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Machine Learning approach for the search of heavy diboson resonances in semi-leptonic final state at $\sqrt{s} = 13$ TeV with the ATLAS detector

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Summary. — A Recurrent Neural Network-based approach has been adopted for the classification of the production mechanisms in the search of heavy resonances decaying in two bosons. The search is performed using proton-proton collision data recorded with the ATLAS detector from 2015 to 2018. The investigated final state is semi-leptonic, where one boson decays in two leptons and the other decays hadronically. No excesses have been found in data with respect to the background-only hypothesis. Upper bounds on the production cross sections of heavy scalar, vector or tensor resonances are derived in the mass range 300–5000 GeV.

1. – Introduction

The Large Hadron Collider (LHC) [1] is a unique facility for the search of heavy resonances that can be directly produced via different mechanisms, such as gluon–gluon fusion (ggF), Drell-Yan (DY) or vector-boson fusion (VBF) (Feynman diagrams are shown in fig. 1). The channels considered consist in the resonance decays into pairs of vector bosons (VV, where V is either W or Z), where one of them decays leptonically ($W \to l\nu$, $Z \to ll$ or $Z \to \nu\nu$) and the other decays hadronically ($W/Z \to qq'$), here l denoting either an electron or a muon [2]. According to the number of charged leptons, three different channels are identified (0-, 1- and 2-leptons). Reference models are Randall-Sundrum (RS) models [3], predicting a neutral scalar Radion, the Heavy Vector Triplet (HVT) framework [4], parameterizing a heavier version of Standard Model (SM) spin-1 W (W′) and Z (Z′) bosons and bulk RS models [5], which predict the existence of a spin-2 Graviton. The hadronic boson decay is reconstructed either as two separate small-radius jets (small-R jets) or as a single large-radius jet (large-R jet). The reconstructed VV

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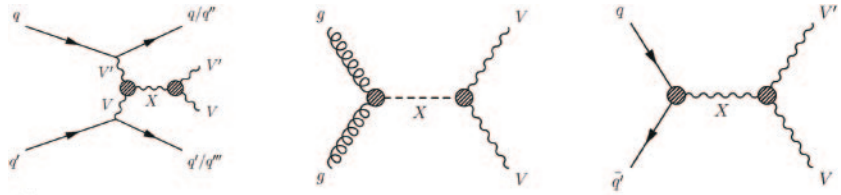


(a) vector-boson fusion (b) gluon-gluon fusion (c) Drell-Yan process

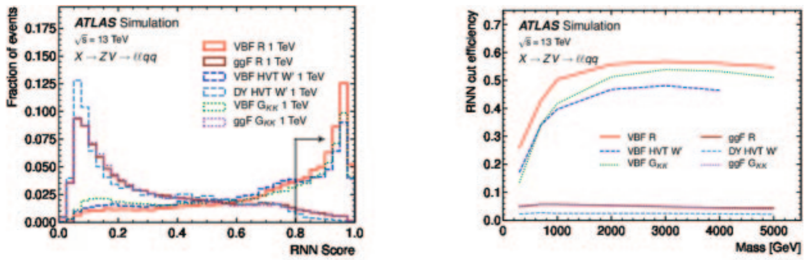
Fig. 1. – Production mechanisms and decays in two vector bosons of the X resonance.

transverse mass or the VV invariant mass are used for signal-background discrimination via maximum-likelihood fits. The investigated mass range is 300–5000 GeV, the search is performed using data collected by ATLAS [6] during the LHC Run-II (from 2015 to 2018), with a pp collisions center-of-mass energy $\sqrt{s} = 13\,\mathrm{TeV}$, corresponding to an integrated luminosity of $L = 139\,\mathrm{fb}^{-1}$. Expected SM background processes are W and Z boson production in association with jets, top-quark production, non-resonant diboson production and multijet production. This analysis exploits a four times larger data set and introduces innovative multivariate techniques with respect to the previous round of the analyses with $36\,\mathrm{fb}^{-1}$ [7, 8].

2. – Event selections and results

The search starts from the selection of the leptonic boson decay. Events are classified into two exclusive VBF and ggF/DY categories, according to their production mechanism, by a Long Short-Term Memory Recurrent Neural Network [9]. Finally, the hadronically decaying boson (V_h) is identified. Multiple signal regions are defined in order to enhance search sensitivities, and the analysis flow is run twice, once for $V_h = W$ and once for $V_h = Z$. The production mechanism is targeted considering the different number of jets between VBF and ggF/DY processes, since in the latter there are two additional jets well separated in pseudorapidity and with a large dijet invariant mass (fig. 1). In this search the classification task has been assigned to a RNN, since it is well suited for a variable-length input sequence such as the number of jets in the event. It is built with the Keras library using the Theano python library as a back end for mathematical computations. The RNN has 2 hidden layers with 25 recurrent cells to exploit the hidden correlation of the input sequence. It takes in input the four-momenta of the small-R jets, and returns the probability for the event to be VBF-like (fig. 2(a)). Training is performed on 1 TeV scalar resonances in the 2-leptons channel and applied on the three leptonic channels, the three resonance models and all resonance masses. An event is classified as a VBF event if its RNN score is >0.8, otherwise as a ggF/DY event. This Machine Learning (ML) approach allows recovering events with only one VBF-tag jet reconstructed (30% of signal events), not selected in the previous searches where two VBF-tag jets were required. In fig. 2(b) efficiency of the RNN score cut as function of the resonance mass is shown.

The hadronic boson decay is first identified as a single large-R jet and the "merged" regime is defined by applying a simultaneous p_T-dependent cut on its mass and the $D2$ variable [10]. In the case the event does not pass the merged selection, the boson decay is reconstructed using two small-R jets. The "resolved" region is defined by applying a fixed mass window on the dijet invariant mass spectrum for V or W decay because the dijet mass resolution is largely independent of the dijet p_T for the resonance masses to which the resolved analysis is sensitive.



(a) (b)

Fig. 2. – (a) RNN score for simulated signals and (b) efficiency of the RNN score cut as function of the resonance mass, for both VBF and ggF production [2].

The fit is performed simultaneously on the mass distributions in the final regions in each leptonic channel using a binned likelihood function.

A profile-likelihood-ratio test statistic is used to test the compatibility of the background-only hypothesis and the observed data, and to test the signal-plus background hypothesis, with the cross section as the parameter of interest.

A good agreement is found between the observed mass distributions and the estimated post-fit background contributions in all regions and limits on the production cross section are calculated (in fig. 3 limits obtained for HVT Z′ and gravitons are shown). When possible, these limits are translated into resonance mass lower limits by comparing them with theoretical cross section predictions. They are found to be significantly more stringent than those published previously from similar searches [7, 8].

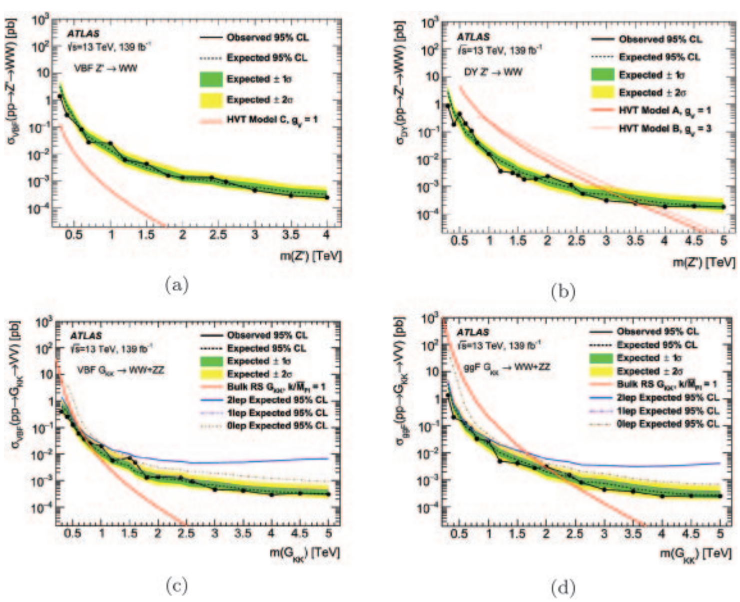


Fig. 3. – Observed (black solid curve) and expected (black dashed curve) 95% CL upper limits on the ggF/DY and VBF production cross section for HVT Z′ ((a) and (b)) and gravitons ((c) and (d)) [2].

3. – Conclusions

A Recurrent Neural Network has been adopted in the search for heavy resonances decaying in two bosons for the classification of production mechanisms. The RNN allows recovering events with a single VBF-tag jet, increasing the VBF event selection efficiency from 10% (5%) at 0.5 TeV to 60% (50%) at 3 TeV for a scalar (spin-1 or spin-2) resonance compared to the previous cut-based selection, with similar background rejections.

The first combined result of diboson searches in the semi-leptonic final states ($l\nu qq, llqq, \nu\nu qq$) has been obtained using the pp collision data recorded at LHC Run-II with the ATLAS detector, corresponding to an integrated luminosity of $139\,\mathrm{fb}^{-1}$ at $\sqrt{s} = 13\,\mathrm{TeV}$ [2]. Data are found to be in good agreement with background predictions. Upper limits on the production cross section of heavy resonances in the mass range 300–5000 GeV through gluon-gluon fusion, Drell-Yan or vector boson fusion processes are derived for SM extensions with an additional neutral scalar, a heavy vector triplet, or warped extra dimensions.

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