

# Reconstructing Inelasticity in IceCube using Deep Neural Networks

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**Massachusetts  
Institute of  
Technology**

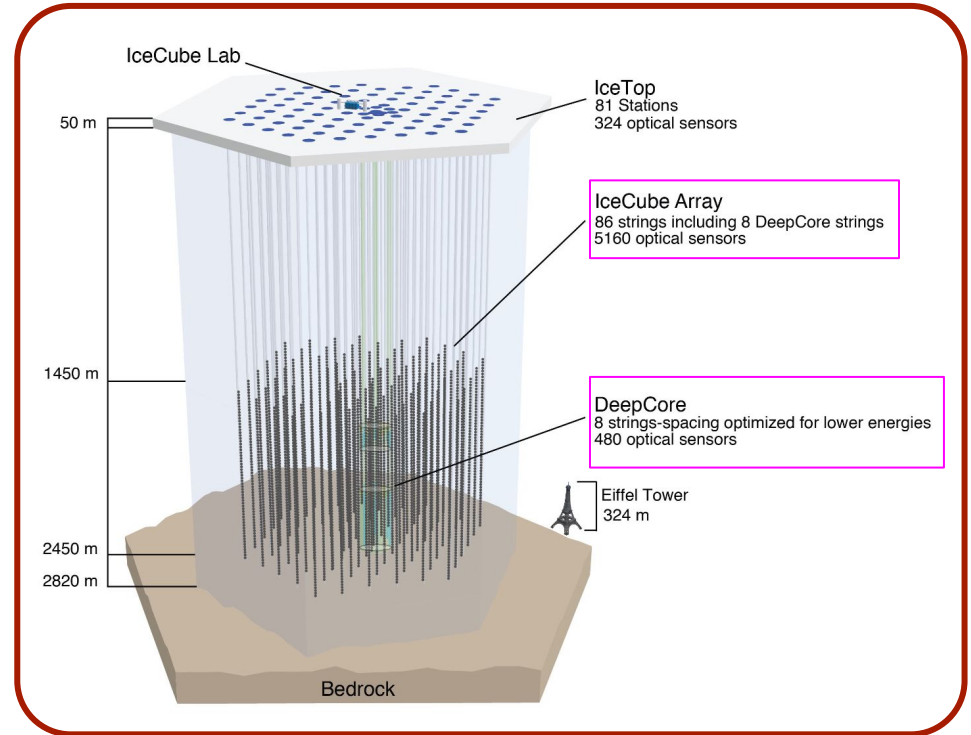


# Overview

1. The IceCube Neutrino Observatory
2. Neutrino Fluxes and Interactions
3. An Approach to Machine Learning in IceCube
4. Inelasticity Reconstruction

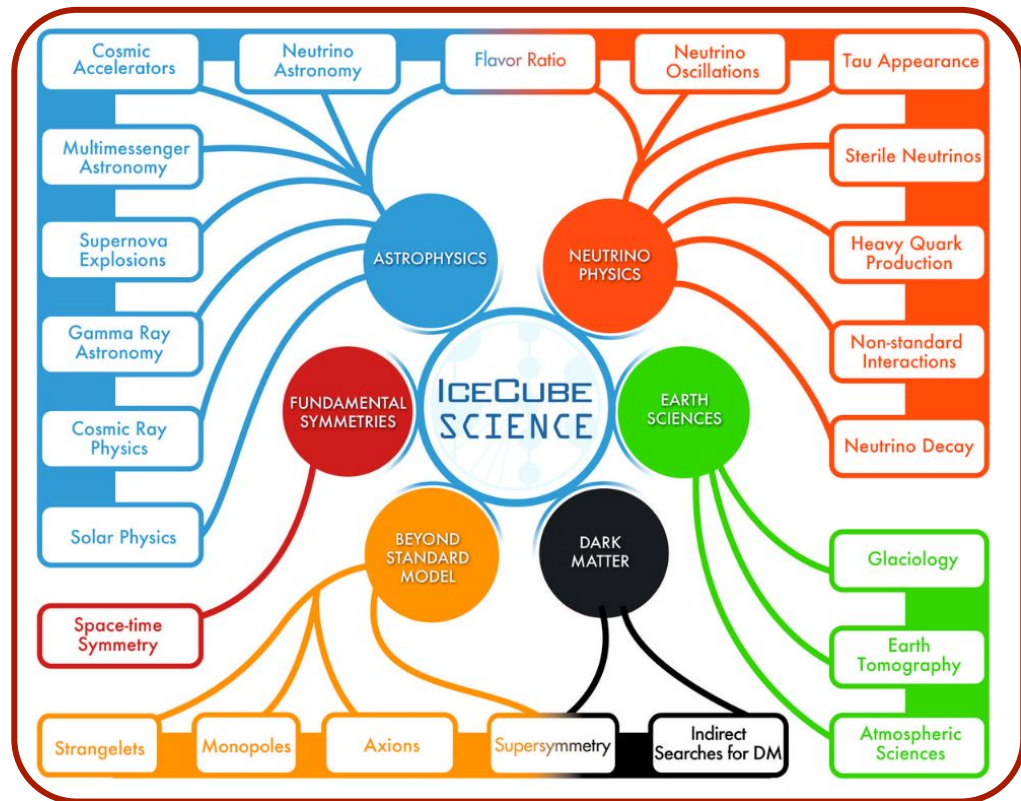
# The IceCube Neutrino Observatory

- IceCube is a cubic kilometer of instrumented ice at the South Pole
- There are 5160 digital optical modules (DOMs) that detect Cherenkov light from charged particles passing through the ice
- For neutrino interactions, these are charged particles resulting from hadronic showers and outgoing charged leptons



# IceCube Science

- The results from our analyses rely strongly on our ability to reconstruct neutrino energies, directions, and particle identification
  - In recent years, these reconstructions have improved greatly with the introduction of machine learning tools



# Recent IceCube Result: Galactic Plane

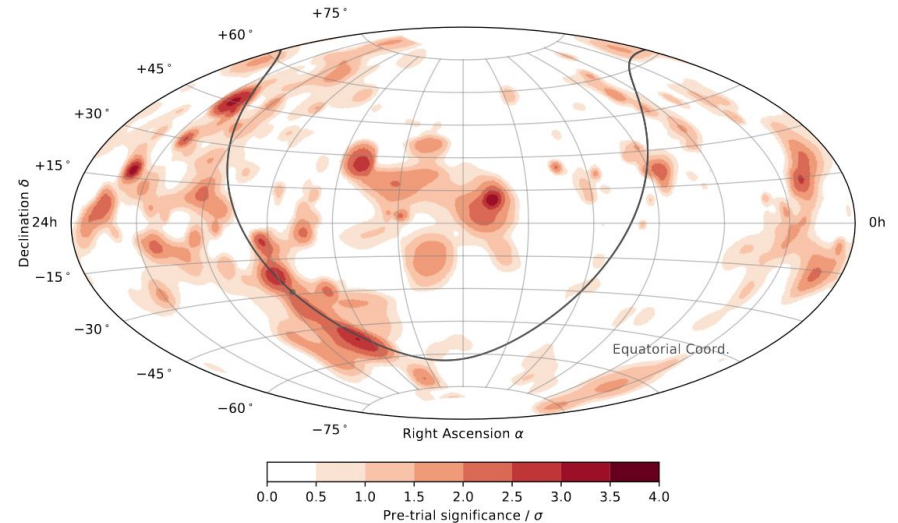
- One of the biggest results from IceCube this year
  - Identification of neutrinos originating from the galactic plane at  $4.5\sigma$
- Analysis relied on many DNN-based reconstructions and hybrid methods
  - See **Mirco Huennefeld's talk from the 2020 NPML for a good overview**
  - I will discuss some of these tools later

## Observation of high-energy neutrinos from the Galactic plane

ICECUBE COLLABORATION R. ABBASI, M. ACKERMANN, J. ADAMS, J. A. AGUILAR, M. AHLERS, M. AHRENS, J. M. ALAMEDDINE, A. A. ALVES JR., [...] AND P. ZHELNIN

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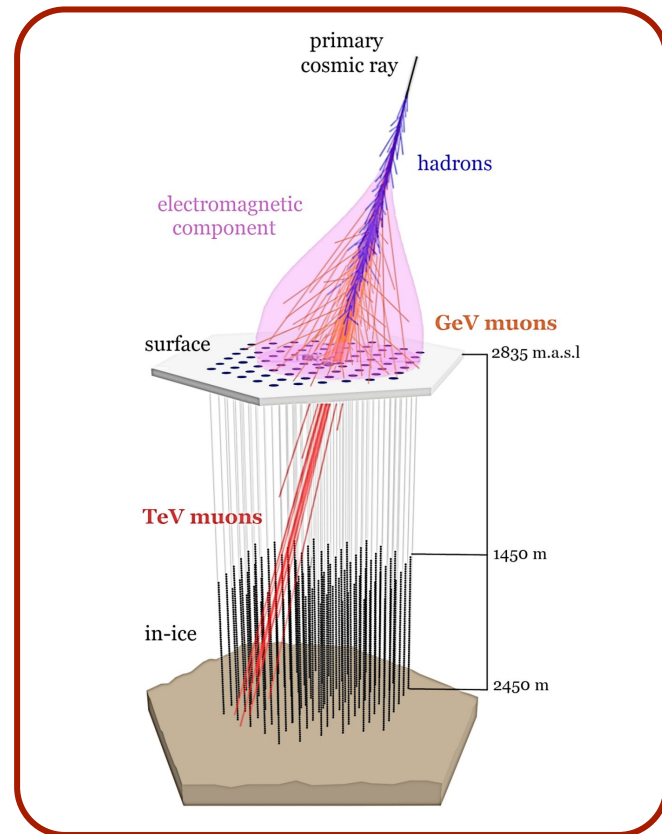
SCIENCE • 29 Jun 2023 • Vol 380, Issue 6652 • pp. 1338-1343 • DOI:10.1126/science.adc9818



Science 380, 1338-1343 (2023)

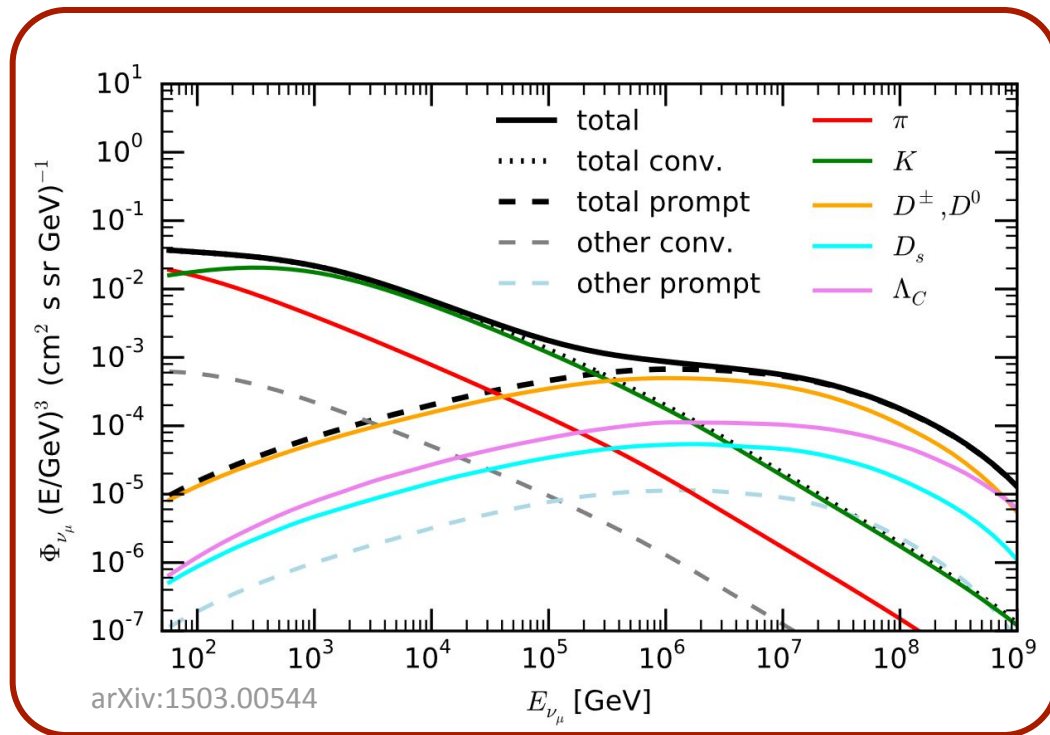
# Atmospheric Muons

- Cosmic rays interact with the atmosphere, producing a large number of secondary particles
- Only muons and neutrinos are able to make to the detector below the ice
  - These atmospheric muons are a large background for many of the neutrino physics analyses
  - The detector triggers on atmospheric muons at a rate of about 3kHz (*Astropart. Phys.* 78 (2016))
    - Example: neutrino rate in the 2020 sterile neutrino analysis: 1.3 mHz (*Phys. Rev. Lett.* 125, 141801)



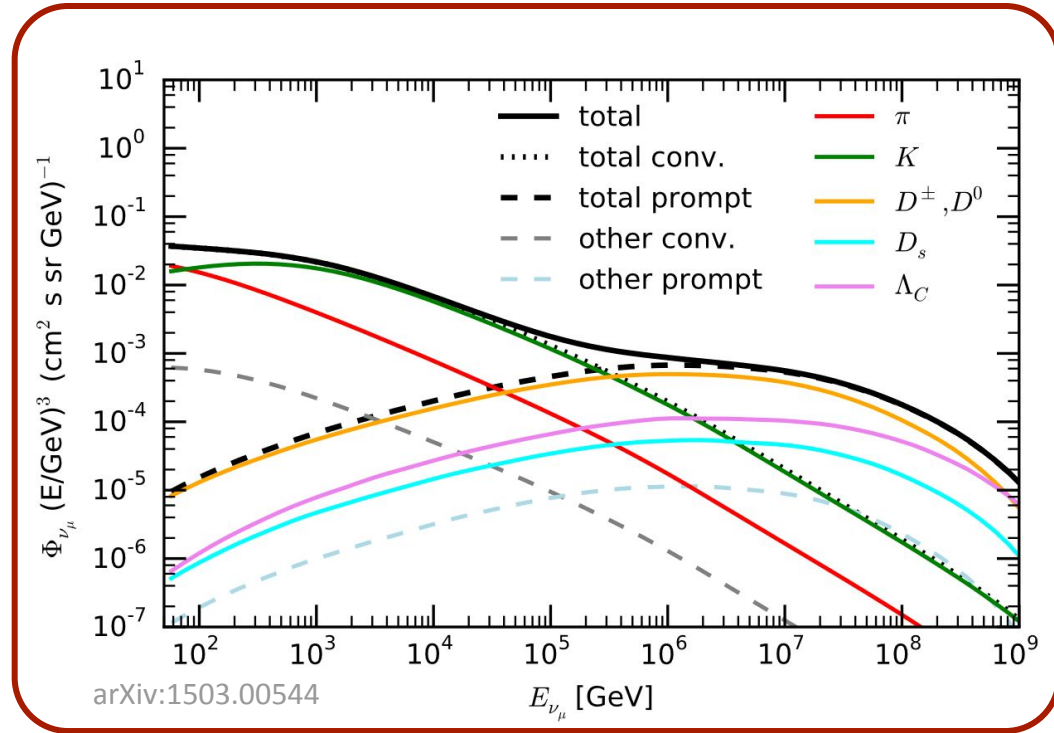
# Atmospheric Neutrino Flux

- Most neutrinos observed in IceCube come from the conventional atmospheric flux
- These neutrinos mostly originate from **pion** and **kaon** decay-in-flight
- Note the factor of  $E^3$ !



# Atmospheric Neutrino Flux

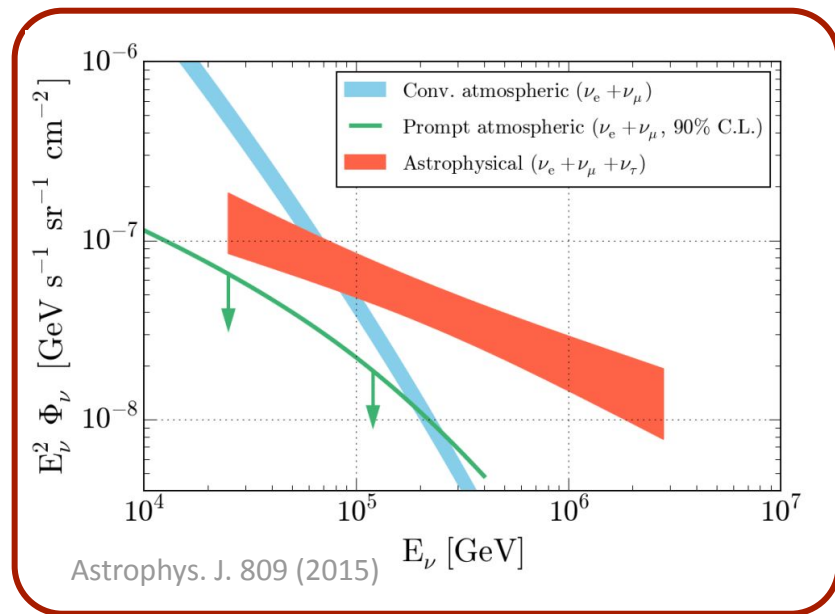
- The prompt atmospheric flux primarily comes from  $D^{\pm/0}/D_s$  meson and  $\Lambda$  baryon decays
  - Simply called “prompt” based on the decay times of these particles
- The prompt component overtakes the conventional component at the highest energies





# Astrophysical Neutrino Flux

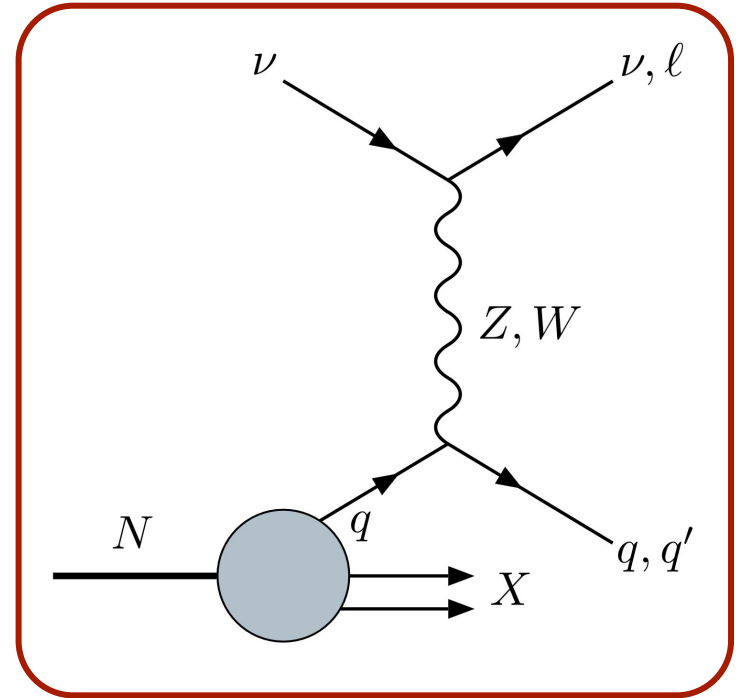
- Above  $\sim 200$  TeV, the diffuse astrophysical flux begins to dominate over the atmospheric flux
  - Diffuse meaning isotropic, neutrinos originating from high energy astrophysical events
  - Origins of these neutrinos are not completely known
- Point Sources:
  - TXS 0506+056
  - NGC 1068
- A fraction also originates from the galactic plane



# Neutrino Deep Inelastic Scattering

- In neutrino deep inelastic scattering (DIS), a neutrino exchanges a W or a Z boson with a quark
  - W boson (CC) → Charged lepton + hadrons out
  - Z boson (NC) → Neutrino + hadrons out
- Inelasticity, labeled  $y$ , is the fraction of energy imparted into the hadrons:

$$y = \frac{E_{\text{had}}}{E_{\nu}}$$



# Neutrino Deep Inelastic Scattering

- The cross section in terms of the structure functions is given by

$$\frac{d^2\sigma^{\nu,\bar{\nu}}}{dx dy} = \frac{G_F^2 M E_\nu}{\pi (1 + Q^2/M_{W,Z}^2)^2} \left[ \begin{array}{c} \frac{y^2}{2} 2xF_1(x, Q^2) + \left(1 - y - \frac{Mxy}{2E}\right) F_2(x, Q^2) \\ \pm y \left(1 - \frac{y}{2}\right) xF_3(x, Q^2) \end{array} \right]$$

- +y for neutrinos, -y for antineutrinos
- The structure functions depend on the parton distribution functions

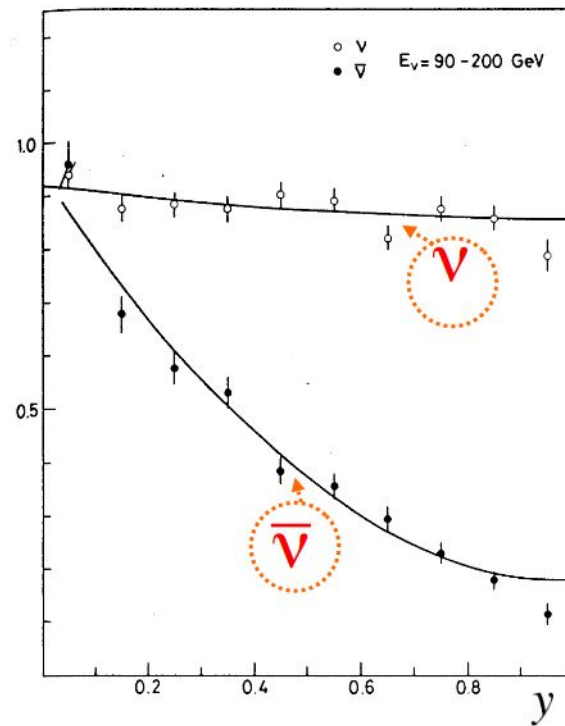
$$F_2(x, Q^2) = 2 \sum_{i=u,d,\dots} (xq(x, Q^2) + x\bar{q}(x, Q^2))$$

$$xF_3(x, Q^2) = 2 \sum_{i=u,d,\dots} (xq(x, Q^2) - x\bar{q}(x, Q^2))$$

# Neutrino Deep Inelastic Scattering

- An interesting feature of DIS is that neutrinos and antineutrinos have differently shaped distributions with respect to inelasticity
  - Note:  $y$ -axis of this plot is proportional to the cross section
- These cross sections are very well understood
  - Uncertainty of DIS cross sections  $\sim$ several %
- This will come up again later!

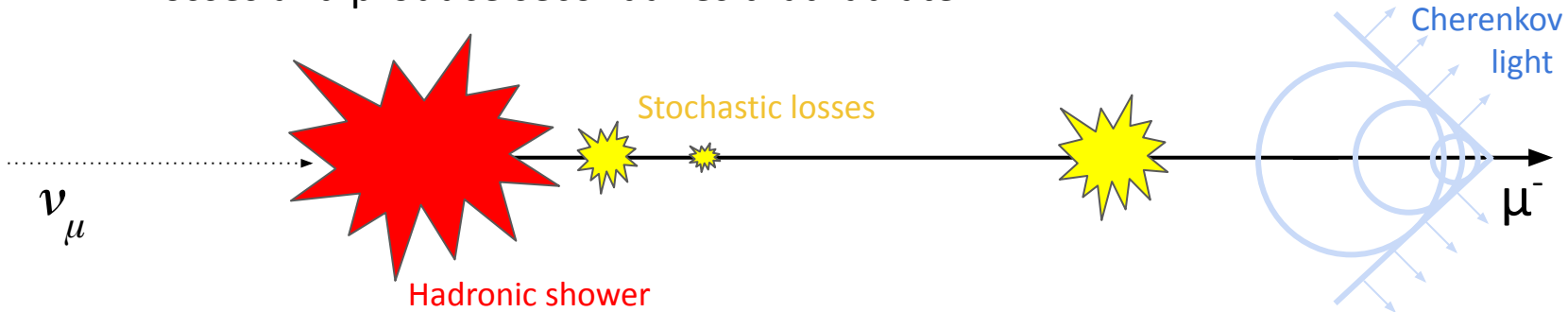
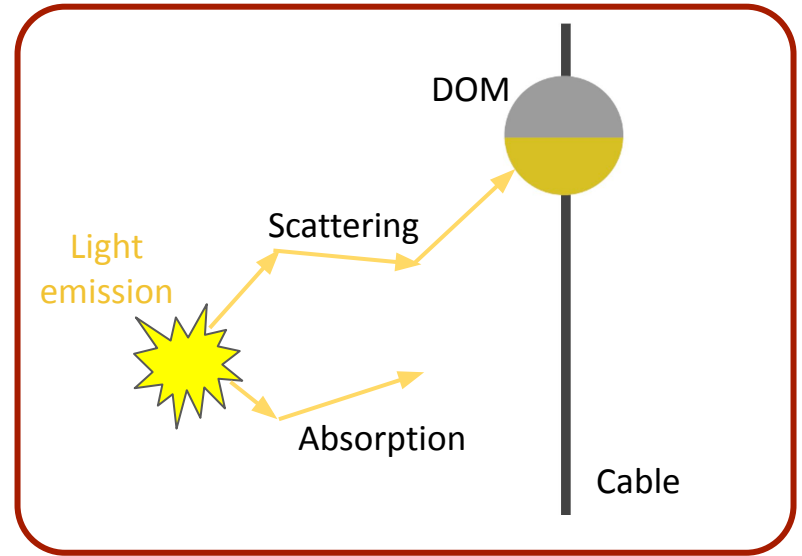
## ● CDHS measured $y$ distribution



J. de Groot et al., Z.Phys. C1 (1979) 143

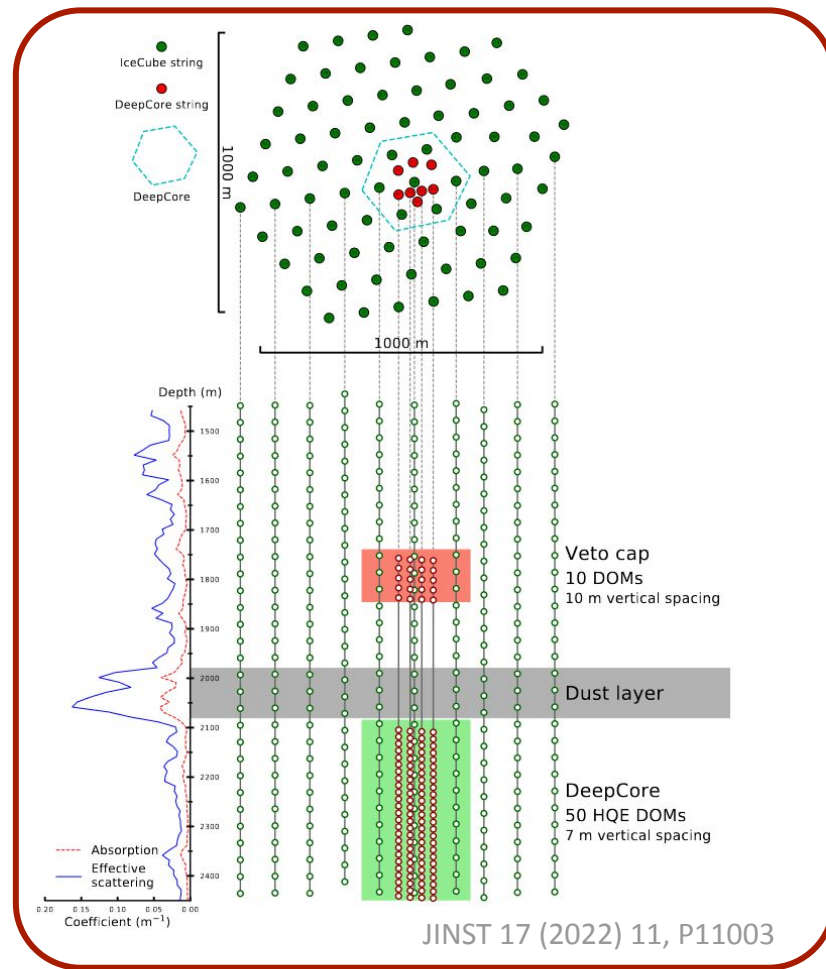
# Light Detection

- Charged particles in the ice can produce Cherenkov light
- The light propagates and scatters until hitting a DOM or absorbed
- At high energies, muons undergo stochastic losses and produce secondaries that radiate



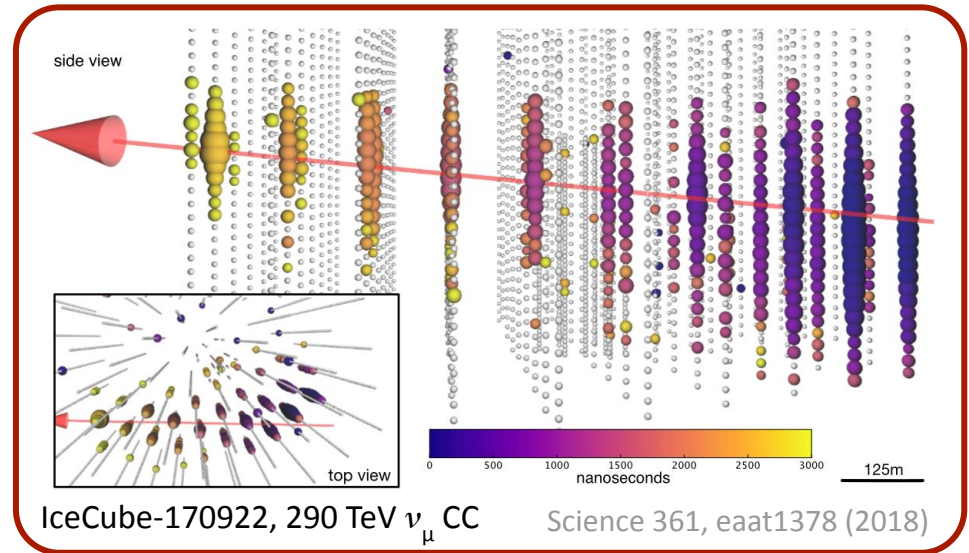
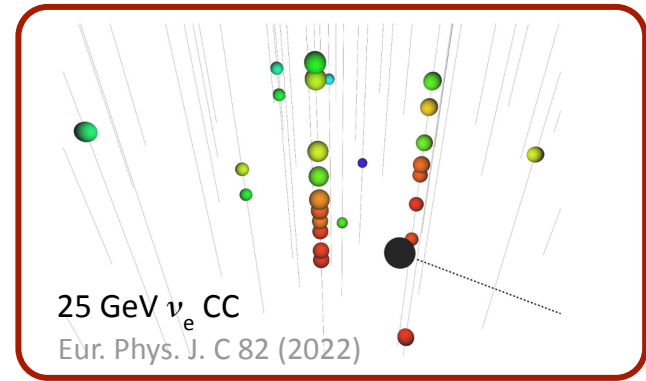
# The Dust Layer

- The ice below the South Pole is typically very transparent, allowing us to observe many of these events
  - However, scattering in the ice obscures the typical Cherenkov rings people would expect
- Additionally, about half-way down the detector, there is an additional layer of dust
  - A region of higher absorption and scattering



# IceCube Events

- IceCube detects events with energies varying over several orders of magnitude
  - ~GeV to ~10 PeV
- The shape and size of these events vary greatly
  - Only DeepCore can really resolve events < 100 GeV (top right)
- $\nu_e$  CC,  $\nu_\tau$  CC, and NC interactions look spherical (showers/cascades)
- $\nu_\mu$  CC are extended (tracks)



# Shaping IceCube Data

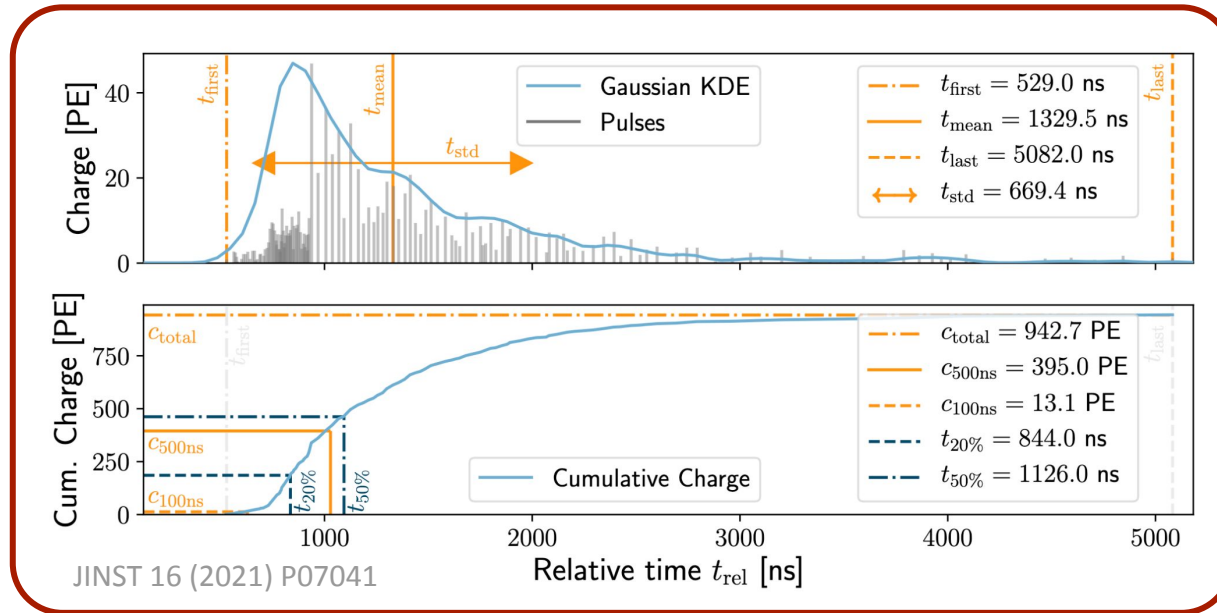
Complication of geometric information and dimensionality:

- Time-series data from DOMs
  - DOMs can have small or very large numbers of pulses
  - For use in a CNN, we need a fixed-length input for each dOM
- Spatial layout of the main array strings
  - Simply mapping the hexagonal geometry to a rectangular array throws away useful geometric information
- DeepCore strings
  - Do not follow the geometrical pattern of the main array strings
  - DeepCore contains a lower and an upper sub-array, which are separated by a layer of dust in the ice



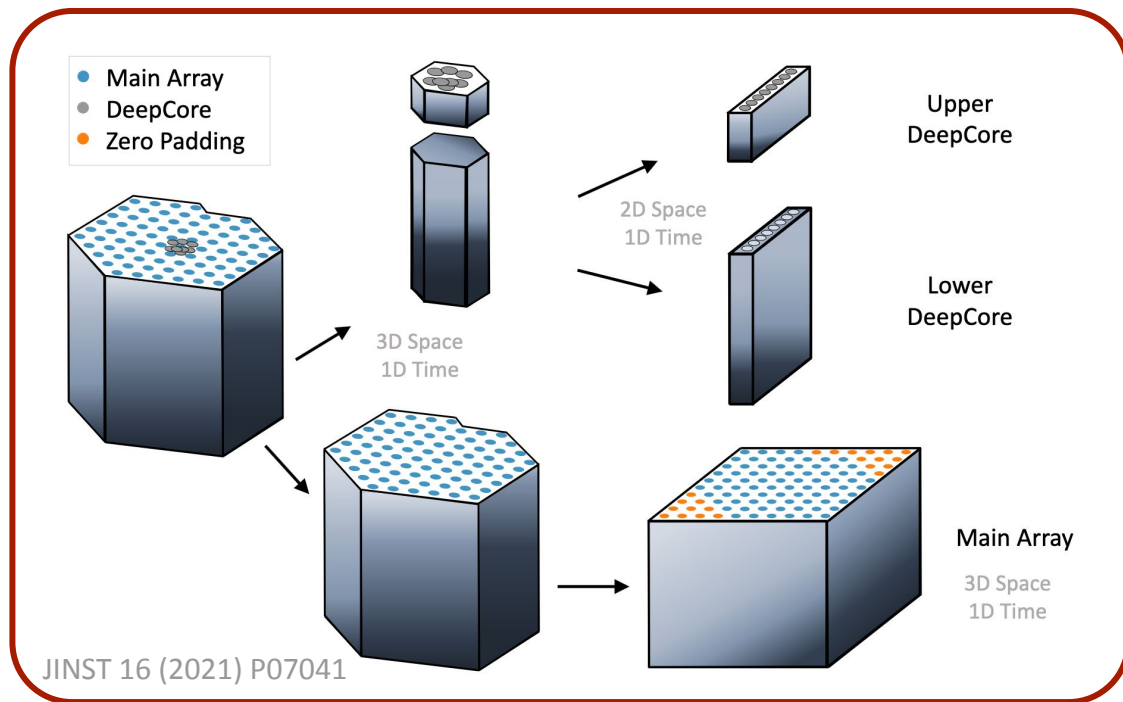
# PMT Pulses to Features

- Pulse data from PMTs are reduced with summary statistics



# PMT Pulses to Features

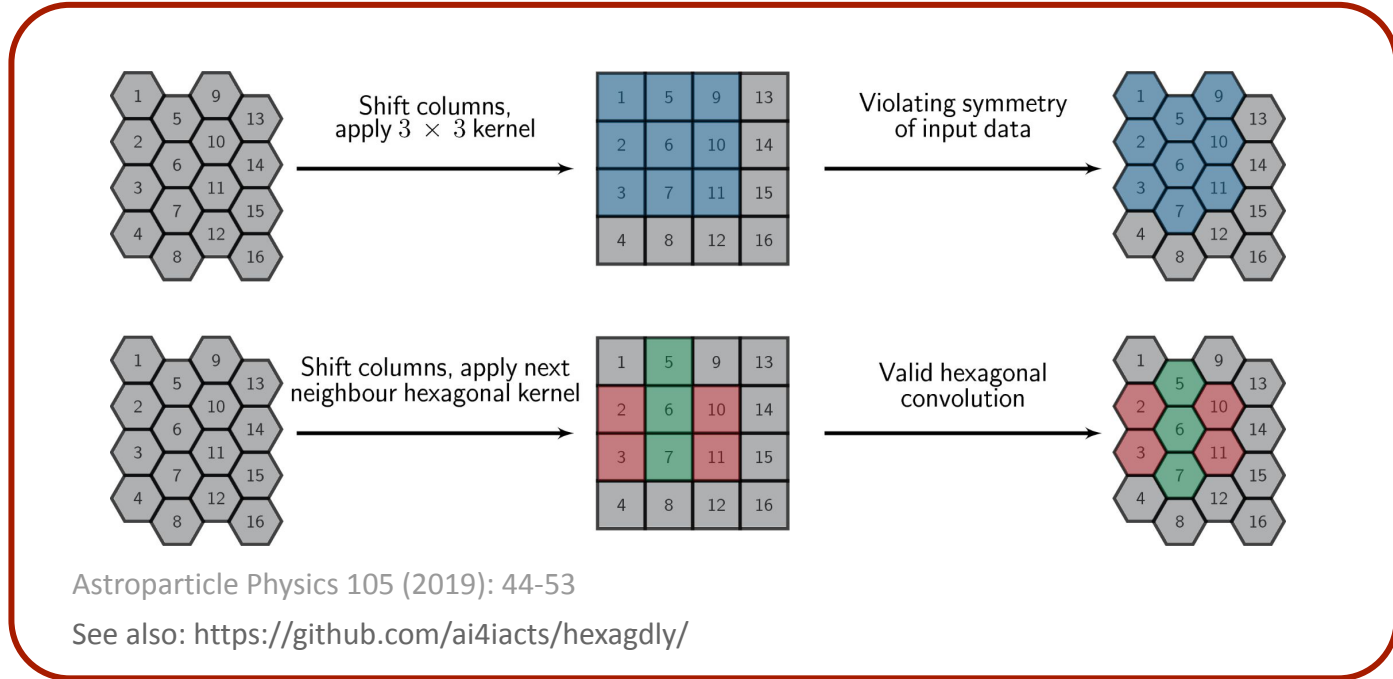
- The DeepCore upper and lower arrays are separated out from the main array
- The IceCube main array is mapped to a zero-padded rectangular array
  - Geometry will be handled by modified convolutions



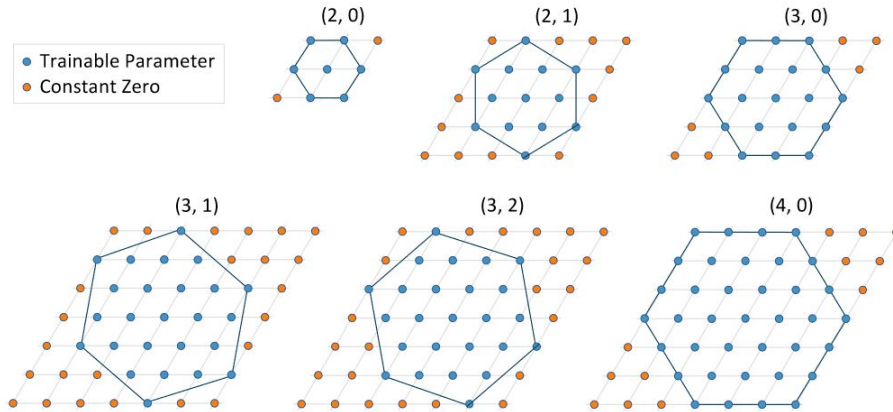
# Hexagonal Convolutional Layers

- Hexagonal convolutions are used to leverage the near-symmetric properties of the IceCube detector
  - Reduces the geometric mismatch when embedding onto the square grid
- This is not an exact symmetry as the spacings between detector strings are not even
- There are several available tools for hexagonal convolutions:
  - hexaconv: <https://github.com/ehoogeboom/hexaconv>
  - TFScripts: <https://github.com/icecube/TFScripts> (used in this work)
  - HexCNN: <https://arxiv.org/abs/2101.10897>
  - hexagdly: <https://github.com/ai4iacts/hexagdly>

# Example: Hexagdy Implementation



# Example: TFScripts Implementation



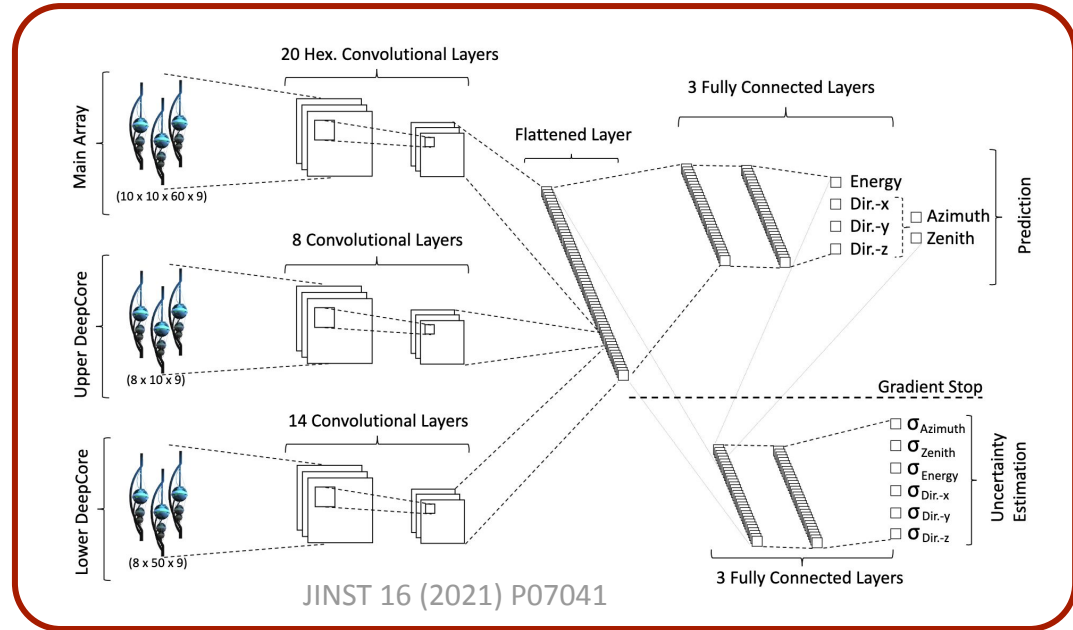
**Figure 7:** An hexagonally shaped kernel can be defined by a tuple of size  $s$  and orientation  $o$ :  $(s, o)$ . For an axis aligned hexagon (orientation  $o = 0$ ), the size parameter  $s$  defines the number of points along an edge of the hexagon.

JINST 16 (2021) P07041

See also: <https://github.com/icecube/TFScripts>

# Neural Network Architecture

- Components of the detector are fed through different sequences of convolutional layers, later flattened and combined
- A sub-network is used to estimate the uncertainty on the prediction
  - A gradient stop is used so the uncertainty estimation does not backprop to the main network

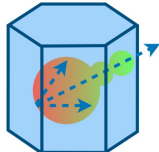
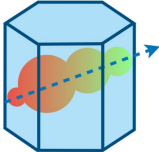


See also: [https://github.com/icecube/dnn\\_reco/](https://github.com/icecube/dnn_reco/)

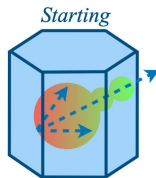
# Event Topologies

- We are interested in CC muon (anti)neutrino interactions which produce an outgoing muon (a “track”) and a hadronic shower
- There are two types of observed event topologies:

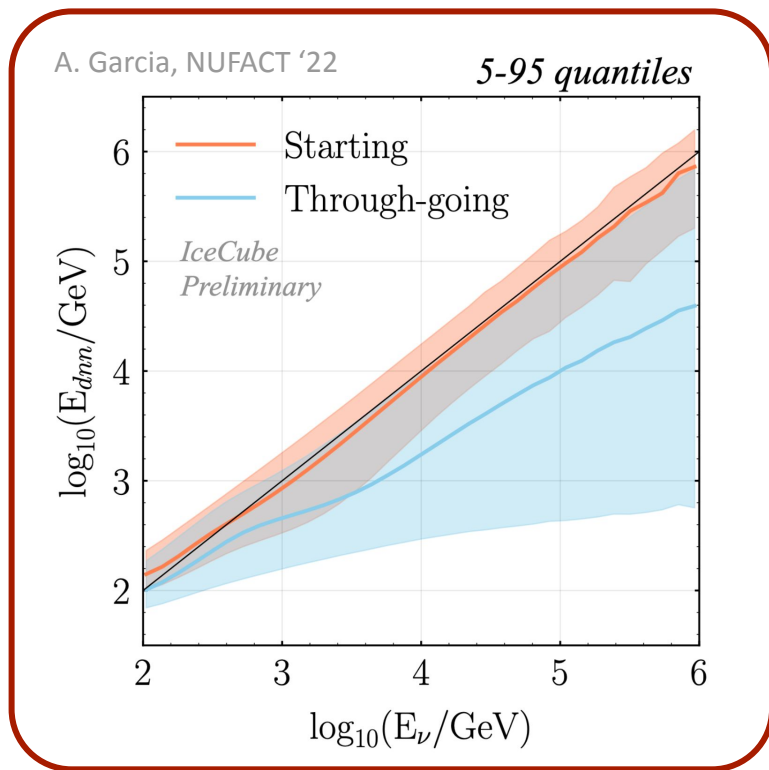
I will be focusing on starting tracks!

 <p><i>Starting</i></p>	<i>Hadronic shower inside detector</i>	<i>Good energy resolution</i>	<i>~20% of events</i>
 <p><i>Through-going</i></p>	<i>Hadronic shower outside detector</i>	<i>Poor energy resolution</i>	<i>~80% of events</i>

# Starting Tracks



- Starting tracks have an interaction vertex inside of the detector volume
  - Most of the hadronic energy is deposited in the detector
- Even though the muon leaves the detector, its energy is proportional to its stochastic energy losses
  - The combination of the hadronic shower and the muon losses allow for a far more accurate reconstruction of the neutrino energy than that of through-going events





# Training Monte Carlo Dataset

- Inelasticity can only be reconstructed if we have information about the hadronic shower at the interaction point
- To train this DNN, we use true starting track ( $\nu_{\mu}$  CC) events
  - These events are generated with energies of 100 GeV to 1 PeV with an  $E^{-2}$  power law spectrum
  - Only simple filtering and precuts are applied to this dataset
- Through-going tracks and other flavor events are not considered in the training
  - Other reconstructions and filters are used to significantly reduce these rates to negligible levels

# Reconstructing Inelasticity

## Approach:

- Reconstruct the energy deposited by the hadronic shower and outgoing muon separately
- Divide the hadronic energy by muon+hadronic to obtain the inelasticity

## Complication:

- Hadronic shower energy is tricky—not all of it will be visible in the detector

# Visible Energy

- A new variable is introduced: visible energy, which equates to an equivalent energy of a purely electromagnetic shower
- This can be calculated by multiplying the total hadronic shower energy by an energy-dependent scaling term determined by simulation:

$$E_{\text{had}}^{\text{vis}} = F_{\text{EM}}(E_{\text{had}})E_{\text{had}}$$

- For a muon, the visible energy is its kinetic energy when it enters the detector
  - Alternatively, its energy when it is created from the interaction if the vertex is within the detector

## Defining Visible Inelasticity

- The visible inelasticity will be defined by using the visible hadronic energy and visible muon energy
  - This proxy for inelasticity is more correlated with the photons observed in the detector

$$y = \frac{E_{\text{had}}}{E_{\nu}} = \frac{E_{\text{had}}}{E_{\mu} + E_{\text{had}}} \longrightarrow y_{\text{vis}} = \frac{E_{\text{had}}^{\text{vis}}}{E_{\mu}^{\text{vis}} + E_{\text{had}}^{\text{vis}}}$$

# Training Information

- Train on 3M simulated true starting track events that pass basic quality cuts
  - Labels: visible track energy, visible hadronic energy, total visible energy
- Adam optimizer,  $\sim 2\text{M}$  steps w/ learning rate scheduler
  - $1\text{e-}5$  to  $1\text{e-}3$  for 1k steps
  - $1\text{e-}3$  to  $1\text{e-}3$  for 1M steps
  - $1\text{e-}3$  to  $1\text{e-}7$  for 1M steps
- Loss function: Gaussian Likelihood
  - Very similar to MSE, but the estimated error from the sub-network is an input to the loss function s.t. the lower the uncertainty the lower the loss
- Total number of parameters:  $\sim 1\text{M}$

## Final Level Dataset

This work uses an event selection designed for an ultra-high purity (>99.9%) muon neutrino dataset, so the performance of this reconstruction will be shown with the following filters/cuts:

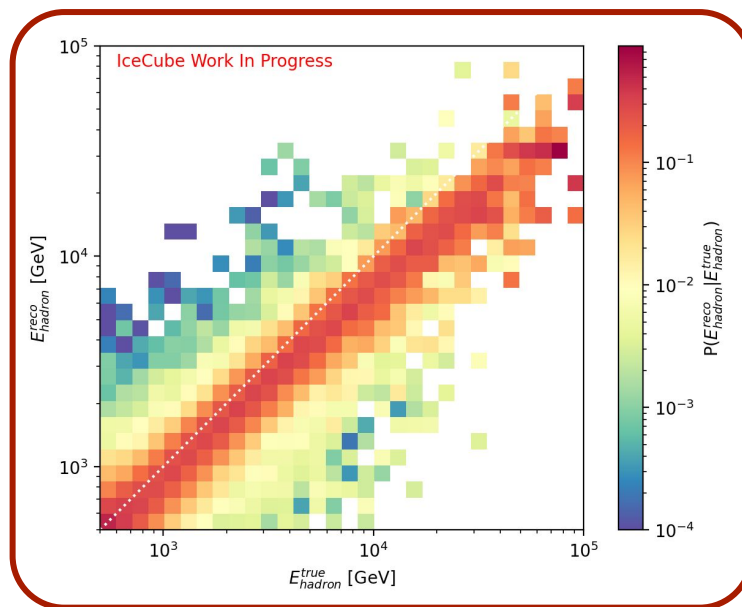
- Events are generated from 100 GeV to 1 PeV with muon neutrinos/antineutrinos
- Precuts are applied to reduce the overall data rate and remove poor quality events
- Events above the horizon are cut to reduce cosmic ray muon background
- Two DNN reconstructions are applied: energy estimator and topology classifier
  - Only classified starting tracks with a reconstructed energy of 500 GeV to 100 TeV pass
- A final level BDT is applied to further reduce background events

# Reconstructing Hadronic Energy

- For a starting track event, the neutrino interaction vertex is inside of the convex hull of the detector, allowing for an accurate reconstruction of the hadronic energy
- Columns are normalized to 1
  - Essentially a pdf in each column

Notes:

1. There is a bias toward predicting a lower hadronic energy, likely due the higher statistics at low energies in the training sample
2. The higher energy region is sparse from the low MC statistics

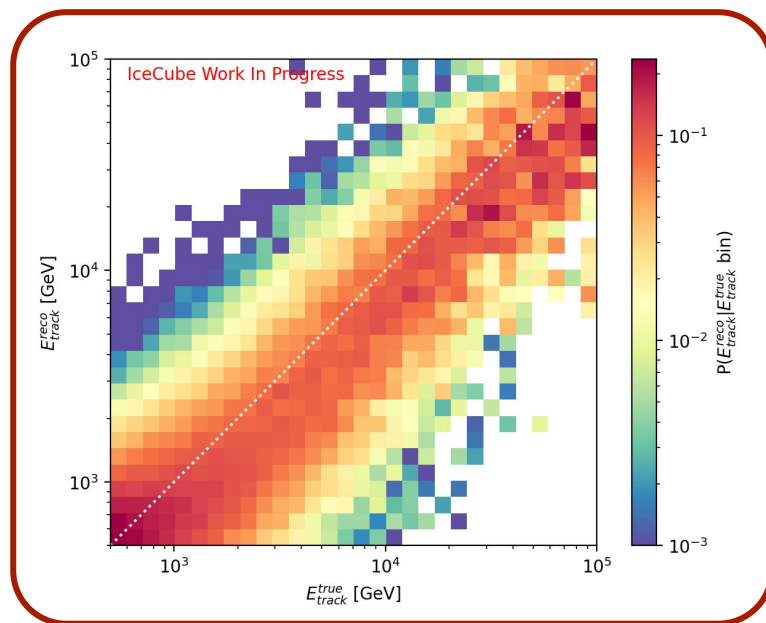


# Reconstructing Track Energy

- High energy muons leave the detector with most of their energy, making it harder to resolve their energy

Notes:

1. Again, the higher energy region is sparse from the low MC statistics



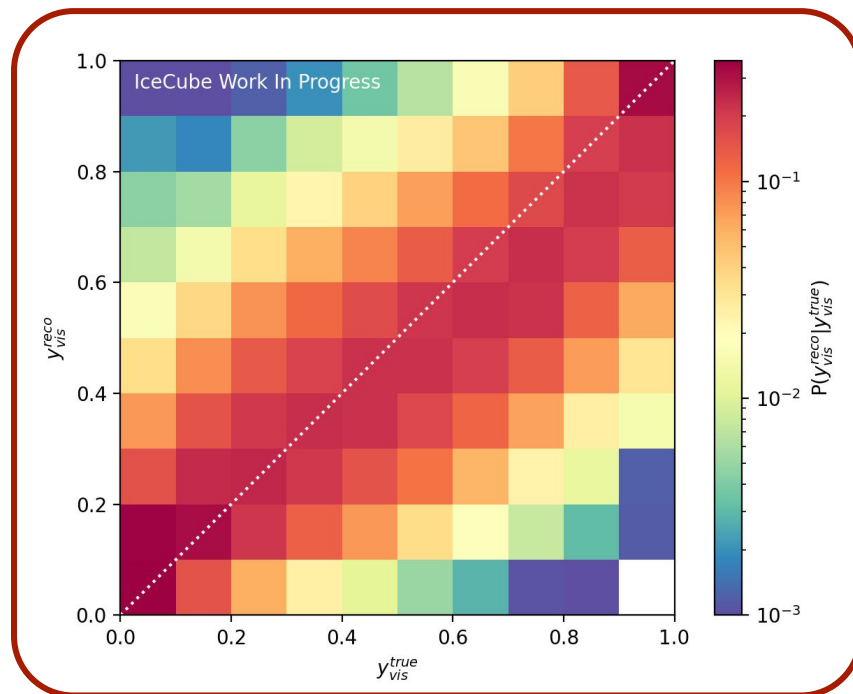


# Reconstructing Visible Inelasticity

- The visible inelasticity can be calculated using the equation from before:

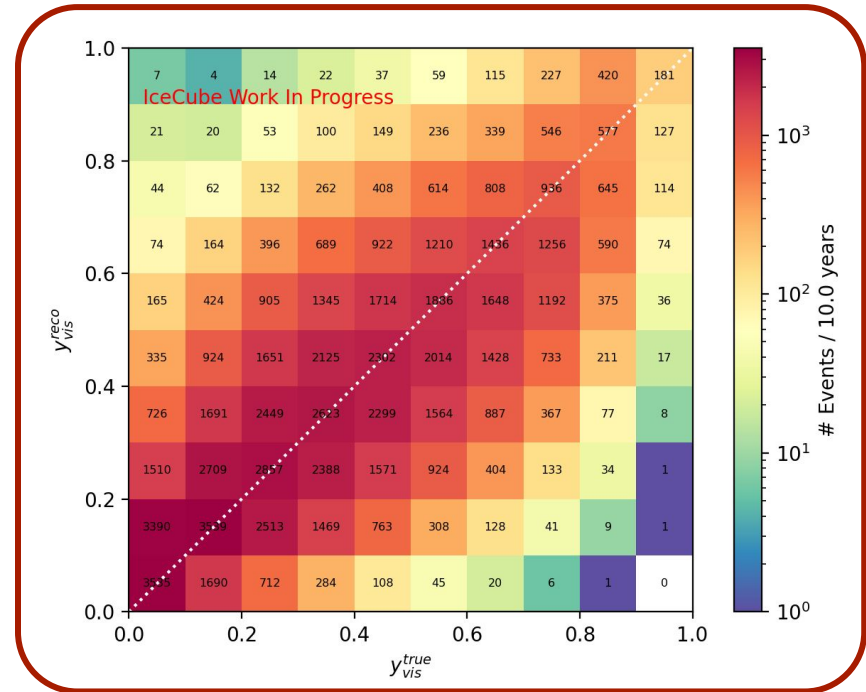
$$y_{\text{vis}} = \frac{E_{\text{had}}^{\text{vis}}}{E_{\mu}^{\text{vis}} + E_{\text{had}}^{\text{vis}}}$$

- Despite poor muon energy resolution, the ability to reconstruct the visible inelasticity is quite good



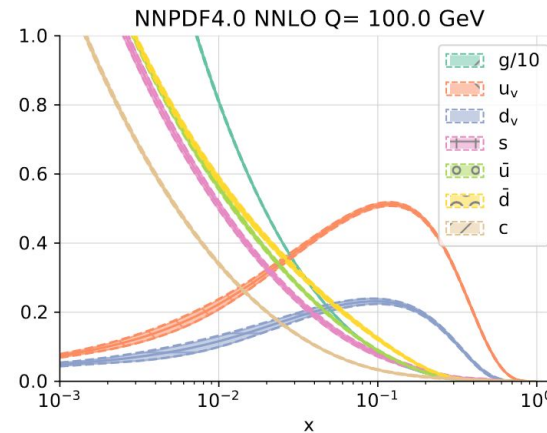
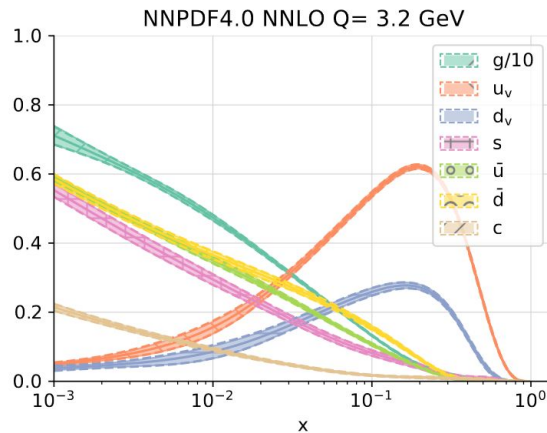
# Number of Events

- Here is the same plot as the previous slide, but showing the expected number of events in 10 years
- There is a noticeable deficit at high visible inelasticity
  - This is caused by the shape of the DIS cross section as well as the precuts that try to remove events that don't look track-like



# What can we do with inelasticity?

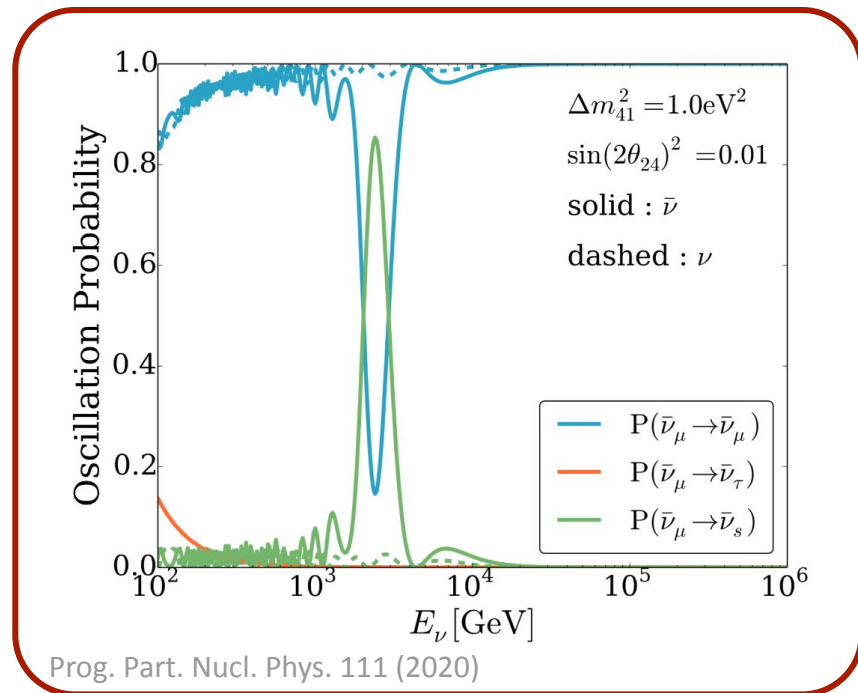
- In general, the visible inelasticity is sensitive to any interaction that looks more shower-like than track-like
  - Tau decays that produce final-state muons will look more shower-like
- Also sensitive to the production of heavy quarks in the hadronic showers
  - Primarily charm production  $\rightarrow$  produces a flatter  $y$  distribution



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# What can we do with inelasticity?

- As mentioned earlier, the cross section as a function of inelasticity differs between neutrinos and antineutrinos
  - This can be used for the statistical separation of  $\nu$  and  $\bar{\nu}$
- One such application is to improve predictions on the atmospheric  $\nu/\bar{\nu}$  ratio
  - This can improve searches for signals that differ w.r.t. neutrinos and antineutrinos
  - e.g. sterile neutrino oscillations with matter effects



# Conclusions

- We have shown that deep neural networks can be effective at reconstructing the visible inelasticity of neutrino deep inelastic scattering events in IceCube
  - This method relies on separating the outgoing muon energy and the hadronic shower energy
- Improvements with regard to network architectures, hyperparameters, etc. are currently being investigated

Thank you for listening!