UPPSALA
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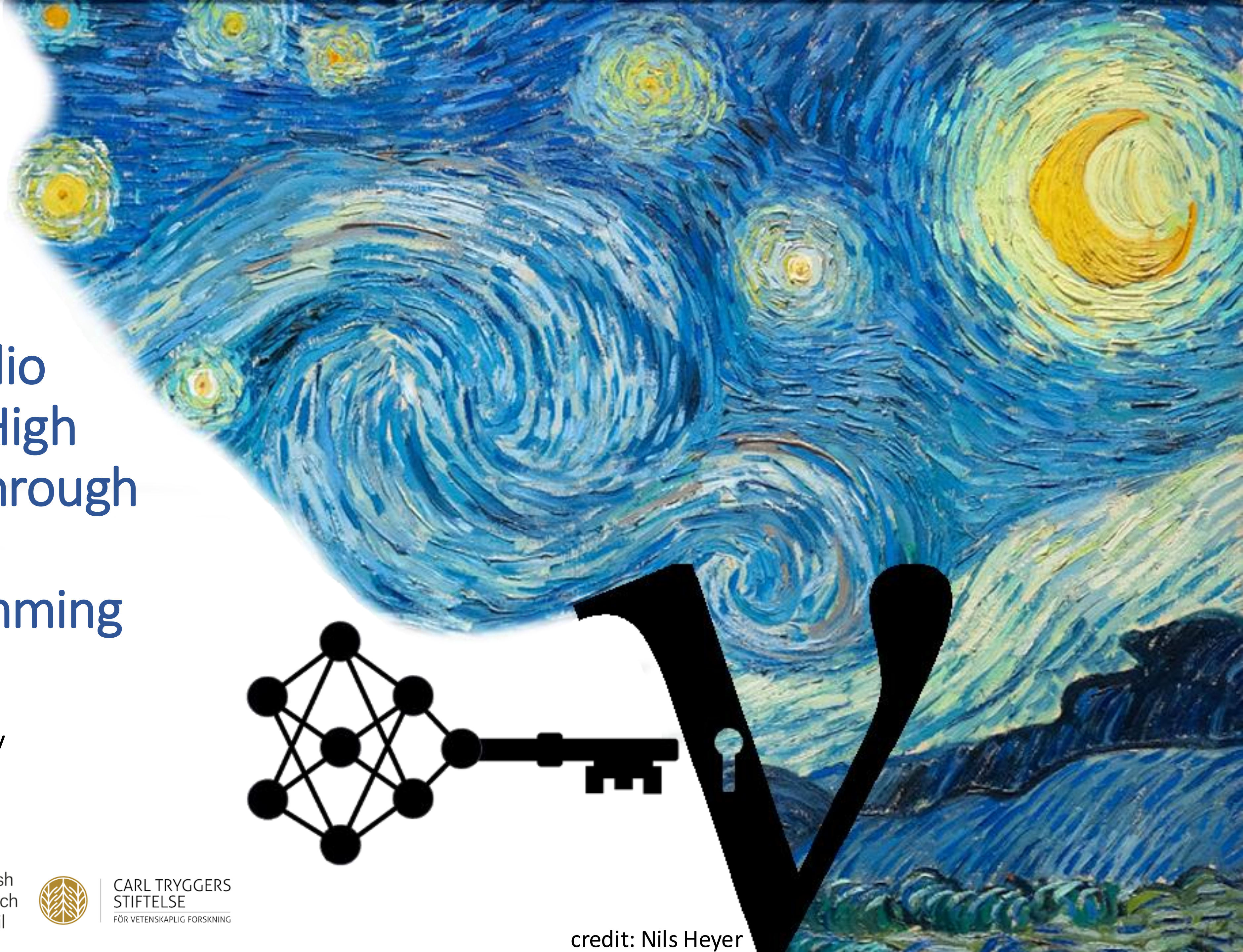
NuRadioOpt: Optimization of Radio Detectors of Ultra-High Energy Neutrinos through Deep Learning and Differential Programming



credit: Nils Heyer

Christian Glaser

Associate Professor, Uppsala Univsersity

Co-funded by the European Union

erc
European Research Council
Established by the European Commission

Swedish Research Council

CARL TRYGGERS STIFTELSE
FÖR VETENSKAPLIG FORSKNING

Executive Summary

NuRadioOpt will improve both key factors that impact the science output

detection rate of UHE neutrinos

→ **objective 1: Deep-Learning-Based Trigger**

precision to determine the neutrino's direction and energy

→ **objective 2: End-to-End Optimization + Deep Learning Reconstruction**

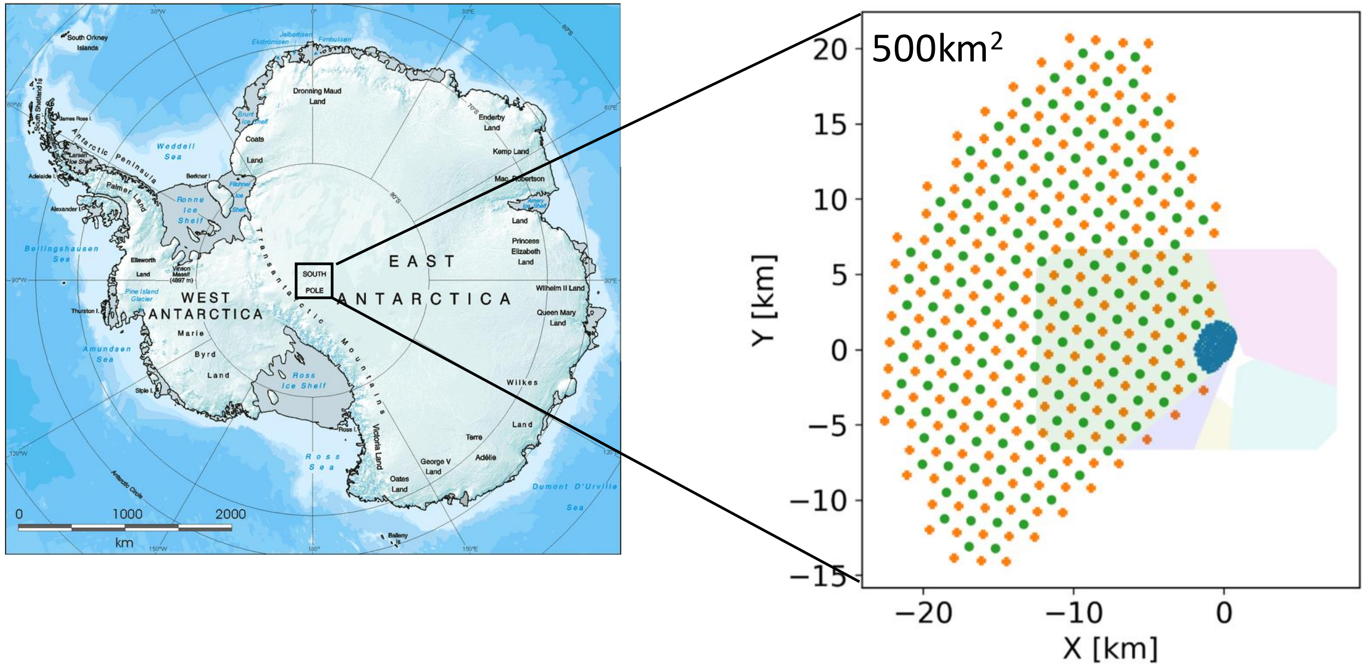
How:
Using Deep Learning and Differential Programming

In-Ice Radio Detection of Ultra-High-Energy Neutrinos

ICECUBE GEN2

RNO-G
Radio Neutrino Observatory - Greenland

In-Ice Radio Detection of Ultra-High-Energy Neutrinos



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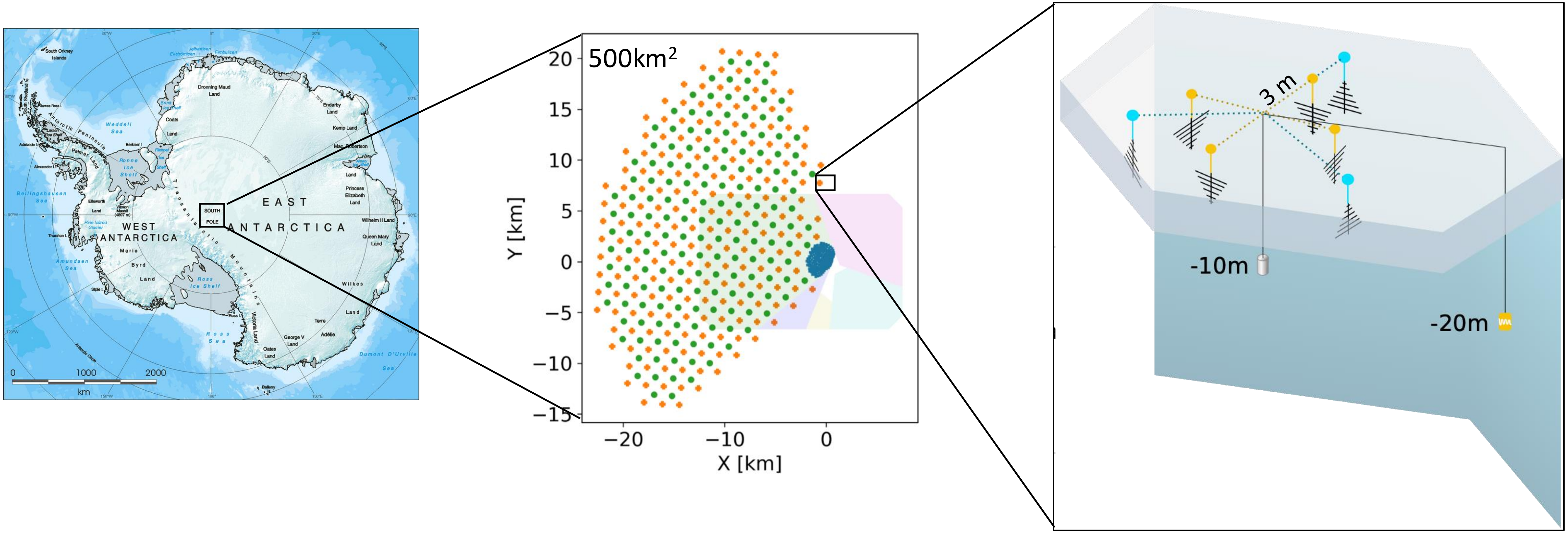
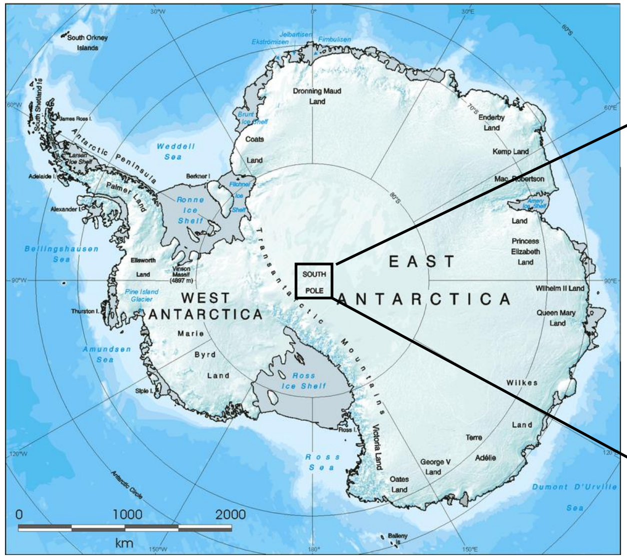
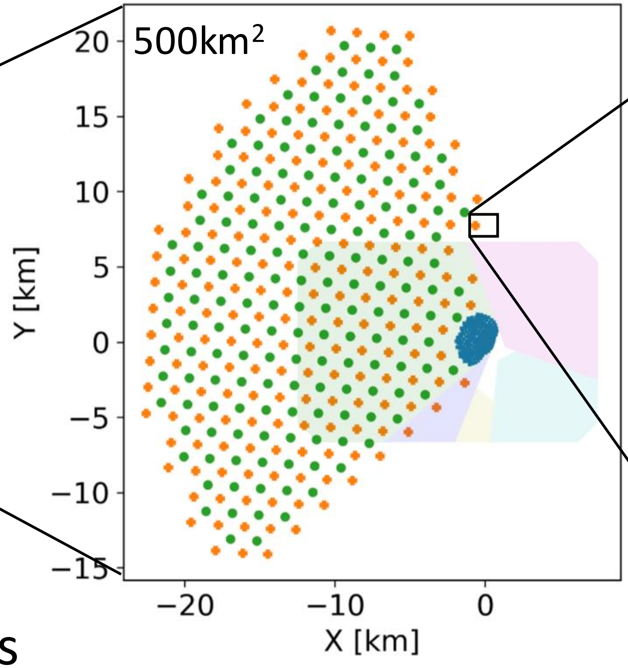
In-Ice Radio Detection of Ultra-High-Energy Neutrinos

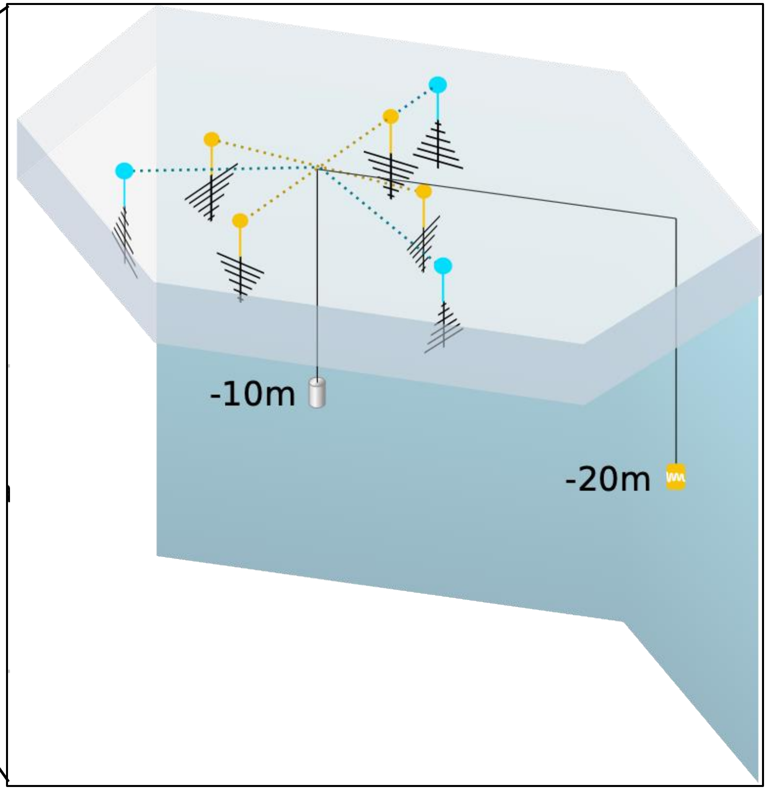


RNO-G site, Summit Station Greenland, summer 2024

In-Ice Radio Detection of Ultra-High-Energy Neutrinos





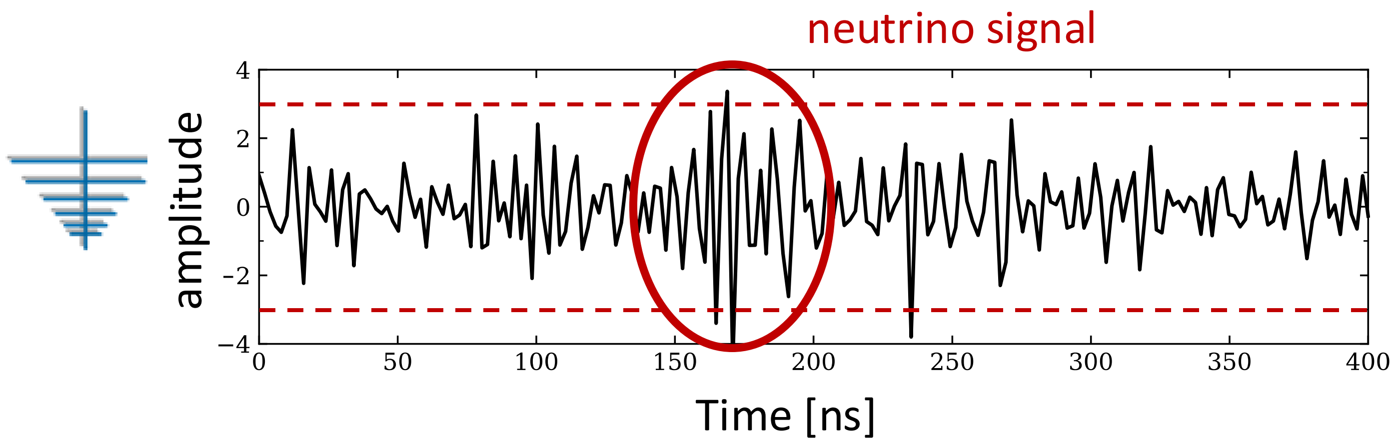


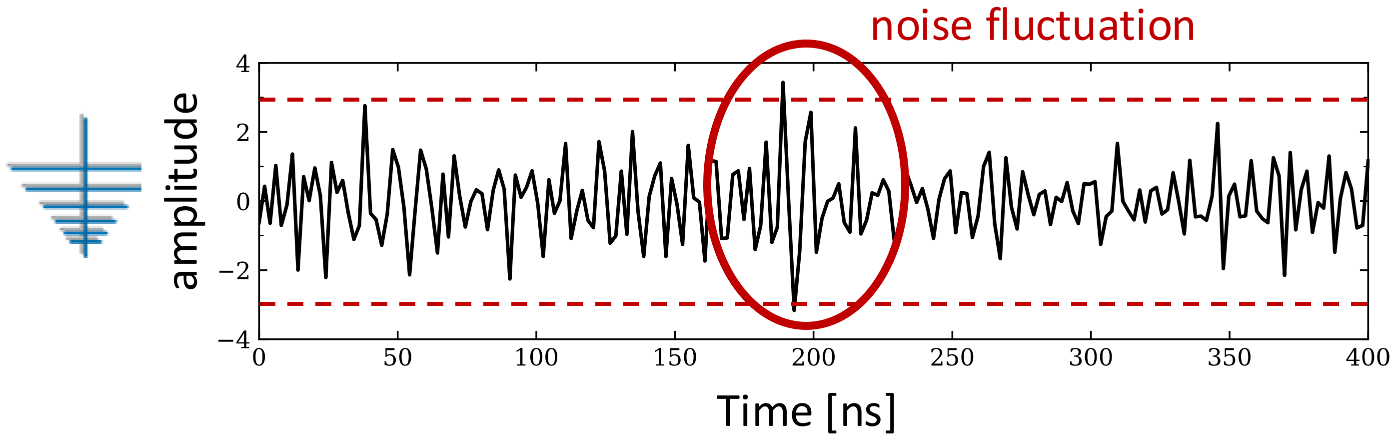
- Autonomous detector stations
  - limited data bandwidth and power budget
- Construction lasts 7 years limited by logistics!
  - detector size can't be increased

→ Only option to accelerate the research field: better detector

Deep-Learning-Based Trigger

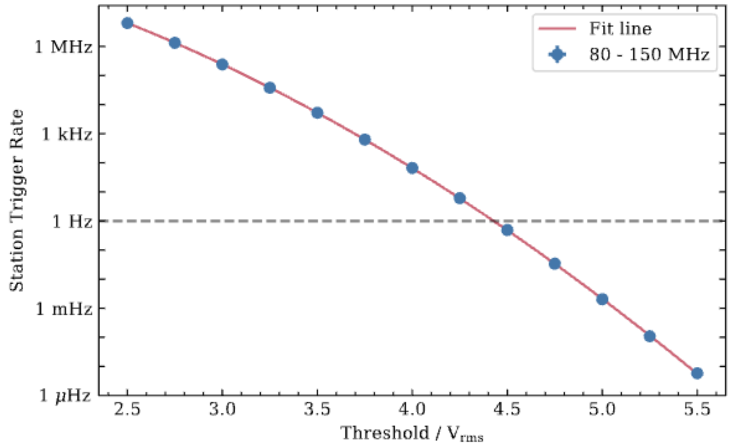
- Data can’t be stored continuously
- Current state of the art: Threshold-based trigger
  - Unavoidable thermal noise fluctuations dominate trigger
  - Thresholds need to be high enough to limit trigger rate on thermal noise



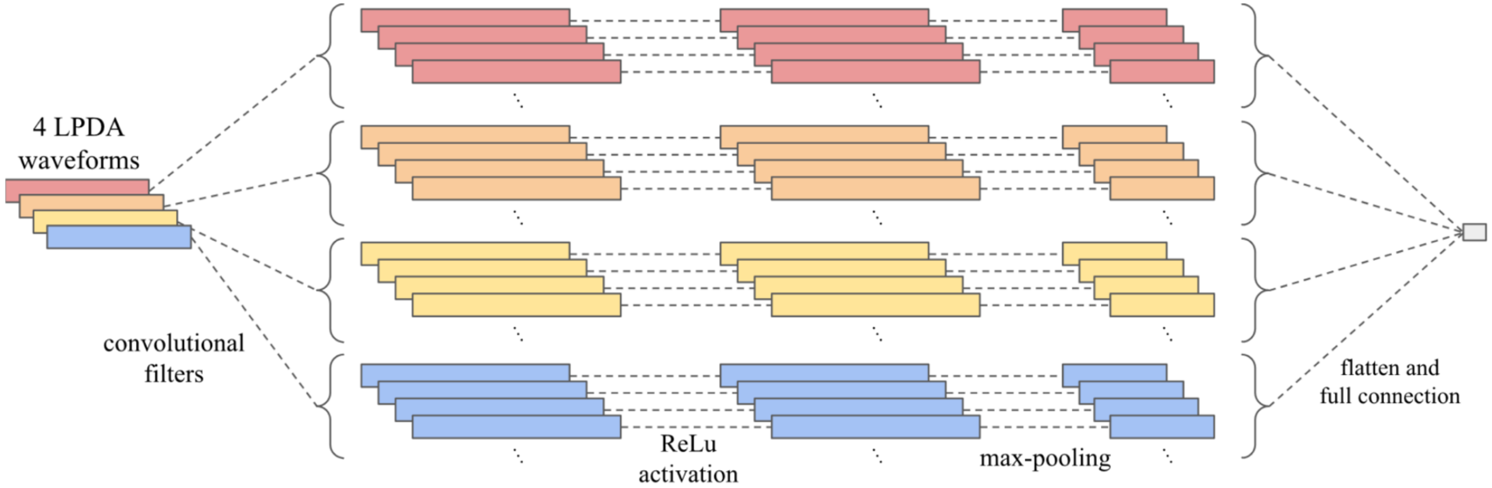


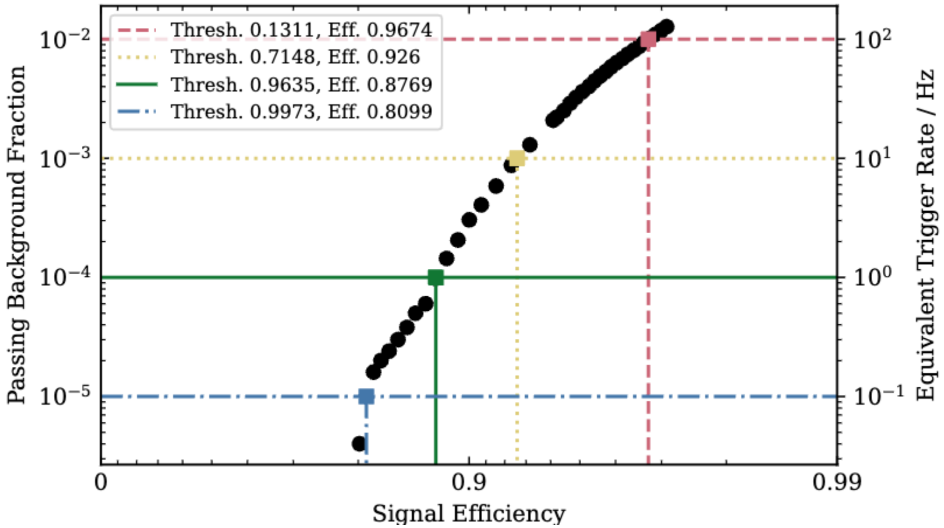
- **Huge potential of improvement:**
  - offline analysis: thermal noise can be rejected with high efficiency
  - Neural networks are very good at classification tasks
  - Proof-of-concept study
    ARIANNA collab. (… C. Glaser, …) , JINST 2022

Option 1: Second Stage Filter



Suitable network: Single CNN layer

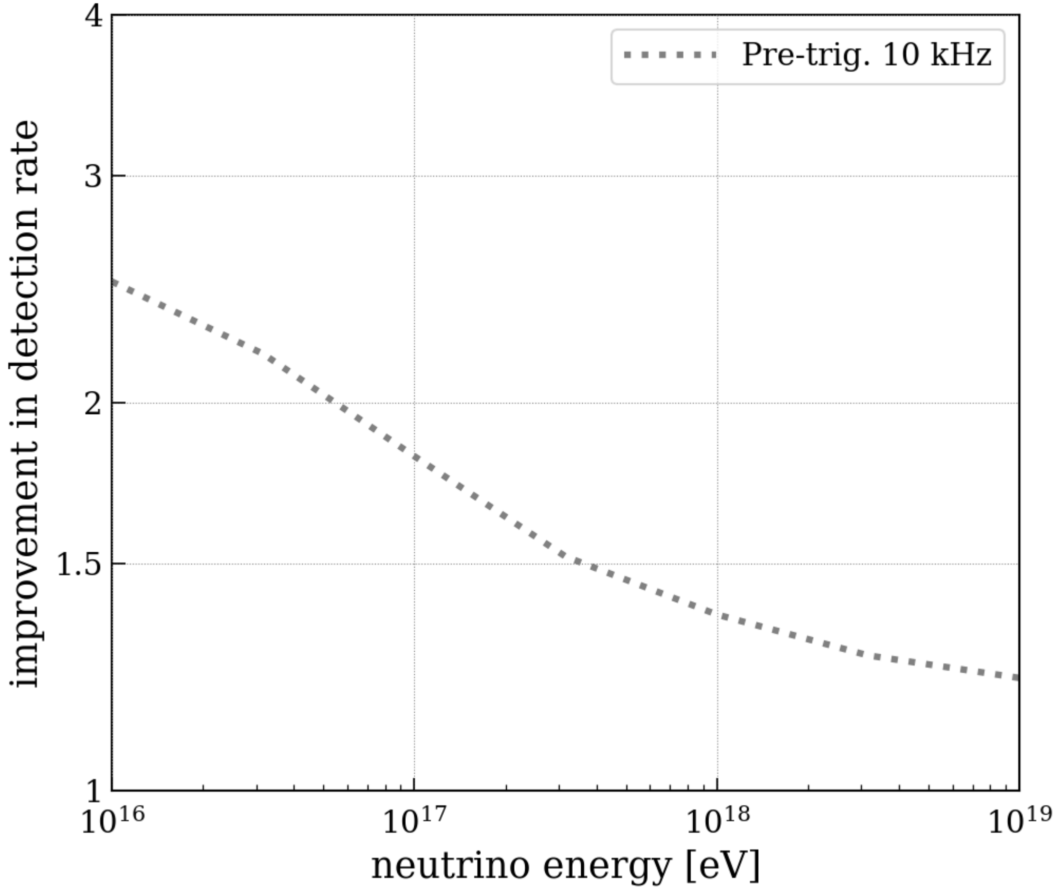




Fits easily on an "old" Cyclone V FPGA

CNN rejects 99.99% of noise at ~90% signal efficiency

Option 1: Second Stage Filter - Performance



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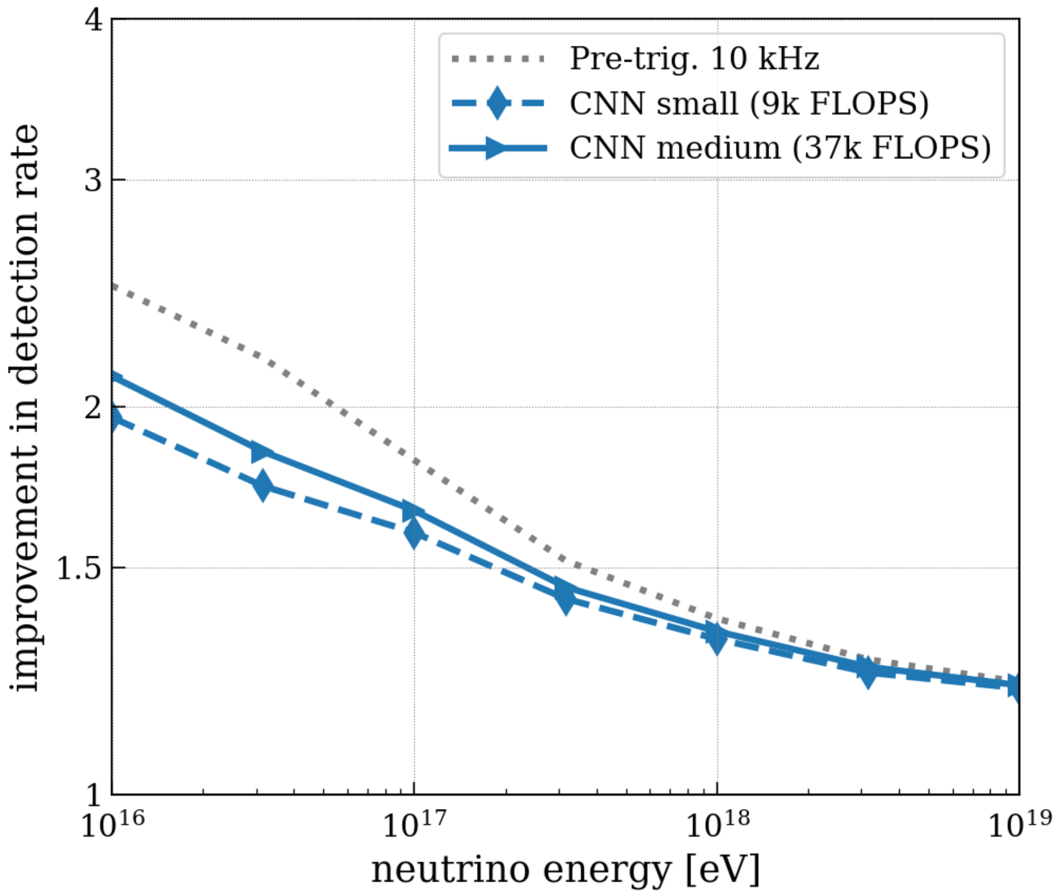

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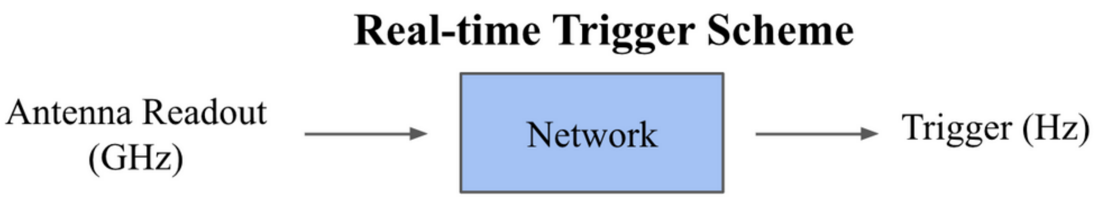
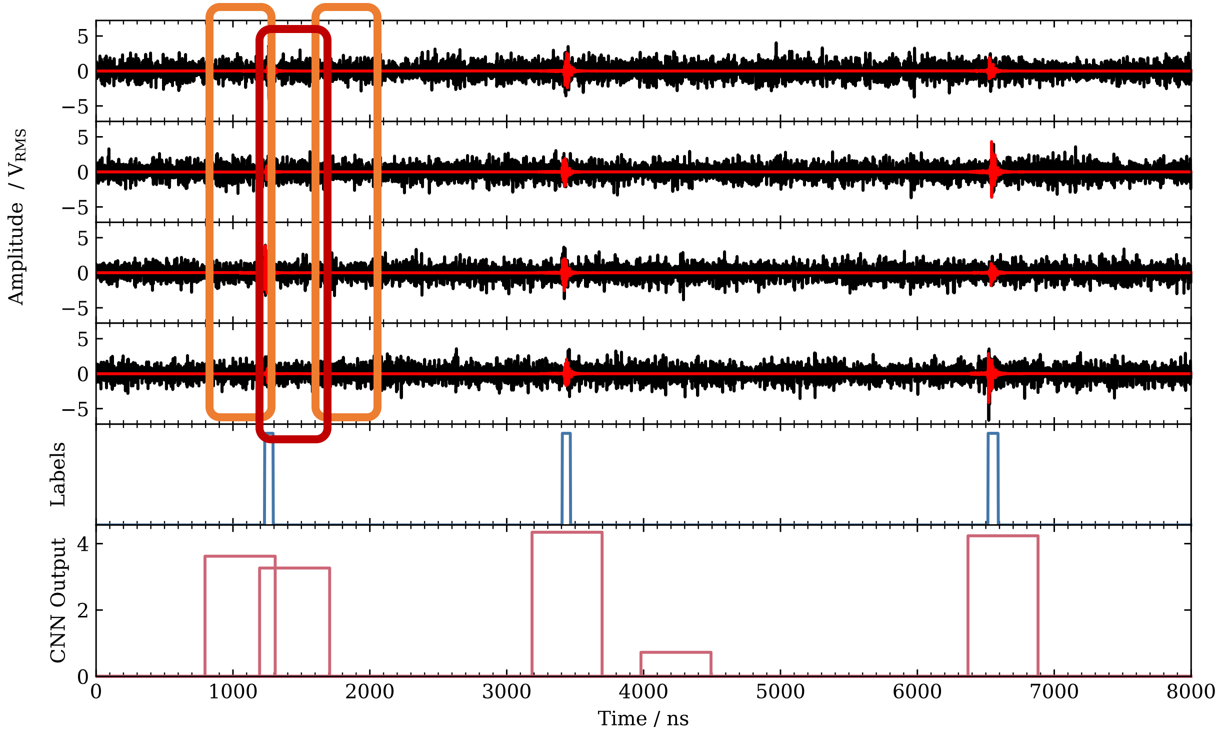
Option 2: Continuous analysis of data stream



- Simplest option:
  - Run CNN on overlapping chunks of data
  - Trigger on CNN output



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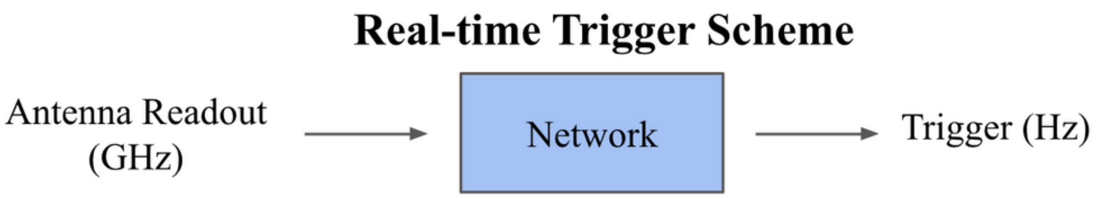
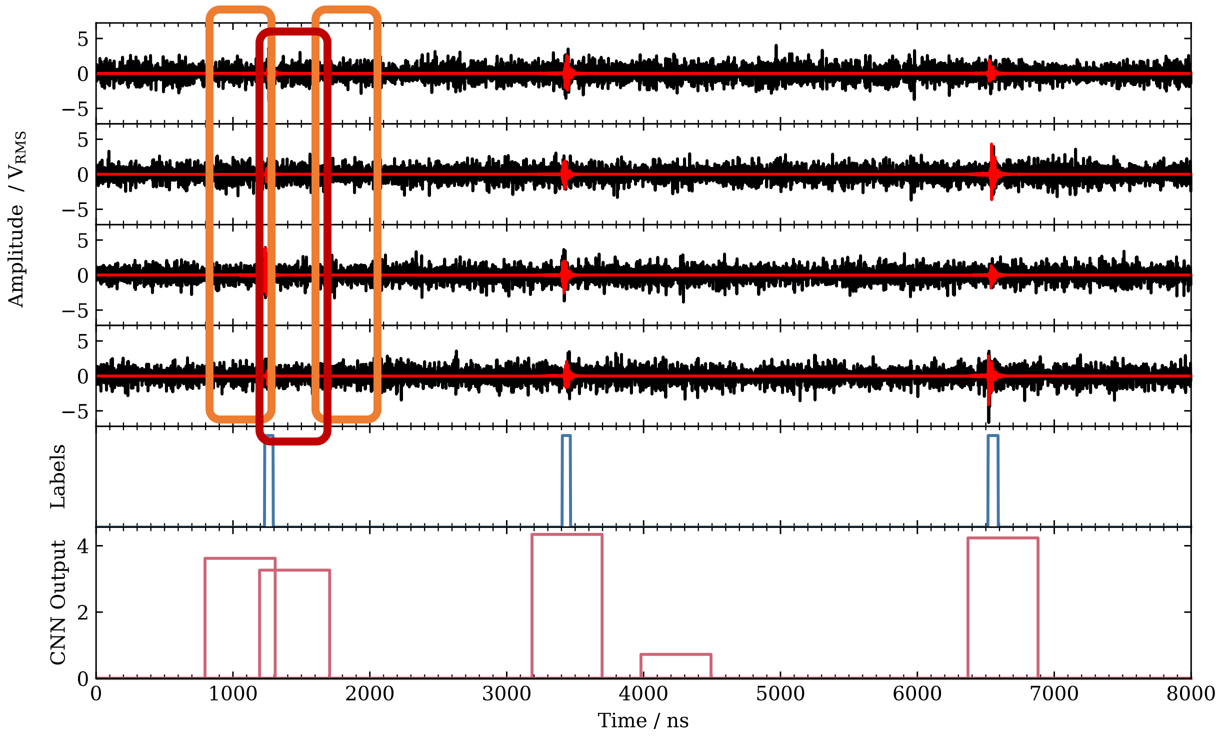


- Simplest option:
  - Run CNN on overlapping chunks of data
  - Trigger on CNN output

- Challenge: threshold set to trigger at 1Hz on thermal noise
  - → 1 trigger every 10^9 samples
  - → 1 trigger every 3.9M data chunks
- Solution:
  - No sigmoid activation
  - Hinge loss (penalize wrong predictions)



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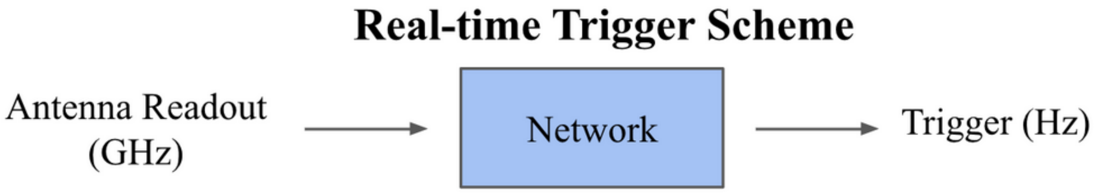


- Simplest option:
  - Run CNN on overlapping chunks of data
  - Trigger on CNN output
- Better: Translation invariant network

Input (N_S, 4, 1)

↓ 1D CNN: N_{f1} x kernel (5,1) — encoding of time series, pattern recognition

(N'_S, 4, N_{f1})

↓ 2D CNN: N_{f2} x kernel (7,4) — time coincidences between antennas

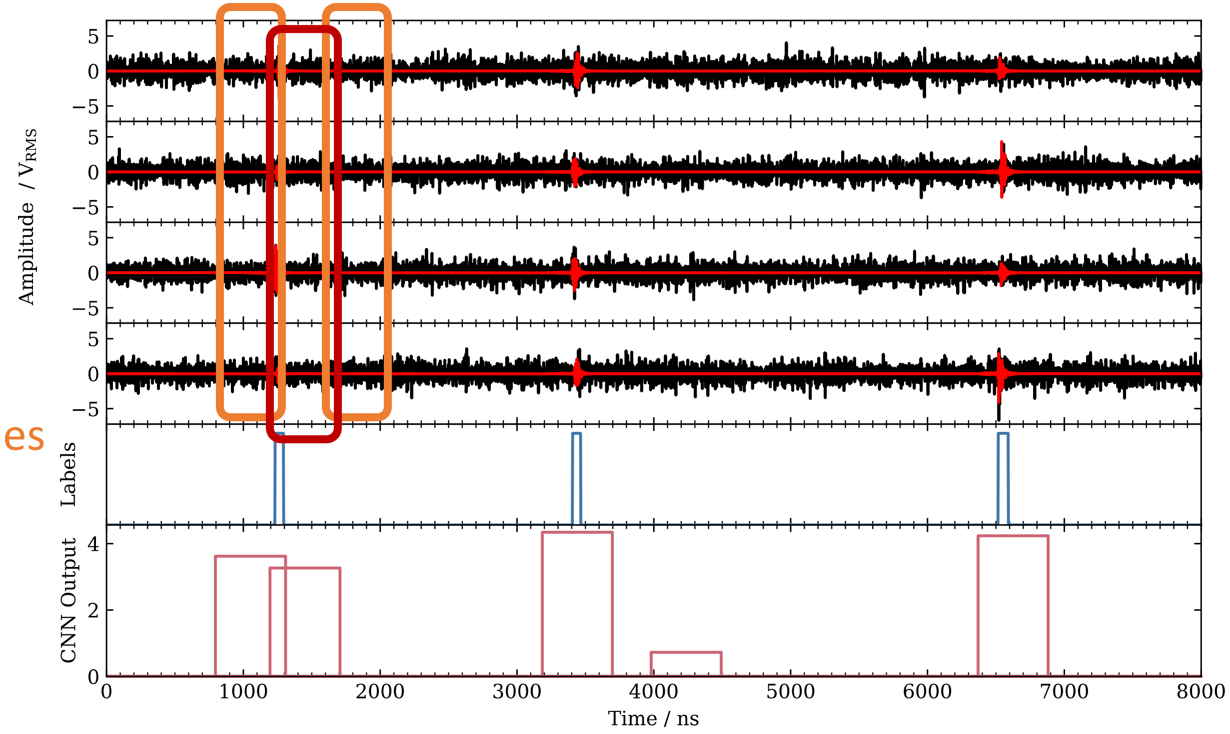
(N''_S, N_{f2})

global maximum ↙ ↘ max pooling

Output (1)

continuous output (N''_S)

trigger on continuous scaler output
reduced sampling rate due to striding



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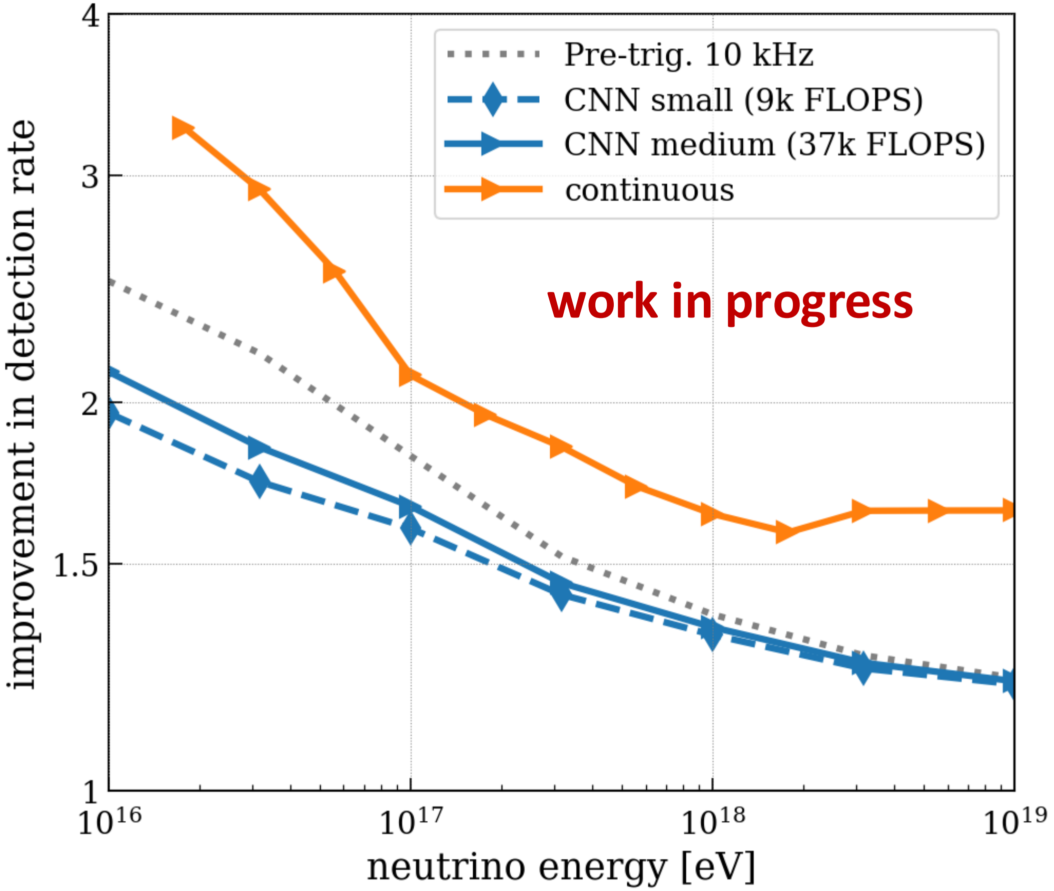

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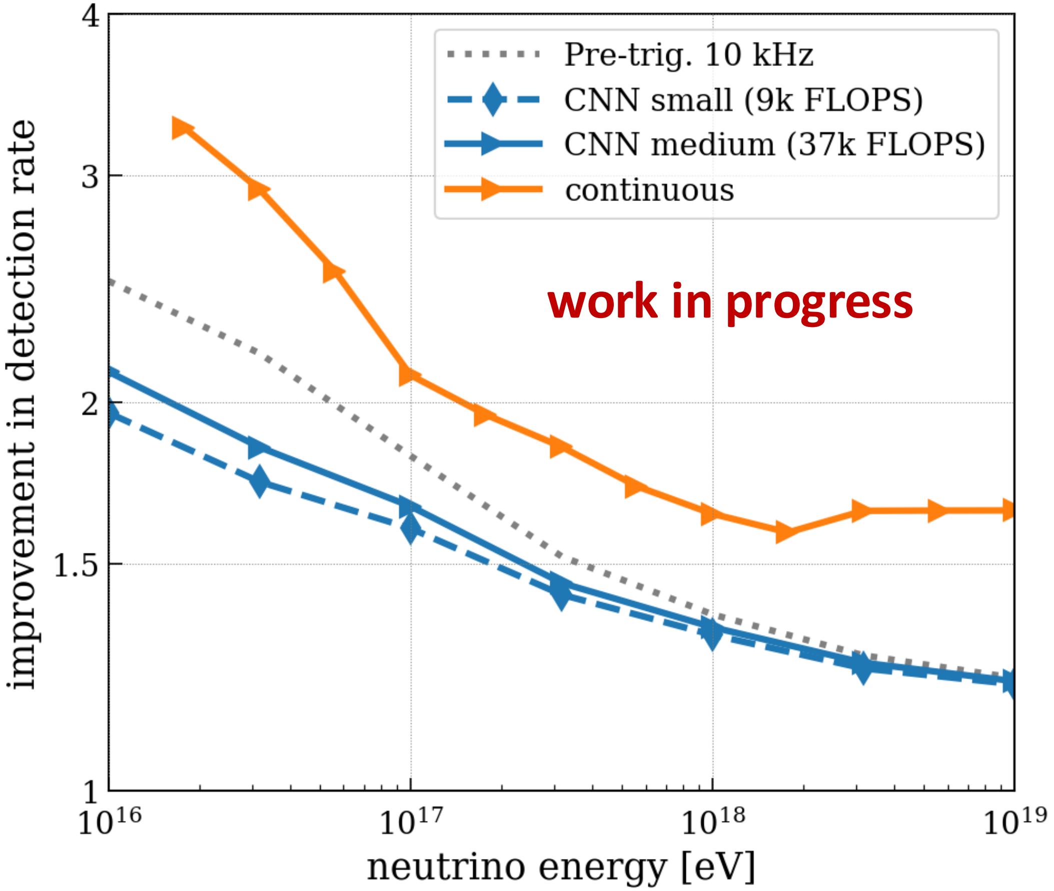
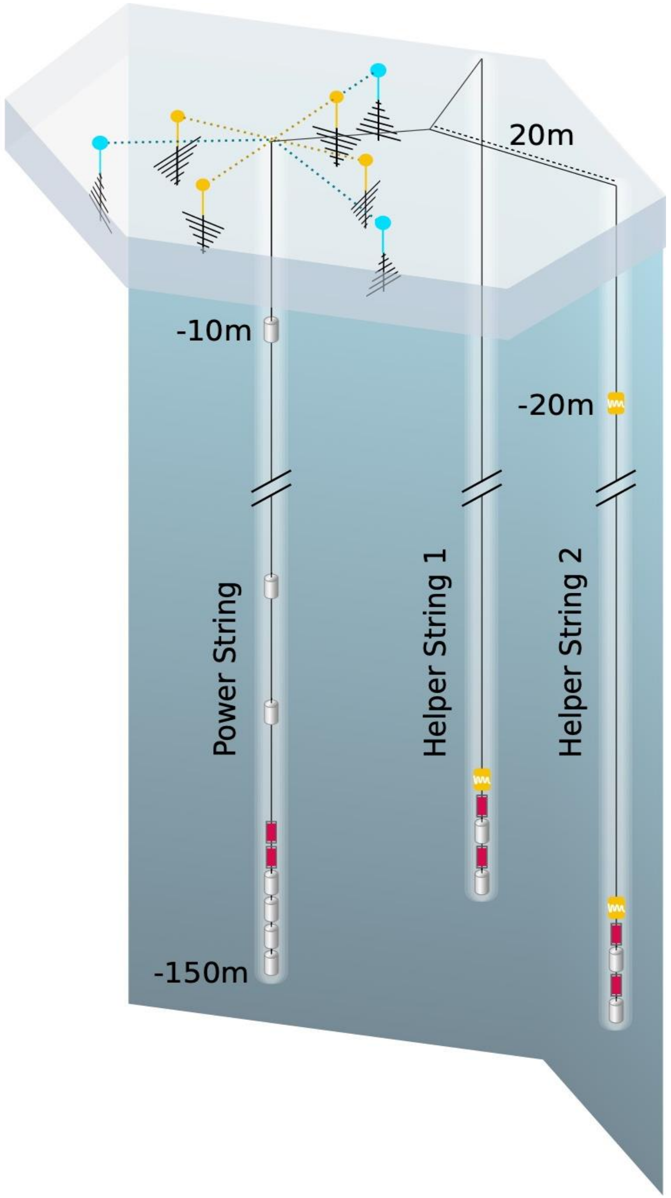


- Future improvements:
  More computing for same power budget
  → **Neuromorphic Computing**
  (collaboration with Tommaso Dorigo and Fredrik Sandin)

End-To-End Optimization

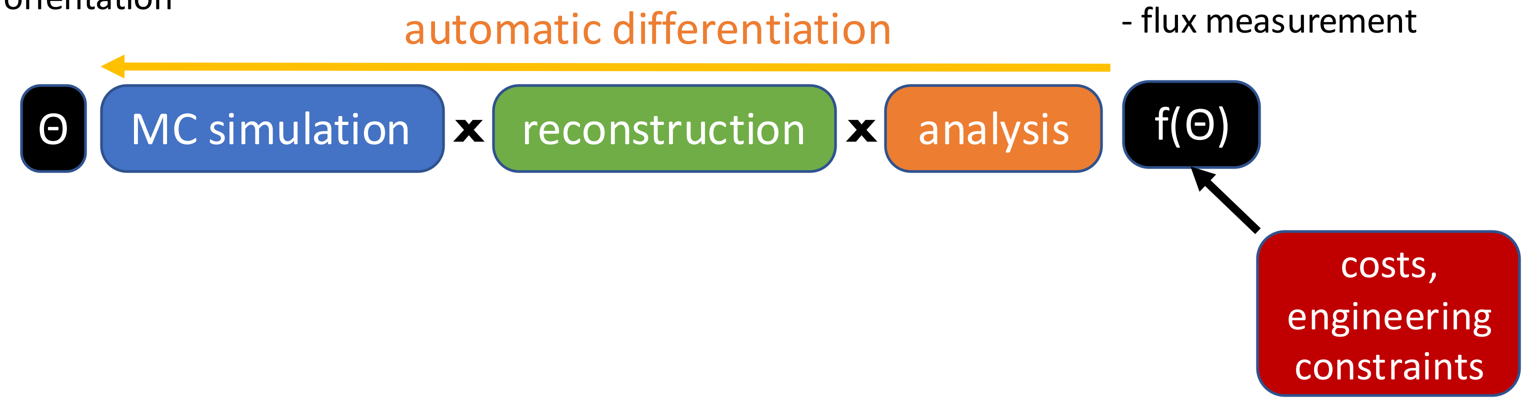


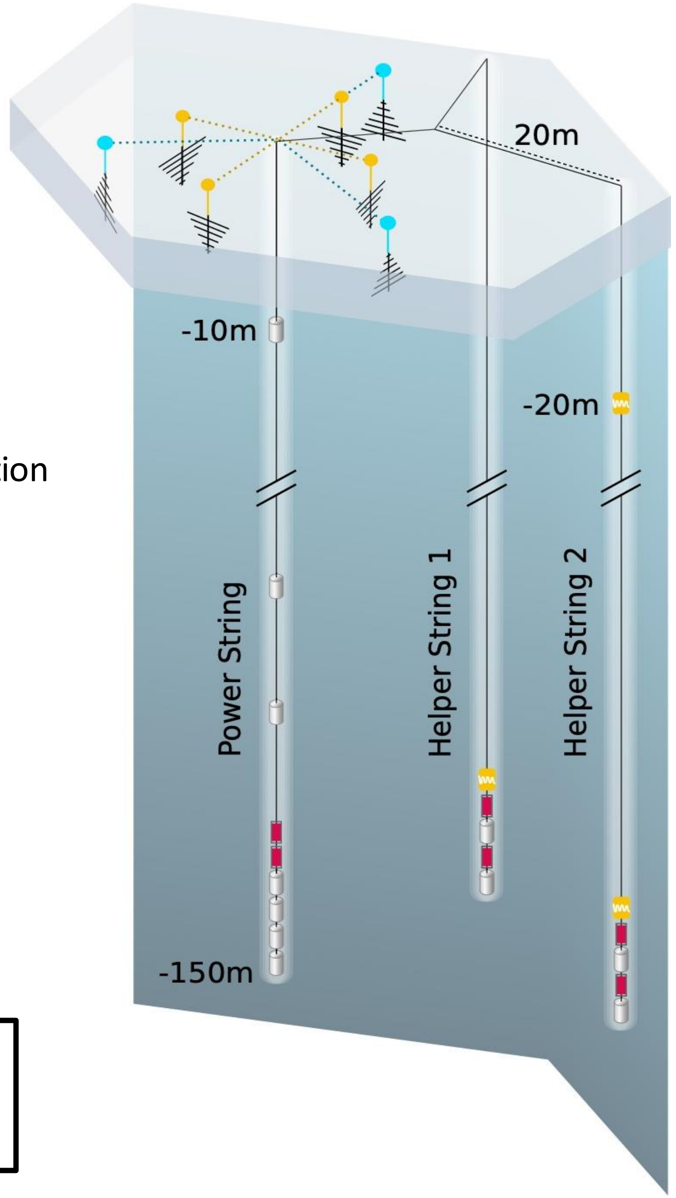
End-To-End Optimization

- Deep learning and differential programming can build an end-to-end optimization pipeline
- Direct optimization of science objective

detector parameters, e.g.,
- antenna positions
- antenna orientation

science output, e.g.,
- neutrino-nucleon cross-section
- source discovery
- flux measurement





→ Expected improvements: up to three times more precise measurement of neutrino direction and energy

Likelihood Reconstruction

- Likelihood for Radio Neutrino Detectors:

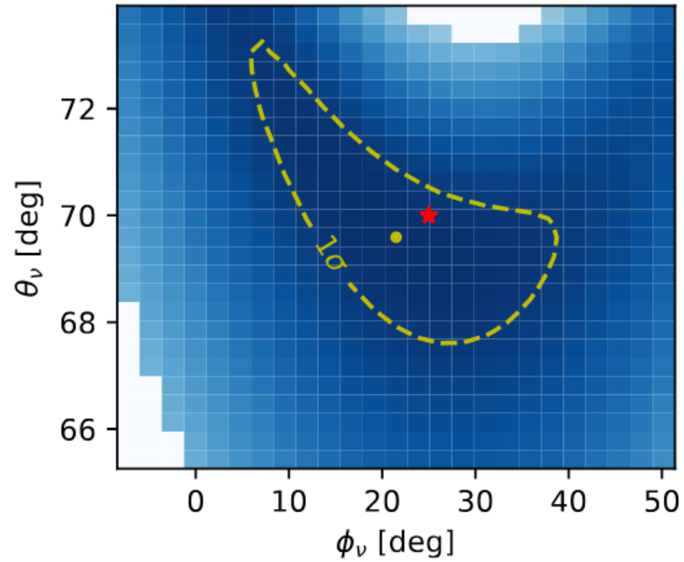
$$p\left(\boldsymbol{x};\boldsymbol{\mu}(\theta),\boldsymbol{\Sigma}\right) = \frac{1}{\sqrt{(2\pi)^{n_t}|\boldsymbol{\Sigma}|}} \exp\left(-\frac{1}{2}\left(\boldsymbol{x}-\boldsymbol{\mu}(\theta)\right)^{\mathsf{T}}\boldsymbol{\Sigma}^{-1}\left(\boldsymbol{x}-\boldsymbol{\mu}(\theta)\right)\right)$$

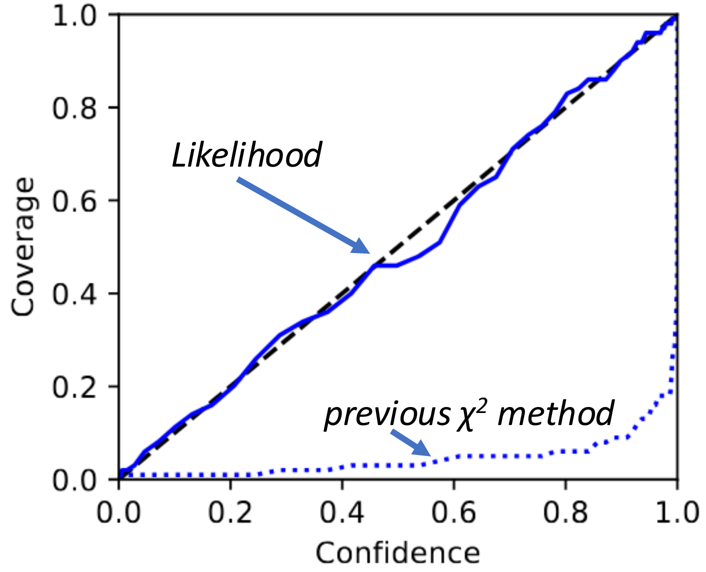
Signal · Trace · Noise

- Key ingredient: Bandwidth-limited noise can be modeled as multi-variate Gaussian

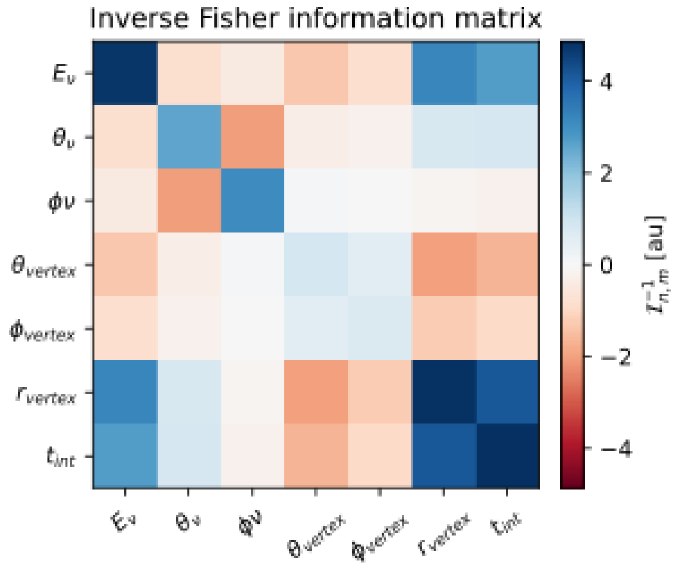
- Minimize to get best-fit parameters and uncertainties

$$-2\ln\mathscr{L}(\boldsymbol{\mu}(\theta);\boldsymbol{x},\boldsymbol{\Sigma}) = \sum_{\text{ant.}} \left(\boldsymbol{x}-\boldsymbol{\mu}(\theta)\right)^{\mathsf{T}}\boldsymbol{\Sigma}^{-1}\left(\boldsymbol{x}-\boldsymbol{\mu}(\theta)\right) + const$$



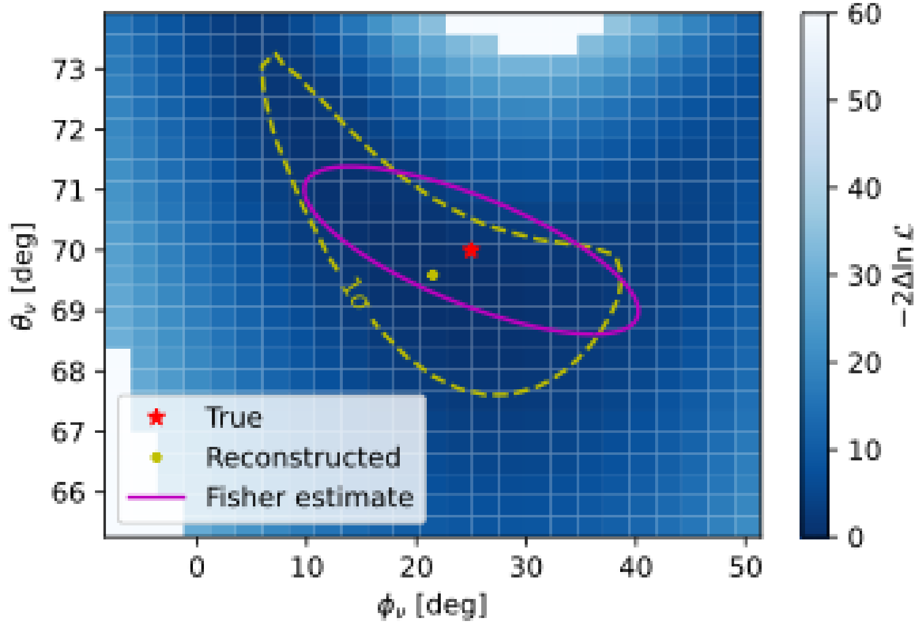


Uncertainty Estimation using Fisher Information



- Fisher Information Matrix can be calculated directly from signal model
  - $$\mathcal{I}_{m,n} = \frac{\partial \boldsymbol{\mu}^{\mathrm{T}}}{\partial \theta_m} \boldsymbol{\Sigma}^{-1} \frac{\partial \boldsymbol{\mu}}{\partial \theta_n}$$
- Inverse gives uncertainty estimate through Cramer-Rao bound
- -> Fast uncertainty estimate for any detector configuration

- Remaining steps to achieve differentiability:
  - Differentiable signal model
    - Electric field generation from particle showers
      → *see Phillips's talk*
    - Signal propagation through ice (ongoing)



Main science objectives of UHE neutrino astronomy:

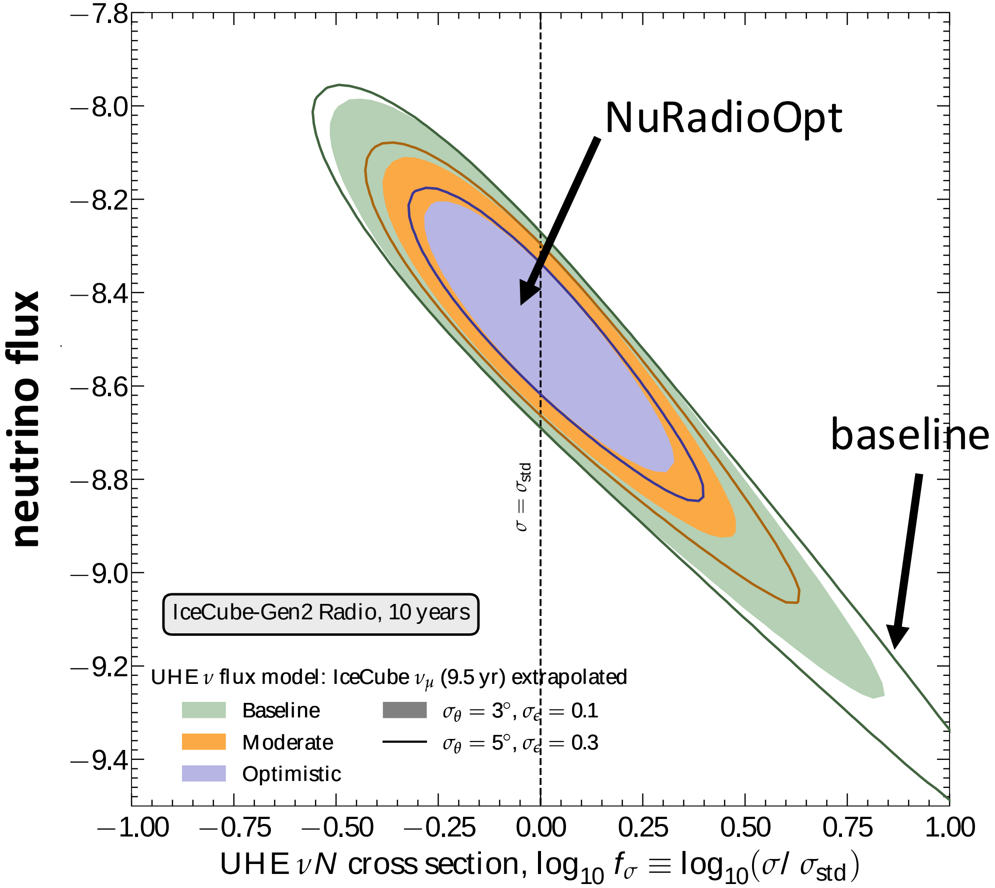
Impact of NuRadioOpt

Neutrino-Nucleon Cross Section

→ 3x more precise measurement

Diffuse Flux

Point Sources



*based on V. Valera, M. Bustamante, **C. Glaser**, JHEP 06 (2022) 105*

Main science objectives of UHE neutrino astronomy:

Impact of NuRadioOpt

Neutrino-Nucleon Cross Section → 3x more precise measurement

*V. Valera, M. Bustamante, **C. Glaser**, JHEP 06 105 (2022)*

Diffuse Flux → expedite the detection of UHE neutrino fluxes by up to a factor of five

*V. Valera, M. Bustamante, **C. Glaser,** PRD 107, 043019 (2023)*

Point Sources → identify sources from deeper in our Universe, increasing the observable volume by a factor of three

D. F. G. Fiorillo, V. Valera, M. Bustamante, JCAP03(2023)026

Main science objectives of UHE neutrino astronomy:

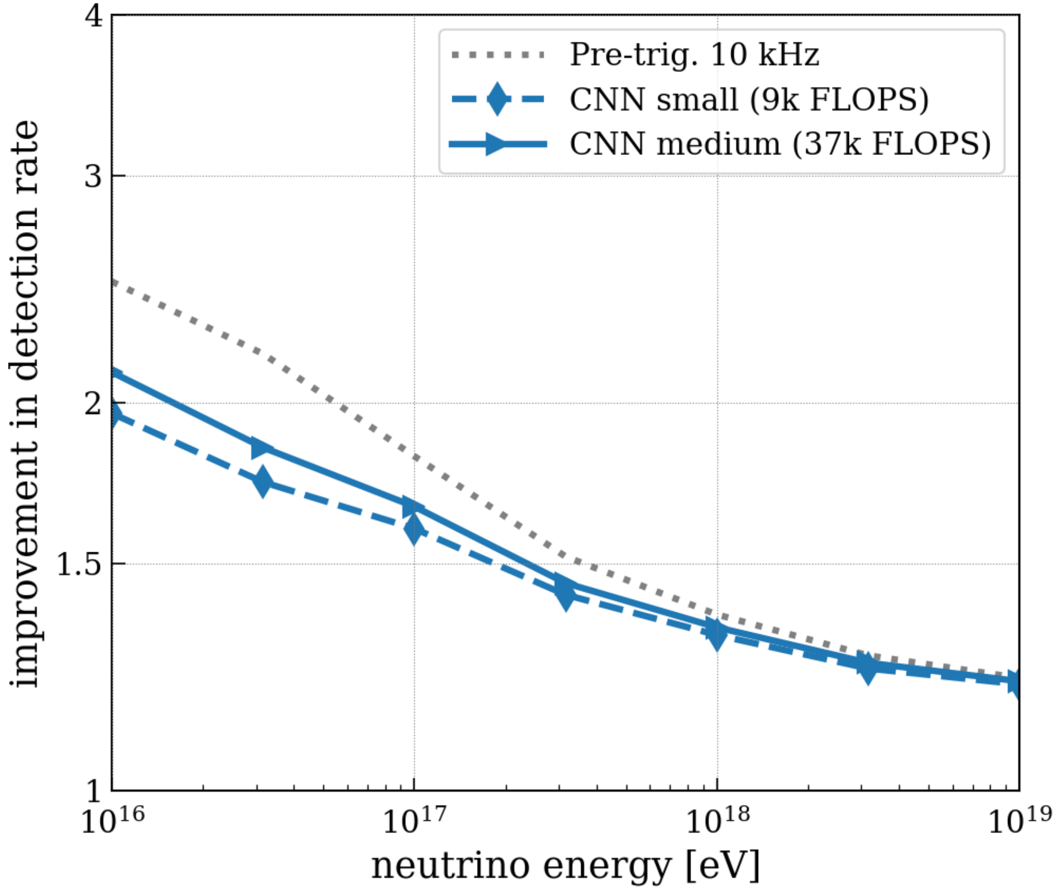
Impact of NuRadioOpt

Neutrino-Nucleon Cross Section	→ 3x more precise measurement *V. Valera, M. Bustamante, **C. Glaser**, JHEP 06 105 (2022)*
Diffuse Flux	→ expedite the detection of UHE neutrino fluxes by up to a factor of five *V. Valera, M. Bustamante, **C. Glaser,** PRD 107, 043019 (2023)*
Point Sources	→ identify sources from deeper in our Universe, increasing the observable volume by a factor of three *D. F. G. Fiorillo, V. Valera, M. Bustamante, JCAP03(2023)026*

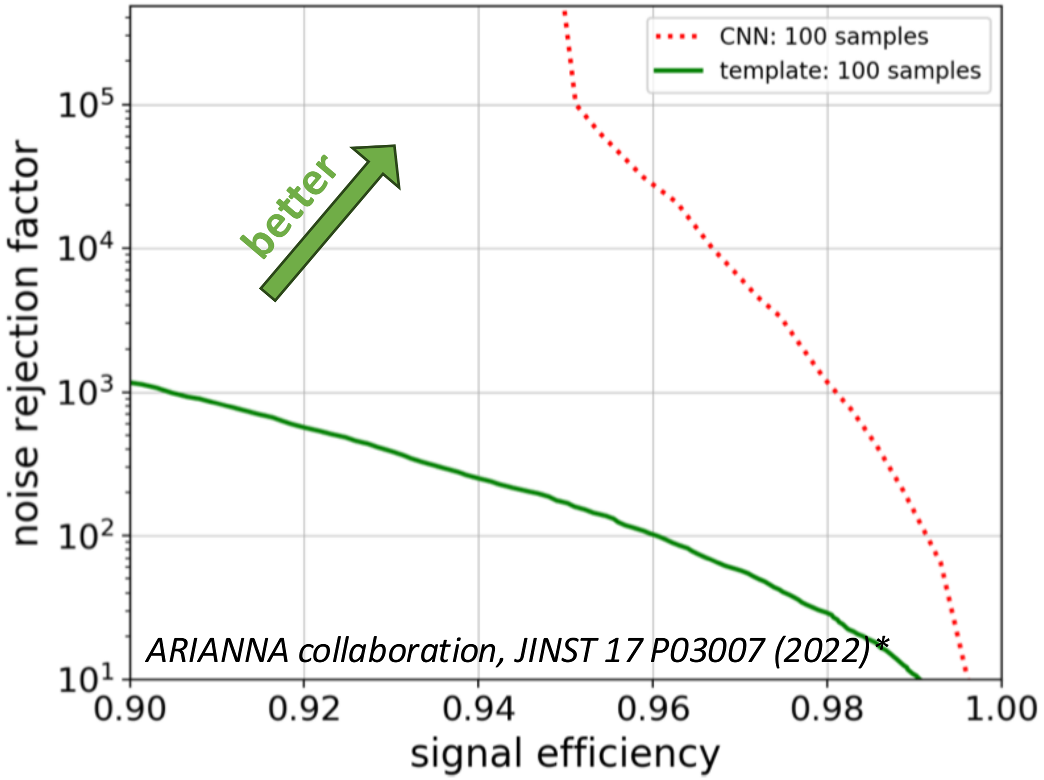
- **Improvements equivalent to building a more than three times larger detector** at essentially no additional costs
- because we are already at the limit of logistical resources at the South Pole, **NuRadioOpt is the only option to accelerate UHE neutrino science in the next decade**

Bonus slides

Option 1: Second Stage Filter - Performance



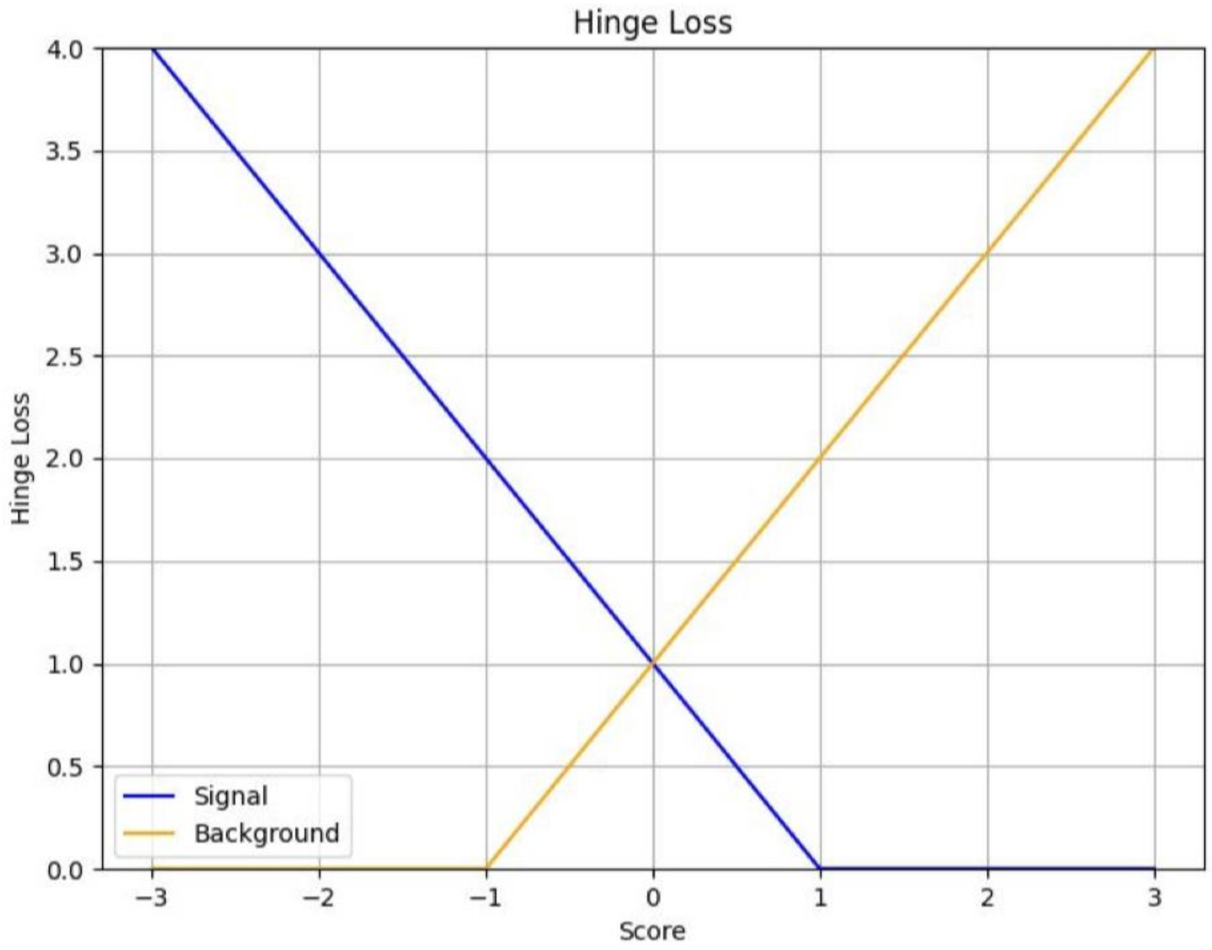
CNN substantially better than template-matching for same runtime



*earlier study on a different/simpler data set. Therefore, signal efficiencies are different than the previously shown result

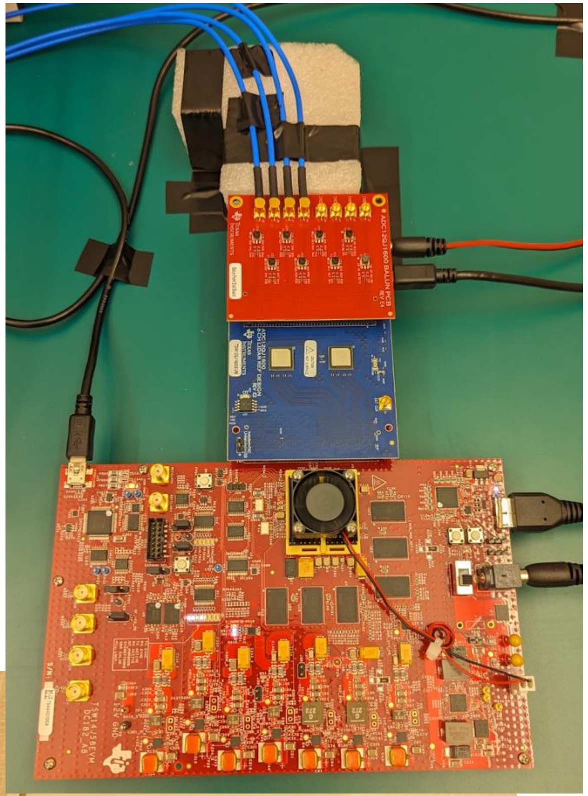
Hinge Loss

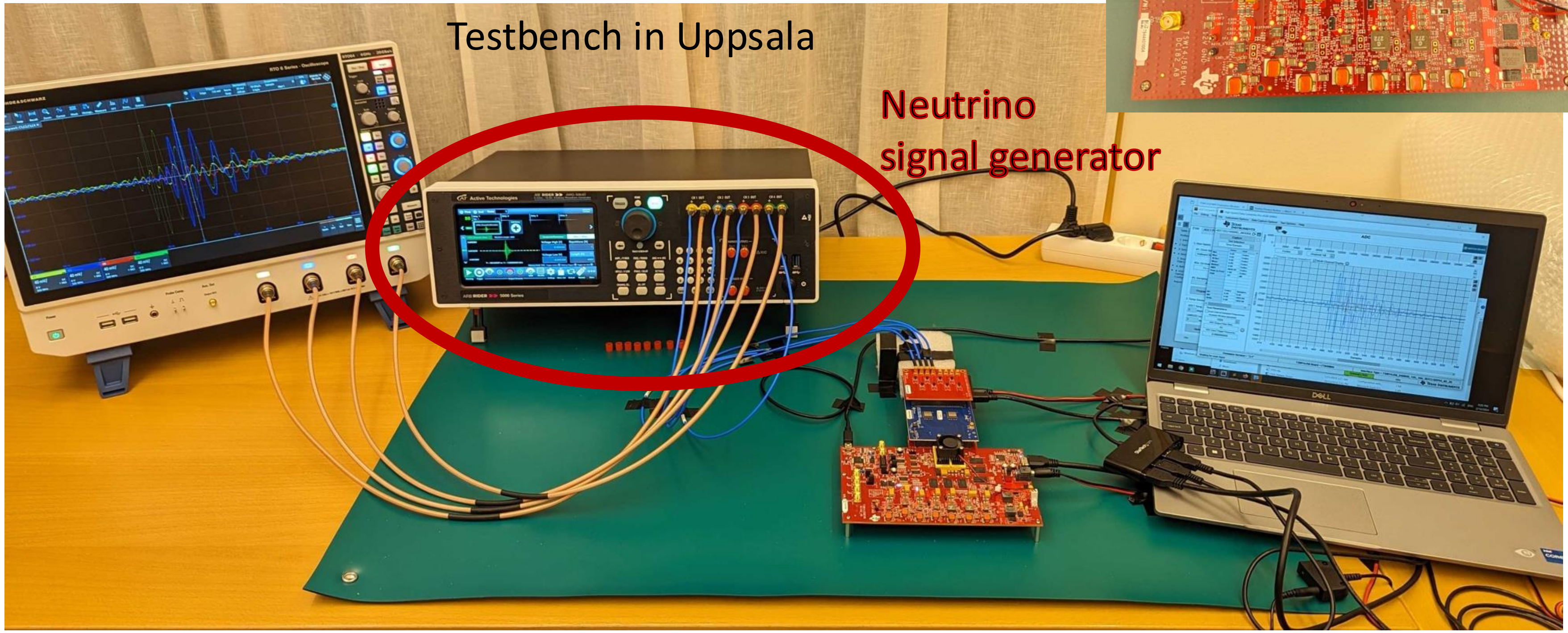
- No sigmoid activation
- Penalize (only) wrong predictions



New DAQ Development

- New ADC generation (JESD204B interface)
  - High speed and low power (~1GHz, 12bit at 0.5W/channel)
  - Simpler compared to custom ASICS of previous hardware
  - Better data quality and opportunities for advanced triggers
- Also looking into Neuromorphic Computing
  (with Tommaso Dorigo + Fredrik Sandin)

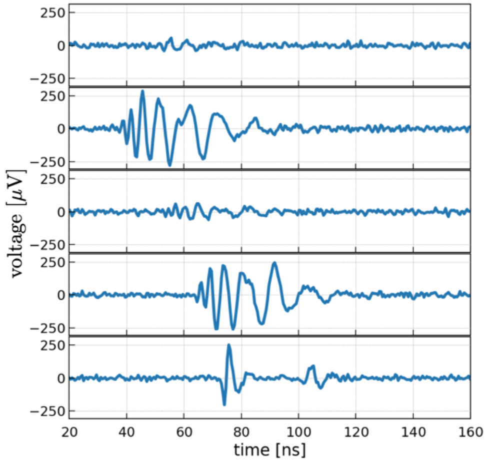




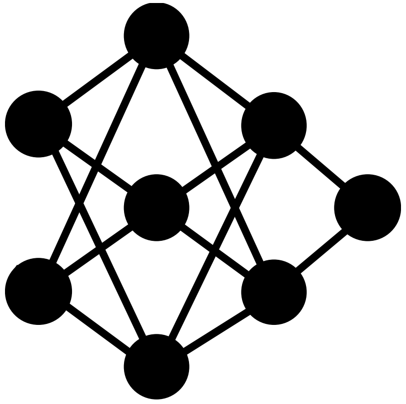
Deep-Learning Reconstruction using Normaling Flows (Simulation-Based Inference)

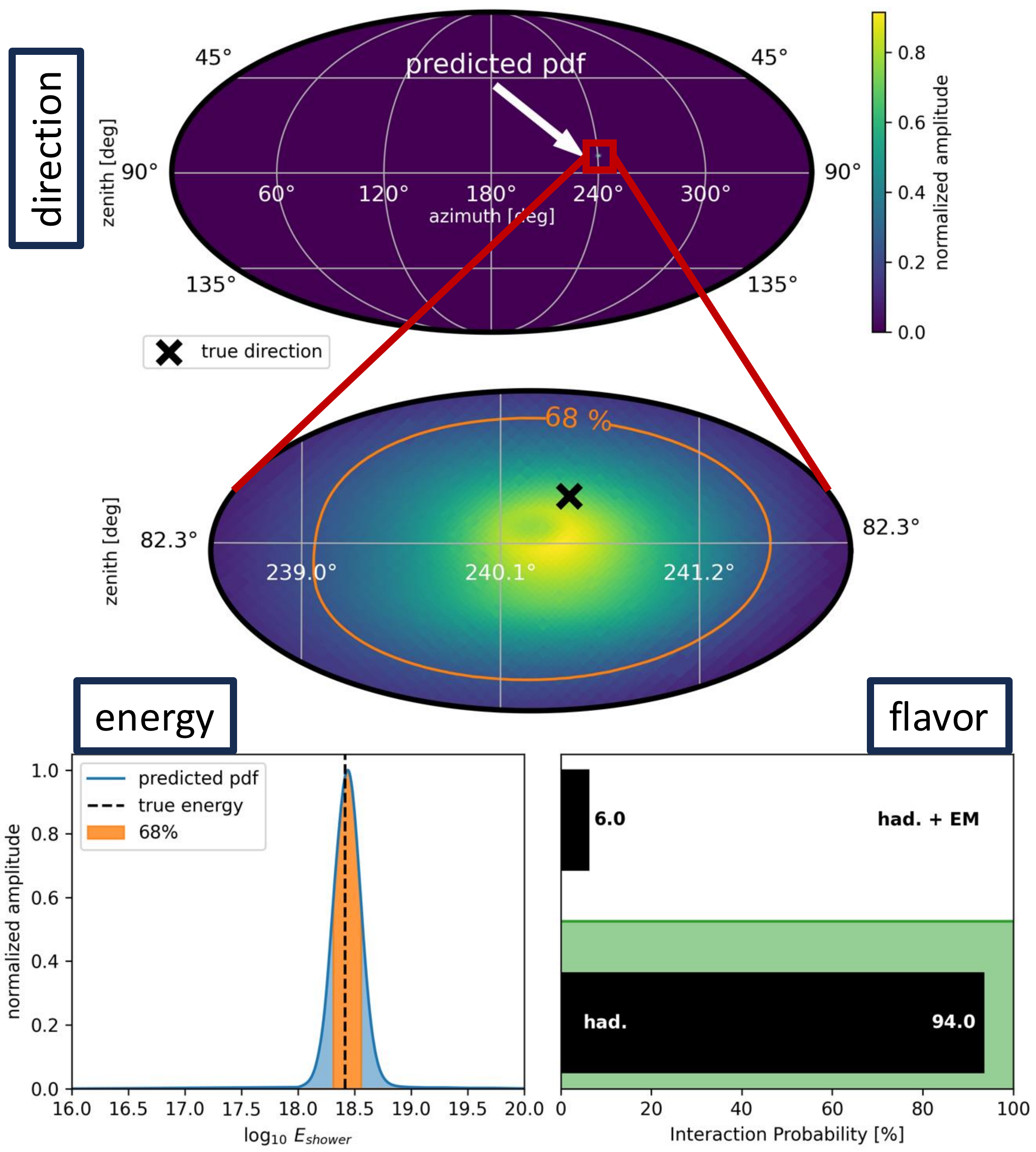
Single Event Reconstruction

raw traces



reconstruction algorithm





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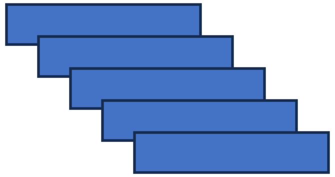
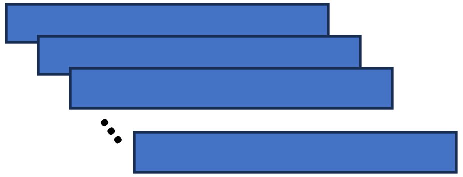
Model architecture

<u>Model Shallow</u>:
1 x 5 x 512



<u>Model Deep</u>:
1 x 16 x 2046

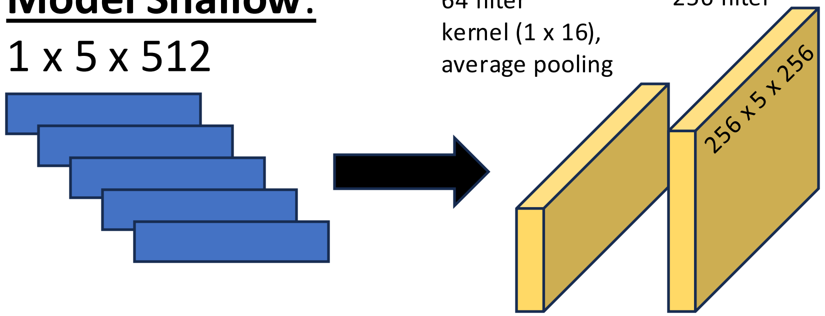


Model architecture

Model Shallow:
1 x 5 x 512

CNN1
4x 1d-conv
64 filter
kernel (1 x 16),
average pooling

CNN2
4x 1d-conv
kernel (1 x 16),
256 filter



Model Deep:
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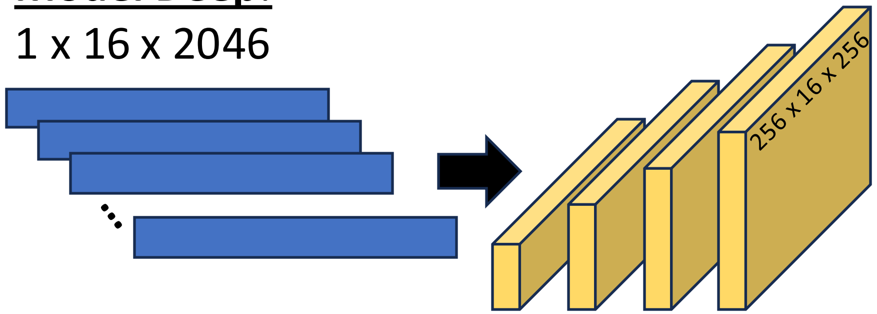
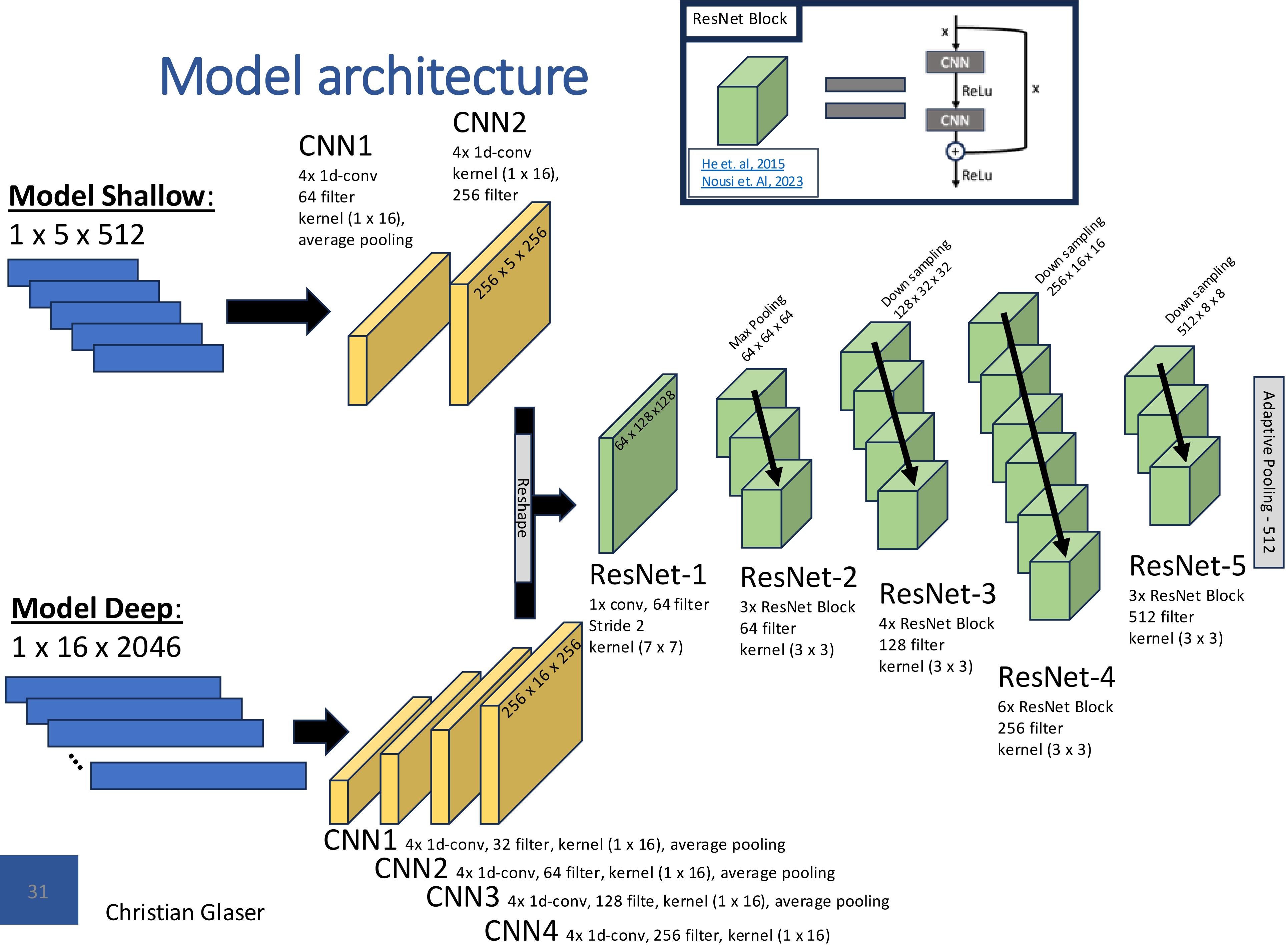


CNN1 4x 1d-conv, 32 filter, kernel (1 x 16), average pooling
CNN2 4x 1d-conv, 64 filter, kernel (1 x 16), average pooling
CNN3 4x 1d-conv, 128 filte, kernel (1 x 16), average pooling
CNN4 4x 1d-conv, 256 filter, kernel (1 x 16)

Model architecture



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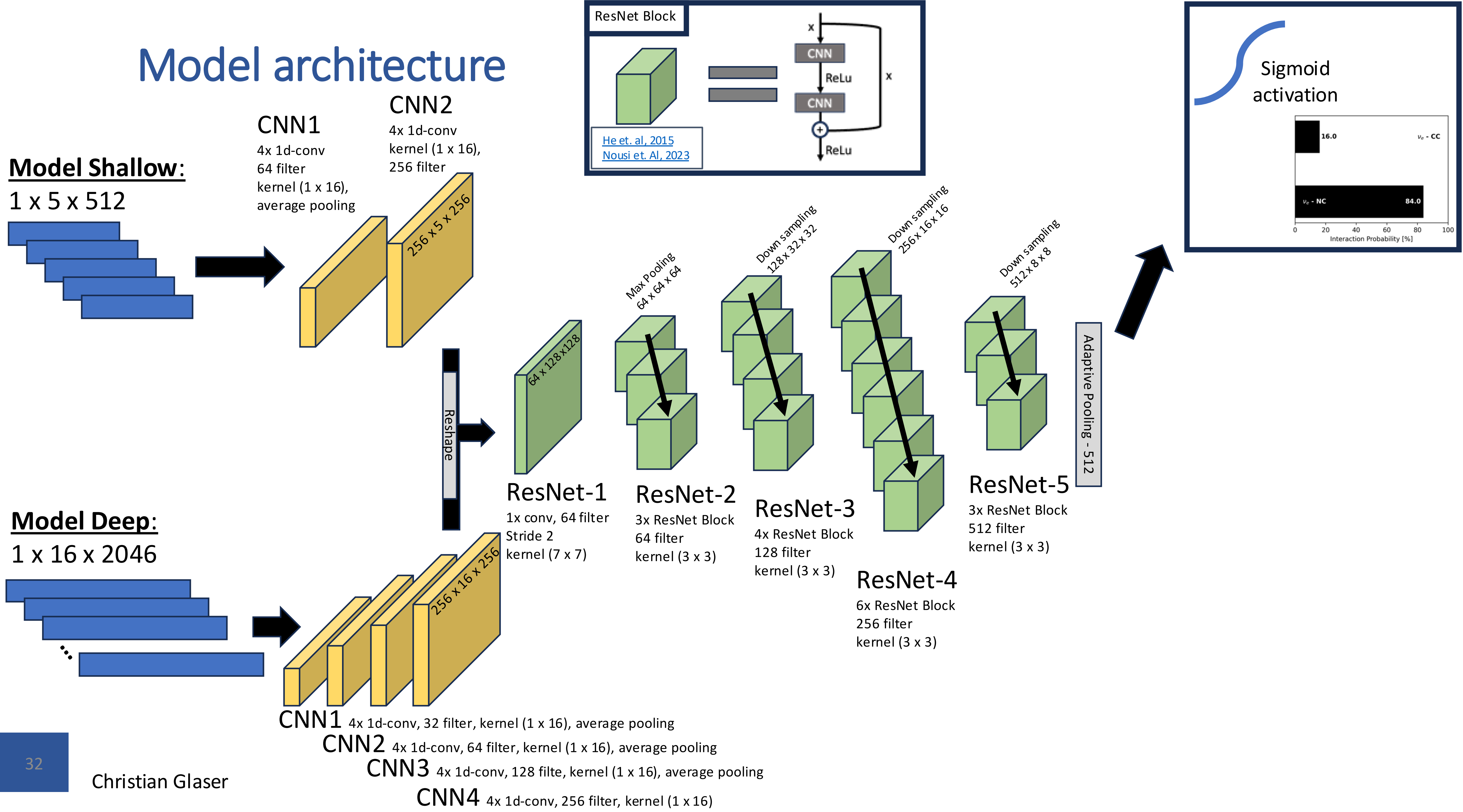
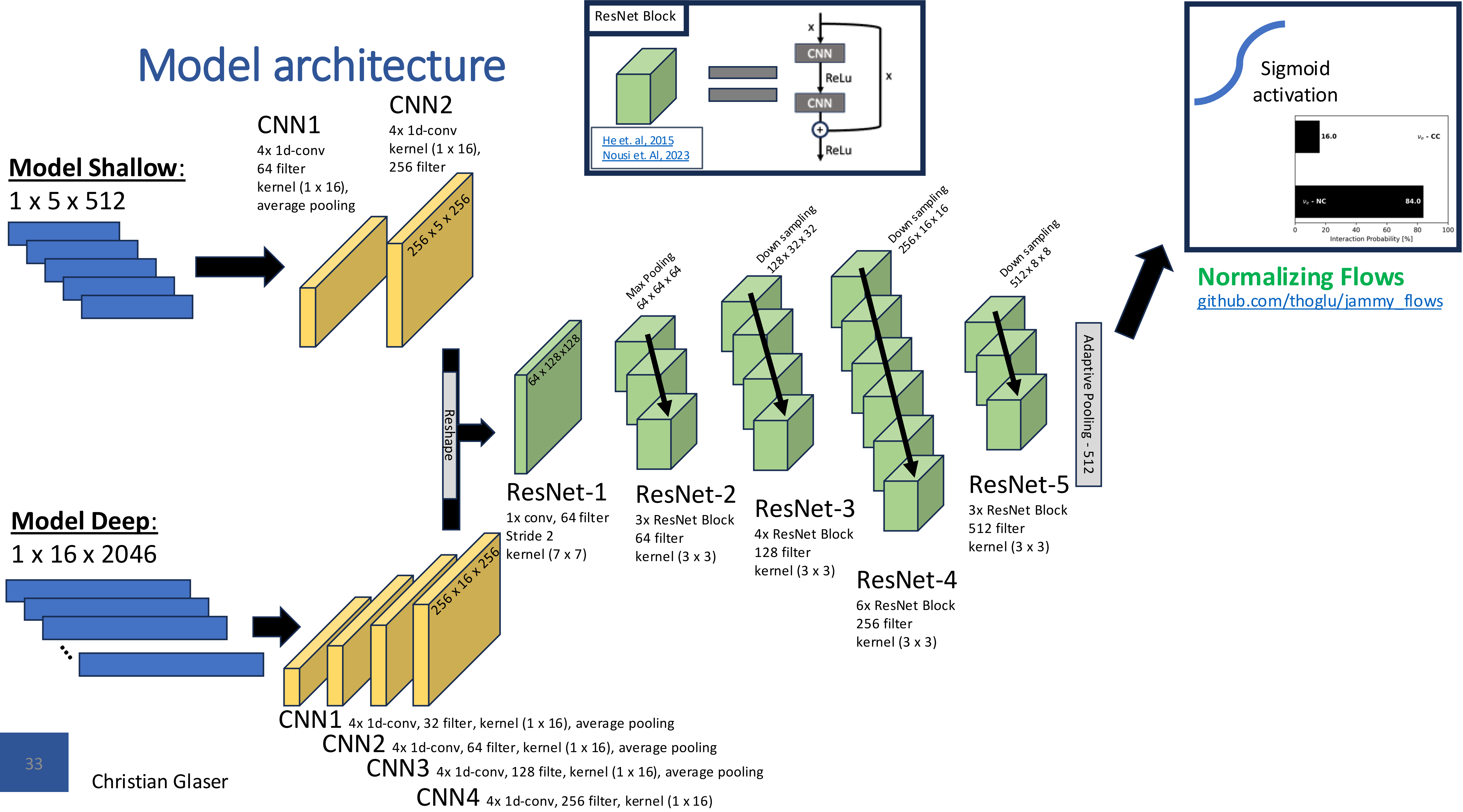


Model architecture



Model architecture

Model Shallow:
1 x 5 x 512

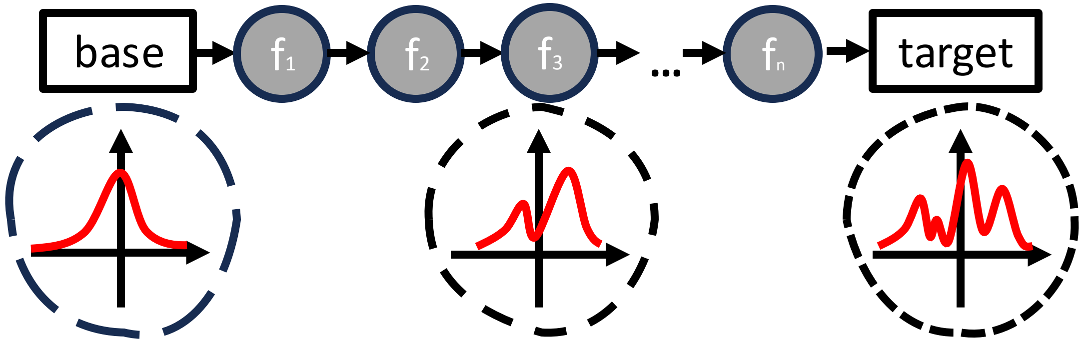
CNN1
4x 1d-conv
64 filter
kernel (1 x 16)
average pooli

CNN2

ResNet Block

Normalizing Flow

- A **function that maps** a gaussian PDF to a non-gaussian target PDF
- Parameters of the flow can be learned by a **neural network**
- Can model **complex PDF shapes**



Sigmoid activation

Adaptive Pooling - 512

Normalizing Flows
github.com/thoglu/jammy_flows

Model Deep:
1 x 16 x 2046

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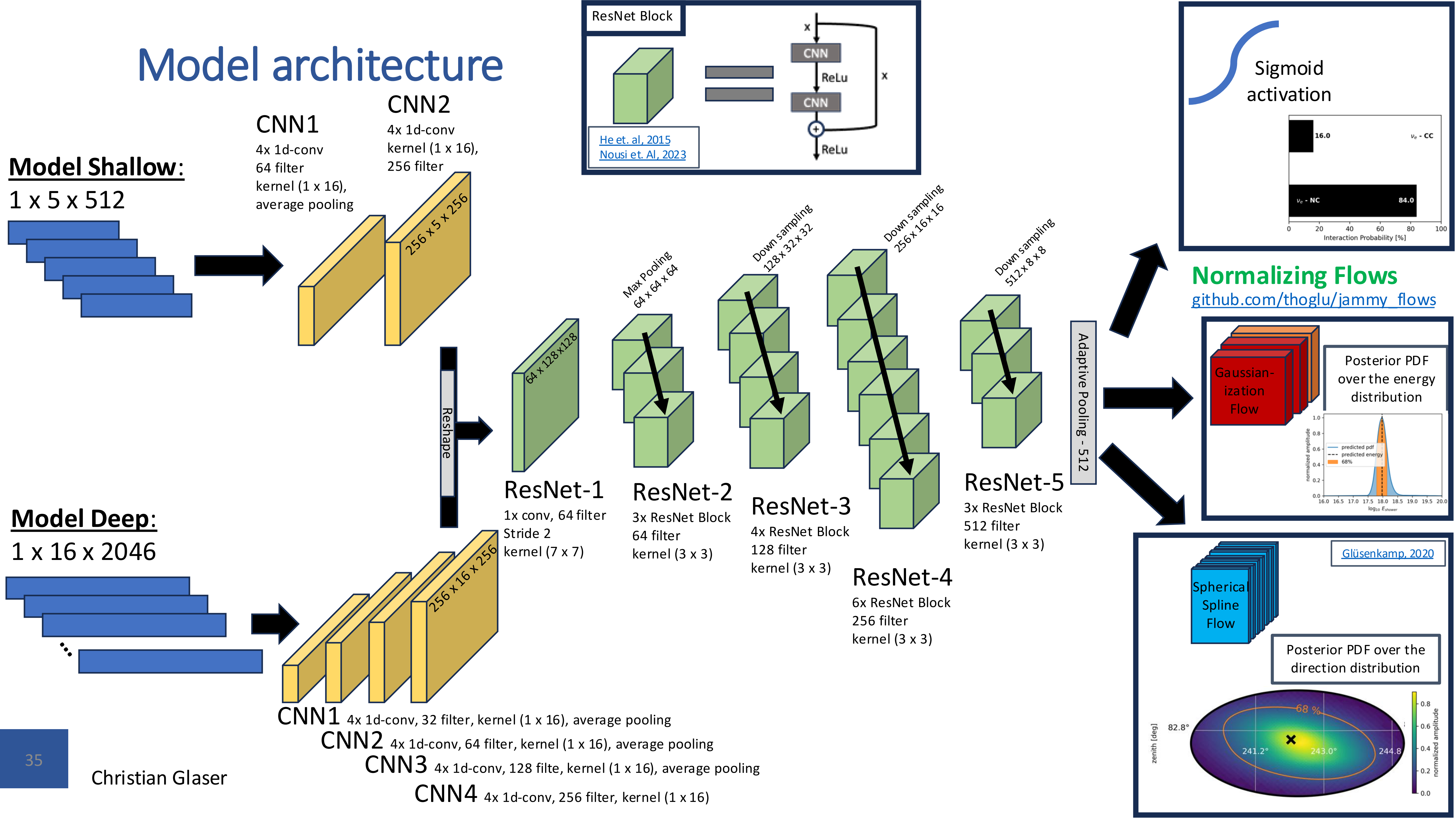
Model architecture



Improvements to previous reconstructions:

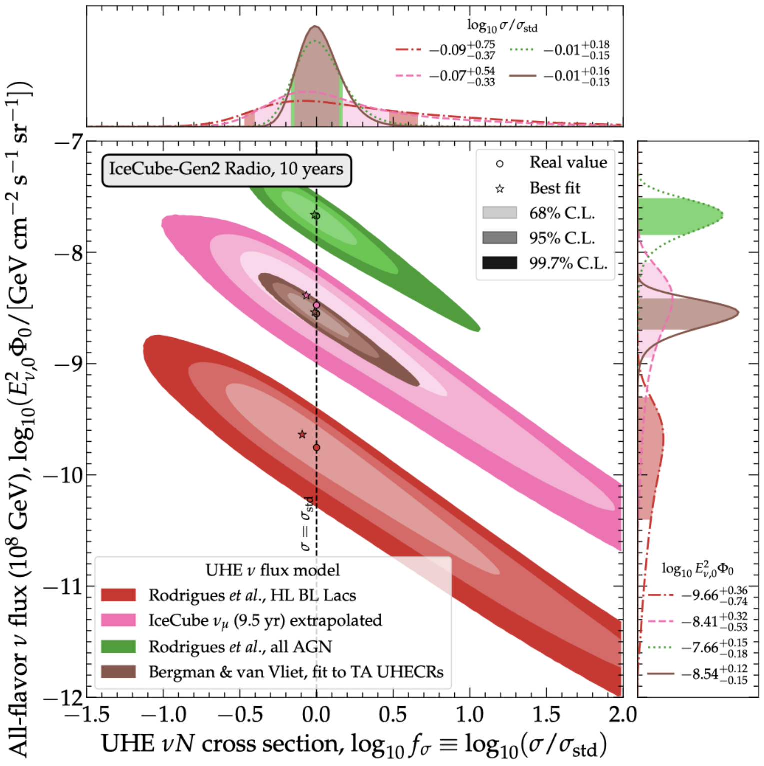
1. Normalizing flows return full posterior PDFs allowing for event-by-event uncertainties (Glüsenkamp, EPJ-C, 2024)
2. Factor 10x improvement in angular resolution (compared to previous best reconstruction of deep stations)
3. No analysis cuts are needed – all neutrino events can be used
4. One model (per station type) to predict all parameters

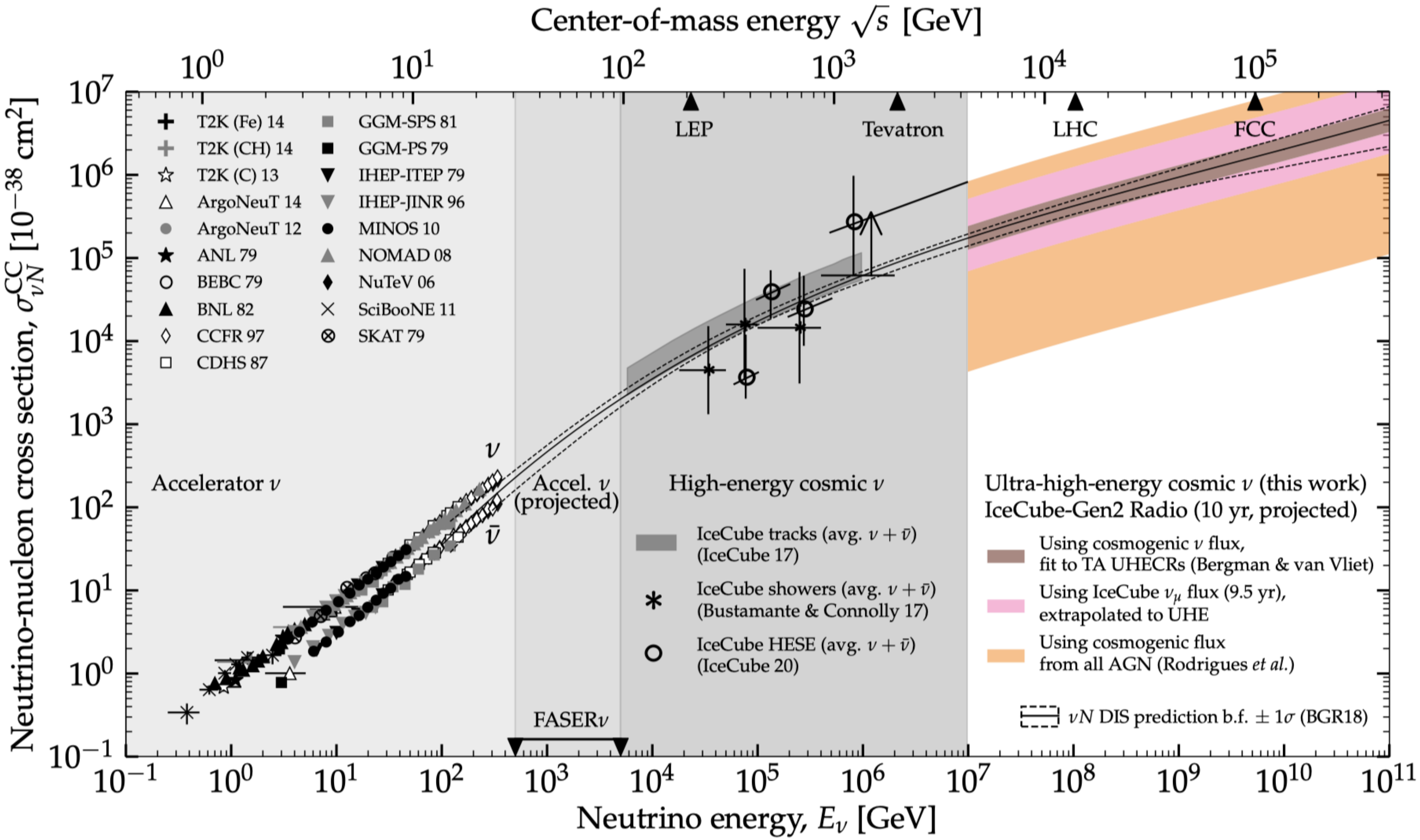
Science Overview: Cross Section

- Sensitivity comes from Earth attenuation
  - Angular resolution important
  - Horizontal events important

$$N_\nu(E_\nu, \theta_z) \propto \Phi_\nu(E_\nu)\sigma(E_\nu)e^{-L(\theta_z)/L_{\nu N}(E_\nu,\theta_z)}$$

$$L_{\nu N} \equiv (\sigma n_N)^{-1}$$





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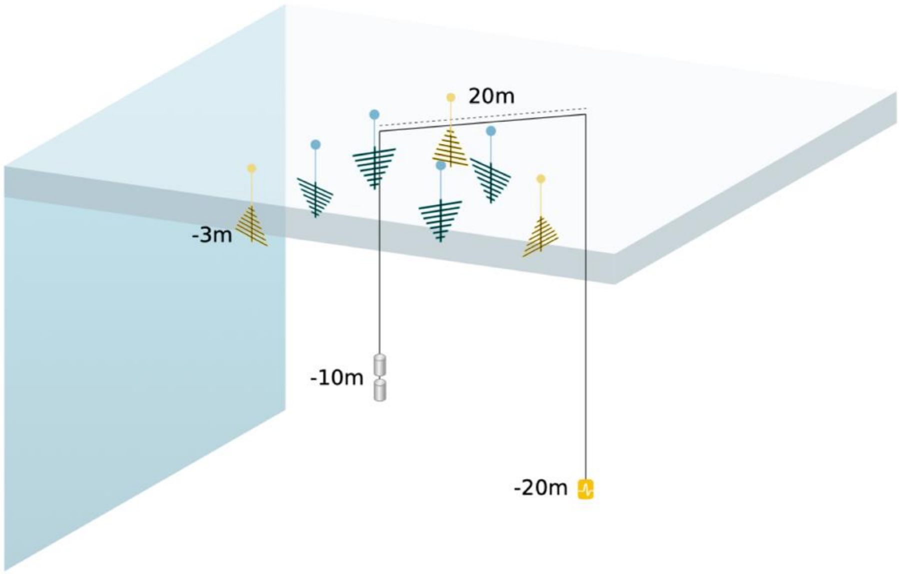
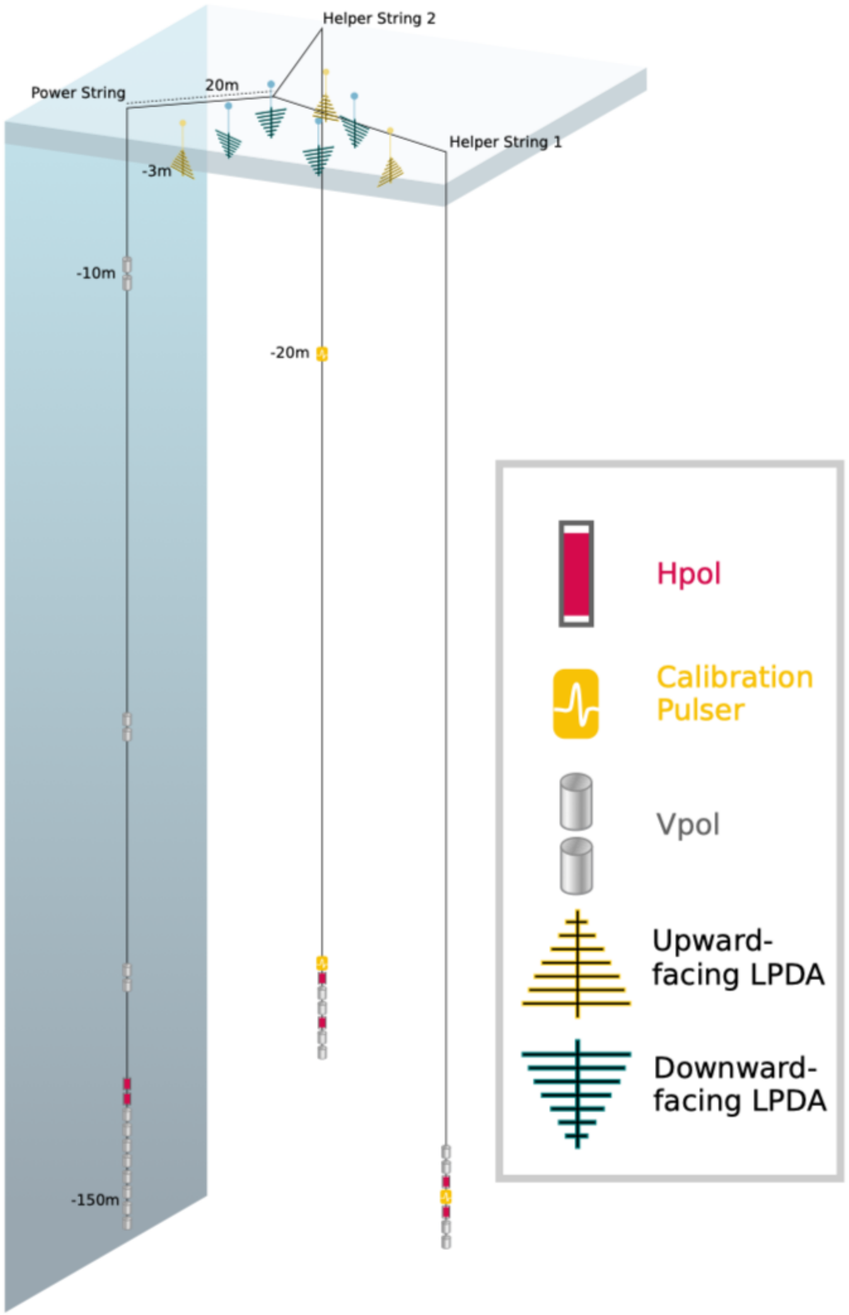
Current Trigger

- Shallow:
  - high/low threshold crossing trigger for each LPDA
  - additional 2/4 time coincidence required
  - effective threshold ~4x Vrms
- Deep: Phased array
  - coherently summed waveforms to increase SNR by sqrt(n_antennas)
  - power integration trigger
  - effective threshold ~2-3* x Vrms





*: not a useful metric because dependent on bandwidth and group delay