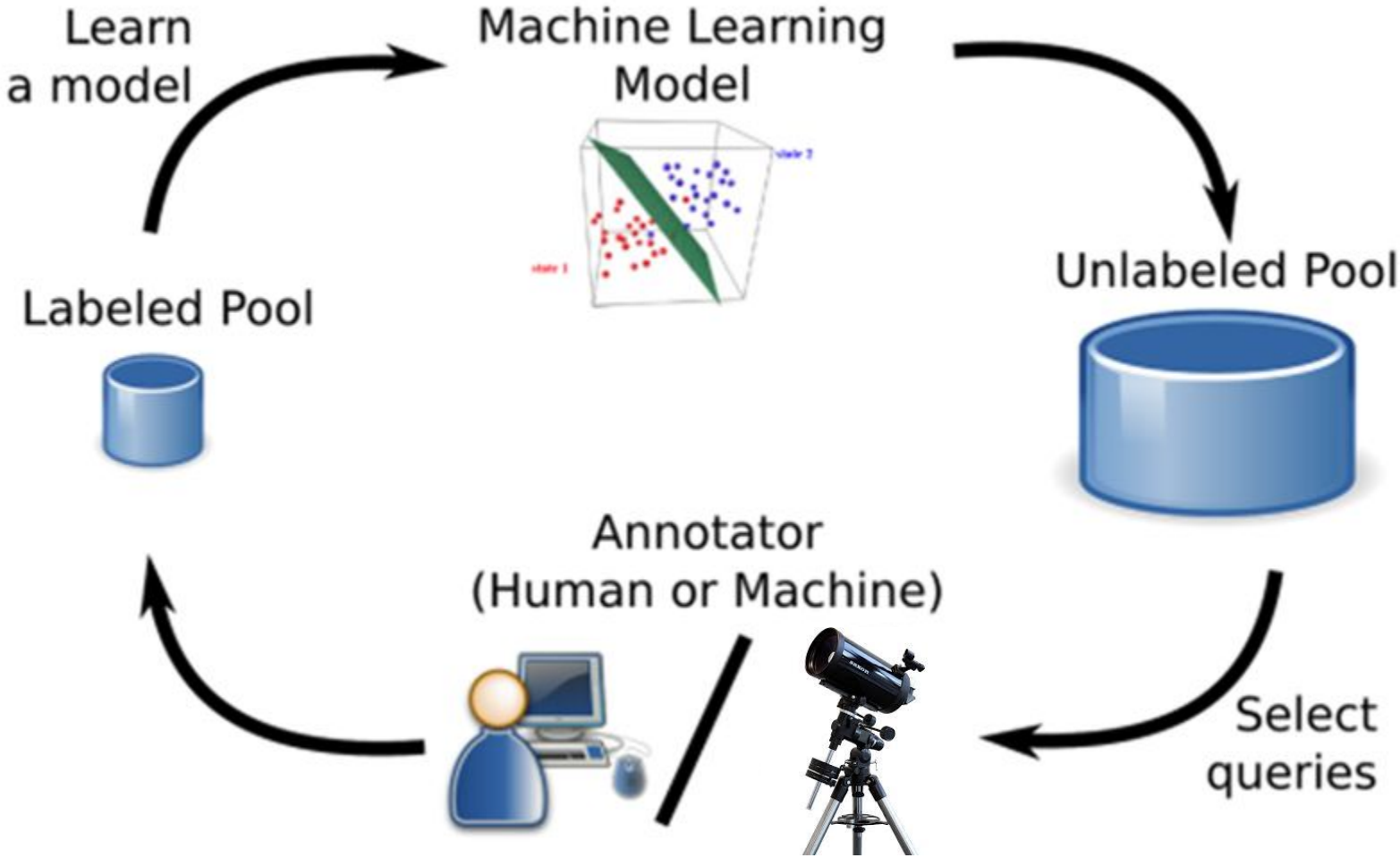


Spectroscopic sample was never meant to be a training set



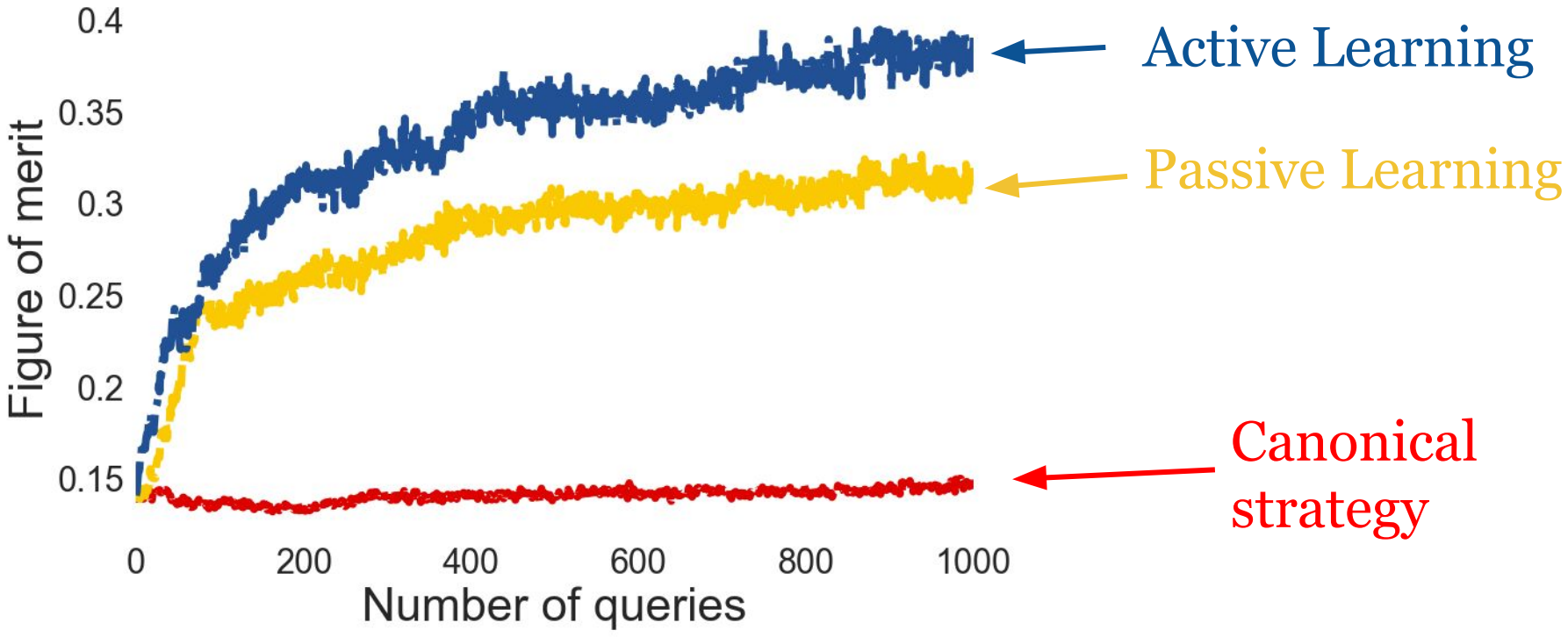
Active Learning

Optimal classification, minimum training



AL for SN classification

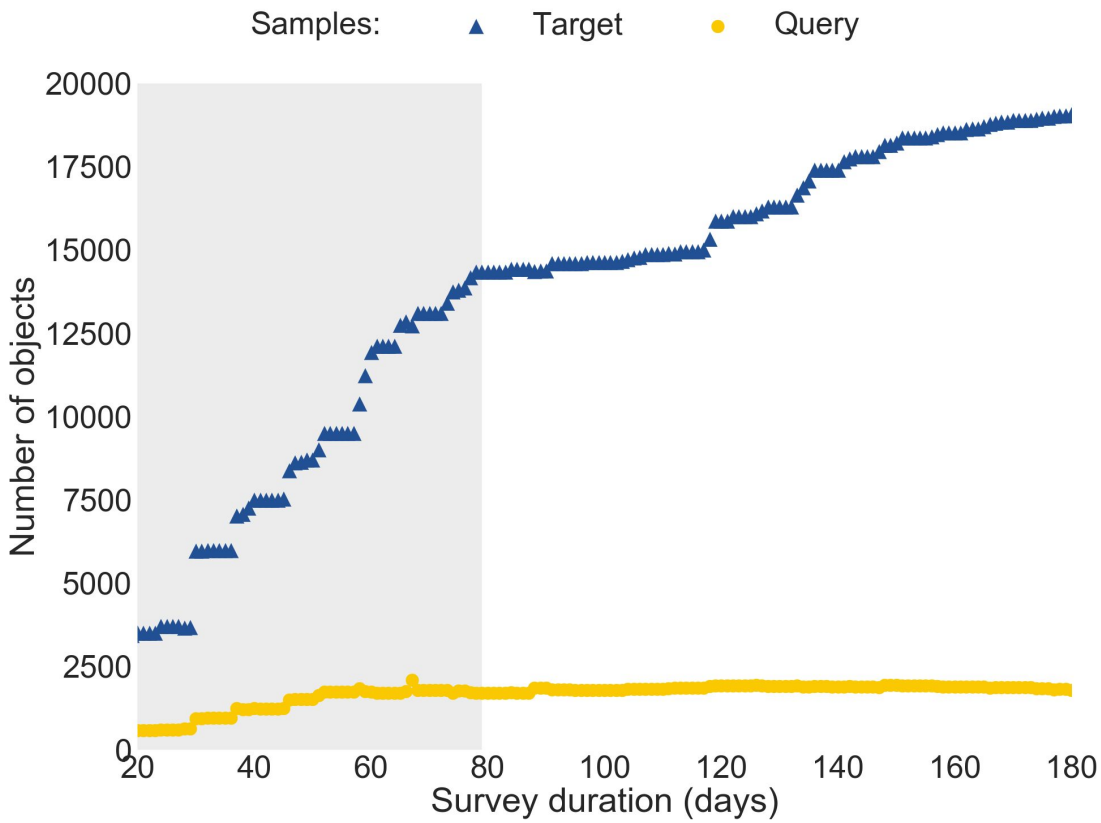
Static results



From COIN Residence Program #4, ***Ishida*** *et al., 2019, MNRAS, 483 (1), 2–18*

SN are transients

Not everything is available for labelling

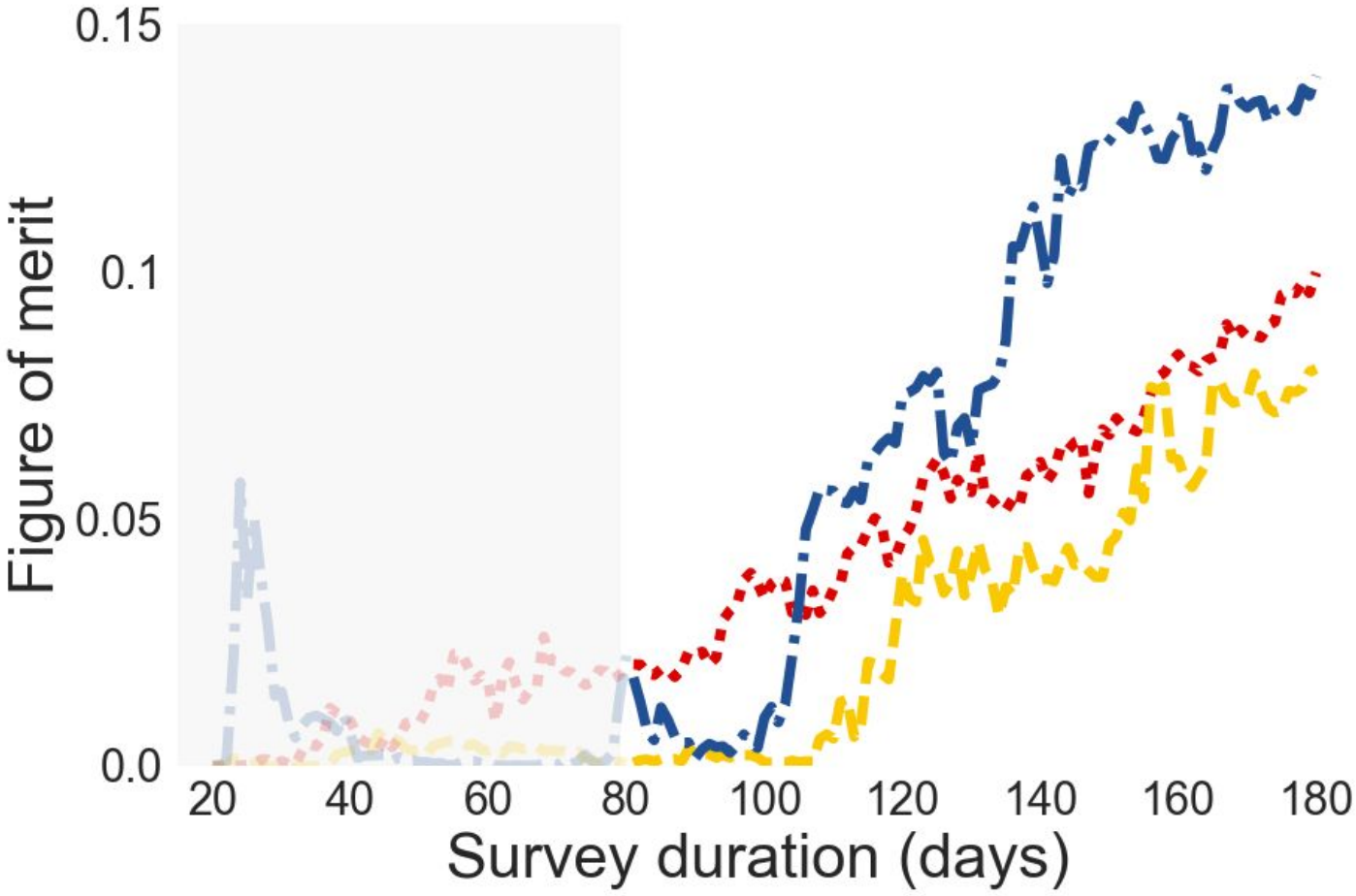


1. Feature extraction done daily **with available observed epochs until then.**

2. Query sample is also re-defined daily: objects with **r-mag < 24**

From COIN Residence Program #4, ***Ishida*** *et al., 2019, MNRAS, 483 (1), 2–18*

Beginning from scratch



From COIN Residence Program #4, ***Ishida*** *et al., 2019, MNRAS, 483 (1), 2–18*

Does this solve the problem completely?

No, it is just the best you can do!

Is this the only way of doing it?

Certainly not!

What is next **for this project**?

- Agreement being drafted with a major telescope to stress test this idea in a more realistic astronomical scenario - world wide coordination with spectroscopic telescopes
- Adapt this to multi-fiber spectrograph - where should I point the telescope?
- Issues still to be tackled:
  - Uncertainties everywhere!
  - Scalability - LSST will have 2 million alerts/night
  - Metrics for different science goals
- Anomaly detection
- Active Learning for Regression
  - Representativeness and correlations in uncertainty space

This is a (very unique) group effort!

What have we learn from the COIN experience so far?

- The human factor needs to be respected
- True interdisciplinary means freedom and requires trust
- The environment is very important (architecture)
- There is human potential waiting to be used in science in the outside world (for free)
- The most efficient way to work with astronomical data is to have an astronomer friend

Next time, up the mountain!

Application deadline, 10 April

https://cosmostatistics-initiative.org/residence-programs/crp6/

THANK YOU

Extra Slides

The COIN Residence Program (CRP)

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CRP #4, 2017, Clermont Ferrand, France

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CRP #3, 2016, Budapest, Hungary

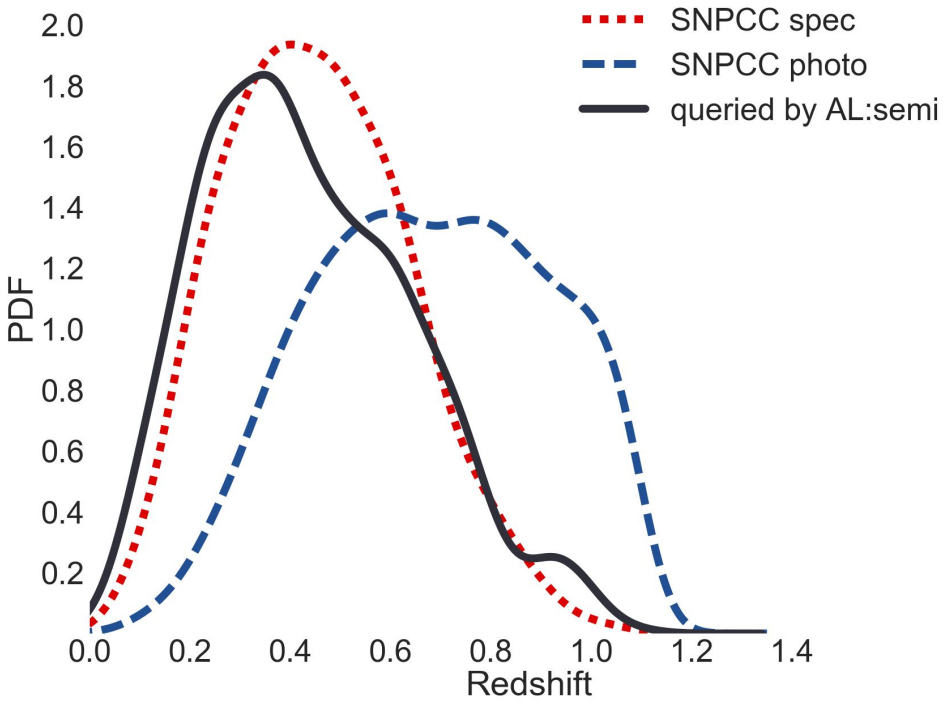
The queried sample

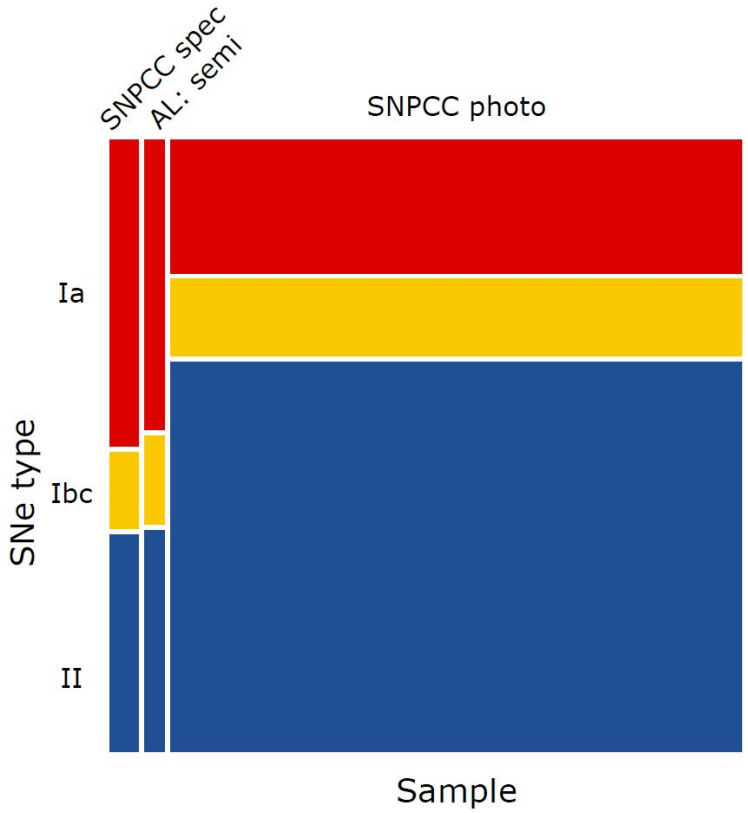
Partial LC, no training, time domain, batch

SNPCC spec:
1103 objects

Queried sample:
800 objects

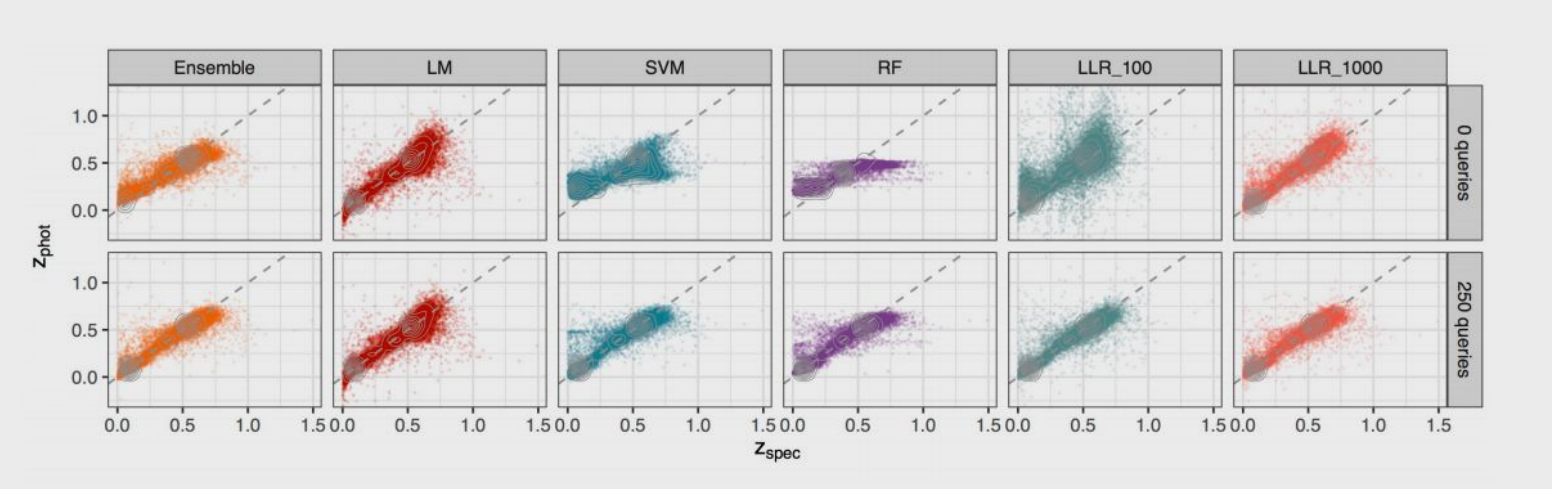
Telescope time:
Queried/spec = 0.999





From COIN Residence Program #4, ***Ishida*** *et al., 2019, MNRAS, 483 (1), 2–18*

AL for Photo-Z



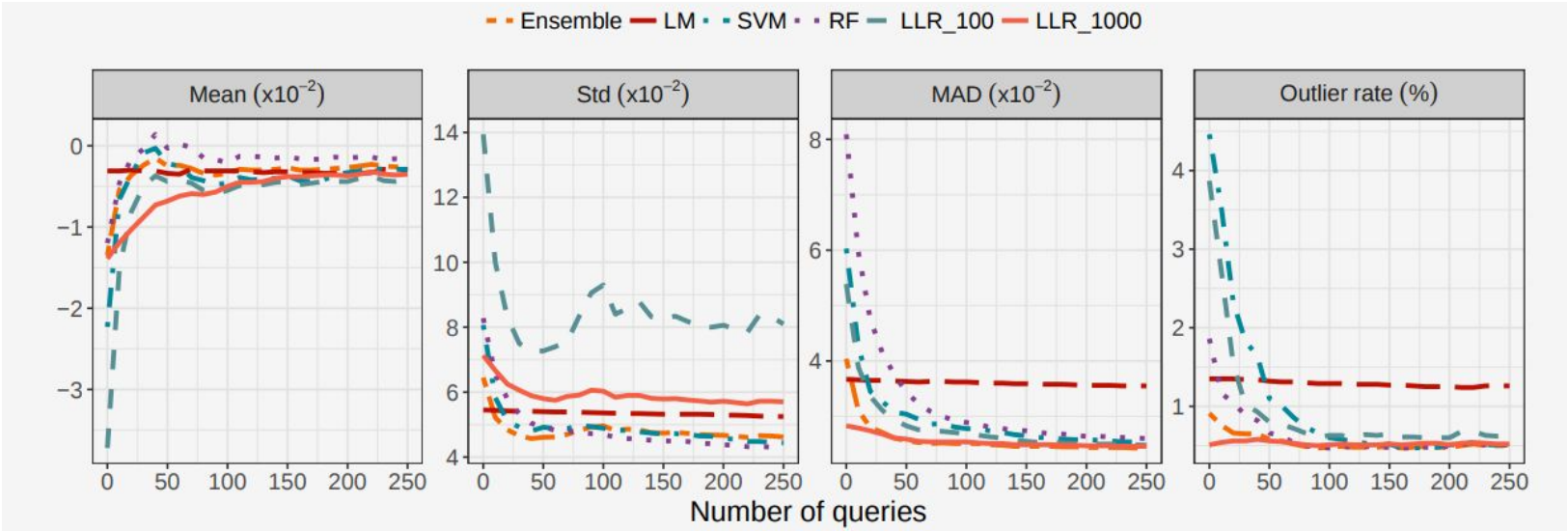
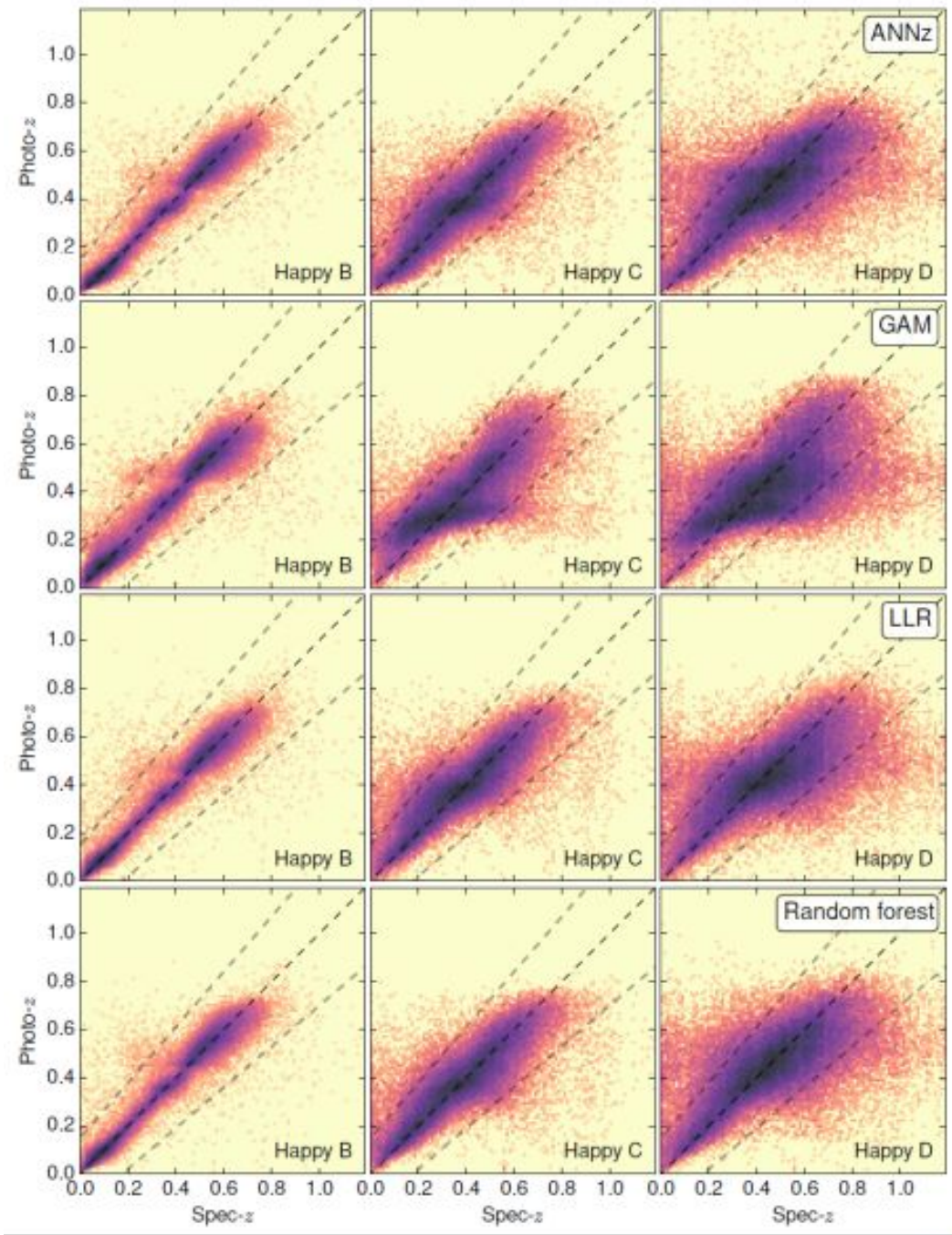


Figure 4. An assessment of the performance of the ensemble model and its constituent models using active learning. Performance diagnostics are shown as a function of the number of queries.

*Vilalta, **Ishida** et al., 2017 IEEE Symposium Series on Computational Intelligence (SSCI)*



Happy catalogue

The effect of coverage + photometric errors

Empirical methods

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

Teddy catalogue

The effect of color coverage

Empirical methods

Method	Set	Diagnostics Mean ($\times 10^{-2}$)	Std ($\times 10^{-2}$)	MAD ($\times 10^{-2}$)	Outlier rate (%)
ANNz	B	0.03	2.35	1.16	0.18
	C	-0.01	2.45	1.15	0.26
	D	-0.08	5.67	3.61	3.09
GAM	B	0.05	2.62	1.34	0.11
	C	0.06	2.79	1.38	0.18
	D	-0.06	3.93	2.23	2.28
LLR	B	0.07	2.35	1.14	0.19
	C	0.05	2.44	1.14	0.28
	D	1.76	4.08	2.46	3.80
Random forest	B	0.03	2.38	1.18	0.17
	C	-0.01	2.49	1.17	0.26
	D	0.16	6.85	5.24	6.70

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

Urgency:

The data Paradigm

year	Number of supernova
1998	42
2014	740
2025	> 10 000

2 million alerts/day
15 TB/day

40 nights of LSST

↓

entire Google database

A. Connelly, TED2014

https://www.kaggle.com/c/PLAsTiCC-2018

Featured Prediction Competition

PLAsTiCC Astronomical Classification

Can you help make sense of the Universe?

$25,000
Prize Money

LSST Project · 1,078 teams · 2 days to go

1,093	1,382	22,430
Teams	Competitors	Entries

Overview | Data | Kernels | Discussion | Leaderboard | Rules | Host

Overview — Edit

- Description
- Evaluation
- Prizes
- Timeline
- PLAsTiCC's Team

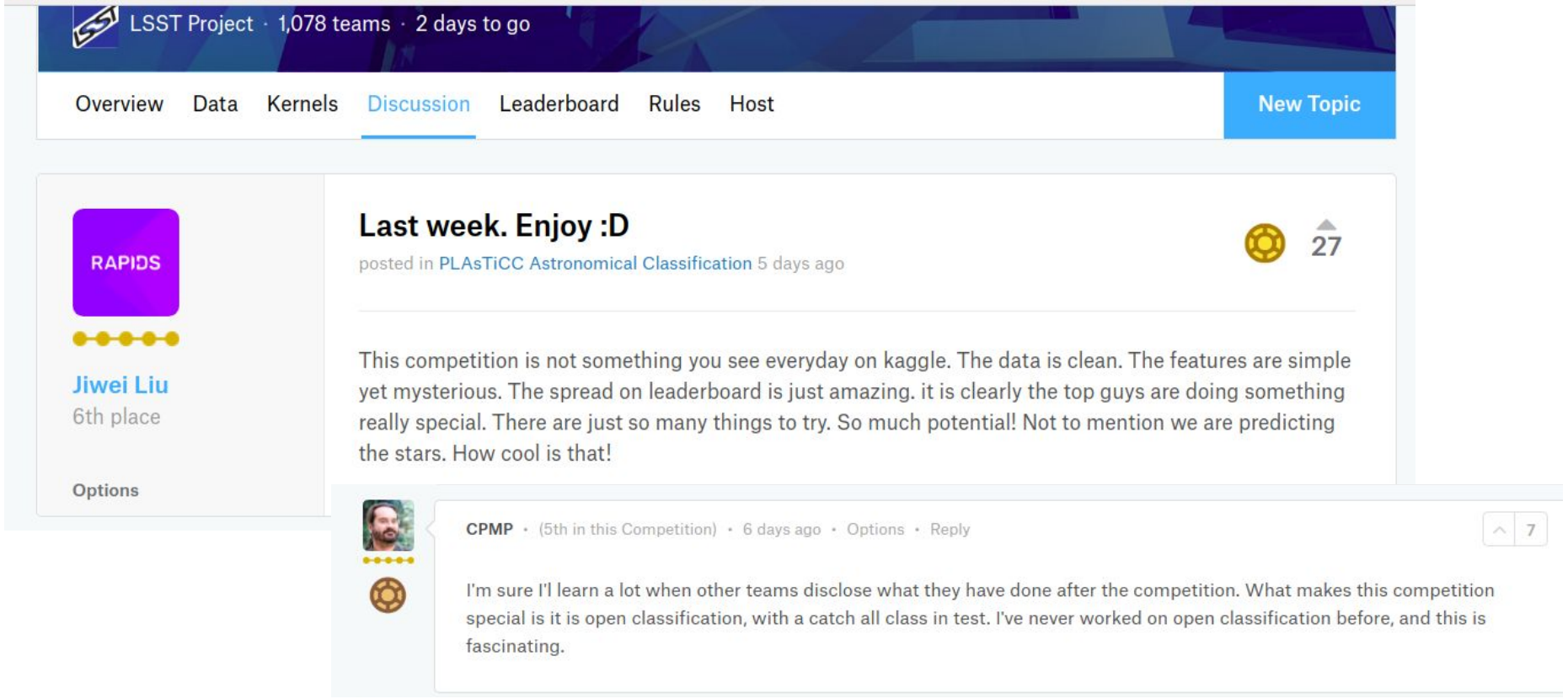
+ Add Page

Help some of the world's leading astronomers grasp the deepest properties of the universe.

The human eye has been the arbiter for the classification of astronomical sources in the night sky for hundreds of years. But a new facility -- the Large Synoptic Survey Telescope (LSST) -- is about to revolutionize the field, discovering 10 to 100 times more astronomical sources that vary in the night sky than we've ever known. Some of these sources will be completely unprecedented!

The Photometric LSST Astronomical Time-Series Classification Challenge (PLAsTiCC) asks Kagglers to help prepare to classify the data from this new survey. Competitors will classify astronomical sources that vary with time into different classes, scaling from a small training set to a very large test set of the type

The repercussion



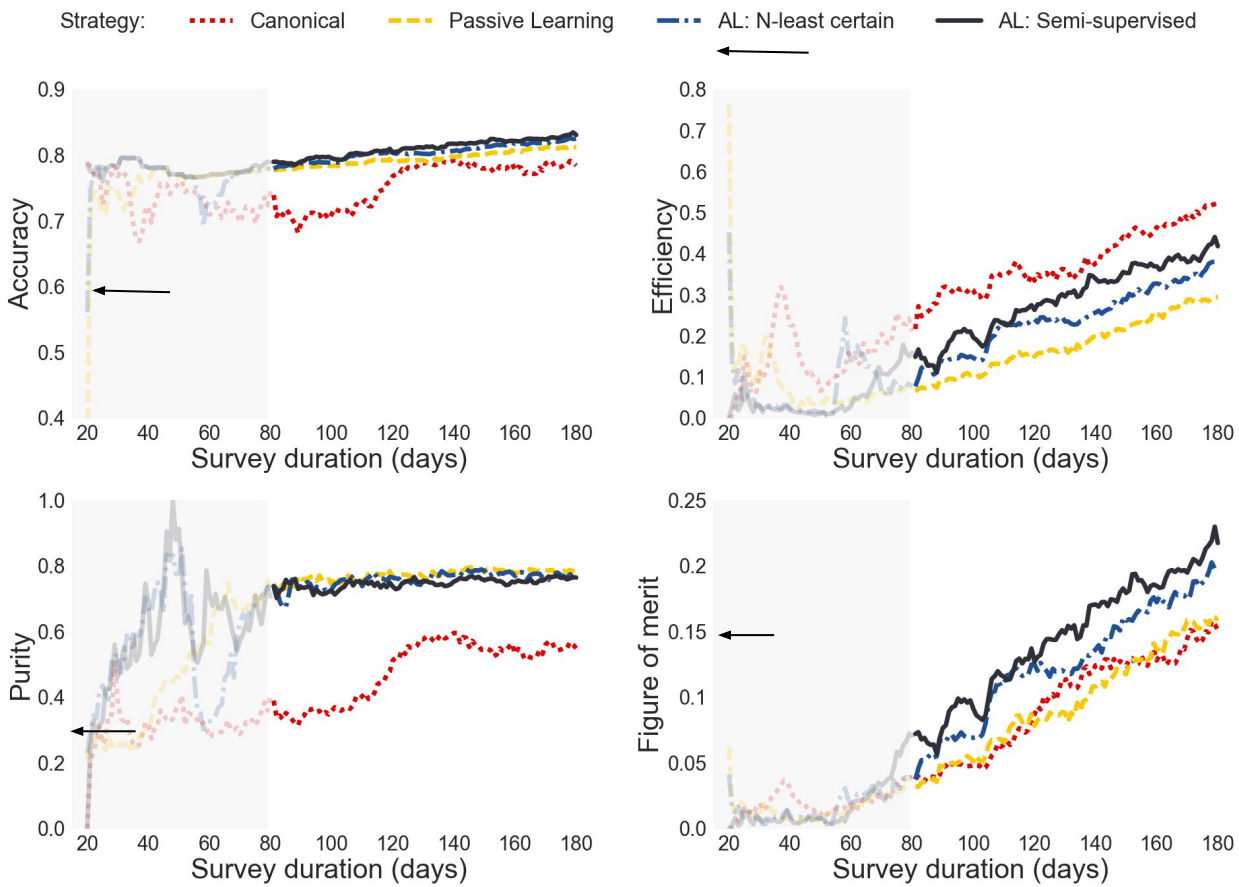
Our data is extremely complex …

...and this is an opportunity...

https://www.kaggle.com/c/PLAsTiCC-2018/discussion/74292

Batch Mode

Partial LC, no initial training, time domain



The arrow shows <u>traditional</u> Full light-curve results with full SNPCC spec

From COIN Residence Program #4, ***Ishida*** *et al., 2019, MNRAS, 483 (1), 2–18*