# Machine Learning in neutrino telescopes

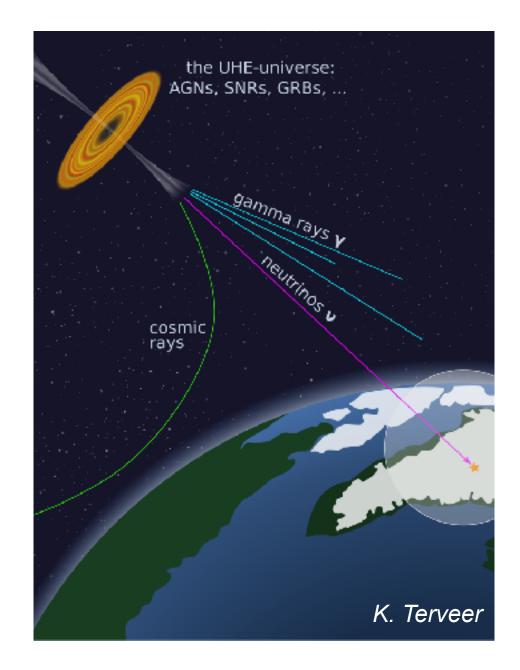
Mostly deep convolutional neural networks

Jakob van Santen APPP Workshop, Zeuthen, 2025-10-07



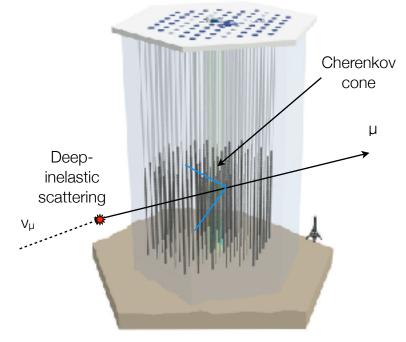
## Why neutrino telescopes

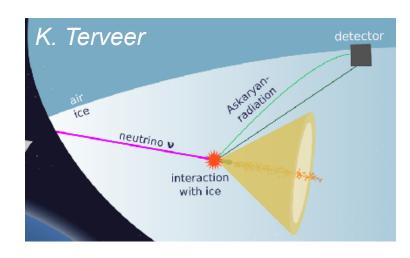
- Where are the sources of high-energy neutrinos?
- What are their properties?
- Along the way: what are the properties of the unresolved sources? (In IceCube jargon: "diffuse analysis")
- Small fluxes -> O(gigaton) target mass -> natural media
- While you're at it:
  - Neutrino properties with atmospheric neutrinos
  - Hadronic physics with air showers
  - [Dark matter, nonstandard interactions, Lorentz invariance violation, etc]



## IceCube & Radio Neutrino Observatory Greenland

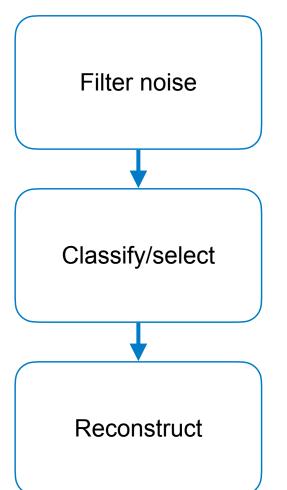
- **IceCube**: PMTs 125 (40-70, 20)\* m apart
- Deep-inelastic scattering in the ice
- Relativistic charged particles induce Cherenkov radiation, detectable O(100 m) away
- Sensitive to neutrinos above ~1000 (100, 30)\* GeV
- Completed in 2012 (Upgrade 2026)
- Cf. KM3NeT, Baikal-GVD, P-ONE
- RNO-G: radio antenna stations 1.25 km apart
- Deep-inelastic scattering in the ice
- Moving charge emits radio pulse, detectable O(1 km) away
- Sensitive to neutrinos above ~1e7 GeV
- Under construction (7/35 stations)
- Cf. ARA, ARIANNA





#### **Tasks**

#### From raw to analysis-ready data



**Physics**: high-energy charged particles in ice **Noise**: everything else

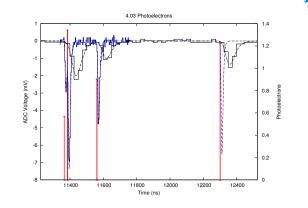
Signal/Background
or
Interaction signature

**Direction:** resolve sources **Energy**: separate from atmospheric backgrounds

#### Focus on IceCube for now

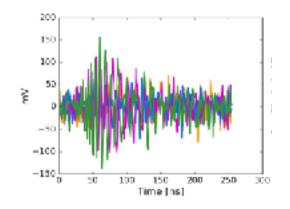
#### IceCube: photons

- Location, time
- Number



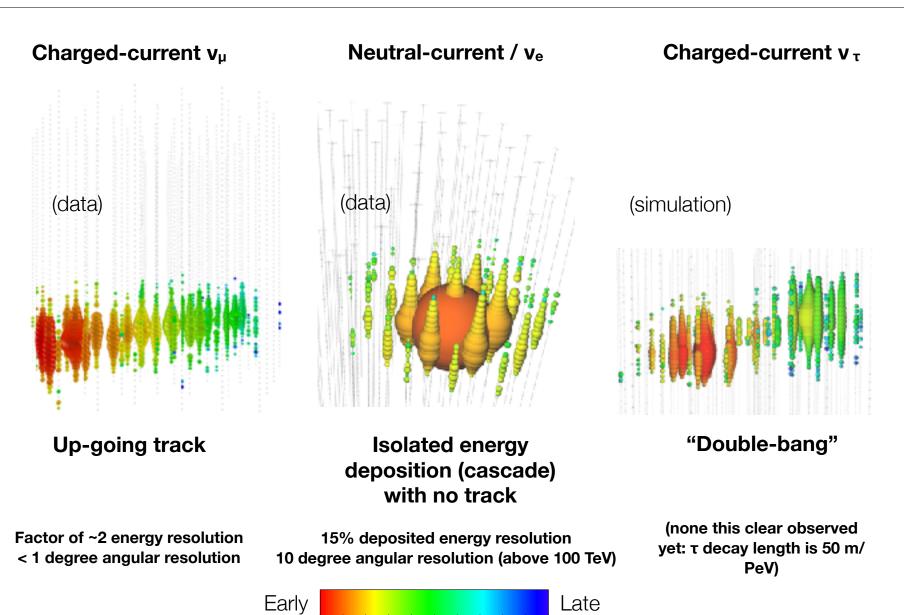
#### **RNO-G: electric field**

- Location, time
- Amplitude
- Polarization



# **Event reconstruction in IceCube**

## Neutrino event signatures (in an optical detector)



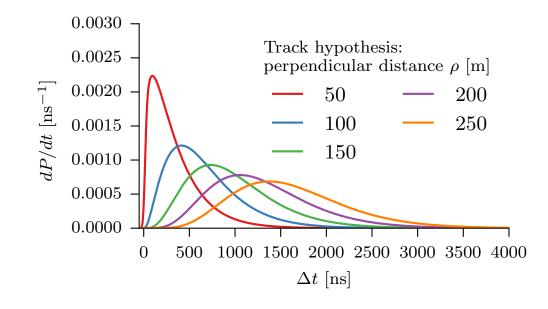




## Accounting for scattering in reconstruction

#### Standard/legacy approach

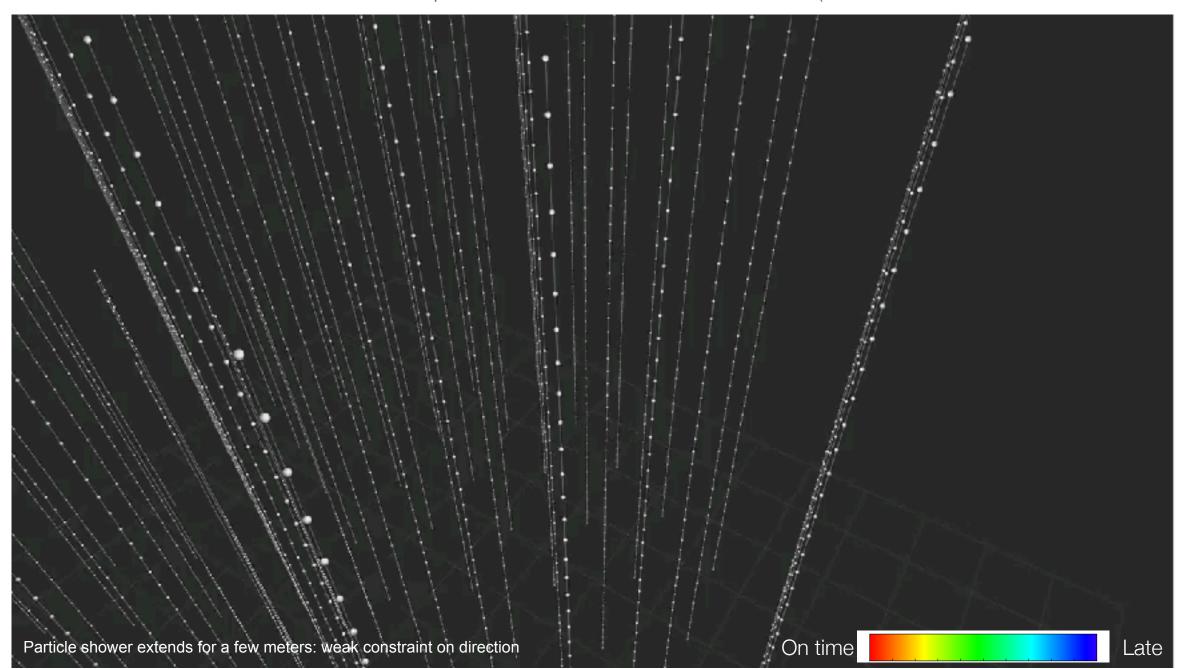
- Use a model of the expected time-delay distribution from a constant-intensity emitter to construct a likelihood for the underlying muon track
- For single photon detection: time distribution of individual photons
- For multiple photon detections: time distribution for first of N photons (order statistic)
- "Easy" for kilometer-long muon tracks: <1 degree angular error</li>



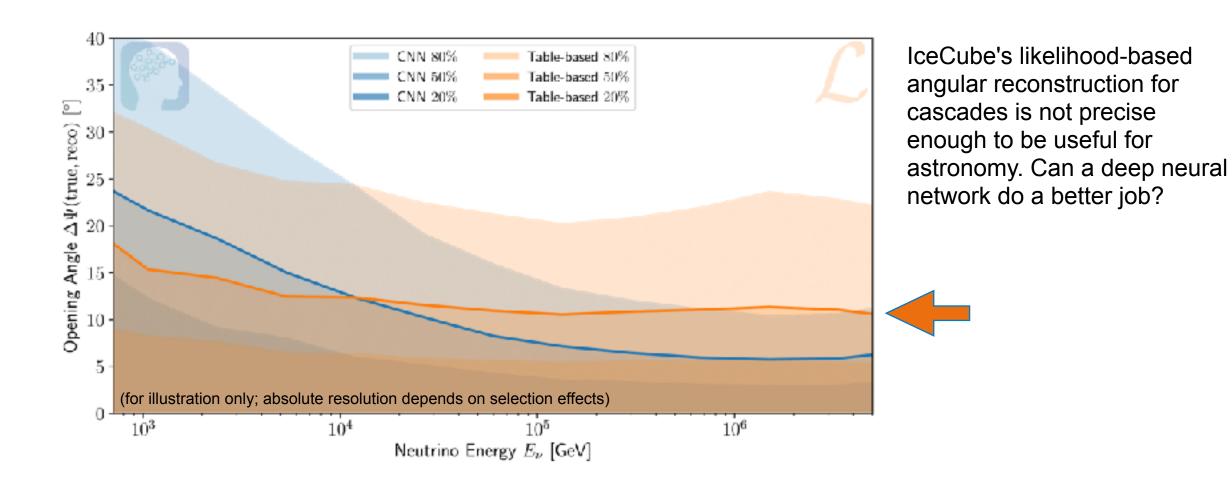
$$L_{\text{SPE1st}}(x) = \prod_{i=1}^{N_{\text{modules}}} dP(t_i - t_{\text{geo},i})/dt$$

$$L_{\text{MPE1st}}(x) = \prod_{i=1}^{N_{\text{modules}}} NdP(t_i - t_{\text{geo},i})/dt \cdot (1 - P(t_i - t_{\text{geo},i}))^{(N-1)}$$

https://arxiv.org/abs/astro-ph/0407044v1



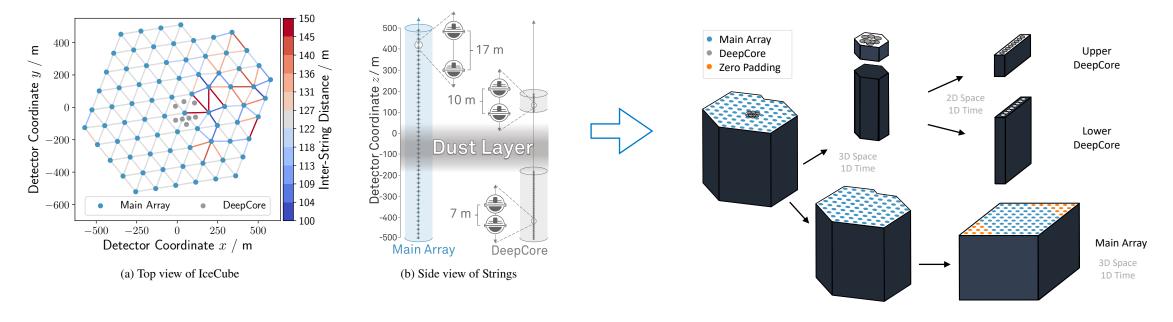
#### **Motivation**



**Challenge: geometry** 

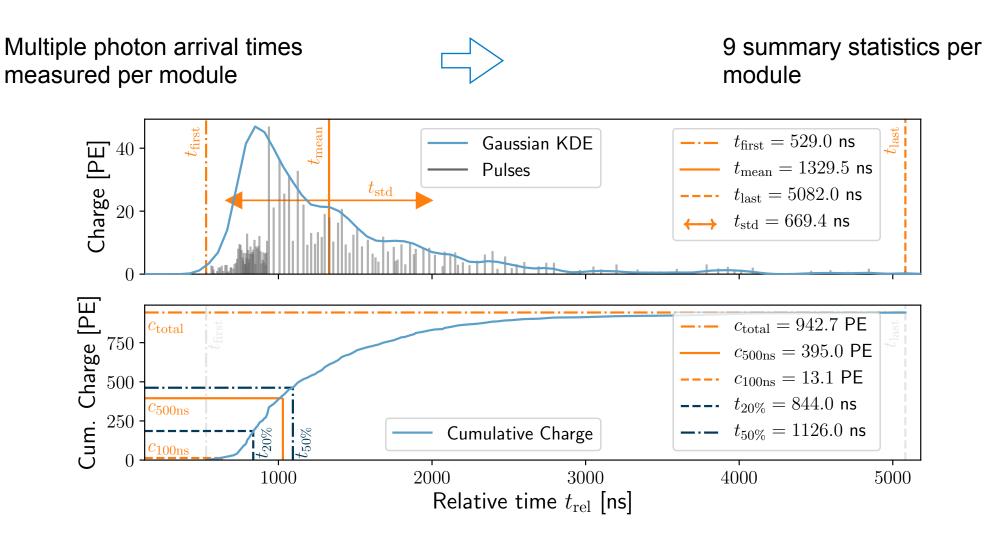
#### Detector is not a cartesian grid

#### Approximate main array as cartesian grid, flatten dense infill

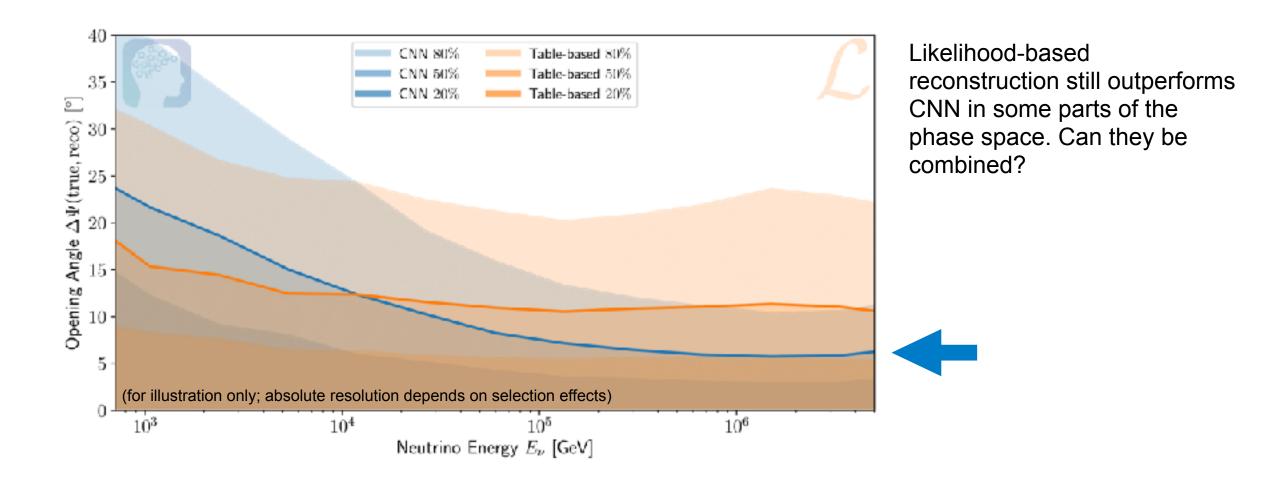


doi:10.1088/1748-0221/16/07/P07041

Challenge: variable-sized input data



#### **Potential for improvement**



DESY.

## Injecting domain knowledge

$$\overrightarrow{\Theta} = f(\overrightarrow{t})$$

 $\overrightarrow{\Theta} = \max_{\overrightarrow{\theta}} \prod_{i} dP(t_i | \overrightarrow{\Theta}) / dt$ 

Point predictor

Maximum likelihood (Learned PDF parameters)

Maximum likelihood (Fixed PDF parameters)

More domain knowledge

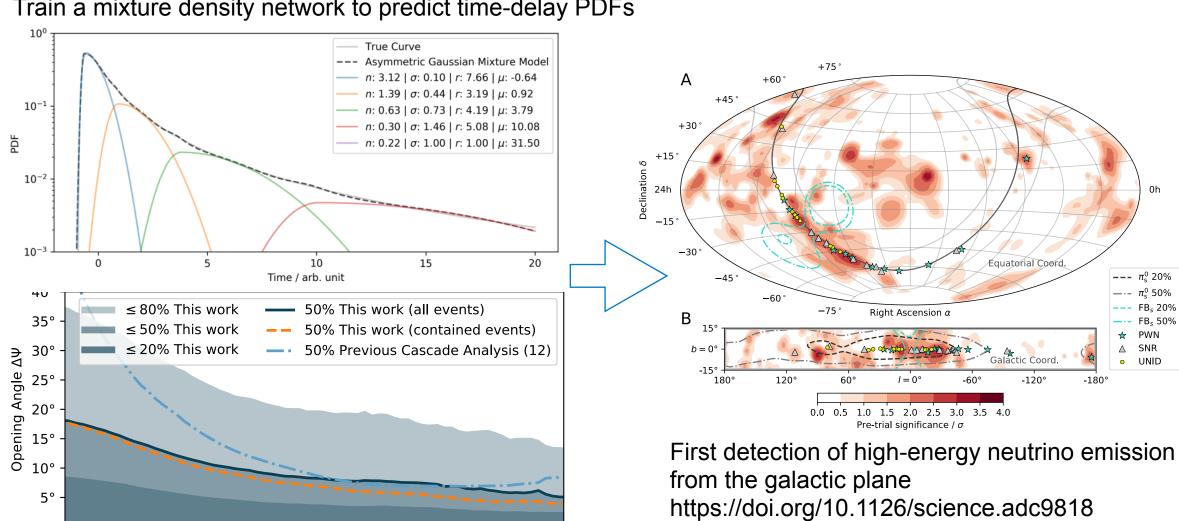
## Hybrid reconstruction with CNN-backed likelihood

#### Train a mixture density network to predict time-delay PDFs

 $10^{5}$ 

Neutrino Energy  $E_{\nu}$  / GeV

 $10^{6}$ 



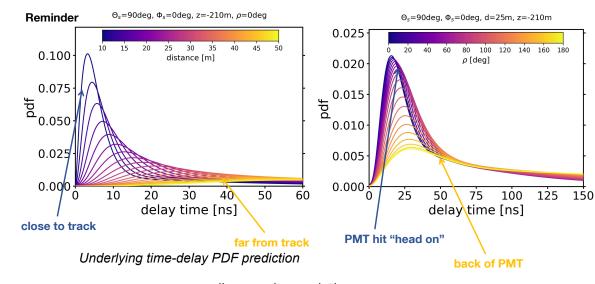
 $10^{3}$ 

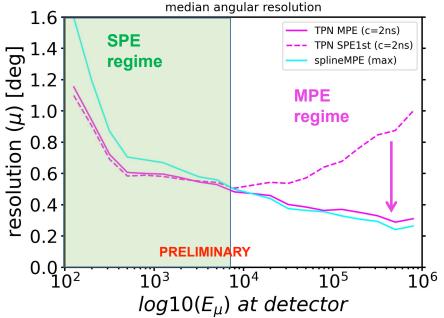
 $10^{4}$ 

#### What about tracks?

- Kilometer-long tracks are the most important sensitive channel for [optical] neutrino telescopes,
   but
- CNN-based point predictors have worse resolution than classical maximum-likelihood reconstruction for track events

- Hybrid likelihood backed by a mixture density network is likely the way forward here, too
- (Work continues)

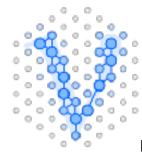




First example of ML-assisted track reconstruction beating legacy method H. Niederhausen, M. Jansson, R. Babu, B. Henke, M. Nisa

#### What about low energies?

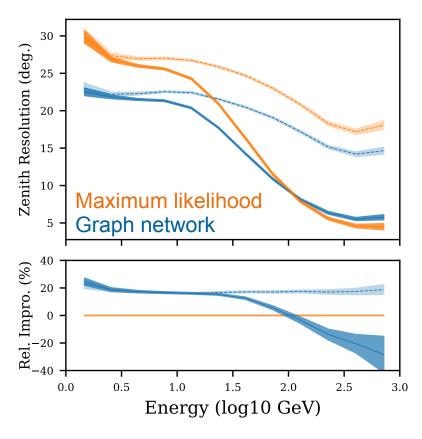
- Most sensitivity below ~300 GeV comes from DeepCore infill array (soon: IceCube Upgrade)
- Special challenges: very sparse data, noise, even more irregular geometry
- Graph CNNs: convolutions with arbitrary (learnable) neighbors
- Graph networks outperform previous maximumlikelihood method
- Multiple applications: noise suppression, segmentation, classification, reconstruction



## GraphNeT

Deep Learning for Neutrino Telescopes

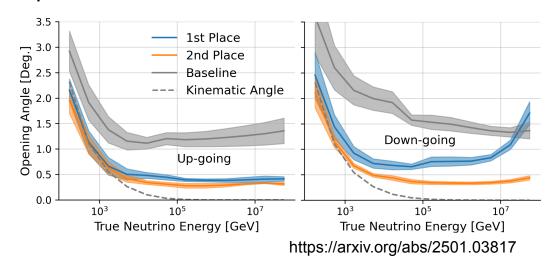
https://github.com/graphnet-team/graphnet

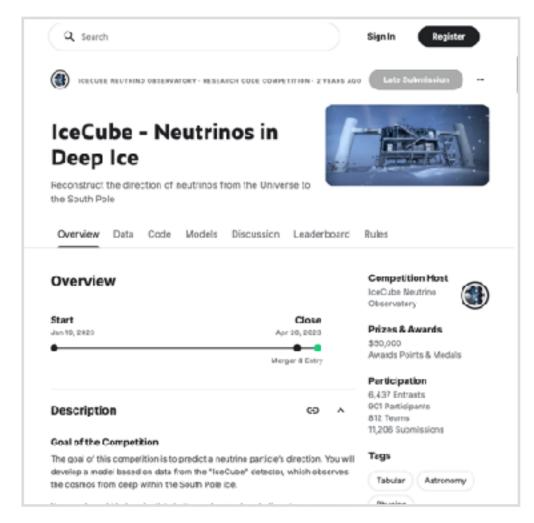


https://doi.org/10.1088/1748-0221/17/11/P11003

## IceCube Kaggle competition

- Public competition to improve IceCube reconstruction
- Provided training data, documentation, baseline solution
- Ran in early 2023, generated 11k submissions from 900 participants
- 1st and 2nd-place solutions implemented in GraphNeT





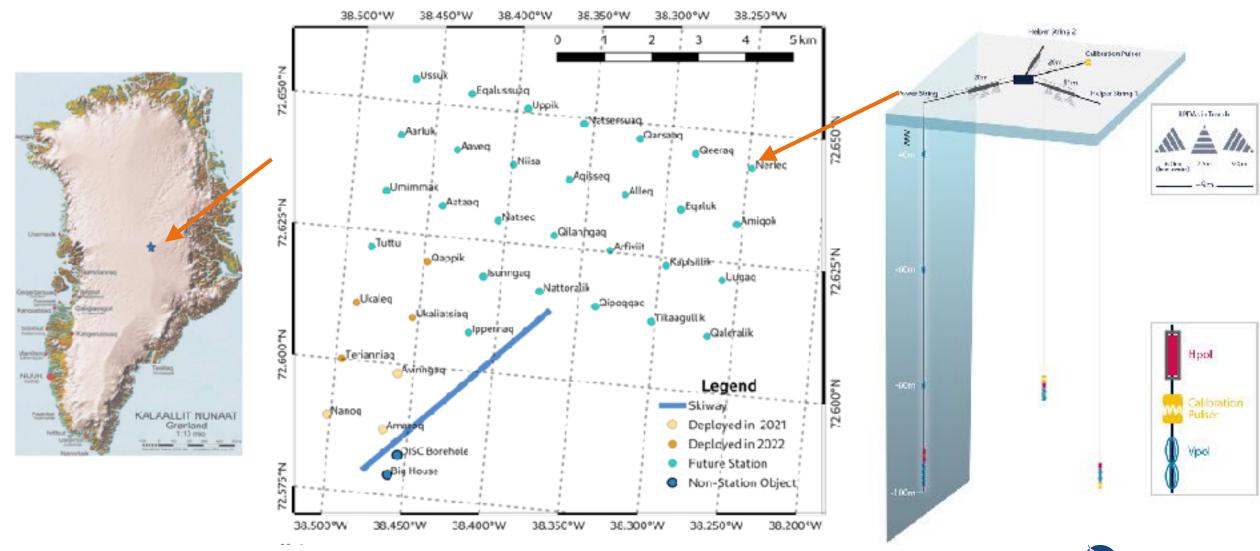
Led by P. Eller (TUM) <a href="https://www.kaggle.com/competitions/icecube-neutrinos-in-deep-ice">https://www.kaggle.com/competitions/icecube-neutrinos-in-deep-ice</a> <a href="https://doi.org/10.22323/1.444.1609">https://doi.org/10.22323/1.444.1609</a>

cf. <a href="https://www.kaggle.com/c/trackml-particle-identification">https://www.kaggle.com/c/trackml-particle-identification</a> cf. <a href="https://www.kaggle.com/competitions/g2net-gravitational-wave-detection">https://www.kaggle.com/competitions/g2net-gravitational-wave-detection</a>

## **RNO-G**

## The Radio Neutrino Observatory in Greenland (RNO-G)

The first large scale implementation



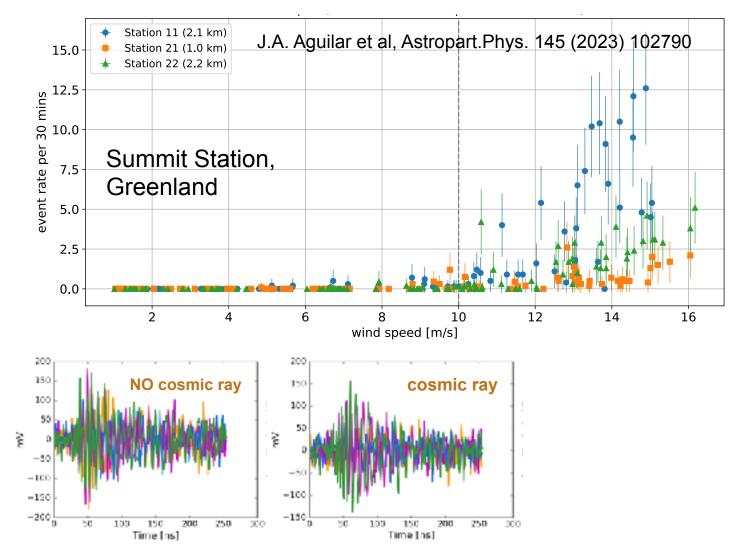
#### **Machine Learning for Radio Detection**

#### Mostly used for two things

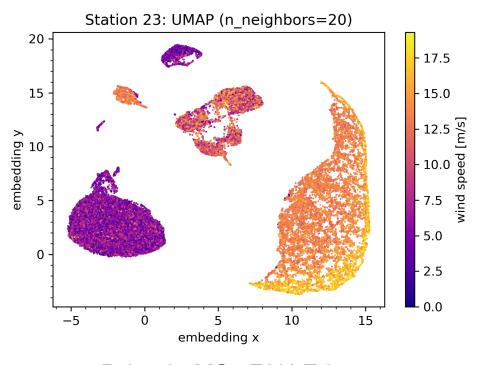
- Background
  - Our triggers are 99.999% useless (little pulses from thermal noise, airplanes, humans, wind, ....)
  - Classify backgrounds, understand backgrounds, mitigate them in instrument
  - Smarter triggering (reduce background at trigger level)

- Reconstruction
  - Signal propagation in ice is complicated and ice not perfectly understood
  - Use ML to reconstruct signals (a bit hypothetical at this point, because not radio emission from a neutrino has been detected)

## Wind noise tagging for RNO-G



- Train variational autoencoder to describe individual waveforms
- Wind-triggered events cluster in latent space



P. Laub, MSc FAU Erlangen

Noise waveforms are very similar to real triggers, but can be distinguished **DESY**.

## **Summary**

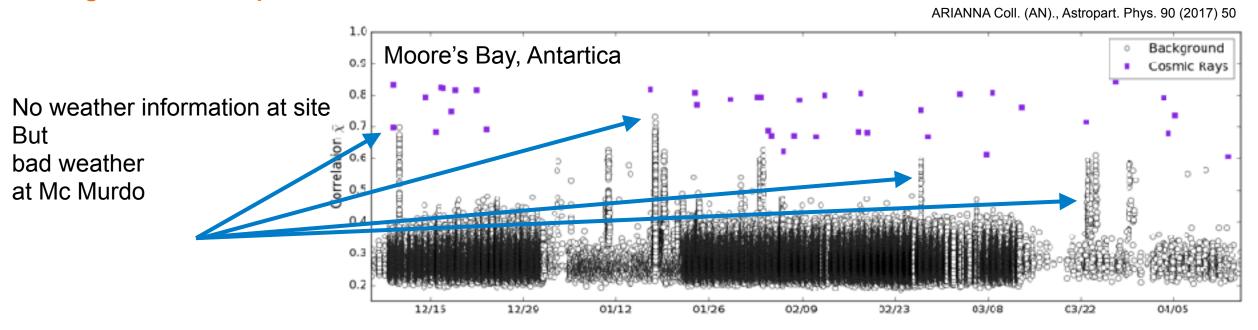
- Machine learning is becoming a workhorse for difficult reconstruction problems in IceCube
- Will likely play a larger role in RNO-G as it grows
- Interesting opportunities for outreach via open data
- Some common challenges:
  - Irregular spatial data
  - Sparse, variable-sized data
  - Industry-standard solutions often need adaptation to our problem domain
  - No calibration source or off-beam data: need to train on simulation.

DESY. 23

## Backup

#### Wind and radio detection

Background events pose a threat to neutrino detection

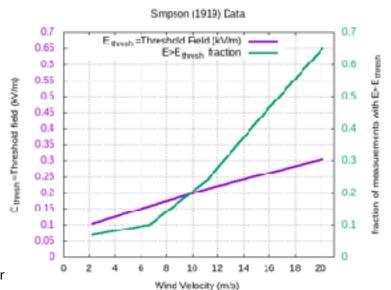


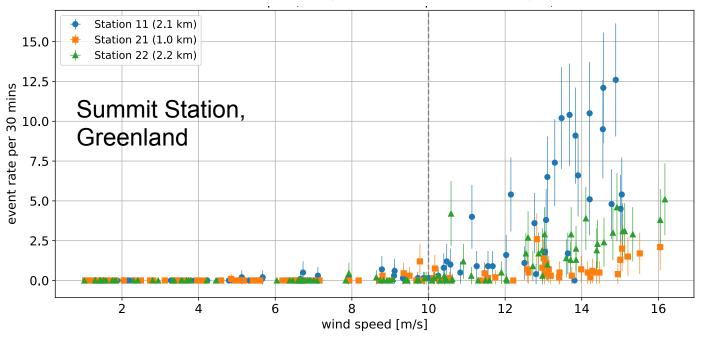
- During periods of bad weather the ARINNA experiment saw an increase in background mimicking neutrino and cosmic ray signals
- Hypotheses: problems with our power or communication system in bad weather

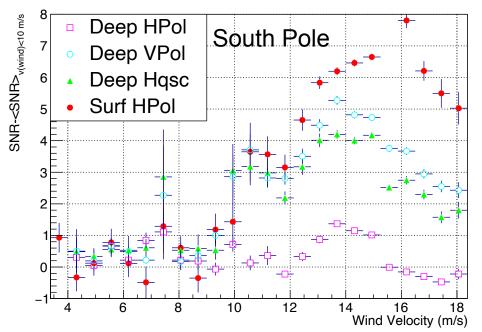
## **Triboelectricity**

#### But the same all around the world

- All prototypes for neutrino detectors see and increase in triggers as function of windspeed
- Anecdotal evidence from radio glaciologists: If the weather is bad, we just don't go out, the data is bad anyway ...
- Even the expedition from Scott to South Pole saw this already







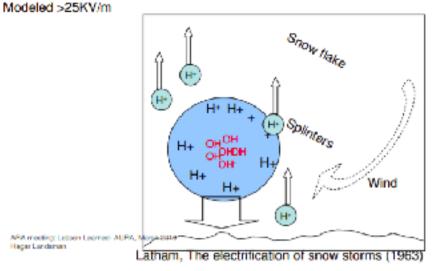
#### Master Thesis, P. Laub, FAU

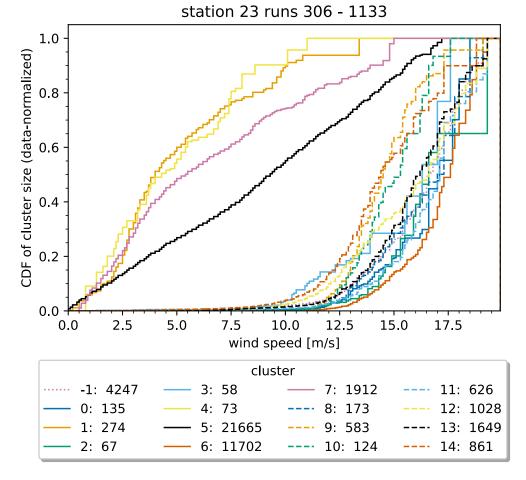
## **Triboelectricity**

#### But what actually causes it?

- If we want to make sure that we can reduce these backgrounds, we need to be able to model them
- Lacks & Shinbrot (2019): We may never be able to model triboelectric charging
- Then we need to understand better, what causes them and what they correlate with

H+ more mobile than OH-Positive charge excess in colder ice ~2dt mV High E field near surface measured.





Clustering using Variational Auto Encoders

There are clearly different event characteristics

So we probably need more than just wind