Machine Learning based jet momentum reconstruction in Pb-Pb collisions in ALICE

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Motivation: Low-$p_T$ jets in heavy-ion collisions

Broad bandwidth of jet measurements:
- Spectra, nuclear modification factors
- Correlation measurements
- Shapes, (sub)structure analyses

Particularly interesting:
Low transverse momenta
→ Medium effects strongest

Main obstacle: Overwhelmingly large background from underlying event of particles uncorrelated with the hard scattering
Huge (charged) particle and energy density from soft processes:

→ Roughly 140 GeV/c per unit area
→ Tracks per event $N = O(2000)$

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

In addition: Large region-to-region fluctuations!

• Random poissonian
• Particle flow
• Detector inhomogenities
• ...

* ALICE Collaboration
JHEP 1203 (2012) 053
Background effect on jet in Pb-Pb (toy background):

- Accumulated particle momentum around jet axis

Background/fluctuations largely affect jet momenta and axes
Background effect on jet in Pb-Pb (toy background):

**Jet** $p_{T,\text{raw}} = 112.9$ GeV/c

**Jet** $p_{T,\text{true}} = 19.3$ GeV/c

**w/ background**

**w/o background**

Example of fluctuated jet

Background/fluctuations largely affect jet momenta and axes
Background effect on jet in Pb-Pb (toy background):

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 correction method

- Event-by-event: Calculate mean background density $\rho$
- Jet-by-jet: Subtract background from jet depending on jet area $A$

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

- Residual fluctuations usually treated statistically in unfolding

Main properties:

- Poor precision on jet energy scale at low-$p_T$
- Method is sensitive to energy-flow
  - Independent on fragmentation changes within jet (good)
  - Combinatorial jets not treated (not so good)

Can we do better?
**ML background estimator: Introduction**

**Idea:** Background different from signal
  → Different particle composition
  → Different spatial distribution

**Ansatz:** Estimate background jet-by-jet
  → Exploit more information from jet
  → Constituent properties, shapes, ...

Perfect candidate for high-dimensional parameter correlations: **Machine Learning (ML)**

Instead of explicit modeling, we learn signal/background relation from jets embedded in background
Method comes with a very general trade-off:
→ Get better performance with more information
→ But also: Potential dependence on jet fragmentation!

- Trained on PYTHIA jets in background
  → Inherently assumes a certain fragmentation of jets
  → Thus, we measure pp-like jets in Pb-Pb

- Uncertainty covers realistic changes in fragmentation
  → We unfolded assuming pure quark-jet fragmentation
Supervised learning approach:
• Mapping raw ↔ corrected jet momentum learned from data
• Regression task: Numerical value is approximated

ML technique:
• We use a shallow neural network (100 → 100 → 50)
• Several algorithms (Random forest, linear regression, …) tested and found to be in agreement

Training data:
• PYTHIA8, $\sqrt{s} = 5.02$ TeV, detector-level rec., embedded in thermal toy model inspired by real Pb-Pb distributions
• Input parameters (found by parameter ranking):
  Area-based jet momentum, $N_{\text{const}}$, angularity, eight leading jet constituent momenta
Data & analysis setup

**Dataset:**
- Pb-Pb, $\sqrt{s_{NN}} = 5.02$ TeV, taken in 2015
- Minimum bias, 0-10% + 30-50% most central collisions
- 0-10%: 7M events, 30-50%: 14M events

**Jet definition:**
- Track-based jets (no neutral particles)
- Fastjet, anti-$k_T$ jets, $R = 0.2, 0.4, 0.6$
- Jet cones fully-contained in acceptance, full azimuth

**Unfolding for detector effects & residual fluctuations:**
- SVD unfolding
- Prior: PYTHIA
- Detector response matrix from matched PYTHIA jets using a full GEANT3 detector model
Estimator performance

Direct measure for residual fluctuations: $\delta p_T$

- Calculated by embedding PYTHIA jets into Pb-Pb events
- $\delta p_T = \text{residual background fluctuation of probe}$
  - Resolution much better for ML-based approach
  - Still centered around zero

Estimator performance

Direct measure for residual fluctuations: $\delta p_T$

- Standard deviation = width of $\delta p_T$
- Smaller = better resolution
- Shown for several jet $R$

→ Good ML estimator performance up to largest $R$
→ Trend shows less progression towards higher $R$

• Results fully compatible with established correction method
• For 0-10%, we gain up to 30 GeV/c towards low $p_T$!
Nuclear modification factor $R_{AA}$

- **New at the LHC**: $R = 0.6$ in Pb-Pb, down to 50 GeV/c!
- **Nuclear modification compatible for** $R = 0.4$ & $R = 0.6$
Nuclear modification factor $R_{AA}$

- New at the LHC: $R = 0.6$ in Pb-Pb, down to 50 GeV/c!
- $R_{AA}$ for $R = 0.6$ still largely suppressed (assuming pp-like jets)

J. Casalderrey-Solana et al., JHEP (2014) 2014: 19
Jet cross-section ratios

- Cross-section ratio not strongly changed compared to pp
- Hint to slightly higher ratio, but covered by uncertainties
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J. Casalderrey-Solana et al., JHEP (2014) 2014: 19

ML-based jet momentum reconstruction

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Summary

Introduced method to correct jets for heavy-ion background:

- ML-based, exploits jet fragmentation properties
- Method shown to be compatible with established area-based correction technique where comparable

Measured charged jets in region of phase space, unconstrained so far by measurements:

- For $R = 0.4$: 40 GeV/c for 0-10%, 30 GeV/c for 30-50% most central collisions
- New in Pb-Pb at the LHC: jets with $R = 0.6$
- Nuclear modification factor $R_{AA}$: No strong radius dependence observed, continues to lower $p_T$
- Cross-section ratios not modified within uncertainties
We still have a lot of ideas to improve the method:

• Impact when unfolding or training assuming e.g. JEWEL fragmentation
• Build a classifier: Instead of approximating background, just discard combinatorial jets
  → Could solve main problem for unfolding
  → Might be less fragmentation dependent
• Try to train deep model that generalizes more on background than on the fragmentation
  → Train with wide variety of fragmentation models

Thank you for your attention!
Backup
Fully corrected charged jet yields

ALICE Pb-Pb 5.02 TeV, 0-10%
Charged jets, anti-$k_T$, $|\eta_{\text{jet}}| < 0.9$ - $R$
ML estimator trained on PYTHIA

$\frac{1}{N_{\text{coll}}} \frac{1}{N_{\text{ev}}} \frac{d^2N_{\text{ch jet}}}{dp_T, ch jet d\eta_{\text{jet}}}$

$R = 0.2$
$R = 0.4$
$R = 0.6$

N_{\text{coll}}$ uncertainty not shown
ALICE Preliminary

$\frac{1}{N_{\text{coll}}} \frac{1}{N_{\text{ev}}} \frac{d^2N_{\text{ch jet}}}{dp_T, ch jet d\eta_{\text{jet}}}$

$R = 0.2$
$R = 0.4$
$R = 0.6$

N_{\text{coll}}$ uncertainty not shown
ALICE Preliminary
Nuclear modification factor $R_{AA}$ for $R=0.2$

**ALICE Pb-Pb 5.02 TeV, 0-10%**
Charged jets, anti-$k_T$, $R = 0.2$, $|\eta_{\text{jet}}| < 0.7$

ML estimator trained on PYTHIA
- ML-based
- Area-based ($p_{T,\text{lead}} > 5 \text{ GeV/c}$, POWHEG ref.)

$T_{AA}$ normalization uncertainty

**ALICE Preliminary**

$R_{AA}$ vs $p_{T,\text{ch jet}}$ (GeV/c)
Systematic uncertainties

Uncertainties summed quadratically

Variations taken into account

- Unfolding method ($\chi^2$-unfolding)
- Unfolding regularization (higher/lower)
- Measured $p_T$ range (higher/lower cut-off)
- Prior (PYTHIA for different radius, steeper/less steep)
- Tracking efficiency uncertainty (4% on tracks)
- Fragmentation uncertainty (response for quark-jets)
The ALICE detector

THE ALICE DETECTOR

1. ITS
2. FMD, T0, V0
3. TPC
4. TRD
5. TOF
6. HMPID
7. EMCal
8. DCal
9. PHOS, CPV
10. L3 Magnet
11. Absorber
12. Muon Tracker
13. Muon Wall
14. Muon Trigger
15. Dipole Magnet
16. PMD
17. AD
18. ZDC
19. ACORDE

a. ITS SPD (Pixel)
b. ITS SDD (Drift)
c. ITS SSD (Strip)
d. V0 and T0
e. FMD

ML-based jet momentum reconstruction

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ML background estimator: Workflow

Toy model dataset

- Toy model creation
- Training and evaluation
- Application on data

ML background estimator (e.g. neural network)

- Training
- Adjust if needed

Real data

- apply

Embedded PYTHIA

- create response

Bkgrd-corrected spectra

- Unfolding

Response matrix

- Unfolding

Final result

arxiv.org/pdf/1810.06324.pdf
“Radiative broadening”:
- For each PYTHIA constituent (above 1 GeV/c), radiate 1 GeV/c particle randomly $\Delta r = 0.6$ with given probability
- Vector calculation of kinematics $\rightarrow$ recoiling constituent
- Jet properties adjusted

This simulates energy loss:
- 1 GeV/c particles radiated dominantly outside jet cone

Would such an effect be correctly reconstructed by the ML estimator?
$\rightarrow$ Yes, see next slide
Fragmentation dependence: Toy model

Toy studies

Even for $p_{\text{loss}} = 100\%$, modification is found with ML estimator!

Same for other $R$
We measure pp-like jets → trained on PYTHIA8

- However, we checked the influence of a different jet assumption
  → Unfold with response for quark-jets in PYTHIA
  → Tested as well unfolding with gluon-jets only ✓

- Leads to a 10-20% uncertainty on the spectra