p_{T} spectra as a function of Multiplicity and Transverse Spherocity in pp collisions using a Bayesian Unfolding

J. David Romo

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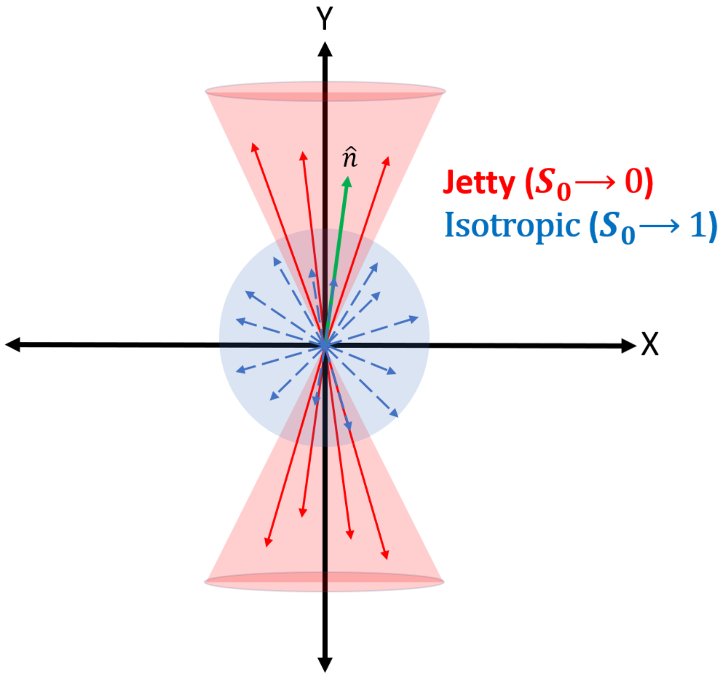
Outline

- Motivation
- Procedure
- Results
- Conclusions

Motivation



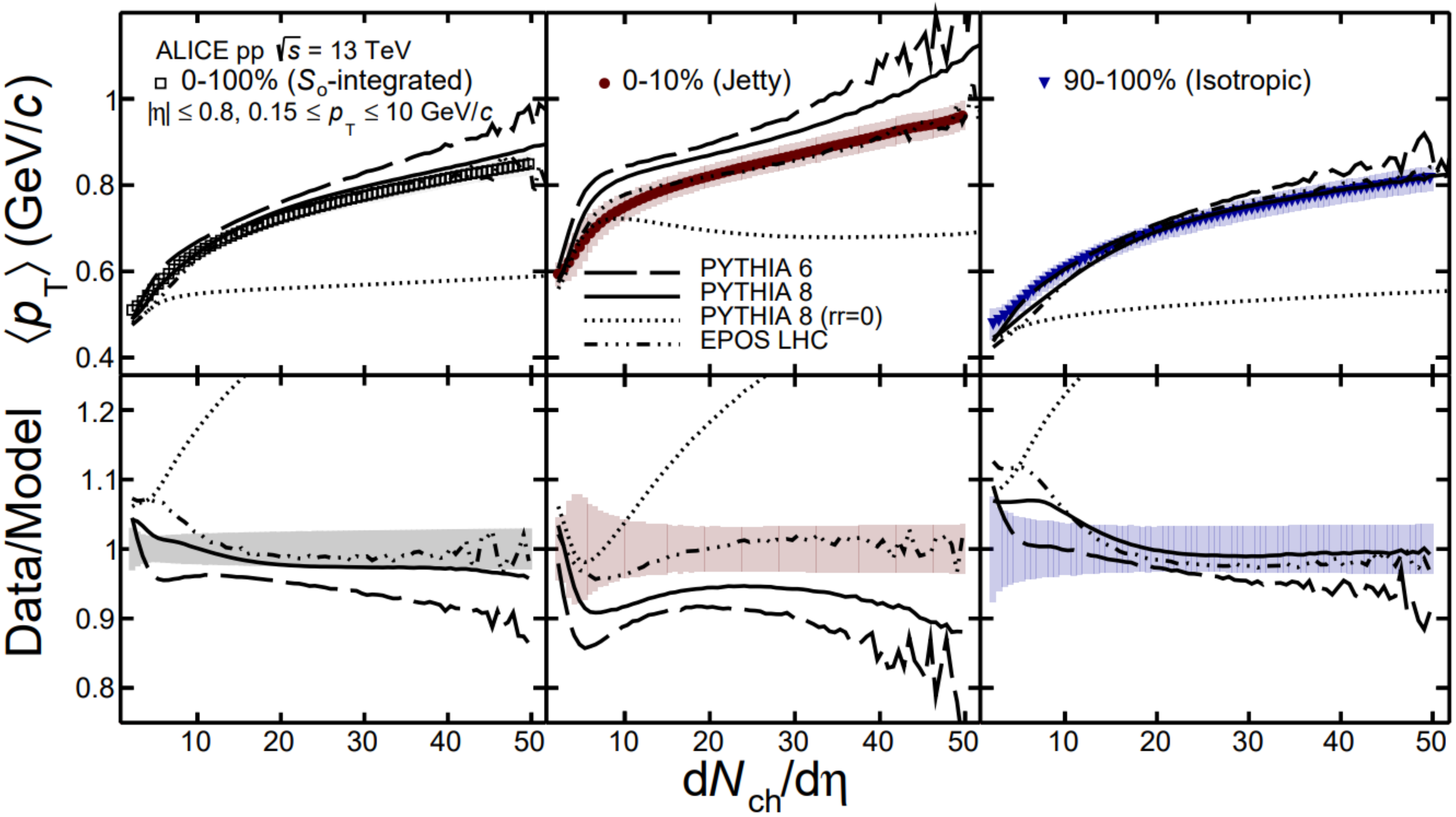
- Heavy ion-like behavior in high multiplicity in pp collisions (like strangeness enhancement and a ridge structure) raise questions about his use as a baseline.

- The event shape transverse spherocity (S_0) can distinguish jet-like ($S_0 \rightarrow 0$) and isotropic event ($S_0 \rightarrow 1$), in which the former is dominated by hard and the latter by soft QCD processes.

$$S_0 = \frac{\pi^2}{4} \min_{\hat{n}_s} \left(\frac{\sum_i |\vec{p}_{\mathrm{T},i} \times \hat{n}_s|}{\sum_i \vec{p}_{\mathrm{T},i}} \right)^2$$

Motivation

- Discrepancy in jetty events (low S_0) between MC Generators and Data at high multiplicity events.
- Unexplained third rise of Average transverse momentum at $dN_{ch}/d\eta > 30$



Acharya, S., Adamová, D., Adhya, S.P. *et al.* *Eur. Phys. J. C* **79,** 857 (2019).
https://doi.org/10.1140/epjc/s10052-019-7350-y

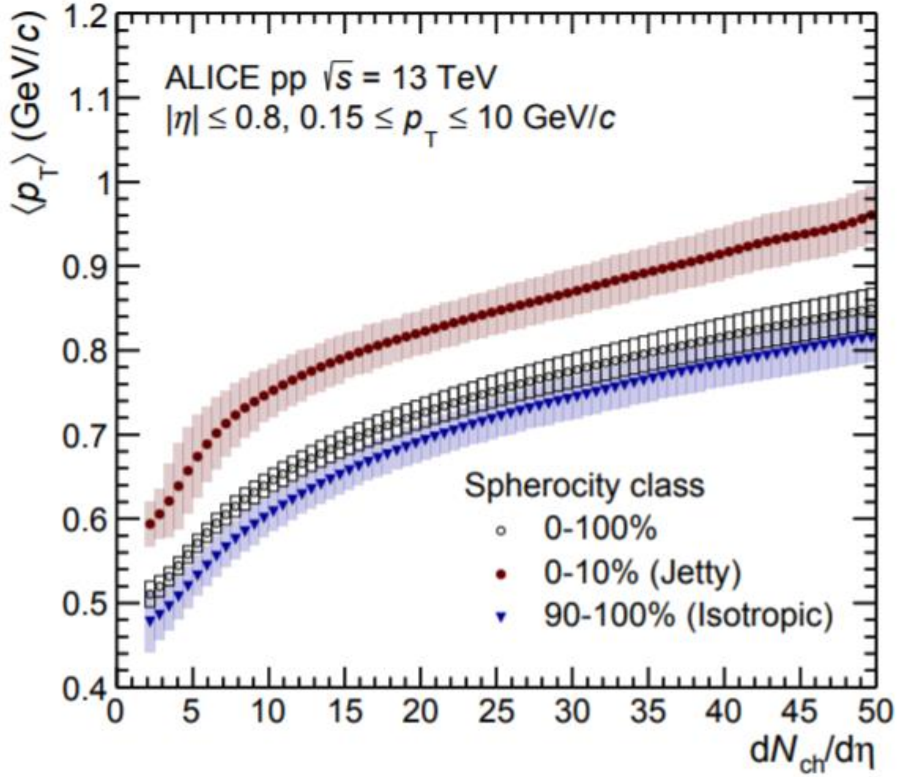
Motivation

- **Previously:** ALICE has reported mean p_T as function of multiplicity and spherocity using a re-weighting procedure.

$$\langle p_T\rangle(N_{ch}, S_0) = \sum_{N_m}\sum_{S_m} R(N_{ch}, N_m)\,\langle p_T\rangle(N_m, S_m) R'(S_0, S_m)$$

- **In this work:** We propose using the **Bayesian Unfolding** to get the p_T spectra as function on Spherocity S_0 and multiplicity N.

$$p(N_m|N_t) = \frac{p(N_t|N_m)p(N_m)}{\sum_m p(N_t|N_m)p(N_m)}$$



1D Bayesian Unfolding

$$p(N_t|N_m) = \frac{p(N_m|N_t)p(N_t)}{\sum_{N_t'} p(N_m|N_t')p(N_t')}$$

$$p_0(N_t)$$

Where $h_{i,l}$ is the l entry in the i iteration of the $n(X_t)$ histogram

while($\chi_i^2 < 1$)

$$\chi_i{}^2 = \frac{1}{N_{bins}} \sum_{l=\#bins} \frac{(h_{i,l} - h_{i-1,l})^2}{\sigma_{i,l}{}^2}$$

$$n(N_t) = \sum_{N_t} p(N_t|N_m)n(N_m)$$

$$p(N_t) = \frac{n(N_t)}{\sum_{N_t'} n(N_t')}$$

Goal: Recover original distribution $n(N_t)$ from the measured one $n(N_m)$, using the MC smearing matrix (in this work from PYTHIA) $n(N_m, N_t)$ to estimate the conditional probability $p(N_m|N_t)$.

For MC simulations, we can verify using a MC Closure Test, **Unfolded/True**

Analysis Procedure

Bayesian Unfolding

Input

MC and Geant Reconstruction

MC Smearing Matrix

Test

MC Closure Test

Compare how well the unfolding can reproduce the full p_T spectra in each Spherocity and Multiplicity Class

Analysis Procedure

Bayesian Unfolding

Input

MC and Geant Reconstruction

ALICE pp collisions

MC Smearing Matrix

Test

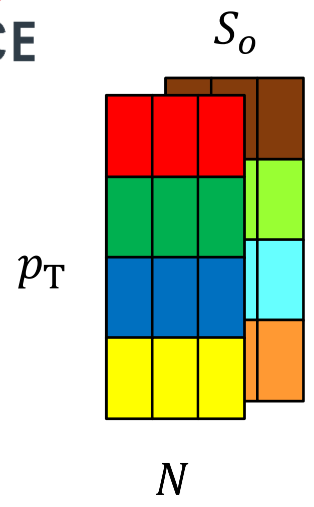
MC Closure Test

Compare how well the unfolding can reproduce the full p_T spectra in each Spherocity and Multiplicity Class

$\langle p_T \rangle$ vs $\langle dN/d\eta \rangle$

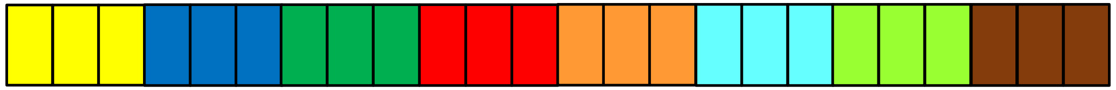
Compare respect the reported mean p_T for pp collisions.

3D Bayesian Unfolding Binning



X

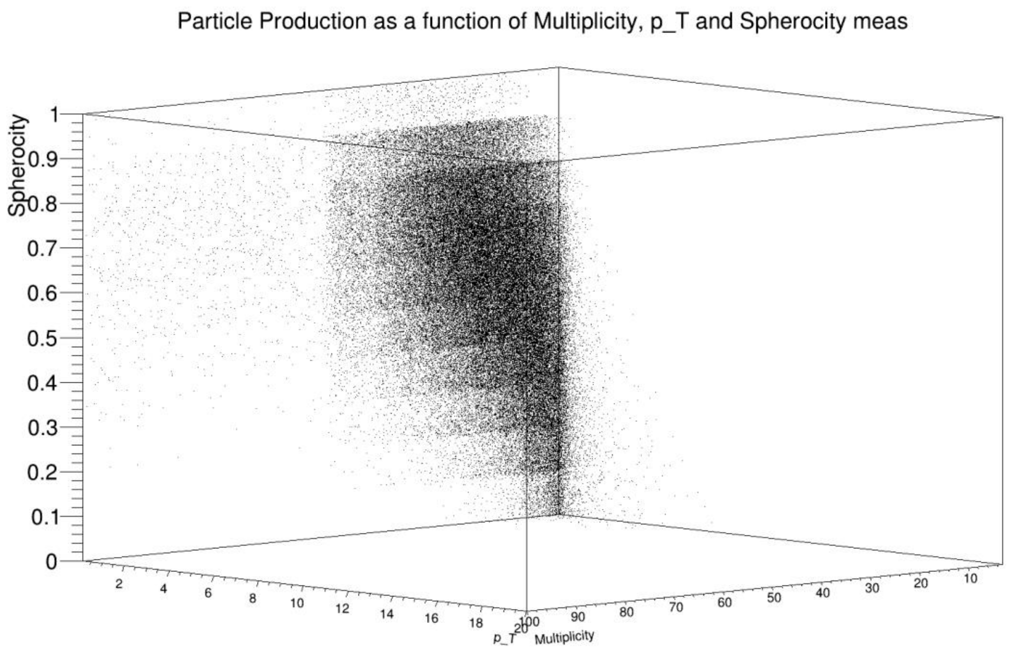
We define a new variable $X(N, p_{\mathrm{T}}, S_o)$, such as



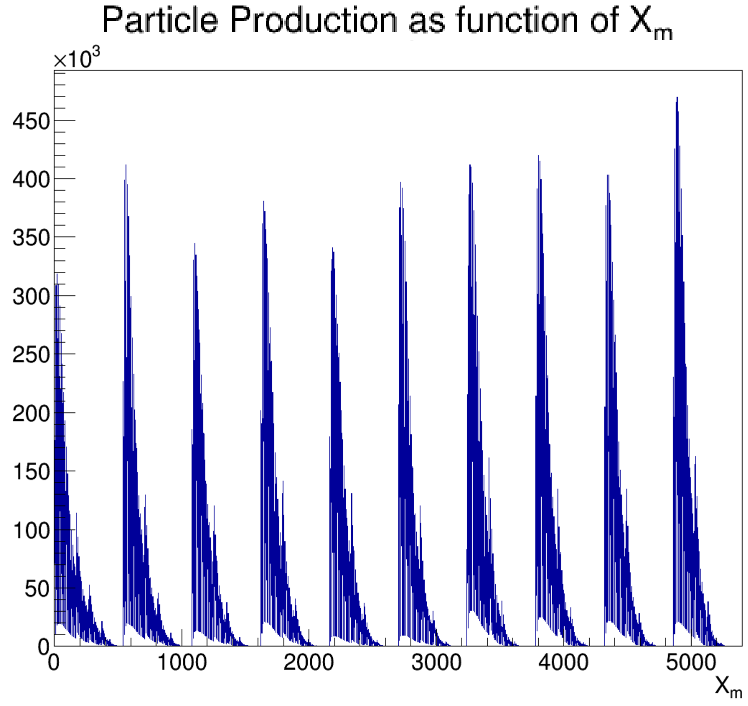
$$X(N, p_{\mathrm{T}}, S_o) = N_{bins\ N} \times N_{bins\ p_T} \times bin_{S_o} + N_{bins\ N} \times bin_{p_T} + bin_N$$

We apply the same strategy

$$\begin{aligned} N_{bins\ X} &= N_{bins\ N} \times N_{bins\ p_T} \times N_{bins\ S_o} \\ &= \mathbf{10} \times \mathbf{54} \times \mathbf{10} \\ &= \mathbf{5400} \end{aligned}$$

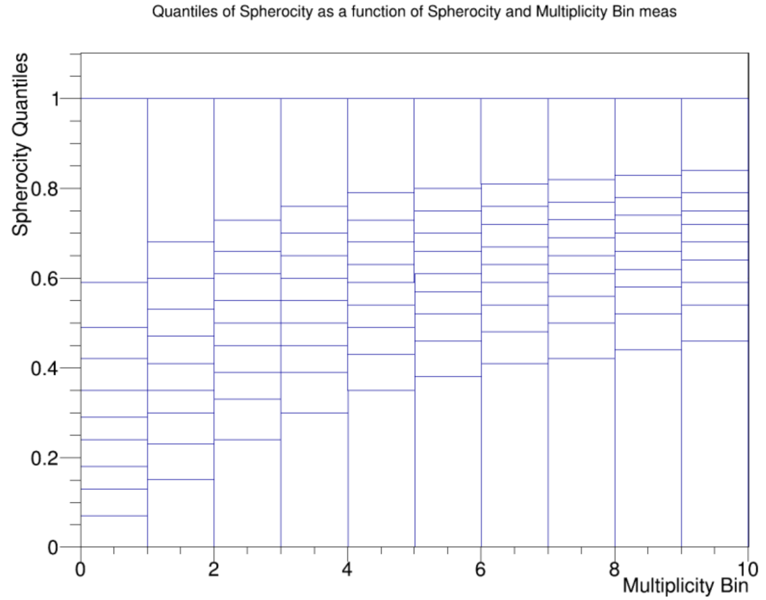


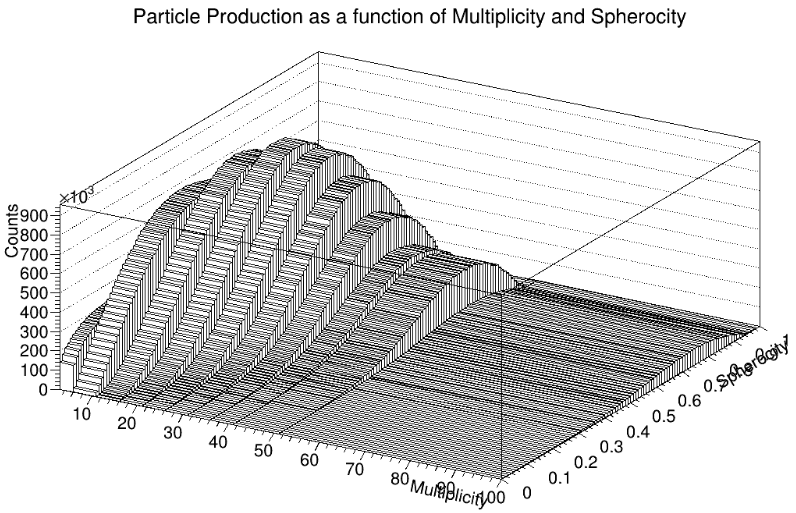
X

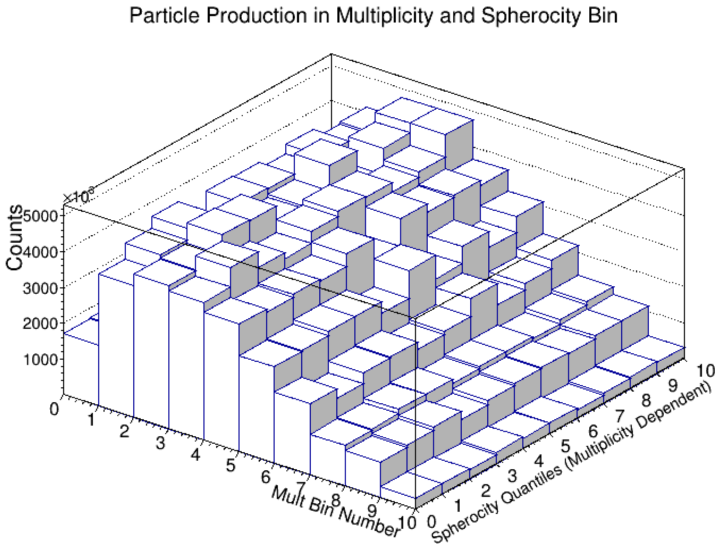


Spherocity Percentiles (Multiplicity Dependent) Preprocessing

Multiplicity Binning: [3, 6, 11, 16, 21, 26, 31, 36, 41, 51, 100]

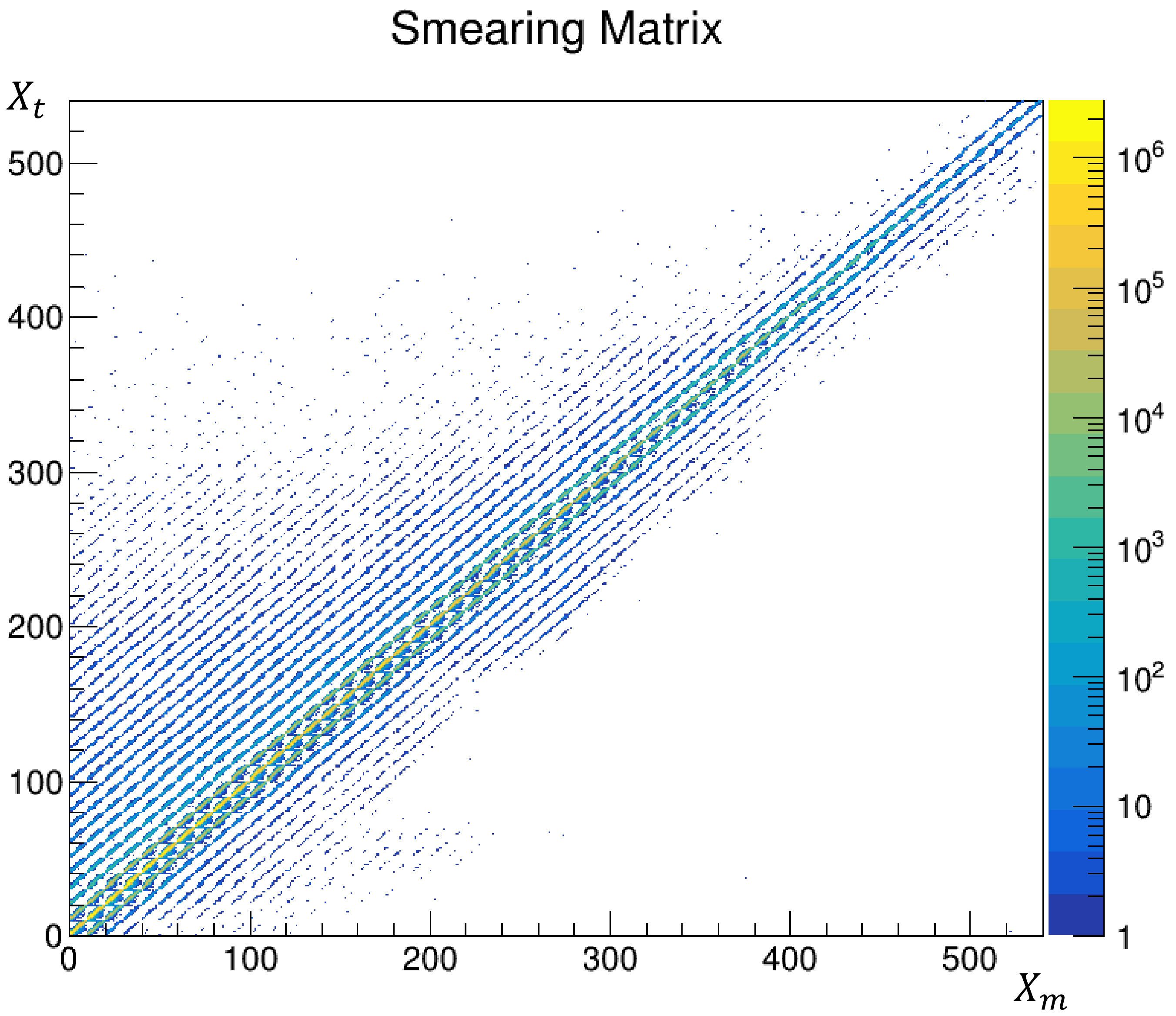






Homogenize Event Distribution by a Multiplicity-Dependent Spherocity Bin

2D Unfolding (1D Rebinning)



In the same manner, we parametrize the Smearing Matrix.

Event and Track Selection

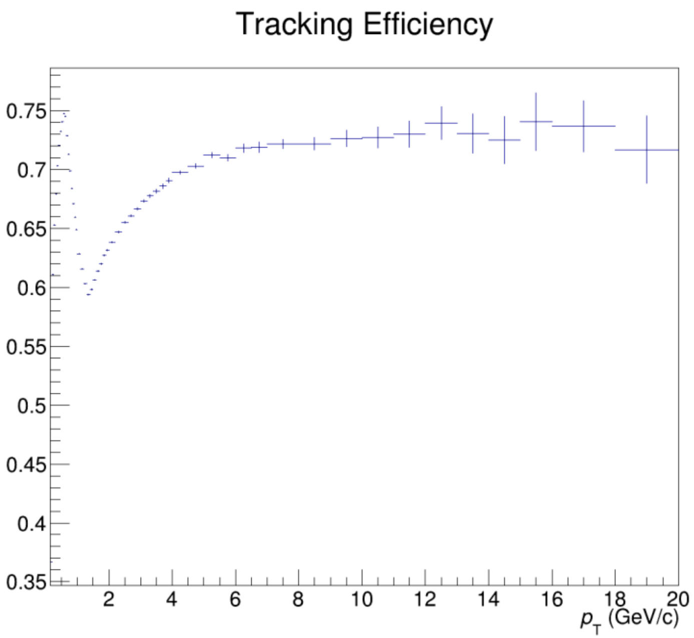
- Event Selection
  - MB trigger condition
  - DAQ Complete
  - Remove Pileup
  - Position reconstructed vertex $|V_z| < 10\ cm$

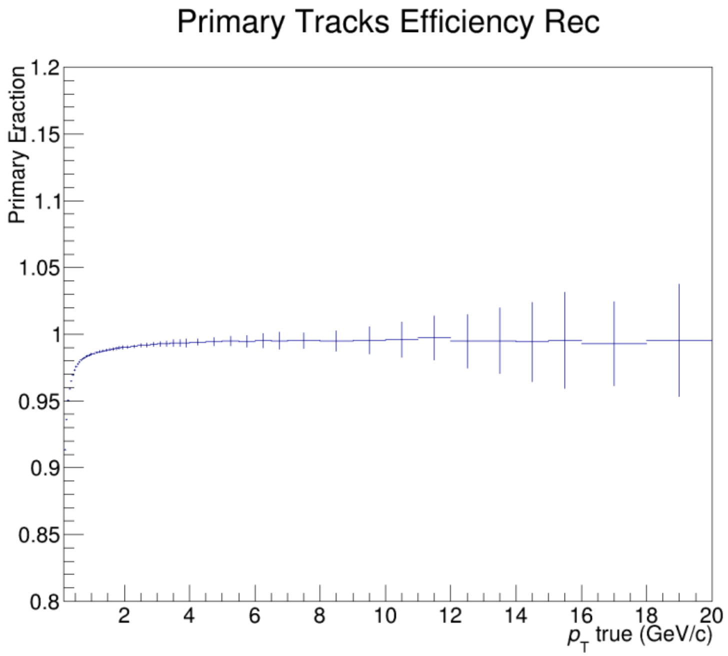
- Track Selection
  - More 70 TPC Clusters
  - Cluster-vs-tracklet background cut
  - χ^2 per TPC Cluster < 4
  - Distance to closest approach $DCA_{xy} < 2.4\ cm$ and $DCA_z < 3.2\ cm$

Data Corrections

$$IY(p_T) = \frac{1}{2\pi p_T}\frac{d^2 n}{d\eta dp_T} = \frac{1}{2\pi p_T}\frac{1}{N_{events}}\frac{N_{tracks,prim}}{\Delta\eta\Delta p_T}\frac{1}{\varepsilon_{track}}\frac{\varepsilon_{ev\ loss}}{\varepsilon_{sg\ loss}}$$

Data Corrections

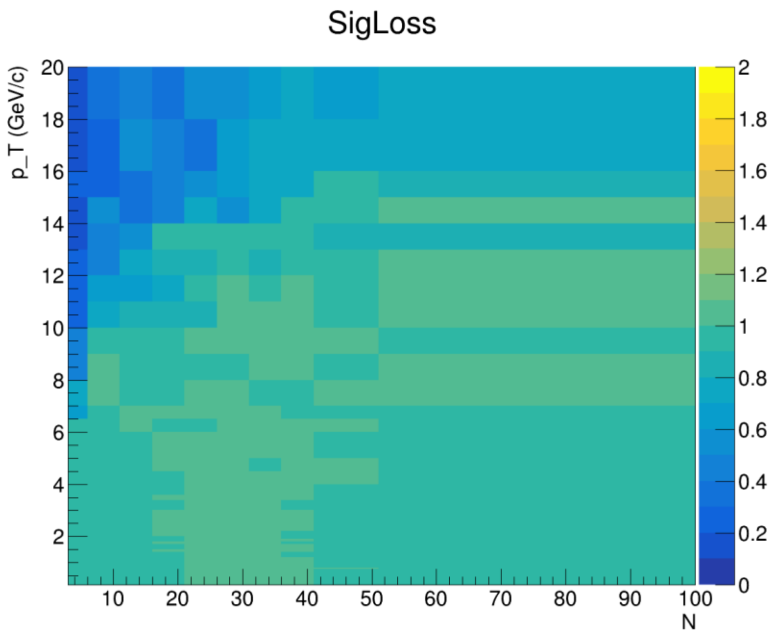


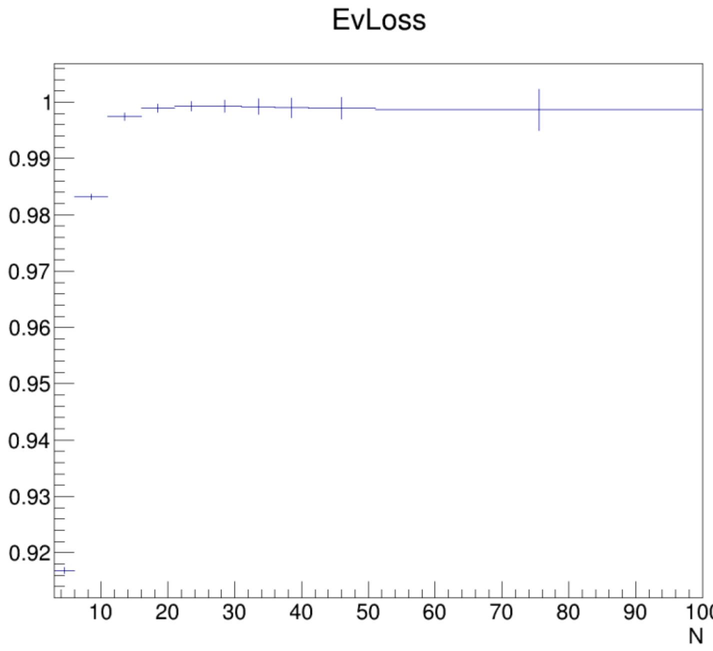


Tracking Efficiency:
Reconstruction of tracklets in the TPC.

Primary Fraction Tracks:
Counts the Secondary Contamination. Quantified with the true variable.

Data Corrections



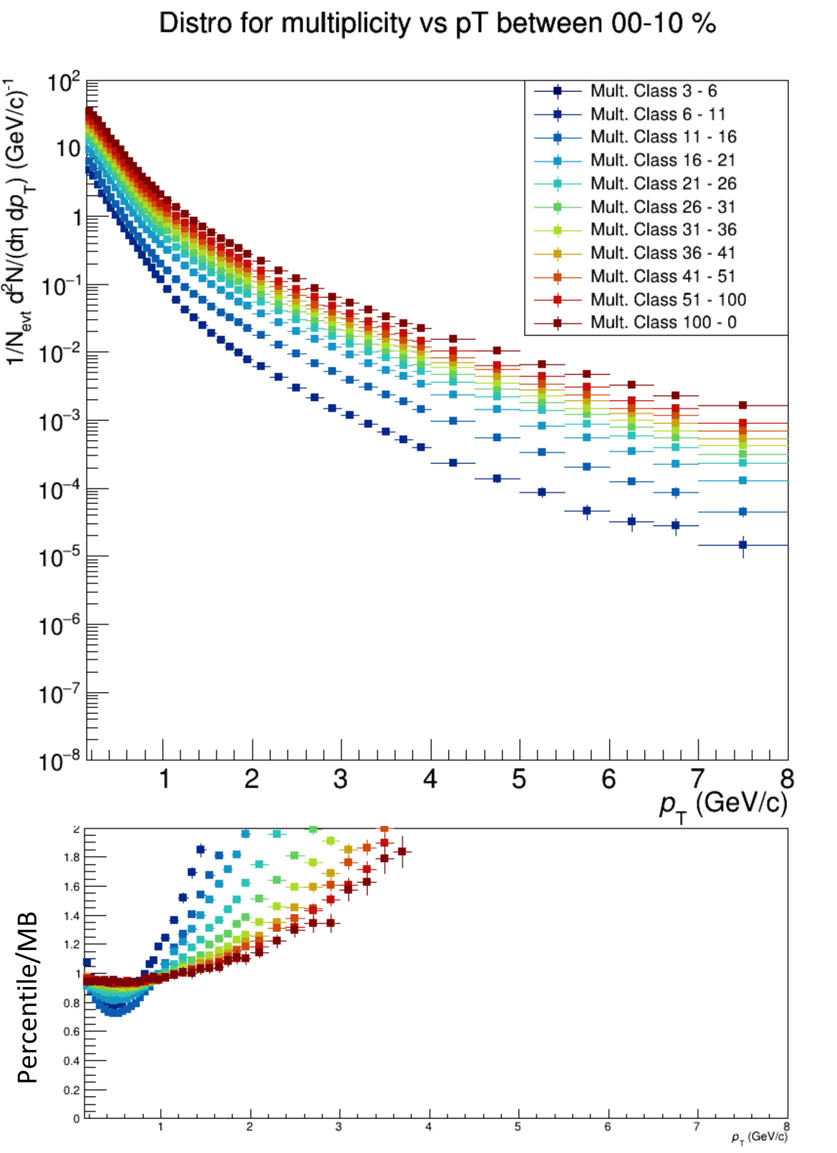


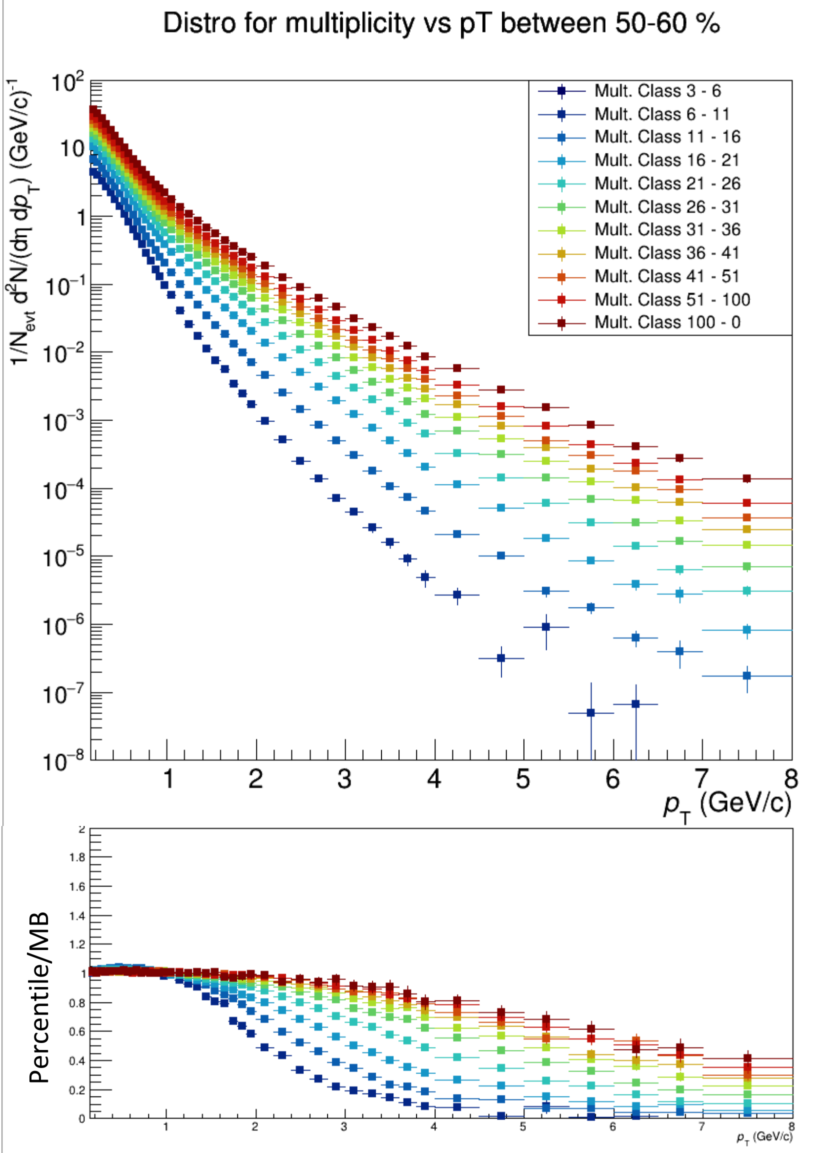
Signal Loss:
Loss of MC particles by event selection

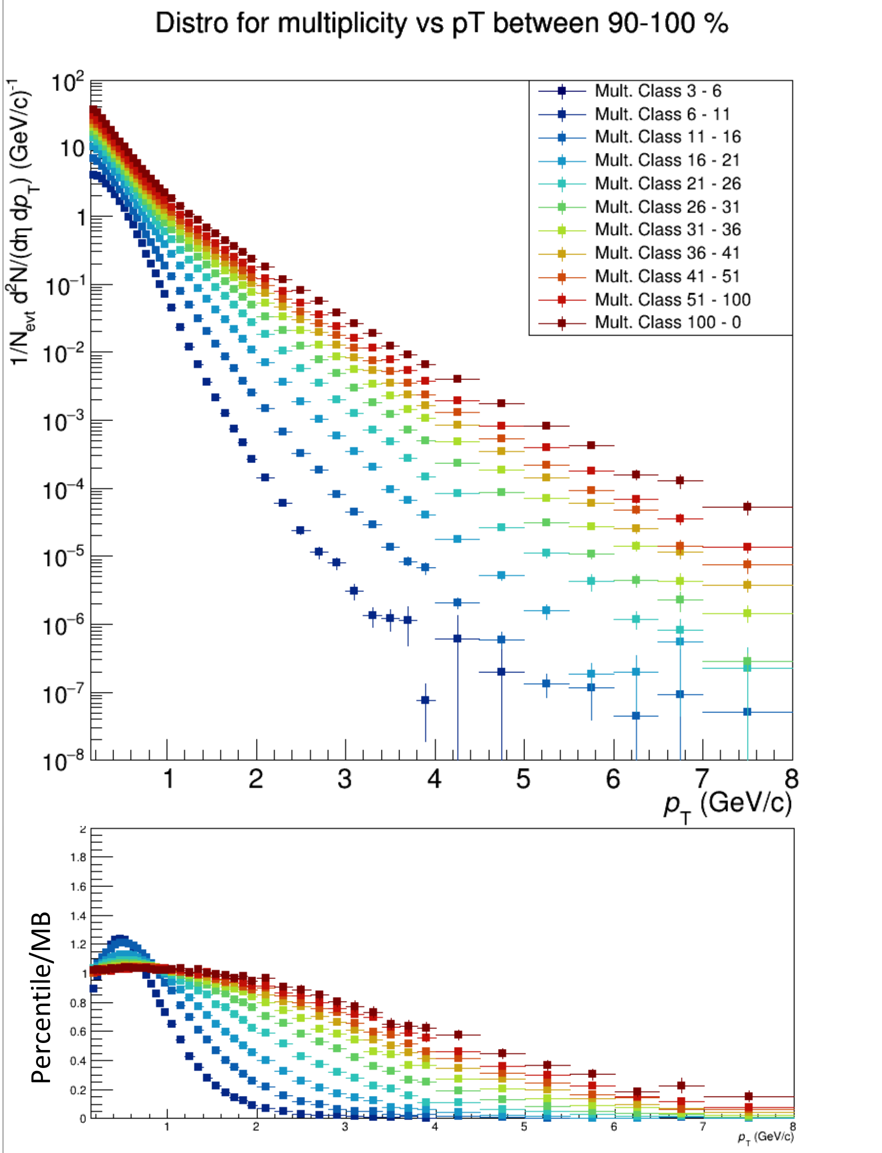
Event Loss:
Loss of MC events by event selection

Results
(MC Analysis)

unfolded p_T spectra



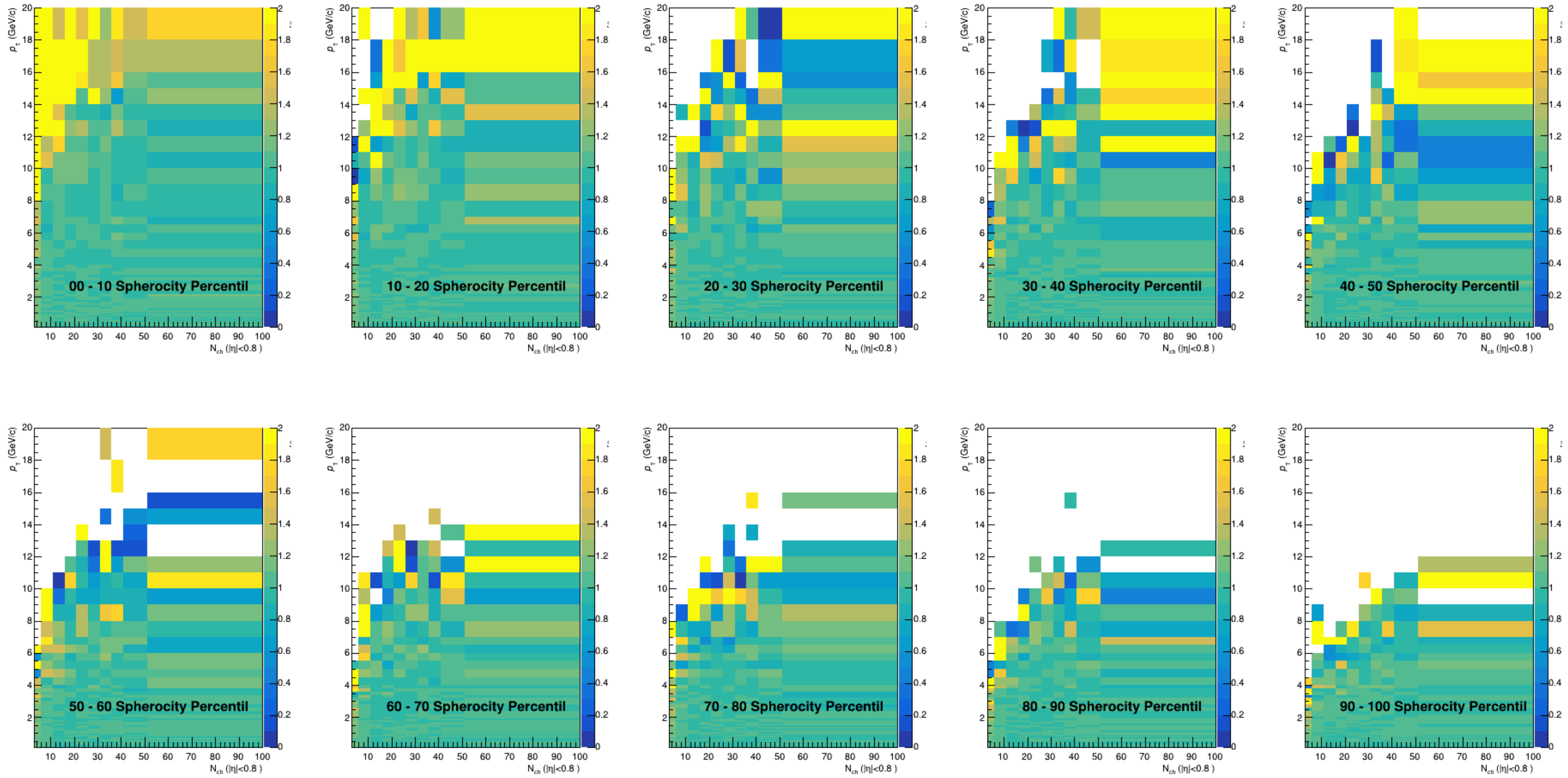




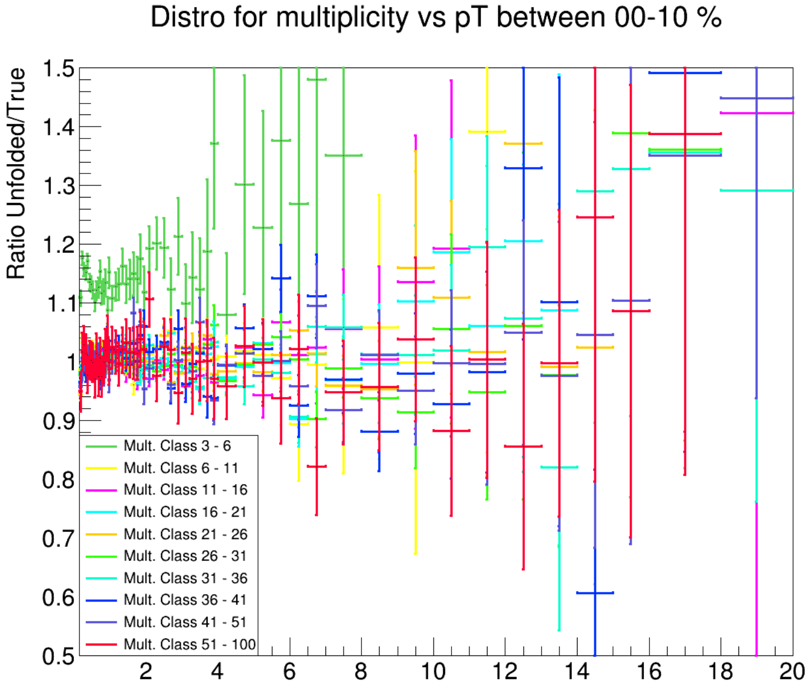
ALICE

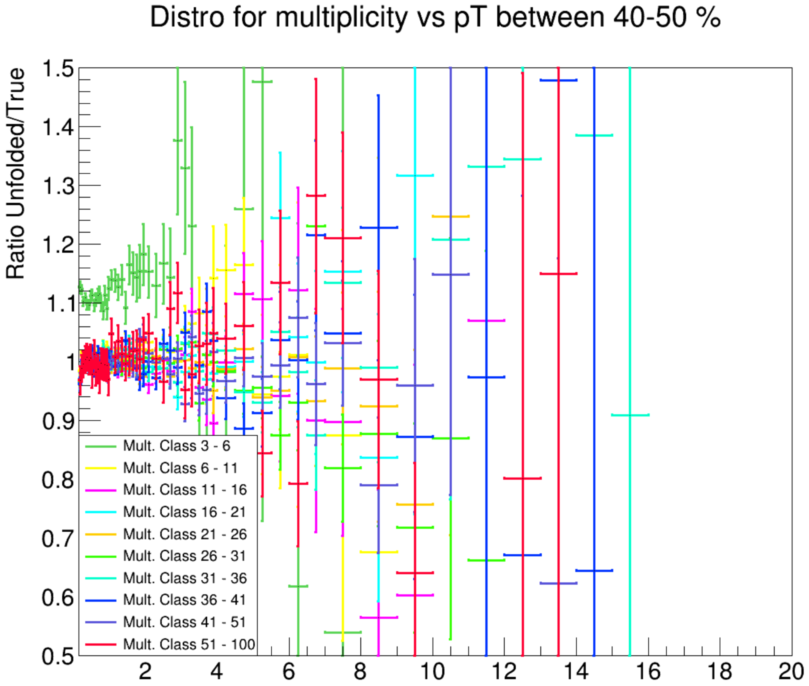
Instituto de Ciencias Nucleares UNAM

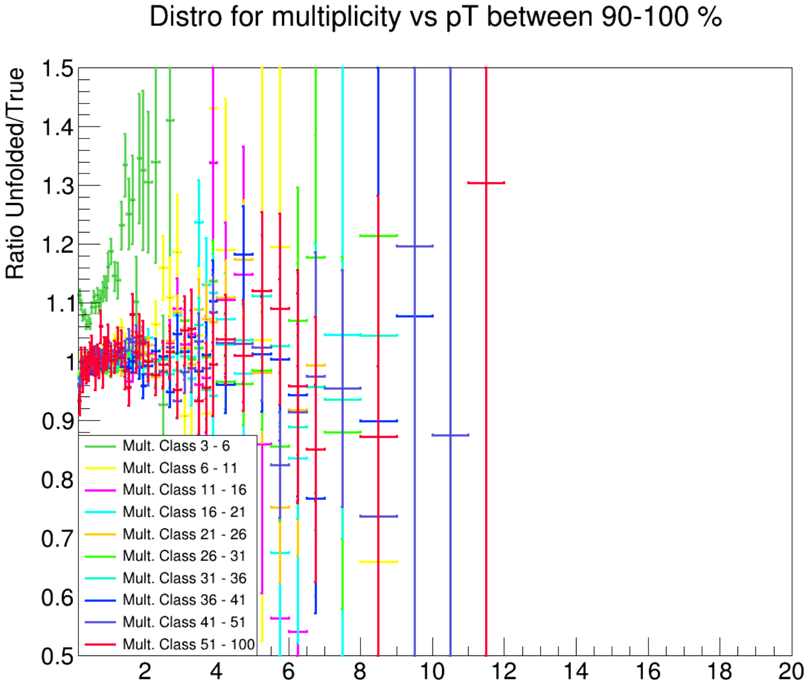
MC Closure Test



MC Closure Test







- Problems with the first multiplicity class, however we expect a better behavoir with hybrid track cuts.

Results

(pp Data Analysis)

Mean multiplicity Density

$$IY(p_T) = \frac{1}{2\pi\, p_T}\frac{d^2N_{ch}(N, p_T, So)}{dp_T d\eta}$$

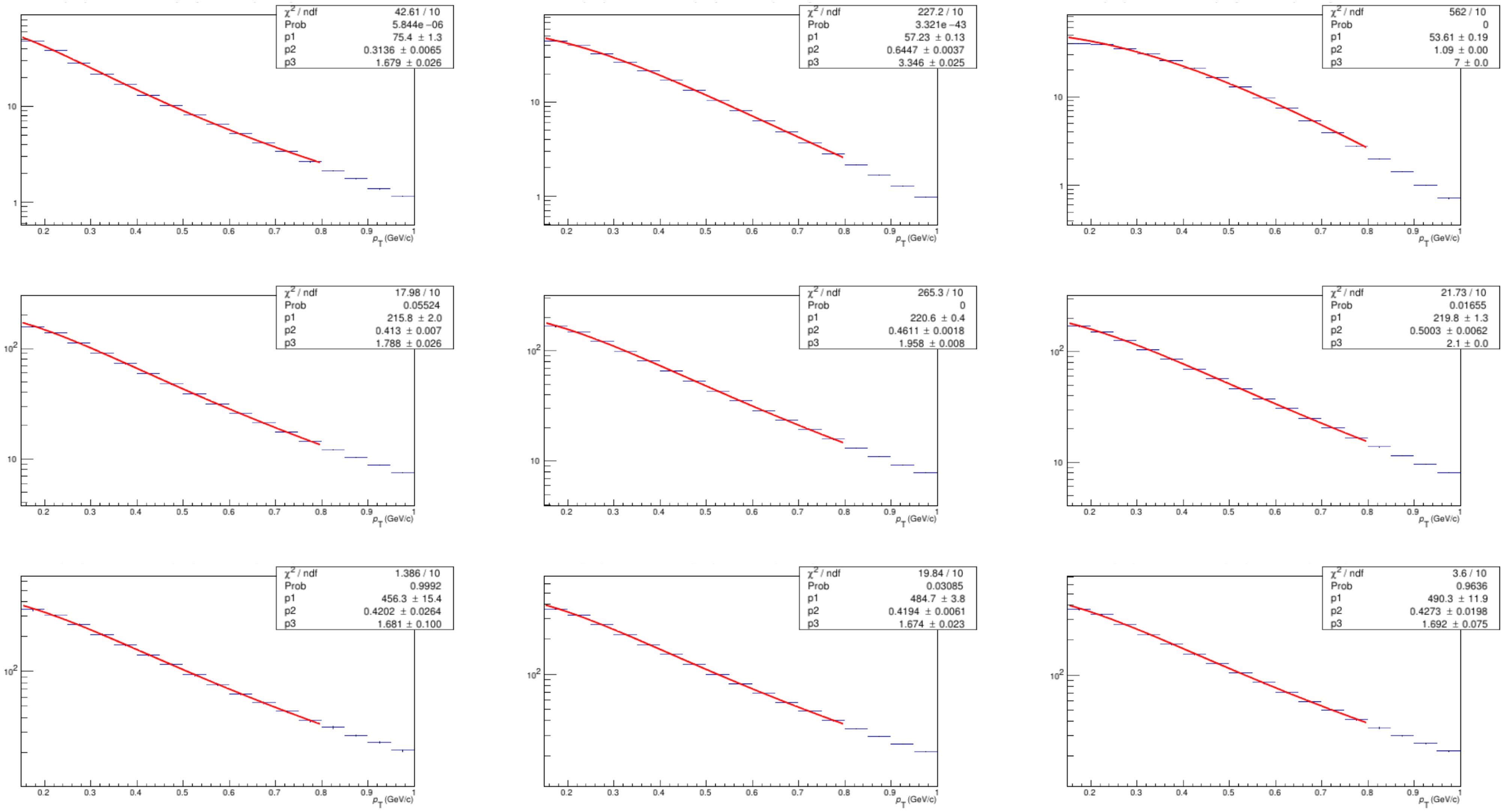
$$\frac{dN_{ch}}{d\eta} = \int 2\pi\, p_T IY(p_T) dp_T$$

$$IY(p_T) = A\left[1 + \left(\frac{p_T}{p_0}\right)^2\right]^{-n}$$

- We estimate the mean multiplicity density of the multiplicity class using a fit of the invariant yield associated to each spherocity and multiplicity class.
- The best function for the fit has been the second modified Hagedorn function, with 3 fitting parameters.

Invariant Yield Fit

	1° S_O Class	Min. Bias	10° S_O Class
1° Mult. Class			
5° Mult. Class			
10° Mult. Class			



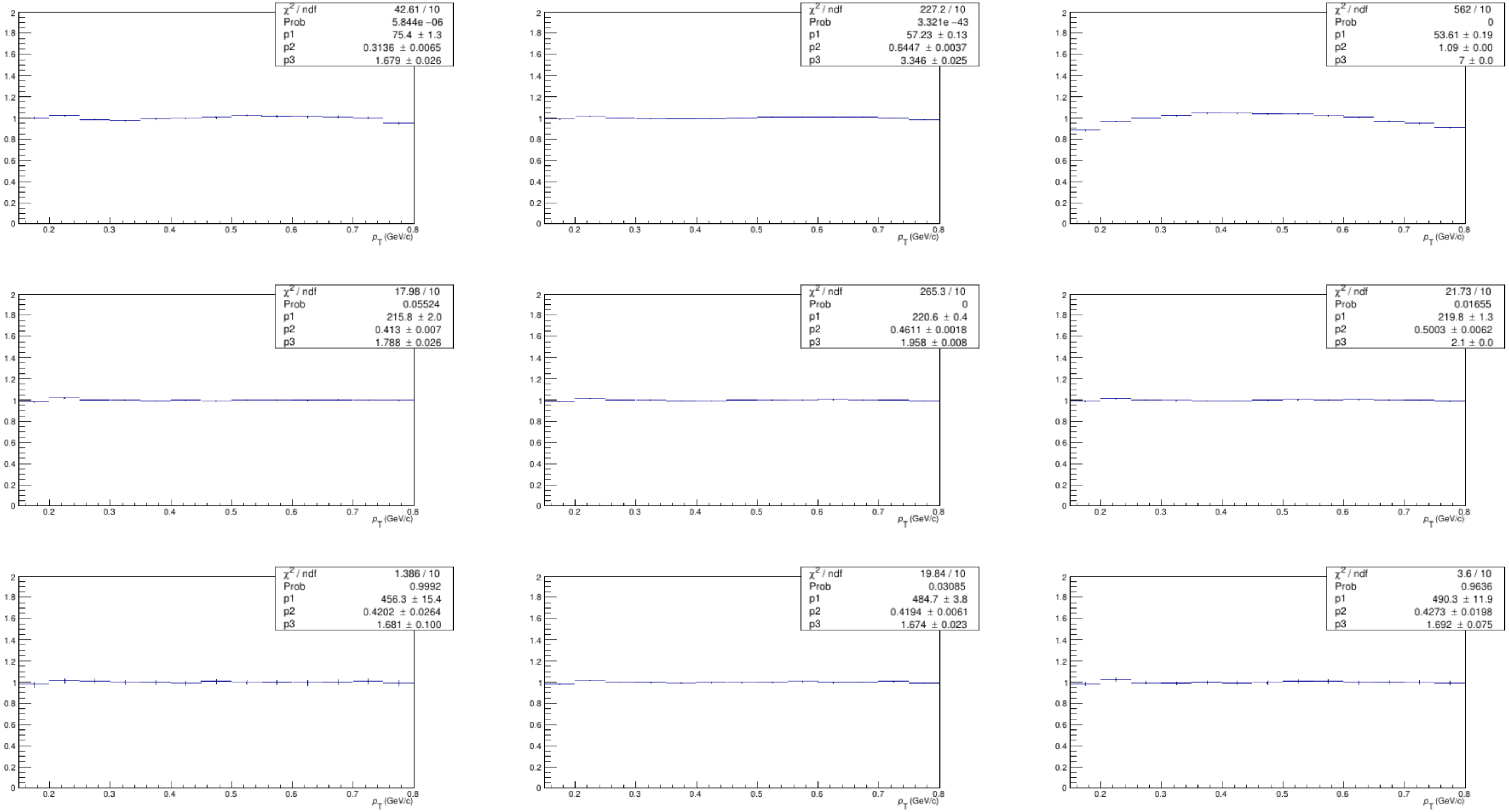
Invariant Yield Fit

1° S_O Class | Min. Bias | 10° S_O Class

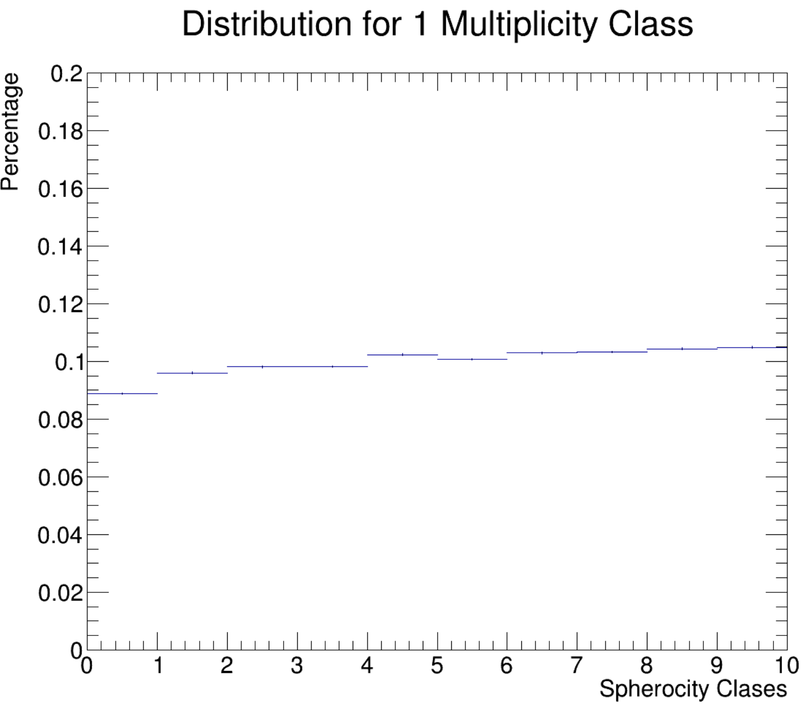
1° Mult. Class

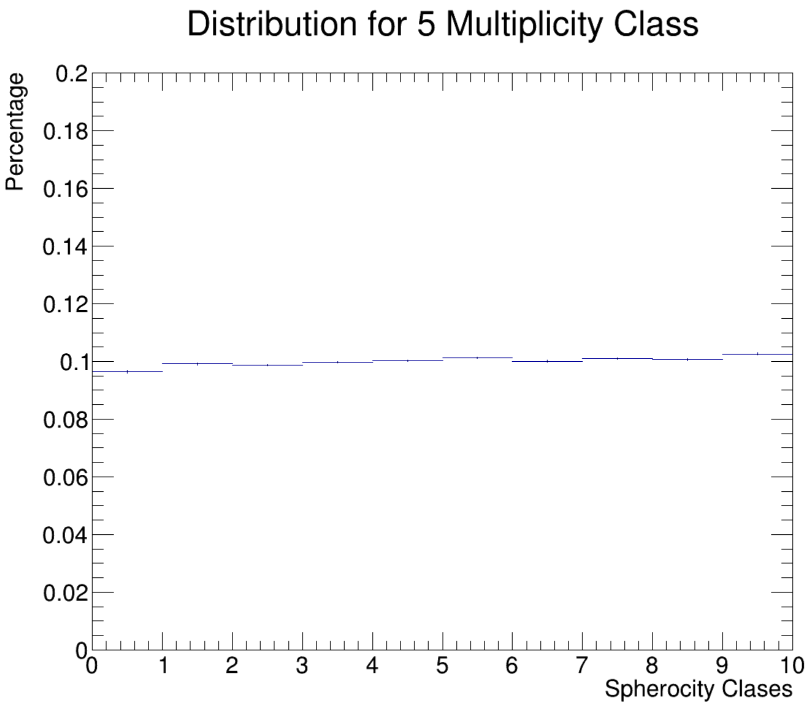
5° Mult. Class

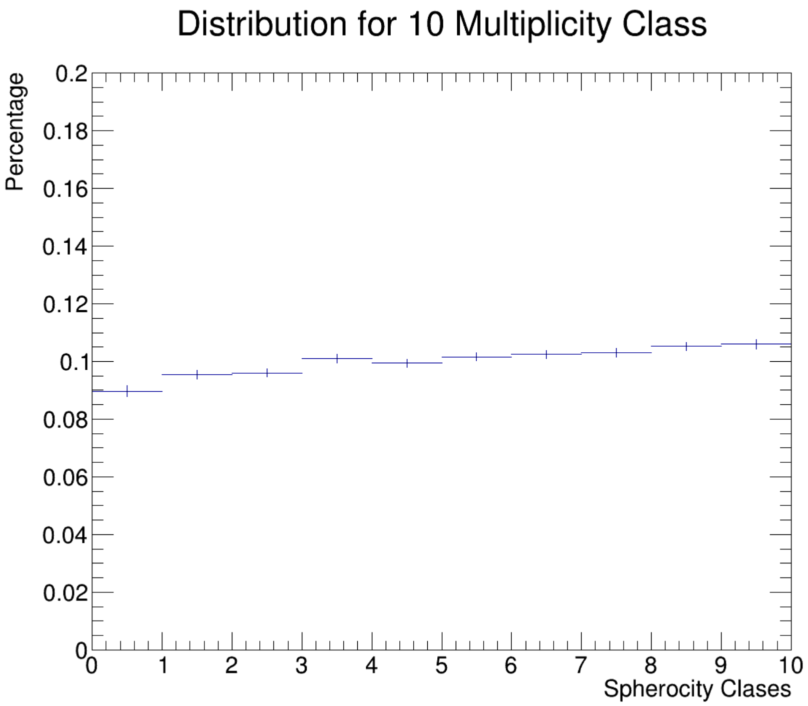
10° Mult. Class



Event Distribution Unfolded



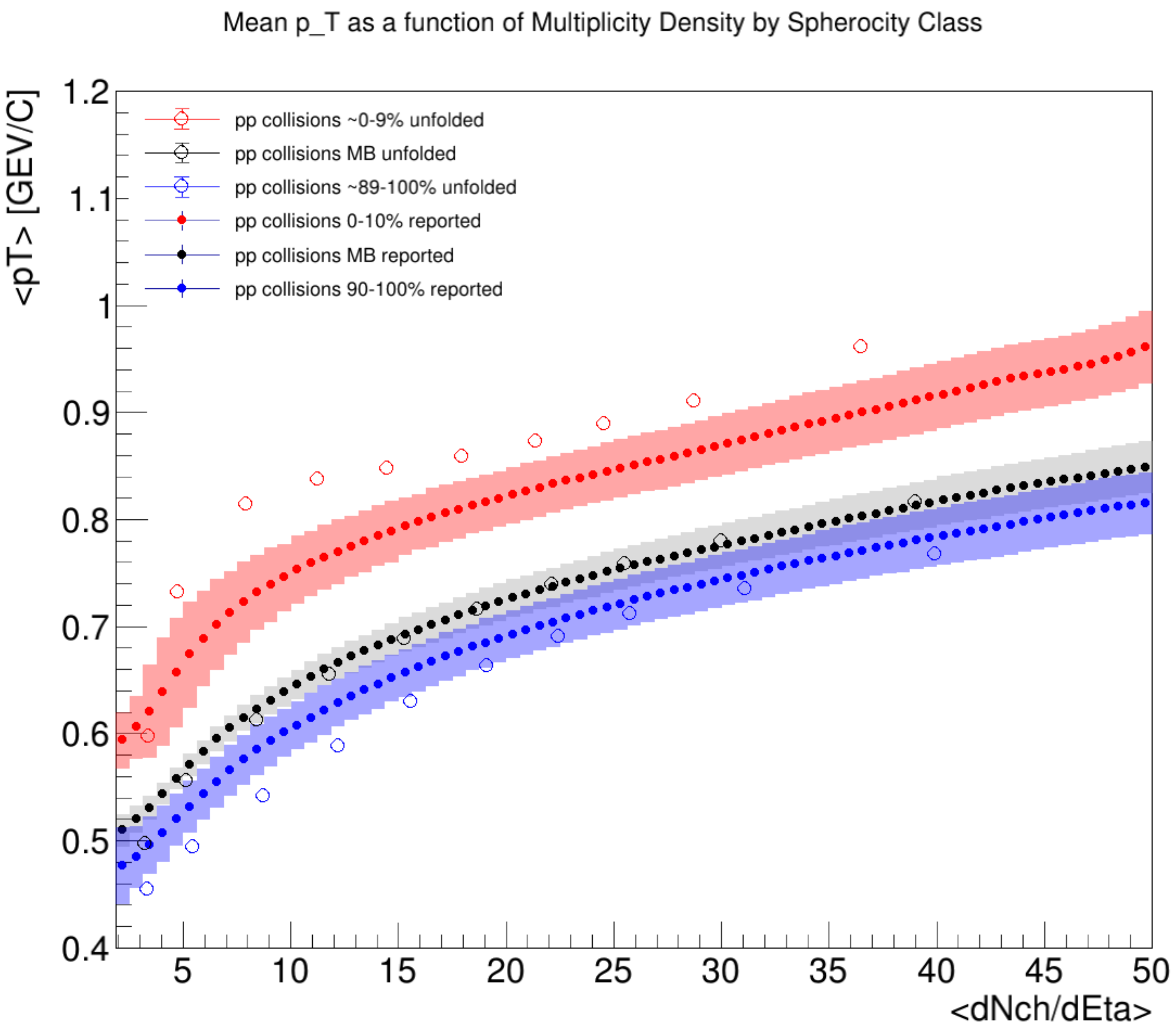




- Although we begin with Spherocity Percentiles Bins from the measure pp collisions, that doesn't mean they are Percentiles in the true distribution.

- For example, in the first multiplicity class, the first Spherocity Class correspond to the 0-9 % most jetty events, meanwhile the last Spherocity Class correspond to the 0-11% most isotropic events.

Mean pT using the Fit <dN/dη> values



Conclusions

- We have been able to reproduce the full p_{T} spectra with the Bayesian Unfolding approach for all multiplicity and spherocity clases from the measure one. The method was proved by the MC Closure Test.

- Using the same smearing matrix, we apply the method to pp collision Data, where we have reproduced the mean p_{T} as a function of multiplicity density for MB, however, there are still disagrements in the most jetty and isotropic data, probably because the change in the percentile selection.

Thanks!