Classifying Charged Particles from High Energy Collisions at the Large Hadron Collider

Justin Anguiano, Margaret Lazarovits

University of Kansas

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Introduction

Overall project goal:

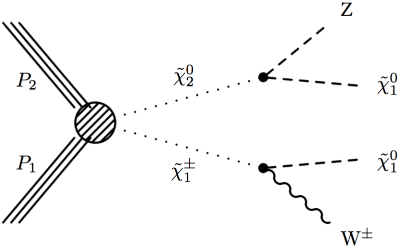
Classify particles better to assist with search for particle darkmatter

Specific focus:

- Discrminate low momentum true muons($\mu^{\pm}$) from particles imitating muons in reconstruction

Motivation

KU CMS analysis in progress – searching for particle dark matter via compressed SUSY models



- Protons P_1, P_2 collide producing SUSY $\tilde{\chi}_1^\pm$,$\tilde{\chi}_2$
- SUSY $\tilde{\chi}_1^\pm$,$\tilde{\chi}_2$ decays to D.M. $\tilde{\chi}_1^0$ and known particles $W^\pm$,Z
- $W^\pm$,Z immediately decay into charged particles($\mu^\pm$) that we see in the detector

A compressed scenario implies $\tilde{\chi}_1^\pm$,$\tilde{\chi}_2$ and $\tilde{\chi}_1^0$ are very close in rest mass

With compression the decay products of $\tilde{\chi}_1^\pm$,$\tilde{\chi}_2$ are soft (low momentum), including ending charged particles

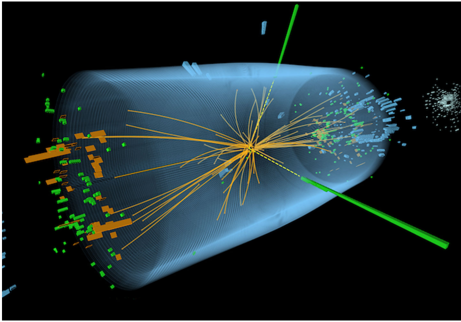
The current CMS detector is less optimized for correctly identifying soft $\mu^\pm$

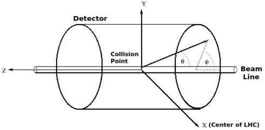
If we can optimize soft charged particle classification, we have a better chance of discovering compressed $\tilde{\chi}_1^\pm$,$\tilde{\chi}_2$, and $\tilde{\chi}_1^0$

Anatomy of an Event

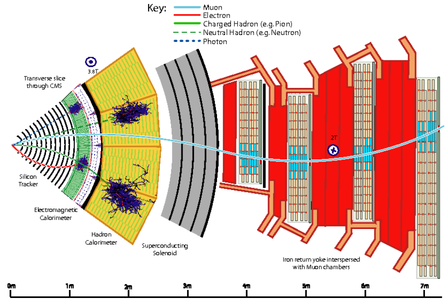
The "physics workflow"

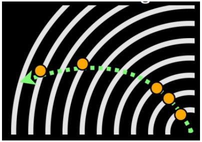
- An event consists of colliding protons which produces particles showering outward(transverse)
- We measure the energy and momentum of all the visible particles in the event
- There are 100s of charged particles per event
- Reconstruct intermediate or invisible particles through momentum and energy conservation





Charged Particle Reconstruction





Charged particles bend in Mag. field and create "tracks"

Tracks are connecting the dots: "hits" that are fit with a curve

Main particle of interest is the Muon($\mu^{\pm}$)

– at high energies μ is easily correctly identified

– low energies leaves room for ambiguity

Sometimes other particles can be reconstructed incorrectly as a muon

– Common fakes: Pion($\pi^{\pm}$), Electron($e^{\pm}$), Kaon($K^{\pm}$), Proton(p), or non physical junk particles

– created from punch through

– junk particles are a result of hit combinatorics

ML Model Introduction

- Deep Neural Network
- Use fully simulated processes to get collections of reconstructed muons
- Reconstructed muons contains both true(Gen.) muons and fakes.
  - This generator information will be our truth, or label, for the network
  - Some particles cant be matched because they are junk – this is unmatched label
- Utilize two types of classification
  1. ID true muons against everything else [Unmatched,π,K,p] – binary classification
  2. ID every particle simultaneously – 5 classes logistic
- Network inputs are measured quantities and track quality metrics

Data Preparation & Network Input

Data Preparation

- Taking data from ROOT trees and converted it to pandas DataFrames
- Evenly sampled among classes from different MC generated processes
  - Each process produces kinematically different muons with different origins
- One-hot encoded the classes for categorical output
- Normalized data

Network Inputs

- Minimal model: variables that can ID a good muon (cut-based benchmark)
- Complex model: energy, position, track information (MVA benchmark)
- Custom: combination of the two
- Evaluate performance with accuracy and loss values and efficiency, purity, and ROC plots

Network Architecture & Training Stats

Architecture

- 4 hidden layers
- 128 neurons/layer
- ReLU activation
- Softmax activation on last layer
- Adam optimizer
- Categorical cross entropy loss

Training

- 35/65 test/training split
- 10/90 validation/training split
- 100 epochs
- 256 batch size

Results: Binary Classifier

Network statistics

Training

- Accuracy: 0.9593
- Loss: 0.1060

Validation

- Accuracy: 0.9299
- Loss: 0.2374

Test

- Accuracy: 0.9244
- Loss: 0.2728

Results: Binary Classifier

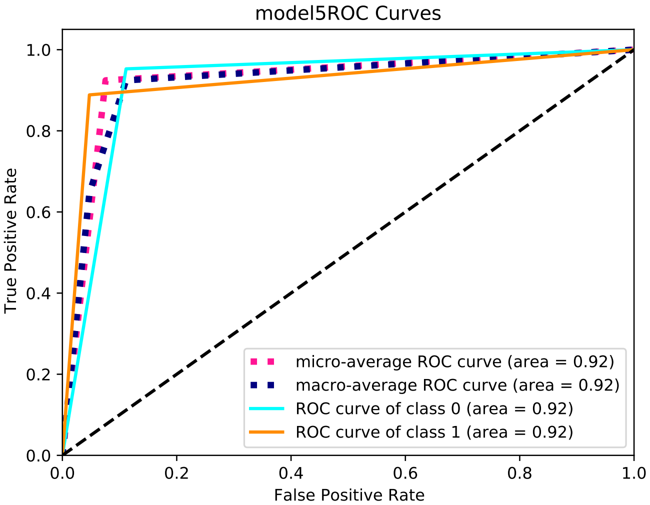
Muon Classification

- Efficiency: 95.274%
  - Purity: 91.540%

$$\text{Efficiency} = \frac{TP}{TP+FN}$$

$$\text{Purity} = \frac{TP}{TP+FP}$$

Results: Binary Classifier



Results: Multiclass Classifier

Network statistics

Training

- Accuracy: 0.6854
- Loss: 0.7739

Validation

- Accuracy: 0.5323
- Loss: 1.2388

Test

- Accuracy: 0.5330
- Loss: 1.2864

Results: Multiclass Classifier

Muon Classification

- Efficiency: 84.032%
- Purity: 87.322%

Pion Classification

- Efficiency: 17.401%
- Purity: 41.398%

Kaon Classification

- Efficiency: 21.601%
- Purity: 33.932%

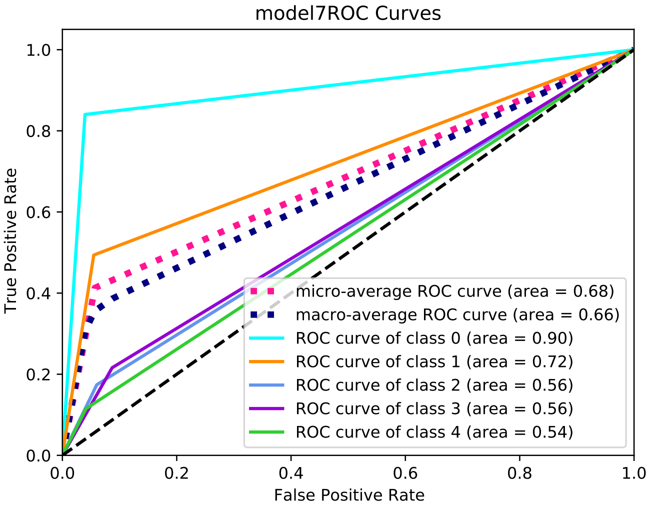
Proton Classification

- Efficiency: 11.496%
- Purity: 4.088%

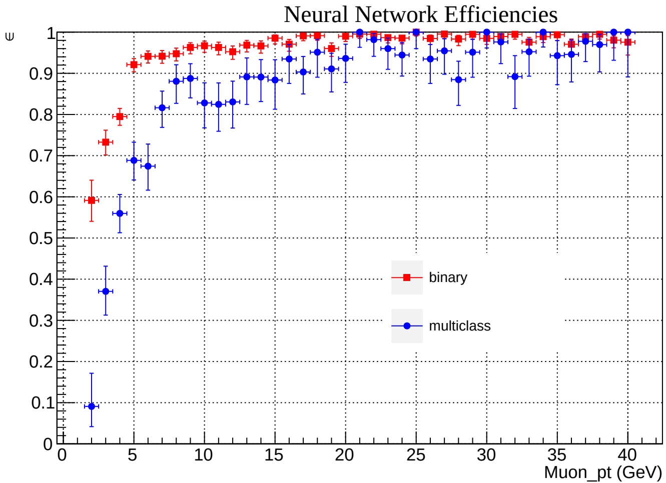
$$\text{Efficiency} = \frac{TP}{TP+FN}$$

$$\text{Purity} = \frac{TP}{TP+FP}$$

Results: Multiclass Classifier

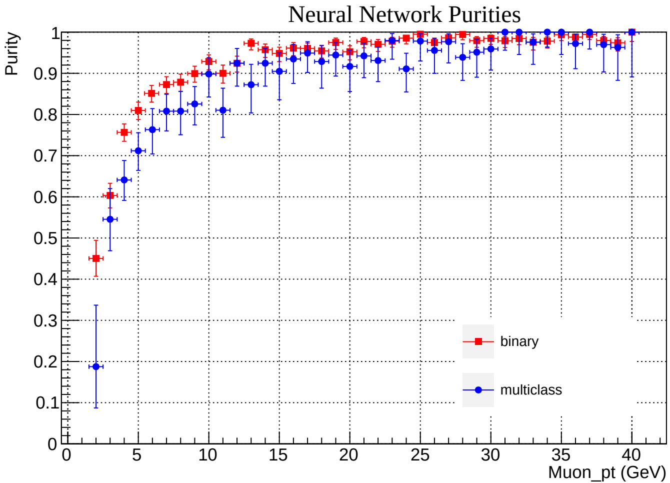


Results: Efficiencies



$\epsilon = \#$ true muons that pass ID$/\#$ true muons

Results: Purities



Purity = # true muons that pass ID/ #reconstructed muons

Benchmark Model

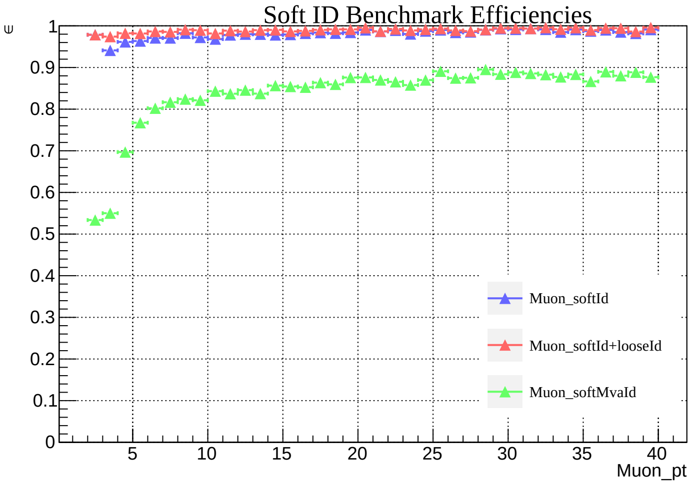
Current techniques to identify low momentum muons are a cut-based ID and a multi-variate analysis (MVA) that uses a gradient boosted regression forest

- Cut-based ID - uses cuts on a few key variables
- MVA - more complex, uses energy and track information

Evaluation Statistics

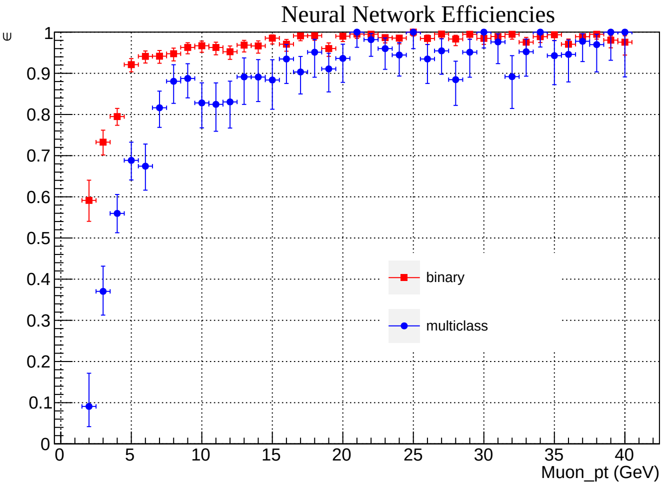
- Efficiency $\epsilon = \#$ true muons that pass ID/$\#$ true muons
- Purity $= \#$ true muons that pass ID/ $\#$reconstructed muons

Benchmark Model: Efficiency



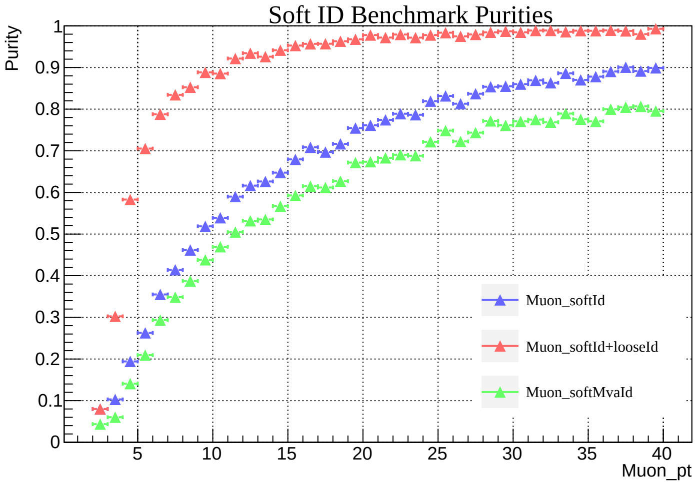
$\epsilon = \#$ true muons that pass ID$/\#$ true muons

Results: Efficiencies



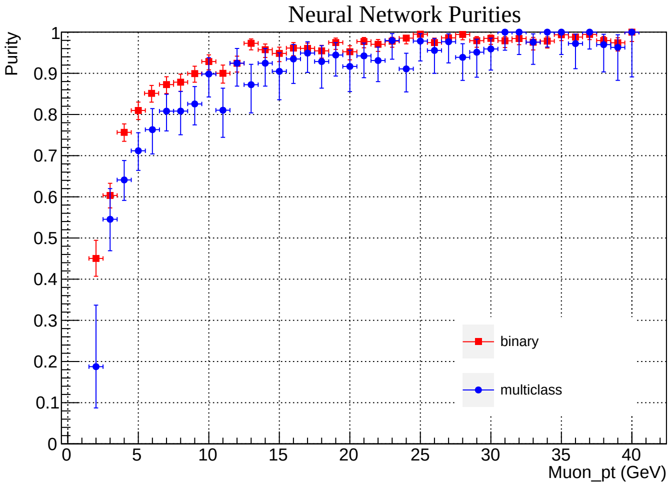
$\epsilon = \#$ true muons that pass ID/$\#$ true muons

Benchmark Model: Purity



Purity = # true muons that pass ID/ #reconstructed muons

Results: Purities



Purity = # true muons that pass ID/ #reconstructed muons

Summary

Goal: correctly classify low momentum muons from proton-proton collisions at the LHC with a neural network

Results

- binary classifier more successful at classifying electrons than multiclass output
  - higher efficiency and purity
- both models competitive with current classification techniques in efficiency
- both models have similar or higher purity than current classification techniques

Future work: integrate classifier into searches for Supersymmetry to find Dark Matter candidates

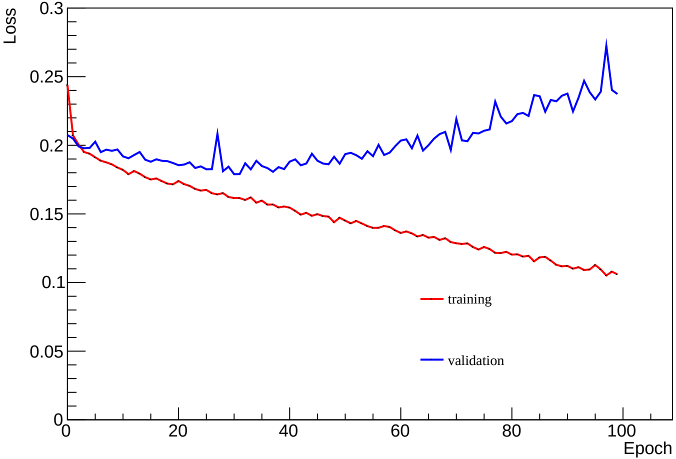
Project Repository: `https://github.com/Jphsx/KUSoftMVA`

Thank You!

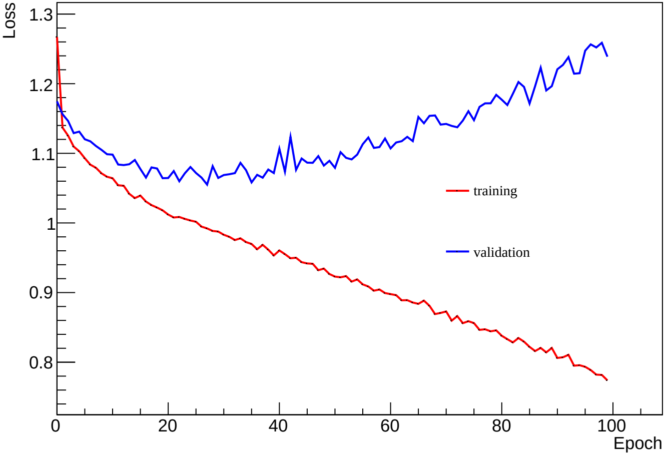
Questions?

Backup

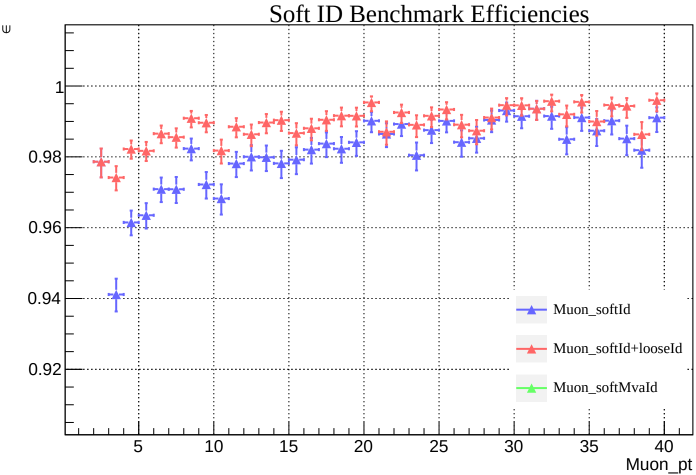
Binary Classifier: Loss



Multiclass Classifier: Loss

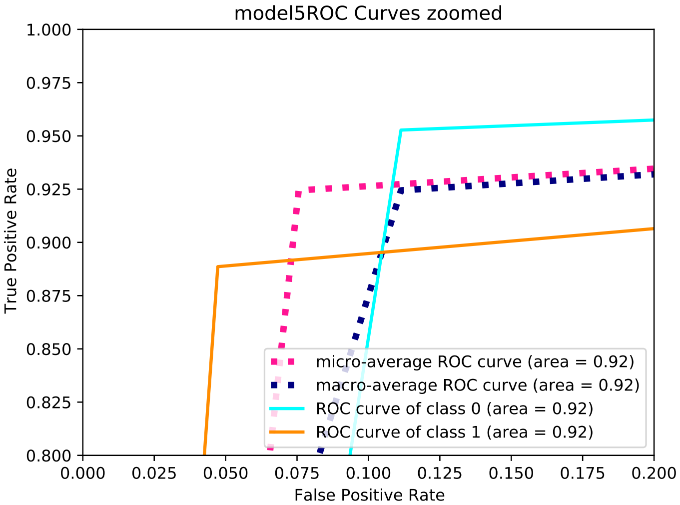


Benchmark Model Performances



$\epsilon = \#$ true muons that pass ID$/\#$ true muons

Results: Multiclass Classifier



Results: Multiclass Classifier