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Eliminating Cosmic Ray Backgrounds for SBND's sub-GeV Dark Matter Search

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Light Dark Matter at SBND

In late Fall 2023 the SBND (Short-Baseline Near Detector) experiment on the Booster Neutrino Beam (BNB) at Fermilab will begin taking data. Fixed-target neutrino experiments can be used to probe the sub-GeV Dark Matter (DM) spectrum.[1] Due to SBND's proximity to the beam target, it will have access to very high statistics, including DM particles produced in the beam. DM scattering events are simulated using the BdNMC event generator.[2] The DM events simulated in SBND are subsequently reconstructed using the Pandora pattern recognition suite of algorithms. In this work we focus on DM-e neutral current (NC) elastic scattering with no other hadronic behavior at the vertex.

Fig. 1

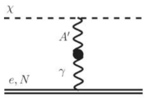


Fig. 2

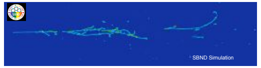
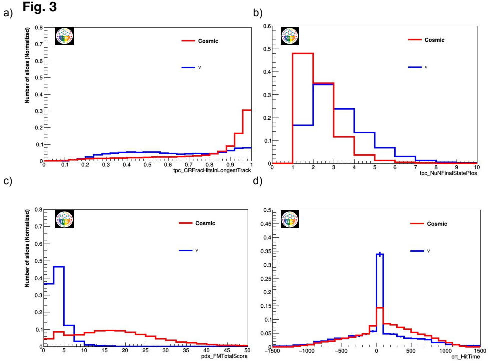


Fig. 1: NC elastic scattering of a theoretical DM particle χ, and an electron or nucleon. The χ particle emits a single dark photon A′ while the SM particle emits a standard photon.

Fig. 2: A simulated DM-e elastic scattering event, appearing as a 'shower-like' object, as we would expect.

We use GENIE generated neutrino event data instead of DM events. We have observed similar behaviors between DM and neutrino events, however, a more rigorous analysis will soon be conducted with DM events.

Fig. 3



CRUMBS Tool for DM Analysis

For DM analysis, a challenge of using a neutrino detector that is on the surface is that we expect a large steady flux of cosmic rays as well as ν-e scattering, among other sources of background. CRUMBS (Cosmic Rejection Using Multi-system BDT Score) is a multivariate based analysis tool, which was developed by H. Lay to select ν_μ charged current events on SBND.[3] CRUMBS successfully combines the three subsystems of SBND: the Photon Detection System, the Time Projection Chamber, and Cosmic Ray Tracker. We input a total of 18 geometric, temporal, and statistical variables from all three systems measured in slices. A slice is a collection of distinct reconstructed objects that are associated to the same interaction. The variables are input simultaneously into a Boosted Decision Tree (BDT), which has proven to give a better background elimination efficiency than previous methods. We implement the use of CRUMBS to differentiate between DM-e-like and cosmic events.

Fig. 3: Four CRUMBS displaying DM-like (blue) and cosmic (red) slices. a) fraction of slice's space-points in the longest track; b) the variable outputs the number of particle flow objects (tracks, showers) within a slice; c) slice's flash match score (this encodes how strong the match was, and whether the associated time sits in the beam window); d) the hit time variable computes the associated time between two matched hits on perpendicular tagger planes.

Fig. 4

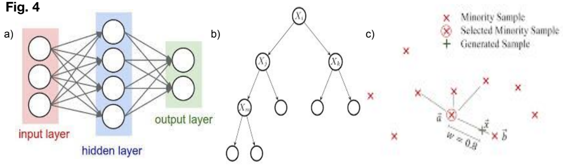


Fig. 4: Architectures of the a) Neural Network (NN), b) BDT, and c) the Synthetic Minority Oversampling Technique (SMOTE) algorithm.[4] The NN is built from four fully-connected layers and uses backpropagation gradient descent to minimize the loss function. Two dropout layers are added to prevent from overfitting and two batch normalizations are made in order to help the model better process the data. The BDT is made using the XGBoost algorithm, which branches out for each decision to a total of 20 trees, each tree learning from the previous ones. The SMOTE algorithm helps avoid pitfalls with an unbalanced data set by generating new DM-like data points, without significantly changing the p-value of the data. New data is generated by convex combination between adjacent data points.

Machine Learning to Eliminate the Cosmic Background

We next implement two models in order to differentiate between the cosmic and DM slices. We build both a traditional BDT, which was used in the original CRUMBS analysis and a more sophisticated nonlinear Neural Network (NN). Both were trained separately on distinctly optimized parameters to perform binary classification between the two types of models. We train both models on 20 epochs and use a 0.35 learning rate for the BDT, compared to a learning rate of 0.001 for the NN.

We use the Binary Cross-Entropy (BCE) loss function for both models,

$$BCE = -\frac{1}{N}\sum_{i=0}^{N} y_i \log(\hat{y}_i) + (1 - y_i) - \log(1 - \hat{y}_i).$$

where N is the number of inputs, y_i is the binary label of an input and $\hat{y}_i$ is the algorithm's probability prediction between 0 and 1.[5] We compare the testing accuracy scores of both models, finding average accuracies of 99.35% for the BDT and 99.40% for the NN.

Var. Name	Importance
fmtotscore	0.45
eigenratio	0.22
fhlt	0.06

Table 1: Top three most important CRUMBS variables as ranked by the BDT, where the maximum feature importance score is one. These were the most useful for background removal. The variables represent (top to bottom) slice's flash match score (this encodes how strong the match was, and whether the associated time sits in the beam window); ratio between the top two eigenvalues of principal component analysis performed on the space-points within 10 cm of the vertex fraction of slice's space-points in the longest track.

Fig. 5

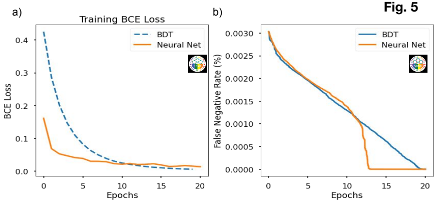


Fig. 5: We compare two key statistics of the NN (blue) and BDT (orange): a) the BCE training loss over 20 epochs and b) the false negative rate computed over the course of training both models on 20 epochs. The false negative rate is the ratio of DM-like slices that are counted as cosmic slices with respect to the total number of DM-like slices.

Conclusions

We find that the CRUMBS tool is useful for eliminating cosmic background from DM-like events on SBND simulations. We also find that both the BDT and NN have high efficiencies, above 99%, and are able to eliminate False-Negative predictions which would harm further analysis due to the low beyond SM statistics in real data. Further work can build on this by adding using DM-e scattering simulations instead of SM events and extending the analysis to ν-e scattering and other Standard Model neutrino-induced backgrounds.

Acknowledgements & Sources

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