Measurement of the Higgs quartic coupling c_{2v} from di-Higgs Vector Boson Fusion in the $bb\tau\tau$ channel

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Outline

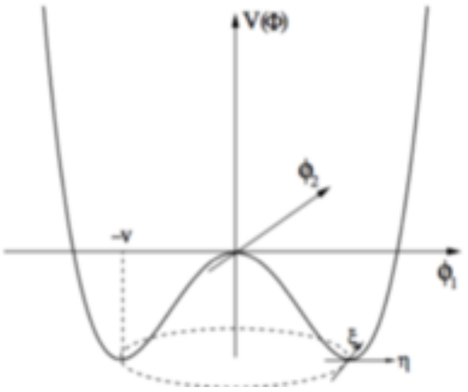
i. Searches for HH and $bb\tau\tau$ analysis introduction
ii. VBF channel event selection
iii. NN design - Input parameters
iv. Hyperparameter Optimization – Results
v. OverTraining tests
vi. Summary

Searches for HH

- The BEH mechanism not only predicts the existence of a massive scalar particle, but also requires this scalar particle to couple to itself.

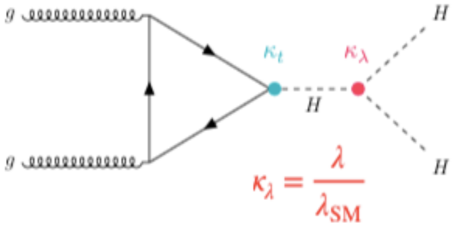
Higgs potential

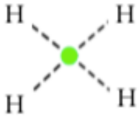
$$V(H) = \frac{m_H^2}{2}H^2 + \lambda v H^3 + \frac{\lambda}{4}H^4 \qquad \text{SM:} \quad \lambda = \frac{m_H^2}{2v^2} = 0.13$$



mass term — triple Higgs coupling — quartic Higgs coupling

$m_H = 125.10 \pm 0.14\,\mathrm{GeV}$
(PDG 2020)

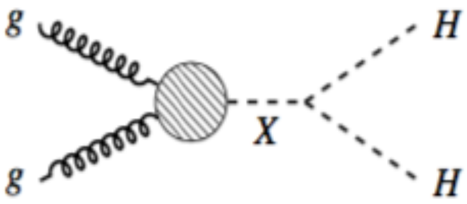




In the SM, pairs of Higgs bosons at the LHC are dominantly produced in **gluon-gluon fusion (ggF)** processes, namely via a loop of top quarks

A direct probe to λ_{HHH} is to measure the non-resonant di-Higgs production via the triangle diagram

BSM theories predict heavy resonances that could decay into a pair of the SM Higgs bosons, such as a heavy spin-0 scalar *X* in two-Higgs-doublet models also it's self-coupling probes shape of potential - **Sensitive to new physics**

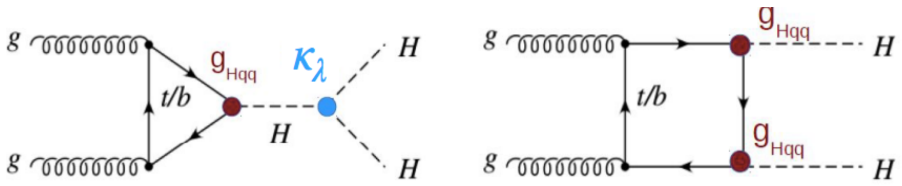


What can we access with HH?

ggF and VBF categories split to enhance sensitivity to SM and BSM

gluon gluon Fusion (ggf)

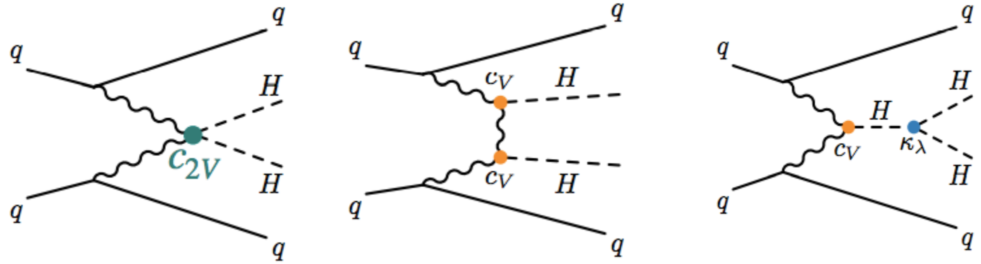
SM cross-section at 13 TeV: 31.05 fb.



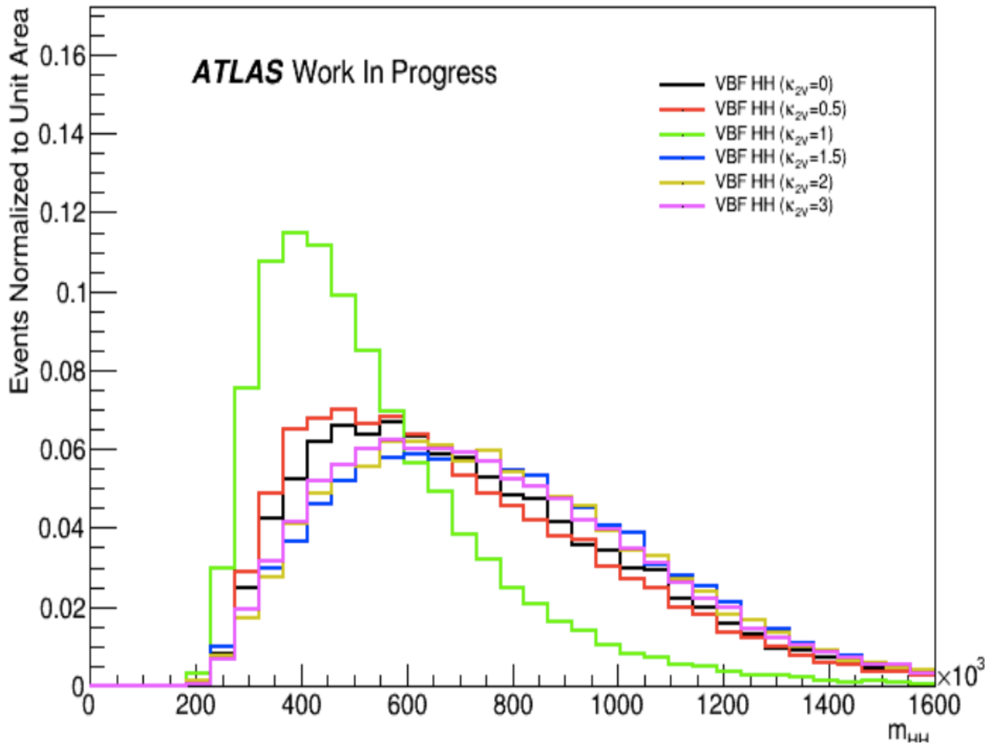
Possible BSM enhancements due to modified coupling strength of κ_λ

Vector Boson Fusion (VBF)

SM cross-section at 13 TeV: 1.73 fb.



Possible BSM enhancements due to modified coupling strength of c_{2v}



Gaining sensitivity to c_{2V} is achieved by reconstructing events with large values of m_{HH}

VBF category will allow us to set limits on c_{2V}

Higgs pair decay and di-Higgs analyses

Main analyses channels:

- bbbb: fully takes advantage of high bb branching ratio
- bbγγ: Excellent trigger and mass resolution for photons
- **And bbττ**

Why $bb\tau\tau$?

- Taus are relatively clean, small background, signal purity
- Relatively high branching ratio
- High trigger efficiency
- b-jets tagging it is very efficient thanks to the precise reconstruction of primary and secondary vertices
- Tau lepton reconstruction is quite challenging but efficient algorithms have been developed

HH: multiple final states

- H→bb is the protagonist

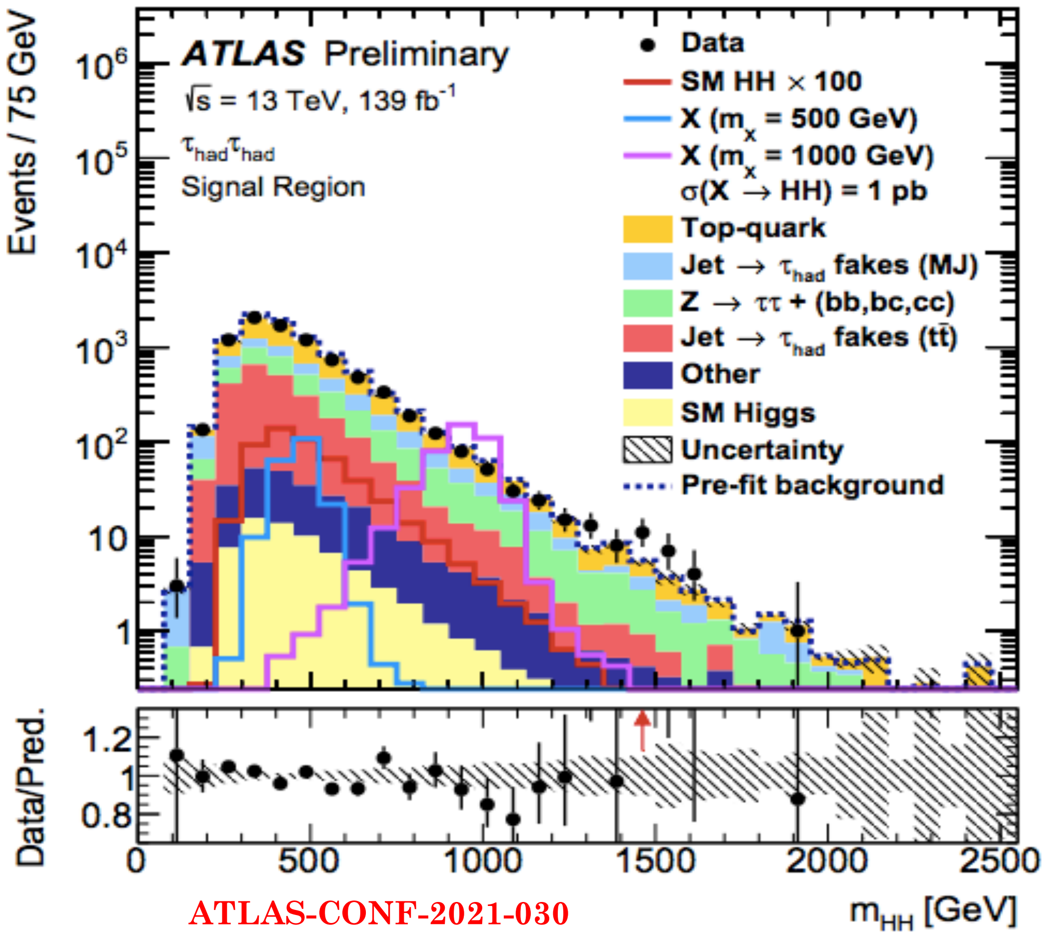
di-Higgs decay BRs given by all possible combinations of observed Higgs decays:

	bb	WW	ττ	ZZ	γγ
bb	33%				
WW	25%	4.6%			
ττ	7.4%	2.5%	0.39%		
ZZ	3.1%	1.2%	0.34%	0.076%	
γγ	0.26%	0.10%	0.029%	0.013%	0.0005%

di-Higgs Analyses bbττ – Event Selection

- **Divided in two channels depending on τ-lepton pair decay mode: $\tau_{lep}\tau_{had}$ and $\tau_{had}\tau_{had}$**

$\tau_{had}\tau_{had}$ (STT / DTT)
single- and di-τ_{had} triggers
exactly two τ_{had}
lepton-veto
trigger dependent thresholds on τ_{had} and jets $m^{MMC}_{\tau\tau} > 60$ GeV OS electric charge of τ_{had} and τ_{had} 2 b-tagged jets (DL1r tagger, 77% WP)



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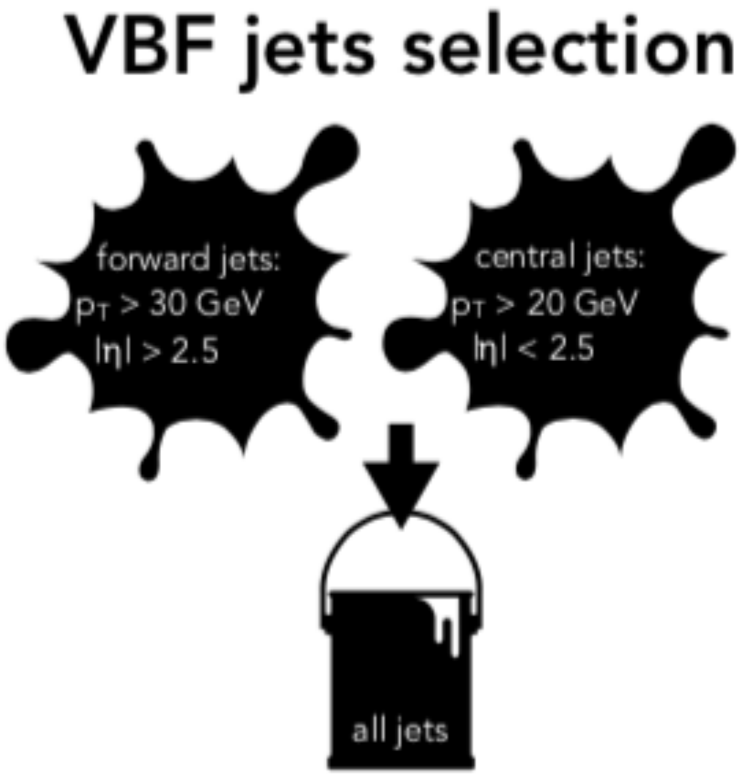
VBF Event Selection



Baseline: Require 2 VBF jets in the event

- Take all forward jets
- Take central jets only if they are non-btagged
- Find jet pairing with highest $\mathbf{m_{jj}}$ pair and in opposite hemispheres, $\mathbf{(\eta^{j1} * \eta^{j2} < 0)}$
- Order VBF jets by p_T

Analyses fw (CxAODReader_bbtautau)

some VBF jets variables driven by (H->tautau)

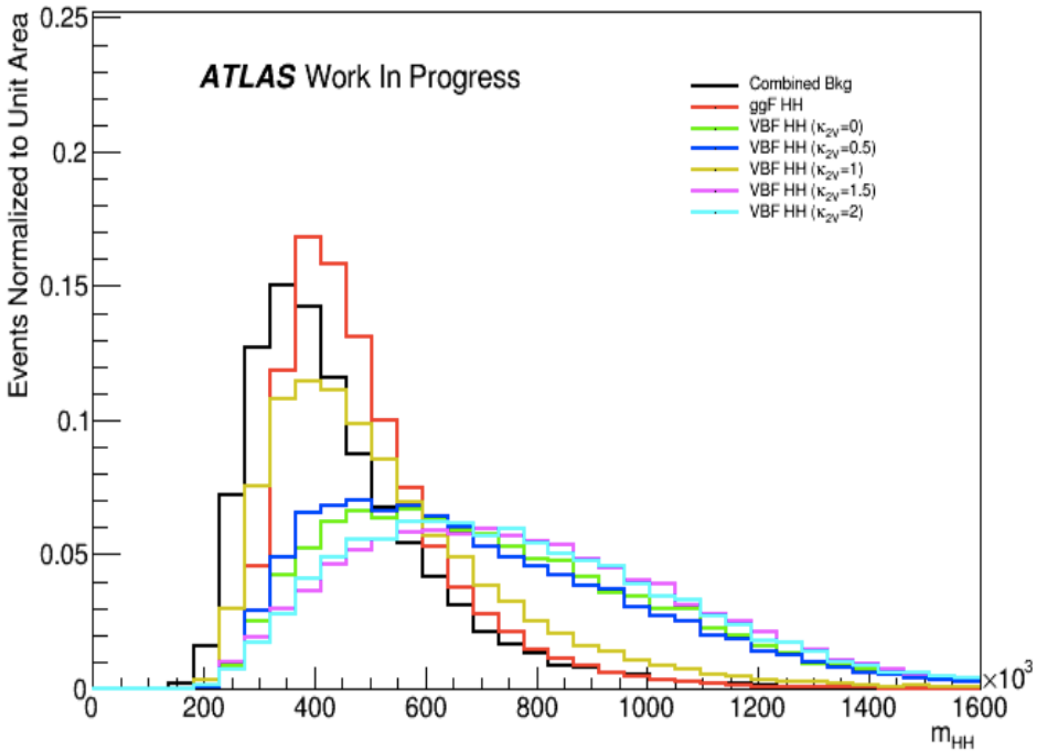
κ_{2V} = {0, 0.5, 1, 1.5, 2, 3}

Events	Total	VBF selection
$VBF_{\kappa=0}$	6.77	4.54
$VBF_{\kappa=1}$	0.167	0.119
$VBF_{\kappa=2}$	4.63	3.125
ggF	5.40	1.57
Combined Bkg	9189.9	3256.9

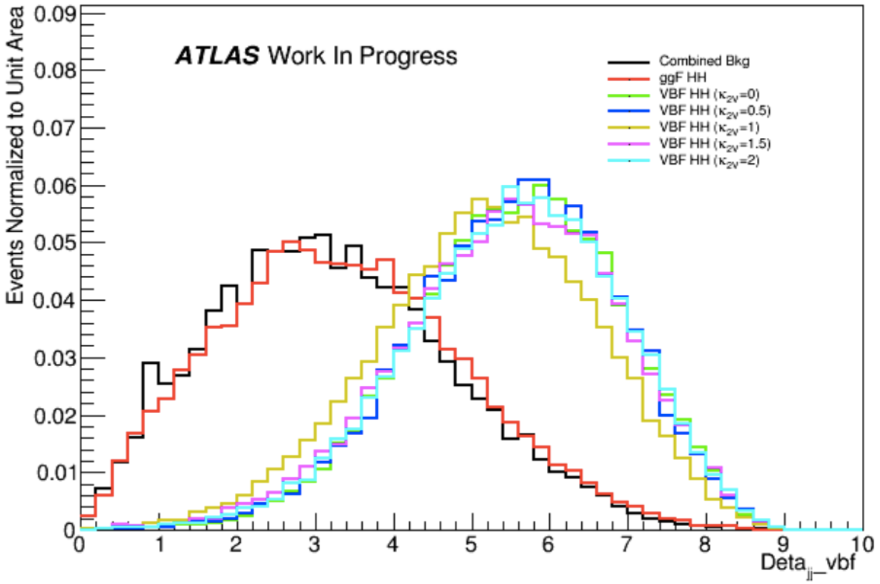
NN design – Input variables

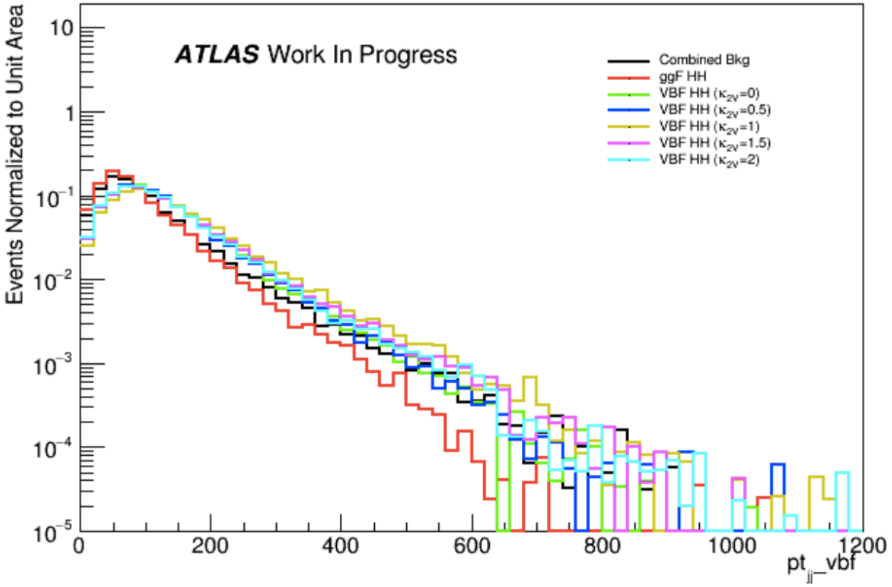
- **Feed Forward NN**

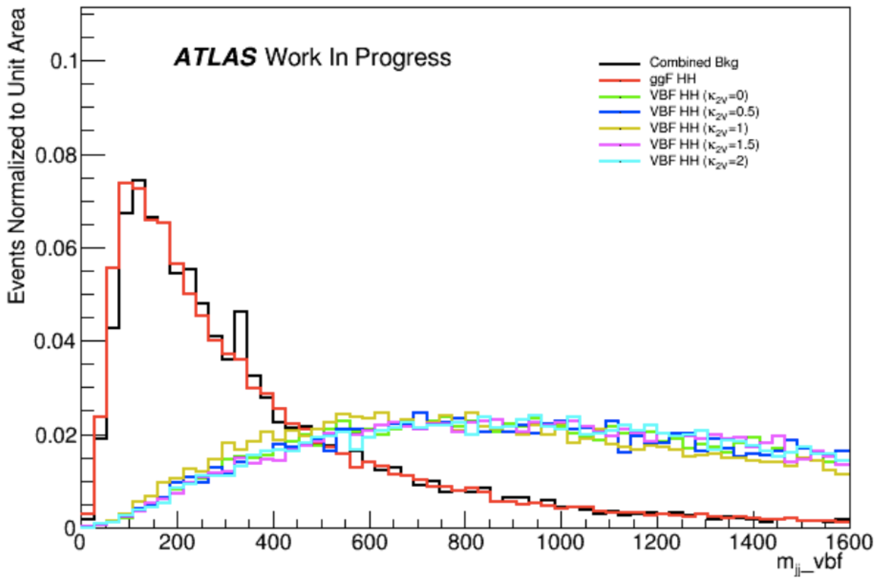
- **Input Variables**
  - m_{HH} : Di-Higgs invariant mass
  - $\Delta R(\tau,\tau)$: The ΔR between the visible-τ decay products
  - $\Delta R(b,b)$: The ΔR between the two b-jets
  - $m_{\tau\tau}^{mmc}$: The invariant mass of the di-τ system, calculated using the MMC momenta of 2 taus
  - m_{bb} : The invariant mass of the di-b-jet system
  - p_T^{jj} : Di-jet (vbf) transverse momentum
  - m_{jj} : The invariant mass of the di-jet(vbf) system
  - $\Delta\eta_{jj}$: The $\Delta\eta$ between the two vbf jets
  - $\eta_{j1} \cdot \eta_{j2}$: Product of η for two vbf jets
  - $Dphi_{jj}$: The $\Delta\phi$ between the two vbf jets
  - $p_T^{\tau\tau}$: The transverse momentum of the two taus
  - p_T^{bb} : The transverse momentum of the two bs
  - $p_T SixObj$: The transverse momentum of the HH+2-VBF jets

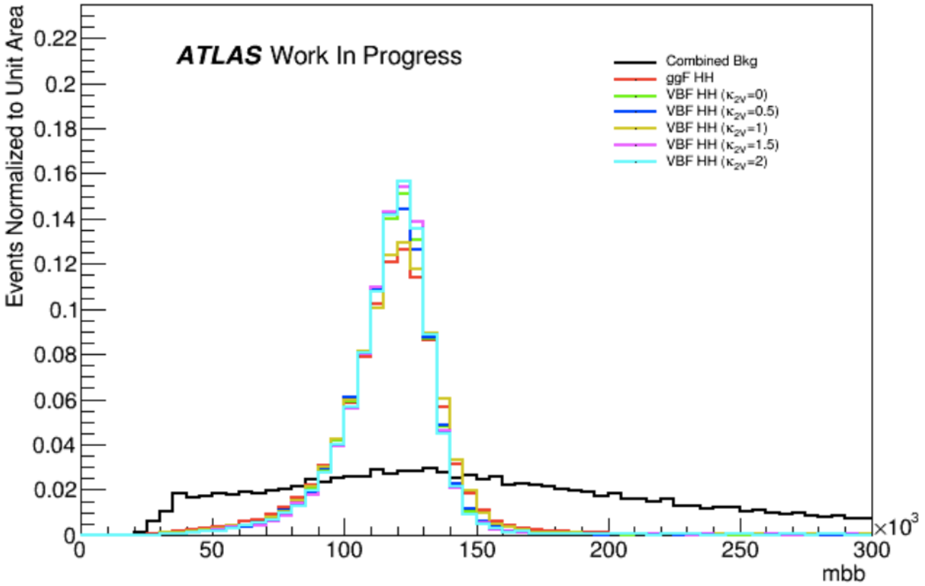


NN design – Input variables

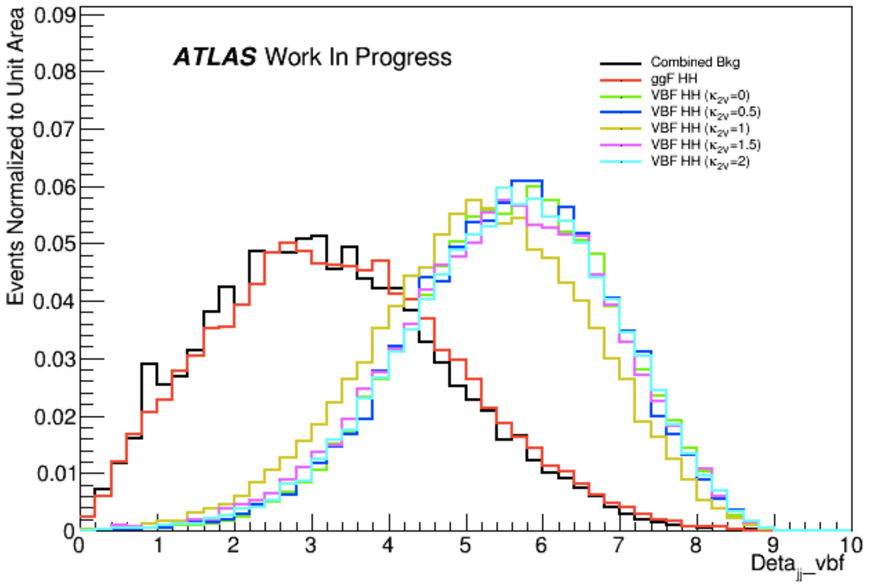


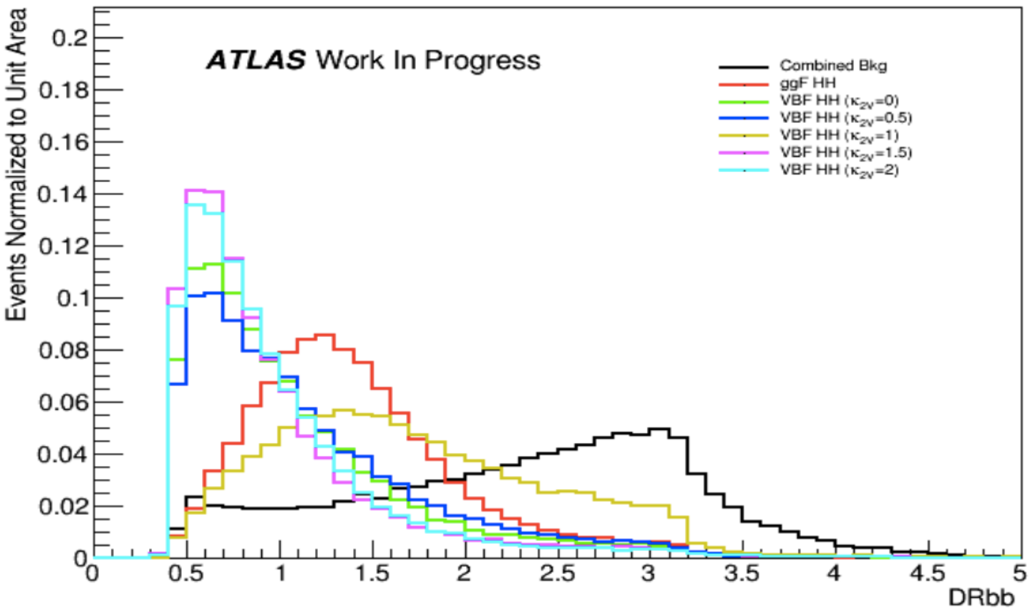


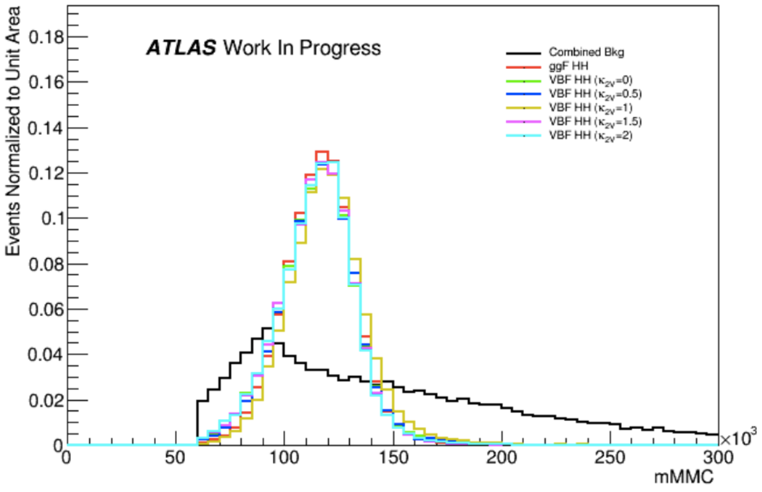


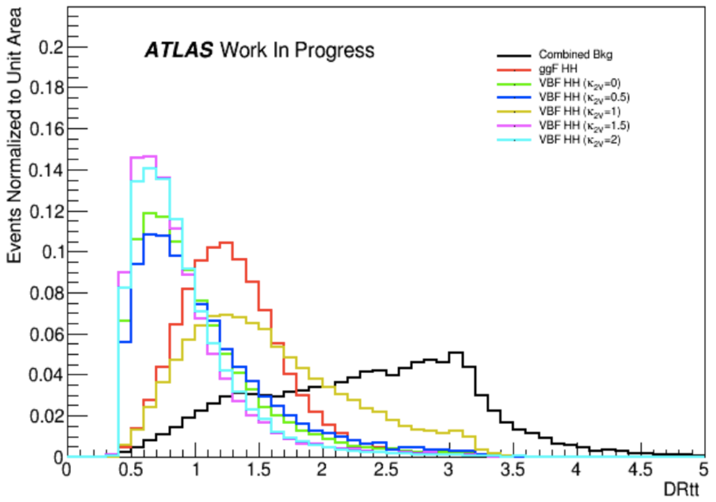


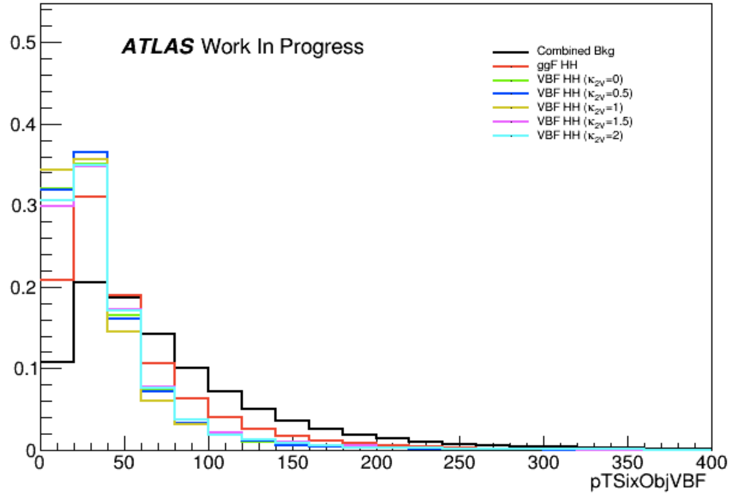
NN design – Input variables











Hyperparameter Optimization Effort

Hyperparameter	Optimization strategy	Implementation
Number of hidden layers	Bayesian optimization	TPE
Number of nodes in each layer	Bayesian optimization	TPE
Activation function	Typical suggestion for FF NN	ReLU
Output activation function	Typical suggestion for multiclassification NN	Softmax
Loss function	Typical suggestion for multiclassification NN	Categorical Cross-Entropy
Loss minimizer	Dynamic adjustment of per-parameter learning rate	ADAM
Regularization method	L2 typically works better than L1/Dropout	L2
Regularization value	Bayesian optimization + fine tuning by hand	TPE
Batch size	Bayesian optimization	TPE
Epochs of training	Best validation loss	EarlyStopping

Hyperparameter Optimization - Bayesian Trials

Tree Parzen Estimator

- Bayesian approach
- Evaluations of a function are used to predict the next set of good hyperparameters
- Better overall performance/Less time required for optimization than random search

Hyperparameters to optimize

- **Neurons/layer : 20 - 40**
- **Layers : 6 - 20**
- **R2 value : 10^{9} - $4*10^{-7}$**
- **Batch size : 4 - 24**

50 Hyperparameter tests with different sets !!!

Maximize signal for 5 bkg events

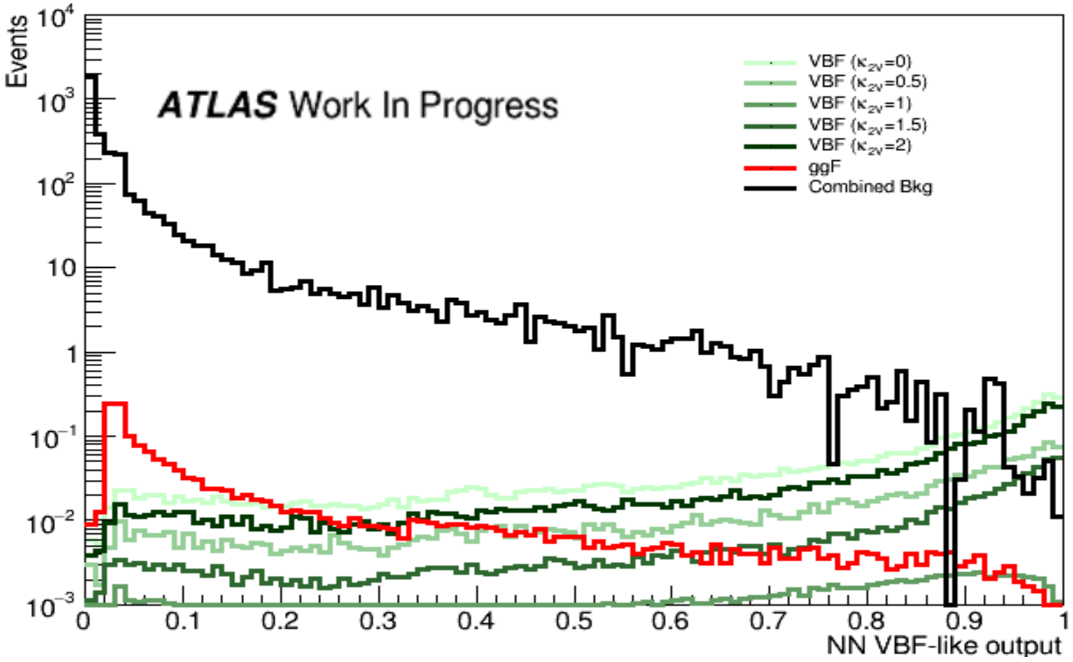
Hyperparameter Optimization – Final Setup

- **Classification strategy**
  - 3-class classification
  - VBF (κ_{2V}=0, κ_{2V}=0.5, κ_{2V}=1.5, κ_{2V}=2 - normalized) / ggF / Bkg
  - Training with even events

- **Input Variables**
  - **m_{HH} , ΔR(τ,τ), ΔR(b,b) , $m_{\tau\tau}^{mmc}$, m_{bb} ,p_T^{jj} , m_{jj} , $\Delta\eta_{jj}$, $\eta_{j1} \cdot \eta_{j2}$, $Dphi_{jj}$, $p_T^{\tau\tau}$, p_T^{bb} , p_TSixObj**

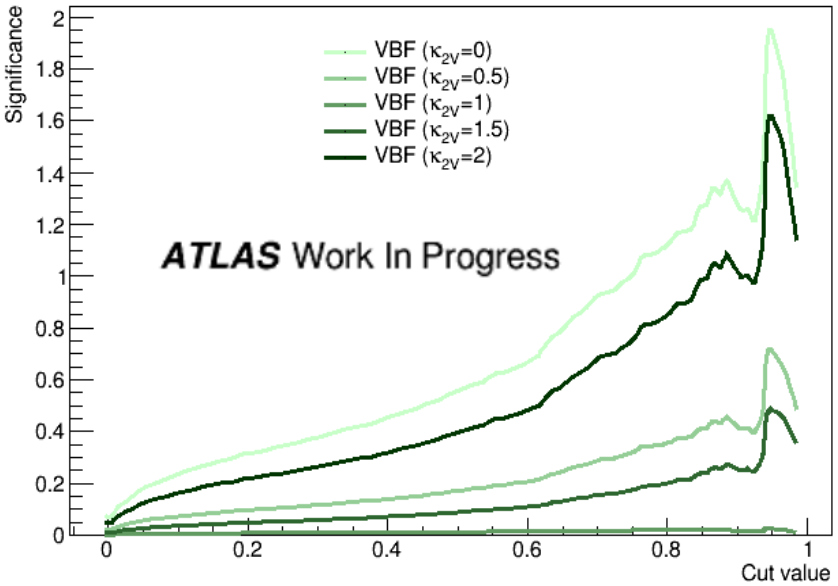
- **MultiLayer Perceptron**
  - Input Layer : 9 Neurons (relu)
  - Hidden Layers : 10 x 35 Neurons (relu)
  - Output Layer : 3 Neuron (softmax)
  - Loss Function : Categorical Crossentropy
  - L2 Regularization for each hidden layer : $3 \cdot 10^{-8}$
  - Loss Optimizer : ADAM
  - Batch size : 16
  - Epochs : 78

Hyperparameter Optimization – Best results



Events	VBF selection
VBFκ=0	4.54
VBFκ=1	0.119
VBFκ=2	3.125
ggf	1.57
Comb. Bkg	3256.9

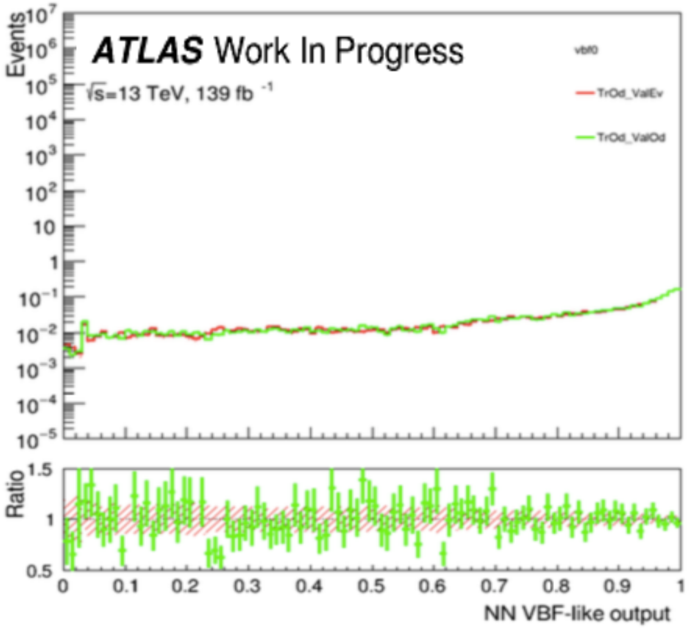
κ_{2V}	Significance	Cut value for 5 bkg events	Signal events passing cut	Bkg events passing cut
0	1.082	0.78	2.820±0.022	5.06±0.784
0.5	0.343	0.78	0.842±0.008	5.06±0.784
1	0.019	0.78	0.045±0.004	5.06±0.784
1.5	0.190	0.78	0.460±0.003	5.06±0.784
2	0.814	0.78	2.076±0.017	5.06±0.784

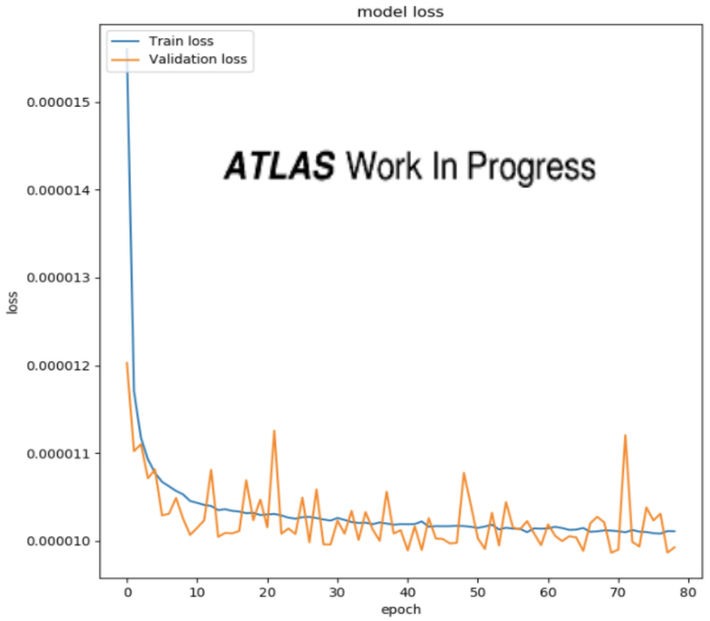


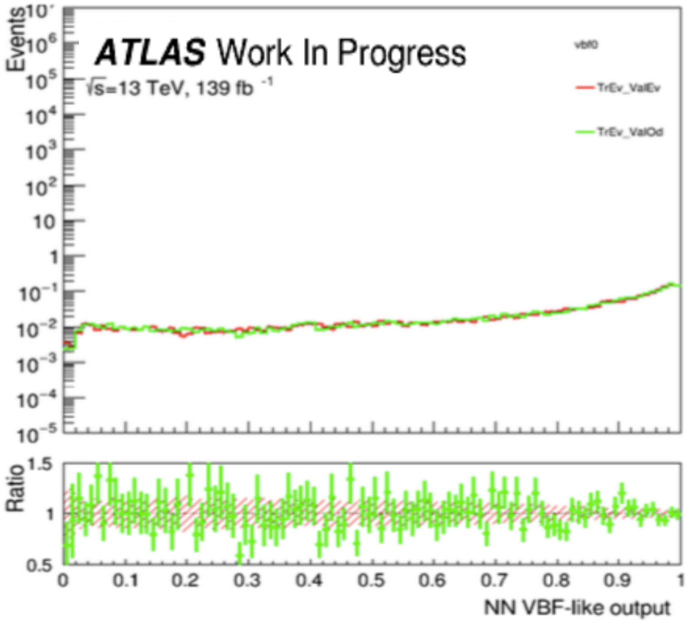
OverTraining Tests

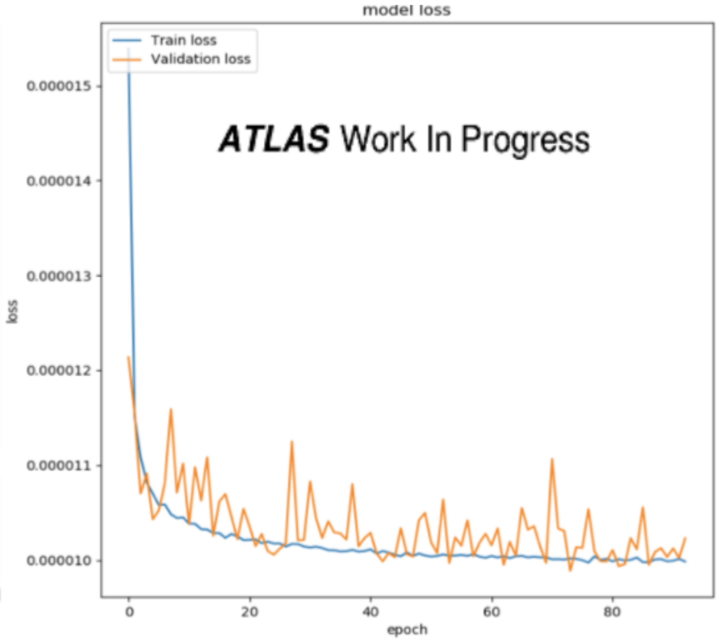
2 NNs trained with the optimal Hyperparameters
One with even and one with odd events

4 Comparisons of events- Val(Train) vs Val(Train)
-Even(Odd) vs Odd(Odd)
-Even(Even) vs Odd(Even)
-Even(Even) vs Even(Odd)
-Odd(Even) vs Odd(Odd)









Summary

- HH studies can access the SM Higgs couplings and BSM physics.
- **VBF category will allow us to set limits on c_{2V}**
- **Feed Forward NN setup design was chosen**
- Set of good Hyperparameters was found
- Optimization variable used was signal for 5 background events
- Additional overfitting checks performed
- NN is implemented in the Analyses framework

- **Fit the NN distributions to get limits for the c_{2v} coupling**