

ICECUBE
NEUTRINO OBSERVATORY



THE
UNIVERSITY
OF UTAH®

Diffuse Astrophysical Neutrinos: Analysis Techniques

Vedant Basu

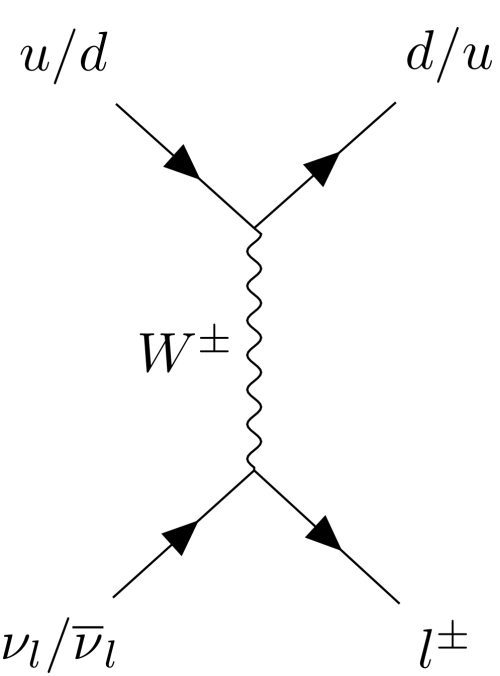
Postdoctoral Researcher, IceCube

Harvard Neutrino Practicum, 2026

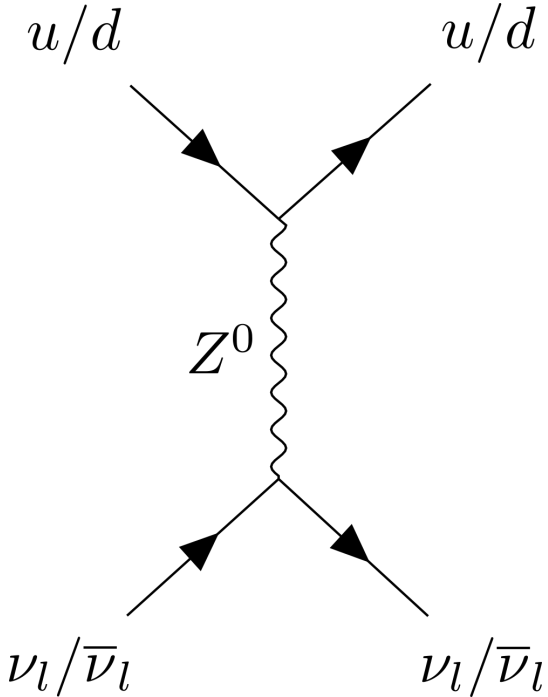
Outline

- **Astrophysical Neutrino Detection at Cherenkov Detectors**
- Event Classification and Selection Techniques
- Neutrino Spectral Measurements
- Fitting a neutrino spectrum!
- Outlook

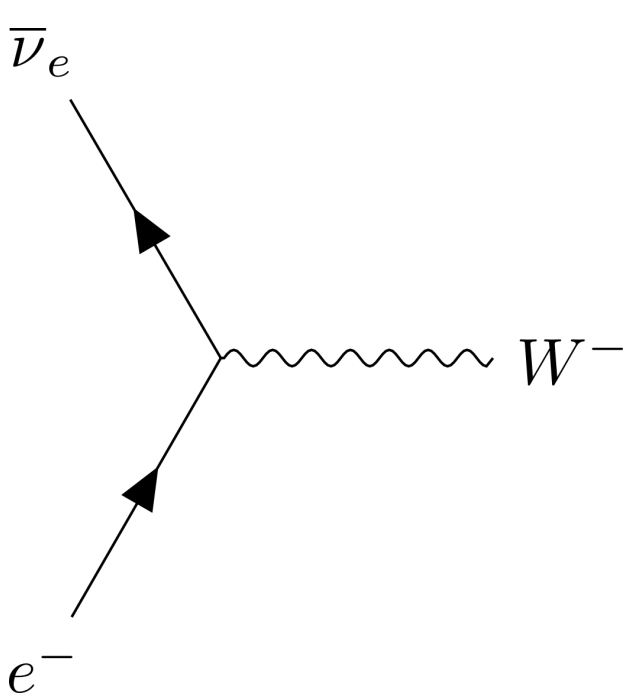
Neutrino Interaction Channels



Charged current interactions yield an outgoing charged lepton and a hadronic shower



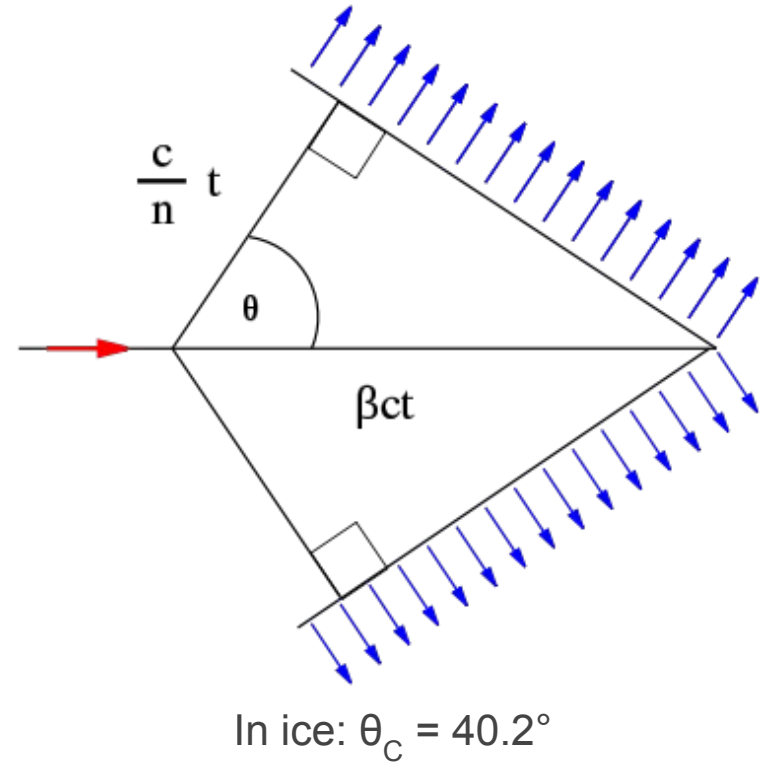
Neutral current interactions have an outgoing scattered hadron and neutrino



Glashow Resonance interactions yield an on-shell W^- boson, which subsequently decays

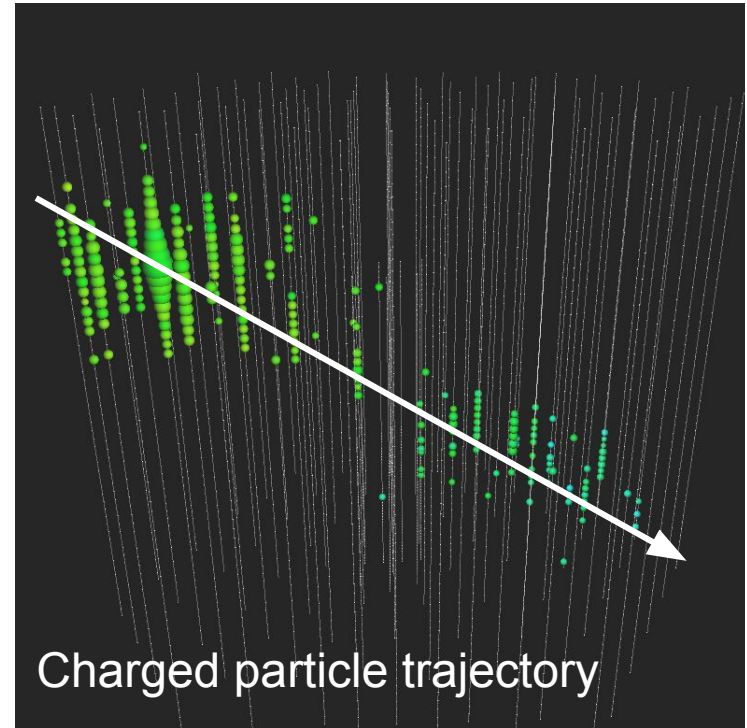
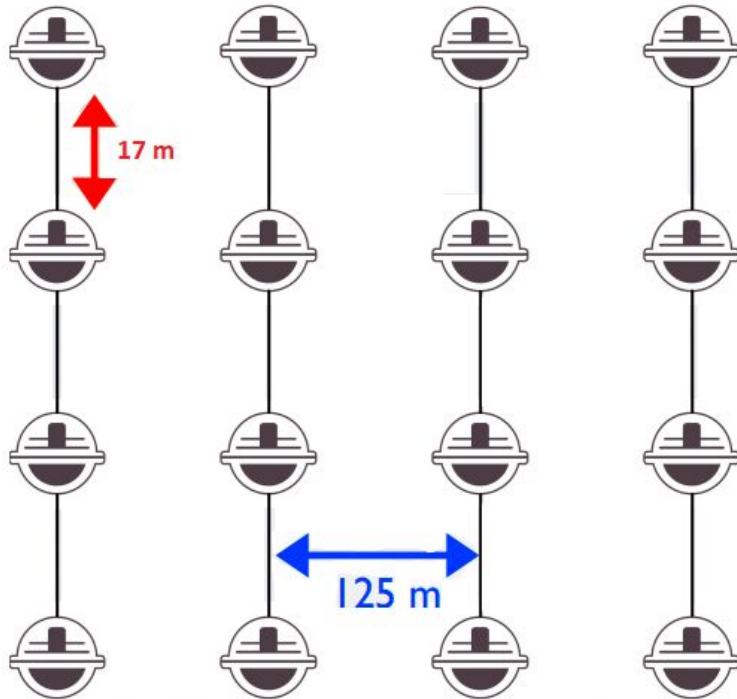
Observing neutrino interactions via the Cherenkov effect

- **Charged particles deposit energy** as they travel through matter
- When charged particles travel faster than the speed of light in a medium, they emit Cherenkov radiation
- A **cone of light is formed** determined by Cherenkov angle, θ_C
- Cherenkov light collected by DOM photomultiplier tubes (PMTs), which convert the optical signal to an amplified electrical signal

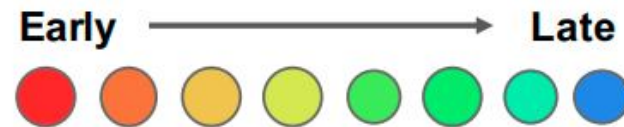


Event Reconstruction

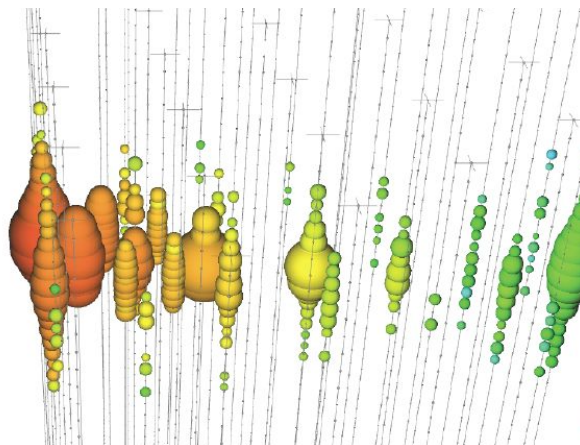
- Number of photons captured $\propto$ deposited energy. Photon arrival times at DOMs helps reconstruct particle trajectory.



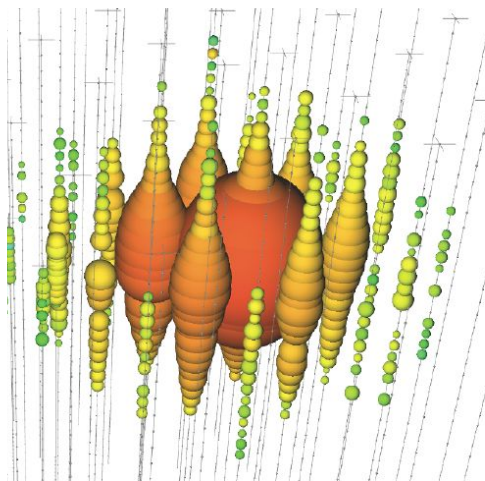
IceCube Event Morphologies



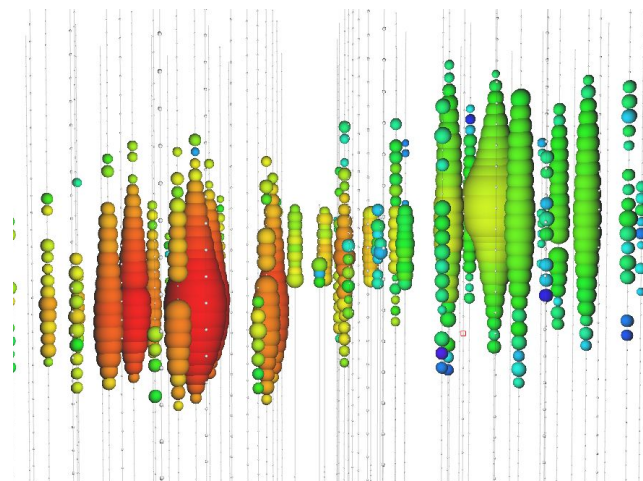
Tracks (Data)



Cascades (Data)



Double Cascade (Simulated)



$$\nu_\mu + X \rightarrow \mu^- + \text{Hadrons}$$

$$\nu_e + X \rightarrow e^- + \text{Hadrons}$$

$$\nu_\tau + X \rightarrow \tau^- + \text{Hadrons}$$

$$\nu_l + X \rightarrow \nu_l + \text{Hadrons}$$

$$\tau^- \rightarrow \nu_\tau + \dots$$

Energy Res. : 0.3 in $\text{Log} \frac{E}{\text{TeV}}$

Energy Res. : 8% @ 100 TeV

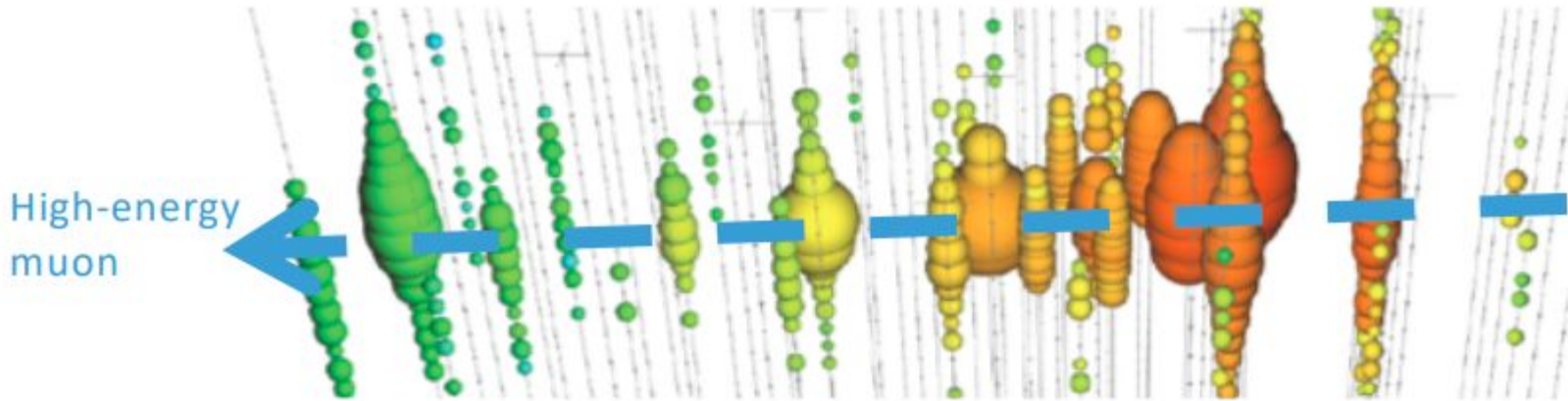
Decay Length : 50 m/PeV

Angular Res. : 0.3°

Angular Res. : 4°

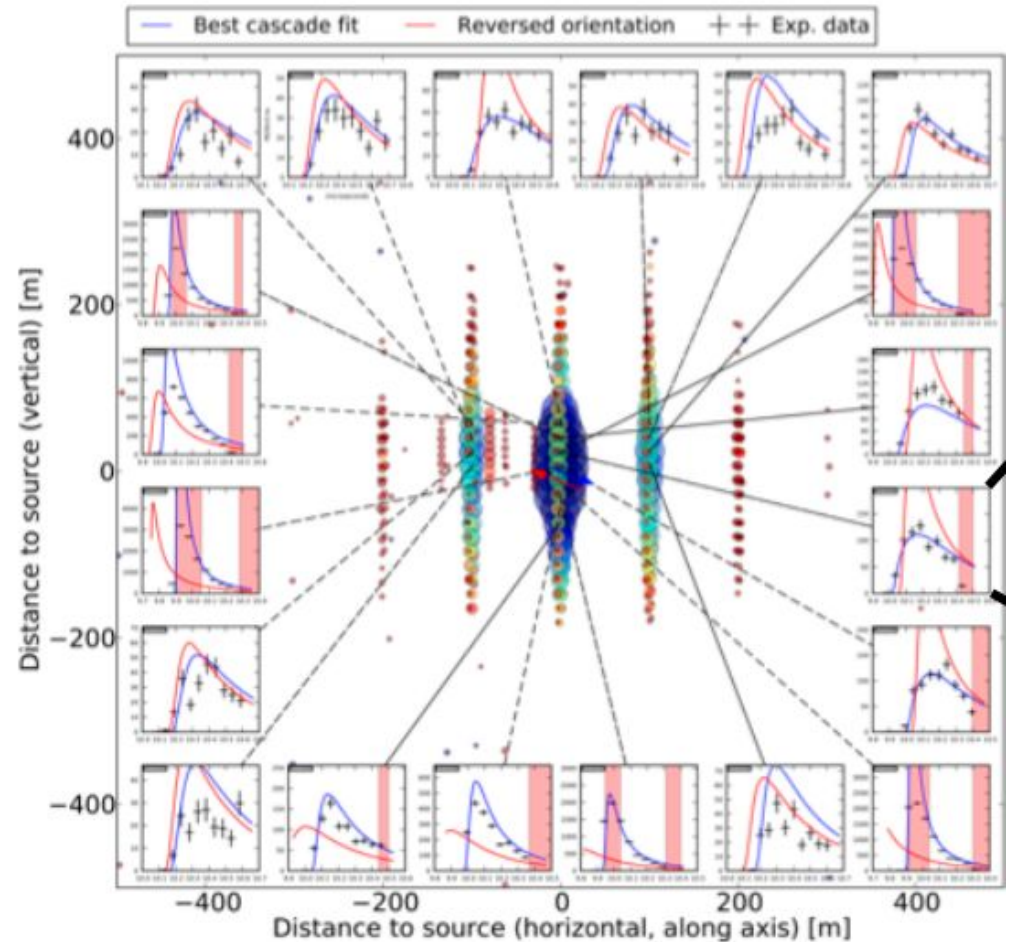
Track Reconstructions

- Use full-waveform information by fitting predicted light yields to what is actually seen
- IceCube's Millipede works for high-energy tracks by breaking it up into multiple cascades along the track due to muon stochastic energy losses



Cascade Reconstructions

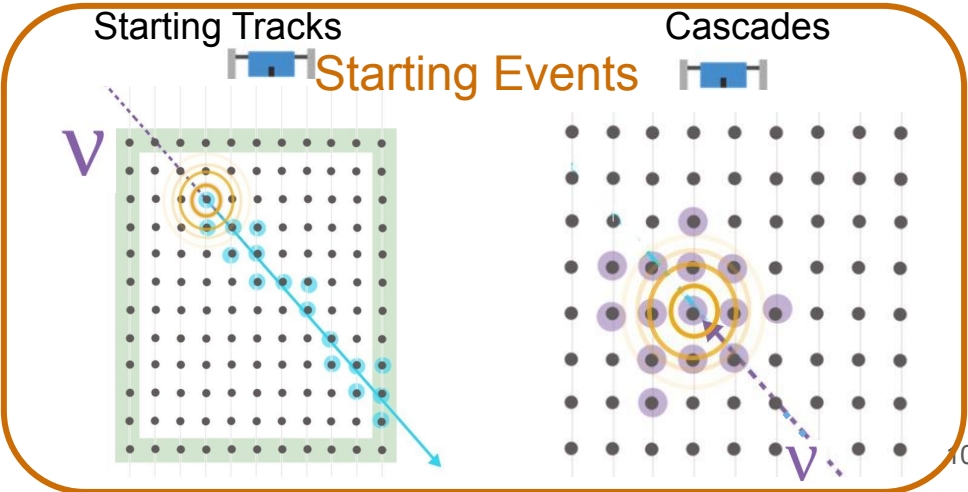
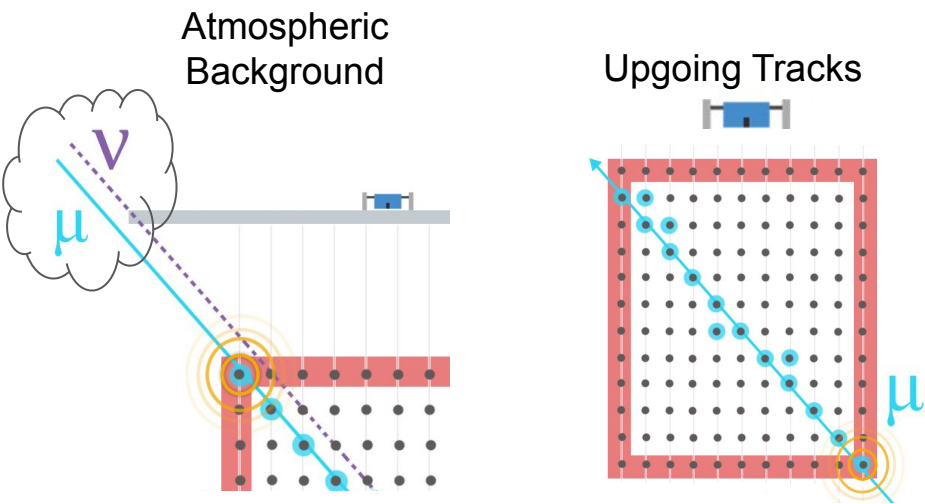
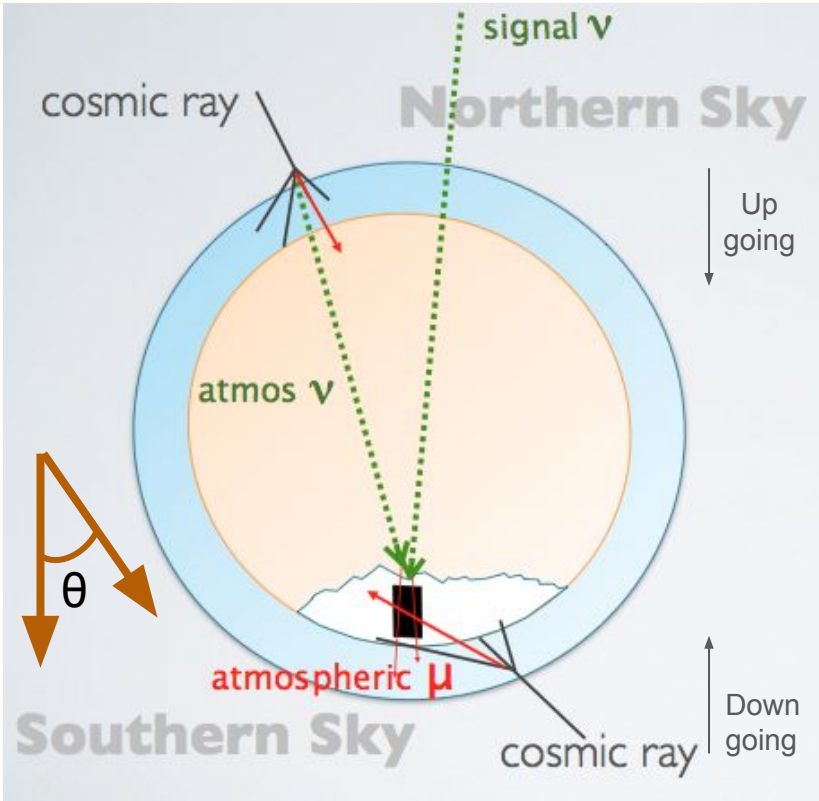
- Large distances between DOMs mean few detected photons
- Sensitivity to asymmetry means high dependence on ice modeling
- IceCube's Monopod algorithm tabulates photon yields for a single ice model



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- Outlook

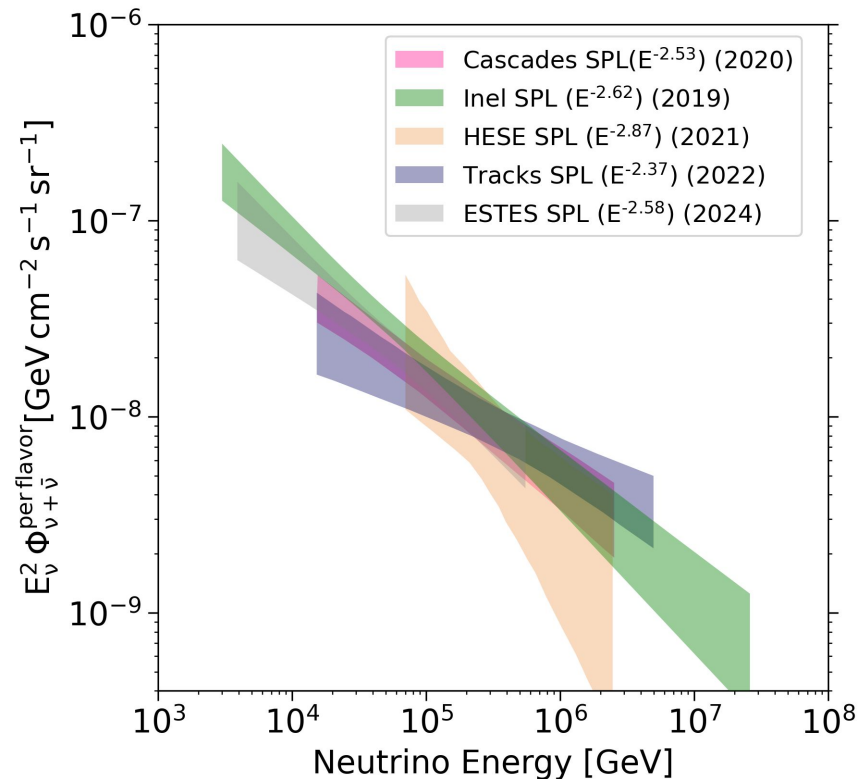
Event Selections



Diffuse Cosmic Neutrino Flux

IceCube measurements of the diffuse spectrum prior to 2026 found a single power law ($E^{-\gamma}$) to be the best fit

- High Energy Starting Event (HESE):
all flavours & all sky, above 60 TeV
- Through-going tracks:
muon neutrinos from the Northern sky
- Cascades:
All sky electron and tau neutrinos, and
muon neutrino NC interactions
- Enhanced Starting Track Event Selection
(ESTES):
All sky muon neutrinos

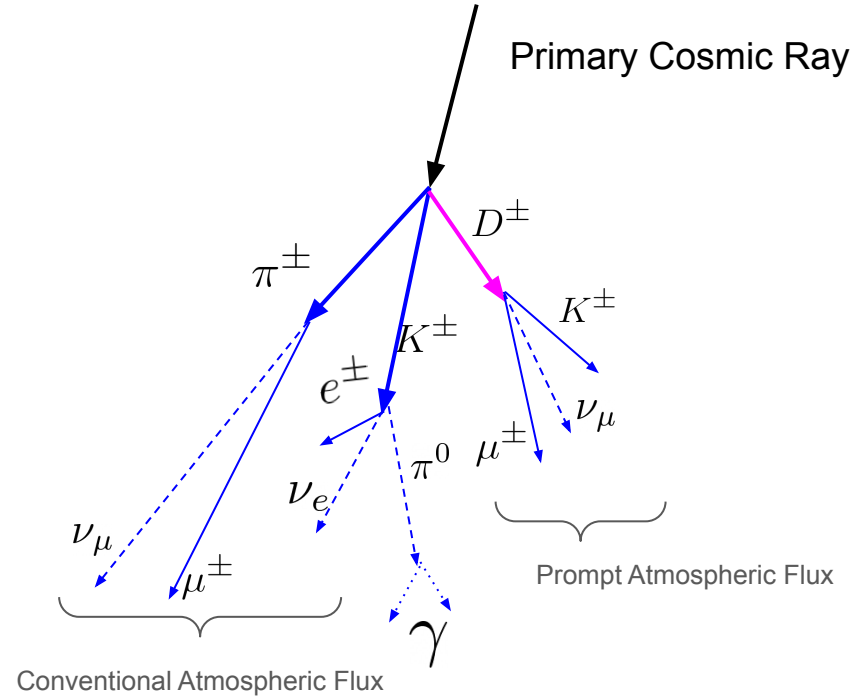


Outline

- Astrophysical Neutrino Detection at Cherenkov Detectors
- Event Classification and Selection Techniques
- **Neutrino Spectral Measurements**
- Beyond Astronomy
- Outlook

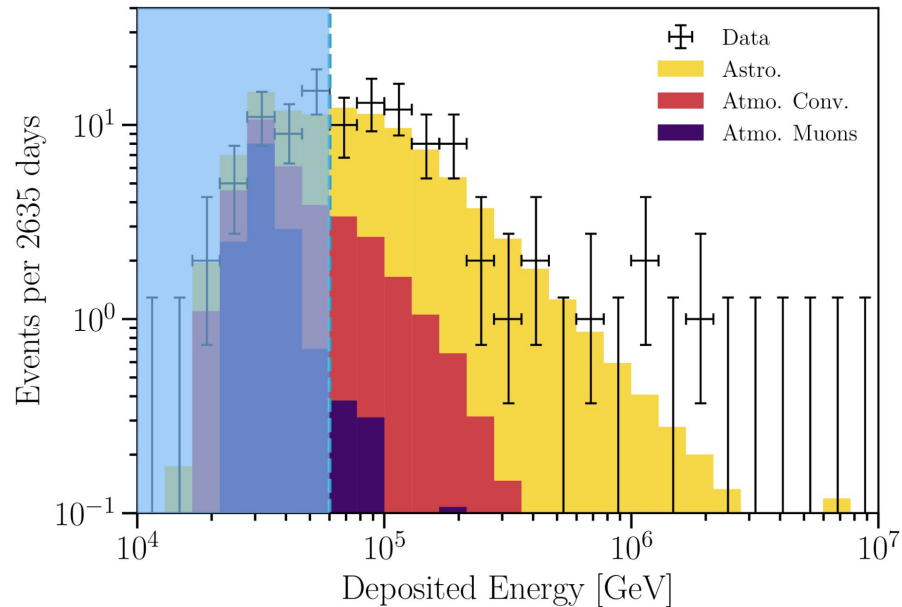
Atmospheric Background

- Main background from atmospheric muons
- Neutrinos also produced in atmospheric cosmic rays interactions.
- Conventional flux from pion/kaon decay follows $\sim E^{-3.7}$
- Prompt contribution from charmed meson decay- follows $\sim E^{-2.7}$
- Q: Why do the conventional and prompt fluxes have different spectra?

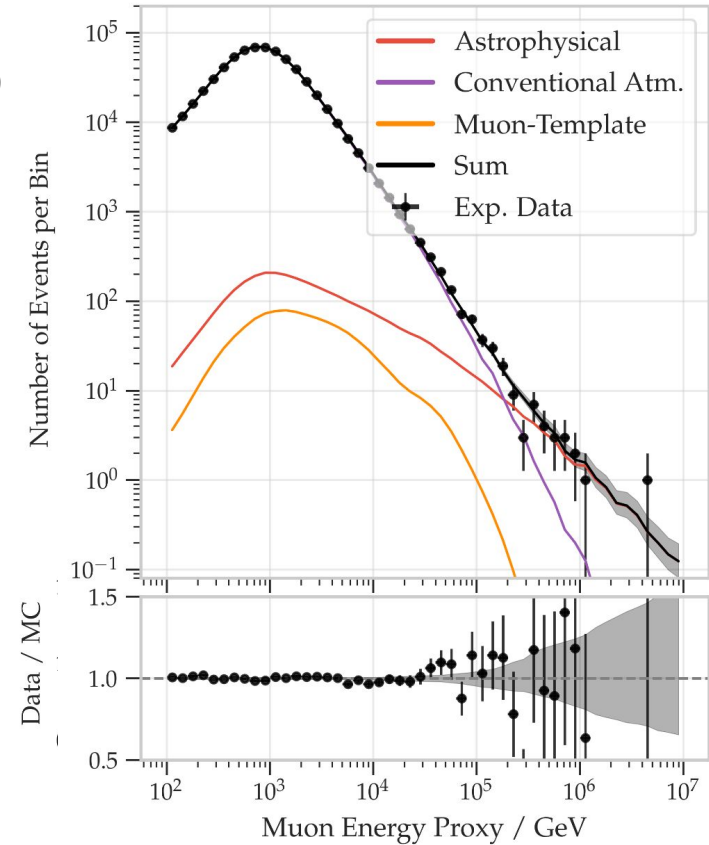


Low energy sensitivity

- The search for structure in the astrophysical neutrino spectrum necessitates pushing the energy threshold lower.
- Tradeoff: Better background rejection/modelling



HESE flux characterization, 7.5 years of data
(events below 60 TeV (shaded) ignored in fit)
IceCube HESE: PRD 104.2 (2021): 022002.

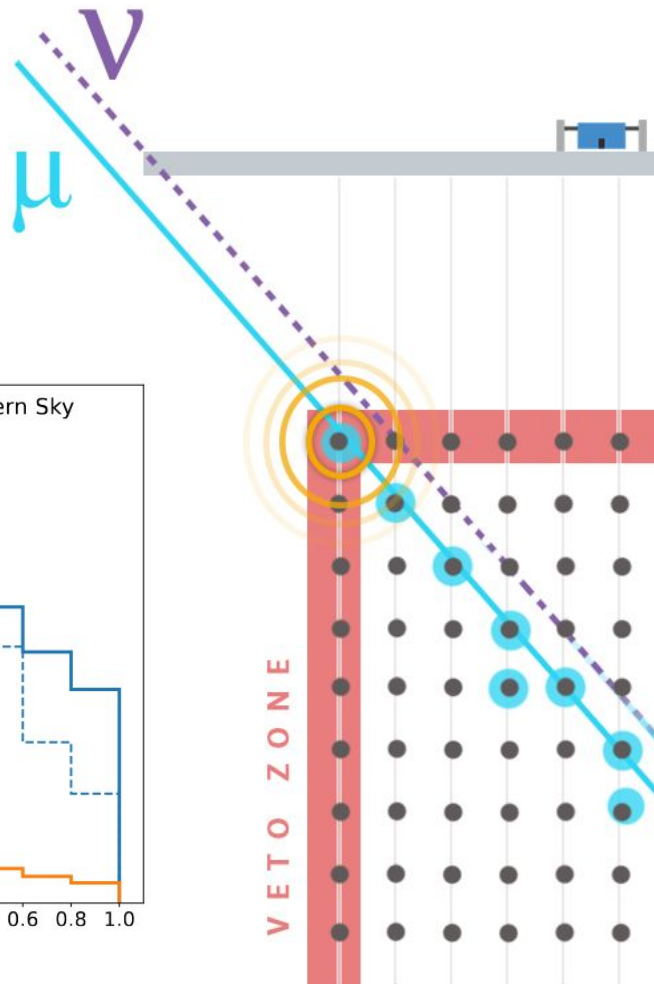
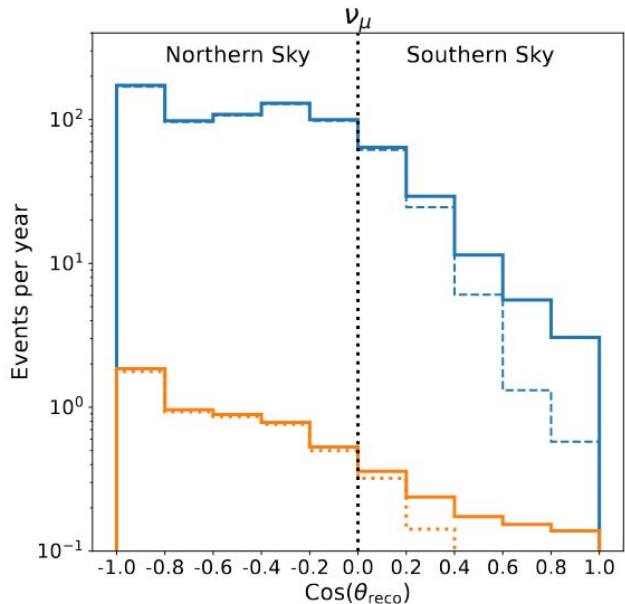
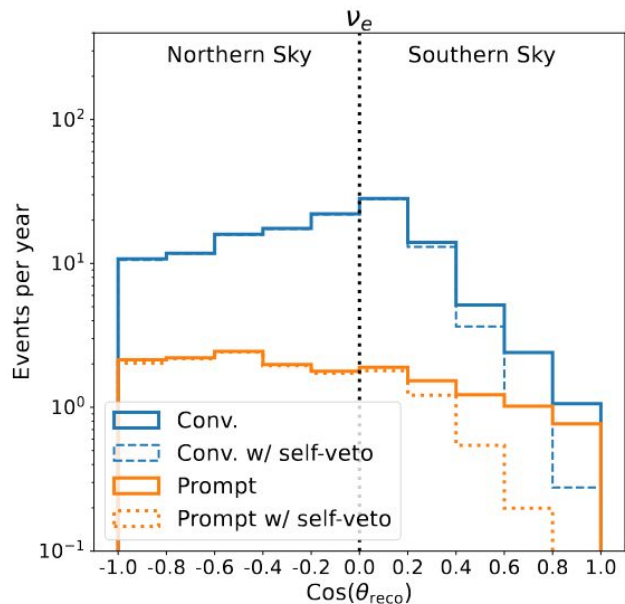


The energy distribution of upgoing tracks for
the period 2010-18

The Astrophysical Journal 928.1 (2022): 50

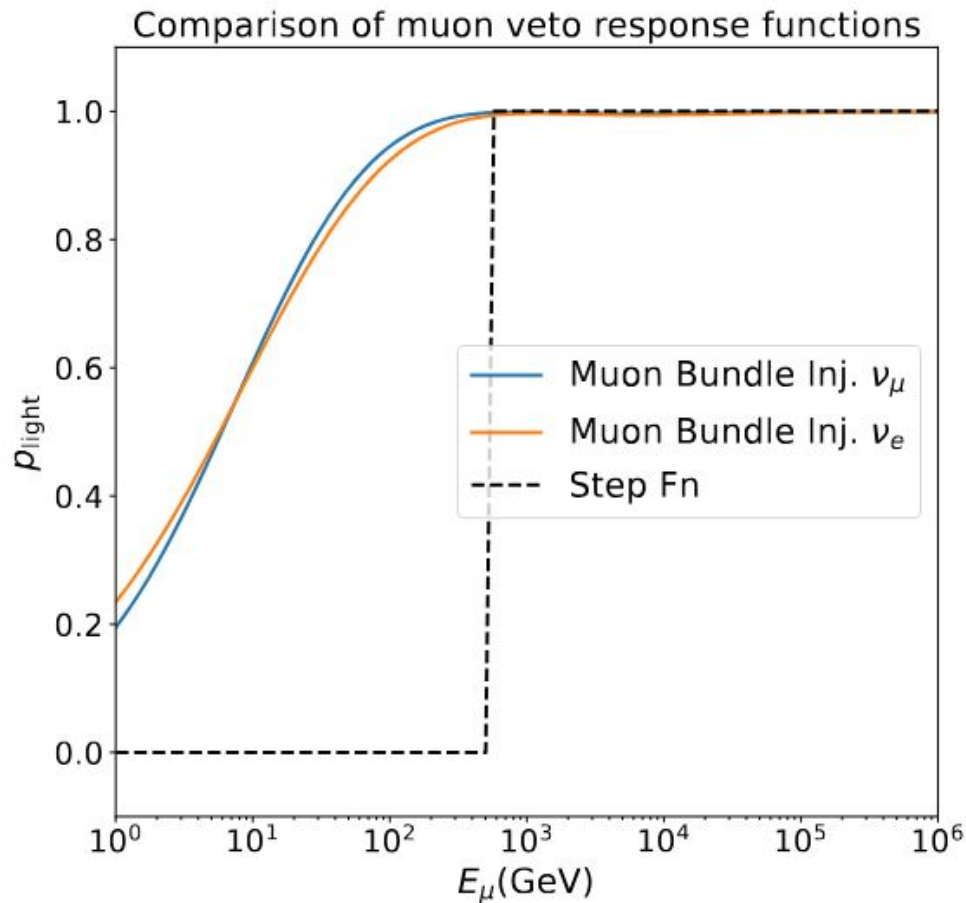
Neutrino self-veto

- Neutrinos from CR showers often accompanied by muons.
- Vetoing these muons suppresses atm. neutrino background
- Accurate modeling of the self-veto suppression via muon bundle injection.



How do we model it?

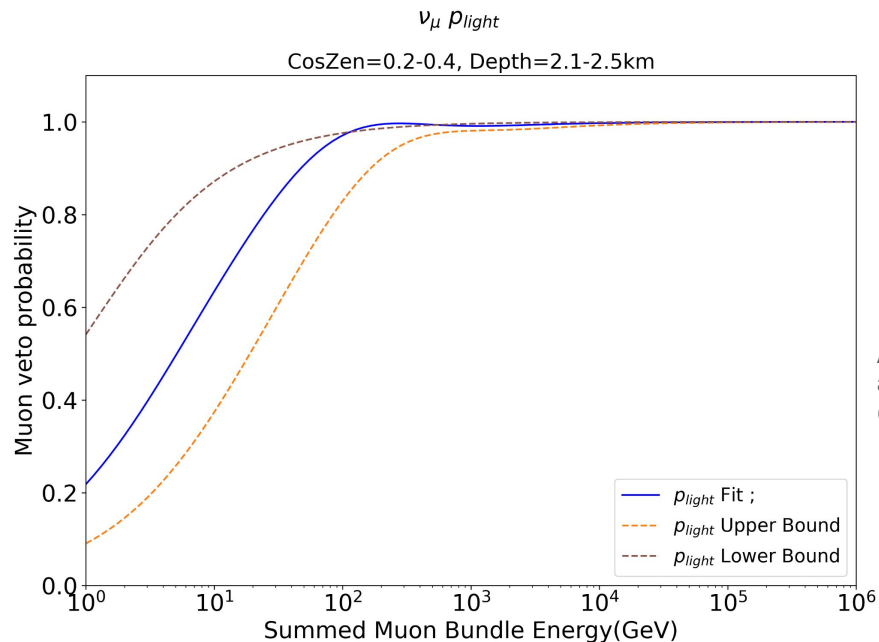
- Need to model detector response to air shower muons
- Generate PDFs of Muon Bundle multiplicity and energy from Corsika MC
- Inject these muons into neutrino events which survive to final level
- Parametrise detector response by reprocessing through event selection, using the P_{light} function



$P_{\text{light}}(E_{\mu})$: fraction of events rejected by addition of accompanying muons

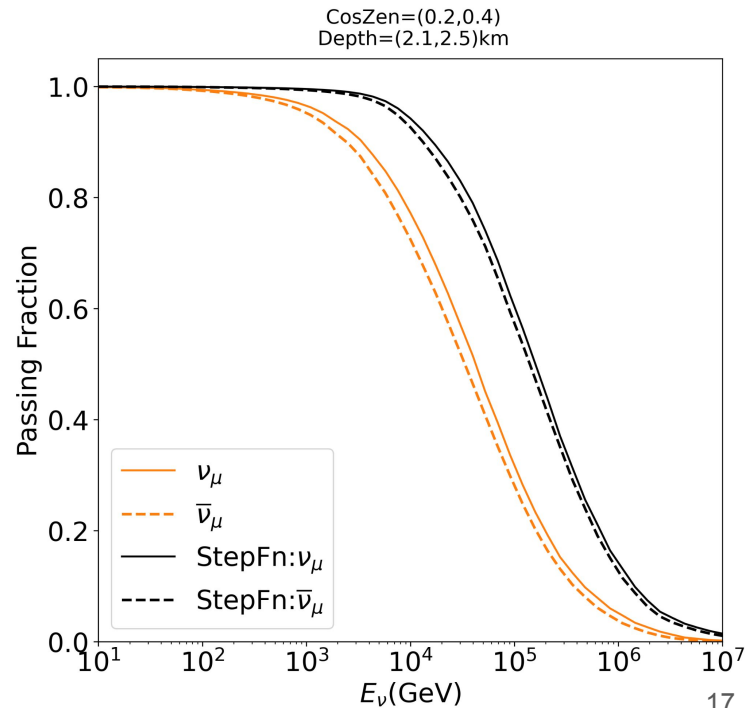
Neutrino passing fractions

- The muon detector response ($P_{\text{light}}(E_\mu)$) evaluated using fraction of neutrino+muon events which survive reprocessing.
- P_{light} is used to calculate **neutrino** passing fractions with the nuVeto package

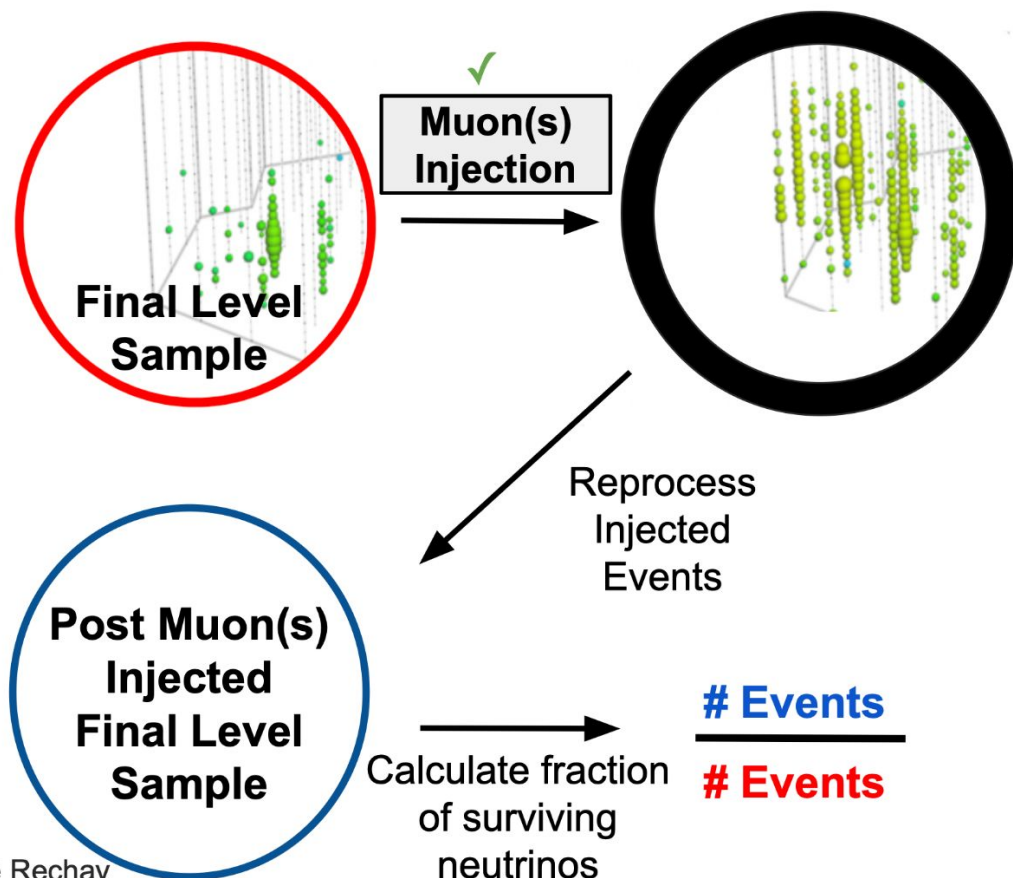


nuVeto

Argüelles, C. A., et al, JCAP 2018.07 (2018): 047.



Muon Bundle Injection



P_{survive} = fraction of neutrino to survive selection with muon(s)

- **# of neutrino events at final level**
- **# of neutrino events with injected muons at final level**

Astrophysical Flux Models

- Single Power Law (SPL):

$$\Phi_{\text{astro}} \left(\frac{E_\nu}{100\text{TeV}} \right)^{-\gamma}$$

- Broken Power Law (BPL):

$$\Phi_{\text{astro}} \left(\frac{E_\nu}{E_{\text{break}}} \right)^{-\gamma_{\text{BPL}}} \left(\frac{E_{\text{break}}}{100\text{TeV}} \right)^{-\gamma_1}$$

$$\gamma_{\text{BPL}} = \begin{cases} \gamma_1 (E_\nu < E_{\text{break}}) \\ \gamma_2 (E_\nu > E_{\text{break}}) \end{cases}$$

- Log Parabola (LP):

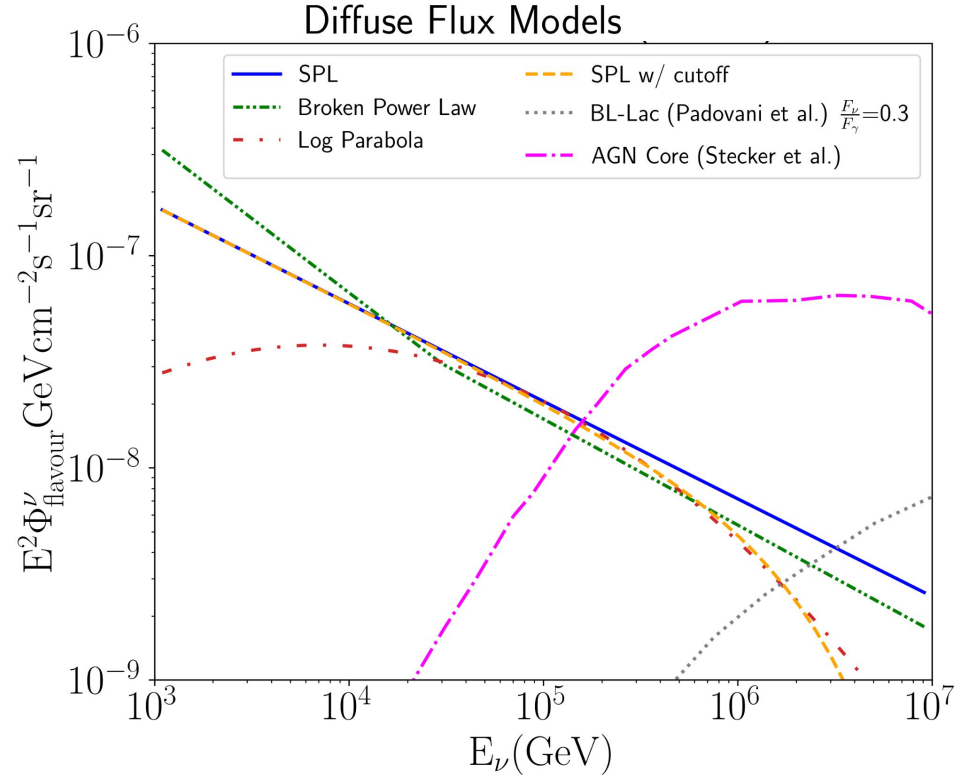
$$\Phi_{\text{astro}} \left(\frac{E_\nu}{100\text{TeV}} \right)^{-\alpha - \beta \log_{10} \left(\frac{E_\nu}{100\text{TeV}} \right)}$$

- SPL+Cutoff:

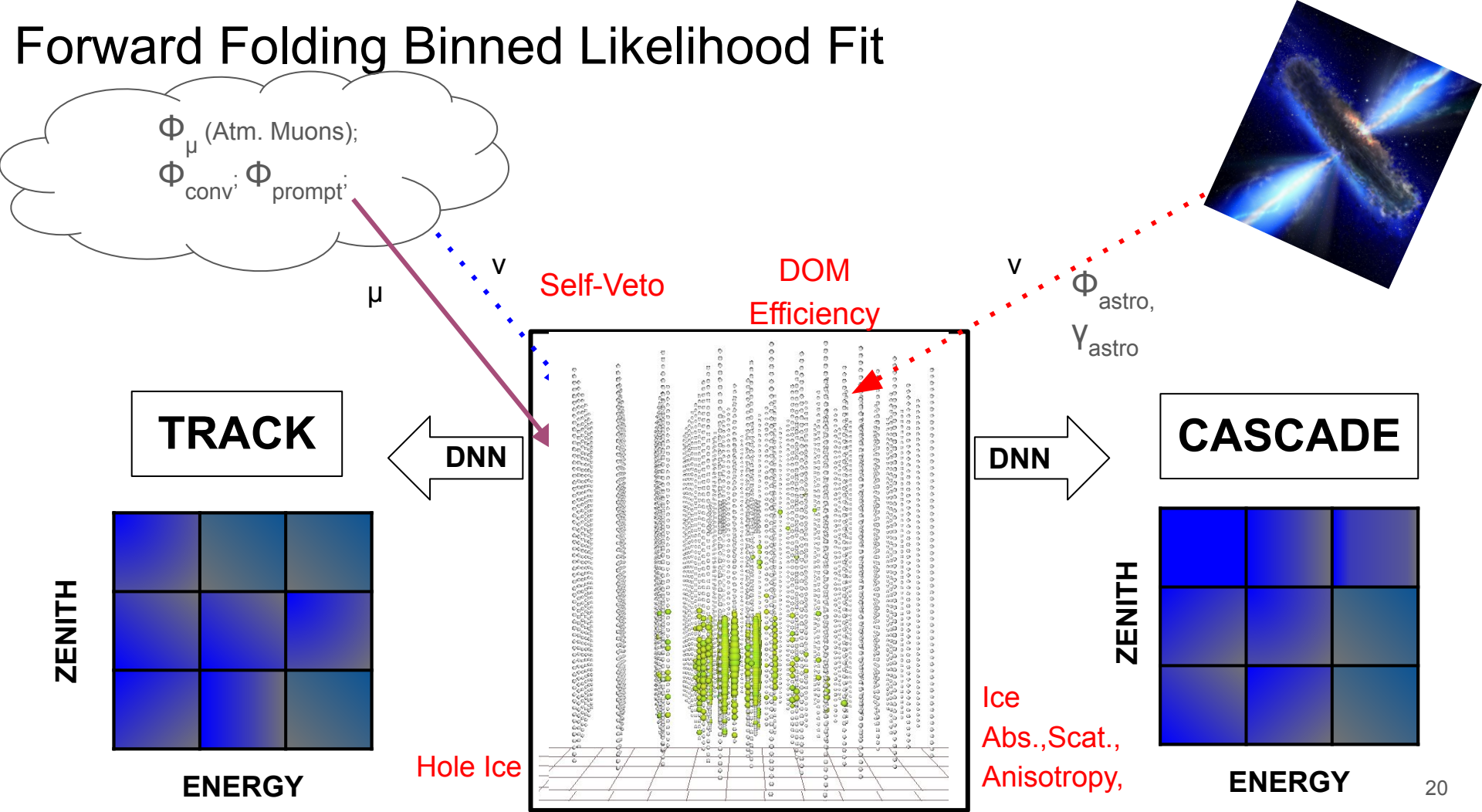
$$\Phi_{\text{astro}} \left(\frac{E_\nu}{100\text{TeV}} \right)^{-\gamma} e^{-\left(\frac{E_\nu}{E_{\text{cutoff}}} \right)}$$

- AGN core neutrino emission (Stecker, F. W. et al, 1991)

- Neutrino emission from BLLac objects (Padovani, P. et al, 2015)

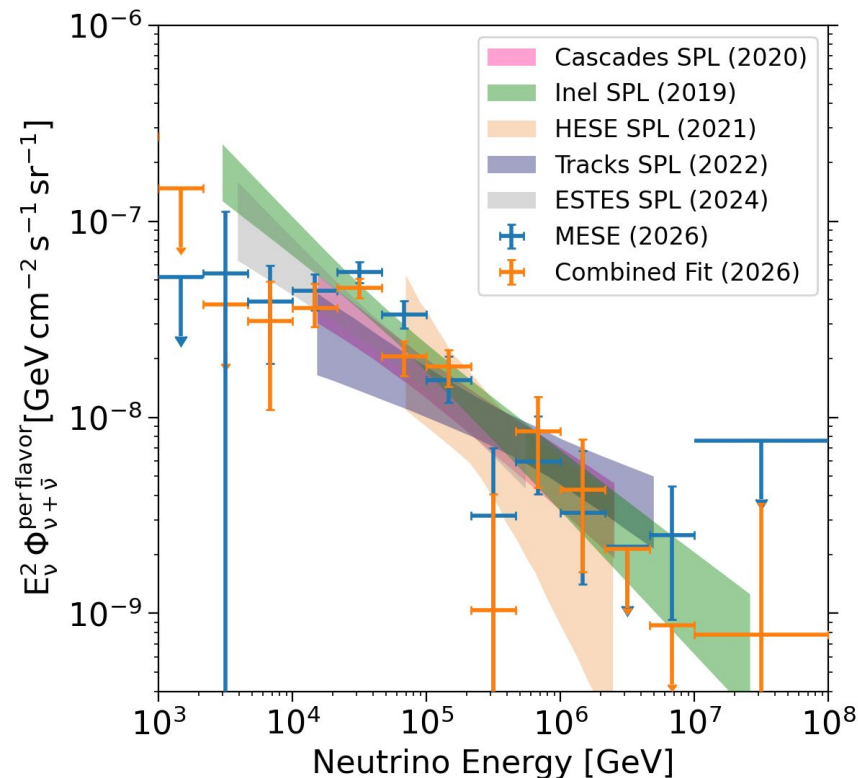


Forward Folding Binned Likelihood Fit



Diffuse Cosmic Neutrino Flux

- In 2026, two analyses were published which observed structure in the Cosmic Neutrino Spectrum
 - MESE: starting events down to 1 TeV
 - Combined Fit: Joint fit of IceCube cascades and upgoing tracks samples
- Reject SPL model for first time by more than 4σ
- Next generation of analyses underway to better resolve features of the neutrino spectrum down to TeV scales

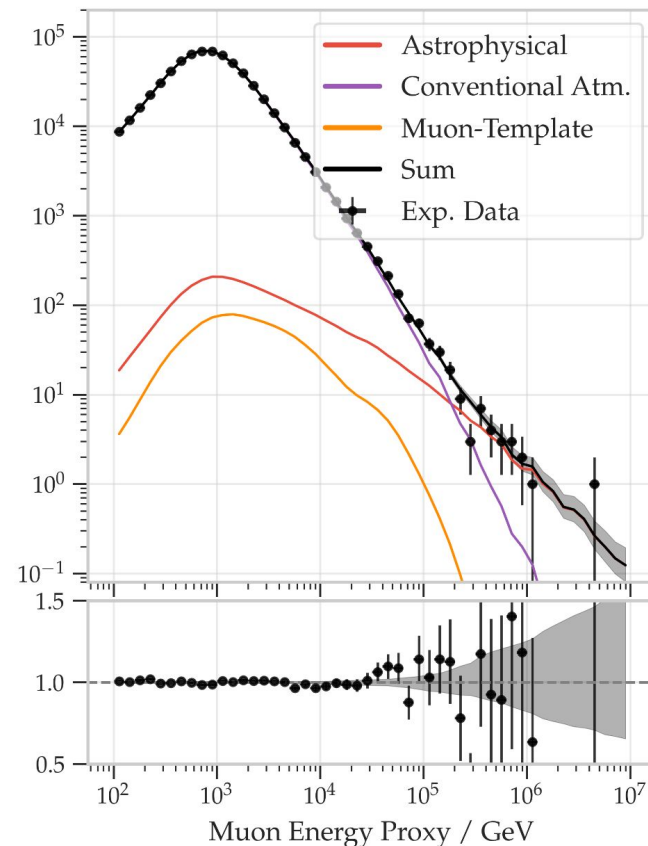


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Components of the astrophysical fit

- Astrophysical Neutrinos: For the purpose of this talk, this is the signal we are trying to measure.
- Atmospheric Neutrinos: An irreducible background
- Atmospheric Muons: Background which can be discriminated and vetoed, but which we will ignore for this exercise



The energy distribution of upgoing tracks for
the period 2010-18

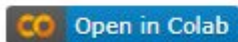
The Astrophysical Journal 928.1 (2022): 50

Link to Notebook

- The practical diffuse exercise is hosted [here](#).
- Plan to run scripts on Google Colab, but you can clone the repository and run it in an environment of your choice.

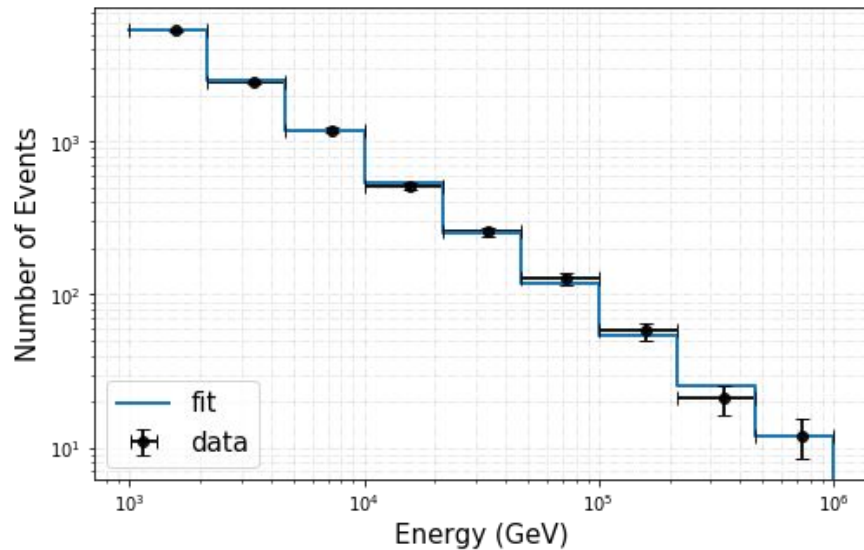
Getting Started

Click the badge below to launch the analysis environment in Google Colab:



Datasets

- *hese_toy_simulation.json*: A pre-made dataset of simulated neutrino events scaled to $E^{-2.5}$
- *hese_toy_data.json*: The data we will try to fit with our simulated neutrino events



Computing expectation values

- Best way to compute an expectation value is to generate Monte Carlo simulation (MC).
 - Start by generating neutrinos and "inject" them near your detector
- You usually inject neutrinos following chosen energy, zenith, azimuthal distributions, and over a certain area of the detector
- Our MC is very resource-intensive to produce-> need to re-use for different astrophysical models
- Solution: Reweighting

Reweighting MC

- We normalize the simulated events to represent different flux models.

- We start by computing the gen-weight for each event

$$\Phi_{generated} = N_{generated} [GeV^{-1} * sr^{-1} * cm^{-2}]$$

- Now we choose a theoretical flux model, either atmospheric or astrophysical. Let us use

$$\Phi_{model} = 2 * 10^{-18} * \left(\frac{E_{\nu}}{100 TeV} \right)^{-2.6} [s^{-1} * GeV^{-1} * sr^{-1} * cm^{-2}]$$

- You can now combine the generated flux and theoretical fluxes to compute event rates
- * Each event will now have it's own expectation rate in units s^{-1} , the weight w

$$w = \frac{\Phi_{model}}{\Phi_{generated}}$$

Binning the data

- We now "bin" the simulation into bins such as energy/zenith/topology, sum all the simulated events within a bin and denote as weight " w_i ", how many neutrinos we expect per second in that bin for our event selection.
- For the total number of events, we add up the total weights from each contributing flux- astrophysical signal and atmospheric backgrounds.
- The dataset we have provided is from the HESE analysis, primarily high energy above 60TeV
- We create bins in energy, cosine zenith, and morphology. The morphologies we consider for the toy analysis are cascades and tracks

Binned Likelihood analyses

- We now define a poissonian likelihood, which is a statement about the probability of a given set of model parameters being correct given the data we observe.
- For a given bin, the probability, of detecting $\mathbf{k}$ counts/s when expecting λ counts/s is

$$P(k|\lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$$

- Given that you already see $\mathbf{k}$ events, we estimate the true expectation to be the value which maximizes the probability of detecting that many events.

$$\mathcal{L}(\lambda|k) = P(k|\lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$$

- Across multiple bins “ i ”, we have

$$\mathcal{L}(\vec{\theta}|\vec{d}) = \prod_i \frac{(\lambda_i)^{k_i} e^{-\lambda_i}}{k_i!}$$

Performing the fit

- As most optimizers are written as minimizers, we define the log-likelihood which turns the product across bins into a sum

$$\log \mathcal{L}(\theta \mid d) = \sum_i k_i \cdot \log(\lambda_i) - \lambda_i - \log \Gamma[k_i + 1]$$

- We then take the negative of the log likelihood, turning the maximum into a minimum, to take advantage of computational minimizers

Hypothesis Testing: Likelihood ratio test

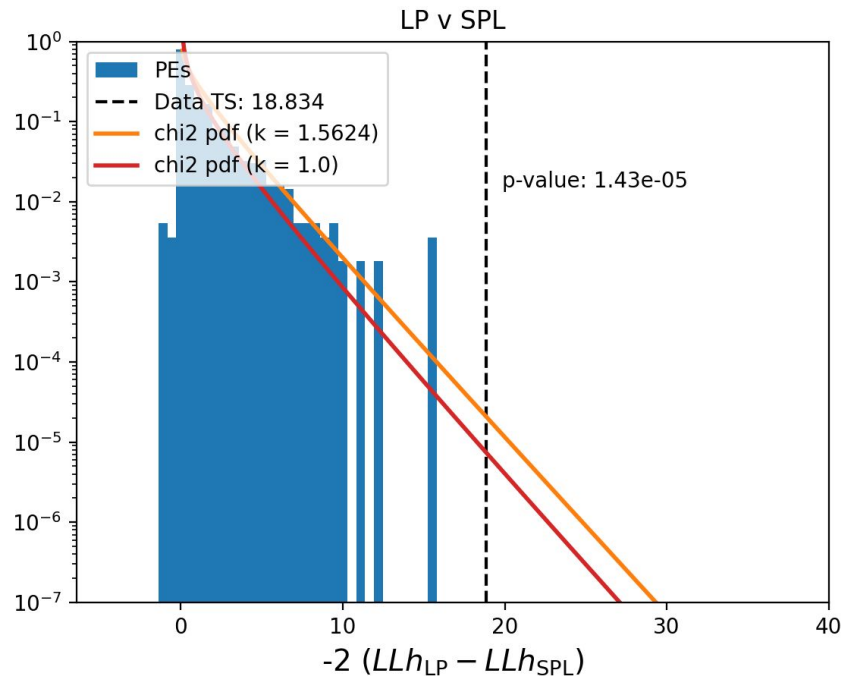
- To test whether a given model fits our data better or worse than another, we run a series of pseudo-experiments with Poisson sampled histograms, and try to fit the test histogram with both models.
- We define our null hypothesis H_0 and our test hypothesis H_1 . Then our Test Statistic is given by

$$TS = 2(\ln \mathcal{L}_{H1} - \ln \mathcal{L}_{H0})$$

- We obtain TS_{data} by fitting our hypotheses to the data histogram, but to determine the statistical significance of our result, we must also obtain a background distribution obtained from fitting a histogram obtained from the null hypothesis

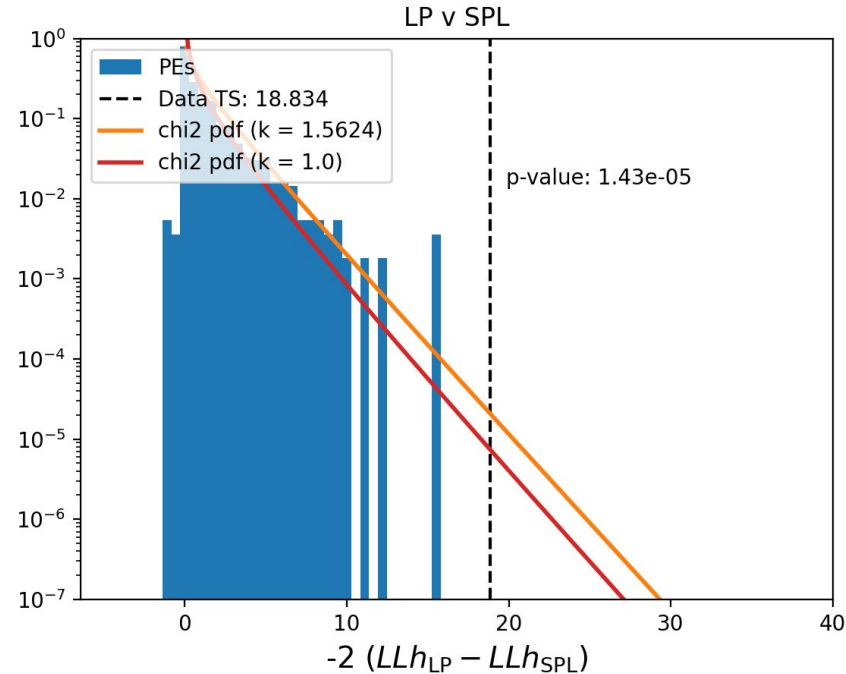
Hypothesis Testing: Background distribution

- We can then define a p-value for our TS_{data} based on the background distribution.
- It becomes computationally very expensive to run pseudo-experiments to map out the tail of the distribution
- We therefore appeal to **Wilks' Theorem**, which provides a model of the underlying background distribution, which we can use for the asymptotes.



Hypothesis Testing: Wilks' Theorem

- The theorem states that, if H_0 is true, then as the sample size grows, the distribution of the TS converges to a chi-square (χ^2) distribution, with degrees-of-freedom equal to the number of extra parameters in H_1 vs H_0 , regardless of the specific details of the tested models.
- Key underlying assumptions:
 - The two models are nested: H_0 must be a special case of the H_1 parameters
 - The true parameter must lie in the interior of the parameter space: Not strictly true for LP vs SPL!
- We use a modification due to **Chernoff**: The distribution is a delta function at zero plus a chi-square.



Outline

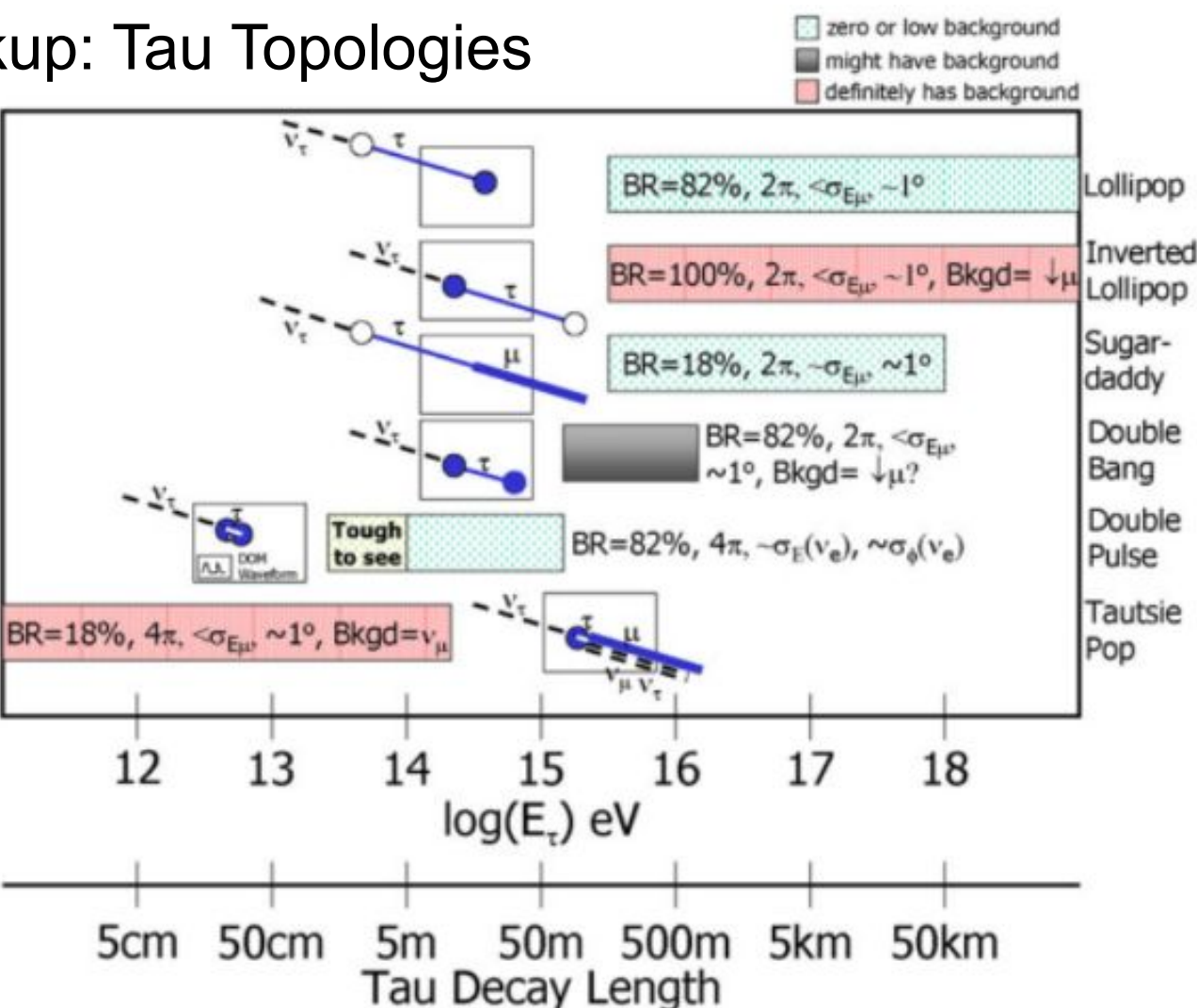
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Outlook

- We have covered the mechanics of performing a simple diffuse fit, along with all the systematic uncertainties that must be accounted for
- New results from IceCube indicate the presence of structure in the diffuse astrophysical neutrino spectrum, with a steep spectrum above ~ 30 TeV and a harder spectrum below that threshold
- New analyses underway to better resolve the low energy spectrum, using machine learning techniques which provide much higher purity neutrino samples!
- Questions?

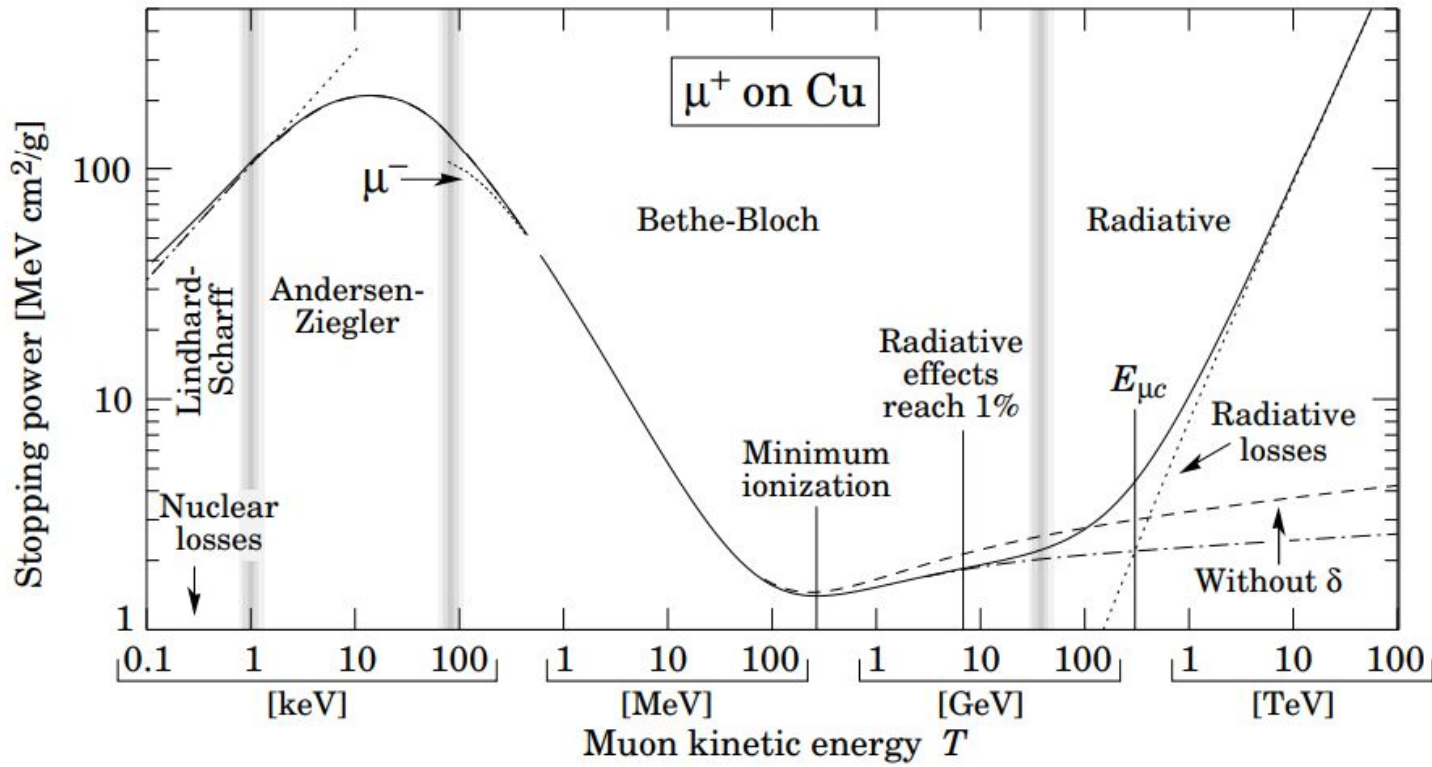
Backup

Backup: Tau Topologies



Cowen, D. F., and IceCube Collaboration. "Tau neutrinos in IceCube." *Journal of Physics: Conference Series*. Vol. 60. No. 1. IOP Publishing, 2007.

Backup: Muon Energy Losses



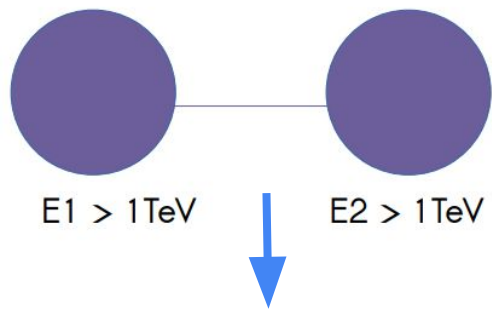
Groom, Donald E., Nikolai V. Mokhov, and Sergei I. Striganov. "Muon stopping power and range tables 10 MeV–100 TeV." Atomic Data and Nuclear Data Tables 78.2 (2001): 183-356.

Systematics: Atmospheric Neutrino Self-Veto

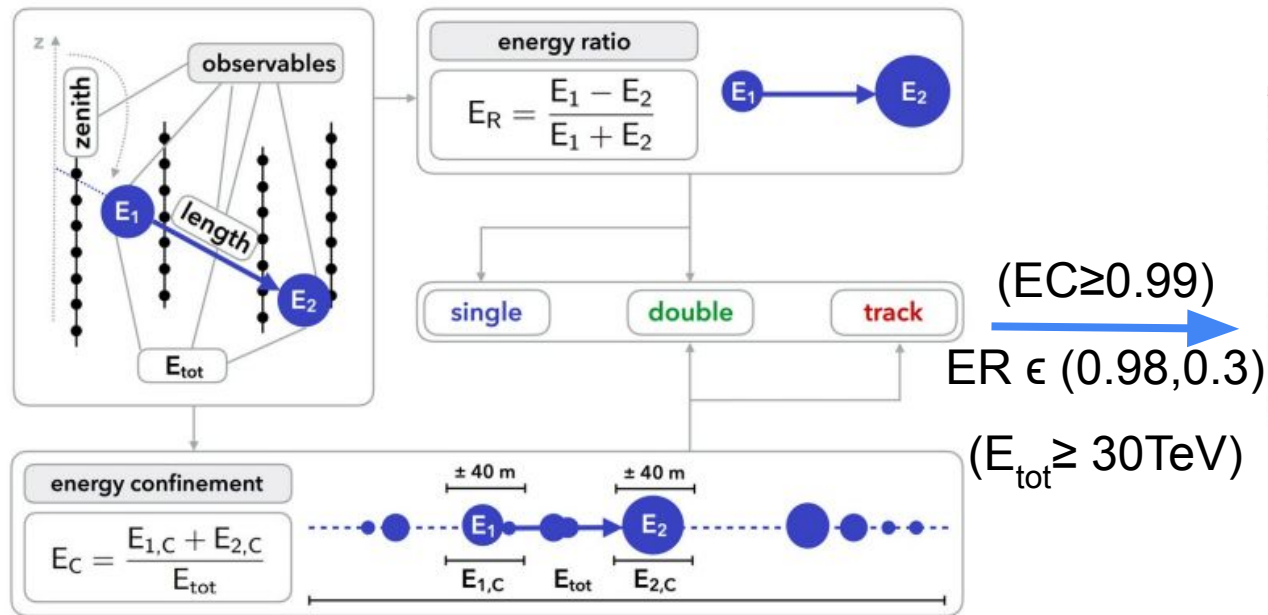
We use the P_{light} as an input to analytically compute the probability of a neutrino with energy E , and zenith angle θ not getting vetoed due to an accompanying sibling muon, this is the passing fraction

$$\mathcal{P}_{\text{pass}}(E_\nu, \theta_z) = \frac{1}{\phi_\nu(E_\nu, \theta_z)} \sum_A \sum_p \int dE_p \int \frac{dX}{\lambda_p(E_p, X)} \int dE_{\text{CR}} \frac{dN_{p,\nu}}{dE_\nu}(E_p, E_\nu) \frac{dN_{A,p}}{dE_p}(E_{\text{CR}}, E_p, X) \phi_A(E_{\text{CR}}) \\ \times \left[1 - \int dE_\mu^i \frac{dN_{p,\mu}}{dE_\mu^i}(E_p, E_\nu, E_\mu^i) \int dE_\mu^f \mathcal{P}_{\text{light}}(E_\mu^f) \mathcal{P}_{\text{reach}}(E_\mu^f | E_\mu^i, \theta_z) \right] e^{-N_{A,\mu}(E_{\text{CR}} - E_p, \theta_z)} \\ \mathcal{P}_{\text{det}}(E_\mu^i, X_\mu(\theta_z))$$

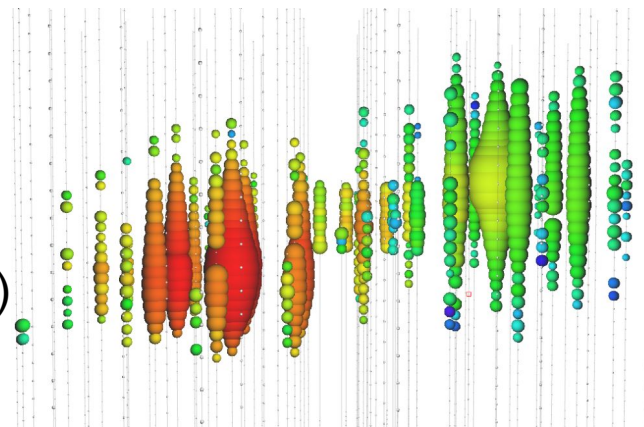
Tau neutrino tagging



- Using Taupede: likelihood-based fitter for double cascades (DC), previously used in HESE (M. Usner DOI:10.18452/19458, J. Stachurska DOI:10.18452/21611)
- As MESE has a DNN-based cascade/track classifier, we use only the DC selection with Taupede



$(EC \geq 0.99)$
 $ER \in (0.98, 0.3)$
 $(E_{\text{tot}} \geq 30\text{TeV})$



Simulated Double
Cascade Event



IceCube Laboratory
Data is collected here and sent by satellite to the data warehouse at UW–Madison



Digital Optical Module (DOM)
5,160 DOMs deployed in the ice

50 m

1450 m

2450 m

Ice Top

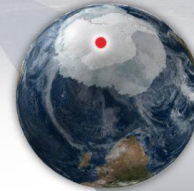
86 strings of DOMs,
set 125 meters apart

IceCube
detector

DeepCore

Antarctic bedrock

Amundsen–Scott South Pole Station, Antarctica
A National Science Foundation-managed research facility



Digital Optical Module

60 DOMs
on each
string

DOMs
are 17
meters
apart

