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Reconstruction improvements for the measurements of the $H \to b\bar{b}$ decay at the ATLAS experiment

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Summary. — The observation of the Higgs boson Yukawa coupling to bottom quarks announced by the ATLAS and CMS experiments in 2018 is one of the most remarkable results obtained at the LHC so far. The main challenge faced to achieve this measurement is the presence of overwhelming backgrounds, which can be greatly reduced requiring two jets initiated by bottom quarks in the final state. Since the time of the observation, the ATLAS Collaboration is pursuing a large experimental effort to improve the heavy-flavoured jets identification techniques. In this context, recent developments exploiting machine-learning algorithms will be presented.

1. – Introduction

The discovery of the Higgs boson is a milestone in particle physics and for fundamental physics in general. Following its discovery [1, 2], the precise measurement of the Higgs boson interactions, which are not governed by symmetries and are not universal, is an outstanding goal in particle physics. In particular, the Yukawa coupling to bottom (Y_b) and charm quarks (Y_c) are some of the most challenging and intriguing measurements to be performed at the LHC.

Among the main production mechanism of the Higgs boson at the LHC, the associated production with a vector boson (VH analysis) is often referred to as the *golden channel* for the measurements of Y_b and Y_c, due to its higher sensitivity [3, 4]. The most up-to-date result produced by the ATLAS Collaboration [5] measured an excess of events compatible with the VH process and $H \to b\bar{b}$ hypothesis with a signal strength of around $\mu = 1.02 \pm 0.18$ [6].

The aforementioned result considered jets reconstructed with a radius parameter $R = 0.4$ (small-R jets) and it is most sensitive to Higgs boson transverse momentum (p_T) in the range 150–300 GeV. To extend the energy reach of these measurements to higher Higgs boson p_T, where the two decaying b-quark are too collimated to be reconstructed as two small-R jets, a different analysis strategy was performed by the ATLAS Collaboration [7]. This analysis is designed to reconstruct the Higgs boson decays into a single jet with a large radius of $R = 1.0$ (large-R jet). Both these analyses rely on the performance of the algorithms used for the identification of heavy-flavoured jets (b-tagging).

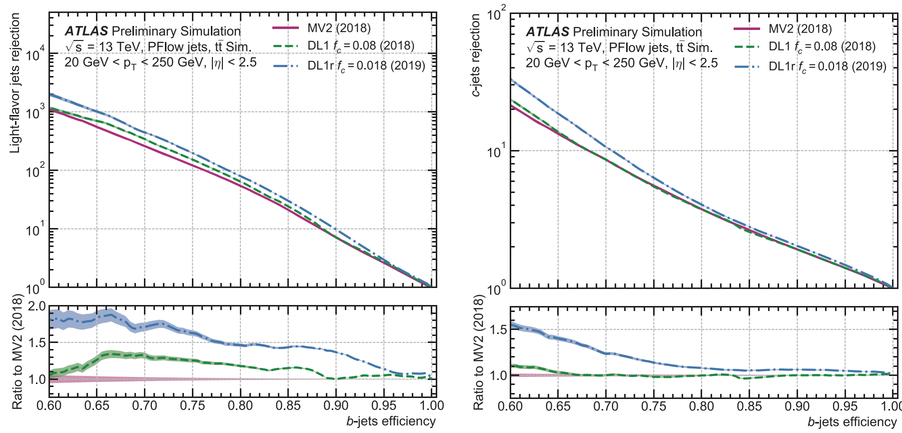

Fig. 1. – Comparison of ROC curves for 2018 recommended versions of MV2 and DL1, and DL1r. The x-axis corresponds to the b-jet efficiency, while the y-axis corresponds to (a) light-flavor jets rejection and (b) c-jets rejection [8].

A novel iteration of the analysis aimed at combining the two reconstruction regimes is currently ongoing. Such an analysis will have the possibility to profit from significant b-tagging improvements mostly arising from machine learning developments.

In the following, the b-tagging improvements will be discussed more in detail for both reconstruction regimes.

2. – Improvements at intermediate Higgs boson energies with small-R jets

For Higgs p_T in the range ≈100–300 GeV, the most sensitive VH analysis considered pairs of small-R jets to define the Higgs boson candidate in an event. Each jet in the pair is required to originate from an heavy-flavoured jet by means of b-tagging requirements.

The b-tagging algorithms exploit the typical life-time of the b-hadron, their fragmentation function, and their high mass by constructing a multivariate tagger based on secondary vertieces and track impact parameter significances. Historically, these variables were combined using a BDT discriminant, referred to as MV2 which will be used as a baseline in the following comparisons. In more recent years, a novel tagger based on deep neural network (DL1) has also been studied and implemented into the ATLAS software infrastructure. An additional variant of the DL1 tagger, named DL1r, has also been deployed. DL1r adds to the DL1 inputs the outputs of a recurrent neural network trained using a set of track features such as the transverse and longitudinal impact parameters.

Figure 1 shows the efficiency as a function of the c- and light-jet rejection, defined as the inverse of the probability to wrongly b-tag a c- or light-jet as a b-jet. The curves are compared to the default MV2 configuration which was also used in the VH analyses mentioned in the introduction. A significant improvement of more than 50% and 30% is observed for light- and c-jet rejections at 70% b-tagging efficiency, respectively.

3. – Improvements at high Higgs boson energy with large-R jets

In general, the angular separation ΔR of the 2-body decay products of a boosted heavy particle is approximately $\Delta R \approx 2m/p_T$. Therefore, for Higgs boson p_T above 250 GeV, the $H \to b\bar{b}$ topology can be reconstructed using a single large-R jet with $R = 1.0$. Such a large radius introduces dependencies between the large-R mass and soft components which leads to instability in the measurements. To mitigate these effects, dedicated grooming and trimming algorithms have been proposed in recent years. The interested reader can find a description of the state-of-the-art techniques used at ATLAS in ref. [9].

To apply b-tagging requirements, jets are built using tracks as input constituents to the anti-k_t clustering algorithm [10]. Two sets of jets are considered depending on the choice of the radius parameter, a single fixed radius (FR) collection with $R = 0.2$, and a more sophisticated algorithm with a variable R (VR) parameter. At high momentum, one would indeed expect the jets to be more collimated as their transverse momentum increases. The (VR) track jets exploits this feature using a clustering algorithm with a variable R parameter function of the jet momentum. VR track jets are the standard jet collection currently used by physics analyses. The reconstructed track jets are finally associated to the large-R jet to form a Higgs candidate jet.

There are two possible strategies to apply the b-tagging requirements to the large-R jet: the first is to apply the b-tagging requirement singularly to the two VR track jets: the second is to optimally exploit the correlation between the b-tagging scores of the VR track jets and the large-R jet kinematics with multivariate techniques.

The first strategy is analogous to what was discussed with small-R jets. The improvements brought by the DL1r algorithms when compared to MV2 are similar to what was obtained in the previous chapter. Additional details can be found in ref. [11]. The main advantage of this approach is the flexibility of its implementation. In particular, well-established calibration analyses used to estimate the b-tagging efficiency in data to correct mis modelling of the Monte Carlo simulation for small-R jets can be easily recast to calibrate VR-track jets.

The second strategy extends the application of b-tagging at the large-R jet level by defining a new algorithm targeting specifically the $H \to b\bar{b}$ topology. This novel tagger, referred to as $D_{X_{bb}}$, combines the flavour information of up to three VR-track jets associated to the large-R jet [12] using a feed-forward neural network. The inputs to the networks are the DL1r outputs scores of each VR track jets and the large-R jet kinematic variables. The inputs variables are carefully chosen to mitigate as much as possible the $D_{X_{bb}}$ dependency on the large-R jet mass. The model is trained to discriminate Higgs jets against boosted top and QCD jets.

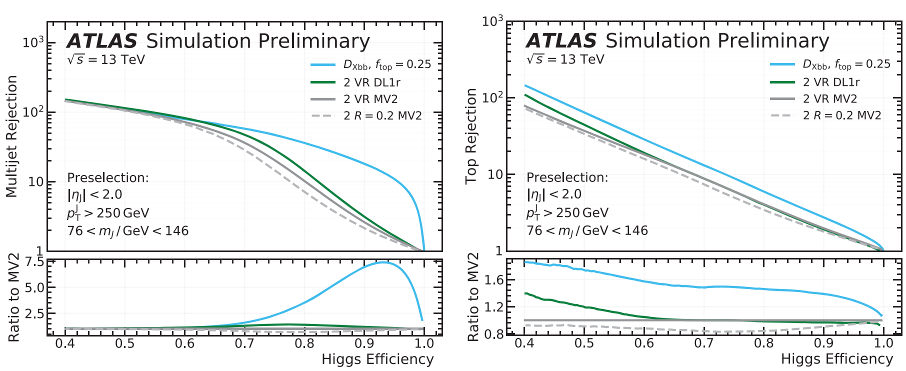

Fig. 2. – QCD multijet (left) and Top jet (right) rejection as a function of the $H \to b\bar{b}$ tagging efficiency, for large R. Performance of the D_{Xbb} algorithm is compared to DL1r and to two variants of MV2, one evaluated on VR jets, the other on FR jets [12].

Figure 2 shows the QCD and top jet rejection as a function of the Higgs tagging efficiency. The MV2 and DL1r performance obtained tagging each sub-jets independently are also shown for comparison. The observed improvement is significant and relevant for the boosted VH channel.

The next challenge for a complete deployment of this algorithm is its calibration. To this end, several analyses aimed at measuring the $D_{X_{bb}}$ efficiency in data using gluon splitting, top and $Z \to b\bar{b}$ events are currently ongoing.

4. – Conclusion

The VH analysis searching for $H \to b\bar{b}$ decays is currently being improved in ATLAS to exploit most of the dataset collected at a center-of-mass energy of 13 TeV. The analysis will profit from several improvements to the b-tagging performance. Preliminary results show a sensitivity improvement of around 20% for both resolved and boosted $H \to b\bar{b}$ analyses. In the boosted regime the analysis sensitivity is further increased thanks to the usage of the boosted b-tagger, $D_{X_{bb}}$, which provides an additional improvement of around 5%.

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