



# Classifiers for centrality determination in proton-nucleus and nucleus-nucleus collisions

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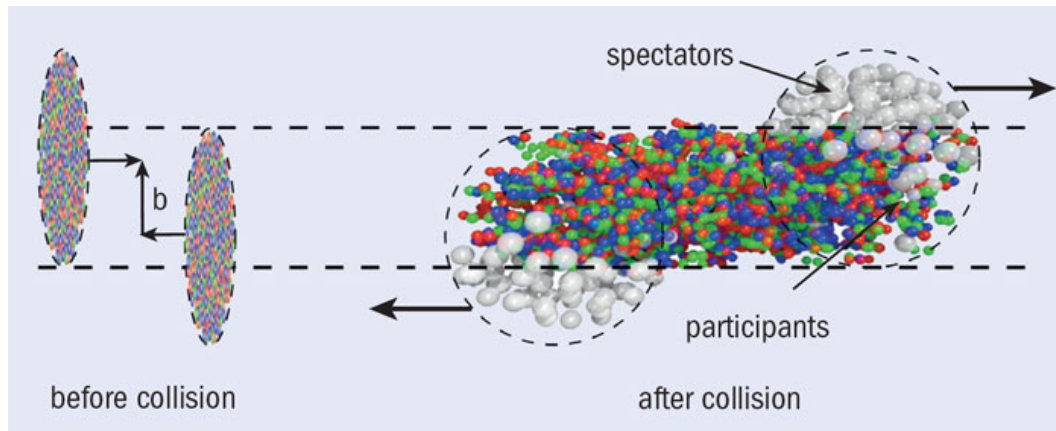
Heavy Flavour Data Mining workshop  
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# Prologue

- ML usage in HEP so far:  
search for rare decays, detector response optimization
- Interesting to find new applications
  - try to address some physics of heavy ion events

# The collision centrality

The **centrality** is a key parameter in the study of the properties of QCD matter at extreme temperature and energy density, because it is directly related to the **initial overlap region of the colliding nuclei**.



The **impact parameter ( $b$ )** is the distance between the centers of the two colliding nuclei.

# The centrality determination in experiment

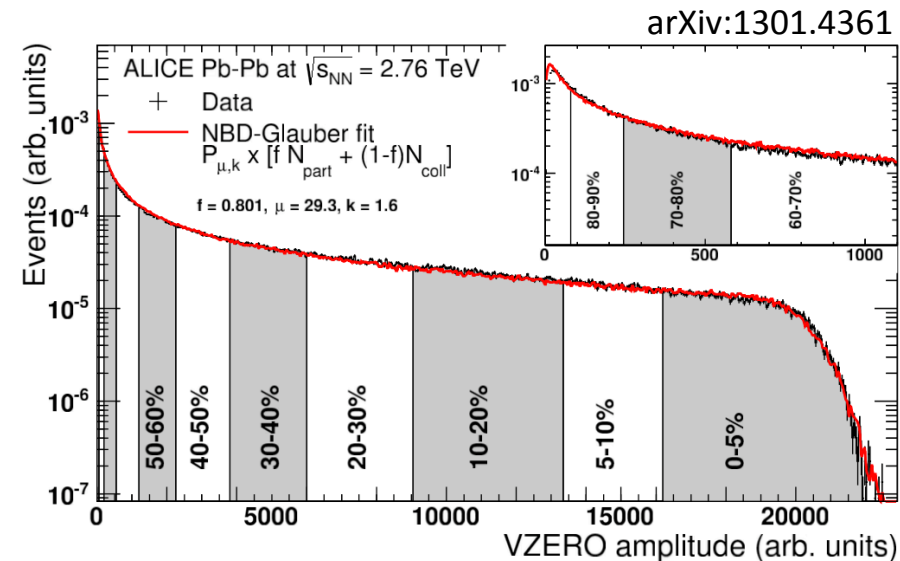
## Receipt:

- Use signal distribution in some detector
- Fit with some geometry-based model
- Split into *centrality classes*.

## In ALICE experiment:

**main method** uses *multiplicity distribution* in (semi-central) **VZERO detector** fitted with the Glauber model.

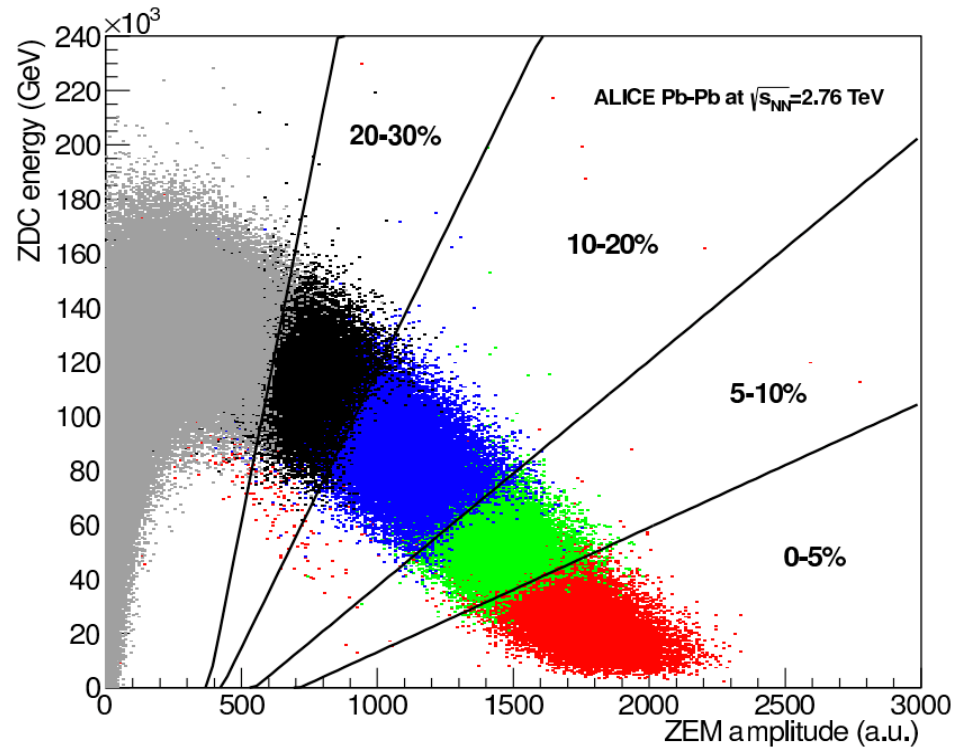
Close to 0% → most central events.



→  $b_{impact}$ ,  $N_{part}$ ,  $N_{coll}$ ,  $N_{spec}$  are deduced from the Glauber model.

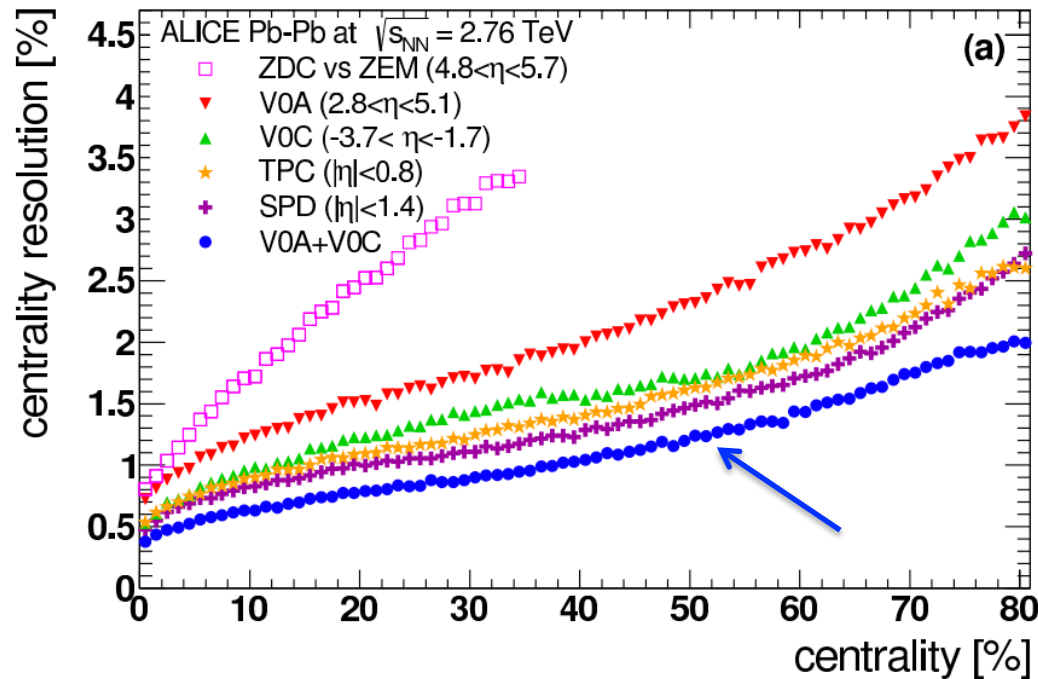
# The centrality determination in experiment

*Second* method of ALICE uses energy from neutrons-spectators in Zero-degree calorimeters (ZDC) coupled with signals in electromagnetic calorimeters (ZEM).



# The centrality determination in experiment

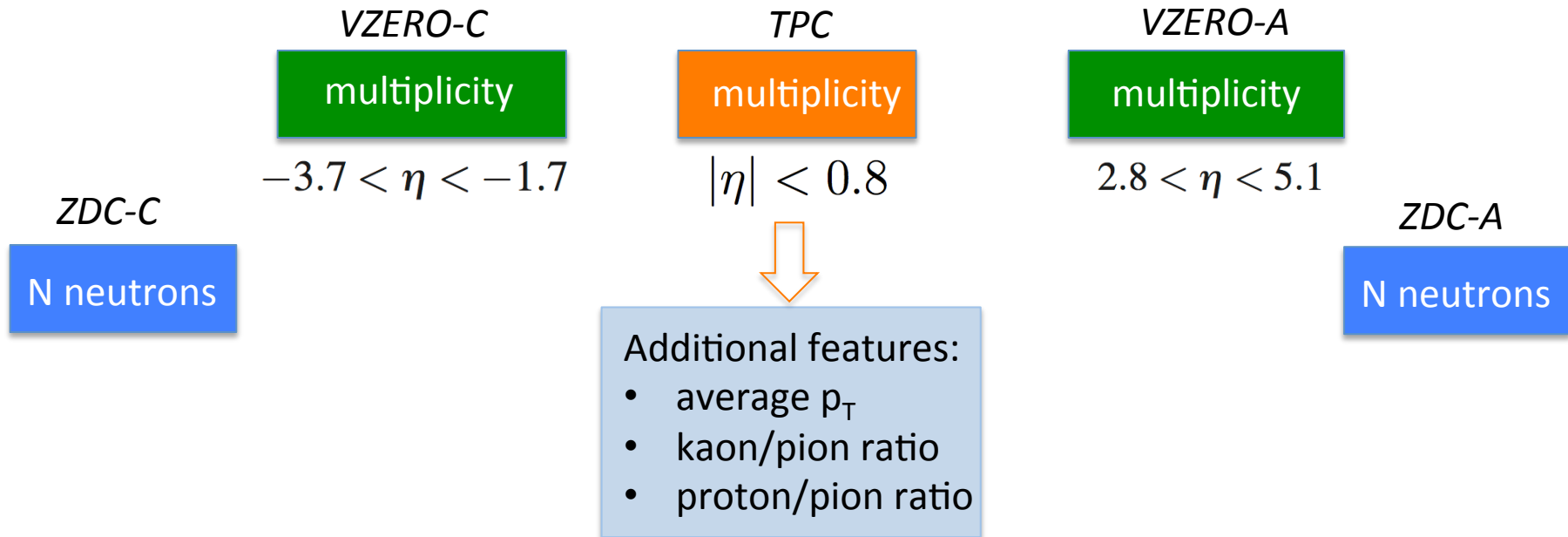
Best centrality resolution is achieved by usage of the **VZERO** estimator:



→ Can we perform better using multiple detectors simultaneously?  
Try machine-learning techniques for that.

# Centrality determination ML task

- Use **AMPT monte-carlo generator** to simulate Pb-Pb events at 2.76 TeV (without detector response) (400k events)
- **5+3 features** are selected in correspondence with the subsystems of the ALICE detector:

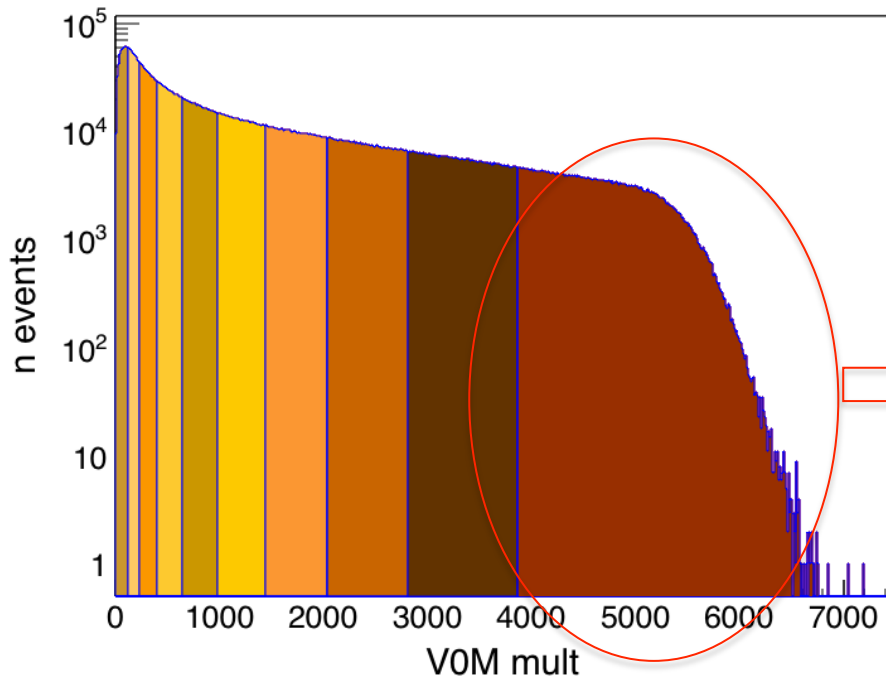


Using TMVA Version 4.2.0

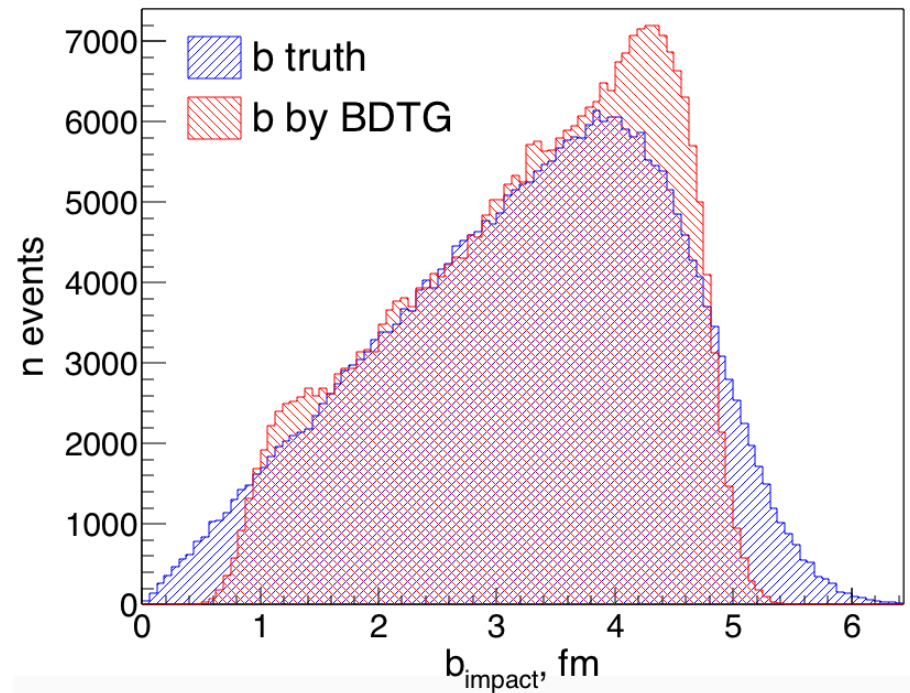
# Target for regression: impact parameter $b$

Pre-selection:

events with 0-10% VOM centrality



True VS estimated by BDTG:

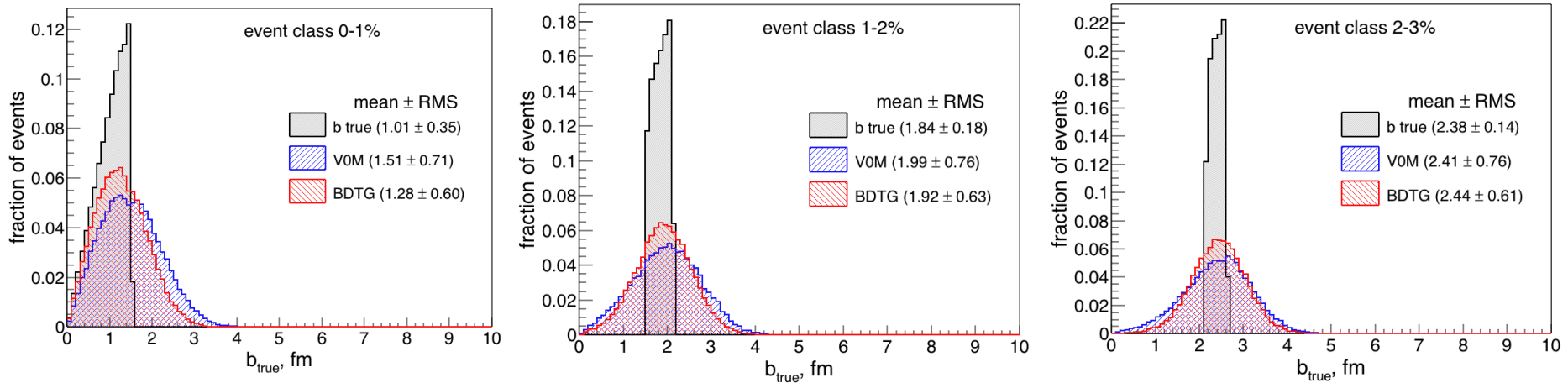


- Estimator: unavoidable “deformation” of the  $b$ -distribution at the edges.

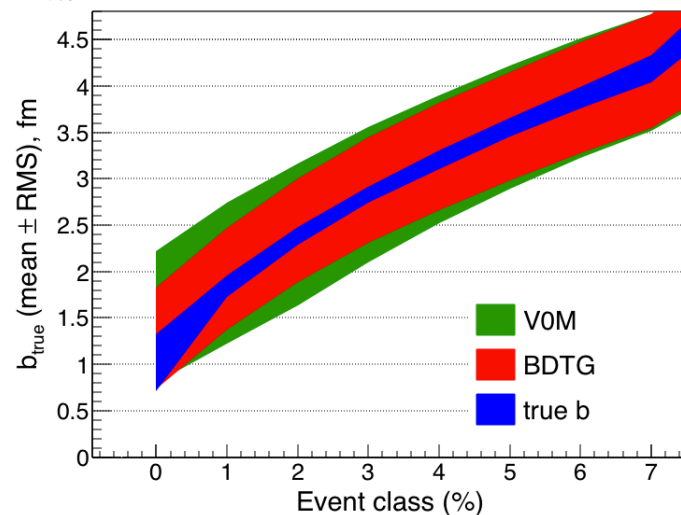


# Estimator performance vs V0M-based selection

- Split the regression output of the estimator into centrality classes
- Look at  $b$  impact distributions:



Mean +/- RMS of  $b$  impact within centrality classes:

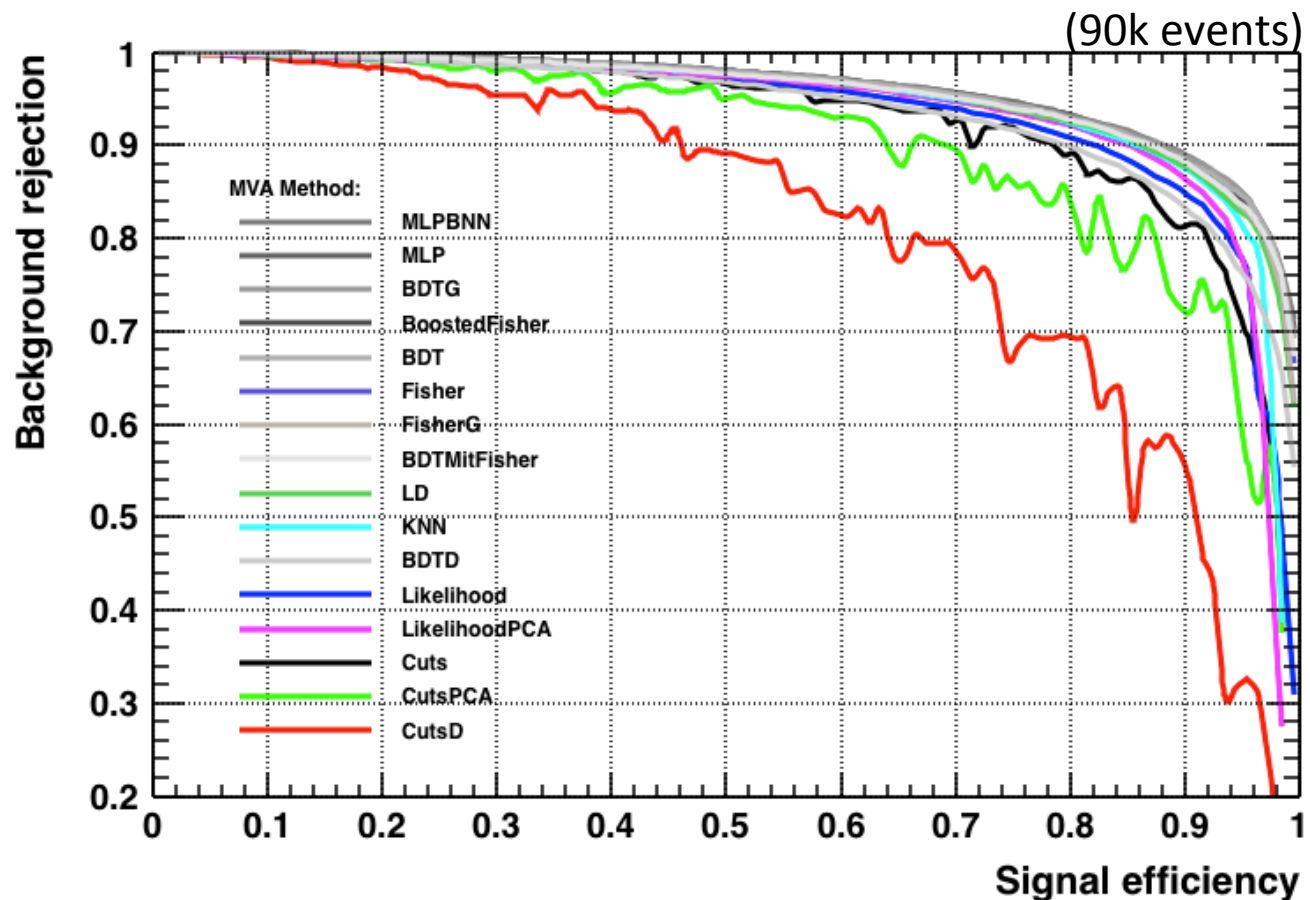


- smaller RMS by estimator than by V0M
- most central 0-1% events by estimator are closer to truth  $b$

# Classification task: find *most central* within 0-10% events

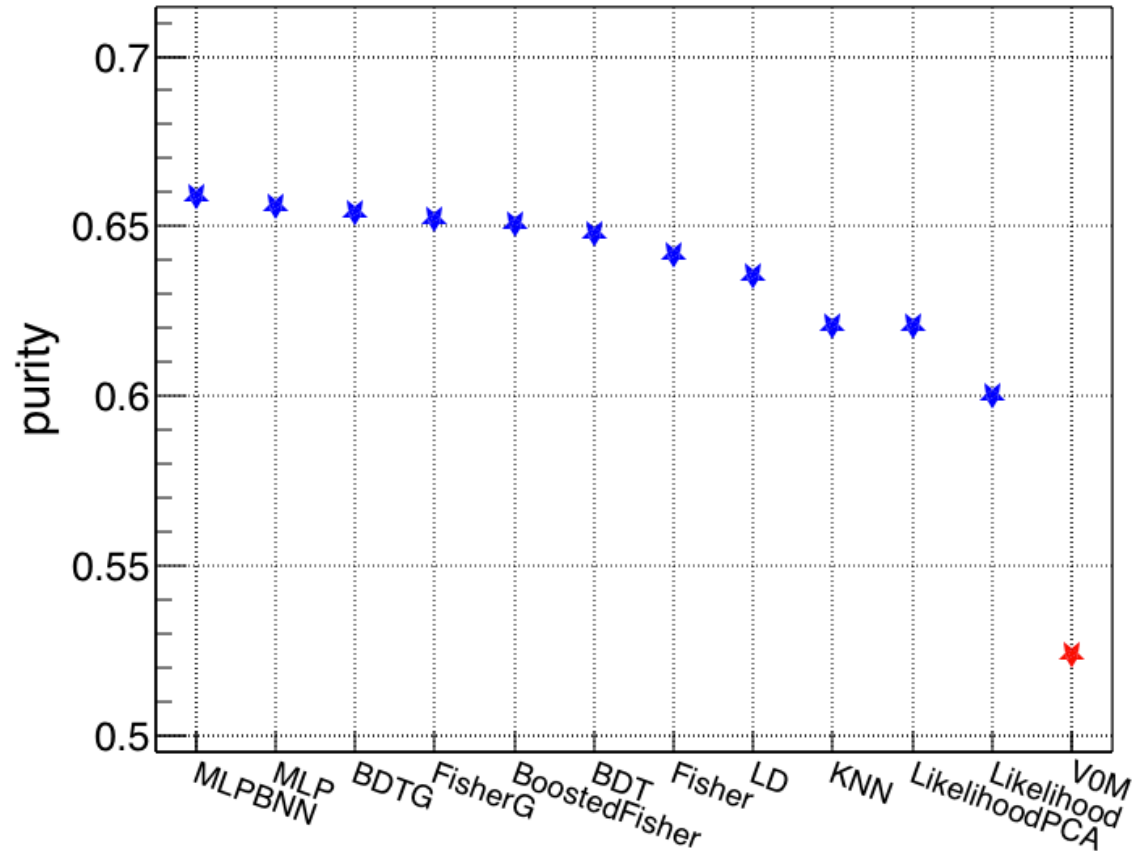
**signal** = 0-1% most central events ( $b_{\text{impact}} < 1.51 \text{ fm}$ )

**background** = 1-10%



- Cut-based classifiers perform worse than others

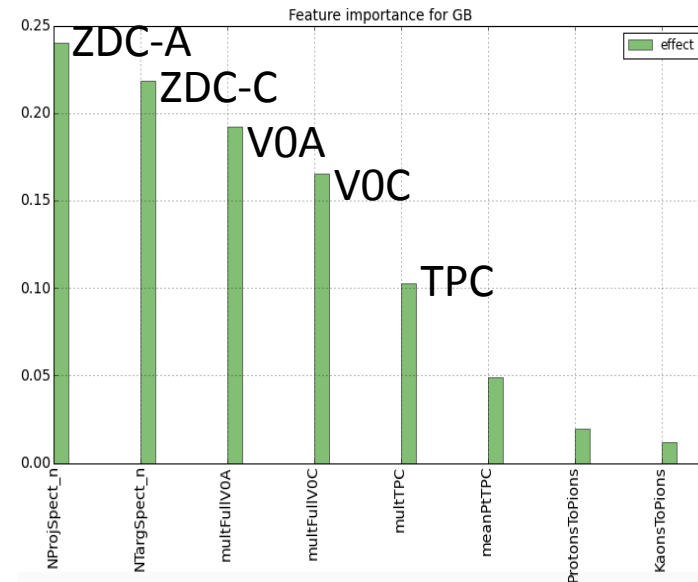
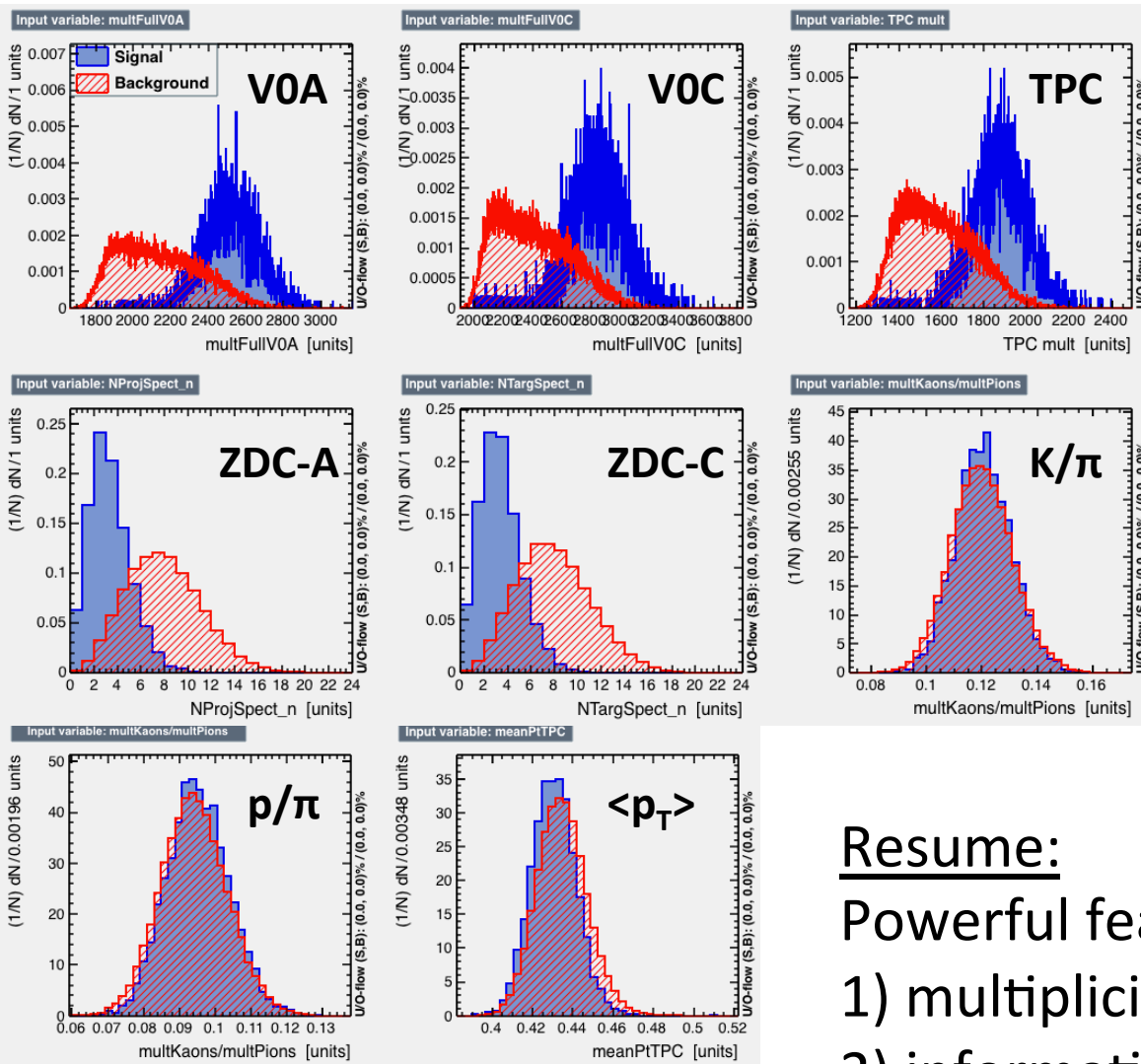
# Fraction of signal events in 0-1% class selected by classifiers output



Purity increased by ~13%.

Significant gain of combined usage of information from several sub-detectors.

# Which features are the most relevant?



## Resume:

Powerful features are:

- 1) multiplicity in large rapidity ranges
- 2) information about spectators

Additional features didn't help.

# Theses

- we want to go back to native definition of the notion of “centrality”: through the *impact parameter*.  
(*possible to perform similar study for  $N$  participants*)
- we want to keep same statistics within centrality classes
  - Machine learning builds decision boundaries for us
  - MC vs Data – how to match?
  
- Accurate centrality is a baseline for many physics analysis:
  - crucial, for example, in fluctuations and correlations studies.