### NMSU Update

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- >> We use Generative adversarial network (GAN) to extract the  $\lambda,\mu,\nu$  values from the reconstructed  $\phi-cos\theta$  histograms. Following modifications are made to the GAN network.
- ightharpoonup Generator is trained with regression step. Therefore criterion is MSELoss. Generator will try to extract the  $\lambda,\mu,\nu$  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.

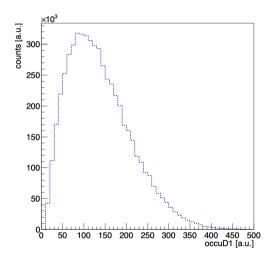
- >> Training histograms;
  - -> About 9k combinations of lambda, mu, nu were created in range [-1., 1.]
  - -> costheta range [-0.6, 0.6]
- >> Test histograms;
  - -> 50 histograms were created with 50K different events.
  - -> 4 different combination of lambda, mu, nu is tested;

		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

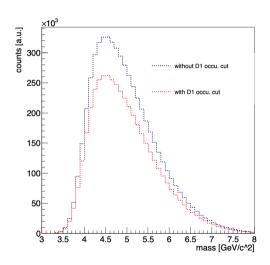
-> These combinations of lambda, mu, nu is not used in training.

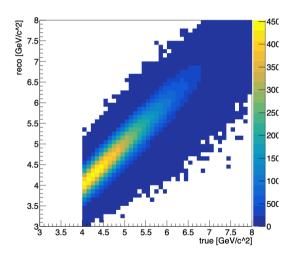
#### D1 Occupancy Cut

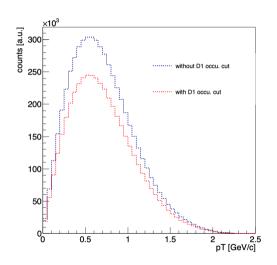
- >> We use the D1 occupancy cut < 200.
- >> We lose about 1M events (out of 5M) due to this cuts.

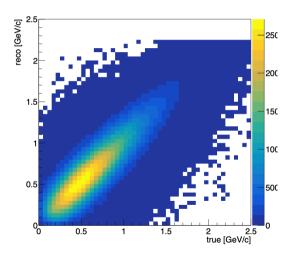


#### mass

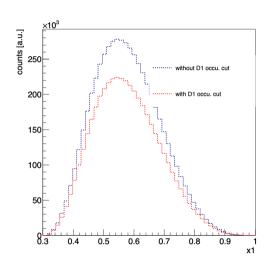


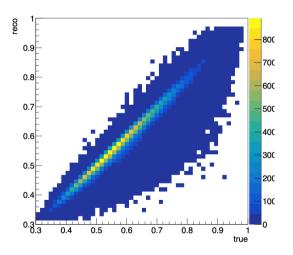




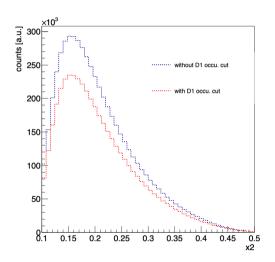


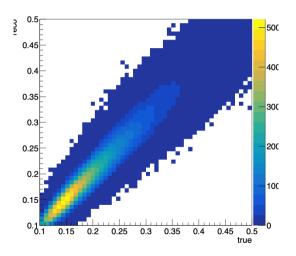




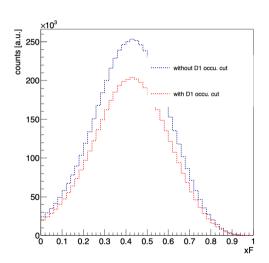


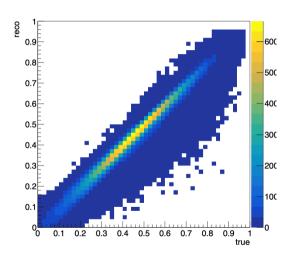




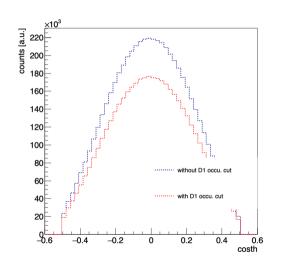


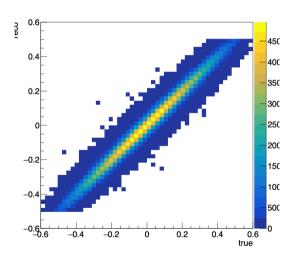




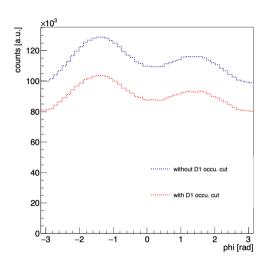


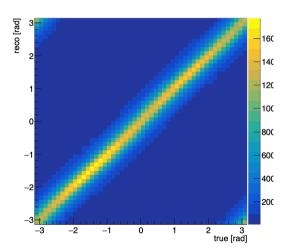
### costh





## phi





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

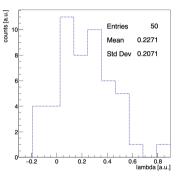


Figure 2: Extracted lambda.

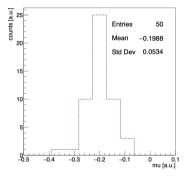


Figure 3: Extracted mu.

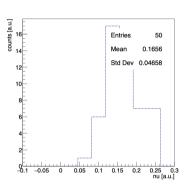
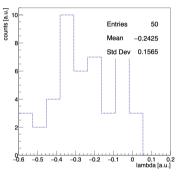


Figure 4: Extracted nu.

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



counts [a.u.] Entries 50 Mean 0.3184 Std Dev 0.04759 0.4 0.45 0.55 0.0 mu [a.u.]

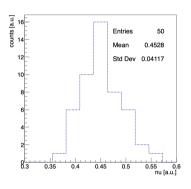
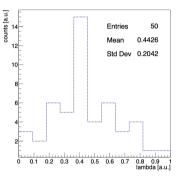


Figure 5: Extracted lambda.

Figure 6: Extracted mu.

Figure 7: Extracted nu.

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



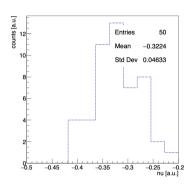
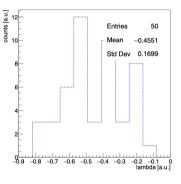


Figure 8: Extracted lambda.

Figure 9: Extracted mu.

Figure 10: Extracted nu.

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



counts [a.u.] 50 Entries Mean 0.115 Std Dev 0.05024 0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 mu [a.u.]

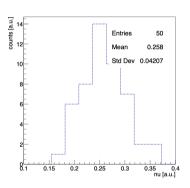


Figure 11: Extracted lambda.

Figure 12: Extracted mu.

Figure 13: Extracted nu.