

# REMOVING RADIO FREQUENCY INTERFERENCE FROM AURORAL KILOMETRIC RADIATION WITH STACKED CONVOLUTIONAL DENOISING AUTOENCODERS

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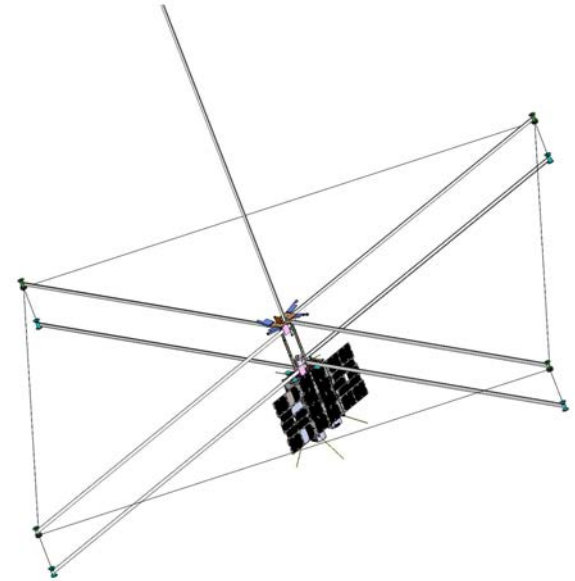
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# AERO-VISTA missions will observe the Earth's auroral region.

- The dominant goal of the AERO-VISTA missions is to study the Earth's auroral zones
- One strong emission is auroral kilometric radiation (AKR), which comes from the electron cyclotron maser mechanism
- One way AKR is downlinked is in the form of time-frequency spectrograms
- However, spectrograms (both observed in space- and ground-level) contain harsh radio frequency interference (RFI) that obscures AKR

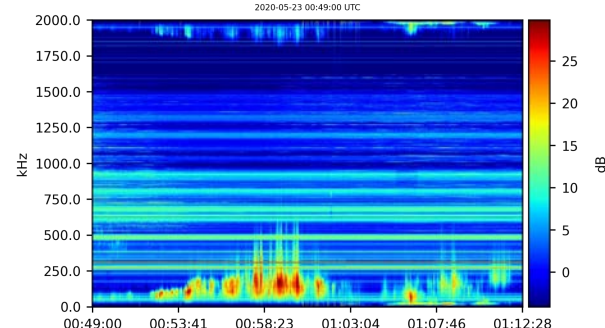
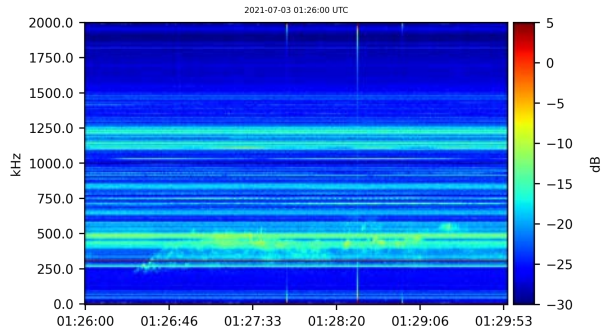
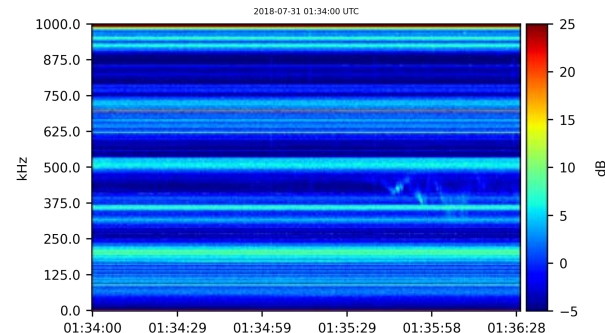
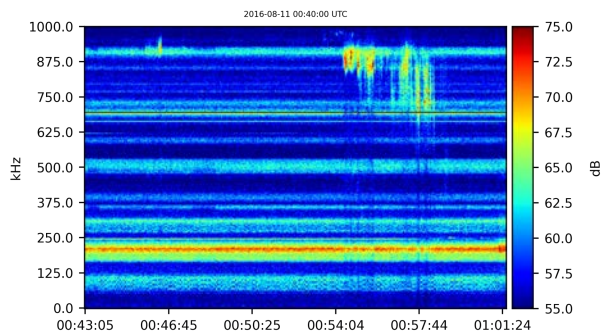


**Fig 1.** The AERO spacecraft  
*AERO-VISTA project*

# AKR observations are corrupted by electronic interference.

- y axis: frequency, typically in the ranges of (0 - 2000 kHz)
- x axis: time
- color: dB intensity

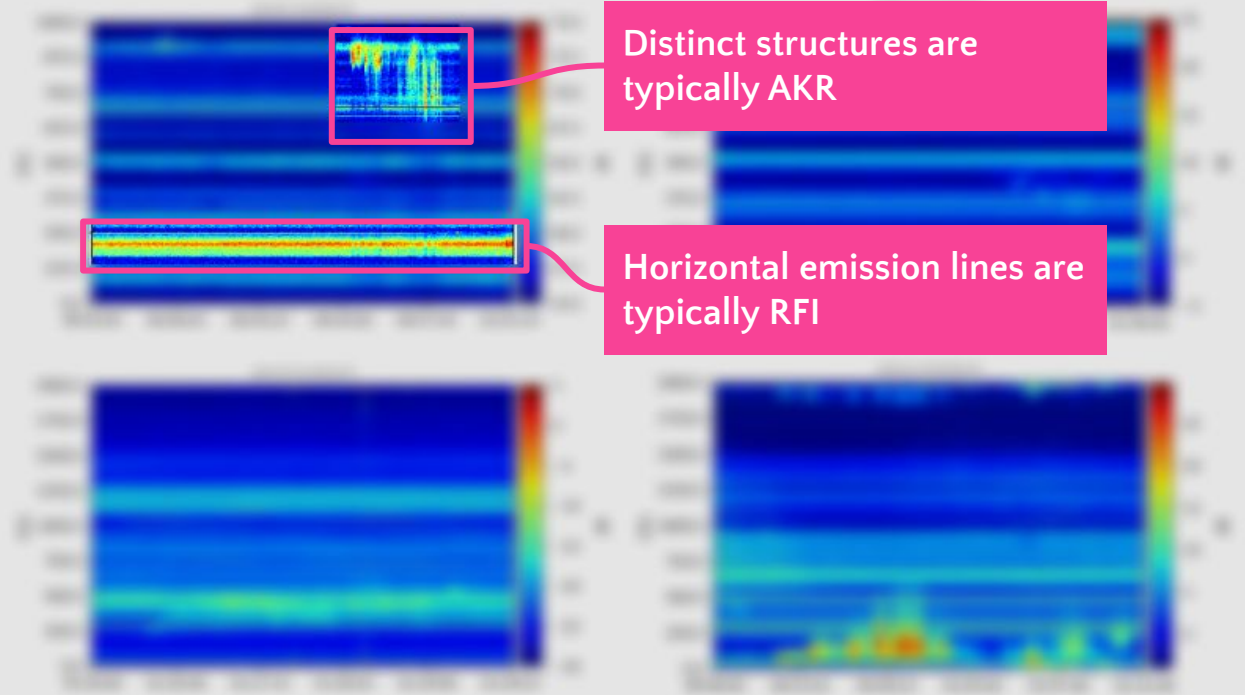
\* plots have different scales



# AKR observations are corrupted by electronic interference.

- y axis: frequency, typically in the range of 10 - 2000 kHz
- x axis: time
- color: dB intensity

\* plots have different scales



# Several motivations exist for noise removal.

- Visual analysis by scientists
- Automatic detection and categorization of auroral radiation
- Unsupervised clustering of emissions with similar characteristics
- Forecasting of future AKR events
- Comparison of AKR across long geographical distances
- Comparison to AKR above the ionosphere
- **(+ any other downstream applications and analysis of AKR data)**

# What can be done about noise?

## Data collection

- ◉ Operate somewhere more silent (such as the South Pole or space)
  - Not a foolproof solution, as seen in the previous plots

## Post-processing

- ◉ Physical cancellation applying convolutions with wavelets (requires knowledge of the exact structure of the noise, assuming the noise structure is constant)
- ◉ Manual instance removal of noise (costly)
- ◉ **Apply existing image denoising techniques to spectrograms (this project)**

# Main computational image denoising methods.

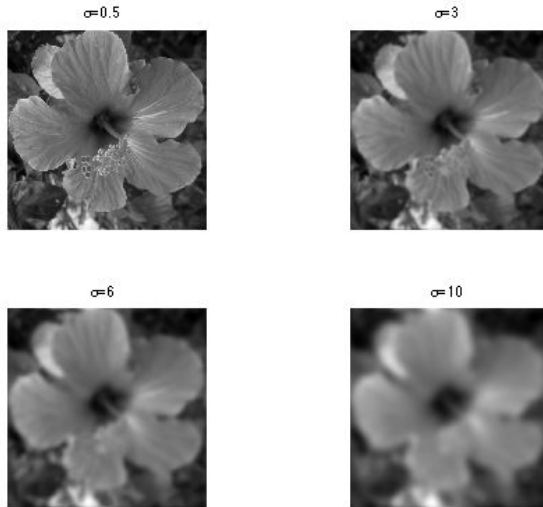


Fig 2. A filtering method

[https://www.numerical-tours.com/matlab/denoising\\_adv\\_8\\_bilateral/](https://www.numerical-tours.com/matlab/denoising_adv_8_bilateral/)

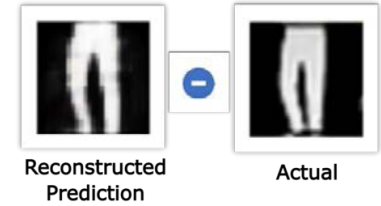
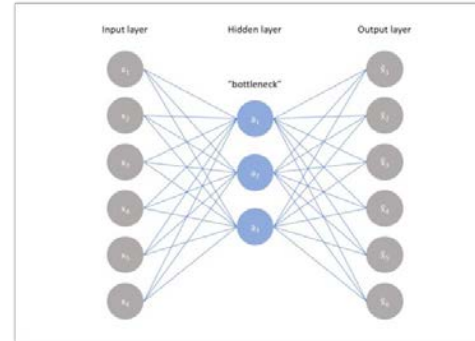


Fig 3. A deep-learning method

<https://towardsdatascience.com/6-applications-of-encoders-every-data-scientist-should-know-dc703cbc892b>

# Main steps in a deep-learning approach.

1. We need a dataset for the denoising model to train from
2. Choose an architecture to denoise with
3. Compare across other denoising algorithms to see if our approach is good



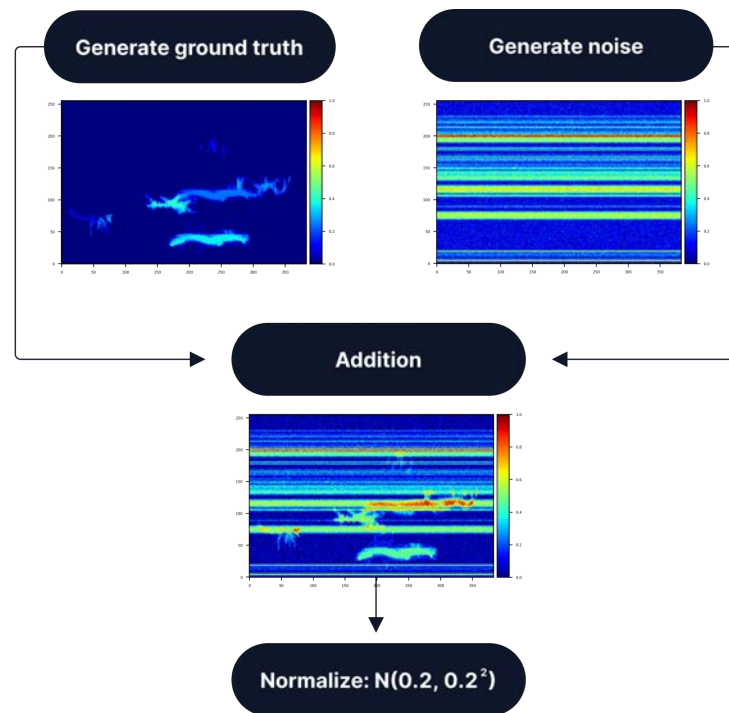
# We synthesized random AKR samples to train from.

Variables used to randomize our ground truths include:

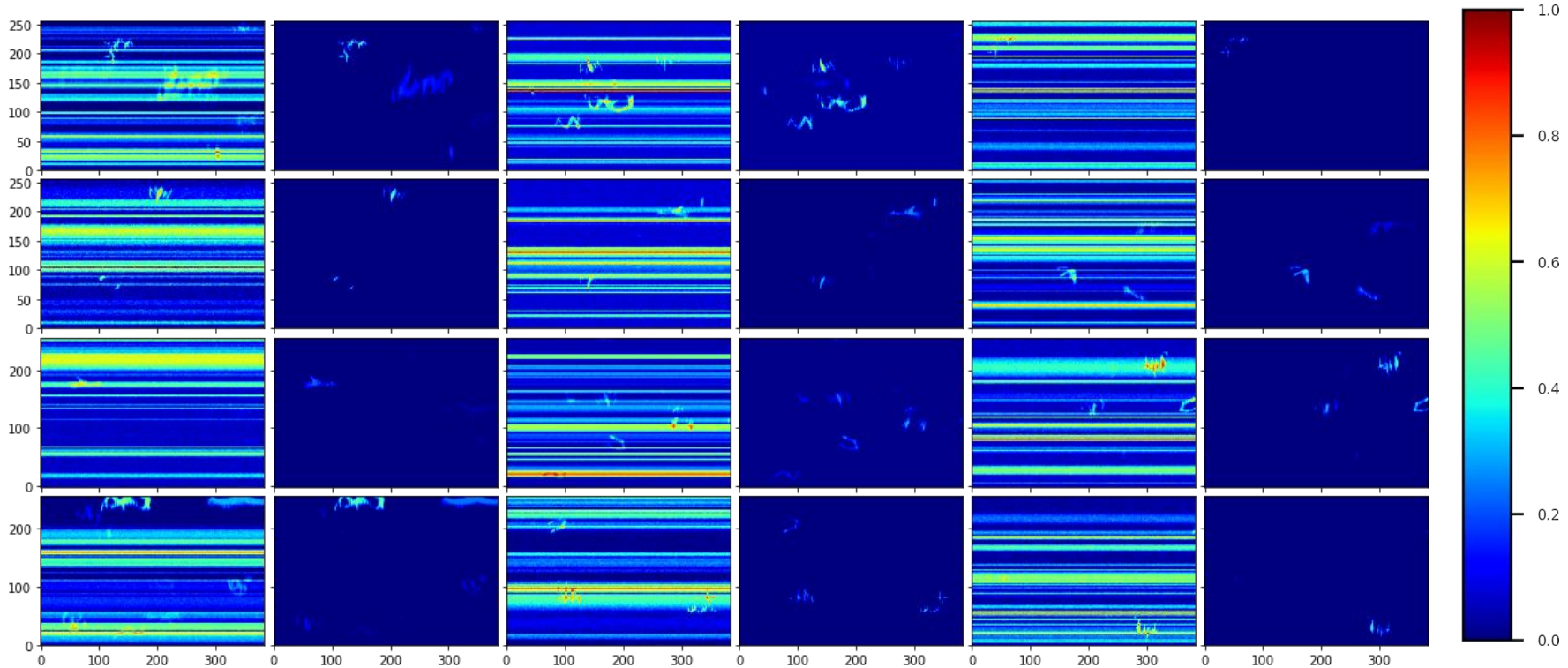
- Background intensity
- Number of AKR
- $\text{AKR}^{(i)}$  position
- $\text{AKR}^{(i)}$  intensity
- $\text{AKR}^{(i)}$  mirroring

Variables used to randomize our noise include:

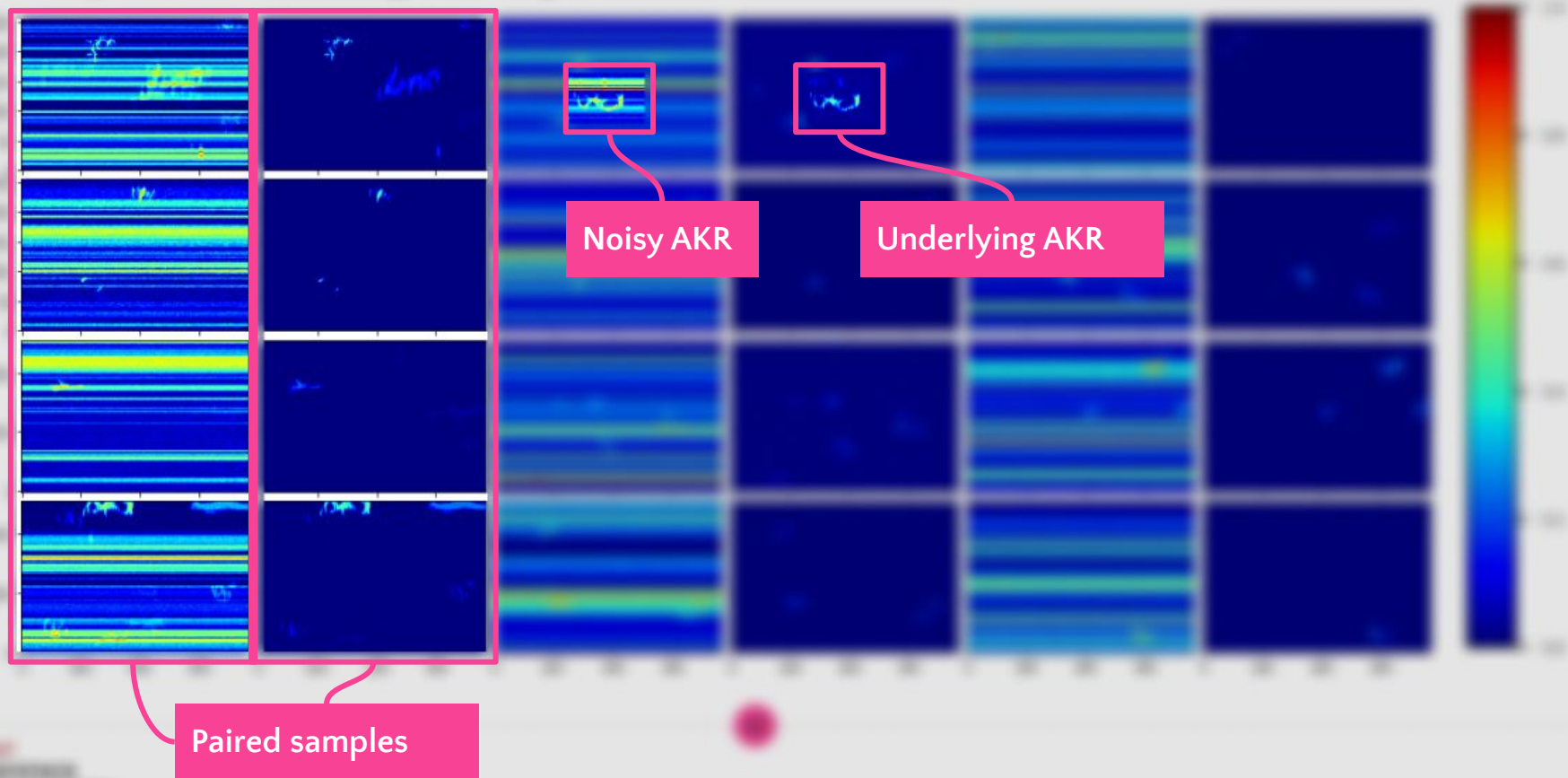
- Gaussian noise intensity
- Overall channel intensity
- $\text{Channel}^{(i)}$  height
- $\text{Channel}^{(i)}$  position
- $\text{Channel}^{(i)}$  intensity



# Sample of training data generated with this method.



Sample of training data generated with this method.



We chose to use a denoising autoencoder, which is the following:

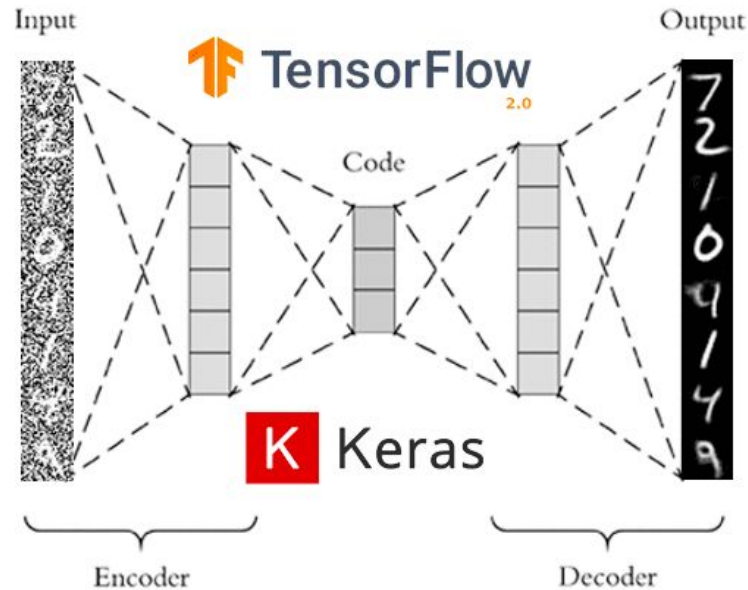
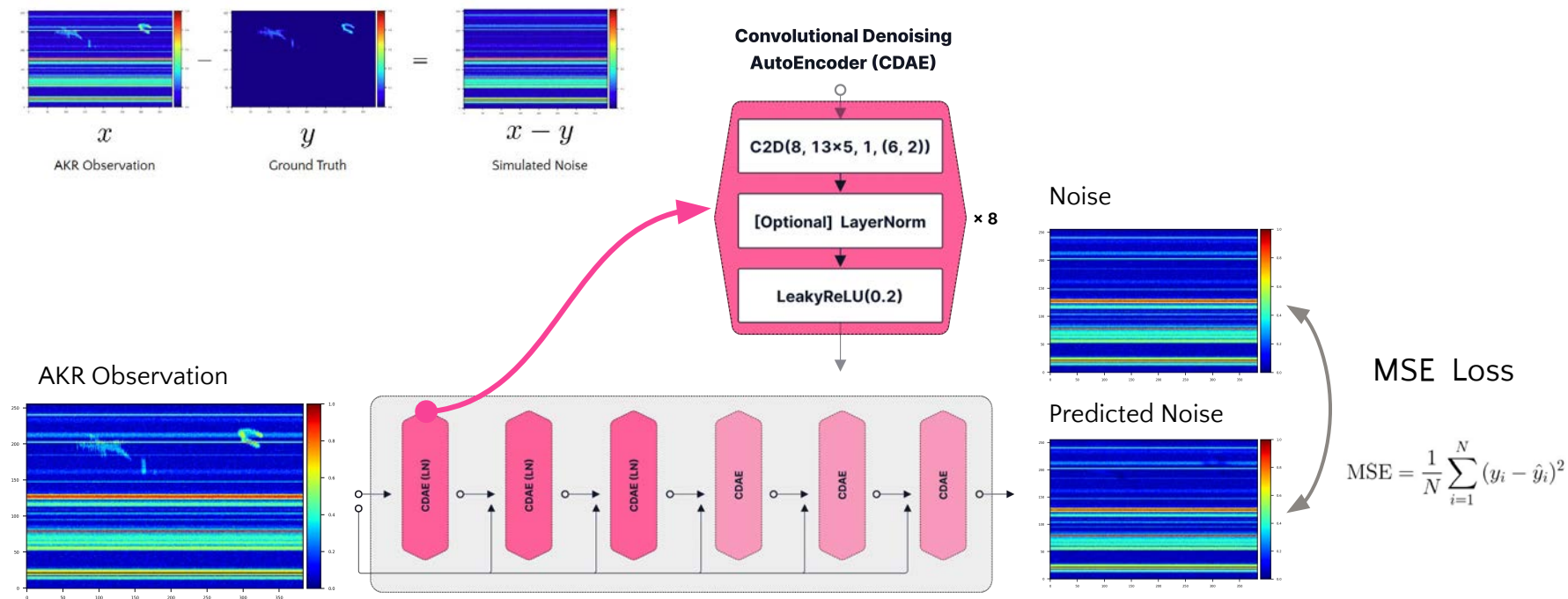


Fig 4. Denoising AutoEncoder

<https://pyimagesearch.com/2020/02/24/denoising-autoencoders-with-keras-tensorflow-and-deep-learning/>

# Denoising Autoencoder for Auroral Radio Emissions (DAARE)



# Denoising Autoencoder for Auroral Radio Emissions (DAARE)

Convolutional layer:

- 8 output channels
- 13 x 5 kernel size
- 1 stride
- 6 x 2 padding

Layer normalization

LeakyReLU activation

Convolutional Denoising  
AutoEncoder (CDAE)

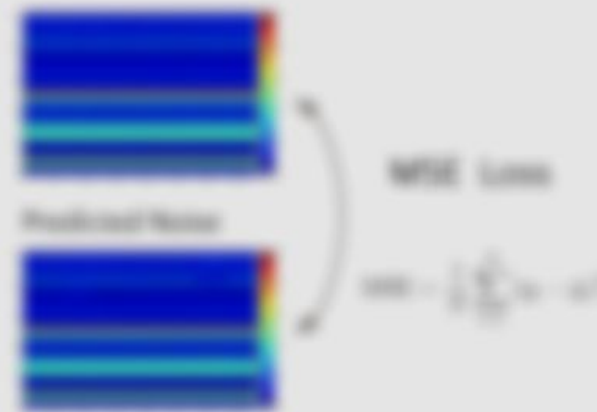
C2D(8, 13x5, 1, (6, 2))

[Optional] LayerNorm

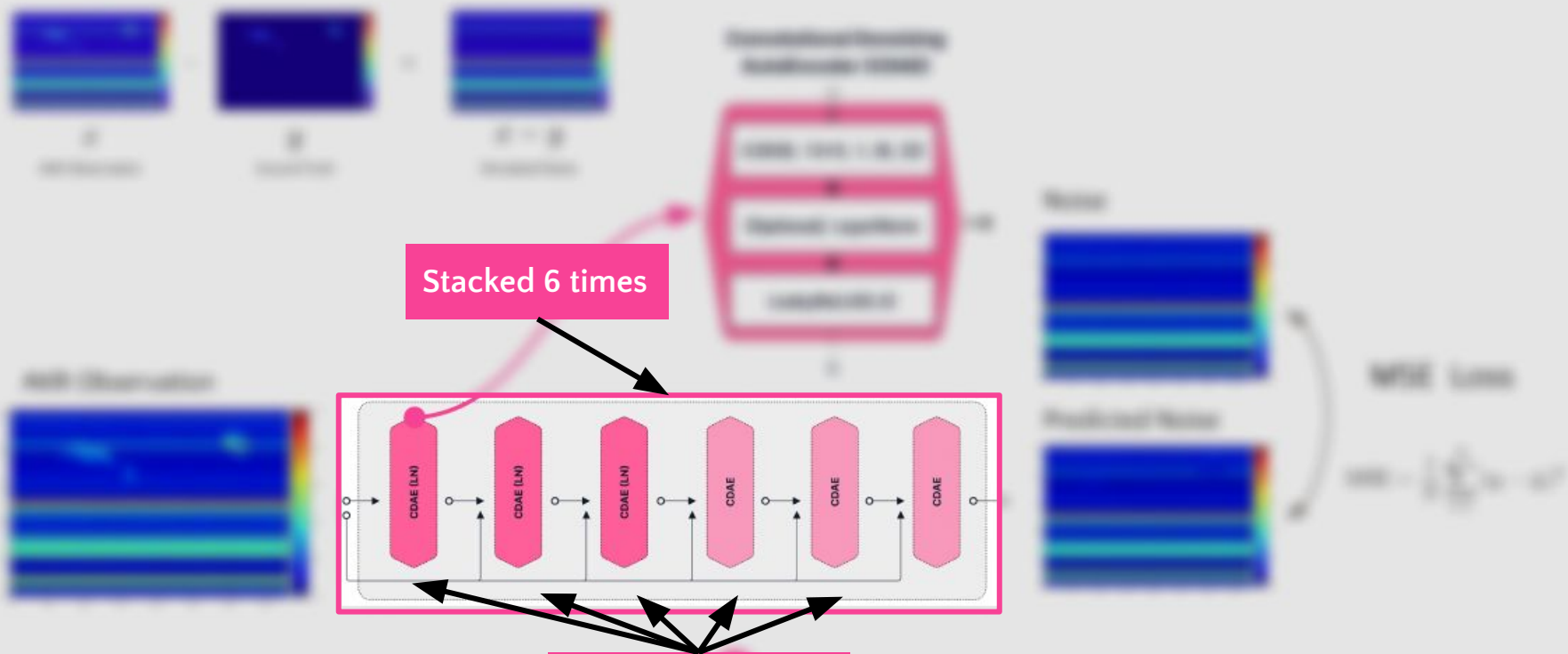
LeakyReLU(0.2)

Stacked 8 times

× 8



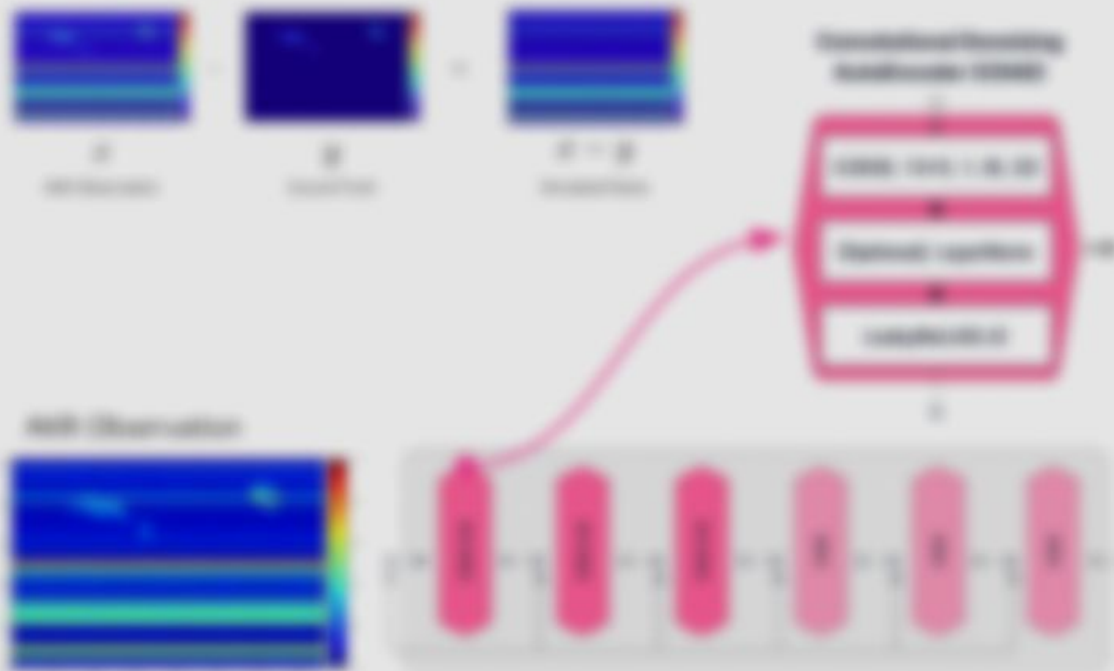
# Denoising Autoencoder for Auroral Radio Emissions (DAARE)



Stacked 6 times

Skip connections

# Denoising Autoencoder for Auroral Radio Emissions (DAARE)



Penalize differences with MSE loss

Noise

Predicted Noise

MSE Loss

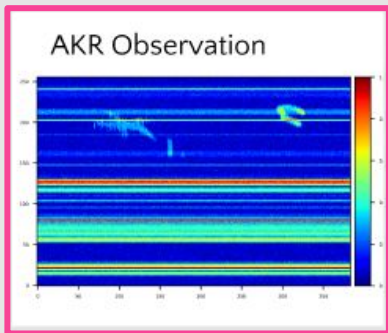
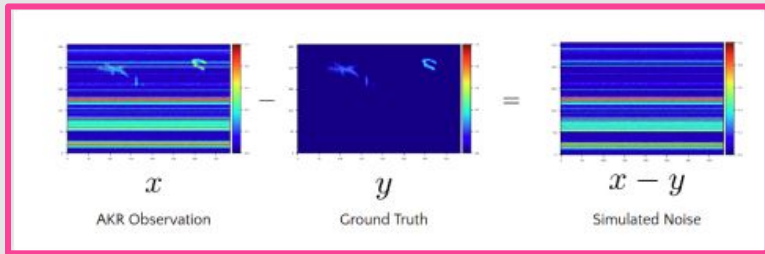
$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

The diagram shows two spectrograms: "Noise" (actual) and "Predicted Noise". A double-headed arrow between them is labeled "MSE Loss". The MSE formula is provided below.



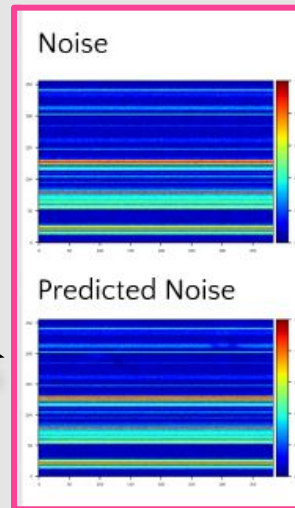
# Denoising Autoencoder for Acoustic Resonance (DAARE)

As long as you have 2, you can calculate the last



DAARE(Observation)  $\rightarrow$  Noise

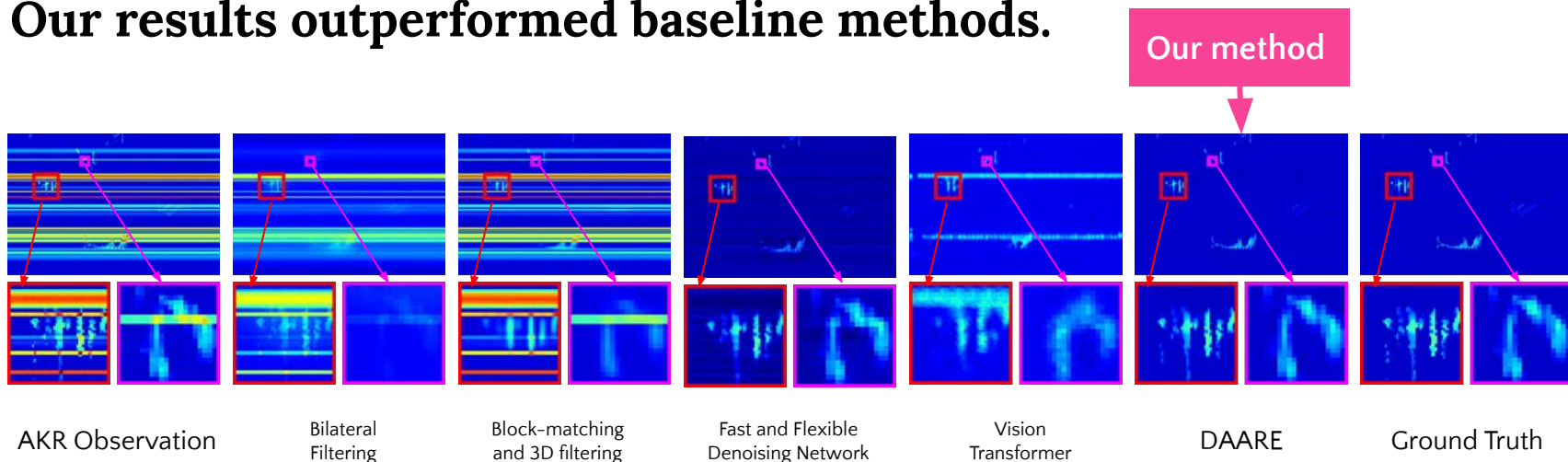
AKR = Observation - Noise



MSE Loss

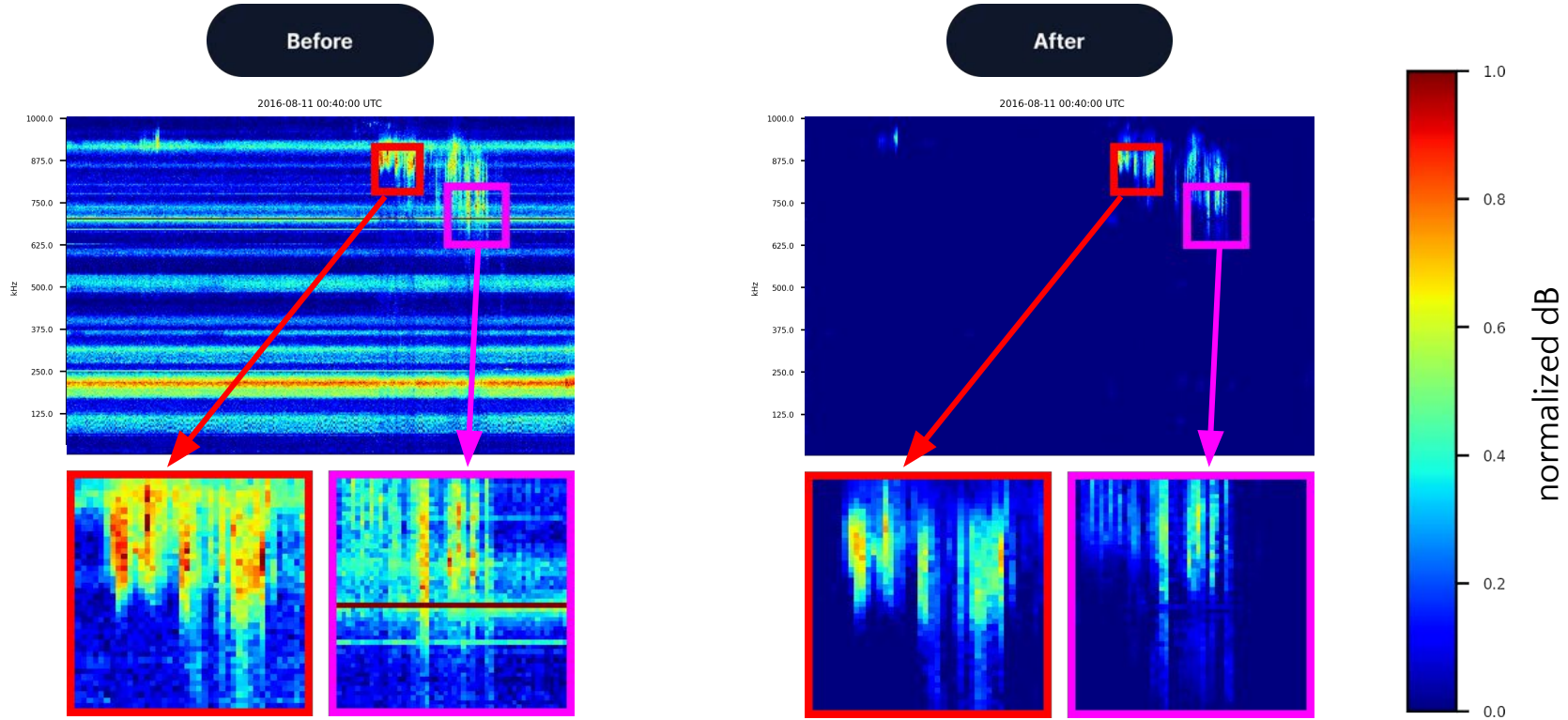
$$\text{MSE Loss} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

# Our results outperformed baseline methods.

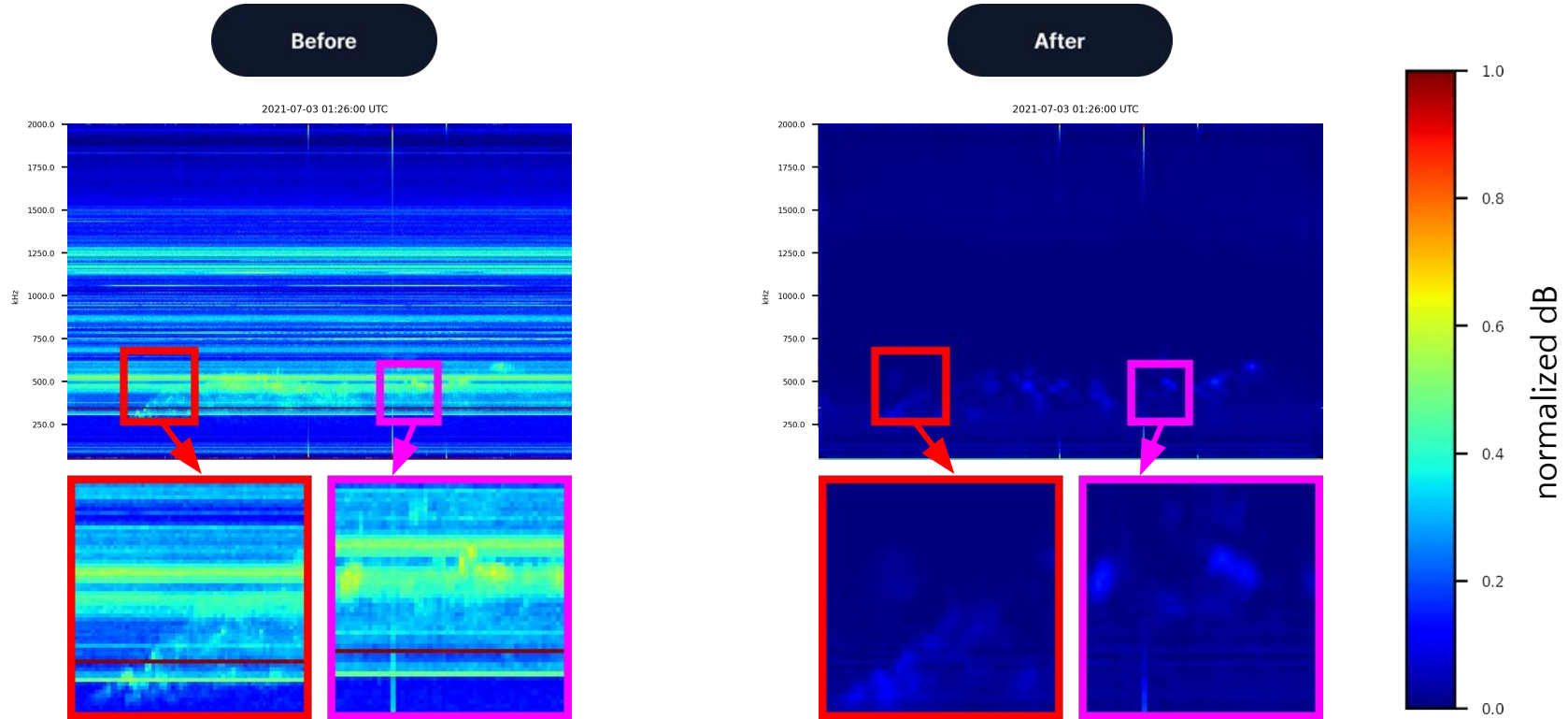


PSNR (dB)		19.8	17.7	38.3	23.5	<b>42.2</b>	$\infty$
SSIM		0.773	0.555	0.917	0.817	<b>0.981</b>	1.00

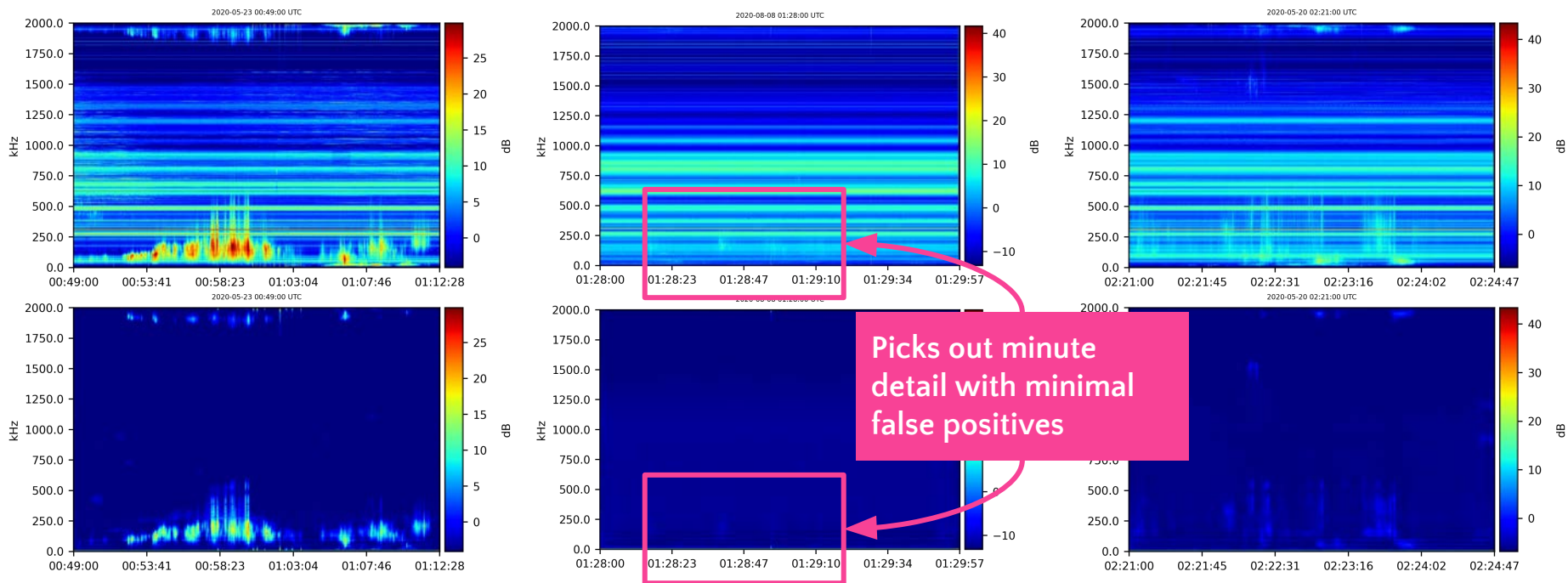
# Real AKR observation: 08-11-2016 00:40 UT



# Real AKR observation: 07-03-2021 01:26 UT



# Denoised spectrograms of other AKR observations



## Main strengths of DAARE:

- ◉ Automated algorithm to denoise AKR spectrograms
- ◉ Efficient
  - Can run in batches and be parallelized
  - Each spectrogram can be processed in < **1 second** (A batch of 16 spectrograms processed in 3.314 seconds without the use of a GPU)

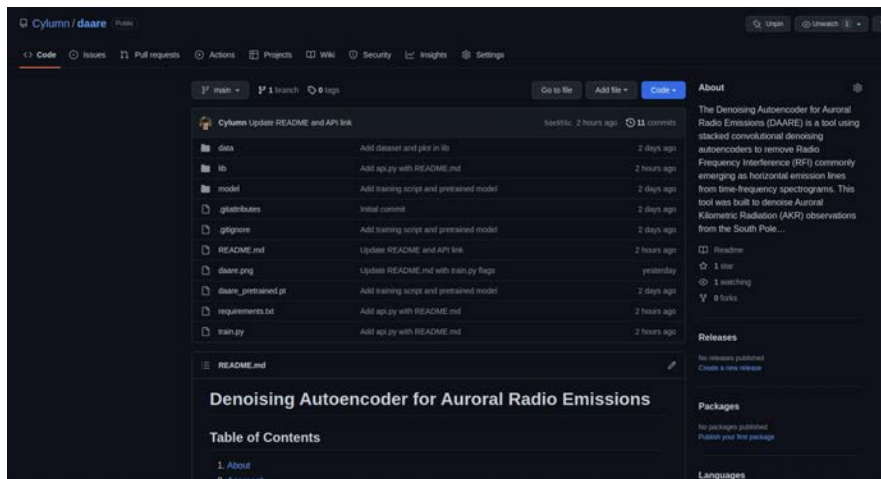
## Main limitations of DAARE:

- ◉ Change in AKR spectra intensity
- ◉ Potential change or loss in AKR features

# Open-Sourcing DAARE

Detailed code and documentation for DAARE can be accessed at: <https://github.com/Cylumn/daare>.

The repository contains detailed comments and instruction to train and use the model, as well as an API to simplify using DAARE without prior knowledge of PyTorch.



# How do we improve DAARE?

- ◉ Improve the training set
  - Manually remove noise for the training set
  - Increase simulation fidelity
- ◉ Specific preprocessing of spectrograms
- ◉ Model architecture search



# Takeaways

- Though AKR observations often contain noise that occlude data, it is possible to remove noise from the data for downstream applications and analysis
- Other radio data with RFI could potentially benefit from applying DAARE
- Future work can apply machine learning to auroral data and ionospheric sciences which has (for the most part) been left untouched



<https://clipart.me/free-vector/aurora>

# Thank you!

## Mentors

Mary Knapp  
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Toby Gedenk  
Philip J. Erickson  
James LaBelle

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Sarah Zhang  
Tal Sternberg

+ everyone else who made this  
REU possible!



DARTMOUTH

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