

# A tale of two jets

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# Acknowledgements



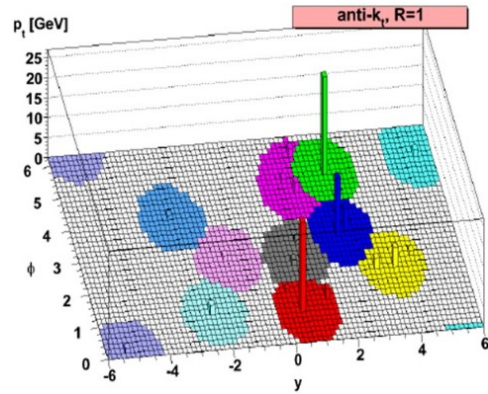
**Antonio Da Silva**



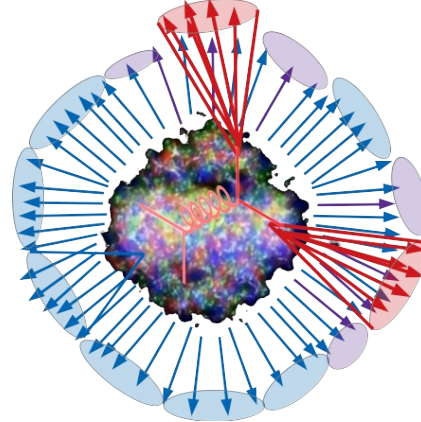
**Patrick Steffanic**



**Charles Hughes**



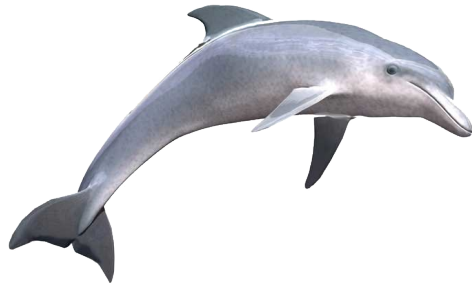
1. What is a jet?



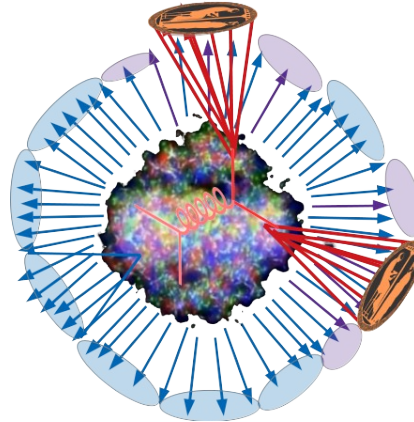
2. Background paradigm



3. Models



4. Suppressing combinatorial jets



5. Correcting for background in MC



6. How to compare to models

# 1. What is a jet?

What is a jet?

# What is a jet?

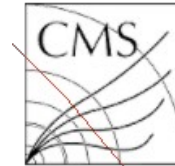
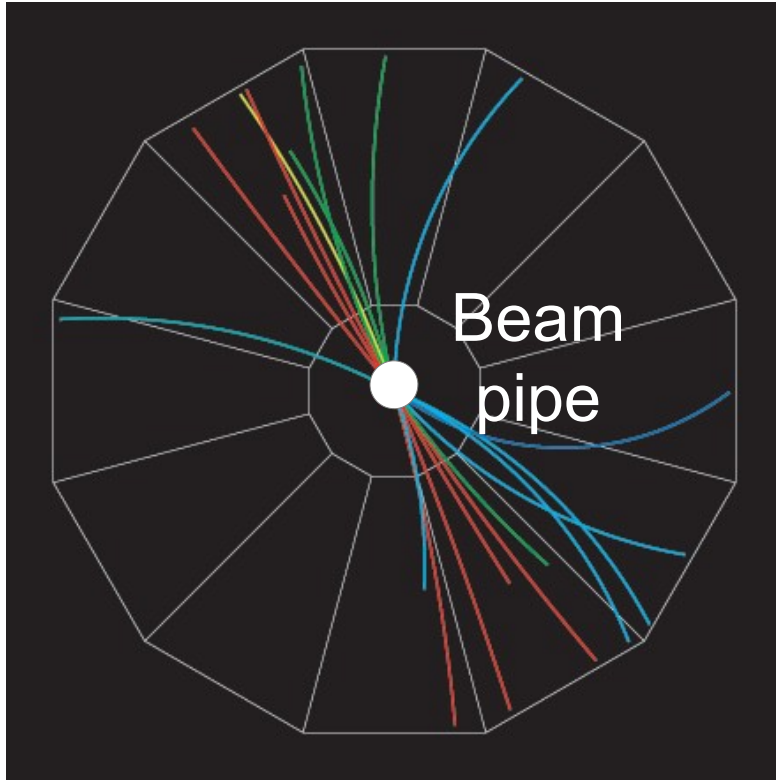
A measurement of a jet is a measurement of a parton.

What is a jet?

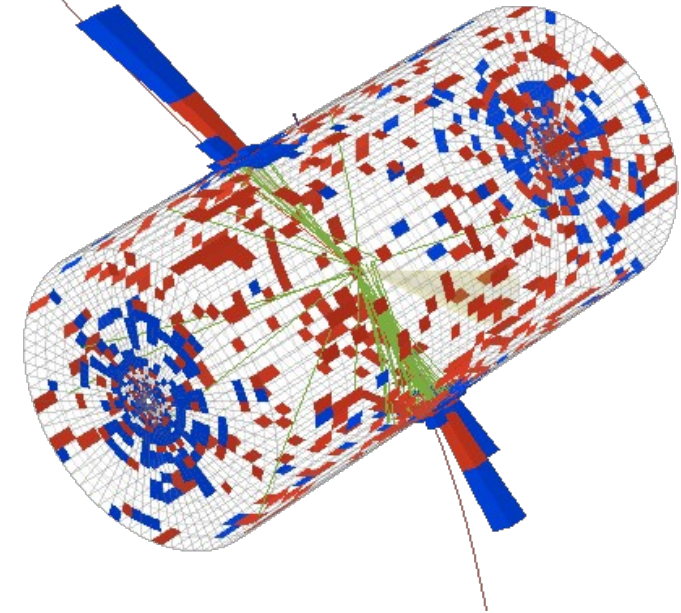
~~A measurement of a jet is a measurement of a parton.~~

# What is a jet?

**p+p dijet**

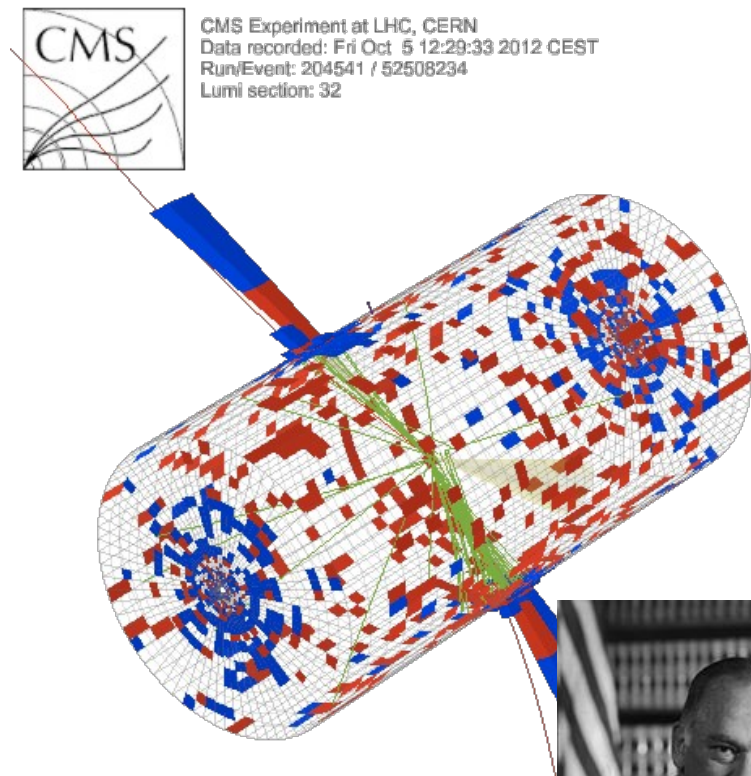
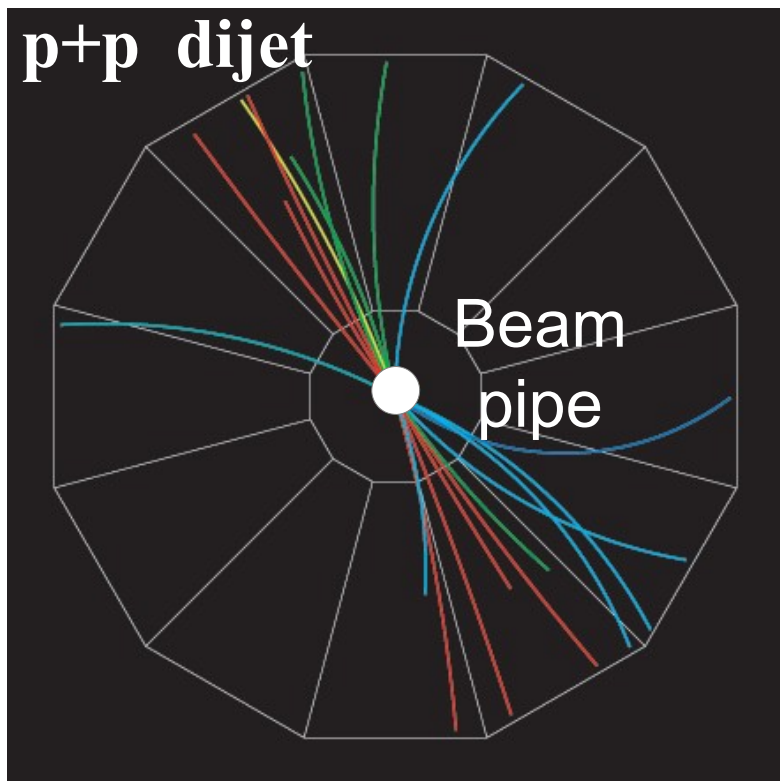


CMS Experiment at LHC, CERN  
Data recorded: Fri Oct 5 12:29:33 2012 CEST  
Run/Event: 204541 / 52508234  
Lumi section: 32



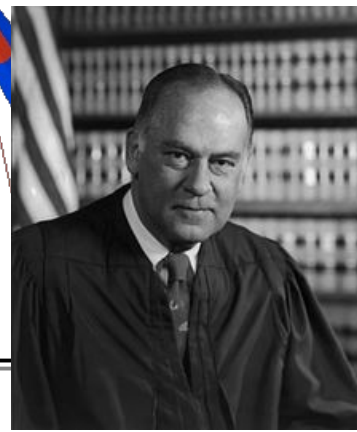


# What is a jet?



“I know it when I see it”

US Supreme Court Justice Potter Stewart, *Jacobellis v. Ohio*



# Jet finding *in pp collisions*

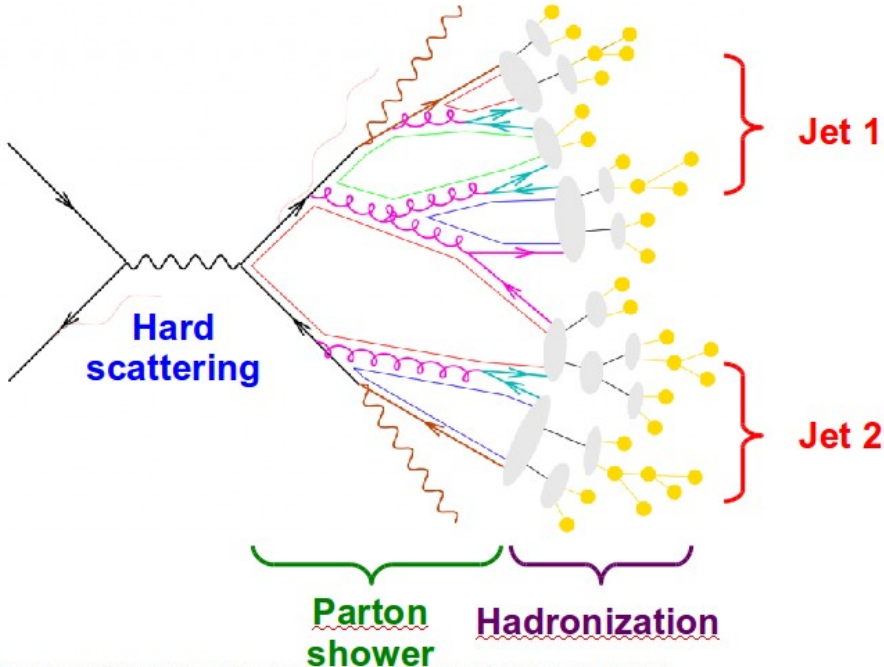


Image from <http://www.gk-eichtheorien.physik.uni-mainz.de/Dateien/Zeppenfeld-3.pdf>

- Jet finder: groups final state particles into jet candidates
  - Anti- $k_T$  algorithm  
JHEP 0804 (2008) 063 [arXiv:0802.1189]
- Depends on hadronization
- Ideally
  - Infrared safe
  - Collinear safe

**Snowmass Accord:** Theoretical calculations and experimental measurements should use the same jet finding algorithm. Otherwise they will not be comparable.

# anti- $k_T$ jet finding algorithm

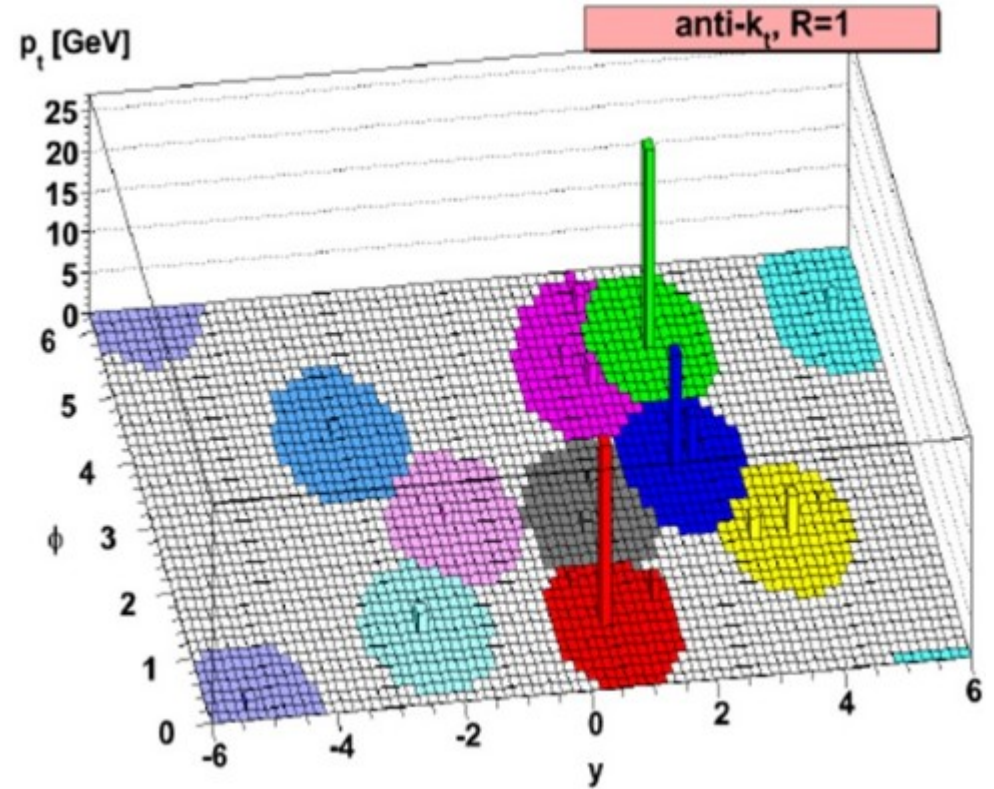
Particles, clusters

## $k_T$ algorithm

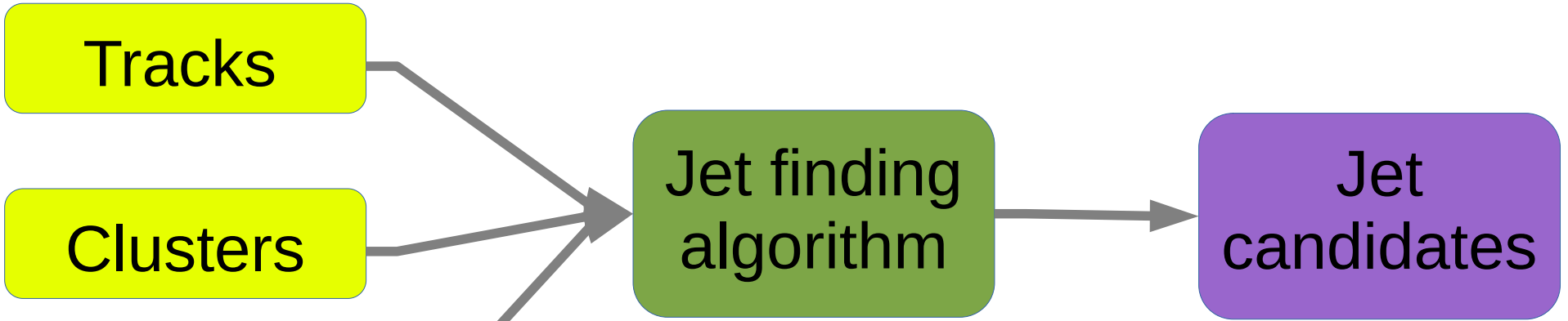
$$k_T = p_T, \Delta R_{ij} = \sqrt{(\eta_i - \eta_j)^2 + (\phi_i - \phi_j)^2}$$

- For all  $i, j$  calculate:  
$$d_{ij} = \min(p_{T,i}^{-2}, p_{T,j}^{-2}) \frac{\Delta R_{ij}^2}{R^2}$$
  - $d_{iB} = p_{T,i}^{-2}$
  - Combine smallest  $d_{ij}$ .  
If  $d_{iB}$  smallest,  $d_{iB} \rightarrow$  jet
- Repeat until no particles left

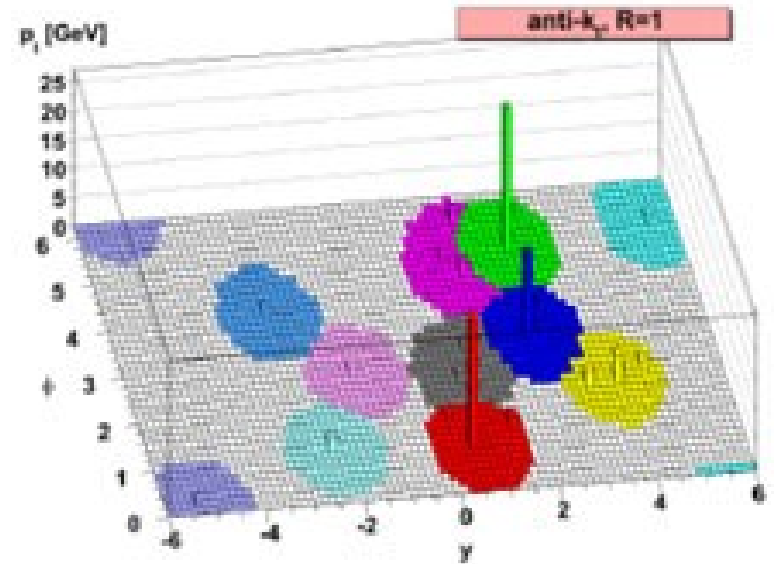
Jet candidates



# Jet finding algorithms



- Any list of objects works as input
- Use the same algorithm on theory & experiment
- Output only as good as input



A jet is what a jet finder finds.

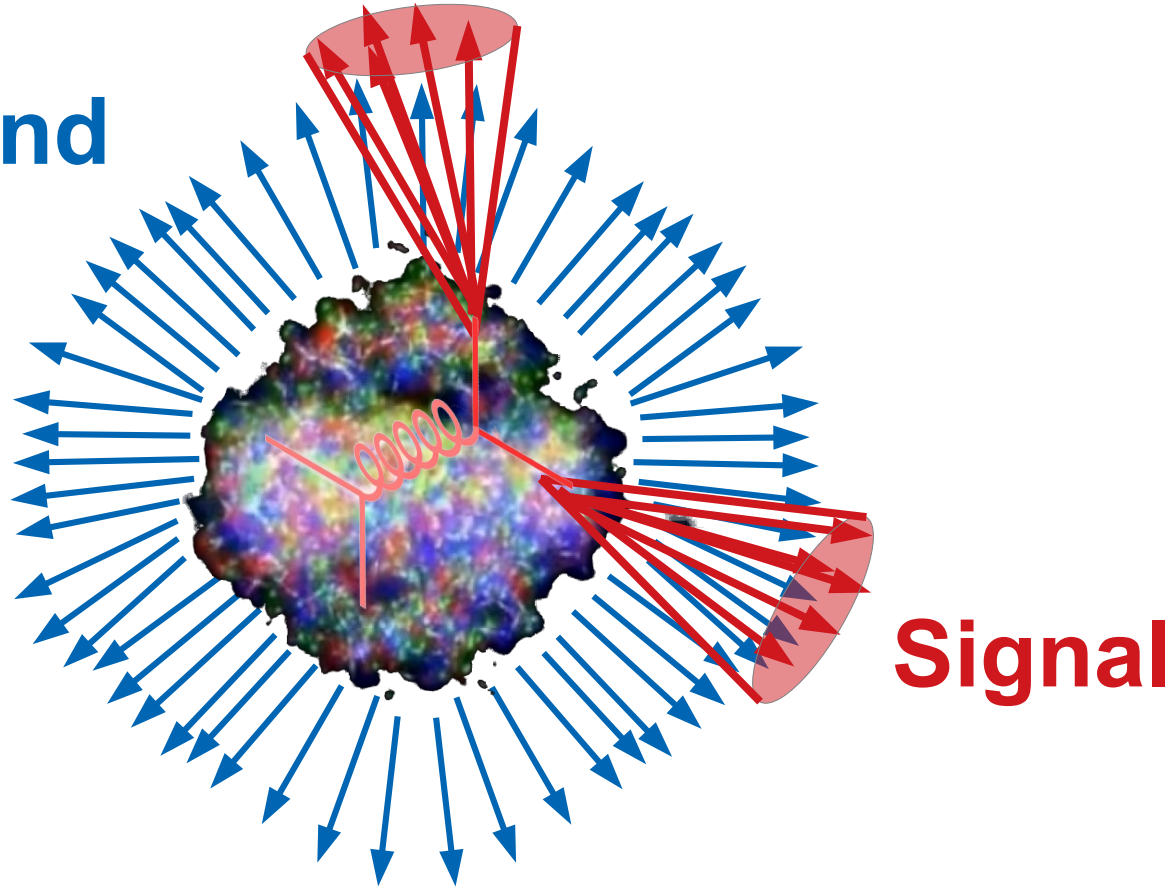
Use the same algorithm on data and the model.  
Then the two will be comparable.

## 2. Standard paradigm of background

# Signal vs Background:

The standard paradigm

**Background**



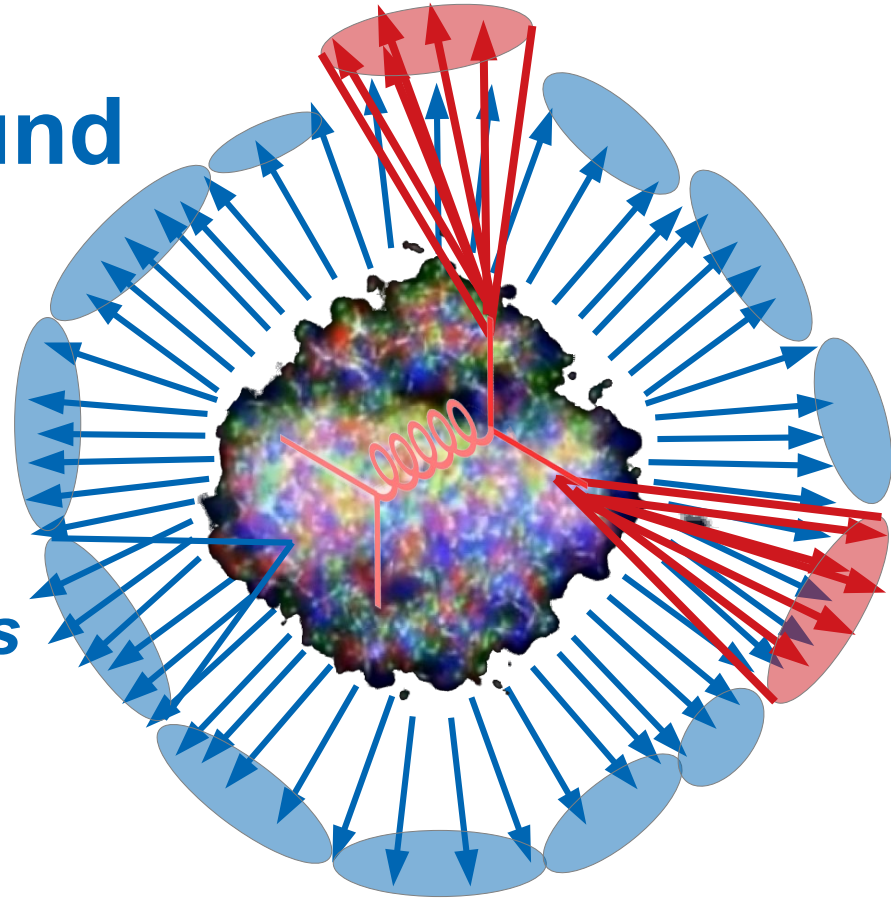


# Signal vs Background:

The standard paradigm

**Background**

**Combinatorial jets**



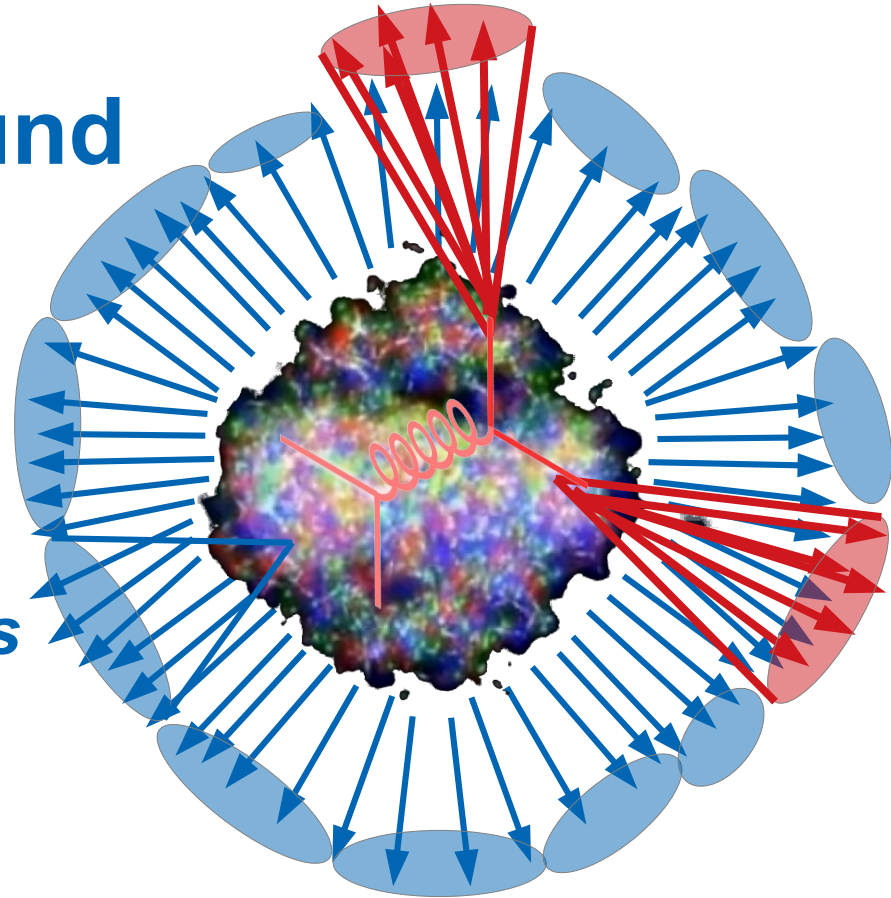
**Signal**

# Signal vs Background:

The standard paradigm

**Background**

**Combinatorial jets  
= “fake” jets**



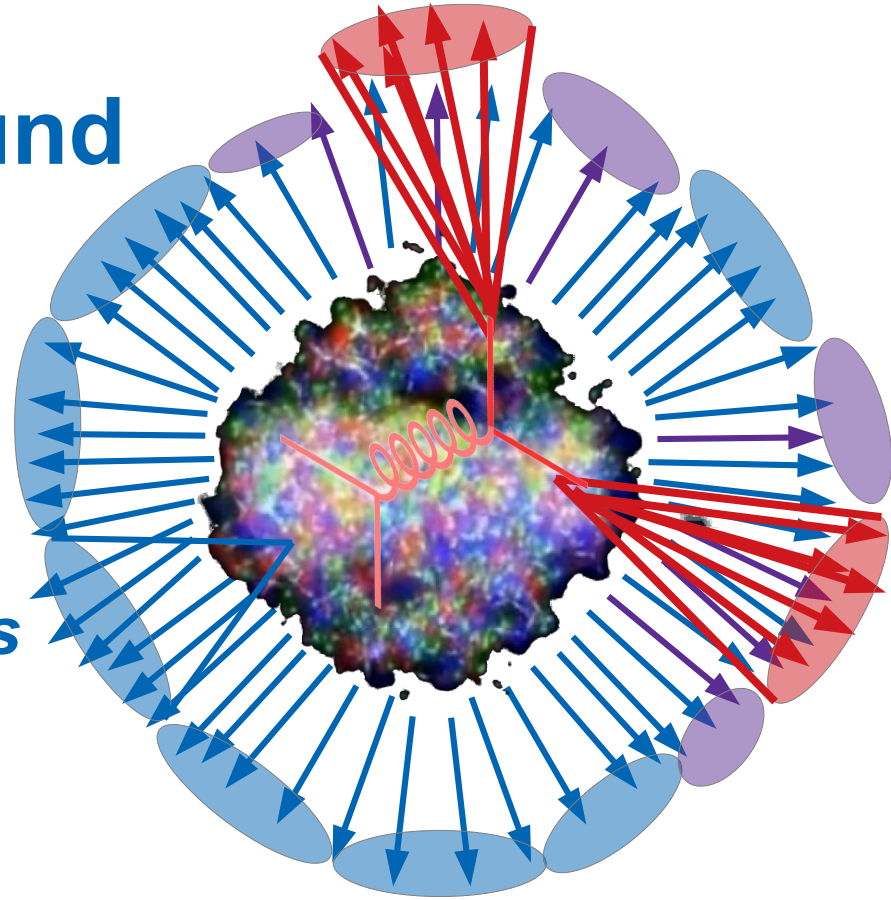
**Signal**

# Signal vs Background:

The standard paradigm

**Background**

**Combinatorial jets**



**Signal**

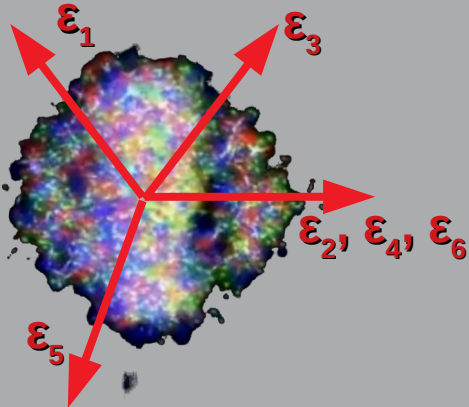
\*Some gray areas

## 3. Models

# TennGen background generator



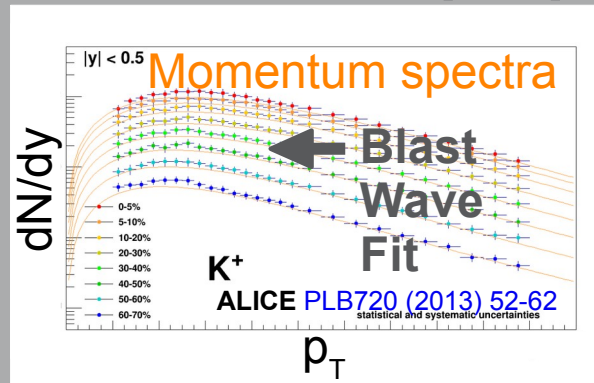
## Event properties



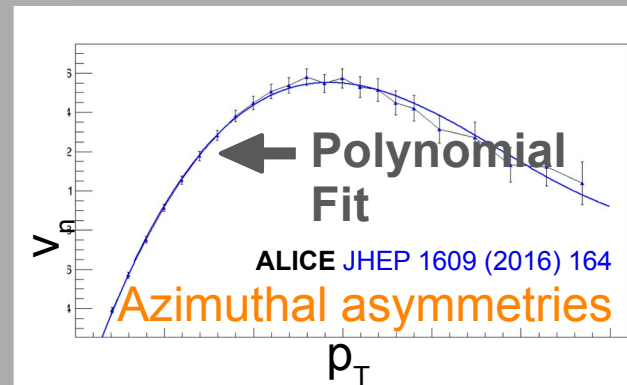
- Even event planes fixed at  $\Psi=0$
- Odd planes at random  $\phi$
- Multiplies from ALICE PRC88 (2013) 044910

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

## Track properties



→ Random  $p_T$



→  $v_n$   
→ Random  $\phi$



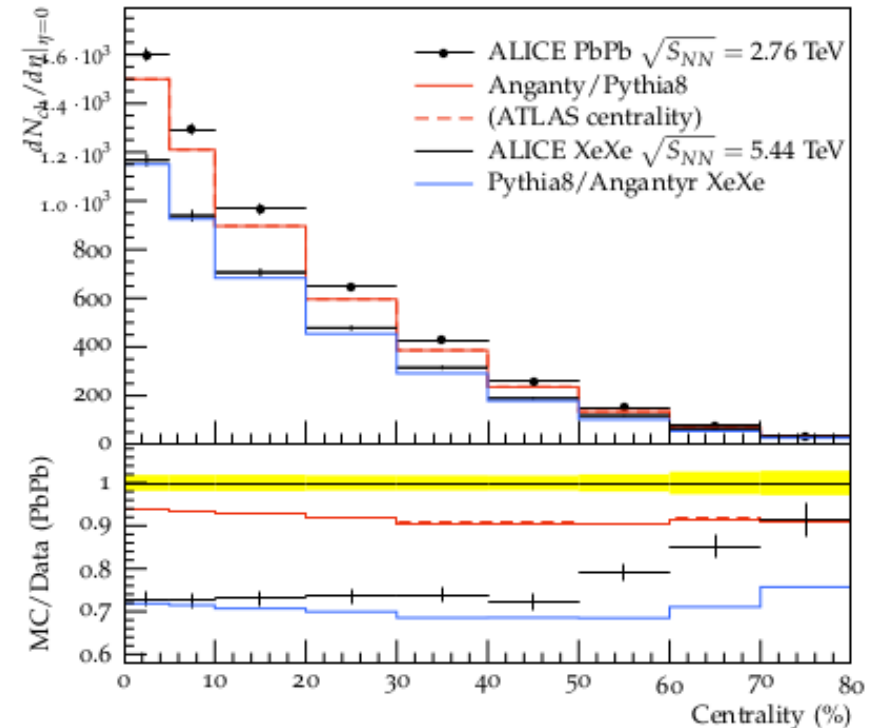
# PYTHIA Angantyr

JHEP (2018) 2018: 134

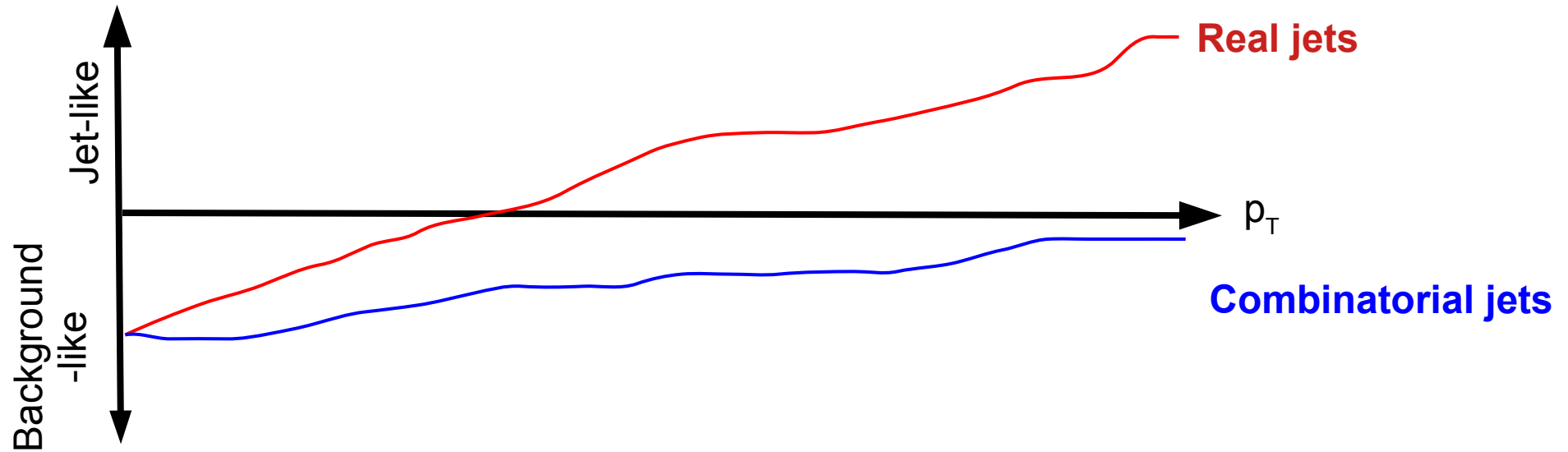


- Based on PYTHIA 8  
Sjöstrand, Mrenna & Skands,  
JHEP05 (2006) 026  
Comput. Phys. Comm. 178 (2008) 852.
- Based on Fritiof & wounded nucleons
- N-N collisions w/fluctuating radii  
→ fluctuating  $\sigma$

**Lots of jets! And resonances!  
No hydrodynamics, no jet quenching**



## 4. Suppressing combinatorial jets



# Technique

- Anti- $k_T$  jet finder,  $|\eta_{\text{jet}}| < 0.5$
- **Combinatorial jets:** Only contain TennGen particles
- **Real jets:** Add a PYTHIA pp event. Real jets contain  $>80\%$  of  $p_{\text{Thard}}^{\text{min}}$
- **Squishy jets:** Everything else
- $R=[0.2,0.3,0.4,0.5,0.6]$ ,  $p_T=[10,20,40,80]$



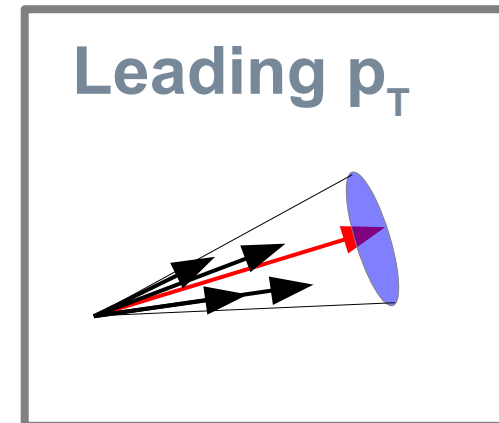
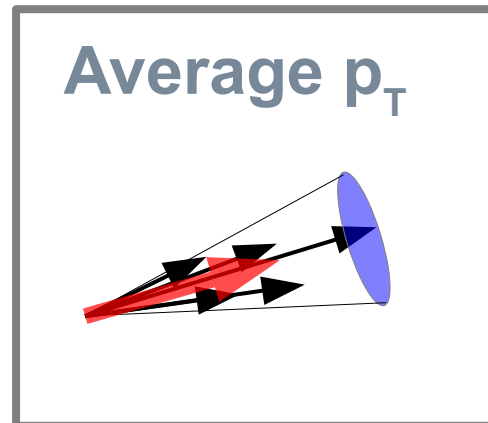
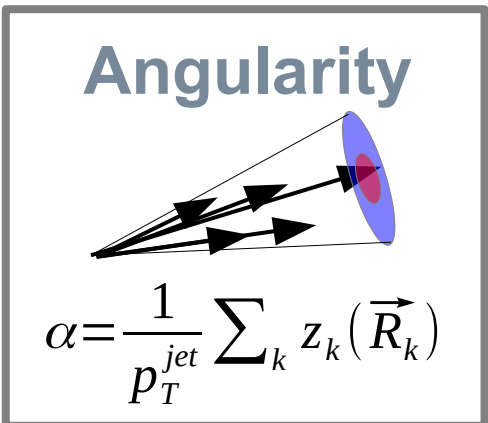
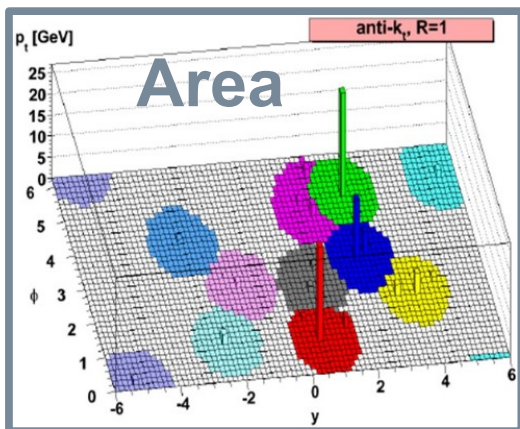
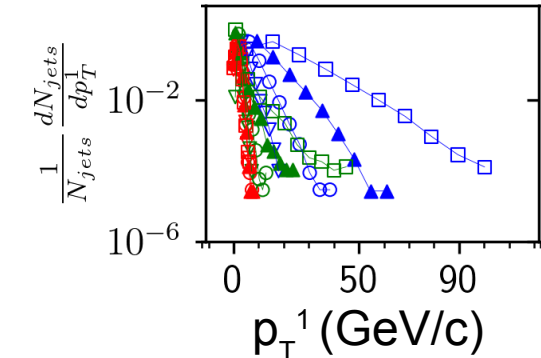
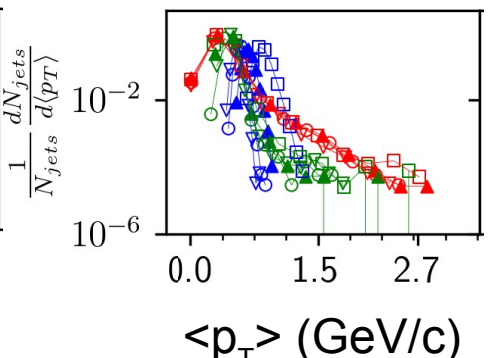
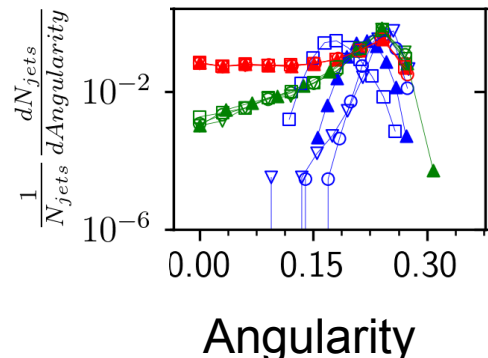
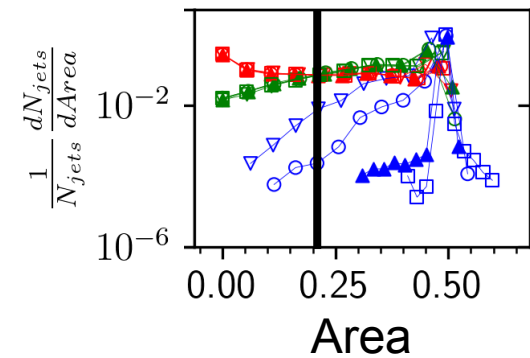
<4% Signal loss  
>50% Comb. loss  
 $Area > 0.6 R$

# Jet properties – R=0.4



▼-Signal ▼-Combinatorial ▼-Squishy

- ▽ 10 GeV/c
- 20 GeV/c
- ▲ 40 GeV/c
- 80 GeV/c



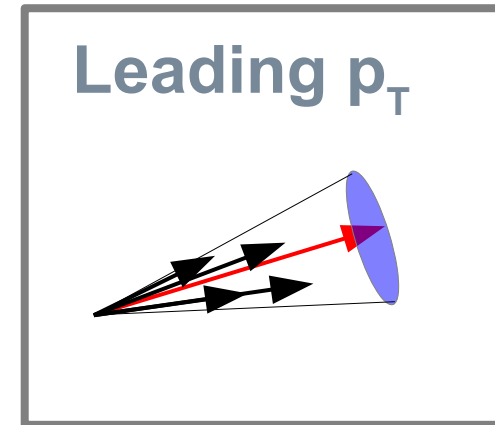
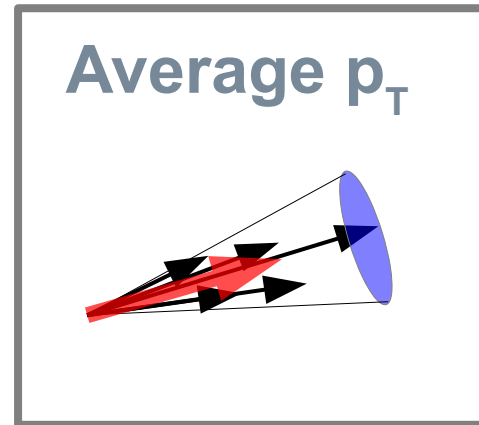
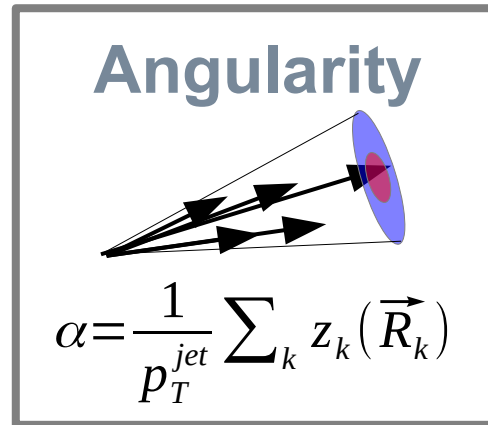
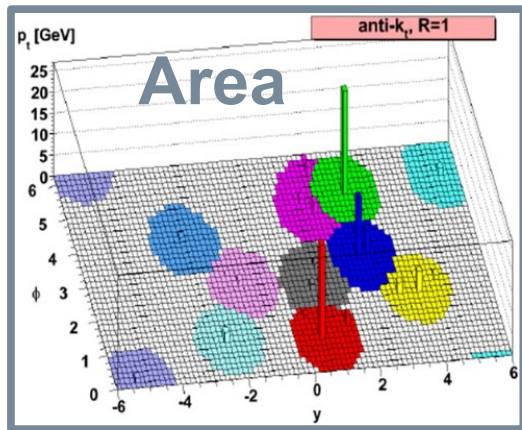
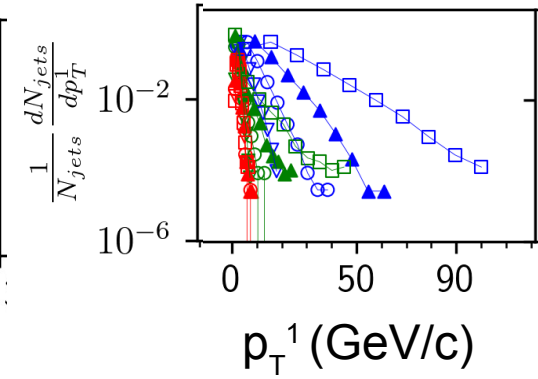
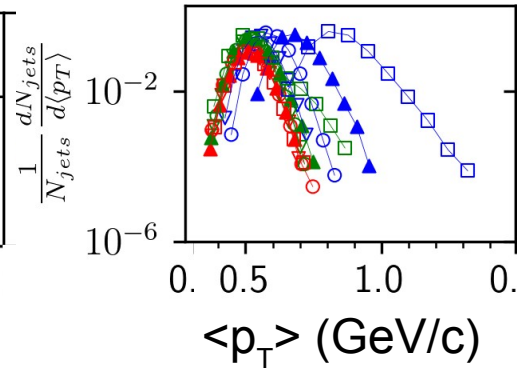
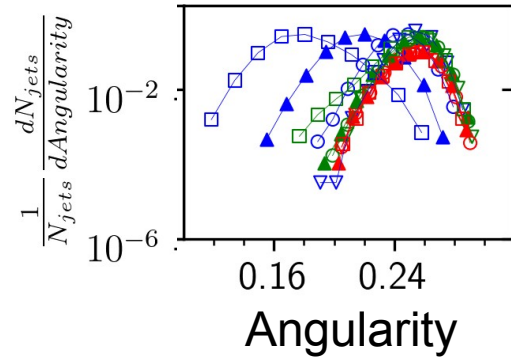
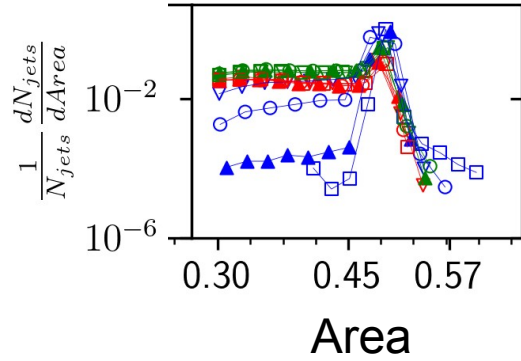
# Jet properties – R=0.4



- ▽ 10 GeV/c
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- 80 GeV/c

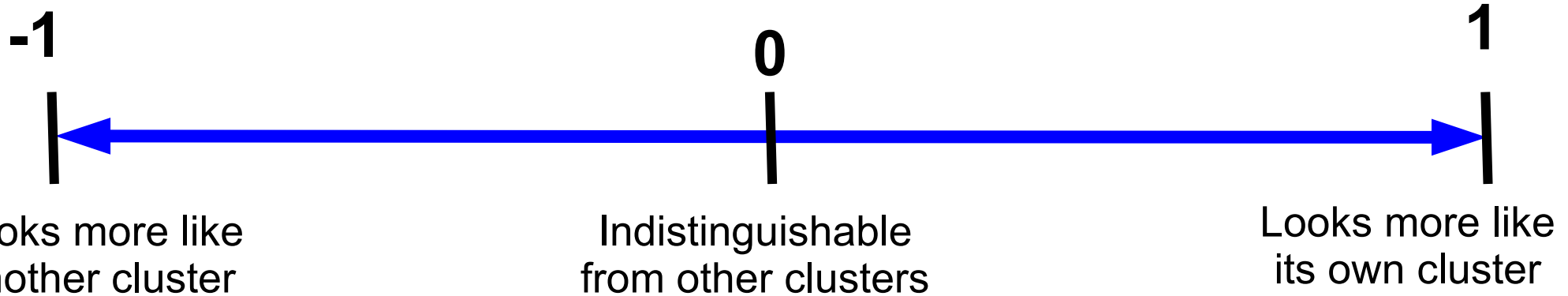
Area > 0.6 R

▼ -Signal 
 ▼ -Combinatorial 
 ▼ -Squishy



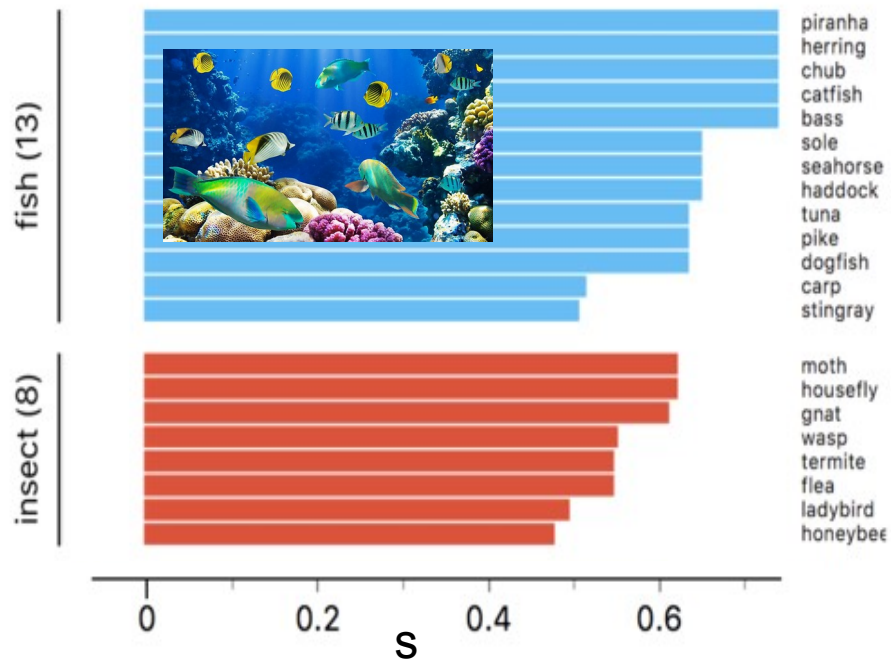
# Silhouette Values

- Average distance between a jet candidate and other jet candidates in its cluster (signal or background)  $a_i = \langle d_{i,j} \rangle_{j \neq i}$
- Average distance between jet candidate and jet candidates in the other cluster  $b_i = \langle d_{i,j} \rangle$
- Silhouette value  $s_i = \frac{b_i - a_i}{\max[b_i, a_i]}$

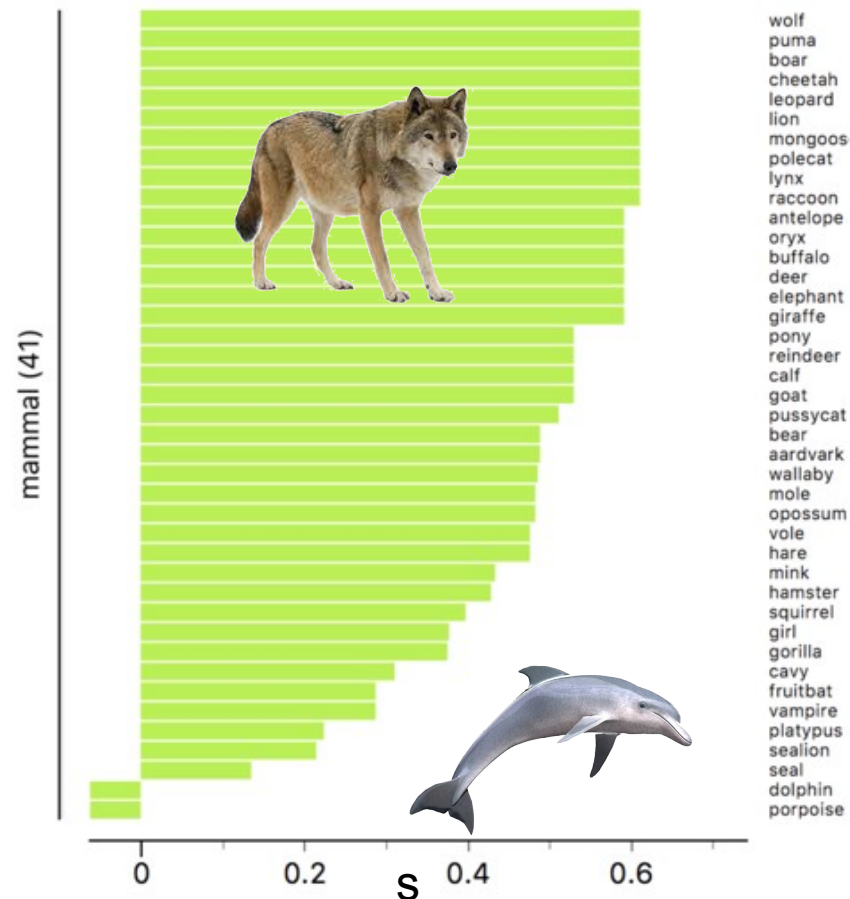


# Silhouette values

## Example from Wikipedia



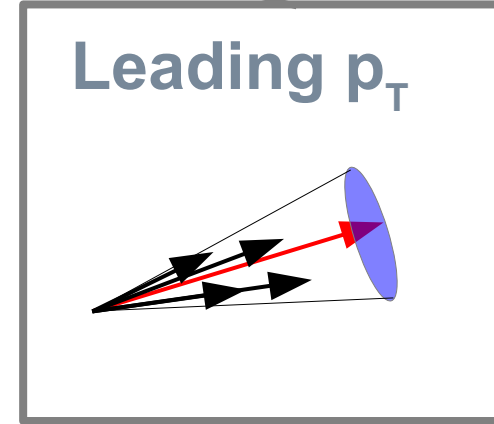
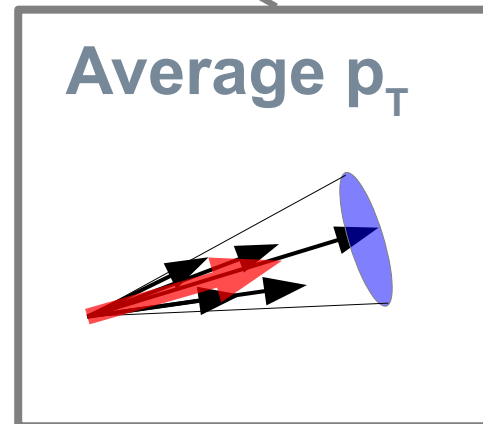
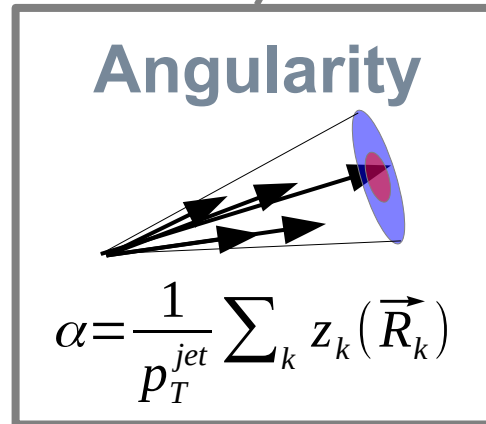
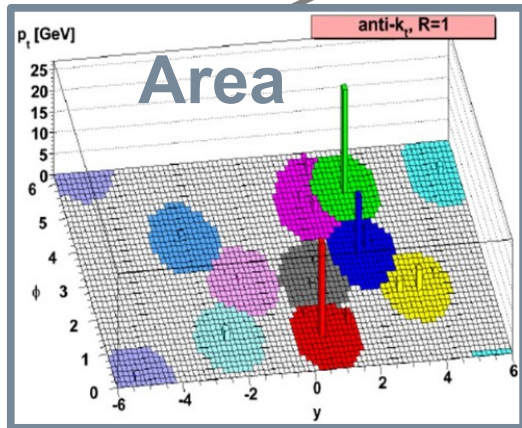
Silhouette scores from three types of animals rendered by [Orange](#) data mining suite.



# Silhouette Values

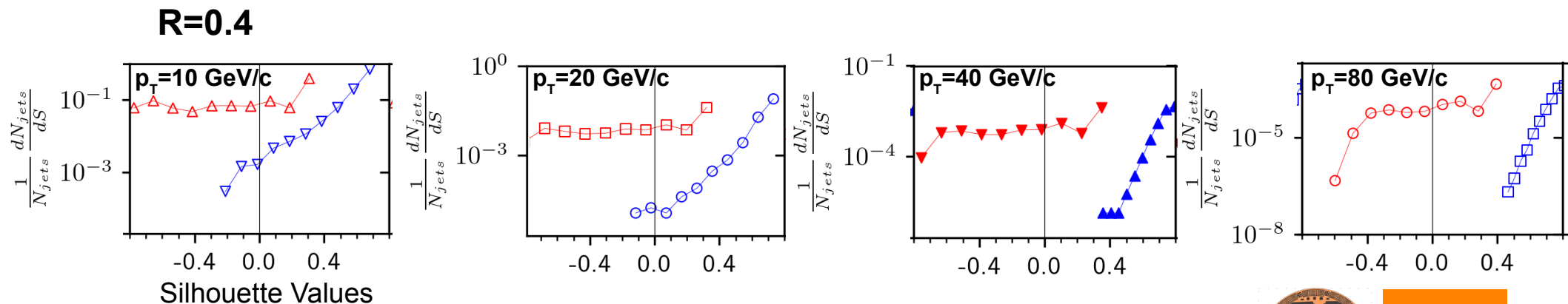
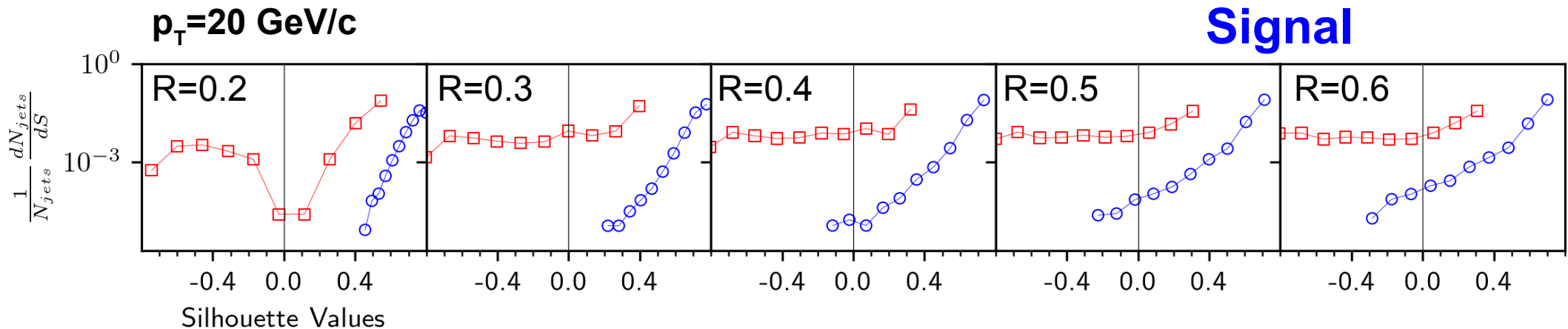
- Define a distance between two jet candidates to determine how similar they are

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



# Before area cut

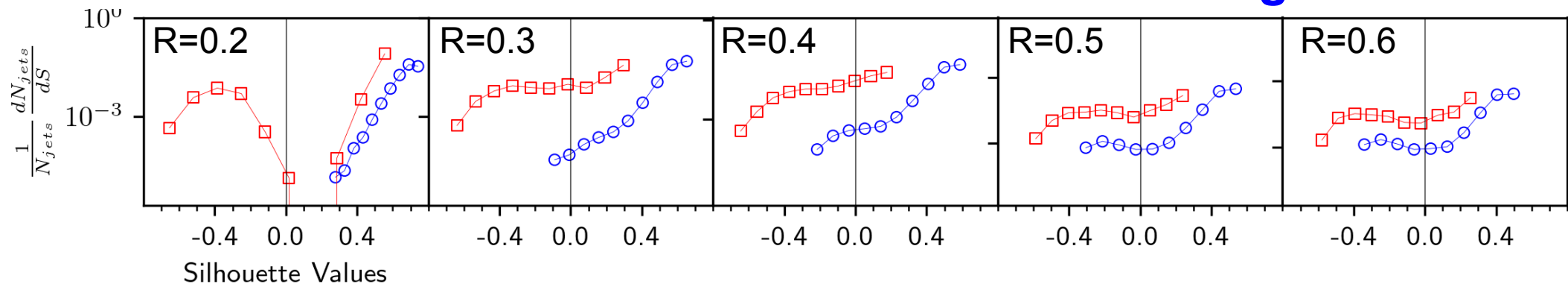
**Combinatorial  
Signal**



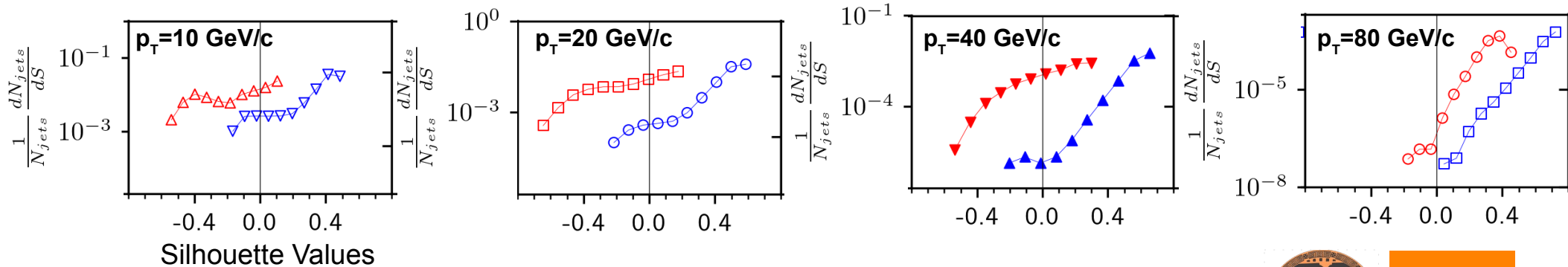
# After area cut

**Combinatorial  
Signal**

**$p_T=20$  GeV/c**



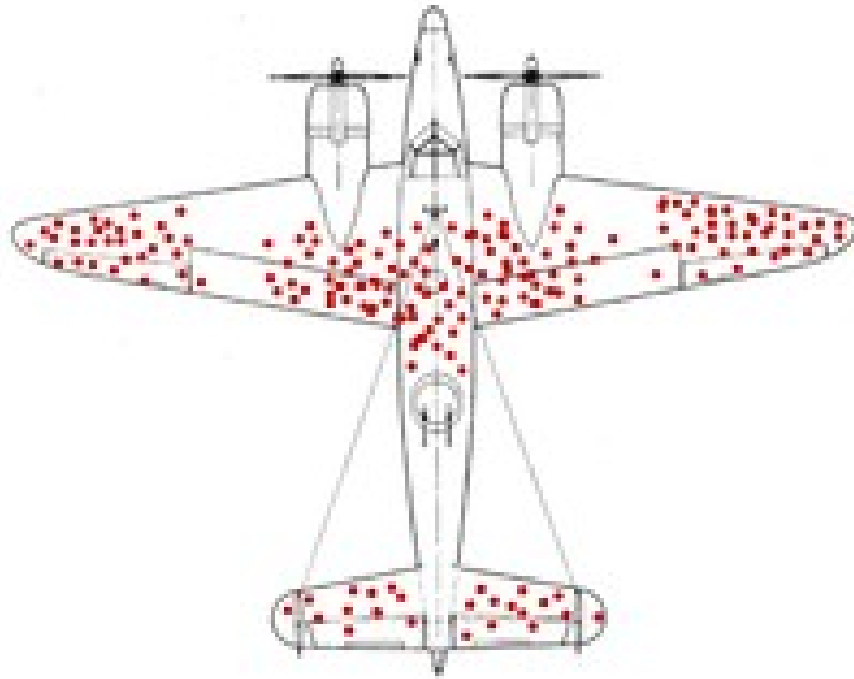
**$R=0.4$**







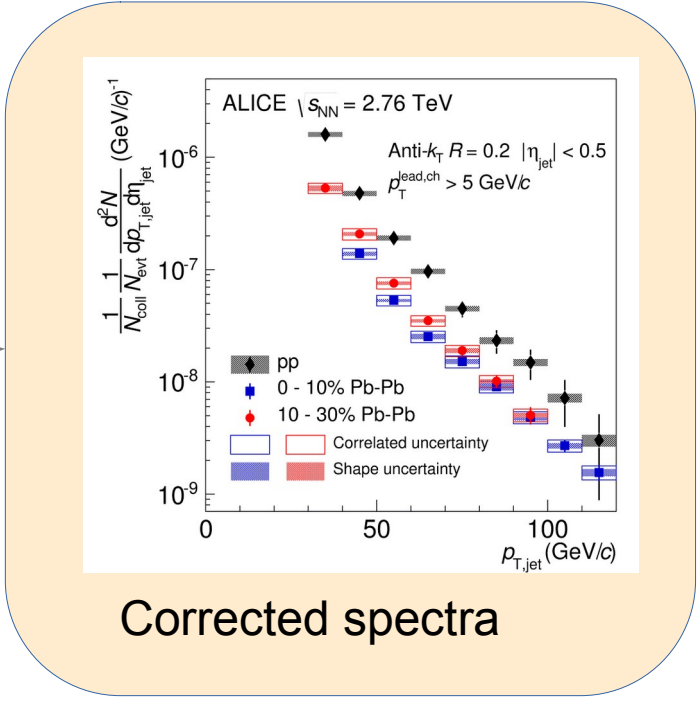
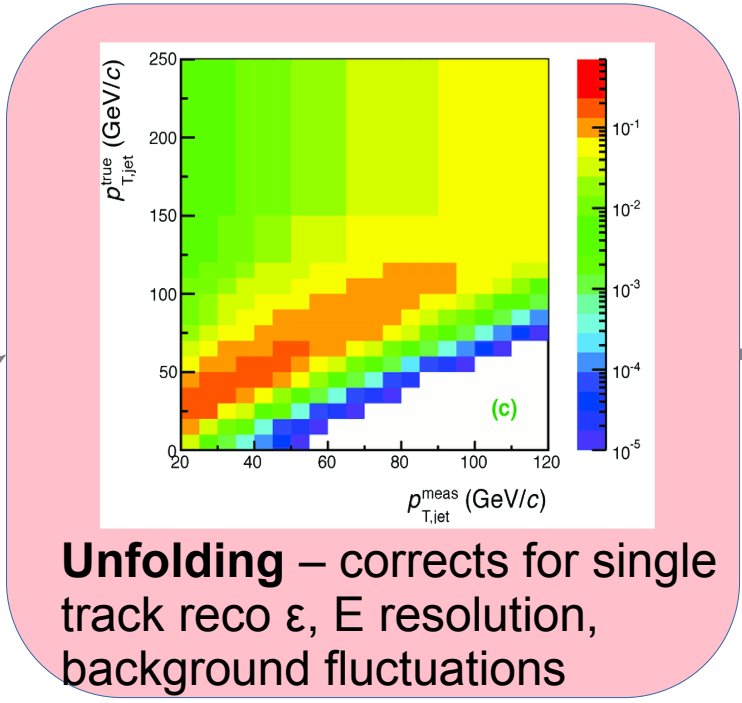
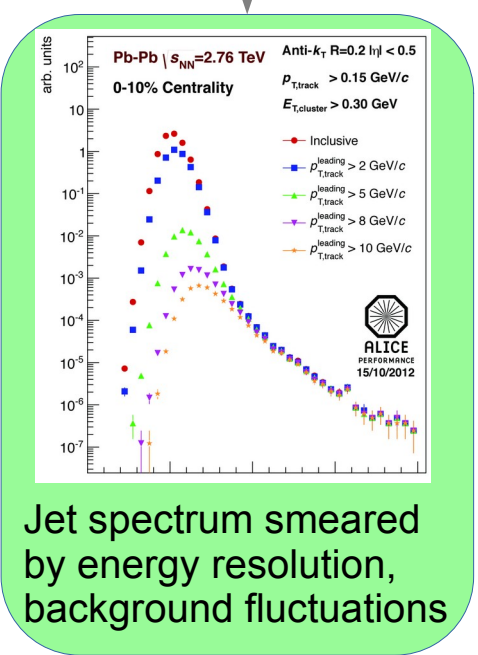
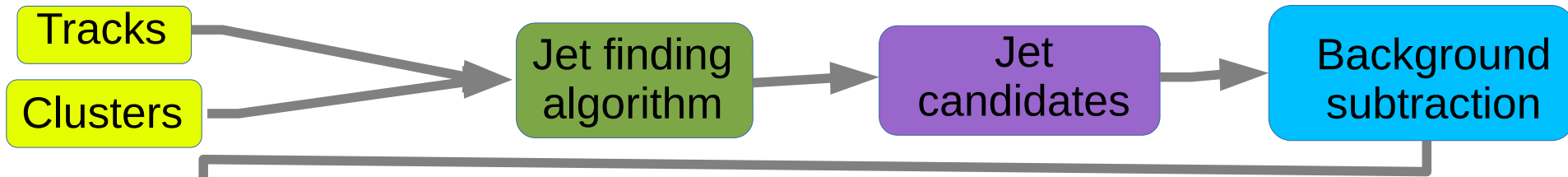
# Survivor bias



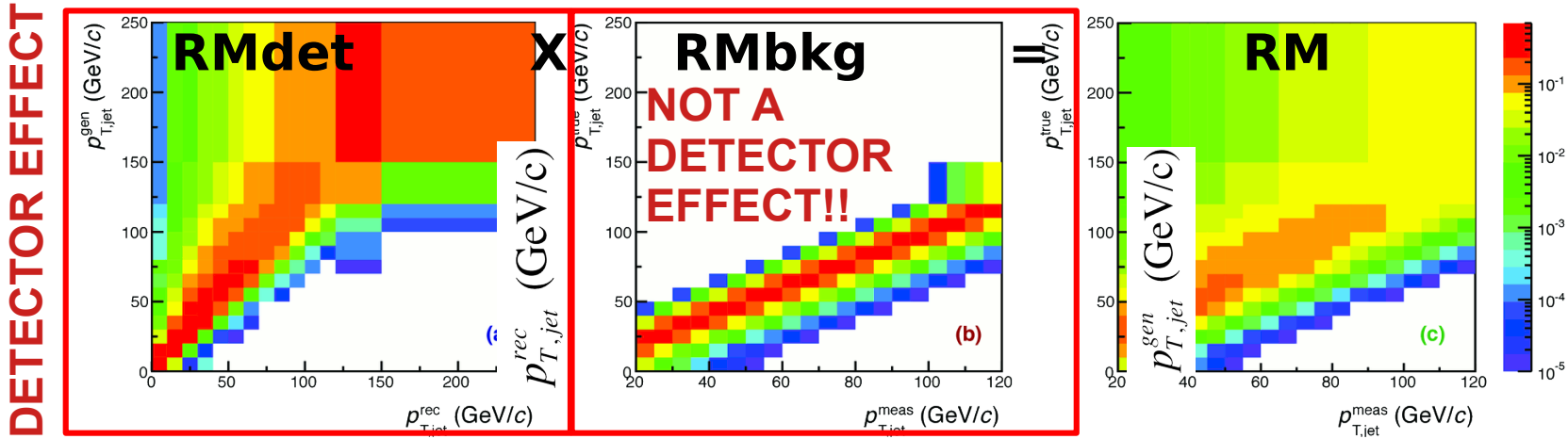
- **WWII Example:** holes planes returning indicate where it's *safer* to get hit
- We're looking at the real and combinatorial jets which *remain*

## 5. Background corrections in Monte Carlo

# Analysis steps



# Jets in ALICE: Response Matrix Construction



**RM<sub>bkg</sub> and RM<sub>det</sub> are approximately factorizable**

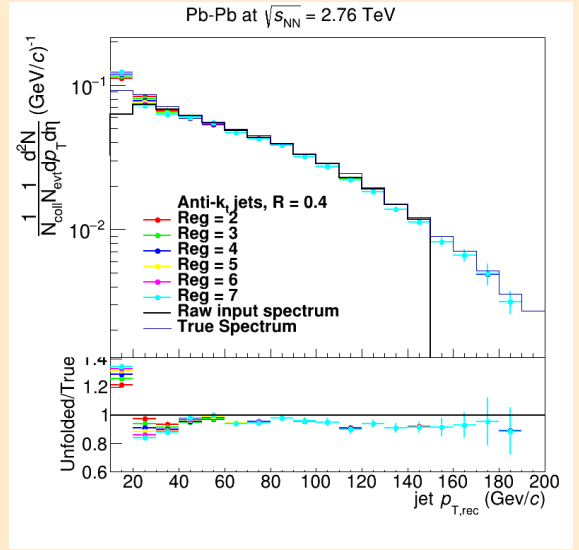
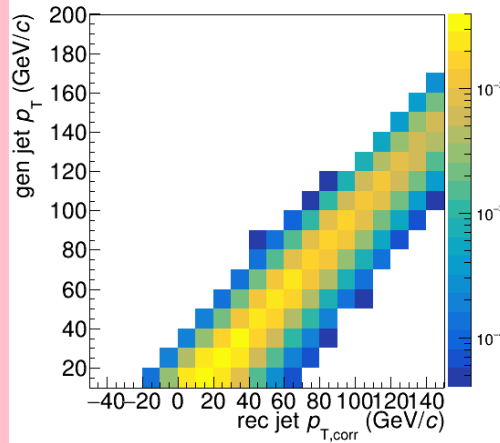
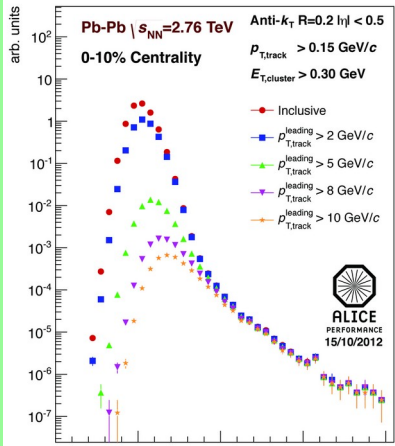
# Analysis steps: Full Monte Carlo

Particles

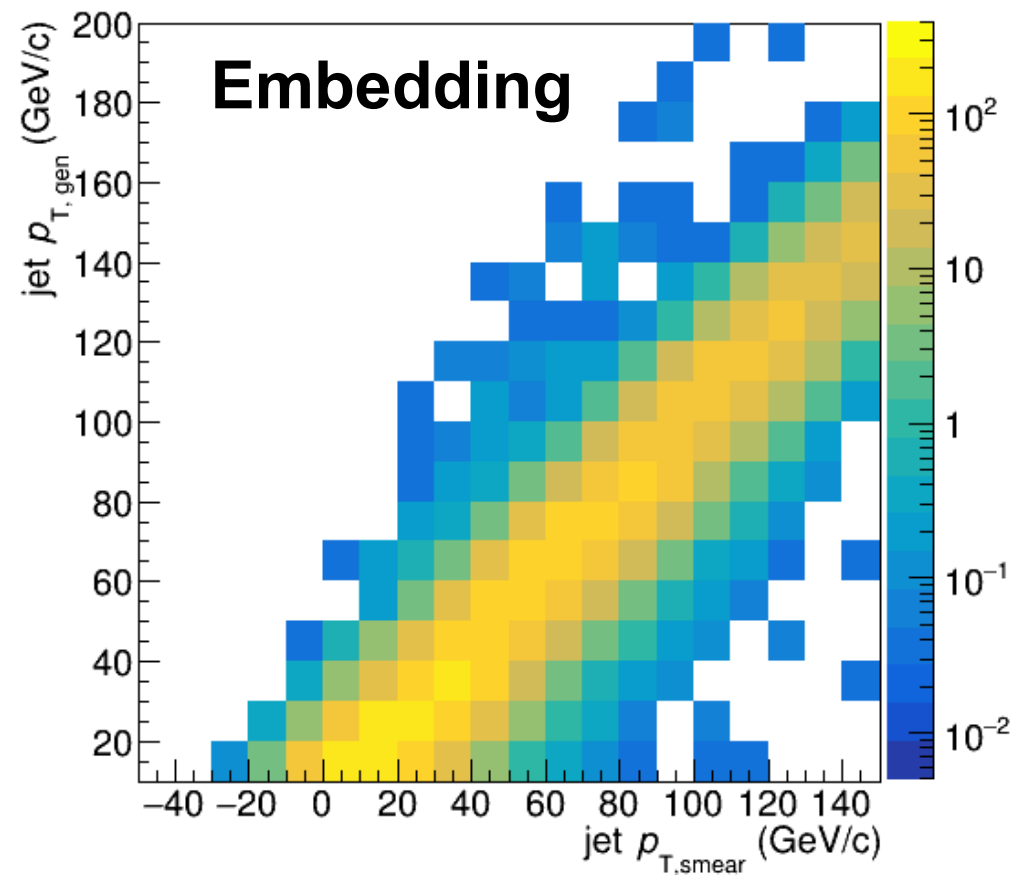
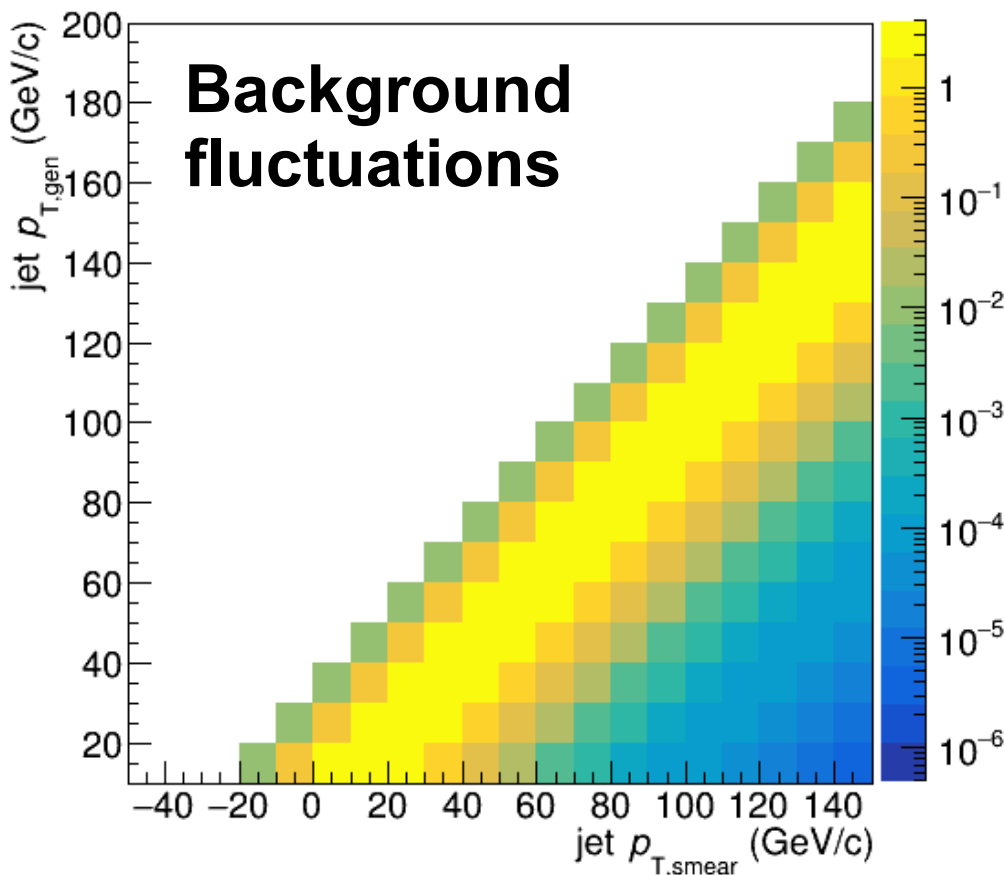
Jet finding algorithm

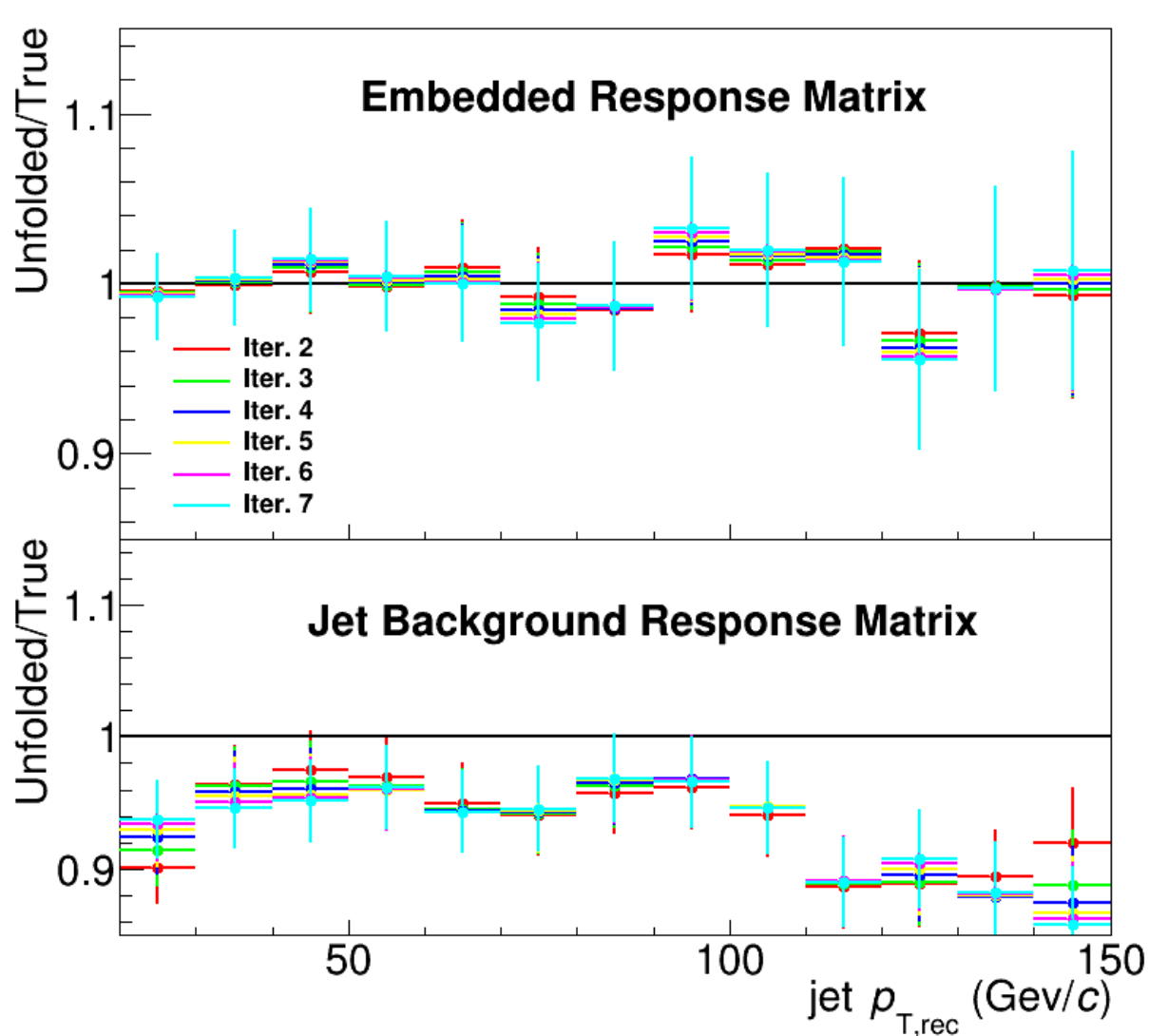
Jet candidates

Background subtraction



# Construct a response matrix in Monte Carlo

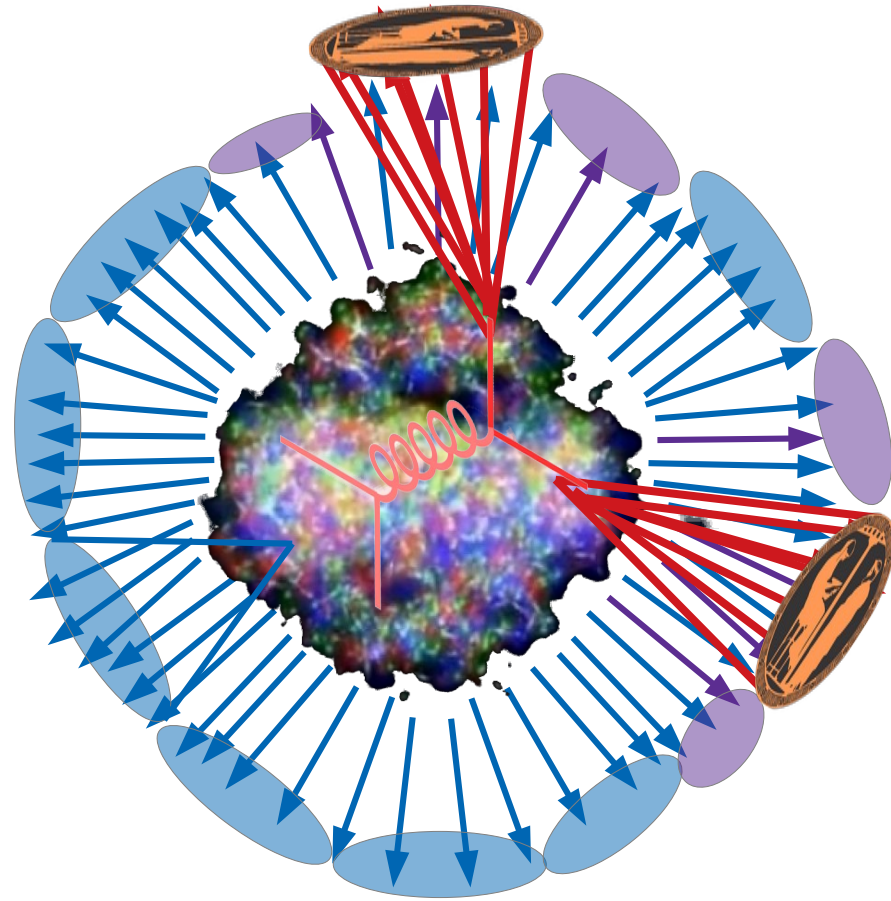




# Closure

- Methods
  - Use  $\delta p_T$  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
- Not due to jet finder behavior in background  $\rightarrow$  interplay between background and jet finder

# Need unfolding and embedding in MC!





## 6. How to compare to models

**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.

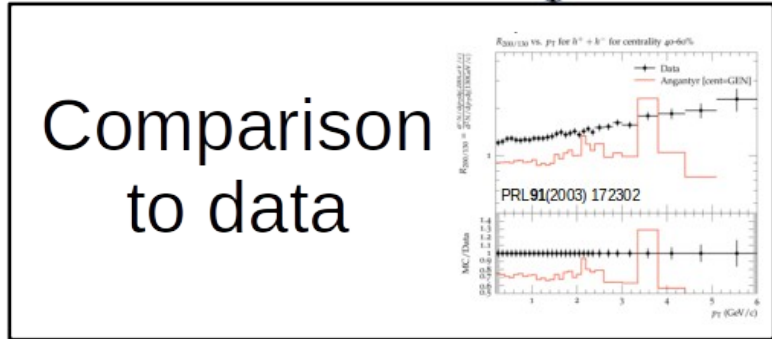
# What is Rivet?

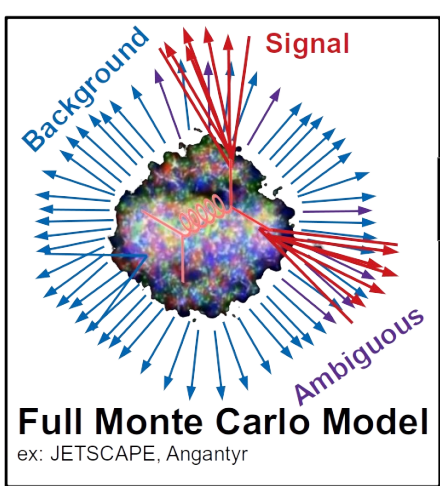


HepMC

HEPData

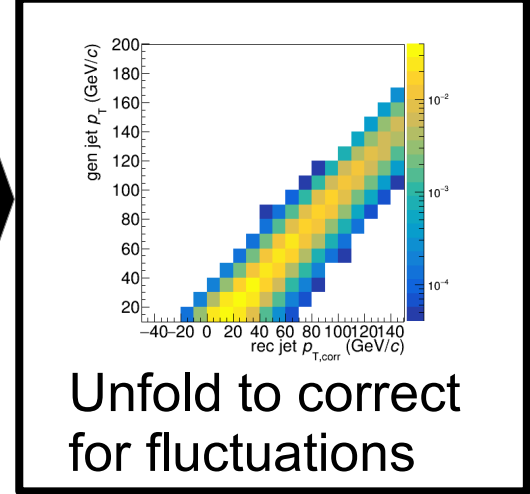
Rivet





**HepMC**

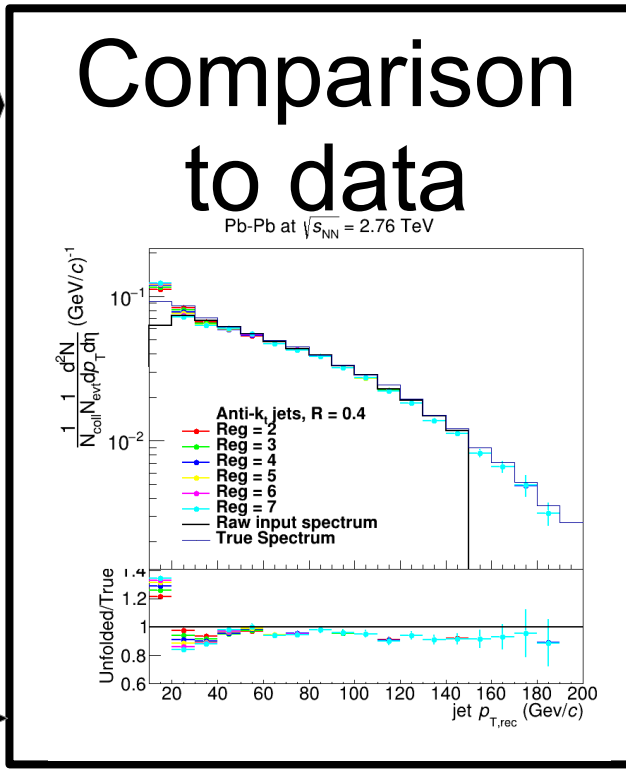
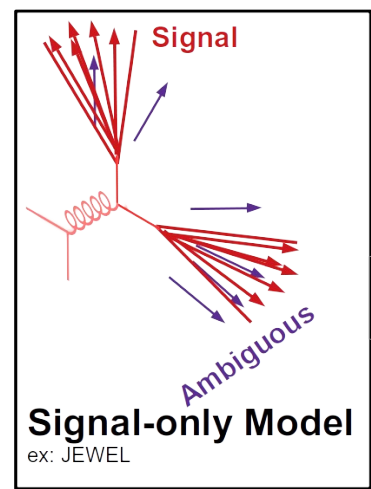
**Rivet**



**HEPData**

**HepMC**

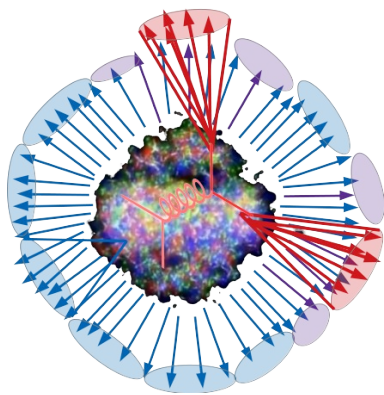
**Rivet**



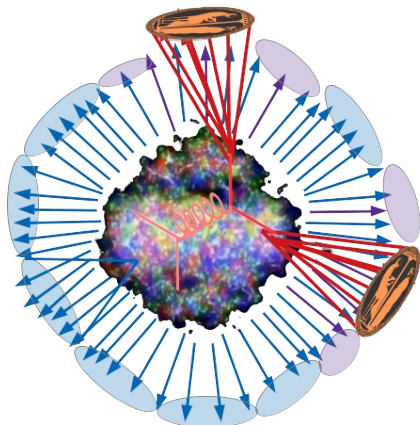
# Why use Rivet?

- Facilitates comparisons between Monte Carlos and data
- It's not that hard
- It preserves analysis details

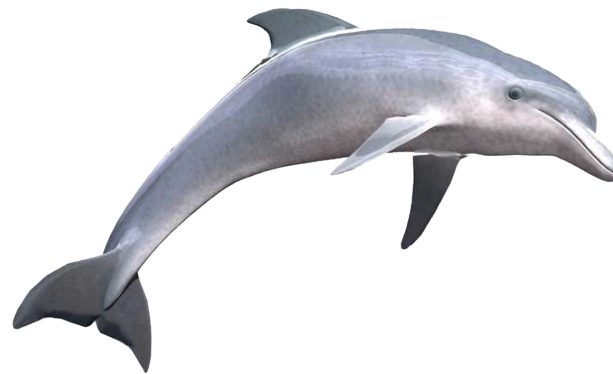
# Conclusions



**Models have background too!**



**Correcting for it requires unfolding, embedding**



**Background suppression → combinatorial jets which look like real jets**



**Treat models like data**

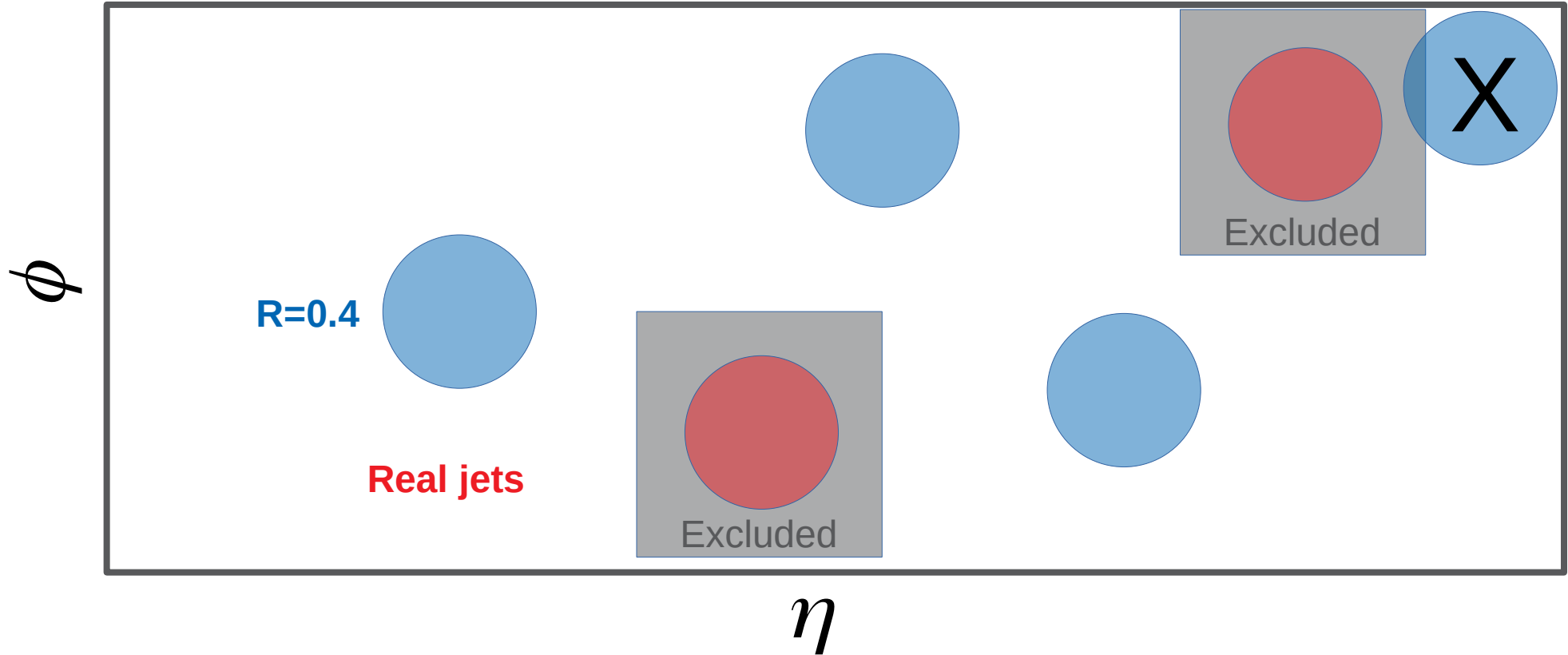
Recorded tutorials from [Rivetizing Heavy Ion Collisions at RHIC](#)



## 4. Background: Not just an experimental problem!

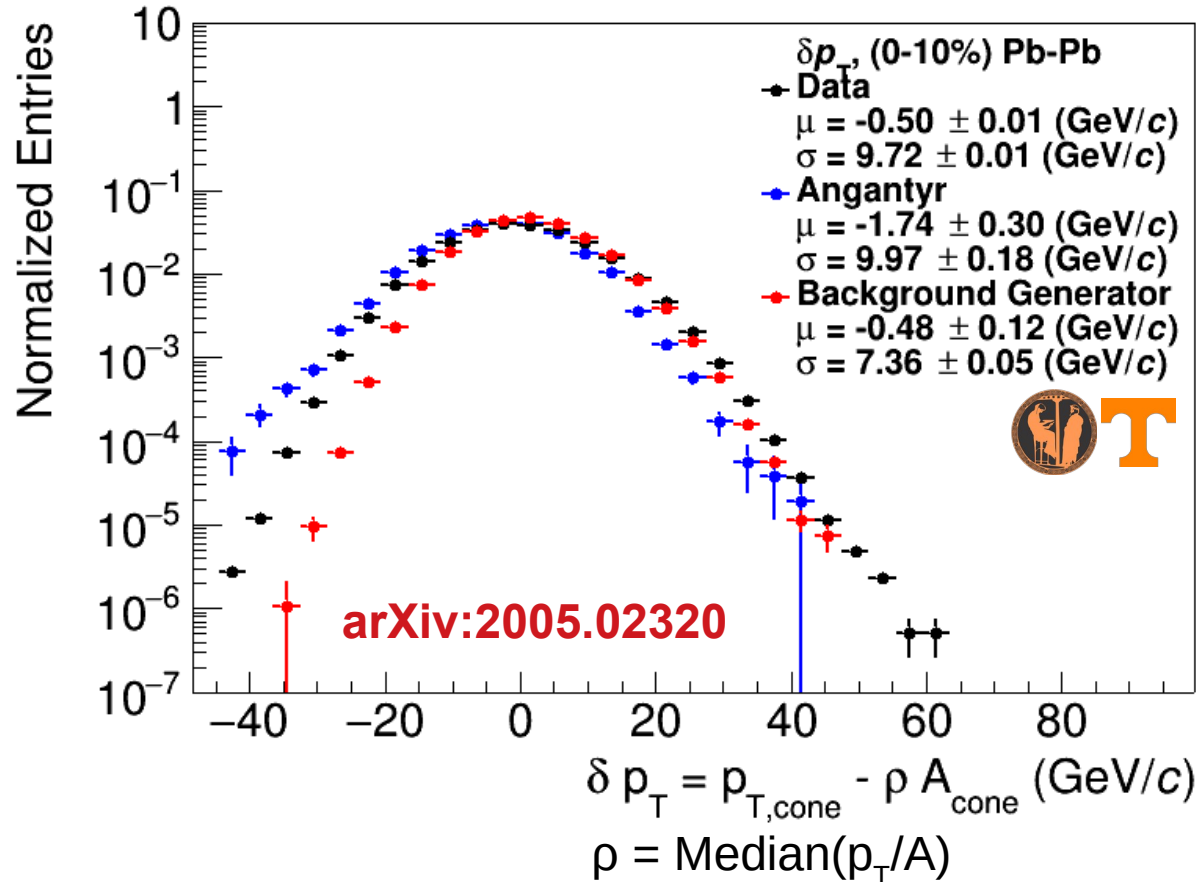
[arXiv:2005.02320](https://arxiv.org/abs/2005.02320)

# Random cones



# Random cones

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



# Shape of width of the distribution

## Single particle spectra

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

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

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

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

**Assumes shape**

## $\Sigma p_T$ of N particles $\rightarrow$ N-fold convolution:

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

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

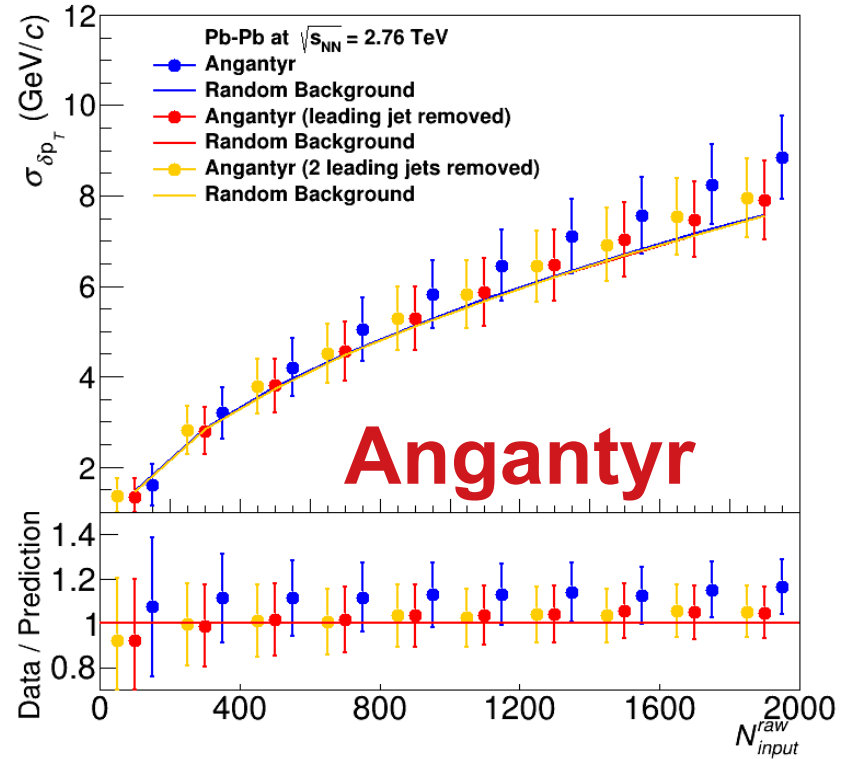
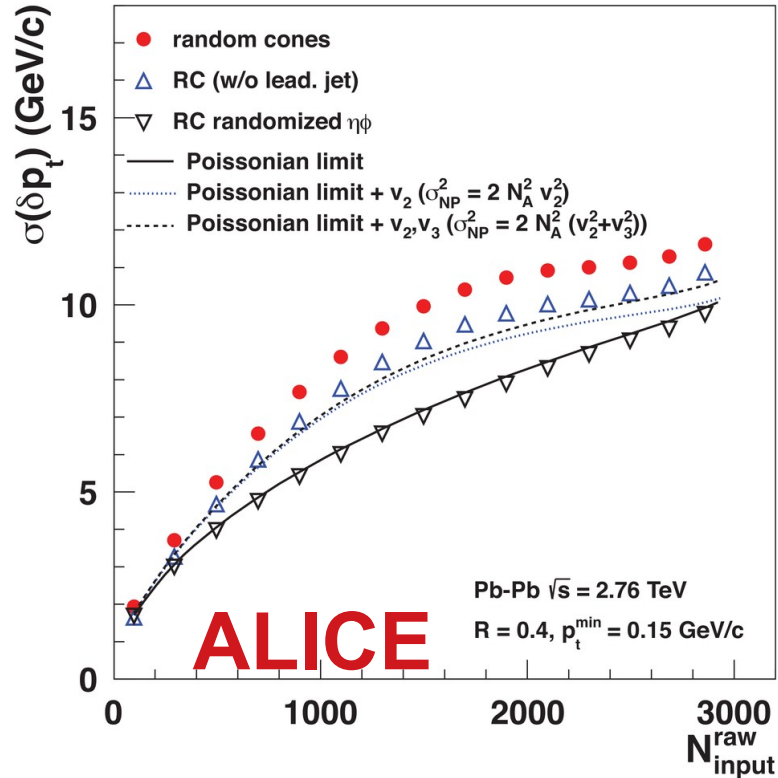
$$\text{Add Poissonian fluctuations in N: } \sigma_{total} = \sqrt{N \sigma_{p_T}^2 + N \mu_{p_T}^2}$$

Add non-Poissonian fluctuations in N due to flow

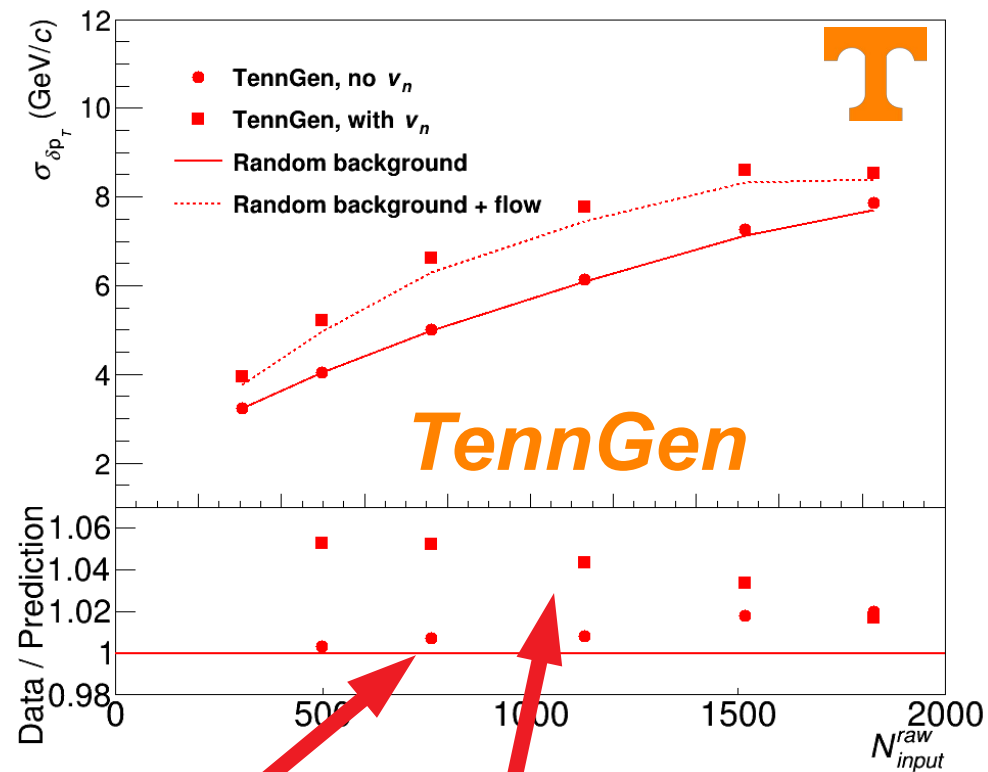
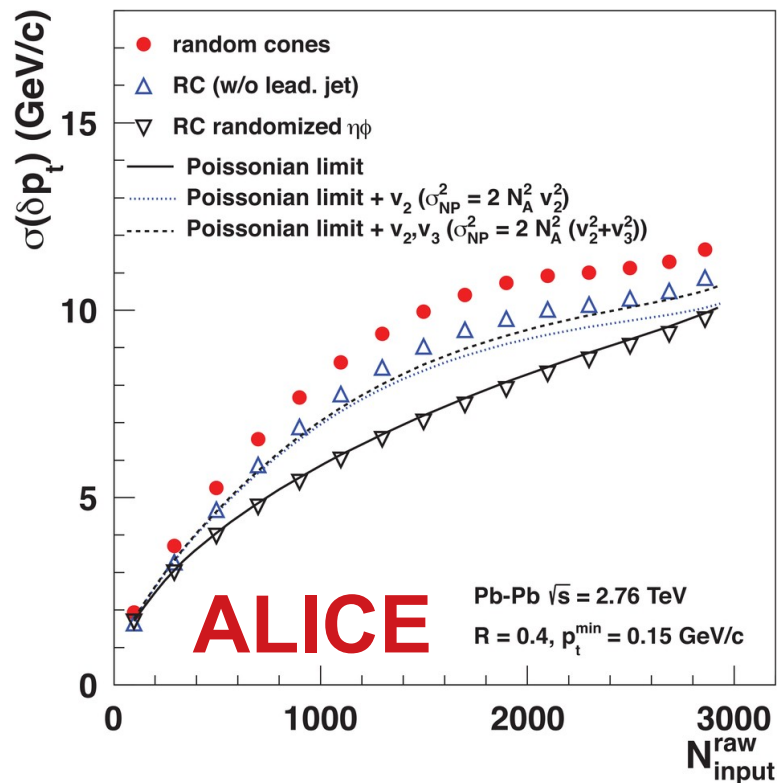
$$\sigma_{total} = \sqrt{N \sigma_{p_T}^2 + \left( N + 2 \sum_n v_n^2 \right) \mu_{p_T}^2}$$

**Assumes uncorrelated number fluctuations**

# Width vs multiplicity



# Width vs multiplicity



Impact of shape of spectrum

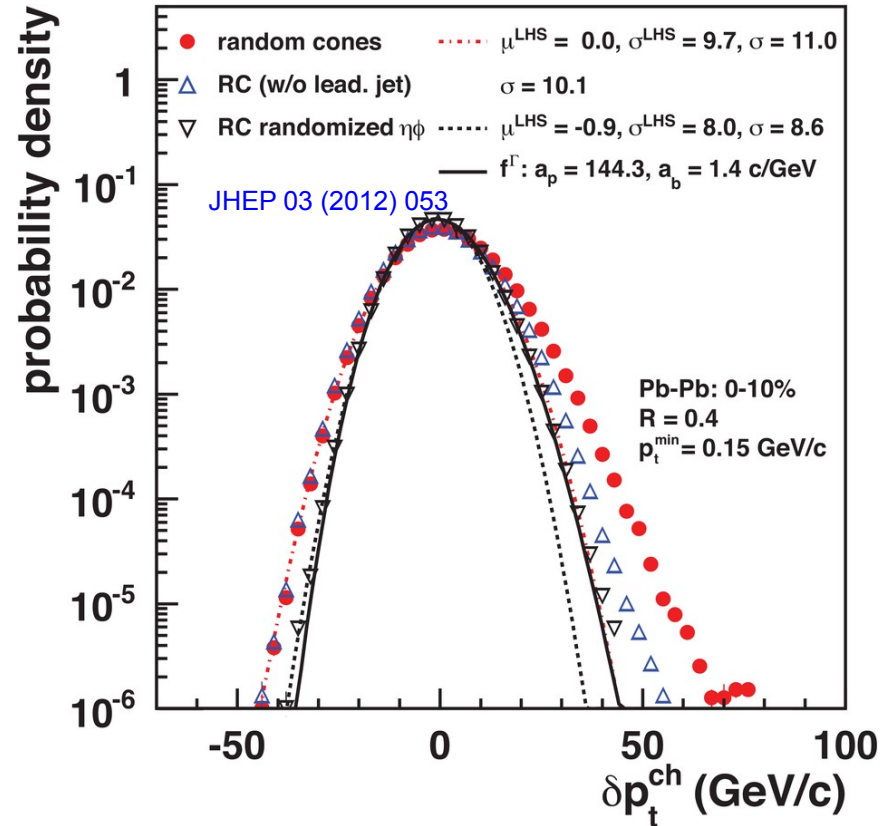
Correlations between event planes

Backup

# Random cones in ALICE

- Estimate  $\rho$ 
  - $k_T$  jet finder  $\rightarrow$  jet candidates
  - $\rho = \text{Median}(p_T/A)$
- Draw Random cone

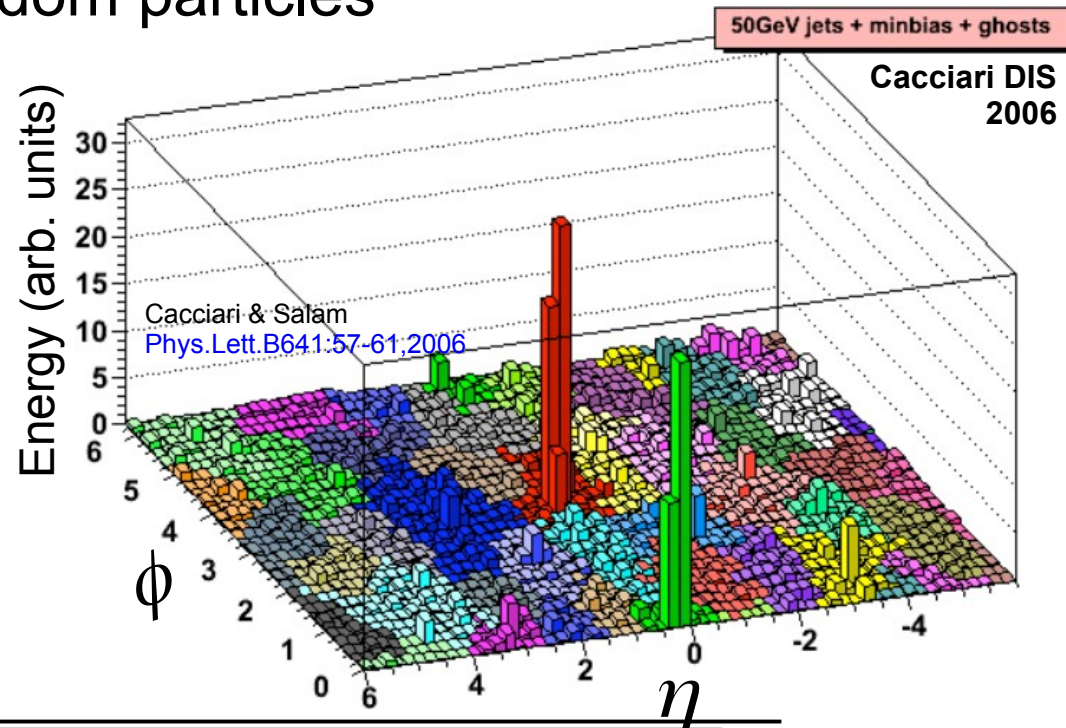
$$\delta p_T = p_T^{\text{reco}} - \rho A$$





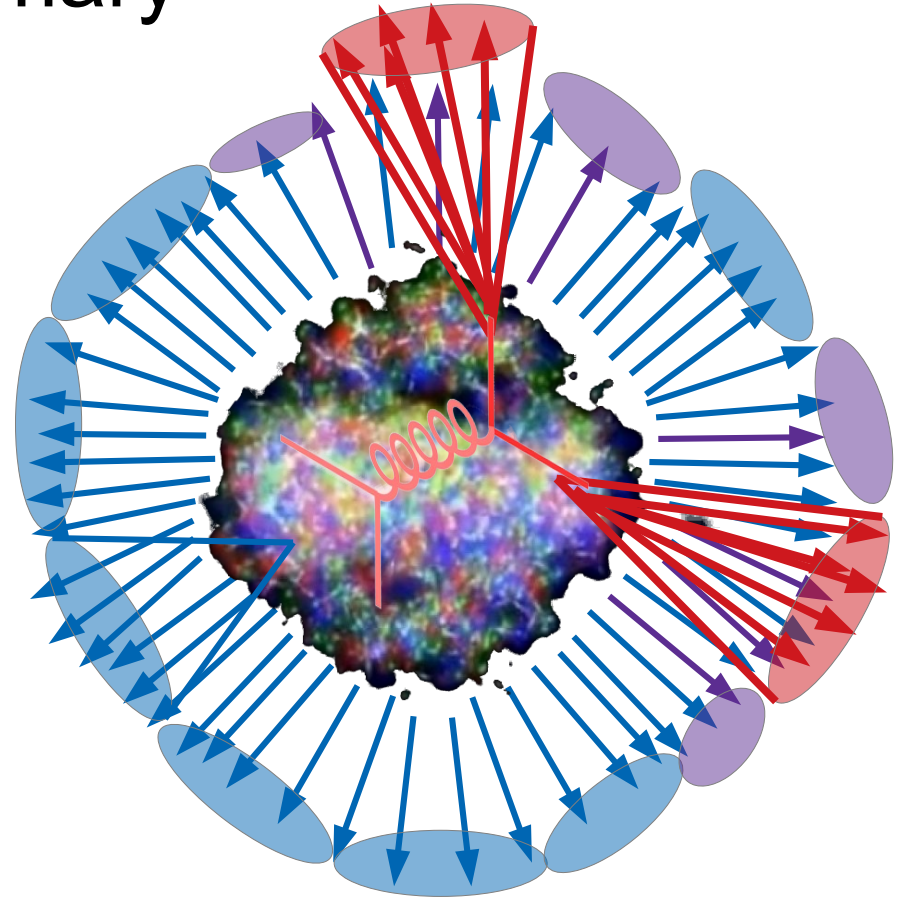
# Mini-summary

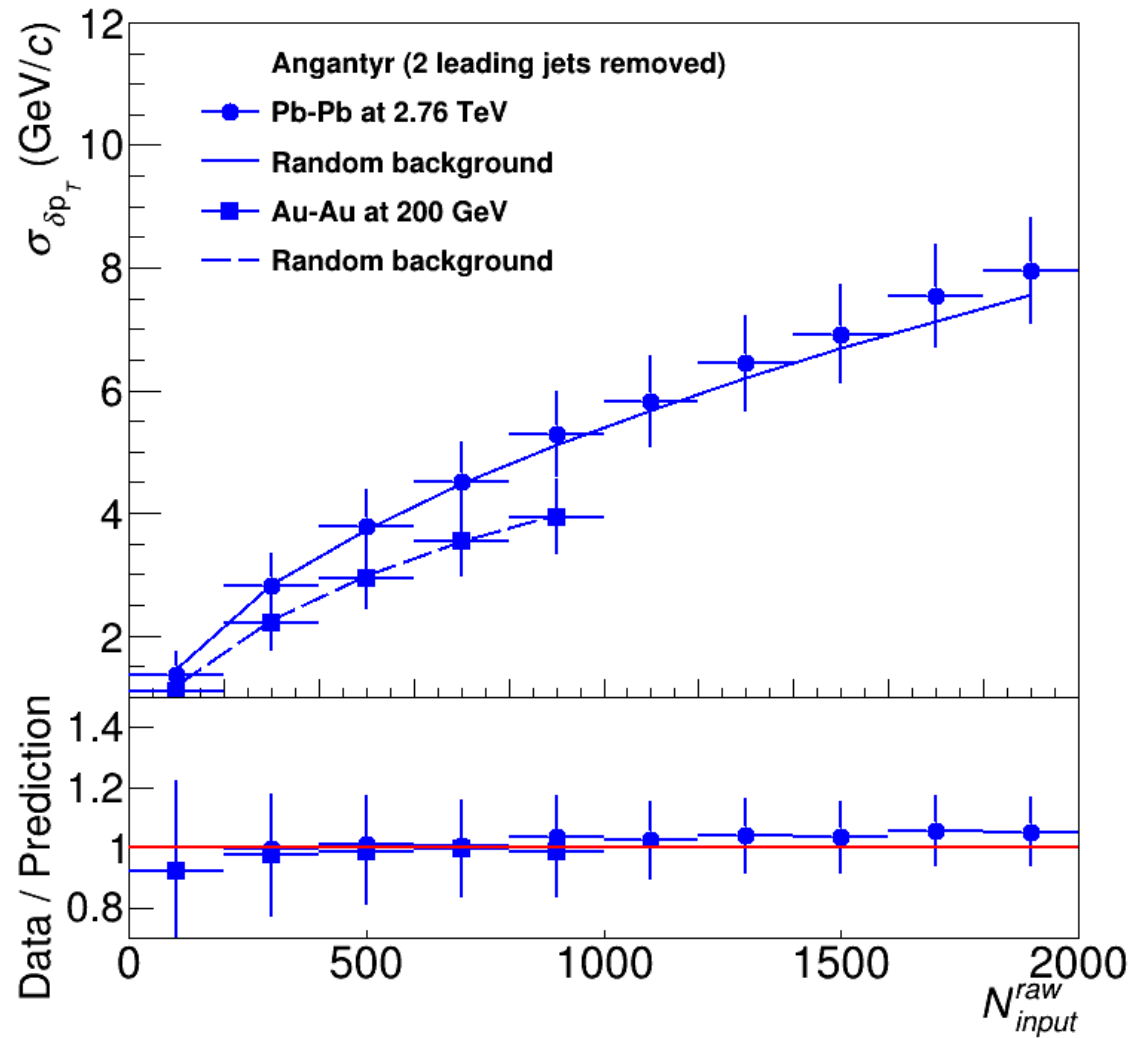
- Jet finders put all input clusters, tracks in a jet candidate
- Background is *dominated* by random particles
  - But ~5% effects from non-Poissonian fluctuations
- Models have background too!
  - Sensitive to multiplicity, implementation of flow

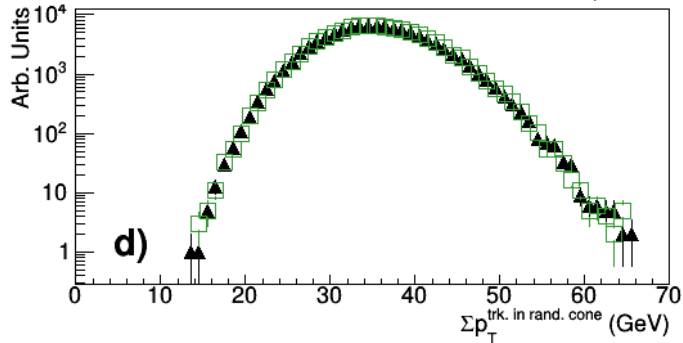
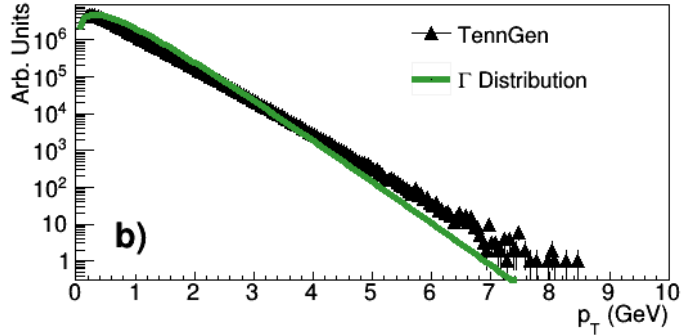
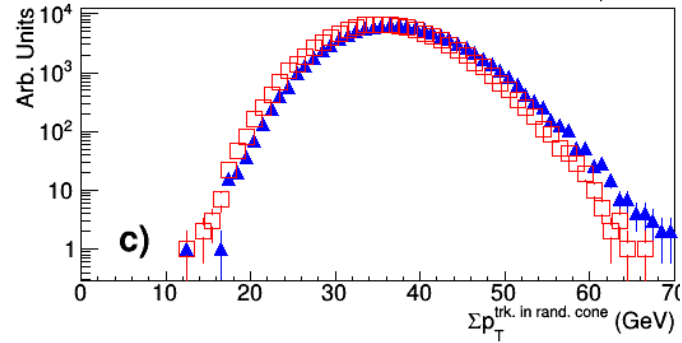
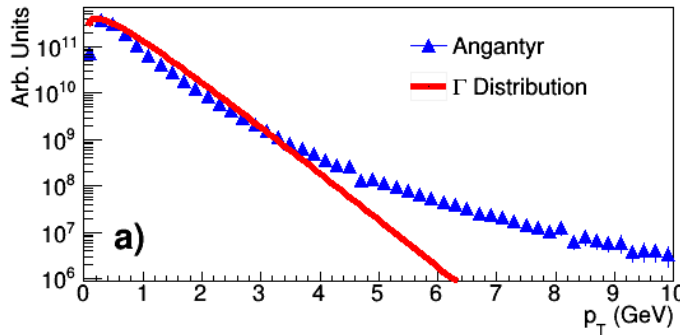
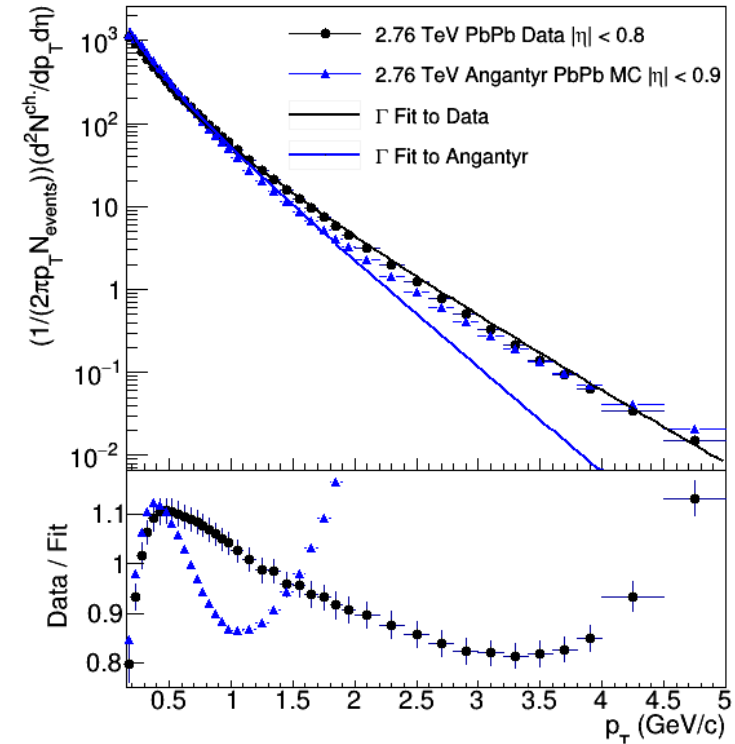


# Mini-summary

- “Signal” and “background” have different properties, but...
- Always overlap somewhat
- Any procedure to remove “background” will also cut signal







# Area-based background subtraction

Cacciari & Salam, [PLB659:119–126,2008](#)

Particles, clusters

## $k_T$ algorithm

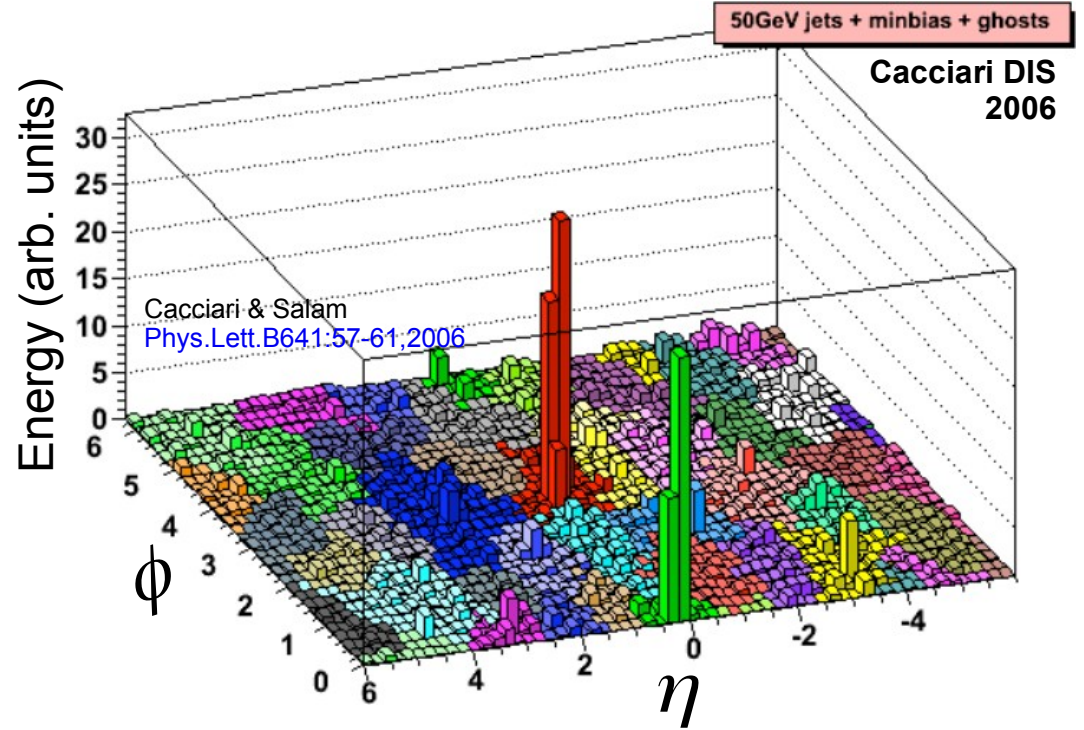
$$k_T = p_T, \Delta R_{ij} = \sqrt{(\eta_i - \eta_j)^2 + (\phi_i - \phi_j)^2}$$

- For all  $i, j$  calculate:
 
$$d_{ij} = \min(p_{T,i}^2, p_{T,j}^2) \Delta R_{ij}^2$$
  - Combine smallest  $d_{ij}$ .  
If  $d_{iB}$  smallest,  $d_{iB} \rightarrow$  jet
- Repeat until no particles left

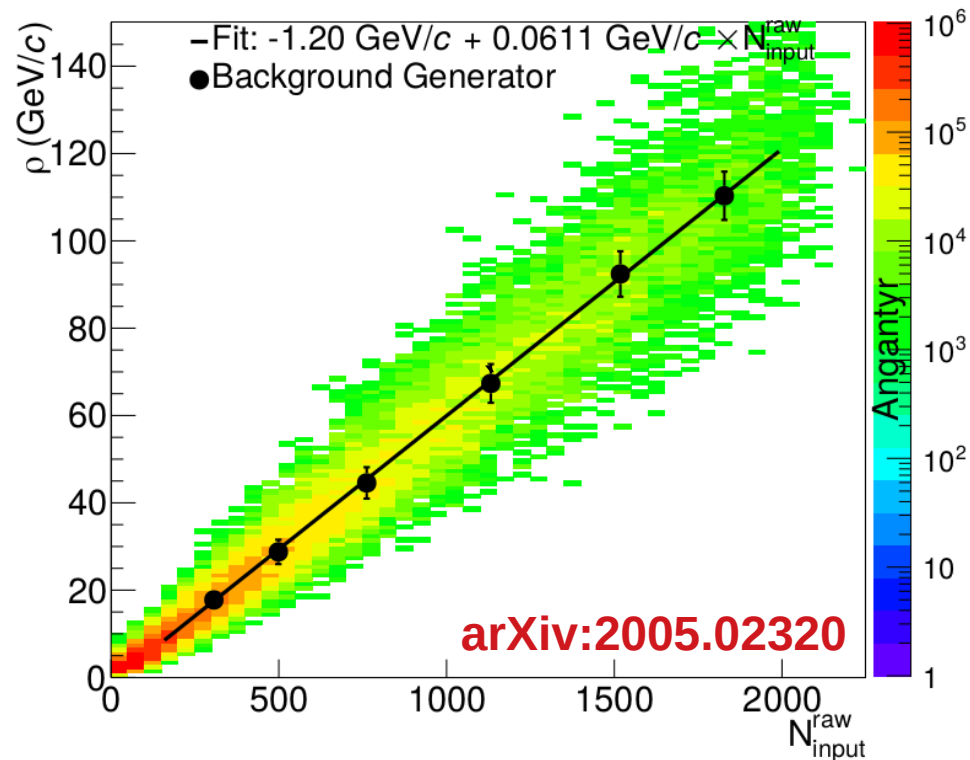
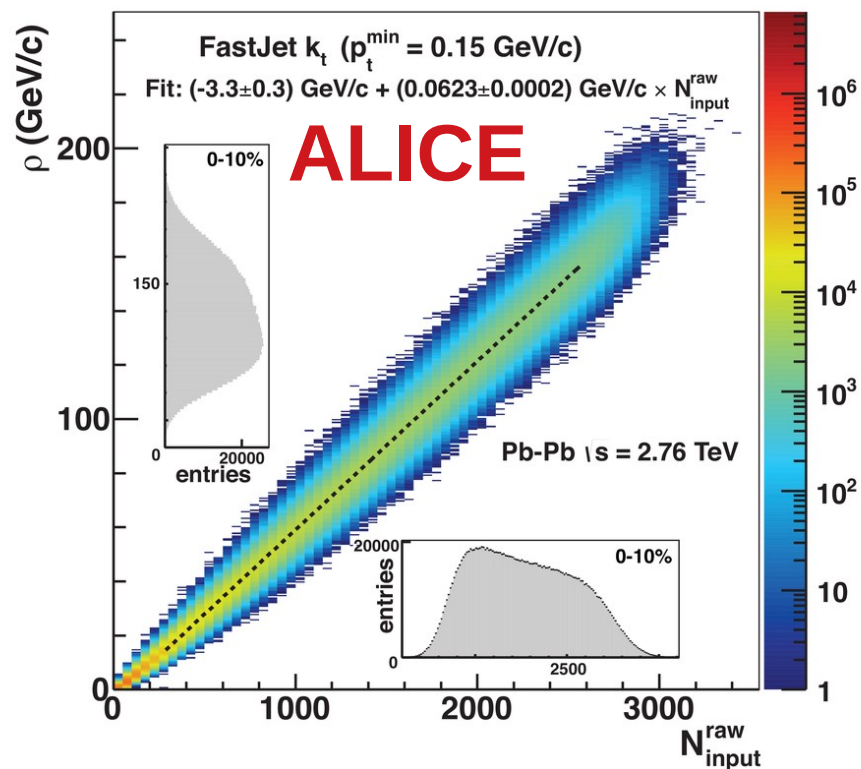
Jet candidates

Median  $\rho = p_T / A$

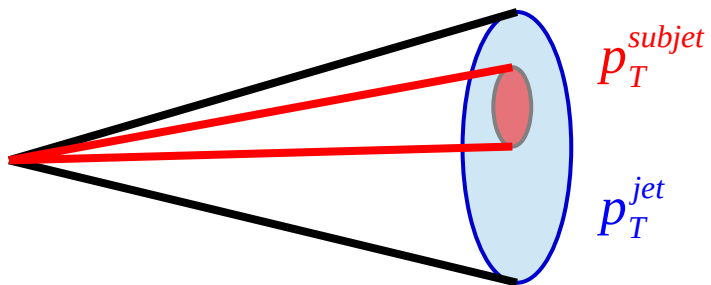
$$p_T^{jet} = p_T^{reco} - \rho_{median} A^{jet}$$



# Background density $\rho$

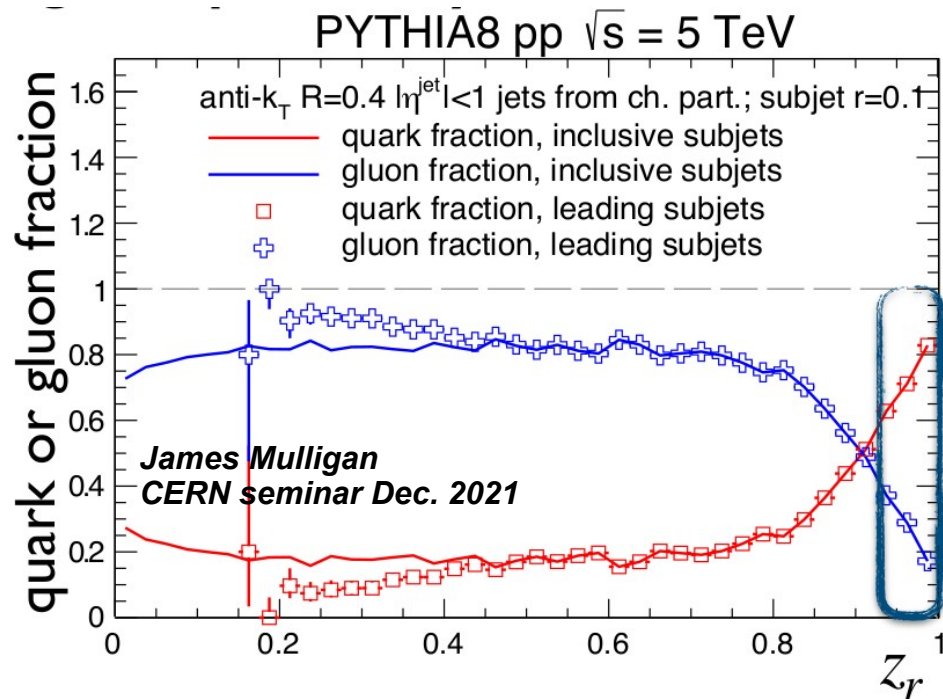


# Subjet z



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

- 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  $R$



# Subjet $z_r$ : Area cut



Subjet  $z_r$ : Leading hadron  $p_T^1$  cut

Subjet  $z_r$ : Leading hadron  $p_T^1$  cut

# Look for a clever solution with Machine Learning

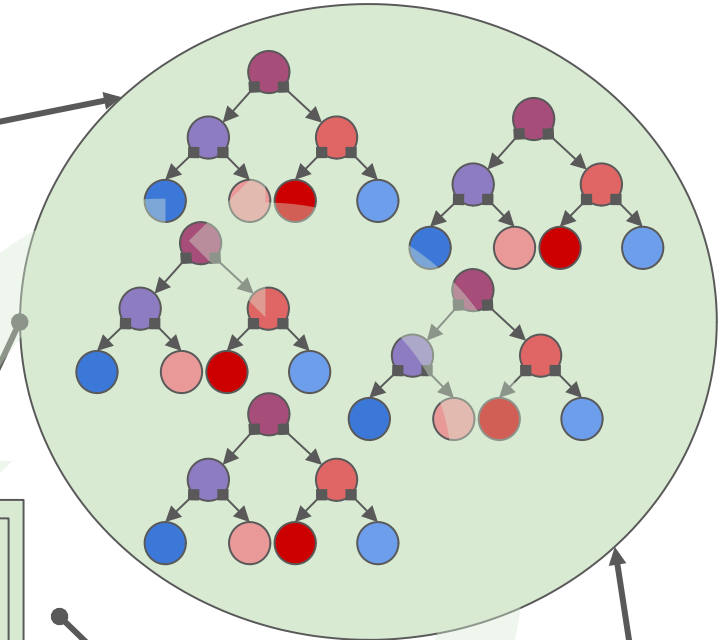
Input Features

Area  
Angular  
Mean Const.  $p_T$   
Leading hadron  $p_T$

Standardize

Scale Max to one and min to zero for each feature

Random Forest



Most effective Kinematic cut

Leading hadron  $p_T > 4.3$  GeV

**75-90% Combinatorial Rejection**  
**40-90% Squishy Rejection**  
**1-15% signal loss**

Oracle

Calculate Loss

Random Forest Prediction: Signal

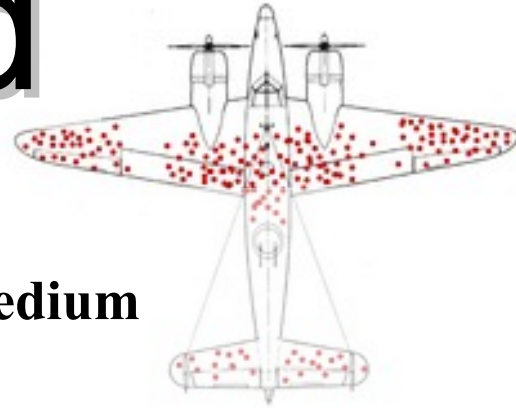
Oracle Prediction: Signal

Random Forest Prediction: Signal

Actual: Squishy

Calculate Loss

# Bias & background



- **Background suppression** → Bias
- **Survivor bias:** Modified jets probably look more like the medium
- **Quark/Gluon bias:**
  - Quark jets are narrower, have fewer tracks, fragment harder [Z Phys C 68, 179-201 (1995), Z Phys C 70, 179-196 (1996), ]
  - Gluon jets reconstructed with  $k_T$  algorithm have more particles than jets reconstructed with anti- $k_T$  algorithm [Phys. Rev. D 45, 1448 (1992)]
  - Gluon jets fragment into more baryons [EPJC 8, 241-254, 1998]
- **Fragmentation bias:** Experimental measurements explicitly select jets with hard fragments