

Data-driven analysis methods for the measurement of reconstructed jets in heavy ion collisions at RHIC and LHC

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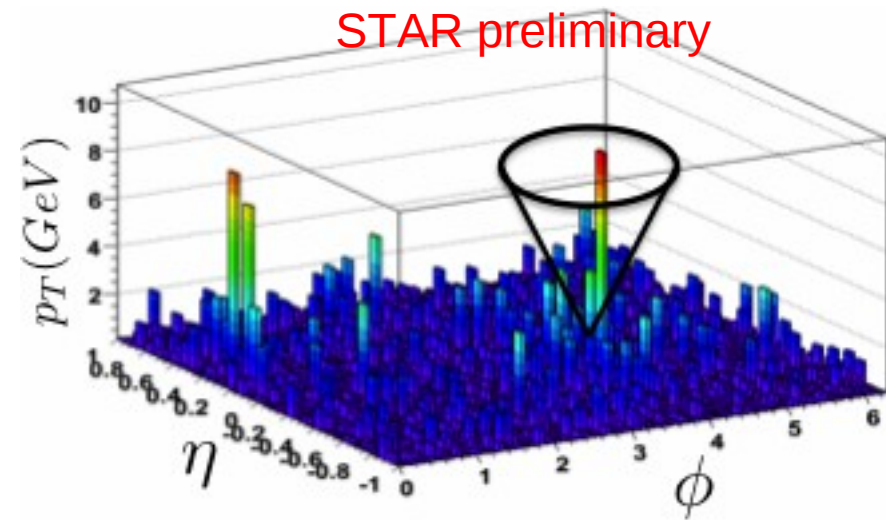
Jet reconstruction in heavy ion collisions

Very challenging task due to large underlying event

Jets are easy to identify but difficult to measure accurately due to large local background fluctuations

Origin of fluctuations: combinatoric “jets”

- random recombination of hadrons from soft background and multiple overlapping true jets
- Experimental noise, no underlying physical distribution



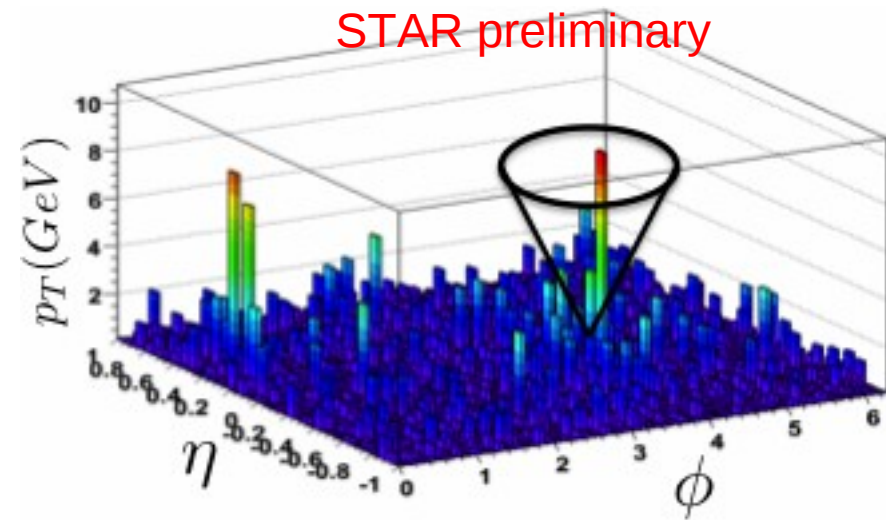
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Experimental approaches thus far:

I. Reduce background fluctuations by suppressing low p_T contribution

Explicitly: cut on hadron p_T or calorimeter cell energy

Implicitly: high B-field, hadronic calorimetry

→ Jet quenching: possibly biased jet population

II. Restrict analysis to very high p_T jets; MC assessment of remaining background systematics

→ Limited applicability (high p_T only); dependence on fragmentation model

HI Jet Reconstruction: a re-assessment

Even in principle:

- Cannot discriminate most hadrons as “jet” or “background” on event-by-event basis
- Cannot know local background density on jet-by-jet basis

Jet quenching has meaning, and can be measured, only on an ensemble-averaged basis

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Therefore, the crucial experimental limitation:

- *is not* the large background relative to signal
- *is* the precision with which we can know the background fluctuations and correct for their effects on an ensemble-averaged basis

Well-defined observables: inclusive cross section, semi-inclusive coincidence rates,...

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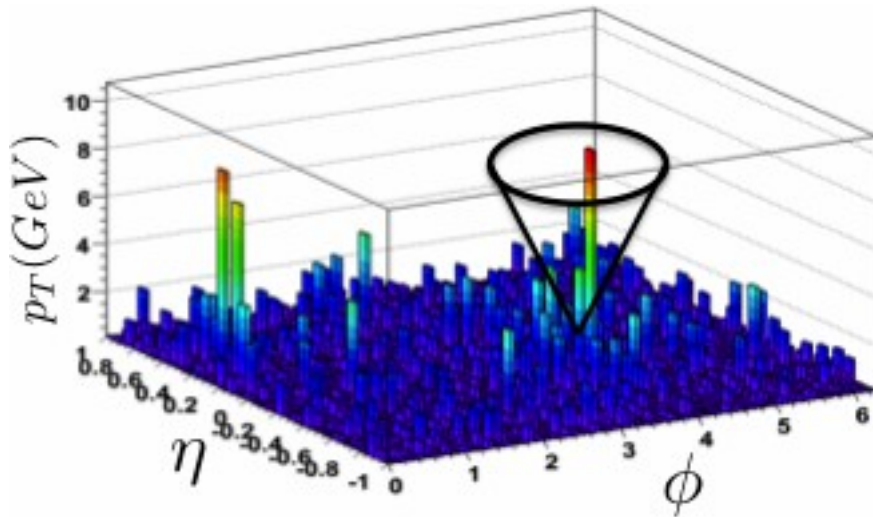
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We seek new HI Jet analysis methods that are systematically well-controlled over a very broad energy range, at both RHIC and LHC

- Fully data-driven: no modeling of backgrounds
- To measure jet quenching: fragmentation biases must be minimal, and transparent
 - To do this: utilize STAR and ALICE capabilities to measure individually almost all jet constituents over a wide p_T range

HI jet reconstruction: FastJet



Jet defined operationally: output of reconstruction algorithm (not necessarily interpretable perturbatively)

FastJet: collect all jets in acceptance $i=1, \dots, N$

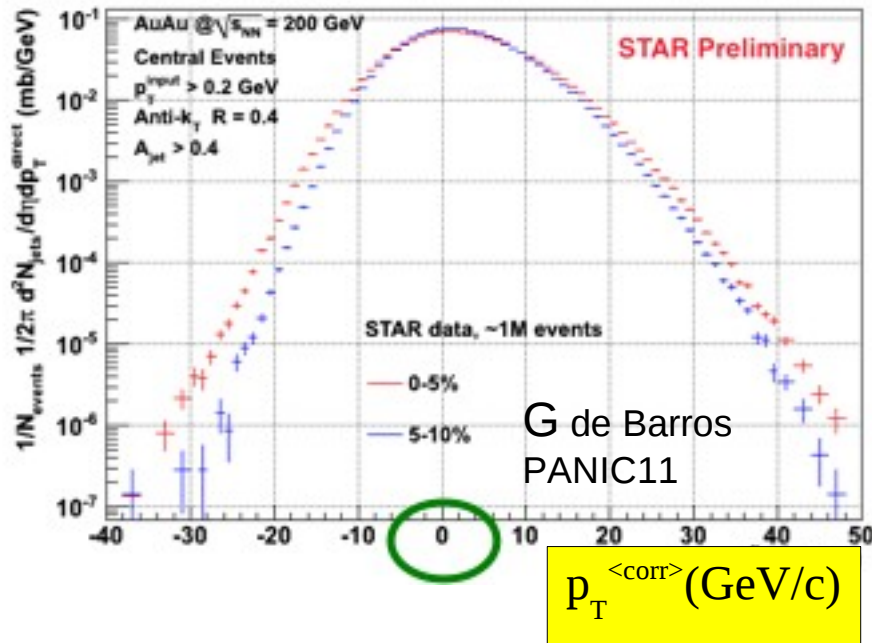
Event-wise estimate of background density:

$$\rho = \text{median} \left\{ \frac{p_{T, \text{jet}, i}}{A_{\text{jet}, i}} \right\}$$

Spectrum **corrected event-wise** for median background density:

$$p_{T, i}^{\langle \text{corr} \rangle} = p_{T, i} - \rho \cdot A_i$$

ρ is median: \sim half the jet population has $p_{T, i}^{\langle \text{corr} \rangle} < 0$



- contains crucial information about background

Toy Model Event Generator

Develop Toy Model Event Generator that

- is simple (and therefore transparent to interpret)
- captures the essential features and complexity of jet reconstruction in the HI background
- approximates experimental conditions at RHIC and LHC
 - apply model to explore algorithms

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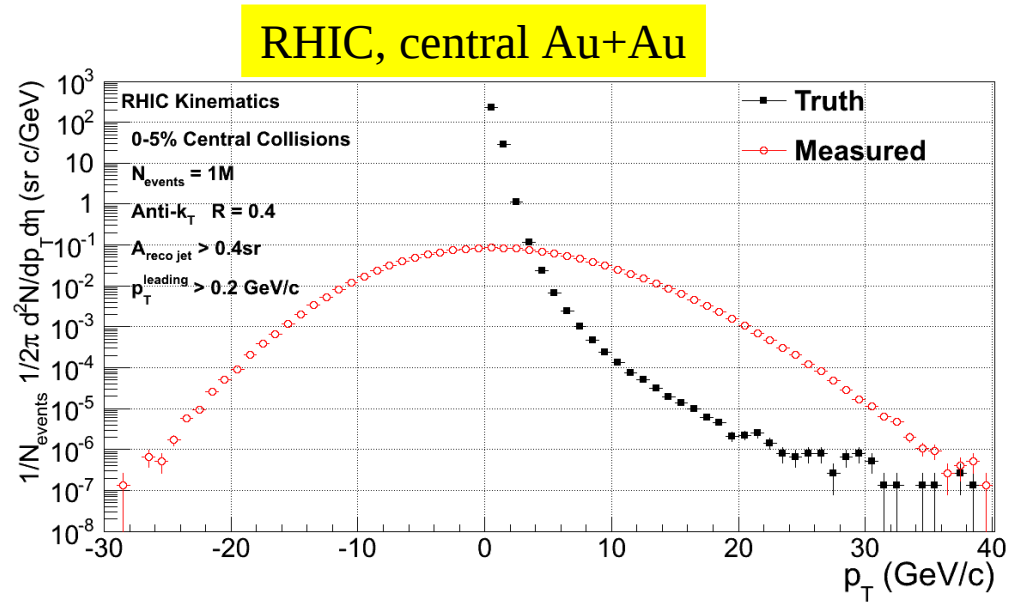
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→ apply model to explore algorithms

- Generic “particles”: primary only, no decays, no detector effects
- Generic acceptance (both RHIC and LHC): $|\eta| < 1.0$, full azimuth
- **Soft component: Boltzmann distribution**
 - RHIC: $\langle p_T \rangle = 500$ MeV
 - LHC: $\langle p_T \rangle = 700$ MeV
- **Hard jet component:**
 - **Distribution:** $T_{AA} * d\sigma_{jet} / dp_T$ (from p+p measurement or PYTHIA)
 - Various fragmentation models (to separate unfolding and fragmentation biases):
 1. *None: jets are modeled as single high p_T particles*
 2. *PYTHIA (vacuum) fragmentation, etc.*
- **“Central” collisions: total multiplicity (charged+neutral) in acceptance**
 - *RHIC, Au+Au 0-5%: $M_{tot} = 2000$*
 - *LHC, Pb+Pb, 0-5%: $M_{tot} = 4800$*
- **throw millions of such events and analyze like data, with anti- k_T , $R=0.4$**

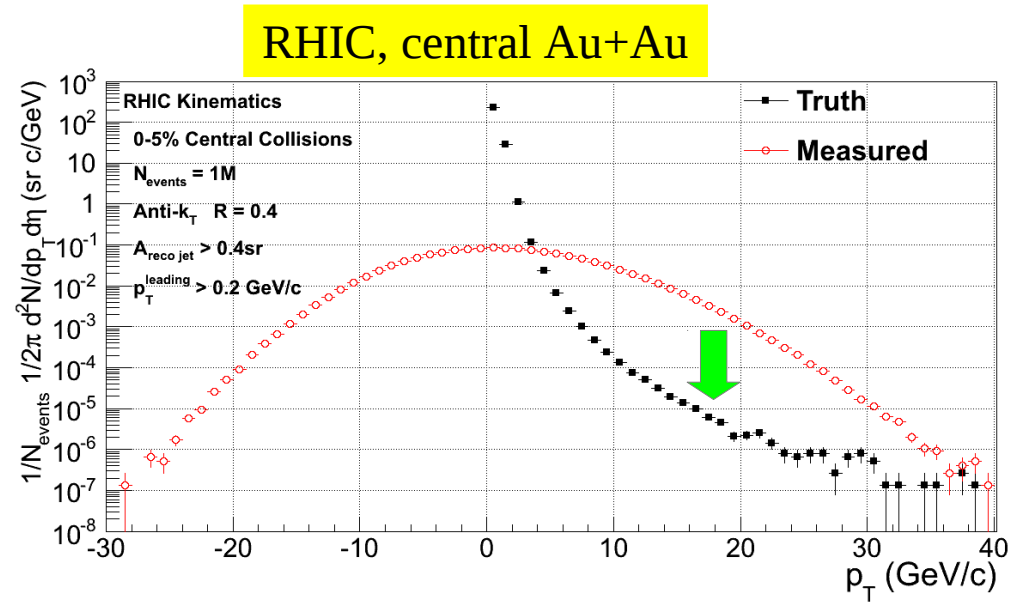
Toy model: inclusive jet spectrum

Dramatic broadening due to HI event background



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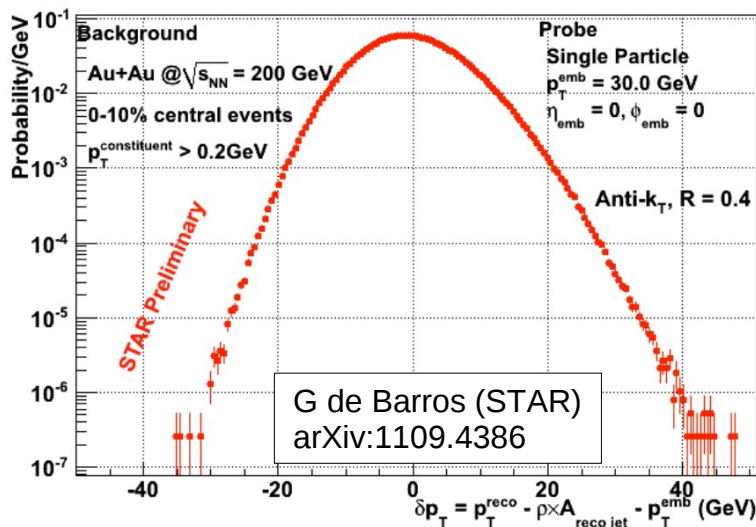
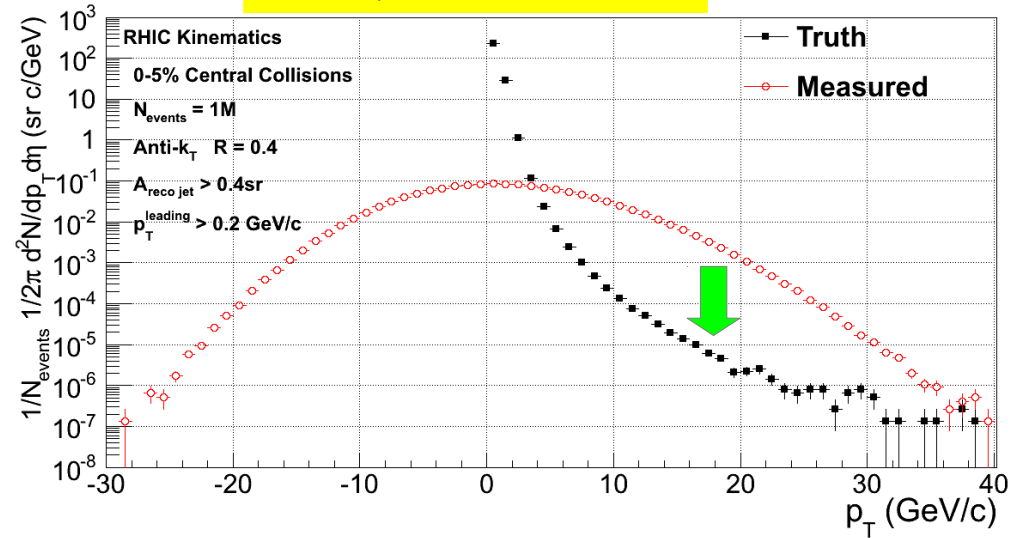
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Dramatic broadening due to HI event background

Measure ensemble-averaged distribution of fluctuations via embedding known probes into real events

$$\delta p_T \equiv p_T^{<corr>} - p_T^{embed} = p_T^{jet} - \rho \cdot A_{jet} - p_T^{embed}$$

RHIC, central Au+Au



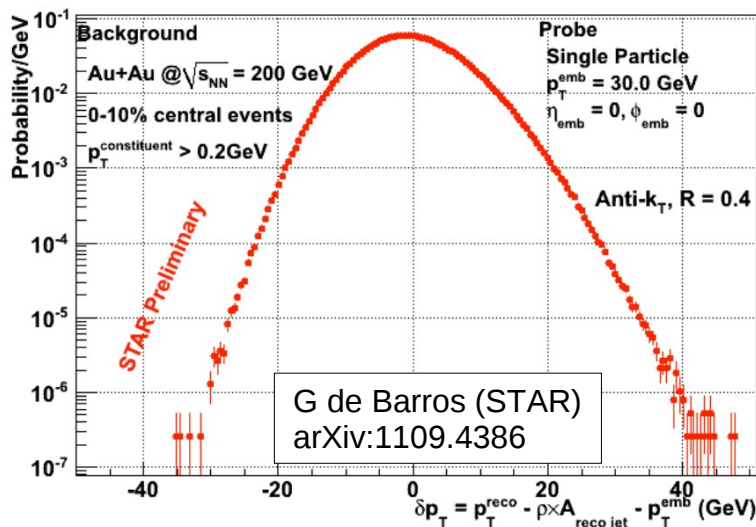
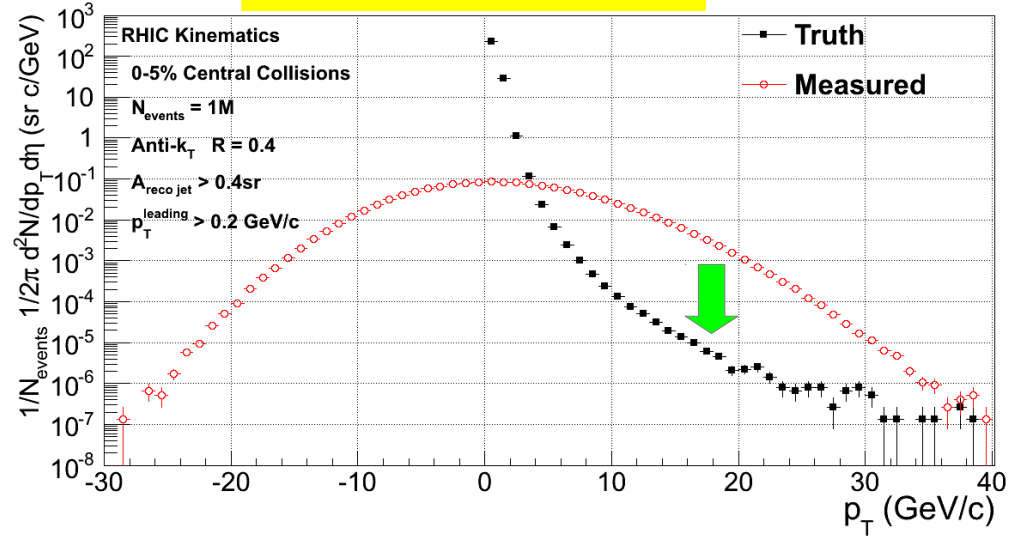
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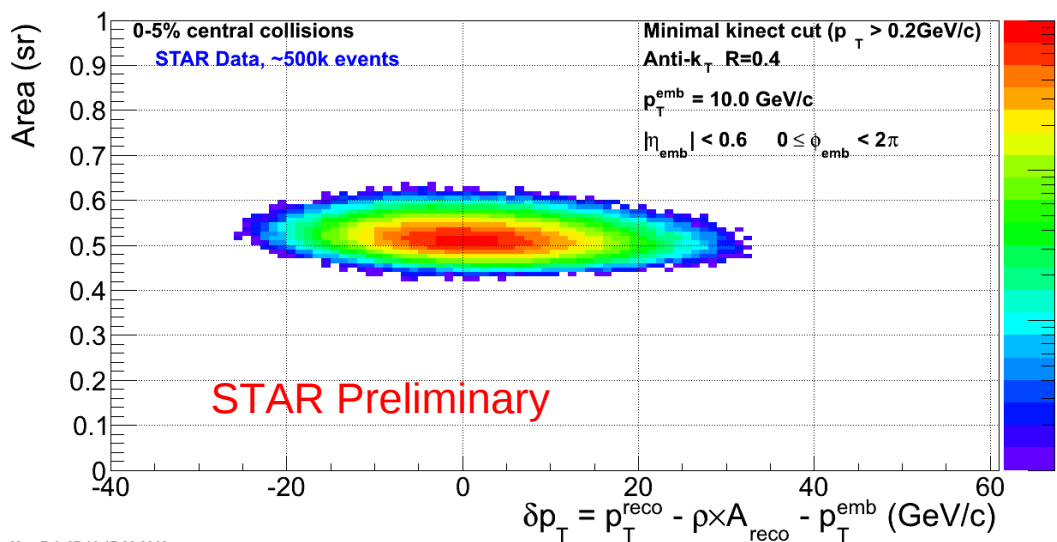
Crucial feature for unbiased measurement: δp_T distribution is independent of fragmentation pattern of embedded jet (G de Barros (STAR) arXiv:1109.4386)

Correction for background fluctuations via “unfolding”

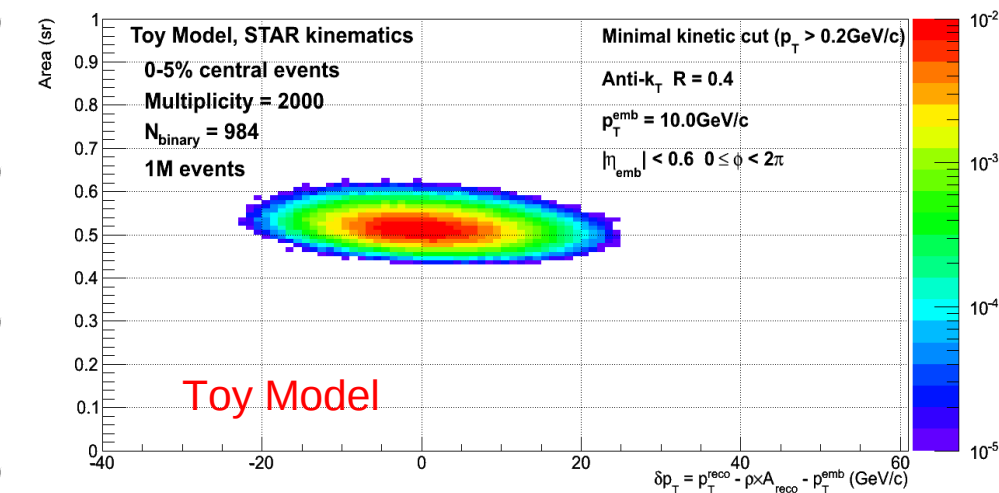
Response matrix: δp_T distribution

Comparison of Toy Model vs Data

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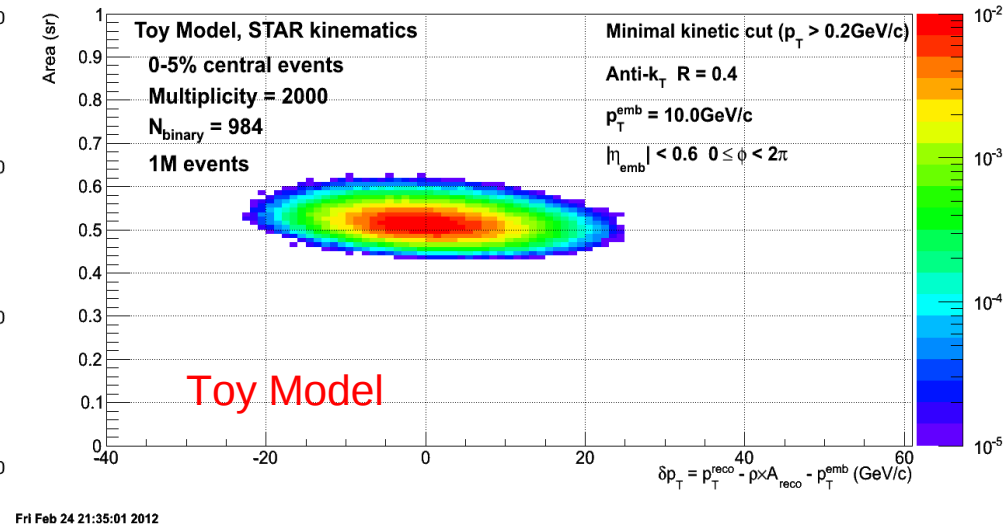
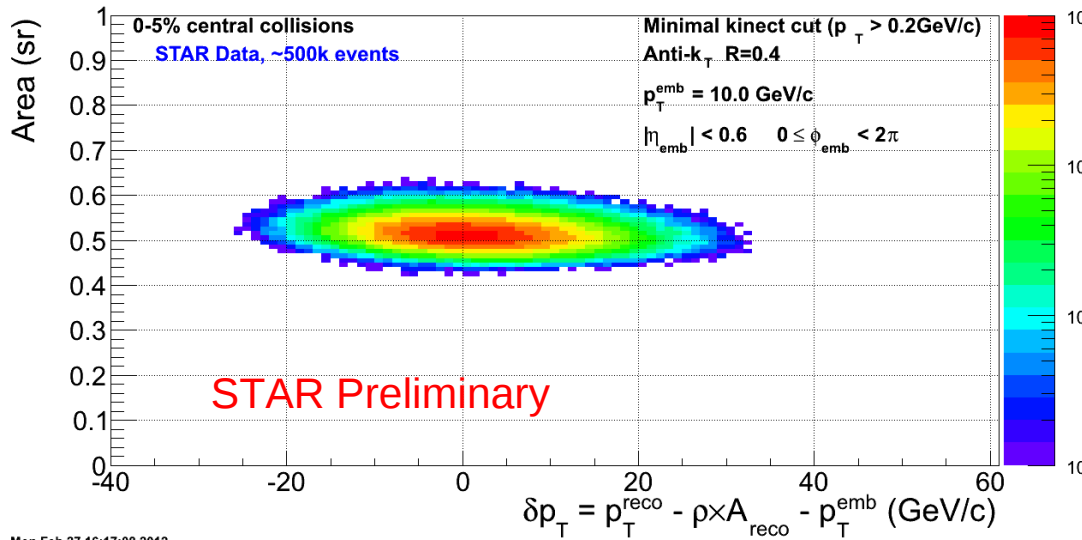
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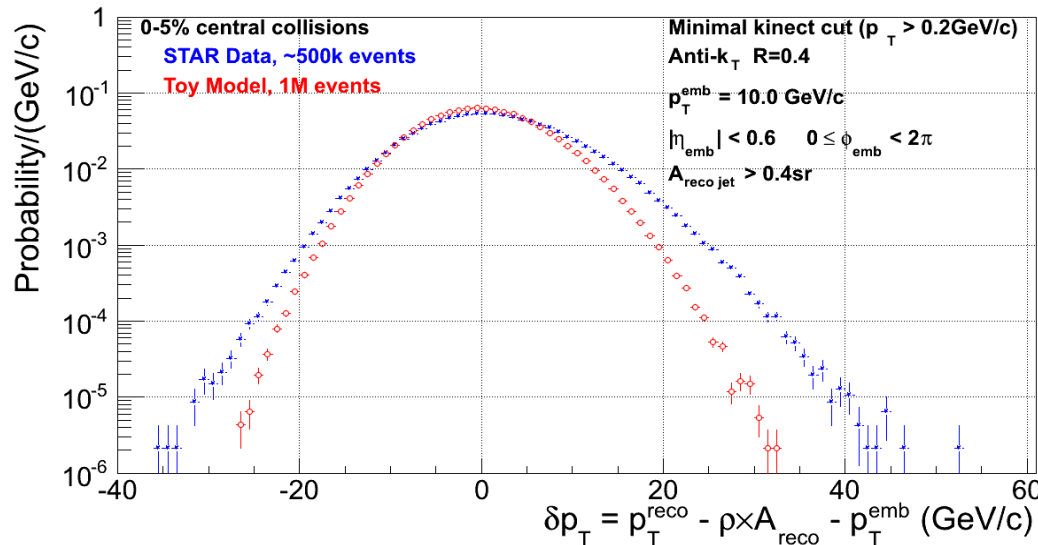
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Comparison of Toy Model vs Data

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Qualitatively similar, differing in detail

- e.g. Toy Model missing flow effects, will account for most of the difference

Current implementation sufficient for generic exploration of problem

- Flow complicates interpretation, leave out for now

Unfolding and Fragmentation Biases

Unfolding: it is essential to limit sensitivity to statistical noise (via regularization)

- Regularization imposes bias (smoothness) in exchange for reduced variance
- Various techniques: we use Iterative Bayesian
 - regularization via number of iterations

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Heavy ion jet reconstruction: two essential biases in the problem

- Fragmentation bias
- Unfolding bias (\sim correction for background fluctuations)

These play against each other:

- Try to lower unfolding bias: suppress background fluctuations via momentum cut on jet constituents
- But this induces fragmentation bias

Jet quenching measurements: essential to minimize fragmentation bias

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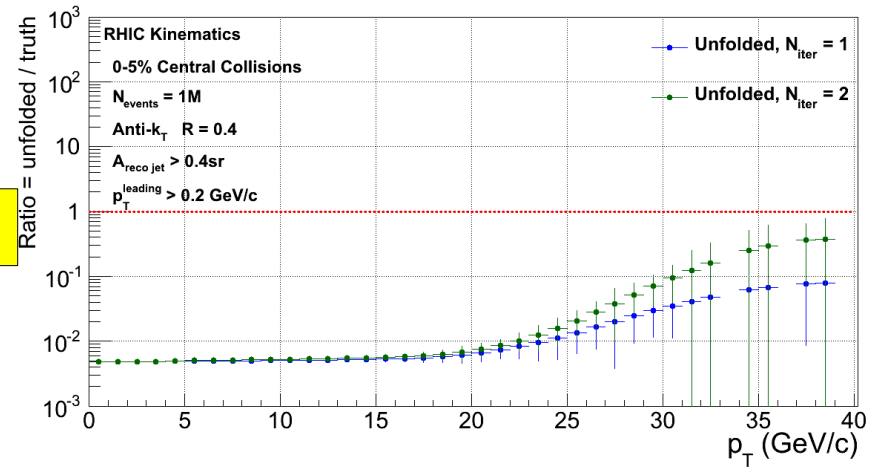
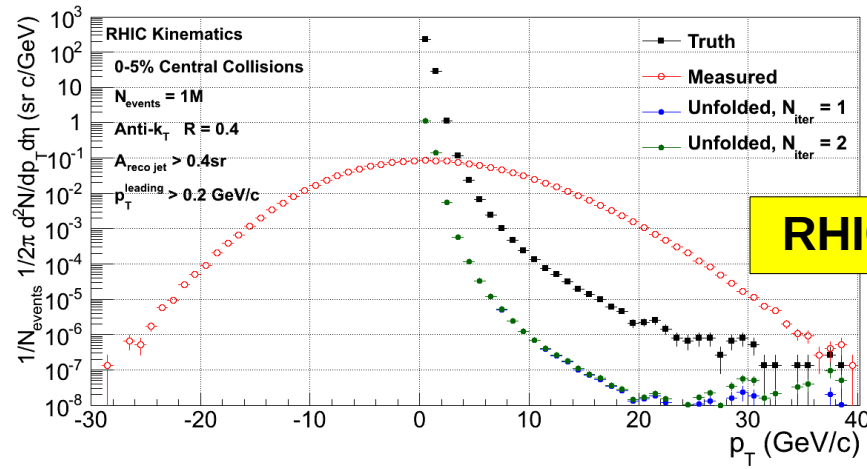
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Jet quenching measurements: essential to minimize fragmentation bias

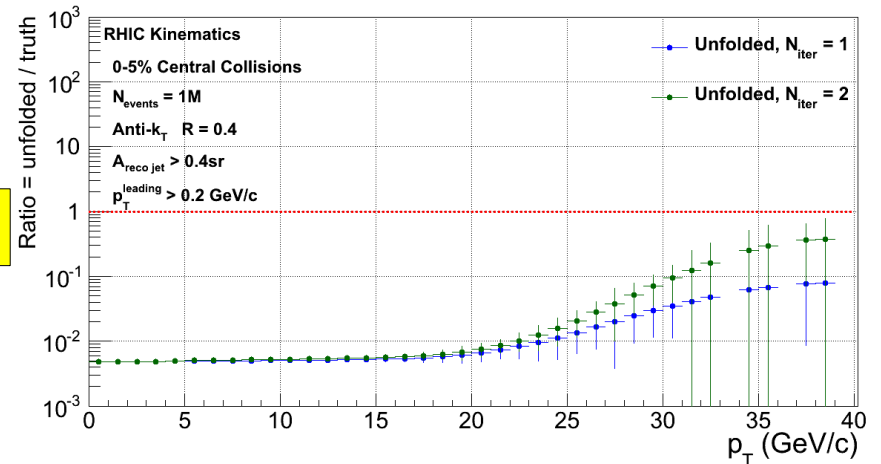
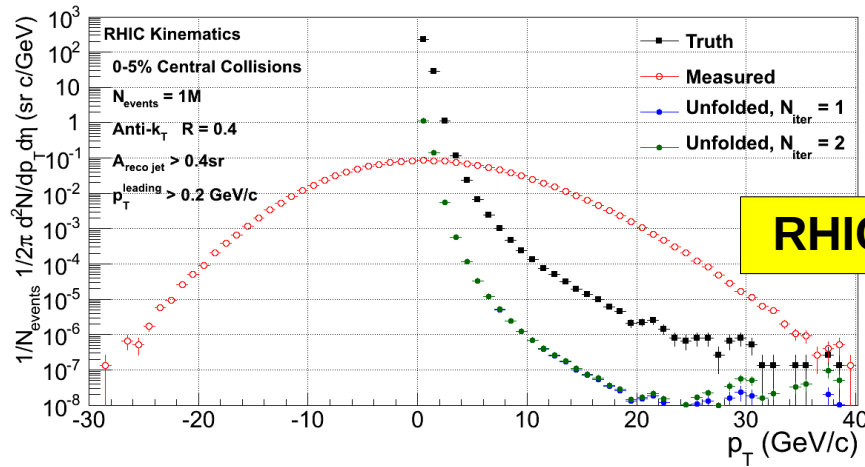
Toy Model study: isolate Unfolding Bias effects by choice of Single Particle fragmentation

- Then assess fragmentation bias by more physical choice of jet fragmentation

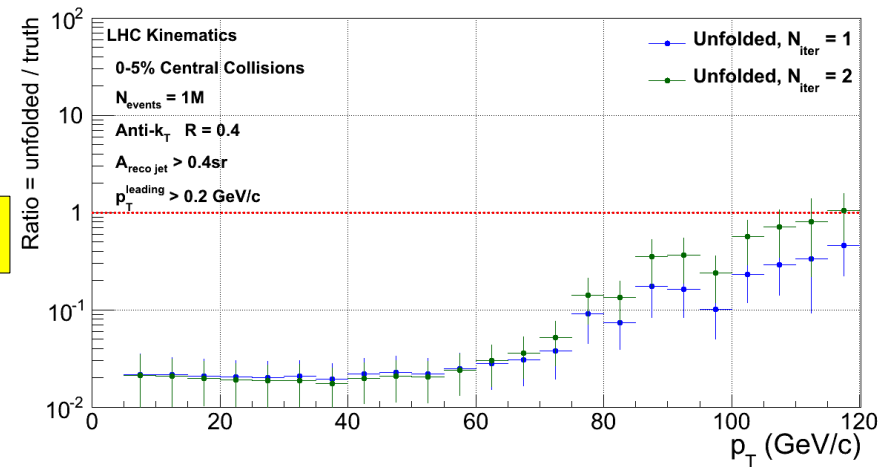
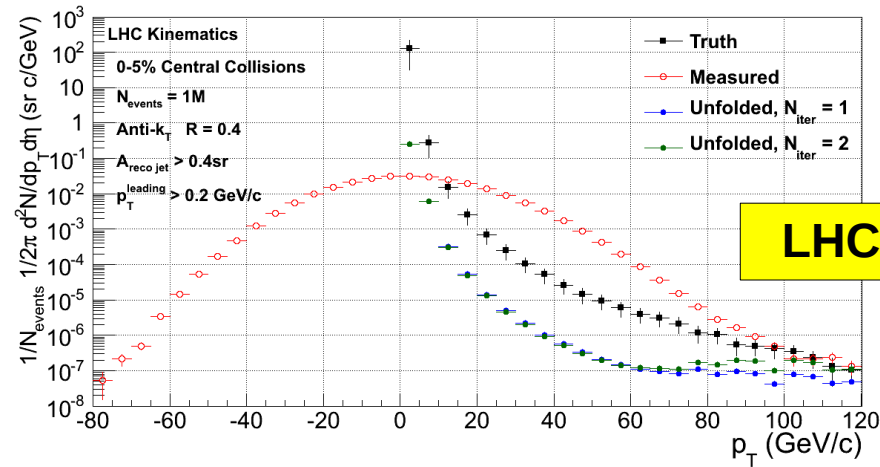
Unfolding of inclusive spectrum



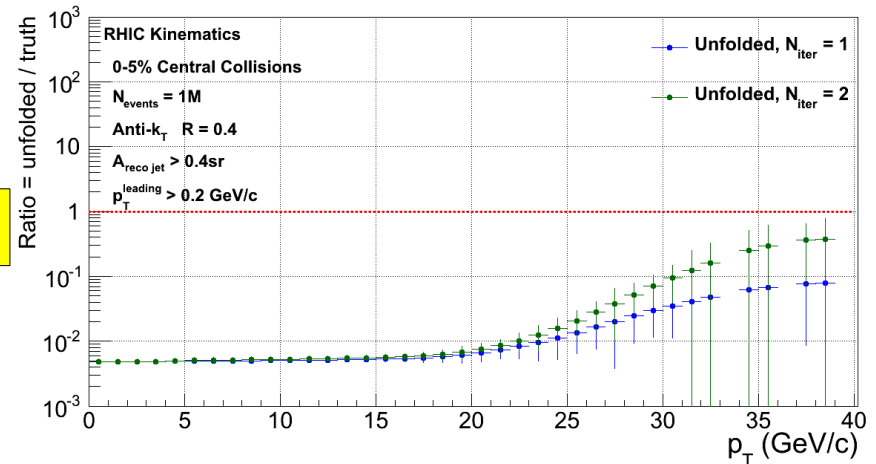
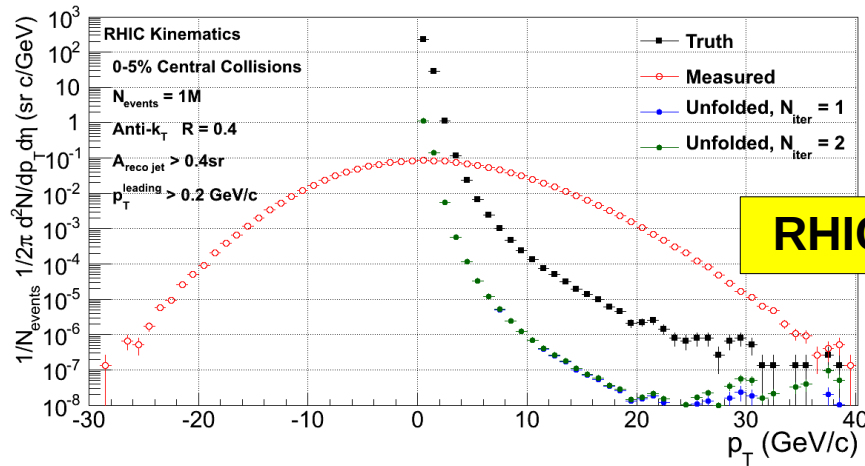
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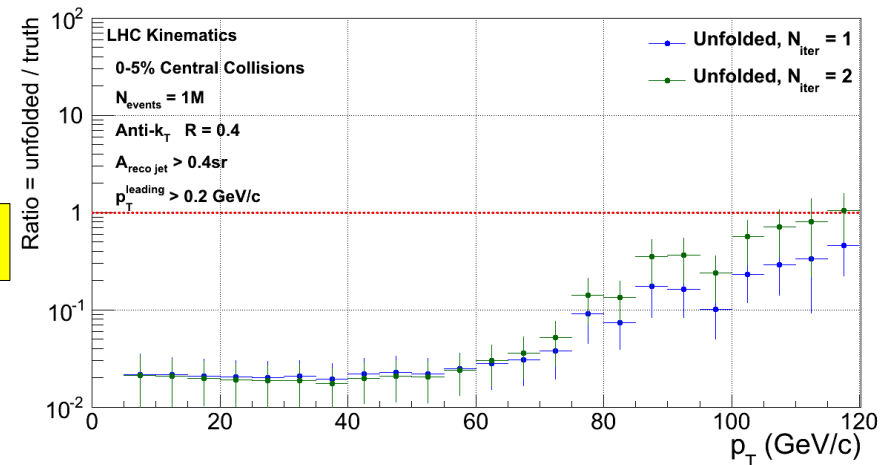
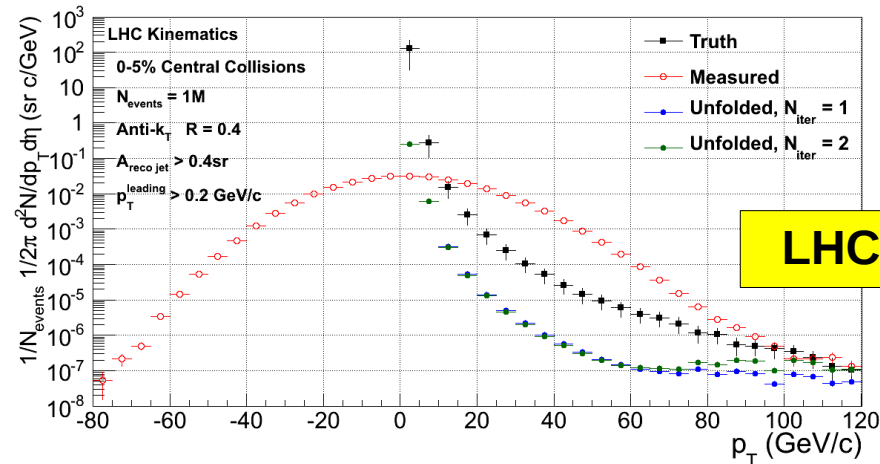
Unfolding does not converge to Truth → highly biased (and wrong) solution



Unfolding of inclusive spectrum



Unfolding does not converge to Truth → highly biased (and wrong) solution



What went wrong? Answer: overwhelming population of combinatoric (noise) “jets”
 no underlying physical distribution, problem not well-posed

Solution: eliminate combinatoric jet population *before* unfolding
 what's left? hard jet population with p_T smeared by background fluctuations:
 → well-posed unfolding problem

Unfolding of inclusive spectrum: suppression of combinatoric jet population

The only available tool for inclusives: impose a fragmentation bias

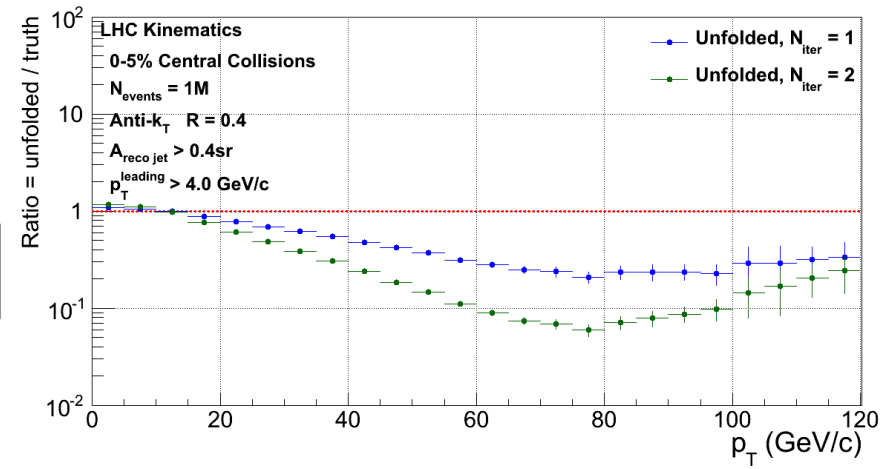
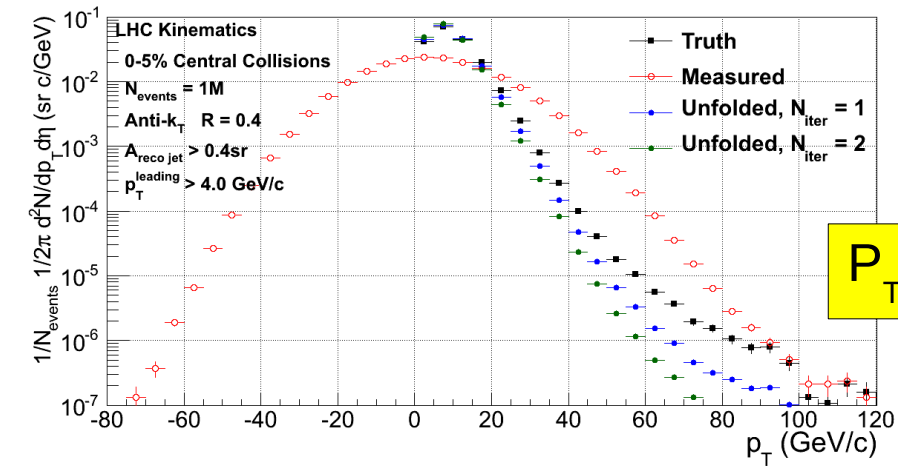
Reasonable choice:

- require accepted jet candidates to have at least one hadron constituent with $p_T > p_T^{\text{threshold}}$ (“ p_T^{leading} ” cut)

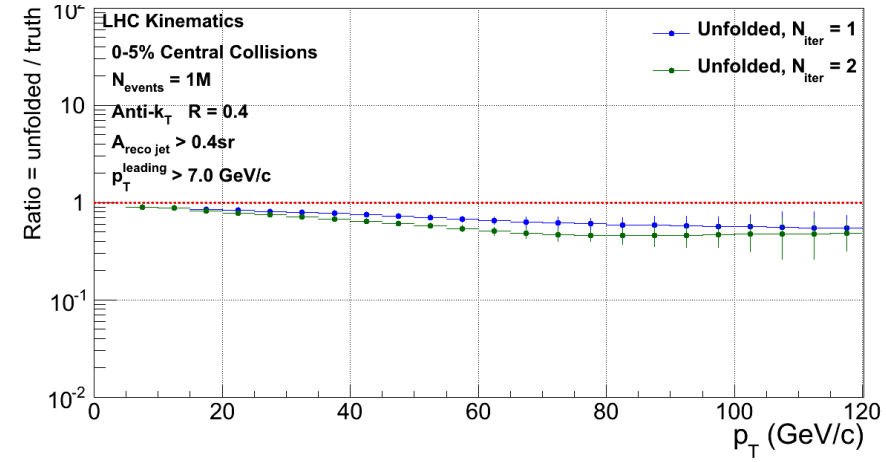
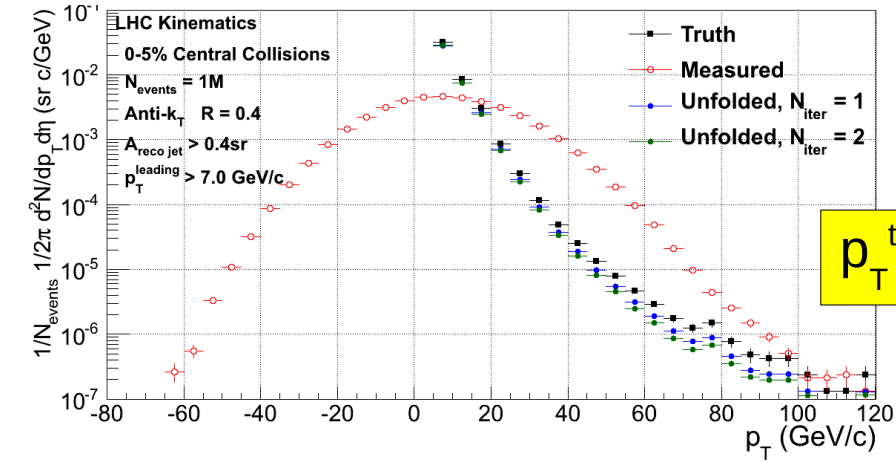
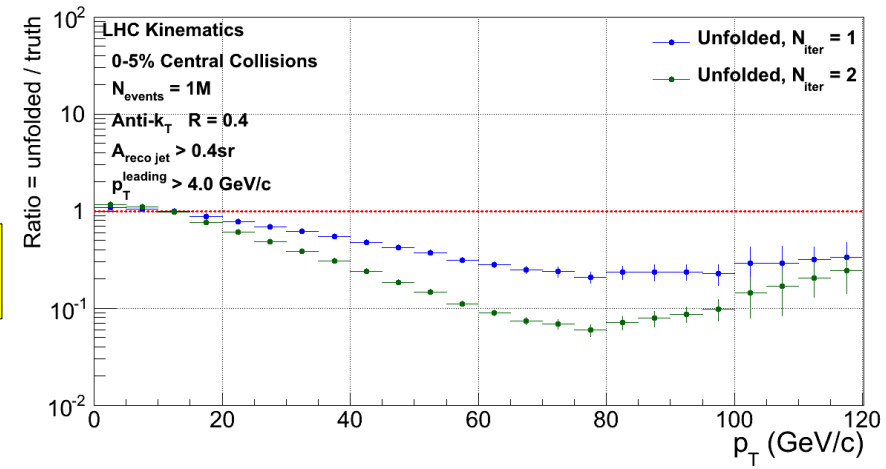
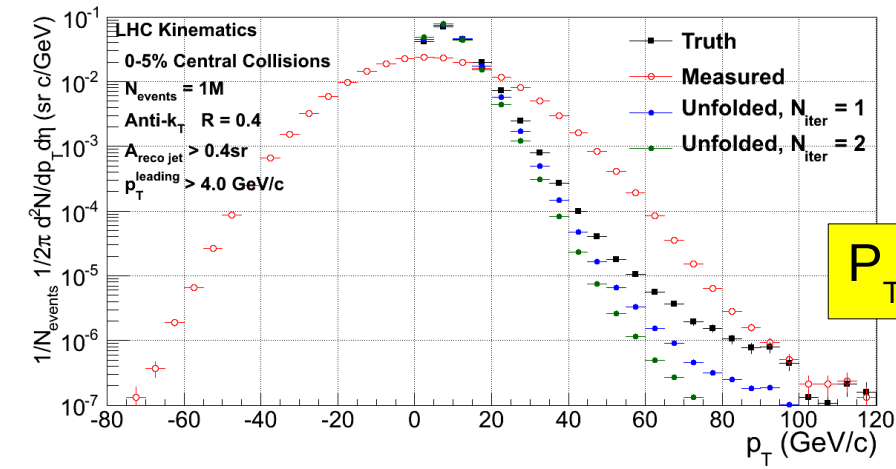
Bias is not zero, but is transparent and may be relatively mild (depends on p_T)

- Jet candidates can still have much of their radiation carried by very soft hadrons

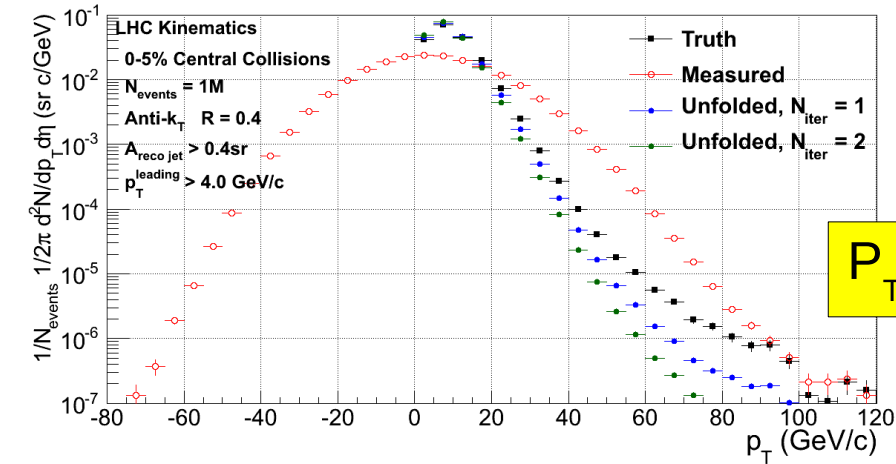
Inclusive spectrum with p_T^{leading} bias: LHC



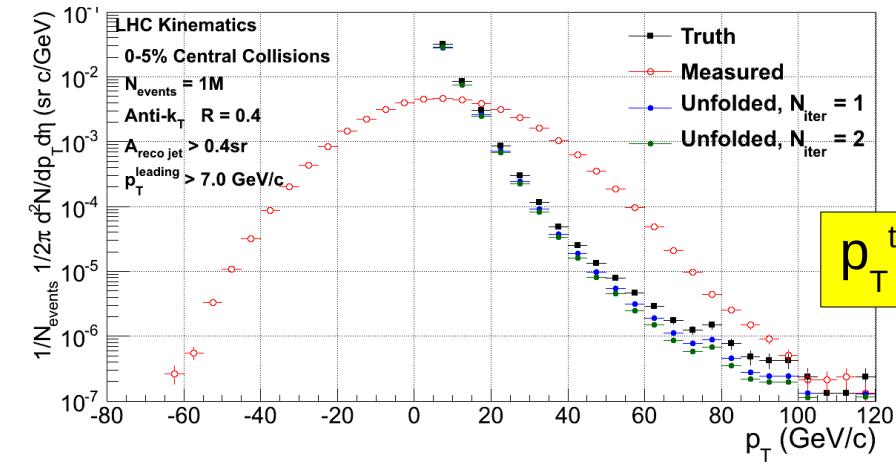
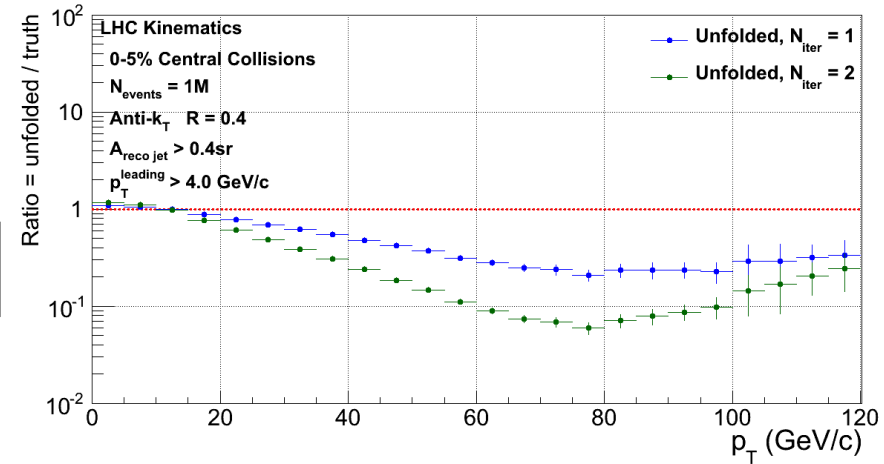
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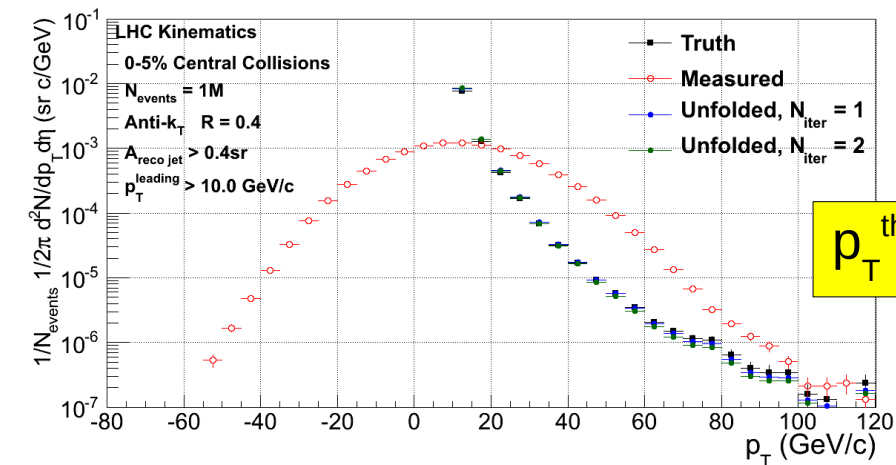
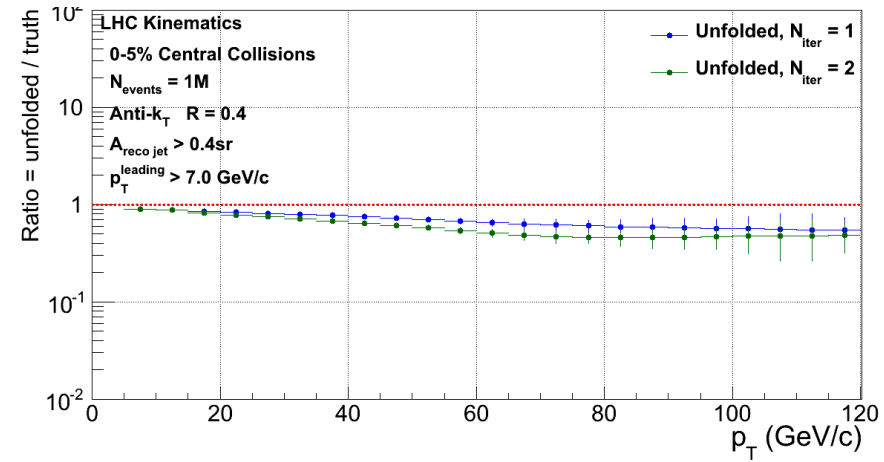
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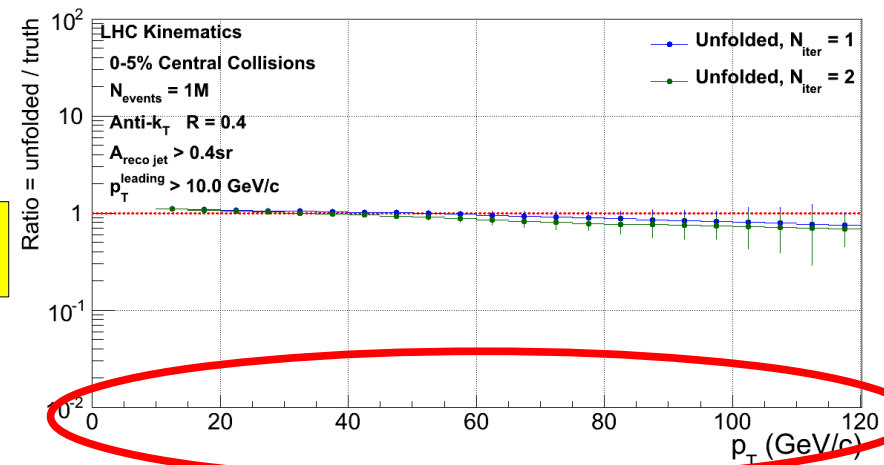
$p_T^{\text{threshold}} = 4\text{GeV}$



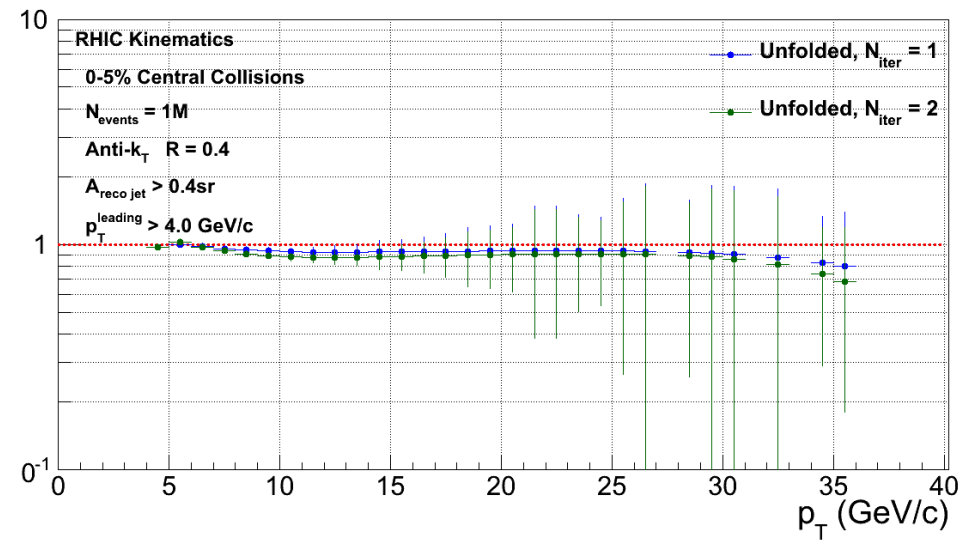
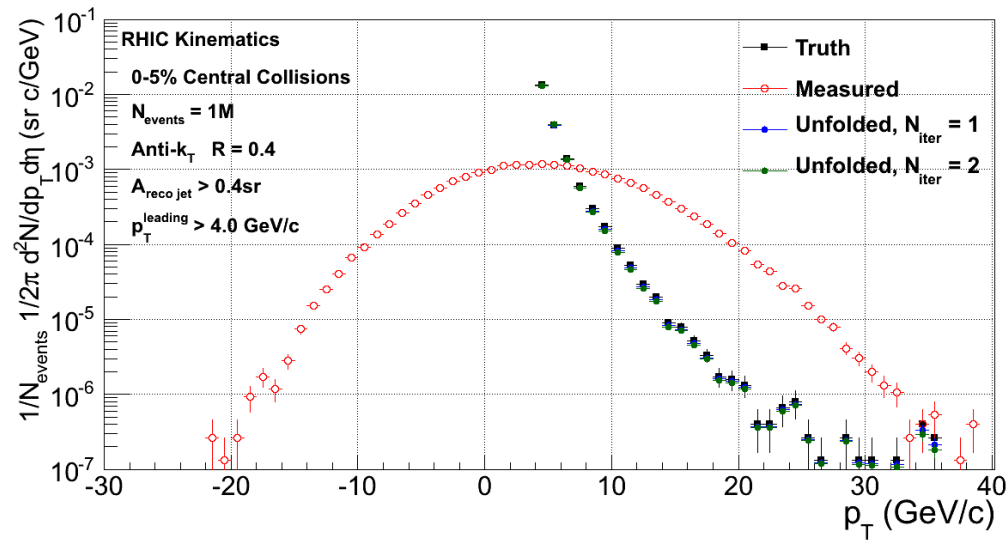
$p_T^{\text{threshold}} = 7\text{GeV}$



$p_T^{\text{threshold}} = 10\text{GeV}$

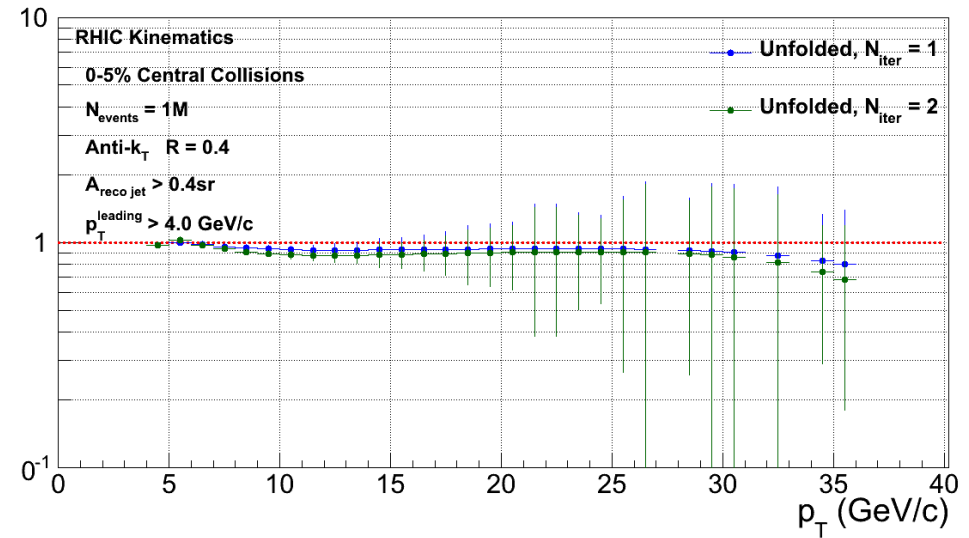
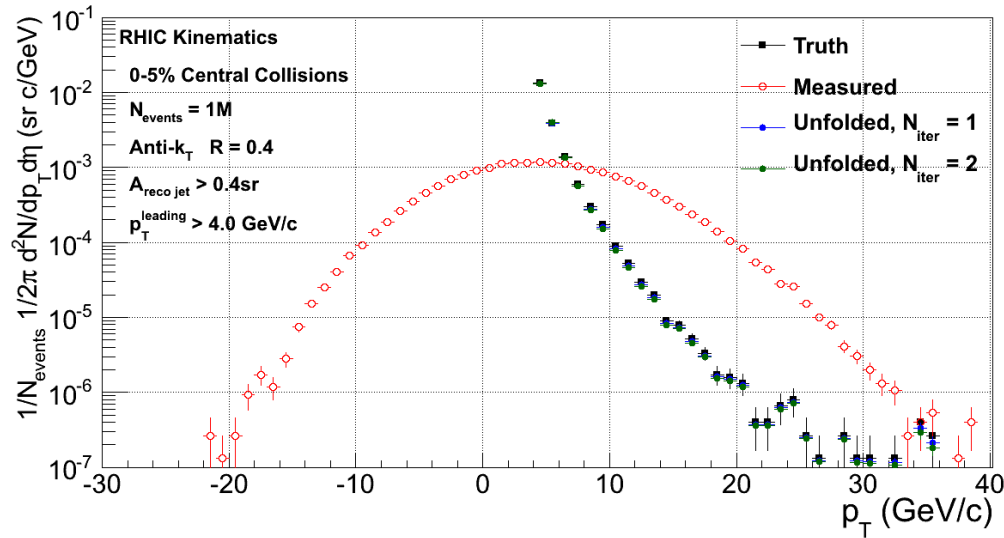


Inclusive spectrum with p_T^{leading} bias: RHIC



Similar result at RHIC (convergence for $p_T^{\text{threshold}} \sim 4\text{ GeV}$)

Inclusive spectrum with p_T^{leading} bias: RHIC



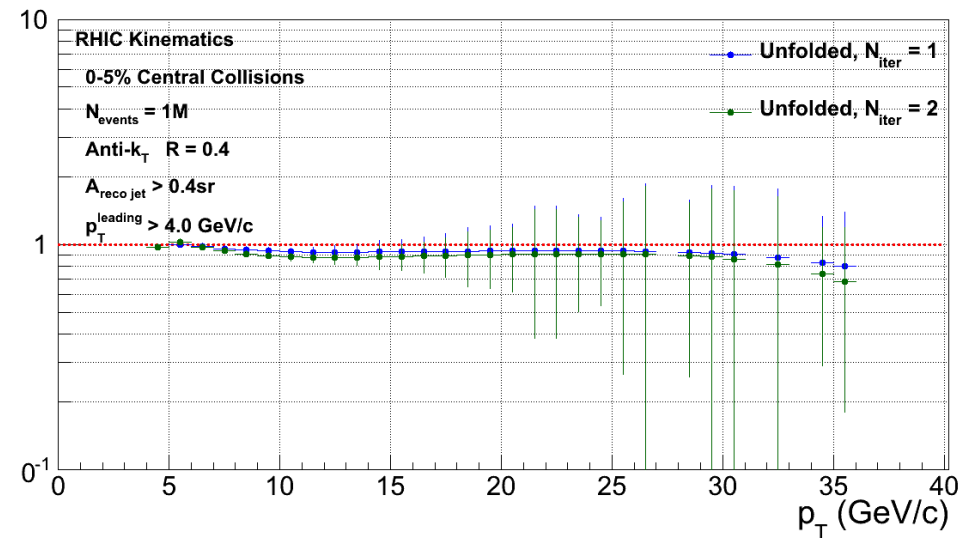
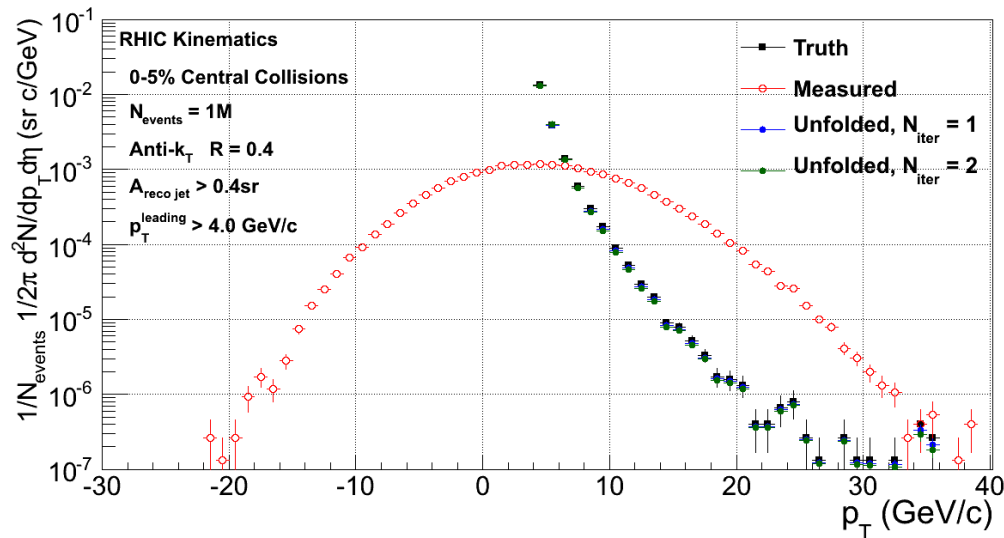
Similar result at RHIC (convergence for $p_T^{\text{threshold}} \sim 4\text{ GeV}$)

Generic observation: transition to correct unfolding solution corresponds to condition:

particle density at $p_T^{\text{threshold}} \ll 1/\text{jet area}$

Rephrase: effective suppression of combinatoric jet population requires fragmentation bias with leading hadron p_T that is “rare” on the scale of jet area

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Caution: current calculation utilizes Single Particle fragmentation to isolate unfolding effects

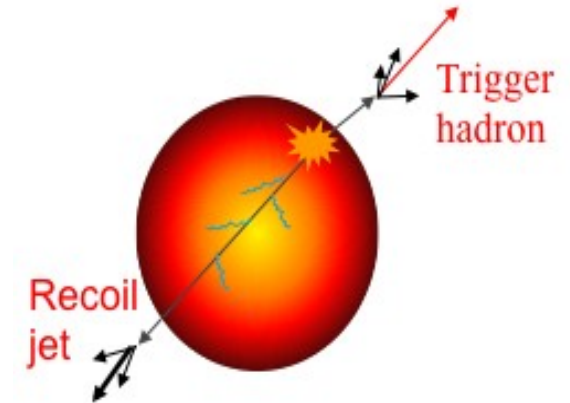


- Spectrum of “particles” is much harder than physical hadron spectrum
- Generically: expect transition in data at lower p_T (PYTHIA-based calculation in progress; quenching models? Ultimately, data will tell us..)

How to beat the fragmentation bias? hadron+jet coincidences

Coincidence of jet recoiling from hadron trigger

- p_T^{trigger} large enough that trigger is likely leading particle of jet
- Trigger imposes surface bias \rightarrow recoil jet traverses maximum path length in medium
- Observable: semi-inclusive recoil jet yield normalized per trigger

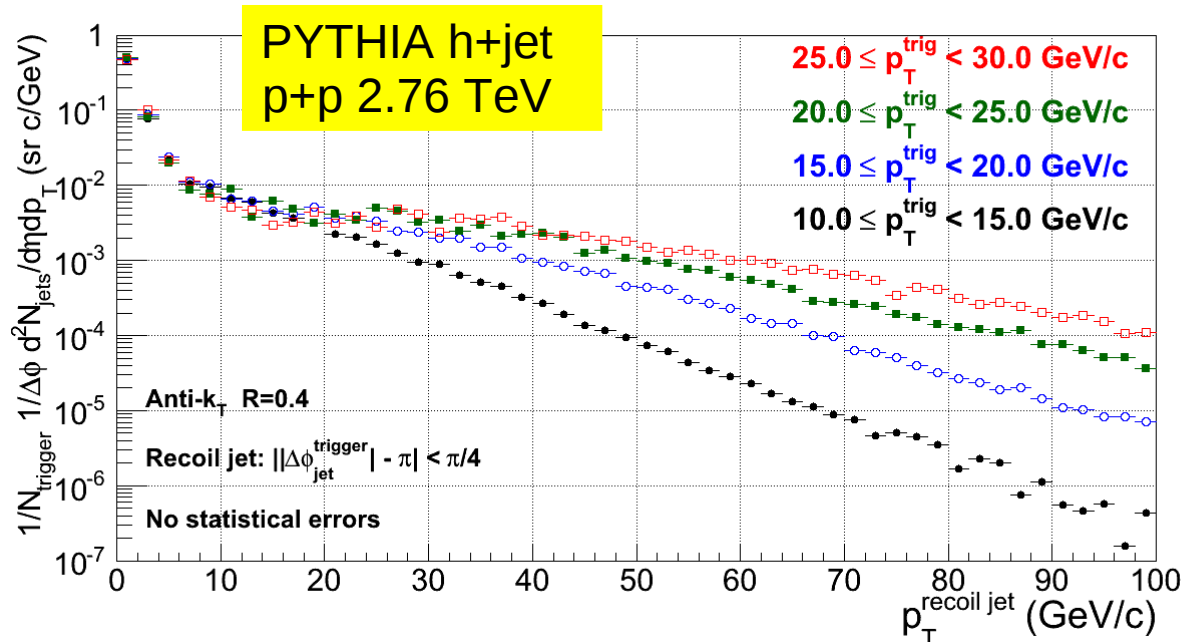
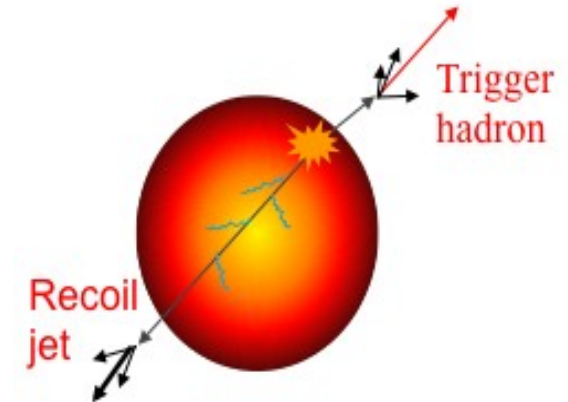


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Heavy ions: hadron trigger isolates a single hard process, rest of event is background

Distribution same as in p+p except for:

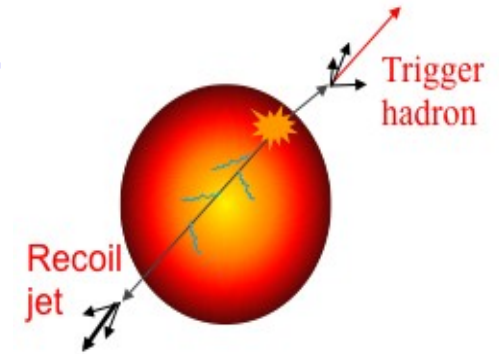
- Jet quenching
- Smearing due to background fluctuations (combinatoric jets)

hadron+jet in heavy ion collisions: new observable

By definition: combinatoric jet distribution is uncorrelated with p_T^{trigger}

Opportunity: compare recoil jet distributions for two different (exclusive) intervals of p_T^{trigger}

- Combinatoric jet part should be identical
- Hard jet part should depend on p_T^{trigger}

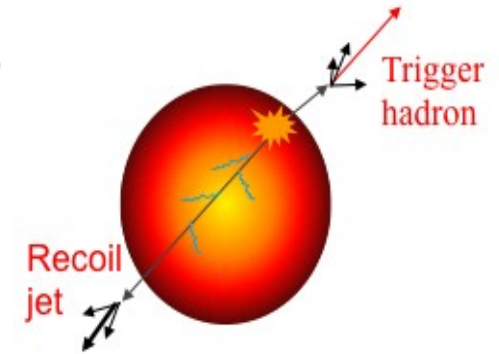


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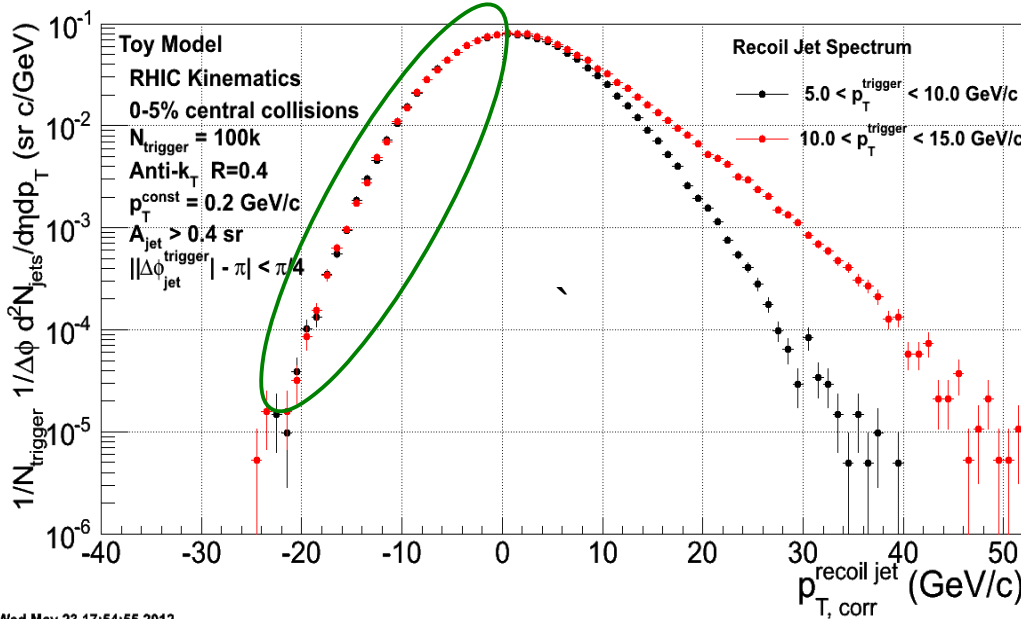
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New observable: difference of the two distributions

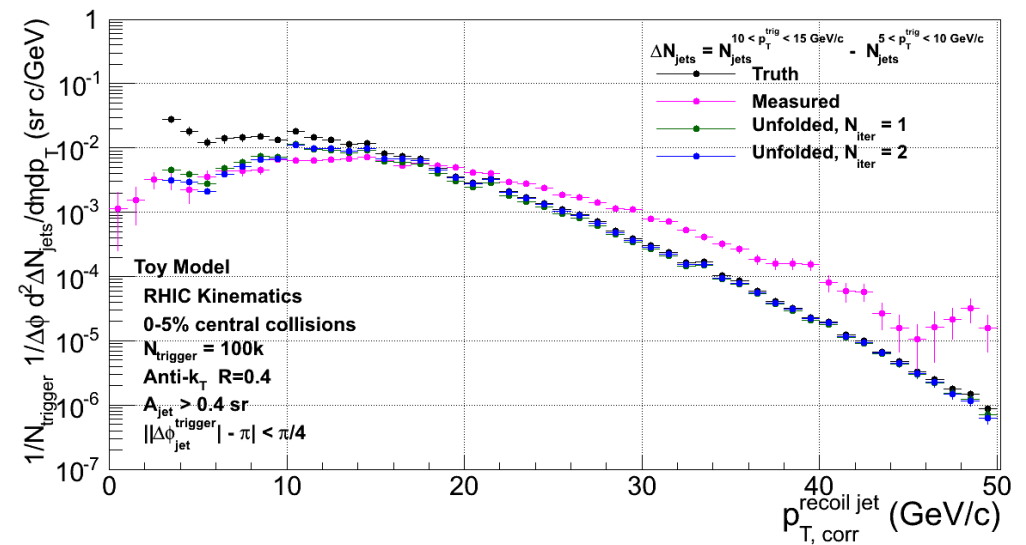
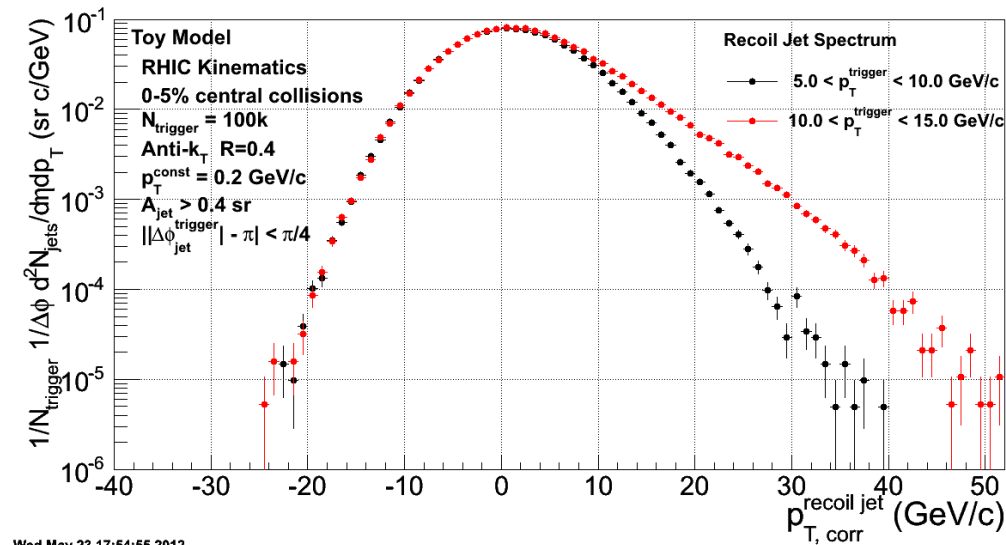


- Combinatorial jet population subtracted in fully data-driven way
- What's left: hard jet distribution smeared by background fluctuations → unfold (!)

What is it?

- The evolution of hard jet distribution as p_T^{trigger} changes
- Unusual, but perfectly legitimate and perturbatively calculable

Differential h+jet coincidence at RHIC: unfolding



Unfolding converges stably to Truth above p_T^{trigger} threshold

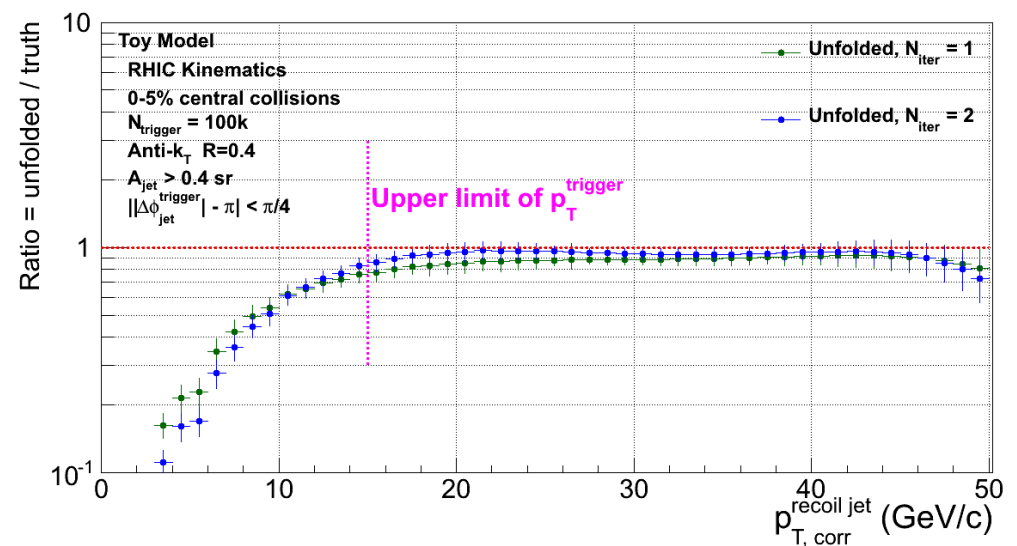
Correct result: subtraction is designed to suppress jet yield below threshold

- physics bias (which is fine, and interesting)

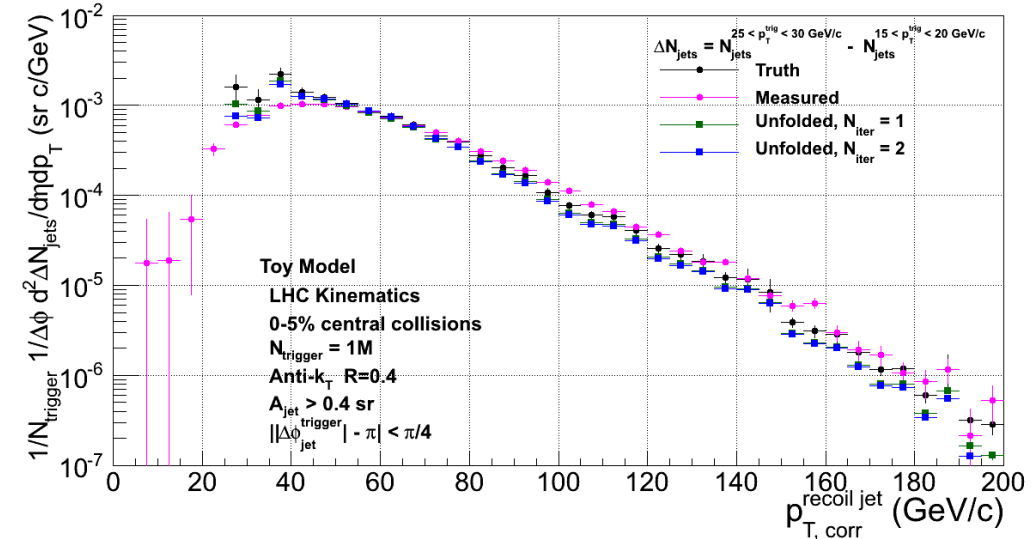
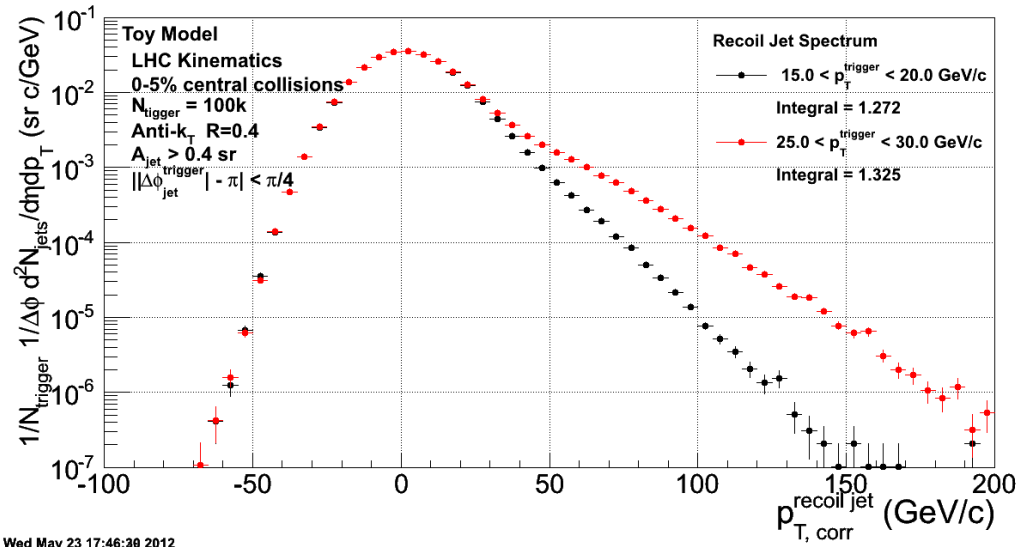
Unfolding bias: minimal

- Unfolded/Truth~1 to better than 10%

Fragmentation bias: none, by design



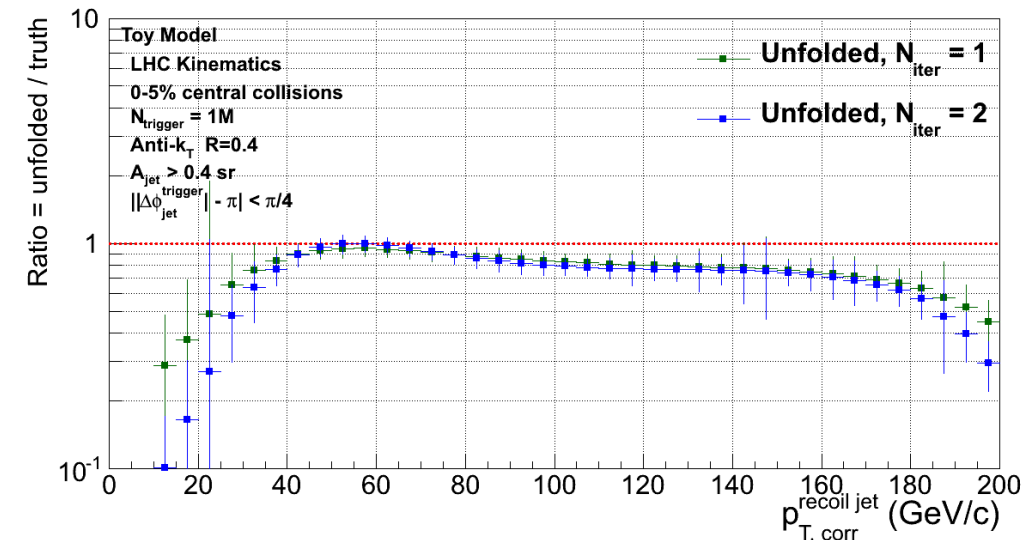
Differential h+jet coincidence at LHC



Similar picture to RHIC: unfolding converges stably to Truth above p_T^{trigger} threshold

Residual unfolding bias $\sim 10\%$ (work in progress)

Fragmentation bias: none, by design



Summary and Outlook

We have reassessed the problem of jet reconstruction in heavy ion collisions

- Key issue: precision with which background fluctuations can be measured and corrected
- Problem recast as minimization of both unfolding and fragmentation biases

New analysis methods proposed to minimize these biases in a transparent way

- Both quasi-inclusive and coincidence observables
- Optimally implemented via STAR/ALICE approach to jet measurements
- Methods were tested on Model studies representative of data
- Methods work well over full jet kinematic range at RHIC and LHC

Next step: apply to data

Backup Slides

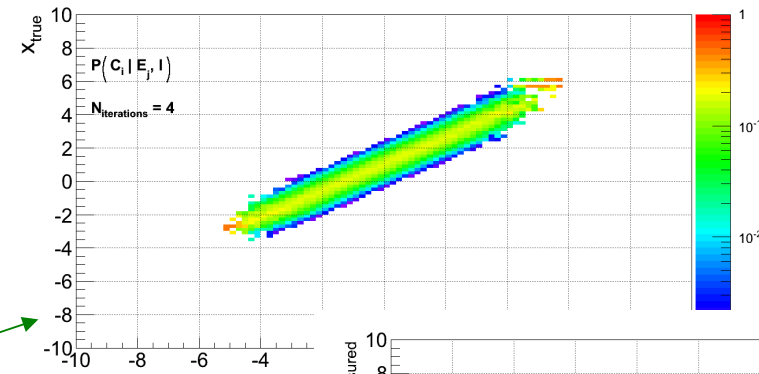
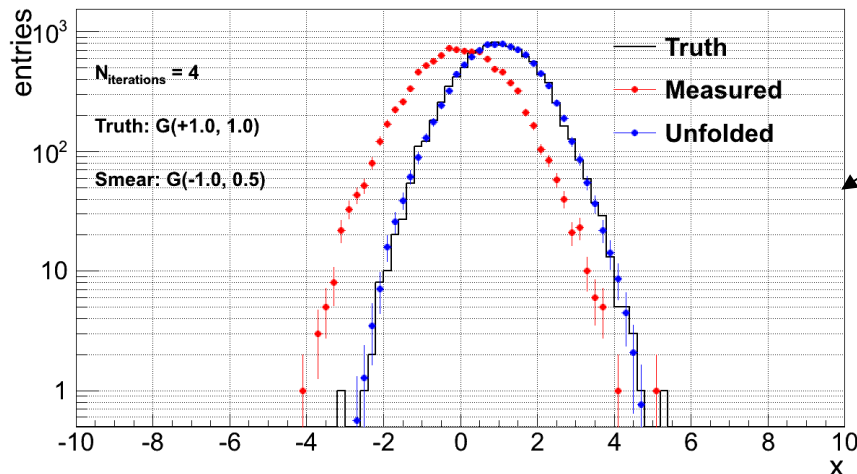
Bayesian Unfolding

$P(E_j|C_i, I)$: probability of **effect j** (E_j) has been caused due **cause i** (C_i)

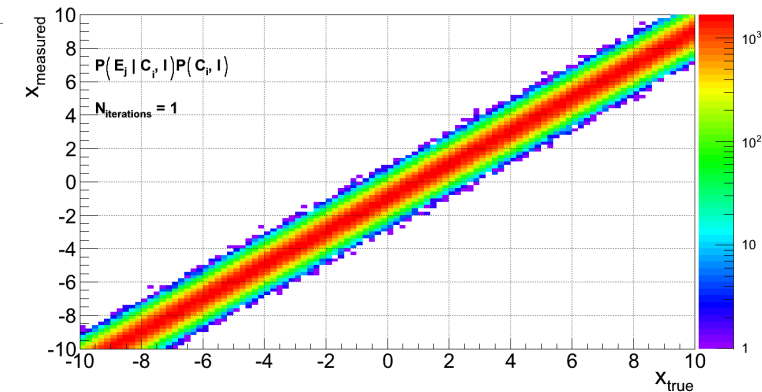
$P(C_i|E_j, I)$: probability of **cause i** (C_i) comes from **effect j** (E_j)

By the knowledge of $P(E_j|C_i, I)$ and a choice of prior distribution, one obtains $P(C_i|E_j, I)$:

$$P(C_i|E_j, I) = \frac{P(E_j|C_i, I) \cdot P_0(C_i, I)}{\sum_{l=0}^{n_C} P(E_j|C_l, I) \cdot P_0(C_l, I)}$$



Thu Nov 24 15:44:13 2011



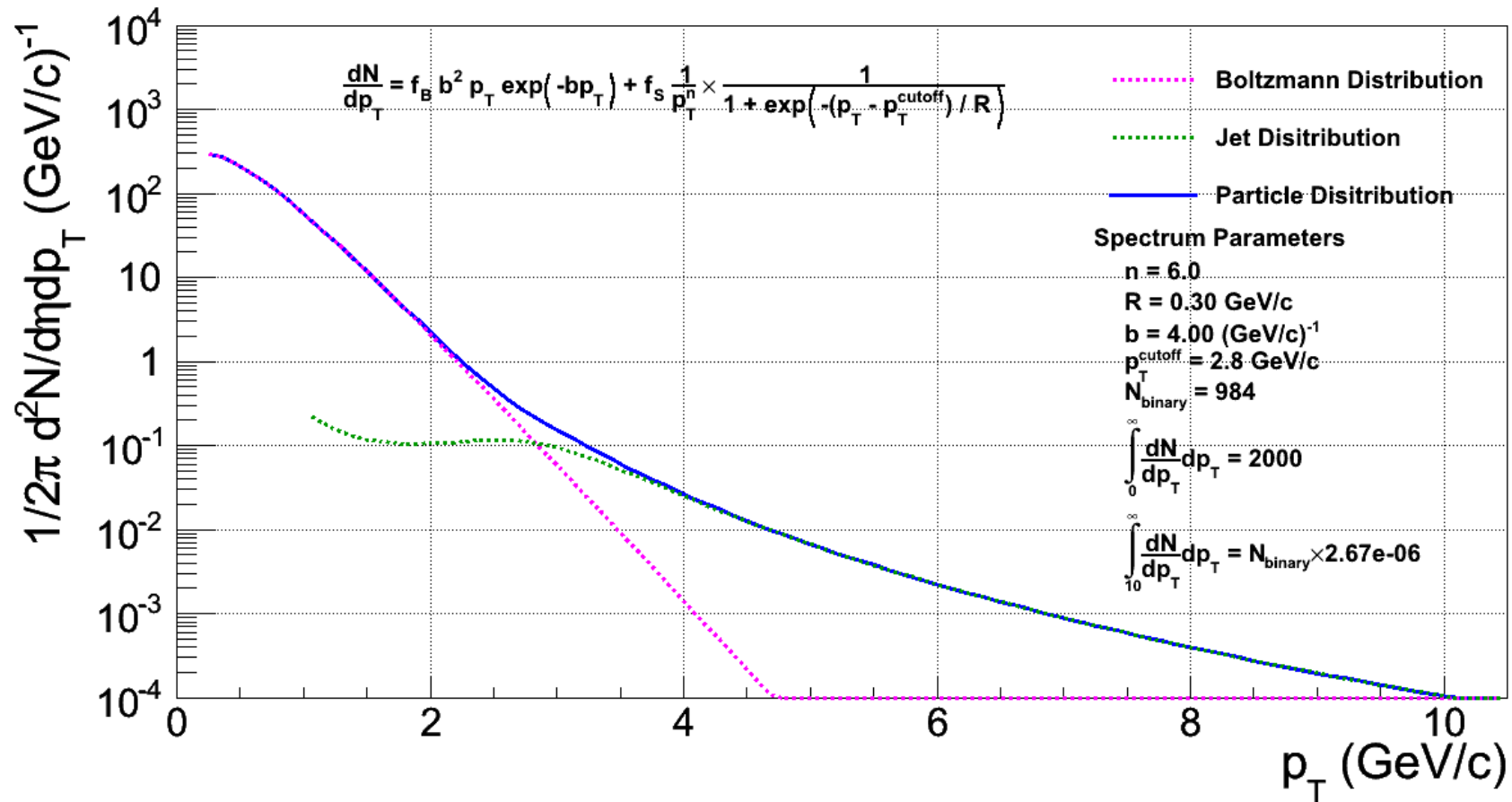
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The **unfolded spectrum** $n(C_i)$ is obtained from the **measured spectrum** $n(E_j)$ by:

$$n(C_i) = \sum_{j=0}^{n_E} P(C_i|E_j, I) \cdot n(E_j)$$

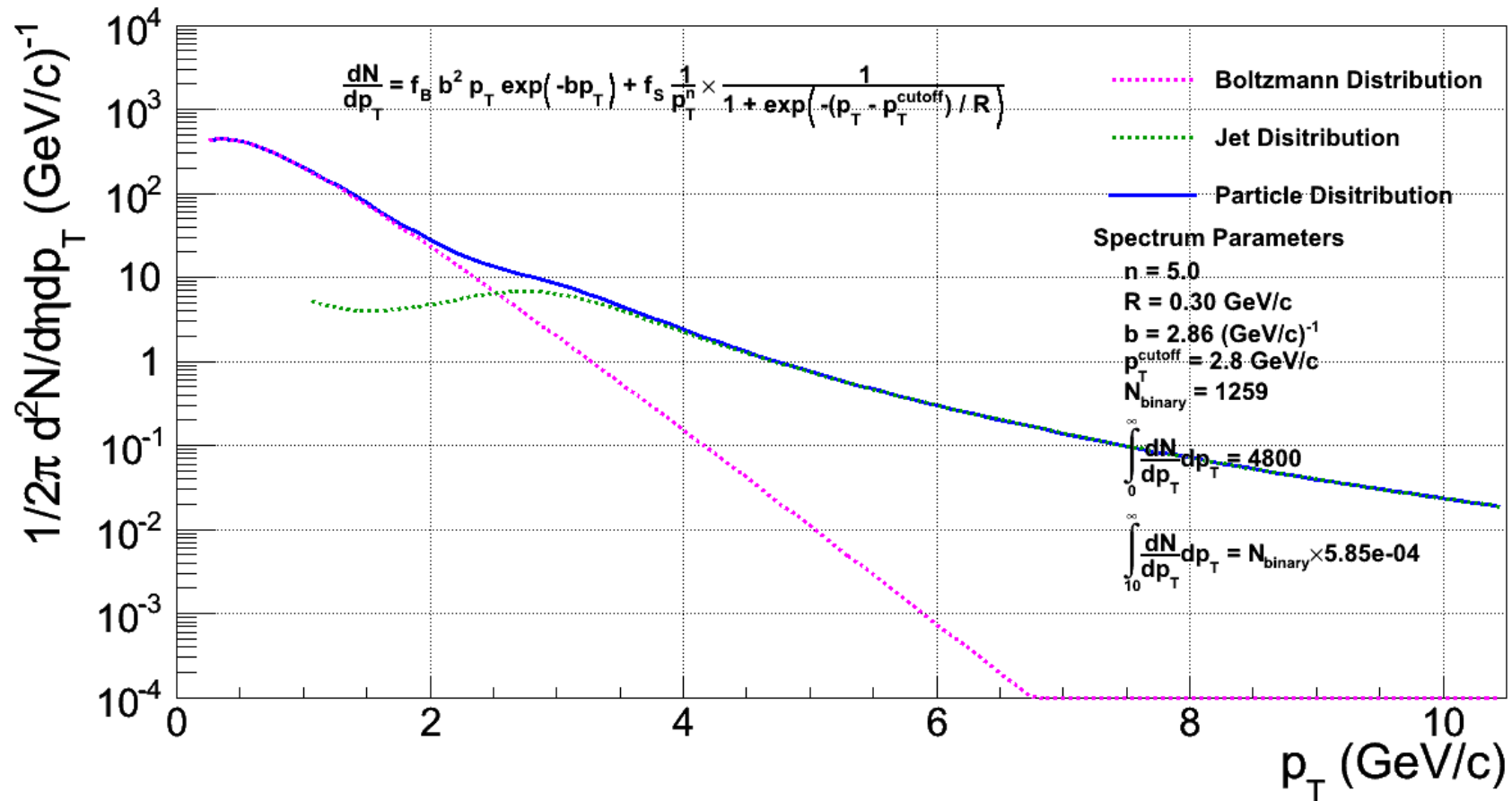
$n(C_i)$ can be used as a **new input for the prior** and unfolding can be done again (iterations) → the number of iterations is the regularization parameter

Toy Model – RHIC



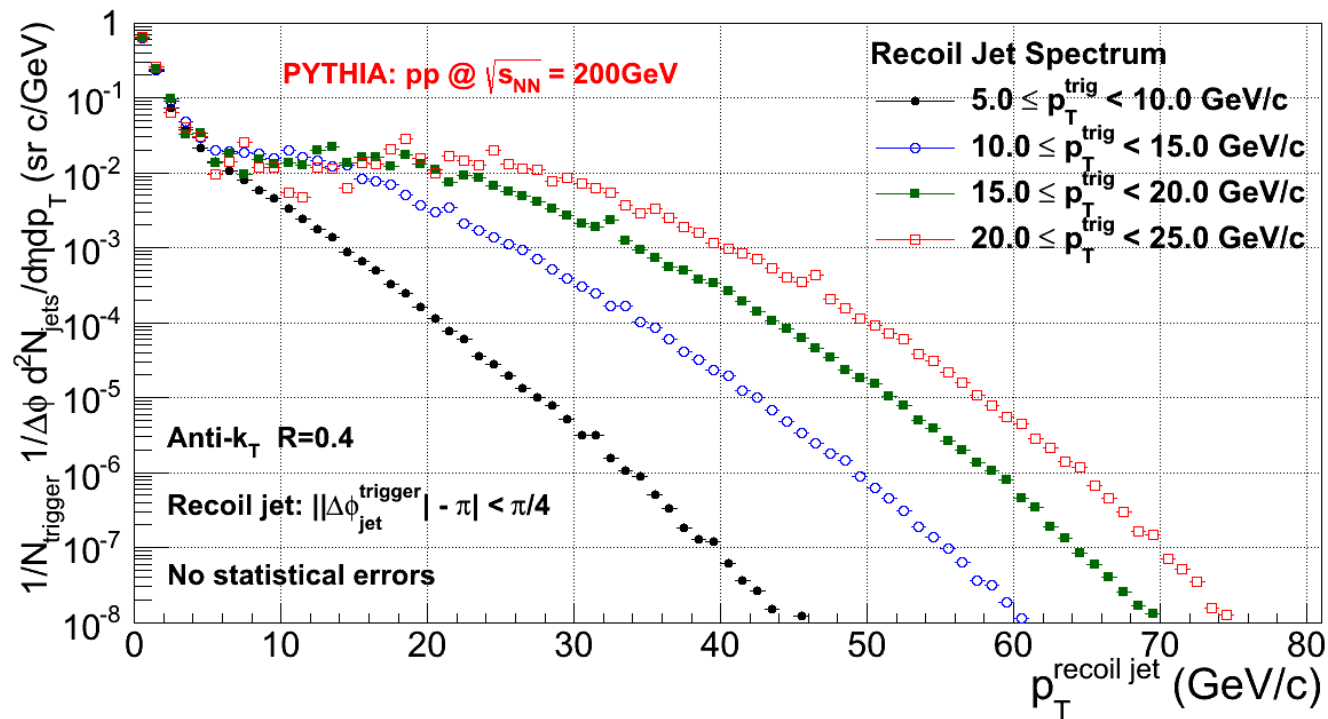
Wed May 23 12:17:15 2012

Toy Model – LHC



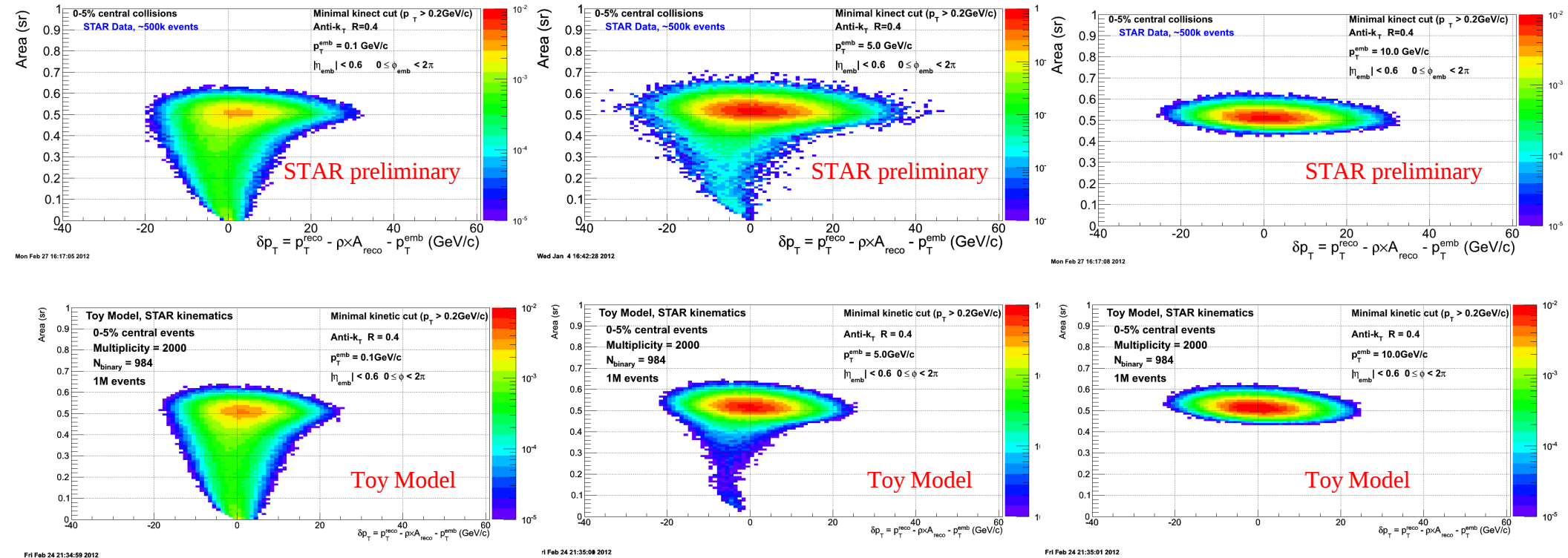
Mon Apr 16 15:47:36 2012

Coincidence Analysis: h+jet (I)



- Trigger on a high p_T particle and report recoil jet
- Utilize exclusive trigger classes
- Allows differential analysis

Toy Model Validation

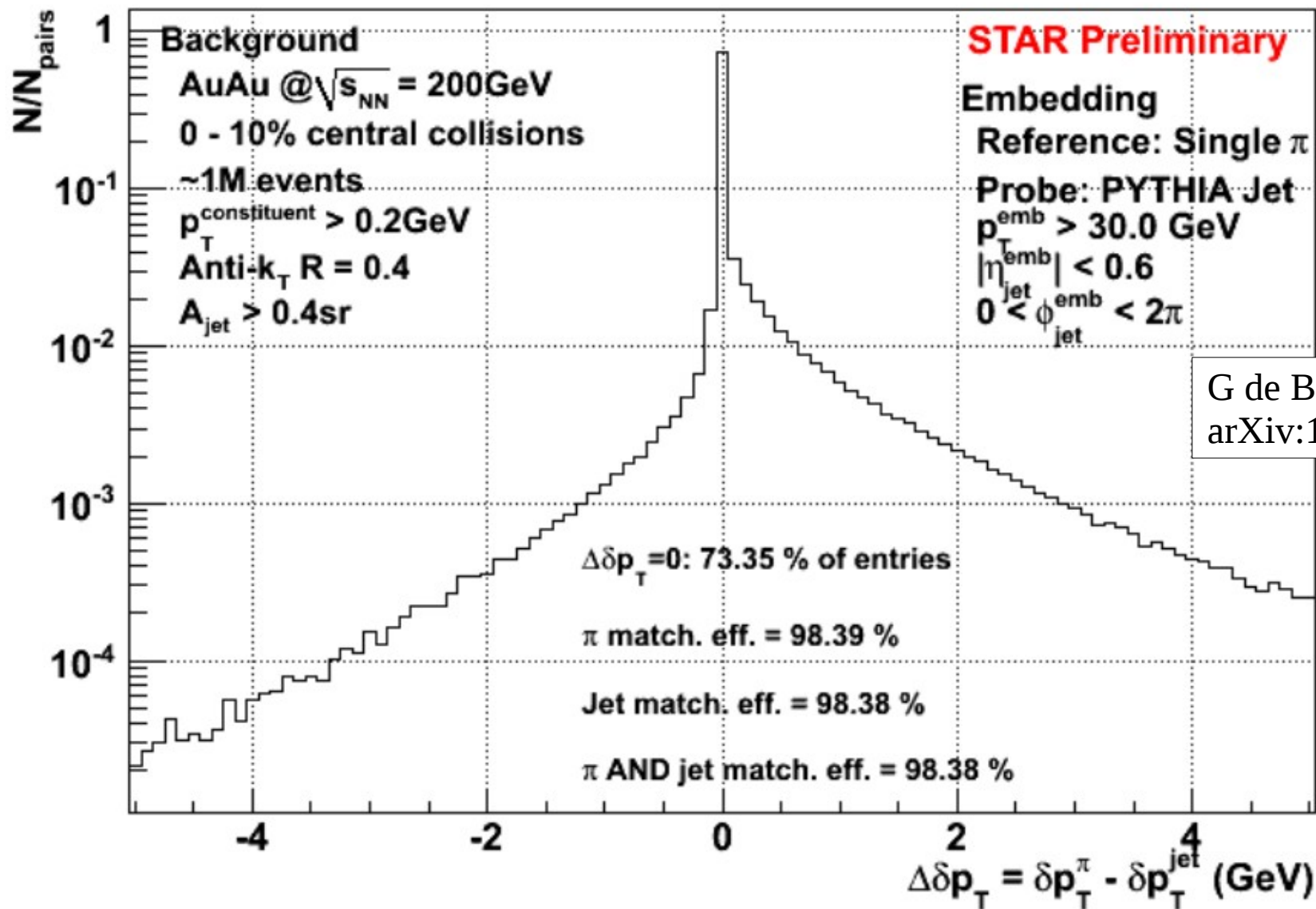


Comparison: delta pT X Jet area:

Same behavior for toy model events as real data

Note transition at $p_{T\text{emb}} = 5 \text{ GeV/c}$.

$$\Delta\delta p_T = \delta p_T^\pi - \delta p_T^{\text{jet}}$$



G de Barros (STAR)
 arXiv:1109.4386