



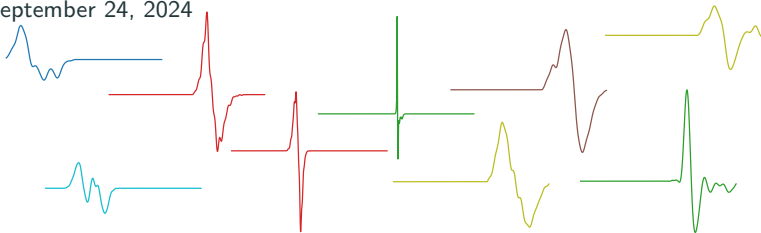
UPPSALA  
UNIVERSITET

# A surrogate model for the generation of radio pulses from neutrinos for IceCube-Gen2

---

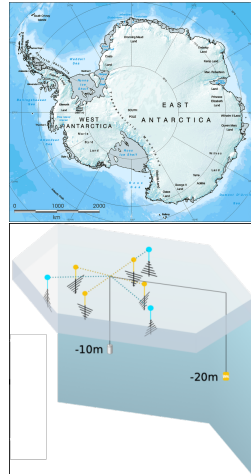
Philipp Pilar, Christian Glaser, Niklas Wahlström

September 24, 2024



# Overview – IceCube-Gen2 detector

- The IceCube detector at the South Pole can detect cosmological high-energy neutrinos.
- IceCube-Gen2 is being developed.
- We consider the radio emission of particle showers.
- Radio detectors can still be optimized.



# Overview – Aim of the project

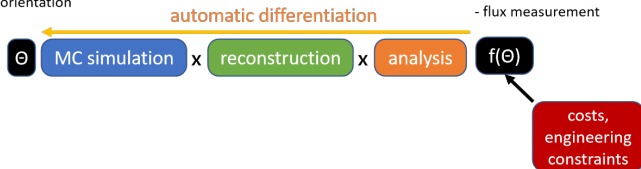
- Part of a bigger aim to create an end-to-end optimization pipeline.  
⇒ NuRadioOpt, see Christian's talk

detector parameters, e.g.,

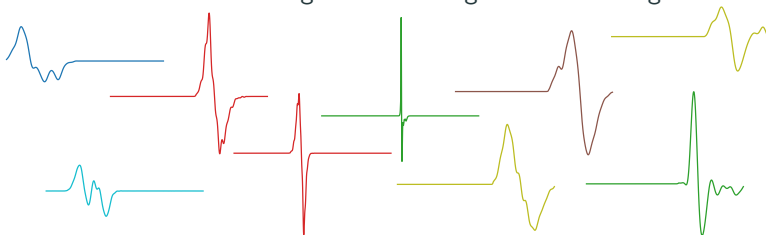
- antenna positions
- antenna orientation

science output, e.g.,

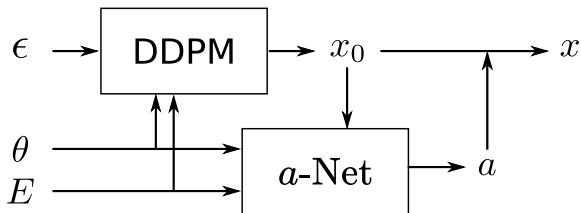
- neutrino-nucleon cross-section
- source discovery
- flux measurement



- We focus on the MC simulation part.
- Train a differentiable surrogate model to generate radio signals.



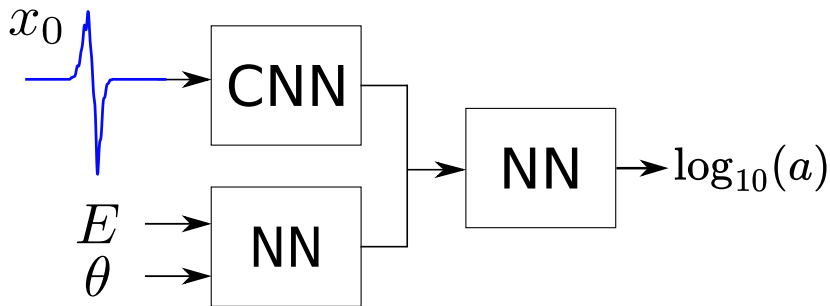
## Model architecture



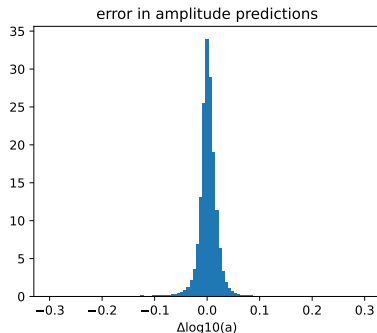
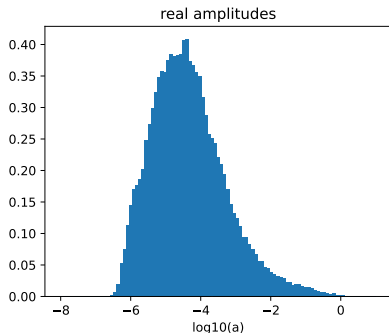
- A denoising diffusion probabilistic model (DDPM) is used to generate normalized samples  $x_0$  from random noise  $\epsilon$ , conditional on the viewing angle  $\theta$  and the energy  $E$ .
- A neural network is employed to predict the amplitude  $a$  of the generated signal ( $a$ -Net).
- Subsequently,  $x_0$  and  $a$  are combined to form the final signal  $x$ .

# Amplitude prediction network (a-Net)

- Normalized waveforms  $x_0$  are fed into a neural network to predict the amplitude.
- Combination of convolutional and fully-connected layers.
- Conditional on  $E$  and  $\theta$ .



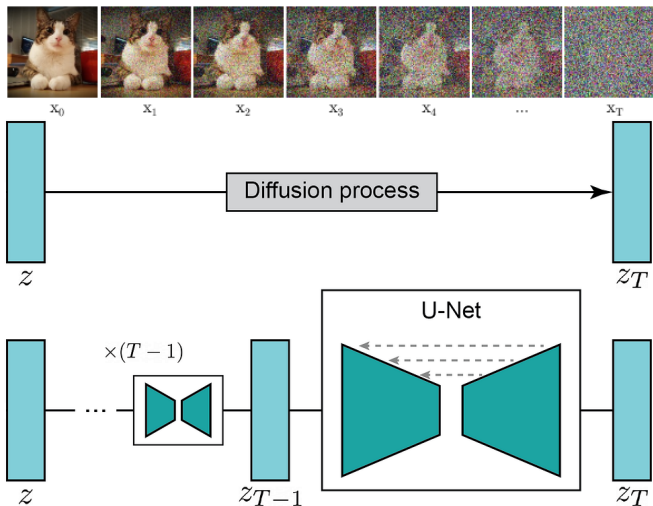
# Results: amplitude prediction



**Left:** the main reason for using the a-Net is the large spread in signal amplitudes.

**Right:** the network manages to predict the amplitudes with high accuracy.

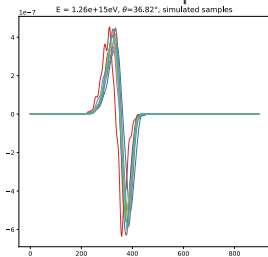
# Denoising diffusion probabilistic models (DDPMs)



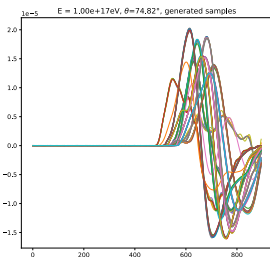
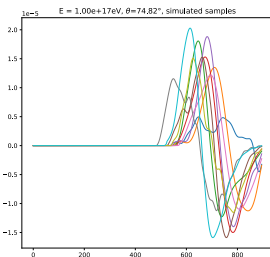
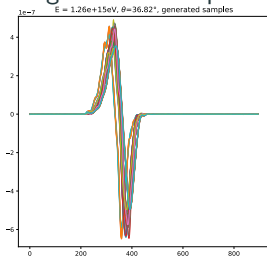
We use the implementation from  
<https://github.com/lucidrains/denoising-diffusion-pytorch>.

# Results: generated samples

## real samples



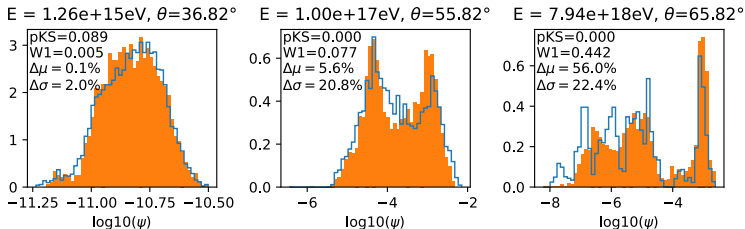
## generated samples





## Results: distribution of summary statistics

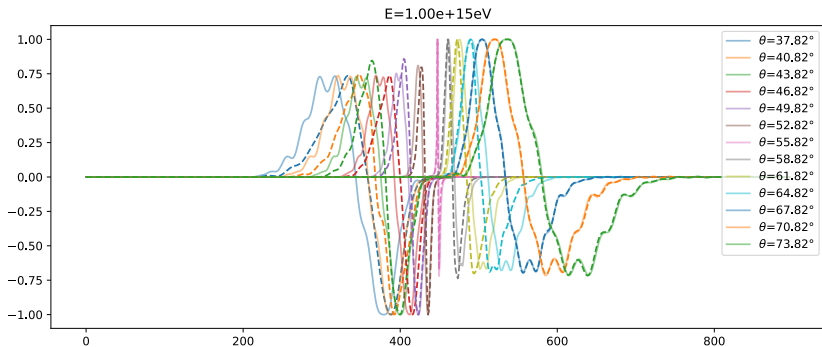
- Use summary statistics to evaluate the accuracy of the generated data distribution.
- E.g., the energy fluence  $\psi$ :



- There generally is a good match for low energies.
- At higher energies, we still often have  $\Delta\mu > 10\%$ .

## Results: $\theta$ -dependence

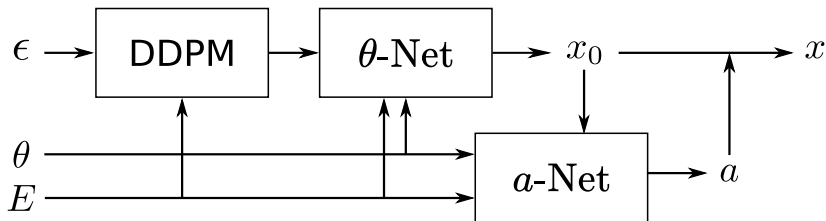
- The model needs to be capable of generating the resulting signals for the same event at different viewing angles  $\theta$ .



- The vanilla DDPM does not automatically learn the correct  $\theta$ -dependence.

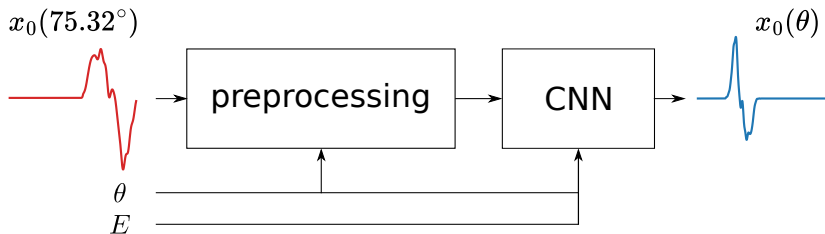
## Model architecture to ensure correct $\theta$ -dependence

We modify the model architecture to enable the correct  $\theta$ -dependence:



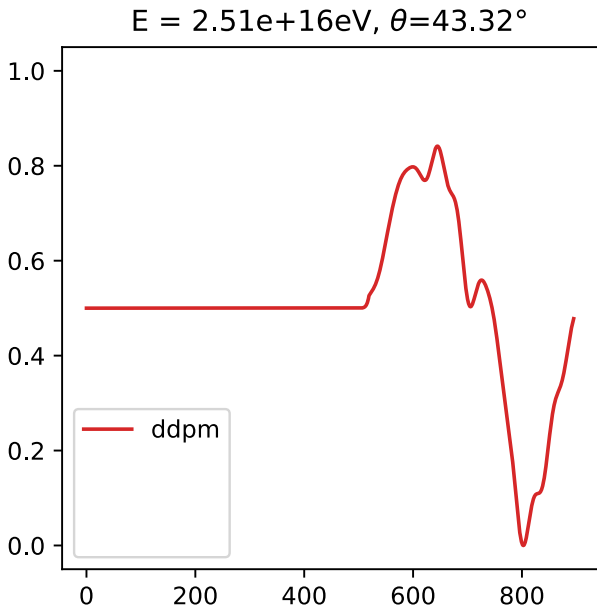
- The DDPM generates samples at a fixed angle  $\theta_0$ .
- A separate network (the  $\theta$ -Net) transforms these samples into the corresponding signals at arbitrary angles  $\theta$ .

## Angle modification network ( $\theta$ -Net)

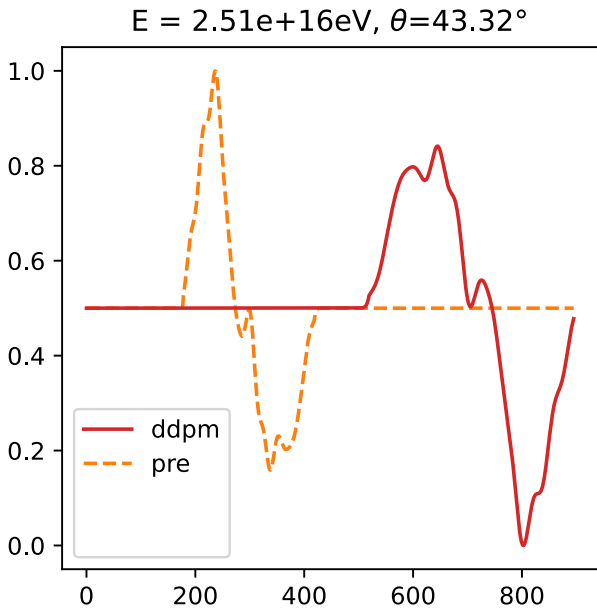


- Samples at the fixed angle  $\theta_0 = 75.32^\circ$  serve as input.
- The samples are preprocessed via a loose geometric relationship.
- A convolutional network finetunes the transformed signals.

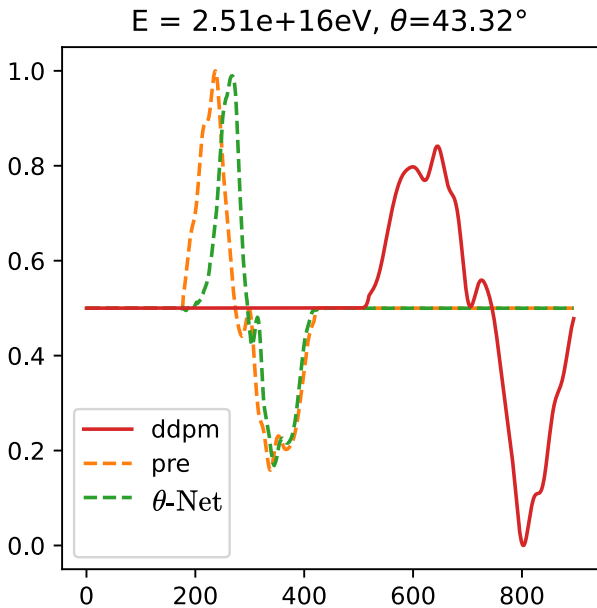
## Generating samples using the $\theta$ -Net



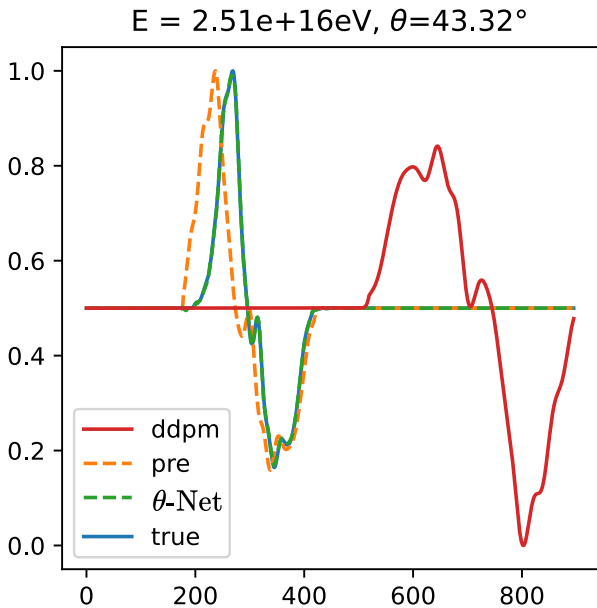
# Generating samples using the $\theta$ -Net



# Generating samples using the $\theta$ -Net



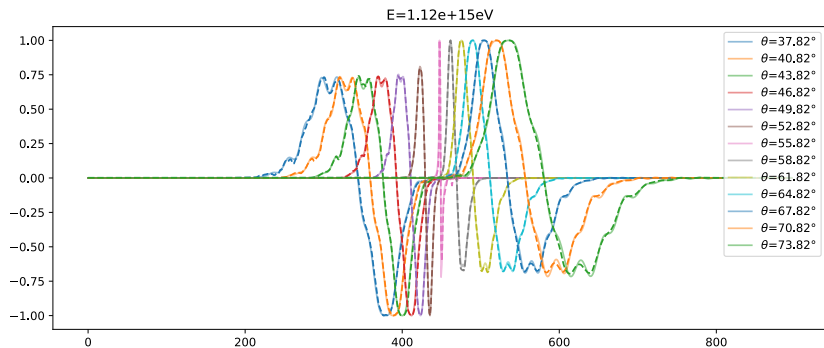
# Generating samples using the $\theta$ -Net





## Results: $\theta$ -dependence with $\theta$ -Net

- Using the  $\theta$ -Net, the correct  $\theta$ -dependence is recovered with high accuracy.



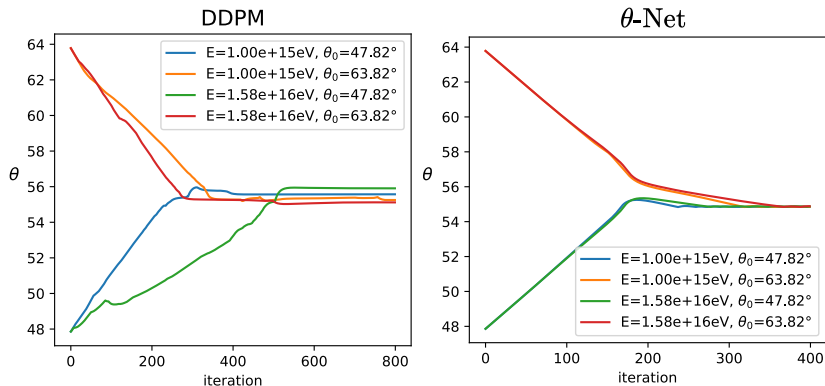
## Simple optimization experiment

- Test whether the backpropagation through the networks yields useful gradients.
- We optimize the viewing angle  $\theta$  to obtain (normalized) signals that are as 'squeezed' as possible.
- That is, we minimize

$$A(x_0(\theta)) = \int_{-\infty}^{\infty} |x_0(t, \theta)| dt \quad (1)$$

with respect to  $\theta$ .

# Results: simple optimization experiment



- Reasonable results with both architectures.
- The model with  $\theta$ -net converges faster and the results are more accurate.
- The VRAM requirements are significantly lower with the  $\theta$ -Net architecture (1GB vs 20GB).

## Summary:

- DDPMs can generate realistic radio signals
- Modular model design improves the results
  - deal with wide range of amplitudes
  - ensure the correct angle-dependence
- Gradients are suitable for optimization

## Summary:

- DDPMs can generate realistic radio signals
- Modular model design improves the results
  - deal with wide range of amplitudes
  - ensure the correct angle-dependence
- Gradients are suitable for optimization

## Outlook:

- Further model tuning to obtain good results at all energies
- Reduce overfit to existing data
- Combine with other elements of optimization pipeline

## Summary:

- DDPMs can generate realistic radio signals
- Modular model design improves the results
  - deal with wide range of amplitudes
  - ensure the correct angle-dependence
- Gradients are suitable for optimization

## Outlook:

- Further model tuning to obtain good results at all energies
- Reduce overfit to existing data
- Combine with other elements of optimization pipeline

# Thanks for your attention!