flavor-tagging in ATLAS

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on behalf of the ATLAS collaboration

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goals

• give a broad overview of flavor-tagging work in ATLAS, especially highlighting the main taggers and some recent results

• topics:
  • algorithm inputs and their simulation
  • mainline algorithms currently in use
  • performance in simulation and data
  • specialized taggers

• obviously I have to leave out some topics and details...

• ... so all public results are available here:
  https://twiki.cern.ch/twiki/bin/view/AtlasPublic/FlavourTaggingPublicResultsCollisionData
algorithm inputs

- our primary $b$-taggers take as inputs **inner-detector (ID) tracks** and **jets**.
- several jet collections have been studied for $b$-tagging, but currently we support:
  - "EMTopo" jets **built from topological clusters**
    - clusters calibrated based on electromagnetic component
    - anti-kt, $R = 0.4$
  - variable-radius (VR) jets **built from ID tracks**
    - anti-kt, $\rho = 30$ GeV, min $R = 0.02$
    - good performance at low-pT and condensed environments
- ID tracks are **associated** to a jet based on a **pT-dependent association cone**:
  - $pT(jet) = 20$ GeV : $\Delta R < 0.45$
  - $pT(jet) \rightarrow \infty$ : $\Delta R < 0.24$
modeling and performance of tracking inputs

• to give an idea of expected **performance of tracking within jets**, there's a very nice PUB note from 2015.

• in general we see reasonable (but **certainly not perfect**) descriptions of low-level tracking inputs to flavor tagging.
• our current track reconstruction procedure has some limitations in extreme kinematic regions inside jets

• this is quite an interesting area to invest in improvements -> especially toward Run III
modeling and performance of tracking inputs

- a lot of effort has gone into **improving the simulation of the inner tracker** (including the IBL)

- **significant improvements in material description** leading up to 2017 data taking

- many of our tagging efficiency **SFs move closer to unity** after these updates
algorithms overview

- **low-level tagging algorithms** take advantage of heavy hadrons’ lifetimes, masses, and decay products
  - track impact parameter (IP) significance
  - secondary and tertiary vertices
  - soft-leptons
- **high-level taggers:**
  - feed observables from low-level taggers into BDT or NN
  - optimize on simulated $tt$ and $Z' \rightarrow qq$ events
low-level taggers: IPTag

ATL-PHYS-PUB-2016-012

- for **IP2D** and **IP3D**, impact parameter significance templates are built from simulation for $b$, $c$, and light jets for tracks with

- $p_T > 1$ GeV; $|d_0| < 1$ mm and $|z_0 \sin\theta| < 1.5$ mm

- where the **IP significances** are defined as $d_0/\sigma(d_0)$ and $z_0 \sin\theta/\sigma(z_0 \sin\theta)$
tracks are further split into 14 categories by quality criteria (number of IBL, B-layer, Pix, and Si hits; number of shared hits, etc).

given the templates for each track category, a likelihood ratio is assigned to each track, and the sum of log-likelihood ratios is used as the discriminant.
in the last few years a **new impact-parameter tagger** using **recurrent neural networks** (RNNs) has been developed.

- the **same tracks** as IPTag, **including track quality categories**, are used as inputs.
- excellent performance w.r.t. IPTag is observed, **especially at high-pT**.
- **first physics results** using this low-level tagger should appear shortly.

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**ATLAS Simulation Preliminary**

\[ \sqrt{s} = 13 \text{ TeV}, t \bar{t} \]

- \( p_T > 20 \text{ GeV}, |\eta| < 2.5 \)
- \( |< 2.5 \eta| > 20 \text{ GeV}, |t| \)

- **ATLAS Simulation Preliminary**

\[ \sqrt{s} = 13 \text{ TeV}, t \bar{t} \]

- \( p_T > 20 \text{ GeV}, |\eta| < 2.5 \)

- Flat 70% b-tagging WP

- **ATLAS Simulation Preliminary**

\[ \sqrt{s} = 13 \text{ TeV}, t \bar{t} \]

- MV2c10
- RNNIP
- IP3D
- SV1

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**light-jet rejection, 1/\( \varepsilon \)**

**b-jet efficiency, \( \varepsilon_b \)**

**b-jet \( p_T \) [GeV]**
low-level taggers: SV1

ATL-PHYS-PUB-2017-011

- **SV1** uses the **single-secondary-vertex-finding** (SSVF) algorithm to identify jets with secondary vertices consistent with a \( b \)-hadron decay.

- in short, all tracks associated to a jet are allowed to form **2-track vertices** which are then **iteratively merged** until one secondary vertex (SV) remains

- \( \chi^2 \) and SV mass requirements are imposed in particular to **remove \( K_s \), \( \Lambda_0 \), and photon conversions**.

- after an acceptable secondary vertex is found, discriminating observables like **SV mass**, **SV energy fraction**, **decay length significance** are constructed.
low-level taggers: JetFitter

JetFitter attempts to reconstruct both the \textit{b-hadron} and \textit{c-hadron} vertices separately, where possible, through the use of an \textit{extended Kalman Filter}.

\textit{ATLAS} Simulation Preliminary
\(\sqrt{s} = 13 \text{ TeV}, t\bar{t}\)

\textit{ATLAS} Simulation Preliminary
\(\sqrt{s} = 13 \text{ TeV}, t\bar{t}\)
similar to SV1, after secondary and tertiary vertices are constructed, discriminating observables are calculated for use in high-level taggers.
we currently use two families of high-level taggers: MV2 (BDT) and DL1 (deep neural network)...

... that take discriminating observables from the low-level taggers as inputs.

as expected, significant gains are achieved by taking advantage of correlations between the outputs of the low-level taggers.
leading up to the 2017 data taking, we started training our taggers on a **hybrid** sample of jets **SM tt** and **Z' -> qq** to better fill out the jet $p_T$ distribution and have more representative $b$-fragmentation.
this resulted in about a factor of two better light-jet rejection in most $b$-jet (from $Z'$) efficiency ranges with the new training.
• we provide "standard" calibrations as a function of jet $p_T$ separately for $b$-, $c$-, and light-jets.

• here "calibration" means we measure in data the probability of a jet passing a cut on the high-level discriminant output distribution and correct the simulation to reflect this with scale factors.

• we calibrate four operating points, corresponding to 60, 70, 77, and 85% $b$-jet efficiency working points in the training sample.
**b-jet calibrations**

- The primary b-jet calibrations are carried out in $tt \rightarrow e\mu b\bar{b}$ events using a likelihood fit over the two jets.

- Calibrations for both VR track jets and EMTopo jets.

- In the past, large uncertainties from light-jet background predictions in $tt$ events, somewhat mitigated now by data-driven constraints.

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**ATLAS** $\sqrt{s} = 13$ TeV, 36.1 fb$^{-1}$

**ATLAS** Preliminary $\sqrt{s} = 13$ TeV, 80.5 fb$^{-1}$

**PERF-2016-05**

**FTAG-2019-002**
**c-jet calibrations**

- the primary $c$-jet calibrations are currently carried out in $tt \rightarrow \ell v c q b b$ events using KLFitter to determine the hadronic $W$ decay products.

- calibrations for both **VR track jets** and **EMTopo jets**.

- largest **uncertainties from $tt$ modeling**.

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*FTAG-2019-003*
• light jet mistag-rate calibrations have always been challenging, in part because it’s difficult to know the flavor-fractions before tagging.

• we have moved to performing the data-based negative tag calibration in Z+jets events, where we have measurements to help us constrain these fractions.

• bottom-up propagation of uncertainties similar to those outlined in ATLAS-CONF-2018-006 continue to be studied.
scale factors so far do not depend strongly on $\langle \mu \rangle$, but we are keeping a close eye on this, especially for mistag rates.
we have several ongoing efforts to provide **non-standard taggers** for particular classes of physics analyses

I'll highlight $X \rightarrow bb$ tagging and **charm tagging** with a few slides.
several charm taggers have been optimized using the DL1 framework, but adding a few additional variables, especially related to JetFitter.

the results look quite promising, and calibrations are underway using similar techniques as for the $b$-tagger calibrations.
**X→bb tagging**

**Z/H/X → bb** reconstruction techniques available for analyses: combination of **b-tagging** and **jet substructure** for discrimination, targeting color singlet signals.

here large-\(R (R = 1.0)\) calorimeter jets are used to identify candidates, and small-\(R (R = 0.2)\) track jets are used for **b-tagging**.

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**ATLAS Simulation Preliminary**

\(p_T > 1000\) GeV, 76 GeV < \(m_{\text{calo}}\) < 146 GeV

- Double b-tag
- Asymm. b-tag (70% wp)
- Single b-tag
- Leading subjet b-tag

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**MV2c10 b-tagging at 77% WP**

- 1 b-tag, Loose \(m_{\text{calo}}\) window
- 2 b-tags, No \(m_{\text{calo}}\) selection
- 2 b-tags, Loose \(m_{\text{calo}}\) window
- 2 b-tags, Tight \(m_{\text{calo}}\) window, \(D_0\) sel.

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**ATLAS-CONF-2016-039**
"advanced" $X \rightarrow bb$ tagging

more sophisticated $Z/H/X \rightarrow bb$ reconstruction techniques being developed and calibrated (VR track jets already in use!)

- center-of-mass (CoM) tagging: boost into resonance rest frame (using reconstructed large-$R$ jet kinematics), perform track-to-jet association, then apply $b$-tagging

- exclusive-kt subjet tagging: apply kt clustering on large-$R$ jet constituents, associate tracks to final two kt subjets, and apply $b$-tagging
technical developments

there have also been some nice developments on the hardware/software side of things:

- DL1 hyperparameter scans are now performed on GPUs distributed over the LHC grid

- this opens up some nice possibilities for more performant taggers, better validation, etc in a reasonable amount of time!
conclusion

• ATLAS has a set of **very performant b-taggers** using primarily inner-detector tracking information seeded by **calorimeter or track jets**.

• there are **many ongoing efforts** to

  • improve performance of input tracks and jets
  • use tracking information more effectively for flavor discrimination
  • develop new low-level taggers
  • improve the way we train high-level taggers
  • provide more precise calibrations
  • foster development of novel taggers for specialized use cases
  • and many more...

• **thanks for your attention!**