E-by-E multiplicity fluctuations from HADES

MARVIN NABROTH
FOR THE HADES COLLABORATION

OUTLINE

- MOTIVATION
- ANALYSIS PROCEDURE
- RESULTS
- SUMMARY AND OUTLOOK

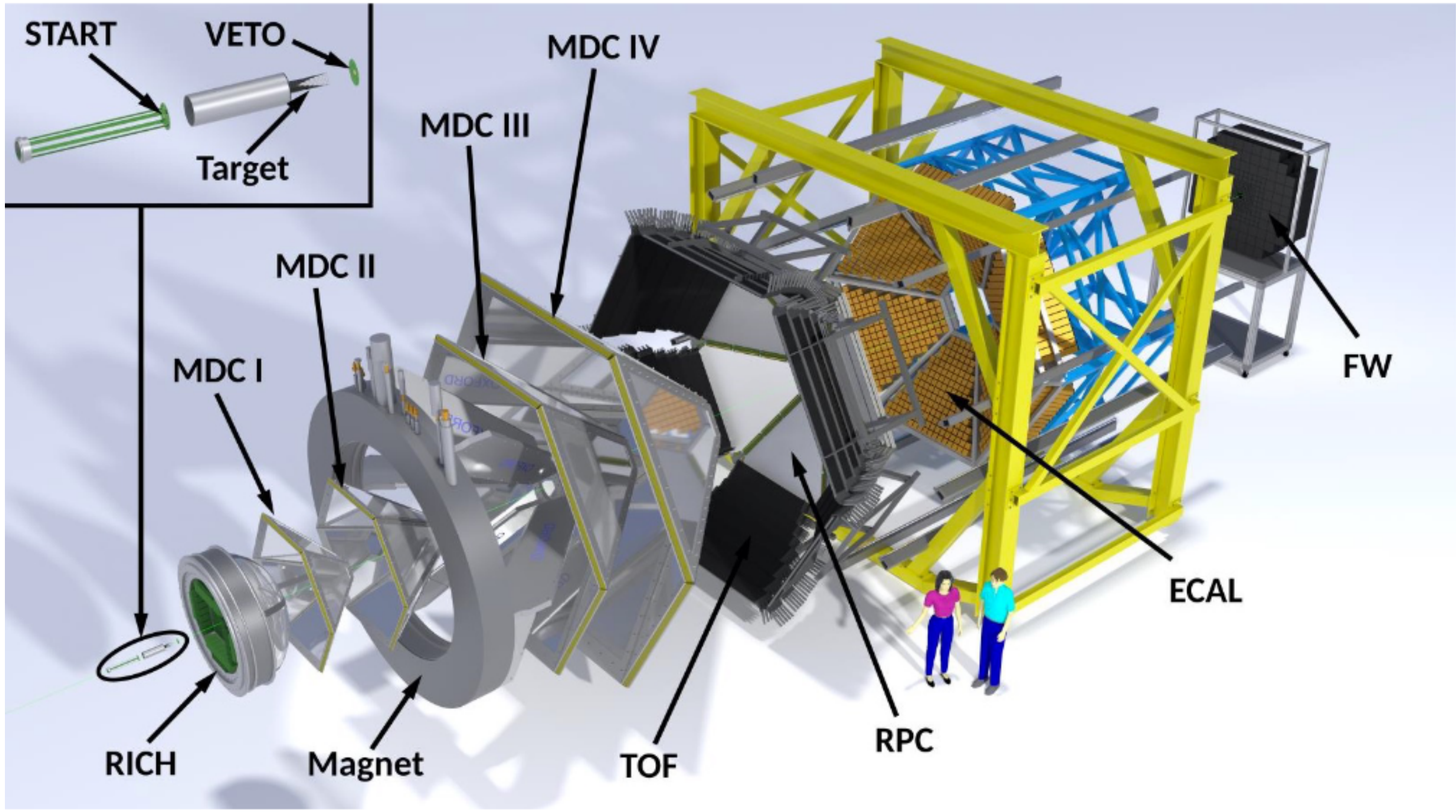

45. CBM Collaboration Meeting
GSI, Darmstadt 16-21 February 2025
Compressed Baryonic Matter
HADES
FAIR
GSI
1: Time-Zero Detector & Beam Diagnostics
2: Silicon Tracking System / Micro Vertex Detector
3: Superconducting Dipole Magnet
4: Muon Chambers
5: Ring Imaging Cherenkov Detector
6: Transition Radiation Detector
7: Time of Flight Detector
8: Forward Spectator Detector

HADES

High-Acceptance-Di-Electron-Spectrometer

- ❑ Fixed target experiment at SIS-18
- ❑ **Momentum reco.** based on toroidal **magnetic spectroscopy** (**MDCs and Magnet**),
- ❑ **Time-of-flight** from **START, RPC and TOF**
- ❑ **Energy-loss measurement** from **MDC** and **TOF**
- ❑ ECAL and hadron-blind RICH detector
- ❑ **Forward Wall** for projectile spectator measurement

- ❖ Almost full azimuthal coverage
- ❖ Polar angle coverage between 18° and 85°



- ❑ New refined simulations with time-differential treatment of Delta-Electrons
- ❑ Up to about 10 % more yield for charged tracks around mid-rapidity

Reminder SIS18/Bevalac energies

Center-of-mass projectile/target velocities < 0.5 c

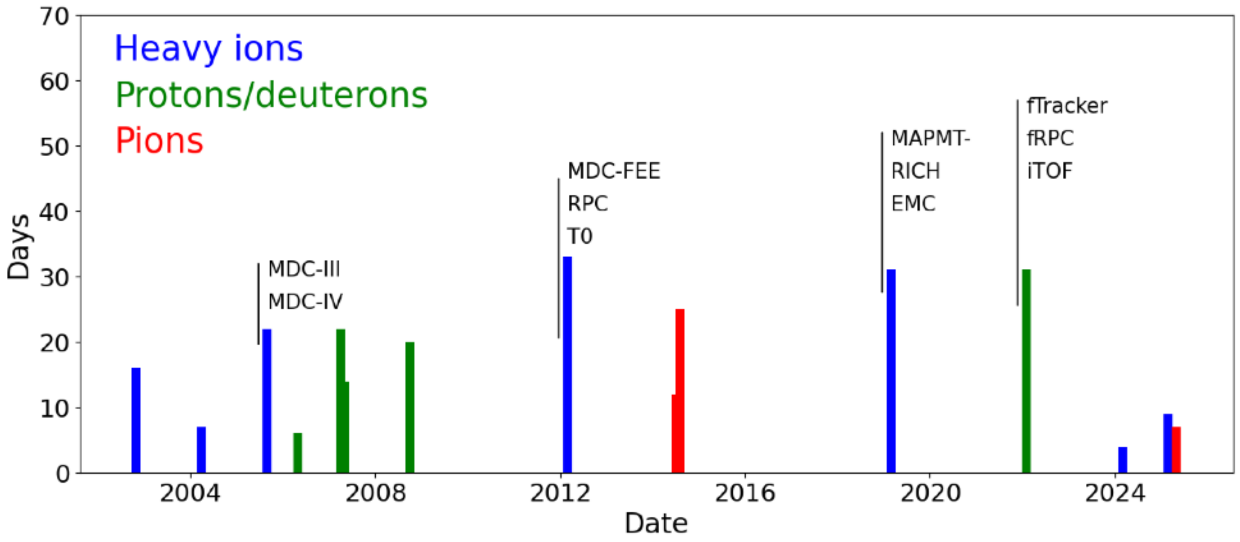
Reduced sensitivity on centrality because of moderate particle multiplicities

Charged-particle multiplicities largely due to stopped baryons (nucleons)

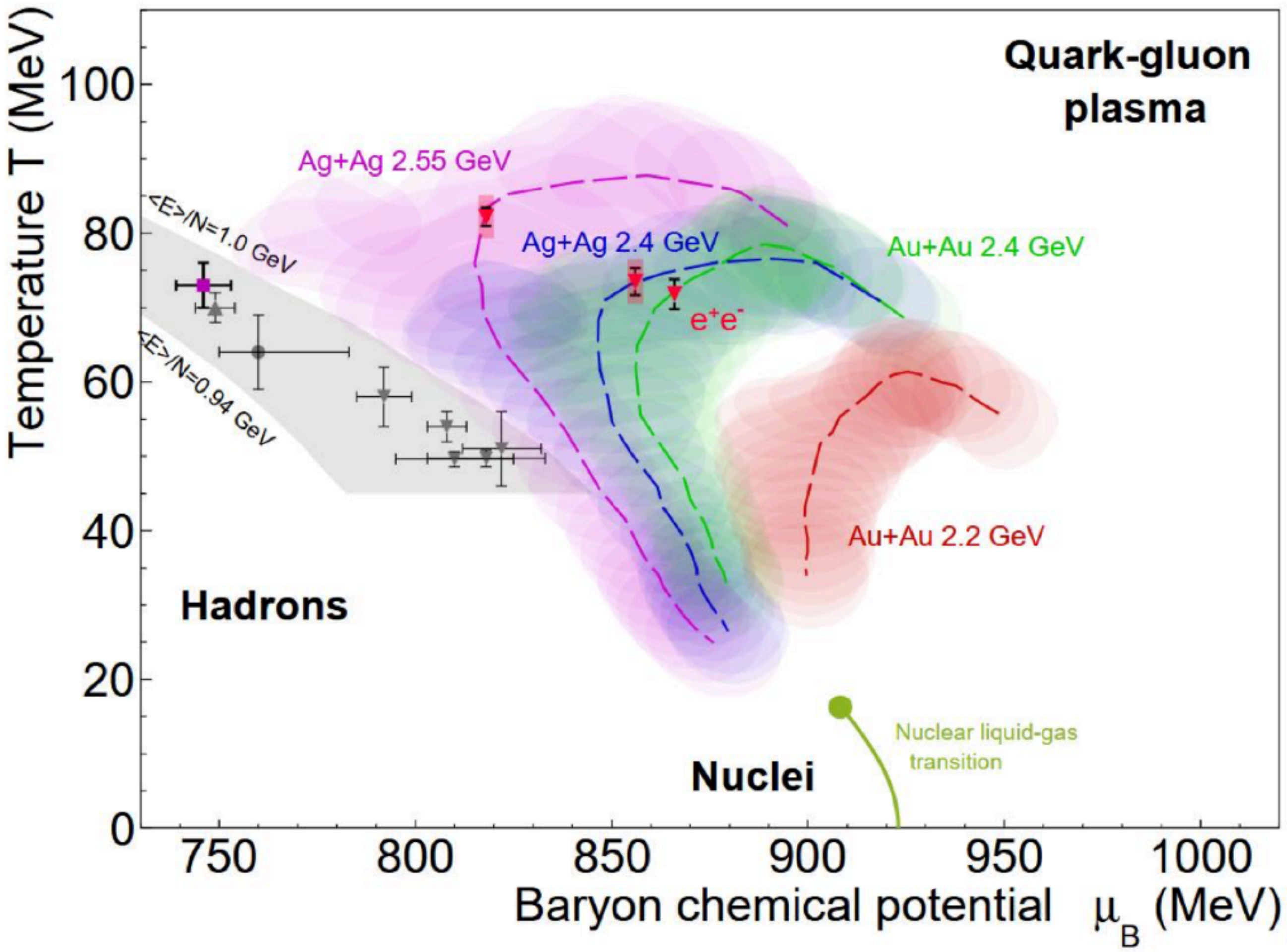
Moderate space-momentum correlation [2201.08486, 2404.00476]

HADES data sets:

Au+Au	$E_{\text{kin}} = 1.23\,A\,\text{GeV}$	(2012)
Ag+Ag	$E_{\text{kin}} = 1.23\,A\,\text{GeV}$	(2019)
Ag+Ag	$E_{\text{kin}} = 1.58\,A\,\text{GeV}$	(2019)
Au+Au	$E_{\text{kin}} = 0.8\,A\,\text{GeV}$	(2019)

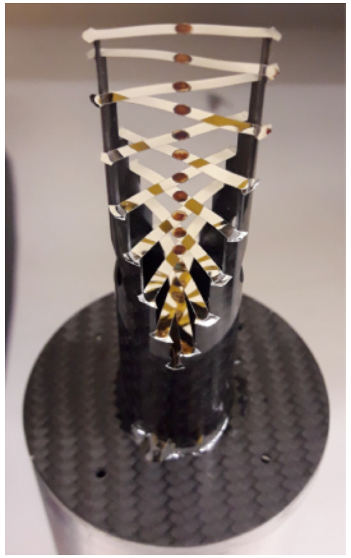


Trajectories from Coarse-grained UrQMD

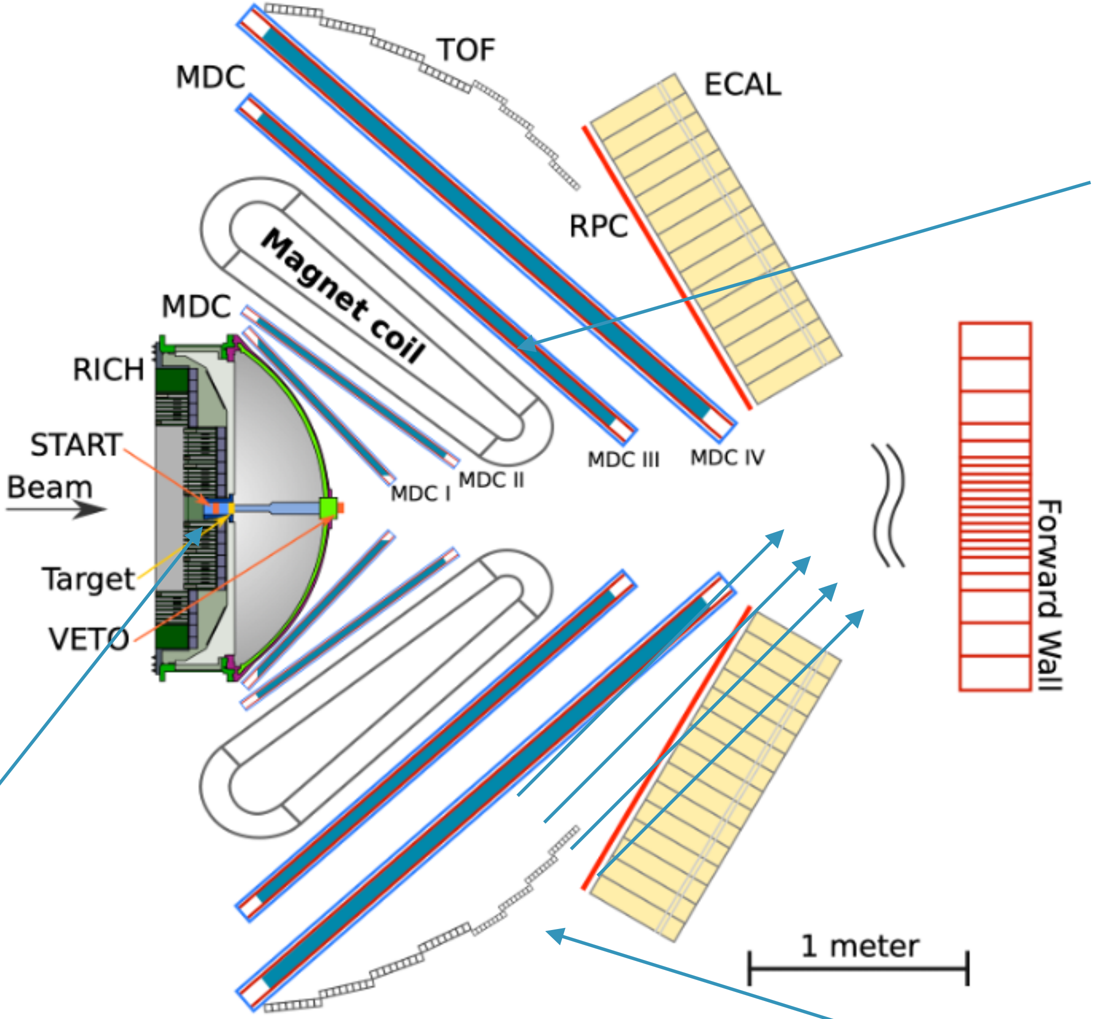


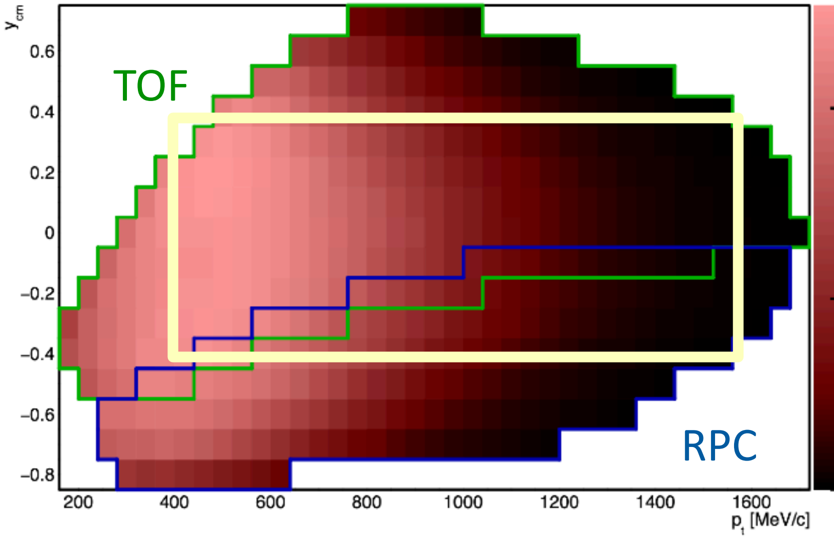
FO curve: J. Cleymans, K. Redlich, Nucl. Phys. A 661 (1999) 379
Au+Au 2.4 GeV data: HADES, Nature Phys. 15(2019) 1040
Eur.Phys.J.A 52 (2016) 5, 131
Phys.Rev.C 106 (2022) 1, 014904
Ag+Ag data: HADES preliminary
figure: F.Seck, T.Galatyuk

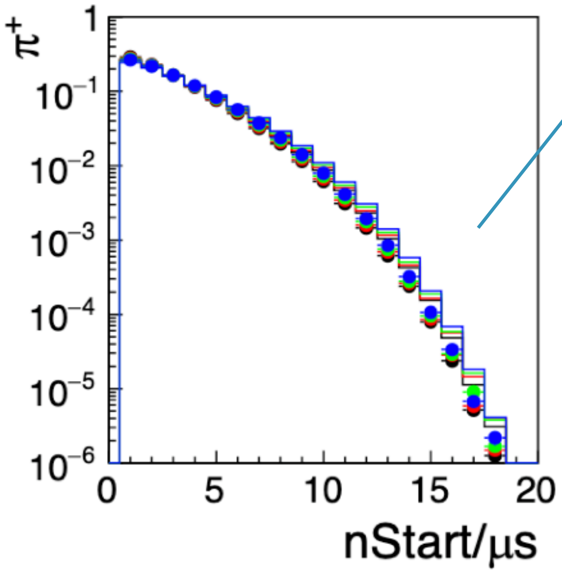
15-fold segmented target

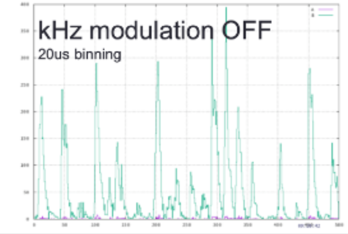


phase space coverage for protons

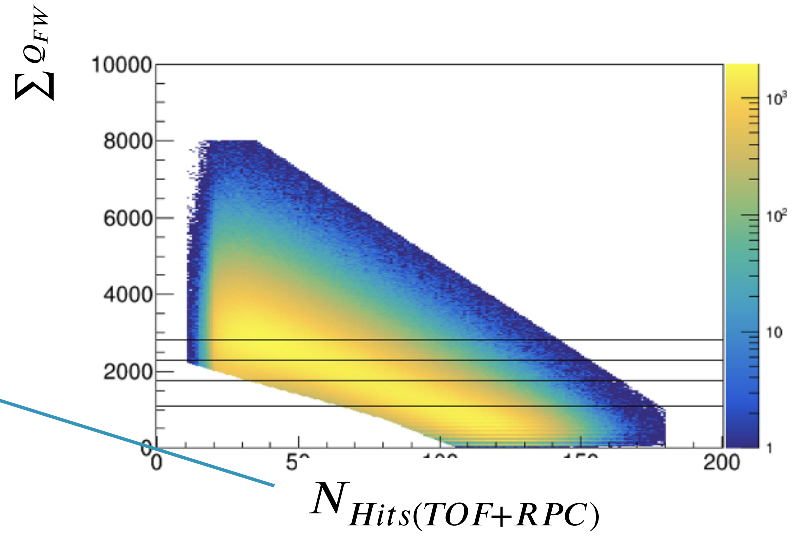




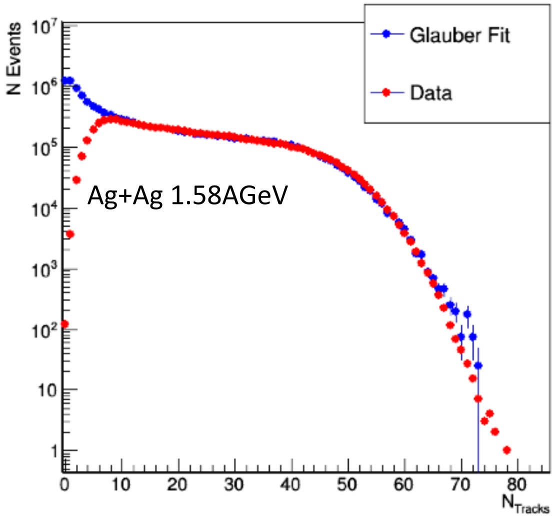


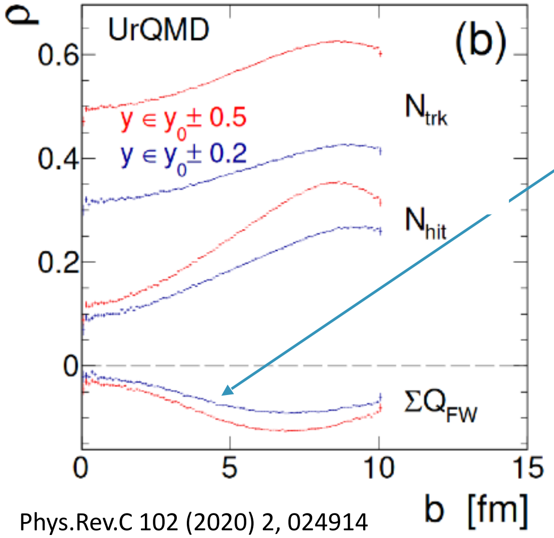


Ag beam: ions/20 us



Centrality Selection for fluctuation analysis

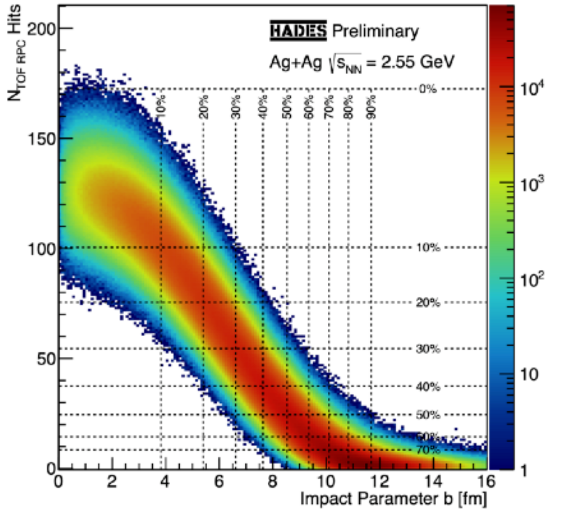


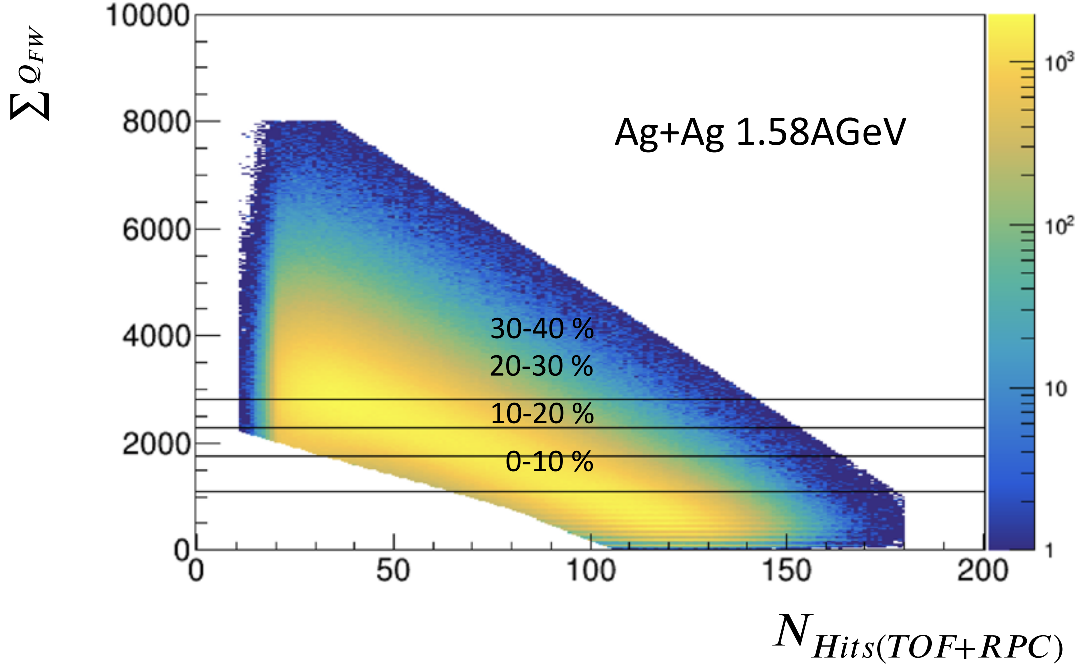


Phys.Rev.C 102 (2020) 2, 024914

Smallest correlation with protons
→ Forward Wall Signal

Glauber MC



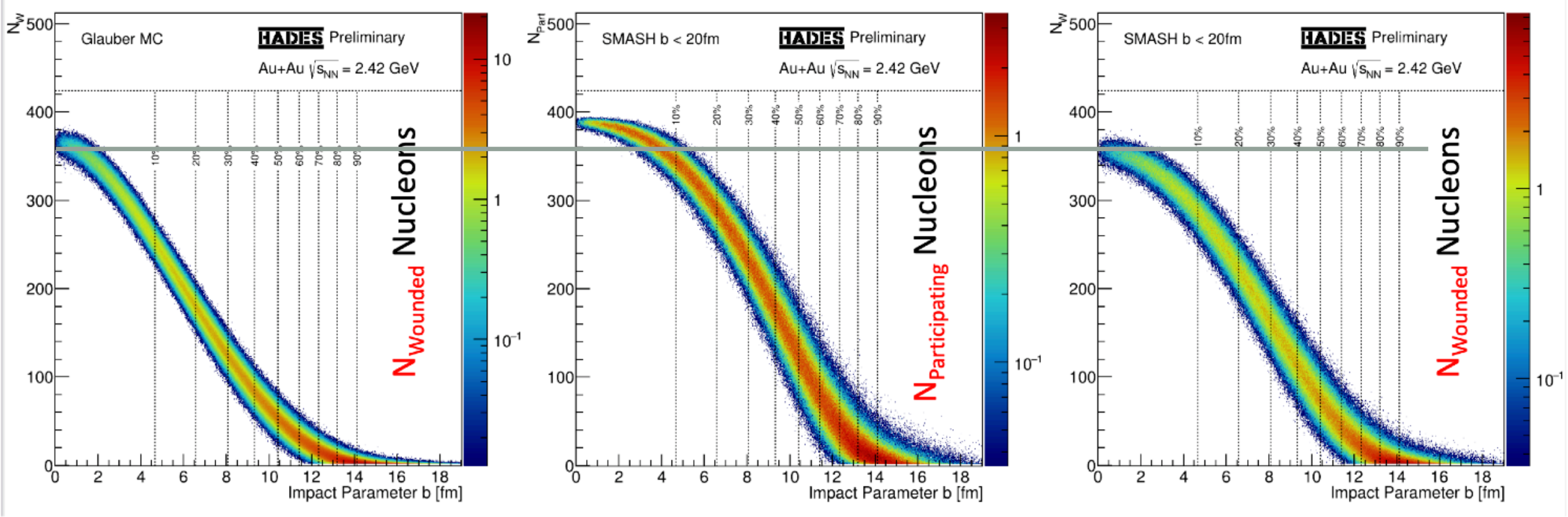


- ❑ Glauber x Neg. Binomial to **charged tracks** and **detector hits**
- ❑ Event selection corresponds to around 55 % most central events
- ❑ For fluctuation analysis, do further centrality binning based on FW signal
- ❑ **Neg. Binomial for charged tracks at HADES is close to Poisson**
  - → **reduce autocorrelation to protons**

The challenge of reducing systematic uncertainties

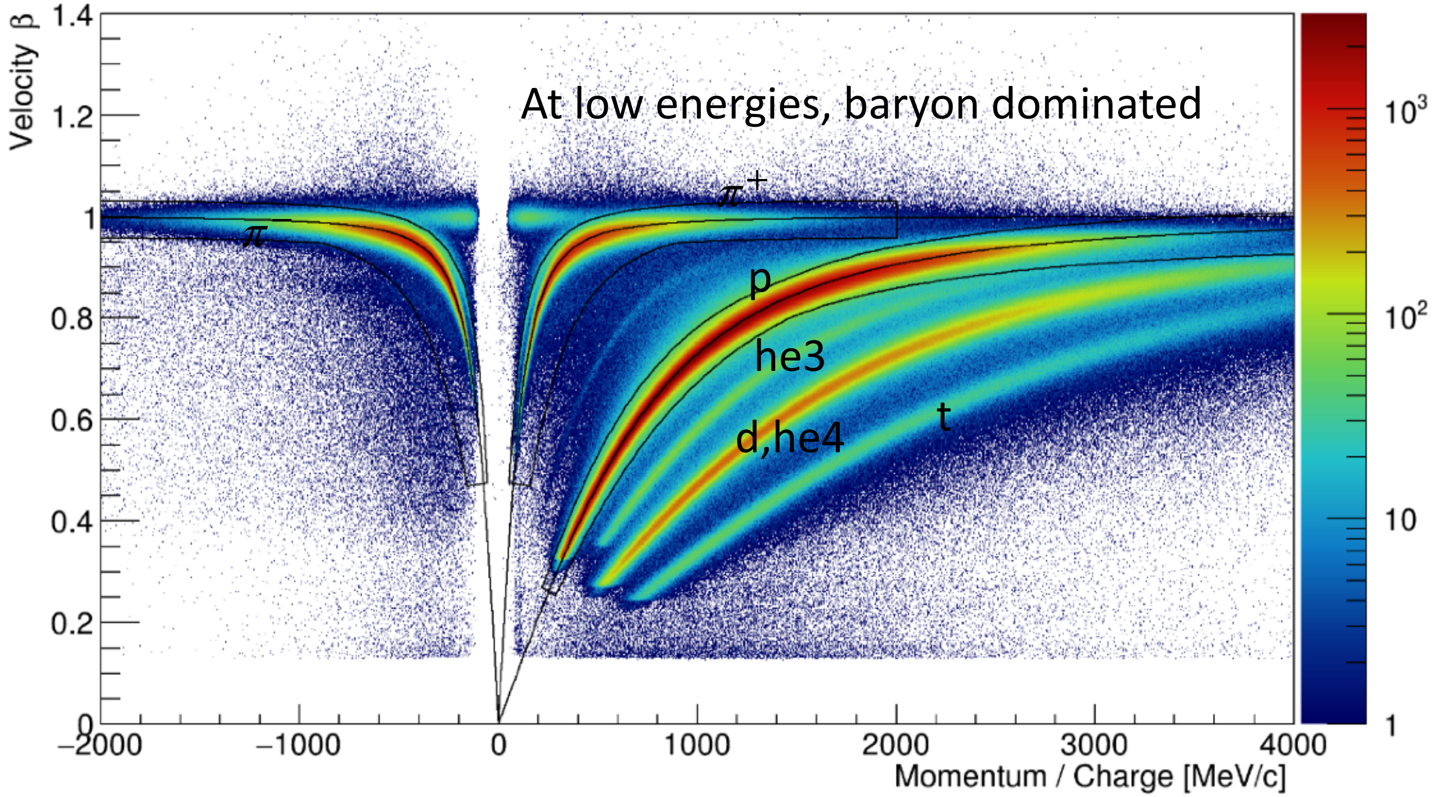
HADES has initiated a reprocessing of data – updated results were shown on QM2025:

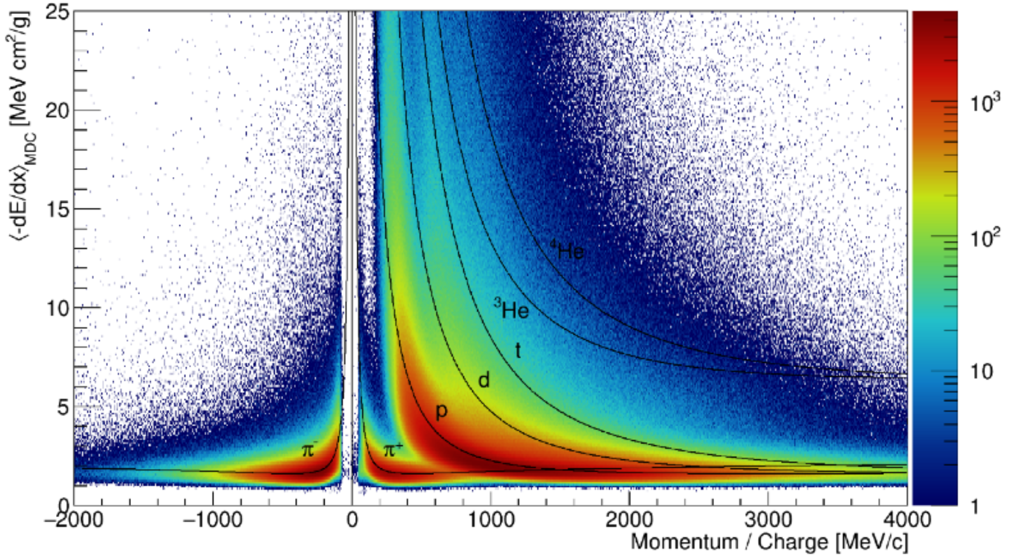
- Refined efficiency models using **multi-hit information of T0 detector**
- **Further rejection** of **critical pile-up** effects
- HADES uses Glauber-MC which is comparable with Transport only if inelastic collisions are counted, i.e.
  $N_{\text{wounded}} \equiv \text{inel. only} \qquad N_{\text{participant}} \equiv \text{el. \& inel.}$



PID

Particle identification at HADES





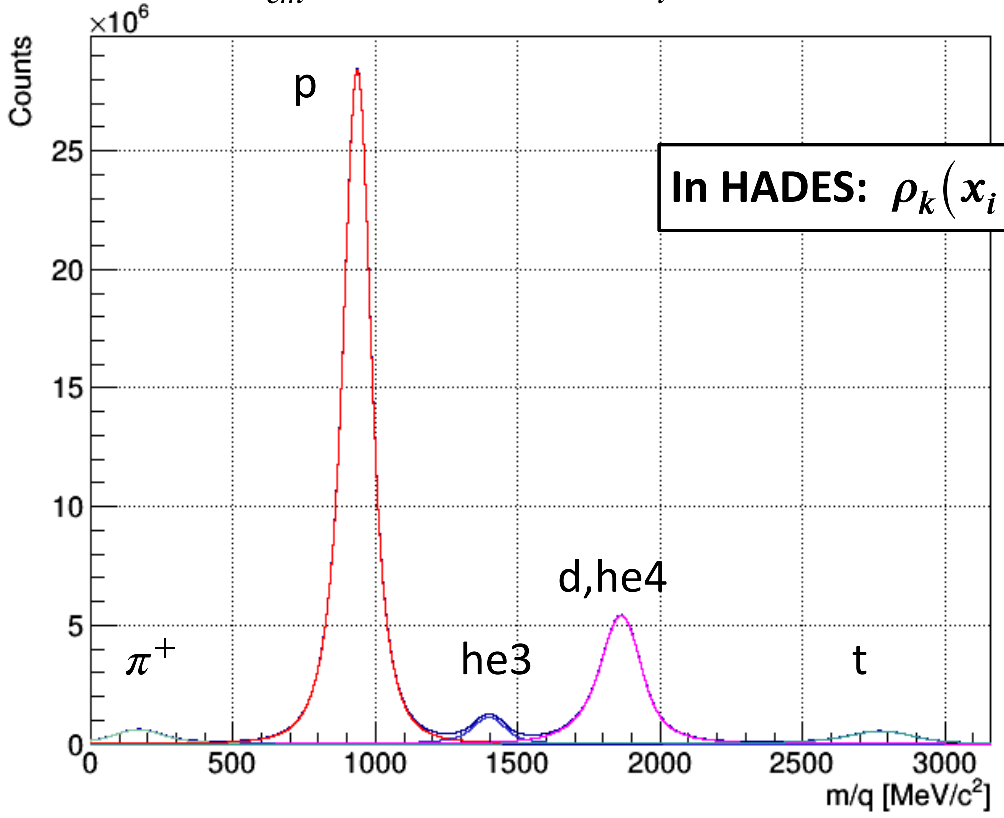
- **MDCs** provide measurement of **specific energy loss**
- In deuteron analysis used as preselection

- PID via **time of flight** (β) and **momentum** measurement → **m/q**
- Time-of-Flight measurement provides good separation

Correcting moments for mis-identification - Fuzzy Logic

Ag+Ag 1.58A GeV

$-0.2 < y_{cm} < 0.2, \quad 400 < p_t < 1600\ MeV/c$



In HADES: $\rho_k(x_i = m/q)$

- ❑ For deuterons, increase separation power by preselection based on dE/dx signal

- ❑ Traditional approach: Hard cuts
- ➢ **Identity method/Fuzzy logic →** Assign PID observable with **degree of membership** to different particles

$$\omega_j(x_i) = \frac{\rho_j(x_i)}{\sum_j \rho_j(x_i)}$$

Event\Proxy quantities

$$W_k = \sum_{i=1}^{N_{tracks}} \omega_k(x_i)$$

Correcting moments for mis-identification - **Fuzzy Logic**

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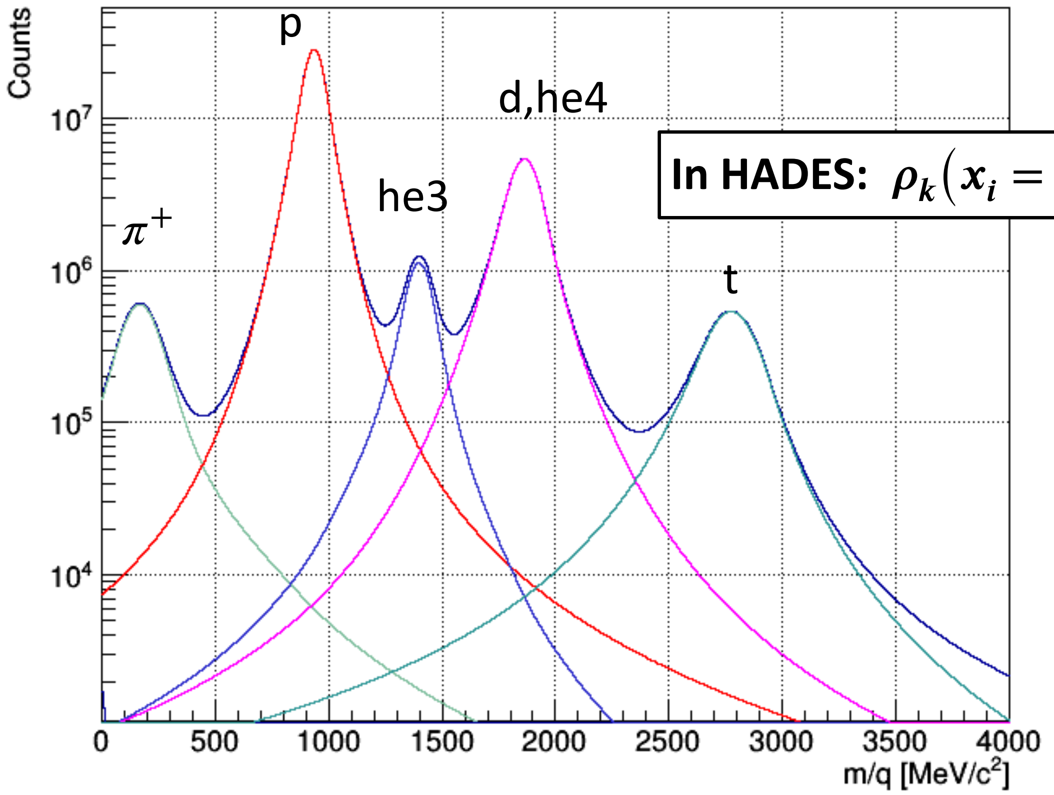

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Correcting moments for mis-identification - **Fuzzy Logic**

- A. Rustamov derived generalized relation between moments of W and N ***Phys.Rev.C*** **110 (2024) 6**

Moment generations function

$$M_W(t_1,t_2,...,t_n) = \sum_{N_1,N_2,...,N_n=0}^{\infty} P(N_1,N_2,...,N_n)\prod_{i=1}^{n}\left[\int_{-\infty}^{+\infty} e^{\sum_{j=1}^{n} t_j\omega_j(x)}\mathcal{P}_i(x)dx\right]^{N_i}$$

→

$$\langle N_1^{i_1}N_2^{i_2},...,N_n^{i_n}\rangle = \left.\frac{\partial^{(i_1+i_2+...+i_n)}M_N(h_1,h_2,...,h_n)}{\partial h_1^{i_1}\partial h_2^{i_2}...\partial h_n^{i_n}}\right|_{\vec{h}=0}.$$

→ **<W> are a linear combination of <N>**

- Inversion procedure to get from <W> to <N> implemented for the first time up to 4. order

$$\langle\vec{W}\rangle = A \times \langle\vec{N}\rangle$$

vector of folded moments = response matrix (A: **Fully defined by mass fit functions**) x vector of true moments

For details, see poster session:

573. Fuzzy logic for reconstructing moments of multiplicity distributions

Anar Rustamov, Joachim Stroth, Marvin Nabroth

- For full efficiency corr. combine with **moment exp**. or **unfolding (Cornish fisher expansion**)

Idea of Moment Exp.: Establish from the detector response matrix a formal relation between corrected and uncorrected moments

T.Nonaka et. al., Nucl.Instrum.Meth.A 906 (2018) 10-17

Fuzzy logic

A.Rustamov, Phys.Rev.C 110 (2024) 6, 064910

- **Relation between W and N is of linear nature**
  → **Translation to regular matrix, inversion possible**

$$\begin{pmatrix} \langle N_a^2\rangle \\ \langle N_b^2\rangle \\ \langle N_a N_b\rangle \end{pmatrix} = \begin{pmatrix} \Omega^{a,a}_{a,a} & \Omega^{a,a}_{b,b} & 2\Omega^{a,a}_{a,b} \\ \Omega^{b,b}_{a,a} & \Omega^{b,b}_{b,b} & 2\Omega^{b,b}_{a,b} \\ \Omega^{a,b}_{a,a} & \Omega^{a,b}_{b,b} & \Omega^{a,b}_{P[a,b]} \end{pmatrix}^{-1} \begin{pmatrix} \langle W_a^2\rangle - \sum_{i=a,b}\langle N_i\rangle\kappa_2(\omega_{a;i}) \\ \langle W_b^2\rangle - \sum_{i=a,b}\langle N_i\rangle\kappa_2(\omega_{b;i}) \\ \langle W_a W_b\rangle - \sum_{i=a,b}\langle N_i\rangle\kappa_{11}(\omega_{ab;i}) \end{pmatrix}$$

Calculating matrix elements by implementing permutation functions

$$\Omega^{a,b}_{P[i,j]} = \Omega^{a,b}_{i,j} + \Omega^{a,b}_{j,i},$$

$$\Omega^{Q[(ab),c]}_{P[i,j]} = \Omega^{(ab),c}_{i,j} + \Omega^{(ab),c}_{j,i} + \Omega^{(ac),b}_{i,j} + \Omega^{(ac),b}_{j,i} + \Omega^{(bc),a}_{i,j} + \Omega^{(bc),a}_{j,i}$$

$$Q[(ab),c] \equiv [(ab),c] + [(ac),b] + [(bc),a]$$

$$Q[(ab),c,d] \equiv [(ab),c,d] + [(ac),b,d]$$

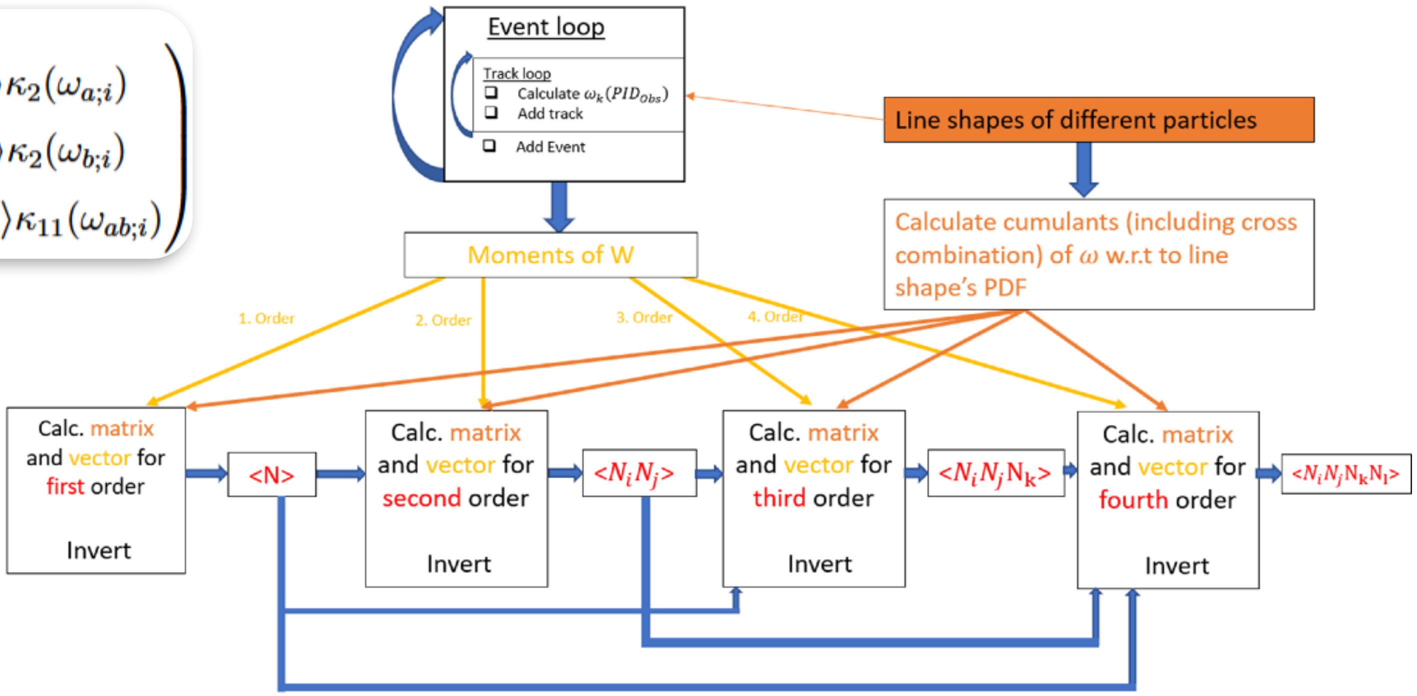
$$P[i,i,j] \equiv [i,i,j] + [i,j,i] + [j,i,i]$$

$$\Omega^{a,b,c}_{i,j,k} = \kappa_1(\omega_{a;i})\kappa_1(\omega_{b;j})\kappa_1(\omega_{c;k}) \ ,$$

$$\Omega^{a,b,c,d}_{i,j,k,l} = \kappa_1(\omega_{a;i})\kappa_1(\omega_{b;j})\kappa_1(\omega_{c;k})\kappa_1$$

Linear coefficients depended on lineshape properties only

Implemented inversion procedure up to 4th order

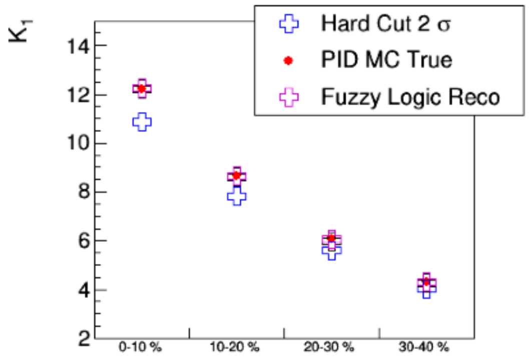


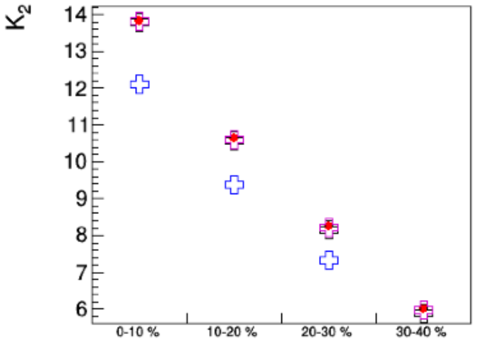
Fuzzy Logic - Performance study in simulation

Ag+Ag 1.58A GeV

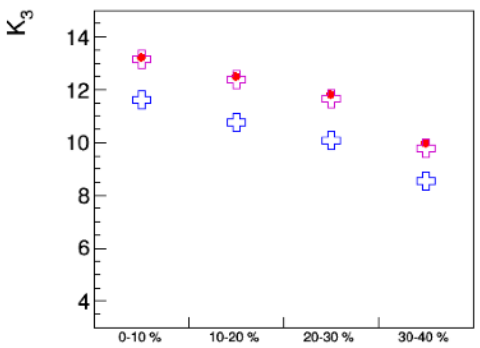
[Smash+Clustering] + HADES GEANT Sim.

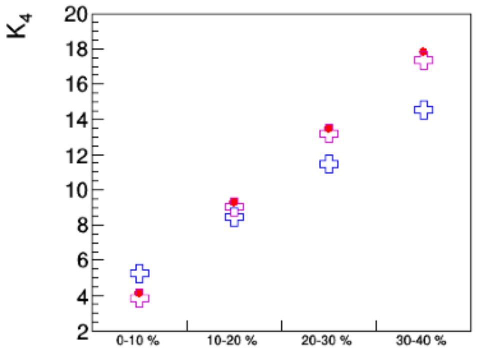
Protons



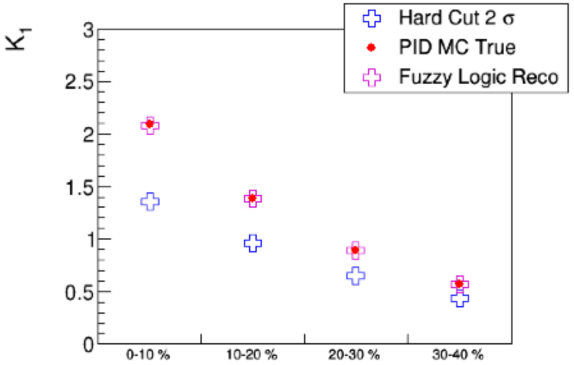


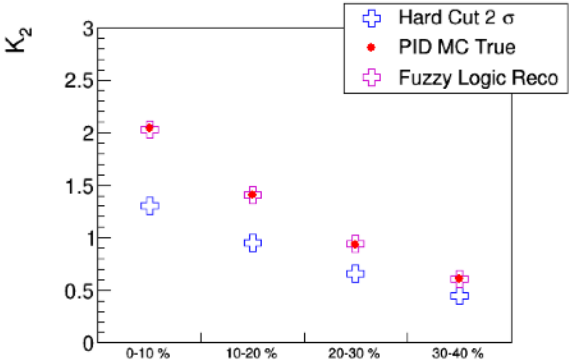
$-0.4 < y_{cm} < 0.4 \;\; 400 < p_t < 1600 \; MeV/c$



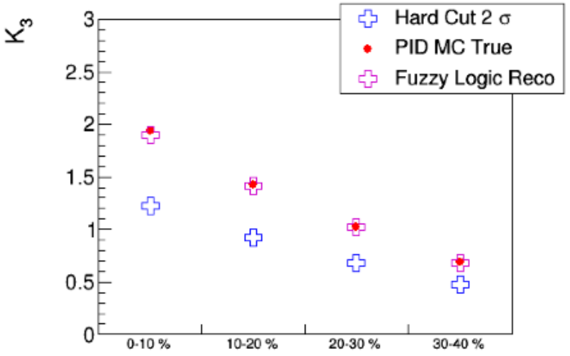


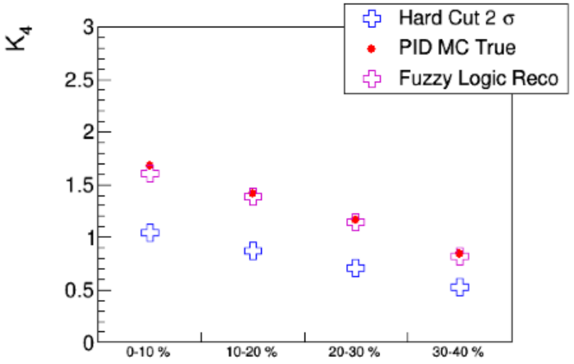
Deuterons





$-0.4 < y_{cm} < 0. \;\; 600 < p_t < 1800 \; MeV/c$



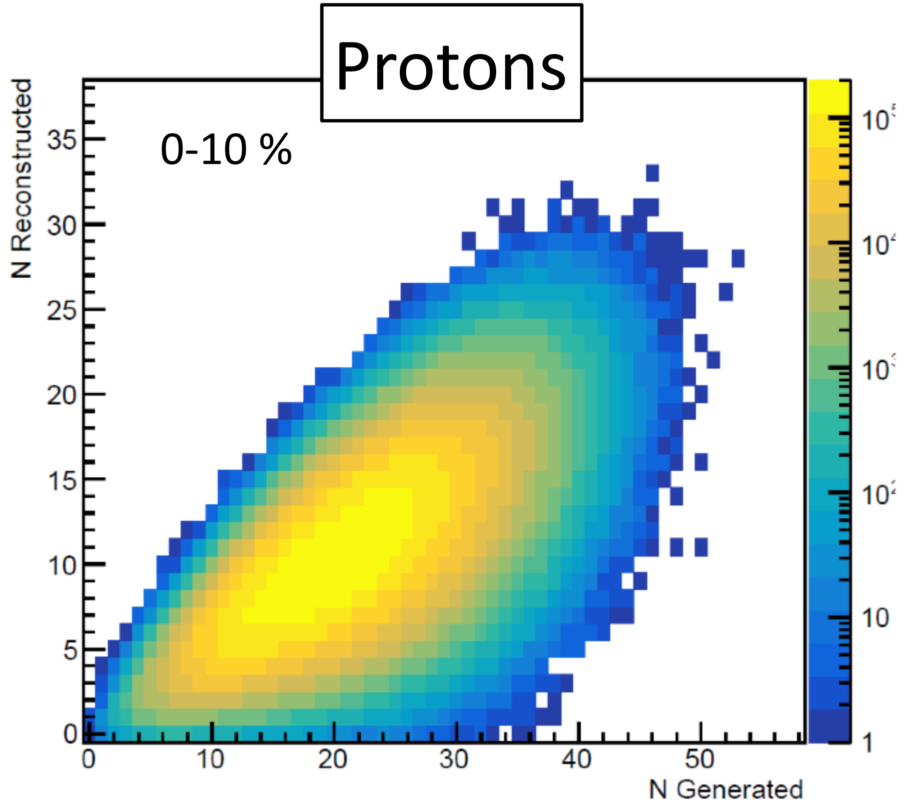


- Good agreement with MC truth, benefit from fuzzy logic compared to hard cuts especially visible for deuterons

Detection efficiency

Efficiency corrections - Response matrices

$N_{generated}$ vs $N_{reconstructed}$ (requires good response simulation / digitisers)



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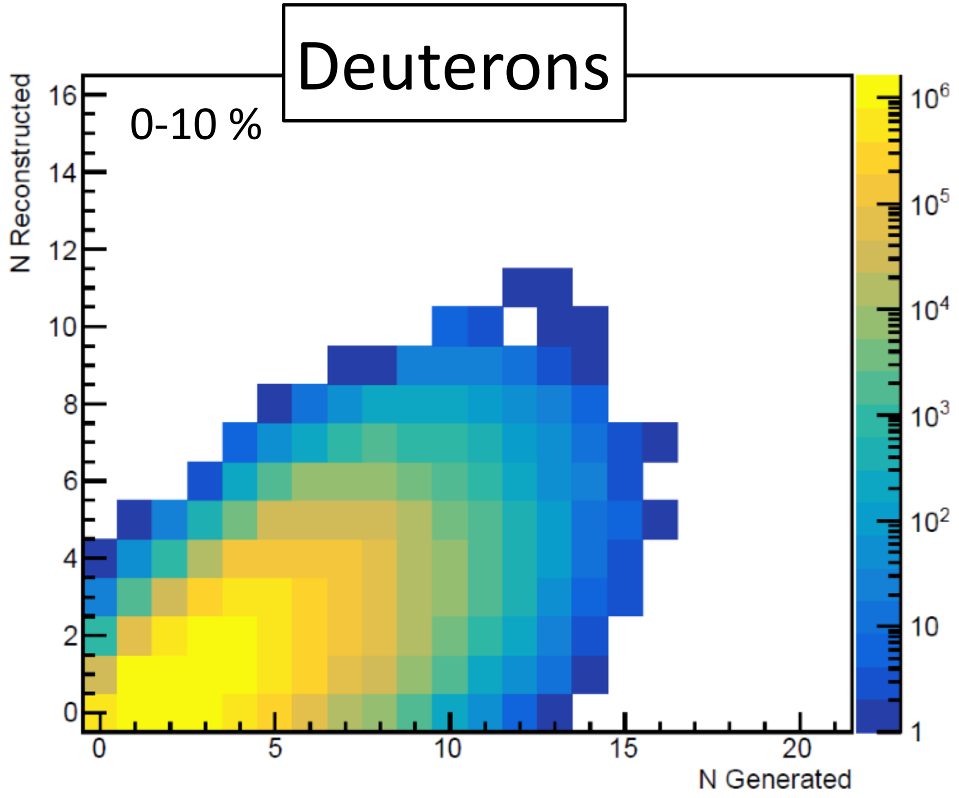


$-0.4 < y_{cm} < 0.,\ 600 < p_t < 1800\ MeV/c$

- 40-50 % average efficiency, non-binomial shape towards tails

Fuzzy-Logic + Efficiency correction

“PID” corrected moments
from Fuzzy Logic/
Identity Method

$\langle \vec{N} \rangle$

Moment Expansion

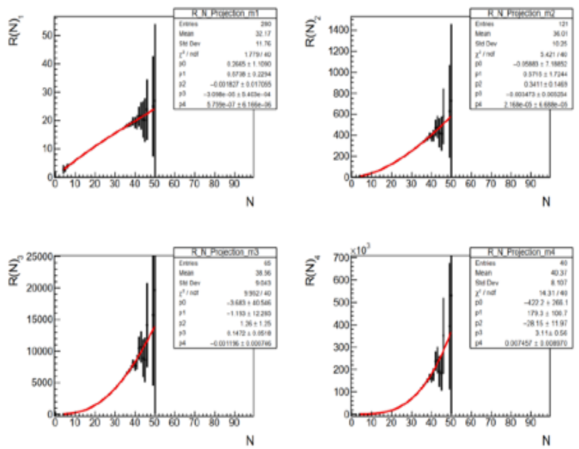
$$< n^m > \; = \sum_N P(N) \sum n^m R(n, N)$$

$$R(N)_m = \sum_N r_{mj} N^j$$

➢**Idea**: Establish from the response matrix a formal relation between corrected and uncorrected moments

➢ True moments are encoded in **column-wise moments** $R_{m(N)}$

➢ Perform **series expansion**



Requires for some bins 6 to 8 expansion terms → Also required from fuzzy logic as input!
(Poissoninan extrapolation possible for higher order)

T.Nonaka et. al.Nucl.Instrum.Meth.A 906 (2018) 10-17

Cornish Fisher Expansion + Distribution Unfolding

➢ Generate distribution having cumulants from fuzzy logic reconstruction

➢ Afterwards perform distribution unfolding → e.g. Bayesian Unfolding

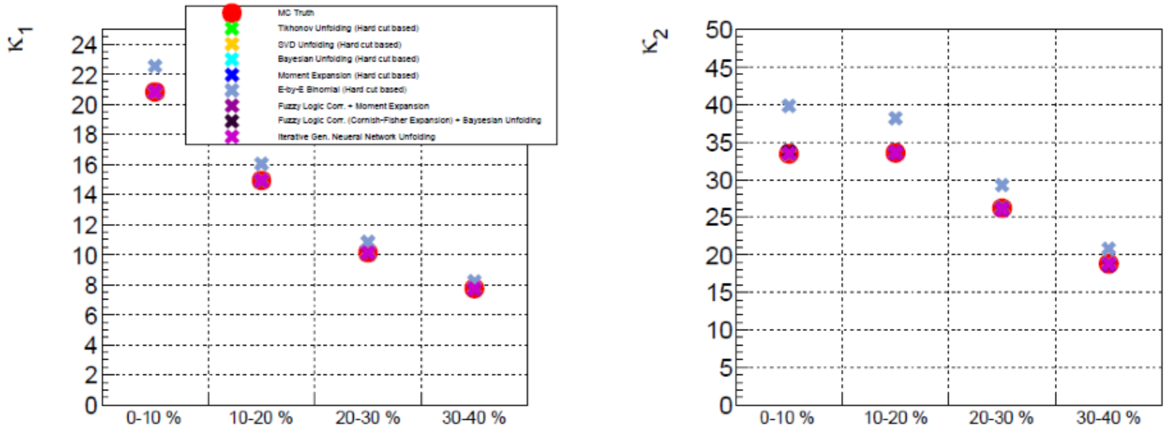
$y_p \approx \mu + \sigma w_p$ where:[3]

$$\begin{aligned} w_p = \quad & x + [\gamma_1 h_1(x)] \\ & + [\gamma_2 h_2(x) + \gamma_1^2 h_{11}(x)] \\ & + [\gamma_3 h_3(x) + \gamma_1 \gamma_2 h_{12}(x) + \gamma_1^3 h_{111}(x)] \\ & + \cdots \end{aligned}$$

Apply transformation on random number sampled from Gaussian

Moments and Cumulants in the Specification of Distributions
E. A. Cornish and R. A. Fisher Vol. 5, No. 4 (Jan., 1938), pp. 307-320

Efficiency corrections: Validation in simulation



Ag+Ag 1.58AGeV, Smash-Clust. + HADES Geant Sim.

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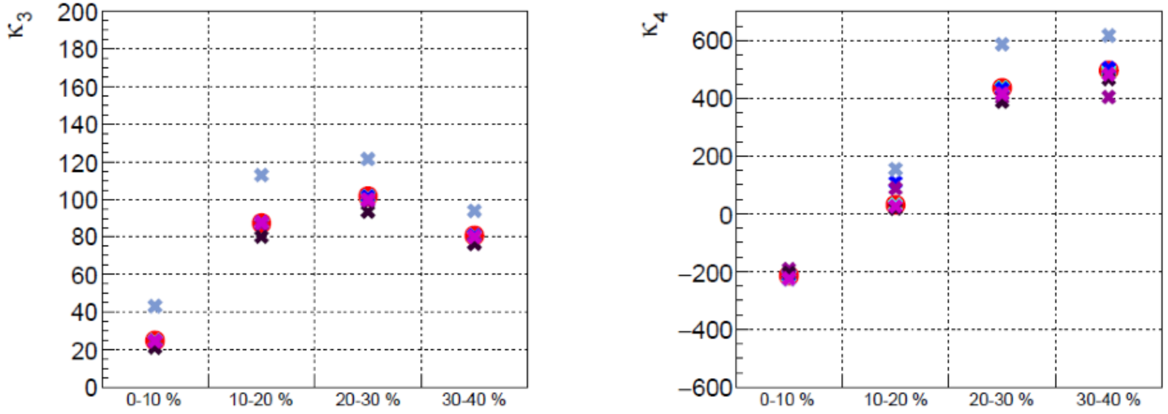


Method	MC Test	Applied on Data
MC Truth		
Tikhonov Unfolding (Hard cut based) [S. Schmitt, J. Instrum. 7, T10003 (2012)]	✓	—
SVD Unfolding (Hard cut based) [A. Höcker and V. Kartvelishvili, Nucl. Instrum. Methods Phys. Res. A 372, 469 (1996)]	✓	—
Bayesian Unfolding (Hard cut based) [G. D'Agostini, Nucl. Instrum. Methods Phys. Res. A A362, 487 (1995)]	✓	✓
Moment Expansion (Hard cut based) [*T.Nonaka et. al.Nucl.Instrum.Meth.A* 906 (2018) 10-17]	✓	✓
E-by-E Binomial (Hard cut based) [Toshihiro Nonaka, Masakiyo Kitazawa, and Shinichi Esumi Phys. Rev. C 95, 064912]	—	—
Fuzzy Logic Corr. + Moment Expansion	✓	✓
Fuzzy Logic Corr. (Cornish-Fisher Expansion) + Baysesian Unf.	✓	✓
Iterative Gen. Neueral Network Unfolding [M. Backes, A. Butter, M. Dunford and B. Malaescu, SciPost Phys.Core 7 (2024) 1, 007]	✓	(✓)

- Tikhonov and SVD Unfolding not applied on data due to instabilities for higher orders
- Moment exp. requires up to 6 orders for stability!
- ➡ Challenging situation
- Binomial (even E-by-E) correction do not perform well for all bins
- ➡ Rely on methods based on response matrix from simulation

Volume fluctuations

Volume Correction

- How to describe **contribution of volume fluctuations** in **observed particle cumulants**?
- Model with simplest assumption:
  - ➡ **Sources of particle production** are **statistical independent**
  - ➡ Moment generating function factorizes [*][**]

$$M_N(t) = [M_N(t)]^{N_{src}}$$

$$\langle N^m(N_{src})\rangle = \frac{d^m}{dt^m}[M_N(t)]$$

$$k_m(N) := Oberserved\ particle\ cumulants$$

$$k_m(n) := Single\ source\ particle\ cumualnts$$

$$k_m(N_{src}) := Cumulants\ of\ sources\backslash participants$$

$$k_1(N) = \langle N_{Src}\rangle\langle n\rangle$$

$$k_2(N) = \langle N_{Src}\rangle k_2(n) + \langle n\rangle^2 k_2(N_{src})$$

$$k_3(N) = \langle N_{Src}\rangle k_3(n) + 3\langle n\rangle k_2(n) k_2(N_{src}) + \langle \mathrm{n}\rangle^3 \mathrm{k}_3(\mathrm{N}_{\mathrm{src}})$$

$$k_4(N) = \langle N_{src}\rangle k_4(n) + 4\langle n\rangle k_3(n) k_2(N_{src}) + 3k_2^2(n) k_2(N_{src}) + 6\langle n\rangle^2 k_2(n) k_3(N_{src}) + \langle n\rangle^4 k_4(N_{src})$$

[*] V. Skokov, B. Friman, K. Redlich, Volume Fluctuations and Higher Order Cumulants of the Net Baryon Number, Phys. Rev. C 88 (2013) 034911. arXiv:1205.4756, doi:10.1103/PhysRevC.88.034911

[**] Bridging the gap between event-by-event fluctuation measurements and theory predictions in relativistic nuclear collisions
P. Braun-Munzinger (Darmstadt, EMMI and Heidelberg U.), A. Rustamov (Heidelberg U. and NNRC, Baku), J. Stachel (Heidelberg U.) Nucl.Phys.A 960 (2017), 114-130

Volume Correction – Data driven approach

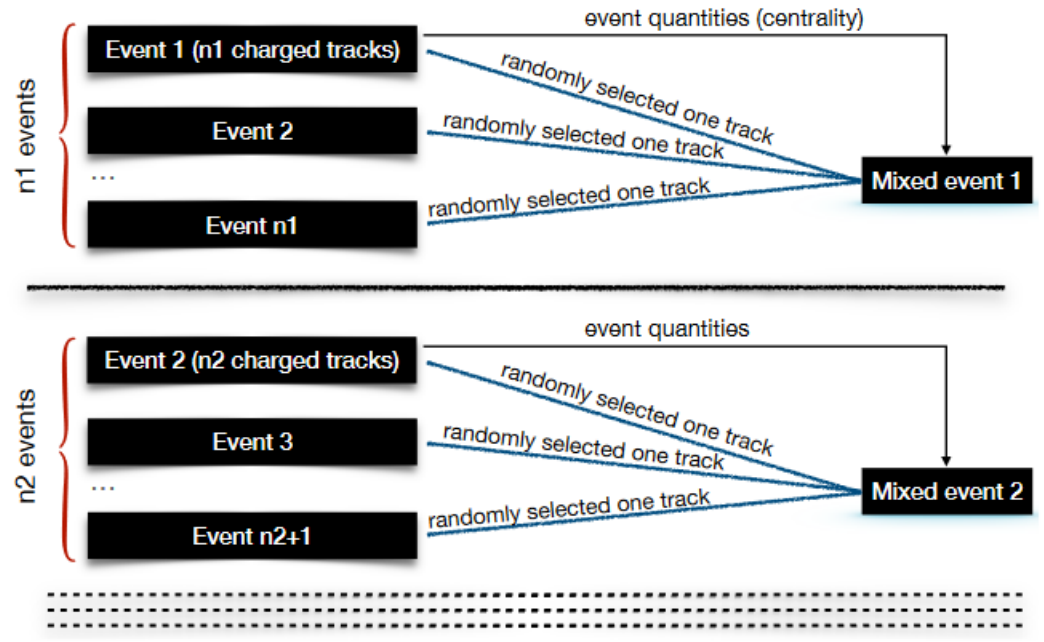


Figure 1: The strategy for event mixing used to remove correlations between particles while preserving participant fluctuations.

- ❑ Event mixing removes correlations between particles
- ➢ In case of **Poisson like behaviour** one expects for the emission per sources:

$$k_m(n) = < n > \quad , \quad cov\left(n_1, n_2\right) = 0$$

- ❑ Event mixing is equivalent to calculations based on charged tracks

$$\frac{\kappa_2[N_w]}{\langle N_w\rangle^2} = \frac{C_2[M] - \bar{C}_2[M]}{\langle M\rangle^2}$$

$$\frac{\kappa_3[N_w]}{\langle N_w\rangle^3} = -3\frac{\bar{C}_2[M]}{\langle M\rangle^2}\frac{\kappa_2[N_w]}{\langle N_w\rangle^2} + \frac{C_3[M] - \bar{C}_3[M]}{\langle M\rangle^3}$$

$$\frac{\kappa_4[N_w]}{\langle N_w\rangle^4} = -6\frac{\bar{C}_2[M]}{\langle M\rangle^2}\frac{\kappa_3[N_w]}{\langle N_w\rangle^3} - \frac{4\bar{C}_3[M]\langle M\rangle + 3\bar{C}_2[M]^2}{\langle M\rangle^4}\frac{\kappa_2[N_w]}{\langle N_w\rangle^2} + \frac{C_4[M] - \bar{C}_4[M]}{\langle M\rangle^4}$$

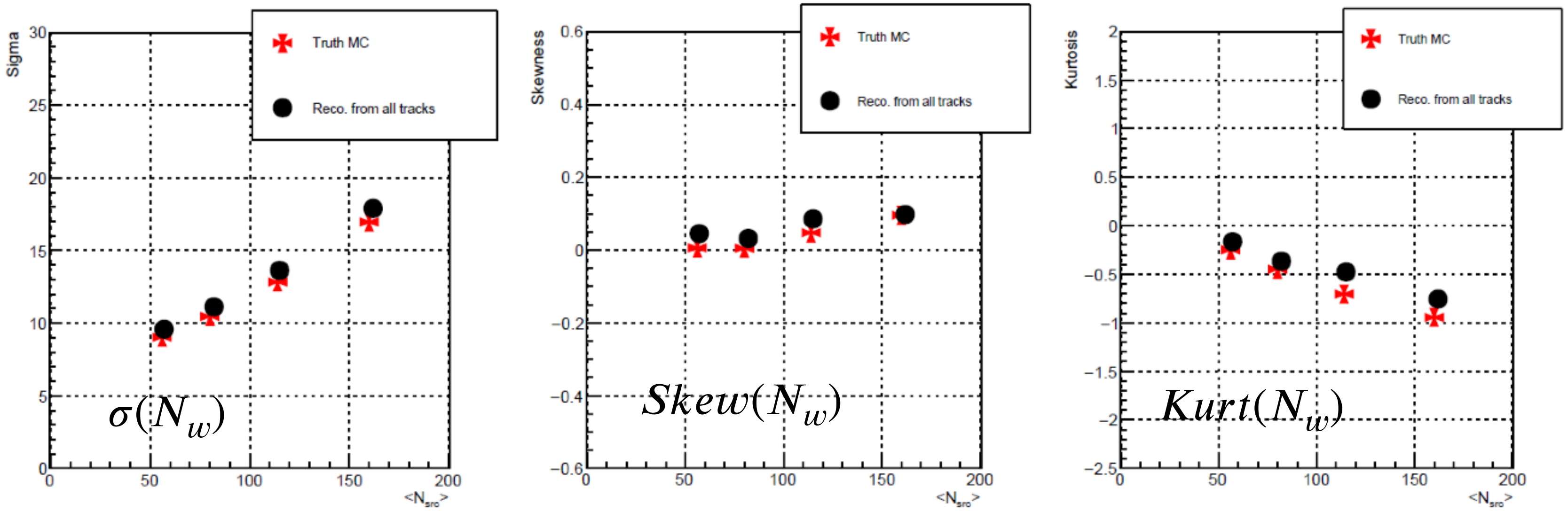
- ❑ Event mixing scheme preserves vol. fluctuations

A model-free procedure to correct for volume fluctuations in E-by-E analyses of particle multiplicities
Anar Rustamov, Joachim Stroth, Romain Holzmann
Nucl.Phys.A 1034 (2023), 122641

Controlling volume fluctuations for studies of critical phenomena in nuclear collisions
Romain Holzmann, Volker Koch, Anar Rustamov, Joachim Stroth
e-Print: 2403.03598 [nucl-th]

Volume Correction – Data driven approach

- ❑ Reconstruction of volume cumulants using mixed particles \ charged tracks in Glauber toy model:



But, is nature at low energies really like Glauber?

- ❑ Interaction of particles with spectators
- ❑ At low energies most of the protons are not produced, but rescattered → protons are significant part of the volume!
- ❑ In transport models, for Apart, assumption of independent emission violated for protons!

- ❑ In HADES: Negative Binomial toy model method exhibits good agreement with MC Truth volume → Negative Binomial close to Poisson

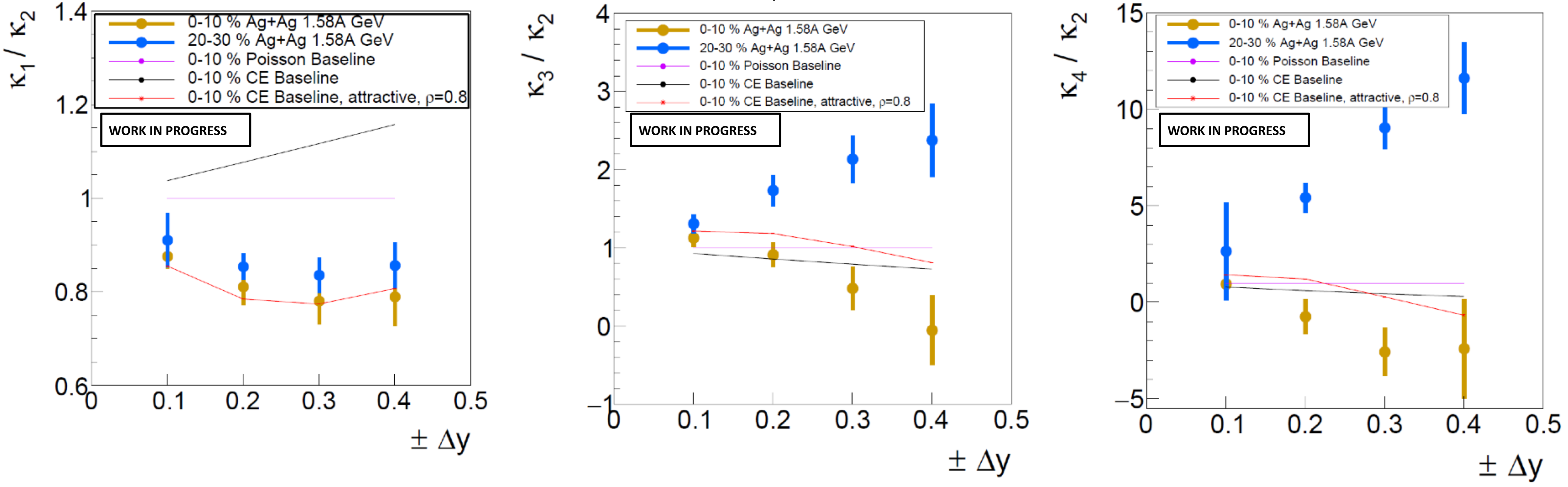
- ❑ **For real data only use mixed-protons due to better understanding of eff. corrections for protons**

Event mixing still so far the best method available, as fully data driven, only independent source assumption!

Proton results for Ag+Ag

Eff. + Volume corrected – proton cumulant ratios

$Ag + Ag\ \sqrt{s_{NN}} = 2.55\ GeV$ $400 < p_t < 1600\ MeV/c$



- ❑ In general convergence towards poisson limit (1) observed
- ❑ κ_3 now mainly positive as opposed to old HADES Au+Au data
- ❑ For higher order, different trend between central and semi-central events → Influence of spectators?

- ❑ CE baseline considering acceptance window only can not describe data, different trend for κ_1/κ_2
- ❑ Trend of rapidity dependence can be described by Canonical baseline considering correlations with an attractive potential (P. Braun-Munzinger, K. Redlich, A. Rustamov, J. Stachel, JHEP 08 (2024) 113)

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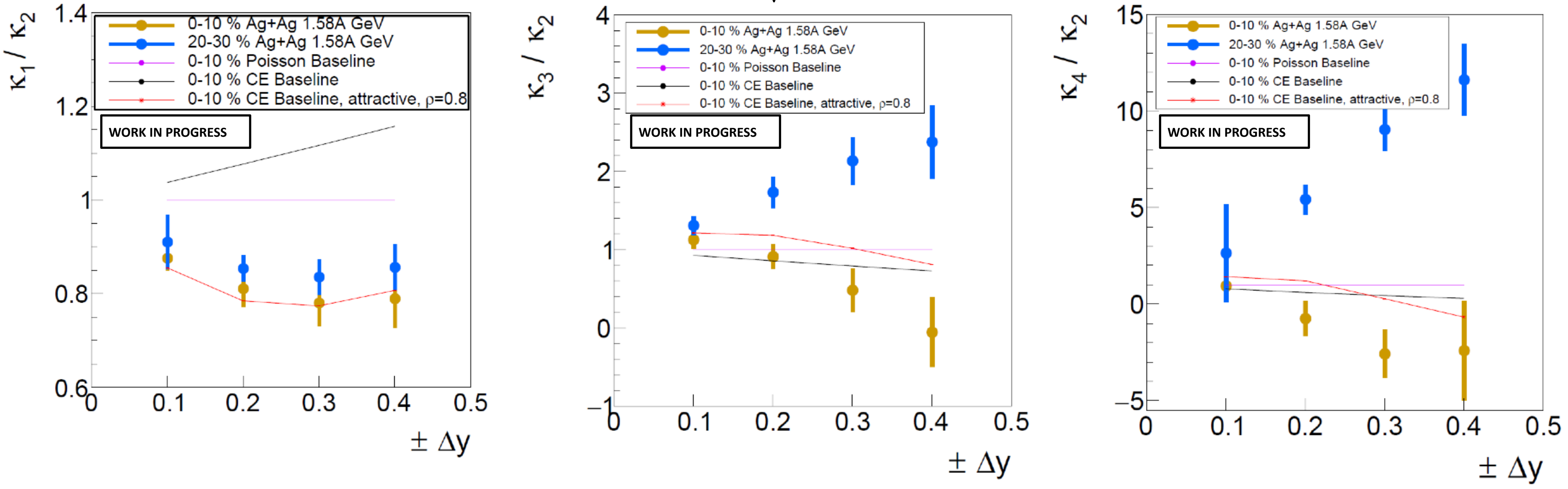

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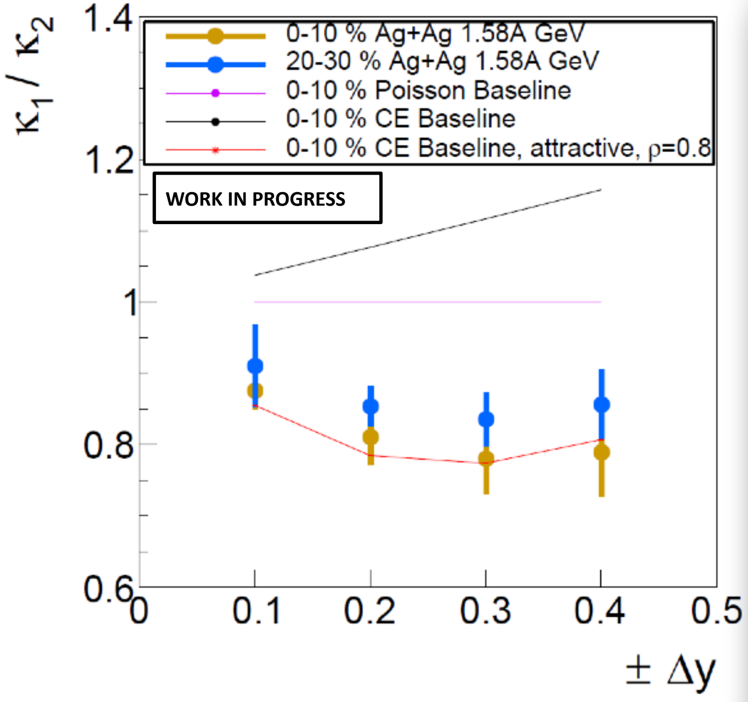
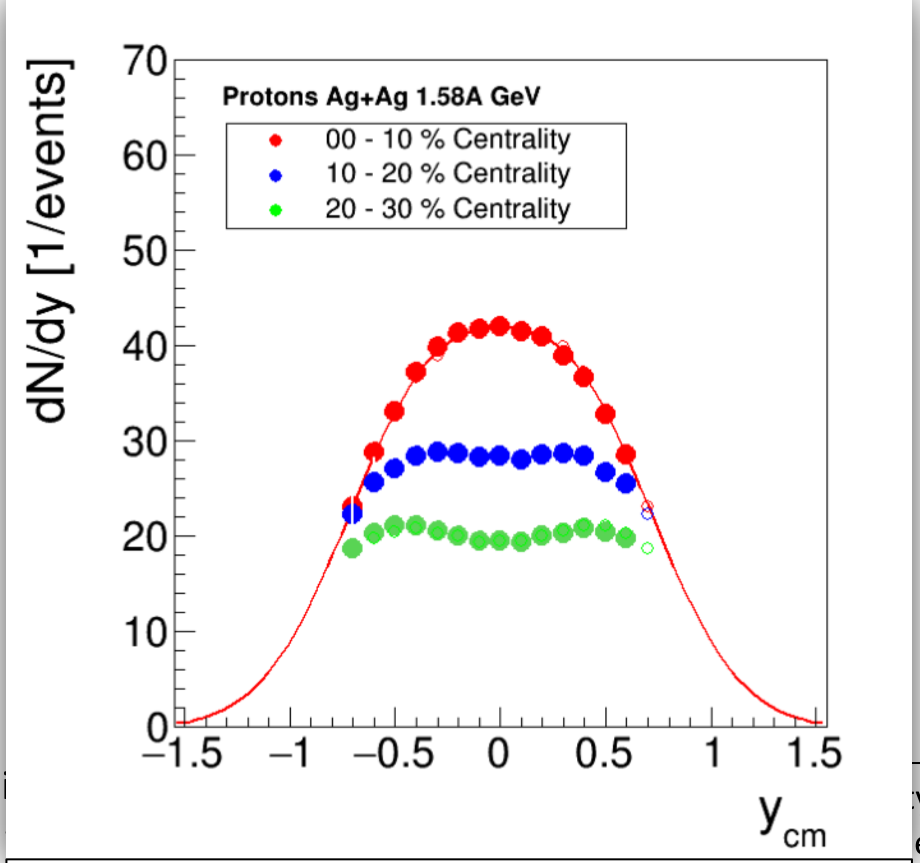
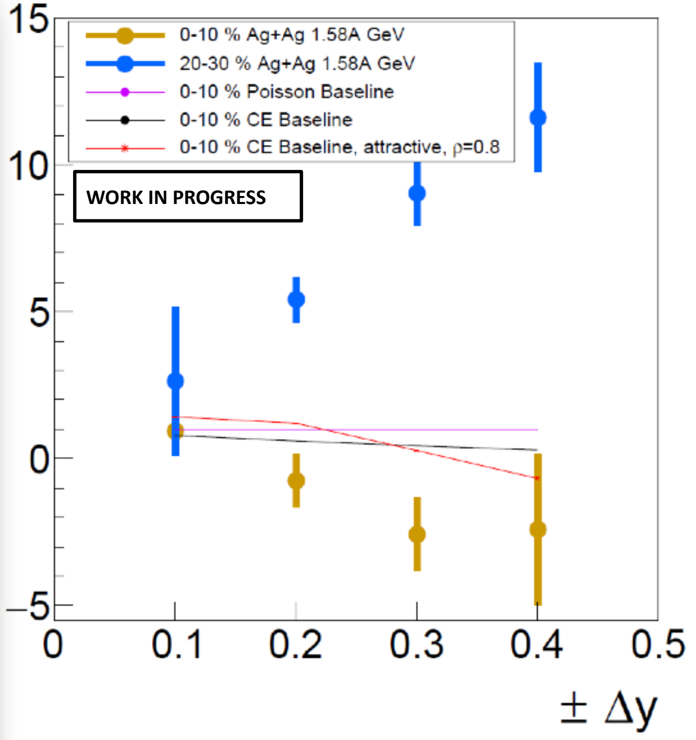
- ❑ κ_1/κ_2 matched by CE model within uncertainties

Eff. + Volume corrected – proton cumulant ratios

$Ag + Ag \sqrt{s_{NN}} = 2.55\ GeV$ $400 < p_t < 1600\ MeV/c$







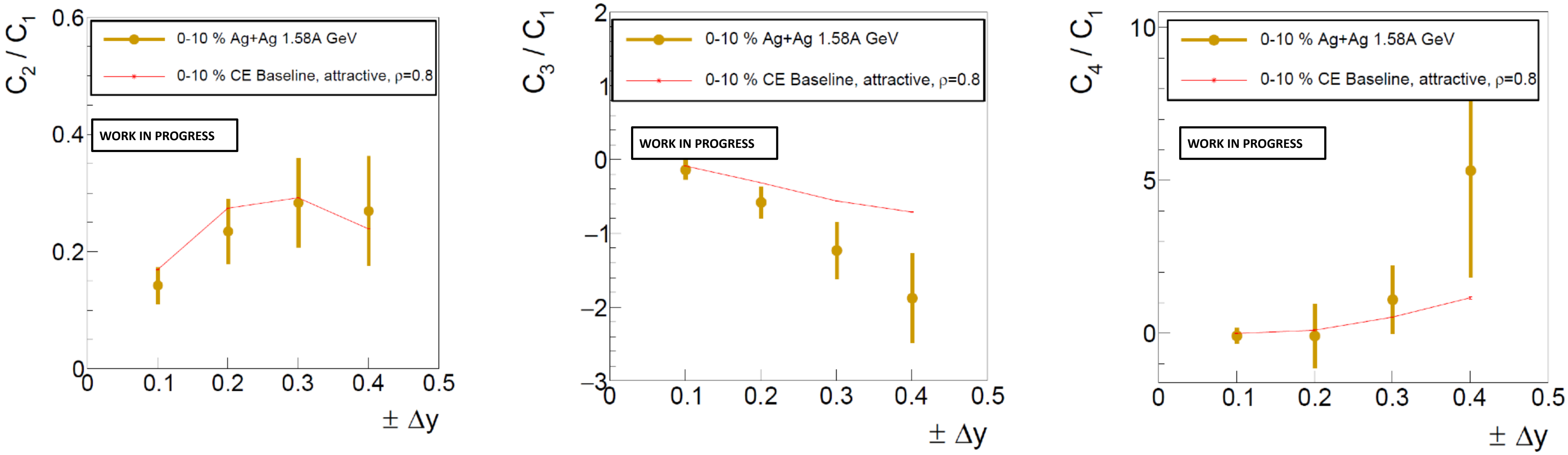
- ❑ In general convergence towards poi
- ❑ κ_3 now mainly positive as opposed
- ❑ For higher order, different trend be events → Influence of spectators

- ❑ Different pattern also apparent in rapidity spectra for semi-central events

y dependence can be described by Canonical
ering correlations with an attractive potential
K. Redlich, A. Rustamov, J. Stachel, JHEP 08 (2024) 113)
by CE model within uncertainties

Eff. + Volume corrected – proton factorial cumulant ratios

”Measure for multi-particle-correlations”



$$C_2 = \kappa_2 - \kappa_1$$
$$C_3 = \kappa_3 - 3\kappa_2 + 2\kappa_1$$
$$C_4 = \kappa_4 - 6\kappa_3 + 11\kappa_2 - 6\kappa_1$$

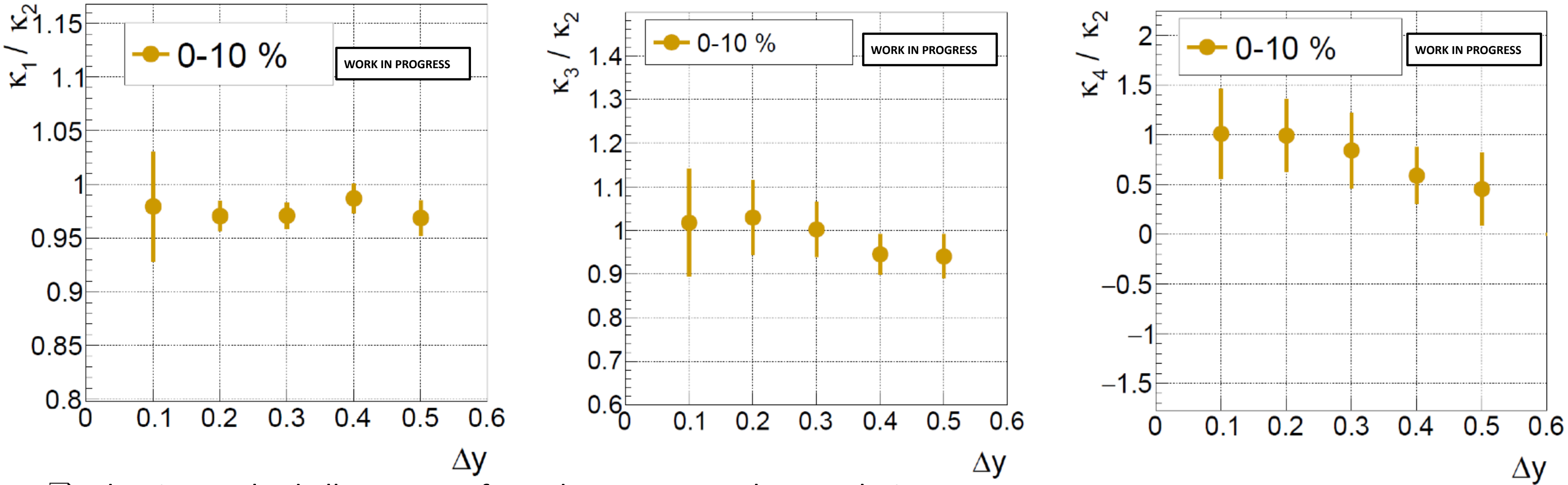
- ❑ Also trend of factorial cumulant ratios as a function of rapidity can be described by Canonical baseline considering correlations with an attractive potential
  [P. Braun-Munzinger, K. Redlich, A. Rustamov, J. Stachel, JHEP 08 (2024) 113]
- ❑ Measurement matched by CE model within uncertainties

Deuteron results for Ag+Ag

Eff. + Volume corrected – deuteron cumulant ratios

$Ag + Ag \sqrt{s_{NN}} = 2.55\ GeV$

$600 < p_t < 1800 \frac{MeV}{c}$



- ❑ Identity method allows to perform deuteron cumulant analysis
- ❑ Ratios are closer to poisson limit compared to protons
  - → smaller phase space coverage ($-0.4 < y_{cm} < 0.1$)
- ❑ Need to establish proper CE baseline

$\Delta y = 0.1: \quad -0.1 < y_{cm} < 0.0$

...

$\Delta y = 0.4: \quad -0.4 < y_{cm} < 0.0$

$\Delta y = 0.5: \quad -0.4 < y_{cm} < 0.1$

Eff. + Volume corrected – deuteron cumulant ratios

$C_2 = \kappa_2 - \kappa_1,$
$C_3 = \kappa_3 - 3\kappa_2 + 2\kappa_1,$
$C_4 = \kappa_4 - 6\kappa_3 + 11\kappa_2 - 6\kappa_1$

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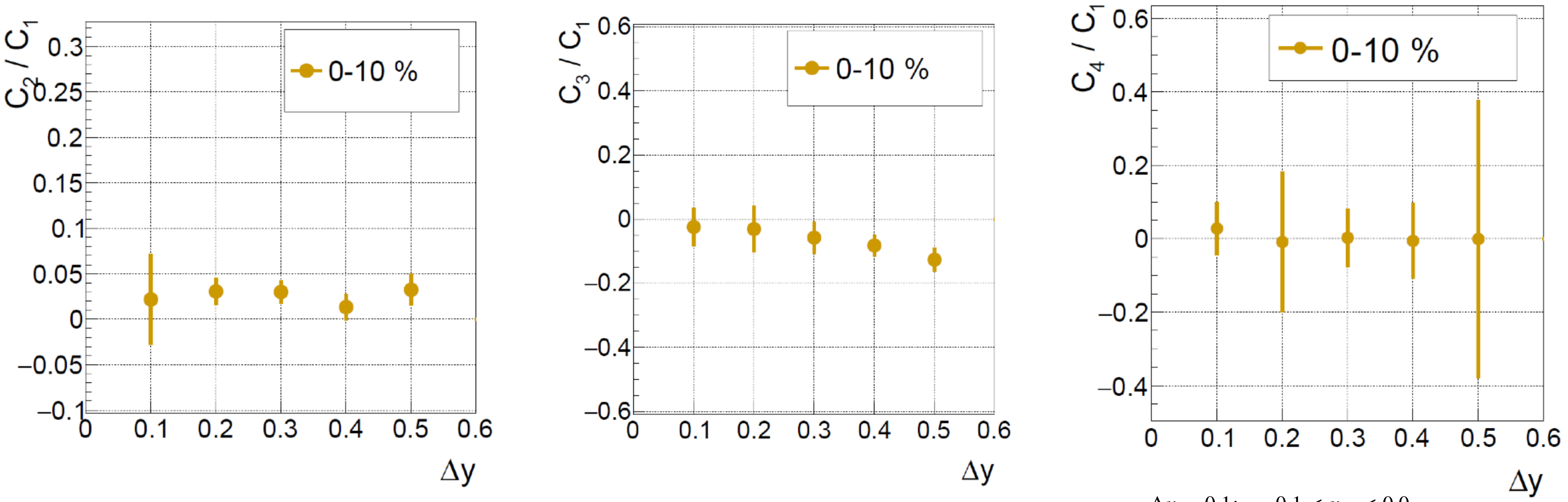

$\Delta y = 0.1: \quad -0.1 < y_{cm} < 0.0$
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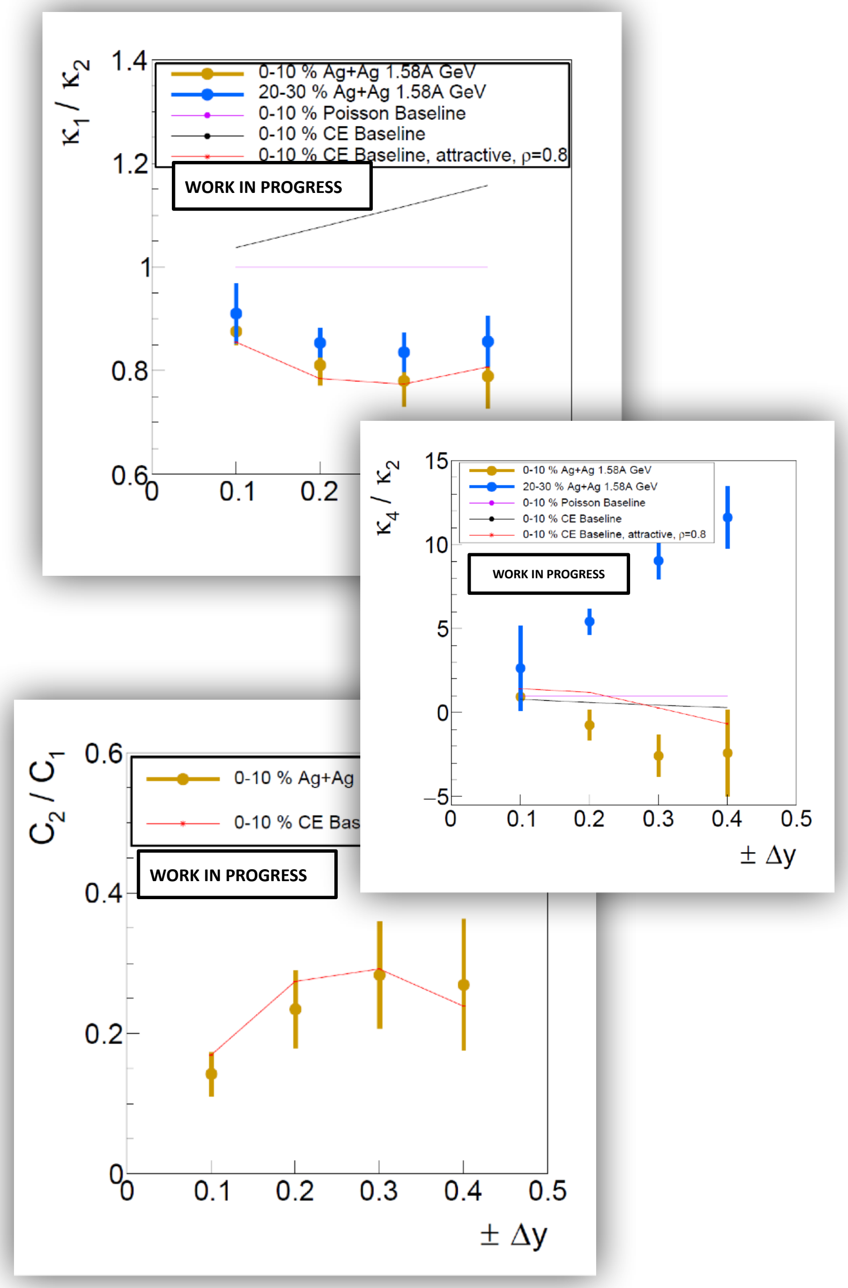
$\Delta y = 0.5: \quad -0.4 < y_{cm} < 0.1$

- ❑ Identity method allows to perform deuteron cumulant analysis
- ❑ Need to establish proper CE baseline

Summary and Outlook

- New refined efficiency corrections in HADES
- Fuzzy logic/Identity method for higher-orders to correct for particle mis-identification
- Full efficiency correction based on unfolding and moment expansion techniques
- Volume correction using mixed events
- **Presented eff. and vol. corrected cumulants and factorial cumulants of protons and deuterons for** $Ag+Ag\ \sqrt{s_{NN}} = 2.55\ GeV$
- **Trend of rapidity dependence of (factorial) cumulant ratios can be described by Canonical baseline considering correlations with an attractive potential**
- **Outlook**
  - (Re)analysis of other HADES data ongoing
    (Au+Au 1.23A GeV, Ag+Ag 1.58A GeV, Au+Au 0.8A GeV)
  - p-d joint-cumulant analysis ongoing
  - Extend cumulants analysis to t and He3, establish baseline
  - Further investigate and refine volume correction method



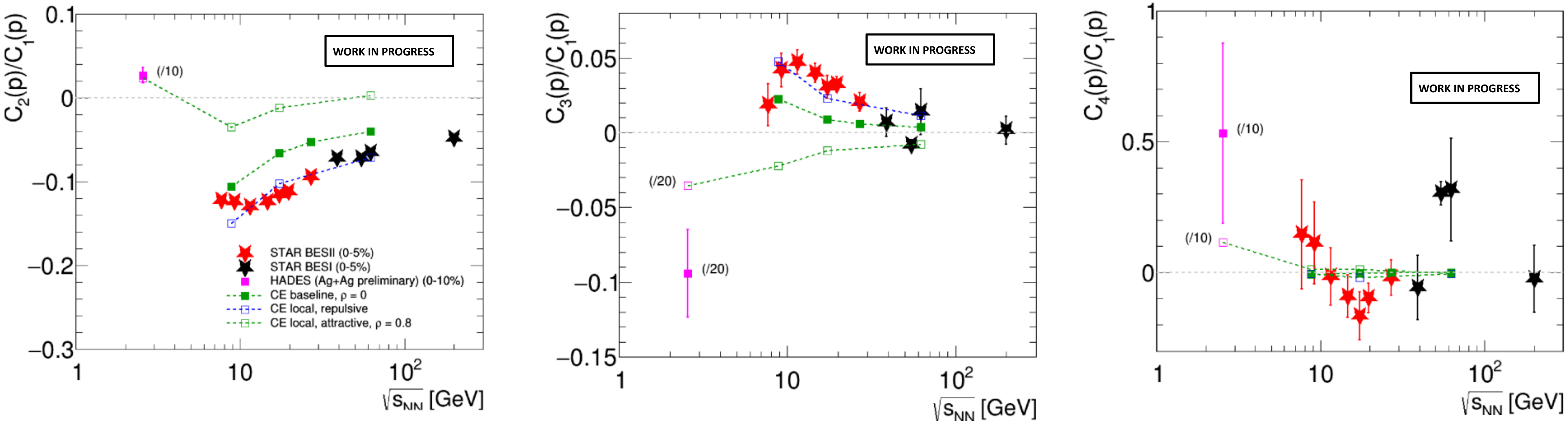
Thank you for your attention!

THE HADES COLLABORATION

Back-Up

Proton Factorial Cumulants - Comparison with STAR

HADES data point for $-0.4 < y_{cm} < 0.4,\ 400 < p_t < 1600\ MeV/c$



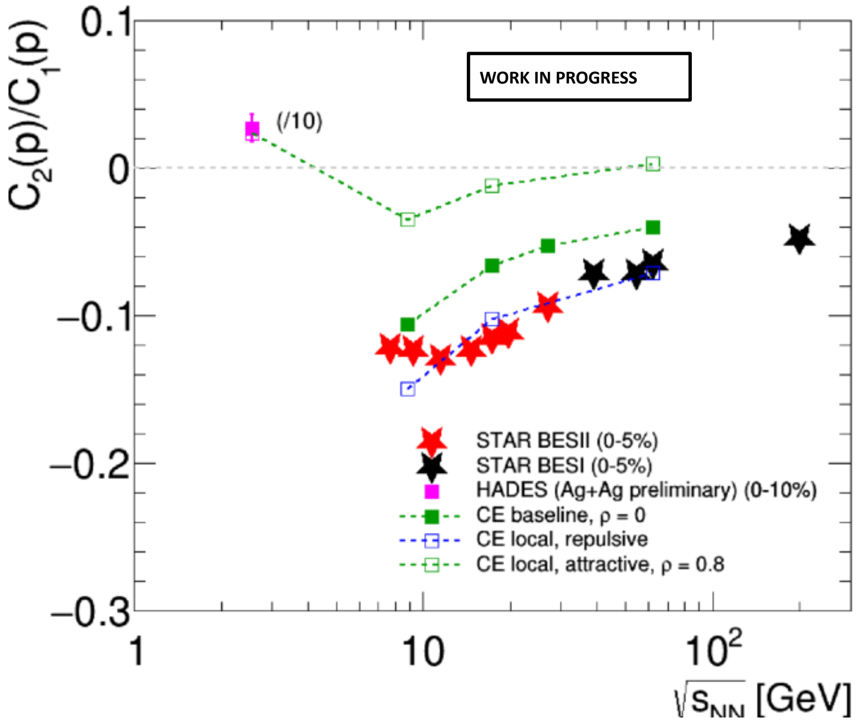
- In general, larger absolute factorial cumulant ratios at HADES energies compared to STAR points at higher energies
- For C_3/C_1 and C_4/C_1, HADES points roughly continue trend observed at START towards lower energies

- Trend of **HADES** point described by correlated CE model with **attractive potential** [P. Braun-Munzinger, K. Redlich, A. Rustamov, J. Stachel, JHEP 08 (2024) 113]
- **STAR** points described by **repulsive potential** [B. Friman, A. Rustamov, K. Redlich (in progress)]

→ Interplay between repulsive and attractive forces

Proton Factorial Cumulants - Comparison with STAR at lower energies

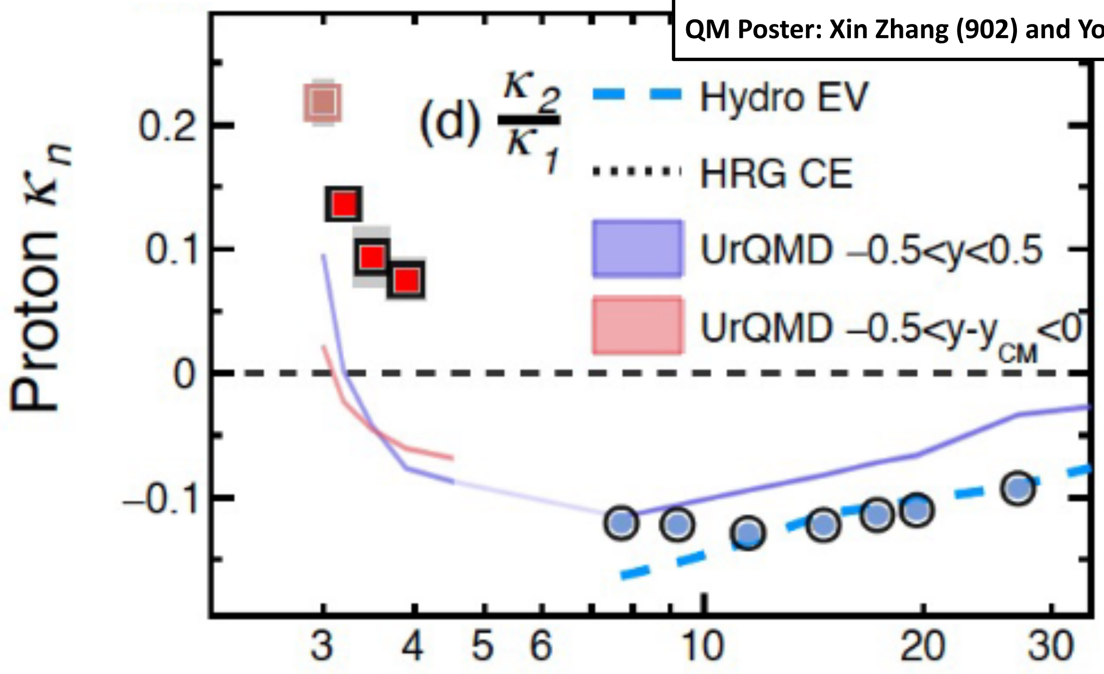
HADES



STAR

QM Talk: Zachary Sweger, Mi 11:10

QM Poster: Xin Zhang (902) and Yongcong Xu (821)

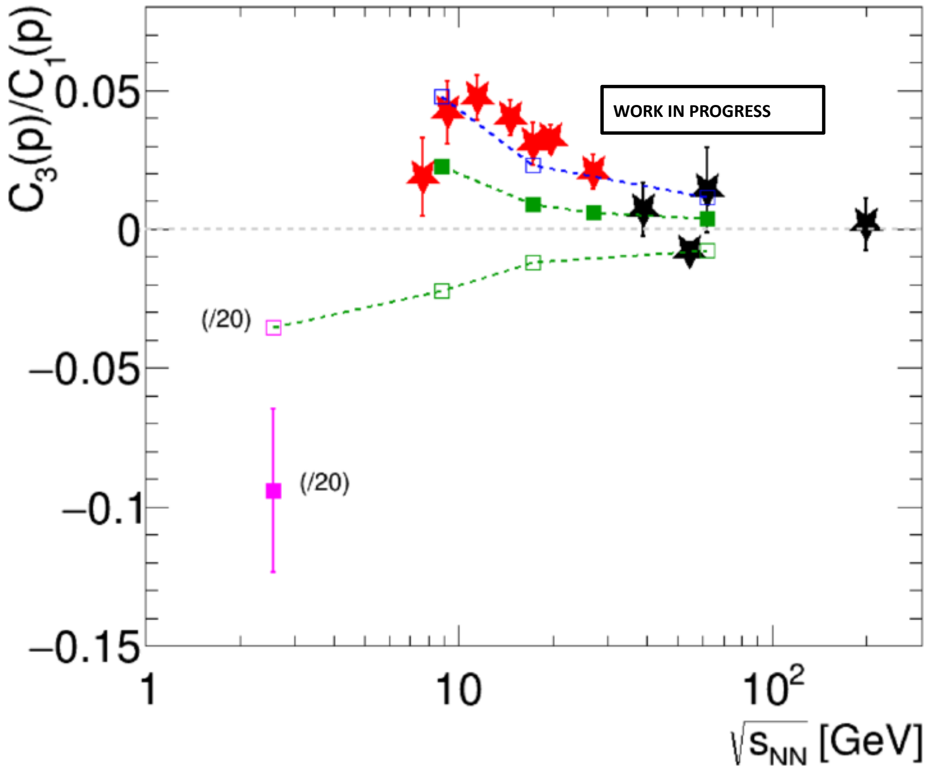


$$\frac{C_2}{C_1}$$

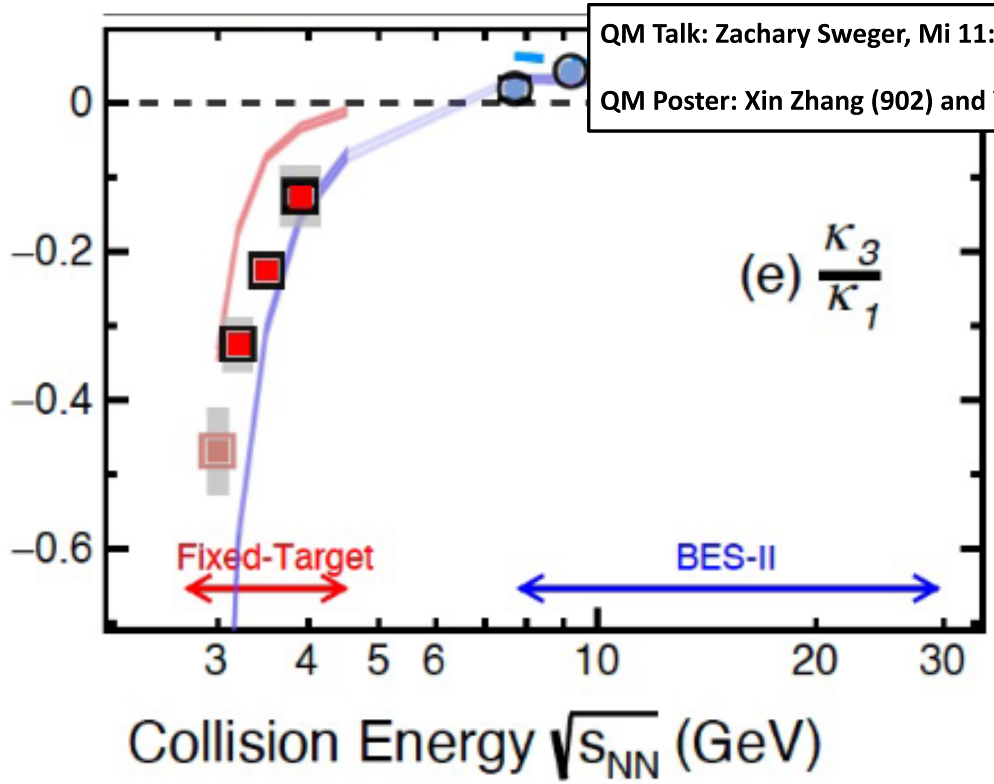
- ❑ Also STAR measured positive C2/C1 for their lower energy points, values are similar to HADES
- → Towards lower energies transition to clustering

Proton Factorial Cumulants
- Comparison with STAR at lower energies

HADES



STAR



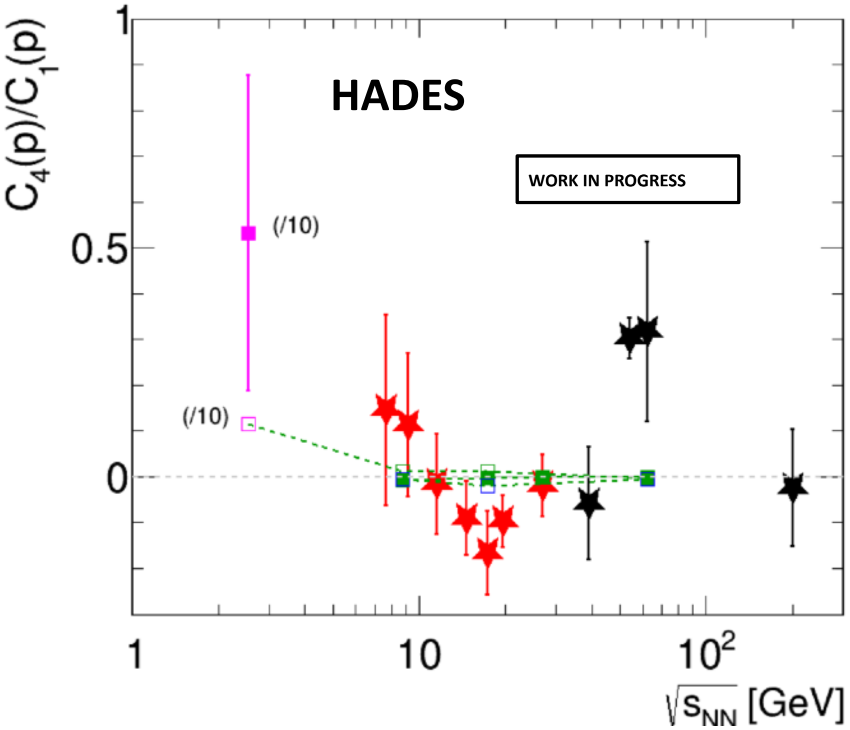
QM Talk: Zachary Sweger, Mi 11:10

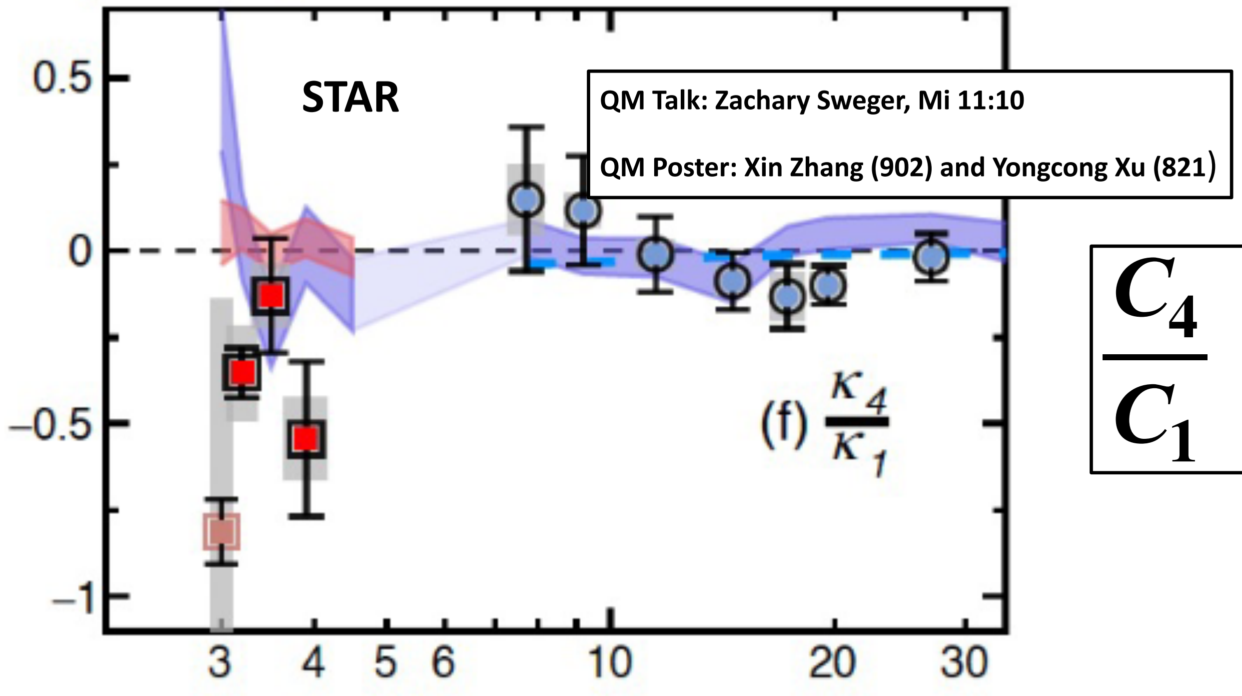
QM Poster: Xin Zhang (902) and Yongcong Xu (821)

$$\frac{C_3}{C_1}$$

- ❑ Negative C3/C2 for lower energy points also observed by STAR → In trend of HADES, but smaller absolute values in STAR

Proton Factorial Cumulants
- Comparison with STAR at lower energies





$$\frac{C_4}{C_1}$$

- ❑Different sign for C4/C2

Potential reasons for deviations

- ❑Different collisions systems are compared, Ag+Ag (HADES) vs. Au+Au (STAR)
- ❑Not the same analysis ranges in pt and y
- ❑Remnants of volume fluctuations? Different methods: Event mixing vs. CBWC
- ❑ ..

Machine Learning based unfolding - Basics

$t_{MC}(x) = Prior\ from\ MC\ Simualtion$

$t_{Experiment}(x) = Prior\ from\ Experiment$

$$d(y) = \int p(y|x)t(x)\,dx$$

Bayse' Theorem

$$p(x|y) = \frac{p(y|x)t(x)}{d(y)}$$

$r(y, x)$ = p(y|x)

$p(y|x)$ from HADES detector simulation

- ➢ Dependence on Prior!
- ➢ Eliminate bias from MC prior by an iterative approach

- ➢ **1. Start with prior from MC or any arbitrary prior**
- ➢ **2. Apply detector response, compare with experimental measurement**
- ➢ **3. Reweight distribution**

Iterative Bayesian Unfolding

Disadvantages

- ➢ Only works with binned data
- ➢ Requires sufficient statistics
- ➢ Unfolding of only one observable possible

➢ **In recent years and month there has been development of brand new ML based unfolding techniques**

The Landscape of Unfolding with Machine Learning

Nathan Huetsch[1], Javier Mariño Villadamigo[1], Alexander Shmakov[2], Sascha Diefenbacher[3], Vinicius Mikuni[3], Theo Heimel[1], Michael Fenton[2], Kevin Greif[2], Benjamin Nachman[3,4], Daniel Whiteson[2], Anja Butter[1,5], and Tilman Plehn[1,6]

arXiv:2404.18807v2 [hep-ph] 17 May 2024

Reweighting - Omnifold

OmniFold: A Method to Simultaneously Unfold All Observables

Anders Andreassen, Patrick T. Komiske, Eric M. Metodiev, Benjamin Nachman, and Jesse Thaler

arXiv:1911.09107v2 [hep-ph] 16 Apr 2020

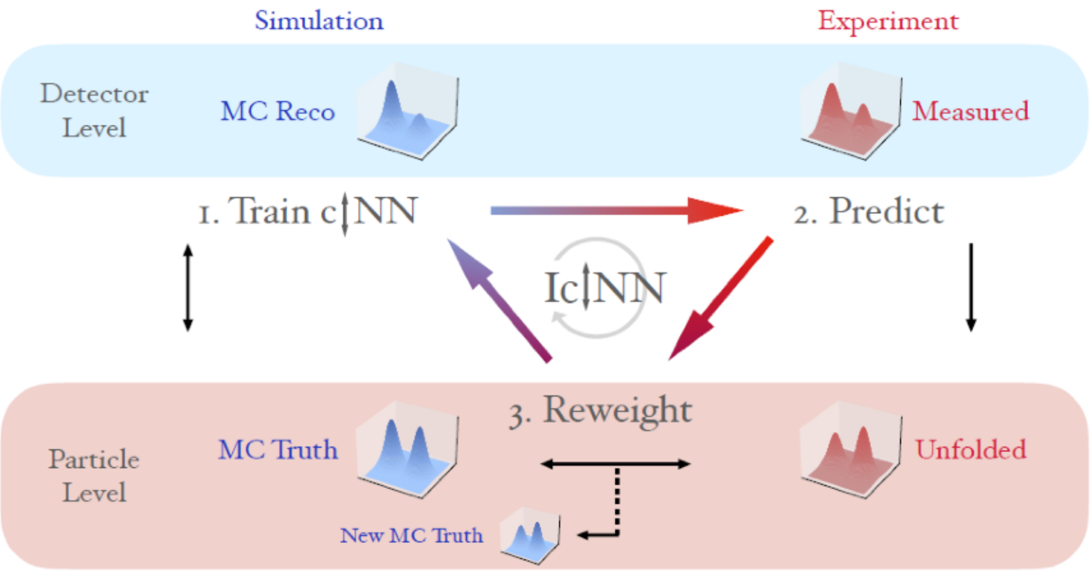
Generative Unfolding

An unfolding method based on conditional Invertible Neural Networks (cINN) using iterative training

Mathias Backes[1], Anja Butter, Monica Dunford, and Bogdan Malaescu

arXiv:2212.08674v3 [hep-ph] 10 Jan 2024

Iterative neural network unfolding

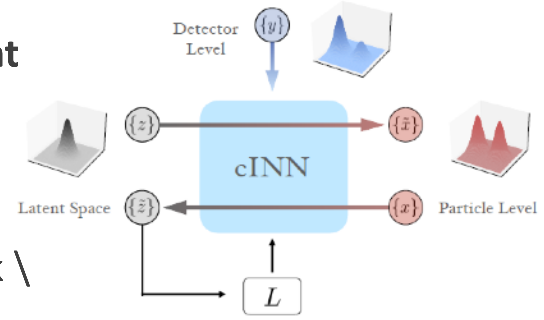


An unfolding method based on conditional Invertible Neural Networks (cINN) using iterative training
Mathias Backes[1], Anja Butter[2,3], Monica Dunford[1], and Bogdan Malaescu[2]
arXiv:2212.08674v3 [hep-ph] 10 Jan 2024

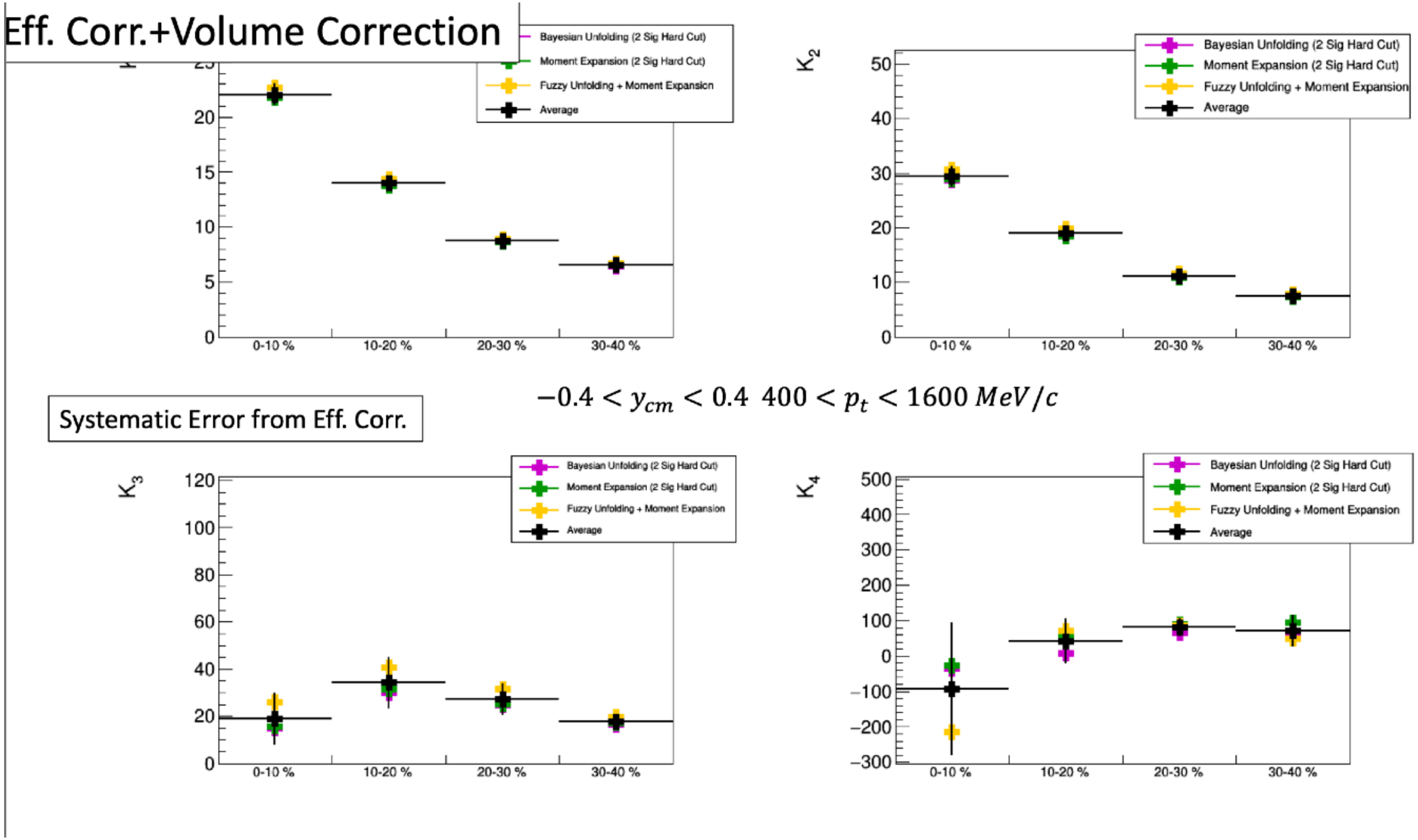
- Train **generative neural network** → Learn $p(N_{Unfolded} | N_{reco})$
- After training predict for given measurement physics level distribution
- Train classifier to predict difference between predicted and initial MC truth
  - Reweight MC truth for next iteration

Generative neural network

- Generate from random noise **(latent space)** + **condition (detector measurement**) data samples for the **truth\physics level**
- Implemented as Invertible Network \ **Normalizing flow network**



Systematics



$$-0.4 < y_{cm} < 0.4 \;\; 400 < p_t < 1600 \; MeV/c$$