IceCube event reconstruction

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IceCube Summer School 2026

ICECUBE

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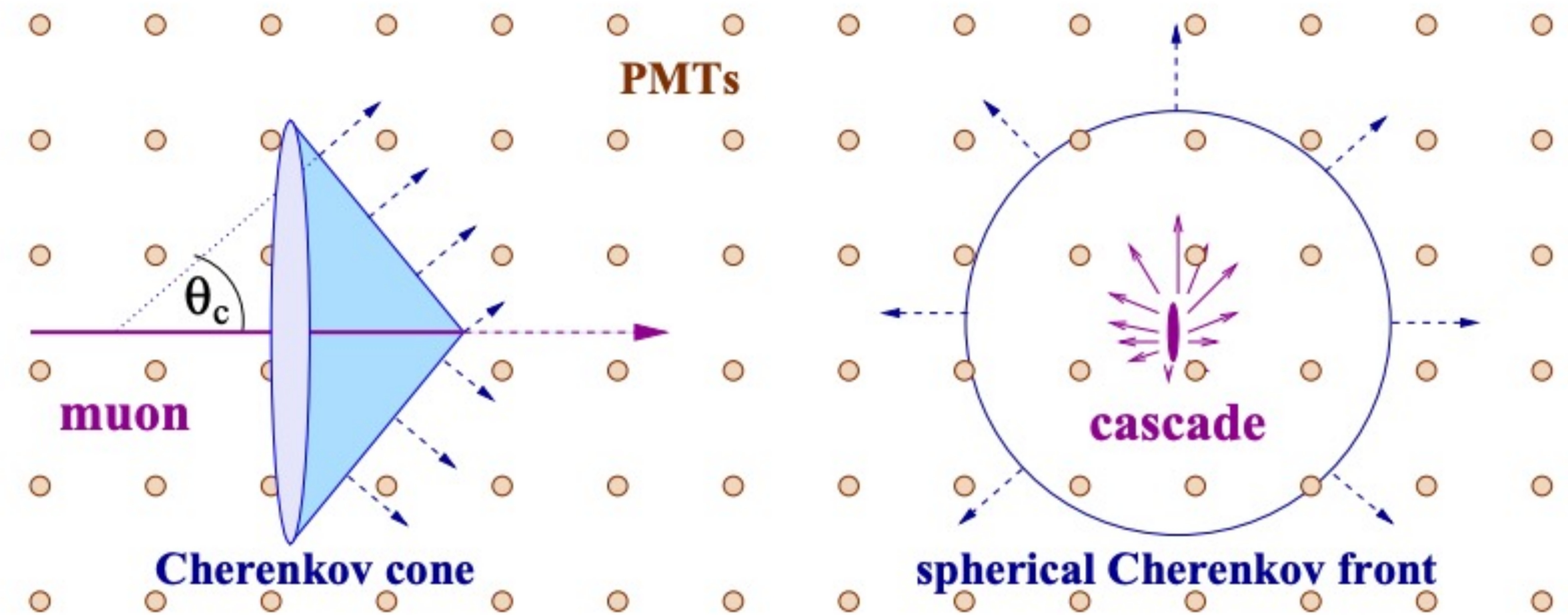
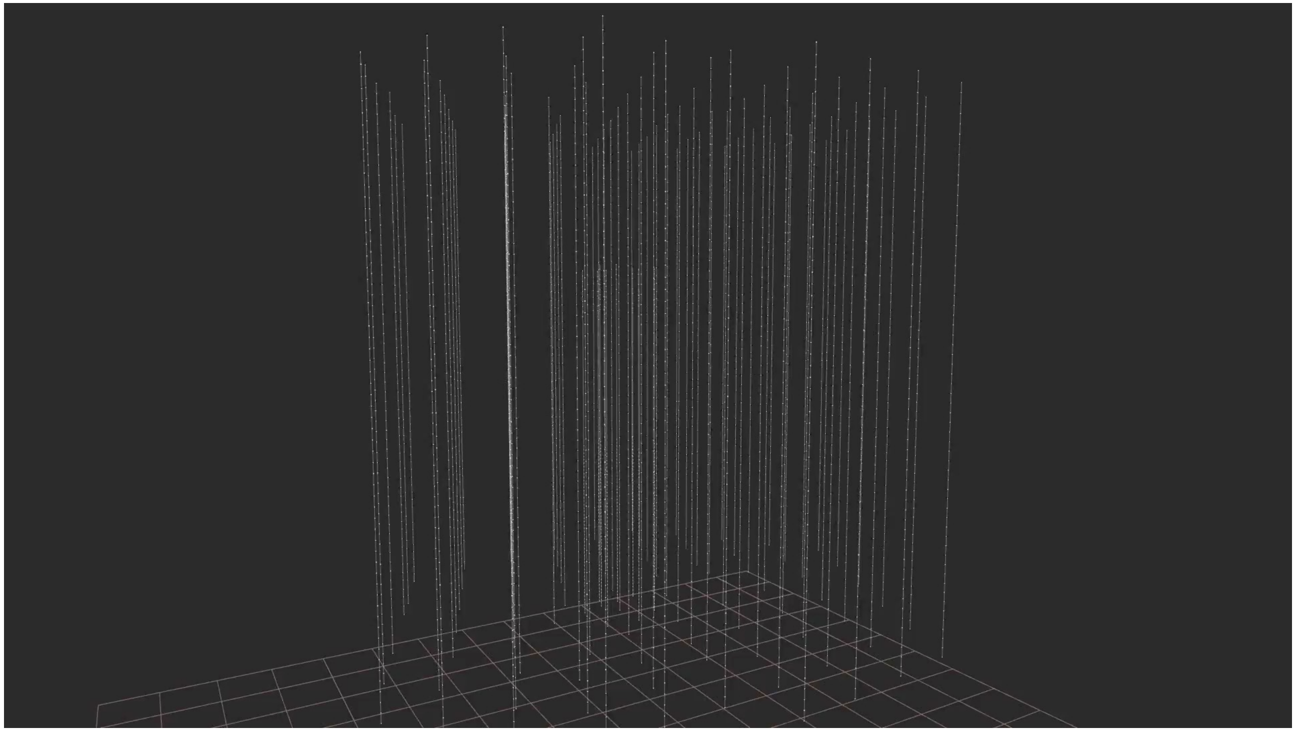
Tracks vs cascades

Tracks can travel large distance ~ first photons on Cherenkov cone

Cascades travel relatively short distance ~ diffuse photons w. spherical front



What do neutrinos look like in IceCube?



muons: long paths in the detector → **track**

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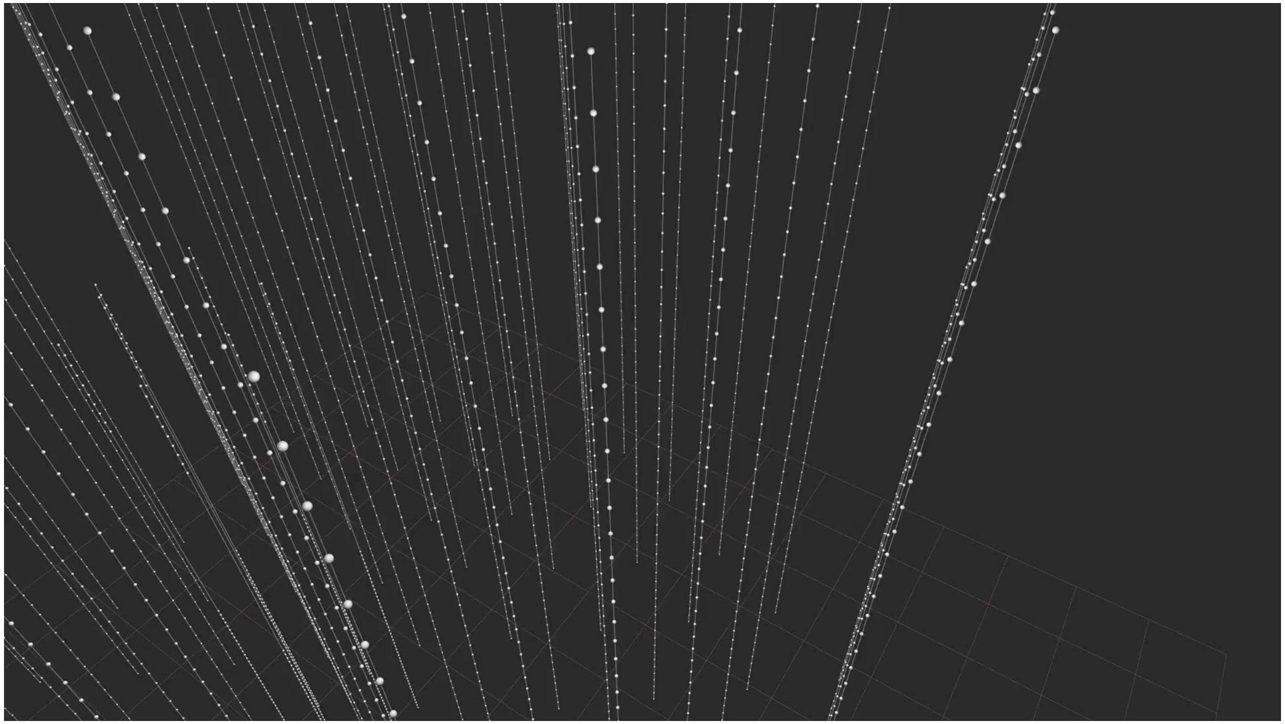
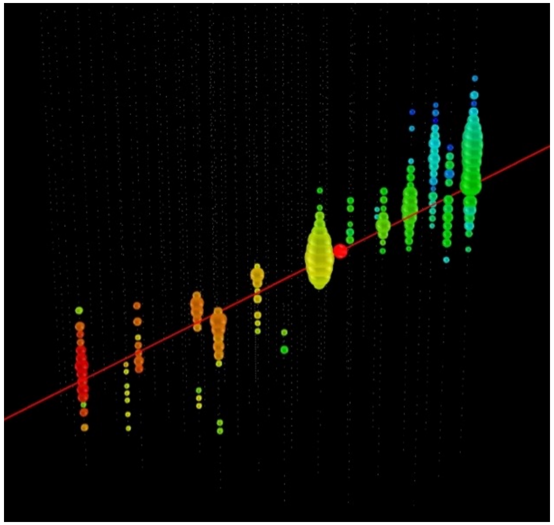


electrons/hadrons: shower of light → **cascade**

What IceCube actually sees (high-energy)

CC muon neutrino

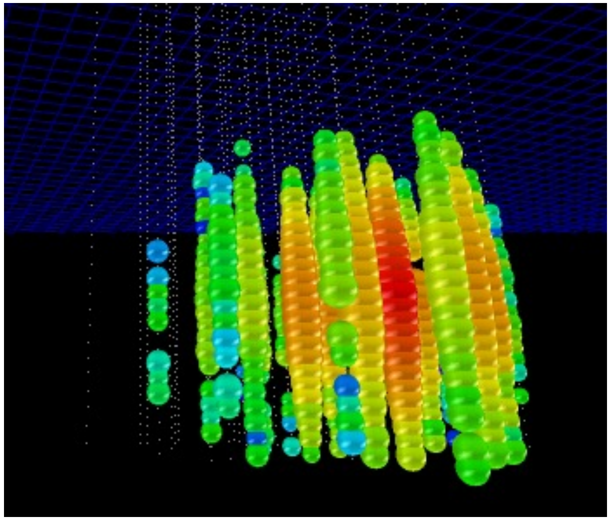


$$\nu_\mu + N \to \mu + X$$

track (data)

angular resolution ~ 0.5°
energy resolution ~ x2

NC or CC electron neutrino

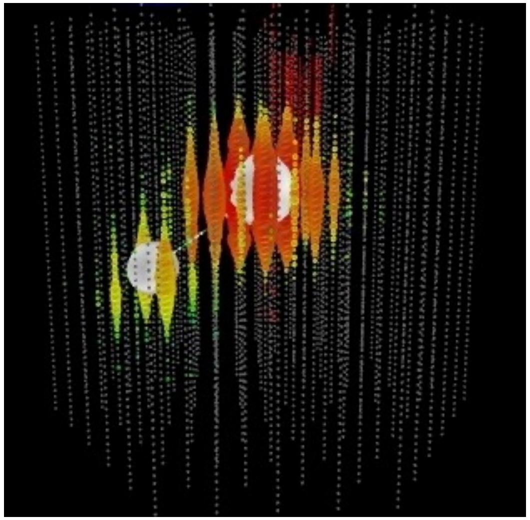


$$\nu_e + N \to e + X$$
$$\nu_x + N \to \nu_x + X$$

shower (data)

angular resolution ~ 10°
energy resolution ~ 15%

CC tau neutrino



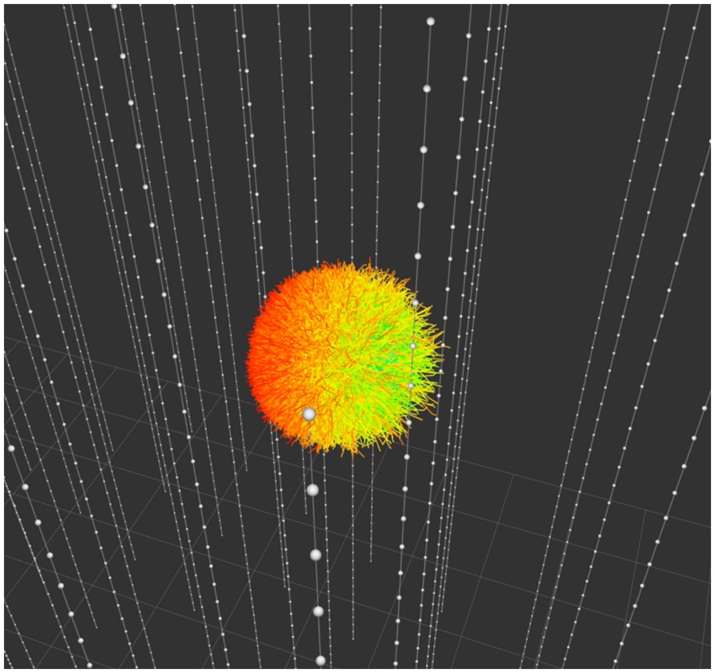
$$\nu_\tau + N \to \tau + X$$

"double-bang"
(simulation)

~2 expected in 6 years

Event reconstruction

Emitted

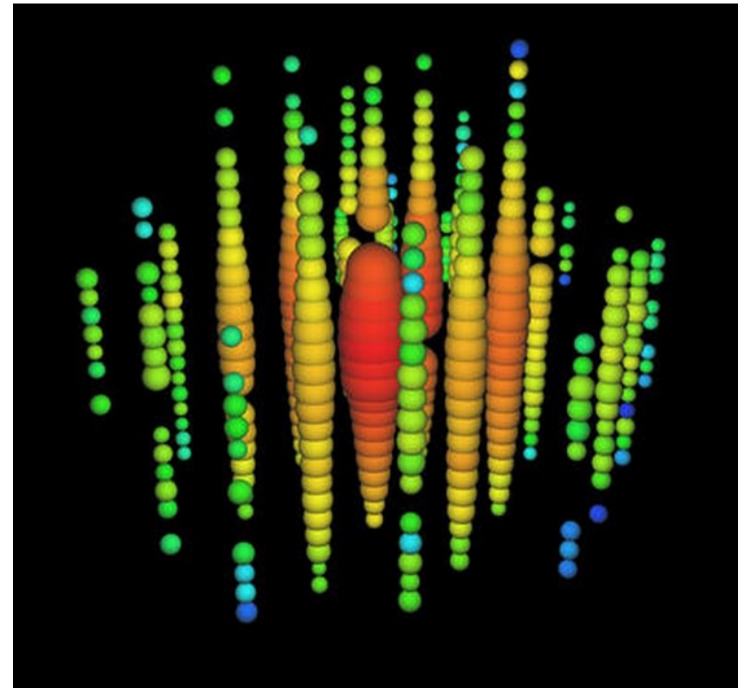


Asymmetry in photon emission helps with directional reconstruction

Information loss

$$\nu_e + N \rightarrow e + X$$
$$\nu_l + N \rightarrow \nu_l + X$$

Detected



Physics model (emission, absorption, scattering)

$$\boldsymbol{\Theta} = (x, y, z, \theta, \phi, E, t)$$

$$X = q_{DOM}\,(t)$$

Maximize $\mathcal{L}(\boldsymbol{\Theta}|\mathrm{X}_{\mathrm{Data}})$ or train ML algorithm

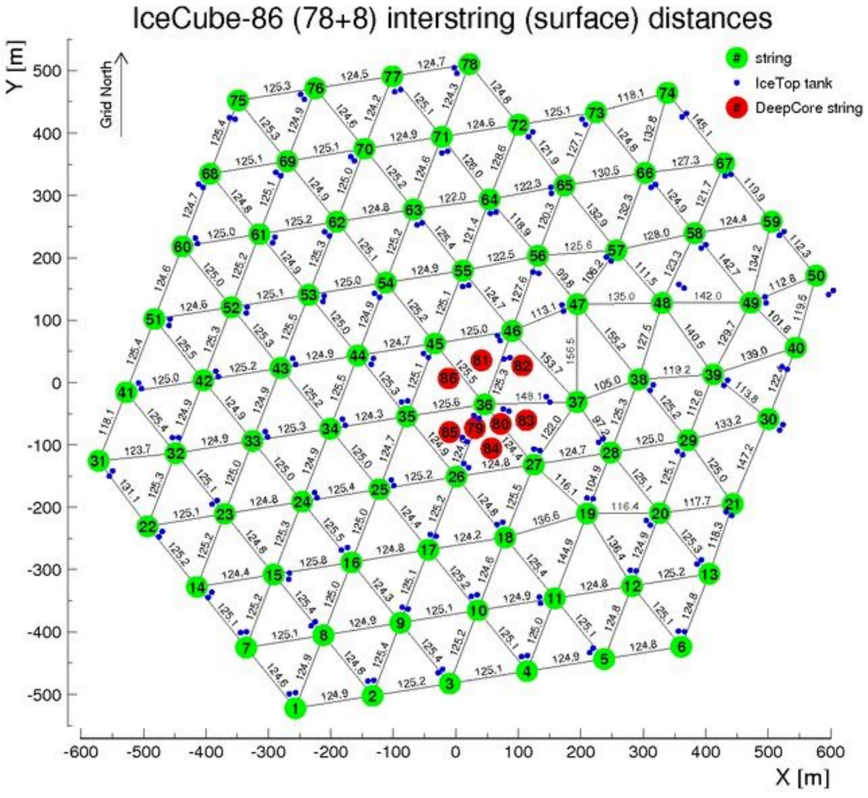
Physics parameters and IceCube coordinates

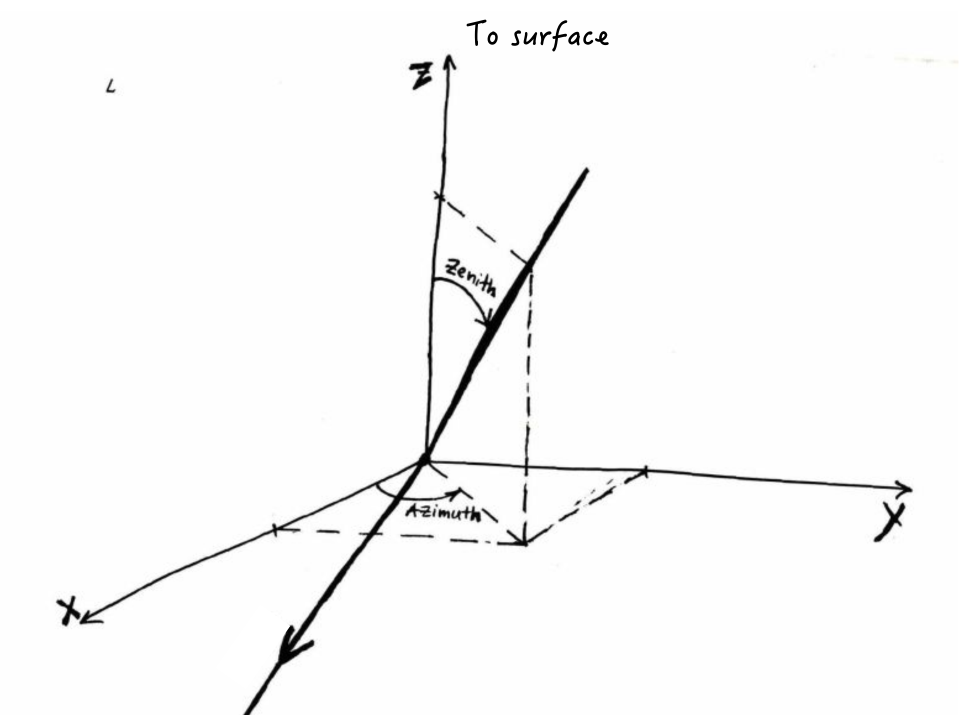
$$\mathbf{\Theta} = (x, y, z, \theta, \phi, E, t)$$

Detector coordinate system centered in middle of detector

(θ, ϕ) = (zenith, azimuth) corresponds to *arrival* direction

Usually, (θ, ϕ, E) are the physics parameters we're most interested in





Approaches for reconstruction

Low energy
High energy

Tracks

- Use **first-hit times** for *directional* reconstruction (SANTA, SplineReco)
- Use **full-waveform** information by fitting predicted light yields to what is actually seen (RetroReco, DirectReco, MuEx, Millipede, DirectFit)
  - Break **high-energy tracks** into multiple cascades along the track due to muon stochastic energy losses
- Likelihood-free inference (FreeDOM)
- Energy reco (TruncatedEnergy)
- ML (FLERCNN, TNF)

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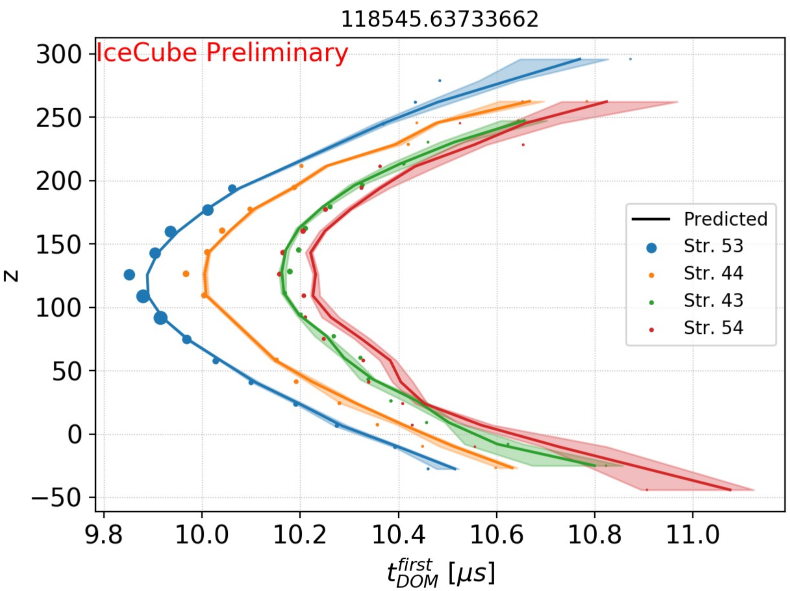
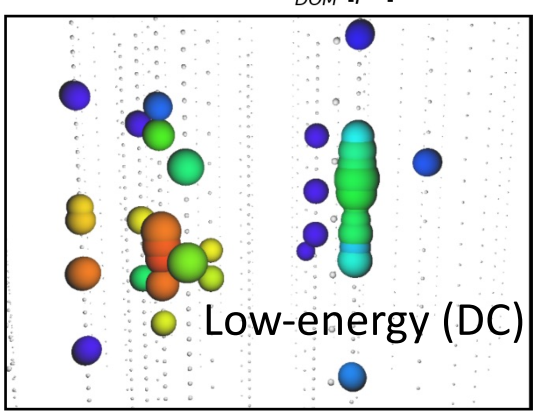
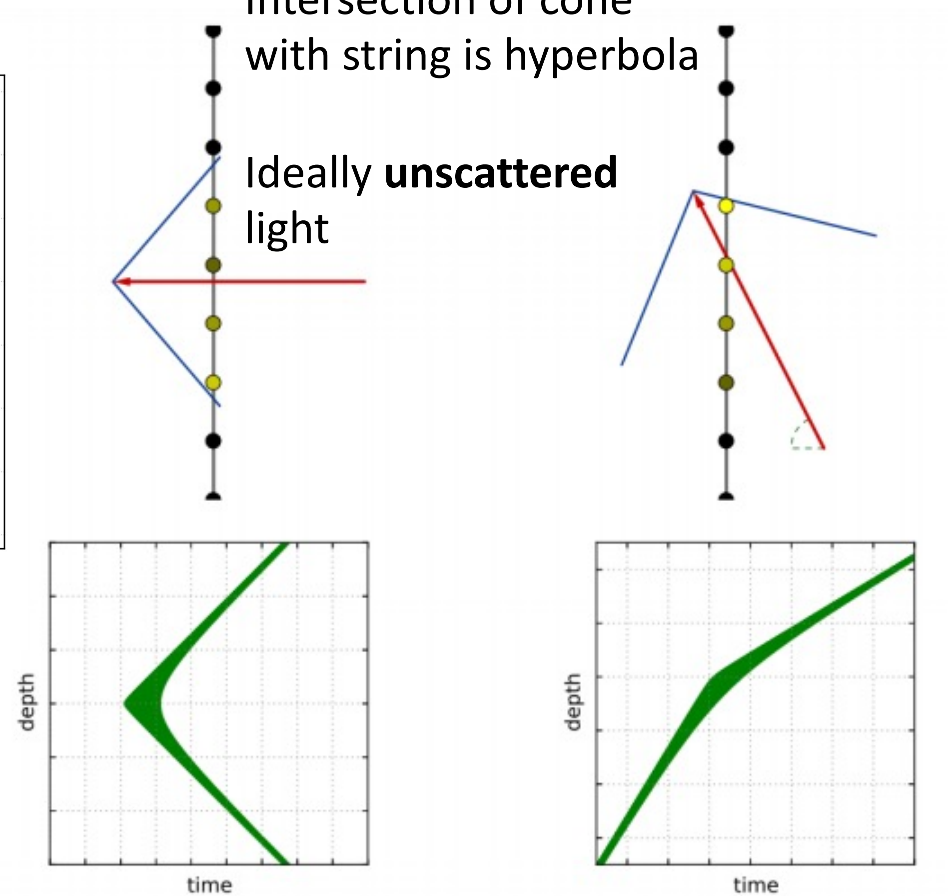






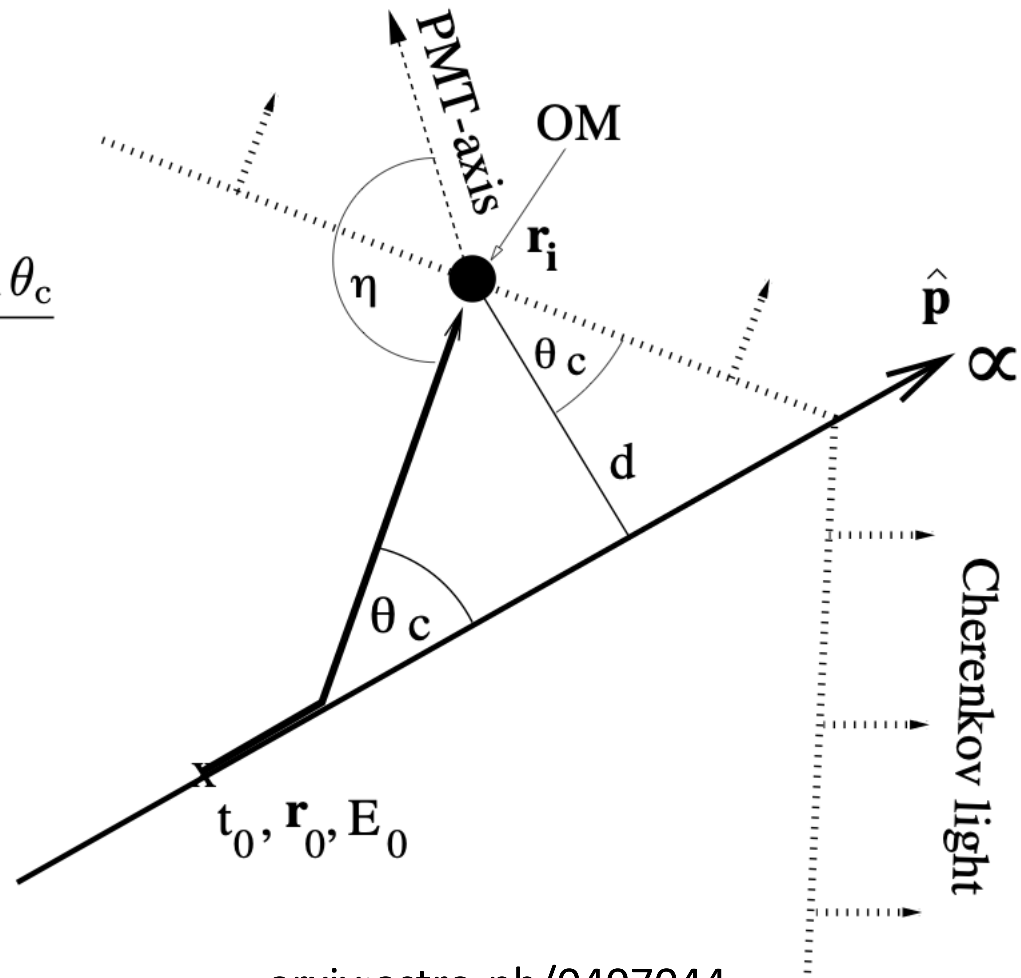
Juan Pablo Yanez

Time residuals

Definition: photon arrival time relative to earliest possible time from geometry

$$t_{\text{geo}} = t_0 + \frac{\hat{\mathbf{p}} \cdot (\mathbf{r_i} - \mathbf{r_0}) + d \tan\theta_c}{c_{\text{vac}}}$$

$$t_{\text{res}} \equiv t_{\text{hit}} - t_{\text{geo}}$$

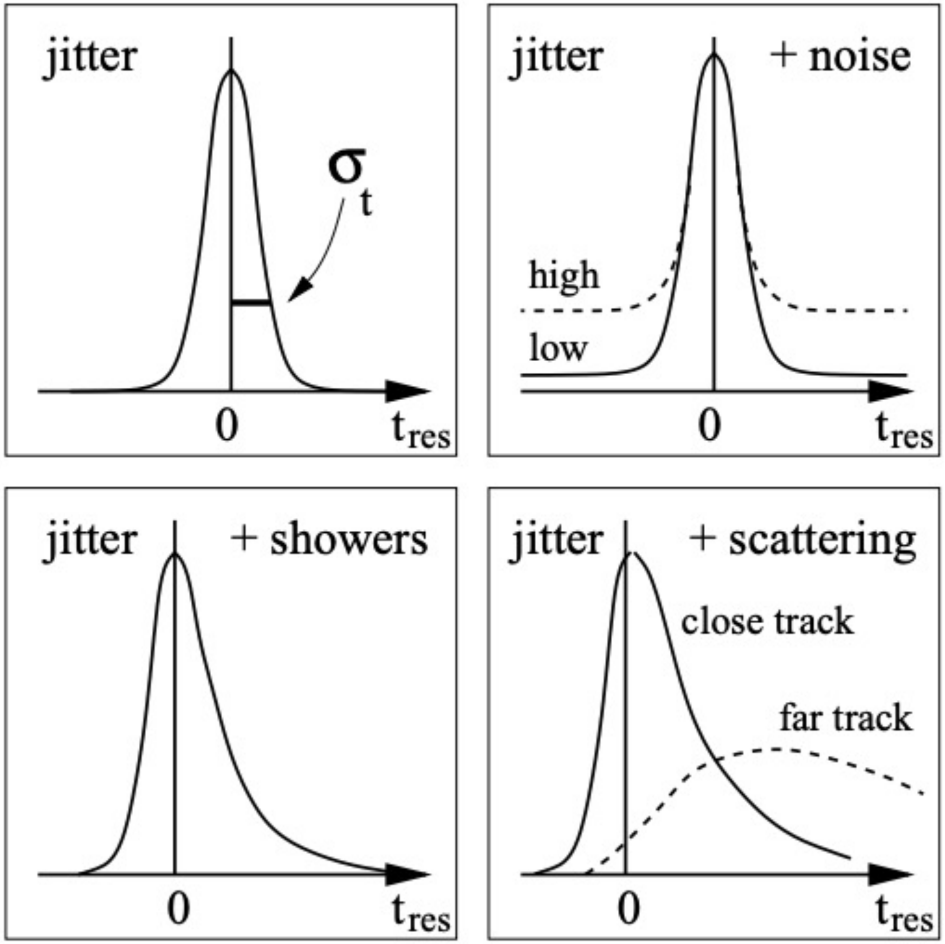


arxiv:astro-ph/0407044

Arrival time-residual pdfs

PMT jitter (Transit time spread) due to spread in initial energies/momenta of photoelectrons

arxiv:astro-ph/0407044



Additional effects due to:

- noise
- additional cascades along track
- scattering

Original analytic parameterization

- "Pandel function" (gamma dist.)

$$p(t_{\text{res}}) \equiv \frac{1}{N(d)} \frac{\tau^{-(d/\lambda)} \cdot t_{\text{res}}^{(d/\lambda-1)}}{\Gamma(d/\lambda)} \cdot e^{-\left(t_{\text{res}} \cdot \left(\frac{1}{\tau} + \frac{c_{\text{medium}}}{\lambda_a}\right) + \frac{d}{\lambda_a}\right)},$$

$$N(d) = e^{-d/\lambda_a} \cdot \left(1 + \frac{\tau \cdot c_{\text{medium}}}{\lambda_a}\right)^{-d/\lambda},$$

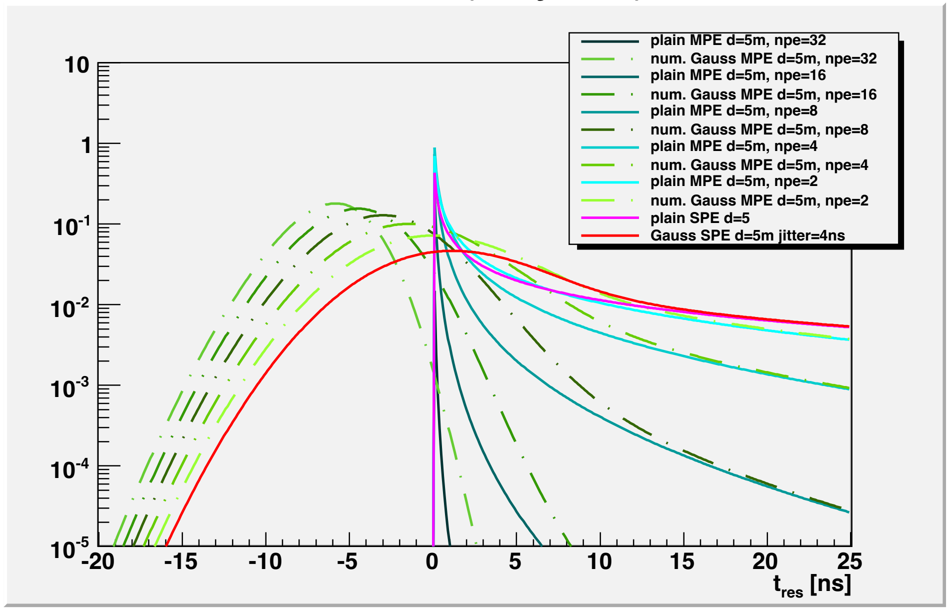
- Now based on splines/NN+basis

MPE Pandel likelihood

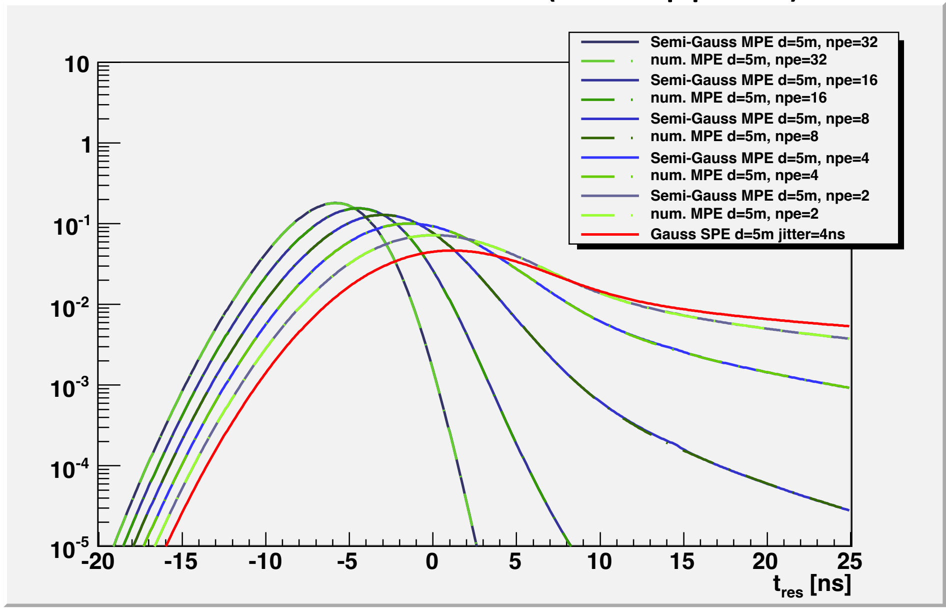
Pandel function cannot cope with negative time residuals so need to convolute with Gaussian

- https://user-web.icecube.wisc.edu/~boersma/PandelUpdates/MPEplots/

Plain MPE (no jitter)

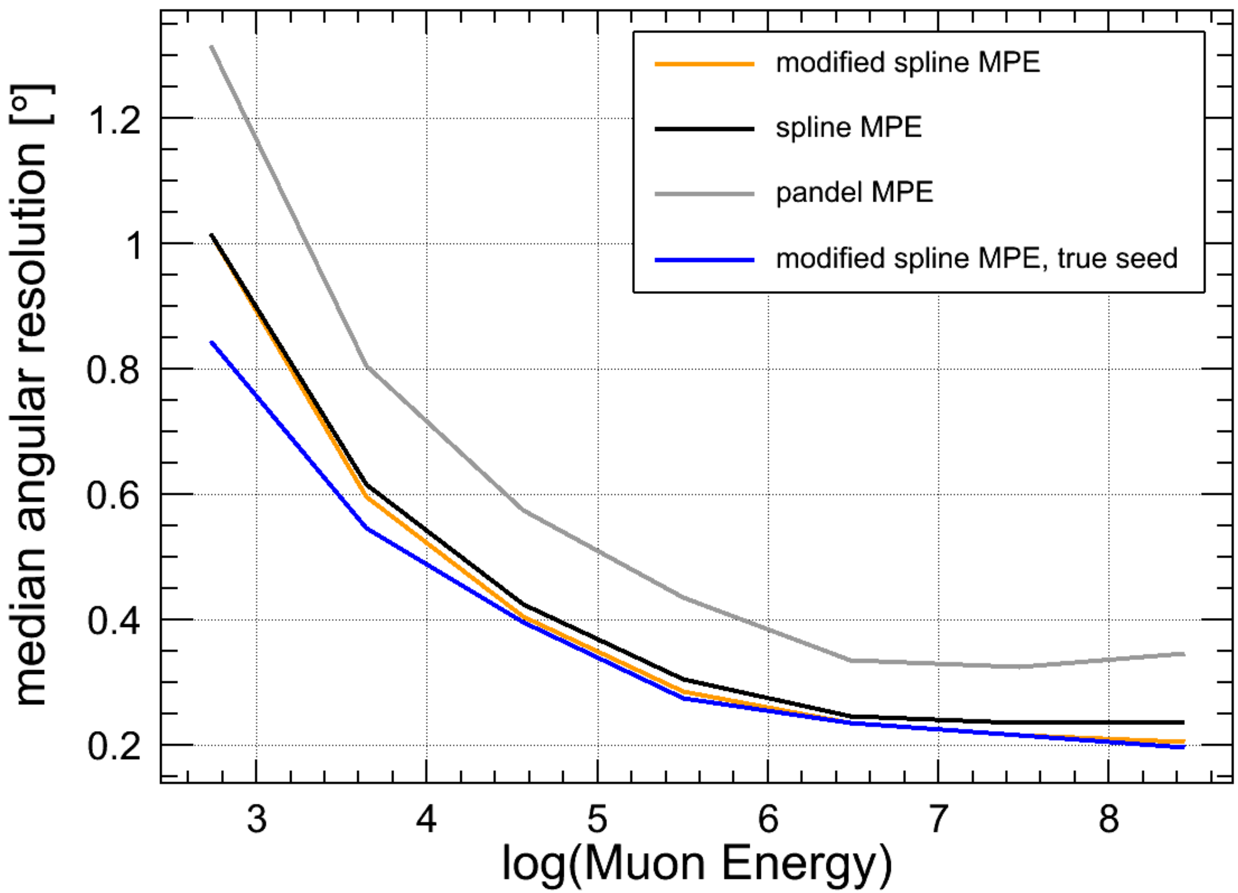


Gauss convoluted (fast-approx.)

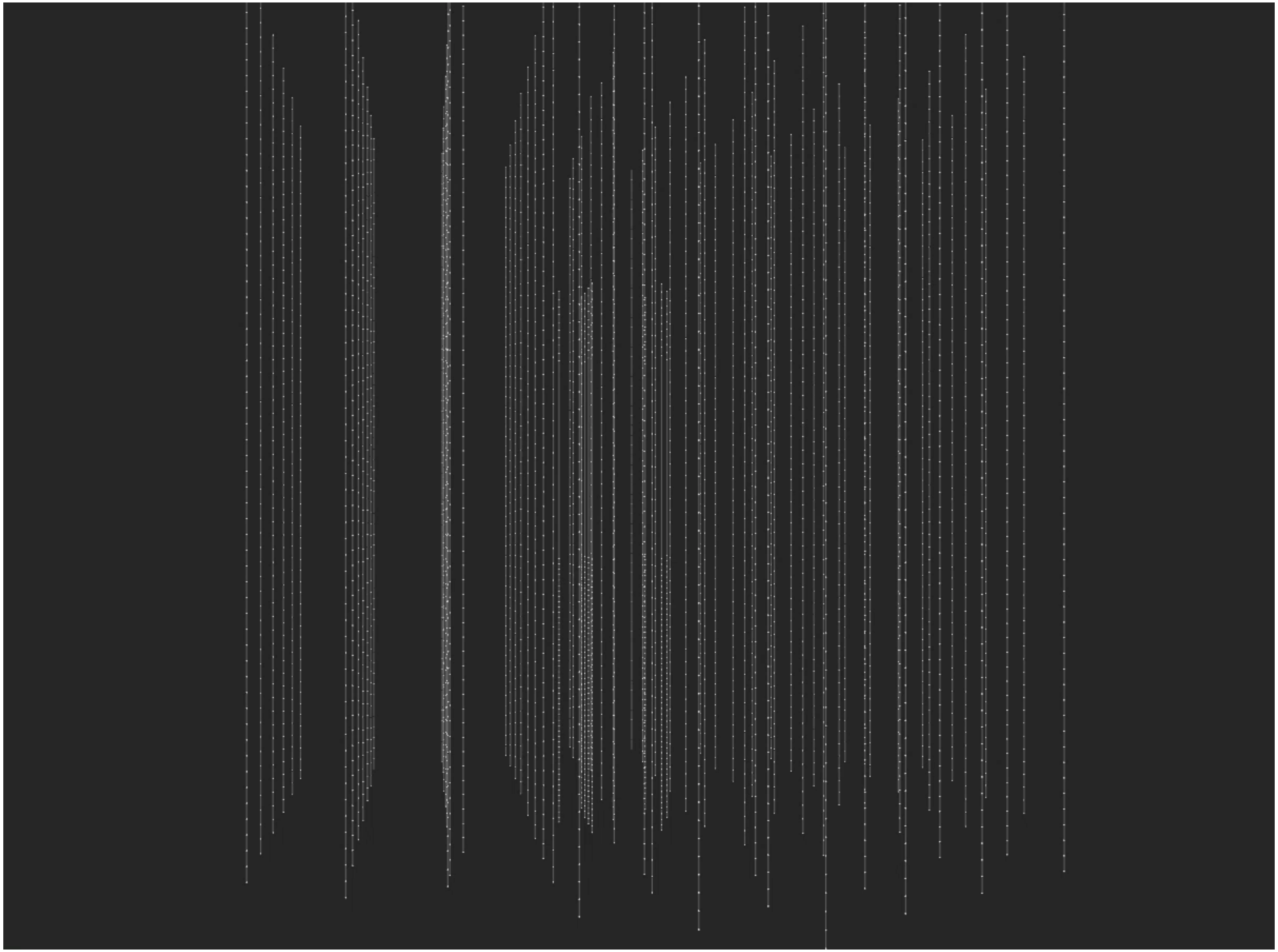


SplineReco Resolutions

Improvements were made by moving to (photo)spline tables based on simulation (c.f. K. Schatto thesis)



Utilizing full-waveform information



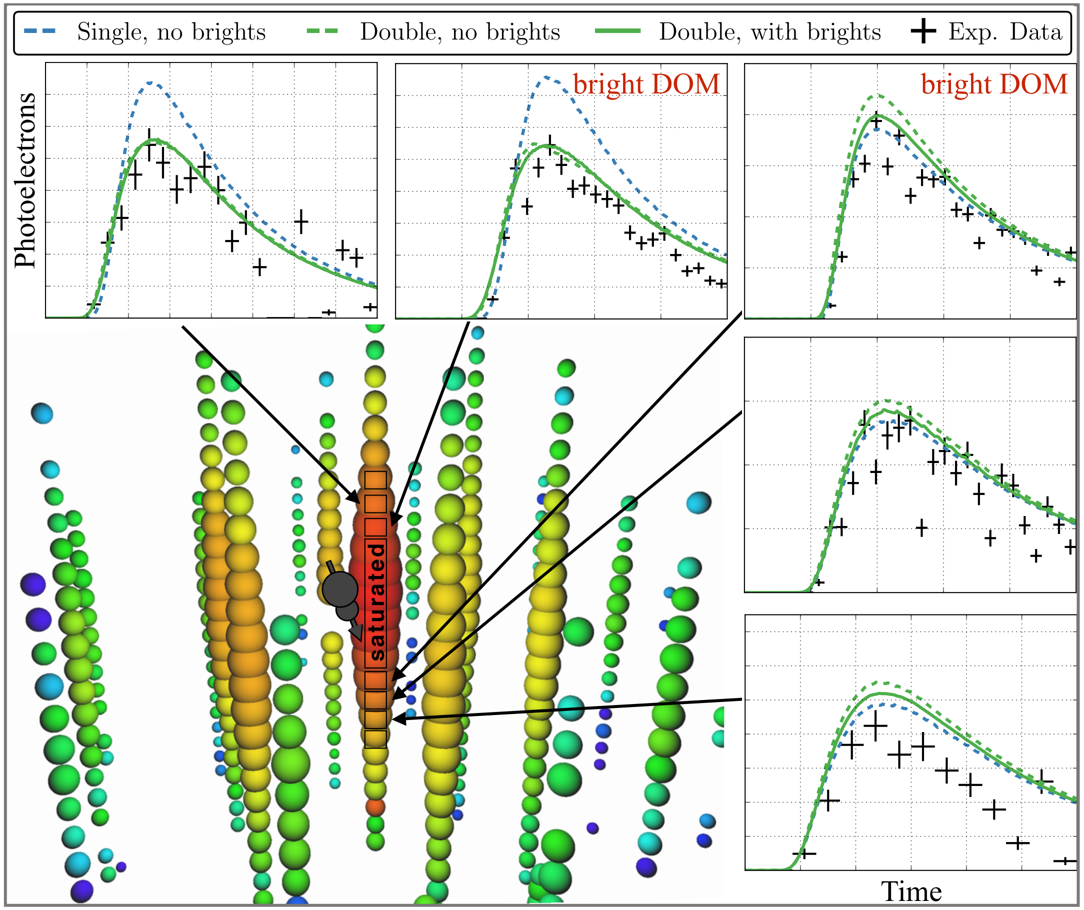
Full-waveform expectations

Tabulated photon yields

- Pros: Fast runtime; gradients
- Cons: Approximate ice model

Direct photon propagation

- Pros: Any ice-model can be used exactly
- Cons: Statistical errors from both data and MC; slow



IC collaboration, 1311.4767
D. Chirkin, arXiv:1304.0735

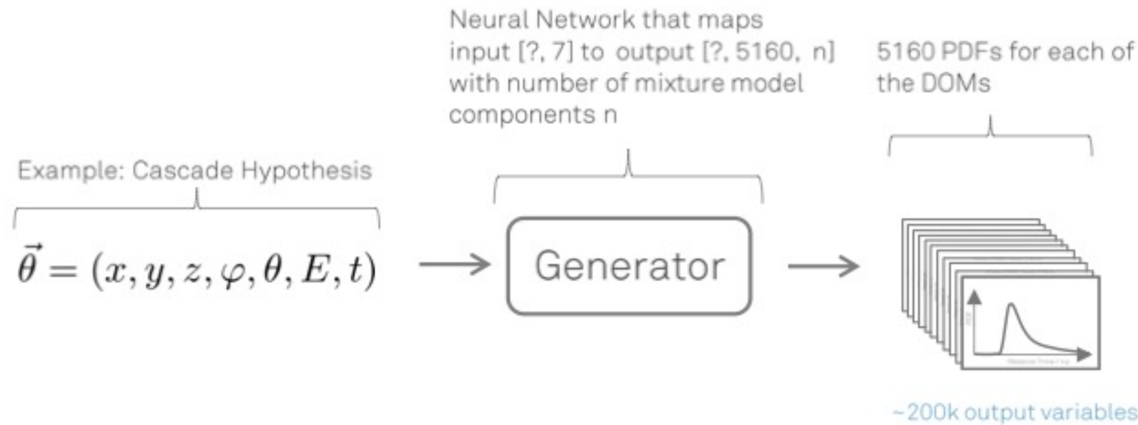
NN modeling (EventGenerator)

Models photoelectron yields with NN using basis functions (e.g. asymmetric gaussian)

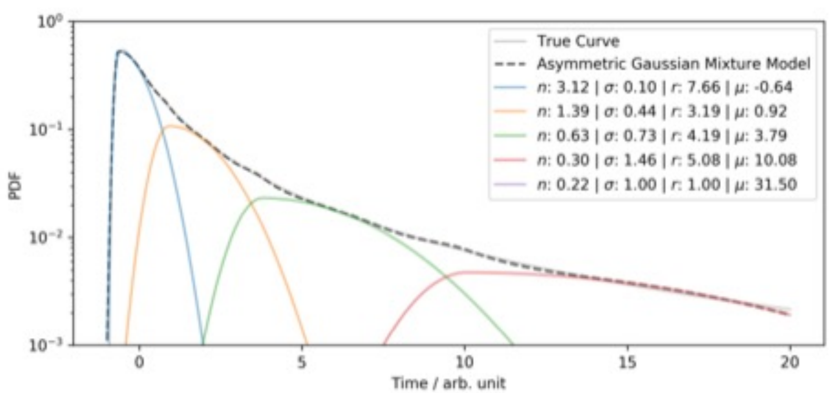
Generator NN learns mapping:

$$f: \vec{\theta} \rightarrow \vec{\lambda},\ \vec{p}(t_i|\vec{\theta})$$

$\vec{\theta}$: source parameters
$\vec{\lambda}$: expected DOM charge
$\vec{p}(t_i|\vec{\theta})$: pulse arrival PDFs



Parameterization of pulse arrival time PDF:



$$g(x|\mu,\sigma,r) = \begin{cases} N \cdot \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right), & x \leq \mu \\ N \cdot \exp\left(-\frac{(x-\mu)^2}{2(\sigma r)^2}\right), & \text{otherwise} \end{cases}$$

$$N = \frac{2}{\sqrt{(2\pi)} \cdot \sigma(r+1)}$$

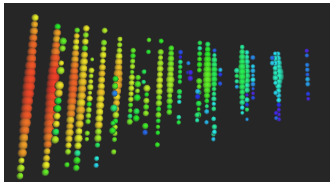
DOI: 10.1007/3-540-70659-3_42

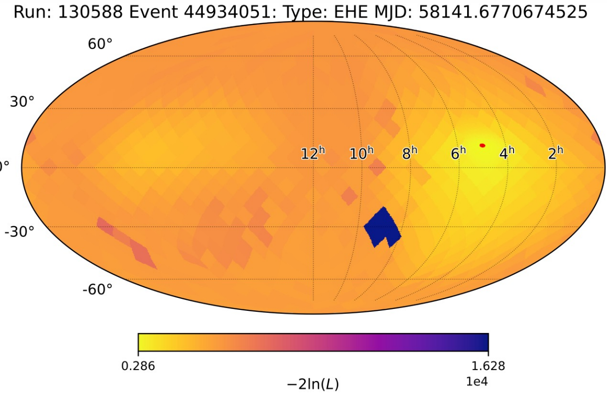
Minimization approaches

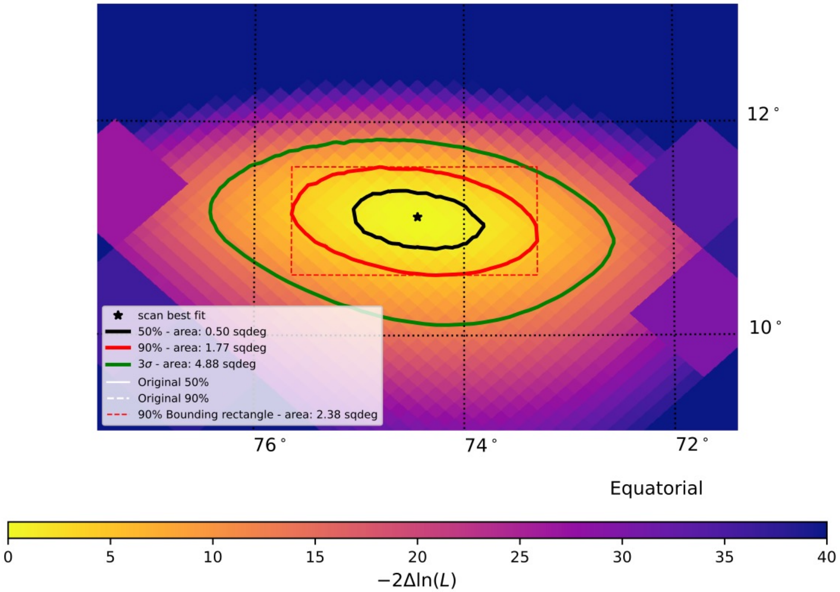
Given a likelihood $\mathcal{L}(\boldsymbol{\Theta}|\mathrm{X}_{\mathrm{Data}})$ as a function of $\boldsymbol{\Theta} = (x, y, z, \theta, \phi, E, t)$, want to find $\boldsymbol{\Theta}_0$ that minimizes the negative likelihood

- Millipede uses **photon tables** which allows for iterative gradient descent

- Can also **brute force** all possible directions (θ, ϕ) to reduce the minimization to only 5 dimensions (realtime alerts)

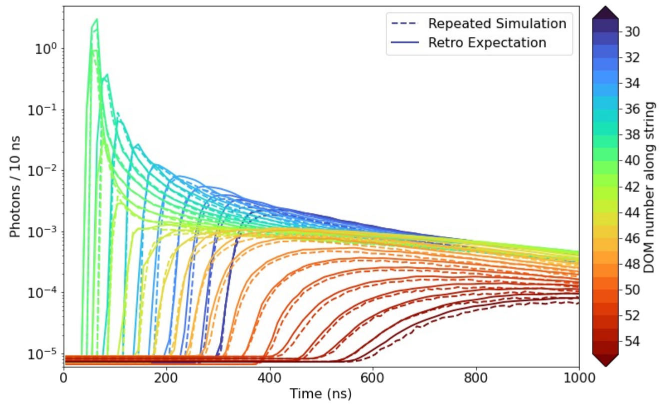


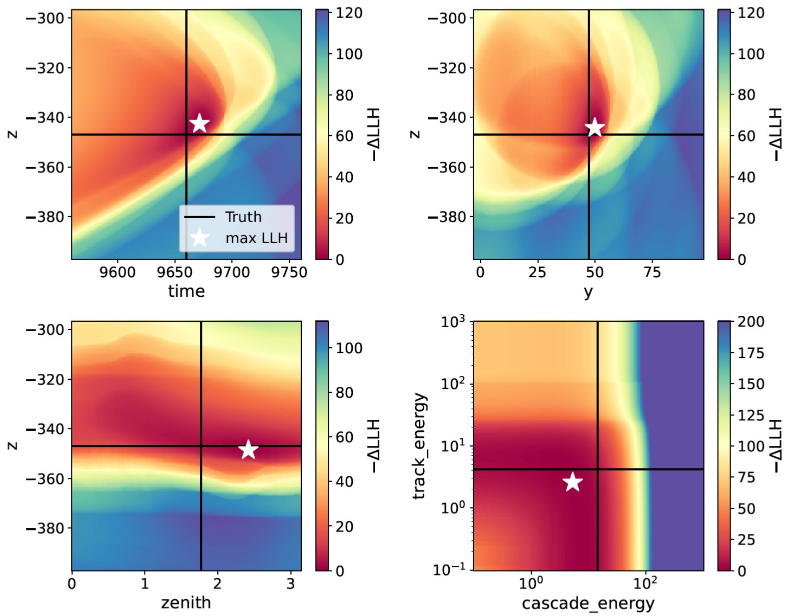




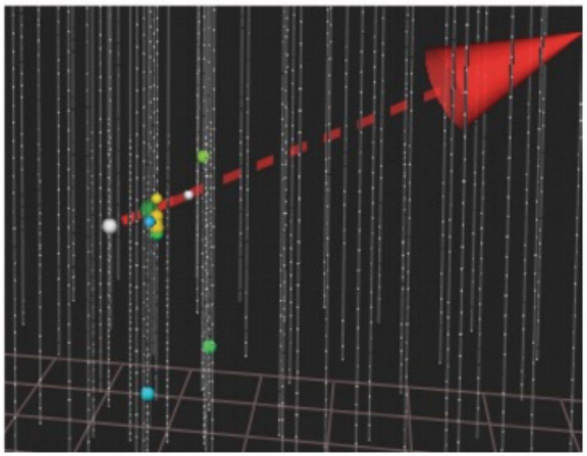
Low-energy reco: RetroReco and DirectReco

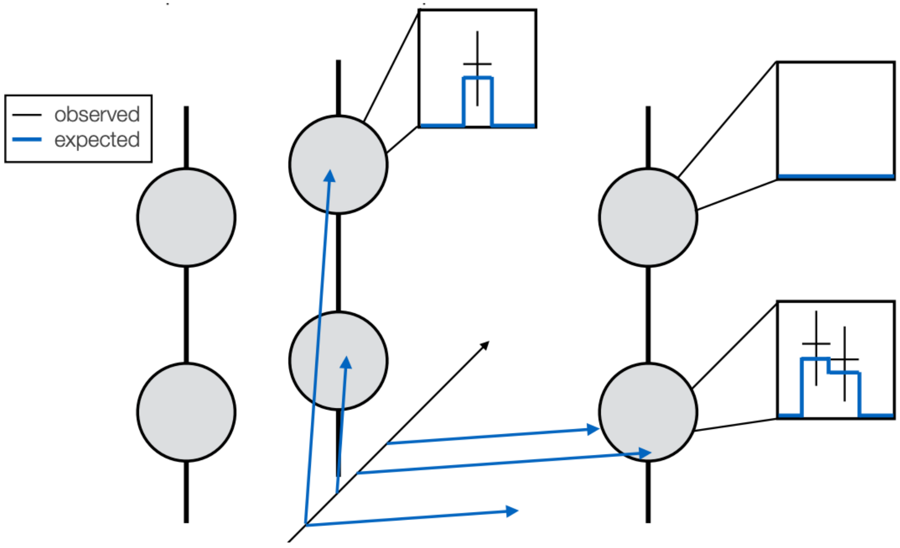
RetroReco: emit photons from DOM and track → then build retro tables





DirectReco: like DirectFit but for lower energies





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High energy

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  - Millipede works for **high-energy tracks** by breaking it up into multiple cascades along the track due to muon stochastic energy losses
- Likelihood-free inference (FreeDOM)
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- ML (FLERCNN, TNF)

Cascades

- Use **full-waveform** information by fitting predicted light yields to what is actually seen (RetroReco, DirectReco, Monopod, DirectFit)
- ML (FLERCNN, DNN, TNF)
- ML+LLH approaches (EventGenerator)
- Likelihood-free inference (FreeDOM)

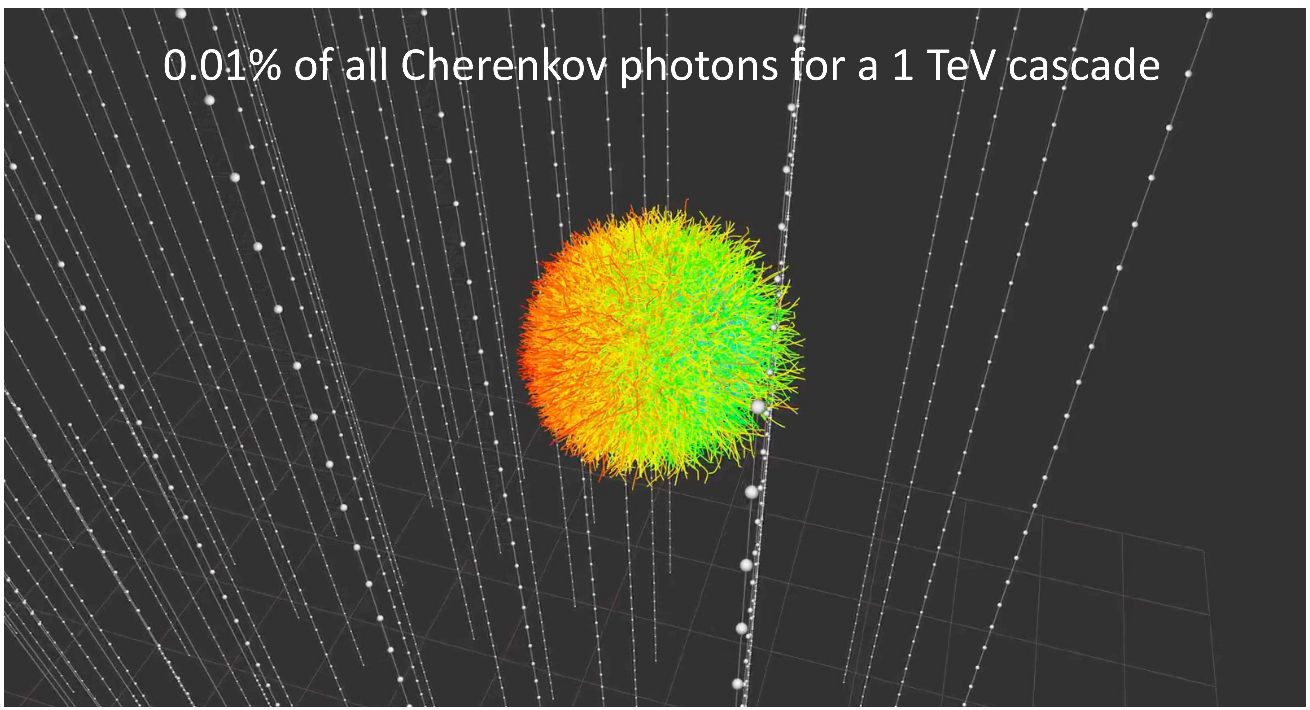
Challenges in cascade reconstruction

Large distances between DOMs means not many detected photons

Small asymmetry means high dependence on ice modeling

Sheer number of photons difficult to simulate

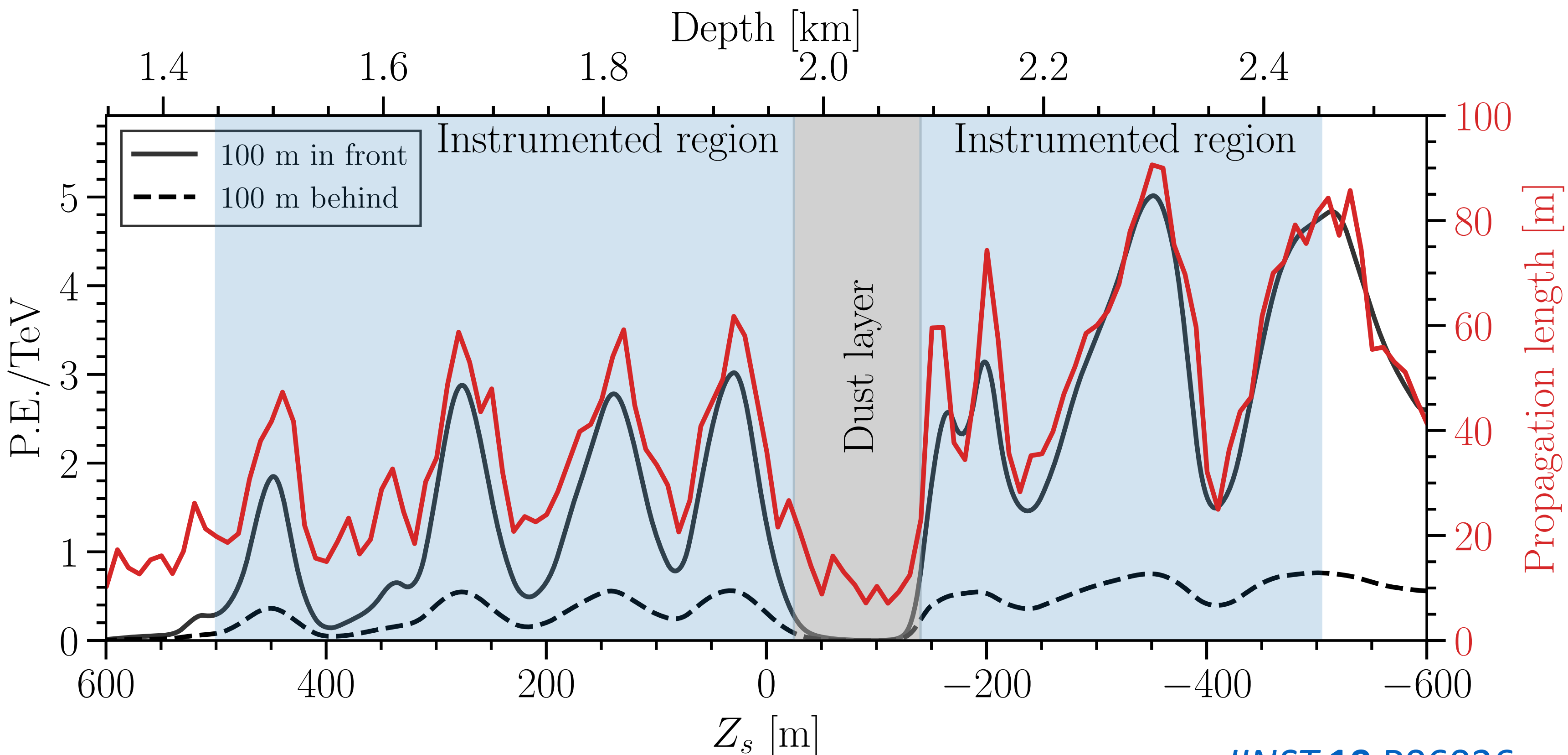
1. Tabulate photon yields for a single ice model (Millipede/Monopod)
   - Fast, table generation time-consuming
2. Directly propagate all photons for any ice model (DirectFit)
   - Slow but accurate



Photon yields vs ice

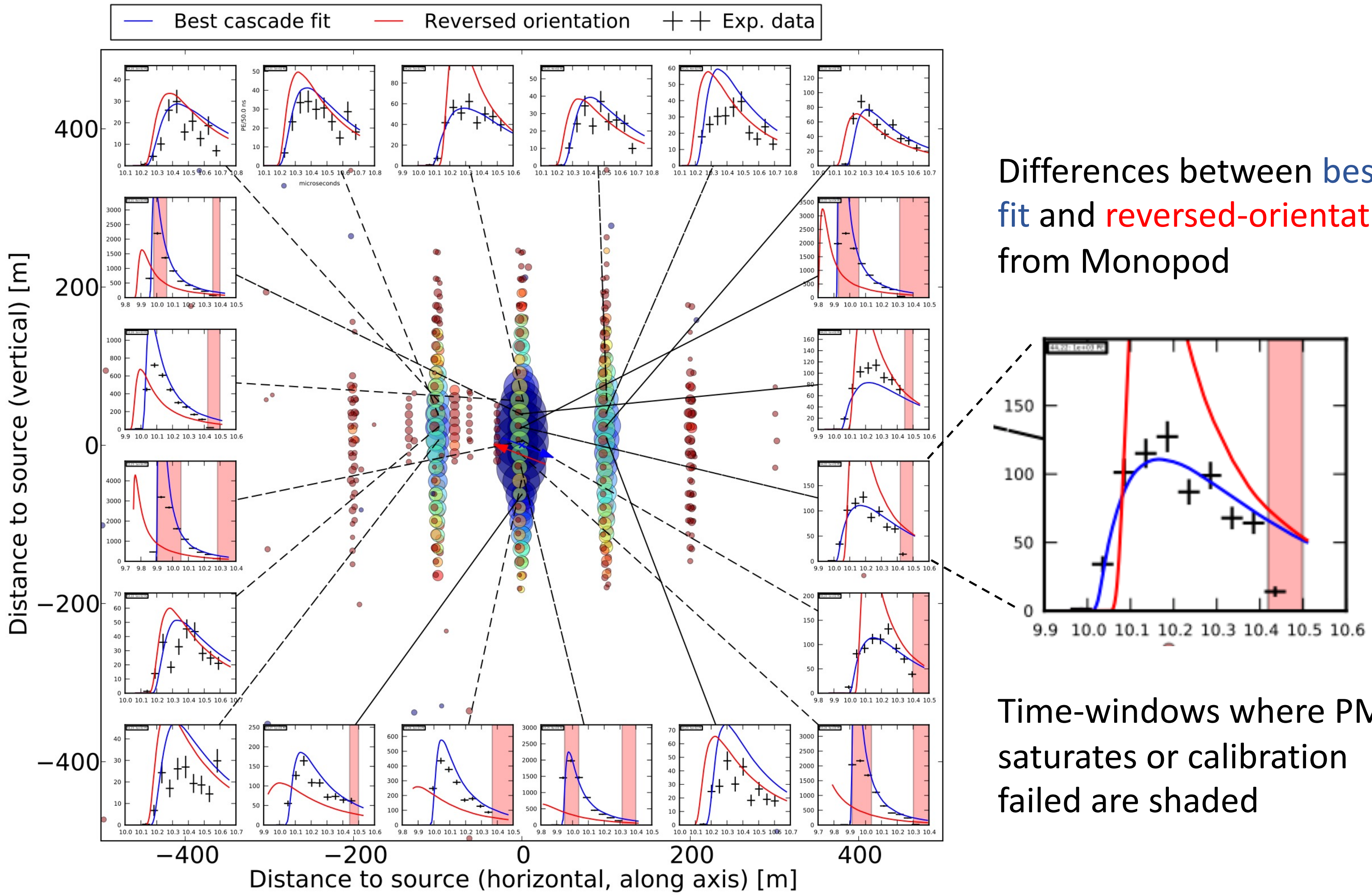
Number of arrival P.E.s shows clear correlation with ice optical properties

Differences between receiver in front of / behind shower allows for directional reconstruction



JINST **19** P06026

Cascade orientation from full-waveform



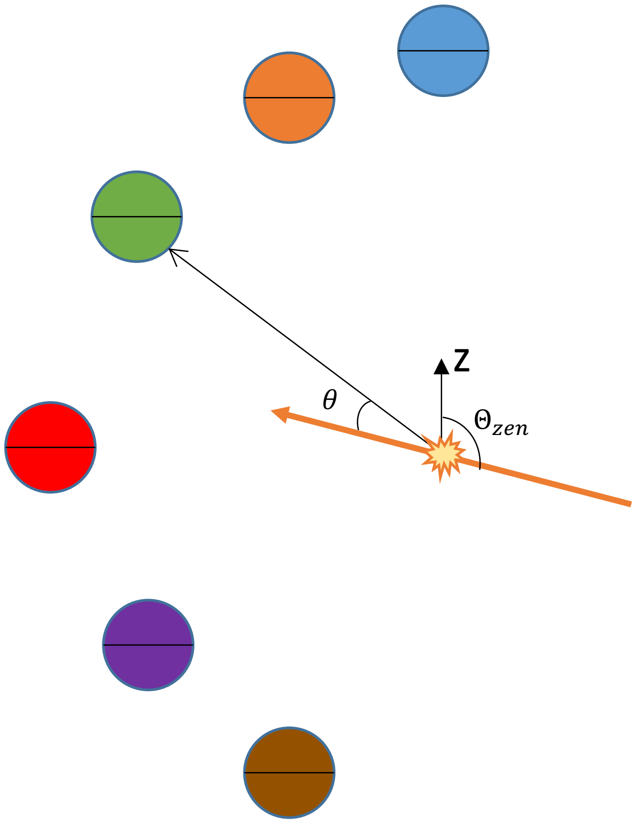
Differences between best-fit and reversed-orientation from Monopod

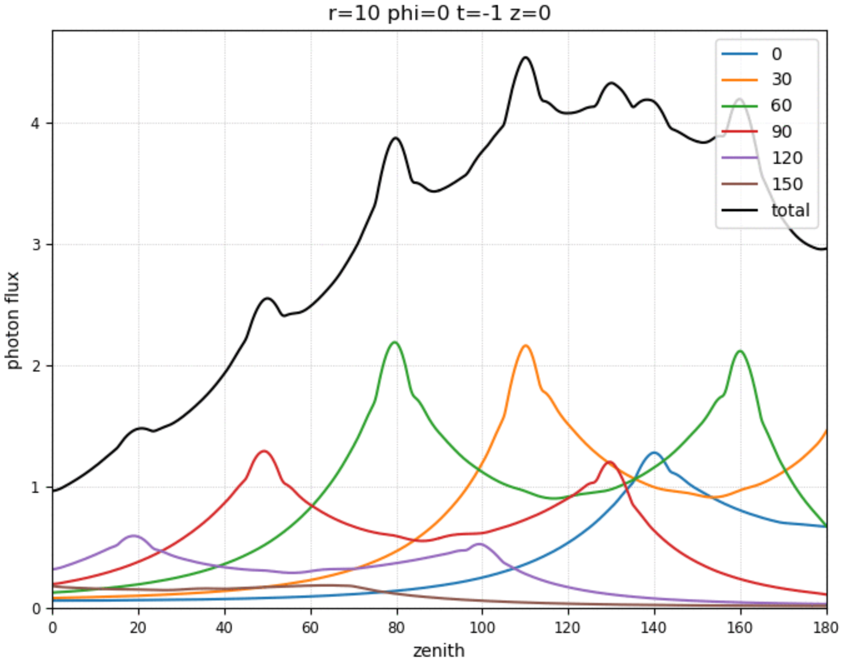
Time-windows where PMT saturates or calibration failed are shaded

Photon amplitudes

Photon flux at different recievers as taken from photospline

Cherenkov peaks visible nearby, falls off rapidly with distance





Minimization approaches

Given a likelihood $\mathcal{L}(\mathbf{\Theta}|\mathrm{X}_{\mathrm{Data}})$ as a function of $\mathbf{\Theta} = (x, y, z, \theta, \phi, E, t)$, want to find $\mathbf{\Theta_0}$ that minimizes the negative likelihood

Need to explore 7D space which is challenging

- Monopod uses **photon tables** which allows for iterative gradient descent
  - May not always find the global minimum

Impact of ice on cascade angular resolution

"Mie model" neglects birefringence and layer undulations

Some slight additional improvement when using two-cascade fit to model shower extension

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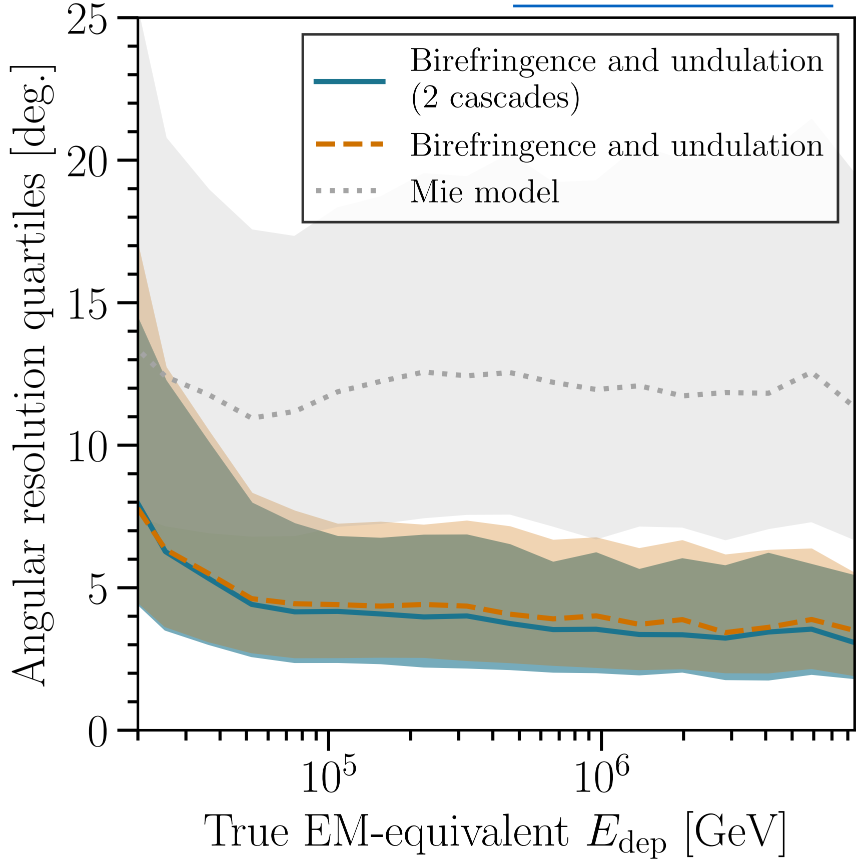

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Need to explore 7D space which is challenging

- Millipede/Monopod uses **photon tables** which allows for iterative gradient descent
  - May not always find the global minimum

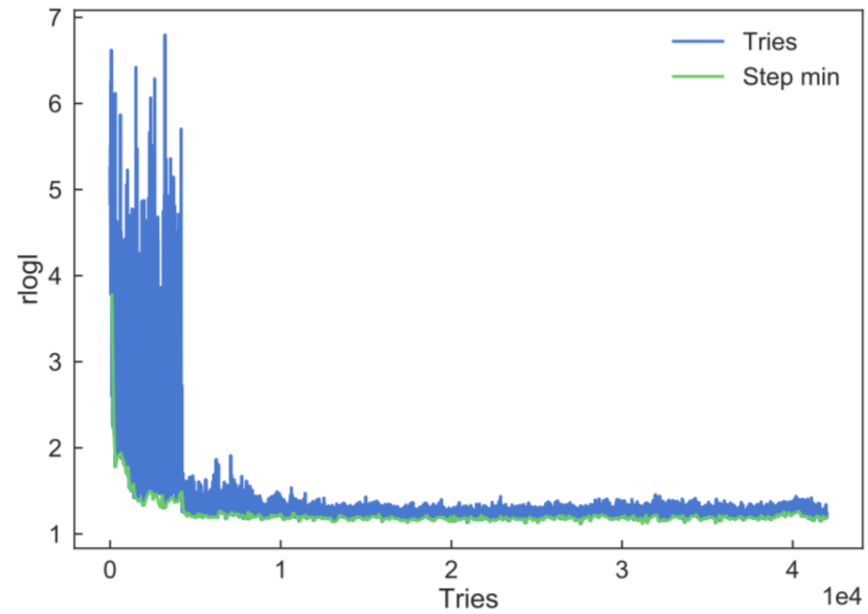
- DirectFit attempts to find minimum using **localized random search**, randomly sampling points in (x, y, z, θ, ϕ) within a "search radius" that is refined iteratively

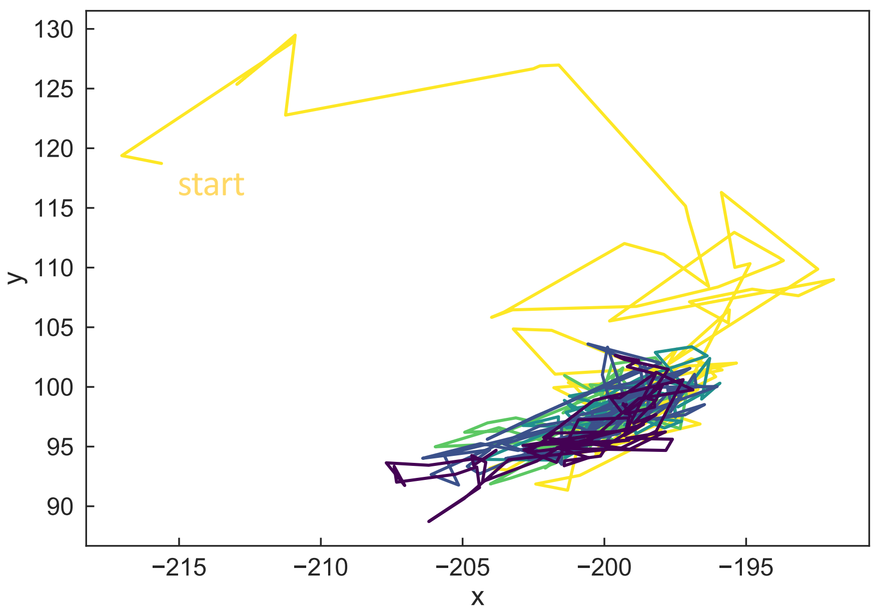
DirectFit minimization

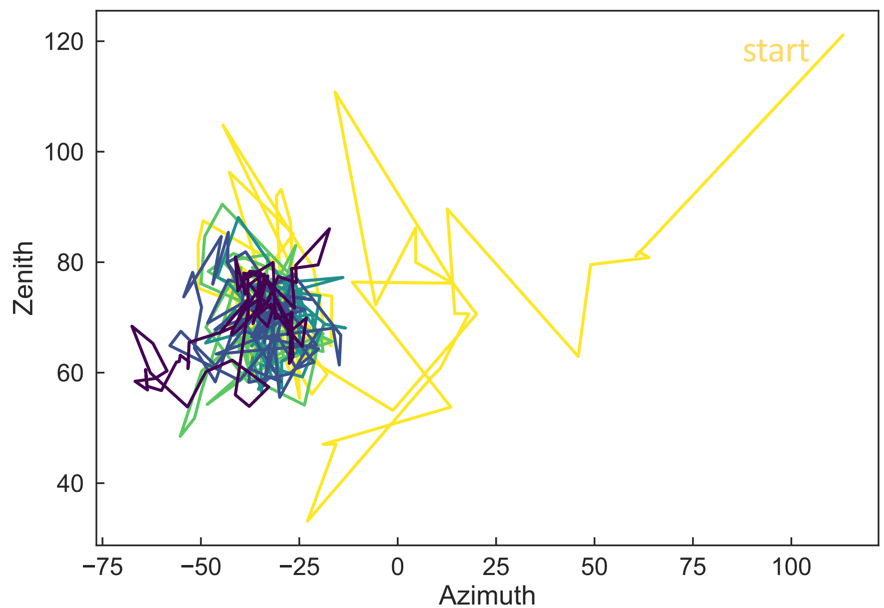
Likelihood gradually improves from start to finish

Following this, MCMC approach to sample from posterior pdf

Ref: D. Chirkin, arxiv:1309.7010

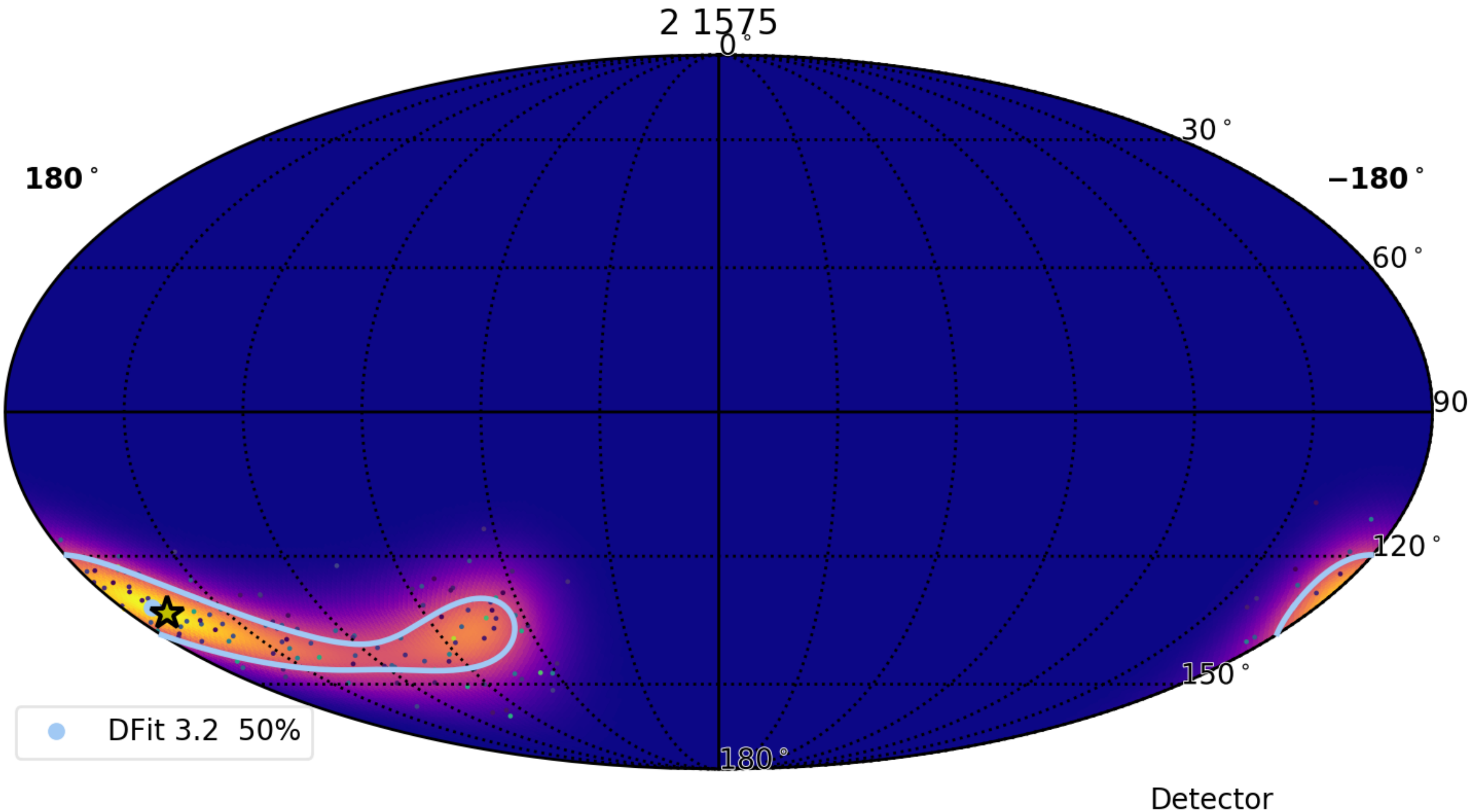






DirectFit with directional PDFs

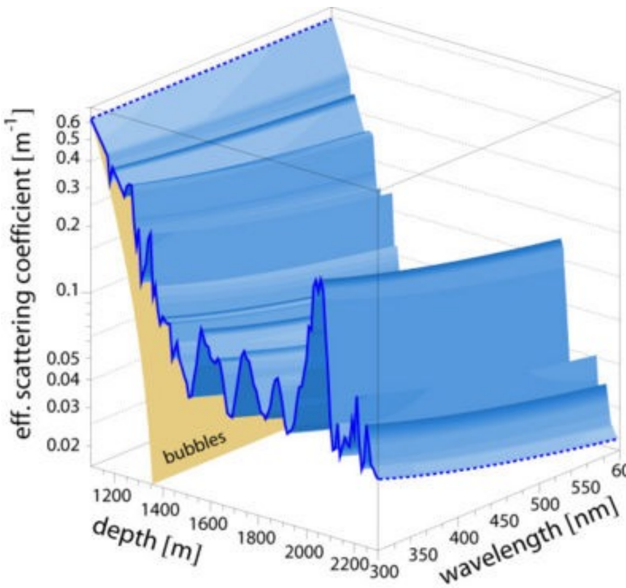
ABC outputs points on unit sphere (simulated event)

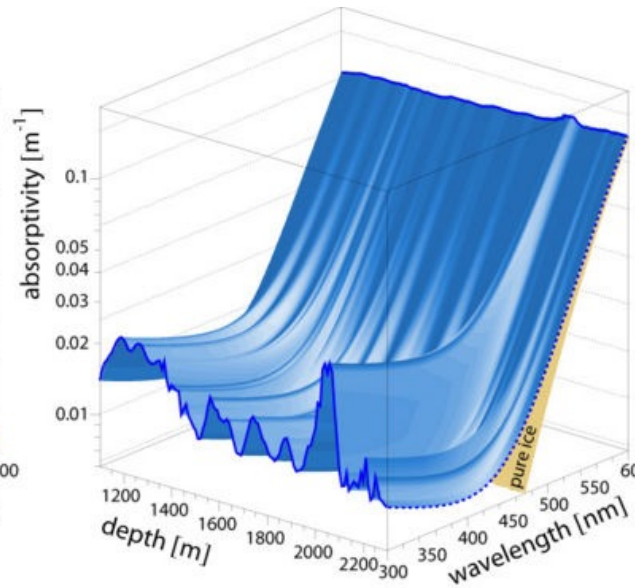


Can then fit a PDF on a sphere to those points

Ice modeling is important!

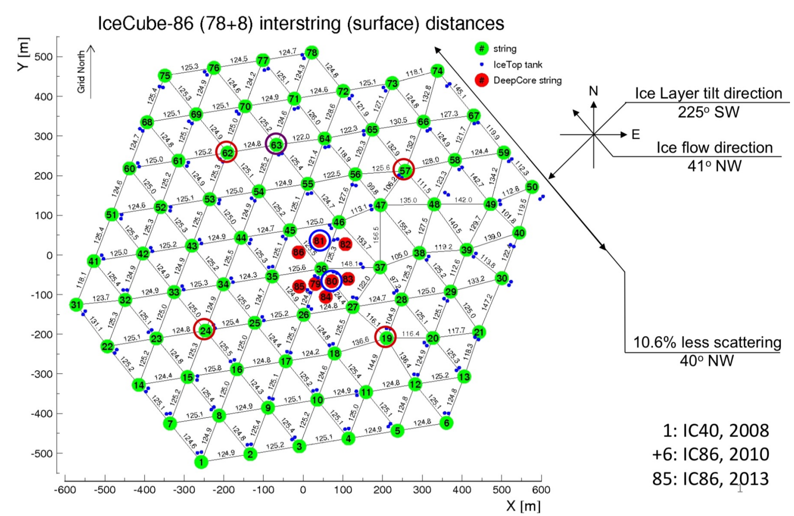
Bulk ice described by scattering and absorption coefficients as a function of depth → these have been refined over time





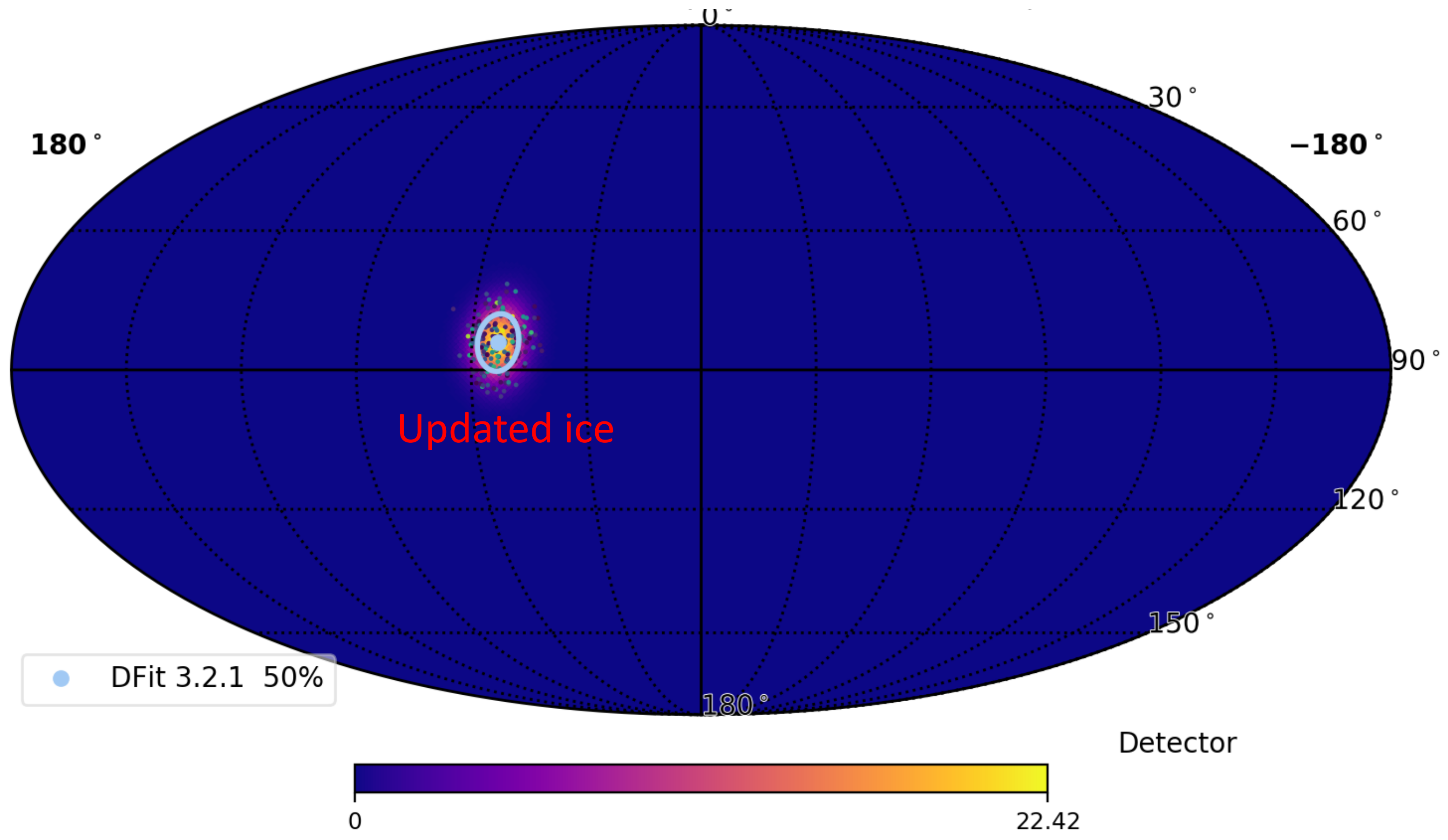
Ice layers were found to be tilted [arXiv:1301.5361]

Ice was also discovered to be anisotropic [ICRC 2013, 0580]



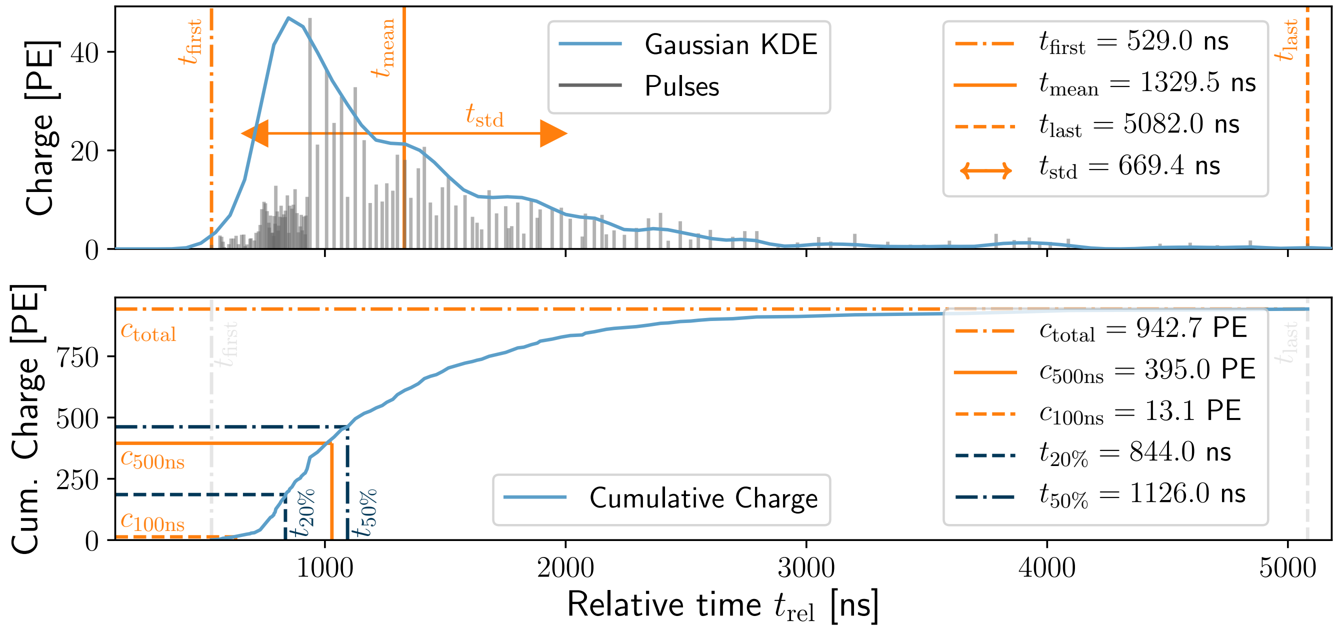
Directional bias due to different ice models

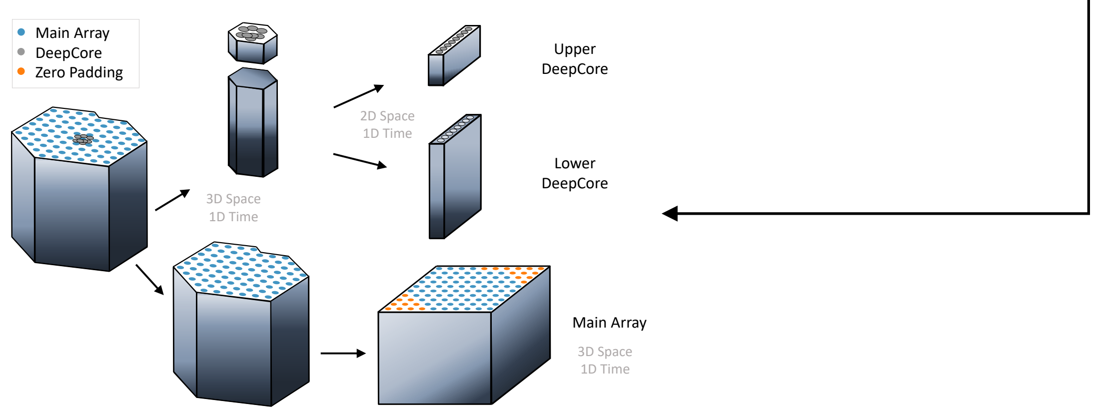
Ice affects cascade reconstruction



One of the early DNN approaches

Input pulse-series features into CNN





JINST 16, 2021

Transformer normalizing flows

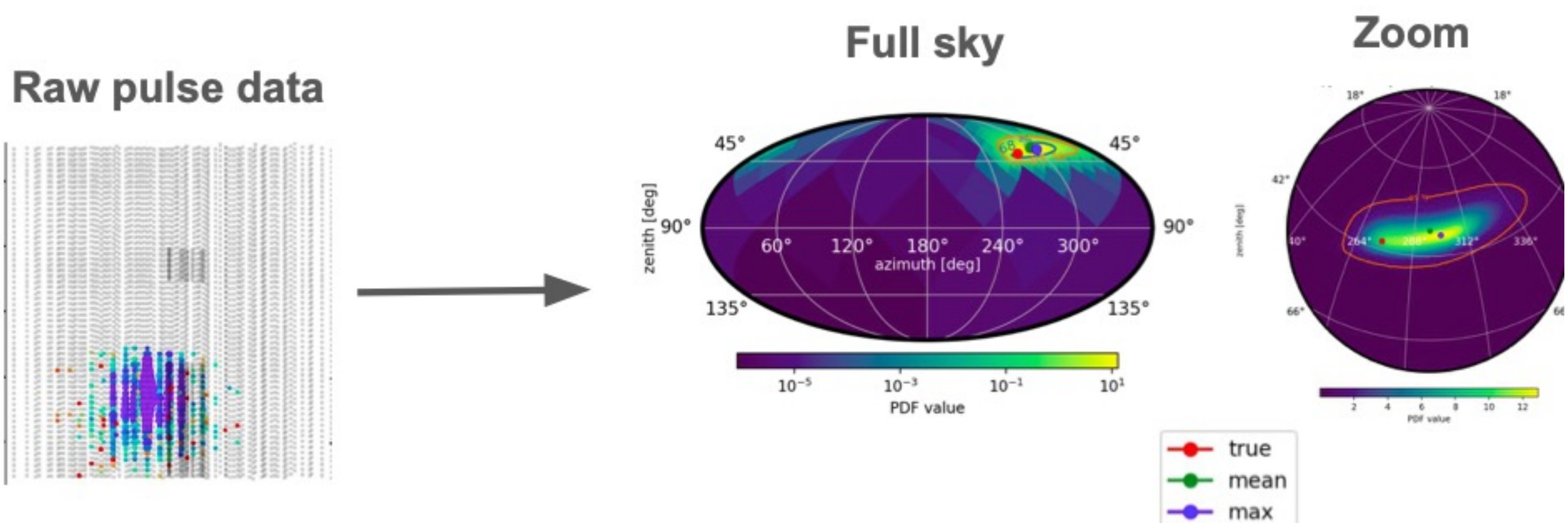
Use transformer architecture to model full posterior distributions with normalizing flows

NN essentially learns joint pdf $f(\boldsymbol{\Theta}, \mathrm{X}_{\mathrm{Data}})$ which can then be conditioned

(conditional) Normalizing flows

powerful machine-learned conditional PDFs from raw data

In particular **posterior distribution** - Example direction: **p(direction|data)**



arXiv:2604.19846

Summary

Reconstruction in IceCube is often a challenge

Many algorithms exist, separable into high-energy/low-energy and track/shower

- Ice modeling is most important for cascades

Traditionally LLH-based approaches; now lots of ML developments (also relevant for future extensions)

Each has pros and cons ~ymmv

New approaches always welcome!

Package reco

pip installable package @https://github.com/icecube/reco

Exe to run optimized millipede, taupede, monopod reconstructions

Can also run semi-optimized SplineMPE reconstruction

Contains library of icetray segments and modules for use outside of exe

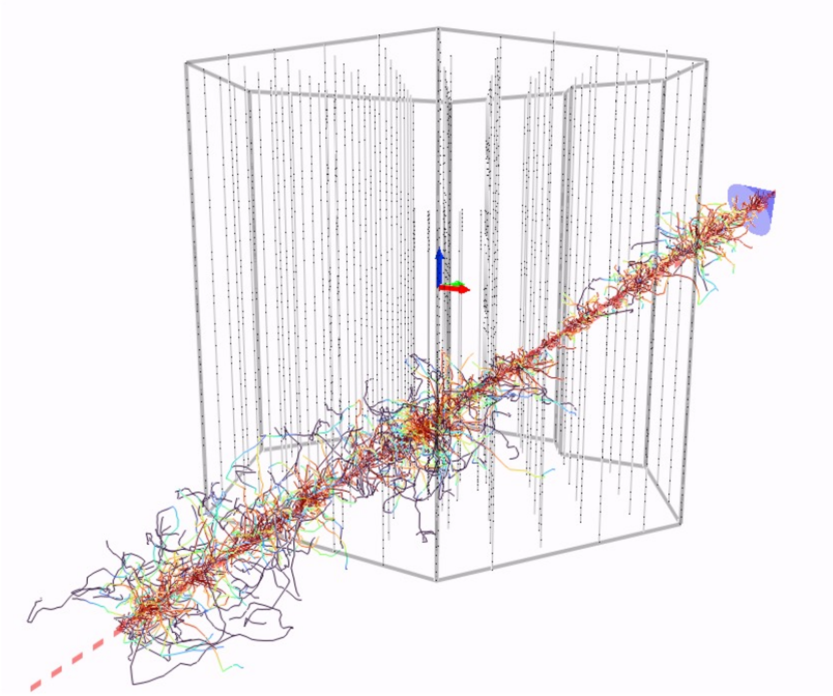
Additionally includes tools for physics event generation and simulation

In addition to reconstruction, the `gen`, `pho` and `det` commands can be used sequentially to generate neutrinos or muons, run photon propagation and process through the detector chain. For example, to simulate a muon neutrino through the dust layer and visualize the photons one can execute the following commands.

```
gen --type numu --location dust --nevents 1 --emin 10e3 --emax 11e3 --gcd /path/to/gcd.i3 -o
```

```
pho gen.i3.zst [--usecpus] --history 100 --gcd /path/to/gcd.i3 --prescale 0.0001 --all --domc
```

The `--usecpus` flag is optional and will work but be slower than gpu. The output can be visualized with `steamshovel /path/to/gcd.i3 pho.i3.zst`.



Batch job submission with HTCondor

There are also two submission scripts for running on clusters with CVMFS. These require an optional dependency, which can be installed from within the repo directory with

References

SANTA: https://doi.org/10.1016/j.astropartphys.2011.01.003

SplineReco: https://docs.icecube.aq/icetray/main/projects/spline-reco/index.html

RetroReco: https://github.com/icecube/retro

DirectReco: https://indico.cern.ch/event/593812/contributions/2499791/attachments/1468178/2270620/snowicki_IC_directreco_CAPtalk2017.pdf

MuEx: https://docs.icecube.aq/icetray/main/projects/mue/muex.html

TruncatedEnergy: https://docs.icecube.aq/icetray/main/projects/truncated_energy/index.html

Millipede: http://dx.doi.org/10.1088/1748-0221/9/03/P03009

Monopod, Taupede: https://doi.org/10.1088/1748-0221/19/06/P06026

DirectFit: http://icecube.wisc.edu/~dima/work/WISC/papers/2013_ICRC/dir/icrc2013-0581.pdf

FLERCNN: https://github.com/jessimic/LowEnergyNeuralNetwork

DNN: https://icecube.wisc.edu/~mhuennefeld/docs/dnn_reco/html/pages/about.html

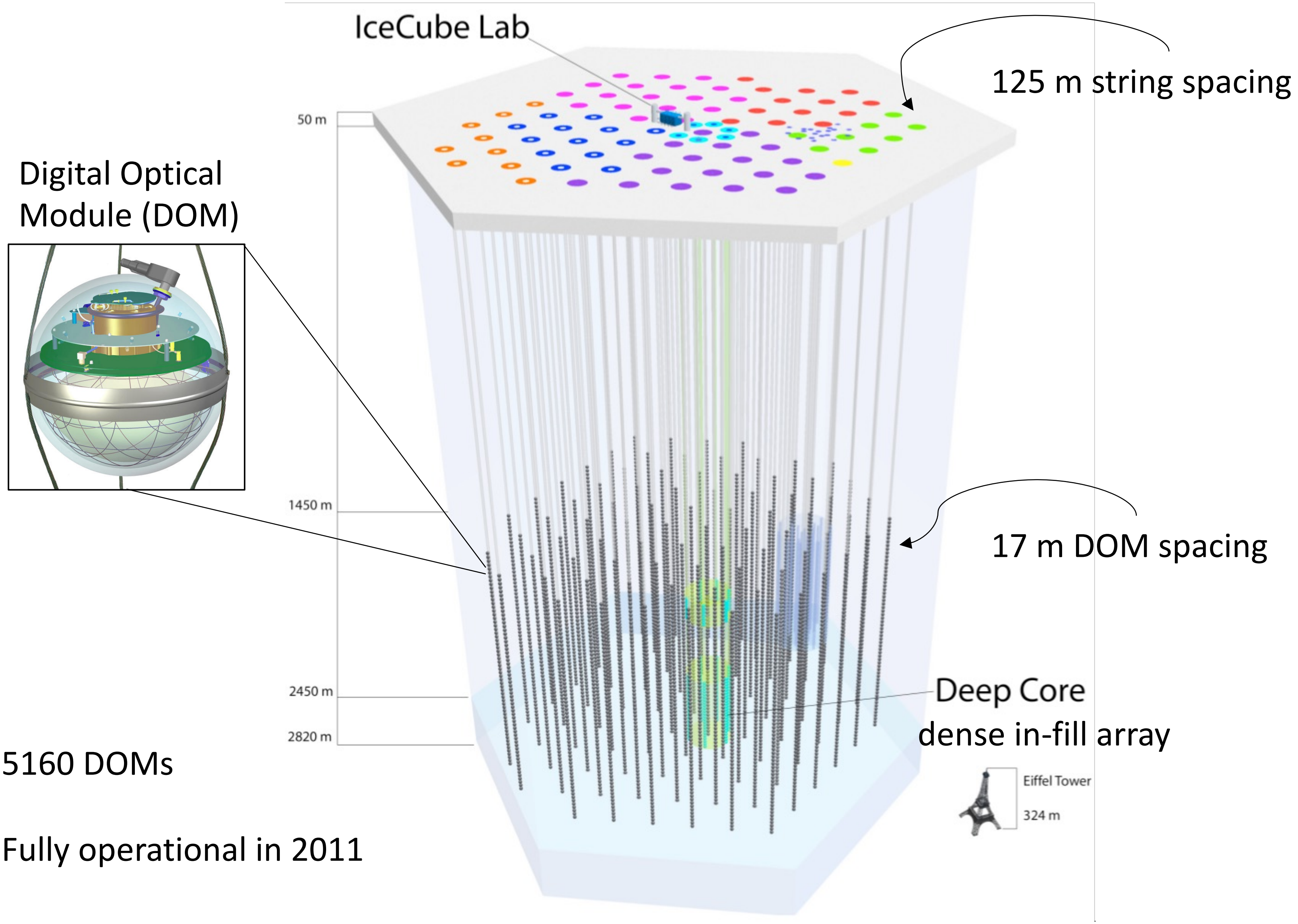
EventGenerator: https://events.icecube.wisc.edu/event/213/contributions/10356/attachments/7984/10418/2024_09_24_IceCube_Madison.pdf

TNF: https://arxiv.org/abs/2604.19846

FreeDOM: https://events.icecube.wisc.edu/event/125/contributions/7228/attachments/5679/6634/fienberg_freeDOM_plenary.pdf

Backups

IceCube



5160 DOMs

Fully operational in 2011

Detection principals

Neutrino interacts via weak force with targets in ice

- At IceCube energies, primarily deep-inelastic scattering (DIS) off nucleons

Nucleon breaks apart; outgoing particles may be charged

Charged particles emit **Cherenkov radiation** detectable by PMTs

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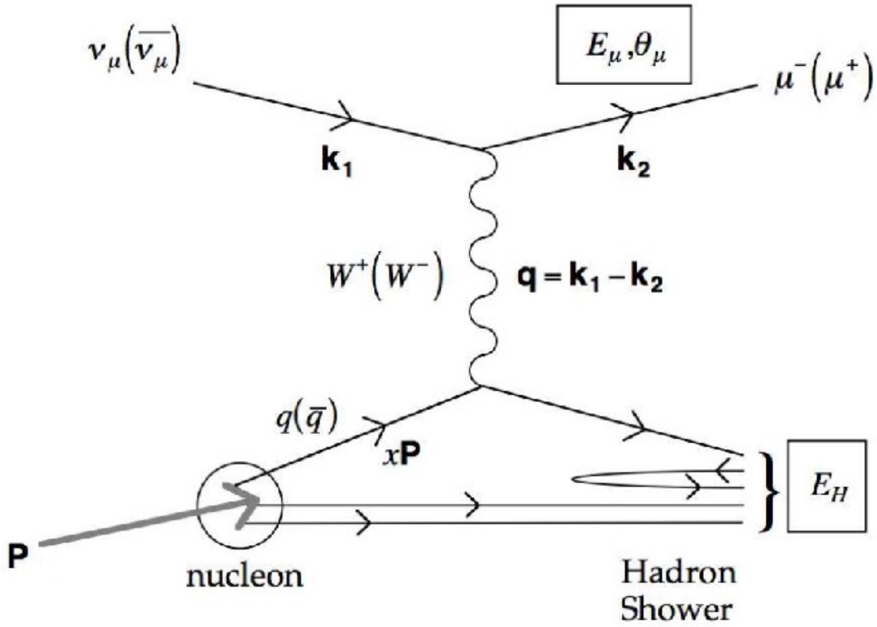
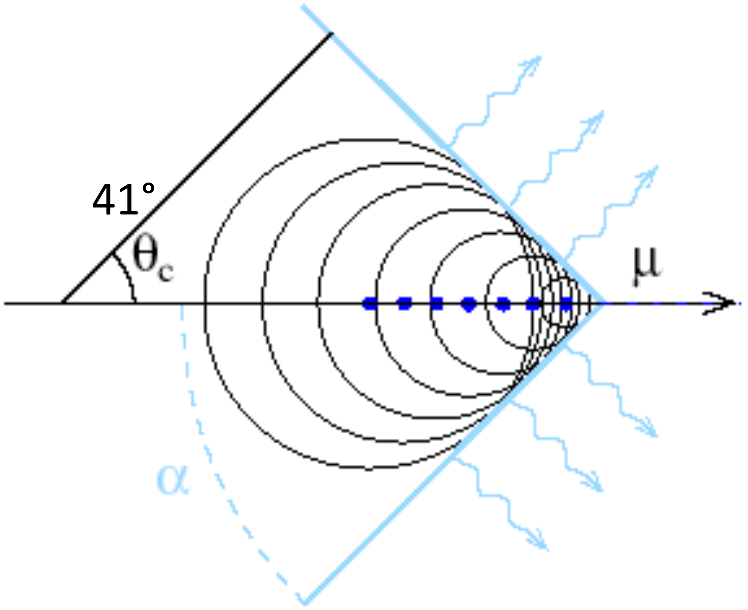




Cherenkov radiation

Occurs when a charged particle travels faster than light-in-medium

Constructive interference of EM-field to form a plane wave

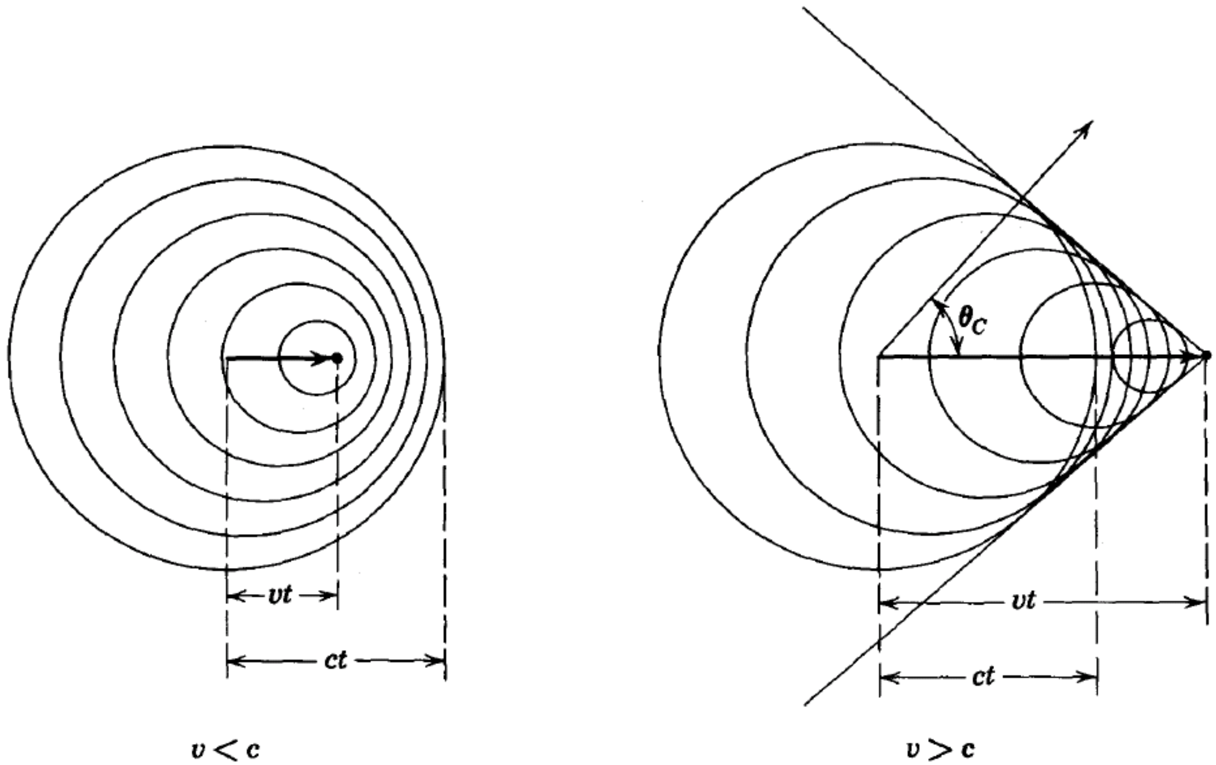


Fig. 14.14 Cherenkov radiation. Spherical wavelets of fields of a particle traveling less than, and greater than, the velocity of light in the medium. For $v > c$, an electromagnetic "shock" wave appears, moving in the direction given by the Cherenkov angle θ_c.

Local effects

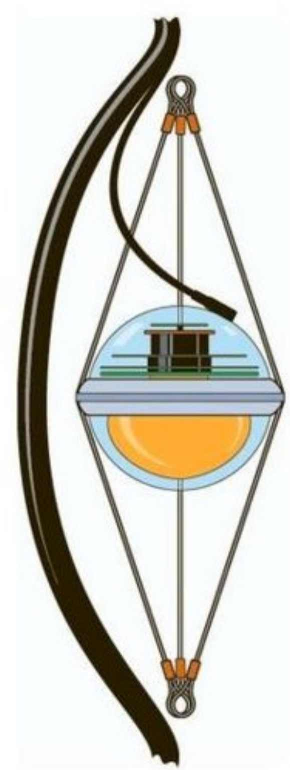
Hole-ice

- Refrozen central column with high scattering

DOM orientation

- Thick, support cable may impede direct photons if vertex is nearby
- A few DOMs may not be perfectly horizontal

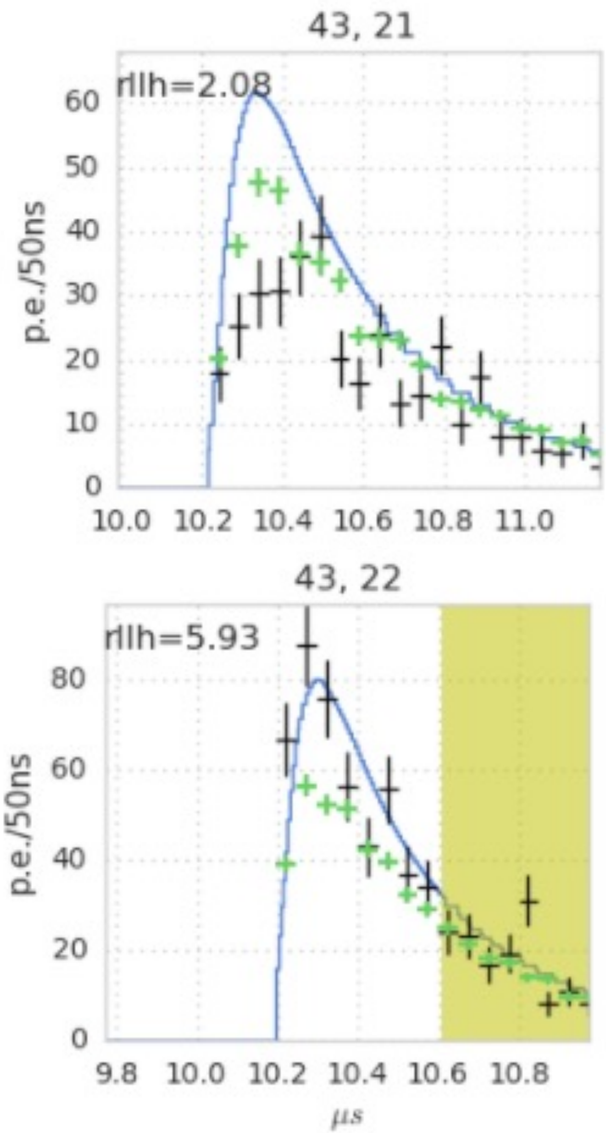
Looking up the string



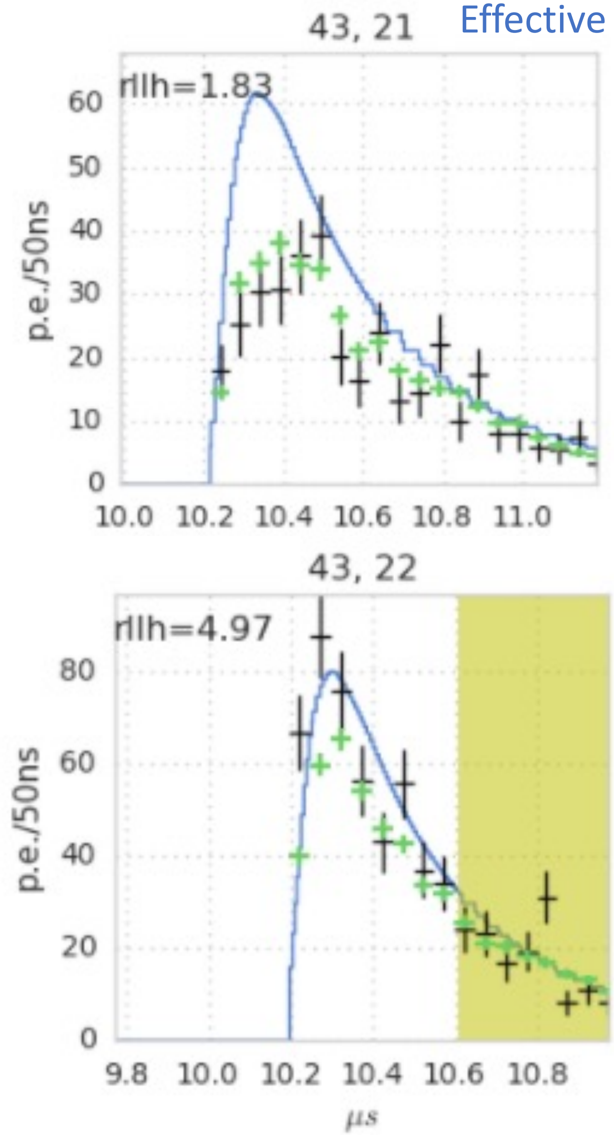
Local effects: DOM orientation and cable position

Bert data
Direct photon MC
Effective photon MC

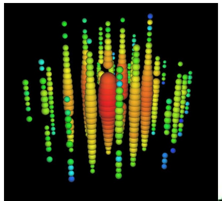
Without local effects



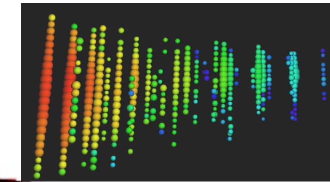
With local effects

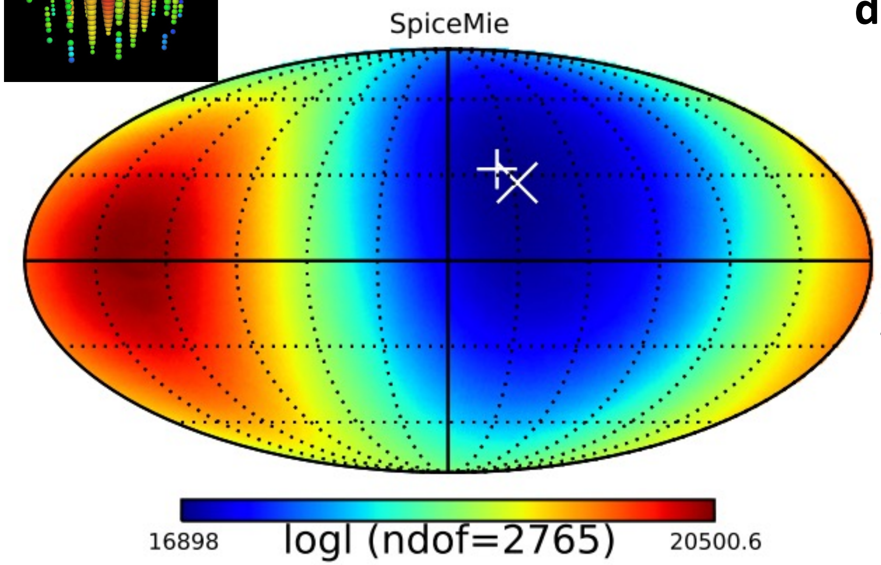


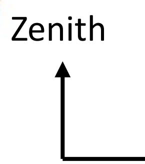
Cascade vs track skymap

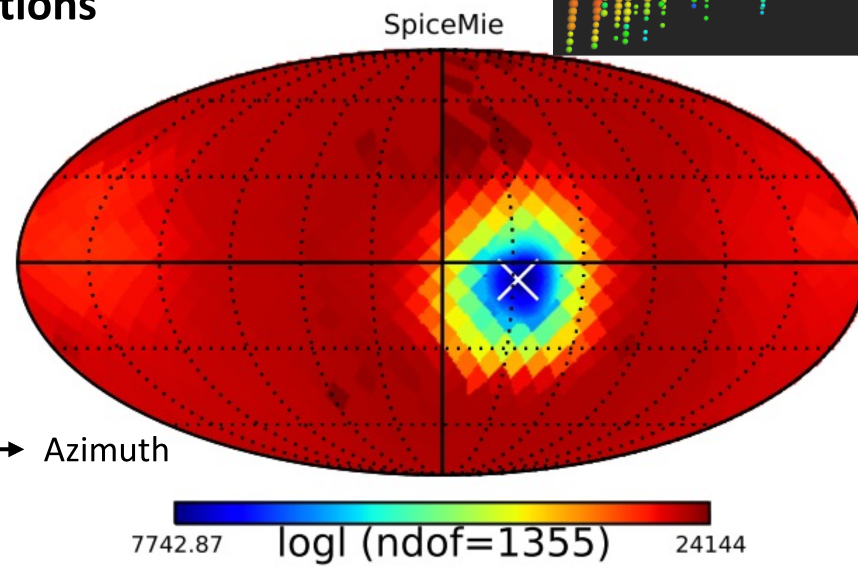


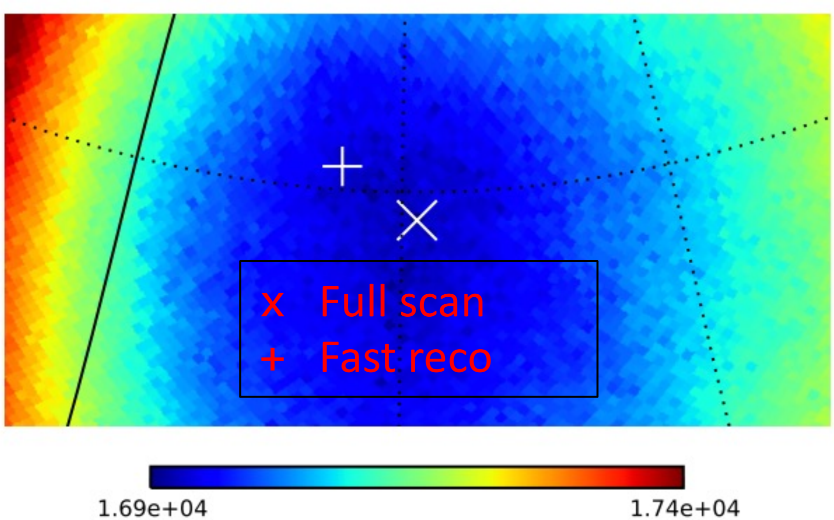
Uses splines from tabulated distributions

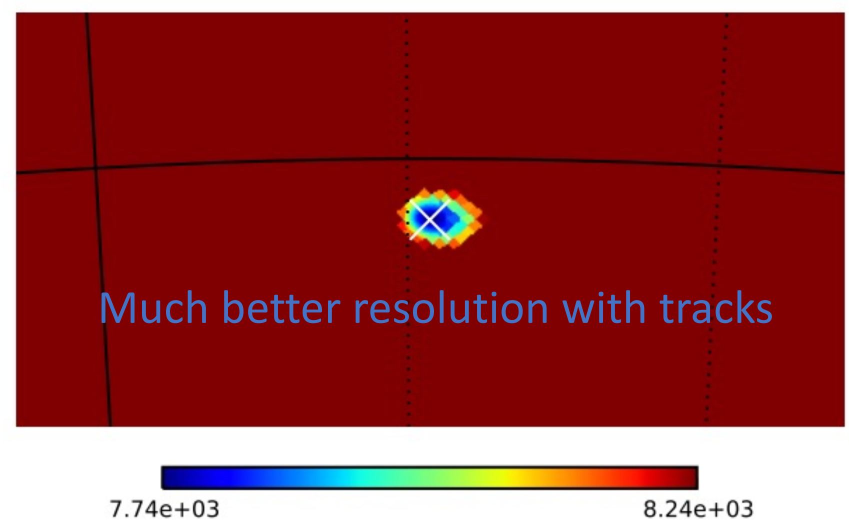








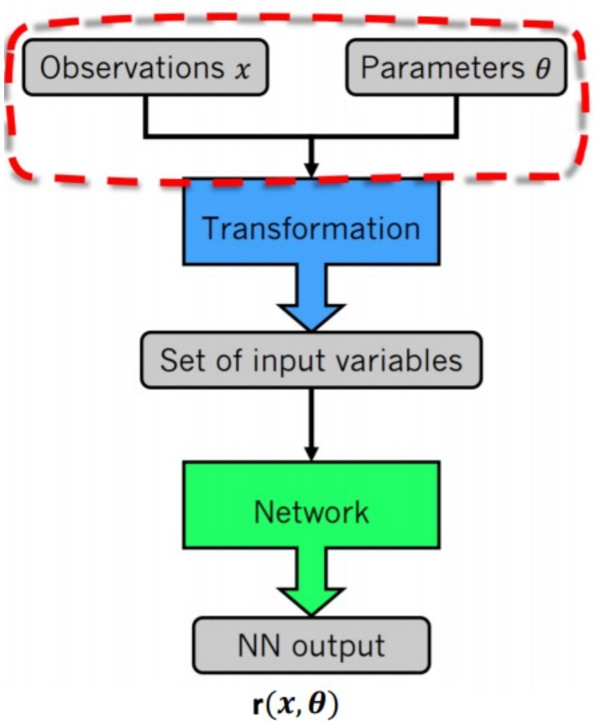




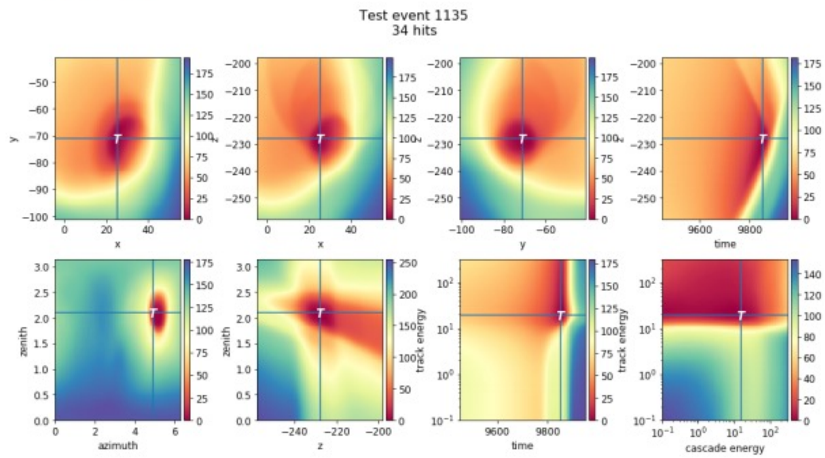
FreeDOM

Likelihood-free inference using NN

Train a binary classifier that can be converted back into a likelihood



- We replace $\frac{\mathcal{L}(\boldsymbol{\theta}|\boldsymbol{x})}{p(\boldsymbol{x})}$ with the output of our neural network, $\boldsymbol{r}(\boldsymbol{x},\boldsymbol{\theta})$
  - $\boldsymbol{r}$ is a ratio estimator; approximates the likelihood-to-evidence ratio
- $\boldsymbol{r}(\boldsymbol{x},\boldsymbol{\theta})$ can be used anywhere you'd typically use a likelihood function
- Evaluating $\boldsymbol{r}(\boldsymbol{x},\boldsymbol{\theta})$ is very fast (tens of microseconds)



T: true parameters

eight hypothesis parameters:
x, y, z, t, azimuth, zenith, cascade energy, track energy

parameters not being scanned are set to their truth values