Study of Mass Composition of Cosmic Rays with IceTop and IceCube

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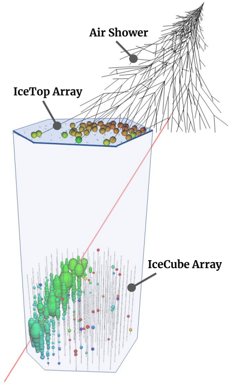
For the IceCube Collaboration

1. Motivation

- Faster and more precise mass-estimation of cosmic ray primary
- Establish analysis framework flexible to detector upgrades
- Extend analysis for sub-PeV cosmic rays

2. Cosmic Rays @ IceCube Observatory



IceTop [1]

- Measures combined signal deposited by EM Component and low energy muons (GeV) by detecting Cherenkov emission
- Primarily uses EM component to reconstruct the primary energy of the shower

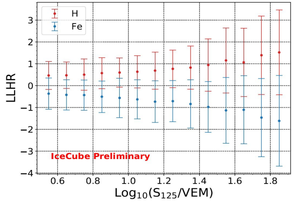
IceCube (in-ice) [2]

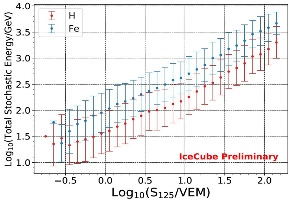
- Detect high-energy muon bundles with energy exceeding 300-400 GeV which penetrate through 1.5 km ice layer to create series of hits
- Combine the measurements and work in synergy with IceTop to detect coincident muons

3. Composition Relevant Parameters

A good separation between H and Fe, in expected output value, is paramount for an air-shower parameter to have good composition sensitivity.

- **S_{125}**= Signal at 125 m from shower axis (energy proxy)
- **Log Likelihood Ratio (LLHR)** of surface signal between H and Fe assumptions
- **Total Stochastic Energy** = Energy of stochastic deposits (in-ice)
- dE/dX_{1500} = Energy deposit at a slant depth of 1500 m in-ice





4. Composition Analysis - Three Modi Operandi

a. Random Forest

- **Baseline Analysis:** Based on [3] using a Random Forest (RF) with S_{125} and zenith from IceTop with the energy deposit dE/dX_{1500} from IceCube
- **Improvement:** RF Analysis includes the calculated LLHR[4] from IceTop
- Meta-parameters same as baseline: 500 trees and a max. depth of 150

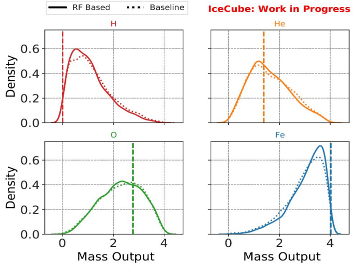
b. Graph Neural Network

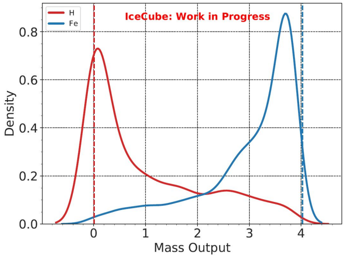
- **Motivation:** Implement analysis method flexible to future detector upgrades and use full signal footprint information
- Treat measured signal in its most natural form, with minimal prior reconstruction
- **Input Features:** Graph Component - Spatio-temporal and charge info; Global event features - S_{125}, dE/dX_{1500}, total stochastic energy

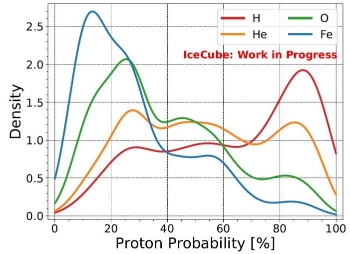
c. BDTs - Low Energy Extension

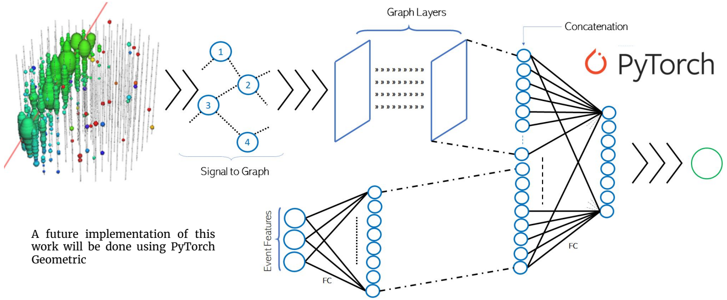
- Dedicated trigger lowers threshold to about 100 TeV
- RFs trained on H and Fe MC-data for core position, zenith and primary energy with surface features
- BDT trained for classifying H and Fe using in-ice features and reconstructed energy
- Applied on He and O simulations, it yields intermediate classification probabilities

5. Results and Outlook









A future implementation of this work will be done using PyTorch Geometric

Significant improvements in per-event based analysis will help to improve our understanding of high-energy cosmic rays. Hence, for a more detailed future composition analysis, Graph Neural Network based method seem to be a viable option. For low-energy extension fast and simple methods like BDTs seem appropriate.

Take Home Messages:

- RF based method is simple and easy to train and shows improvement over the baseline analysis.
- Preliminary results for graph-based method show major improvement over other methods.
- BDTs are fast and easy way to extend current high-energy composition analysis to sub-PeV air showers.

References

[1] IceCube Collaboration, R. Abbasi et al., Nucl Instr. and Meth.A 700 (2013) 188−220
[2] IceCube Collaboration, M. G. Aartsen et al., JINST 12 (2017) P03012
[3] IceCube Collaboration, M. G. Aartsen et al., Phys.Rev.D (2019) 100, 082002
[4] IceCube Collaboration, H. Pandya PoS ICRC2017 (2018) 514.

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