Probing Higgs Boson Properties With Boosted Objects at the CMS Experiment



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Higgs potential and BSM opportunity August 29, 2021



INTRODUCTION

- Boosted objects: powerful tools for new physics searches and standard model measurements at the LHC
- Hadronic decays of highly boosted heavy particles (Higgs/W/Z/ top) lead to large-R jets with distinctive characteristics:
 - different radiation patterns ("substructure")
 - 3-prong (top), 2-prong (W/Z/H) vs 1-prong (gluon/light quark jet)
 - different **flavor** content: existence of one or more b-/c-quarks
 - simultaneously exploiting both substructure and flavor to maximize the performance
 - significant performance leap thanks to new machine learning (ML) techniques









... in action!



DEEPAK8

- Advanced deep learning-based algorithm for boosted object tagging, using AK8 (anti-k_T R=0.8) jets
 - multi-class classifier for top quark and W, Z, Higgs boson tagging
 - sub-classes based on decay modes (e.g., $H \rightarrow bb, H \rightarrow cc, H \rightarrow VV^* \rightarrow 4q$)
 - output scores can be aggregated/transformed for different tasks -> highly versatile tagger
 - directly uses jet constituents (particle-flow candidates / secondary vertices)
 - ID convolutional neural network (CNN) based on the ResNet [arXiv: 1512.03385] architecture
 - significant performance improvement



DEEPAK8-MD

- The nominal version of DeepAK8 shows significantly improved performance, but also features strong "mass sculpting"
 - i.e., jet mass shape of the background becomes similar to that of the signal after selection with the tagger
- Mass-decorrelated tagger: "DeepAK8-MD"
 - mitigate mass sculpting using "adversarial training" [arXiv: 1611.01046]
 - added a mass prediction network to predict the jet mass from the learned features
 - higher mass prediction accuracy -> stronger correlation w/ the jet mass
 - accuracy of the mass prediction included in the loss function as a penalty
 - minimizing the joint loss -> improving classification accuracy while preventing mass correlation
 - significantly reduced mass sculpting yet still strong performance





PARTICLENET

 $\mathbf{X}_{j_{i3}}$

X

- ParticleNet [Phys. Rev. D 101, 056019 (2020)]
 - treating a jet as an unordered set of particles in space

 $\mathbf{X}_{j_{il}}$

EdgeConv

using permutation-invariant oraph neural networks



- multi-class tagger for t/W/Z/H tagging
- same inputs as DeepAK8 (PF candidates + secondary vertices)
- significant performance improvement



 $\mathbf{X}_{j_{i2}}$

 $\mathbf{e}_{ij_{i1}}$

e_{iji3}

e_{*ij*_{*i*⁴}}

ParticleNet architecture

PARTICLENET-MD

- ParticleNet-MD
 - exploiting a dedicated signal sample for training:
 - hadronic decays of a spin-0 particle X
 - $X \to b\bar{b}, X \to c\bar{c}, X \to q\bar{q}$
 - flat mass spectrum: $m_X \in [15, 250]$ GeV
 - in addition: signal/background samples reweighted to a \sim flat (p_T, m_{SD}) distribution to aid the training
 - both signal and background have the same mass spectrum, thus no sculpting can form during the training





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Mass Regression

- Jet mass: one of the most powerful observables for boosted jet tagging
 - characteristic mass peak for top/W/Z/H jets v.s. continuum for QCD jets
 - grooming technique (e.g., soft drop) typically used to reduce sensitivity to unrelated radiations (initial-state radiation, underlying event, pileup, etc.)
- Mass regression
 - exploit the ParticleNet architecture to predict the jet mass directly from jet constituents
 - similar setup as the ParticleNet-MD tagger (inputs, training samples, etc.)
 - regression target
 - signal: generated particle mass (pole mass) of X [ranging from 15-250 GeV]
 - background: soft drop mass of the particle-level jet
 - loss function

LogCosh:
$$L(y, y^p) = \sum_{i=1}^{n} \log(\cosh(y_i^p - y_i))$$

focus on Higgs (or generally 2-prong jets) for now





https://www.cs.cornell.edu/courses/cs4780/2015fa/ web/lecturenotes/lecturenote10.html

MASS REGRESSION: PERFORMANCE

CMS DP-2021/017







- Substantial improvement in both mass scale and resolution, especially for signal jets
- Tails in m_{SD} also significantly reduced
- Up to ~20-25% improvement in analysis sensitivity with H->bb/cc

VH(H→CC)

- First direct search for $H \rightarrow cc$ in CMS
 - VH channel: V (W, Z) \rightarrow ll, lv, vv
 - two complimentary approaches to fully explore the H→cc decay topologies
 - Resolved-jet topology
 - $H \rightarrow cc$ decay reconstructed with two resolved jets (R=0.4)
 - charm quark jets identified with DNN-based DeepCSV algorithm
 - analysis strategy similar to the VH(H→bb) analysis [PRL 121, 121801 (2018)]
 - fit to BDT shapes to extract the VH($H \rightarrow cc$) signal
 - Merged-jet topology
 - $H \rightarrow cc$ decay reconstructed with one large-R jets
 - using **R=1.5** (instead of R=0.8) to increase acceptance at lower p_T (~200−300 GeV)
 - the DeepAK8-MD algorithm adapted to select cc-jet and suppress light-/bb-flavor jets
 - fit to the mass of the large-R jet (Higgs boson candidate) to extract the VH(H→cc) signal

(13 TeV) efficiency CMS 1.4 Resolved Simulation Merged ($\Delta R < 1.5$) 1.2 Preliminary Merged ($\Delta R < 0.8$) ZH events 0.8 0.6 0.4 0.2 0 $\begin{array}{r} 250 & 350 \\ \text{Higgs boson } \text{p}_{\text{T}} \left[\begin{array}{c} \text{GeV} \end{array} \right] \end{array}$ 250 50 150 Ό

IHEP 03 (2020) 131



$H \rightarrow CC: ANALYSIS STRATEGY$

Analysis strategy of the merged-jet topology

<u>JHEP 03 (2020) 131</u>

- event-level kinematic BDT developed in each channel to better suppress the dominant backgrounds (V+jets, ttbar)
 - using only event kinematics, NOT the intrinsic properties (e.g., flavor/mass) of the Higgs candidate (H_{cand})
- cc-tagging discriminant used to select cc-flavor jets and reject light/bb-flavor jets
- distinct m(H_{cand}) shapes between signal and V+jets/ttbar background:
 - fit the m(H_{cand}) shape to extract the $H \rightarrow cc$ signal
- Kinematic BDT, cc-tagging discriminant and m(H_{cand}) largely independent of each other
 - allowing for a simple and robust strategy for background estimation and signal extraction



$H \rightarrow CC: RESULTS$

Results from the two approaches combined for the final results

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- resolved-jet topology : p_T(V) < 300 GeV; merged-jet topology : p_T(V) > 300 GeV
- using **35.9 fb**⁻¹ data (2016)

95% CL exclusion limit on $\mu_{VH(H\to c\bar{c})}$								
	Resolved-jet	Merged-jet	Combination					
	$(p_{\rm T}({\rm V}) < 300 {\rm GeV})$	$(p_{\rm T}({\rm V}) \ge 300 {\rm GeV})$	0L	1L	2L	All channels		
Expected	45^{+18}_{-13}	73^{+34}_{-22}	79^{+32}_{-22}	72^{+31}_{-21}	57^{+25}_{-17}	37^{+16}_{-11}		
Observed	86	75	83	110	93	70		

cf. ATLAS [ATLAS-CONF-2021-021, **139** fb⁻¹]: $\mu_{VH(H \rightarrow cc)}$ < 26 (31) obs. (exp.)





VBF HH(→4b)



VBF di-Higgs production: a unique channel to probe the hhVV quartic coupling (K_{2V})



- very rare process in SM: $\sigma \sim 1.7$ fb
- however, if the hhVV coupling deviates from the SM ($\kappa_{2V} \neq 1$), the cross section can be enhanced
 - meanwhile, a significant fraction of signal becomes highly boosted -> enhanced sensitivity using boosted objects for Higgs boson reconstruction



VBF HH(\rightarrow 4b):ANALYSIS STRATEGY

- First search for non-resonant VBF HH production **in the boosted topology**
- Analysis strategy
 - Higgs bosons reconstructed as two high p_T AK8 jets (p_T > 500/400 GeV)
 - **H→bb tagging** with the ParticleNet algorithm
 - 3 WPs: signal efficiencies ~ 60%, 80%, 90% at QCD mis-id. rate ~0.3%, 1% and 2%
 - Higgs jet mass reconstructed with the ParticleNet mass regression (~20% improvement w.r.t soft drop algorithm)
 - = selection of **VBF topology**: two AK4 jets with dijet mass > 500 GeV and $|\Delta \eta| > 4$
 - Background estimation
 - ttbar background estimated from simulation, with corrections derived from a top-enriched region
 - QCD multijet background estimated with a data-driven method
 - using QCD-enriched "fail" region by inverting the ParticleNet bb-tagging selections
 - Signal extraction
 - by fitting to m_{HH} in three search categories of increasing purity



m_{нн} [GeV]

VBF HH(\rightarrow 4b): RESULTS

- Most stringent constraint on κ_{2V} to date: **0.6 < \kappa_{2V} < 1.4**
 - κ_{2V} = 0 excluded for the first time!
 - cf. ATLAS [IHEP 07 (2020) 108]: -0.43 (-0.55) < κ_{2V} < 2.56 (2.72) obs. (exp.)

SUMMARY

- Lots of progress in boosted object techniques in recent years
 - substantial performance improvements with the introduction of novel machine learningbased approaches
 - performance gains confirmed in real data, and led to significantly increased sensitivity in relevant analyses
 - Advances in boosted object techniques brought new opportunities for Higgs physics
 - measurement of the Higgs couplings, complementary to the resolved-jet approach
 - VH(H→cc) [<u>JHEP 03 (2020) 131</u>]
 - VBF HH(→4b) [<u>CMS-PAS-B2G-21-001</u>]
 - probing Higgs boson production in the boosted regime [JHEP 12 (2020) 085]
 - search for new resonances decaying into Higgs bosons [CMS-PAS-B2G-20-007, CMS-PAS-B2G-20-004, ...]
 - ... and more to come!

VBF HH(\rightarrow 4b): RESULTS

2D limit scan excludes $\kappa_{2V} = 0$ for $\kappa_V > 0.5$ (with other couplings fixed to SM values)

VBF HH(\rightarrow 4b): BACKGROUND ESTIMATION

$H \rightarrow CC: FIT STRATEGY$

- Dedicated control regions are set up to measure the normalizations of major backgrounds (W/Z+jets, ttbar)
 - simultaneous fit of signal regions and control regions to constrain BKGs and extract the signal

- Dominant sources of uncertainties:
 - size of the MC simulation / data control samples
 - charm tagging efficiencies
 - simulation modeling

Uncertainty source	$\Delta \mu \mid \mu = 37$		
Statistical	+17.3	-17.1	
Background normalisations	+10.1	-10.2	
Experimental	+7.6	-8.2	
Charm tagging efficiencies	+5.6	-4.8	
Simulation modeling	+4.2	-5.1	
Jet energy scale and resolution	+2.4	-2.8	
Lepton identification efficiencies	+0.4	-1.8	
Luminosity	+1.6	-1.7	
Statistics of the simulated samples	+0.5	-1.9	
Theory	+6.5	-4.6	
Signal	+5.0	-2.5	
Backgrounds	+4.3	-3.9	
Total	+20.0	-19.5	

MASS REGRESSION: PERFORMANCE (II)

CMS DP-2021/017

Consistent improvements in all jet flavors

MASS REGRESSION: PERFORMANCE (III)

<u>CMS DP-2021/017</u>

- Mass resolution more stable vs m_X compared to soft drop
- No signs of mass sculpting even for very tight tagger selections
- Up to ~20-25% improvement in analysis sensitivity with H->bb/cc

PERFORMANCE IN DATA

<u>JINST 15 (2020) P06005</u>

TAGGER CALIBRATION IN DATA

- Crucial to calibrate these taggers in real data for them to be used in analyses
 - Top/W tagging efficiency

<u>JINST 15 (2020) P06005</u>

- measured using the single-µ sample enriched in semi-leptonic ttbar events
- fit jet mass templates in the "pass" and "fail" categories simultaneously to extract efficiency in data
 - simulation-to-data scale factors SF := eff(data) / eff(MC) derived to correct the simulation
- jet mass scale and resolution scale factors can also be extracted
- H->bb/H->cc tagging efficiency: measured via proxy jets, gluon->bb/cc, using a di-jet sample Mistag rates of background jet typically derived directly from analysis-specific control regions