PAIReD jet:

A calibratable, Lorentz-boost independent, multi-pronged resonance tagging strategy

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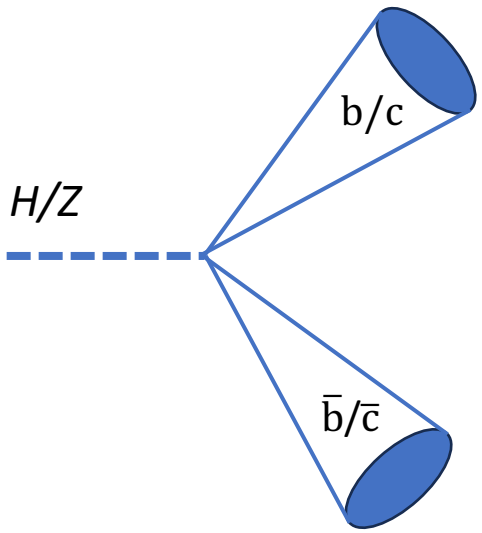
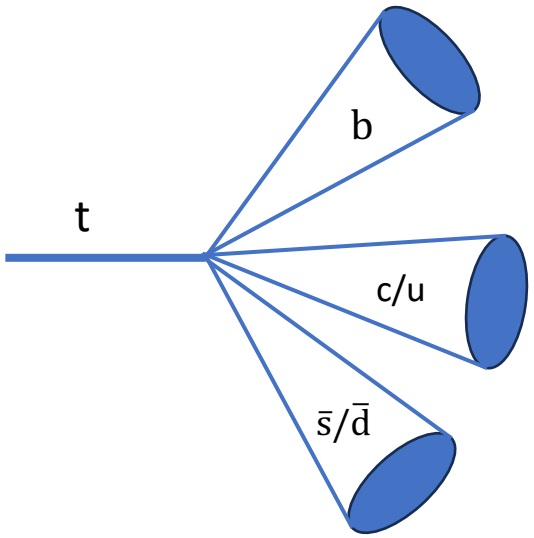
Introduction

- Identifying heavy particles is crucial for the LHC physics program
- Hadronic decays identified from “jets”

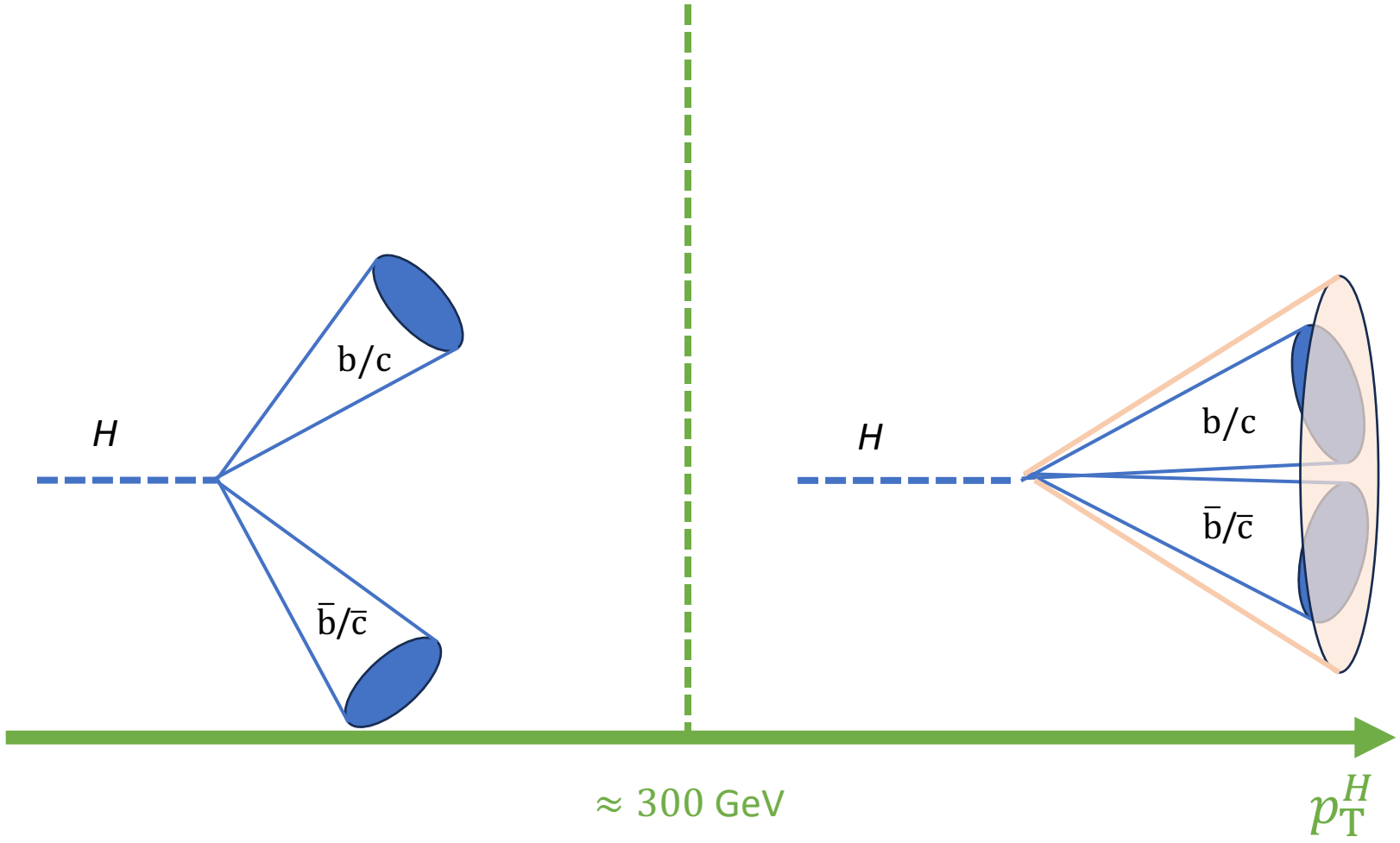




- 2 or 3 (or more) quark final-states

Resolved vs. Boosted

- Angular separation of partons, $\Delta R \sim \frac{m}{p_{\mathrm{T}}}$

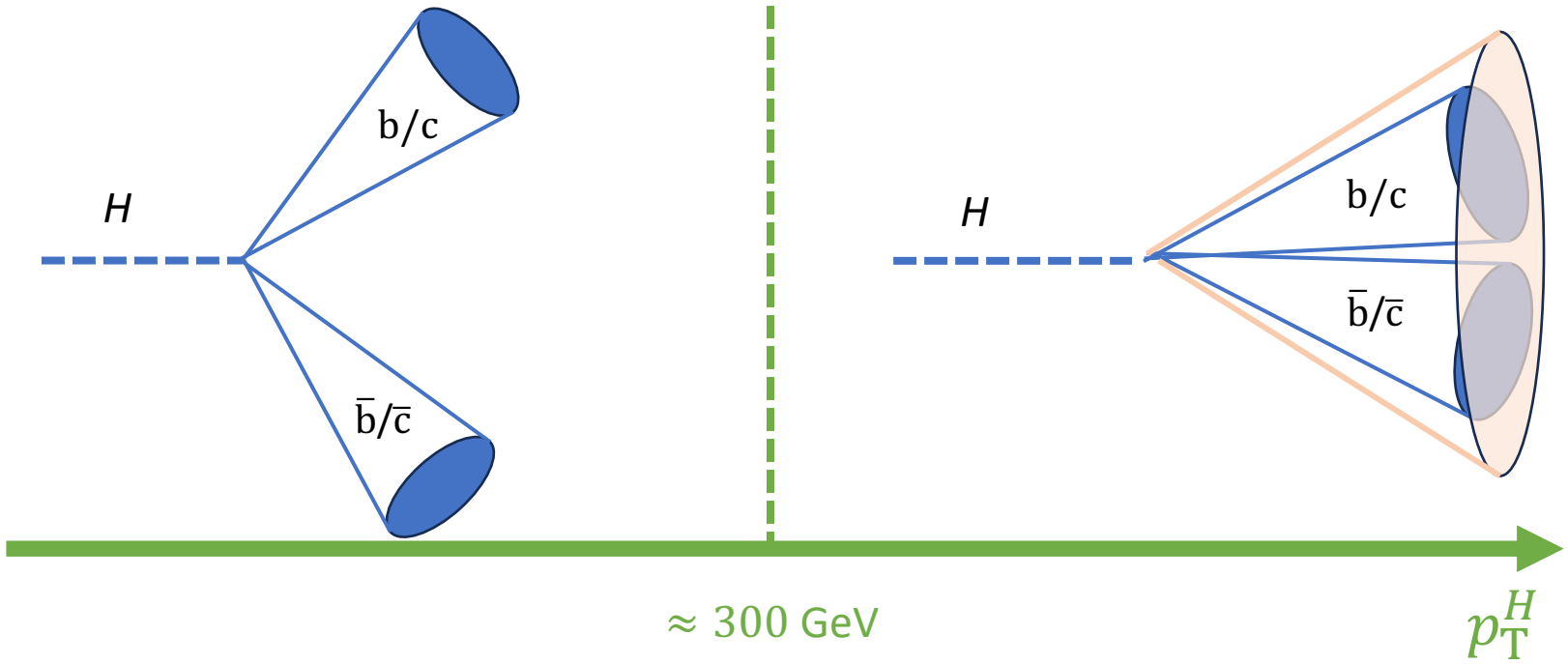


Resolved vs. Boosted

- Tagging strategy:

  - Two thin-radius (AK4) jets
  - Flavour tag them individually
  - Use events where both jets tagged

  - One large-radius (AK8/AK10/AK15) jet
  - Tag full jet as bb/cc
  - Use jets that pass



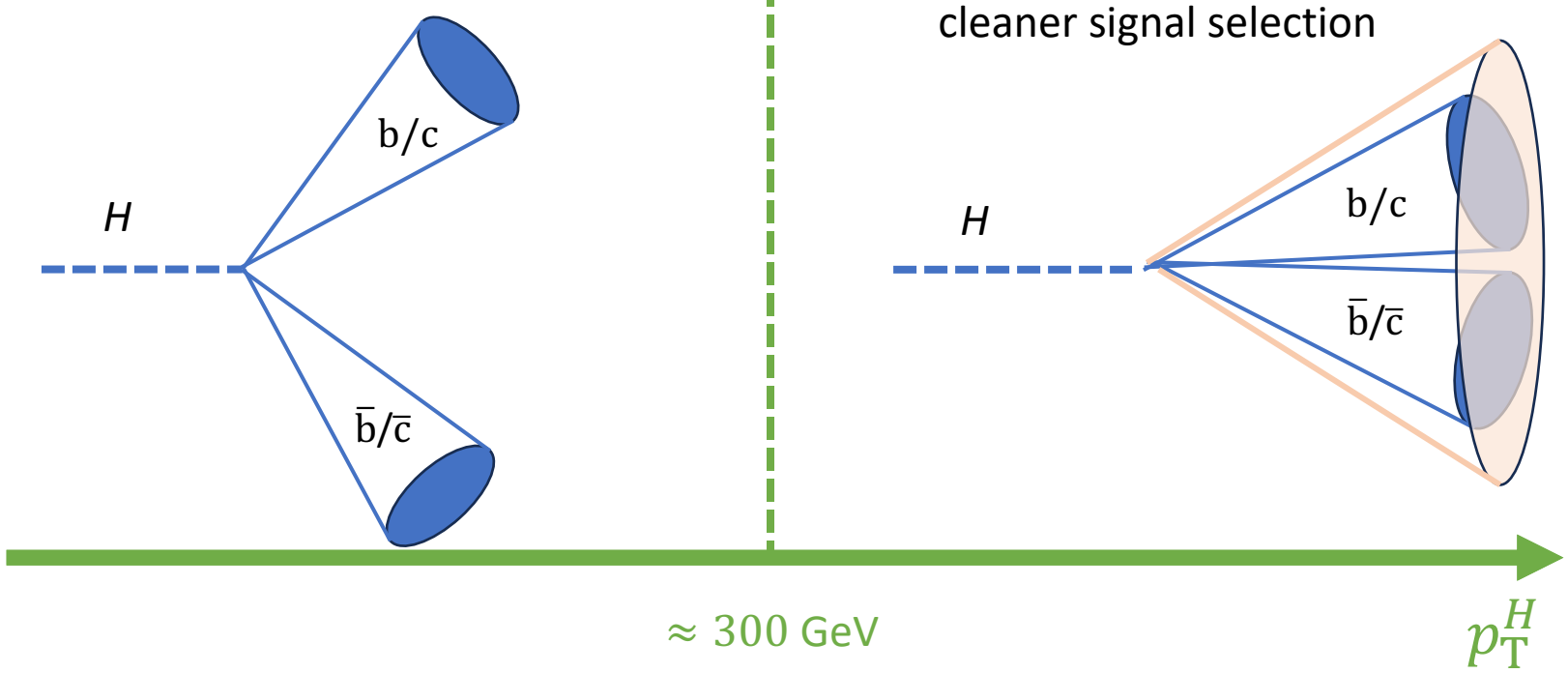
Resolved vs. Boosted

- Advantages:

🤩 Caters to a large part (~95%) of the signal phase space

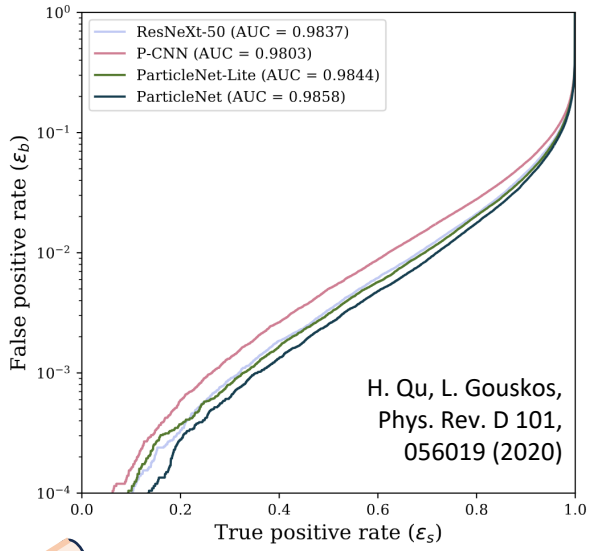
🤩 Exploits correlations between decay products of two quarks: More information for jet tagging

🤩 Lower background at high boosts – cleaner signal selection

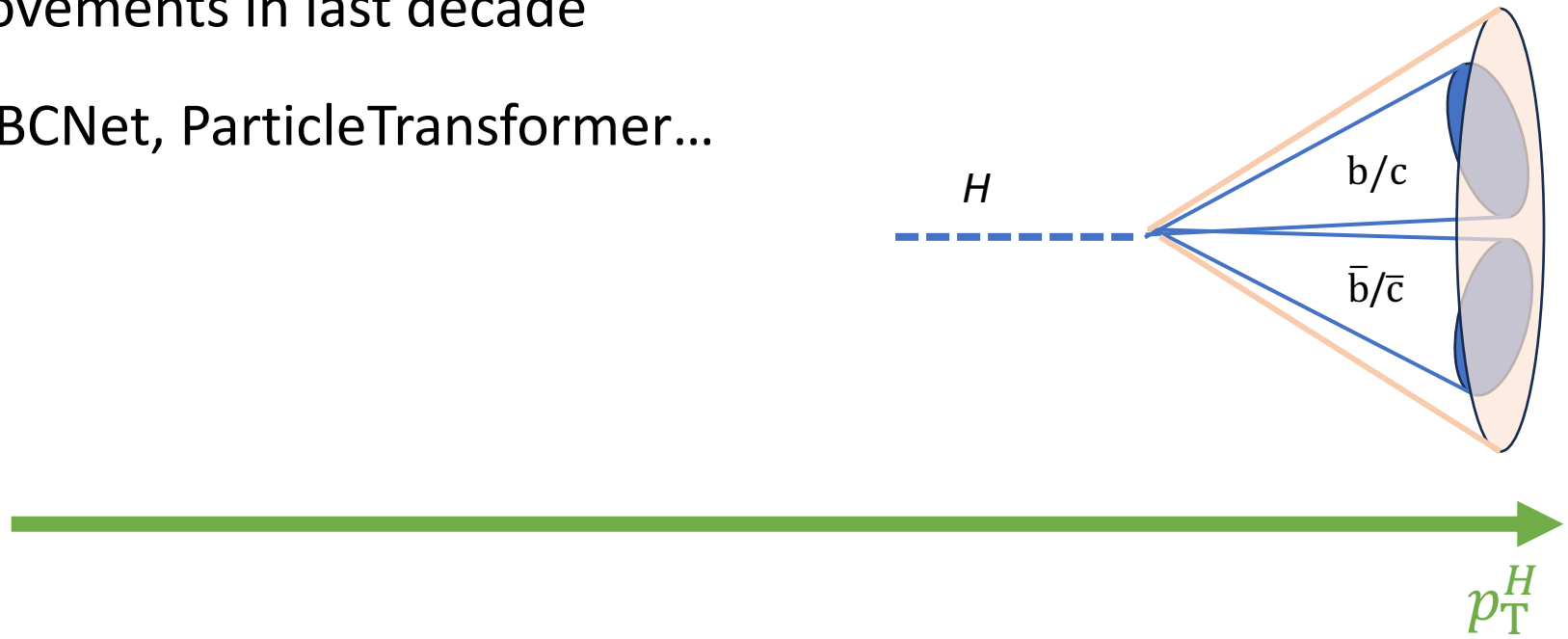


Resolved vs. Boosted

- Several approaches to optimize large-radius jet tagging
  - Jet substructure methods (physics motivated)
  - ML-based discrimination (leverage low-level information)
  - Combination (smaller number of inputs)
- Massive improvements in last decade
- ParticleNet, ABCNet, ParticleTransformer…

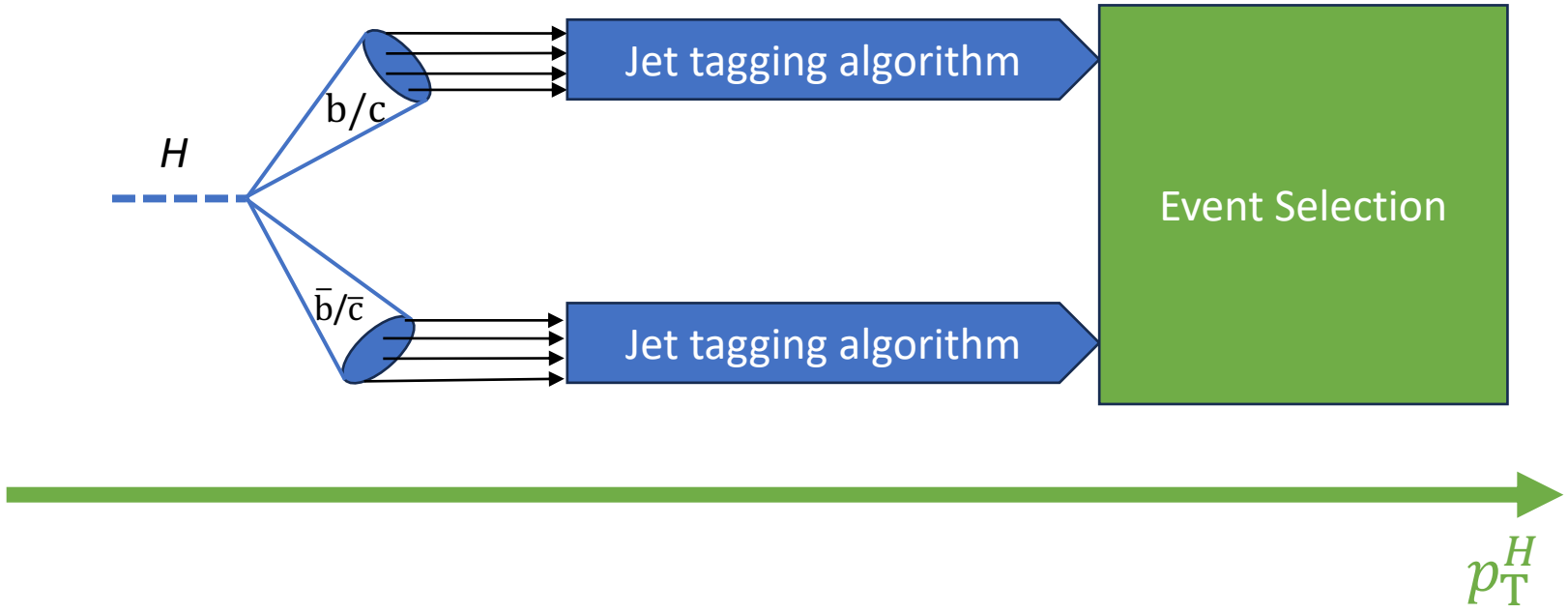


H. Qu, L. Gouskos, Phys. Rev. D 101, 056019 (2020)



Problem statement

- Same novel algorithms used for thin jets
- Improves per-jet tagging performance



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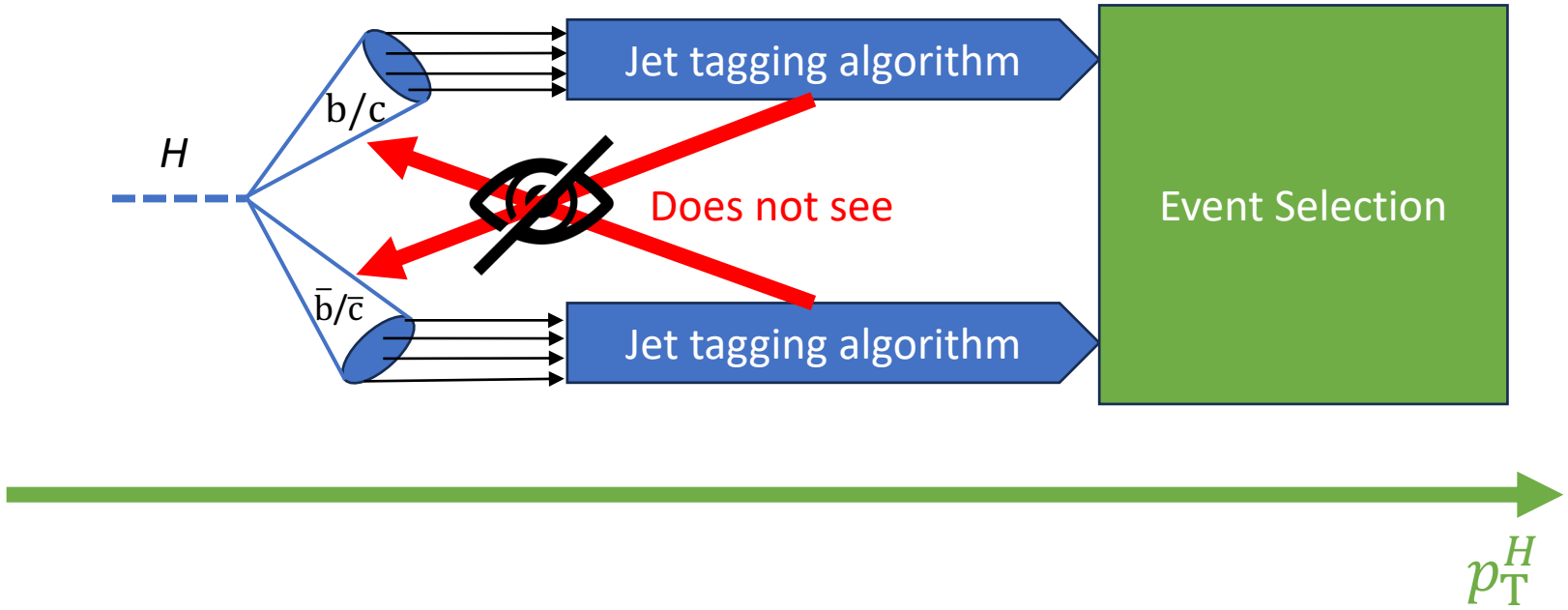
- Algorithm has no information about the other thin jet!



Problem statement

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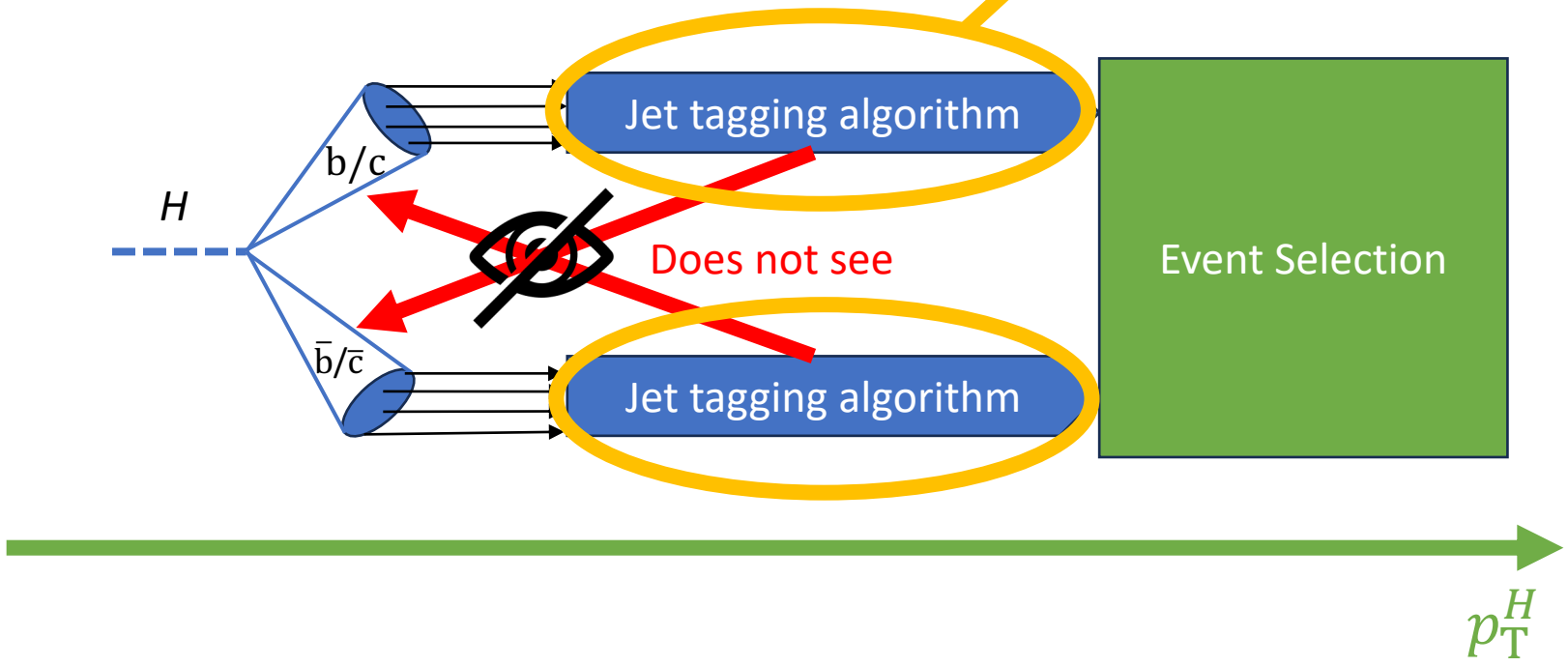
- Improves per-jet tagging performance
- Algorithm has no information about the other thin jet!

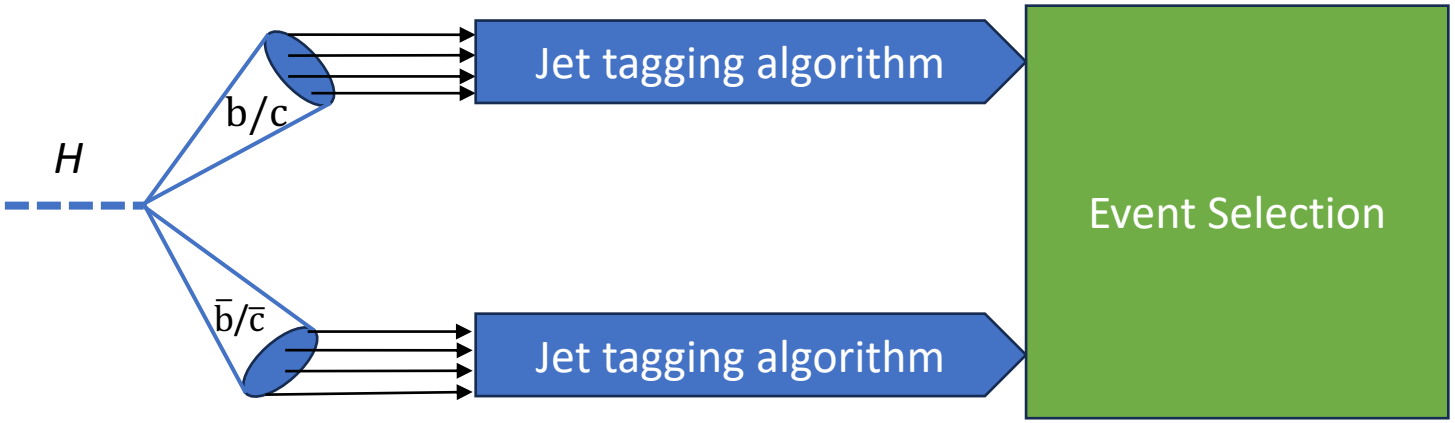
No matter how good the algorithm is, there is inevitable loss of information!

A fundamental limitation of the strategy!

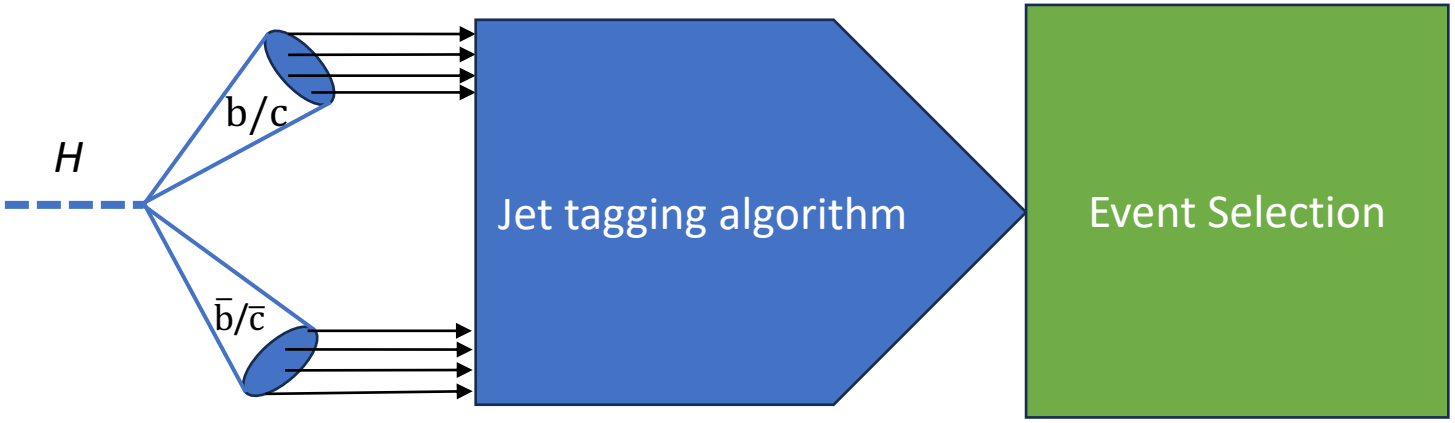


Proposed strategy

- Traditional resolved-jet approach:

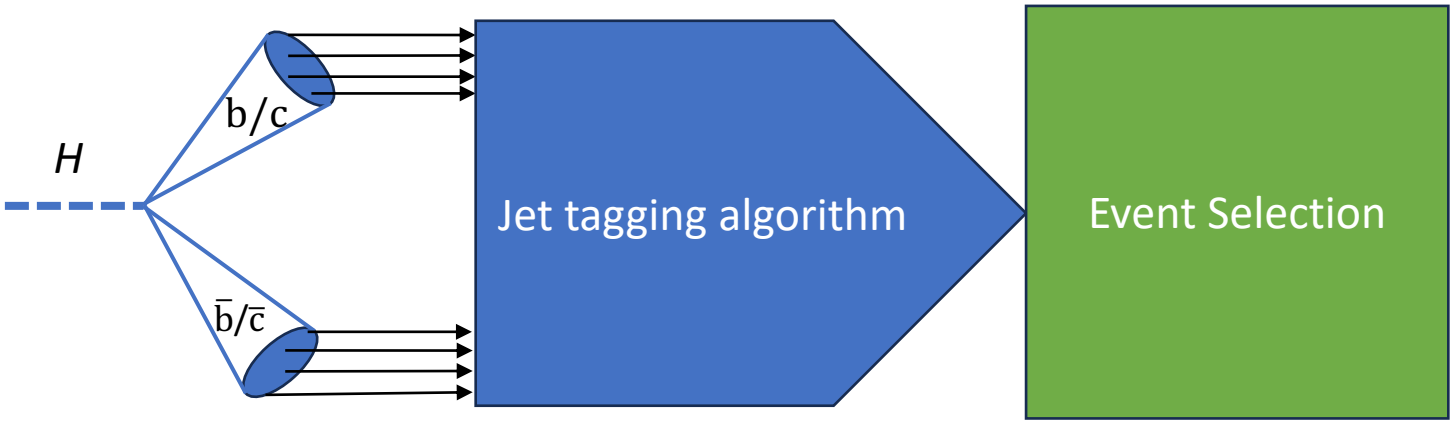


- The ***first variant*** of the PAIReD approach to event reconstruction:



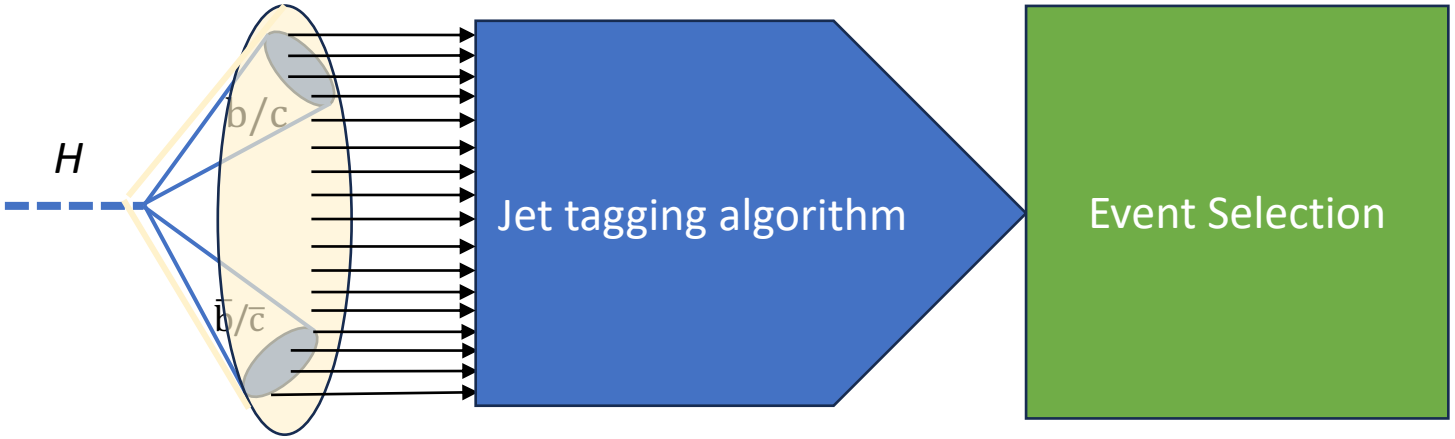
Proposed strategy

- Construct every pair of jets possible from all reconstructed AK4 jets in an event
- Train algorithms with low-level features of two jets simultaneously
  - Access to information from both jets: particle kinematics, trajectory displacements, pair-wise features…
  - Not limited to narrow range of particle boosts



Proposed strategy

- Construct every pair of jets possible from all reconstructed AK4 jets in an event
- Train algorithms with low-level features of two jets simultaneously
  - Access to information from both jets: particle kinematics, trajectory displacements, pair-wise features…
  - Not limited to narrow range of particle boosts
- ***Second variant***: PAIReDEllipse jet
  - Define an ellipse in η–ϕ plane encompassing two AK4 jets

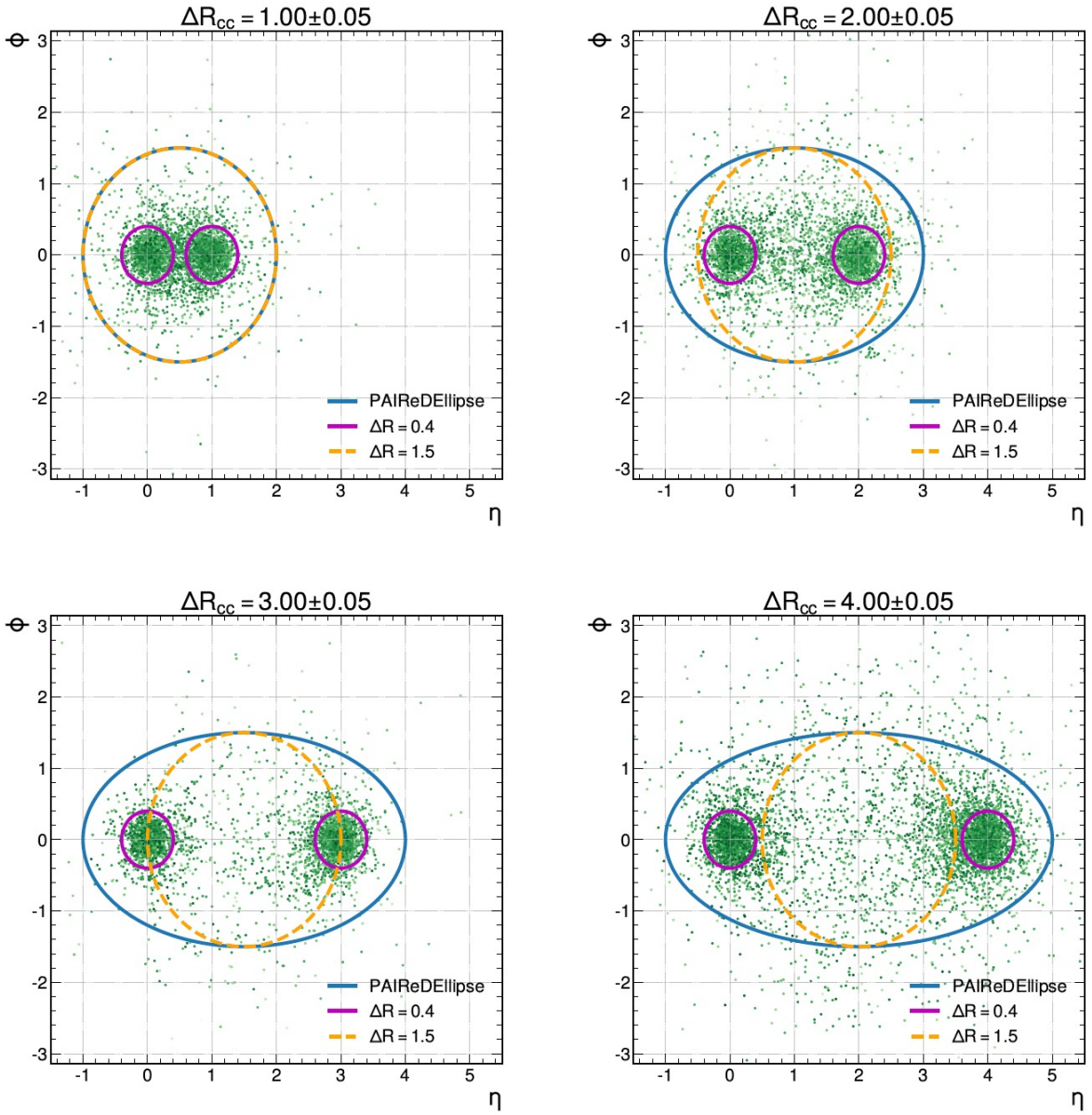


- ➢ AK4 jets used as "seeds" to define elliptical area
- ➢ No reclustering

Proposed strategy

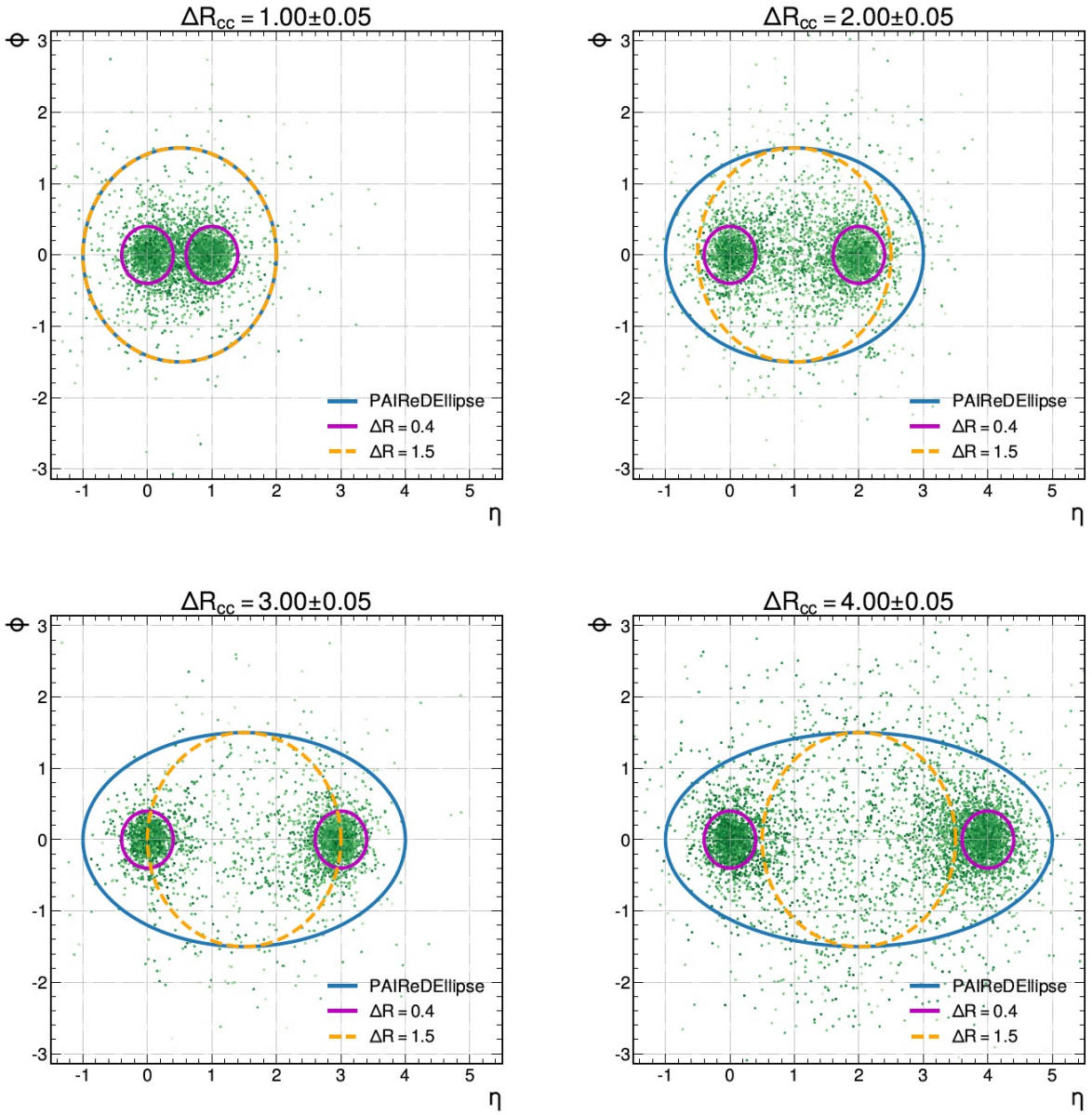
- Compare strategies
  - Use simulated ZH(H → $c\bar{c}$) events (as example)
  - MadGraph5 + Pythia8
  - Delphes with CMS configuration
  - Plot particles generated from Higgs in η–ϕ plane
  - Translate and rotate the plane such that higher-p_T c is at (0,0), second c on η-axis, for each event
  - Overlay events with similar angular separations, $\Delta R_{c\bar{c}}$

Each plot shows 800 ZH(H → $c\bar{c}$) events (with similar $\Delta R_{c\bar{c}}$) superimposed on top of one another



Proposed strategy

- AK15 limited to small range of $\Delta R_{c\bar{c}}$
- AK4, PAIReD and PAIReDEllipse can reconstruct the decay at all $\Delta R_{c\bar{c}}$ values
- PAIReDEllipse encompasses full decay
  - Not IRC safe
  - More pileup particles



Neural network training

- We use ParticleTransformer [H. Qu, C. Li, S. Qian, PMLR 162:18281-18292, 2022]
  - State of the art
  - Evaluate different strategies against **fixed choice of architecture**
- Signal
  - Simulated ZH($H \to b\bar{b}$) and ZH($H \to c\bar{c}$) events (~15M each)
  - Mass of generated Higgs varied between 10 and 500 GeV to achieve mass decorrelation
- Background
  - Simulated Z+jets samples (~30M)
- Inputs: Particle kinematics and trajectory displacement

Performance metrics

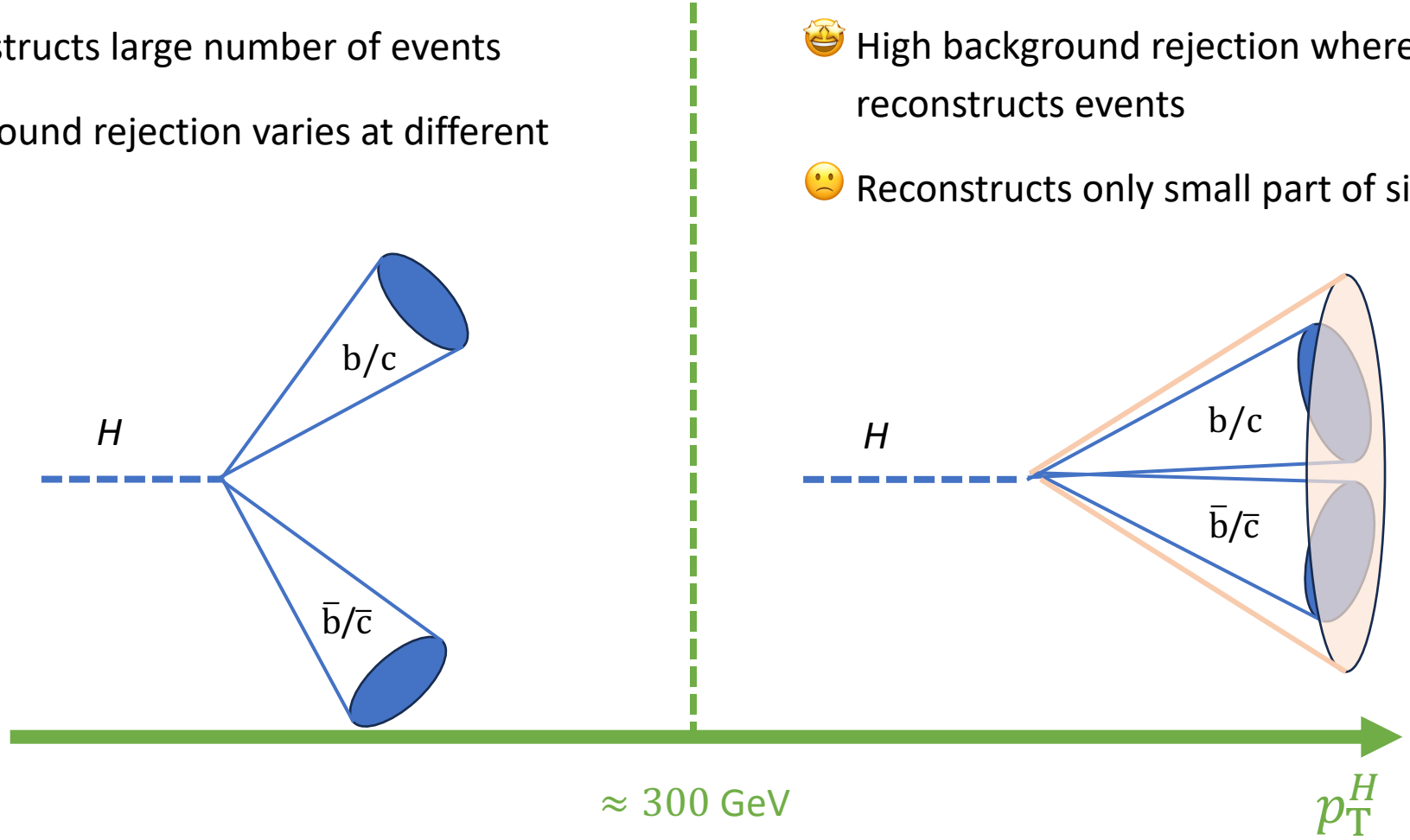
- Difficult to make apple-to-apple comparison across strategies with just ROC curves

🤩 Reconstructs large number of events

🙁 Background rejection varies at different boosts

🤩 High background rejection where it reconstructs events

🙁 Reconstructs only small part of signal



Performance metrics

- Difficult to make apple-to-apple comparison across strategies with just ROC curves
- Propose **end-to-end event signal efficiency** and **end-to-end background rejection rates**

End-to-end efficiency = Efficiency factor from correct event reconstruction $\otimes$ Efficiency after cutting on tagger score

- Can be applied to any reconstruction strategy
- Can be plotted as function of p_{T}
- Each component can also be studied independently

Performance metrics

- Difficult to make apple-to-apple comparison across strategies with just ROC curves
- Propose **end-to-end event signal efficiency** and **end-to-end background rejection rates**

Depends on how many events *can* be reconstructed

End-to-end efficiency = Efficiency factor from correct event reconstruction
$\otimes$ Efficiency after cutting on tagger score

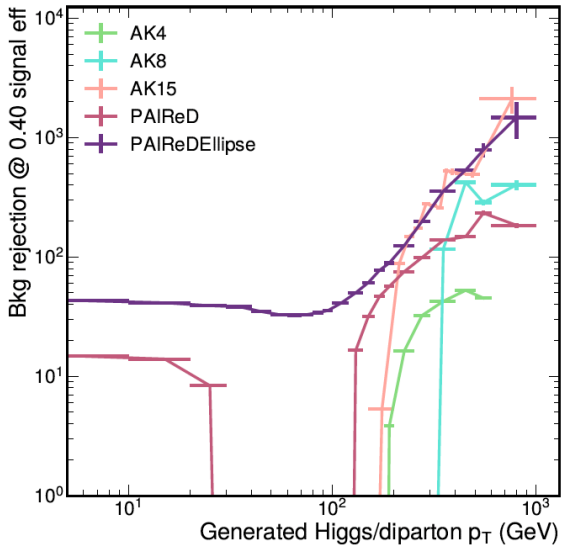
Depends on classifier performance

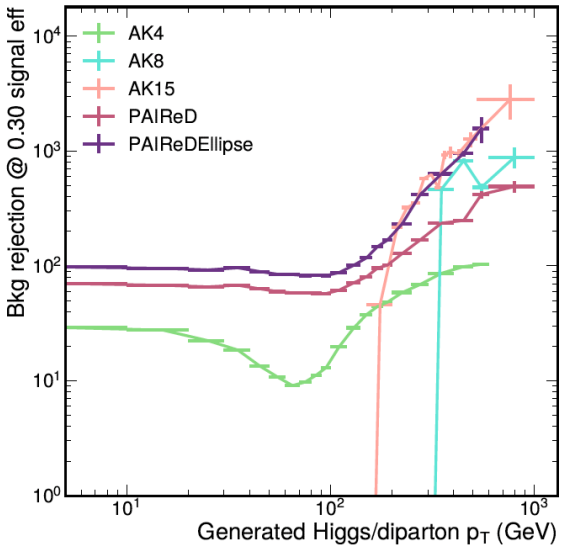
- Can be applied to any reconstruction strategy
- Can be plotted as function of p_{T}
- Each component can also be studied independently

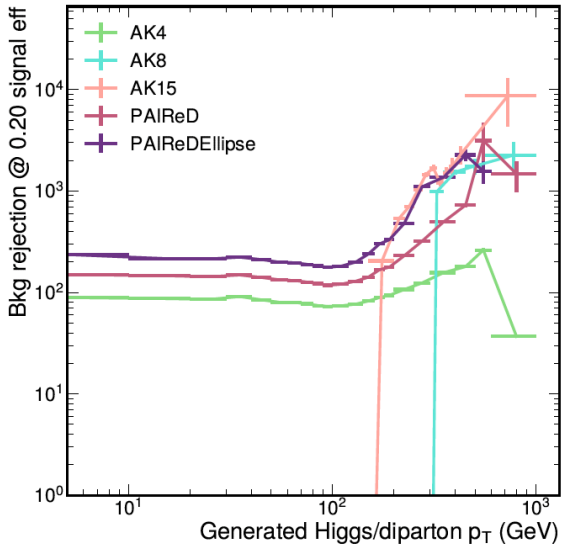
Neural network training: Classification

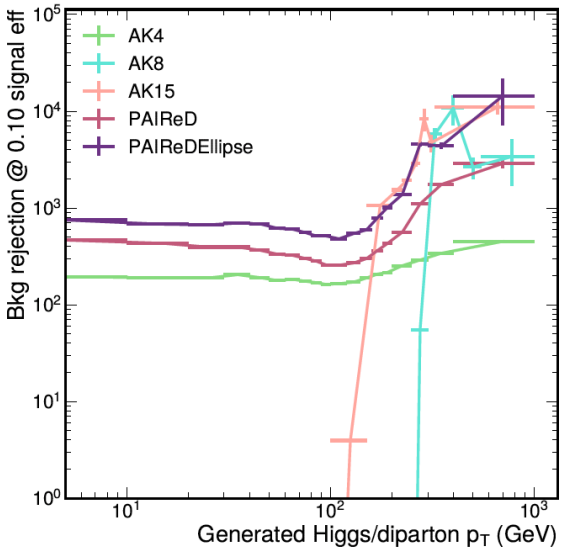
- Classifier trained such that mass metric has a flat distribution
- Three classes: bb, cc, $\ell\ell$
- Validate using $m_H = 125$ GeV samples
- Performance evaluated as **end-to-end background rejection** at a **given end-to-end signal efficiency**
  - as a function of generated Higgs p_{T} (for signal) or proxy diparton p_{T} (for background)
- Apply event selections (2 AK4 jets/1 fat jet, m_H cut) and apply cut on jet tagger score to achieve target end-to-end signal efficiency

Neural network validation: Classification









- Low boosts:
  - PAIReDEllipse outperforms AK4-based approach by a factor of 2–4.
  - AK8/AK15 have no role.
- High boosts:
  - PAIReDEllipse performs similar to AK8 and AK15 based approach.
  - AK4 worse.
- PAIReDEllipse outperforms PAIReD despite potentially containing more pileup particles and soft radiations

Calibratibility

- Energy calibration:
  - PAIReD and PAIReDEllipse jet energies can be calibrated using AK8/AK15 energy calibration methods
  - E.g., balance momentum of Z($\ell\ell$)+qq system
- Flavour tagger calibration:
  - Use proxy jet methods, similar to AK8/AK15 flavour tagging calibration methods
  - E.g., soft-muon tagged jets, calibration using Z(bb), etc.
- Unlike full event taggers, PAIReD(Ellipse) jets are fully calibratable while leveraging larger fractions of detector volume than traditional object-based approaches

Summary

- We propose a new reconstruction strategy for hadronic decays of heavy particles
  - PAIReD treats two-small radius jets as a single entity and performs tagging
  - PAIReDEllipse forms a large unconventional jet using AK4 jet seeds to perform tagging
- Both methods can be used at all Lorentz-boosts of parent heavy particle
- Both PAIReD and PAIReDEllipse outperform standard methods at low boosts
  - 2 to 4 times better background rejection
- PAIReDEllipse has similar performance as fatjet tagging at high boosts
- The approach is fully calibratable using real collision data

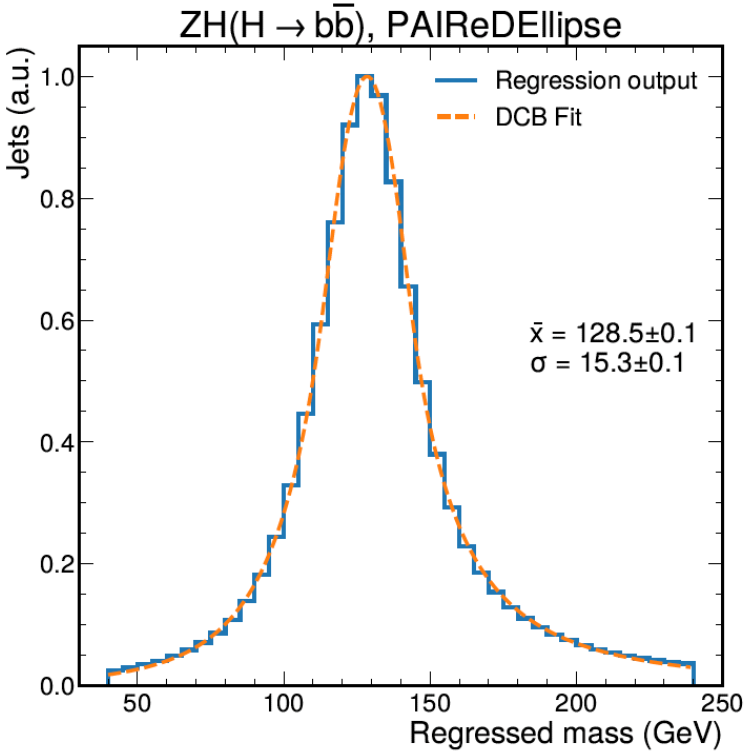
Outlook

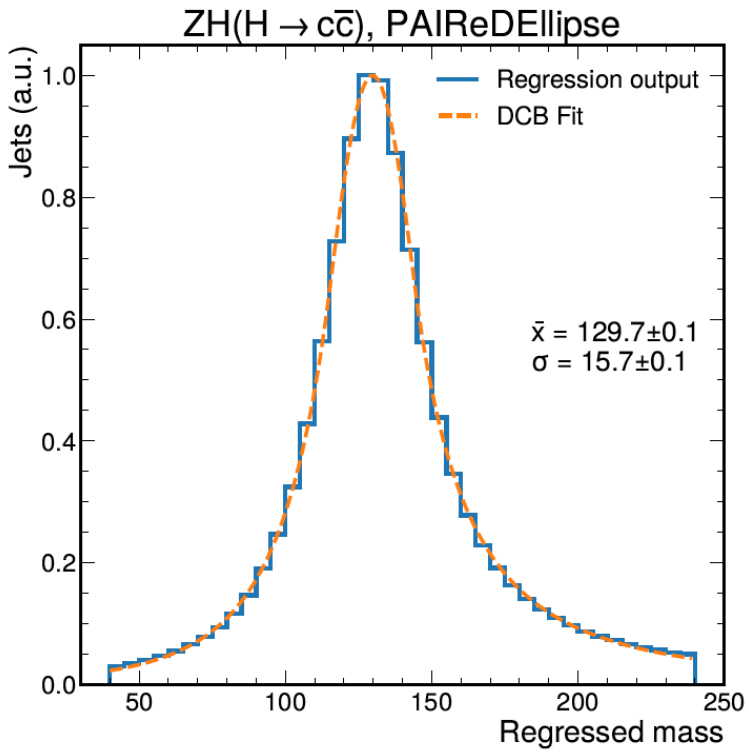
- H → $c\bar{c}$ is only one example. Can be extended to H → $b\bar{b}$, Z → $b\bar{b}/c\bar{c}$, HH → 4b, …
- Can be trained for any flavour pair (e.g., $H^{\pm} \rightarrow c\bar{s}$).
- Can be extended to 3-pronged decays.
- Also suitable for 4-pronged decays (e.g., $H \rightarrow ZZ \rightarrow$ qqqq) which have very low reconstruction efficiencies in fatjets; or event can be factorized to two pairs of PAIReD jets.
- Regression methods can be used to predict parent particle mass
- New method expected to improve sensitivity at low boosts and make previously-inaccessible kinematic regions accessible and competitive.

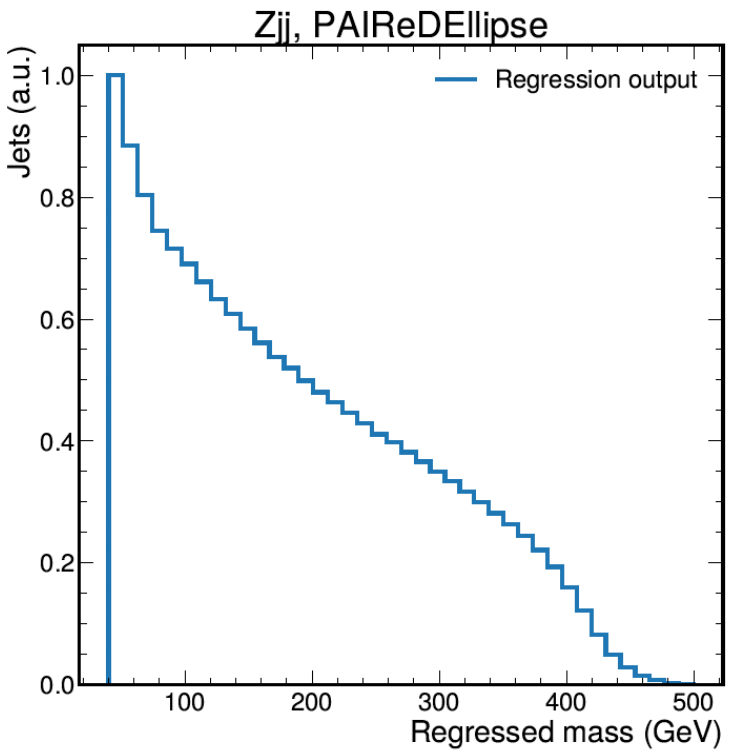
Backup

Neural network validation: Regression

- Regression validated with $m_H = 125$ GeV samples







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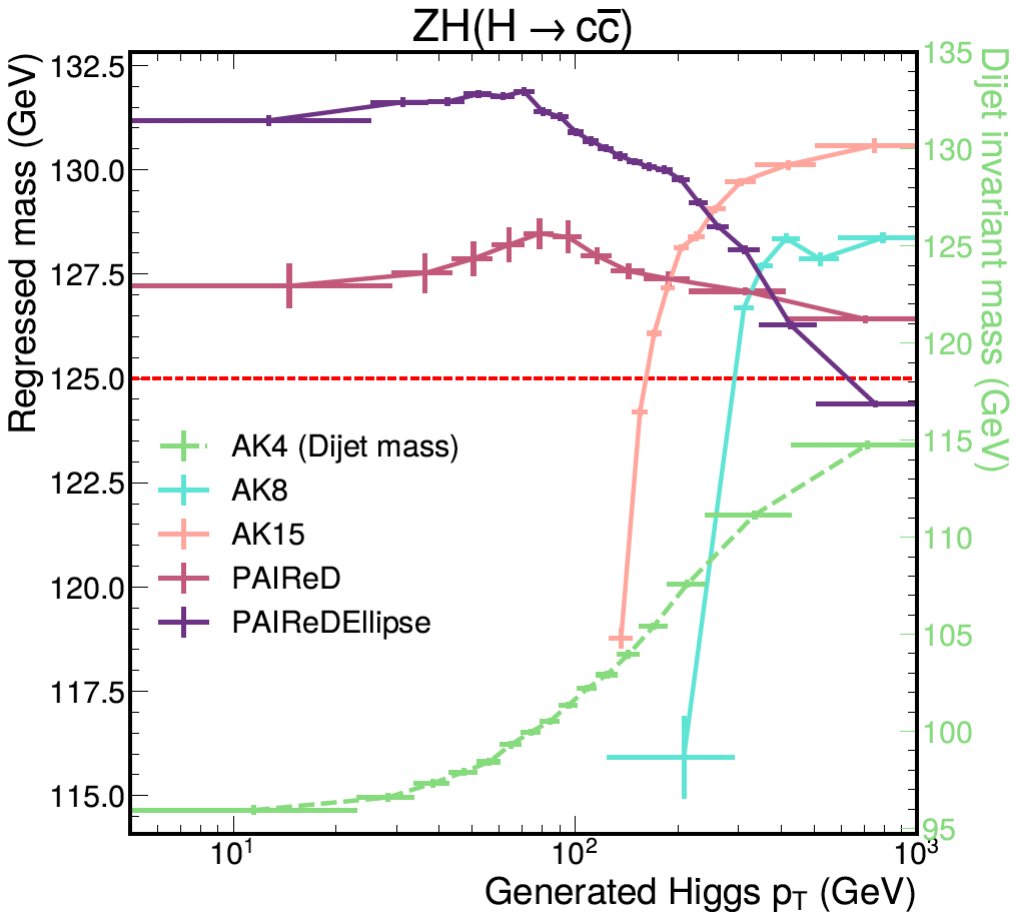
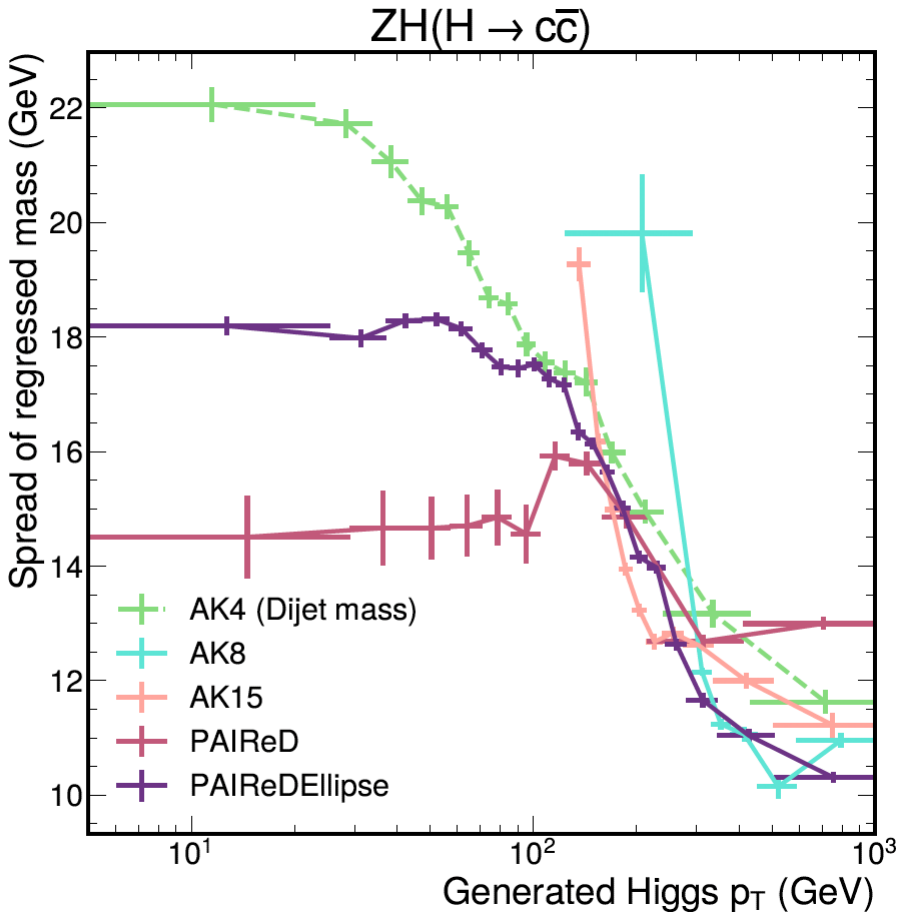
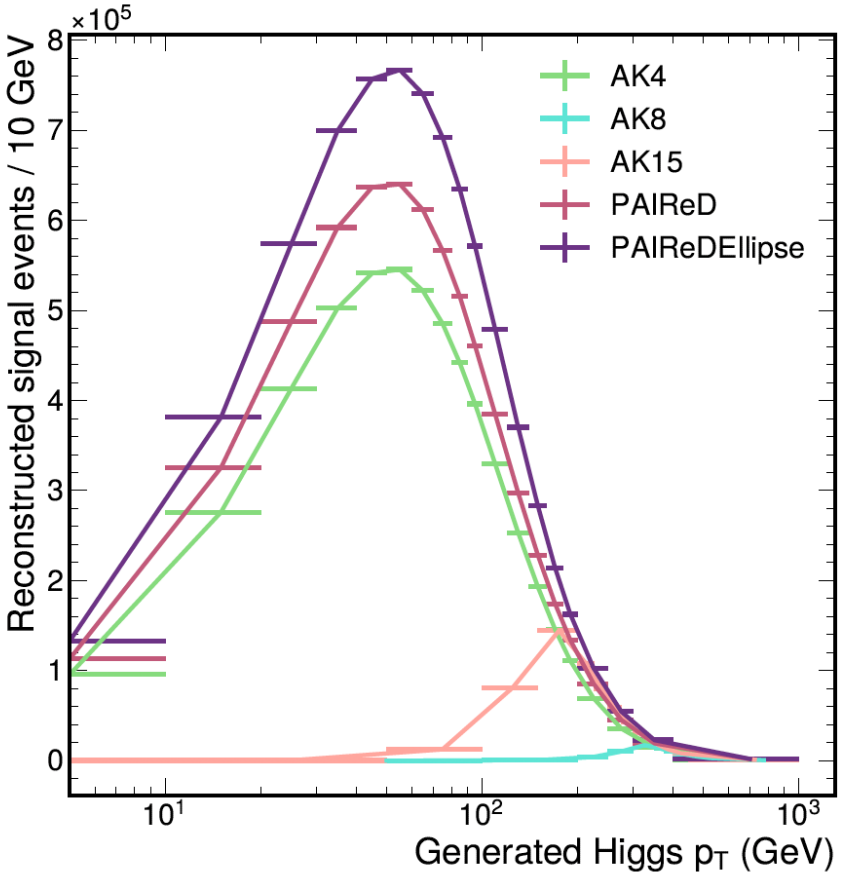


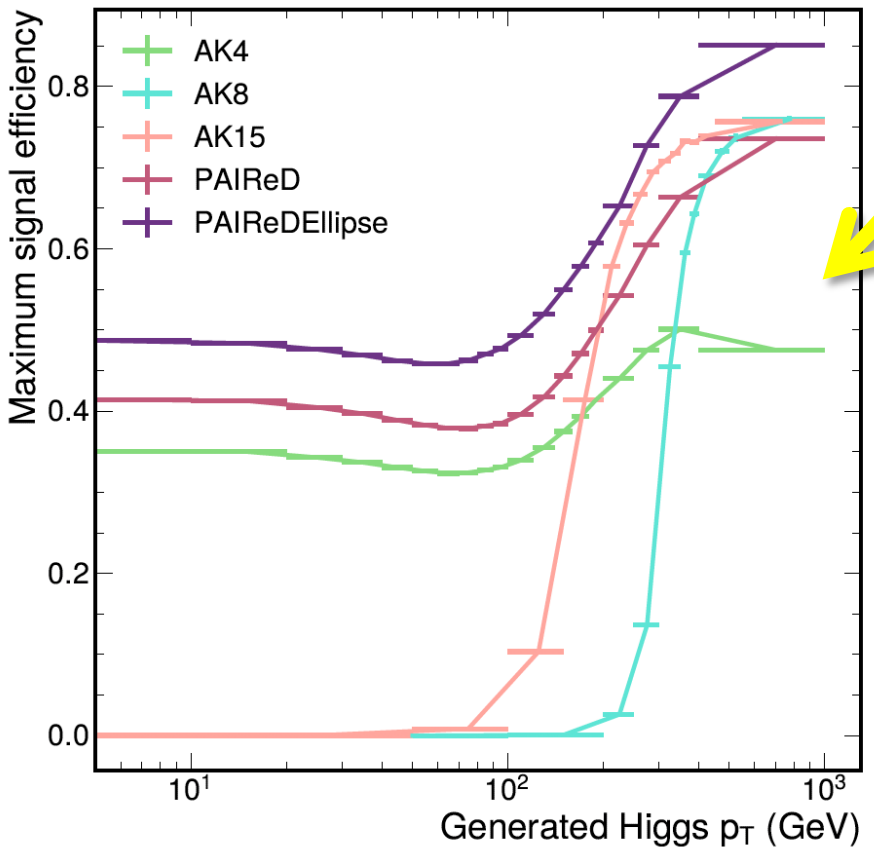


Event Reconstruction

End-to-end efficiency = Efficiency factor from correct event reconstruction

⊗ Efficiency after cutting on tagger score





Neural network validation: Classification

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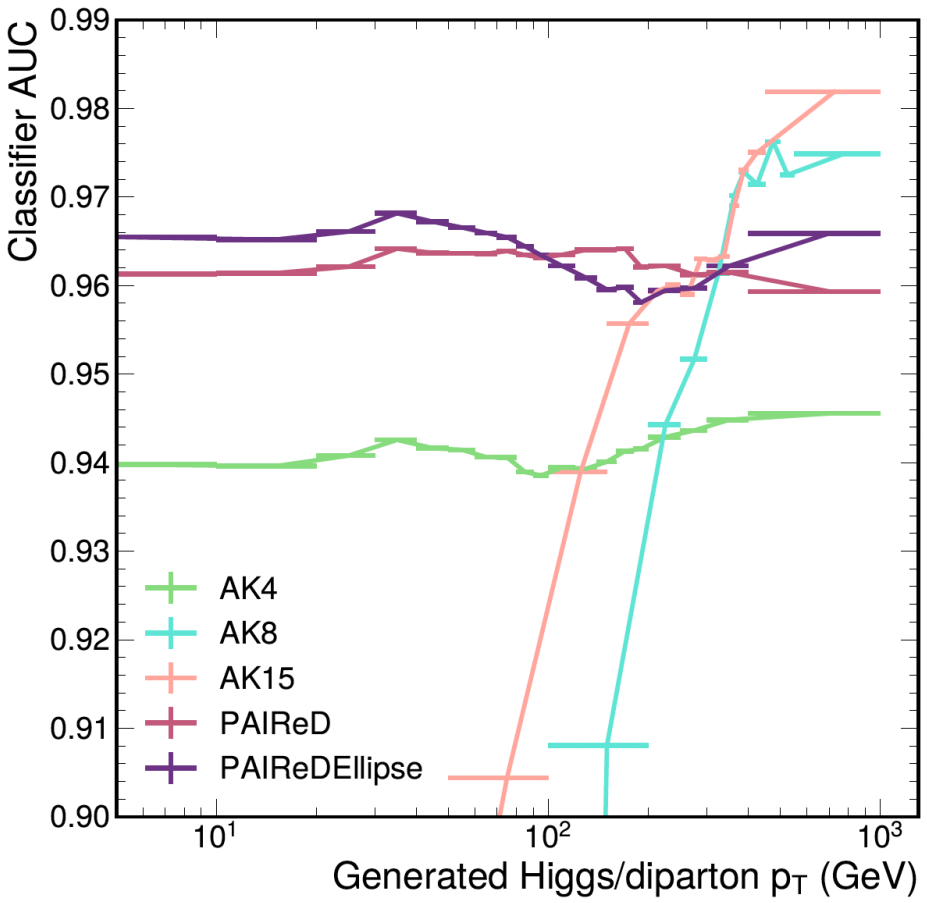
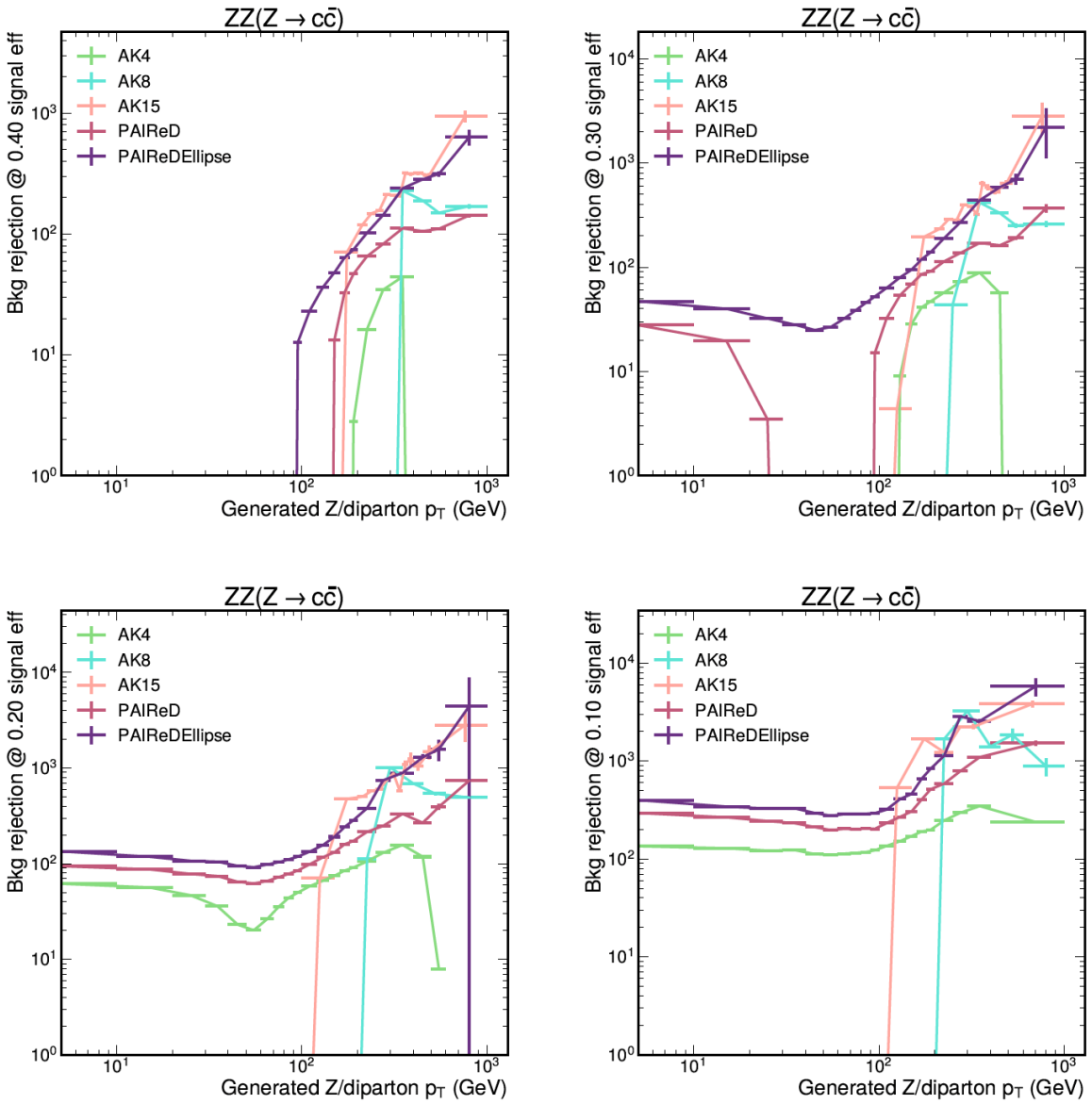


(Quantified in terms of area under the ROC curves)

$ZZ(Z \to c\bar{c})$


ZZ(Z → cc̄)
Bkg rejection @ 0.40 signal eff
Bkg rejection @ 0.30 signal eff
Bkg rejection @ 0.20 signal eff
Bkg rejection @ 0.10 signal eff
AK4
AK8
AK15
PAIReD
PAIReDEllipse
Generated Z/diparton p_T (GeV)