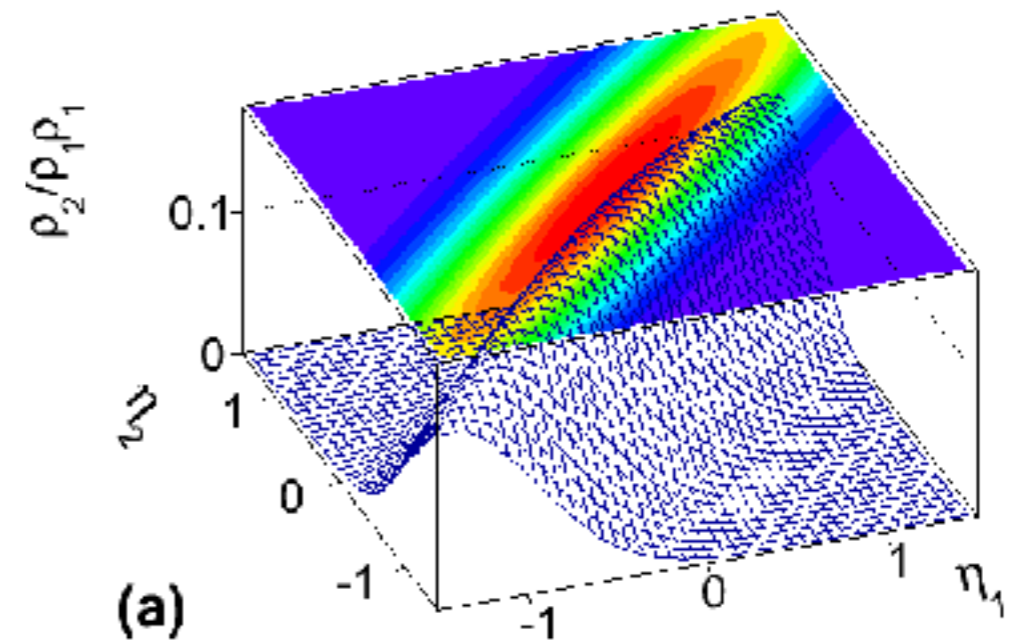




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# Lessons from Differential Correlation Measurements

EMMI Workshop, Wuhan, China  
Oct 2017

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## Outline

- A. Some *not so random* thoughts...
- B. Controlling errors w/ Differential Correlations
- C. **Differential Identity Method**

# Definitions (I)

- **Definition: Single & Pair Densities**

**Single Density:**  $\rho_1(\phi_i, \eta_i) = \langle N(\phi_i, \eta_i) \rangle / \Delta\phi\Delta\eta$

Histogram — number of singles per event normalized per bin width

Histogram — number of pairs per event normalized per bin width

**Pair Density:**  $\rho_2(\phi_1, \eta_1, \phi_2, \eta_2) = \langle N(\phi_1, \eta_1)N(\phi_2, \eta_2) \rangle / \Delta\phi^2 \Delta\eta^2$

- **Factorize average yield and kinematic dependence**

Single Probability Distribution

$$\rho_1(\phi_i, \eta_i) = \langle N \rangle P_1(\phi_i, \eta_i)$$

1st Moment: Avg Multiplicity

$$\langle N \rangle = \int_{\text{accept}} \rho_1(\phi_i, \eta_i) d\phi_i d\eta_i$$

$$1 = \int_{\text{accept}} P_1(\phi_i, \eta_i) d\phi_i d\eta_i$$

$$\rho_2(\phi_1, \eta_1, \phi_2, \eta_2) = \langle N(N-1) \rangle P_2(\phi_1, \eta_1, \phi_2, \eta_2)$$

2nd Factorial:  
Avg Number of Pairs

$$\langle N(N-1) \rangle = \int_{\text{accept}} \rho_2(\phi_1, \eta_1, \phi_2, \eta_2) d\phi_1 d\eta_1 d\phi_2 d\eta_2$$

$$1 = \int_{\text{accept}} P_2(\phi_1, \eta_1, \phi_1, \eta_1) d\phi_1 d\eta_1 d\phi_2 d\eta_2$$

Pair Probability Distribution

# Definitions (II)

- Two-Particle Cumulant

$$C_2(\phi_1, \eta_1, \phi_2, \eta_2) = \rho_2(\phi_1, \eta_1, \phi_2, \eta_2) - \rho_1(\phi_1, \eta_1)\rho_1(\phi_2, \eta_2)$$

$$C_2(\Delta\phi, \Delta\eta) = \int_{\text{Accept}} C_2(\phi_1, \eta_1, \phi_2, \eta_2) \delta(\Delta\phi - \phi_1 + \phi_2) \delta(\Delta\eta - \eta_1 + \eta_2) d\phi_1 d\eta_1 d\phi_2 d\eta_2$$

- Normalized Cumulant

Differential:

$$R_2(\phi_1, \eta_1, \phi_2, \eta_2) = \frac{C_2(\phi_1, \eta_1, \phi_2, \eta_2)}{\rho_1(\phi_1, \eta_1)\rho_1(\phi_2, \eta_2)} = \frac{\rho_2(\phi_1, \eta_1, \phi_2, \eta_2)}{\rho_1(\phi_1, \eta_1)\rho_1(\phi_2, \eta_2)} - 1$$

Integral:

$$\bar{R}_2 = \frac{\langle N(N-1) \rangle}{\langle N \rangle^2} - 1$$

# Part I: Some not so random thoughts...

- Role of Conservation Laws
- Role of the Acceptance
- Flow vs Non-Flow:
  - Collective vs. Non-Collective
  - System wide vs. Non-Flow
- “Mediumization”



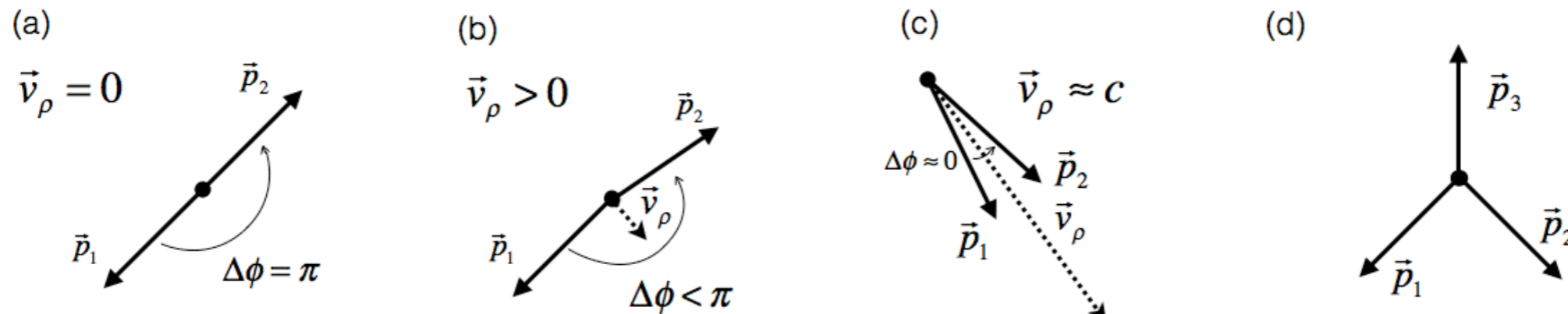


# Role of Conservation Laws (1)

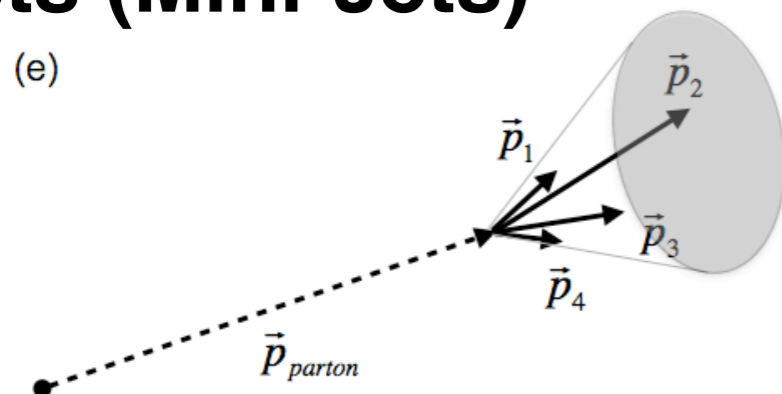
Conservation laws and particle production processes determine correlations and fluctuations .

Energy Momentum Conservation  
 Charge Conservation  
 Strangeness Conservation  
 etc...

Resonance decays, Finite Temperature Emission, Radial Flow:



## Jets (Mini-Jets)

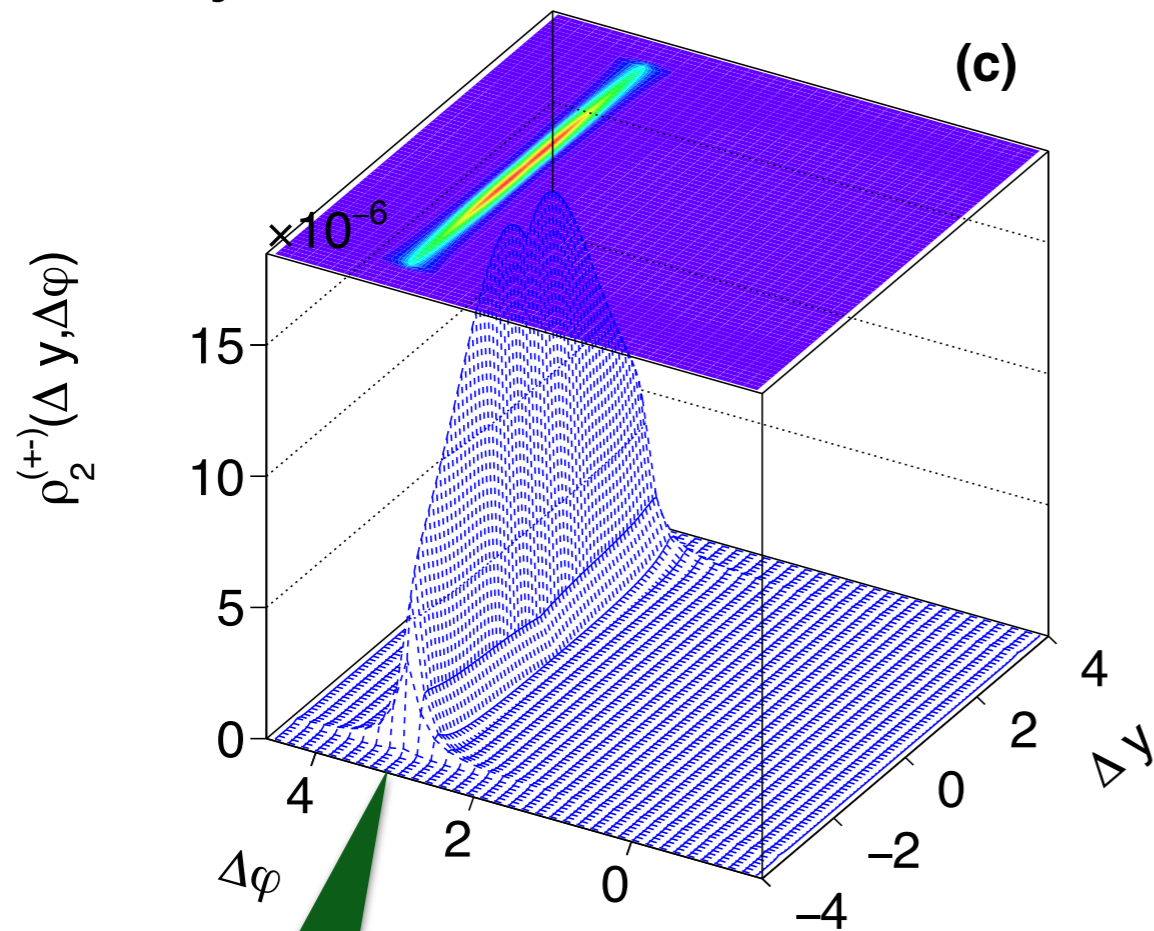


Number of pairs, triplets, etc within fixed acceptance depends on temperature, flow boost, jet energy, etc

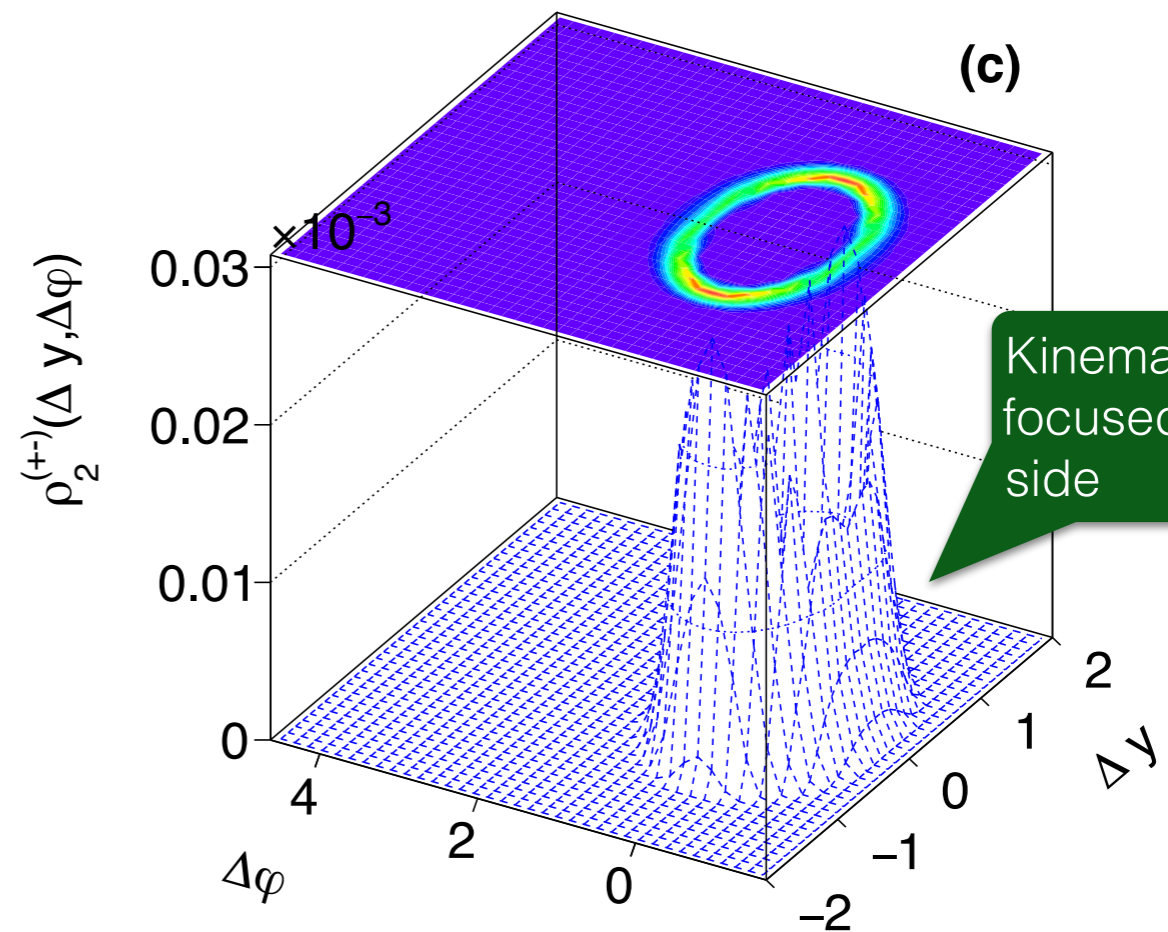
# Example: $\rho^0 \rightarrow \pi^+ + \pi^-$ Decays

Decay at rest:

Transverse Boost:  $\beta \sim 0.9$



Back-to-back in azimuth



Kinematically focused to near-side

$\Delta y$  range determined by resonance mass, system temperature, radial boost velocity...

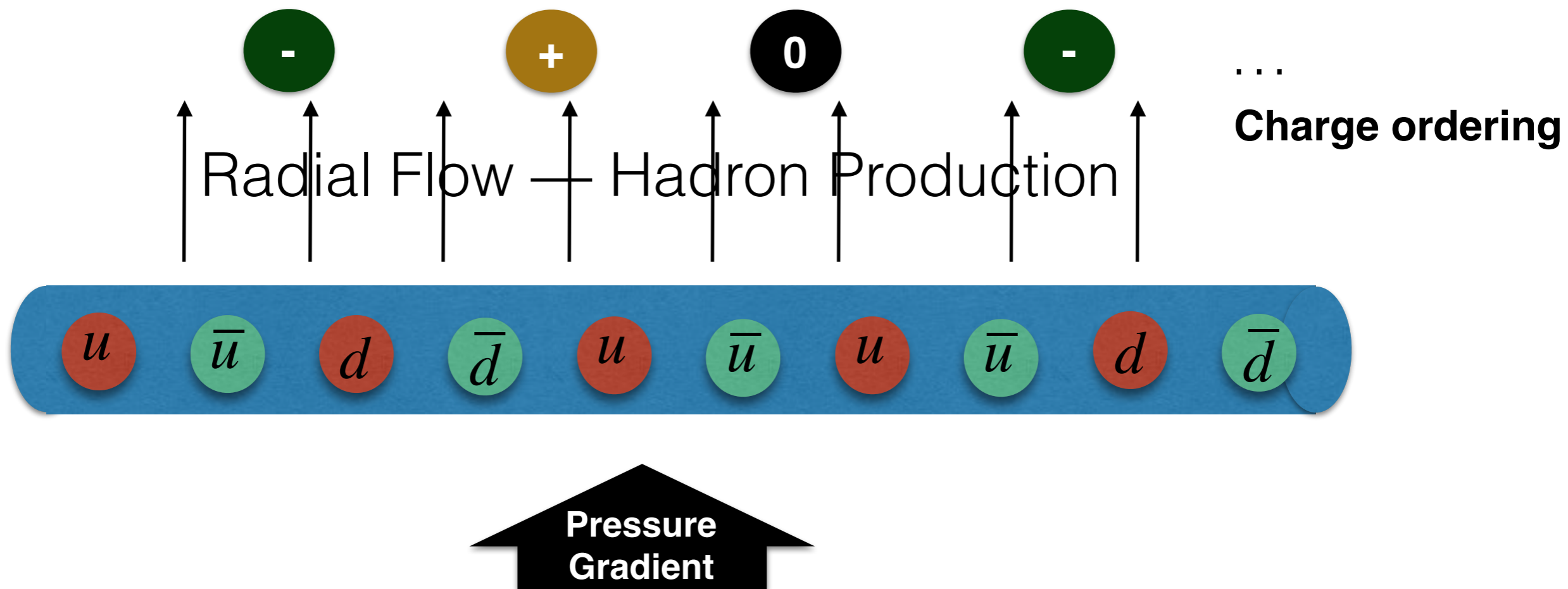
==> Net charge fluctuations.



# Role of Conservation Laws (2)

Conservation laws and particle production processes determine correlations.

## String Fragmentation, Color Tube Fragmentation

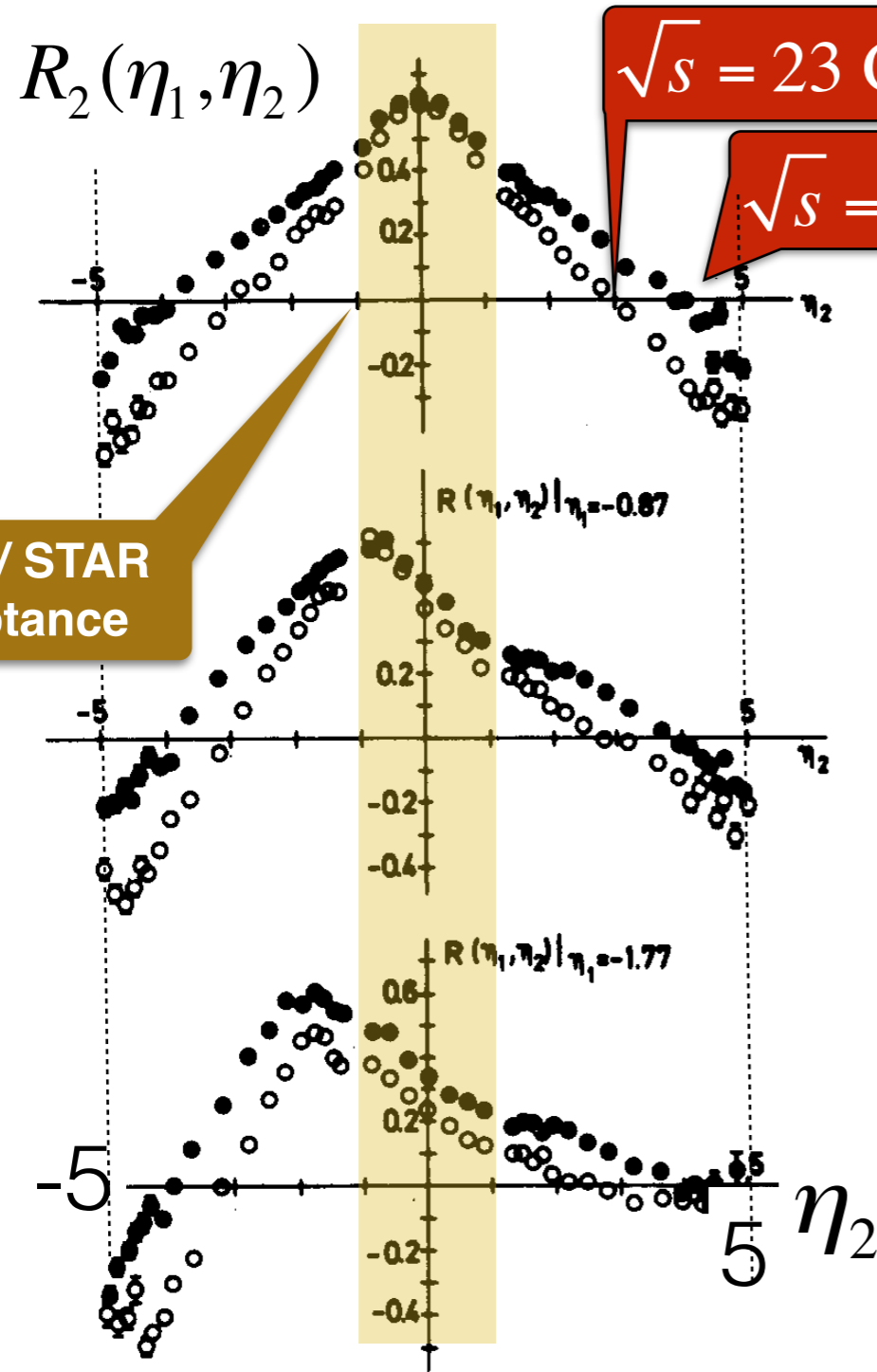


Multi-particle Longitudinal Long Range Correlations  
Anisotropic Flow  
Number of pairs, triplets depend on the acceptance...

# Example: ISR Results (p+p)

- S. R. Amendolia et al., PLB 48 (1974)

## Charge particles Longitudinal Correlations



- Correlations extend over wide range of rapidities
  - Also in p-pBar @FNAL.
- Such **long range correlations must persist in A+A**
  - Indicator: **Lack of flow plane decorrelation vs. eta gap.**
- Maybe modified by nuclear stopping, radial flow, late QGP hadronization, etc BUT they do NOT vanish...
- They underlie fluctuation measurements....
- Note: **Integral correlations for small eta range ARE NOT Poisson.**

# Poisson vs. Non-Poisson...

- Fluctuations do not become Poissonian when the acceptance is reduced.

- Two particle density:  $\rho_2(\phi_1, \eta_1, \phi_2, \eta_2) = \langle N(N-1) \rangle P_2(\phi_1, \eta_1, \phi_2, \eta_2)$

- Poisson realized if:  $P_2(\phi_1, \eta_1, \phi_2, \eta_2) = P_1(\phi_1, \eta_1)P_1(\phi_2, \eta_2)$

## Statistical Independence

$$\rho_2(\phi_1, \eta_1, \phi_2, \eta_2) = \rho_1(\phi_1, \eta_1)\rho_1(\phi_2, \eta_2)$$

$$\langle N(N-1) \rangle = \langle N \rangle^2$$

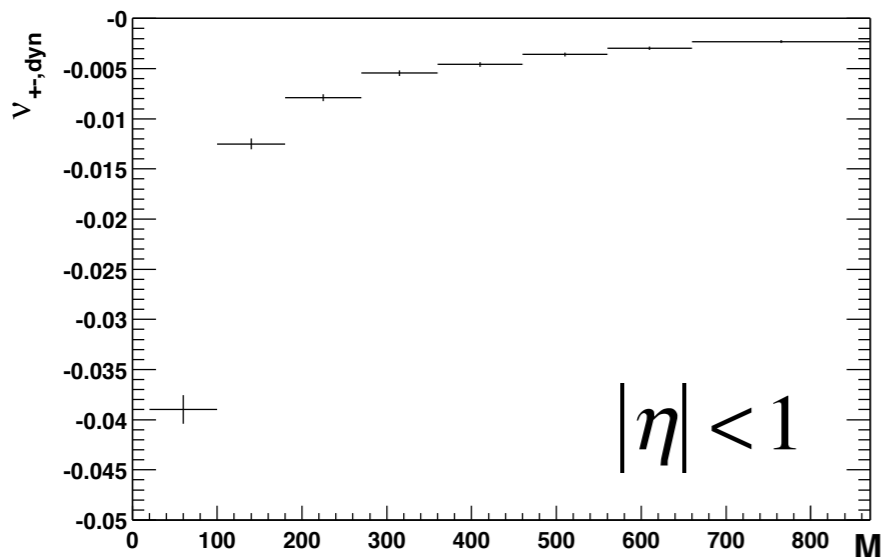
- If the differential correlation functions are **non-poisson**, **so are the integrals...**
- **But distinguishing non-Poisson from Poisson fluctuations** may be challenging with integral correlations and finite statistics - when the acceptance is reduced.
- **Go differential!!!**



# Two-Body Correlations Dilution vs System Size

Multiplicity fluctuations in Au+Au collisions at  $\sqrt{s_{NN}} = 130$  GeV

STAR, Phys.Rev. C68 (2003) 044905



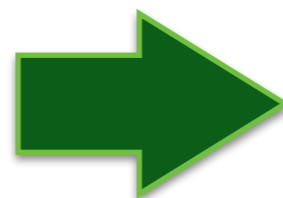
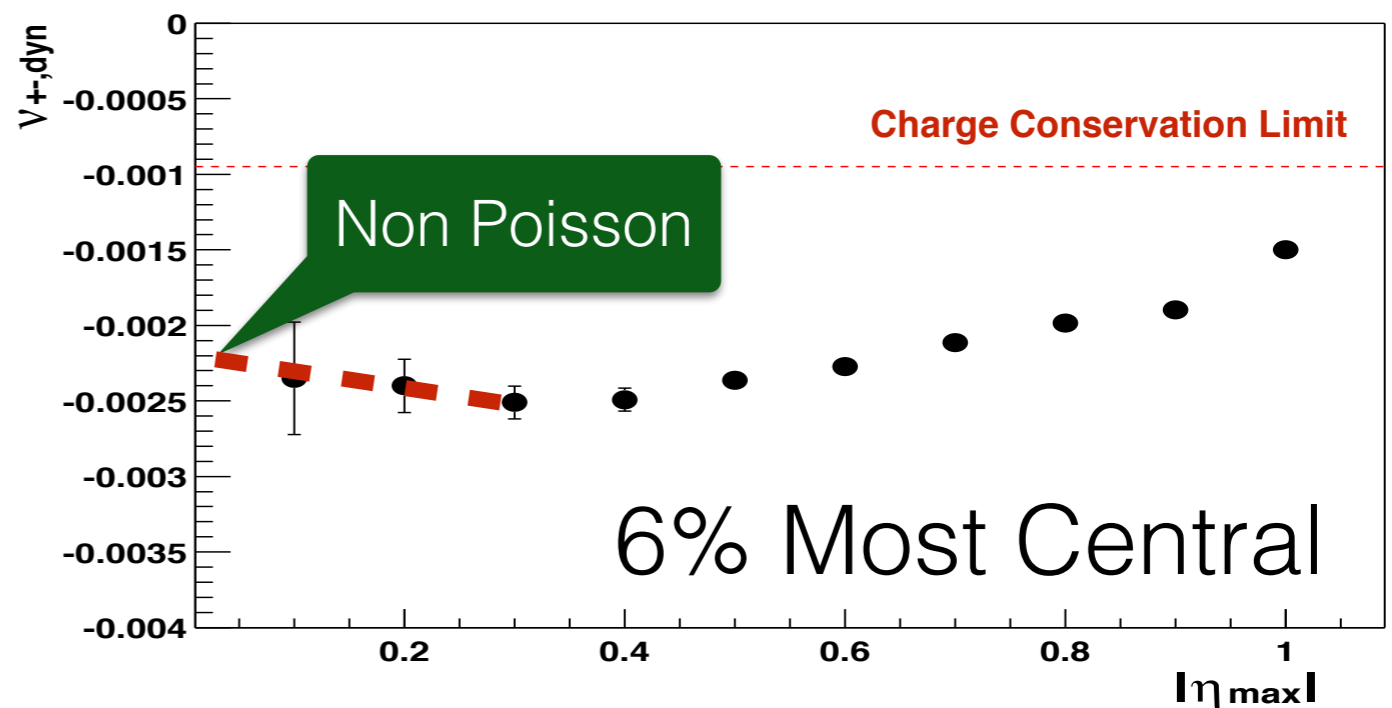
(a)

$$v_{dyn}^{(+-)} = \bar{R}_2^{(++)} + \bar{R}_2^{(--)} - 2\bar{R}_2^{(+-)}$$

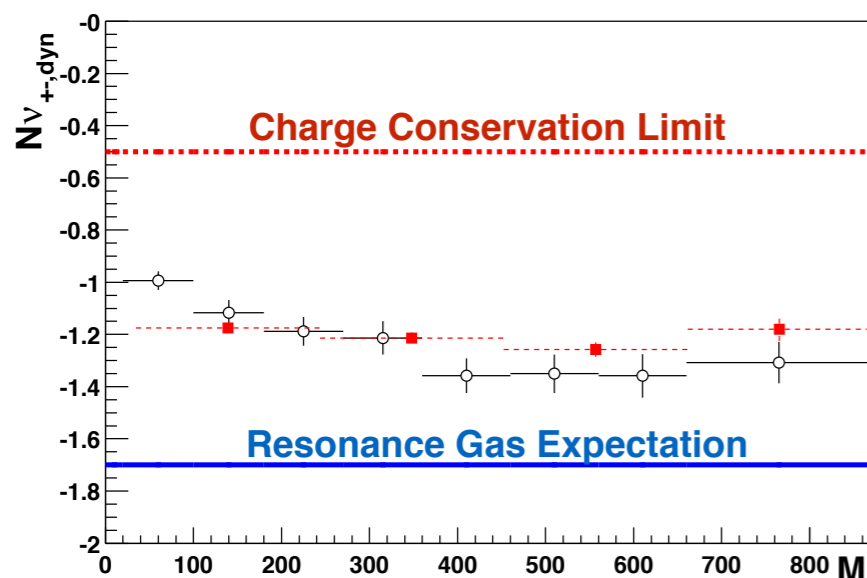
Two-body correlation dilution:

$$v_{dyn}^{(+-)}(AA) \propto \frac{1}{m_s} v_{dyn}^{(+-)}(pp)$$

Number of "sources"



Width of the Acceptance Matters



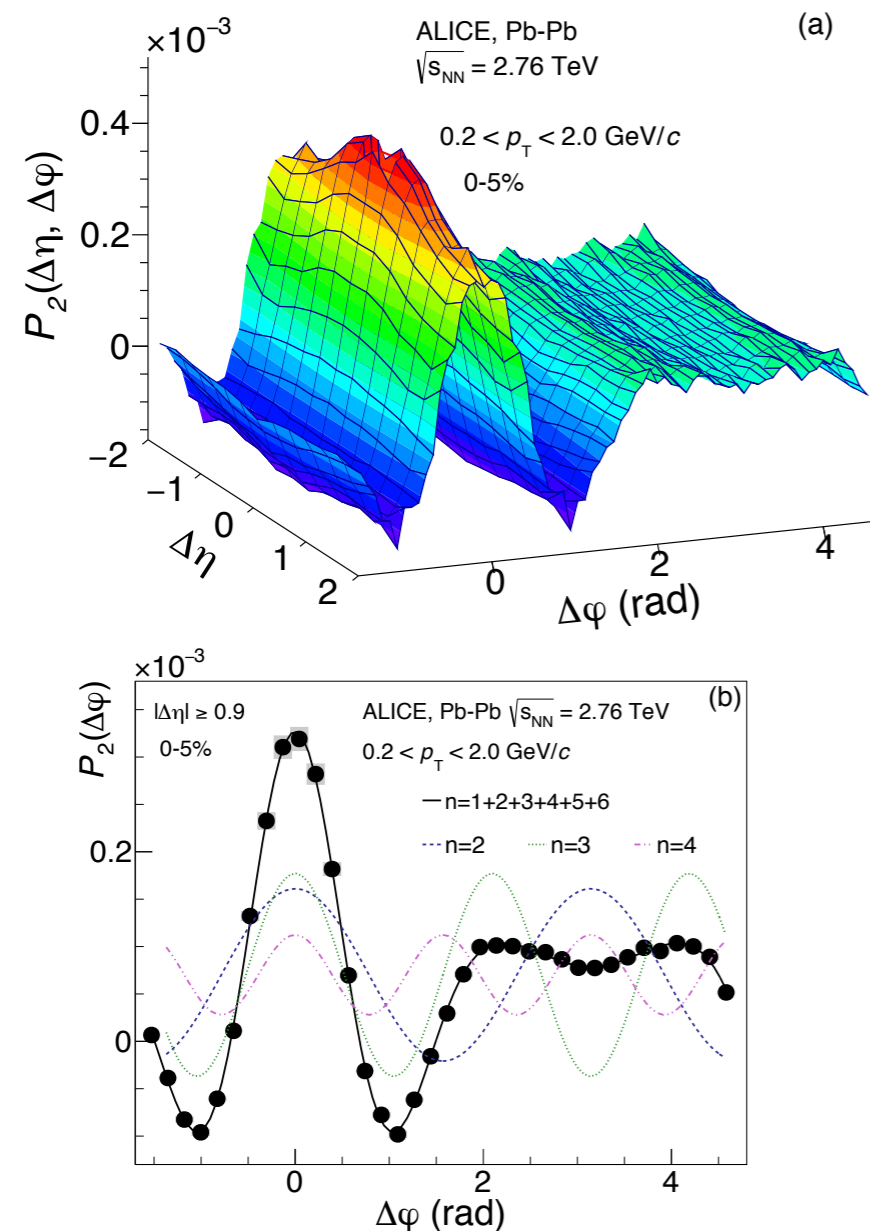
(b)



# Flow vs. Non-Flow

## Collective vs. Non-Collective: System Wide (Properties) vs. Elementary Processes

Flow dominance and factorization of transverse momentum correlations in Pb-Pb collisions at the LHC  
**ALICE, Phys. Rev. Lett. 118 (2017)162302.**



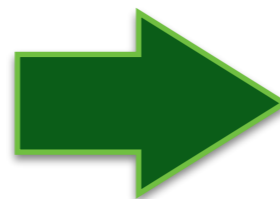
## Transverse Momentum Correlations

$$P_2 = \frac{\langle \Delta p_T \Delta p_T \rangle (\Delta\eta, \Delta\phi)}{\langle p_T \rangle^2} = \frac{1}{\langle p_T \rangle^2} \frac{\int_{p_{T,\min}}^{p_{T,\max}} \rho_2(\vec{p}_1, \vec{p}_2) \Delta p_{T,1} \Delta p_{T,2} dp_{T,1} dp_{T,2}}{\int_{p_{T,\min}}^{p_{T,\max}} \rho_2(\vec{p}_1, \vec{p}_2) dp_{T,1} dp_{T,2}}$$

## Flow Ansatz

$$v_n[P_2] \cong v_n^{p_T} / \langle p_T \rangle - v_n$$

$$v_n^{p_T} = \int \rho_1 v_n(p_T) p_T dp_T / \int \rho_1 dp_T$$

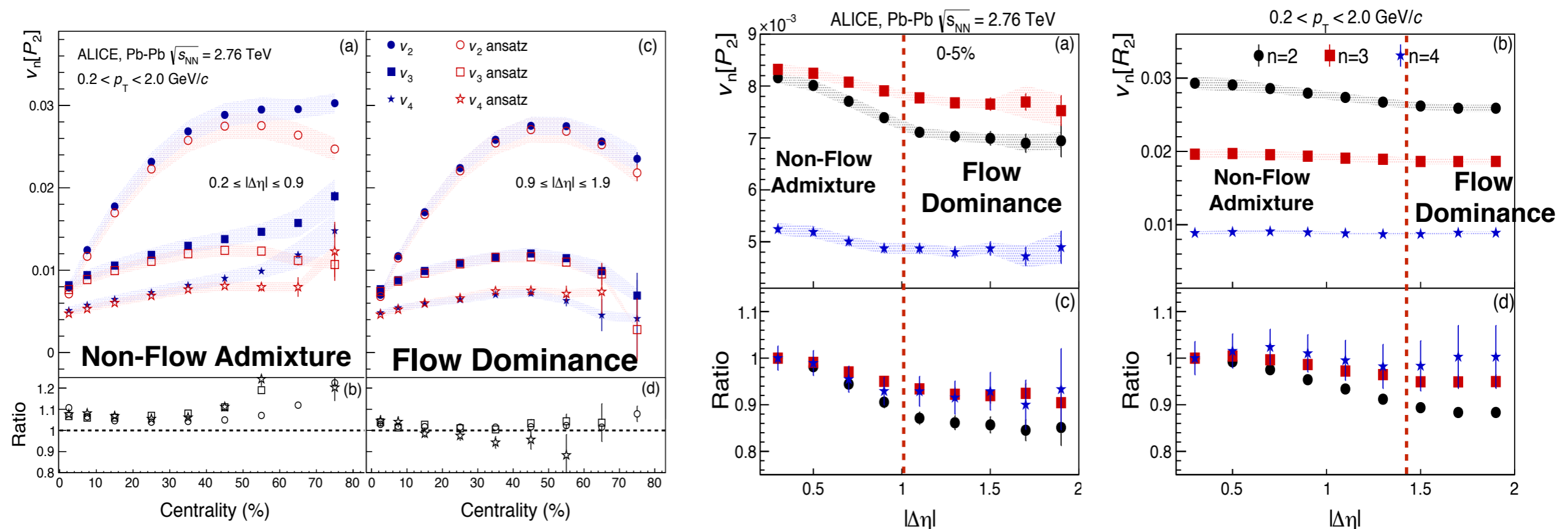


**Pt Correlations more sensitive to v3 than number correlations**

# Flow vs. Non-Flow

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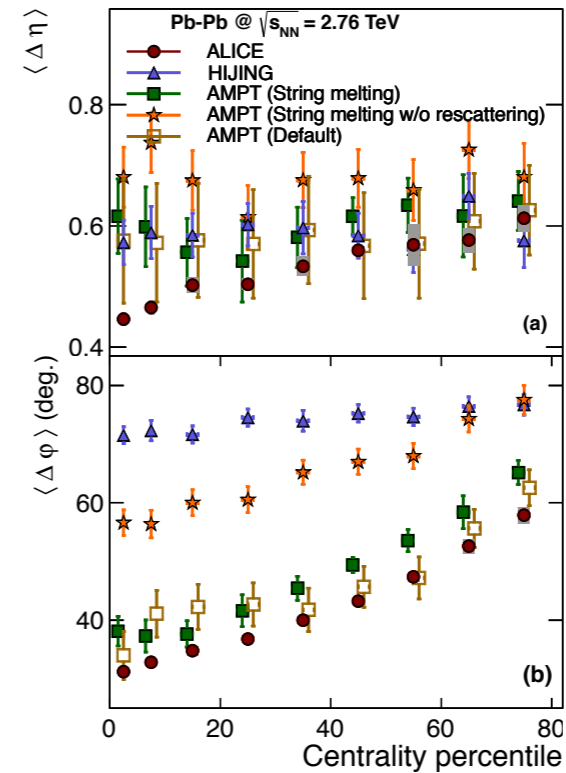
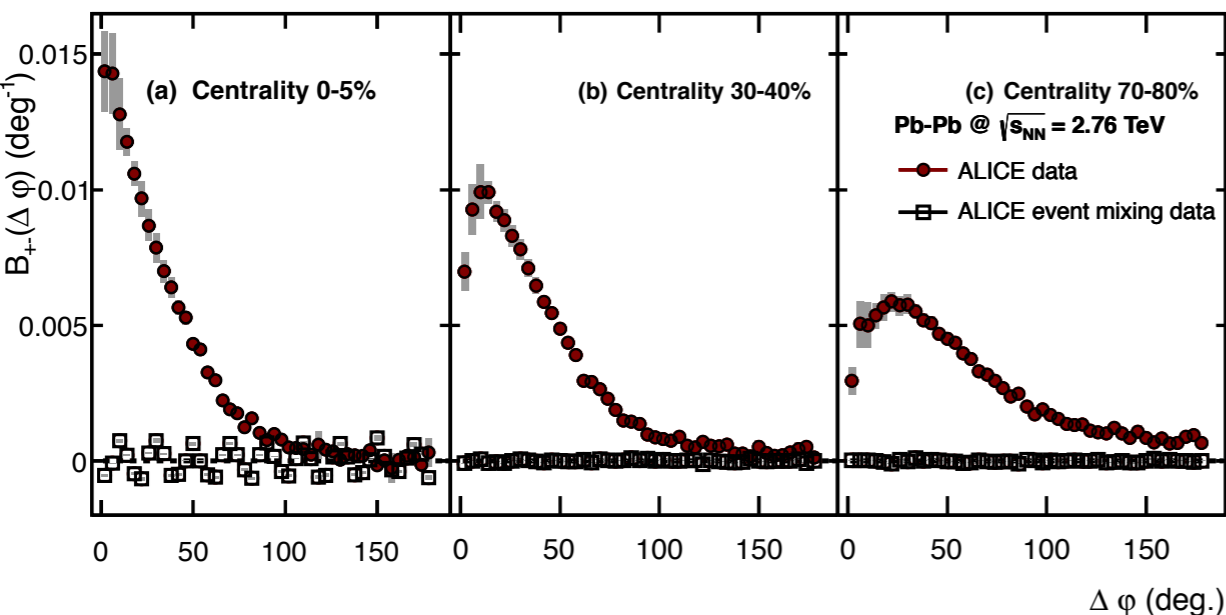
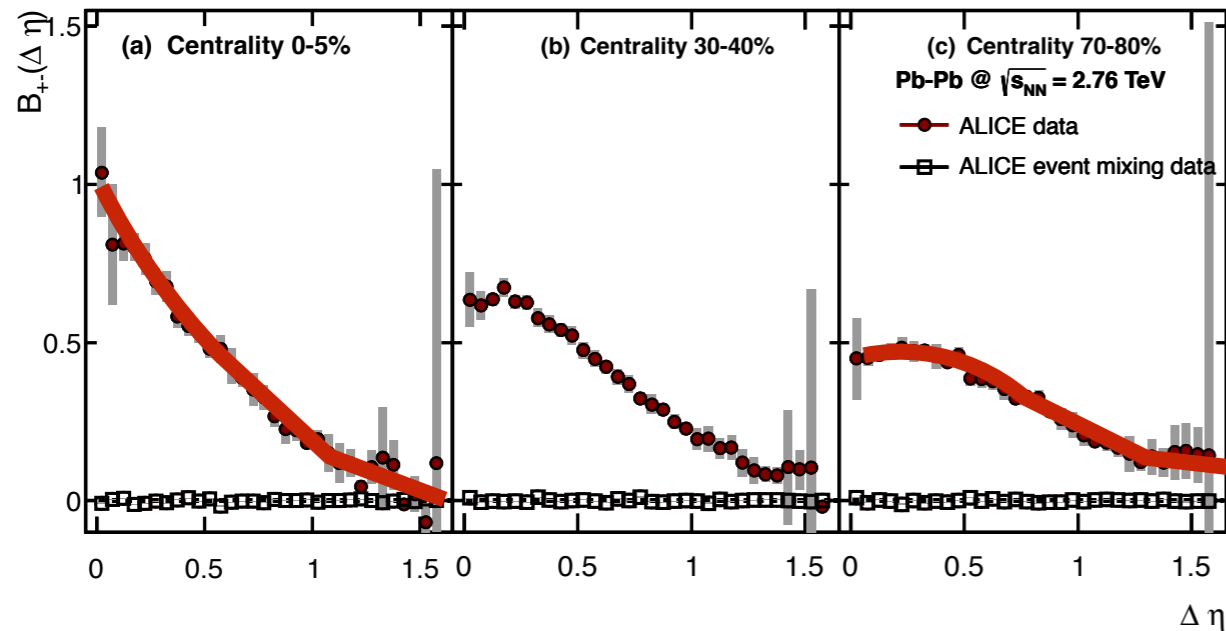
- A pair “eta gap” is required to suppress non-flow effects in differential  $R_2$  or  $P_2$  correlations & flow measurements.
- So why not in integral correlation measurements???



# Example (2): Balance Function

Charge correlations using the balance function in Pb–Pb collisions at 2.76 TeV

ALICE, Phys. Lett. B723 (2013) 267



- Radial Flow
- Delayed Hadronization
- Effective Temperature
- Effective Mass

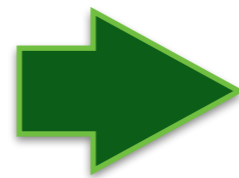


**Width of BF depends on centrality.**  
**Fluctuations depend on radial flow.**

# Balance Functions

$$R_2^{(CD)}(\Delta\phi, \Delta\eta) = \frac{1}{2} \left[ R_2^{(US)}(\Delta\phi, \Delta\eta) - R_2^{(LS)}(\Delta\phi, \Delta\eta) \right]$$

$R_2^{(CD)}(\Delta\phi, \Delta\eta) \propto$  Balance Function

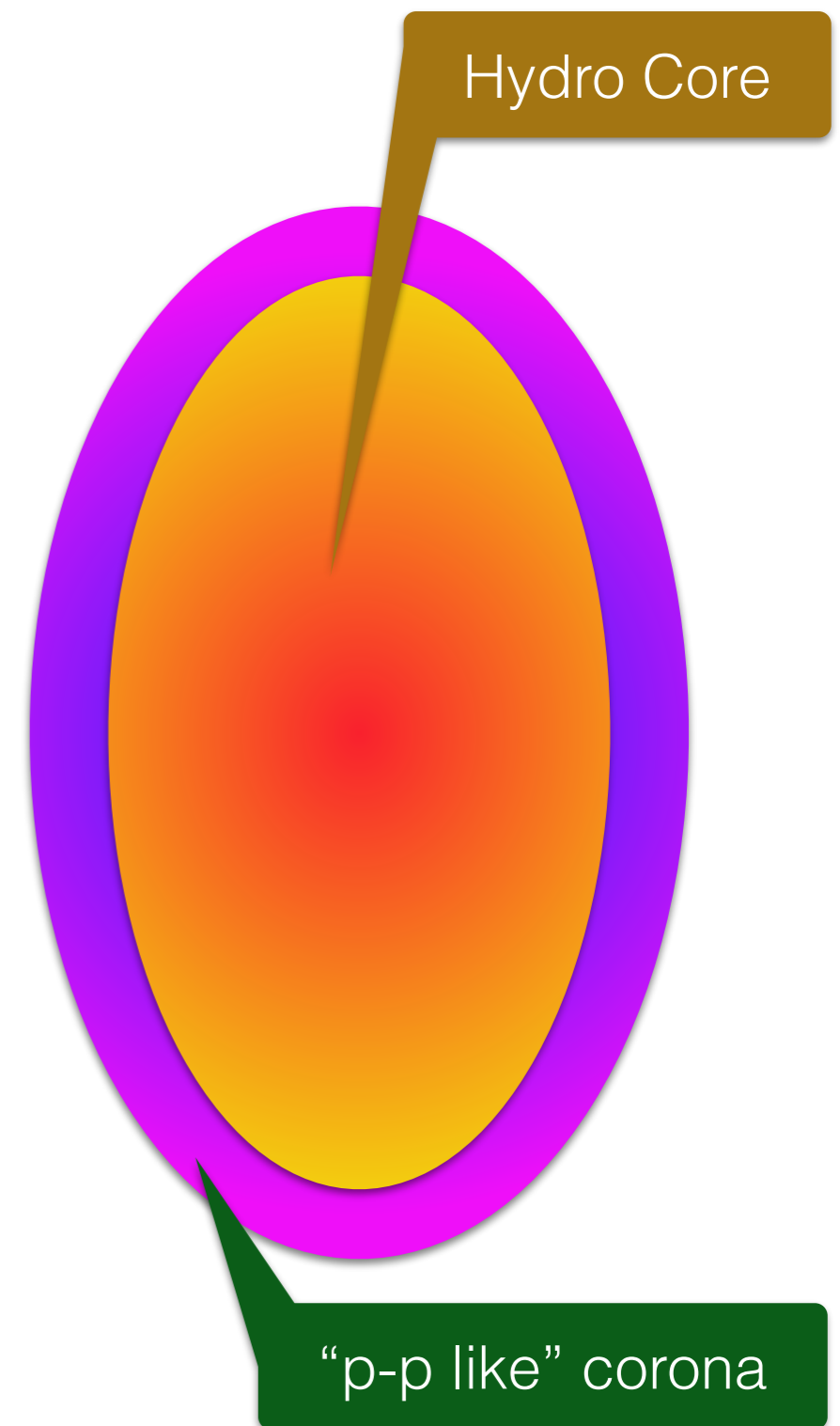


- **Width of Balance Function depends on centrality, radial boost, life time of system (delayed hadronization)**
- **Effective Charge conservation effects change w/ system size, impact parameter, beam energy.**
- **The Acceptance Width Matters But its effects can be measured and modeled.**
- **The model is better if based on a measurement!**



# Core/Corona Contributions

- EPOS 3.0 reproduces many observables
  - Particle yields, Species ratios, Average Momentum, Anisotropic flow
  - For small and large systems, collision centrality dependence
- Suggests/Implies
  - Core/Corona **contributions and distinctions** are “real”
  - **Core vs. Corona contributions to charge/strangeness/baryon correlations and fluctuations** may be different and thus must be accounted for.
  - One must understand the **energy dependence of the core vs. corona contributions** to charge correlations/fluctuations.
- But...

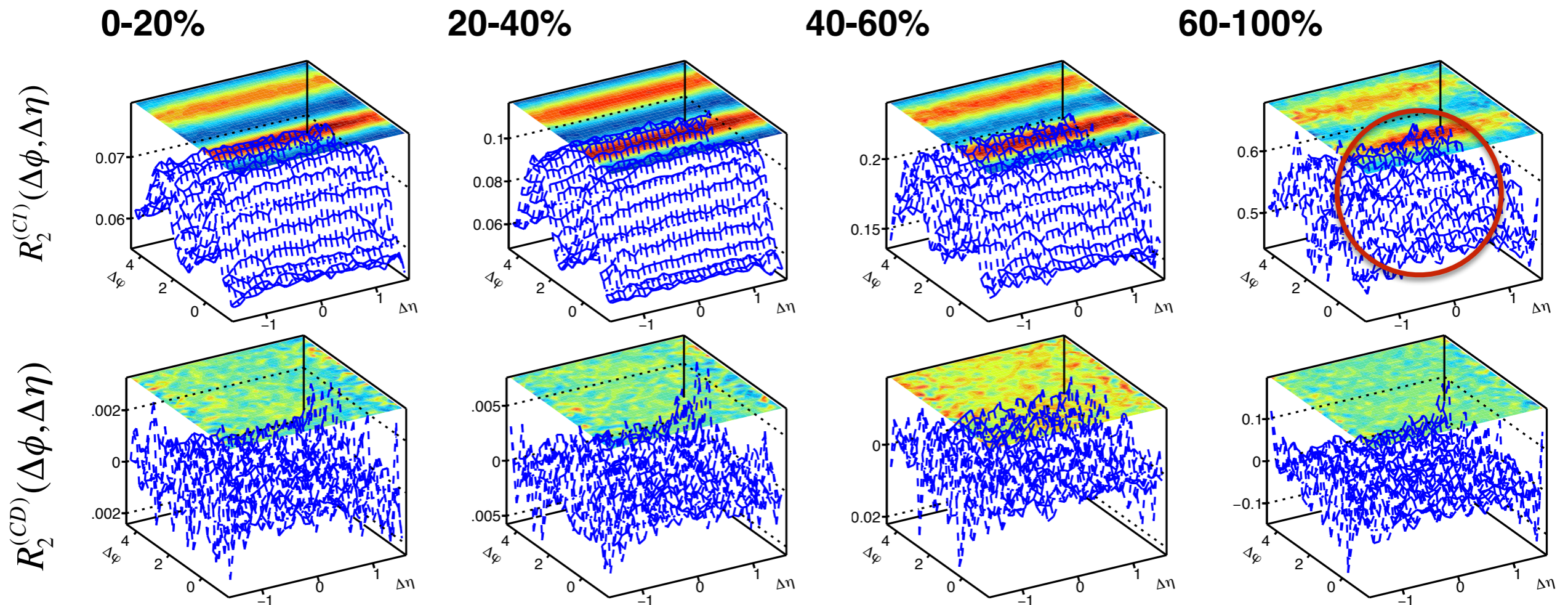


# Core/Corona Contributions

Unfortunately **EPOS does not reproduce CI or CD charge R2 correlation functions** in peripheral to central collisions.

Pb-Pb @ 2.76 TeV

S. Basu, V. Gonzalez, C.P., et al., in preparation



**Fails to reproduce ALICE data.**

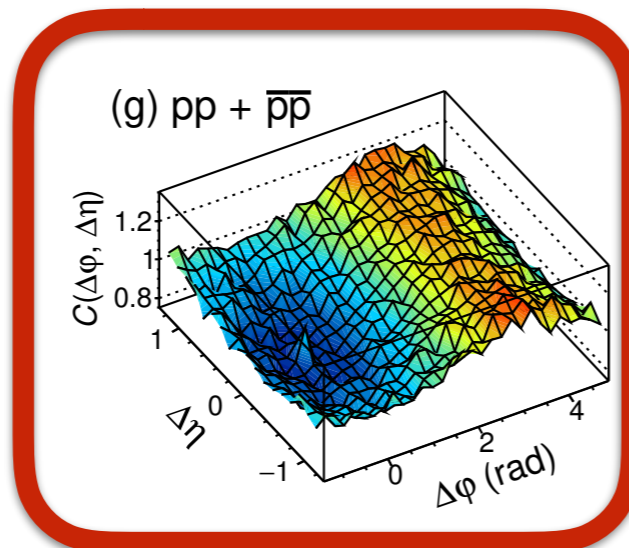
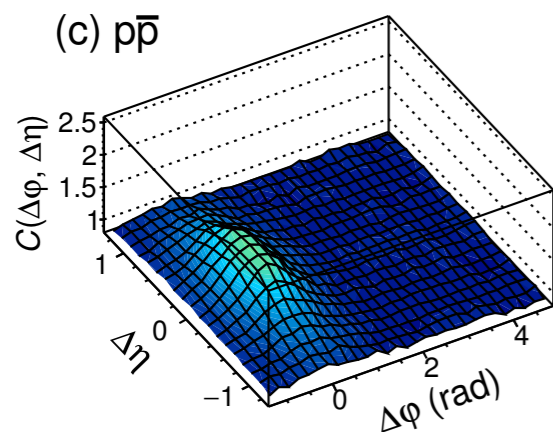
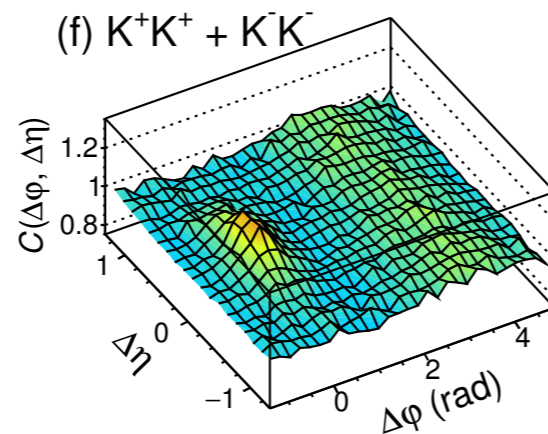
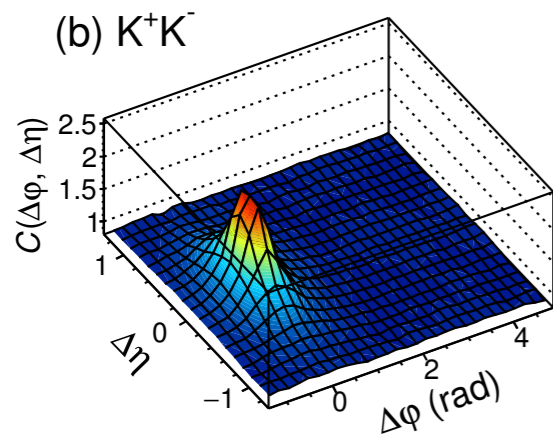
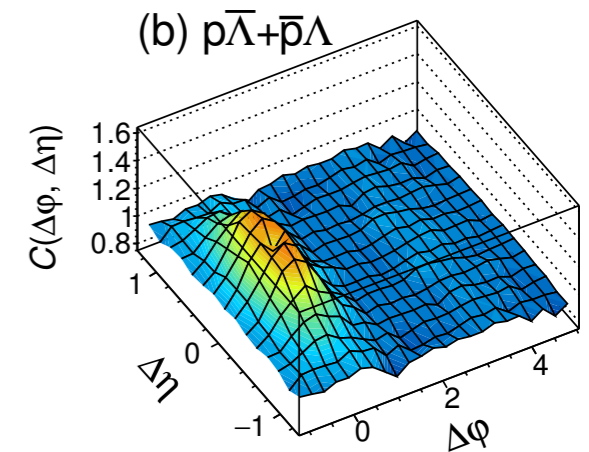
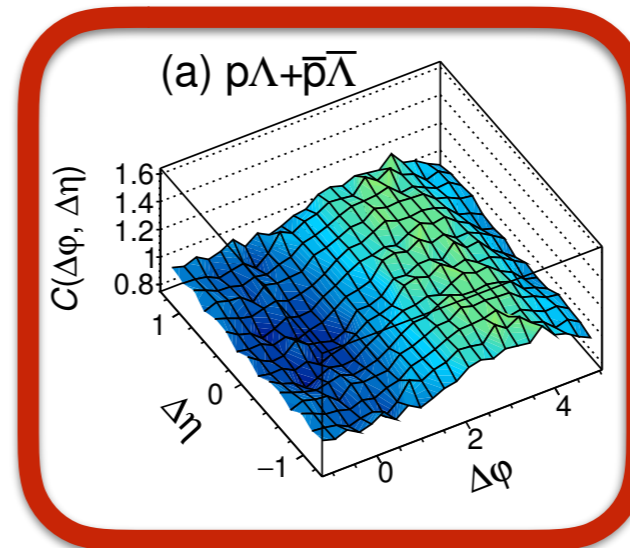
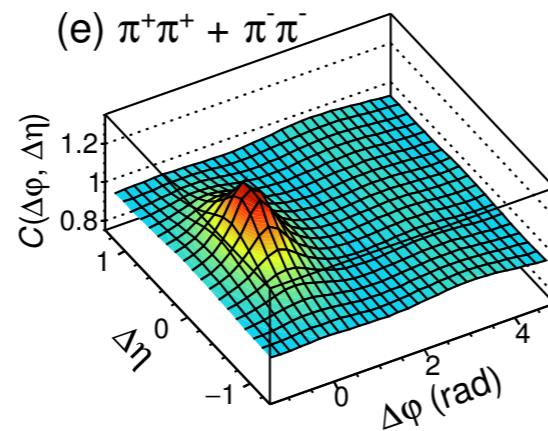
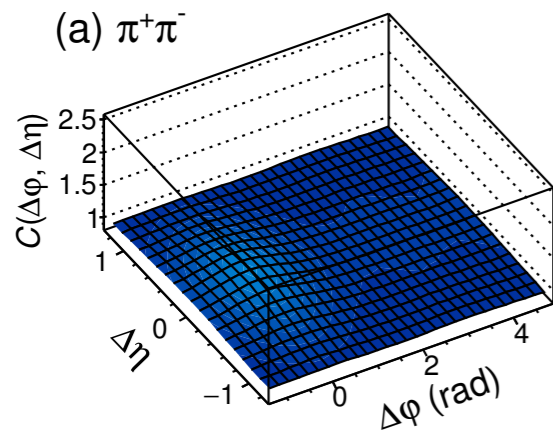
**Core contributions mishandled by Cooper-Frye prescription?**



# Some surprises too

Insight into particle production mechanisms via angular correlations of identified particles in pp collisions at 7 TeV

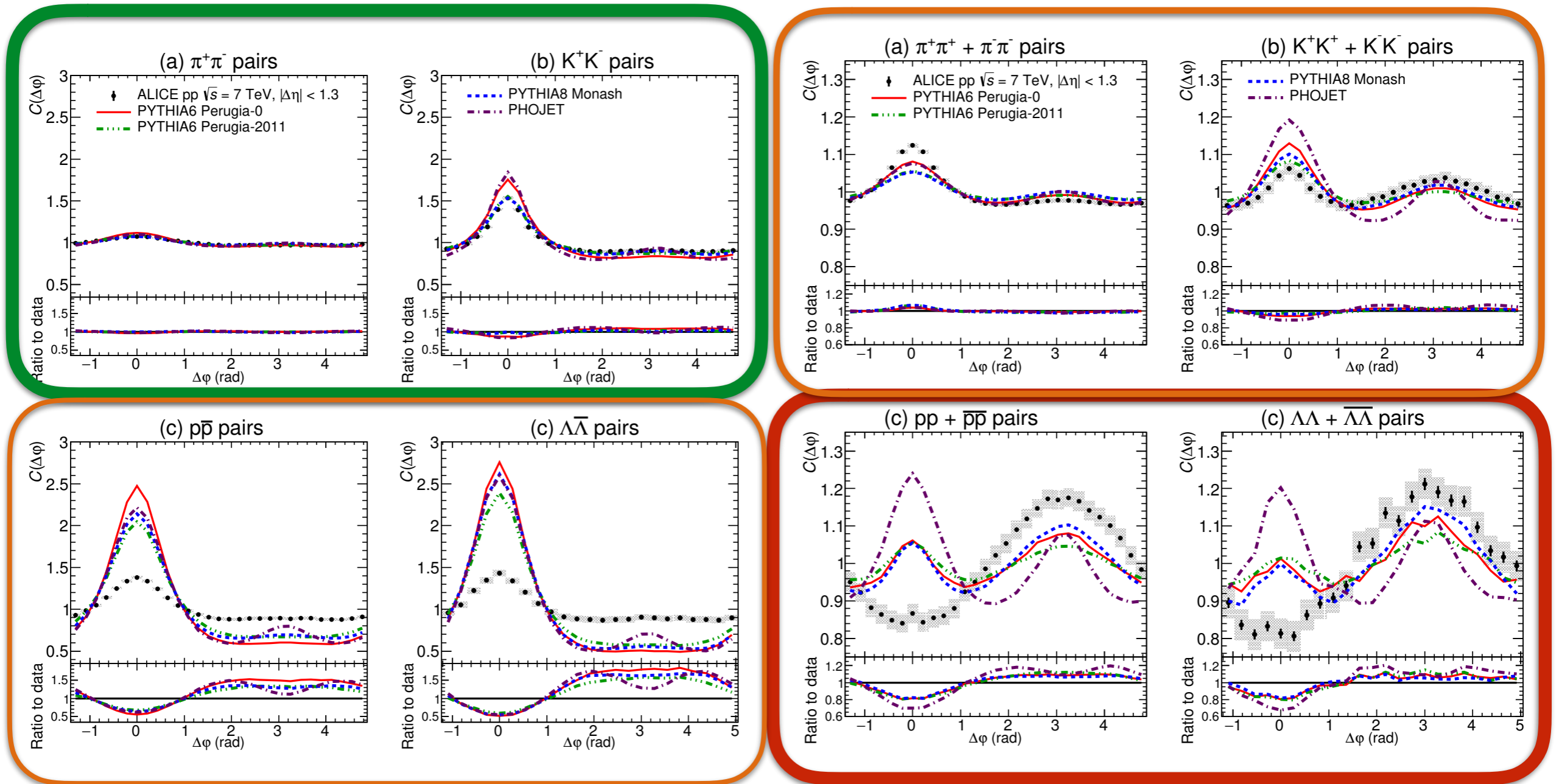
ALICE, arXiv:1612.08975v1



p+p @ 7 TeV

# Other models get it wrong ;-)

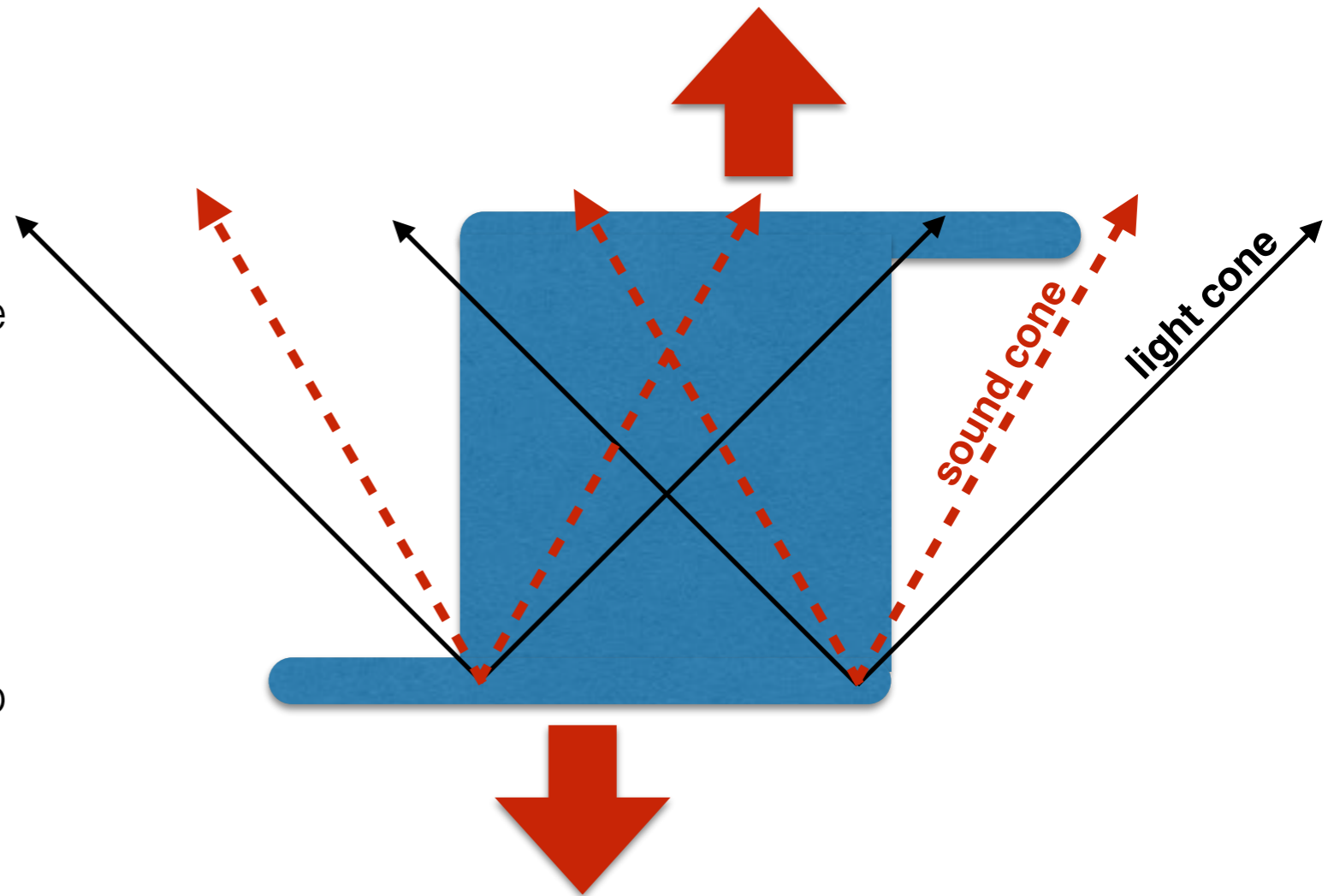
PYTHIA, p+p @ 7 TeV



p-p “base-line” rather unexpected even at 7 TeV!!!

# System Size & Lifespan

- Inclusive particle production, e.g., strangeness saturation, suggests local thermalization is achieved rather rapidly.
- Yet, if one probes the long distance scale behavior, there has to be time for the system to relax into a medium, i.e., to “**mediumize.**”
  - This should be particularly important for the spatial correlation length one wishes to probe with fluctuations.
  - But even at the speed of light, opposing sides of the collision systems remain causally disconnected until freeze out — and the **speed of sound is likely more relevant in this context...**

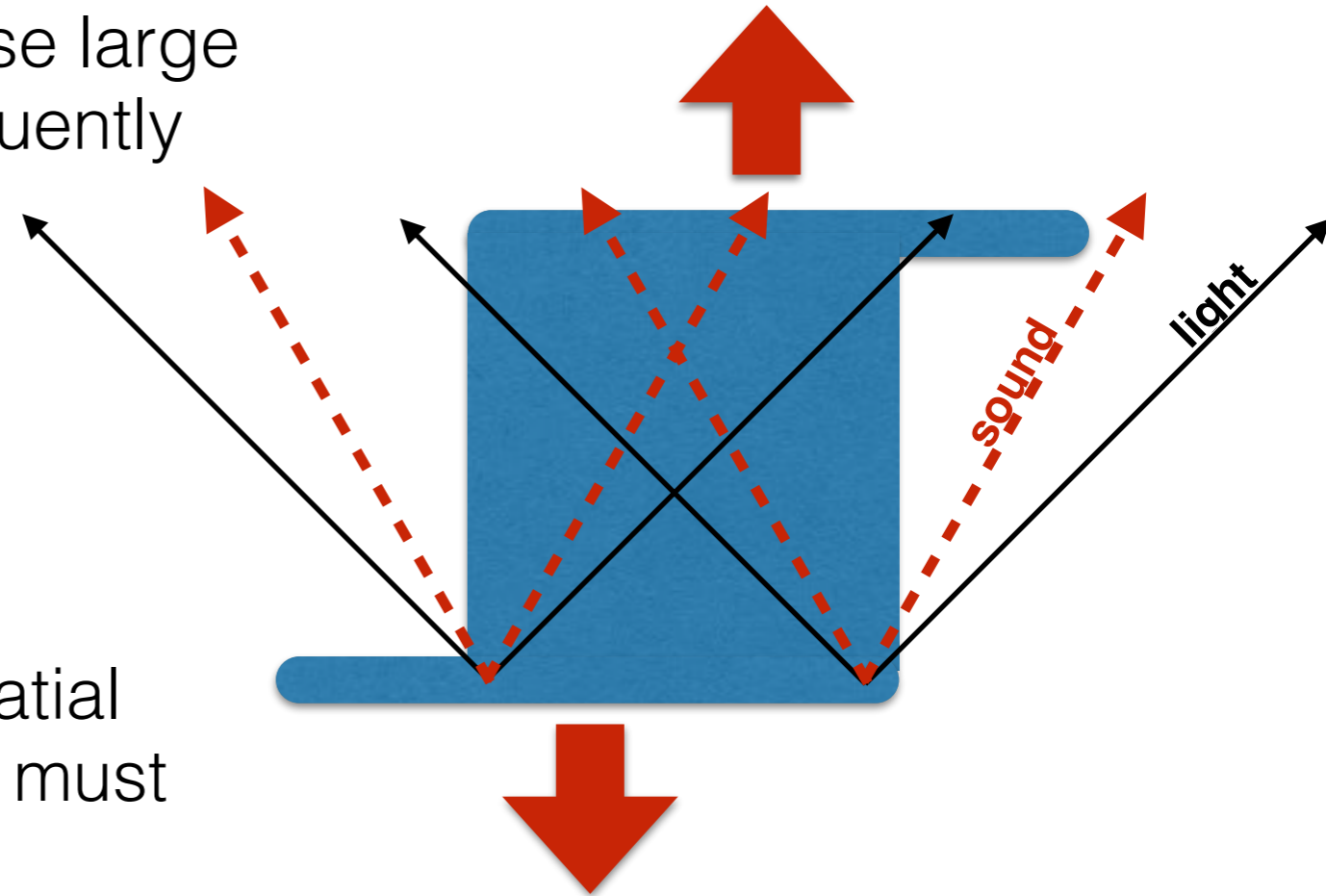


- The left end side is not “informed” of the right end side until the system freezes out.
- Transverse long range behavior does not materialize before system break-up
- The correlation length actually probed is probably quite short.



# System Size & Lifespan (2)

- Capacity to mediate and sense large correlation lengths must consequently depend on
  - collision centrality
  - system size
  - system lifetime
- Sensitivity to variations of the spatial correlation length consequently must depend on
  - produced multiplicity
  - system size
  - beam energy
  - as well as EOS and proximity to C.P.



**Berdnikov-Rajagopal (2000):**  $\xi \sim 2 - 3 \text{ fm}$



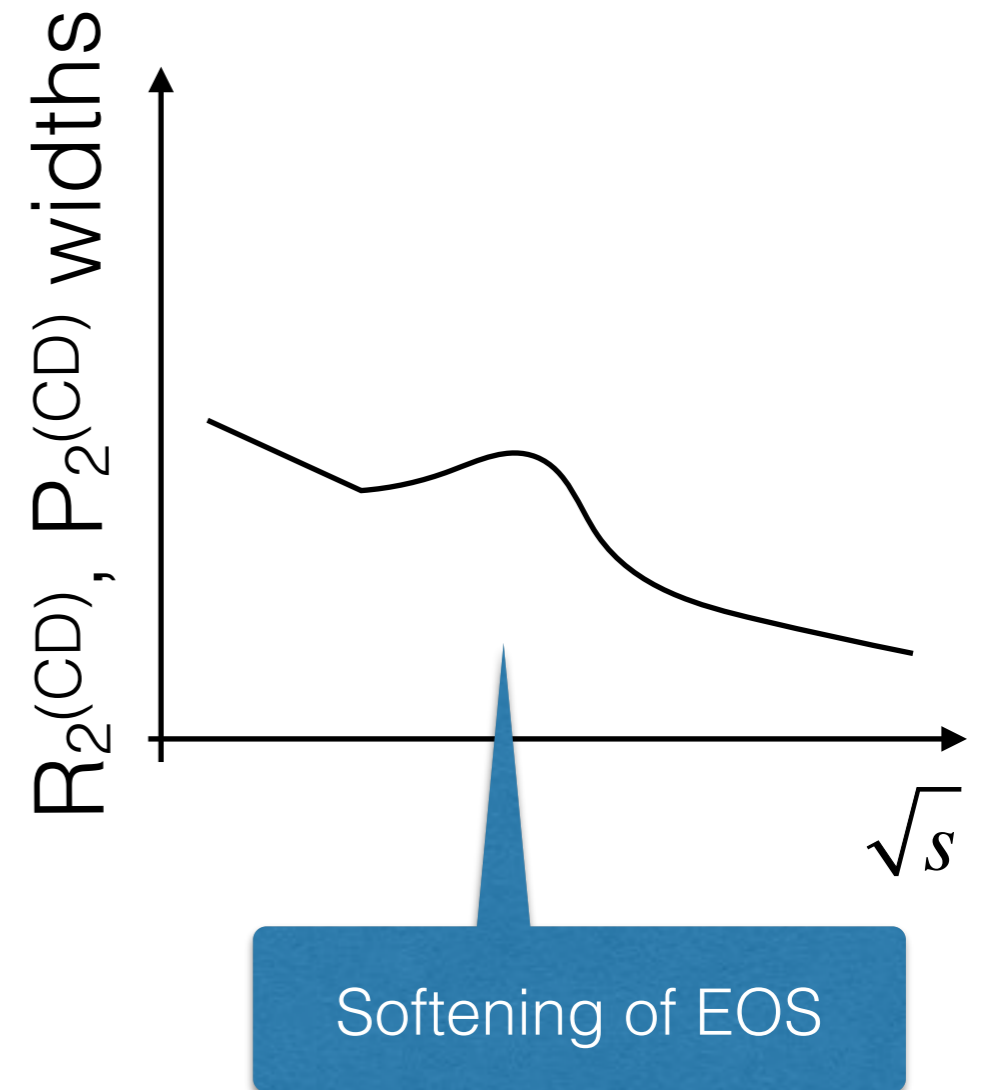
# Measure Factorial Moments and Corr Fct.

- Integral correlations are
  - (slow) **functions of the acceptance**
  - PARTLY determined by non-flow phenomena, not just system wide properties.
- **Eliminate/Suppress non-flow effects**
  - Require an eta-gap in measurement of cumulants?
  - Better still: measure differential correlations
    - e.g.,  $R_4$  (Differential version of Volker/Adam's  $C_4$ ) suppress non-flow thereby focusing on system wide properties.
    - Side benefit: differential correlations are more easily corrected for detector effects.
    - **Factorial moments are more robust** than integral cumulants
- **Note: Puzzling features of STAR's  $R_2$  Measurement at 19.6 GeV ... show  $R_2$  is more sensitive to details of the detector response BUT when these details are understood, the integral of  $R_2$  shall be more reliable.**



# Diversify Types of Measurements

- For instance:
  - Width and strength of Balance Functions of  $R_2$  and  $P_2$  vs. beam energy
- Softening of the equation implies change in radial flow which implies
  - changes in kinematic focusing
  - broadening of the width of balance function
- Caveat:
  - reduction in beam energy implies changes in particle production mechanisms that may feature different rapidly spans.



Study  $R_2$ ,  $P_2$  amplitude also

## Part II: Some Technical Considerations

- Acceptance:
  - **Cannot be corrected** for but can be varied or averaged across, e.g., vs.  $\bar{\eta} = (\eta_1 + \eta_2) / 2$
- Efficiency:
  - Single and Pair Efficiencies can be accounted for with robust ratios, weight technique, etc.
- Contamination:
  - Secondaries contamination identifiable as extra features or correlation shape changes in differential correlation functions.

S. Ravan, P. Pujahari, S. Prasad, C.A.P., Phys.Rev. C89 (2014) 024906

# Efficiency & Robustness (I)

- Model the Probability of observing  $n$  particles given  $N$  (in a given “bin”) were produced with binomial distribution.

$$P_{\text{det}}(n | N; \varepsilon) = \frac{\varepsilon^N (1 - \varepsilon)^{N-n}}{n!(N - n)!}$$

- Model the Probability of observing particle fluctuations...

- Singles

$$P_M(n(\eta_1) | N(\eta_1); \varepsilon_1) = \sum_{N_1=1}^{\infty} P_T(N(\eta_1)) \frac{\varepsilon_1^{N(\eta_1)} (1 - \varepsilon_1)^{N(\eta_1) - n(\eta_1)}}{n(\eta_1)! (N(\eta_1) - n(\eta_1))!}$$

Measured Probability distribution

True Probability distribution

- Pairs

$$P_M(n(\eta_1), n(\eta_2) | N(\eta_1), N(\eta_2); \varepsilon_1, \varepsilon_2) = \sum_{N_1, N_2=1}^{\infty} P_T(N(\eta_1), N(\eta_2)) \frac{\varepsilon_1^{N(\eta_1)} (1 - \varepsilon_1)^{N(\eta_1) - n(\eta_1)}}{n(\eta_1)! (N(\eta_1) - n(\eta_1))!} \frac{\varepsilon_2^{N(\eta_2)} (1 - \varepsilon_2)^{N(\eta_2) - n(\eta_2)}}{n(\eta_2)! (N(\eta_2) - n(\eta_2))!}$$

Measured Probability distribution

True Probability distribution

# Efficiency & Robustness (I)

- Singles Average

- True

$$\langle N \rangle = \int P_T(N) N dN$$

- Measured

$$\langle n \rangle = \int P_M(n) n dn$$

$$\langle n \rangle = \int P_T(N) dN \int n P_{\text{det}}(n | N; \varepsilon) dn = \varepsilon \int P_T(N) N dN$$

$$\langle n \rangle = \varepsilon \langle N \rangle$$

- Pair Averages

- True

$$\langle N_1 N_2 \rangle = \int P_p(N_1, N_2) N_1 N_2 dN_1 dN_2$$

- Measured

$$\langle n_1 n_2 \rangle = \int P_m(n_1, n_2) n_1 n_2 dn_1 dn_2$$

$$\langle n_1 n_2 \rangle = \varepsilon_1 \varepsilon_2 \langle N_1 N_2 \rangle$$

Correct for any True PDF  
Only requires binomial sampling.

# Efficiency & Robustness (III)

- Correlation function measurement

- Goal:

$$C_2^{(True)}(\eta_1, \eta_2) = \rho_2(\eta_1, \eta_2) - \rho_1(\eta_1)\rho_1(\eta_2)$$

True

- “Raw” Measurement

$$\begin{aligned} C_2^{(measured)}(\eta_1, \eta_2) &= \frac{1}{\Delta\eta^2} \langle n(\eta_1)n(\eta_2) \rangle - \langle n(\eta_1) \rangle \langle n(\eta_2) \rangle \\ &= \frac{1}{\Delta\eta^2} \varepsilon_1(\eta_1)\varepsilon_2(\eta_2) \{ \langle N(\eta_1)N(\eta_2) \rangle - \langle N_1(\eta_1) \rangle \langle N_2(\eta_2) \rangle \} \end{aligned}$$

Measured

- Ratio Fct

$$\begin{aligned} R_2^{(Measured)}(\eta_1, \eta_2) &= \frac{\langle n(\eta_1)n(\eta_2) \rangle}{\langle n(\eta_1) \rangle \langle n(\eta_2) \rangle} - 1 \\ &= \frac{\varepsilon_1(\eta_1)\varepsilon_1(\eta_2) \langle N(\eta_1)N(\eta_2) \rangle}{\varepsilon_1(\eta_1)\varepsilon_1(\eta_2) \langle N(\eta_1) \rangle \langle N(\eta_2) \rangle} - 1 = \frac{\langle N(\eta_1)N(\eta_2) \rangle}{\langle N(\eta_1) \rangle \langle N(\eta_2) \rangle} - 1 \end{aligned}$$

$$R_2^{(Measured)}(\eta_1, \eta_2) = R_2^{(True)}(\eta_1, \eta_2)$$

Efficiencies cancel >>> Robust Observable

# Folding of Singles vs Event Mixing

- Ratio R requires product of single yields
  - Can be obtained from actual singles

$$R_M(\eta_1, \eta_2) = \frac{\langle n_1(\eta_1)n_2(\eta_2) \rangle}{\langle n_1(\eta_1) \rangle \langle n_2(\eta_2) \rangle} - 1$$

- Can be obtained from mixed events

$$R_M^{(mixed)}(\eta_1, \eta_2) = \frac{\langle n_1 n_2(\eta_1, \eta_2) \rangle}{\langle n_1(\eta_1) \rangle \langle n_2(\eta_2) \rangle} = \frac{\langle n_1 n_2(\eta_1, \eta_2) \rangle_{\text{same}}}{\langle n_1 n_2(\eta_1, \eta_2) \rangle_{\text{mixed}}} - 1$$

No event  
mixing  
required

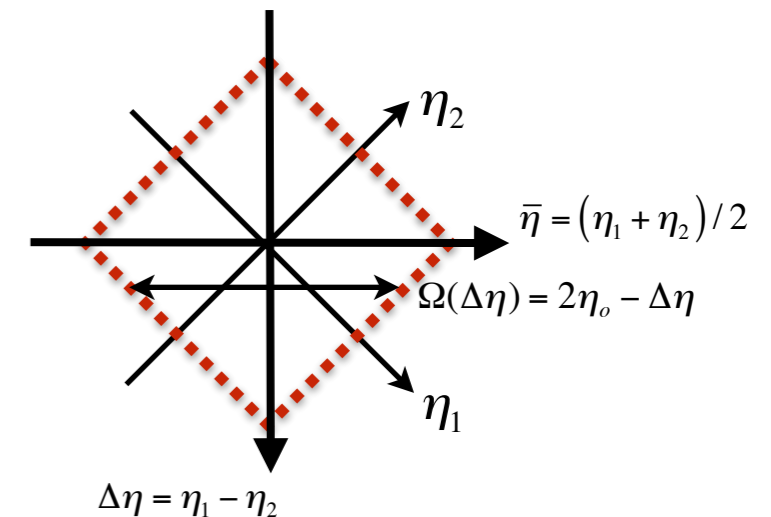
Greater  
flexibility  
w/ cuts

# Evaluation of Normalized Cumulants Two Methods

- **Method 1: Ratio of averages (Common Approach)**

- Measure pair yields (same and mixed) directly vs  $\Delta\eta$ .
- Calculate  $R(\Delta\eta)$  by taking the ratio of same to mixed.

$$R_M(\Delta\eta) = \frac{\frac{1}{\Omega(\Delta\eta)_{accept}} \int \rho_2(\Delta\eta, \bar{\eta}) d\bar{\eta}}{\frac{1}{\Omega(\Delta\eta)_{accept}} \int \rho_1 \otimes \rho_1(\Delta\eta, \bar{\eta}) d\bar{\eta}} - 1$$



- **Method 2: Average of Ratio**

- Measure  $R(\eta_1, \eta_2)$  by taking the ratio of same to mixed.
- Average out  $\bar{\eta}$  dependence, i.e. project onto  $\Delta\eta$  to get  $R(\Delta\eta)$

$$R_M(\Delta\eta) = \frac{1}{\Omega(\Delta\eta)_{accept}} \int R_2(\Delta\eta, \bar{\eta}) d\bar{\eta} = \frac{1}{\Omega(\Delta\eta)_{accept}} \int \left( \frac{\rho_2(\Delta\eta, \bar{\eta})}{\rho_1 \otimes \rho_1(\Delta\eta, \bar{\eta})} - 1 \right) d\bar{\eta}$$

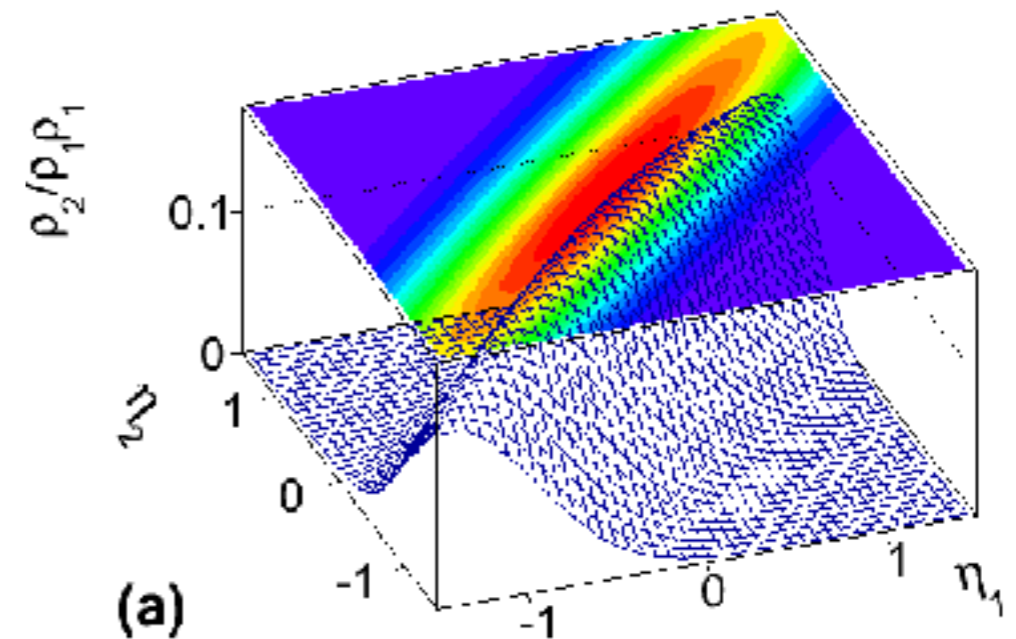
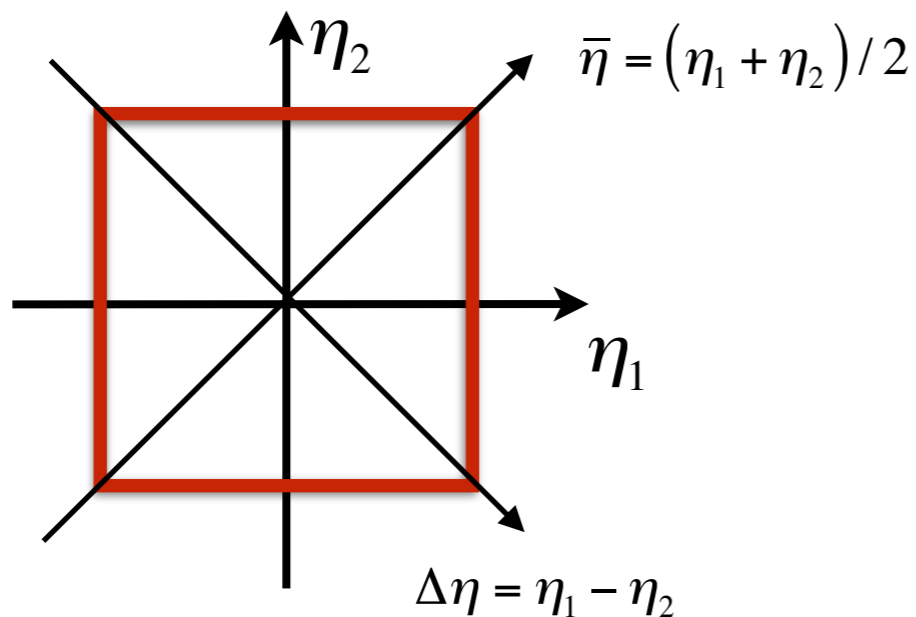


# Method 1 vs. Method 2: Correlation Model

- Correlation Model:
  - Longitudinal Model w/ Two-particle emission correlated vs.

$$C(\Delta\eta, \bar{\eta}) \propto \exp\left(-\frac{\Delta\eta^2}{2\sigma_{\Delta\eta}^2}\right) \exp\left(-\frac{\bar{\eta}^2}{2\sigma_{\bar{\eta}}^2}\right)$$

- Assumed factorization of the dependence on the relative and average pseudorapidity.
- **Factorization may not be realized in practice**

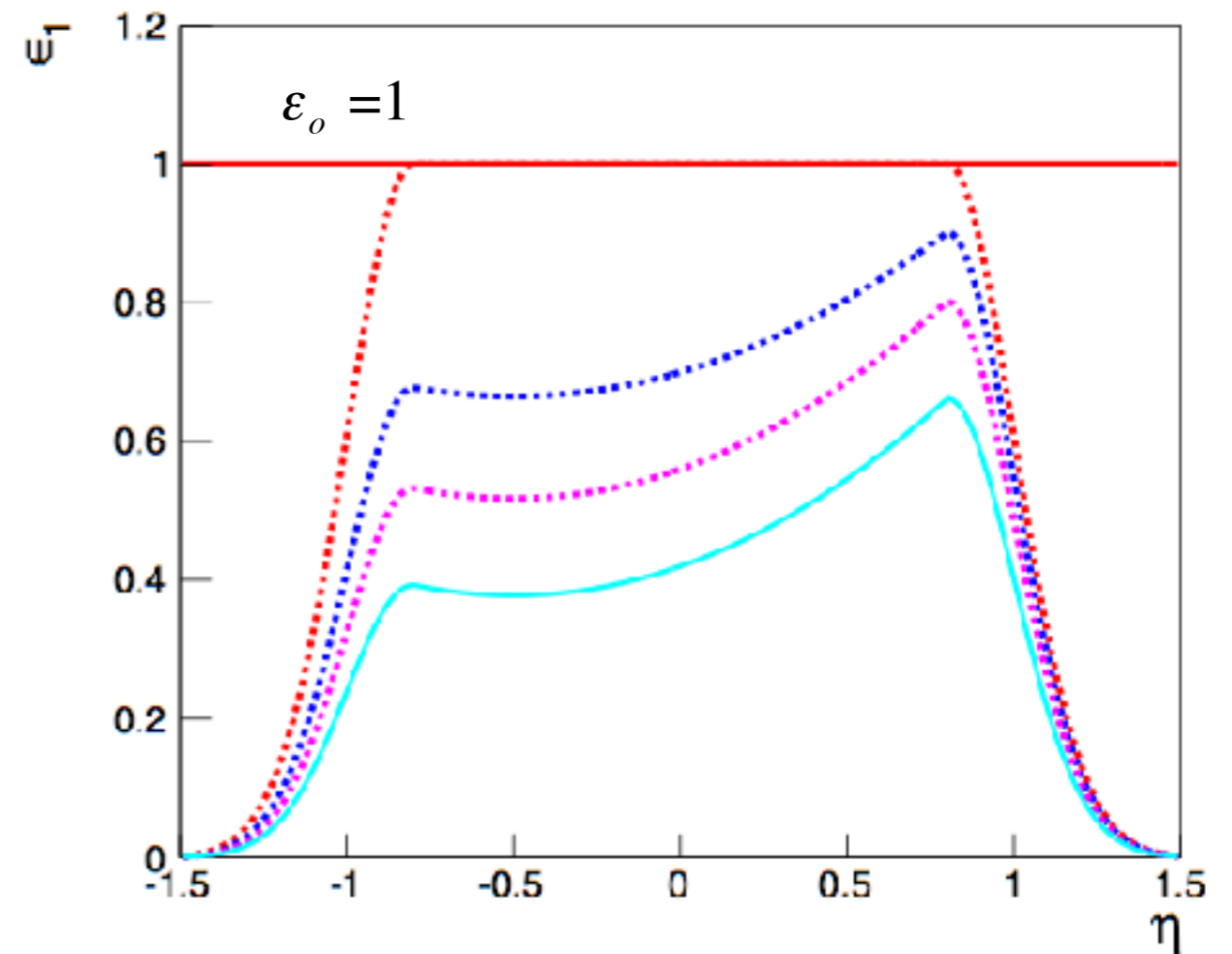


# Method 1 vs. Method 2: Efficiency Model

- Use a simple but non trivial correlation model
- Use a simple model of the detection efficiency and edge effects.

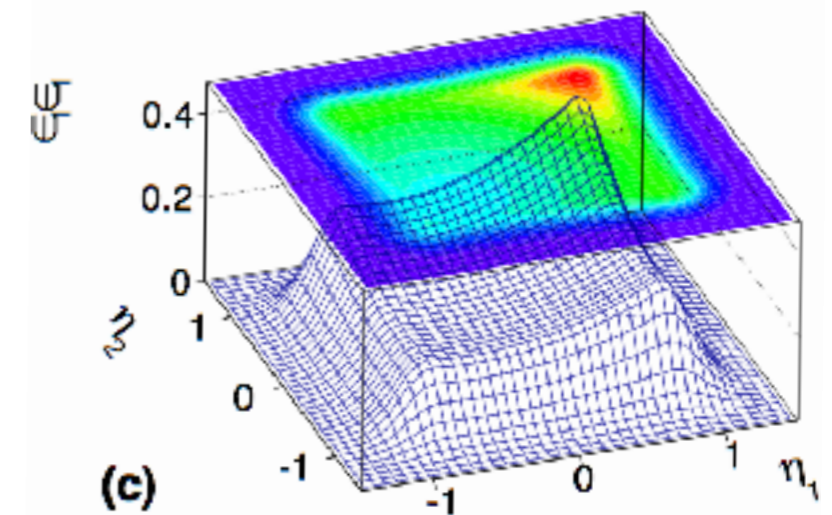
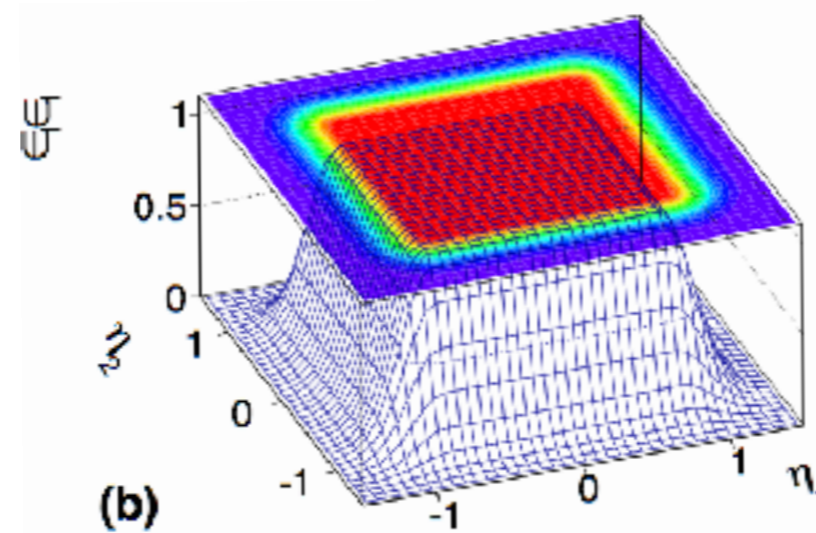
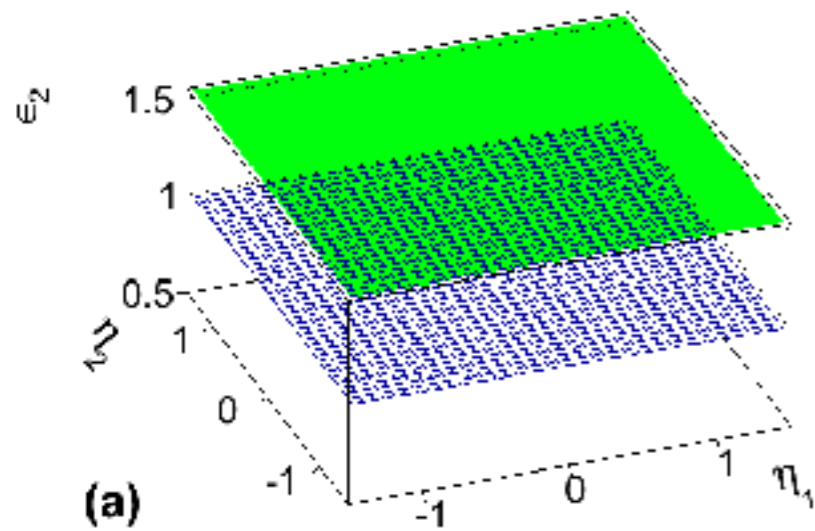
$$\begin{aligned}\varepsilon(\eta) &= \varepsilon_q(\eta) \exp\left(-\frac{(\eta - \eta_<)^2}{2\sigma_\varepsilon^2}\right) && \text{for } \eta < \eta_< \\ &= \varepsilon_q(\eta) && \text{for } \eta_< < \eta < \eta_> \\ &= \varepsilon_q(\eta) \exp\left(-\frac{(\eta - \eta_>)^2}{2\sigma_\varepsilon^2}\right) && \text{for } \eta > \eta_>\end{aligned}$$

$$\varepsilon_q(\eta) = 1 + \alpha(\eta - \eta_o) + \beta(\eta - \eta_o)^2$$

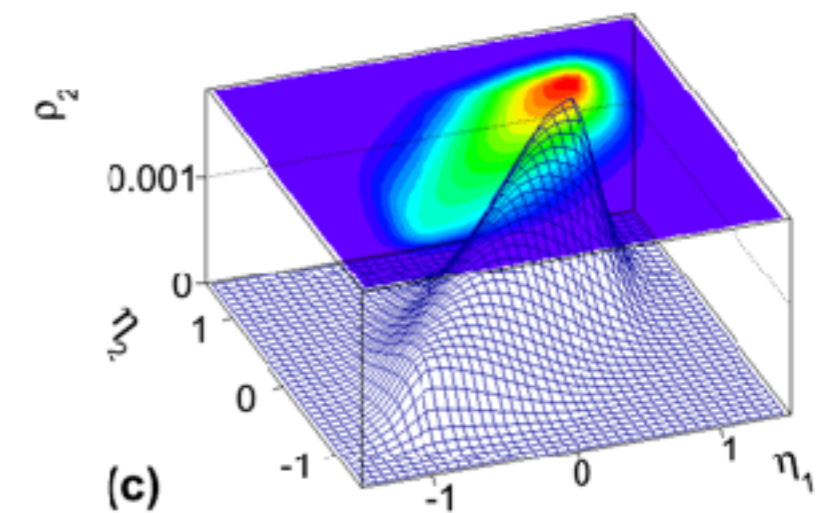
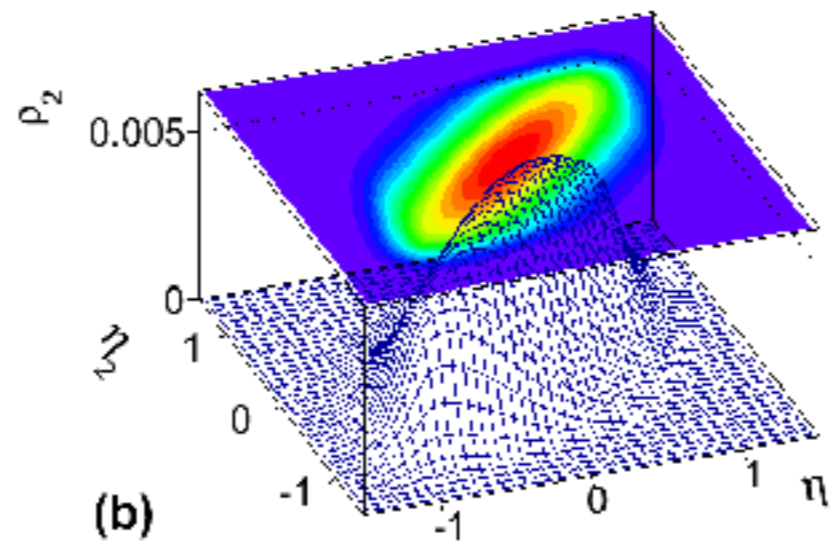
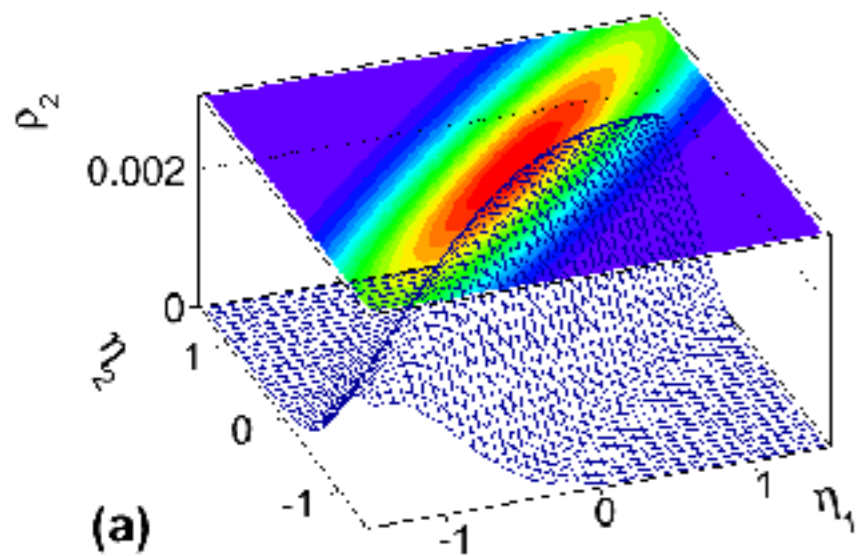


# Efficiency, Pair Yield

- Efficiency



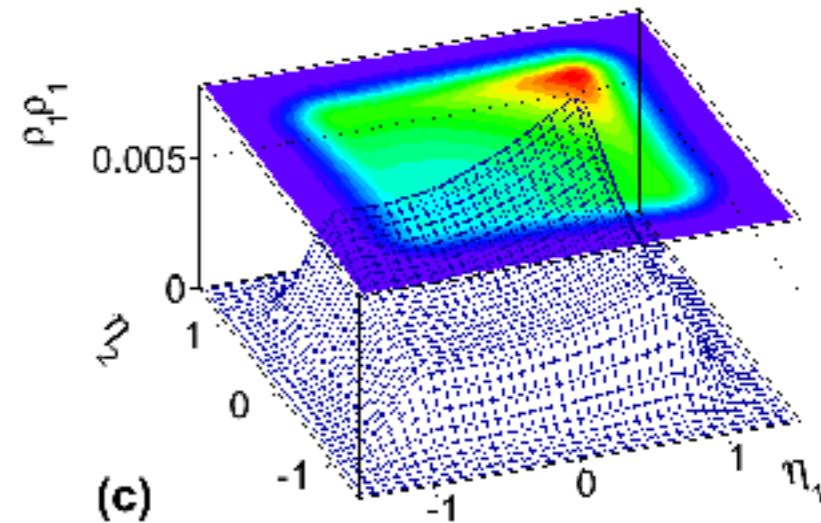
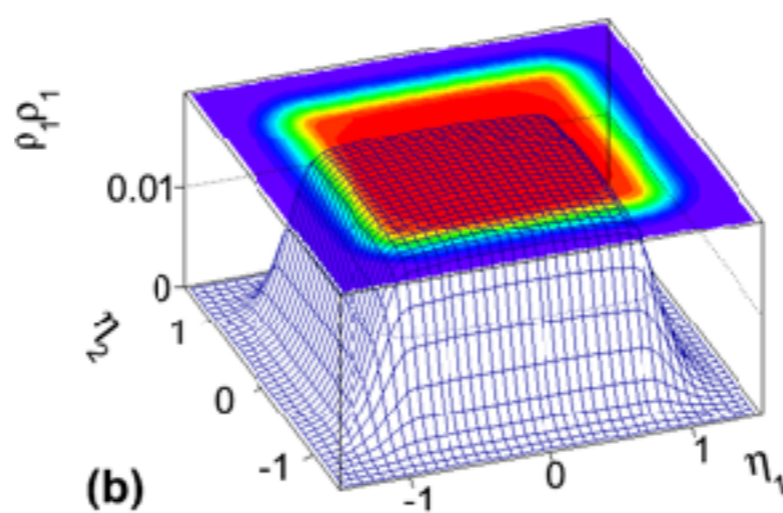
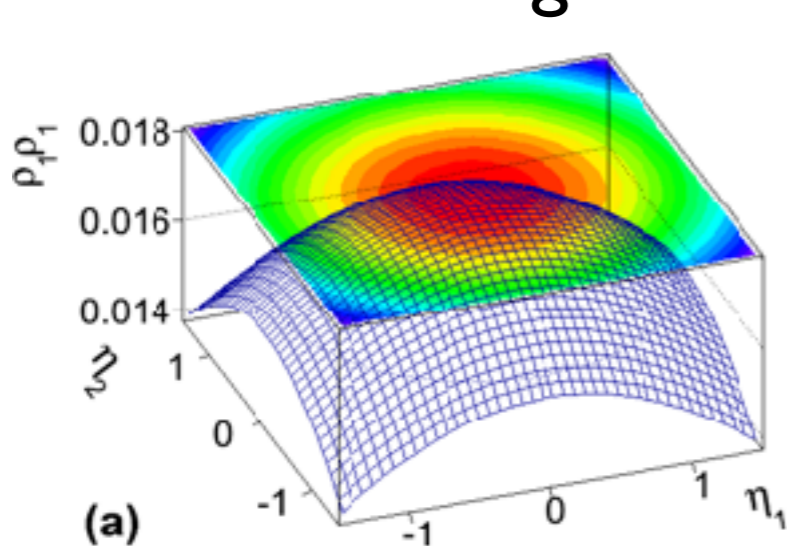
- Pair Yield





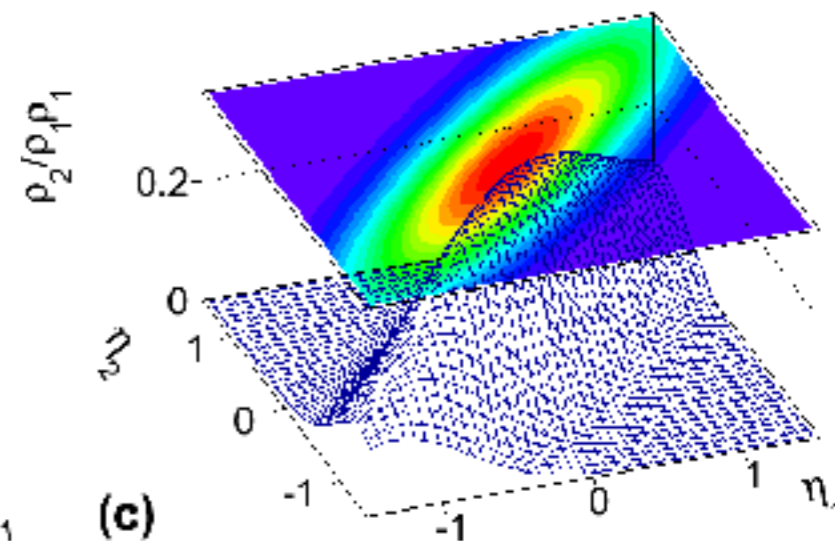
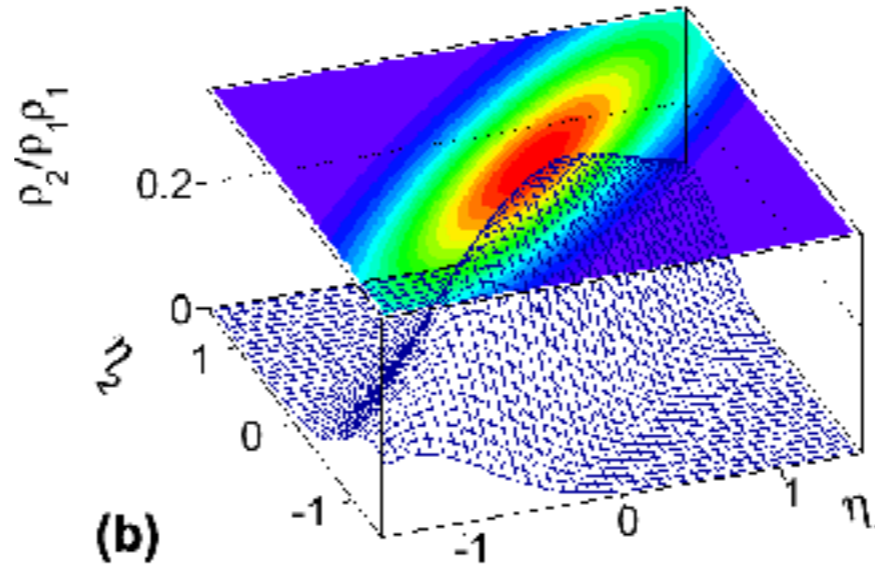
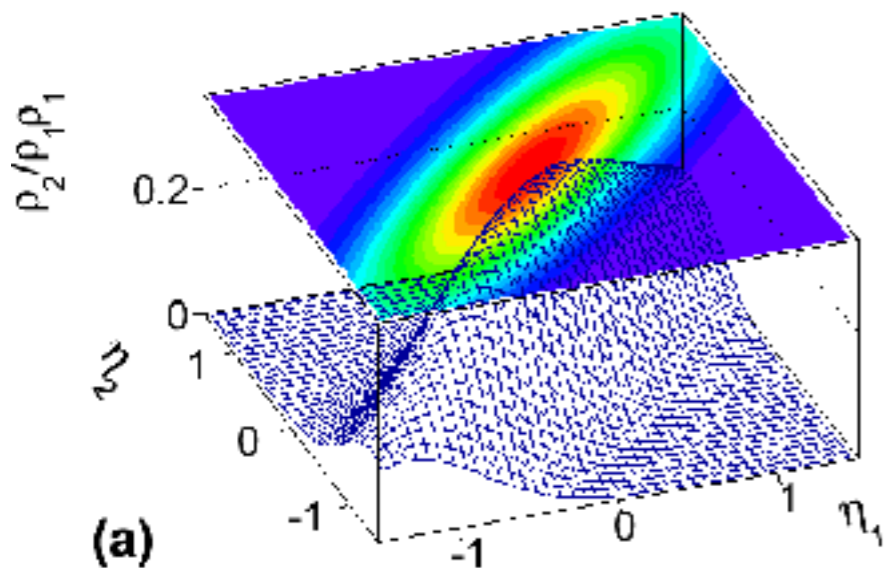
# Method 2: Results

## Product of singles

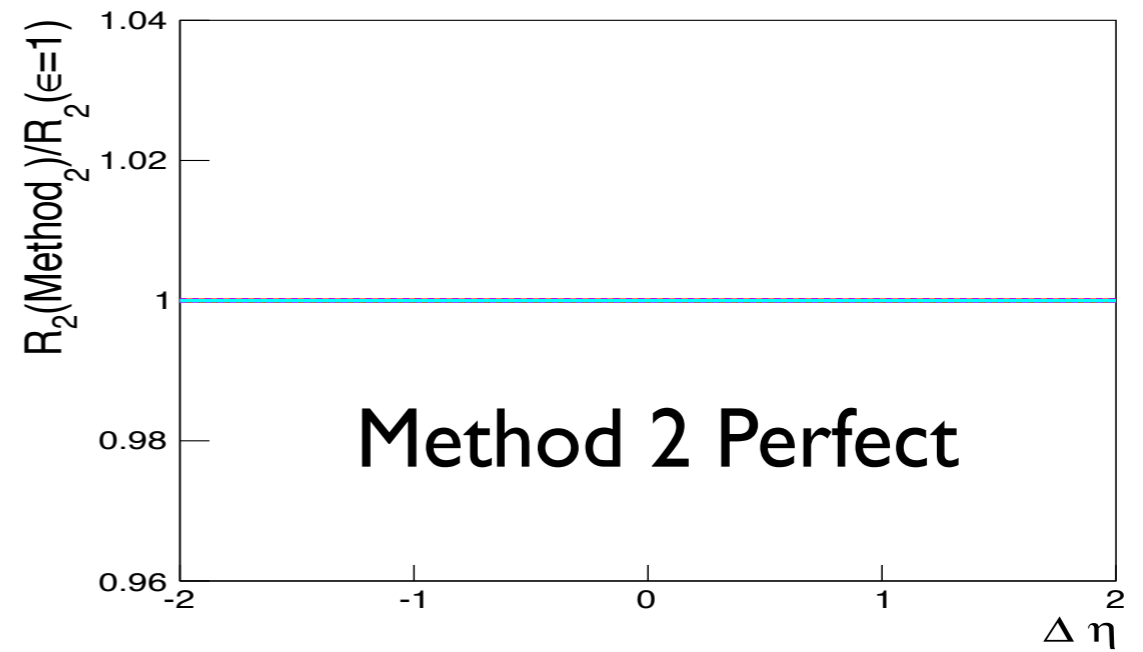
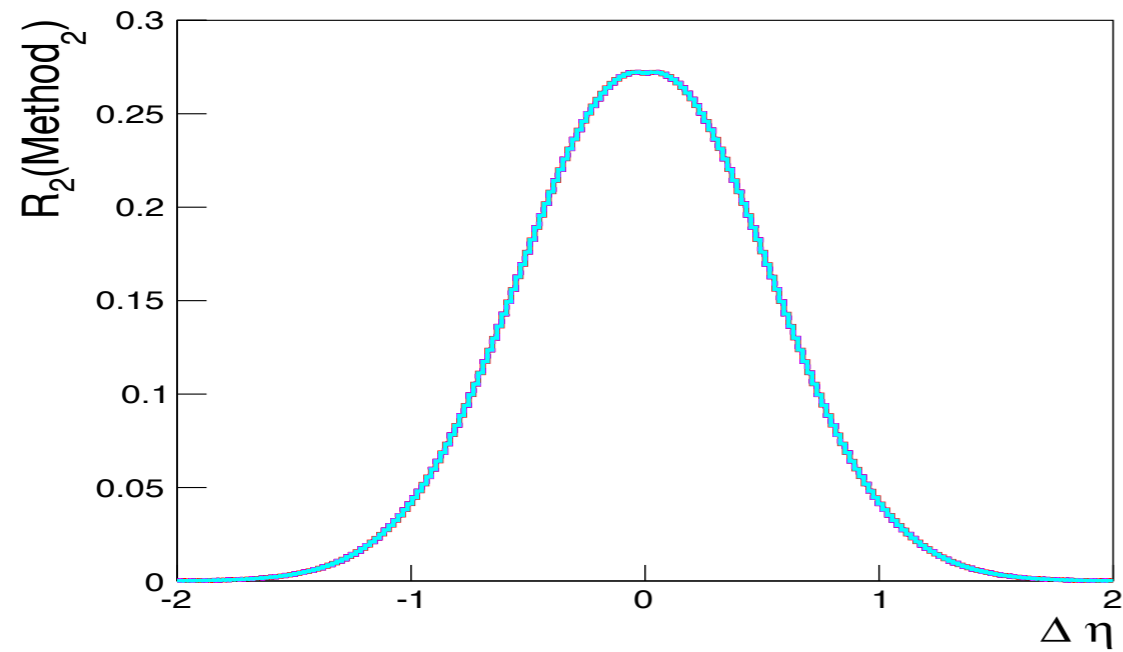


## R2 (Method 2)

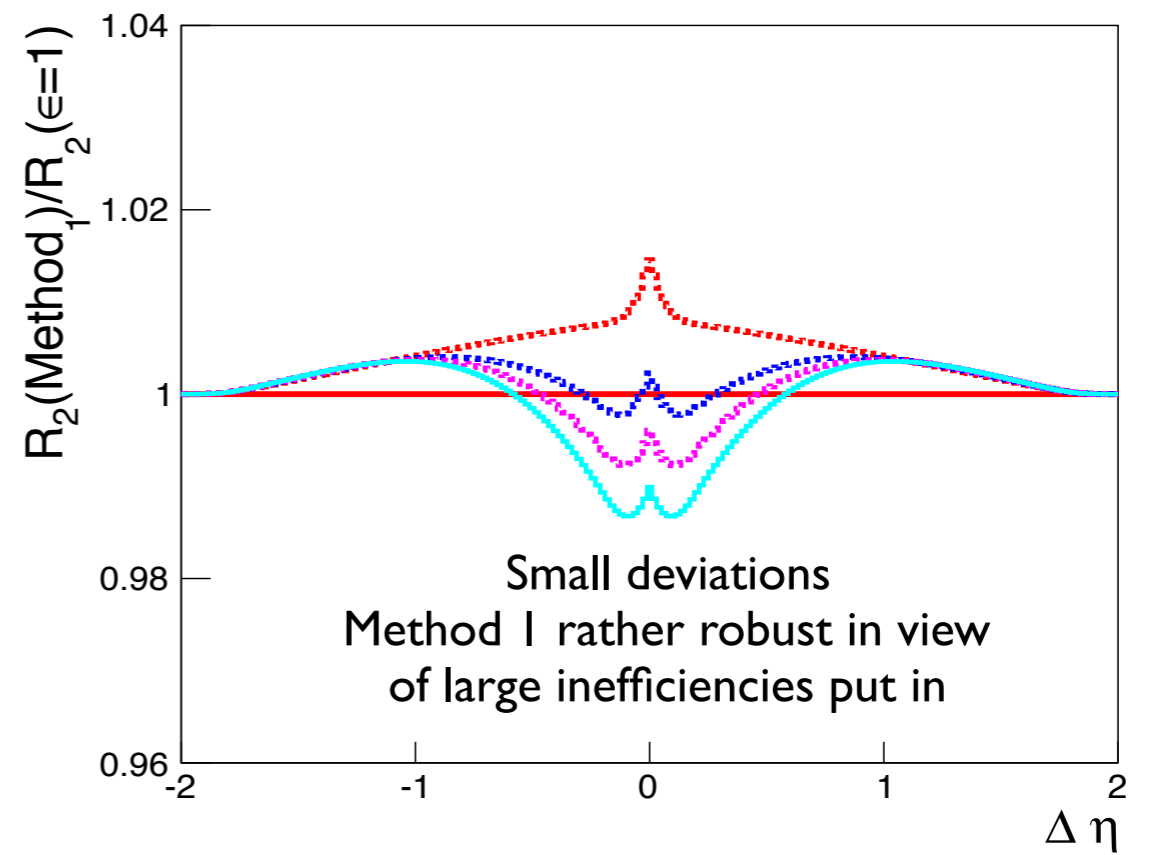
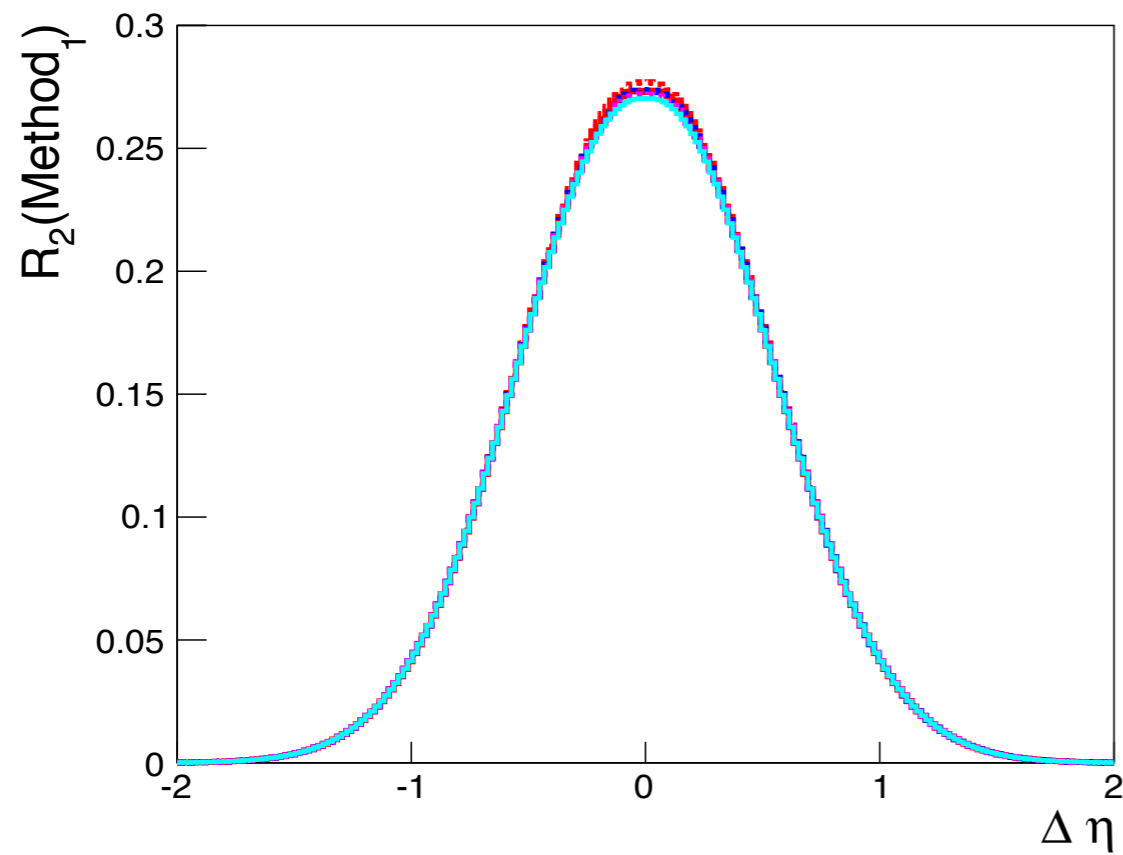
Perfect Reconstruction for any factorized efficient model w/ sufficient statistics



# R2( $\Delta\eta$ ) Method 2



# R2( $\Delta\eta$ ) Method 1



# Why?

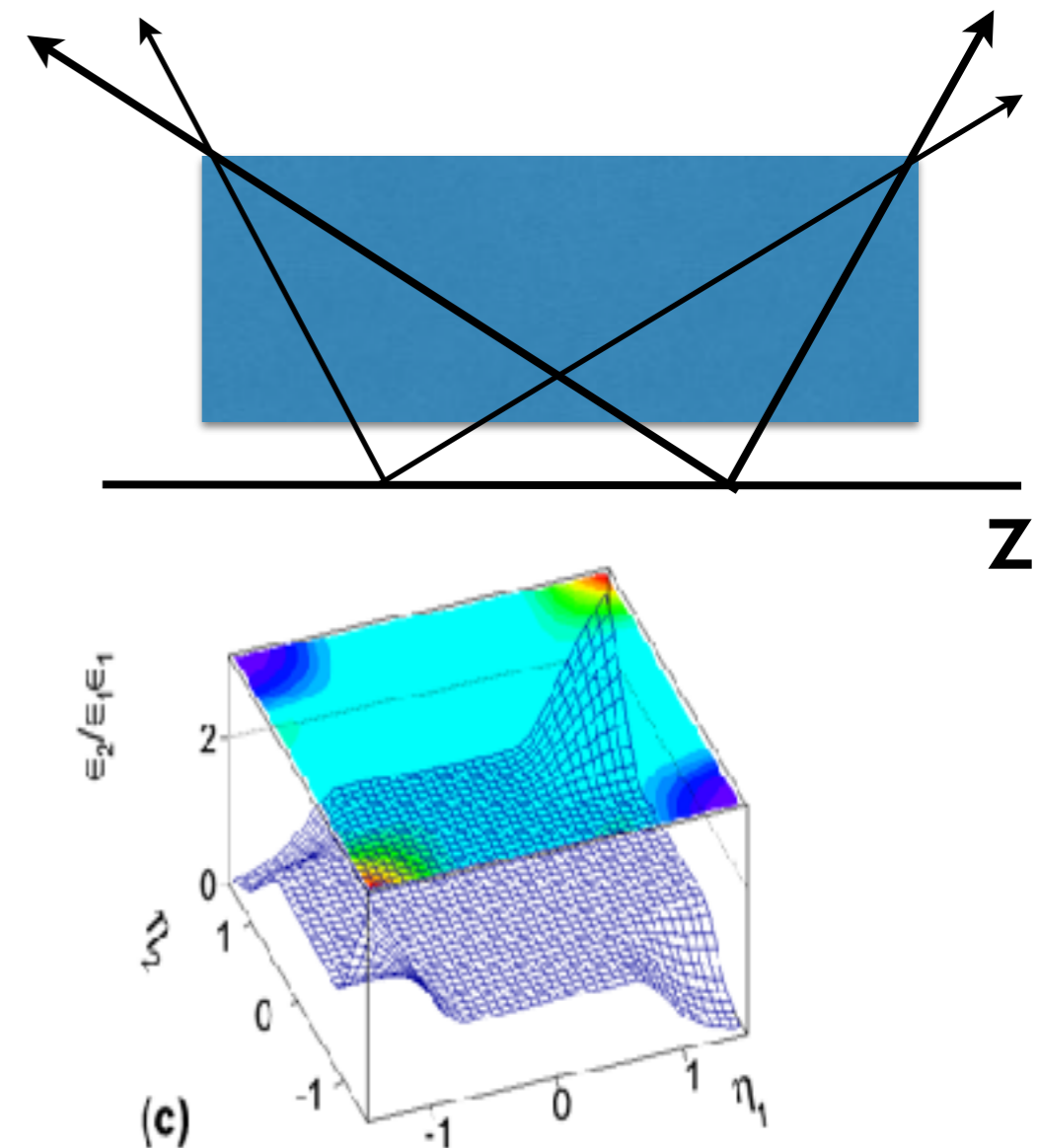
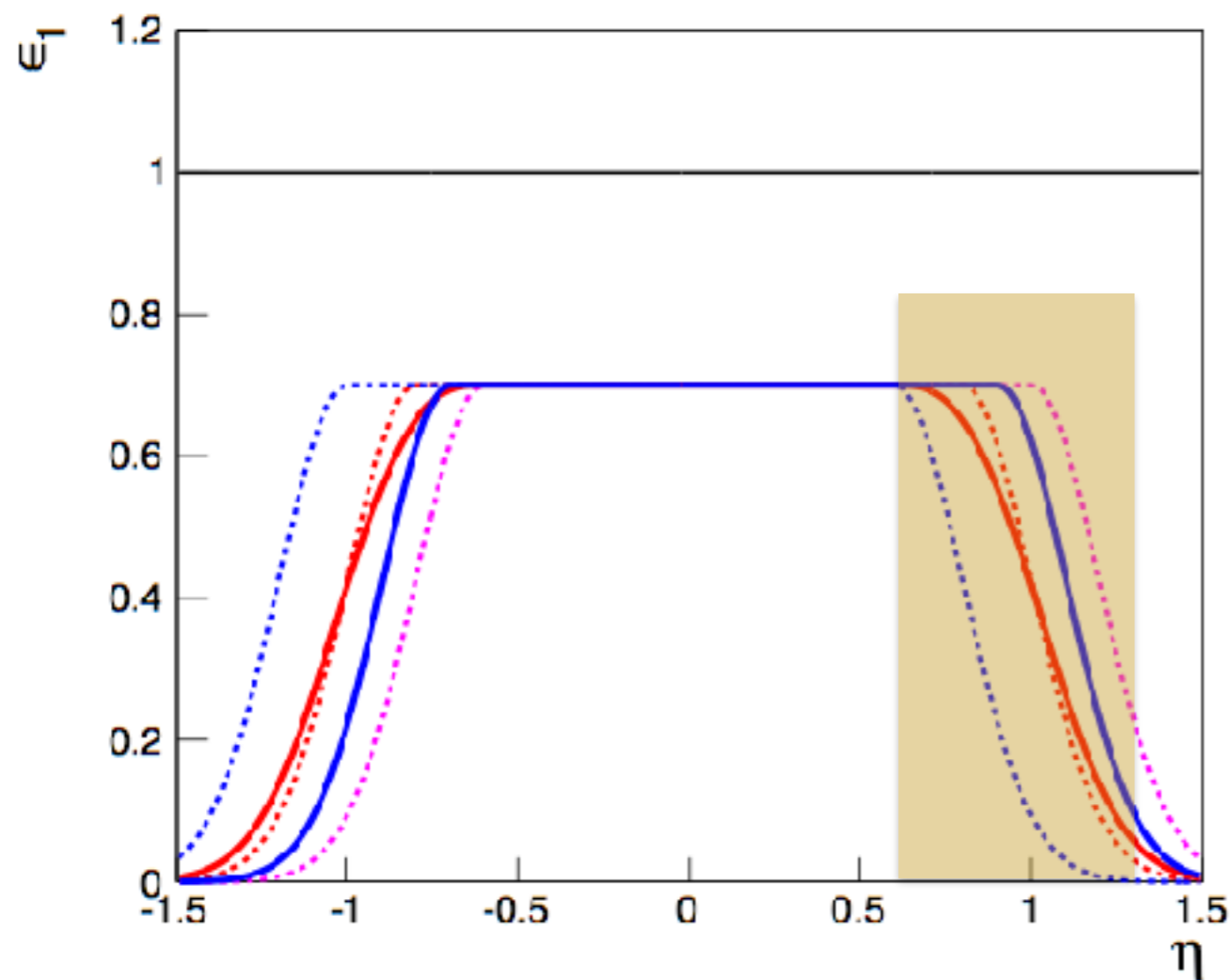
$$R_2(\Delta\eta)^{Method1} = \frac{\int g(\Delta\eta, \bar{\eta}) R_2^{true}(\Delta\eta, \bar{\eta}) d\bar{\eta}}{\int g(\Delta\eta, \bar{\eta}) d\bar{\eta}}$$

$$g(\Delta\eta, \bar{\eta}) = \varepsilon_1(\eta_1) \rho_1(\eta_1) \otimes \varepsilon_1(\eta_2) \rho_1(\eta_2)$$

- If efficiency, yield, or correlation varies with avg-rapidity, then  $g$  or  $R_2$  cannot be factorized out of the integrals.
  - The numerator and denominator are in general NOT equal.
- Method 1 is only approximately robust - for slow varying functions
- Note: not a problem in azimuthal correlation because of periodic boundary conditions.

# Dependence on z-vertex

- ALICE, STAR Acceptances are functions of the vertex position.
- Use a simple model as before...



# Efficiency Factorization???

- Local Factorization:

$$\epsilon_{pair}(\eta_1, \eta_2 | z) = \epsilon_1(\eta_1 | z) \times \epsilon_1(\eta_2 | z)$$

- Loss of “Global” Factorization:

$$\langle n_1(\eta_1) \rangle = K \int_{z_{min}}^{z_{max}} P_c(z) \epsilon(\eta_1 | z) \langle N_1(\eta_1) \rangle dz = \langle N_1(\eta_1) \rangle f_1(\eta_1)$$

$$\langle n_2(\eta_1, \eta_2) \rangle = K \int_{z_{min}}^{z_{max}} P_c(z) \epsilon(\eta_1 | z) \times \epsilon(\eta_2 | z) \langle N_2(\eta_1, \eta_2) \rangle dz = \langle N_2(\eta_1, \eta_2) \rangle f_2(\eta_1, \eta_2)$$

$$f_1(\eta_1) = K \int_{z_{min}}^{z_{max}} P_c(z) \epsilon(\eta_1 | z) dz$$

$$f_2(\eta_1, \eta_2) = K \int_{z_{min}}^{z_{max}} P_c(z) \epsilon(\eta_1 | z) \times \epsilon(\eta_2 | z) dz$$

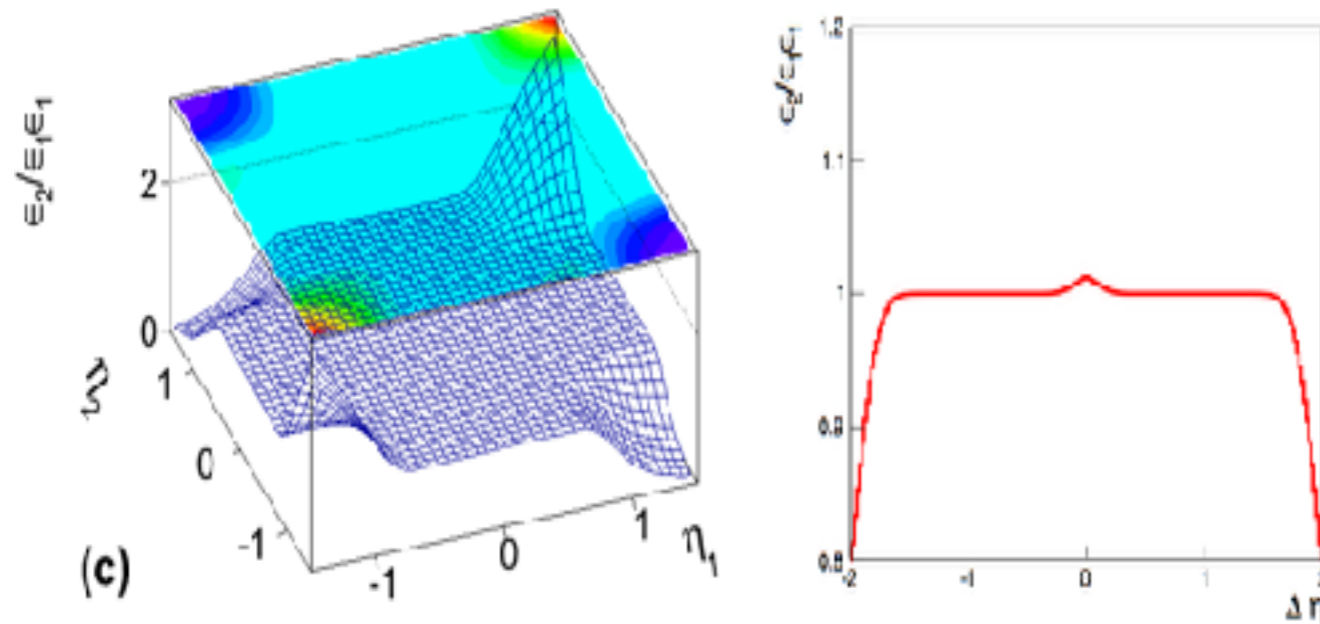
$$K^{-1} = \int_{z_{min}}^{z_{max}} P_c(z) dz$$

$$R_2(\eta_1, \eta_2) = \frac{f_2(\eta_1, \eta_2)}{f_1(\eta_1) f_1(\eta_2)} \frac{\langle N_2(\eta_1, \eta_2) \rangle}{\langle N_1(\eta_1) \rangle \langle N_1(\eta_2) \rangle}$$

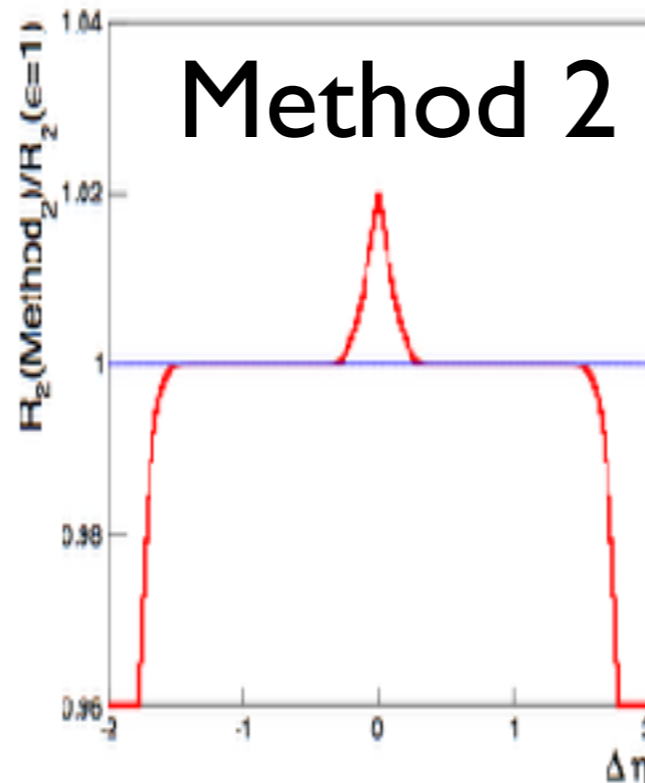
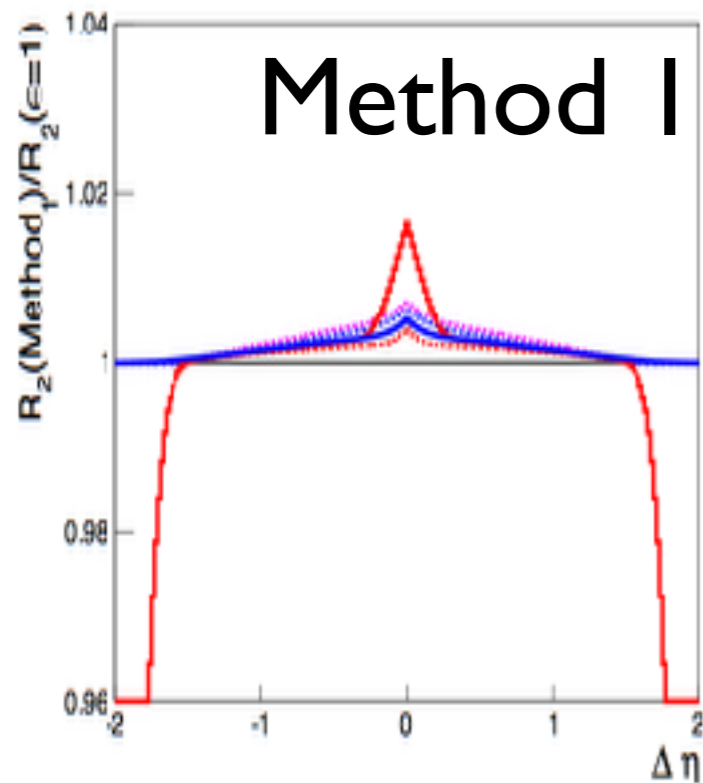
Neither Methods Robust



# How this works...



Efficiency dependence on “z-vertex”, with gaussian edges, but flat in the fiducial volume.



# Recovery...

- Method 2:
  - Carry analysis in fine (narrow)  $z$  bins.
  - Apply local efficiency factorization.

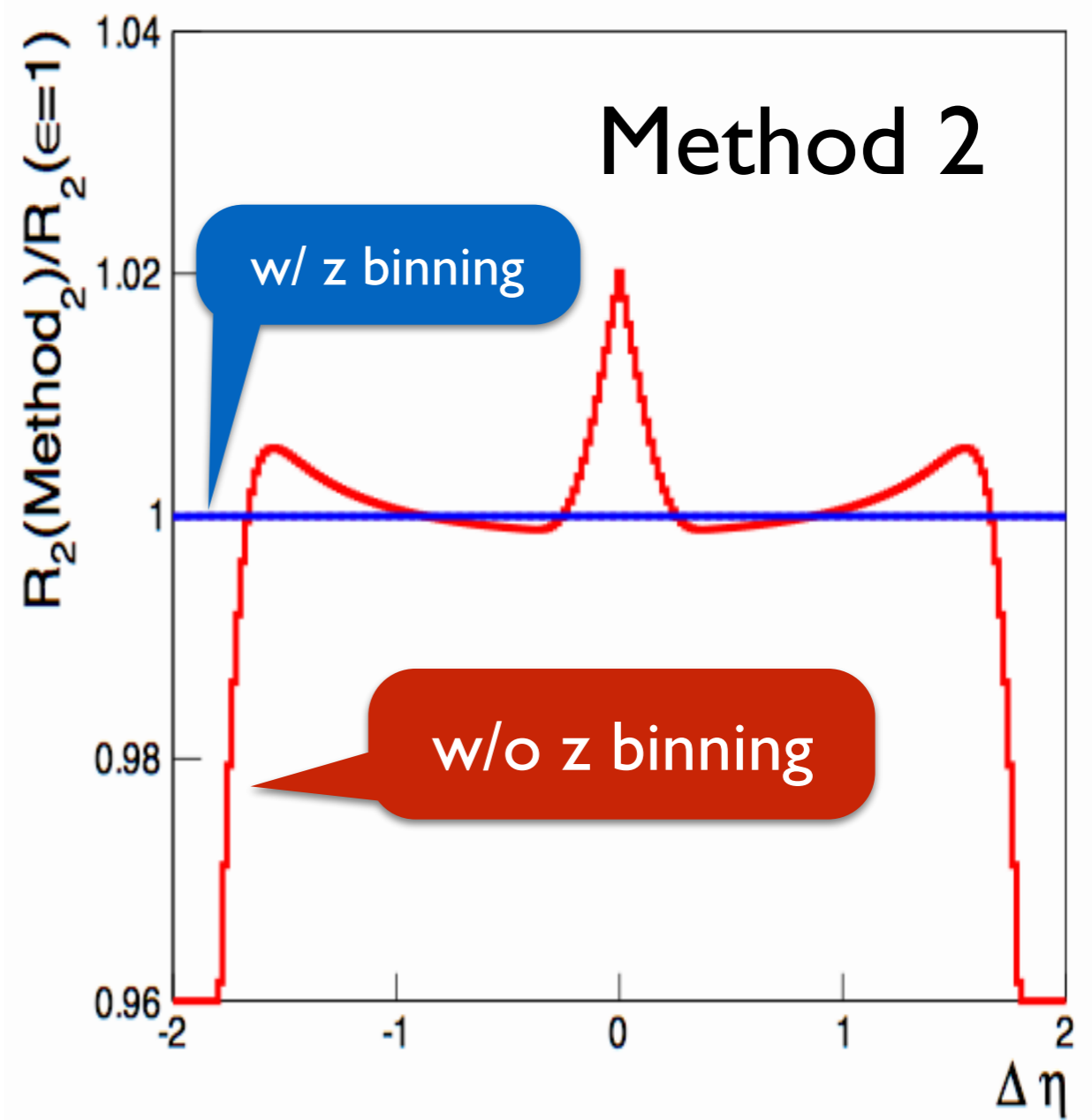
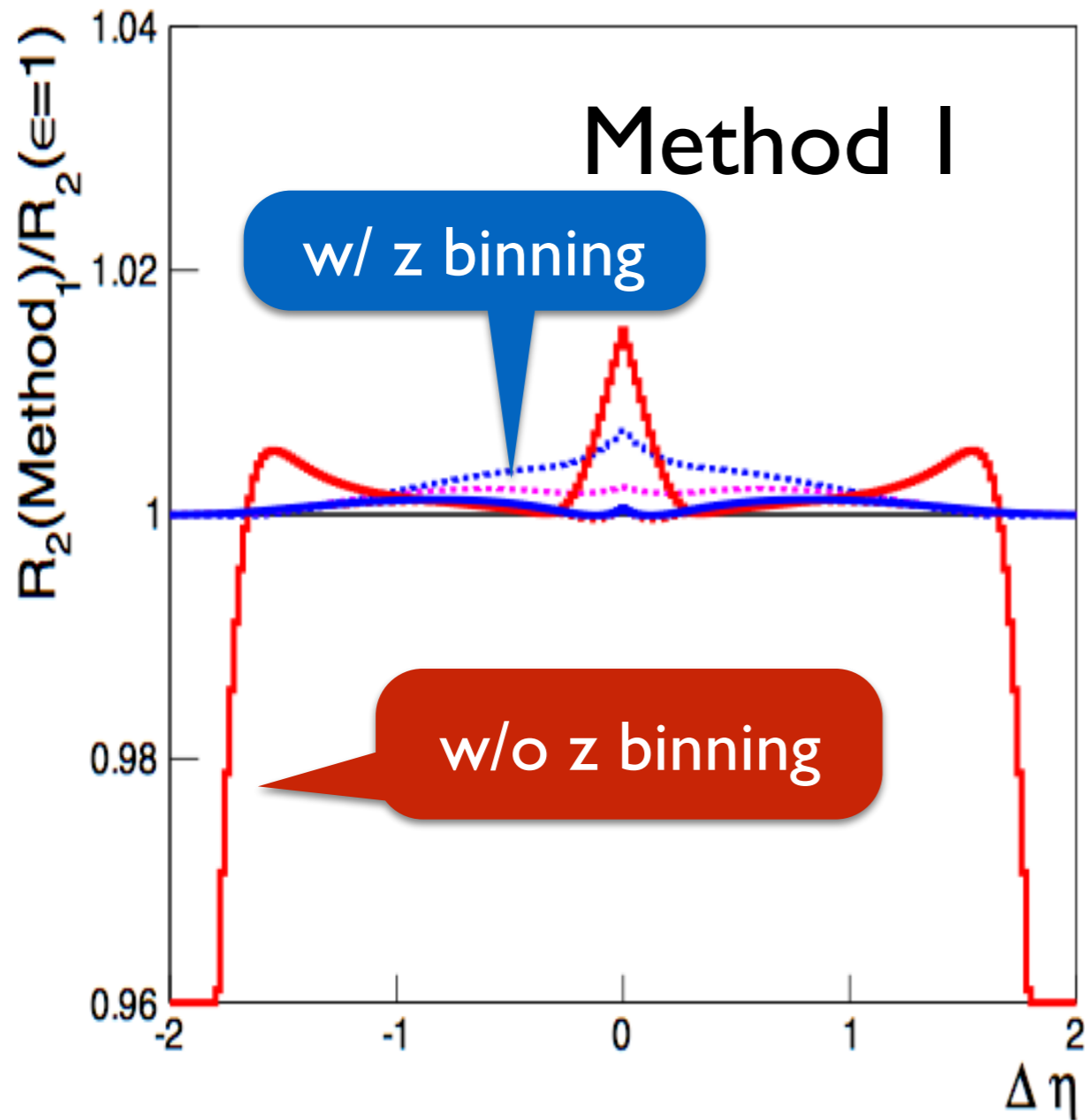
$$R_2(\eta_1, \eta_2) = K \int_{z_{min}}^{z_{max}} P_c(z) \quad (49)$$
$$\times \frac{\epsilon(\eta_1|z) \times \epsilon(\eta_2|z) \langle N_2(\eta_1, \eta_2) \rangle}{\epsilon(\eta_1|z) \times \epsilon(\eta_2|z) \langle N_1(\eta_1) \rangle \langle N_1(\eta_2) \rangle} dz$$

$$R_2(\eta_1, \eta_2) = K \frac{\langle N_2(\eta_1, \eta_2) \rangle}{\langle N_1(\eta_1) \rangle \langle N_1(\eta_2) \rangle} \int P_c(z) dz$$
$$= \frac{\langle N_2(\eta_1, \eta_2) \rangle}{\langle N_1(\eta_1) \rangle \langle N_1(\eta_2) \rangle}$$

- Method 1:
  - This “recipe” not strictly valid for method 1

# Method 1 and 2

Efficiency dependence on “z-vertex”, with gaussian edges, but **quadratic** dependence on eta in the fiducial volume.



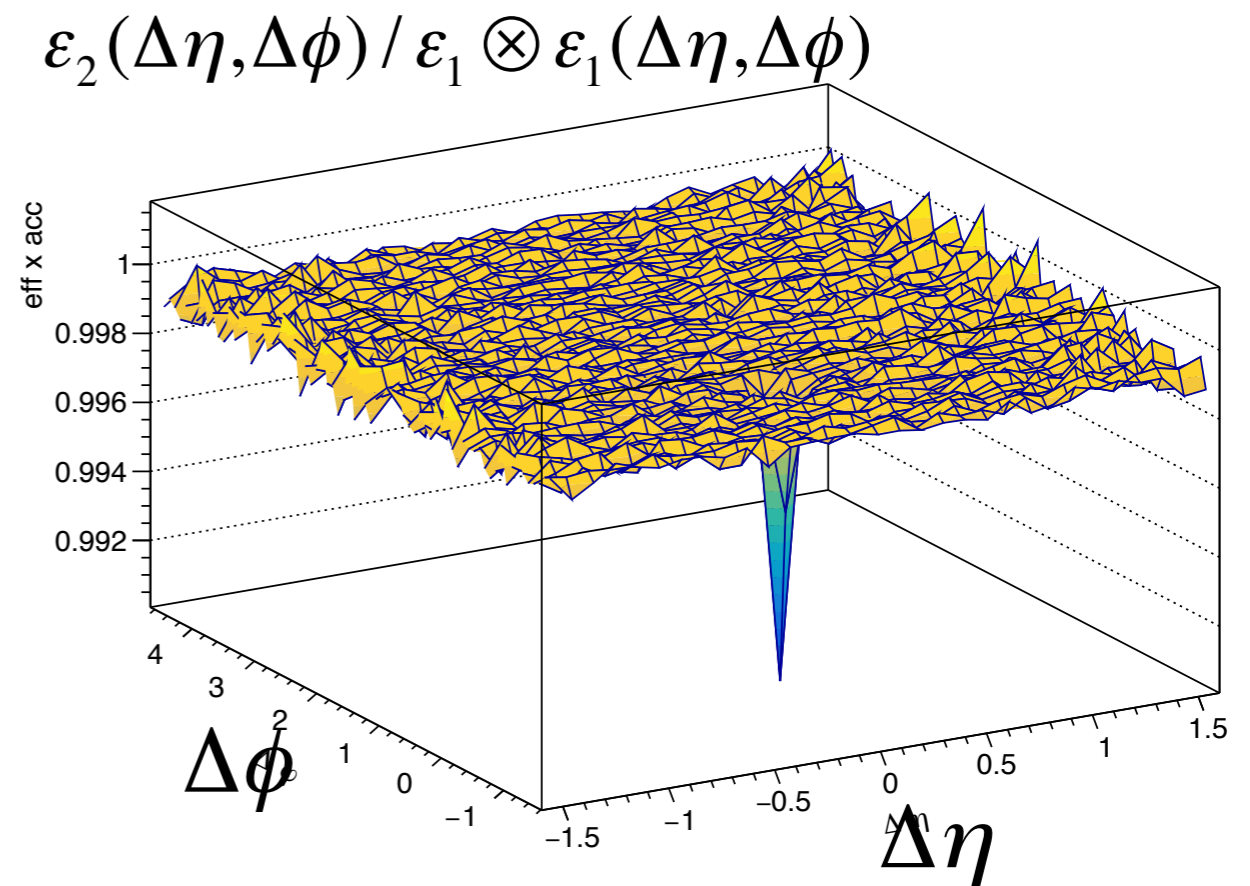
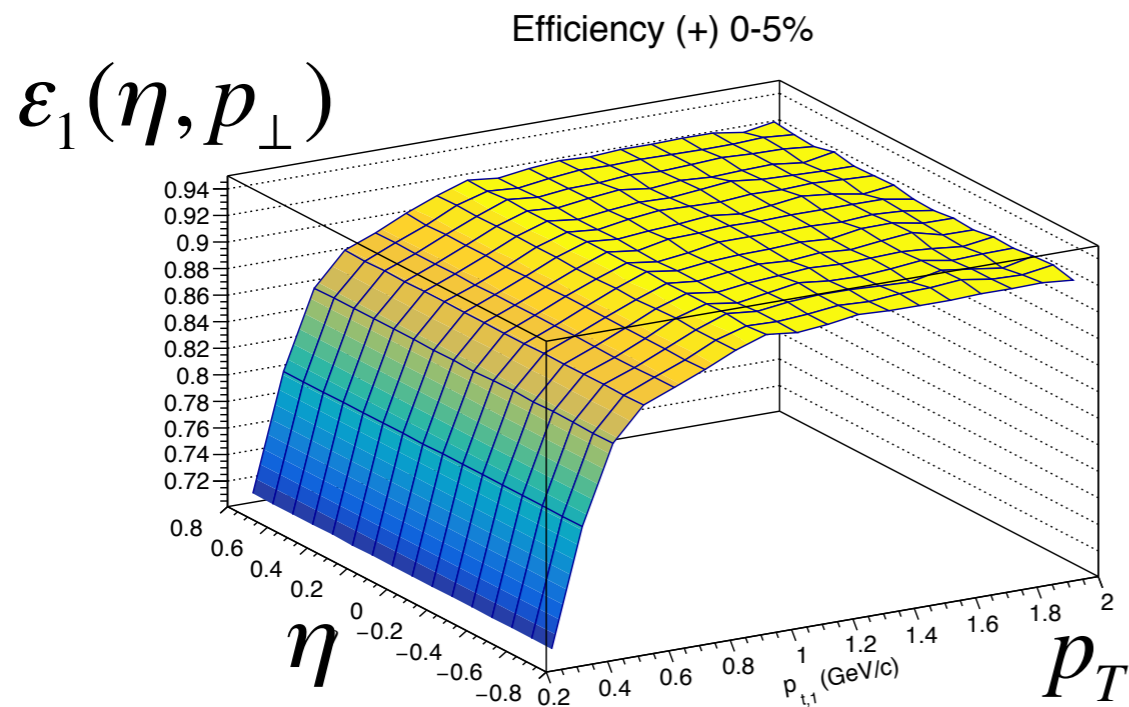
Both methods fail if efficiency is dependent on “z”.

**Approximate** recovery with fine z-bins using Method 1

Complete recovery with fine z-bins using Method 2

# What about momentum dependence and pair losses

- Example from ALICE detector
- Determined from HIJING events propagated through detector simulation with GEANT and detector response simulator



- **Technique:**

- Discretize the densities in  $p_T$  also
- Use eta, phi,  $p_T$  dependent weights proportional to inverse of efficiencies.

# Part II: Conclusions

- **Method 2 Robust**
  - unless efficiency has dependence on z-vertex
  - but recovery possible for analysis in narrow z-bins
- **Method 1 Only Approximately Robust**
  - Robustness lost if singles, correlation, or efficiency are function of avg-eta
  - Approximate Robustness lost if dependence on z-vertex
  - “Partial” recovery possible for analysis in narrow z-bins
- **Bigger Point:**
  - With differential correlations, it is possible to identify detector features more readily than with integral correlations.
  - Integral correlations average over detector issues, they DO NOT eliminate them.

# Part III: The Identity Method - Revisited/Extended

## C.A.P, arXiv:1706.01333

- Context:
  - Identity Method developed by **Marek Gazdzicki** to study fluctuations of the multiplicity of particle species w/o loss of statistics and in cases where the PID signals (dE/dx, TOF, or mass) associated with different species might overlap significantly and lead to considerable ambiguities.
  - Method developed first for PID problems involving two species (A Method to study chemical equilibration in nucleus-nucleus collisions), Eur. Phys. J. C8 (1999) 131.
  - Extended to “n” species by **M. Gorenstein** (Identity Method for Particle Number Fluctuations and Correlations) Phys. Rev. C84 (2011) 024902.
  - Extended to “n” species and arbitrary orders by **A. Rustamov** and **M. Gorenstein** (Identity Method for Moments of Multiplicity Distribution) Phys. Rev. C86 (2012) 044906.
  - BUT: Method outlined in these papers does not explicitly account for particle losses.
- C.A.P, **arXiv:1706.01333**
  - **Identity method extended to account for particle losses.**
- **This presentation:**
  - **Extending identity method to differential correlation functions.**

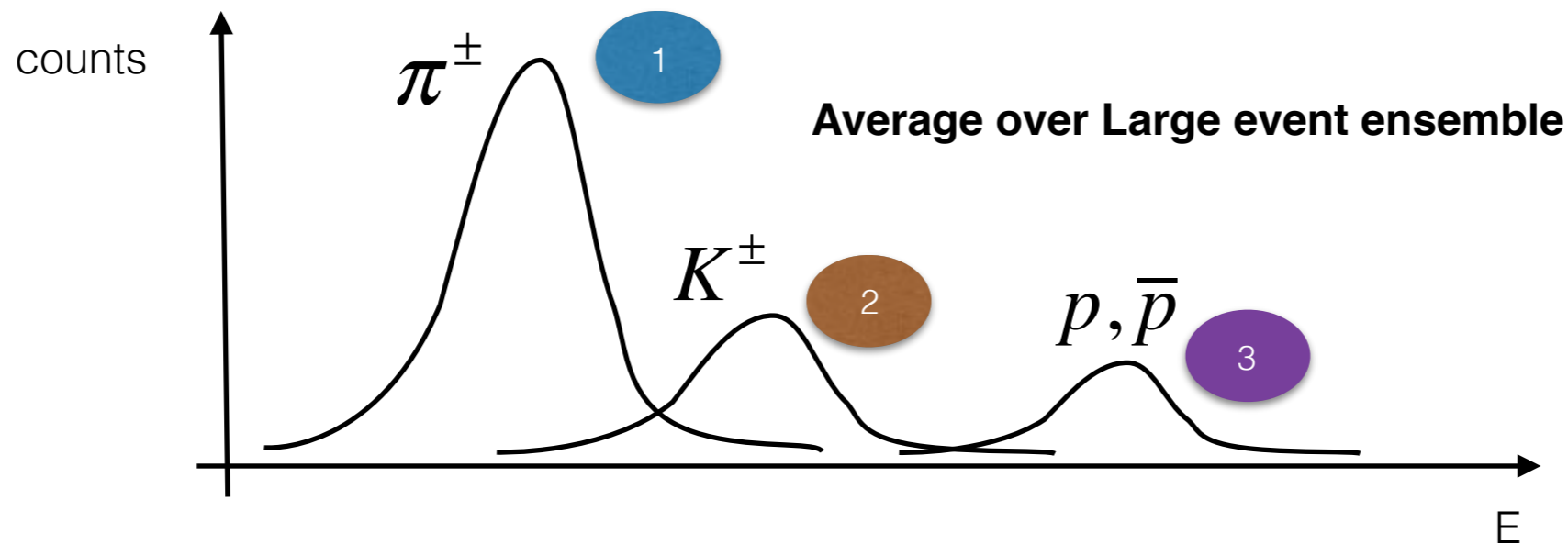


# PID Disambiguation ....

- Goal: Measure moments of e-by-e yield fluctuations of different species

$$v_{dyn} = \frac{\langle N_1(N_1 - 1) \rangle}{\langle N_1 \rangle^2} + \frac{\langle N_2(N_2 - 1) \rangle}{\langle N_2 \rangle^2} - \frac{\langle N_1 N_2 \rangle}{\langle N_1 \rangle \langle N_2 \rangle}$$

- where  $N_1, N_2$ : number of particles of types “1” and “2” measured e-by-e,
- Species identified with some PID detector that produces a signal  $E$  with distributions that are nominally distinct for different species but some overlap.



- Tracks may be lost because of detector or algorithm artifacts. The detection efficiency  $\varepsilon_i$  is species dependent - and momentum dependent.



# Moments of produced/measured multiplicities

- Probability of producing multiplicities  $N_1, N_2, \dots, N_K$  of all species is denoted by  $P_T(N_1, N_2, \dots, N_K)$
- Probability of measuring multiplicities  $n_1, n_2, \dots, n_K$  of all species is denoted by  $P_M(n_1, n_2, \dots, n_K)$
- Moments are calculated according to

$$\langle N_p \rangle \equiv \sum_{N_1, N_2, \dots, N_K}^{\infty} P_T(N_1, N_2, \dots, N_K) N_p$$

$$\langle n_p \rangle \equiv \sum_{n_1, n_2, \dots, n_K}^{\infty} P_M(n_1, n_2, \dots, n_K) n_p$$

$$\langle N_p^2 \rangle \equiv \sum_{N_1, N_2, \dots, N_K}^{\infty} P_T(N_1, N_2, \dots, N_K) N_p^2$$

$$\langle n_p^2 \rangle \equiv \sum_{n_1, n_2, \dots, n_K}^{\infty} P_M(n_1, n_2, \dots, n_K) n_p^2$$

$$\langle N_p N_q \rangle \equiv \sum_{N_1, N_2, \dots, N_K}^{\infty} P_T(N_1, N_2, \dots, N_K) N_p N_q$$

$$\langle n_p n_q \rangle \equiv \sum_{n_1, n_2, \dots, n_K}^{\infty} P_M(n_1, n_2, \dots, n_K) n_p n_q$$

and similarly for higher moments ...



# Moments of measured multiplicities (2)

- Particle Loss Model:

$$P_M(n_1, n_2, \dots, n_k) = \sum_{N_1=0}^{\infty} \sum_{N_2=0}^{\infty} \dots \sum_{N_k=0}^{\infty} P_T(N_1, N_2, \dots, N_k) B(n_1|N_1, \varepsilon_1) B(n_2|N_2, \varepsilon_2) \times \dots \times B(n_k|N_k, \varepsilon_k).$$

- Calculations yields:
 
$$\langle n_p \rangle = \varepsilon_p \langle N_p \rangle$$

$$\langle n_p^2 \rangle = \varepsilon_p (1 - \varepsilon_p) \langle N_p \rangle + \varepsilon_p^2 \langle N_p^2 \rangle$$

$$\langle n_p n_q \rangle = \varepsilon_p \varepsilon_q \langle N_p N_q \rangle.$$

$$\langle n_p (n_p - 1) \rangle = \varepsilon_p^2 \langle N_p (N_p - 1) \rangle.$$

$$R_2 = \frac{\langle n_p (n_p - 1) \rangle}{\langle n_p \rangle^2} = \frac{\langle N_p (N_p - 1) \rangle}{\langle N_p \rangle^2}$$

$$V_{dyn}^{(measured)} = V_{dyn}^{(true)}$$

Factorial Moments are well behaved

Robust Ratio (R2)

Nu-dyn is ROBUST

However: Must discretize measurement to correct for efficiency momentum dependence (weight technique)

# Identity Method: PID weight

- Counting probabilities rather than integer instances
- Assume one knows the probability of observing **signal E** given **species "p"**:  $P_p(E)$
- Define the Line Shape (Density):

$$\rho_p(E) = \langle n_p \rangle P_p(E)$$

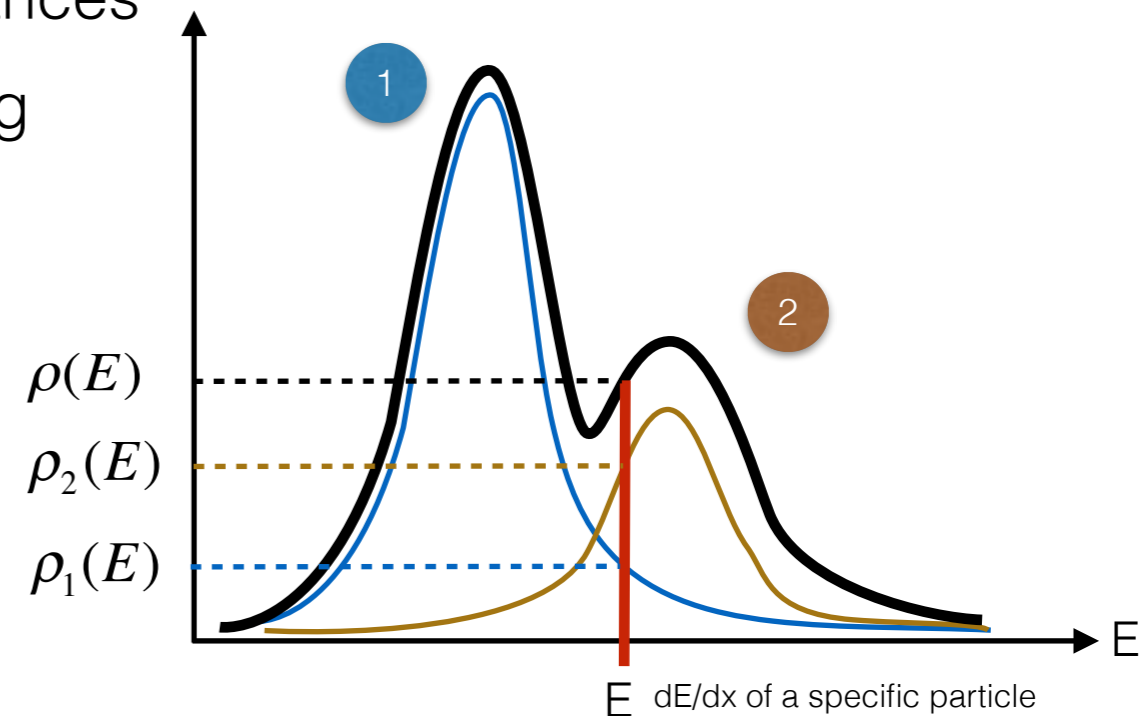
- Normalization:

$$\rho(E) = \sum_{p=1}^K \rho_p(E) = \sum_{p=1}^K \langle n_p \rangle P_p(E)$$

- Probability of signal being due to species "p" given PID signal E.

$$P(p | E) = \frac{\rho_p(E)}{\rho(E)} \equiv \omega_p(E)$$

**For each particle and each candidate species**



In the absence of overlap  
(unambiguous PID):  $\omega_p(E) = 0$  or  $1$

In most cases  
(ambiguous PID):  $0 \leq \omega_p(E) \leq 1$

# Identity Variable

- Definition: Identity Variable (particle and event):

$$W_p = \sum_{i=1}^n \omega_p(E_i)$$

**For each of the K candidate species: sum weights of all n particles of an event.**

- In the absence of overlap (unambiguous PID):

$$W_1 = n_1 \quad n_1 \text{ particles of type 1}$$

$$W_2 = n_2 \quad n_2 \text{ particles of type 2}$$

$$\dots \quad n = n_1 + n_2 + n_K$$

- w/ ambiguous PID:

$$0 \leq W_p \leq n$$

# Identity Variables Moments

Calculation of 1st, 2nd, and covariances of the identity variables

1st Moments: 
$$\langle W_p \rangle = \frac{1}{N_{events}} \sum_{i=1}^{N_{events}} W_p^{(i)}$$

2nd Moments: 
$$\langle W_p^2 \rangle = \frac{1}{N_{events}} \sum_{i=1}^{N_{events}} (W_p^{(i)})^2$$

Covariances: 
$$\langle W_p W_q \rangle = \frac{1}{N_{events}} \sum_{i=1}^{N_{events}} W_p^{(i)} W_q^{(i)}$$

These moments are **linear combinations of moments of the measured multiplicities** — proportional to moments of the **produced multiplicities**.



# Identity Method w/o Losses (1)

- One finds:

$$\begin{aligned}
 \langle W_p \rangle &= \sum_{i_1=1}^{n_1} \sum_{n_1=0}^{\infty} \sum_{n_2=0}^{\infty} P_T(n_1, n_2) u_{p1} + \sum_{i_2=1}^{n_2} \sum_{n_1=0}^{\infty} \sum_{n_2=0}^{\infty} P_T(n_1, n_2) u_{p2} \\
 &= \sum_{n_1=0}^{\infty} \sum_{n_2=0}^{\infty} P_T(n_1, n_2) n_1 u_{p1} + \sum_{n_1=0}^{\infty} \sum_{n_2=0}^{\infty} P_T(n_1, n_2) n_2 u_{p2} \\
 &= u_{p1} \langle n_1 \rangle + u_{p2} \langle n_2 \rangle
 \end{aligned}$$

Linear Equations

$$\begin{aligned}
 \langle W_1 \rangle &= u_{11} \langle n_1 \rangle + u_{12} \langle n_2 \rangle \\
 \langle W_2 \rangle &= u_{21} \langle n_1 \rangle + u_{22} \langle n_2 \rangle
 \end{aligned}$$

Matrix Form

$$\begin{pmatrix} \langle W_1 \rangle \\ \langle W_2 \rangle \end{pmatrix} = \begin{pmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \end{pmatrix} \begin{pmatrix} \langle n_1 \rangle \\ \langle n_2 \rangle \end{pmatrix}$$

Matrix Inversion

$$\begin{pmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \end{pmatrix}^{-1} \begin{pmatrix} \langle W_1 \rangle \\ \langle W_2 \rangle \end{pmatrix} = \begin{pmatrix} \langle n_1 \rangle \\ \langle n_2 \rangle \end{pmatrix}$$

**Example for two species**

# Identity Method with Efficiency Losses (2)

$$\langle W_p \rangle = \sum_{N_1=0}^{\infty} \sum_{N_2=0}^{\infty} P_T(N_1, N_2) [u_{p1} \epsilon_1 N_1 + u_{p2} \epsilon_2 N_2] = u_{p1} \epsilon_1 \langle N_1 \rangle + u_{p2} \epsilon_2 \langle N_2 \rangle$$

$$\langle W_p^2 \rangle = \sum_{j=1}^2 u_{pj}^2 \epsilon_j \langle N_j \rangle + \sum_{j=1}^2 (u_{pj})^2 \epsilon_j^2 \langle N_j(N_j - 1) \rangle + 2u_{p1}u_{p2} \epsilon_1 \epsilon_2 \langle N_1 N_2 \rangle$$

$$\langle W_p W_q \rangle = \sum_{j=1}^2 u_{pqj} \epsilon_j \langle N_j \rangle + \sum_{j=1}^2 u_{pj} u_{qj} \epsilon_j^2 \langle N_j(N_j - 1) \rangle + (u_{p1}u_{q2} + u_{q1}u_{p2}) \epsilon_1 \epsilon_2 \langle N_1 N_2 \rangle$$

Trick is to absorb the efficiency and define N' quantities

$$\langle W_p^2 \rangle = \sum_{j=1}^2 u_{pj}^2 \langle N'_j \rangle + \sum_{j=1}^2 (u_{pj})^2 \langle N_j(N_j - 1)' \rangle + 2u_{p1}u_{p2} \langle N'_1 N'_2 \rangle$$

$$\langle W_p W_q \rangle = \sum_{j=1}^2 u_{pqj} \langle N'_j \rangle + \sum_{j=1}^2 u_{pj} u_{qj} \langle N_j(N_j - 1)' \rangle + (u_{p1}u_{q2} + u_{q1}u_{p2}) \langle N'_1 N'_2 \rangle$$

One can then write

$$b_p = \langle W_p^2 \rangle - \sum_{j=1}^k u_{pj}^2 \langle N'_j \rangle, \quad a_j^i = (u_{ij})^2, \quad 1 \leq i, j, \leq k;$$

$$b_{pq} = \langle W_p W_q \rangle - \sum_{j=1}^k u_{pqj} \langle N'_j \rangle, \quad a_i^{pq} = 2u_{ip}u_{iq}, \quad 1 \leq p < q \leq k, i = 1, \dots, k;$$

$$a_{pq}^i = u_{pi}u_{qi}, \quad 1 \leq p < q \leq k, i = 1, \dots, k;$$

$$a_{pq}^{ij} = u_{pi}u_{qj} + u_{pj}u_{qi}, \quad 1 \leq p < q \leq k, 1 \leq i < jk.$$

$$\mathbf{N} = \begin{pmatrix} \langle N_1(N_1 - 1)' \rangle \\ \vdots \\ \langle N_k(N_k - 1)' \rangle \\ \langle N'_1 N'_2 \rangle \\ \vdots \\ \langle N'_{k-1} N'_k \rangle \end{pmatrix}, \quad \mathbf{B} = \begin{pmatrix} b_1 \\ \vdots \\ b_k \\ b_{12} \\ \vdots \\ b_{(k-1)k} \end{pmatrix}$$

$$\mathbf{N} = \mathbf{A}^{-1} \mathbf{B}.$$

# Differential Correlations (Discretization)

- Discretize momentum space (single particle level)
  - Rapidity:  $-\eta_0 \leq \eta \leq \eta_0 \longrightarrow \alpha = 1, \dots, m_\alpha$
  - Azimuth:  $0 \leq \phi \leq 2\pi \longrightarrow \beta = 1, \dots, m_\beta$
  - Transverse Momentum:  $p_{\perp, \min} \leq p_{\perp} \leq p_{\perp, \max} \longrightarrow \gamma = 1, \dots, m_\gamma$
- Single Particle Density:  $\rho_1^{(p)}(\eta, \phi, p_{\perp}) \longrightarrow \hat{\rho}_1^{(p)}(\alpha, \beta, \gamma)$
- Pair Density:  $\rho_2^{(pq)}(\eta_1, \phi_1, p_{\perp, 1}, \eta_2, \phi_2, p_{\perp, 2}) \longrightarrow \hat{\rho}_2^{(pq)}(\alpha_1, \beta_1, \gamma_1, \alpha_2, \beta_2, \gamma_2)$

$$\hat{\rho}_1^{(p)}(\alpha, \beta, \gamma) = \frac{1}{N_{events}} \sum_{i=1}^{N_{events}} \frac{N_{1,(i)}^{(p)}(\alpha, \beta, \gamma)}{\varepsilon_1^{(p)}(\alpha, \beta, \gamma)} \frac{1}{\Delta\eta\Delta\phi\Delta p_{\perp}}$$

Detection Efficiency for Species (p)

$$\hat{\rho}_2^{(pq)}(\alpha_1, \beta_1, \gamma_1, \alpha_2, \beta_2, \gamma_2) = \frac{1}{N_{events}} \sum_{i=1}^{N_{events}} \frac{N_{1,(i)}^{(p)}(\alpha_1, \beta_1, \gamma_1)}{\varepsilon_1^{(p)}(\alpha_1, \beta_1, \gamma_1)} \frac{N_{1,(i)}^{(q)}(\alpha_2, \beta_2, \gamma_2)}{\varepsilon_1^{(q)}(\alpha_2, \beta_2, \gamma_2)} \frac{1}{\Delta\eta^2\Delta\phi^2\Delta p_{\perp}^2}$$

use N(N-1) is all indices are equal.



# Marginalization (integrating pT)

- Integrals replaced by sums...

$$\hat{\rho}_1^{(p)}(\alpha, \beta) = \sum_{\gamma=1}^{N_\gamma} \hat{\rho}_1^{(p)}(\alpha, \beta, \gamma)$$

$$\hat{\rho}_2^{(pq)}(\alpha_1, \beta_1, \alpha_2, \beta_2) = \sum_{\gamma_1, \gamma_2=1}^{m_\gamma} \hat{\rho}_2^{(pq)}(\alpha_1, \beta_1, \gamma_1, \alpha_2, \beta_2, \gamma_2) = \sum_{\gamma_1=1}^{m_\gamma} \hat{\rho}_2^{(pq)}(\alpha_1, \beta_1, \gamma_1, \alpha_2, \beta_2, \gamma_1) + \sum_{\gamma_1 \neq \gamma_2=1}^{m_\gamma} \hat{\rho}_2^{(pq)}(\alpha_1, \beta_1, \gamma_1, \alpha_2, \beta_2, \gamma_2)$$

$$R_2^{(pq)}(\Delta\alpha, \Delta\beta) = \frac{\sum_{\alpha_1, \alpha_2}^{m_\alpha} \sum_{\beta_1, \beta_2}^{m_\beta} \hat{\rho}_2^{(pq)}(\alpha_1, \beta_1, \alpha_2, \beta_2) \delta(\Delta\alpha - \alpha_1 + \alpha_2) \delta(\Delta\beta - \beta_1 + \beta_2)}{\sum_{\alpha_1, \alpha_2}^{m_\alpha} \sum_{\beta_1, \beta_2}^{m_\beta} \hat{\rho}_1^{(p)}(\alpha_1, \beta_1) \hat{\rho}_1^{(q)}(\alpha_2, \beta_2) \delta(\Delta\alpha - \alpha_1 + \alpha_2) \delta(\Delta\beta - \beta_1 + \beta_2)} - 1$$



# Differential Identity Method w/ Losses

Moments of the identity variables in differential bins

$$\langle W_p(\alpha, \beta, \gamma) \rangle = \sum_{j=1}^K u_{pj}(\alpha, \beta, \gamma) \varepsilon_1^{(j)}(\alpha, \beta, \gamma) \langle N_1^{(j)}(\alpha, \beta, \gamma) \rangle$$

$$\begin{aligned} \langle W_p(\alpha, \beta, \gamma)^2 \rangle &= \sum_{j=1}^K u_{pj}^{(2)}(\alpha, \beta, \gamma) \varepsilon_1^{(j)}(\alpha, \beta, \gamma) \langle N_1^{(j)}(\alpha, \beta, \gamma) \rangle \\ &+ \sum_{j=1}^K \left[ u_{pj}(\alpha, \beta, \gamma) \varepsilon_1^{(j)}(\alpha, \beta, \gamma) \right]^2 \langle N_1^{(j)}(\alpha, \beta, \gamma) [N_1^{(j)}(\alpha, \beta, \gamma) - 1] \rangle \\ &+ \sum_{j \neq j'=1}^K u_{pj}(\alpha, \beta, \gamma) \varepsilon_1^{(j)}(\alpha, \beta, \gamma) u_{pj'}(\alpha, \beta, \gamma) \varepsilon_1^{(j')}(\alpha, \beta, \gamma) \langle N_1^{(j)}(\alpha, \beta, \gamma) \rangle \end{aligned}$$

$$\begin{aligned} \langle W_p(\alpha_1, \beta_1, \gamma_1) W_q(\alpha_2, \beta_2, \gamma_2) \rangle &= \sum_{j=1}^K u_{pqj}(\alpha, \beta, \gamma) \varepsilon_1^{(j)}(\alpha, \beta, \gamma) \langle N_1^{(j)}(\alpha, \beta, \gamma) \rangle \\ &+ \sum_{j=1}^K u_{pj}(\alpha, \beta, \gamma) \varepsilon_1^{(j)}(\alpha, \beta, \gamma) u_{qj}(\alpha, \beta, \gamma) \varepsilon_1^{(j)}(\alpha, \beta, \gamma) \langle N_1^{(j)}(\alpha, \beta, \gamma) [N_1^{(j)}(\alpha, \beta, \gamma) - 1] \rangle \\ &+ \sum_{j \neq j'=1}^K u_{pj}(\alpha, \beta, \gamma) \varepsilon_1^{(j)}(\alpha, \beta, \gamma) u_{qj'}(\alpha, \beta, \gamma) \varepsilon_1^{(j')}(\alpha, \beta, \gamma) \langle N_1^{(j)}(\alpha, \beta, \gamma) \rangle \end{aligned}$$

Matrix Inversion provides differential moments:  $N = A^{-1}B$

# Part III: Summary

- The Identity method extended to account for rapidity, azimuth, and  $p_T$  dependent detection efficiency...
  - for fluctuation measurements
  - for differential correlation measurements
  - flow measurements (not discussed here).



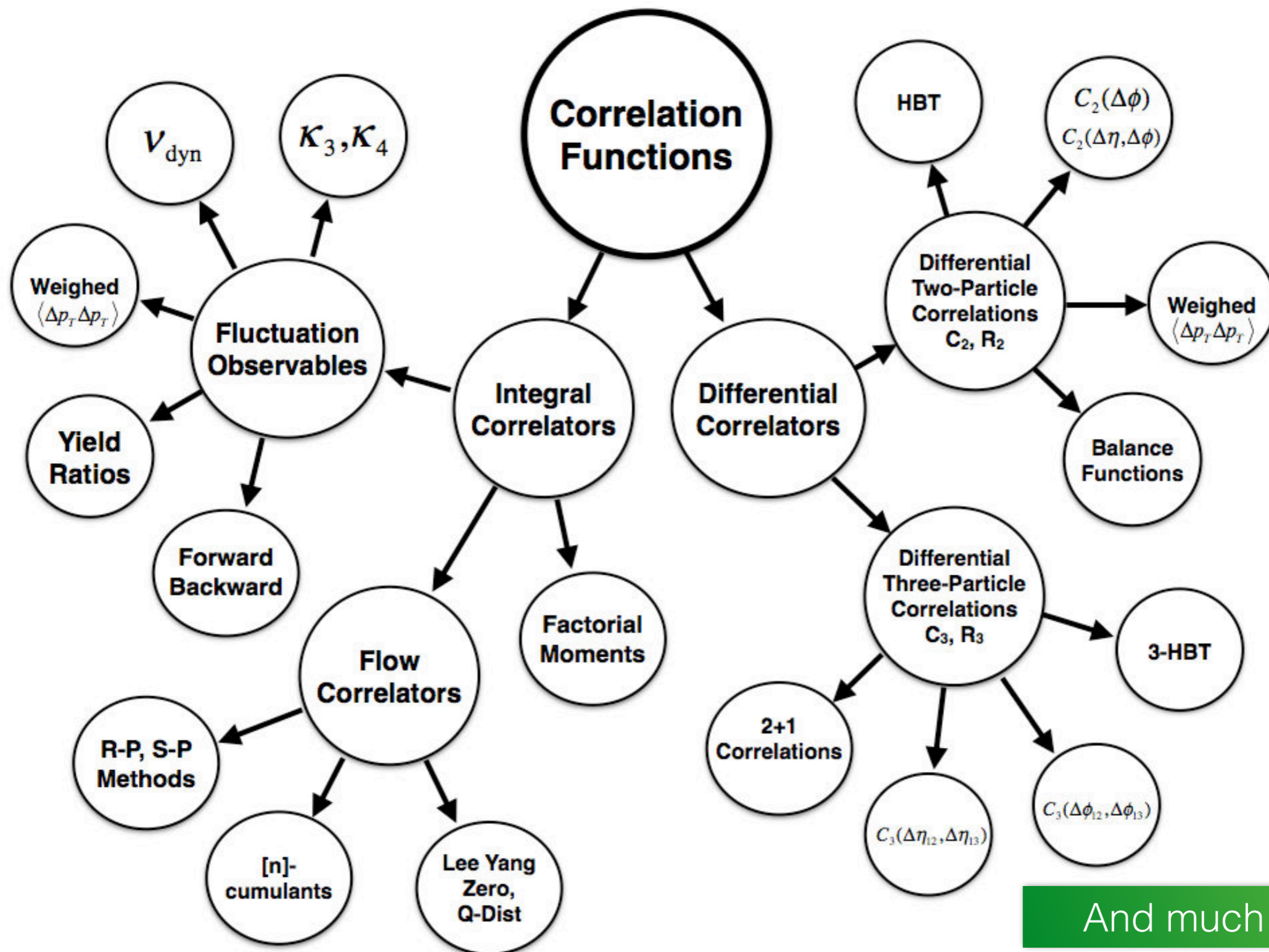


# Summary

- Observing anomalies in the BES of fluctuations is rather challenging.
- I argued to
  - diversify observables used in the search
  - **include differential observables and their basic characteristics (amplitude, width) with system size, beam energy, etc.**
- I showed that differential correlations can be measured robustly — even when the efficiency is a complicated function of momentum or detector conditions..
- I extended the identity method
  - to account for particle losses — that vary across the acceptance.
  - to differential correlation measurements
    - maximize use of the accumulated statistics
    - extend pT range of differential correlation measurements

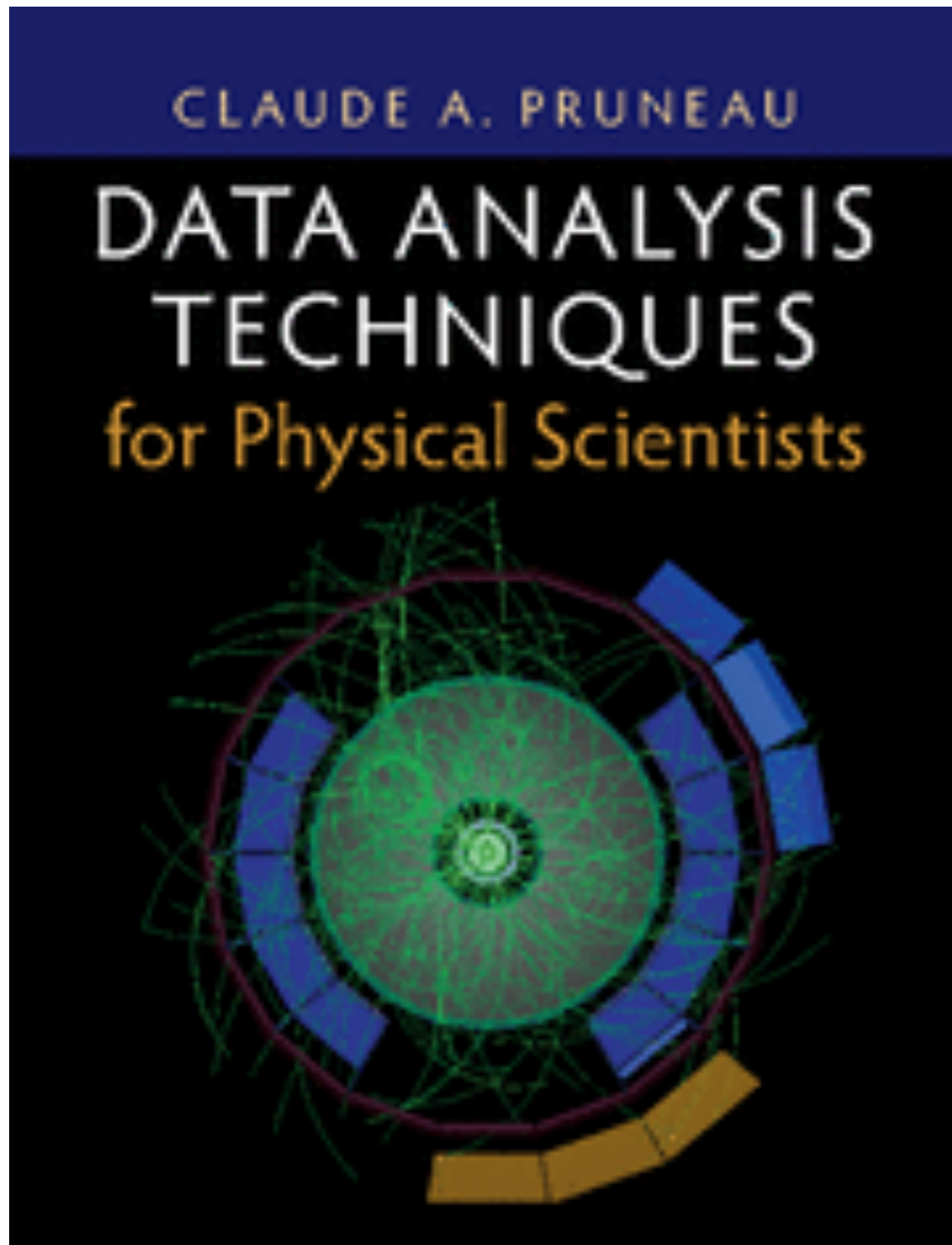


# The Multiple Facets of Correlation Functions



And much more ...

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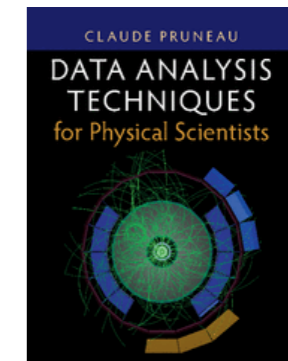
## Data Analysis Techniques for Physical Scientists

Claude A. Pruneau

Wayne State University, Michigan

A comprehensive guide to data analysis techniques for physical scientists, providing a valuable resource for advanced undergraduate and graduate students, as well as seasoned researchers. The book begins with an extensive discussion of the foundational concepts and methods of probability and statistics under both the frequentist and Bayesian interpretations of probability. It next presents basic concepts and techniques used for measurements of particle production cross-sections, correlation functions, and particle identification. Much attention is devoted to notions of statistical and systematic errors, beginning with intuitive discussions and progressively introducing the more formal concepts of confidence intervals, credible range, and hypothesis testing. The book also includes an in-depth discussion of the methods used to unfold or correct data for instrumental effects associated with measurement and process noise as well as particle and event losses, before ending with a presentation of elementary Monte Carlo techniques.

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