Cumulants of the multiplicity distributions of identified particles measured in heavy-ion collisions by HADES

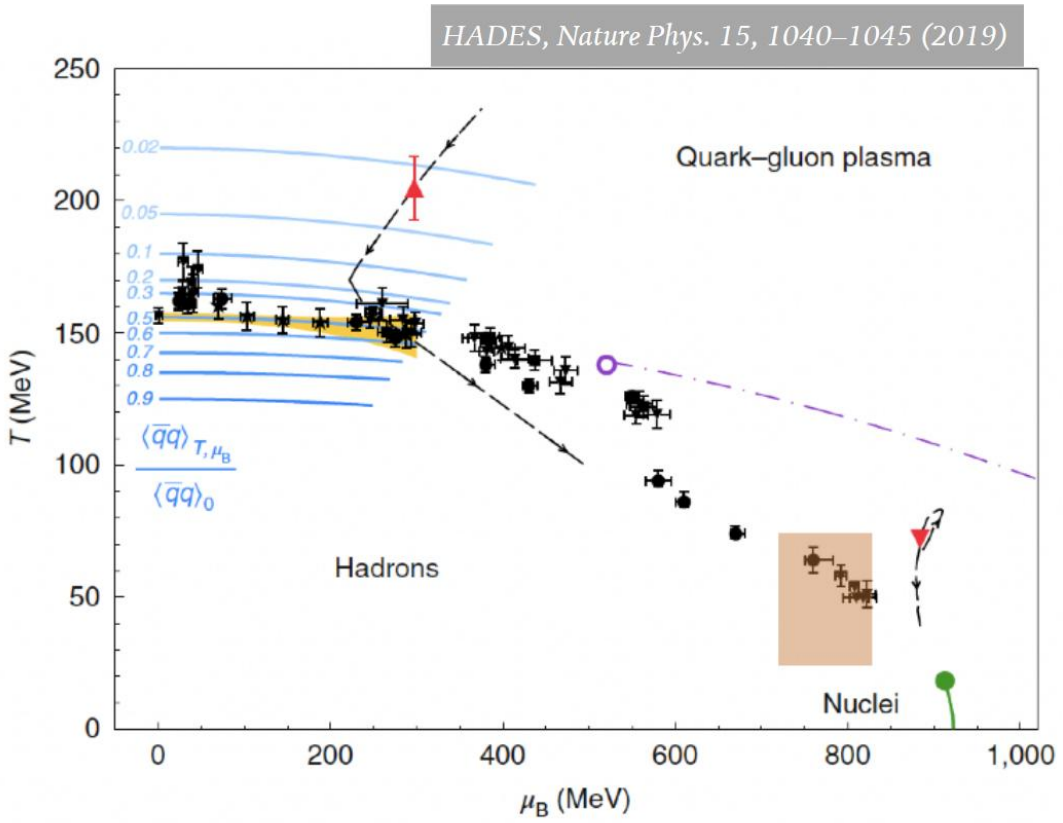
MARVIN NABROTH FOR THE HADES COLLABORATION

OUTLINE

- MOTIVATION
- ANALYSIS PROCEDURE
- RESULTS
- SUMMARY AND OUTLOOK

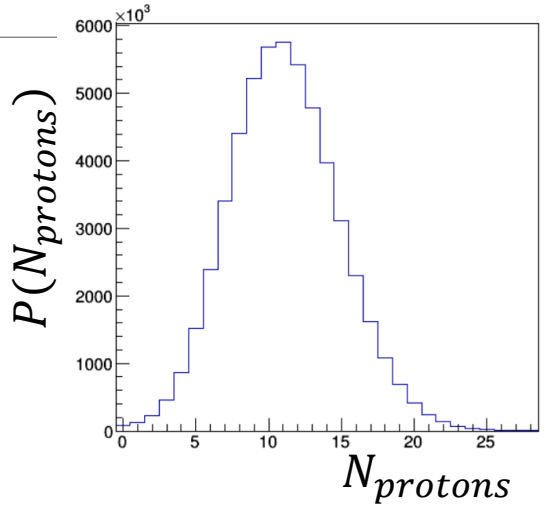
Motivation – QCD at high μ_B

- Expected first order phase transition ending in a conjectured critical end point towards lower μ_b
- High μ_b-region is not accessible by Lattice QCD calculations (sign-problem)
  - Effective approaches, functional methods
- **Experimental Access: Heavy-Ion collisions at energies of a few GeV**
  → 40 % of protons are bound
- **Experimental observables:**
  - Particle yields, Emisson spectra, Anisotropic flow, Femtoscopy and **E-by-E fluctuations of baryon number → Decipher properties of phase transition**



Event-by-Event Fluctuations

- Basic idea: **Count number of baryon** emitted per event, extract moments or other distribution measures
- Study QCD phase structure of freeze-out in detail by looking at **higher order moments of particle yields → related to derivates of partition Function Z w.r.t** μ_B



$$\langle N \rangle = \frac{\partial \ln(Z)}{\partial\left(\frac{\mu}{T}\right)} \qquad \langle N^2 \rangle - \langle N \rangle^2 = \frac{\partial^2 \ln(Z)}{\partial\left(\frac{\mu}{T}\right)^2} \ \ldots$$

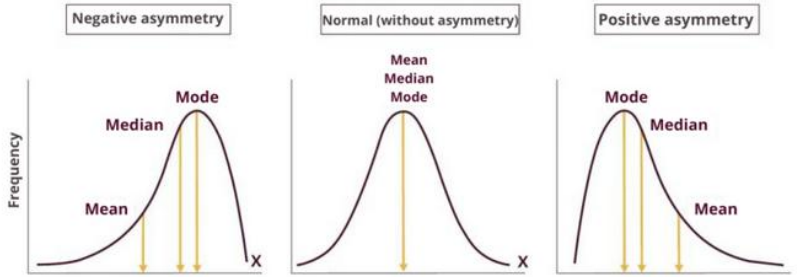
Cumulants

- $\kappa_1 = \langle N \rangle$
- $\kappa_2 = \langle N^2 \rangle - \langle N \rangle^2$
- $\kappa_3 = \langle N^3 \rangle - 3\langle N^2 \rangle \langle N \rangle + 2\langle N \rangle^3$
- $\kappa_4 = \langle N^4 \rangle - 4\langle N^3 \rangle \langle N \rangle - 3\langle N^2 \rangle^2 + 12\langle N^2 \rangle \langle N \rangle^2 - 6\langle N \rangle^4$

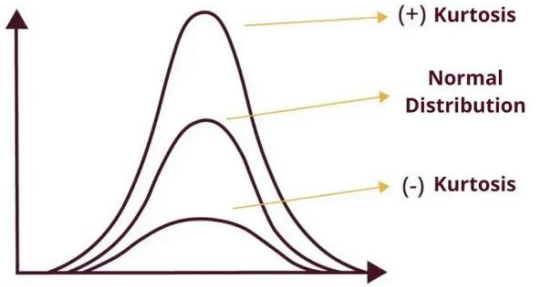
Factorial Cumulants

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

Skewness $= \frac{\kappa_3}{\sigma^3}$

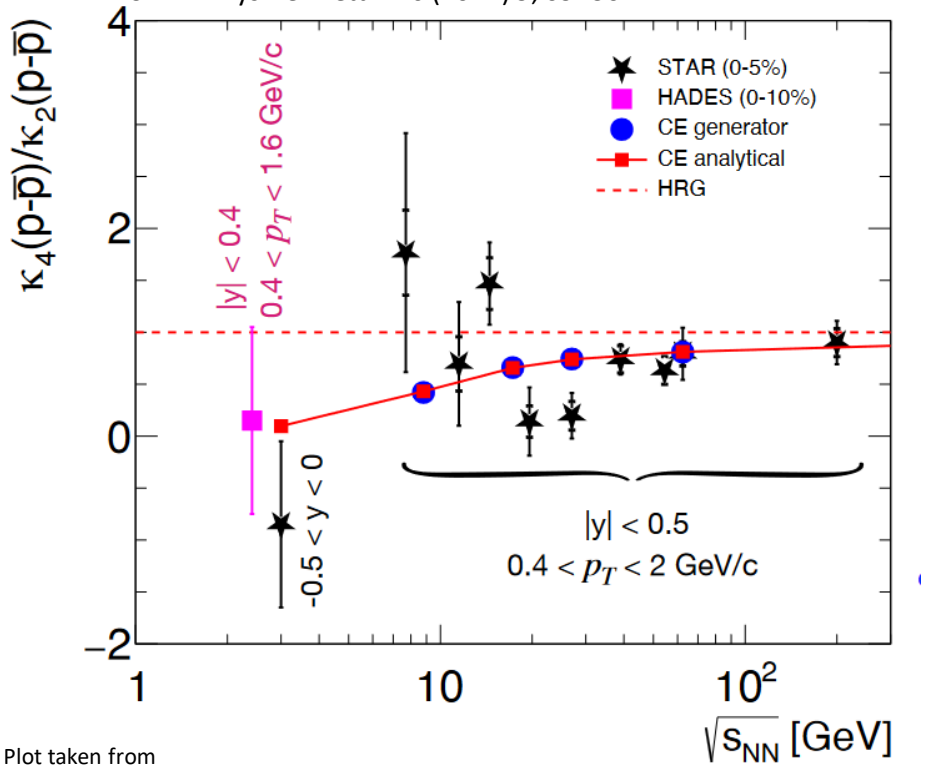


Kurtosis $= \frac{\kappa_4}{\sigma^4}$



Experimental goal:
Extract higher order cumulant ratios

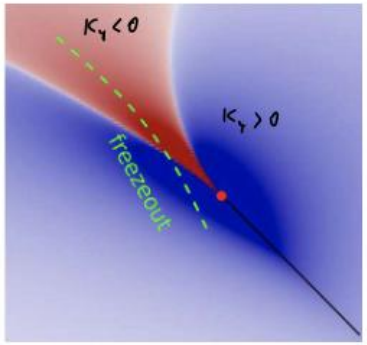
HADES: Phys.Rev.C 102 (2020) 2, 024914
STAR: Phys.Rev.Lett. 126 (2021) 9, 092301

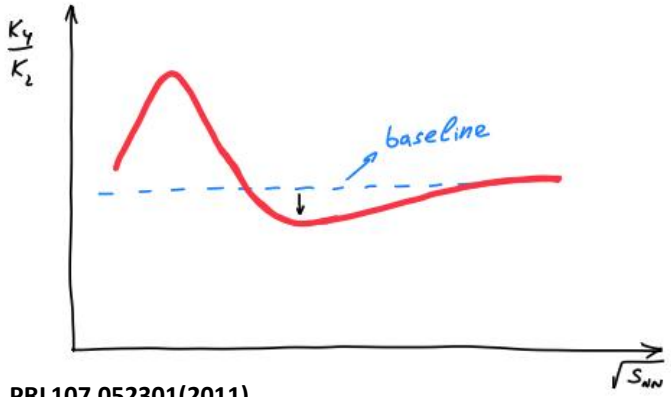


Plot taken from
Anar Rustamov DOI: 10.1051/epjconf/202327601007, EPJ Web Conf. 276 (2023) 01007)

- Measure energy excitation function of **higher-order cumulant ratios of baryons** (protons, light nuclei as proxy in experiment)

→ Expected non-monotonic trend for critical behaviour





M. Stephanov, PRL102.032301(2009), PRL107.052301(2011)
M.Cheng et al, PRD79.074505(2009)

- More recently focus on: **Factorial cumulant ratios, joint cumulants**

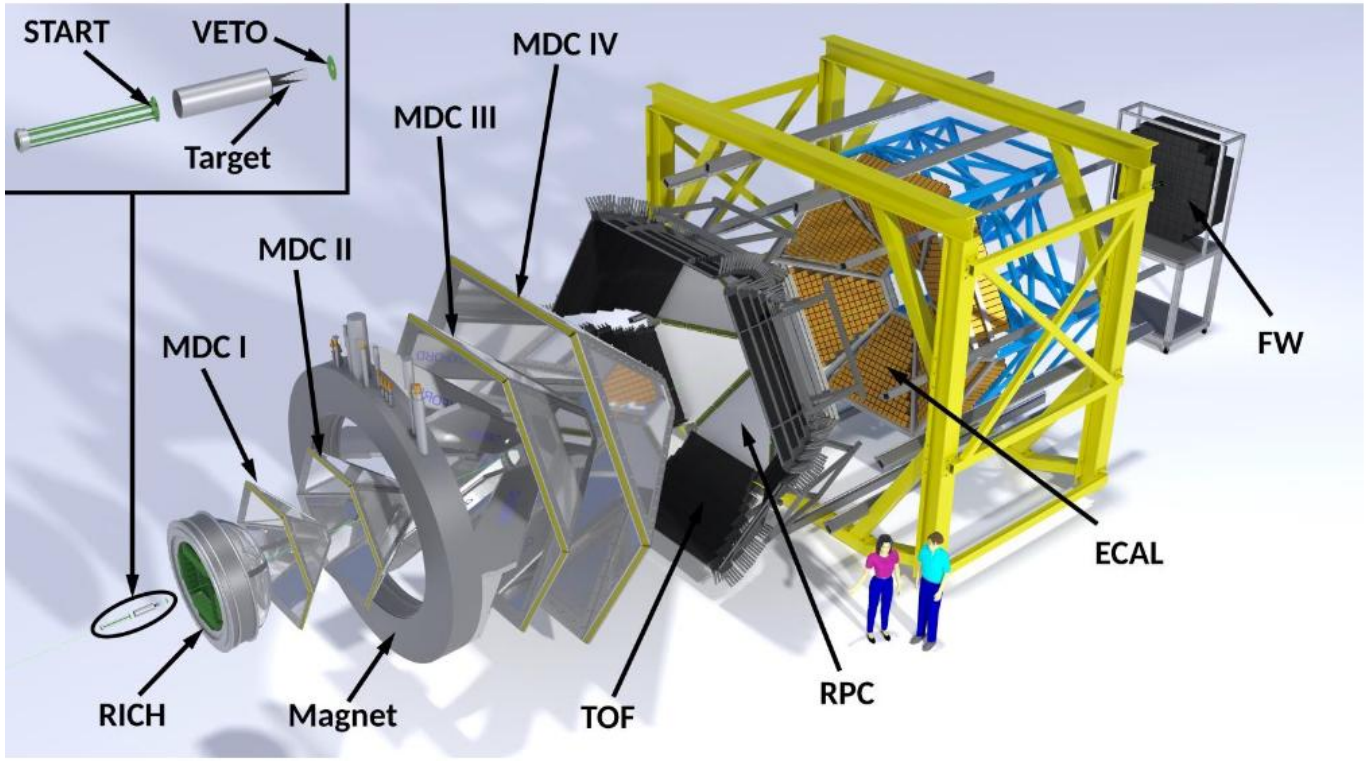
- **Experimental challenge: Disentangle non-critical from critical fluctuations**
  - Distortion from volume fluctuations, limited detector efficiencies and impurities in particle identification

High-Acceptance-Di-Electron-Spectrometer

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

Available measurement of low energy heavy-ion collisions

- Au+Au $E_{kin} = 1.23A\ GeV$ *(2012)*
- Ag+Ag $E_{kin} = 1.23A\ GeV$ (2019
- Ag+Ag $E_{kin} = 1.58A\ GeV$ (2019)
- Au+Au $E_{kin} = 0.8A\ GeV$ (2024)



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

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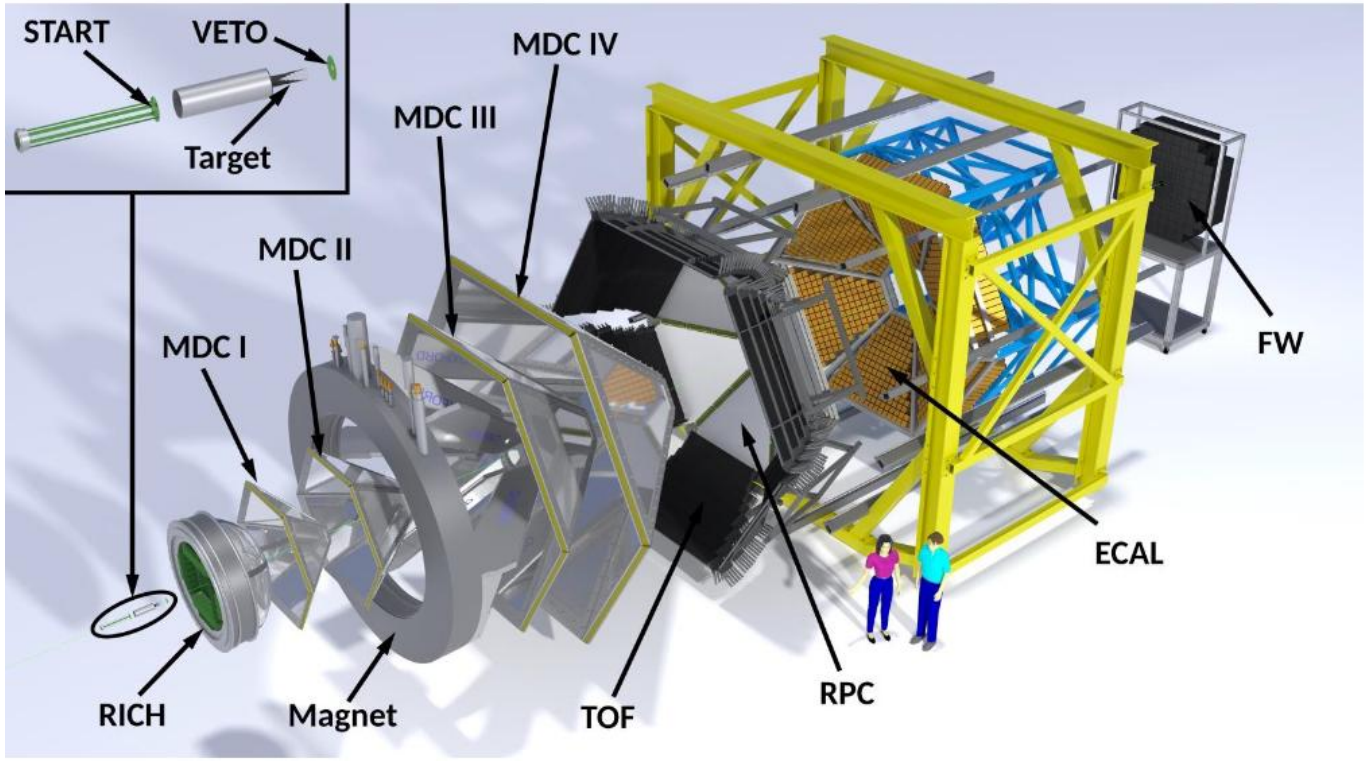
- New refined simulations considering properly Delta-Electrons caused by beam ions
- Previous simulation estimated too low efficiencies
- → approx. 10 % more yield around mid-rapidity



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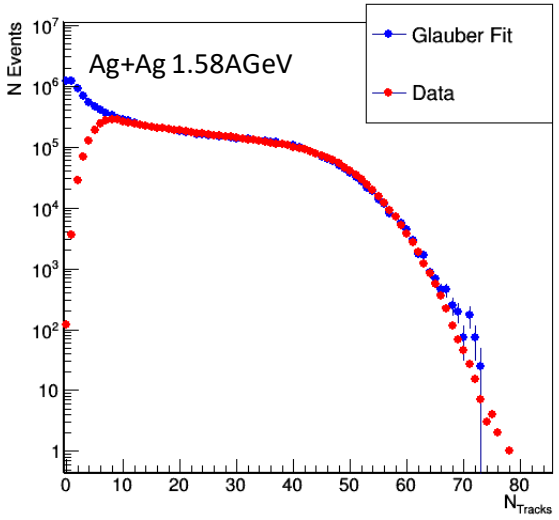
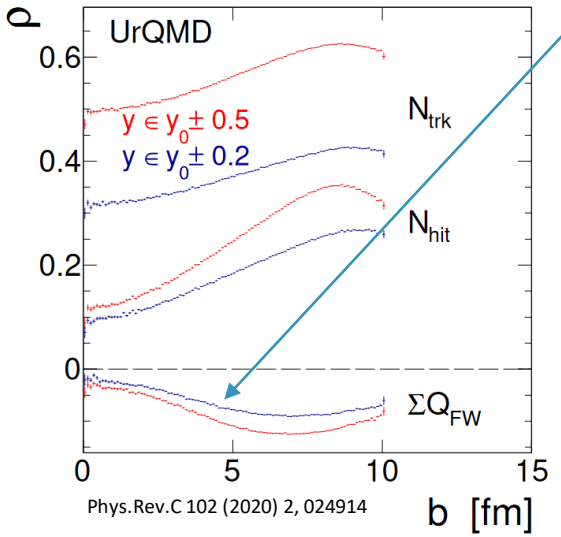
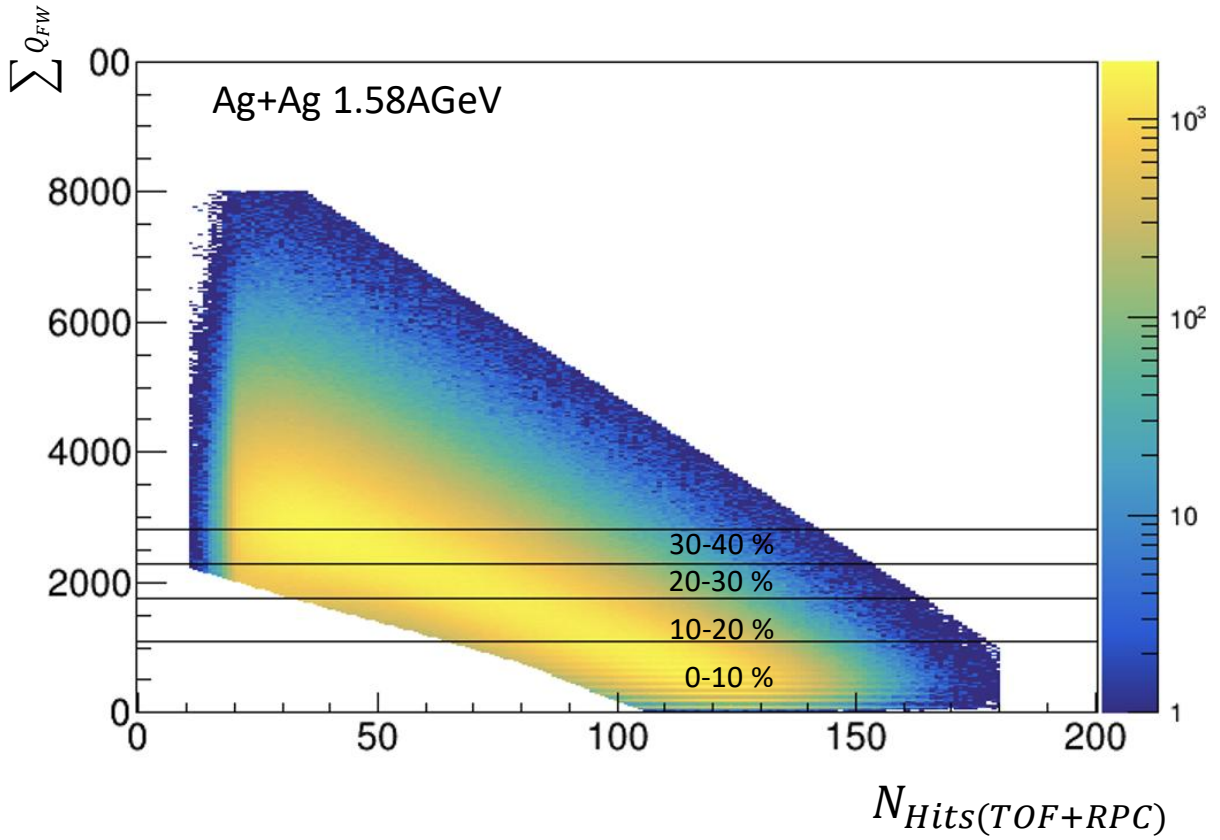
Centrality Selection for fluctuation analysis

Smallest correlation with protons
→ Forward Wall Signal

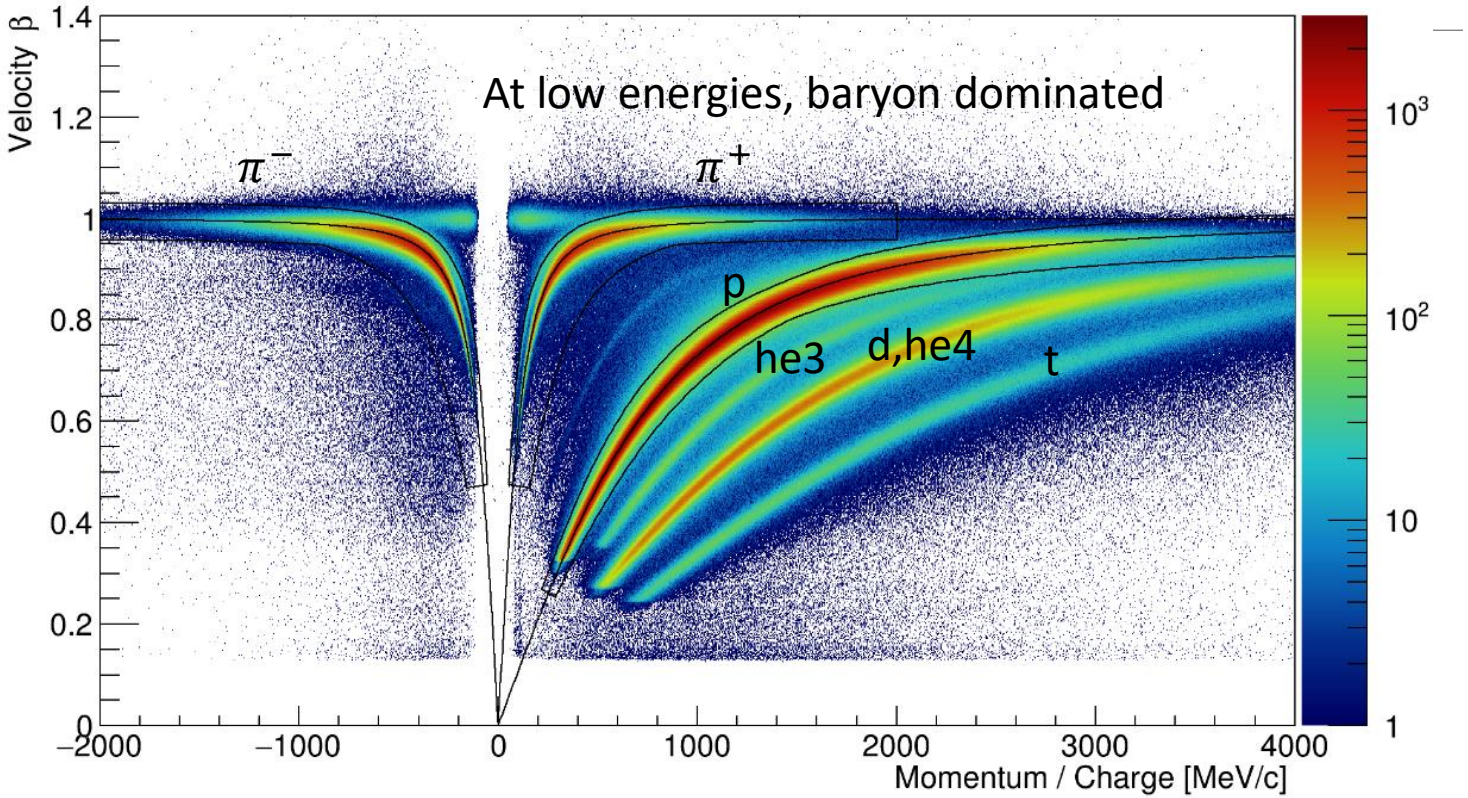




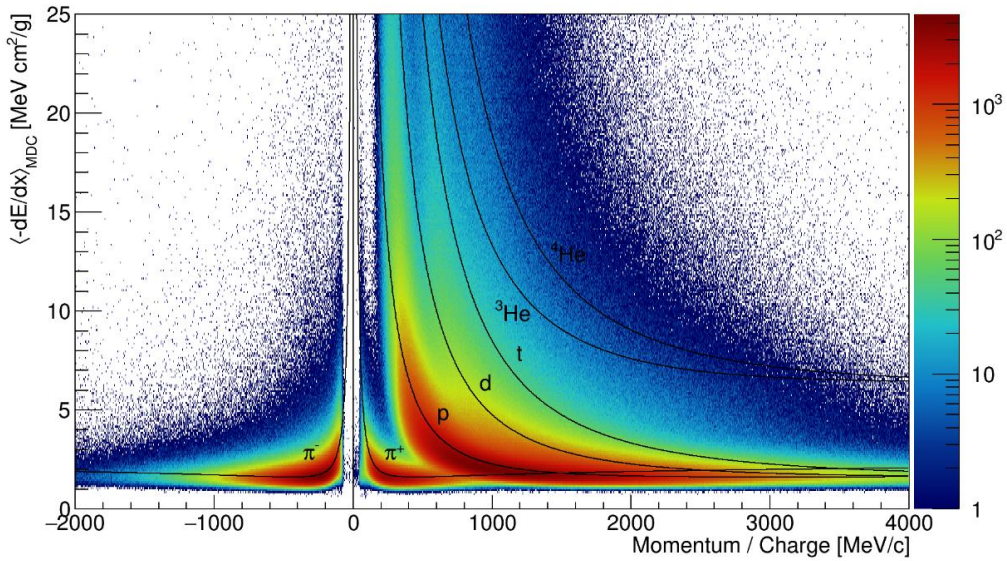


- Glauber x Neg. Binomial to **charged tracks** and **detector hits**
  - Event selection corresponds to around 55 % most central events
- For fluctuation analysis, do further centrality binning based on FW signal
- **Neg. Binomial for charged tracks at HADES is close to Poisson**
  → **reduce autocorrelation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

Particle identification at HADES



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

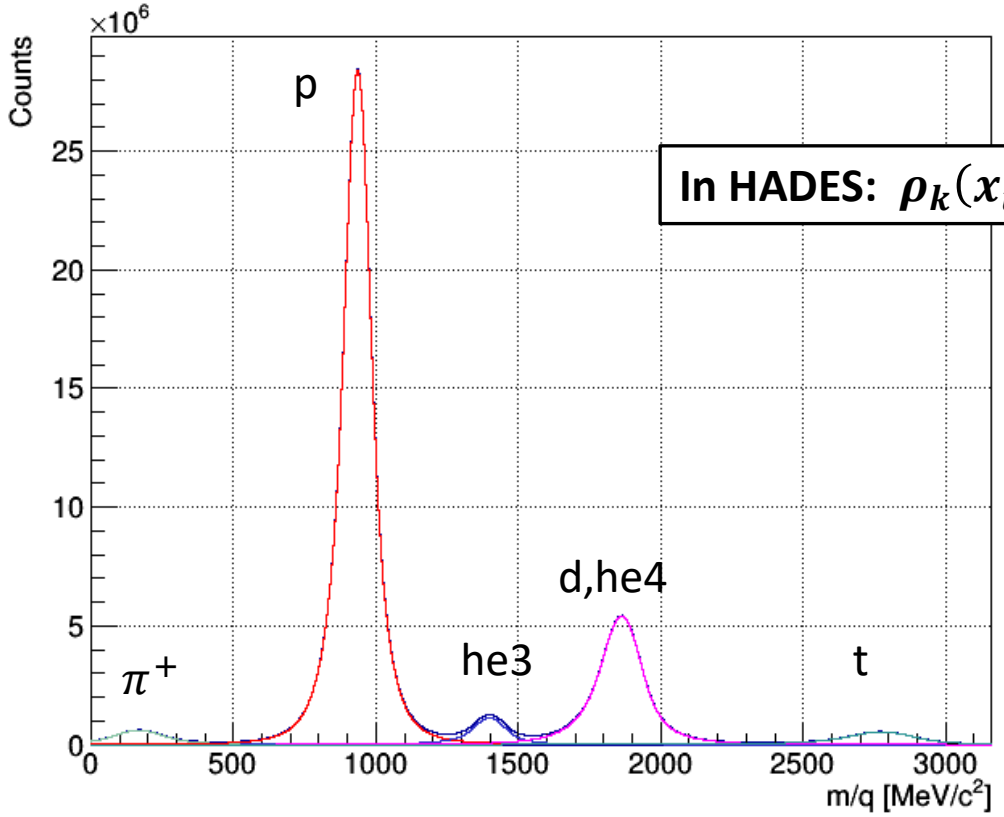


- **MDCs** provide measurement of **specific energy loss**
- In deuteron analysis used as preselection

Correcting moments for mis-identification - Fuzzy Logic

Ag+Ag 1.58A GeV

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



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

$$\omega_k = \frac{\rho_k(x_i)}{\sum \rho_l(x_i)}$$

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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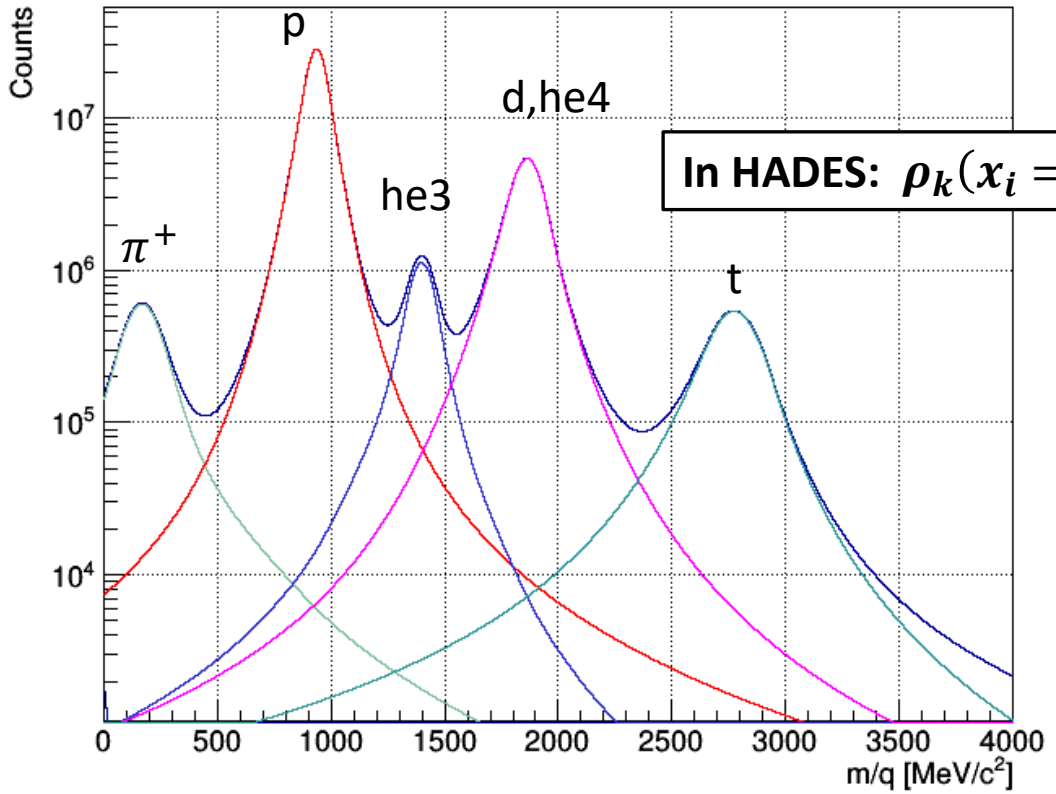

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Correcting moments for mis-identification - Fuzzy Logic

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

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

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

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

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

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

Fully defined by mass fit functions

vector of folded moments | response matrix | vector of true moments

- 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

For details, see poster session:

573. Fuzzy logic for reconstructing moments of multiplicity distributions

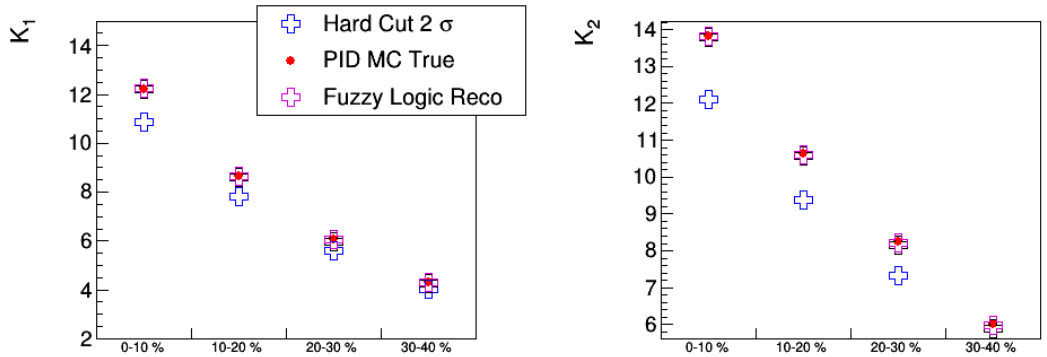
Anar Rustamov, Joachim Stroth, Marvin Nabroth

Fuzzy Logic - Performance study in simulation

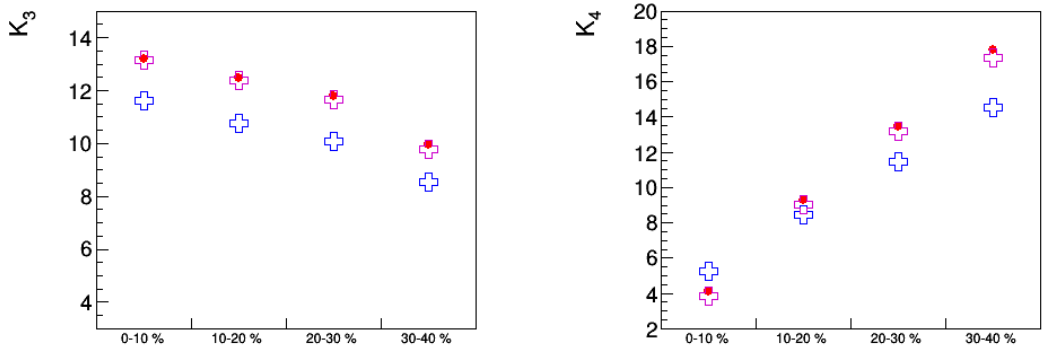
Ag+Ag 1.58A GeV

[Smash+Clustering] + HADES GEANT Sim.

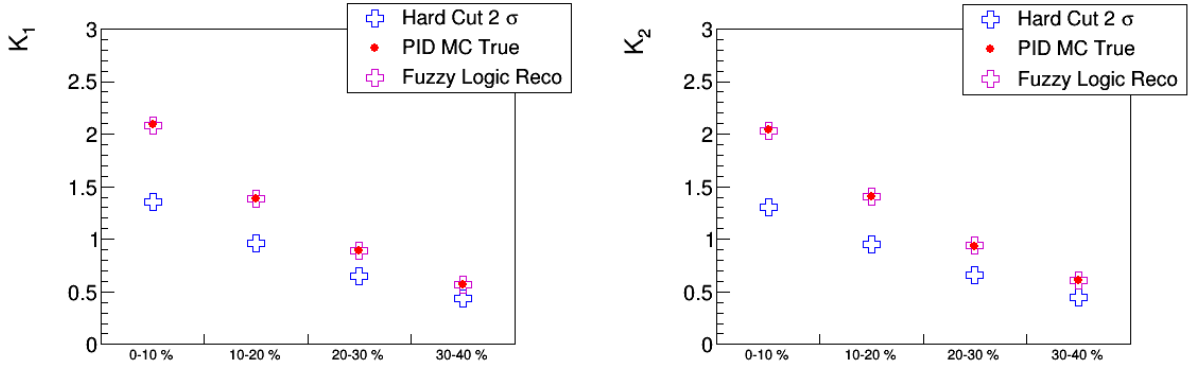
Protons



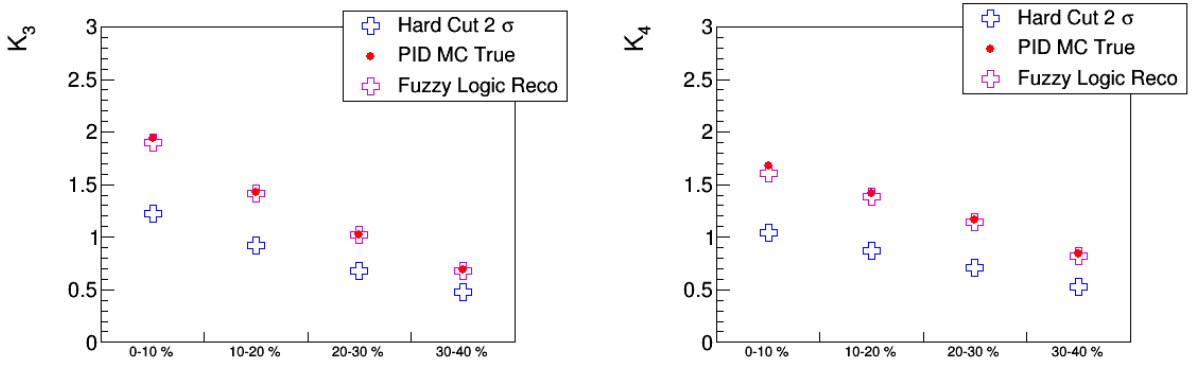
$-0.4 < y_{cm} < 0.4 \;\; 400 < p_t < 1600 \; MeV/c$



Deuterons

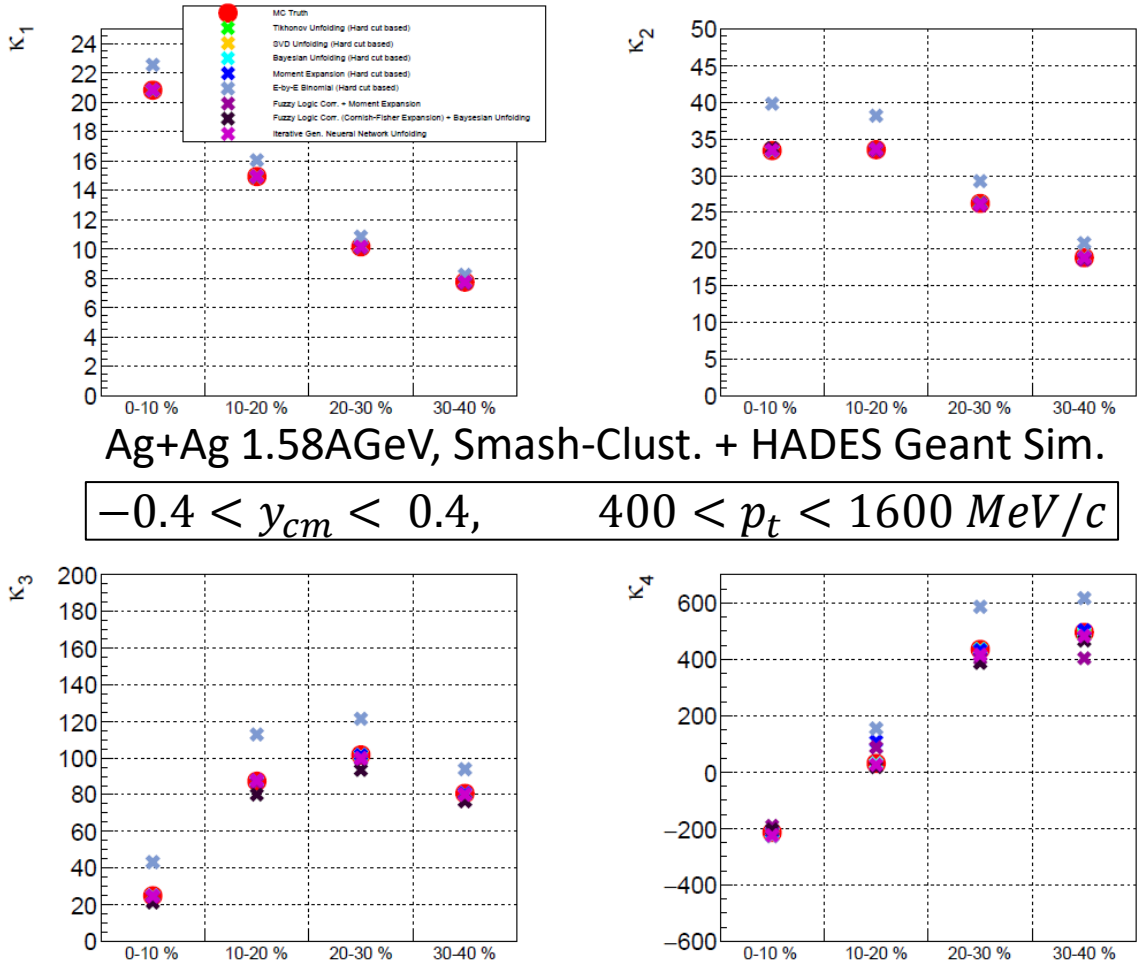


$-0.4 < y_{cm} < 0. \;\; 600 < p_t < 1800 \; MeV/c$



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

Efficiency corrections: Validation in simulation



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

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

	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]	✓	(✓)

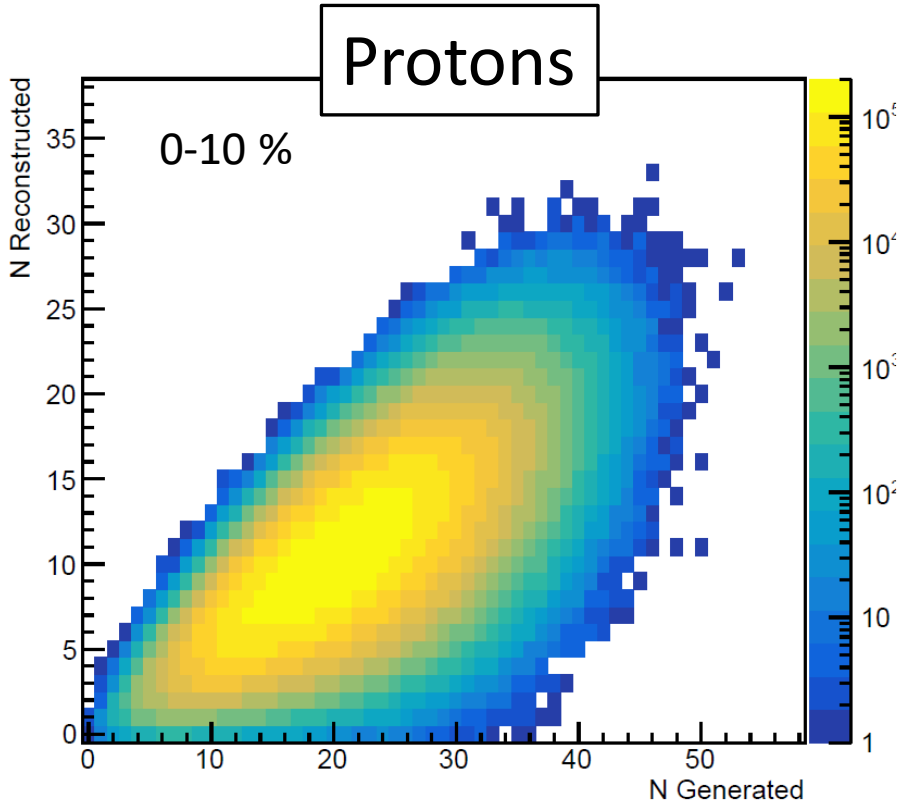
- ❑ Tikhonov and SVD Unfolding not applied on data due to instabilities for higher orders
- ❑ Moment exp. requires up to 6 orders for stability!

→Challenging situation

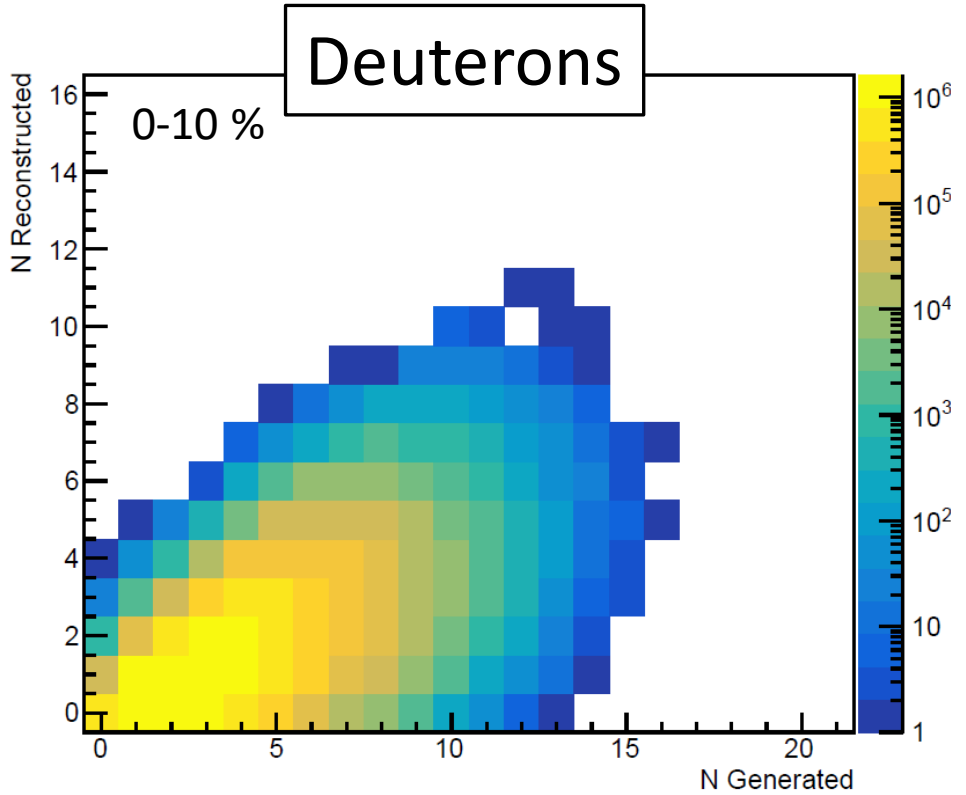
- ❑ Binomial (even E-by-E) correction do not perform well for all bins

→ Rely on methods based on response matrix from simulation

Efficiency corrections
- Response matrices $N_{generated}$ vs $N_{reconstructed}$



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



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

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

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

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

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

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

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

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

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

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

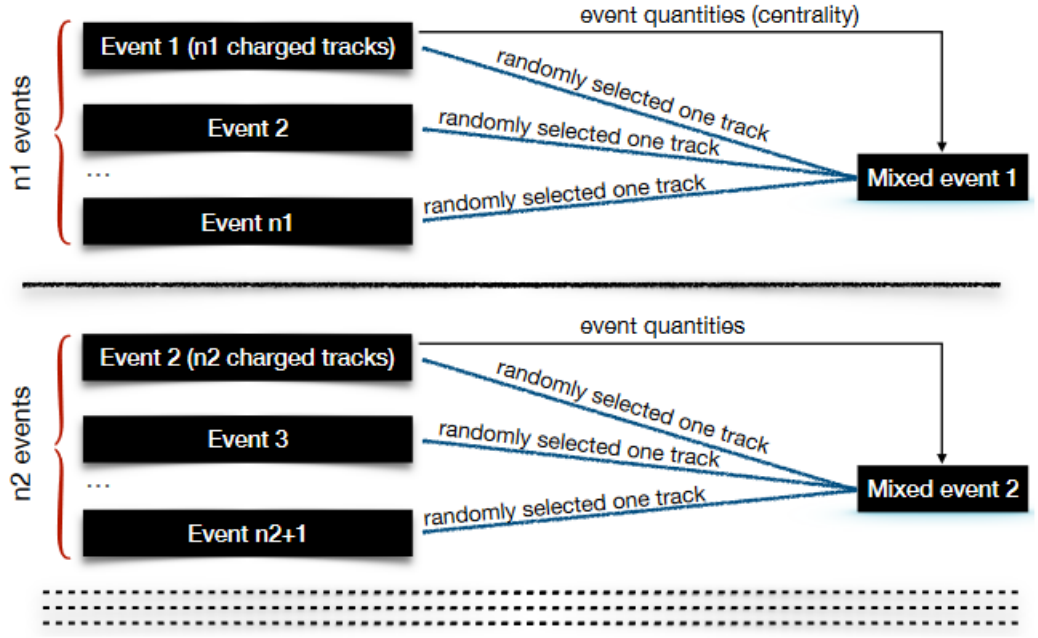
$k_m(n) :=$ *Single source particle cumualnts*

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

[*] 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



- 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

- Event mixing removes correlations between particles
  - In case of **Poisson like behaviour** one expects for the emission per sources:
    - $\boldsymbol{k_m(n) =< n >,\ cov(n_1, n_2) = 0}$

- Event mixing is equivalent to calculations based on charged tracks

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

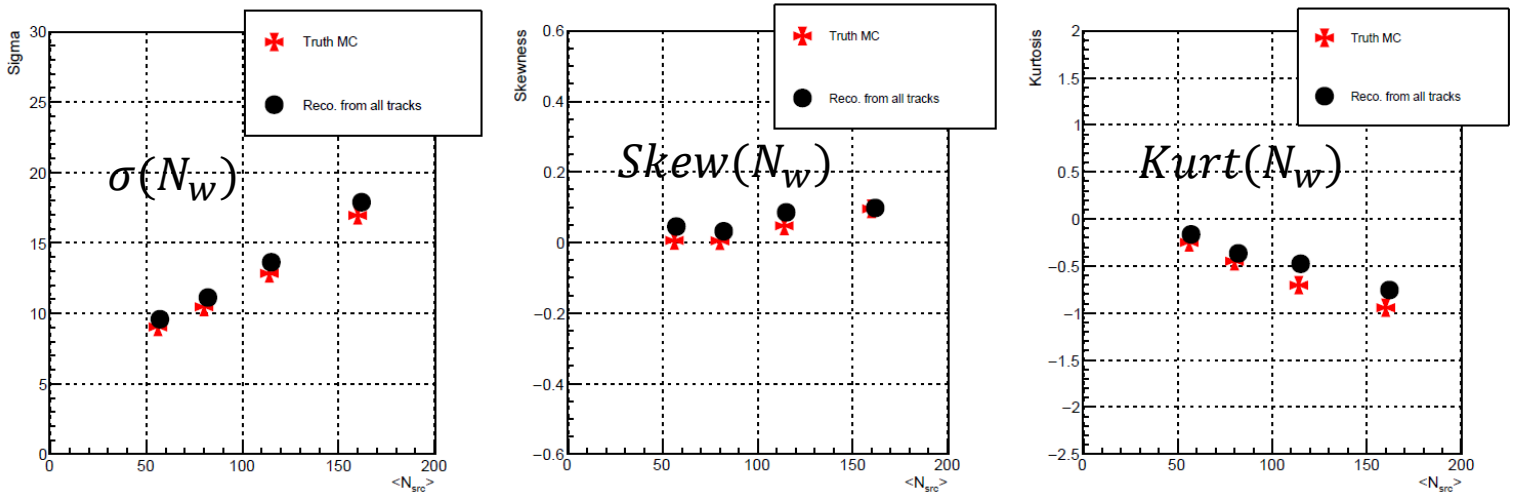
$$\frac{\kappa_3[N_w]}{\langle N_w\rangle^3} = -3\frac{\bar{C}_2[M]}{\langle M\rangle^2}\frac{\kappa_2[N_w]}{\langle N_w\rangle^2} + \frac{C_3[M] - \bar{C}_3[M]}{\langle M\rangle^3}$$

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

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:



- In HADES: Negative Binomial toy model method exhibits good agreement with MC Truth volume → Neg Bino. close to Poisson
- **For real data only use mixed-protons due to better understating of eff. corrections for protons**

But, is nature at low energies really like Glauber?

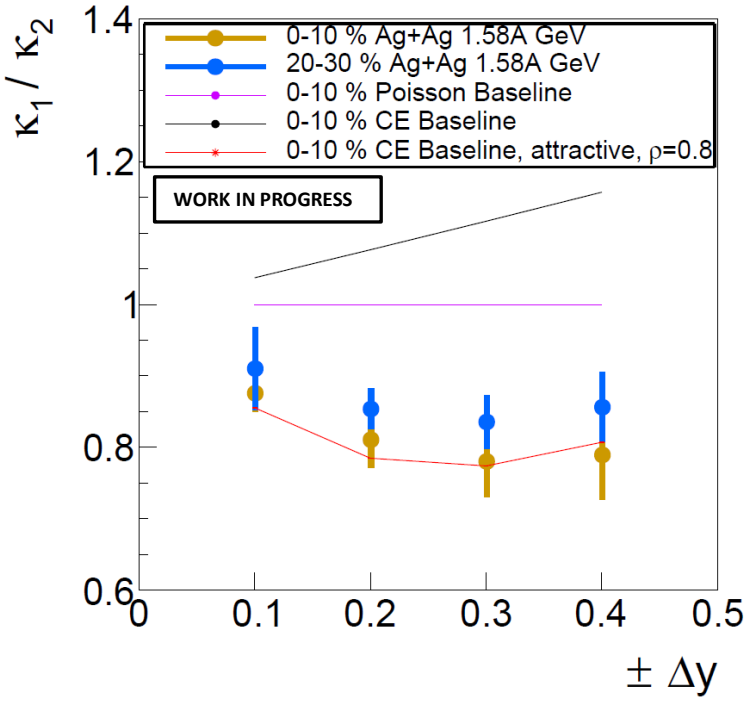
- Interaction of particles with spectators
- At low energies most of the protons are not produced, but rescattered → protons are significant part of the volume!
- In transport models, for Apart, assumption of independent emission violated for protons!

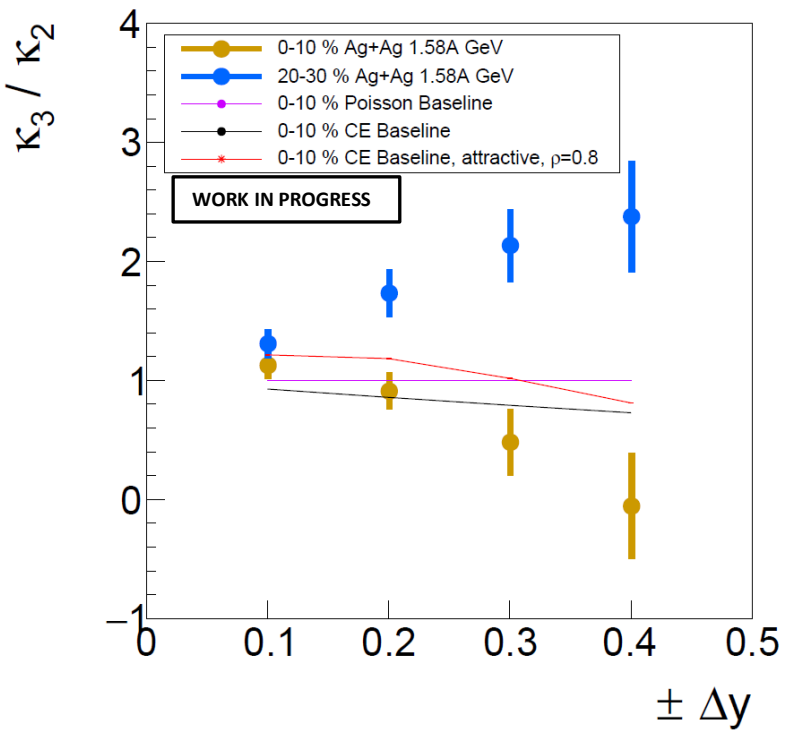
Event mixing still so far the best method available, as fully data driven, only independent source assumption!

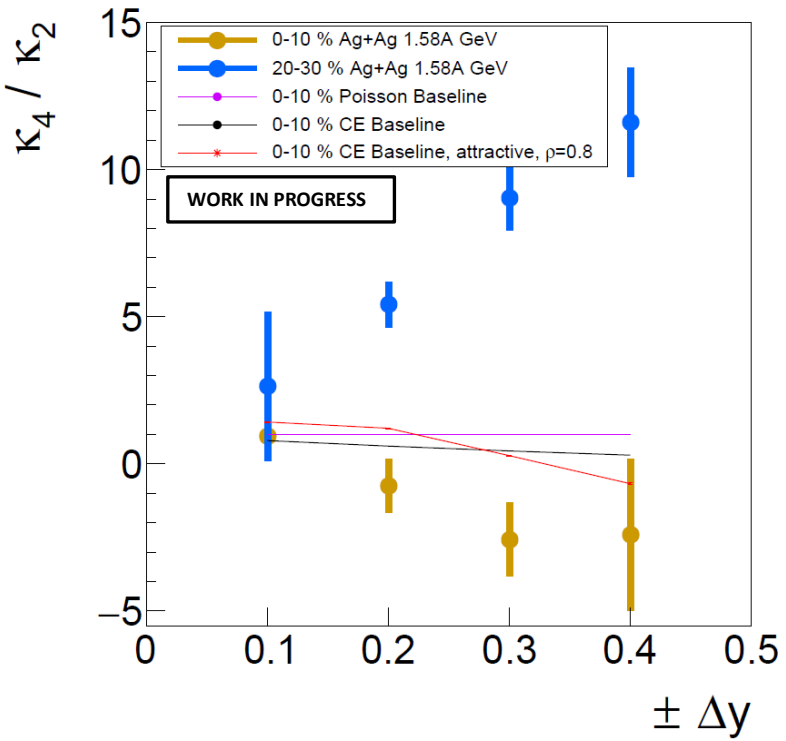
Eff. + Volume corrected – proton cumulant ratios

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

$$400 < p_t < 1600\ MeV/c$$







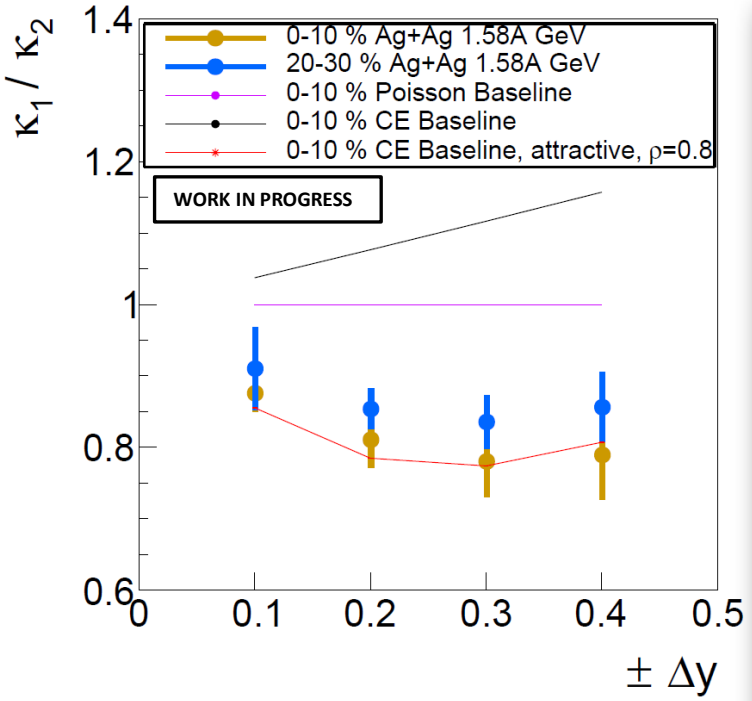
- In general convergence towards poisson limit (1) observed
- κ_3 now mainly positive as opposed to old HADES Au+Au data
- For higher order, different trend between central and semi-central events → Influence of spectators?

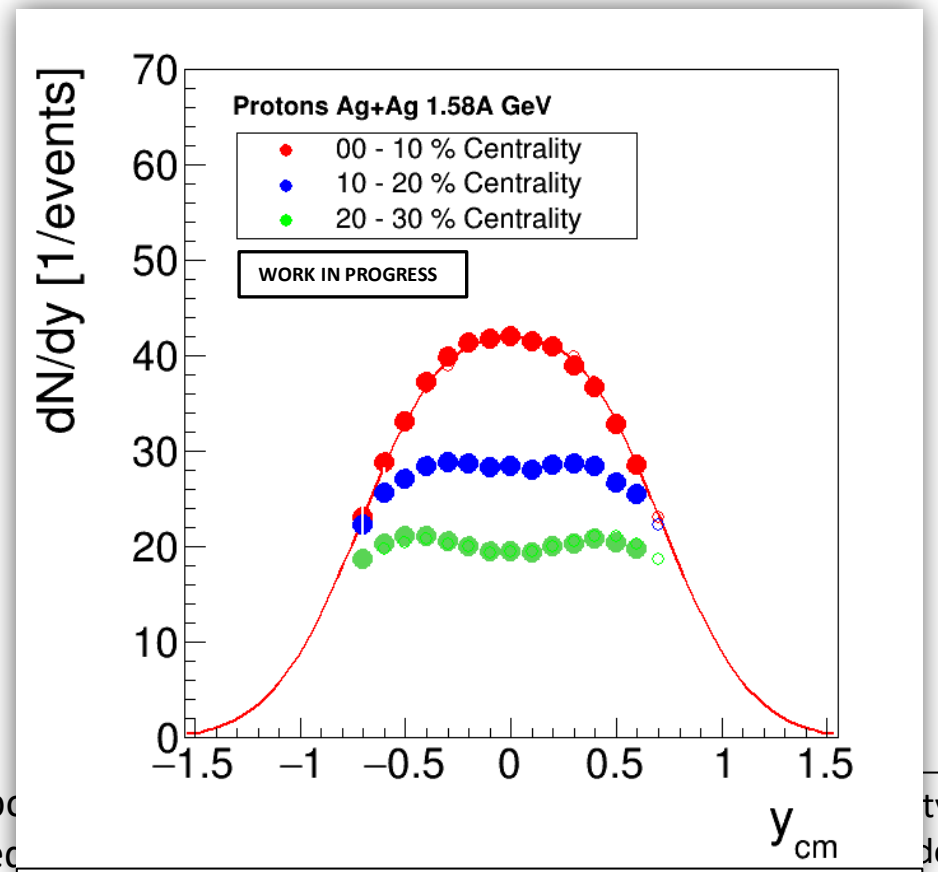
- CE baseline considering acceptance window only can not describe data, different trend for κ_1/κ_2
- Trend of rapidity dependence can be described by Canonical baseline considering correlations with an attractive potential (P. Braun-Munzinger, K. Redlich, A. Rustamov, J. Stachel, JHEP 08 (2024) 113)

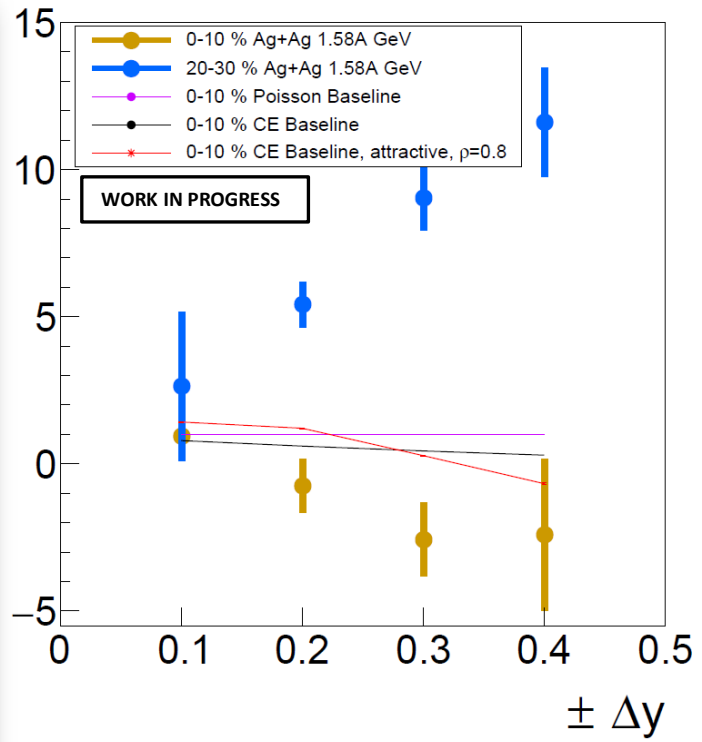
Eff. + Volume corrected – proton cumulant ratios

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

$$400 < p_t < 1600\ MeV/c$$







- In general convergence towards po
- 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

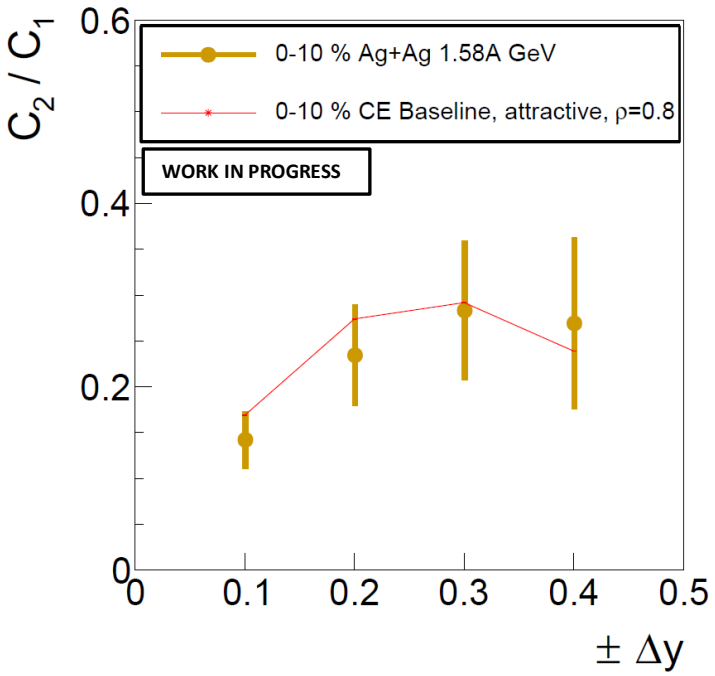
ty dependence can be described by Canonical dering correlations with an attractive potential (P. Redlich, A. Rustamov, J. Stachel, JHEP 08 (2024) 113) d by CE model within uncertainties

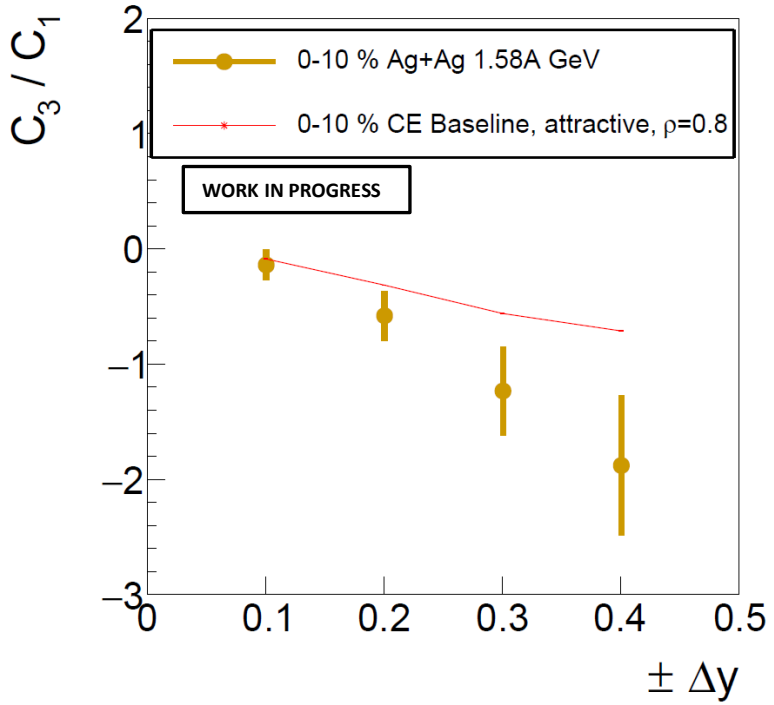
Eff. + Volume corrected – proton factorial cumulant ratios

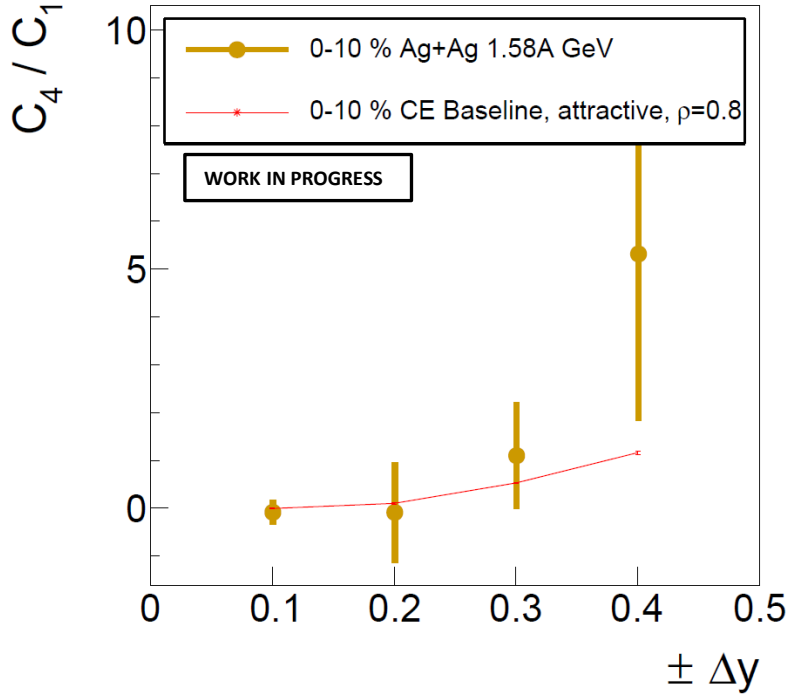
$$C_2 = \kappa_2 - \kappa_1$$
$$C_3 = \kappa_3 - 3\kappa_2 + 2\kappa_1$$
$$C_4 = \kappa_4 - 6\kappa_3 + 11\kappa_2 - 6\kappa_1$$

→"Measure for multi-particle-correlations"

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



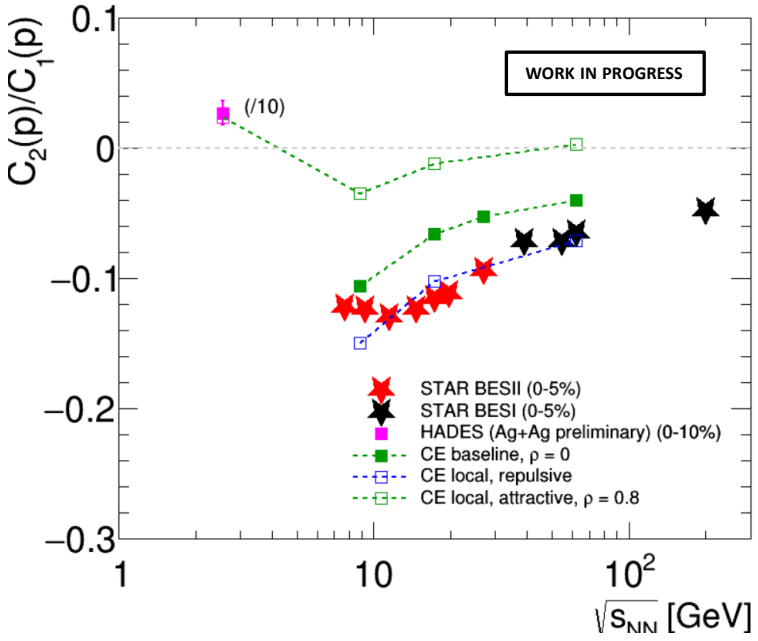


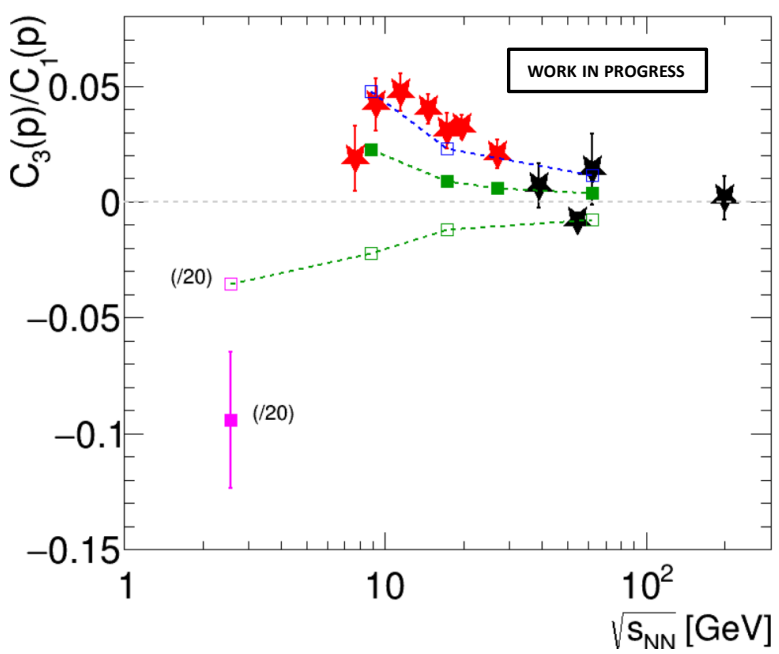


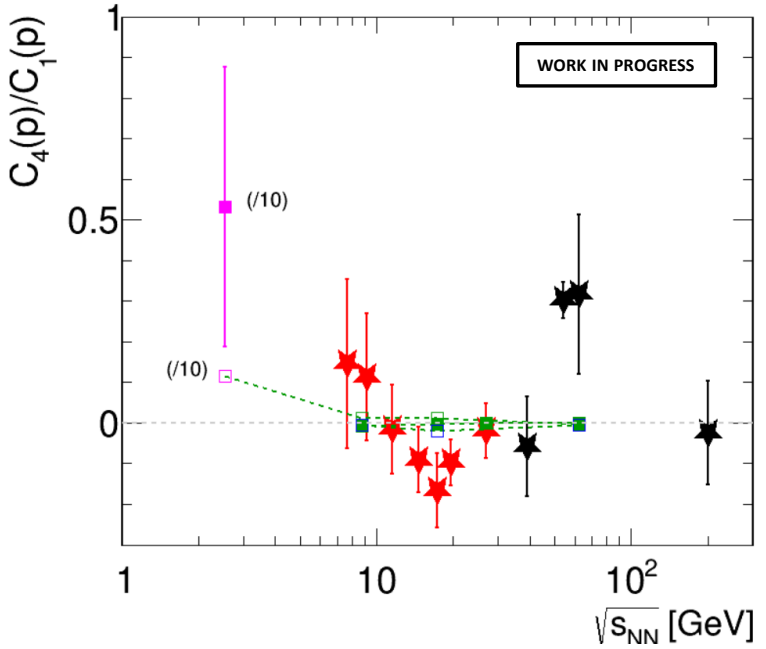
- Also trend of factorial cumulant ratios as a function of rapidity can be described by Canonical baseline considering correlations with an attractive potential
  [P. Braun-Munzinger, K. Redlich, A. Rustamov, J. Stachel, JHEP 08 (2024) 113]
- Measurement matched by CE model within uncertainties

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

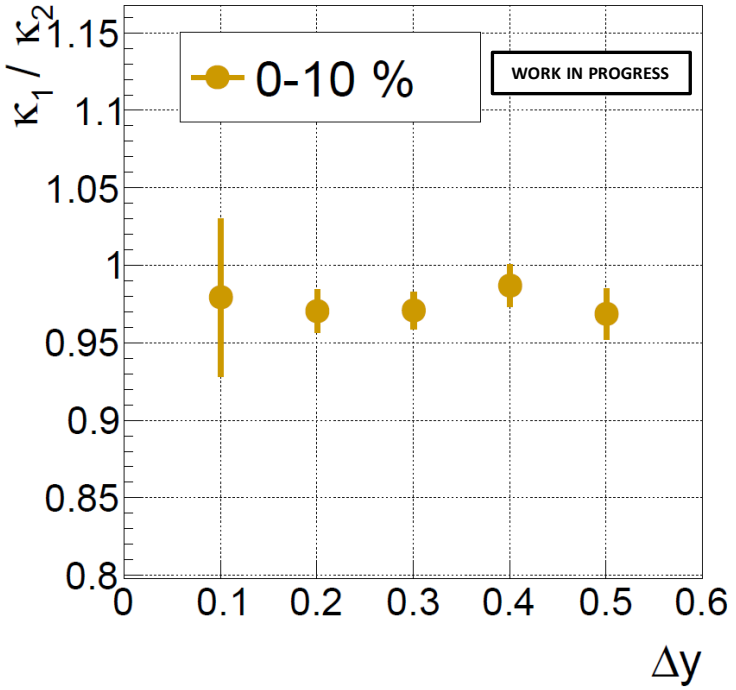
- Trend of **HADES** point described by correlated CE model with **attractive potential** [P. Braun-Munzinger, K. Redlich, A. Rustamov, J. Stachel, JHEP 08 (2024) 113]
- **STAR** points described by **repulsive potential** [B. Friman, A. Rustamov, K. Redlich (in progress)]

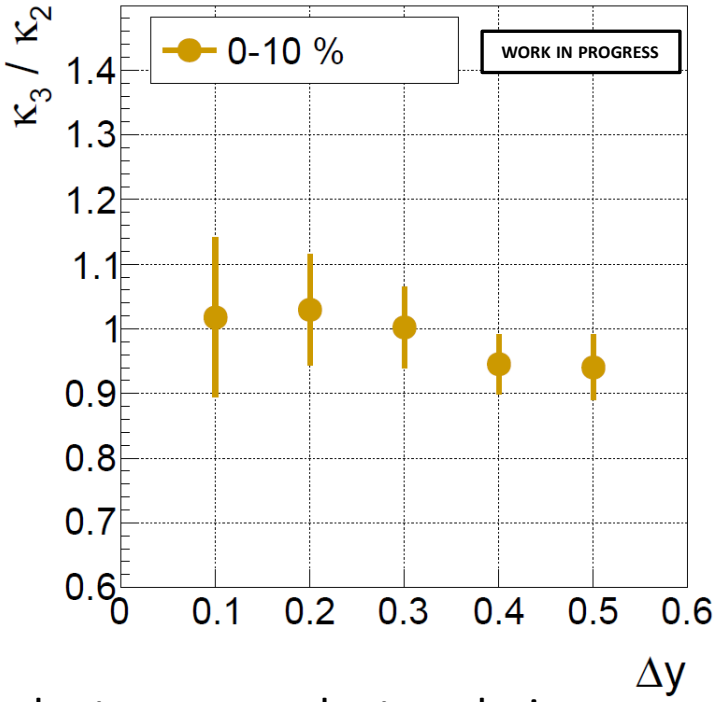
→ Interplay between repulsive and attractive forces

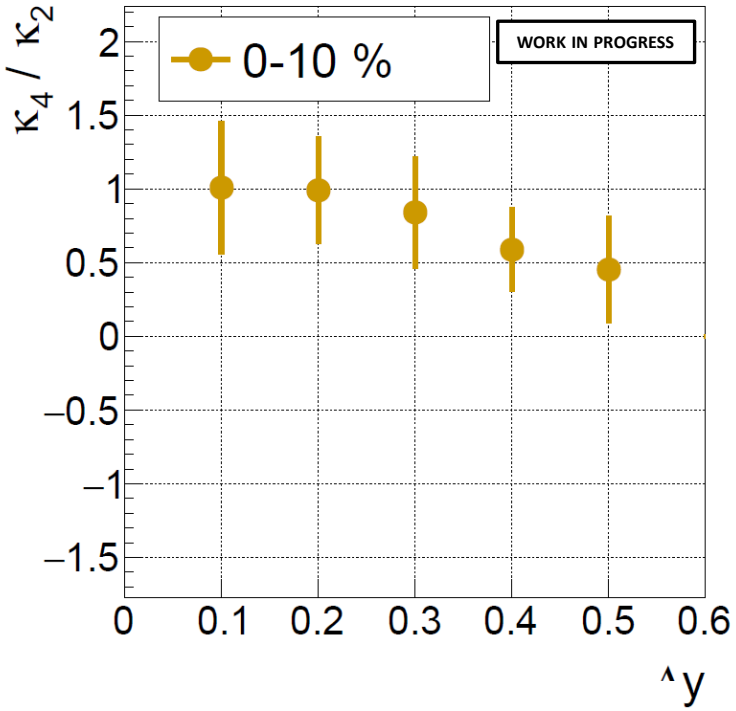
Eff. + Volume corrected – deuteron cumulant ratios

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

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







- 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

$\Delta y = 0.1$: $-0.1 < y_{cm} < 0$

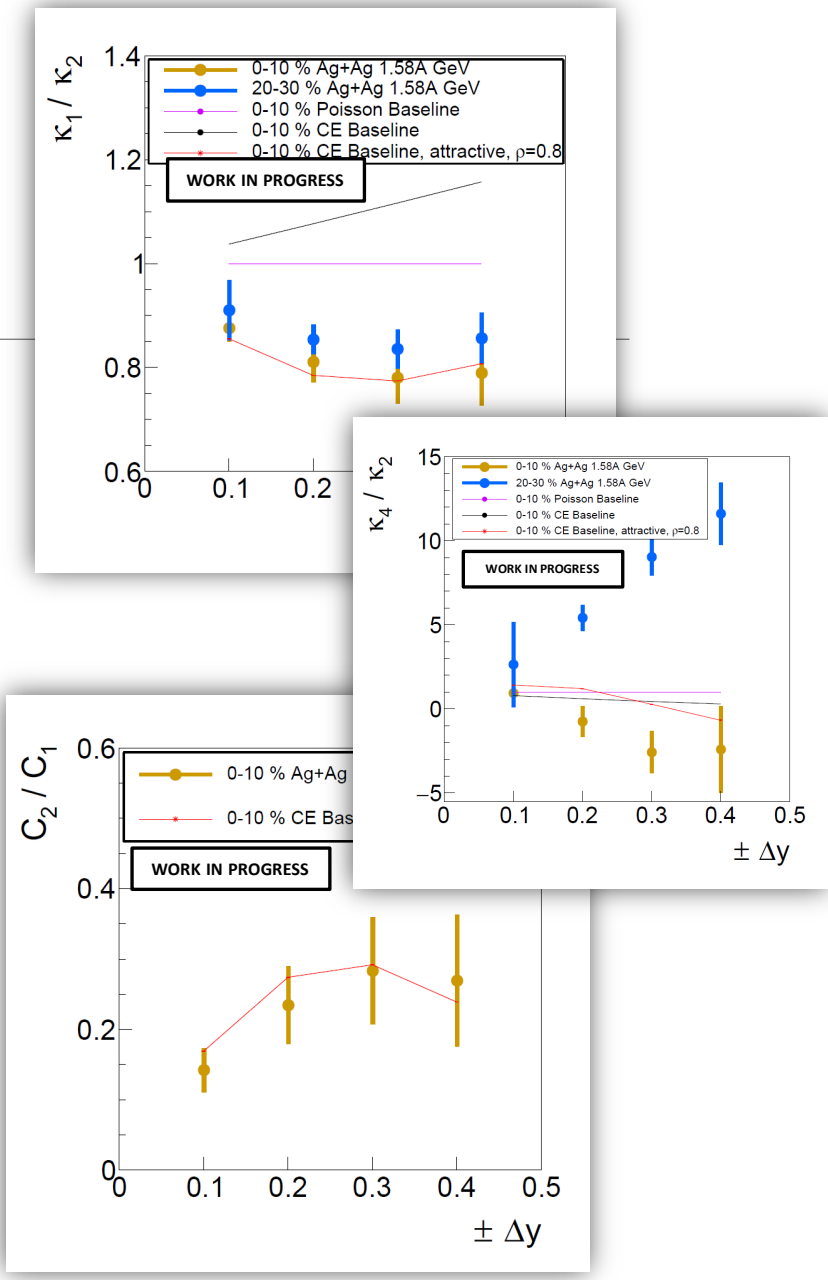
...

$\Delta y = 0.4$: $-0.4 < y_{cm} < 0$

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

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 (Au+Au 1.23A GeV, Ag+Ag 1.58A GeV, Au+Au 0.8A GeV) ongoing
  - p-d joint-cumulant analysis ongoing
  - Extend cumulants analysis to t and He3, establish baseline
  - Further investigate and refine volume correction method



HADES

Thank you for your attention!

THE HADES COLLABORATION

Back-Up

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**

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

Calculating matrix elements by implementing permutation functions

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

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

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

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

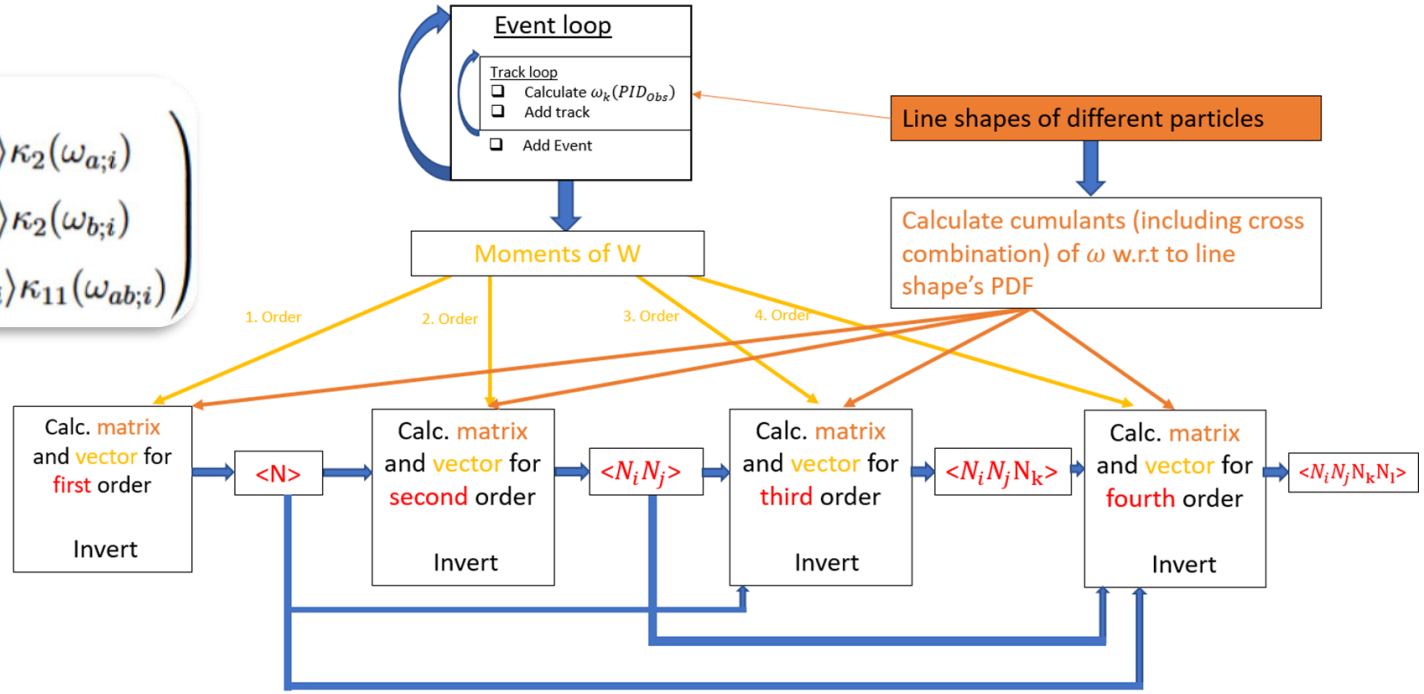
$$P[i,i,j] \equiv [i,i,j] + [i,j,i] + [j,i,i]$$

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

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

Linear coefficients depended on lineshape properties only

Implemented inversion procedure up to 4th order



Fuzzy-Logic + Efficiency correction

"PID" corrected moments from Fuzzy Logic/ Identity Method

$\langle \vec{N} \rangle$

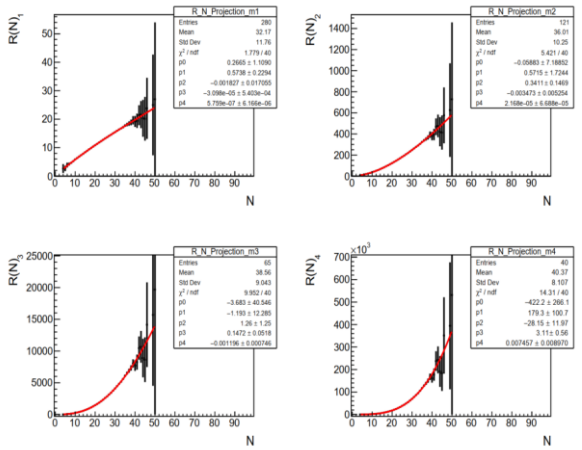
Moment Expansion

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

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

➢ **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 **simple series expansion**



Requires for some bins 6 or 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

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

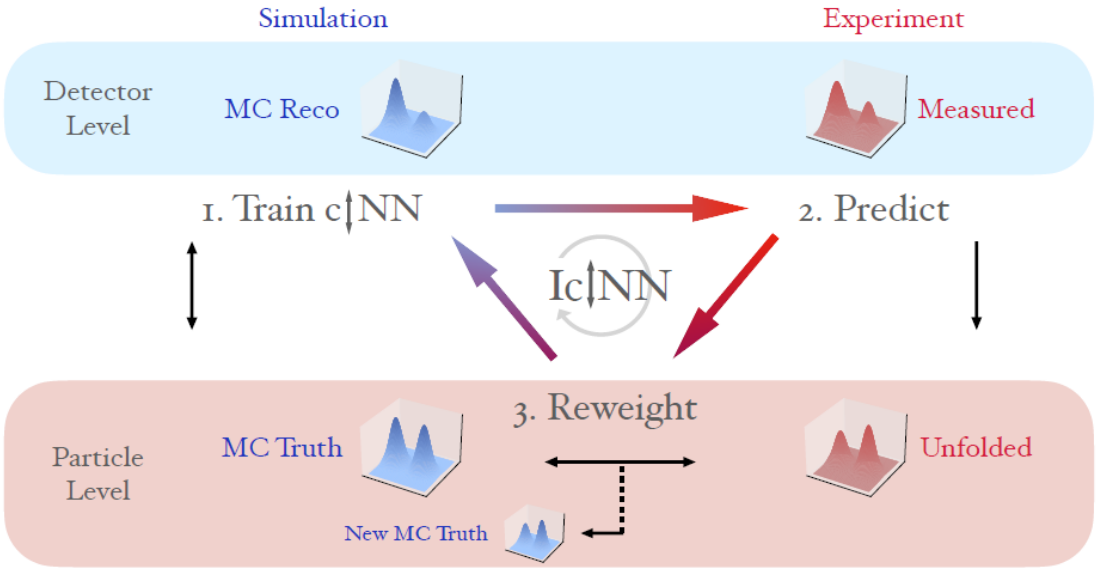
Reweighting - Omnifold

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

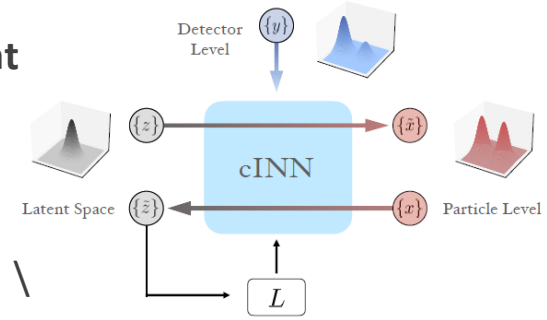


An unfolding method based on conditional Invertible Neural Networks (cINN) using iterative training

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**