

Quarks and gluons in the Lund plane

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based on arXiv:2112.09140

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- 1 A few word about quark v. gluon tagging
- 2 The **Lund plane** representation of jets (and events)
- 3 **Using Lund variables to tag quarks and gluons**
 - An approach using perturbative QCD
 - An approach using Deep Learning
- 4 Applications and results
 - Validation (in the collinear limit)
 - Boosted jets at the LHC
 - a (preliminary) FCC-ee application

Discriminate quark-initiated jets from gluon-initiated ones

generic tool with many applications:

coll	q	g
any	BSM	QCD
hh	VBF H	$gg \rightarrow H$
ee	$Z \rightarrow q\bar{q}$	$H \rightarrow gg$

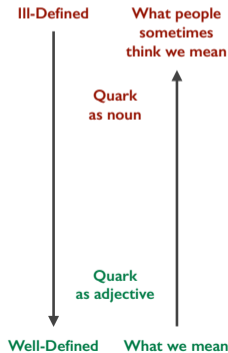
Intrinsic limitation:

- q and g not really well defined
e.g. a “gluon jet” is different in $q\bar{q} \rightarrow Zg$ or in $gg \rightarrow gg$
- cross-section in q/g -enriched region is well-defined

see e.g. [arXiv:1704.03878](https://arxiv.org/abs/1704.03878)

What is a Quark Jet?

From lunch/dinner discussions



A quark parton

A Born-level quark parton

The initiating quark parton in a final state shower

An eikonal line with baryon number 1/3 and carrying triplet color charge

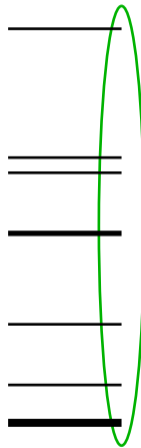
A quark operator appearing in a hard matrix element in the context of a factorization theorem

A parton-level jet object that has been quark-tagged using a soft-safe flavored jet algorithm (automatically collinear safe if you sum constituent flavors)

A phase space region (as defined by an unambiguous hadronic fiducial cross section measurement) that yields an enriched sample of quarks (as interpreted by some suitable, though fundamentally ambiguous, criterion)

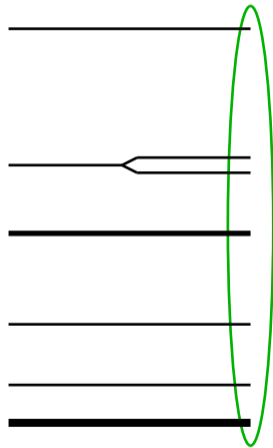
The Lund plane(s) representation (1/3)

use Cambridge/Aachen to iteratively recombine the closest pair



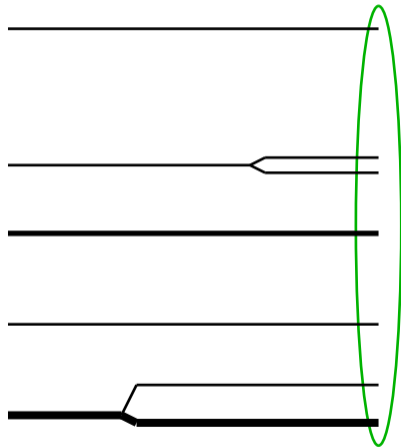
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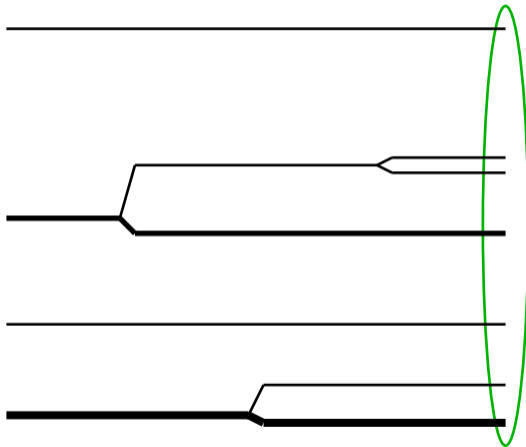
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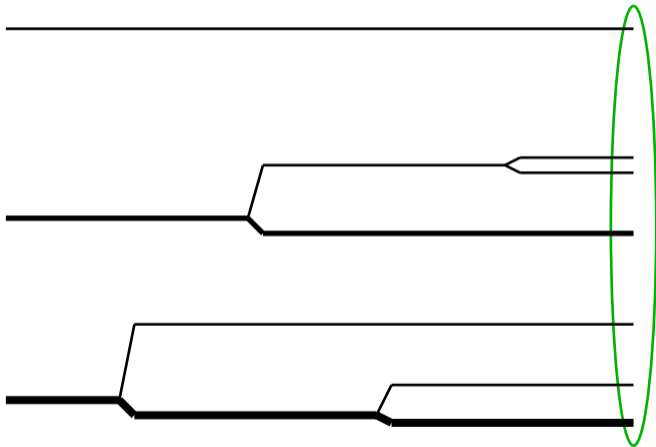
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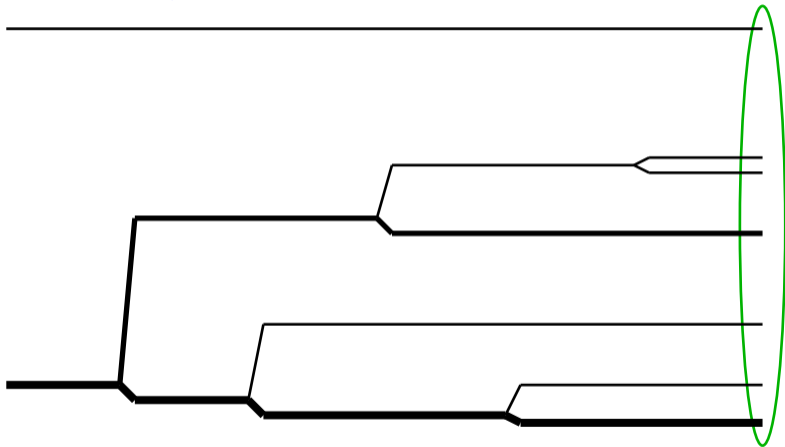
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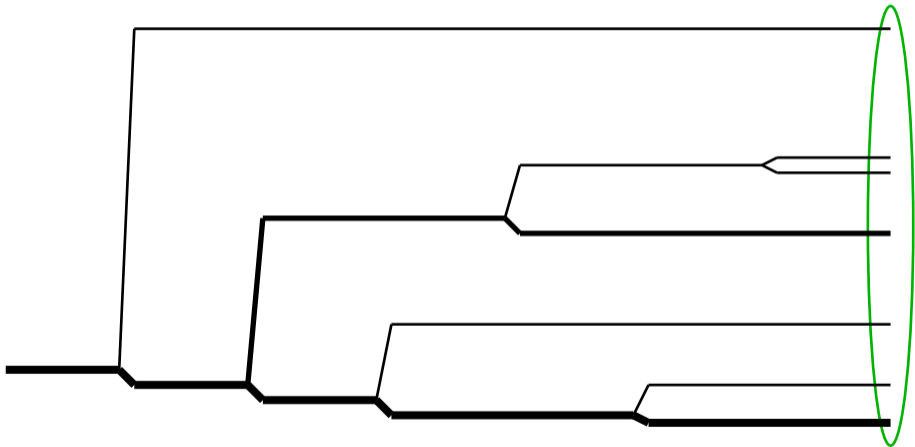
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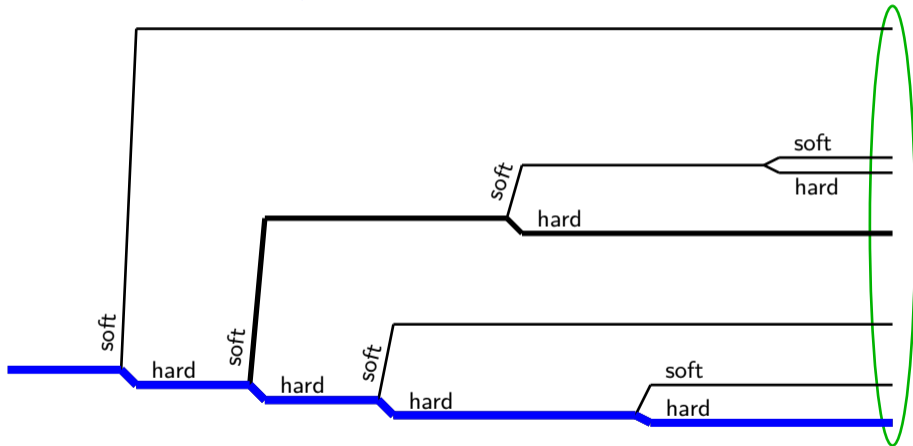
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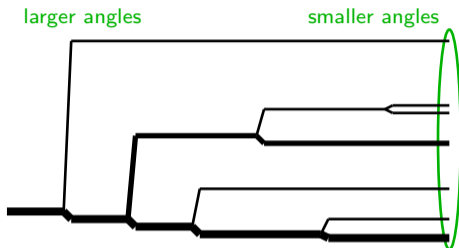
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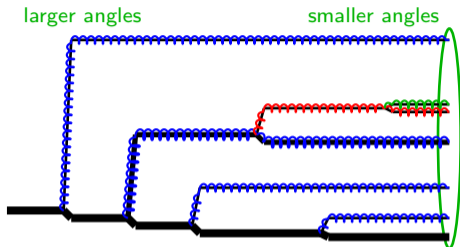
E.g.: conceptually the largest-energy (p_t or z) branch \equiv emissions from the “leading parton”

The Lund plane(s) representation (2/3)

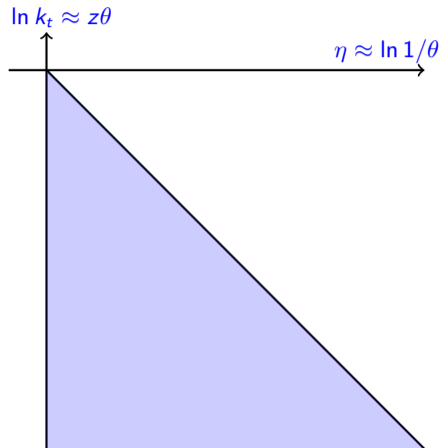


- closely follow our beloved angular ordering

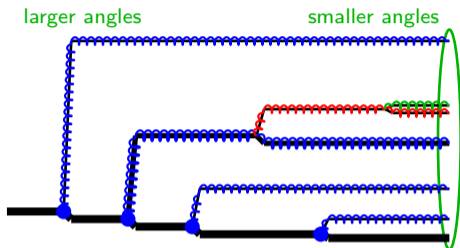
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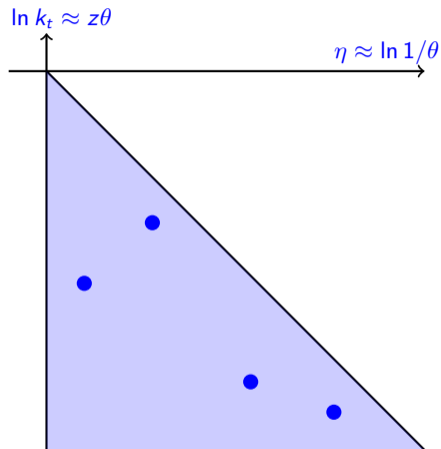
- closely follow our beloved angular ordering
- i.e. mimics partonic cascade
- can be organised in Lund planes



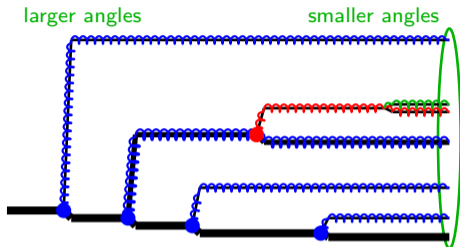
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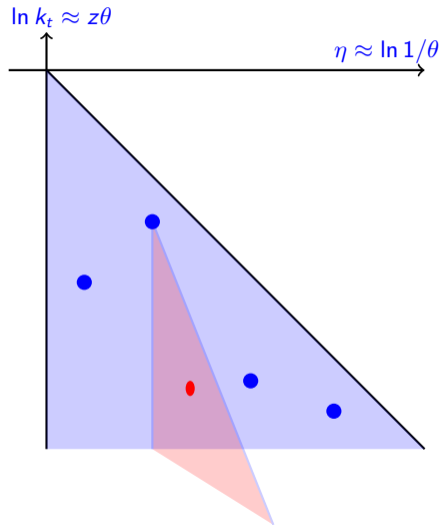
- closely follow our beloved angular ordering
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- can be organised in Lund planes
 - primary



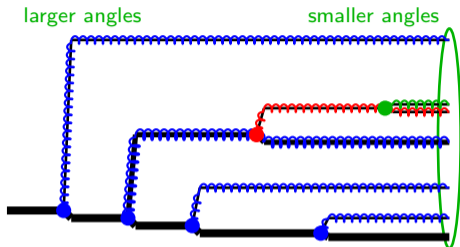
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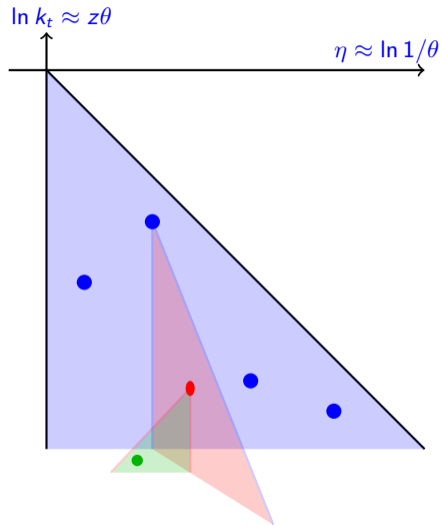
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- can be organised in Lund planes
 - primary
 - secondary



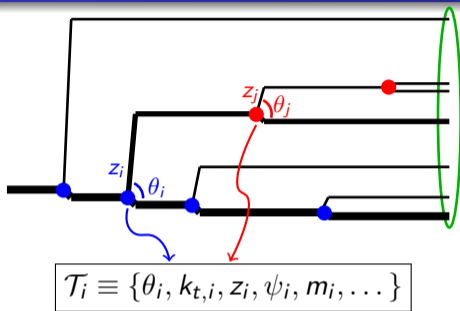
The Lund plane(s) representation (2/3)



- closely follow our beloved angular ordering
- i.e. mimics partonic cascade
- can be organised in Lund planes
 - primary
 - secondary
 - ...



The Lund plane(s) representation (3/3)



Two different structures

“primary plane”
(follow hard branch)

OR

full (de-)clustering tree

$$\mathcal{L}_{\text{prim}} \equiv \{\mathcal{T}_i\}$$

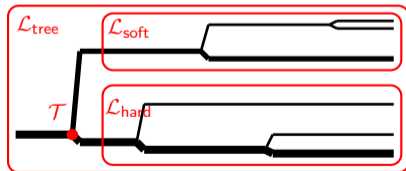
$$\mathcal{L}_{\text{tree}} \equiv \{\mathcal{T}, \mathcal{L}_{\text{hard}}, \mathcal{L}_{\text{soft}}\}$$

for *ee* events: (similar for jets in *pp*)

$$k_t = E_{\text{soft}} \sin \theta,$$

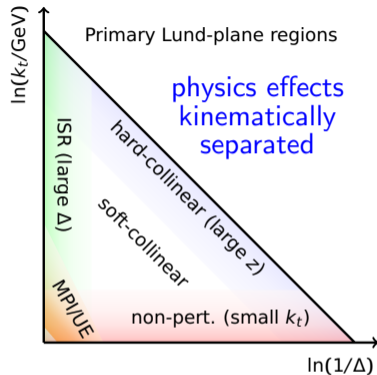
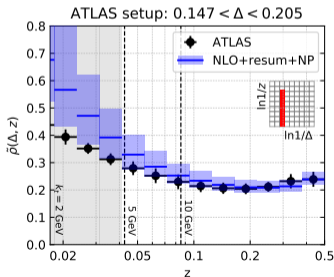
$$z = \frac{E_{\text{soft}}}{E_{\text{parent}}}$$

$\psi \equiv$ azimuthal angle



(A wide range of) Lund plane applications

- Tagging: q v. g [this talk+⁶], W ^[1,4], t ^[4], ...
- Monte Carlo constraints^[1]
- pQCD v. data^[2,3]
- study quark-gluon plasma^[5]
- inputs for Deep Learning^[1,4,6]



- 1 F.Dreyer, G.Salam, GS, arXiv:1807.04758
- 2 ATLAS, CERN-EP-2020-030
- 3 A.Lifson, G.Salam, GS, arXiv:2007.06578
- 4 F.Dreyer, H.Qu, arXiv:2012.08526
- 5 Alice, ALICE-PUBLIC-2021-002
- 6 F.Dreyer, GS, A.Takacs, arXiv:2112.09140

Quark/gluon tagging in the Lund plane

Basic approaches

Idea: gluons radiate more than quarks

- shapes (angularities, energy-energy correlations,...)
- multiplicities (n_{chg} , Iterated SoftDrop, ...)

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ML approaches

Idea: train a Neural Network

- EFN/PFN ([1810.05165](#))
- ParticleNet (next talk)

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This approach/talk

Discriminate quarks and gluons
based on Lund declusterings
(primaries $\mathcal{L}_{\text{prim}}$, or full tree $\mathcal{L}_{\text{tree}}$)

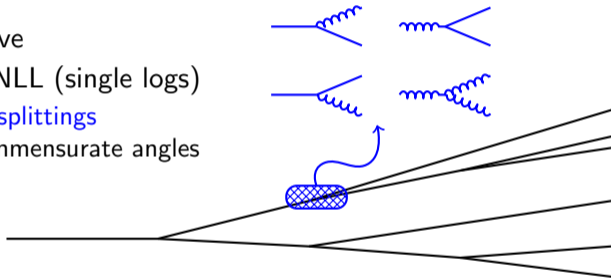
Idea: best discriminant given
by the likelihood ratio

$$\mathbb{L}_{\text{prim,tree}} = \frac{p(g|\mathcal{L}_{\text{prim,tree}})}{p(q|\mathcal{L}_{\text{prim,tree}})}$$

Approach #1: compute $p(q, g|\mathcal{L})$ in perturbative QCD

Calculation ingredients:

- Consider $k_t \geq k_{t,\text{cut}}$ to stay perturbative
- Resum logs to all orders in α_s , up to NLL (single logs)
 - ▶ single logs from “DGLAP” collinear splittings
 - ▶ some single logs for emissions at commensurate angles



Comments:

- LL (double logs) equivalent to the Iterated SoftDrop multiplicity
- Paper focused on jets in pp (would apply to FCC- hh) where large-angle and fixed-order corrections are process-dependent (and thus neglected)

Approach #2: input the Lund coordinates in a Neural Network

Primary Lund plane

Ingredients:

- LSTM network
- inputs: $\ln \theta$, $\ln k_t$, $\ln z$, Ψ
- with or without a k_t cut

Comments:

- DNN, CNN tried but less effective
- Could use Attention instead

Full Lund tree

Ingredients:

- Lund-Net (graph) network
- inputs: $\ln \theta$, $\ln k_t$, $\ln z$, Ψ
- with or without a k_t cut

Comments:

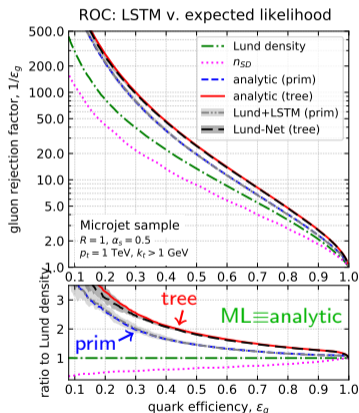
- similar to Particle-Net but the Lund structure is simpler
- Could add PDG-ID info

Validation in the collinear limit

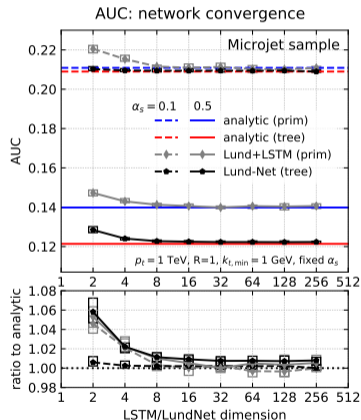
our analytic discriminant is exact/optimal in the dominant collinear limit $\theta_1 \gg \theta_2 \gg \dots \gg \theta_n$
 \Rightarrow ML expected to give the same performance

Validation in the collinear limit

our analytic discriminant is exact/optimal in the dominant collinear limit $\theta_1 \gg \theta_2 \gg \dots \gg \theta_n$
 \Rightarrow ML expected to give the same performance



Microjet
 \equiv
pure-collinear



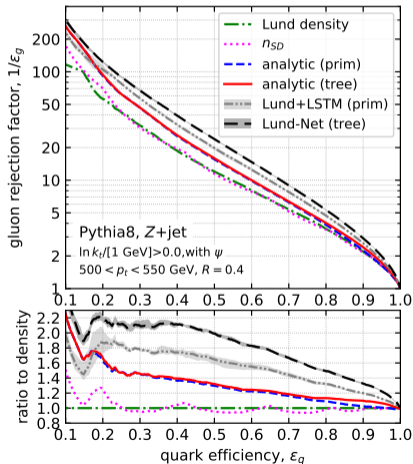
ROC curves agree

Converges for large-enough networks

Jet tagging at the LHC

$pp \rightarrow Zq$ v. $pp \rightarrow Zg$ ($p_t \sim 500$ GeV, $R = 0.4$)

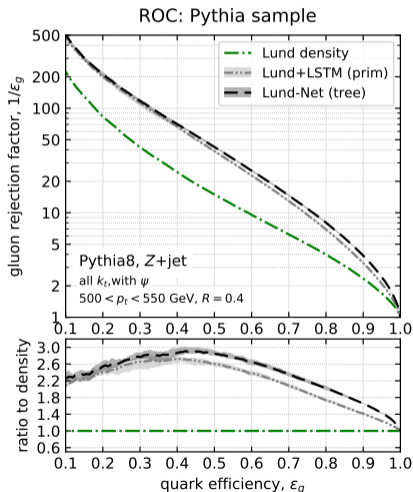
ROC: Pythia sample



- clear performance ordering:

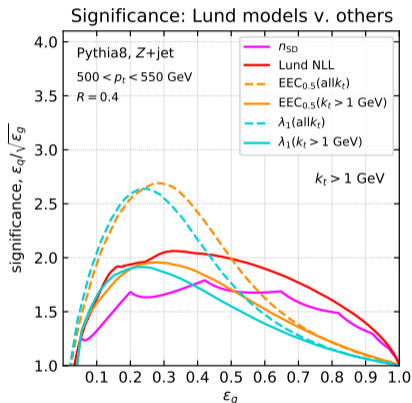
- 1 Lund+ML $>$ Lund analytic $>$ ISD
- 2 tree $>$ prim

$pp \rightarrow Zq$ v. $pp \rightarrow Zg$ ($p_t \sim 500$ GeV, $R = 0.4$)



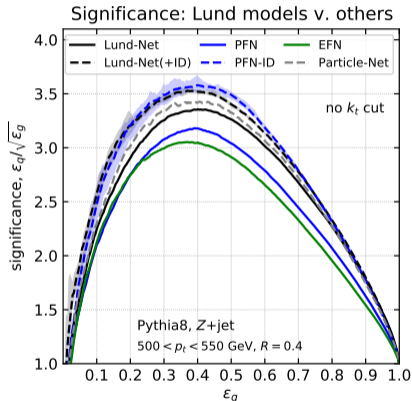
- clear performance ordering:
 - 1 Lund+ML $>$ Lund analytic $>$ ISD
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- larger gains with no k_t cut

$$pp \rightarrow Zq \text{ v. } pp \rightarrow Zg \quad (p_t \sim 500 \text{ GeV}, R = 0.4)$$



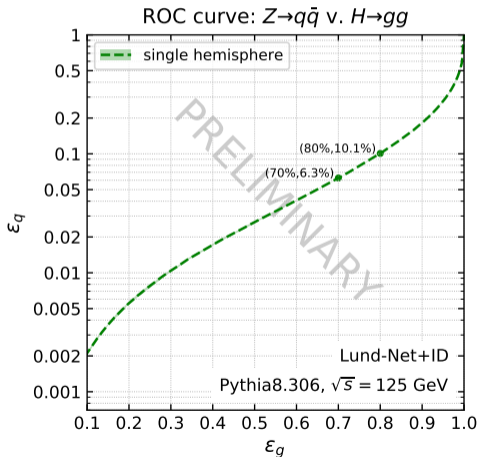
- clear performance ordering:
 - 1 Lund+ML > Lund analytic > ISD
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- Analytic approach shows gains for $k_t > 1 \text{ GeV}$
(shapes improve at small ε_q by adding smaller k_t)

$$pp \rightarrow Zq \text{ v. } pp \rightarrow Zg \quad (p_t \sim 500 \text{ GeV}, R = 0.4)$$



- clear performance ordering:
 - 1 Lund+ML > Lund analytic > ISD
 - 2 tree > prim
- larger gains with no k_t cut
- Analytic approach shows gains for $k_t > 1 \text{ GeV}$
(shapes improve at small ϵ_q by adding smaller k_t)
- ML performance on par with PFN, slightly better than Particle-Net
(treatment of PDG-ID could maybe be improved)

$e^+e^- \rightarrow Z \rightarrow q\bar{q}$ v. $e^+e^- \rightarrow H \rightarrow gg$ ($\sqrt{s} = 125$ GeV, no ISR)



observed performance:

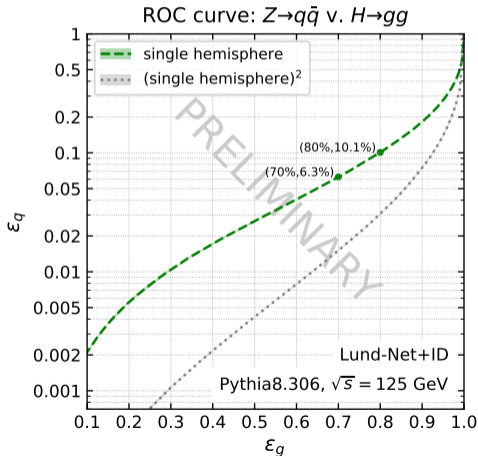
- **Lund-Net in single jet/hemisphere**
6% (10%) quark mistag for
70% (80%) gluon efficiency

Not quite the 1% quark mistag in 2107.02686
(see also David d'Enterra's talk)

In agreement with numbers from June 2021
FCC week (see also Giovanni Marchiori's talk)

Watch out: $H \neq HZ$

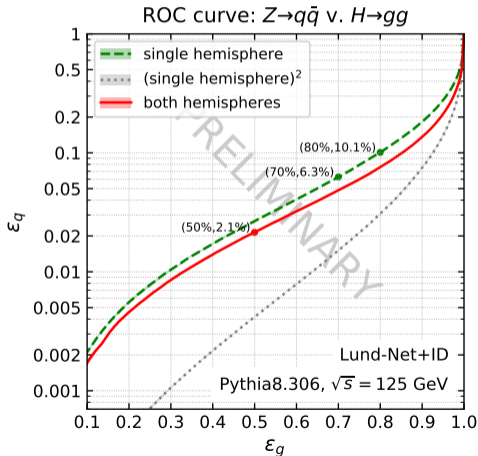
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observed performance:

- Lund-Net in single jet/hemisphere
- assuming 2 independent tags (not physical)

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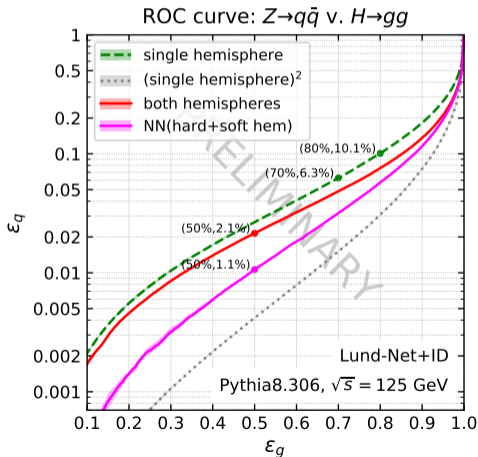


observed performance:

- Lund-Net in single jet/hemisphere
- assuming 2 independent tags (not physical)
- tagging both hemispheres
i.e. both jets should be tagged

full event clearly worse than (jet)²

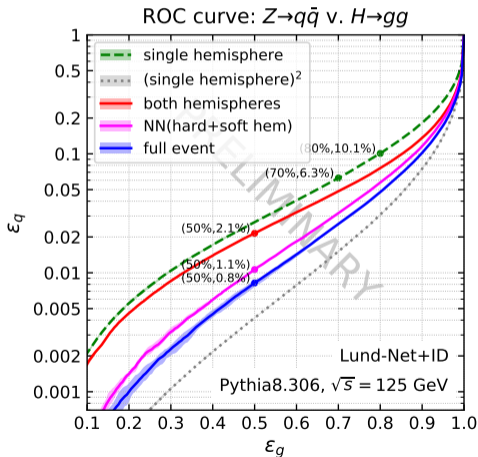
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observed performance:

- Lund-Net in single jet/hemisphere
 - assuming 2 independent tags (not physical)
 - tagging both hemispheres
 - double Lund-Net tag
- train separately on hard & soft hemispheres
use another NN (or MVA) to combine the two
- clear performance gain

$e^+e^- \rightarrow Z \rightarrow q\bar{q}$ v. $e^+e^- \rightarrow H \rightarrow gg$ ($\sqrt{s} = 125$ GeV, no ISR)



observed performance:

- Lund-Net in single jet/hemisphere
 - assuming 2 independent tags (not physical)
 - tagging both hemispheres
 - double Lund-Net tag
 - Lund-Net for the full event
- Another performance gain

Watch out: numbers to be taken with care

- fixed-order corrections are relevant at large ϵ_g
- no ISR, no detector effects, ...

① Quark/gluon discrimination is a complex task with many applications

② Lund declusterings apply to many domains of jet physics
⇒ broad usefulness for LHC/FCC-ee/FCC-hh

③ Focus on Lund declusterings for quark/gluon tagging:

- ▶ maximise likelihood ratio either in pQCD or with ML
- ▶ good performance seen at the LHC

④ Preliminary FCC-ee study gives

$\lesssim 1\%$ $Z \rightarrow q\bar{q}$ mistag rate for $\sim 50\%$ $H \rightarrow gg$ signal efficiency

How much better can we do with better theory understanding (higher fixed-order, better parton shower, better tunes, more restrictive tagging, better PID, , ...)?

