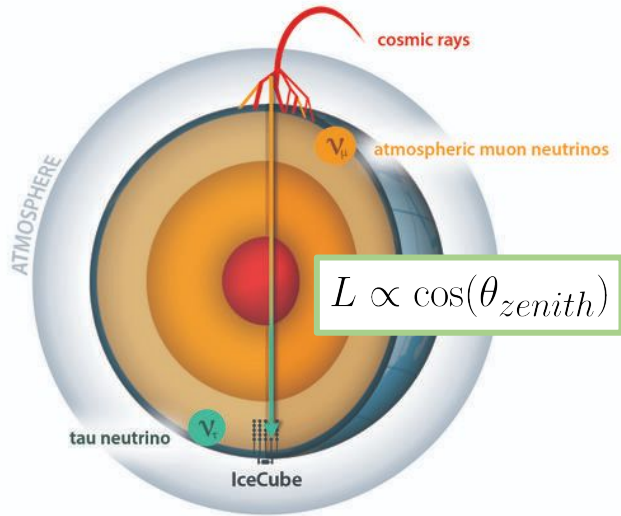


Current and Future Neutrino Oscillation Measurements using IceCube DeepCore

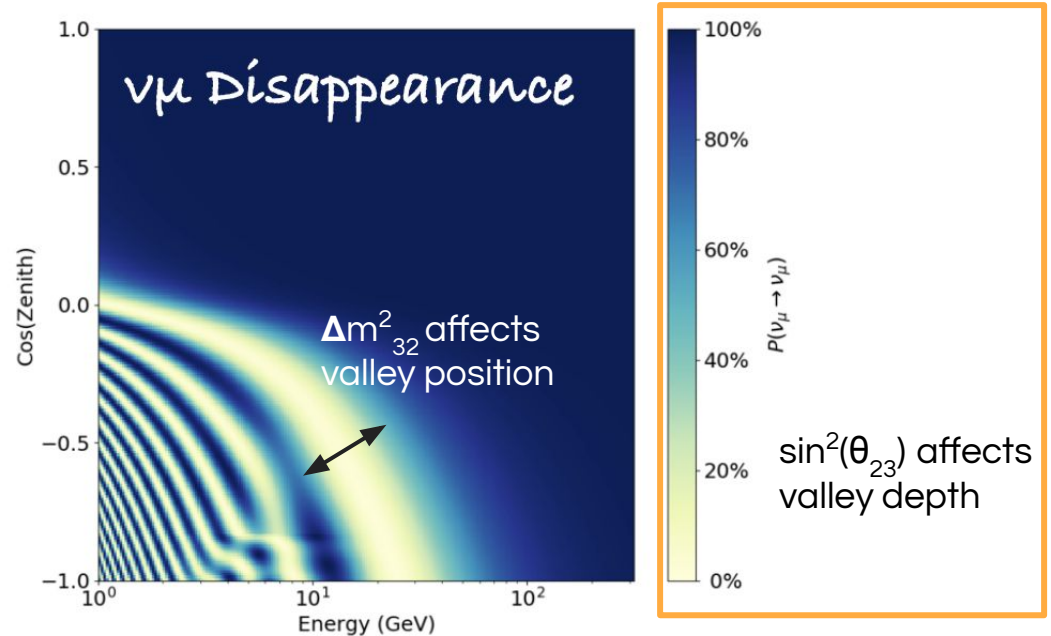
Jessie Micallef
Michigan State University
micall12@msu.edu



Energies for Atmospheric Neutrino Oscillation



$$P_{\nu_\mu \rightarrow \nu_\mu}(L) \approx 1 - \sin^2 2\theta_{23} \cdot \sin^2 \left(\frac{1}{4} \cdot \Delta m_{32}^2 \cdot \frac{L}{E} \right)$$

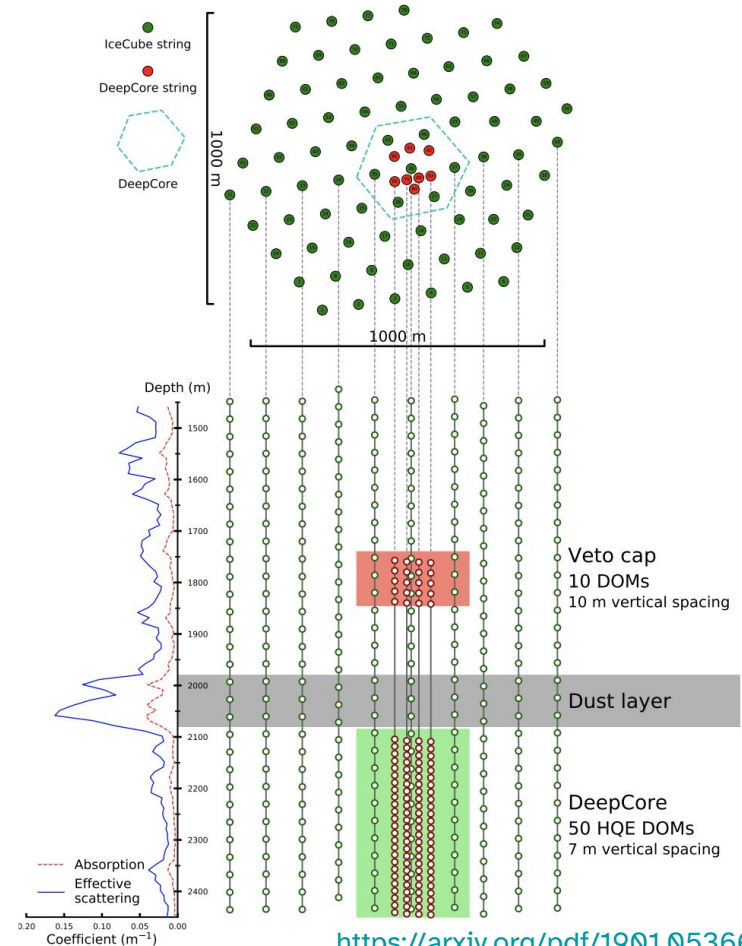


→ Measuring atmospheric neutrino oscillation requires identifying neutrinos at energies < 100 GeV

[DOI: 10.1016/j.nima.2020.164332](https://doi.org/10.1016/j.nima.2020.164332)

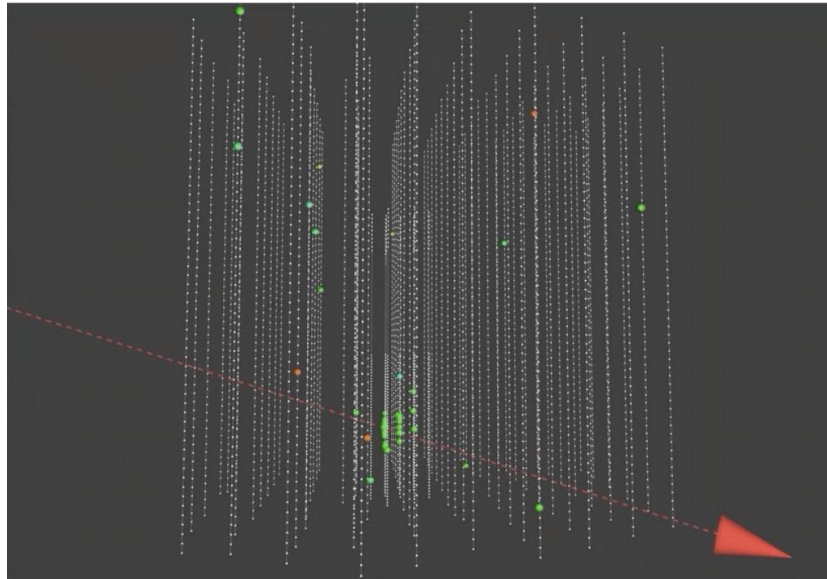
IceCube and DeepCore

- Instruments 1 km³ of ice at South Pole
- 5160 Digital Optical Modules (DOMs) detect Cherenkov light
- DeepCore:
 - Center 8 strings and nearby IceCube strings
 - Densely arranged DOMs with higher photo sensitivity
 - Detects atmospheric neutrinos from GeV - 100 TeV



<https://arxiv.org/pdf/1901.05366.pdf>

IceCube Events at 10-GeV Scale



*Average about 17 pulses
and 14 DOMs hit per event

- Less light produced per event means fewer DOMs record pulses
- Must leverage DeepCore array
- Need to optimize reconstructions specifically for these events

IceCube's Low Energy Reconstructions

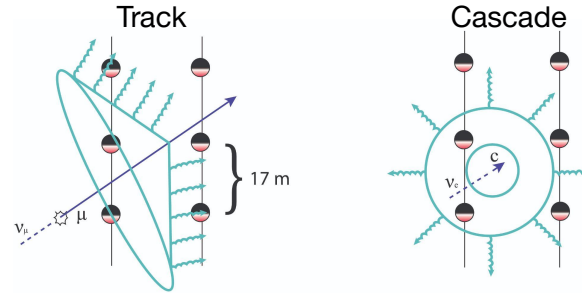
→ Accuracy: Handle input from only dozen DOMs

→ Speed: Monte Carlo and systematics require reconstructing $O(10^8)$ events

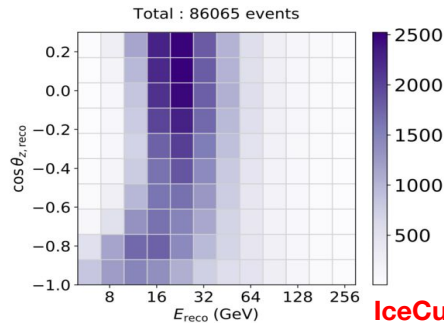
Reconstructions	Pros	Cons	Average time per event (s)
Direct Photons	- Speed	- Only ~30% of events pass direct photon selection	5
Likelihood Table-Based	- Accuracy	- Limited by information stored in tables - Speed	40
Convolutional Neural Network (CNN) <small>J. Micallef, et al. https://pos.sissa.it/395/1053/pdf https://pos.sissa.it/395/1054/pdf</small>	- Speed - Adaptable for future geometries	- Extensive development and training needed	0.007 (GPU) 0.015 (CPU)

IceCube ν_μ Disappearance Analysis Procedure

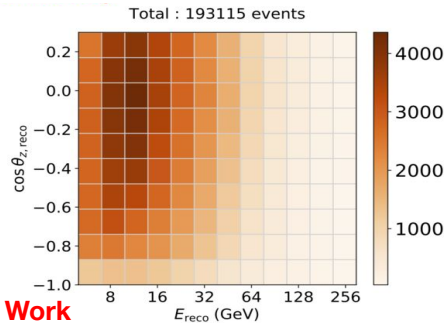
1. Event selection to remove background
2. Separate in event type (flavor)
3. Bin in energy and cosine zenith



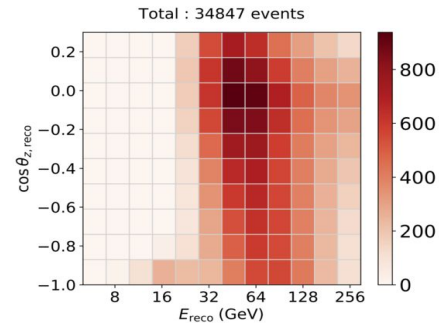
Cascades
(ν_e CC, ν_τ CC, all NC)



Mixed
(indistinguishable)



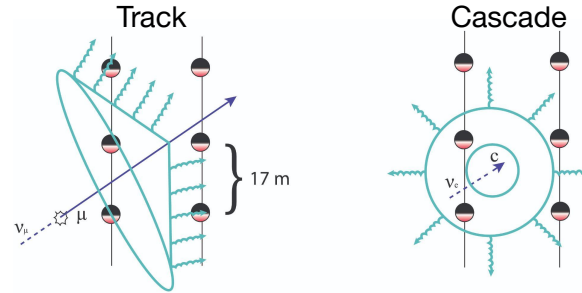
Tracks
(ν_μ CC)



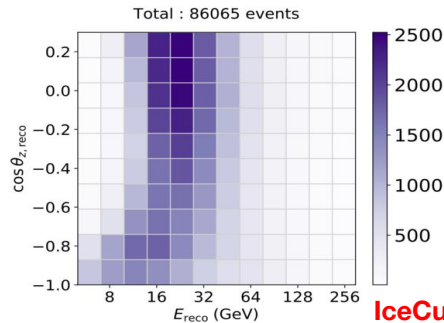
IceCube Work
In Progress

IceCube ν_μ Disappearance Analysis Procedure

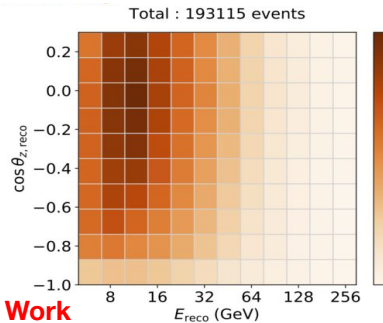
1. Event selection to remove background
2. Separate in event type (flavor)
3. Bin in energy and cosine zenith



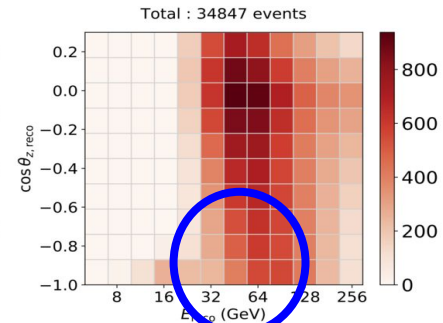
Cascades
(ν_e CC, ν_τ CC, all NC)



Mixed
(indistinguishable)



Tracks
(ν_μ CC)

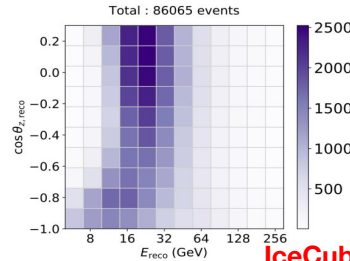


IceCube Work
In Progress

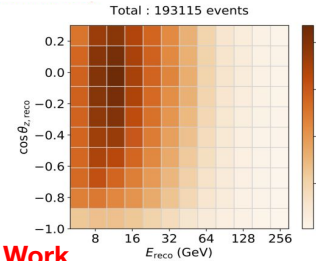
IceCube ν_μ Disappearance Analysis Procedure

4. Explore systematic effects with pulls from nominal set
5. Compare data to no oscillation hypothesis

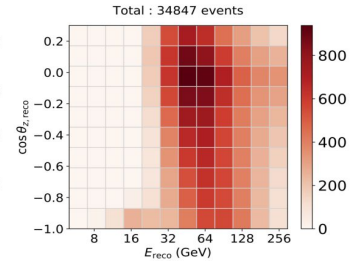
Cascades
(ν_e CC, ν_τ CC, all NC)



Mixed
(indistinguishable)



Tracks
(ν_μ CC)

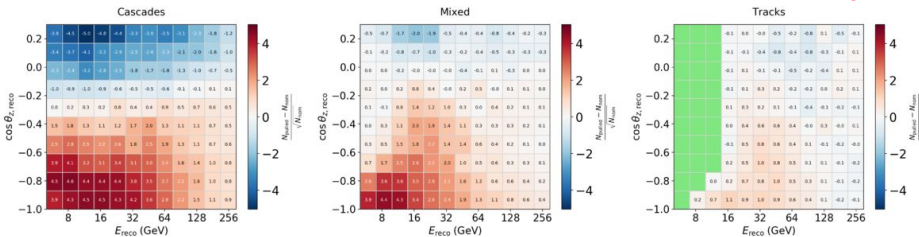


**IceCube Work
In Progress**

Major detector systematic: hole ice p1 parameter

$\Delta(\text{Hole ice, } p_1) = +0.1 : -0.0493 \rightarrow 0.0507$

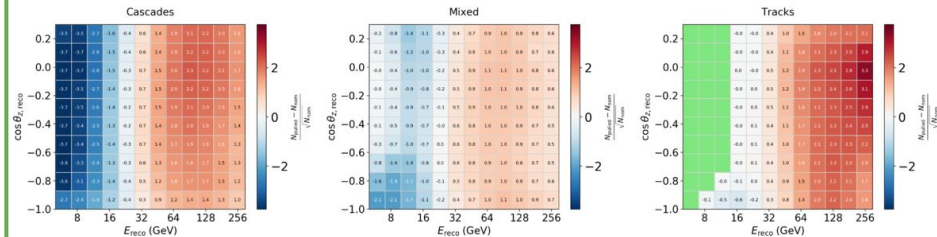
IceCube Work In Progress



Systematic: neutrino flux spectral index

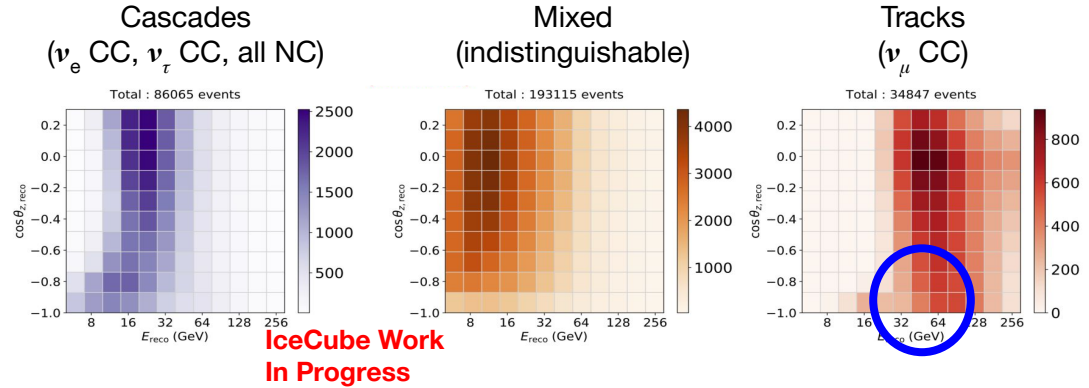
$\Delta(\Delta\gamma_\nu) = +1\sigma : 0 \rightarrow 0.1$

IceCube Work In Progress

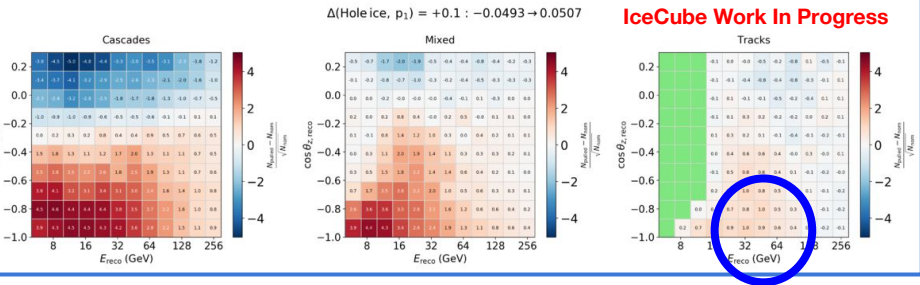


IceCube ν_μ Disappearance Analysis Procedure

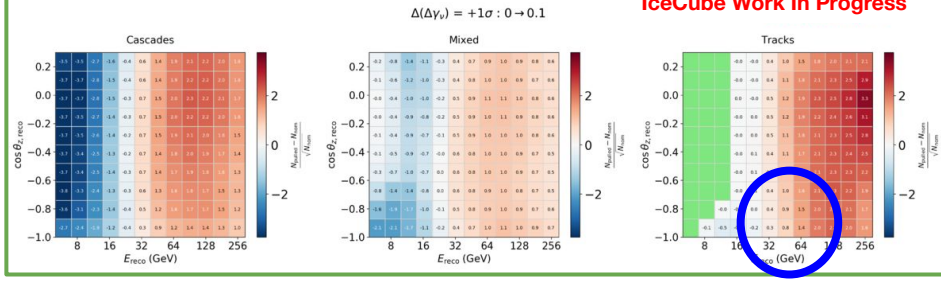
4. Explore systematic effects with pulls from nominal set
5. Compare data to no oscillation hypothesis



Major detector systematic: hole ice p1 parameter



Systematic: neutrino flux spectral index



Focusing on Direct Photons Reconstruction Result

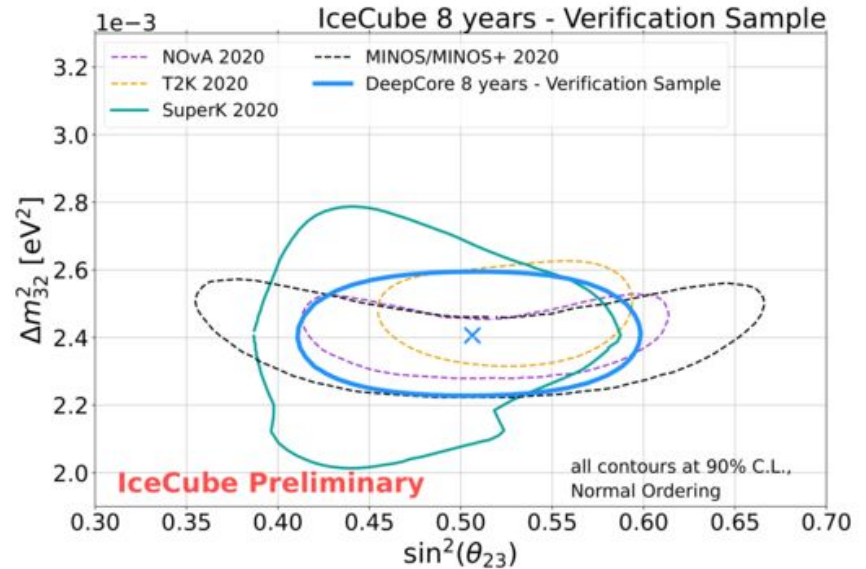
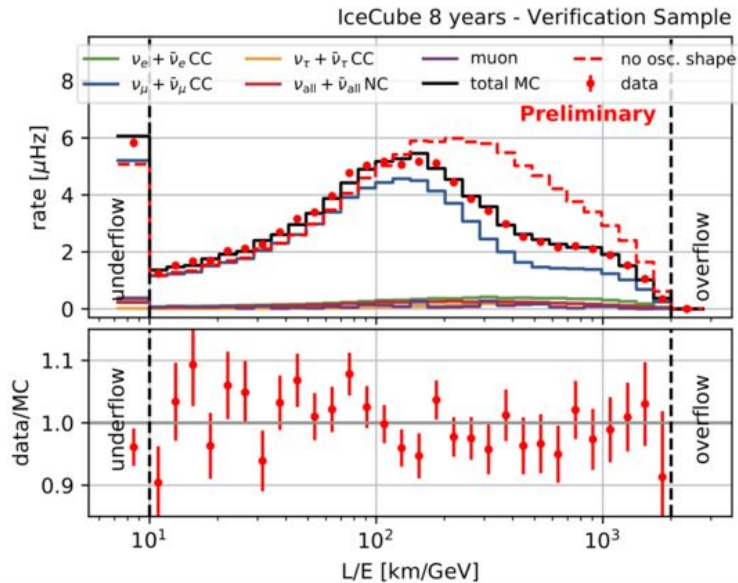
→ Accuracy: Handle input from only dozen DOMs

→ Speed: Monte Carlo and systematics require reconstructing $O(10^8)$ events

Reconstruction	Pros	Cons	Average time per event (s)
Direct Photons	- Speed	- Only ~30% of events pass direct photon selection	5
Likelihood Table-Based	- Accuracy	- Limited by information stored in tables - Speed	40
Convolutional Neural Network (CNN) <small>J. Micallef, et al. https://pos.sissa.it/395/1053/pdf https://pos.sissa.it/395/1054/pdf</small>	- Speed - Adaptable for future geometries	- Extensive development and training needed	0.007 (GPU) 0.015 (CPU)

ν_μ Disappearance Result using Direct Photons Reconstruction

- About 10% of full dataset
 - Called “verification sample” here
- Stable data/MC agreement for L/E
- Agrees with global neutrino experiments



Best fit of verification sample:

$$\sin^2 \theta_{23} = 0.505_{-0.050}^{+0.051} \text{ and } \Delta m_{32}^2 = 2.41_{-0.084}^{+0.084} \times 10^{-3} eV^2$$

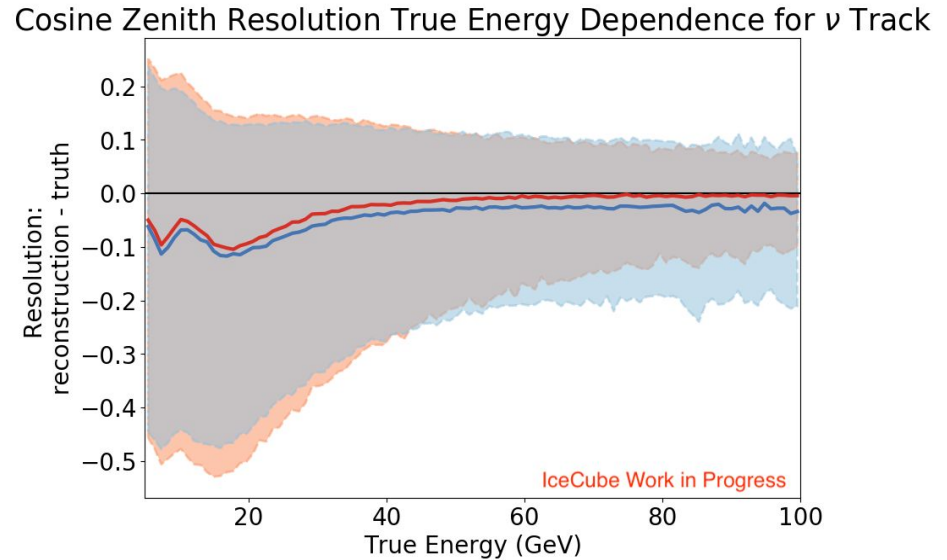
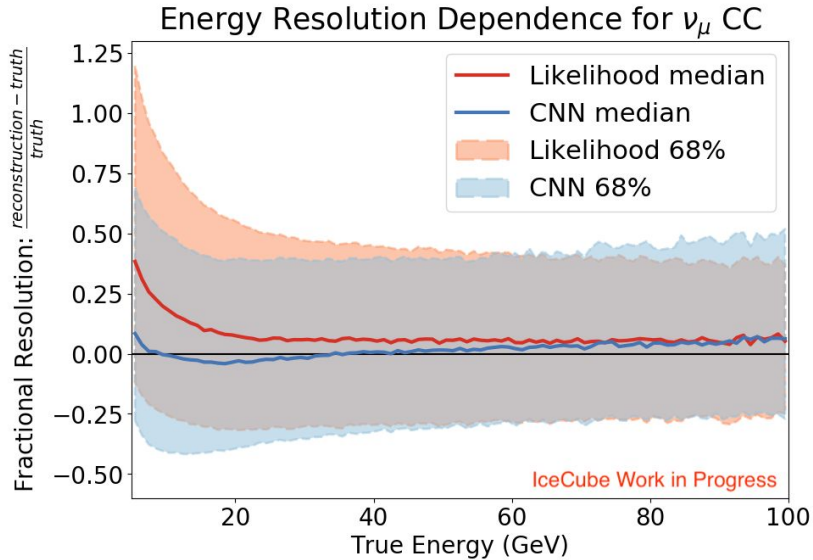
Future Analysis Methods: Likelihood and CNN

→ Accuracy: Handle input from only dozen DOMs

→ Speed: Monte Carlo and systematics require reconstructing $O(10^8)$ events

Reconstruction	Pros	Cons	Average time per event (s)
Direct Photons	- Speed	- Only ~30% of events pass direct photon selection	5
Likelihood Table-Based	- Accuracy	- Limited by information stored in tables - Speed	40
Convolutional Neural Network (CNN) <small>J. Micallef, et al. https://pos.sissa.it/395/1053/pdf https://pos.sissa.it/395/1054/pdf</small>	- Speed - Adaptable for future geometries	- Extensive development and training needed	0.007 (GPU) 0.015 (CPU)

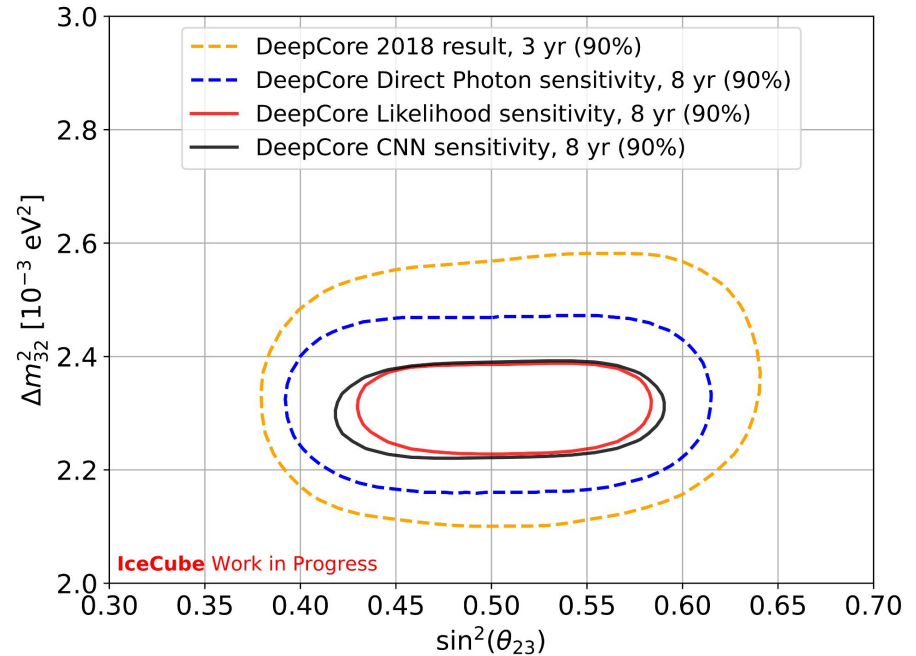
Performance for Full Sample Selections



- Likelihood and CNN have comparable resolutions for ν_μ CC (tracks)
- Lowest energy events typically provide most difficulty

Projected ν_μ Disappearance Sensitivity Improvement for Full Sample Selections

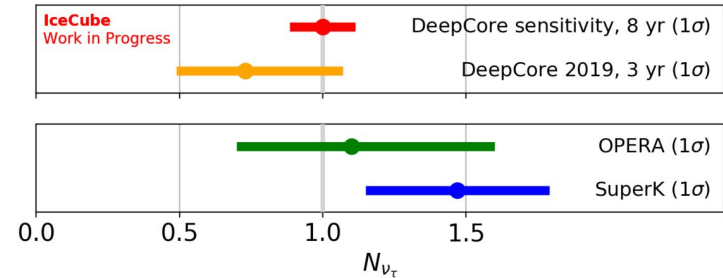
- Projected sensitivity for full sample with improved reconstructions
- Expect improvement from 3 year result and from Direct Photon reconstruction
- Sensitivities projected from DeepCore 2018, 3 yr best fit point



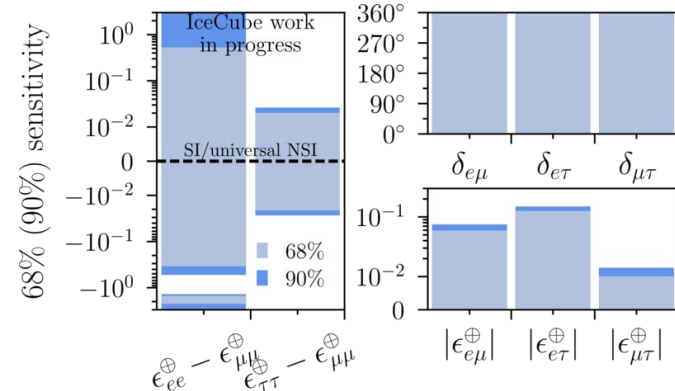
Additional DeepCore Studies on the Horizon

- Tau Neutrino Appearance
- Neutrino mass ordering
- Non-Standard Interactions
(<https://pos.sissa.it/398/245/pdf>)
- Search for sterile neutrinos
(<https://doi.org/10.1088/1748-0221/16/09/C09005>)
- Neutrino decoherence

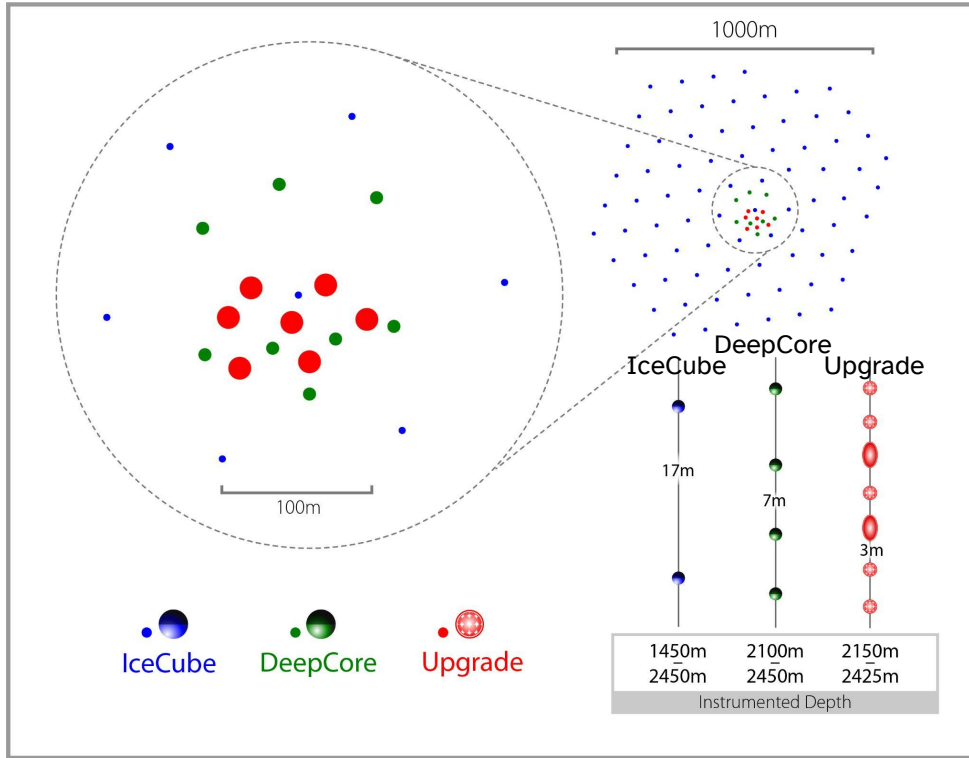
Tau Neutrino Appearance Sensitivity



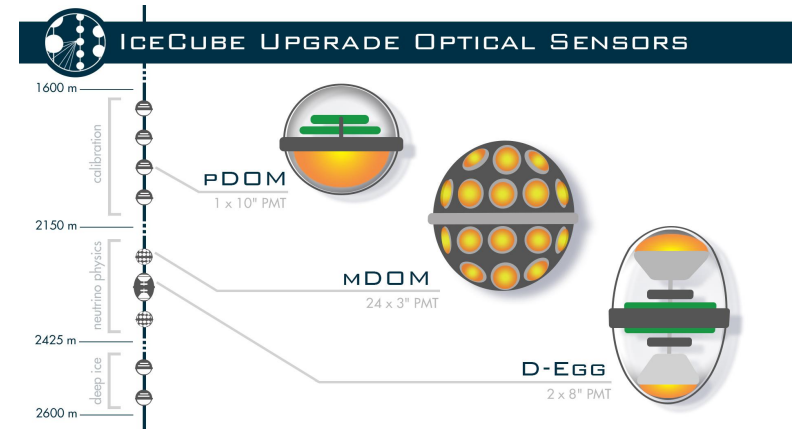
Non-Standard Interactions Sensitivity



IceCube Upgrade

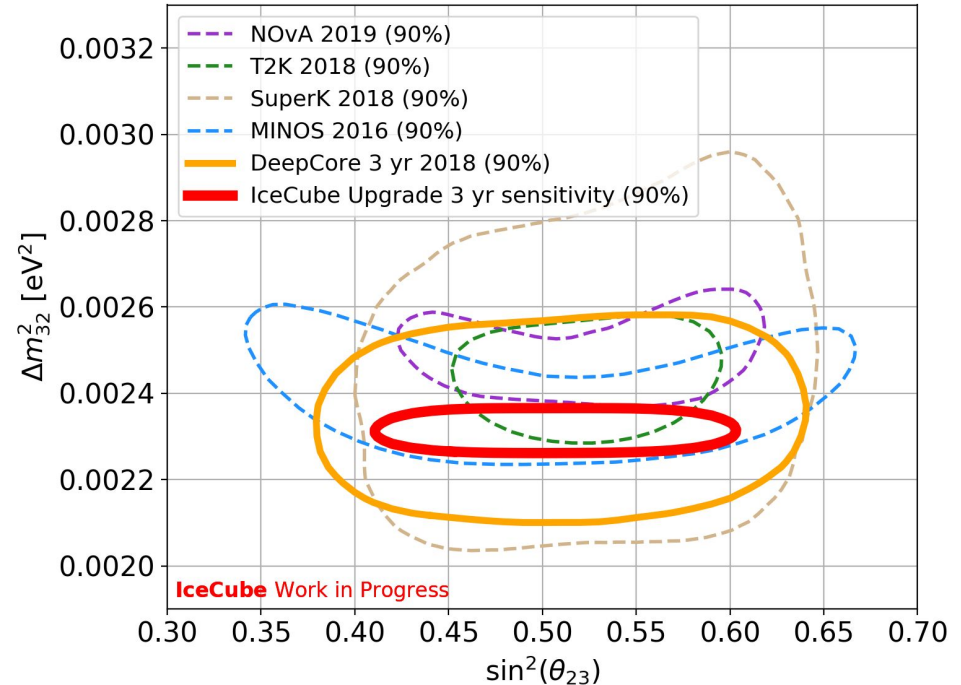


- Additional strings
 - Increased instrumented density near center
- Multi-PMT DOM designs



Improved Sensitivity from IceCube Upgrade

- New reconstructions currently being developed
 - Machine learning based
- Projected sensitivity is a conservative estimate after only 3 years of Upgrade running
- Further constraints expected from improved calibration and systematics



Conclusion

- IceCube's current ν_{μ} disappearance constraints on Δm_{23}^2 and $\sin^2(\theta_{32})$ agree with global experiments
 - New reconstructions using full 8 year low energy IceCube sample expects improvement
- Expect competitive constraints on ν_{τ} appearance and BSM phenomena
- ML reconstruction methods have comparable resolution and fast run times
 - Paving the way for the future in IceCube and IceCube Upgrade
- IceCube Upgrade expects further improvement in sensitivity and understanding of neutrino properties

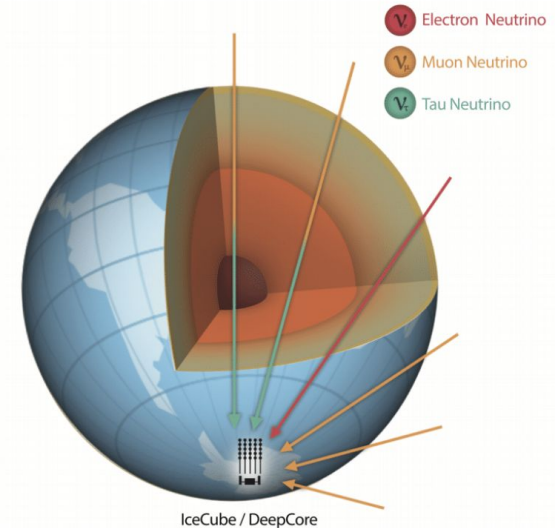


Backup

Oscillation from Atmospheric Neutrinos

- Source flavor: mostly ν_μ
 - Look for $\nu_\mu \rightarrow \nu_\tau$
 - Can also look for ν_τ appearance
- Not fixed baseline
 - Neutrinos from different distances
 - Use neutrino angle in detector to determine L

→ 2D measurement: varying L & E



List of Some Typical Systematics For IceCube Oscillation Analysis

Flux and cross section uncertainties (highly degenerate)	Typical prior/method
Overall neutrino rate	unconstrained
Linear energy-dependent effects (flux spectral index, DIS effects)	± 0.10 in index
hadronic flux effects (17 Barr variables)	from Barr et al. 2006
Axial vector mass M_A (some effect for resonances, negligible for CCQE)	from GENIE
NC normalization	$\pm 20\%$
Detector/background uncertainties	
DOM overall sensitivity	$\pm 10\%$
DOM angular-dependent response: two parameters	from LED data
Photon scattering and absorption in glacial ice: two parameters	$\pm 5\%$
Atmospheric muon normalization	unconstrained
Atmospheric muon background shape (rate unconstrained)	from MC

CNN Input Variables

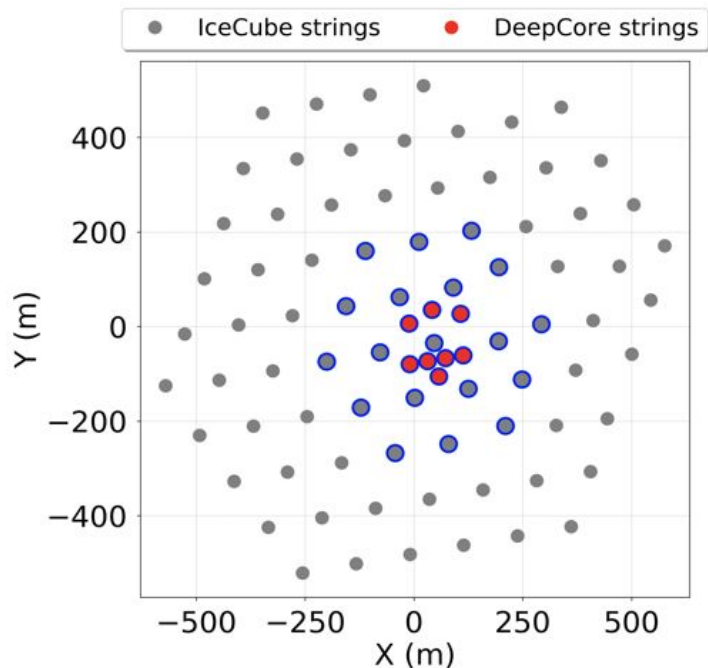
CNN uses per-DOM approach: summarize all pulses that hit each DOM

- Sum of charge
- time of first hit
- time of last hit
- charge weighted mean
- charge weighted σ

→ Structure of input array for each event has 5 summary variables per DOM per string =

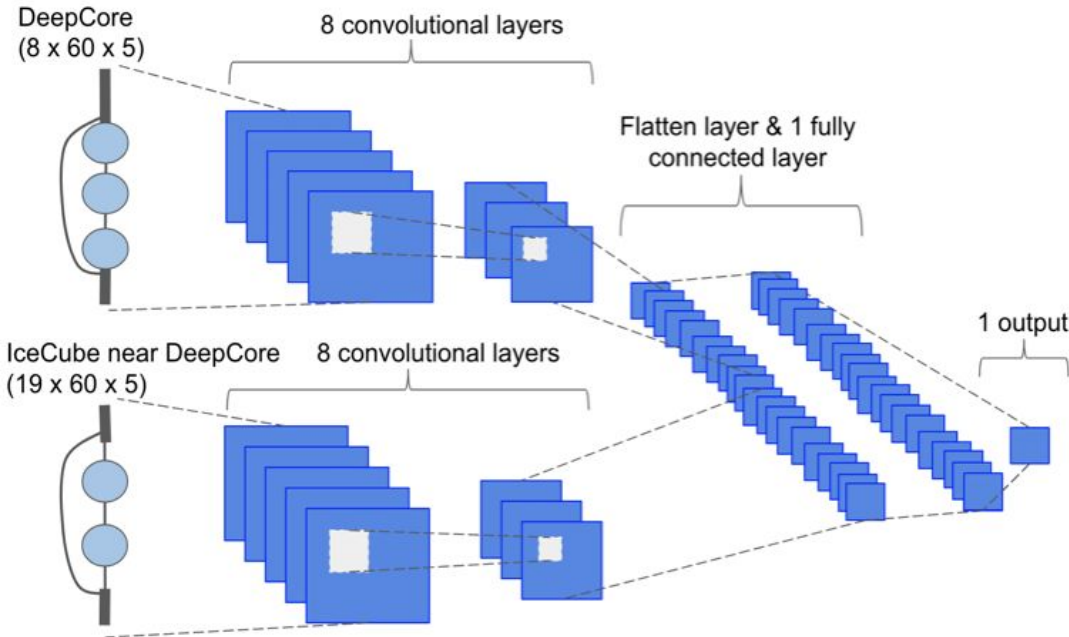
[string ID x DOM ID x summary variable]

[8 DC/19 IC x 60 x 5]



→ Strings used for CNN input highlighted in blue

GeV-Scale CNN Architecture



Five separate CNNs trained & optimized for “single” output.

Regressions:

1. **Energy**
2. **Zenith**
3. **Interaction Vertex**
→ (x, y, and z)

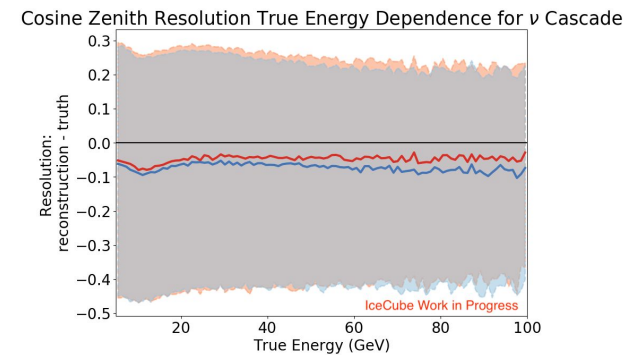
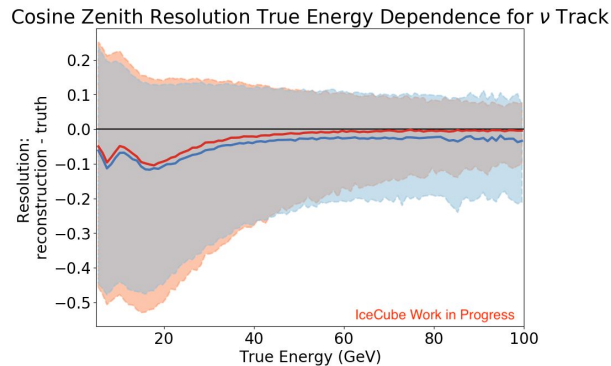
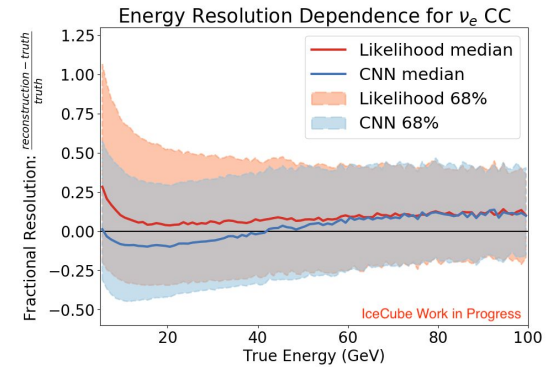
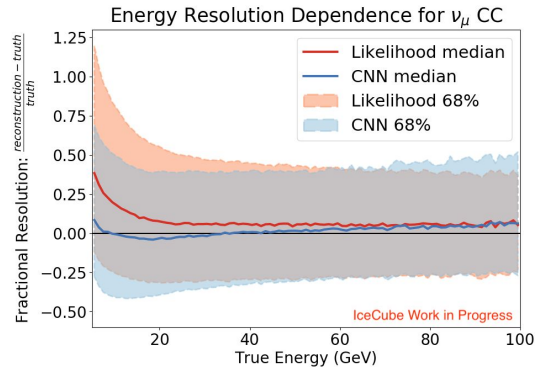
Classifications:

4. **Track vs Cascade (flavor)**
5. **Atmospheric Muon vs Neutrinos**

→ **Everything we need for oscillations analysis** (+ more!)

Resolutions for Full Sample Reconstructions

- Resolutions for oscillation variables: energy & cosine zenith
- Comparable resolutions for Likelihood and CNN across target energies



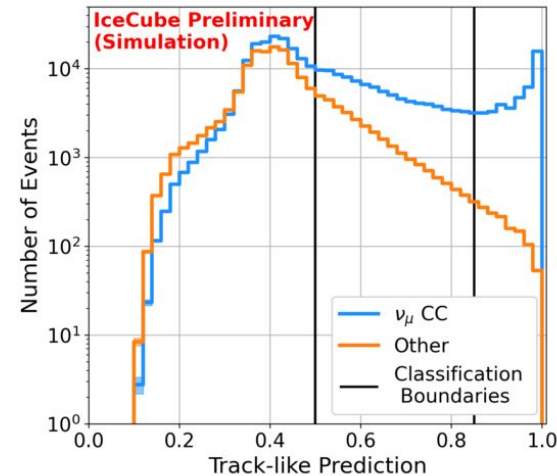
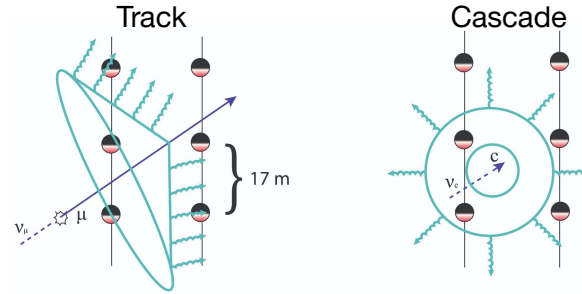
Particle Identification (PID)

Topology:

- Tracks are ν_{μ} CC
- Cascades are ν_e CC, ν_{τ} CC, all NC

Identifying PID at lowest energy difficult with only a few pulses:

- Low energy tracks look like cascades
- “Cascades” analysis bin includes low energy tracks
- “Mixed” bin has more tracks than cascades
- “Tracks” bin dominated by tracks



Full Sample Reconstruction Projections vs. Global Results

- Likelihood and CNN reconstructions projected sensitivities
 - Generated using best fit from DeepCore 2018, 3 year result
- Agrees with global results

