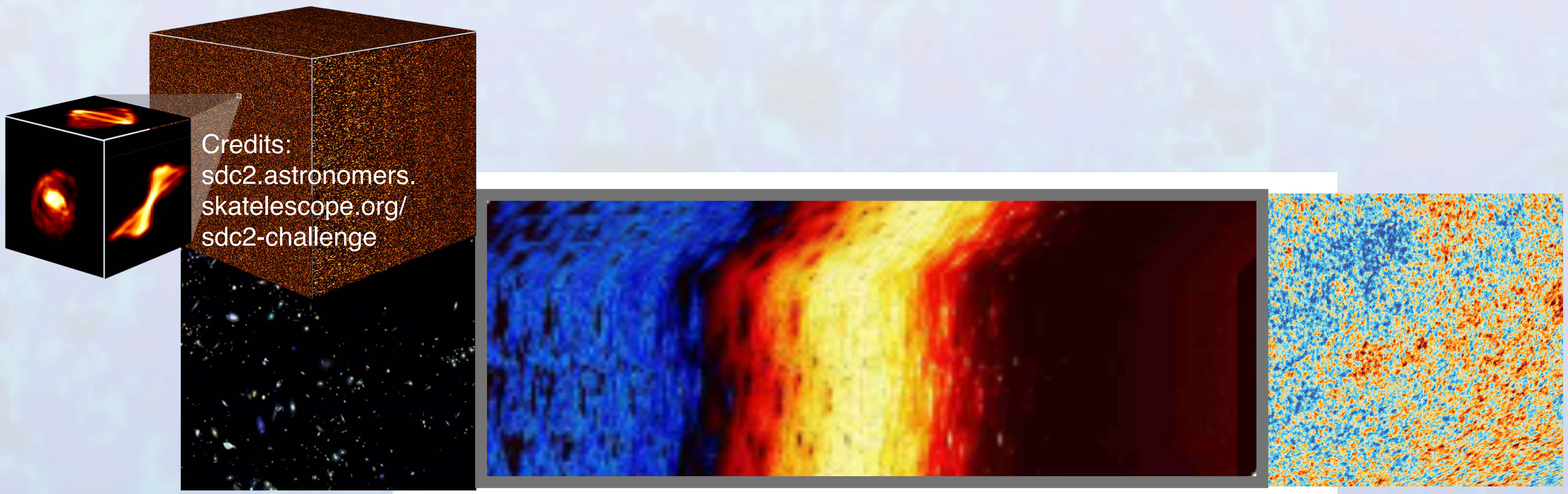
Learning from 3D tomographic 21cm maps



Credits: ESO

Credits: Planck, ESA

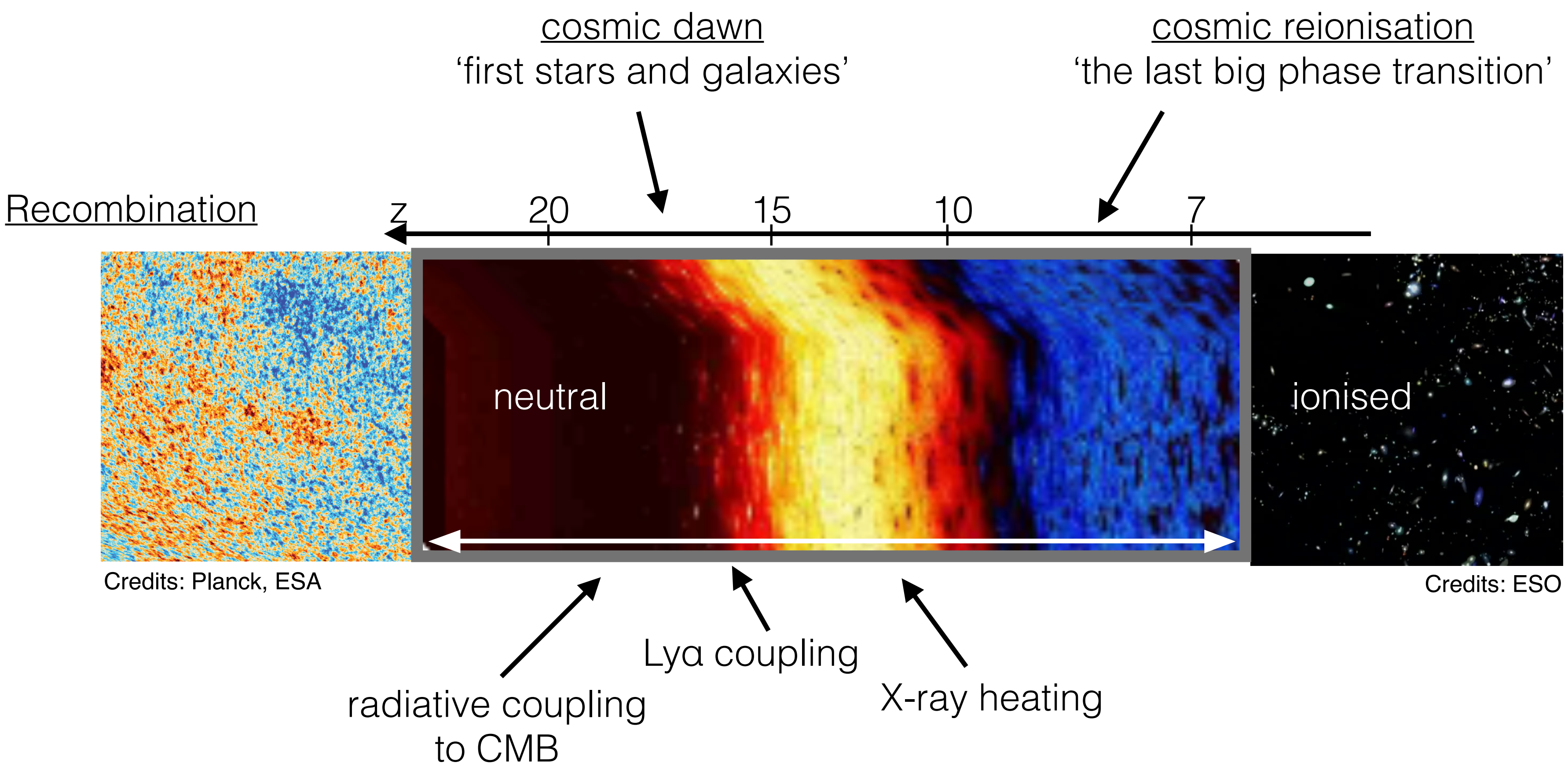
Caroline Heneka, Hamburg University & Observatory, EXC Quantum Universe

2021 IAP colloquium, October 18th 2021

Collaborators: Steffen Neutsch (UHH), Marcus Brüggen (UHH), Michele delle Veneri (U. Naples), Bernardo Fraga (CBPF Brazil), Andrew Soroka (CMC MSU), Fedor Gubanov (CMC MSU), Clecio de Bom (BBPF Brazil), Alex Meshcheryakov (CMC MSU)

3D lightcones to track the history of the Universe

What is the cosmology at high redshifts? ‘gap’ between CMB and galaxy surveys
What properties do the very first stars and galaxies have?



21-cm lightcone*
generated with 21cmFAST

*lightcone = 2D spatial + 1D frequency information

blue = emission
red / yellow = absorption against the CMB

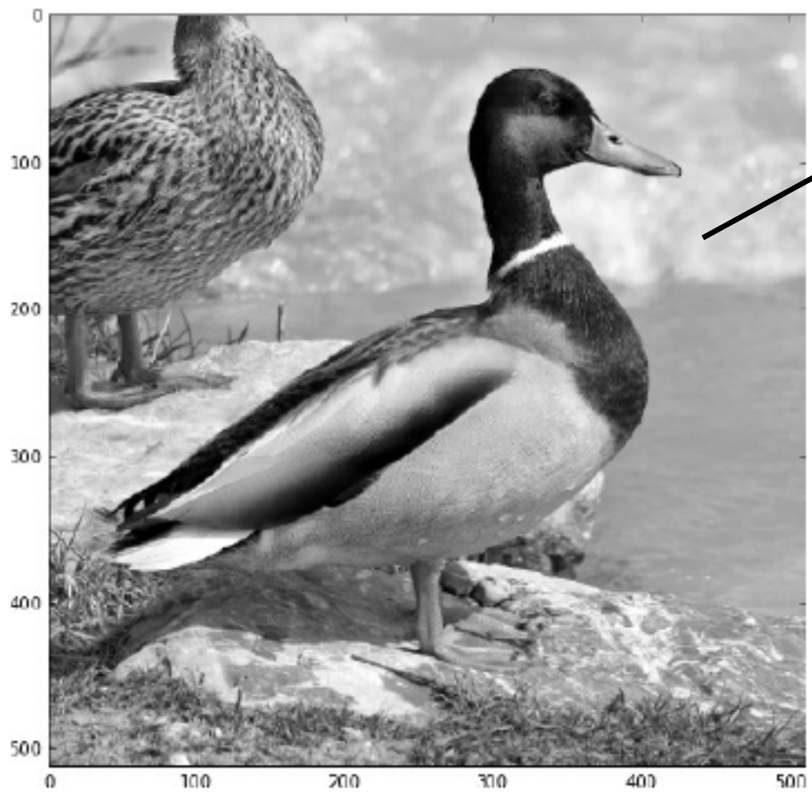
Galaxy surveys: Identify individual sources

IM: Measure emission fluctuations over ‘large’ areas

Example: Planck satellite for the CMB

Why (deep) learning?

The duck example of (Non-)Gaussianity

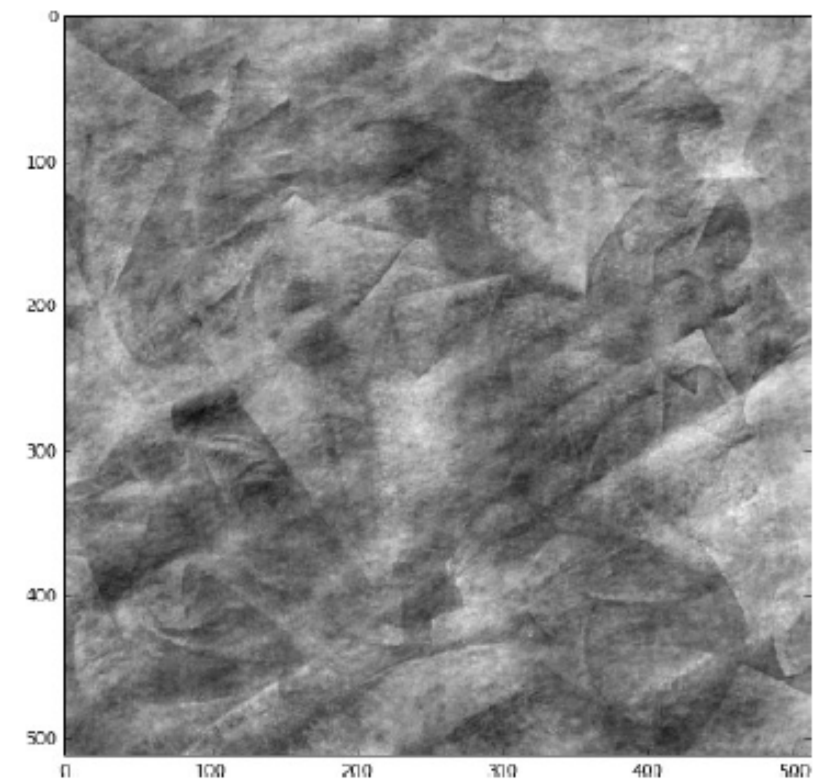


The duck: highly non-Gaussian

parameters
(size, color, background)

randomise phases

Same 2D
power spectrum



The Gaussian duck

Credit: G. Bernardi
D. Prelogovic

- Picks up non-Gaussian information
- Representation learning

Applications:

1. **Inference** (what duck? what properties? what shapes?)
2. Detect the duck (or galaxy, or signature)

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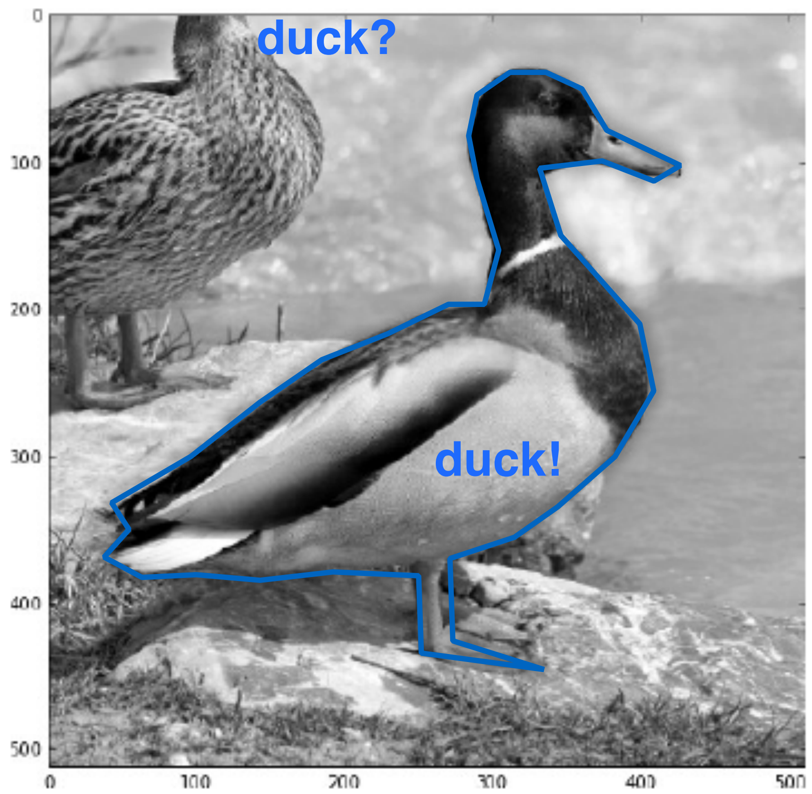

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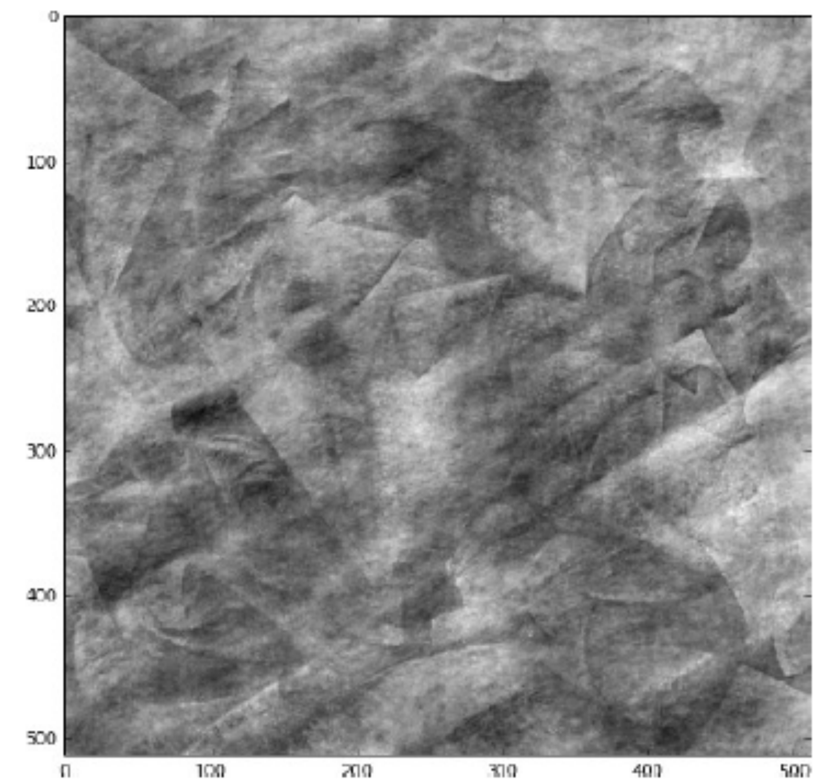

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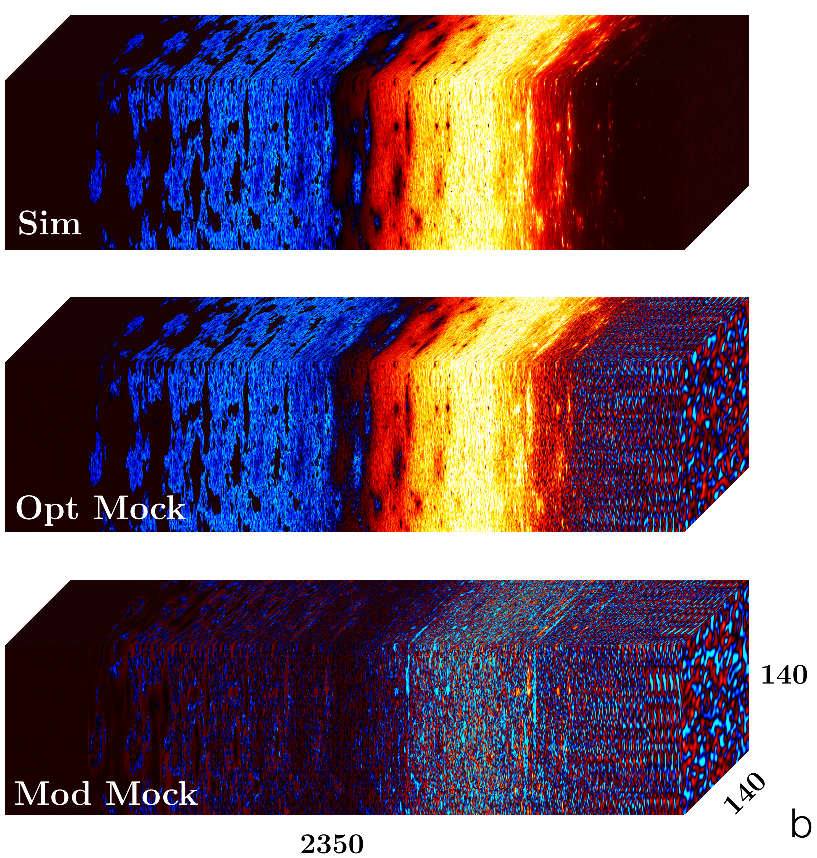
Inference from (mock) 3D tomographic cubes

Direct likelihood-free inference from 3D tomographic mock cubes (21cm IM)

Goal to infer astrophysical and cosmological key parameters
directly from intensity lightcones $(\Omega_{\mathrm{m}},\, \zeta,\, T_{\mathrm{vir}},\, L_{\mathrm{X}},\, E_0,\, m_{\mathrm{WDM}})$

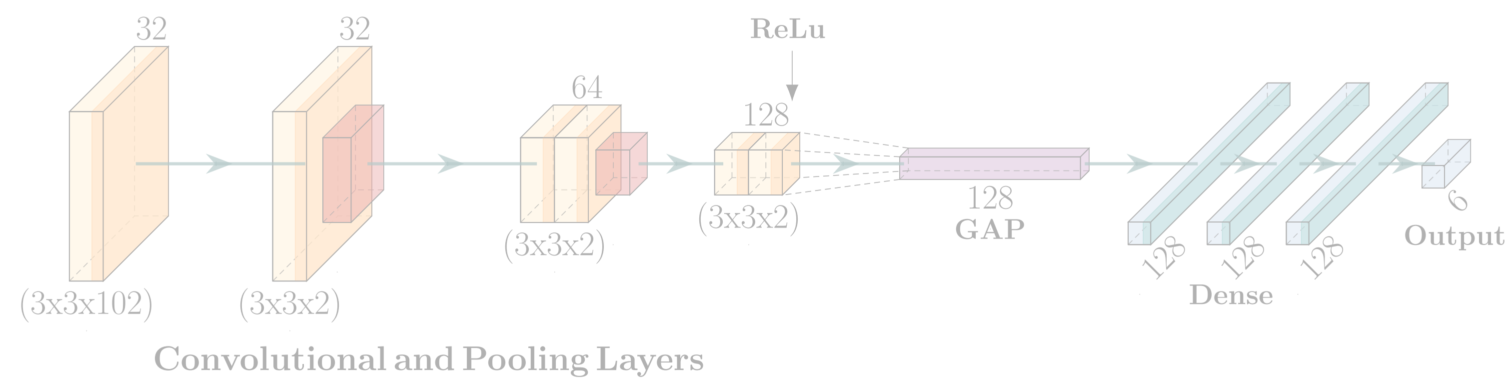
<u>cosmic reionisation</u>
'the last big phase transition'

<u>cosmic dawn</u>
'first stars and galaxies'



21-cm lightcone
generated with 21cmFAST

Mocks created with
21cmSense for SKA1-Low



blue = emission
red / yellow = absorption
against the Cosmic Microwave Background

Neutsch, Heneka, Brüggen, in prep

Inference from 3D tomographic cubes

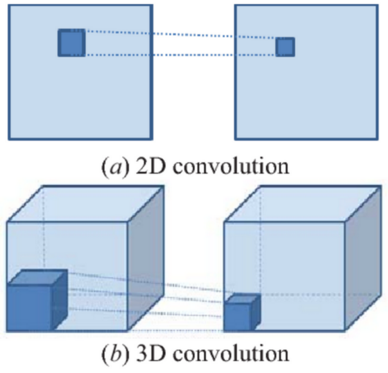
Direct likelihood-free inference from 3D tomographic cubes (21cm IM)

Various Options:

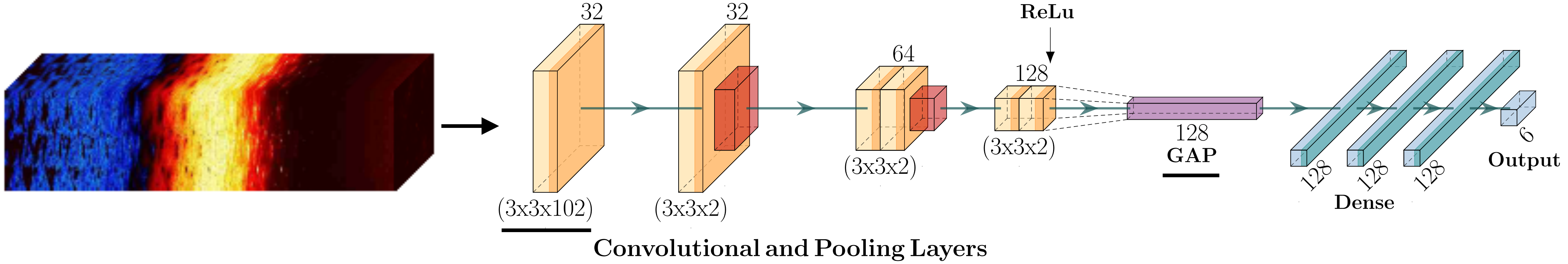
- Slicing and treatment with 2D CNN as image → 'standard' **2D CNN**, residual (skip connections) **ResNet**
- Time series (frequency) of co-eval images → **LSTM** network
- Full 3D convolution → 3D CNN:

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

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



Best-performing: simple Conv3D architecture



Database of ~5000 lightcones
140x140x2350 pix, 1.4 Mpc resolution
Training (K80 GPU): ~20min/epoch, ~30 epochs

Neutsch, Heneka, Brüggen, in prep

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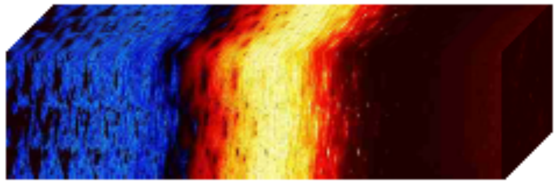
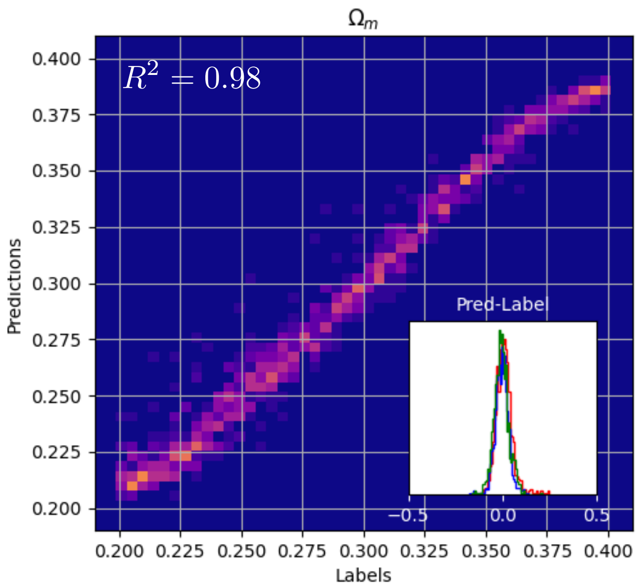
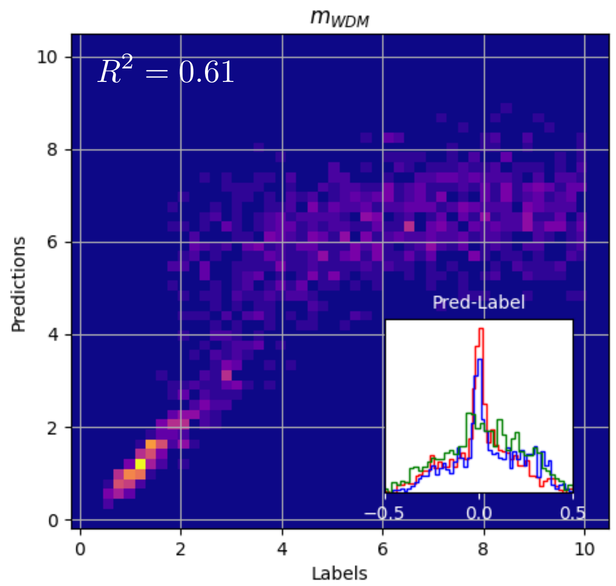


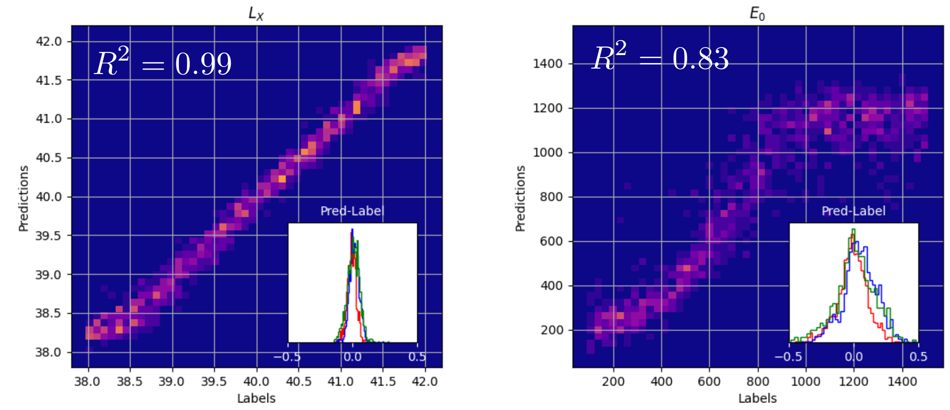
$$(\Omega_\mathrm{m},\, \zeta,\, T_\mathrm{vir},\, L_\mathrm{X},\, E_0,\, m_\mathrm{WDM})$$



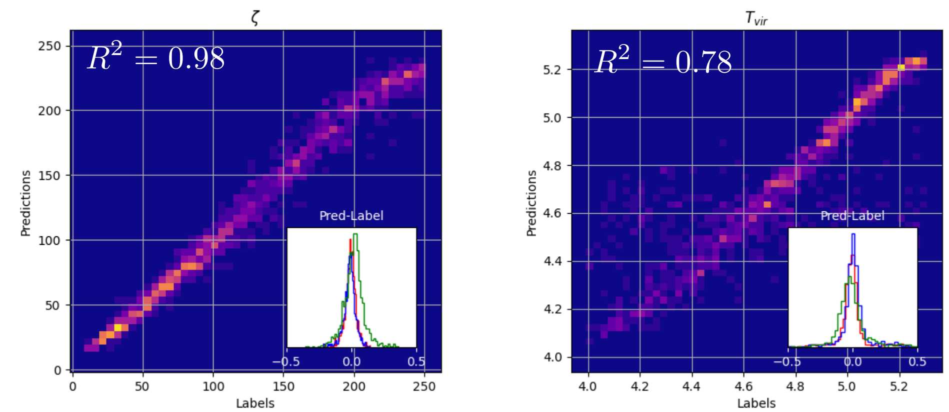


Cosmology

Cosmic Dawn



Reionisation



Directly constrain cosmology, cosmic dawn and reionisation astrophysics

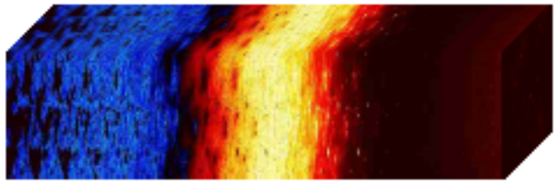
Also tested: 'astro-only' inference

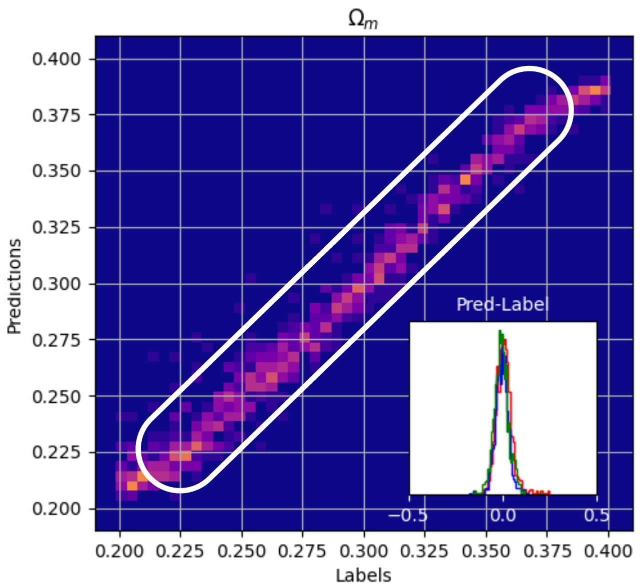
Neutsch, Heneka, Brüggen, in prep

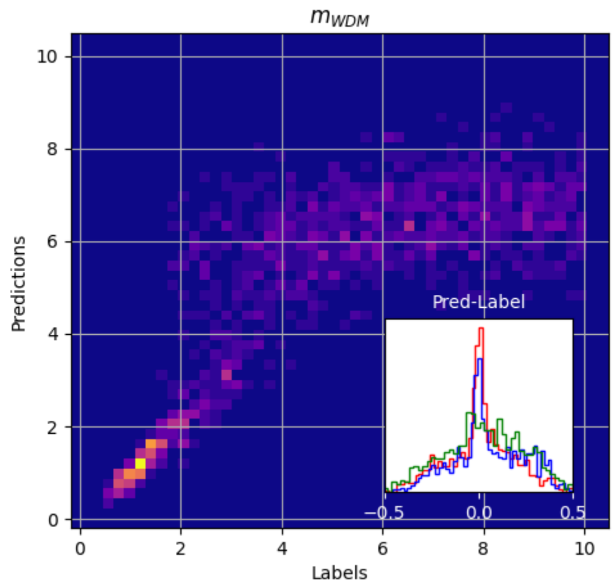
Inference from 3D tomographic cubes

Direct likelihood-free inference from 3D tomographic mock cubes (21cm IM)

$$(\Omega_{\rm m},\, \zeta,\, T_{\rm vir},\, L_{\rm X},\, E_0,\, m_{\rm WDM})$$



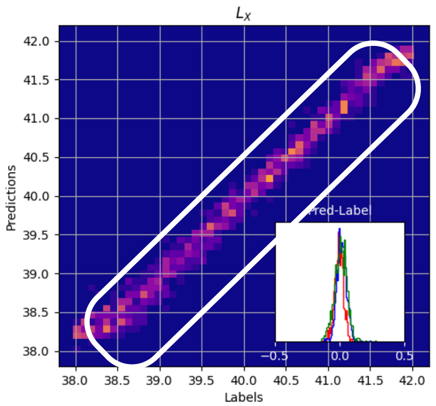


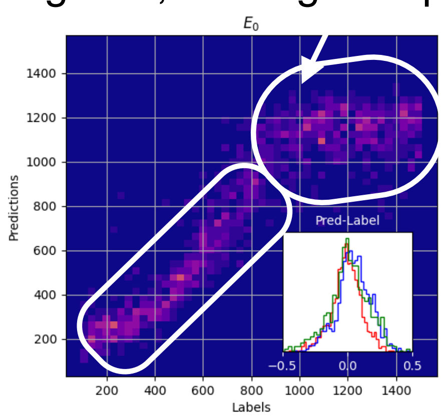


Cosmology

Cosmic Dawn

high E0, nothing escapes





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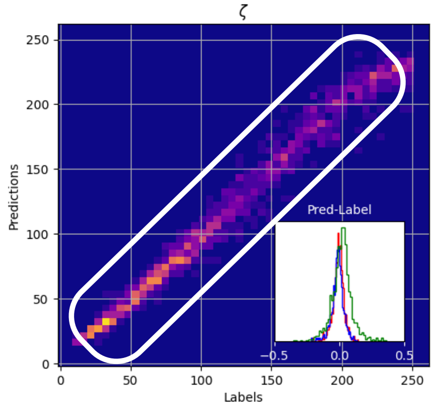

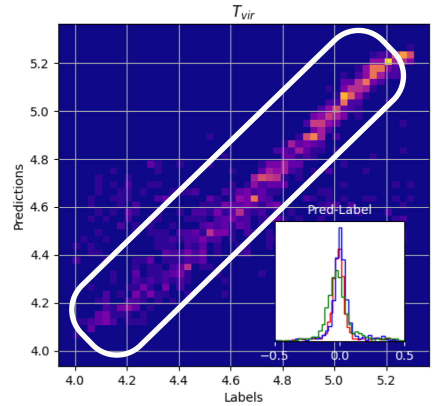

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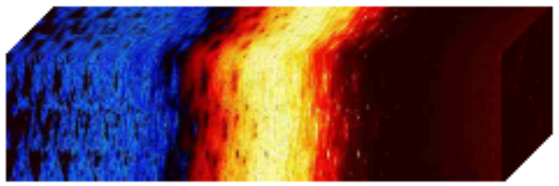
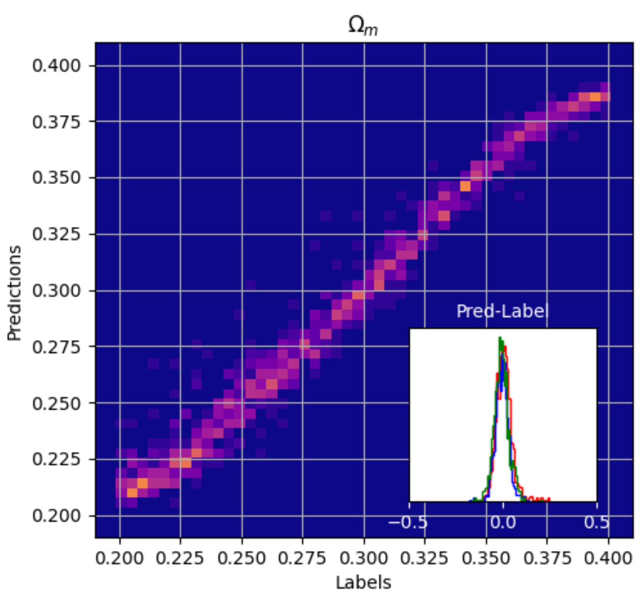
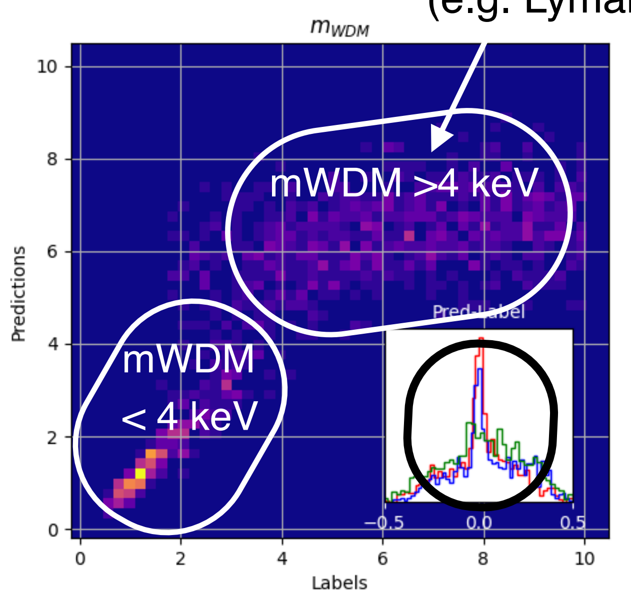
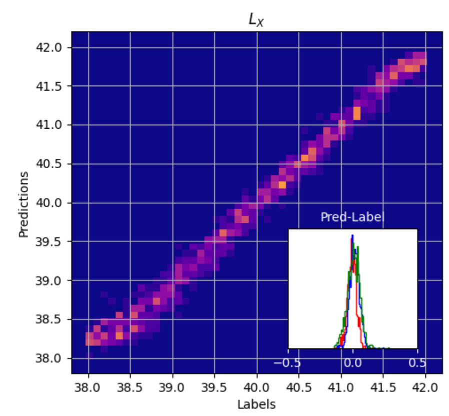


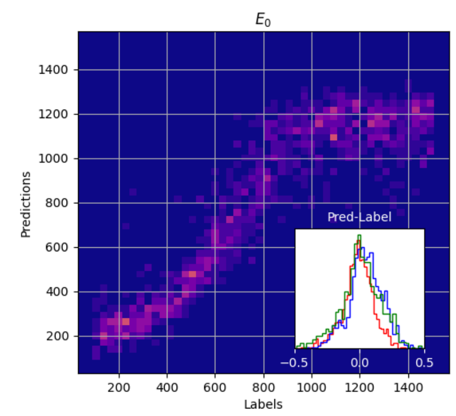
~results from other studies
(e.g. Lyman-forest)





Cosmic Dawn



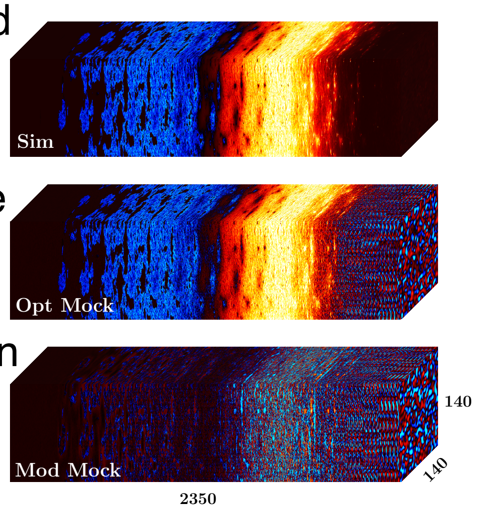


Cosmology

red

blue

green



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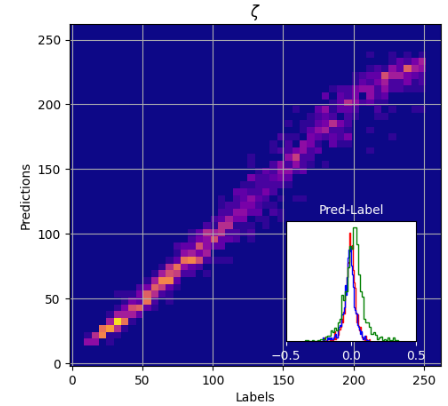
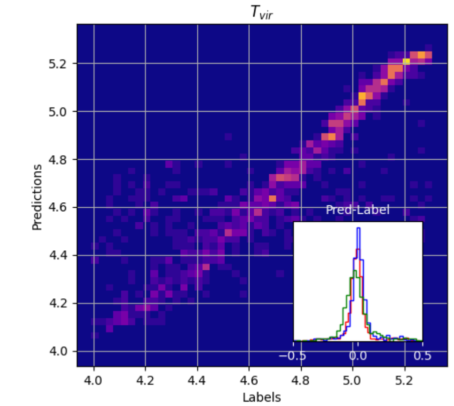
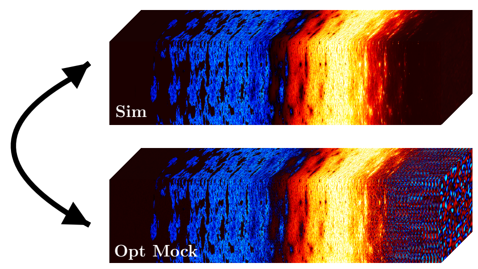




Neutsch, Heneka, Brüggen, in prep

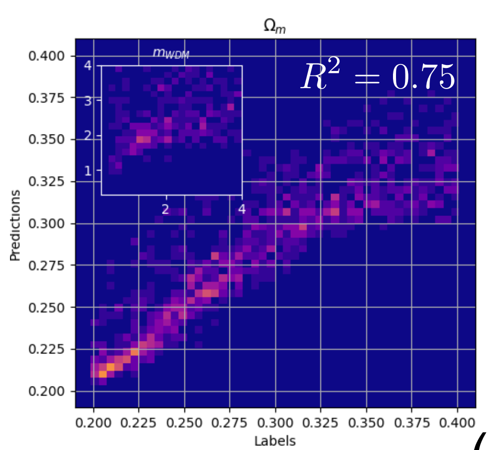
Testing robustness & interpretability

1) Transfer learning Sims & Mocks

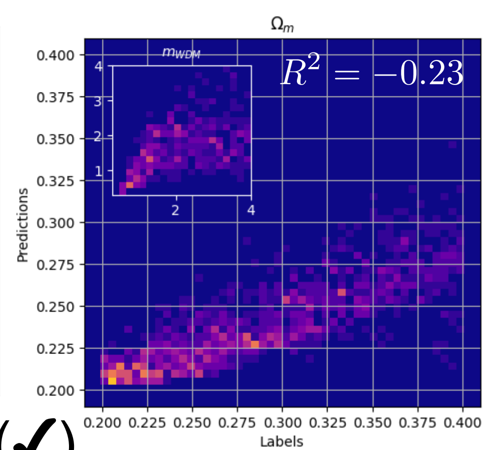


Sim -> Mock

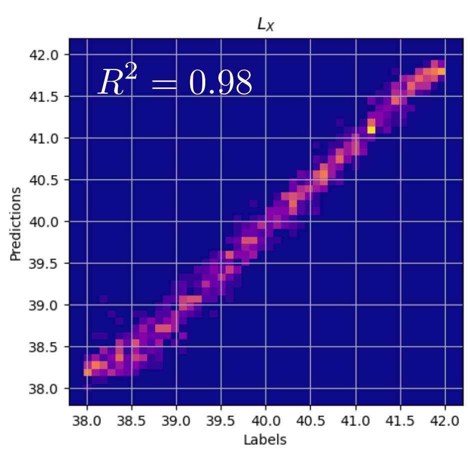
Mock -> Sim



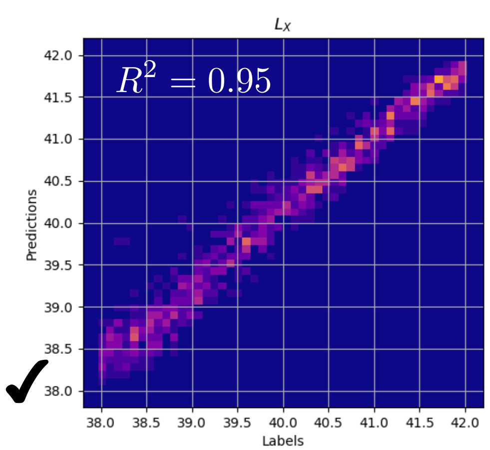
(✓)



✗

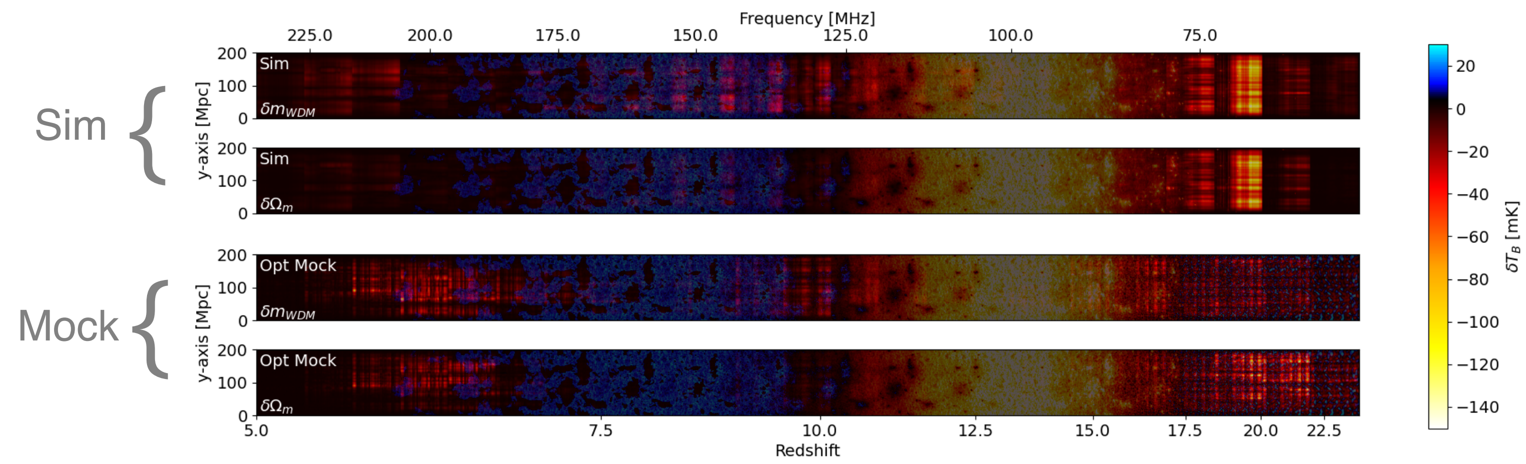


✓

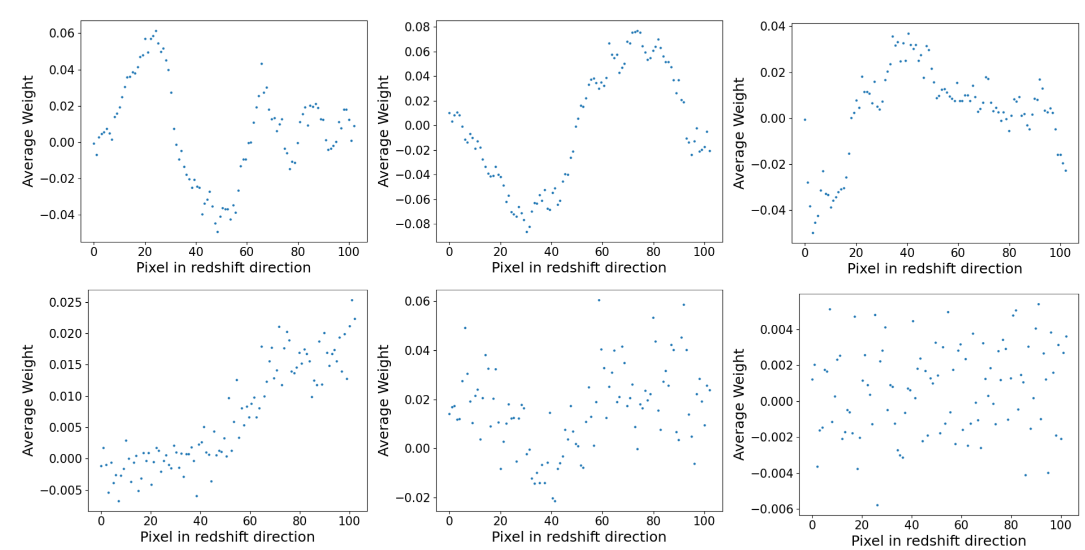


✓

2) Gradient-based saliency maps



+ check your filters



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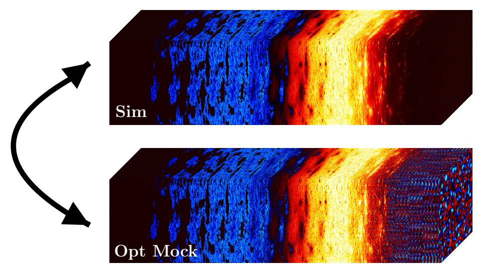

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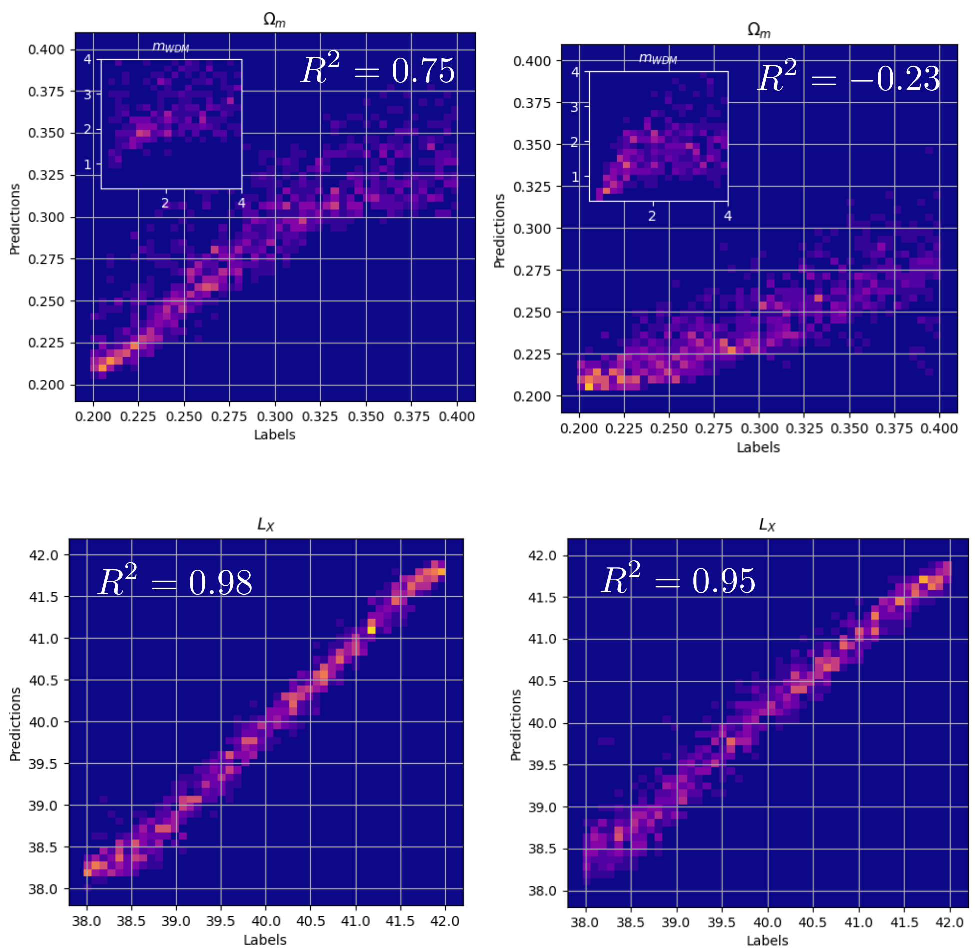

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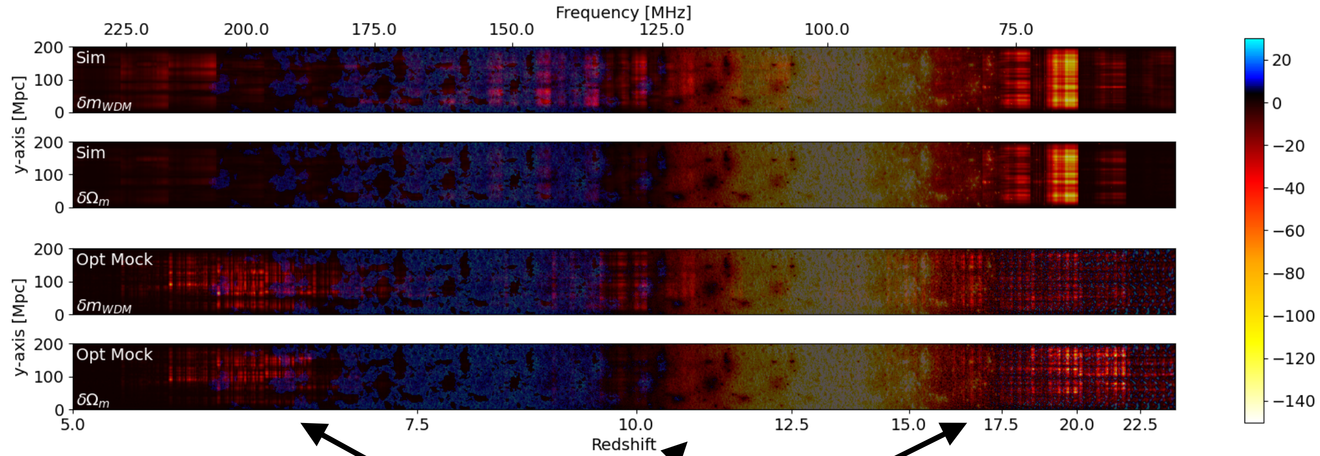
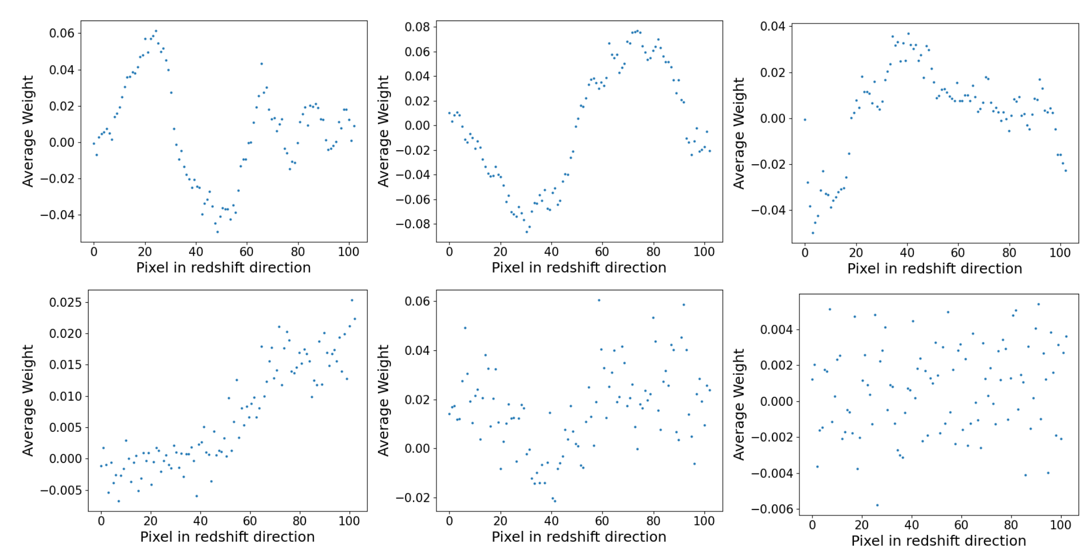


'transitions'

also seen for Fisher forecasts:
Heneka & Amendola 2018
Liu, Heneka, Amendola 2020

+ check your filters



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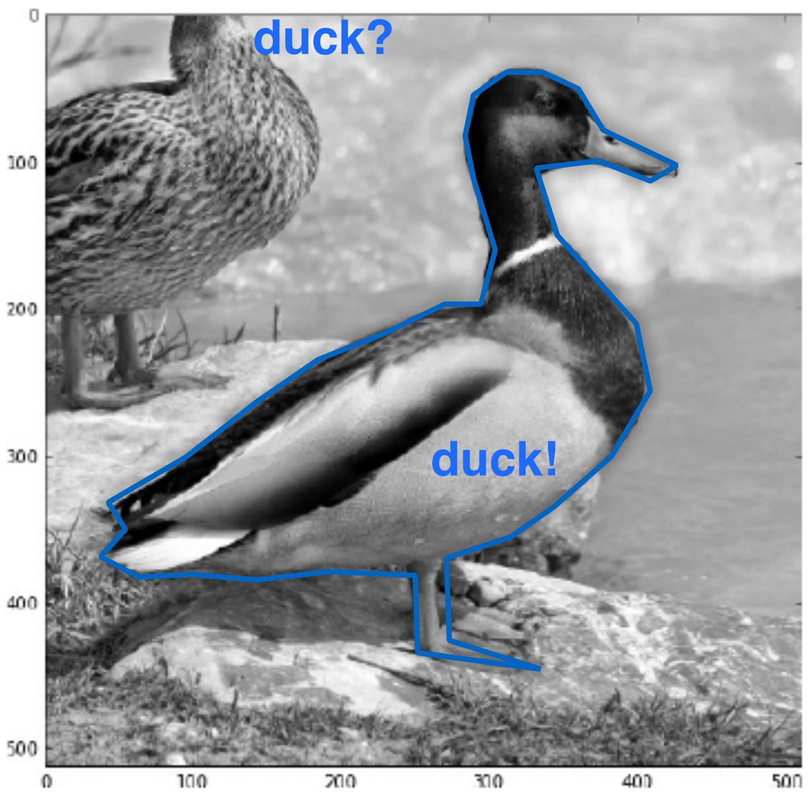
Why (deep) learning?

The duck example of (Non-)Gaussianity



The duck: highly non-Gaussian

randomise phases

Same 2D
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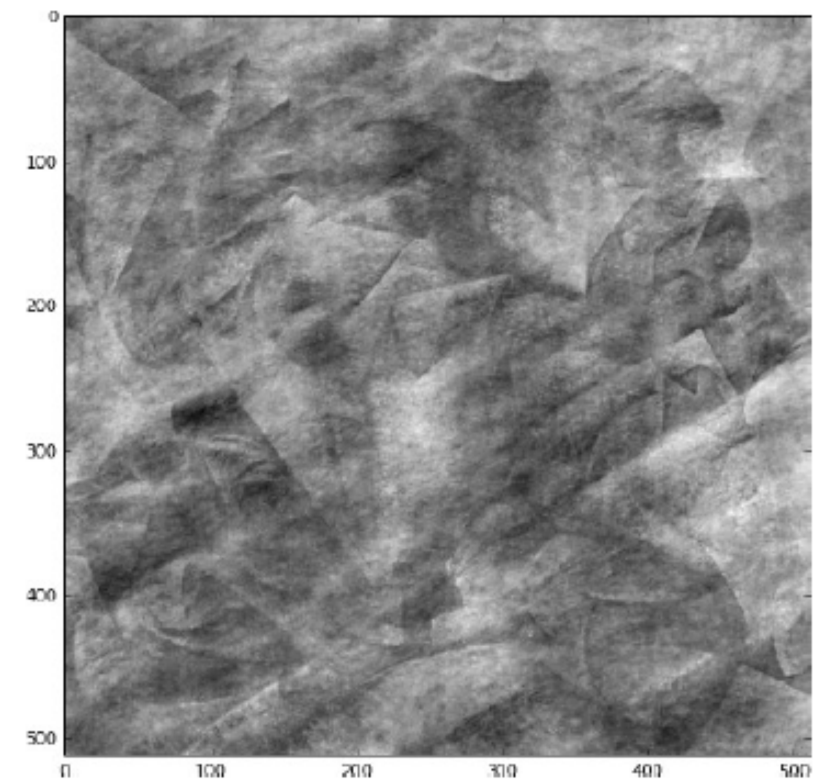

Credit: G. Bernardi

The Gaussian duck

- Picks up non-Gaussian information
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Applications:

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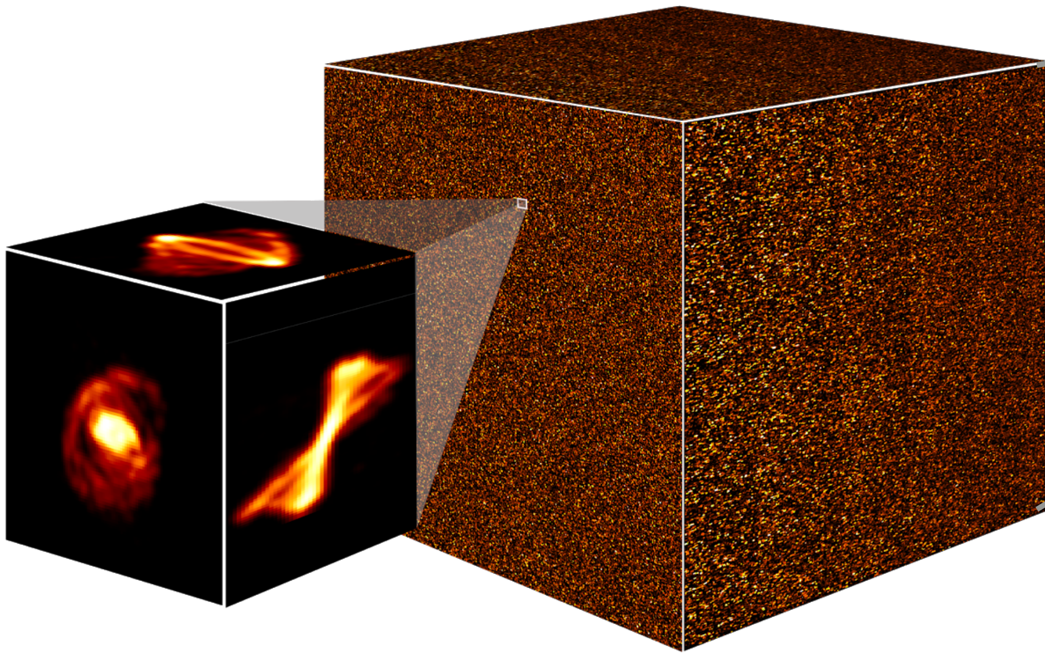
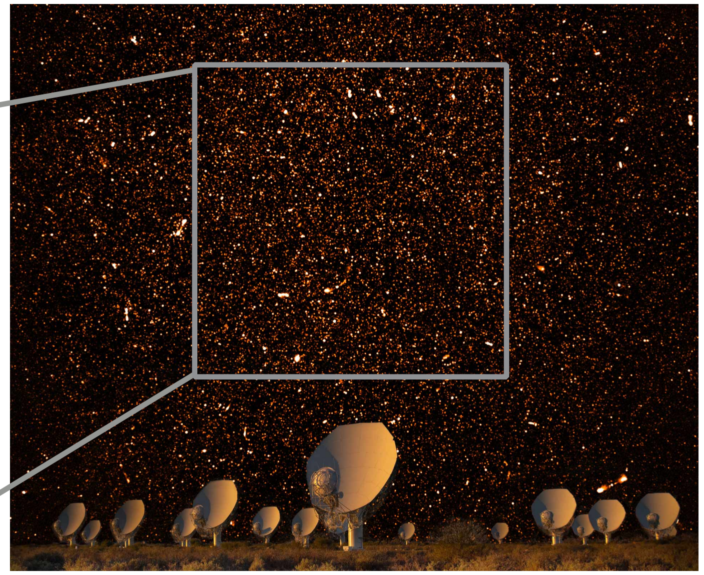
Source Finding: SKA Science Data Challenge



Credit: https://sdc2.astronomers.skatelescope.org/sdc2-challenge/data



Composite MeerKAT dishes and observations.
Credit: South African Radio Astronomy Observatory (SARAO)

SKA -
The Square Kilometre Array

An international effort to build the world's largest radio telescope

Expected data rate in full operation: 1 TB/s

Key science goals include:
Galaxy Evolution, Reionisation, Cosmology, Astroparticles

Goal is source finding and characterisation

(+ test of computing nodes on the way to SKA)

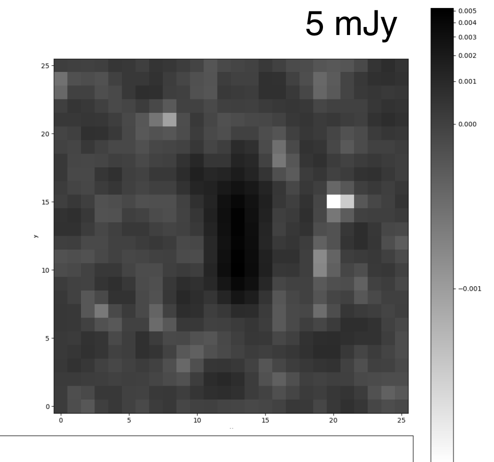
https://sdc2.astronomers.skatelescope.org/computational-resources

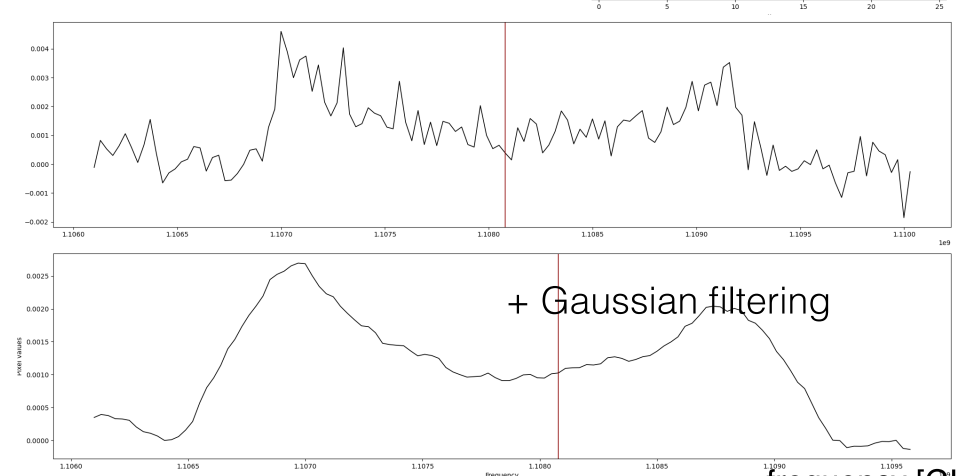
The challenging HI sources:

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

see also: 1905.01324 (optical, detection & de-blending)

The brightest HI source





SKA Science Data Challenge

Machine learning and deep learning come together?

Team: Michelle delle Veneri, Andrew Soroka, Bernardo Fraga, Fedor Gobanov, Clecio de Bom, Alex Meshcheryakov

DL source detection & characterisation:

Best performing: full 3D approaches (U-Net type)

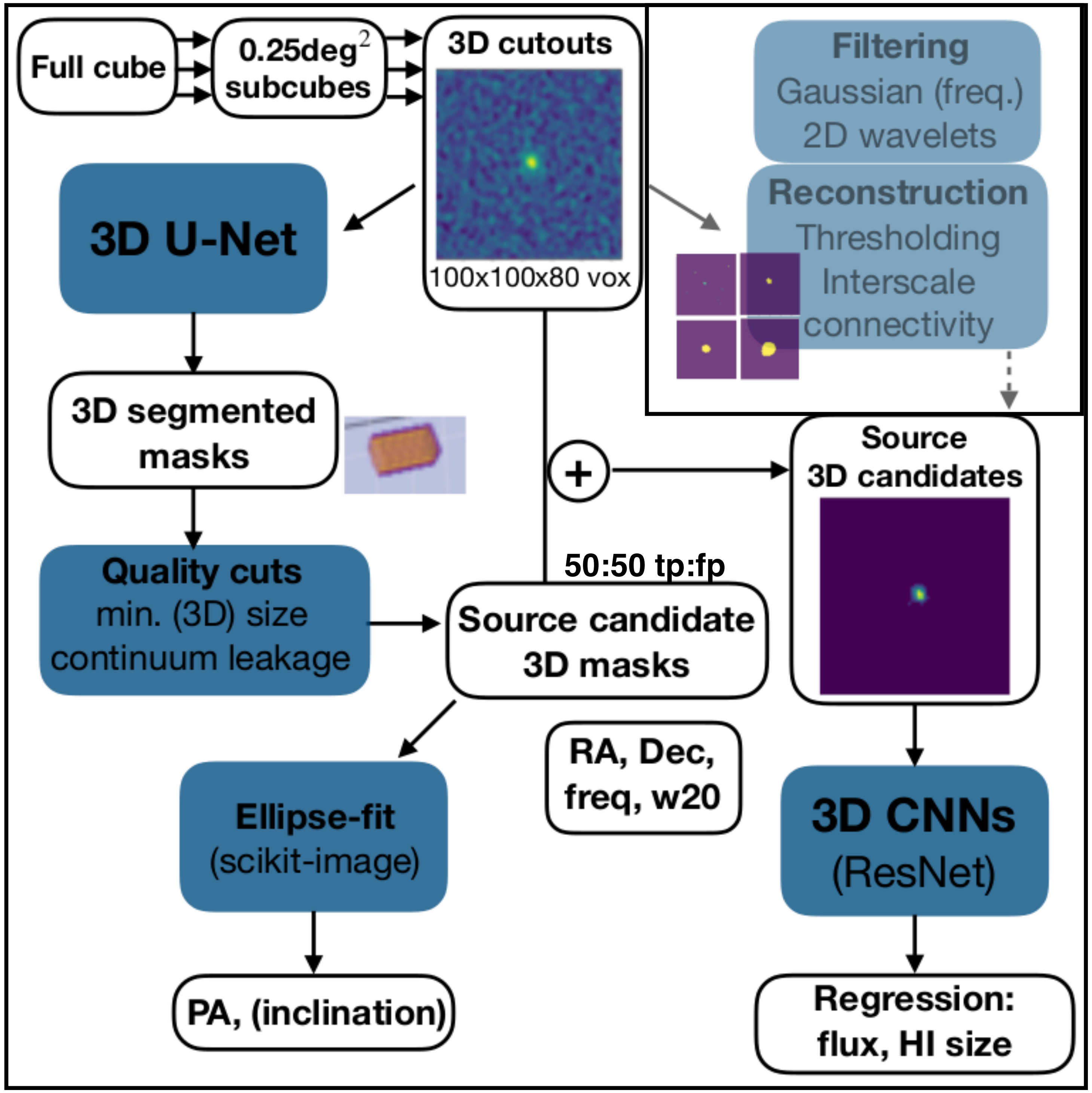
Trials: 2D/3D variants of U-Net, R-CNN, inception network

+ Trial source detection baseline

Wavelet denoising & Multi-scale model

Our pitfalls:

- **Pre-processing, noise model(s)**
- **High sparsity**
- **Choice of training set**
- **Needs multi-step and/or ensemble decision**



Conclusion & Outlook: 21cm tomography with nets

Main take-aways:

- Beyond Gaussianity: Direct inference from tomography with nets
- Avenue to jointly constrain astrophysics and cosmology at Cosmic Dawn and Reionization
- 3D net for 3D data
- SKA source detection: pitfalls in low S/N regime

Ongoing & future steps:

- 3D-21cmPIE-Net Private - public soon on Github
- Test of Bayesian network for errors on parameters
- Test on data from SKA precursors & improved mocks

Thank you!

caroline.heneka@uni-hamburg.de, www.caroline-heneka.de