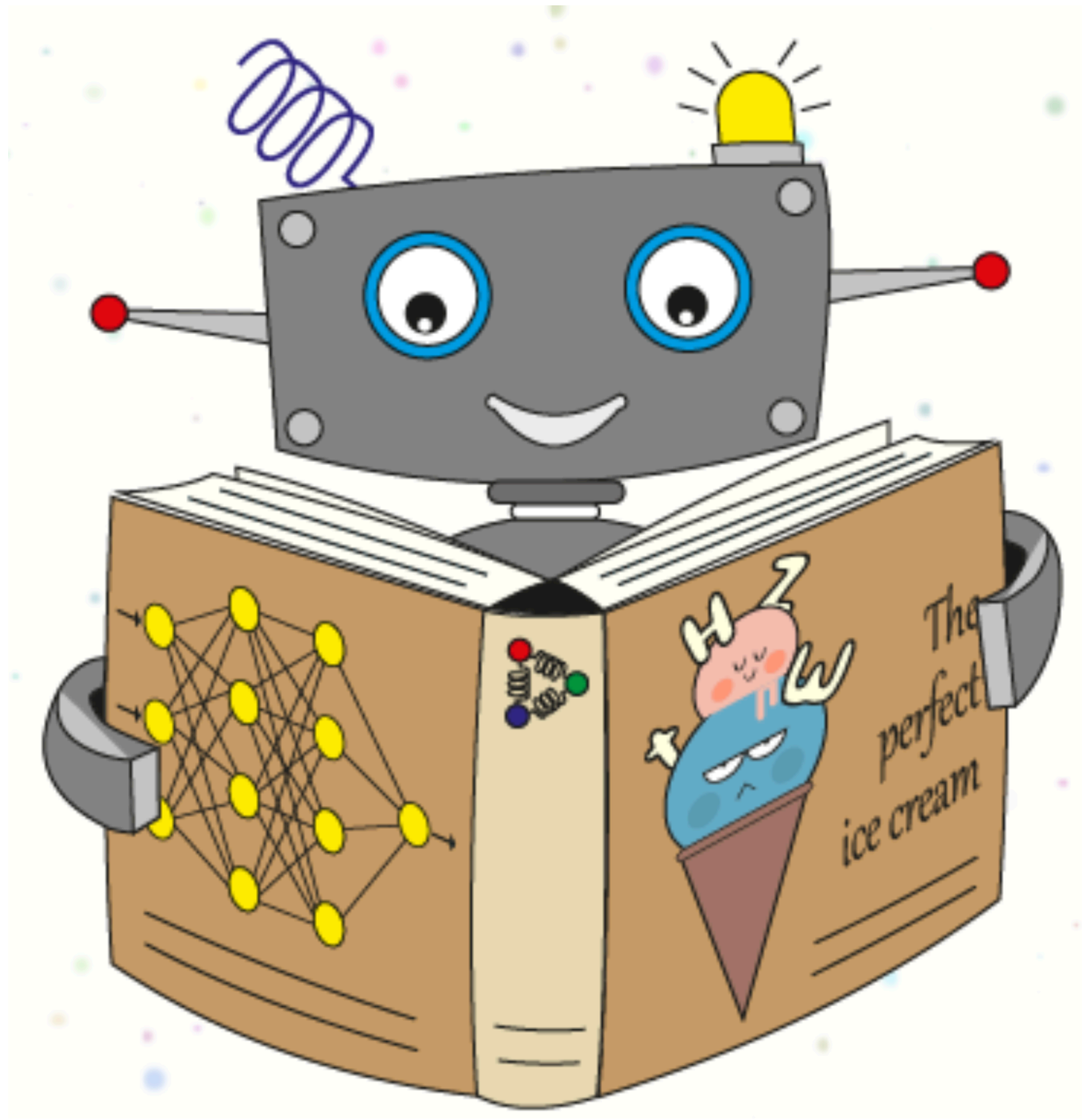
BDT, shallow and deep neural network techniques for analysis and detector reconstruction



Gian Michele Innocenti (CERN)

Machine Learning in HEP
A conversation over ice-cream
October 5, 2021

Special thanks to Hannah Bossi, Fabio Catalano, Maja Kabus for the material and the useful discussions

Overview of the talk

- **A short introduction to heavy-ion (HI) physics and its analysis/reconstruction challenges**

- **Few selected examples of BDT/network techniques applied to HI physics**

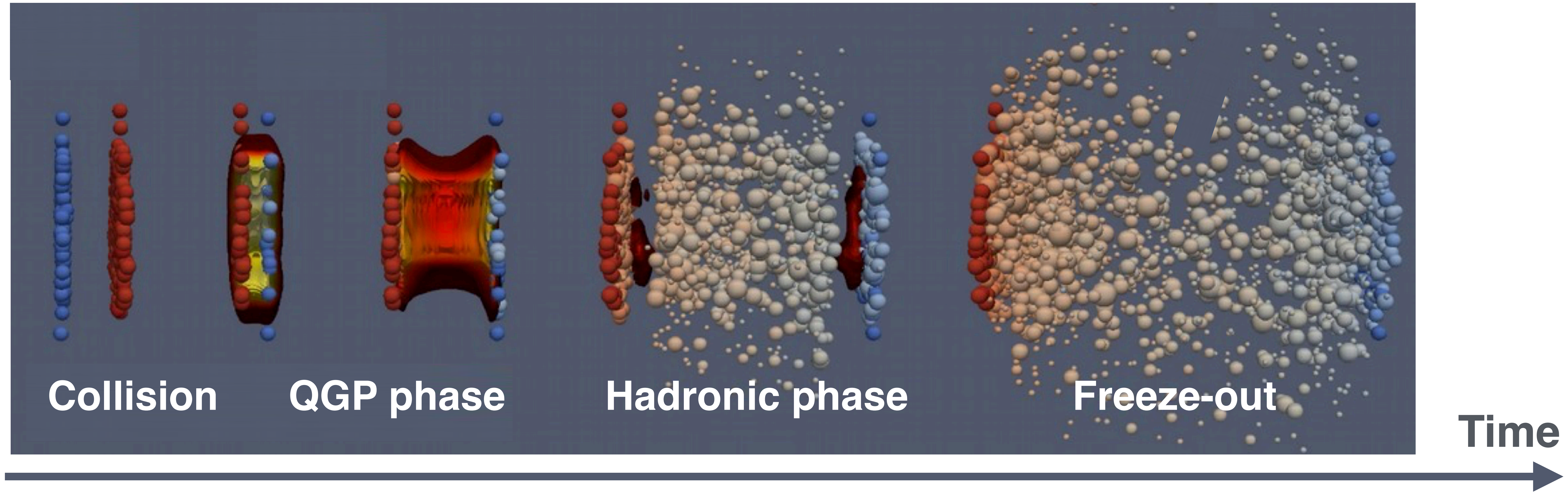
  - BDT analyses for “rare” hadron identification in PbPb collisions
  - Shallow neural networks for jet physics in HI
  - DNN for detector calibration of Time-Projection-Chamber for Run3 data taking

- **Conclusions and future challenges/opportunities**

Heavy-ion physics in a nutshell

→ QCD at extreme temperature and density (Quark Gluon Plasma) to study quark deconfinement (and more)

MADAI Collaboration



Quark-gluon plasma radiation and restoration of chiral symmetry

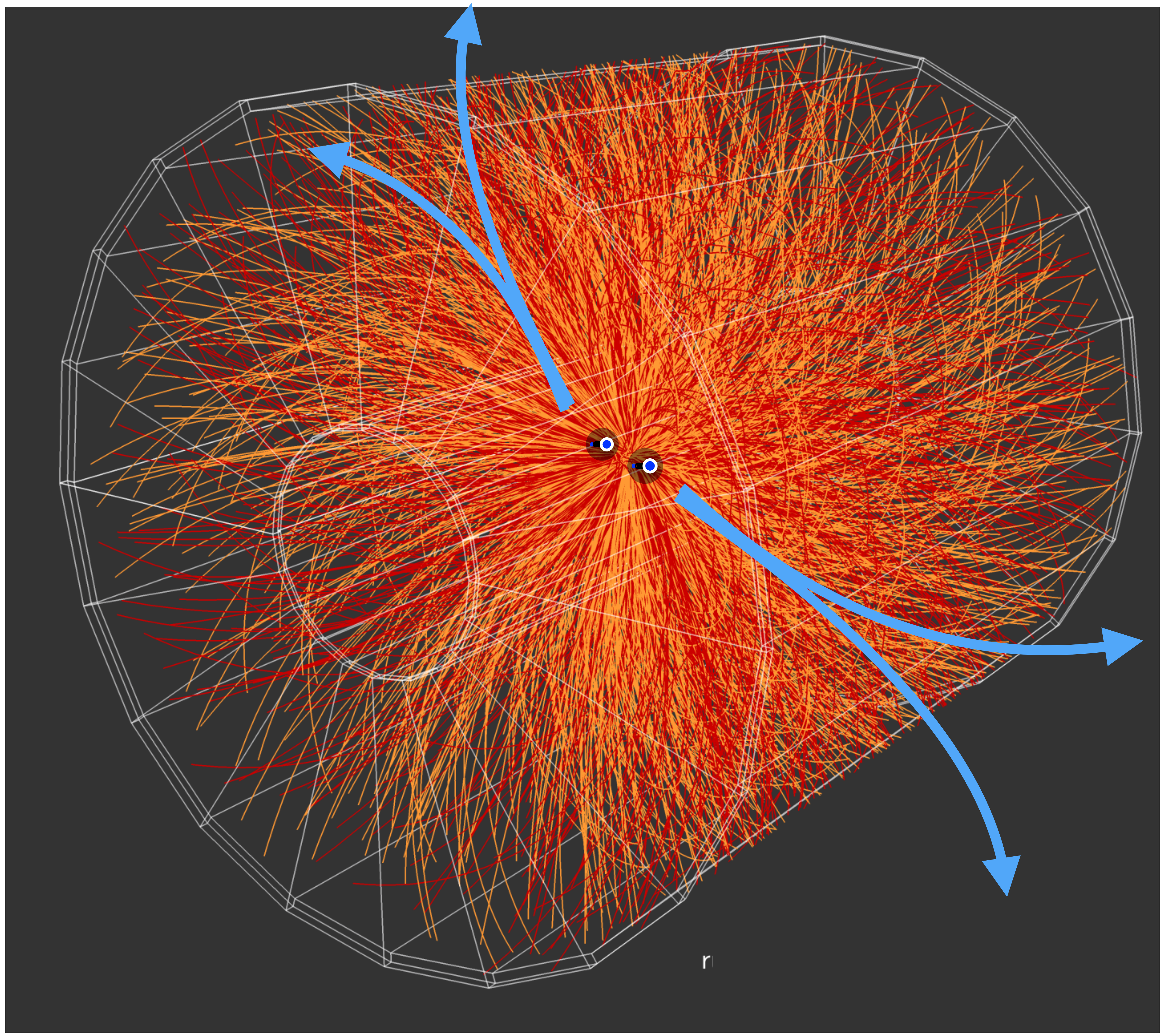
QGP microscopic "structure" and access to quasi-particles with quenching measurements

Hadronization beyond in-vacuum fragmentation

→ **Indirect probes**:
- suppression of high-p_T probes (heavy-flavor or jets)
- particle correlations to study fluid-like
- EM probes (W, photons, …)

Heavy- ion challenges and ML techniques

Large ion collisions (PbPb or AuAu) produces thousands of particles!



High-particle density:
- O(100) more particles than in pp collisions

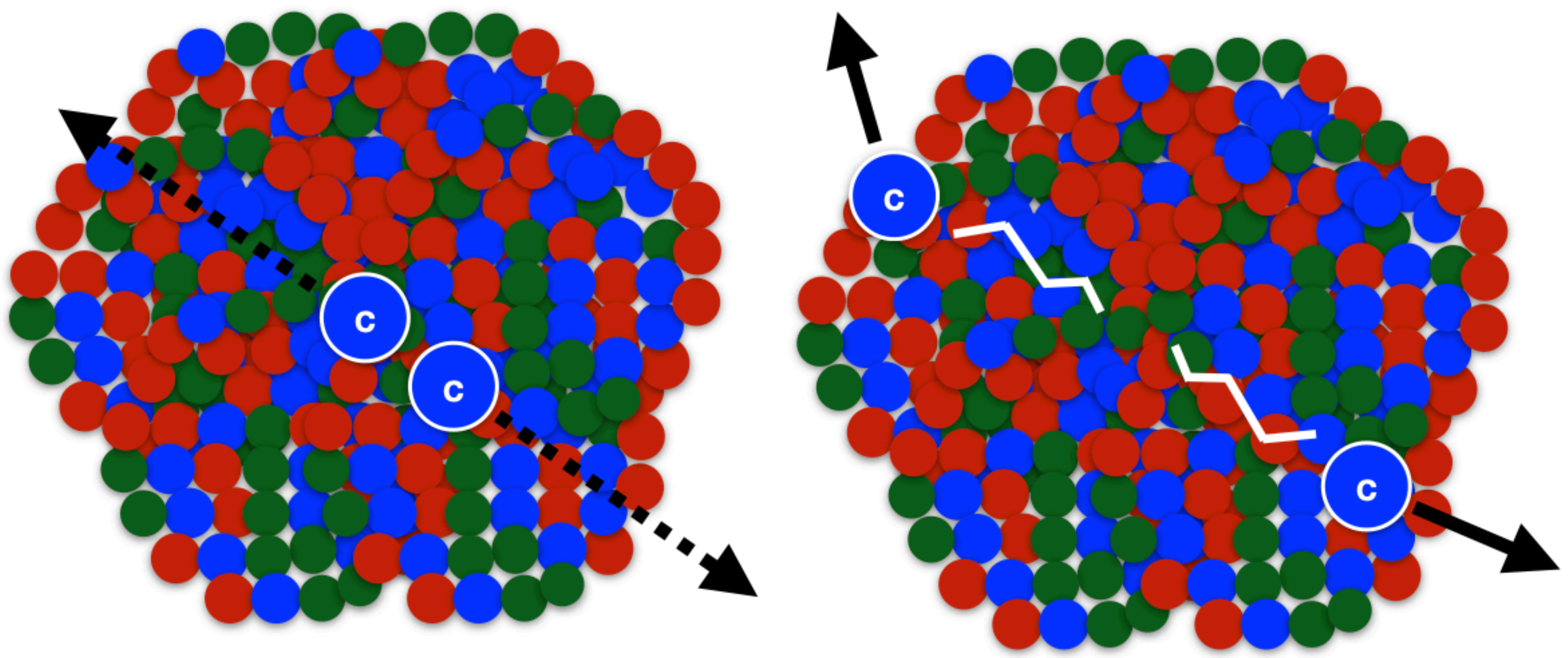
Interest in low-p_T probes and correlations:
- e.g. few GeV hadrons, D, B mesons
- low-p_T jets

→ Large background contamination and low S/B
→ Need for detectors with high tracking accuracy and PID capabilities at low p_T

ML techniques offer unique opportunities to overcome these challenges:
→ few (selected) examples in the upcoming slides!

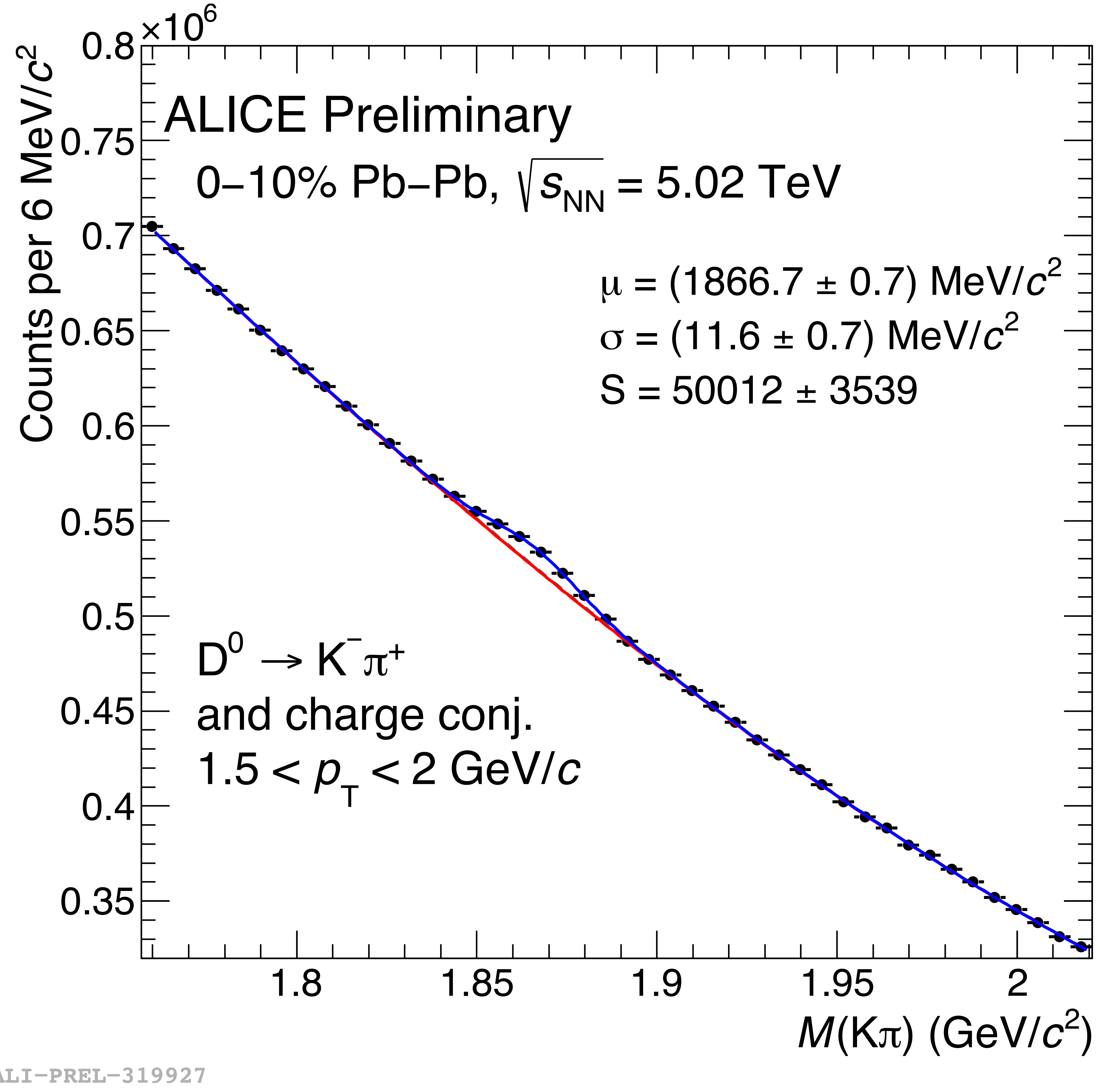
BDT techniques for “rare" signal measurements at low p_T

BDT for heavy-flavor measurements



Modification of heavy-flavor hadron yields in PbPb vs pp:

- information about the medium density and properties
- low $p_T \sim m_c$ is of highest interest



→ D/B mesons in HI are affected by huge backgrounds at low-p_T mostly from uncorrelated pair/triplet combination

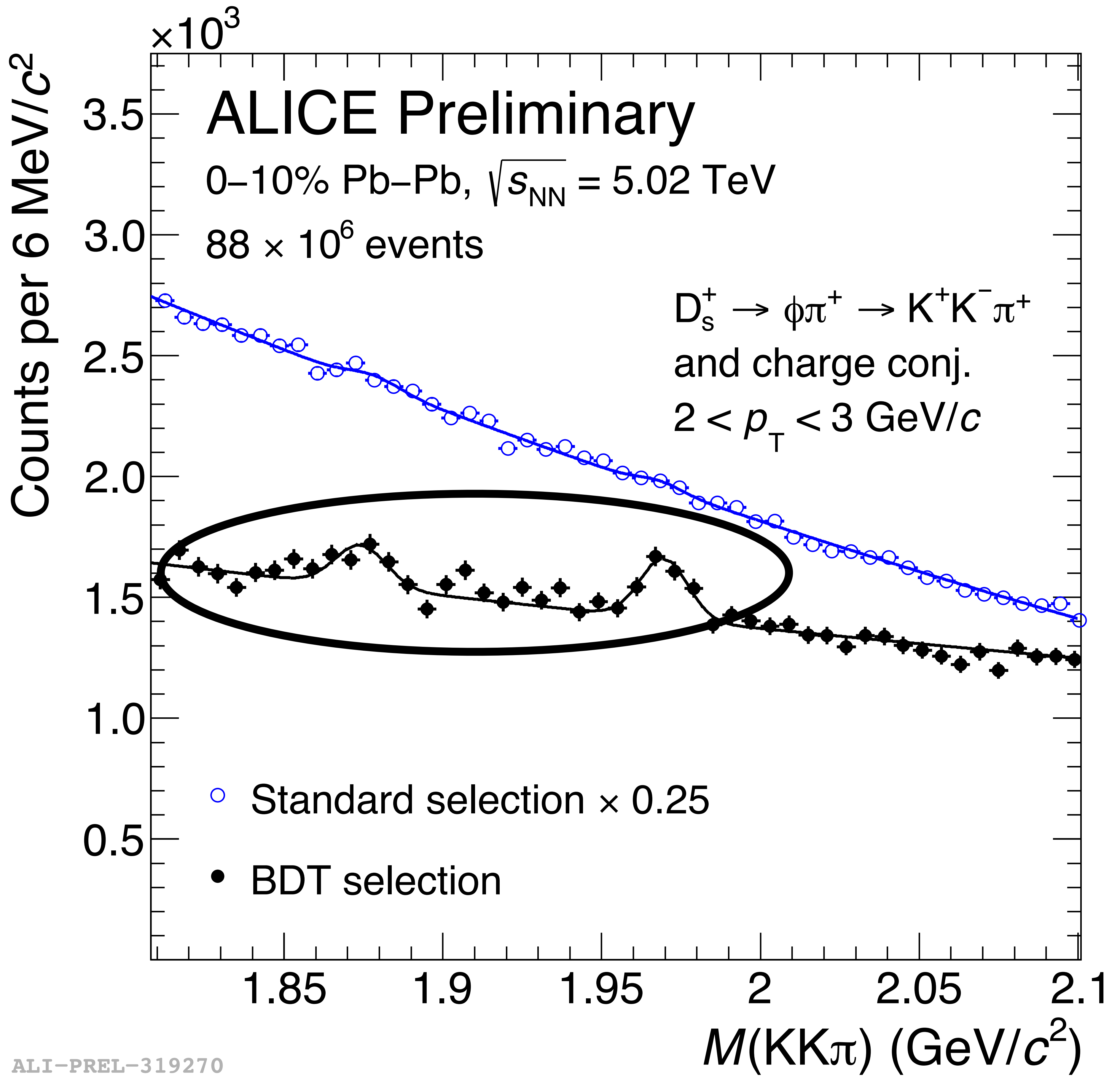
→ **Signal / Background down to 10^{-6}**

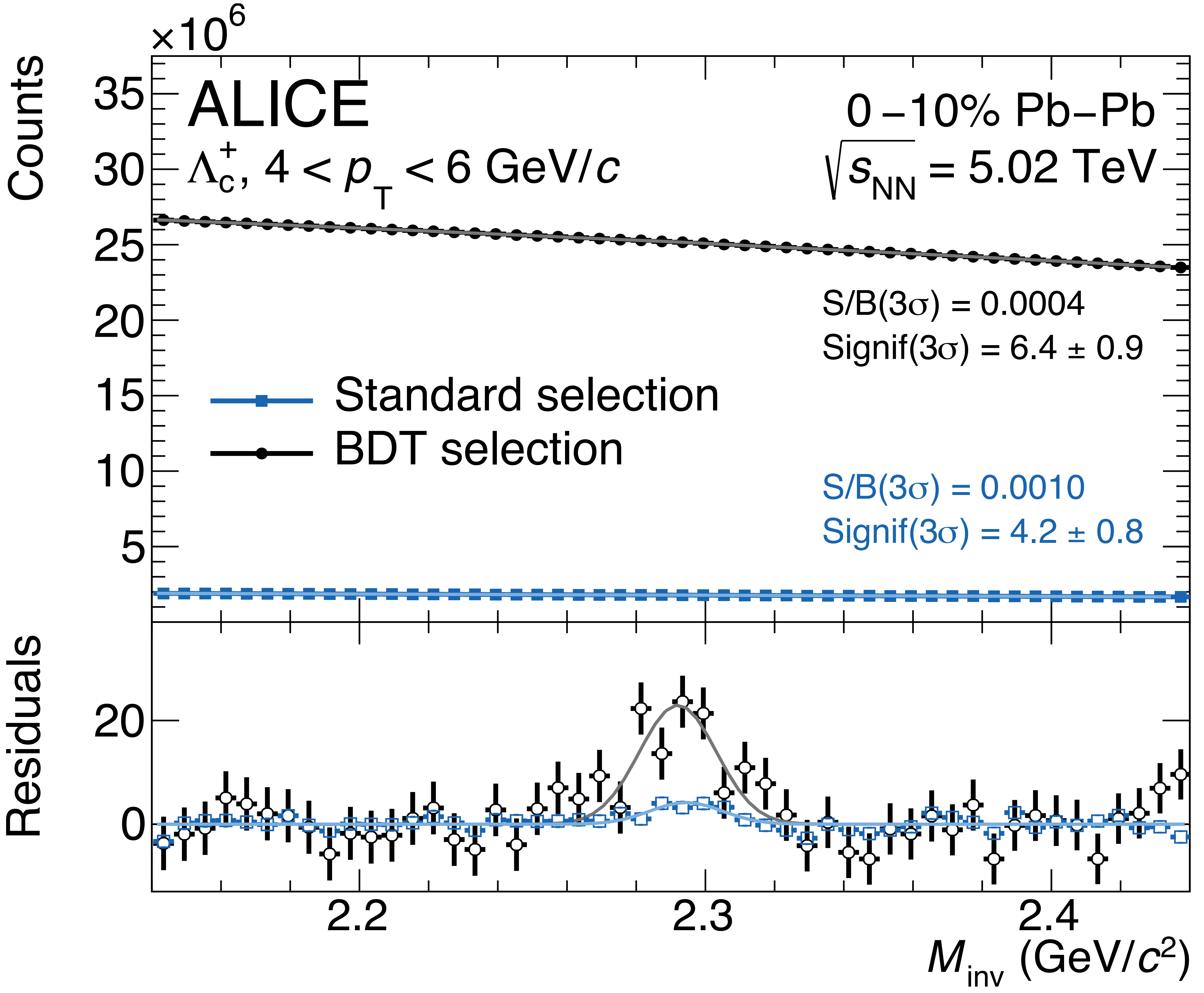
→ **High-purity selection is critical**

BDT for D_s, Λ_c measurements in PbPb

BDT performed with a combination of PID and topological selections:

→ measurement to the very low-p_T regime, **not accessible without ML techniques**



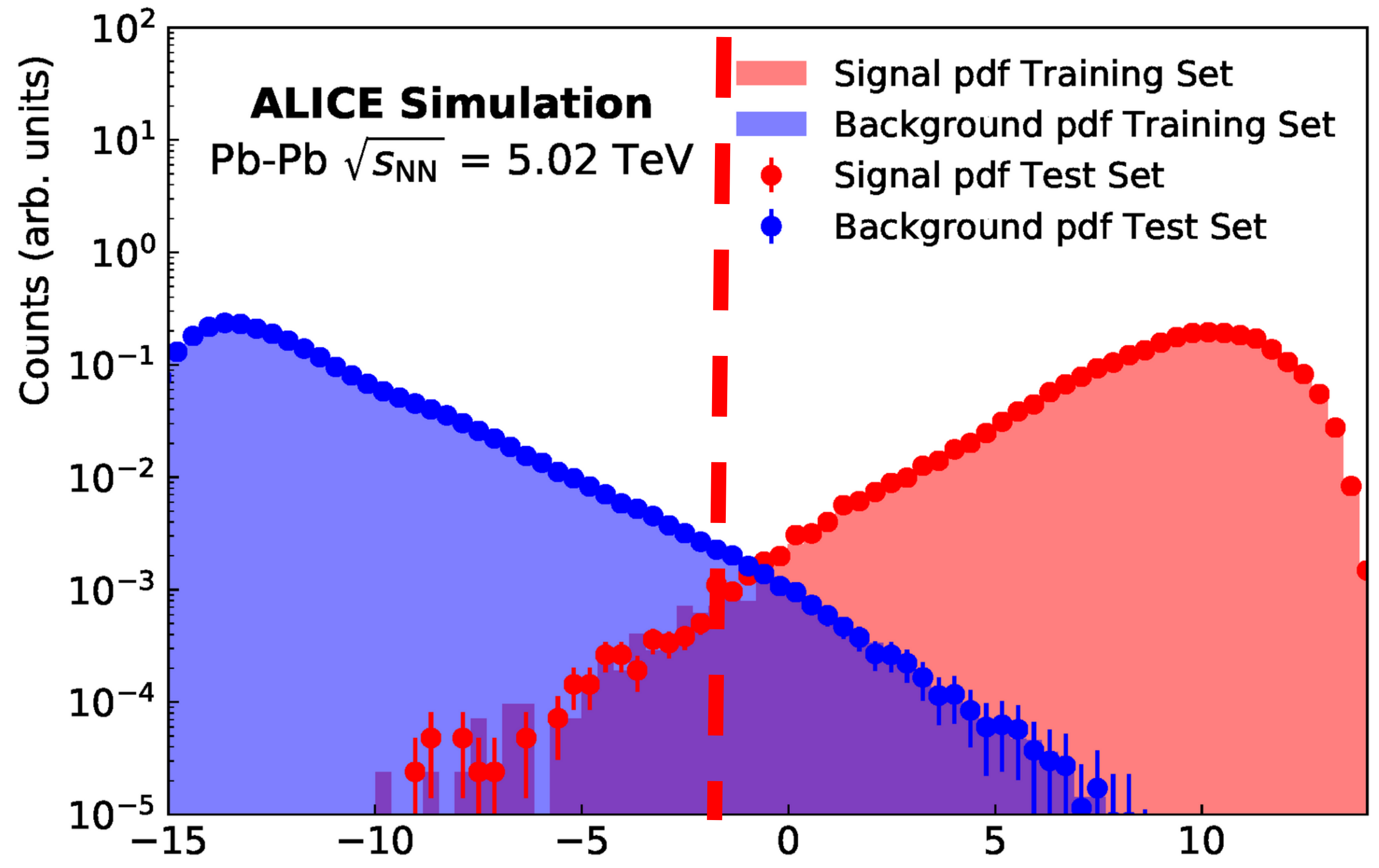


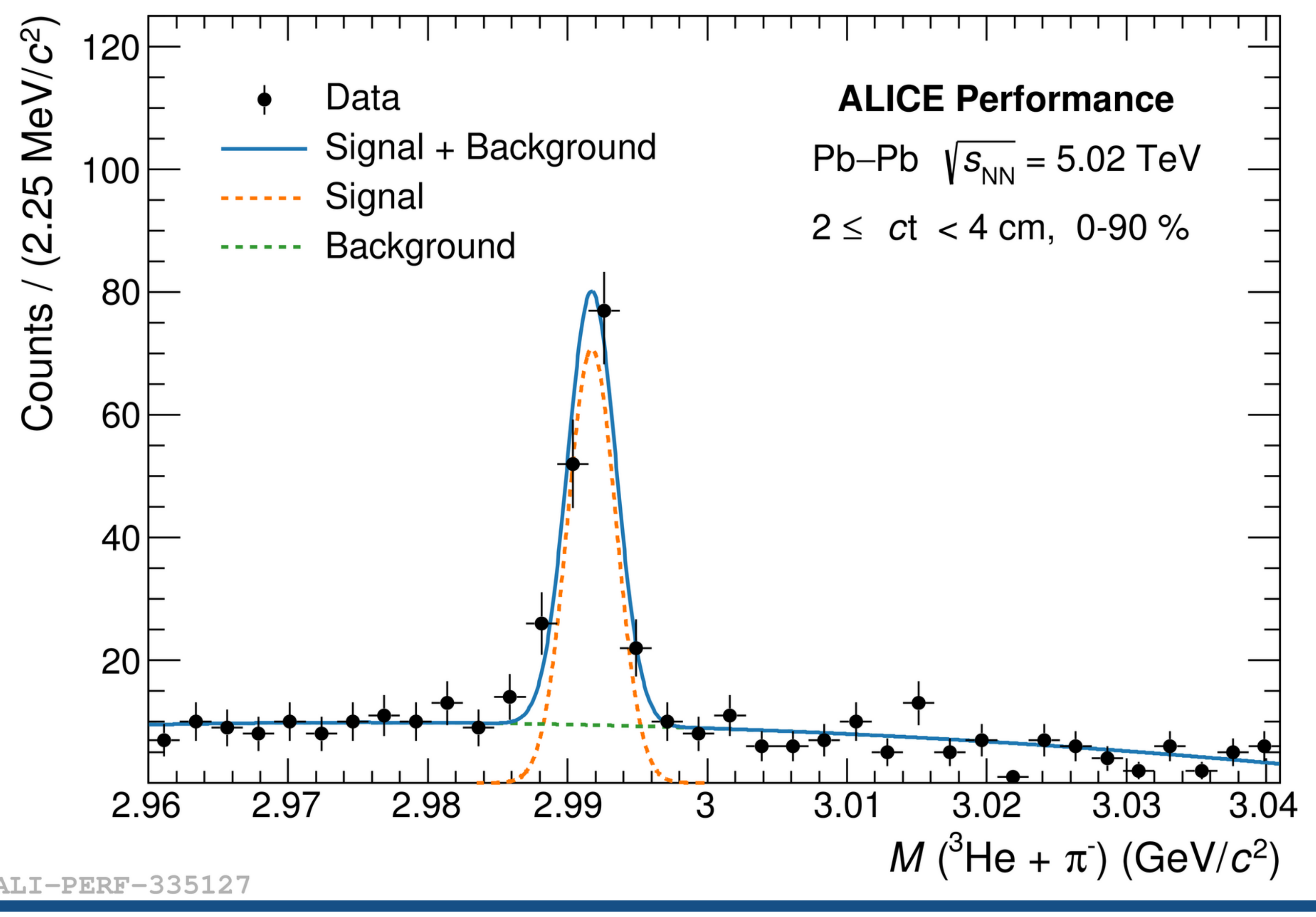
Challenges:

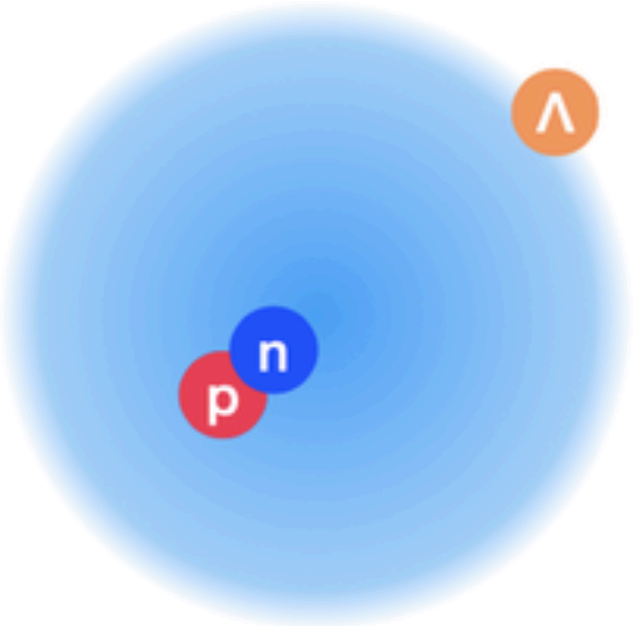
- MC/data reweighing, systematic evaluation in p_T interval where no standard analysis was possible, …

$^{3}_{\Lambda}$H selection: BDT approach

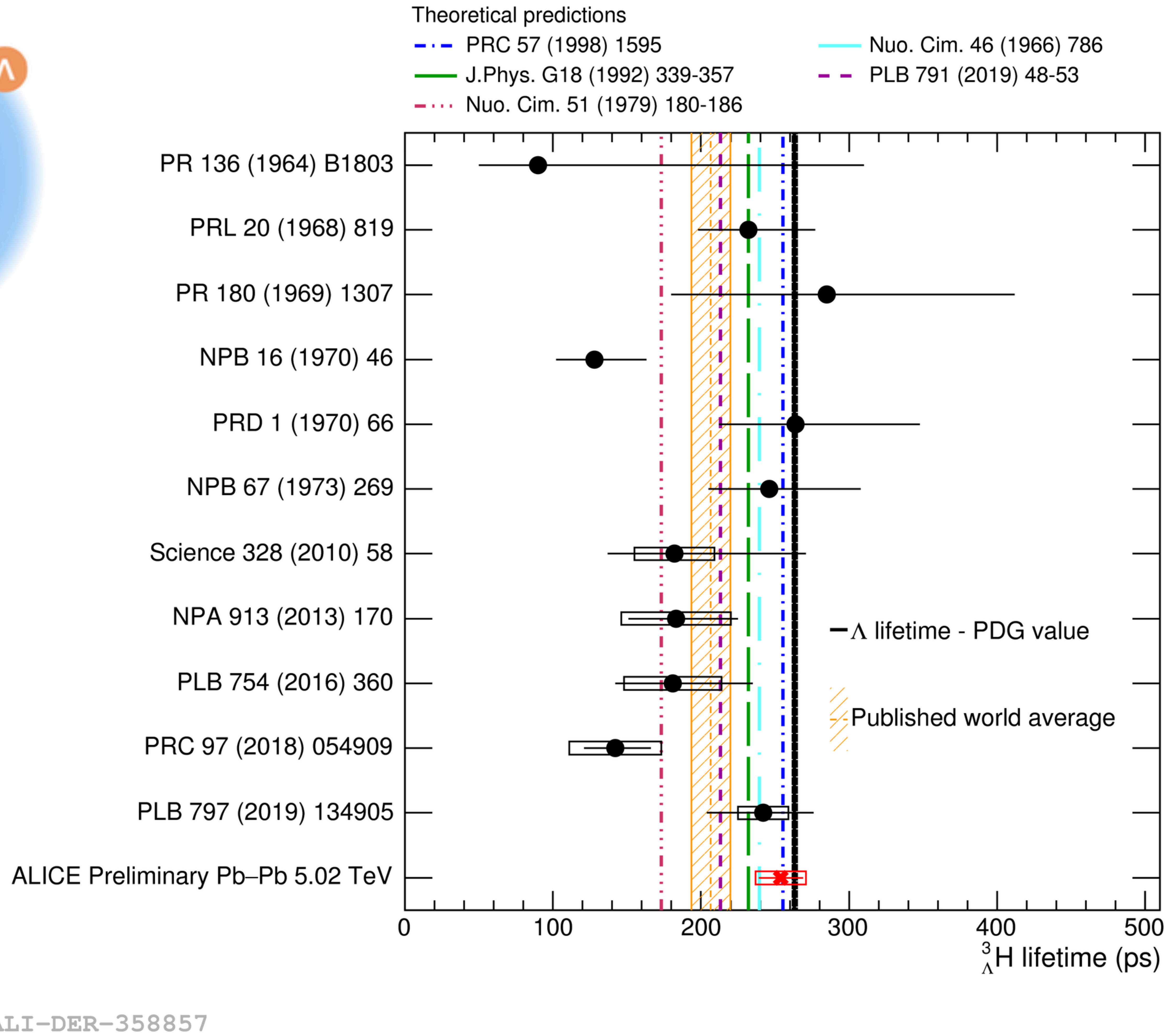
Selection applied on the BDT score, computed from PID and topological features
- maximisation of the expected significance (assuming thermal production)







$r = 10.79^{+3.04}_{-1.53}$ fm

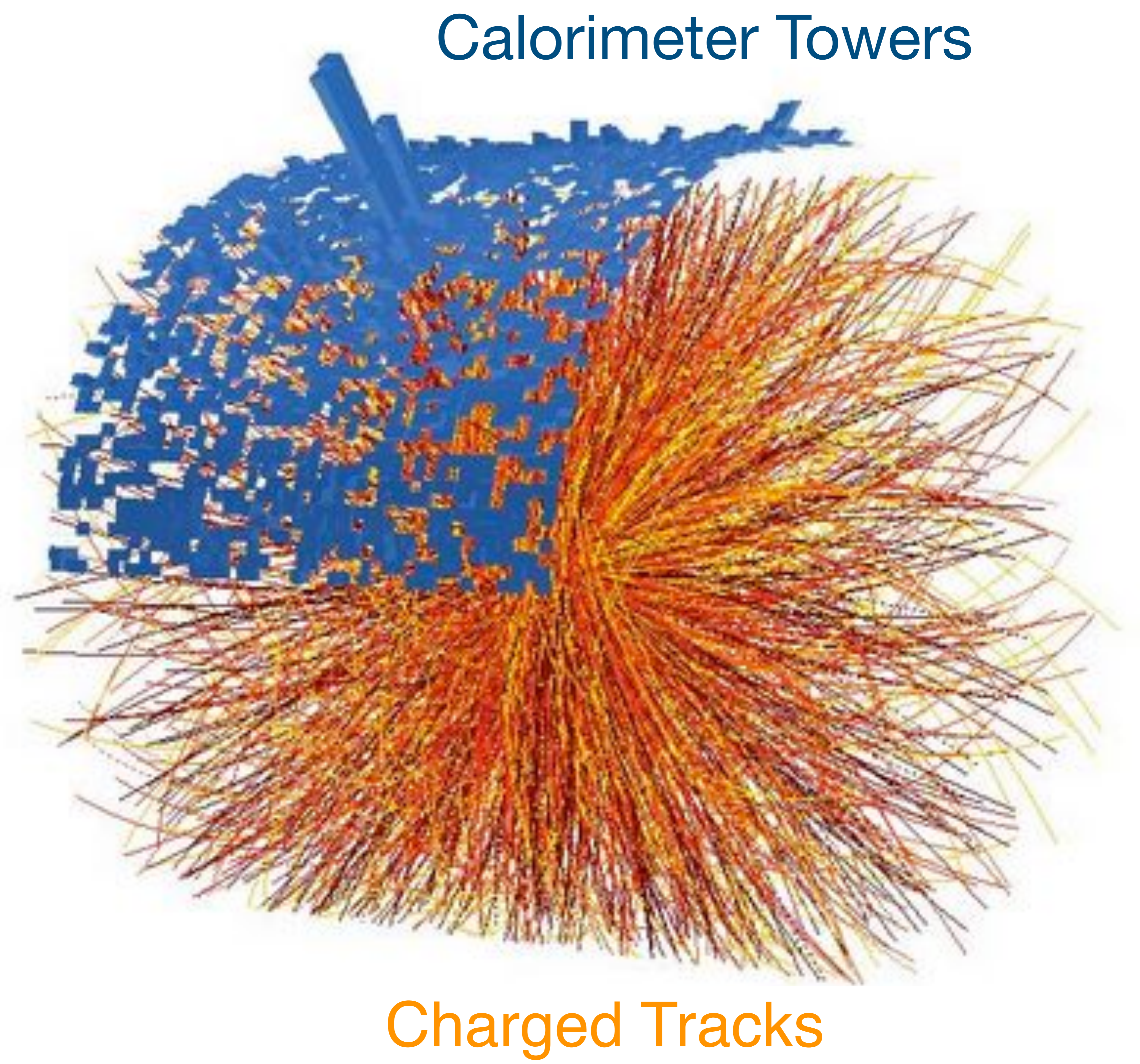


Shallow neural networks for HI jet physics

Underlying Event (UE) subtraction for HI jets

Reconstruction of inclusive jet p_{T} in HI made difficult by the large fluctuating background from the underlying event.

For low p_{T} jets, fluctuations can be on the order of jet itself!
→Need to subtract the large fluctuating background
→very challenging to low p_{T} (tens GeV) and wide jets (up to R=1)



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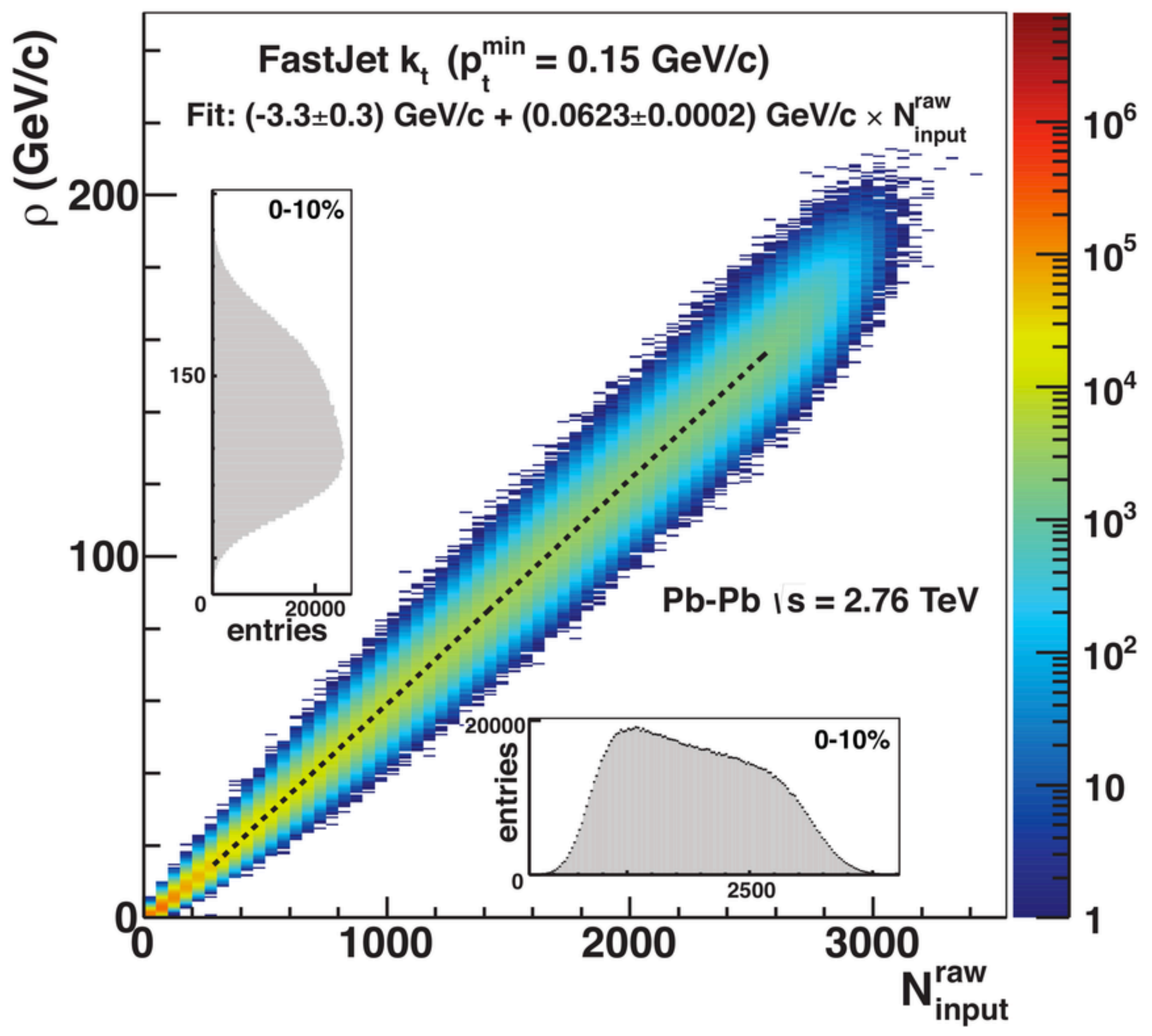


"Classic"Area based method:
Pedestal subtraction of event-averaged momentum density.

1. Estimate and subtract the pedestal

$$p_{\mathrm{T,rec}} = p_{\mathrm{T,raw}} - \rho A$$

2. Leading track bias to remove fake contributions

3. Correct for residual fluctuations via unfolding

UE subtraction with ML techniques

Use machine learning (ML) to create a mapping to correct the jet for the background

Jet Properties

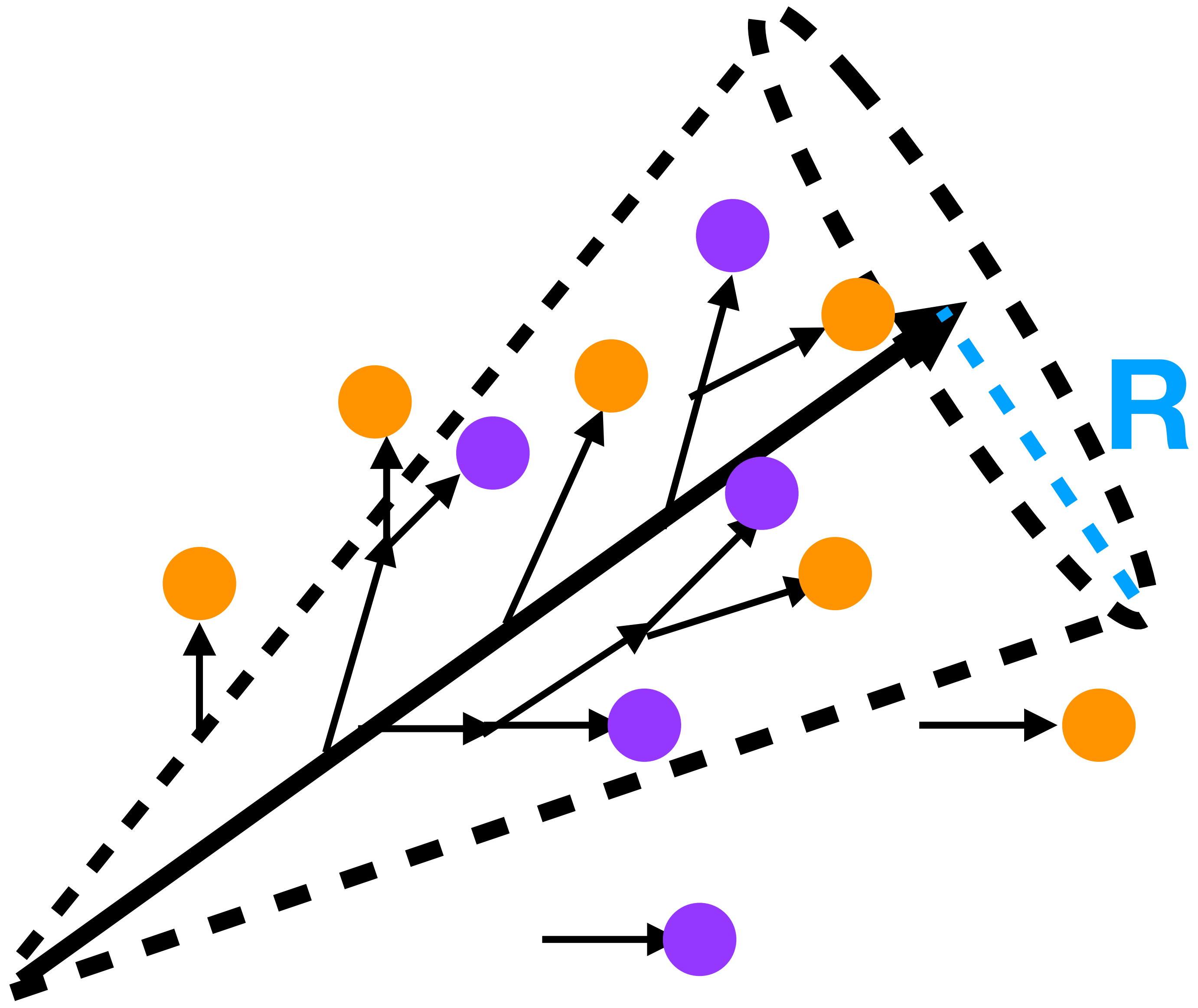
(Including constituent properties)

ML →

Corrected Jet p_{T}

→

Unfold for fluctuations and detector effects



R.Haake, C. Loizides Phys. Rev. C 99, 064904 (2019)

UE subtraction with ML techniques

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Jet Properties

(Including constituent properties)

ML →

Corrected Jet p_{T}

→

Unfold for fluctuations and detector effects

Training (PYTHIA fragmentation)

Train on "hybrid event" created by embedding PYTHIA jets into Pb-Pb Background

Shallow neural network implemented in *scikit-learn*.

3 layers [100,100,50] nodes

Testing

Apply ML estimator to hybrid events not used in training.

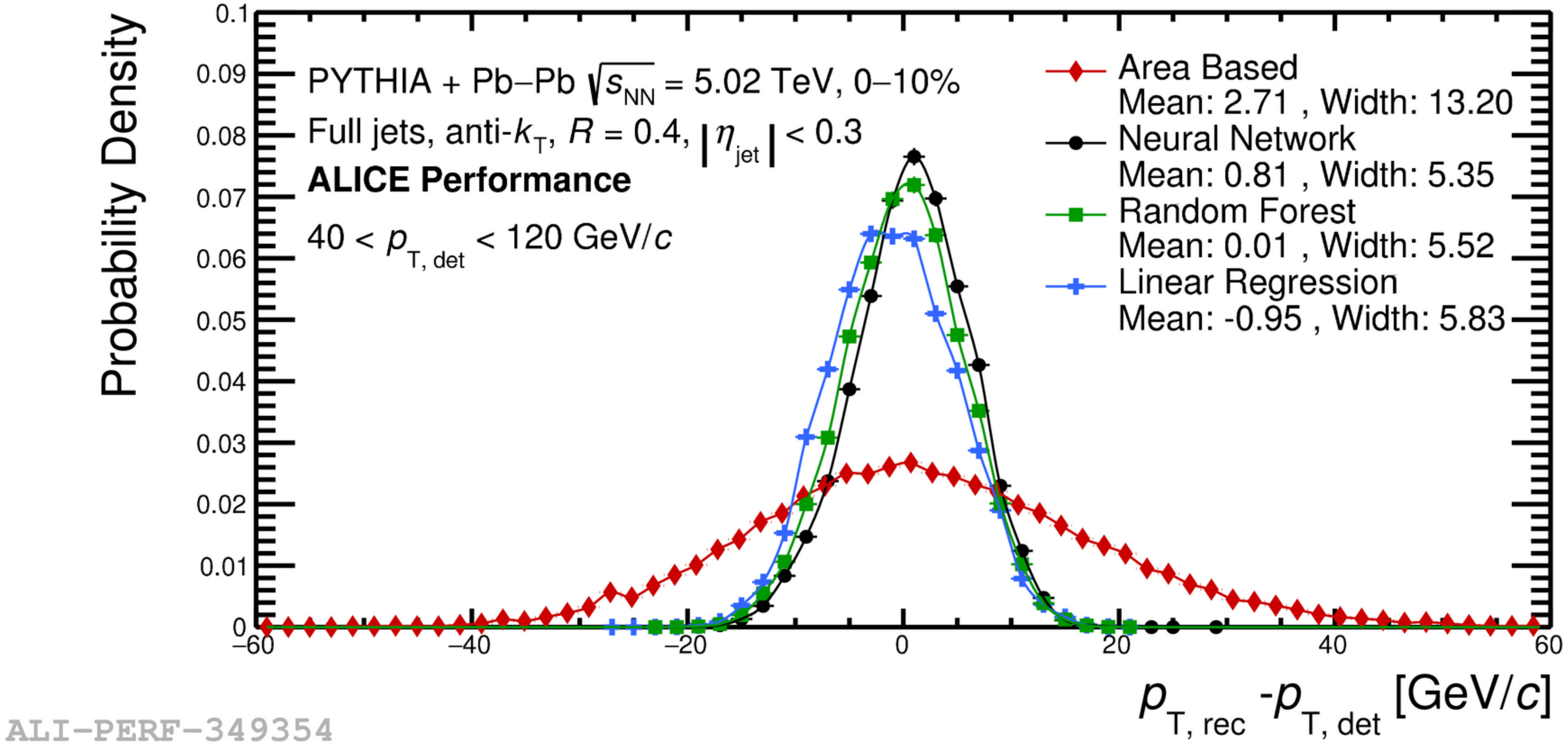
R.Haake, C. Loizides Phys. Rev. C 99, 064904 (2019)

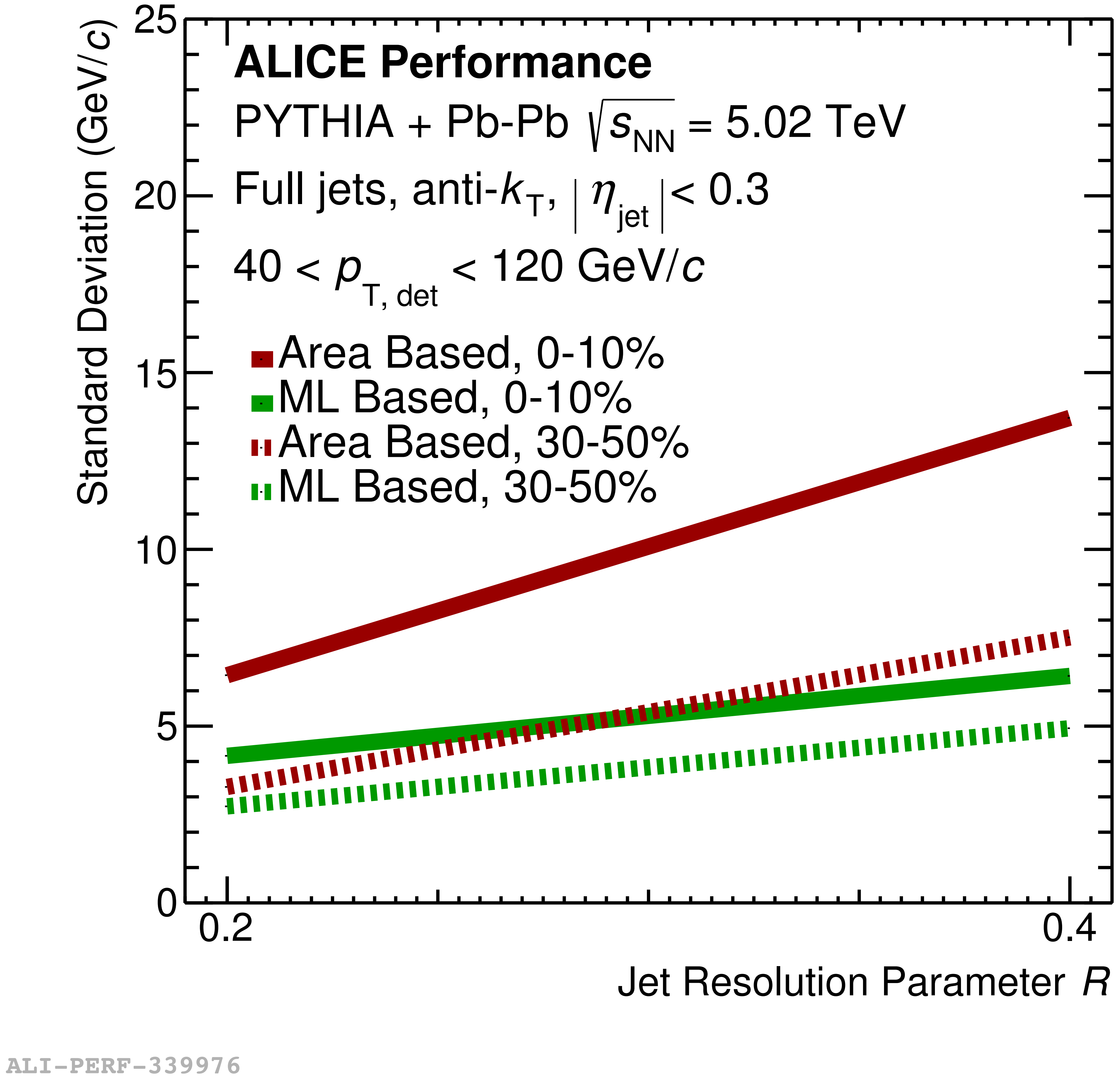
Comparison with standard analysis subtraction

Full Jets

$$\delta p_{\mathrm{T}} = p_{\mathrm{T,rec}} - p_{\mathrm{T,true}}$$

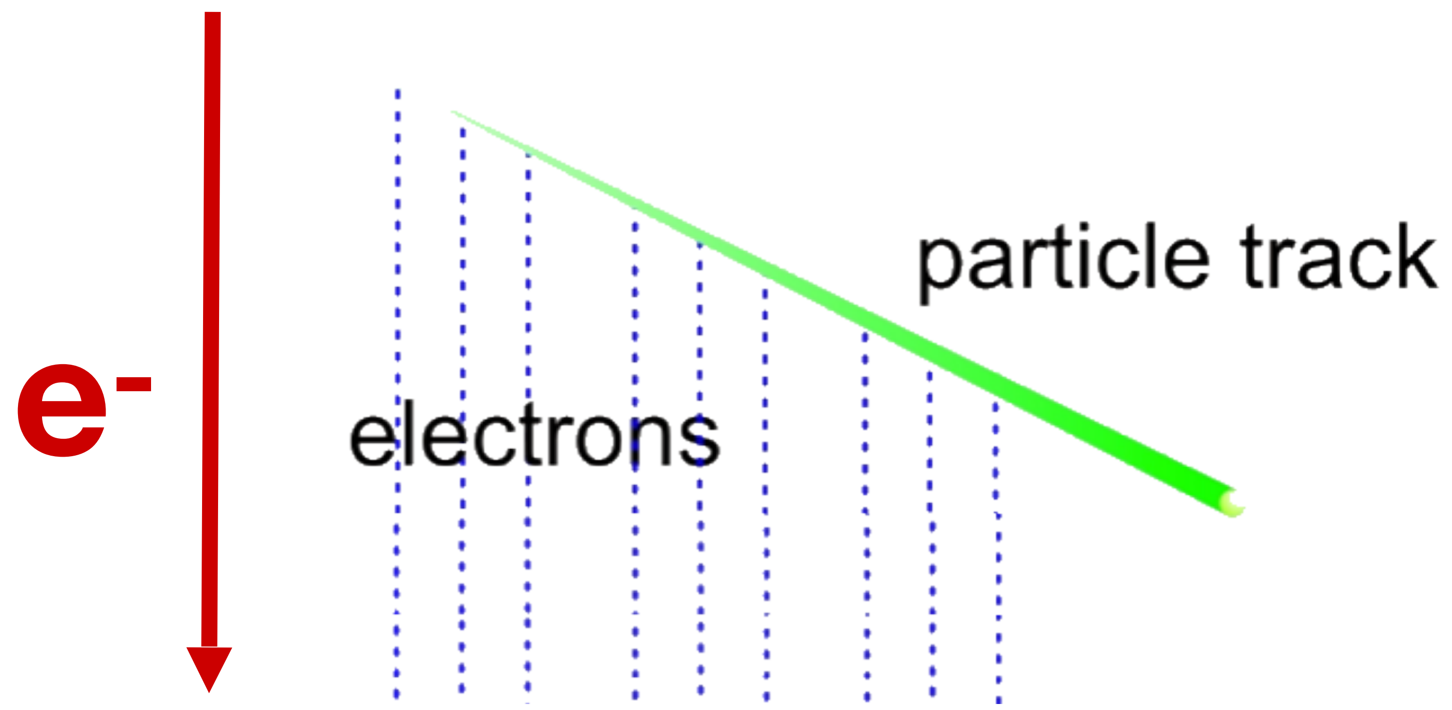
Are we getting back to the “truth” (matched PYTHIA detector level jet)?



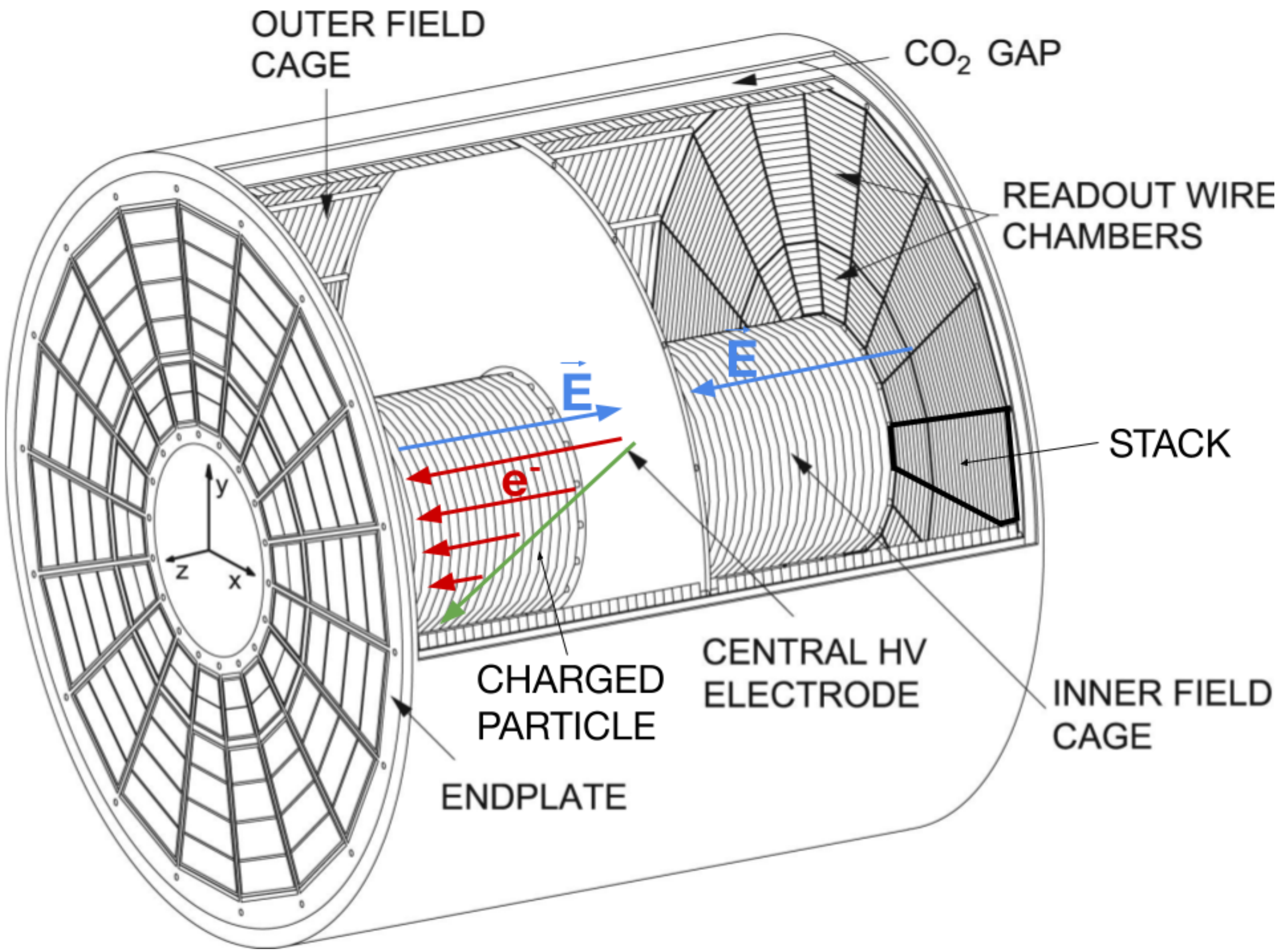


Narrow δp_{T} → Reduced residual fluctuations

Deep neural networks for Time-Projection-Chamber calibrations in Run3



Time-projection chamber for ALICE tracking



Gas ionization by charged particles.

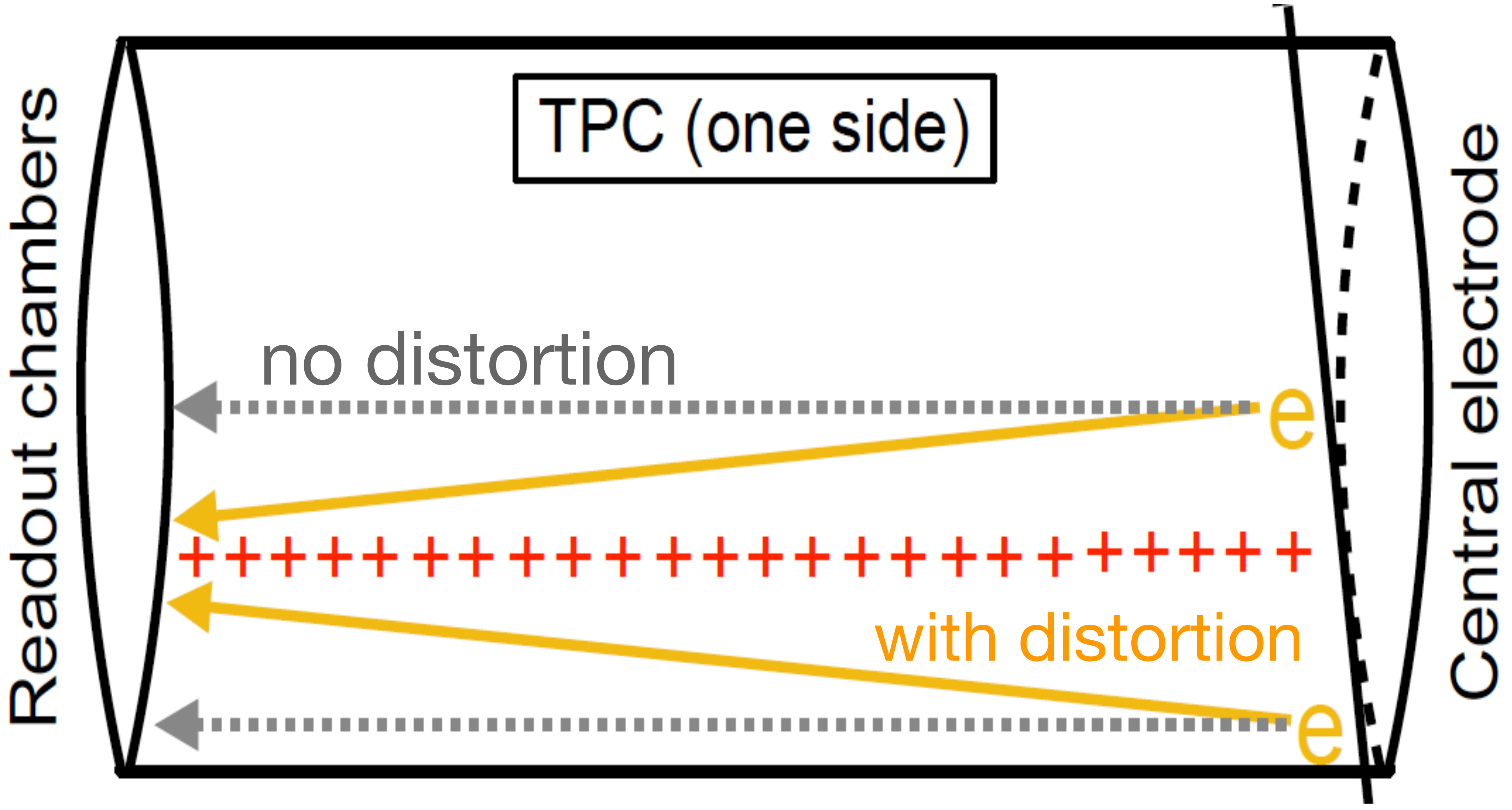
1. The drift of the ionization electrons to the readout chambers.
2. Signal amplified and collected.

3D information for each track point:

- $r\varphi$ via the position in the readout chamber
- z via speed and time of drift, $s = vt$

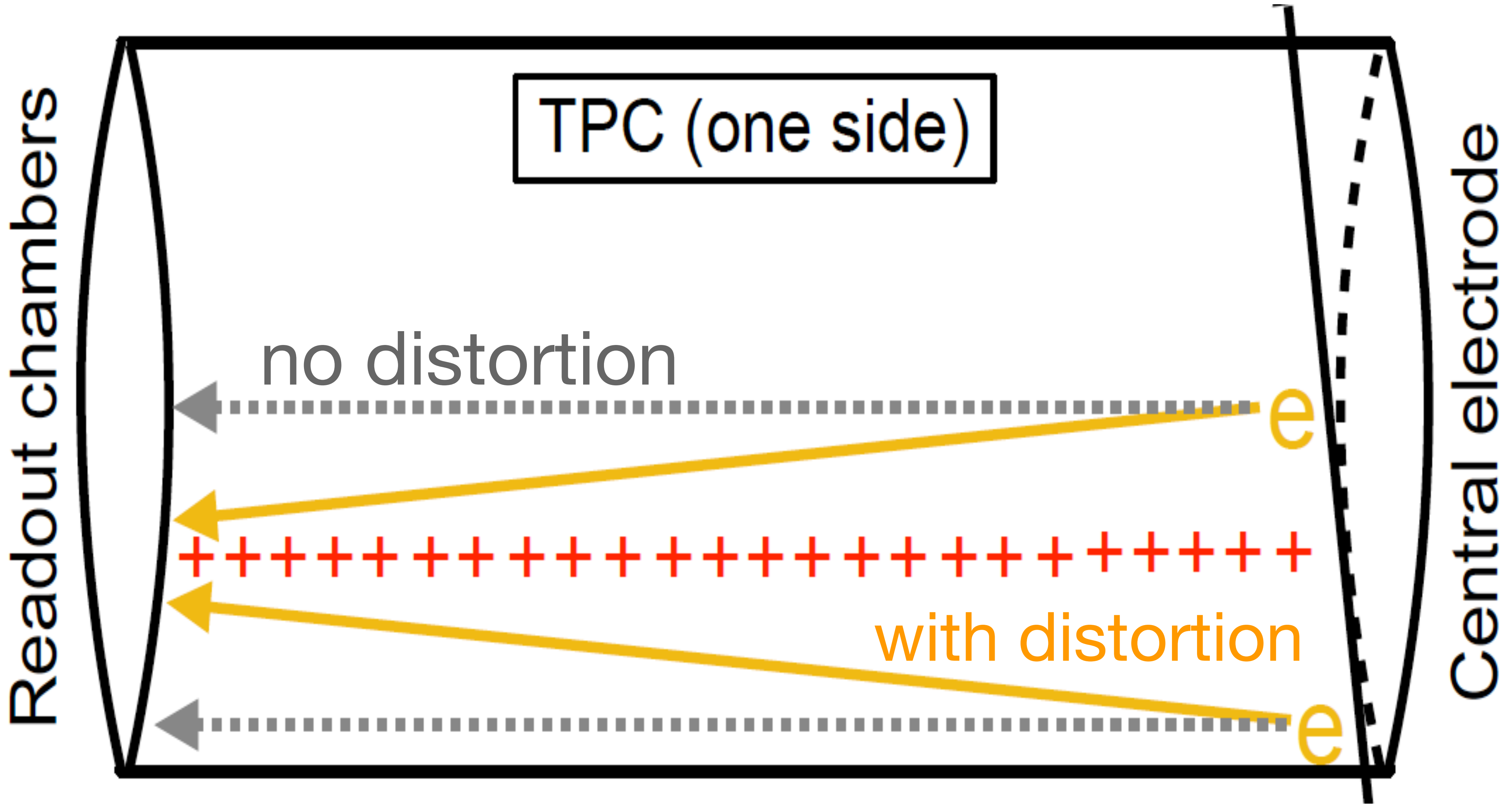
Ideally: a very **uniform** electric field –> accurate tracks measurements

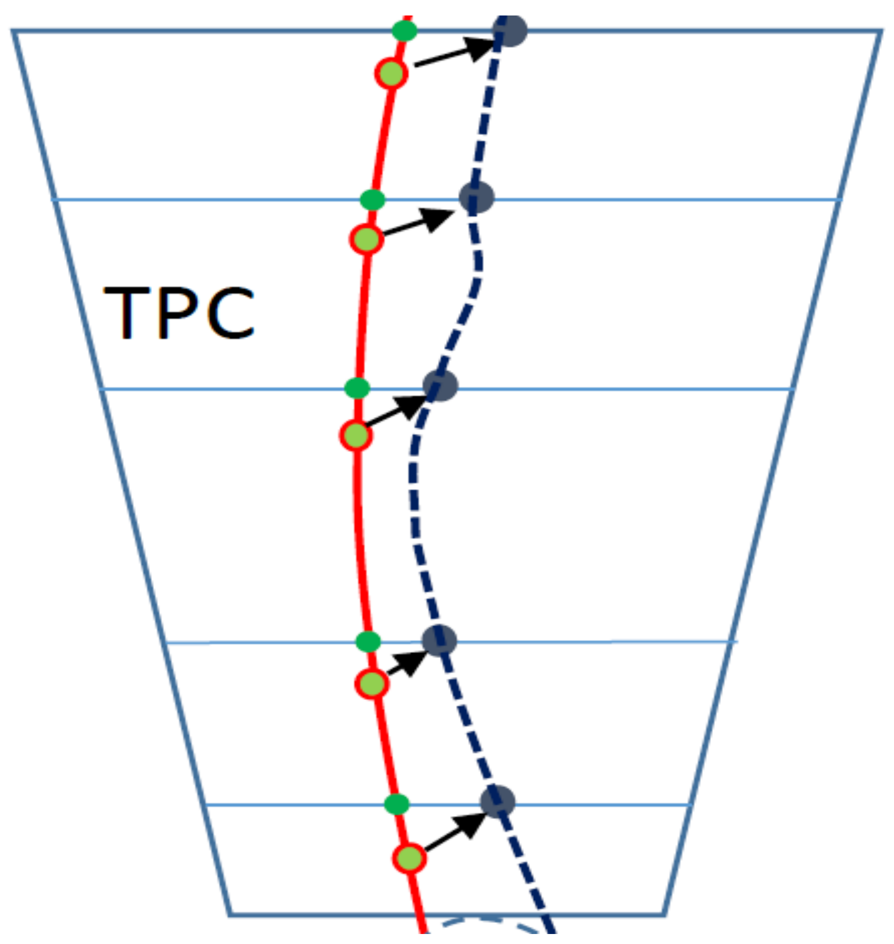
Distortion and distortion fluctuations in Run3 TPC



The positive ions are very slow and distort the electric field lines.
→ The electric field is **not constant** and **not uniform!**

Distortion and distortion fluctuations in Run3 TPC





with distortions
no distortions

Shifted reconstructed point positions
→ worse reconstruction accuracy.

The positive ions are very slow and distort the electric field lines.
→ The electric field is **not constant** and **not uniform!**

- distortions ($\vec{E}$ not uniform)
- distortion fluctuation ($\vec{E}$ not constant over time) – **most difficult** to correct

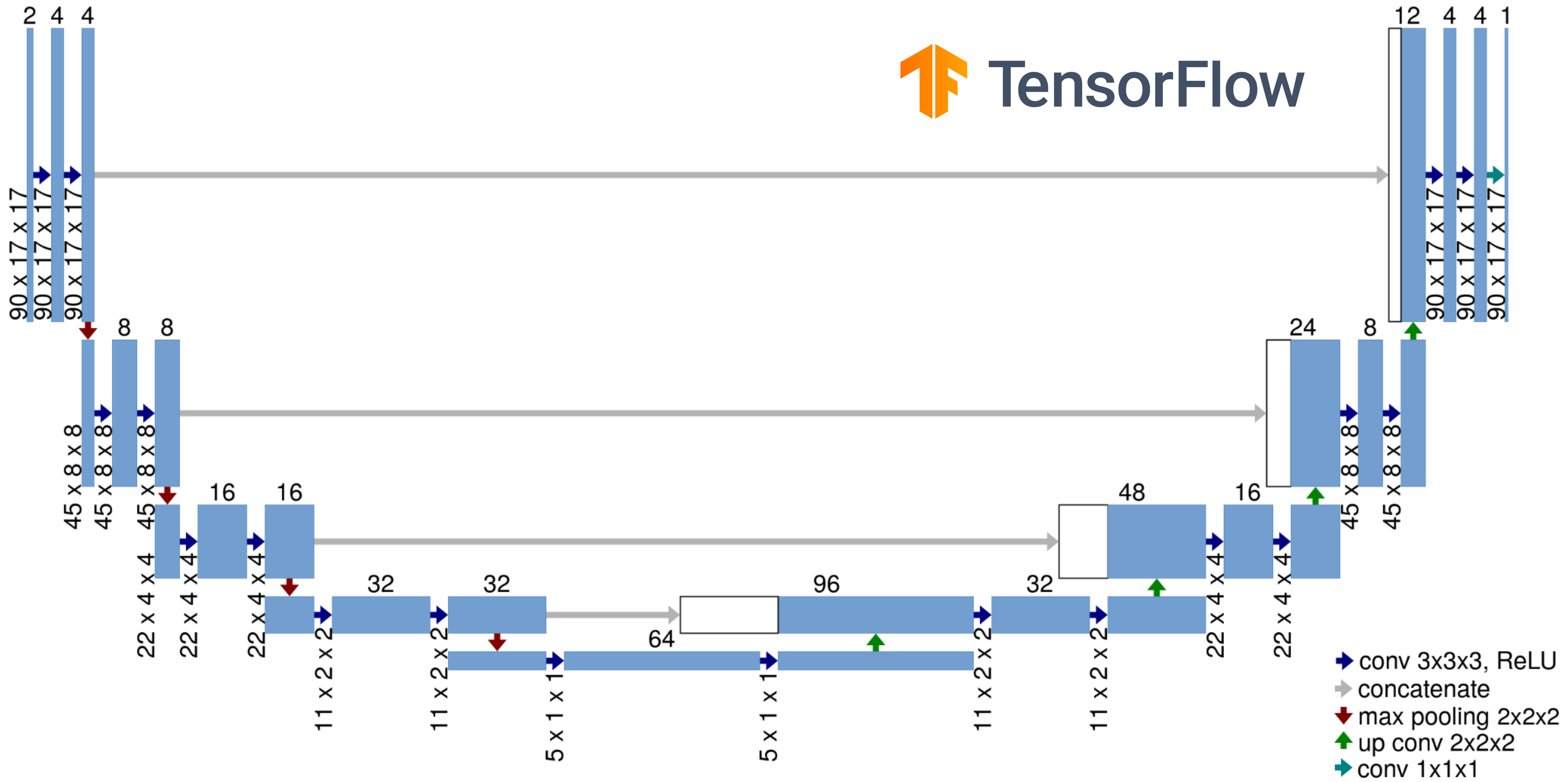
CRITICAL: No proper correction → no precise reconstruction of particle trajectories
→ cannot perform almost **any physics analysis!**

Fluctuation corrections with deep learning

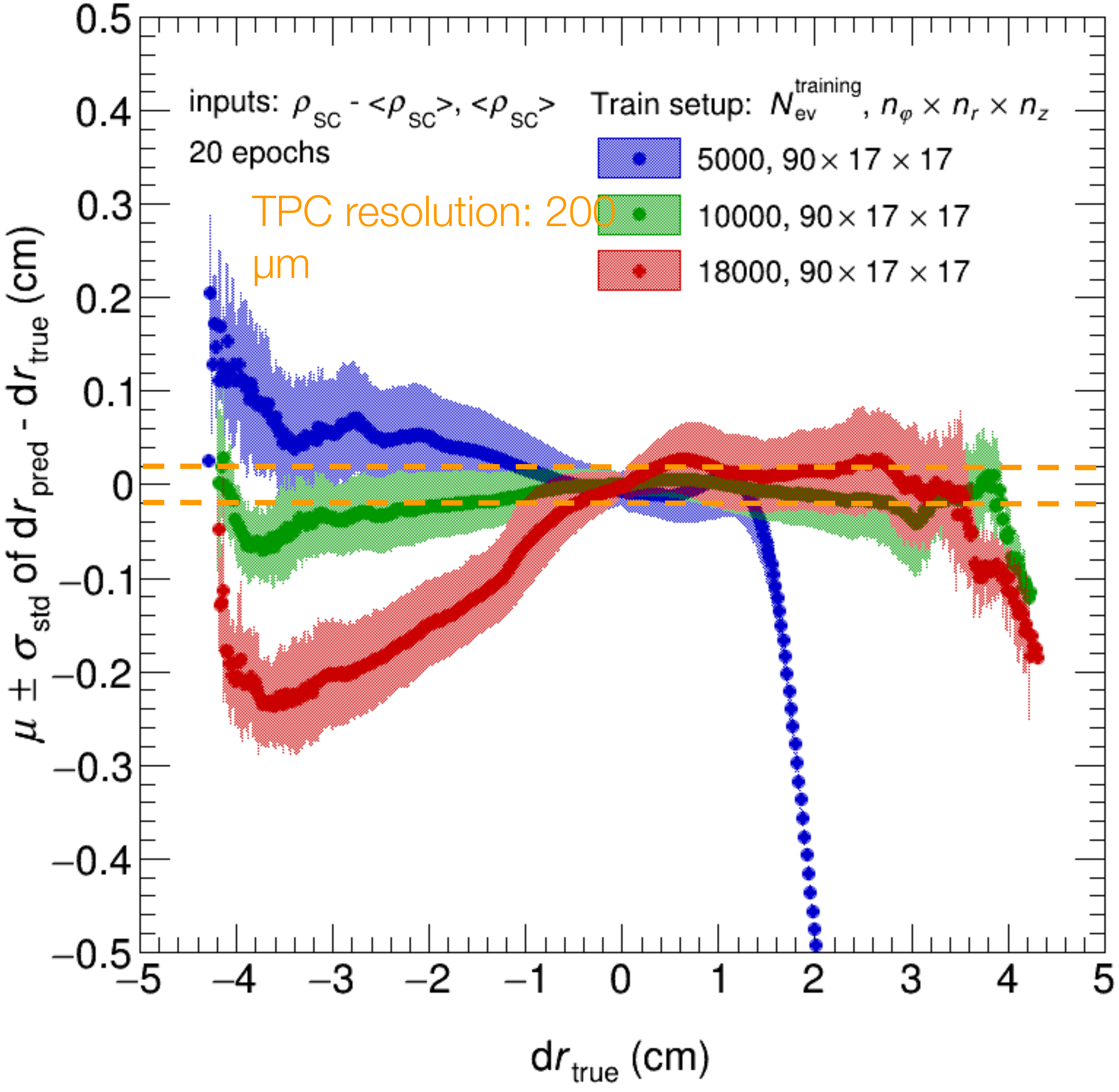
Why not using analytic calculations? too slow ***for a real-time calibration*** and potentially less accurate

Input: **~ion "current" in each TPC 3D point**
Output: correction of local **distortion fluctuations** in each direction in 3D space

U-Net: a convolutional neural network for biomedical image segmentation.



Preliminary results on DNN corrections



Preliminary results!

- with proper tuning procedures, **the DNN can predict the distortion fluctuations** within the TPC resolution (200 microns)

Challenges:

- "Semi-online"
- Optimize granularity of input data
- data augmentation for larger training samples
- speed-up training
- data-driven training inputs ….

Conclusions and outlook

- **BDT and network techniques quickly becoming very important tools for heavy-ion physicists**
  - Strong impact on current analyses and critical relevance for future high-luminosity runs

- **Growing impact on detector reconstruction and calibration in high-multiplicity environments**

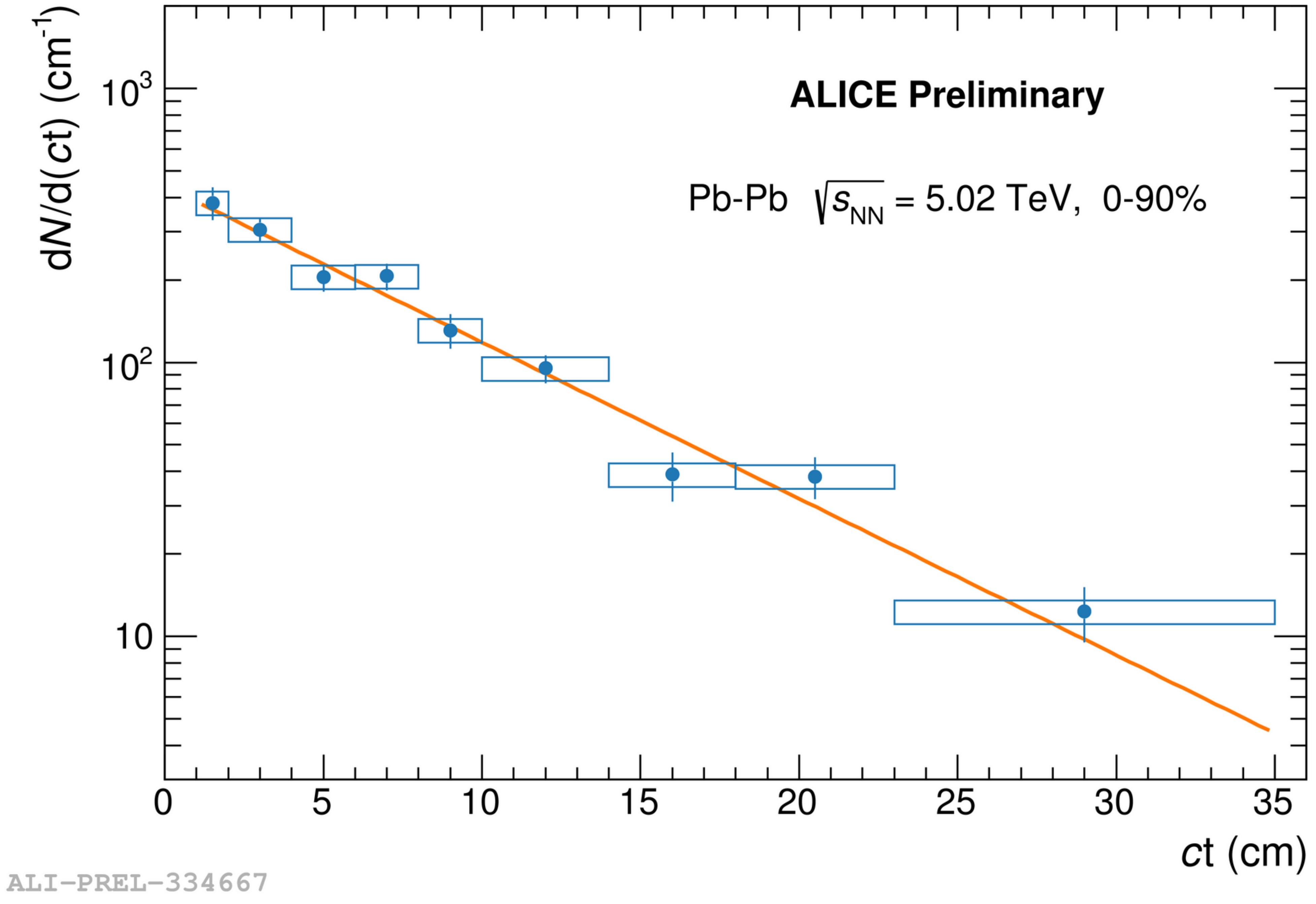
- **Next few years full of challenges and opportunities for ML in HI:**
  - so far for “selection” tasks BDT are still outperforming DNN. Will this change?
  - Accuracy of MC simulations as the biggest limiting factor in HI analyses with high-statistics Run3 data:
    → ML-based MC reweighing techniques could have a strong impact on our analyses!
  - Detector reconstruction and simulation with ML will profit from the large GPUs facilities of LHC experiments
  - Need for deeper understanding of systematic “errors” on ML predictions
  - ….

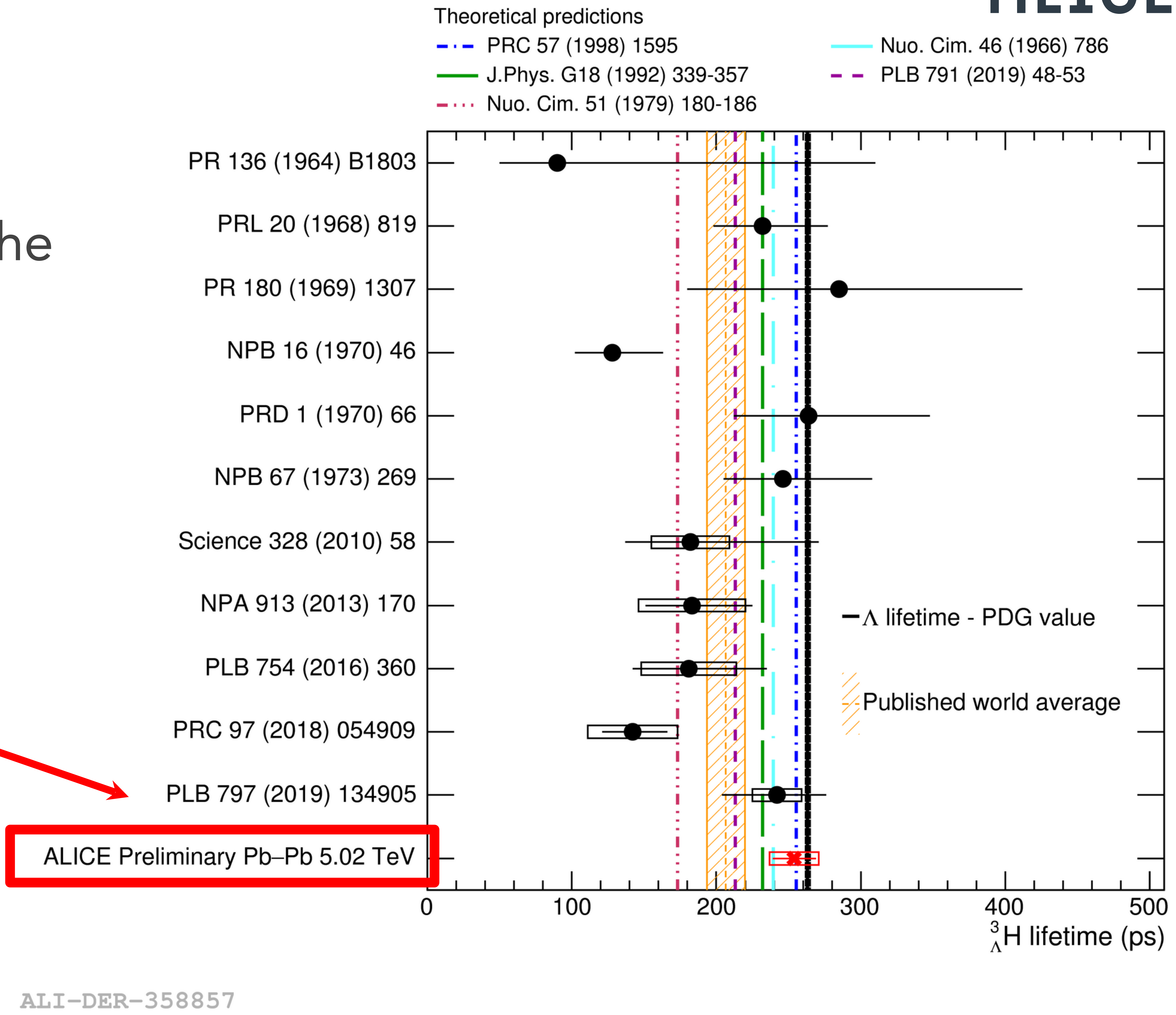
Thanks for your attention!

BACKUP

$^{3}_{\Lambda}H$ Lifetime

- Most precise measurement available
- Statistical uncertainty lower than the published world average uncertainty
- Models predicting lifetime to be near to the free Λ one are favoured





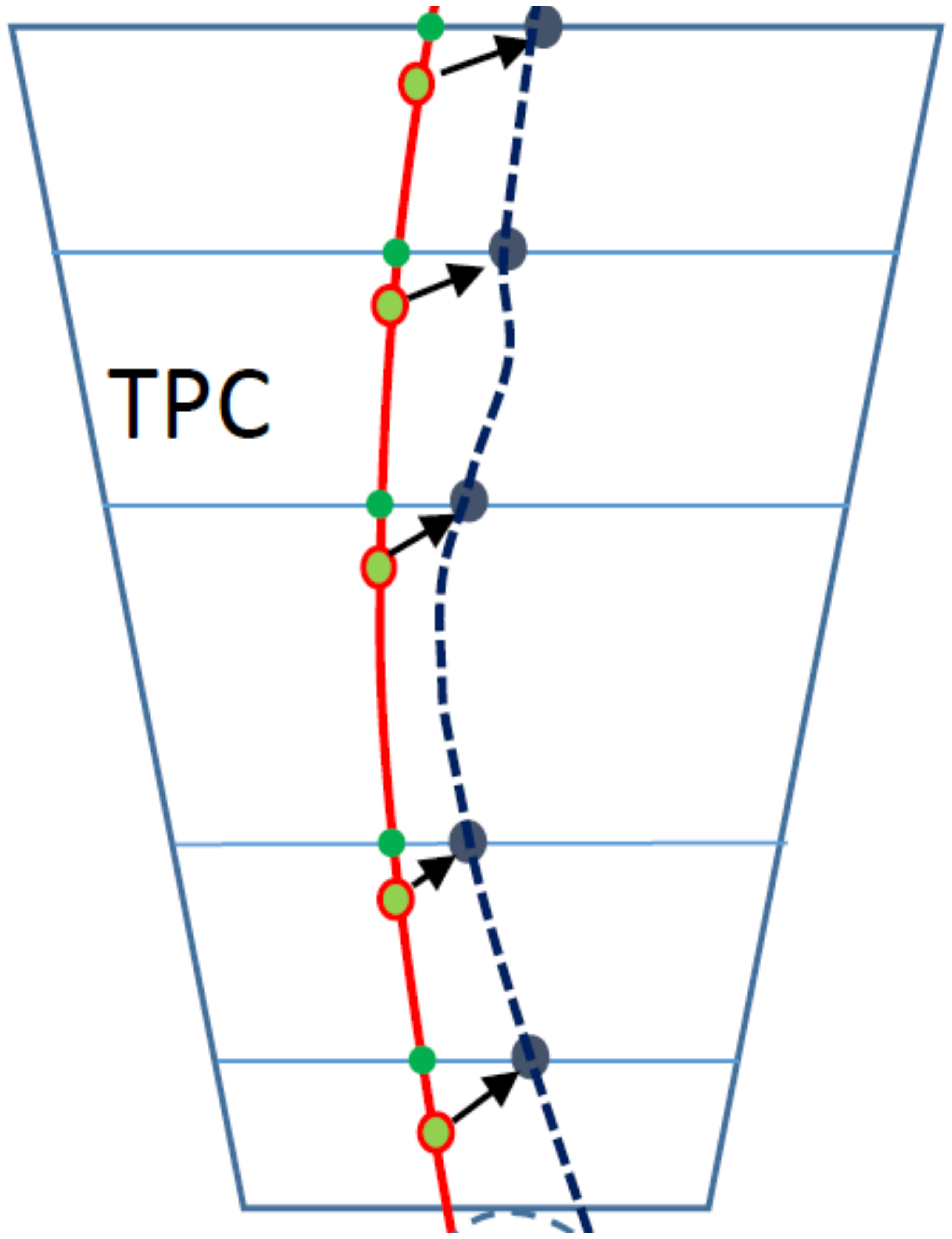
Distortion and distortion fluctuations in Run3 TPC

Problem: calculate the correction of the **distortions** and **distortion fluctuations** from the electric field modifications

Requirements:
- precision **~200 μm** (TPC resolution)
- new distortion correction for each **~5 ms** data interval

Analytic calculations: too slow and potentially less accurate

ML and DNN: effective and fast methods for correcting the **fluctuations**



with distortions
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