Closing Report (02/2006 – 01/2007)
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MiniBooNE Neutrino Physics at The University of Alabama

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This report summarizes the activities conducted by the UA group under the auspices of the DoE/EPSCoR grant number DE–FG02–04ER46112 since the date of the previous progress report, i.e., since November 2005. It also provides a final report of the accomplishments achieved during the entire period of this grant (February 2004 to January 2007). The grant has fully supported the work of Dr. Yong Liu (postdoctoral research assistant – in residence at Fermilab) on the MiniBooNE reconstruction and particle identification (PID) algorithms.

Briefly, the MiniBooNE (E–898) experiment at the Fermi National Accelerator Laboratory is a direct search for neutrino oscillations, looking for the ν_e appearance in a ν_μ beam. The ν_e presence in the detector is evidenced by the detection of an isolated electron in the tank's fiducial volume, via (primarily) the charged-current reaction $\nu_e C \rightarrow e^- X$. Particle identification plays a crucial role in determining the experiment's sensitivity to neutrino oscillations, as it dictates the level at which the potential signal (the electrons) can be extracted from the background muons and neutral pions generated by the overwhelming ν_μ flux through charged- and neutral-current reactions on the carbon atoms of the mineral oil. The UA group has been responsible for both particle reconstruction and identification within the MiniBooNE experiment. The PI has concentrated mainly on the reconstruction, whereas Dr. Liu has worked mainly on the PID.

The major effort of this group during the last year has been concentrating on the PID algorithms, while the reconstruction has remained relatively stable. During this period of time there have been three significant changes to the underlying MiniBooNE simulations package, in December 2005, April 2006, and May 2006. After each release, a significant amount of time has been spent by this group in retuning the reconstruction software and retraining the PID algorithms. Dr. Liu's work has contributed to continuously increasing the performance of the PID algorithms, first by transitioning from artificial neural networks (ANNs) to boosted decision trees (BDTs), as reported in Ref. [1], and second by developing a novel training method for pattern recognition methods, the cascade training technique, as reported in Ref. [2]. The reconstruction and particle identification software developed by this group have formed the basis of the first physics publication by the MiniBooNE collaboration, as reported in Ref. [3]. Now that the first neutrino oscillations analysis has been completed, the collaboration is focusing on other physics analyses, and several papers are expected to be finalized before the end of the year.

Dr. Liu's work has been essential to achieving a sensitivity to neutrino oscillations which surpassed the original design parameters of this experiment, despite the fact that the beam-induced backgrounds have been higher than anticipated, and the fact that the experiment received a lower amount of protons on target as originally requested. During his detailed studies of the boosted decision trees and systematic effort of improving their performance we have learned a lot regarding this novel and powerful pattern recognition method. In particular, it was believed that because of the fact that most of the underlying input variables depend strongly on both event energy and event location/direction in the MiniBooNE detector, explicitly adding one of these parameters to the list of BDT inputs, their performance would improve. As explicitly shown in

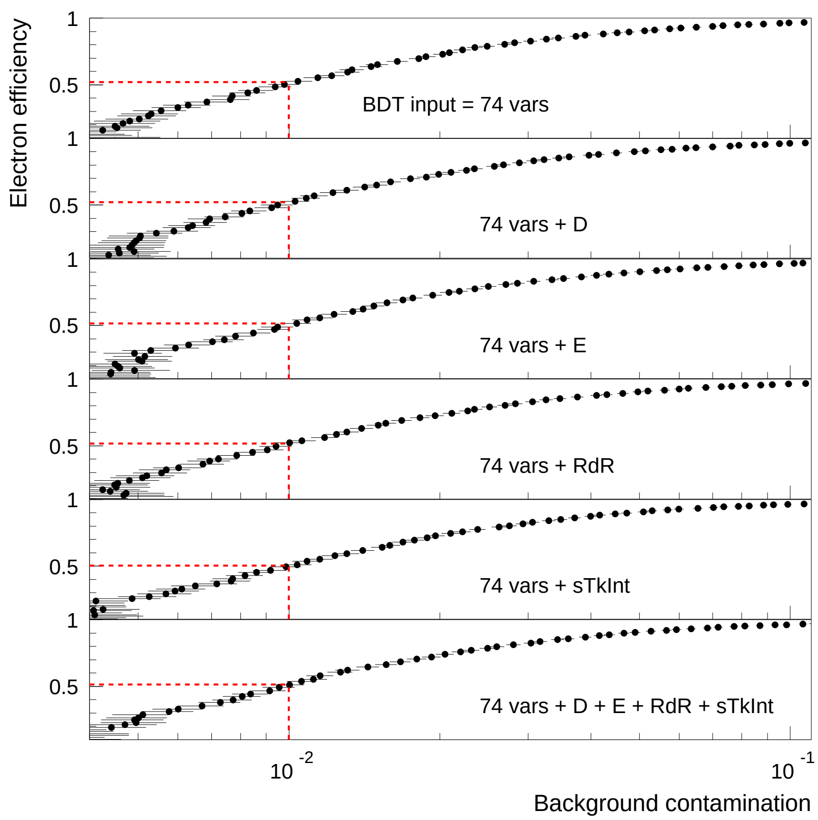

Figure 1: BDT performance with and without energy/geometrical inputs.

Fig. 1, Dr. Liu has demonstrated that the boosted decision trees are intelligent enough to learn the differences induced by energy and geometrical effects directly from the input variables, while their explicit addition does not improve the overall performance of the BDTs. The same conclusion has been reached while training the algorithms in different energy or geometrical bins, as shown in Figs. 2 and 3, respectively. Here RdR

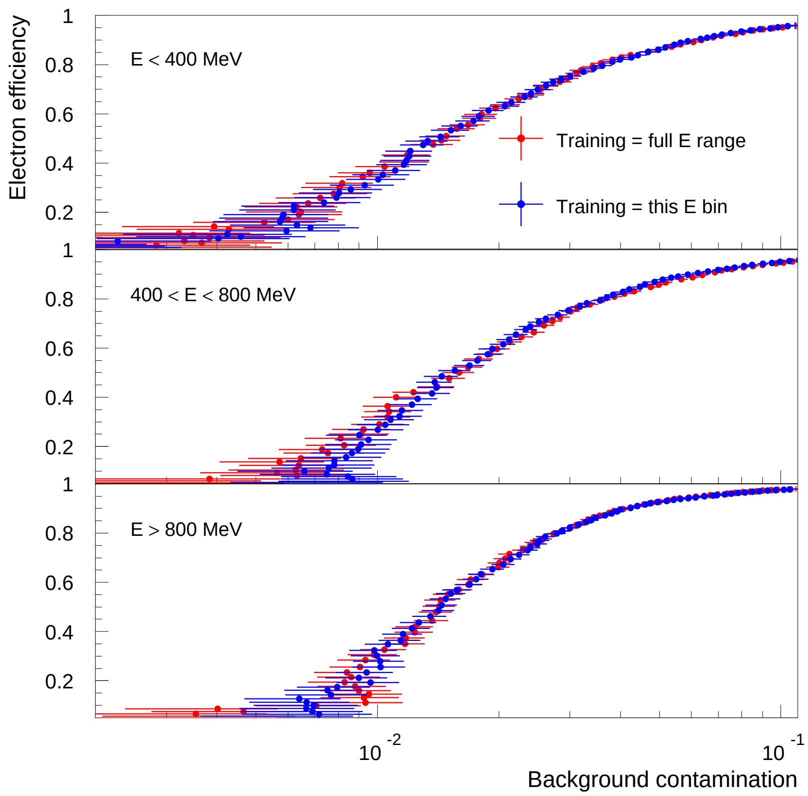

Figure 2: BDT performance trained over the entire energy range as compared to specific energy bins, as labeled.

quantifies the event location and orientation in the MiniBooNE detector, and is just the scalar product between the event position vector and its reconstructed direction.

In further studies Dr. Liu has investigated the performance of a single BDT trained on the entire beam-induced background "cocktail" as the background sample, as compared to a combination of BDTs which were trained each on a specific background only, such as μ-only, or π-only, etc. The conclusion of this lengthy exercise was that the training on the "all-background" sample performed equally well as the combination trained on the individual backgrounds. Nonetheless, these latter algorithms have proven quite useful in other physics analyses than neutrino oscillations.

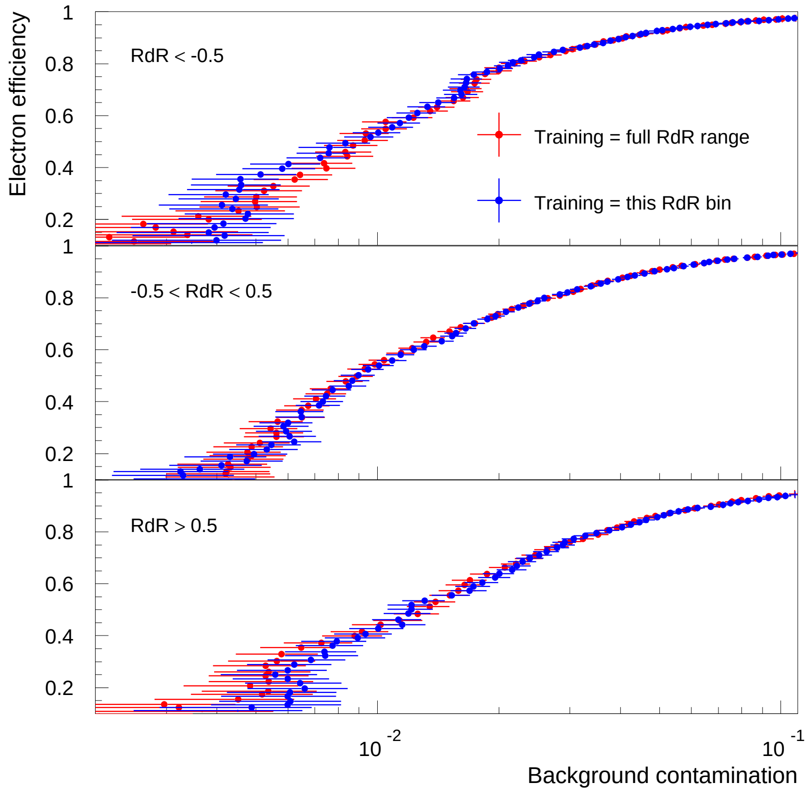

Figure 3: BDT performance trained over the entire RdR range as compared to specific RdR bins, as labeled.

References

[1] B. P. Roe, H. J. Yang, J. Zhu, Y. Liu, I. Stancu, and G. McGregor, *"Boosted Decision Trees as an Alternative to Artificial Neural Networks for Particle Identification"*, Nucl. Inst. Methods **A543**, 577–584 (2005).

[2] Y. Liu and I. Stancu, *"Cascade Training Technique for Particle Identification"*, to appear in Nucl. Inst. Methods.

[3] A. A. Aguilar-Arevalo *et al.* (MiniBooNE Collaboration), *"Search for Electron Neutrino Appearance at the $\Delta m^2 \sim 1\, eV^2$ Scale"*, submitted to Phys. Rev. Letters.

In conclusion, the support of Dr. Liu's work has been of essence to MiniBooNE achieving the desired neutrino oscillations sensitivity, has lead to finalizing the experiment's first neutrino oscillations analysis and paper, and has lead to the development of a new training technique in pattern recognition algorithms, which applies not only to boosted decision trees, but to a large class of other methods.
