

How to make valid comparisons between data and models



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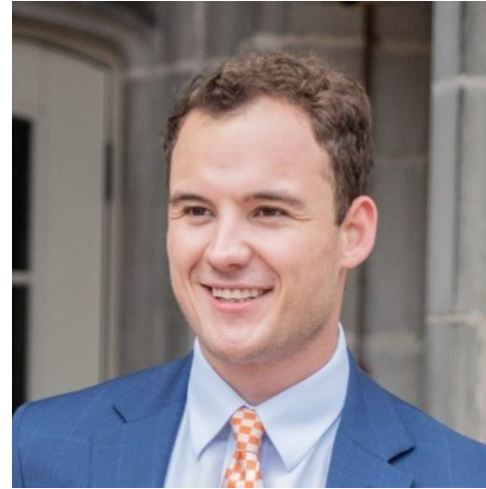
Acknowledgements



Antonio Da Silva



Patrick Steffanic



Tanner Mengel



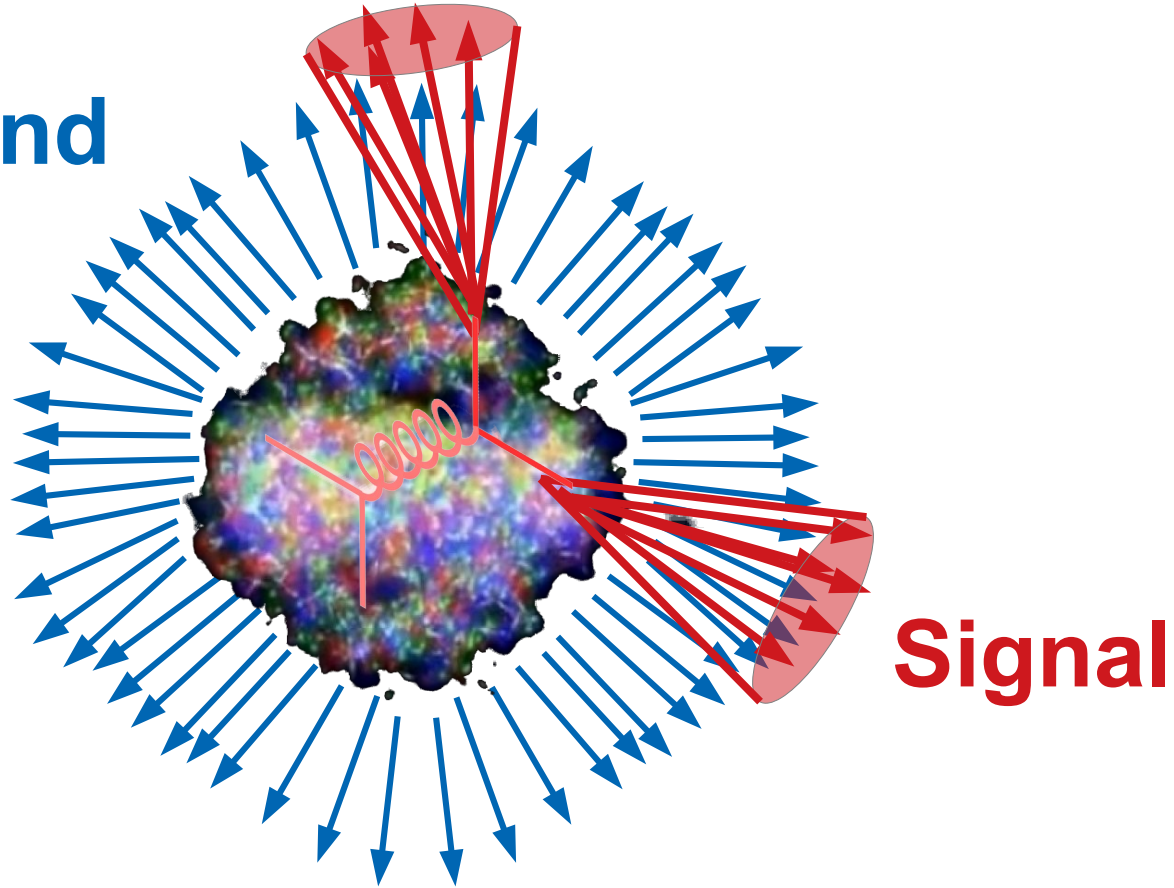
Charles Hughes

1. Standard paradigm of background

Signal vs Background:

The standard paradigm

Background

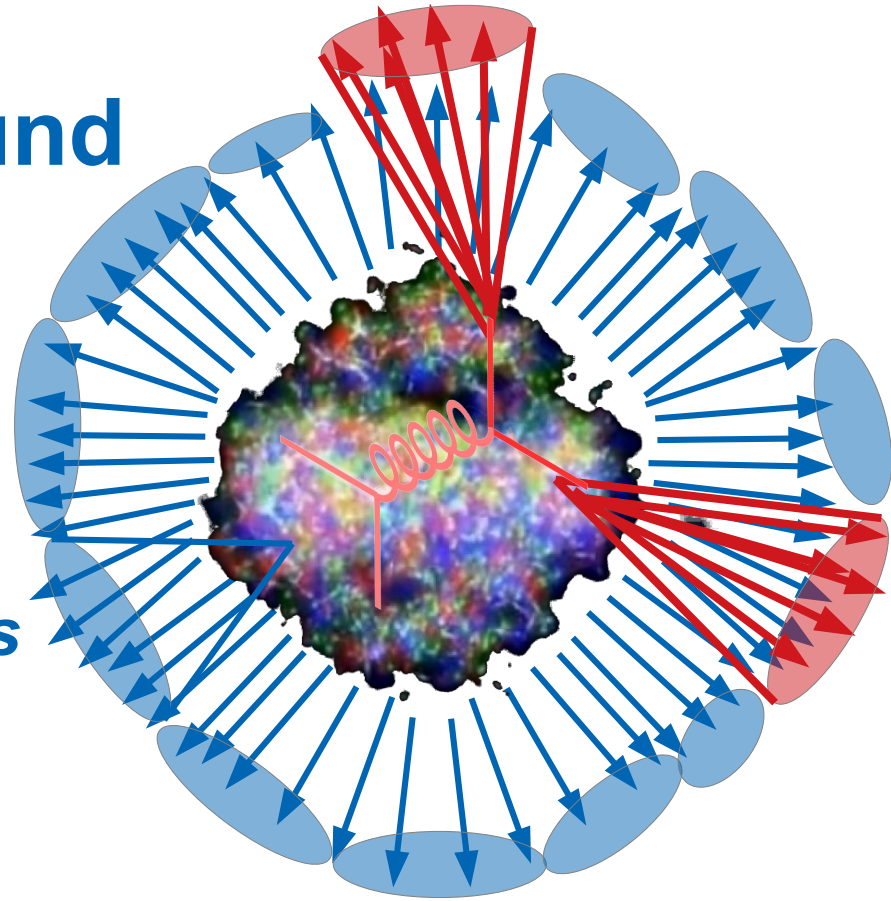


Signal vs Background:

The standard paradigm

Background

Combinatorial jets



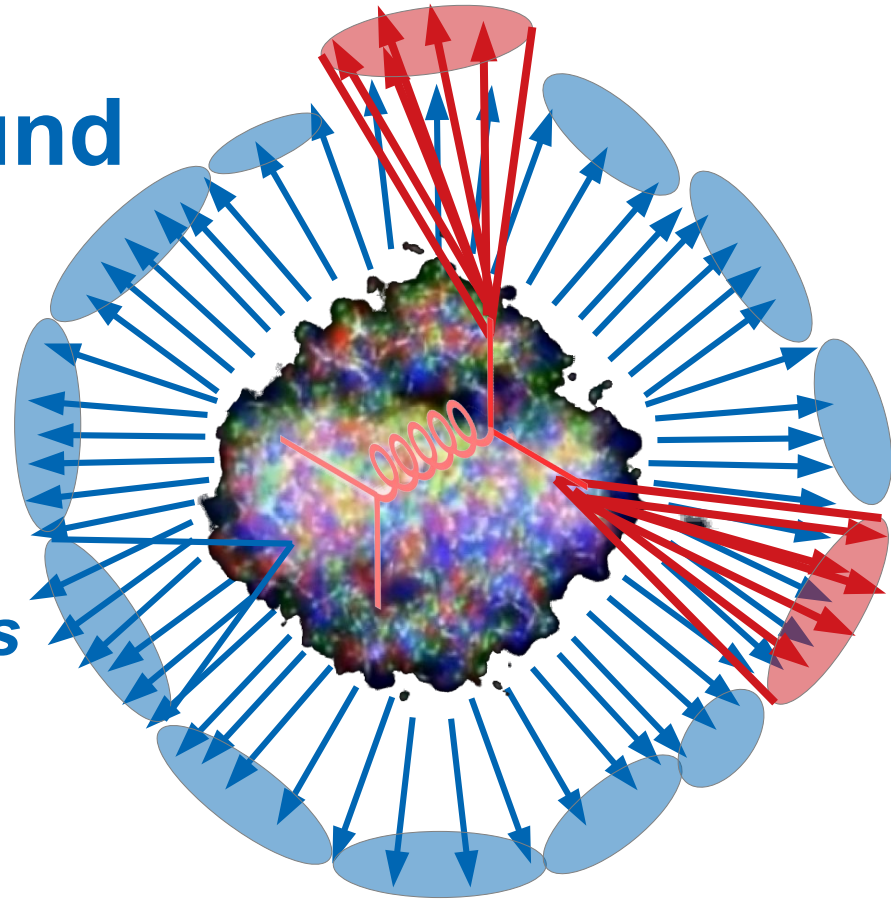
Signal

Signal vs Background:

The standard paradigm

Background

**Combinatorial jets
= “fake” jets**



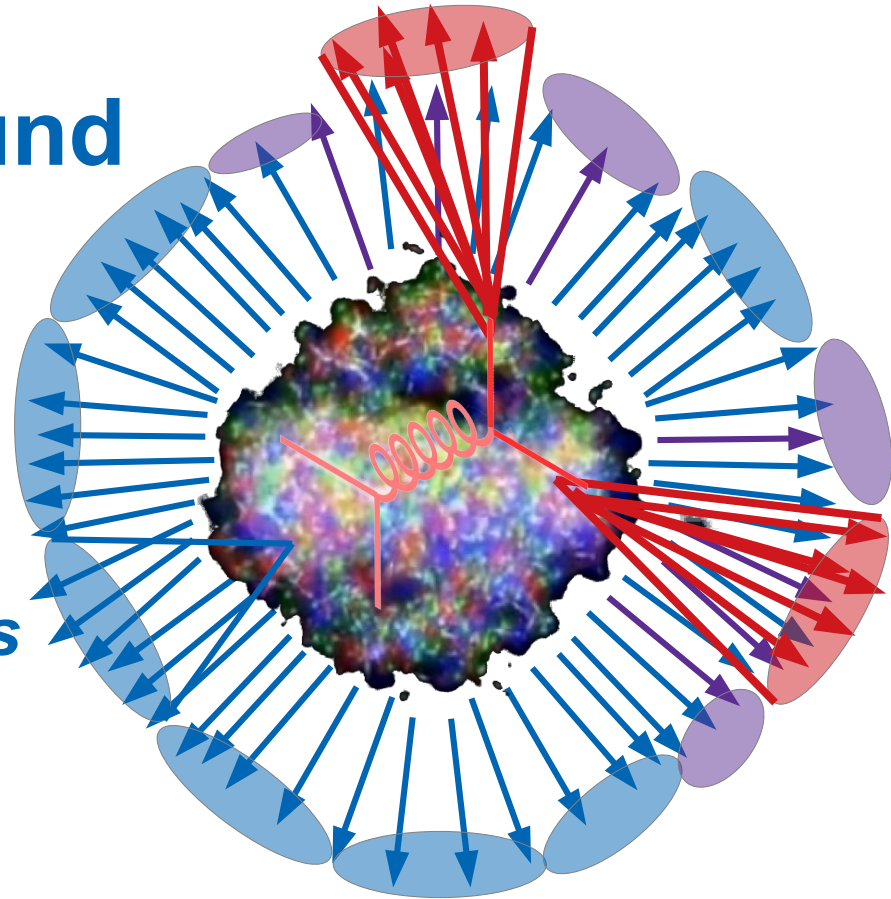
Signal

Signal vs Background:

The standard paradigm

Background

Combinatorial jets



Signal

*Some gray areas

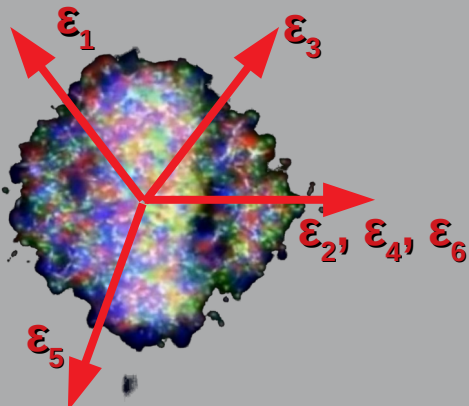
A jet is what a jet finder finds.

2. Models

TennGen background generator



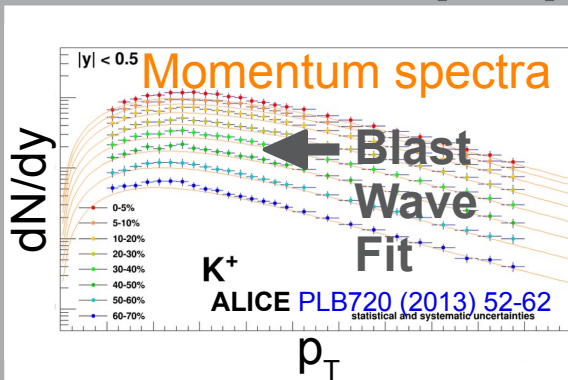
Event properties



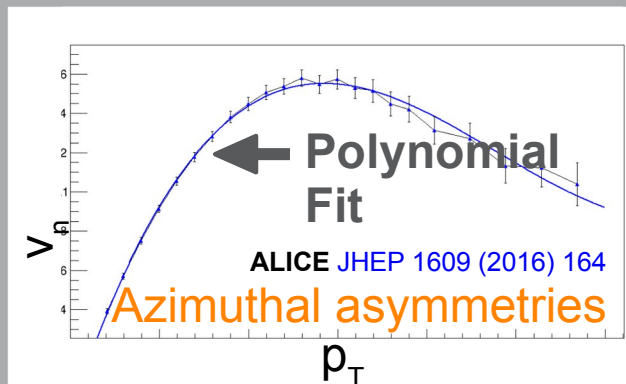
- Even event planes fixed at $\Psi=0$
- Odd planes at random ϕ
- Multiplies from ALICE PRC88 (2013) 044910

**No jets! No resonances
Emulates hydro correlations**

Track properties



→ Random p_T



→ v_n
→ Random ϕ

TENNGEN



Mix TennGen with PYTHIA

- Merge PYTHIA pp collisions into TennGen heavy ion background
- Find charged anti- k_T jets in merged event and geometrically match them back to PYTHIA jets
- Use matched PYTHIA jet momentum as ground truth



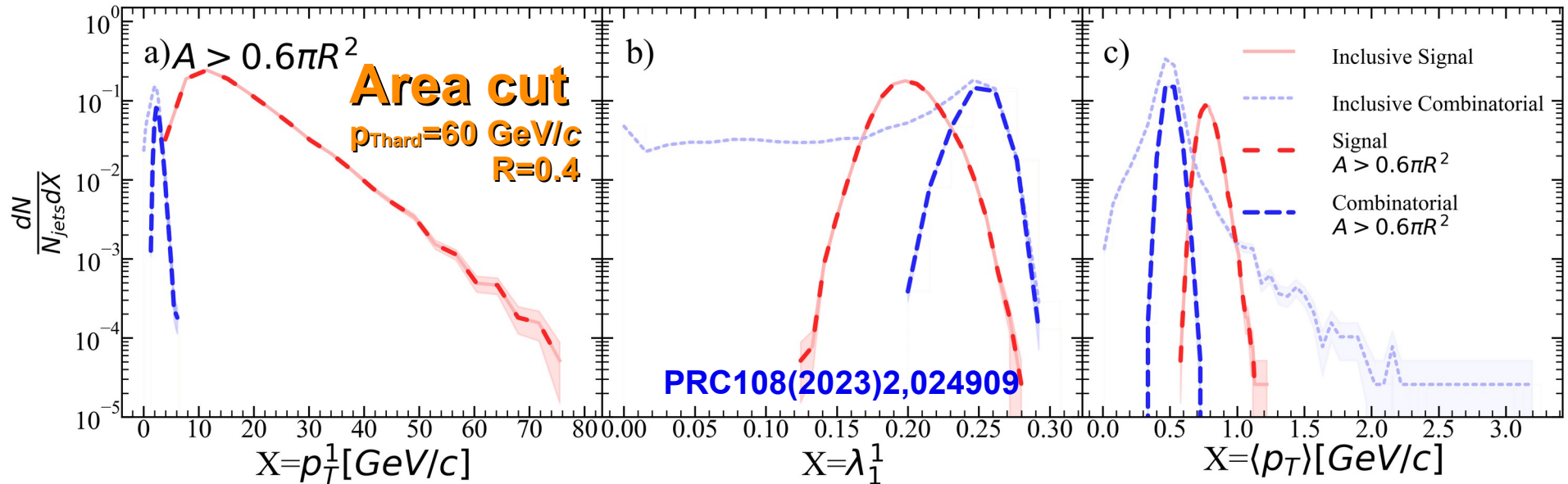
+

TENNGEN



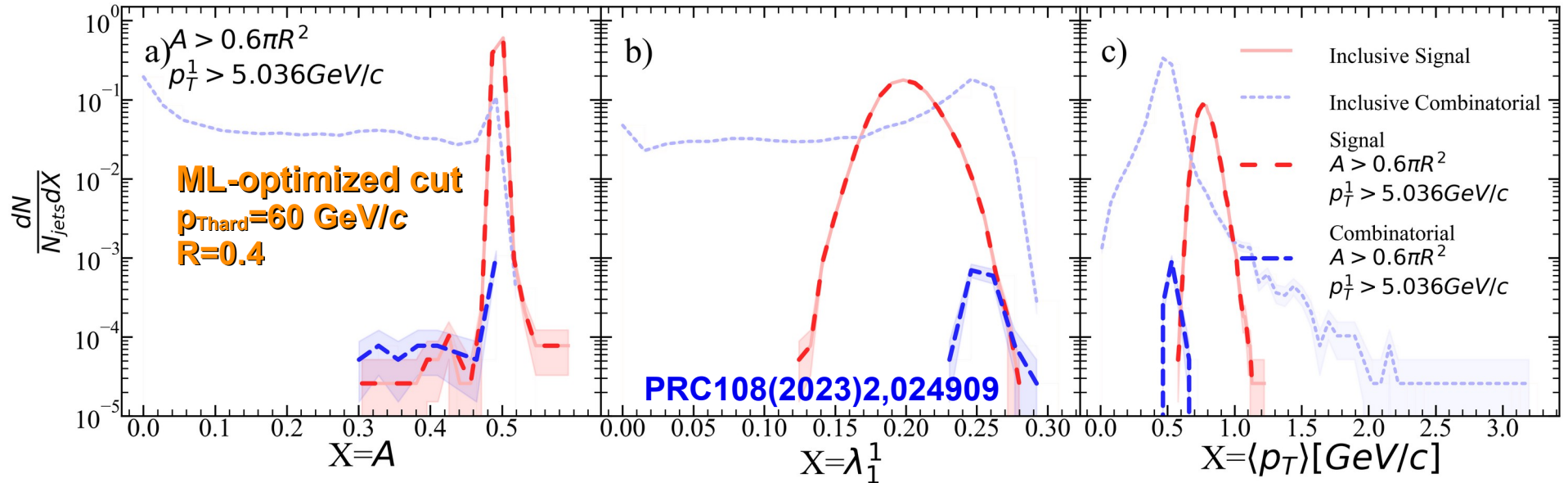
3. Background and signal overlap

What happens to jet properties when you cut background?



Remaining background jets look like signal

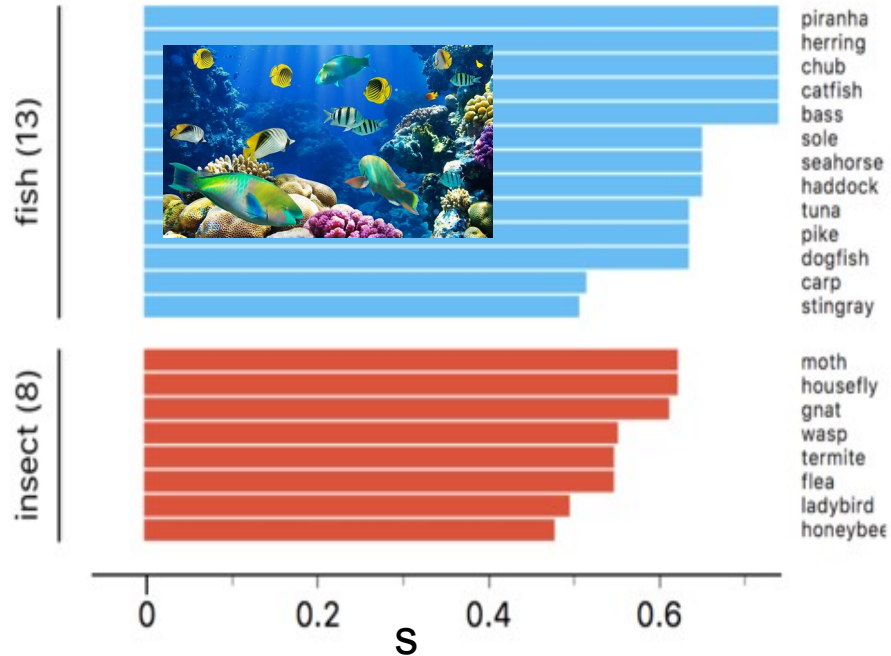
What happens to jet properties when you cut background?



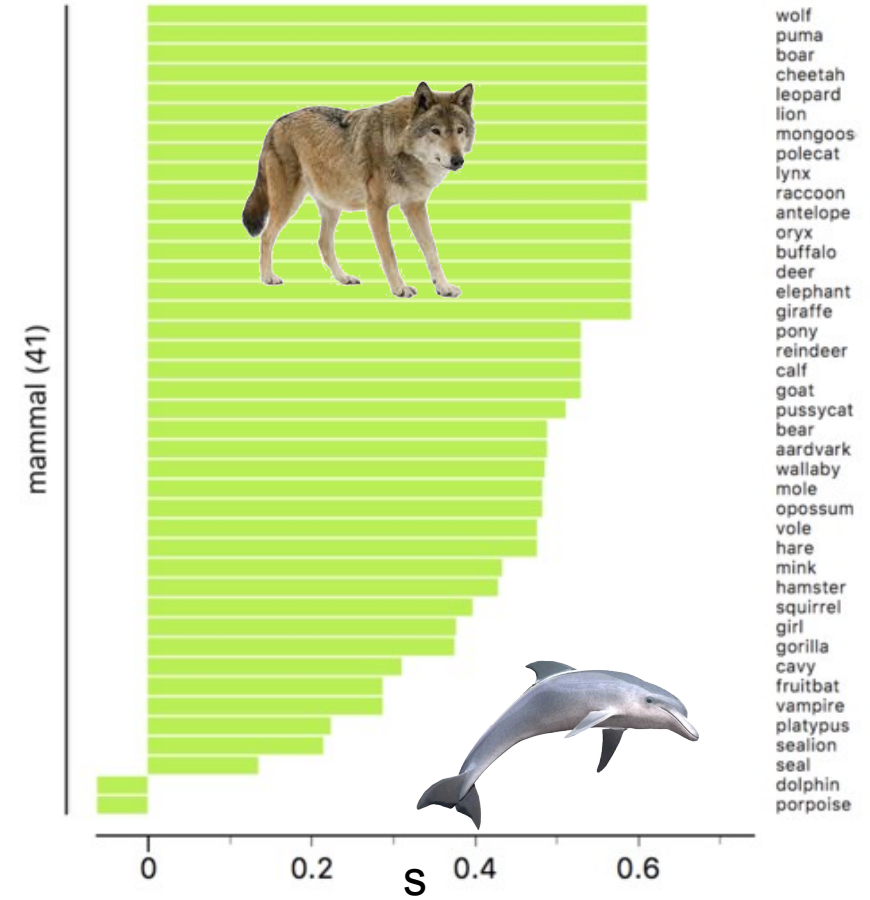
Remaining background jets look like signal

Silhouette values

Example from Wikipedia



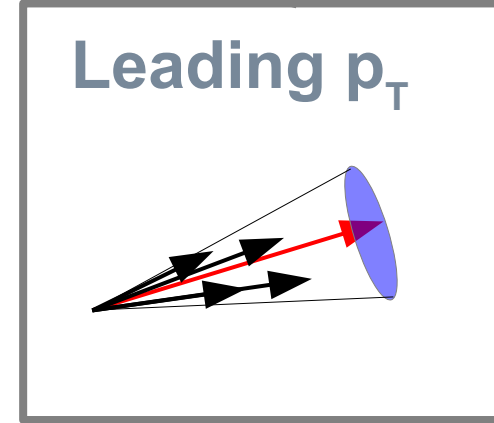
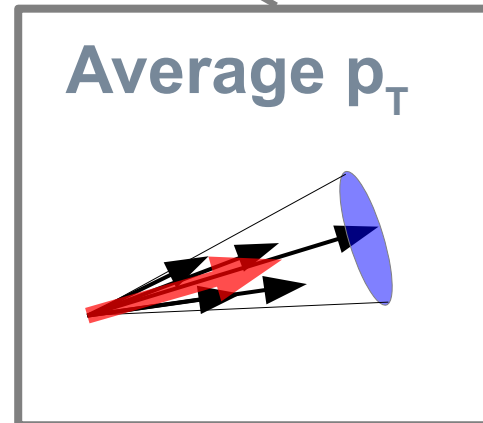
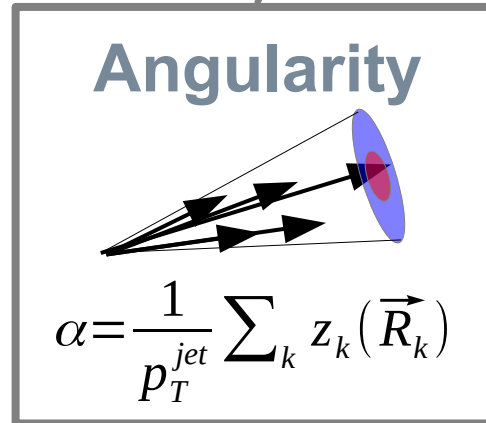
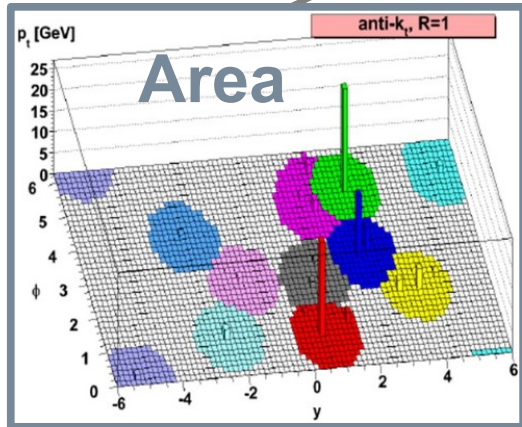
Silhouette scores from three types of animals rendered by Orange data mining suite.



Silhouette Values

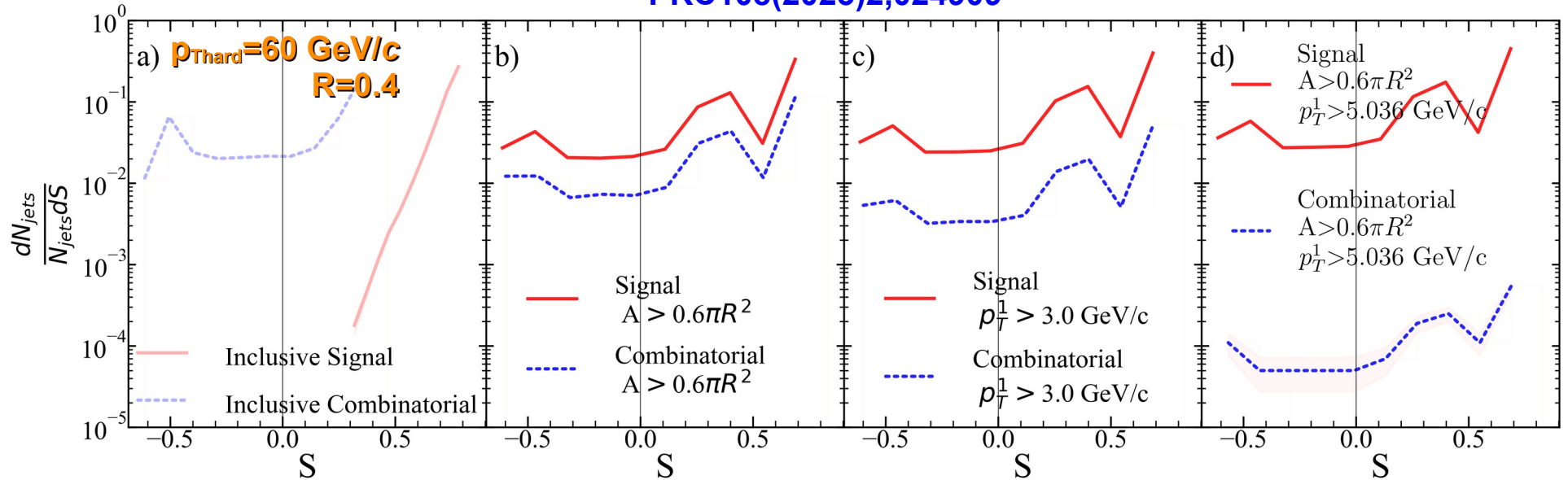
- Define a distance between two jet candidates to determine how similar they are

$$d_{i,j} = \sqrt{\left(\frac{A_i - A_j}{A^{\max} - A^{\min}}\right)^2 + \left(\frac{\alpha_i - \alpha_j}{\alpha^{\max} - \alpha^{\min}}\right)^2 + \left(\frac{\langle p_T \rangle_i - \langle p_T \rangle_j}{\langle p_T \rangle^{\max} - \langle p_T \rangle^{\min}}\right)^2 + \left(\frac{p_{T,i}^L - p_{T,j}^L}{p_T^{L,\max} - p_T^{L,\min}}\right)^2}$$



What happens to jet properties when you cut background?

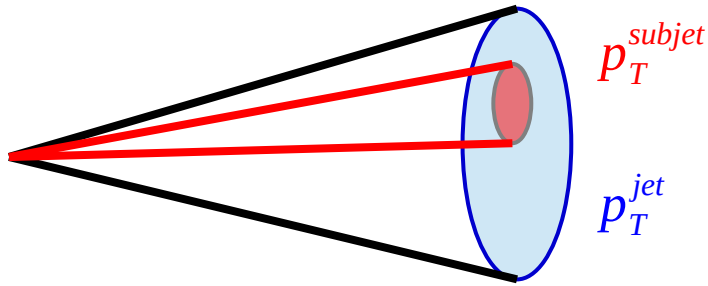
PRC108(2023)2,024909



Yes, you can cut background, but it comes at a cost. Background jets which look like signal remain.



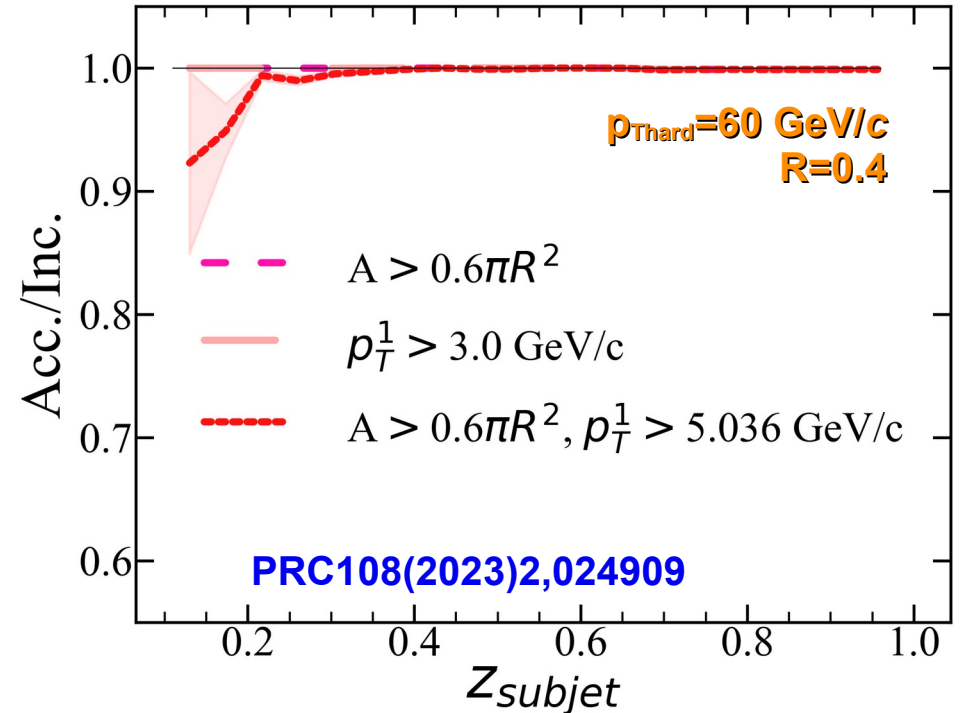
What's left is biased towards quark-like jets



$$z_r = \frac{p_T^{\text{subjet}}}{p_T^{\text{jet}}}$$

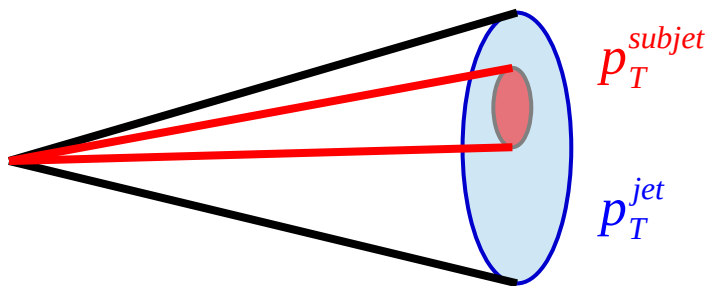
Subjet z

Calculated using PYTHIA particles only



Gluon-like ← → Quark-like

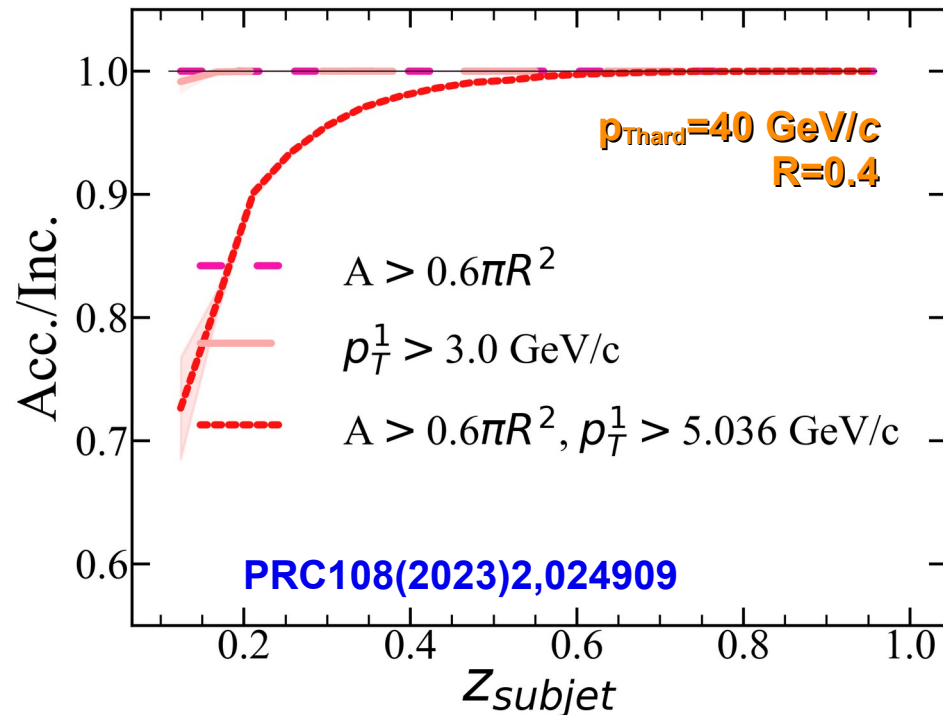
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Subjet z

Calculated using PYTHIA particles only

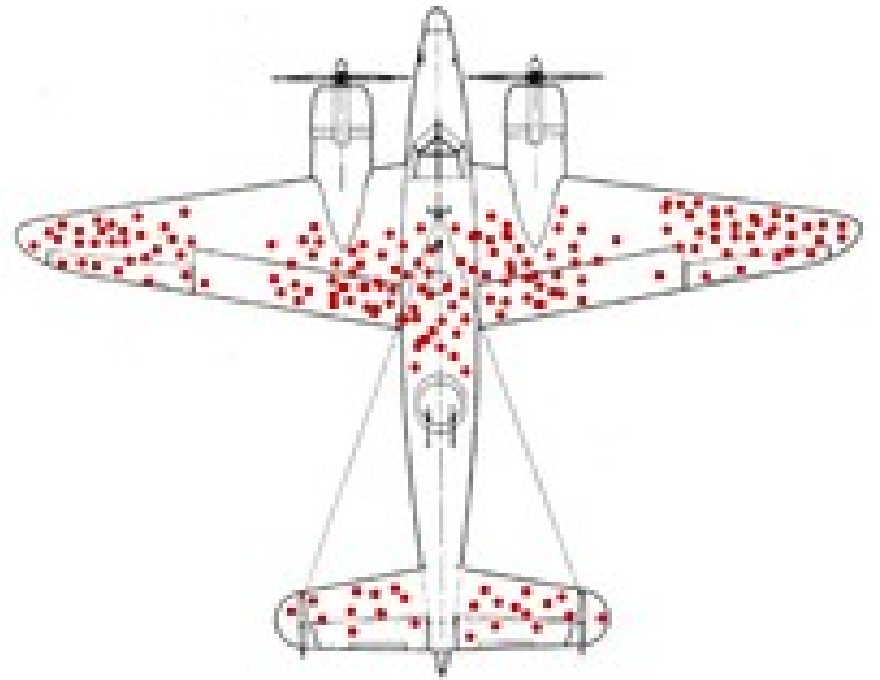


Gluon-like ←  → Quark-like

Survivor bias

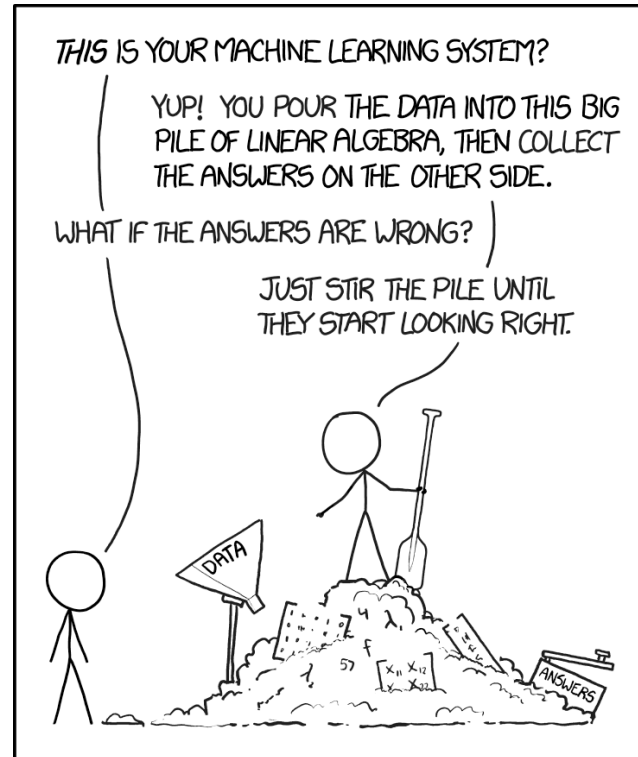
First use of the term for jets in heavy ion collisions?

Rev. Mod. Phys. 90, 025005 (2018)

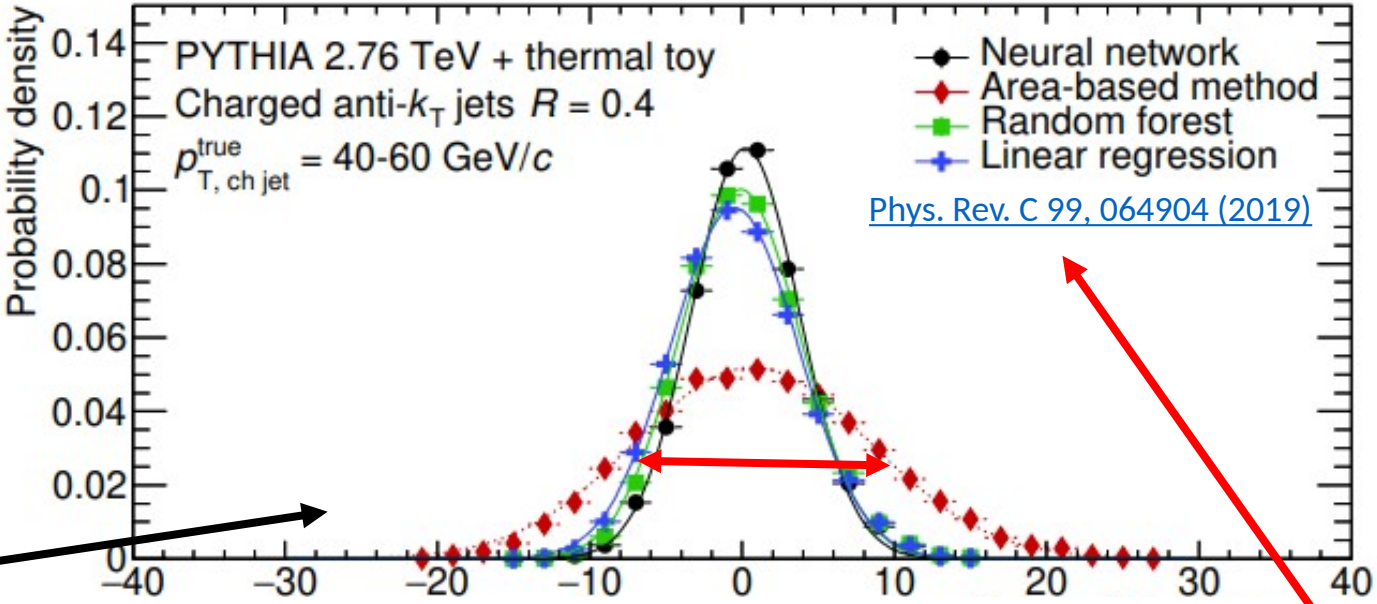


- **WWII Example:** holes planes returning indicate where it's *safer* to get hit
- We're looking at the jets which *remain*

4. Machine learning only teaches you what you already know!



Observation – ML does better at background



[Phys. Rev. C 99, 064904 \(2019\)](#)

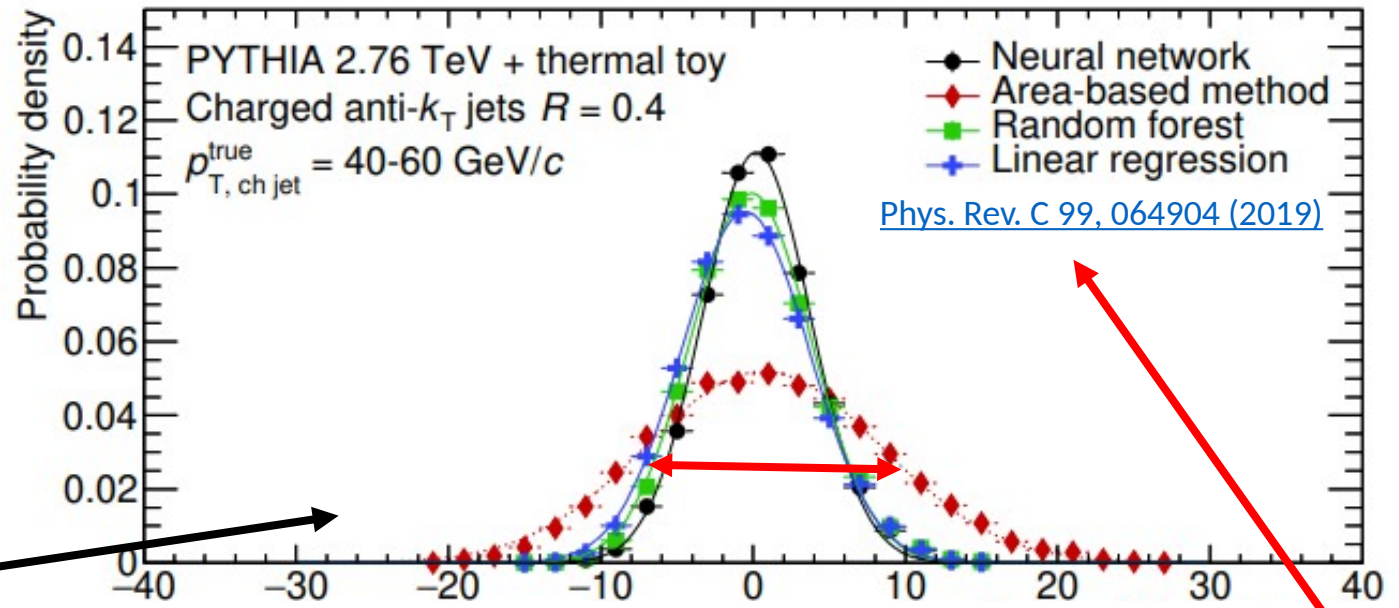
Width of determines momentum resolution of method.

$$\delta p_T = (p_{T, jet}^{pred.} - p_{T, jet}^{truth})$$

$$p_T^{Corr.} = p_T^{raw.} - \rho A_{jet}$$

Applied to data in ALICE Collaboration, PLB 849 (2024) 138412

Observation – ML does better at background



Width of determines momentum resolution of method.

$$\delta p_T = (p_{T, \text{jet}}^{\text{pred.}} - p_{T, \text{jet}}^{\text{truth}})$$

$$p_T^{\text{Corr.}} = p_T^{\text{raw.}} - \rho A_{\text{jet}}$$

Applied to data in ALICE Collaboration, PLB 849 (2024) 138412

A better method?

- Random cone:

$$p_T^{corr} = p_T^{raw} - \rho_A A$$

Also confirmed in
PRC 106, 044915 (2022)

$$\sigma_{total} = \sqrt{N \sigma_{p_T}^2 + (N + 2N^2 \sum_n v_n^2) \mu_{p_T}^2}$$

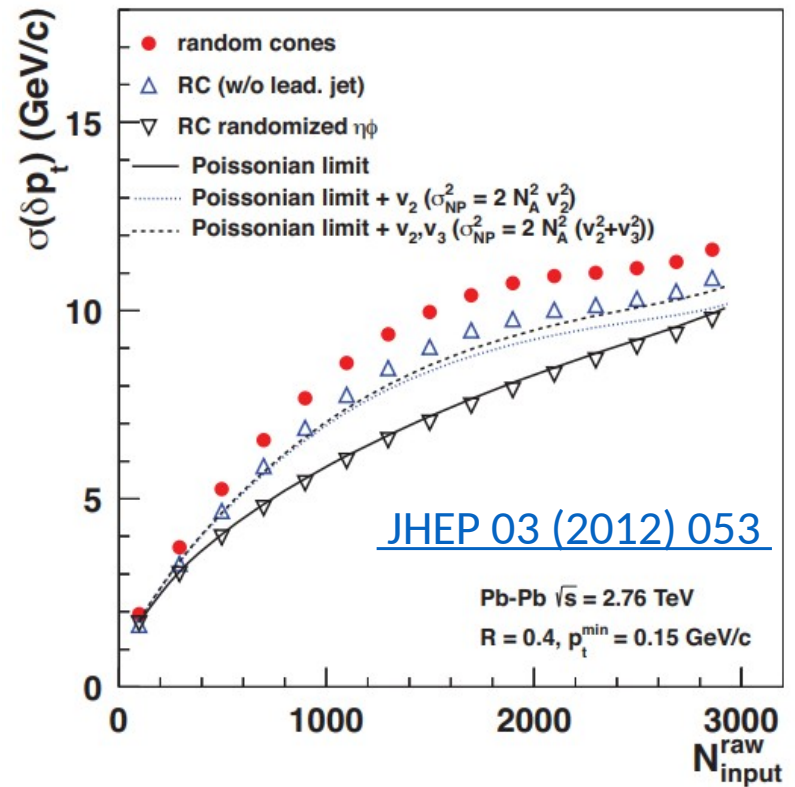
Tannenbaum, PLB(498),1-2,Pg.29-34(2001)

- Multiplicity method:

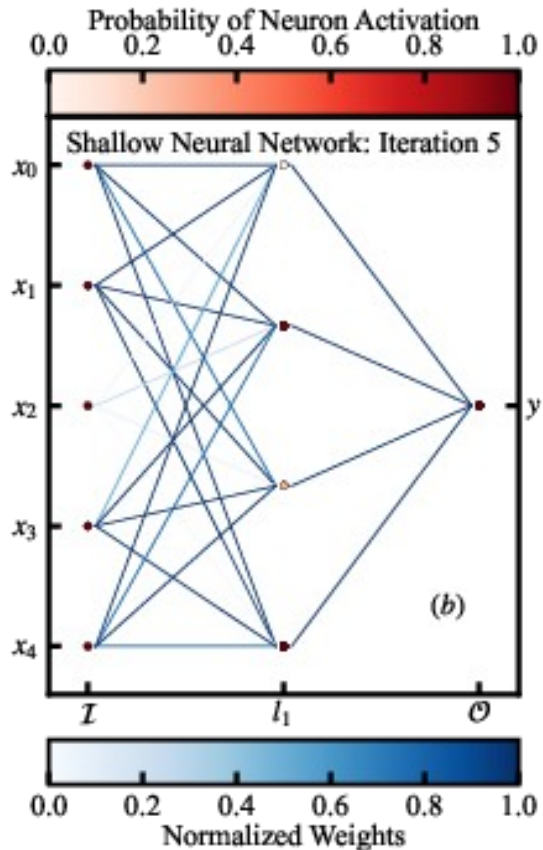
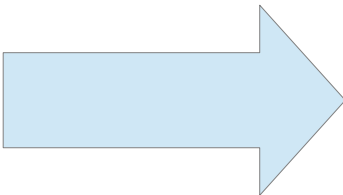
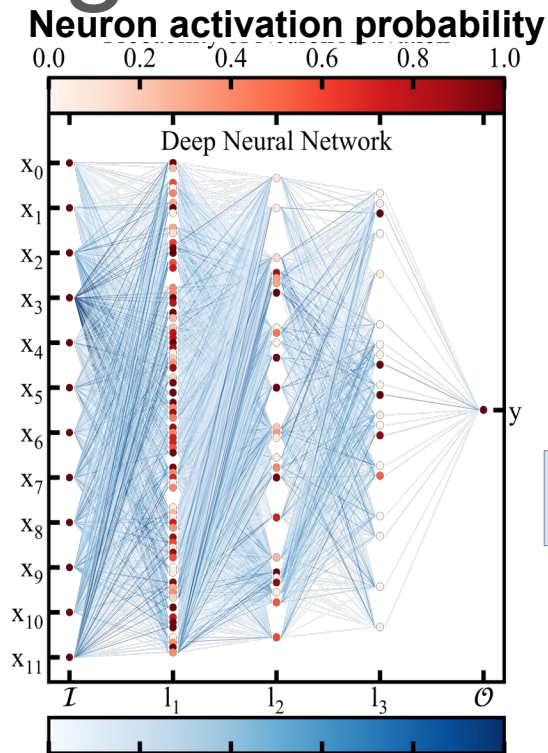
$$p_T^{corr} = p_T^{raw} - \rho_N (N_{tot} - N_{sig})$$

$$\sigma_{total} = \sqrt{N \sigma_{p_T}^2}$$

PRC.108.L021901(2023)6



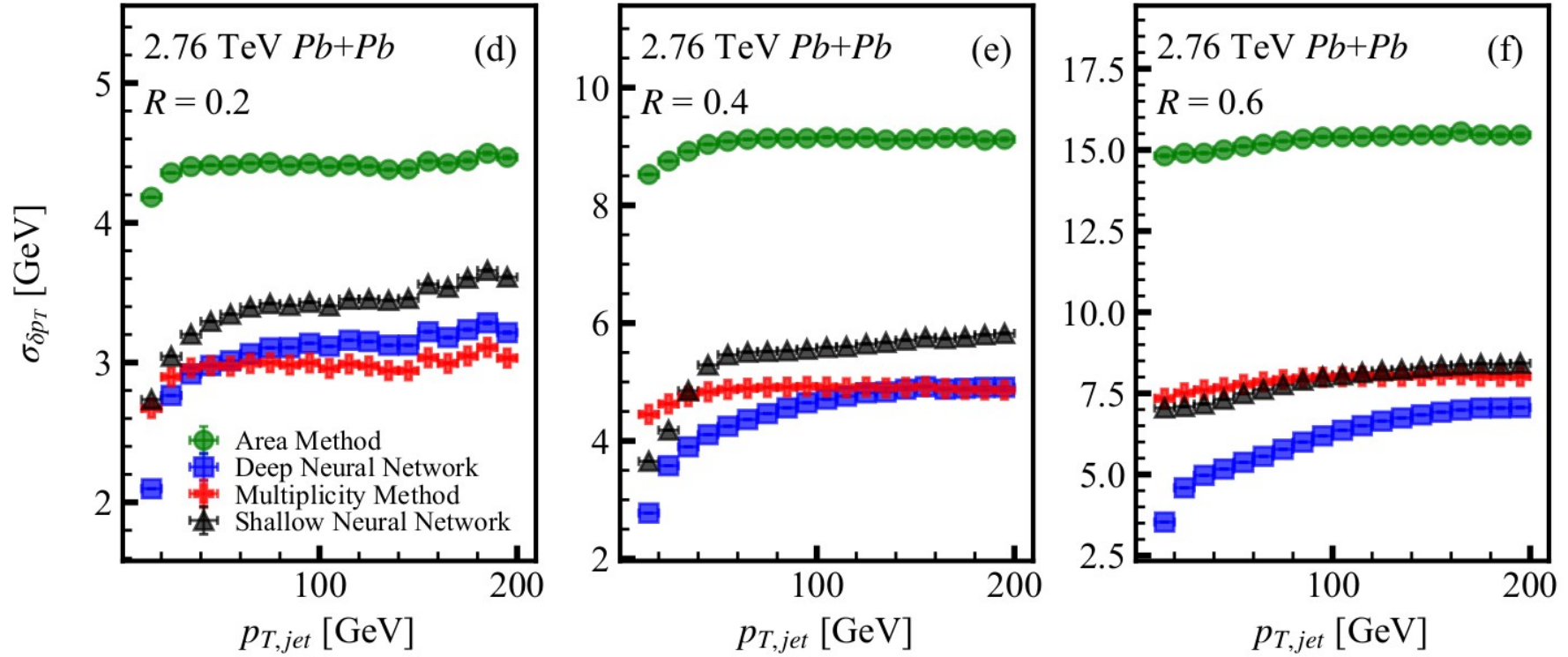
Trimming the network



Information flows forward from layer to layer
Nodes are connected by weights

Follow up to
[PRC.108.L021901\(2023\)6](#)
Arxiv pending

Algorithm Performance



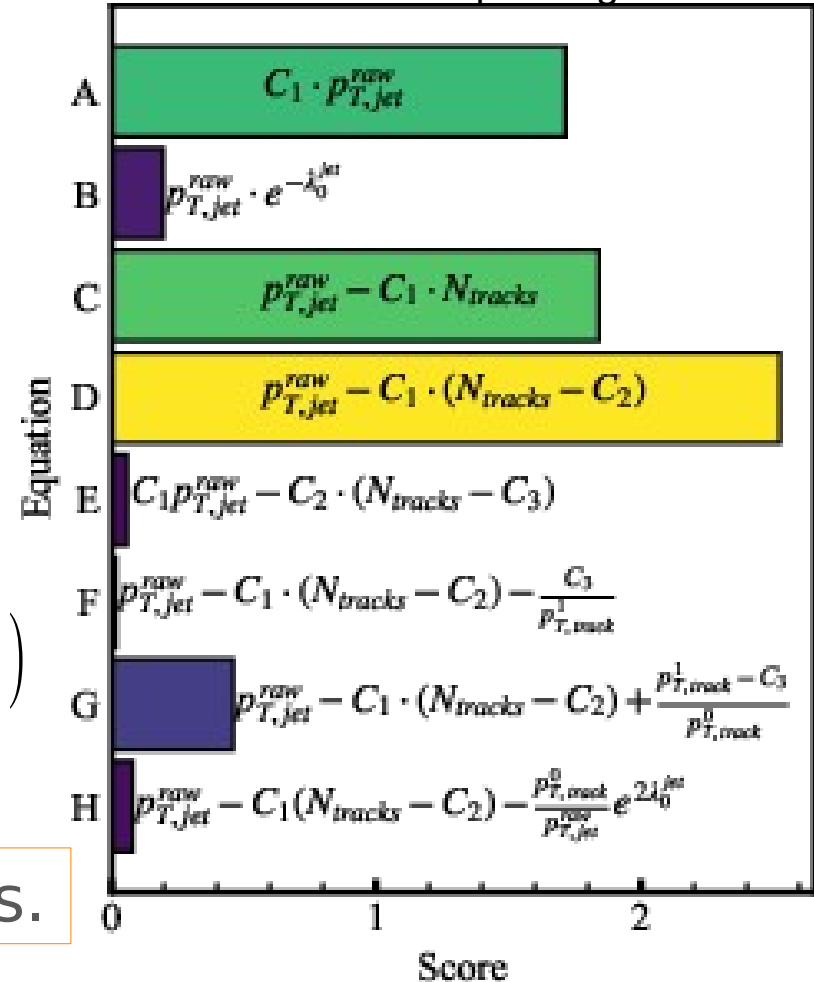
Symbolic regression

- Analytical approximation
- Trained on **all input jet features** with exponential, trigonometric, and arithmetic operations.
- The best result was a linear combination.**

Jet multiplicity

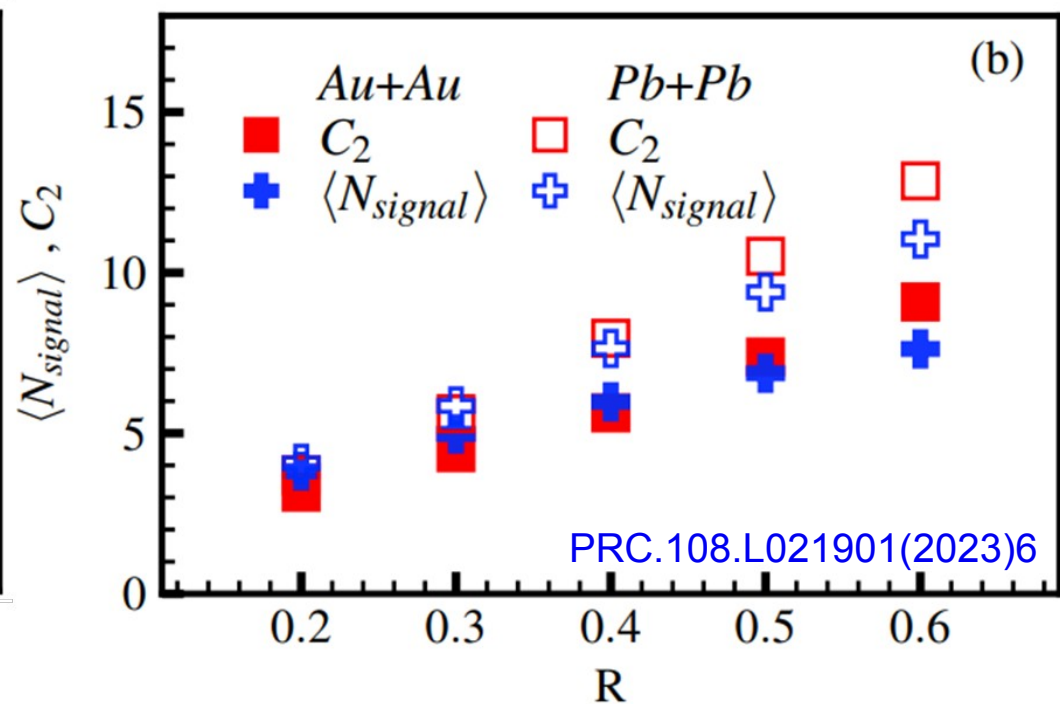
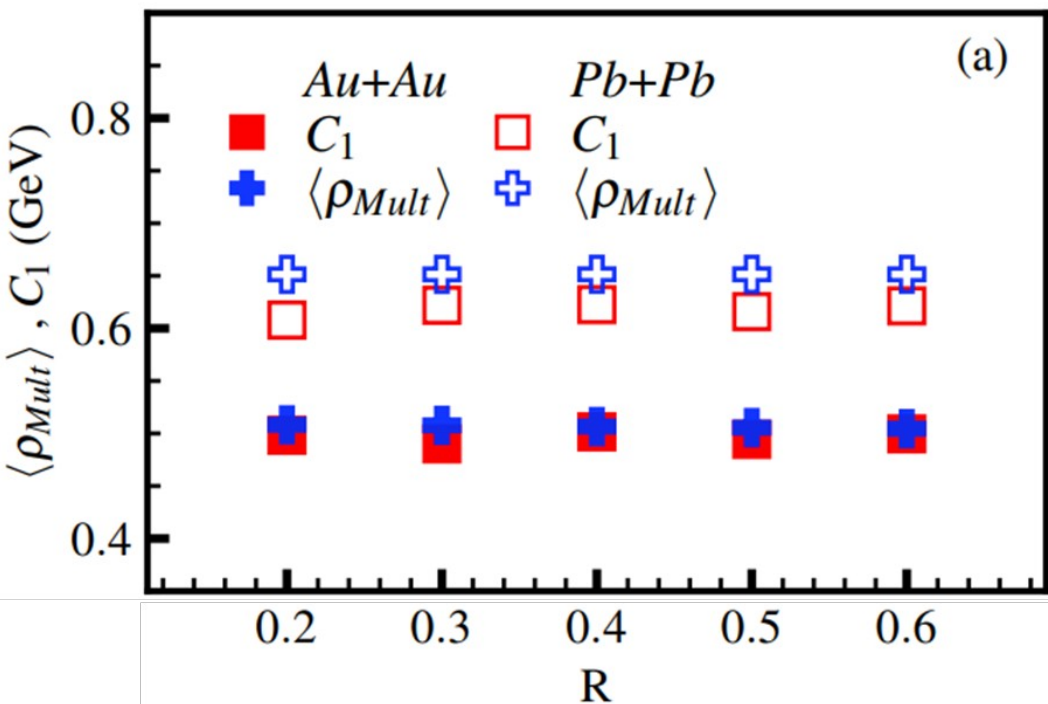
$$p_T^{corr.} = p_T^{raw} - C_1 \cdot (N - C_2)$$

Learned optimization constants.



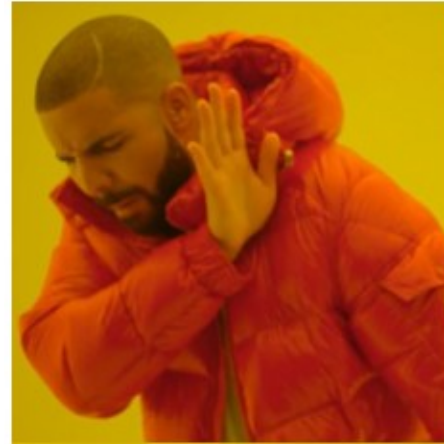
Neural network \approx Multiplicity method

- Constants learned by PySR are approximately the terms used in multiplicity background subtraction method.



Interpretable ML

1. Method must be equivalently applicable to data and simulation.
2. Predictions must be understood outside the range of training set.
3. Systematic uncertainties can be assessed for predictions.
4. Learned relationships can be directly observed.



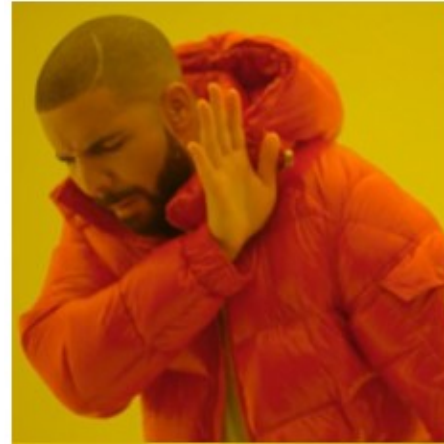
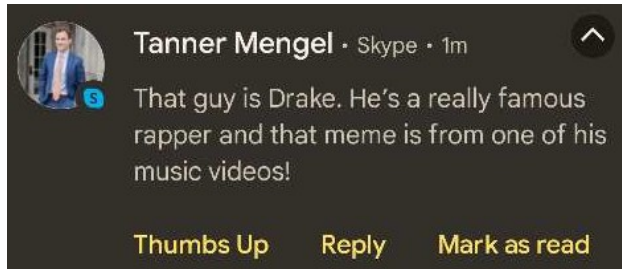
Machine Learning



Interpretable Machine Learning

Interpretable ML

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Machine Learning

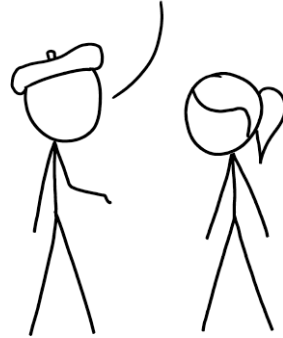


Interpretable Machine Learning

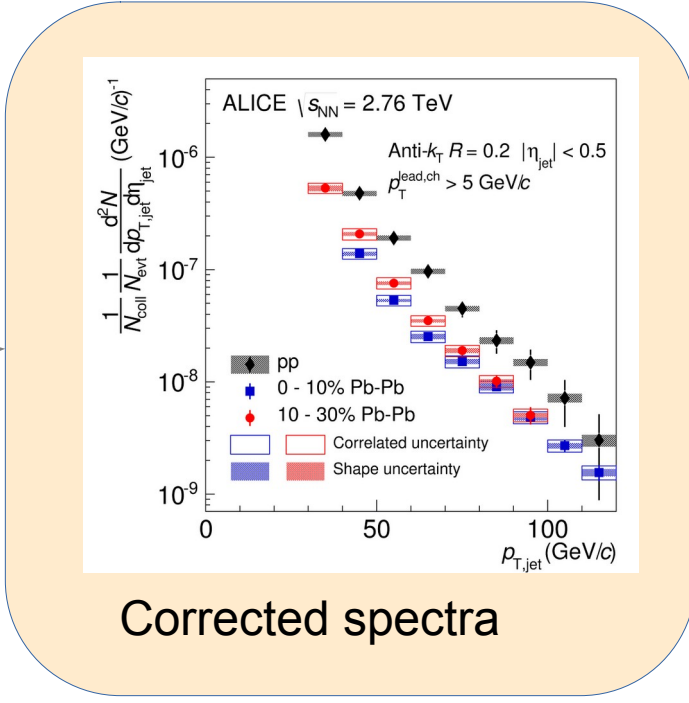
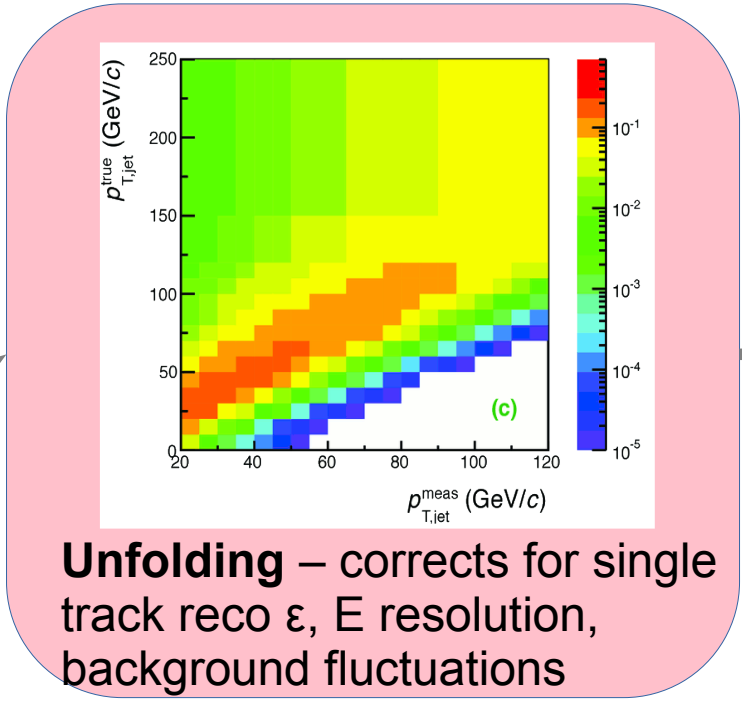
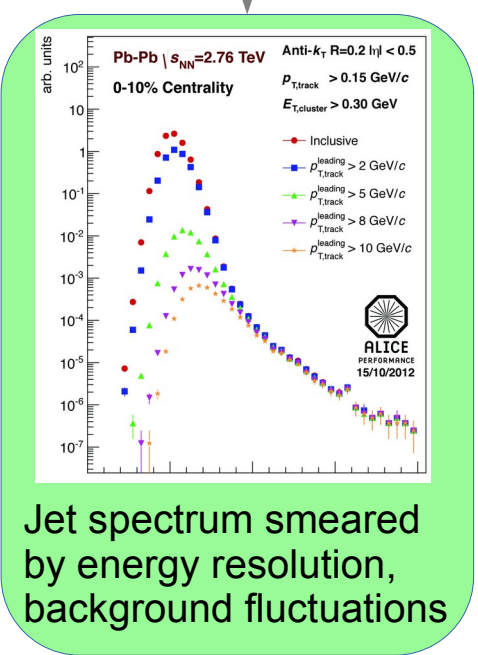
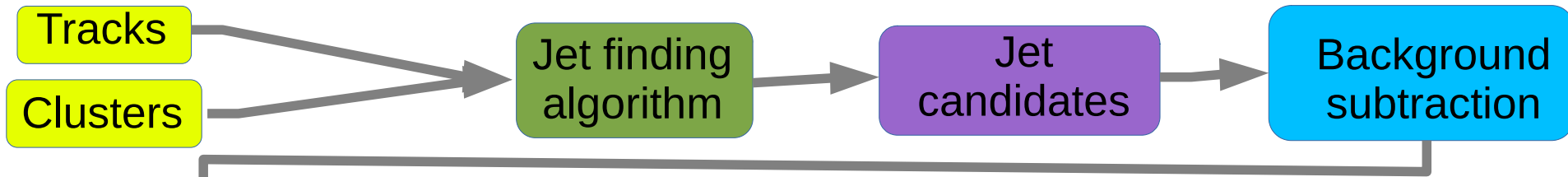
5. How should you compare to models?

WE DON'T WANT TO REINVENT THE WHEEL,
SO EVERY DAY WE GOOGLE IMAGE SEARCH
"WHEEL," AND WHATEVER OBJECT COMES UP,
THAT'S WHAT WE ATTACH TO OUR VEHICLES.

SURE, EXTERNAL DEPENDENCIES
CARRY RISKS, BUT SO FAR THEY'VE
ALL BEEN PRETTY GOOD WHEELS.



Analysis steps



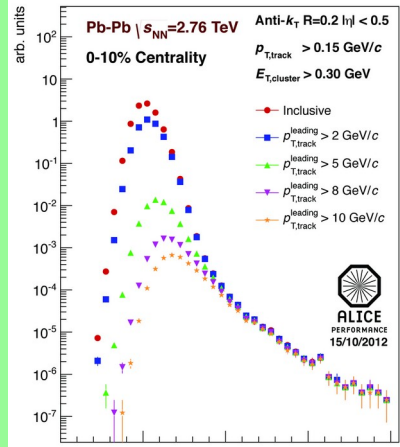
Analysis steps: Full Monte Carlo

Particles

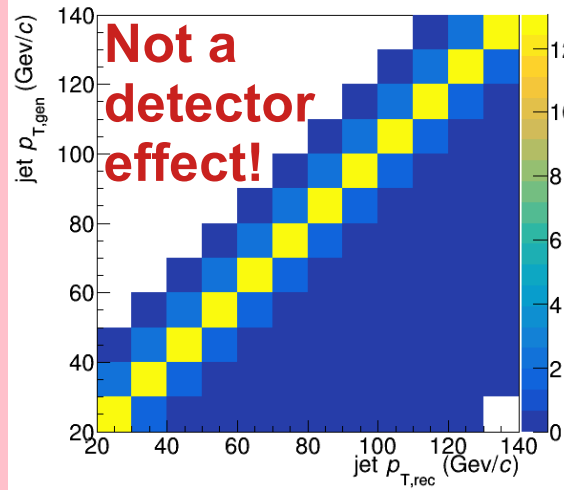
Jet finding algorithm

Jet candidates

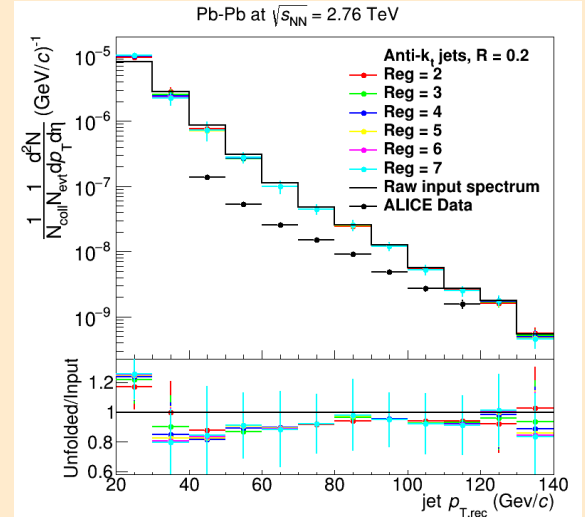
Background subtraction



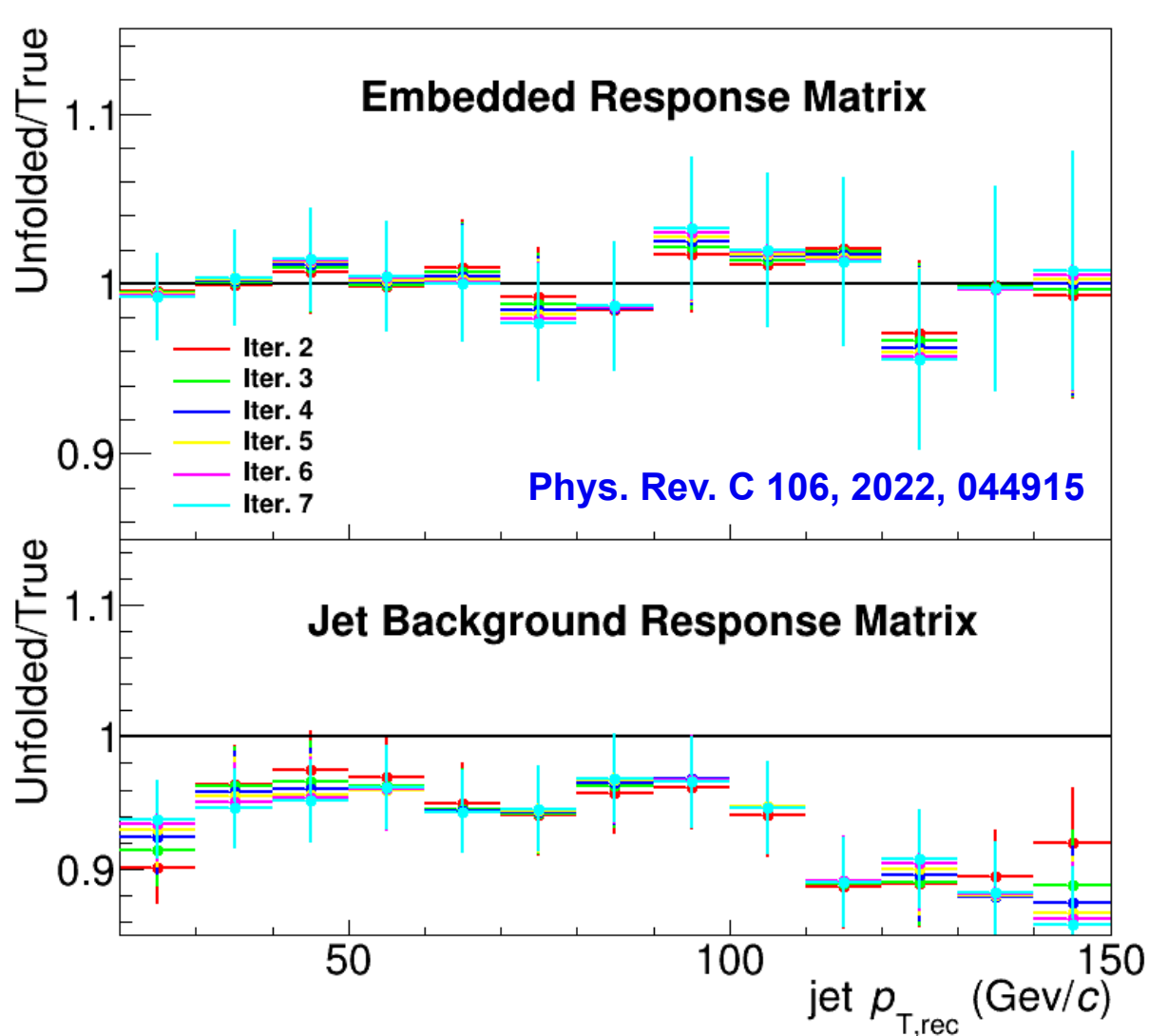
Jet spectrum smeared by energy resolution



Unfolding – corrects for background fluctuations



Corrected spectra



Closure

- Methods
 - Use δp_T method to measure width of fluctuations with varying numbers of leading jets (LJ) discarded
 - Embed PYTHIA event into heavy ion event
- **Only embedding leads to full closure in Monte Carlo**

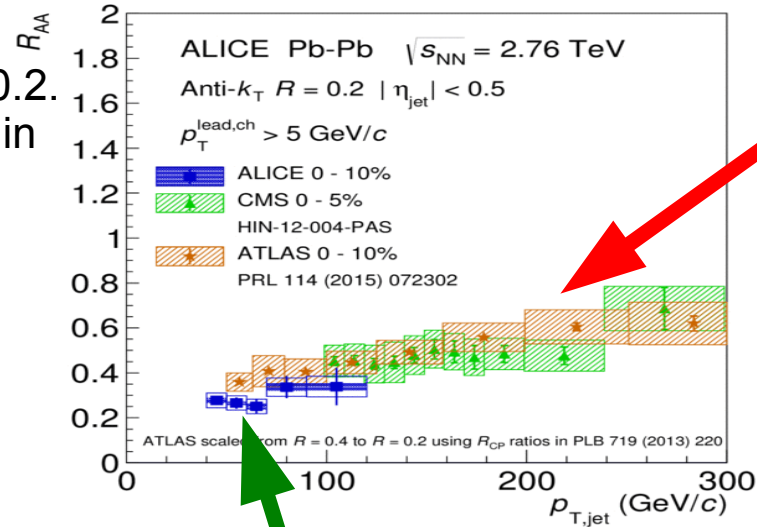
ATLAS

Background subtraction method:

- Iterative procedure
 - **Calorimeter jets:** Reconstruct jets with $R=0.2$. v_2 modulated $\langle \text{Bkgd} \rangle$ estimated by energy in calorimeters excluding jets with at least one tower with $E_{\text{tower}} > \langle E_{\text{tower}} \rangle$
Track jets: Use tracks with $p_T > 4$ GeV/c
 - Calorimeter jets from above with $E > 25$ GeV and track jets with $p_T > 10$ GeV/c used to estimate background again.

- Calorimeter tracks matching one track with $p_T > 7$ GeV/c or containing a high energy cluster $E > 7$ GeV are used for analysis down to $E_{\text{jet}} = 20$ GeV

Phys. Lett. B 719 (2013) 220-241



Constituent biases don't matter that much up here

But they do matter down here!

Snowmass Accord: Apply the same algorithm to data and your model. Then the measurement and the calculation are the same.

Rivet: Apply the same algorithm to data and your model. Then the measurement and the calculation are the same.

This is **also** what people have learned in the soft sector in heavy ion collisions.



The Lisbon Accord

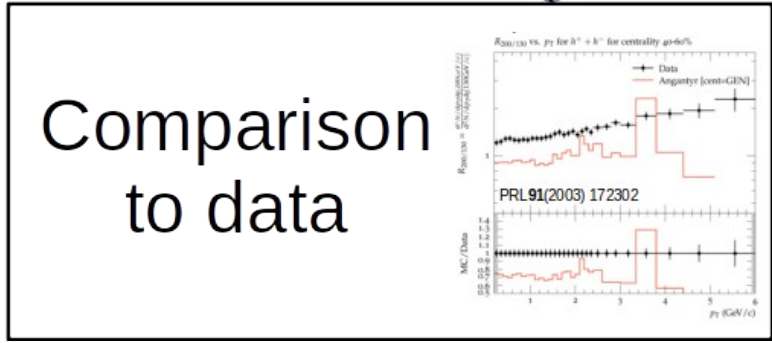
- [Lisbon Accord](#) proposed that heavy ion analyses adopt RIVET in July 2014



HepMC

HEPData

Rivet



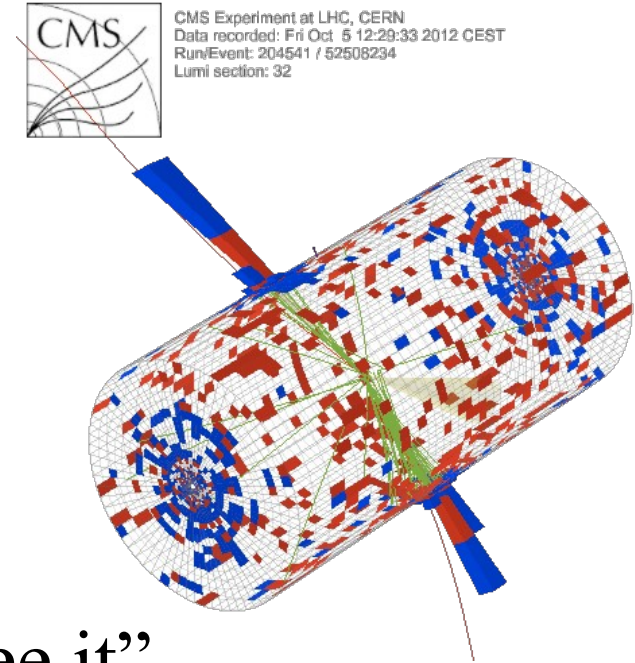
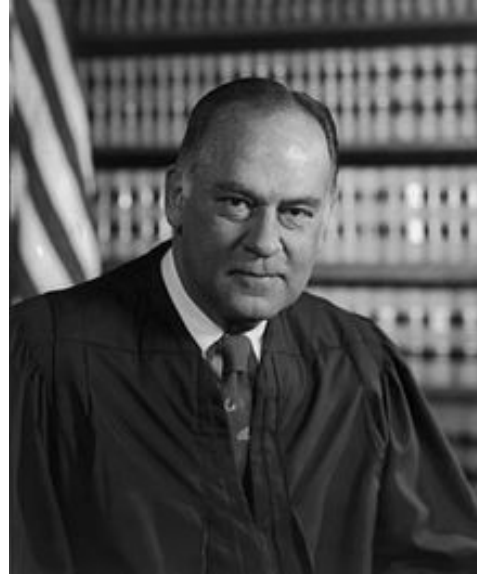
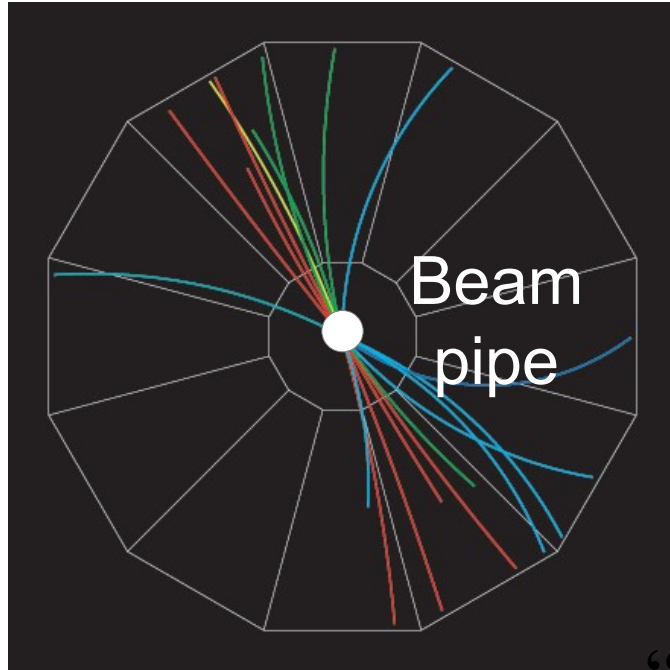
How should you compare to models?
Let's not reinvent the wheel!



This bike works!

What is a jet?

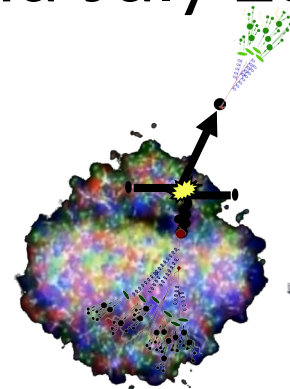
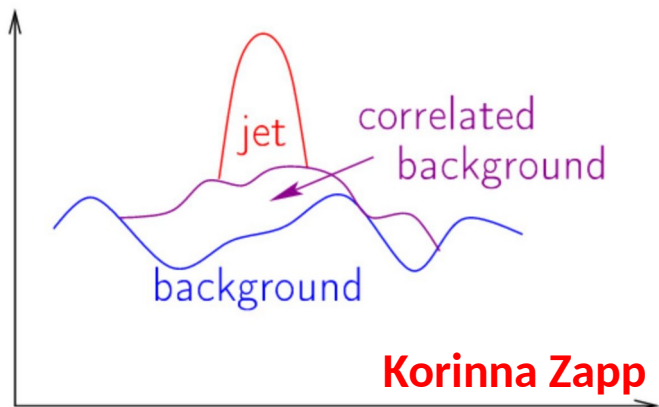
p+p dijet



“I know it when I see it”

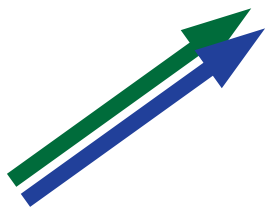
US Supreme Court Justice Potter Stewart,
Jacobellis v. Ohio

Definition of Jets in a Large Background July 25-27, 2018

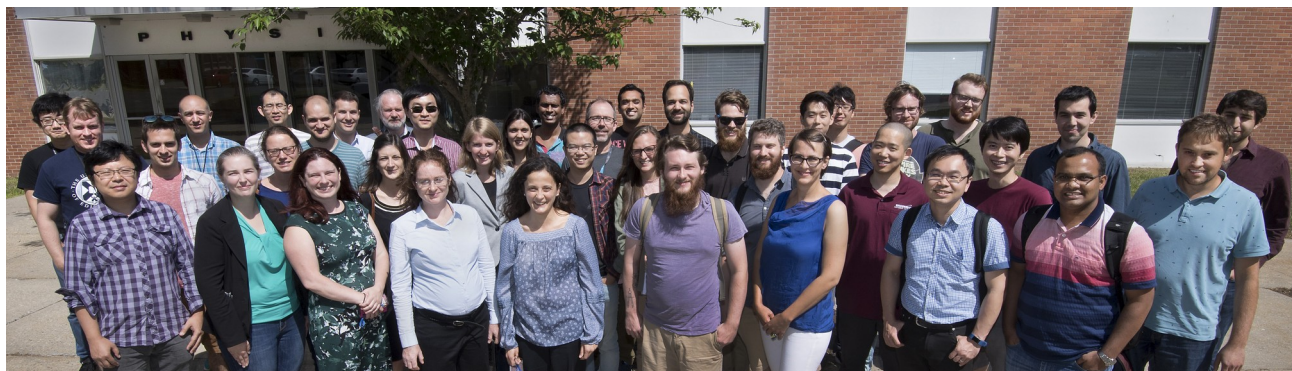


Include anything correlated in definition of jet

Provide enough details to make comparisons between data and models



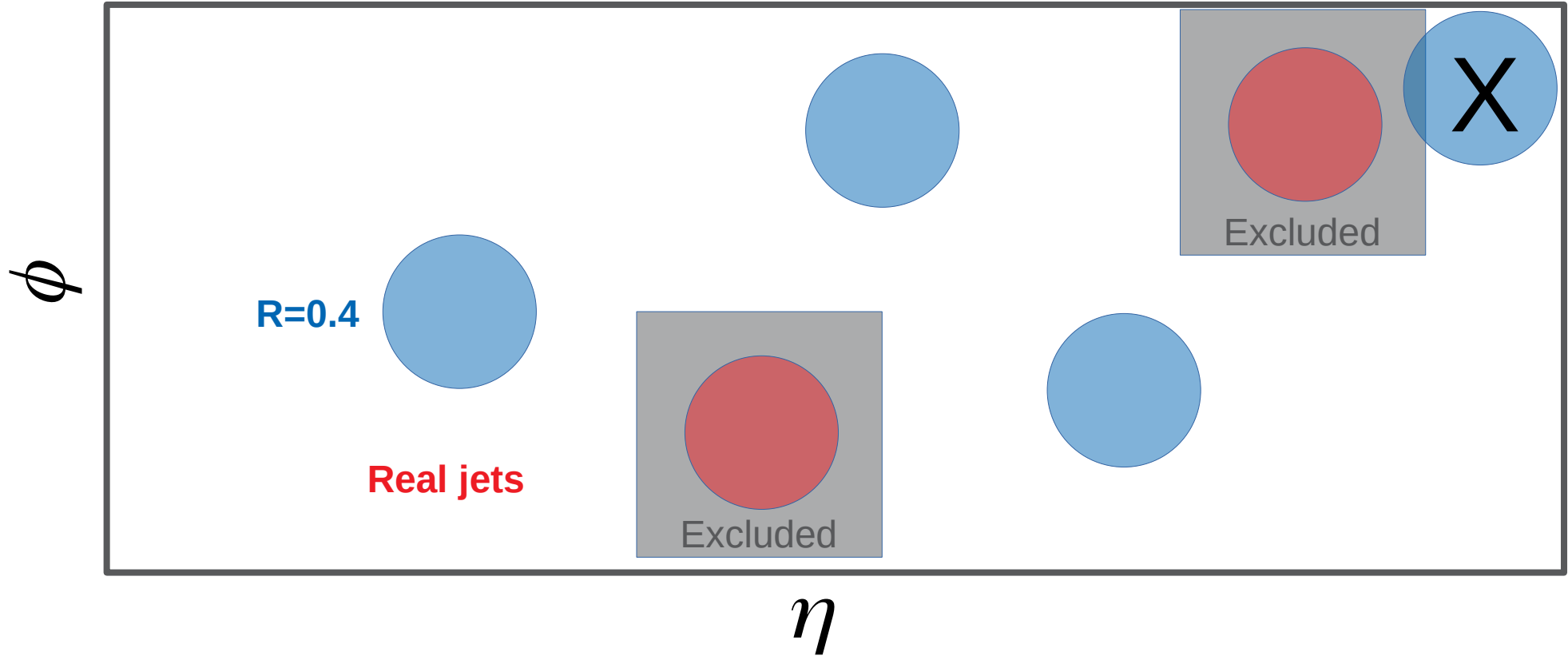
Reconsider role of collinear safety



Discuss and put effort into the problem

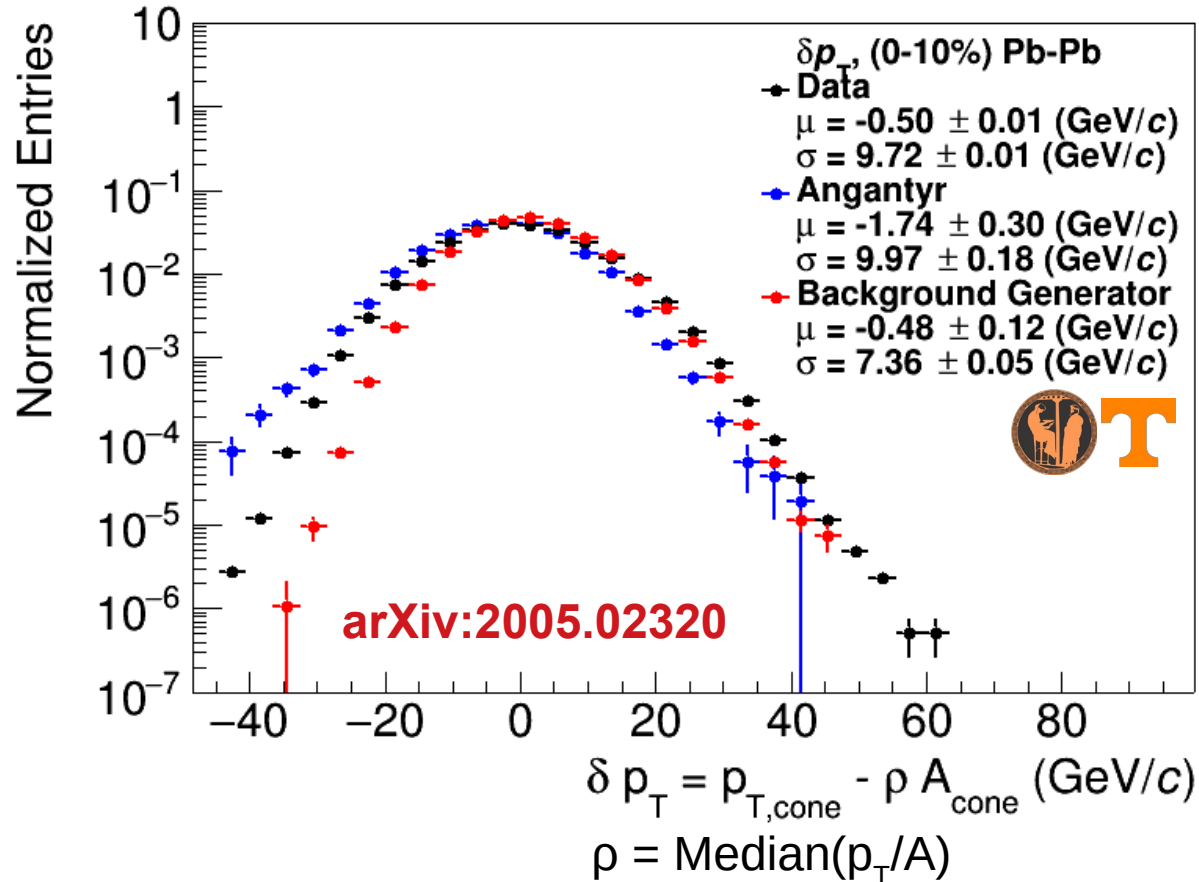
Backup

Random cones

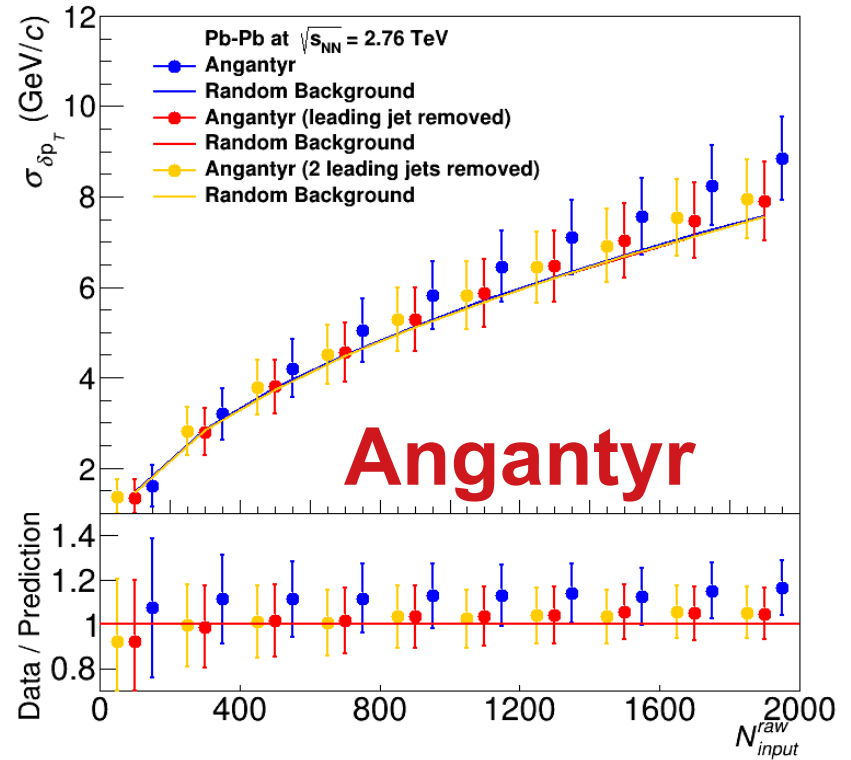
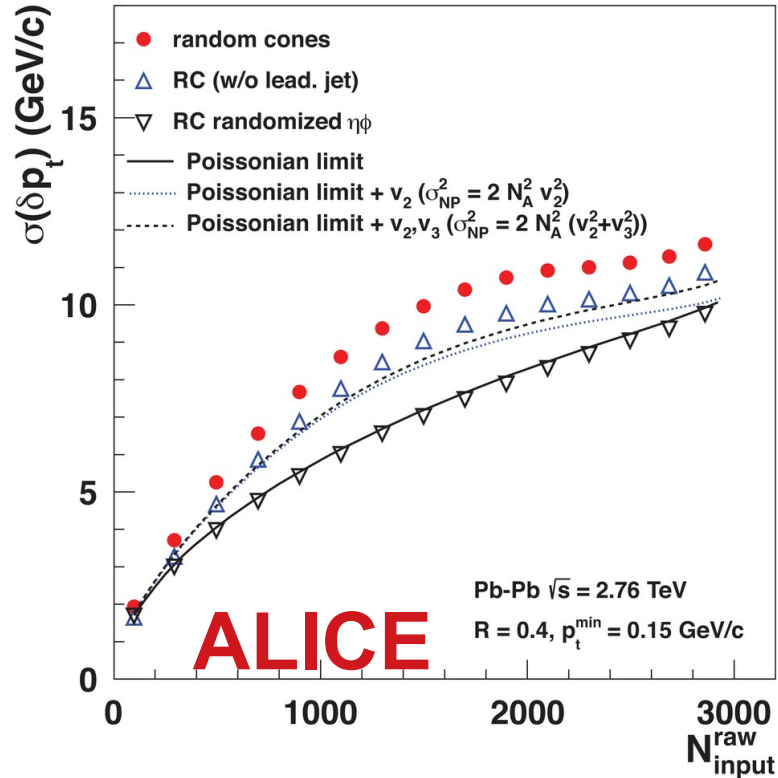


Random cones

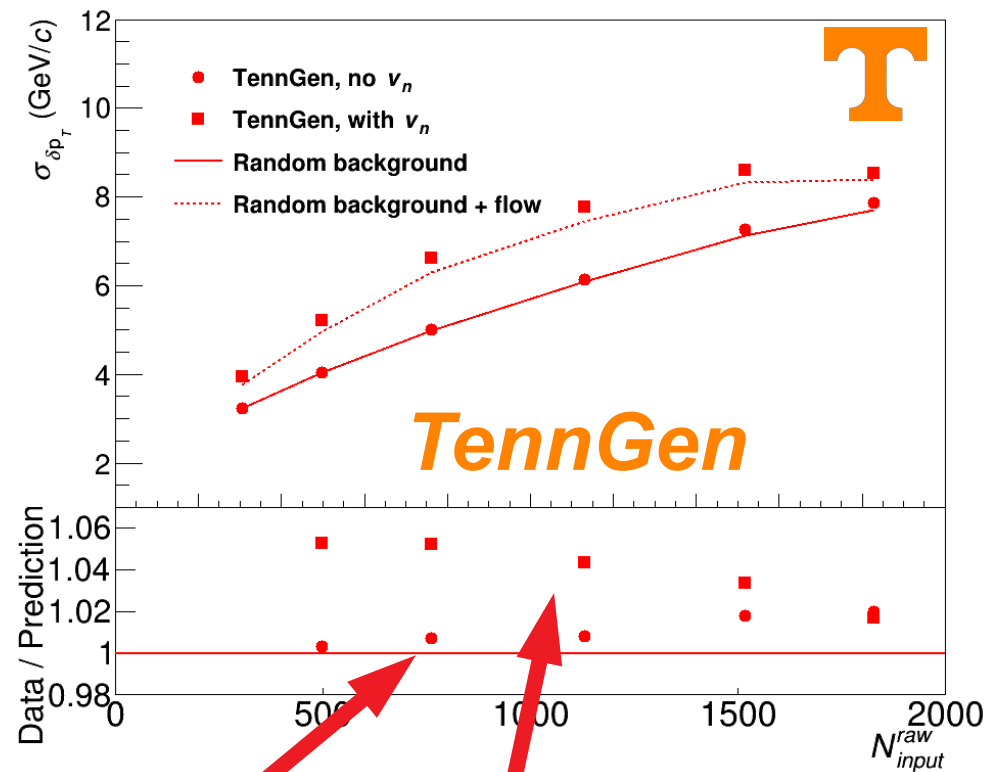
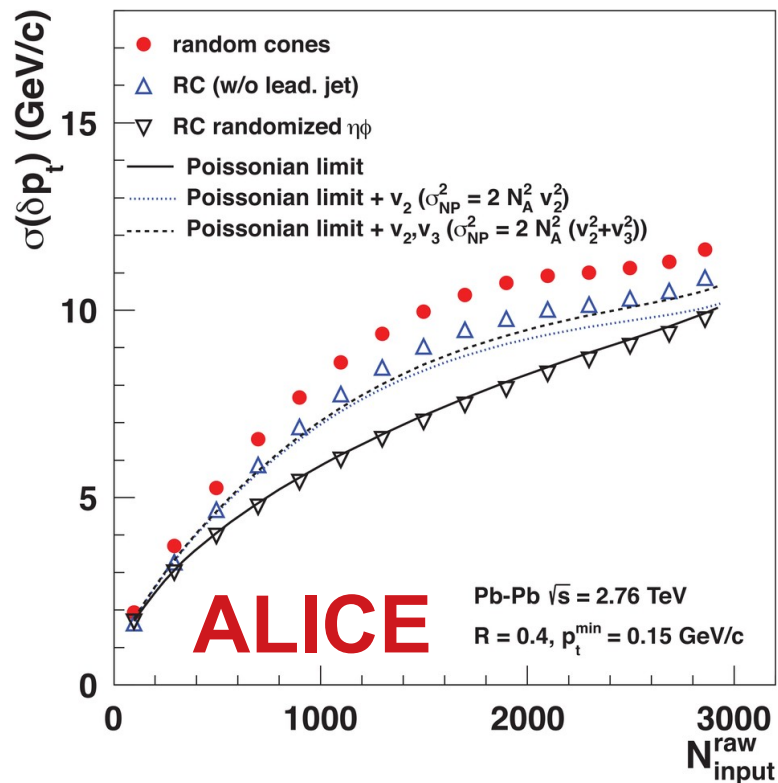
ALICE Data: [JHEP 03 \(2012\) 053](#)



Width vs multiplicity



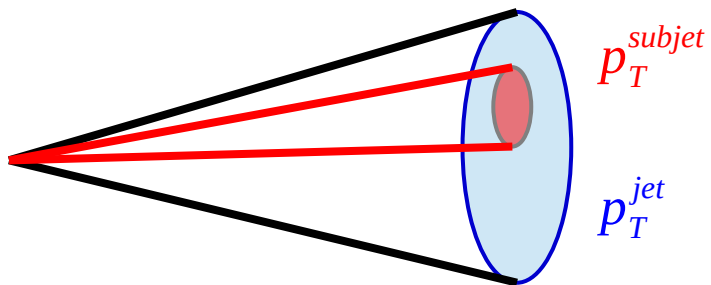
Width vs multiplicity



Impact of shape of spectrum

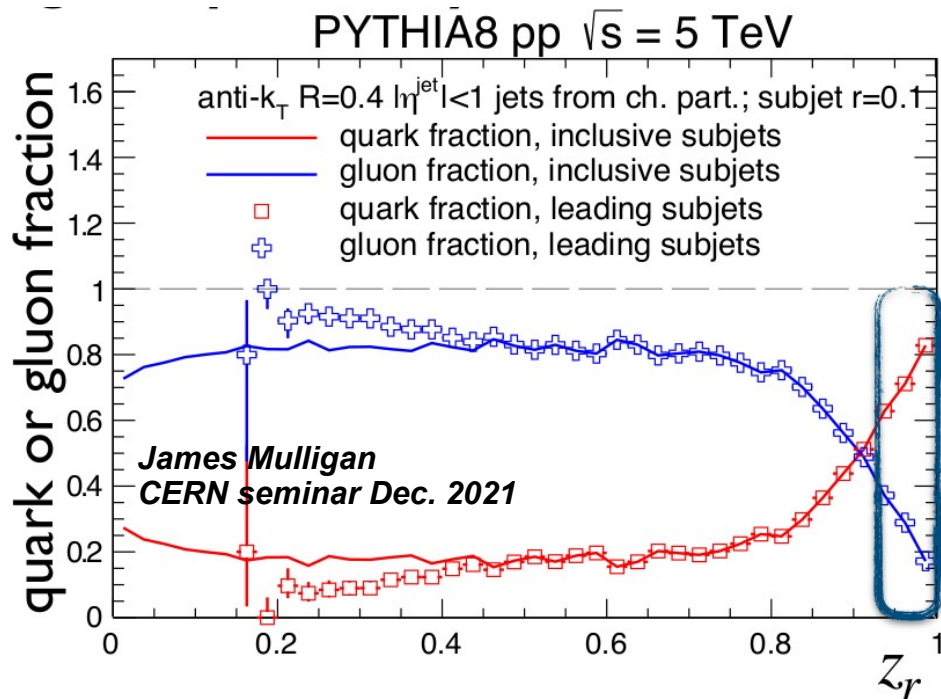
Correlations between event planes

Subjet z

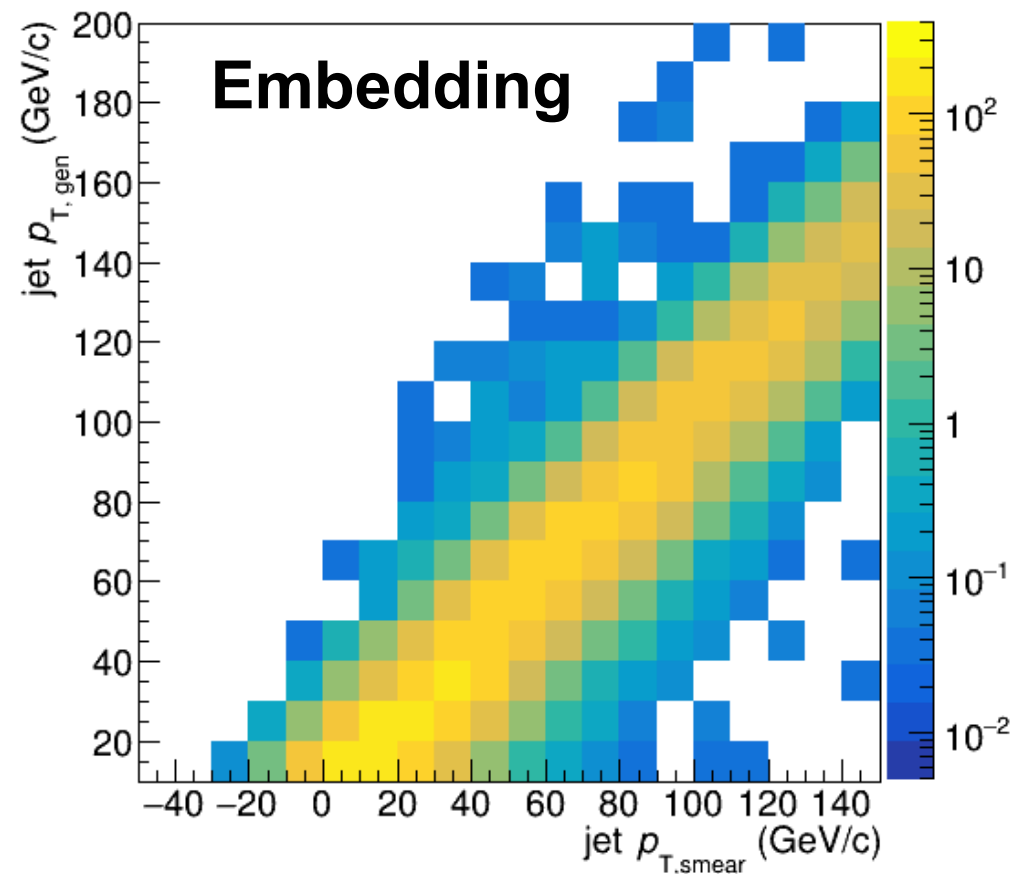
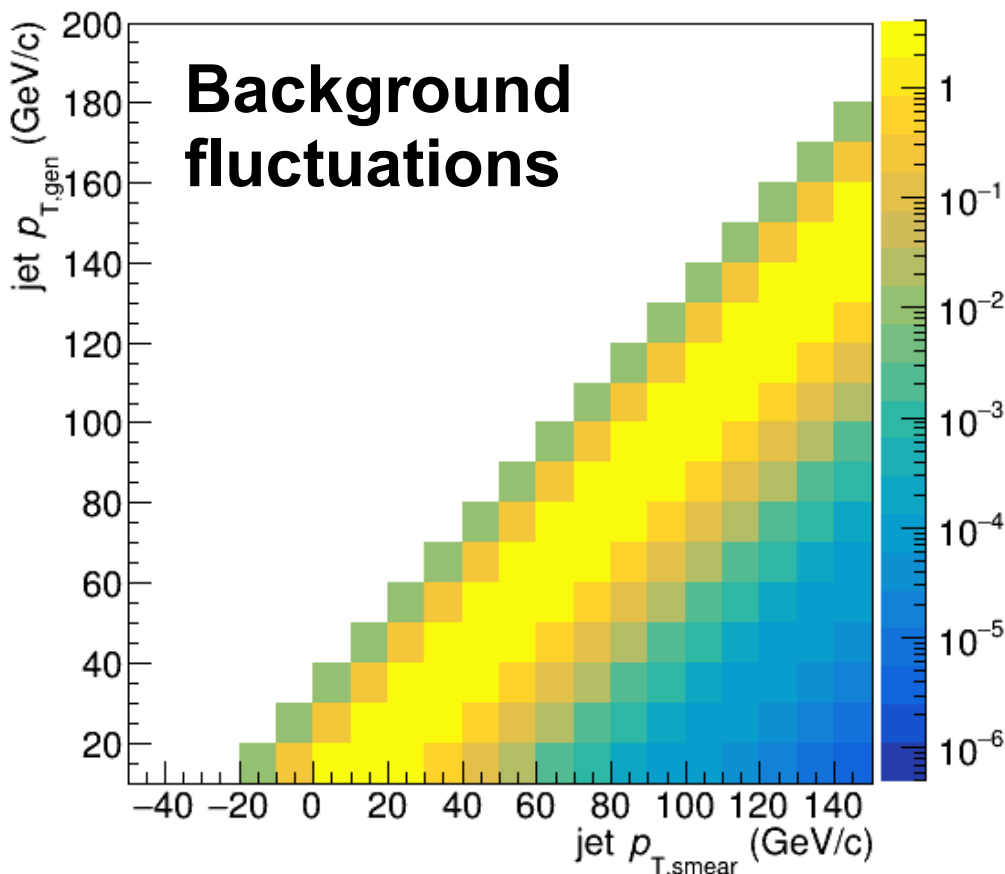


$$z_r = \frac{p_T^{\text{subjet}}}{p_T^{\text{jet}}}$$

- Cluster jets with anti- k_T with resolution parameter R
- Recluster constituents with anti- k_T with resolution parameter r
- Some discriminating power between quark-like and gluon-like jets
 - Strained at low momentum, small R



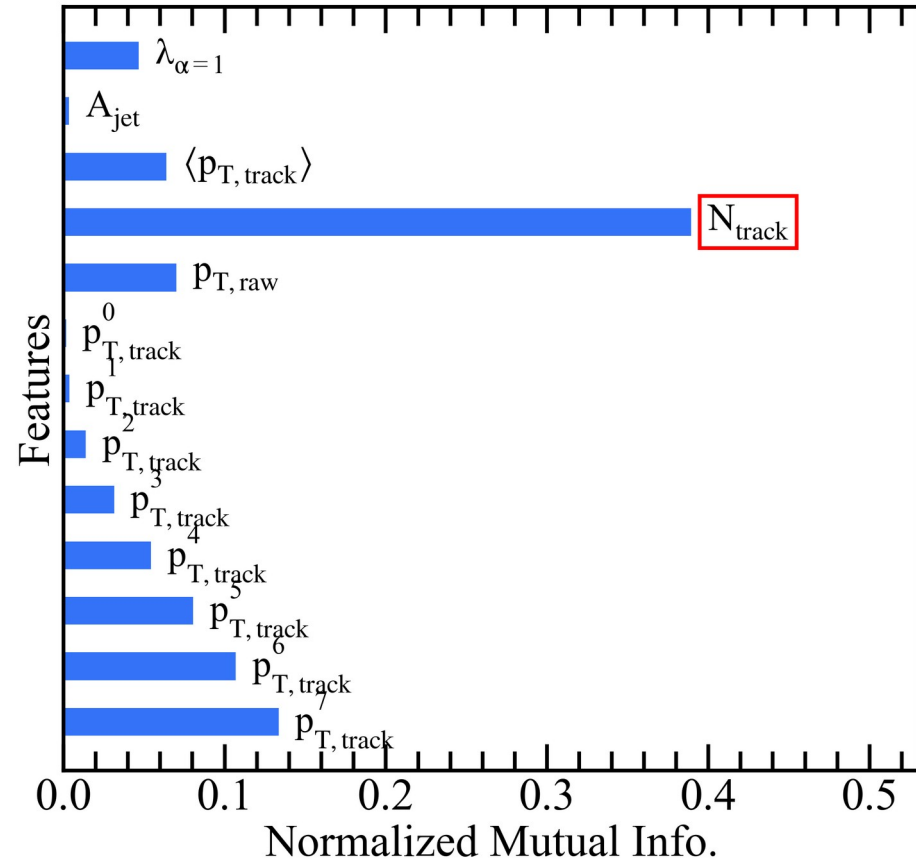
Construct a response matrix in Monte Carlo



Designing a better method

- Jet multiplicity largest mutual information w/jet momentum .
- Background fluctuations are well described by multiplicity fluctuations.

[JHEP 03 \(2012\) 053](#),
[Phys. Rev. C 106, 044915 \(2022\)](#),
[Physics Letters B 498, 29 \(2001\)](#).



Definition of Jets in a Large Background July 25-27, 2019

- **Organizers:** M. Connors, G. Milhano, C. Nattrass, R. Reed, S. Salur
- **Spectra conveners:** R. Kunnawalkam Elayavalli, Y. Mehtar-Tani (R. Bertens)
- **Correlation conveners:** J. Noronha-Hostler, J. Huang
- **Substructure conveners:** Y. Lee, Y. Chien

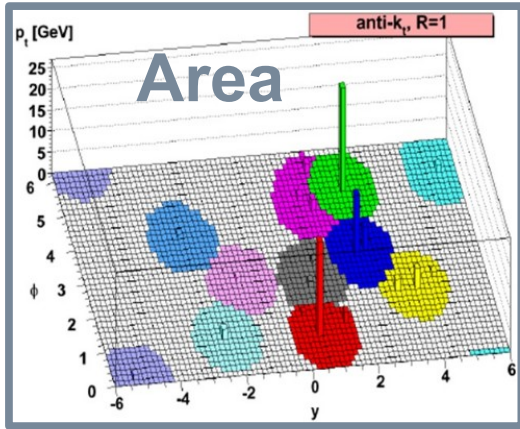


Extensively discussed the interplay between experimental techniques and theoretical calculations with the aim of **reaching an agreement*** on the way forward for extracting jet measurements from large background events such as those in heavy ion collisions and high luminosity p-p or electron-ion collisions.

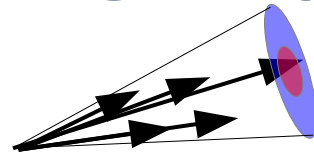
***Consensus on some points**

62 Registered but due to various visa & travel complications: 45 + several BNL employees attended.

Jet properties

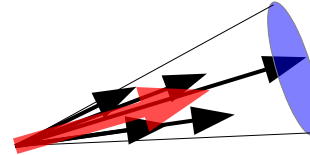


Angularity

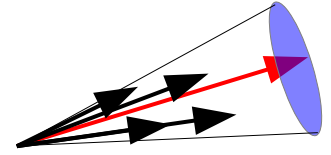


$$\alpha = \frac{1}{p_T^{jet}} \sum_k z_k (\vec{R}_k)$$

Average p_T



Leading p_T



Shape of width of the distribution

Single particle spectra

$$f_{\Gamma}(p_T, p, b) = \frac{b}{\Gamma(p)} (b p_T)^{p-1} e^{-b p_T}$$

$$\frac{dN}{dy} \propto f_{\Gamma}(p_T, 2, b) = b^2 p_T e^{-b p_T}$$

$$\mu_{p_T} = \frac{p}{b}, \sigma_{p_T} = \frac{\sqrt{p}}{b}$$

Tannenbaum, PLB(498),1-2, Pg.29-34(2001)

Confirmed in

JHEP 03 (2012) 053 ALICE

PRC 106, 044915 (2022) Hughes et al

Σp_T of N particles \rightarrow N-fold convolution:

$$f_N(p_T, p, b) = f_{\Gamma}(p_T, Np, b) \quad \frac{dp_T^{total}}{dy} \propto f_N(p_T, Np, b)$$

$$N = \frac{N_{total}}{A_{total}} \pi R^2 \quad \mu_{total} = \frac{Np}{b} = N \mu_{p_T}, \sigma_{total} = \frac{\sqrt{Np}}{b} = \sqrt{N} \sigma_{p_T}$$

Add Poissonian fluctuations in N: $\sigma_{total} = \sqrt{N \sigma_{p_T}^2 + N \mu_{p_T}^2}$

Add non-Poissonian fluctuations in N due to flow

$$\sigma_{total} = \sqrt{N \sigma_{p_T}^2 + (N + 2N^2 \sum_n v_n^2) \mu_{p_T}^2}$$