A Boosted Event Shape Tagger for Heavy Object Classification

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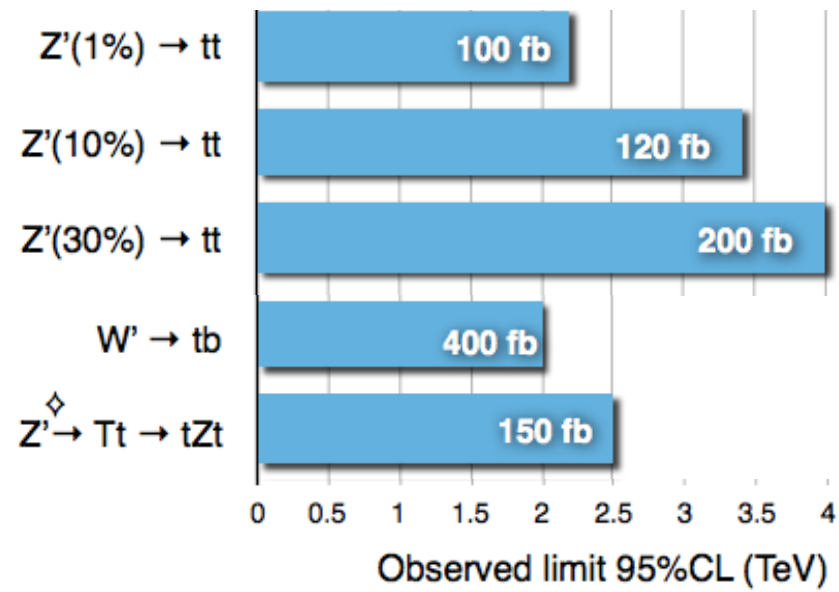
Introduction

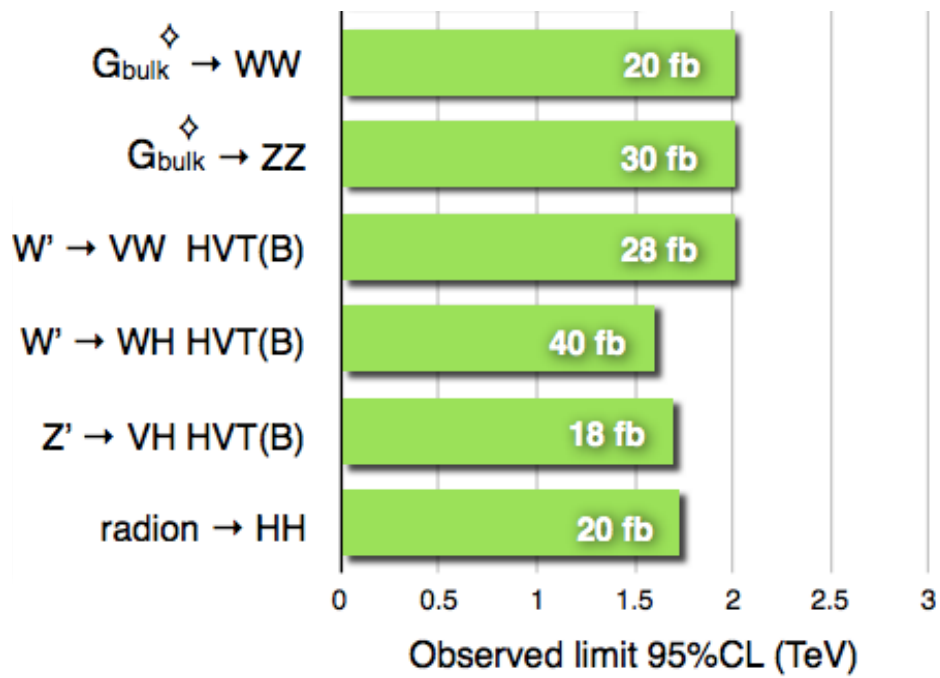
- Searches for new physics at the LHC continue to push exclusion limits higher and higher

- High resonance mass → high energy, collimated SM decay products

- **Jet substructure** techniques critical to maintain search sensitivity to these unique signatures
  - Identify hadronic decays of high-p_T, heavy SM objects
    - Top quarks, W, Z, H bosons

  - Already prevalent in CMS analyses, becoming more widespread
    - Also powerful for pileup mitigation





Jet Substructure

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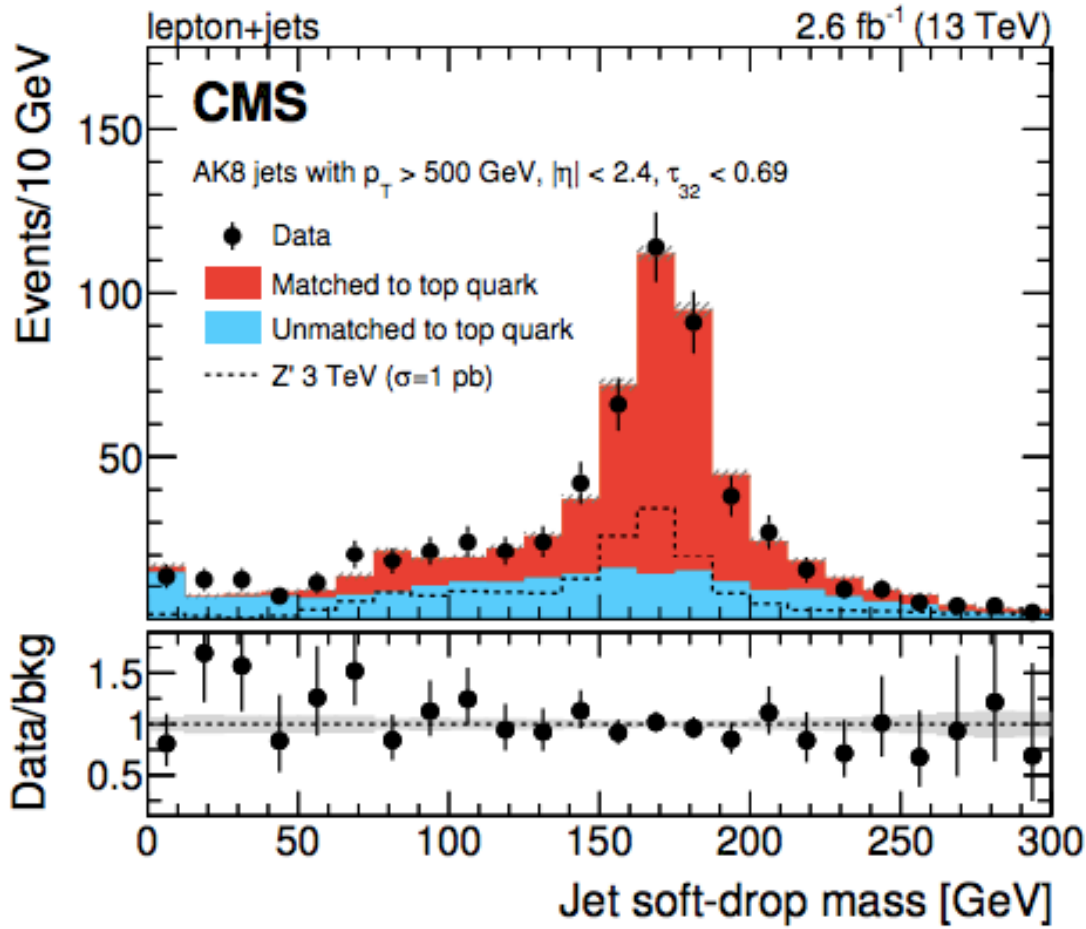
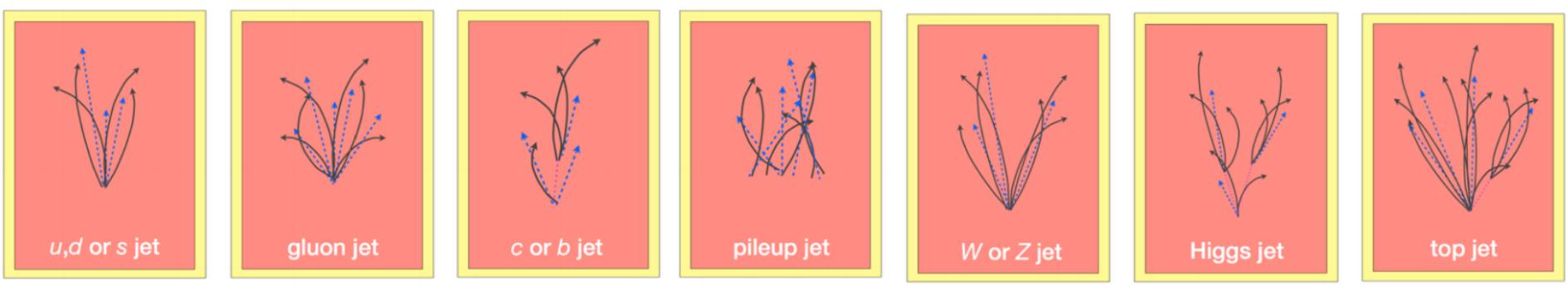
- **Jet substructure signatures are discovery signatures!**
  - Use information within a jet to identify hadronic decays of heavy objects
    - Choose large jet cone size to capture all decay products
    - R = 0.8 →
      - Merged W at p_T = 200 GeV
      - Merged top at p_T = 400 GeV
    - "Top jet", "W jet", etc.



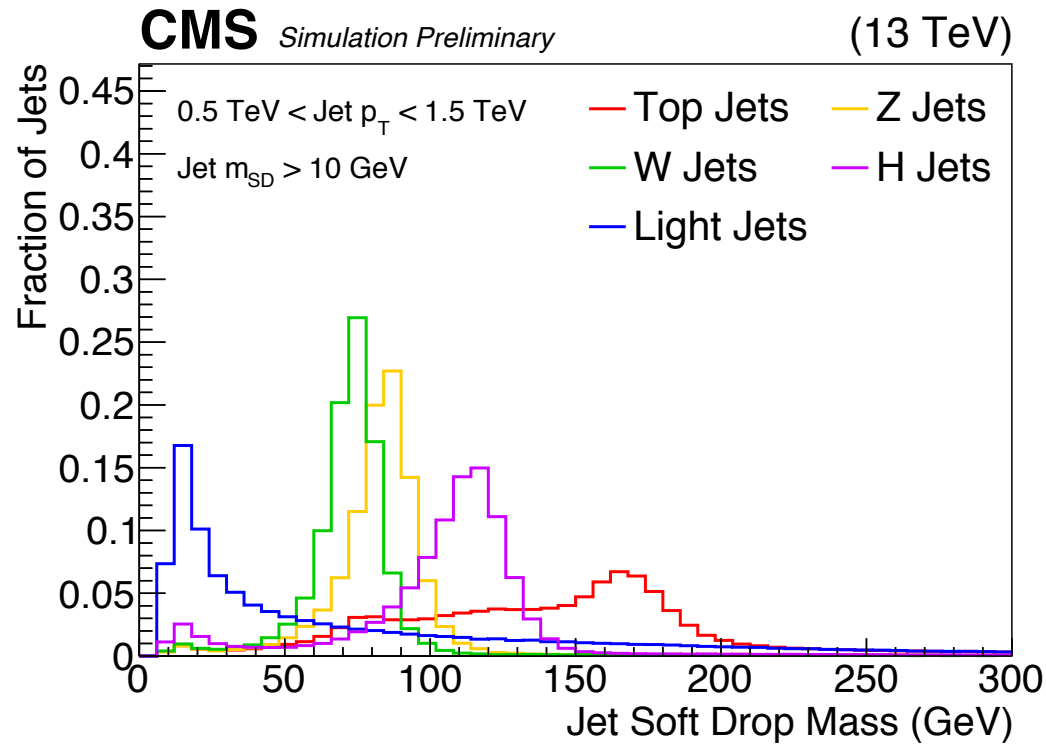
- Several algorithms in use in CMS targeting individual particles
  - Well-validated in data



N. Tran

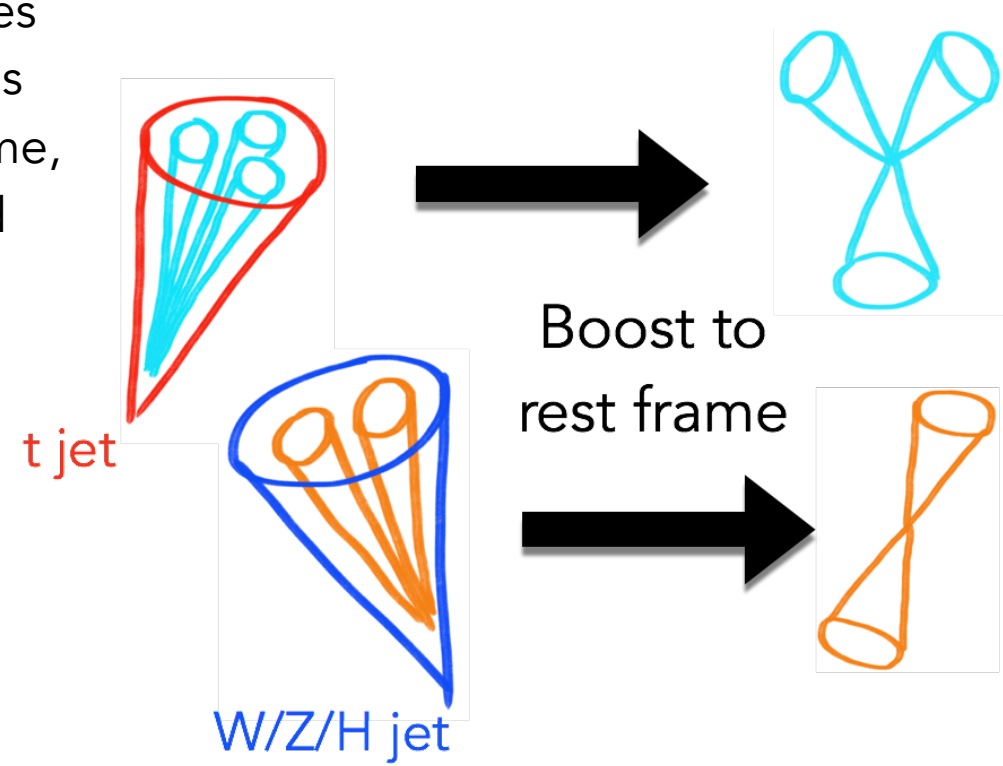
New Idea

- We present a new algorithm to **simultaneously** classify jets according to heavy object type
- **Boosted Event Shape Tagger (BEST)**
  - Consider top quarks, W, Z, H bosons
  - Light jets from QCD processes as background



- Use different hypothesized reference frames corresponding to the heavy particle masses
  - When boosting to the 'correct' rest frame, jet constituents should be isotropic and show the expected N-prong structure

- Based on fall 2016 phenomenology paper [1], now implemented using full CMS simulation and reconstruction



[1] PRD 94 094027 (2016)

Methodology

Public Material in CMS Detector Performance Note CMS-DP-2017/027

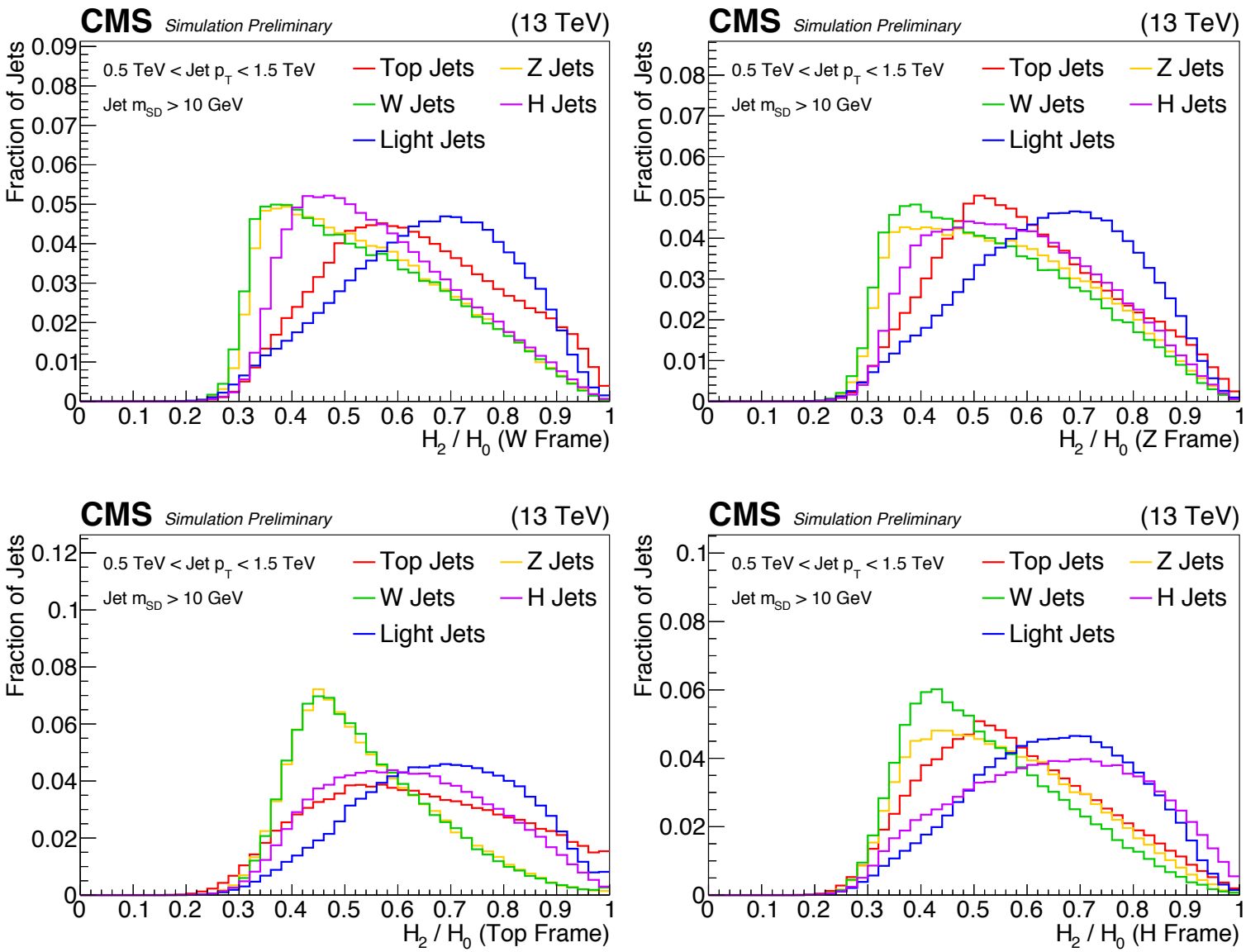
- Select an anti-kT R = 0.8 (AK8) jet with $p_T > 500$ GeV, $|\eta| < 2.4$
- Define four reference frames based on hypothesized particle origins of jet
  - Assume mass of top, Z, W, H; with same jet momentum
- Boost all jet constituents into each of the 4 hypothesized reference frames
- Compute angular and kinematic quantities in each frame
  - Four distributions of same quantity for each jet in respective frames
  - Recluster constituents in boosted frame (relative to boost axis) with smaller distance parameter R = 0.4 (AK4 jets)
- Train a neural network using these observables
- Obtain discrimination between heavy object jets and light jets; particle origin classification from NN outputs

NN Input Quantities	
Sphericity (t, W, Z, H)	Jet Soft-Drop Mass
Isotropy (t, W, Z, H)	Jet p_T (flattened)
Aplanarity (t, W, Z, H)	Jet η
Thrust (t, W, Z, H)	Jet τ_{21}
Jet Asymmetry A_L (t, W, Z, H)	Jet τ_{32}
Fox-Wolfram H_1/H_0 (t, W, Z, H)	Fox-Wolfram H_3/H_0 (t, W, Z, H)
Fox-Wolfram H_2/H_0 (t, W, Z, H)	Fox-Wolfram H_4/H_0 (t, W, Z, H)

Inputs - Fox-Wolfram Moments

- Related to Legendre polynomials
  - Angular moments of the distribution of particles

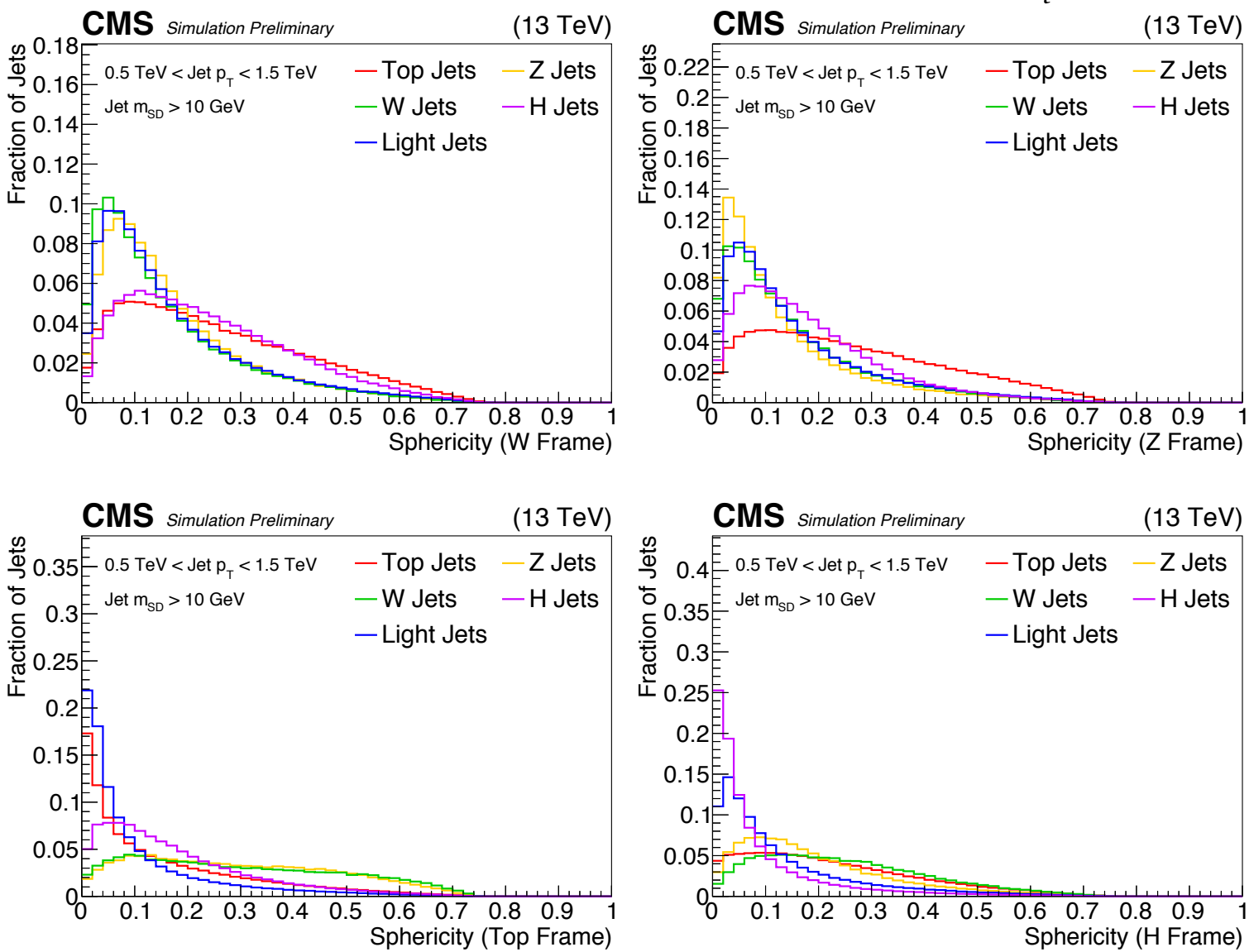
$$H_\ell = \sum_{i,j} \frac{|\vec{p}_i||\vec{p}_j|}{s} \cdot P_\ell(\cos(\phi_{i,j}))$$



Inputs - Sphericity Tensor

- Measure of how uniformly distributed a set of particles is
  - 0 → Spherical, 1 → Collimated

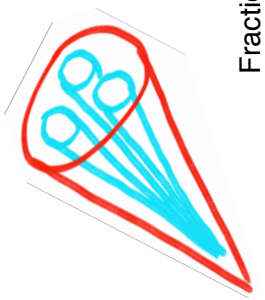
$$S^{\alpha,\beta} = \frac{\sum_i p_i^\alpha p_i^\beta}{\sum_i |\vec{p}_i|^2}$$

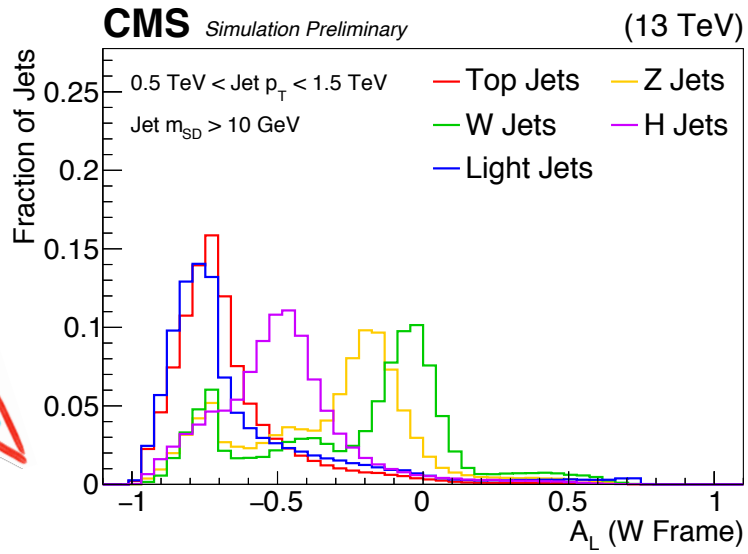


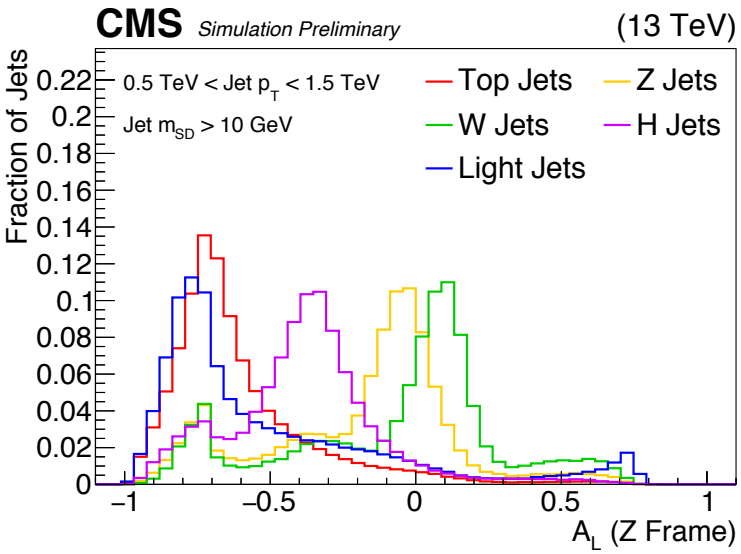
Inputs - Jet Asymmetry

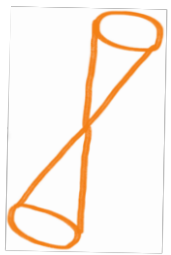
- Use the AK4 jets reclustered in boosted frames
  - In 'correct' frame, $A_L \rightarrow 0$

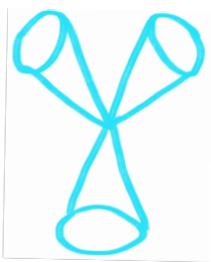
$$A_L = \frac{\sum_{jet} p_z^{jet}}{\sum_{jet} p^{jet}}$$

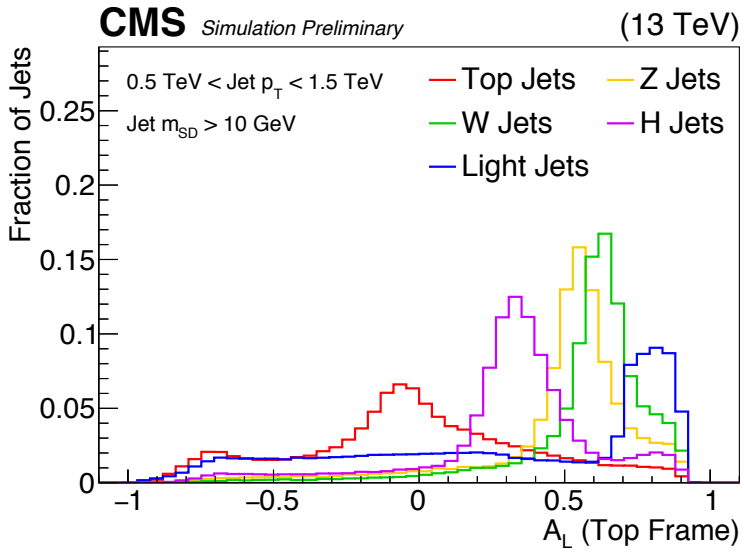


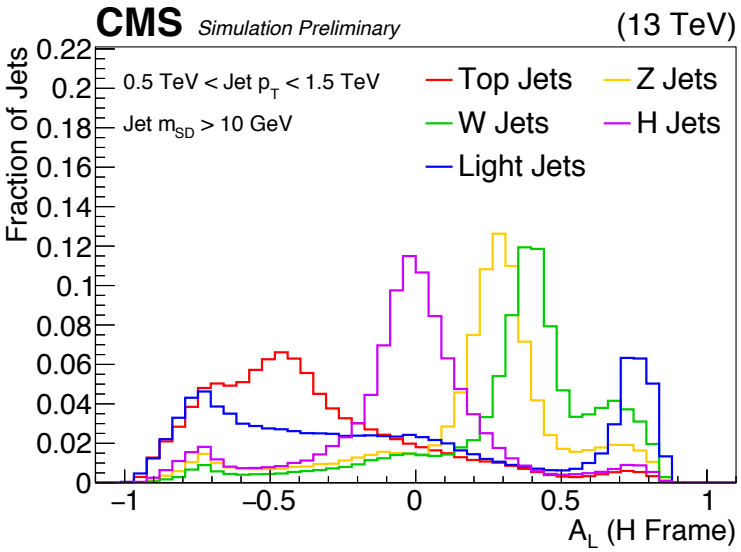


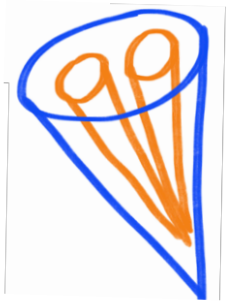






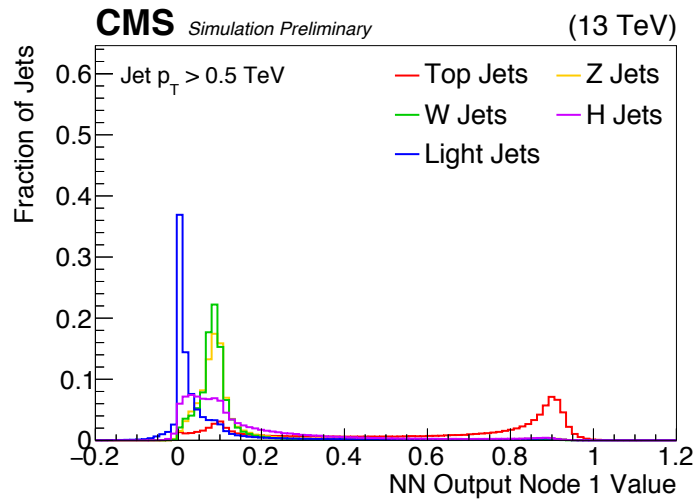


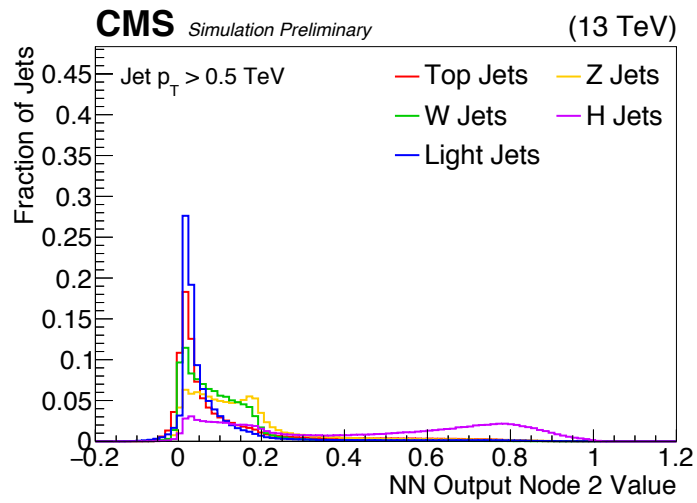


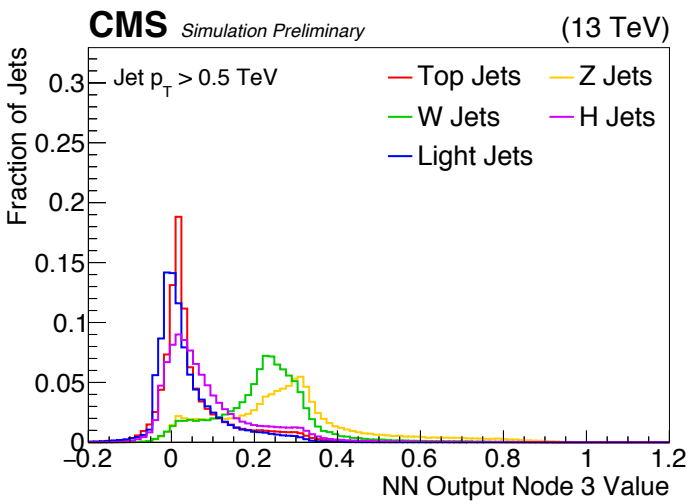


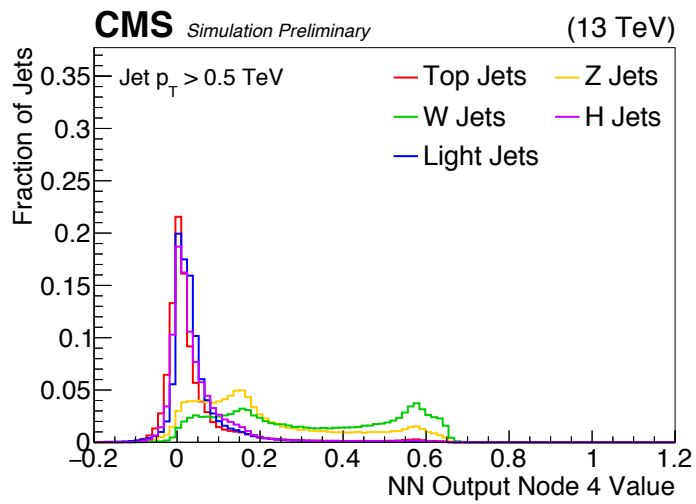
Neural Network

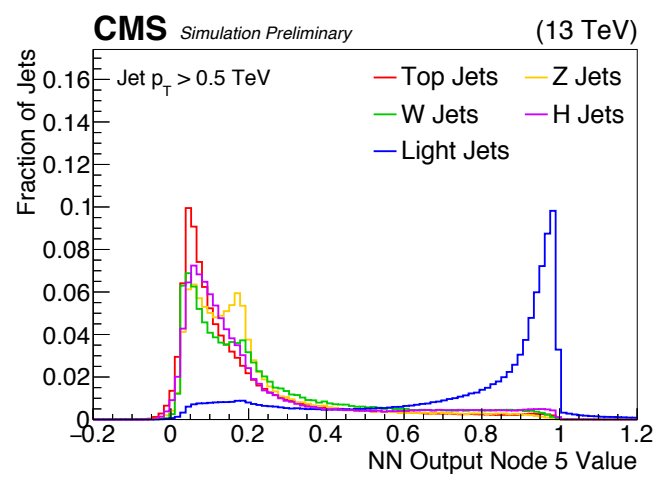
- We train a NN using the TMVA software package
  - 41 input nodes for the input distributions
  - 2 x 20-node hidden layers
  - 5 output nodes
    - One target each for t, W, Z, H jets and light-flavor jets from QCD
- 100k individual jets used for training
  - 20k from each particle species
- Outputs show good separation!





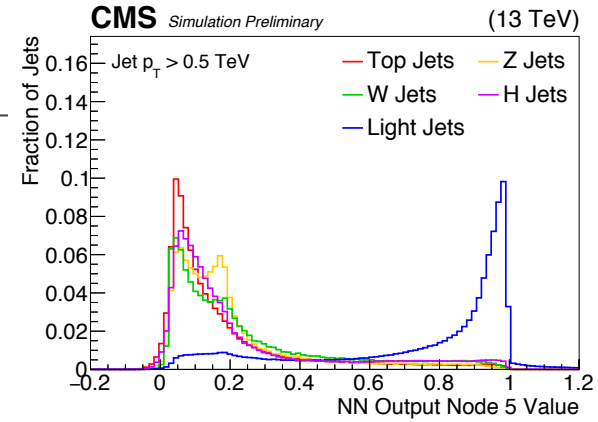


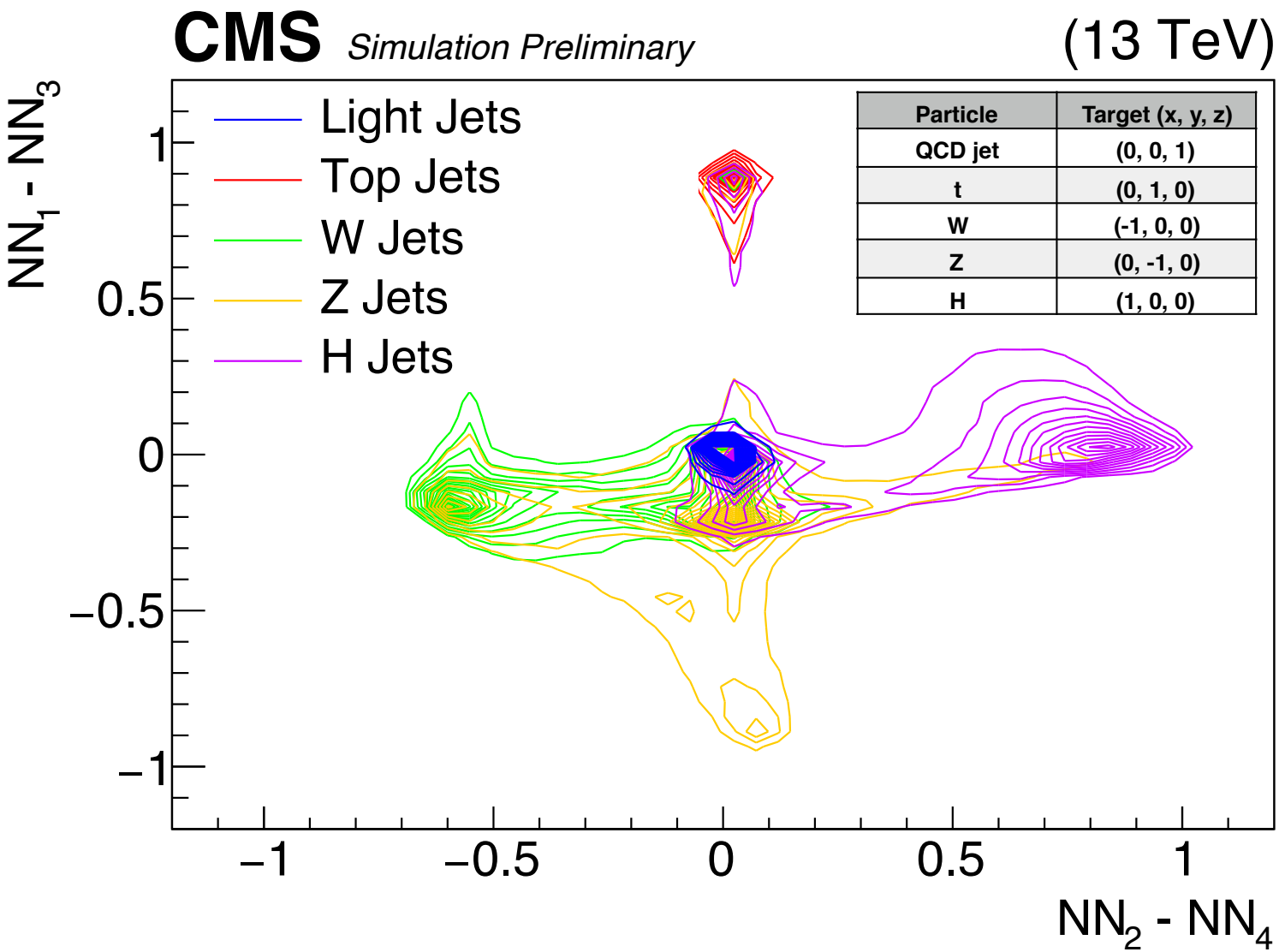




Neural Network

- Two-dimensional visualization of the 5D space shows simultaneous separation of the species
  - QCD will fall out of the page

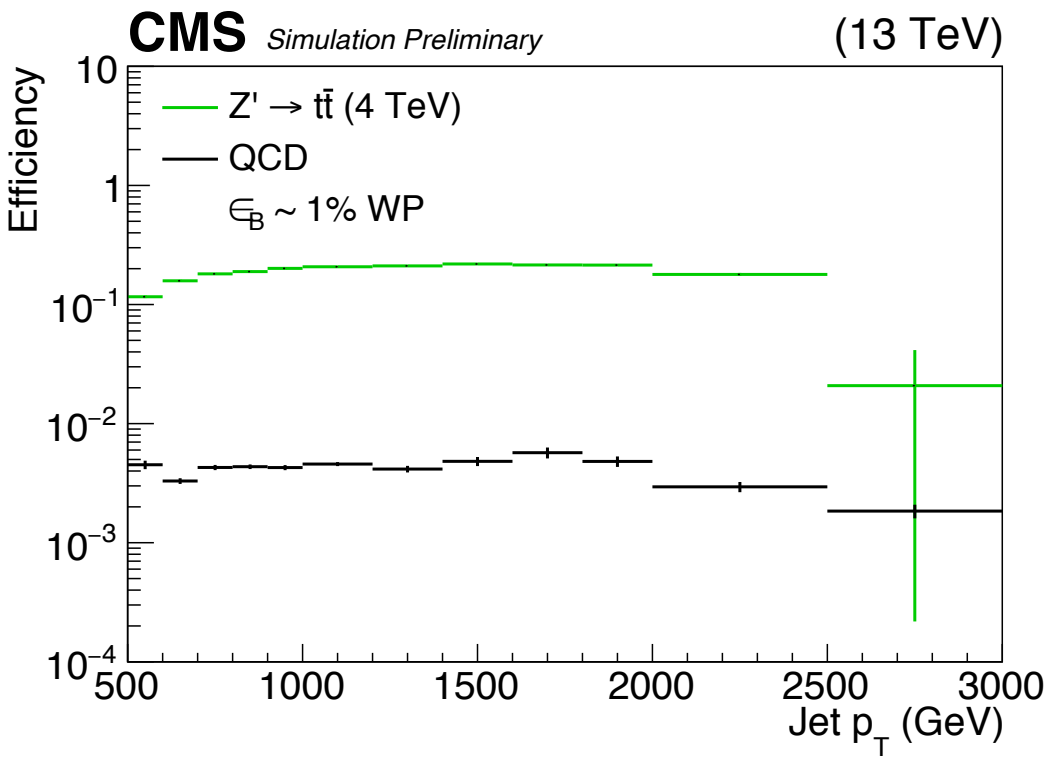


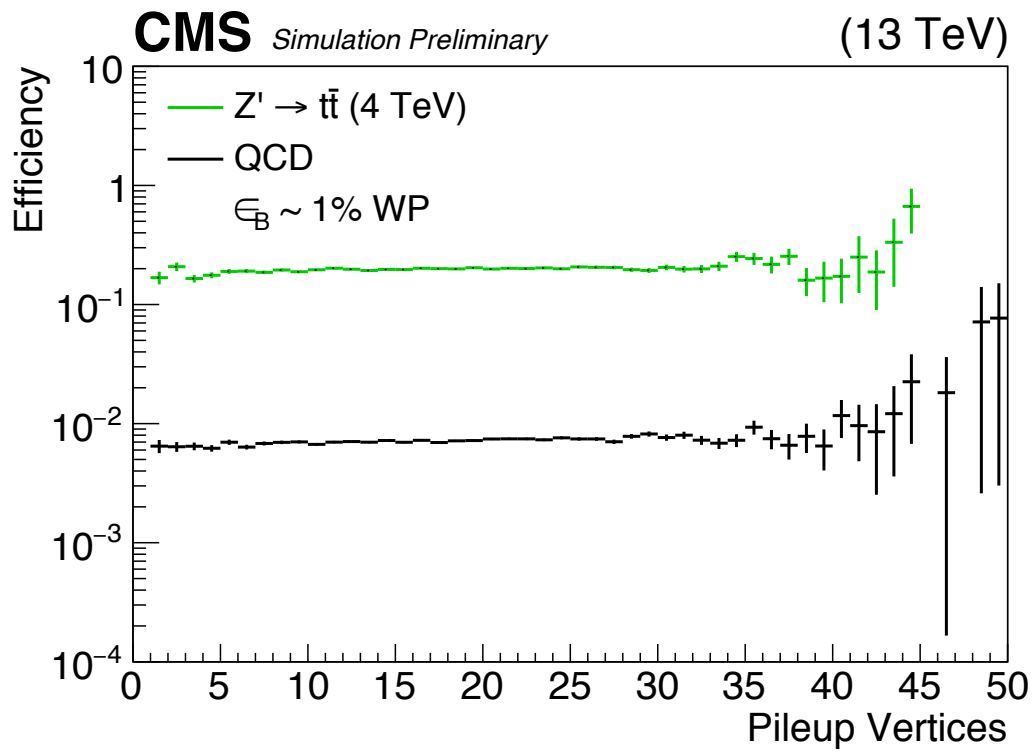


Particle	Target (x, y, z)
QCD jet	(0, 0, 1)
t	(0, 1, 0)
W	(-1, 0, 0)
Z	(0, -1, 0)
H	(1, 0, 0)

Extension to Analysis

- To use in an analysis, we can create working points for identifying the different objects, e.g. top-tagging
  - Combining cuts on the NN outputs with existing methods (jet soft-drop mass, N-subjettiness) gains performance
- Efficiency is stable as a function of p_T and pileup activity
  - ~25% top-tagging efficiency for <1% background efficiency

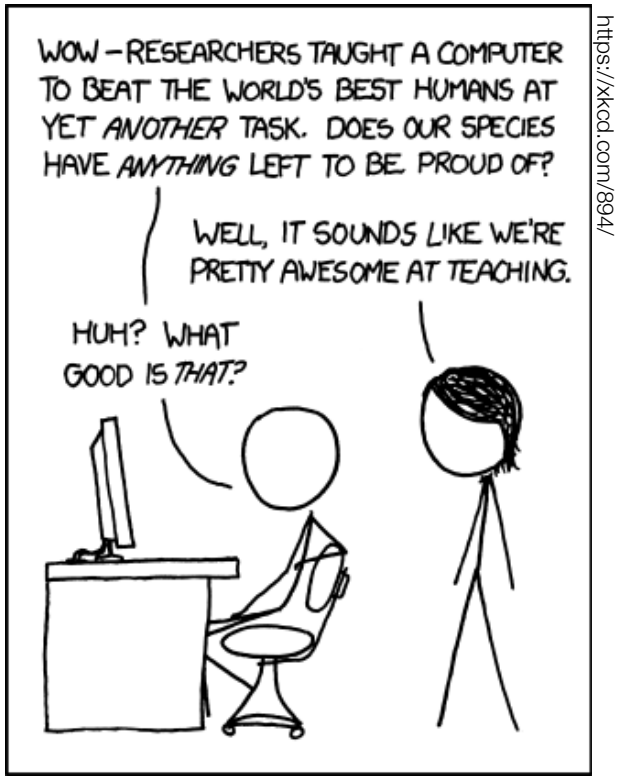




Conclusions

PRD 94 094027 (2016)
Public Material in CMS Detector
Performance Note CMS-DP-2017/027

- We have demonstrated the Boosted Event Shape Tagger (BEST) in CMS simulation/reconstruction
  - Achieved simultaneous classification of t/W/Z/H jets and discrimination of light-flavor jet background
- Useful for high-multiplicity final states, e.g. vector-like quark searches (TT→tZtH, bWtZ, etc.)
- Can also be used for single-particle identification through cuts on NN outputs
  - Improve top-pair resonance searches, diboson resonance searches, e.g.
- Next steps
  - Optimize input variables to remove redundant information
  - Validation in data events
  - Performance comparisons to existing tools
  - Commission in analysis scenario



https://xkcd.com/894/