$Z \to \tau\tau$ Reconstruction and Tagging at FCC-ee

Results of `SimpleNN` model

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Overview

- Introduction
  - Goal
  - Dataset
- SimpleNN Model
  - Model Architecture
  - Training
  - Performance
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All code can be found on GitLab. The dataset is at
`/ceph/xzuo/FCC_ntuples/tau_reco/ntuples_20240415/`

Introduction

Goal

- Study the tagging of $Z \to \tau\tau$ events at FCC-ee
- Differentiate between $Z \to \tau\tau$ and $Z \to q\bar{q}$ events
  - Subgoal: Differentiate the quark flavor
- Use a simple neural network model for tagging

Dataset

- Simulated $Z \to xx$ events at FCC-ee with $x = \tau, u, d, s, c, b$
- $E_{\text{cm}} = 91\,\text{GeV}$
- jet clustering and particle flow reconstruction
  $\Rightarrow$ **exclusive** and inclusive jets
- $\mathcal{O}(180)$ variables per event
  - event variables: $n_\mu, n_e, E_{\text{miss}}, \ldots$
  - jet variables: $p_T, \eta, \phi, m, \ldots$
  - pfcandidate variables: $p_T, \eta, \phi, m, \text{type}, \ldots$

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  - pfcandidate variables: $p_T, \eta, \phi, m, \text{type}, \ldots$
- **Focus:** Use only the jet variables, especially pfcandidate variables
  - max. 6 pfcandidates per jet
  - Missing values are filled with -4 (out of range)

Distributions of important input variables External: Distributions of all input variables

Dataset

Qualitative Overview of Variables

- Large differences between leptonic decays and quark decays
- Small differences between quark flavors
- For comparison of jet algorithms, sorting of inclusive jets is necessary $\Rightarrow$ skipped

Distributions of important input variables | External: Distributions of all input variables

Detailed Overview of Variables

Table 1: Particle Flow Candidate Variables (used)

Symbol	Variable Name	Description
E_{rel}	`pfcand_erel(_log)`	Energy of the particle relative to the jet energy
$\mathcal{O}_{\text{ch}}, \mathcal{O}_\gamma, \ldots$	`pfcand_is*`	Particle type in one hot encoding
$\Delta\theta$	`pfcand_thetarel`	Angle between the jet and the particle
E	`pfcand_e`	Energy of the particle
p	`pfcand_p`	Momentum of the particle
θ	`pfcand_theta`	θ angle of the particle
$\frac{\mathrm{d}N}{\mathrm{d}x}$	`pfcand_dndx`	Number of primary ionisation clusters
$m_{\text{t.o.f.}}$	`pfcand_mtof`	Mass of the particle from time of flight
d_z	`pfcand_dz`	longitudinal impact parameter
d_{xy}	`pfcand_dxy`	transverse impact parameter

SimpleNN Model

SimpleNN Model

- Simple feed-forward neural network
- 3 hidden layers with 128 neurons each
- ReLU activation function
- Binary classification
- Input: 6 pfcandidates + 2 jet variables
- Output: $Z \to xx$ with $x = \tau, u/d, s, c, b$

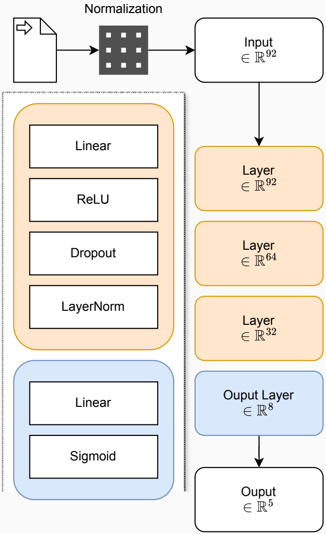


Figure 1: Visualization of the SimpleNN model

Training

- Training on 600k events, 200k $Z \to \tau\tau$, 400k $Z \to q\bar{q}$
- Fast decay of loss function
- 10 epochs, batch size 128

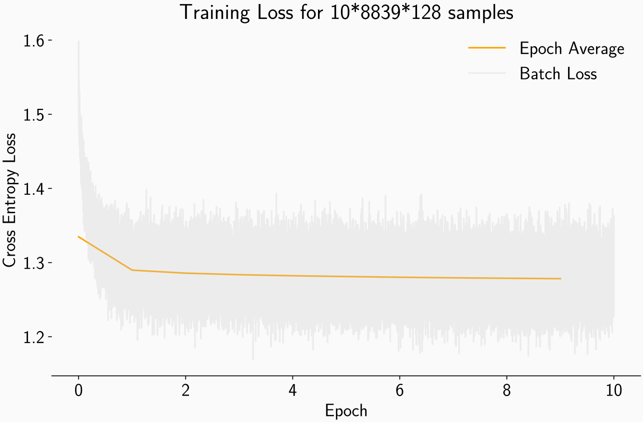


Figure 2: Loss function during training

Performance

Table 2: Results for classification of $Z \to xx$ events

	Accuaracy[1]	Repr Testset	Wrong per Million
$Z \to \tau\tau$	96.9 %	0.170864	30916.402380
$Z \to ss$	56.6 %	0.207284	434083.701262
$Z \to bb$	57.6 %	0.207284	423574.404577
$Z \to cc$	44.7 %	0.207284	553251.248886
$Z \to ud$	54.7 %	0.207284	453216.010613

[1] Accuracy A: $f(p,a) \equiv \theta(p-0.5) - a$ with $p =$ prediction, $a =$ actual

$$A = \frac{1}{N} \sum_{i=1}^{N} \begin{cases} 1 & f(p,a) = 0 \\ 0 & \text{otherwise} \end{cases}$$

Performance

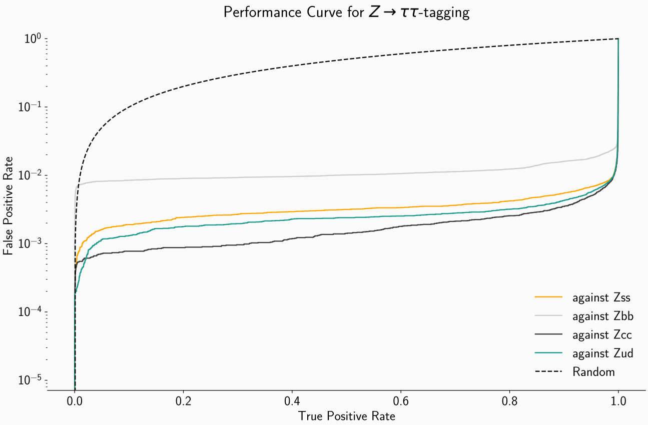


Figure 3: Performance curve for classification of $Z \rightarrow \tau\tau$ events

More Performance curves

Performance

- High accuracy for $Z \to \tau\tau$ events
- Low accuracy for $Z \to q\bar{q}$ events

  $\Rightarrow$ Model is biased towards $Z \to \tau\tau$

  $\Rightarrow$ largely different input distributions

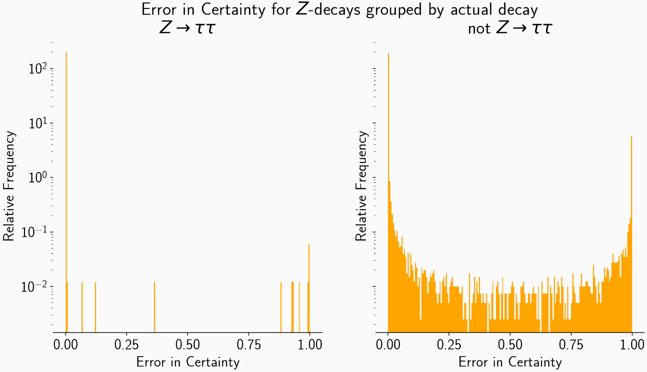


Figure 4: Error in certainty for $Z \to \tau\tau$ and $Z \to q\bar{q}$ events

Explicit Reconstruction

$\tau \to 3\pi$ Reconstruction Algorithm

Determine if a vertex is candidate for $\tau \to 3\pi$ decay

1. vertex is primary
2. vertex with 3 tracks
3. all tracks have PDG ID 211
4. $|q| = 1$

Table 3: Rates for candidates of $\tau \to 3\pi$ events

	$n = 0$	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
$Z \to \tau\tau$	0.8304	0.1695	0.0000	0.0000	0.0000	0.0000
$Z \to ud$	0.9959	0.0039	0.0003	0.0000	0.0000	0.0000
$Z \to ss$	0.9953	0.0044	0.0003	0.0000	0.0000	0.0000
$Z \to cc$	0.8824	0.1136	0.0039	0.0000	0.0000	0.0000
$Z \to bb$	0.6533	0.2929	0.0498	0.0038	0.0002	0.0000

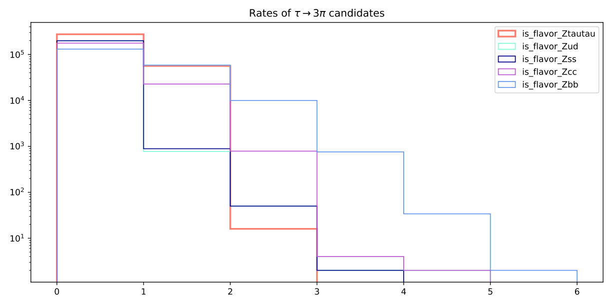


Figure 5: Rates for candidates of $\tau \to 3\pi$ events in $Z \to \tau\tau$ and $Z \to q\bar{q}$ events

Candidate Evaluation

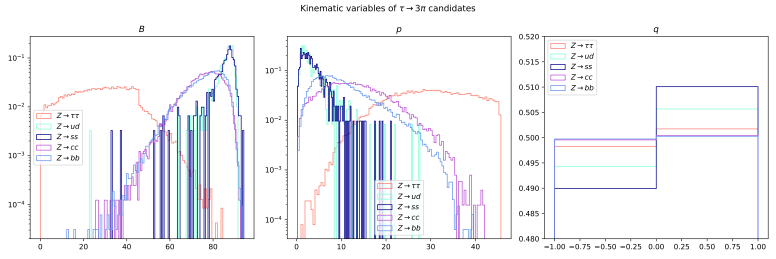
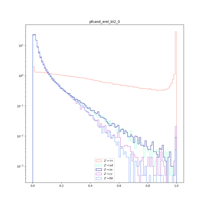


Figure 6: Distributions of kinematic variables for $\tau \to 3\pi$ candidates

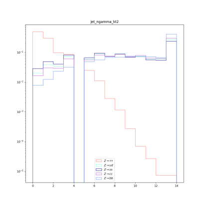
- Noticable differences between $Z \to \tau\tau$ and $Z \to q\bar{q}$ events
- especially in B, p
- effects of small statistics in q visible

Appendix

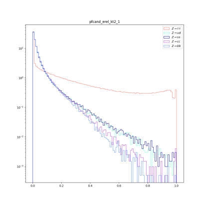
Distributions of input variables



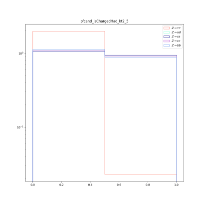
(a) pfcand_erel_kt2_0



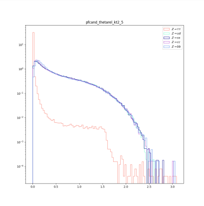
(b) jet_ngamma_kt2



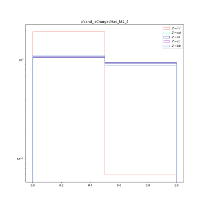
(c) erel_kt2_1



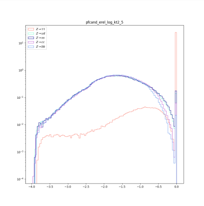
(d) isChargedHad_kt2_5



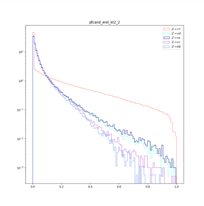
(e) thetarel_kt2_5



(f) isChargedHad_kt2_4



(g) erel_log_kt2_5



(h) erel_kt2_2

Figure 7: 8 most important input variables

Performance Curves

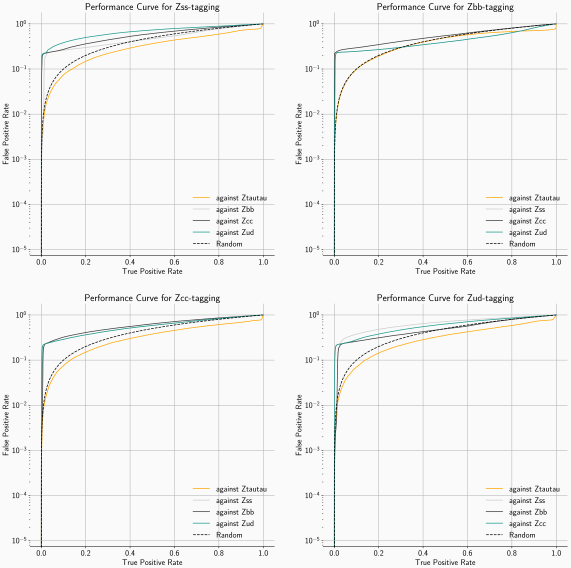


Figure 8: Performance curve for $Z \to xx$ events in one-on-one comparison