Test towards a new training of the track/shower BTD algorithm in Pandora

Mattia Sotgia*, Alice Campani** (University of Genoa and INFN), Angela Fava (FNAL) Midterm internship report (Aug. 23rd, 2024)

Fermilab



Event reconstruction in LArTPCs: ICARUS event reconstruction chain

ICARUS analysis is performed trough a chain of subsequent algorithms, performing all the steps from clustering of hits (portions of waveforms with a signal) in 3D to reconstructing the event hierarchy.

From the **Hits** of the single wires, the **2D reconstruction** for each wire plane is performed, and then the **3D Clusters** are made. These then are used as inputs for two different reconstruction algorithms.



Event reconstruction in LArTPCs: ICARUS event reconstruction chain

ICARUS implements the Pandora-based reconstruction algorithm

• Based on *clusters, slices* (reconstructed interactions, i.e. groups of particles linked with the same interaction) and pattern recognition

There are two main stages of the reconstruction

• **PandoraCosmic** (stage 0) where the cosmic-like hits are clustered from the 2D hits and are separated from the Event

Track (p), daughter of primary p

• **PandoraNu** (stage 1) where the reconstruction of the ν candidates happen

Track (p), primary daughter of v_{μ}

Parent ν_{μ} interaction vertex

Reco PFP Shower (e^+), daughter of primary π^+ Track (π^+) , primary daughter of ν_{μ}

Track (μ), primary daughter of ν_{μ}

Boosted Decision Trees (BDTs) are used **1.** in candidate ν /cosmic selection, **2.** in finding the true interaction vertex and 3. in the track/shower discrimination







Track/shower discrimination BDT: testing a new dataset

- The third BTD algorithm is the one responsible for the shower/track discrimination
- The BDT algorithm was last trained on a previous version of the code (with a BNB ν -only sample). This outperformed the precedent training (SBND MC sample), with a classification efficiency of ~80 %.
 - Good performance with track like particles (p, π^{\pm}, μ^{-})
 - A slight decrease in performance for shower like particles (e^-, γ, π^0)

See <u>SBN-doc-34318-v2</u> for further details

- A new MC dataset from the ICARUS ML working group was made also available
 - Less biased than a BNB/NuMI beam simulation, since particles are not generated from the BNB beam but with a uniform energy distribution (no dependence on the signal model)
- In this talk we compare two samples, BNB (ν -only) and the ML sample (ν + cosmic), with the aim of finding the most suitable to perform a re-training of the BDT algorithm.







Comparing the BNB MC and ML MPVMPR MC datasets Charge end fraction

- The distributions are more peaked in the ML sample than those in the BNB sample, though the separation is actually similar.
- The overall shape is more 'Gaussian-like', as no weird features are visible in the ML data sample.





Comparing the BNB MC and ML MPVMPR MC datasets Linear fit RMS

- A greater number of shower like events in the MPVMPR sample
- like particles



• Fewer contaminations of shower like particles in the area populated mostly by track



Comparing the BNB MC and ML MPVMPR MC datasets BDT Track Score

- Showing greater separation (although this variable is actually the output of the previous training on both samples and needs to be evaluated after the re-training)
- Overall with the current training of the algorithm the MLM MPVMPR sample is promising





- The ML MPVMPR sample has shown greater discrimination power in some BDT variables
- - The track/shower ratio is lower than the BNB MC sample ratio_{MPVMPR} = $\frac{\text{#track-like}}{\text{#shower-like}} \Big|_{\text{MPVMPR}} \simeq \frac{9052}{6978} \simeq 1.3$ $\frac{\text{\#track-like}}{\text{\#shower-like}} \Big|_{\text{BNB}} \simeq \frac{64972}{704} \simeq 92.3$ instead of ratio_{BNB} = \cdot
 - count of the BNB MC
 - roughly 200 000 tracks and 150 000 showers per cryostat

The ML MPVMPR sample has also a better balance between track-like and shower-like particles contribution

The MPVMPR sample analyzed consist of 325535 events, which is overall lower in respect to the event

In the view of the training a new MC sample with larger statistic has been produced. The sample contains



- A new training will be performed with all the BDT variables, with the ML MPVMPR sample
- Some of the variables showed a less than acceptable discrimination power
 - Vertex distance
 - Conicalness
 - Concentration
 - Halo total ratio
 - Linear fit length



Testing to be done on the BNB sample

A new training will be also performed without these 5 variables



Thank you for the attention!

Test towards a new training of the track/shower **BTD** algorithm in Pandora

Mattia Sotgia, Alice Campani (University of Genoa and INFN), Angela Fava (FNAL) ICARUS ML Working Group meeting (Aug. 21st, 2024)

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Backup Slides

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Backup 1: **Definition of hit purity and completeness**

Compare MC particles and reconstructed PFPs (Particle Flow Particles, Pandora Objects)

Definitions

Matched hits \equiv hits_{MC} particle \cap hits_{reco} pfp-

For the example on the side Matched hits_{*i*} \rightarrow 6 and Matched hits_{*k*} \rightarrow 2

$$\begin{aligned} \mathbf{Purity} &\equiv \frac{\mathsf{hits}_{\mathsf{MC}} \; \mathsf{particle} \cap \mathsf{hits}_{\mathsf{reco}} \; \mathsf{pfp}}{\mathsf{hits}_{\mathsf{reco}} \; \mathsf{pfp}} \\ \mathsf{For the example on the side Purity}_{j} &\to \frac{6}{9} \simeq 67 \; \% \; \text{ and Purity}_{k} \to \frac{2}{9} \simeq 22 \; \% \\ \mathbf{Completeness} &\equiv \frac{\mathsf{hits}_{\mathsf{MC}} \; \mathsf{particle} \cap \mathsf{hits}_{\mathsf{reco}} \; \mathsf{pfp}}{\mathsf{hits}_{\mathsf{MC}} \; \mathsf{particle}} \\ \mathsf{For the example on the side Completeness}_{j} \to \frac{6}{9} \simeq 67 \; \% \; \mathsf{and} \\ \mathsf{Completeness}_{k} \to \frac{2}{2} \simeq 100 \; \% \end{aligned}$$





Reconstructed track Hits with match in particle j Hits with match in particle k MC hits in particle j MC hits in particle k



Backup 2: The Boosted Decision Tree algorithm



BDT variables: charge variables and cone charge variables

The current version of the BDT track/shower algorithm implements 13 variables (hyper parameters) to perform the cuts of the decision tree

All the BDT charge variables are computed on the Hits of the induction 1 wire plane. The other make use of the full 3D information from the reconstructed PFFs.

The first two are the 'charge-based variables'.

- pfp.
- whereas showers are expected in > 1.

1. Charge end fraction (BDT.chendfrac), defined as the ratio of the deposited charge in the last 10% of the PFP hits, over the total deposited charge. Tracks are expected to have a more uniform charge distribution than showers. For this variable the expected values are in the range [0, 1]. Smaller values mean a less uniform charge distribution trough the length of the

2. Charge fraction spread (BDT.chfracspread), defined as the ratio of the variance of the deposited charge of the hits to the deposited charge mean value. Showers are expected to have a more spread variety of charge related to the hits. It is a ratio but it is not normalized (i.e. the range is not in [0, 1]). The binning is chosen to be in [0, 2.5]. Tracks are expected in < 1,



BDT variables: charge variables and cone charge variables

The last update of the BDT algorithm introduced three new variables, called 'cone charge variables' Defining the chargeCore (the hits inside the 20% of the direction of the primary eigenvector) and

Defining the chargeCore (the hits inside the 20% chargeHalo (hits beyond the 20% threshold)

3. Concentration (BDT.concentration), defined as

Values are expected in the range [0, 100]

4. Halo total ratio (BDT.halototratio), defined as -

is the sum of the Hits inside the cone. It being a ratio, the values are expected in the range [0, 1].

5. Conicalness (BDT.conicalness), defined as

Its values are expected in the range [0, 600].





BDT variables: linear and geometrical variables

There are also the linear variables

- smaller.
- [0, 0.15] [arb. U.] both for showers and tracks.
- is in the centimeters, so the range is [0, 0.5] cm.
- showers are expected in [~1, ~5].

6. Linear fit length (BDT.linfitlen), defined as the length of the reco particle. The long tracks (μ, π^{\pm}) can be some ~1 m, protons are usually shorter and showers are

7. Linear fit difference (BDT.linfitdiff), defined as the difference in linearity variation, between the end and the start point. This is expected to be quite small, in the range

8. Linear fit gap length (BDT.linfitgaplen), defined as the gap between the hits on the linear fit. Tracks are expected to have smaller gap length. The common gap length

9. Linear fit RMS (BDT.linfitrms), defined as the RMS of the fit. Tracks are expected to have smaller RMS. The binning is in [0, 5], tracks are expected in [0, ~1], and



BDT variables: linear and geometrical variables

And also the geometrical parameters

- events which were otherwise not included.

angle between the two eigenvectors. The chosen range is in $[0, \sim 35]$ deg, but most events are to be expected in the [0, 20] deg range.

10. Distance from vertex (to BDT.vtxdist), defined as the distance from the reconstructed vertex and its closest hit. This is usually very short for tracks and normally the distance of an electromagnetic shower from the reconstructed interaction vertex is greater. The range is chosen [0, 200] cm to account for

12. PCA2 ratio (BDT.pca2ratio), defined as the ratio of the eigenvalue v_2 over the eigenvalue v_1 obtained from the Principal Component Analysis (PCA) algorithm, describing the orientation of the hits in space.

13. PCA3 ratio (BDT.pca3ratio), defines as the ration of the third eigenvalue over the first. It is expected to be a good variable, being shower more tridimensional than tracks, since this value highlight the 3D aspect of the cluster, along with the PCA2 ratio. The chosen range is to get all the events plotted.

14. Opening angle difference (BDT.openanglediff), defined as $\tan^{-1} \left(\sqrt{PCA2} \sin \theta \right)$, where θ is the



The datasets: MC fractional population of shower- and track-like particles

The simulations were made for the BNB dataset and for the MPVMPR dataset with the particle composition shown on the top right

Two datasets:

- **BNB MC** created for the study on Central Value (CV) systematics for ulletNeutrino 2024 icaruspro_production_v09_89_01_01_2024A_ICARUS_MC_CV_Sys_2024 A_MC_CV_Sys_flatcaf
- **MPVMPR MC** samples, produced by the ICARUS ML WG acampani_training_caf_default_v09_89_01_01_mpvmpr

BNB sample is ν -only, whereas ML MPVMPR (Multi Particle Vertex, Multi Particle Rain) is ν + cosmic.

A cut (wellRecoCut) is applied to only select well reconstructed particles, which have *hit completeness* and *purity* above 80% (more of their definition) is in backup). This avoids biasing the result of the comparison with other mis-reconstruction effects, such as clustering issues, track-splitting, ...

Shower-like

Track-like

noSpillCut						
	BNB (total 213512)		MPVMPR (total 66331)			
	Fraction	(events)	Fraction	(events)		
protons	0.527	(112594)	0.429	(28455)		
charged_pi	0.121	(25925)	0.223	(14822)		
muons	0.237	(50707)	0.018	(1221)		
electrons	0.003	(610)	0.092	(6074)		
photons	0.111	(23676)	0.238	(15759)		

wellRecoCut						
	BNB (total 65676)		MPVMPR (total 16030)			
	Fraction	(events)	Fraction	(events)		
protons	0.391	(25704)	0.377	(6050)		
charged_pi	0.073	(4807)	0.153	(2450)		
muons	0.525	(34461)	0.034	(552)		
electrons	0.005	(313)	0.119	(1911)		
photons	0.006	(391)	0.316	(5067)		

SBN-doc-34318-v2

둘 <u>Neutrino 2024</u>

ML sample update SBN-doc-35469-v1





BNB data: Plot of BDT_{var} comparing the distributions for shower/track like particles

Comparing track like (p, π^{\pm}, μ^{-}) and shower like (e^{-}, γ) particles



BNB data sample (samweb definition icaruspro_production_v09_89_01_01_2024A_ICARUS_MC_CV_Sys_2024A_MC_CV_Sys_flatcaf)



MPVMPR data: Plot of BDT_{var} comparing the distributions for shower/track like particles

Comparing track like (p, π^{\pm}, μ^{-}) and shower like (e^{-}, γ) particles



MPVMPR data sample (samweb definition acampani_training_caf_default_v09_89_01_01_mpvmpr)





Comparing the BNB MC and ML MPVMPR MC datasets Charge fraction spread

two population arises



• With a larger statistics in the ML sample a better separation between the



Comparing the BNB MC and ML MPVMPR MC datasets Linear fit gap length

two population arises



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Comparing the BNB MC and ML MPVMPR MC datasets PCA2 ratio and PCA3 ratio

- No major difference is evident, but overall the shape has changed a bit, especially for the PCA3 ratio
- Plots are in logY scale.
- Still interesting for the possibility of a joint cut alongside another variable.

2D plots are work in progress





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Training to be done on the BNB sample



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Training to be done on the BNB sample





Generation of the ML MPVMPR data sample ML MPVMPR Working Group

The MC sample data is generated with the Multi Particle Vertex Multi Particle Rain module in <u>sbncode/EventGenerator/Multipart/</u> gen mpvmpr.fcl

The data is in the samweb definition icaruspro_production_2024A_MPVMPR_MC_v09_89_01_01_stage1

It is generated in three steps

- - The energy range is taken from the expected energies in the BNB
 - BNB is 1.6 µs)
- the kind of cosmic we could see.
 - Generated in time (during the beam spill)
 - Generated in a larger volume than the TPC fiducial (+20 cm each direction)
- kind of cosmic we could see.
 - Generated out of time (not during the beam spill)
 - Generated in a smaller volume than the TPC fiducial (-20 cm each direction)

Further details in <u>ML sample SBN-doc-35469-v1</u>

1. One Multi-Particle Vertex is generated, random number (with a flat distribution) of particles sampled from a uniform energy distribution

- The beam spill is set similar, but slightly longer than NuMI, so MPV are generated in the [0, 10] µs range (NuMI is 9.5 µs, whereas

2. A random number (flat distribution in [3, 5]) of single particles sampled from different energy distribution is generated (rain2), covering

3. A random number (flat distribution in [2, 4]) of single particles sampled from different energy distribution is generated (rain), covering the



Comparing the BNB MC and ML MPVMPR MC datasets Linear fit difference

 Not so much improvement, it shows in both cases a potential discrimination power



