

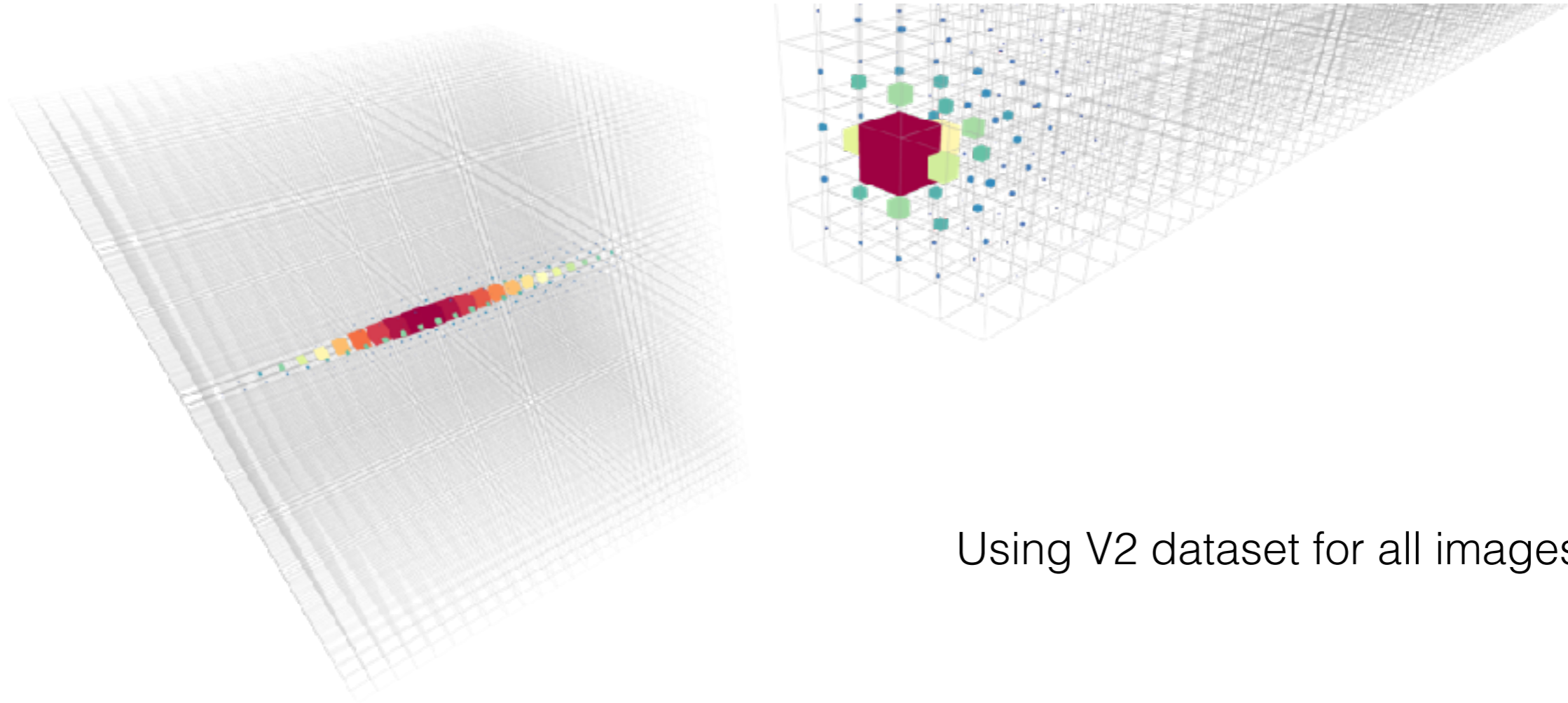


SUMMARY OF CURRENT PROGRESS

MATT ZHANG



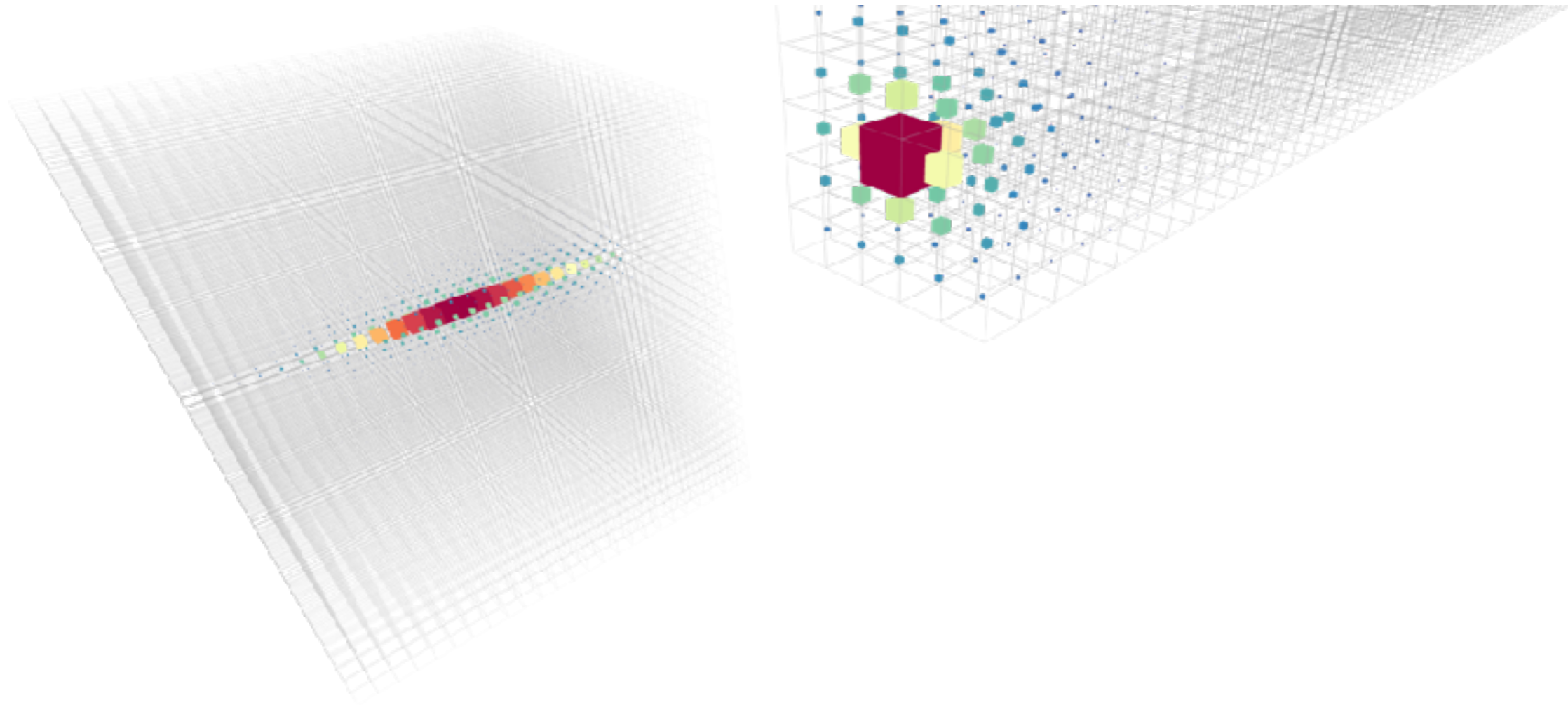
Average 60 GeV electron



Using V2 dataset for all images

Images generated by Wei

Average 105 GeV charged pion



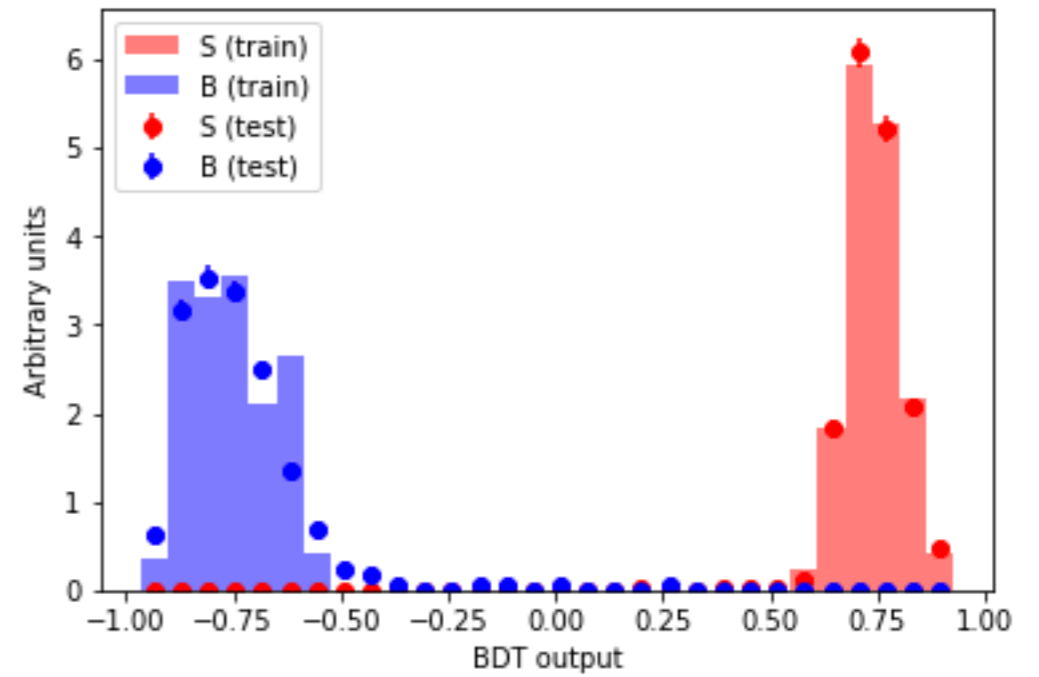
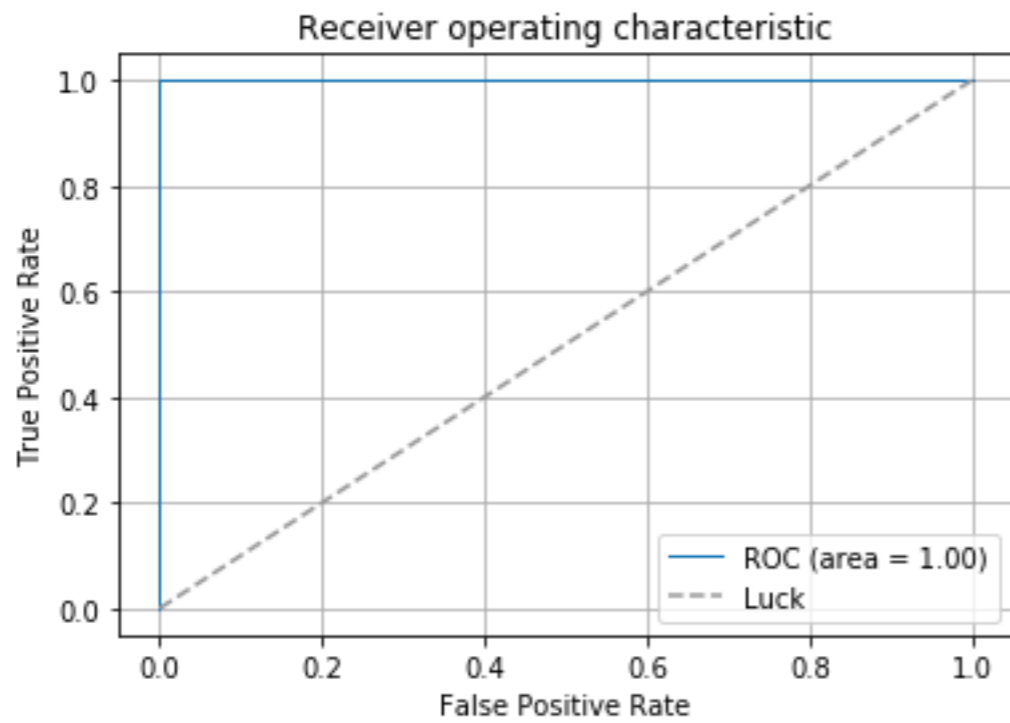
Images generated by Wei

The charged pion deposits its energy further in the ECAL than the electron, and leaves a more diffuse signature in the HCAL, even with the same ECAL/HCAL ratio.

Electron / ChPi discrimination seems easy to do.

	precision	recall	f1-score	support
charged pion	1.00	0.99	1.00	395
electron	1.00	1.00	1.00	3275
avg / total	1.00	1.00	1.00	3670

Area under ROC curve: 1.0000

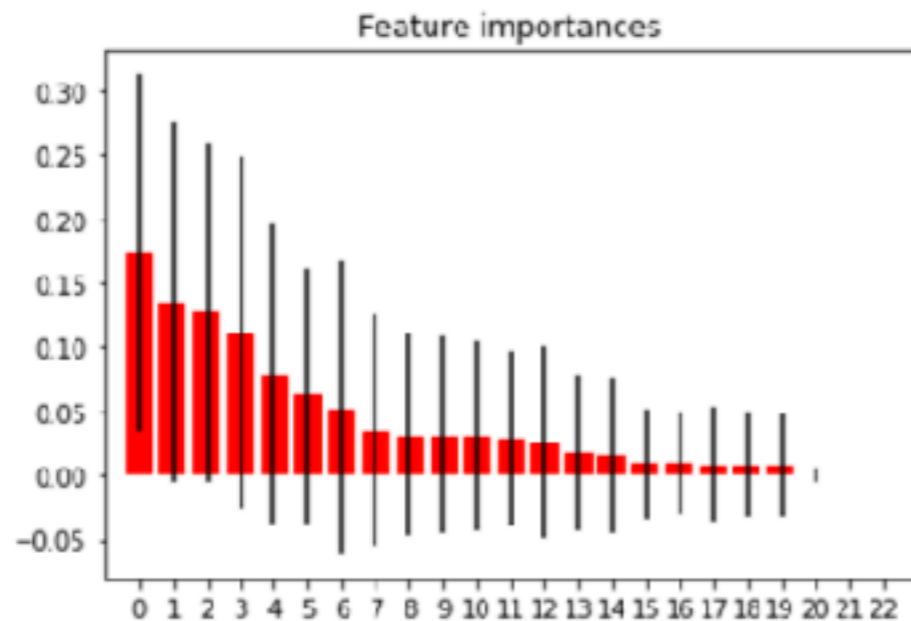


E - ChPi BDT

Feature ranking:

1. HCAL_nHits (0.173457)
2. ECAL_E (0.135110)
3. ECALmomentZ1 (0.126652)
4. ECALmomentY5 (0.110985)
5. ECAL_nHits (0.078583)
6. HCAL_E (0.062295)
7. ECAL_ratioFirstLayerToTotalE (0.052166)
8. ECALmomentX1 (0.035415)
9. HCAL_ECAL_ERatio (0.031651)
10. ECALmomentY4 (0.031493)
11. ECALmomentZ2 (0.030736)
12. HCAL_ratioFirstLayerToTotalE (0.028296)
13. ECALmomentX5 (0.025176)
14. ECALmomentY3 (0.017541)
15. ECALmomentX3 (0.015427)
16. ECALmomentX2 (0.009514)
17. ECALmomentY2 (0.009445)
18. ECALmomentX4 (0.008819)
19. ECALmomentZ3 (0.008803)
20. ECALmomentY1 (0.008007)
21. ECALmomentZ4 (0.000430)
22. ECALmomentZ5 (0.000000)
23. HCAL_ECAL_nHitsRatio (0.000000)

data may be fishy - needs further investigation

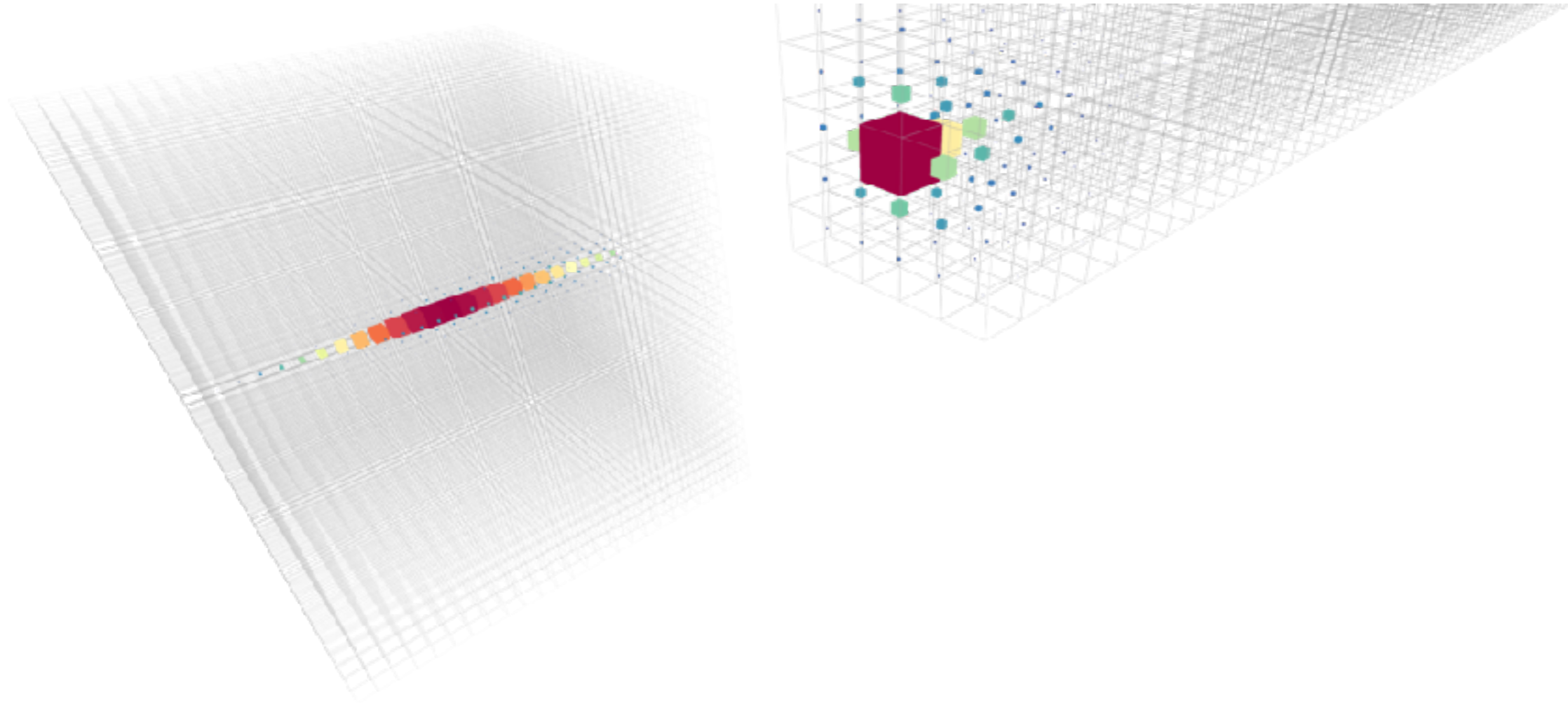


γ - π^0 BDT

E - ChPi DNN

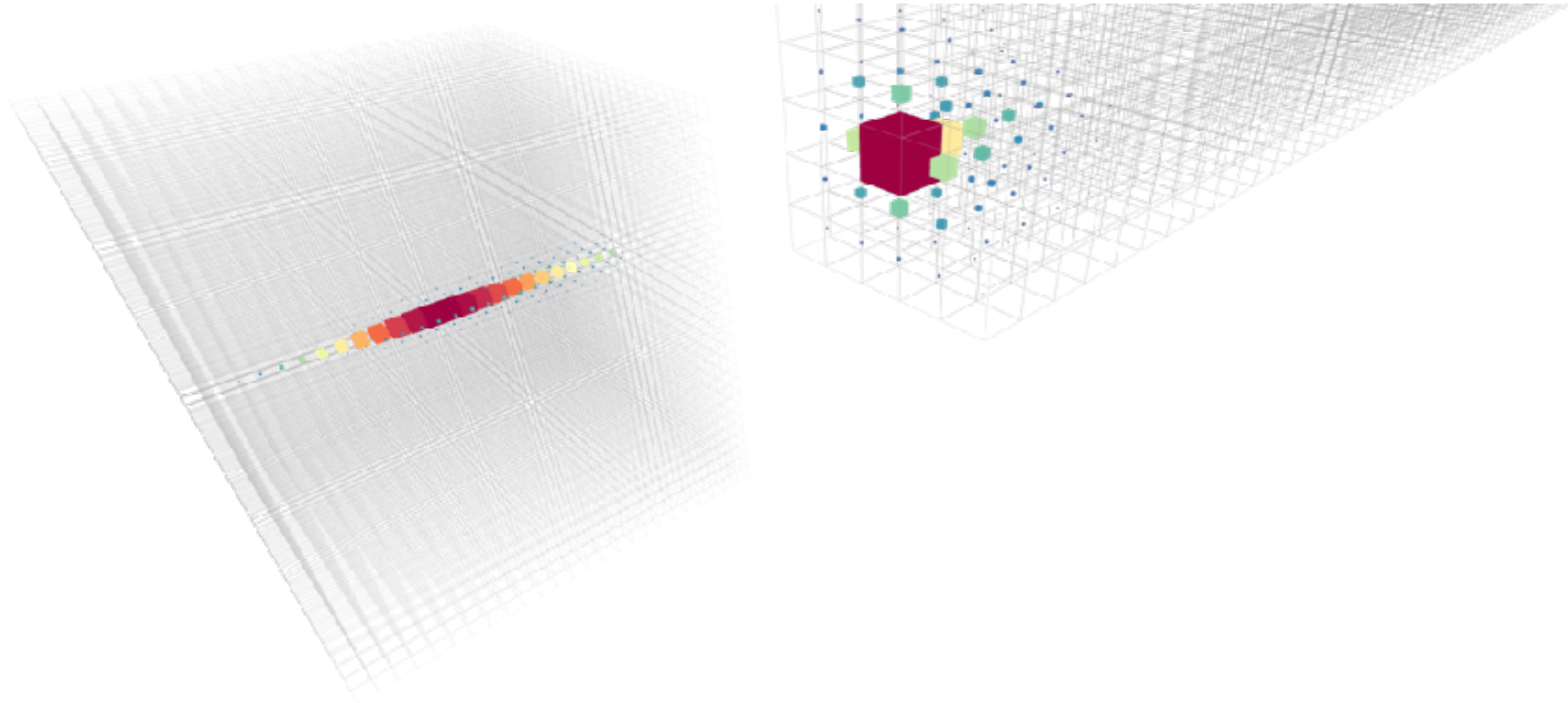
Technical problems - plot not available.
See backup for details.

Average 60 GeV photon



Images generated by Wei

Average 60 GeV neutral pion



Images generated by Wei

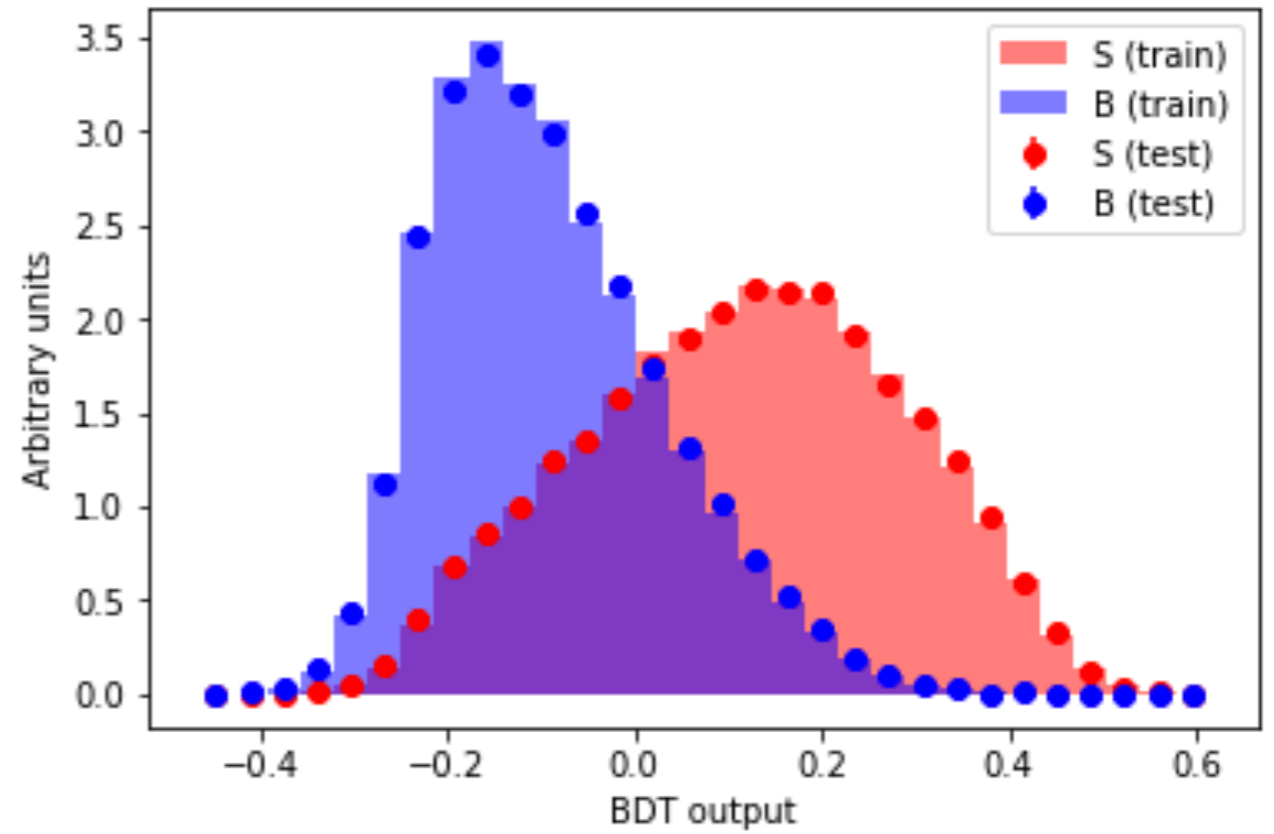
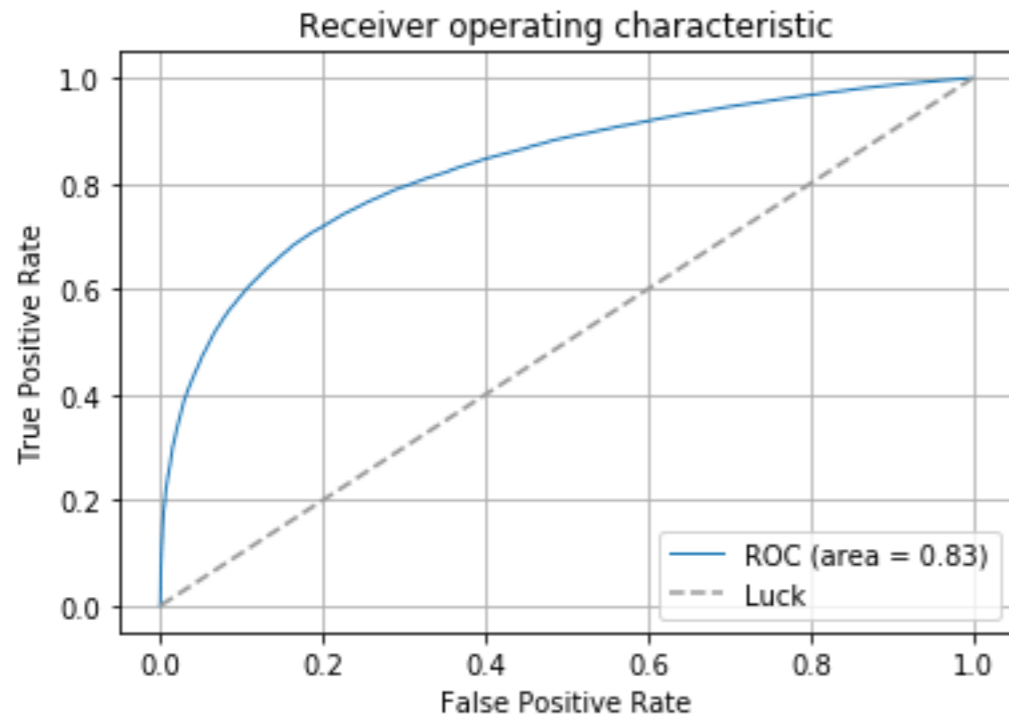
Difference is subtle, but the $\text{Pi}0 \rightarrow \gamma\gamma$ is more spread out in both ECAL and HCAL.

The opening angle for these $\text{Pi}0$ events is less than 0.01 radians.

typo

	precision	recall	f1-score	support
photon	0.75	0.78	0.76	44400
electron	0.77	0.74	0.75	44040
avg / total	0.76	0.76	0.76	88440

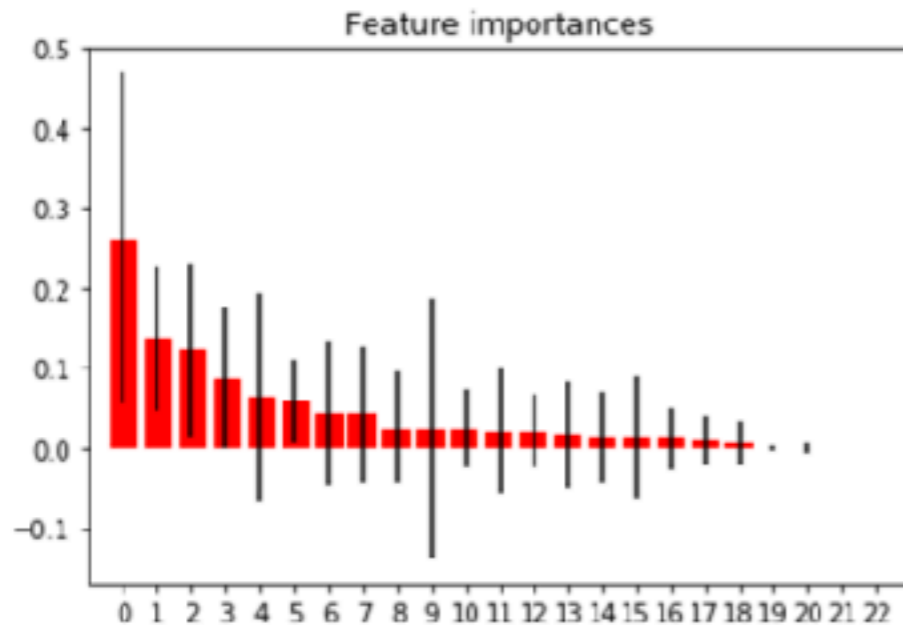
Area under ROC curve: 0.8311



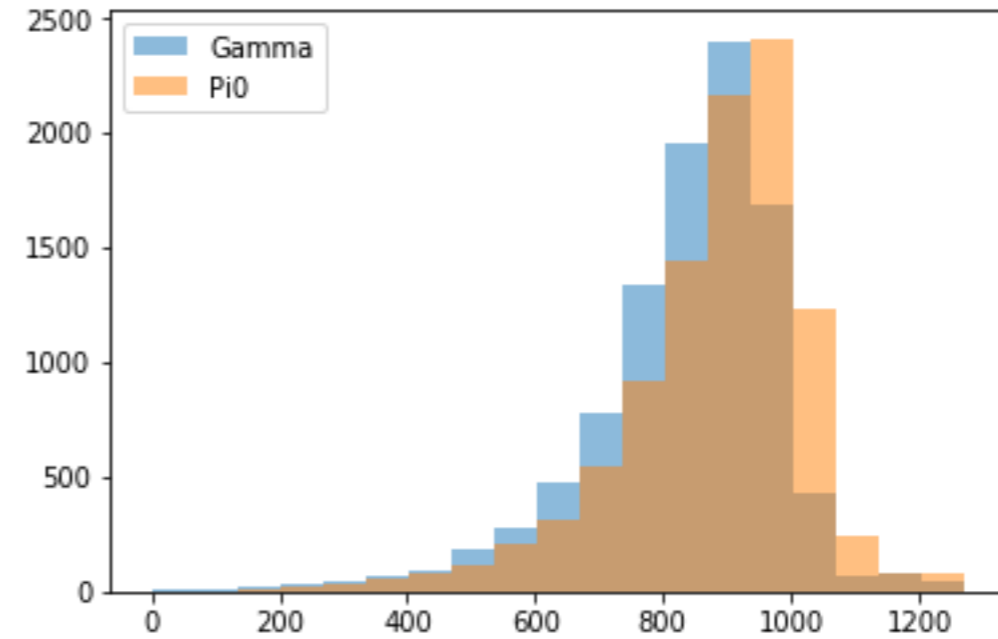
γ - π^0 BDT

Feature ranking:

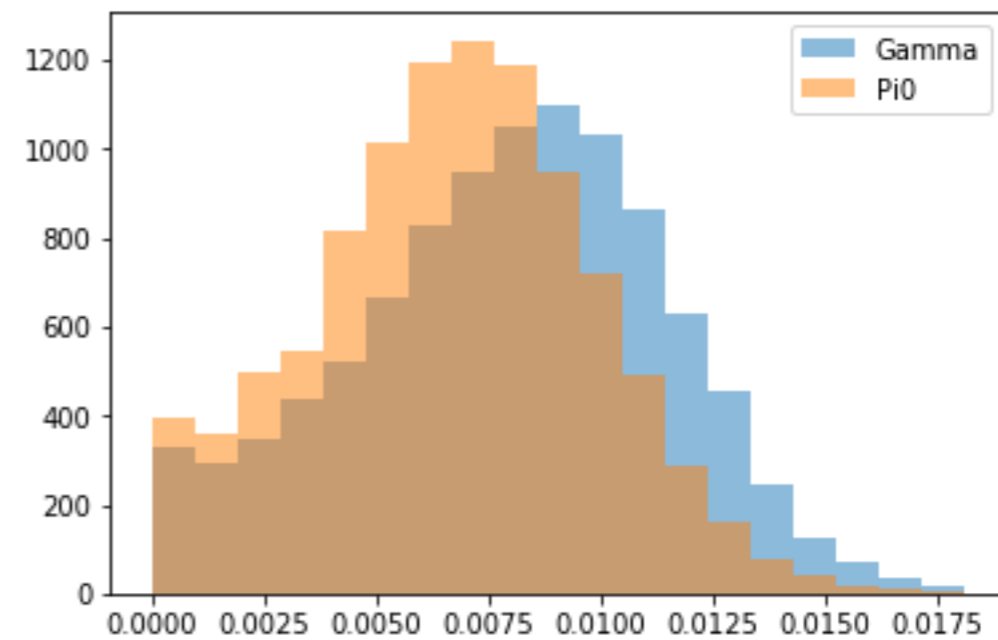
1. ECAL_nHits (0.262327)
2. ECALmomentY5 (0.136302)
3. ECAL_E (0.121541)
4. ECALmomentZ1 (0.087116)
5. ECALmomentY1 (0.063538)
6. ECALmomentX5 (0.058756)
7. HCAL_nHits (0.042656)
8. ECALmomentY4 (0.041717)
9. ECALmomentY2 (0.026004)
10. ECAL_ratioFirstLayerToTotalE (0.024097)
11. ECALmomentY3 (0.023396)
12. ECALmomentZ2 (0.021951)
13. ECALmomentX4 (0.021255)
14. ECALmomentX1 (0.016328)
15. ECALmomentX2 (0.013603)
16. HCAL_ratioFirstLayerToTotalE (0.012366)
17. HCAL_E (0.011821)
18. ECALmomentX3 (0.008615)
19. HCAL_ECAL_ERatio (0.006148)
20. ECALmomentZ3 (0.000224)
21. HCAL_ECAL_nHitsRatio (0.000159)
22. ECALmomentZ4 (0.000000)
23. ECALmomentZ5 (0.000000)



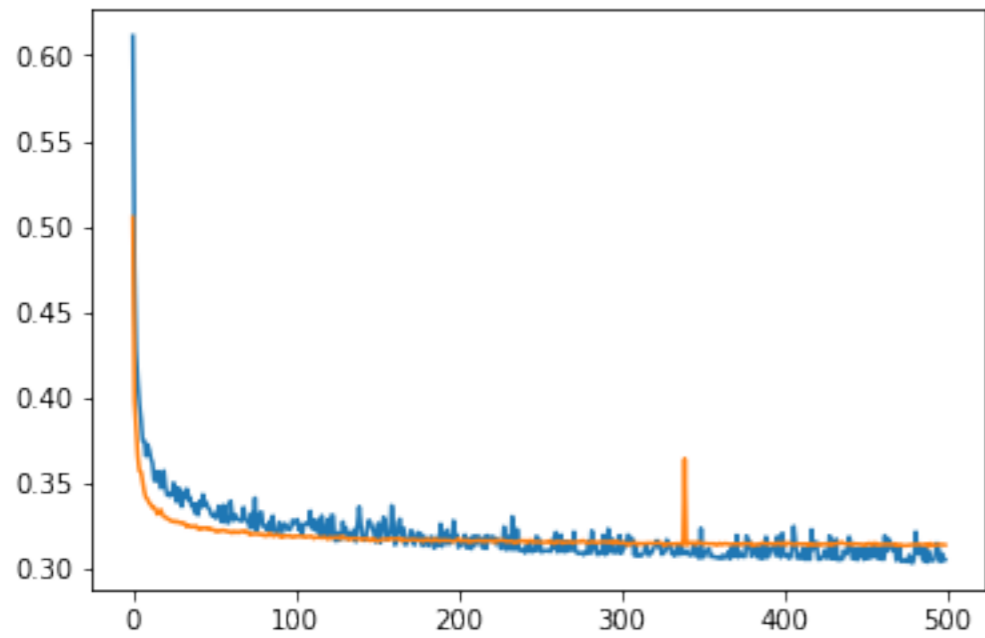
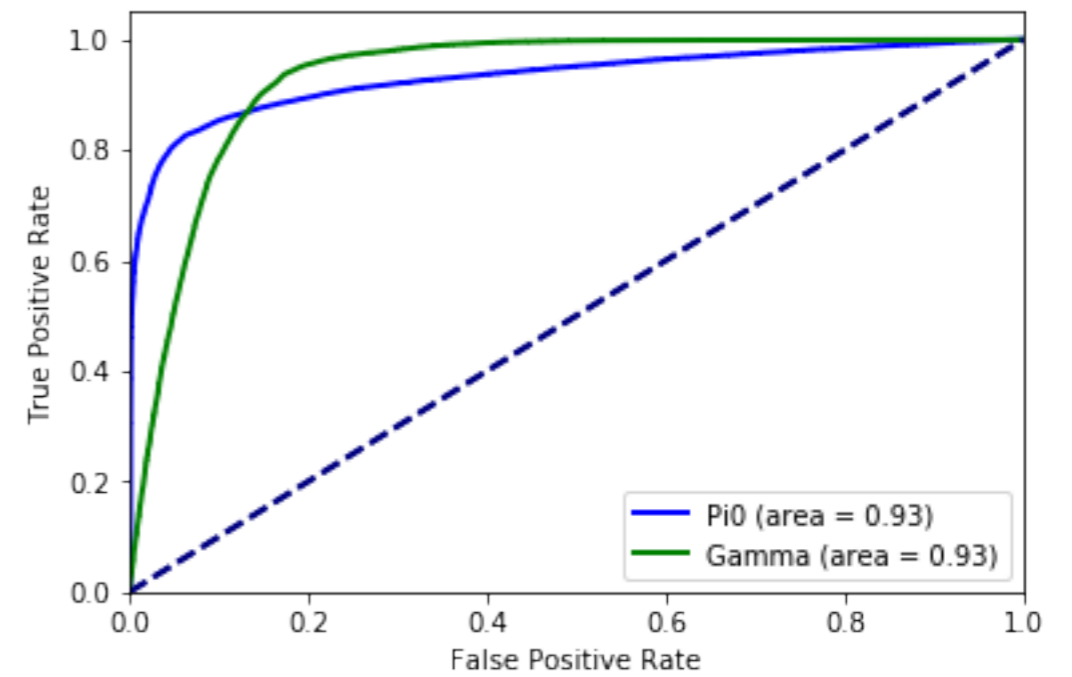
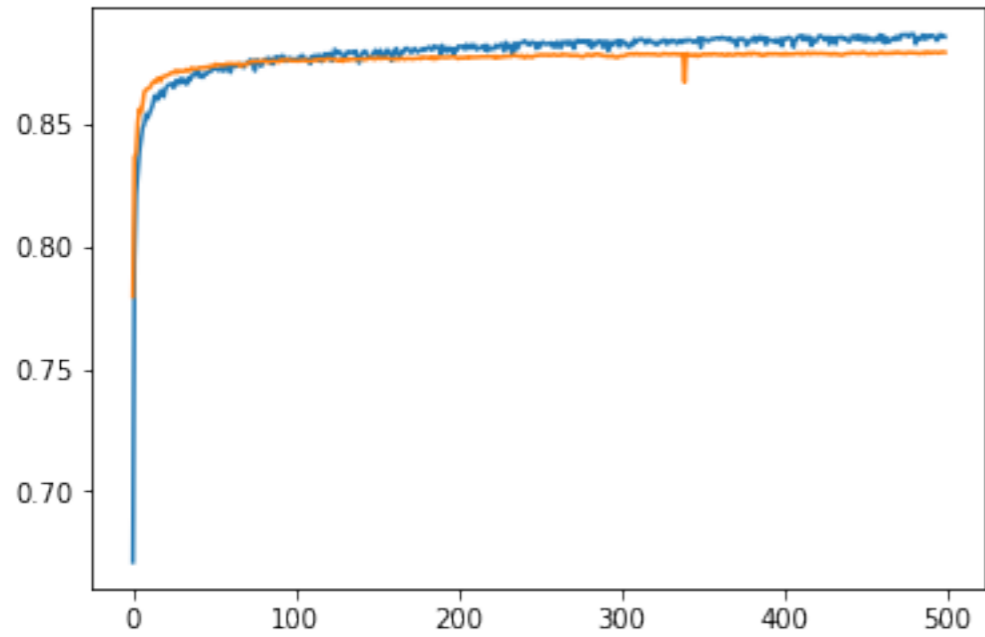
ECAL_nHits



ECALmomentY5



γ - π^0 BDT



γ - π^0 DNN

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 25, 25, 25)	0	
input_2 (InputLayer)	(None, 5, 5, 60)	0	
flatten_1 (Flatten)	(None, 15625)	0	input_1[0][0]
flatten_2 (Flatten)	(None, 1500)	0	input_2[0][0]
activation_1 (Activation)	(None, 15625)	0	flatten_1[0][0]
activation_4 (Activation)	(None, 1500)	0	flatten_2[0][0]
dense_1 (Dense)	(None, 64)	1000064	activation_1[0][0]
dense_3 (Dense)	(None, 32)	48032	activation_4[0][0]
activation_2 (Activation)	(None, 64)	0	dense_1[0][0]
activation_5 (Activation)	(None, 32)	0	dense_3[0][0]
dropout_1 (Dropout)	(None, 64)	0	activation_2[0][0]
dropout_3 (Dropout)	(None, 32)	0	activation_5[0][0]
dense_2 (Dense)	(None, 64)	4160	dropout_1[0][0]
dense_4 (Dense)	(None, 32)	1056	dropout_3[0][0]
activation_3 (Activation)	(None, 64)	0	dense_2[0][0]
activation_6 (Activation)	(None, 32)	0	dense_4[0][0]
dropout_2 (Dropout)	(None, 64)	0	activation_3[0][0]
dropout_4 (Dropout)	(None, 32)	0	activation_6[0][0]
concatenate_1 (Concatenate)	(None, 96)	0	dropout_2[0][0] dropout_4[0][0]
dense_5 (Dense)	(None, 2)	194	concatenate_1[0][0]

γ - π^0 DNN

Paper Outline

1. Background and purpose
2. Brief description of how machine learning techniques work
3. Description of areas where improved particle ID can be beneficial
4. Dataset generation using the CLIC LCD detector
5. Examination of generated data
6. Description of BDT baseline
7. Description of DNN
8. Description of CNN
9. Comparison of results
10. Conclusion



Need some help here (Ben?)

Maybe could add an appendix on data handling, generators, etc. (Amir?)

Outstanding To-Do Items

- Improve and test n-subjettiness in BDT → Matt, Wei
- Fix generator issue → Amir, Matt
- Improve CNN architecture → Matt, Ryan, Amir
 - I tried a few architectures, but they currently train slower than DNN and get worse results
 - Trying out inference-layer architecture from GoogleNet, but have not been able to train on it yet
 - Generate CNN plots for paper
- Generate and validate new samples → Maurizio, Matt
- Write up paper sections → Everyone
- (Not for paper) Create samples at multiple p_T points, and also for μ and τ → Maurizio, Wei
- (Not for paper) Create samples with pileup → Maurizio, Wei
- (Not for paper) Create samples at multiple incident angles → Maurizio, Wei
- (Not for paper) Use semantic segmentation algorithms to identify object locations in calorimeter → Matt, Ryan, Amir

Backup

Bugs

- “top” on UTA cluster reveals that I have several python processes in uninterruptible sleep - requires hard reboot of cluster.
- I can not open files to read into Keras net as of two days ago, probably due to this issue.