

PAPER

Low energy event classification in IceCube using boosted decision trees

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Low energy event classification in IceCube using boosted decision trees

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ABSTRACT: The DeepCore sub-array within the IceCube Neutrino Observatory is a densely instrumented region of Antarctic ice designed to observe atmospheric neutrino interactions above 5 GeV via Cherenkov radiation. An essential aspect of any neutrino oscillation analysis is the ability to accurately identify the flavor of neutrino events in the detector. This task is particularly difficult at low energies when very little light is deposited in the detector. Here we discuss the use of machine learning to perform event classification at low energies in IceCube using a boosted decision tree (BDT). A BDT is trained using reconstructed quantities to identify track-like events, which result from muon neutrino charged current interactions. This new method improves the accuracy of particle identification compared to traditional classification methods which rely on univariate straight cuts.

KEYWORDS: Neutrino detectors; Particle identification methods

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1 Introduction

The IceCube detector is a kilometer-scale detector located at the South Pole containing 5160 optical modules designed to observe Cherenkov light from neutrino interactions [1]. Within IceCube is a subarray called DeepCore which has a much denser spacing between modules than the rest of the array [2]. The dense spacing allows DeepCore to detect events at much lower energies compared to the rest of IceCube, even down to a few GeV. The main physics goal of DeepCore is to measure neutrino flavor oscillations using atmospheric muon neutrinos which travel through the Earth and oscillate to tau neutrinos. This has been measured previously in DeepCore in [3, 4]. For Earth-crossing muon neutrinos, this oscillation maximum occurs at $E \sim 25$ GeV. Measuring this deficit of muon neutrinos due to oscillations requires accurate identification of muon neutrino events.

2 Event signatures in IceCube DeepCore

The neutrino interactions we observe are deep inelastic scattering (DIS) off atomic nuclei, and occur as either neutral current (NC) interactions in which the outgoing particle is a neutrino, or as charged current (CC) interactions in which the outgoing particle is a charged lepton. DIS dissociates the nucleus, producing a hadronic shower with a cascade-like signature at the interaction vertex for all events. For NC events, this is the only visible light. For ν_e^{CC} events, the outgoing e induces an electromagnetic shower which cannot be resolved from the hadronic shower at the interaction vertex, so this also appears as a single cascade. For ν_τ^{CC} events, the outgoing τ produces a shower when it decays, although this also appears as a single cascade in DeepCore because the tau decay length at these energies is $\mathcal{O}$ (mm). The outgoing μ in ν_μ^{CC} events leaves a long track which can extend beyond the cascade at the interaction vertex if the μ has enough energy. A small fraction of track events are due to ν_τ^{CC} events in which the outgoing tau decays into a muon. Schematics of these various event signatures can be seen in figure 1. To summarize, all events contain a cascade portion and events with outgoing muons contain both track and cascade components. To simplify notation, we will henceforth refer to cascade-only events as *true cascades* and cascade + track events as *true tracks*. Distinguishing these event types is difficult at low energies due to the low

signal present per event. Sample event displays comparing a high energy event in IceCube and a low energy event in DeepCore are shown in figure 2.

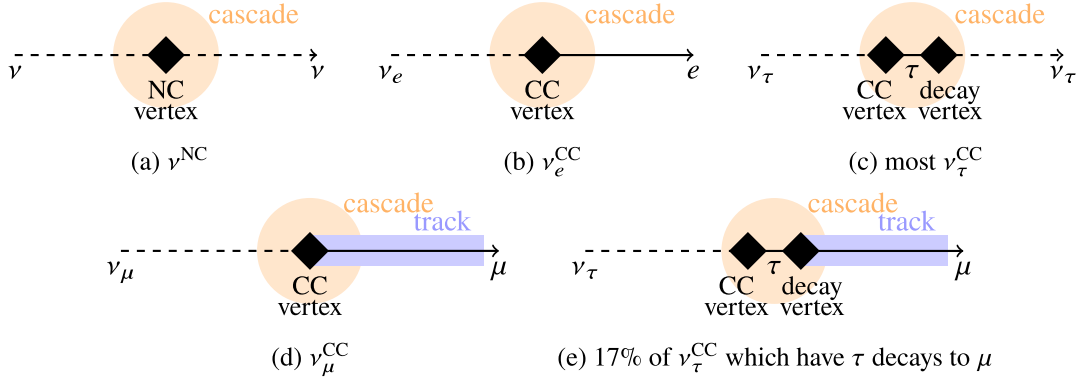


Figure 1. Sketch of event signatures (not to scale).

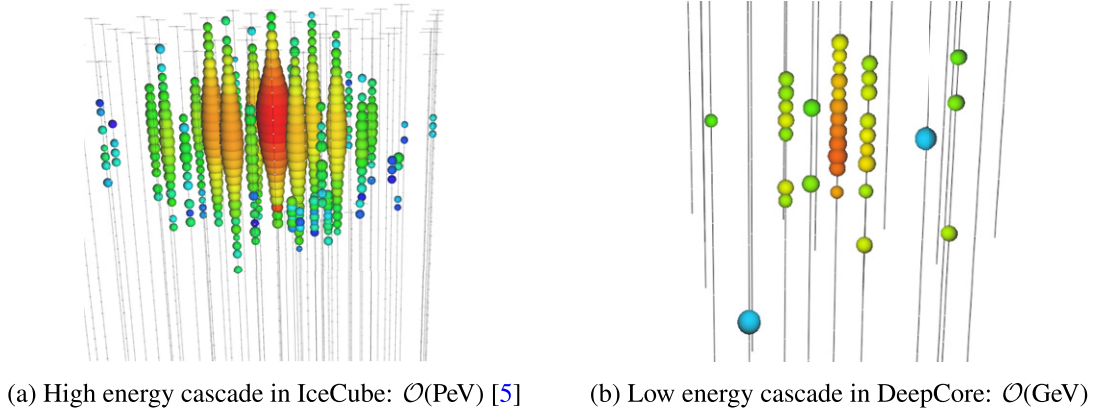


Figure 2. Sample event displays for cascades at high and low energies.

3 Event classification using a boosted decision tree

Events are reconstructed using a cascade + track hypothesis with 8 parameters: the interaction vertex (x, y, z, t) , the direction of the incoming neutrino (zenith θ and azimuth ϕ), the amount of visible energy in the cascade E_{cascade} , and the length of the track component L_{track} . Event classification uses reconstructed parameters to determine whether events are cascade-like or track-like.

There are two main methods that have been used previously in DeepCore to perform event classification. One method used in [4] is to simply use the reconstructed track length L_{track} where events with $L_{\text{track}} > 50$ m are labeled tracks and $L_{\text{track}} < 50$ m are cascades. A second method used

in [3, 4] is based on the difference in log-likelihood, ΔLLH , between the best-fit reconstruction and a reconstruction in which the track length has been fixed to zero. This comparison between the cascade + track hypothesis and a cascade-only hypothesis allows us to quantify the importance of the track component in describing the event well; if the fit gets significantly worse by removing the track portion, then the event is likely a track, and if the LLH remains almost unchanged after eliminating the track component, then the event is likely a cascade.

The event classification technique used in current state-of-the-art analyses expands on these previous methods and introduces machine learning for the first time into IceCube DeepCore event classification. This method uses a boosted decision tree (BDT) with the XGBoost algorithm [6]. The following reconstructed quantities are used as input features to the BDT:

- L_{track} : A long reconstructed track likely indicates the presence of a muon in the event.
- E_{cascade} : An estimate of how much light is in the cascade portion of the event.
- $\Delta\text{LLH} = \ln \mathcal{L}_{\text{cascade+track}} - \ln \mathcal{L}_{\text{cascade-only}}$: Log-likelihood difference between the full reconstruction and a cascade-only hypothesis in which $L_{\text{track}} = 0$.
- Zenith: Because of the geometry of the detector, tracks that are nearly up-going or down-going are easier to identify than horizontal ones. (The spacing between adjacent DOMs in the vertical direction is much smaller than in the x - y direction.)
- Zenith spread: This quantity is calculated from the distribution of points traversed by the minimizer before convergence. Tracks are typically associated with better pointing resolution due to their longer lever arm, so events with a smaller zenith spread are often more track-like.

The classifier is trained on a cleaned Monte Carlo sample containing only ν_{μ}^{CC} and ν_e^{CC} events with energies of 5–500 GeV. Events are weighted according to the Honda flux [7] with an unoscillated spectrum to avoid introducing any artificial dependence on the oscillation parameters when this method is later used for oscillation analyses. Sample balancing is performed for the relative contributions between flavors so equal weight is given to tracks and cascades during training. The cleaned sample is divided and 50% of events are used for training, and 50% for testing the model.

The output score of the BDT is a number between 0 and 1 indicating how track-like an event is, with 1 being the most track-like. Figure 3 shows the distribution of classifier scores for true tracks and cascades, separated by training and testing samples. The training and testing distributions are virtually indistinguishable, which indicates no overfitting. As we expect, there is a peak at 1 in the track distribution and the cascades dominate at the lowest scores, but in the middle is a region of confusion. The events in the confusion region tend to be the lowest energy events with very few hits in the detector. With such little information, the two event types become indistinguishable and this degeneracy results in the BDT never being able to assign with certainty an event as a cascade (score near 0) and instead gives an intermediate score peaking near 0.4. Different analyses may place the threshold cut at different values, in order to optimize the sensitivity for each analysis. For an example threshold of 0.5, everything below the threshold is labeled a cascade and everything above is labeled a track. We can use this sample cut to evaluate the performance of the classifier as a function of energy; see figure 4. We find that at the lowest energies almost everything is classified as a cascade and at the highest energies, the vast majority of events are classified correctly.

For the analysis measuring atmospheric neutrino flavor oscillations mentioned in section 1, we find that the greatest sensitivity occurs when using 3 bins with cuts placed at 0.5 and 0.85, rather than only 2 bins. This results in a mixed bin, a low purity track bin, and a high purity track bin, with track purities of 53%, 72%, and 97% respectively. The third extremely pure ν_μ^{CC} bin provides improved sensitivity to the physics parameters of interest, reducing the widths of the 90% uncertainty contours by about 10–15% for $\sin^2(\theta_{23})$ and Δm_{32}^2 , compared to only using two bins.

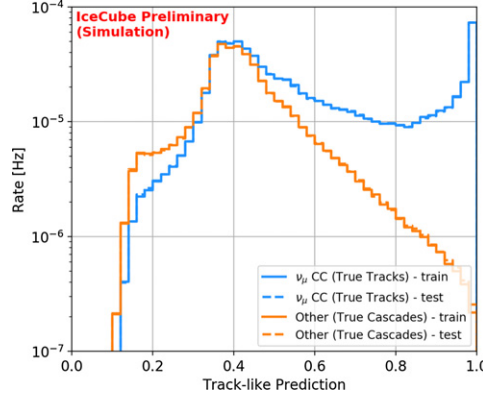


Figure 3. Distribution of PID scores for tracks and cascades.

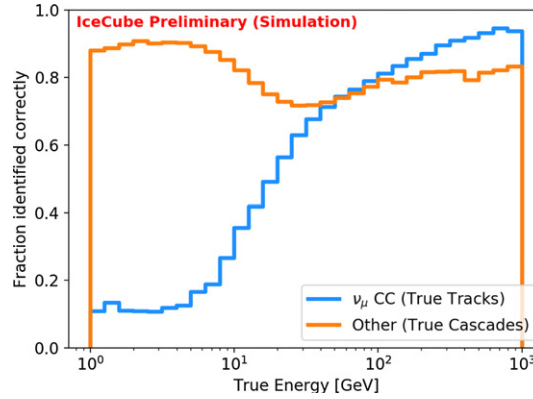


Figure 4. Fraction of events classified correctly as a function of energy.

4 Summary and outlook

This new classification technique for distinguishing low energy tracks and cascades in IceCube DeepCore expands on previous methods and introduces machine learning methods for the first time. A boosted decision tree is trained to identify track-like events. We find that the ability to identify tracks correctly depends highly on the true energy of the event. This method is being

used in a forthcoming data sample of 8 years of IceCube DeepCore data designed to measure atmospheric neutrino oscillations. In the near future, additional efforts are underway to expand the use of machine learning in IceCube DeepCore, with future methods using neural networks to perform reconstruction and event classification [8, 9]. Looking beyond DeepCore, low energy event classification will greatly improve with the IceCube Upgrade — a seven string infill within DeepCore. The increased module density of the Upgrade will result in more hits per event and provide a greater level of detail than we have with DeepCore alone.

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