Inclusive jet $p_T$ reconstruction at $\sqrt{s_{NN}} = 5.02$ TeV with ALICE using machine learning techniques

June 2nd, Hard Probes 2020, Austin, Texas (Remote)

Hannah Bossi for the ALICE Collaboration
Reconstructing jet $p_T$

Reconstruction of inclusive jet $p_T$ in heavy-ion collisions is made difficult by the large fluctuating background from the underlying event. Fluctuations can be on the order of jet itself!

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

1. Estimate and subtract the pedestal

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

2. Leading track bias to remove fake contributions

3. Correct for residual fluctuations via unfolding
Where are we now in ALICE?

Inclusive Jet Measurement Summary

<table>
<thead>
<tr>
<th>Lower $p_T$ Cutoff (GeV/c)</th>
<th>Charged Particle Jets</th>
<th>Full Jets</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.2</td>
<td>30</td>
<td>40</td>
</tr>
<tr>
<td>0.3</td>
<td>50</td>
<td>60</td>
</tr>
<tr>
<td>0.4</td>
<td>N/A</td>
<td>60</td>
</tr>
<tr>
<td>0.6</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Limited by large fake jet contribution at lower $p_T$!

For low $p_T$ : see Jamie Norman’s talk about jets recoiling from high $p_T$ hadron!

Jet quenching and acoplanarity via hadron+jet measurements in pp and Pb-Pb collisions at 5.02 TeV with ALICE
Hybrid Model

Allow for comparisons with jets at RHIC.

Low $p_T$ and large $R$ are less studied regions with inclusive jet probes.

Modification varies at different scales.

Allow for comparisons with jets at RHIC.

Are large $R$ jets modified?

For more on the modification of jet substructure, check out talks by James Mulligan and Raymond Ehlers!

Jet substructure measurements in Pb-Pb collisions at 5.02 TeV with ALICE

Exploring large-$R$ jets and substructure in Pb-Pb collisions at 5.02 TeV with ALICE

Phys. Rev. Lett. 124, 052301
Pushing to low $p_T$ and large $R$

Low $p_T$ and large $R$ are less studied regions with inclusive jet probes, lots of recent experimental efforts to extend measurements to these regions!

ALICE: Low $p_T$, Large $R$, Charged Particle Jets

→ Extend to full jets!

CMS: High $p_T$, Large $R$, Full Jets
Analysis details

Inclusive Pb—Pb jet sample at $\sqrt{s_{\text{NN}}} = 5.02$ TeV with the ALICE detector in 2015.

anti-$k_T$ jets with various resolution parameters $R$ and centralities

Charged particle jets $\rightarrow$ contain the charged component of the jet $\rightarrow$ measured with tracking detectors

Full jets $\rightarrow$ contain charged and neutral components of the jet $\rightarrow$ measured with electromagnetic calorimeter $\rightarrow$ limited to fiducial phi acceptance
Machine learning background estimator

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

Does this method reduce residual fluctuations, allowing the measurement to be pushed to lower $p_T$ with reduced systematic uncertainties?

Does using constituent information in training introduce a fragmentation bias?

New: Extending method to full jets and exploration of potential fragmentation bias!

Process

Training (PYTHIA fragmentation)

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

Can either be Pb-Pb data or thermal toy background.

Key is that this background is realistic.

Testing

Shallow neural network implemented in scikit-learn.

3 layers [100,100,50] nodes

Apply ML estimator to hybrid events not used in training.

Do we get back the signal we put in?

Regression target is PYTHIA jet $p_T$.

Iterative process to decide on optimal set of features, full list in backup!
Evaluating the performance

\[ \delta p_T = p_{T,\text{rec}} - p_{T,\text{true}} \]

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

Narrow \( \delta p_T \rightarrow \) Reduced residual fluctuations

Residual fluctuations significantly reduced!
Evaluating the performance

\[
\delta p_T = p_{T, \text{rec}} - p_{T, \text{true}}
\]

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

Narrow \(\delta p_T \rightarrow \) Reduced residual fluctuations

Residual fluctuations significantly reduced!
Results - inclusive jet spectra

Charged Particle Jets

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

Able to extend measurements to lower $p_T$ and larger $R$!

Full Jets

Unfolding systematics dominate at lower $p_T$.
Tracking efficiency systematics dominate at high $p_T$.

New Preliminary!

ALICE Pb-Pb $\sqrt{s}_{NN} = 5.02$ TeV, 0-10%
Full Jets, anti-$k_T$ $R = 0.4$, $|\eta_{jet}| < 0.7 - R$
ML Estimator Trained on PYTHIA

<table>
<thead>
<tr>
<th>Lower $p_T$ Cutoff (GeV/c)</th>
<th>Charged Particle Jets</th>
<th>Full Jets</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>20</td>
<td>40</td>
</tr>
<tr>
<td>0.3</td>
<td>50</td>
<td>60</td>
</tr>
<tr>
<td>0.4</td>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>0.6</td>
<td>50</td>
<td>N/A</td>
</tr>
</tbody>
</table>
**Results - jet $R_{AA}$**

$R_{AA} = \frac{1}{N_{ evt}} \frac{d^2 N_{PbPb}}{dp_T dy} \bigg|_{cent} = \frac{\left< T_{AA} \right>}{d^2 \sigma_{PP}^{jet}} \frac{d^2 N_{jet}}{dp_T dy}$

**Charged Particle Jets**

ALICE Pb-Pb 5.02 TeV, 0-10%
Charged jets, anti-$k_T$, $R = 0.4$, $|\eta_{jet}| < 0.5$
ML estimator trained on PYTHIA
- ML-based
- Area-based ($p_{T,lead} > 7$ GeV/c)

**Full Jets**

ALICE Pb-Pb $\sqrt{s_{NN}} = 5.02$ TeV, 0-10%
Full Jets, anti-$k_T$, $R = 0.4$, $|\eta_{jet}| < 0.7 - R$
ML Estimator Trained on PYTHIA

See significant jet suppression down to 40 GeV/c!

Systematic uncertainties are reduced.

New Preliminary!
Learning on constituents introduces a fragmentation bias.

We learn on a PYTHIA fragmentation.

We know that fragmentation in heavy-ion collisions is modified by the presence of the medium.

We want to investigate how this impacts the final result we get with ML!
Toy model studies

We study a toy model with three different ways to alter constituents of the jet, changing the fragmentation.

Fractional Mostly In-Cone Energy Loss

Fractional Mostly Out-of-Cone Energy Loss

BDMPS-Motivated

Use prior knowledge of behavior at intermediate \( p_T \) to create a variation in the fragmentation!
Modification to the fragmentation function

8 leading particles are what we chose to train on.
Looking at $R_{AA}^{toy}$

1. Modify PYTHIA jets
2. Apply ML trained on unmodified PYTHIA
3. Look at $R_{AA}^{toy} = \frac{\text{Modified}}{\text{Unmodified}}$

Here, we focus on the difference between PYTHIA and Embedded (ML).

Largest difference for the mostly in cone case.

Will we see similar biases in the final result if we trained on modified toy?
Illustration of potential bias

Train on the modified toy model and apply to data; measure bias.

Method is relatively robust to the explored biases!

Lower $p_T$ is a largely unexplored region. Machine learning provides us with an opportunity to study this.
Comparing to models

Keeping previous studies in mind, let’s compare to models!

Aiming to constrain models at low $p_T$ with new measurement technique!

### JEWEL: Scattering and radiative energy loss, with/without recoiling medium.

JHEP 1707 (2017) 141

### SCETg: Interactions with medium mediated by Glauber gluon exchange.

JHEP 07 (2019) 148

### Hybrid Model: medium response via wake. AdS/CFT non-pert. regime.

Phys. Rev. Lett. 124, 052301

### LBT: hydrodynamic medium, jet-medium interactions, recoils.

Summary and conclusion

We present a novel machine learning based background correction, which allows for the extension of inclusive jet measurements to lower $p_T$ and larger $R$ than previously possible in ALICE.

See significant jet suppression down to $p_T$ accessible by RHIC.

We study the fragmentation bias introduced by training the neural network on the constituents from PYTHIA using a toy model with three different modifications, estimating the effect of these modifications on the $R_{AA}$.

Future: Expand full jet results to more resolution parameters and centralities.
Extend tests of fragmentation with a quenched MC.

Thanks!
Backup
Technical Details of the ML

Regression task where the regression target is the detector level jet $p_T$.

Here we are prioritizing a simple model!

Training sample 10%, testing sample 90%.

Implemented in *scikit-learn*. Default parameters used unless otherwise specified.

**Shallow Neural Network**
Shallow, 3 layers with [100, 100, 50] nodes
ADAM optimizer, stochastic gradient descent algorithm.
Nodes/neurons activated by a ReLU activation function.

**Linear Regression**
Normalization set to true by default.

**Random Forest**
Ensemble of 30 decision trees.
Maximum number of features set to 15.

Hannah Bossi
Features for training

Ask ourselves two questions

- How important is the feature to the model? → Feature Scores
  - Higher the feature score, more often variable is used in training.

- How correlated is the feature with other features?

<table>
<thead>
<tr>
<th>Feature</th>
<th>Score</th>
<th>Feature</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jet $p_T$ (no corr.)</td>
<td>0.1355</td>
<td>$p^1_{T,\text{const}}$</td>
<td>0.0012</td>
</tr>
<tr>
<td>Jet mass</td>
<td>0.0007</td>
<td>$p^2_{T,\text{const}}$</td>
<td>0.0039</td>
</tr>
<tr>
<td>Jet Area</td>
<td>0.0005</td>
<td>$p^3_{T,\text{const}}$</td>
<td>0.0015</td>
</tr>
<tr>
<td>Jet $p_T$ (area based corr.)</td>
<td>0.7876</td>
<td>$p^4_{T,\text{const}}$</td>
<td>0.0011</td>
</tr>
<tr>
<td>LeSub</td>
<td>0.0004</td>
<td>$p^5_{T,\text{const}}$</td>
<td>0.0009</td>
</tr>
<tr>
<td>Radial moment</td>
<td>0.0005</td>
<td>$p^6_{T,\text{const}}$</td>
<td>0.0009</td>
</tr>
<tr>
<td>Momentum dispersion</td>
<td>0.0007</td>
<td>$p^7_{T,\text{const}}$</td>
<td>0.0008</td>
</tr>
<tr>
<td>Number of constituents</td>
<td>0.0008</td>
<td>$p^8_{T,\text{const}}$</td>
<td>0.0007</td>
</tr>
<tr>
<td>Mean of constituent $p_T$'s</td>
<td>0.0585</td>
<td>$p^9_{T,\text{const}}$</td>
<td>0.0006</td>
</tr>
<tr>
<td>Median of Constituent $p_T$'s</td>
<td>0.0023</td>
<td>$p^{10}_{T,\text{const}}$</td>
<td>0.0007</td>
</tr>
</tbody>
</table>

*Iteratively remove unimportant or highly correlated features!*

Features for training

Ask ourselves two questions

- How important is the feature to the model? → Feature Scores
  Higher the feature score, more often variable is used in training.

- How correlated is the feature with other features?

Final List: Prioritizing a simple model!

- Jet $p_T$ (area-based corrected)
- Number of Constituents within Jet
- Jet Angularity
- $p_T$ of 12 Leading Constituents
Evaluating the performance

\[ \delta p_T = p_{T,\text{rec}} - p_{T,\text{true}} \]

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

Narrow \( \delta p_T \rightarrow \) Reduced residual fluctuations

Charged Particle Jets

Residual fluctuations significantly reduced!
BDMPS Toy Model Modification

\[ P(\theta_g, \omega) = \alpha \omega \theta_g^3 \sqrt{\frac{2\omega}{\hat{q}}} L e^{-\theta_g^2\omega^2 / \sqrt{2\omega\hat{q}}} \]

Modify the constituents of the jet by sampling the BDMPS gluon emission spectrum in the emission angle and energy.

For this study we use values of \( \hat{q} = 2 \) and \( L = 7 \) fm and \( p_{loss} = 1.0 \).

Motivation behind this is to emit from a probability distribution dictated by quenching theory.