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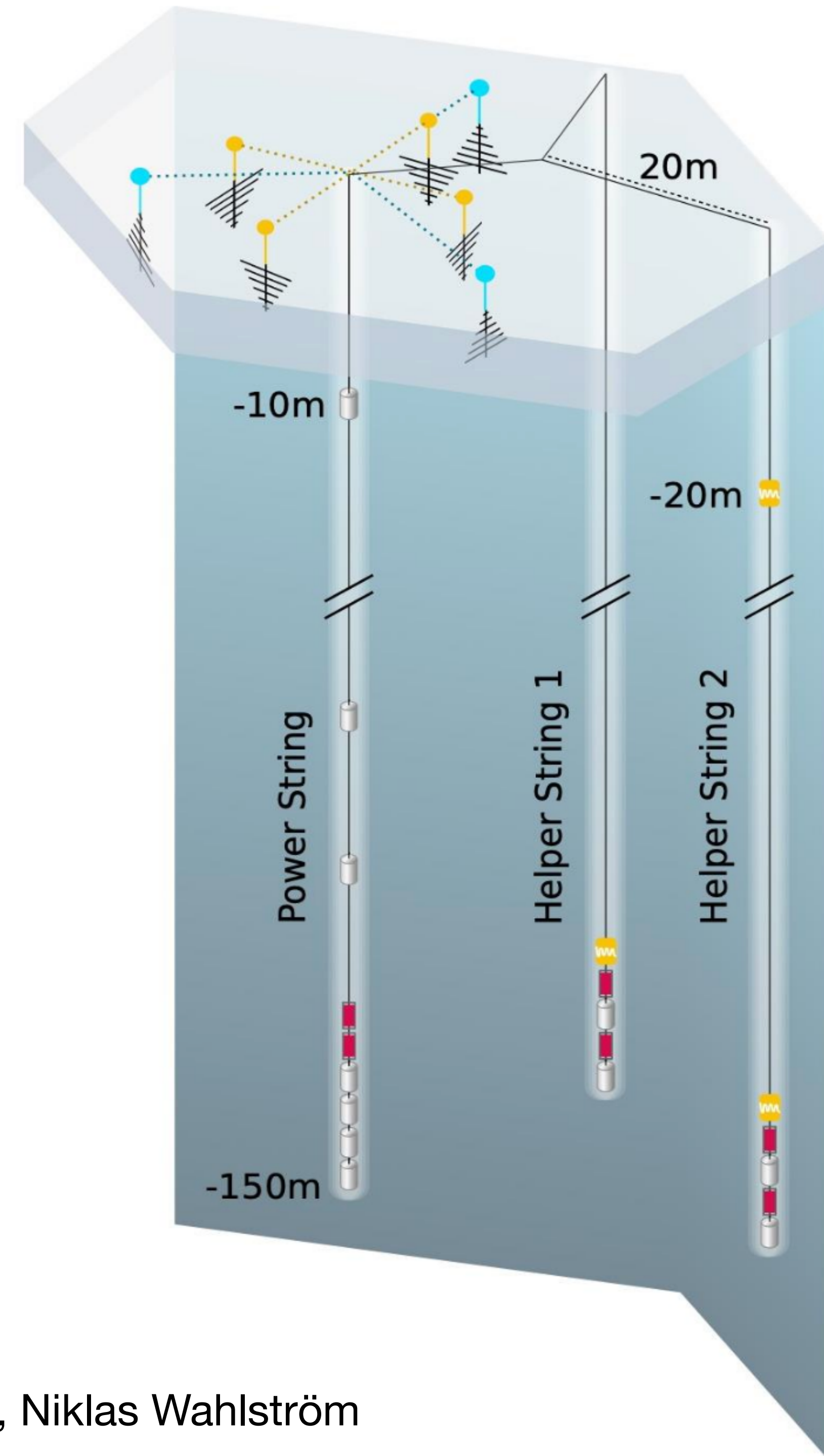
European Research Council
Established by the European Commission



Swedish
Research Council

Differentiable end-to-end optimization for in-ice radio neutrino detectors

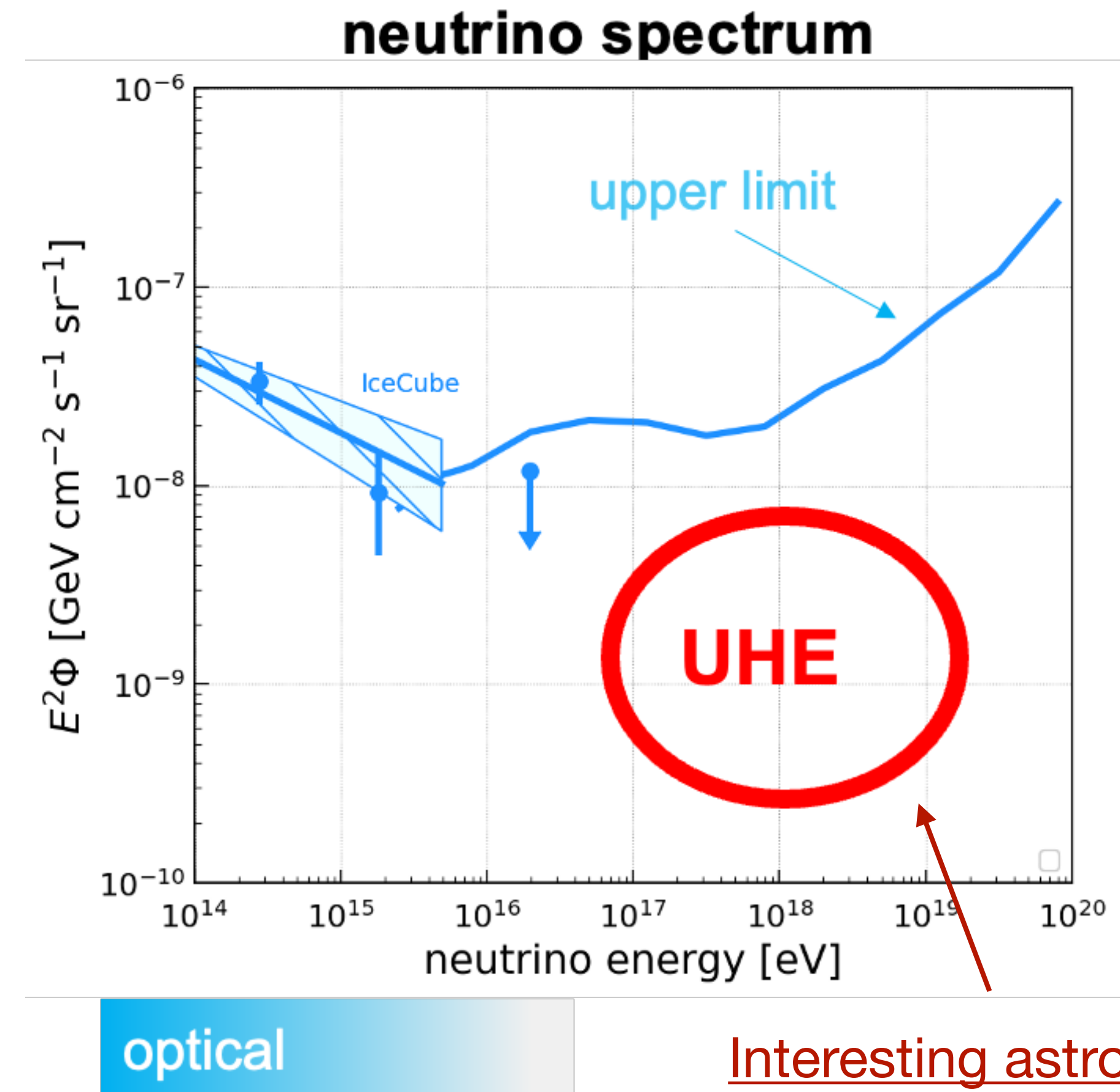
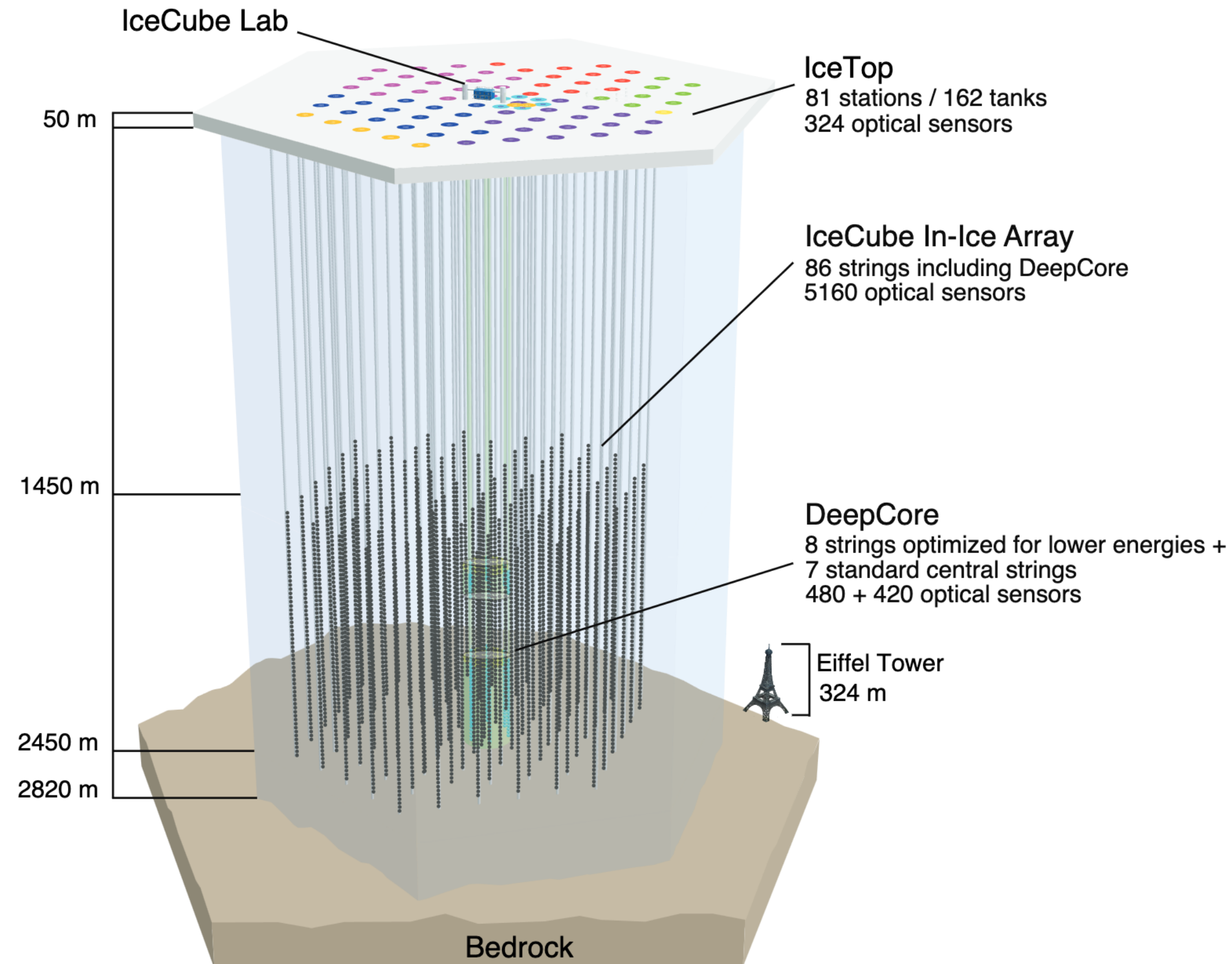
NBI Neutrino Summer School
2025-07-10



Martin Langgård Ravn, Philipp Pilar, Christian Glaser, Thorsten Glüsenkamp, Niklas Wahlström

Ultra-high energy neutrino detection

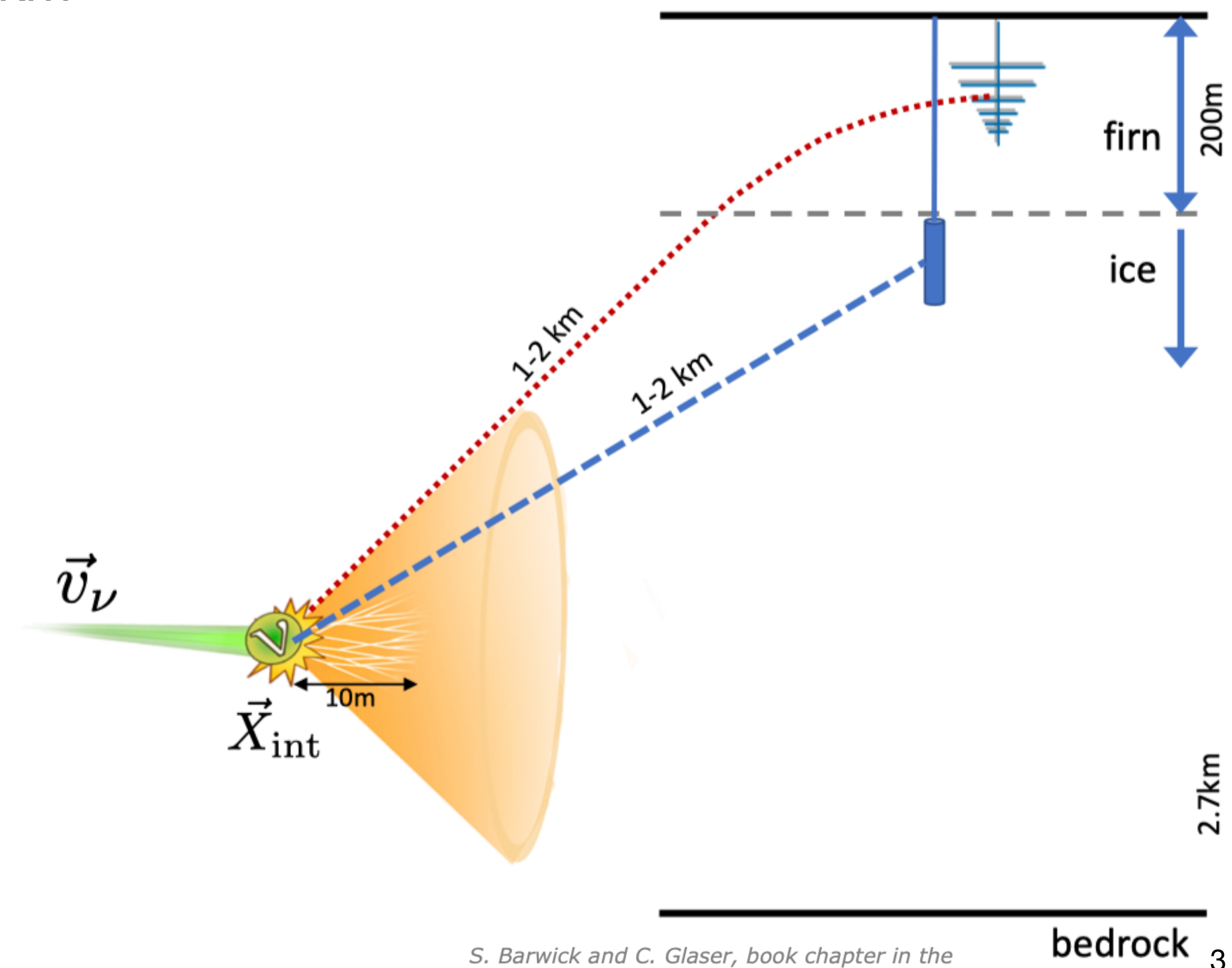
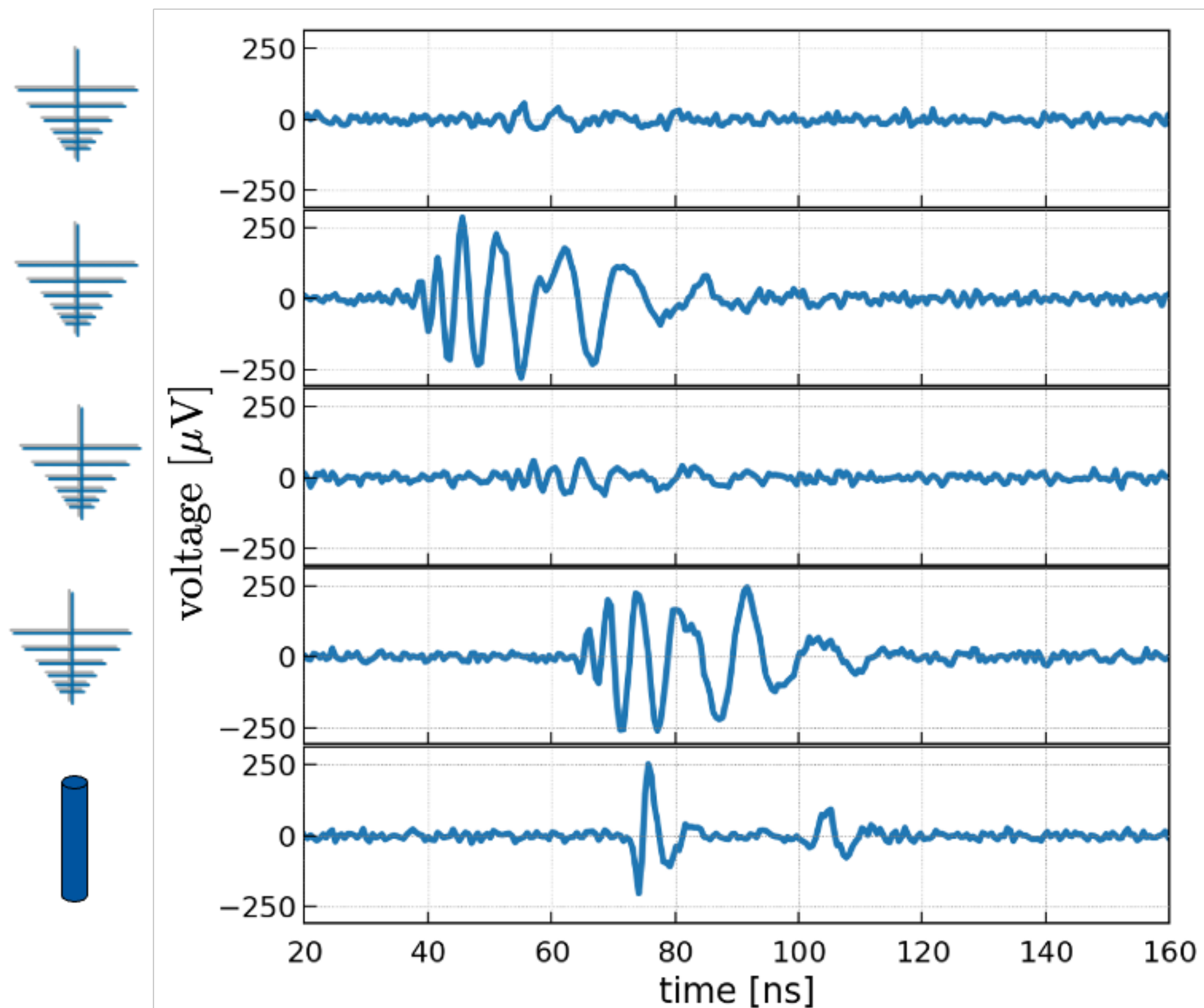
- Ultra-high energy ($> \text{PeV}$) neutrino flux is too low for IceCube to measure
- 100 times the effective volume is needed



Interesting astrophysics:
Active galactic nuclei, gamma
ray bursts, pulsars, blazars,
cosmogenic neutrinos, etc.

Radio detection of neutrinos

- Askaryan effect produces radio emission at $E_\nu > 10^{15}$ eV
- Attenuation length of radio signals in ice is 1-2 km

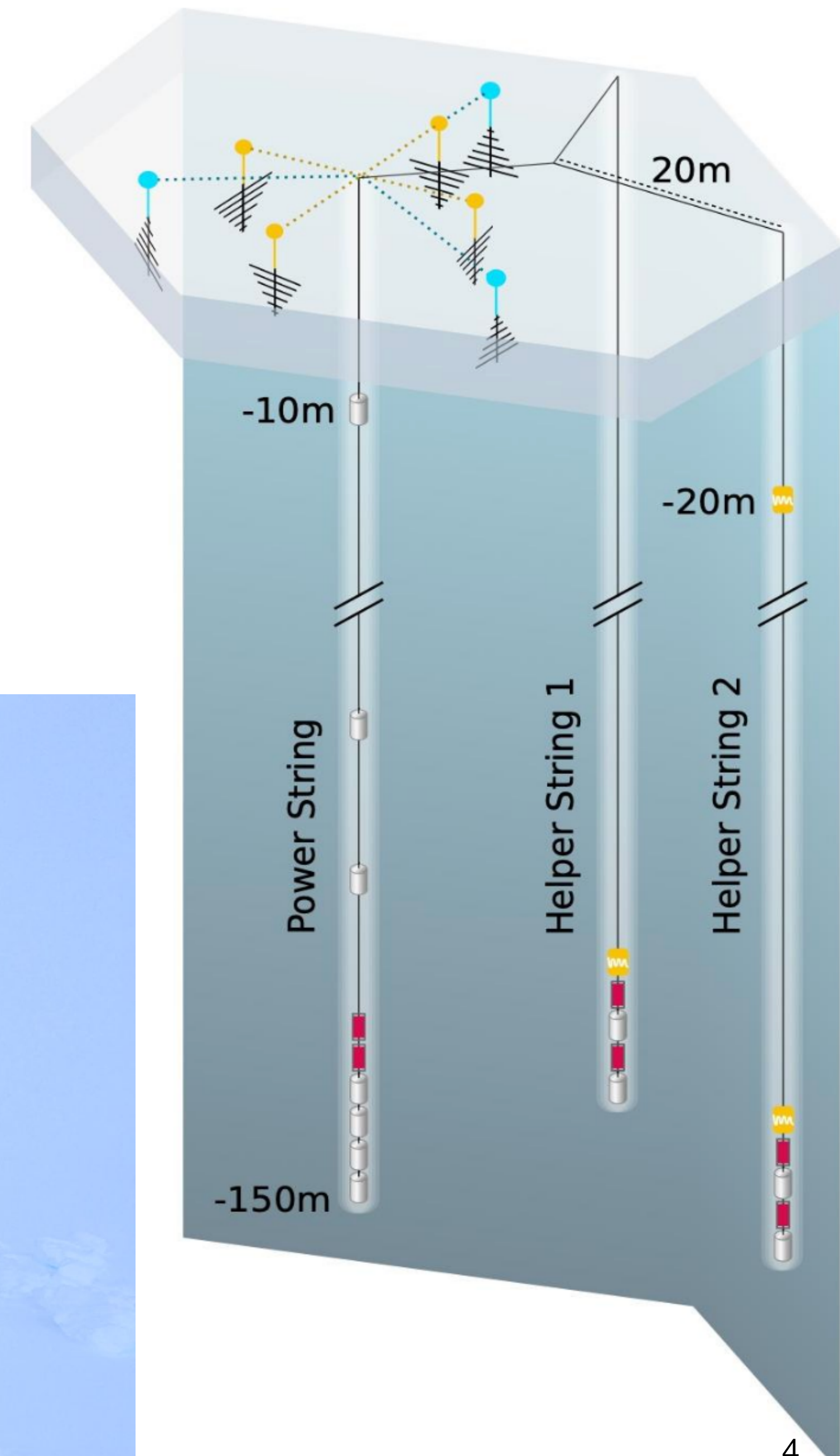


Experimental landscape

- In-ice radio detection:
 - ARIANNA
 - ARA
 - **RNO-G** (8 out of 35 stations deployed)
 - Future: IceCube-Gen2 Radio (~350 stations)

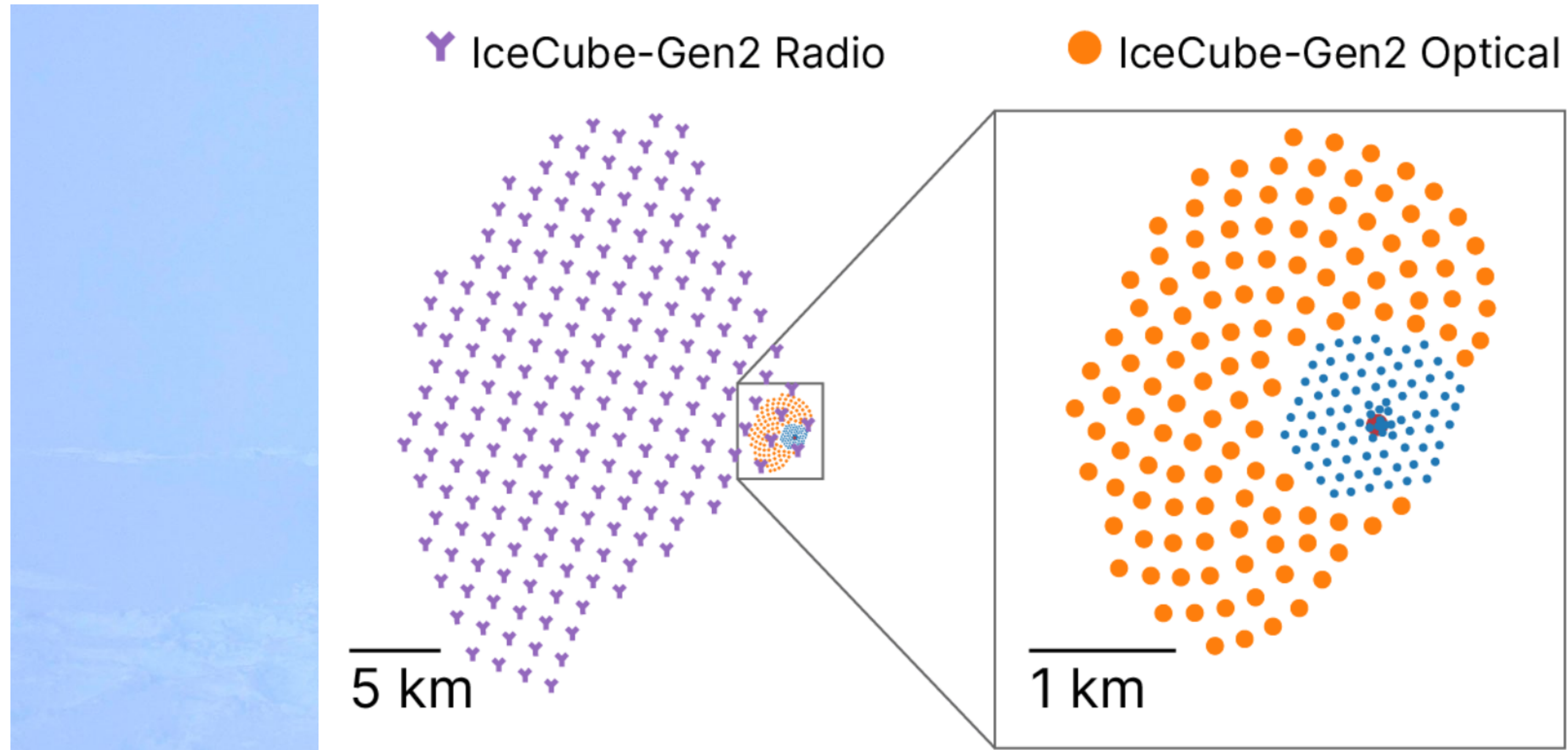


In-ice radio station:

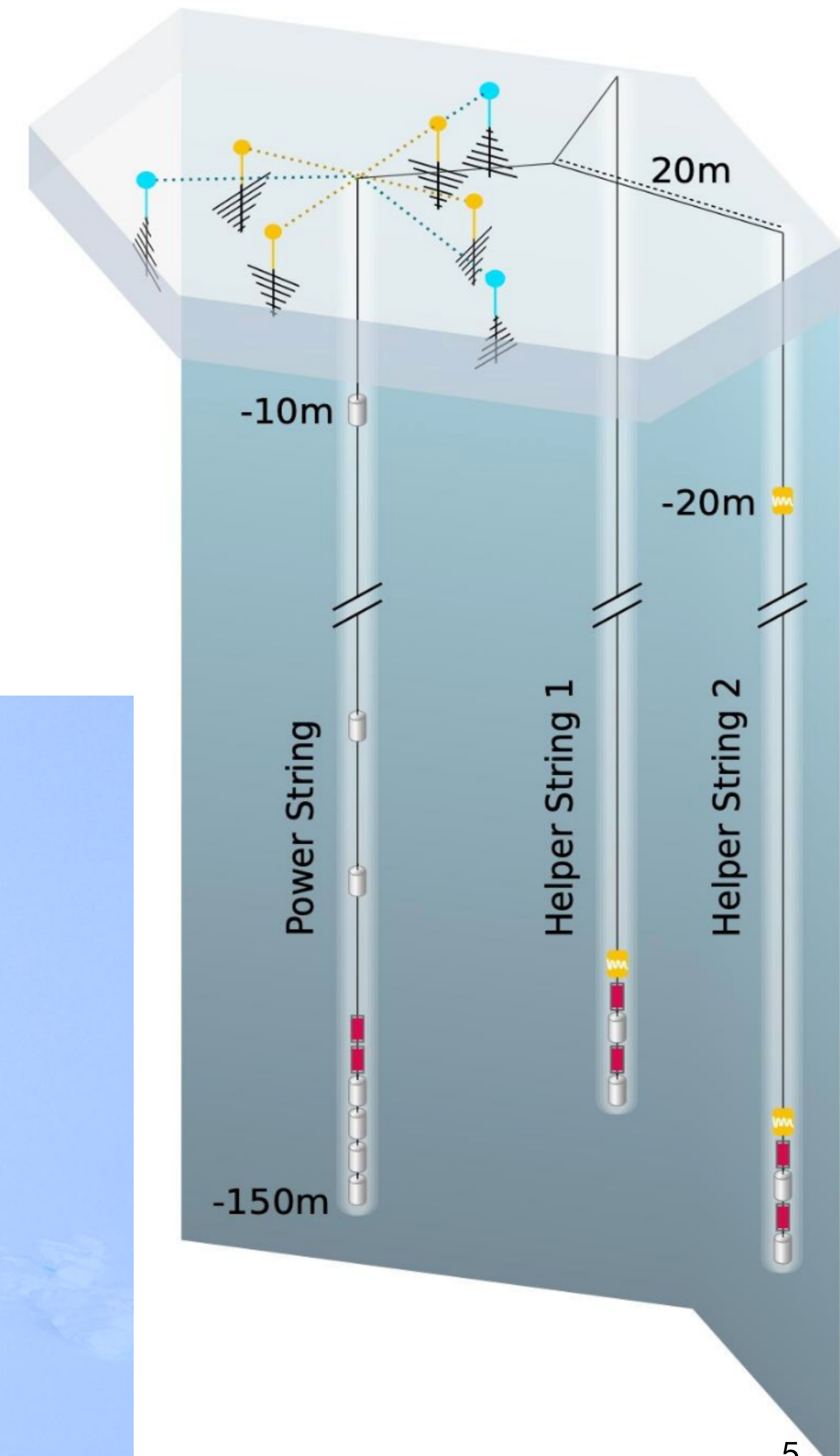


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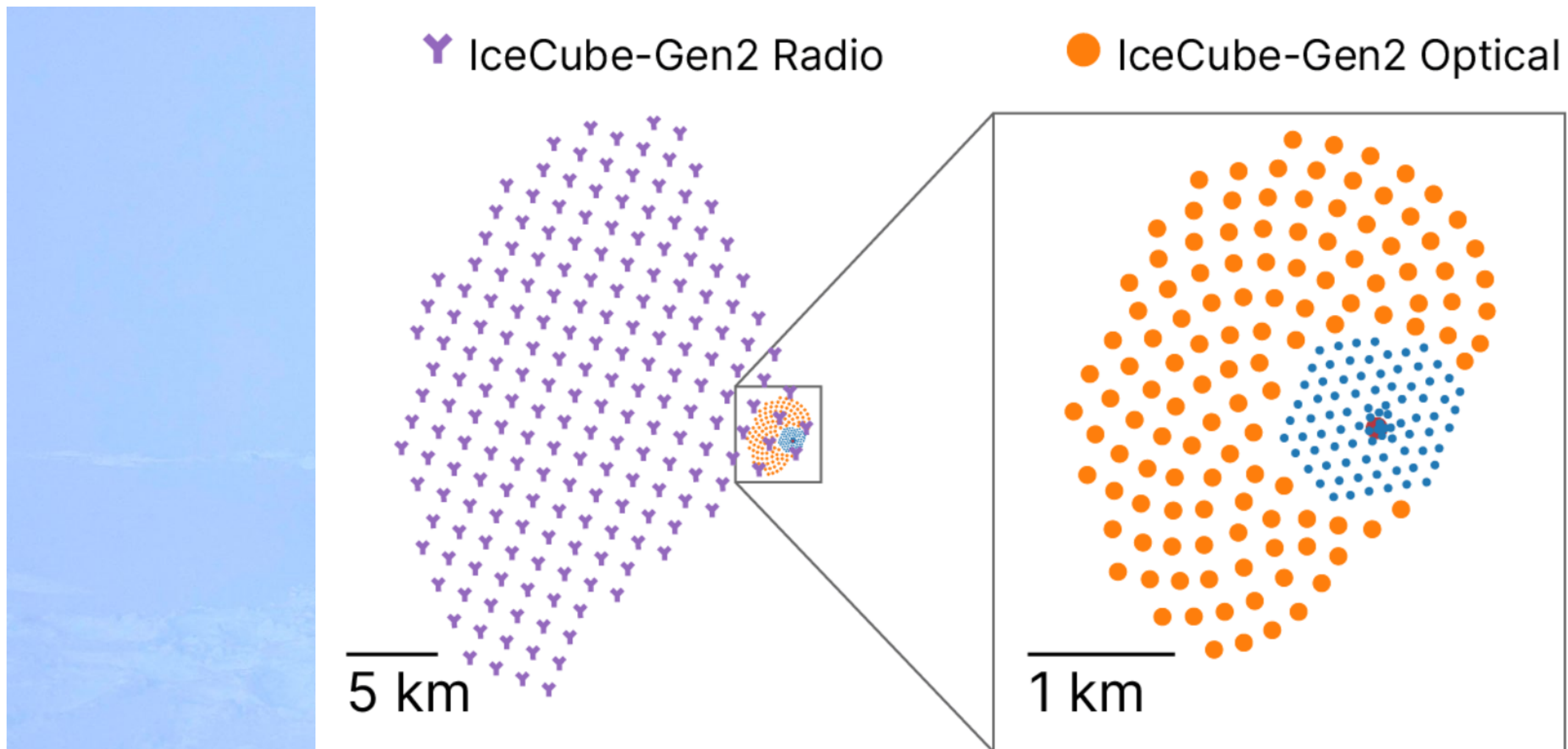


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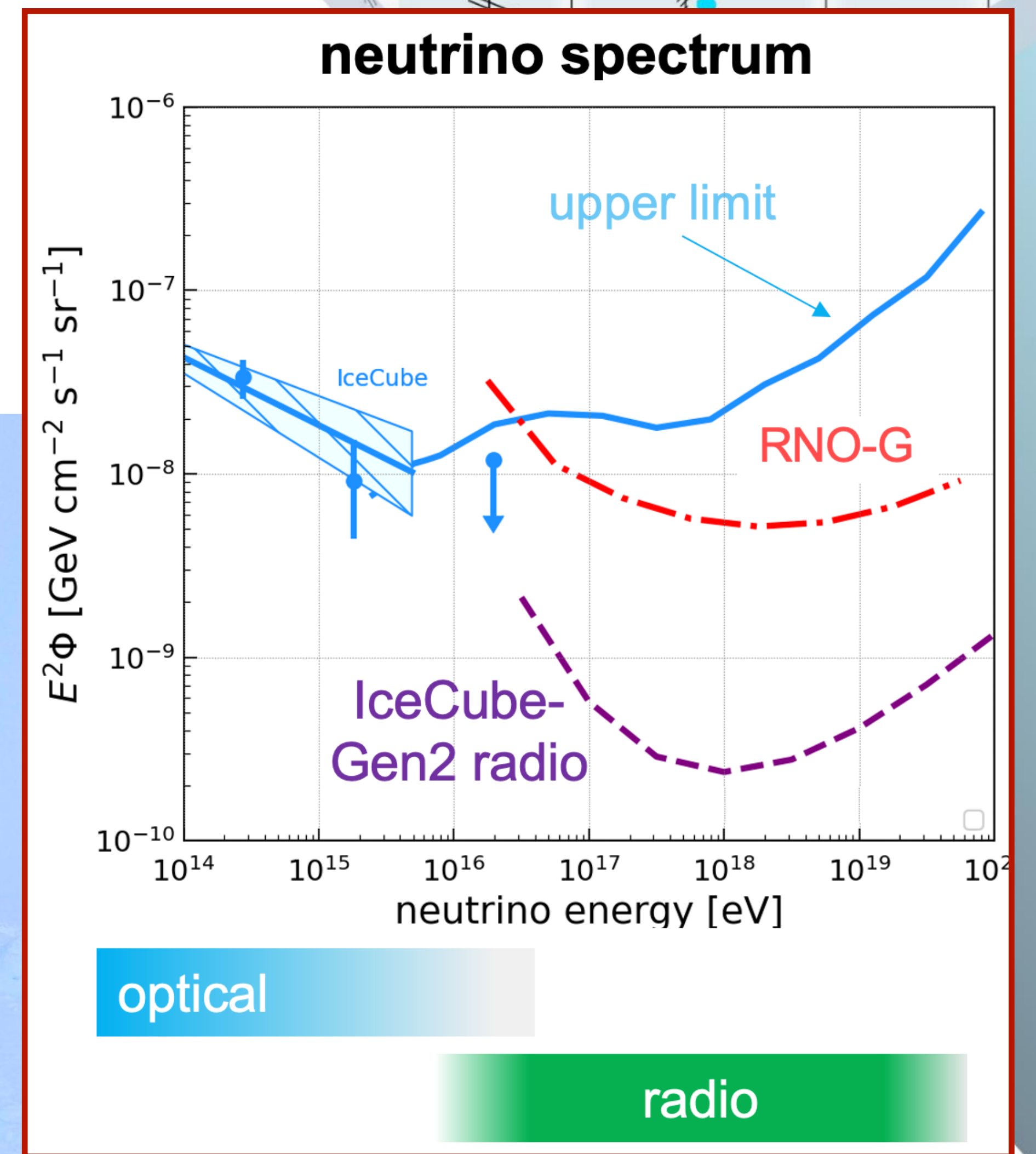
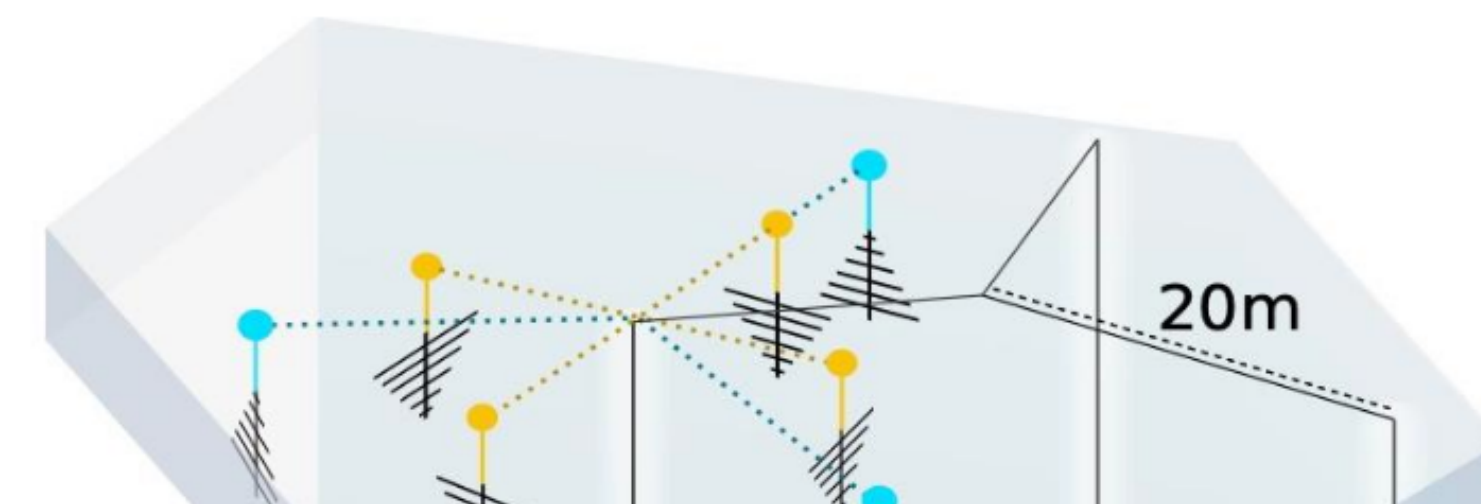


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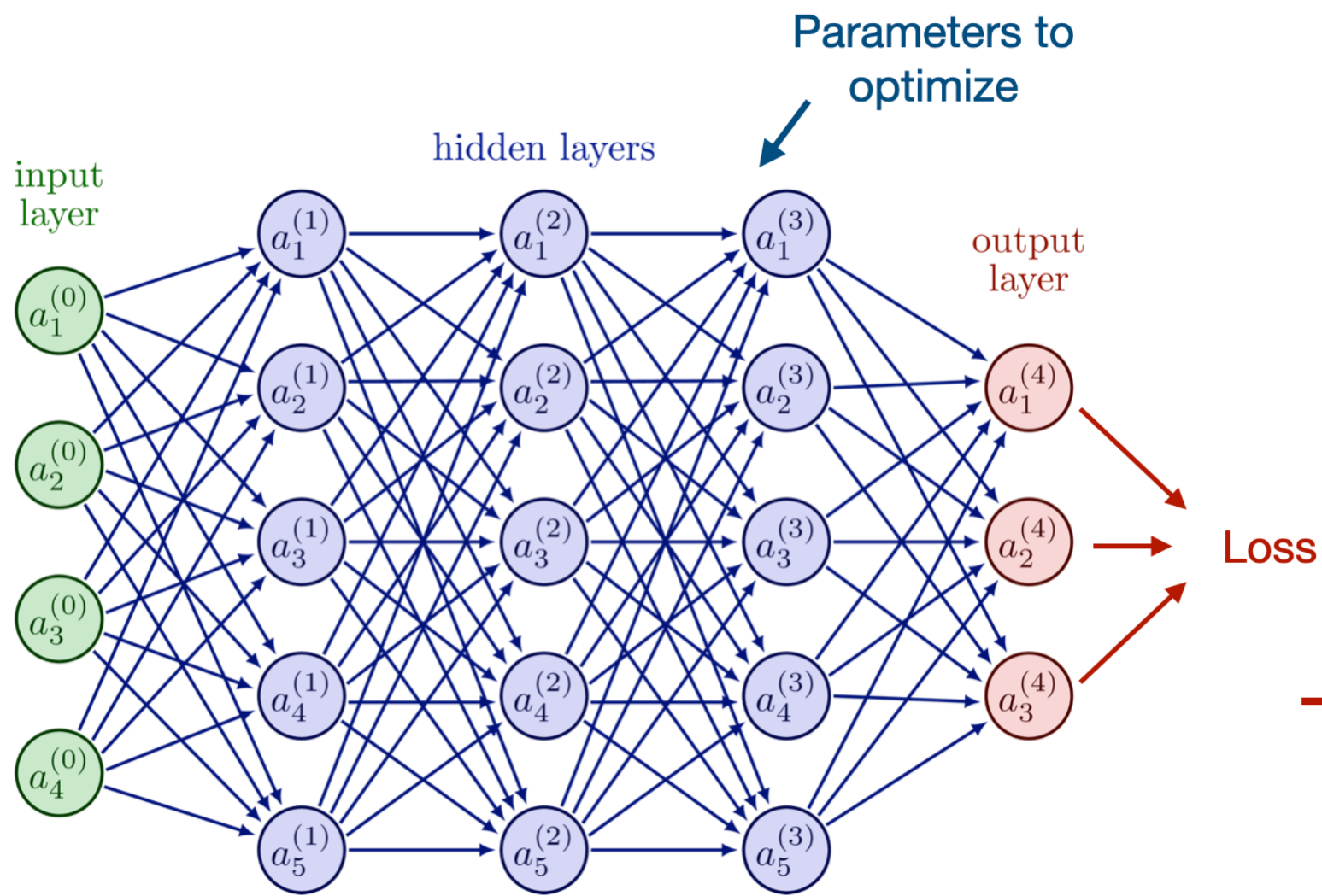
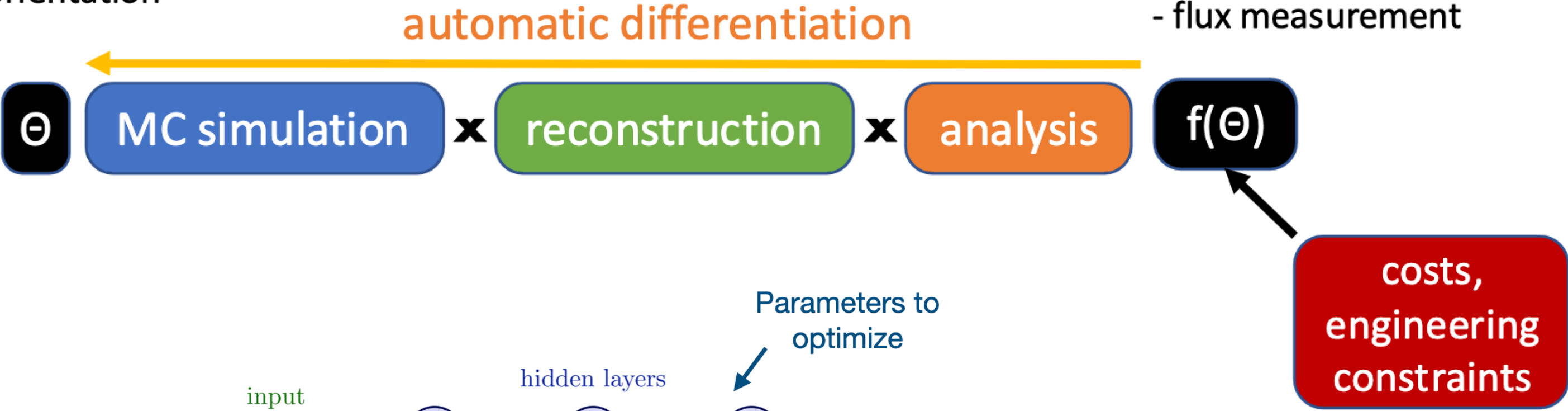
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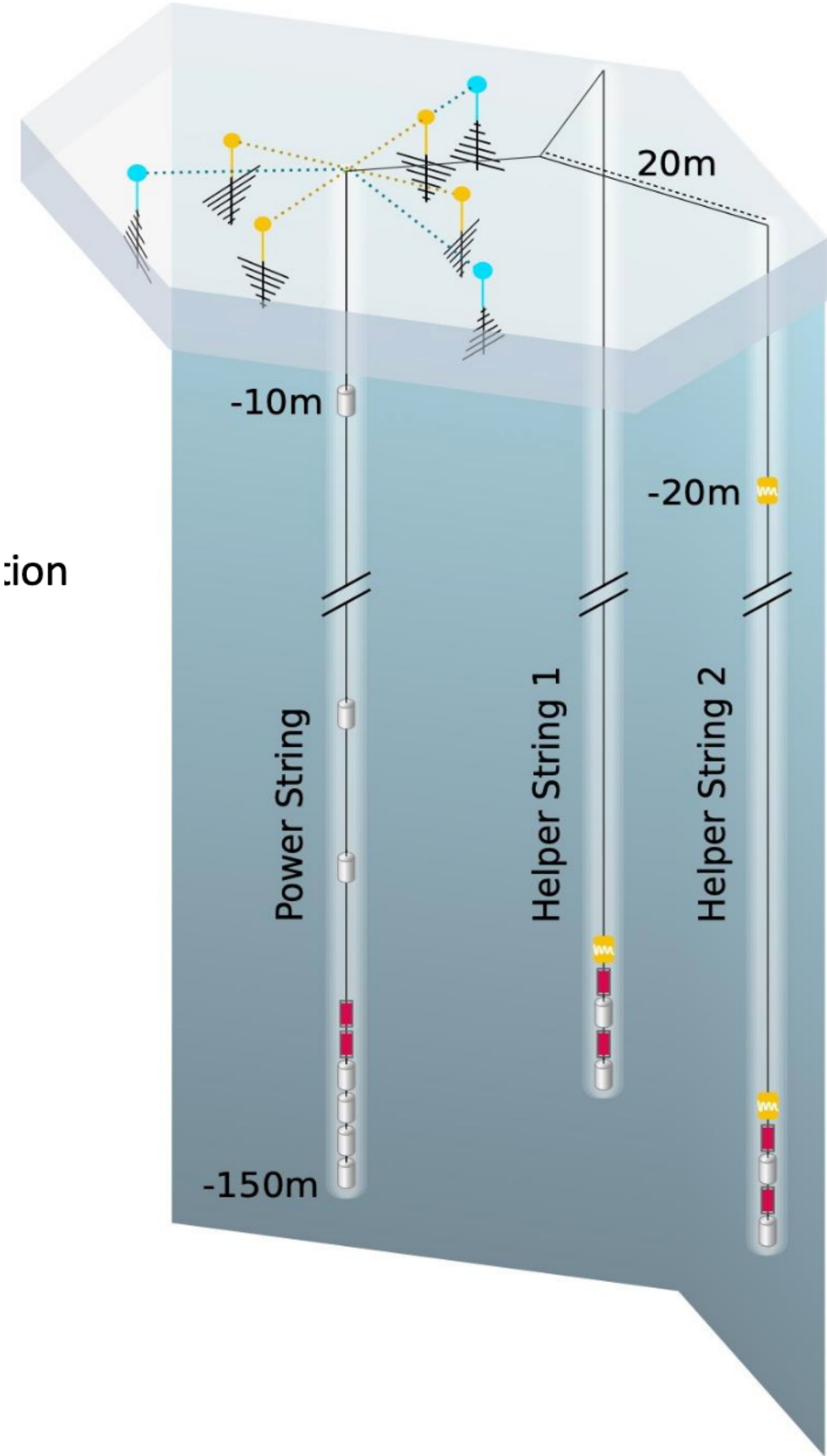
IceCube-Gen2 Radio detector design

- Traditional **detector optimization** is slow
- Make pipeline **differentiable** using PyTorch

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

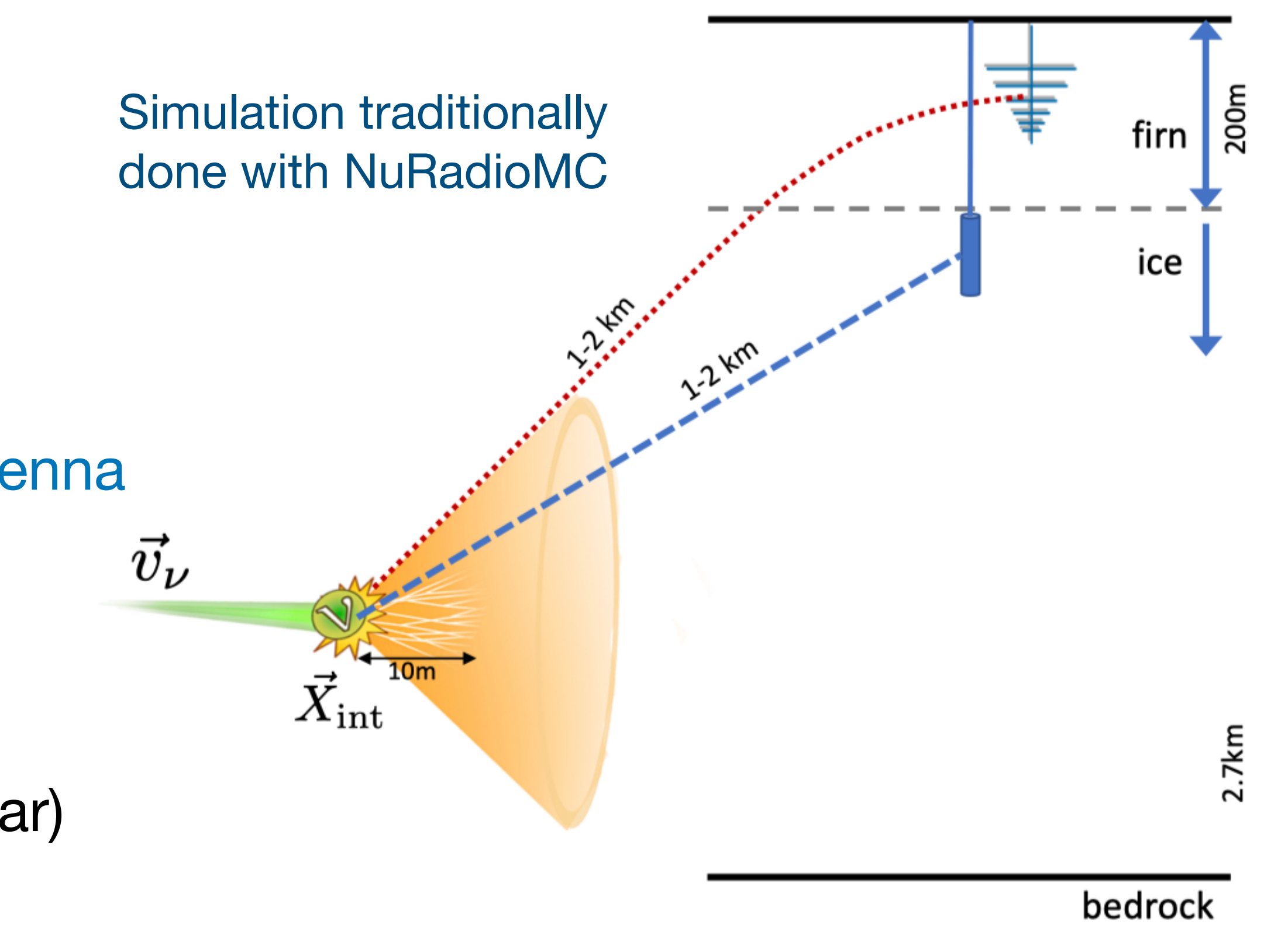


Train detector like
neural network

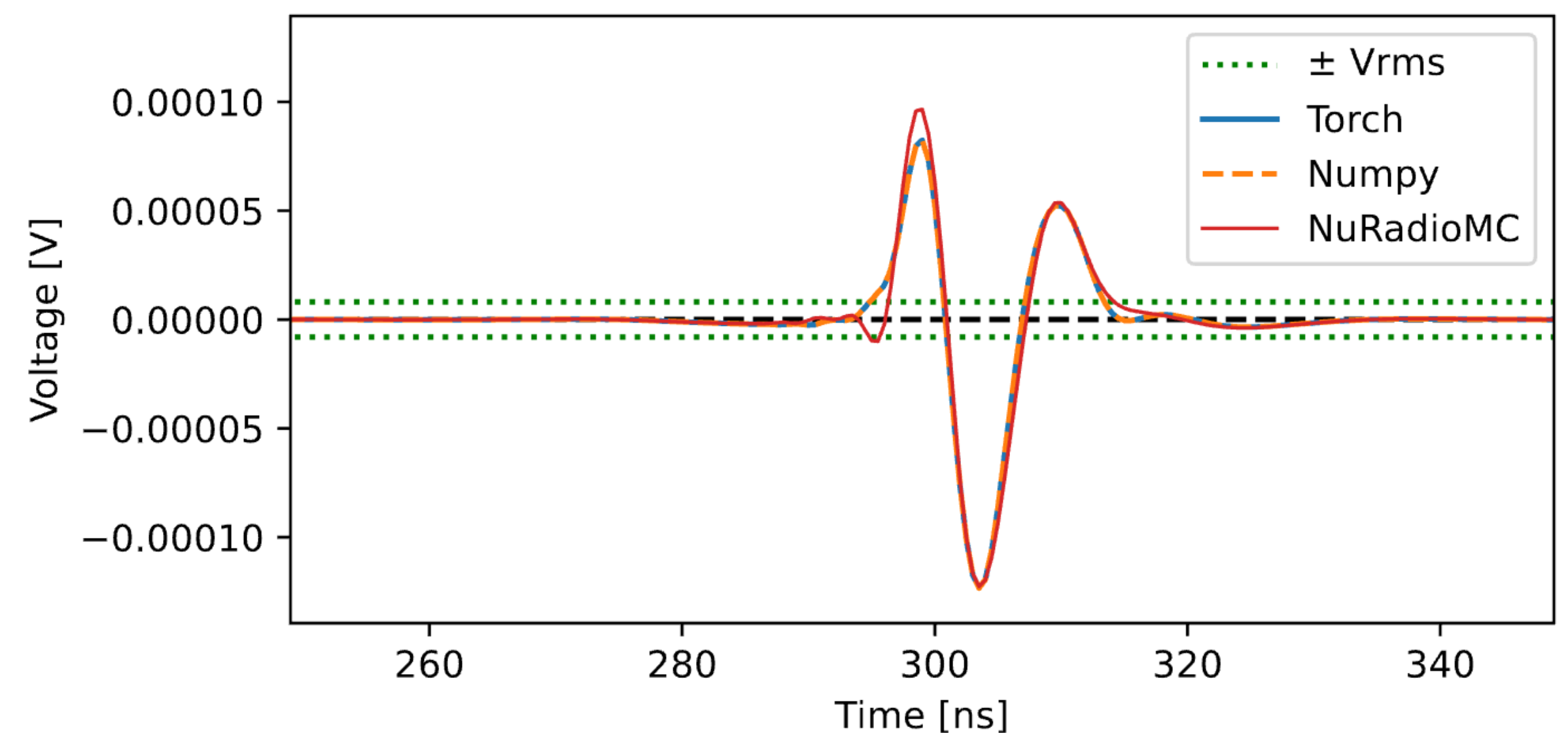


Differentiable simulation pipeline

- Input: Neutrino and detector parameters:
 - E_{shower} , θ_ν , ϕ_ν , x_ν , y_ν , z_ν , t_0 , `xyz_antenna`, `ori_antenna`
- Simulation implemented in PyTorch:
 - Event geometry
 - Askaryan emission (Diffusion model by Philipp Pilar)
 - Propagation (straight line - constant n)
 - Detection (LPDAs)
- Output:
 - Voltage traces**

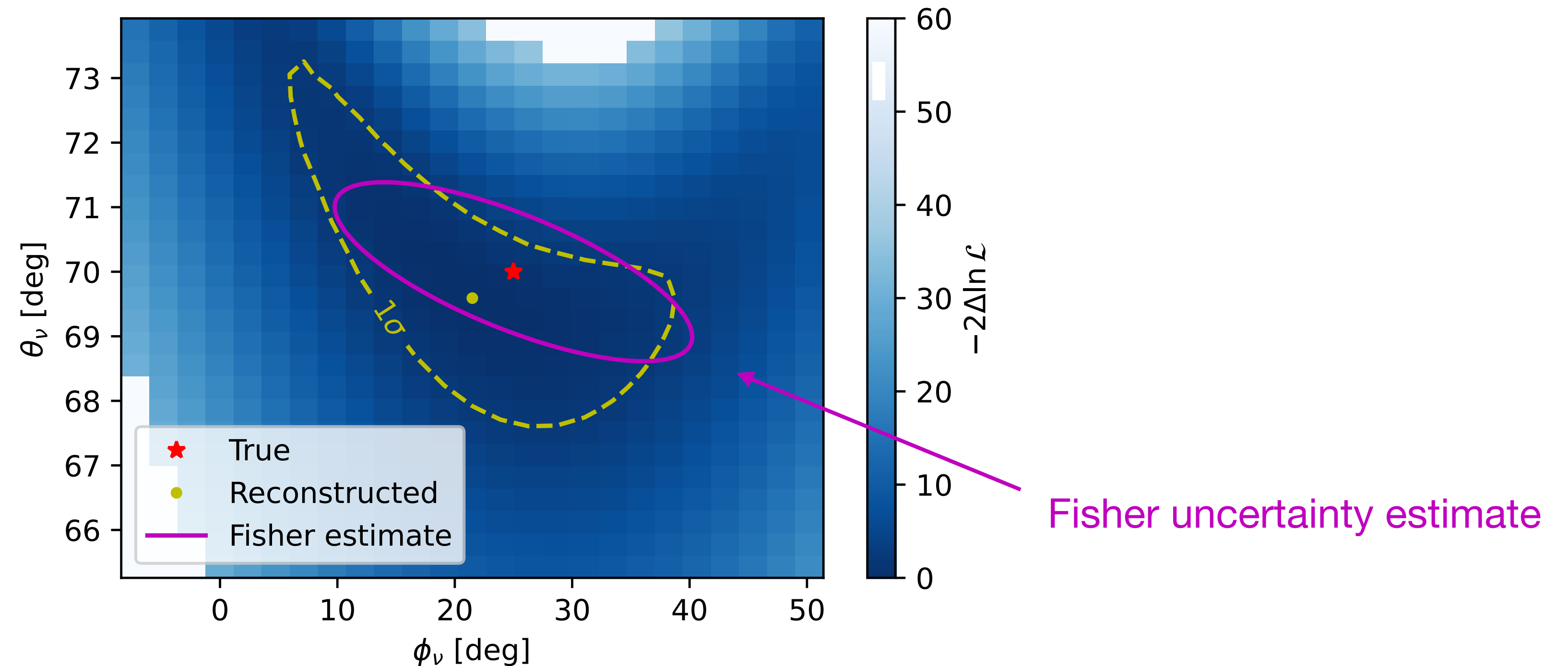


Example simulation:



Reconstruction uncertainty estimation

- Reconstruction of MC **neutrino arrival direction** in in-ice radio detector:



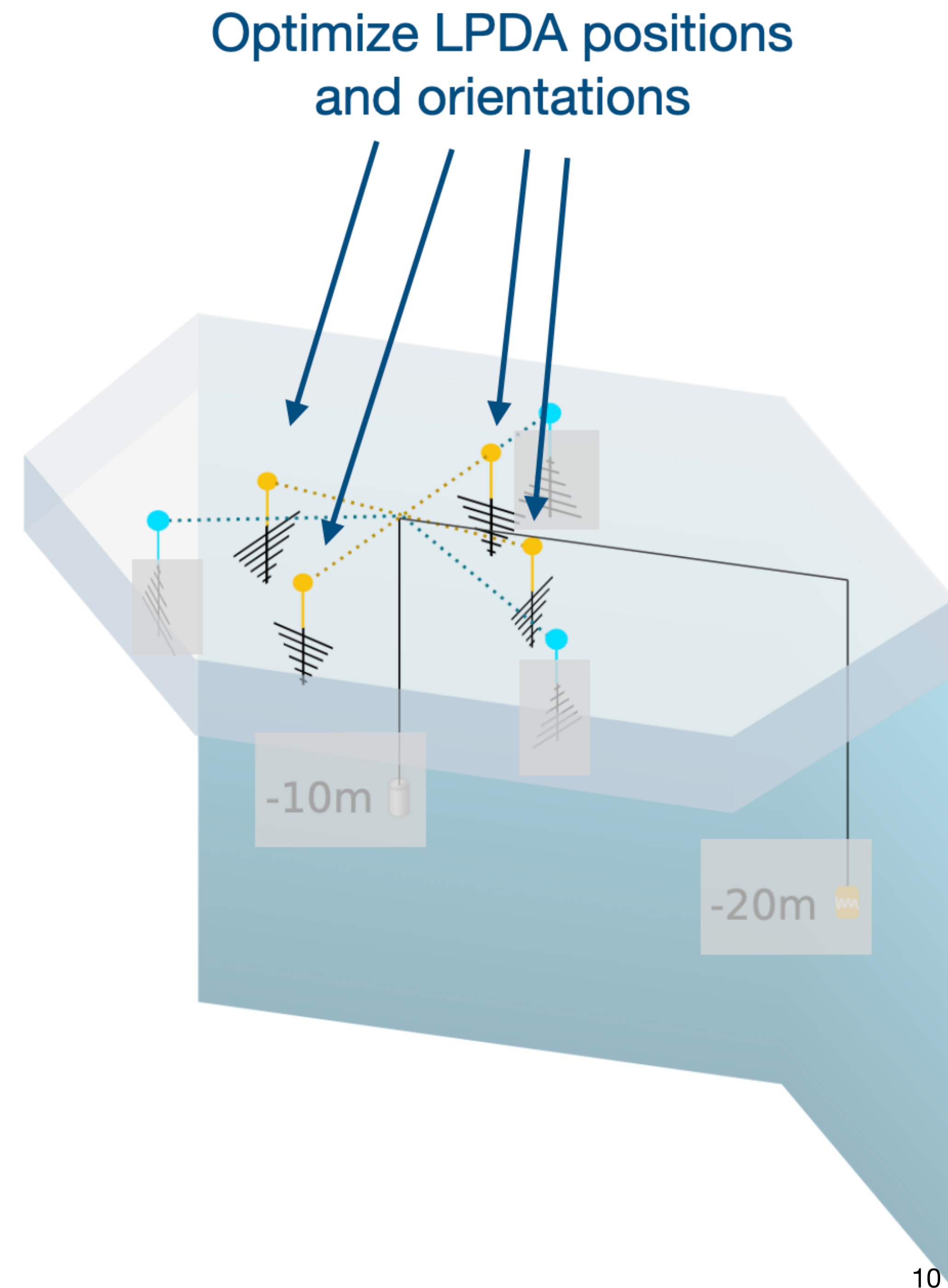
- Uncertainty can be estimated with **Fisher information**
- Orders of magnitude faster than full reconstruction
- Implemented in PyTorch

$$\mathcal{I}_{m,n} = \sum_{ant.} \frac{\partial \boldsymbol{\mu}^T}{\partial \theta_m} \boldsymbol{\Sigma}^{-1} \frac{\partial \boldsymbol{\mu}}{\partial \theta_n}$$

$$\sigma^2 = \left(\mathcal{I} \right)^{-1}$$

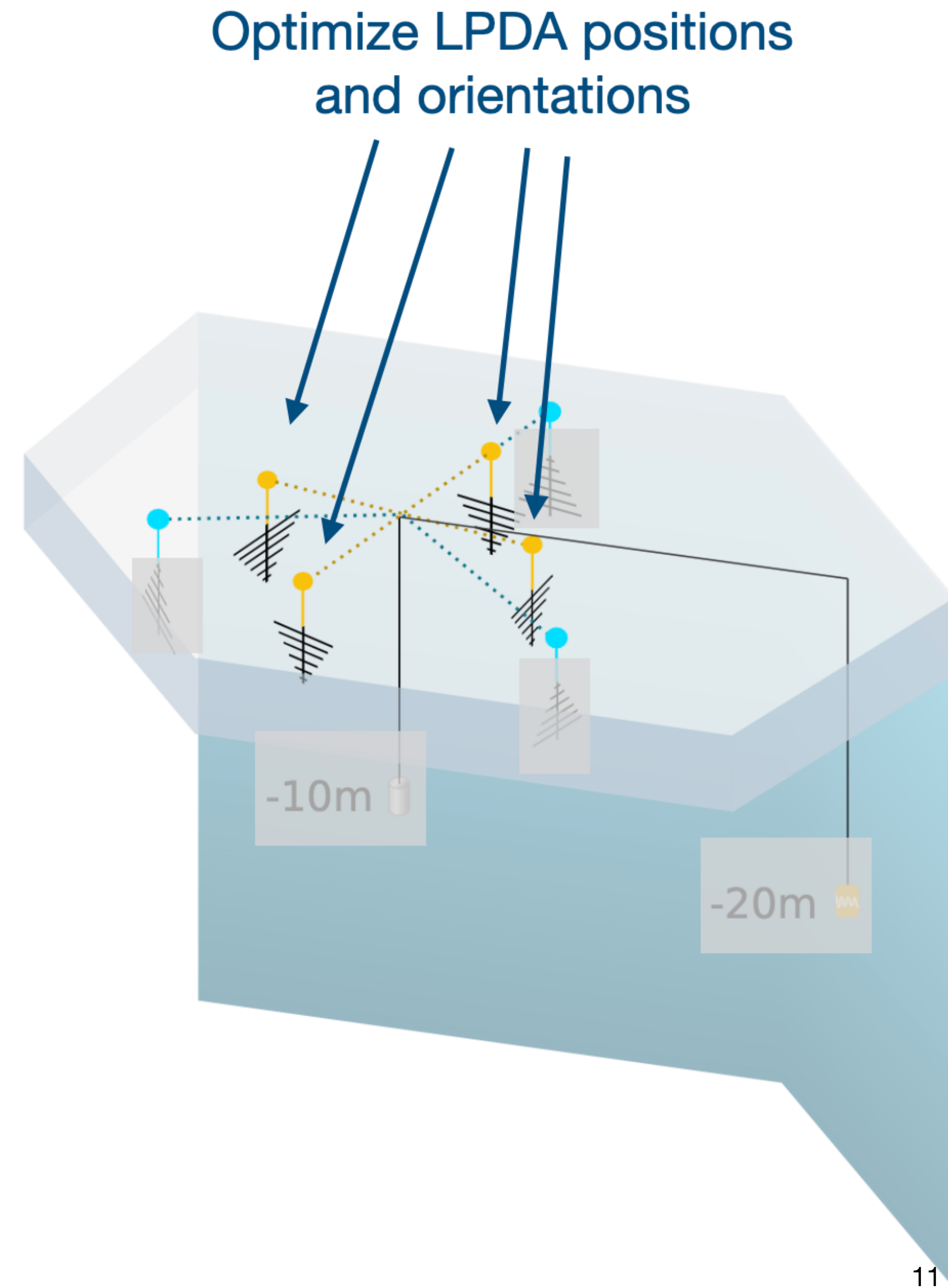
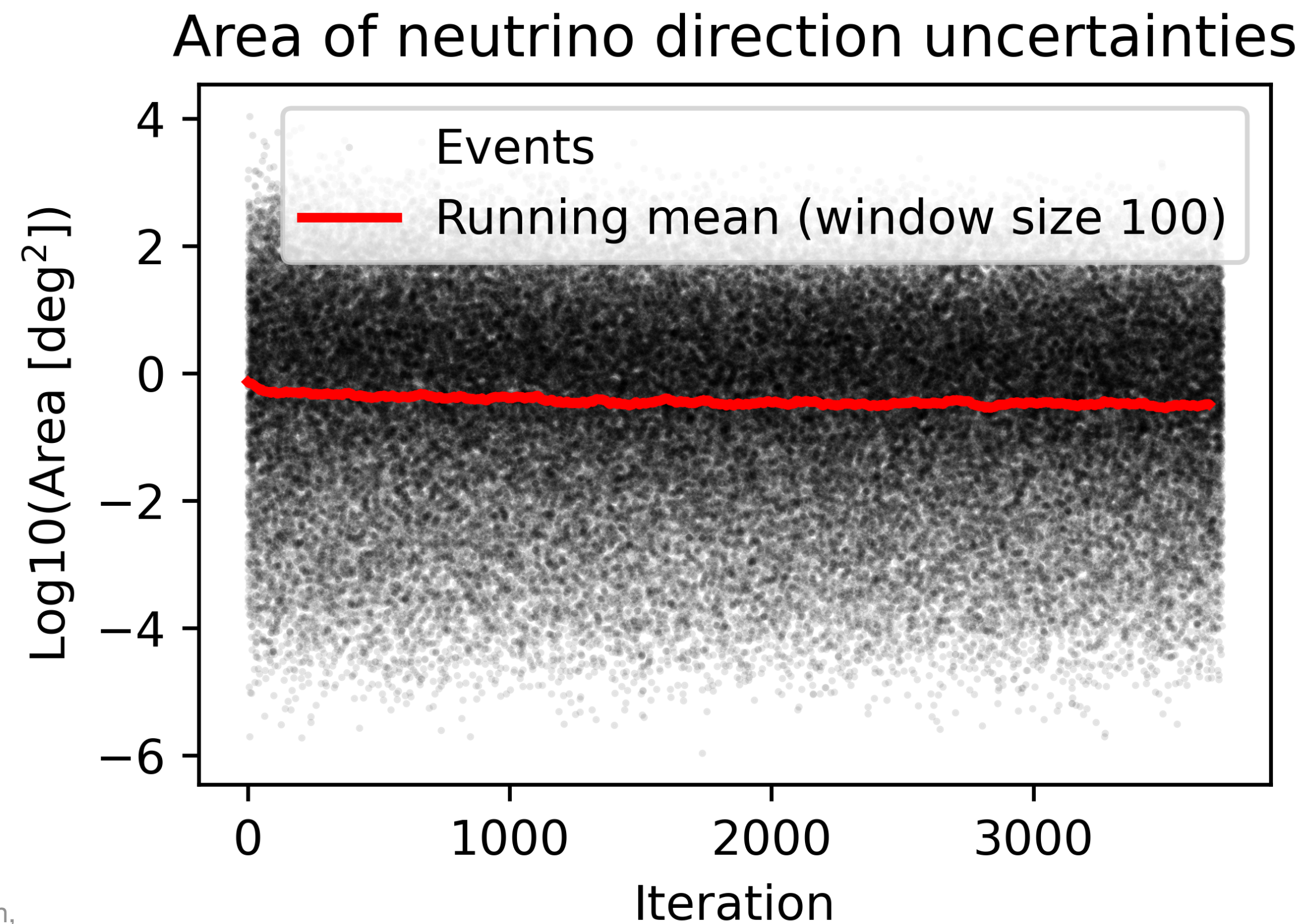
Proof of concept optimization

- Optimize antenna **positions and orientations**
- **Batch**: 28 random neutrino events
- **Loss**: $\log(\text{reconstructed direction uncertainty area})$



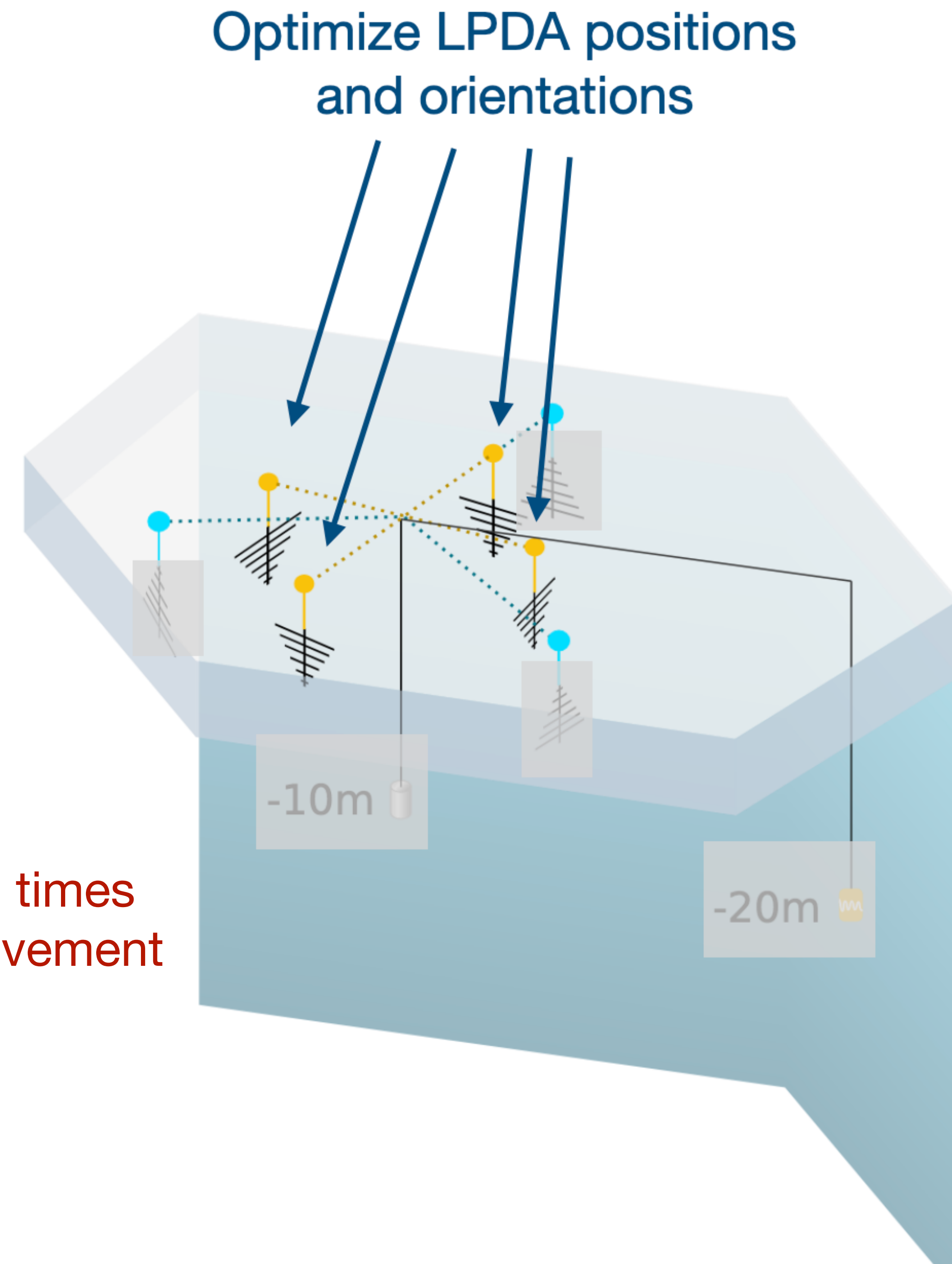
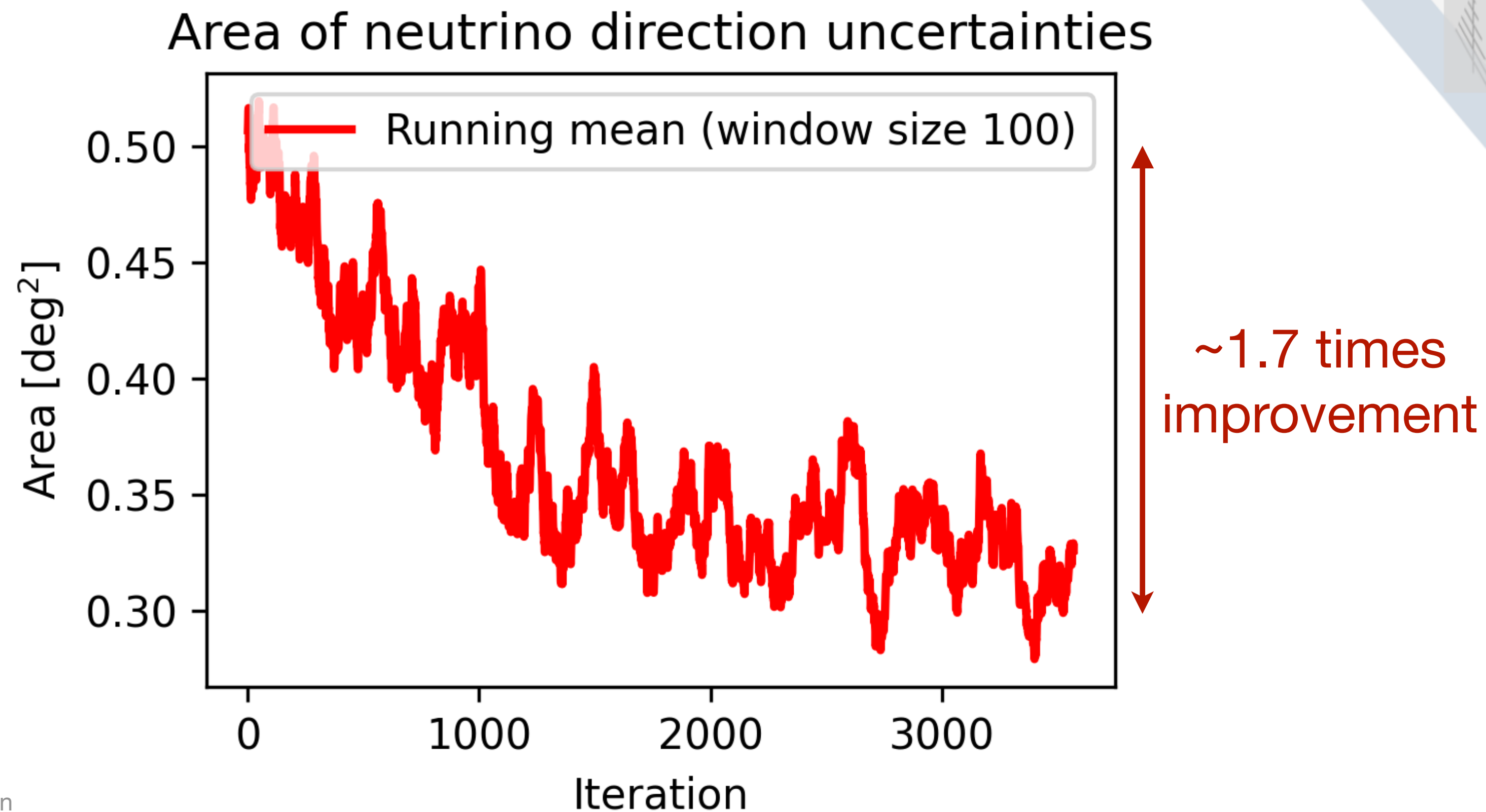
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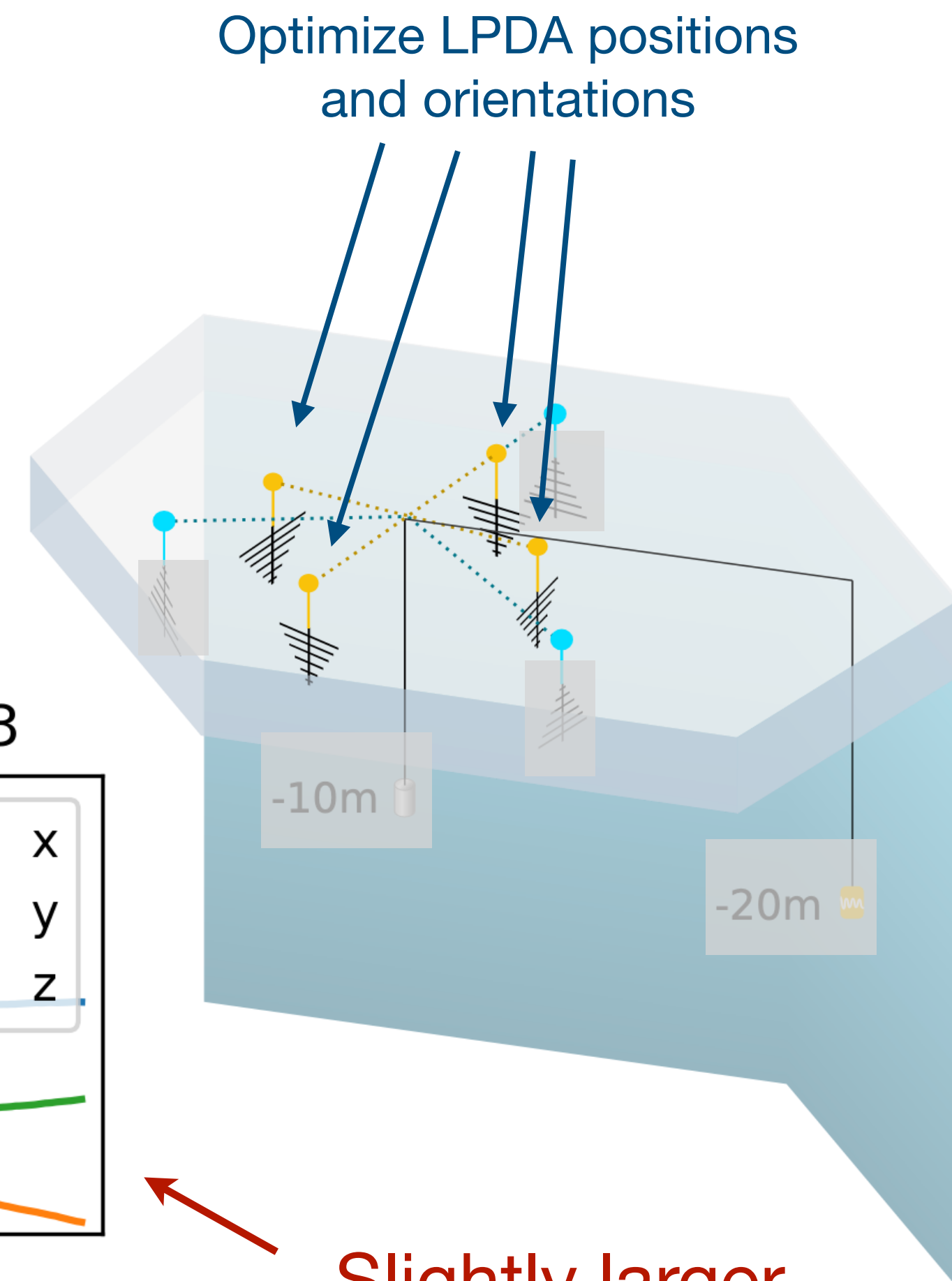
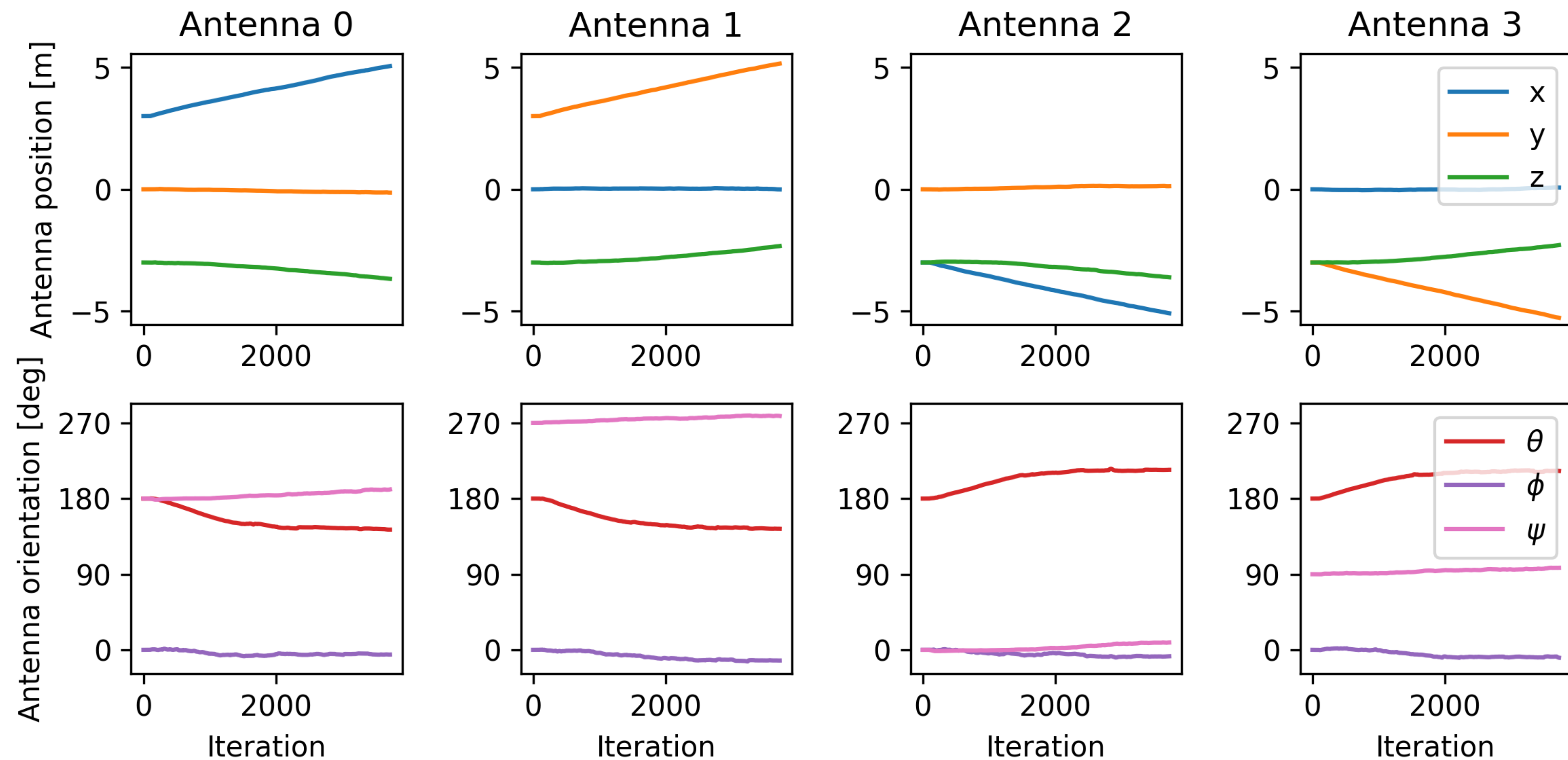
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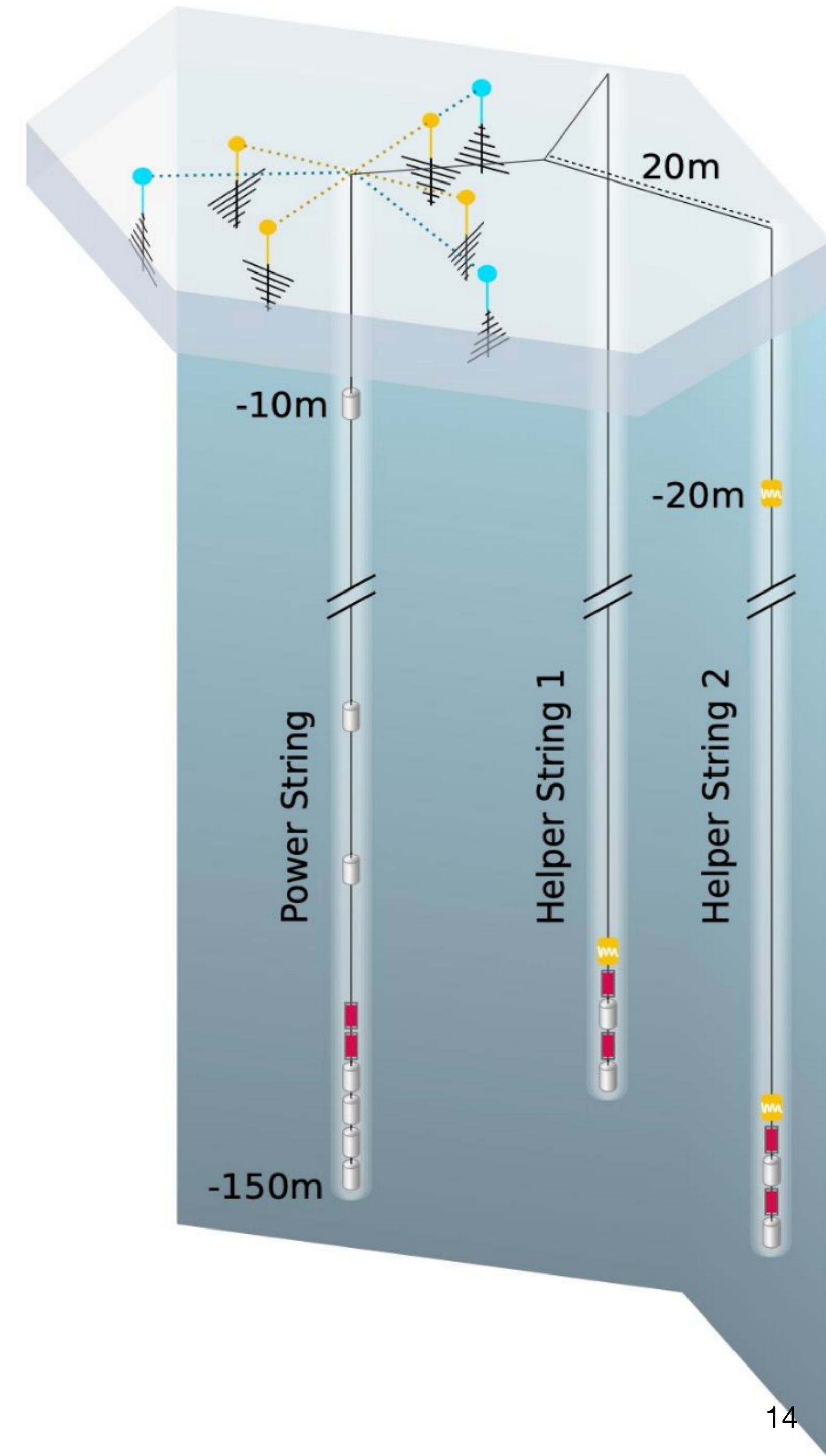
Slightly larger detector

Slightly less downward-facing

Sensible results!

Conclusions

- (Slightly simplified) differential radio neutrino simulation and reconstruction pipeline in PyTorch is ready
- Proof of concept: differentiable end-to-end optimization works
- Next steps:
 - Increase realism of the differentiable signal model (in particular in-ice ray-tracing with surrogate model)
 - Use large event sample with realistic neutrino distributions
 - Optimize more complex stations with more antennas
 - Full end-to-end optimization of the RNO-G and Gen2 radio stations



Extra slides

NuRadioOpt

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

This talk

Main science objectives
of UHE neutrino astronomy:

Neutrino-Nucleon
Cross Section

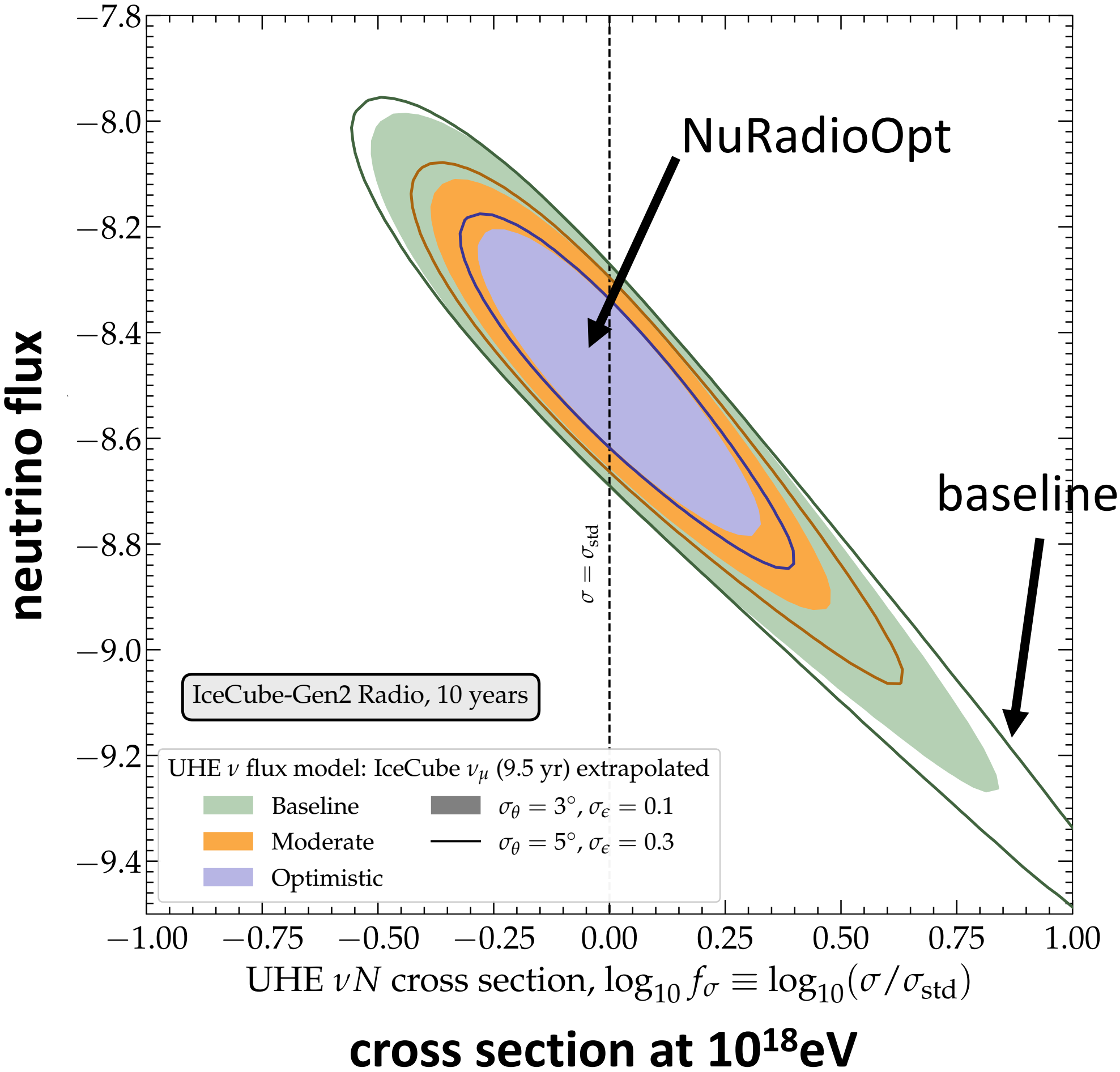
Diffuse Flux

Point Sources

Impact of NuRadioOpt

→ 3x more precise measurement

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



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

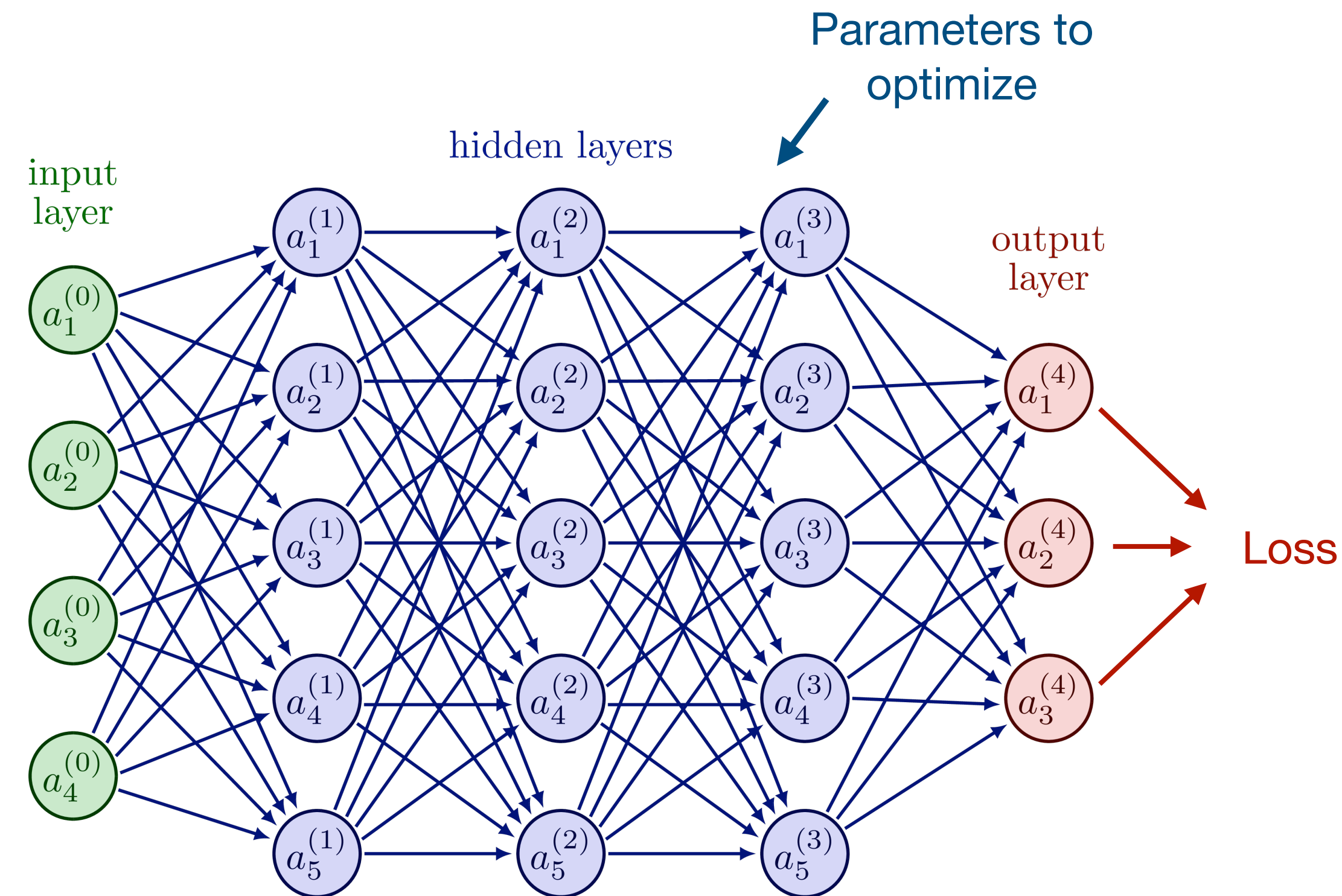
→ identify sources from deeper in our Universe,
increasing the observable volume by a factor of three

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

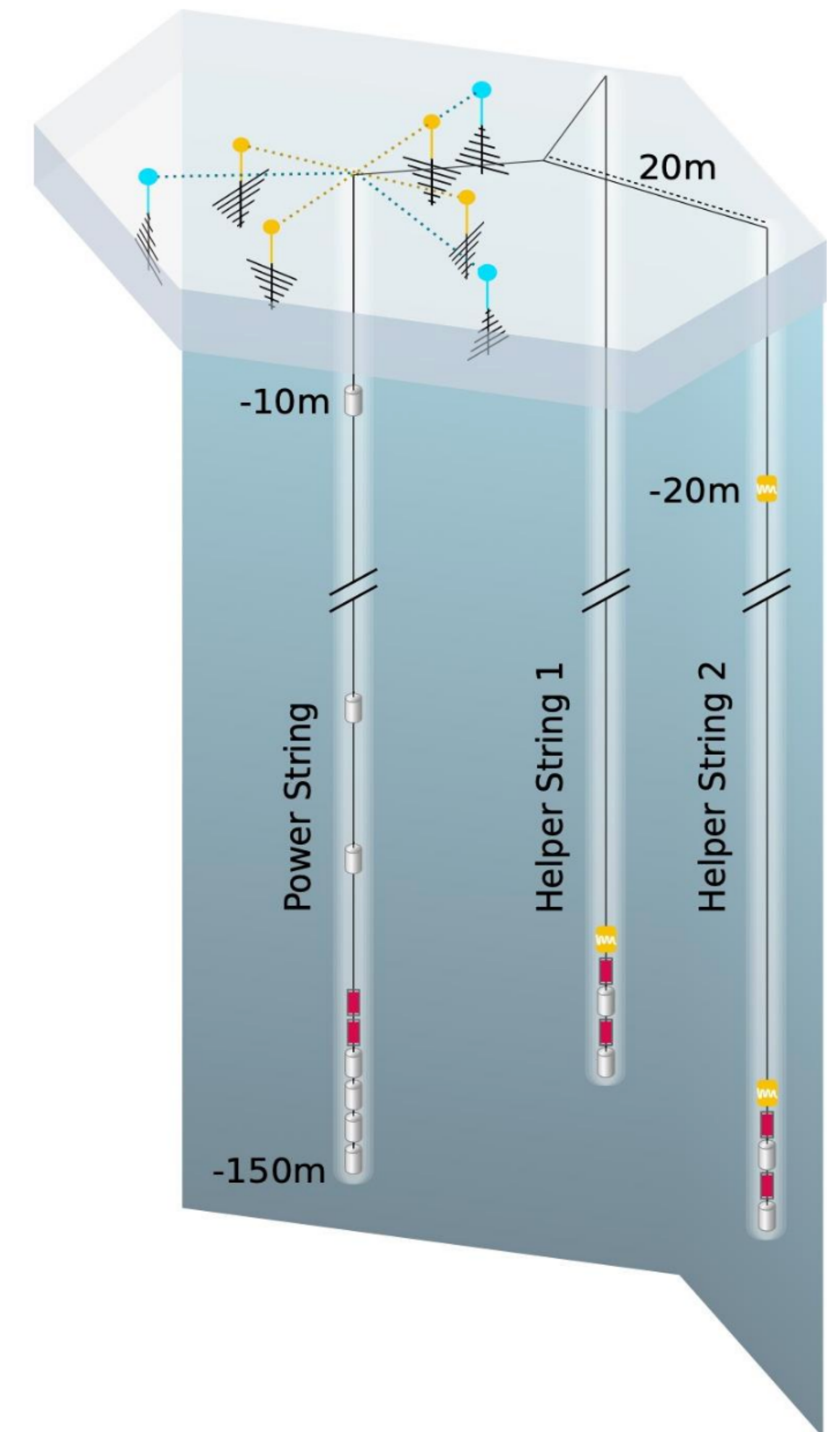
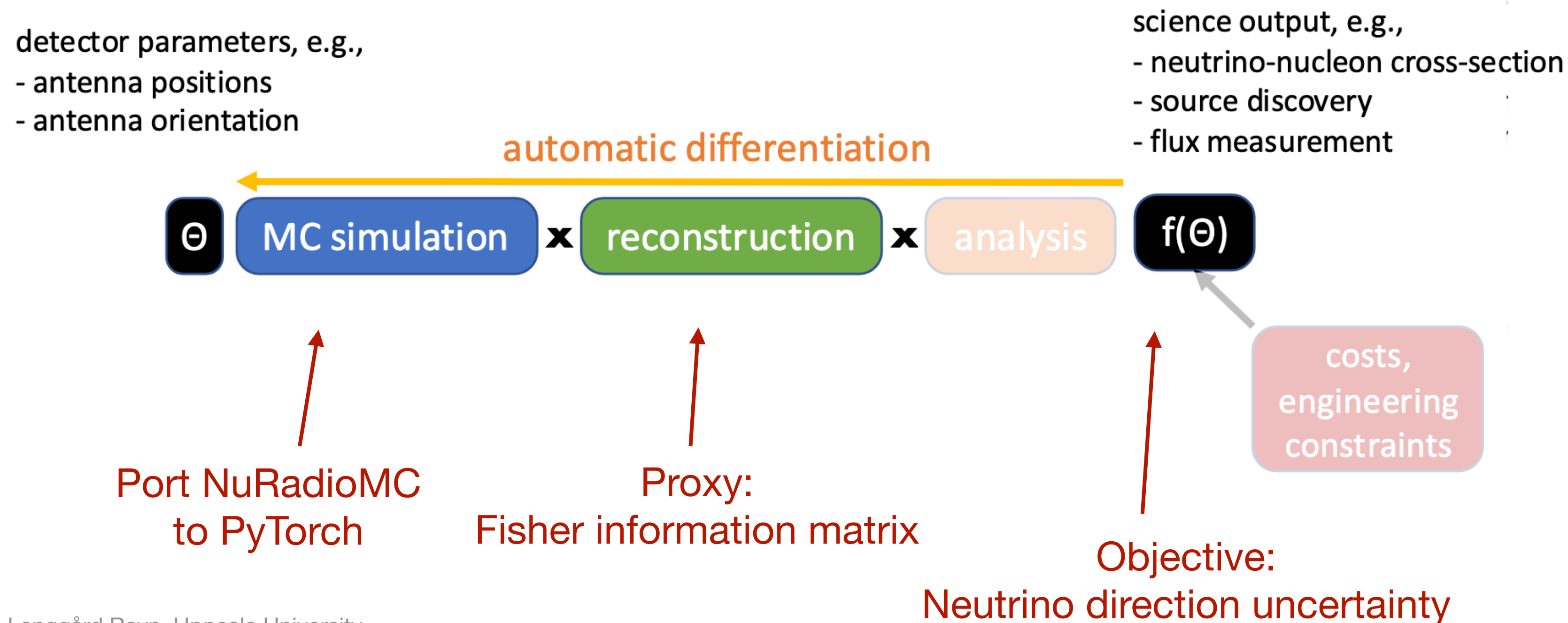
Differentiable programming

- Central concept in machine learning
- Automatically calculate and save derivatives of output w.r.t. parameters in forward pass
- Calculate gradient of loss w.r.t. parameters in backpropagation (chain rule)
- Take step opposite gradient to optimize network
- Use for detector optimization:
 - Network is simulation pipeline
 - Input is neutrino parameters
 - Parameters are detector parameters
 - Loss is neutrino reconstruction uncertainty
- We can utilize differential programming frameworks to optimize detector layouts



IceCube-Gen2 Radio detector design

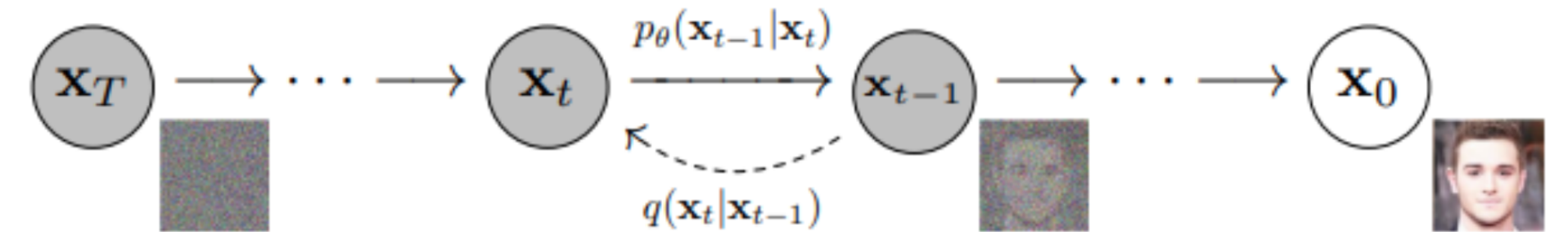
- Traditional detector optimization is slow
- Deep learning and differential programming can build an end-to-end optimization pipeline
- Direct optimization of science objective



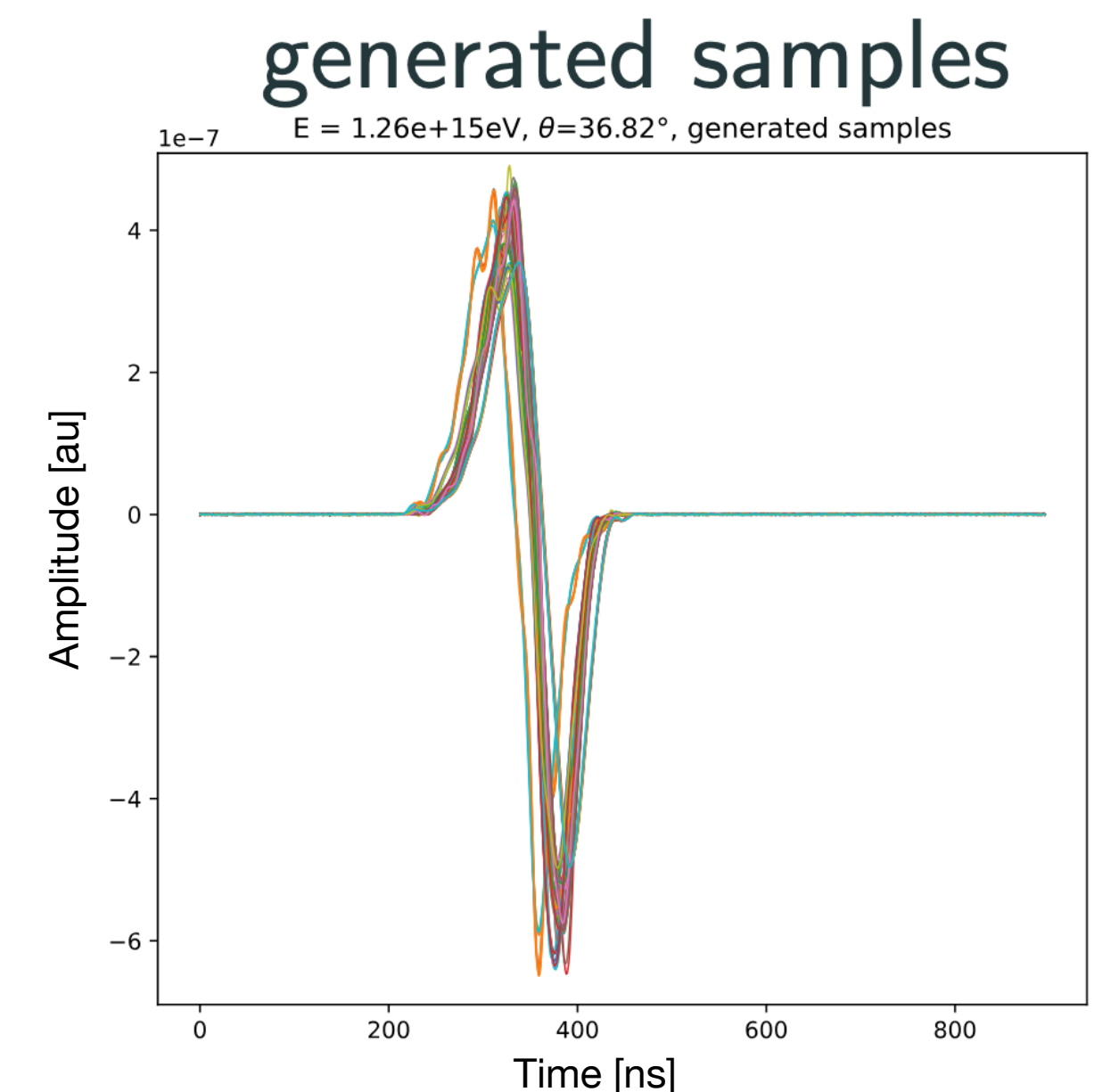
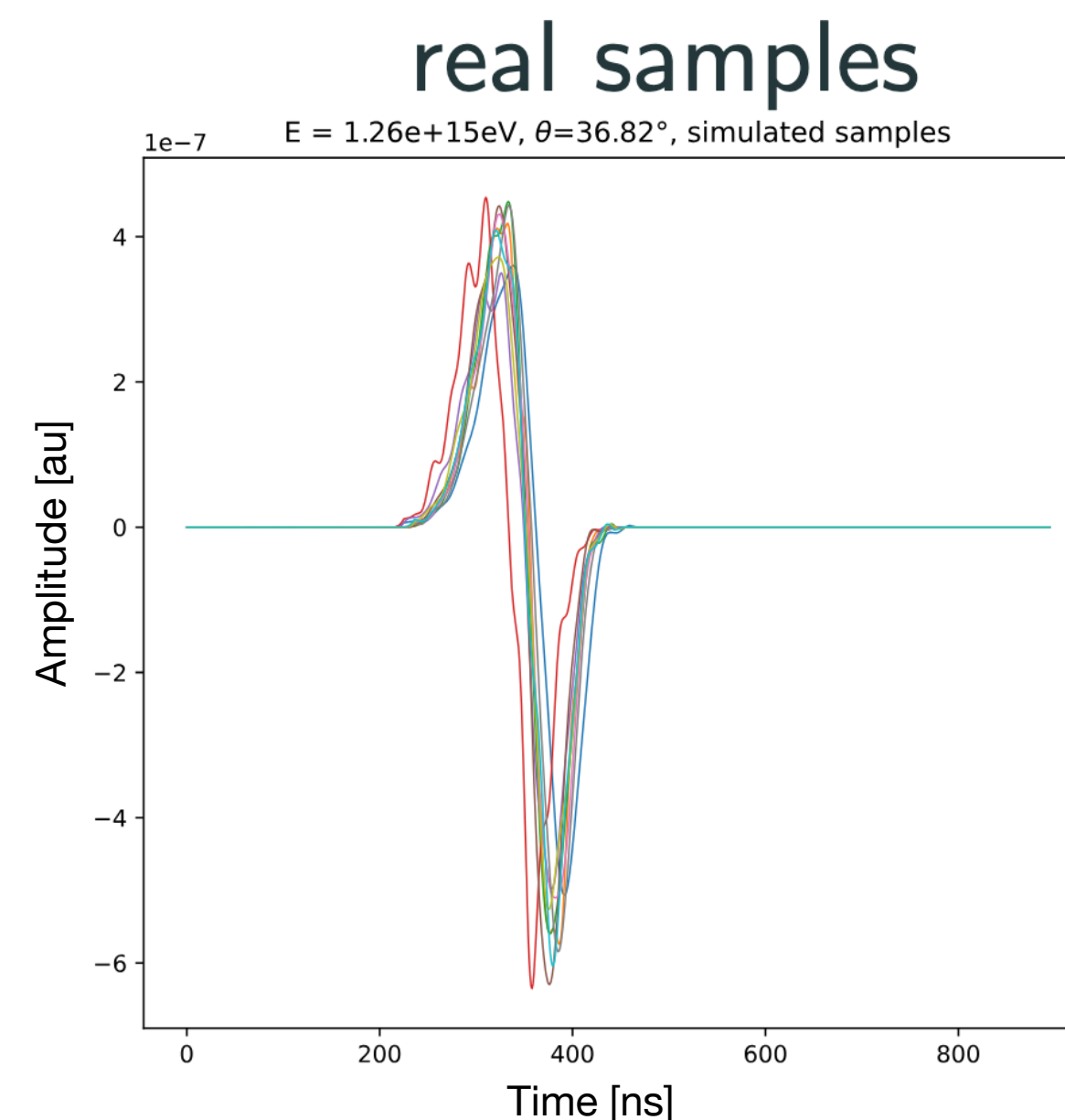
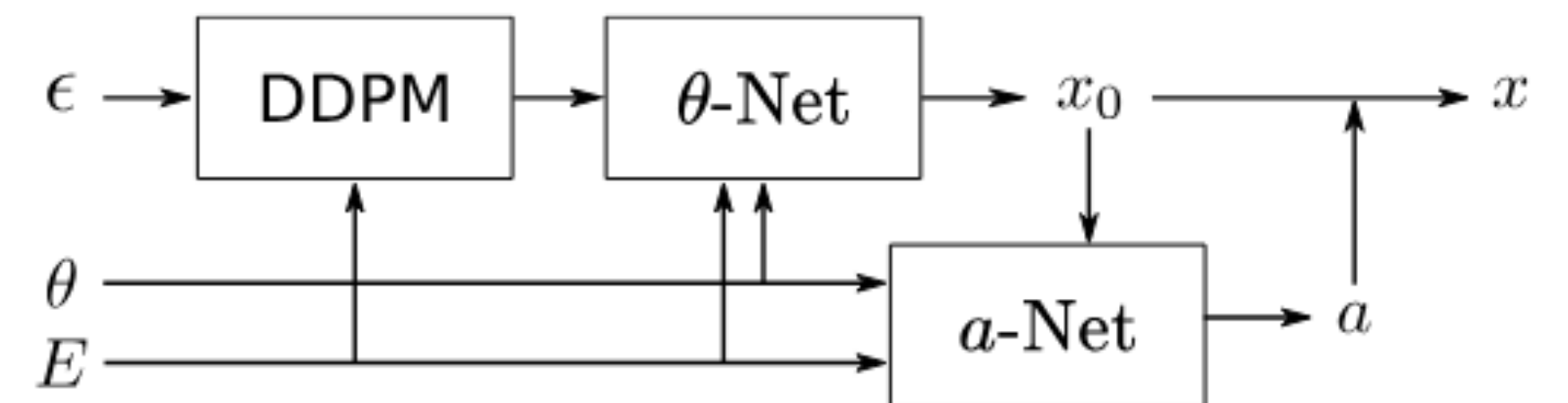
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Shown at last year's MODE Workshop:



Diffusion model trained to generate Askaryan emission (surrogate model):



Likelihood Reconstruction

- Likelihood for Radio Neutrino Detectors:

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

Diagram illustrating the components of the likelihood function:

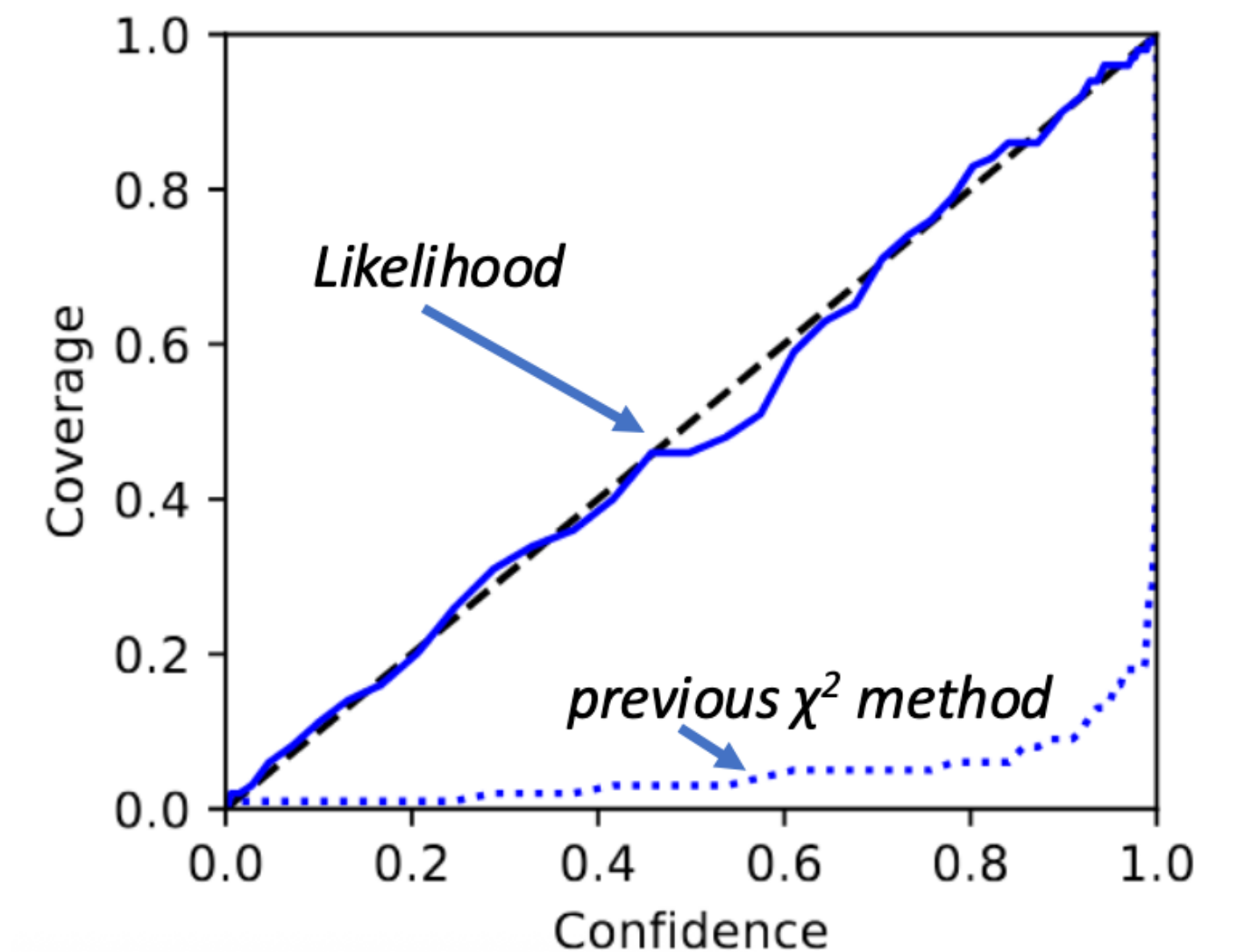
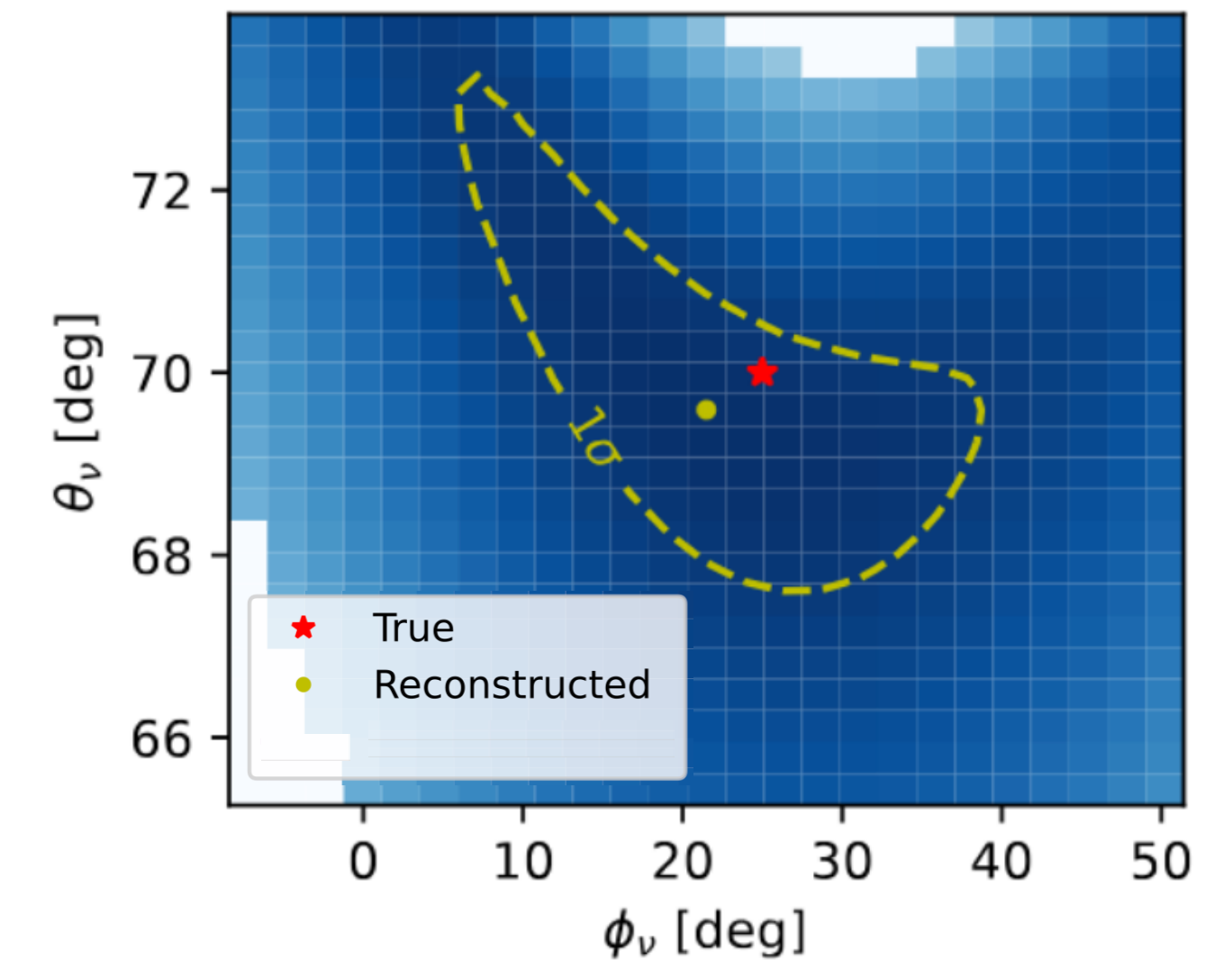
- Signal**: Points to $\boldsymbol{\mu}(\theta)$ (green).
- Trace**: Points to $\mathbf{x}$ (blue).
- Noise**: Points to $\boldsymbol{\Sigma}^{-1}$ (red).

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

- Minimize to get best-fit parameters and uncertainties

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

arxiv: 2409.11888



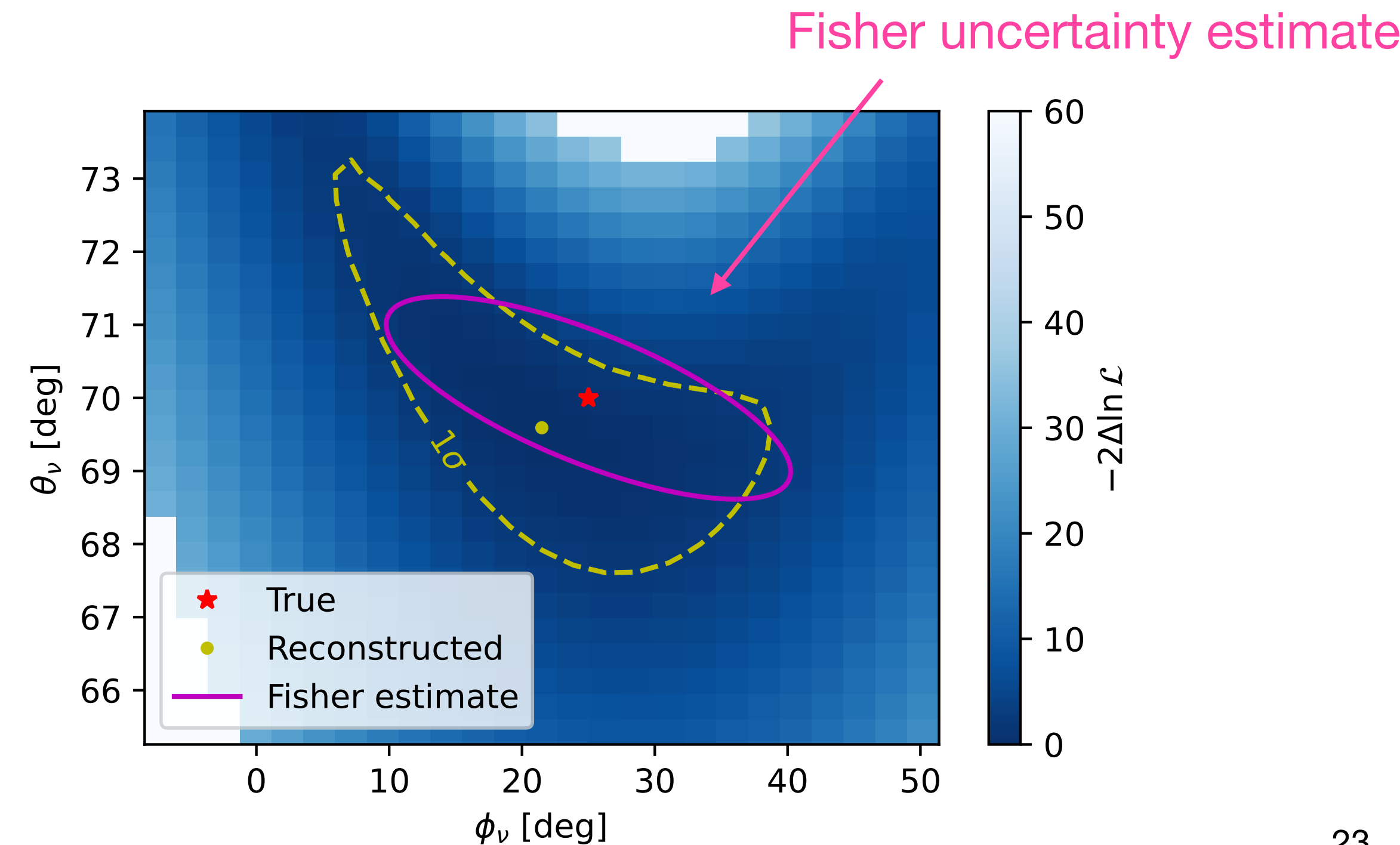
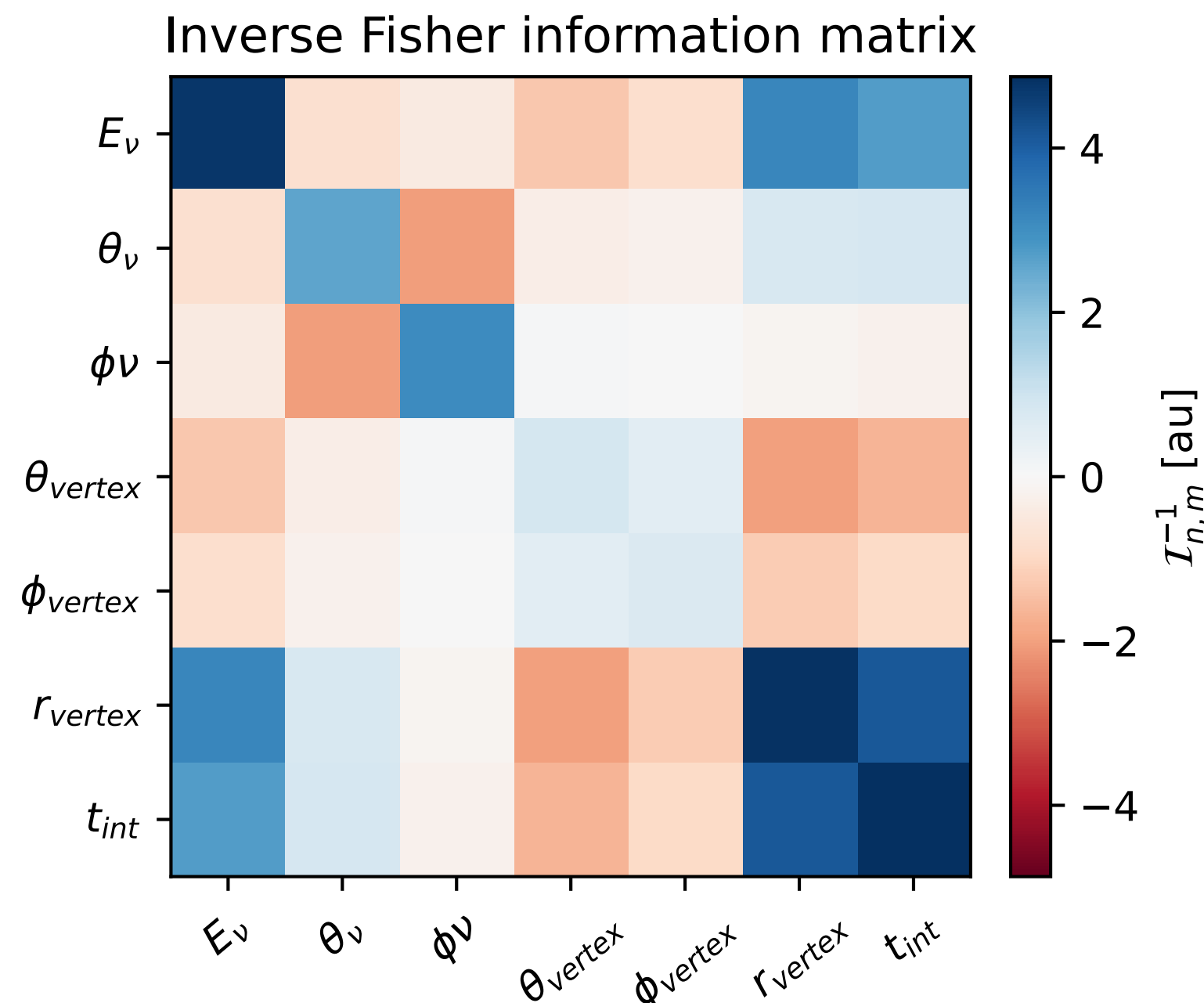
Uncertainty estimation with Fisher information matrix

- Fisher Information Matrix can be calculated directly from signal model:

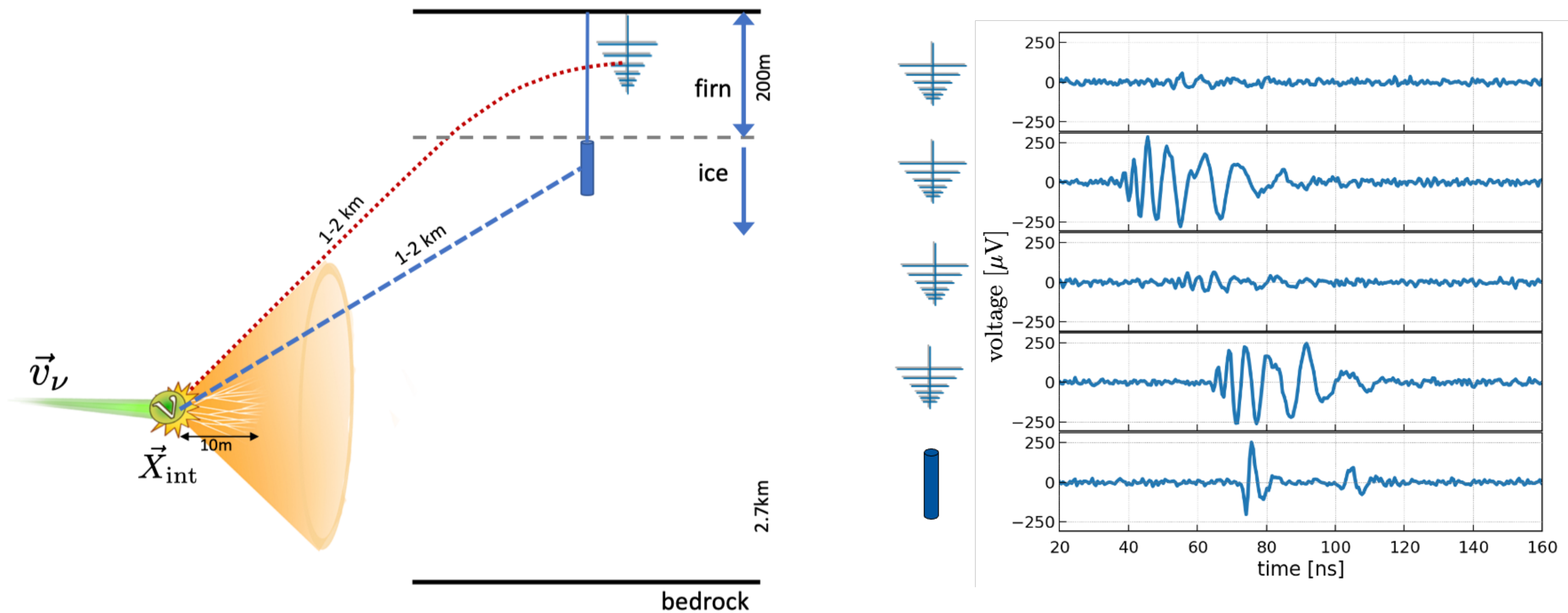
$$\mathcal{I}_{m,n} = \sum_{ant.} \frac{\partial \mu^T}{\partial \theta_m} \Sigma^{-1} \frac{\partial \mu}{\partial \theta_n} \quad \sigma^2 = \left(\mathcal{I} \right)^{-1}$$

Implemented in PyTorch:
Autodiff (in forward mode) or
Finite difference (shown here)

- Inverse gives uncertainty estimate through Cramer-Rao bound
- Depends only on neutrino and detector parameters → fast uncertainty estimation



Radio neutrino simulation and reconstruction



Neutrino parameters:

E_ν
 θ_ν, ϕ_ν
 x_ν, y_ν, z_ν
 t_0

Simulation with NuRadioMC

Reconstruction

$V(t)$

Probabilistic noise model

- Covariance matrix:

$$\Sigma = \begin{pmatrix} \text{Var}(t_0, t_0) & \dots & \text{Cov}(t_n, t_0) \\ \vdots & \ddots & \vdots \\ \text{Cov}(t_0, t_n) & \dots & \text{Var}(t_n, t_n) \end{pmatrix}$$

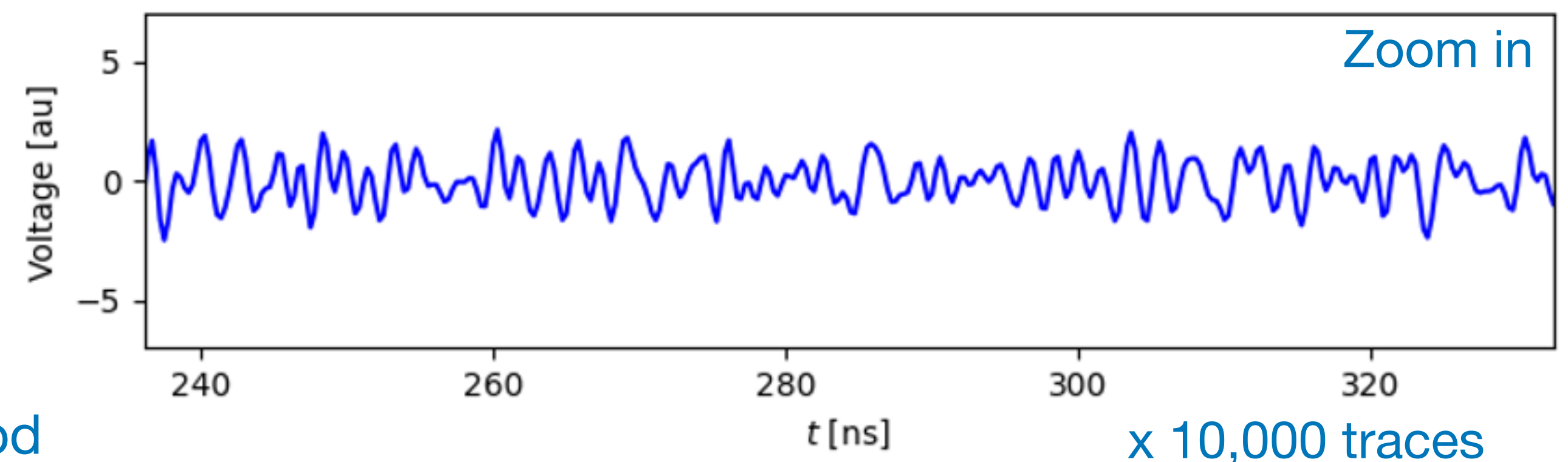
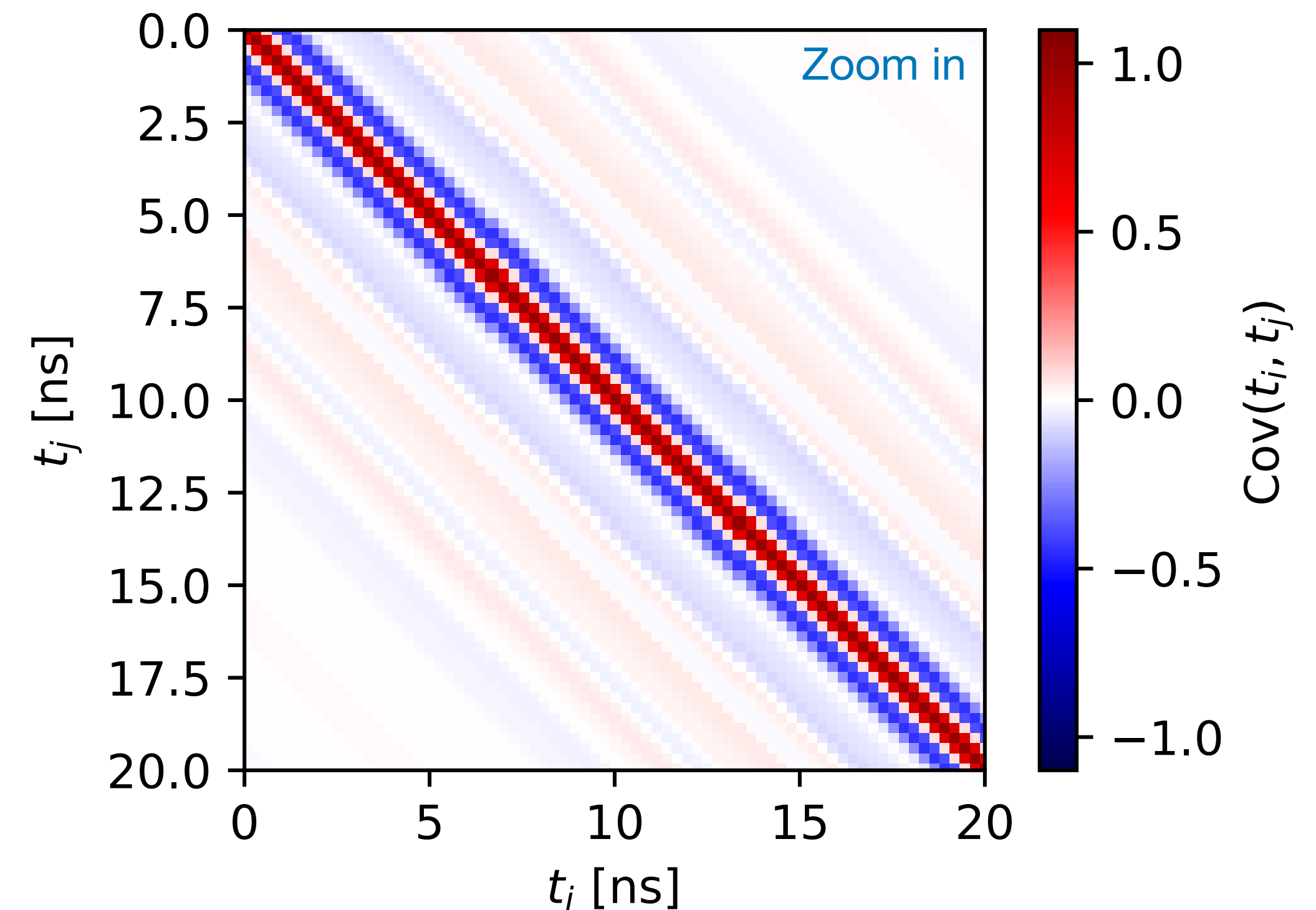
- Calculate from traces:

$$\text{Cov}(t_i, t_j) = \frac{1}{N} \sum_{n=1}^N (x_{n,i} - \mu_i)(x_{n,j} - \mu_j),$$

- Has been verified against data
- Probability is likelihood:

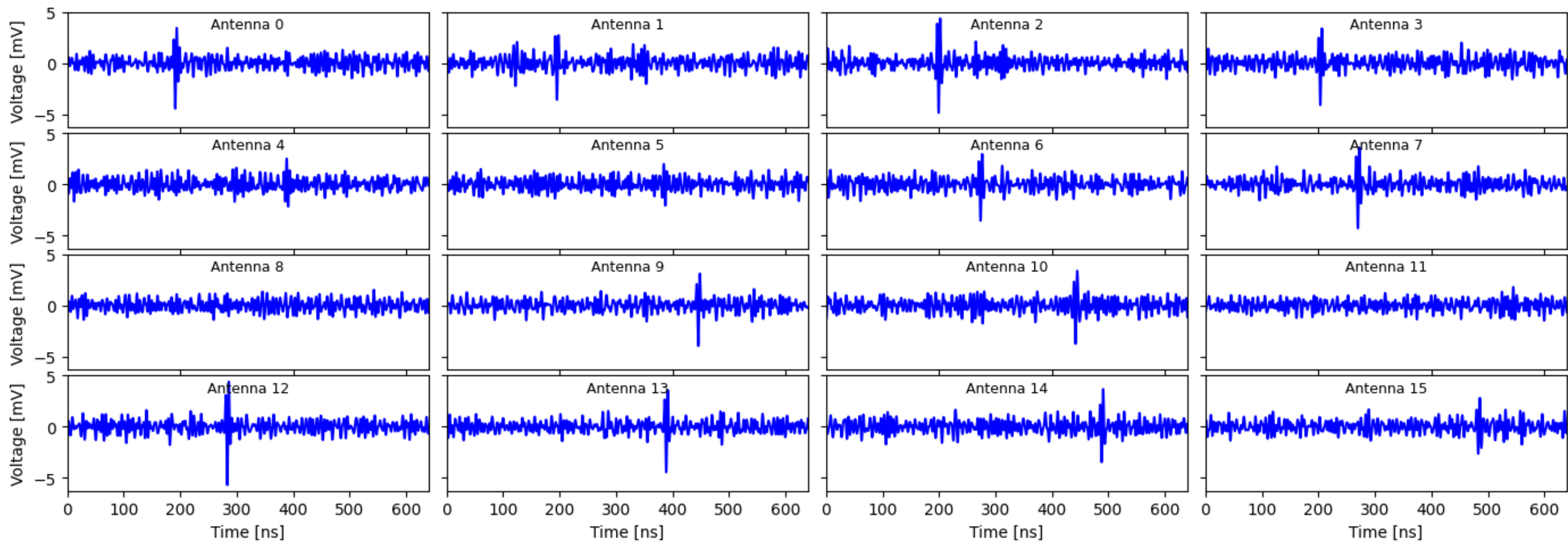
$$p(\mathbf{x}; \boldsymbol{\mu}(\theta), \boldsymbol{\Sigma}) = \mathcal{L}(\boldsymbol{\mu}(\theta); \mathbf{x}, \boldsymbol{\Sigma})$$

Likelihood

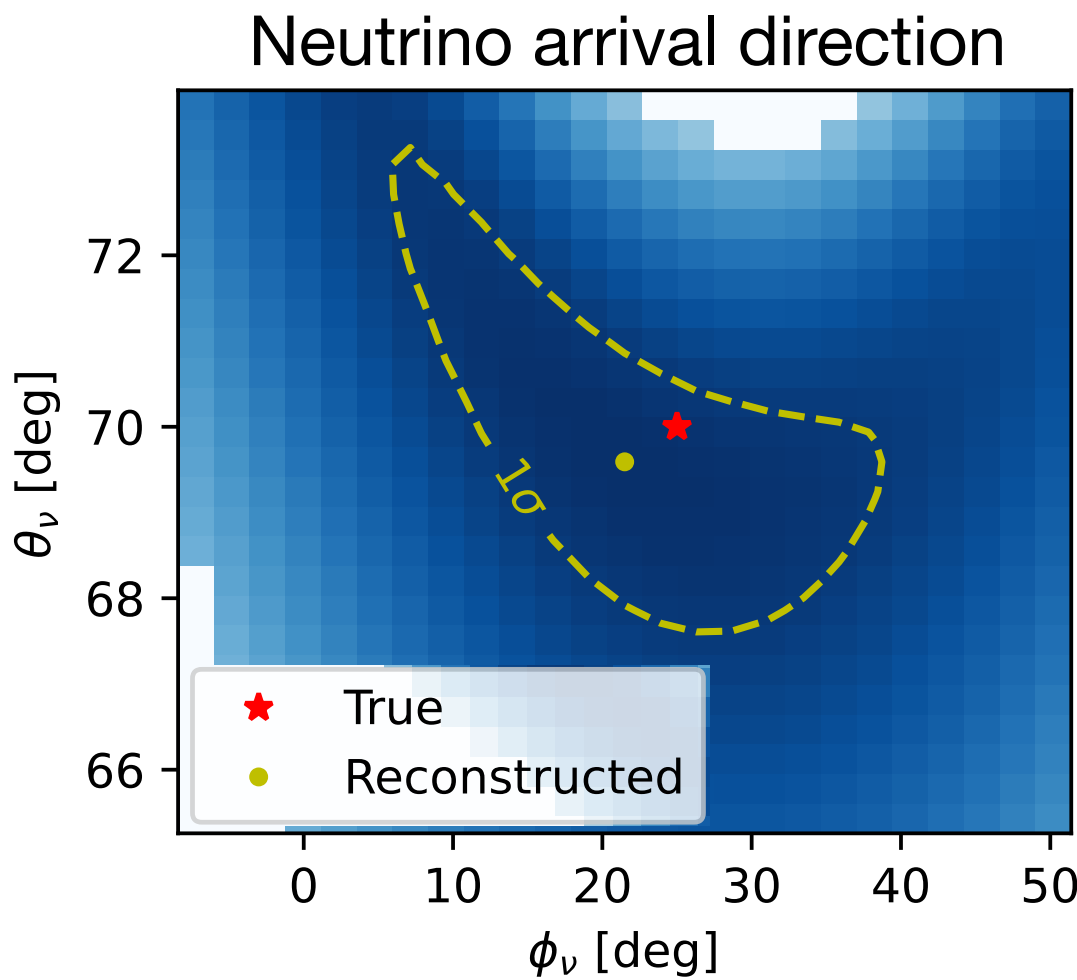


RNO-G reconstruction

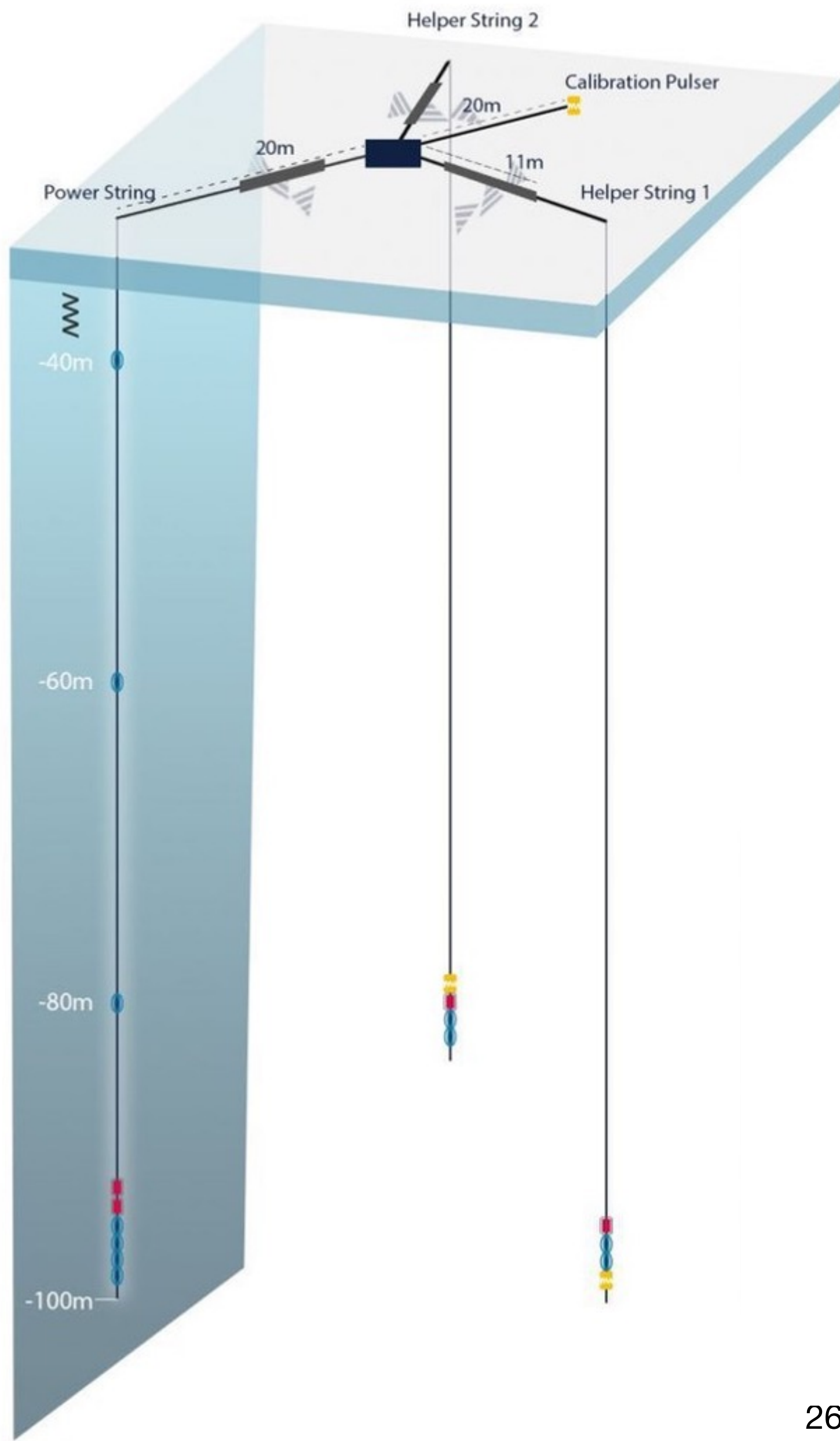
- Example event in deep detector simulated with NuRadioMC:



↓ Likelihood reconstruction



RNO-G station:



Fisher information matrix contour

- Four different ways of estimating uncertainties

