## Track vs. Shower Identification Improvements using ML in Pandora

Mousam Rai 6th Jan 2020 / DUNE FD Sim-Reco Meeting / Supervisor - Dr John Marshall

DEEP UNDERGROUND NEUTRINO EXPERIMENT

## Roadmap for this presentation

- Aim
- Variables
- Current and Proposed approach to track/shower ID in Pandora for DUNE FD
- Performance plots for proposed implementation
- Summary/Future Works


## Aim

- Take particles reconstructed by Pandora and tag them as "track-like" or "shower-like"


## Variables

- MicroBooNE variables $\rightarrow 8$ Topological and 2 Calorimetric variables
- Additional variables $\rightarrow 3$ Hierarchy variables



## Distributions for selected variables


charge2 - Ratio of charge in the last $10 \%$ of the PFO and the mean charge in the collection plane

daughterParentNhitsRatio - 3D hits ratio between all downstream daughter pfos and parent pfo.

## Current and Proposed approach to track/shower ID in Pandora

- Current Implementation
- Basic cut flow approach
- MicroBooNE $\rightarrow$ Support Vector Machine approach
- Looking to implement similar ML approach for DUNE FD
- Proposed Implementation
- Boosted Decision Tree approach using SciKit-Learn which Pandora supports
- 13 variables
- Training $\rightarrow 50 \%$ numu and 50\% nue DUNE FD 1X2X6 MCC11 samples, completeness and purity $\geq 80 \%$, fiducial volume cuts
- Testing $\rightarrow$ 50\% numu and 50\% nue DUNE FD 1X2X6 MCC11 samples, no completeness and purity cuts, no fiducial volume cuts


## SKLearn BDT Distribution



## Efficiency Numbers

| Key $\quad \mathrm{T}=$ Tracks | S = Showers | TT = True Tracks |  | TS = True Showers |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| T/S Characterisation Approach | TT as T (\#Pfos) | TT as S (\#Pfos) | Efficiency (T only) | TS as S (\#Pfos) | TS as T (\#Pfos) | Efficiency (S only) | $\begin{aligned} & \text { Total } \\ & \text { (\#Pfos) } \end{aligned}$ | Efficiency <br> (All Pfos) |
| Cut Based Approach | 212900 | 100588 | $\begin{aligned} & 0.679 \pm \\ & 0.0008 \end{aligned}$ | 149980 | 13774 | $\begin{gathered} 0.916 \pm \\ 0.0007 \end{gathered}$ | 477242 | $\begin{aligned} & 0.760 \pm \\ & 0.0006 \end{aligned}$ |
| Root TMVA BDT | 283724 | 29764 | $\begin{gathered} 0.905 \pm \\ 0.0005 \end{gathered}$ | 128639 | 35115 | $\begin{gathered} 0.786 \pm \\ 0.0010 \end{gathered}$ | 477242 | $\begin{gathered} 0.864 \pm \\ 0.0005 \end{gathered}$ |
| SKLearn BDT | 290678 | 22810 | $\begin{aligned} & 0.927 \pm \\ & 0.0005 \end{aligned}$ | 120746 | 43008 | $\begin{gathered} 0.737 \pm \\ 0.0011 \end{gathered}$ | 477242 | $\begin{gathered} 0.862 \pm \\ 0.0005 \end{gathered}$ |

## Efficiency vs nHits



## Summary/Future Works

- Cut Flow $\rightarrow$ BDT approach (SKLearn)
- Significant Improvements
- Test on ProtoDUNE MC/data
- Use Andy Chappell's work
- Alan Turing Institute (mid-Jan 2020)
- Any questions or comments are deeply appreciated


## BACK UP SLIDES

the university of warwick

## Correlation Matrix for 13 variables

## Correlation Matrix (signal)

| laughterParentNhitsRatio | Linear correlation coefficients in \% |  |  |  |  |  |  |  |  |  |  |  |  | 100 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | -4 | 1 | 8 |  |  | 4 | 1 |  |  | 7 | 16 | 58 | 100 |  |
| nHilts3DDaughterTotal | -2 | -3 |  | 4 | -2 | 2 | 2 |  | 7 | -1 | 55 | 100 | 58 | 80 |
| nAllDaughter | 5 | -6 | -9 | 2 | -5 | -3 |  | -1 | 8 | -9 | 100 | 55 | 16 | 60 |
| charge2 | -46 | 14 | 46 | -4 |  | 10 | 1 | 3 | -5 | 100 | -9 | -1 | 7 | 40 |
| charge 1 | 1 | 14 | 4 | 16 |  | 15 | 12 | 8 | 100 | -5 | 8 | 7 |  |  |
| pca2 | -3 | 22 | 16 | 36 | 1 | 19 | 52 | 100 | 8 | 3 | -1 |  |  | 20 |
| pca1 | -4 | 32 | 15 | 47 | 4 | 28 | 100 | 52 | 12 | 1 |  | 2 | 1 | 0 |
| diffAngle | -9 | 31 | 22 | 27 | 7 | 100 | 28 | 19 | 15 | 10 | -3 | 2 | 4 | -20 |
| vertexDistance | 2 |  |  | 3 | 100 | 7 | 4 | 1 |  |  | -5 | -2 |  |  |
| rms |  | 21 | 12 | 100 | 3 | 27 | 47 | 36 | 16 | -4 | 2 | 4 |  | -40 |
| gap | -42 | 29 | 100 | 12 |  | 22 | 15 | 16 | 4 | 46 | -9 |  | 8 | -60 |
| diff | -23 | 100 | 29 | 21 |  | 31 | 32 | 22 | 14 | 14 | -6 | -3 | 1 | -80 |
| length | 100 | -23 | -42 |  | 2 | -9 | -4 | -3 | 1 | -46 | 5 | -2 | -4 |  |
|  | length alif |  | $9{ }^{\text {a }}$ | rms |  |  |  |  |  |  |  |  |  |  |

## Definition of the variables

- length - 3D length of the PFO
- diff - Mean difference between the position of the hits and a straight line, divided by the straight line length
- gap - Average max gap distance, divided by straight line length
- rms - Average root mean square of linear sliding fit, divided by straight line length
- vertexDistance - Distance between the PFO vertex and the primary vertex
- diffAngle - Difference between the opening and closing angles calculated over 50\% of the pfo closest and furthest from the vertex.
- pca1 - Ratio between the second largest and the largest PCA eigenvalue
- pca2 - Ratio between the third largest and the largest PCA eigenvalue
- charge1 - Ratio between sigmaCharge ((charge - meanCharge) ${ }^{2}$ ) and the mean charge in collection plane.
- charge 2 - Ratio of charge in the last $10 \%$ of the PFO and the mean charge in the collection plane
- nAllDaughter - total number of all downstream daughter pfos
- nHits3DDaughterTotal - total number of 3D hits in all downstream daughter pfos
- daughterParentNhitsRatio - 3D hits ratio between all downstream daughter pfos and parent pfo.


## T/S Distribution for Kinetic Energy



## T/S Distribution for nHits



