

Run 15 ZDC A_N vs. P_T Unfolding

Spin PWG Meeting

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9:00 AM (KST/JST)

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Content

Unfolding overview

- Statistical fluctuations and migrations

One- and two-dimensional unfolding cases

- Generated transverse momentum
- Smeared transverse momentum
- Smearing response matrix
- Closure test

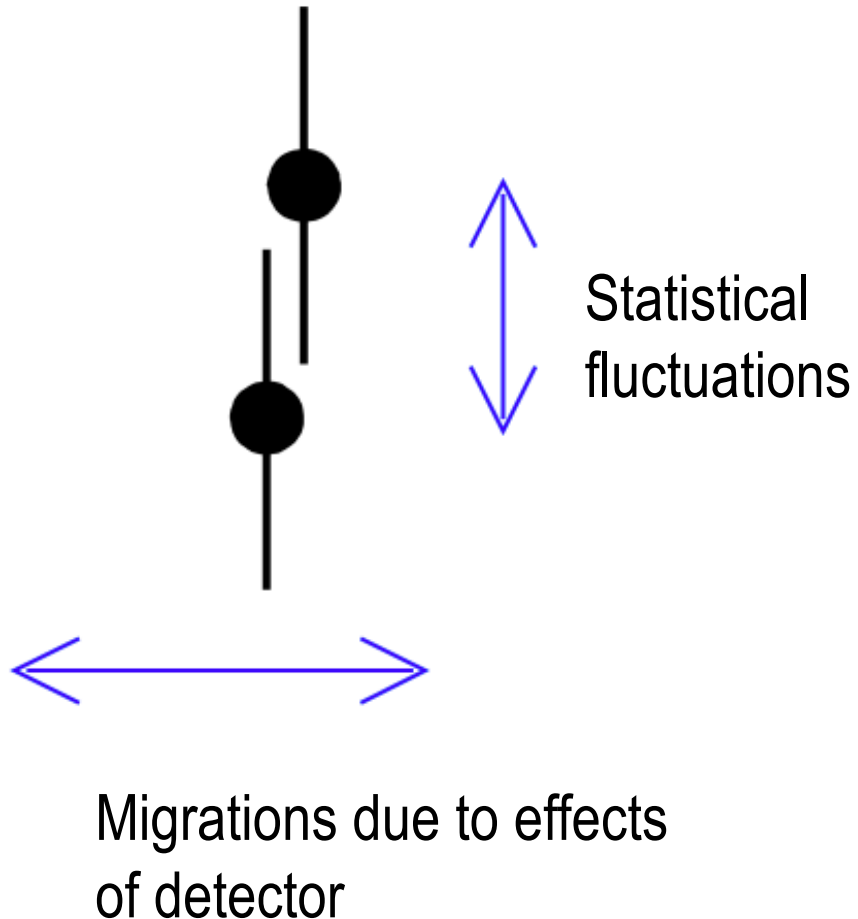
Unfolding neutron asymmetry for inclusive pp collisions in the ZDC

- Strategy
- Asymmetry extraction and reweighting

Conclusions

- Summary
- To-do-list

Unfolding overview – Statistical fluctuations and migrations due to detector effects



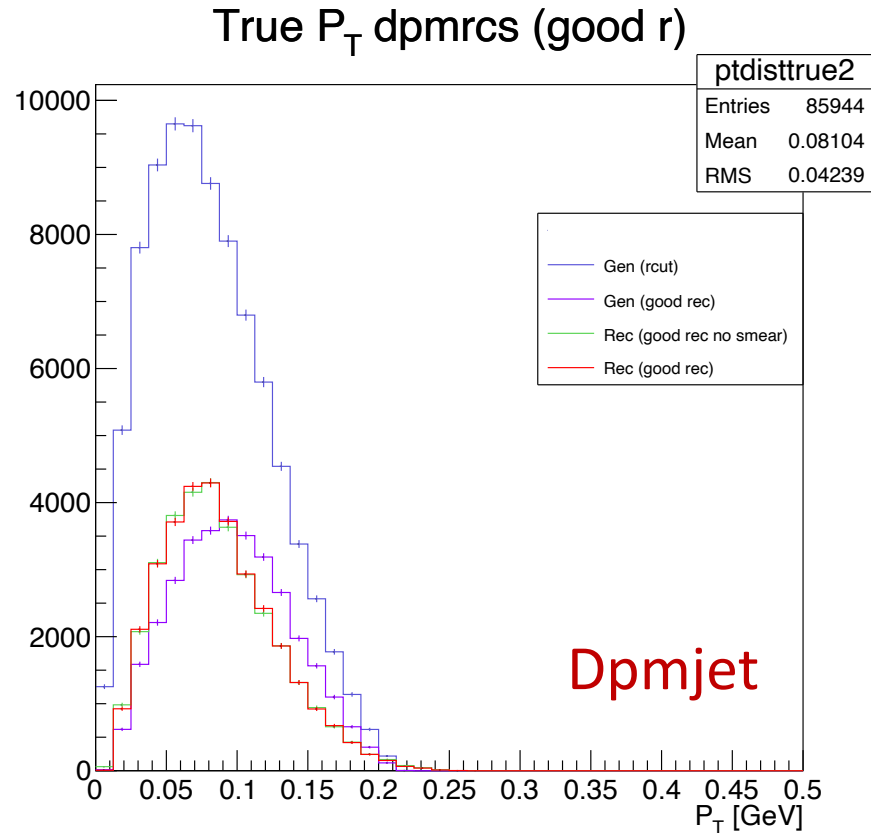
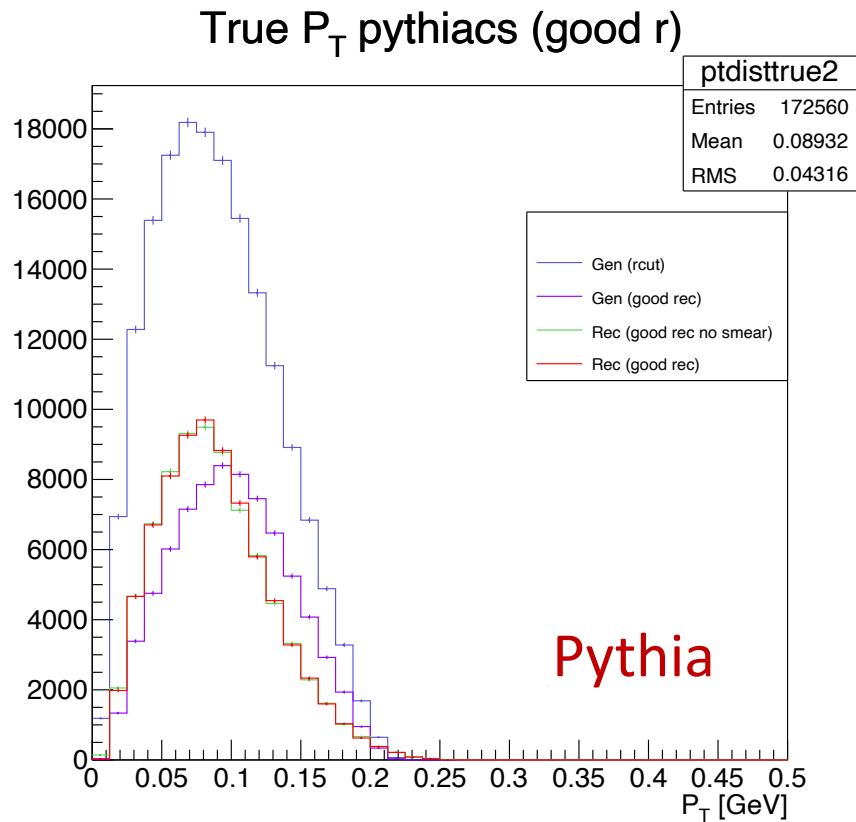
Unfolding:

- Is used to correct for migration effects in the presence of statistical fluctuations.

Result:

- Is an estimation of the “truth” distribution.
- Covariance matrix (statistical uncertainties)

One - dimensional pt unfolding closure test – Unfolding inputs using Pythia and DPMJET

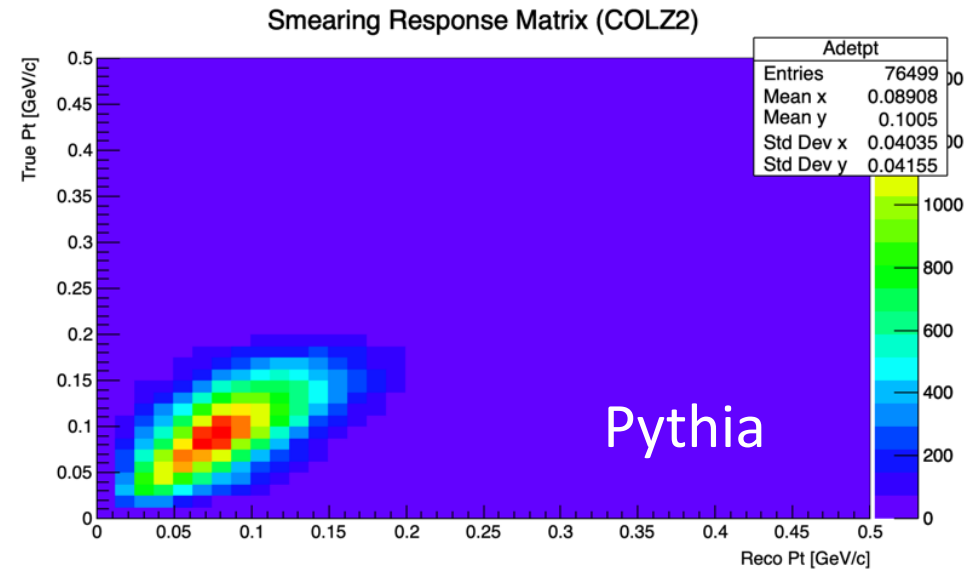


1. Gen (rcut) : Blue line with $r_{min} < 0.5$ and $r_{max} < 4.0$ cm
2. Gen (good rec): Purple line with cuts: r_{cut} , $E_{min} > 20$ GeV and $E_{max} < 120$ GeV, $E_{ZDC2}/E_{ZDC1} > 0.03$, $N_x N_y > 1$ fired above $E_{smdxy} = 0.003$ GeV
3. Rec (good rec no smear): Green line – no smearing
4. Rec (good rec): Red line – is reconstructed.

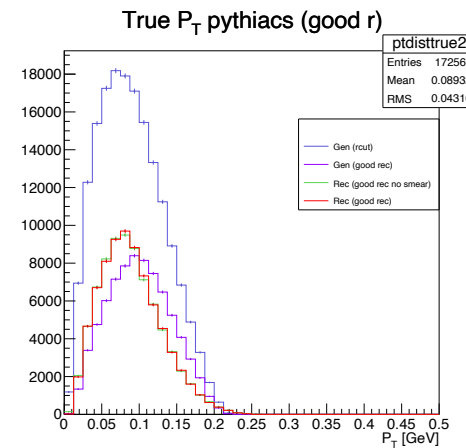
$$P_{T(True)} = \sqrt{p_x * p_x + p_y * p_y}$$

$$P_{T(Reco)} = \frac{r E_{reco}}{IP_{To_ZDC}} \quad \text{with } r = \sqrt{x_{ev} * x_{ev} + y_{ev} * y_{ev}} \quad \text{and IP is the distance from the collision point to ZDC)}$$

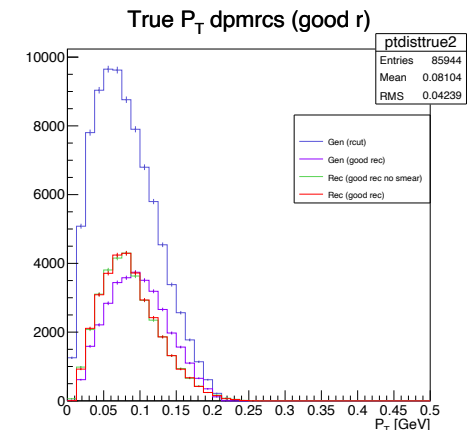
One-dimensional pt unfolding closure test – Unfolding inputs using Pythia and DPMJET



- Detector smearing matrix from pythia Monte Carlo.
- It maps the smeared (reco) pt in red line to the true pt in purple line of Pythia Monte Carlo sample.

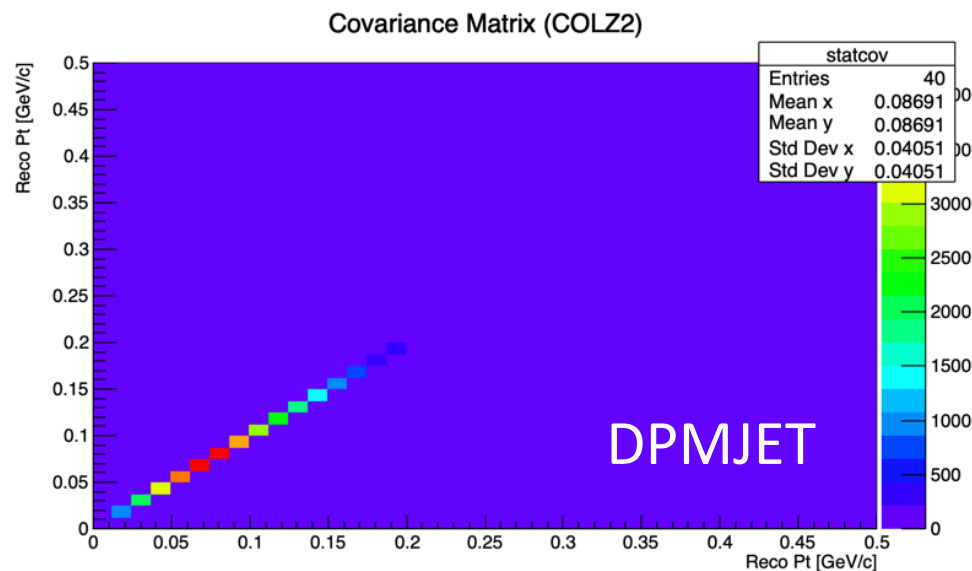


Pythia



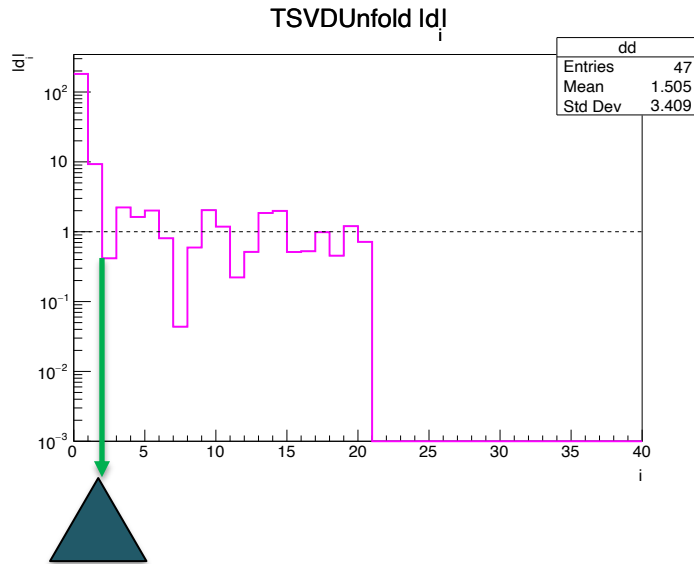
Dpmjet

- Input covariance matrix obtained from the square of the errors of the smeared pt (red line) from dpmjet.
- Unfolding is based on the singular value decomposition(SVD) of detector response matrix.



One-dimensional pt unfolding closure test – using pythia and dpmjet MC

Unfolding is performed with an optimal regularization parameter obtained from a d vector distribution for a regularized system:



$$d_i = z_i^\tau \frac{s_i^2 + \tau}{s_i}, \quad i = 1, \dots, \text{Nbin}$$

$\tau = \text{Kreg}$ (regularization parameter)

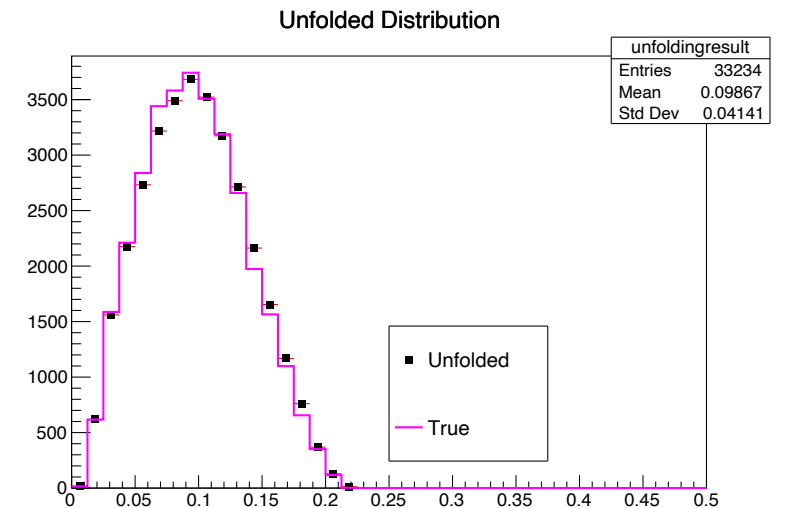
s_i = positive diagonal elements (singular values of response matrix)

τ = nonzero (regularized system)

= zero (non-regularized system), $d_i = s_i \cdot z_i^{(0)}$ (diagonal systems - not useful)

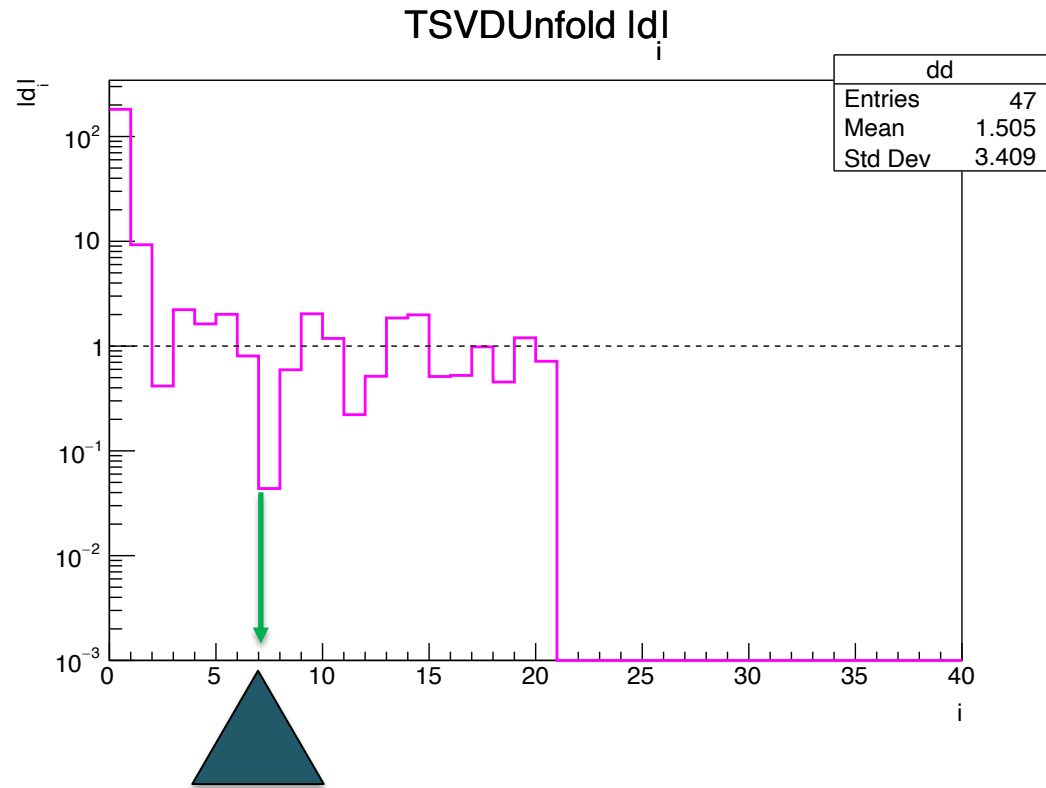
Unfolded the measured pt distribution using regularization parameter = 2

Parameter = 2 gives the best **minimum curvature = 0.000007** and is chosen as the optimum value.



Magenta line: True spectrum from dpmjet MC.

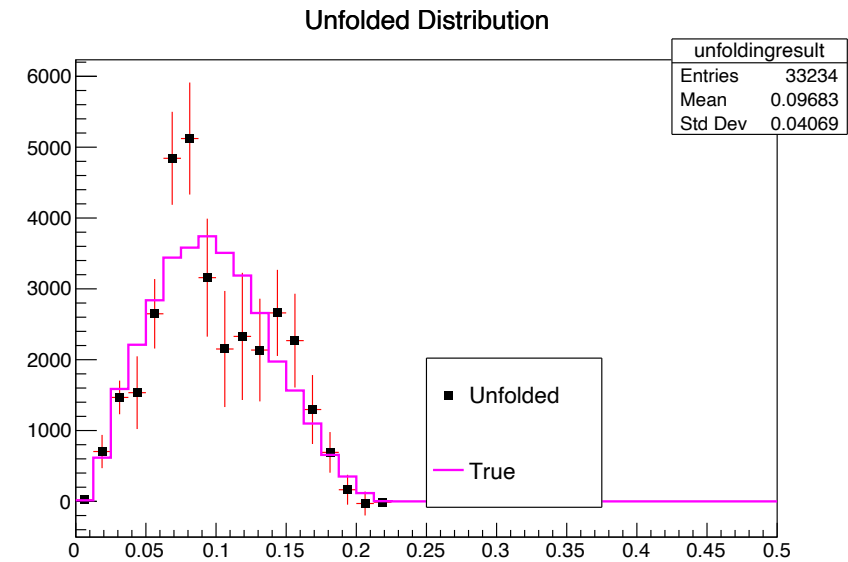
One-dimensional pt unfolding closure test – using pythia and dpmjet MC



Unfolded the measured pt distribution using **regularization parameter = 7**

Regularization parameter = 7 gives a large **minimum curvature = 0.343233**.

Best minimum curvature should be almost zero but not zero.

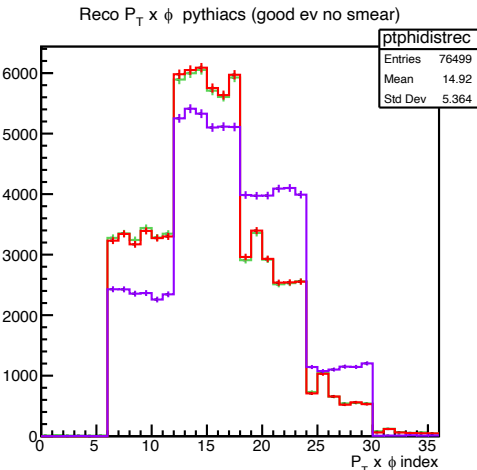
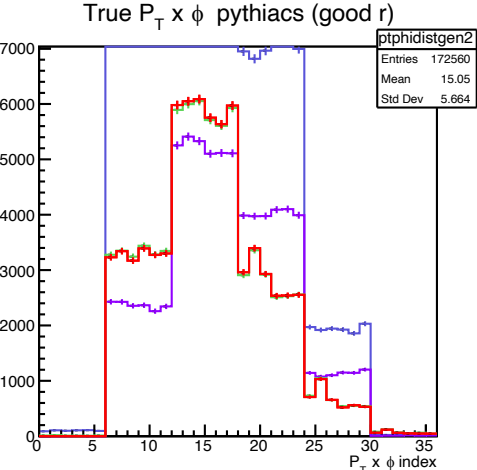
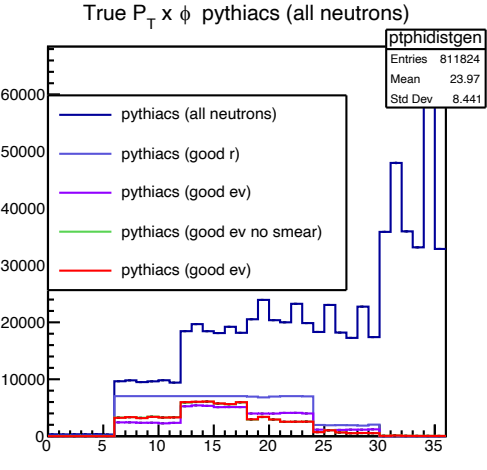


Magenta line: True distribution from dpmjet MC.

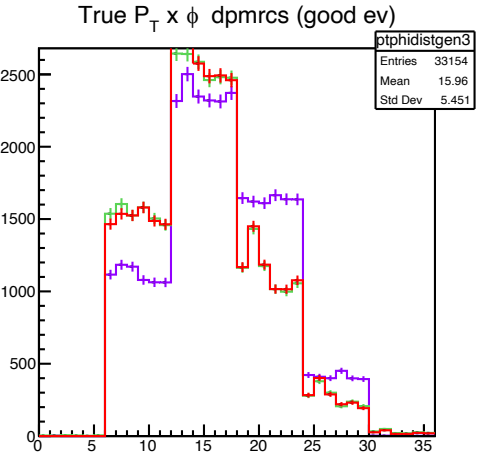
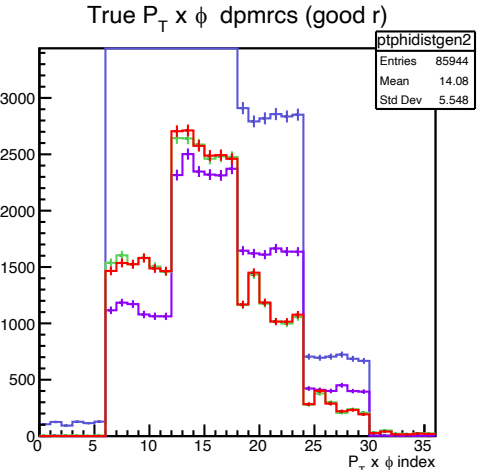
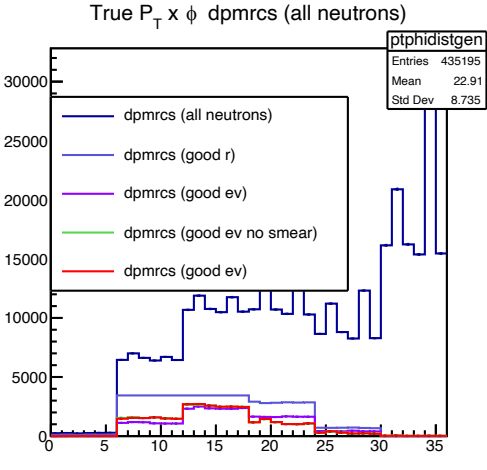
Solid black boxes: Unfolded distribution.

Unfolded distribution has been scaled to match the statistics between dpmjet and pythia.

Two-dimensional pt unfolding closure test – Unfolding inputs

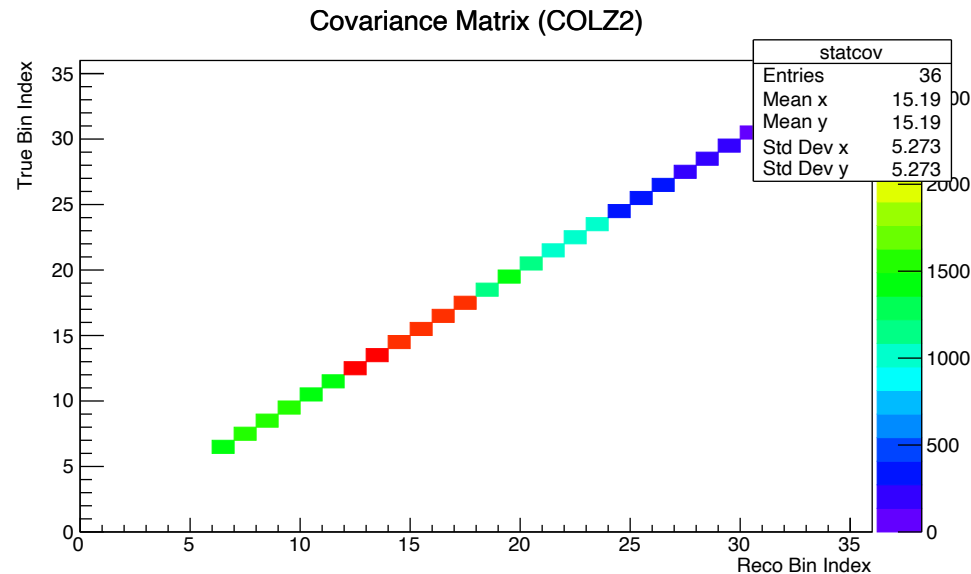
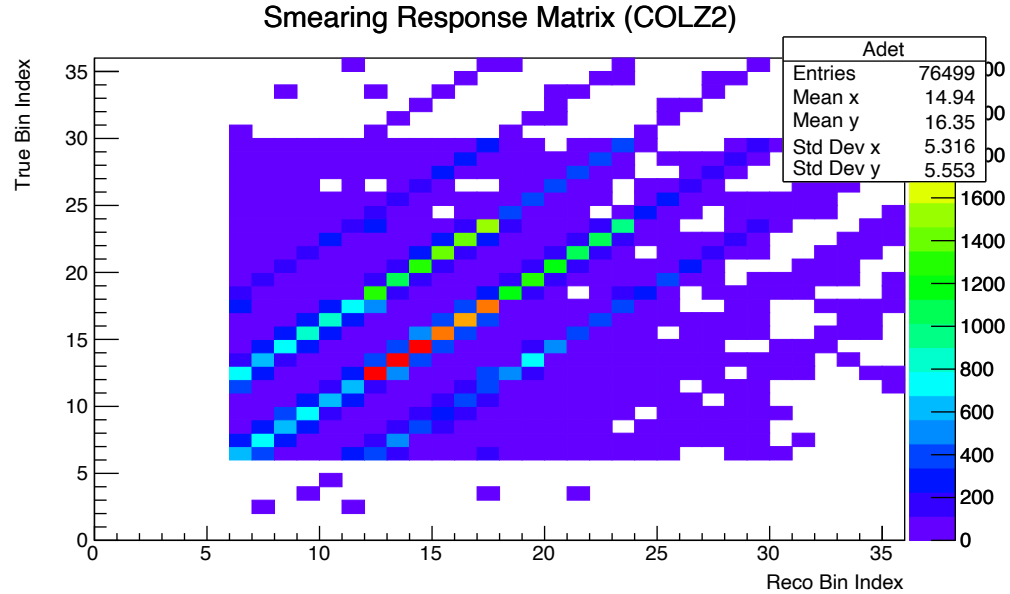


Pythia



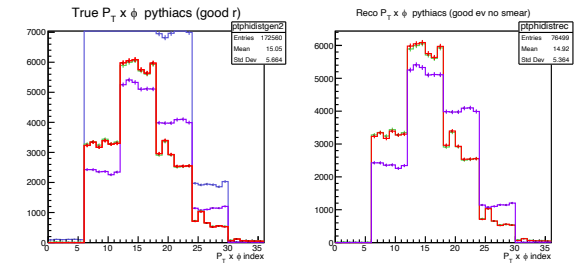
Dpmjet

Two-dimensional pt unfolding closure test – Unfolding input observables

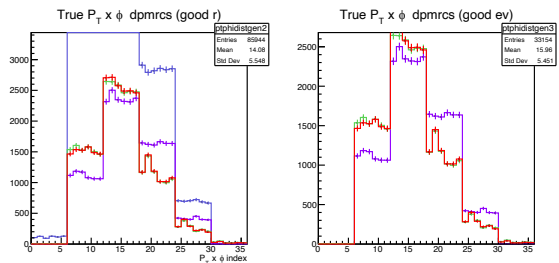


- Correlation matrix between true and measured pt in phi distributions.
- Two variables are being used here pt and azimuth (phi)

Pythia

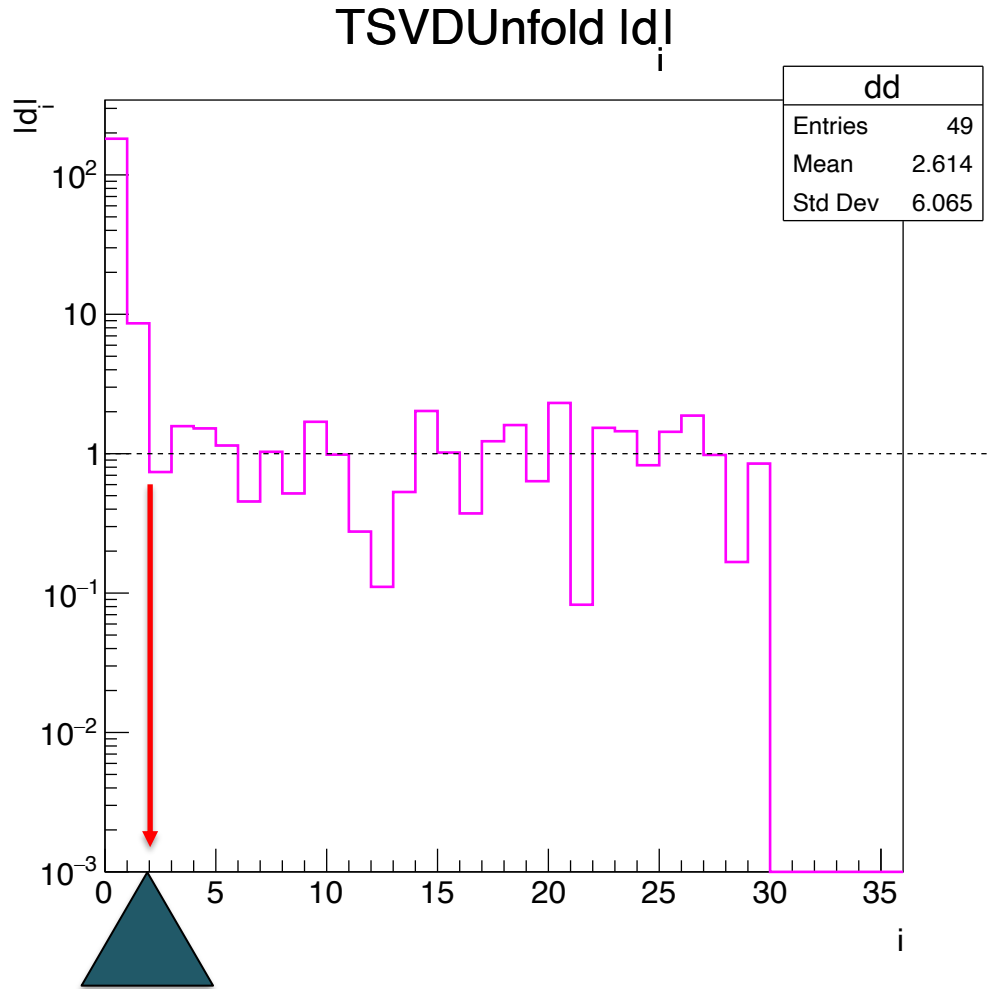


Dpmjet

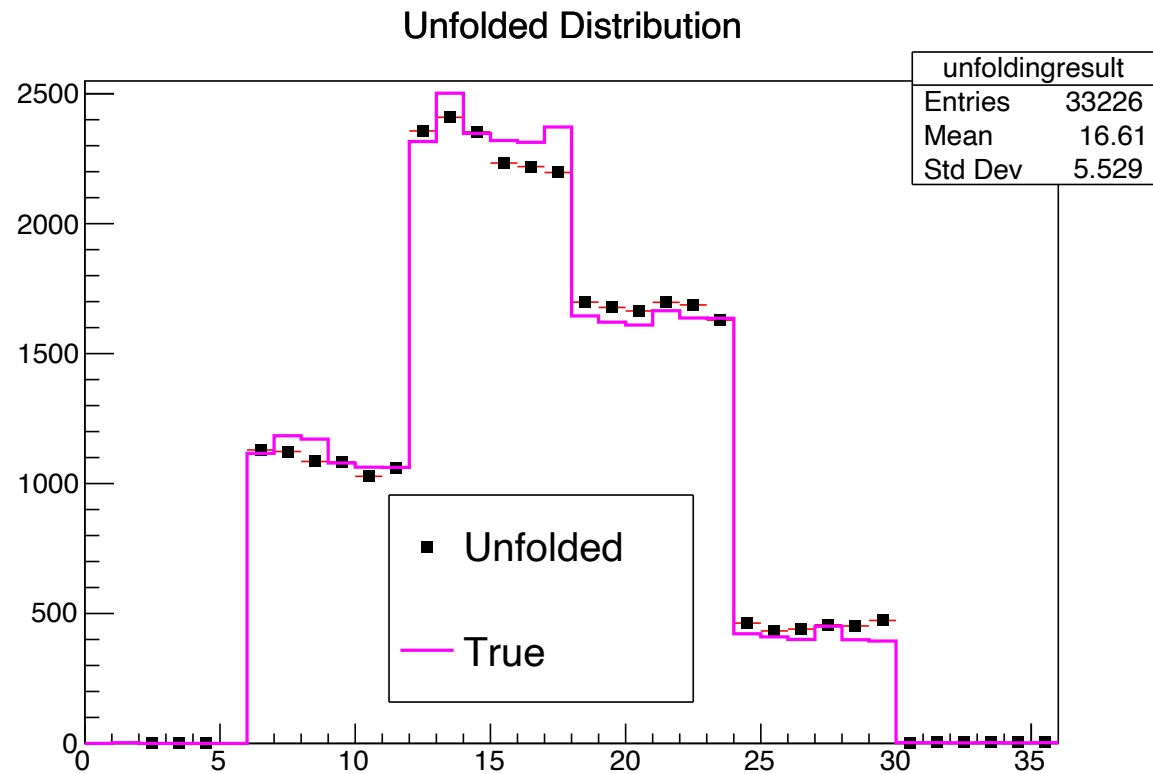


- Input covariance matrix obtained from the square of the errors of the reconstructed pt distribution (red line) from the Dpmjet Monte Carlo sample.

Two-dimensional pt unfolding closure test – Regularization parameter = 2



Unfolded the measured pt distribution using regularization parameter = 2
Minimum curvature = 0.000002

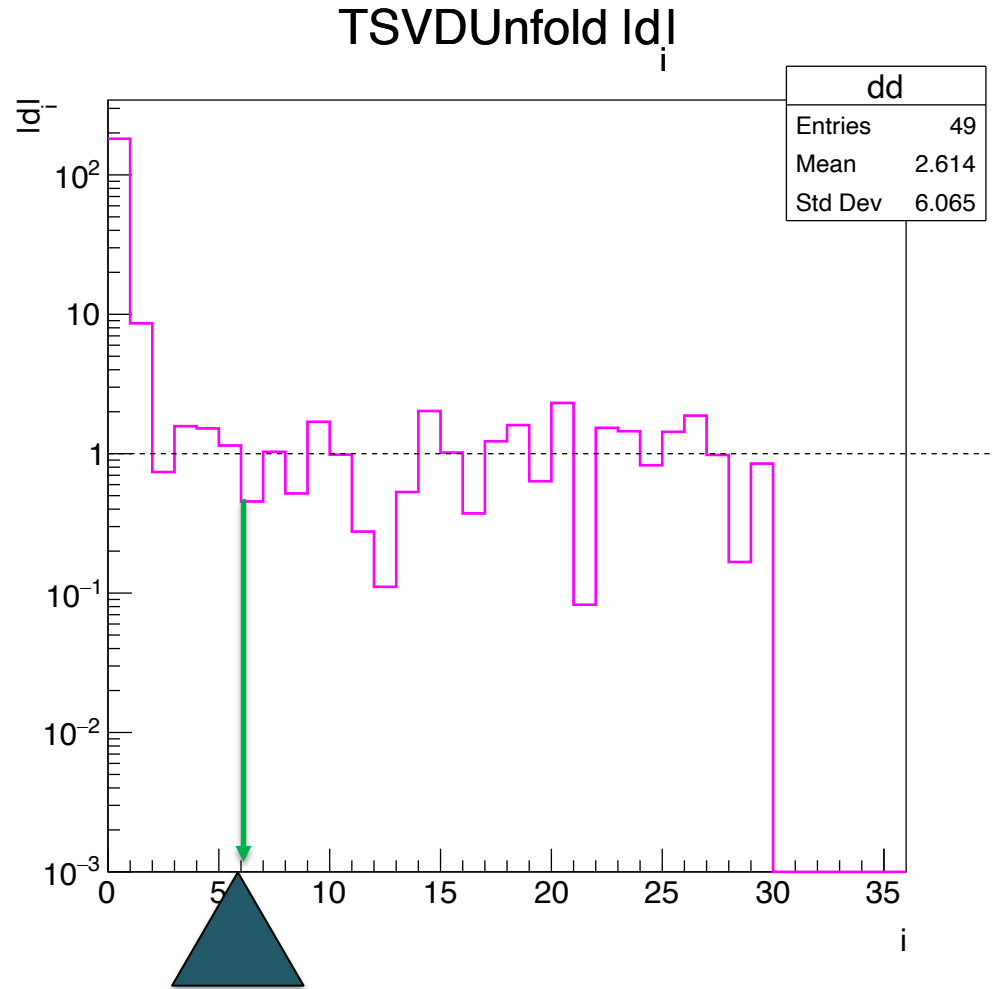


Magenta line: True distribution from dpmjet MC.

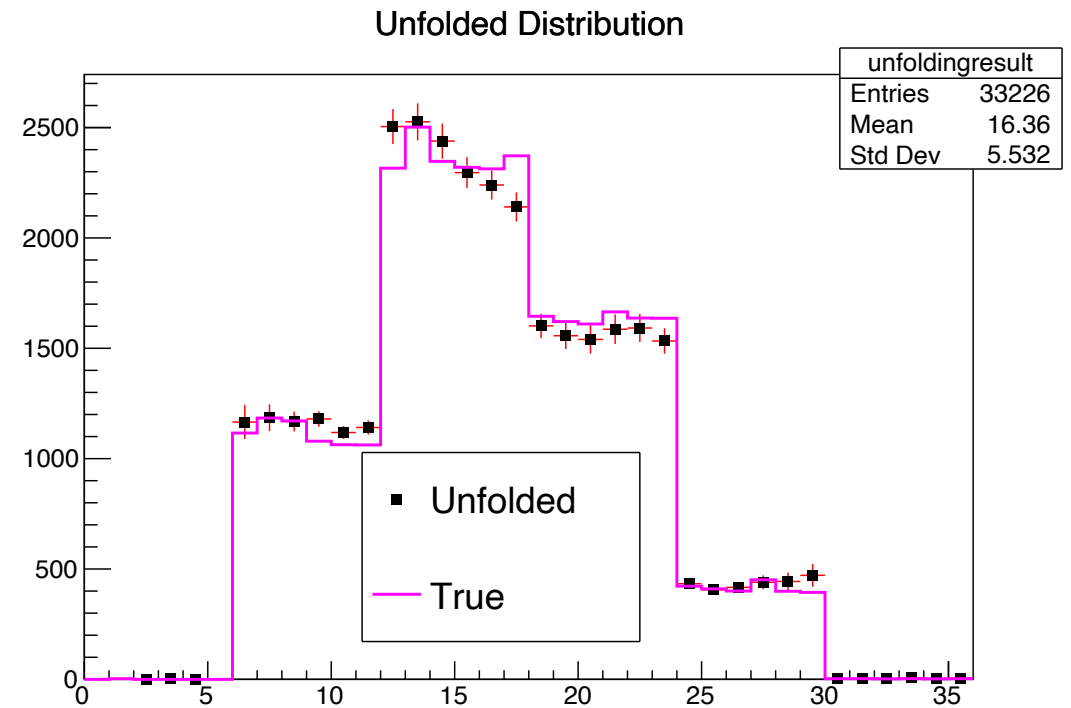
Solid black boxes: Unfolded distribution.

Unfolded distribution has been scaled to match the statistics between dpmjet and pythia.

Two-dimensional pt unfolding closure test – Regularization parameter = 6



Unfolded the measured pt distribution using regularization parameter = 6
Minimum curvature = 0.000331

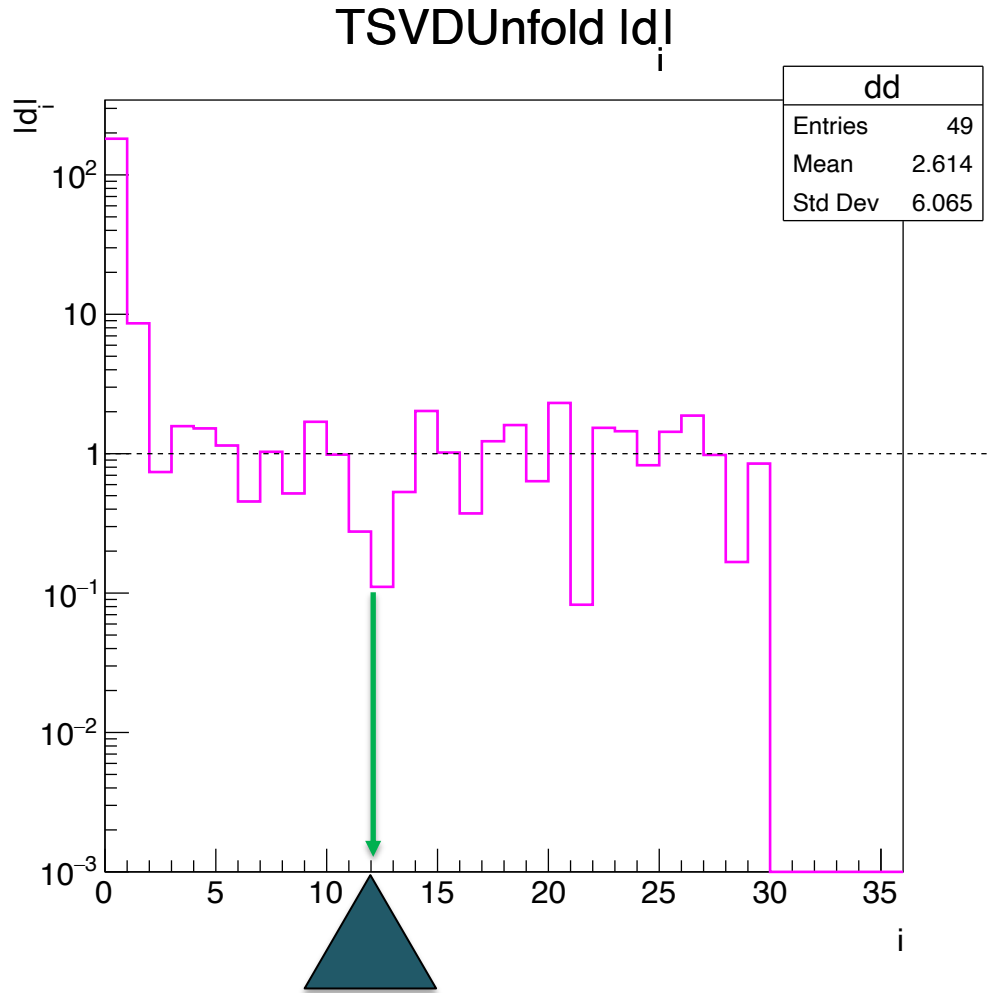


Magenta line: True distribution from dpmjet MC.

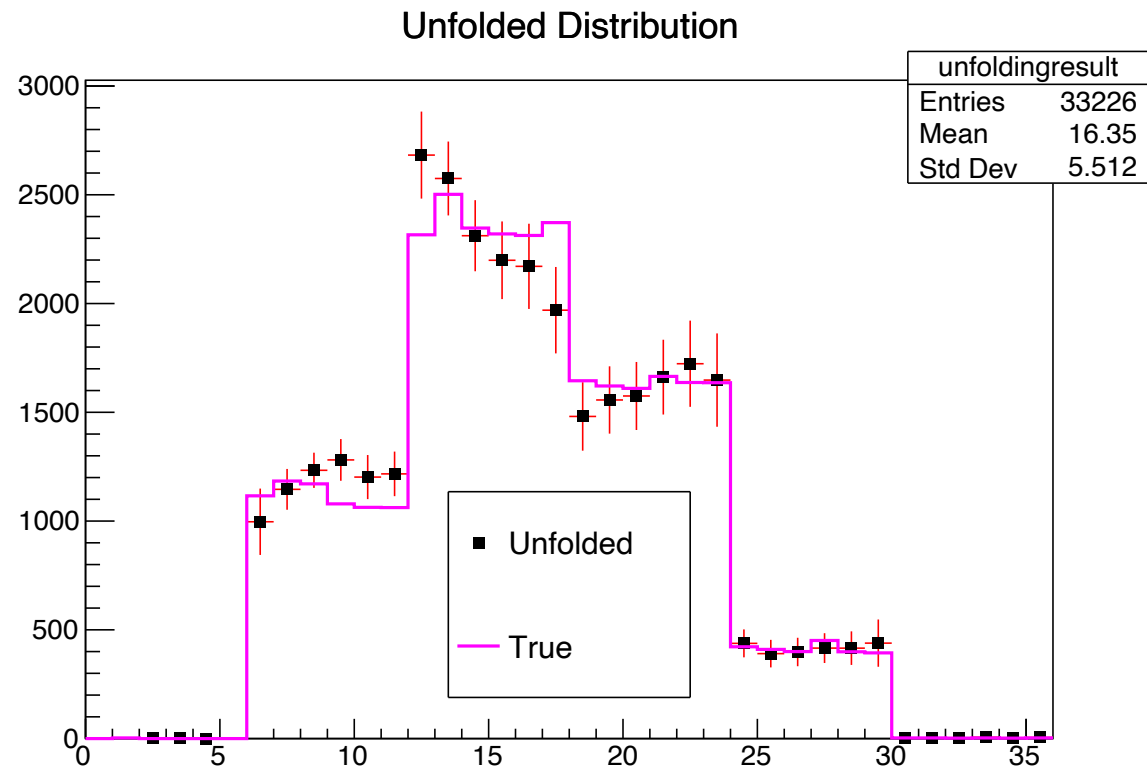
Solid black boxes: Unfolded distribution.

Unfolded distribution has been scaled to match the statistics between dpmjet and pythia.

Two-dimensional pt unfolding closure test – Regularization parameter = 12



Unfolded the measured pt distribution using regularization parameter = 12
Minimum curvature = 0.009416

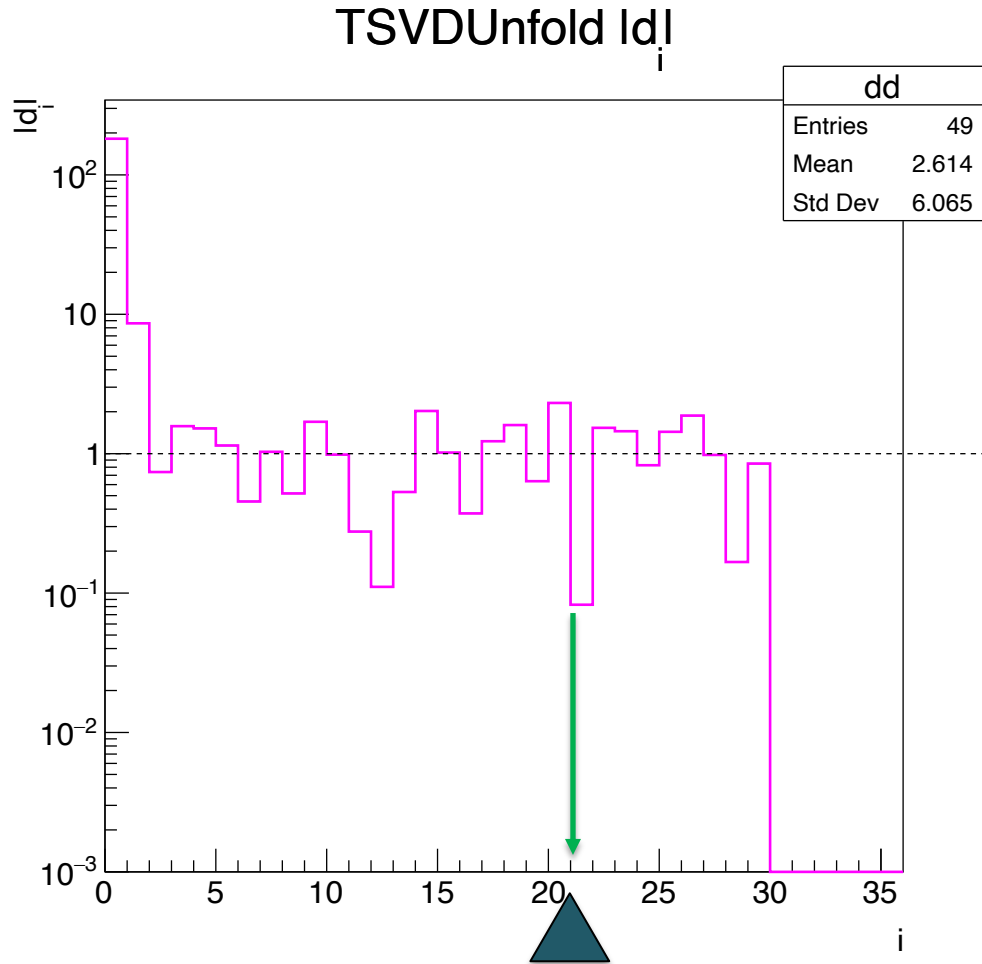


Magenta line: True distribution from dpmjet MC.

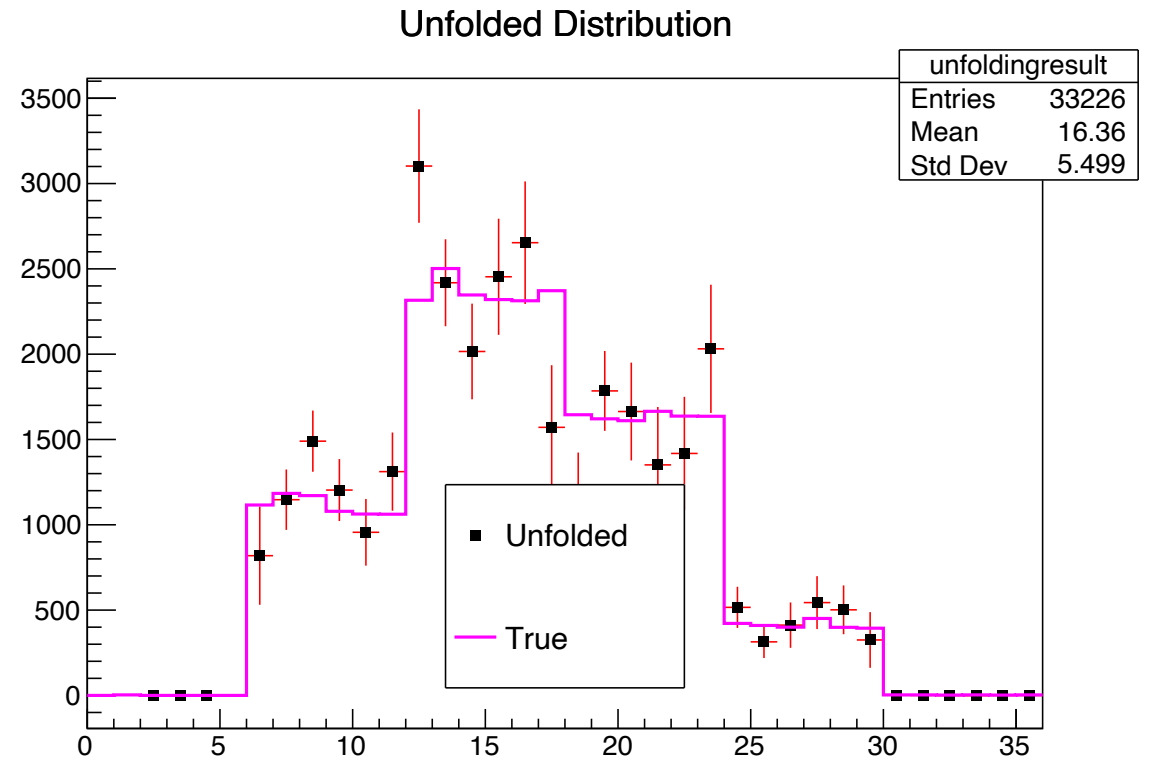
Solid black boxes: Unfolded distribution.

Unfolded distribution has been scaled to match the statistics between dpmjet and pythia.

Two-dimensional pt unfolding closure test – Regularization parameter = 21



Unfolded the measured pt distribution using regularization parameter = 21
Minimum curvature = 0.583



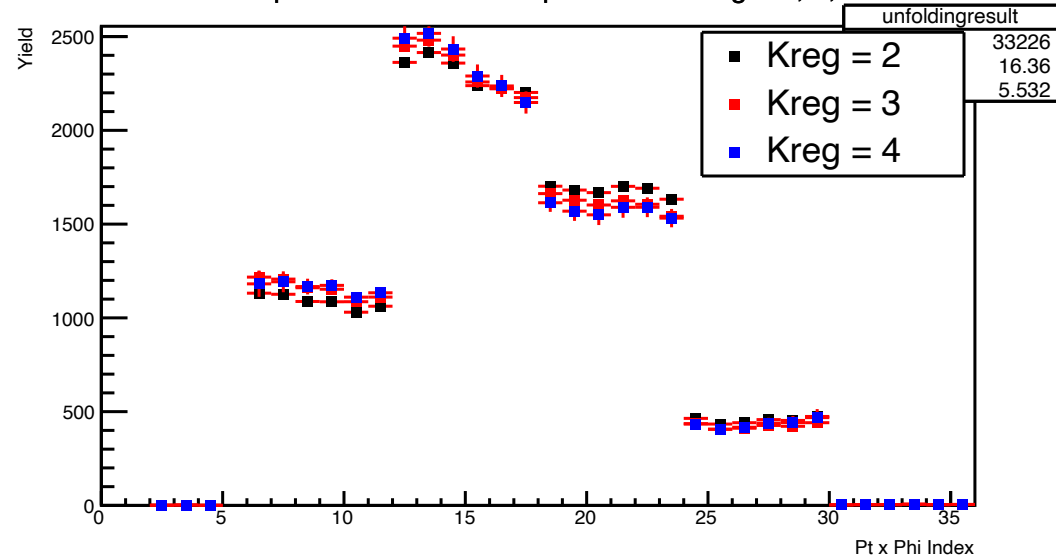
Magenta line: True distribution from dpmjet MC.

Solid black boxes: Unfolded distribution.

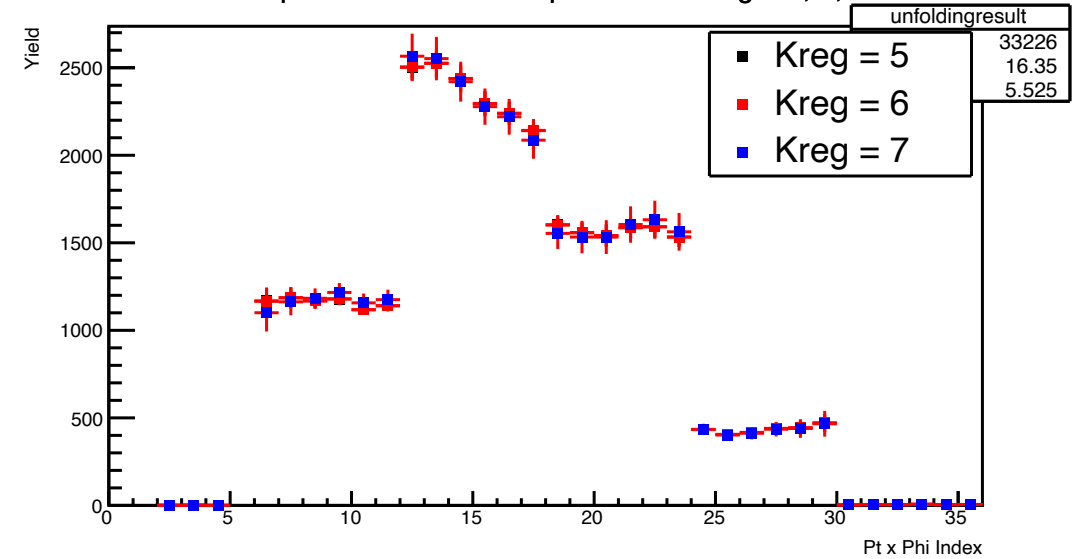
Unfolded distribution has been scaled to match the statistics between dpmjet and pythia.

Two-dimensional pt unfolding closure test – All possible parameter comparison

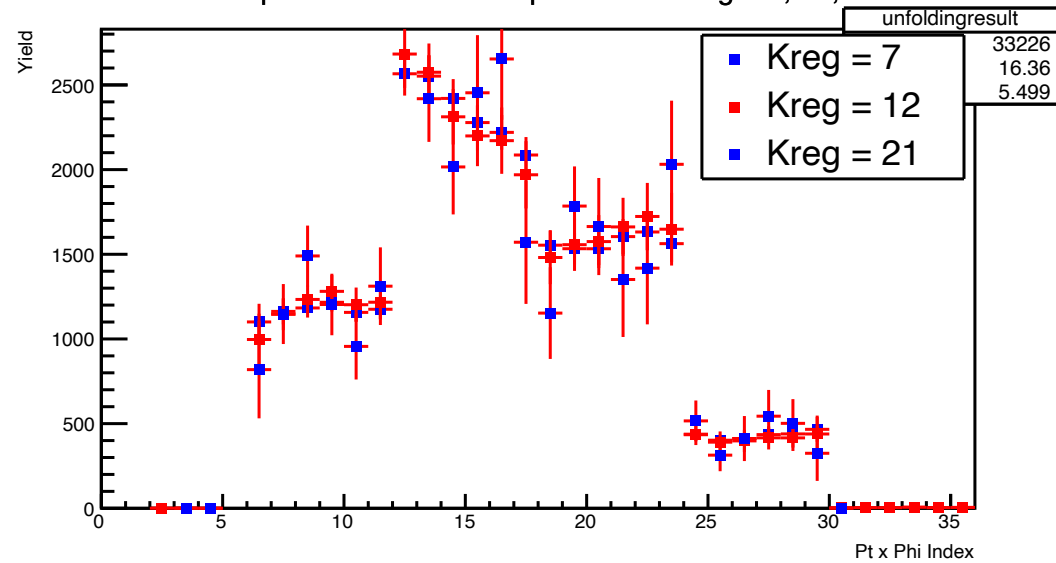
Comparison of unfolded spectra with kreg = 2, 3, 4



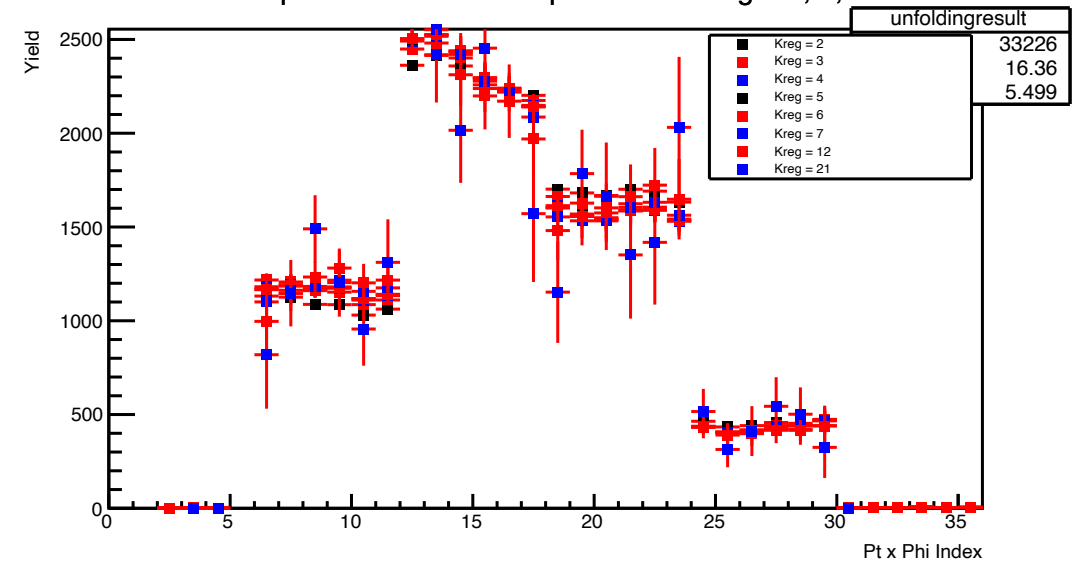
Comparison of unfolded spectra with kreg = 5, 6, 7



Comparison of unfolded spectra with kreg = 7, 12, 21



Comparison of unfolded spectra with kreg = 2, 3, 4



One and two-dimensional pt unfolding closure test

Summary of all possible kreg values and their corresponding minimum curvature values

Regularization parameter, Kreg	Minimum curvature value determines best optimum regularization parameter, the closer the value to zero the better			
2	1D		2D	
	0.000002	Best value	0.000002	Best value
3			0.000010	
4			0.000201	
5			0.000307	
6			0.000331	
7	0.343233.	~34%	0.009416	
12			0.009416	
21			0.583000	~ 60%

Run 15 neutron asymmetry for inclusive pp collisions in the ZDC – 2D Unfolding

Strategy

Currently available is Minjung's ZDC neutron asymmetry for inclusive pp collisions run 15 data. The strategy is to:

- Translate the available pt dependent A_N 's into yields.
- Apply the 2D unfolding in P_T and azimuth, Φ
- Extract the unfolded asymmetries (A_N 's)

Above strategy requires creation of artificial asymmetries and reweighting procedures of pp monte carlo samples such as pythia, dpmjet and the one pion exchange (OPE).

Algorithm

Asymmetry creation and and extraction algorithm is as follows:

Algorithm

1. Create two spin states using TRandom Number Generator:
Spin down (0)
Spin up (1)
2. Create spin depended weight according to Taylor series of a polynomial in the form:

$$w = 1 + (a + b * P_{T,T} + c * P_{T,T}^2 + d * P_{T,T}^3) \cos(\varphi_T + spin * \pi)$$

the parameters are:

a = constant

b = linear

c = quadratic

d = cube

spin * pi = phase shift

spin = 0 (down)

1 (up)

Note: Other functional forms can also be scanned and tried to describe data asymmetries.

Algorithm...

3. Scan parameters for different functional forms over a wide range using chi-square based on the reconstructed asymmetries from pp collision monte carlo samples and run 15 pp asymmetry results (Minjung's result) to find the best parameter, i.e. parameter with lowest,

$$\chi^2 = \sum_i \frac{(A_{N,i}^{Minjung} - A_{N,i}^{w,reco})^2}{(\Delta A_{N,i}^{2,Minjung} + \Delta A_{N,i}^{2,w,reco})}$$

4. Extract the asymmetry using the best Chi-squared parameters,

$$A_N = \frac{N_{\Phi\uparrow} - N_{\Phi\downarrow}}{N_{\Phi\uparrow} + N_{\Phi\downarrow}}$$

A Quick Scan of Created Asymmetries – Pythia, Dpmjet and OPE

Scanned neutron asymmetries based on the following functions;

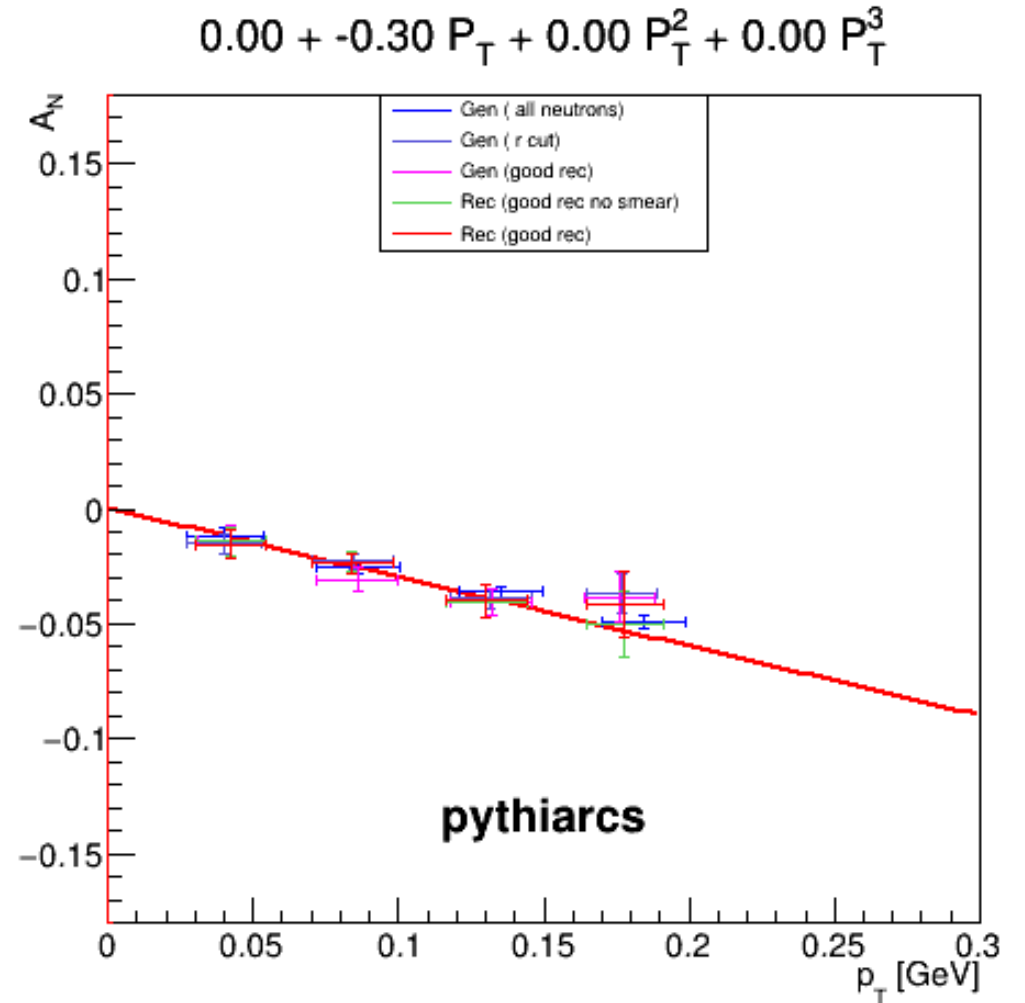
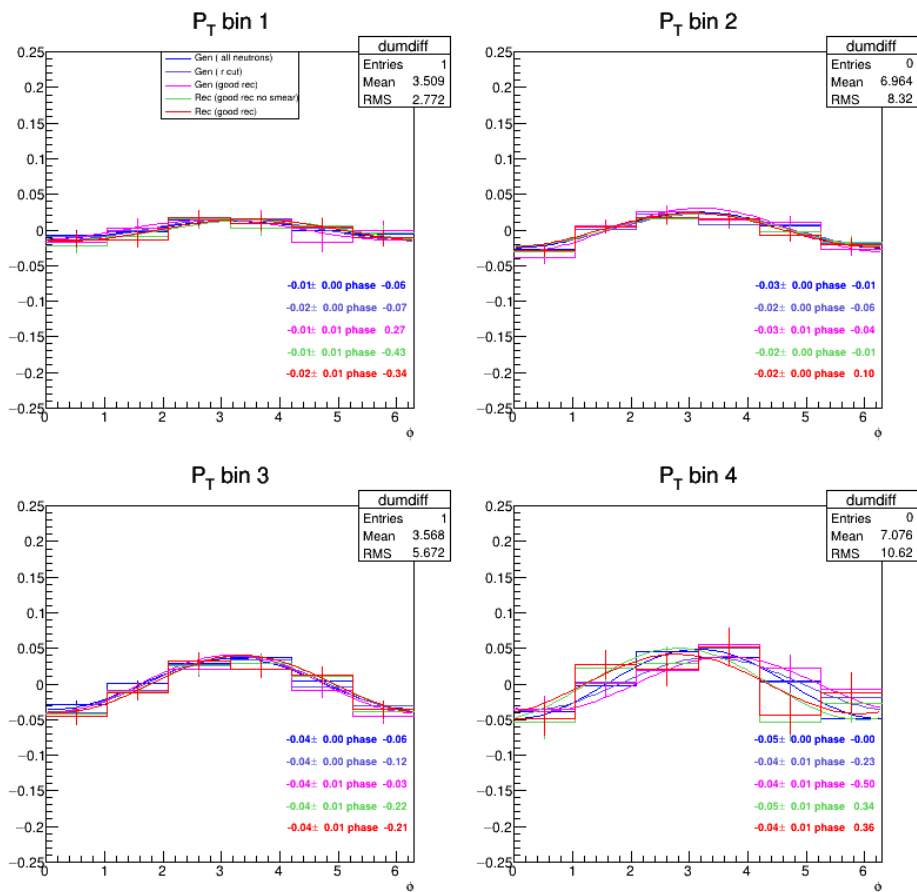
- Quadratic function
- Linear function

Based on Minjung's Pt binning:

- $(0, 0.01)$, $(0.01, 0.06)$, $(0.06, 0.11)$, $(0.11, 0.16)$, $(0.16, 0.21)$, $(0.21, 0.40)$
- First and last bins are ignored. Hence,
- $(0.01, 0.06)$, $(0.06, 0.11)$, $(0.11, 0.16)$, $(0.16, 0.21)$

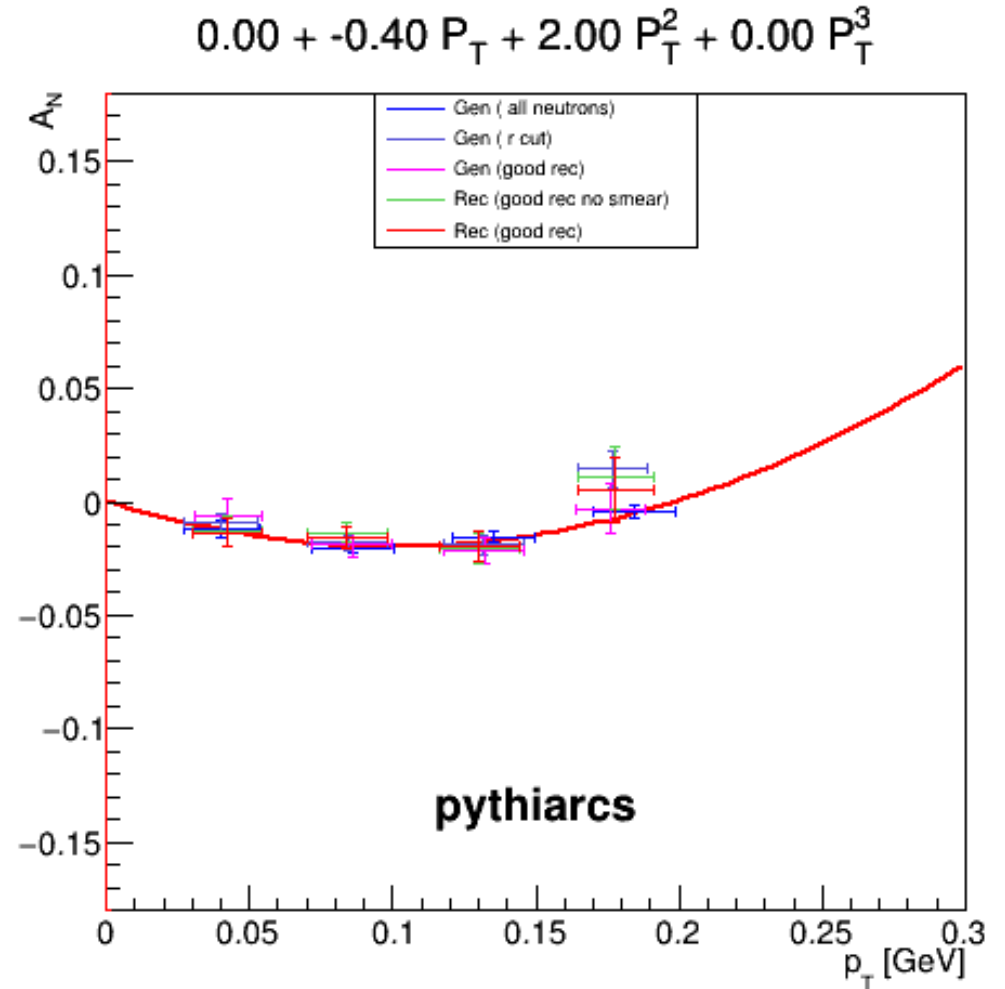
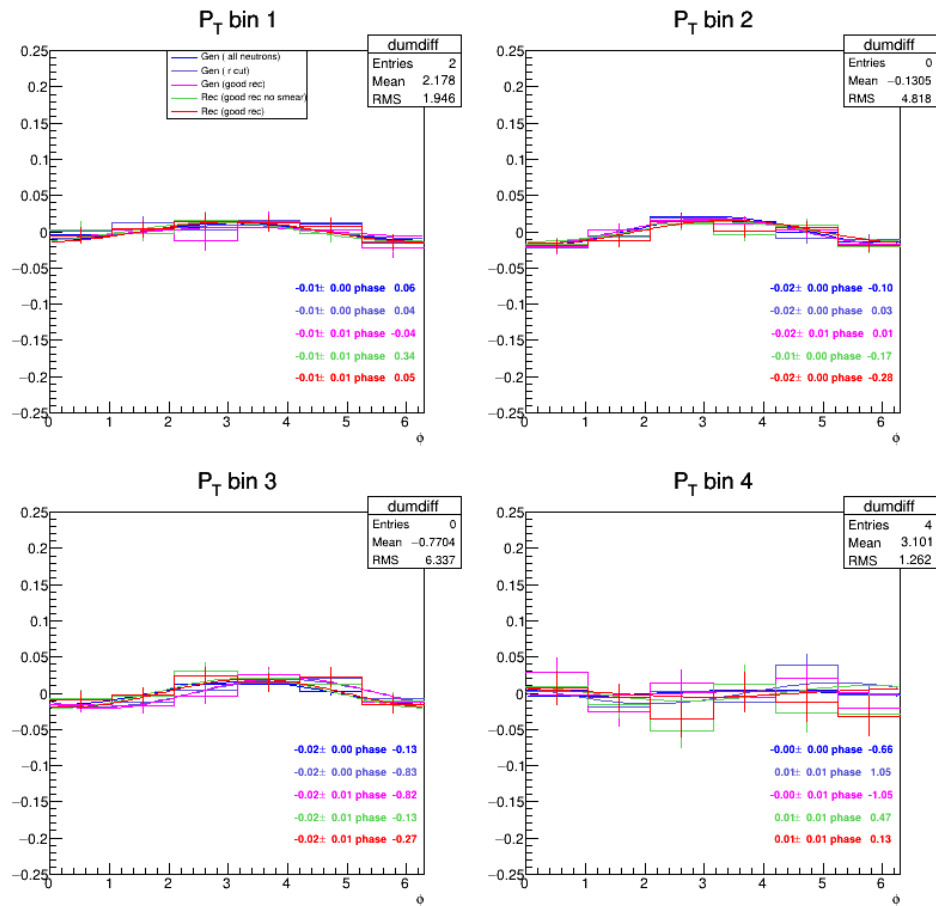
A Quick Scan of Created Asymmetries – Pythia Monte Carlo Sample

Asymmetry based on linear function



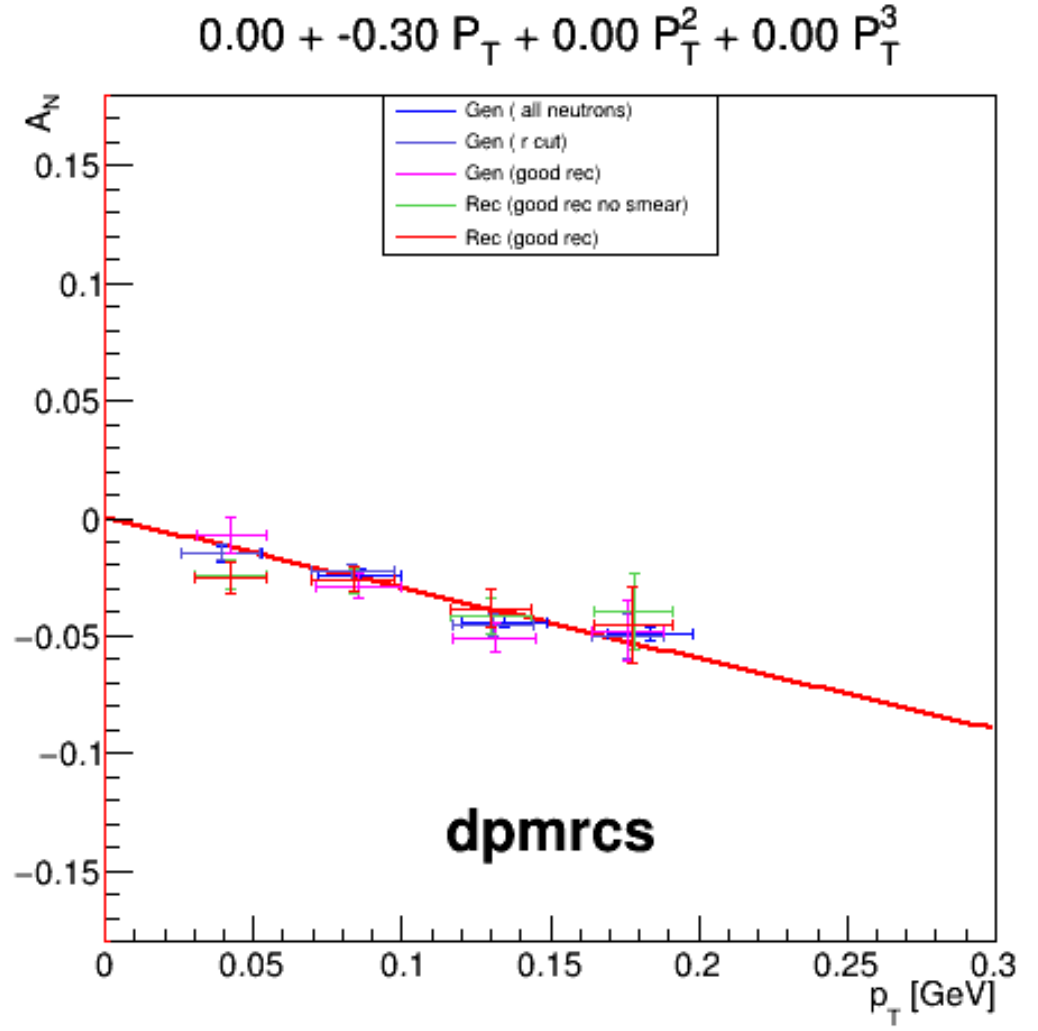
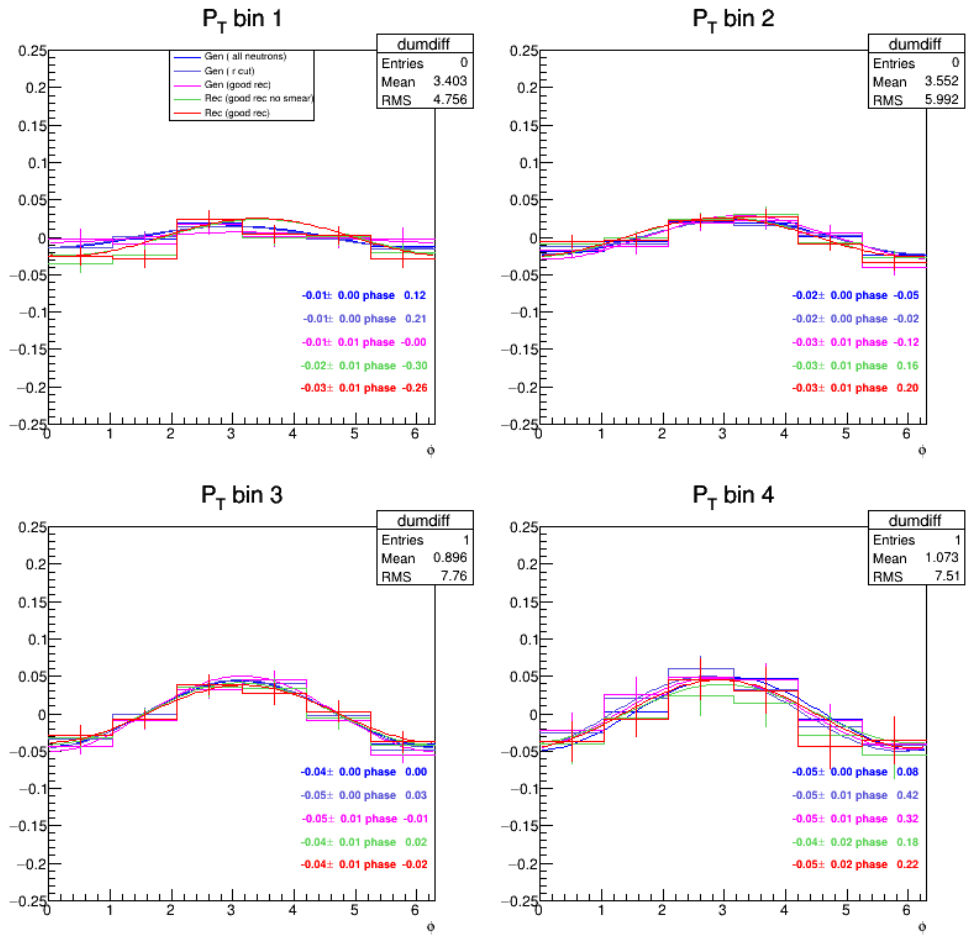
A Quick Scan of Created Asymmetries – Pythia Monte Carlo Sample

Asymmetry based on quadratic function



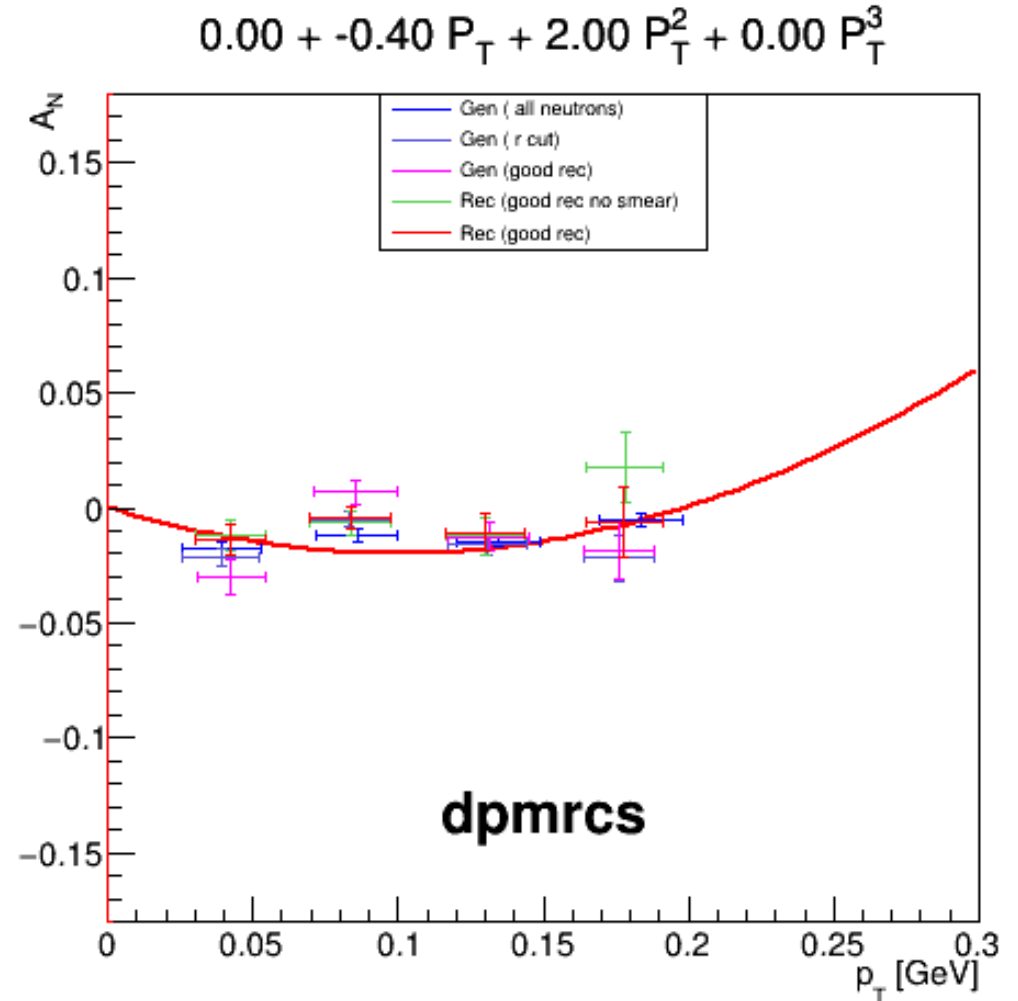
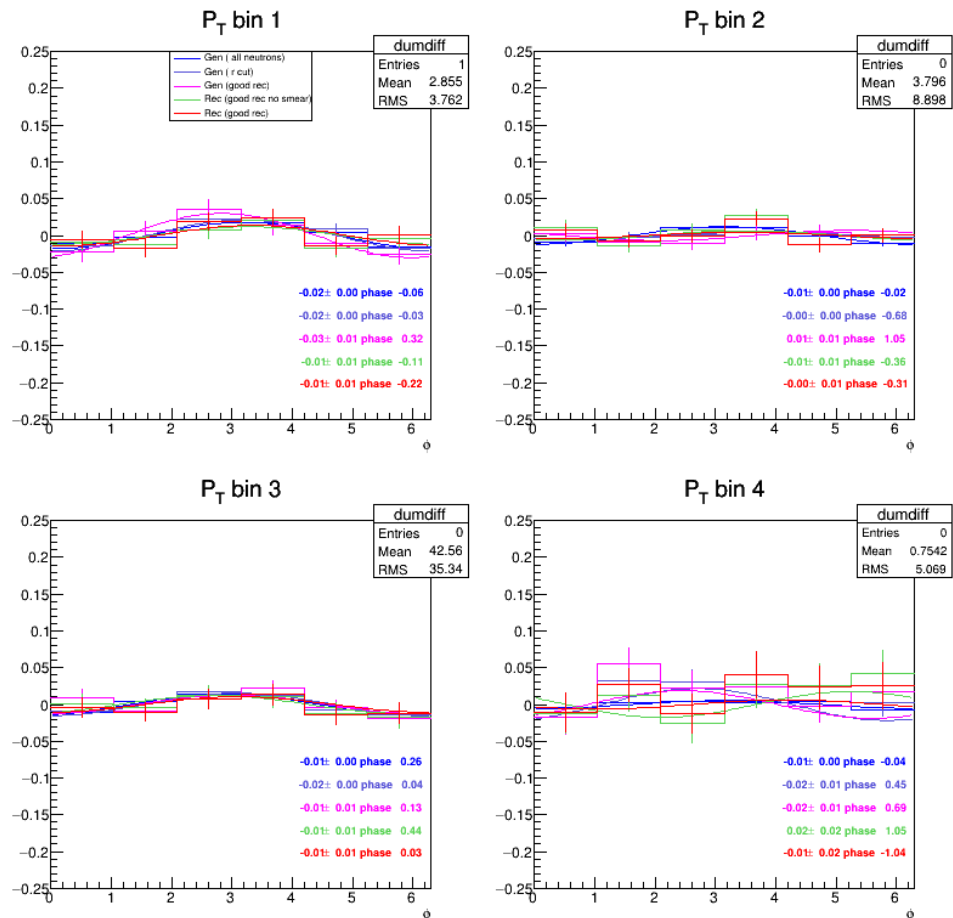
A Quick Scan of Created Asymmetries – Dpmjet Monte Carlo Sample

Asymmetry based on linear function



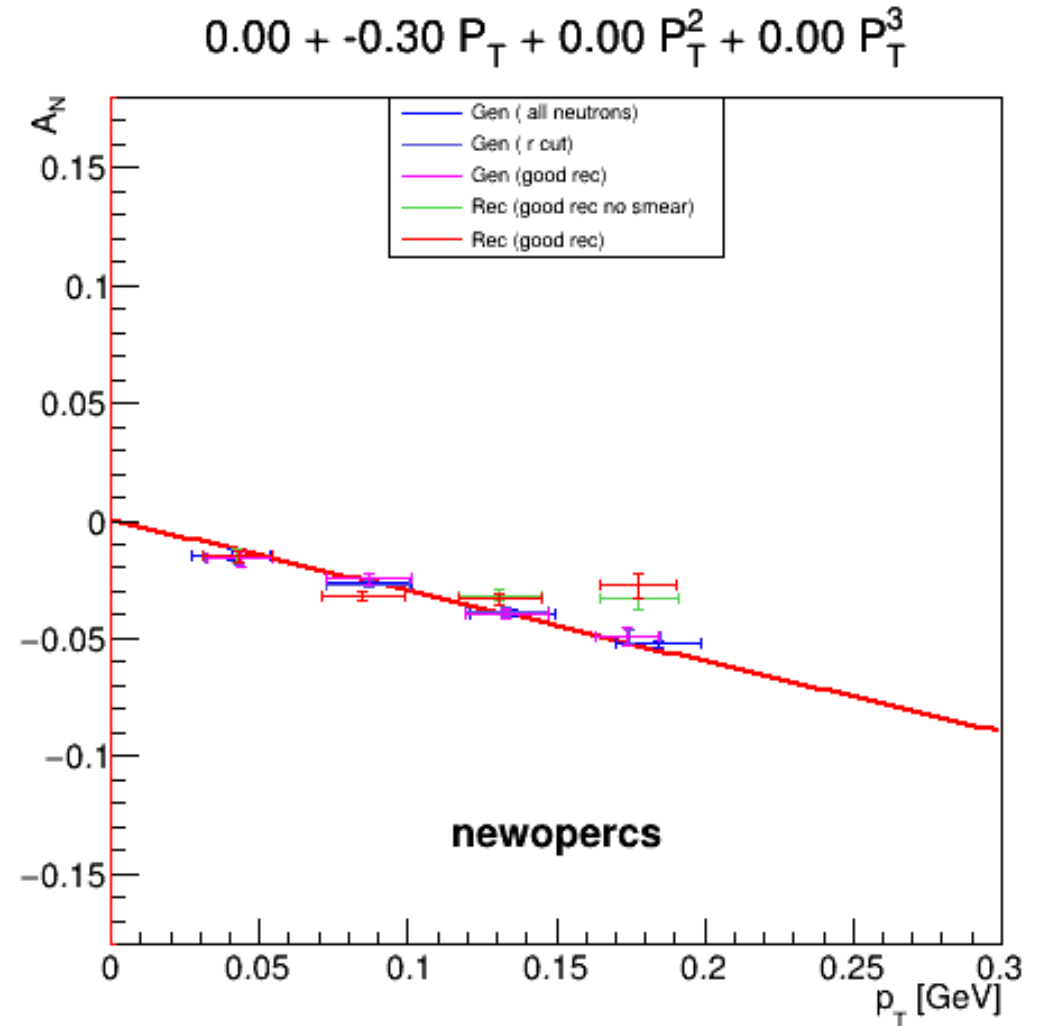
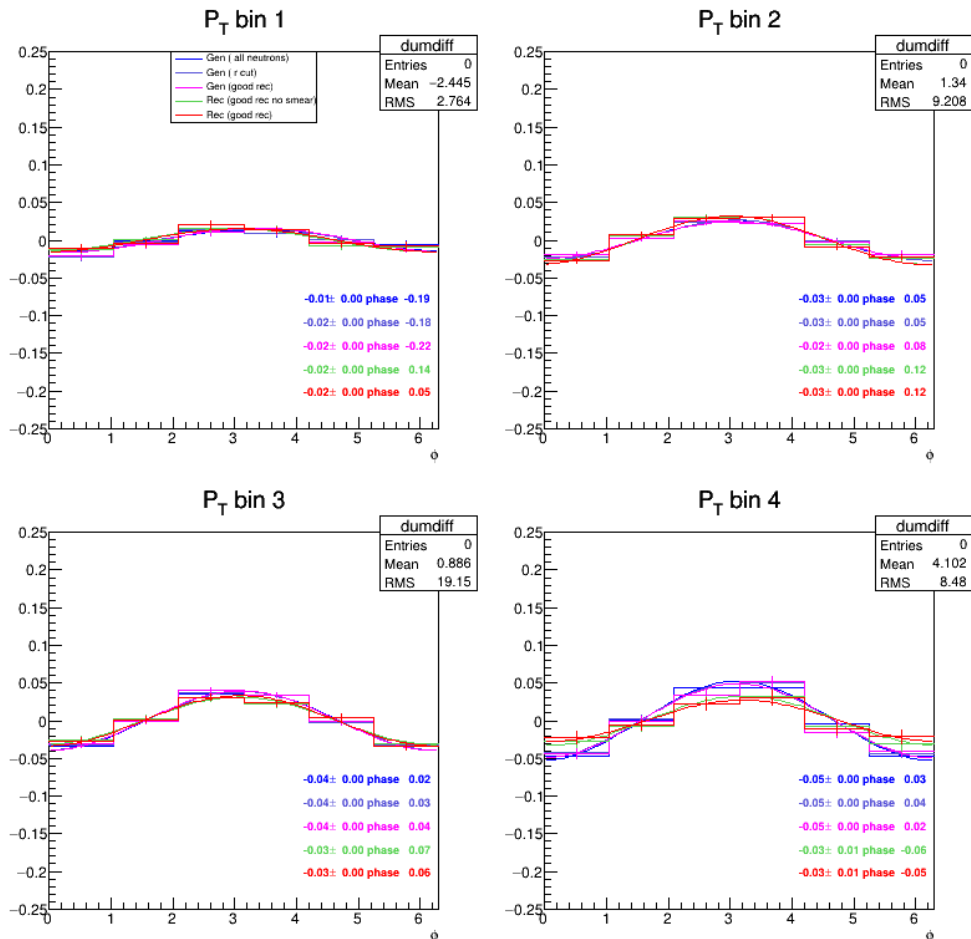
A Quick Scan of Created Asymmetries – Dpmjet Monte Carlo Sample

Asymmetry based on quadratic function



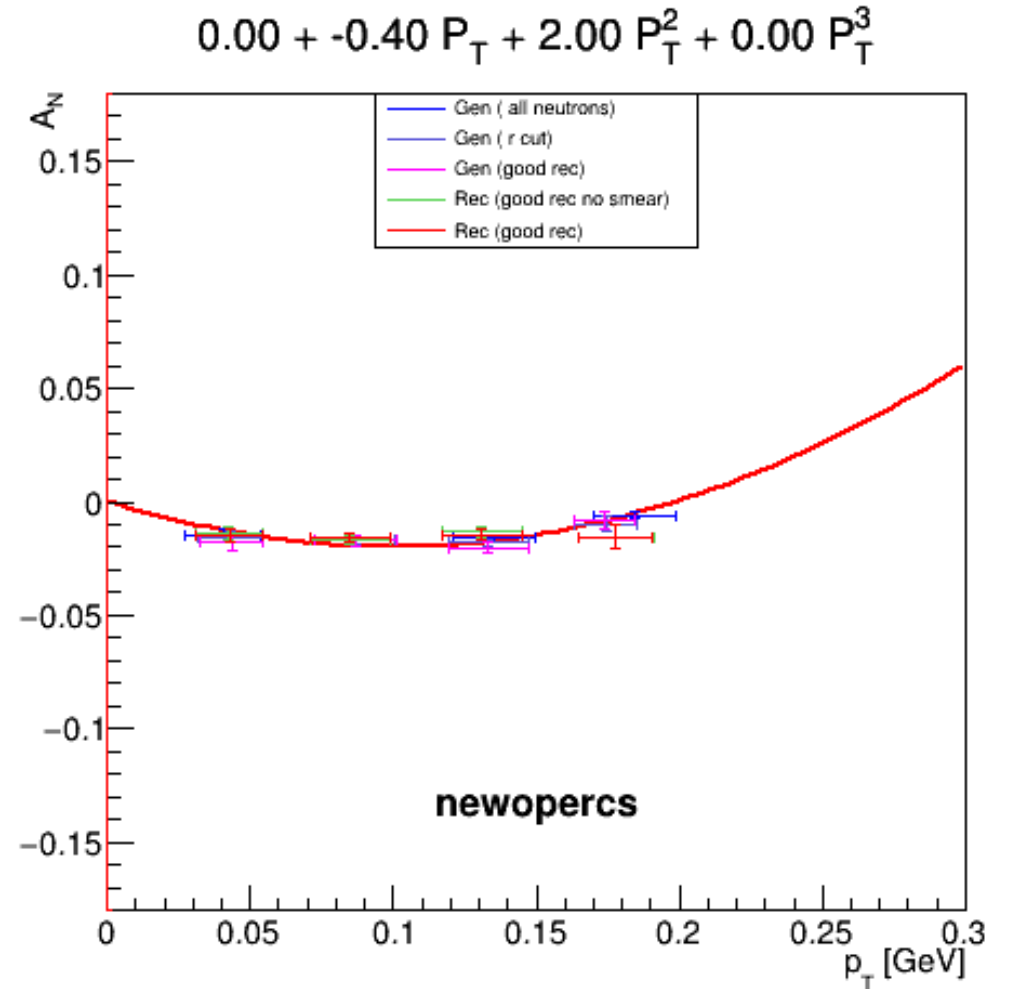
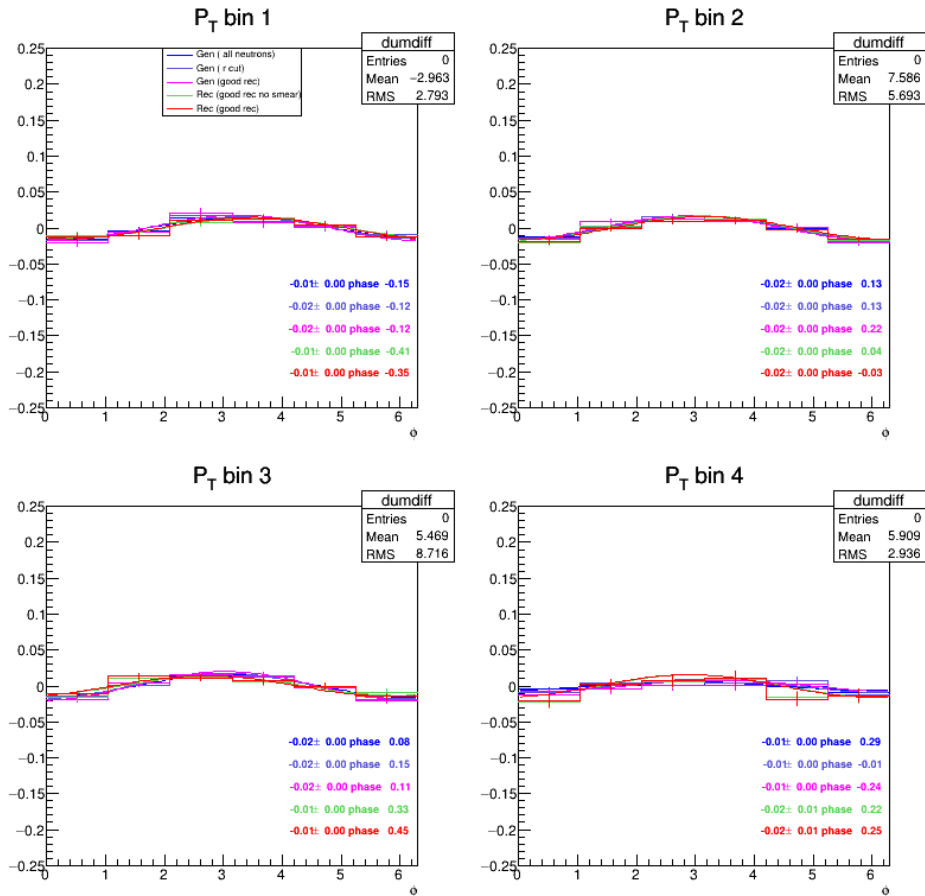
A Quick Scan of Created Asymmetries – One Pion Exchange (OPE) MC

Asymmetry based on linear function



A Quick Scan of Created Asymmetries – One Pion Exchange (OPE) MC

Asymmetry based on quadratic function



Summary

- Closure test seems to work well at small regularization parameter = 2 than at larger regularization parameter = 7 where it fails for the 1D case with increased statistical fluctuations.
- Similar trend for the 2D case. Lower values of regularization seem to agree better than larger values.
- The statistical fluctuations at small kreg parameters are smaller than at larger values of regularization.
- Scanned neutron asymmetries for linear and quadratic functions for Pythia, Dpmjet and OPE using parameters chosen intuitively.

To Do List

Period	Task
June 18 ~ June 24	<ul style="list-style-type: none">▪ Optimization of weight to mimic the actual pT dependence of pp data using best parameters from Chi-square.
June 15 ~ June 30	<ul style="list-style-type: none">▪ Apply best parameters to extract neutron asymmetries that mimic pp data asymmetries