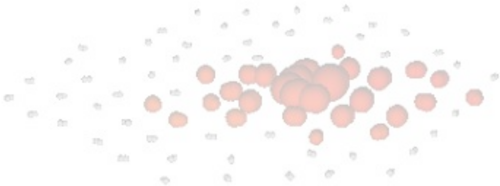
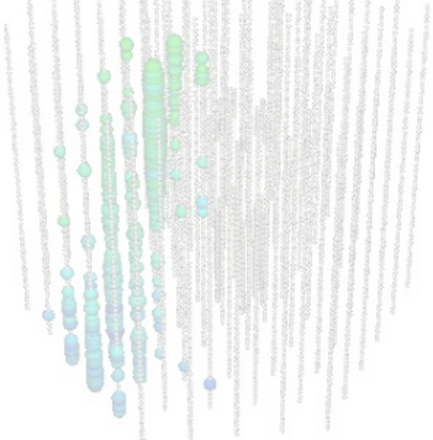


Measurement of the High-Energy Muon Multiplicity in Air Showers with IceTop and IceCube using Neural Networks

Stef Verpoest for the IceCube Collaboration

Workshop on Machine Learning for Cosmic-Ray Air Showers
February 1st, 2022

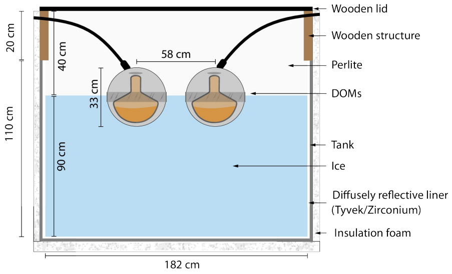


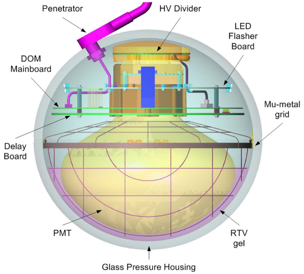
IceCube
Neutrino Observatory

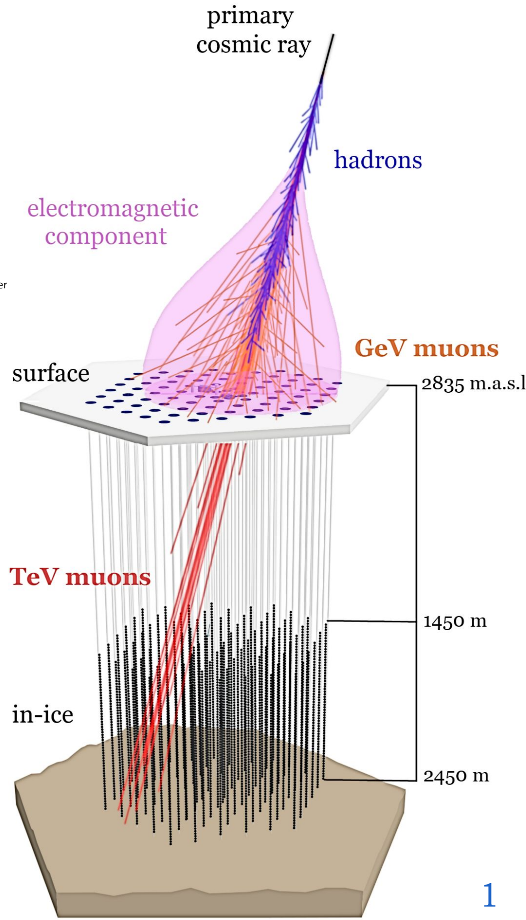
Ghent University

Cosmic rays with IceTop & IceCube

- ➢ IceTop
  - ○ ~ 1 km^2
  - ○ 81 x 2 water Cherenkov tanks
  - ○ EM & low-energy muons (~GeV)
- ➢ IceCube
  - ○ ~ 1 km^3
  - ○ 5160 DOMs on 86 strings
  - ○ High-energy muon bundle (≳400GeV)

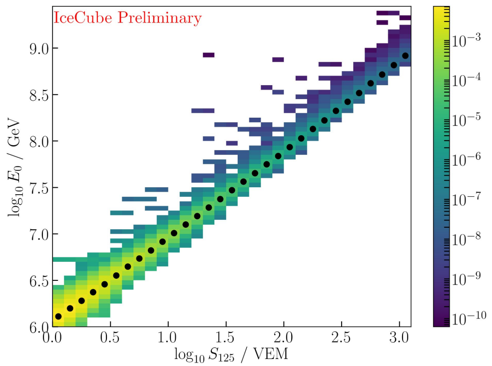


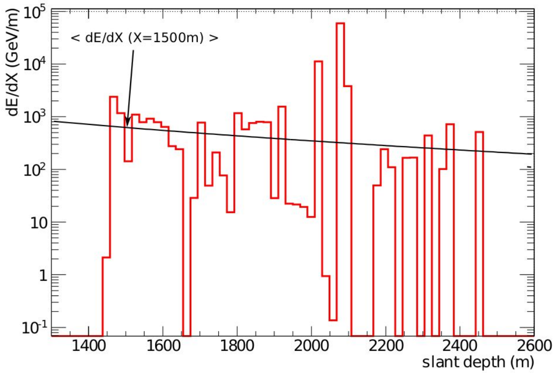


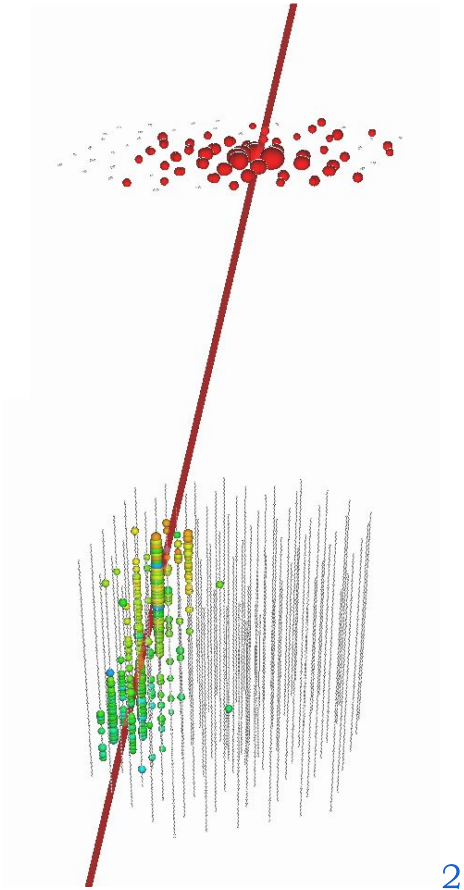


Cosmic rays with IceTop & IceCube

- IceTop
  - Lateral charge distribution fit
  - CR energy estimator S_{125}
  - CR direction
- IceCube
  - Likelihood reconstruction of deposited energy along track

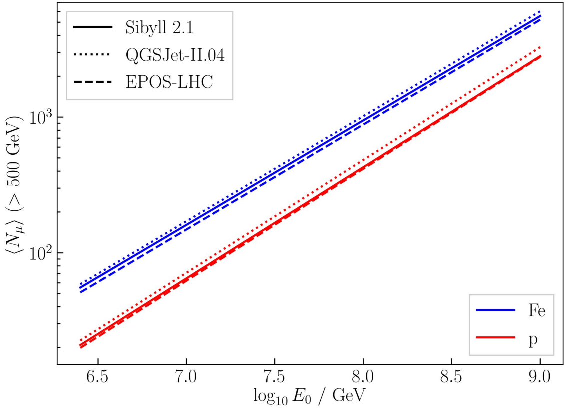


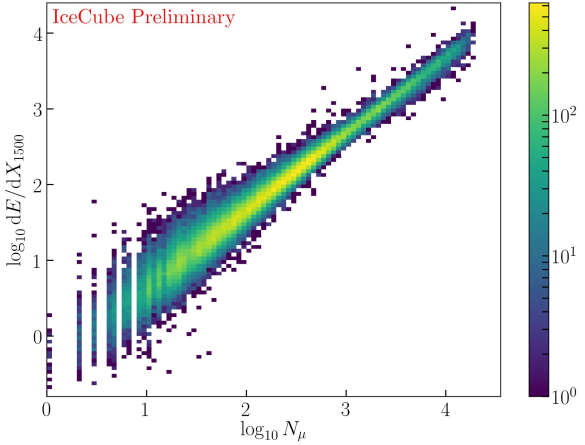




High-energy muon multiplicity

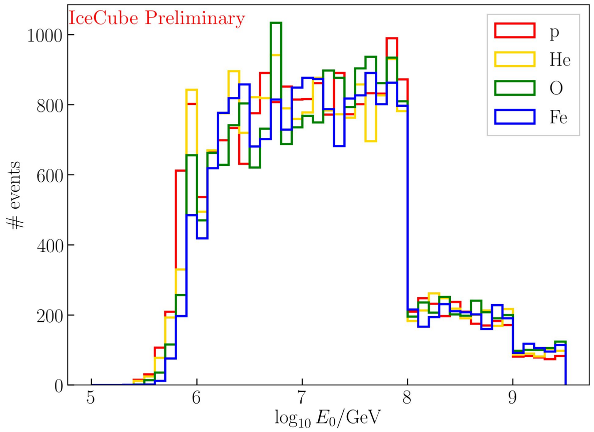
- ➢ High-energy muon bundle
  - Composition
  - Hadronic interaction models
  - …
- ➢ Multiplicity measurement
  - Vertical showers ($\cos\theta > 0.95$)
  - IceTop & IceCube containment
  - N_μ > 500 GeV at surface
  - Correlated with <dE/dX>
  - Improve using full energy loss reconstruction

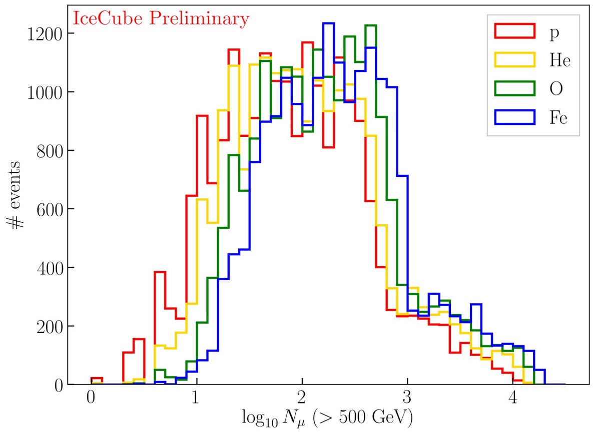




Neural network approach

- ➢ Dataset
  - ○ CORSIKA simulation
  - ○ Sibyll 2.1
  - ○ p, He, O, Fe
- ➢ Training
  - ○ 60%/40% train/test split
  - ○ Regression on $\log_{10}N_\mu$: MSE loss function
- ➢ Two methods
  - ○ *"NNN"* model: IceCube input → N_μ
  - ○ *"NENN"* model: IceCube + IceTop input → N_μ, E_0



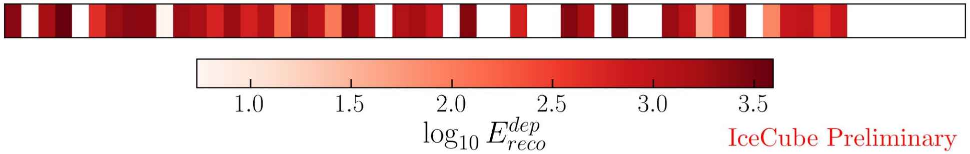


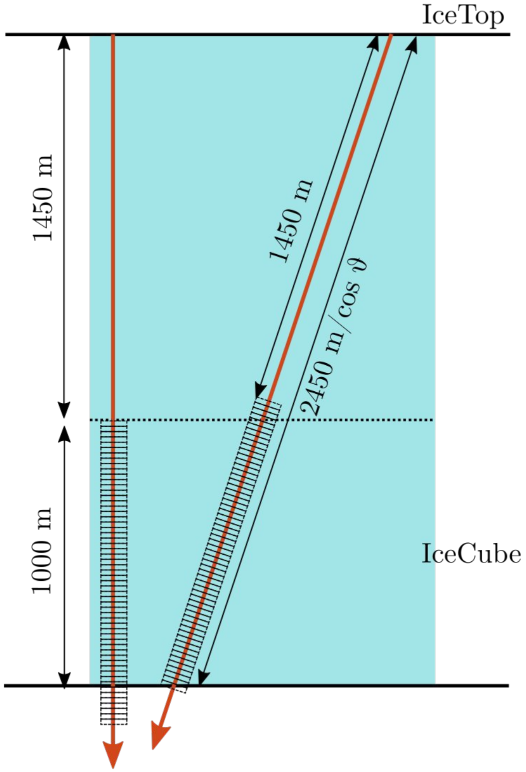
Neural network input

➢ IceCube input

- Energy loss reconstruction (20m segments)
- Fixed length vector: $\dfrac{2450\ \mathrm{m}/\cos\theta - 1450\ \mathrm{m}}{20\ \mathrm{m}} \approx 57$
- Zero-padding based on geometry

Example: proton, $\log_{10}E_0$ = 7.5, θ = 1°, N_μ = 163





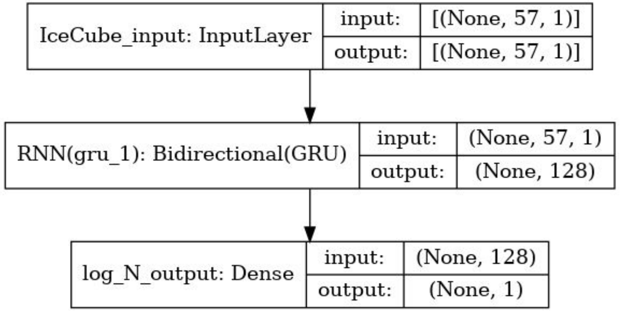
→ Perfect for 1D Convolutional or Recurrent Neural Network

NNN model: architecture & training

➢ Type of model

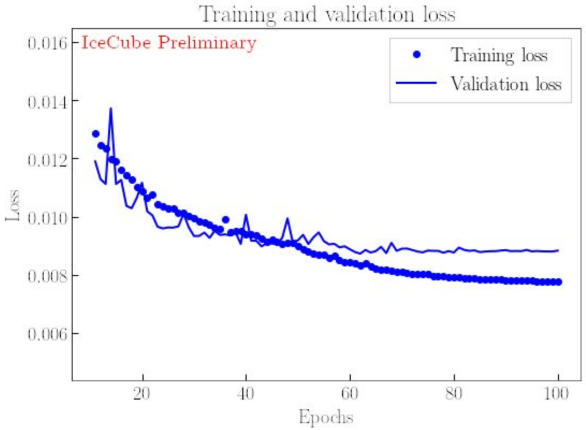
- 1D CNN: fast, needs tuning for optimal results
- RNN: slower, matches CNN performance out of the box

→ Use RNN (bidirectional GRU)



➢ Training

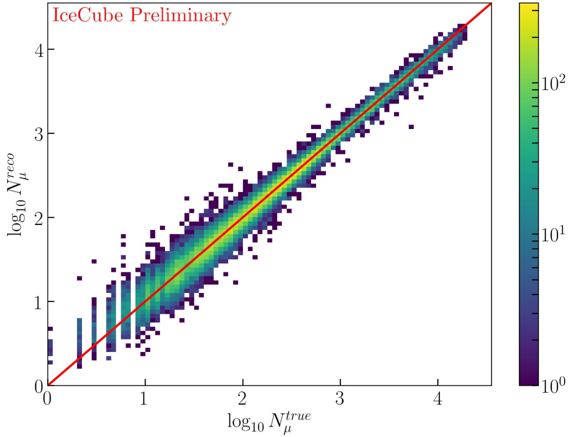
- 100 epochs
- Decreasing learning rate exponentially
- No issues with overfitting

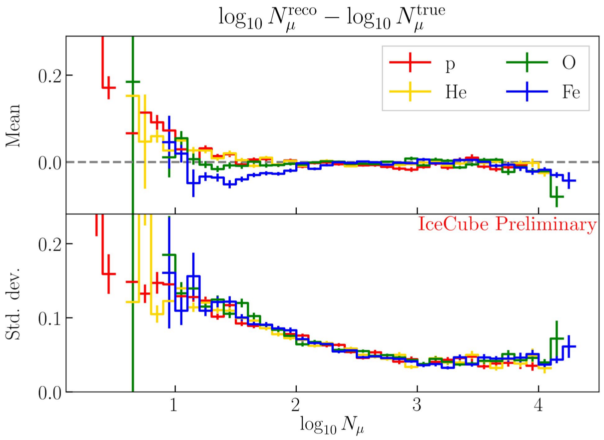


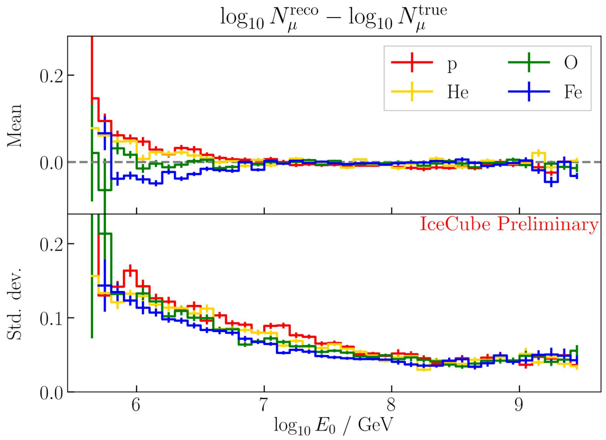
NNN model: performance

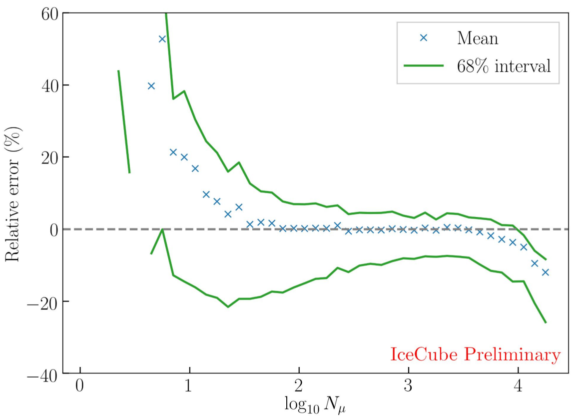
➢ Performance on test set

- Correlation plot $\log_{10} N_\mu$ (all elements)
- Relative error N_μ (all elements)
- Bias & resolution $\log_{10} N_\mu$ (4 components)
  - vs true N_μ
  - vs true E_0



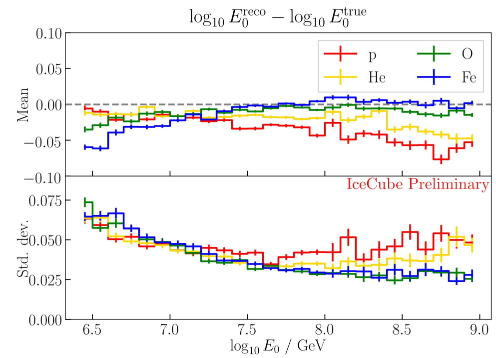




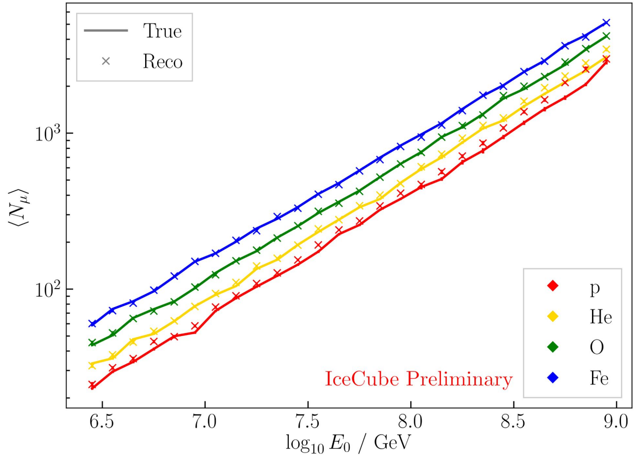


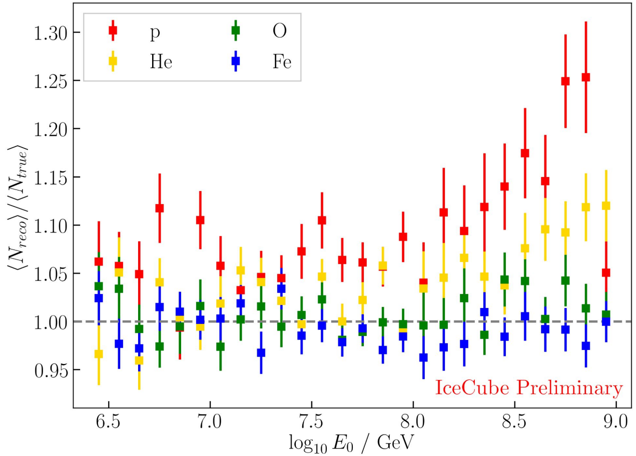
NNN model: ⟨N⟩ vs E

- ➢ Combine with energy reconstruction
  - ○ S_{125} - E_0 conversion from H4a weighted MC →

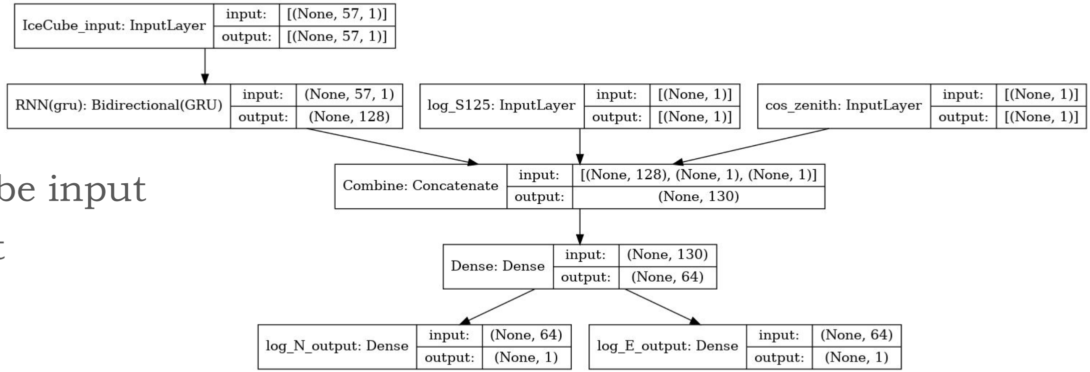


- ➢ ⟨N⟩ vs E measurement
  - ○ Composition dependent biases
  - ○ Need for calibration



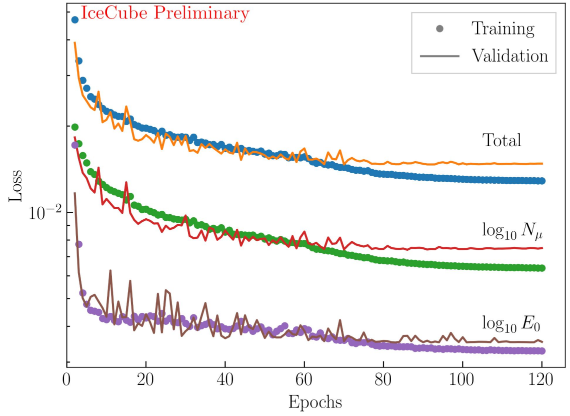


NENN model: architecture & training



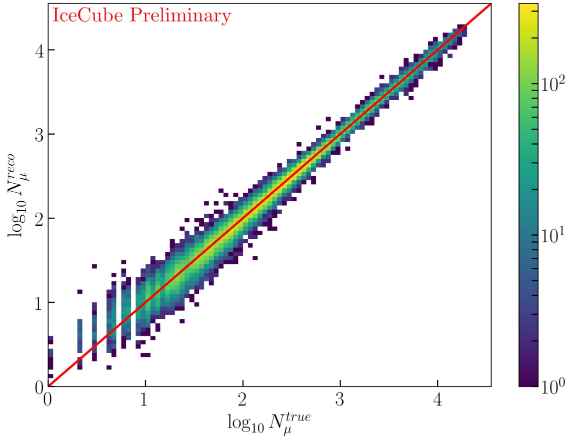
- **Architecture**
  - Same RNN as before for IceCube input
  - Concatenate with IceTop input
    - Energy estimator S_{125}
    - Zenith angle θ
  - Feed to Dense layer & 2 outputs

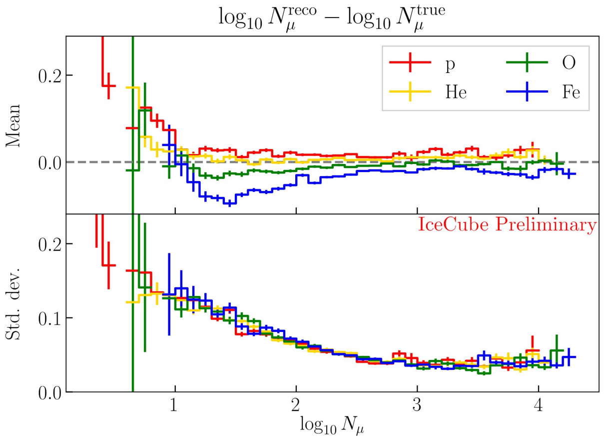
- **Training**
  - Double regression:
    - $\log_{10}N_\mu$
    - $\log_{10}E_0$
  - Loss function: MSE with 1.5x weight for N_μ

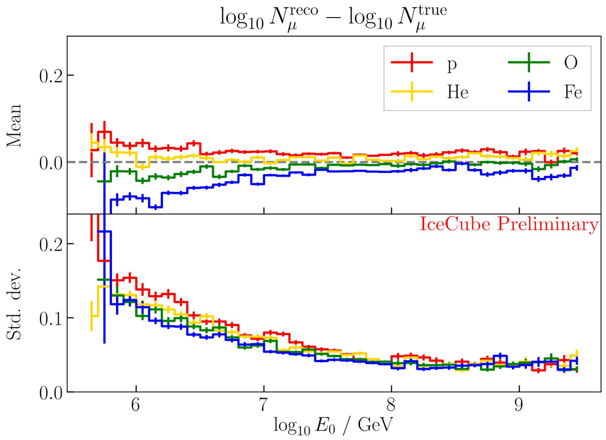


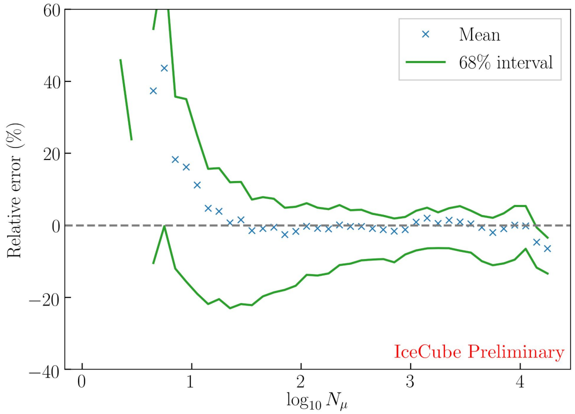
NENN model: performance (N)

- ➢ Performance on test set
  - ○ Correlation plot $\log_{10}N_\mu$ (all elements)
  - ○ Relative error N_μ (all elements)
  - ○ Bias & resolution $\log_{10}N_\mu$ (4 components)
    - · vs true N_μ
    - · vs true E_0





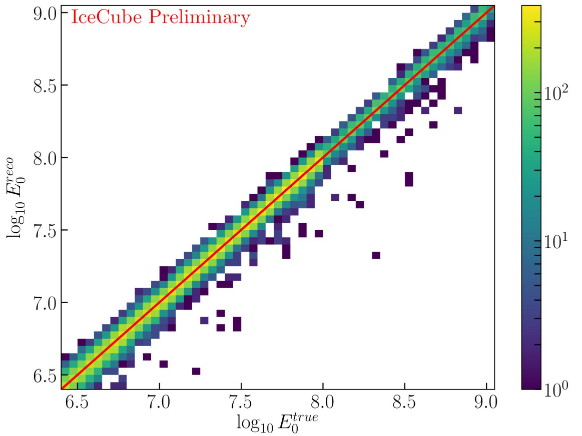


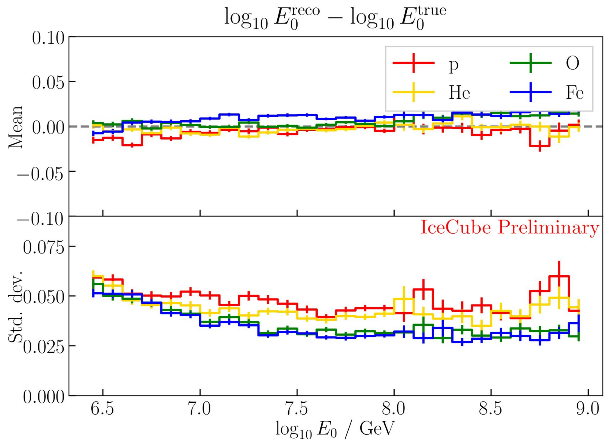


NENN model: performance (E)

- ➢ Performance on test set
  - ○ Correlation plot $\log_{10}E_0$ (all elements)
  - ○ Bias & resolution $\log_{10}E_0$ (4 components)
    - · vs true E_0

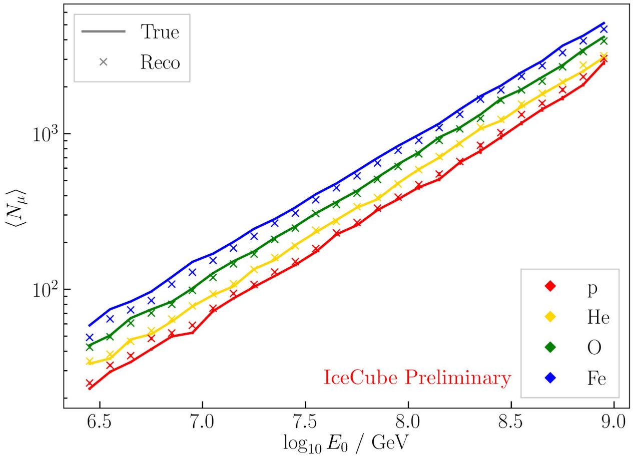
- ➢ Comparison to NNN model
  - ○ Improved energy estimator
  - ○ Slight improvement in resolution
  - ○ Stronger composition dependent bias in multiplicity reconstruction

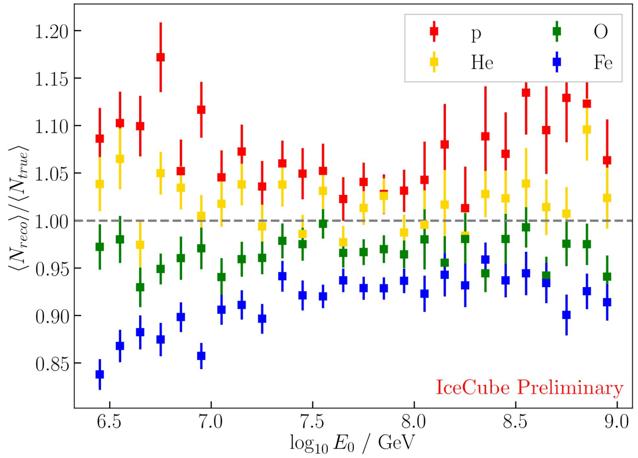




NENN model: ⟨N⟩ vs E

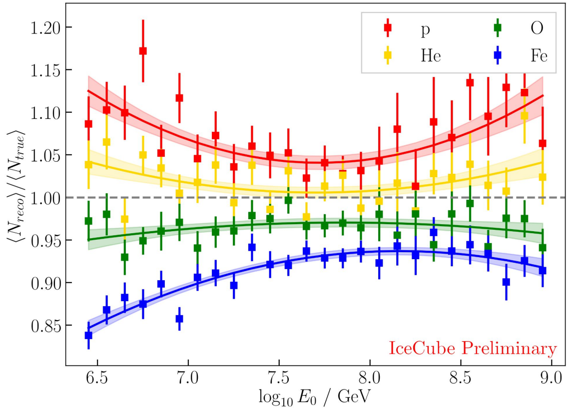
- ⟨N⟩ vs E measurement
  - Over/underestimation in light/heavy elements
  - ~ average relation between multiplicity and primary energy

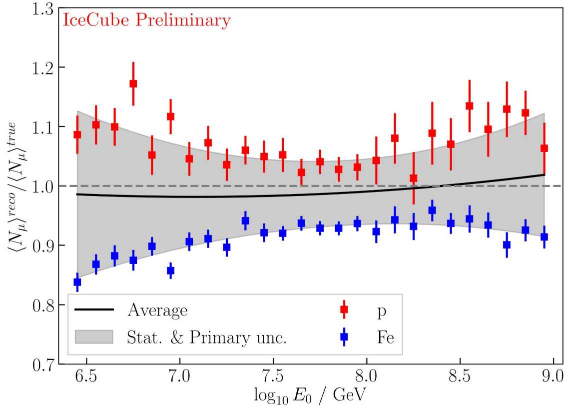




Calibration

- ➢ Calibration factor
  - ○ Fit reconstructed/true in MC
  - ○ Combine based on composition
  - ○ Multiply with measurement to remove bias
- ➢ Composition dependence
  - ○ Currently: average p & Fe with large uncertainty
  - ○ Work in progress: iterative method



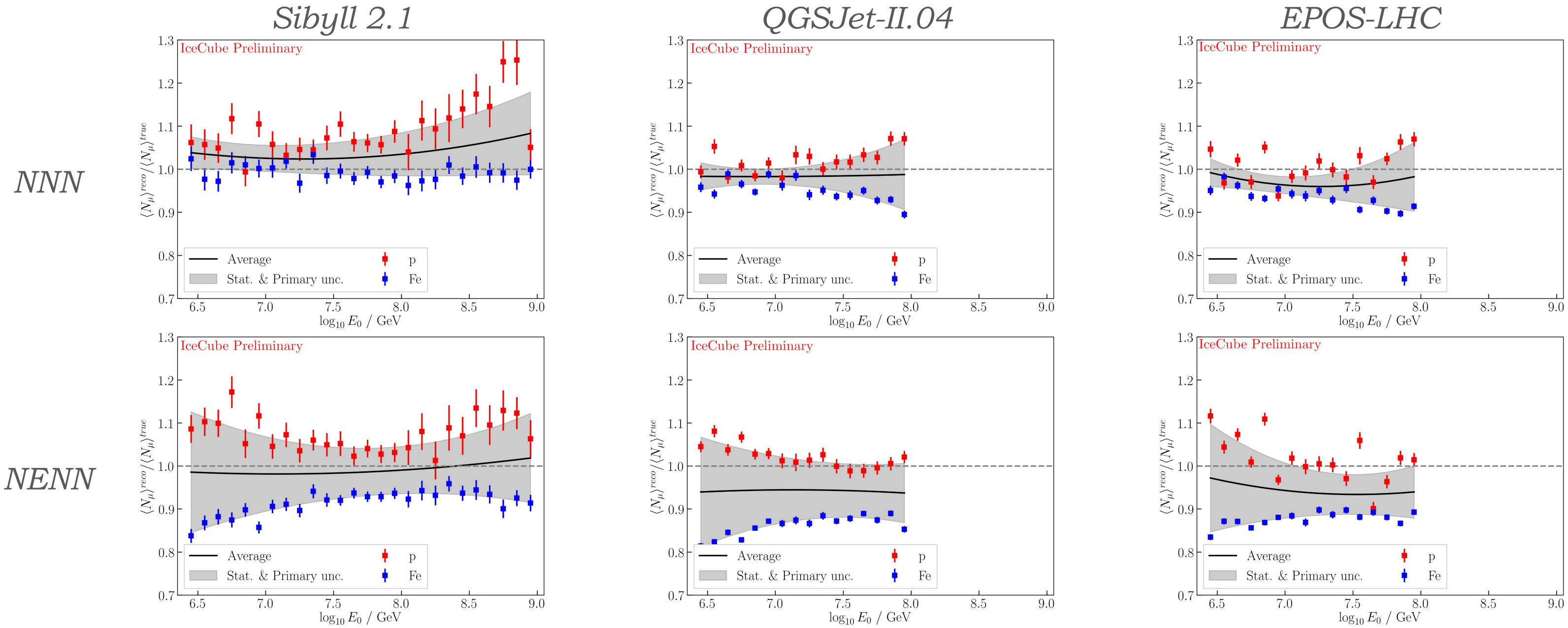


Calibration

➢ Hadronic model dependence

- Reconstruction based on Sibyll 2.1
- Derive calibration factors for other hadronic model

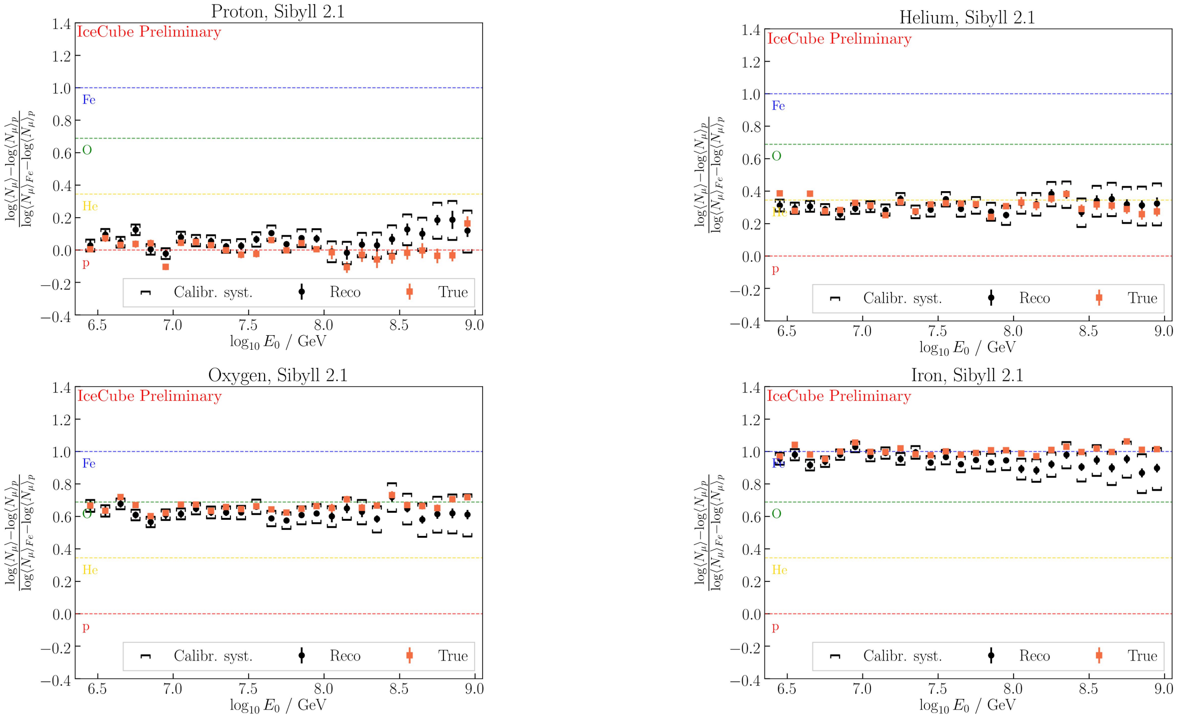
→ Model dependent interpretation of data



Results (NNN)

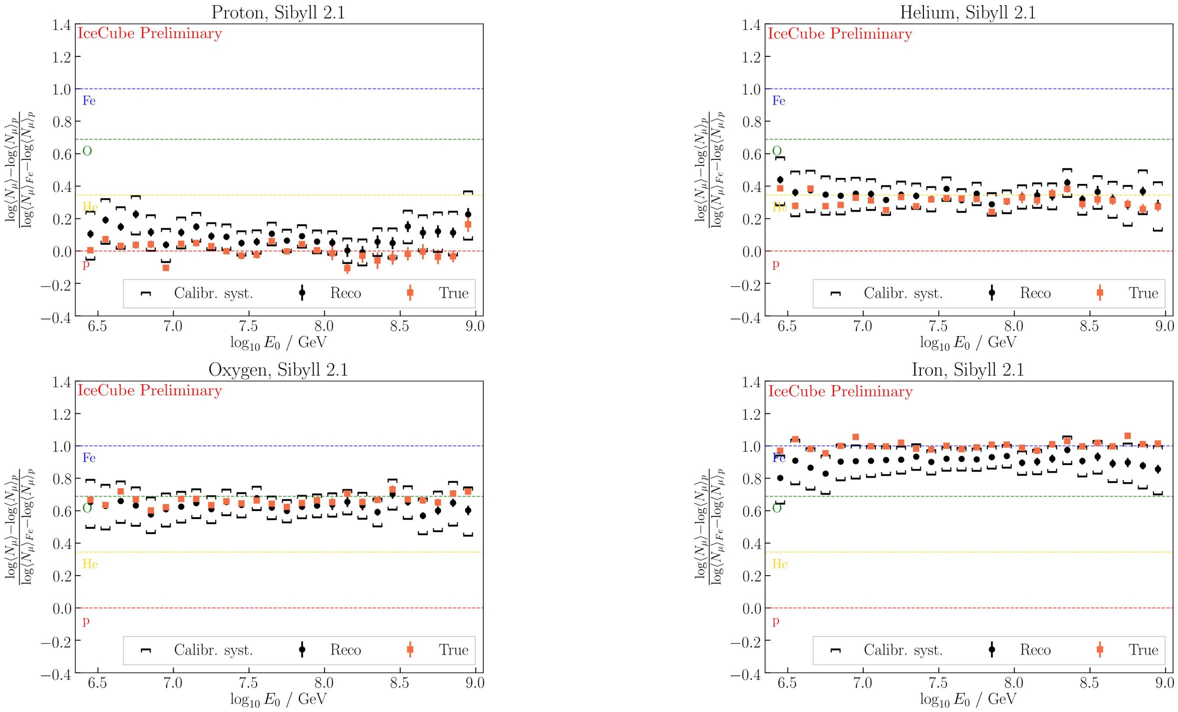
➢ Tests of reconstruction & calibration

- Apply E & N reconstructions + calibration factor to MC (pure composition)
- Calibration uncertainty given by brackets



Results (NENN)

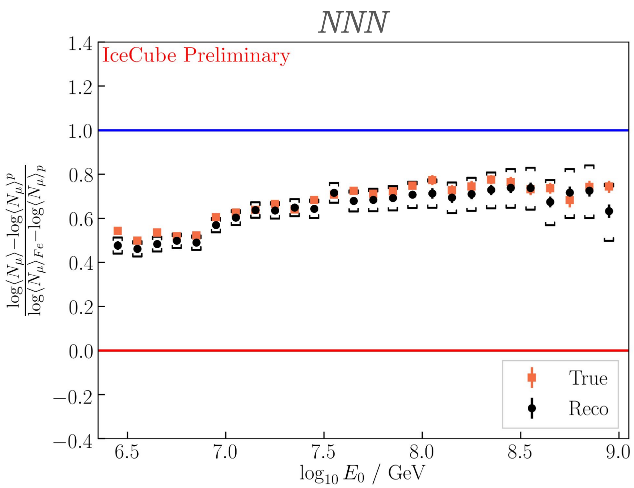
- Tests of reconstruction & calibration
  - Apply E & N reconstructions + calibration factor to MC (pure composition)
  - Calibration uncertainty given by brackets

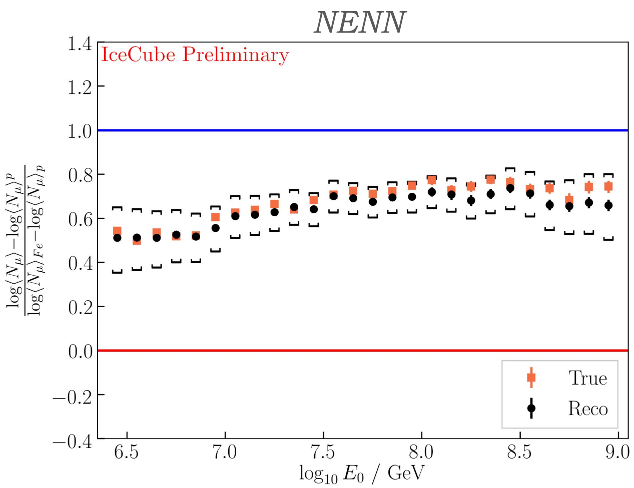


Results

➢ Tests of reconstruction & calibration

- Apply E & N reconstructions + calibration factor
- MC weighted to realistic composition model (H4a)
- Calibration uncertainty given by brackets

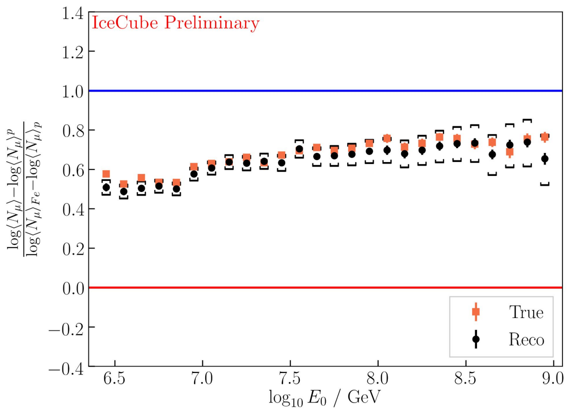




Summary & outlook

- ➢ Muon multiplicity reconstruction
  - ○ IceTop & IceCube coincident events
  - ○ Segmented reconstruction (ML) of bundle energy loss
  - ○ Good results with 2 approaches based on CNN / RNN:
    - · Single-output regression: N_μ
    - · Multi-output regression: N_μ & E_0

- ➢ $\langle N_\mu \rangle$ vs E_0 measurement
  - ○ Calibration factor from MC
  - ○ Hadronic interaction model dependent measurement
  - ○ Good agreement between true & reconstructed in MC



- ➢ Going forward
  - ○ Study neural network input variations
  - ○ Expand phase space
  - ○ Iterative calibration method

Backup

IceCube input distributions

- ➢ Distribution of energy loss values in input vectors
  - ○ Number of entries = length input vector (57) × number of events
  - ○ Modifications for easier training:
    - ■ Shift & scale so that mean ≅ 0 and standard deviation ≅ 1
    - ■ Low energy noise replaced by fixed value