Elliptic Flow Fluctuations with the PHOBOS detector

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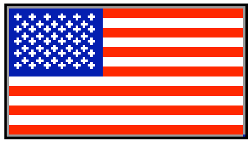
PHOBOS Collaboration





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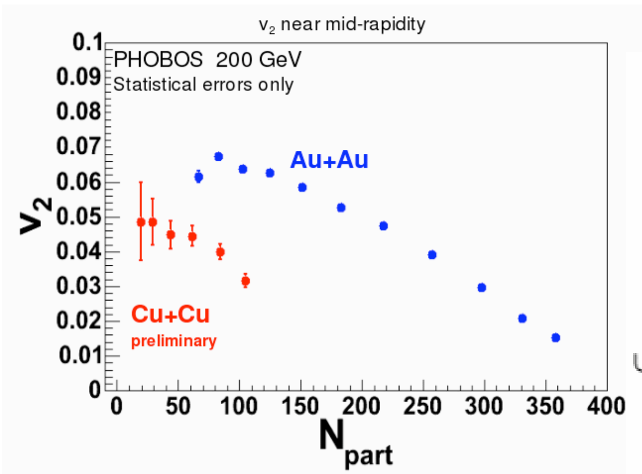
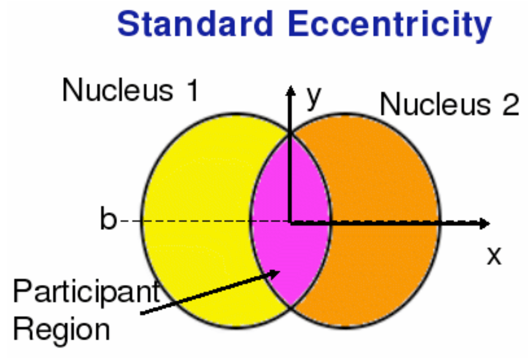
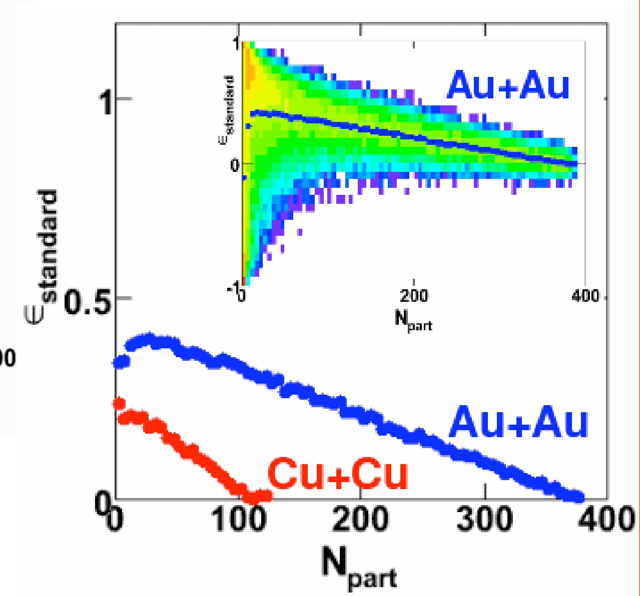
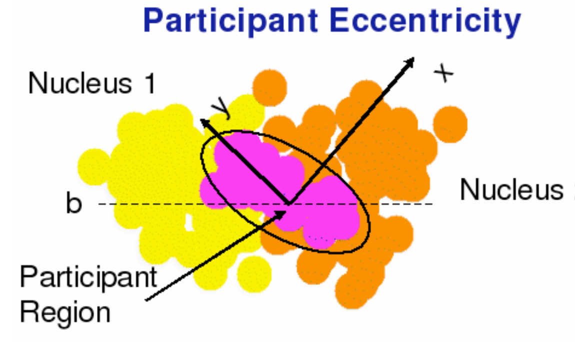
Motivation

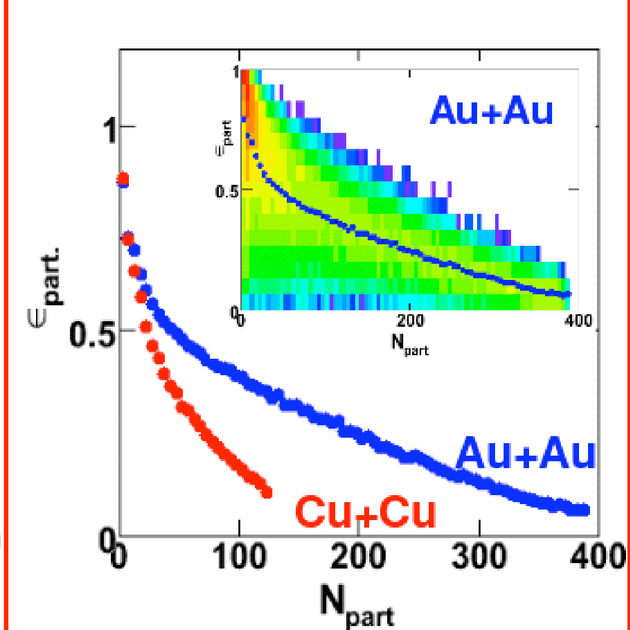
High v_2 observed in CuCu can be explained by fluctuations in initial collision region.









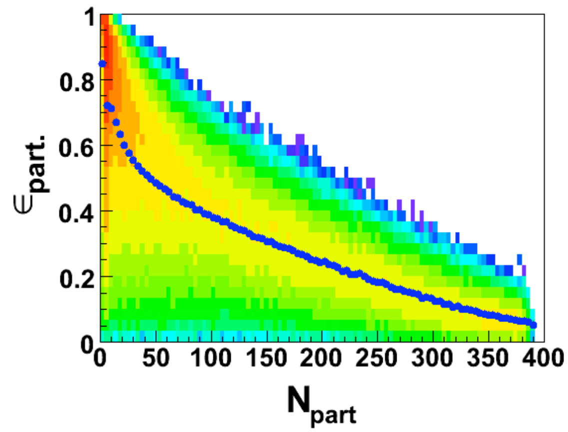


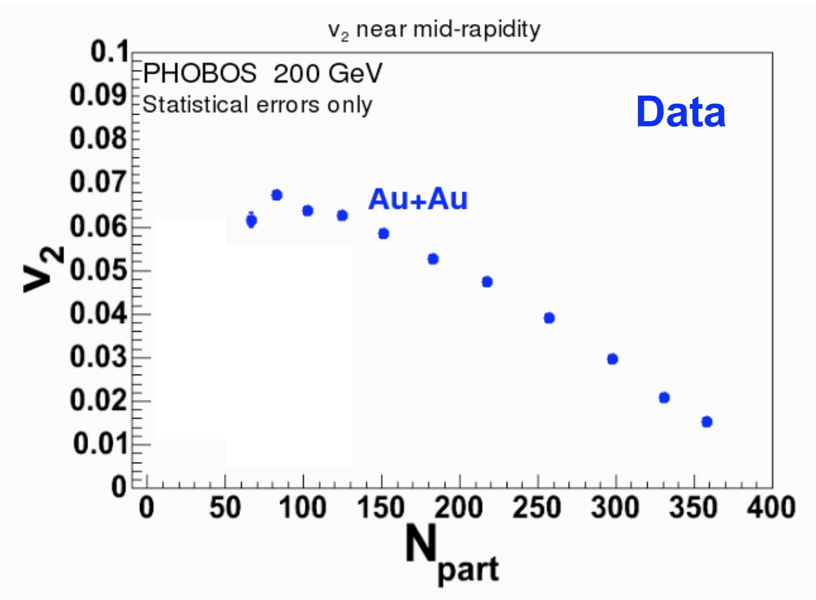
Can we test the Participant Eccentricity Model?

Expected fluctuations

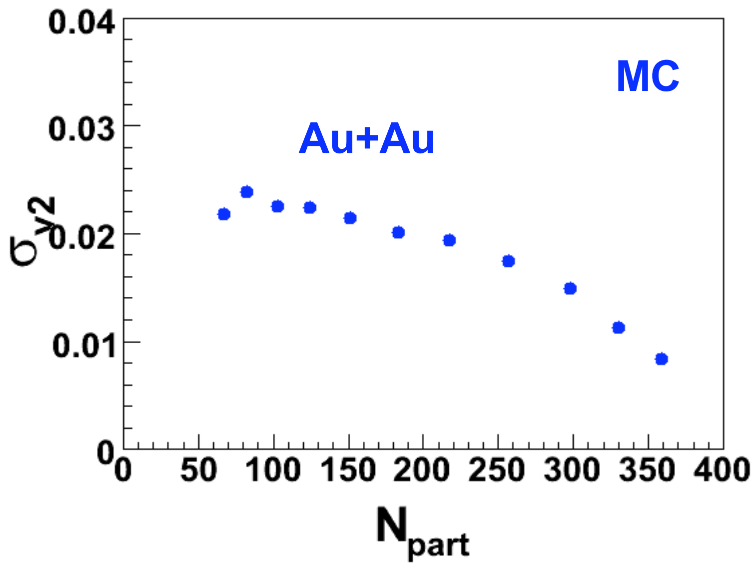
Assuming $v_2 \propto \varepsilon_{part}$, participant eccentricity model predicts v_2 fluctuations

$$\frac{\sigma_{v_2}}{v_2} = \frac{\sigma_\epsilon}{\epsilon}$$





Expected σ_{v2} from fluctuations in ε_{part}



Measuring v_2 Fluctuations

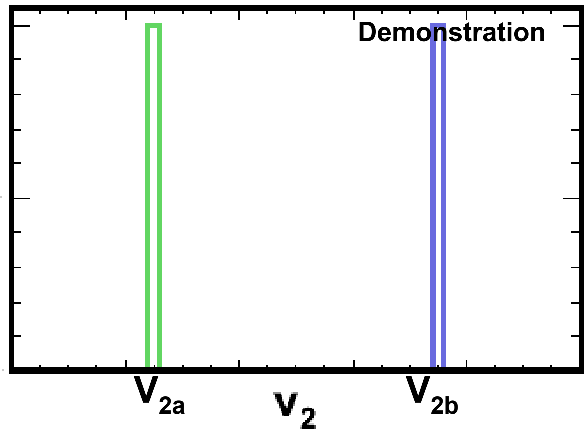
- **We have considered 3 different methods**
  - **2 particle correlations → $\langle v_2^2 \rangle$**
    - c.f. S. Voloshin nucl-th/0606022
    - $\sigma_{v2}^2 = \langle v_2^2 \rangle - \langle v_2 \rangle^2$
    - Do systematic errors cancel?
  - **2 particle correlations → v_2^2 event by event**
    - Mixed event background generation is possible
    - Reduces fit parameters to 1 (no reaction plane)
    - Hard to untangle acceptance effects event by event
  - **v_2 event by event**
    - This is the method we are pursuing

Measuring v_2 Fluctuations - Today's Talk

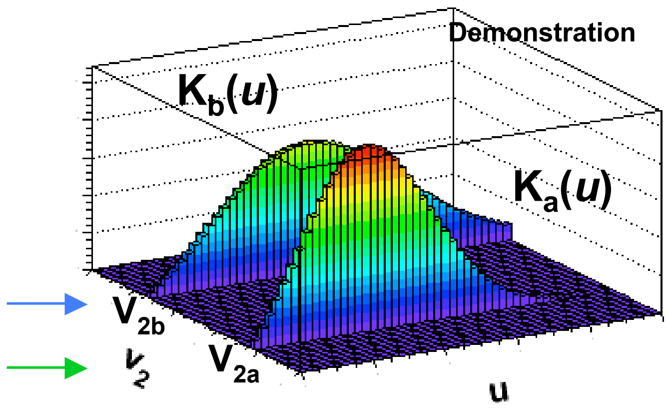
- Measuring v_2 event by event
- Ongoing analysis on 200GeV Au-Au
- Today
  - How we are planning to make the measurement
  - Studies on fully simulated MC events
    - Modified Hijing - Flow
    - Geant

Method Overview - Simplified Example

2 possible v_2 values



Event by Event measurement

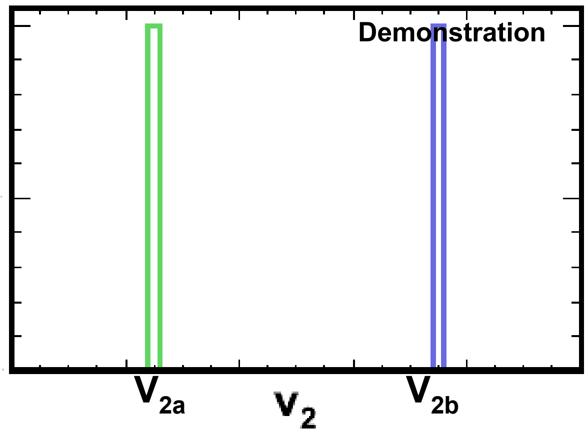


$u = v_{2obs.}$

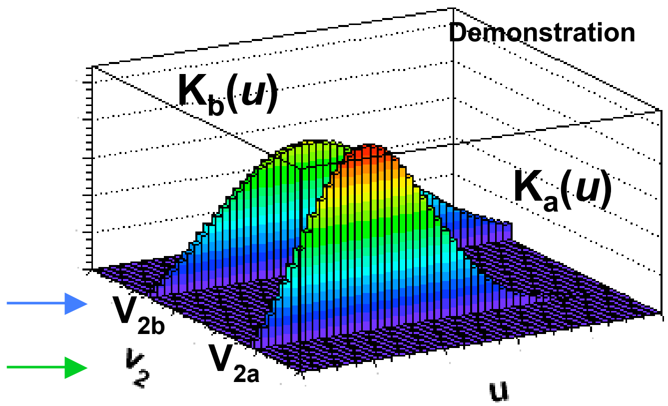
or $u = v_2{}^2{}_{obs.}$
or $u = q_{obs.}$

Method Overview - Simplified Example

2 possible v_2 values



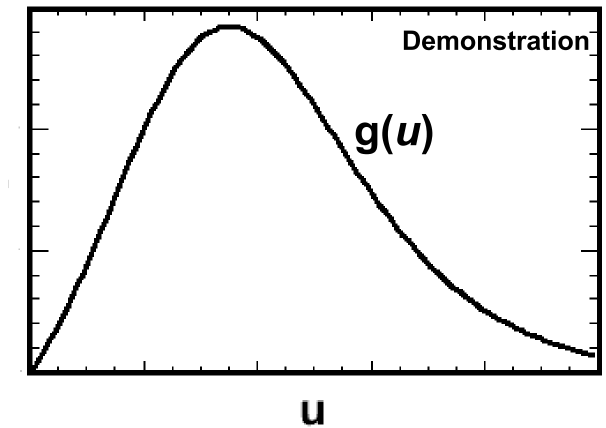
Event by Event measurement



$u = v_{2obs.}$

or $u = v_2^2{}_{obs.}$
or $u = q_{obs.}$

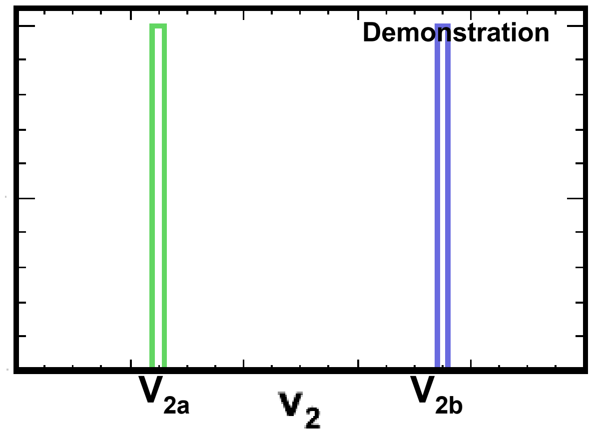
Measured u distribution in a sample



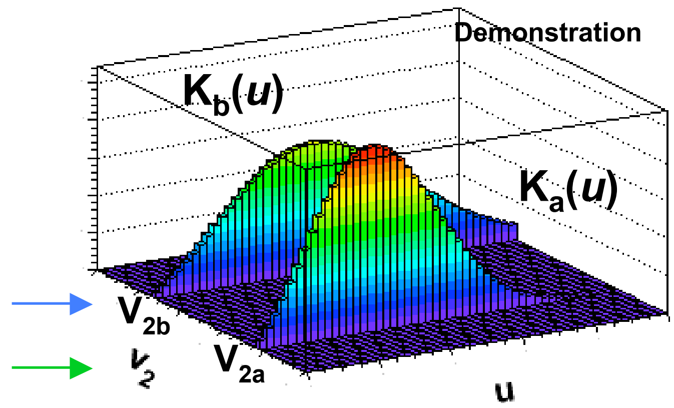
Question: What is the relative abundance of v_{2a} to v_{2b} in the sample?

Method Overview - Simplified Example

2 possible v_2 values



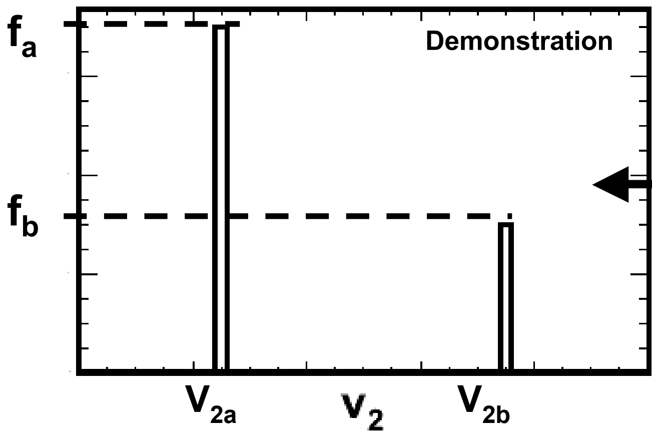
Event by Event measurement



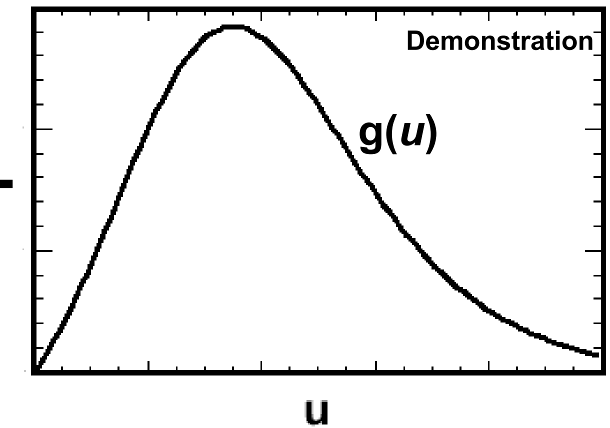
u=$v_{2obs.}$

or u = $v_2{}^2{}_{obs.}$
or u = $q_{obs.}$

Extracted v_{2true} distribution from sample



Measured u distribution in a sample

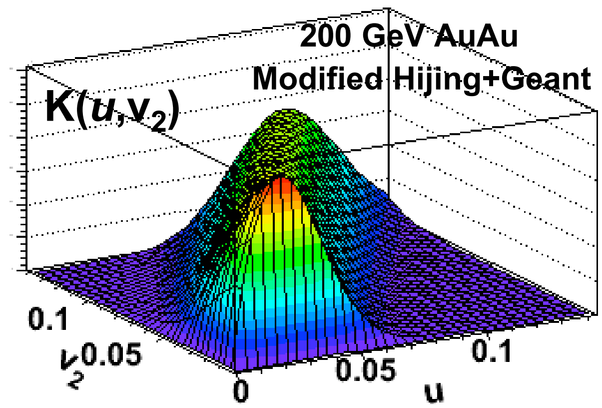


Question: What is the relative abundance of v_{2a} to v_{2b} in the sample?

$$g(u)=f_aK_a(u) + f_bK_b(u)$$

Method Overview

Kernel

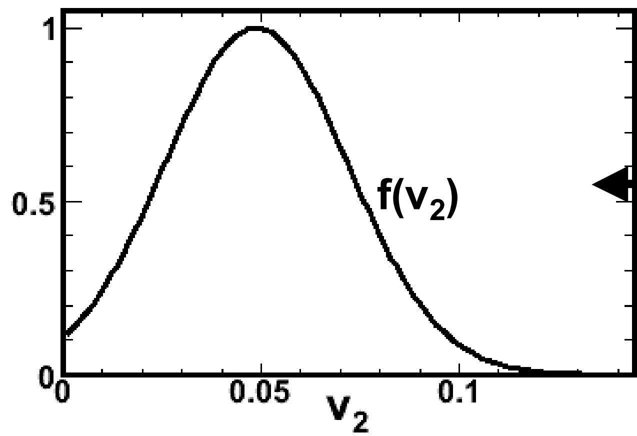


$u = v_{2obs.}$

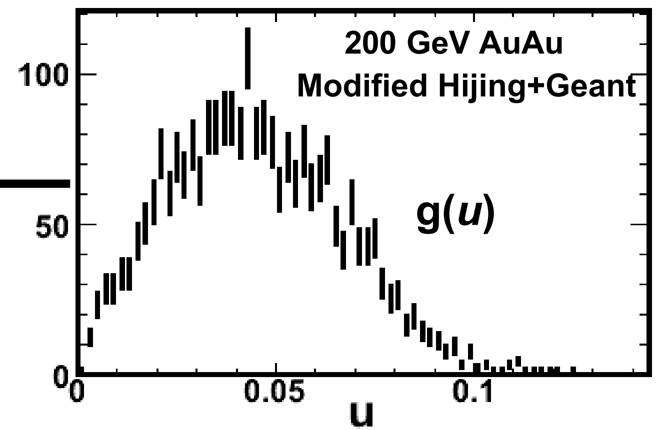
In real life v_2 can take a continuum of values

$$g(u) = \int_0^\infty K(u, v_2) f(v_2) dv_2$$

Extracted v_{2true} distribution from sample



Measured *u* distribution in a sample



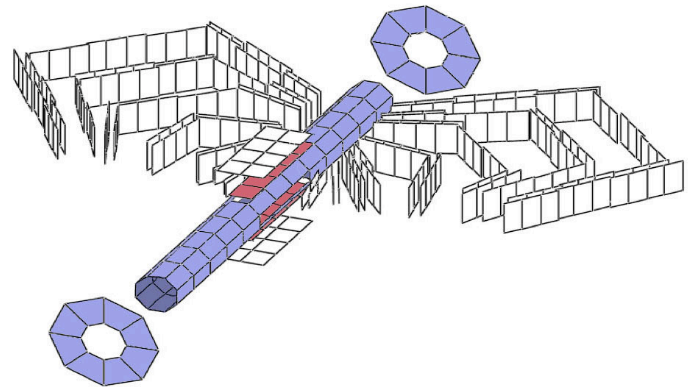
Method Overview

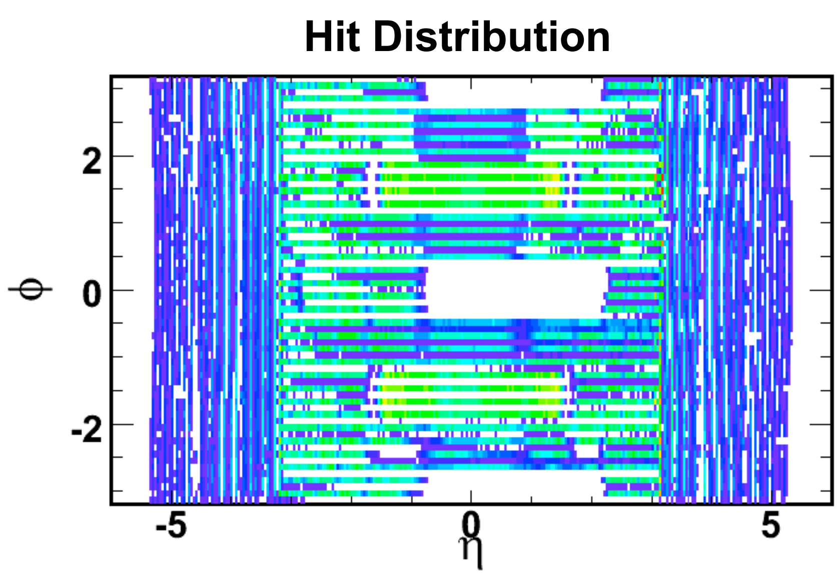
- **3 Tasks**
  - **Measure *u* event-by-event g(*u*)**
  - **Calculate the kernel K(*u*,v_2)**
  - **Extract dynamical fluctuations f(v_2)**

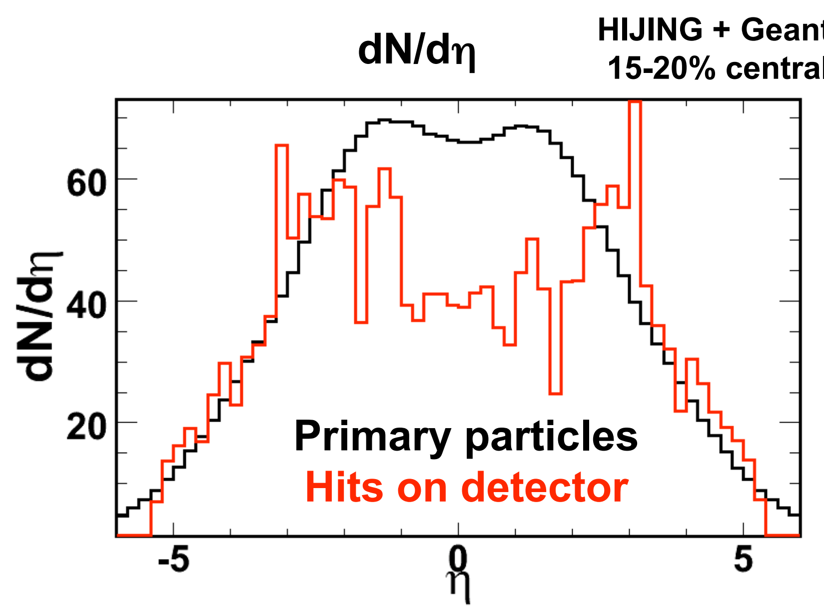
$$g(u) = \int_0^\infty K(u, v_2) f(v_2) dv_2$$

PHOBOS Detector

- **PHOBOS Multiplicity Array**
  - -5.4<η<5.4 coverage
  - -Holes / granularity differences
- **Idea: Use all available information in event to read off single *u* value**



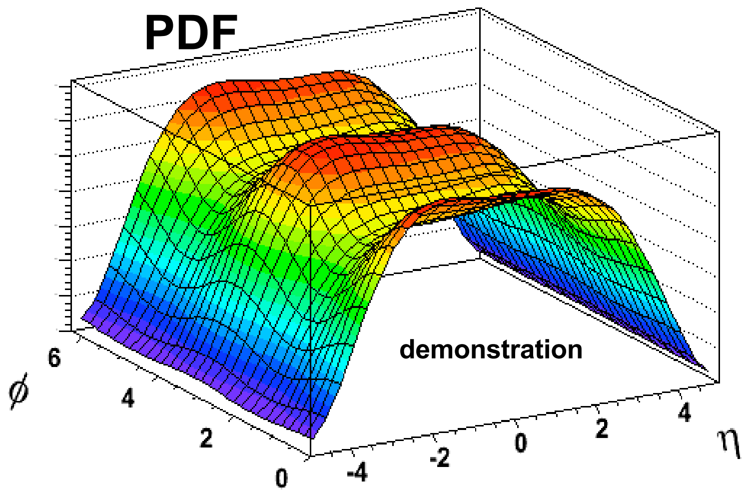




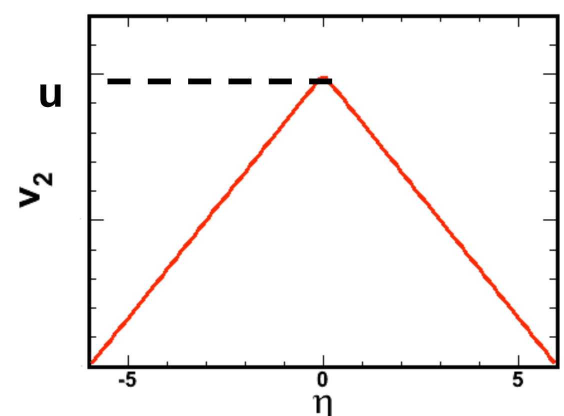
Measuring $u=v_{2obs}$ Event by Event I

- **Probability Distribution Function (PDF) for hit positions:**

$$P(\eta,\phi|u,\phi_0) = \underbrace{p(\eta)}_{\text{Probability of hit in } \eta}\underbrace{[1+2v_2(\eta)cos(2(\phi-\phi_0))]}_{\text{Probability of hit in } \phi}$$



$$v_2(\eta) = u(1-|\eta|/6)$$



- **Define likelihood of u and ϕ_0 for an event:**

$$L(u,\phi_0) = \prod_{i=1}^{n} P(\eta_i,\phi_i|u,\phi_0)$$

Measuring $u = v_{2obs}$ Event by Event II

$$L(u, \phi_0) = \prod_{i=1}^{n} p(\eta_i)[1 + 2\,u\,(1 - |\eta_i|/6)\,cos(2(\phi_i - \phi_0))]$$

- **Maximize likelihood to find "most likely" value of *u***
- **Comparing values of *u* and ϕ_0**
  - **In an event, $p(\eta_i)$ is same for all *u* and ϕ_0.**
  - **PDF folded by acceptance must be normalized to the same value for different *u* and ϕ_0's**

Acceptance

$$s(u, \phi_0|\eta) = \int A(\eta, \phi) \cdot [1 + 2\,u\,(1 - |\eta|/6)\,cos(2(\phi - \phi_0))]\,d\phi\,d\eta$$

Measuring $u=v_{2obs}$ Event by Event II

$$L(u,\phi_0)=\prod_{i=1}^{n} p(\eta_i)[1+2\,u\,(1-|\eta_i|/6)\,cos(2(\phi_i-\phi_0))]$$

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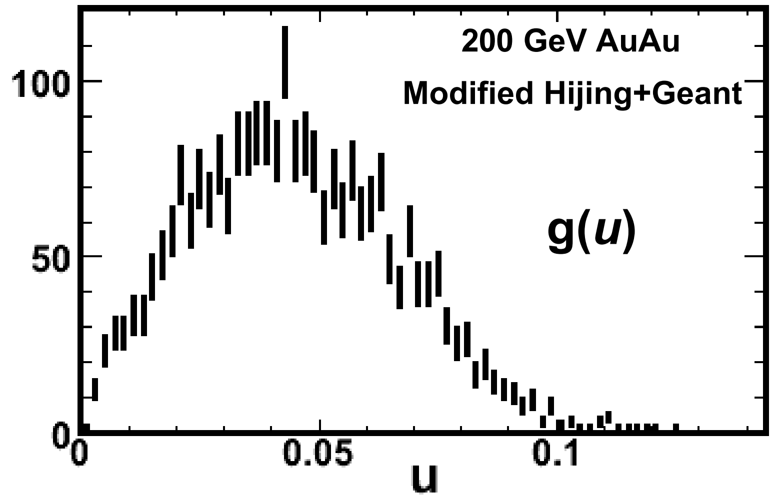
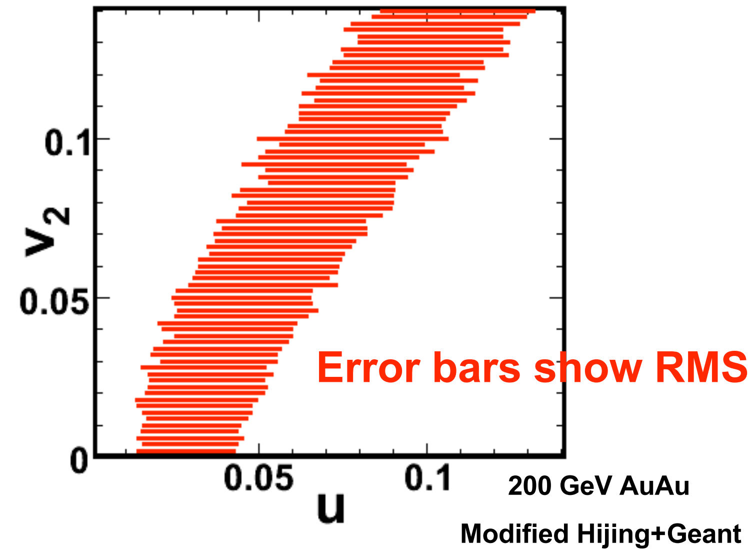
$$L(u,\phi_0)=\prod_{i=1}^{n}\frac{1}{s(u,\phi_0|\eta_i)}[1+2\,u\,(1-|\eta_i|/6)\,cos(2(\phi_i-\phi_0))]$$

Measuring $u=v_{2obs}$ Event by Event III

Observed *u* distribution in a sample



Mean and RMS of *u* in slices of v_2

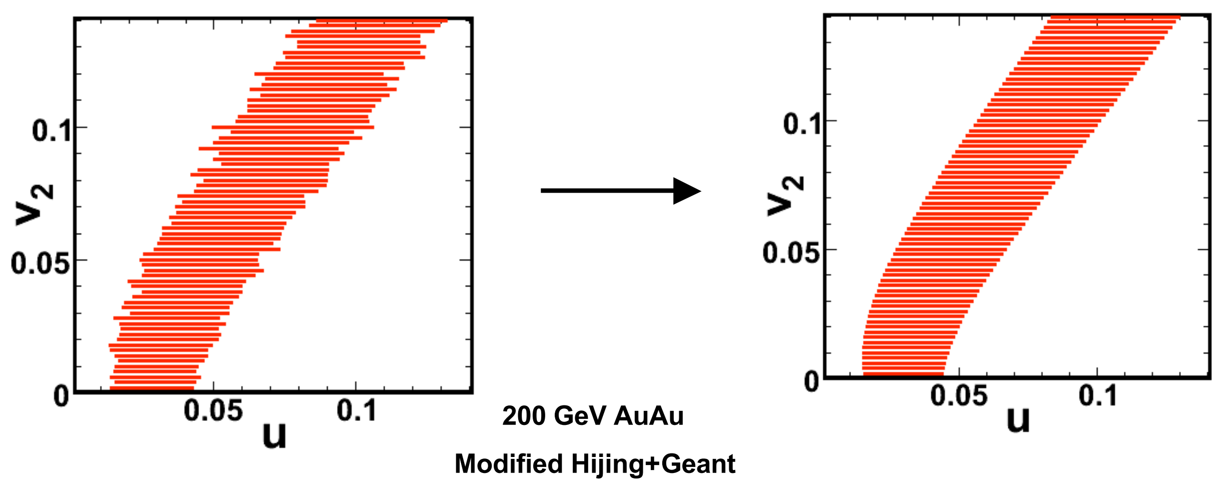


Next Step: Construct the Kernel to unfold g(*u*)

$$g(u) = \int_0^\infty K(u, v_2) f(v_2) dv_2$$

Calculating the Kernel I

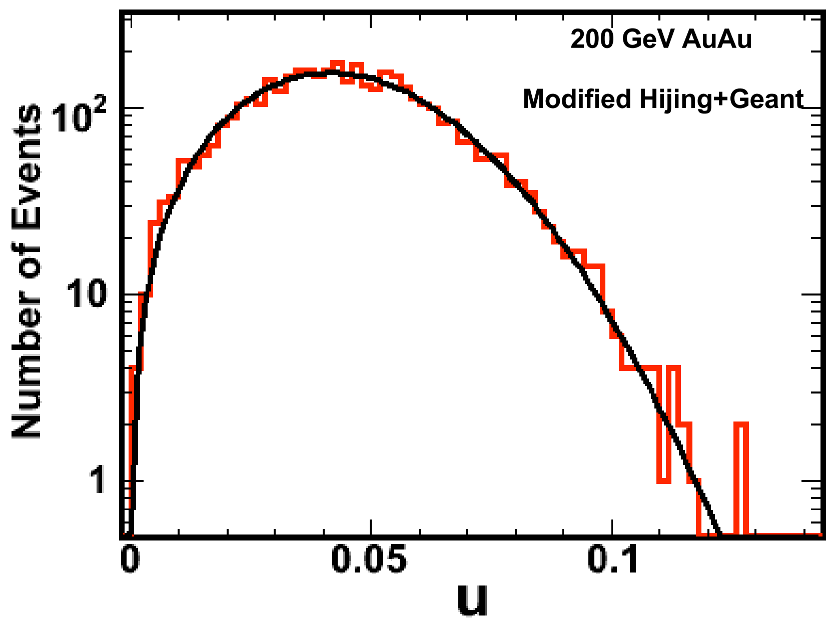
- **Simple: Measure *u* distribution in bins of v_2**
- **2 small complications**
  - **Kernel depends on multiplicity: K(u,v_2,n)**
    - ***n* = number of hits on the detector**
    - **Measure *u* distribution in bins of v_2 and *n*.**
  - **Statistics in bins can be combined by fitting smooth functions**



Calculating the Kernel II

- In a single bin of v_2 and *n*

u* distribution with for fixed v_2 and *n



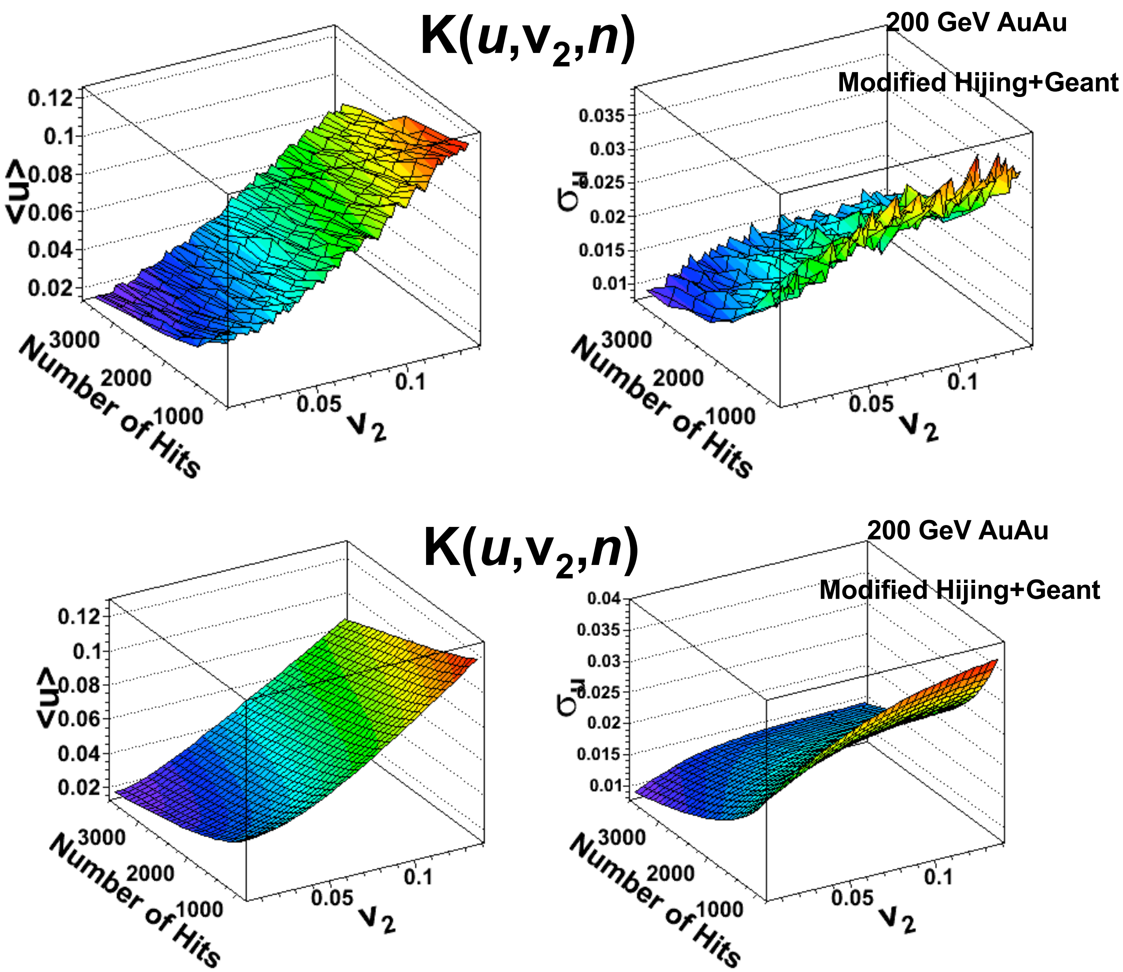
$$K(u)|_{v_2,n} = u \cdot exp\left(-\frac{u-a^2}{2b^2}\right)$$

(a, b) ↔ (<*u*>,σ_u)

- Distribution is not Gaussian
- But can be parameterized by <*u*> and σ_u

Calculating the Kernel III

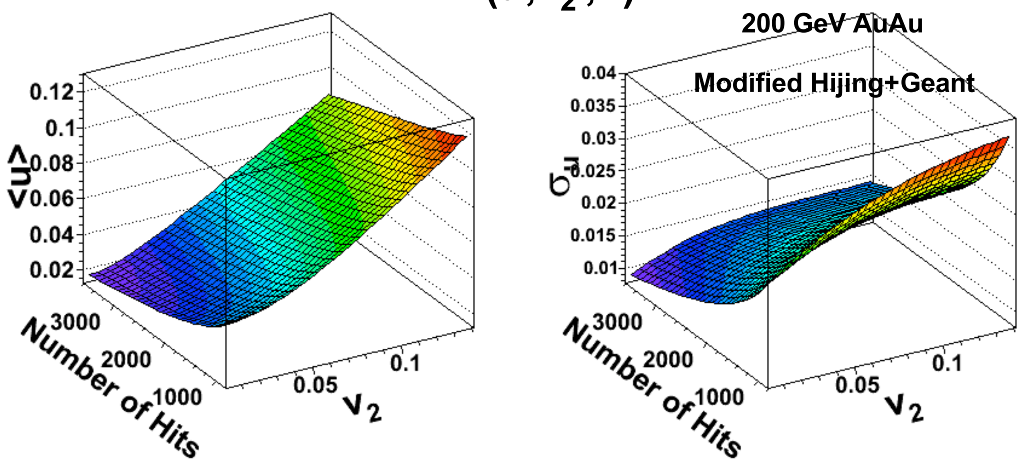
- Measure $\langle u \rangle$ and σ_u in bins of v_2 and n
- Fit smooth functions



Calculating the Kernel IV

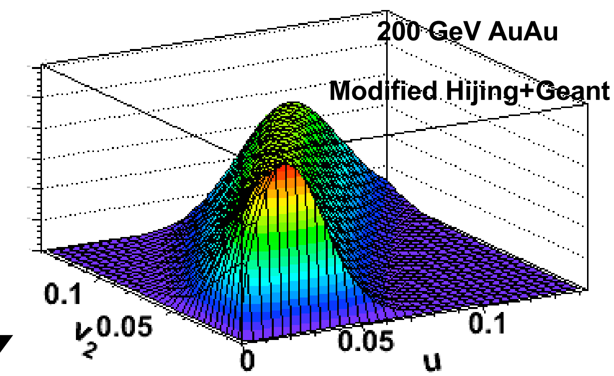
- **Multiplicity dependence can be integrated out**

K(*u*,v$_2$,*n*)

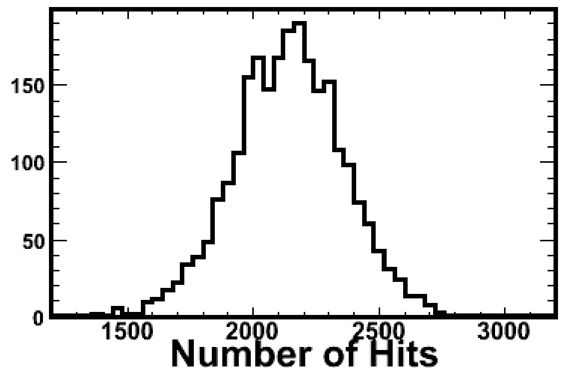


$$K(u,v_2) = \int K(u,v_2,n)N(n)dn$$

K(*u*,v$_2$)



N(*n*) = Number hits distribution in sample



Extracting dynamical fluctuations

$$\underline{g(u)} = \int_0^\infty \underline{K(u,v_2)}\,\underline{f(v_2)}dv_2$$

known

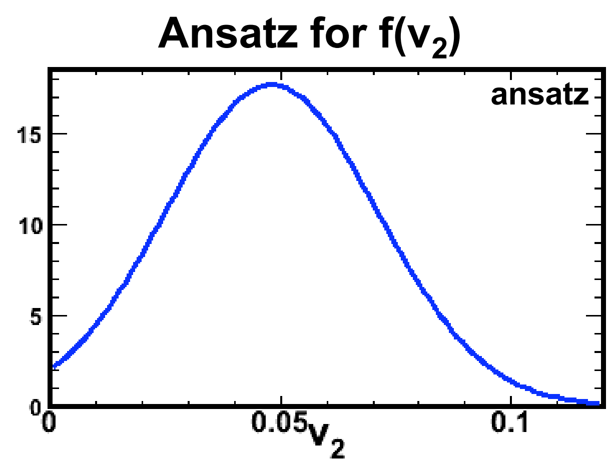
?

Extracting dynamical fluctuations

$$\underline{g(u)} = \int_0^\infty \underline{K(u,v_2)}\,\underline{f(v_2)}\,dv_2$$

known ?

Ansatz with two parameters: $f(v_2) = exp(-\frac{(v_2 - <v_2>)^2}{2\sigma_{v_2}^2})$



Extracting dynamical fluctuations

$$\underline{g(u)} = \int_0^\infty \underline{K(u, v_2)}\,\underline{f(v_2)}dv_2$$

known ?

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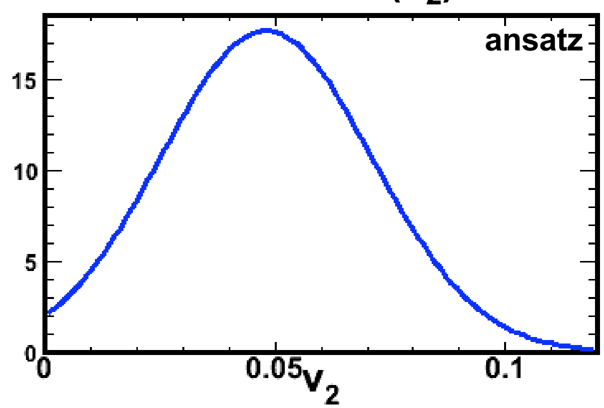
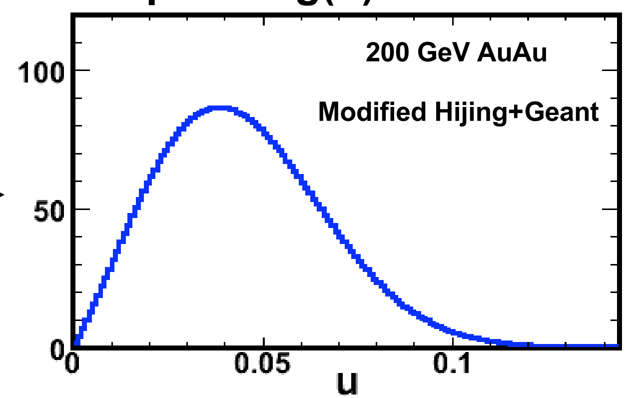
Ansatz for f(v_2)



integrate

Expected g(*u*) for Ansatz

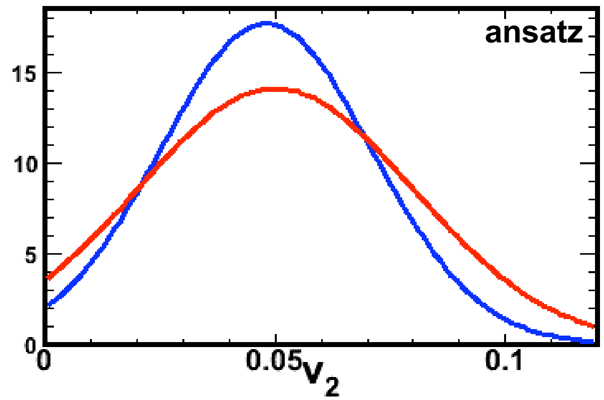


Extracting dynamical fluctuations

$$\underbrace{g(u)}_{\text{known}} = \int_0^\infty \underbrace{K(u, v_2)}_{\text{known}} \underbrace{f(v_2)}_{?} dv_2$$

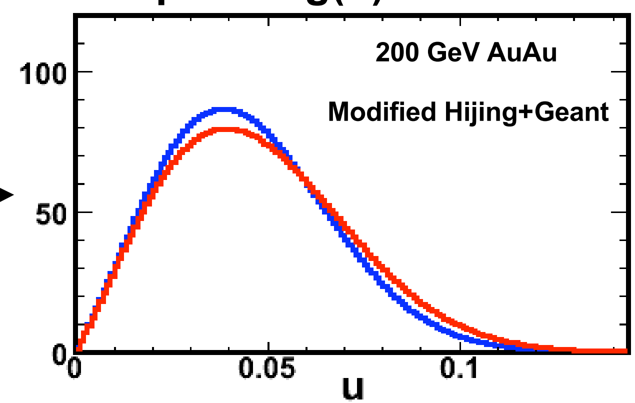
Ansatz with two parameters: $$f(v_2) = exp(-\frac{(v_2 - <v_2>)^2}{2\sigma_{v_2}^2})$$

Ansätze for $f(v_2)$



integrate

Expected g(*u*) for Ansätze



Extracting dynamical fluctuations

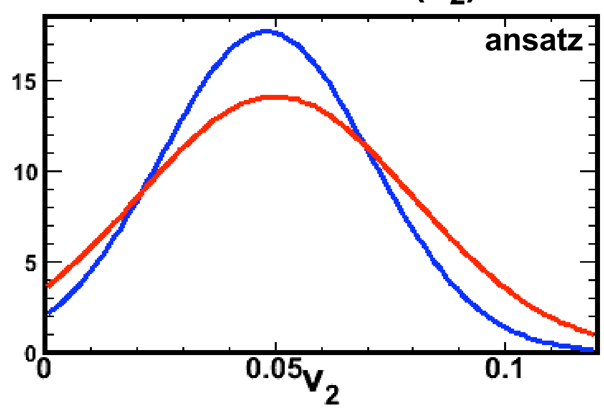
$$\underline{g(u)} = \int_0^\infty \underline{K(u, v_2)}\, \underline{f(v_2)} dv_2$$

known

?

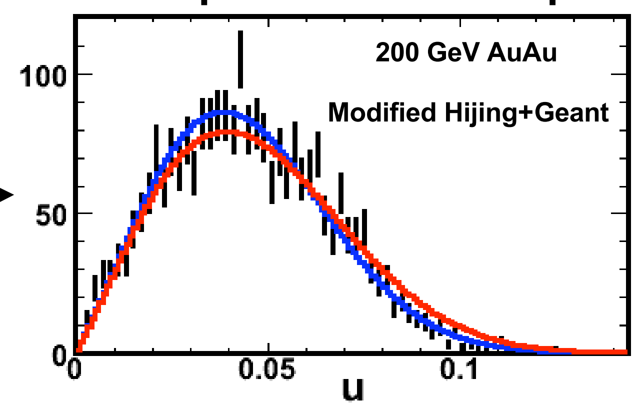
Ansatz with two parameters: $f(v_2) = exp(-\frac{(v_2 - < v_2 >)^2}{2\sigma_{v_2}^2})$

Ansätze for $f(v_2)$



integrate

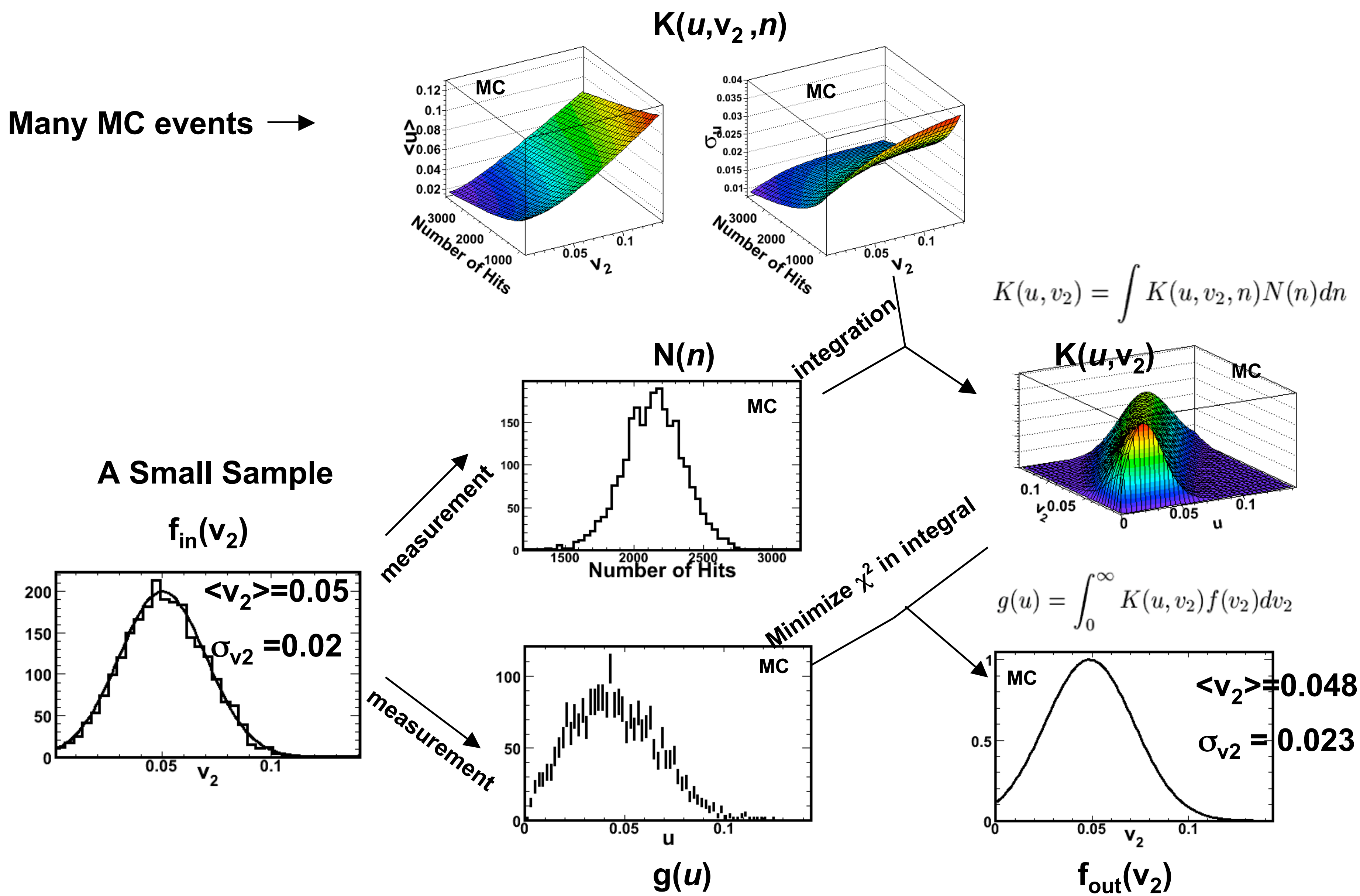
Comparison with sample



Compare expected g(u) for Ansatz with measurement

Minimum $\chi^2 \rightarrow \langle v_2 \rangle$ and σ_{v2}

Method Summary

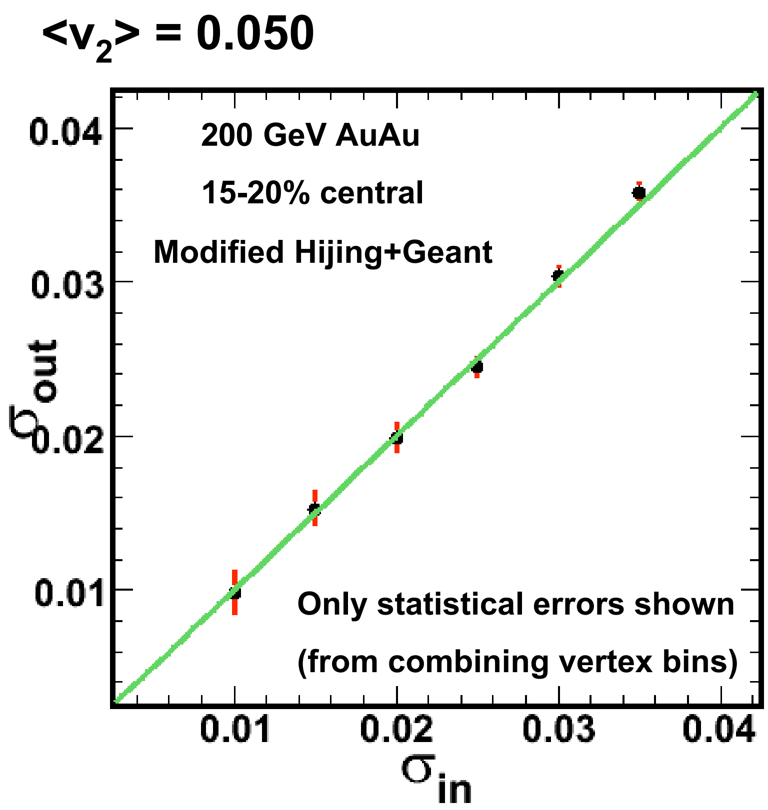


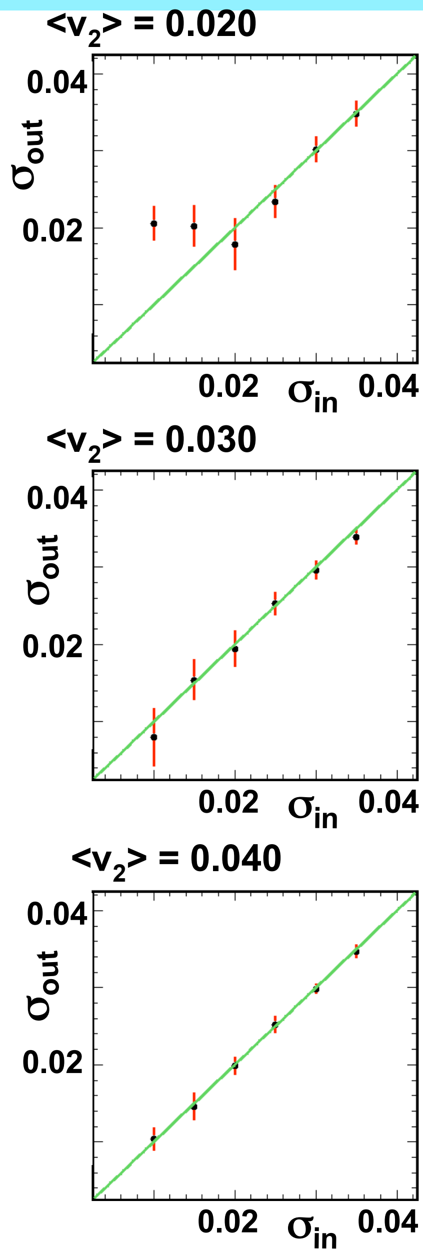
Verification

- **Ran this analysis on Modified Hijing**
  - **$v_2(\eta) = v_2(0) \cdot (1-|\eta|/6)$**
    - **Same as the assumption in our fit**
  - **$v_2(0)$ given by a Gaussian distribution in each sample**
    - **Same as our Ansatz**
  - **Analysis done in 10 collision vertex bins**
    - **Final results are averaged**
  - **0-40% central events used to construct Kernel**
  - **15-20% central events used as sample**

Verification

- **Ran this analysis on Modified Hijing**
  - **The input fluctuations are reconstructed successfully**

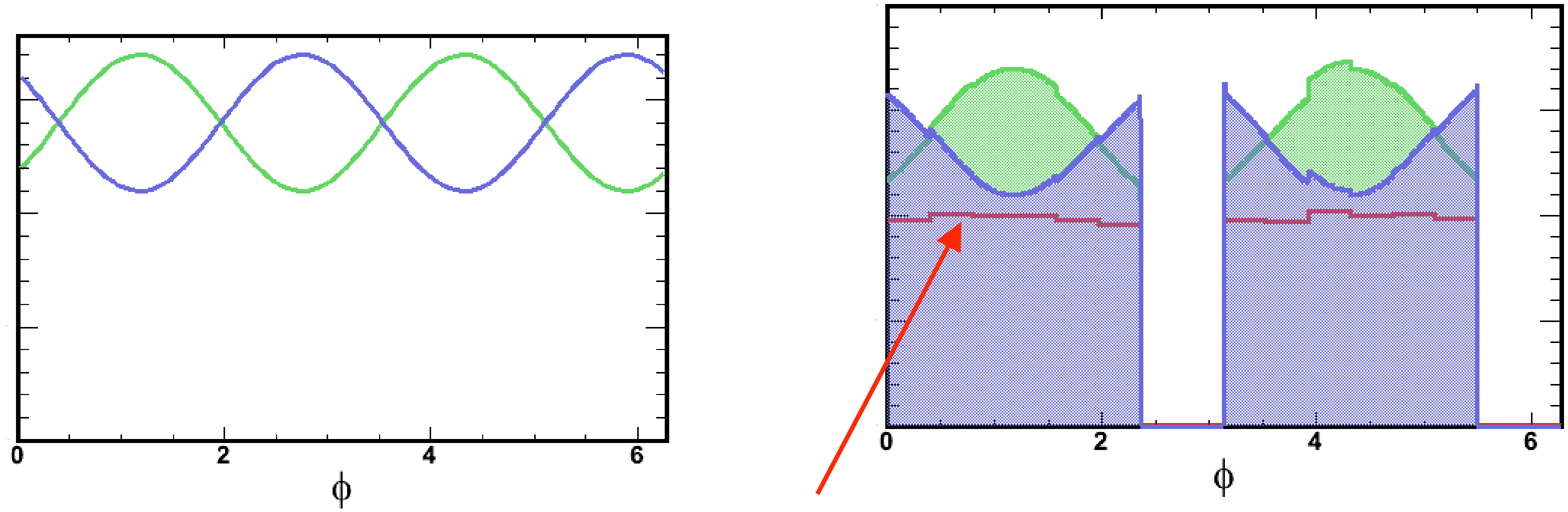




Conclusion / Outlook

- A new method to measure elliptic flow fluctuations is developed.
- Fluctuations in MC simulations are successfully reconstructed.
- Ready to apply the method to extract dynamical fluctuations in DATA.
  - Important part will be to estimate systematic uncertainties due to the MC/DATA differences
    - $dN/d\eta(\eta)$
    - $v_2(\eta)$
    - Non-flow in data
      - Should show up in reaction plane resolutions

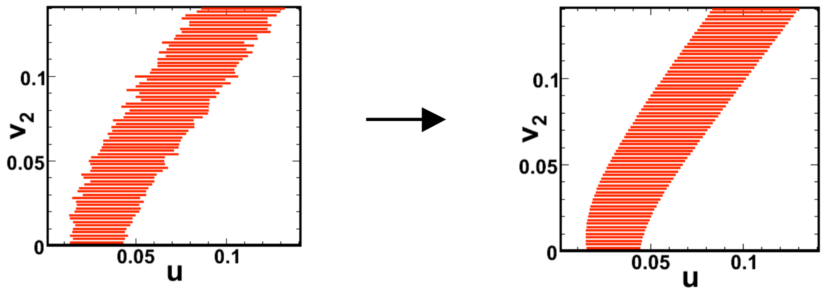
Likelihood Fit Normalization



$$s(u, \phi_0 | \eta) = \int A(\eta, \phi) \cdot [1 + 2\, u\, (1 - |\eta|/6)\, cos(2(\phi - \phi_0))]\, d\phi\, d\eta$$

$$L(u, \phi_0) = \prod_{i=1}^{n} \frac{1}{s(u, \phi_0 | \eta_i)} [1 + 2\, u\, (1 - |\eta_i|/6)\, cos(2(\phi_i - \phi_0))]$$

Calculating the Kernel. Functions observed to fit the Kernel



$$< u > (v_2)|_n = \sqrt{m_1 \cdot v_2^2 + m_2}$$

$$\sigma_u(v_2)|_n = \frac{1}{r_1 + \frac{2}{3}\, e^{r_2 v_2}}$$

$$< u > (v_2, n) = \sqrt{(M_1 n^2 + M_2 n + M_3) \cdot v_2^2 + (M_4 * n + M_5)}$$

$$\sigma_u(v_2, n) = \frac{R_1}{(R_2\sqrt{n} + 1) \cdot (1 + \frac{2}{3}\, e^{(R_3 n + R_4) v_2})}$$