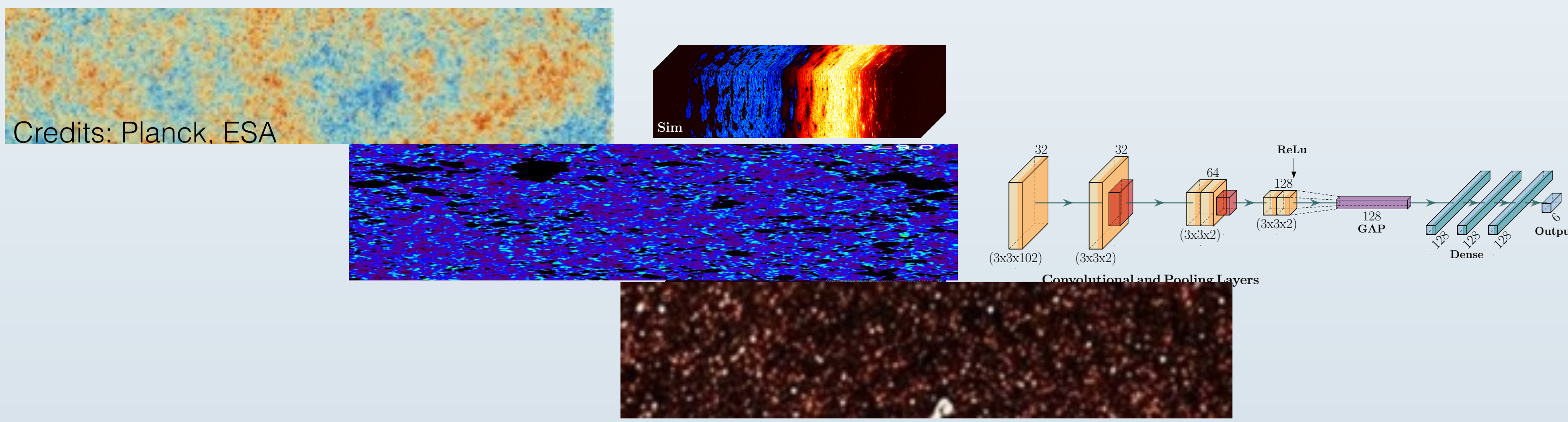
Machine Learning in Astrophysics and Astronomy



Caroline Heneka, ITP Heidelberg
Group 'Computer Vision Astrophysics and Cosmology'

ML4Jets 2023, DESY, Hamburg, Nov 8th 2023

Where we stand: The cosmic timeline

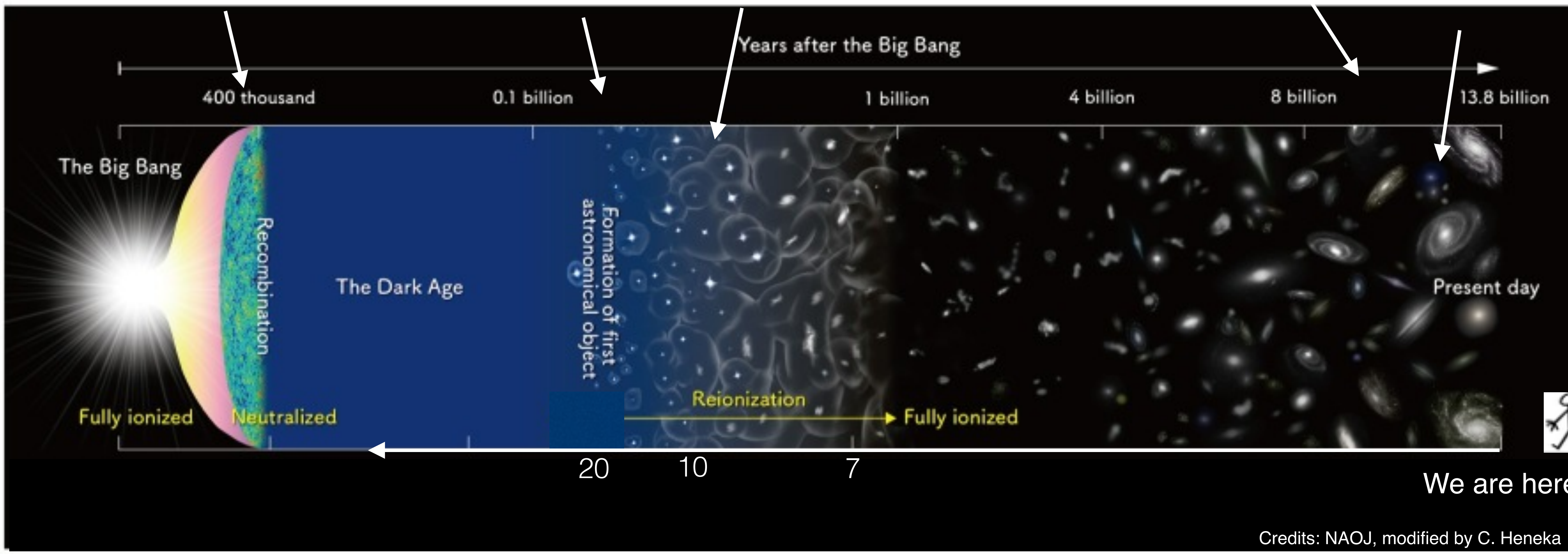
recombination
CMB

cosmic dawn CD
'first stars and galaxies'

reionisation EoR
'the last big phase transition'

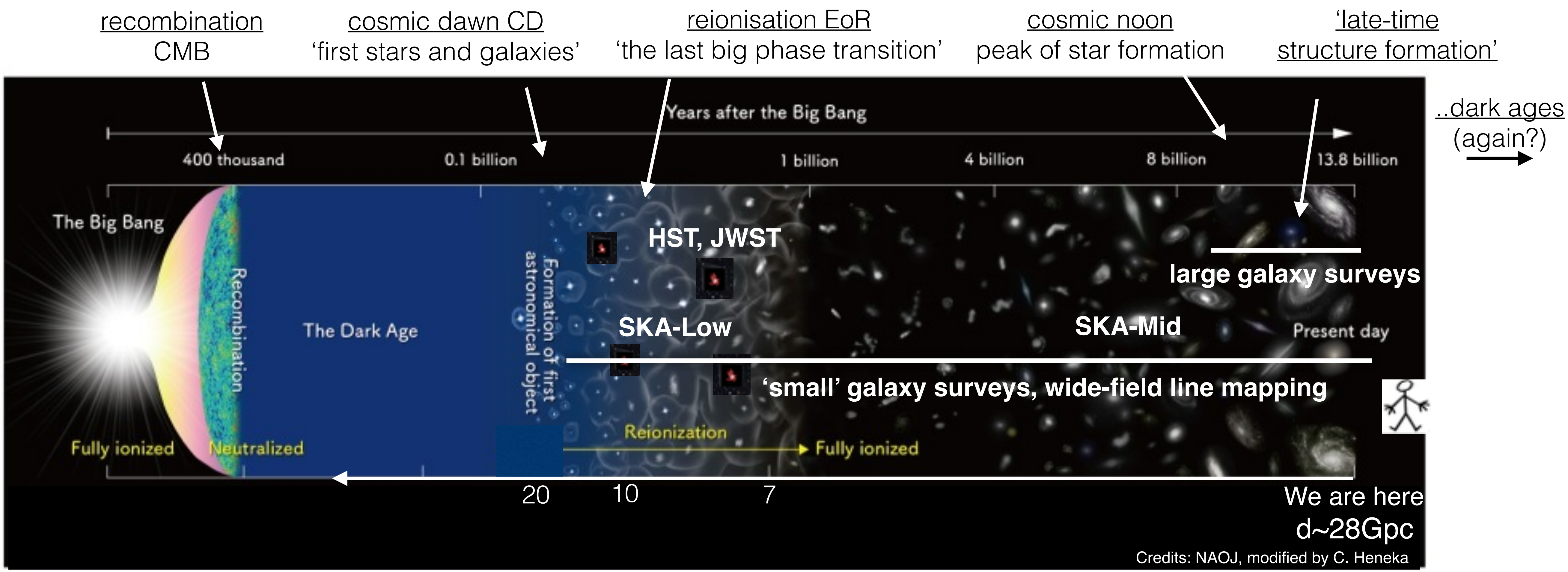
cosmic noon
peak of star formation

'late-time
structure formation'



..dark ages
(again?)

Where we stand: Astronomical surveys



Goal:

Test astrophysical processes of galaxy evolution, the intergalactic medium (IGM) as well as cosmological structure formation from the Epoch of Reionisation (EoR) to the present.

Coming decade: push to map up to **80% of the observable Universe**

Why ML/DL for astrophysics and astronomy

One big goal?

Test astrophysical processes of galaxy evolution, the intergalactic medium (IGM) as well as cosmological structure formation from the Epoch of Reionisation (EoR) to the present.

No, really - many goals, …

… and instruments

… and (types) of data

- imaging
- spectra
- tomography, IFS and IM
- time series

… datarates, scales, signal-to-noise

Datarates: Space typical ~Mbps, SKA TB/s

Scales: Stars to galaxies 3-4 orders, 10^9-10^{10} modes
Galaxies (kpc) to large-scale structure 3-4 orders
Large-scale structure to Hubble size 3-4 orders

Signal-to-noise: from many low SN to fewer high SN signals

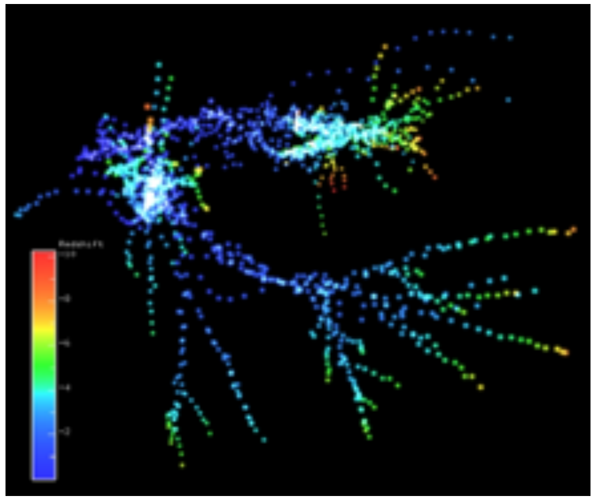
Why ML/DL for astrophysics and astronomy

… and therefore a zoo of applications!

- detection, segmentation
- classification
- regression, inference
- anomaly detection
- generation, emulation, …

+ plenty of inverse problems

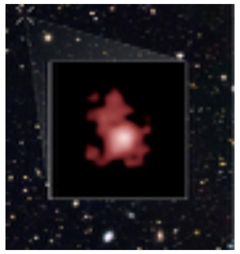
$$I^D(x, y) = R \times I(x, y) + n$$



@Chris Fluke, Swinburne University of Technology

Hierarchical

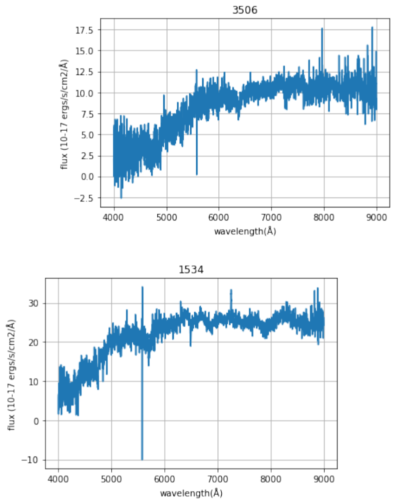
@Hubble, NASA



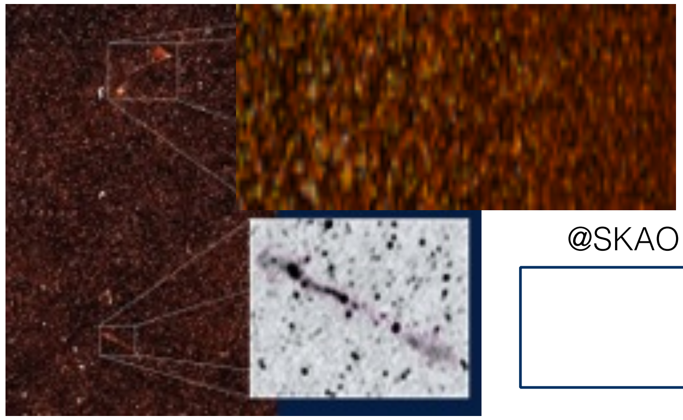
@Hubble, NASA

High-dim. correlations

Representation learning



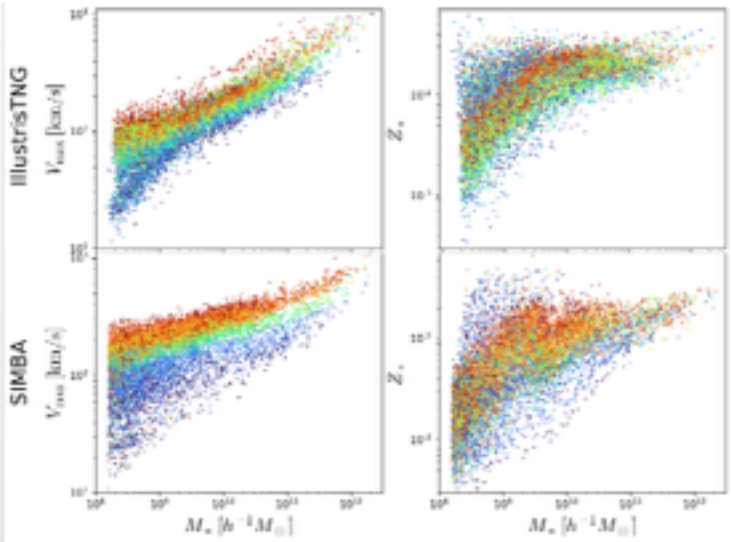
@SDSS



@SKAO

@MeerKAT

Non-linear, non-Gaussian



arXiv:2201.02202

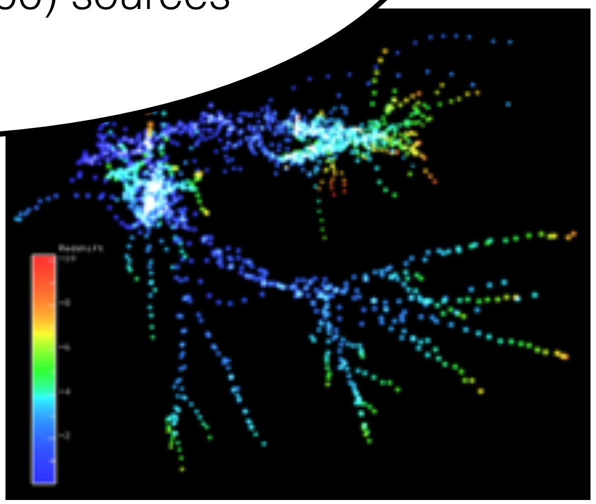
Why ML/DL for astrophysics and astronomy

Examples:

few sec: Classification 40.000 spectra
few sec: 7-parameter regression O(100)MB cube
few sec: detection, segmentation & flux measurement on O(100) sources

… and therefore a zoo of applications!

- detection, segmentation
- classification
- regression, inference
- anomaly detection
- generation, emulation, …



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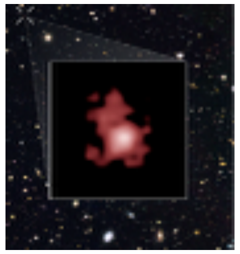
Hierarchical

@Hubble, NASA



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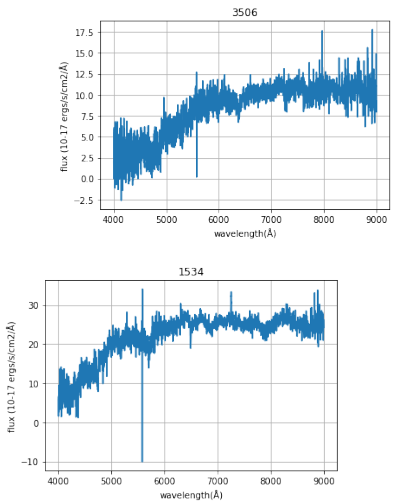

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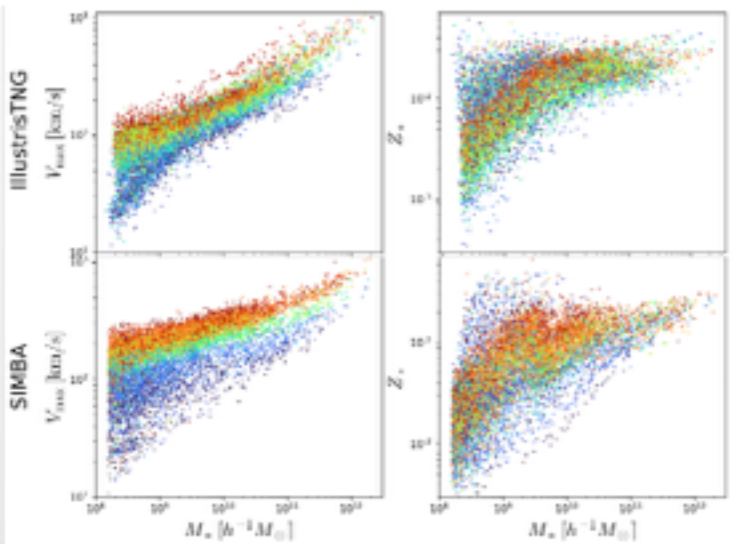
Representation learning

High-dim. correlations



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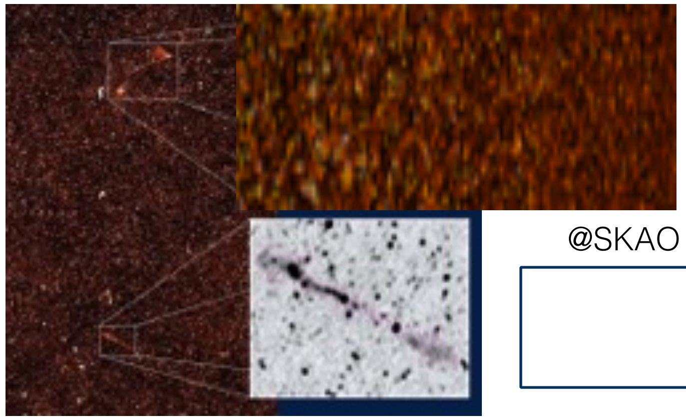

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Non-linear, non-Gaussian

Machine learning in Astrophysics and Astronomy

… and therefore a zoo of applications!

- detection, segmentation
- classification
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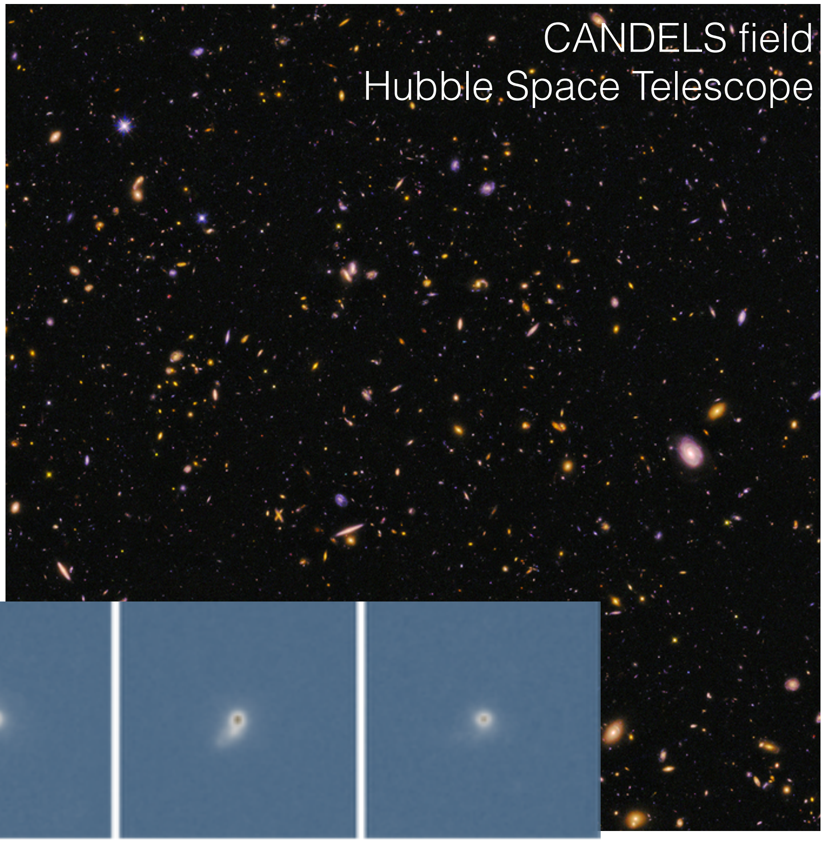
- generation, emulation, …

1) The deblending problem of biased photometry
2) Detection & regression for tomography
3) Inference when faced with intractable likelihoods
4) On-the-fly classification of the unexpected (spectra)
5) Cosmology with one galaxy

Machine learning in Astrophysics and Astronomy

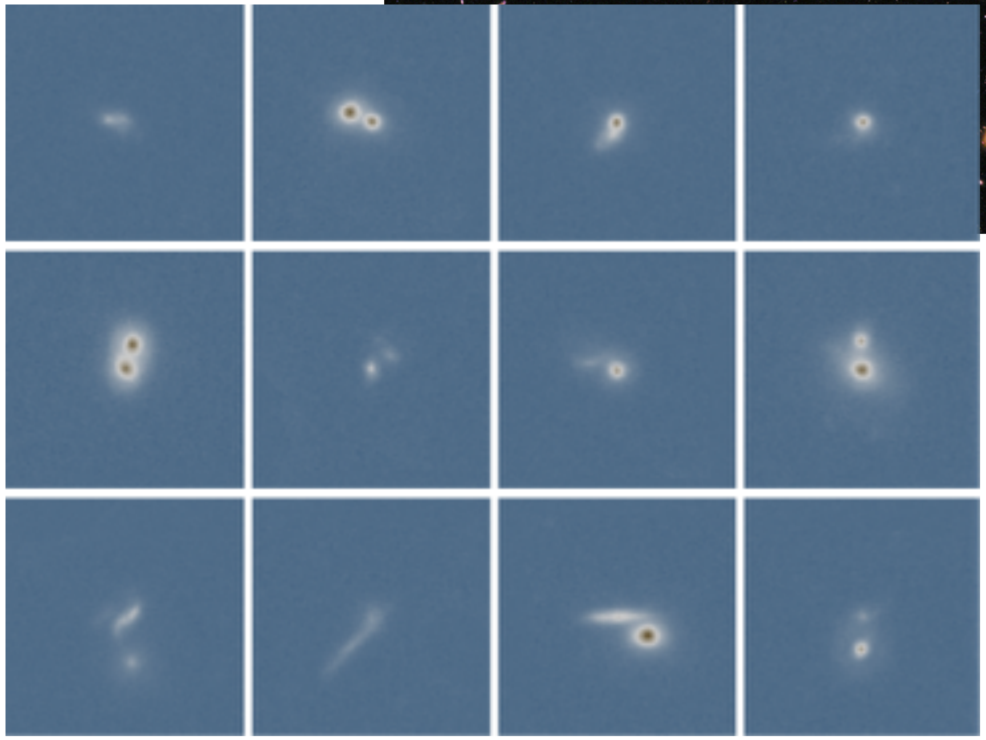
1) The deblending problem of biased photometry



Goal: ‘Good’ photometry for surveys with high blended fraction (expected), e.g. SDSS, LSST and Euclid

Add-on: Galaxy segmentation and morphology / shape (also prior for ‘classic’ methods)

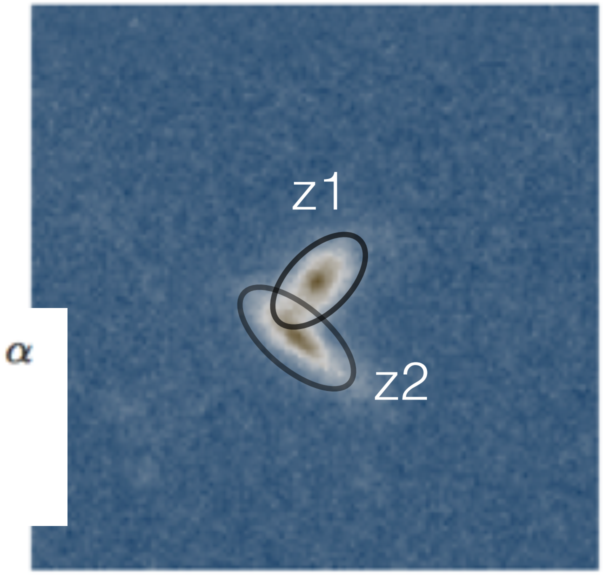
Challenge: Galaxies are ‘transparent’, separating flux in overlapping regions is difficult



‘Classic’:
Fit ellipse(s)
and profile(s)

e.g. Einasto (‘65):

$$\frac{d\log(\rho)}{d\log(r)} = -2\left(\frac{r}{r_s}\right)^{\alpha}$$



Machine learning in Astrophysics and Astronomy

1) The deblending problem of biased photometry

Credit: Euclid, ESA

Goal:
(expected), e.g. SDSS, LSST and Euclid

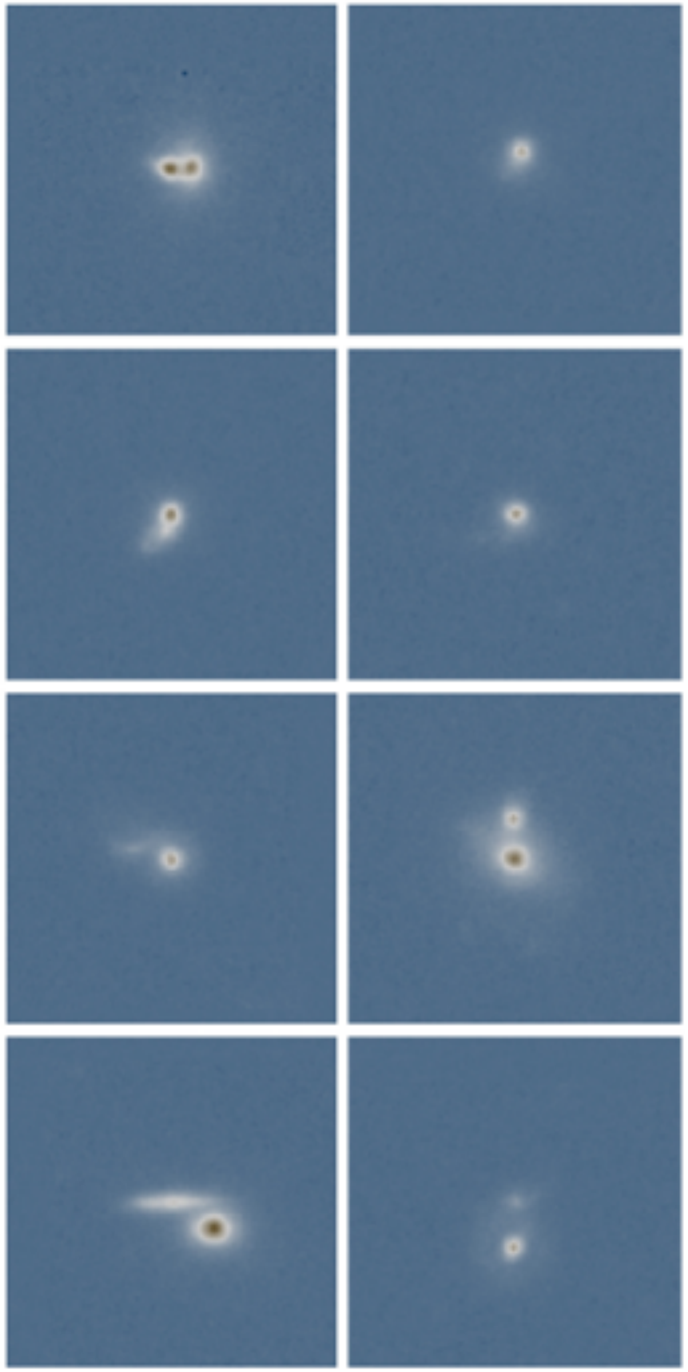
Add-on:
(also prior for ‘classic’ methods)

Machine learning in Astrophysics and Astronomy

COIN -
Cosmostatistics Initiative

A worldwide endeavour to create an interdisciplinary community around data-driven problems in Astronomy

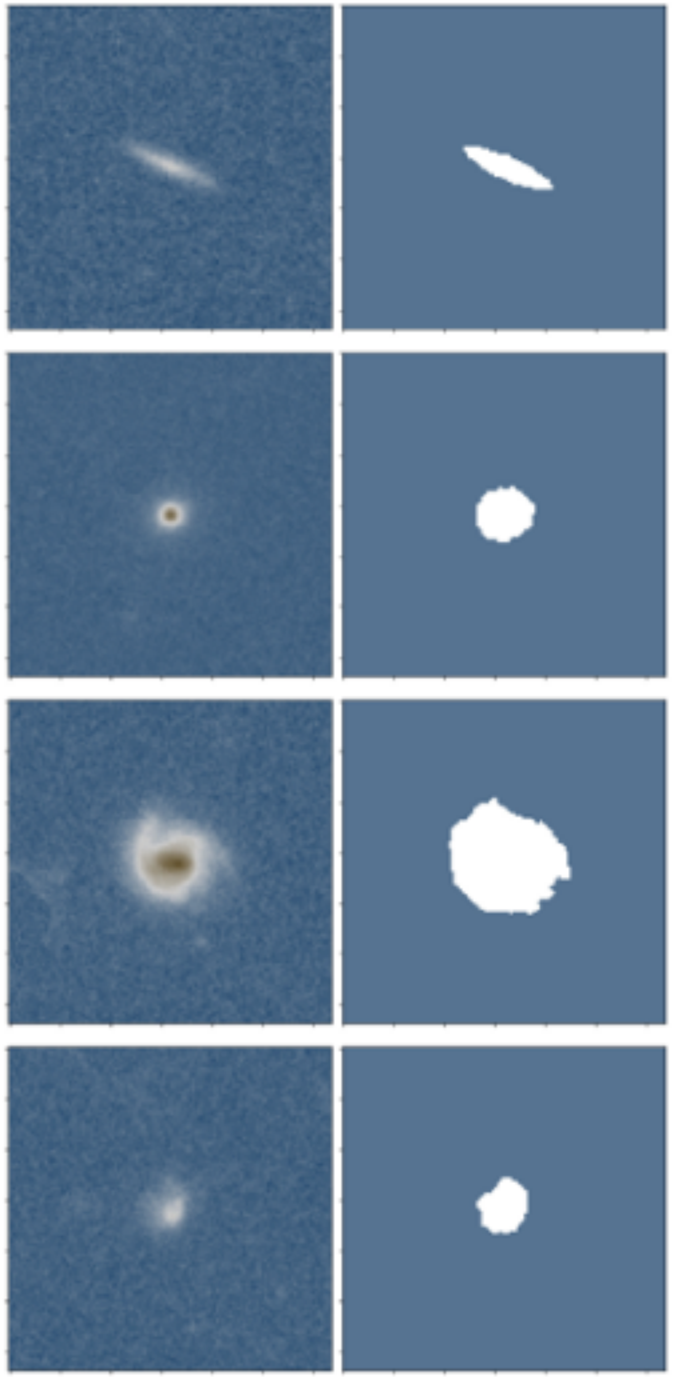
1) The deblending problem of biased photometry



Get the correct photometry

Derive masks

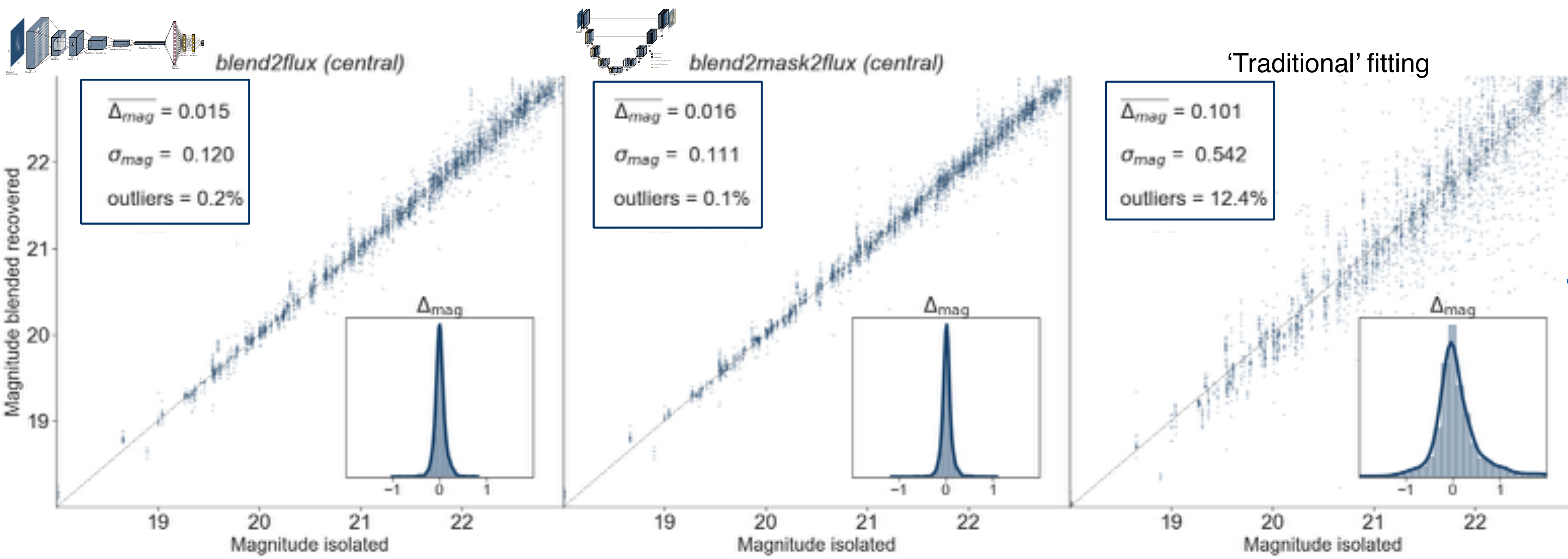
..and do so bias-free



Boucaud, Huertas-Company, Heneka+ 20

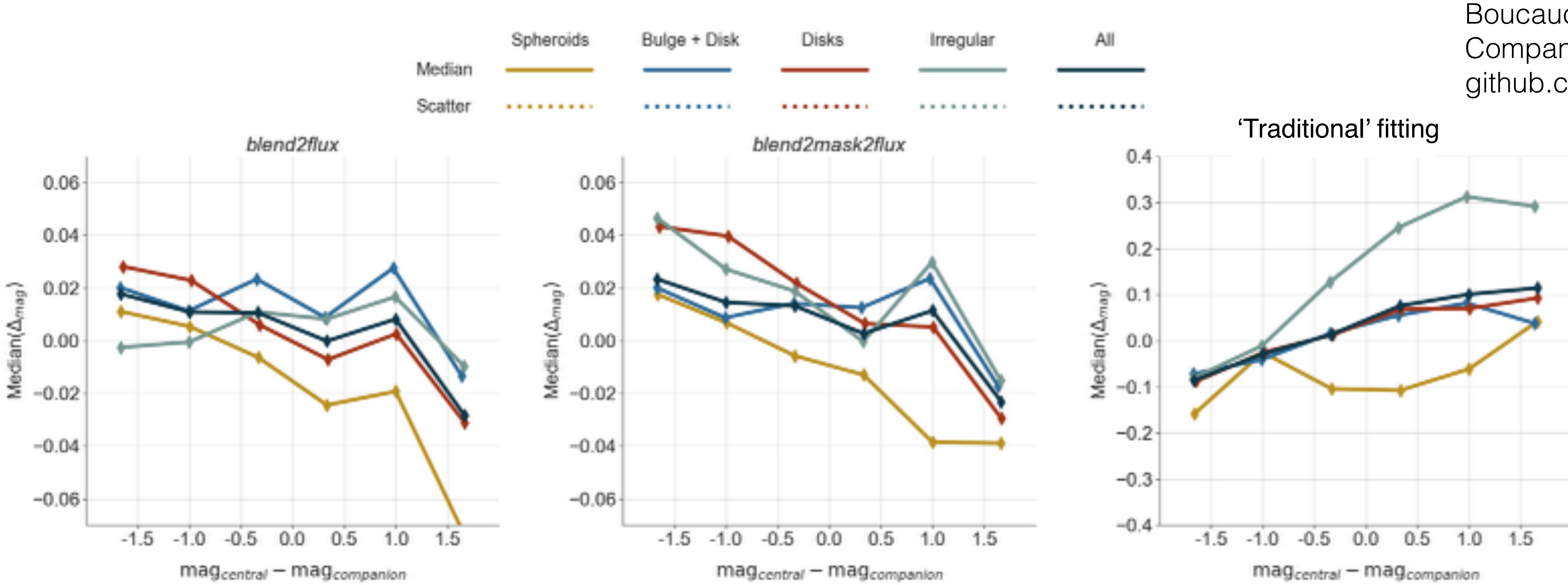
Machine learning in Astrophysics and Astronomy

1) The deblending problem of biased photometry



→ uncertainty 0.1mag << conventional

Boucaud, Huertas-Company, Heneka+ 20
github.com: coindeblend



→ small bias

Note: Trade-off segmentation vs.photometry

Machine learning in Astrophysics and Astronomy

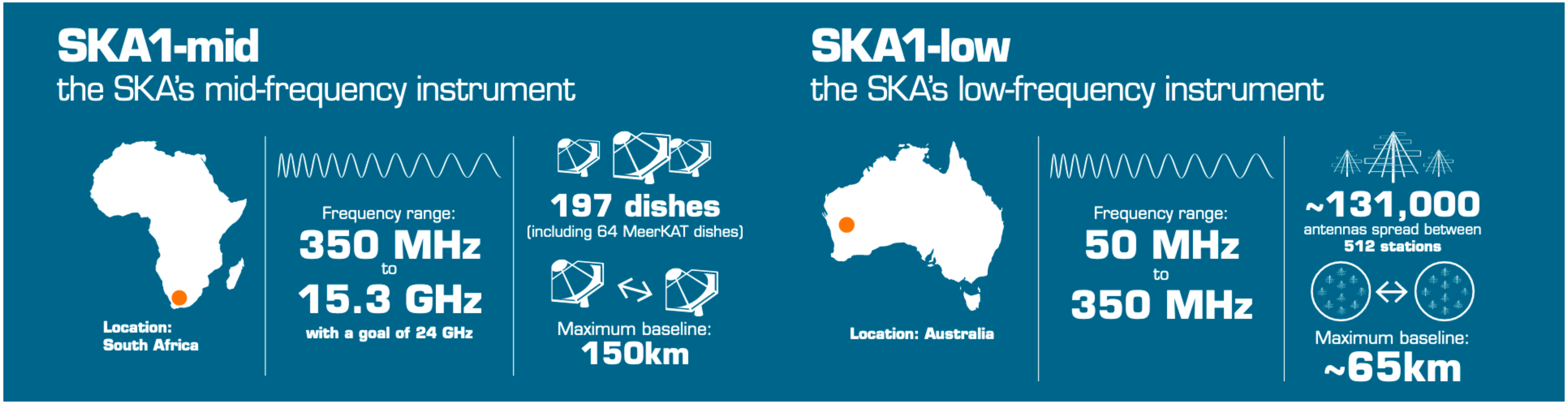
2) Detection & regression for tomography

The Square Kilometre Array (SKA) - in one slide

2) Detection & regression for tomography

SKA in numbers
- Currently 16 member countries, >100 member organisations
- Routine science observations are expected to start in the late 2020s
- Consists of thousands of dishes and up to 1 million antennas, >1km^2 collecting area
- Expected data rate in full operation: 1 TB/s

SKA-LOW SKA-MID Credits: SKAO



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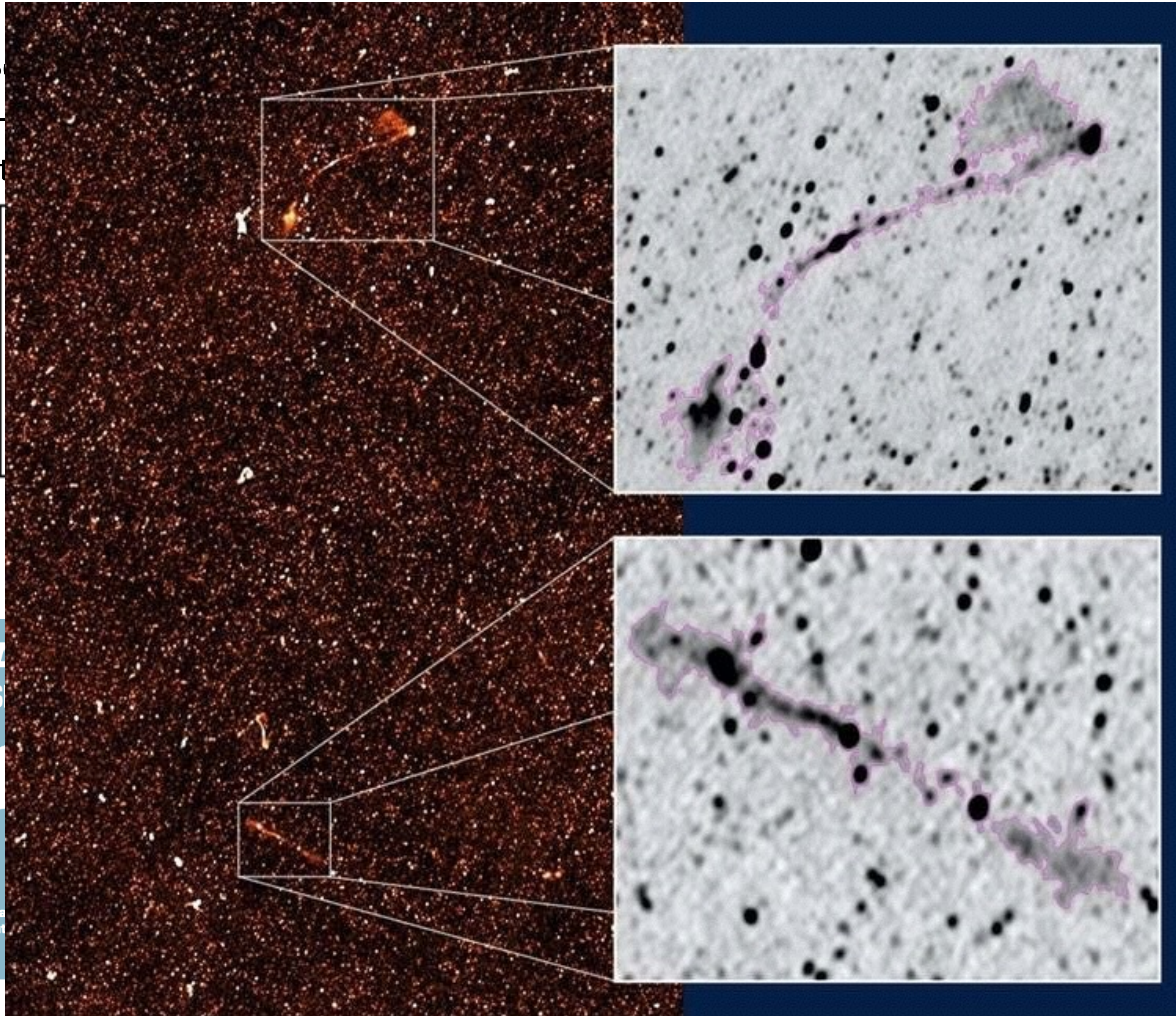

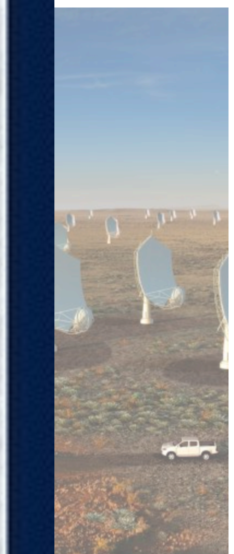

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@MeerKAT, https://doi.org/10.1093/mnras/staa3837

Machine learning in Astrophysics and Astronomy

2) Detection & regression for tomography

Source finding

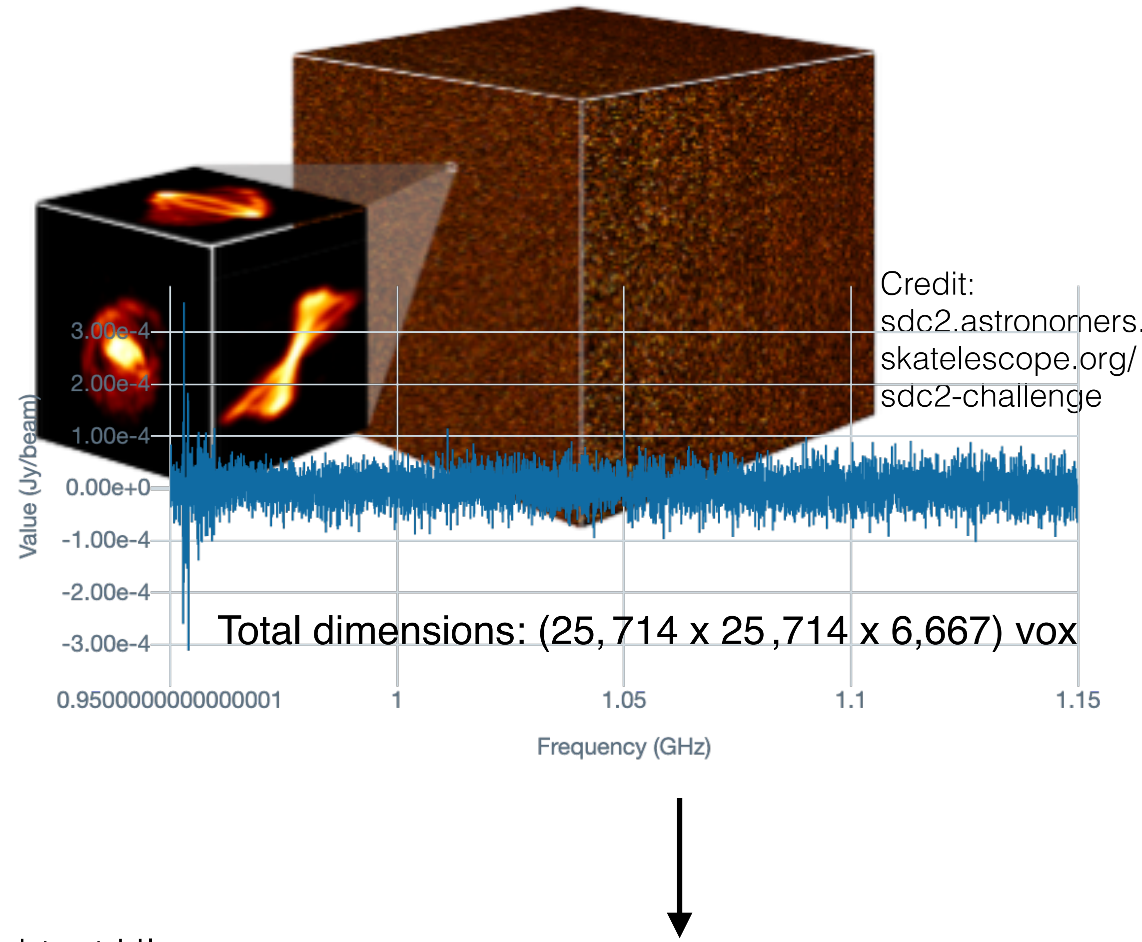
Location in RA, Dec,
central frequency (Hz)

Characterisation

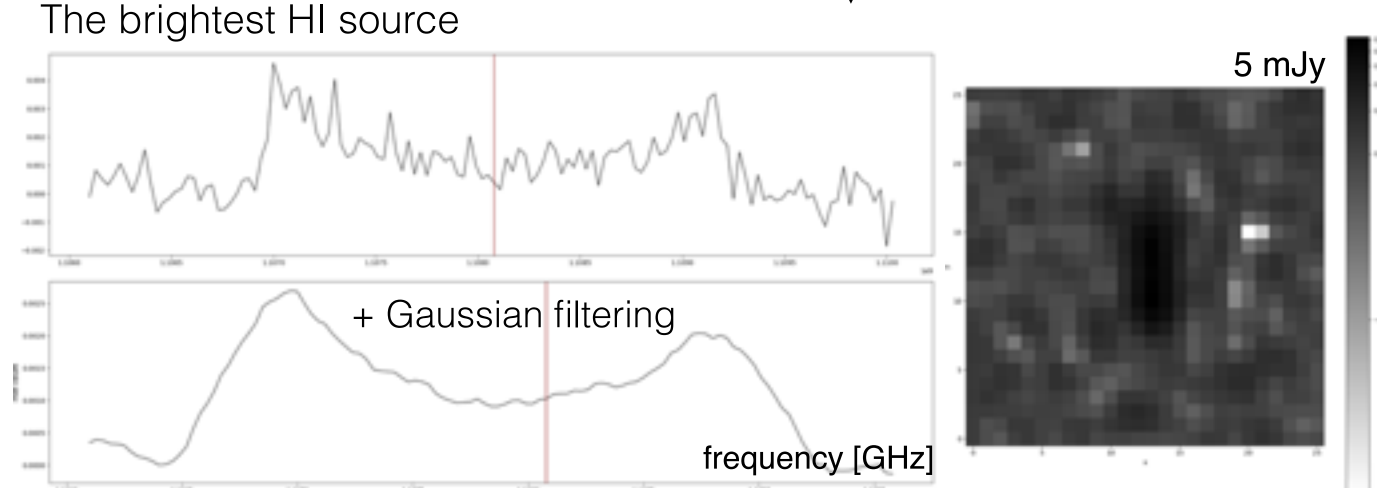
- Integrated line flux (Jy Hz)
- Line width (km/s)
- HI major axis diameter (arcsec)
- Position angle (degrees)
- Inclination angle (degrees)

The challenging HI sources:

- **low S/N**
- **small spatial size**
- **systematics**



The brightest HI source



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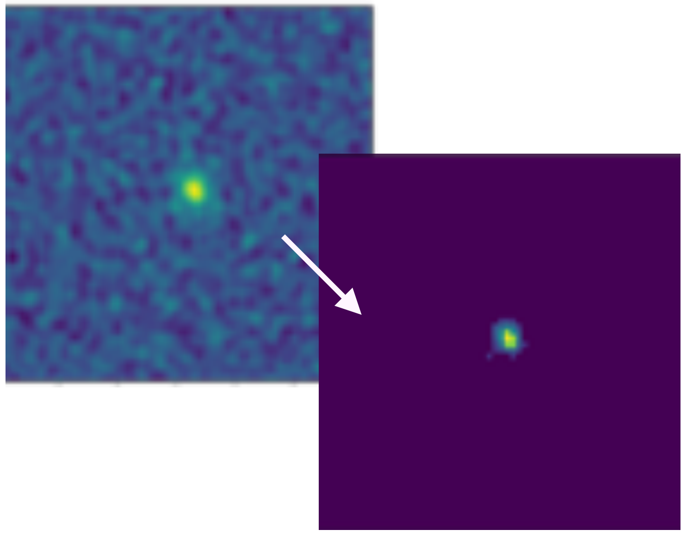
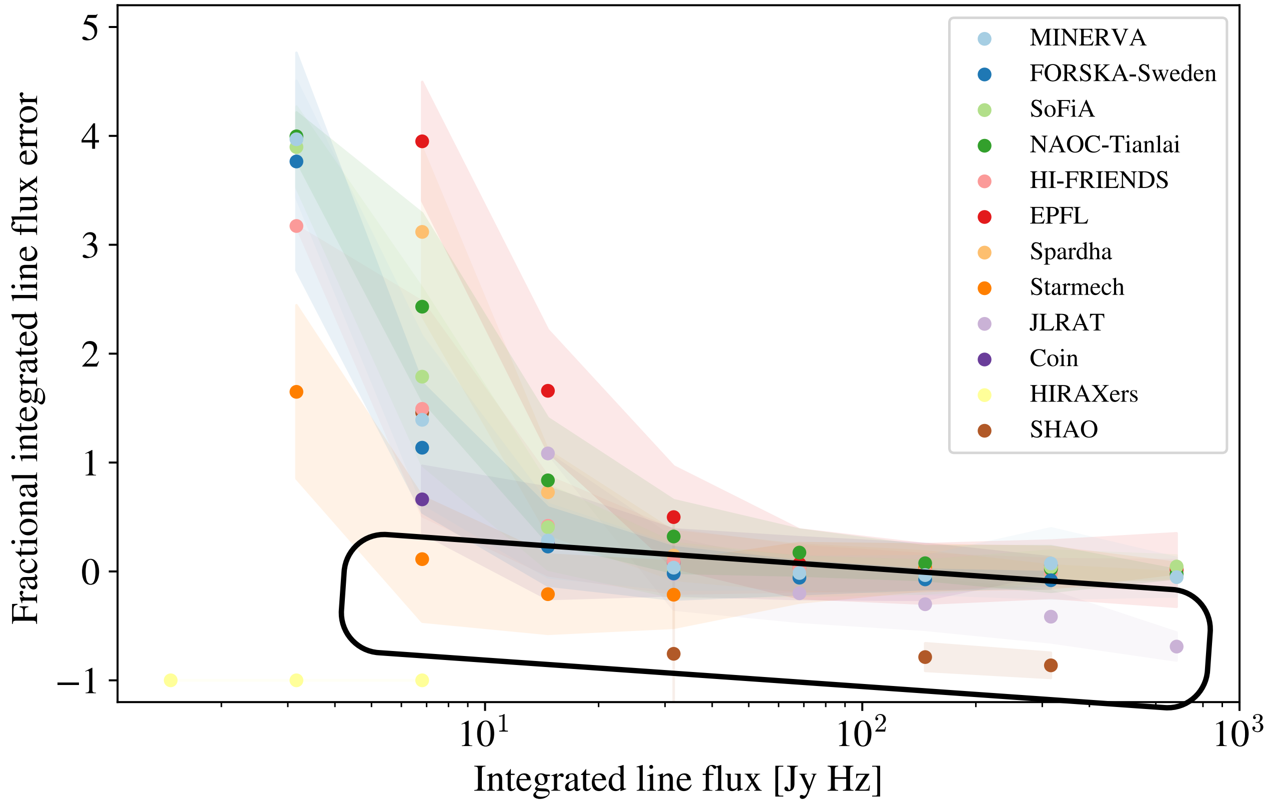
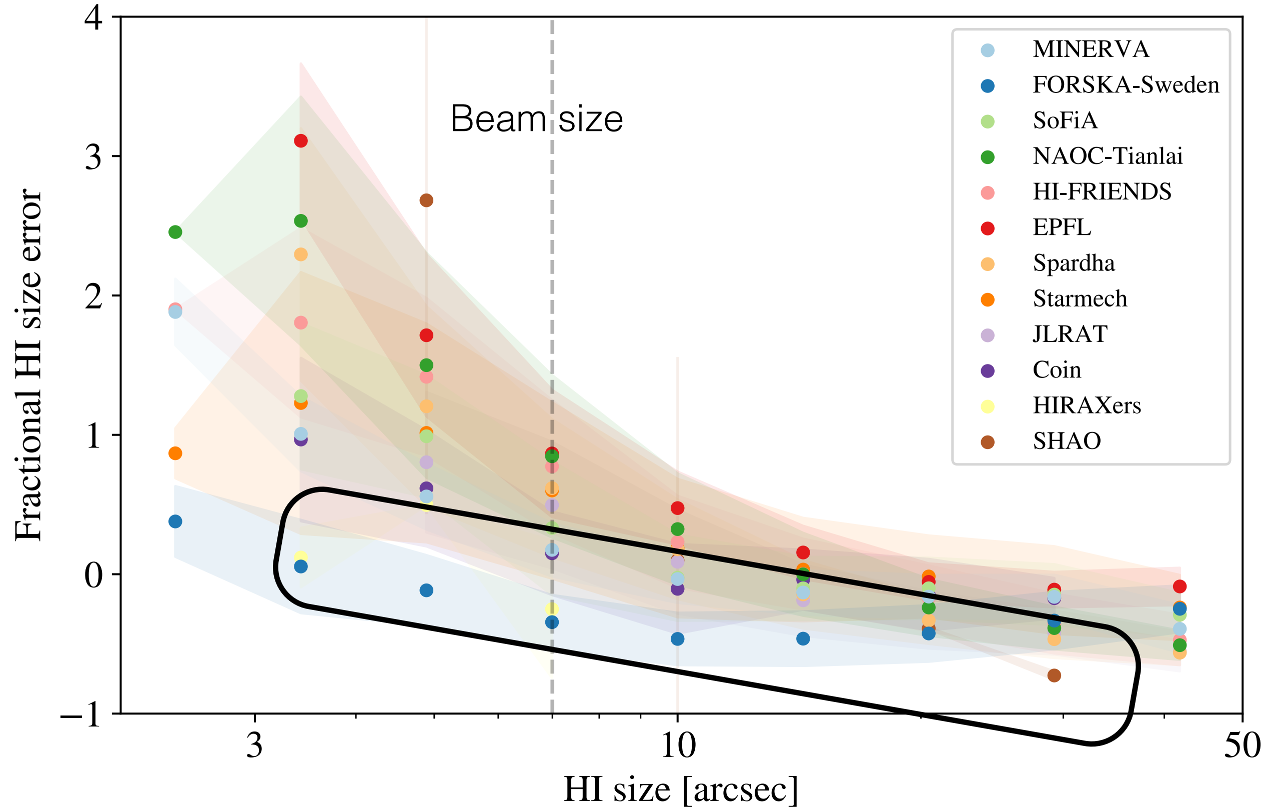
2) Detection & regression for tomography

- 3D better than stitching of 2D + 1D
- High-fidelity 3D reconstructions
- **Good prior for characterisation tasks via nets:**



Hartley+23, arXiv:2303.07943





→ Recovery across wide range in HI flux and size

Pushing to low S/N recovery came at a cost (FPs)

Take-aways:
- **Choice of training set**
  (partly) self-supervised
- Multi-step and/or ensemble decision

Machine learning in Astrophysics and Astronomy

3) Inference when faced with intractable likelihoods

Machine learning in Astrophysics and Astronomy

3) Inference when faced with intractable likelihoods

<u>Tomographic surveys of the large-scale structure:</u>

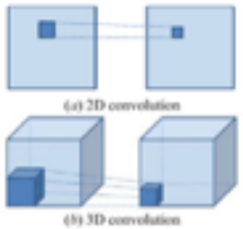
MCMC not feasible anymore
Covariance intractable

Various Options:

- Slicing and treatment with 2D CNN as image → ‘standard’ **2D CNN**, residual (skip connections) **ResNet**
- Time series (frequency) of co-eval images → **LSTM** network
- Full 3D convolution → 3D CNN:

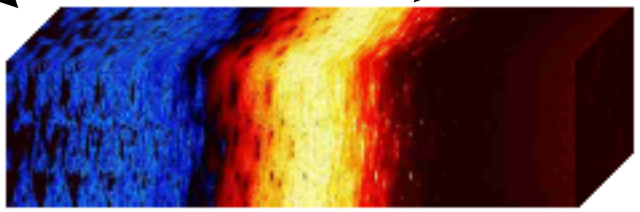
[see e.g. Prelogovic+ arXiv: 2107.00018, Gillet+2019]

Moving from **2D to full 3D convolution**



<u>cosmic reionisation</u>
‘the last big phase transition’

<u>cosmic dawn</u>
‘first stars and galaxies’



parameter regression ?

likelihood inference →

See talk by
Benedikt Schosser

3D-21cmPIE-Net

Neutsch, Heneka, Brüggen
MNRAS (2022)
arXiv:2201.07587

Machine learning in Astrophysics and Astronomy

4) On-the-fly classification of the unexpected (spectra)

Machine learning in Astrophysics and Astronomy

4) On-the-fly classification of the unexpected (spectra)

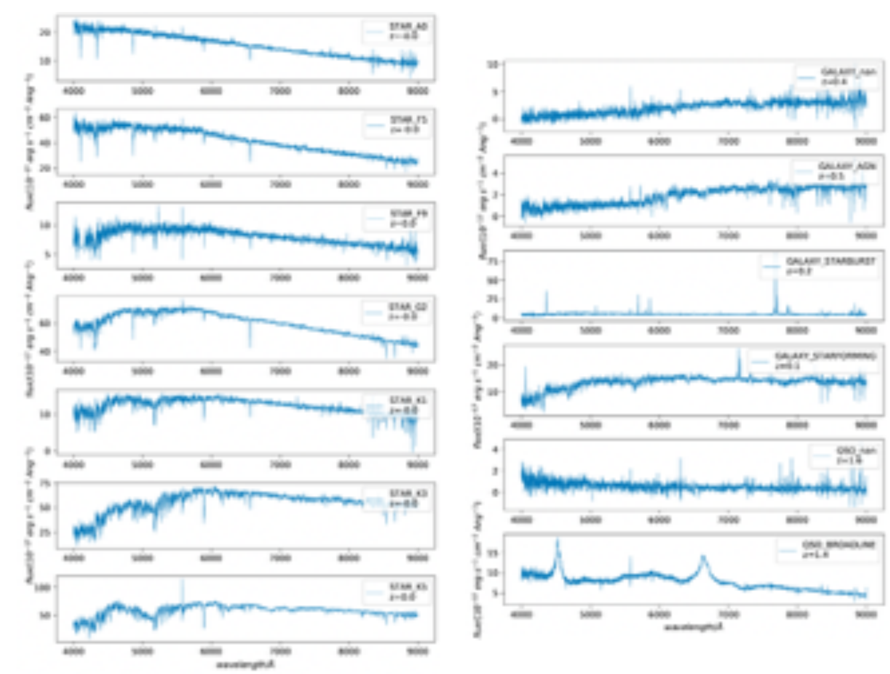
https://www.4most.eu Credit: ESO

- 5-year survey
- wide-field, fibre-fed, optical spectroscopy
- on ESO's 4-m-class telescope VISTA
- 2.5-degree diameter field-of-view, 2436 fibres
- HRS R ≈ 18000 – 21000, LRS R ≈ 4000 – 7500
- 20mio. (LRS), 3mio. (HRS) sources

Goal: Data-driven classification layer between L1 and L2 pipelines

- **Galactic & extragalactic source classification**

  → Probabilistic multiclassifier



- **Feedback on a) targets, b) 'unknown' class**

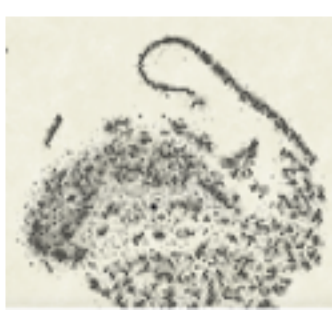
  Currently set-up:

  4MOST explorer t-SNE

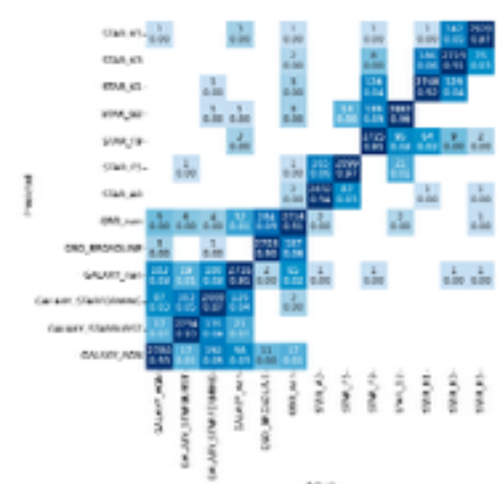
  (Gregor Traven, Gal Matijevic)

  arXiv: 1612.02242

  VAE network in testing



Benchmark with SDSS spectra: Convolutional network variants, BNN class uncertainties

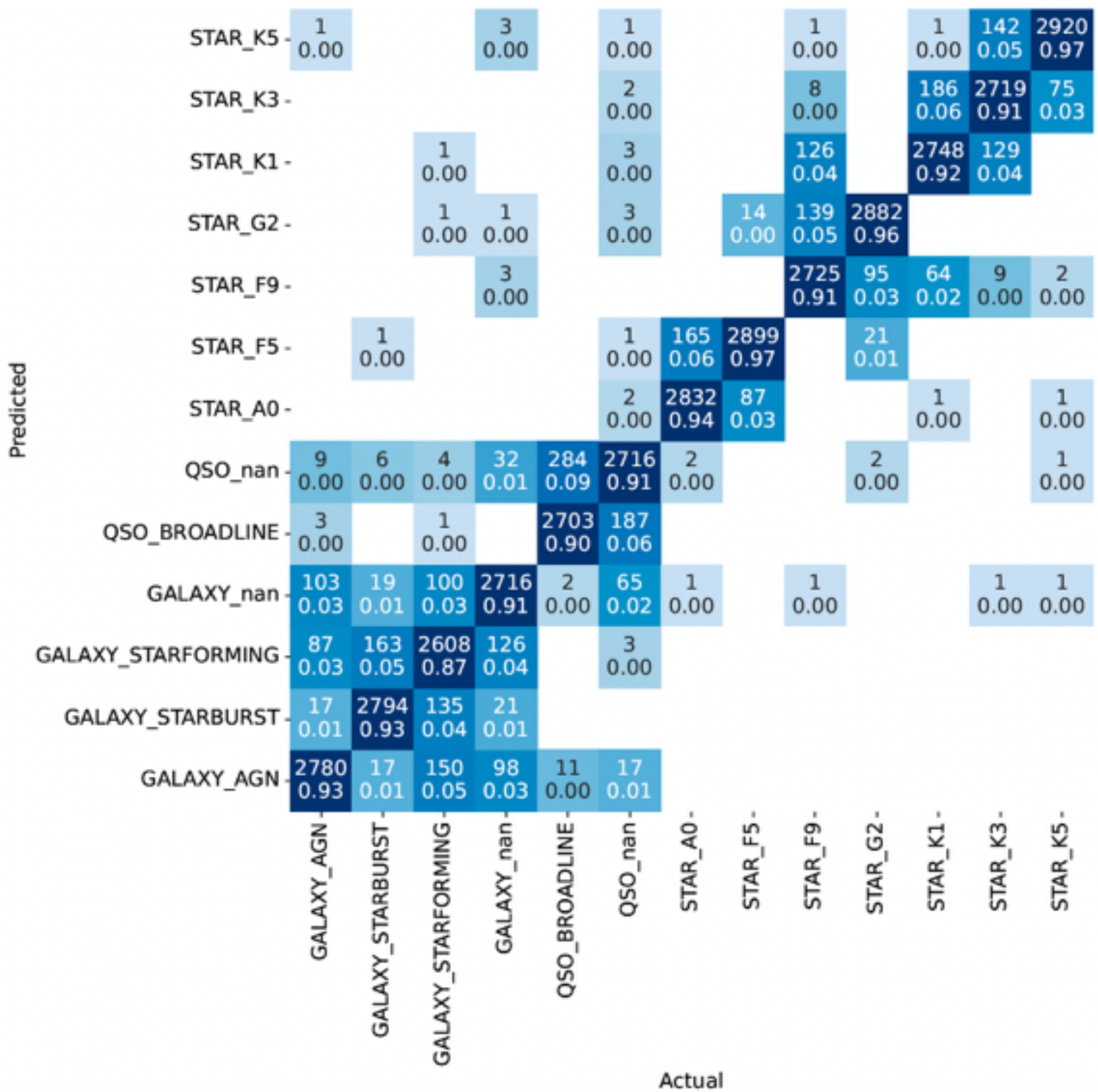


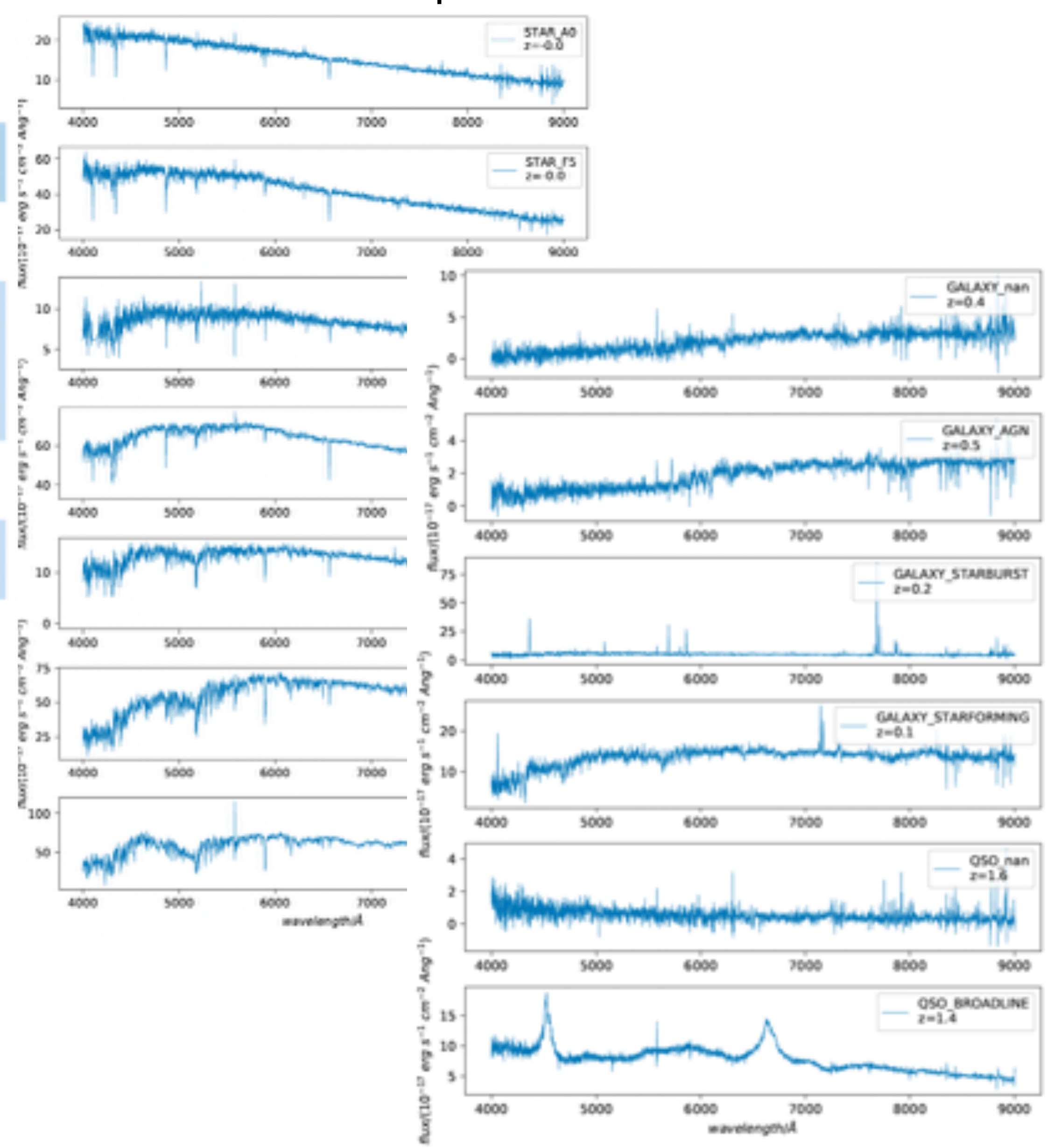
@Fucheng Zhong, arXiv:2311.033xx

Machine learning in Astrophysics and Astronomy

https://www.4most.eu Credit: ESO

4) On-the-fly classification of the unexpected (spectra)





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Machine learning in Astrophysics and Astronomy

From problems to the unexpected & new

5) Cosmology with one galaxy

Machine learning in Astrophysics and Astronomy

= Cosmology and Astrophysics with MachinE Learning Simulations

https://camels.readthedocs.io

5) Cosmology with one galaxy

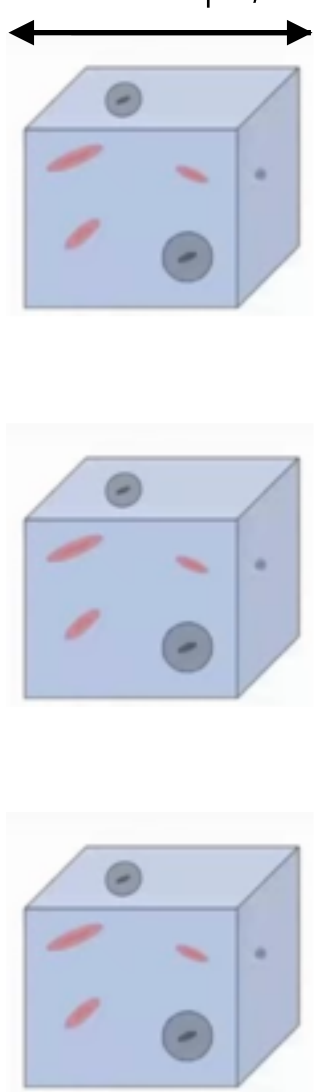
How many galaxies do we need to constrain e.g. Ω_m?

25cMpc/h

$\Omega_m = 0.27$
$\sigma_8 = 0.85$
$A_{SN1} = 0.7$
$A_{SN2} = 0.9$
$A_{AGN1} = 1.4$
$A_{AGN2} = 0.8$

$\Omega_m = 0.4$
$\sigma_8 = 0.65$
$A_{SN1} = 1.1$
$A_{SN2} = 0.9$
$A_{AGN1} = 1.1$
$A_{AGN2} = 0.9$

$\Omega_m = 0.2$
$\sigma_8 = 0.95$
$A_{SN1} = 1.8$
$A_{SN2} = 0.5$
$A_{AGN1} = 3.0$
$A_{AGN2} = 1.5$



random galaxy: $\longrightarrow$ galaxy properties

$$\begin{bmatrix} M_* \\ \mathrm{K} \\ M_g \\ Z_g \\ V_{max} \\ Z_* \\ \mathrm{g} \\ \sigma_v \\ R_* \\ M_t \\ \mathrm{U} \\ R_t \\ R_{max} \\ \mathrm{SFR} \\ J \\ \mathrm{V} \\ M_{bh} \end{bmatrix}$$

O(10^4) galaxies per cube

Machine learning in Astrophysics and Astronomy

5) Cosmology with one galaxy

How many galaxies do we need to constrain e.g. Ω_m?

= Cosmology and Astrophysics with MachinE Learning Simulations

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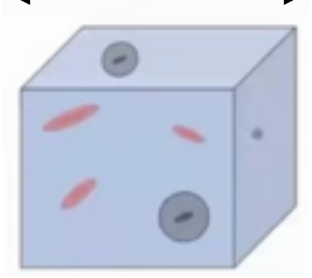

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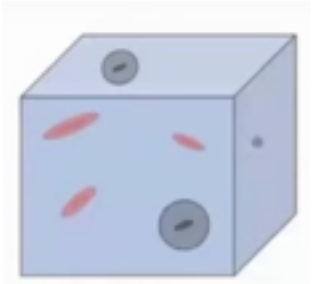

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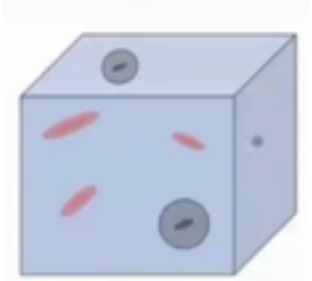
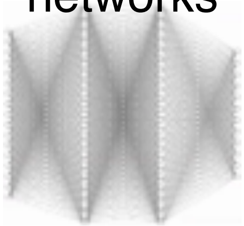


O(10^4) galaxies per cube

random galaxy: → galaxy properties

$$\begin{bmatrix} M_* \\ K \\ M_g \\ Z_g \\ V_{max} \\ Z_* \\ g \\ \sigma_v \\ R_* \\ M_t \\ U \\ R_t \\ R_{max} \\ SFR \\ J \\ V \\ M_{bh} \end{bmatrix}$$

Moment density networks



arXiv:2011.05991

→ ?

Ω_m
$\delta\Omega_m$

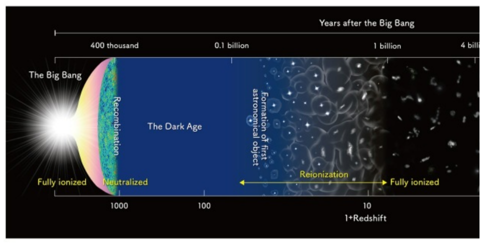
~10% uncertainty

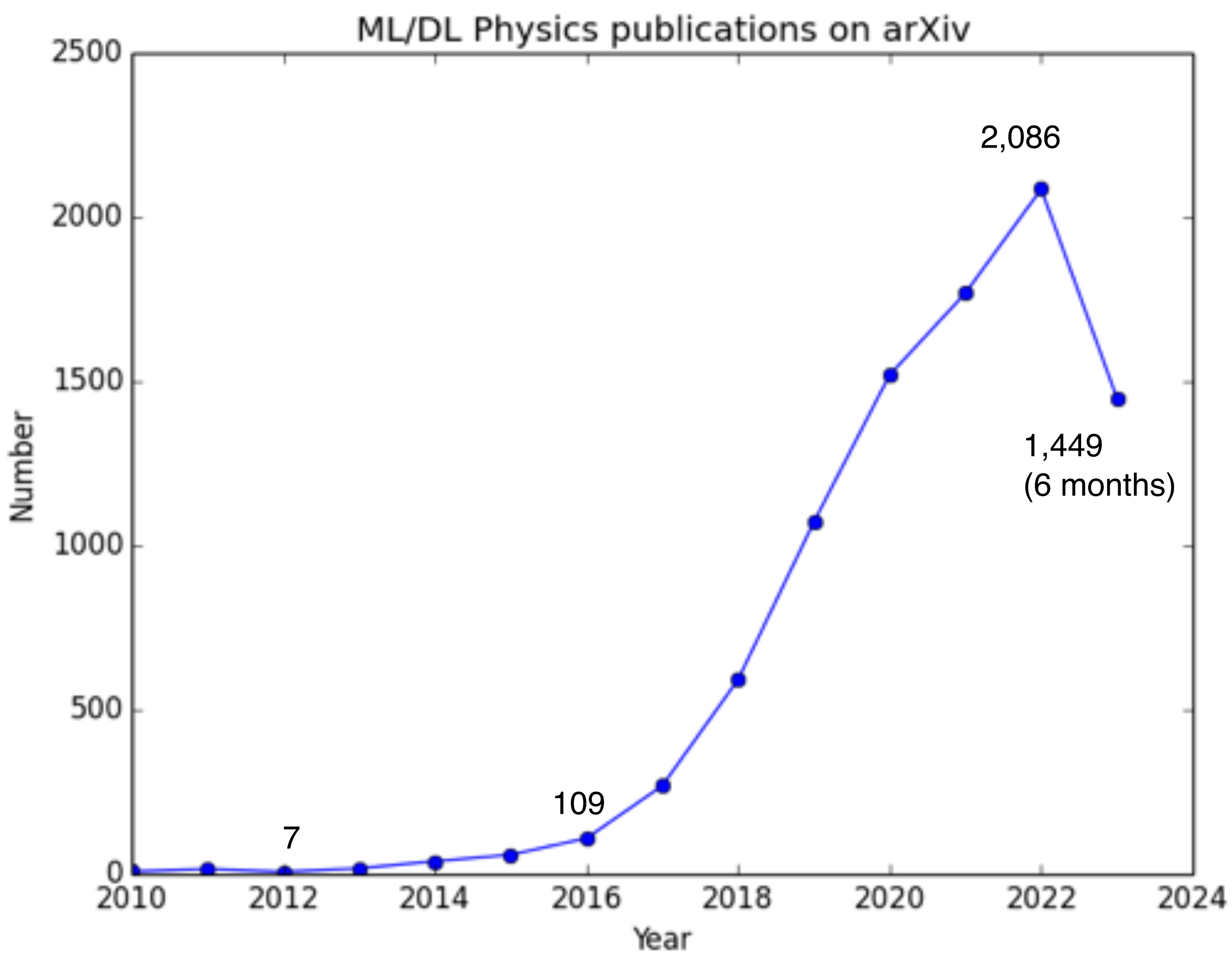
recovery of matter density for very different masses (and environments)
<u>also</u>: holds for redshifts other than z=0

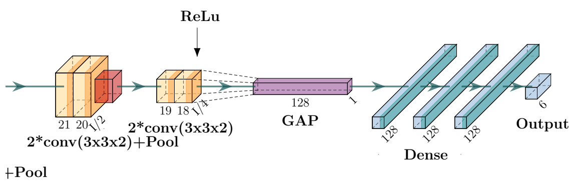
connections on a high dimensional manifold?

Machine learning in Astrophysics and Astronomy

Why care?



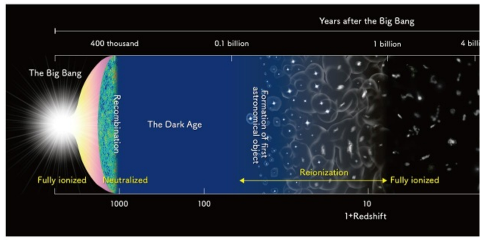


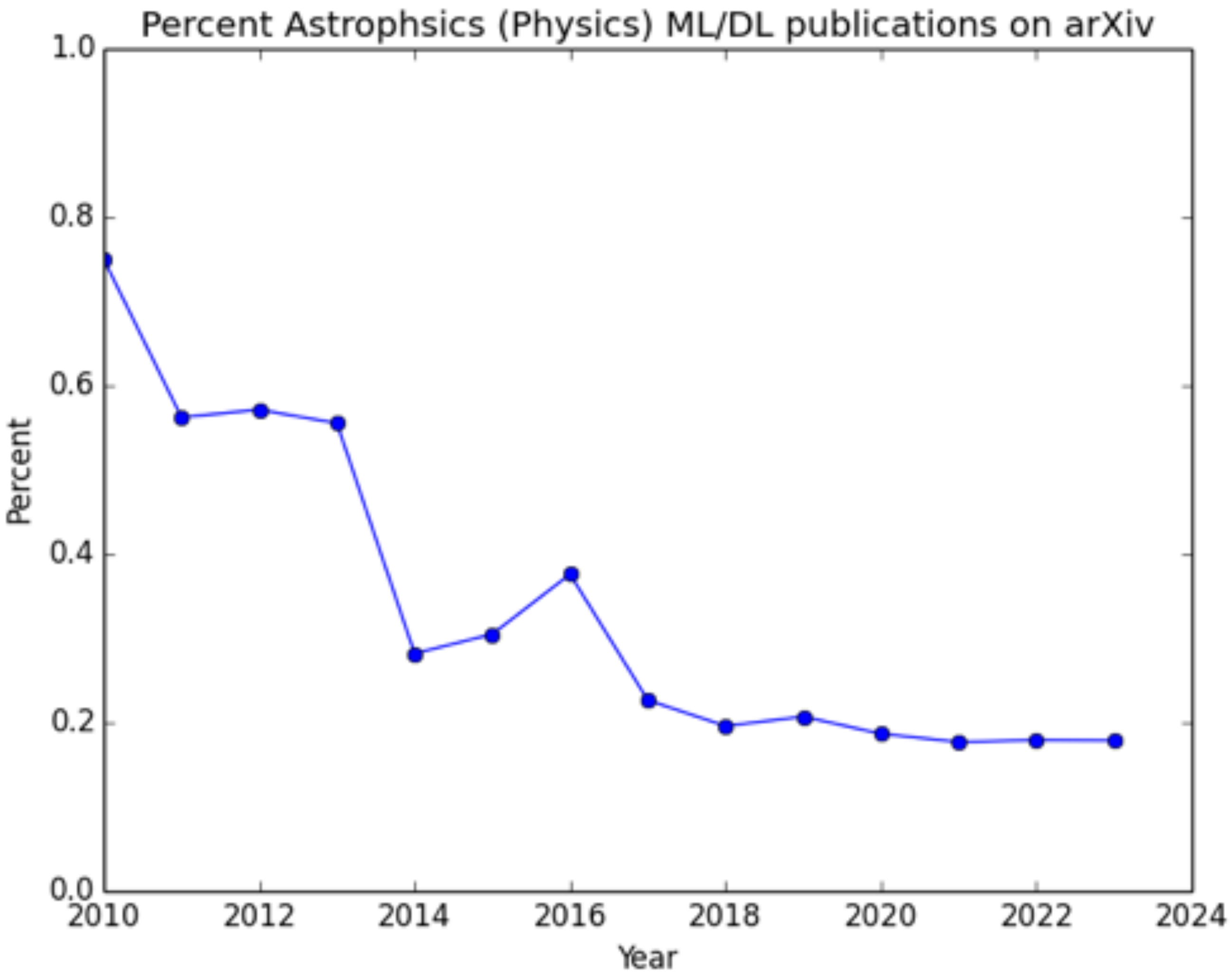


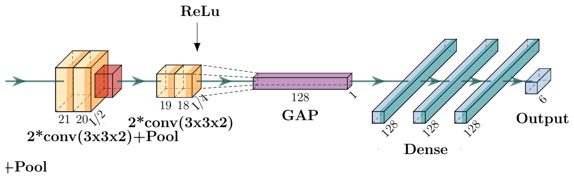
From: 17.07.2023 Astrophysics & ML/DL - MITP Summer School

Machine learning in Astrophysics and Astronomy

Why care?





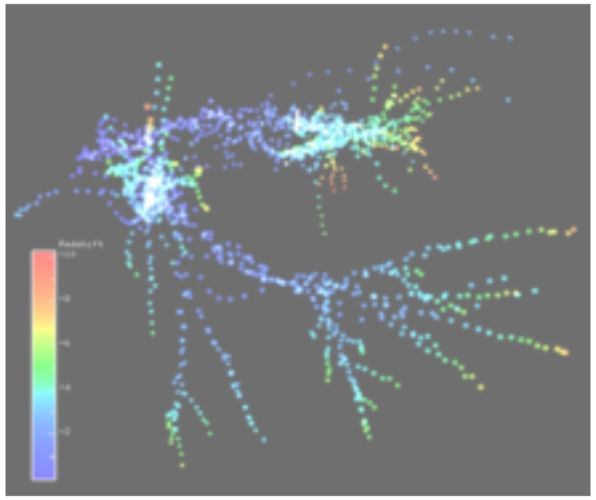


From: 17.07.2023 Astrophysics & ML/DL - MITP Summer School

Machine learning in Astrophysics and Astronomy

A zoo of applications and data is waiting for you!

- detection, segmentation
- classification
- regression, inference
- anomaly detection
- generation, emulation, …

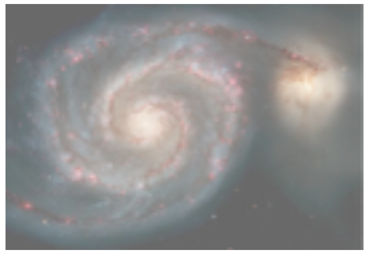


@Chris Fluke, Swinburne University of Technology

+ plenty of inverse problems

$$I^D(x, y) = R \times I(x, y) + n$$

Hierarchical



@Hubble, NASA

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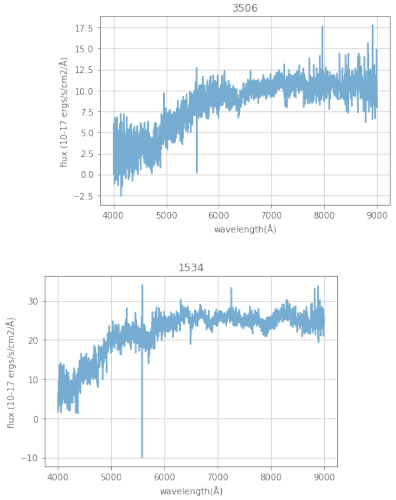
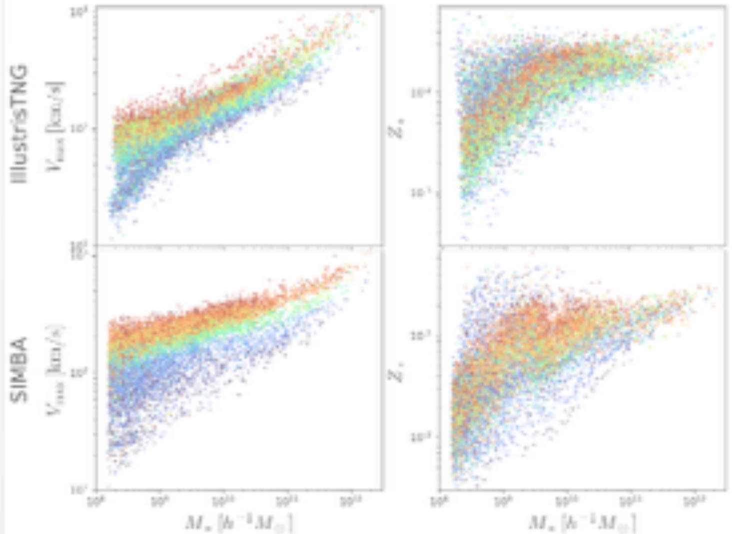


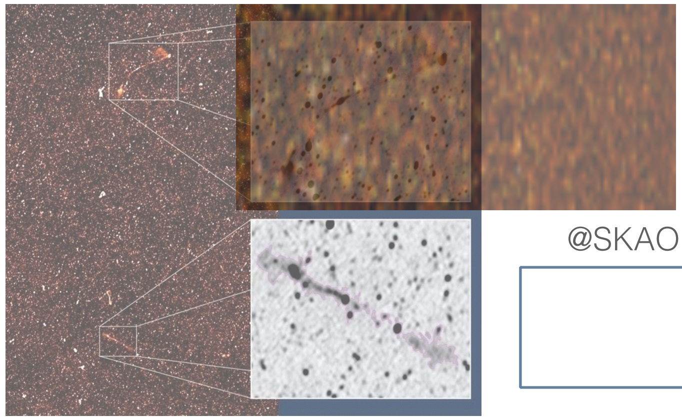
@SDSS

Representation learning

High-dim. correlations



arXiv:2201.02202



@SKAO

@MeerKAT

Non-linear, non-Gaussian