





Human in the Loop: Active Learning for Astronomy

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First things first

Acknowledgements

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Konstantin Malanchev (UIUC) 😌 SVAD Maria Pruzhinskaya (LPC) and everyone in the **SNAD** collaboration



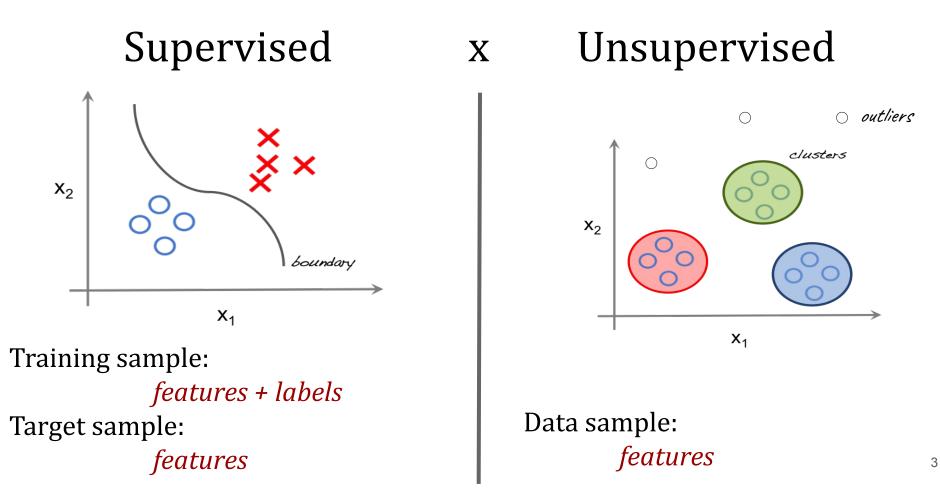
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> Alex I. Malz (CMU) Mi Dai (JHU) Kara Ponder Amanda Wasserman (UIUC) and all those working in the **RESSPECT team**





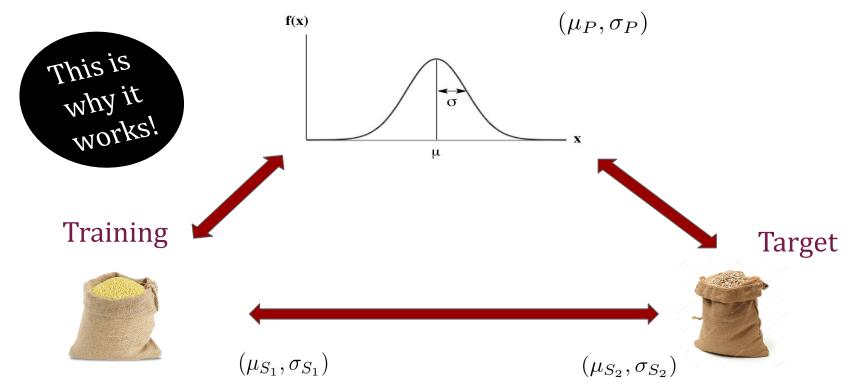
Categories of Machine Learning:



From yesterday ...

Representativeness

Probability distribution, P



Ideal Supervised learning situation eov Training sample Images, colors,

light curves, etc.

Classes

sample

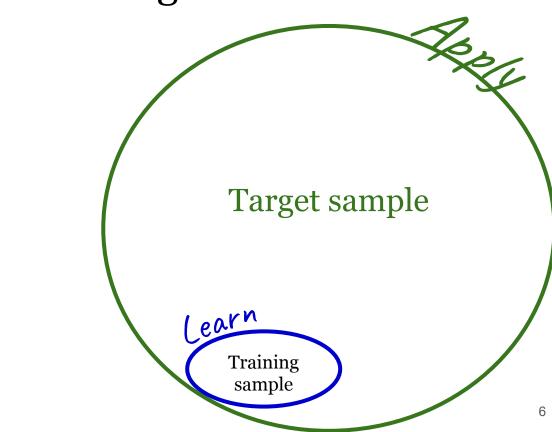
Images,

colors, light

curves, etc.

In astro, training means spectra

Real astro-learning situation

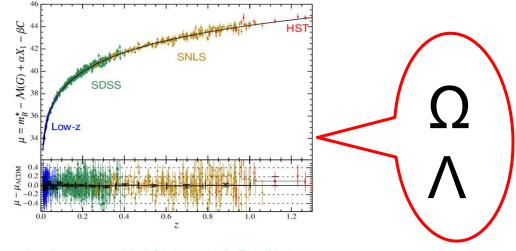


Example science case:

Type Ia supernova cosmology

Standard candles used to measure cosmological distances

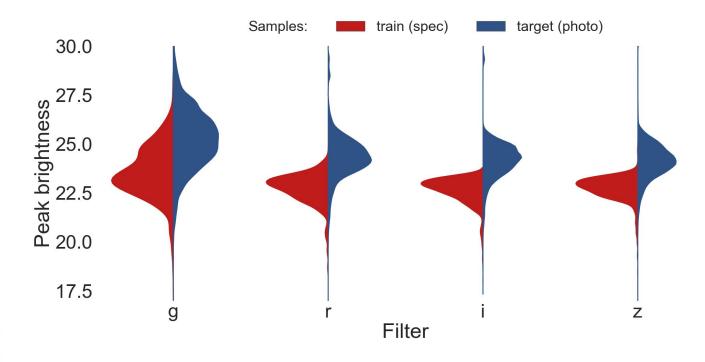




http://supernovae.in2p3.fr/sdss_snls_jla/ReadMe.html



Real astro-learning situation





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

Very common situation

Labels are often far too expensive!





Given limited resources, we need recommendation systems!



35% of Amazon's revenue are generated by it's recommendation engine.

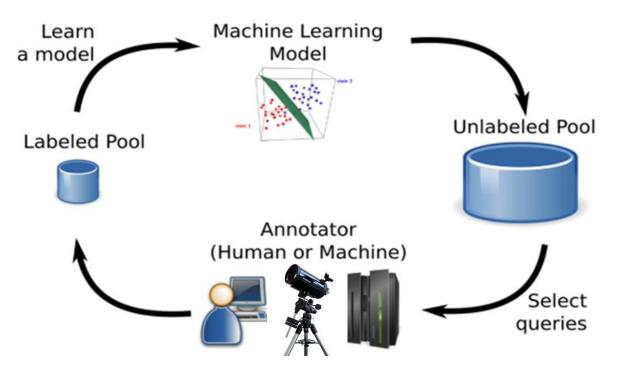




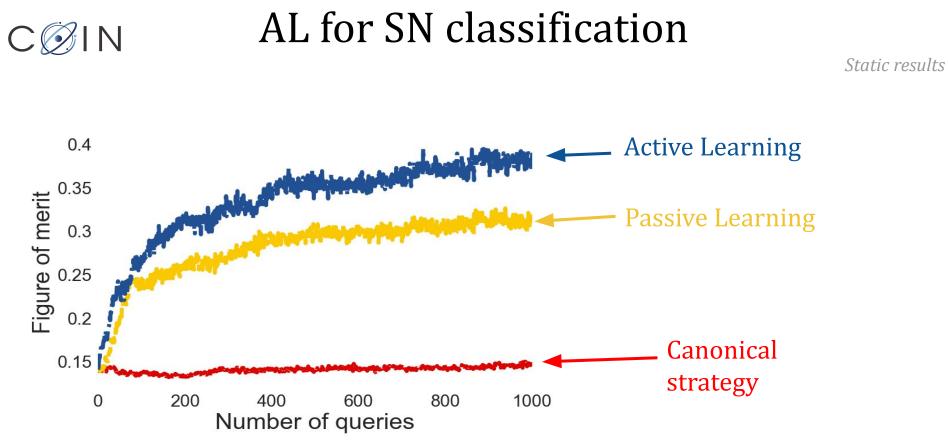
Strategy

Active Learning

Optimal classification, minimum training



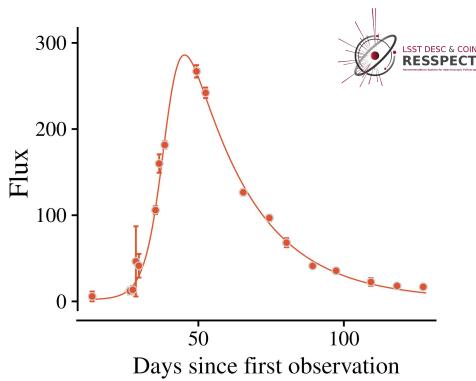
Strategy 2



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

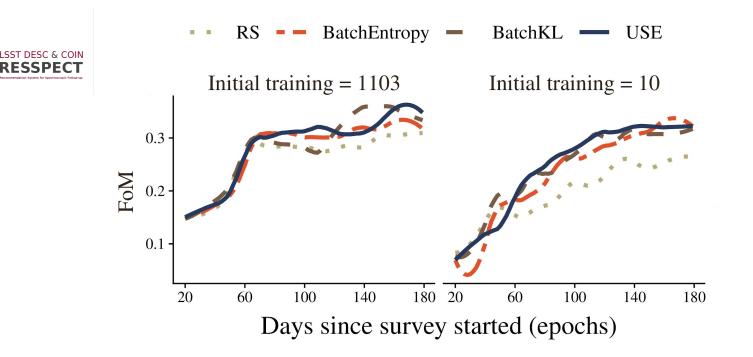
If only it were that simple ...

- Window of Opportunity for Labelling
- Evolving Samples
 - We must make query decisions before we can observe the full LC
- Multiple Instruments for labelling
- Evolving budget
 - Other people want to use the telescope
- Evolving Costs
 - Observing costs for a given object changes as it evolves.



<u>Kennamer, Ishida_et al., 2020 - arXiv:astro-ph/2010.05941</u> - The RESSPECT team: LSST-DESC and COIN, IEEE Symposium on Computational Intelligence for Astroinformatics, 2020, Canberra, Australia

Start from scratch, do not overcomplicate



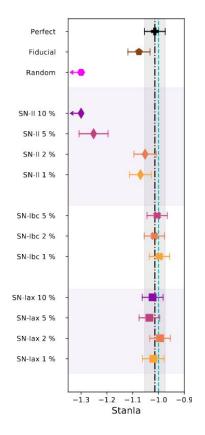
<u>Kennamer, Ishida_et al., 2020 - arXiv:astro-ph/2010.05941</u> - The RESSPECT team: LSST-DESC and COIN, IEEE Symposium on Computational Intelligence for Astroinformatics, 2020, Canberra, Australia

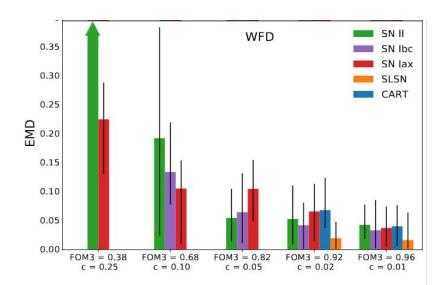
What about science?

Cosmology results from photometrically classified SN IA Trained -0.75 Photo-classified SN machine ≥ -1.00 SN la candidates learning -1.25 classifier -1.50 0.2 0.3 Ω.... 2. Impacts learning this algorithm LSST DESC & COIN +RESSPE Training Recommendation System for Spectroscopic Follow-up 1. Different choices of sample this!

What about science?

Good classification might not be enough



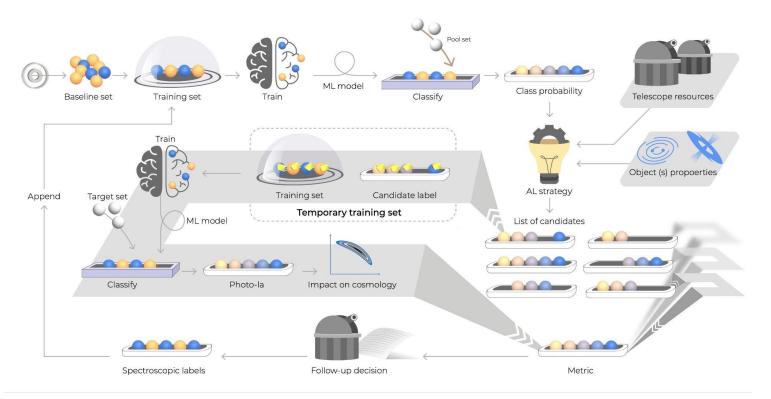


LSST DESC & COIN RESSPECT

Malz et al., 2023 - <u>arXiv:astro-ph/2305.14421</u> - The RESSPECT team: LSST-DESC and COIN, Are classification metrics good proxies for SN Ia cosmological constraining power? -- submitted to A&A

What about science?

The RESSPECT workflow



https://github.com/COINtoolbox/RESSPECT



The difficult part is data treatment/gathering

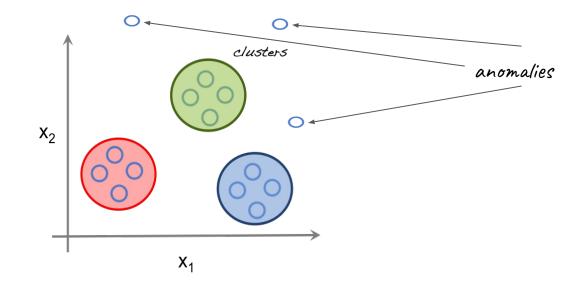
- The power of machine learning is in its connection with domain knowledge
- There are caveats in using machine learning and we should avoid off-the-shelf and black bloxes applications
- ML for science must be personalized

The beauty of an observational science

"... telescopes that merely achieve their stated science goals have probably failed to capture the most important scientific discoveries available to them."

Norris, R. (2017). Discovering the Unexpected in Astronomical Survey Data. Publications of the Astronomical Society of Australia, 34, E007. doi:10.1017/pasa.2016.63 Statistically,

Anomaly Detection

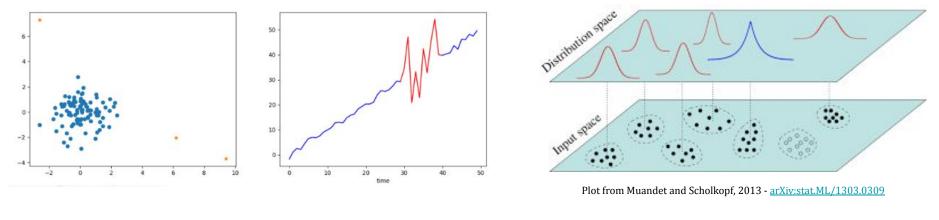


"An anomaly is an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism"

Statistically,

Anomaly Detection

"An anomaly is an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism" *Hawkins, 1980*



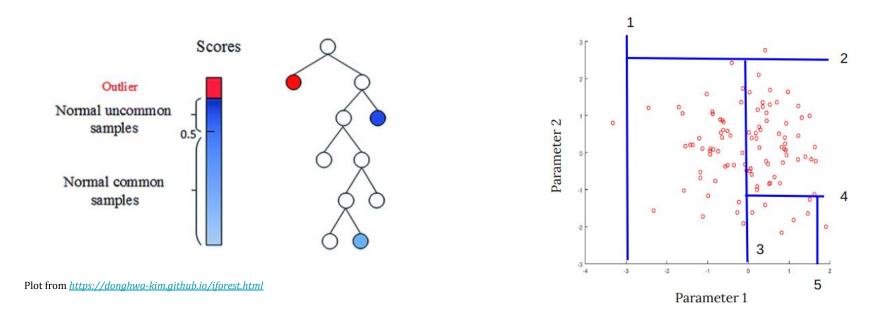
isolation

behaviour

group

Example of an automatic search for anomalies,

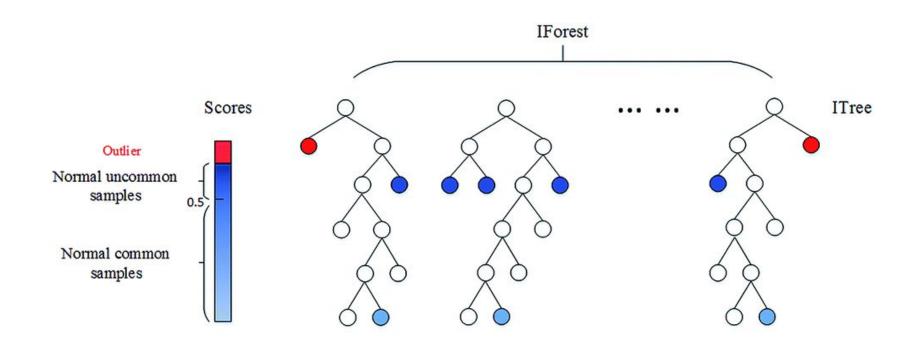
Isolation tree



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Example of an automatic search for anomalies,

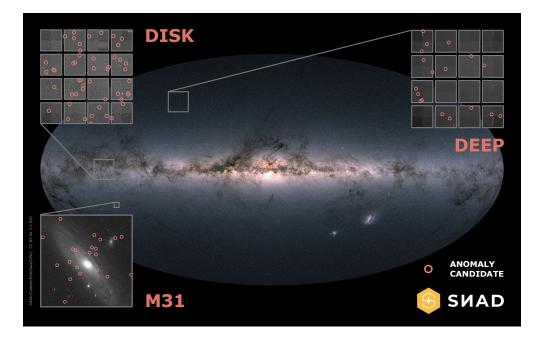
Isolation forest



Anomaly detection on real data



Zwicky Transient Facility DR3



- Survey currently in operation, telescope in California
- 3 fields from Dara Release 3 (DR3)

After selection cuts and feature extraction, **2.25 million objects**

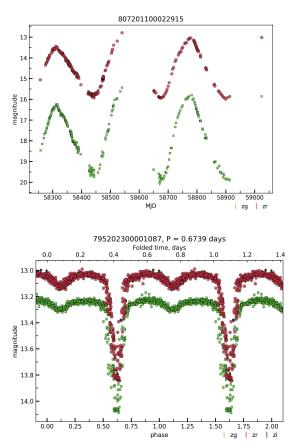
Malanchev et al., 2021 - MNRAS - https://arxiv.org/abs/2012.01419

Figure by Maria Pruzhinskaya

Example: nominal objects

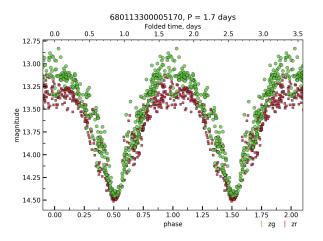


Zwicky Transient Facility DR3



expected to contain stars and periodic variables (no transients)

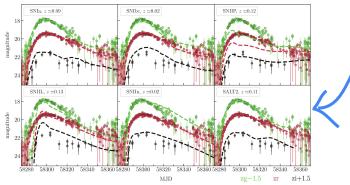
Visualization generated with the SNAD ZTF viewer: https://ztf.snad.space/

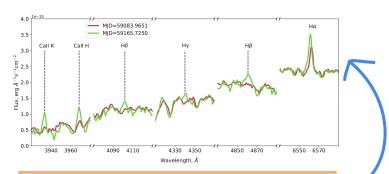




Zwicky Transient Facility DR3

- Feature extraction
- Anomaly detection algorithms:
 - Isolation Forest
 - Local Outlier Factor
 - Gaussian Mixture Model
 - One-Class Support Vector Machine
- Initial data: 2.25 million objects
- Expert analysis: 277 objects





- 1 RS Canum Venaticorum star
- 1 red dwarf flare
 - 4 Supernova candidates

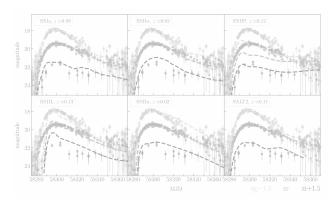
Results:

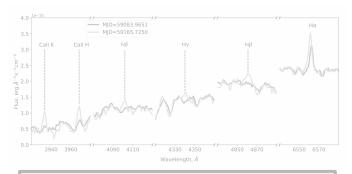
- 68 % (188) artifacts, bogus
- 24 % (66) previously cataloged
- 8 % (23) discoveries <



Zwicky Transient Facility DR3

- Feature extraction
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Philosophically,

Stages of discovery in astronomy:

Detection

Interpretation

Understanding Acceptance

It is about Discovery

"An anomaly is an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism"

Which mechanism? Is it something we are familiar with but fail to proper model or recognise? Is it something we have never seen before?

Is there something new for us to learn?



In order to identify the unusual we need to have a clear ideal of what is usual ...

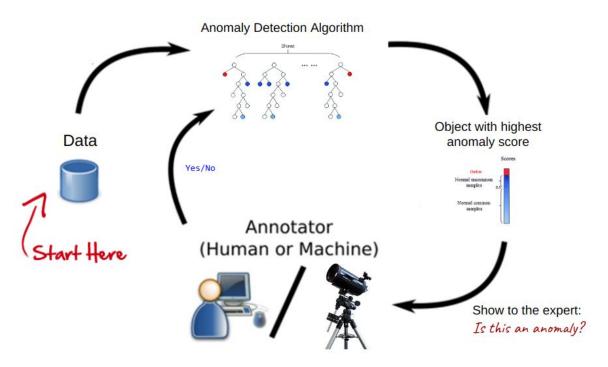


.. and that is a social construct. It changes and adapts with time!

Discovery and Classification in Astronomy - by Steven Dick - Cambridge University Press (2013)

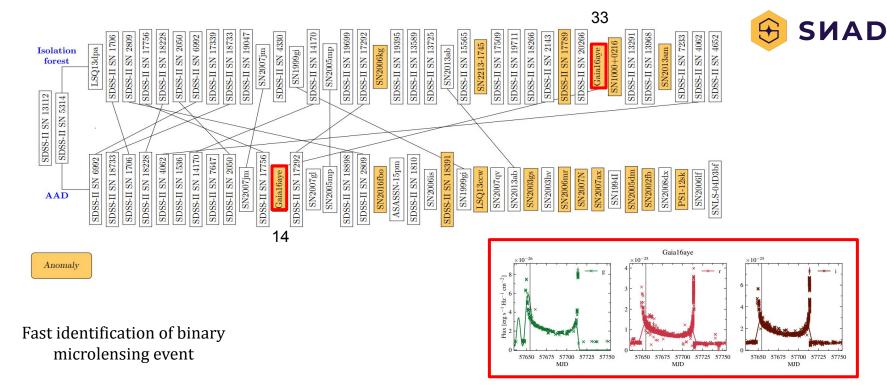
Human-oriented search

Active Anomaly Detection



Plot modified from <u>Chowdhury et al., 2021, SPIE Medical Imaging</u> Algorithm from Das, S., et al., 2017, in Workshop on Interactive Data Exploration and Analytics (IDEA'17), KDD workshop, <u>arXiv:cs.LG/1708.09441</u> Try the SNAD implementation: <u>https://coniferest.readthedocs.io/en/latest/tutorial.html</u>

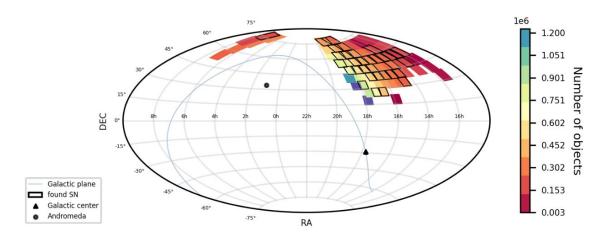
AAD on real data: The Open Supernova Catalog



Second try:



AAD on real data: ZTF data releases



- March December/2018
- 70 fields
- 30 objects/field
- Total 2100 objects inspected



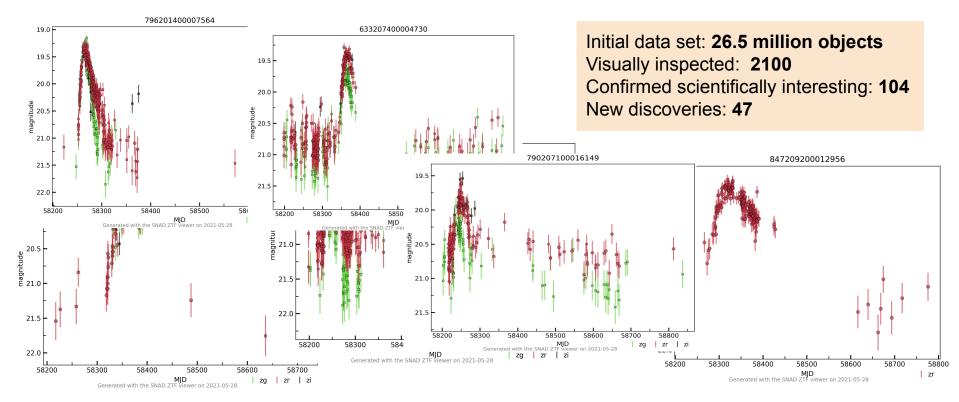
- 100 SN-like objects
 - 46 already catalogued
 - 54 newly discovered
- The SNAD catalog: <u>https://snad.space/catalog/</u>

AAD on real data: ZTF DR3



"There are no new supernova-like objects in ZTF DR"

Basically everyone to whom we mentioned we were looking for them.

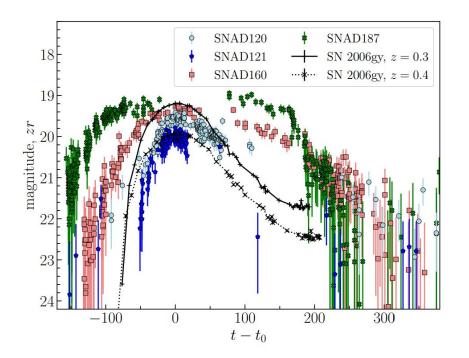


Catalog of lost transients: https://snad.space/catalog/

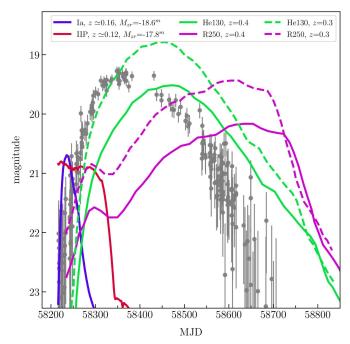
Pruzhinskaya et al., 2023, A&A - arXiv:astro-ph/2208.09053



Interesting SLSN candidates







Pruzhinskaya et al., 2023, A&A 672, A111 (2023), arXiv:astro-ph/2208.09053

Problem:

AAD is very expensive

Algorit	hm 2 Active Anomaly Discovery (AAD)
	ut: Dataset H, budget B
Init	ialize the weights $\mathbf{w}^{(0)} = \{\frac{1}{\sqrt{m}},, \frac{1}{\sqrt{m}}\}$
Set	t = 0
Set	$\mathbf{H}_A = \mathbf{H}_N = \emptyset$
wh	ile $t \leq B$ do
t	= t + 1
S	et $\mathbf{a} = \mathbf{H} \cdot \mathbf{w}$ (i.e., \mathbf{a} is the vector of anomaly scores)
	et z_i = instance with highest anomaly score (where $i = rg \max_i(a_i)$)
C	Get feedback { 'anomaly'/ 'nominal'} on z_i
it	$f z_i$ is anomaly then
	$\mathbf{H}_A = \{\mathbf{z}_i\} \cup \mathbf{H}_A$
e	lse
	$\mathbf{H}_N = \{\mathbf{z}_i\} \cup \mathbf{H}_N$
	nd if
5: W	$\mathbf{w}^{(t)} = \text{compute new weights; normalize } \ \mathbf{w}^{(t)}\ = 1$
end	l while

$l(q, \boldsymbol{w}; z_i, y_i) =$

(0 if 0 if		$\boldsymbol{w} \cdot \boldsymbol{z}_i \geq q$	and	$y_i = anomaly$	
J	0 if		$\boldsymbol{w} \cdot \boldsymbol{z}_i < q$	and	$y_i = normal$	
)	$q - \boldsymbol{w} \cdot \boldsymbol{z}_i$	if	$\boldsymbol{w} \cdot \boldsymbol{z}_i < q$	and	$y_i = anomaly$	
l	$\boldsymbol{w} \cdot \boldsymbol{z}_i - q$	if	$\boldsymbol{w} \cdot \boldsymbol{z}_i \geq q$	and	y_i = anomaly y_i = normal	

$$\begin{split} \mathbf{w}^{(t)} &= \arg\min_{\mathbf{w},\,\xi} \frac{C_A}{|\mathbf{H}_A|} \left(\sum_{\mathbf{z}_i \in \mathbf{H}_A} \ell(\hat{q}_{\tau}(\mathbf{w}^{(t-1)}), \mathbf{w}; (\mathbf{z}_i, y_i)) \right) \\ &+ \frac{1}{|\mathbf{H}_N|} \left(\sum_{\mathbf{z}_i \in \mathbf{H}_A} \ell(\hat{q}_{\tau}(\mathbf{w}^{(t-1)}), \mathbf{w}; (\mathbf{z}_i, y_i)) \right) \\ &+ \frac{C_{\xi}}{|\mathbf{H}_A|} \left(\sum_{\mathbf{z}_i \in \mathbf{H}_A} \ell(\mathbf{z}_{\tau}^{(t-1)} \cdot \mathbf{w}, \mathbf{w}; (\mathbf{z}_i, y_i)) \right) \\ &+ \frac{C_{\xi}}{|\mathbf{H}_N|} \left(\sum_{\mathbf{z}_i \in \mathbf{H}_N} \ell(\mathbf{z}_{\tau}^{(t-1)} \cdot \mathbf{w}, \mathbf{w}; (\mathbf{z}_i, y_i)) \right) \\ &+ \|\mathbf{w} - \mathbf{w}_p\|^2 \end{split}$$
(2)

,

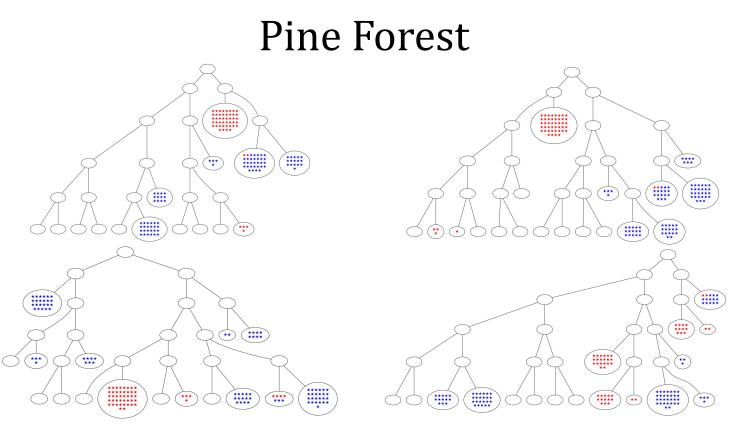


Aiming at bigger data

- Requires optimization
- Smooth incorporation of expert knowledge

Filtering only interesting trees





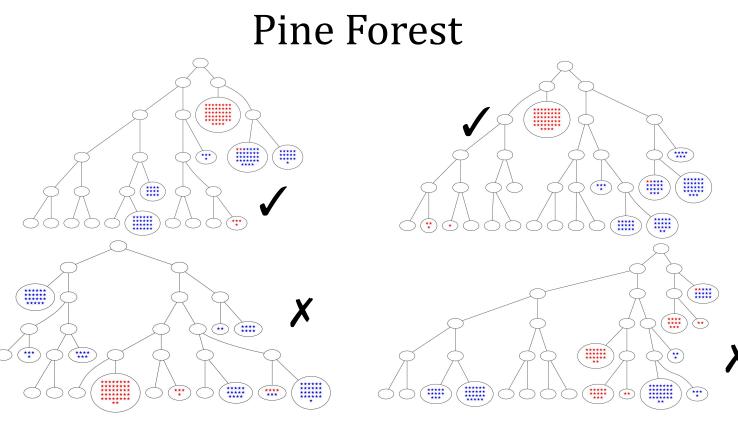
Scientifically interesting anomalies

Statistical outliers

Illustration and algorithm by Vladimir Korolev

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Scientifically interesting anomalies

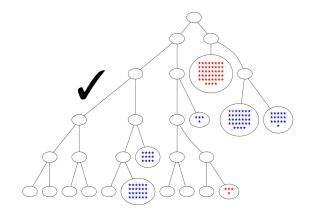
Statistical outliers

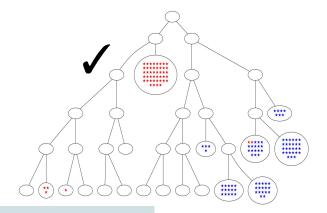
Illustration by Vladimir Korolev

Filtering only interesting trees



Pine Forest





Generate new random trees and filter again

Scientifically interesting anomalies

Illustration and algorithm by Vladimir Korolev

Break



Active Anomaly Detection tutorial

Remember to: File \rightarrow Save a copy to drive

https://colab.research.google.com/drive/1LvC a8QE7Q5MECL5uOAdze xGgRSS4bm?usp=sharing



Active Anomaly Detection tutorial

- The coniferest package: <u>https://coniferest.readthedocs.io/en/latest/tutorial.html</u>
- To use with your own data:
 - **Features** (called data in the tutorial) \Rightarrow 2D pandas dataframe 1 line per object, 1 column per feature
 - If you are using light curves, you might want to check the light_curve package for optimized feature extraction: <u>https://github.com/light-curve/light-curve</u>
 - \circ Metadata \Rightarrow 2D array

1 line per object: it may contain any information that will identify the candidate so you can make a decision.

For ZTF (26.5 million light curves) we need more infrastructure



The SNAD viewer



Malanchev et al., 2023, PASP, Volume 135, Issue 1044, id.024503, 18 pp, arXiv:astro-ph/2211.07605

Preparing for the future:

The knowledge database

SNAD160 - 821207100004043

dge			
Tags	Description	Changed by	Changed at
SN, uncertain	SNAD160	maria	2021-11-11T11:07:27.753Z
AGN, SN, uncertain	SNAD160	maria	2021-11-09T21:42:36.314Z
AGN, SN, uncertain, non-catalogued		maria	2021-11-08T13:33:49.098Z
	SN, uncertain AGN, SN, uncertain	SN, uncertain SNAD160 AGN, SN, uncertain SNAD160	SN, uncertain SNAD160 maria

SUBMIT

RESET

More than 2000 objects already tagged by experts

Explore the boundaries of your knowledge

- In the era of Rubin, serendipitous discoveries will not happen
- Domain experts **must be included** in the development of new techniques **from the first stages**. They should supervise the first prototypes.

Explore the boundaries of your knowledge

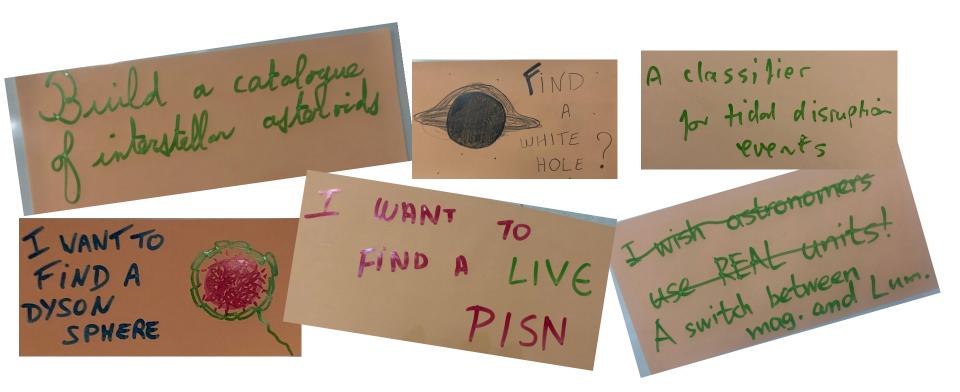
- In the era of Rubin, serendipitous discoveries will not happen
- Domain experts **must be included** in the development of new techniques **from the first stages**. They should supervise the first prototypes.

It is crucial to know what you are looking for

Get inspired

#FinkDreamShots





From OzFink 2023 - Melbourne, Australia - <u>https://www.ozgrav.org/ozfink-workshop-2023.html</u>

What do you want to see?

