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

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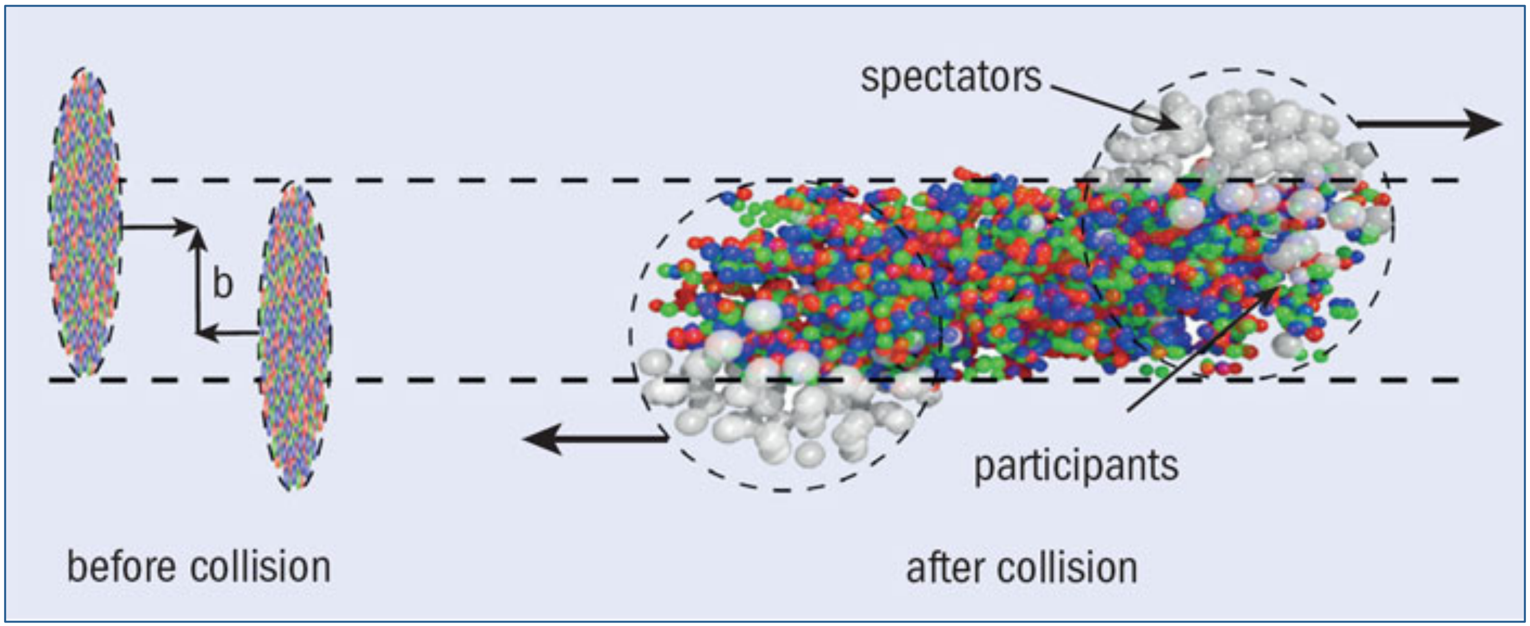
Prologue

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

The collision centrality

The centrality is a key parameter in the study QCD matter at extreme energy densities, 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 colliding nuclei.

Centrality determination in experiment

Usual receipt:

- use distribution of a signal in some detector
- fit with some geometry-based model
- split into *centrality classes* (0-100%)

In ALICE for Pb-Pb:

use *multiplicity distribution* in (semi-central) **VZERO detector** + Glauber fit

(-3.7<η<-1.7 and 2.8<η<5.1)

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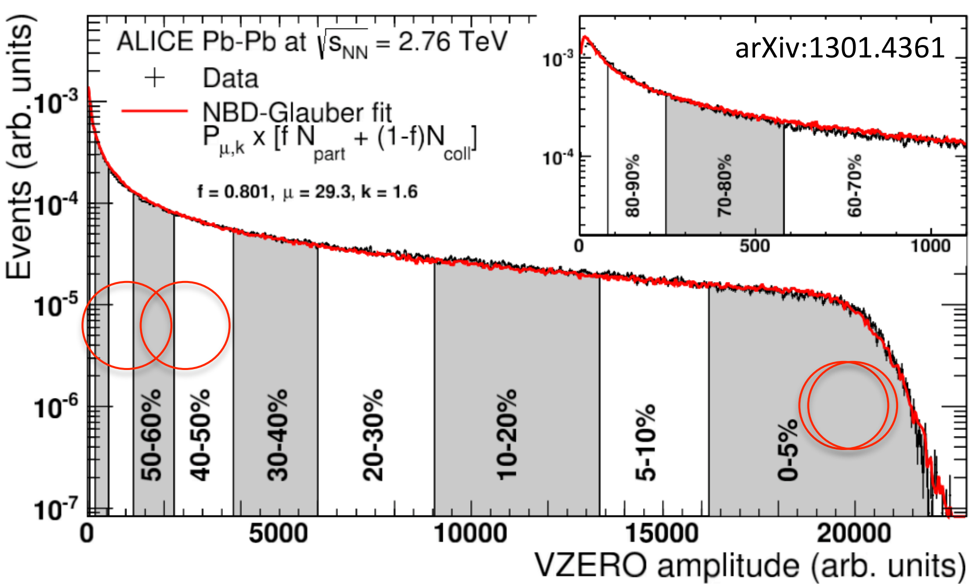


(-3.7<η<-1.7 and 2.8<η<5.1)

close to 0% → most **central** events

closer to 100% → **peripheral** events

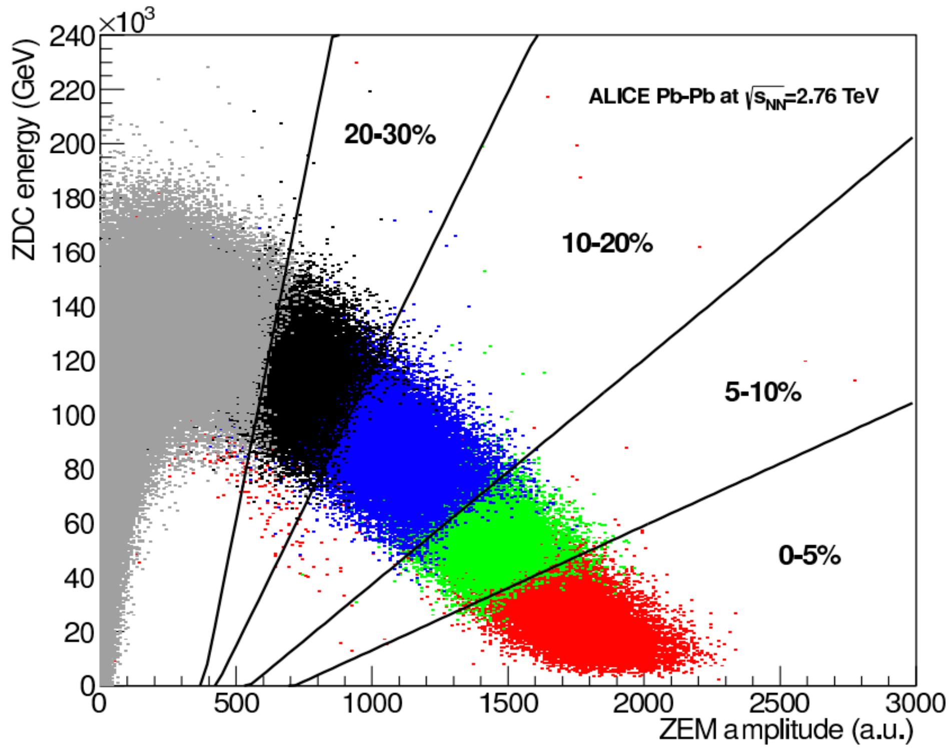
→ b_{impact}, N_{part}, N_{coll}, N_{spec} are not directly measurable and are deduced from the Glauber model.

Alternative method in ALICE

Based on 2D distribution of signals from two detectors:

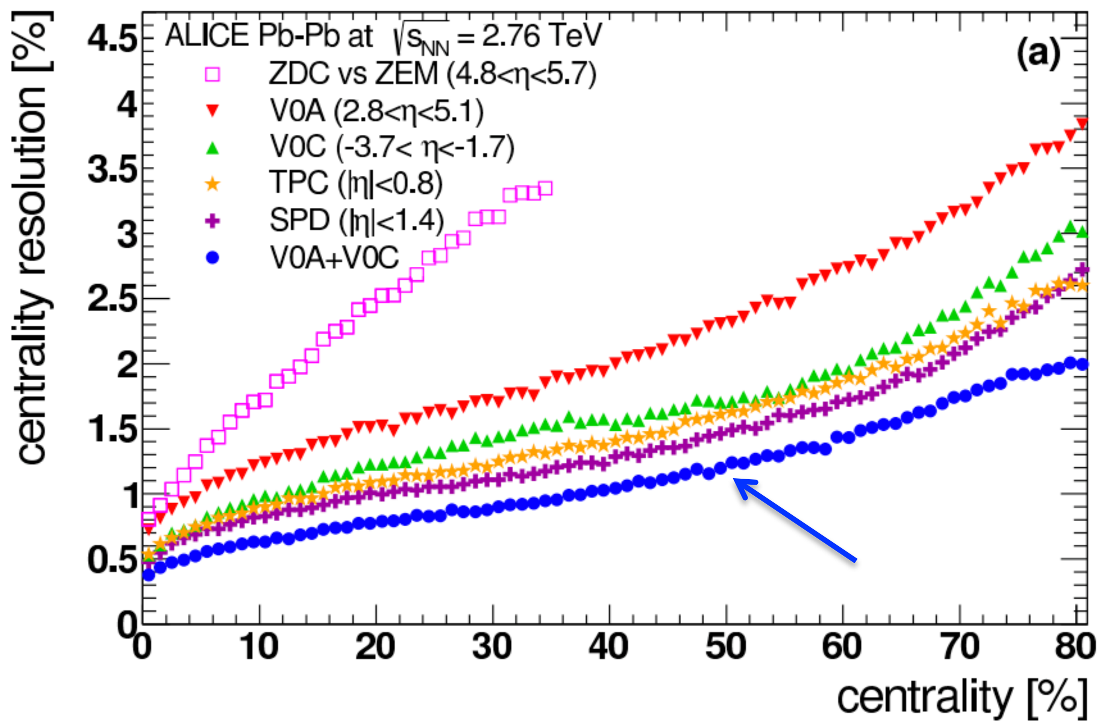
energy from neutrons-spectators in Zero-degree calorimeters (**ZDC**) && signals in electromagnetic calorimeters (**ZEM**)

(4.8<η<5.7)



Splitting in centrality classes is done by drawing (arbitrary) lines.

Centrality resolution in experiment



Best centrality resolution is achieved by usage of the VZERO estimator.

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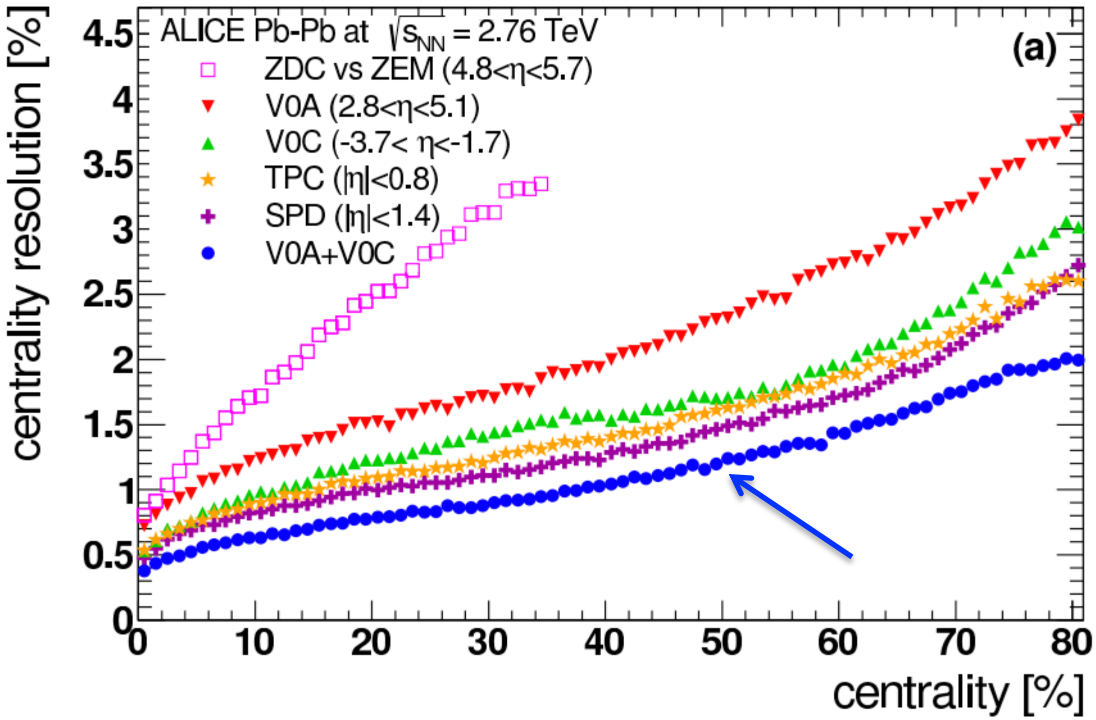

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Can we perform better using multiple detectors simultaneously?
Try machine-learning techniques for that.

Centrality determination as a Machine-Learning task

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

ZDC-C
N neutrons

VZERO-C
multiplicity
$-3.7 < \eta < -1.7$

TPC
multiplicity
$|\eta| < 0.8$

VZERO-A
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ZDC-C
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ZDC-A
N neutrons

+3 additional features:
- average p_T
- kaon/pion ratio
- proton/pion ratio

Target for regression: **impact parameter *b***

(using TMVA Version 4.2.0)

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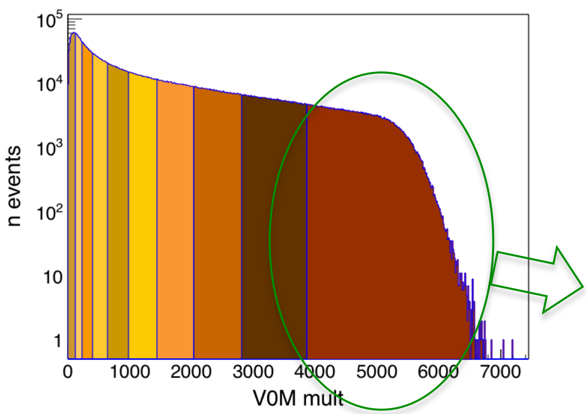
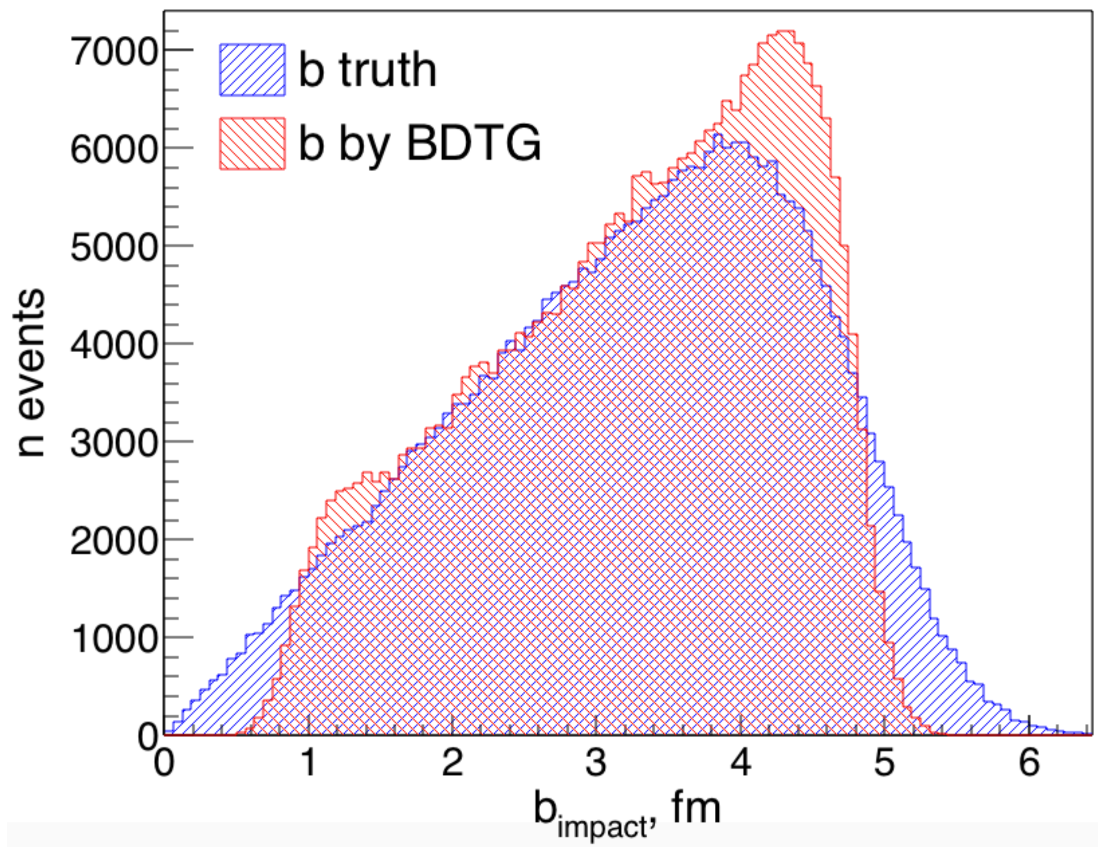
pre-selection:
events class **0-10%** (V0M)



True distribution *VS* estimated by Boosted Decision Tree:



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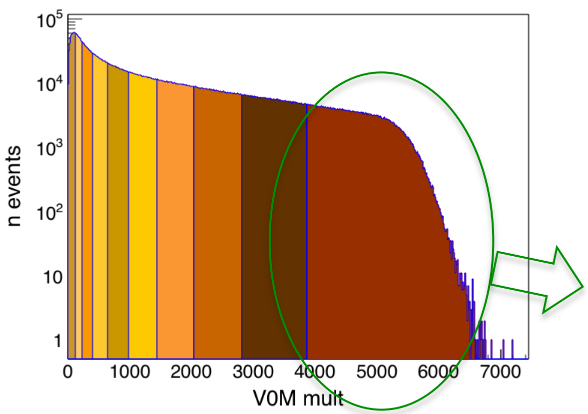

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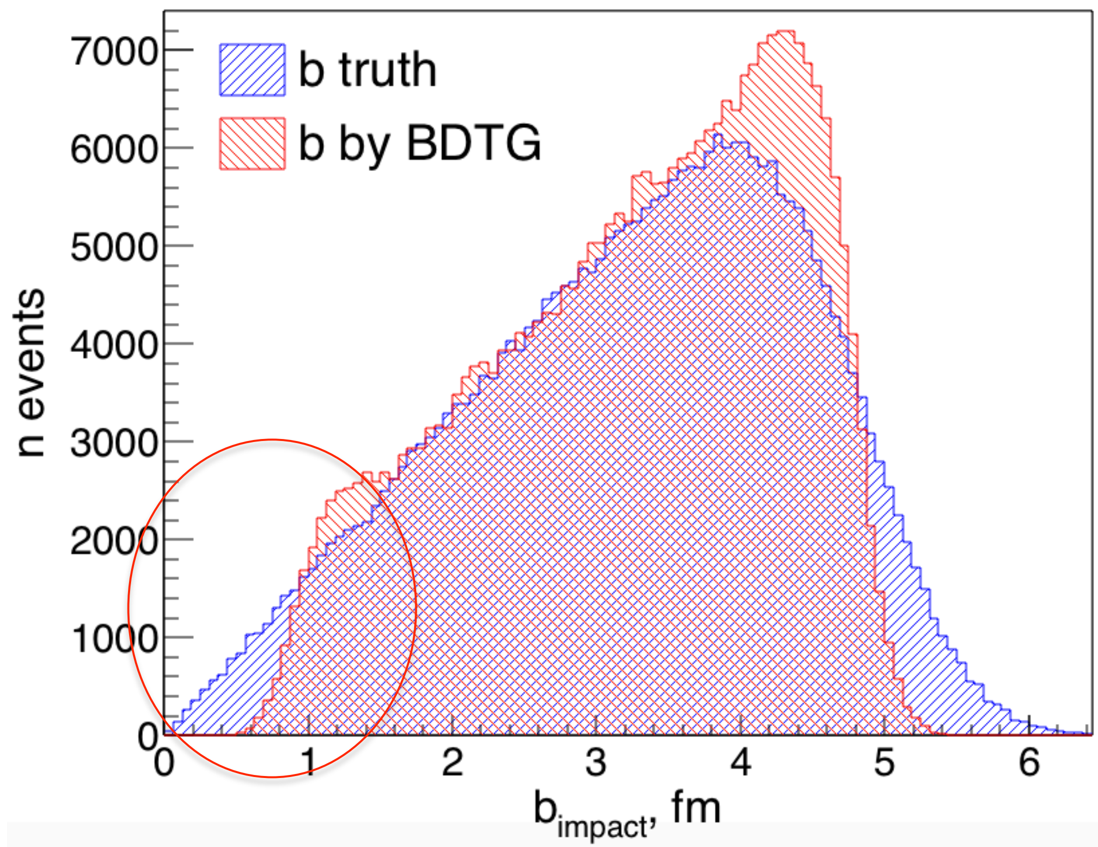
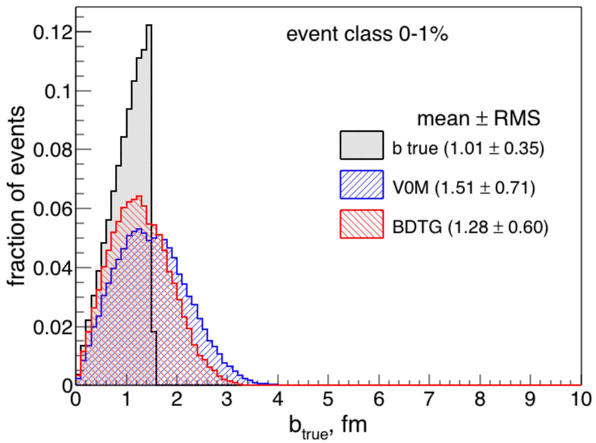
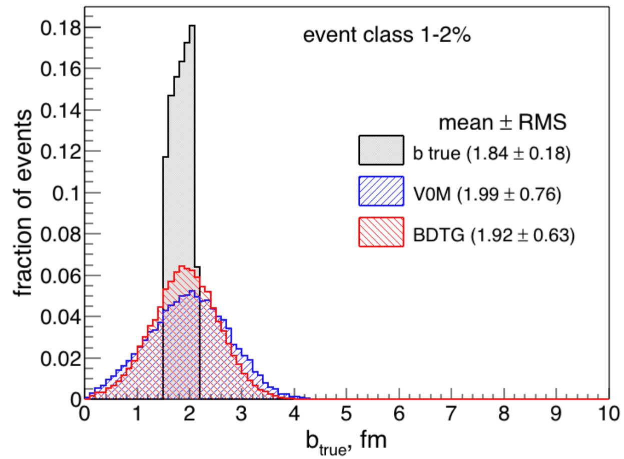


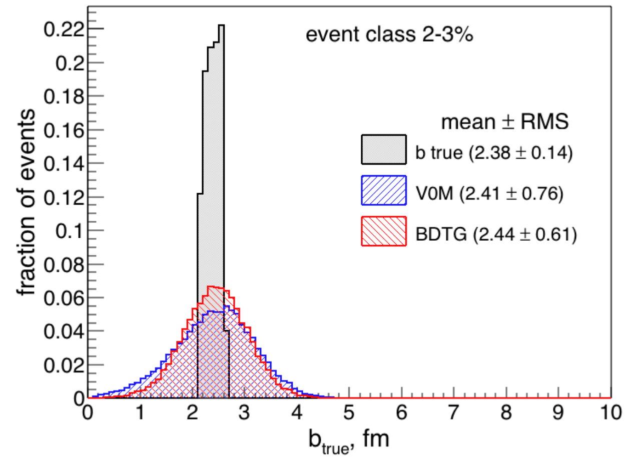
Regression by ML estimator: unavoidable "deformation" of the *b*-distribution at the edges.

ML estimator *vs* V0M-based selection

- Split the regression output of the estimator into centrality classes of 1% width
- Look at *b impact* distributions:







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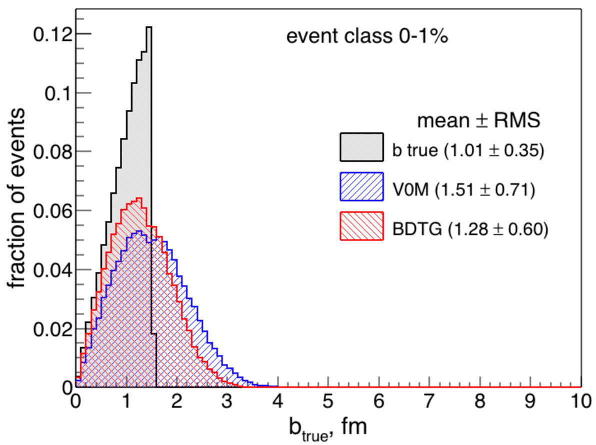
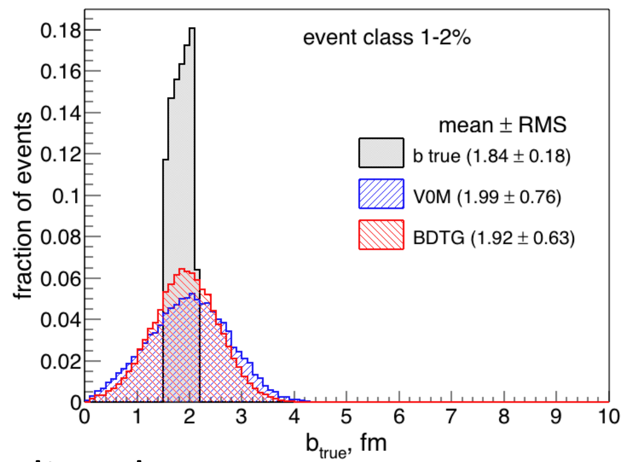
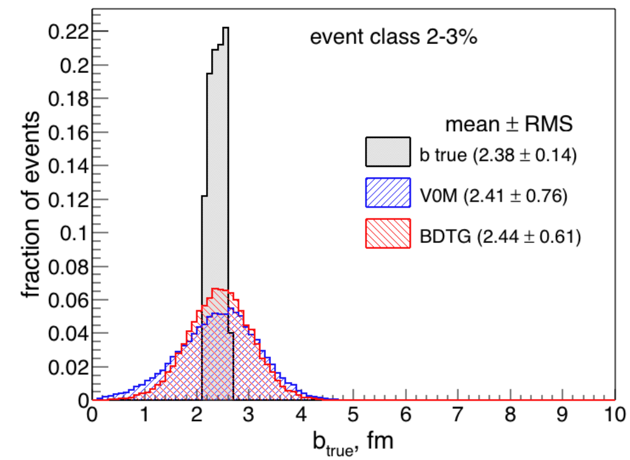
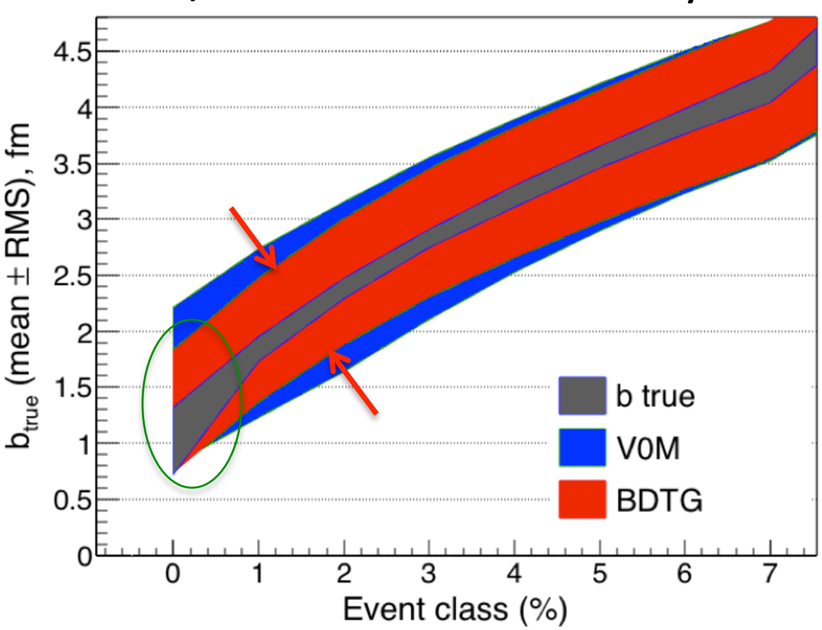






Mean +/- RMS within centrality classes:



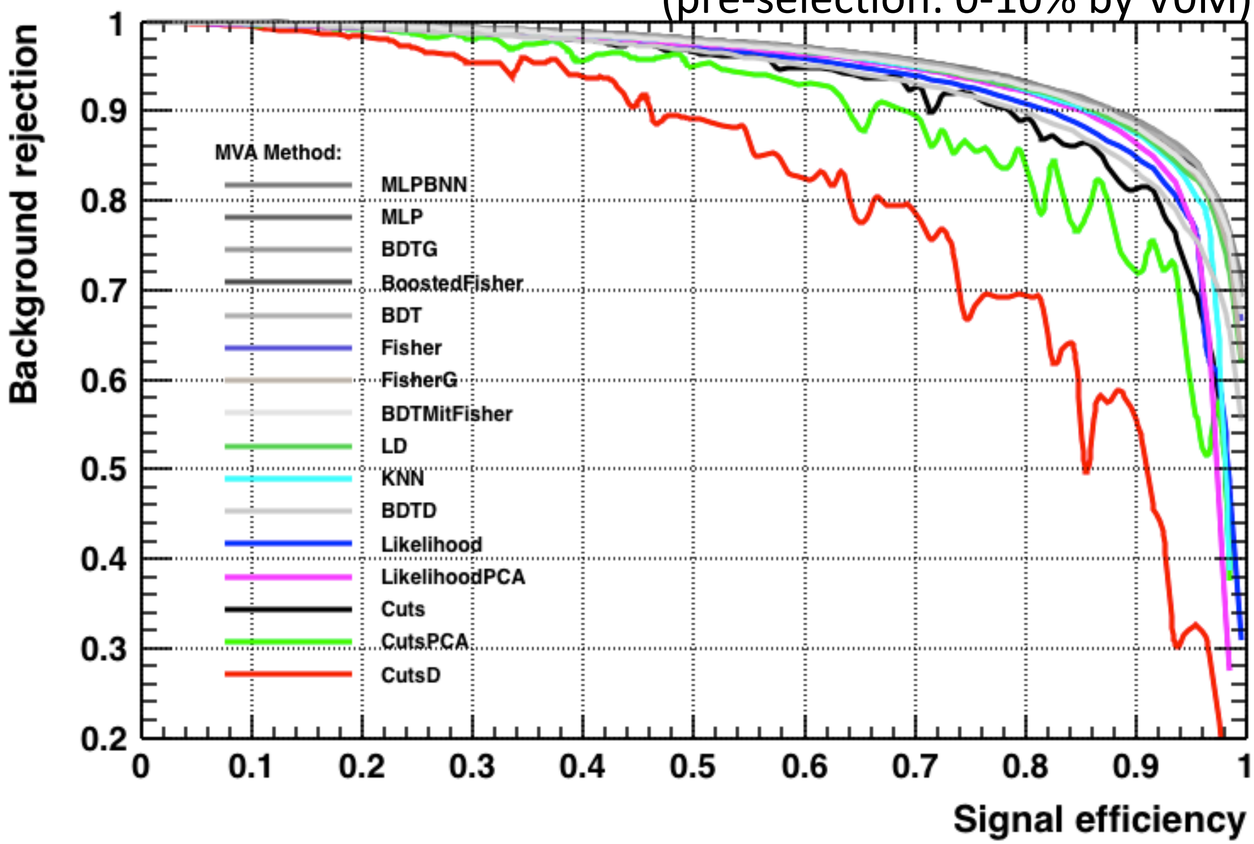
- *narrower* RMS by ML estimator than by V0M
- most central 0-1% events by estimator are *closer to truth* b

Study in terms of $\mathbf{N_{part}}$ should go even closer to truth!

Now try <u>classification</u> task: find *most central* events

signal = 0-1% most central events (b_{impact} < 1.5 fm)
background = other events

(pre-selection: 0-10% by V0M)



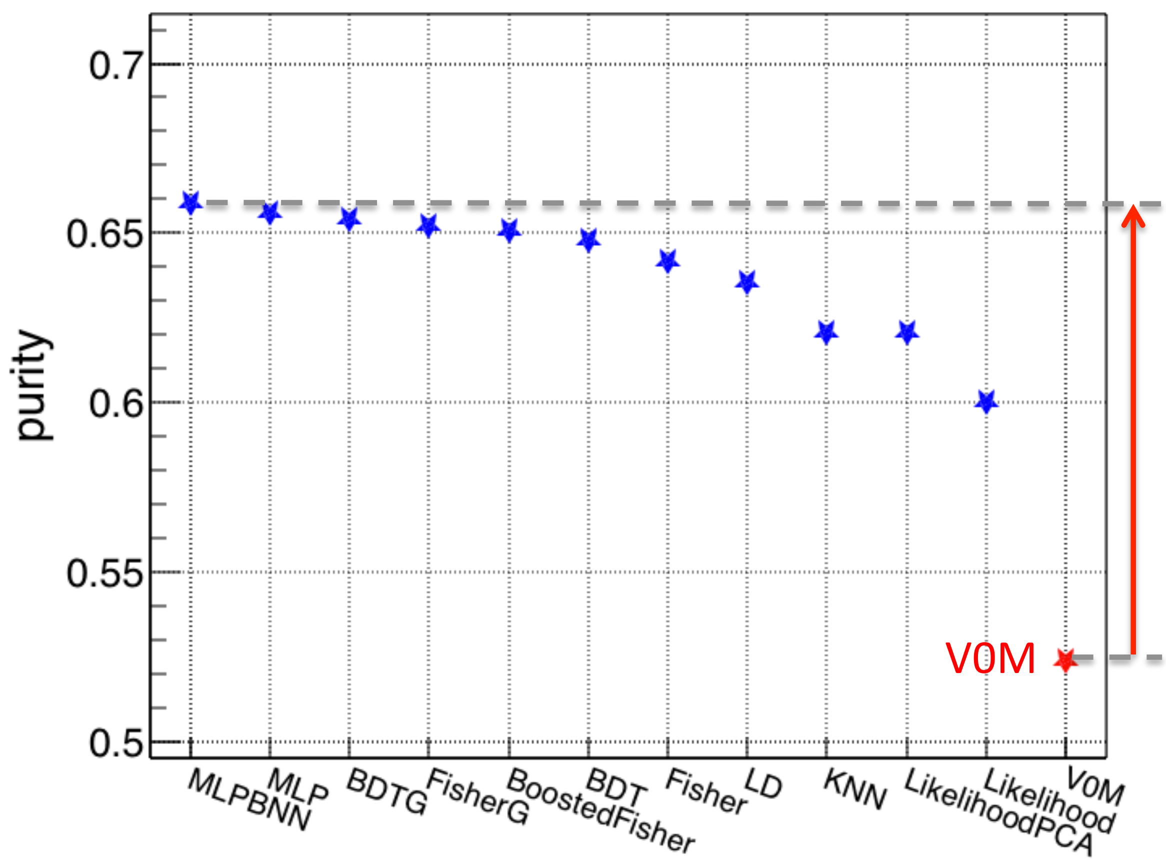
90k events

- Similar performance for the most of estimators
- Cut-based classifiers perform worse than others

Fraction of "signal" events selected by classifiers output

(="purity")

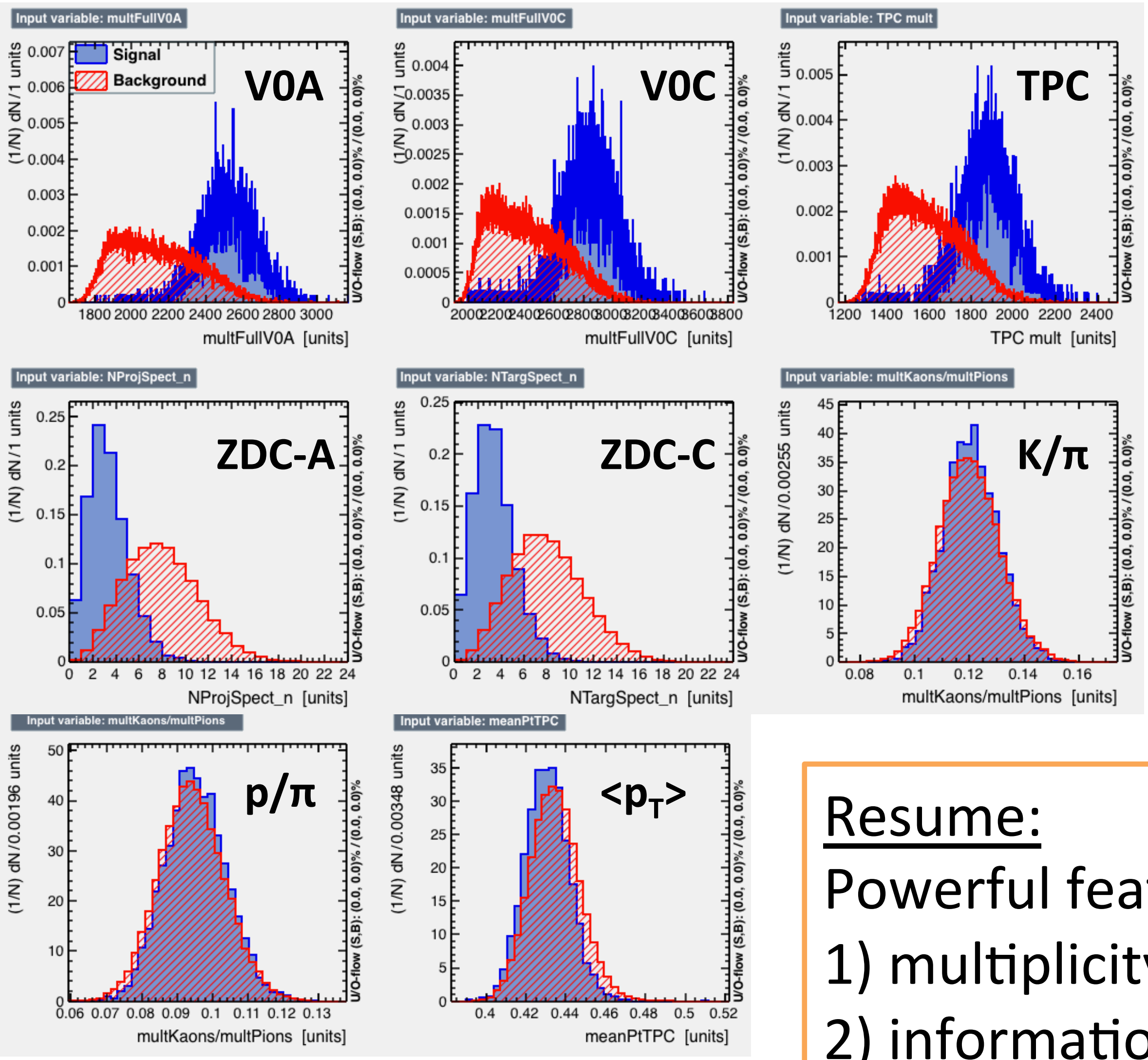
signal = 0-1% most central events (b_{impact} < 1.5 fm)

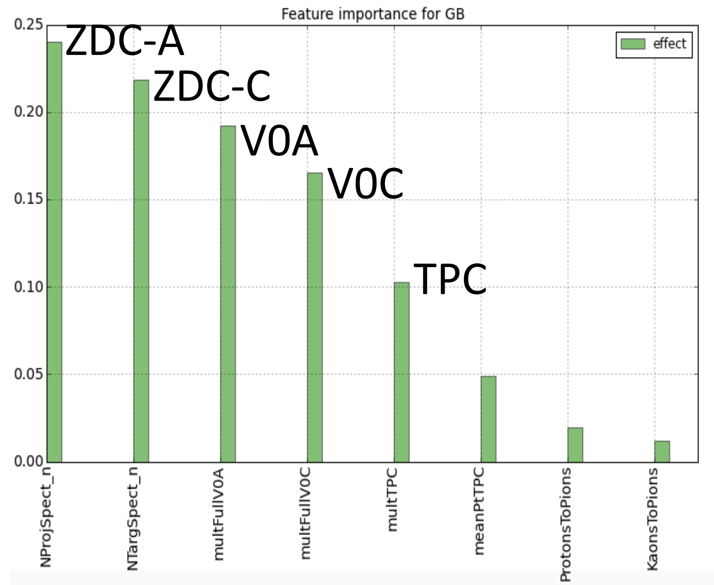


Compare to V0M estimator: purity is increased by ~13%.

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

Which features are the most relevant?





<u>Resume:</u>

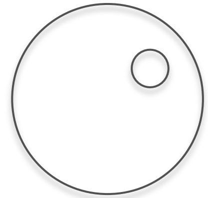
Powerful features are:

1) multiplicity in large rapidity ranges

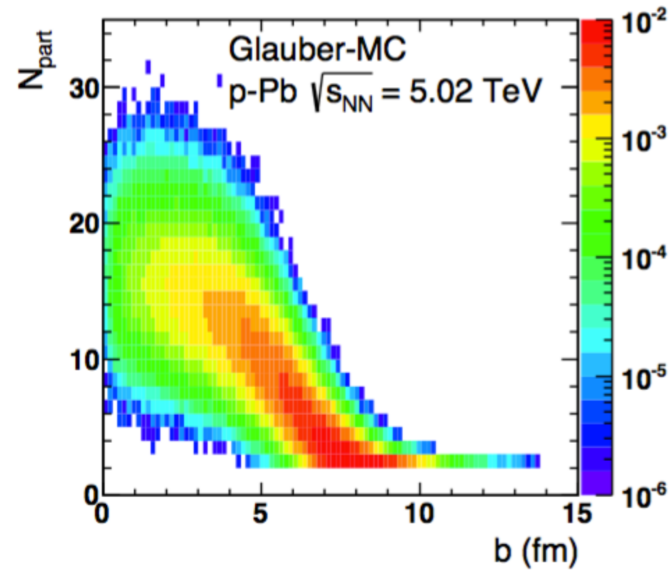
2) information about spectators

Additional features do not help.

From Pb-Pb to p-Pb collisions



centrality in p-Pb (ALICE)
arXiv:1412.6828



p-Pb collisions:

- larger fluctuations in Npart
- More bias from multiplicity-based estimators
- N_{part} is more reliable *target* than b_{impact}

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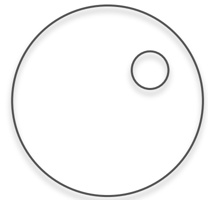

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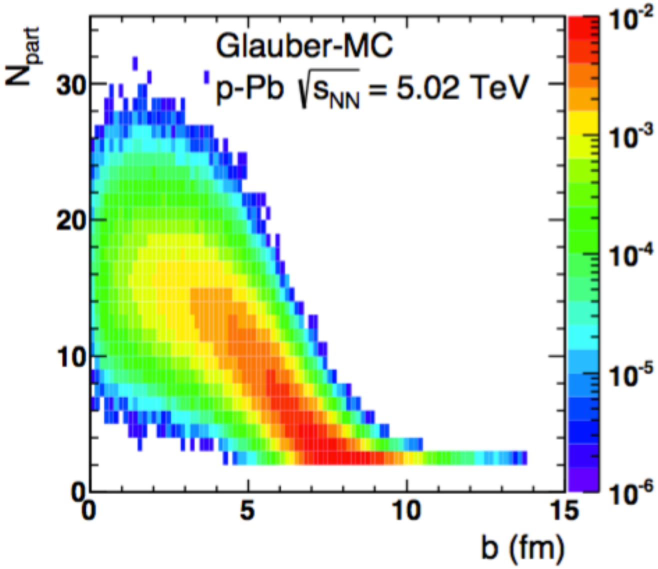

p-Pb collisions:

- larger fluctuations in Npart
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- N_{part} is more reliable *target* than b_{impact}

Try ML classification task with N_{part} as a target:

split all events into 5 classes
0-20, 20-40, 40-60, 60-80, 80-100%,
0-20% = most central
How often do we get true N_{part} in 0-20% using estimator output?

Use for that 5 *mln* AMPT p-Pb events

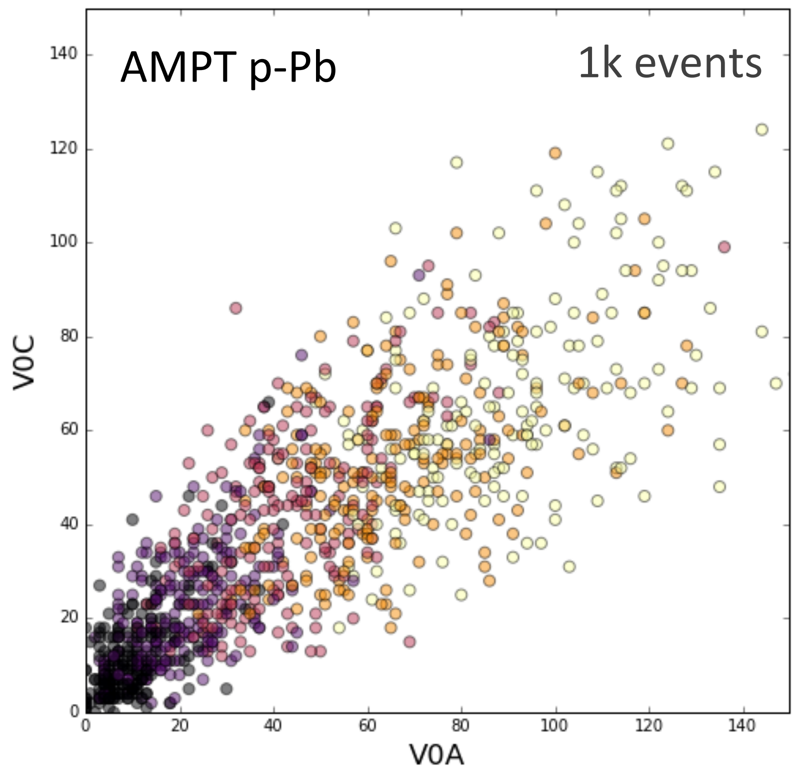
Visualize decision boundaries

p-Pb

Two features: mult in VZERO-C && mult in VZERO-A

$-3.7 < \eta < -1.7$ $\quad$ $2.8 < \eta < 5.1$

Target: N_{part}



Colors:
5 true centrality classes

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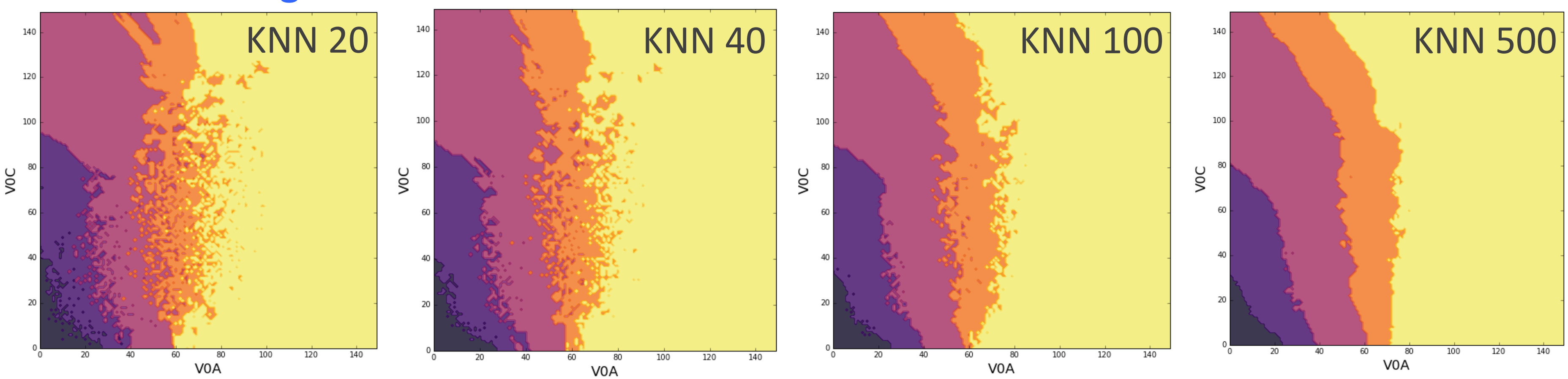
(using scikit-learn library)

K-nearest neighbors:



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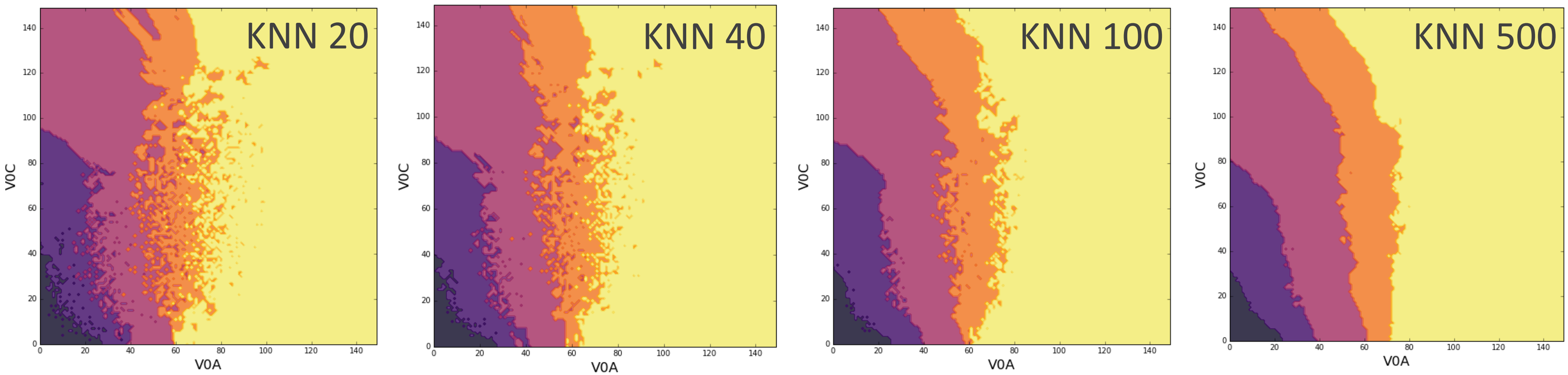
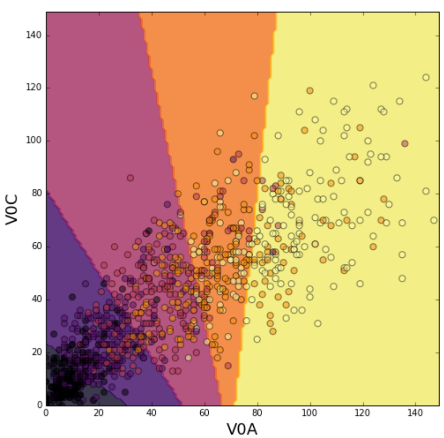
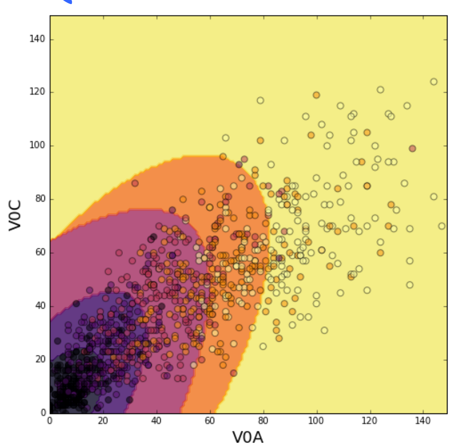


Linear Discriminant:



Quadratic Discriminant:



Visualize decision boundaries (other features)

p-Pb

Two other features: mult in VZERO-A && ZDC-neutrons

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$2.8 < \eta < 5.1$

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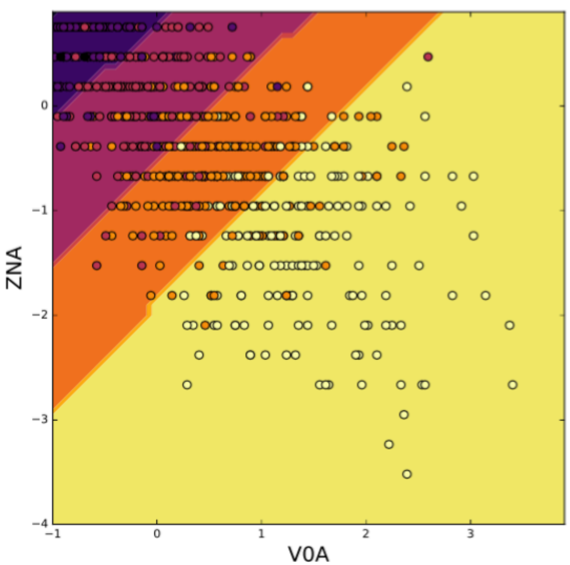

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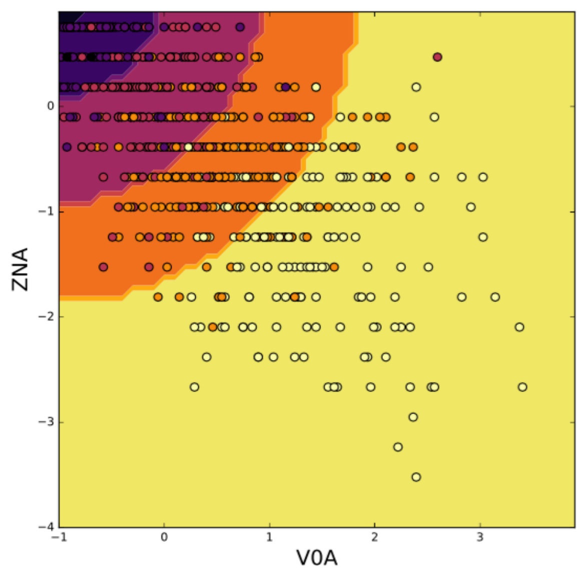

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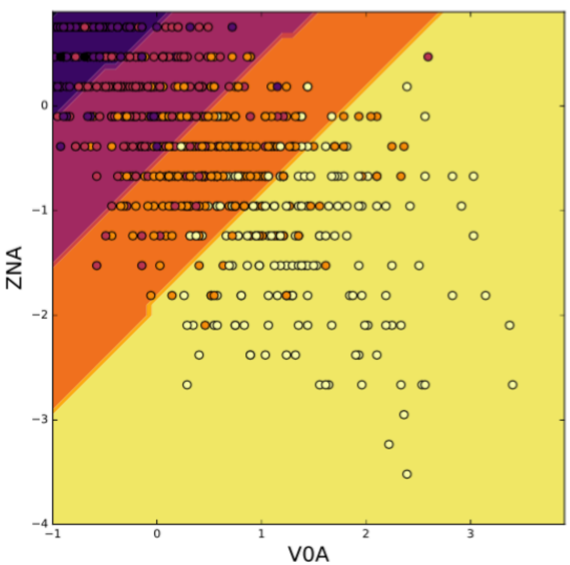

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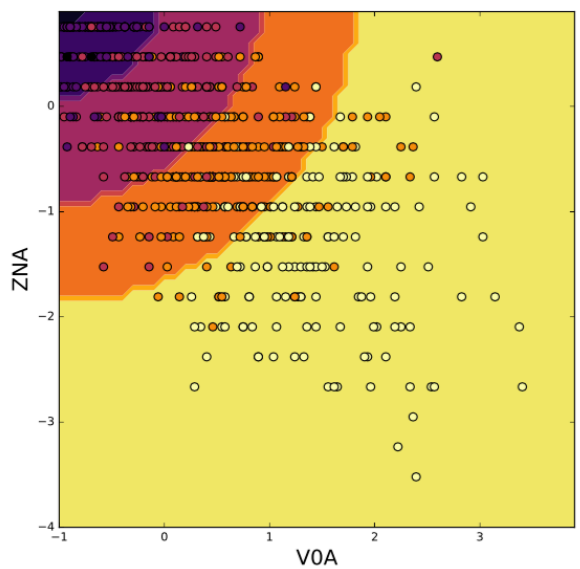
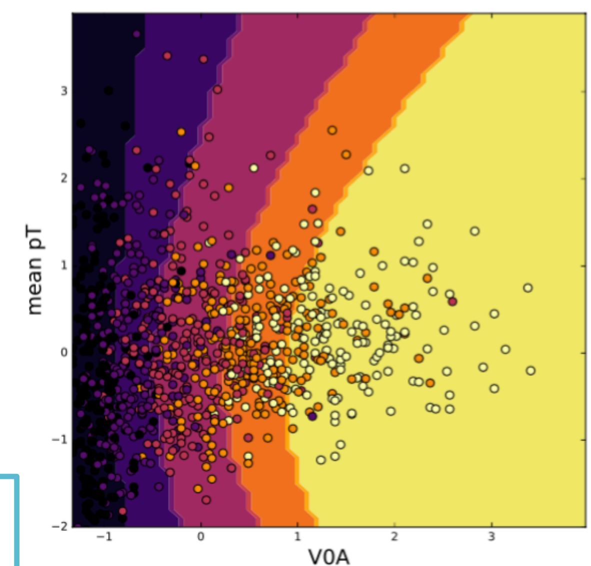


Try another feature: mean p_T (vs V0A)

Quadratic Discriminant:



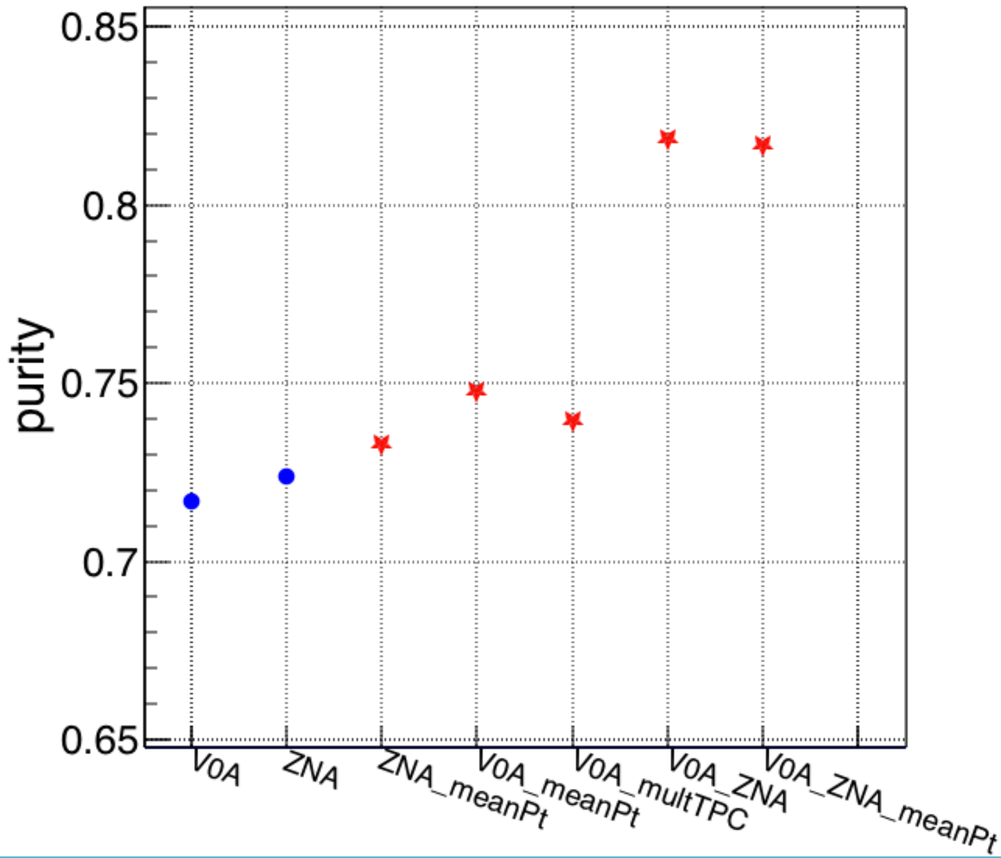
Task:
how often do we get true N_{part} in 0-20% using estimator output?

"Purity" of selection events in 0-20% by N_{part}

p-Pb

Compare different feature sets
basing on Quadratic Discriminant classification:

(target: N_{part})

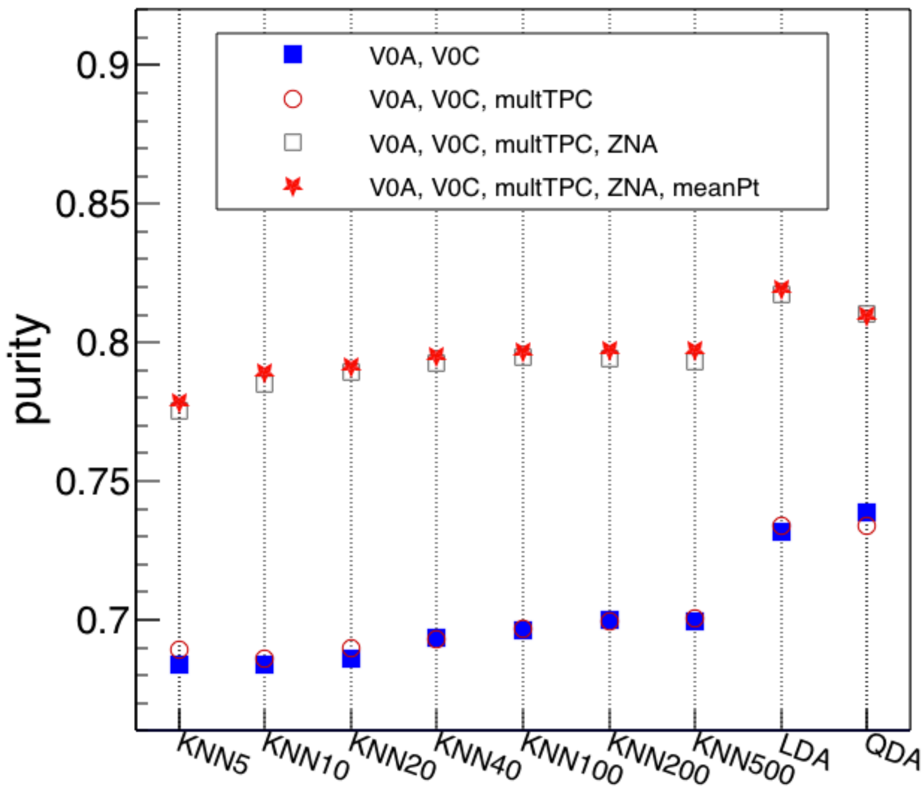


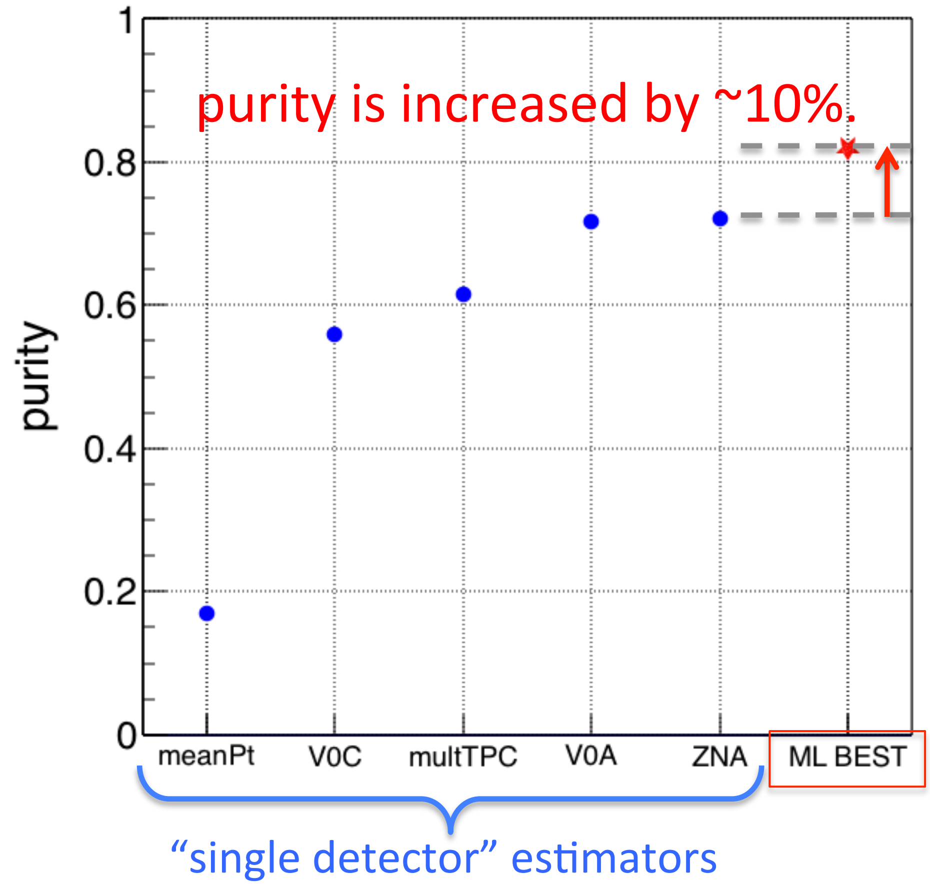
- Combination V0A && ZNA provides best results
  - Other features are almost irrelevant

"Purity" of selection events in 0-20% by N_{part}

p-Pb

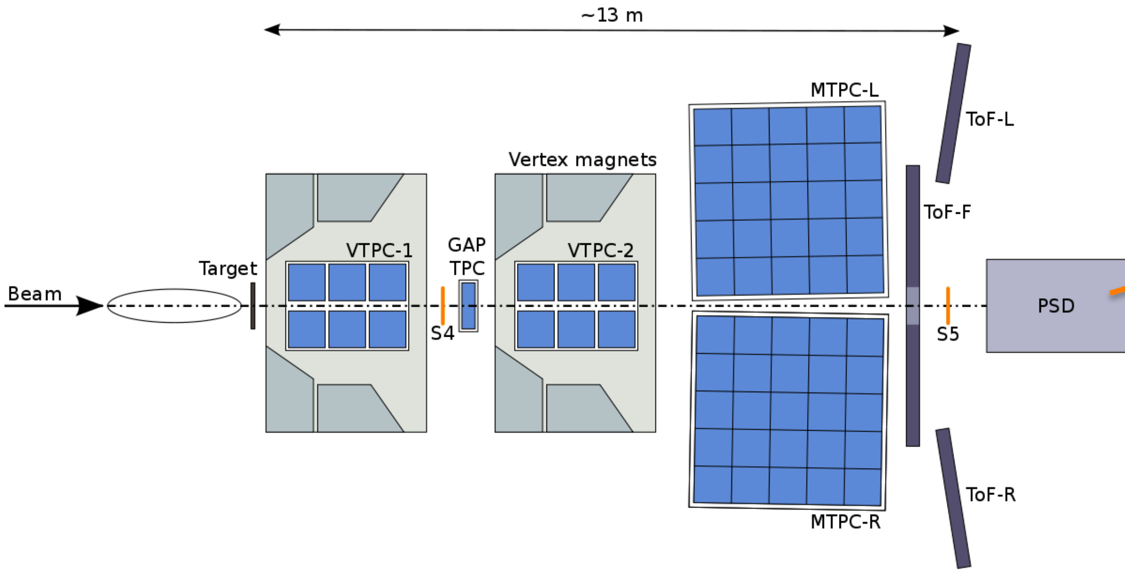
Different feature sets and several ML algorithms:



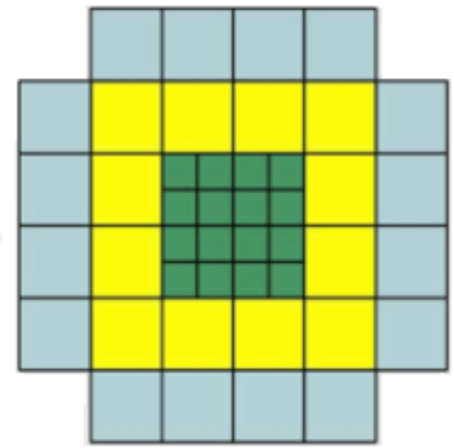


ML-based classification allowed to increase purity of 0-20% class in terms of N_{part} by ~10%.

Possible ML task in fixed target experiment NA61/SHINE



Projectile Spectator Detector (PSD)



http://shine.web.cern.ch

- Centrality in AA collisions in NA61 experiment is determined by energy in modules of PSD (possibly in combination with data from TPC's).
- Modules in PSD are fired by spectators **and** particles born in collision.

→ Possibilities to use ML classifiers to cope with these conditions and increase resolution of centrality selection?

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- ML algorithms are able to select most central events with higher “purity” without loss of statistics using info from several detectors.
- In this exploratory work, increase in purity is ~10-13%
  → possible to gain more?.
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Thanks for your attention!