

Jet Momentum Background Estimation using Machine Learning with ALICE

ORNL Nuclear Physics Seminar

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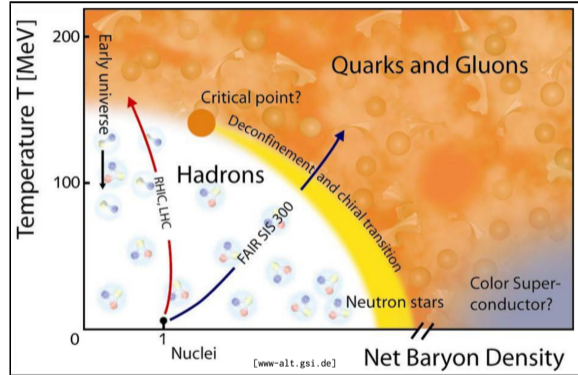
¹Oak Ridge National Lab

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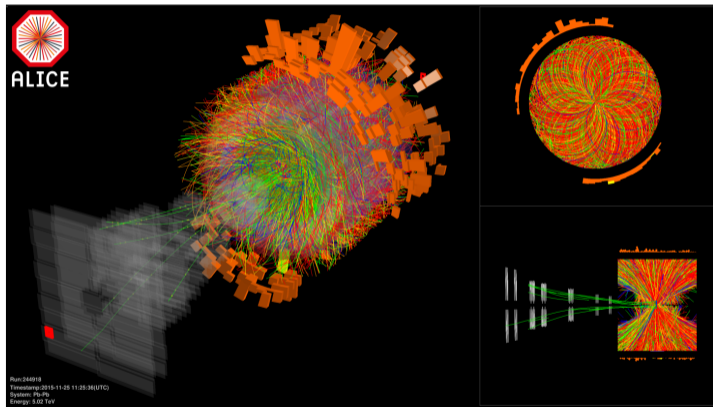
QCD Phase Diagram and the Quark Gluon Plasma (QGP)

- At high temperatures, hadrons melt into their constituent quarks and gluons.
- The quarks and gluons are deconfined in a strongly coupled state known as the **Quark Gluon Plasma (QGP)**.
- Phase transition occurs around a temperature of $T \sim 150$ MeV.
 - Smooth crossover phase transition near net baryon density of ~ 0 .
- Trajectories through the phase-space are experimentally accessible in heavy-ion collisions.



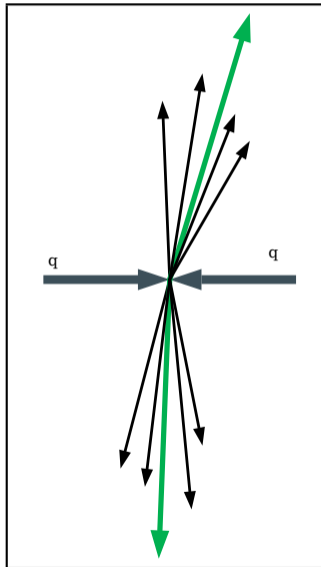
High Momentum Transfer Processes

- Heavy ion collisions involve a variety of physical processes.
 - → We need tools to isolate properties of interest.
- My focus: **High momentum transfer processes** which provide a built-in probe of the QGP.
- The experimental signature of high momentum transfer processes is known as a **jet**.



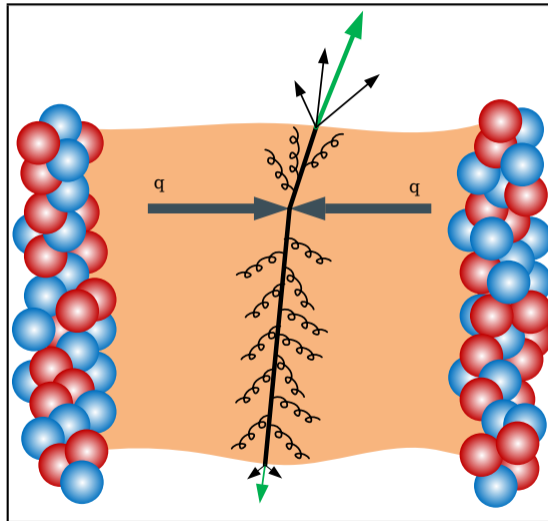
Jets and Jet Quenching

- Jets are collimated sprays of particles produced by the fragmentation of a parton from a high momentum transfer scattering.
 - Experimentally defined by a jet clustering algorithm with a resolution parameter, R .



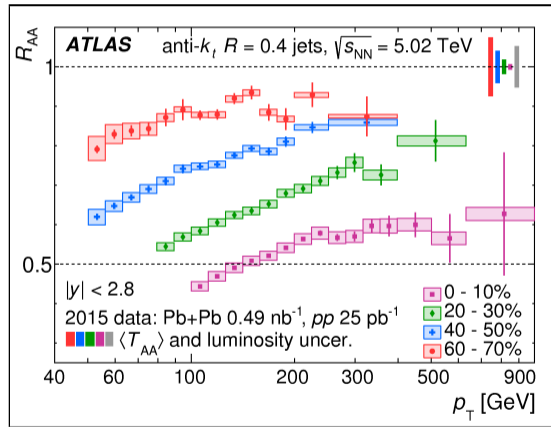
Jets and Jet Quenching

- Jets are collimated sprays of particles produced by the fragmentation of a parton from a high momentum transfer scattering.
 - Experimentally defined by a jet clustering algorithm with a resolution parameter, R .
- In heavy-ion collisions, jets are produced before the QGP forms and then propagate through it, **losing energy**.
- Jet-medium interactions are expected to **modify the internal structure** of the jet.
 - Jets probe multiple scales during propagation.
- The impact of these interactions are collectively known as **jet quenching**.



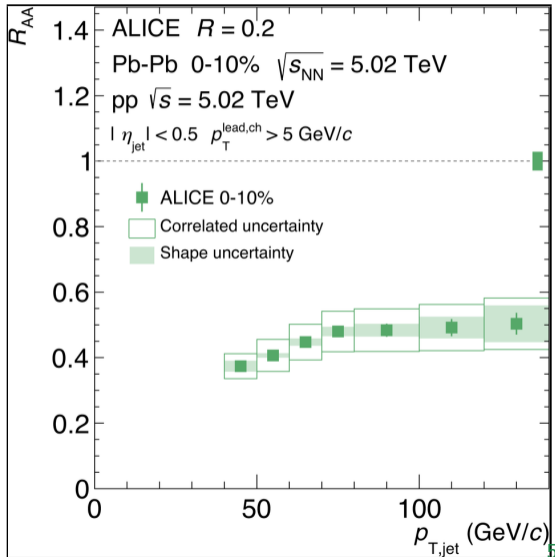
Jet Quenching: R_{AA}

- Jet nuclear modification factor, R_{AA} , compares the jet spectra between Pb–Pb and pp collisions scaled by the number of binary collisions.
 - $R_{AA} = 1$ corresponds to no modification.
- Many measurements show **significant suppression** of jets in Pb–Pb over a wide jet p_T range.
 - Suppression decreases in more peripheral collisions.
- Don't yet have jet p_T overlap between RHIC and LHC.



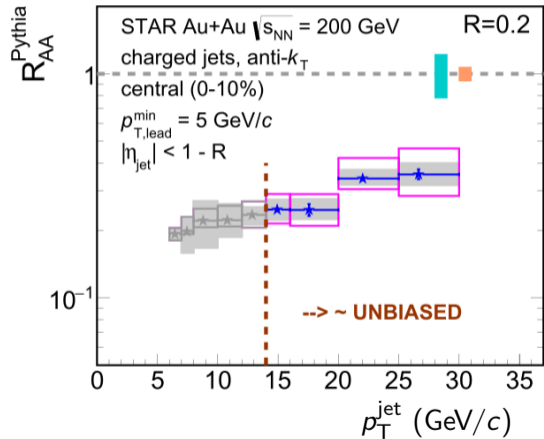
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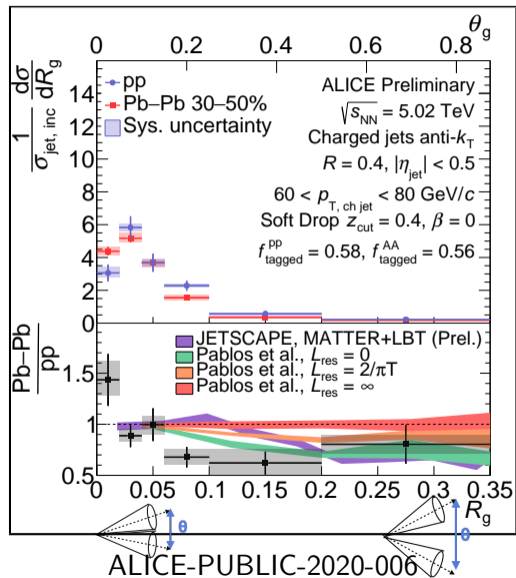
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Further Jet Measurements

- There are a plethora of jet measurements:
 - Jet substructure
 - Jet shapes
 - Jet-x correlations
 - etc...
- Different measurements add different constraints to properties of the QGP.
- All of these measurements depend on our ability to measure jets effectively.
- → **How do we measure jets?**
 - What are the difficulties?
 - Can we improve our techniques?



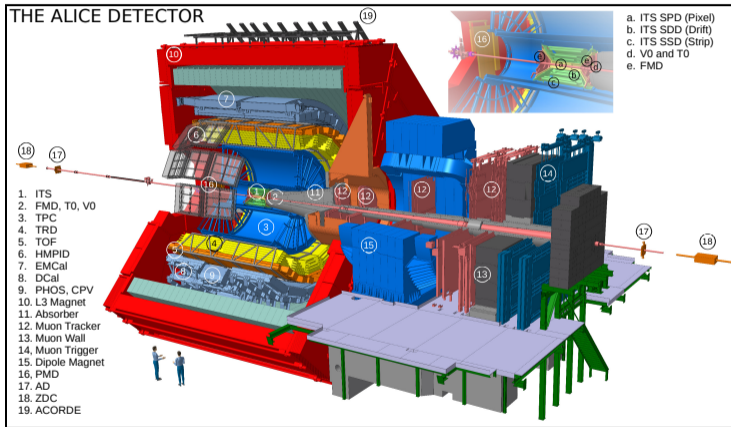
How Do We Measure Jets in ALICE?

- ALICE performs two kinds of jet measurements:
 - Charged-particle jets.
 - Full jets (see Hannah's talk).

Why charged-particle jets?

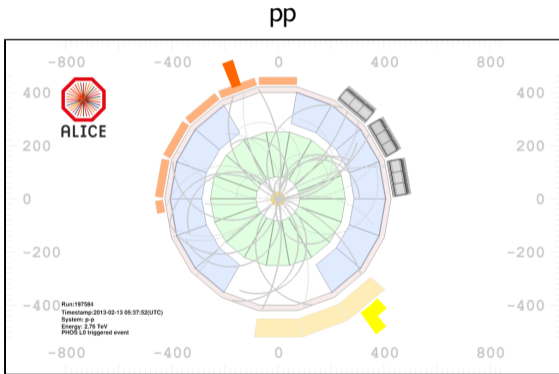
ALICE central barrel tracking is based around the ITS and TPC.

1. Measure charged particles with precise angular resolution down to $p_T > 150$ MeV/c.
2. Larger acceptance.



How Do We Measure Jets?

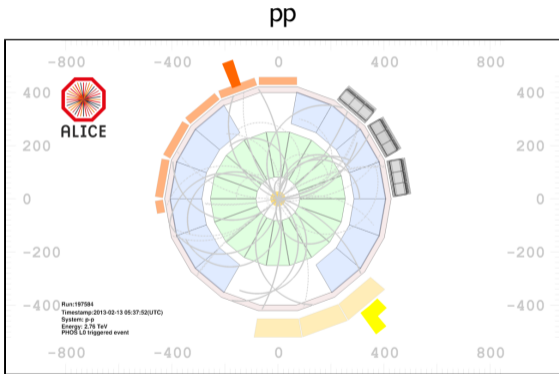
- Looking for collimated sprays of particles.



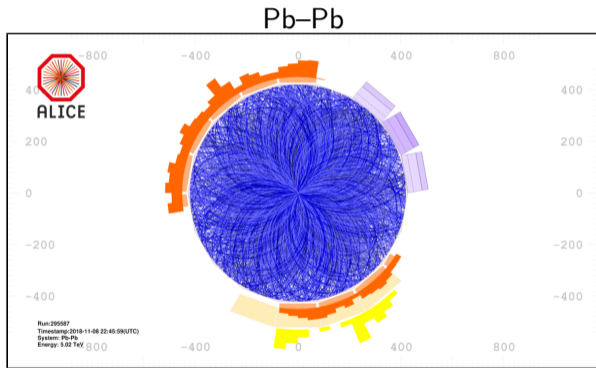
→ Can roughly jet find by eye.

How Do We Measure Jets?

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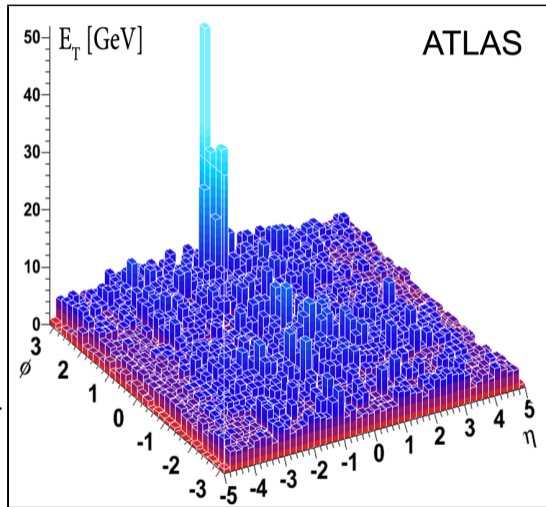
→ Can roughly jet find by eye.



→ Not so much here. . .

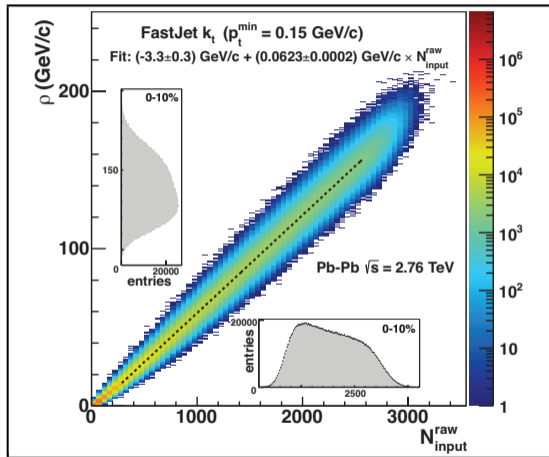
Background Contributions to HI Jets

- The jet is composed of the particles from the high momentum transfer process as well as the medium response.
- There is an additional **large, fluctuating background** from the underlying event (soft interactions, particles from the QGP, etc).
- Two main background components:
 1. Event-averaged pedestal
 2. Residual fluctuations
- Background limits possible jet R and min jet p_T .
 - Contaminates larger jets.
 - Fluctuations limit jet p_T reach.



Accounting for the HI Background

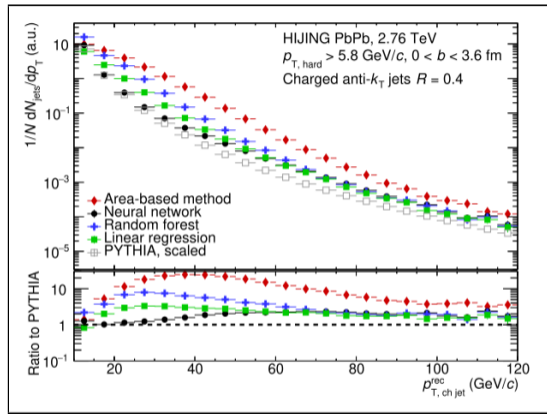
- The pedestal usually accounted for with area-based subtraction:
 1. Determine the event-averaged momentum density, ρ .
 2. Determine the jet area.
 3. Subtract the pedestal via
$$p_{T,rec} = p_{T,raw} - \rho A.$$
- Fluctuations accounted for via **unfolding** (along with detector effects).
- **Limited** to $p_{T,jet} = 60 \text{ GeV}/c$ for $R = 0.4$ charged-particle jets in 0-10%.
- Can we do better?



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Machine Learning for Background Subtraction

- We have a **highly and non-trivially correlated problem** with lots of available information.
 - Too complex for experts to disentangle.
- Background fluctuations **statistically limited** the AB method from going to lower $p_{T,\text{jet}}$.
- → Can we take advantage of machine learning (ML) techniques?
 - Utilize **more jet properties** than $p_{T,\text{jet}}$.
- On a jet-by-jet basis, can ML correct $p_{T,\text{jet}}$?
- Goal: Increase jet R and jet p_T range by reducing residual background fluctuations.
 - Unfolding will still be necessary.



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064904 (2019)

Guiding Principles for Jet Background ML

- ML has been broadly adopted in HEP, but is relatively new in HI collisions.
- For example, we don't yet have a comprehensive MC event generator.
- → Use **simpler ML techniques**: linear regression, random forest, shallow neural network.
- Note: We perform supervised learning using jets from the MC event generator PYTHIA.
 - Potentially dependent on the PYTHIA fragmentation.
- → Use **minimal jet properties**.

Machine Learning based jet momentum reconstruction in heavy-ion collisions

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¹Yale University, Wright Laboratory, New Haven, CT, USA

²ORNL, Physics Division, Oak Ridge, TN, USA

(Dated: June 24, 2019)

The precise reconstruction of jet transverse momenta in heavy-ion collisions is a challenging task. A major obstacle is the large number of (mainly) low- p_T particles overlaying the jets. Strong region-to-region fluctuations of this background complicate the jet measurement and lead to significant uncertainties. In this paper, a novel approach to correct jet momenta (or energies) for the underlying background in heavy-ion collisions is introduced. The proposed method makes use of common Machine Learning techniques to estimate the jet transverse momentum based on several parameters, including properties of the jet constituents. Using a toy model and HIJING simulations, the performance of the new method is shown to be superior to the established standard area-based background estimator. The application of the new method to data promises the measurement of jets down to extremely low transverse momenta, unprecedented thus far in data on heavy-ion collisions.

INTRODUCTION

In ultrarelativistic heavy-ion collisions a new state of nuclear matter is created: the Quark-Gluon Plasma (QGP) [1]. In the QGP, deconfined quarks and gluons interact strongly and form a hot and dense medium that can be approximately described by hydro- and thermodynamics. The regime of strong coupling at large distances, especially in systems of high temperature or large energy densities, is still not well understood in Quantum Chromodynamics (QCD). An ideal self-generated probe to explore the properties of the medium and its interactions are particle jets [2]. Reconstructed in the detector as collimated sprays of color-neutral particles, jets are created in a large-momentum-transfer scattering of partons in the early stage of a high-energy collision. Their production is well understood within the framework of QCD and their rates can be perturbatively calculated in vacuum. In a heavy-ion collision, jets traverse the strongly-interacting medium and interact mainly non-perturbatively and, thus, can serve as valuable probes of the QGP.

The reconstruction of particle jets in heavy-ion collisions is a complex task. The main obstacle is the overwhelmingly

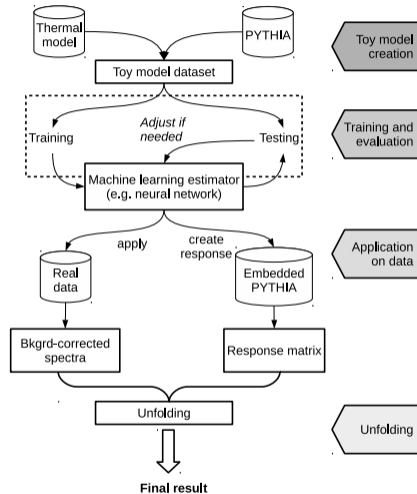
finding algorithm and eventually result in large uncertainties on the final measurements. An approach to at least lower the impact of the background at the expense of a potential fragmentation bias is a higher p_T -cut for constituents used in the jet finding algorithm. This massively reduces the background, which mostly consists of low- p_T particles, but it also discards the low- p_T parts of the jet. The treatment of the background and its fluctuations depends on the observable under study. In this paper, the focus is on the correction of observables based on jet momentum, i.e. the correction of the jet energy scale, without applying a particular constituent cut. The impact of the background on the jet (sub)structure, e.g. by distorting the jet axis, is not discussed here.

In the standard method for jet spectra measurements in ALICE, the background momentum density per unit area is calculated on an *event-by-event* basis. Each jet is then corrected by taking into account the event-averaged density multiplied by the jet area. The area-based method corrects the jet momentum for the average background but leads to large residual fluctuations. These residual fluctuations are then typically corrected for on a statistical basis in an unfolding procedure, see for instance Ref. [3].

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Machine Learning Procedure

- Event consists of PYTHIA events embedded into real Pb-Pb data.
- Extract features which are important for model performance, avoiding highly-correlated or unimportant features.
 - AB Jet p_T , constituent p_T , etc.
- Test/train split: 90/10%
 - Matches the statistics in data.
- NN with [100, 100, 50] layers.
- Regression task to predict the corrected jet p_T .
 - True jet p_T corresponds to PYTHIA at detector level.



Machine Learning Inputs

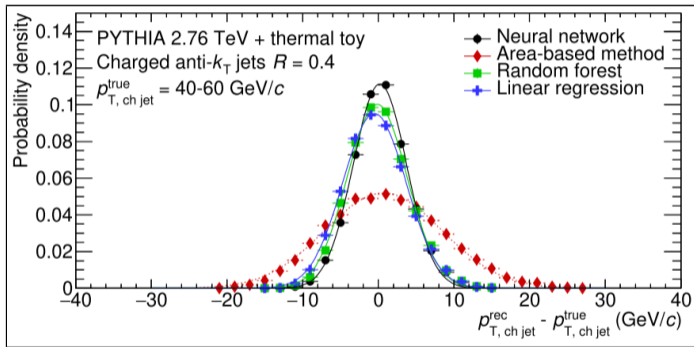
- **Optimize the included jet parameters** by evaluating feature importance using the random forest.
 - Not identical to NN, but the models are simple enough that they are expected to be simple.
- Remove parameters without importance, or that are highly correlated with other features.
- Parameters utilized:
 - Area based jet p_T
 - Number of jet constituents
 - Jet angularity
 - Constituent p_T for leading eight tracks.

| Feature | Score | Feature | Score |
|------------------------------|---------------|----------------------------|---------------|
| Jet p_T (no corr.) | 0.1355 | $p_{T, \text{const}}^1$ | 0.0012 |
| Jet mass | 0.0007 | $p_{T, \text{const}}^2$ | 0.0039 |
| Jet area | 0.0005 | $p_{T, \text{const}}^3$ | 0.0015 |
| Jet p_T (area-based corr.) | 0.7876 | $p_{T, \text{const}}^4$ | 0.0011 |
| LeSub | 0.0004 | $p_{T, \text{const}}^5$ | 0.0009 |
| Radial moment | 0.0005 | $p_{T, \text{const}}^6$ | 0.0009 |
| Momentum dispersion | 0.0007 | $p_{T, \text{const}}^7$ | 0.0008 |
| Number of constituents | 0.0008 | $p_{T, \text{const}}^8$ | 0.0007 |
| Mean of const. p_T | 0.0585 | $p_{T, \text{const}}^9$ | 0.0006 |
| Median of const. p_T | 0.0023 | $p_{T, \text{const}}^{10}$ | 0.0007 |

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Evaluating Background Subtraction Performance: ML vs AB

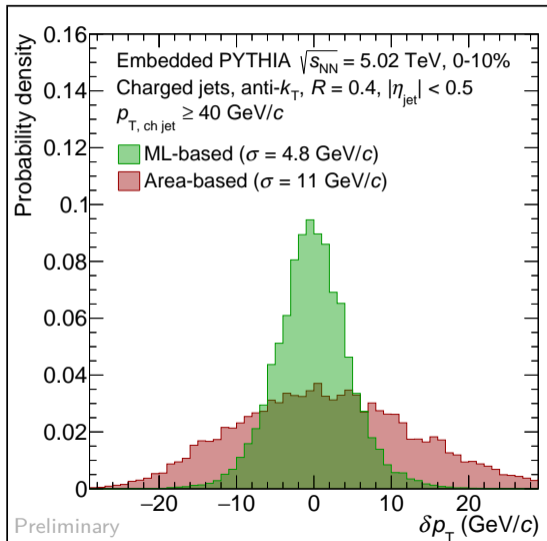
- Performance characterized by $\delta p_T = p_{T,\text{rec}} - p_{T,\text{true}}$.
 - $p_{T,\text{rec}}$: $p_{T,\text{jet}}$ corrected for background.
 - $p_{T,\text{true}}$: True $p_{T,\text{jet}}$.
- Characterized by putting known jets into a HI-like background.
- Zero mean indicates no overall $p_{T,\text{jet}}$ bias.
- Width characterizes background fluctuations.



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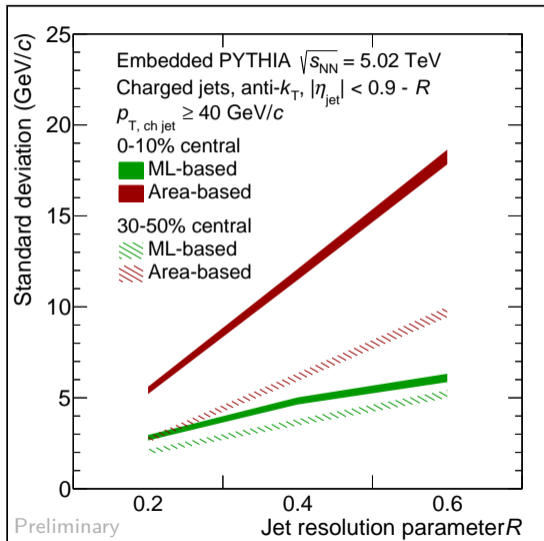
Evaluating ML vs AB Performance with data embedding

- Performance characterized by $\delta p_T = p_{T,rec} - p_{T,true}$.
- Measured by embedding known pythia jets into **real Pb–Pb data**.
- NN introduces **no additional bias** to the mean.
- NN shows a **clear improvement** over area based for background fluctuations.
- Improvements for all jet R , centralities.



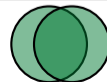
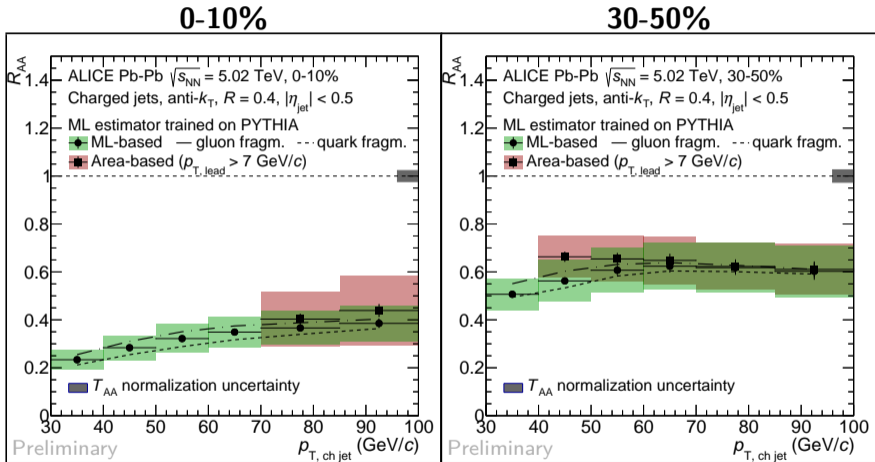
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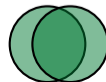
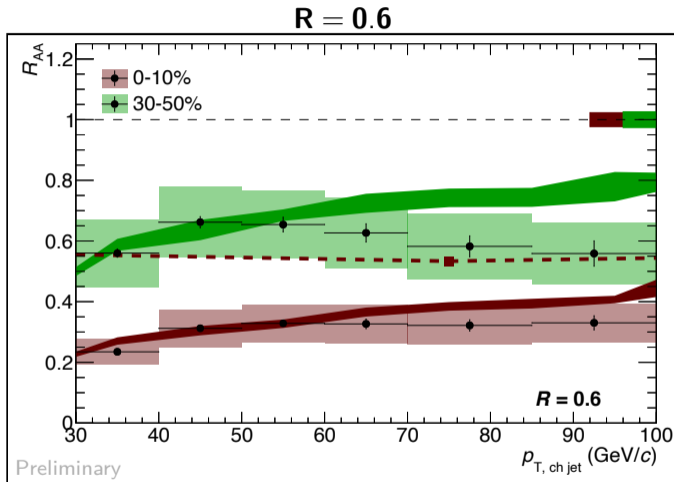
Jet Nuclear Modification Factor - $R = 0.4$

- **Consistent** with existing area-based measurements.
- Extend to **lower jet p_T** : 30 GeV/c.
- Quark or gluon only fragmentation biases are within uncertainties.



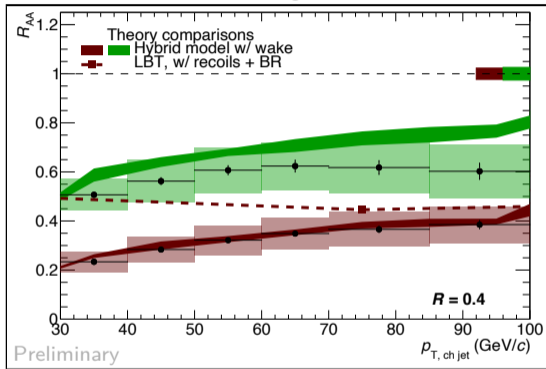
Jet Nuclear Modification Factor - $R = 0.6$

- **First** measurement of $R = 0.6$ at **low jet p_T** at the LHC.
- Extends down to 30 GeV/c!
- Increasing suppression for more central collisions.
- R_{AA} consistent with flat evolution with jet p_T .

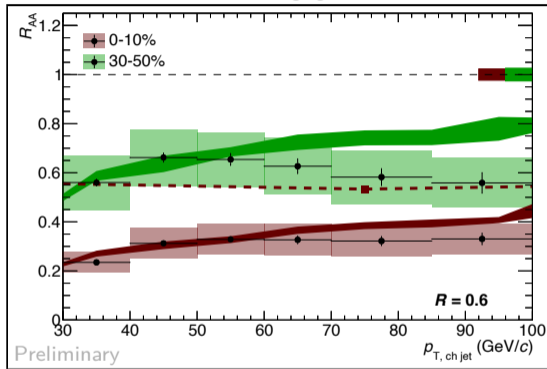


Jet Nuclear Modification Factor - $R = 0.4$ and $R = 0.6$

$R = 0.4$



$R = 0.6$

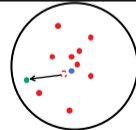
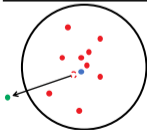
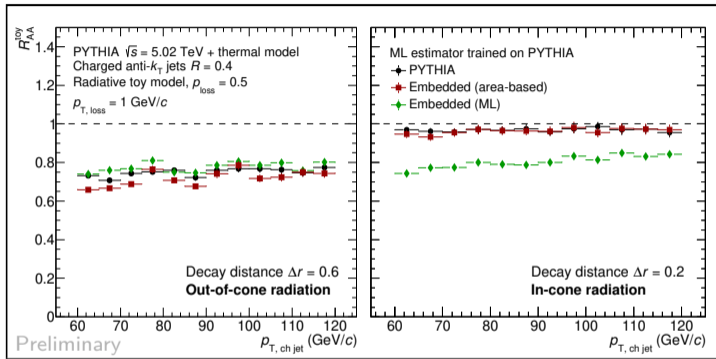


- Suppression is consistent between $R = 0.4$ and $R = 0.6$.
- May help differentiate models at low jet p_T .



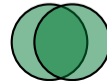
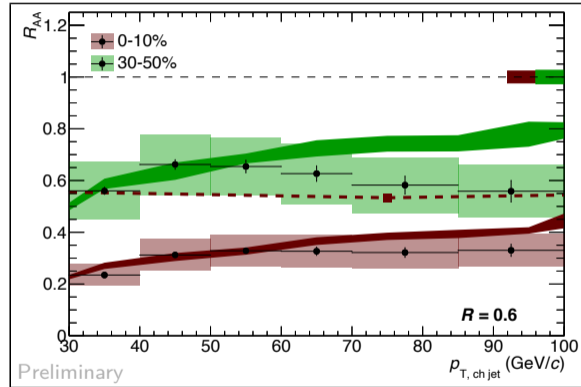
Fragmentation Bias Studies

- The ML techniques explicitly relies on PYTHIA fragmentation patterns.
- It's possible that fragmentation in HI collisions is significantly different than training data
 - Manually modify jet fragmentation to test for this possibility.
- Explore broadening both within and outside the jet cone.
 - Much more in Hannah's talk.



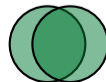
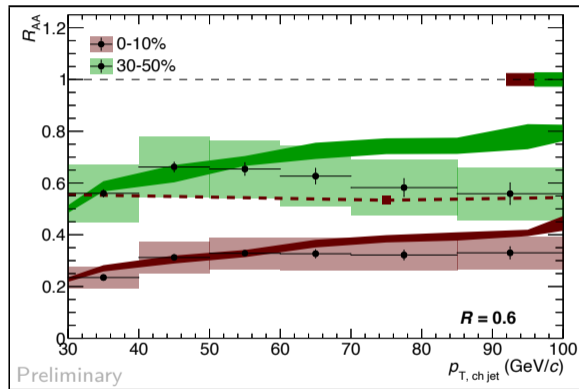
Conclusions

- We have developed machine learning methods to correct the background contribution to jets measured in heavy ion collisions.
- These techniques enable charged-particle jet spectra measurements at the LHC to extend to lower jet p_T and larger jet R than previously possible.
 - Down to $p_{T,\text{jet}} = 30 \text{ GeV}/c$ for $R = 0.6$ jets.
- Enables improved understanding of jet energy loss, thereby improving characterization of QGP properties.



Outlook

- Next steps include:
 - Further fragmentation bias studies
 - Full jets
 - Extensions to jet substructure, shapes, etc.
- → Hannah's talk.



Backup

Machine Learning Settings

- All implemented via `scikit-learn` with defaults unless specified.
- Training sample 10%, testing sample 90%.

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

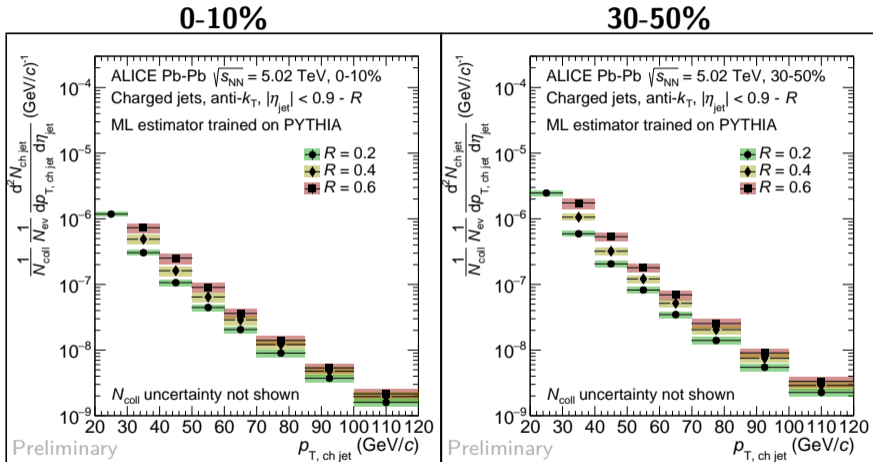
- Normalization set to true by default.

Random Forest

- Ensemble of 30 decision trees.
- Maximum number of features set to 15.

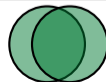
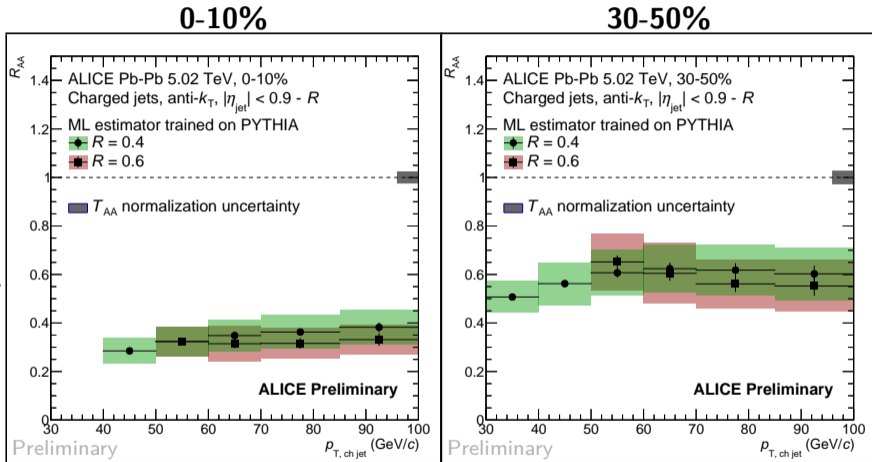
Inclusive Jet Spectra

- Spectra measured for 0-10% and 30-50% centralities.
- Measured down to 30 GeV/c for $R = 0.6$ jets!
- **Expands jet p_T range and jet R .**



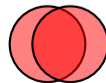
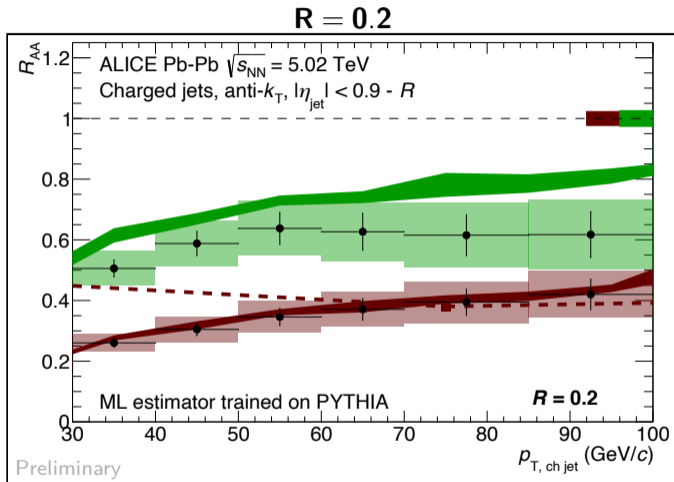
Jet Nuclear Modification Factor - $R = 0.4$ vs $R = 0.6$

- **First** measurement of $R = 0.6$ at **low jet p_T** at the LHC.
- Similar suppression for $R = 0.4$ and $R = 0.6$.



Jet Nuclear Modification Factor - $R = 0.2$

- $R = 0.2$ measurement extends down to 30 GeV/c!
- Increasing suppression for more central collisions.
- Largest suppression decreases with increasing jet p_T .



Jet Cross Section Ratios

- Many uncertainties cancel for CSR, so it can provide strong constraints for QCD.
- pp and Pb-Pb are largely consistent within uncertainties.
- Hybrid model describes $R = 0.2/R = 0.4$, but overpredicts $R = 0.2/R = 0.6$.

