Graph Neural Network for τ identification

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Introduction

		τ Decay Mode	Branching Fraction (%)
Leptonic		$\tau^\pm \to e^\pm + \overline{\nu}_e + \nu_\tau$	17.84 ± 0.04
		$\tau^\pm \to \mu^\pm + \overline{\nu}_\mu + \nu_\tau$	17.41 ± 0.04
Hadronic	One-prong	$\tau^\pm \to \pi^\pm + (\geq 0\,\pi^0) + \nu_\tau$	49.46 ± 0.10
		$\tau^\pm \to \pi^\pm + \nu_\tau$	10.83 ± 0.06
		$\tau^\pm \to \rho^\pm(\to \pi^\pm + \pi^0) + \nu_\tau$	25.52 ± 0.09
		$\tau^\pm \to a_1(\to \pi^\pm + 2\pi^0) + \nu_\tau$	9.30 ± 0.11
		$\tau^\pm \to \pi^\pm + 3\pi^0 + \nu_\tau$	1.05 ± 0.07
		$\tau^\pm \to h^\pm + 4\pi^0 + \nu_\tau$	0.11 ± 0.04
Hadronic	Three-prong	$\tau^\pm \to \pi^\pm + \pi^\mp + \pi^\pm + (\geq 0\pi^0) + \nu_\tau$	14.57 ± 0.07
		$\tau^\pm \to \pi^\pm + \pi^\mp + \pi^\pm + \nu_\tau$	8.99 ± 0.06
		$\tau^\pm \to \pi^\pm + \pi^\mp + \pi^\pm + \pi^0 + \nu_\tau$	2.70 ± 0.08

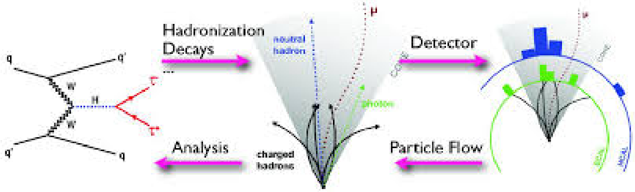
- Goal of our work is to discriminate hadronically decaying tau from quark and gluon jets using graph learning techniques
- As a baseline, DeepPF network and MVA classifier are used

MC samples

Samples from 2016 MC are used. True tau are selected from DY MC samples, fake from W+jet MC samples. In both cases, only decays into one charged hadron (decay mode 0), one charged hadron and a neutral pion (decay mode 1), or three charged hadrons (decay mode 10) are selected

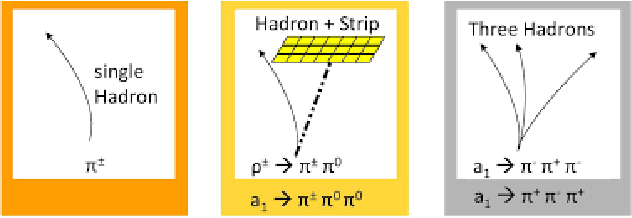
Reweighting is applied to flatten in tau p_T spectrum

PF algorithm



The Particle Flow event reconstruction aims at reconstructing all stable particles arising from collisions, using combined response from all the CMS sub-detectors. This list of individual particles is then used to build jets, to determine the missing transverse energy, to reconstruct and identify taus from their decay products, etc.
https://cds.cern.ch/record/2029414/

Hadron Plus Strip



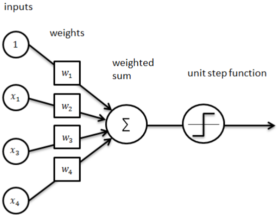
The HPS algorithm uses PF candidates to check whether the combined topology is compatible with one of the hadronic decay modes

Tau Isolation Discriminators

Different discriminators were developed to discriminate τ_h from jets, e and μ

- Cut-based discriminator
- MVA: boosted decision trees - based discriminator
- DeepPF: DNN-based discriminator with 10 convolutional layers and 4 fully-connected layers
- DeepTau ID v1, v2: DNN-based discriminators

Artificial Neural Networks

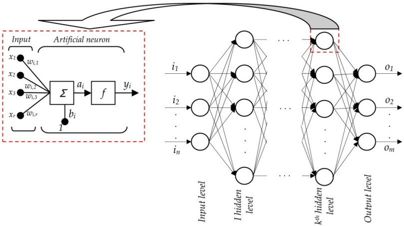


Linear model is able to approximate simple functions

Several linear models with nonlinear activations between them can approximate arbitrary functions (Universal approximation theorem)

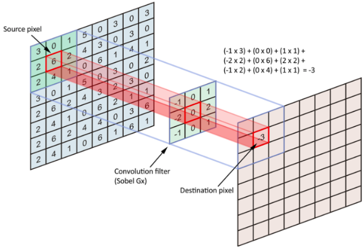
Loss function is introduced to describe the value of model's prediction error:

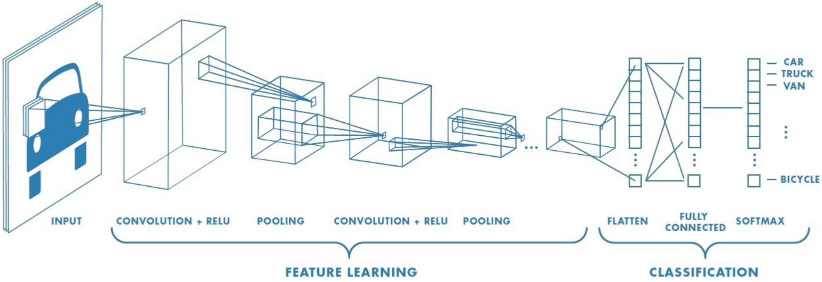
$$BCE = \frac{1}{N}\sum_{i=0}^{N} y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)$$



Model training is the minimization of the loss function, usually with different modifications of gradient descent

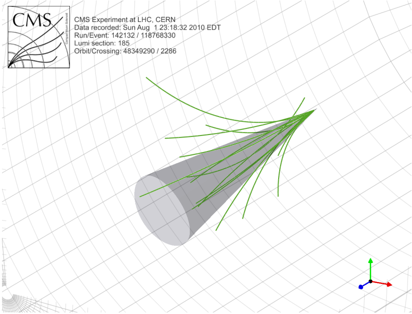
Convolutional Neural Networks





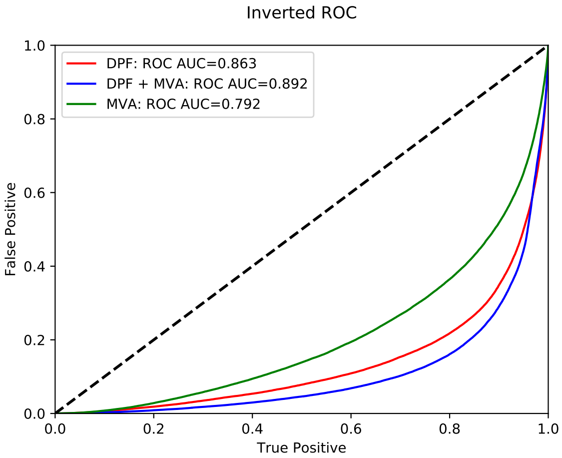
DPF network (Author: Owen Colegrove)

- tau are reconstructed from particle flow particles
- Variables from particles contained in cone centered on the tau are formatted into a 2-D table and fed into a Deep Neural Network
- Each event are represented as matrix 60*47(number of particles - 60; number of features - 47)
- If number of particles in cone is less then 60, the last rows of table are filled with zeroes



Particles	feature1	...	featureN
p1	f1,p1		fN,p1
...			
pm	f1,pm		fN,pm

DPF performance

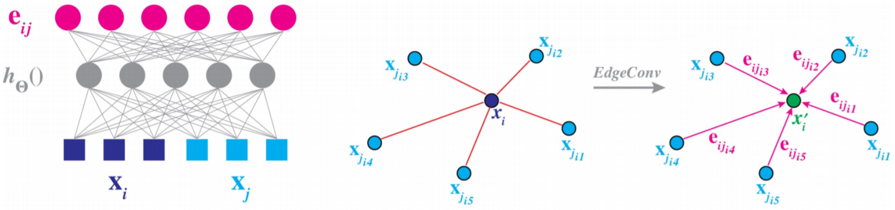


Graph Convolutional Network

- The same data and the same features as in DPF network are used
- Variables from particles contained in cone centered on the tau are represented as a point cloud (each particle represented as a one point)
- Graph is constructed from a particle cloud as k-nearest neighbour graph
- Graph fed into Graph Convolutional Neural Network, which consists of graph convolutional layers and FC layers

EdgeConv Layer

https://arxiv.org/abs/1801.07829



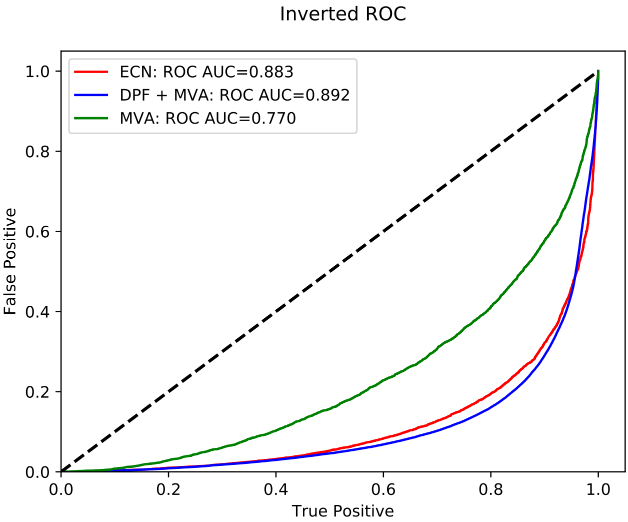
Edge features are defined as:

$$e_{ij} = h_\Theta(x_i, x_j)$$

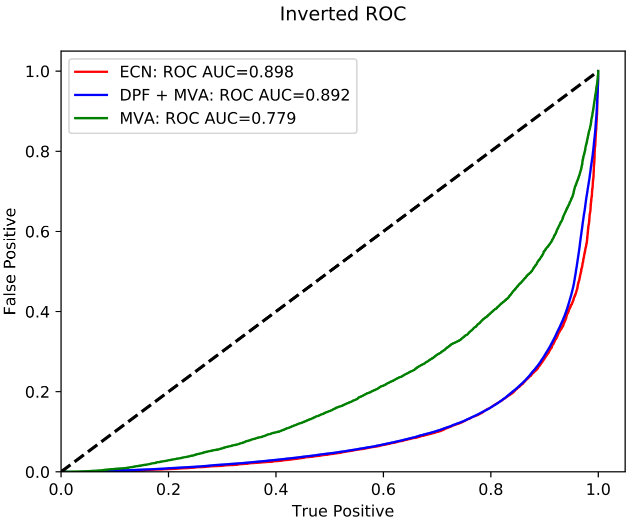
EdgeConv operation is defined by applying a symmetric aggregation operation $\square$ (e.g., $\sum$ or max):

$$x'_i = \square h_\Theta(x_i, x_j)$$

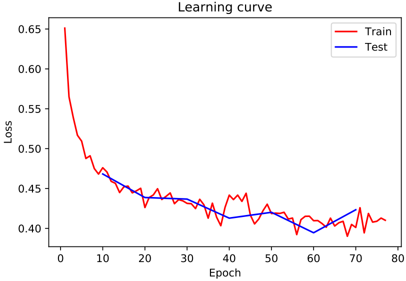
ECN performance (1 Convolutional layer)

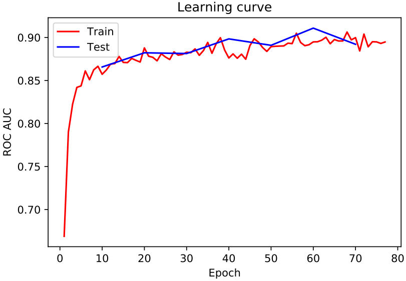


ECN performance (3 Convolutional layers)

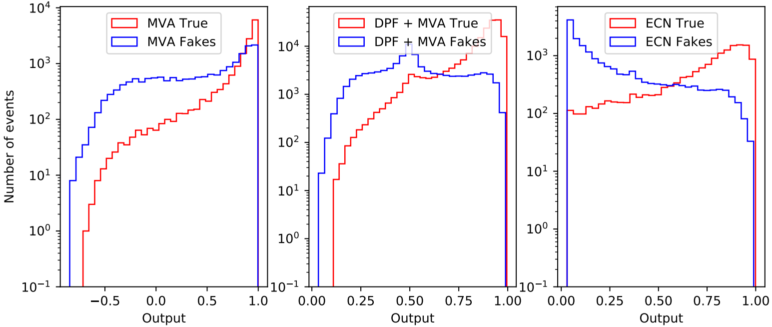


Learning curves for ECN with 3 layers





Output distribution



Output distributions for different decay modes

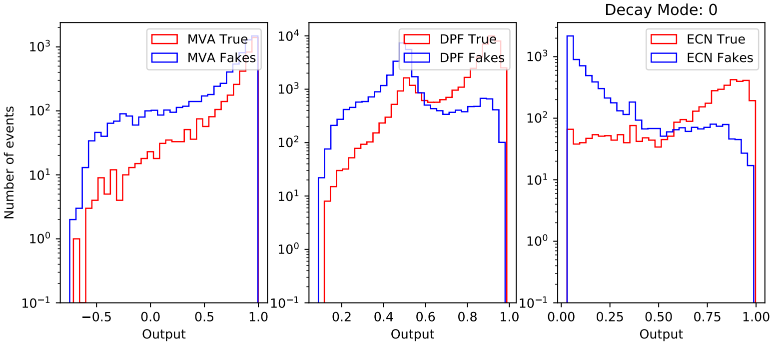


Figure: Output distribution for decay mode 0 (into one charged hadron)

Output distributions for different decay modes

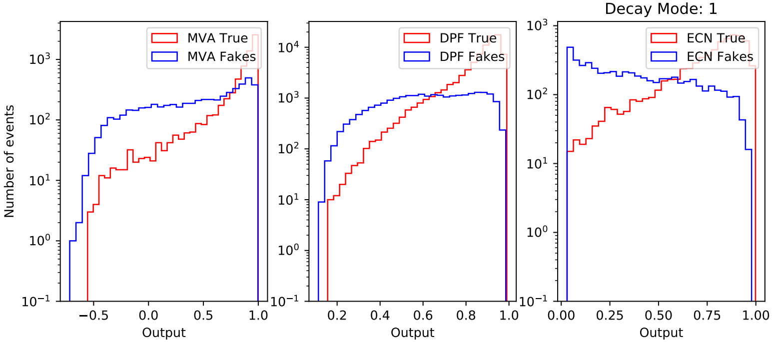


Figure: Output distribution for decay mode 1 (into one charged hadron and a neutral pion)

Output distributions for different decay modes

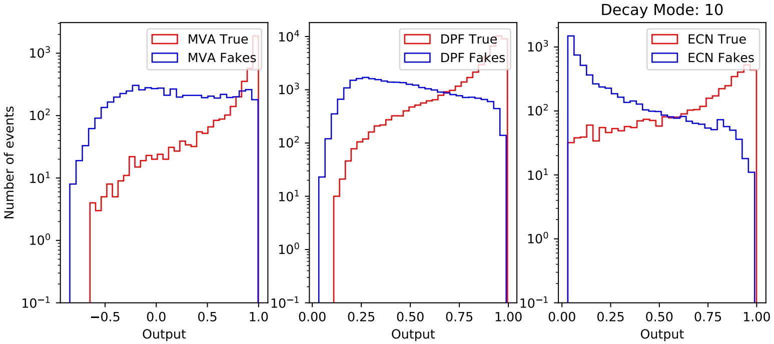
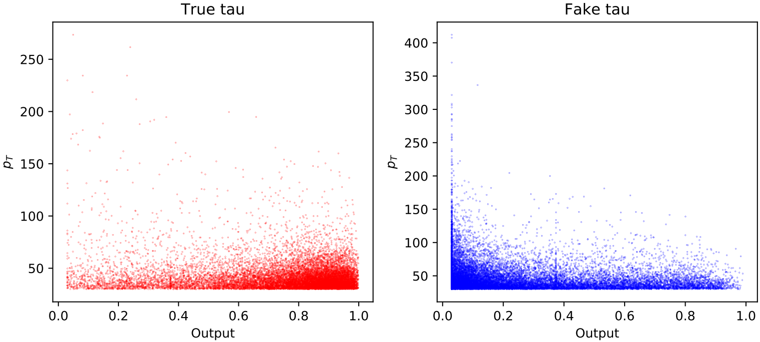


Figure: Output distribution for decay mode 10 (into three charged hadrons)

p_T dependence



Results

Architecture	ROC AUC score	Number of parameters	Time [ms]
MVA	0.792	-	-
DPF	0.863	8838945	166
DPF + MVA	0.892	-	-
ECN (1 layer)	0.883	**49283**	**0.6**
ECN (3 layers)	**0.898**	223939	2.6

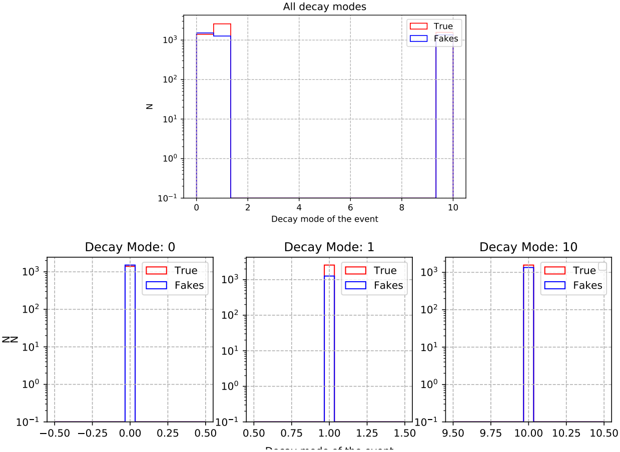
Time was evaluated on CPU Intel Xeon E5-2650 with 1 thread and batch size of 2048

Conclusions

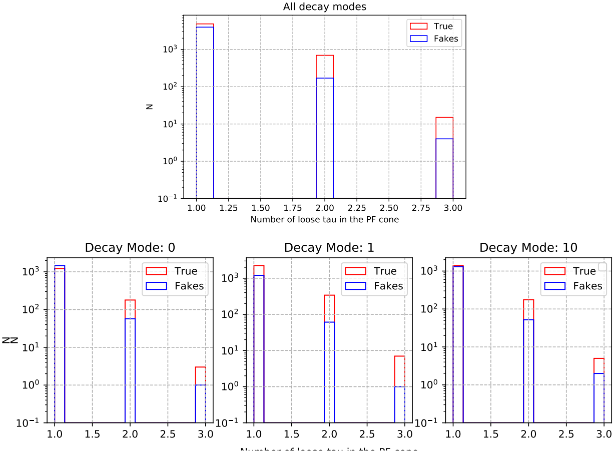
- DNN-based methods have better performance than BDT-based
- Neural Network with Graph Convolutions has performance close to the one of DPF while having much less number of parameters

Backup

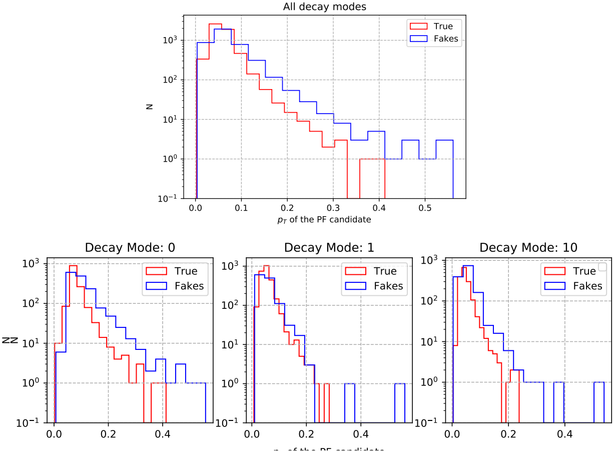
Feature: Decay mode of the event



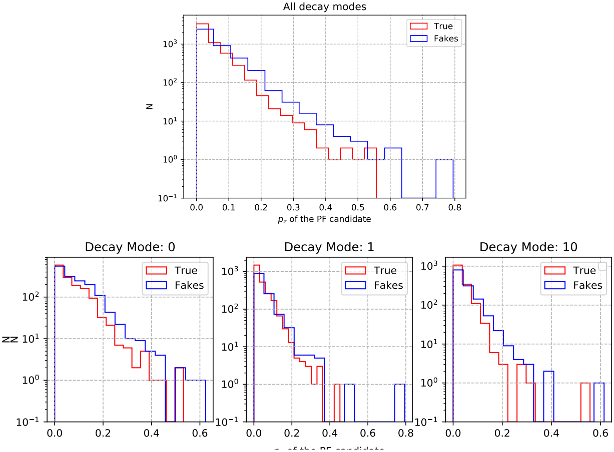
Feature: Number of loose tau in the PF cone



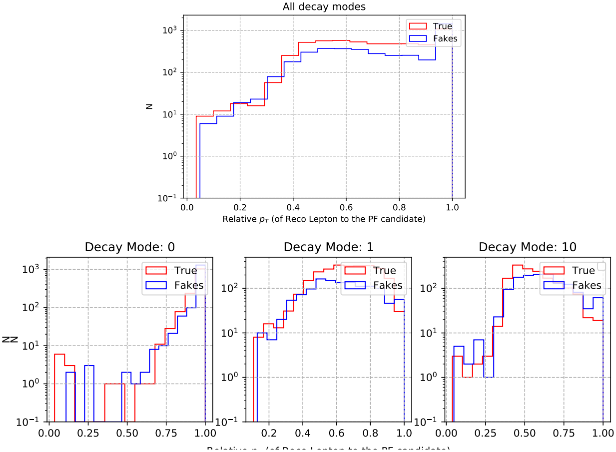
Feature: p_T of the PF candidate



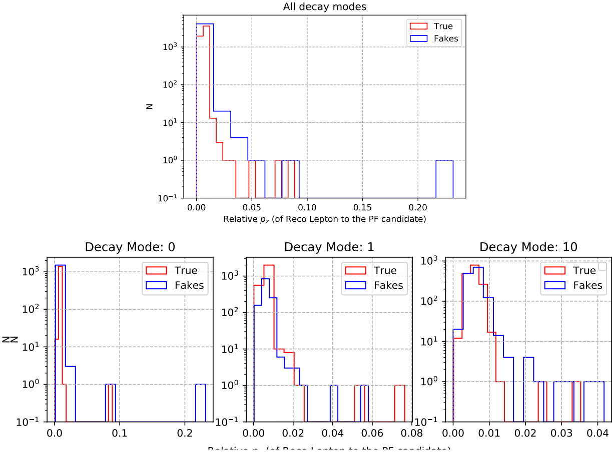
Feature: p_z of the PF candidate



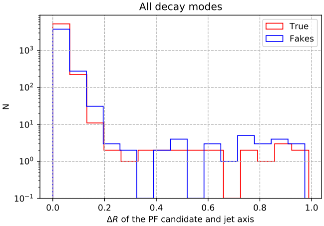
Feature: Relative p_T (of Reco Lepton to the PF candidate)

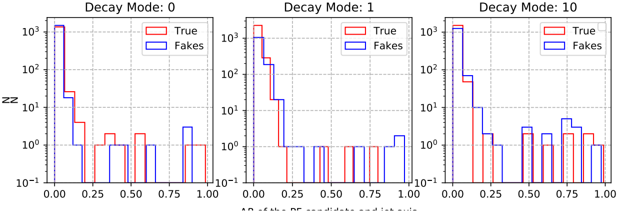


Feature: Relative p_z (of Reco Lepton to the PF candidate)

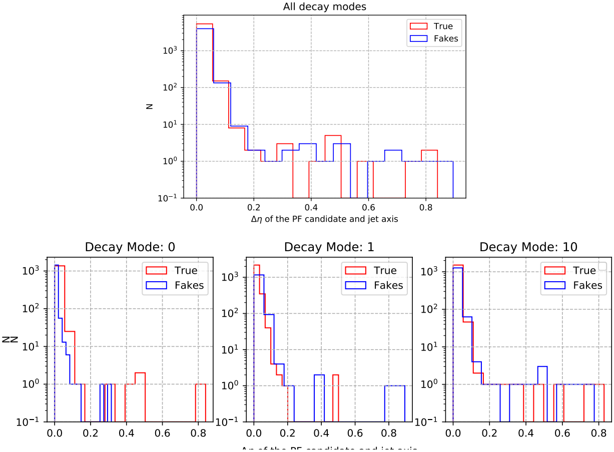


Feature: ΔR of the PF candidate and jet axis

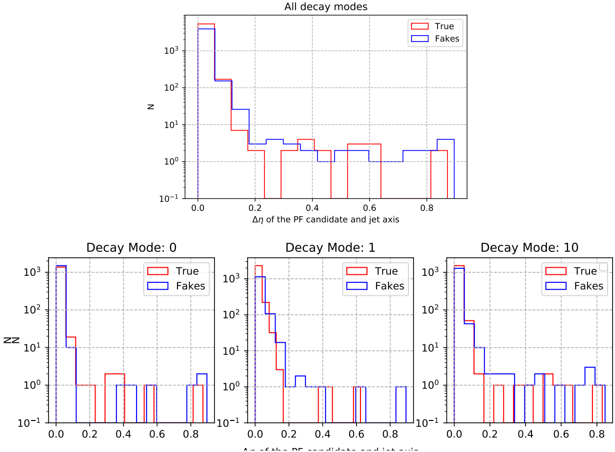




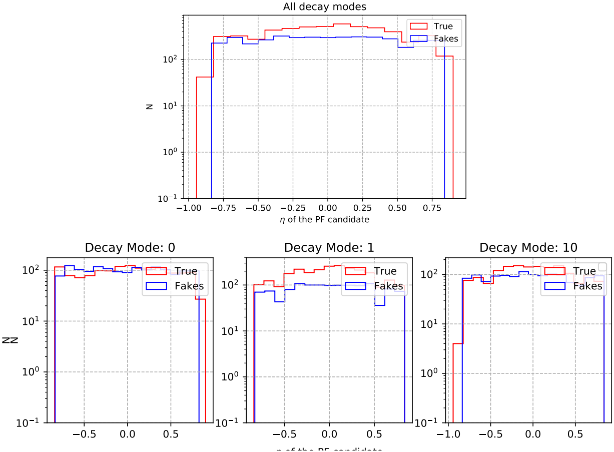
Feature: $\Delta\eta$ of the PF candidate and jet axis



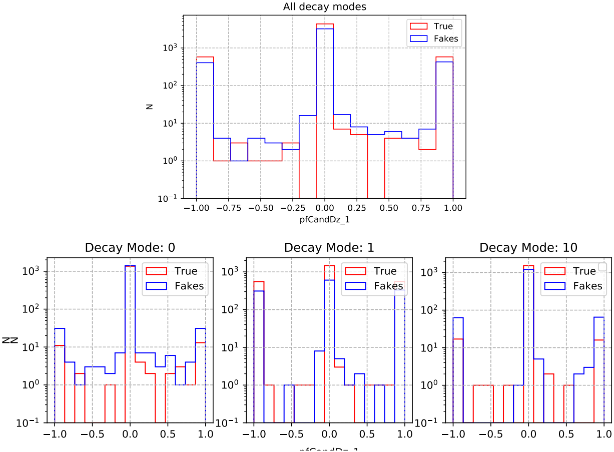
Feature: $\Delta\phi$ of the PF candidate and jet axis



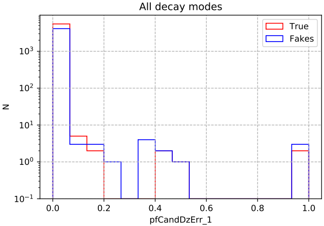
Feature: η of the PF candidate

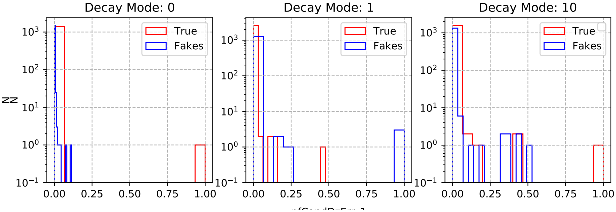


Feature: pfCandDz_1

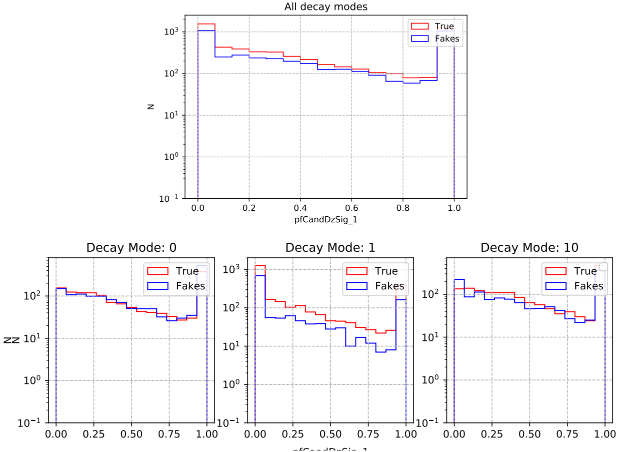


Feature: pfCandDzErr_1

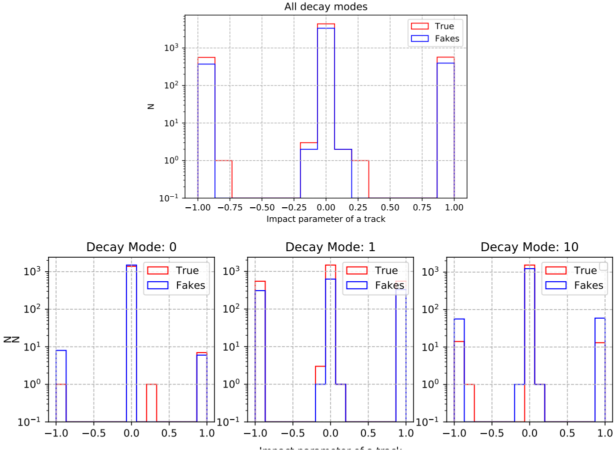




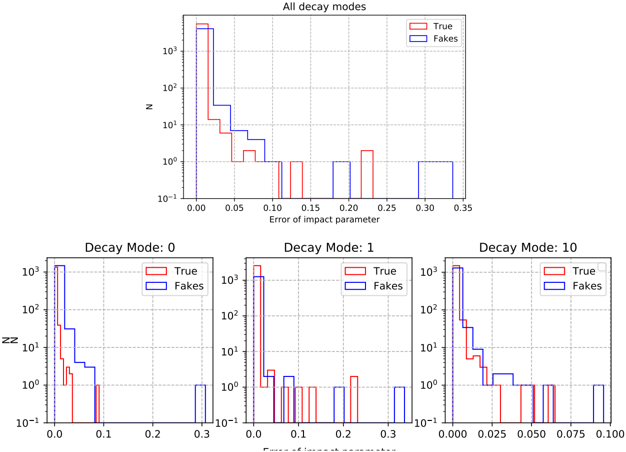
Feature: pfCandDzSig$_1$



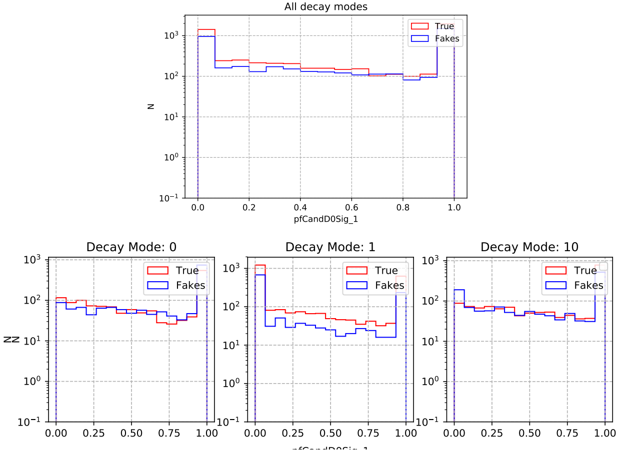
Feature: Impact parameter of a track



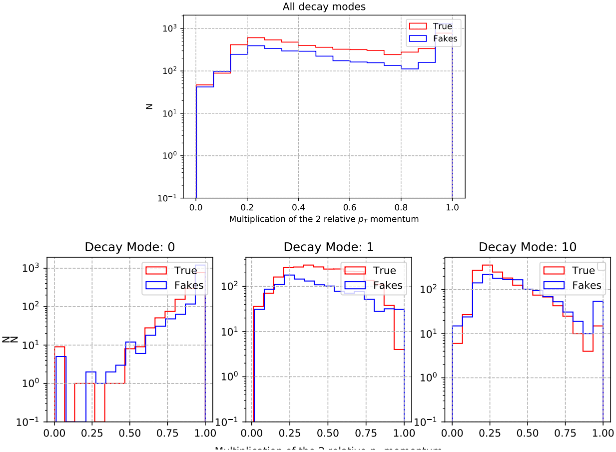
Feature: Error of impact parameter



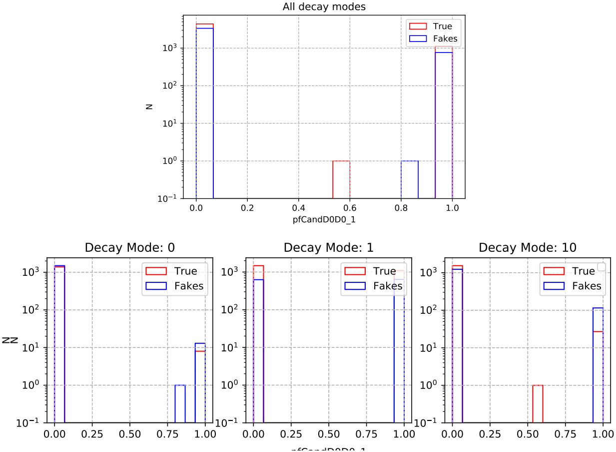
Feature: pfCandD0Sig$_1$



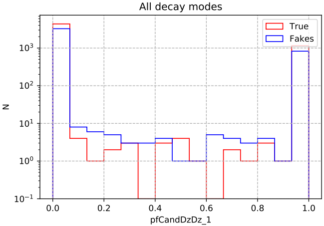
Feature: Multiplication of the 2 relative p_T momentum

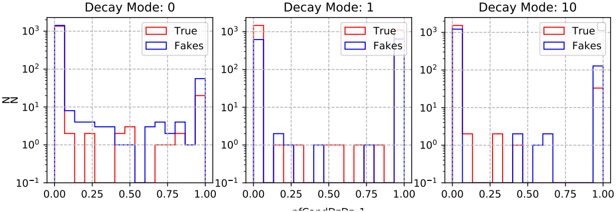


Feature: pfCandD0D0$_1$

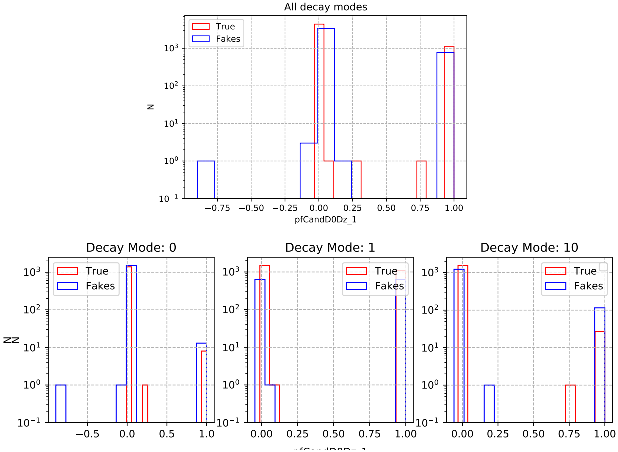


Feature: pfCandDzDz$_1$

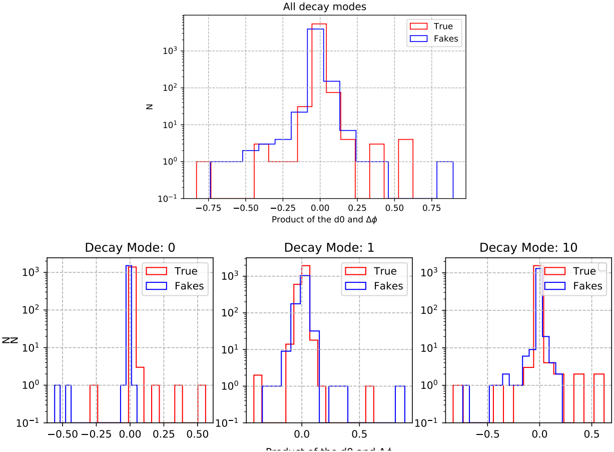




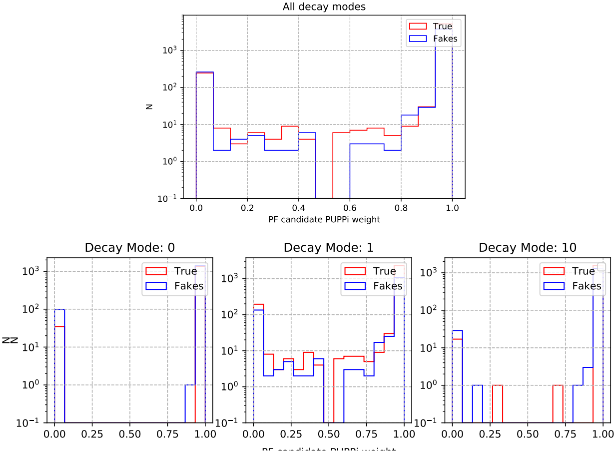
Feature: pfCandD0Dz$_1$



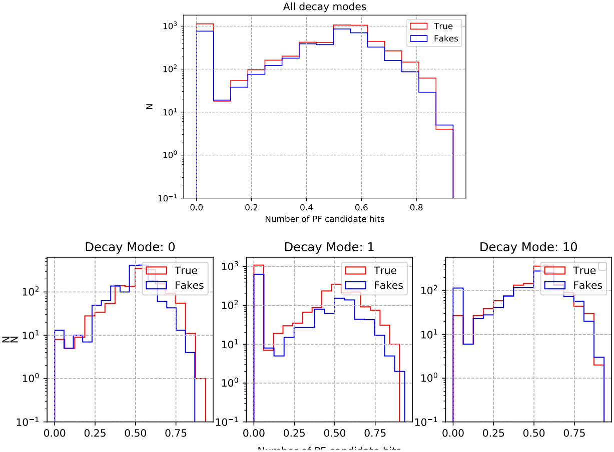
Feature: Product of the d0 and $\Delta\phi$



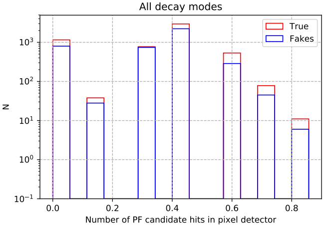
Feature: PF candidate PUPPi weight

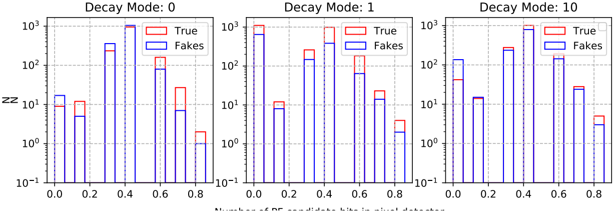


Feature: Number of PF candidate hits

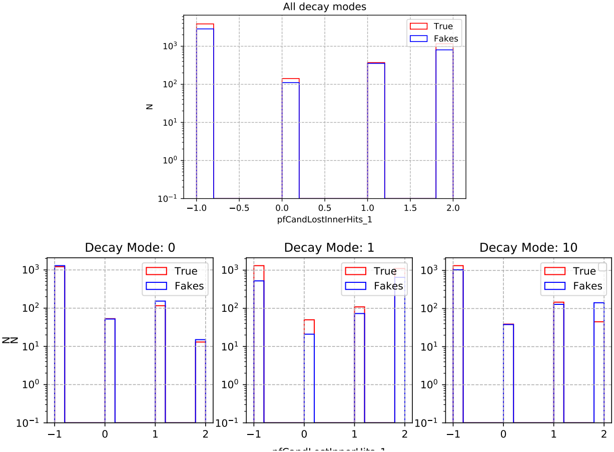


Feature: Number of PF candidate hits in pixel detector

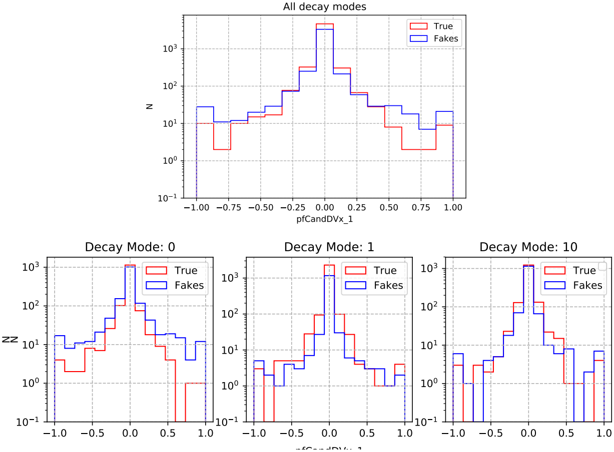




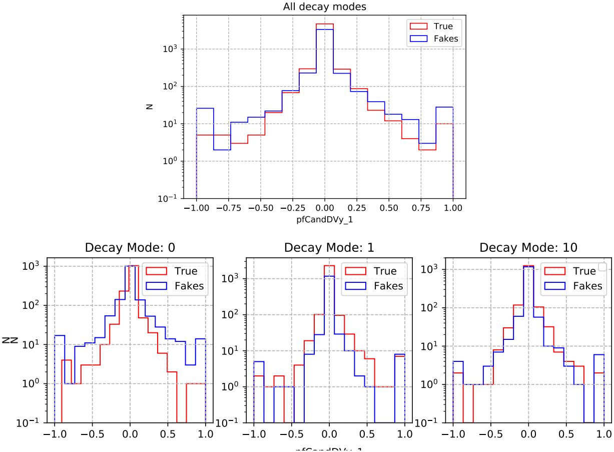
Feature: $\text{pfCandLostInnerHits}_1$



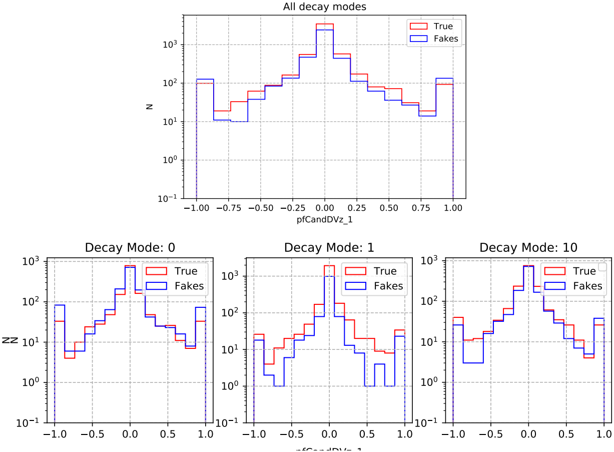
Feature: pfCandDVx$_1$



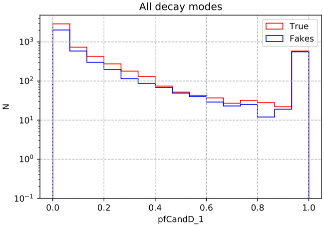
Feature: pfCandDVy_1

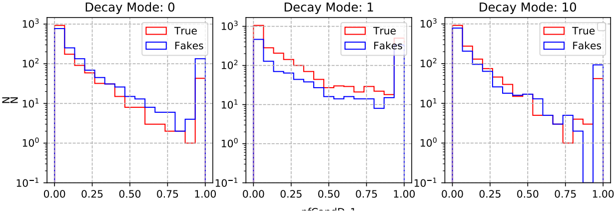


Feature: pfCandDVz$_1$

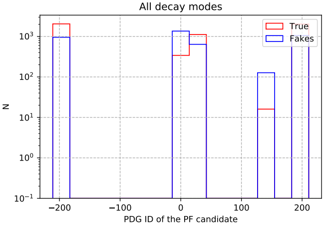


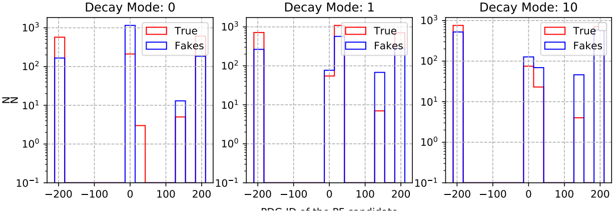
Feature: pfCandD_1



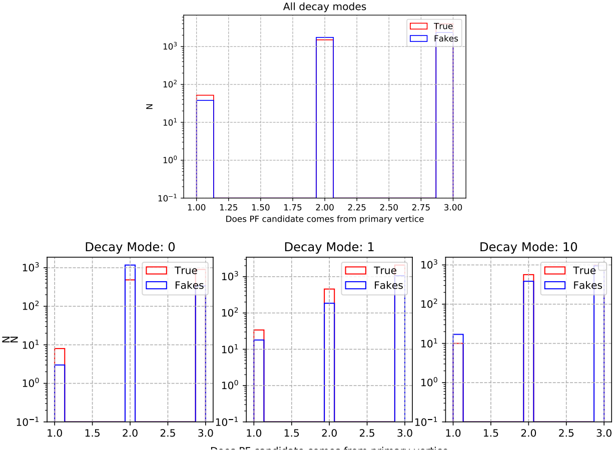


Feature: PDG ID of the PF candidate

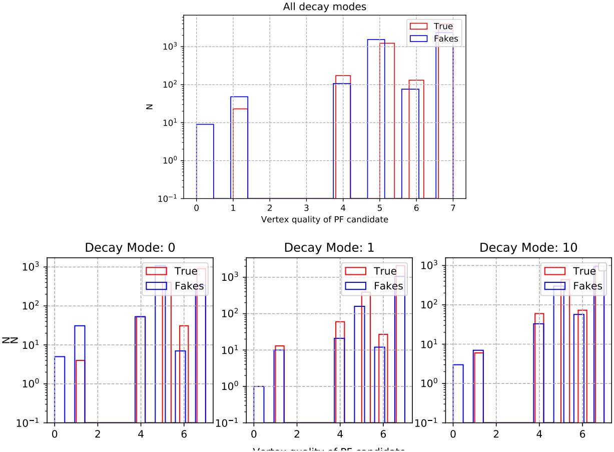




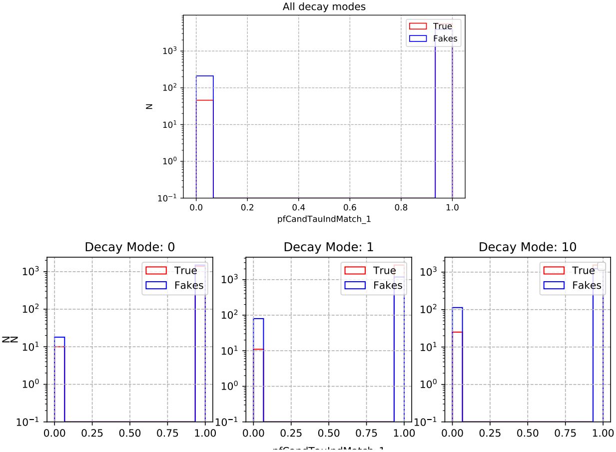
Feature: Does PF candidate comes from primary vertice



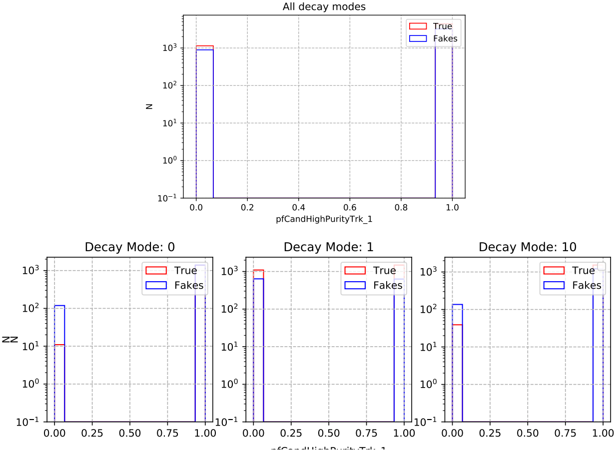
Feature: Vertex quality of PF candidate



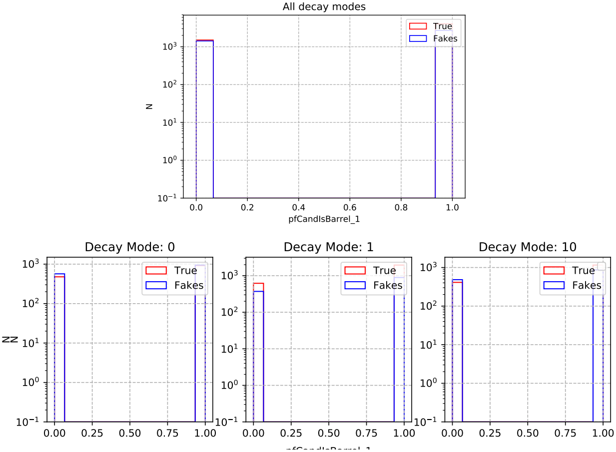
Feature: pfCandTauIndMatch$_1$



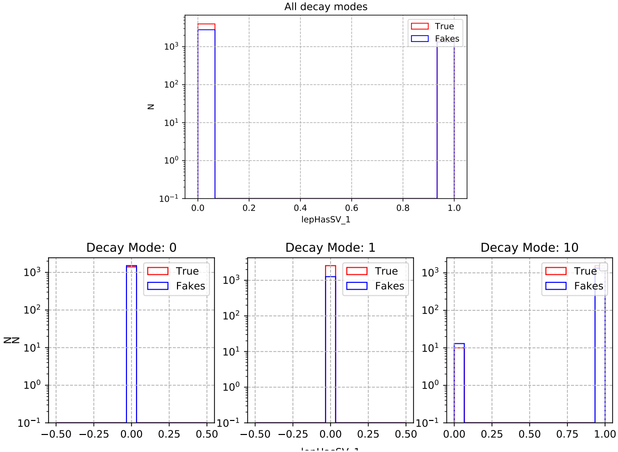
Feature: pfCandHighPurityTrk$_1$



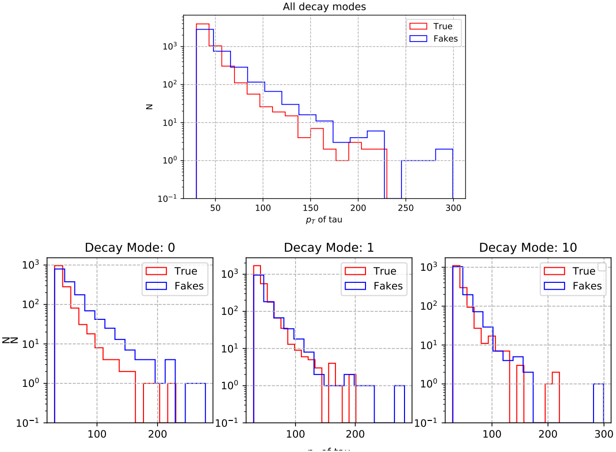
Feature: pfCandIsBarrel$_1$



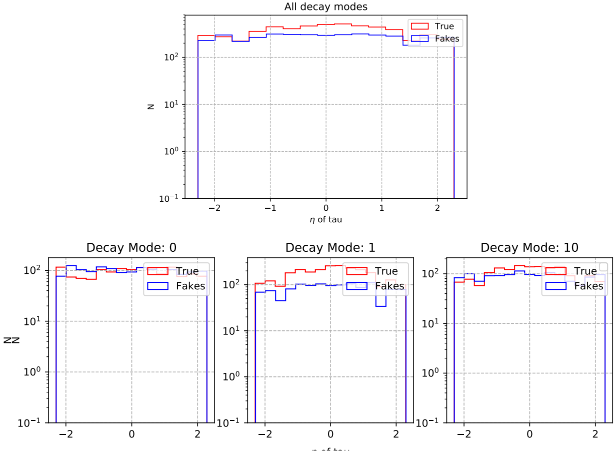
Feature: lepHasSV_1



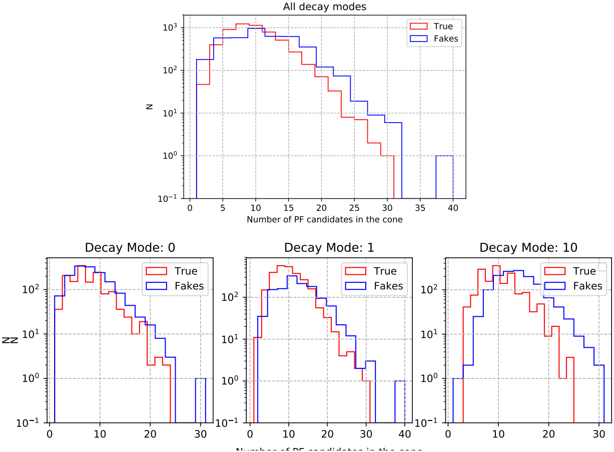
Feature: p_T of tau



Feature: η of tau



Feature: Number of PF candidates in the cone



Feature: Charge of the PF candidate