Quarks and gluons in the Lund plane

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Based on arXiv:2112.09140

Classifying q/g jets

- q/g tagging: QCD bkg of jet studies, jet quenching, etc.

The definition of q/g jet is not trivial.

- Discriminators up to now:

1. Jet substructure: angularity, E-E-correlation, jet charge, Lund plane
2. Neural networks (NN): CNN, RNN, energy-flow, GNN

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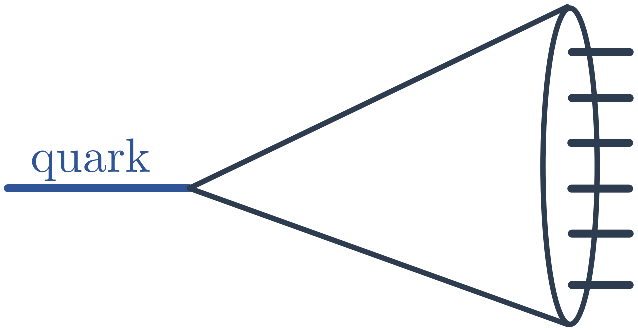

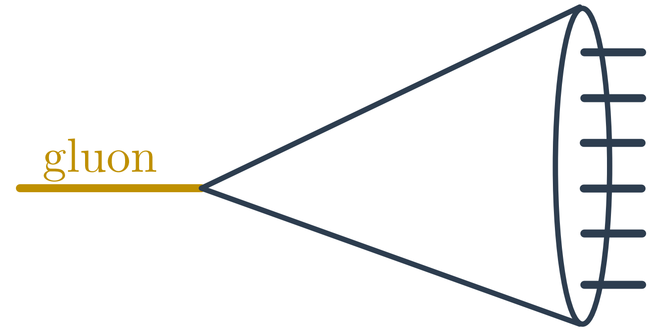

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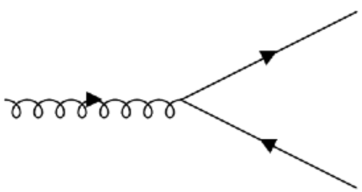

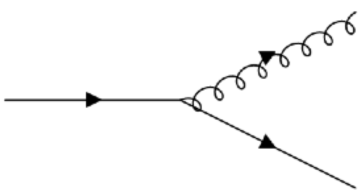

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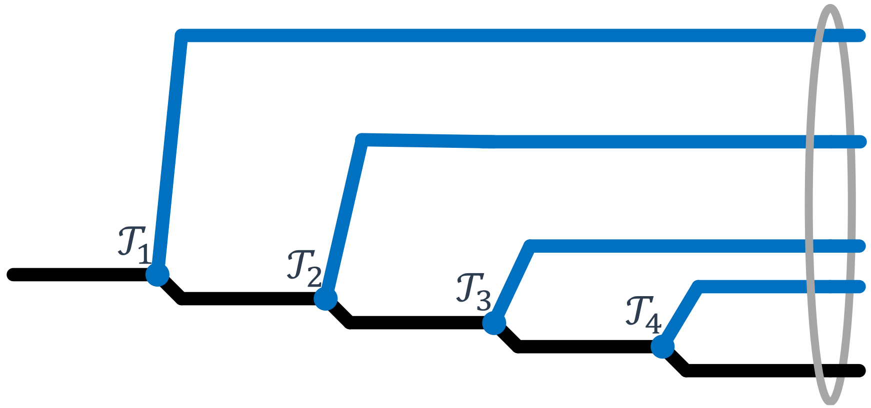
C/A declustering history

1. Find a jet
2. Recluster with C/A:

$$\mathcal{T}_j = \{\Delta_j, z_j, \psi_j, \ldots\}$$

$$\mathcal{L}_{prim}(j) = [\mathcal{T}_1, \mathcal{T}_2, \ldots, \mathcal{T}_j]$$



Exclusive probability

Declustering history = graph

$p_{fin}(\mathcal{L}_{tree})$

Graph neural network (LundNet)
Train on generated and labeled events
[F.Dreyer,H.Qu, 2012.08526]

Likelihood ratio:

$$\mathbb{L}_{tree} = \frac{p_q(\mathcal{L}_{tree})}{p_g(\mathcal{L}_{tree})}$$

ideal discriminant at NLL!

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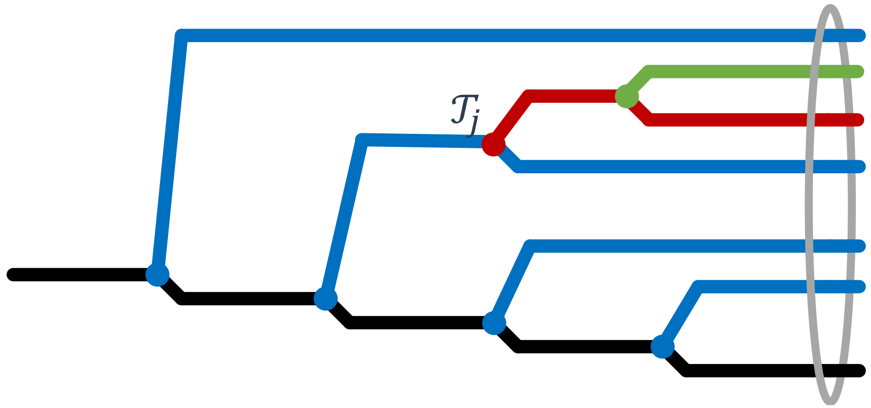

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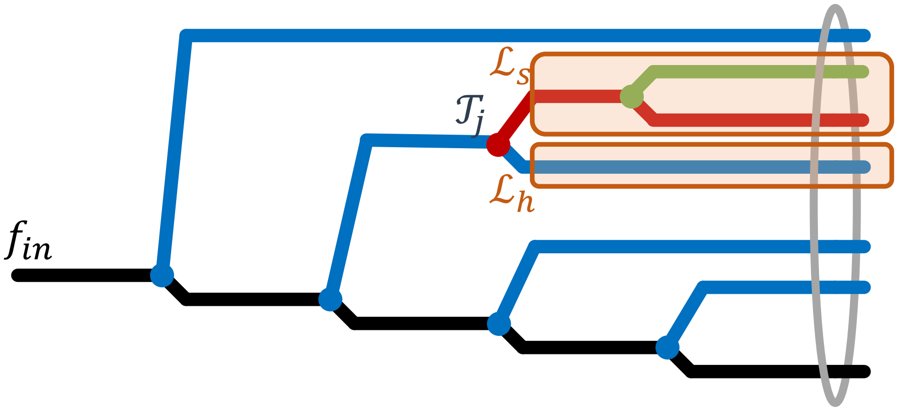

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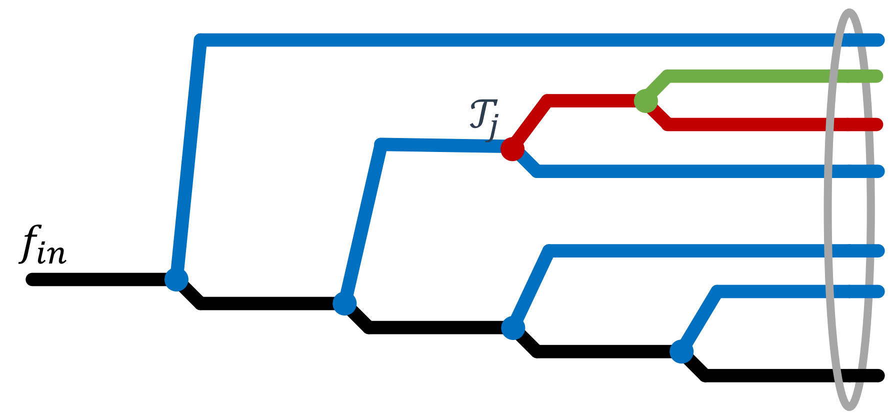

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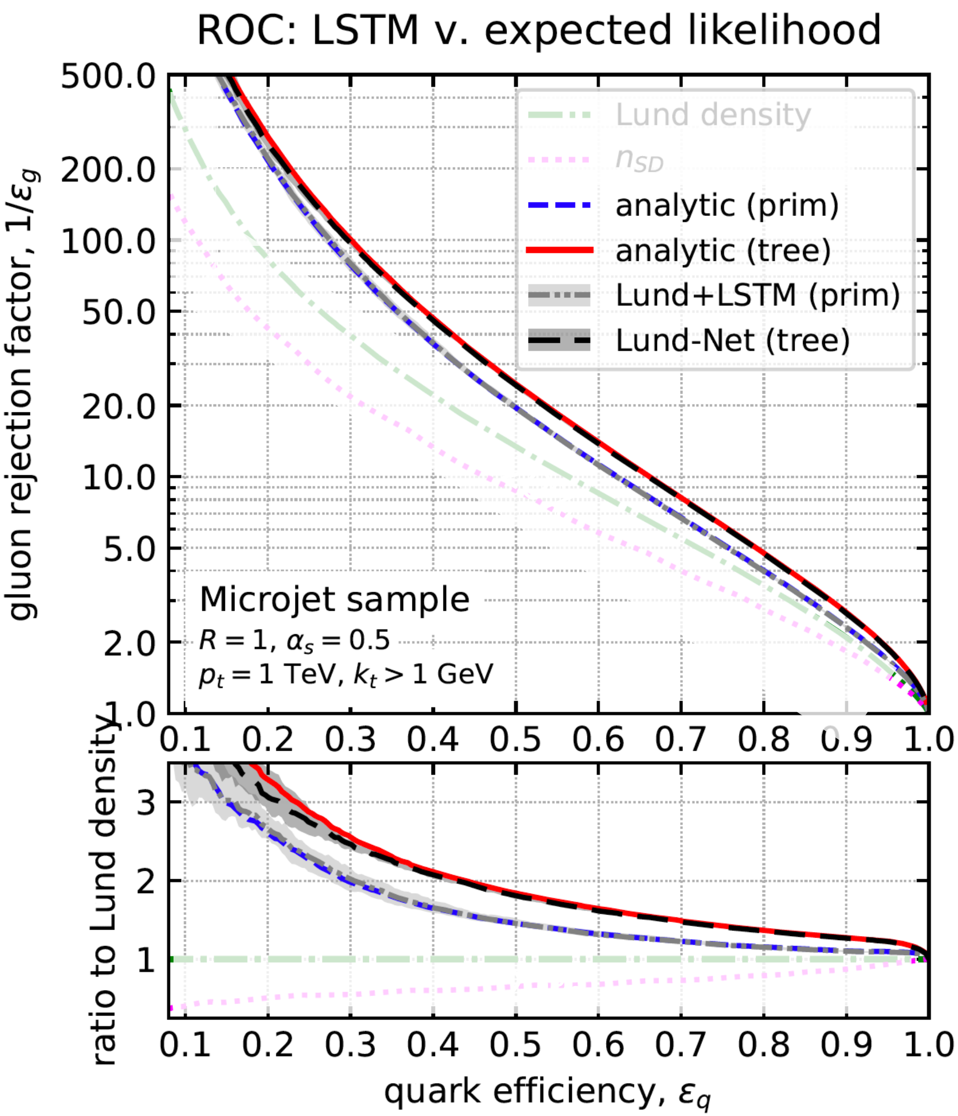
Equivalence of NN and NLL 1.

Train on NLL collinear splittings.

ROC curve:

better

discriminant



Performance:

- primary < tree
- analytic = NN

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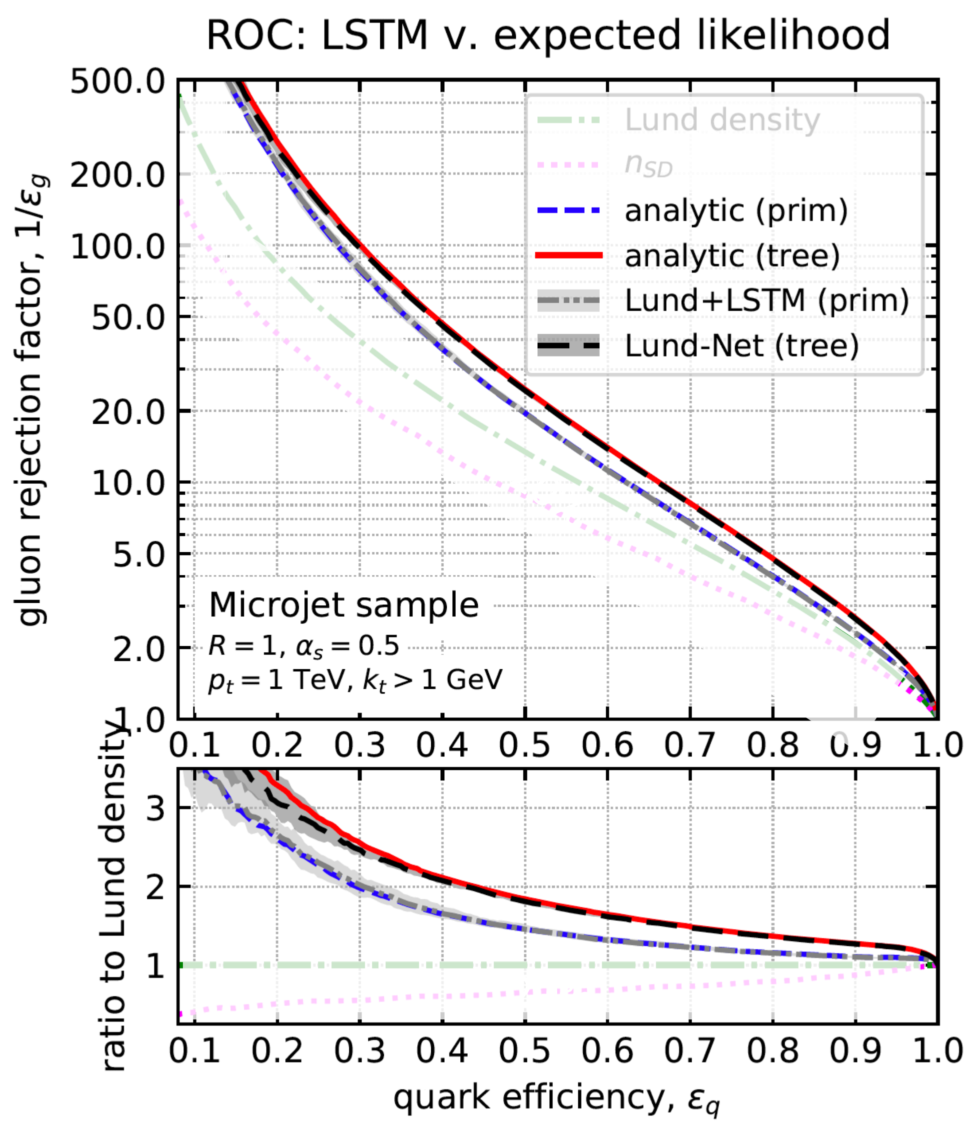

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Performance test

Re-train on Pythia jets.

ROC curve:

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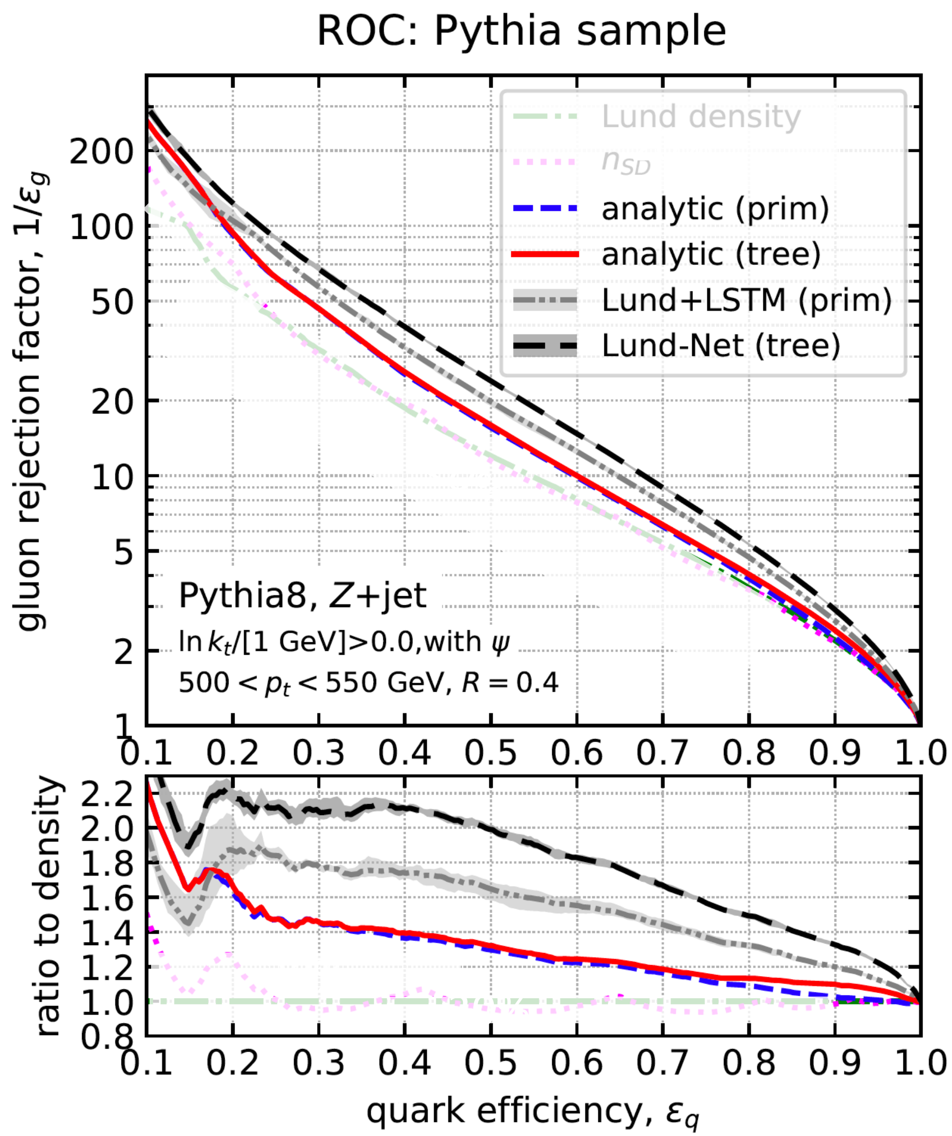

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Where is the improvement from?

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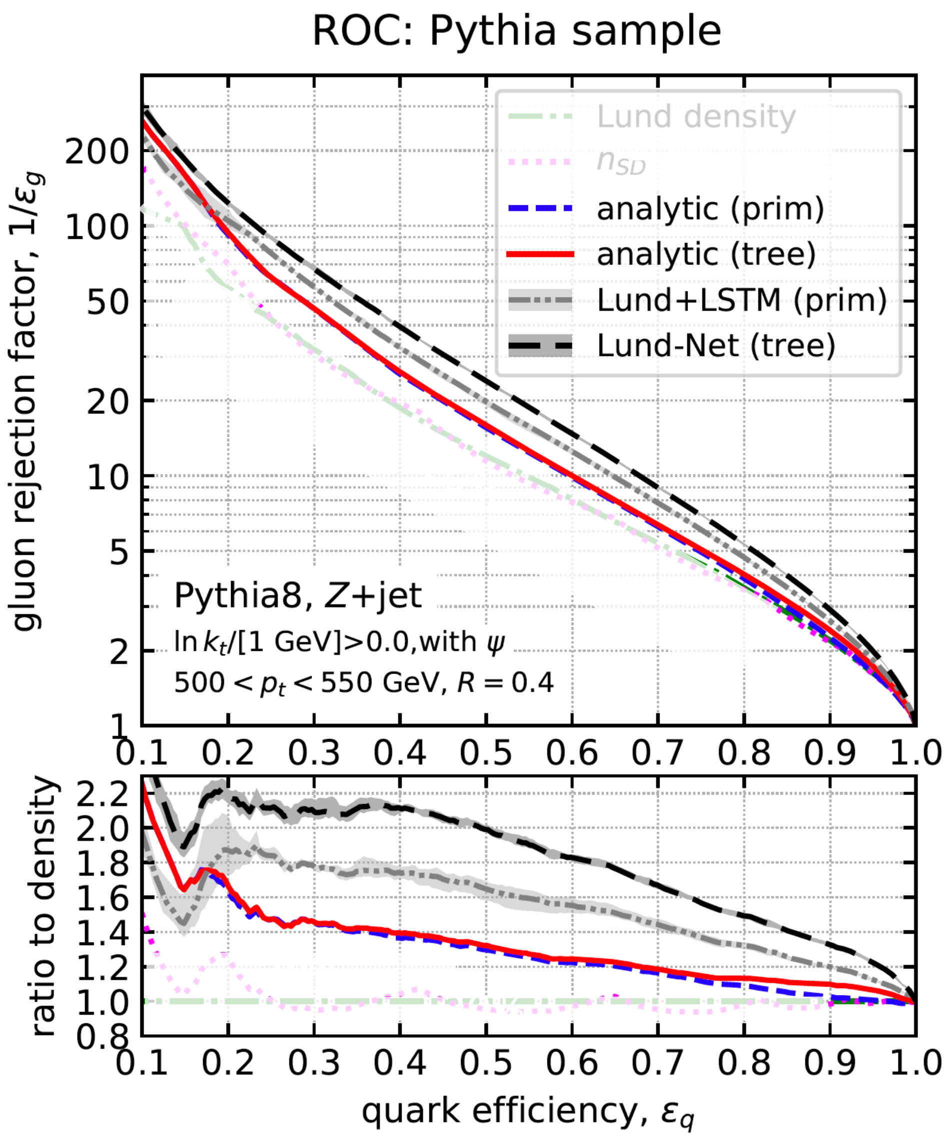

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Equivalence of ML and NLL 2.

NLL accuracy test: [PanScales 2002.11114]

$$\alpha_s(p_T R) \to 0$$

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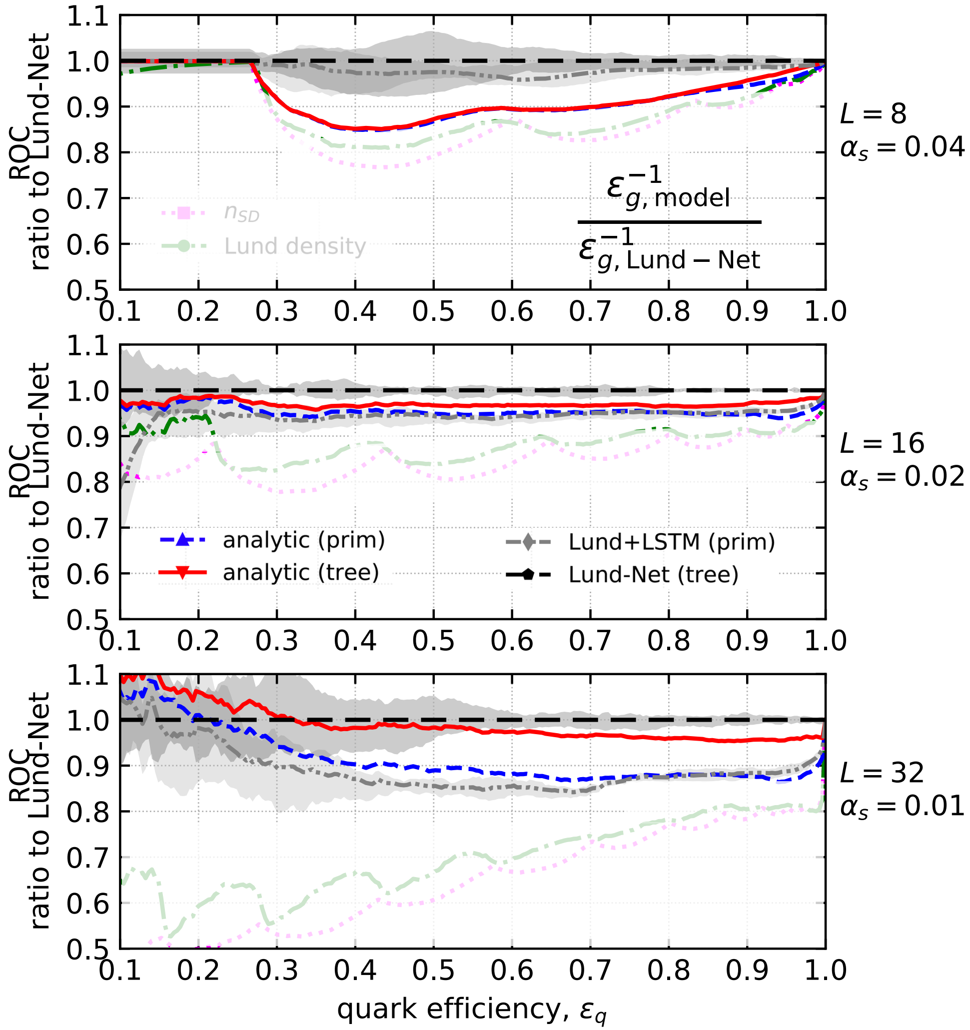
- the NN gains from
  1. subleading terms
  2. non-perturbative physics
  3. etc.



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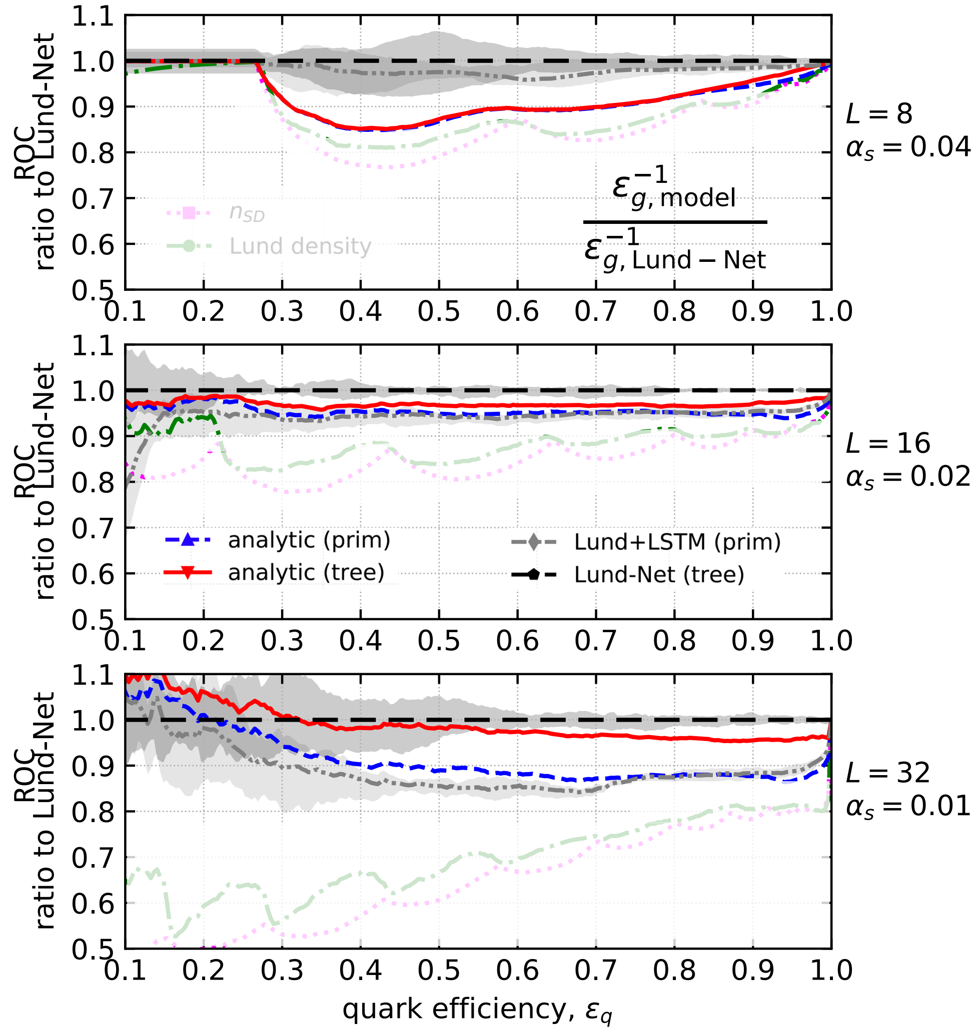


Summary

- q/g jet likelihood is calculated at NLL accuracy.
- NN is constructed to do the same (state-of-the-art tagger).
- NN $=$ analytics in the NLL limit!
- Performance: NN $>$ analytic
- Resilience: NN $<$ analytic

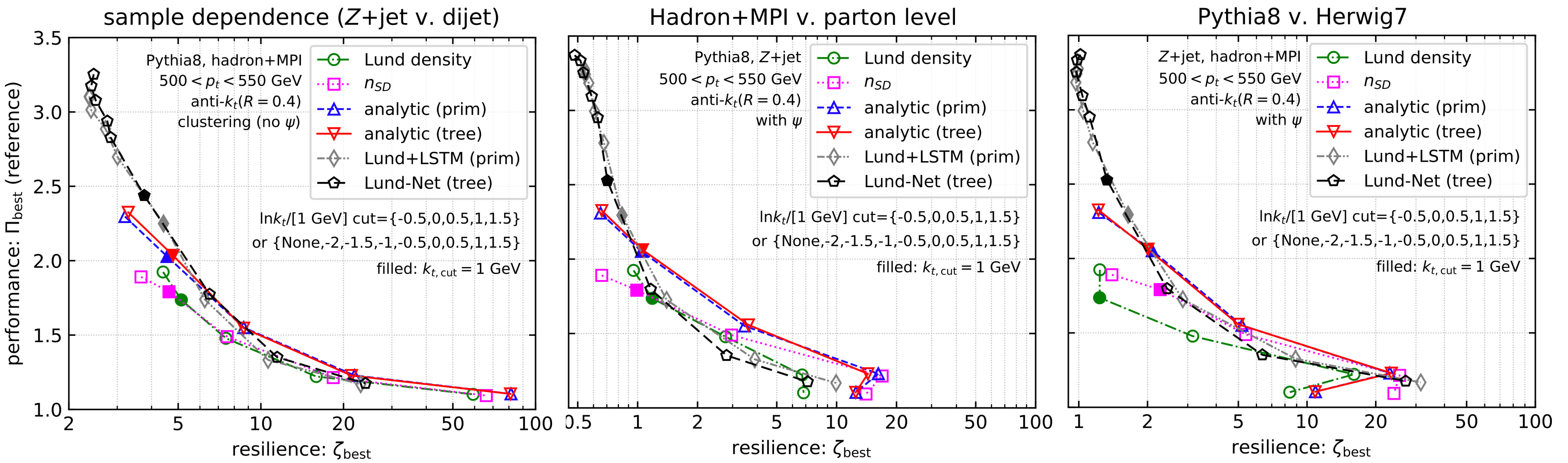
subleading terms, NP effects

Thank you for your attention!

Backup: Test of resilience

Studies:

- sensitivity to the hard process (dijet vs. Z+jet)
- sensitivity to non-perturbative effects (MPI, hadronization)
- sensitivity to the MC (Pythia8 vs. Herwig7)



primary ~ tree

NN < analytic