NMSU Update

Dinupa

March 26, 2023

- We use Generative adversarial network (GAN) to extract the λ, μ, ν values from the reconstructed $\phi - cos\theta$ histograms. Following modifications are made to the GAN network.
- Generator is trained with regression step. Therefore criterion is MSELoss. Generator will try to extract the λ, μ, ν values from the input histogram.

```
Generator(
(conv): Sequential(
  (0): Conv2d(1, 32, kernel_size=(5, 5), stride=(1, 1))
  (1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (2): ReLU()
  (3): Conv2d(32, 64, kernel_size=(5, 5), stride=(1, 1))
  (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (5): ReLU()
)
(fc): Sequential(
  (0): Linear(in_features=256, out_features=64, bias=True)
  (1): ReLU()
  (2): Linear(in_features=64, out_features=32, bias=True)
  (3): ReLU()
  (4): Linear(in_features=32, out_features=3, bias=True)
)
)
```

- Discriminator will try to classify whether the output from the Generator is real or fake. Therefore criterion is BCELoss.

```
Discriminator(
  (model): Sequential(
    (0): Linear(in_features=3, out_features=20, bias=True)
    (1): ReLU()
    (2): Linear(in_features=20, out_features=1, bias=True)
    (3): Sigmoid()
  )
)
```

- We can understand the behavior of GAN as a con artist trying to fake a painting (generator) while a detective trying to identify if the painting is fake or real (discriminator). Artist will succeed his work when he was able to fool the detective. This is what we try to achieve by training GAN.
- Our goal is to extract the angular coefficients from the new histograms using a trained GAN.

Training histograms;

-> About 9k combinations of lambda, mu, nu were created in range [-1., 1.]

-> costheta range [-0.6, 0.6]

Test histograms;

-> 50 histograms were created with 50K different events.

-> 4 different combination of lambda, mu, nu is tested;

	lambda	mu	nu
test 1	0.25	-0.15	0.15
test 2	-0.25	0.35	0.45
test 3	0.45	0.15	-0.35
test 4	-0.45	0.15	0.25

-> These combinations of lambda, mu, nu is not used in training.

D1 Occupancy Cut

- We use the D1 occupancy cut < 200.
- We lose about 1M events (out of 5M) due to this cuts.

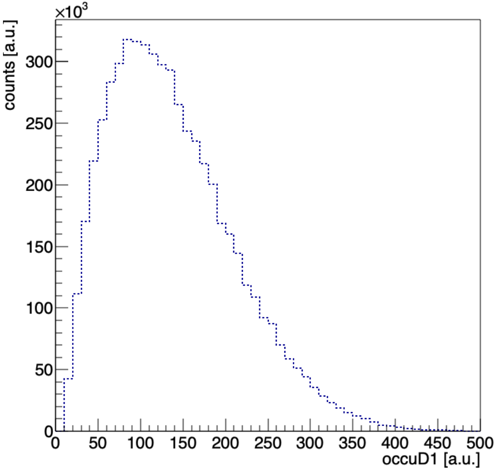
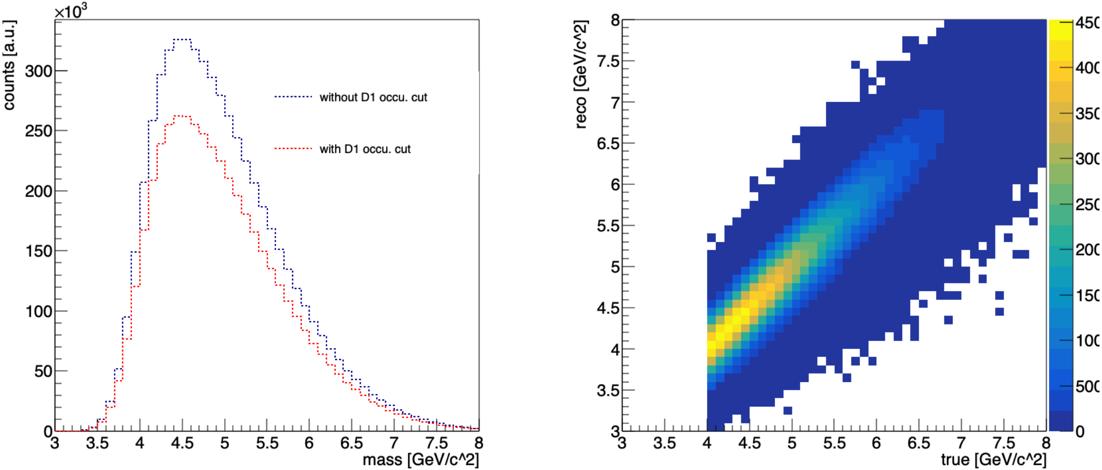


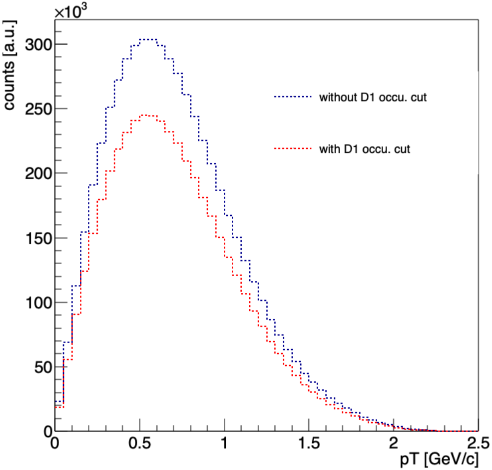
Figure 1: D1 occupancy.

mass

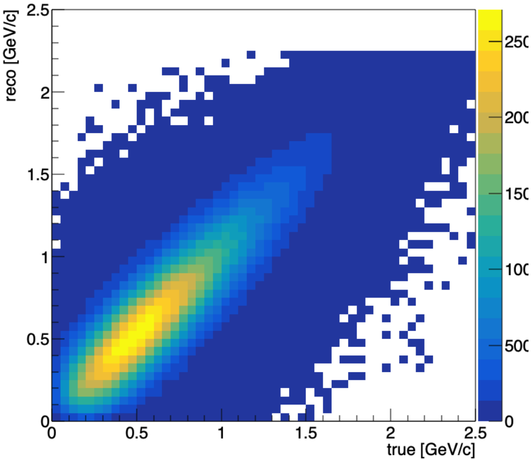


×10^3
counts [a.u.]
300
250
200
150
100
50
0
3
3.5
4
4.5
5
5.5
6
6.5
7
7.5
8
mass [GeV/c^2]
without D1 occu. cut
with D1 occu. cut
reco [GeV/c^2]
true [GeV/c^2]
450
400
350
300
250
200
150
100
500
0

pT

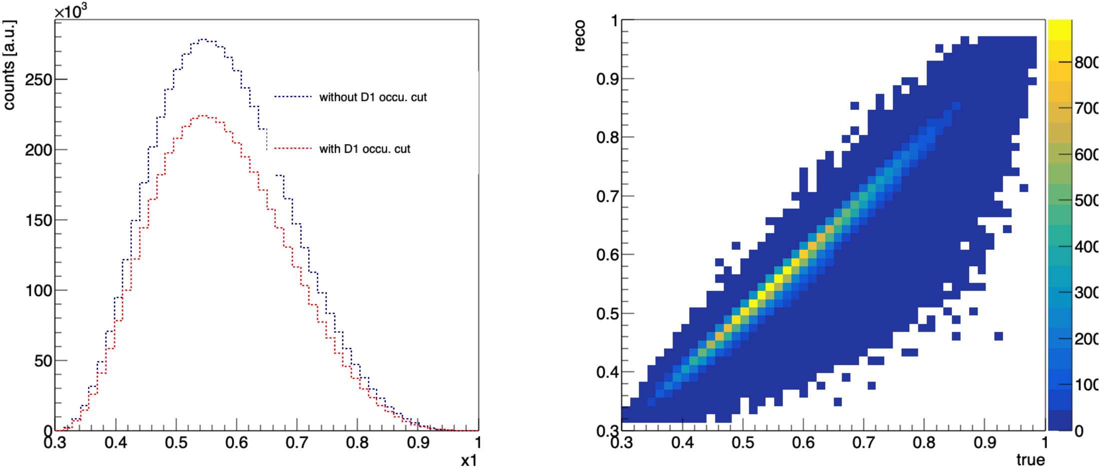


$\times10^3$
counts [a.u.]
300
250
200
150
100
50
0
0
0.5
1
1.5
2
2.5
pT [GeV/c]
without D1 occu. cut
with D1 occu. cut

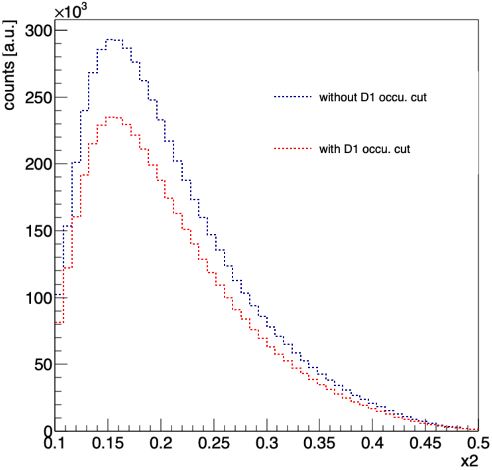


reco [GeV/c]
2.5
2
1.5
1
0.5
0
0
0.5
1
1.5
2
2.5
true [GeV/c]
250
200
150
100
500
0

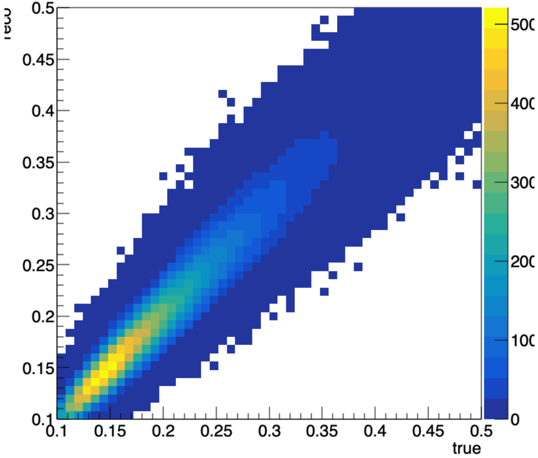
x1


×10³
counts [a.u.]
250
200
150
100
50
0
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
x1
without D1 occu. cut
with D1 occu. cut
reco
true
800
700
600
500
400
300
200
100
0

x2

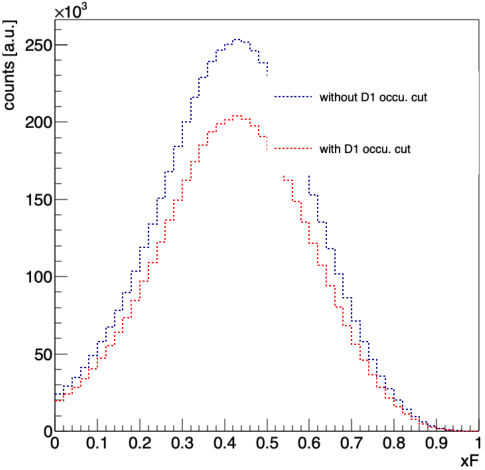


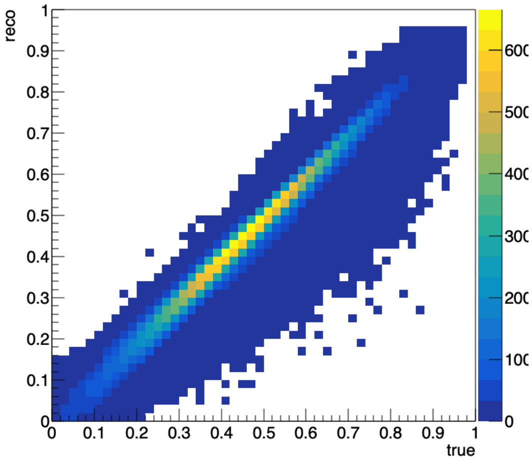
×10³
300
250
200
150
100
50
0
counts [a.u.]
without D1 occu. cut
with D1 occu. cut
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
x2



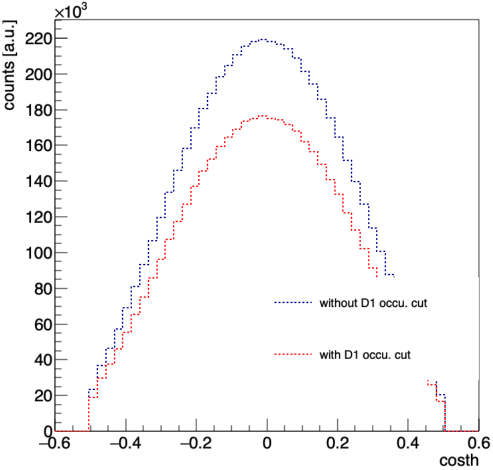
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
true
0

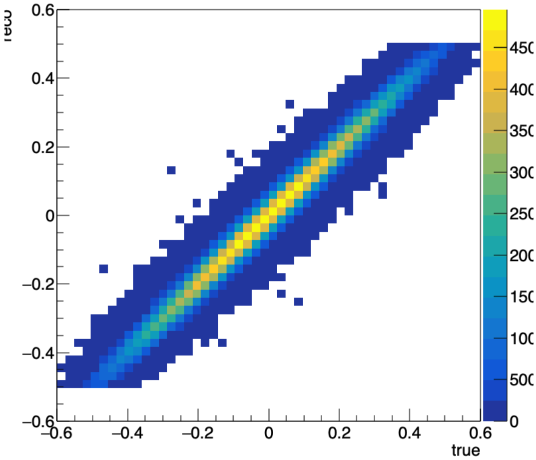
xF


×10³
counts [a.u.]
250
200
150
100
50
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
xF
without D1 occu. cut
with D1 occu. cut

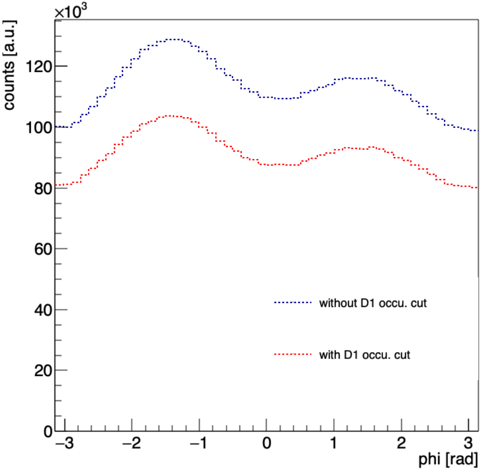

reco
true
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

costh

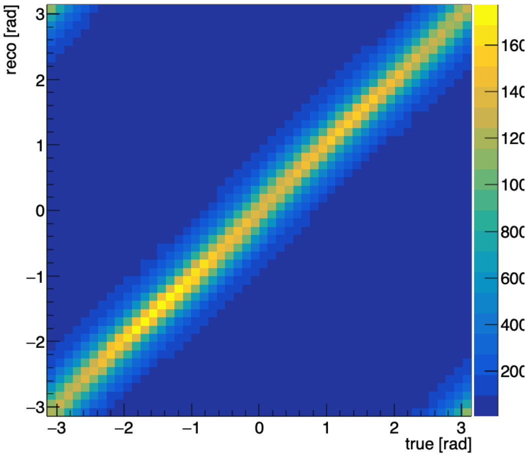

×10^3
counts [a.u.]
220
200
180
160
140
120
100
80
60
40
20
0
−0.6
−0.4
−0.2
0
0.2
0.4
0.6
costh
without D1 occu. cut
with D1 occu. cut


reco
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
−0.6
−0.4
−0.2
0
0.2
0.4
0.6
true
450
400
350
300
250
200
150
100
500
0

phi



$\times 10^3$
counts [a.u.]
120
100
80
60
40
20
0
−3
−2
−1
0
1
2
3
phi [rad]
without D1 occu. cut
with D1 occu. cut



reco [rad]
3
2
1
0
−1
−2
−3
true [rad]
160
140
120
100
800
600
400
200

$$[\lambda, \mu, \nu] = [0.25, -0.15, 0.15]$$

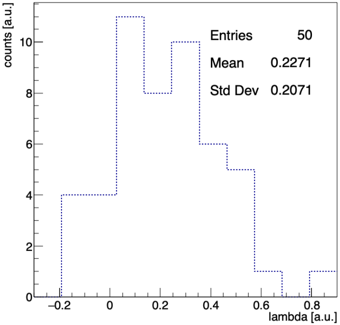


Figure 2: Extracted lambda.

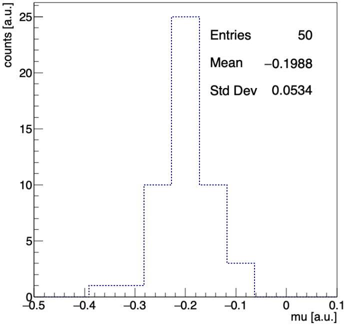


Figure 3: Extracted mu.

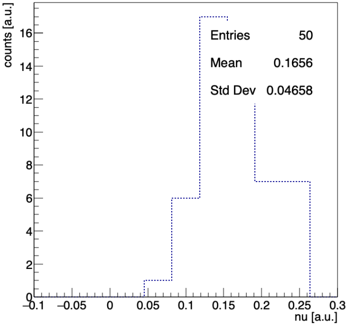


Figure 4: Extracted nu.

$$[\lambda, \mu, \nu] = [-0.25, 0.35, 0.45]$$

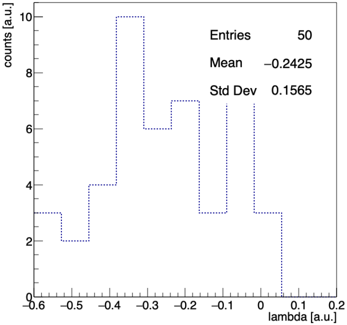


Figure 5: Extracted lambda.

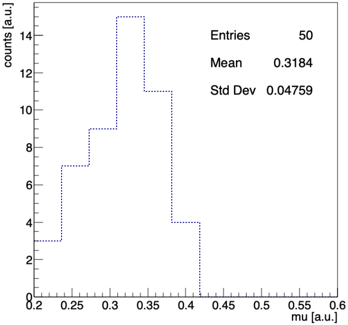


Figure 6: Extracted mu.

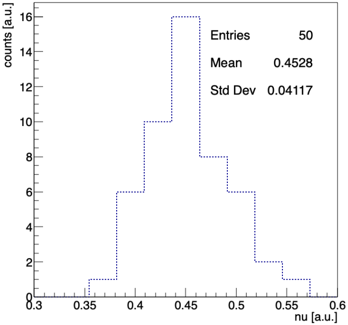


Figure 7: Extracted nu.

$$[\lambda, \mu, \nu] = [0.45, 0.15, -0.35]$$

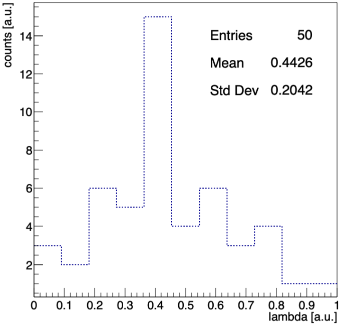


Figure 8: Extracted lambda.

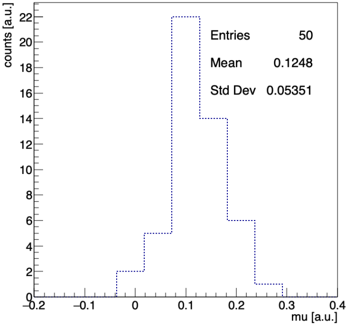


Figure 9: Extracted mu.

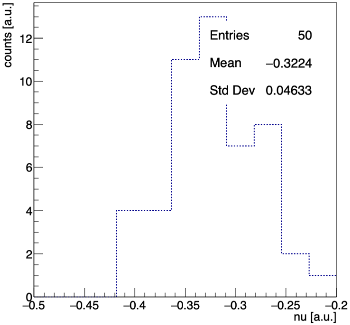


Figure 10: Extracted nu.

$$[\lambda, \mu, \nu] = [-0.45, 0.15, 0.45]$$

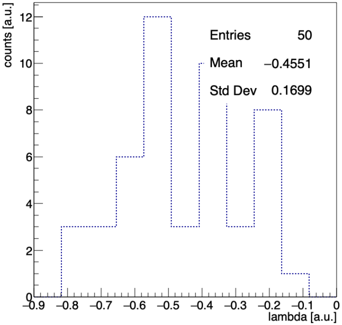


Figure 11: Extracted lambda.

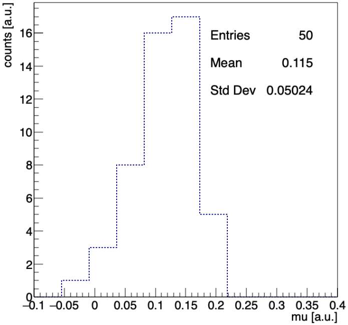


Figure 12: Extracted mu.

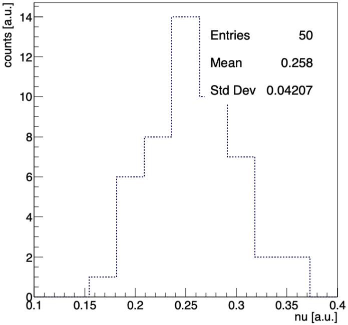


Figure 13: Extracted nu.

Summary

- With D1 occupancy cut, neural network was able to predict μ and ν accurately.
- Next: extract the angular coefficients for binned data.