



Networks Learning the Universe:

From 3D (cosmological inference) to 1D (classification of spectra)

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‘Computer Vision Astrophysics’ and observational cosmology group
@Institute for Theoretical Physics, Heidelberg University

EuCAIFcon2024, Amsterdam, April 30th 2024

Collaborators and students* (non-comprehensive):

Lara Alegre, Benedikt Schosser*, Tilman Plehn, Yannic Pietschke*, Tim Ullrich*,
Steffen Neusch*, Marcus Brüggen, Fucheng Zhong*, Nicola Napolitano, Simon Barton*



Our goal

Learn about cosmology, large-scale structure, and galaxy evolution using data from large astronomical surveys and developing the suitable modern ML & AI toolkit.

Our research:

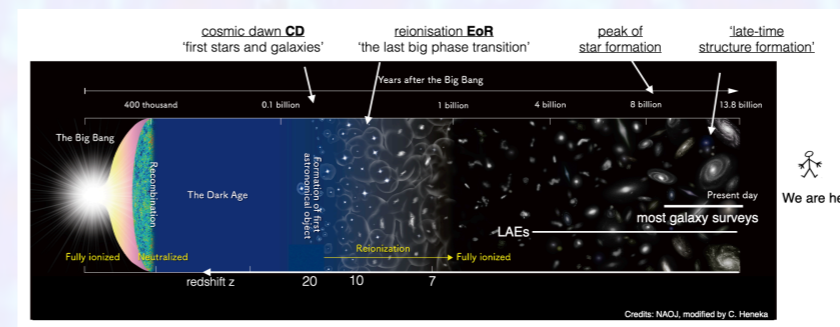
- Computational astrophysics / cosmology
- Intensity mapping
- Large (radio) surveys, SKA & LOFAR

Specifically the modern ML toolkit for cosmology and large-scale surveys:

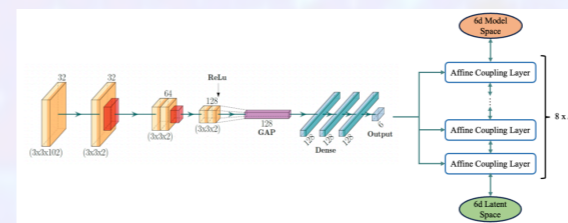
- Emulation, generation
- Inference

Also:

- Classification, anomaly detection
- **Computer Vision tasks in astronomy**



+



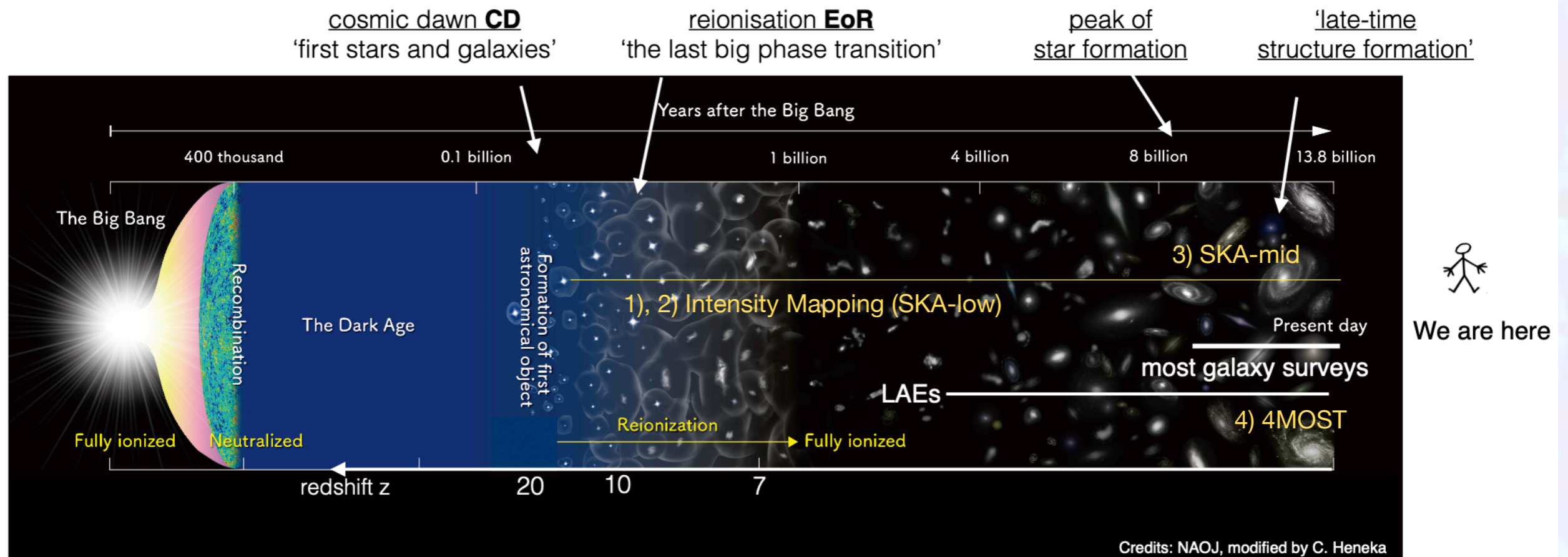
Group 'Computer Vision Astrophysics' and observational cosmology:

Lara Alegre (postdoc), Yannic Pietschke (PhD student), Vrund Patel (PhD student), Tom Schlenker (M.Sc. student), Abdulmalik Kara (M.Sc. student), Thomas Blankenburg (M.Sc. student), Marius Booz (B.Sc. student), Maitri Purohit (student assistant)



This Talk

- 1) Simulation-based inference (SBI) in 3D
- 2) Generative methods for simulation
- 3) Source detection & characterisation
- 4) Classification / Triggering



1) Simulation-based inference (SBI) for intensity mapping (3D)

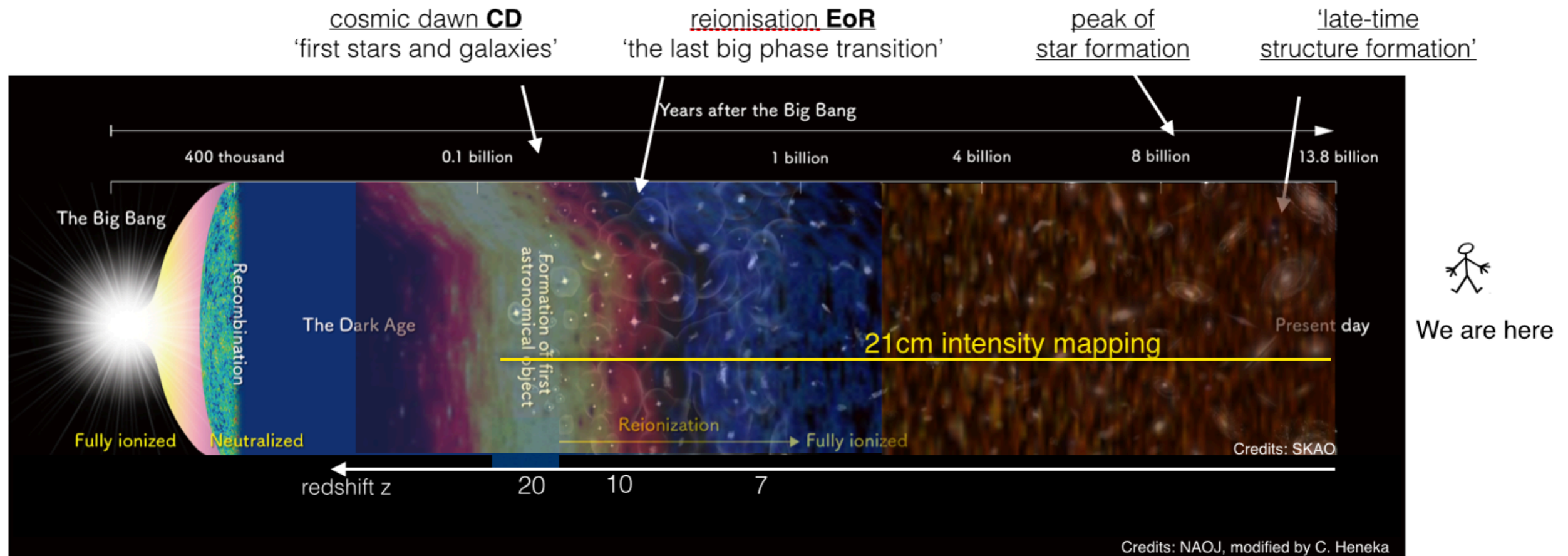
21cm signal

a tracer of neutral hydrogen:

$$\delta T_b(\nu) = \frac{T_S - T_\gamma}{1+z} (1 - e^{-\tau_{\nu 0}})$$

$$\propto x_{\text{HI}} (1 + \delta_{\text{nl}}) \left(\frac{H}{dv_r/dr + H} \right)$$

Why care?
Tomography of >80% of the Universe



1) Simulation-based inference (SBI) for intensity mapping (3D)

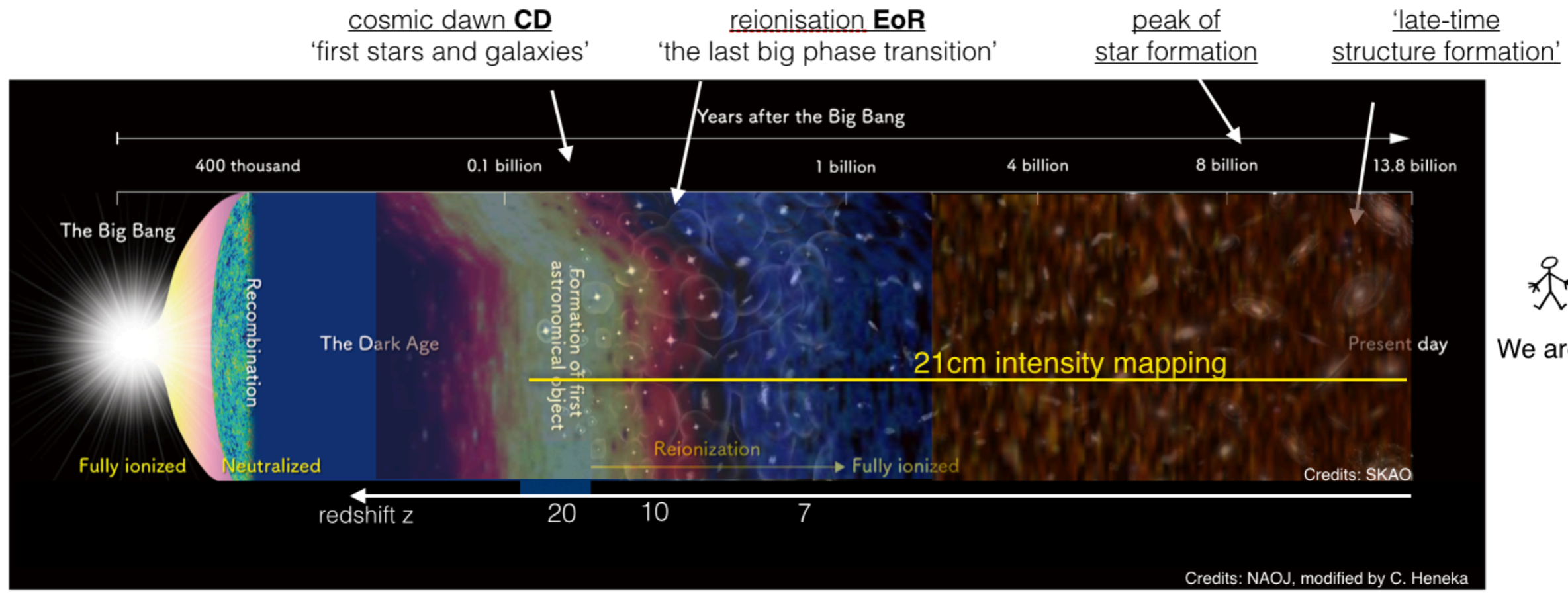


Why care?
 Tomography of >80% of the Universe
 Square Kilometre Array - true 'Big Data'
 non-linear, non-Gaussian signal

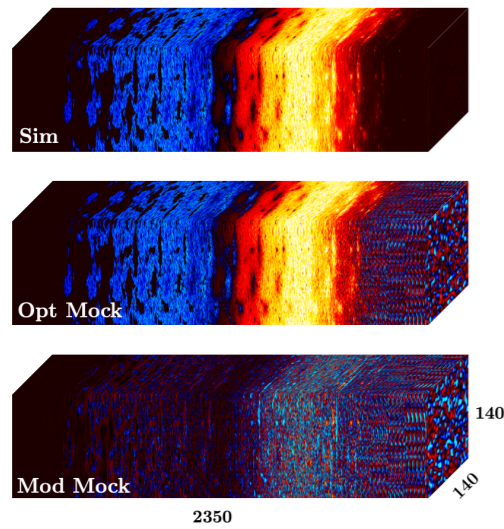
Expected data SKA rate:
 TB/s, few EB/day
 Archive: ~700 PB/yr



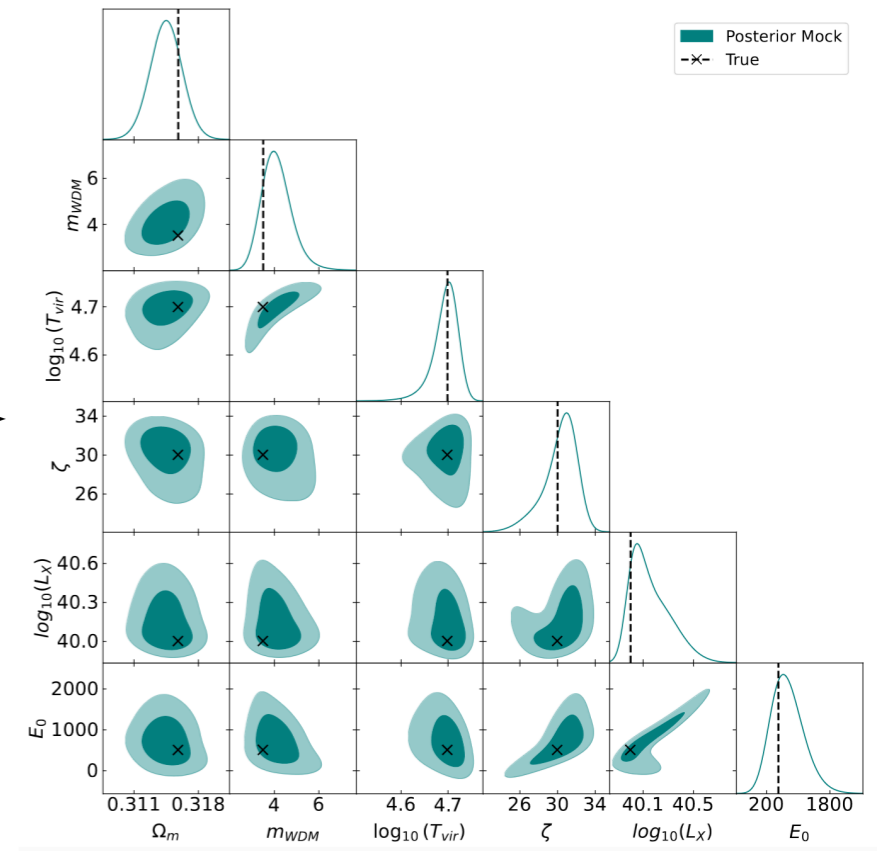
Move to full likelihood inference with networks



1) Simulation-based inference (SBI) for intensity mapping (3D)



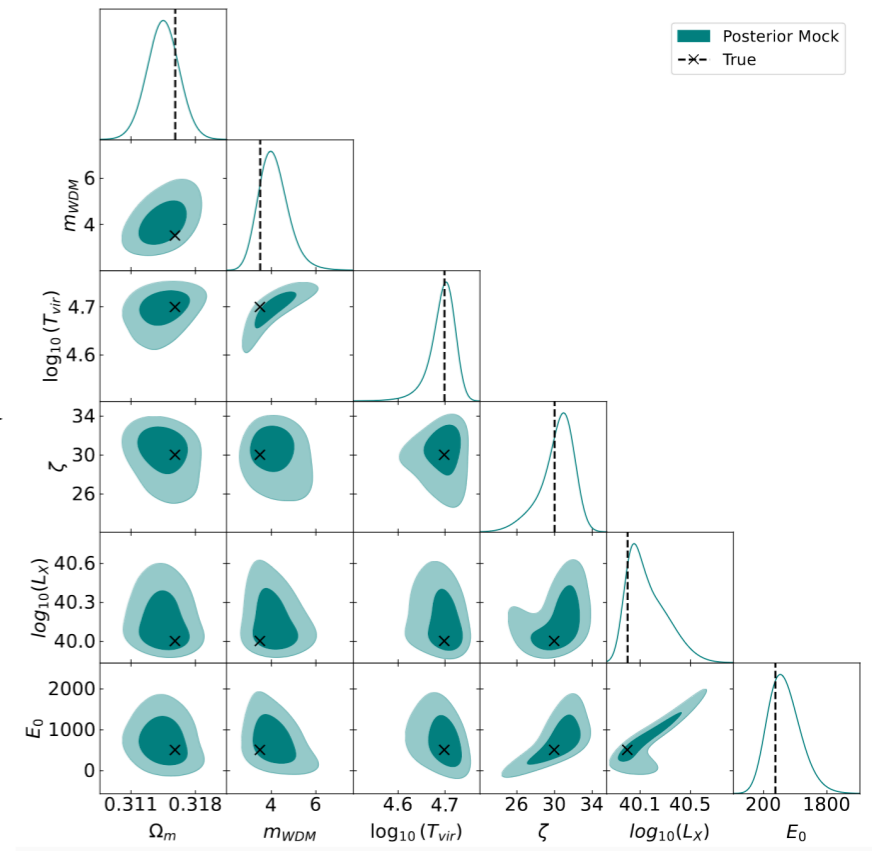
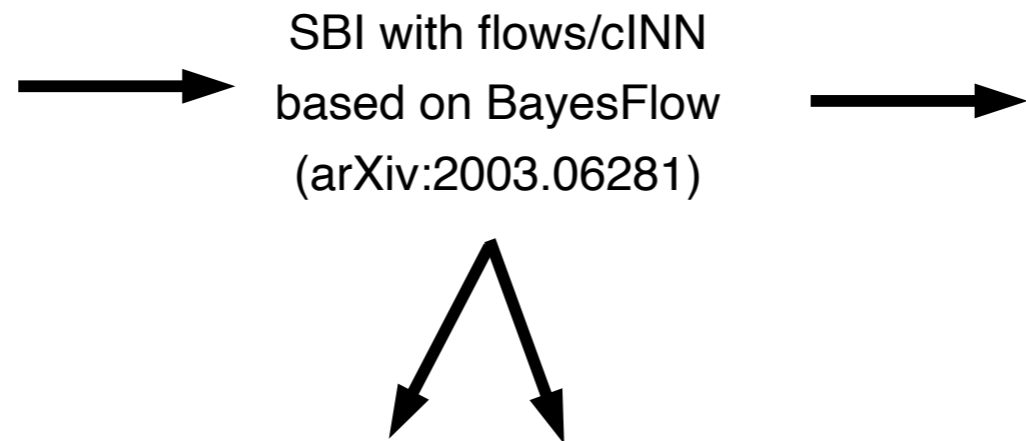
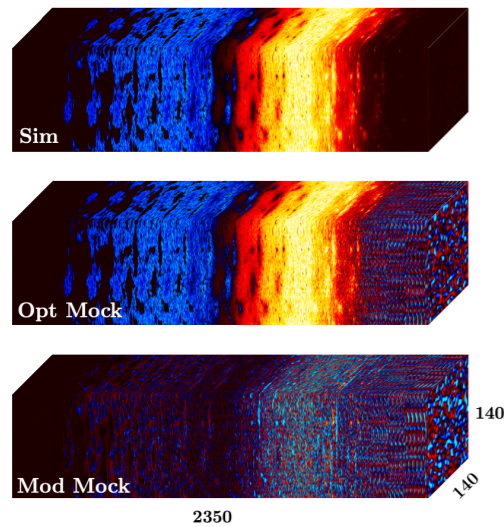
?




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

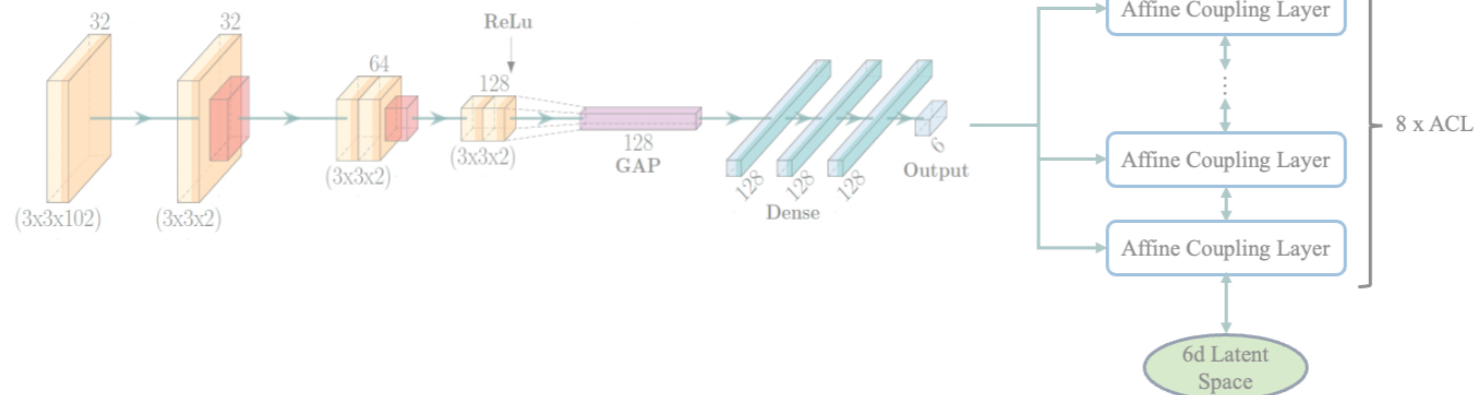
Schosser, Heneka, Plehn, arXiv:2401.04174

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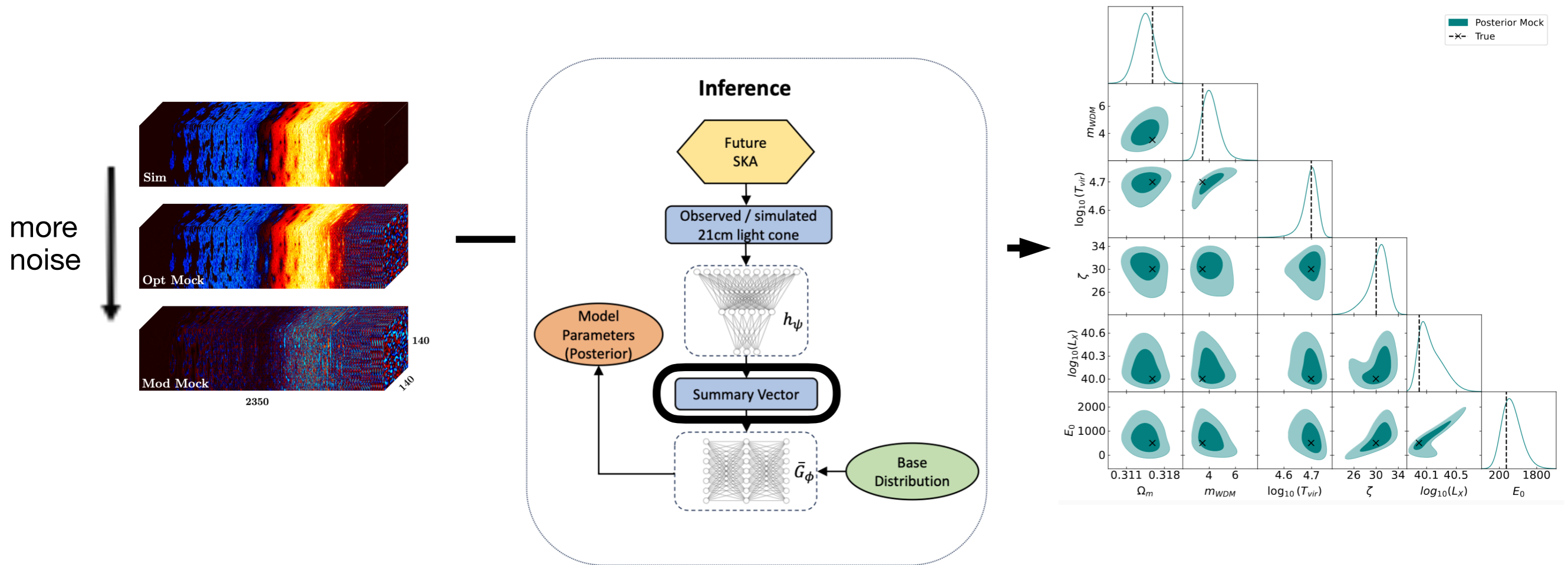


 3D-21cmPIE-Net (public)
Neutsch, Heneka, Brüggem (2022)
arXiv:2201.07587

+  21cm-cINN (public when published)
Schosser, Heneka, Plehn, arXiv:2401.04174



1) Simulation-based inference (SBI) for intensity mapping (3D)



BayesFlow, arXiv:2003.06281

Neutsch, Heneka, Brügger (2022), arXiv:2201.07587

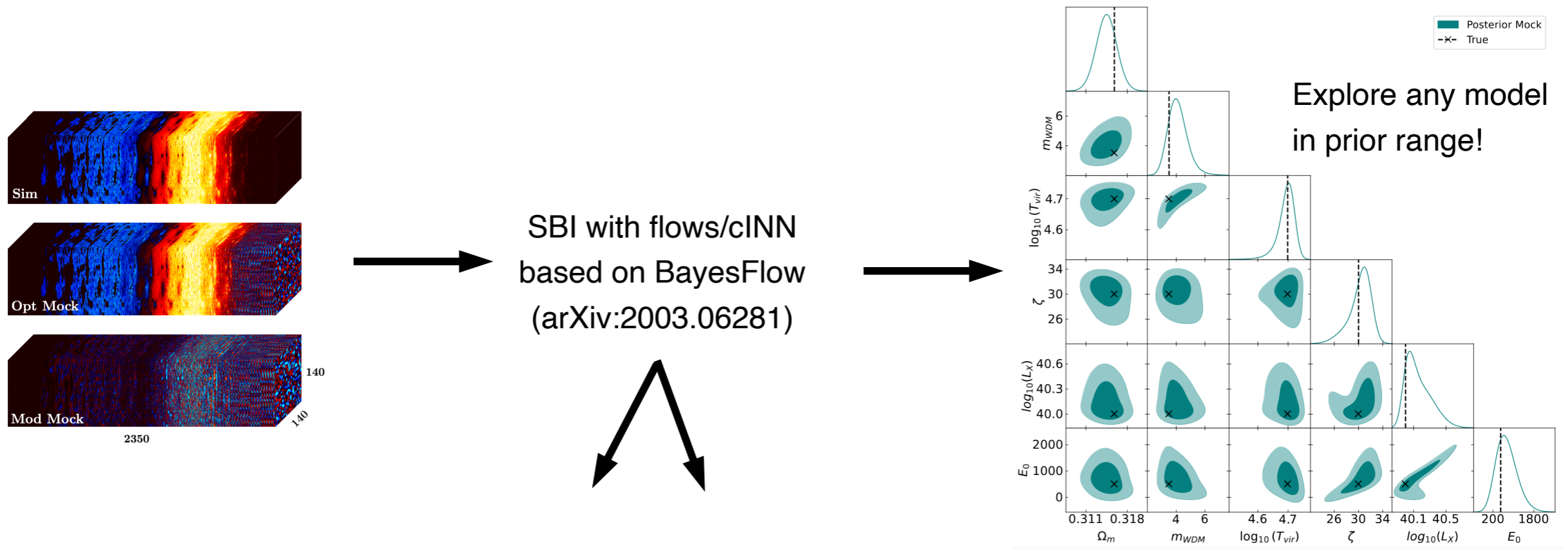
Schosser, Heneka, Plehn, arXiv:2401.04174

Sim: Summary stays close to original
 Mock: Heavy adjustment of summary vector



We profit from learned summary in presence of noise (more).

1) Simulation-based inference (SBI) for intensity mapping (3D)



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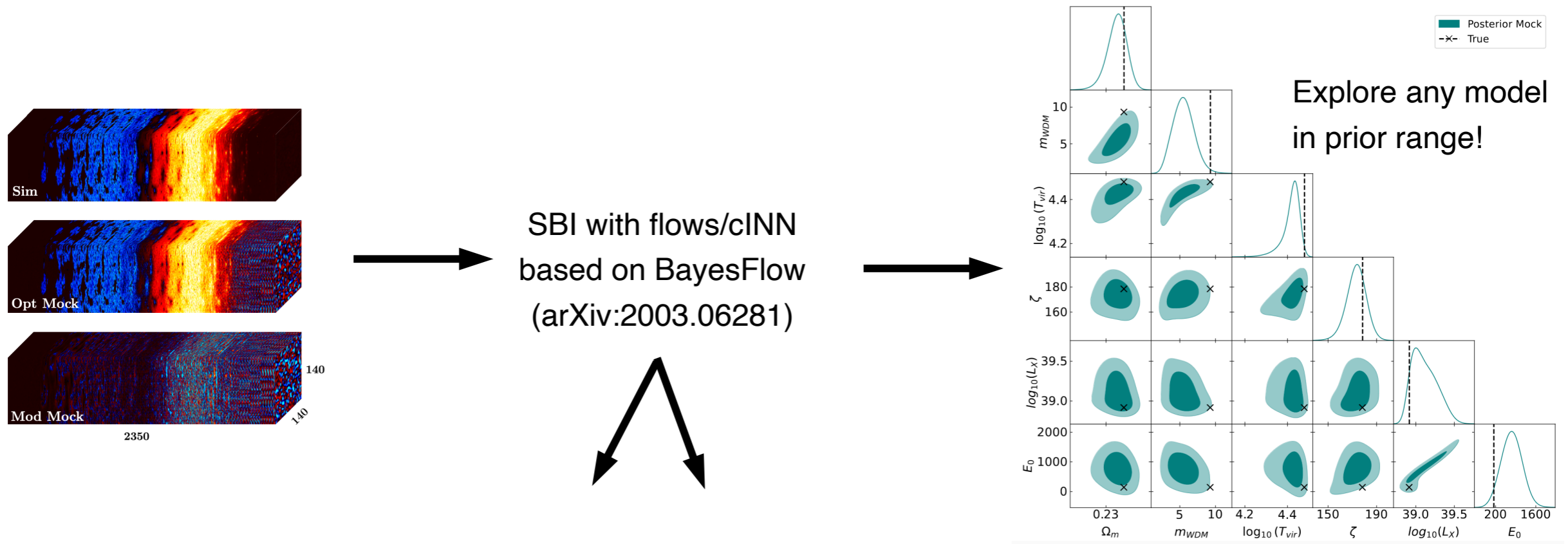
21cm-cINN (public when published)


Schosser, Heneka, Plehn (2024), arXiv:2401.04174

Learn more here: Poster location 108, Poster by Benedikt Schosser

'Optimal, fast, and robust inference of reionization-era cosmology with the 21cmPIE-INN'

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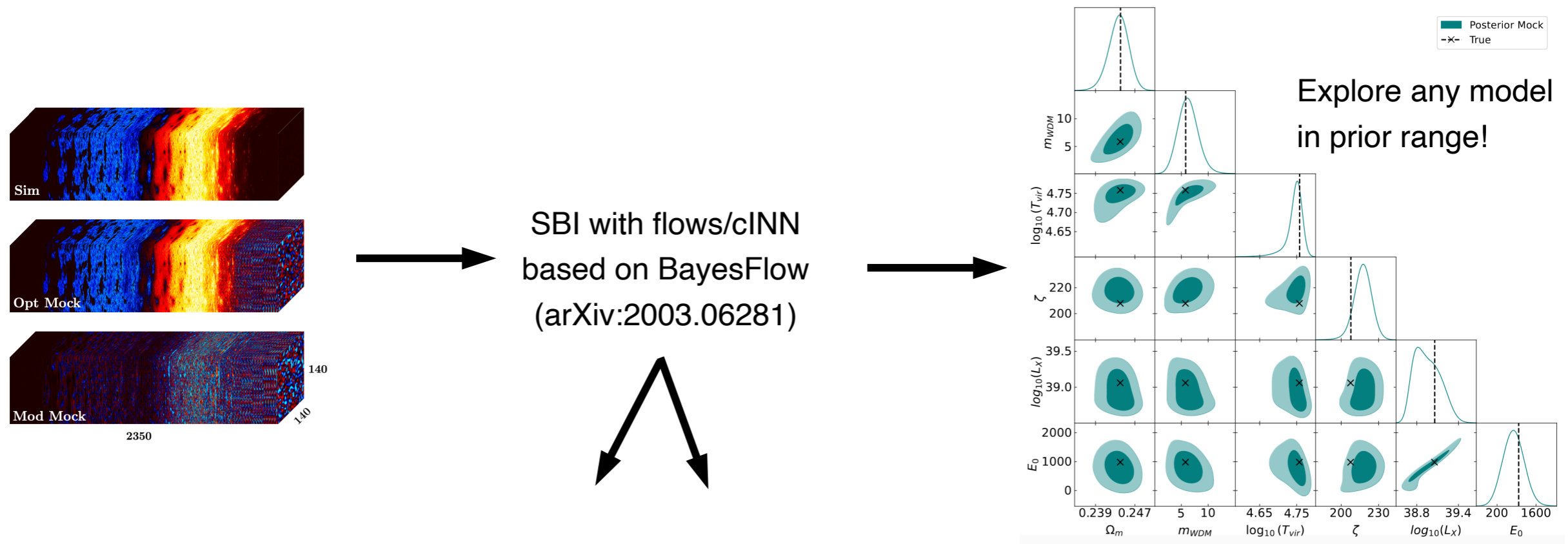
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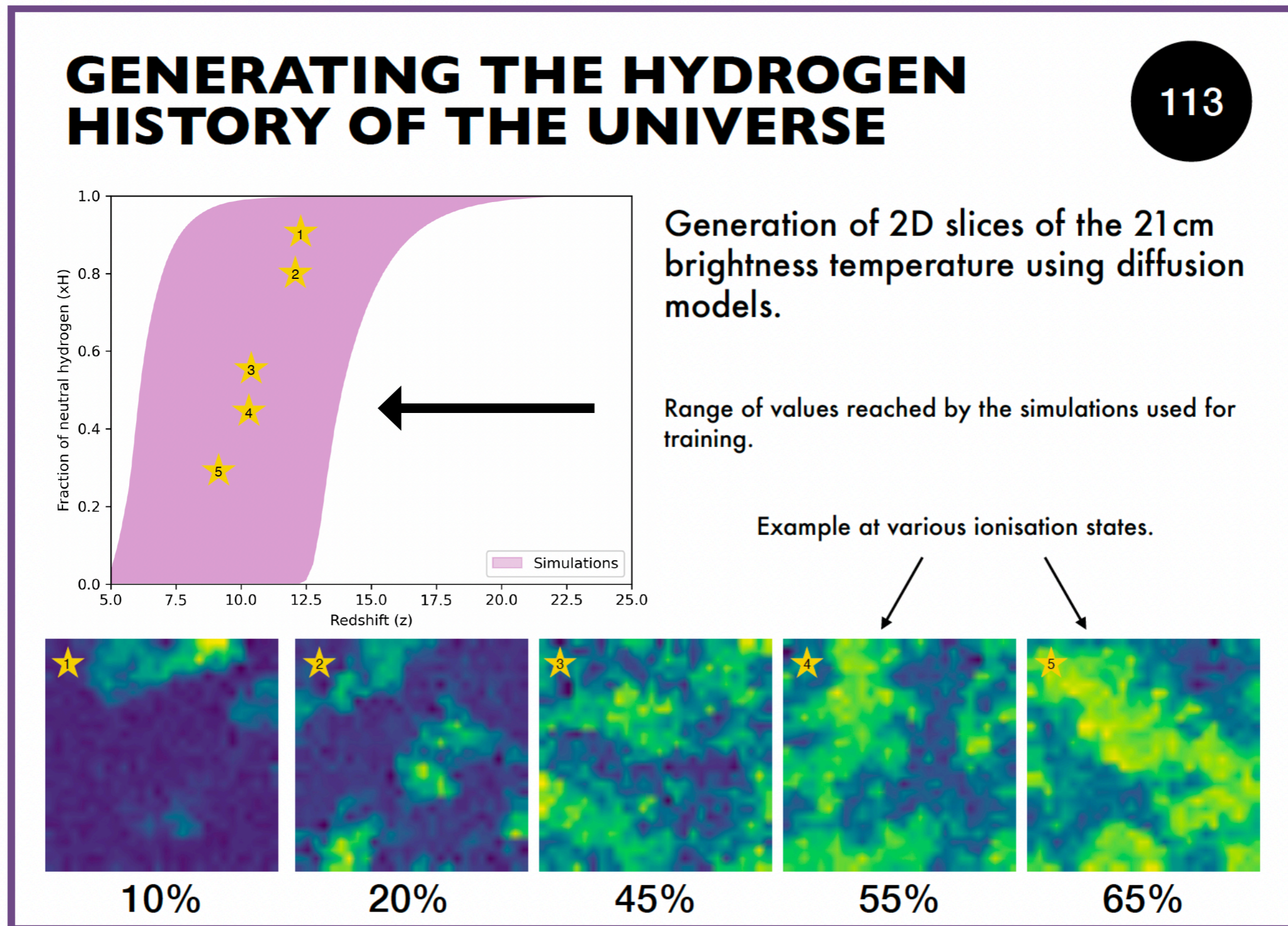
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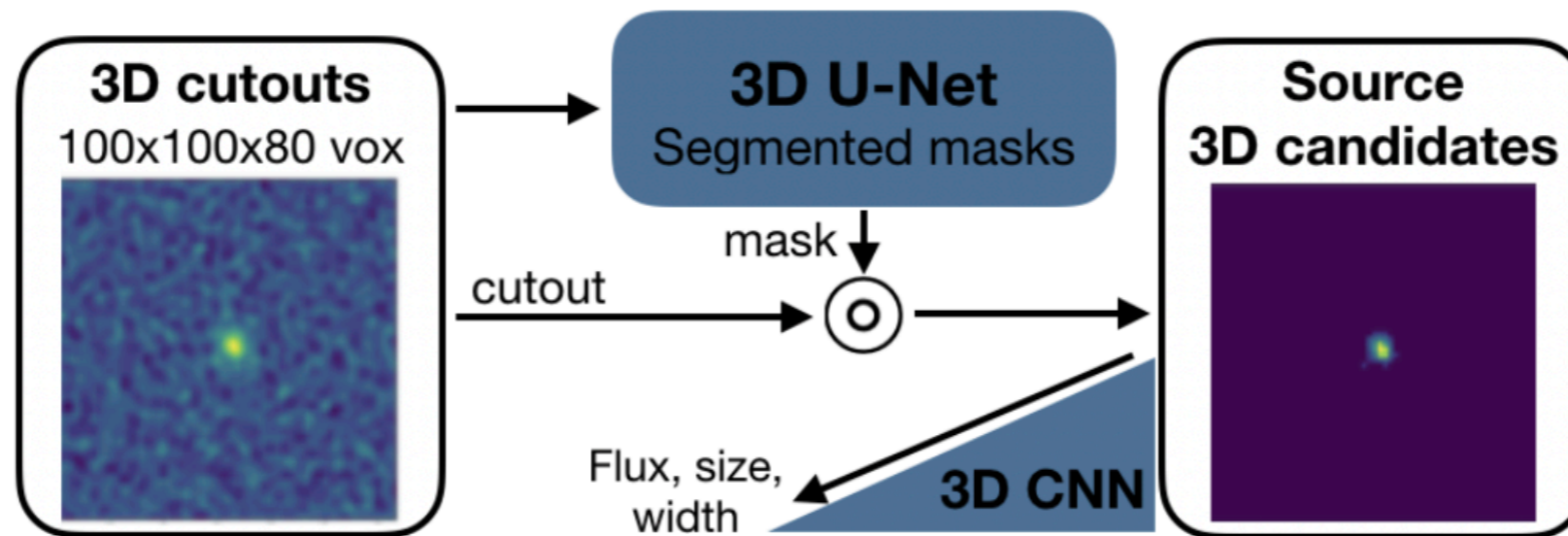
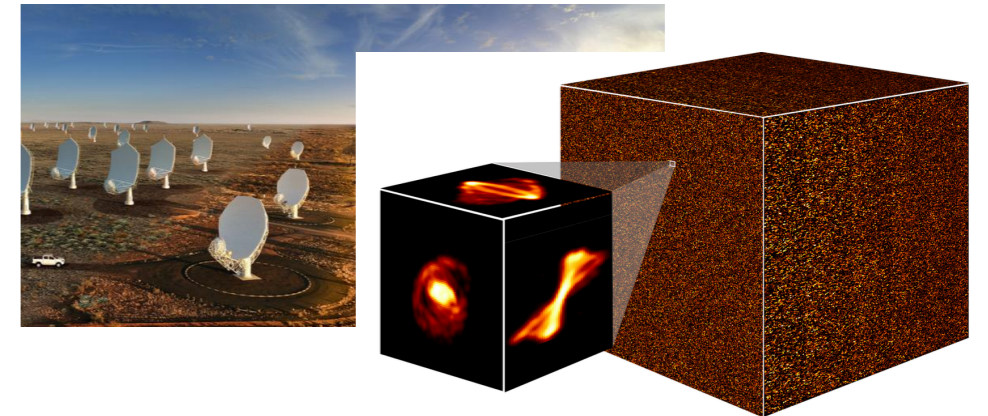
2) Generative methods for simulation (of the 21cm signal)



To learn more, see poster by: Lara Alegre, poster location 113

3) Radio source detection and characterisation

Example: Source detection in 3D tomographic data



Main take-aways:

- 3D better than stitching 2D (spatial) + 1D (frequency/time)
- High-fidelity 3D reconstructions, unbiased prior for characterisation
- Push to low signal-to-noise regime
- High S/N training data, ensemble decision

Hartley+ 23 (incl. Alegre, Heneka), arXiv:2303.07943
Heneka 22, arXiv:2311.17553

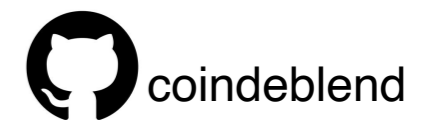
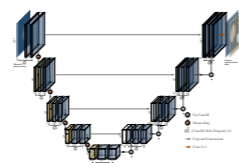
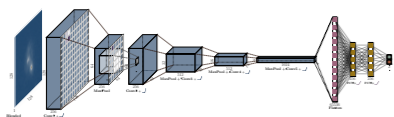
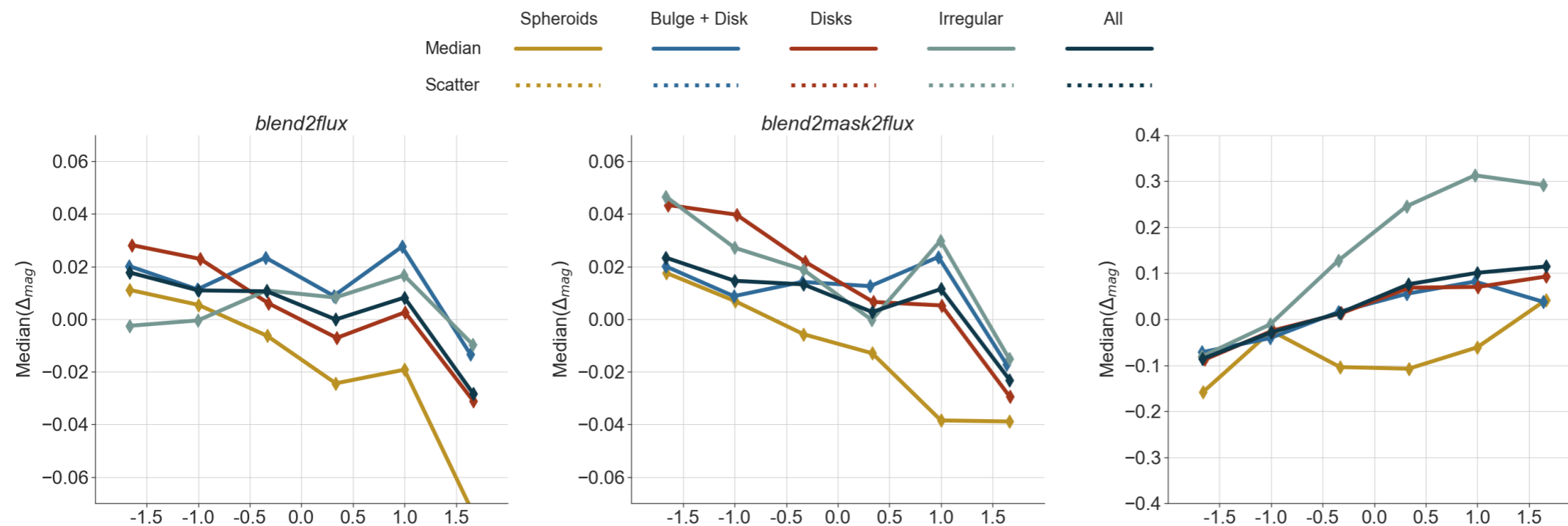
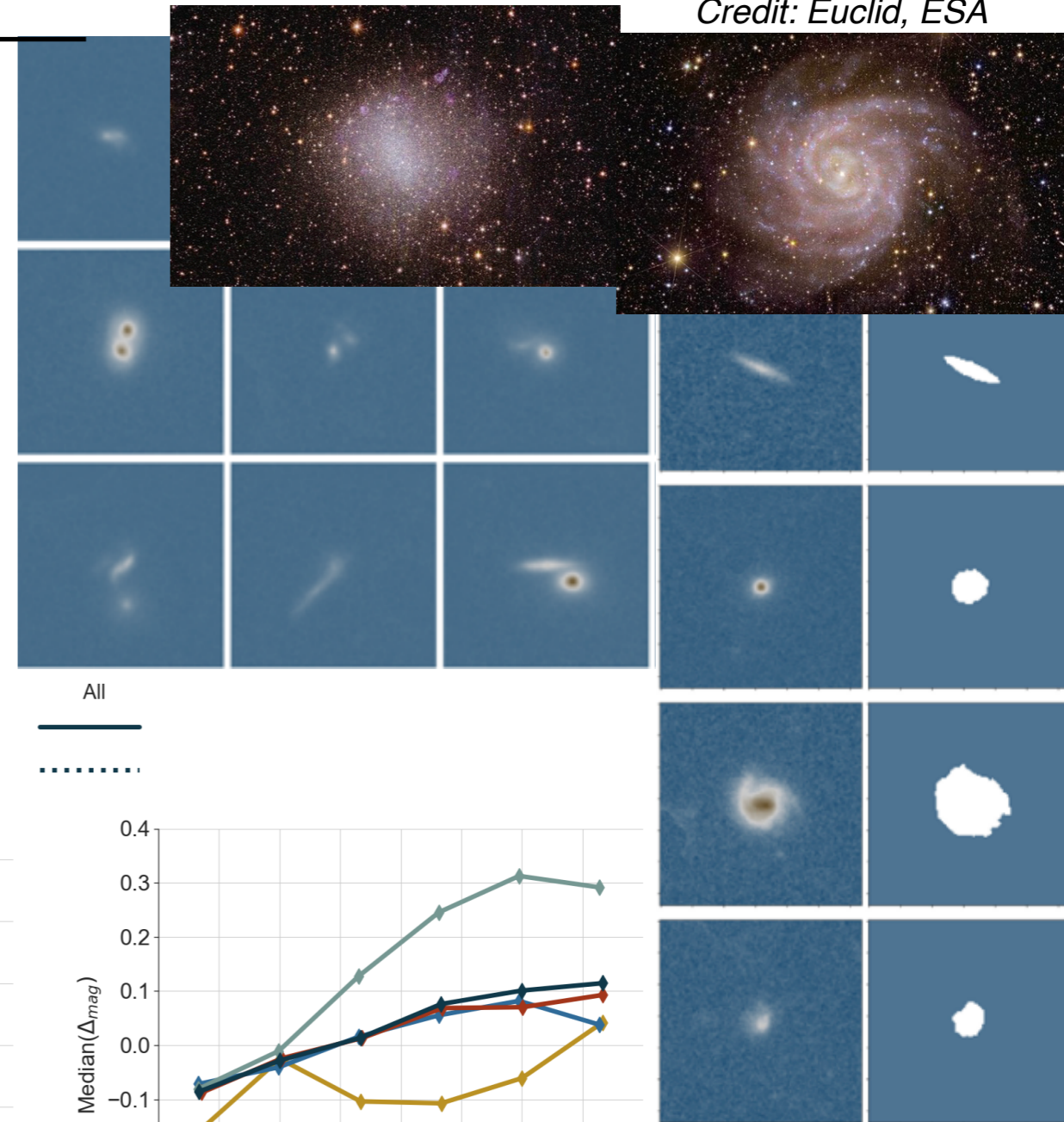
3) Optical source detection and characterisation

Credit: Euclid, ESA

Example: Source detection in imaging data

Main take-aways:

- ~factor 5 more precise photometry
- Order of magnitude less bias!
- Good performance also for irregular type

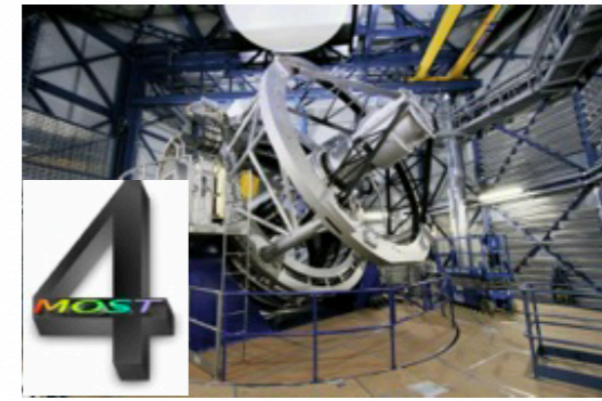


Boucaud, Huertas-Company, Heneka+ 20, arXiv:1905.01324

4) Classification and triggering for large astronomical surveys

4MOST: On-the-fly classification of spectra (1D)

- 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 \approx 18000 – 21000, LRS R \approx 4000 – 7500
- 20mio. (LRS), 3mio. (HRS) sources



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

Goal: Data-driven classification pipeline layer (galactic & extragalactic sources)

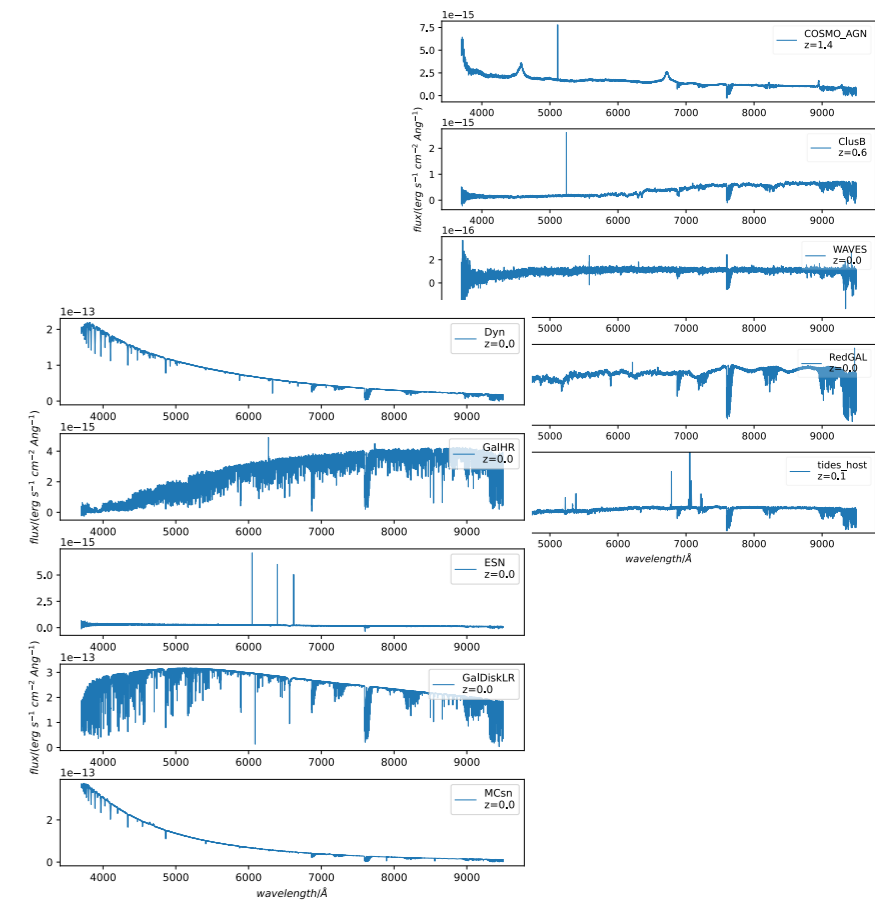
Classification infrastructure working group, led by: N. Napolitano & C. Heneka

➔ Probabilistic multi-classifier

Benchmark with SDSS archival spectra: Convolutional network variants, BNN + contrastive learning for class uncertainties

- competitive with template fitting

STAR_K5	1	0.00	3	0.00	1	0.00	1	0.00	1	0.00	142	2920
STAR_K3					2	0.00			8	0.00	186	2719
STAR_K1			1	0.00	3	0.00			126	0.04	2748	129
STAR_G2			1	0.00	3	0.00			14	0.00	139	2882
STAR_F9									2725	0.91	95	64
STAR_F5			1	0.00					21	0.01	21	0.00
STAR_A0					2	0.00			2832	0.87	87	0.00
QSO_nan	9	0.00	6	0.00	4	0.00	32	0.01	284	0.09	2716	2
QSO_BROADLINE	3	0.00			1	0.00			2703	0.90	187	0.06
GALAXY_nan	103	0.03	19	0.01	100	0.03	2716	0.91	2	0.00	65	1
GALAXY_STARFORMING	87	0.03	163	0.05	2608	0.87	126	0.04			3	0.00
GALAXY_STARBURST	17	0.01	2794	0.93	135	0.04	21	0.01				
GALAXY_AGN	2780	0.93	17	0.01	150	0.05	98	0.03	11	0.00	17	0.01
GALAXY_AGN												
GALAXY_STARFORMING												
GALAXY_BROADLINE												
QSO_nan												
STAR_A0												
STAR_F5												
STAR_F9												
STAR_G2												
STAR_K1												
STAR_K3												
STAR_K5												



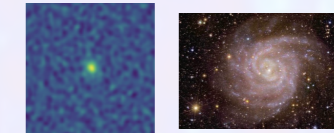
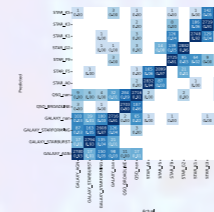
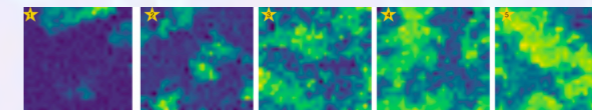
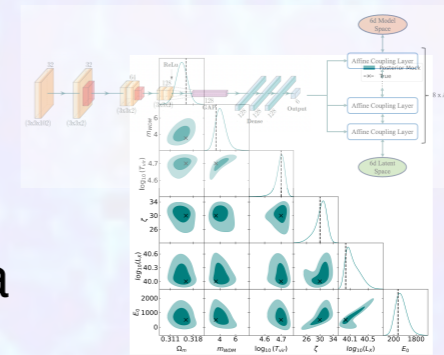
Zhong, Napolitano, Heneka+ arXiv:2311.04146

Summary and conclusions

Use data from large astronomical surveys to learn about astrophysics + cosmology.

Important tasks are

- Inference: SBI in 3D from non-Gaussian tomographic data
- Simulation: Produce large range of reionization topologies
- Detection & Characterisation: Unbiased measurements from diverse sources (galaxies)
- Classification: Online classifier and triggering



ML/DL/AI has come to stay when dealing with astronomical survey data.

Neutsch, Heneka, Brüggem 22, arXiv:2201.07587
Schosser, Heneka, Plehn, arXiv:2401.04174
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Thank you for your attention!