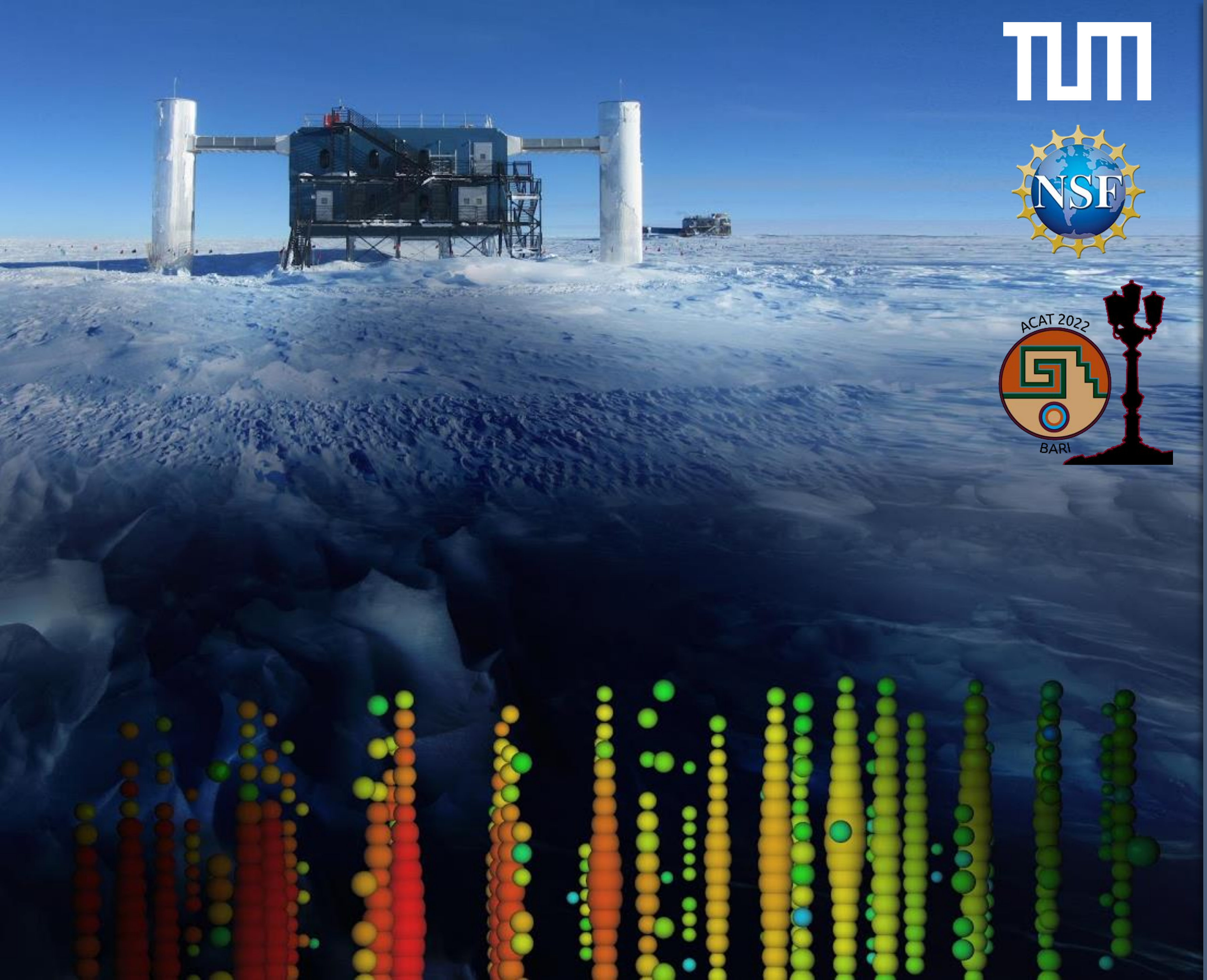
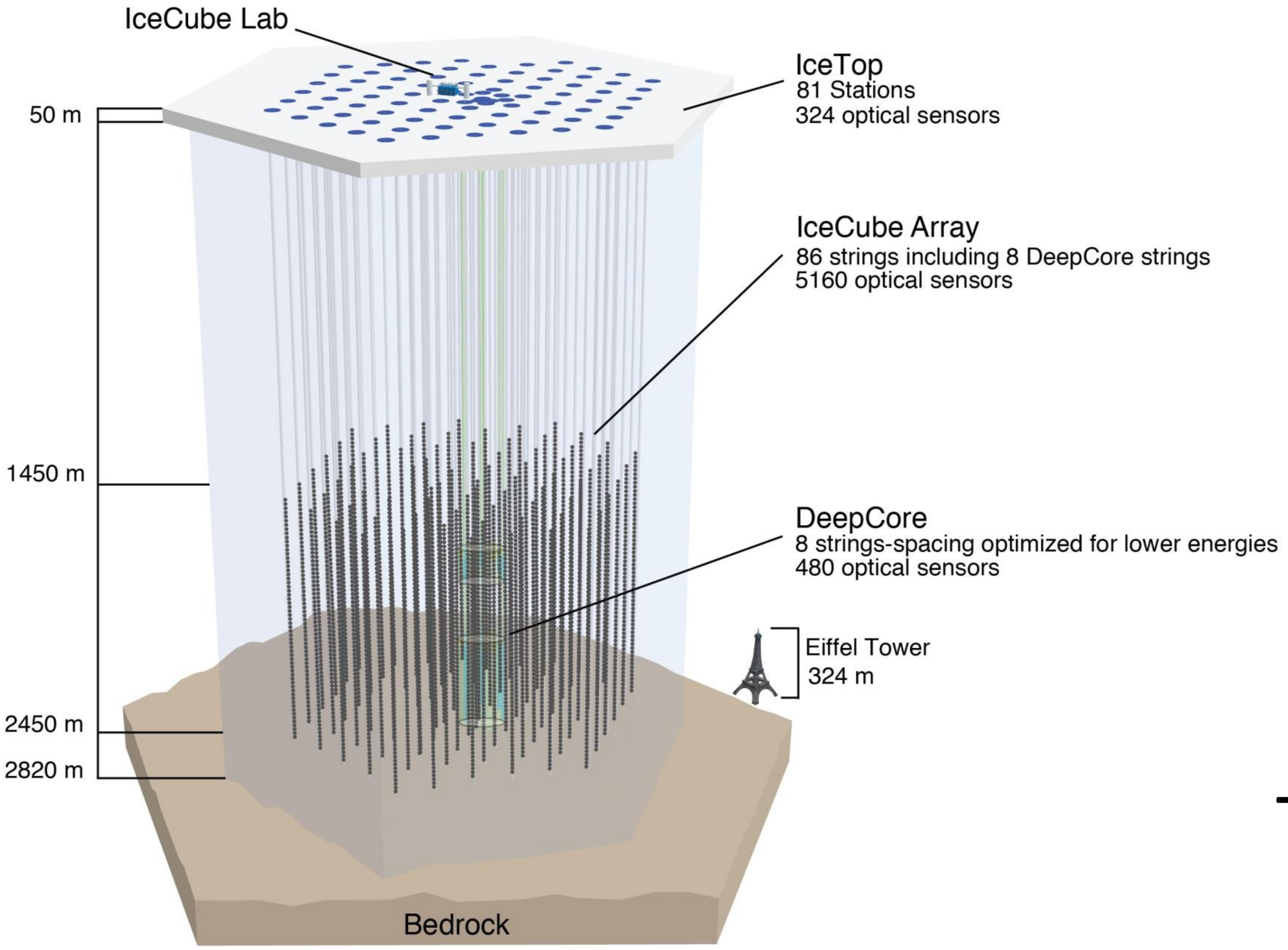


Graph Neural Networks and their application in IceCube

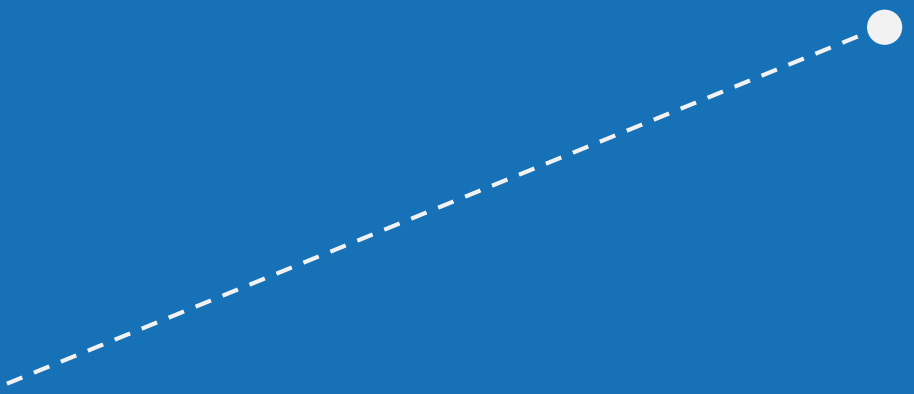
Martin Ha Minh
Technical University of Munich

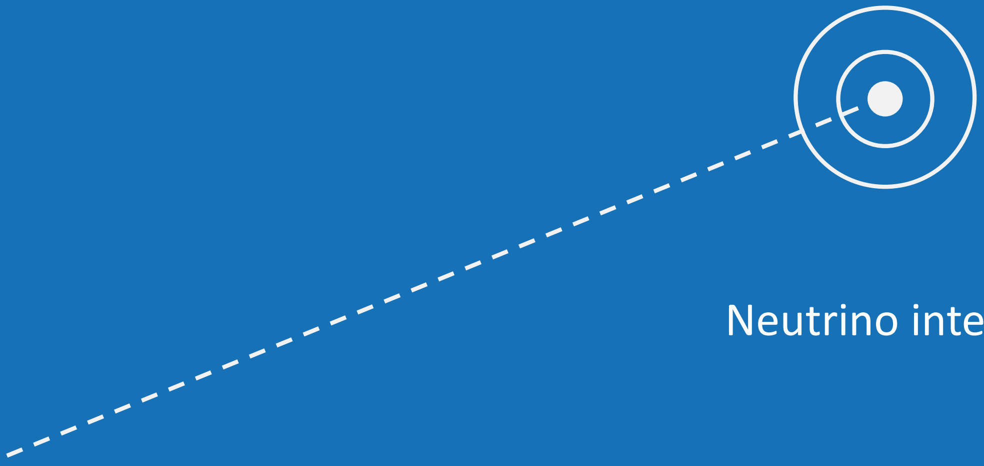
21st International Workshop on Advanced Computing and Analysis Techniques in Physics Research
27th October 2022



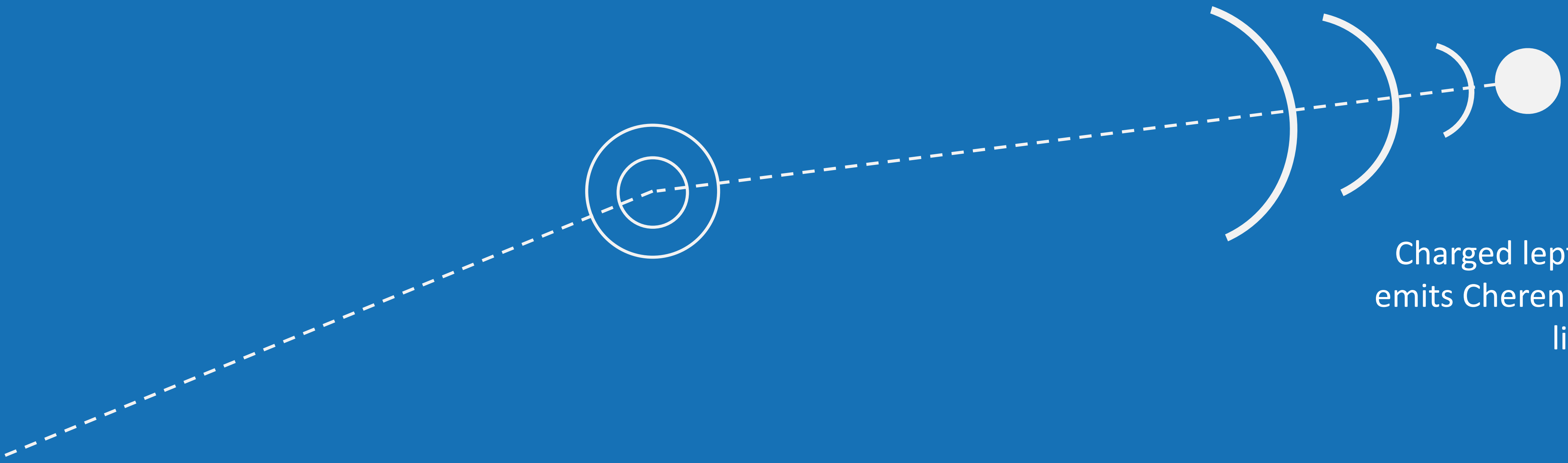
The IceCube detector

Neutrino traveling in ice

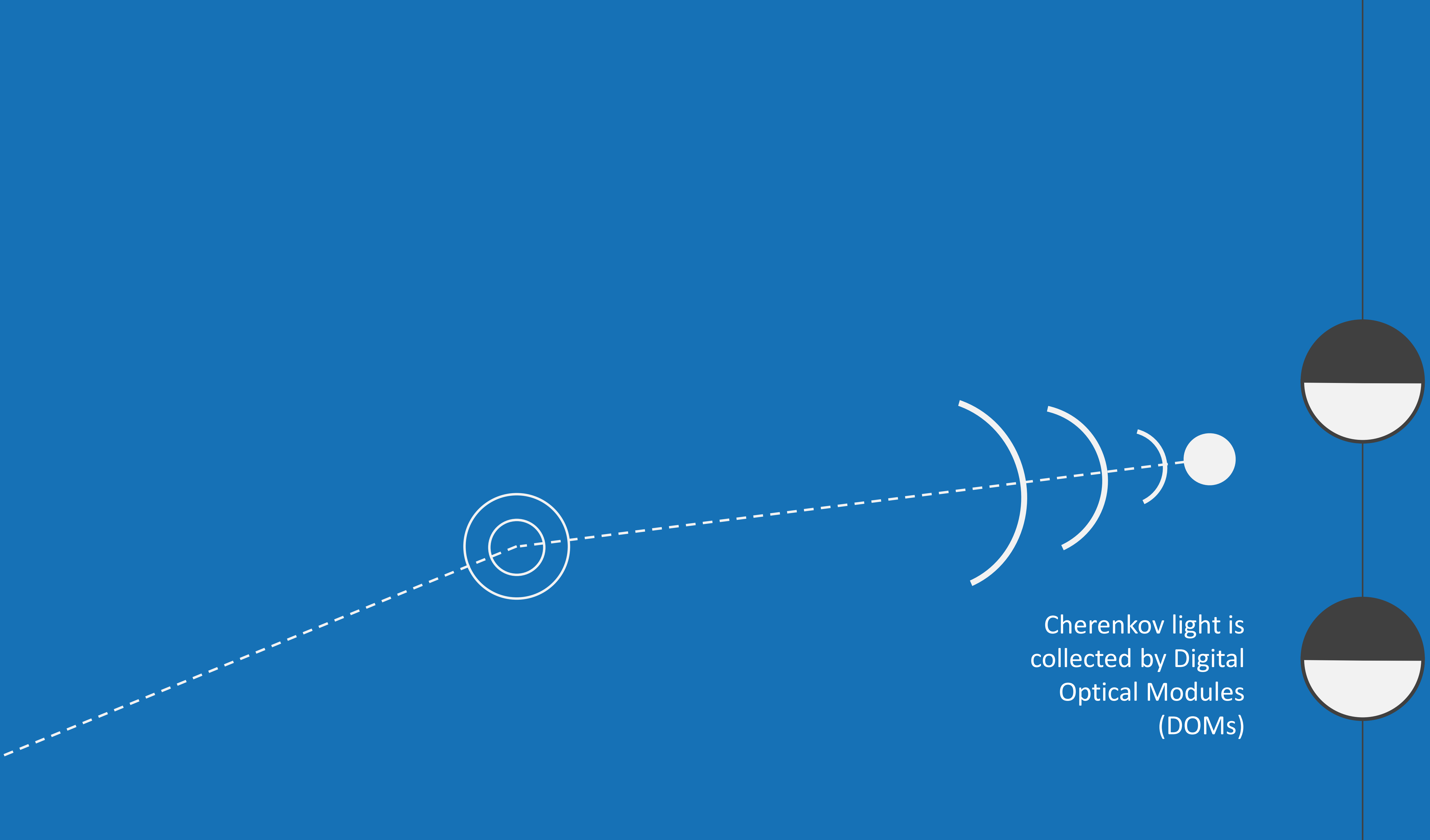


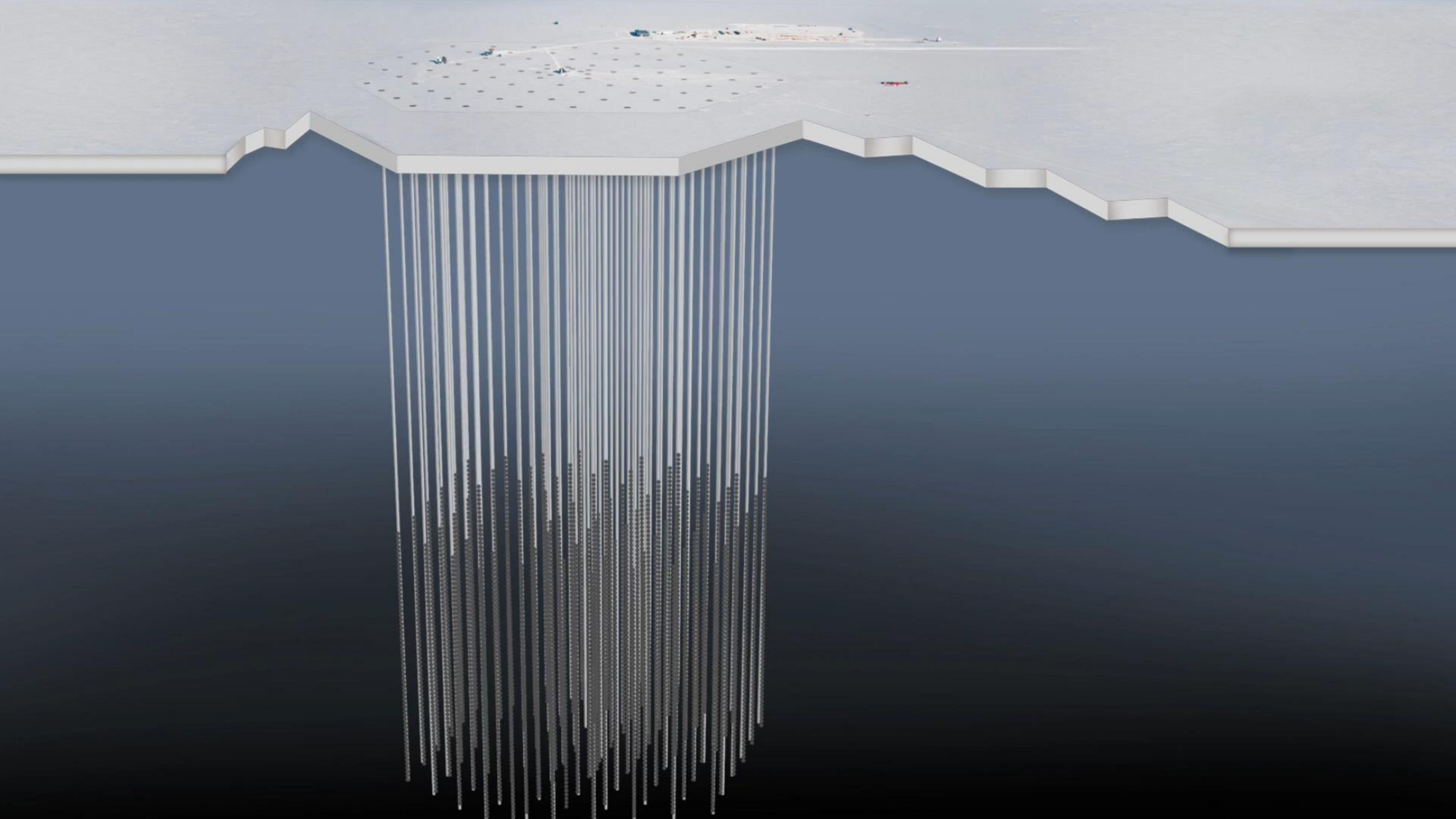


Neutrino interacts with medium

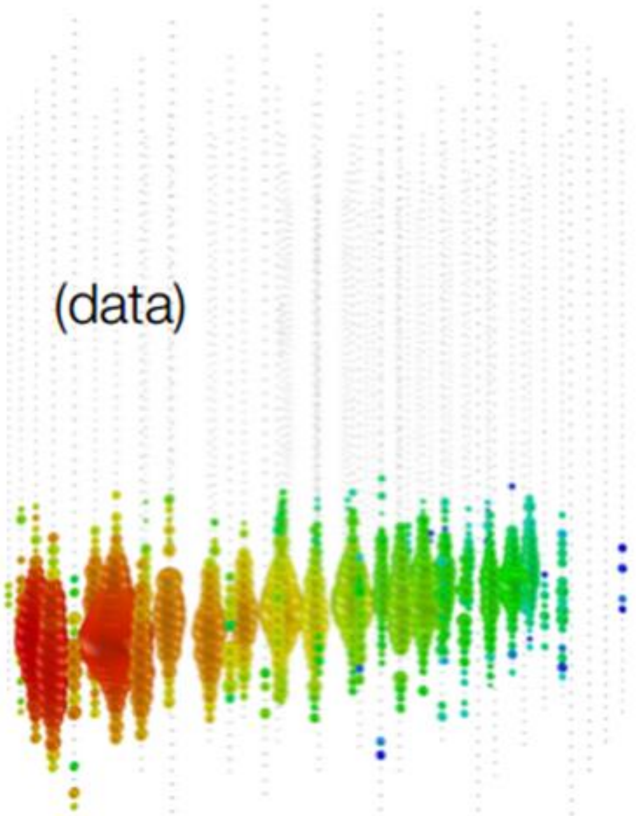


Charged lepton emits Cherenkov light


Cherenkov light is
collected by Digital
Optical Modules
(DOMs)

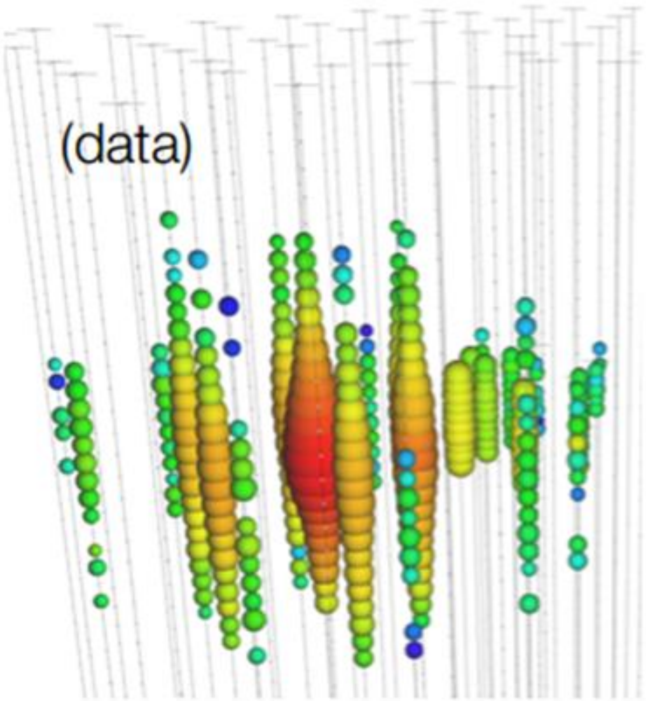


Charged-current ν_μ

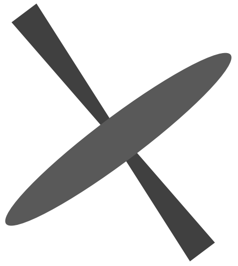


Up-going track

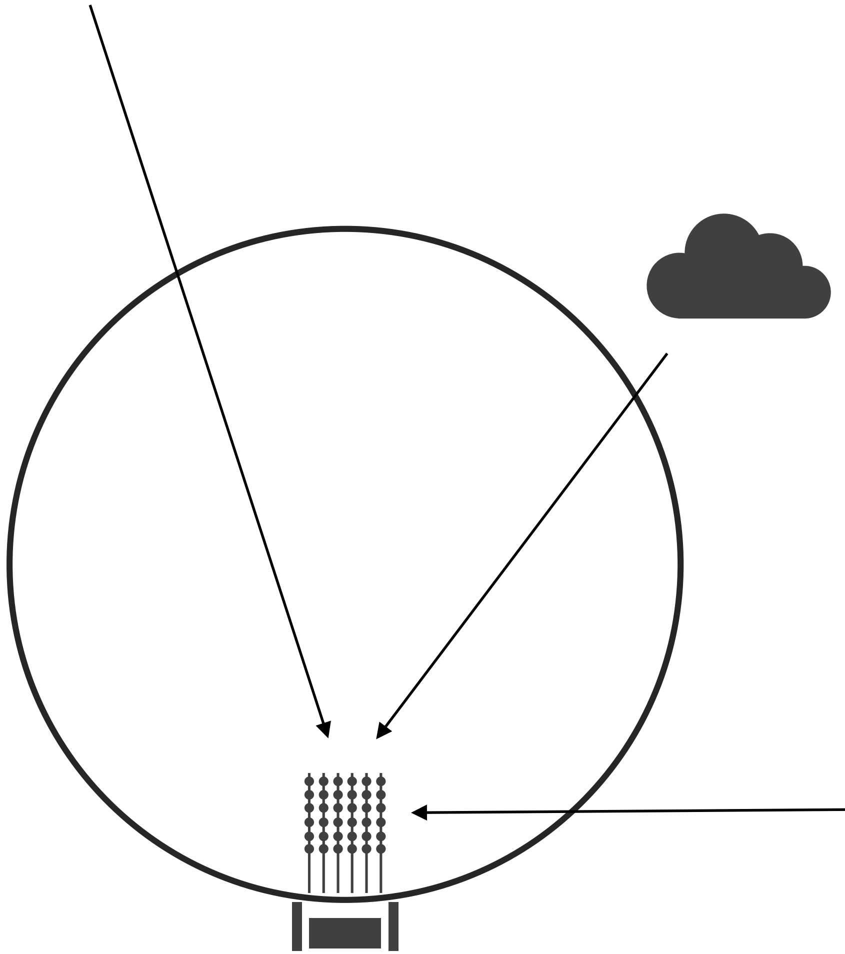
Neutral-current / ν_e



Isolated energy deposition (cascade) with no track



Neutrino astronomy
Finding source candidates that produce neutrinos, such as Active Galactic nuclei

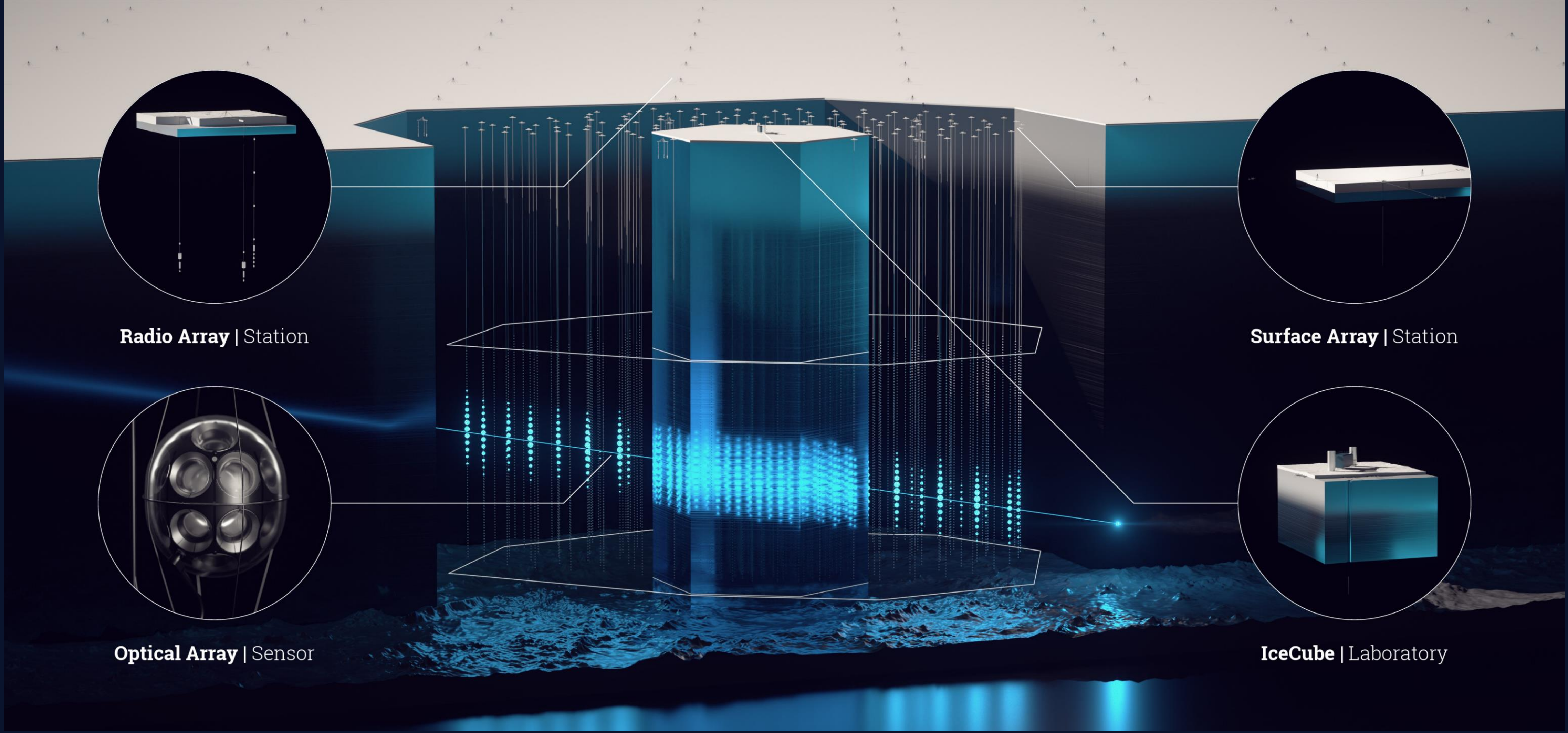


Neutrino oscillations
Studying the particle’s properties with neutrinos produced in atmospheric particle showers

?

Beyond the standard model
Looking for dark matter, SUSY particles, non-standard interactions, etc.

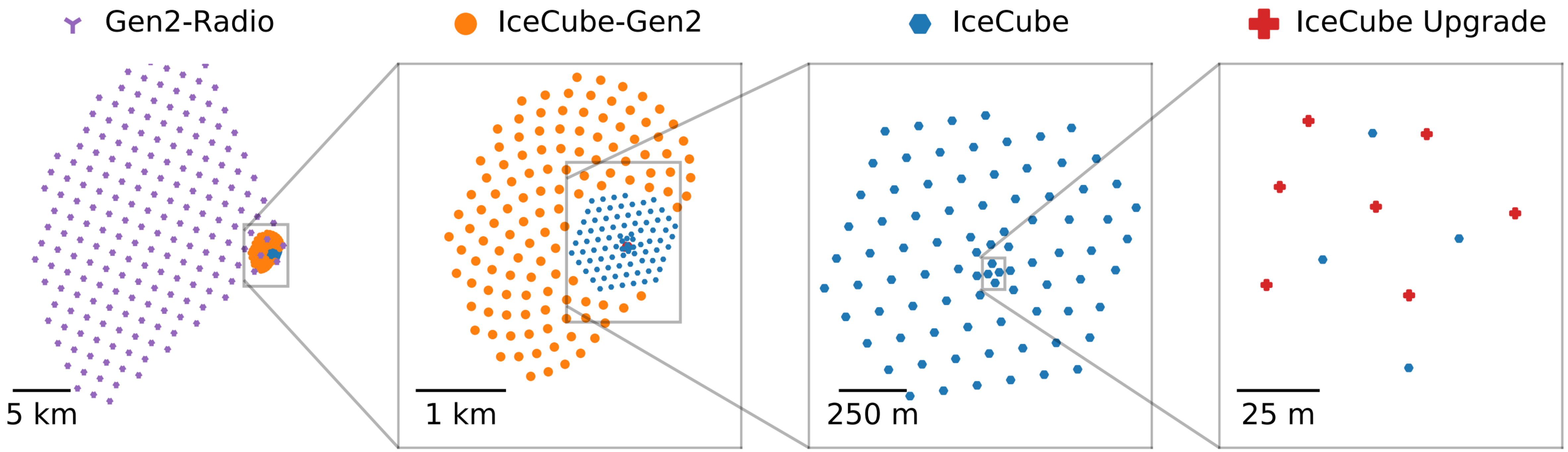
IceCube-Gen2



- 120 optical strings
- 200 radio detection stations

- 7.9x larger than current IceCube
- 500 km² in area

Expected to be deployed 2034



Bird's eye view of IceCube string configurations

IceCube Upgrade

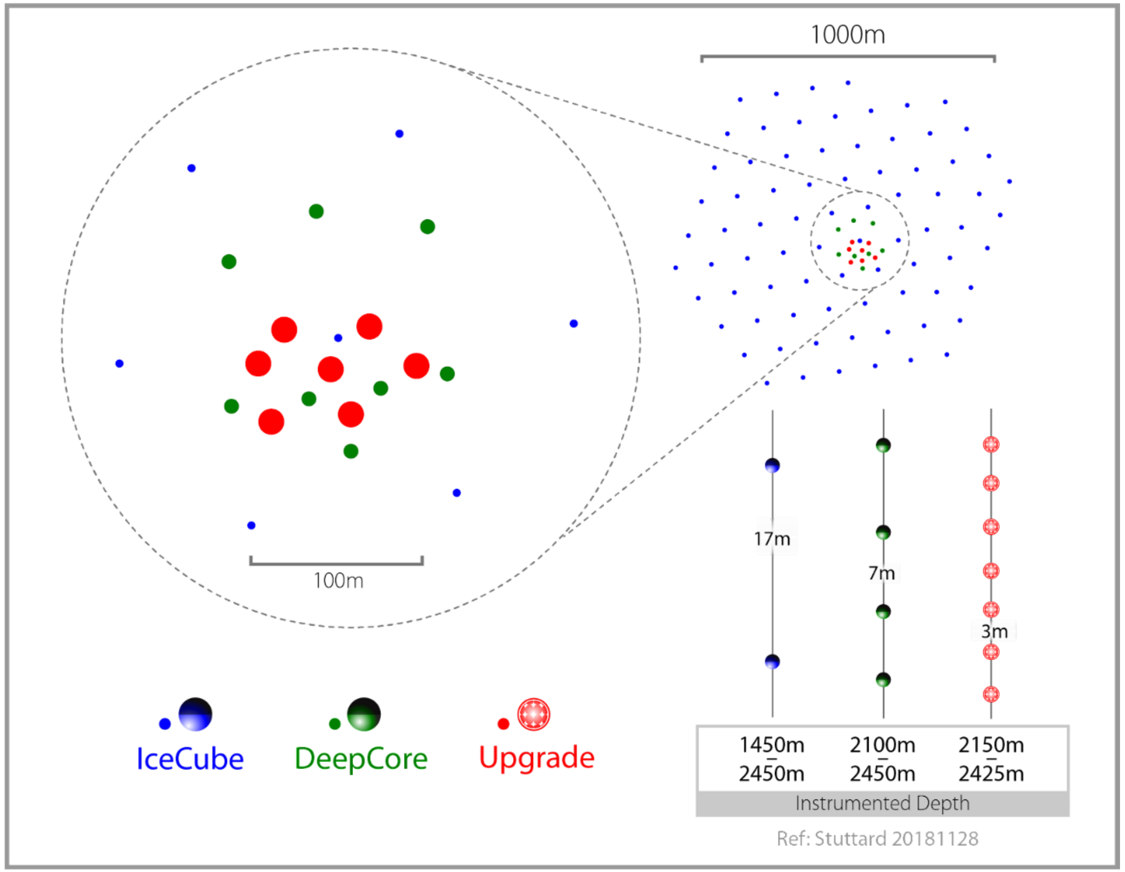
Pathfinder project for the Gen2

Testing of new optical modules

Includes dedicated calibration modules

Expands IceCube detection range towards lower energies

Expected to be deployed 2025/26

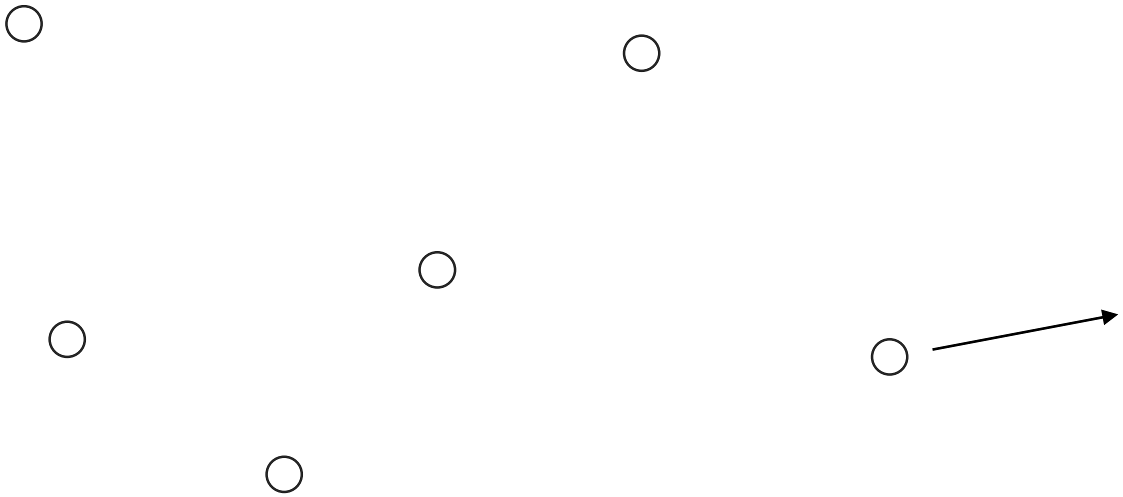


However:

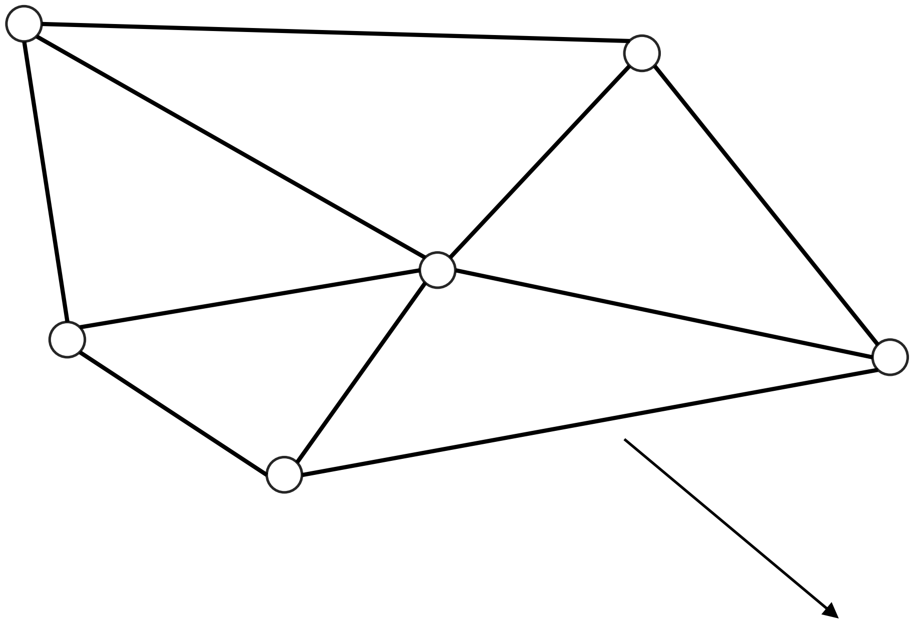
Current baseline reconstruction method unfeasible with photomultiplier tubes pointing in multiple directions!

Alternative method greatly needed!

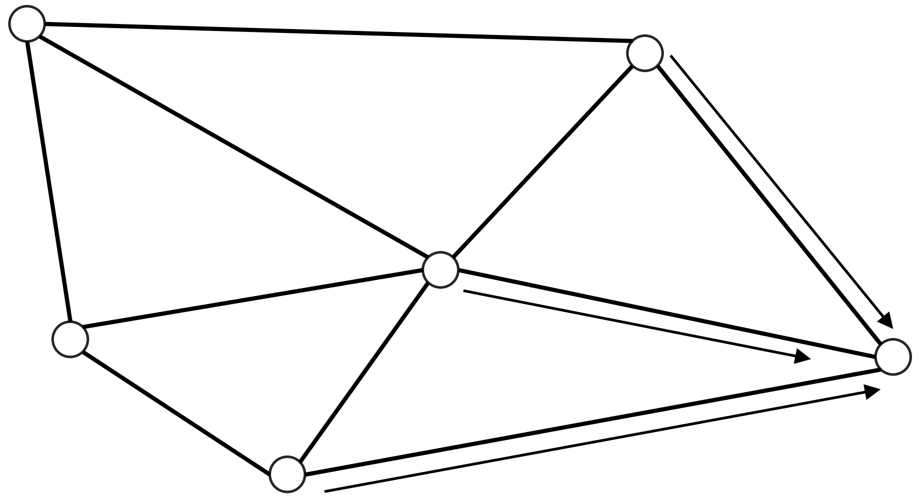
Graph neural networks



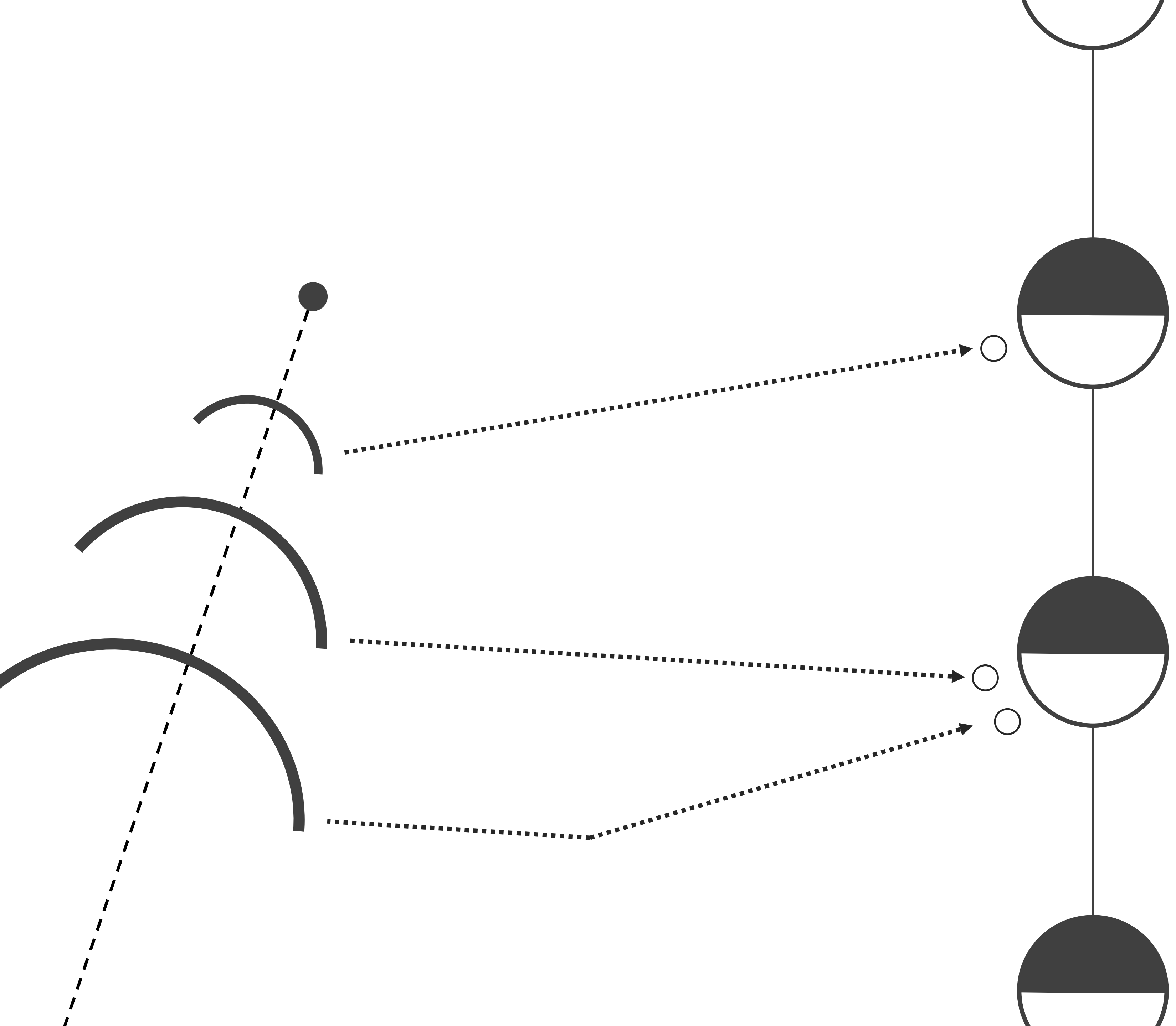
Node: Input vector x_i



Edges: Connection
between nodes

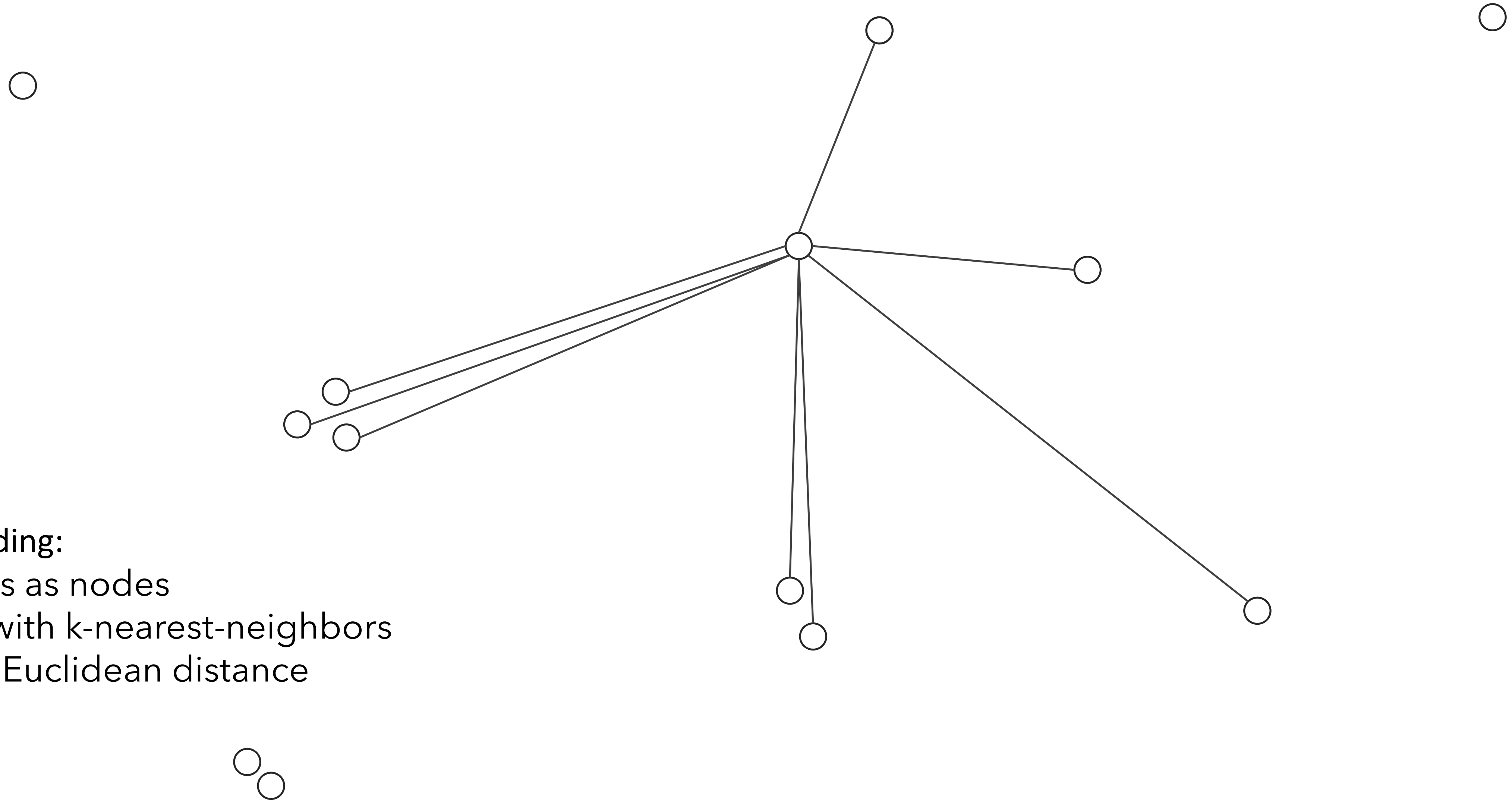


Message passing:
Graph is convolved by aggregating the neighborhood of each node

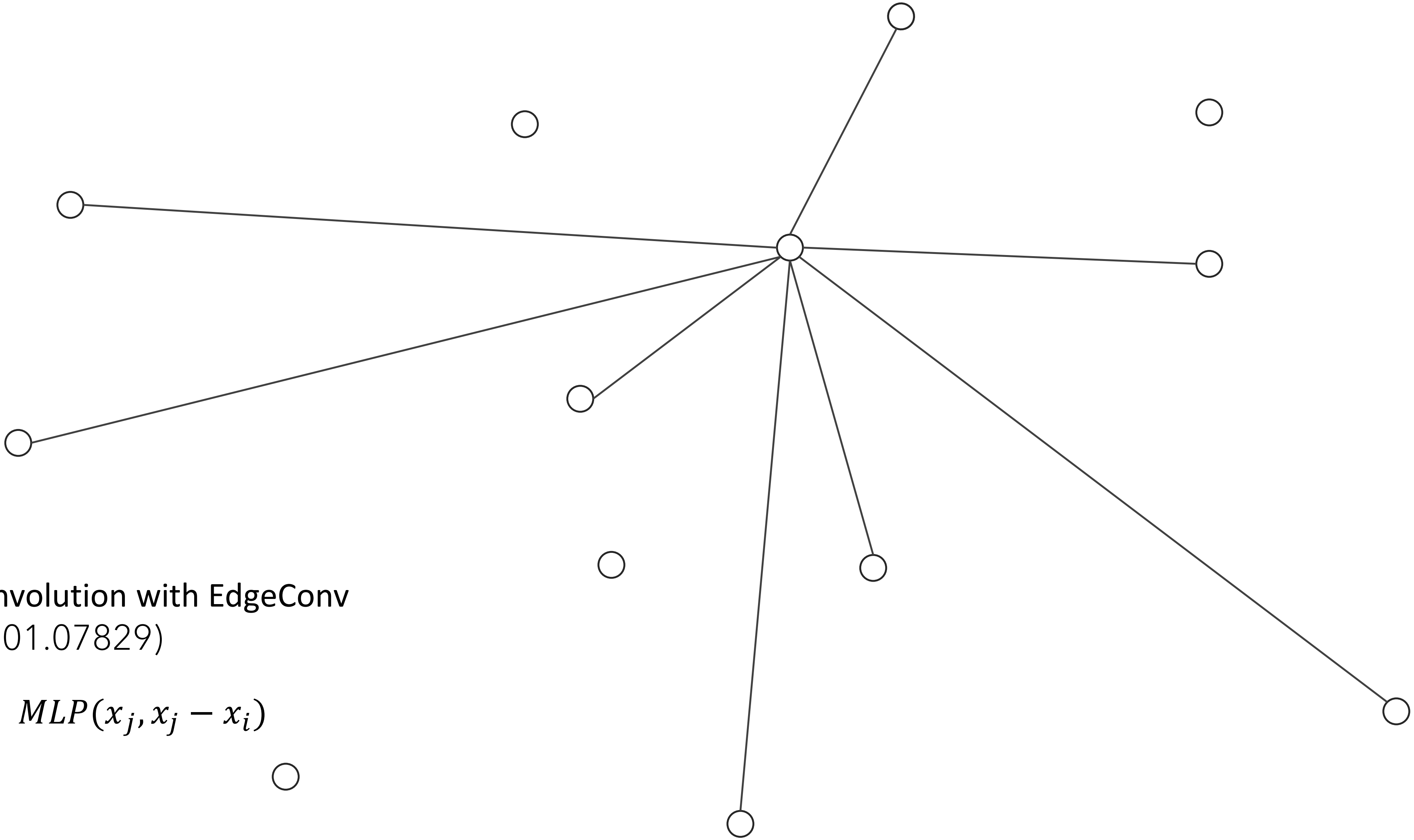


Recorded pulse $x_j =$

$$\begin{pmatrix} xyz \\ t \\ q \\ QE \end{pmatrix} \begin{array}{l} \text{DOM position} \\ \text{Time} \\ \text{Charge} \\ \text{Quantum efficiency} \end{array}$$

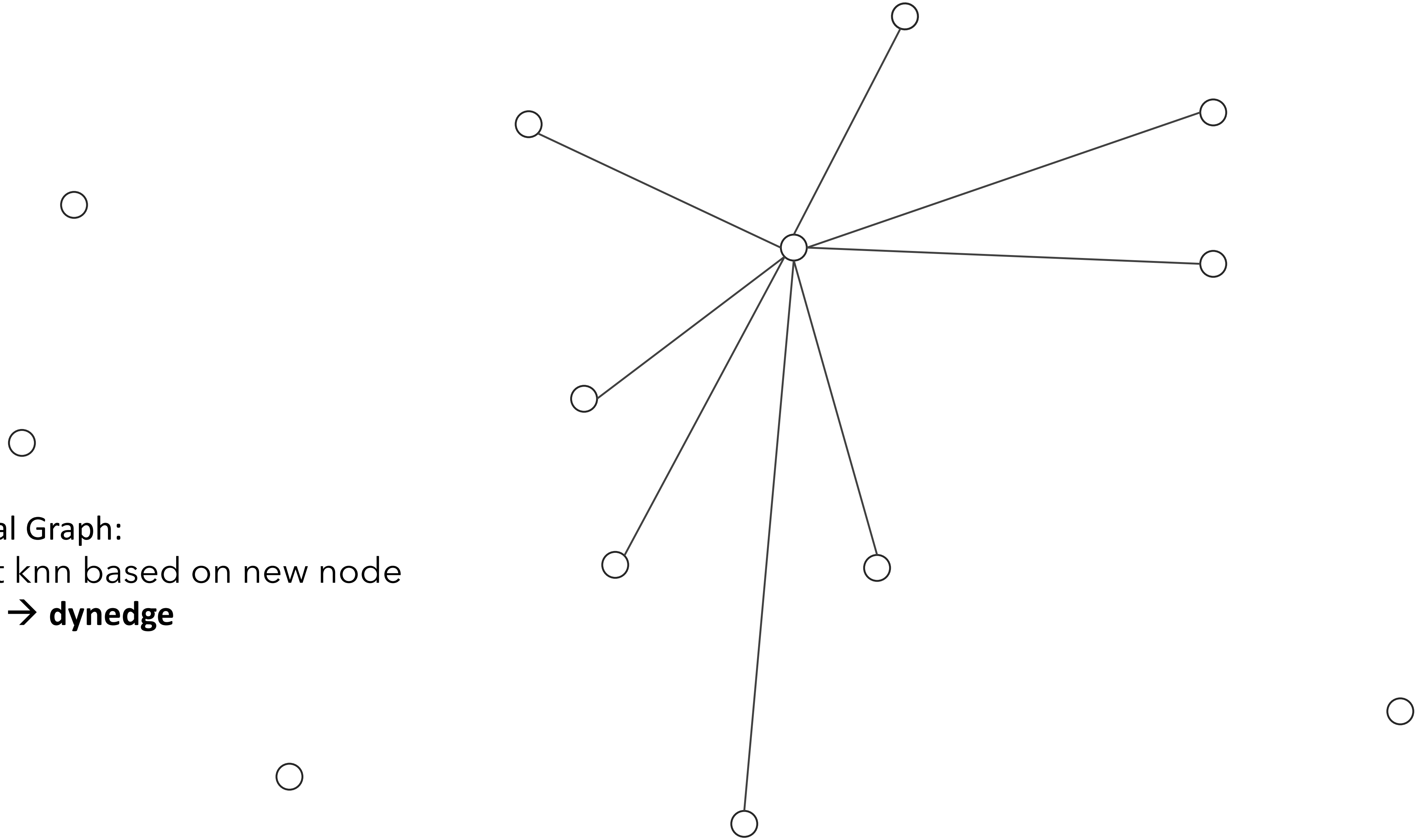


Graph building:
Use pulses as nodes
Connect with k-nearest-neighbors
based on Euclidean distance

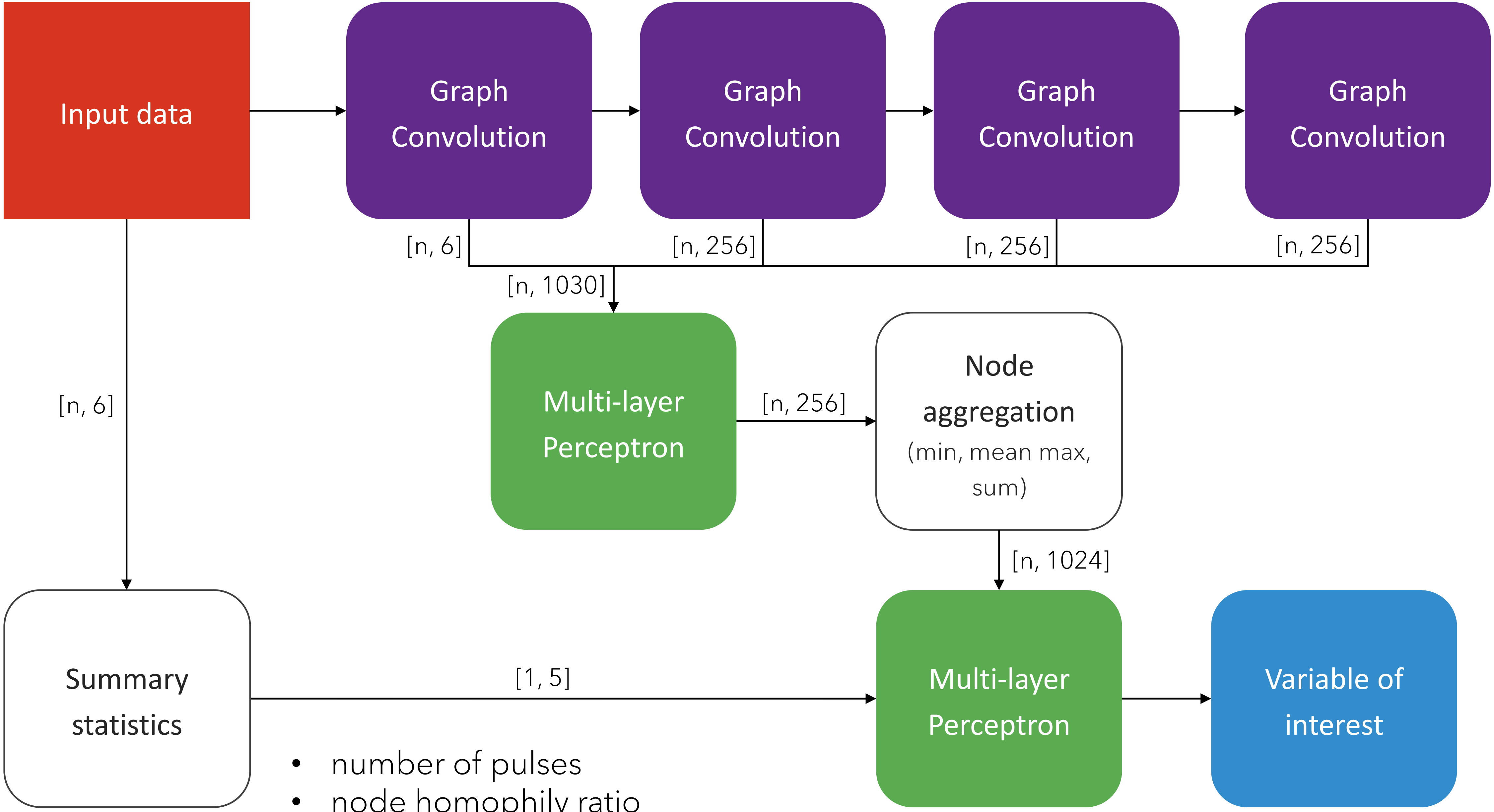


Graph convolution with EdgeConv
(arXiv:1801.07829)

$$\tilde{x}_j = \sum_i MLP(x_j, x_j - x_i)$$

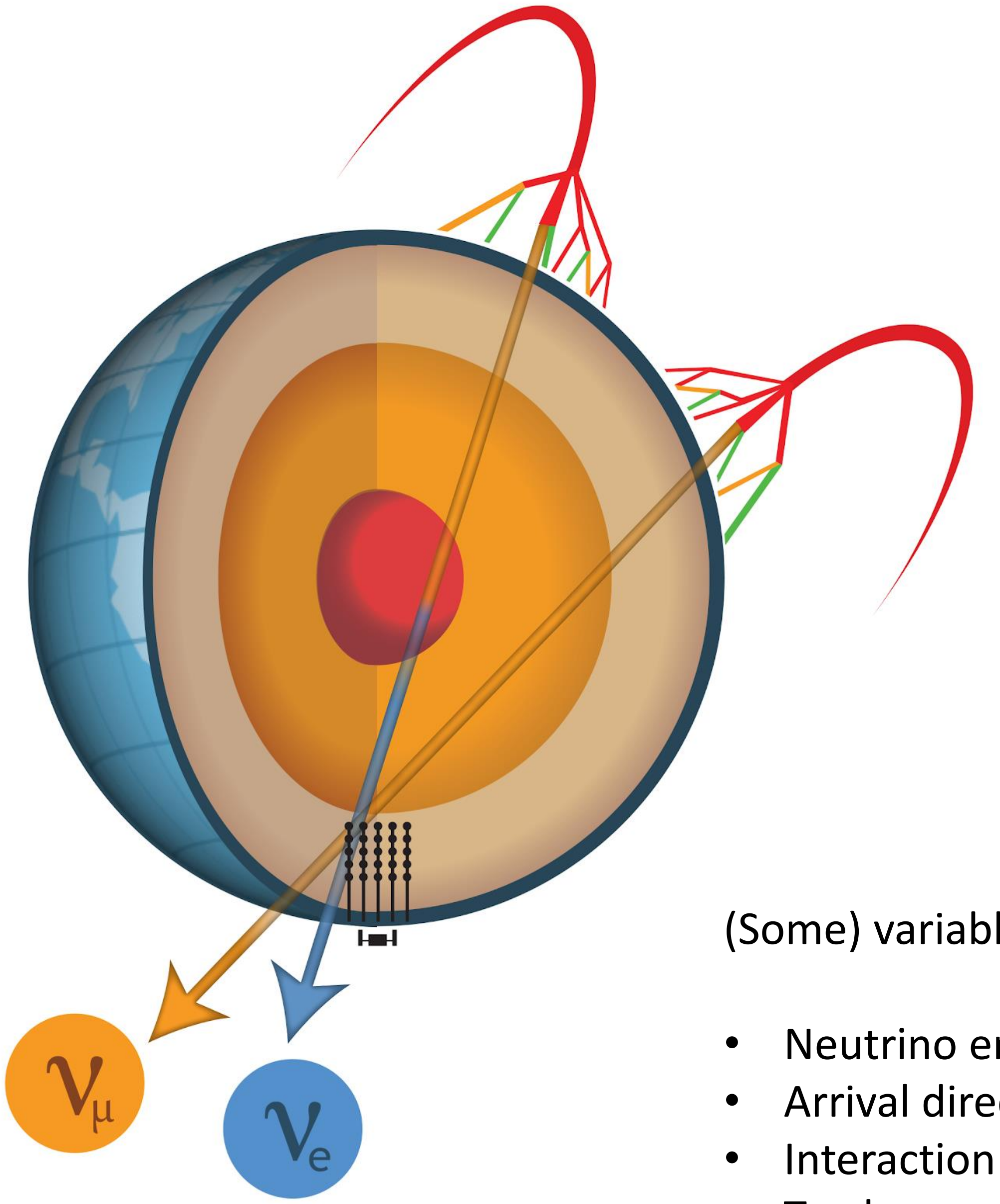


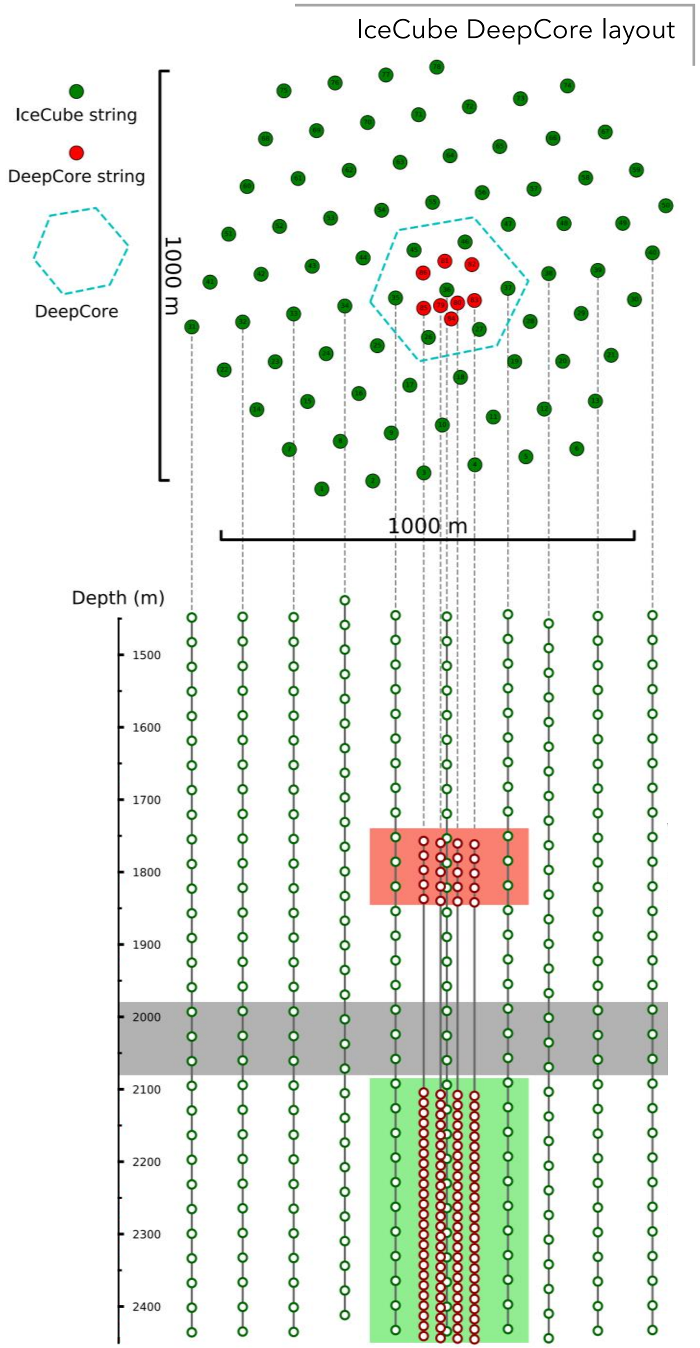
Dynamical Graph:
Connect knn based on new node features → **dynedge**



- number of pulses
- node homophily ratio in xy, z, and t

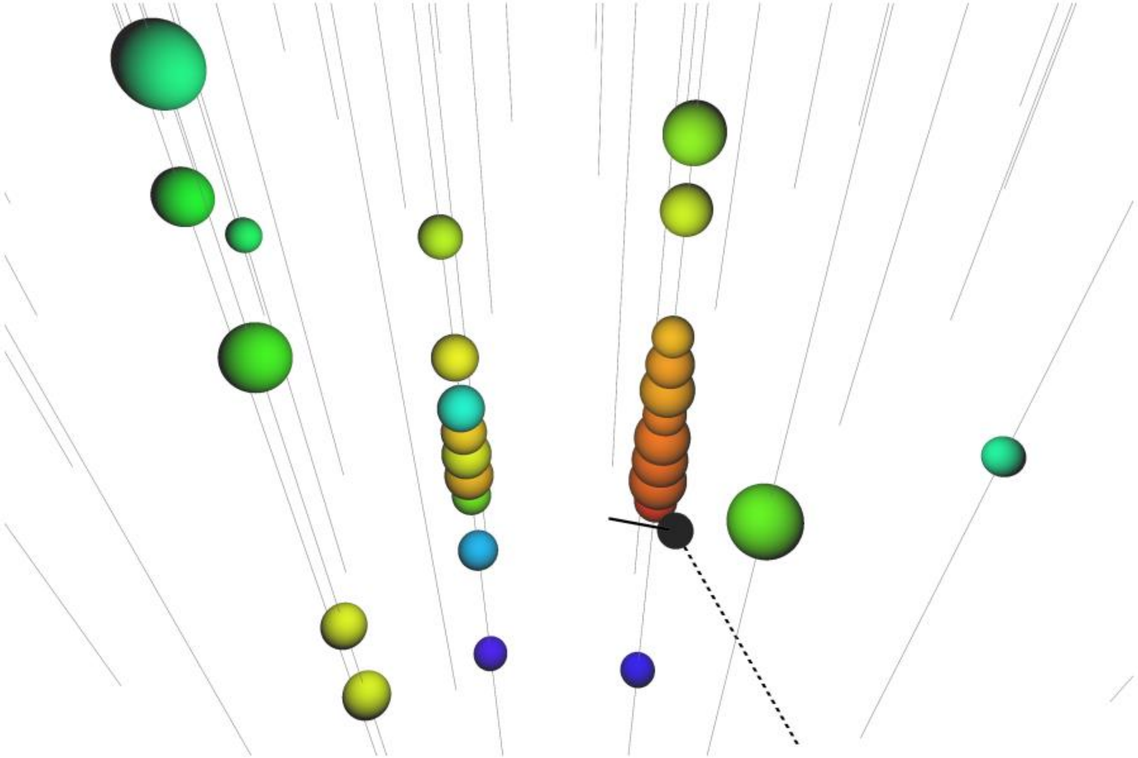
First application: Atmospheric neutrinos with DeepCore





(Some) variables of interest:

- Neutrino energy
- Arrival direction
- Interaction vertex
- Track- or cascade-like signature
- Neutrino / muon classification


Simulated event at 25 GeV

Challenges of neutrino oscillation event reconstruction:

- Comparatively low in energy
  → Event information very sparse
- High number of events (>10^8)
  Current baseline algorithm takes ~40s per event reconstruction!

Train network on neutrino oscillation MC and compare our GNN dynedge with baseline algorithms:

(Low energy event reconstruction in IceCube DeepCore. Eur. Phys. J. C 82, 807 (2022))

- Neutrino event parameter regression (energy, direction, vertex):

  Retro

  (non-ML likelihood-based algorithm)

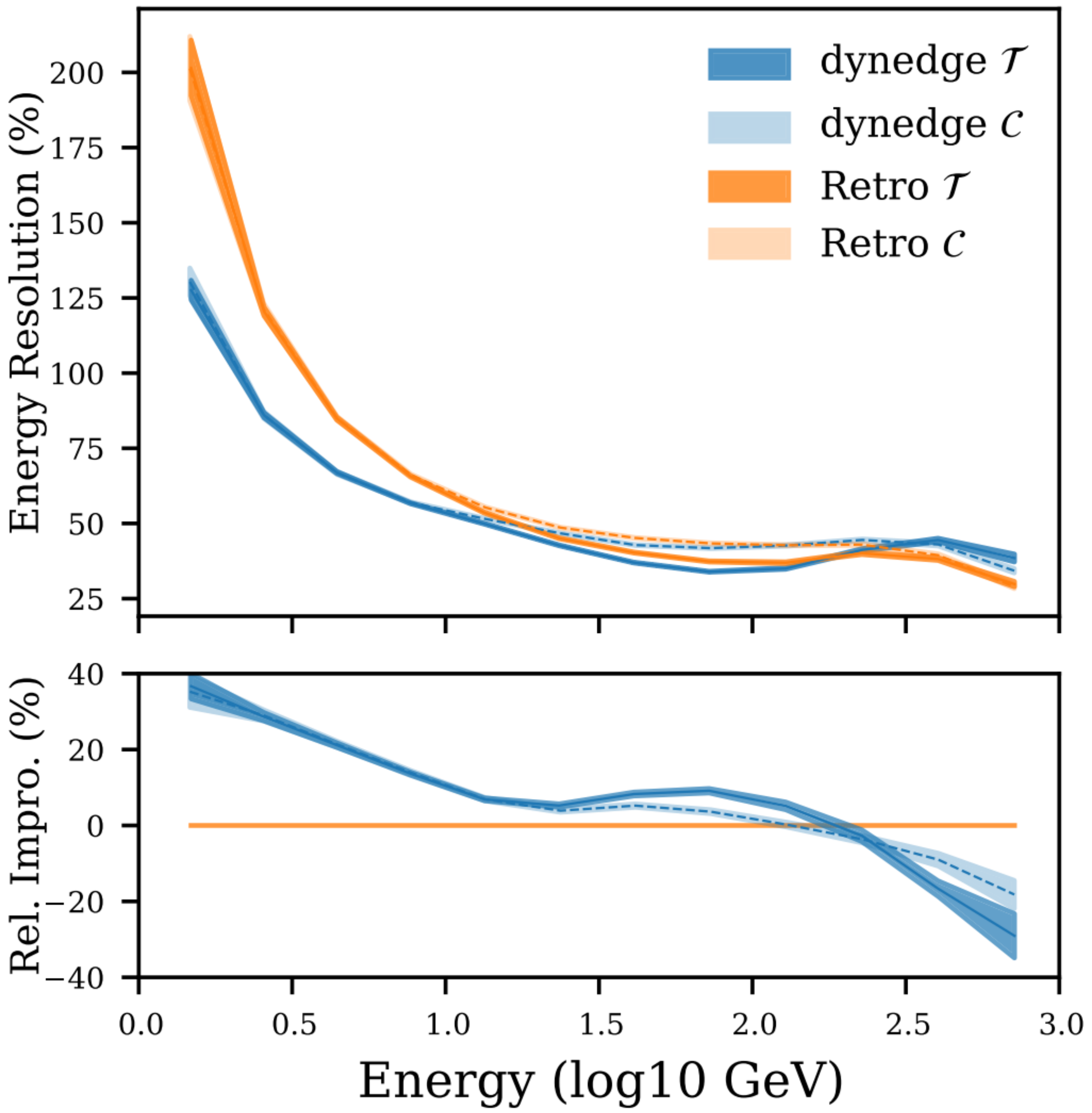
- Track- vs cascade-like (T/C) signature &

  Neutrino vs muon (ν/μ) classification (i.e., background rejection):

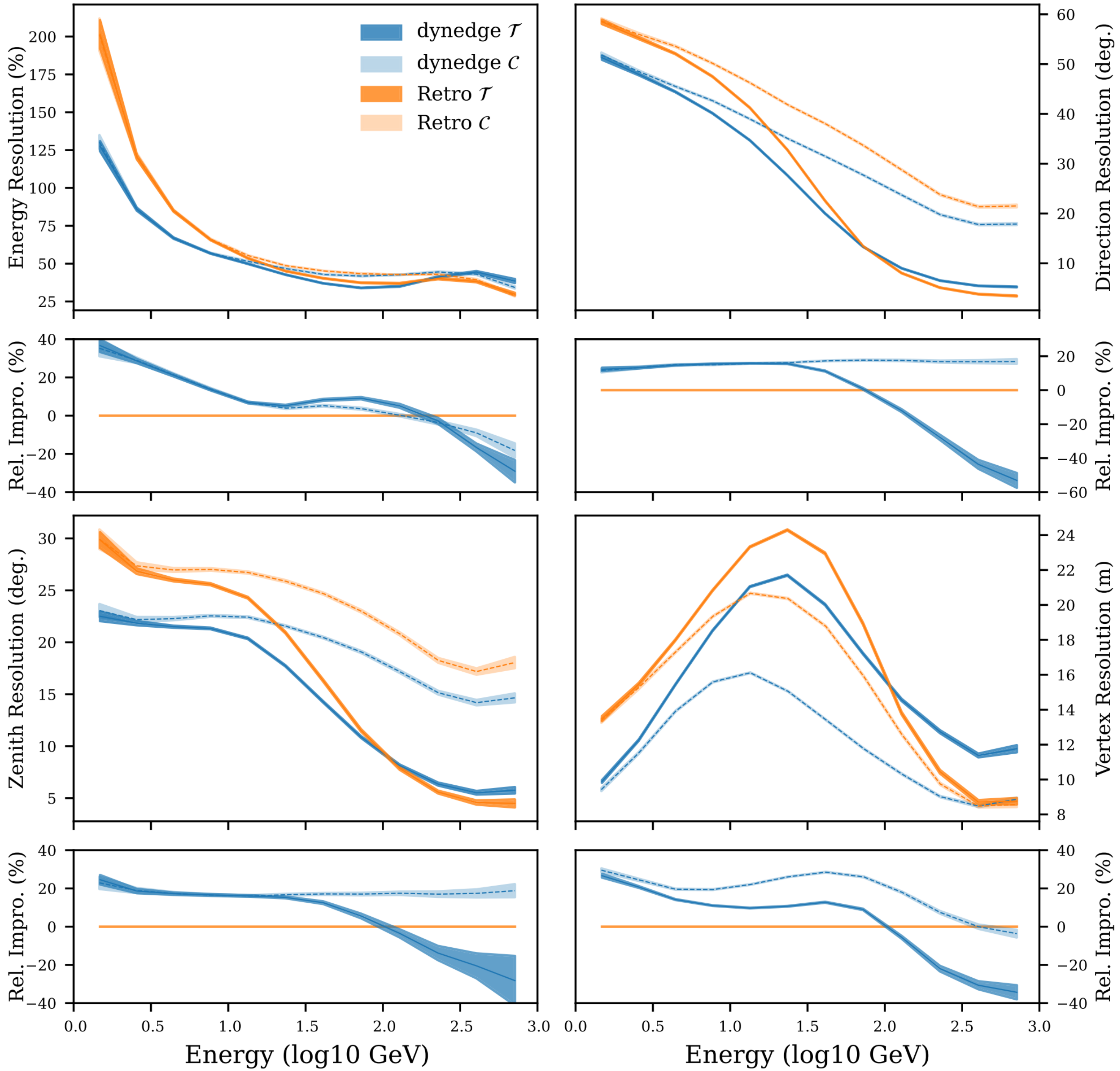
  Boosted Decision Trees

  (separate BDTs using summary statistics from pulses and/or reconstructed variables)

Regression


dynedge $\mathcal{T}$
dynedge $\mathcal{C}$
Retro $\mathcal{T}$
Retro $\mathcal{C}$
Energy Resolution (%)
200
175
150
125
100
75
50
25
Rel. Impro. (%)
40
20
0
−20
−40
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Energy (log10 GeV)

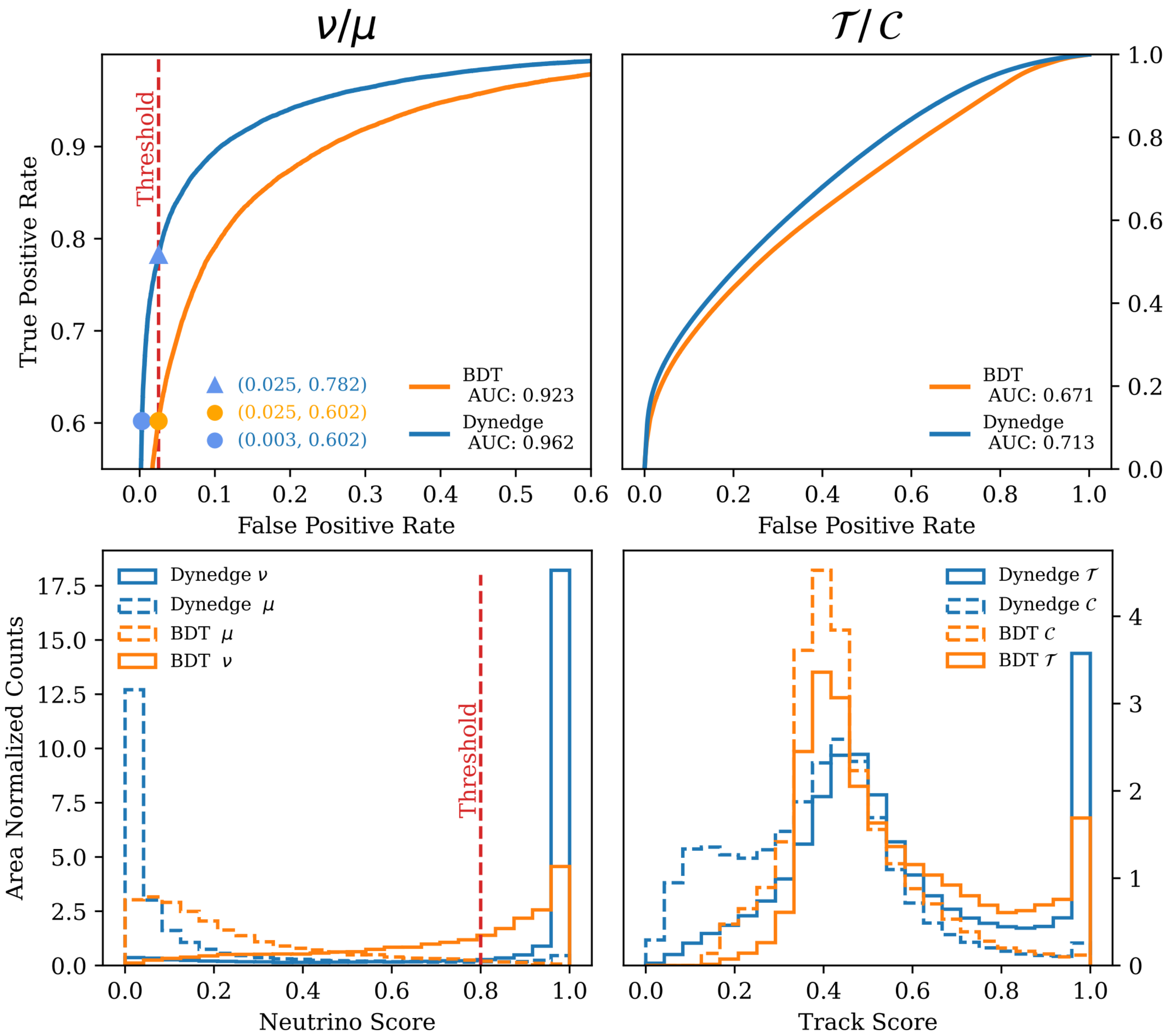
Regression


dynedge $\mathcal{T}$
dynedge $\mathcal{C}$
Retro $\mathcal{T}$
Retro $\mathcal{C}$
Energy Resolution (%)
Direction Resolution (deg.)
Rel. Impro. (%)
Zenith Resolution (deg.)
Vertex Resolution (m)
Energy (log10 GeV)

Classification

Neutrino / Muon

Track-like / Cascade-like



Improvement of resolution and classification power in all tasks and at most neutrino energies!

Not only that, but also speed increase on the order of 10^4!
With ~30 kHz per reco variable, full realtime reconstruction is possible

Additional question:
How stable is our algorithm to real-world variations?

Two tests:

Vary systematics:

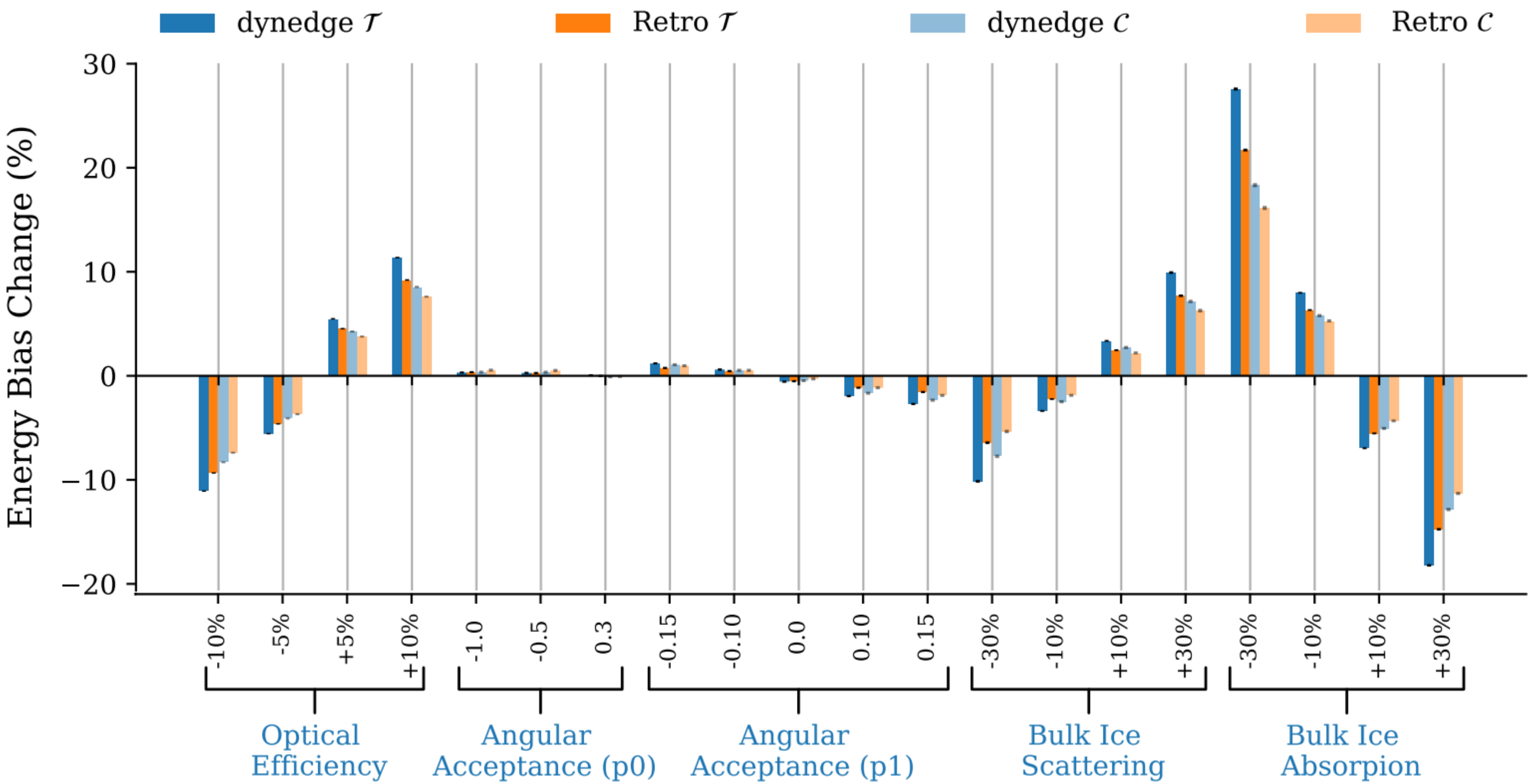
Apply GNN (trained with baseline MC) on simulations created with varied systematic parameters, such as:

- Optical efficiency
- Angular acceptance
- Ice scattering and absorption

Perturb input data:

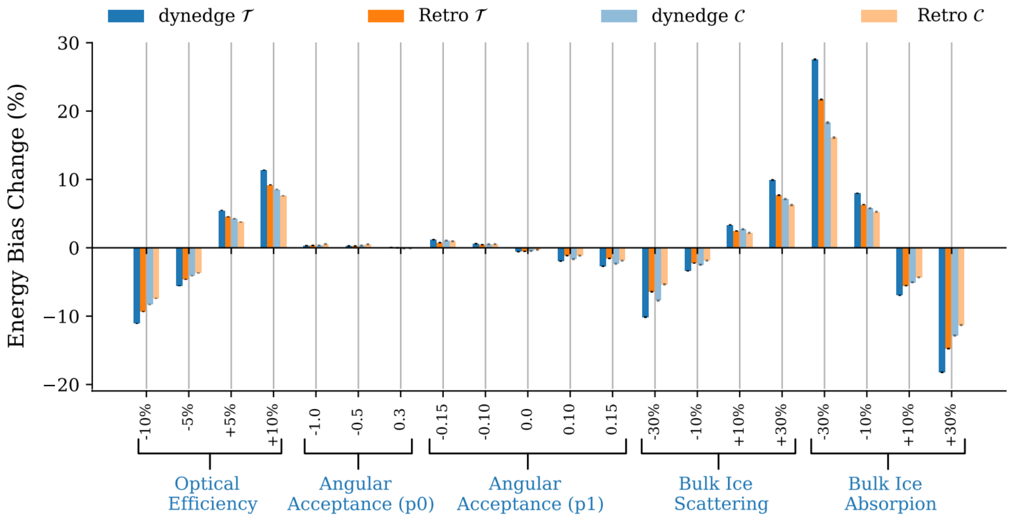
Slightly vary certain input features by a random amount based on real-life measurement uncertainties

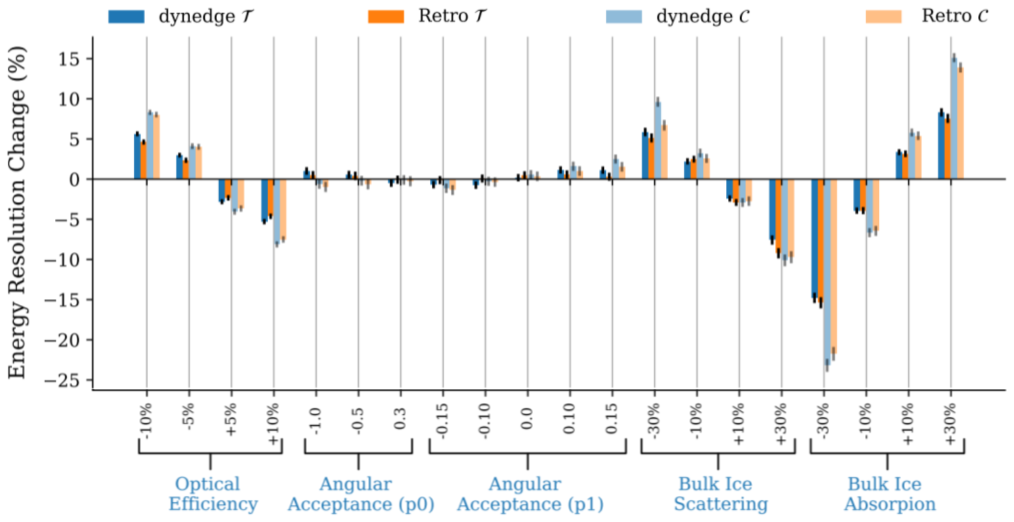
1) Applying the GNN on simulations with different systematics



Bias:
Shift in the median of predictions compared to truth

1) Applying the GNN on simulations with different systematics

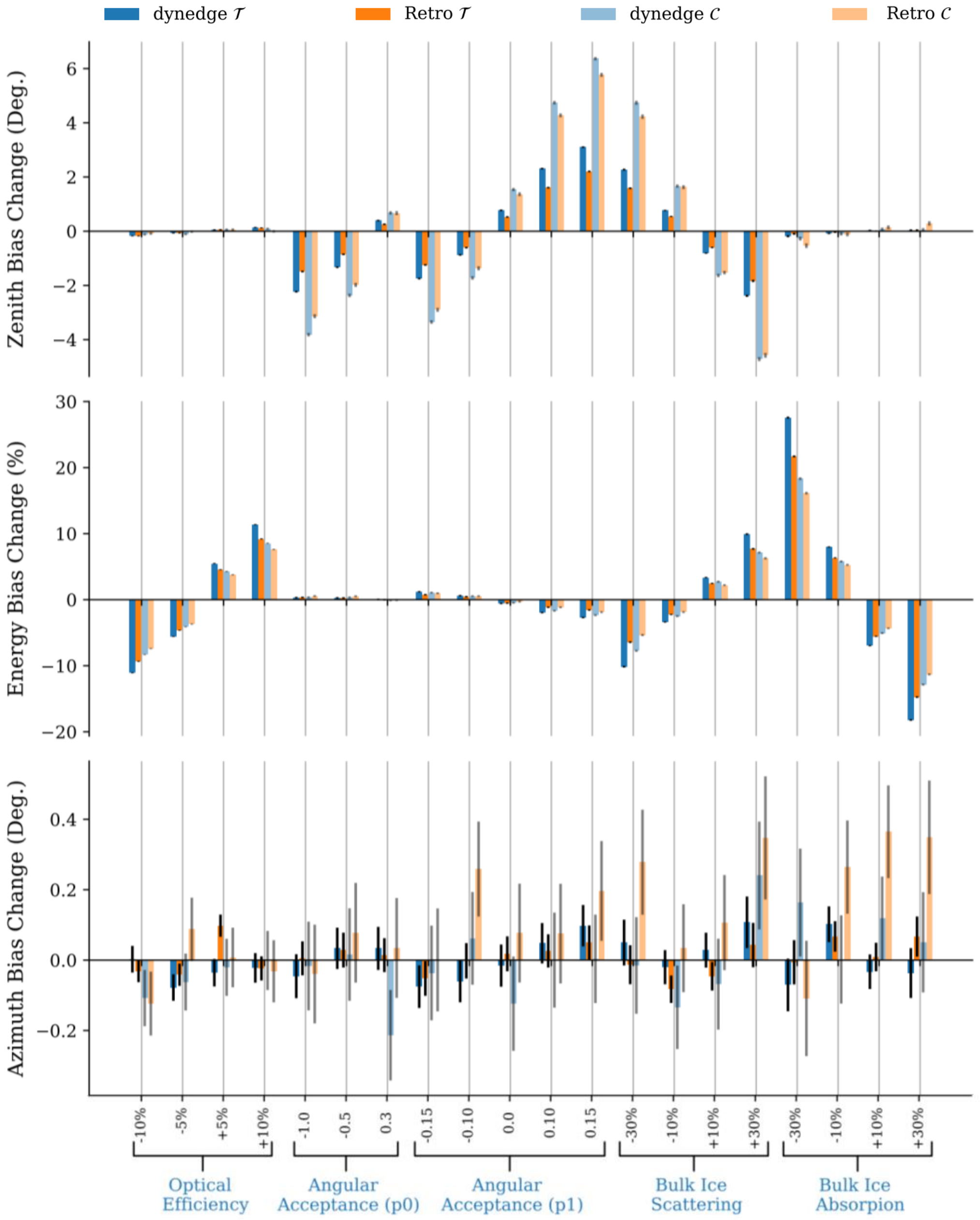


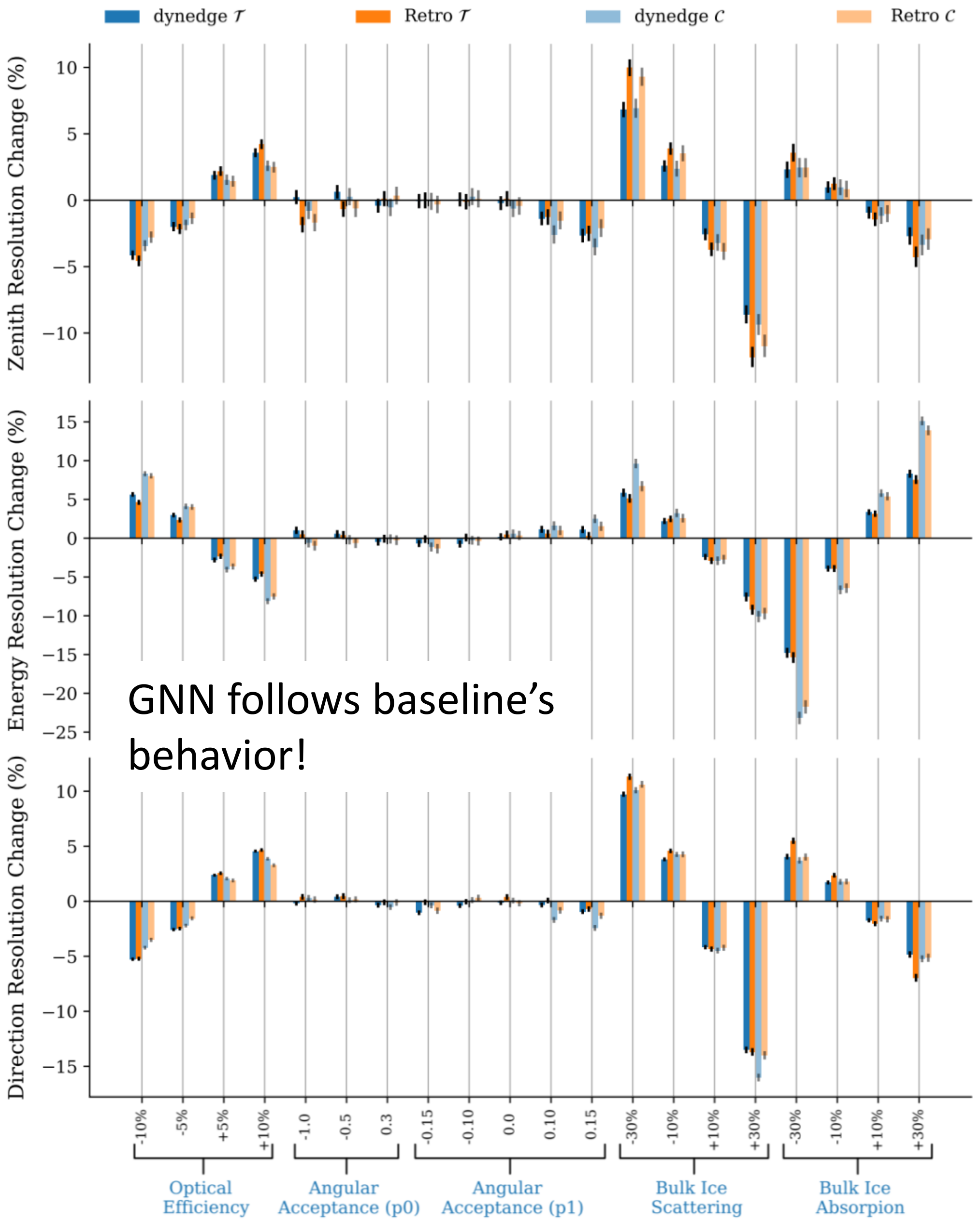


Bias:
Shift in the median of predictions compared to truth

Resolution:
Width of the central 68% bands of the predictions

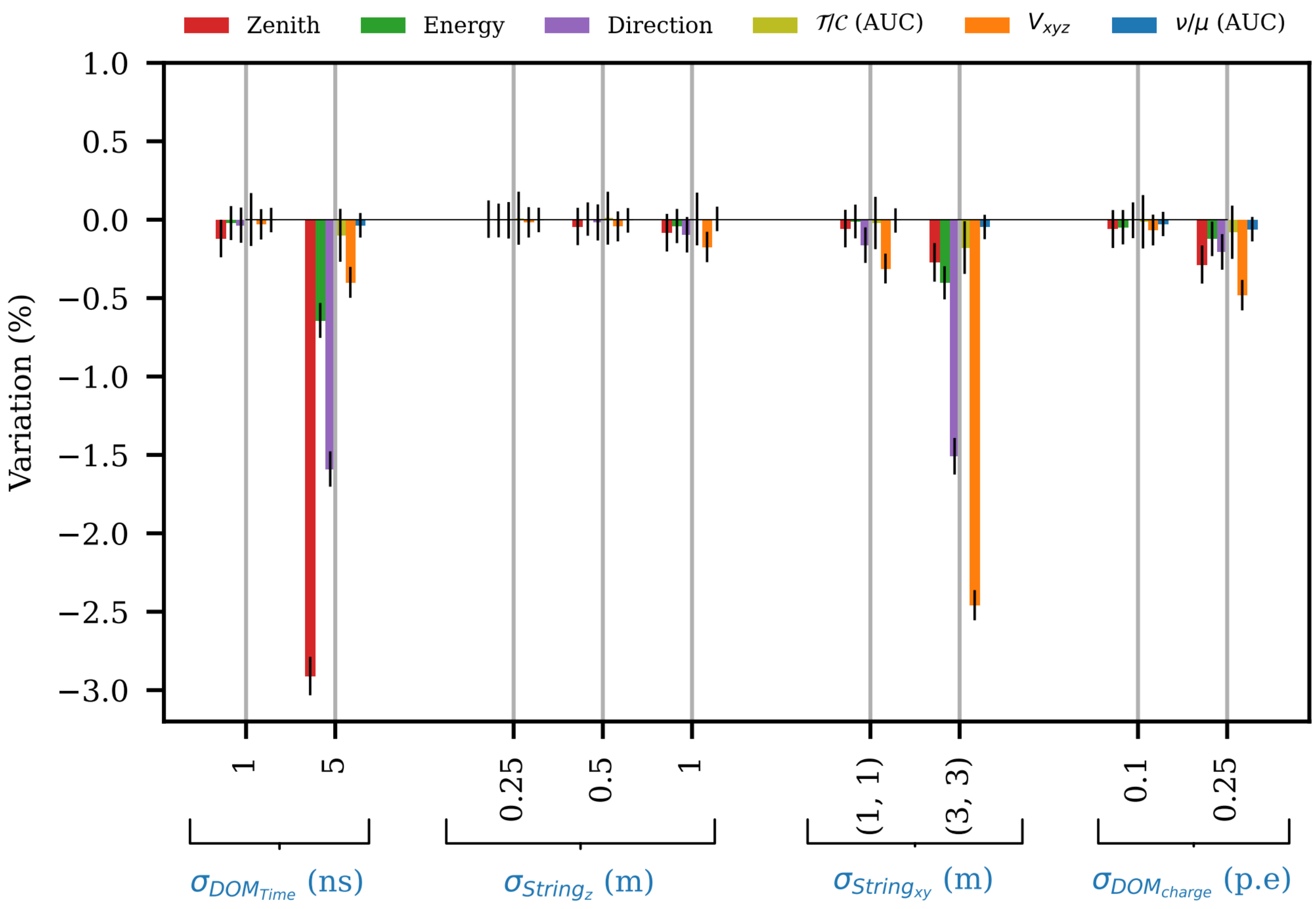
1) Applying the GNN on simulations with different systematics





GNN follows baseline's behavior!

2) Randomly perturb input features according to real-life uncertainties



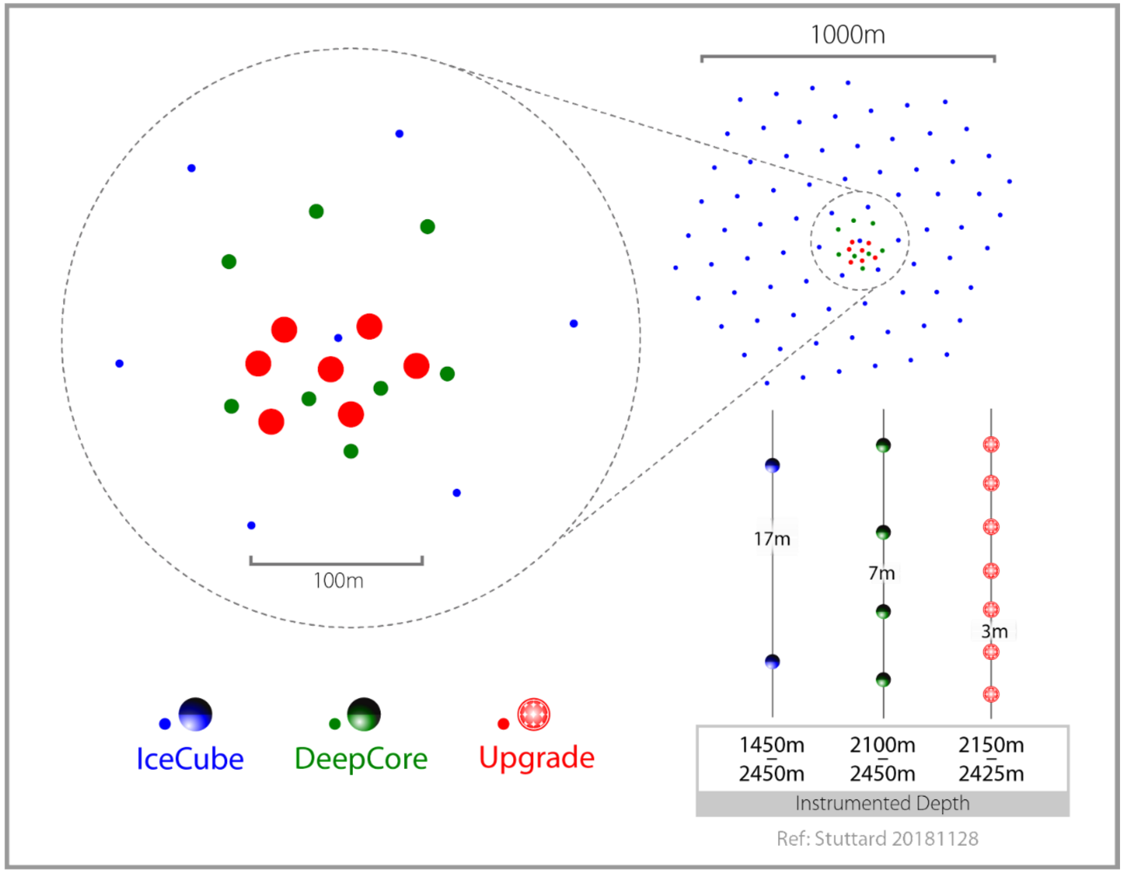
Conclusions:

- Our GNN rivals and often surpasses the baseline algorithms in resolution
- Offers a speed-up on the order of 10^4
- Behaves similar to our baseline reconstruction when faced with systematic variations
- Perturbation of input parameters according to measurement uncertainties show only marginal effect
- These results are from our paper, recently accepted by JINST

Graph Neural Networks for
Low-Energy Event
Classification & Reconstruction
in IceCube
arXiv:2209.03042

A look into the future: IceCube Upgrade

Martin Ha Minh (TUM) mhaminh@icecube.wisc.edu

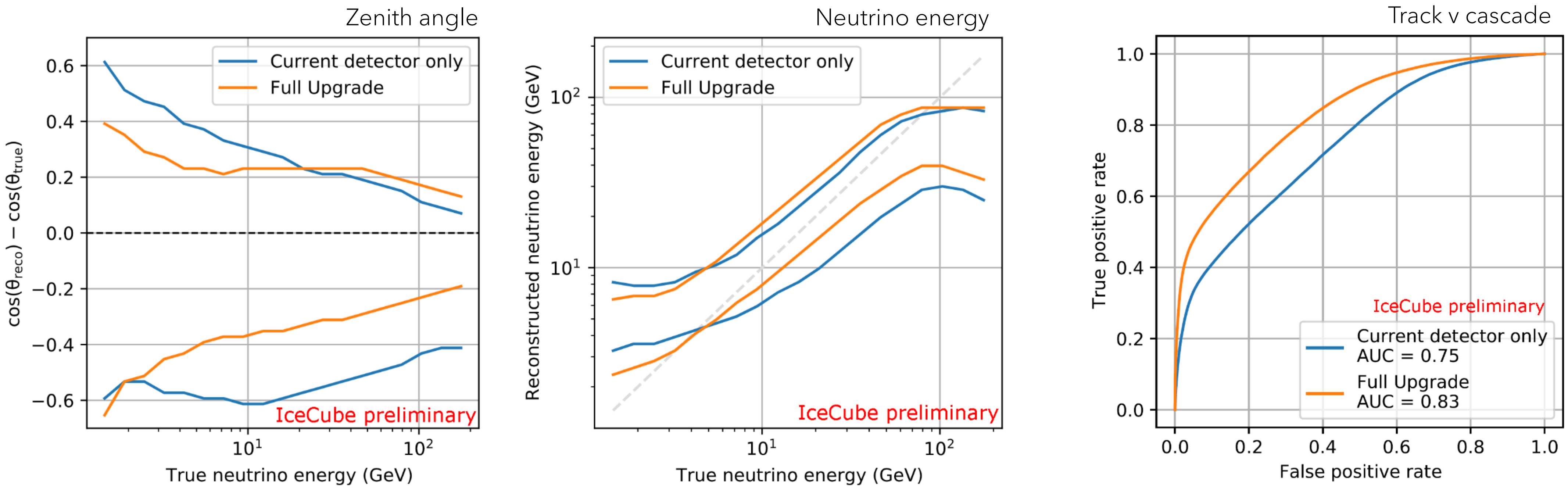


Reminder:

IceCube Upgrade (and Gen2) has additional strings with new detector modules, equipped with PMTs pointing in multiple directions

Current reconstruction algorithms would have to be greatly revamped and would still be too slow!

GNN does not have this problem: Simply introduce PMT angles as input features



Very early tests show that GNN are able reconstruct IceCube Upgrade events!

Work in progress on premature simulations and event selections, not to be compared with previous results

Reconstruction of Neutrino Events in IceCube using Graph Neural Networks
ICRC 2019
https://pos.sissa.it/395/1138/

Our GNN is already compatible with future IceCube extensions: Among the first to be able to reconstruct simulated events

Another strong message:
We're able to reconstruct neutrino events from two virtually different detectors using the same approach

The development of our GNN led to the creation of GraphNeT

Idea: Provide an
- easy-to-use framework for GNN development and application
- not only for IceCube, but for any other neutrino telescope

Currently a 10+ person team with its main locations at the
Niels Bohr Institute Copenhagen and Technical University of Munich

Any interest in developing or using our algorithms is welcome!


Troels Petersen (Assoc. Prof.)


Andreas Søgaard (PostDoc)


Philipp Eller (PostDoc)


Martin Ha Minh (PhD)


Rasmus Ørsøe (PhD)

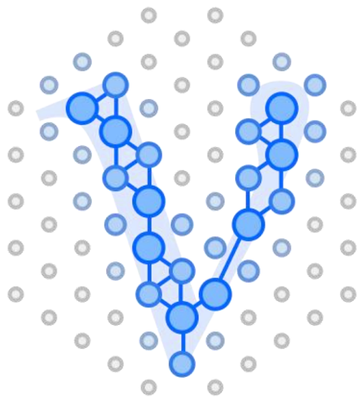
and many more!

github.com/graphnet-team/graphnet

GraphNeT
Graph Neural Networks for
Neutrino Telescope Event Reconstruction

Future detectors
Our approach allows us to provide realistic sensitivity studies for IceCube Upgrade and Gen2

Expand range of application
Investigate possibilities in BSM searches and neutrino astrophysics

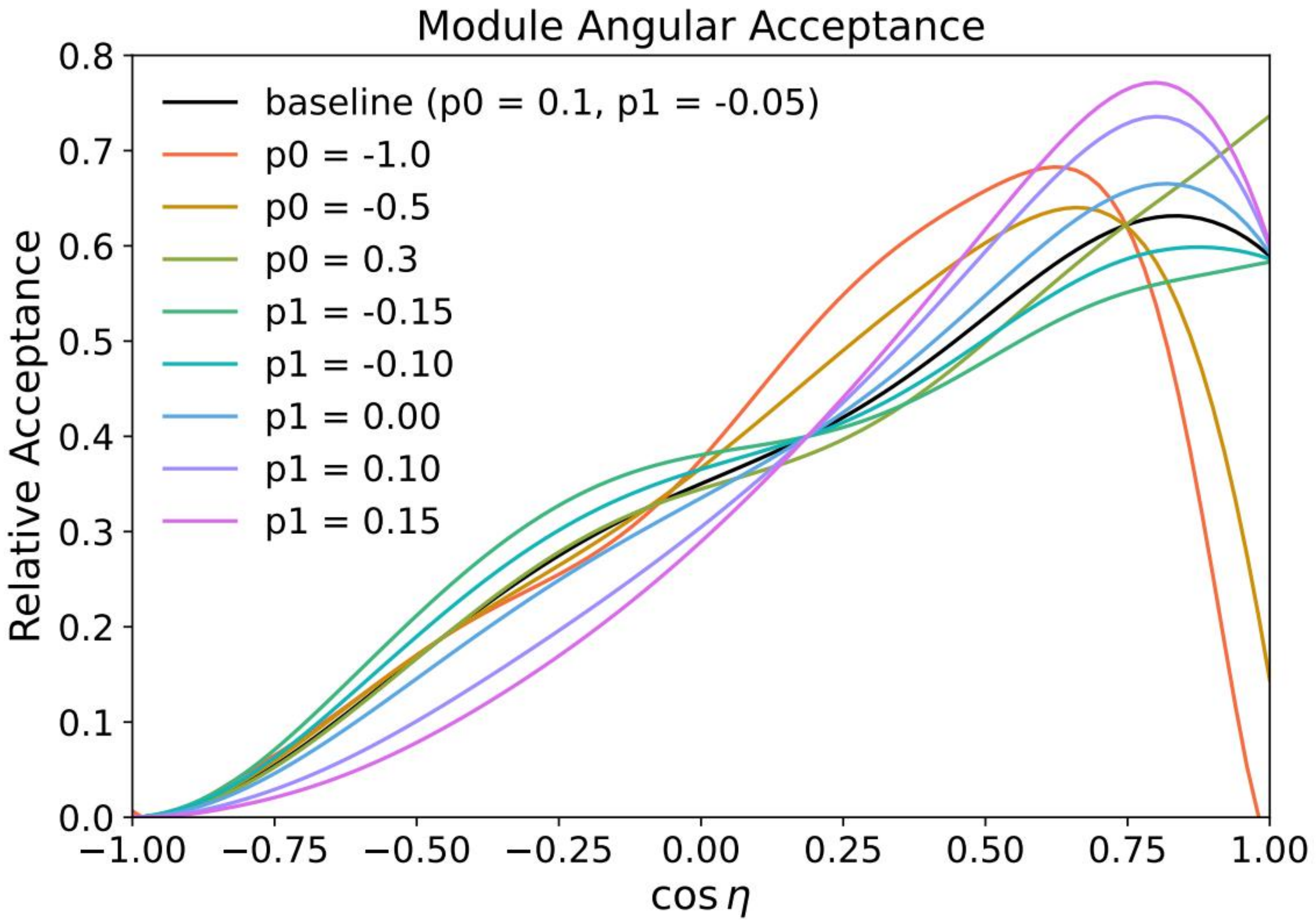


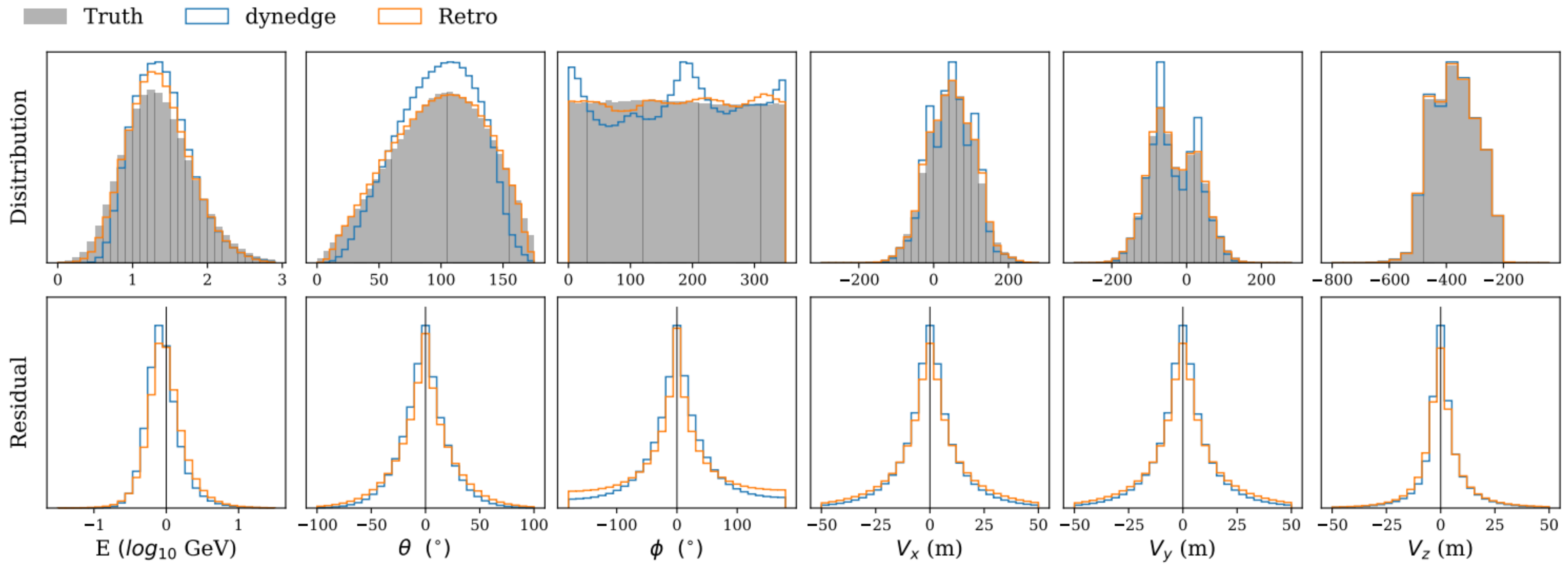
Optimize network
Introduce and test bleeding-edge machine learning techniques

Thanks for listening!

Training samples

Task	Total	ν_e^{NC}(%)	ν_e^{CC} (%)	ν_μ^{NC}(%)	ν_μ^{CC}(%)	ν_τ^{NC}(%)	ν_τ^{CC}(%)	μ (%)
ν/μ (Train)	215k	1.6	15.0	1.6	15.0	4.4	12.3	50.1
ν/μ (Test)	106k	1.6	15.1	1.5	15.3	4.5	12.2	49.8
Reconstruction (Train)	3.76M	3.2	30.0	3.1	30.3	9.0	24.4	
Reconstruction (Test)	4.37M	1.4	12.8	6.6	64.3	4.0	11.0	
$\mathcal{T}/\mathcal{C}$ (Train)	731k	16.7	16.7	16.7	49.9			
$\mathcal{T}/\mathcal{C}$ (Test)	7.4M	0.8	21.2	3.9	48.2	7.0	18.9	


Module Angular Acceptance
baseline (p0 = 0.1, p1 = -0.05)
p0 = -1.0
p0 = -0.5
p0 = 0.3
p1 = -0.15
p1 = -0.10
p1 = 0.00
p1 = 0.10
p1 = 0.15
Relative Acceptance
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
$\cos\eta$



Truth
dynedge
Retro
Disitribution
Residual
E (log_{10} GeV)
θ (°)
ϕ (°)
V_x (m)
V_y (m)
V_z (m)