CMS HL-LHC PROJECTION FOR NON-RESONANT DI-HIGGS PRODUCTION IN THE $b\bar{b}\tau\bar{\tau}$ DECAY CHANNEL

A summary of the analysis documented in CMS-PAS-FTR-18-019 [1], performed on behalf of the CMS Collaboration by:

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I—INTRODUCTION

- One parameter of the Higgs boson which we have yet to measure is the strength at which the Higgs boson couples to itself, λ_{hhh}
- Precise measurements of the Higgs self-coupling are most easily performed using events in which two Higgs boson are produced
- The tiny cross-sections for such events mean that only the HL-LHC and beyond will be capable of detecting a statistically significant number of them
- In this analysis we performed a projection of the sensitivity of the HL-LHC to di-Higgs production using decays to $bb\tau\tau$, a channel which offers
  - The high branching ratio of $h\rightarrow bb$ (58.24%)
  - The QCD-suppressing source of light leptons of $h\rightarrow\tau\tau$ (BR = 6.23%)
- The results of this analysis are then combined with orthogonal analyses for other di-Higgs decay channels

II—DATA & SELECTION

- 14 *TeV* signal and background Monte Carlo samples are generated
  - Signal production cross-section = 36.69 *fb* x $\mathrm{BR}_{bb\tau\tau}$ [2]
- Delphes [3] detector simulation is used to reconstruct objects, using dedicated tagging efficiencies
  - *b*-tagging assumes the MIP timing detector exists
  - τ-tagging assumes an MVA-based discriminator
- Object selection assumes an L1 trigger menu with similar thresholds to those of Run-II
- Kinematic selection follows the Run-II analysis [4] with the exception that no cuts are applied to the masses of the Higgs bosons
- We select events into one of three exclusive categories according to the $\tau\tau$ decay channel:

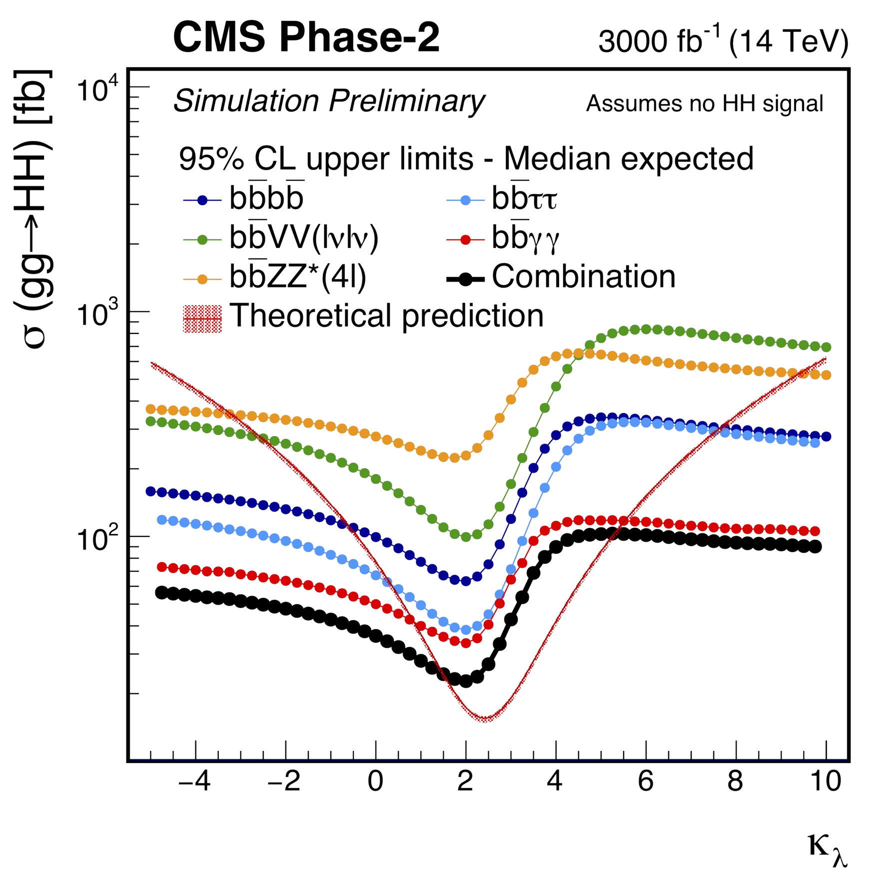
Channel	# events events @$\mathscr{L}_{\mathrm{int.}}$ = 3000 fb^{-1}	
	Signal	Background
$\mu\tau_h$	100	4.3×10^6
$e\tau_h$	70	2.9×10^6
$\tau_h\tau_h$	60	1.3×10^5

III—DNN DEVELOPMENT

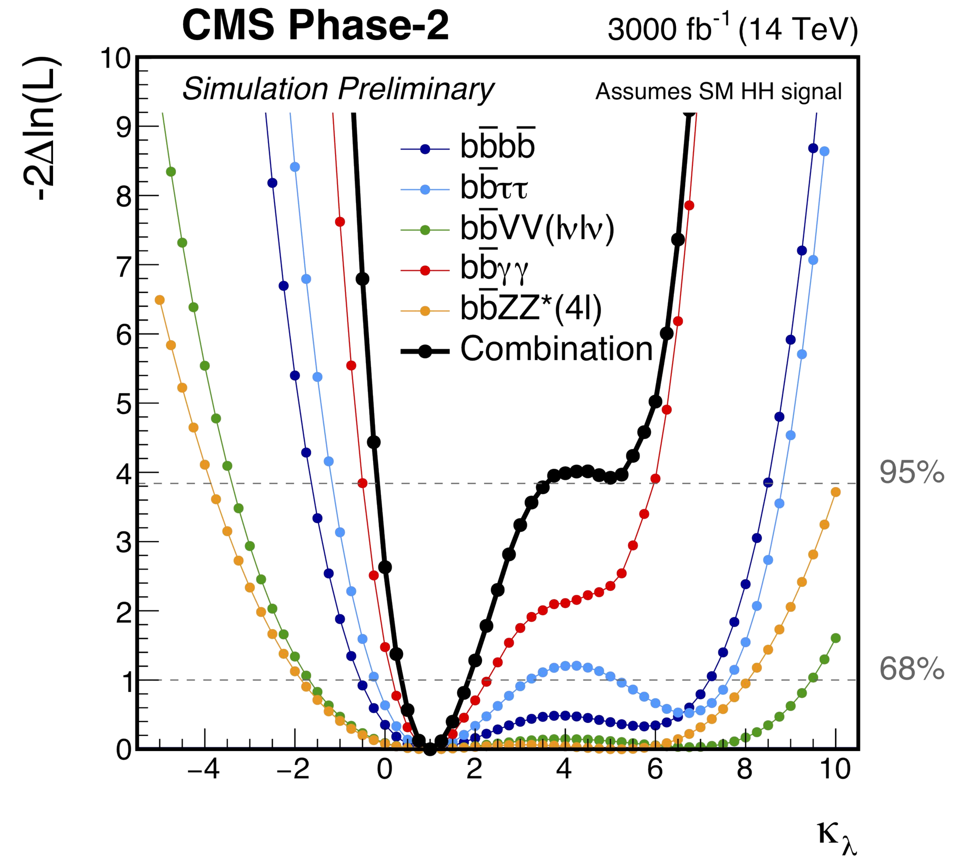
- The dataset of simulated signal and background events was divided into two equally sized subsamples
  - A pair of discriminators are trained, one on each half of the data
  - A total of 52 input variables were used, split into :
    - *basic* (27), e.g. final state 4-momenta and p_T^{Miss}
    - *high-level-reconstructed* (21), e.g. Higgs 4-momenta
    - *high-level-global* (4), e.g. s_T and jet multiplicity
- The final architecture consists of a pair of weighted ensembles of 10 fully-connected Deep Neural Networks (DNN), each with:
  - 3 hidden layers of 100 neurons
  - SELU activation functions [5]
  - NADAM optimisation [6]
  - Single sigmoid output - signal or background
- Models are trained via cross-validation
  - An Initial pre-training is run without sample weights
  - The main training phase with sample weights is then performed
  - The learning-rate follows a cosine cycle with warm restarts [7]
  - Data augmentation is applied to events during training and inference, consisting of
    - rotations over the azimuthal angle, ϕ
    - *x*- and *y*-axis reflections
- Implemented in Keras [8] with Tensorflow backend [9]

IV—RESULTS

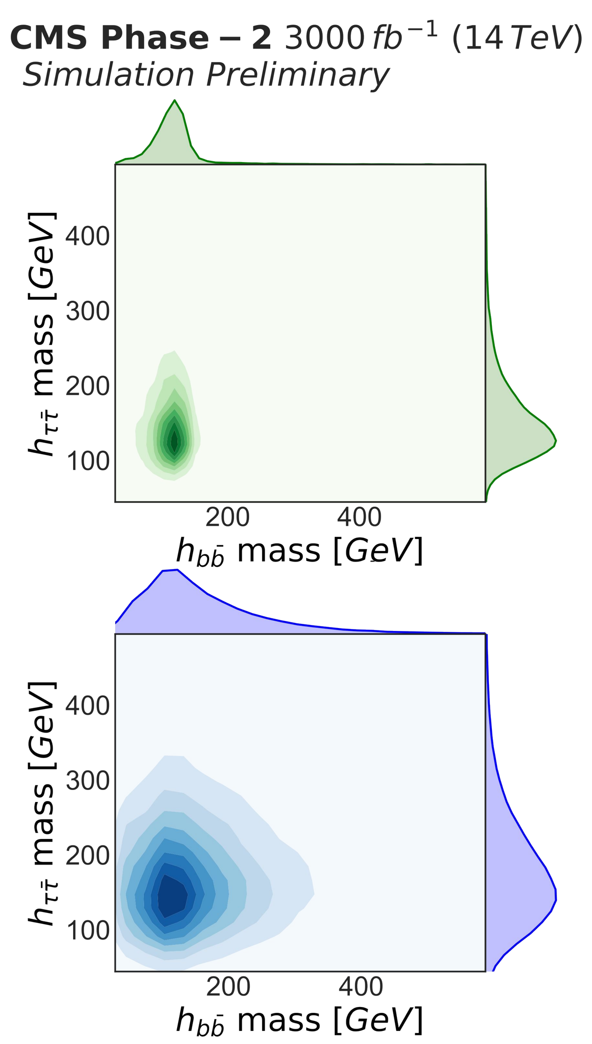
- The class prediction per event of the DNN ensembles is used as a summary statistic of the data
  - The distributions of class prediction in each of the three channels are binned as histograms
  - A shape analysis is performed using all three channels simultaneously
  - Expected systematic uncertainties are accounted for during the fit
- For standard model coupling we expect a signal significance of 1.4 (1.6) σ with(out) systematic uncertainties
- In absence of standard model non resonant production, this would correspond to 95% CL cross-section upper limits of 1.4 (1.3) times the standard model cross-section with(out) systematic uncertainties
- We then extend these results for a range of κ_λ by reweighting the signal events to match different coupling values

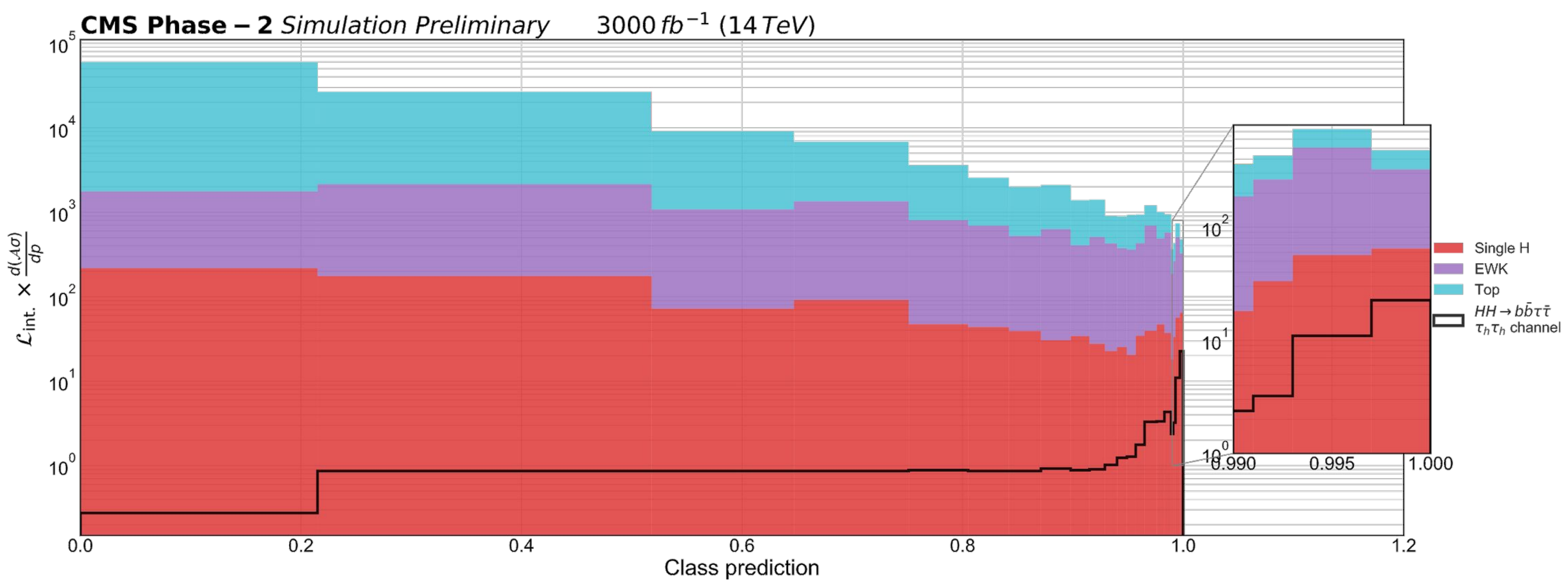


κ_λ scan for the expected median cross-section upper limits for di-Higgs production at 95% confidence



Negative log-likelihood for κ_λ assuming standard model di-Higgs production





Left: 2D Higgs mass distributions for signal (top) and background (bottom)
Above: Example prediction distribution shown for events in the $bb\tau_h\tau_h$ channel

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