

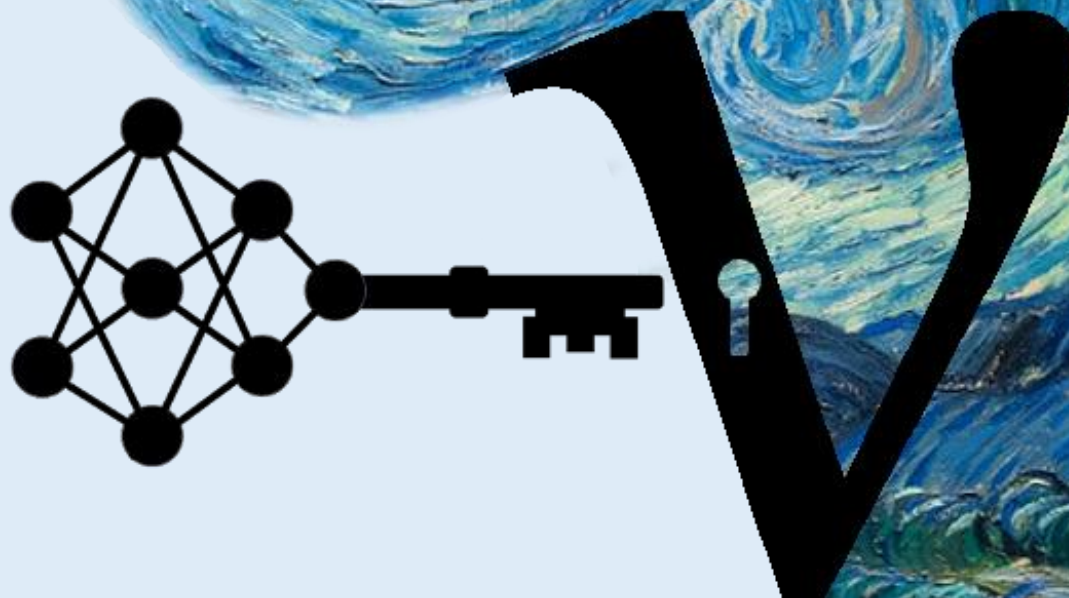


UPPSALA
UNIVERSITET

Deep Learning Reconstruction of in-ice Radio Neutrino Signals

Astroparticle School 2024,
Obertrubach-Bärnfels

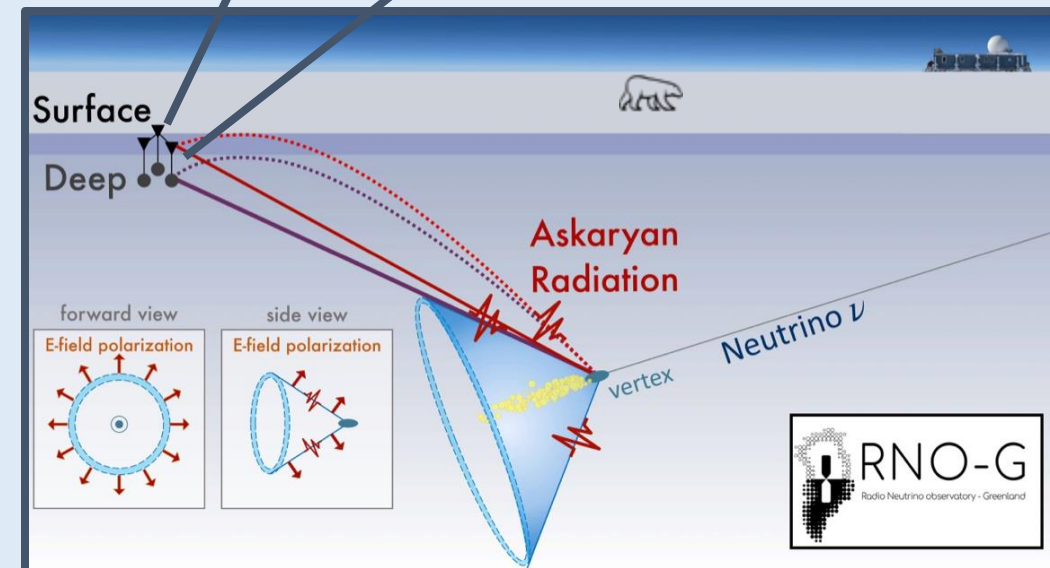
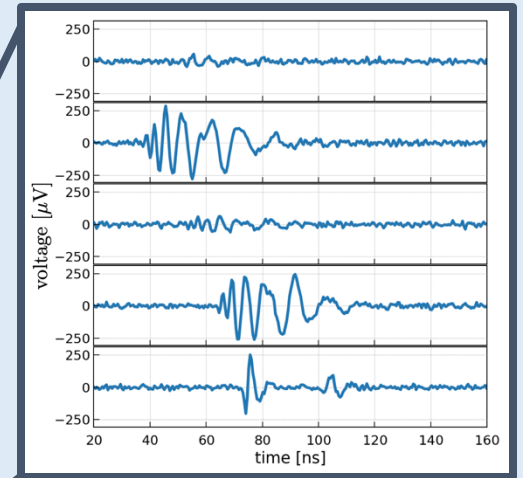
Nils Heyer





Radio Detection of Cosmic Neutrinos

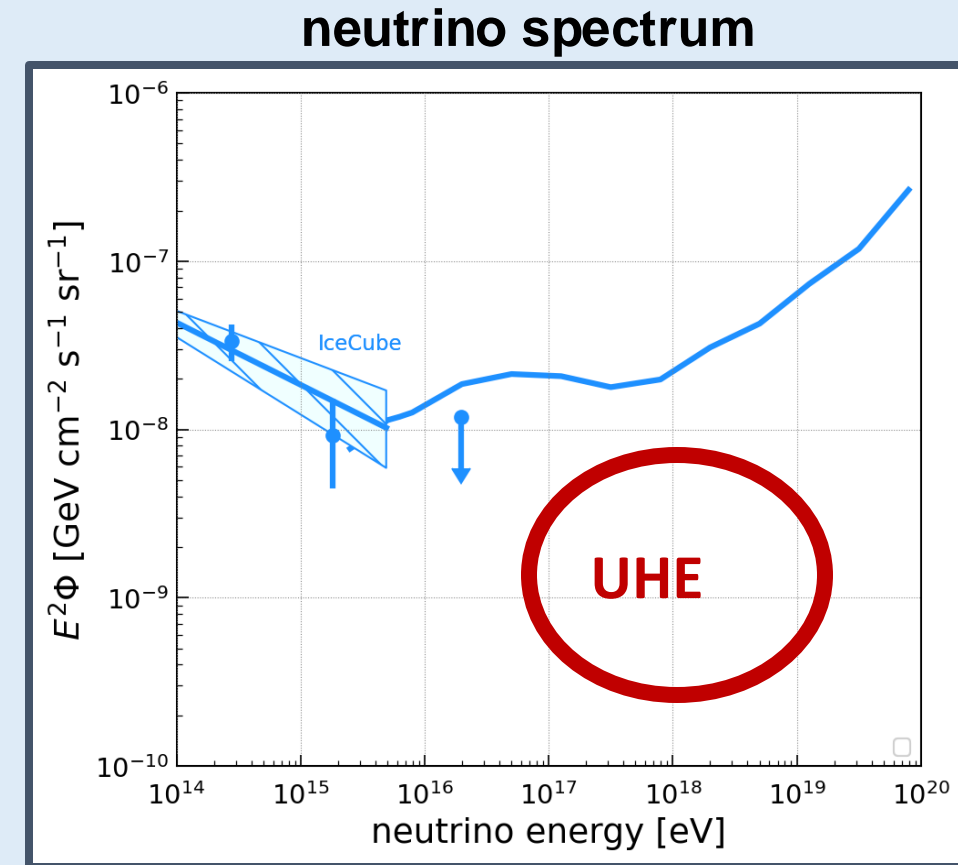
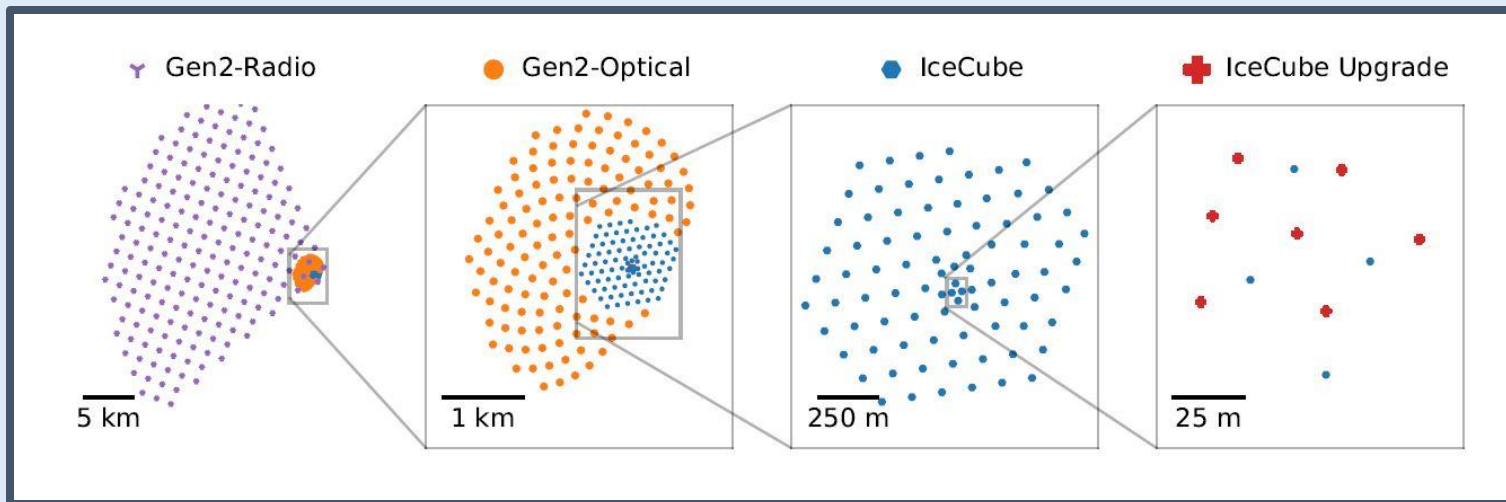
- The **neutrino collides** with a nucleus in the ice
- The collision induces a **particle shower**
- The particle shower creates a radio pulse via **Askaryan emission**
- The radio **pulses propagate** through the ice until reaching an antenna
- The pulse is measured by one or multiple **radio antennas**





IceCube - Gen2 Radio

- Is planned to instrument $\sim 500 \text{ km}^3$ of ice
- Its sensitivity is expected to tap into the predicted UHE neutrino flux
- Counting experiment or neutrino observatory?

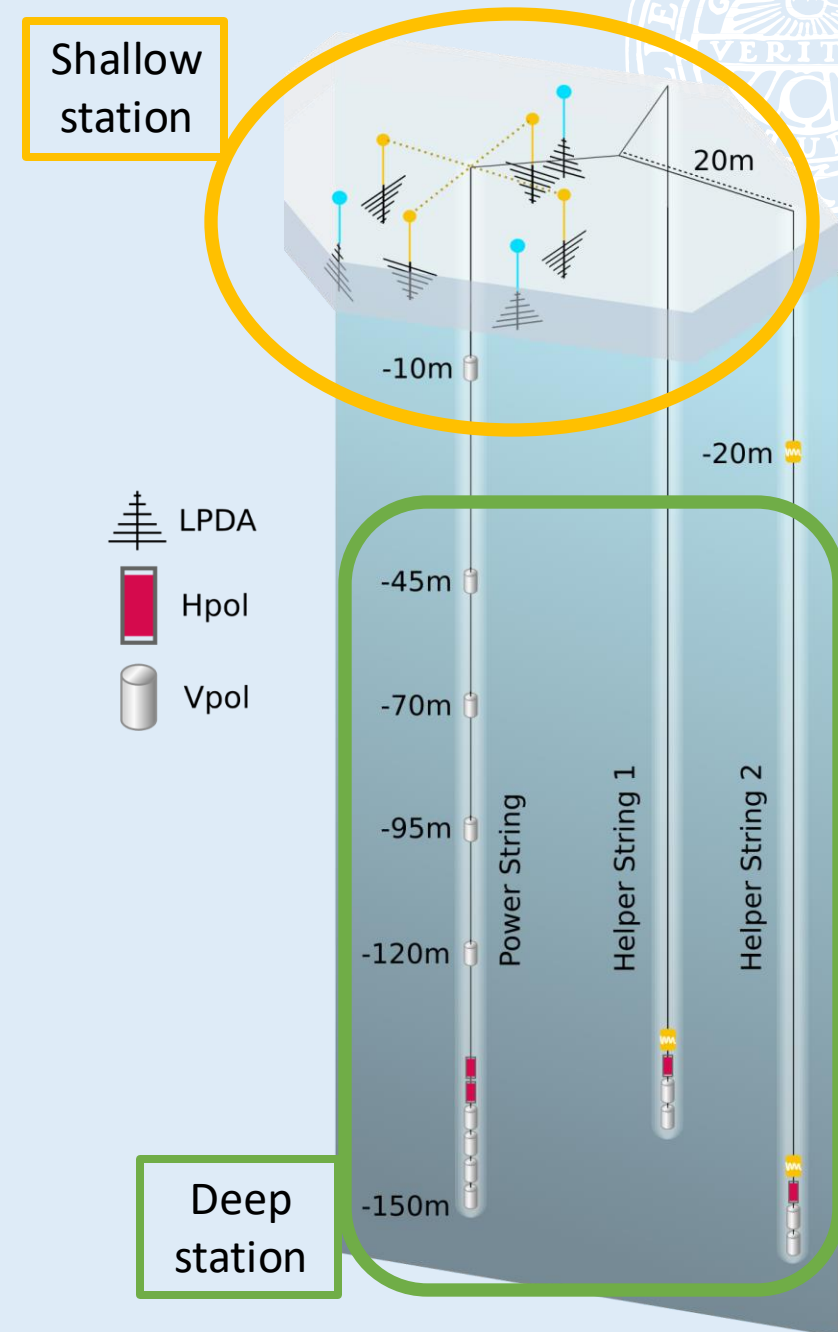


optical

radio

Two Different Station Designs

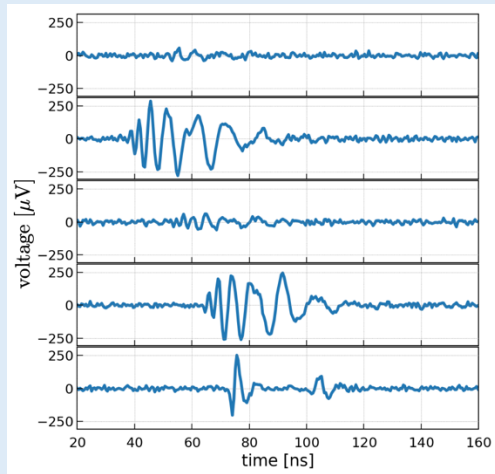
- MC generated events for a single station @South Pole
- The events have a **uniform shower energy distribution**
- Single station event topologies:
 1. Hadronic shower ($\nu_{e,\mu,\tau} - NC, \nu_{\mu,\tau} - CC$)
 2. Hadronic shower + EM shower ($\nu_e - CC$)
- The current IceCube Gen2 station:
 - Shallow – 5 antennas
 - Deep – 16 antennas
 - **2.1 million neutrino events** for each station layout





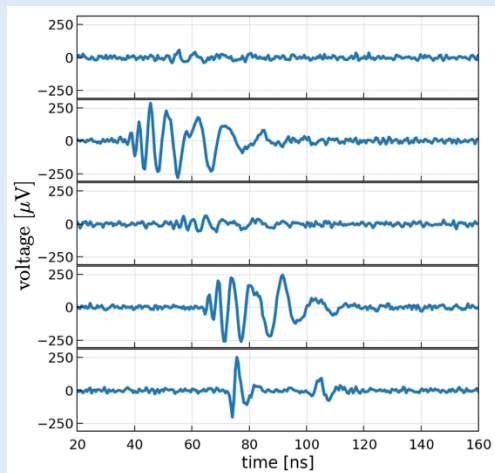
What will we do after measuring the first neutrino?

raw traces

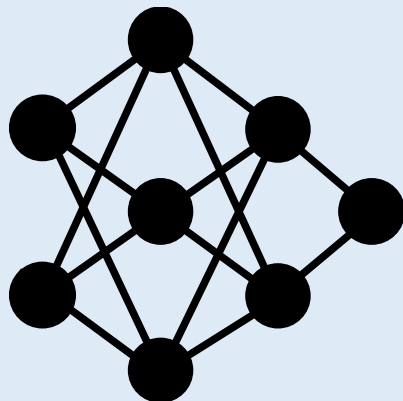


What will we do after measuring the first neutrino?

raw traces

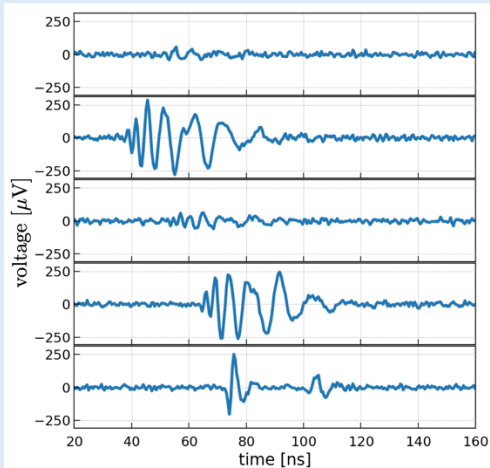


reconstruction algorithm

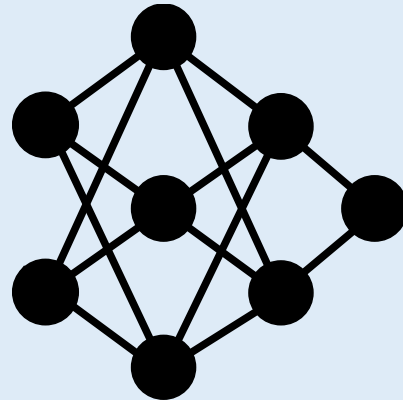


What will we do after measuring the first neutrino?

raw traces

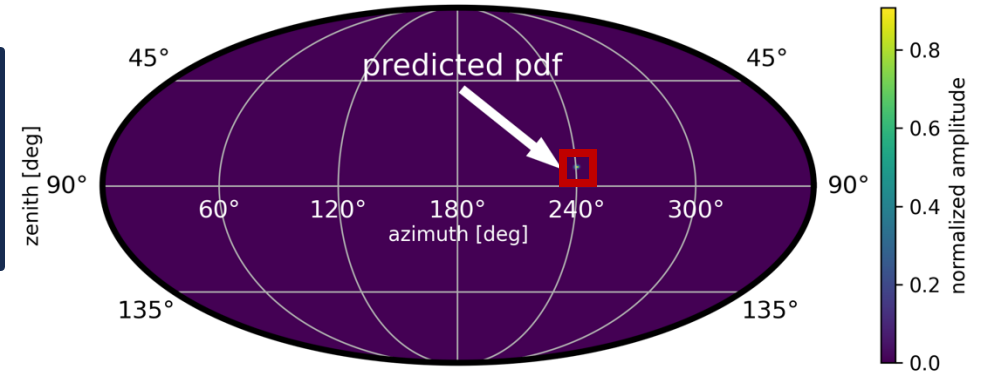


reconstruction algorithm



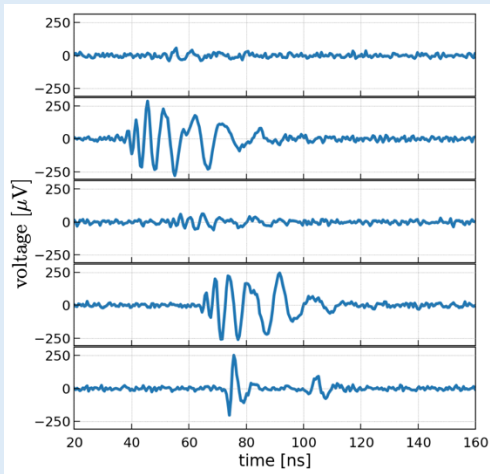
Single Event Reconstruction

direction

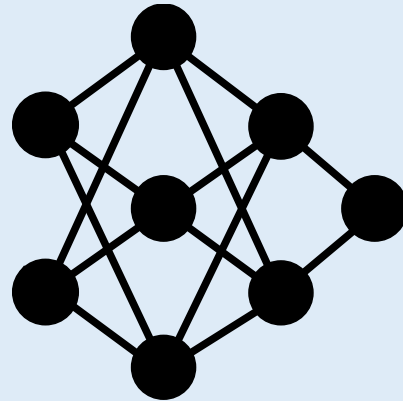


What will we do after measuring the first neutrino?

raw traces

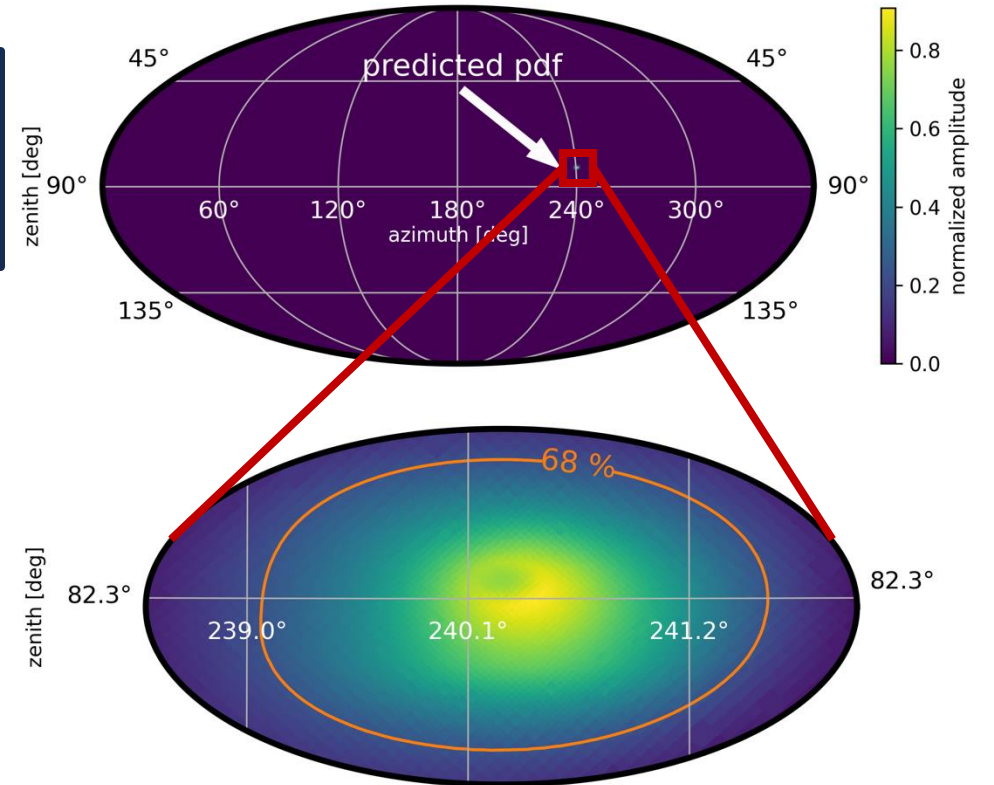


reconstruction algorithm



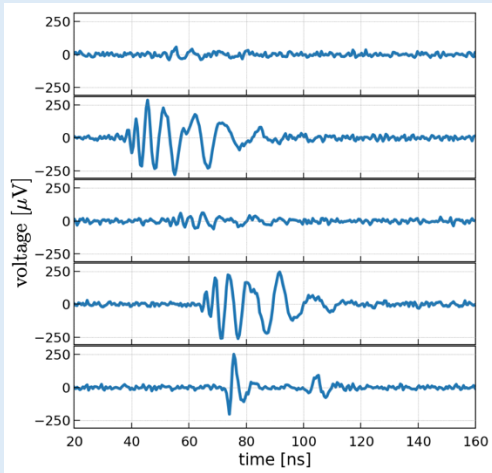
Single Event Reconstruction

direction

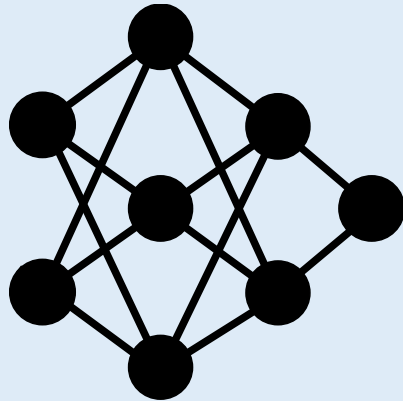


What will we do after measuring the first neutrino?

raw traces

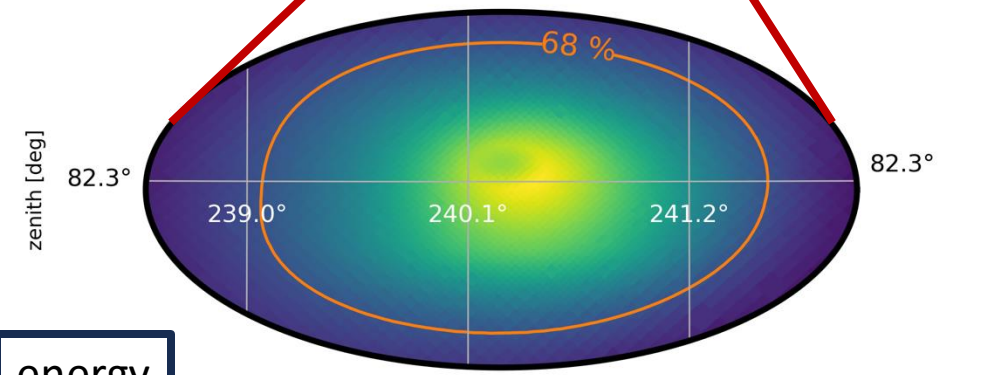
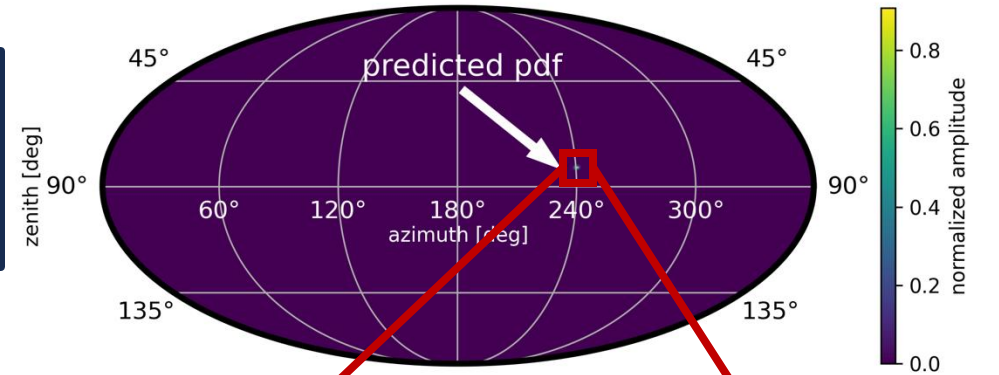


reconstruction algorithm

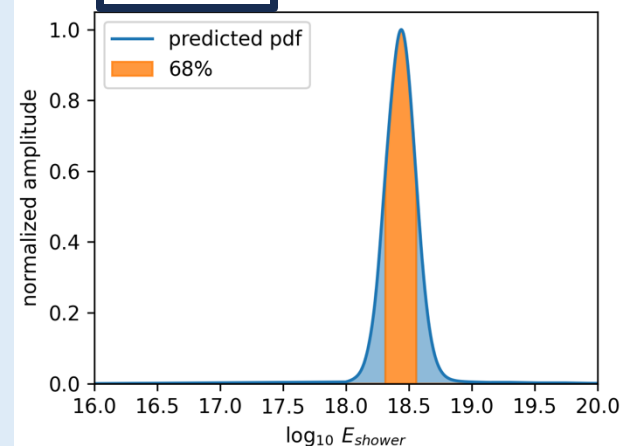


Single Event Reconstruction

direction

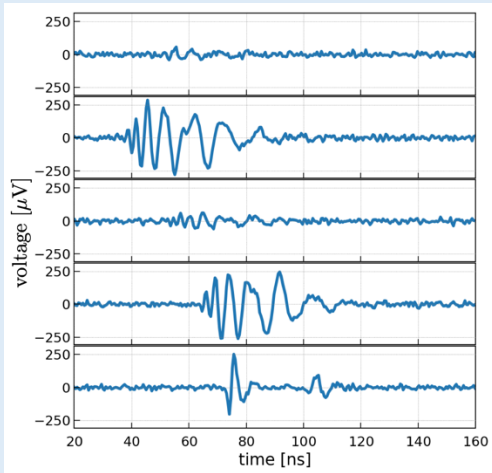


energy

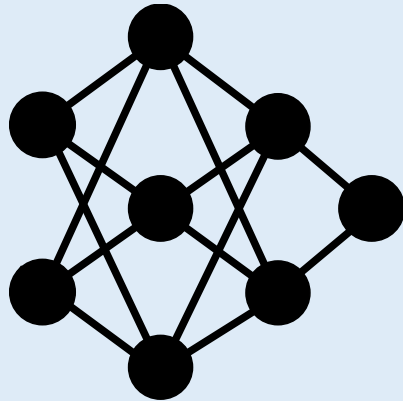


What will we do after measuring the first neutrino?

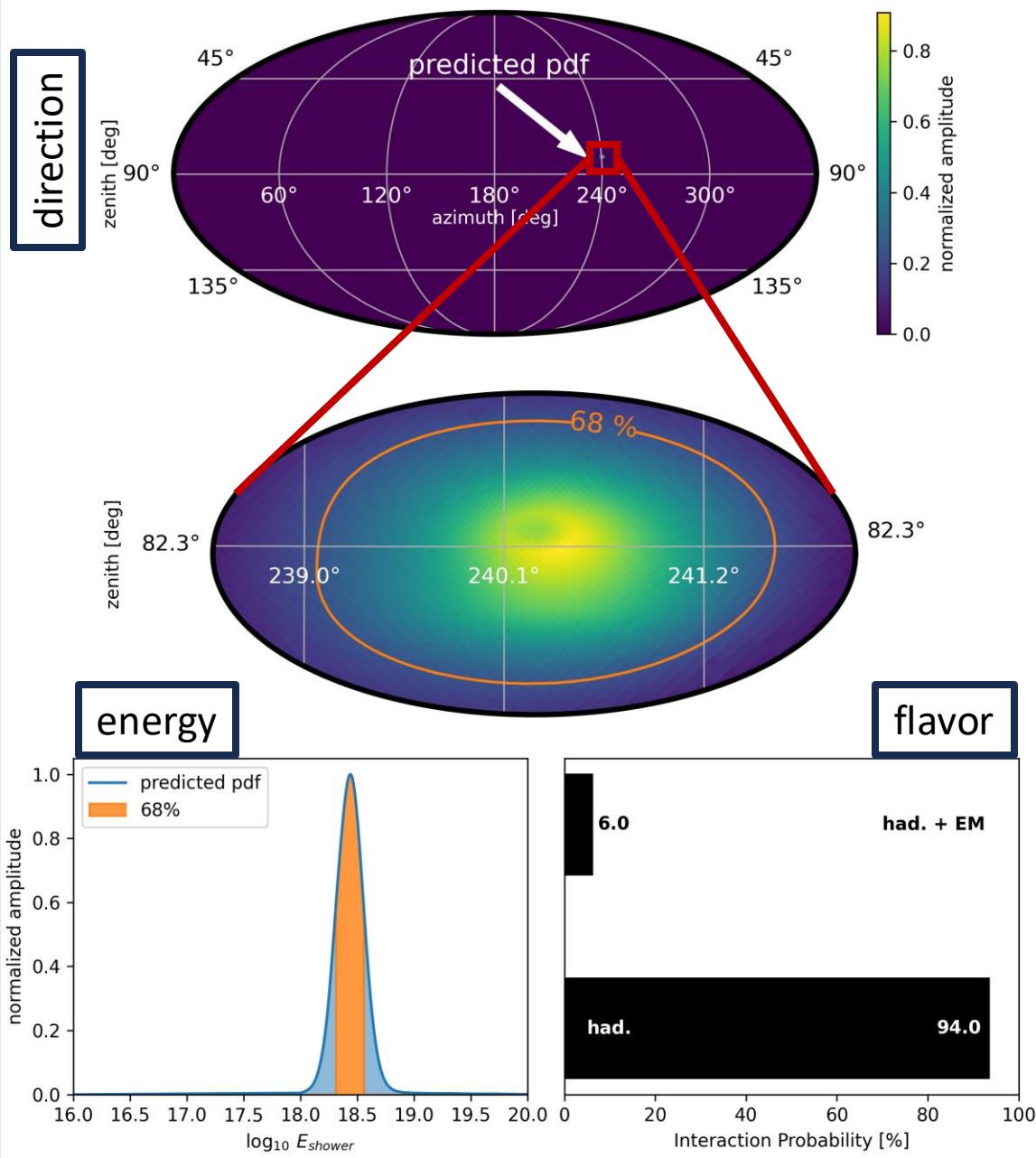
raw traces



reconstruction algorithm

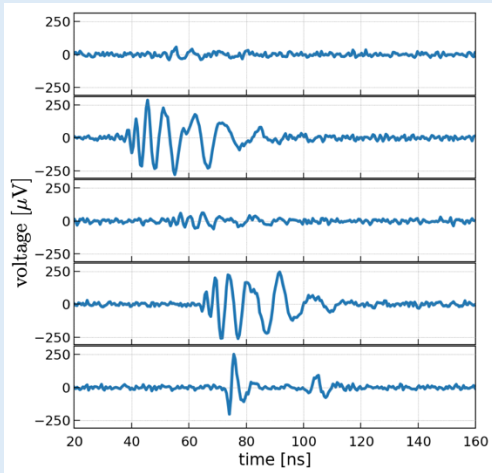


Single Event Reconstruction

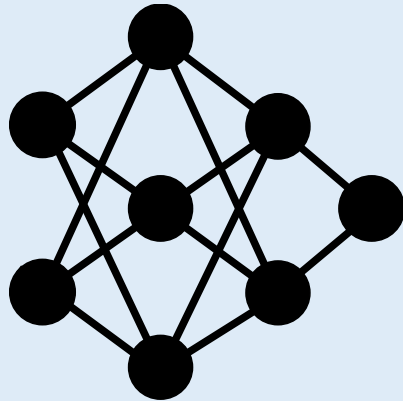


What will we do after measuring the first neutrino?

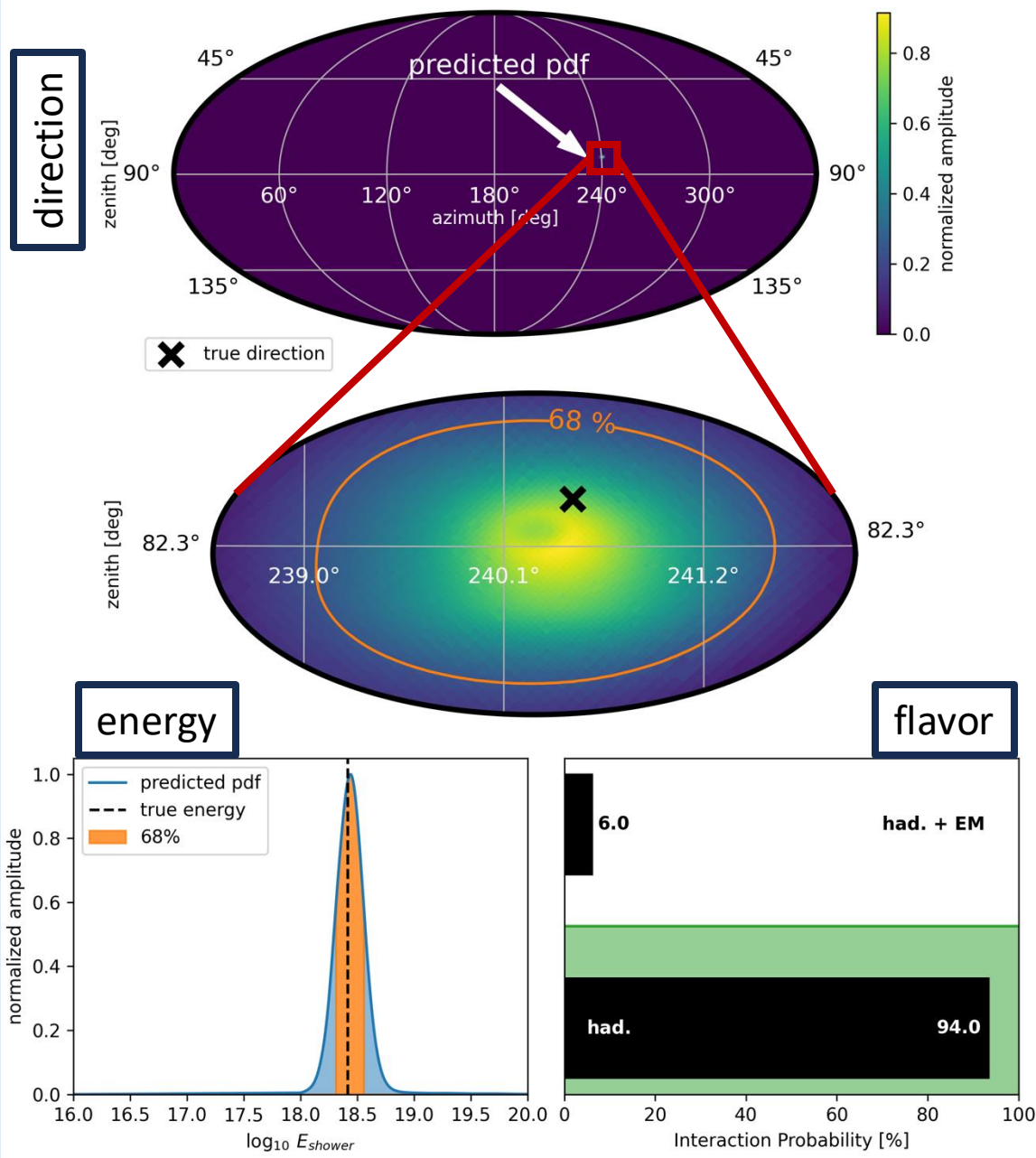
raw traces



reconstruction algorithm



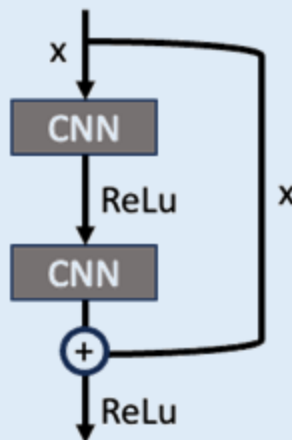
Single Event Reconstruction



Important Deep Learning Concepts

ResNet

- Developed for **image classification**
- Allows for very deep networks **without vanishing gradients**
- Previously used for **GW detection**

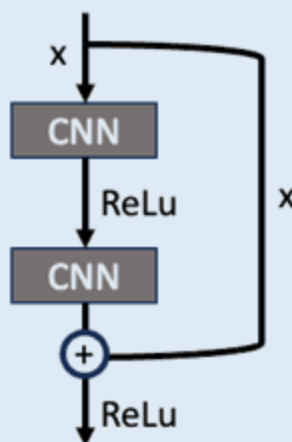




Important Deep Learning Concepts

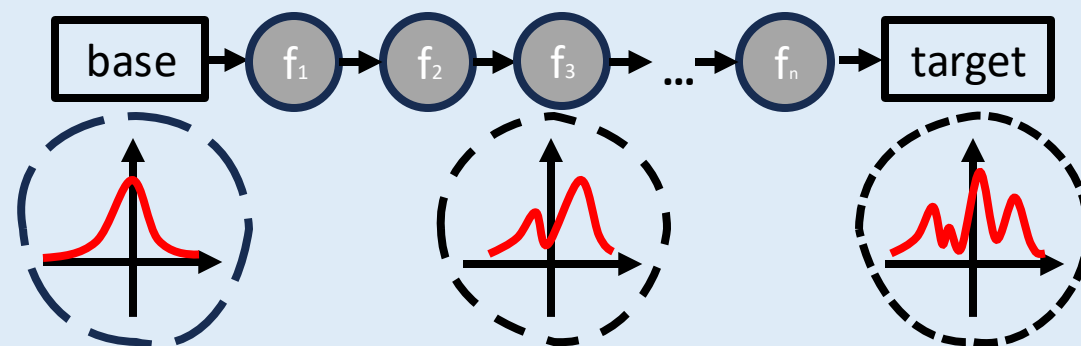
ResNet

- Developed for **image classification**
- Allows for very deep networks **without vanishing gradients**
- Previously used for **GW detection**



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**

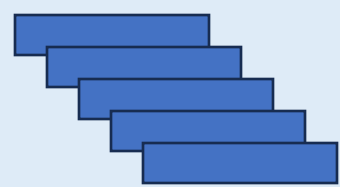


Model architecture



Model Shallow:

1 x 5 x 512



Model Deep:

1 x 16 x 2046

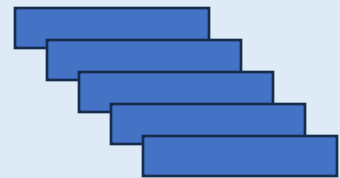




Model architecture

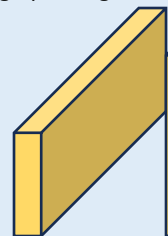
Model Shallow:

1 x 5 x 512



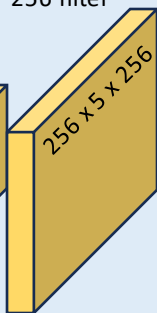
CNN1

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

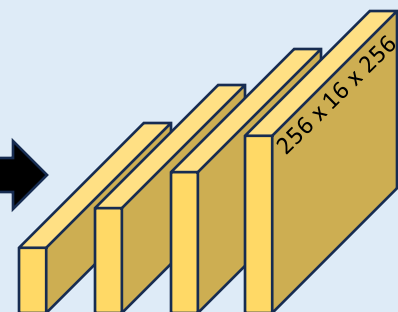
4x 1d-conv, 64 filter, kernel (1 x 16), average pooling

CNN3

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

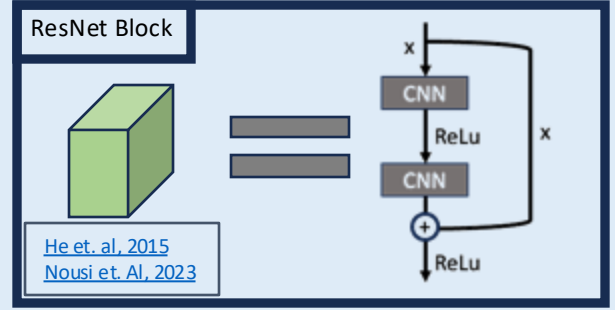
CNN4

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





Model architecture



Model Shallow:

1 x 5 x 512

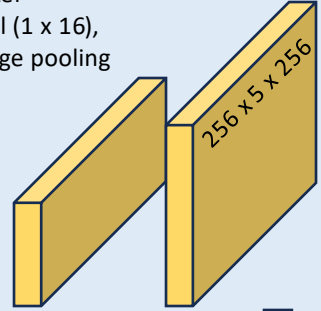


CNN1

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

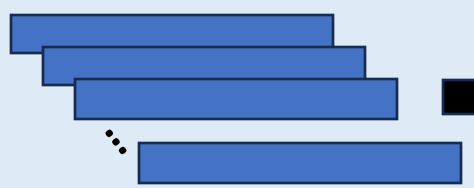
CNN2

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



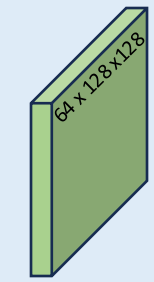
Model Deep:

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)

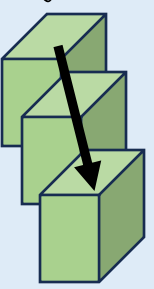
Reshape



ResNet-1

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

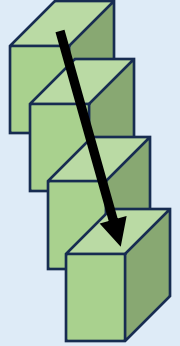
Max Pooling
64 x 64 x 64



ResNet-2

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

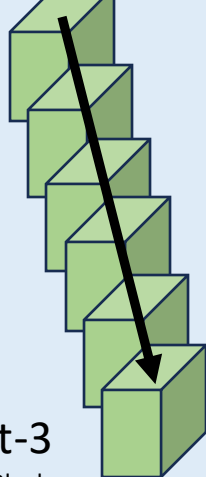
Down sampling
128 x 32 x 32



ResNet-3

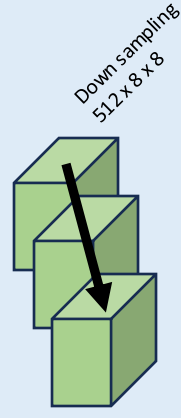
4x ResNet Block
128 filter
kernel (3 x 3)

Down sampling
256 x 16 x 16



ResNet-4

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



ResNet-5

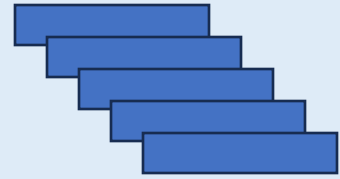
3x ResNet Block
512 filter
kernel (3 x 3)

Adaptive Pooling - 512

Model architecture

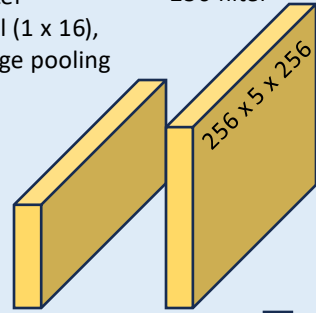
Model Shallow:

1 x 5 x 512



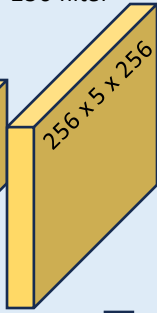
CNN1

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



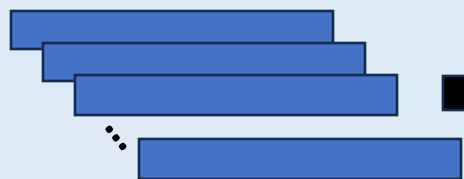
CNN2

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



Model Deep:

1 x 16 x 2046

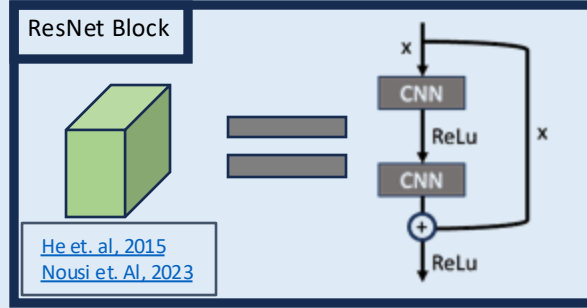


CNN1 4x 1d-conv, 32 filter, kernel (1 x 16), average pooling

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

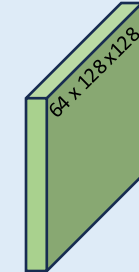
CNN3 4x 1d-conv, 128 filter, kernel (1 x 16), average pooling

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



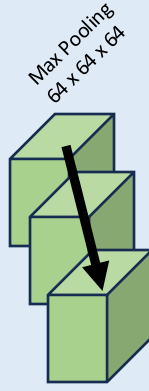
ResNet-1

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



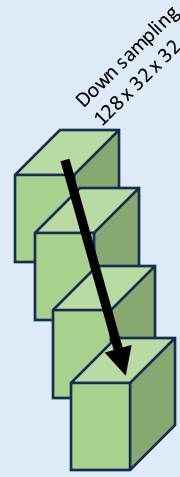
ResNet-2

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



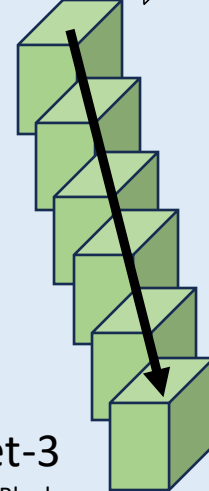
ResNet-3

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



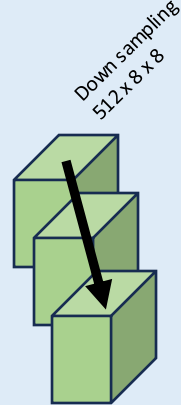
ResNet-4

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

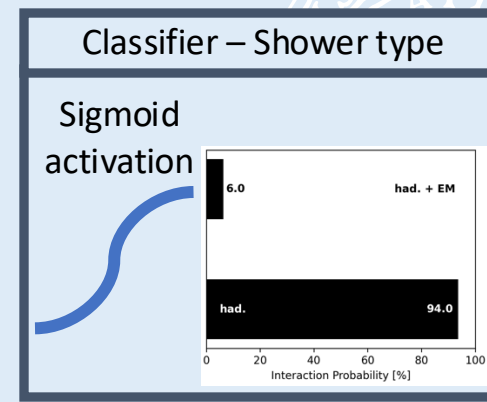


ResNet-5

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



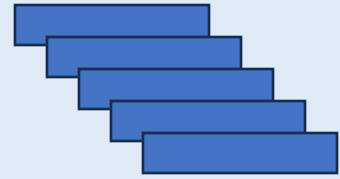
Adaptive Pooling - 512



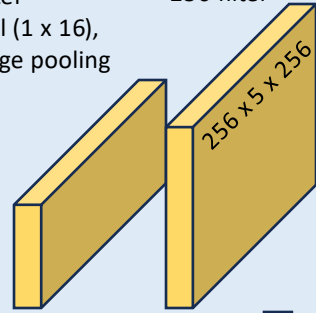
Model architecture

Model Shallow:

1 x 5 x 512



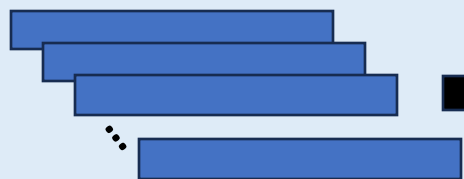
CNN1
4x 1d-conv
64 filter
kernel (1 x 16),
average pooling



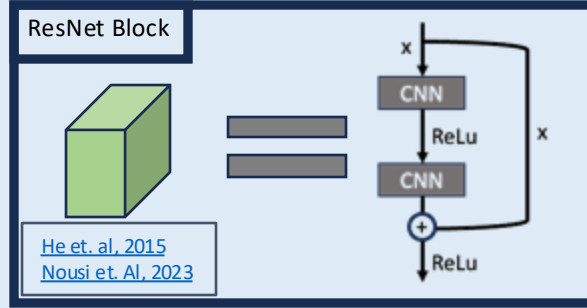
CNN2
4x 1d-conv
kernel (1 x 16),
256 filter

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)

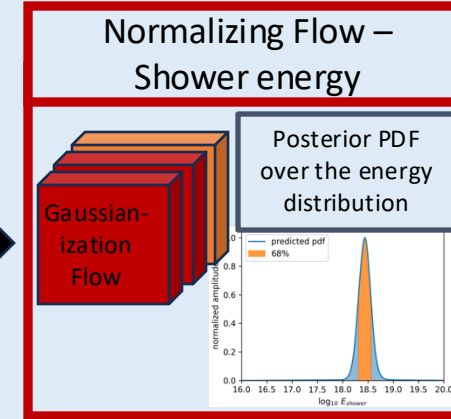
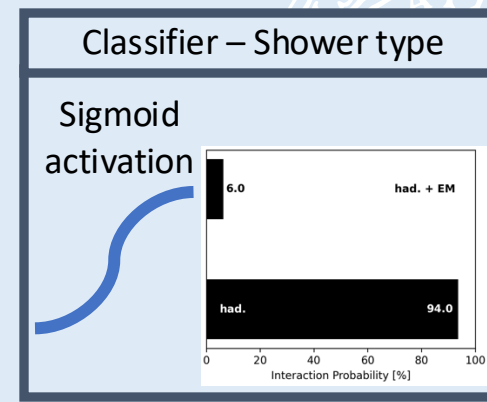
ResNet-2
3x ResNet Block
64 filter
kernel (3 x 3)

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)

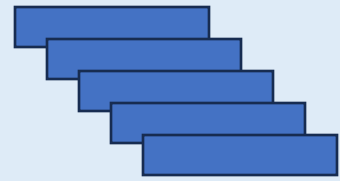
Adaptive Pooling - 512



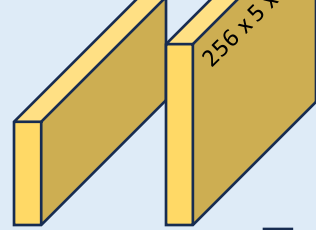
Model architecture

Model Shallow:

1 x 5 x 512



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

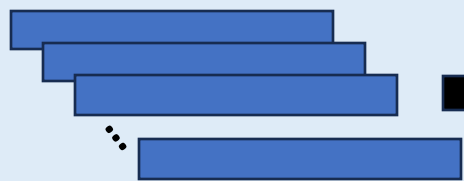


CNN2
4x 1d-conv
kernel (1 x 16),
256 filter



Model Deep:

1 x 16 x 2046

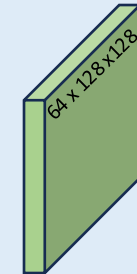
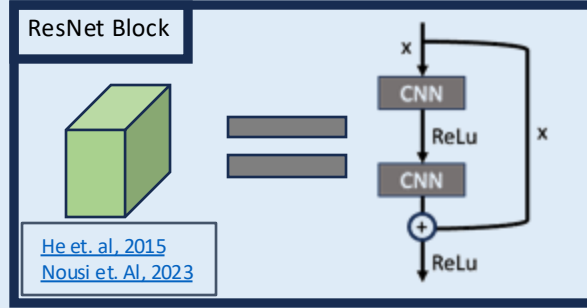


CNN1 4x 1d-conv, 32 filter, kernel (1 x 16), average pooling

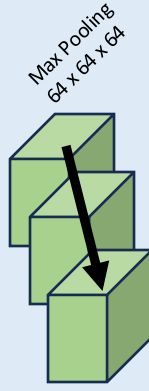
CNN2 4x 1d-conv, 64 filter, kernel (1 x 16), average pooling

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

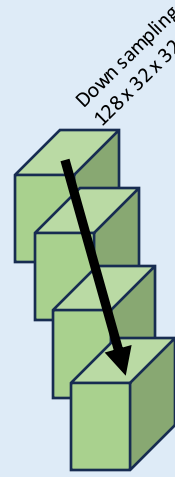
CNN4 4x 1d-conv, 256 filter, kernel (1 x 16)



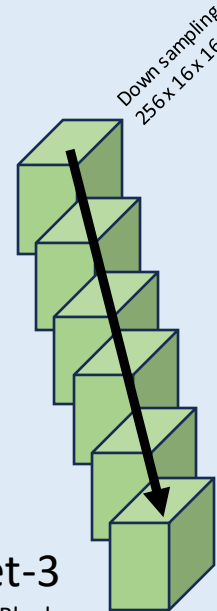
ResNet-1
1x conv, 64 filter
Stride 2
kernel (7 x 7)



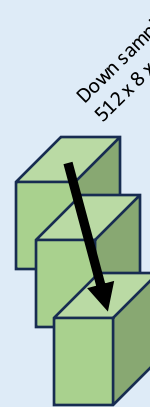
ResNet-2
3x ResNet Block
64 filter
kernel (3 x 3)



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

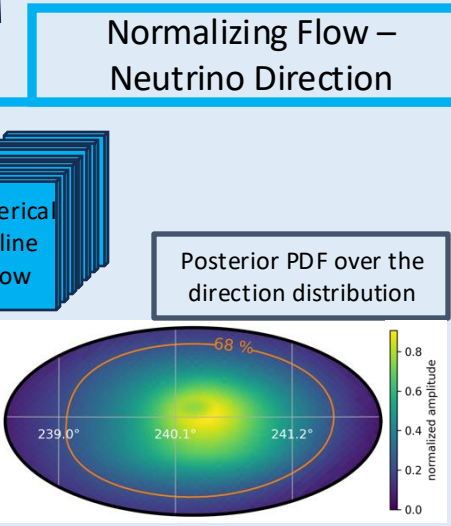
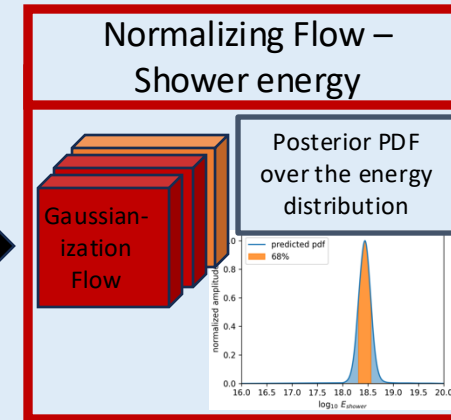
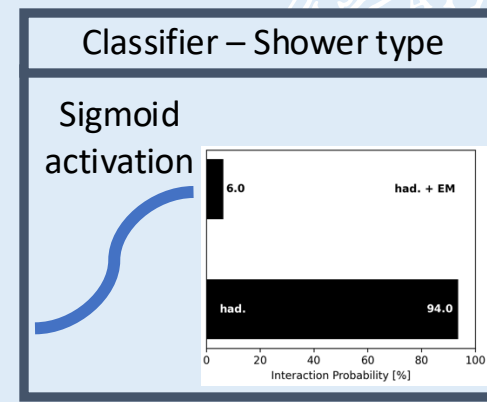


ResNet-4
6x ResNet Block
256 filter
kernel (3 x 3)



ResNet-5
3x ResNet Block
512 filter
kernel (3 x 3)

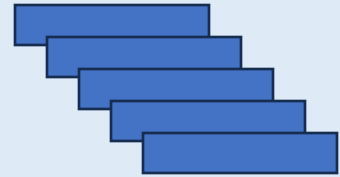
Adaptive Pooling - 512



Model architecture

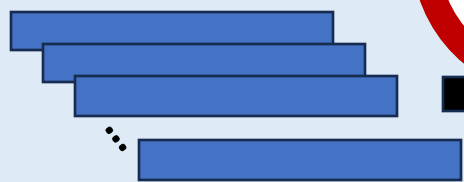
Model Shallow:

1 x 5 x 512



Model Deep:

1 x 16 x 2046



CNN1

4x 1d-conv
64 filter

CNN2

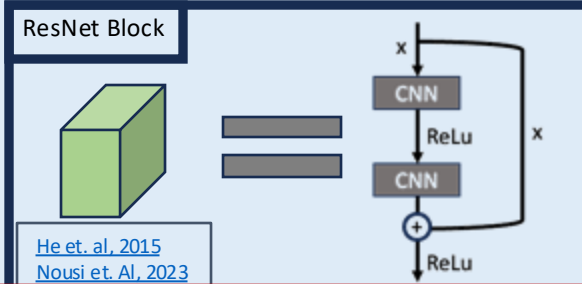
4x 1d-conv
kernel (1 x 16),
64 filter

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

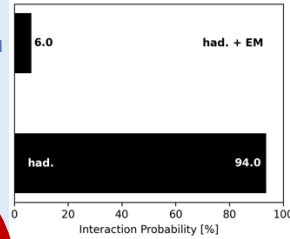
CNN4 4x 1d-conv, 256 filter, kernel (1 x 16)



He et. al, 2015
Nousi et. Al, 2023

Classifier – Shower type

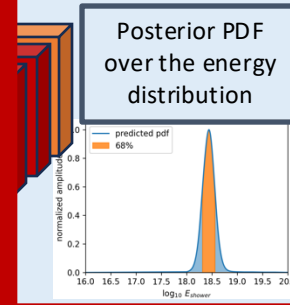
Sigmoid
activation



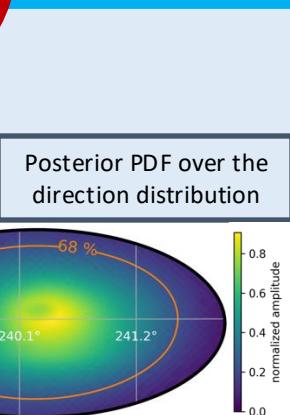
Improvements to previous reconstructions:

1. **One model** (per station type) to predict all parameters
2. Normalizing flows return **full posterior PDFs** allowing for event-by-event uncertainties
3. The model has no prior knowledge of the shower type
4. **No analysis cuts are needed** – all neutrino events can be used

Normalizing Flow –
Shower energy



Normalizing Flow –
Neutrino Direction



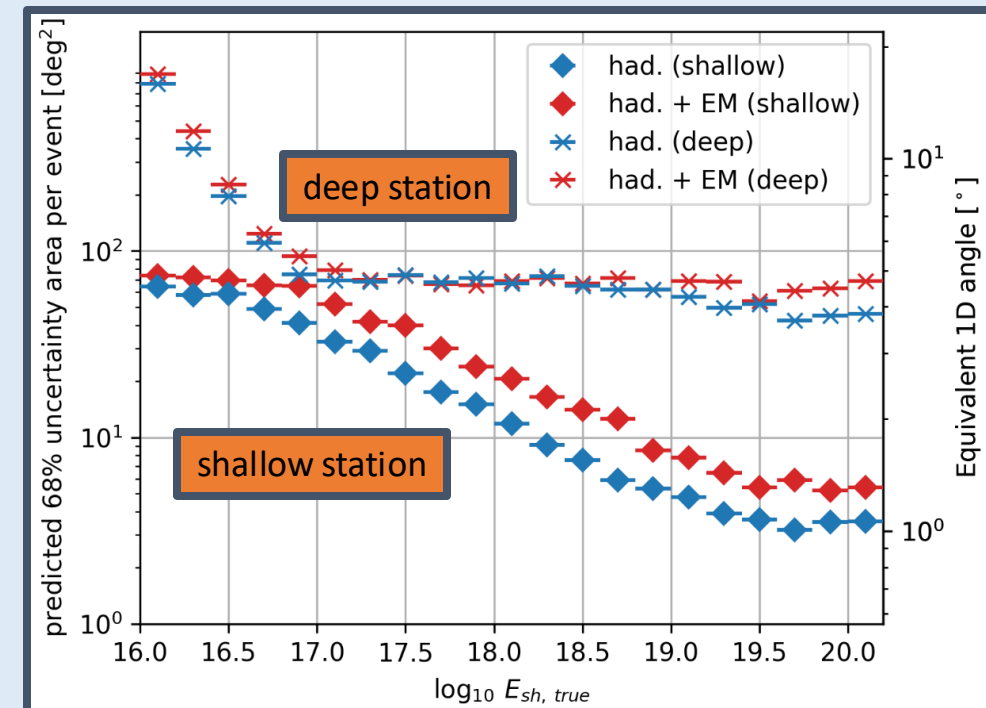
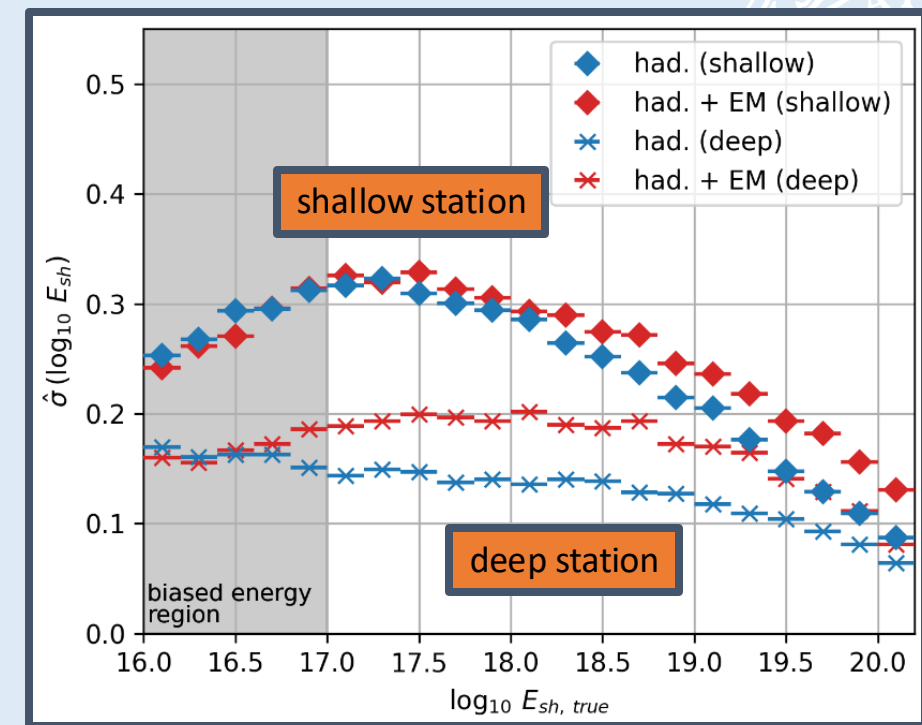
Spherical
Spline
Flow

kernel (3 x 3)

Results

– Energy and Direction

- Quantifying the size of our **uncertainties**
- Performance gets better with shower energy
- **Hadronic showers** are easier to reconstruct but don't tell us as much about the neutrino
- 'deep' stations have better **energy resolution**
- 'shallow' stations have better **direction resolution**





Summary & Outlook

- **Radio Neutrino** Detectors can instrument enormous volumes of ice
- After the first detection **reconstruction** will become a priority
- I created a model that can reconstruct all relevant properties
- Resolution at 1EeV shower energy:

| Resolution at 1EeV (had.) | Shallow Station | Deep Station |
|---------------------------|----------------------|----------------------|
| Shower Energy | 0.3 log E | 0.15 log E |
| 68% Uncertainty size | ~10 deg ² | ~70 deg ² |

- Next up:
 - Nice statistical uncertainties, but what about **systematics**?
 - How similar is a measured event to our Monte Carlo simulations?
 - What are the effects of **birefringence**?

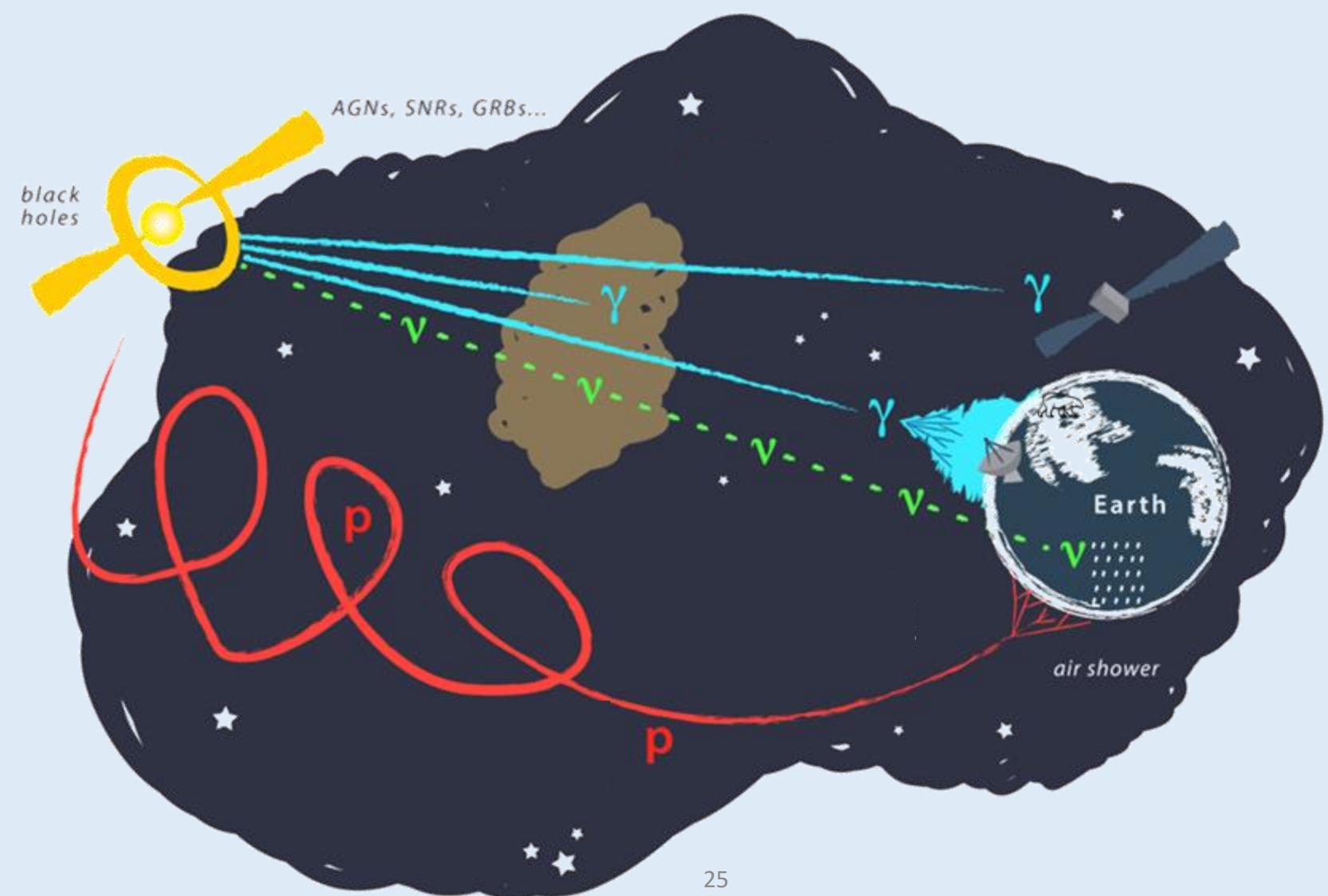
Thank you!



Usually we attack the science,
but sometimes science strikes back



Why measure Cosmic Neutrinos?

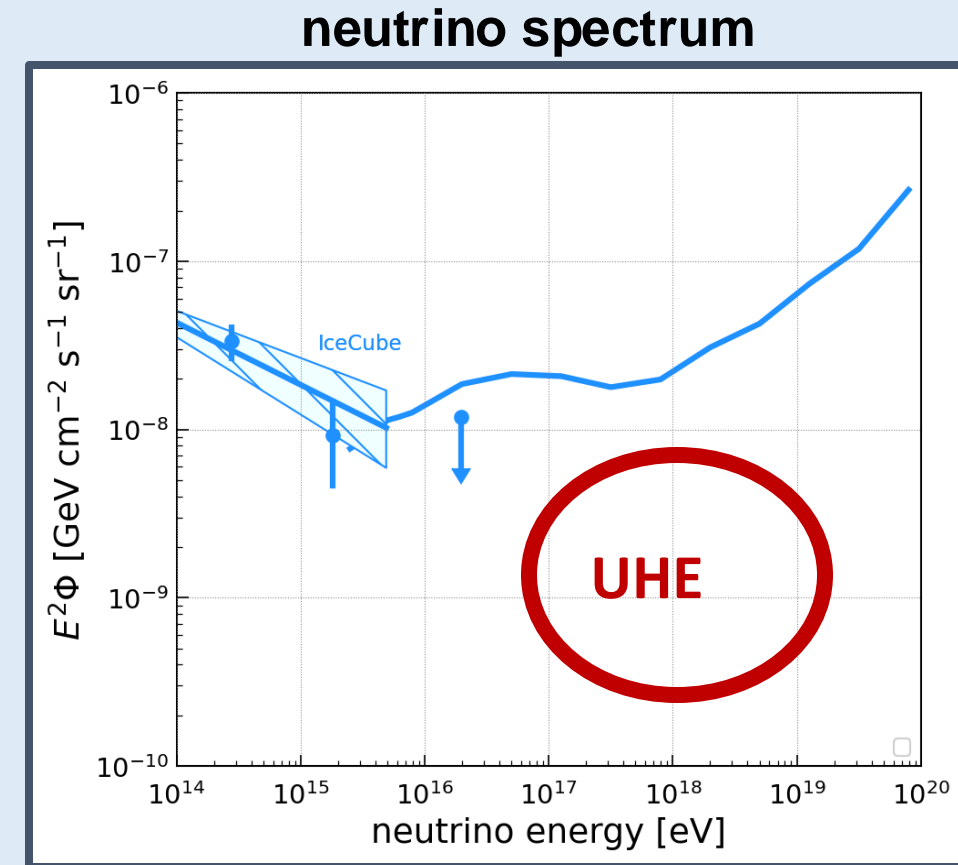
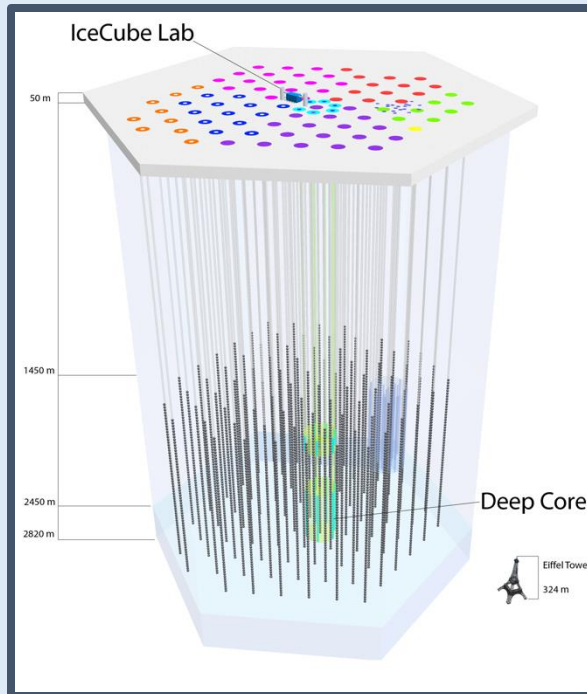




IceCube – The km³ Neutrino Telescope

- Instruments a **cubic kilometre** of ice
- Successfully measured the cosmic neutrino flux in the **TeV-PeV range**
- Detected point sources of neutrinos (**NGC1068, TXS 0506+056**)

But there is more...



optical

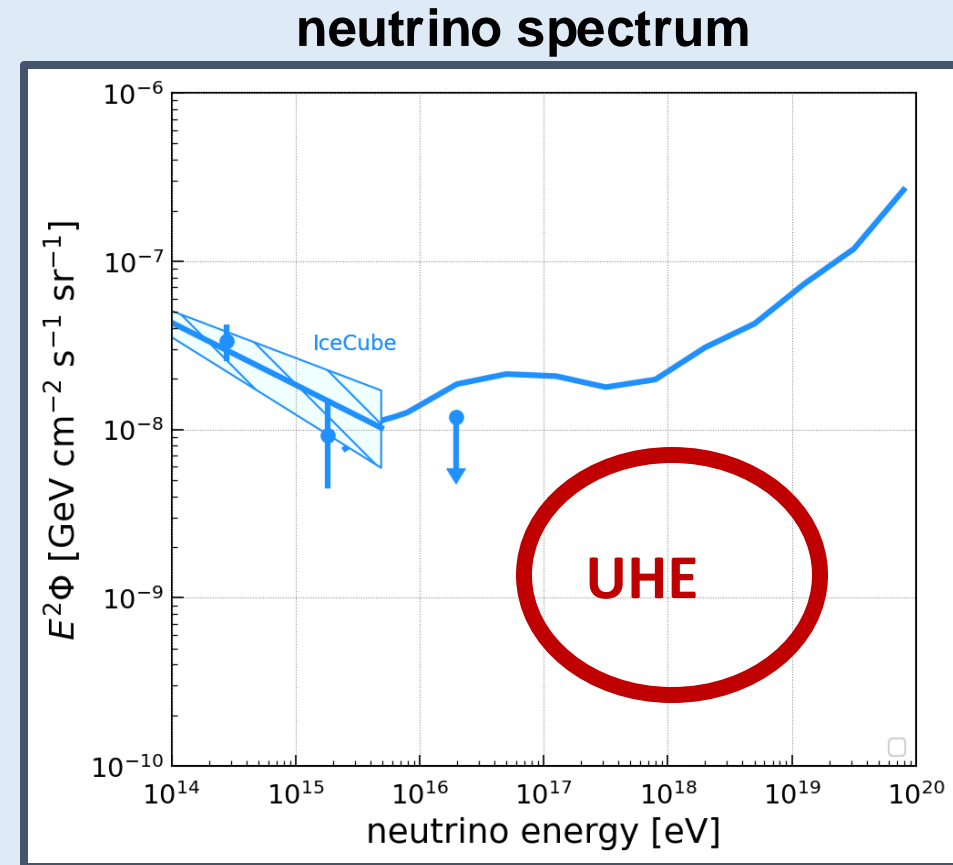
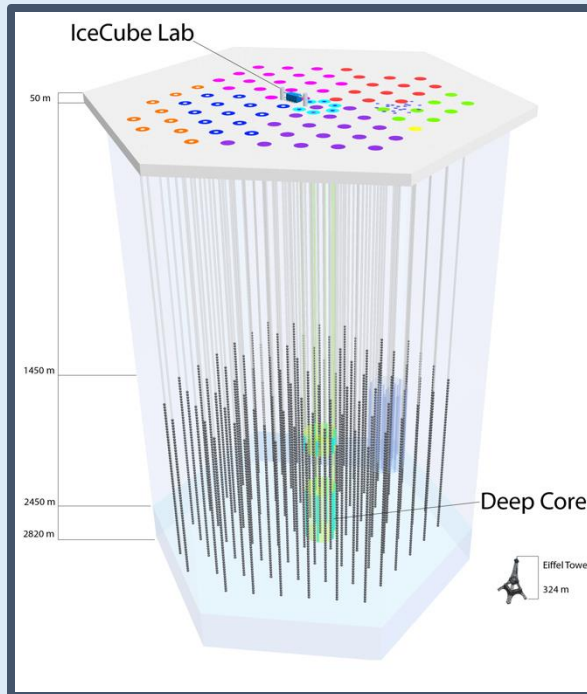


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But there is more...

- Radio neutrino detection extends the reach into the **EeV range**
- Can cost effectively instrument **hundreds of cubic kilometres of ice**



optical

radio