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

- 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
      - \( R = 0.8 \rightarrow \)
        - 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
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

Methodology

- 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

<table>
<thead>
<tr>
<th>Sphericity (t, W, Z, H)</th>
<th>Jet Soft-Drop Mass</th>
</tr>
</thead>
<tbody>
<tr>
<td>Isotropy (t, W, Z, H)</td>
<td>Jet $p_T$ (flattened)</td>
</tr>
<tr>
<td>Aplanarity (t, W, Z, H)</td>
<td>Jet $\eta$</td>
</tr>
<tr>
<td>Thrust (t, W, Z, H)</td>
<td>Jet $\tau_{21}$</td>
</tr>
<tr>
<td>Jet Asymmetry $A_L$ (t, W, Z, H)</td>
<td>Jet $\tau_{32}$</td>
</tr>
<tr>
<td>Fox-Wolfram $H_1/H_0$ (t, W, Z, H)</td>
<td>Fox-Wolfram $H_1/H_0$ (t, W, Z, H)</td>
</tr>
<tr>
<td>Fox-Wolfram $H_3/H_0$ (t, W, Z, H)</td>
<td>Fox-Wolfram $H_3/H_0$ (t, W, Z, H)</td>
</tr>
</tbody>
</table>
Inputs - Fox-Wolfram Moments

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

\[ H_\ell = \sum_{i,j} \frac{\vec{p}_i \cdot \vec{p}_j}{s} \cdot P_\ell (\cos(\phi_{i,j})) \]
Inputs - Sphericity Tensor

- Measure of how uniformly distributed a set of particles is
  - \(0 \to\) Spherical, \(1 \to\) Collimated

\[
S^{\alpha,\beta} = \frac{\sum p_i^\alpha p_i^\beta}{\sum_i |\vec{p}_i|^2}
\]
**Inputs - Jet Asymmetry**

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

\[
A_L = \frac{\sum p_{jet}^z}{\sum p_{jet}^z}
\]
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

**CMS Simulation Preliminary**

<table>
<thead>
<tr>
<th>Particle</th>
<th>Target (x, y, z)</th>
</tr>
</thead>
<tbody>
<tr>
<td>QCD jet</td>
<td>(0, 0, 1)</td>
</tr>
<tr>
<td>t</td>
<td>(0, 1, 0)</td>
</tr>
<tr>
<td>W</td>
<td>(-1, 0, 0)</td>
</tr>
<tr>
<td>Z</td>
<td>(0, -1, 0)</td>
</tr>
<tr>
<td>H</td>
<td>(1, 0, 0)</td>
</tr>
</tbody>
</table>
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

‣ 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\rightarrow 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