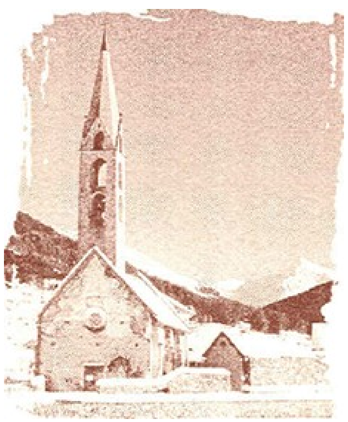
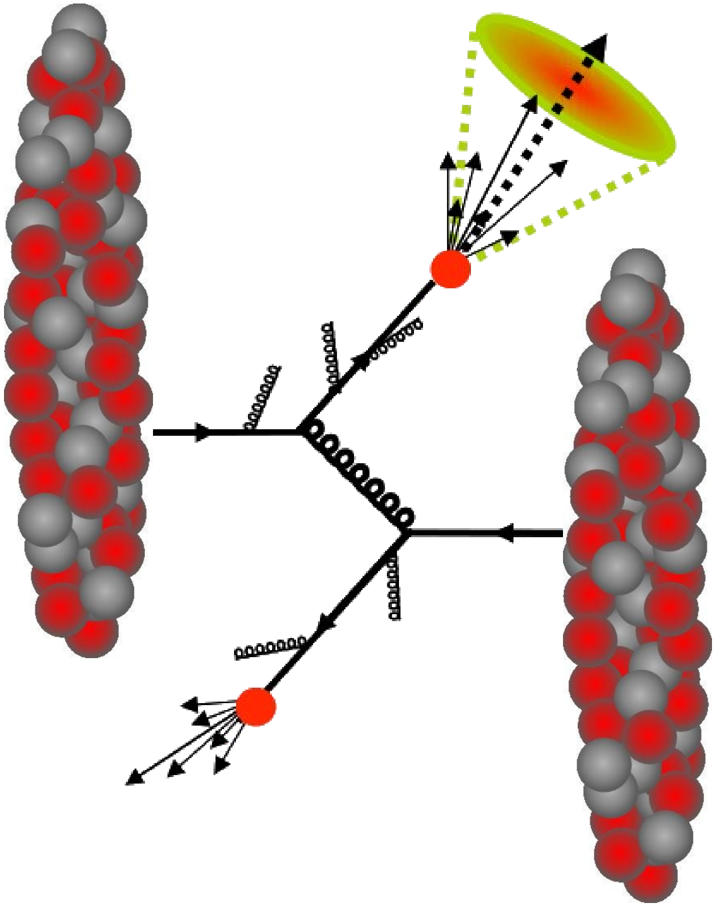
Machine Learning based jet momentum reconstruction in heavy-ion collisions



57. International Winter Meeting on Nuclear Physics
Bormio, Italy

Rüdiger Haake (Yale University)
(23.01.2019)

Motivation



- Jets = collimated sprays of particles created in hard interactions
- Interesting for heavy-ion collision:
  Calibrated probes of medium!

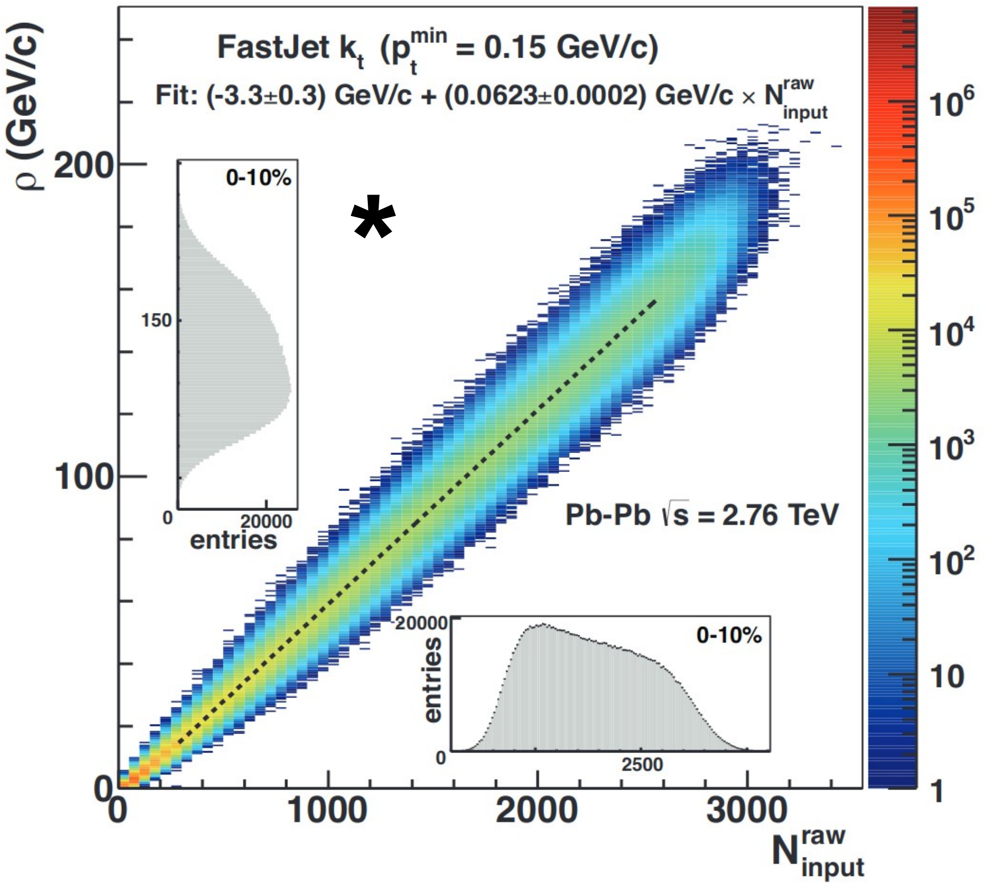
Broad bandwidth of measurements:

- Spectra, nuclear modification factors
- Correlation measurements
- Shapes, (sub)structure analyses

Particularly interesting: Low transverse momenta
→ Medium effects strongest

Main obstacle: Overwhelmingly large background of particles not originating from hard parton interactions

Jets in heavy-ion background I



Huge (charged) particle and energy density from soft processes:

→ Roughly 140 GeV/c per unit area

→ Tracks per event $N = O(2000)$

($p_{T,track}$ > 0.15 GeV/c, $\sqrt{s_{NN}}$ = 2.76 TeV)

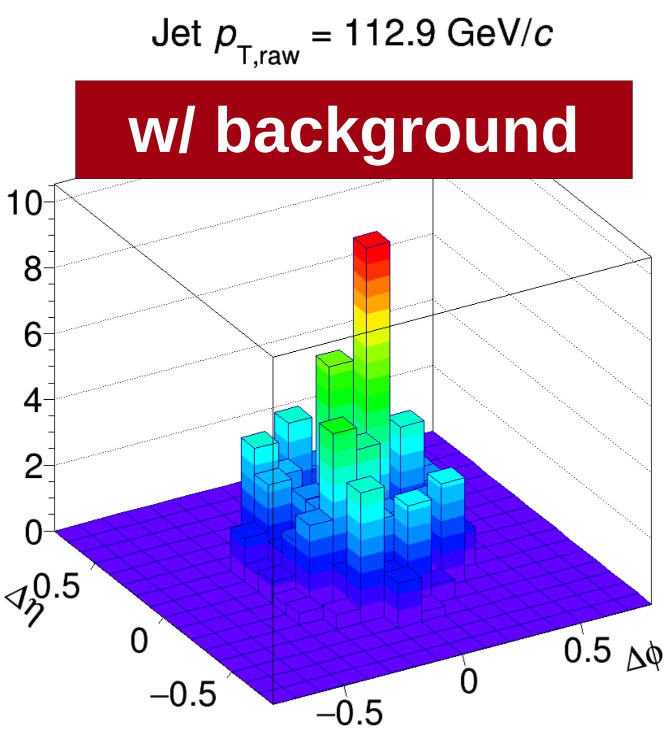
In addition: Large region-to-region fluctuations!

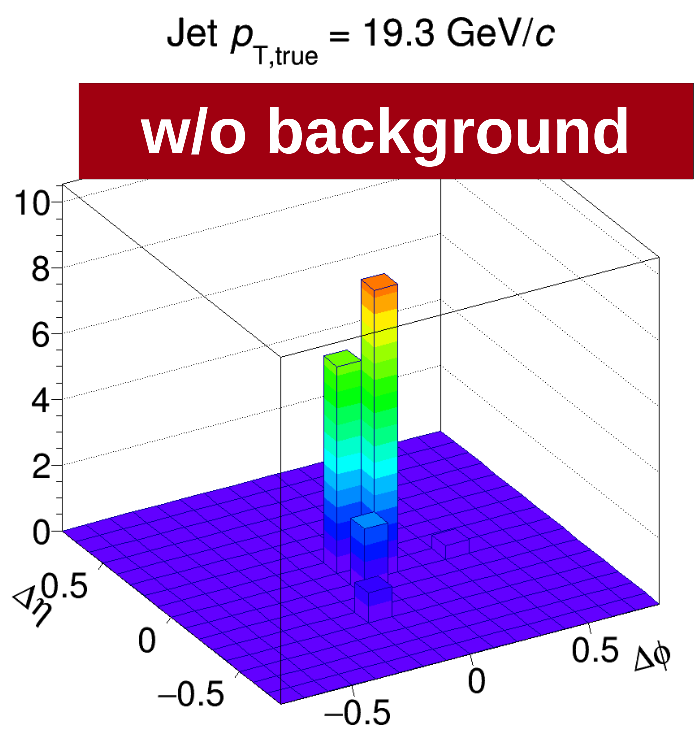
- Random poissonian
- Particle flow
- Detector inhomogenities
- …

[*] **https://arxiv.org/abs/1201.2423**

Jets in heavy-ion background II

Background effect on jet in Pb-Pb (toy background):



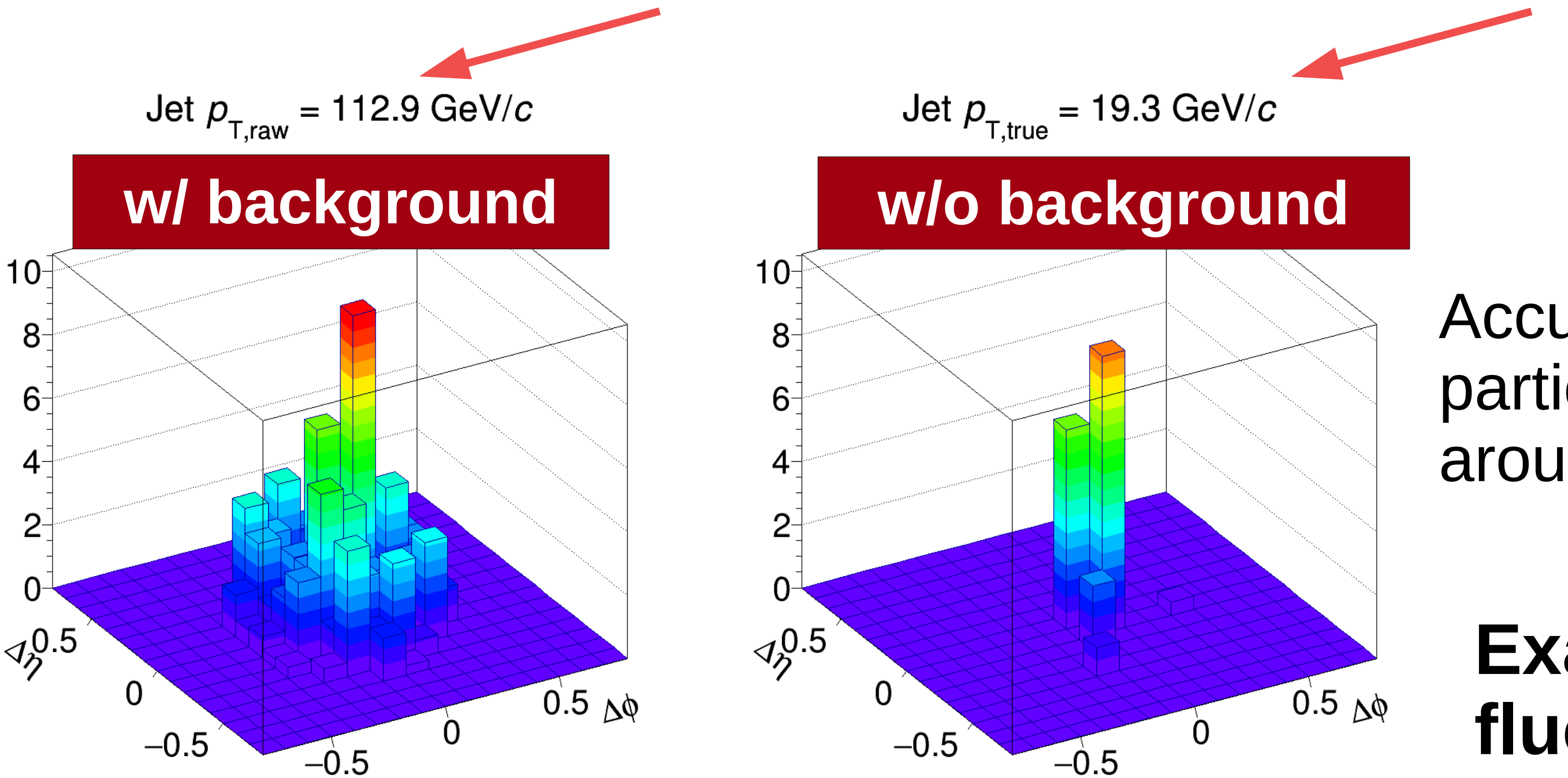


Accumulated particle momentum around jet axis

Background/fluctuations largely affect jet momenta and axes

Jets in heavy-ion background II

Background effect on jet in Pb-Pb (toy background):

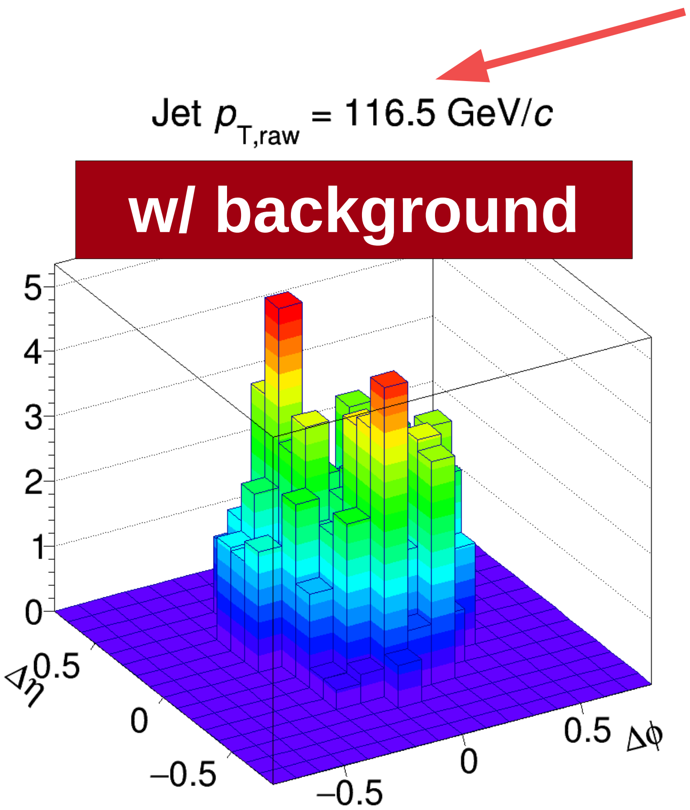


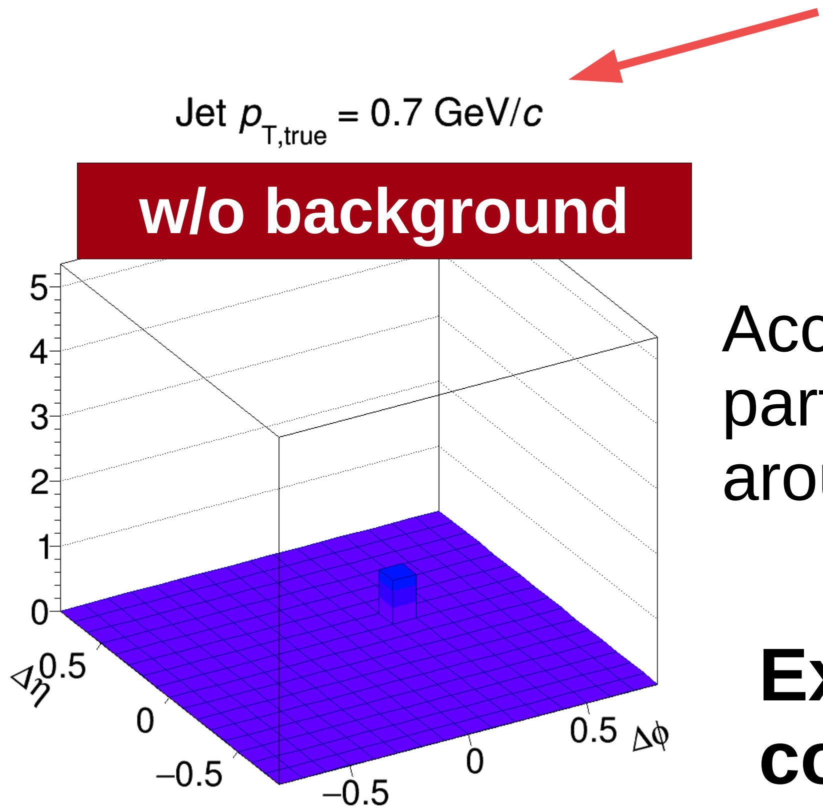
Accumulated particle momentum around jet axis

Example of fluctuated jet

Background/fluctuations largely affect jet momenta and axes

Background effect on jet in Pb-Pb (toy background):





Accumulated particle momentum around jet axis

Example of combinatorial jet

Background/fluctuations largely affect jet momenta and axes

How to correct jets for background?

De facto standard method in ALICE:

Area-based background correction method

- Event-by-event: Calculate mean background density
- Correct each jet p_T by subtracting background density x jet area:

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

- Residual fluctuations usually treated statistically in unfolding

Main caveats:

- Poor precision on jet energy scale at low-p_T
- Combinatorial jets not treated

We can do better!

ML background estimator: Introduction

Idea: Some information on background encoded in jet

- Background conceptually different than signal
  → Different spectrum, spatial distribution

- However, relation of the input parameters not trivial

  Perfect candidate to exploit complex high-dimensional parameter correlations: **Machine learning**

Method described here is fully described in paper which we submitted to PRC

Preprint on arXiV: https://arxiv.org/pdf/1810.06324.pdf

ML background estimator: Introduction

Ansatz: Use machine learning techniques to calculate background on jet-by-jet basis (instead of event-by-event)

Supervised learning approach:

- Mapping of raw and corrected jet momentum is learned from model data, not modeled itself
- Regression task: Numerical value is approximated

Several estimators evaluated, all widely used in HEP:

- Shallow neural networks ($100 \rightarrow 100 \rightarrow 50$)
- Random forests
- Linear regression
- …

ML background estimator: Toy model

Toy model used for training:

- PYTHIA jets, $\sqrt{s}$ = 2.76 TeV, in thermal background
- Fastjet anti-k_T jets, $R = 0.4$
- Charged jets (no neutral particles)
  (extension to full jets straightforward)
- Thermal background multiplicity distribution roughly as in central Pb-Pb collisions
  (Gaussian distribution, mean: 1800, width: 200)
- Particle momentum distribution modeled to coincide data at low p_T, but to fall much quicker for higher momenta $\gtrapprox$ 4 GeV/c
- Many cross checks done, estimators very robust for different thermal background definitions!

ML background estimator: Parameters

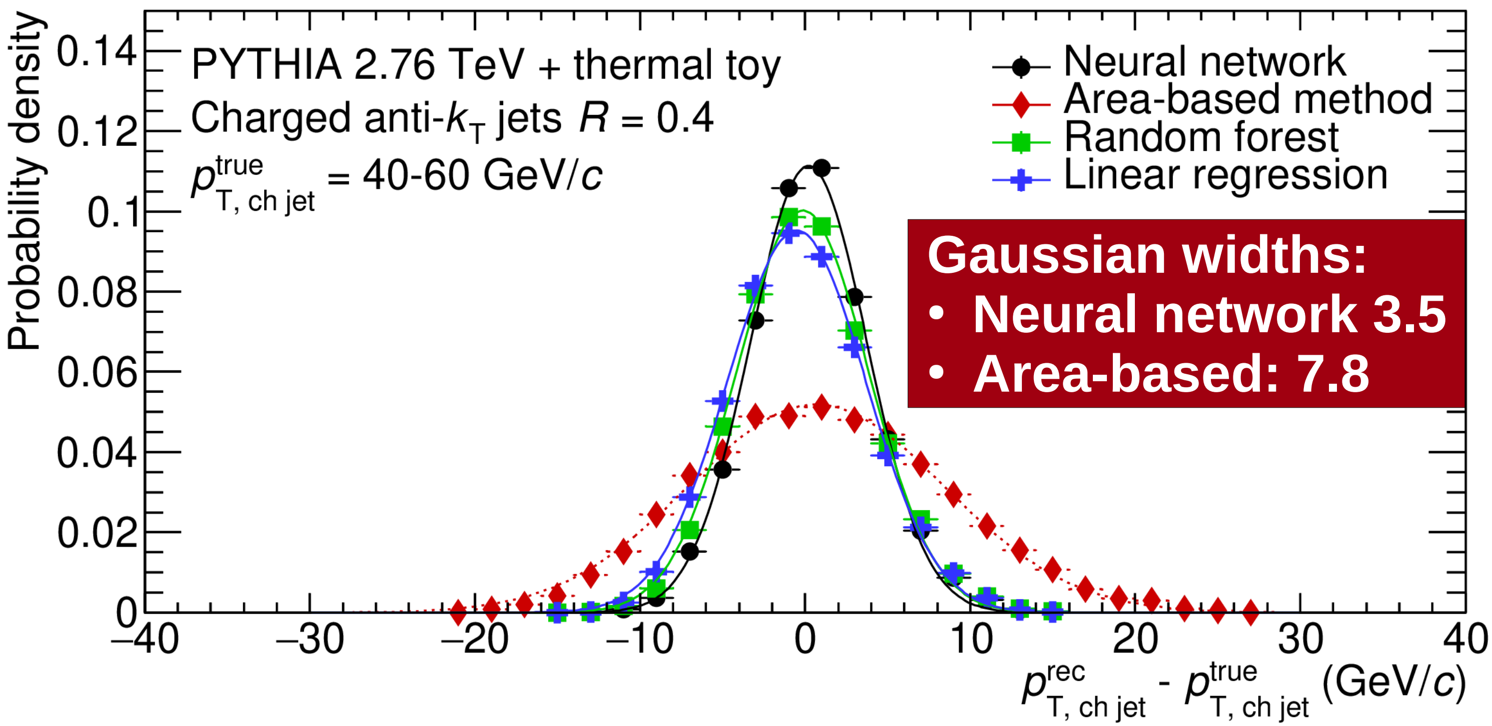
Input parameters to the estimator:

- Jet momentum
  - uncorrected from jet finder
  - corrected w/ established area-based method
- Selected jet shapes (mass, radial moment, momentum dispersion, LeSub)
- Number of constituents, mean + median of const. momenta
- First ten leading constituent momenta

We also did a feature importance analysis:

Established correction brings a lot of separation!

Performance on toy: Method comparison



Gaussian widths:
- **Neural network 3.5**
- **Area-based: 7.8**

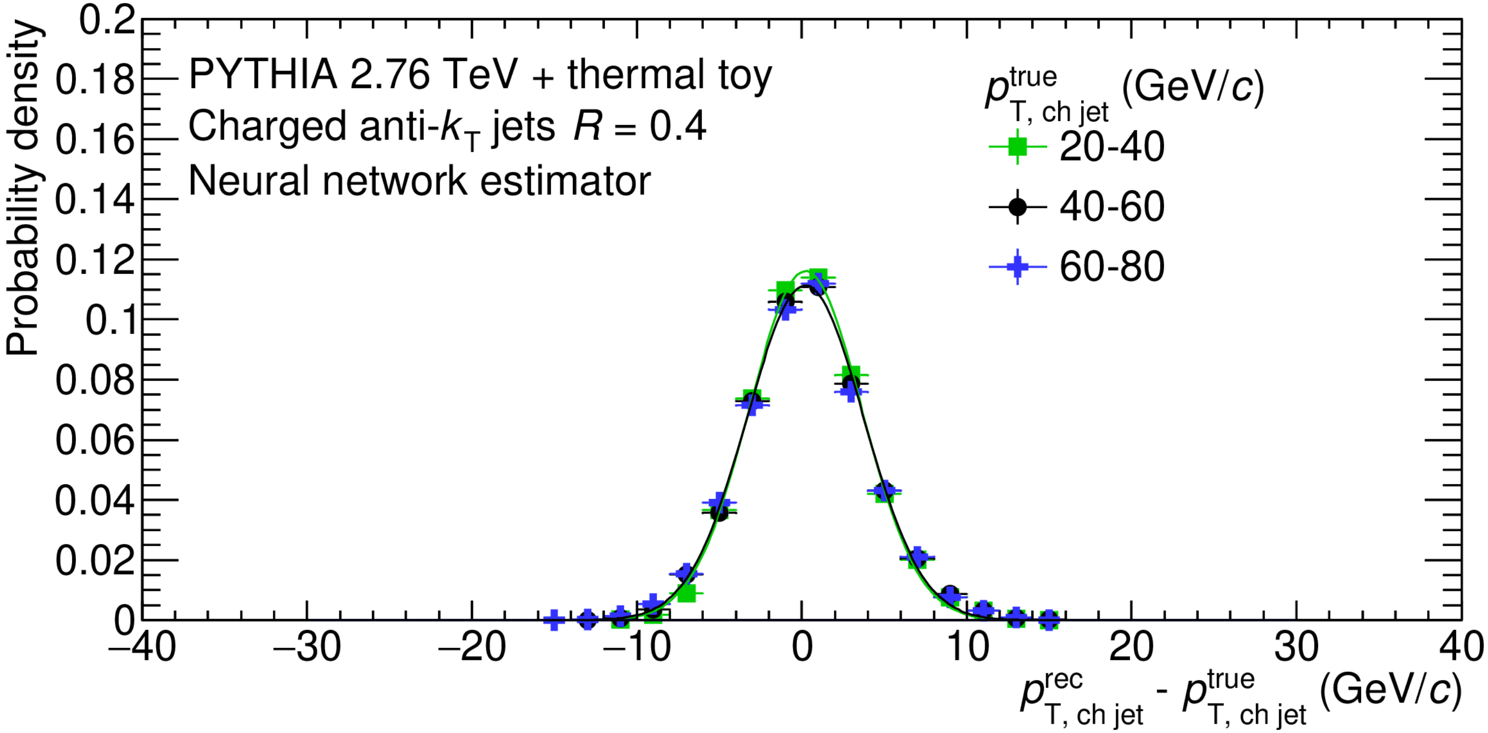
Performance indicator: Residual difference of corrected vs. true jet p_T

Example for perfect estimator: δ-peak around zero

Comparison of area-based method to several ML methods:

ML methods all perform much better:
- Higher resolution (less residual fluctuations)
- Still centered around nominal zero
- Neural network estimator works particularly well

Performance on toy: Different momenta



Performance indicator: Residual difference of corrected vs. true jet p_T

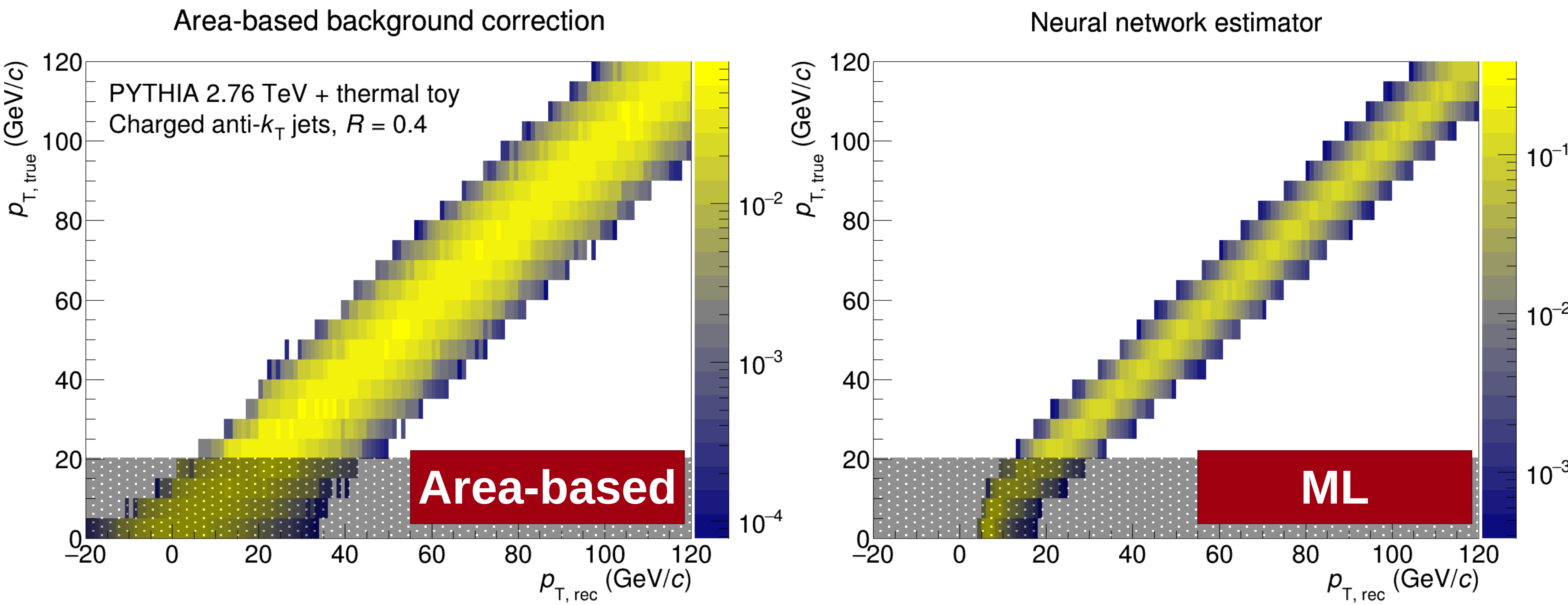
Example for perfect estimator: δ-peak around zero

Comparison of different jet transverse momenta:

Roughly same performance for full considered range

Note: Results shown for NN estimator, but similar results also for other estimators

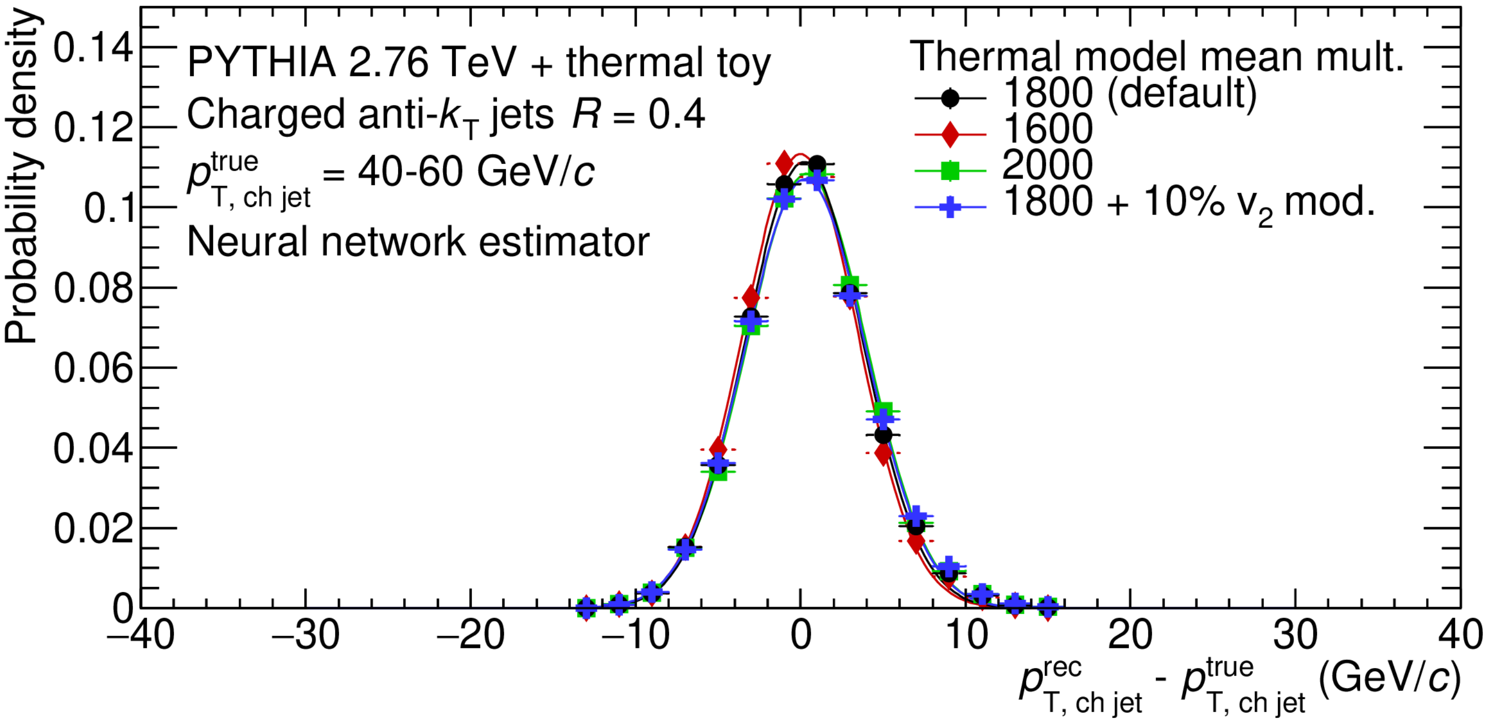
Performance on toy: Method comparison



Comparison of response matrix true vs. reconstructed jet p_T:

Clearly huge performance gain for all momenta

Model robustness: Thermal model



Performance indicator: Residual difference of corrected vs. true jet p_T

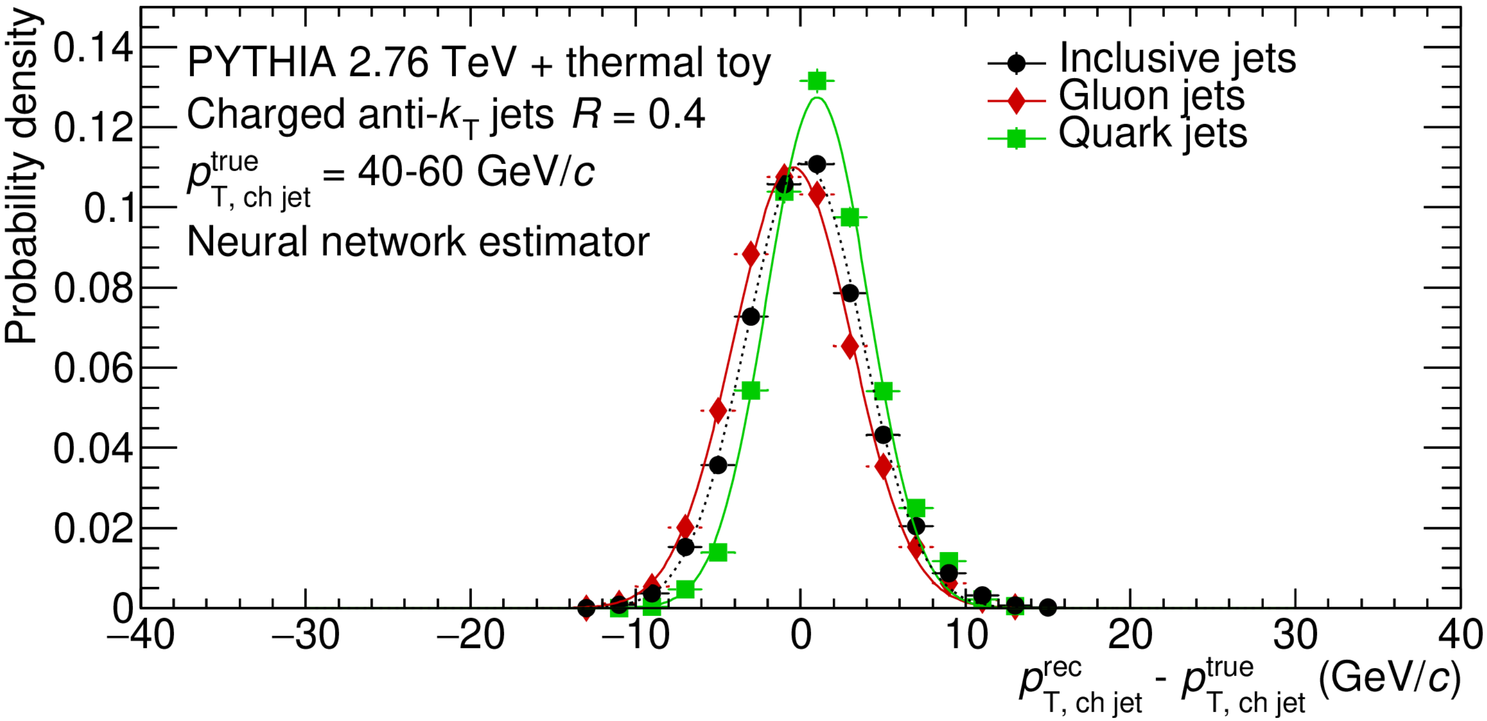
Example for perfect estimator: δ-peak around zero

Train estimator on one background but test on another:

Same performance for different backgrounds:

- Different (never trained) multiplicities perform as well
- No influence from hydrodynamic particle flow
- Many further tests show robustness (different toy p_T distributions, training on flat multiplicity distributions, ...)

Model robustness: Fragmentation



Performance indicator: Residual difference of corrected vs. true jet p_T

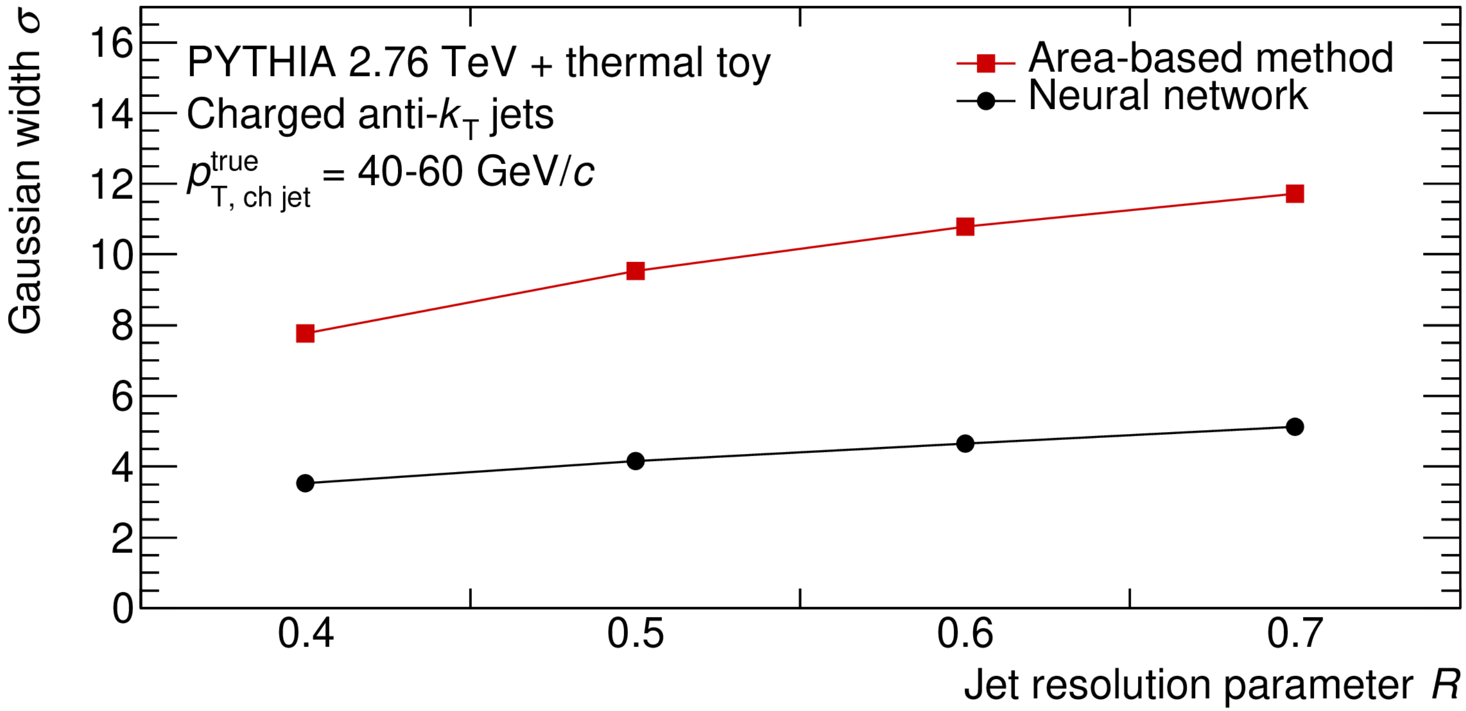
Example for perfect estimator: δ-peak around zero

Check effect of different fragmentation on performance
→ Train on inclusive jets, evaluate extreme cases of *q*/*g*-jets

No strong dependence on fragmentation:

- Tests indicate a few percent effect on spectrum (worst case)
- Residual effects can be corrected for in unfolding procedure

Model robustness: Resolution parameters



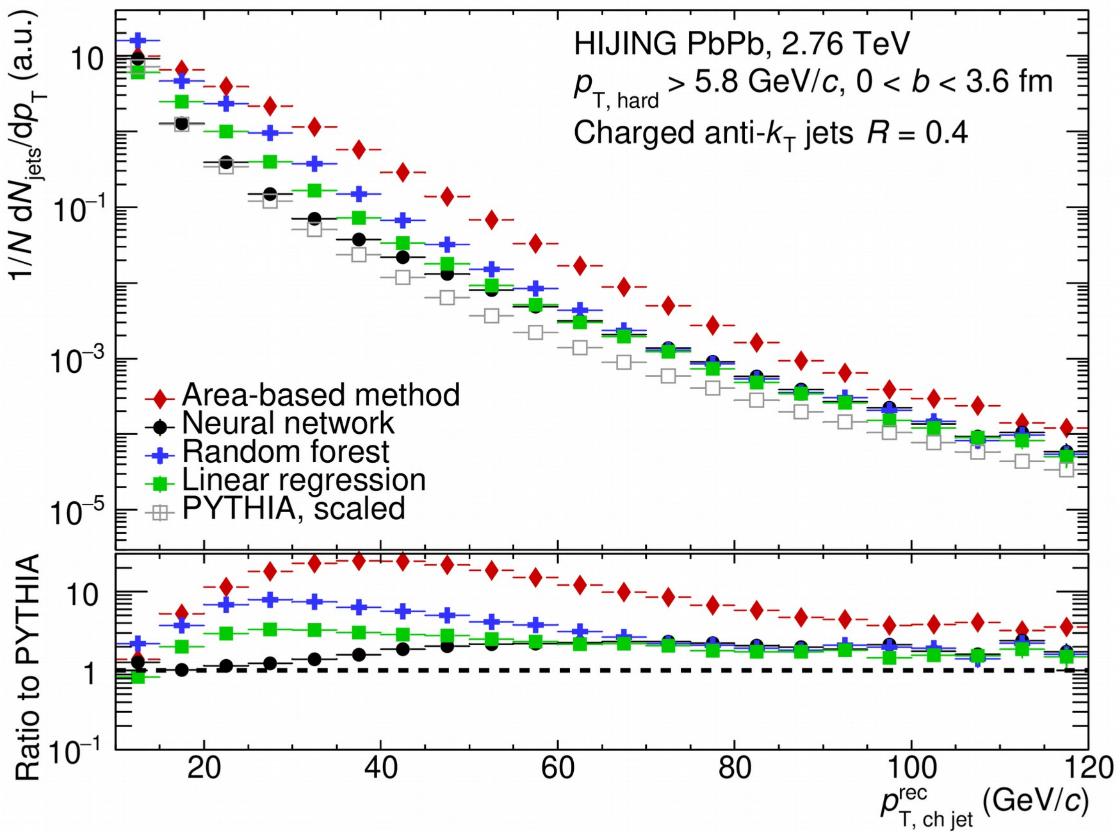
Width of residual distribution = Resolution of method

Behavior for different jet resolution parameter (“jet radii”):

Good ML estimator performance up to largest *R*:

- Trend shows less progression towards higher *R*

Performance on other MC



Jet spectra on MC data

- HIJING Pb-Pb, 2.76 TeV (heavy-ion MC events)
- No jet quenching used
- Tweaked to roughly reproduce data distributions & central multiplicities
- Estimator has never seen this type of data

- Ratio to PYTHIA shows: ML estimators much closer to the truth than standard method
- Cross checked w/ further HIJING settings

Outlook

Several analyses using ML estimator ongoing in ALICE

Stay tuned for EPS-HEP 2019!

What else:

- Measure jet mass as cross check → ”Full jet 4-vector”
- Even better: Two-parameter regression
  → Background correction for p_T and mass at the same time
- “Jet denoiser”
  - Clean jet at constituent-level
  - Nice use case for deep learning (e.g. deep autoencoder)
    → Explorative: Just an idea at the moment...
    → Needs much more computation power for training

Summary

- We introduced a novel method to correct jet p_T
  - → using common ML techniques
  - → correction done on jet-by-jet basis
- Toy model analysis indicates superior performance of new approach
- Supported by independent HIJING MC studies
- No strong bias for differently fragmented jets
- Application to real heavy-ion data promising:
  - → higher precision, particularly at low transverse momentum
  - → a lot ongoing in ALICE

Thank you for your attention!