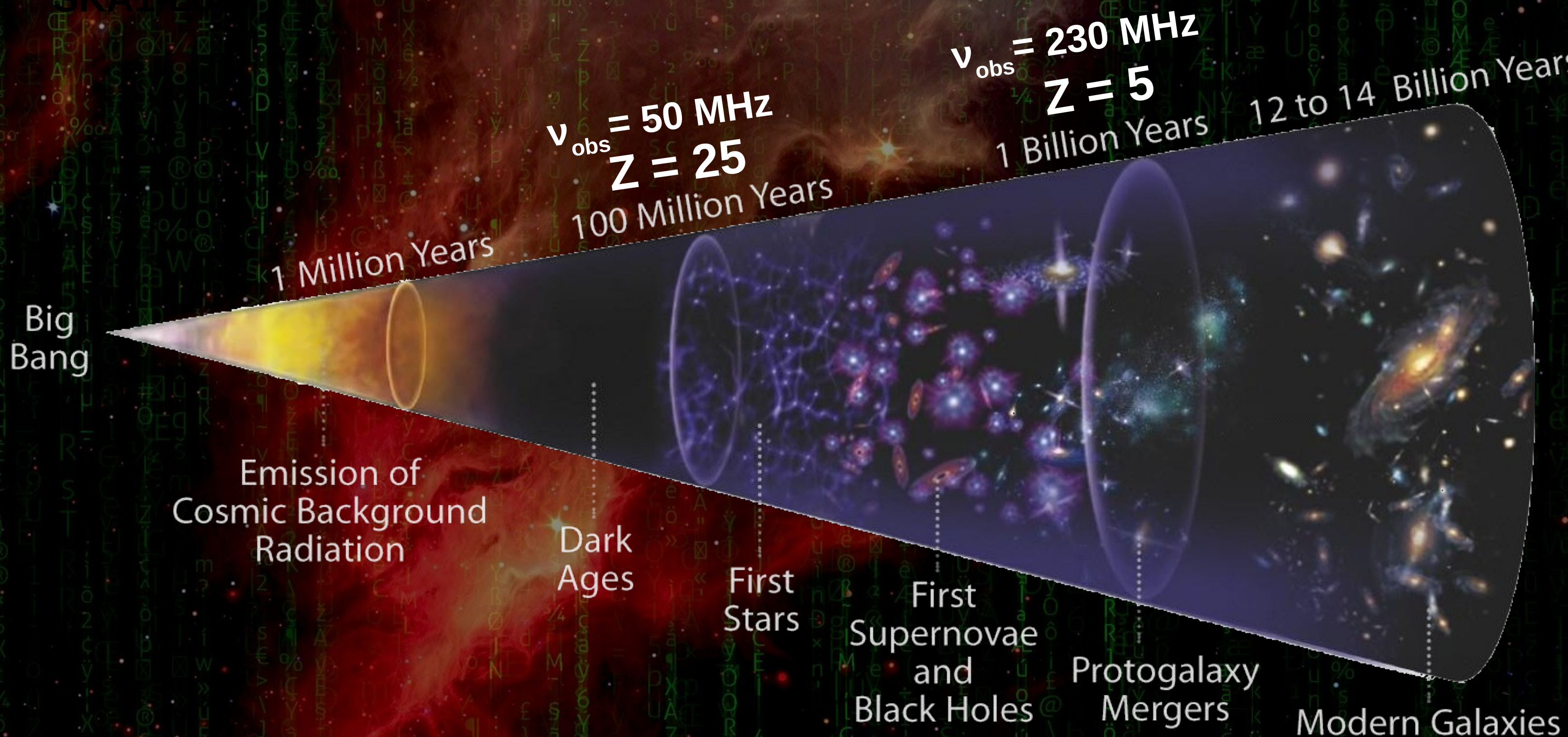
Deep Learning approach for HI regions identification and 21-cm signal recover from SKA-Low observations

Michele Bianco

David Prelogović (SNS Pisa), Tianyue Cheng (EPFL), Sambit K. Giri (University Zurich), Emma Tolley (EPFL), Andrei Mesinger (SNS Pisa)

The Epoch of Cosmic Reionisation



- Transition the Universe from a cold, neutral state to hot and ionised
- Detect 21-cm signal from hydrogen in the Intergalactic Medium (IGM)

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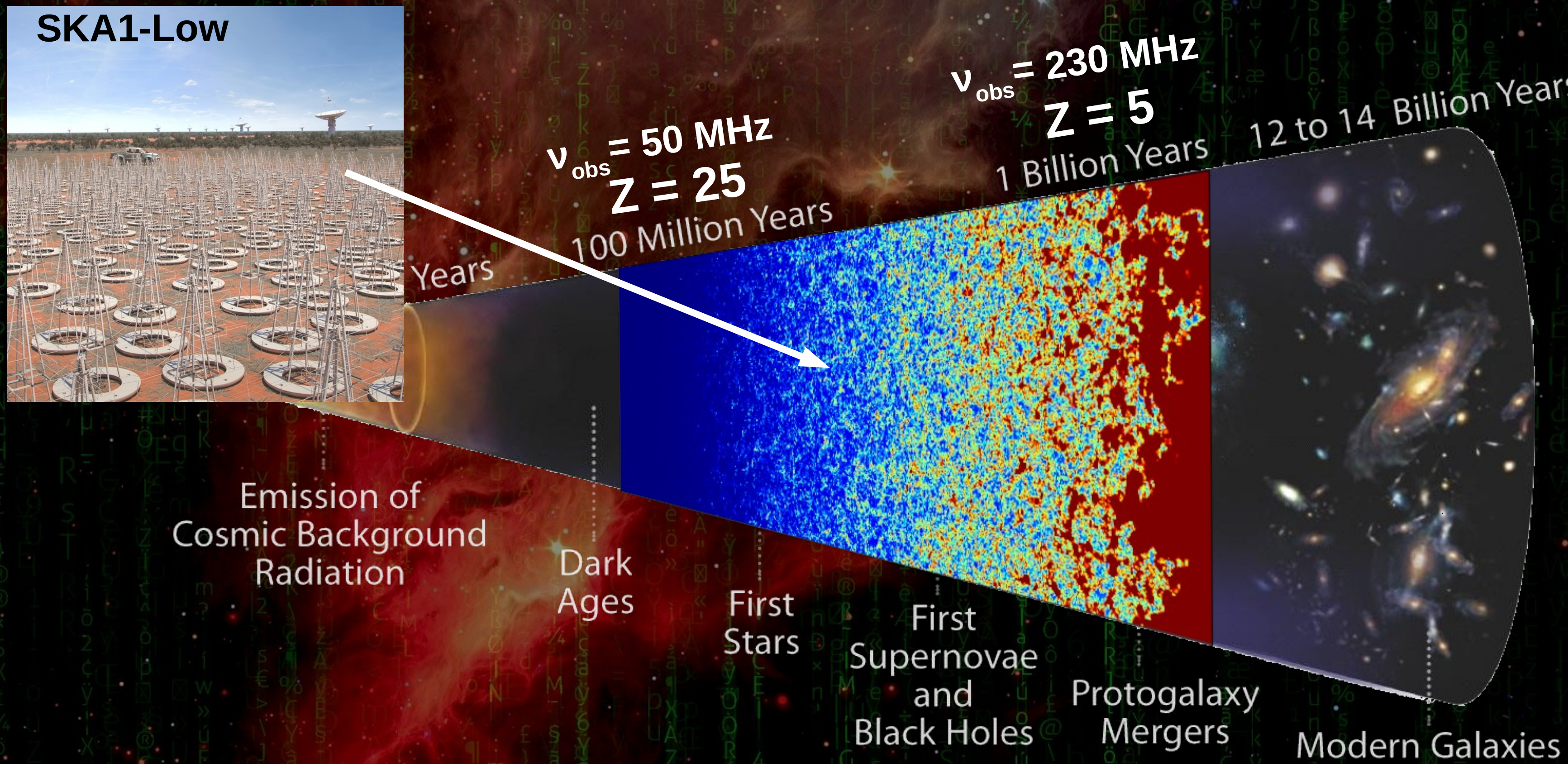

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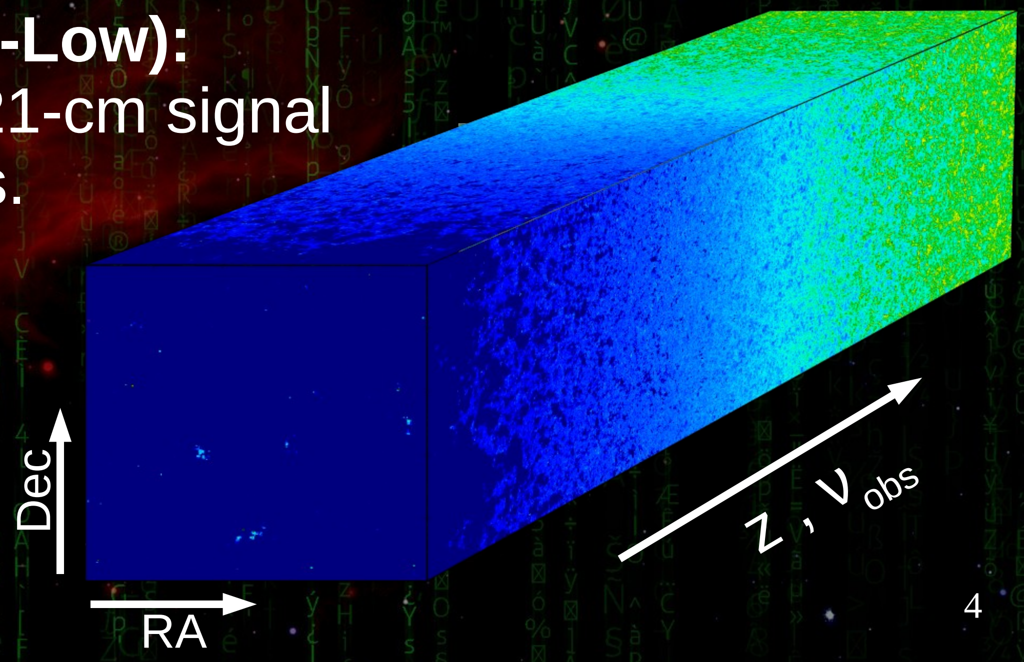
Tomographic imaging of the 21-cm signal

Probe reionization process by observing the redshifted 21-cm signal

$$\delta T_b(\theta, z) \propto x_{\rm HI}(\theta, z)$$

Square Kilometre Array (SKA1-Low):
Images sequence of redshifted 21-cm signal at different observed frequencies.

3D tomographic dataset or
a.k.a. 21-cm lightcones



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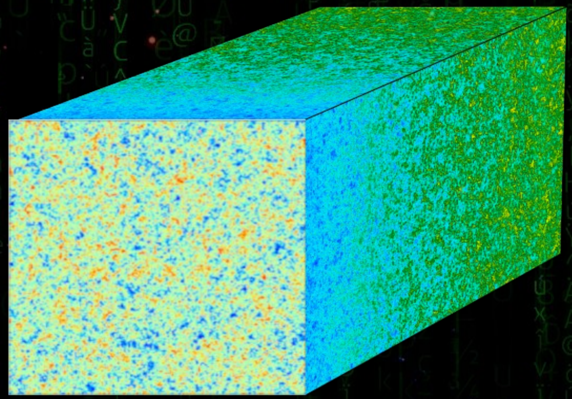

$z = 13.2$
$\nu_{obs} = 100$ MHz

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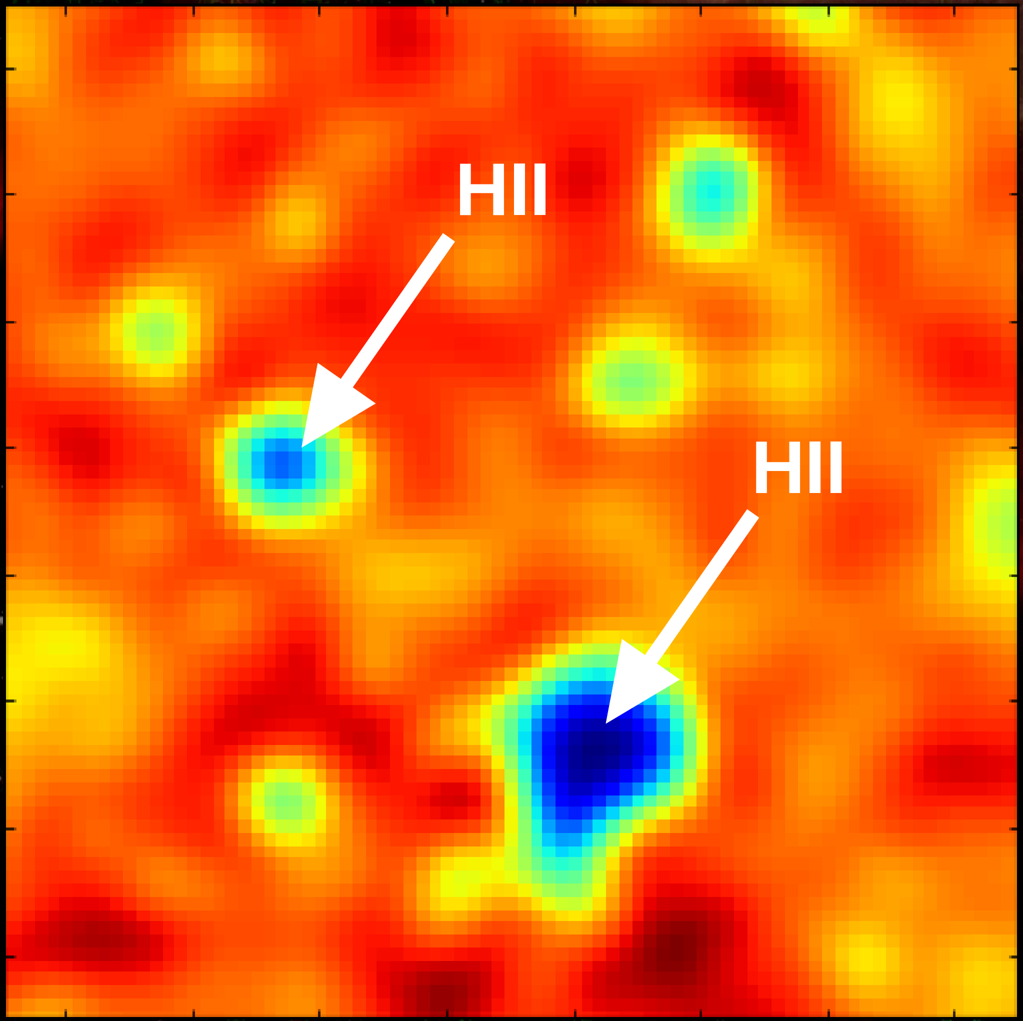

simulated **SKA1-Low** 21-cm images from tomographic data:

- $z = 10$ ($\nu_{obs} = 130$ MHz)
- Field of View ~ 1 deg
- Angular resolution ~ 42 arcsec

Isolated Ionised regions (bubble) indicate presence of galaxy cluster and/or primordial black hole.

No differential brightness:

$$\delta T_b = 0\,\mathrm{mK}$$

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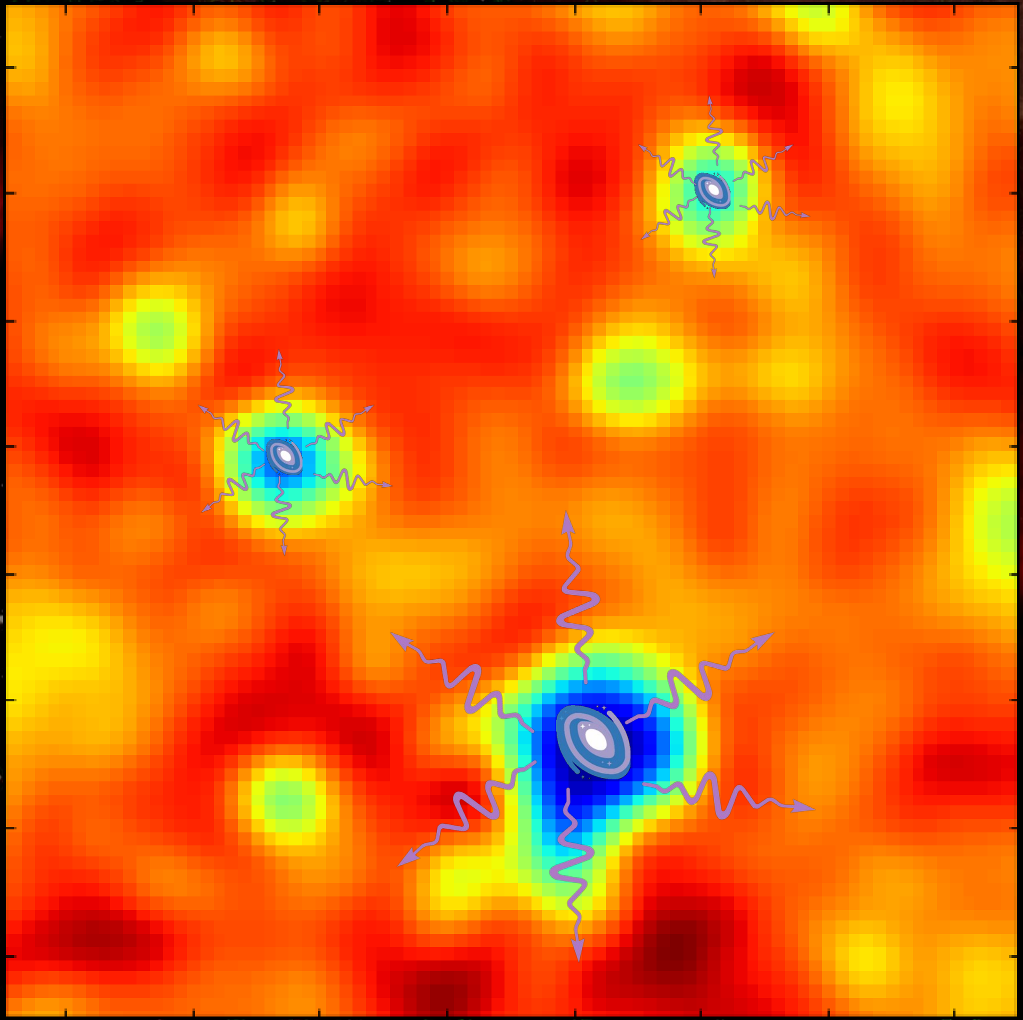

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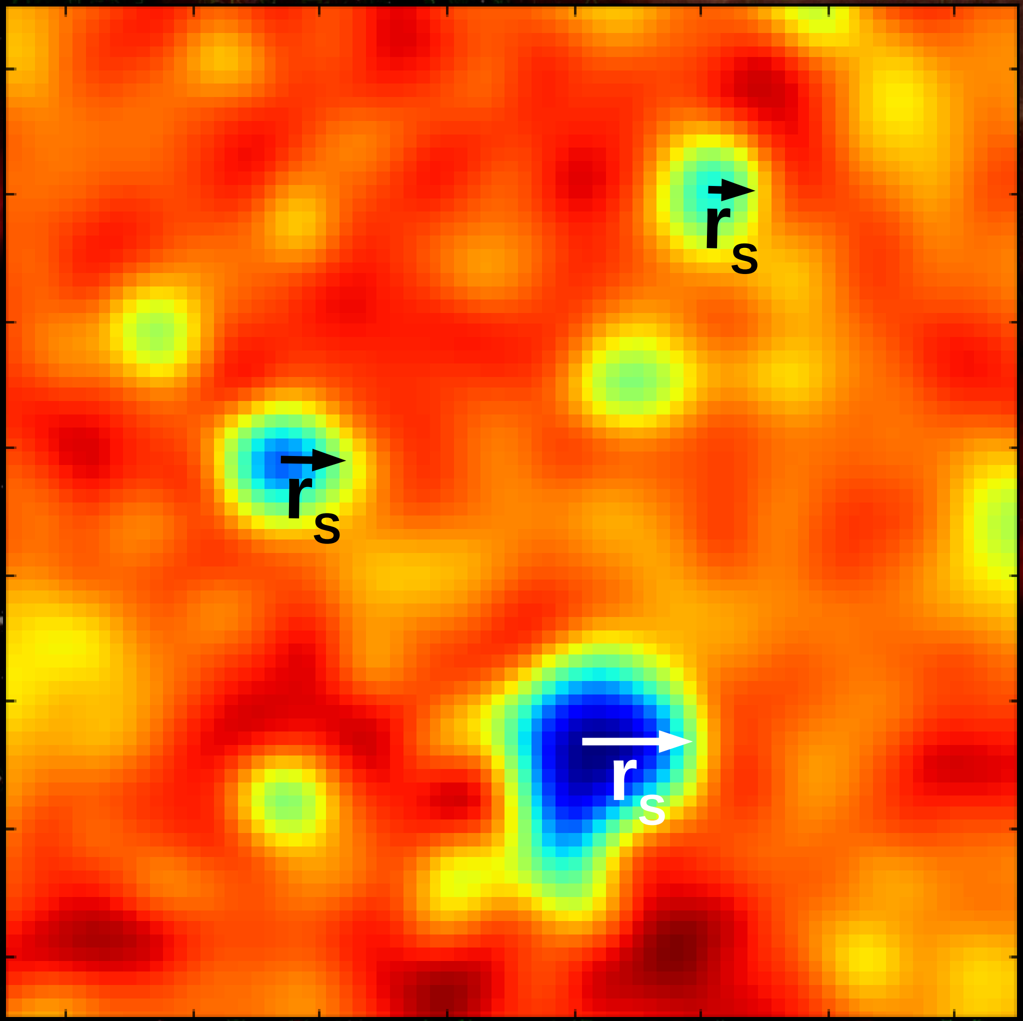

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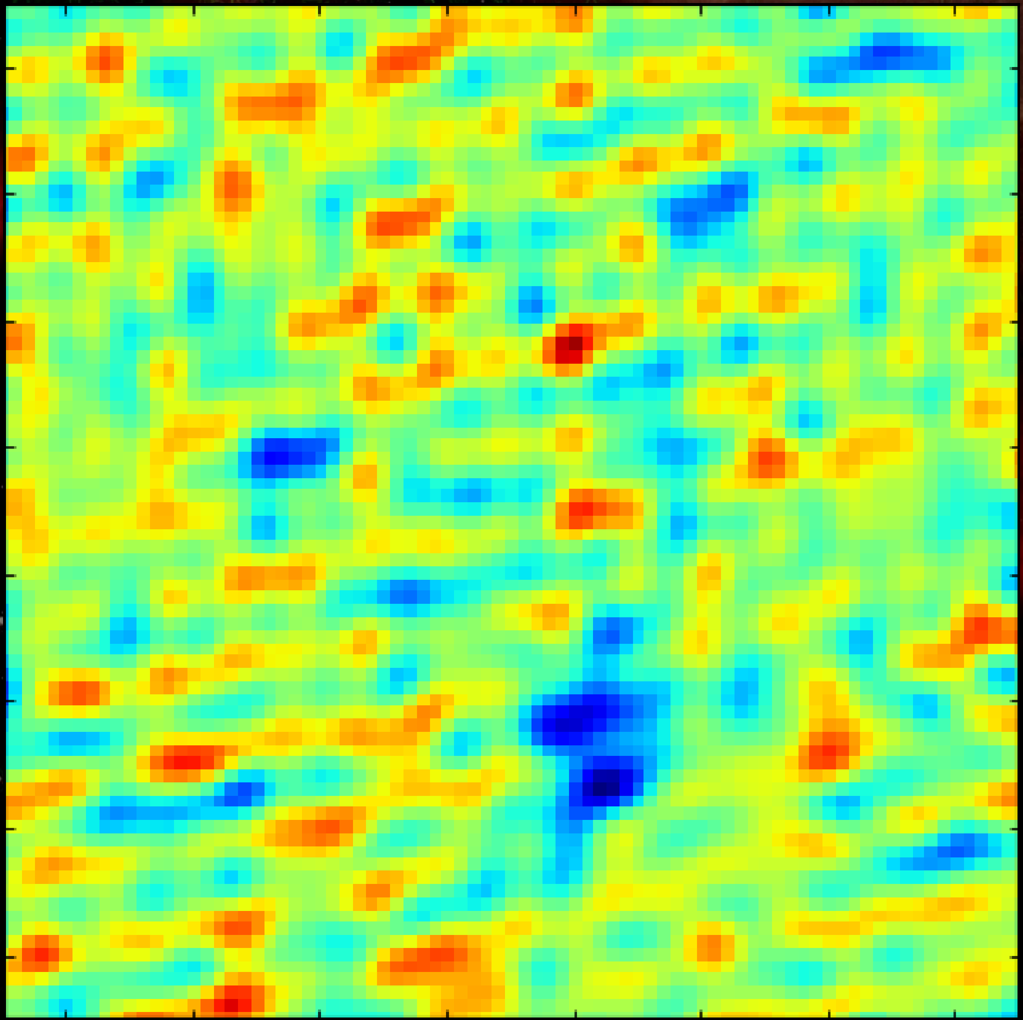
Relation between the size of the ionised volume and the sources proprieties

$$r_S \simeq \left(\frac{3\, N_{ion,tot}}{4\pi \, \langle n_{\mathrm{H}} \rangle} \right)^{1/3}$$

Tomographic imaging of the 21-cm signal



simulated **systematic noise map** after 1000 h observation:

- $z = 10$ (ν_{obs} = 130 MHz)
- Field of View ~ 1 deg
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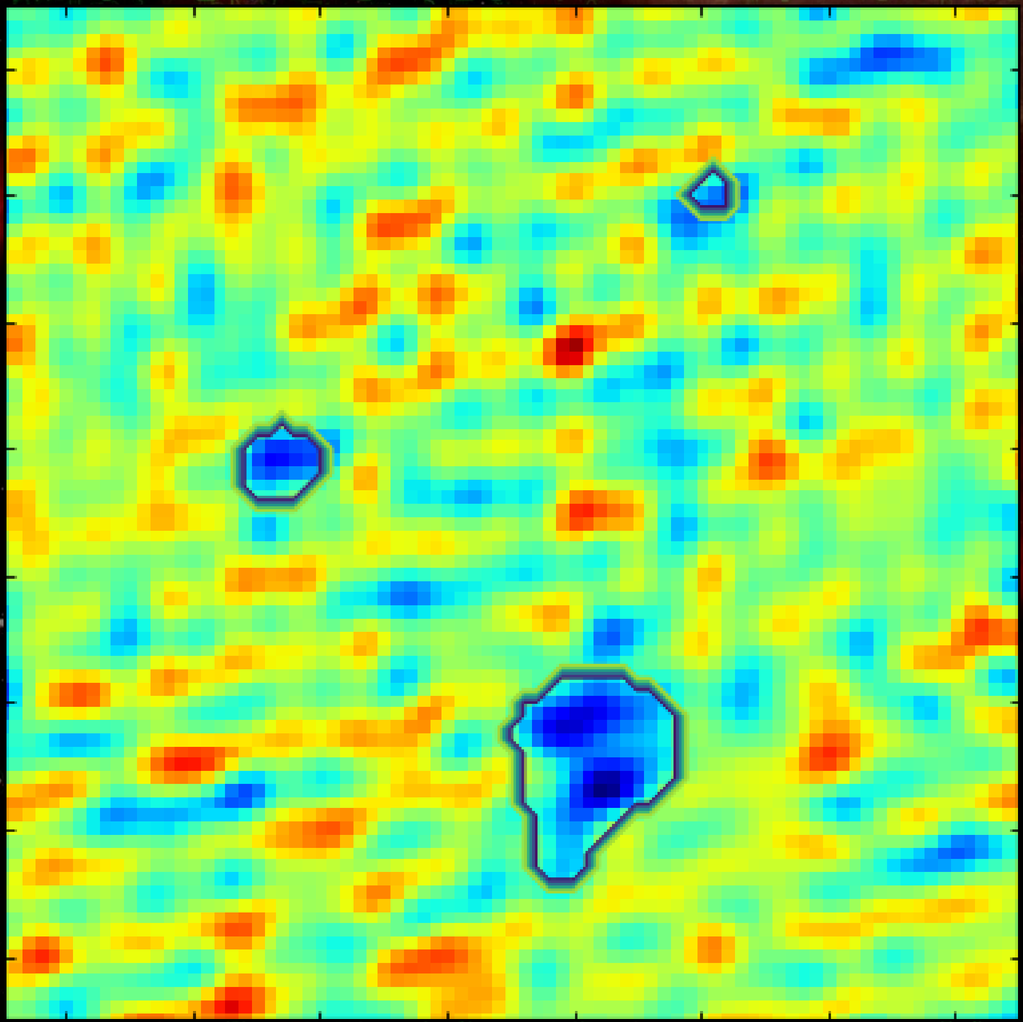
Systematic noise corrupts the 21-cm image and detection of ionised bubble becomes non trivial

Measurement of the bubble radius r_s becomes also non trivial

Tomographic imaging of the 21-cm signal



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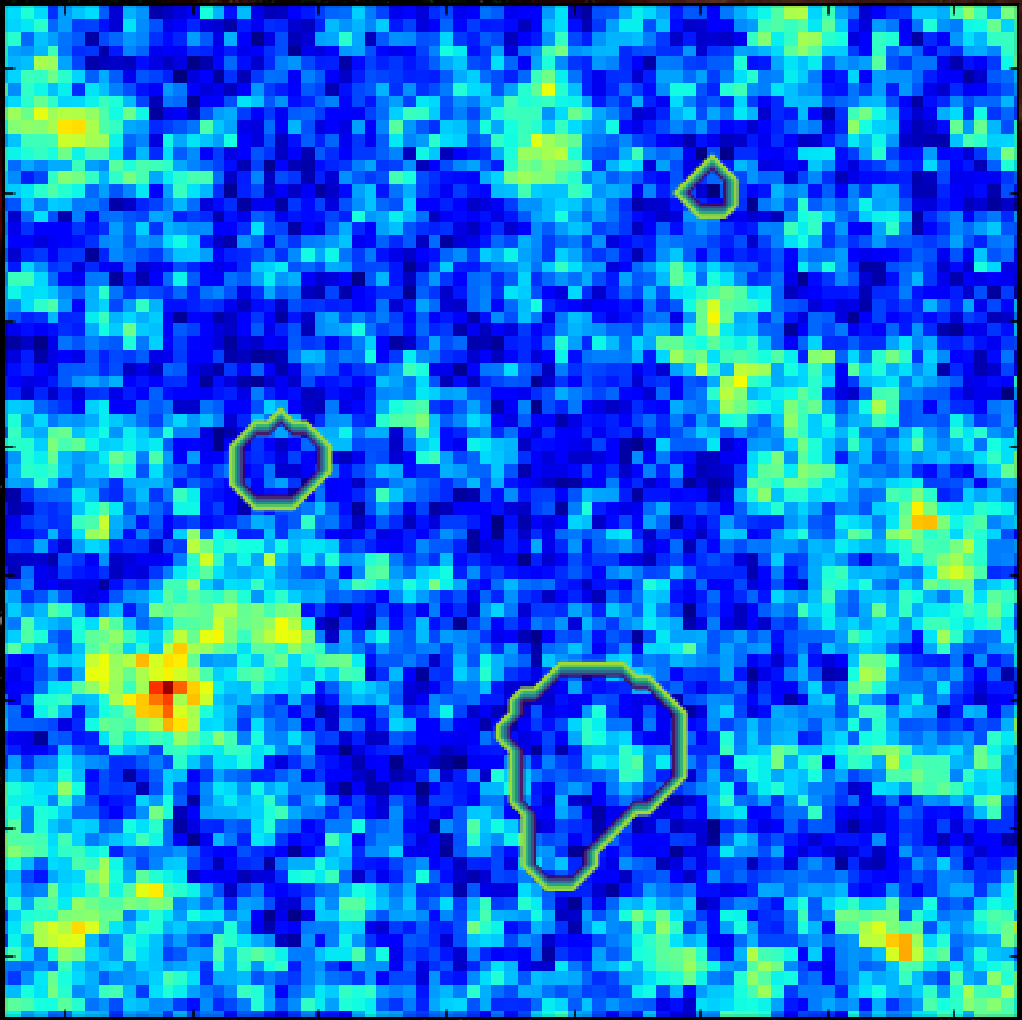


simulated **foreground map** for tomographic data:

- $z = 10$ ($\nu_{obs} = 130$ MHz)
- Field of View ~ 1 deg
- Angular resolution ~ 42 arcsec

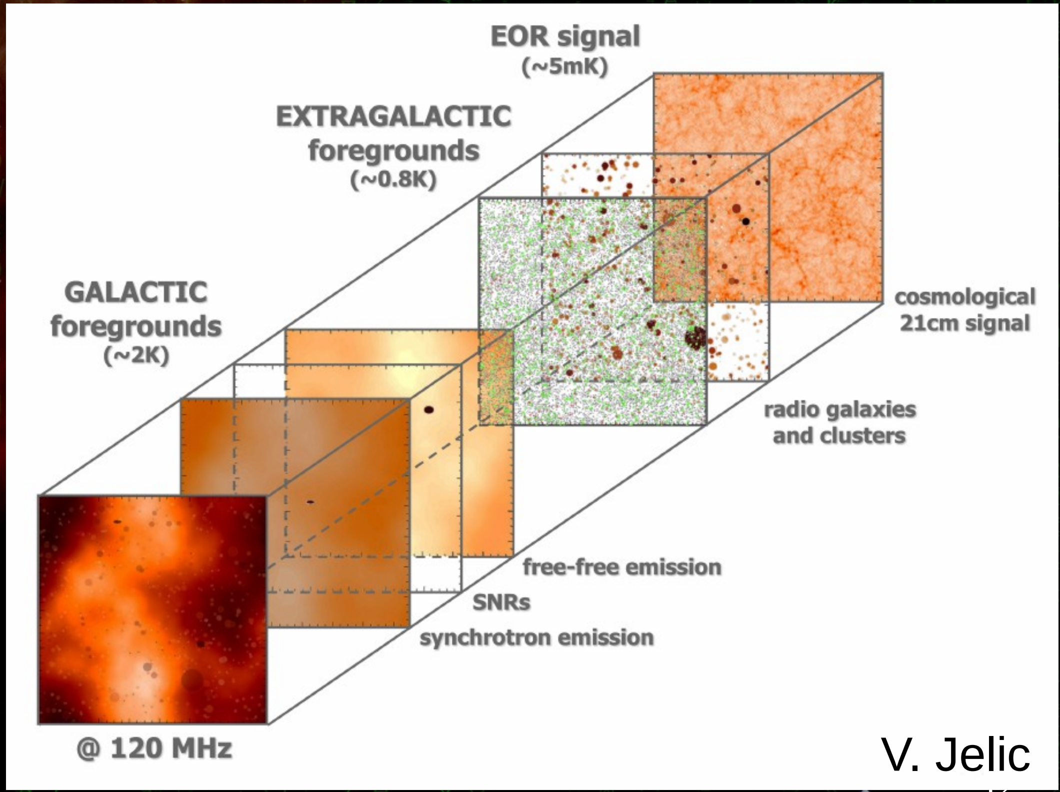
Contributions from the Galactic synchrotron radiation outshines the 21-cm signal of the order ~10^6

Impossible identification and measurement of bubbles radius $\mathbf{r_s}$

Tomographic imaging of the 21-cm signal

SKA1-Low tomographic images of redshifted 21-cm signal challenges:

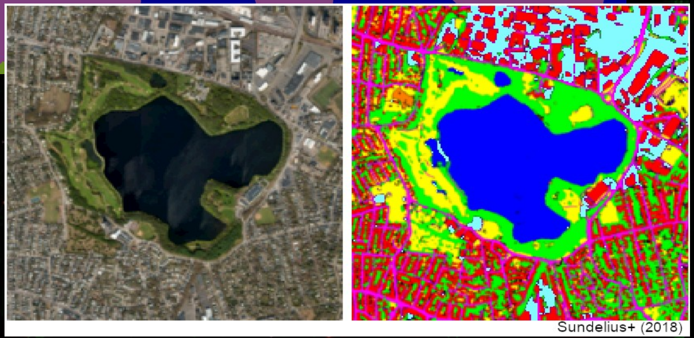
- Instrumental noise (signal ~ 5 K)
- Foreground emission (signal ~ 1 - 1000 K)
- Antennas gain errors
- Ionospheric refraction effects
- Radio frequency interference
- And more ...



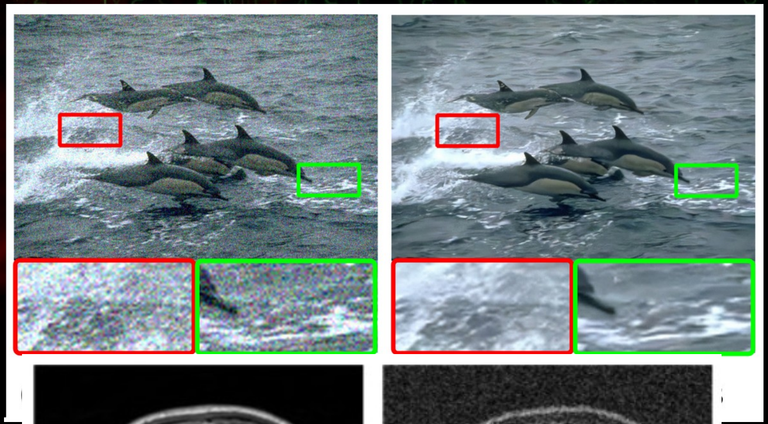
Deep Learning algorithm with Convolutional Neural Networks

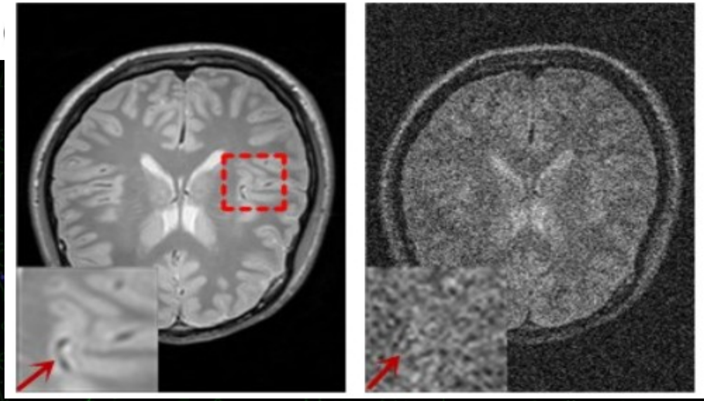
Modern Computer Vision technology based on AI and deep learning methods are able to **identify object** and/or **de-noise** images with great precision. (e.g.: self-driving cars, image satellites, medical image, etc...)

Image segmentation



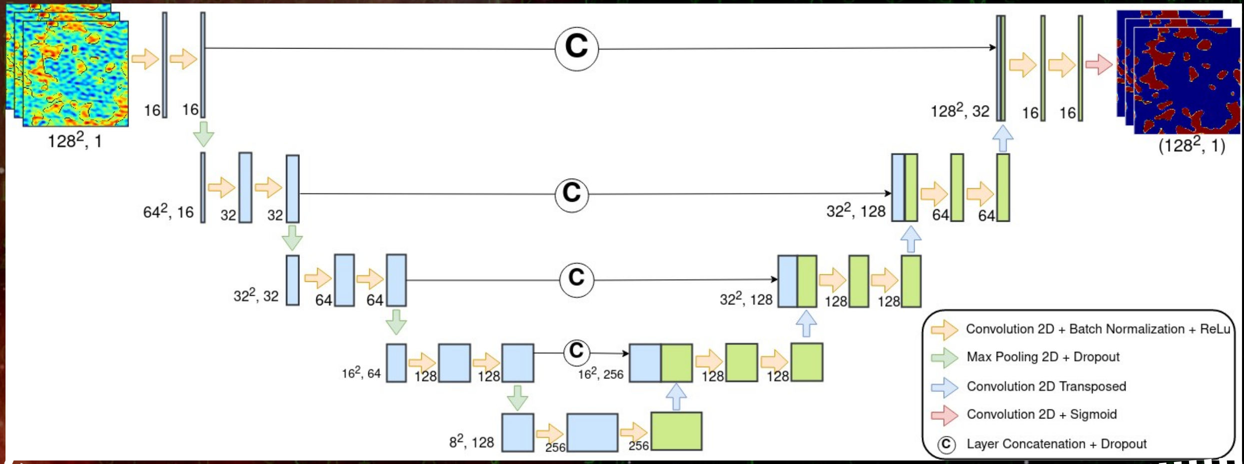
de-noising images

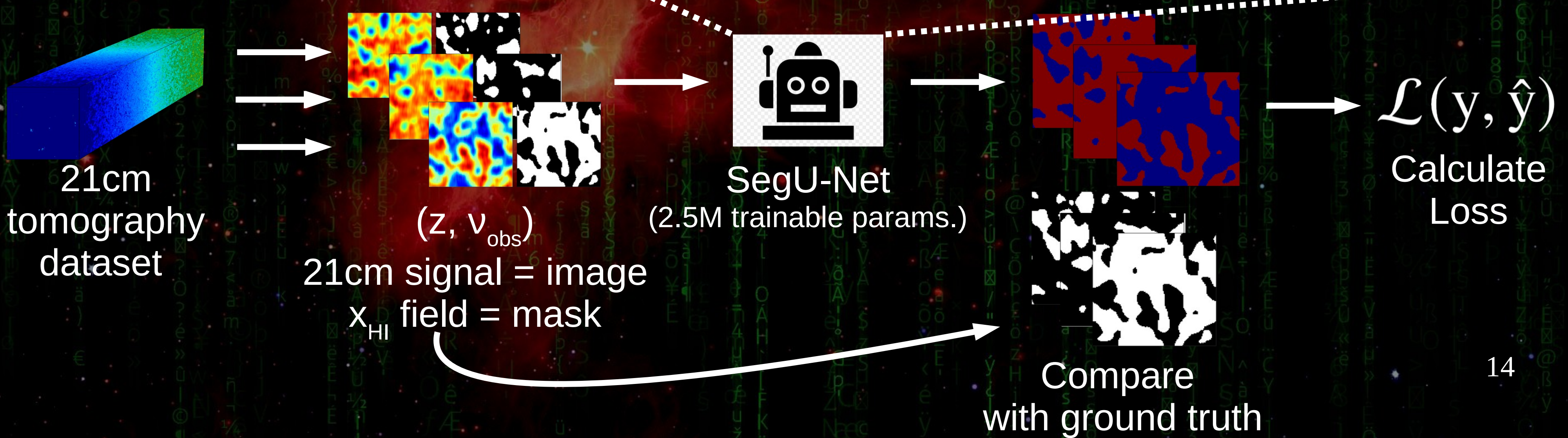




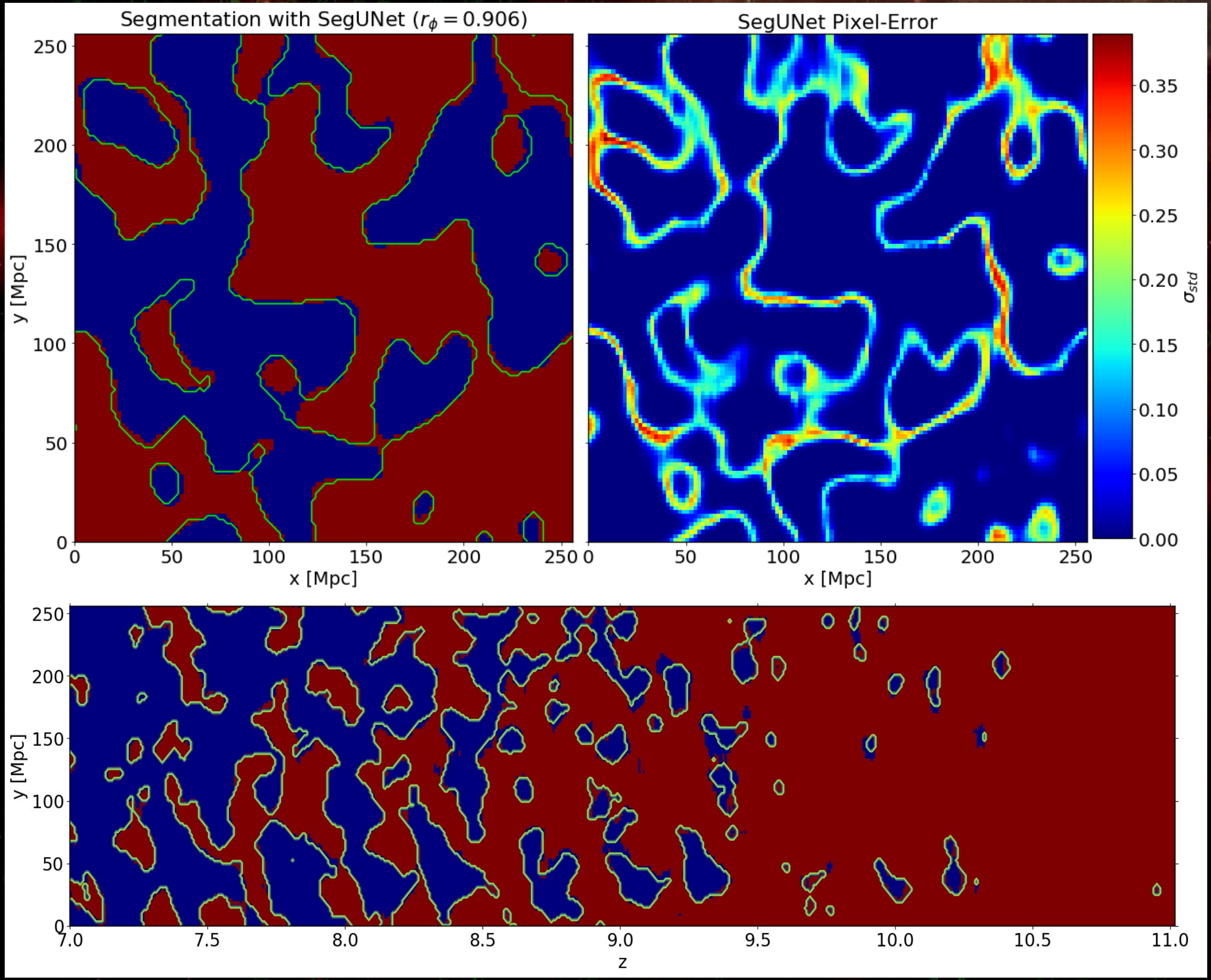
SegU-Net: Segmentation with U-Net for EoR
(Bianco+ 2021) arXiv:2102.06713

- U-Net:
  Network with interconnected encoder/decoder layers
- Convolutional layers on 2D slice of tomographic dataset (rolling procedure along z-axis)



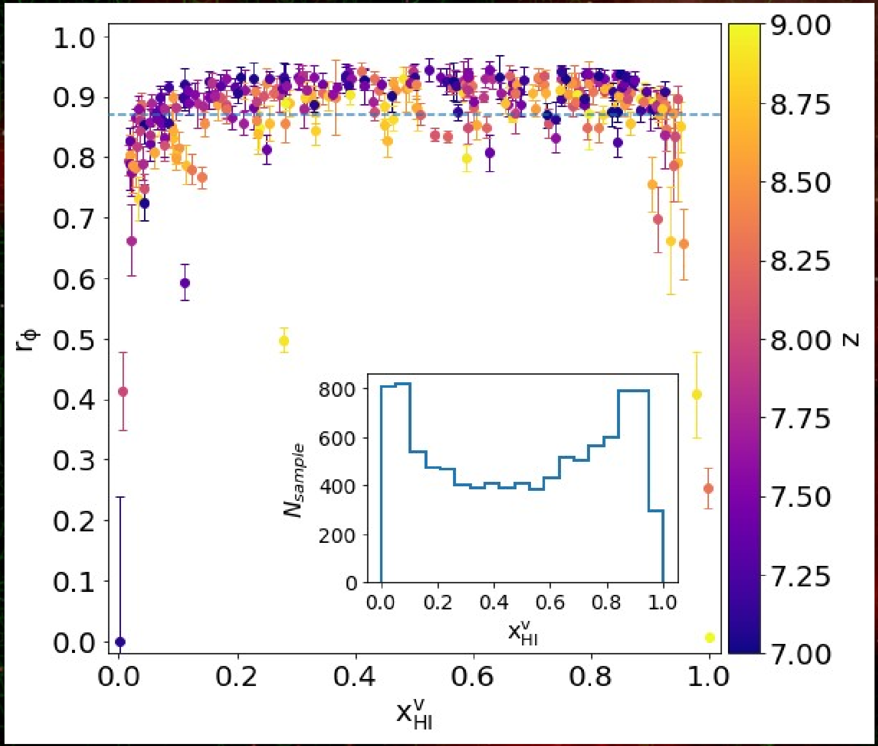


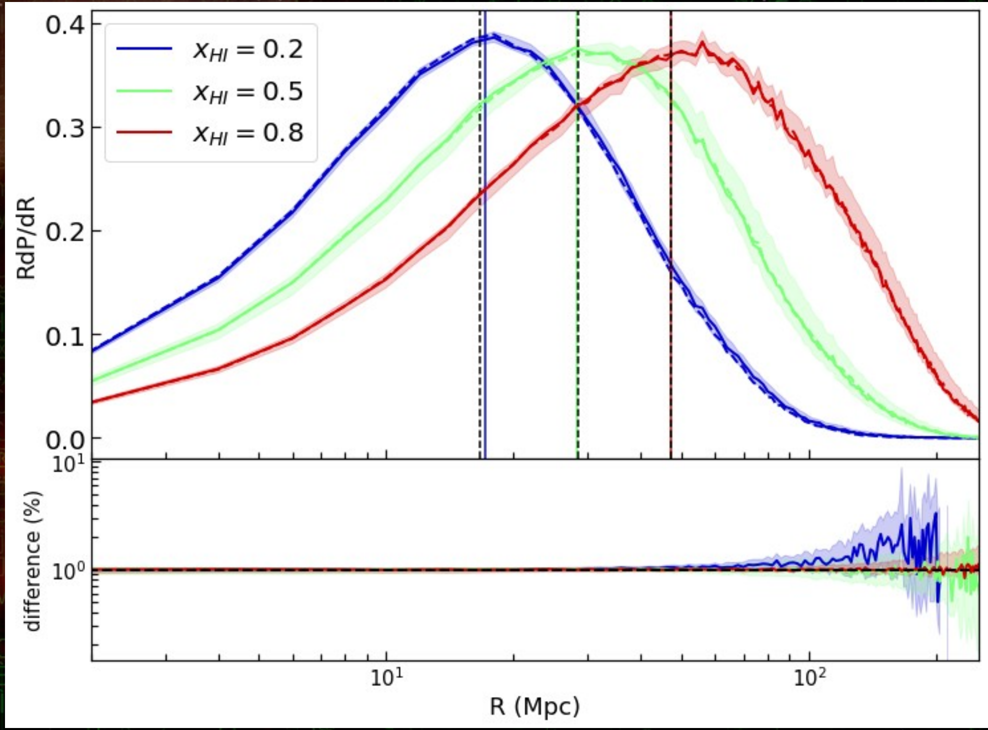
SegU-Net Results: Visual Evaluation & Uncertainty-map



- Network binary field recovers with "confidence" large interconnected ionised/neutral regions
- Higher uncertainty at Bottleneck and regions with low-dynamic range

SegU-Net Results : Correlation Coefficient r_Φ and HI size distribution





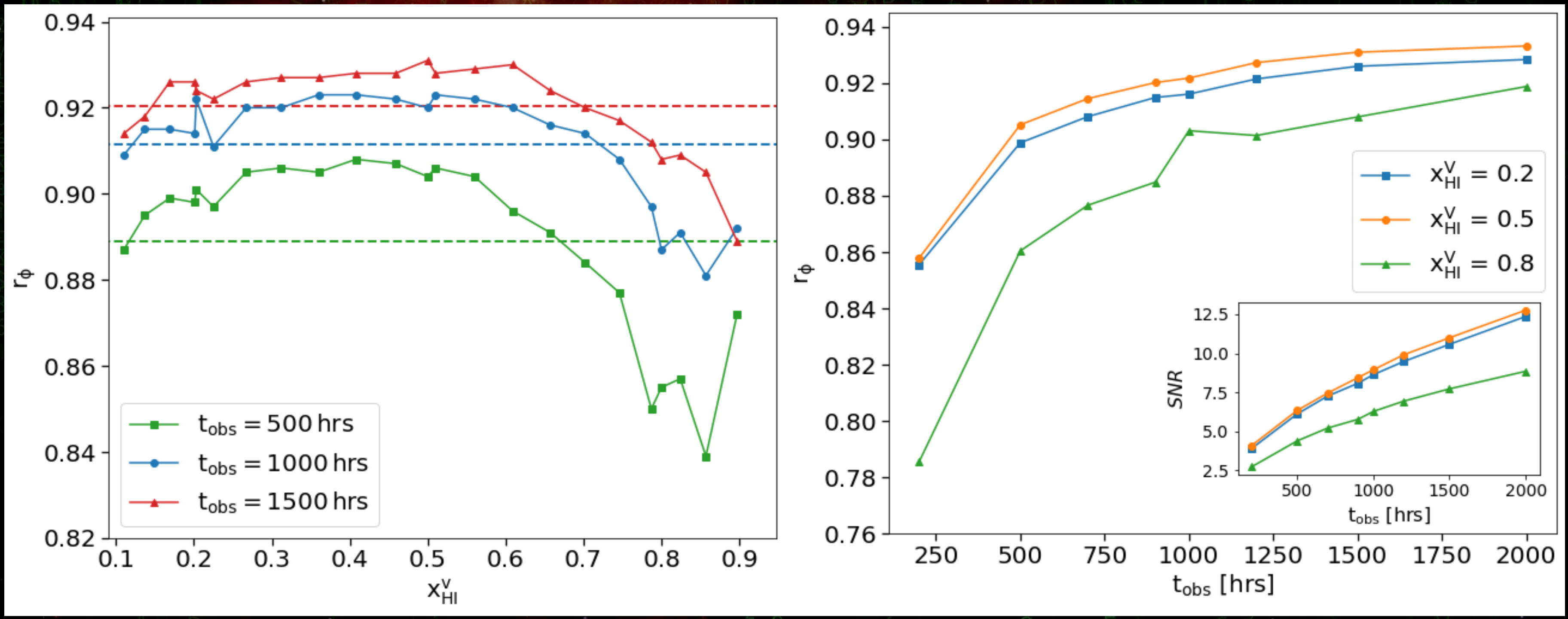
Average accuracy: 85% better than state-of-the-art algorithm for segmentation

Estimations are consistent troughout EoR history. Difference to ground truth is within ~5%

SegU-Net Results: Response to Noise level

Test on different instrumental noise level: under- or over-estimate

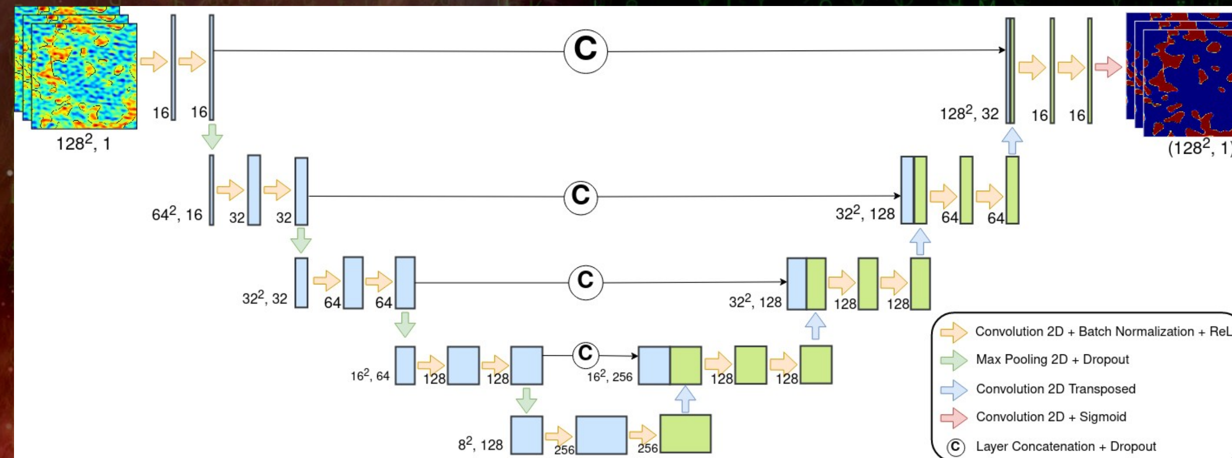
- Predictions on un-trained data with t_{obs} = **500 - 2000 hrs**
- $\mathbf{t_{obs}}$ > 500 hrs (SNR>3) same level of accuracy (~85%) as in the training
- Network accuracy affected by the **dynamic range** in the images



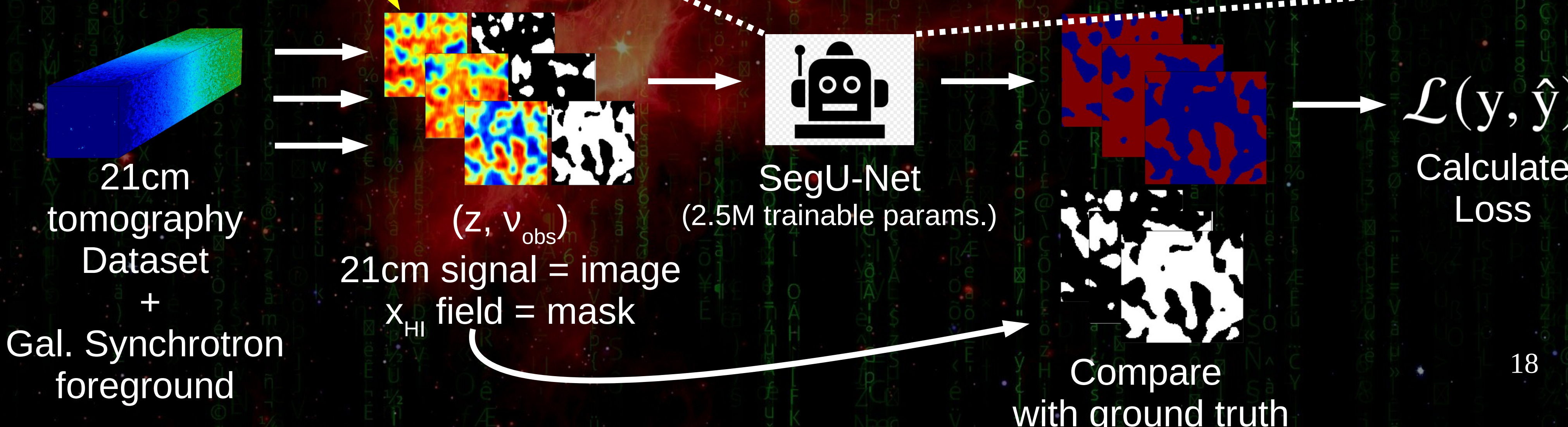
SegU-Net v2.0: foreground contamination

(Bianco+ in prep.)

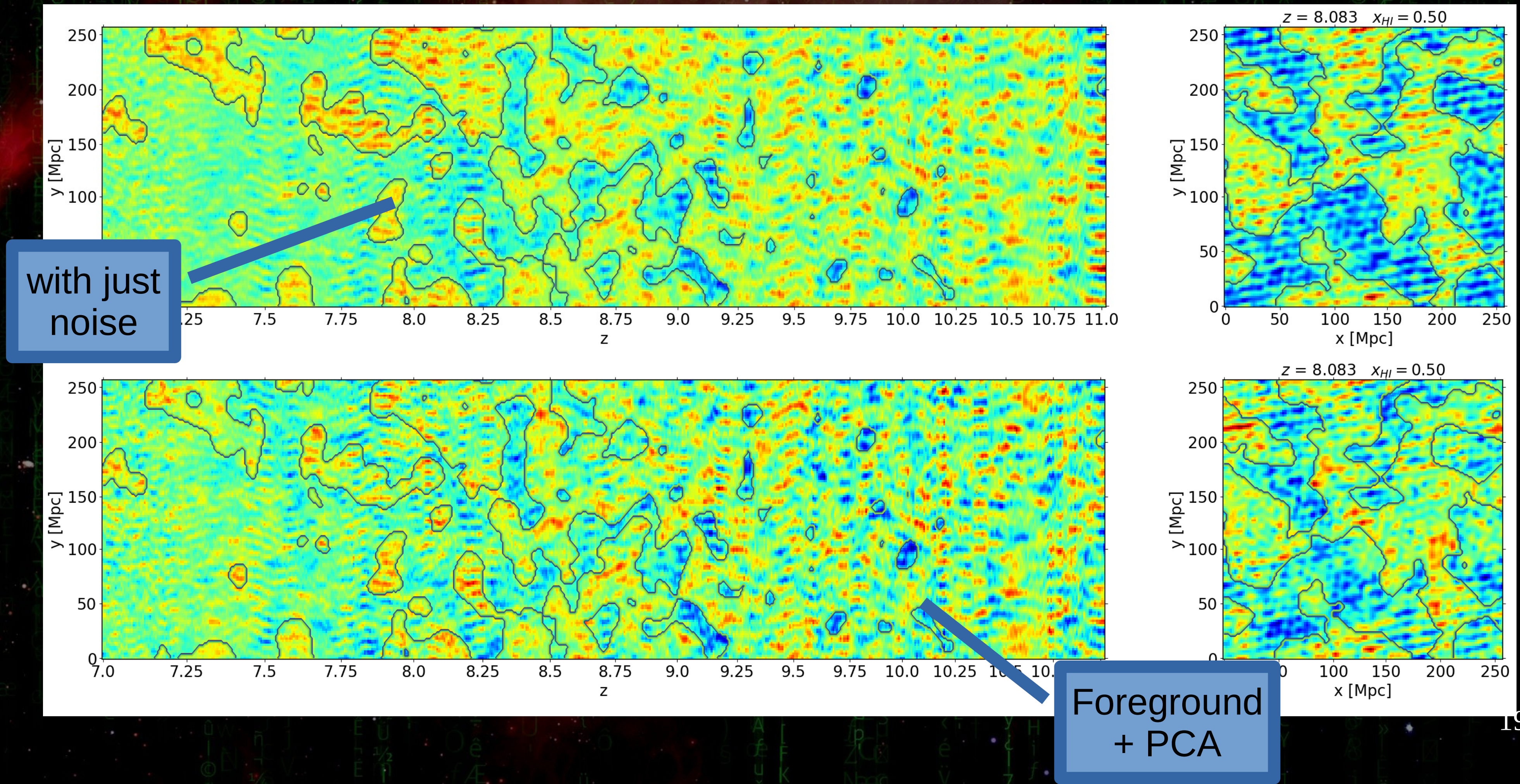
- U-Net:
  Network with interconnected encoder/decoder layers



add PCA pre-process step that decreases image dynamic range



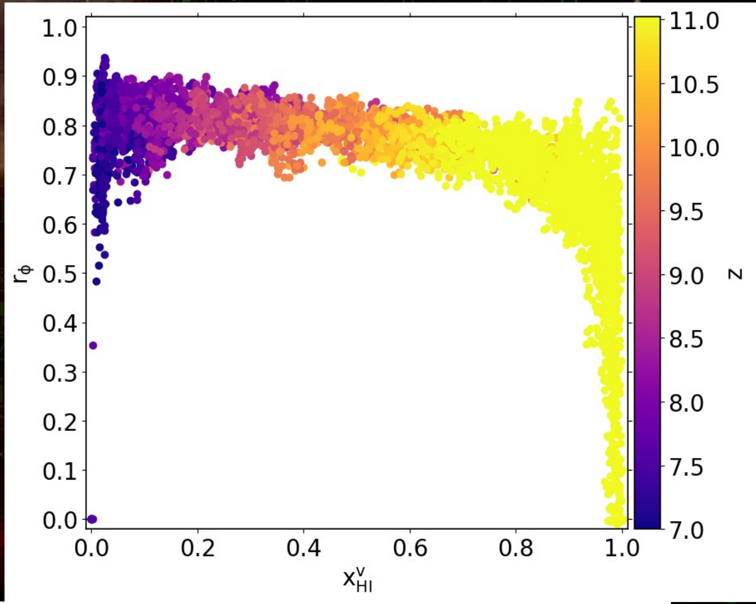
Reduce dynamic range in foreground contaminated 21-cm image with PCA

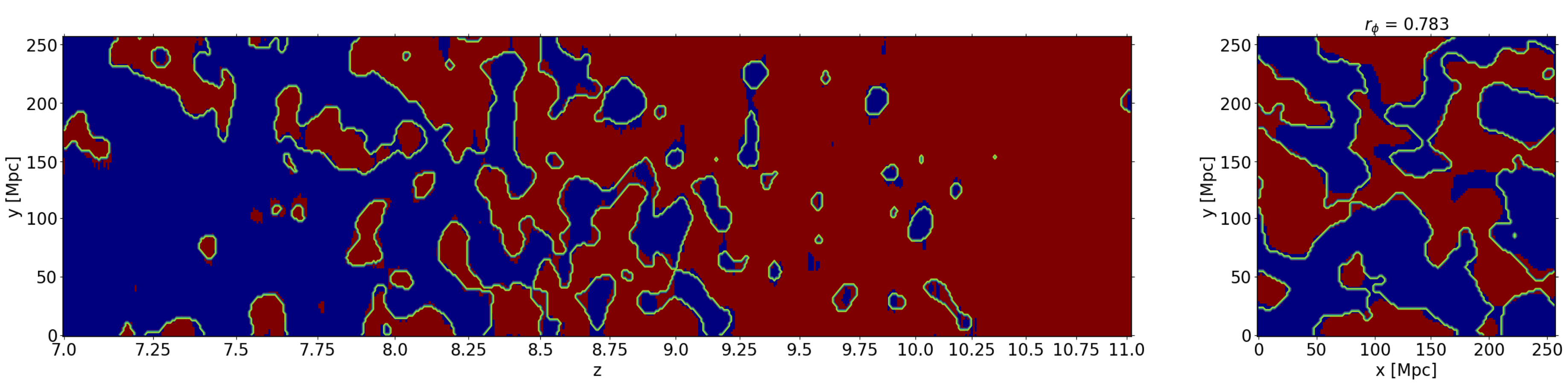


SegU-Net v2.0 Result: segmentation with foreground contamination

PCA+SegU-Net obtains accuracy level on the same level of our previous wor

PCA decreases the dynamic range to manageable levels for SegU-Net to recover tomographic binary data



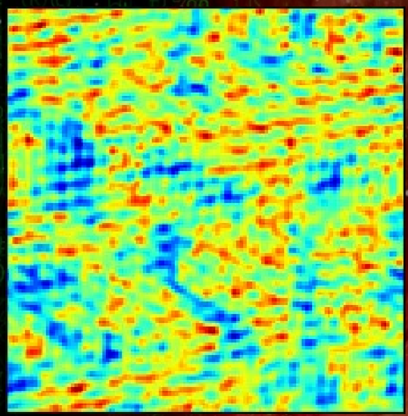


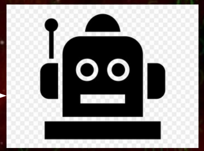
The Next Goal of the Project

Deep learning approach for HI regions identification….

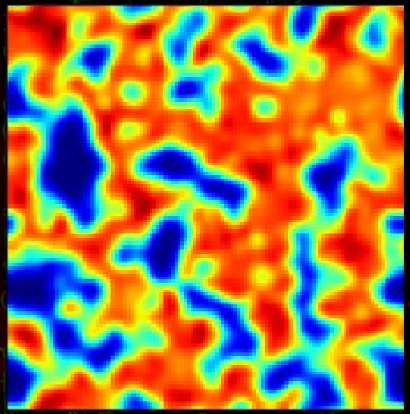
…. and 21-cm signal recover from SKA-Low observations

Corrupted 21cm image





Deep Learning Networks



simulated 21cm image

1) Use accurate modelling of the foreground and interferometry instrumental response (incomplete uv-coverage)

2) Data pre-process for foreground avoidance (wedge removal) and/or foreground mitigation techniques (PCA)

3) Use identified HI regions as prior information in the training process of the 21-cm recover network (RecU-Net)

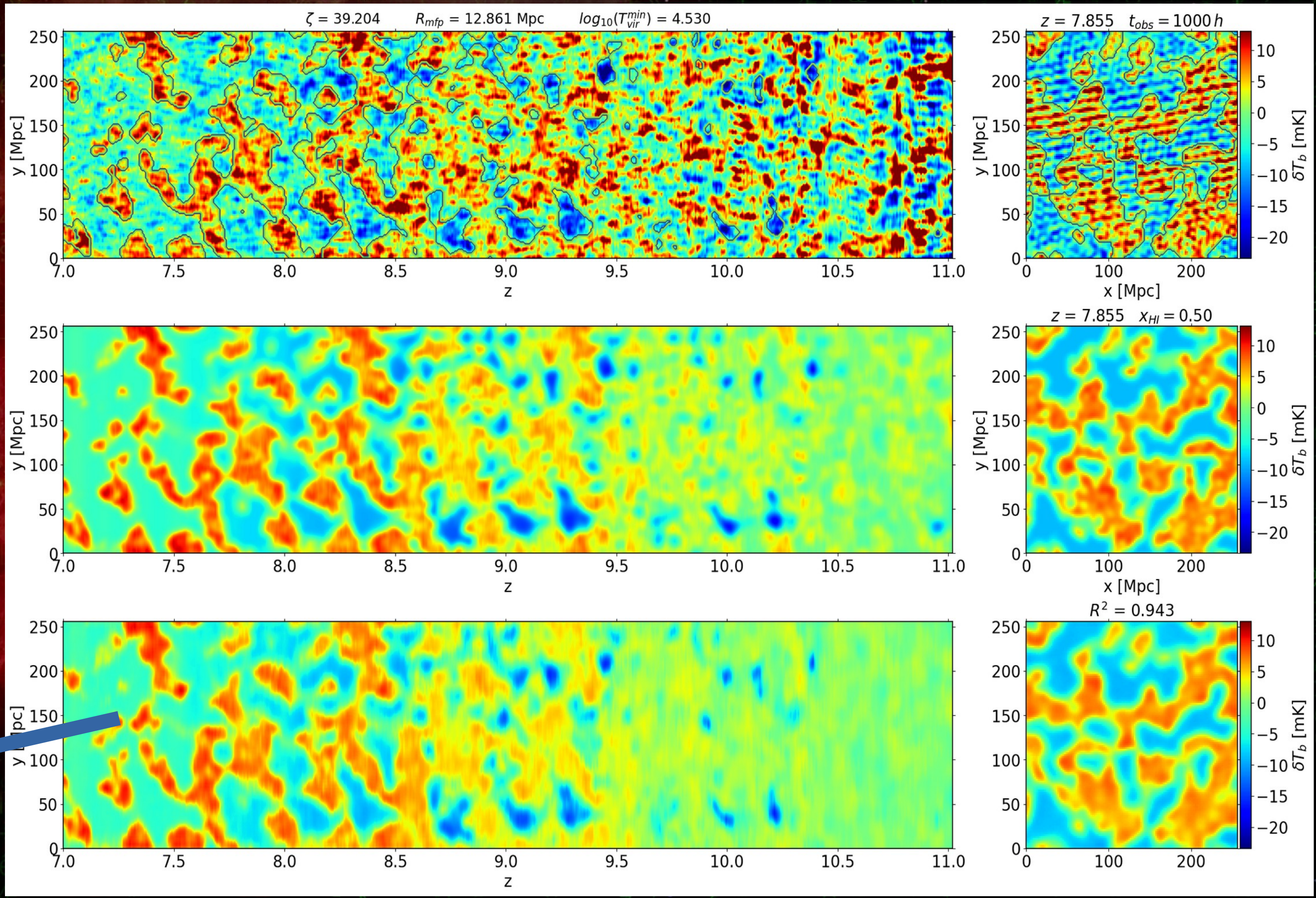
RecU-Net Results: 21-cm Visual comparison

A first test:

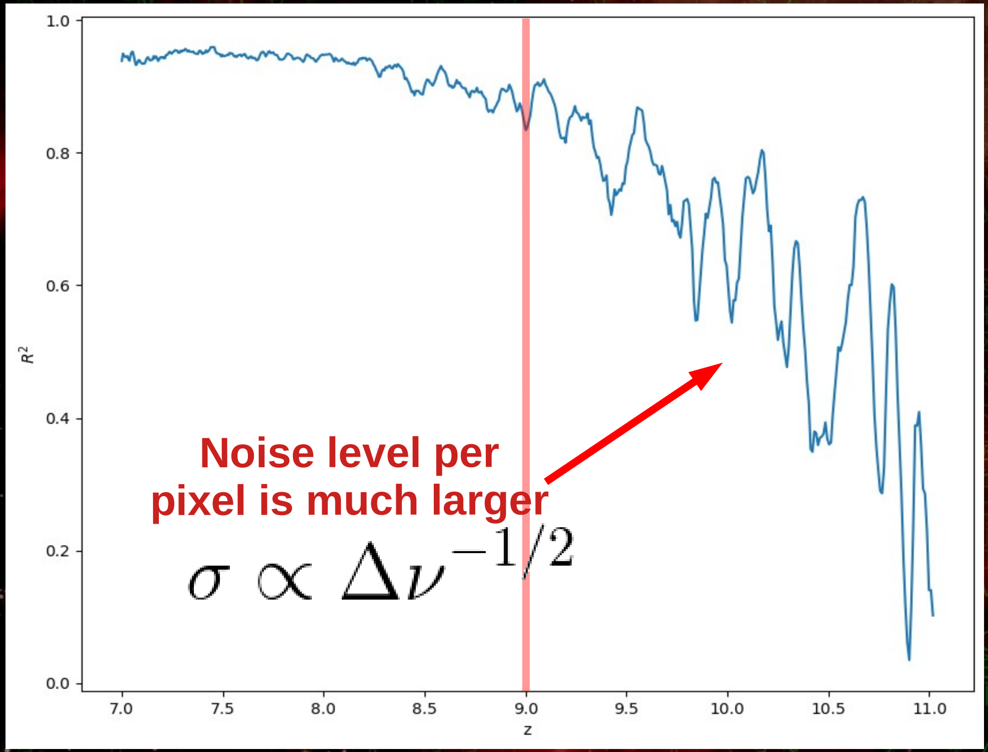
- RecU-Net≈SegU-Net
  1) final activation
  2) changed target
  3) different loss

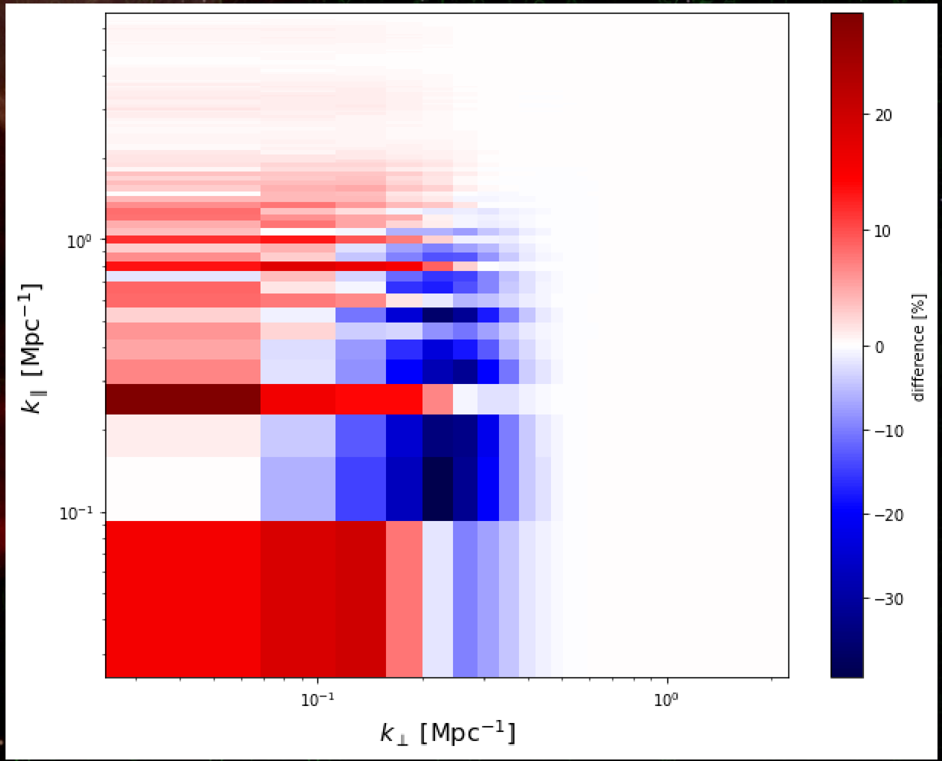
- Recover 21cm signal from images with SKA-Low instrumental noise

This is RecU-Net prediction



RecU-Net Results: r_Φ and x_{HI} on entire Tomographic data



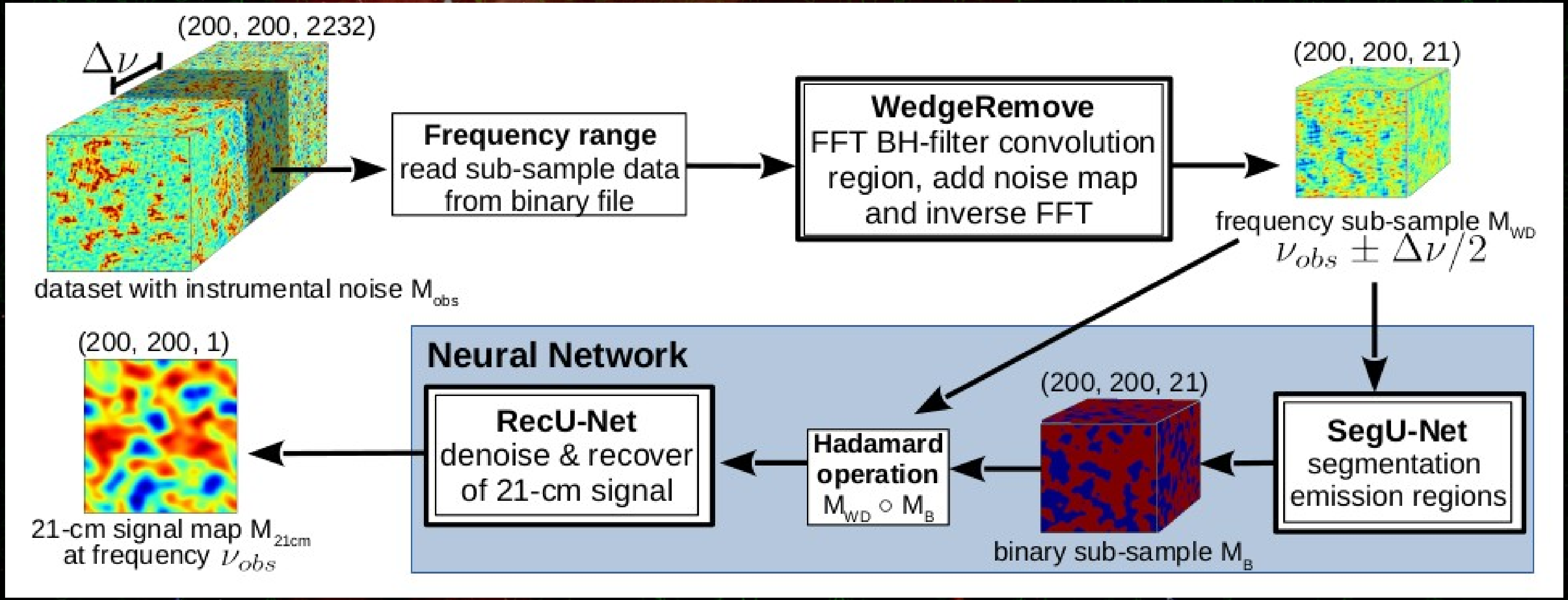


RecU-Net is extremely accurate ($R^2 \sim$ 92%) redshift range **7 < z < 9**

21-cm Power spectra (top) recover within ~5% small scale correlation, k > 0.2 Mpc^{-1} and redshift z < 9

SERENEt
Segmentation and Regression NEtwork

Combine the prediction of SegU-Net as additional input in Rec-Unet training step in order to include prior in the network training.



Proposal accepted for SKACH large HPC allocation projects
at Pitz Daint @ CSCS (started 1th of August)

Summary & Future Work

Work done so far:

- SegU-Net is a powerful tools for segmentation on noisy 21-cm images.
- Existing technique can be employed to pre-process data before training. to reduce the dynamic range of foreground contamination.
- SegU-Net v2.0 can also be use on foreground contaminated images
- UNets can be employed to recover 21-cm signal from noisy data.

Open challenges list:

- Employ OSKAR simulation for radio interferometery effects.
- Feed prior information in training (combination of Seg and RecU-Net).
- Impact of the foreground pre-process step on the training and prediction.
- Study a combination of foreground subtraction algorithm (PCA, Wedge,…
- Strategise training bias of SegU-Net v2.0
- Publish paper on SegU-Net v2.0