



UPPSALA
UNIVERSITET

Advancing Ultra-High Energy Neutrino Astronomy through Deep Learning and Differential Programming

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Co-funded by
the European Union



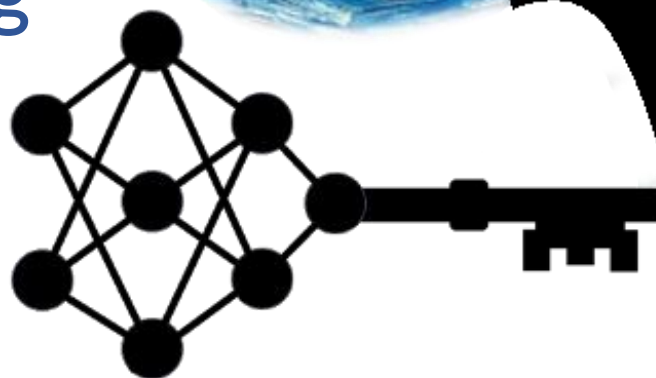
European Research Council
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CARL TRYGGERS
STIFTELSE
FÖR VETENSKAPLIG FORSKNING



credit: Nils Heyer

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

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How:
Using Deep Learning and
Differential Programming

MODE collaboration <https://mode-collaboration.github.io/>

4th MODE workshop, Valencia, 23.-25. Sept <https://indico.cern.ch/event/1380163/>

EuCAIF working group 2

The need to detect UHE ($E_\nu > 10^{17}$ eV) neutrinos

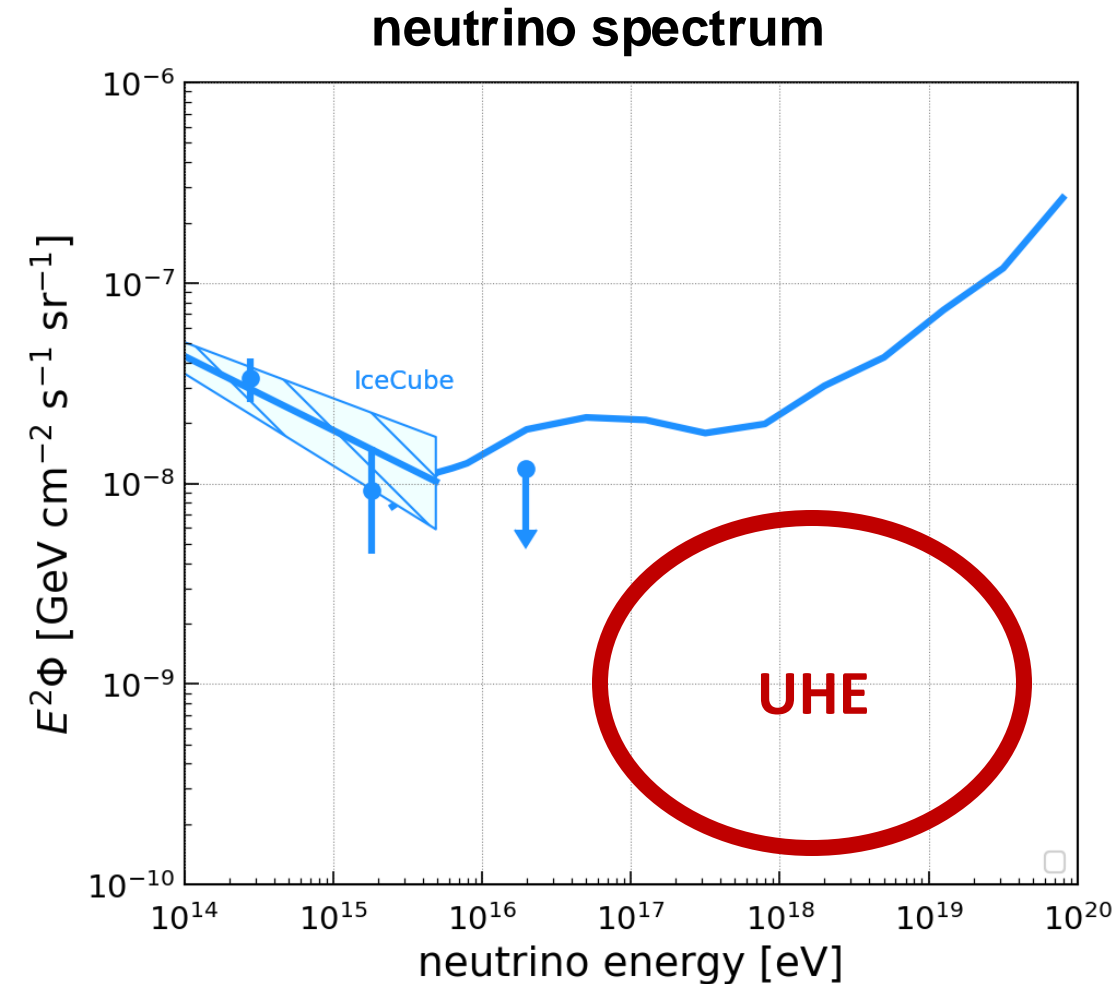
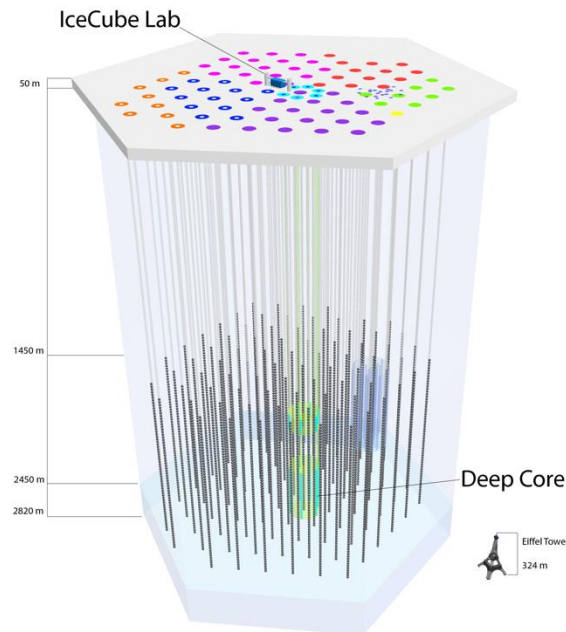
- Breakthrough in astroparticle physics
- New Window to the Universe
- Excellent probes of astroparticle and high-energy physics

The need to detect UHE ($E_\nu > 10^{17}$ eV) neutrinos

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TeV – PeV energies

- IceCube: Currently world's largest neutrino telescope
- Breakthrough discoveries



optical/IceCube

The need to detect UHE ($E_\nu > 10^{17}$ eV) neutrinos

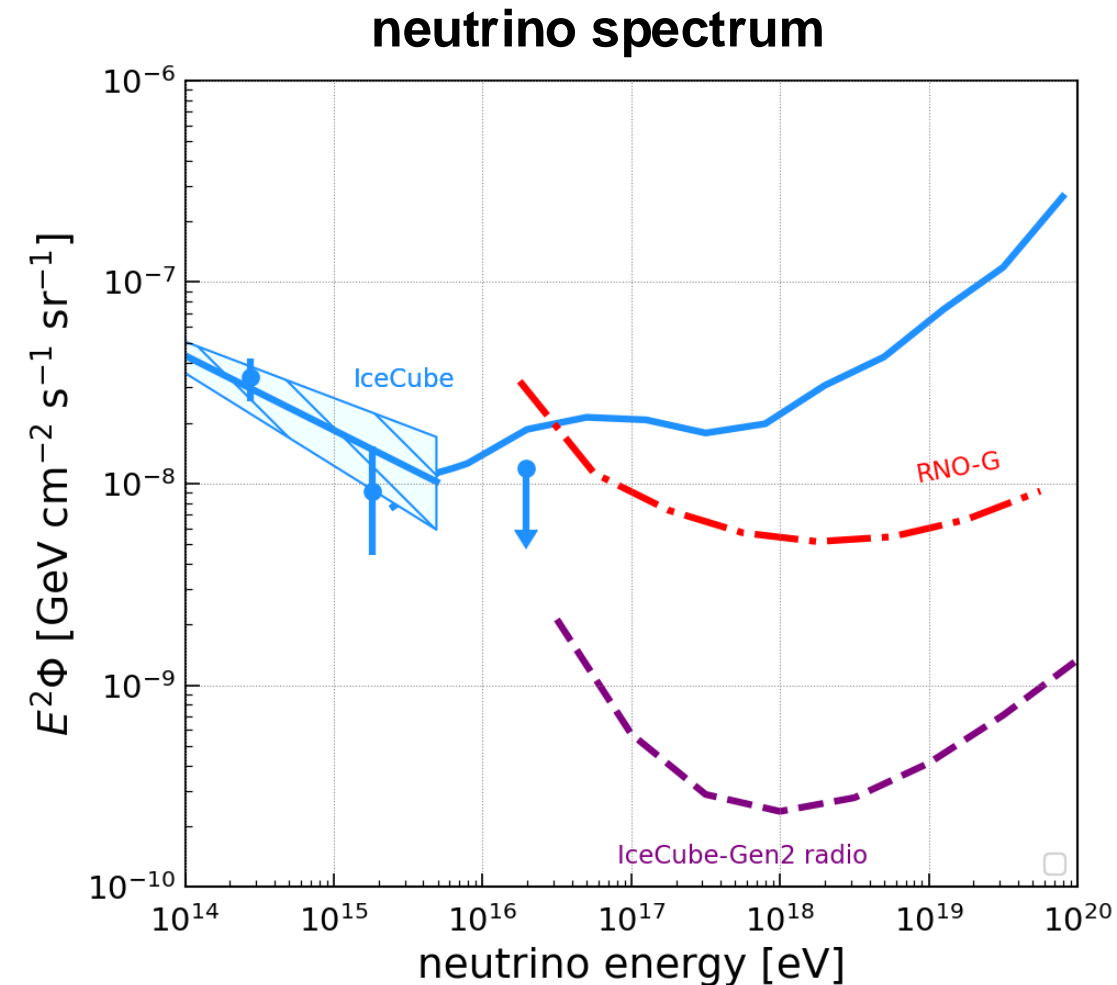
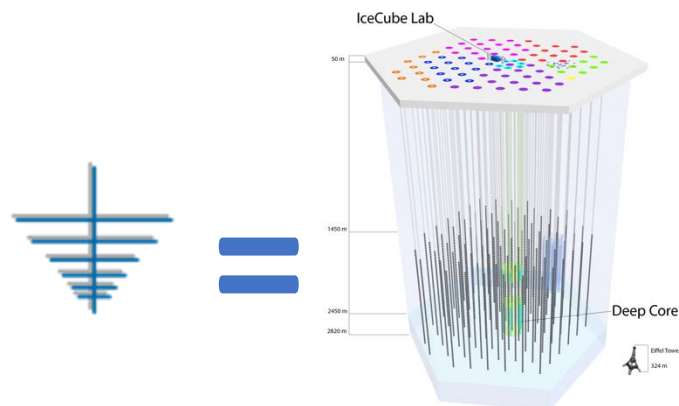
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EeV

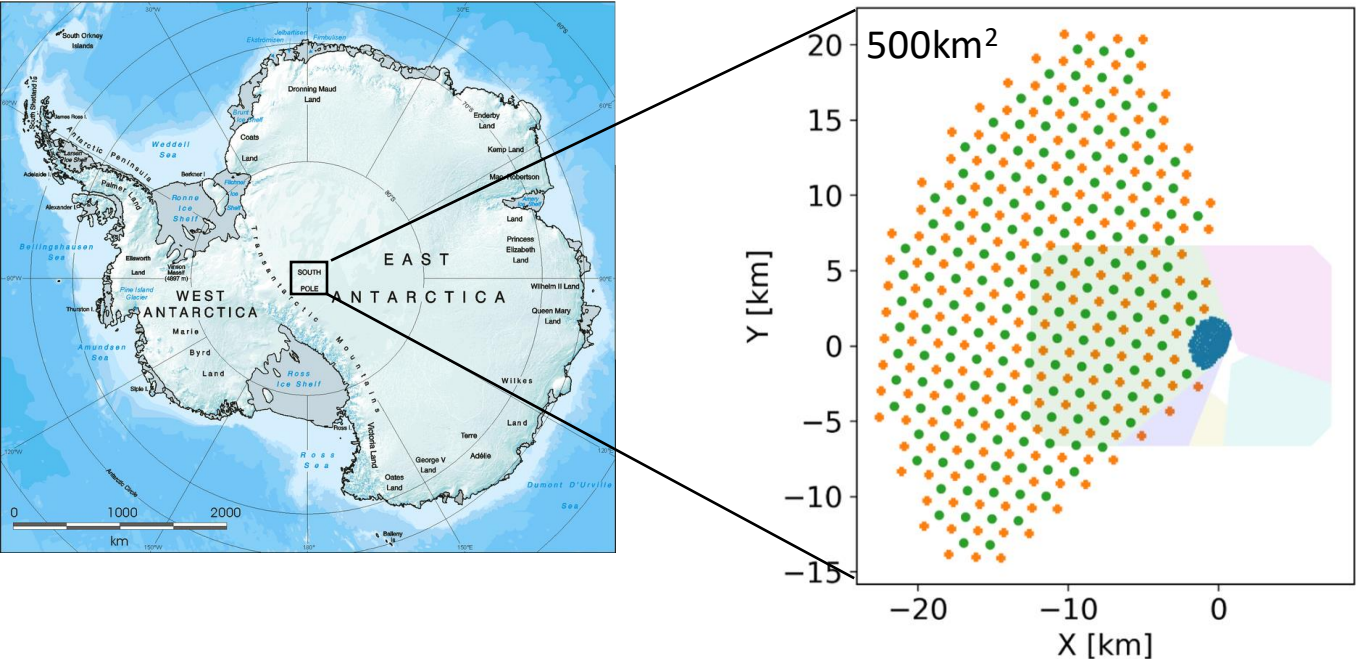
- **Solution: radio technique**
 - Large attenuation length in ice (>1 km)



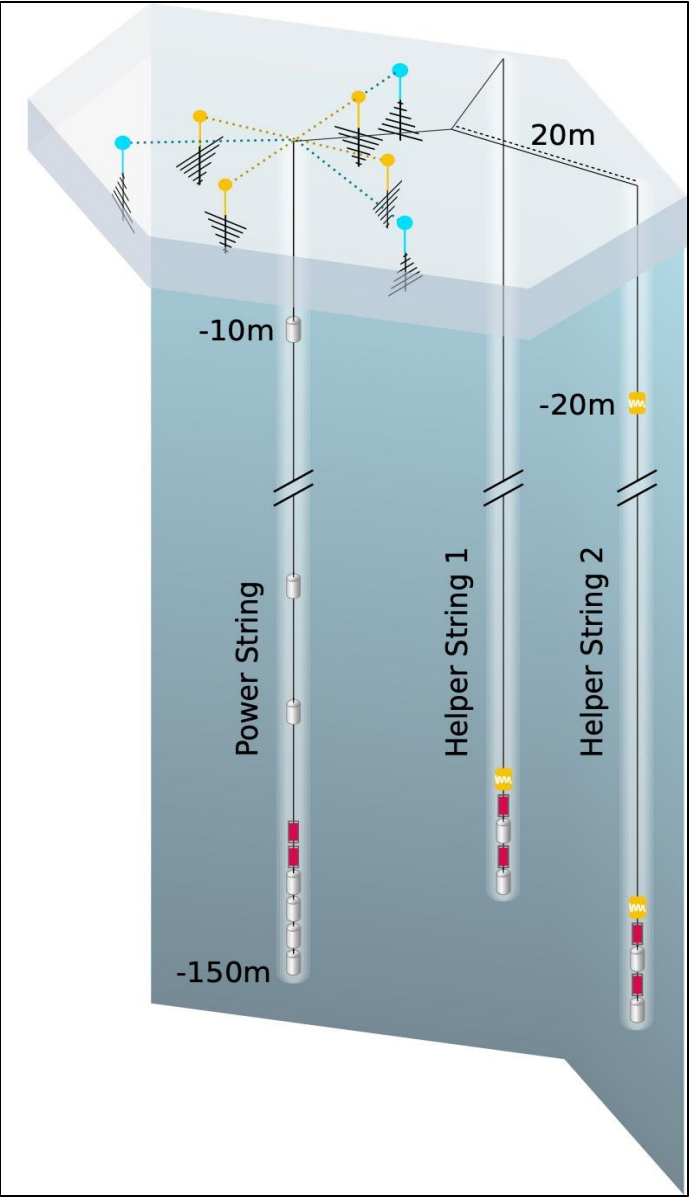
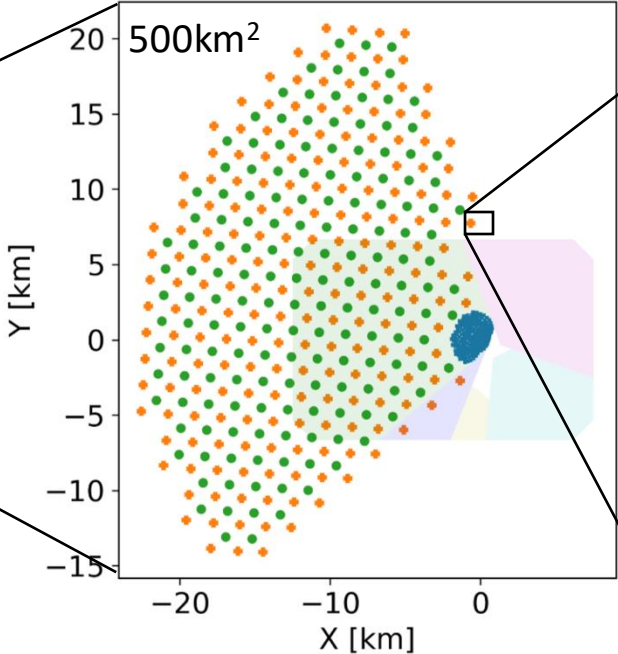
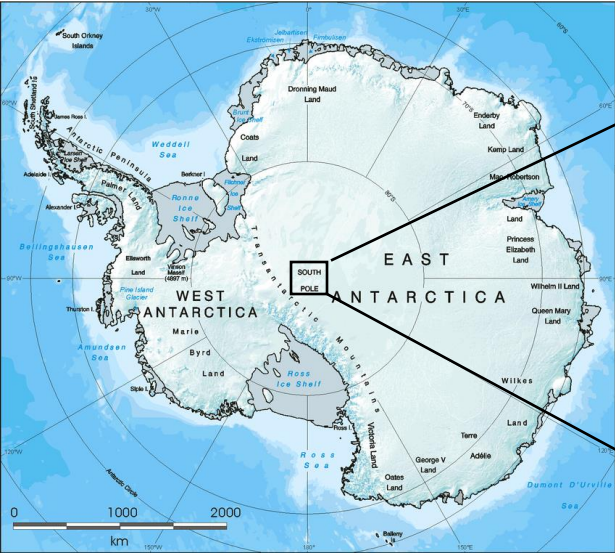
optical/IceCube

radio

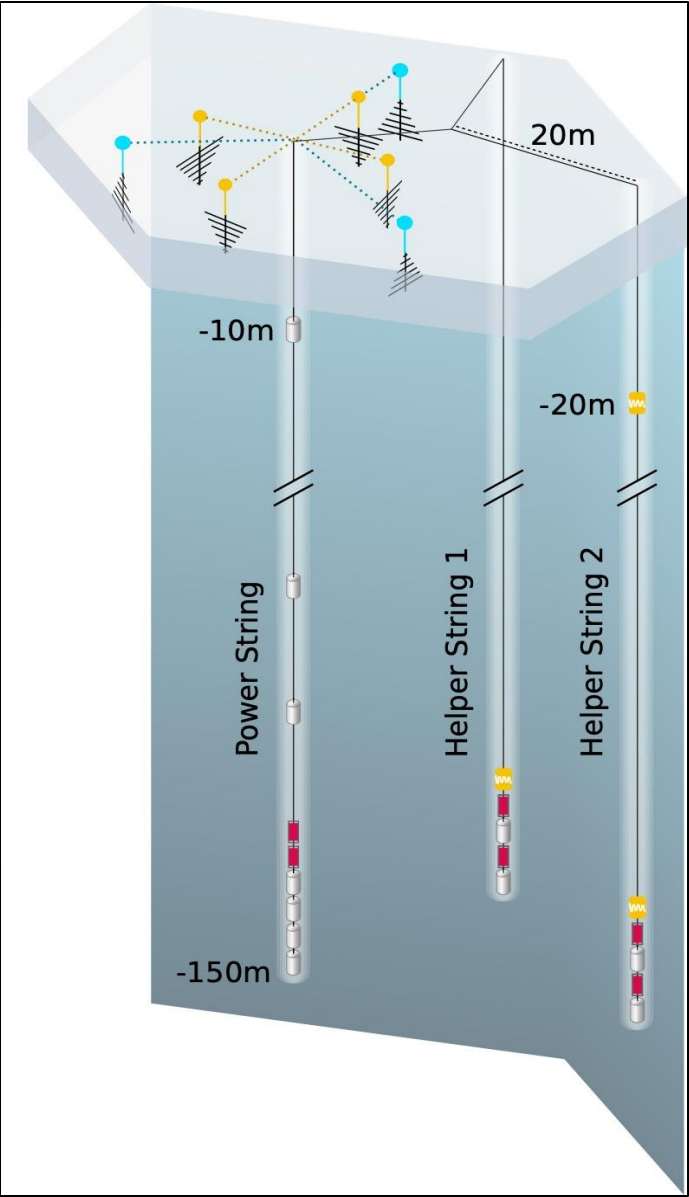
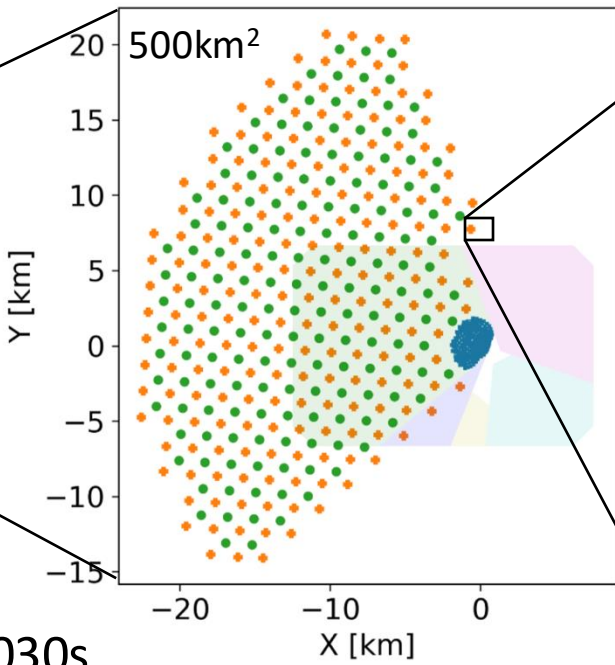
IceCube-Gen2 radio



IceCube-Gen2 radio

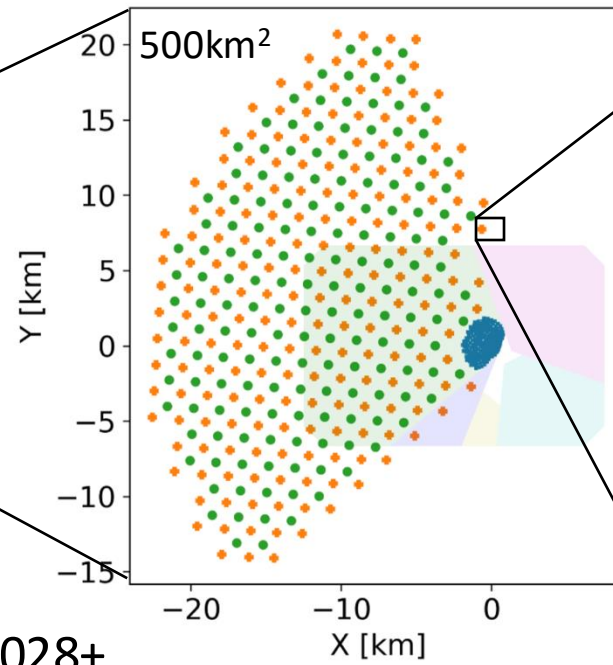
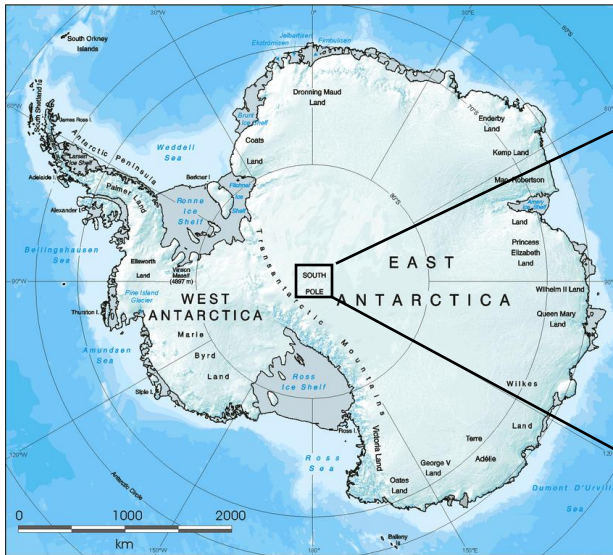


IceCube-Gen2 radio



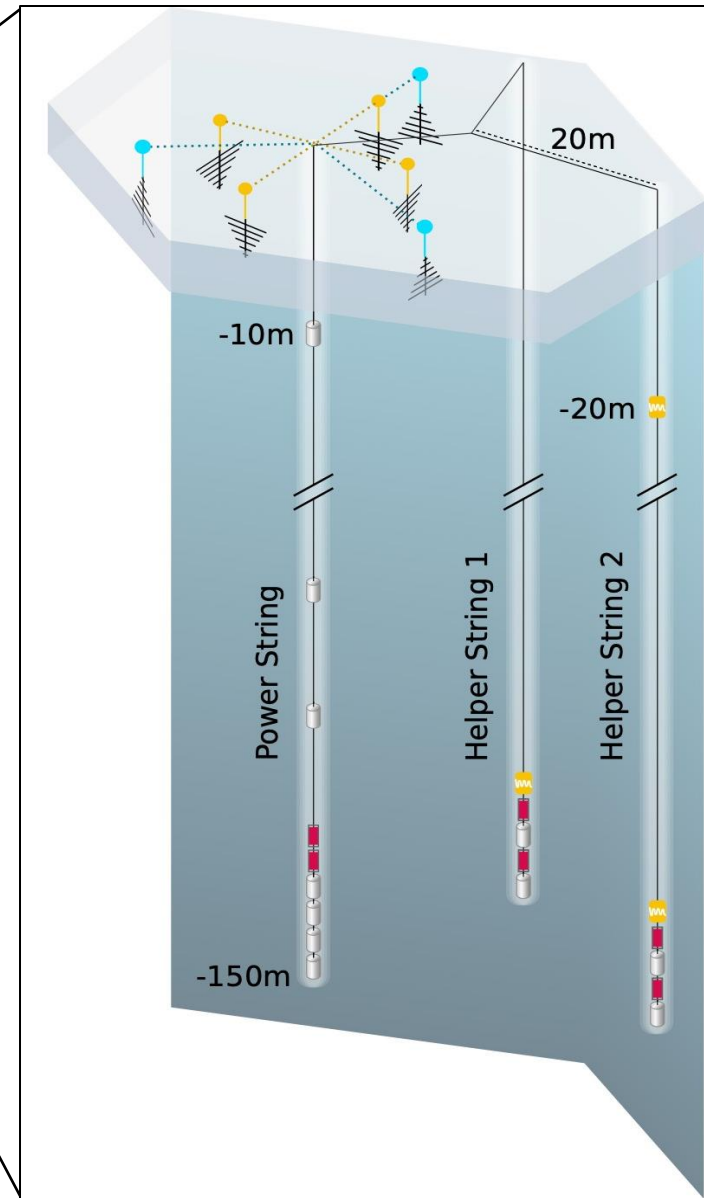
- Timeline: Start of construction 2030s
 - Unique opportunity to influence large astroparticle observatory

IceCube-Gen2 radio



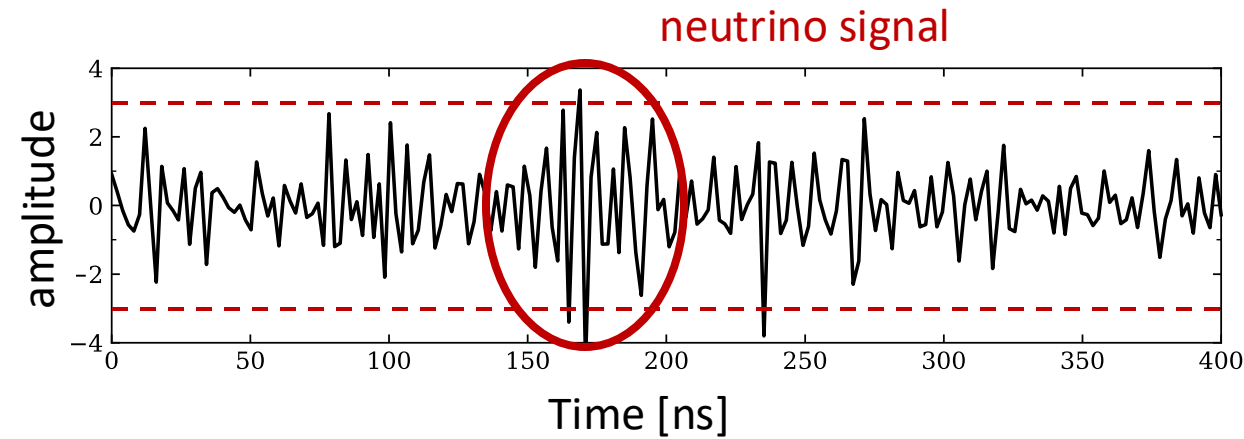
- Timeline: Start of construction 2028+
 - **Unique opportunity to influence large astroparticle observatory**
- Autonomous detector stations
 - limited data bandwidth and power budget
- IceCube-Gen2 construction lasts 7 years limited by logistics!
 - detector size can't be increased

→ **Only option to accelerate the research field: better detector (this project)**



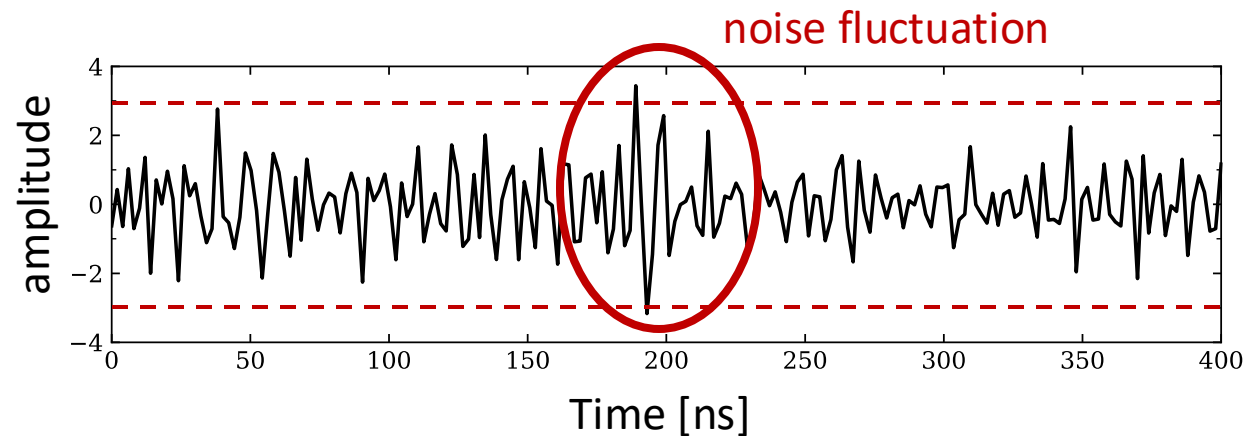
Deep-Learning-Based Trigger

- 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

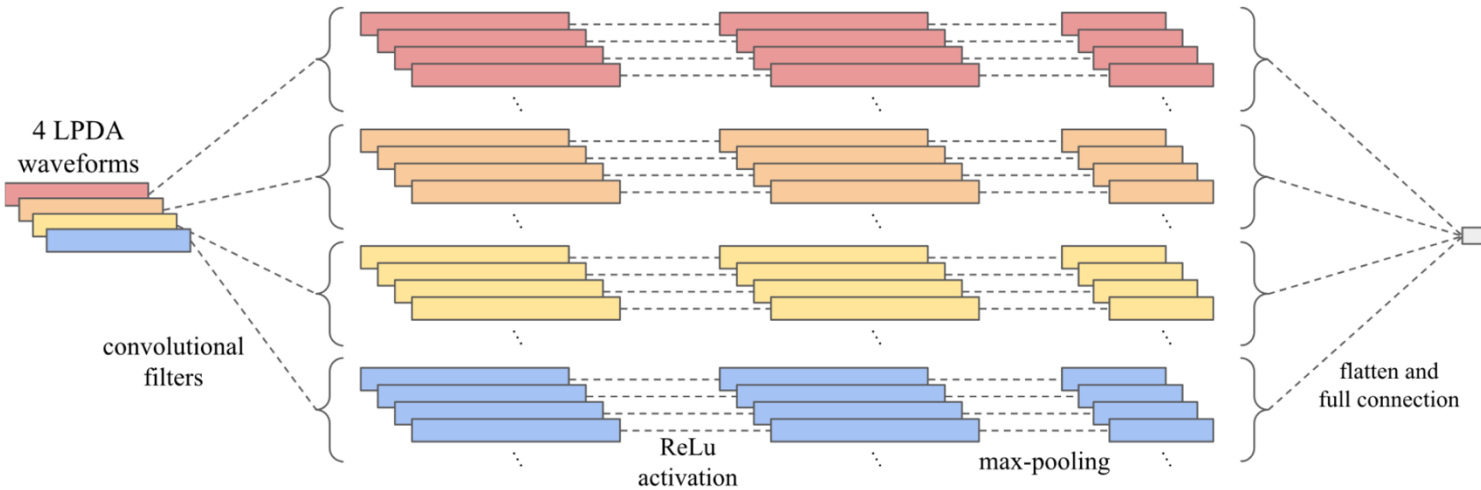
ARIANNA collab. (... C. Glaser, ...), JINST 2022



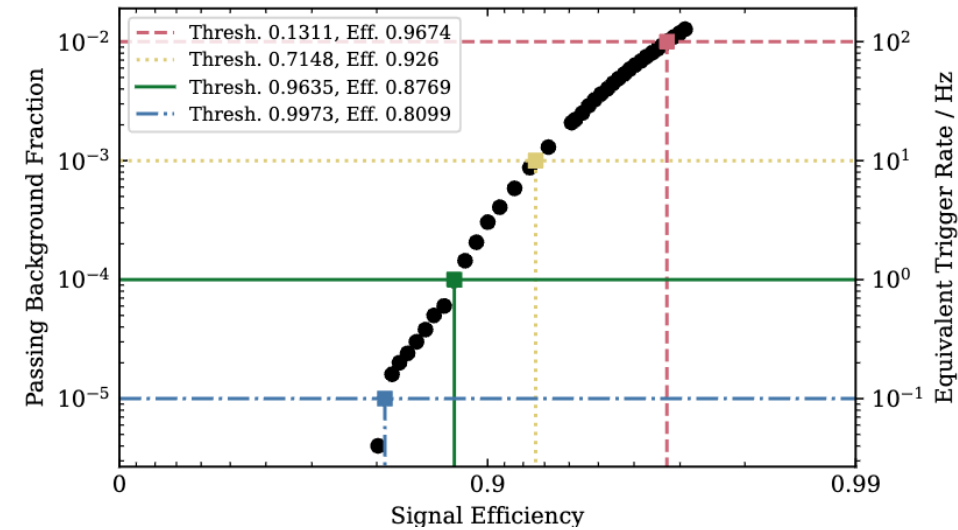
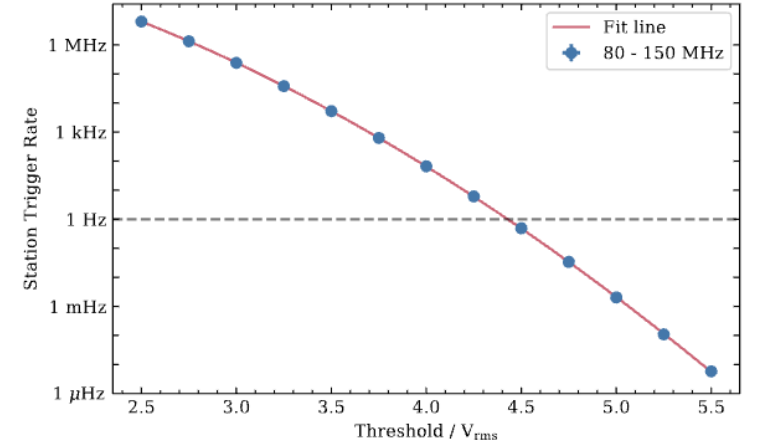
Option 1: Second Stage Filter



Suitable network: Single CNN layer

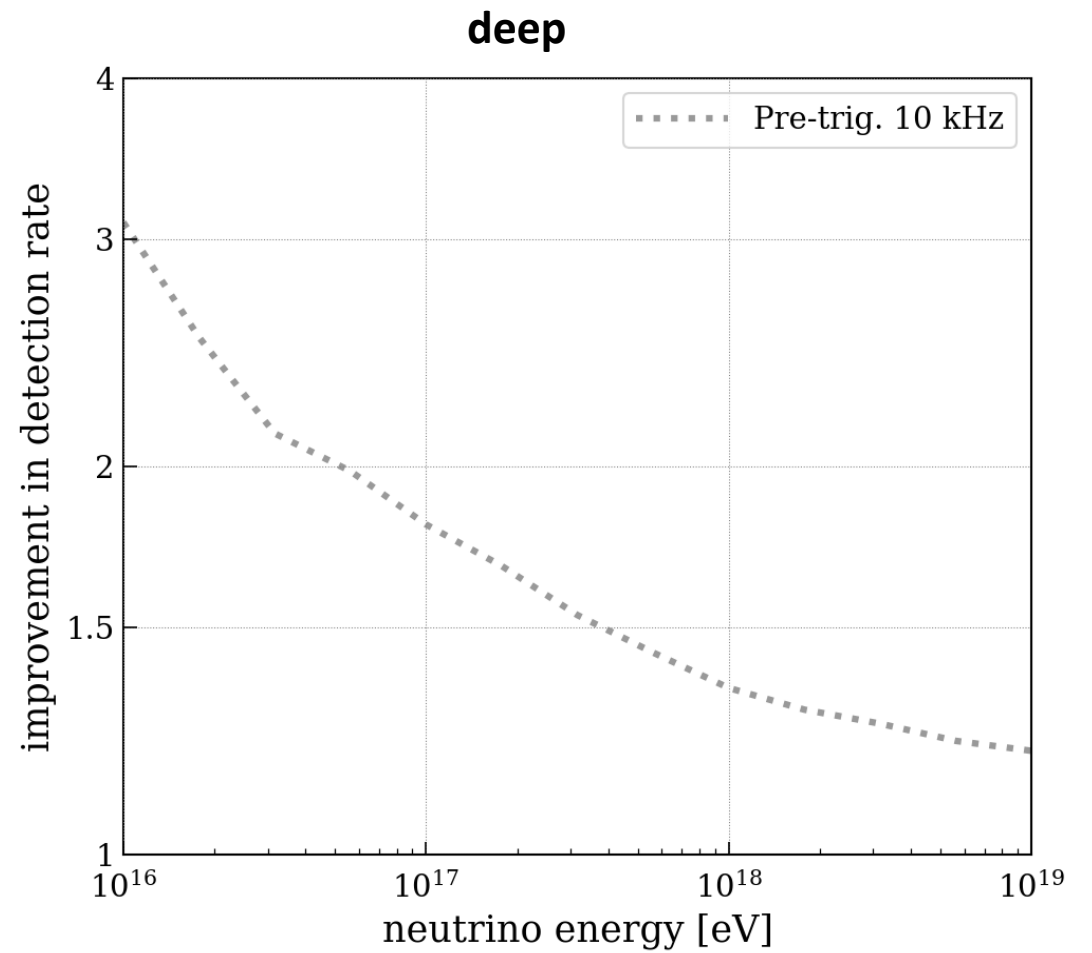
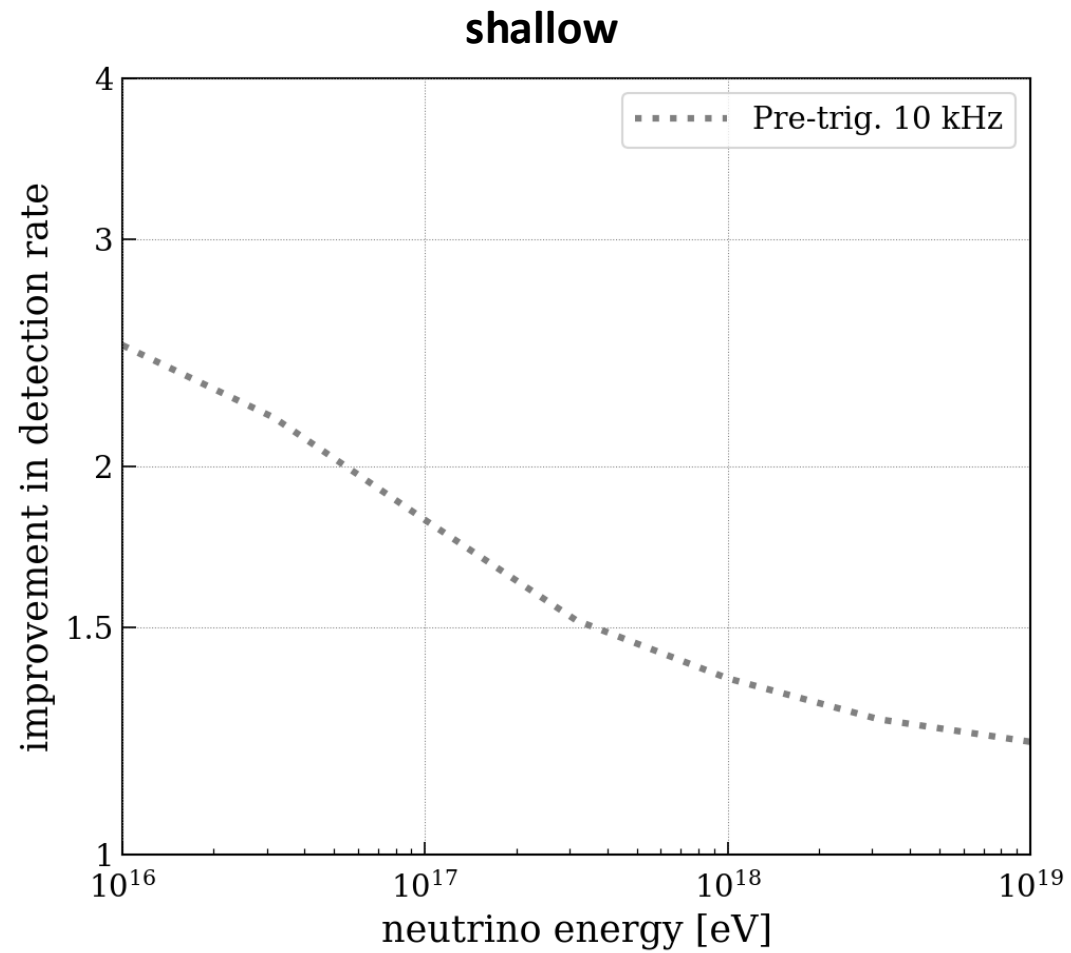


Fits easily on an "old" Cyclone V FPGA

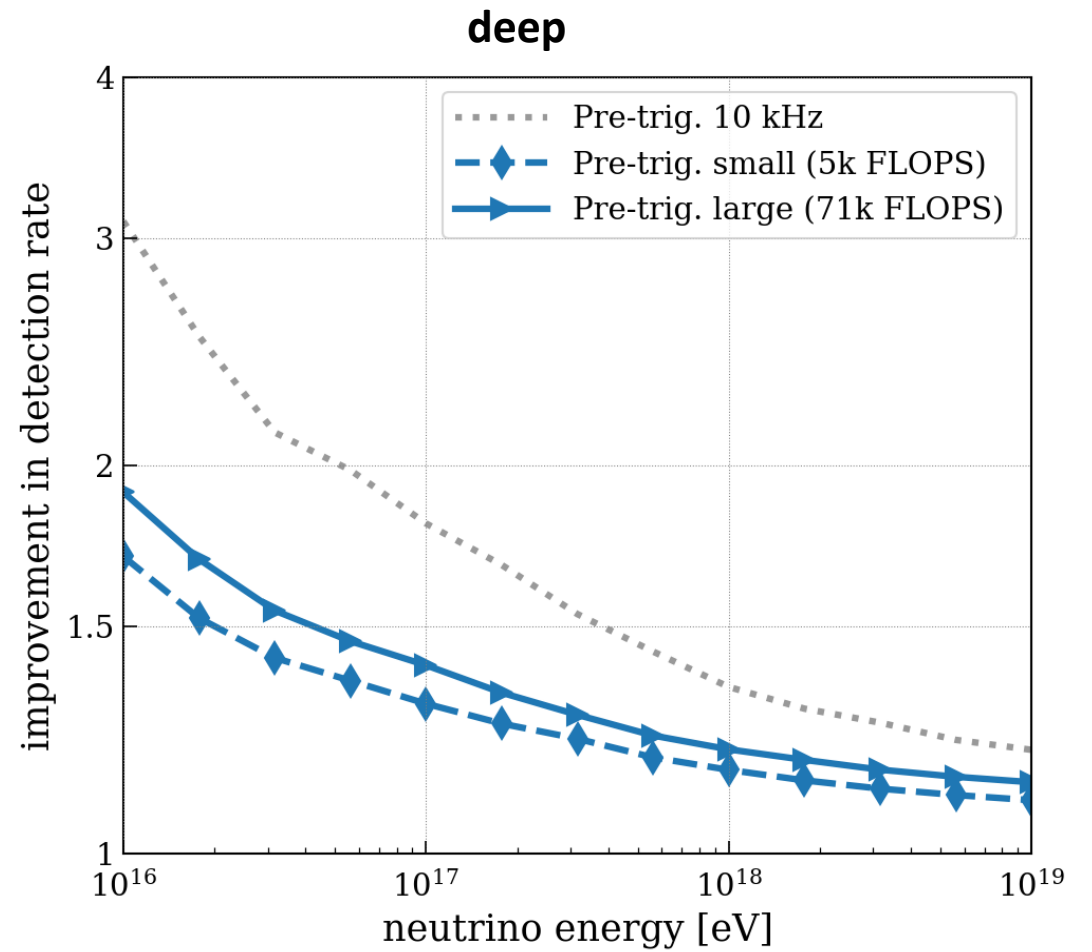
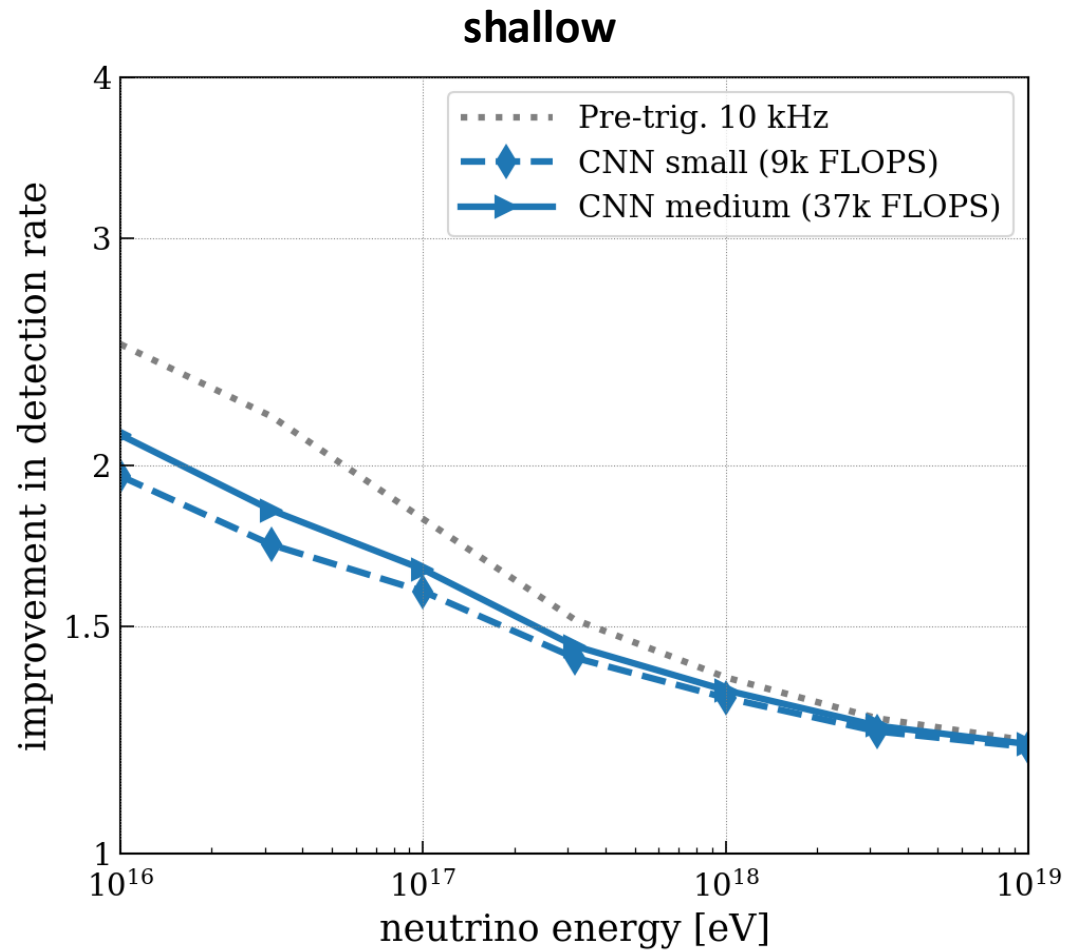


CNN rejects 99.99% of noise at ~90% signal efficiency

Option 1: Second Stage Filter - Performance

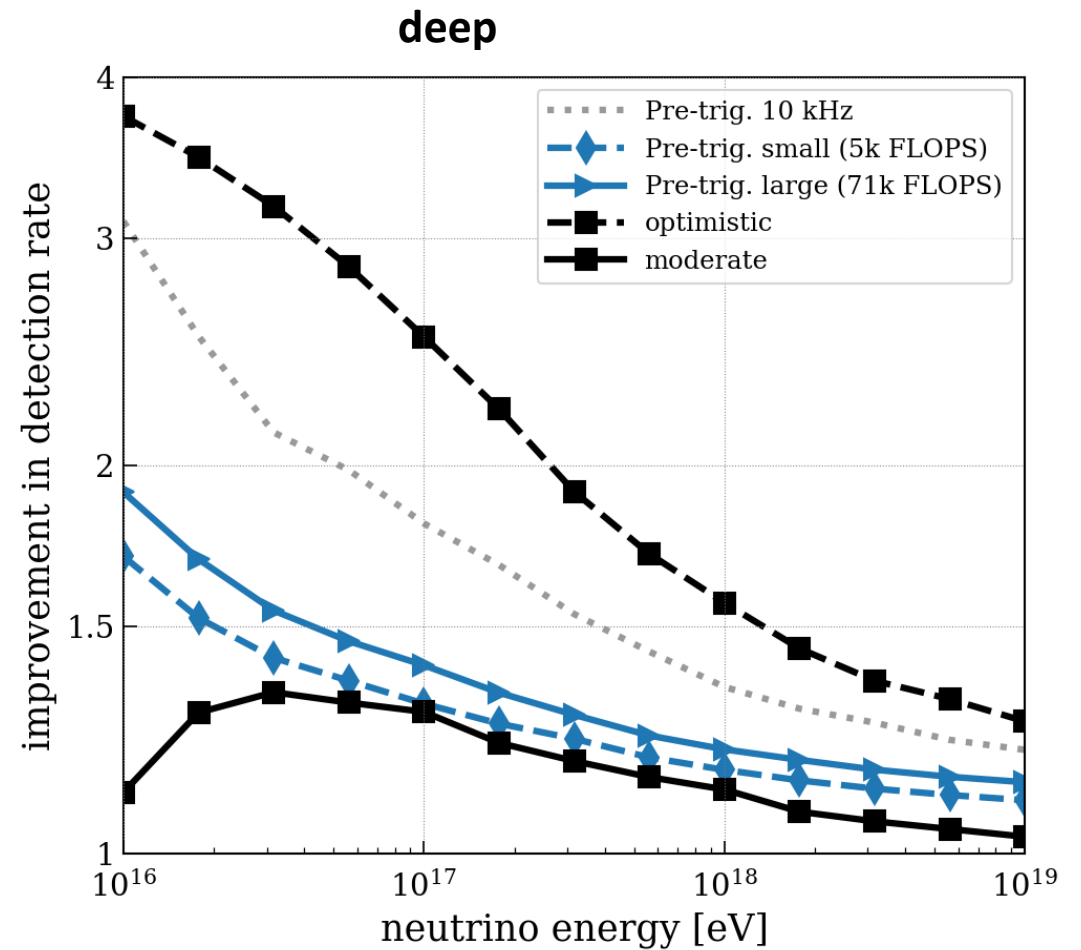
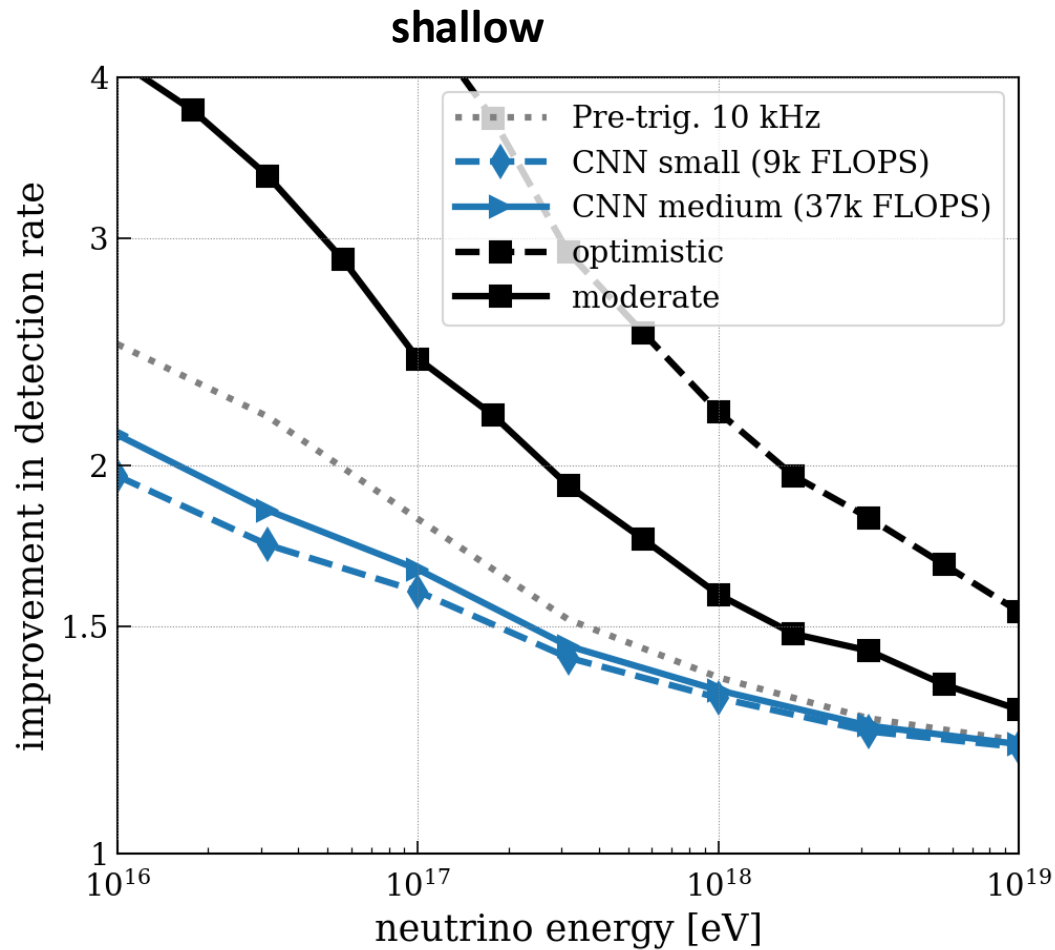


Option 1: Second Stage Filter - Performance

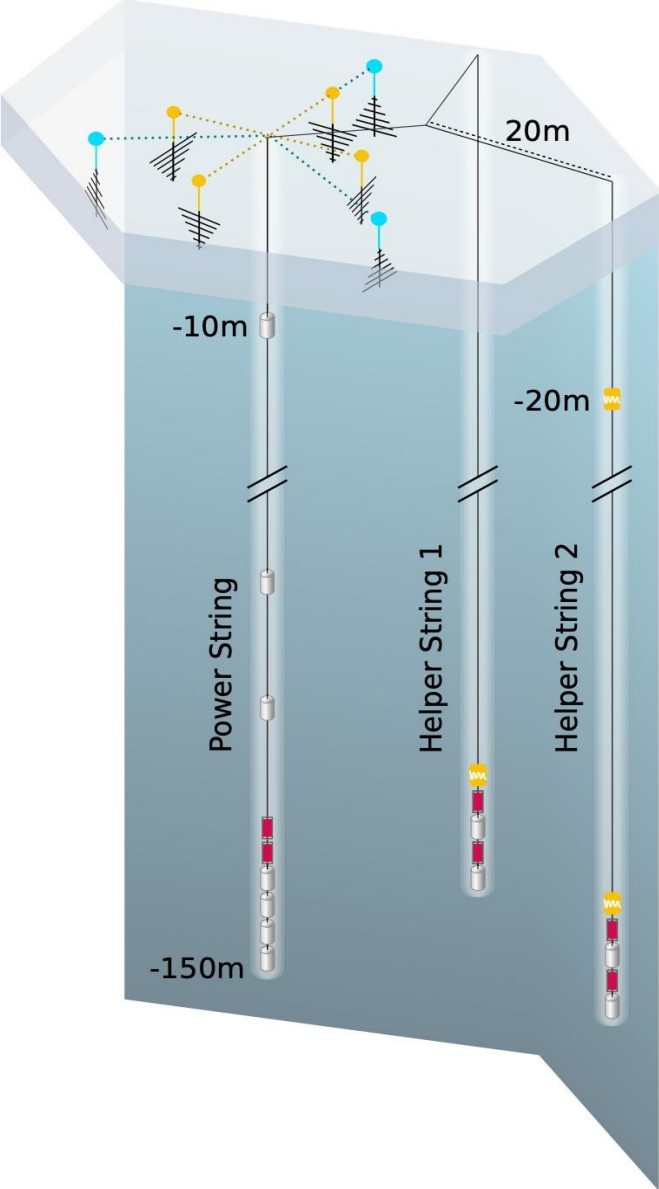


Option 2: Continuous analysis of data stream

work in progress



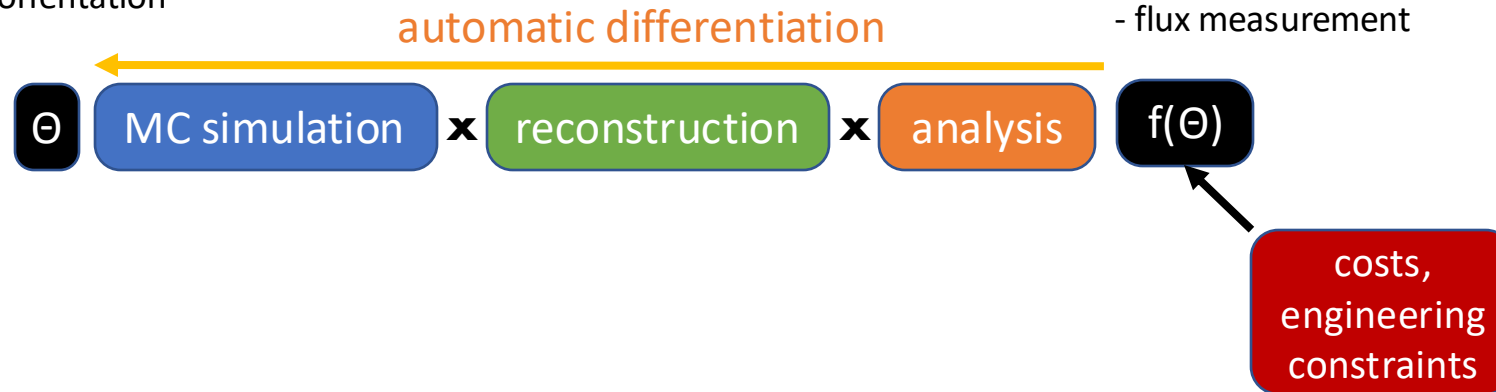
Objective 2: End-To-End Optimization



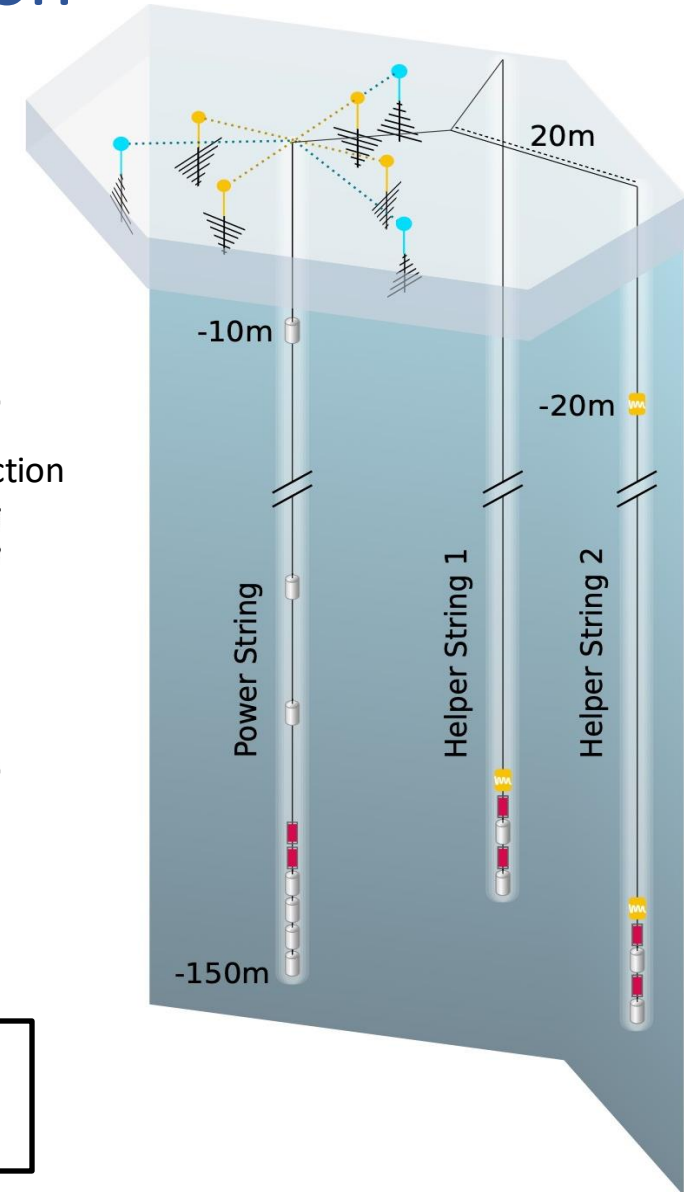
Objective 2: End-To-End Optimization

- 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

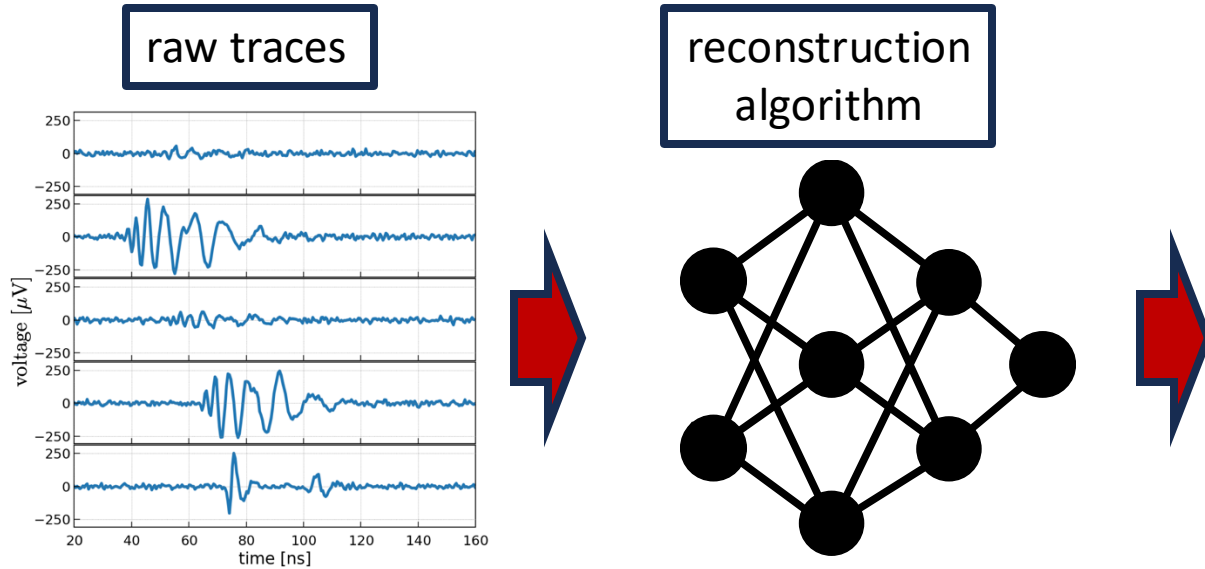


science output, e.g.,
- neutrino-nucleon cross-section
- source discovery
- flux measurement

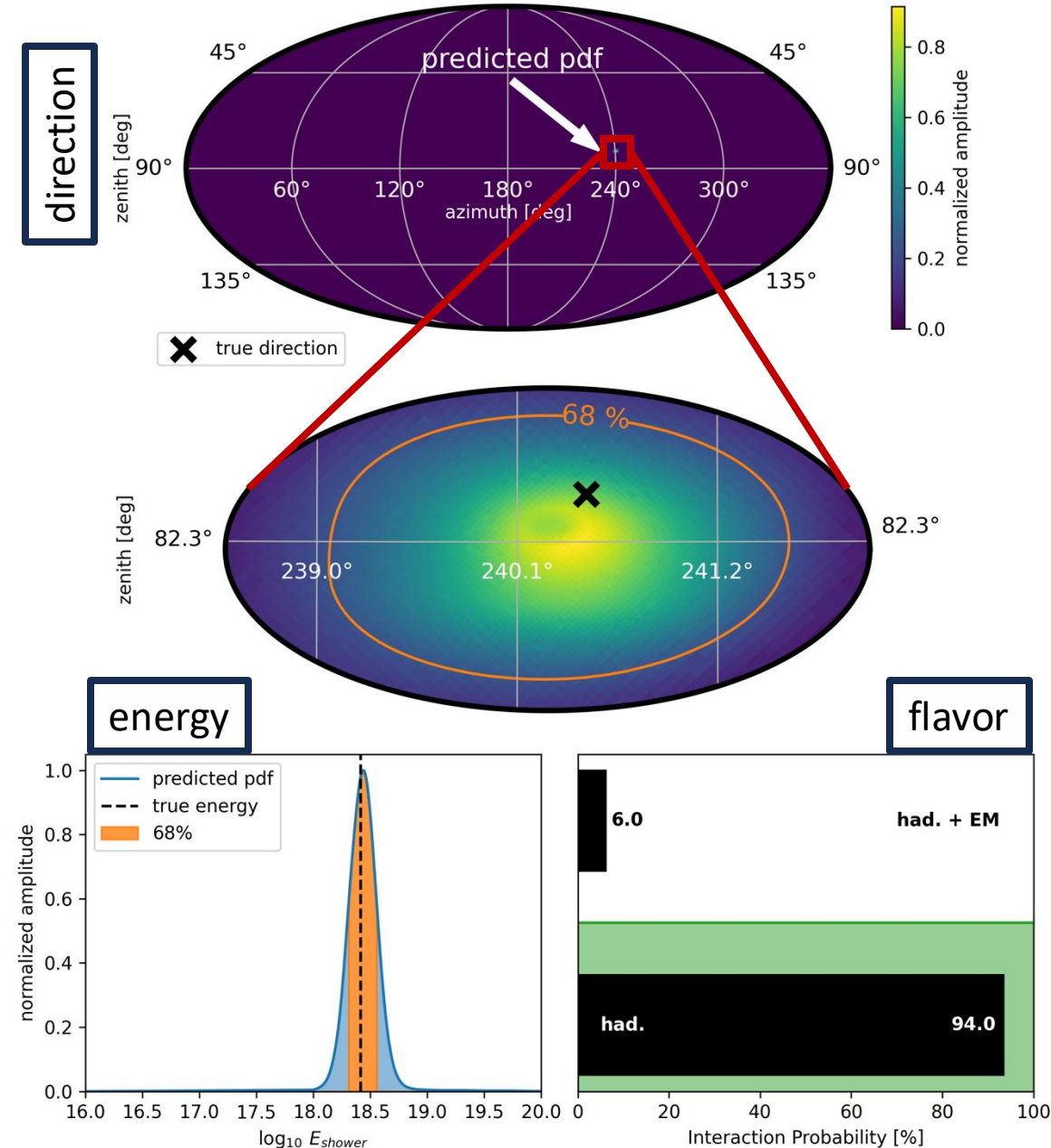


→ Expected improvements: up to three times more precise measurement of neutrino direction and energy

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



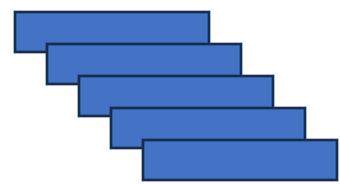
Single Event Reconstruction



Model architecture

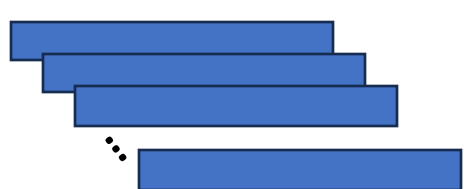
Model Shallow:

1 x 5 x 512



Model Deep:

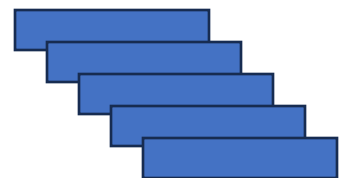
1 x 16 x 2046



Model architecture

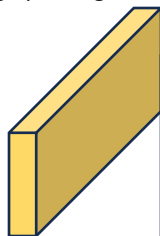
Model Shallow:

1 x 5 x 512



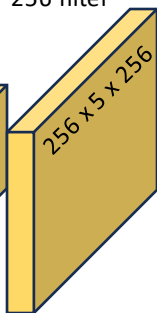
CNN1

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



CNN2

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



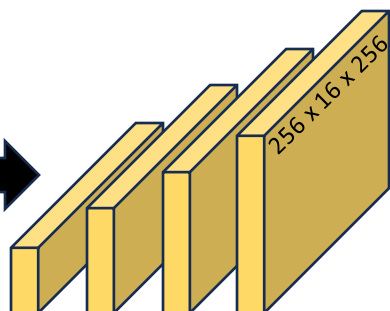
Model Deep:

1 x 16 x 2046



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 filter, kernel (1 x 16), average pooling

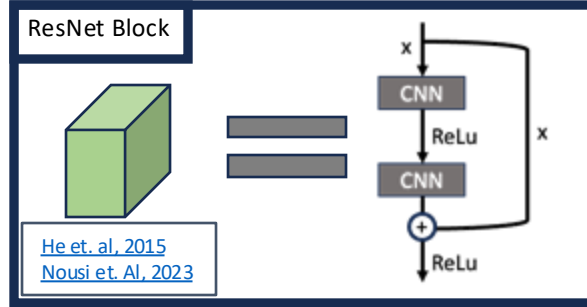


CNN4

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

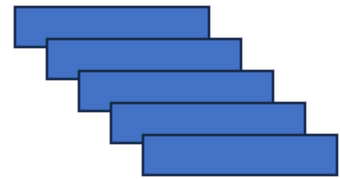


Model architecture



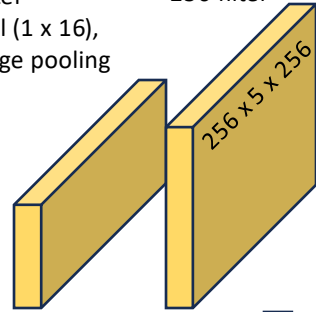
Model Shallow:

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

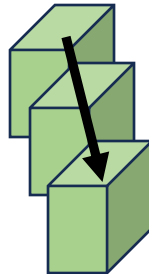
Reshape



ResNet-1

1x conv, 64 filter
Stride 2
kernel (7 x 7)

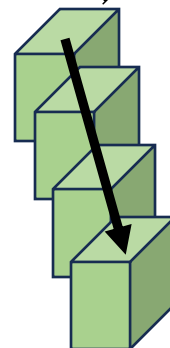
Max Pooling
64 x 64 x 64



ResNet-2

3x ResNet Block
64 filter
kernel (3 x 3)

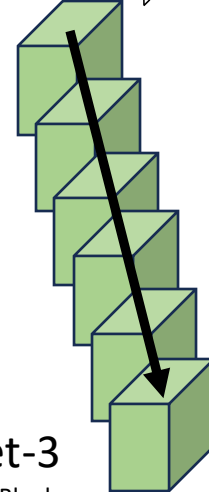
Down sampling
128 x 32 x 32



ResNet-3

4x ResNet Block
128 filter
kernel (3 x 3)

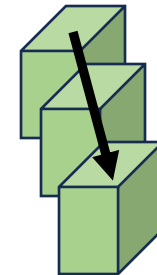
Down sampling
256 x 16 x 16



ResNet-4

6x ResNet Block
256 filter
kernel (3 x 3)

Down sampling
512 x 8 x 8



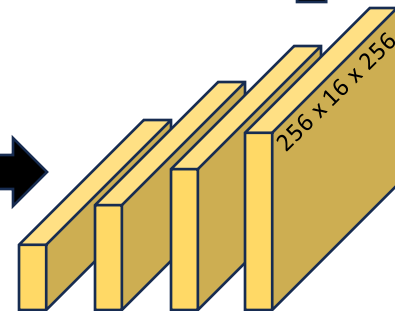
ResNet-5

3x ResNet Block
512 filter
kernel (3 x 3)

Adaptive Pooling - 512

Model Deep:

1 x 16 x 2046



CNN1 4x 1d-conv, 32 filter, kernel (1 x 16), average pooling

CNN2 4x 1d-conv, 64 filter, kernel (1 x 16), average pooling

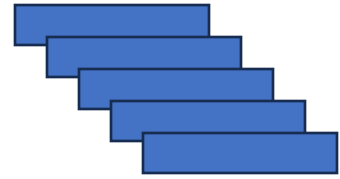
CNN3 4x 1d-conv, 128 filter, kernel (1 x 16), average pooling

CNN4 4x 1d-conv, 256 filter, kernel (1 x 16)

Model architecture

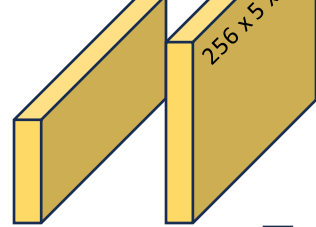
Model Shallow:

1 x 5 x 512



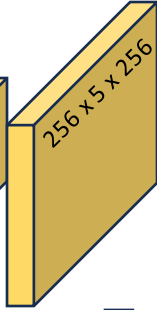
CNN1

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



CNN2

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



Model Deep:

1 x 16 x 2046



CNN1

4x 1d-conv, 32 filter, kernel (1 x 16), average pooling

CNN2

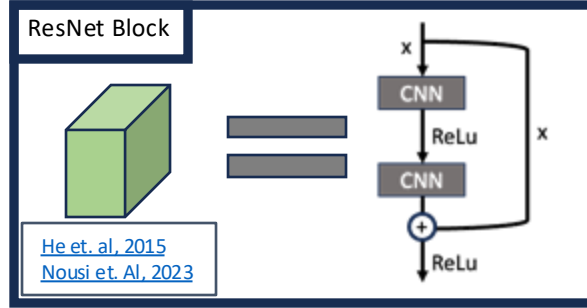
4x 1d-conv, 64 filter, kernel (1 x 16), average pooling

CNN3

4x 1d-conv, 128 filter, kernel (1 x 16), average pooling

CNN4

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



ResNet-1

1x conv, 64 filter
Stride 2
kernel (7 x 7)

ResNet-2

3x ResNet Block
64 filter
kernel (3 x 3)

ResNet-3

4x ResNet Block
128 filter
kernel (3 x 3)

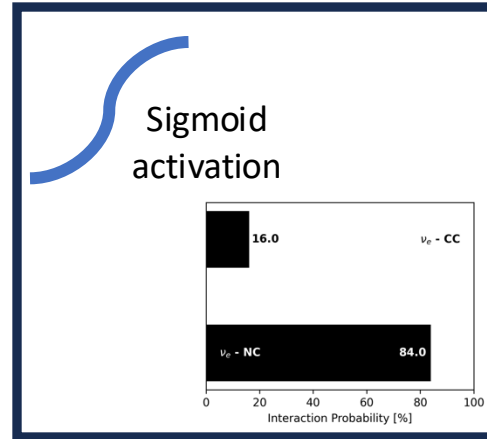
ResNet-4

6x ResNet Block
256 filter
kernel (3 x 3)

ResNet-5

3x ResNet Block
512 filter
kernel (3 x 3)

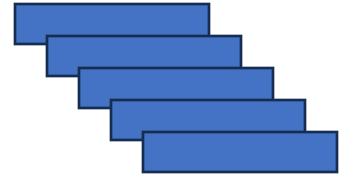
Adaptive Pooling - 512



Model architecture

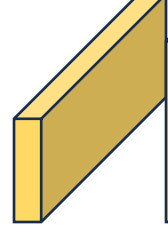
Model Shallow:

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CNN1

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



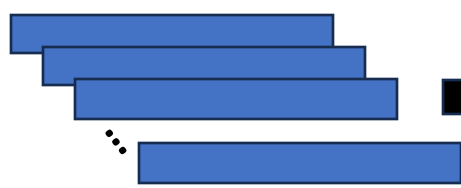
CNN2

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



Model Deep:

1 x 16 x 2046



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 filter, kernel (1 x 16), average pooling

CNN4

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

ResNet-1

1x conv, 64 filter
Stride 2
kernel (7 x 7)

ResNet-2

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64 filter
kernel (3 x 3)

ResNet-3

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128 filter
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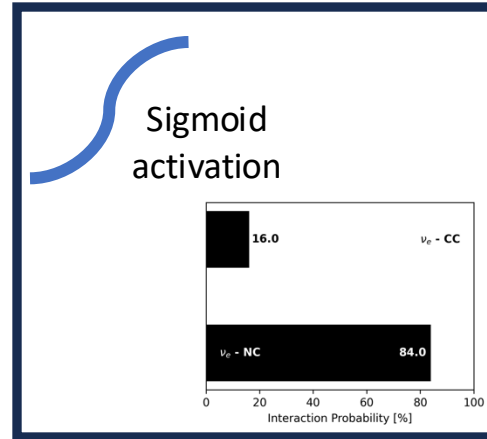
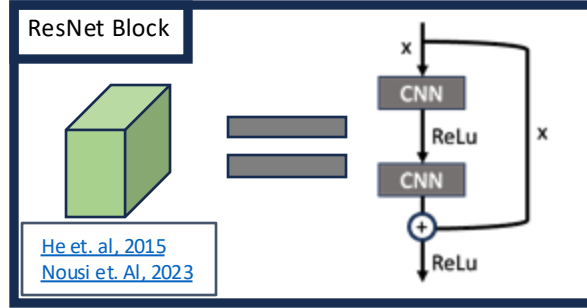
ResNet-4

6x ResNet Block
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kernel (3 x 3)

ResNet-5

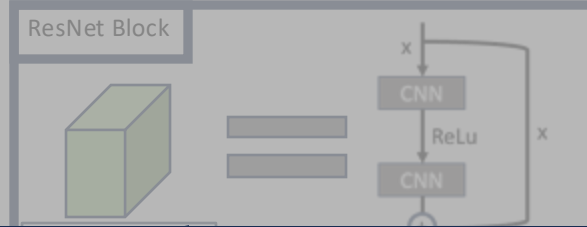
3x ResNet Block
512 filter
kernel (3 x 3)

Adaptive Pooling - 512



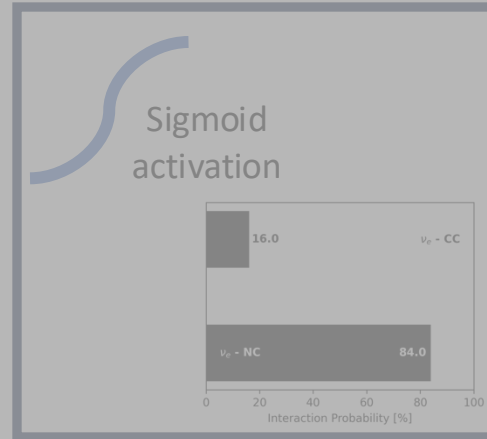
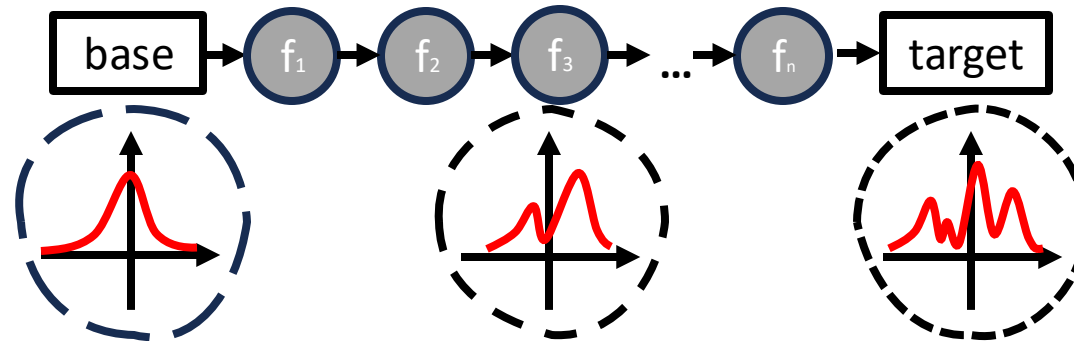
Normalizing Flows
github.com/thoglu/jammy_flows

Model architecture



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**



Normalizing Flows
github.com/thoglu/jammy_flows

Model Shallow:

1 x 5 x 512

CNN1

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

CNN2

4x 1d-conv

Model Deep:

1 x 16 x 2046

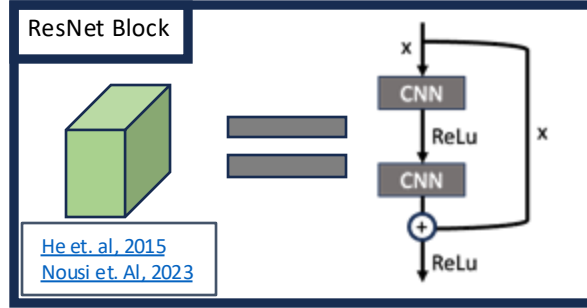
CNN1 4x 1d-conv, 32 filter, kernel (1 x 16), average pooling

CNN2 4x 1d-conv, 64 filter, kernel (1 x 16), average pooling

CNN3 4x 1d-conv, 128 filter, kernel (1 x 16), average pooling

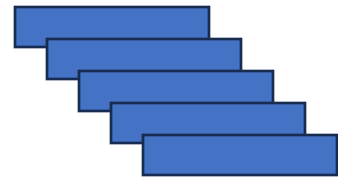
CNN4 4x 1d-conv, 256 filter, kernel (1 x 16)

Model architecture



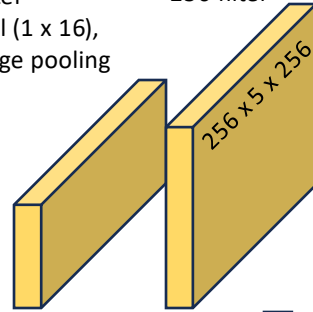
Model Shallow:

1 x 5 x 512



CNN1

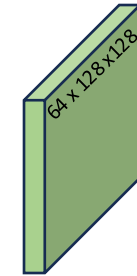
4x 1d-conv
64 filter
kernel (1 x 16),
average pooling



CNN2

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

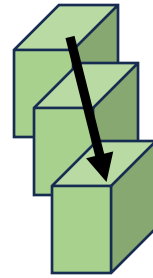
Reshape



ResNet-1

1x conv, 64 filter
Stride 2
kernel (7 x 7)

Max Pooling
64 x 64 x 64



ResNet-2

3x ResNet Block
64 filter
kernel (3 x 3)

ResNet-3

4x ResNet Block
128 filter
kernel (3 x 3)

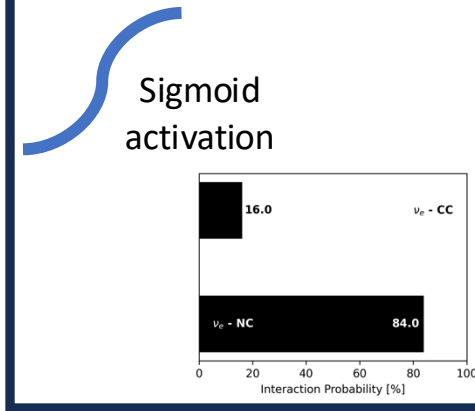
ResNet-4

6x ResNet Block
256 filter
kernel (3 x 3)

ResNet-5

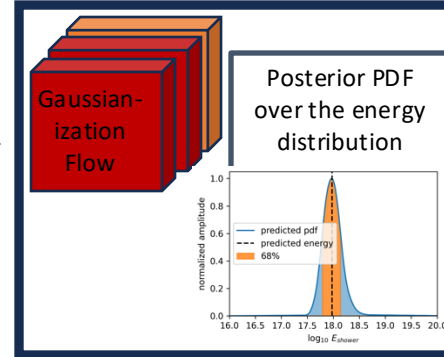
3x ResNet Block
512 filter
kernel (3 x 3)

Adaptive Pooling - 512



Normalizing Flows

github.com/thoglu/jammy_flows



Model Deep:

1 x 16 x 2046

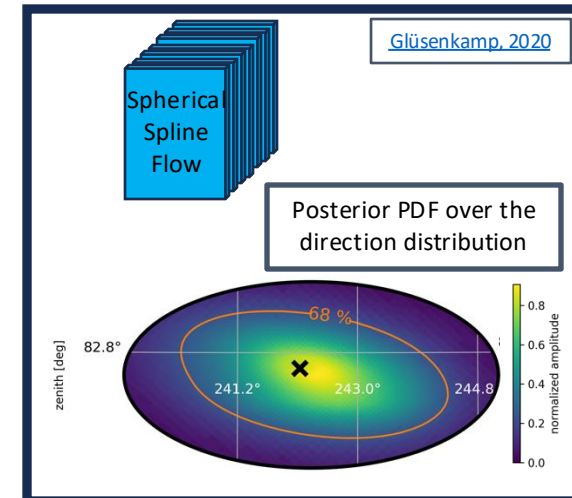


CNN1 4x 1d-conv, 32 filter, kernel (1 x 16), average pooling

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CNN3 4x 1d-conv, 128 filter, kernel (1 x 16), average pooling

CNN4 4x 1d-conv, 256 filter, kernel (1 x 16)

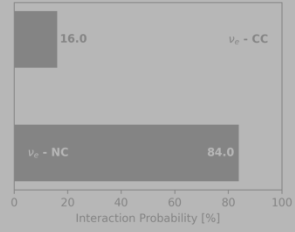


Model architecture

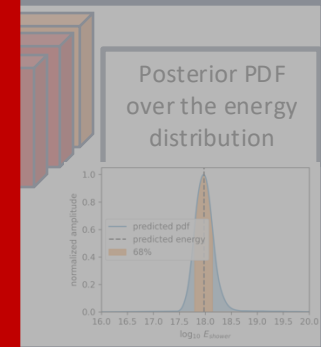
CNN2



Sigmoid activation

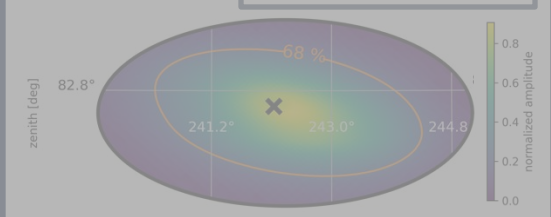


Normalizing Flows
[/thoglu/jammy_flows](#)



Glüsenkamp, 2020

Posterior PDF over the direction distribution



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

Model Shallow:

1 x 5 x 512

Model Deep:

1 x 16 x 2046

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 filter, kernel (1 x 16), average pooling

CNN4 4x 1d-conv, 256 filter, kernel (1 x 16)

Main science objectives of UHE neutrino astronomy:

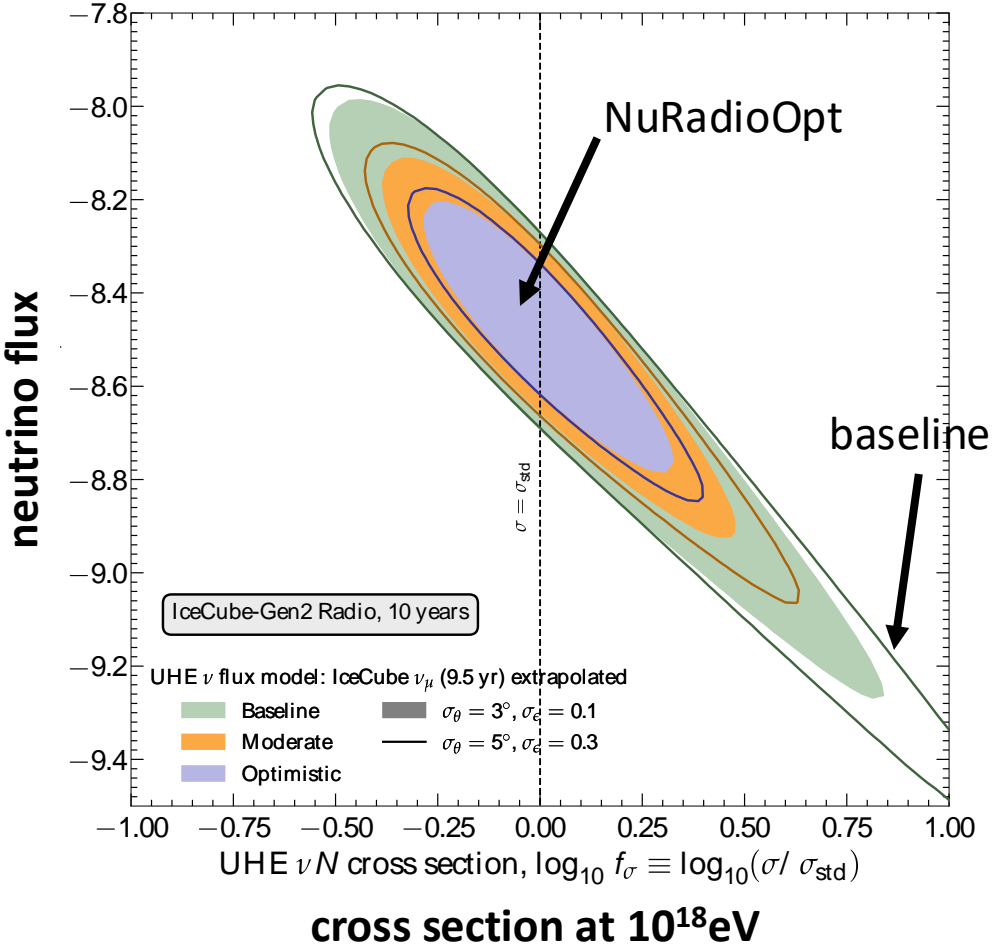
Neutrino-Nucleon Cross Section

Diffuse Flux

Point Sources

Impact of NuRadioOpt

→ 3x more precise measurement



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

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Neutrino-Nucleon
Cross Section

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V. Valera, M. Bustamente, 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. Bustamente, 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. Bustamente, JCAP03(2023)026

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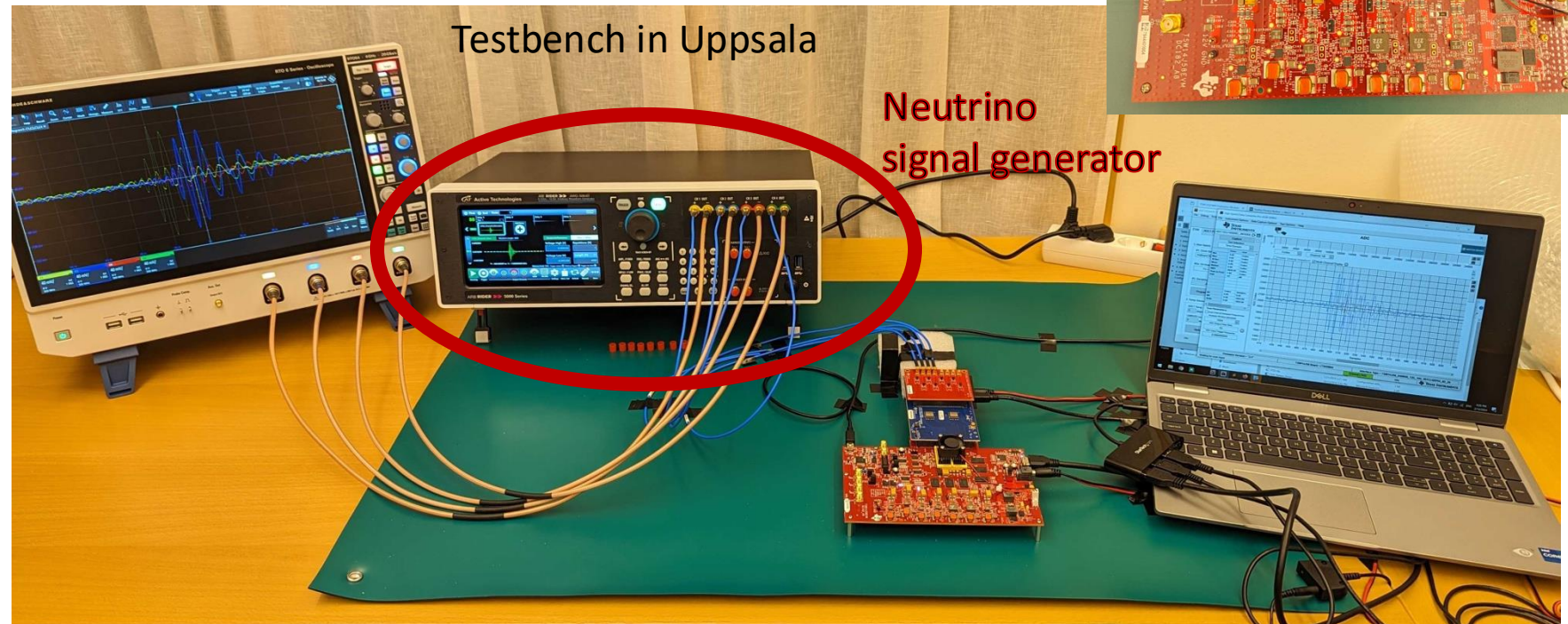
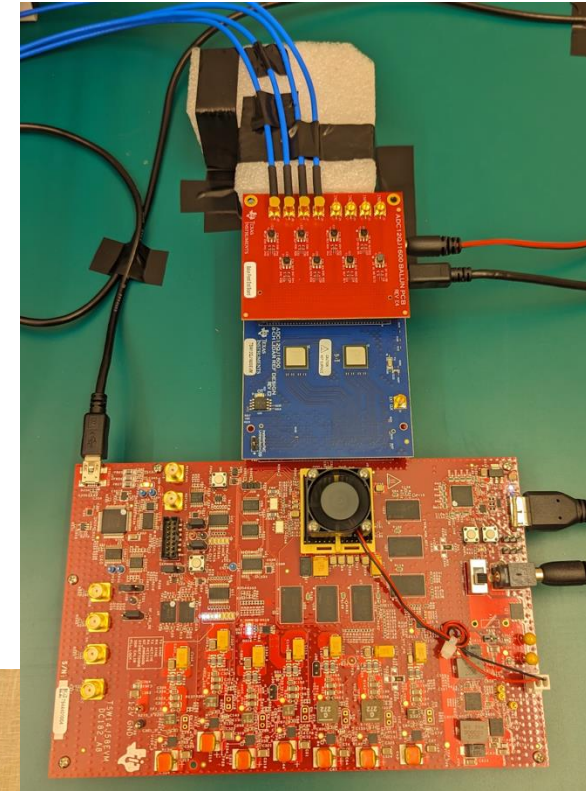
D. F. G. Fiorillo, V. Valera, M. Bustamante, JCAP03(2023)026

- **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**
- **Deep Learning and Differential Programming will Accelerate Science** (reanalysis of existing data, better trigger, better detector design)

Bonus slides

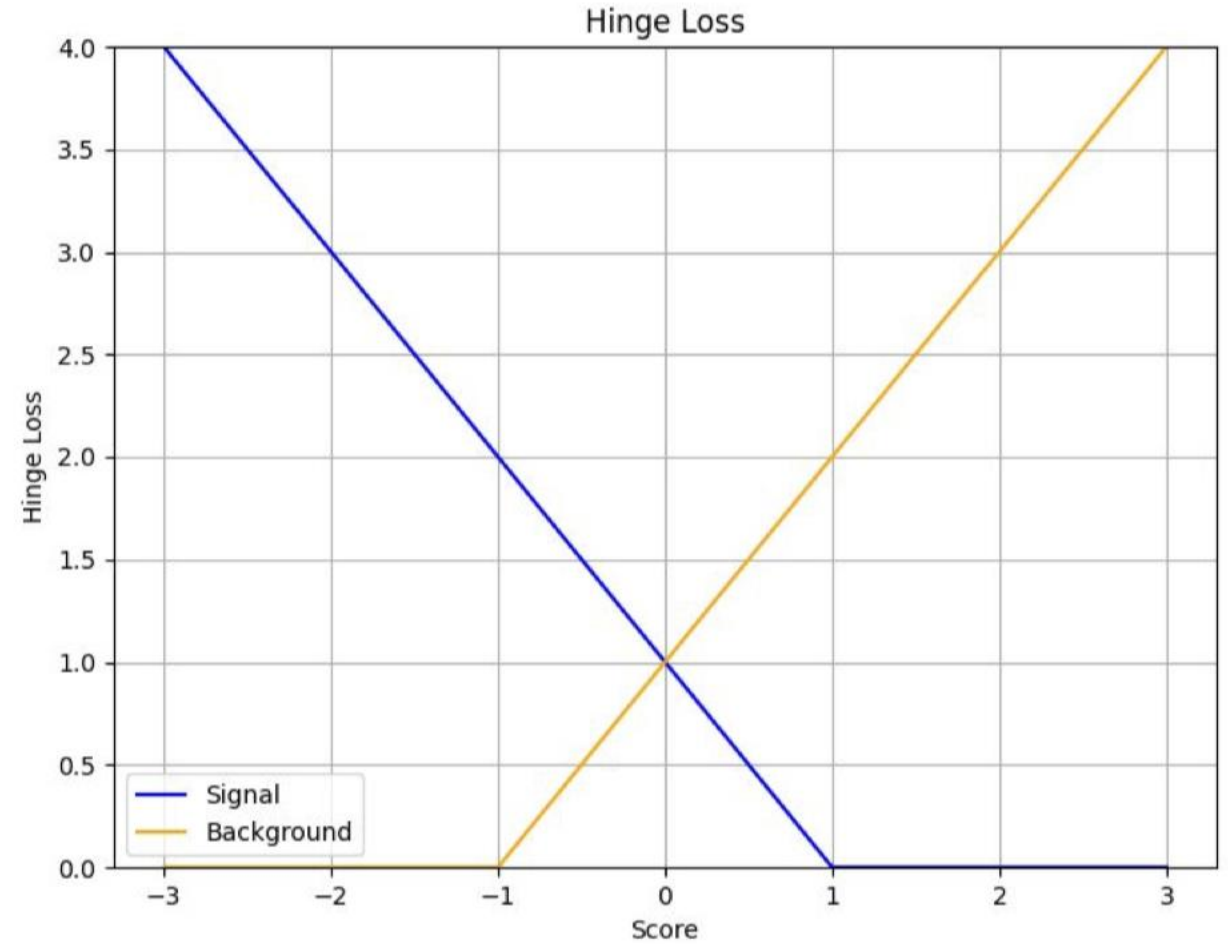
New DAQ Development

- New ADC generation (JESD204B interface)
 - High speed and low power ($\sim 1\text{GHz}$, 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)



Hinge Loss

- No sigmoid activation
- Penalize (only) wrong predictions

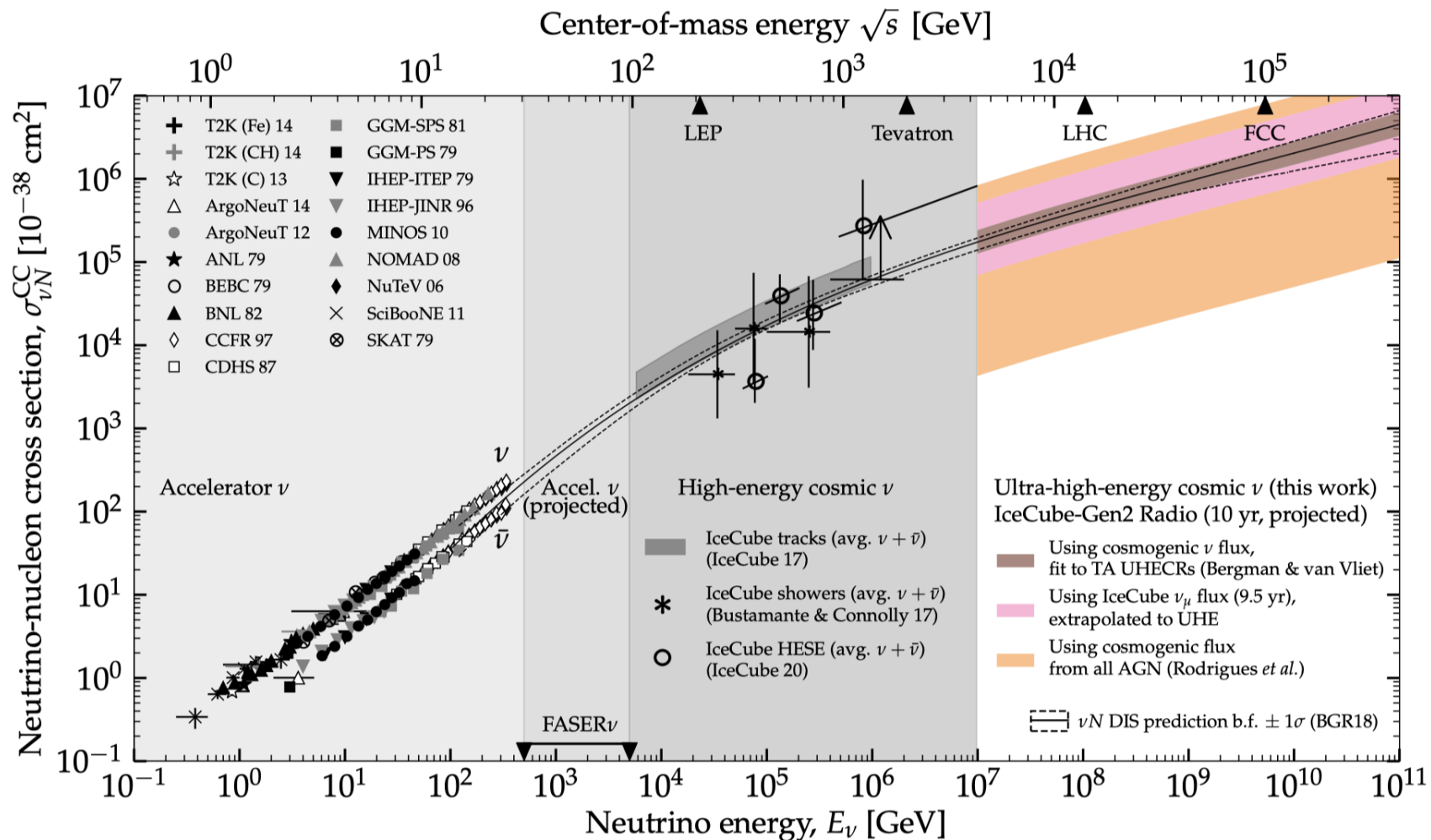
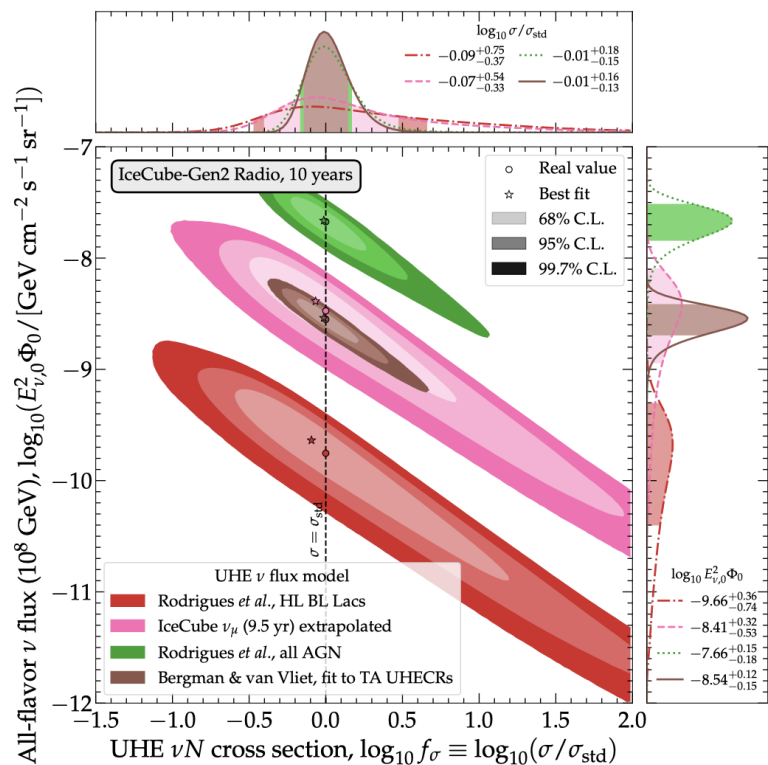


Science Overview: Cross Section

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

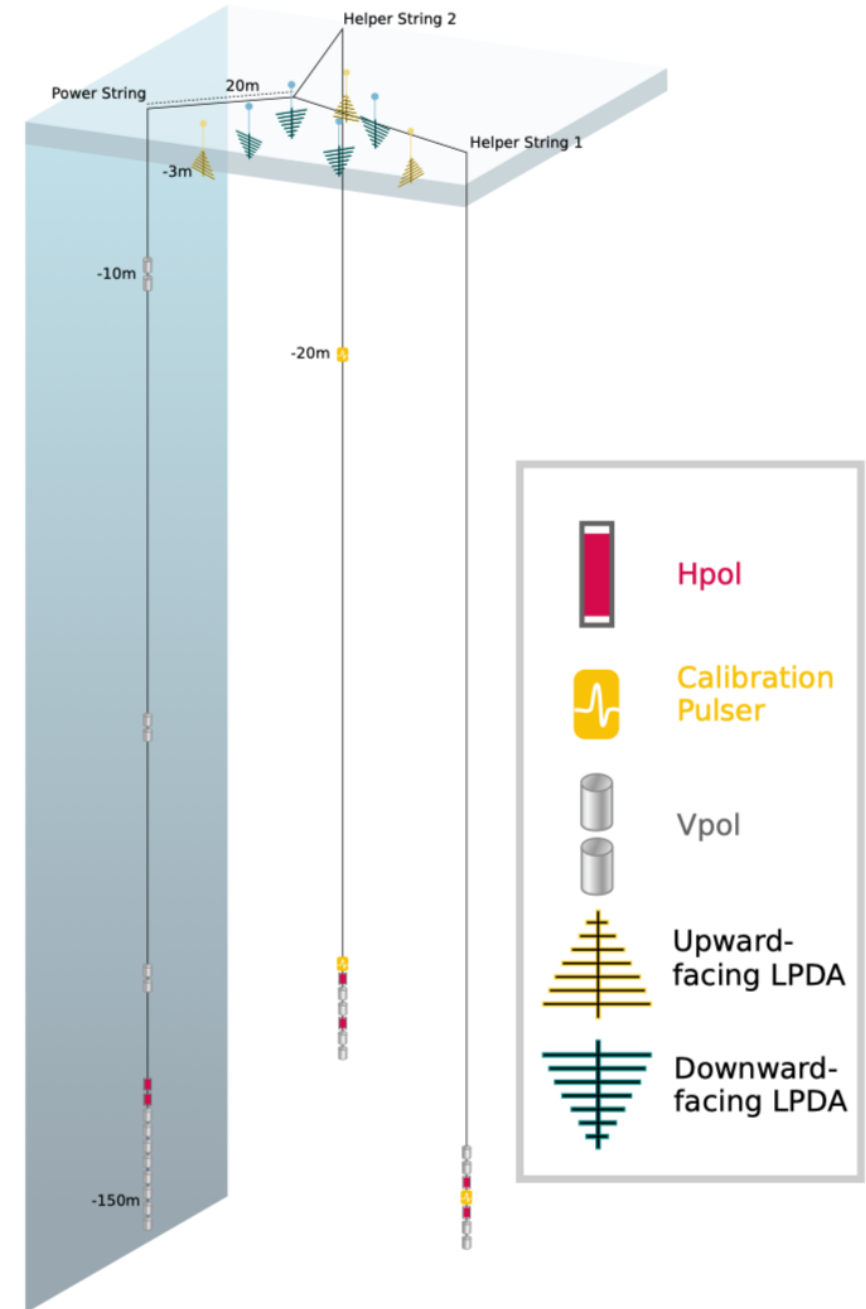
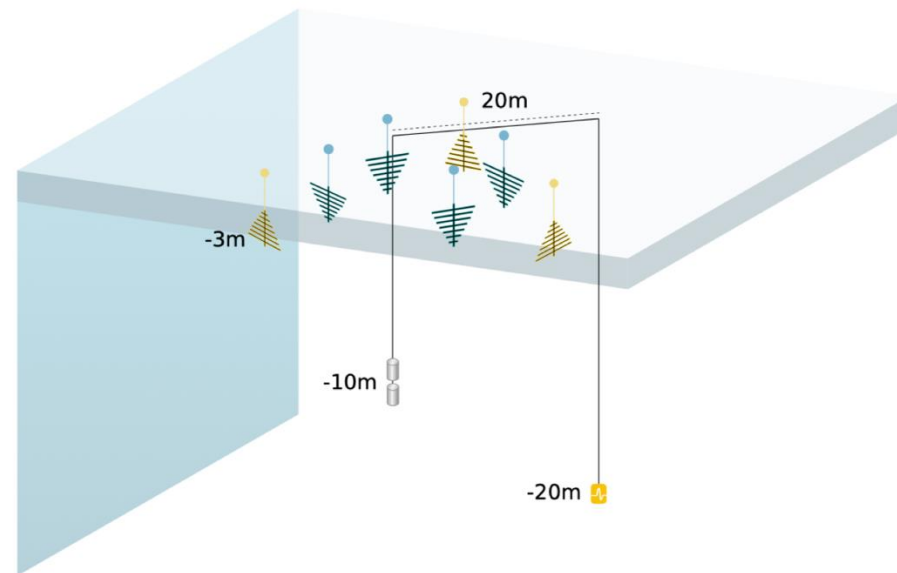
$$N_\nu(E_\nu, \theta_z) \propto \Phi_\nu(E_\nu) \sigma(E_\nu) e^{-L(\theta_z)/L_{\nu N}(E_\nu, \theta_z)}$$

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



Current Trigger

- Shallow:
 - high/low threshold crossing trigger for each LPDA
 - additional 2/4 time coincidence required
 - effective threshold $\sim 4x V_{rms}$
- Deep: Phased array
 - coherently summed waveforms to increase SNR by $\sqrt{n_{antennas}}$
 - power integration trigger
 - effective threshold $\sim 2-3^* \times V_{rms}$



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