q/g Discrimination and Jet Pull with ATLAS

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Today’s Talk

- ATLAS is continuing to refine our understanding of jet substructure observables
  - As the analysis of the Run I dataset finishes, we are able to make some of the most complex and interesting studies yet
- Showing results on two new ATLAS performance measurements today:

1. **Quark/Gluon Discrimination**
   - Introduction
   - Templates and Validation
   - Tagger and Performance

2. **Jet Pull**
   - Overview
   - Resolution Effects
   - Data/MC
Quark/Gluon Discrimination

hep-ex:1405.6583
History and Motivation

- Quark-initiated and gluon initiated jets have long been known to have different properties
  - Well measured at PETRA, SLAC, LEP, others
- Two papers from Schwartz and Gallicchio in 2011, along with previous efforts in ATLAS, led to a push for creating and commissioning a quark-gluon tagger
  - Theory paper (1106.3076) investigated the best variables to use to train a tagger, in parallel to our own efforts
- Many potential applications in searches for new physics and standard model measurements
  - Separate (resolved) hadronically decaying bosons from gluon dominated backgrounds (diboson searches, Higgs, etc.), improve discrimination in dijet searches, monojet characterization, many more
Variable Selection

- Important to choose pileup robust variables: **use only tracking**
- Need strong performance across wide range of $p_T$: $n_{trk}$ has best performance at highest, track width better at low
- EEC variables have good separation as well— but have systematic issues (more in backup)
- We use a **likelihood** combining $n_{trk}$ and track width
Template Methods

- Significant data/MC disagreement for the input variables required the use of a data-driven template technique

\[
\begin{align*}
\text{quarks} & \quad 60\% & + & 40\% & = & \gamma + \text{jet} \\
\text{gluons} & \quad 40\% & + & 60\% & = & \text{dijet}
\end{align*}
\]

- Take percentages from MC, measure \(\gamma + \text{jet}\) and \(\text{dijet}\) in data: solve for quark and gluon distributions in data

- More information on method in backup
Templates with Data

- Pythia disagrees with data in $n_{trk}$, leading to worse separation than expected.
- Track Width has better agreement, though not good at high $p_T$.
Purified Samples

- Are the data templates correct? How can we test these derived shapes?
- Define **topological/kinematic regions** where jets are more likely to be quark-initiated or gluon-initiated
  - Trijet sample, with $\zeta = |\eta_3| - |\eta_1| - |\eta_2| < 0$ is gluon-like
  - $\gamma+2\text{jet}$ sample, with $\xi = \eta_{\text{jet1}} \times \eta_\gamma + \Delta R(\text{jet2}, \gamma) < 1$ is quark-like
  - See arXiv:1104.1175 for more details
- These regions have purity of $\sim 90\%$—good regions for **validation of templates**!
  - Not enough statistics to derive 2D templates, but enough to be useful for validation
Pure Shapes: $n_{trk}$

- Shapes from topologically purified samples generally agree with extracted templates to 1 $\sigma$
  - Shapes also agree for Track Width
- Independent sample confirms difference between data and MC
• Define $L = \frac{q}{q+g}$ separately in data and MC

**Data**

ATLAS Discriminant for Data-Driven Tagger

$\mathcal{L}(\text{d}t = 4.7 \text{ fb}^{-1}, \sqrt{s} = 7 \text{ TeV})$

anti-$k_T$, $R=0.4$, $|\eta| < 0.8$

$160 \text{ GeV} < p_T < 210 \text{ GeV}$

**MC**

ATLAS Simulation

Discriminant for MC-Based Tagger

Pythia MC11, $\sqrt{s} = 7 \text{ TeV}$

anti-$k_T$, $R=0.4$, $|\eta| < 0.8$

$160 \text{ GeV} < p_T < 210 \text{ GeV}$

• Immediately can see that while shapes are similar, performance is much worse in data

• Still enough to be useful! Define a tagger at 4 operating points: 0.3, 0.5, 0.7, and 0.9 quark efficiency
Systematic Uncertainties

- Many different sources of error considered for the tagger:
  1. PDF variations– affect $q/g$ fractions
  2. $\gamma$ purity– affects data input
  3. Heavy flavor shapes/fraction– affects MC inputs
  4. Madgraph/Pythia fraction differences– affect $q/g$ fractions
  5. Non-closure/ sample dependence– affects data inputs
Here, show **breakdown of systematics** for 50% quark-like o.p.

- **Sample dependence** is by far the largest effect
  - Quarks/gluons from γ+jet do not look exactly like quarks/gluons from dijets (in both Pythia and Herwig)
  - Need to understand this effect to apply this tagger to other topologies
Overview of Performance

- For measuring performance, we will show several different tests together:
  - **Red points** indicate performance of data tagger, tested on data templates
    - **Red lines** on those points indicate statistical uncertainties
  - **Teal band** indicates systematic uncertainties
  - **Blue points** indicate performance of pythia tagger, tested on pythia templates
  - **Magenta points** indicate performance of data tagger, tested on purified data samples
Gluon Efficiency vs. Quark Efficiency

- Purified samples show slightly worse gluon efficiency than data, but agreement within $1\sigma$.
- Data shows worse performance than Pythia—generally greater than $1\sigma$ disagreement.
  - Data lies between discrimination of Pythia and Herwig++. 

ATLAS
anti-$k_{T}$, $R=0.4$, $|\eta| < 0.8$
60 GeV-$p_{T} < 80$ GeV
$\int L \, dt = 4.7 \, fb^{-1}$, $\sqrt{s} = 7 \, TeV$
Pythia MC11 Simulation

Pythia
Herwig++
Syst.

Data + Stat.

MC

Enriched Data
Jet Pull
ATLAS-CONF-2014-048
Overview

- Jet pull is designed to be sensitive to the **superstructure** of the event: the color connection *between jets*
  - Combines substructure information of one jet, with the full topology of the event
- Can we measure the orientation of the energy in one jet relative to another?
  - DØ had a measurement in 2011, but ATLAS (and CMS) have many more events, and potentially more sensitive detectors
- Today: a detailed study of the performance of pull
Our System: $t\bar{t}$

- Use semi-leptonic ($\mu$ only) selection
  - Jets and $\mu$ have $> 25$ GeV, 2 b-tags, $E_T^{\text{miss}} > 20$ GeV, $E_T^{\text{miss}} + M_T > 60$ GeV
- Pull measures relationships **between jets**
  - Top provides many pairs of jets to use—$W$ daughters, which should be connected, and $b$-jets, which should not
Our Measurement

Jets: Calculate pull of $J_1$ with respect to $J_2$

Jet constituents: calorimeter clusters, (ghost associated) tracks, or stable particles (truth jets)

$$\vec{r}_i = (\Delta y_i, \Delta \phi_i)$$ with respect to the jet position.

Pull (Vector)

$$v_P(J) = \sum_{i \in J} \frac{p_T^i |\vec{r}_i|}{p_T^j} \vec{r}_i$$

$\theta_P \sim 0 \rightarrow \text{‘color-connected’}$

$\Delta y = y - y_{J_1}$

Legend
- $\Rightarrow$ Pull Vector $v_P(J_1)$
- $\theta_P$ jet pull angle
- Constituent of $J_1$ (size weighted by $p_T$)
First Look: $J_1$ vs $J_2$ and $J_1$ vs $B_1$

- Large difference between the two topologies, and **very large** shift from truth to reconstructed
- **A large caveat:** kinematics and topology are very important, and can sculpt the pull angle dramatically
Dependence on $\Delta R$

- $\Delta R$, for example, has a large effect on the variable
  - Closer-by jets have larger peak at 0
- $W$-daughters tend to be close by, so the previous effect is partly attributable to just topology
Resolution

- The **Pull Angle Resolution** is also an important part of any physics measurement.
- Unfortunately, RMS is $O(1)$ rad—detector causes significant smearing.
- Using **tracks** can improve resolution significantly:
  - Tracks have more accurate position measurement than calorimeter clusters.
  - Lose some discrimination power from ignoring neutrals.

![Resolution Graph](image-url)

**ATLAS Simulation Preliminary**

$s = 8$ TeV

<table>
<thead>
<tr>
<th>Track $\theta(J_{i},J_{j})$</th>
<th>Calorimeter $\theta(J_{i},J_{j})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Response Mean; RMS</td>
<td></td>
</tr>
<tr>
<td>0.02; 0.88</td>
<td>-0.01; 0.86</td>
</tr>
<tr>
<td>0.07; 1.08</td>
<td>-0.05; 1.08</td>
</tr>
</tbody>
</table>
Improving Resolution

- Cutting on jet $p_T$ and **pull vector magnitude** can significantly improve resolution
- Higher $p_T$, broader jets, have more accurately measured pull angle
Data/MC Agreement: Pull Vector Magnitude

- Very good agreement in pull vector magnitude, for both tracking and calorimeter measurement
- JES, JER, $t\bar{t}$ cross-section, and luminosity uncertainties included
  - Other selection uncertainties are sub-dominant
Data/MC Agreement: Pull Angle

- Very good data/MC agreement observed in pull angle (and magnitude)!
- Agreement consistent over range of $p_T$
Conclusions
Summary

- ATLAS has a rich program in understanding the performance of complex jet substructure observables
- A data-driven quark/gluon tagger has been developed, validated, and calibrated
  - Performance generally lower than expected compared to MC
- The performance of jet pull has been assessed in $t\bar{t}$ events
  - Understanding the very broad resolution is critical for future physics measurements
  - Good data/MC agreement is observed
- New physics measurements coming soon!
Thank You For Your Attention!
Backup
Defining Quark/Gluon Initiated Jets

- Need to use a consistent definition across generators for defining a quark/gluon initiated jet
- We use: “a jet is defined by the flavor of the highest energy parton inside the jet”
  - This labelling is studied in Madgraph to determine how often it matches the Matrix Element: 95 – 99% of the time
Extracting Templates

- Goal: to better understand quark/gluon shapes in data, extrapolate data to 100% purity with fractions from MC

- Ideally, solve for $q/g$ on bin-per-bin basis from:

$$\begin{align*}
h^{\gamma+j} &= P_Q^{\gamma+j} q + P_G^{\gamma+j} g \\
h^{dijet} &= P_Q^{dijet} q + P_G^{dijet} g
\end{align*}$$

$$P_Q = \text{percentage quark} \quad h = \text{histogram value} \quad q/g = \text{templates}$$

$$\frac{(\gamma + \text{jet})}{(\text{dijet})} = \text{different sample}$$

- But, need to account for $b$ and $c$ fractions (for now, taken from MC):

$$\begin{align*}
h^{\gamma+j + \text{jet}} &= P_Q^{\gamma+j+\text{jet}} q + P_G^{\gamma+j+\text{jet}} g + P_B^{\gamma+j+\text{jet}} b + P_C^{\gamma+j+\text{jet}} c \\
h^{dijet} &= P_Q^{dijet} q + P_G^{dijet} g + P_B^{dijet} b + P_C^{dijet} c
\end{align*}$$

From Data

From MC

Solving for This

- Then, compare pure data shapes to pure MC shapes (used for training tagger)
Testing Method in MC

- MC-labeled distributions in $\gamma+$jet and dijets agree very well with templates derived in MC
  - Disagreement at low $p_T$ will be discussed at length soon
- Gives us confidence that the algorithm is doing something sensible
Shapes from topologically purified samples generally agree with extracted templates to 1 σ

Independent sample confirms difference between data and MC
• **Significantly reduced** performance in data
  • But enough to still make something useful!
• Purified samples show slightly worse gluon efficiency than data, but agreement within $1\sigma$.

• Data shows worse performance than Pythia—generally greater than $1\sigma$ disagreement.
  • Data lies between discrimination of Pythia and Herwig++.
Performance vs. Jet $p_T$

- Left shows 30% quark point, right shows 50%
- Results are consistent across $p_T$: purified samples measurement generally agree with data, but MC significantly overestimates performance.
Performance vs. Jet $p_T$

- Left shows 70% quark point, right shows 90%
- Results are consistent across $p_T$: purified samples measurement generally agree with data, but MC significantly overestimates performance
Angularities

- New class of variables, called “Energy Correlation Angularities,” described in arXiv:1305.0007
- Defined with free parameter $\beta$:

  \[
  \text{Ang} = \frac{\sum_i \sum_j p_{T,i} p_{T,j} (\Delta R(i,j))^{\beta}}{(\sum p_{T,i})^2}
  \]  

- How does gluon efficiency change with $\beta$, and how large are the systematics?
Angularity Performance

- **NB:** 1 - Gluon Efficiency shown
- **Significant differences** between data and MC performance, and **systematics are larger** than for the likelihood
  - Sample dependence is **very large** for angularities, at least with **$\beta < 1$**
  - **$\beta = 0.2$** is slightly optimal in MC, but difficult to tell trend in data
Systematics Summary: 30% Operating Point

- Similar effects as at other operating points: largest here at low efficiency
Systematics Summary: 70% Operating Point

- Similar effects as at other operating points
Systematics Summary: 90% Operating Point

- Similar effects as at other operating points
Nonclosure: 30% Operating Point

- Breakdown of Pythia/Herwig++ disagreements with their respective templates
Nonclosure: 50% Operating Point

- Breakdown of Pythia/Herwig++ disagreements with their respective templates
Nonclosure: 70% Operating Point

- Breakdown of Pythia/Herwig++ disagreements with their respective templates
Nonclosure: 90% Operating Point

- Breakdown of Pythia/Herwig++ disagreements with their respective templates
Sensitivity Pileup

- Pull angle resolution is not strongly affected by pileup, even with calorimeter only measurement.
Data/MC Agreement, Powheg+Pythia

- Very good data/MC agreement observed in pull angle (and magnitude)!
  - Agreement consistent over range of $p_T$
Data/MC Agreement: Pull Vector Magnitude

- Very good data/MC agreement observed in magnitude
  - Agreement consistent over range of $p_T$
Correlation of $J_1$ to $J_2$

- **Angle of both jets** is useful— not just the leading jet
Pull as a Tagger

- Also measured pull angle’s performance as a tagger—here using truth to maximize power
  - Can we identify the daughters of the $W$ in a top event using only pull angle information?

- Tagger performance is somewhat limited: pull, and color connection in general, is a subtle effect

\[
\theta_p(J_t, \diamondsuit) \quad \theta_p(\diamondsuit, J_t) \quad \text{Optimal Combination} \quad \text{Random Match}
\]