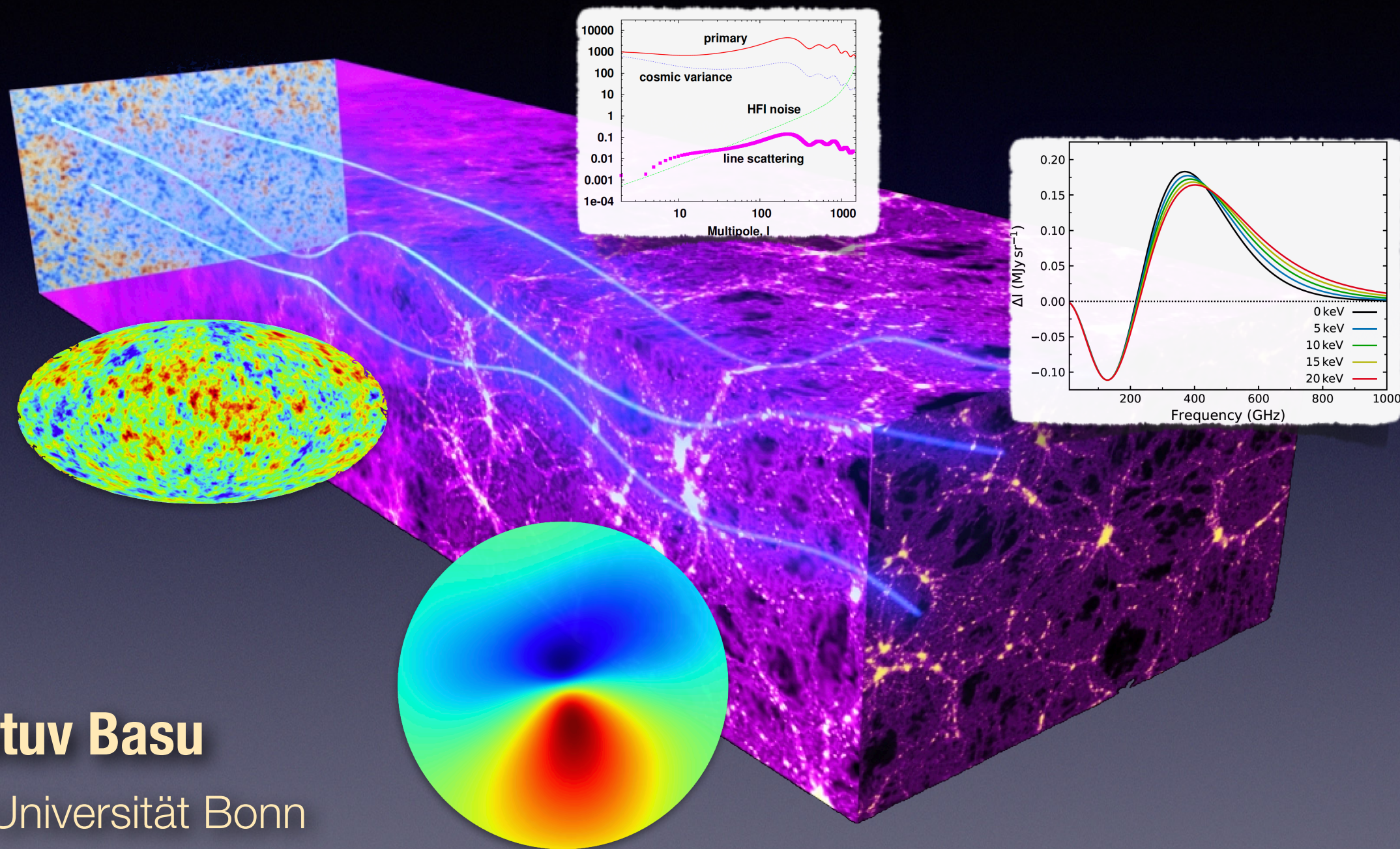


Deep Learning on the CMB:

How to learn more from the oldest light



Kaustuv Basu

AlfA, Universität Bonn

kbasu@uni-bonn.de

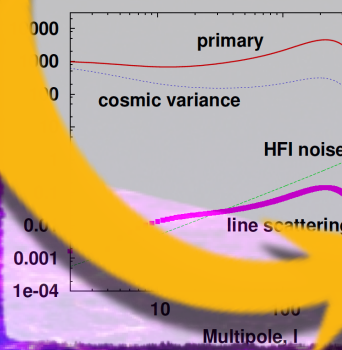
Deep Learning on the CMB:

How to learn more from the oldest light

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Goal: We want to determine the masses of every major galaxy cluster in the Universe!

M_{250c}

T_i

T_{dipole}

ResNet I

ResNet II

DEEP LEARNING ON THE CMB

Dr. Kaustuv Basu kbasu@uni-bonn.de

AlfA, Universität Bonn

Scientific Background

The Cosmic Microwave Background (CMB), the oldest light in the Universe, shines behind every astronomical object. Among these objects are the massive clusters of galaxies, which distorts the background light via gravitational lensing.

- The lensing signatures of galaxy clusters are useful for inferring their (dark matter) mass, which is the most important ingredient of doing cosmological analysis with these objects (and also the most difficult to measure). The current methods are not very efficient, requiring 1000s of objects to make any significant detection of CMB-lensing.
- The very unique lensing distortion feature (which looks like a dipole) makes it an ideal test-case for computer vision! The global lensing signal (i.e. the convergence maps) can directly be used to model the total mass distribution in the Universe.
- Additional applications of deep learning on CMB are: Component separation (i.e. separating the CMB and foreground signals), de-noising (suppressing the detector and atmospheric noise), and image upscaling (i.e. improving the angular resolution).

Methods & Questions

Application of deep learning (via ResNet and other CNN architectures) on CMB images is nothing new: At least two papers used it for galaxy cluster masses, and well over a dozen for CMB map reconstruction in general. We are testing the mResUNet architecture proposed by Gupta & Reichardt (2021)

Many possibilities, which road to take?

- Use GANs for image generation, or move to vision transformers?
- How to use data from multiple frequencies to remove contaminating signals, or even do spectral fitting?
- Can we employ specific Fourier-domain filtering techniques (like matched filtering) in the convolutional layers?

None of these methods (specifically on cluster mass modelling) have yet been applied on real data! One of our objectives is to make use of the amazing new data that will be collected from the Fred Young Submillimeter Telescope (image on the right), starting 2024 or early 2025. Hence the need for hurrying up!

Challenges to Overcome

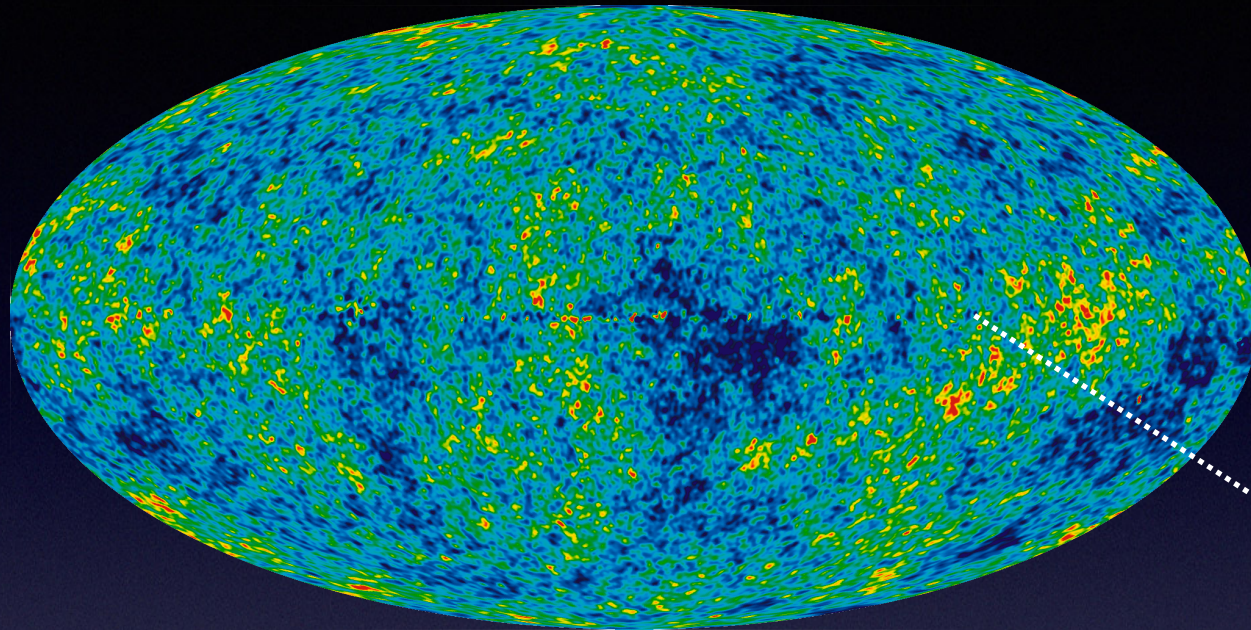
Some specific challenges for CMB-lensing (and other CMB-vision tasks):

- The lensing signal is too small, typically $10 \mu K$ signal hidden under $100 \mu K$ noise, and in polarization the signal is 10-100 times smaller. Hence, it can be very difficult to avoid over-fitting or eliminate biases. What are the best methods to work in such low signal-to-noise regime?
- De-noising approaches are further complicated by the atmosphere, whose noise properties are not very well understood. Can we be agnostic about the noise correlations or other specific details?
- Real-life data are still not plentiful enough to run multiple training-tests independently.

Last but not the least, compute time scales up dramatically when training with higher-resolution images (necessary for capturing CMB-lensing features). Where to find the appropriate GPU resources?!

Gravitational lensing of CMB

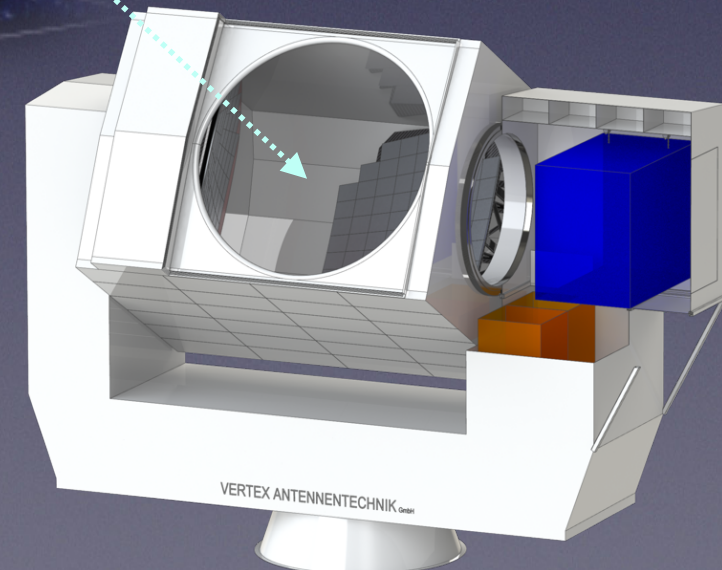
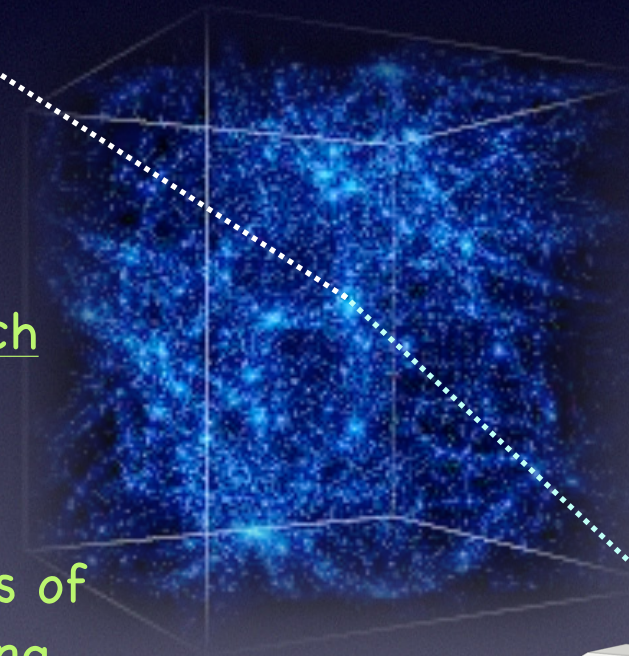
The Cosmic Microwave Background (CMB) is the remnant of the hot, early phase of the Universe. On their journey to our telescopes, the CMB photons get deflected by gravitational lensing (and scattering).



- Lensing of the CMB by galaxy clusters is useful for inferring the total (dark matter) mass of clusters, which is the most important ingredient of doing cosmological analysis with these objects.
- Current methods are not very efficient, requiring 1000s of objects to make any significant detection of CMB-lensing.

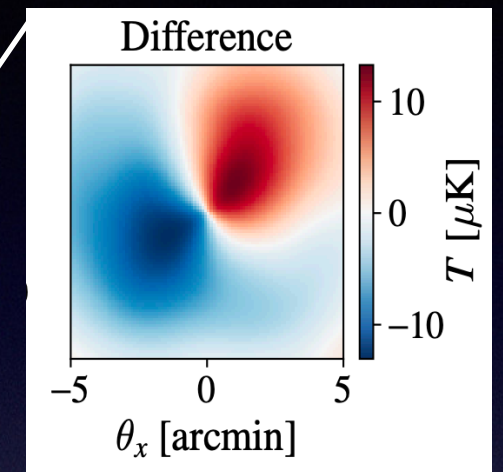
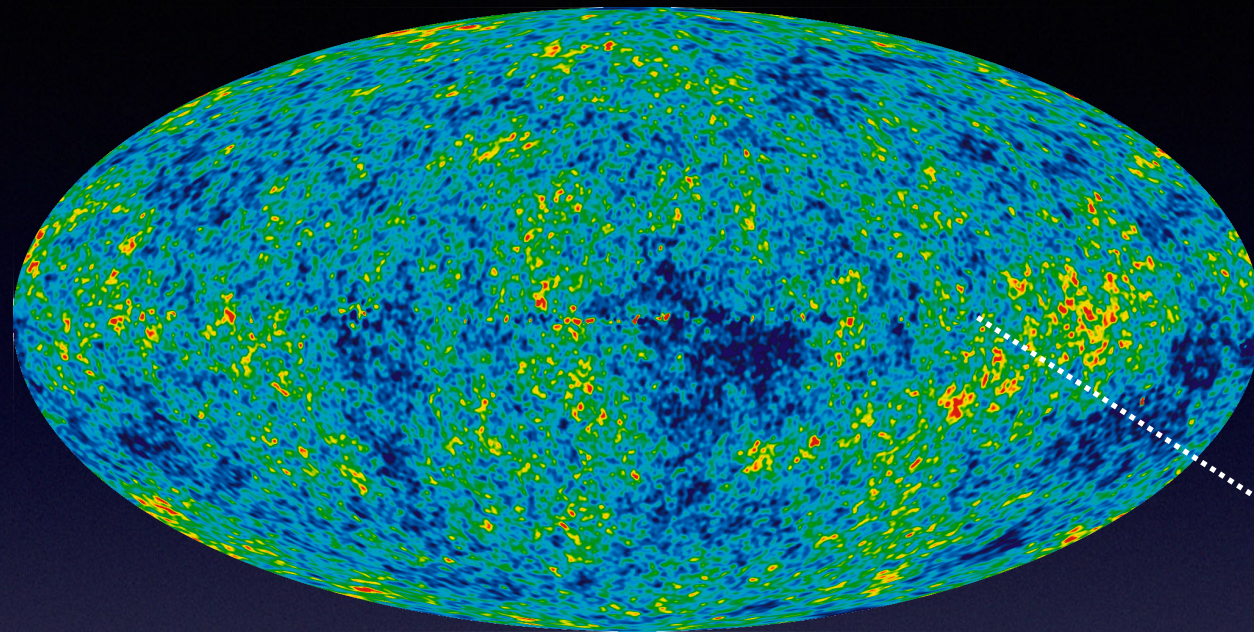
Additional applications of deep learning on the CMB:

Component separation (i.e. separating the CMB and foreground signals), de-noising (suppressing the detector and atmospheric noise), and image upscaling (i.e. improving the angular resolution).



Gravitational lensing of CMB

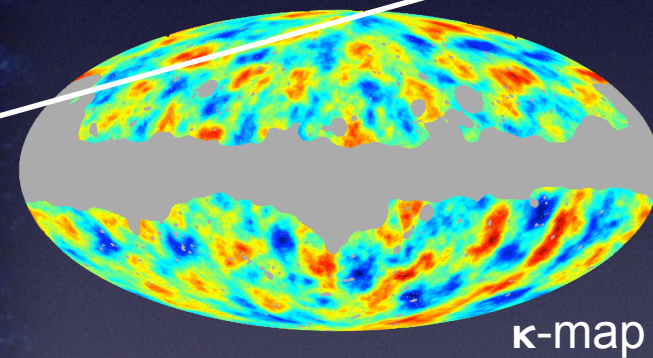
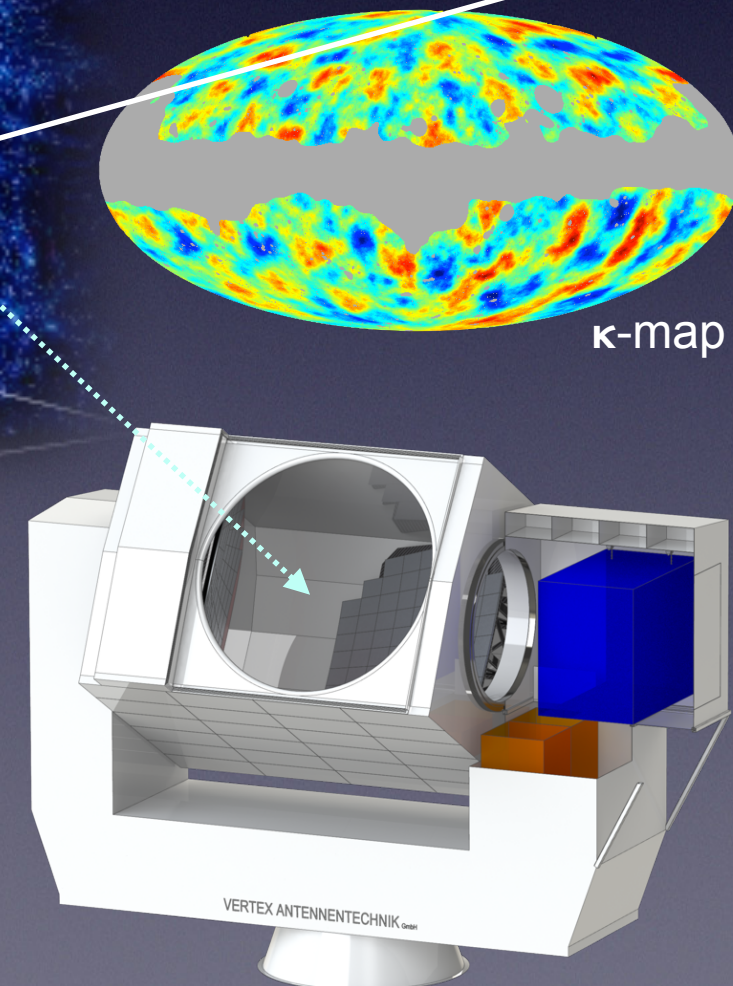
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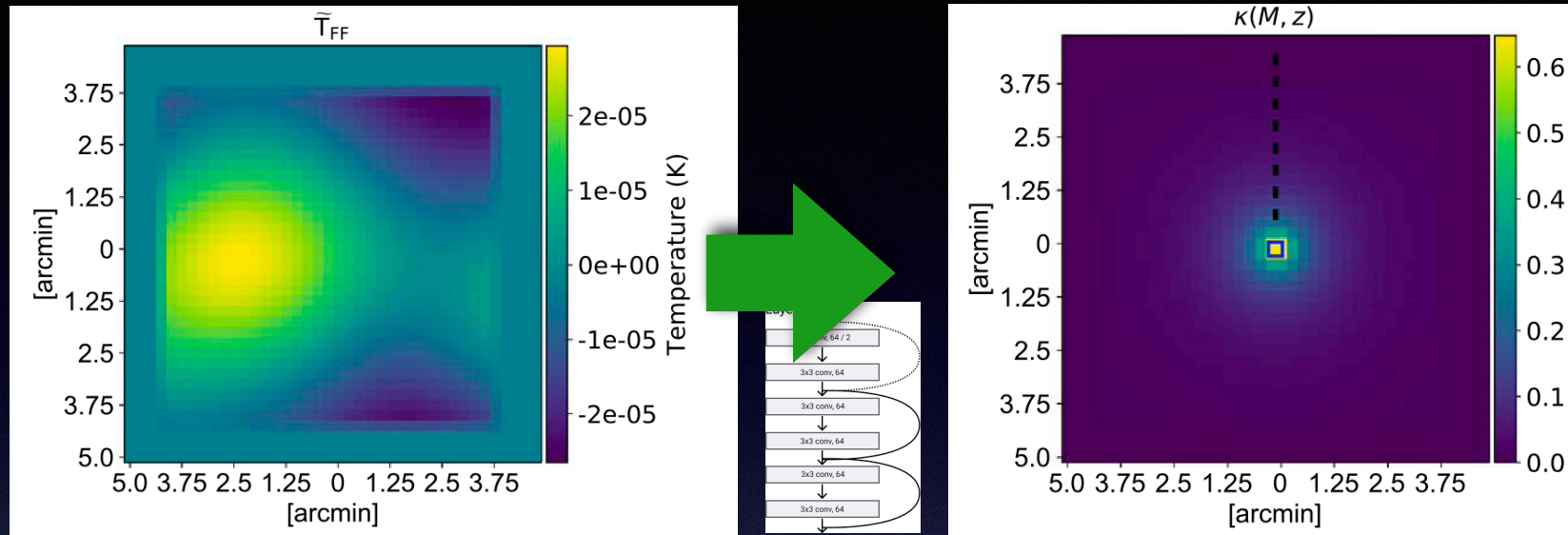
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Our work with Skynet ResNet

How to determine the masses of every major galaxy cluster in the Universe (via CMB-lensing)?



Application of deep learning (via ResNet and other deep-neural architectures) on CMB is not new. At least two papers used it for galaxy cluster mass, and well over a dozen papers or CMB map reconstruction. **No application on real data so far!**

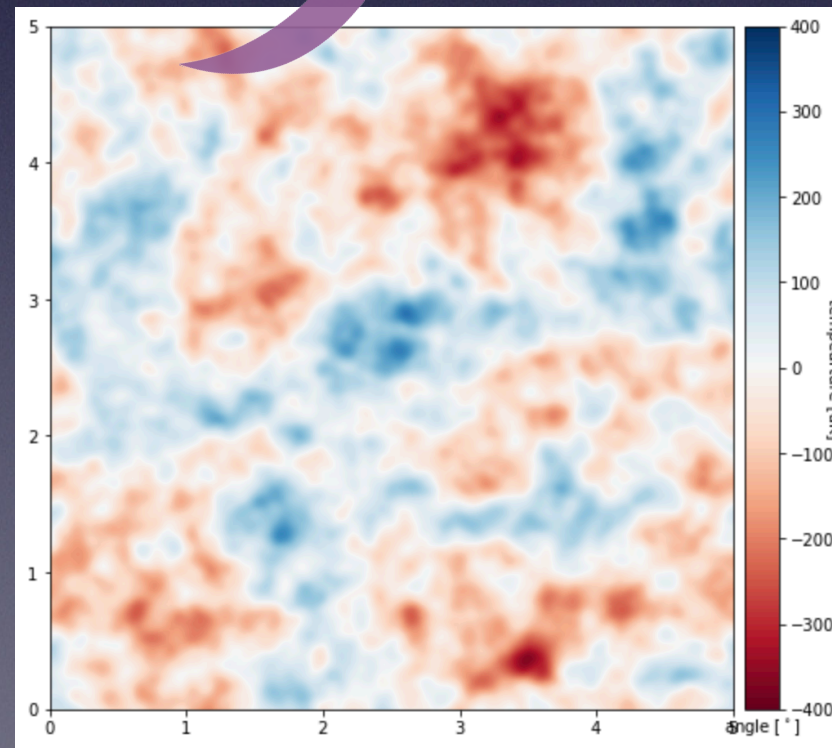
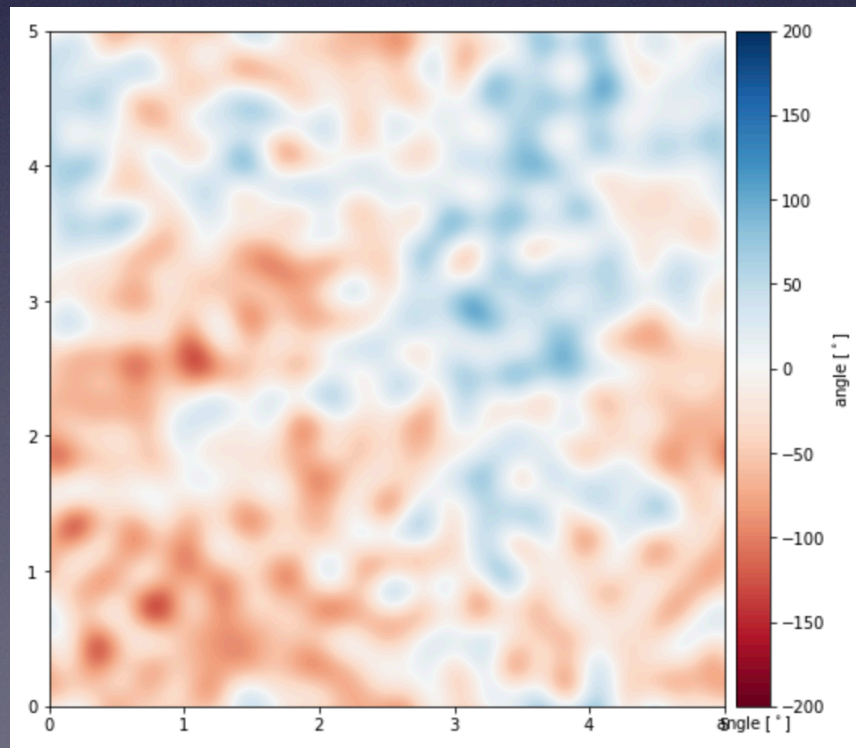
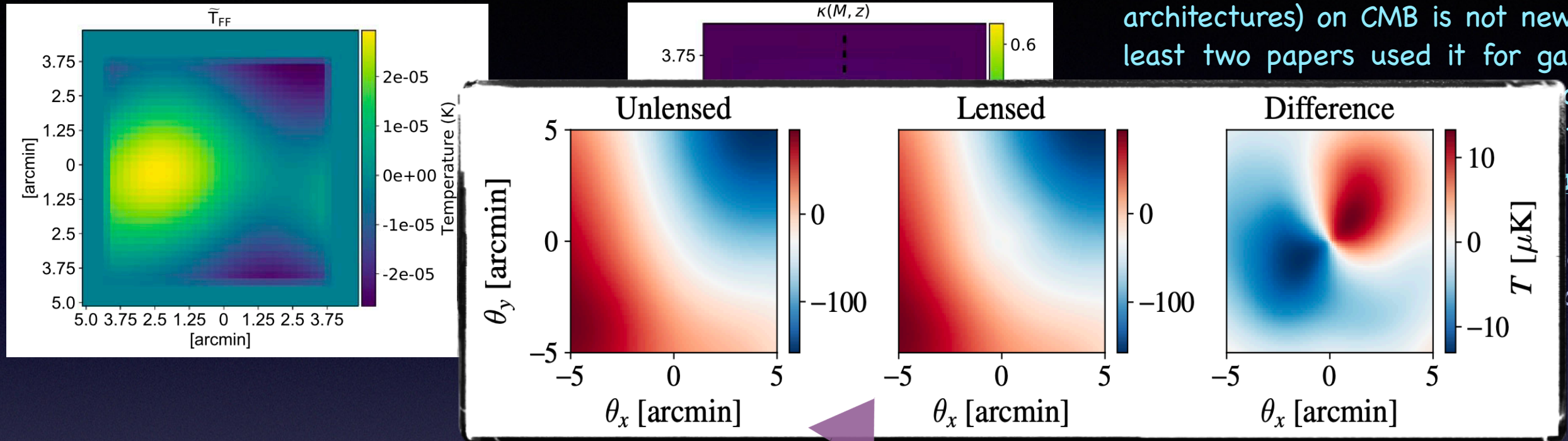
We are using the mResUNet model proposed by Gupta & Reichardt (2021), implemented in PyTorch.

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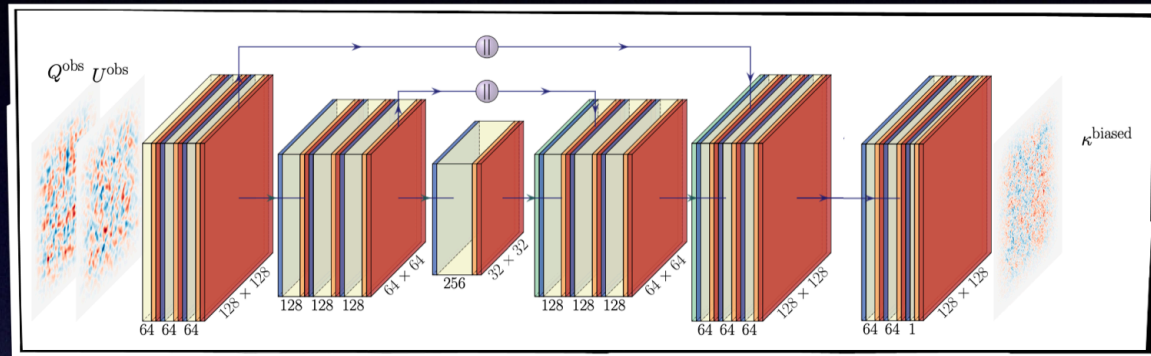


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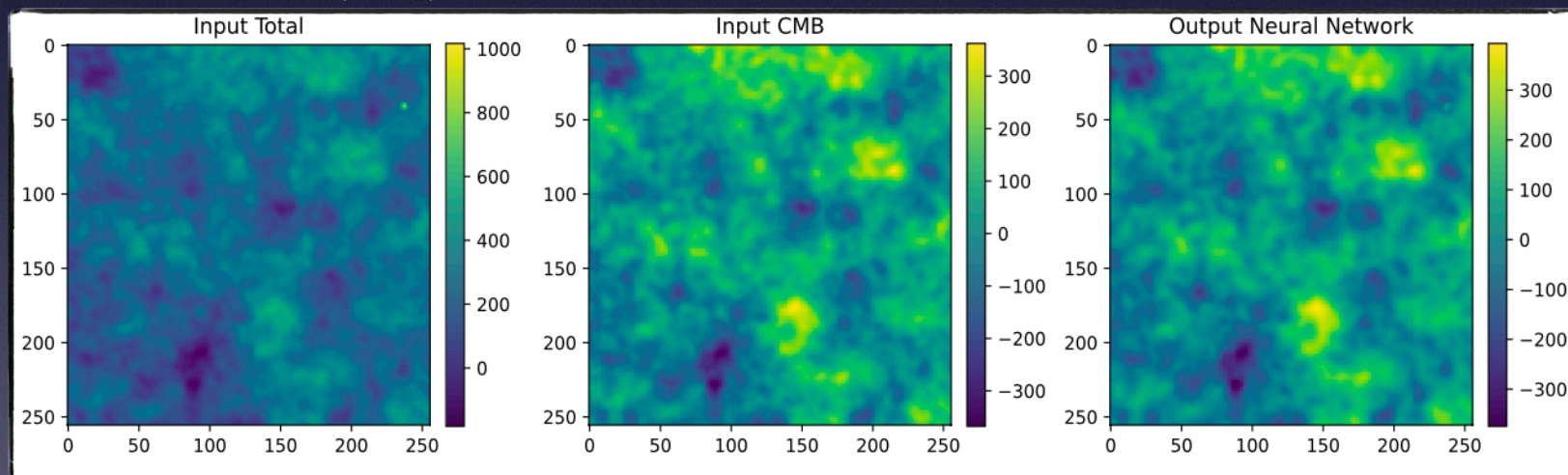
Challenges to solve (& questions to the experts)

We want to move further and make high-resolution CMB maps for upcoming sky surveys, removing the astrophysical foregrounds along the process. This poses many questions:



Adapted from Guzman & Mayers (2021)

CENN: Casas et al. (2022)



None of these approaches have yet been applied on real data! One of our objectives is to make use of the amazing new data that will be collected from the Fred Young Submillimeter Telescope (image on the right), starting 2024 or early 2025.

- Use GANs for image generation, or move to vision transformers?
- How to use data from multiple frequencies to remove contaminating signals (or even to do spectral fitting) ?
- Can we employ specific filtering techniques (like matched filtering) in the convolutional layers? Can we speed-up the whole learning process by running ResNet in the Fourier domain??

Rendition of the Fred Young Submillimeter Telescope (FYST) at Chilean Atacama desert at 5600 meters altitude

