IceCube-Upgrade Reconstructions using Recurrent Neural Networks

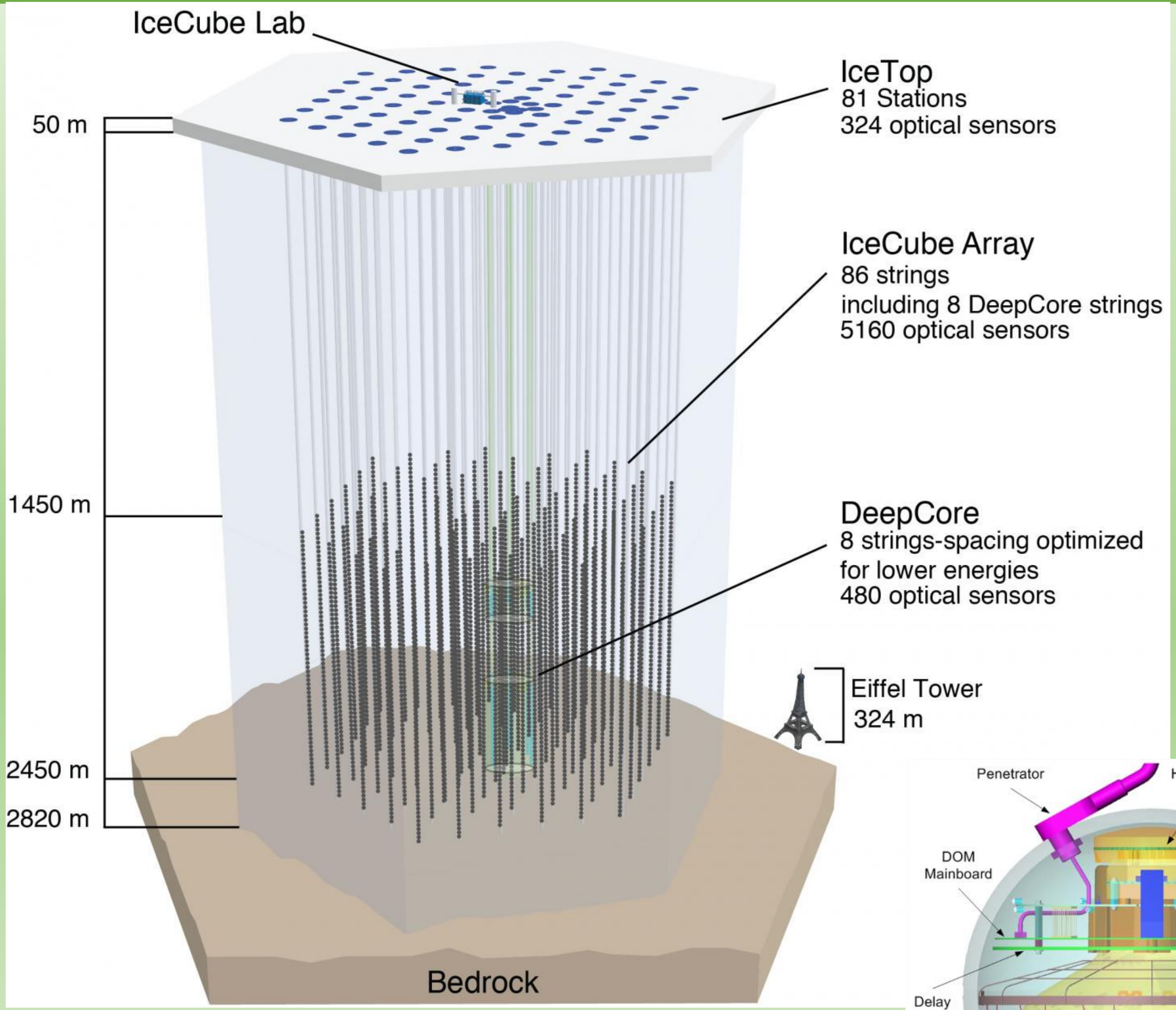
Brandon Pries for the IceCube Collaboration

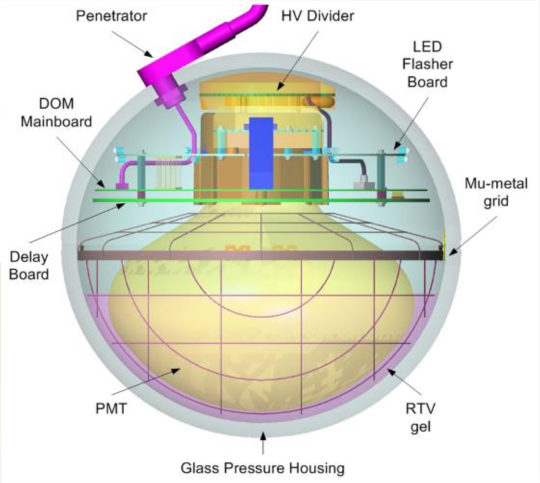
Michigan State University

APS DPF 7-14-21

IceCube Detector[1]

- Cubic-kilometer neutrino detector at South Pole
  - Detects Cherenkov radiation from neutrino interactions within the ice
- Currently uses 5,160 Digital Optical Modules (DOMs) on 86 strings
  - DOMs located 1.5-2.5 km beneath the surface
  - DOMs record time and intensity of light for each detection ("hit")
- Central area of the detector is called DeepCore
  - Higher instrument density for better resolution of low-energy events
- IceCube struggles to reconstruct lowest-energy events
  - DOM spacing optimized for high-energy events
  - DeepCore helps down to ~5 GeV



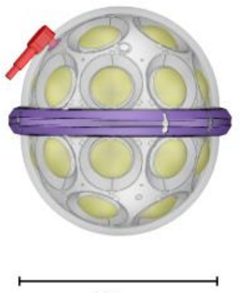


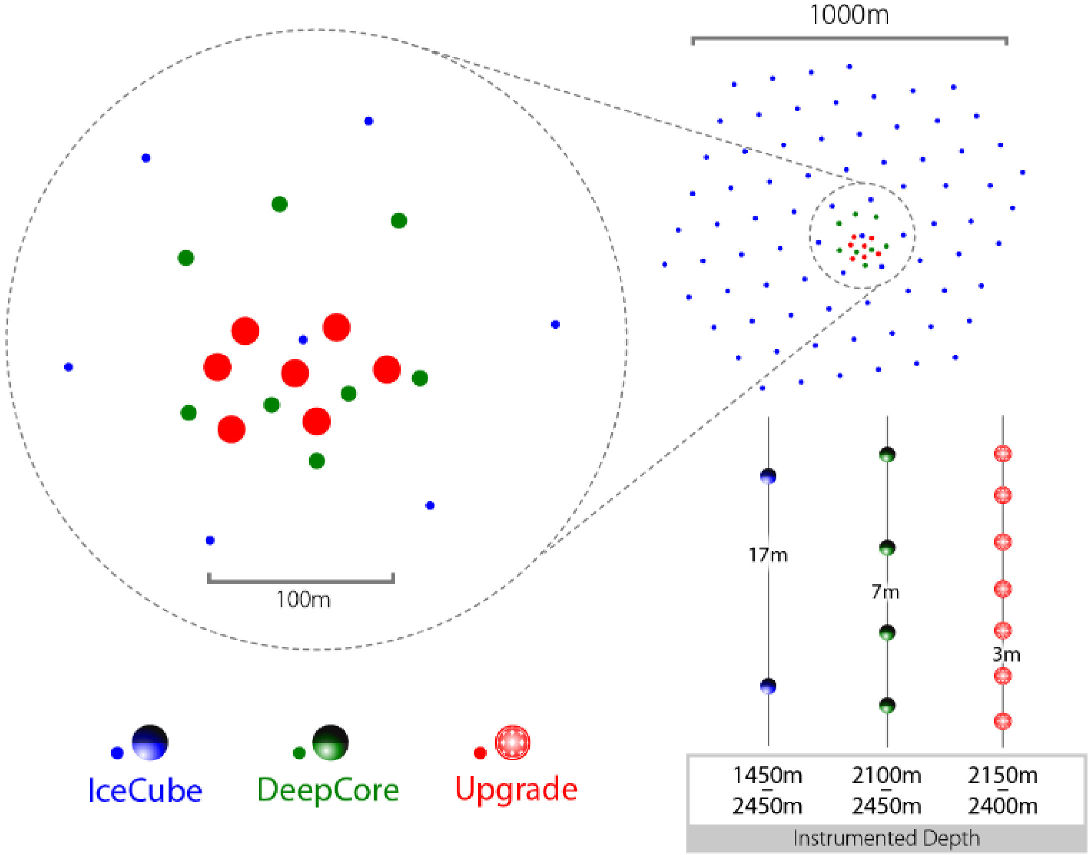
IceCube-Upgrade[2]

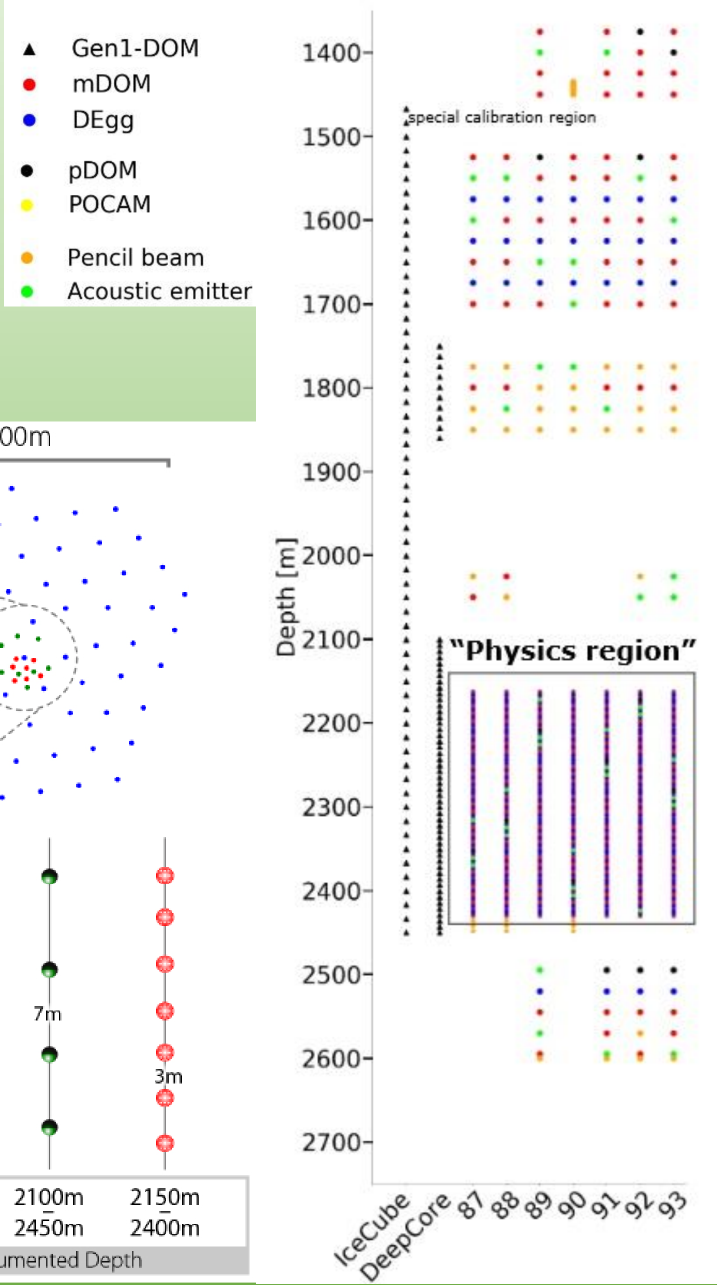
- 7 additional strings in development to be added to detector
  - Each string has approximately 100 DOMs
- Upgrade will feature multi-PMT DOMs (D-Egg and mDOM)
  - D-Egg has 2 PMTs (top and bottom)
  - mDOM has 24 PMTs (roughly isotropic)
- Upgrade is expected to improve event resolution down to energies below 5 GeV
- Scheduled deployment during 2022/2023 Austral summer

D-Egg
(277 modules)

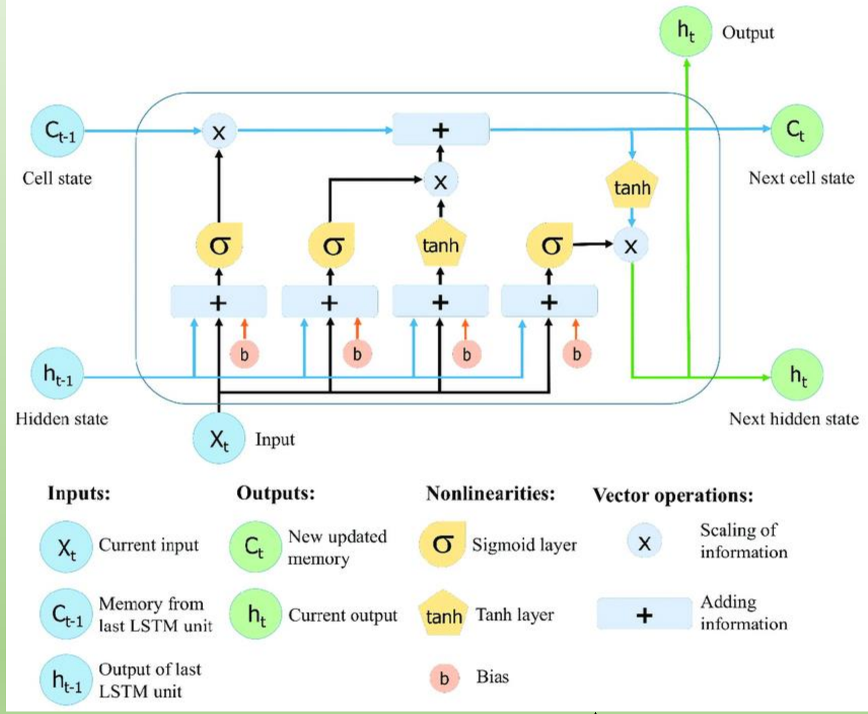
mDOM
(403 modules)







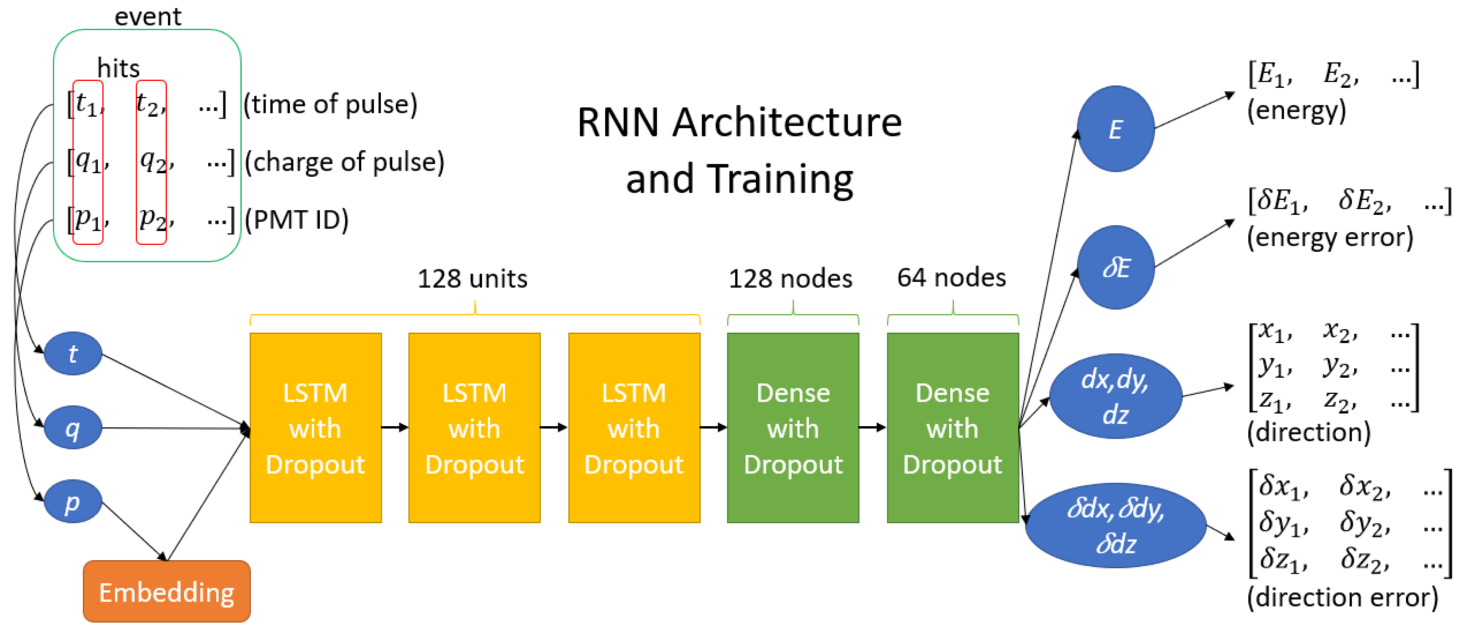
Recurrent Neural Networks



- RNNs are a machine learning algorithm designed for sequential data (time)
  - Great for IceCube data (time is a primary variable)
- RNNs less dependent on detector geometry
  - IceCube is hexagonal, not grid-like
  - Advantage over other neural network designs like CNNs
- Main component of RNNs are Long Short-Term Memory (LSTM) layers
  - Weight information from input sequences based on correlation to outputs
- Current RNN design implemented in Python with Keras/Tensorflow architecture

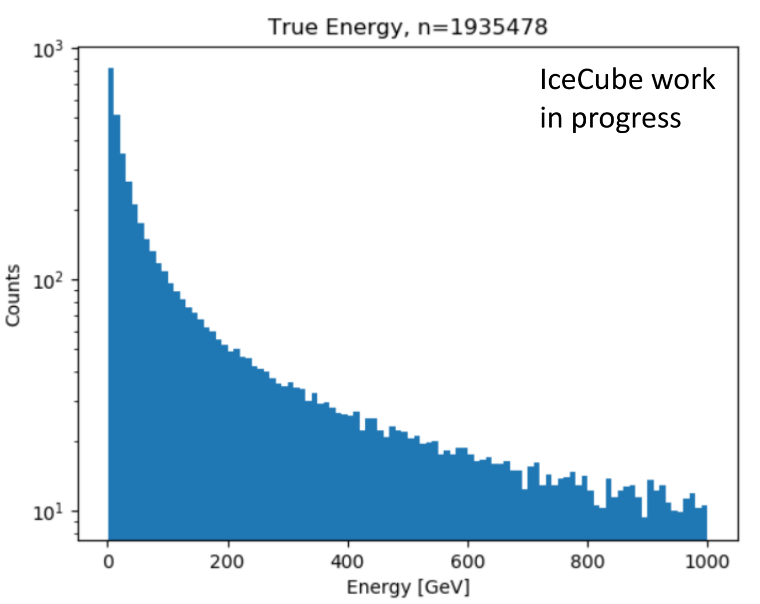
IceCube-Upgrade RNN

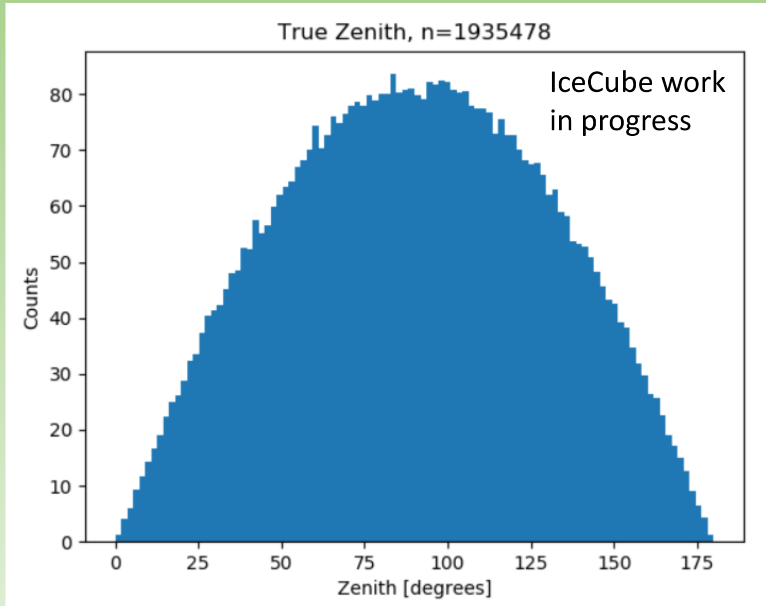
- Inputs are arrays of hits (time, charge, and PMT for each hit)
  - Input sequences are padded/truncated to specific length (250 hits)
    - Studies showed no significant difference between front/back truncation
- Outputs are energy and dx/dy/dz direction (all with error estimates)

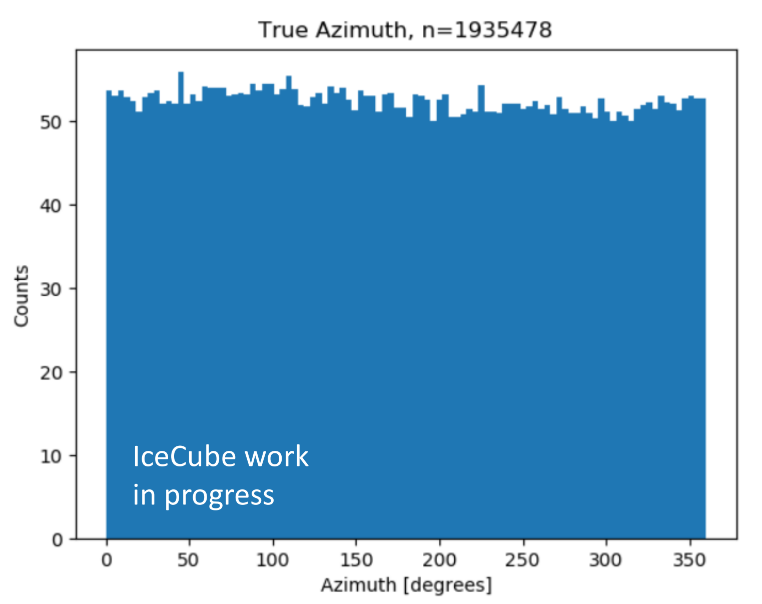


Data Sample

- Simulated NuMu CC events, Upgrade geometry
- Data quality similar to raw IceCube data
- Preliminary noise cleaning, cut for vertex starting in DeepCore

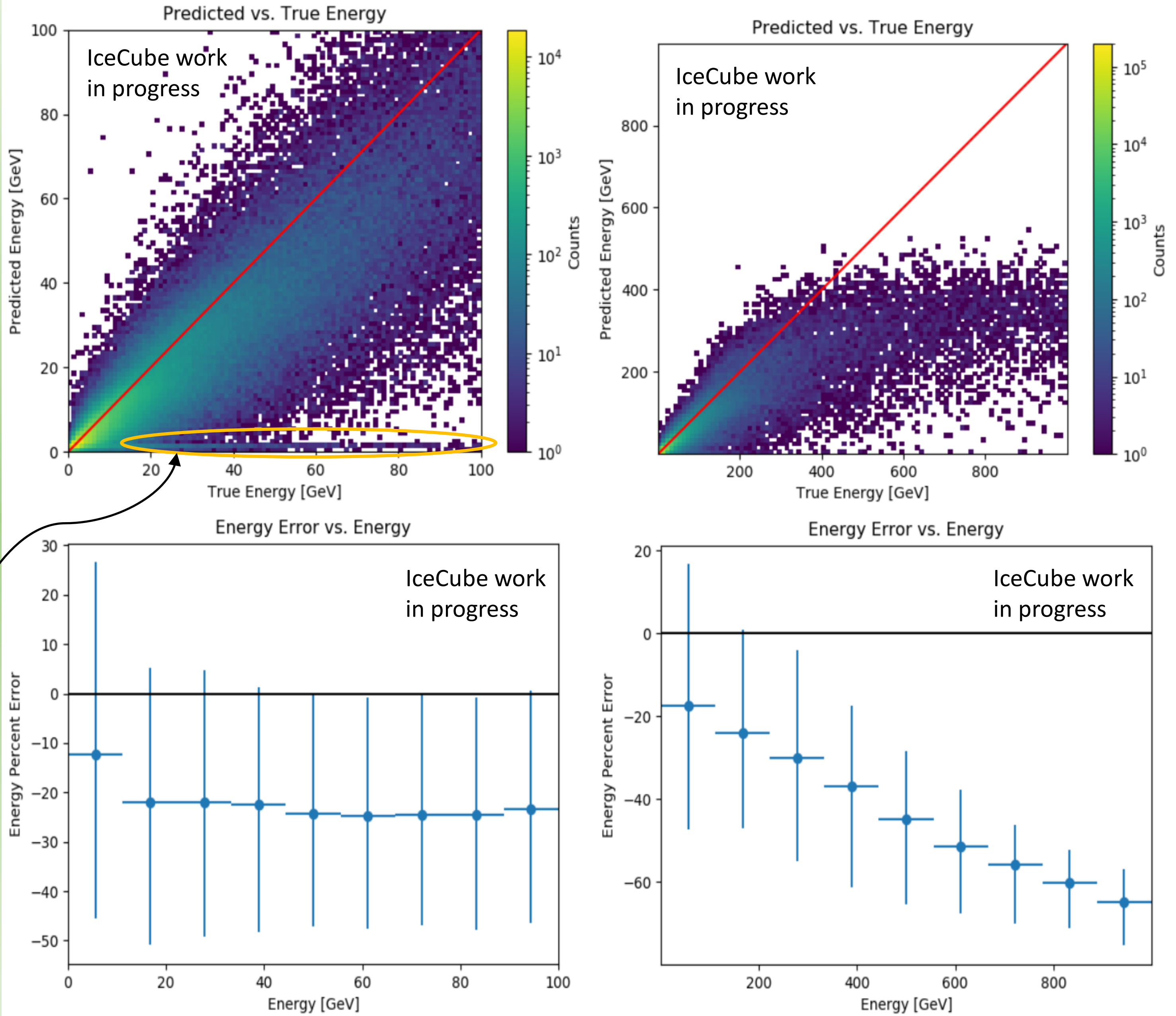






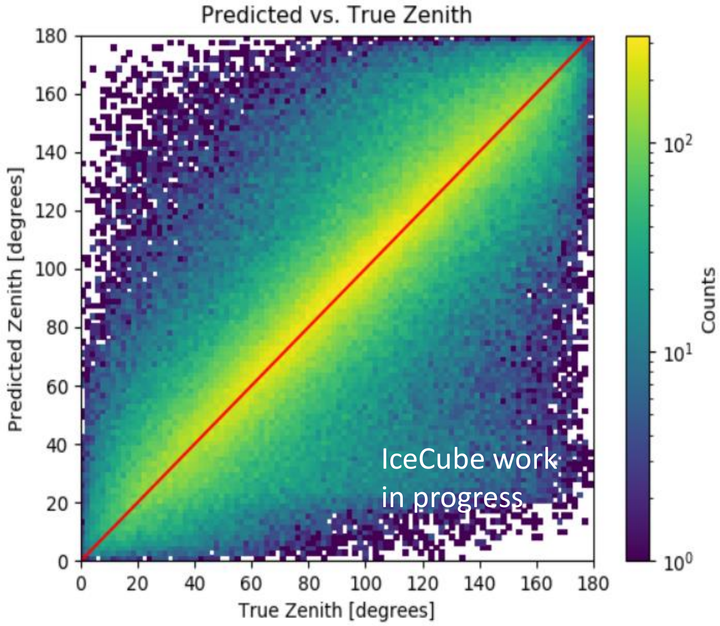
Energy Reconstructions

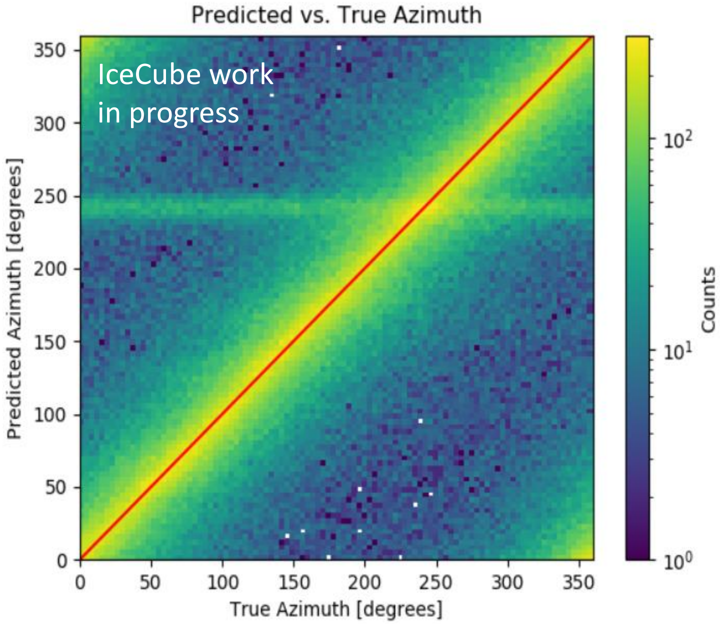
- RNN under-reconstructs majority of events
  - Underpredicts by ~12% for events between 0-10 GeV
  - Underpredicts by ~22% for events between 10-100 GeV
- Reconstructions become worse at higher energies
  - Artifact of loss function (Mean Absolute Percentage Error)
    - Creates shoulder in predicted energy distribution
  - Could also be caused by:
    - Biased energy distribution
    - Truncating hits for events with >250 hits
- Subset of events predicted at low energies regardless of true energy
  - These may be noise-dominated/ noise-only (“non-reconstructable”)

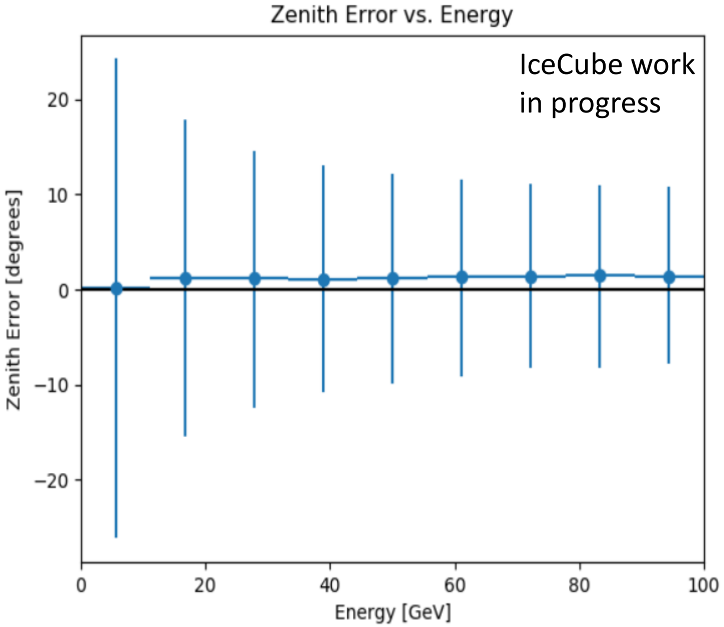


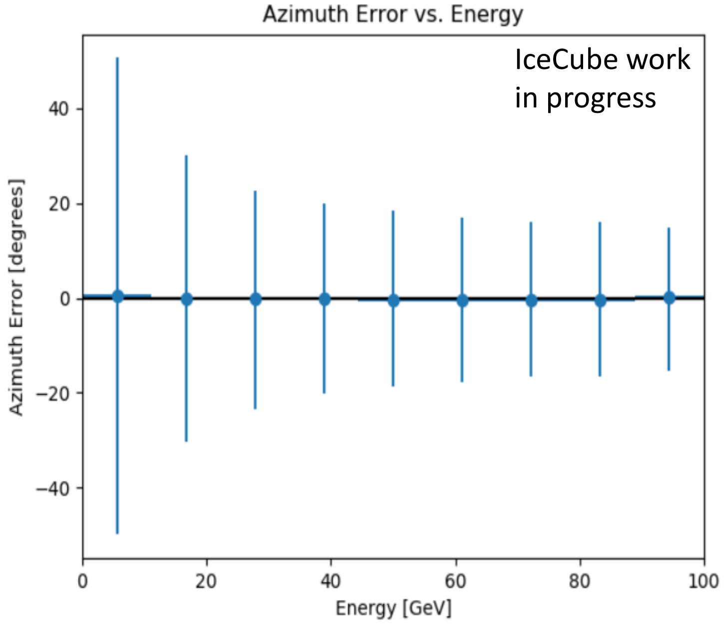
Directional Reconstructions

- Directional reconstructions significantly more accurate than energy
- Both zenith and azimuth median reconstructions are within a few degrees of truth up to 100 GeV
  - Zenith 1σ bands up to ~25° at lowest energies, ~10° at higher energies
  - Azimuth 1σ bands up to ~50° at lowest energies, ~20° at higher energies
- Activity in off-corners due to phase space of azimuth (0° = 360°)
- Band of events at 240° azimuth may be non-reconstructable events
  - Believe this corresponds to events with high directional uncertainties



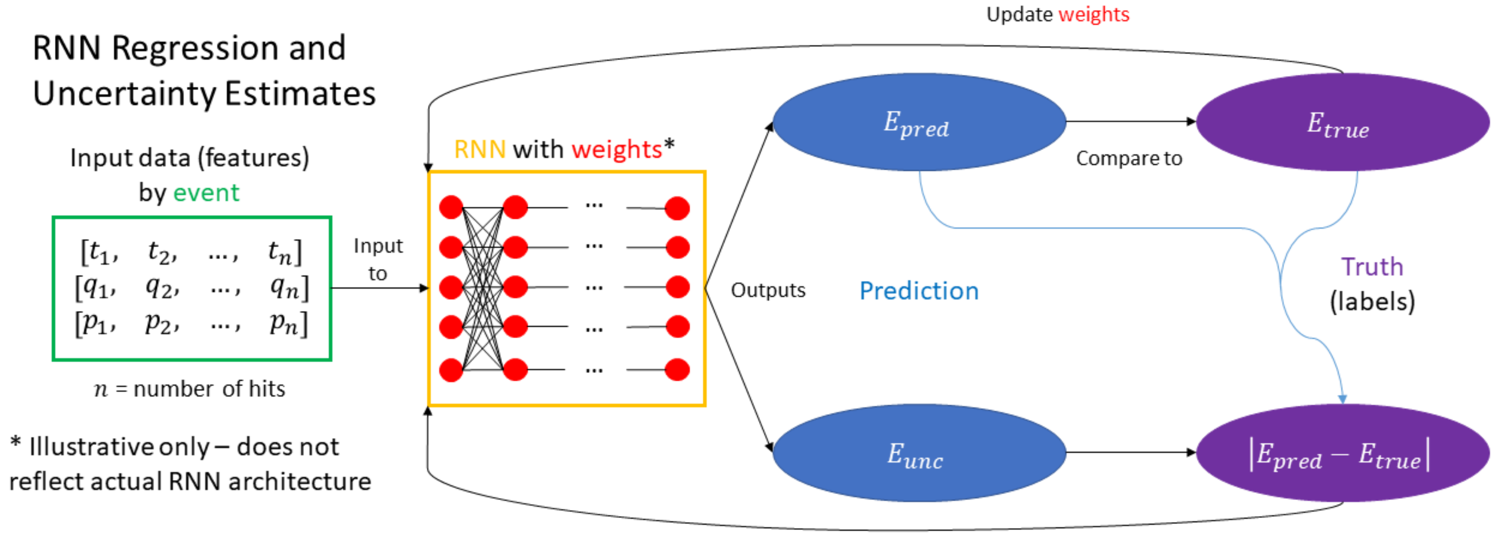






RNN Regression for Uncertainties

- RNN performs "regression on regression" for uncertainty calculations
  - Uses truth E_{true} to predict E_{pred}
  - Uses truth $|E_{pred} - E_{true}|$ to predict E_{unc}

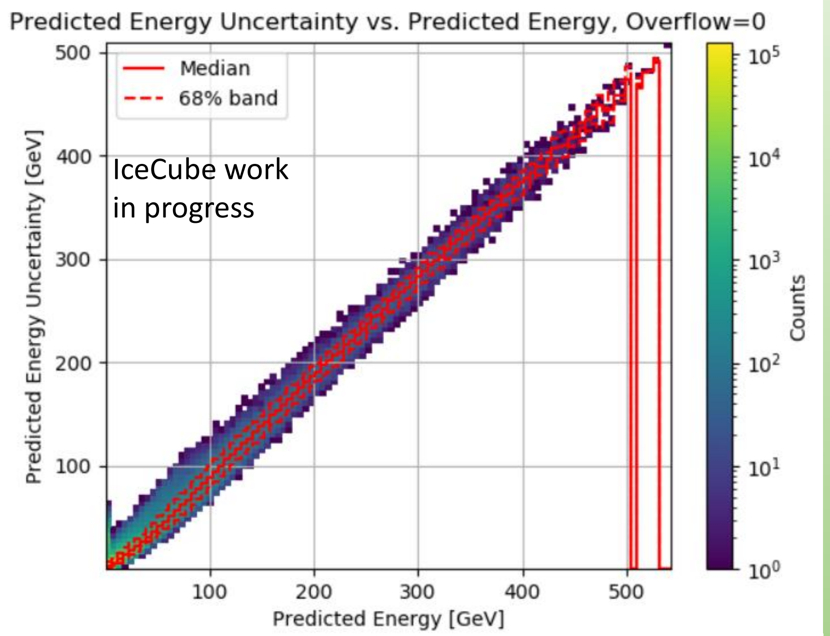


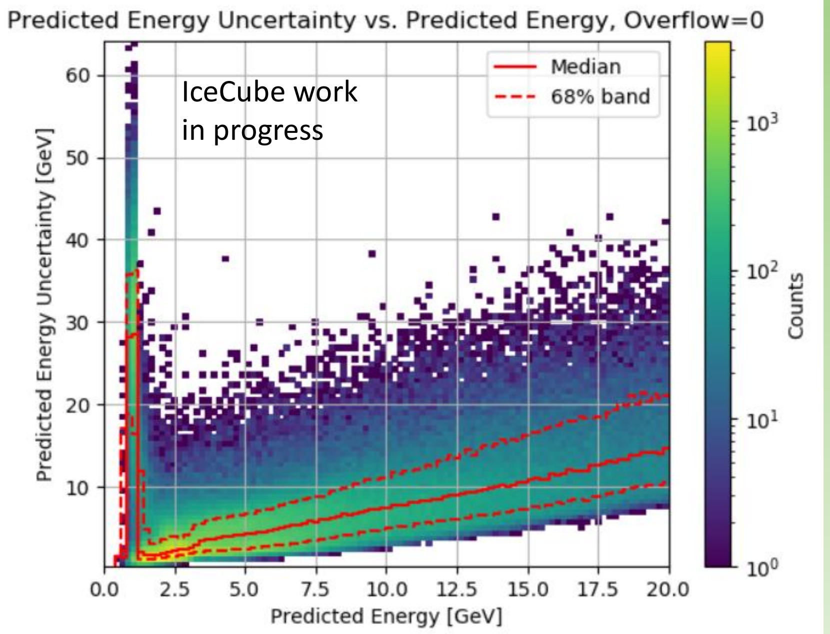
Why RNN Uncertainties Matter

- Non-reconstructable events consistently predicted at low energies, regardless of true energy
  - Non-reconstructable events should have low E_{pred}, high E_{true}
  - High $\left|E_{pred} - E_{true}\right| \Longrightarrow$ high E_{unc}
- Want to find features of predicted uncertainty as a function of predicted energy

RNN Uncertainty Distributions

- Very high correlation between predicted energy and predicted energy uncertainty
    - Events with lowest energy uncertainties predicted at ~2 GeV
- Plots highlight spike in predicted uncertainty at low predicted energies
    - Spike appears to be over ~0-2 GeV in predicted energies
    - This may correspond to the non-reconstructable events



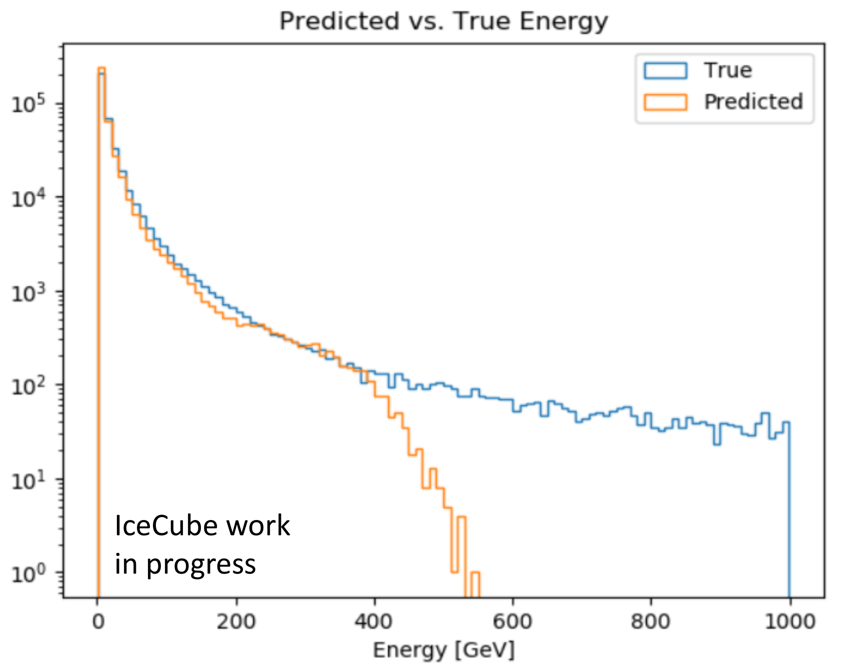


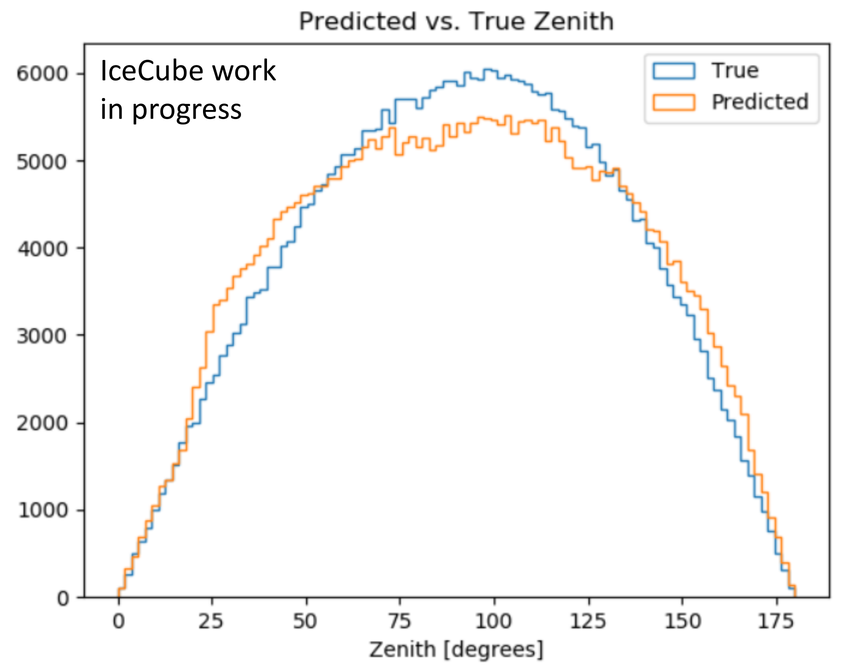
Summary

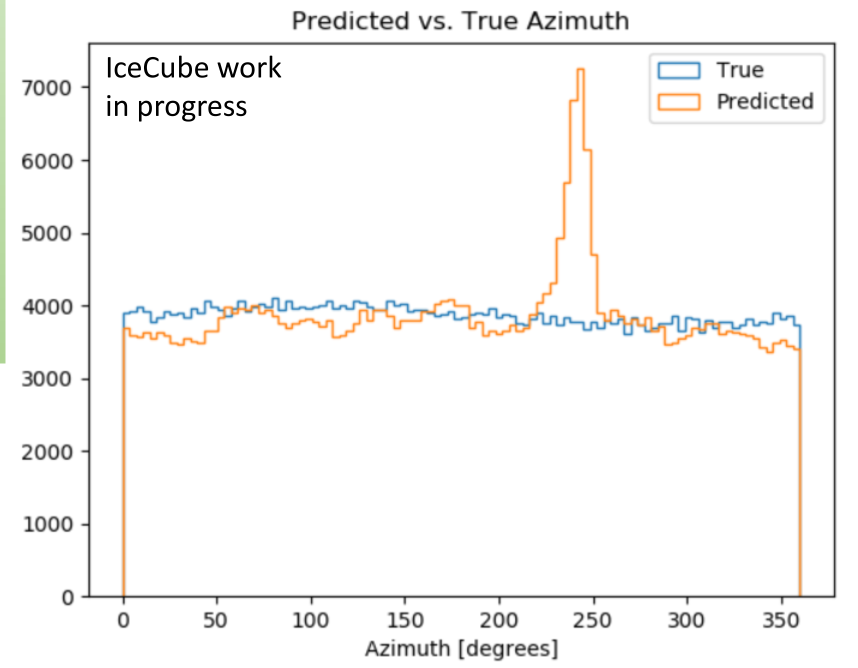
- RNN currently consistently under-reconstructs energy outside lowest true energies
  - Could be combination of loss function (MAPE), biased sample, hit limit
- RNN directional reconstruction shows much higher accuracy
  - ~68% of events predicted within 10^{o} (zenith) and 20^{o} (azimuth) of truth
- Non-reconstructable events may have high predicted uncertainties
  - Could use this correlation to develop quality cut for sample

Backup

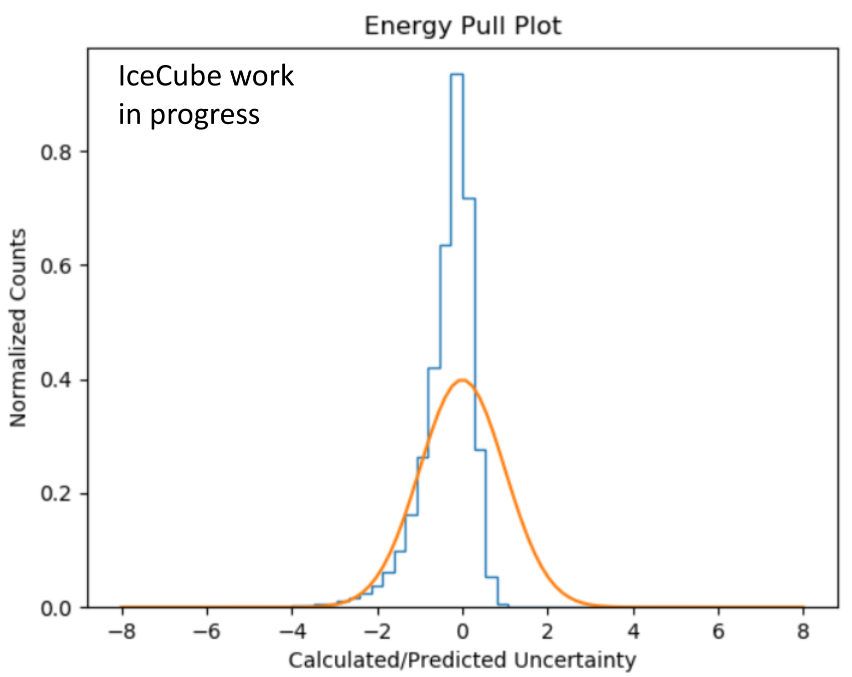
Energy/Direction 1D Distributions

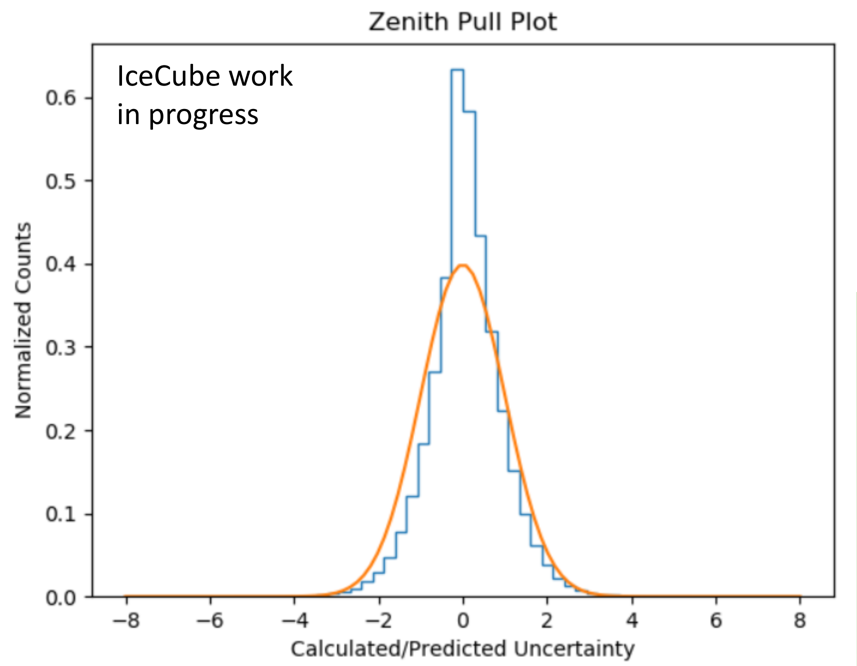


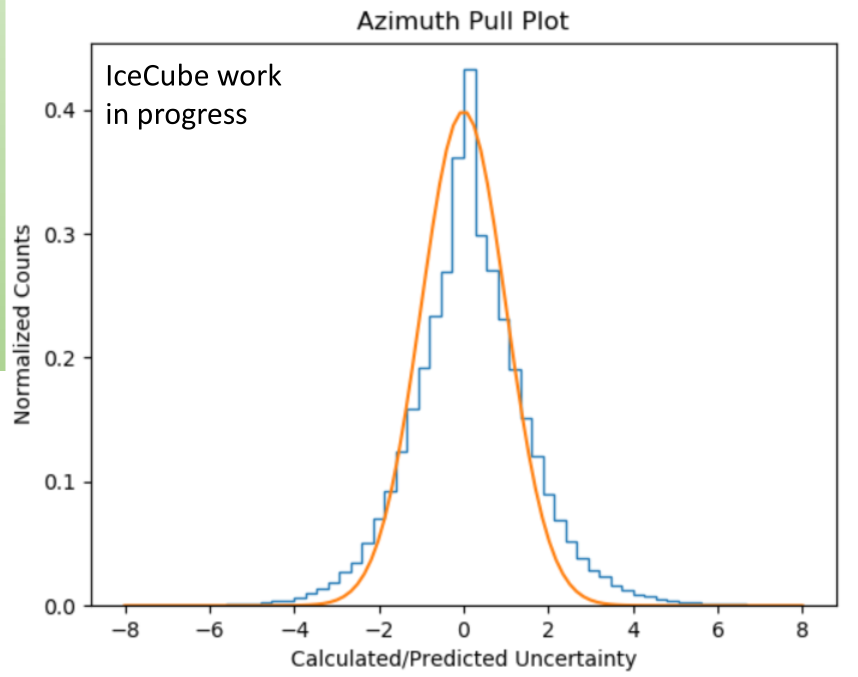




Pull Plots


Energy Pull Plot
IceCube work
in progress
0.0
0.2
0.4
0.6
0.8
Normalized Counts
−8
−6
−4
−2
0
2
4
6
8
Calculated/Predicted Uncertainty


Zenith Pull Plot
IceCube work
in progress
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Normalized Counts
−8
−6
−4
−2
0
2
4
6
8
Calculated/Predicted Uncertainty


Azimuth Pull Plot
IceCube work
in progress
0.0
0.1
0.2
0.3
0.4
Normalized Counts
−8
−6
−4
−2
0
2
4
6
8
Calculated/Predicted Uncertainty

References/Links

- [1] M.G. Aartsen et. al. The IceCube Neutrino Observatory: Instrumentation and Online Systems. *JINST*, Vol. 12, 2017. DOI 10.1088/1784-0221/12/03/P03012
- [2] Aya Ishihara. The IceCube Upgrade – Design and Science Goals. *PoS*, 2019. arXiv: 1908.09441

Acknowledgements

This work is supported by Michigan State University through the Professorial Assistantship Program, as well as the National Science Foundation under Grant No. 1913607. Any opinions, findings, conclusions or recommendations in this material are those of the author and do not necessarily reflect the views of the National Science Foundation.

Thank you to MSU's Institute for Cyber-Enabled Research (ICER) for the computing resources necessary for this project.

Thank you to IceCube mentors Claudio Kopper, Brian Clark, and Jessie Micallef.

Thank you to Johannes Wagner (UC-Berkeley, formerly Drexel) for developing RNN framework.

Thank you to Nathan Willey for results on further studies of front/back truncation (slide 5) azimuth band (slide 8).