Disentangling and Quantifying Jet Quenching with Generative Deep Learning

João A. Gonçalves

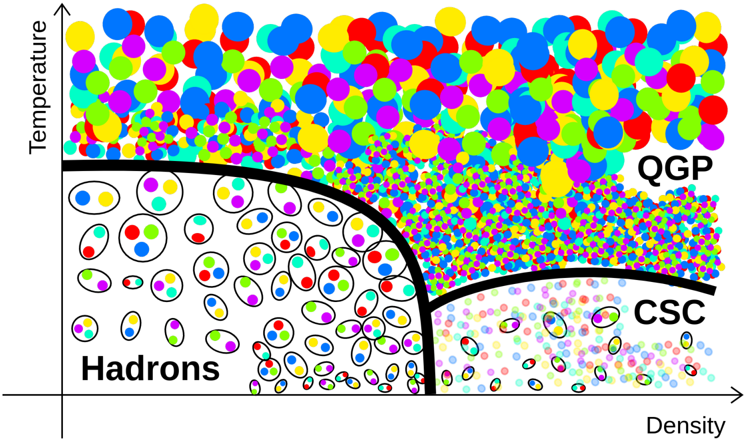
September 6, 2021

Overview

1. Quark Gluon Plasma, how to make it and how to study it
2. Generative Deep Learning
3. Conclusions

Quark Gluon Plasma, how to make it and how to study it

Quark Gluon Plasma



Quark Gluon Plasma, how to make it and how to study it

How to make it

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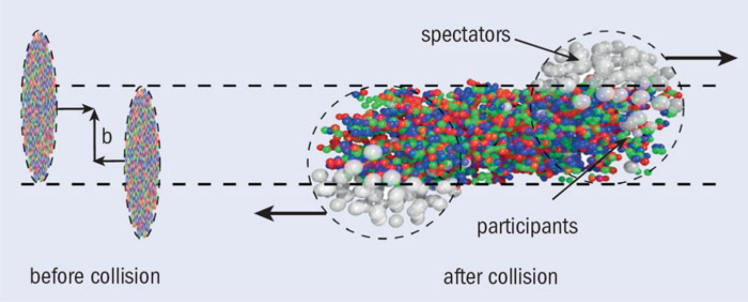
How to make it



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How to study it

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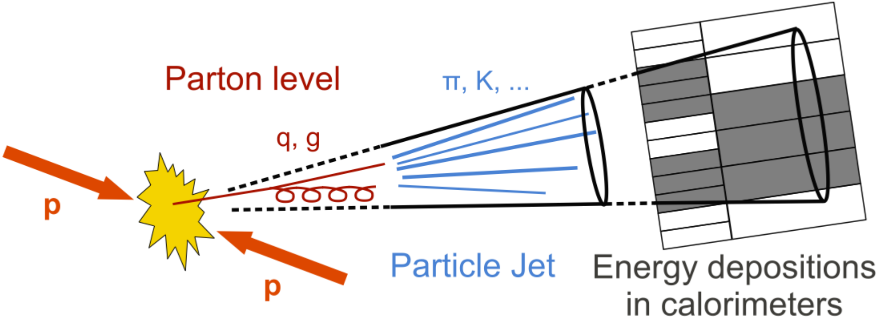

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Generative Deep Learning

Informally, Generative Deep Learning corresponds to a, generally unsupervised, area of Machine Learning (ML), where the main goal is typically to learn the true underlying distributions of the data, using many-layer models.

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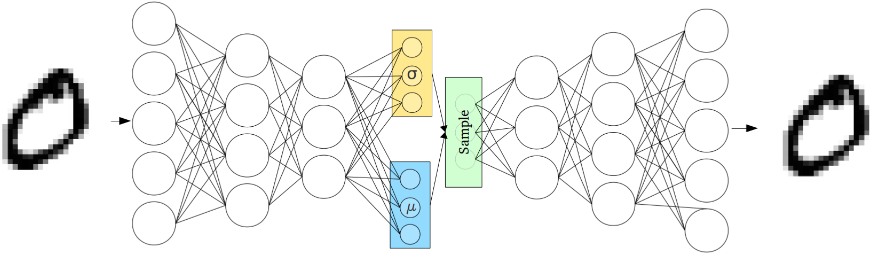

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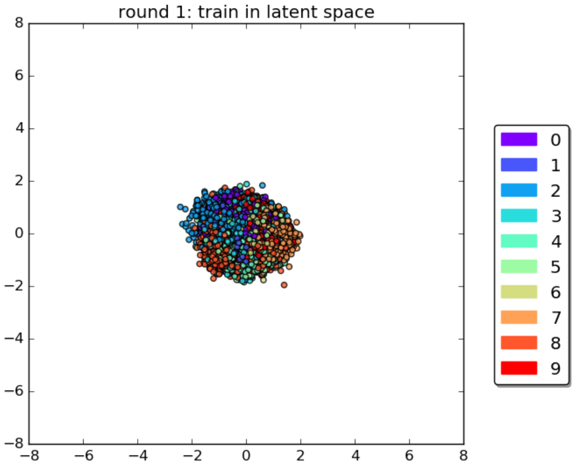
Generative Deep Learning



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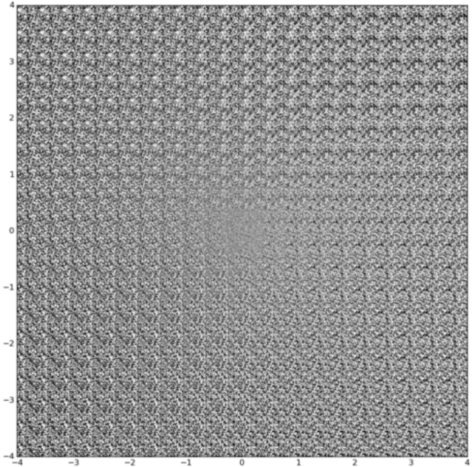
Generative Deep Learning



REF

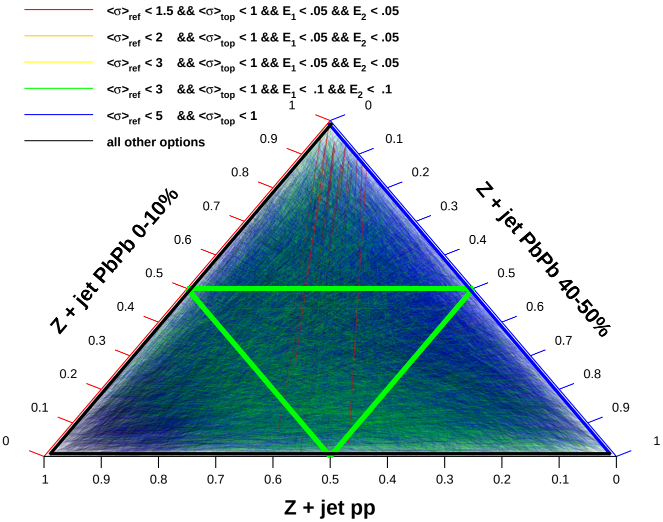
Conclusions

- Generative Deep Learning allows us to look at the problem of quantifying Jet Quenching in a different light than before.
- The minimum dimension of the latent space that maintains performance may have deep physical significance.
- Connection of analytical jet variables to this latent space, will be of crucial interest more downstream.

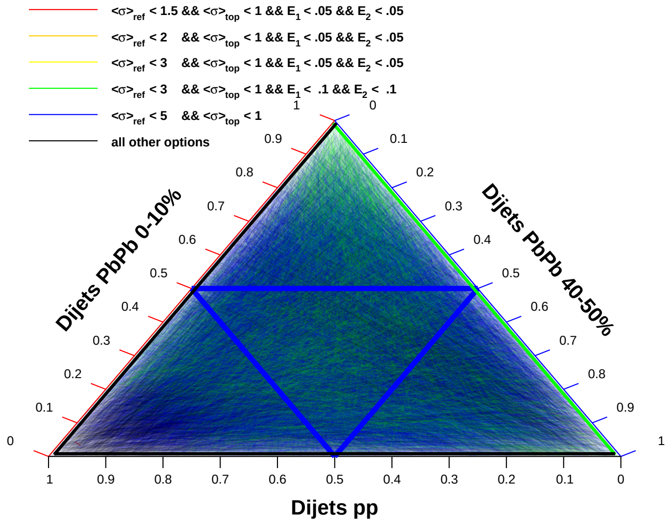
Thank you for your attention.

Backup

Results for modified/unmodified Z + jet with three samples



Results for modified/unmodified Dijets with three samples



Reducibility factors and residues

$$\kappa(p_1|p_2) = max\{\kappa \in [0,1] | \exists \text{ a distribution } G \text{ s.t. } p_1 = (1-\kappa).G + \kappa.p_2\}$$

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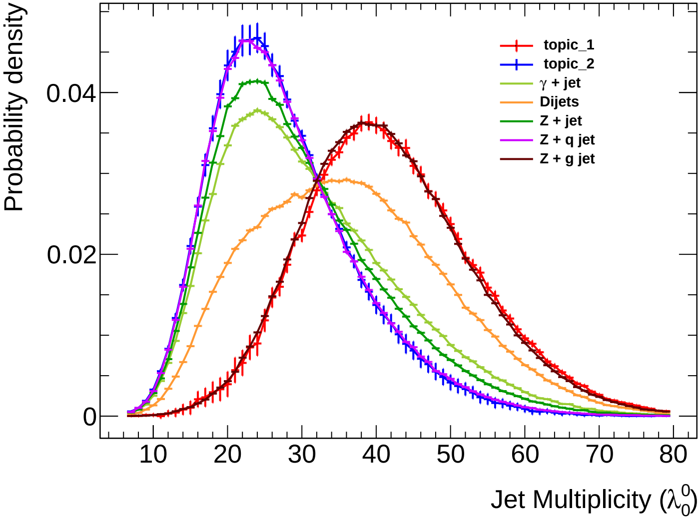
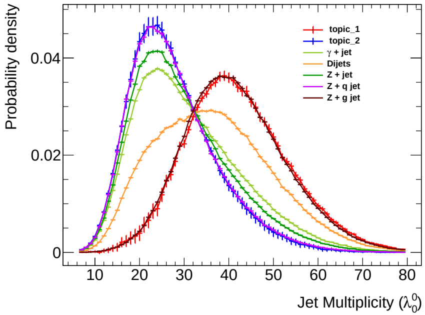
$$p_{k=1} = \frac{p_{i=1}(x) - \kappa(1|2)p_{i=2}(x)}{1-\kappa(1|2)} \qquad p_{k=2} = \frac{p_{i=2}(x) - \kappa(2|1)p_{i=1}(x)}{1-\kappa(2|1)}$$

The Generalization

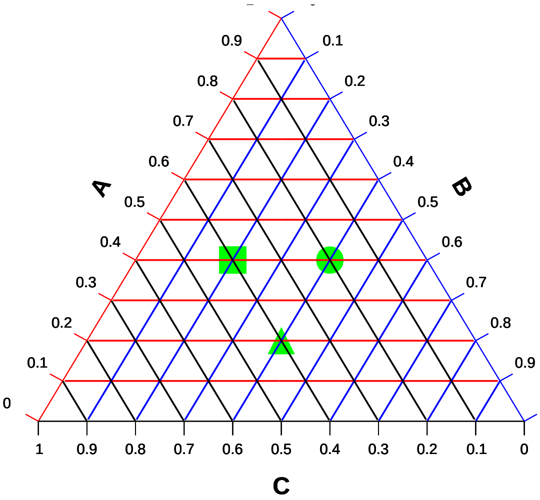


The Generalization (Cont.)



$$conv(S) = \left\{ \sum_{i}^{|S|} \alpha_i x_i \middle| \sum_{i}^{|S|} \alpha_i = 1 \land \forall i : \alpha_i > 0 \right\}$$

The Generalization (Cont.)



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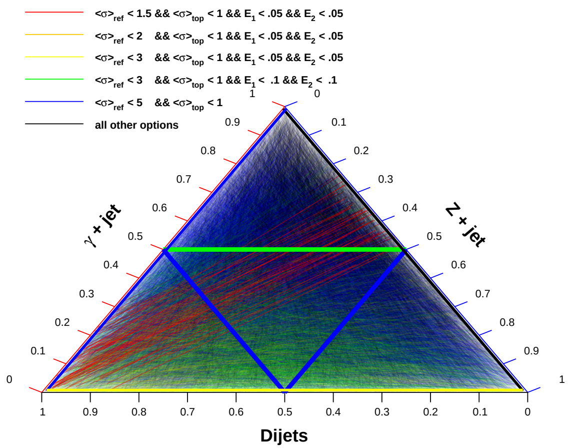
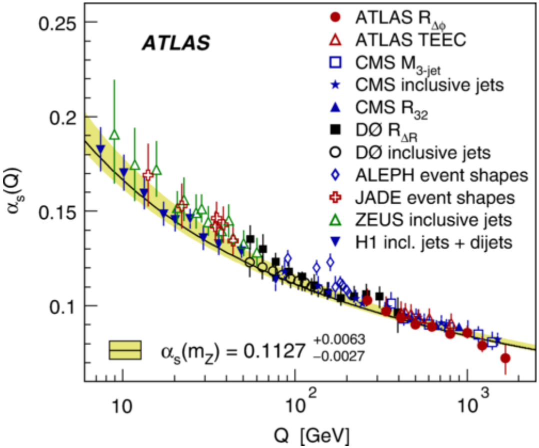
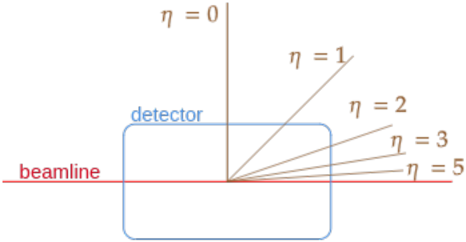


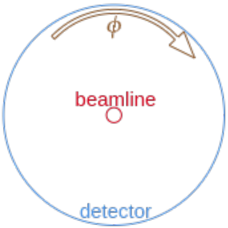
The running of the coupling constant



Measurements of the running of the coupling constant from multiple experiments throughout the years. Image taken from here.

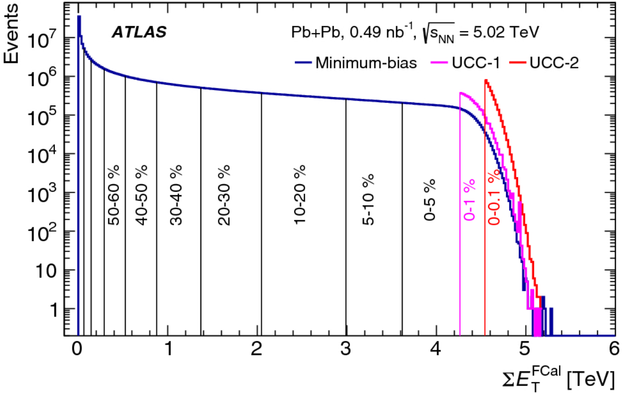
Cylindrical Detector Coordinates





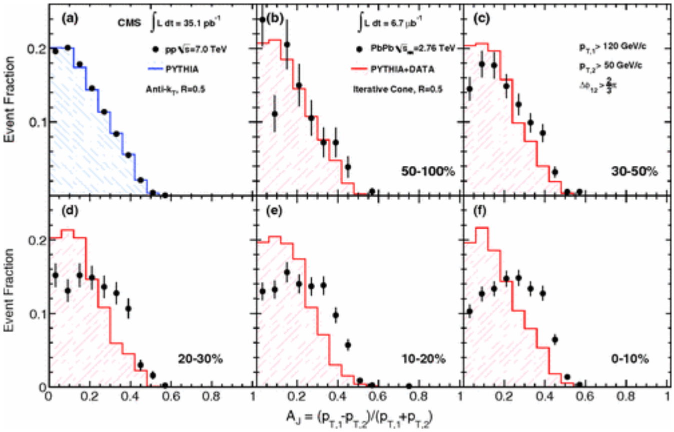
Phase space variables in a cylindrical detector. To the left we have the pseudorapidity, represented in a plane containing the beamline as a horizontal line; to the right, we have the azimuthal angle in the transverse plane of a detector, where the beamline corresponds to a point in the centre of the circle.

Centrality



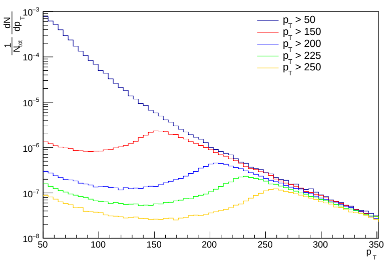
The sum of the transverse energy deposited in the ATLAS FCal, and centrality bins considered. The plot considers three different triggers, but we only present it to introduce the concept of centrality and so, we refrain from further explaining the considered triggers. Plot taken from reference.

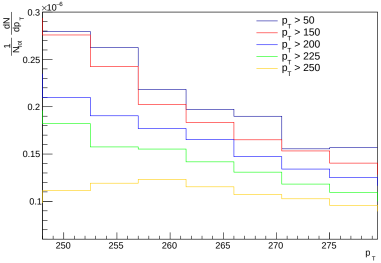
Dijet Asymmetry (measurement)



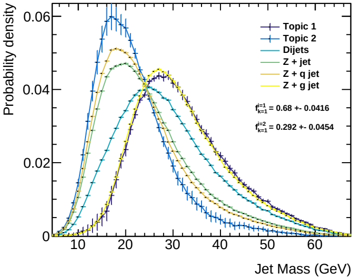
Proposed strategy

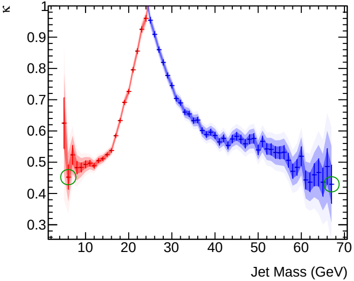
$\hat{p}_T$ lower bond



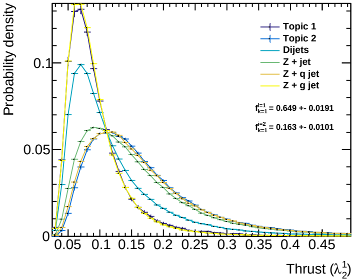


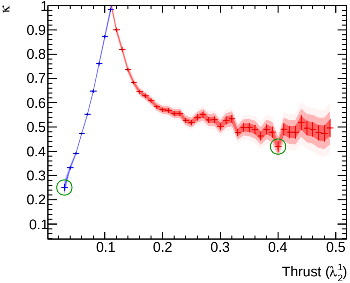
Jet mass for q/g discrimination in pp



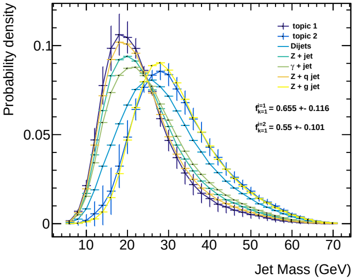


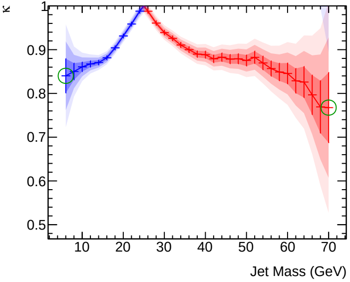
Jet thrust for q/g discrimination in pp



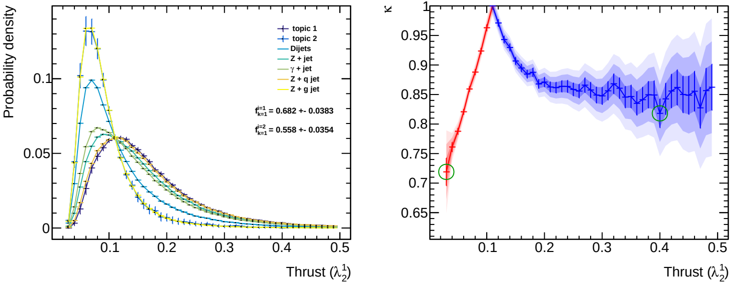


Jet mass for q/g discrimination with three samples in pp

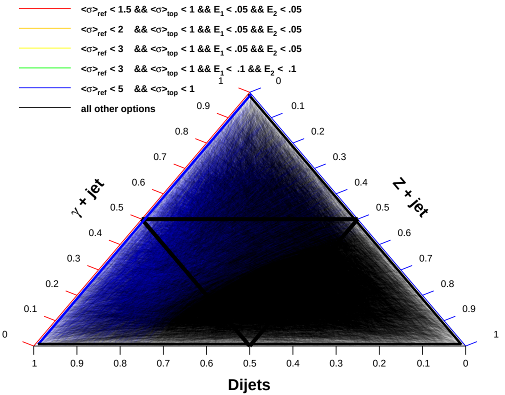




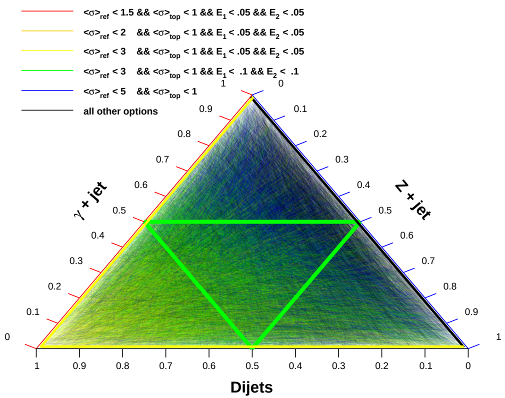
Jet thrust for q/g discrimination with three samples in pp



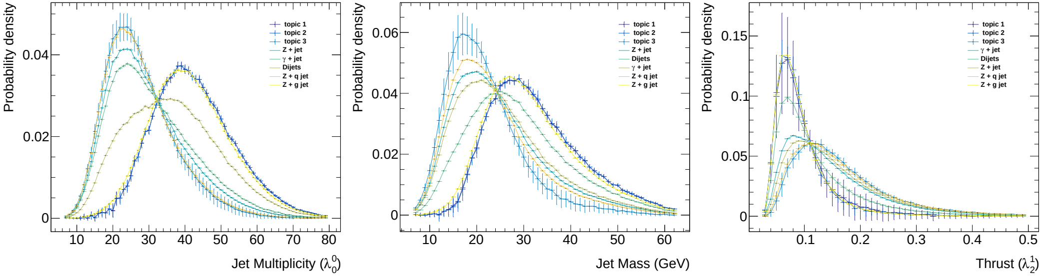
Ternary plot for the jet's mass, for q/g discrimination in pp



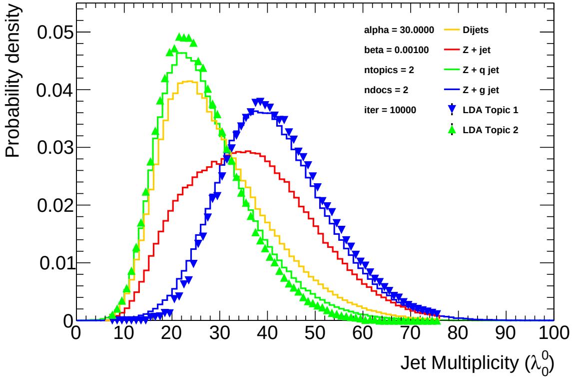
Ternary plot for the jet's thrust, for q/g discrimination in pp



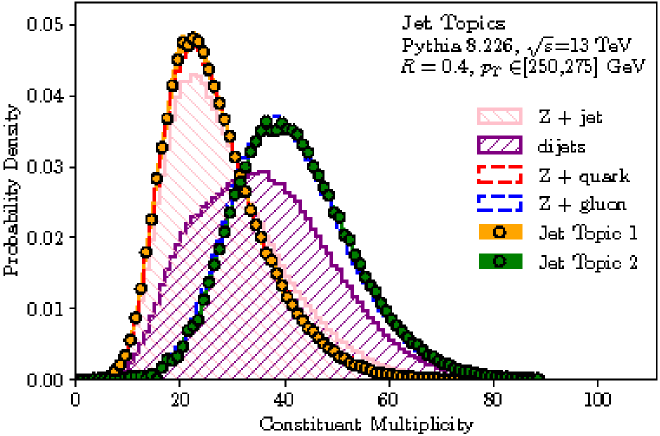
Extracting 3 topics from 3 samples in q/g discr.



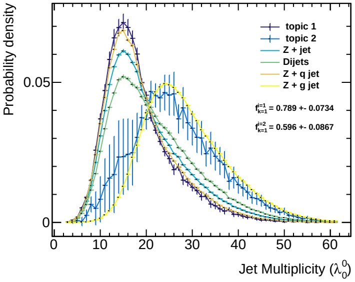
Latent Dirichlet Analysis (LDA)

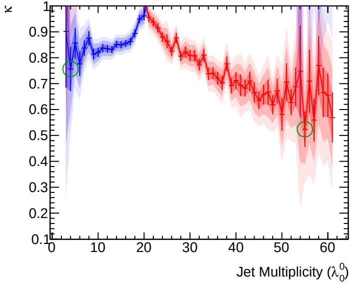


Reference for implementation validation

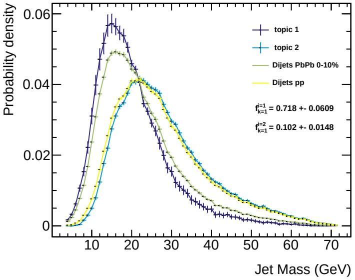


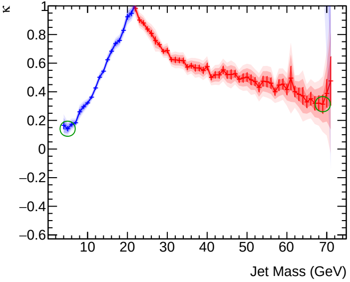
Jet's multiplicity for q/g discrimination in PbPb



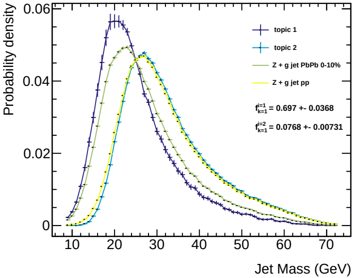


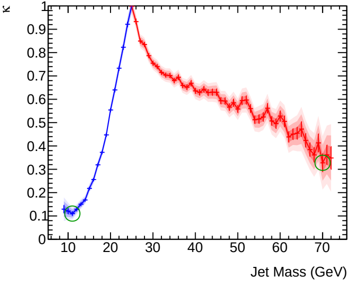
Quenched unquenched separation of quark jets



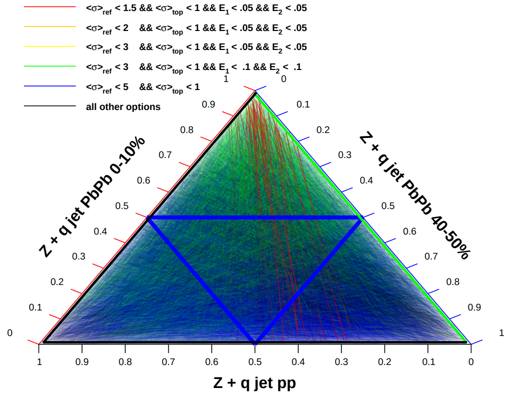


Quenched unquenched separation of gluon jets



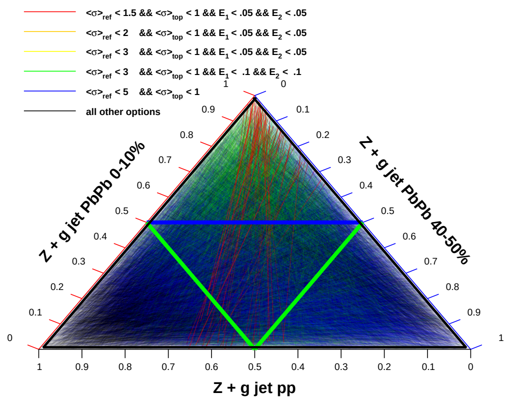


Ternary plot for quenched unquenched separation of quark jets



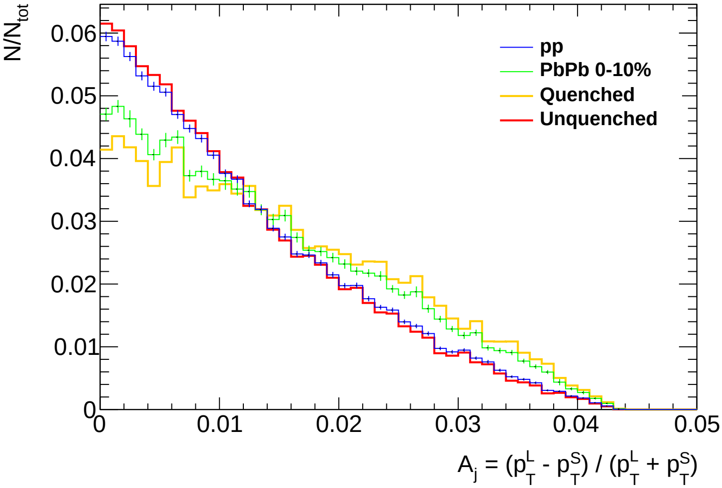
Ternary plot for Z + quark jet's mass.

Ternary plot for quenched unquenched separation of gluon jets



Ternary plot for Z + gluon jet's mass.

Dijet Asymmetry (reconstructed from extracted fractions)



Stating the Problem (Cont.)

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$$N_{jets}^{PbPb}(p_T \in [p_T^i, p_T^f]; N_{jets}^{pp}(p_T \geq p_T^i)) =$$

Stating the Problem (Cont.)

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$$N_{jets}^{unquenched}(p_T \in [p_T^i, p_T^f]; N_{jets}^{pp}(p_T \in [p_T^i, p_T^f]))$$

The Results

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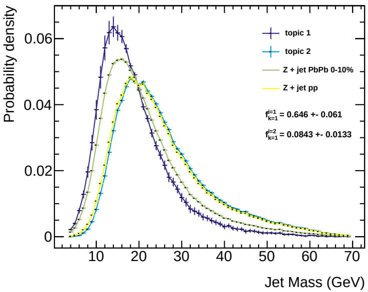
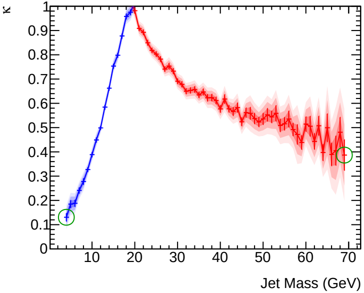
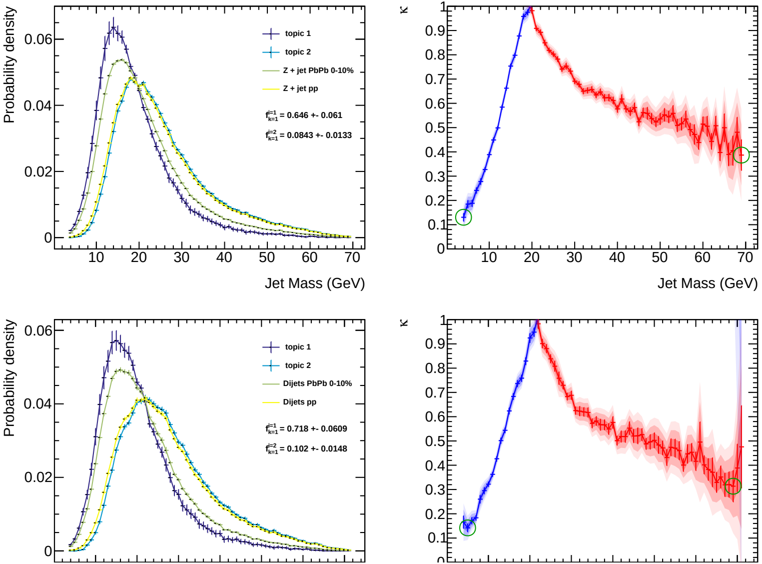

Probability density
0.06
0.04
0.02
0
10
20
30
40
50
60
70
Jet Mass (GeV)
topic 1
topic 2
Z + jet PbPb 0-10%
Z + jet pp
$f^{i=1}_{k=1}$ = 0.646 +- 0.061
$f^{i=2}_{k=1}$ = 0.0843 +- 0.0133


κ
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
10
20
30
40
50
60
70
Jet Mass (GeV)

The Results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0.5
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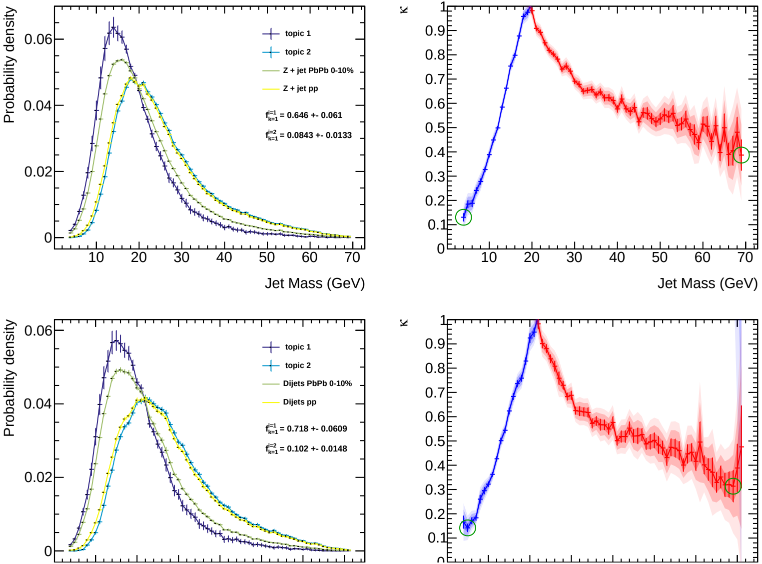
0
Jet Mass (GeV)
Dijets PbPb 0-10%
Dijets pp
$f^{i=1}_{k=1}$ = 0.718 +- 0.0609
$f^{i=2}_{k=1}$ = 0.102 +- 0.0148

The Results



Probability density
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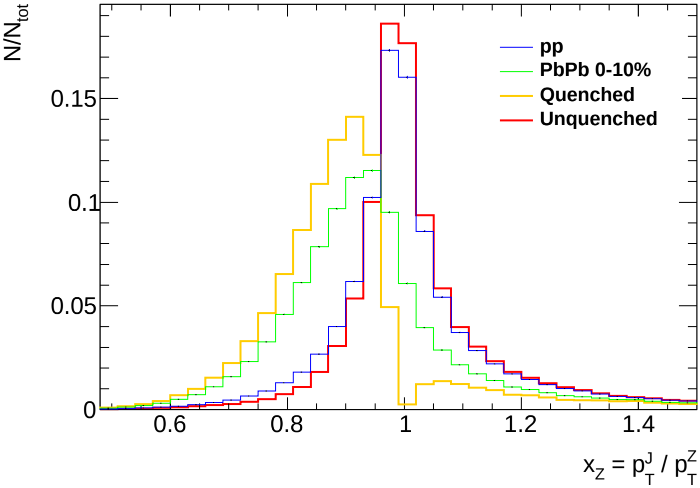

N/N_{tot}
0.15
0.1
0.05
0
0.6
0.8
1
1.2
1.4
$x_Z = p_T^J / p_T^Z$
pp
PbPb 0-10%
Quenched
Unquenched