Apples to Apples in Jet Quenching

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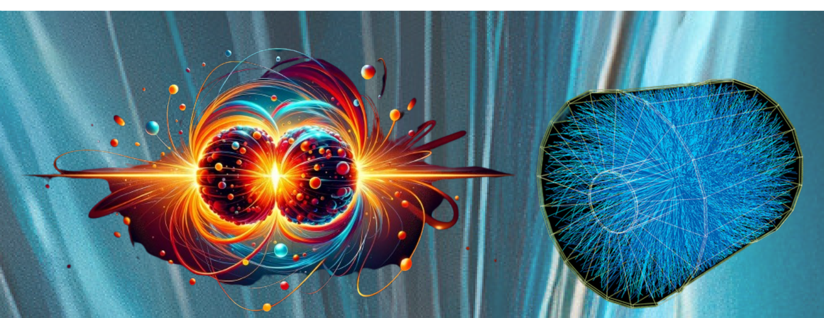
Introduction and Motivation

Context

In central Heavy-Ion Collisions (HIC), a large and strongly fluctuating Underlying Event (UE) is produced, often, along with jets emerging from a hard scattering. The UE arises from the rapid expansion and cooling of the produced Quark-Gluon Plasma (QGP) Currently, a constituent-based algorithm is used to subtract this UE. However, this algorithm is not flawless, and because of the fluctuating nature of the UE, the subtracted jets still exhibit fluctuations.

Studying the QGP

The study of the QGP through the modifications it induces in the produced jets, is done by comparing these with jets produced in pp collisions, where we have a great experimental and theoretical control over them.



True Modifications and ML

For ML algorithms in particular, models could learn to distinguish jets from PbPb and pp collisions solely on the presence of subtraction induced fluctuations in the PbPb jets. To mitigate this effect, pp jets should be embedded in a as-close-to-experimental-data-as-possible UE and subtracted the same way as PbPb jets. Only modifications that survive this subtraction are truly jet modifications, not stemming from procedural differences on the two samples.

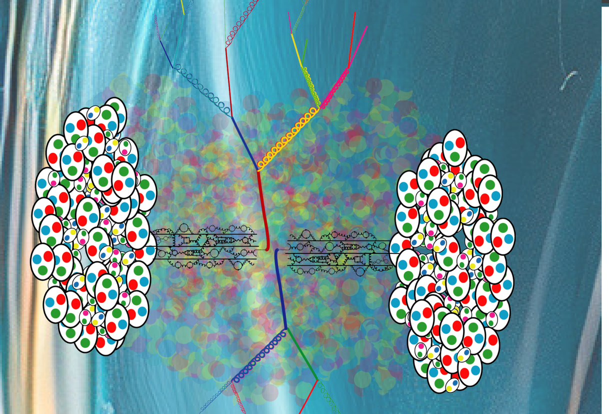
Our Aim

In this work we aim to build an UE generation procedure from experimental measurements and study the robustness of jet modifications to the subtraction in both pp and PbPb jets across a wide range of observables. We furthermore study the impact of the subtraction on a range of ML algorithms, including several Neural Network (NN) architectures such as convolutional, energy flow and particle flow networks, in supervised and unsupervised scenarios.

Procedures

Work Pipeline

GEN: Generate pp and PbPb (with recoils) jets through JEWEL [1].
GEN: Generate as many UEs as events.
SUB: Apply JEWEL's recoil subtraction.
EMB: Embed both pp jets and PbPb (after rec. sub.) in the UEs.
SUB: Subtract the whole event through ICS [2].
ANA: Reconstruct dijet system and study jet observables.
ANA: Produce jet representations and apply ML algorithms.

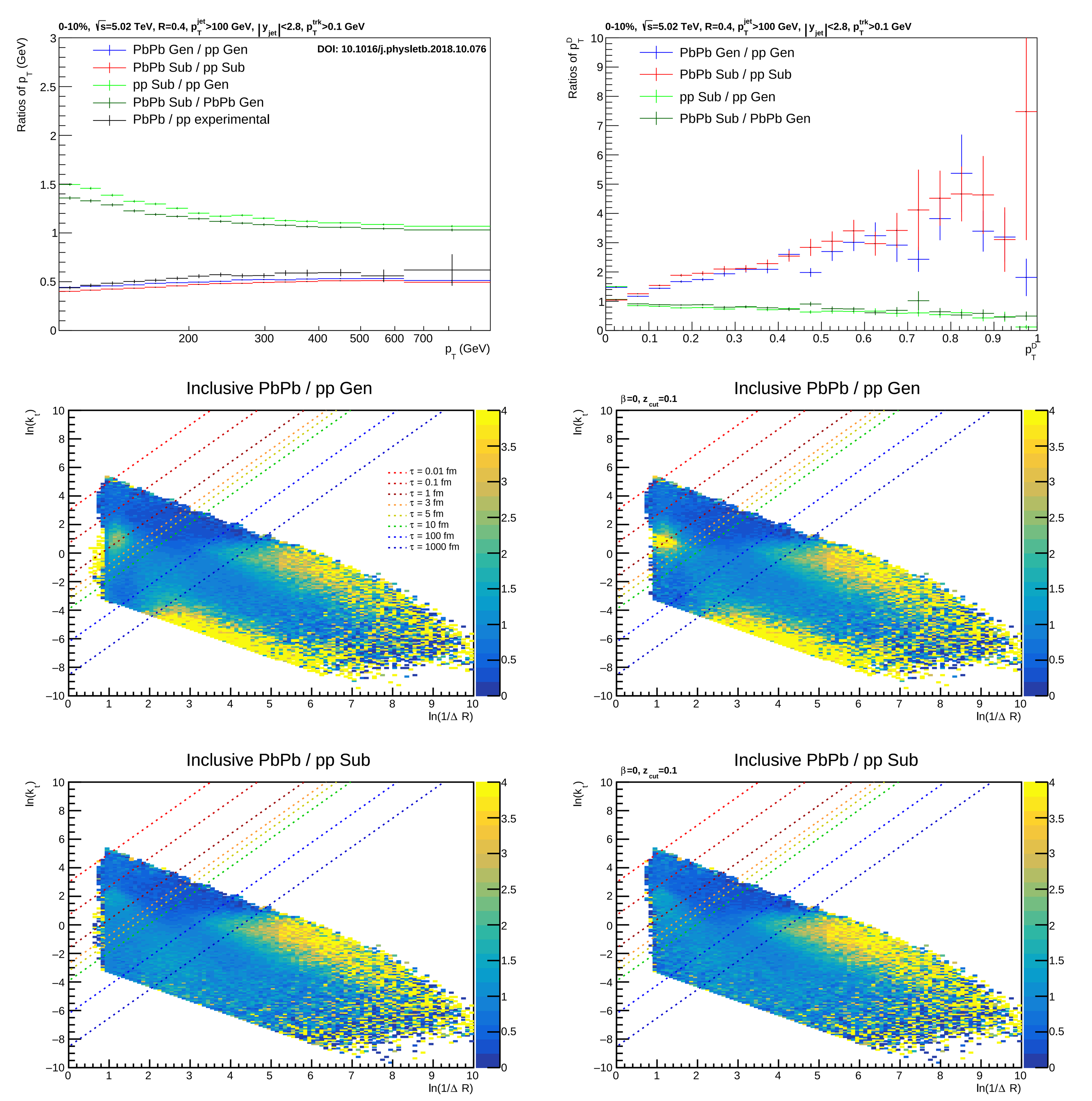


UE Generation

FIT: Fit the pseudo-rapidity spectrum of the UE measured in [3] and take ϕ uniform.
FIT: Fit the transverse momentum spectrum of the UE measured in [4].
INT: Integrate the η spectrum and scale by 1.5 to include neutrals, to obtain an average value of particles to be produced per event.
SAM: Sample the number of particles from a gaussian distribution with the average value obtained, and its squared root as a std. dev..
SAM: Sample p_T, η and ϕ form the considered spectra.
SAM: Sample uniformly an id from the three species of pions.

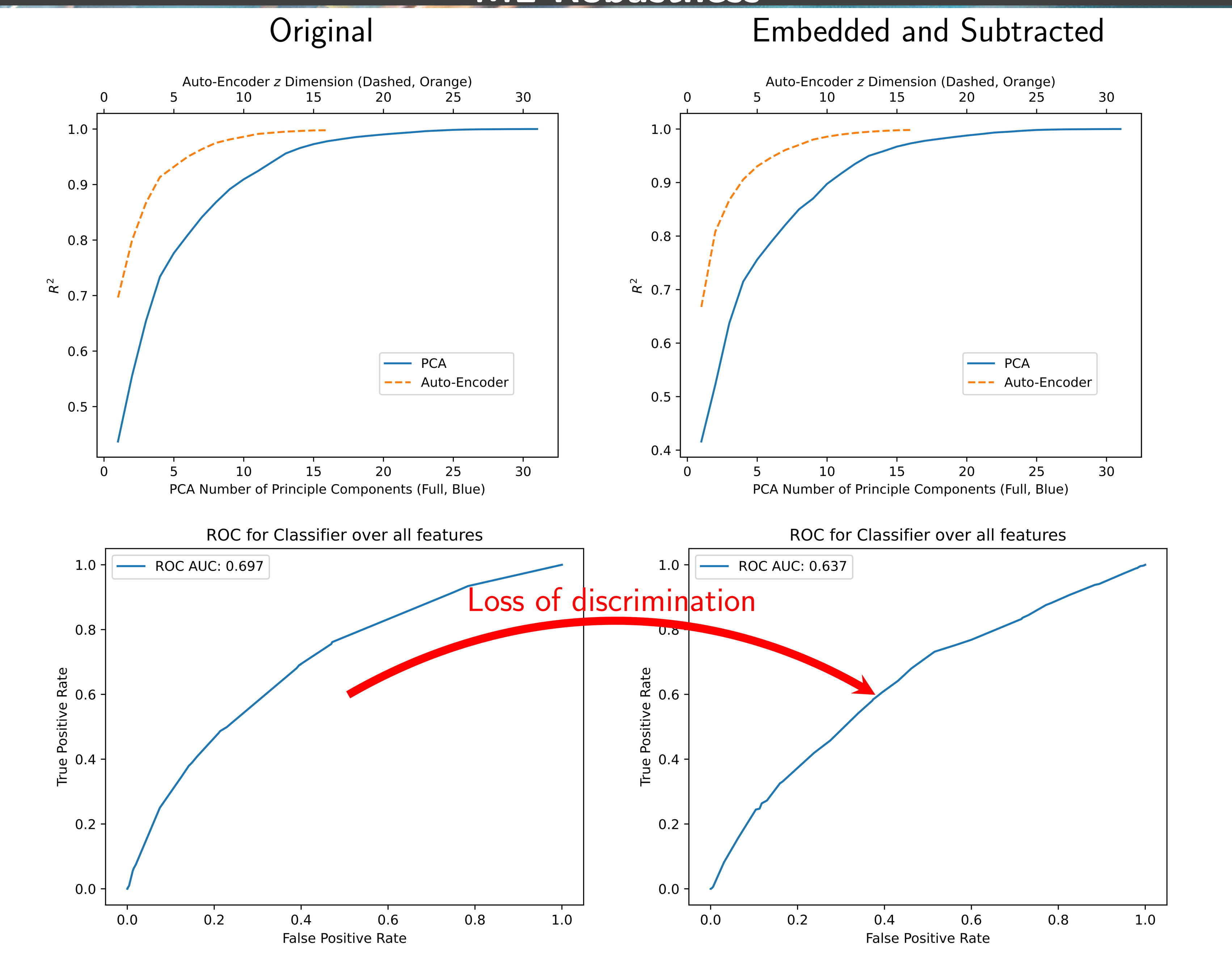
Results

Observable Robustness



[5]

ML Robustness



Comments:

- Observables modified by the method in a similar manner in both samples, are robust.
- In these cases the ratios of these observables should themselves be robust.
- Grooming seems to mimic the effect of the jet modification in the Lund Plane.
- Both of these effects are suppressed after the embedding and subtraction procedure.
- In ML, [6], the procedure leads to a degradation of performance in a supervised setting.

Conclusions

- The advantages of this procedure over full UE generators such as HYDJET, MUSIC or others, comes from the simplicity of the procedure, and subsequent fast performance.
- Furthermore, the direct reliability on experimental results, published by LHC experiments, ensures a model-agnostic, "as-faithful-as-possible" to experiments, UE.
- A rather large survey of the jet Quenching Phenomena, robust to this embedding and subtraction procedure, across a multitude of observables has been performed, revealing, in general, higher robustness from groomed observables than standard ones.
- Towards ML robustness, we have found stronger robustness on the unsupervised analysis in comparison to the supervised analysis.
- Further work to study the robustness of other unsupervised, supervised and semi-supervised ML algorithms to this procedure is on the way.

References

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