ATLAS and CMS non-resonant HH→bb$\tau\tau$

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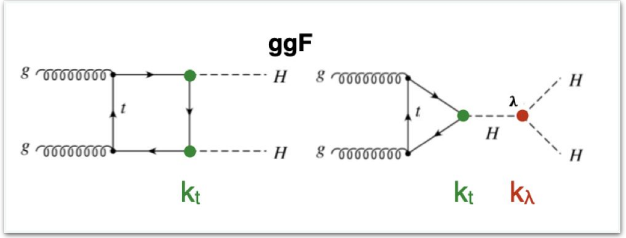
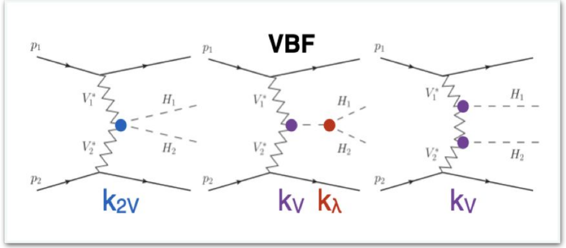
on behalf of the ATLAS and CMS Collaborations

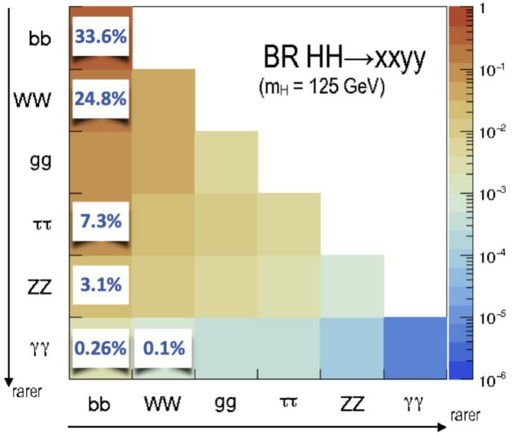
Introduction

- Higgs pair-production allows to directly measure κ_λ and κ_{2V}
  - *ggF*: 31.05 fb, *VBF*: 1.73 fb





- $bb\tau\tau$ final state:
  - 7.3%, large BR
  - relatively clean signature compared to other channels with higher BR



- Analysis performed in two channels depending on $\tau\tau$ decay:
  - $\tau_{had}\tau_{had}$ (BR: 42%)
  - $\tau_{lep}\tau_{had}$ (BR: 45.6%) $\rightarrow$ split in $\tau_e\tau_h/\tau_\mu\tau_h$ for CMS

Trigger Strategy

ATLAS and CMS use a similar trigger strategy based only on leptons and τ_{had}

ATLAS

- $\tau_{had}\tau_{had}$:
  - single τ trigger with p_T of 80-160 GeV
  - di-τ trigger with p_T of 35 and 25 GeV
    - In 2016, 1 jet (> 25 GeV) at L1
    - 2017-2018, 1 jet (> 25 GeV) or 2 jets (> 12 GeV) at L1
- $\tau_{lep}\tau_{had}$:
  - **SLT**: single lepton trigger with 24-26 (20-26) GeV for e (μ);
  - **LTT**: lepton+τ_{had} trigger with 17 (14) GeV for e (μ) and 25 GeV for τ_{had}
    - From 2017, 1 jet (> 25 GeV) or 2 jets (> 12 GeV) at L1

CMS

- $\tau_{had}\tau_{had}$:
  - di-τ trigger with p_T>35 GeV
  - di-τ (p_T>25 GeV) + 2 jets (p_T>45/115 GeV)
- $\tau_{lep}\tau_{had}$:
  - single-e with p_T>25 (32) GeV (2017-2018)
  - e-τ trigger with
    - ele p_T>24 GeV
    - τ p_T>30 GeV
  - Single-μ with p_T>22 (24) GeV (2017-2018)
  - μ-τ trigger with
    - μ p_T>19 (20) GeV (2017-2018)
    - τ p_T>20 (27) GeV (2017-2018)

Event Selection

ATLAS EXPERIMENT

- 2 b-jets (DNN-based tagger, 77%)
  - Mis-tag rate for light jet is 0.06%
- 2 τ_{hads} or 1τ_{had}+ 1 e/μ with OS
  - τ_{had}: RNN-based Loose WP (1-p: 85%, 3-p: 75%)
- Trigger-dependent p_T on e/μ/τ_{had} and jets
- e/μ veto applied for $\tau_{had}\tau_{had}$
- Exactly 1 e/μ and 1 τ_{had} for $\tau_{lep}\tau_{had}$
- $m_{\tau\tau}$ (from MMC) > 60 GeV
- m_{bb} < 150 GeV for $\tau_{lep}\tau_{had}$

CMS

- 2 jets with p_T>20 GeV and |η|<2.5
  - Select 2 b-jet candidates with a dedicated recurrent NN (HH-bTag)
  - Efficiency to tag H→bb ~95%
- Two isolated and OS leptons
  - p_T threshold dependent on trigger
  - τ_{had} candidates discriminated vs e/μ/jets using DeepTau NN (CMS-TAU-20-001)
    - Medium WP (70% eff vs jets)
  - Extra lepton veto for all channels
- Elliptical mass cuts on $m_{\tau\tau}/m_{bb}$

CMS: Mass Cuts

- Elliptic mass cut on $m_{\tau\tau}$ (SVFit algo.) and m_{bb} (jet vis. mass sum)
  - Minimize background and keep signal efficiency > 90%
  - Removes significantly outlying background events where no signal is expected
  - Actual discrimination between signal and background is left to the DNN

- Optimized for different categories

- Resolved categories : $$\frac{(m_{\tau\tau} - 129\ GeV)^2}{(53\ GeV)^2} + \frac{(m_{bb} - 169\ GeV)^2}{(145\ GeV)^2} < 1$$

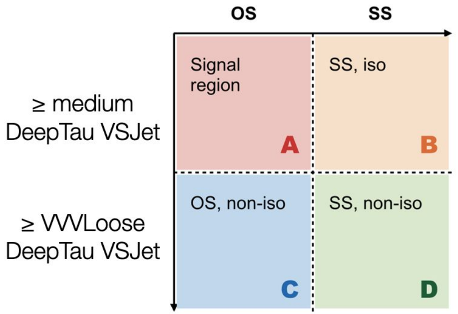
- Boosted category : $$\frac{(m_{\tau\tau} - 128\ GeV)^2}{(60\ GeV)^2} + \frac{(m_{bb} - 159\ GeV)^2}{(94\ GeV)^2} < 1$$

- No mass cut is applied in the VBF categories

Background Estimation

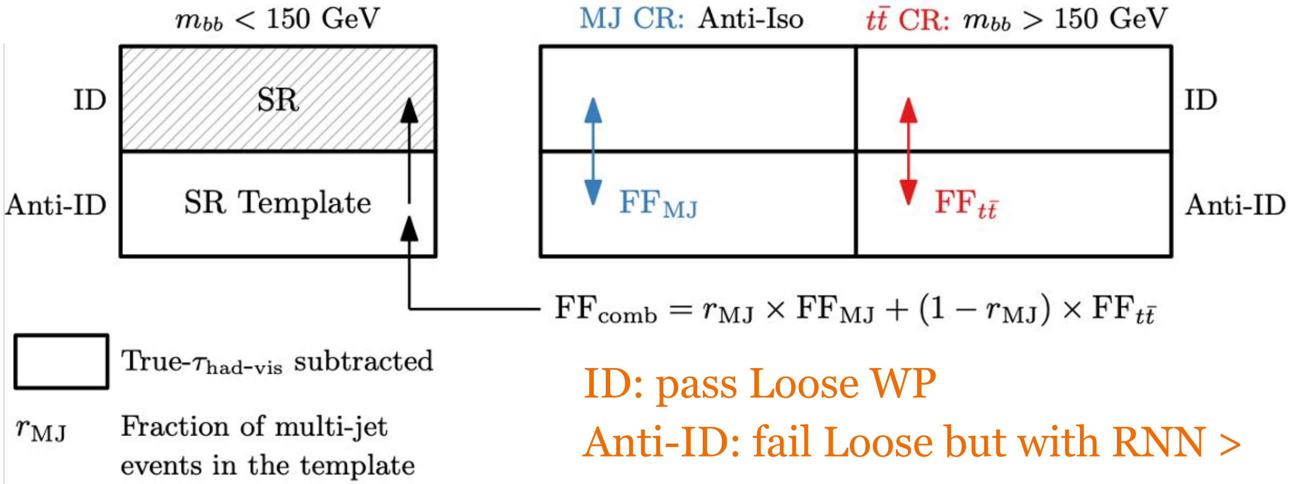
- ttbar with true τ_{had} and Z + heavy-flavor: shape from simulation, normalizations determined in the fit
- Single Higgs and other processes from simulation
- Jets→fake τ_{had} background: estimated with data-driven approach (more details in the coming slides)

- ttbar and DY+jets from simulation with norm. corrected from data CR
  - 18 Z→μμ+jets CRs for DY
  - 2 b-tag + inv. mass cut for ttbar
- QCD multijet fully data-driven
  - ABCD method inverting tau pair selections



- Other backgrounds from simulation
- No special treatment for fake τ_{had}

ATLAS: Fake Background in $\tau_{lep}\tau_{had}$

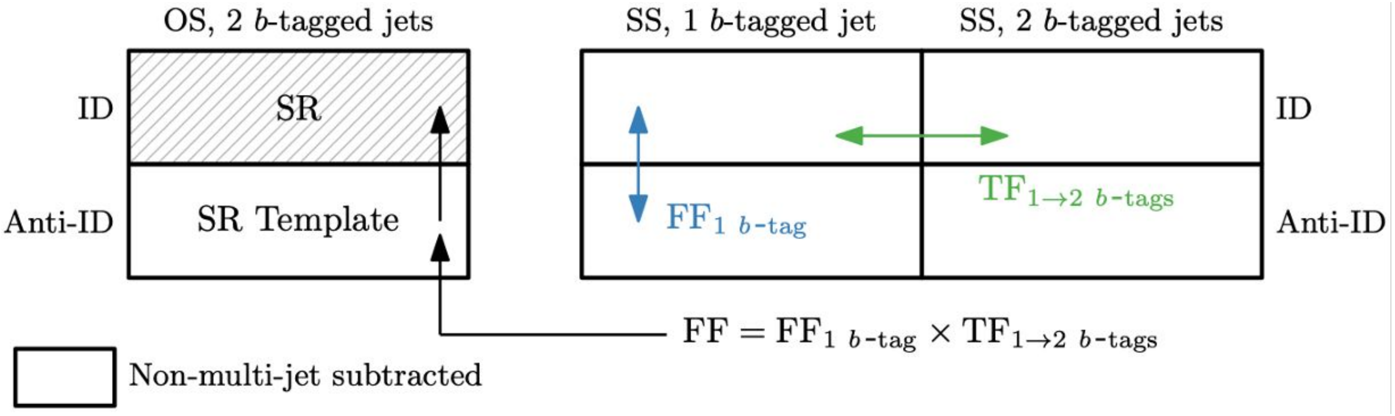


ID: pass Loose WP

Anti-ID: fail Loose but with RNN > 0.01

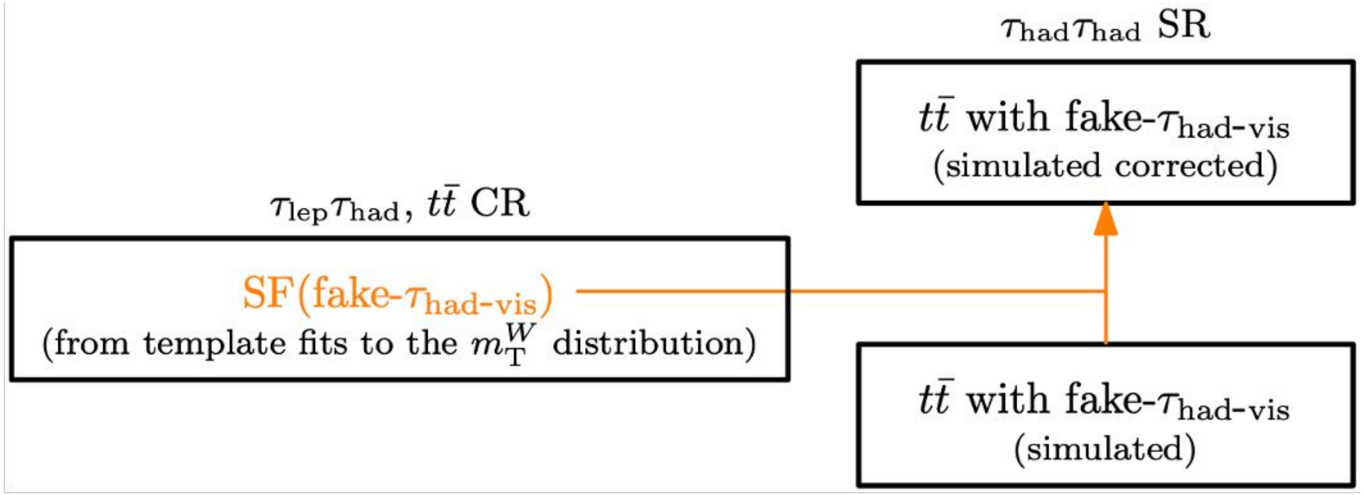
- Fake factor (FF) derived for ttbar and multi-jet separately
  - Split in 1/3-prong and derived as a function of p_T
- Combined FFs applied to scale Anti-ID SR template to obtain fake background in SR

ATLAS: Multi-jet Fake Background in $\tau_{had}\tau_{had}$



- For multi-jet, FF derived in 1 b-tag same-sign CR
- Transfer factors derived to account for extrapolation from 1 b-tag to 2 b-tag events

ATLAS: ttbar Fake Background in $\tau_{had}\tau_{had}$



- For ttbar, fake τ_{had} from simulation
- Scale factors: applied to correct τ_{had} misidentification efficiencies
    - 1-prong: ~1 for <40 GeV, ~0.6 for >70 GeV
    - 3-prong: ~20% larger than 1-prong

Event Categorization

- Three trigger-dependent categories: $\tau_{had}\tau_{had}$, $\tau_{lep}\tau_{had}$ SLT and $\tau_{lep}\tau_{had}$ LTT

- SLT and LTT are orthogonal with LTT only including low p_T e/μ

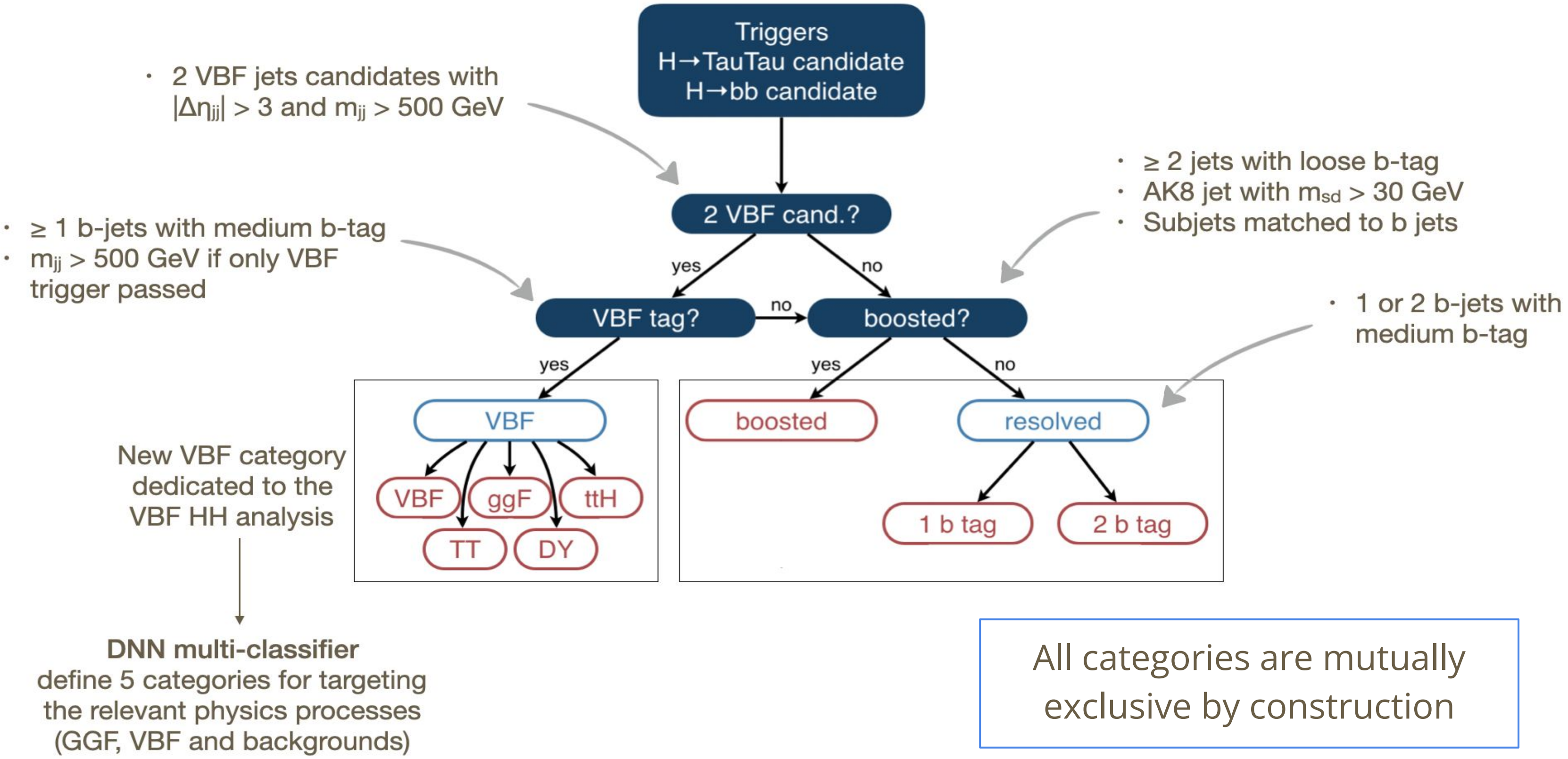
- 3 channels based on the tau pair decay
  - $\tau_{had}\tau_{\mu}$: single lep. and lep.+tau triggers
  - $\tau_{had}\tau_{e}$: single lep. and lep.+tau triggers
  - $\tau_{had}\tau_{had}$: di-tau and di-tau+VBF triggers

- Further categorization based on the number and flavor of the jets
  - Resolved, boosted and VBF-like
  - 8 categories defined

- 3 channels x 8 categories x 3 years for a total of 72 categories in the final fit

CMS: Event Categorization

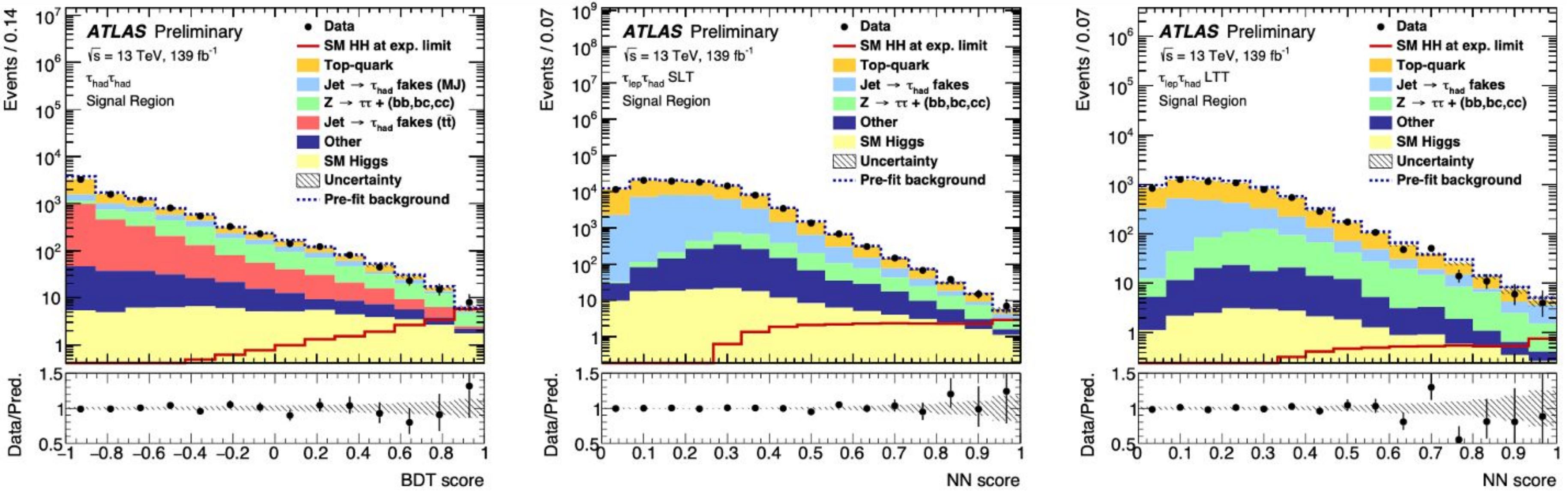
Event categorization is based on the number and nature of the jets tagged in the event



All categories are mutually exclusive by construction

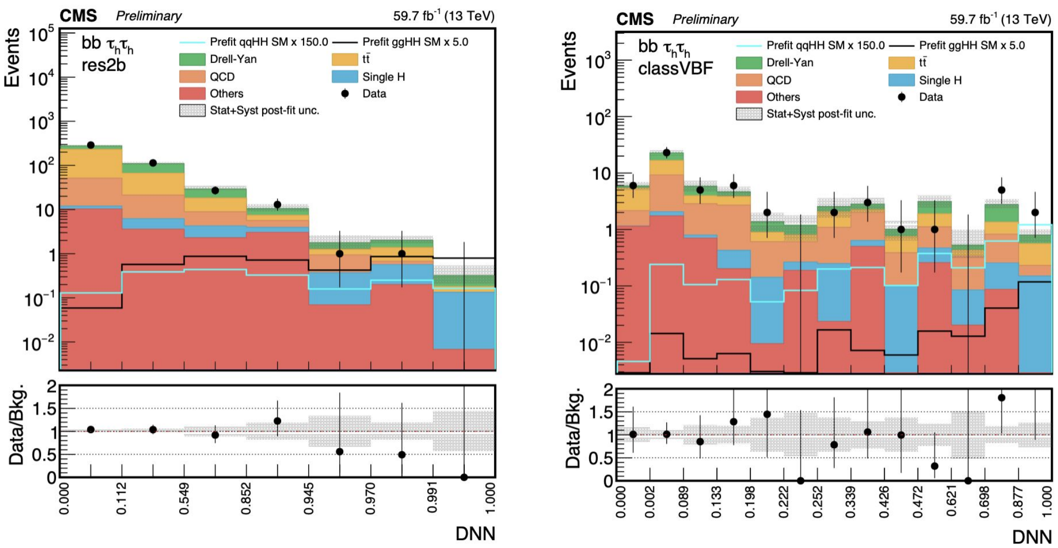
ATLAS Signal Extraction

- MVA trained in each category to separate SM signal and total background
- $\tau_{had}\tau_{had}$: boosted decision tree, $\tau_{lep}\tau_{had}$: neural network
- MVA output used as discriminant for fitting

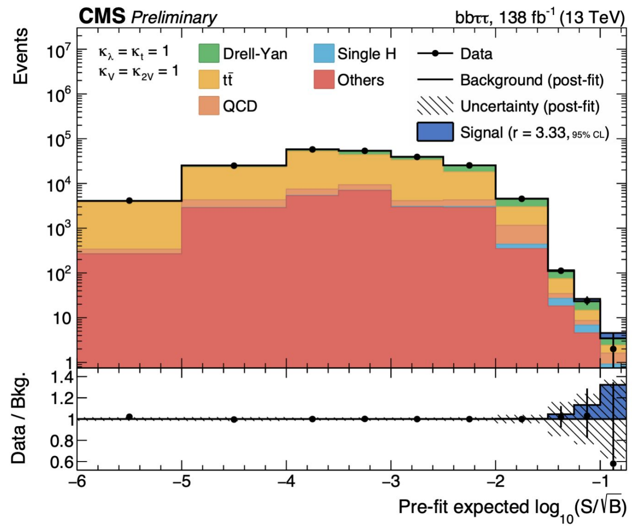


CMS: Signal Extraction

- DNN trained to separate SM non-resonant signal vs all backgrounds
  - All channels and categories are considered in the training together
  - “Categorical” feature used as input (year, category, channel…)
- Binned DNN score distribution used as final discriminant for signal extraction



DNN scores of the two most sensitive categories for the ggF (left) and VBF (right) searches



Cumulative Run 2 DNN score bins ordered by their pre-fit S/B ratio split into physics processes

Input Variables for Training

ATLAS EXPERIMENT

CMS

Variable	$\tau_{had}\tau_{had}$	$\tau_{lep}\tau_{had}$ SLT	$\tau_{lep}\tau_{had}$ LTT
m_{HH}	✓	✓	✓
$m_{\tau\tau}^{MMC}$	✓	✓	✓
m_{bb}	✓	✓	✓
$\Delta R(\tau, \tau)$	✓	✓	✓
$\Delta R(b, b)$	✓	✓	
$\Delta p_{T}(\ell, \tau)$		✓	✓
Sub-leading b-tagged jet p_{T}		✓	
m_{T}^{W}		✓	
E_{T}^{miss}		✓	
$\mathbf{p}_{T}^{miss}$ ϕ centrality		✓	
$\Delta\phi(\ell\tau, bb)$		✓	
$\Delta\phi(\ell, \mathbf{p}_{T}^{miss})$			✓
$\Delta\phi(\ell\tau, \mathbf{p}_{T}^{miss})$			✓
S_{T}			✓

Input Features	
Continuous	Categorical
b-tag score of 1^{st} b-jet	Event is *boosted* or not
m_{HH} kinematic fit	Presence of VBF-candidates
χ^2 kinematic fit	$\tau\tau$ decay mode
$m_{\tau\tau}^{SVfit}$	Highest b-tag WP of 1^{st} b-jet
$\Delta R(\tau,\tau) \cdot p_T(H_{\tau\tau}^{SVfit})$	Highest b-tag WP of 2^{nd} b-jet
$\Delta R(\tau,\tau)$	Year
m_T and p_T of both taus	
$\Delta\phi(H_{\tau\tau}^{SVfit}, MET)$	
m_{bb}	
$\Delta\phi(H_{\tau\tau}^{SVfit}, H_{bb})$	
$p_T(H_{bb})$	

Final continuous features selected from a starting pool of over a 100 features

Uncertainties

Uncertainty source	Non-resonant HH
Data statistical	81%
Systematic	59%
$t\bar{t}$ and Z + HF normalisations	4%
MC statistical	28%
Experimental	
Jet and $E_{\mathrm{T}}^{\mathrm{miss}}$	7%
b-jet tagging	3%
$\tau_{\text{had-vis}}$	5%
Electrons and muons	2%
Luminosity and pileup	3%
Theoretical and modelling	
Fake-$\tau_{\text{had-vis}}$	9%
Top-quark	24%
$Z(\rightarrow \tau\tau)$ + HF	9%
Single Higgs boson	29%
Other backgrounds	3%
Signal	5%

- Main sources of syst. unc.:
  - Theory uncertainty on ggF HH cross section:

    $^{+6\%}_{-23\%}(\text{scale} + m_t) \pm 3\,\%\,(\text{PDF} + \alpha_S)$
  - Statistical fluctuations affecting multijet bkg estimation
  - Uncertainties on mis-modeling of jet and tau ID and reco in simulation.
- Total effect of syst. unc. on final limit is ~15%

Upper limit on Cross Section

ATLAS-CONF-2021-030
(soon to be submitted to journal)

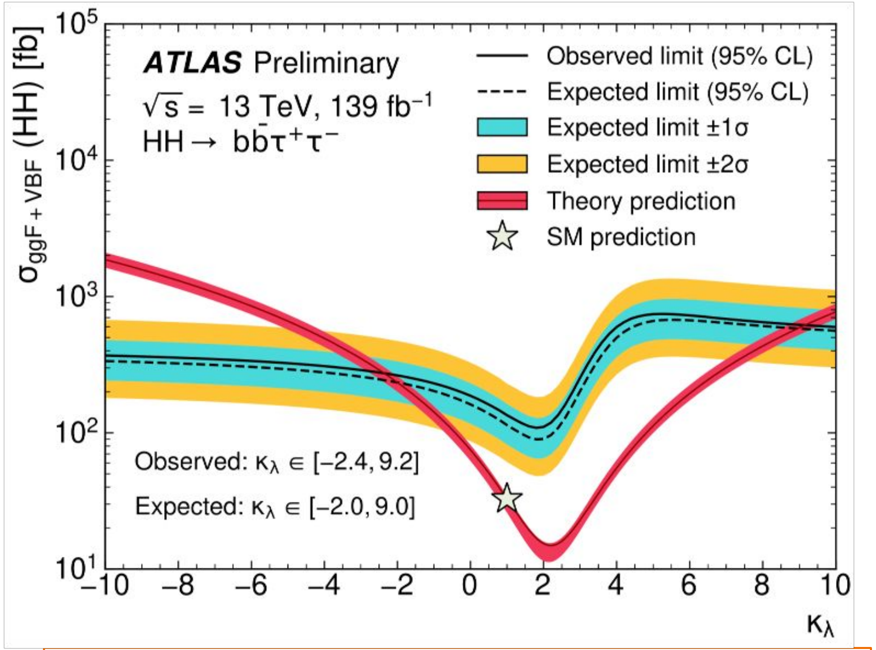
- Obs. (exp.) limit at 95% CL:
  4.7 (3.9) × σ_{SM}
  - 4x improvement over 36.1 fb^{-1} result (obs.: 12.7, exp.: 14.8)
- Around half of the gain from improved reconstruction and identification of τ_{had} and b-jets, as well as the MVA and fake strategy

CMS-PAS-HIG-20-010
(soon to be submitted to journal)

- Obs. (exp.) limit at 95% CL:
  3.3 (5.2) × σ_{SM}
  - 5x improvement over 35.9 fb^{-1} PLB publ. (obs.: 30, exp.: 25)
- Improvement mainly from:
  - Renewed trigger strategy
  - Large use of DNNs for:
    - Obj. reco and identification
    - Signal vs bkg. discrimination

Constraint on k_λ

ATLAS-CONF-2021-052

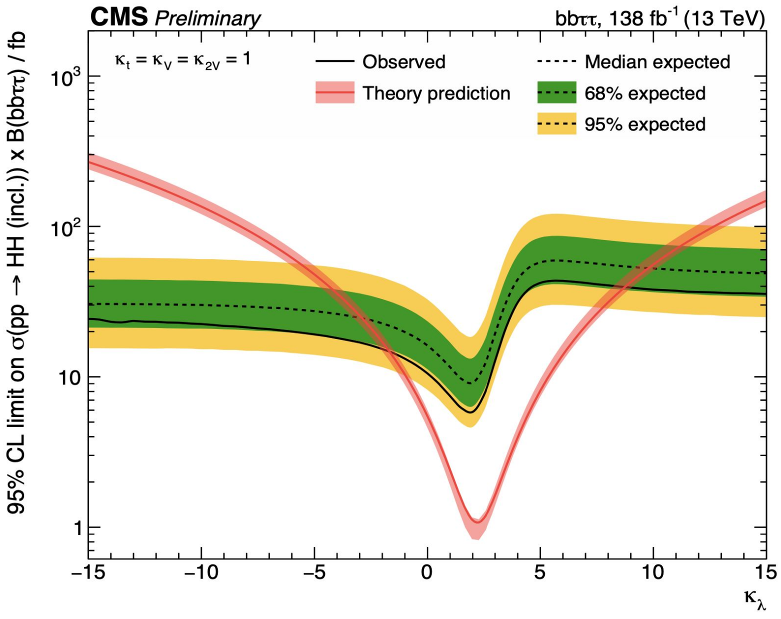


Obs. (exp.) constraint on κ_λ:

$-2.4 \leq \kappa_\lambda \leq 9.2$ ($-2.0 \leq \kappa_\lambda \leq 9.0$)

CMS-PAS-HIG-20-010

(soon to be submitted to journal)

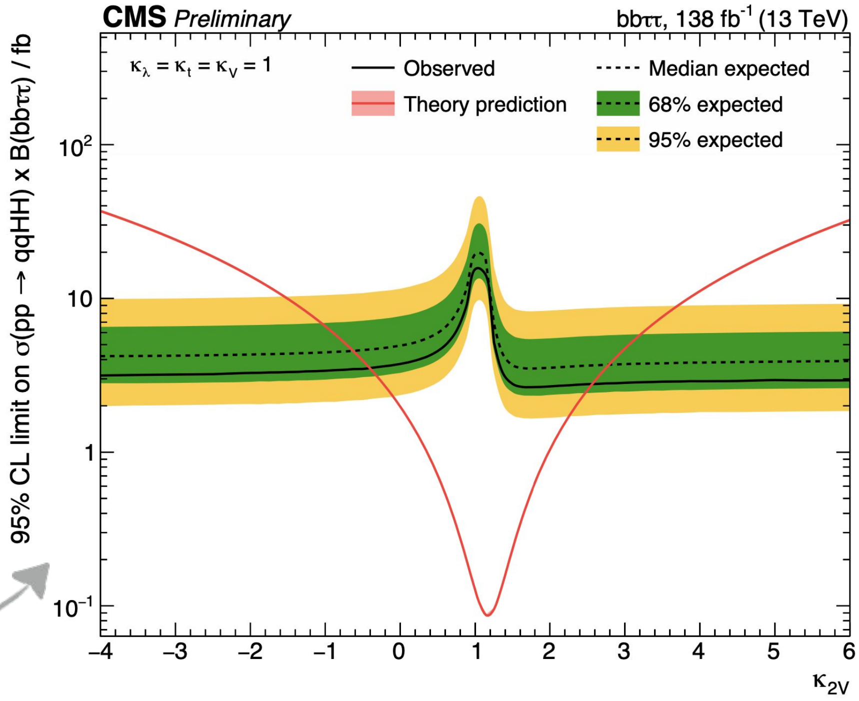


Obs. (exp.) constraint on κ_λ:

$-1.8 \leq \kappa_\lambda \leq 8.8$ ($-3.0 \leq \kappa_\lambda \leq 9.9$)

CMS: VBF HH Results

- Dedicated VBF HH analysis
  - Ad hoc triggers and categorization
- Obs. (exp.) limit at 95% CL:
  124 (154) × σ_{SM}^{VBF}
  - Most stringent limit 95% CL on *σ(pp→qqHH)* at the moment
- Obs. (exp.) constraint on κ_{2V}:
  $-0.4 \leq \kappa_{2V} \leq 2.6$ $(-0.6 \leq \kappa_{2V} \leq 2.8)$



Summary

The ATLAS and CMS HH→bb$\tau\tau$ non-resonant analyses with Run 2 data have been presented

- Main similarities
  - Trigger strategy based on lepton/tau-triggers
  - Signal extraction based on MVA methods (BDT, DNN)
- Main differences
  - Background estimation:
    ATLAS has dedicated jets→fake τ_{had} method
  - Event categorization:
    CMS has 3 channels ($\tau\tau$ DM) x 8 categories (jets) + dedicated VBF search
- Results
  - ATLAS and CMS sets comparable limits on inclusive HH production and κ_λ
    - ATLAS: 4.7 (3.9) × σ_{SM}, $-2.4 \leq \kappa_\lambda \leq 9.2$ ($-2.0 \leq \kappa_\lambda \leq 9.0$)
    - CMS : 3.3 (5.2) × σ_{SM}, $-1.8 \leq \kappa_\lambda \leq 8.8$ ($-3.0 \leq \kappa_\lambda \leq 9.9$)
  - CMS also sets limit on VBF HH production and κ_{2V}: 124 (154) × σ_{SM}^{VBF}
    ATLAS: new non-resonant analysis with optimization on $\kappa_\lambda/\kappa_{2V}$ using ggF/VBF is underway

Backup

ATLAS HL-LHC Projection

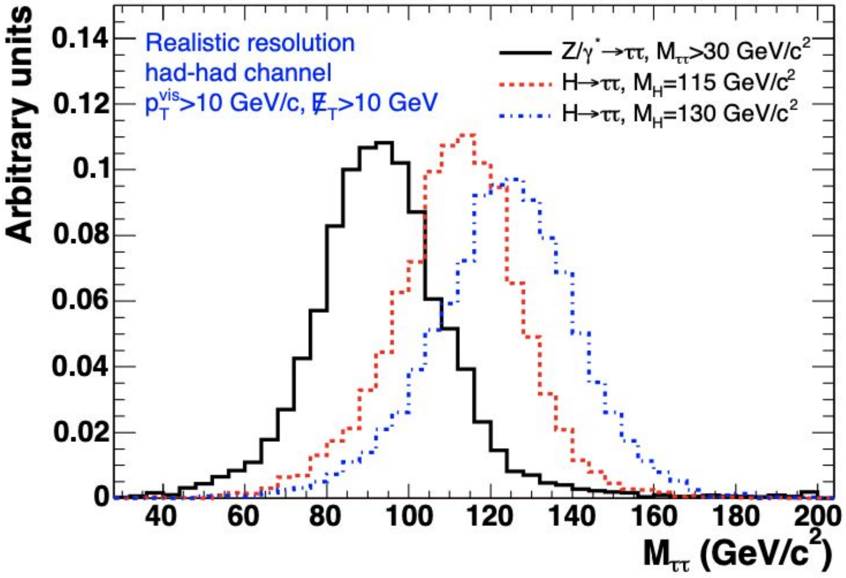
Uncertainty Scenario	95% CL Upper Limit	Significance [σ]	Signal Strength Precision
No syst. unc.	0.49	4.0	0.27
Baseline	0.71	2.8	0.39
Run 2 syst. unc.	1.37	1.5	0.69
MC stat. unc. neglected	0.99	2.2	0.51
Theoretical unc. halved	1.07	1.7	0.58

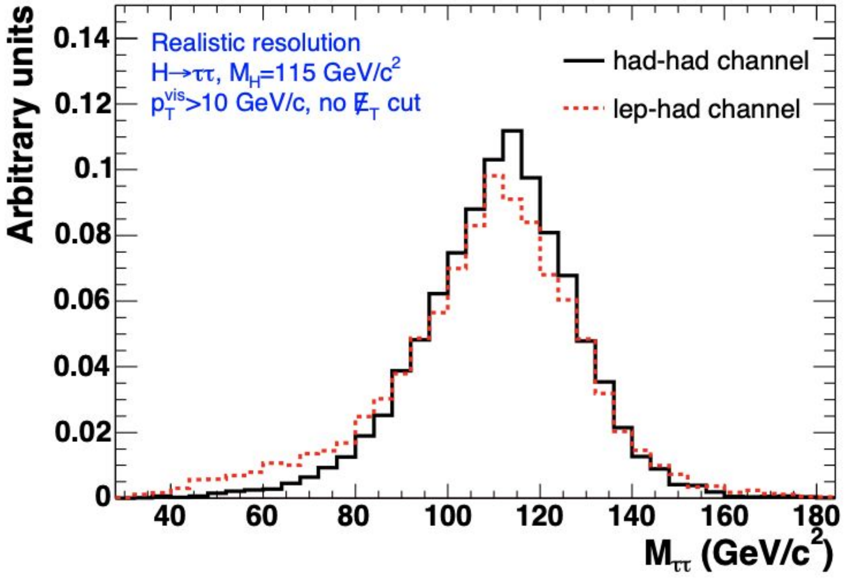
Uncertainty Scenario	Likelihood Scan 1σ CI	Likelihood Scan 2σ CI
No syst. unc.	$[0.5, 1.6]$	$[0.1, 2.5] \cup [4.5, 6.5]$
Baseline	$[0.3, 1.9] \cup [5.2, 6.7]$	$[-0.3, 7.4]$
Run 2 syst. unc.	$[-0.2, 7.3]$	$[-1.2, 8.3]$
MC stat. unc. neglected	$[0.0, 2.2] \cup [4.9, 7.1]$	$[-0.8, 8.0]$
Theoretical unc. halved	$[0.0, 2.9] \cup [4.2, 7.1]$	$[-0.8, 7.9]$

ATL-PHYS-PUB-2021-044

Missing Mass Calculator

- Allows for a complete reconstruction of event kinematics in $\tau\tau$ final state

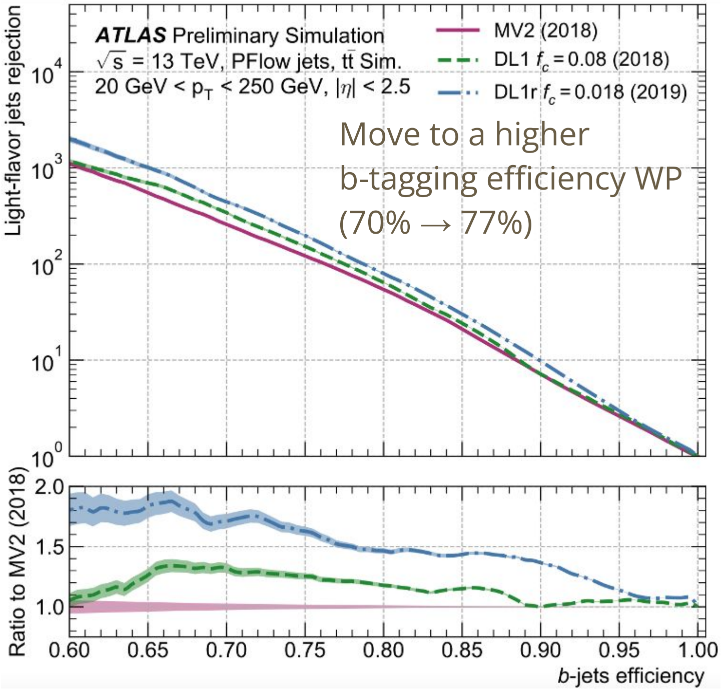


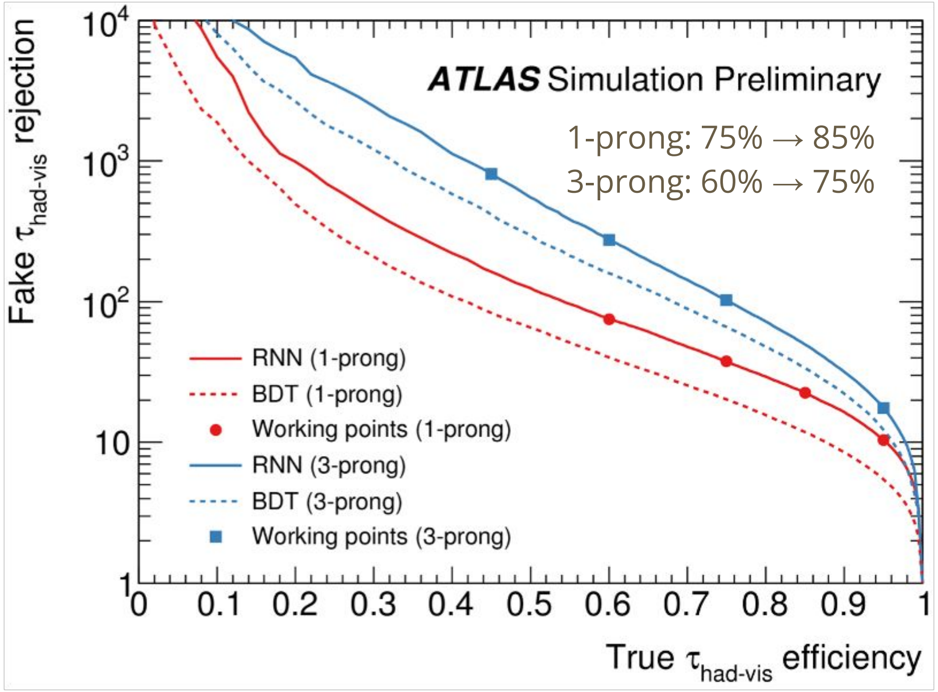


arXiv:1012.4686

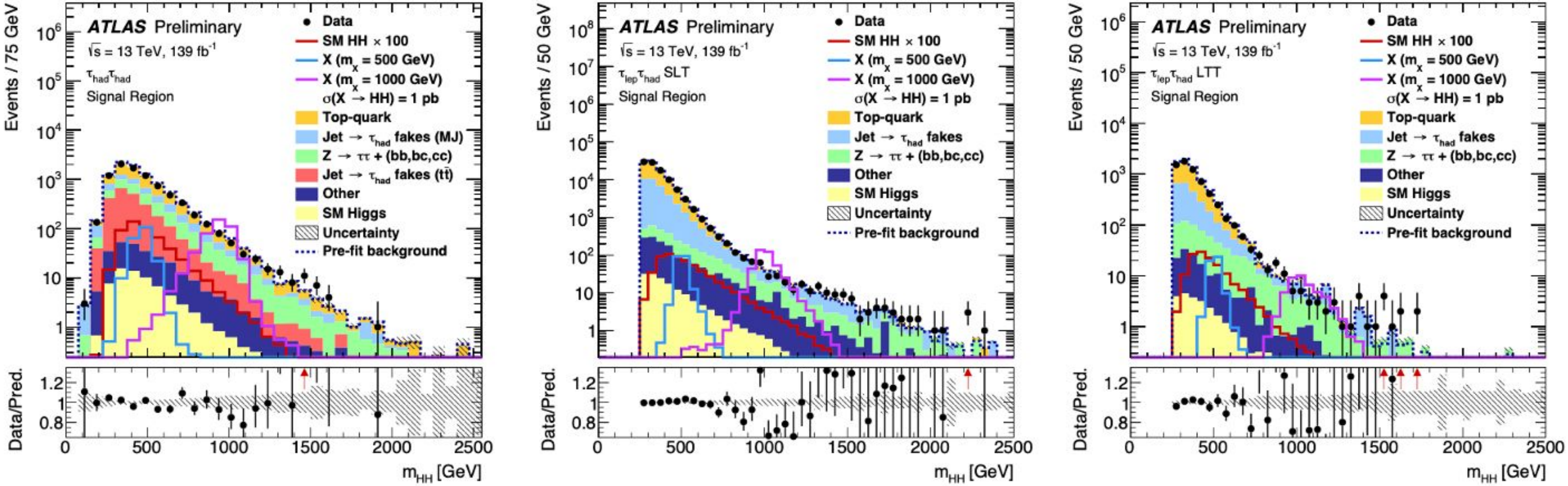
ATLAS Signal Acceptance × Efficiency

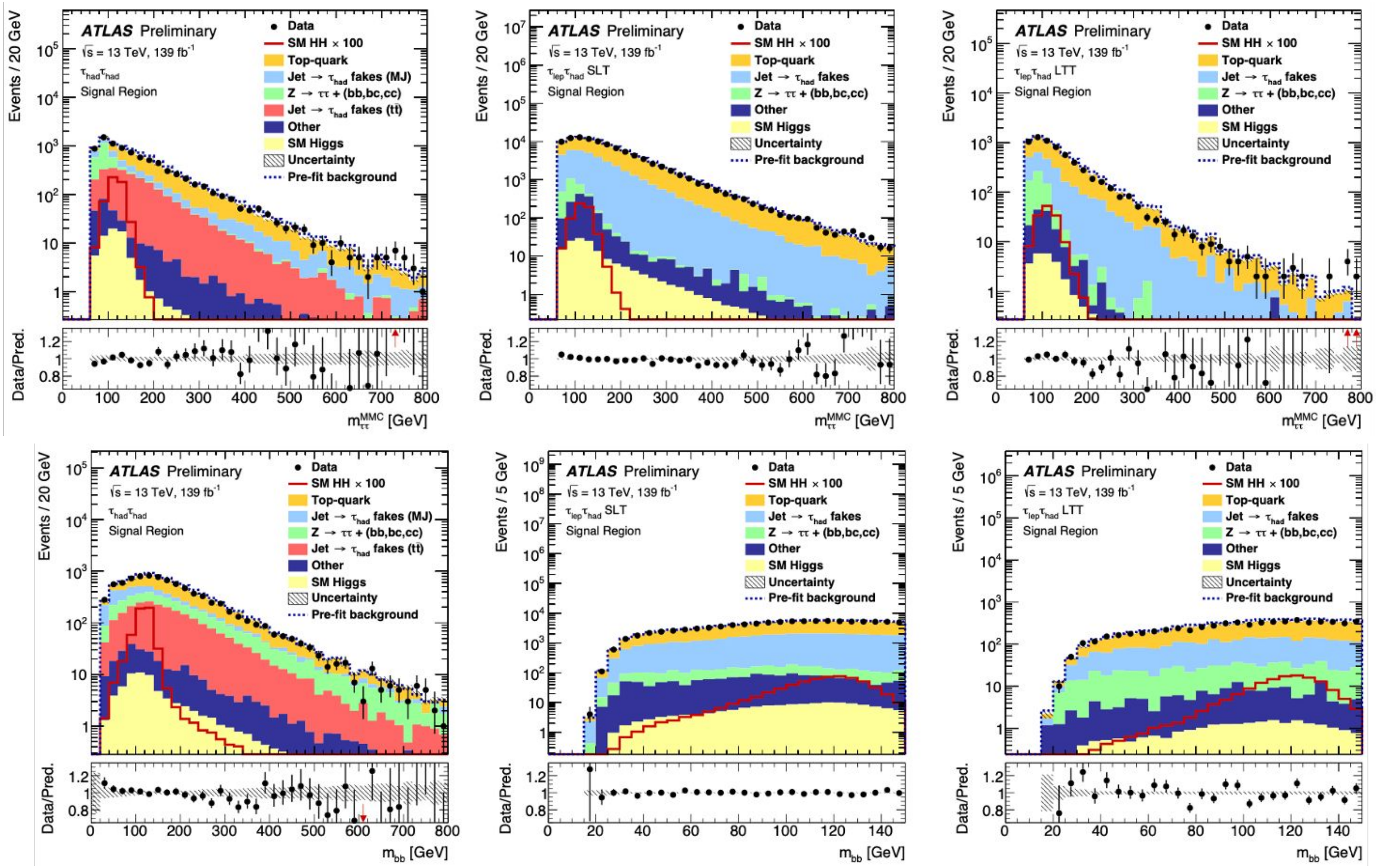
- The acceptance times efficiency for the non-resonant ggF+VBF evaluated w.r.t. targeted τ decay modes
- $\tau_{had}\tau_{had}$: 4.0%, $\tau_{lep}\tau_{had}$ SLT: 4.0%, $\tau_{lep}\tau_{had}$ LTT: 1.0%





mHH Distributions



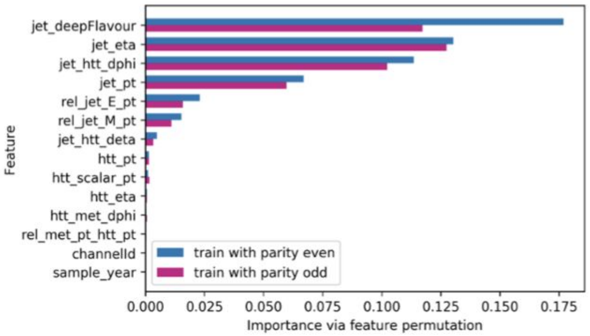

ATLAS Preliminary
√s = 13 TeV, 139 fb-1
τhadτhad
τlepτhad SLT
τlepτhad LTT
Signal Region
Data
SM HH × 100
Top-quark
Jet → τhad fakes (MJ)
Jet → τhad fakes
Z → ττ + (bb,bc,cc)
Jet → τhad fakes (tt̄)
Other
SM Higgs
Uncertainty
Pre-fit background
Events / 20 GeV
Events / 5 GeV
Data/Pred.
mττMMC [GeV]
mbb [GeV]

CMS: HH-bTag

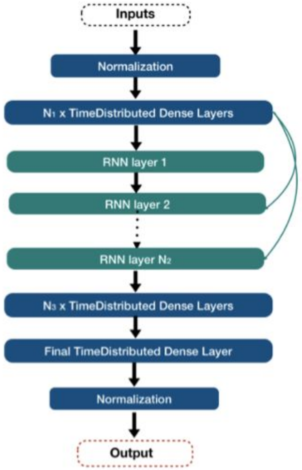
To **identify the b-jet pair** from $H \rightarrow bb$ for the $HH \rightarrow bb\tau\tau$ final state we use specially trained DNN (**HH-btag**)

- Using information about b tag quality as well as the kinematic of the event as NN inputs
- Generator level information is used as the ground truth
- The training and testing were done using all available nonresonant and resonant $HH \rightarrow bb\tau\tau$ Run 2 sample
- Recurrent NN assigns a score to each jet in the event
- Bayesian optimization to chose best NN hyperparameters

NN input features ranked by importance



NN architecture

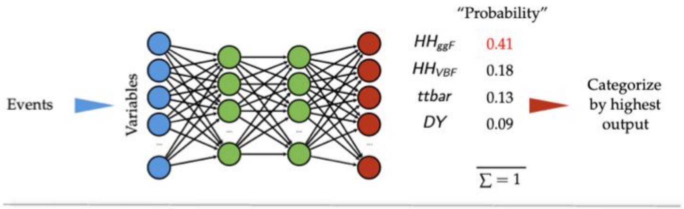


Final NN parameters:
5 LSTM layers (75 units/layer)
13 dense layers (15 units/layer)
Trainable params $\approx 225k$

CMS: multi-classification DNN

- We define **5 VBF categories** associated to the relevant **physics processes**
  - see slide 13
- Each event is assigned a probability estimate to belong to categories using **multi-class DNN**

Concept of the DNN-based event categorization



DNN architecture