

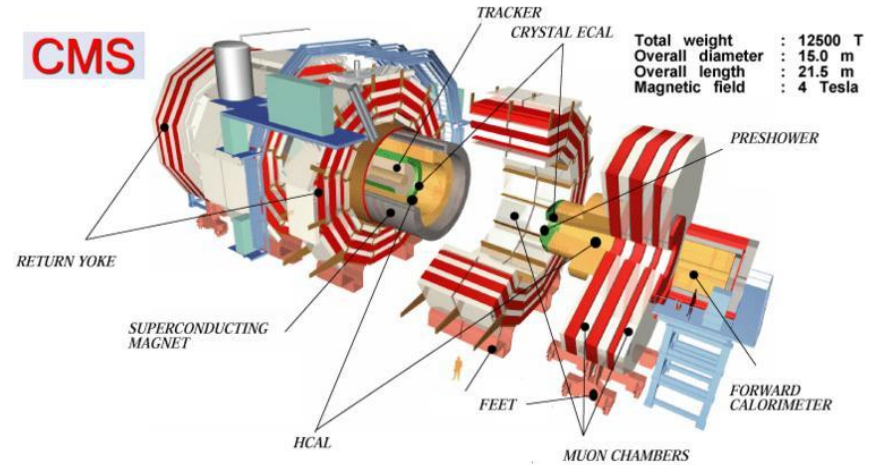
Search for the decay of a heavy Higgs boson into two lighter Higgs bosons of different mass in final states with b quarks and tau leptons at the LHC

23.05.22

In this talk...

A beyond-Standard-Model search for additional Higgs bosons:

- Inspired by the next-to-minimal supersymmetric Standard Model (NMSSM)
- Majority of background estimation from data
- Multiclassification using a neural net
- Statistical inference to set upper exclusion limits on the signal cross section \times BR



Why search for BSM physics?

The Standard Model (SM) provides our current best description of fundamental particles

However: SM has experimental and theoretical shortcomings (e.g. Gravitation, Dark Matter) → search for SM extension or new fundamental theory

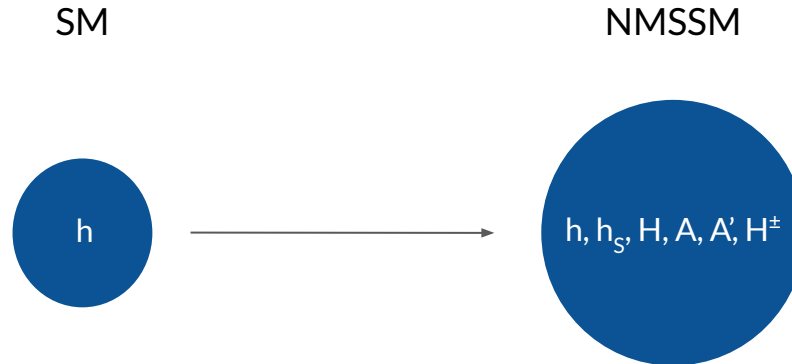
Supersymmetric theories:

- Class of SM extensions
- Imposes additional symmetry on SM → new particles
- Can be parametrised in many ways e.g. the next-to-minimal supersymmetric Standard Model (**NMSSM**)

The NMSSM Higgs Sector (1)

Next-to-minimal realisation of supersymmetry. Extends the SM Higgs sector with an additional SU(2) doublet + singlet

→ **NMSSM Higgs Sector contains 7 Higgs boson with rich phenomenology**



The NMSSM Higgs Sector (2)

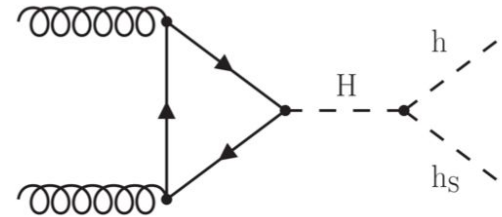
Next-to-minimal realisation of supersymmetry. Extends the SM Higgs sector with an additional SU(2) doublet + singlet

→ **NMSSM Higgs Sector contains 7 Higgs boson with rich phenomenology**

We consider the 3 scalars in this analysis:

- Consider h to have properties of previously discovered Higgs boson
- h_s is considered 'light', H is considered 'heavy'
- $m(h_s)$ and $m(H)$ are free parameters

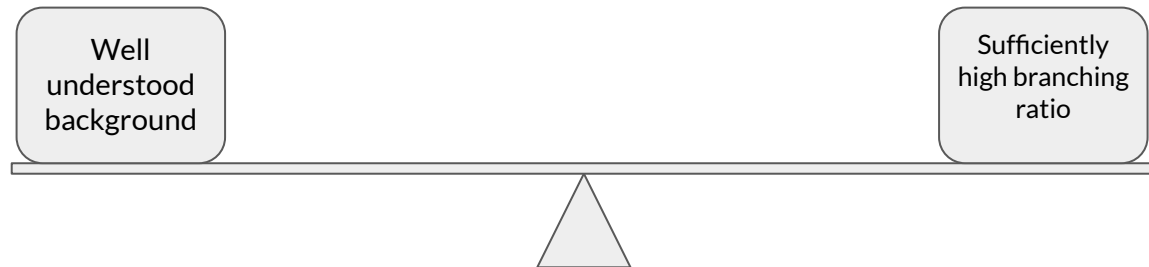
Scalars: h, h_s, H
Pseudoscalars: A, A'
Charged: H^\pm



$H \rightarrow hh_s$ final states with b quarks and tau leptons (1)

We target final states with a b quark and tau lepton pair (i.e. $H \rightarrow hh_s \rightarrow b\bar{b}\tau\tau$).

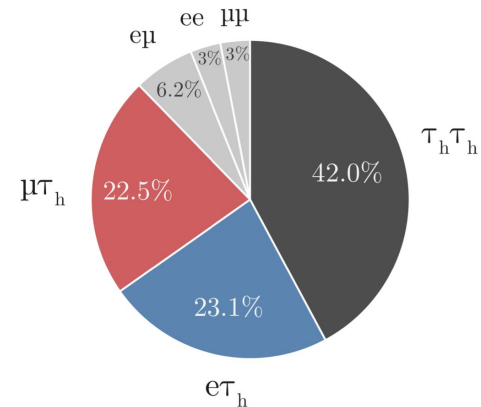
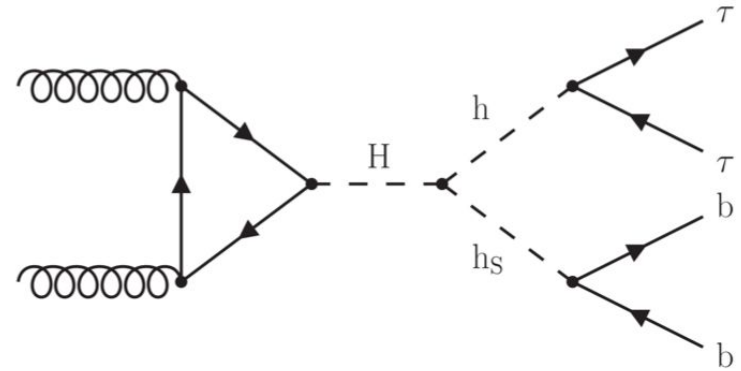
- Decays to b quarks (which hadronise to form b-jets):
 - (+) **high branching ratio**
 - (-) less well understood background
- The τ leptons are identified via their decay products (e, μ , hadrons):
 - (+) **well understood background**
 - (-) lower branching ratio



$H \rightarrow hh_s$ final states with b quarks and tau leptons (2)

An analysis targeting $H \rightarrow h(\tau\tau)h_s(bb)$ was published in 2021 by the CMS collaboration [1]:

- Considered to full CMS Run-2 data (2016 + 2017 + 2018 data taking periods)
- Targets 3 most common τ -pair decay modes



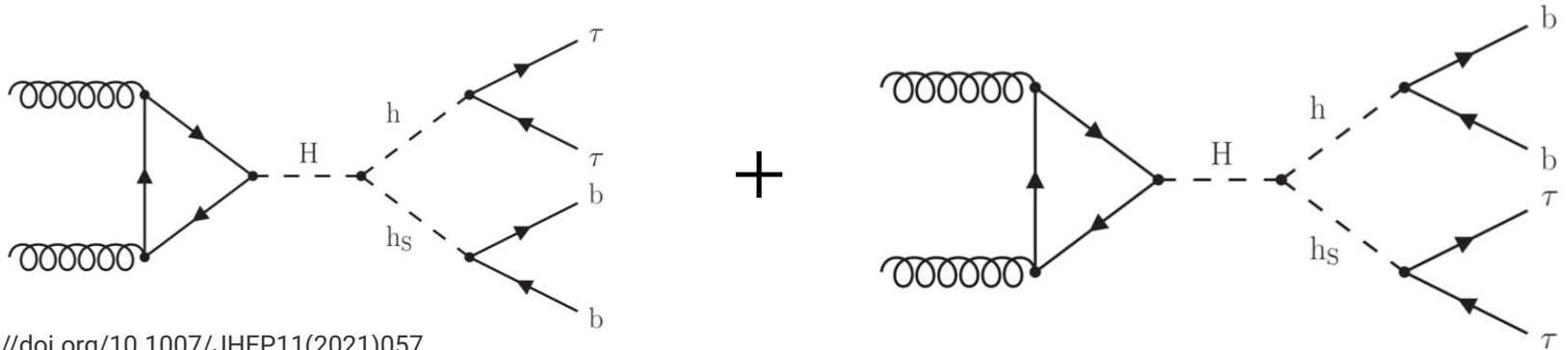
[1] [https://doi.org/10.1007/JHEP11\(2021\)057](https://doi.org/10.1007/JHEP11(2021)057)

$H \rightarrow hh_s$ final states with b quarks and tau leptons (3)

This analysis is a proof of concept to extend [1] with the $H \rightarrow h(bb)h_s(\tau\tau)$ final state.

A number of simplifications w.r.t original analysis are made:

- Only consider 2018 period
- Only consider $\tau_h\tau_h$ decay mode

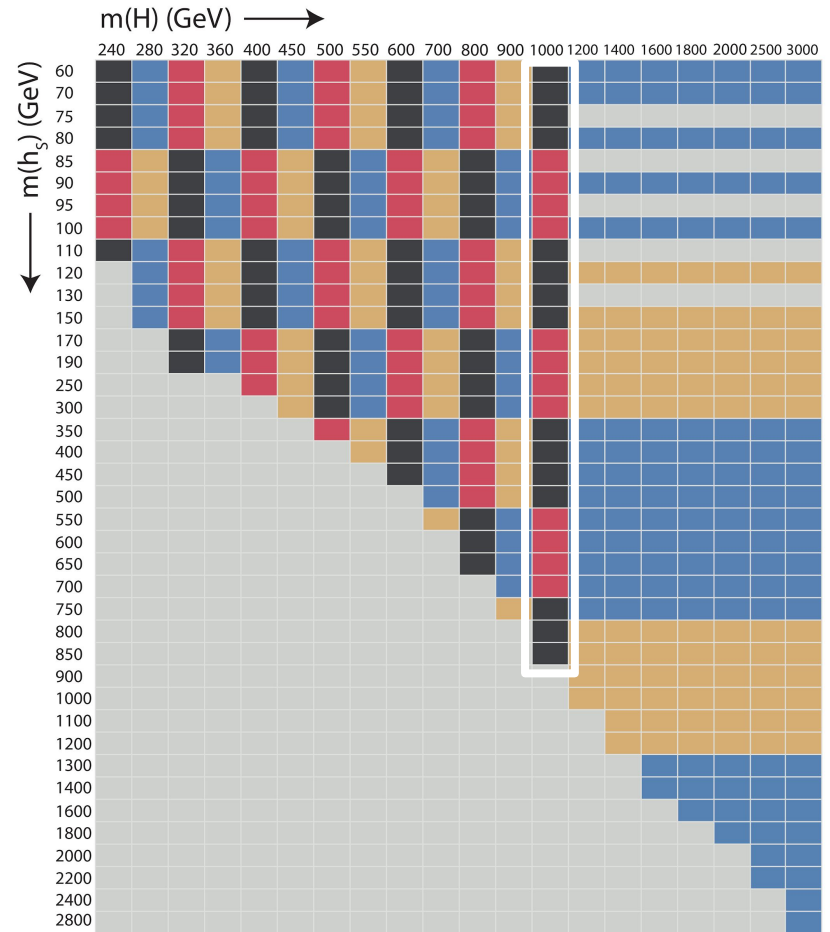


[1] [https://doi.org/10.1007/JHEP11\(2021\)057](https://doi.org/10.1007/JHEP11(2021)057)

Signal Simulation

$H \rightarrow h(bb)h_s(\tau\tau) / h(\tau\tau)h_s(bb)$ samples
have been privately produced:

- MadGraph5_aMC@NLO
- 27 mass combinations with $m(H) = 1000$ GeV and $m(h_s) = [60, 850]$ GeV were produced (on-shell)
- 200,000 events for each mass point
- Production required $\sim 100,000$ CPU hours (local resources, NEMO)



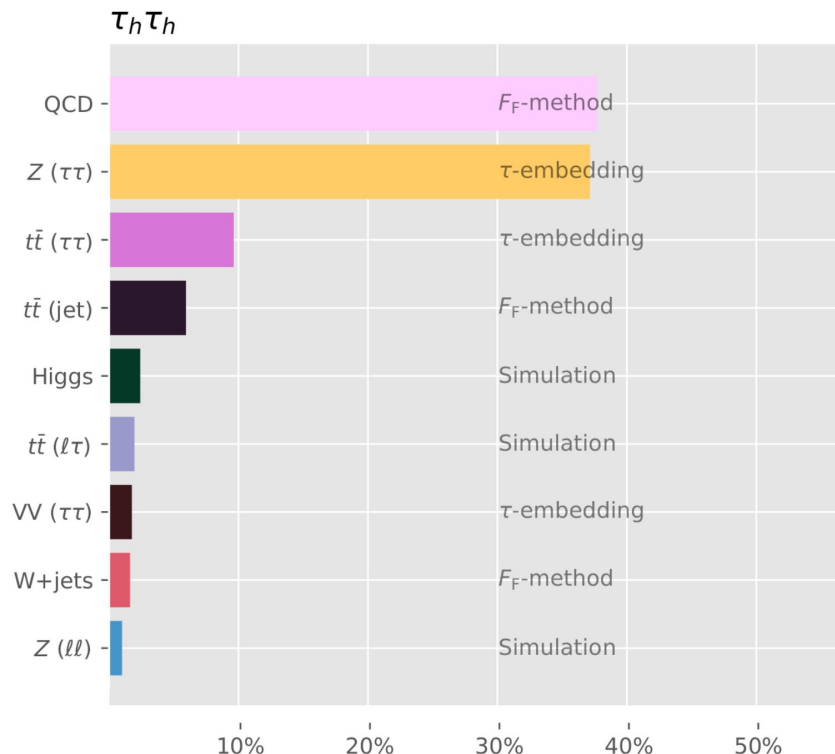
Background Estimation (1)

Processes that produce

- A genuine or 'fake' tau lepton pair
- A genuine or 'fake' b-Jet pair

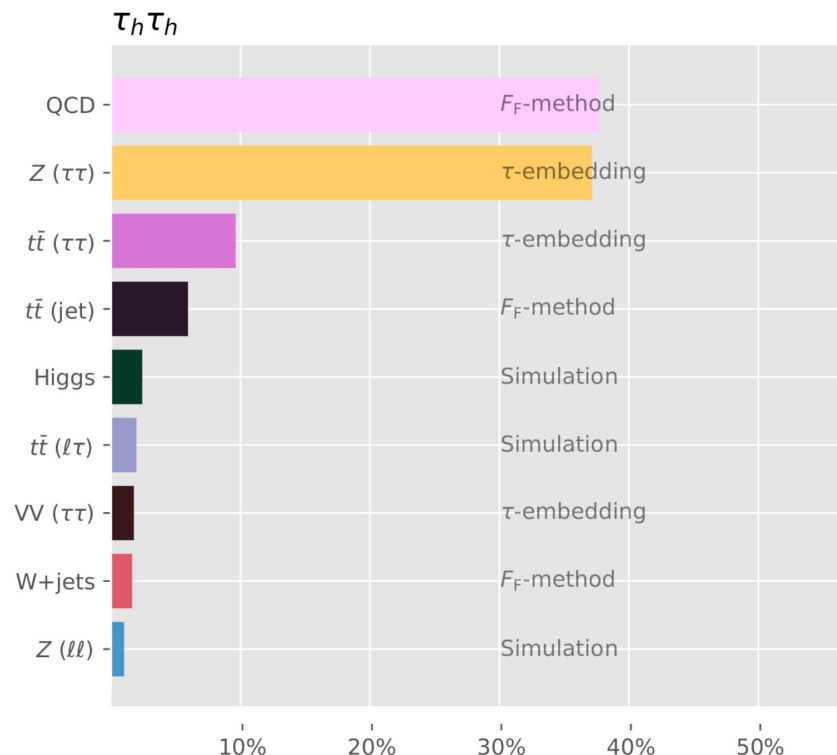
Most prominent in $\tau_h \tau_h$ channel:

- QCD multijet production
- $Z \rightarrow \tau\tau$



Background Estimation (2)

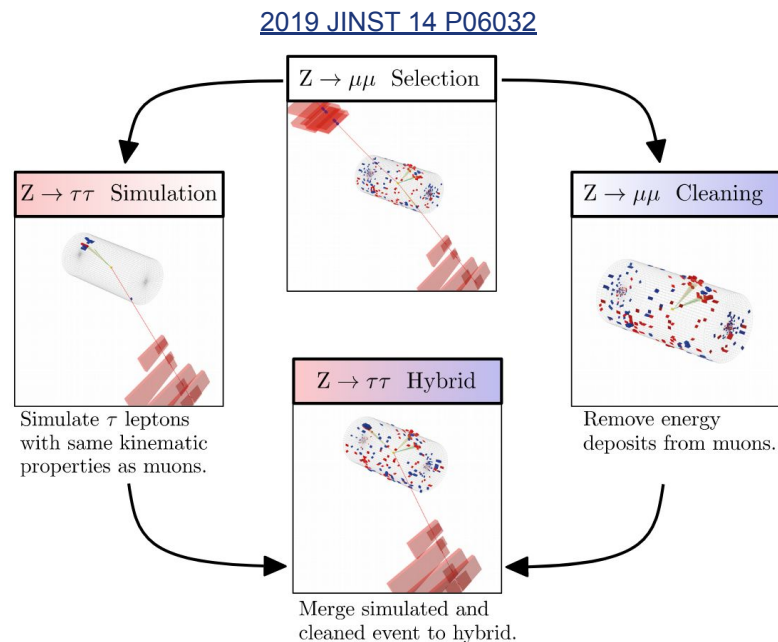
1. **τ -embedding** for all events with two genuine tau leptons
2. **F_F method** for events entering the analysis due to misidentified quark/gluon induced jets
3. **Monte Carlo (MC) simulation** for SM $h \rightarrow \tau\tau$ events + misc.



Background Estimation: Tau-Embedding

Used to model background processes with genuine τ -pairs:

1. Selecting $\mu\mu$ events from data
2. Remove muon energy deposits
3. Simulate τ -leptons in place of muons
4. Merge simulation with original event



Reduced associated uncertainties vs full MC estimation

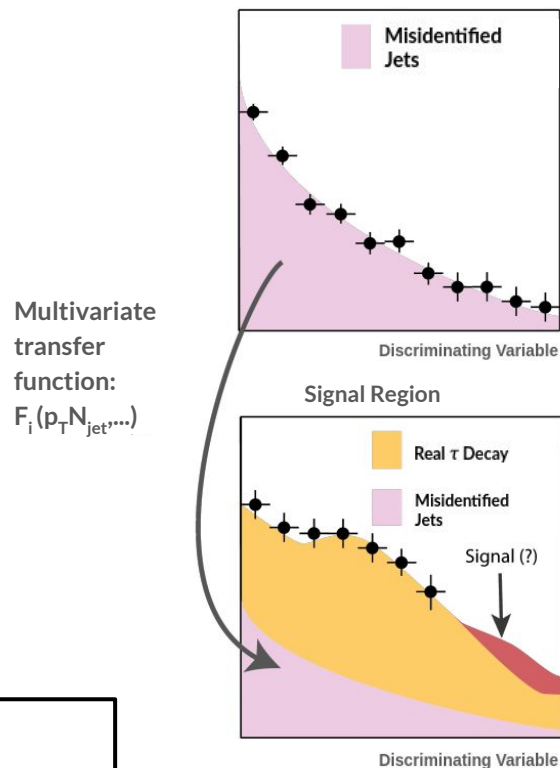
Background Estimation: F_F Method

Used to model jets incorrectly identified as τ_h :

1. Bckgd. processes are selected by process specific properties e.g.:
 - QCD: same sign
 - tt : additional leptons
2. Define sideband region enriched in misidentified jets
3. Calculate multivariate transfer function F_i
→ apply to sideband region

No MC corrections needed in estimating signal region

Sideband region: e.g. same sign QCD taus



Background Estimation: Simulation

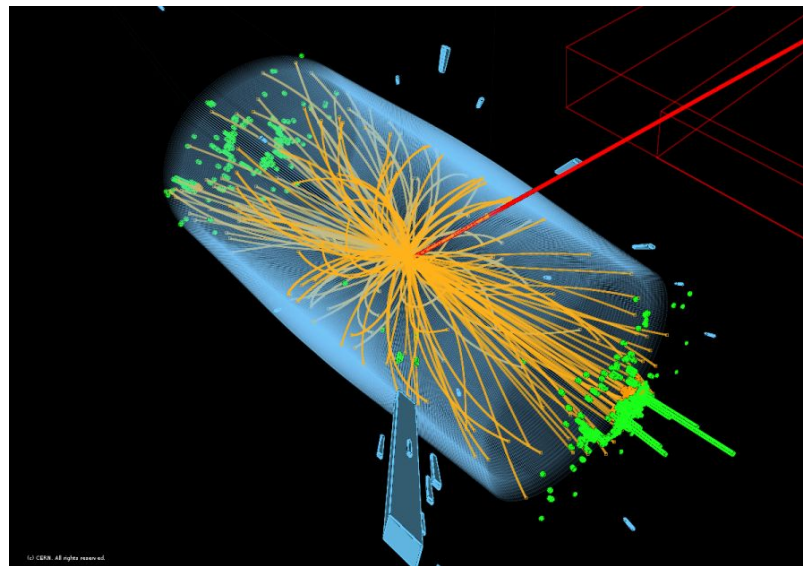
Used to estimate a number of minor backgrounds e.g.:

- SM $h \rightarrow \tau\tau$
- $Z \rightarrow ee, Z \rightarrow \mu\mu$
- $tt(l\tau)$

Events are weighted with a factor

$$\beta = L_{\text{int}} \cdot \sigma \cdot \frac{1}{N_{\text{sim}}}$$

- L_{int} : Integrated luminosity
- σ : process cross section
- N_{sim} : # of sim. events



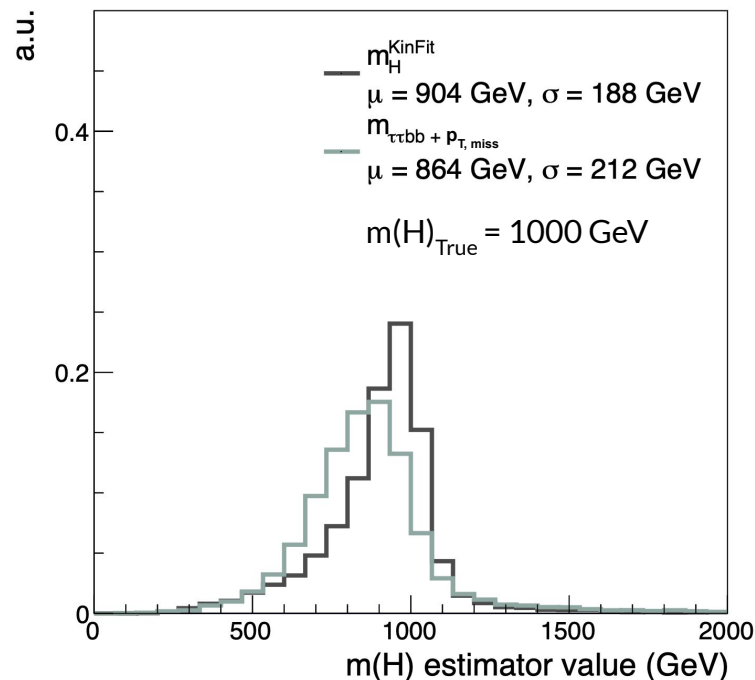
Kinematic Fit of $bb + \tau\tau$ Mass (1)

χ^2 estimate of the mass of the $bb\tau\tau$ -system:

- Minimise χ^2 for range of $m(h_s)$ hypotheses ([30 GeV, 3000 GeV])
- Fit with lowest minimal χ^2 value is chosen
- Output: $m(H)$ estimator, $m(h_s)$, χ^2 value of fit
- Improves resolution of the reconstructed mass $m_{bb\tau\tau}$

$$\chi^2 = \chi_{b_1}^2 + \chi_{b_2}^2 + \chi_{\text{recoil}}^2$$

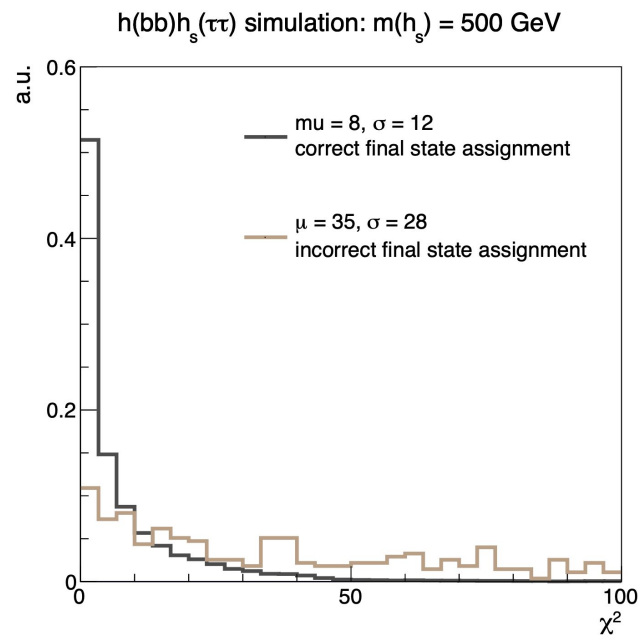
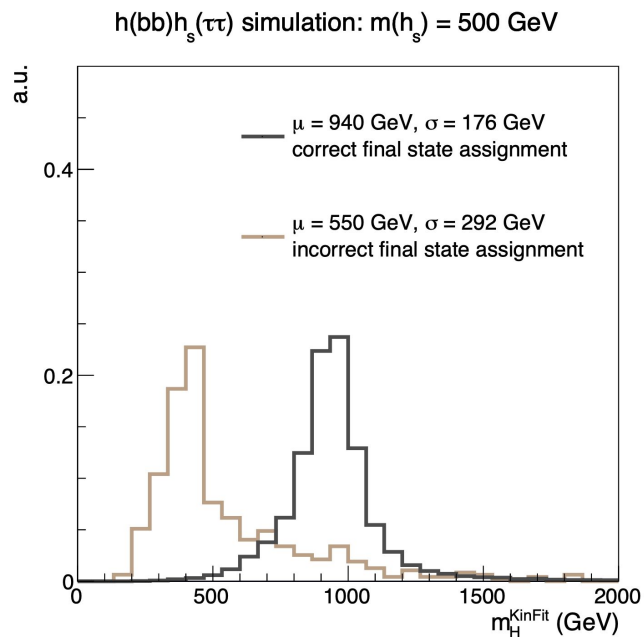
$h(\tau\tau)h_s(bb)$ simulation: $m(h_s) = 500$ GeV



CMS Simulation: Work in Progress

Kinematic Fit of $bb + \tau\tau$ Mass (2)

Fit performed once for each signal final state, outputs of both are saved

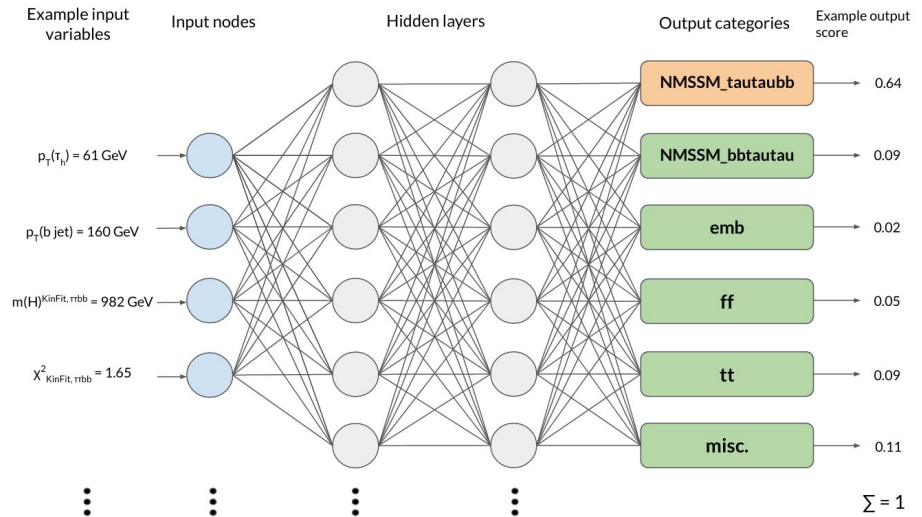


CMS Simulation: Work in Progress

Event Classification (1)

Multiclass classification based on **Neural Net (NN)** with 4 background categories and 2 signal categories:

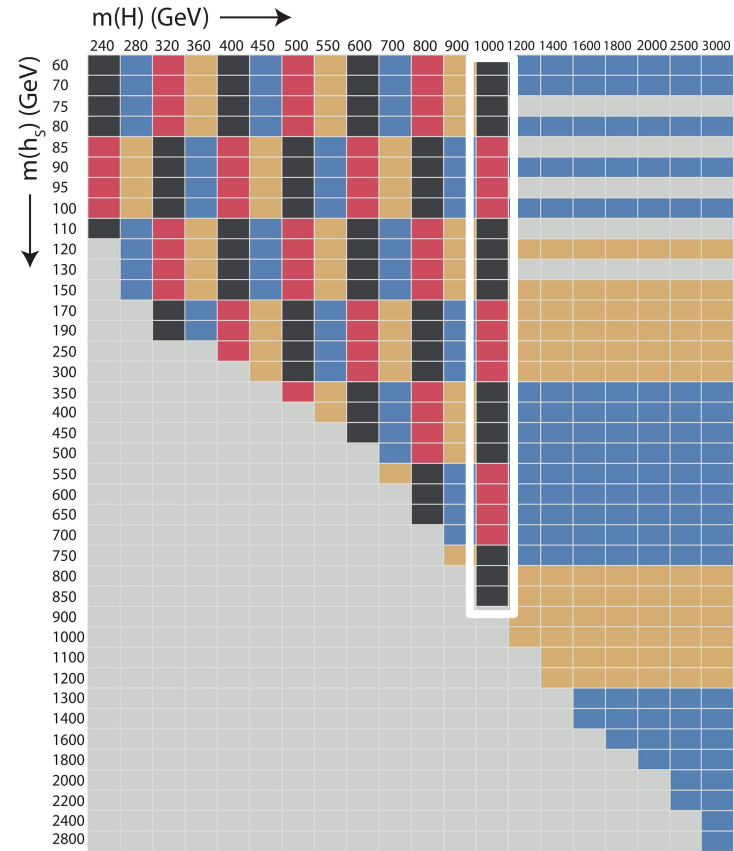
- 28 Input features
- NN returns a probability-like score for each category. The event is assigned to category with highest score with value NN_{\max}



Event Classification (1)

Multiclass classification based on **Neural Net (NN)** with 4 background categories and 2 signal categories:

- 28 Input features
- NN returns a probability-like score for each category. The event is assigned to category with highest score with value NN_{\max}
- 7 NNs are trained for 7 different mass groupings

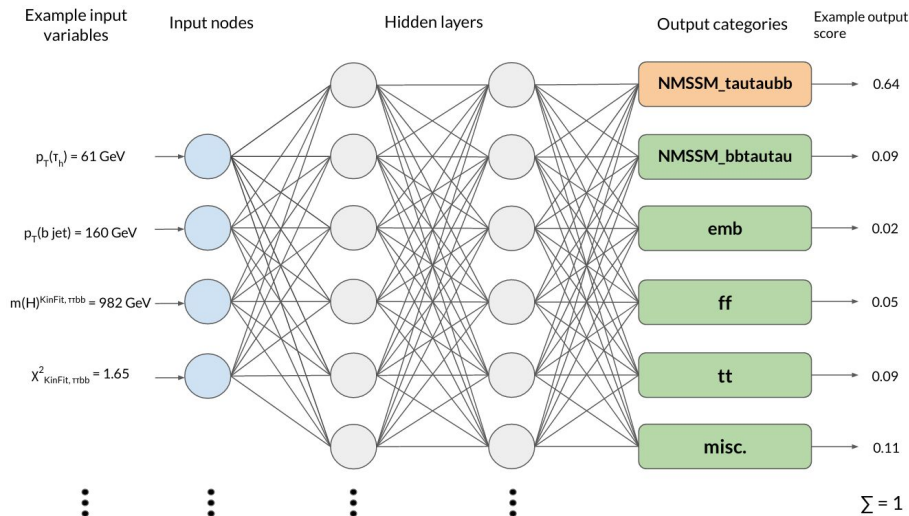


Event Classification (2)

NN features:

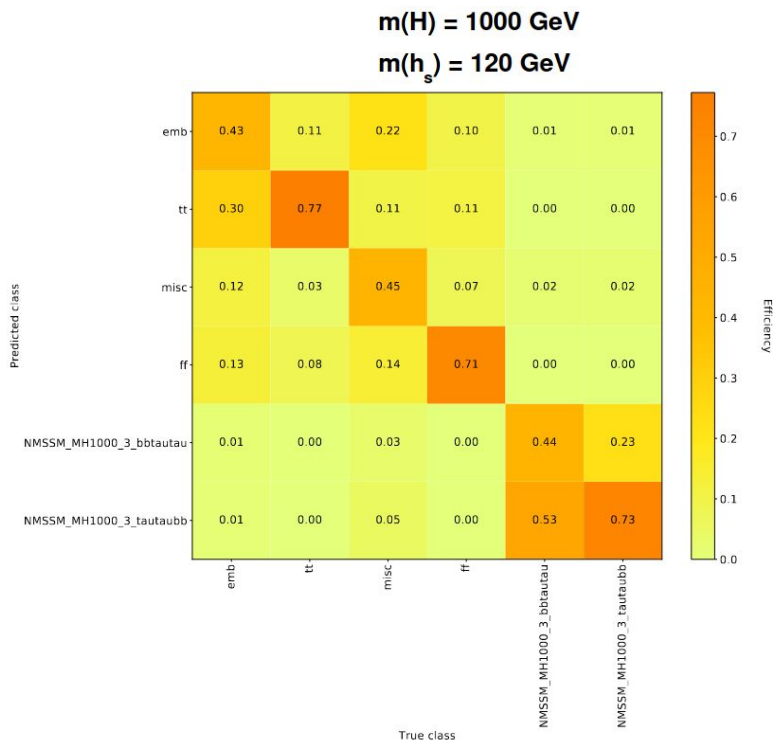
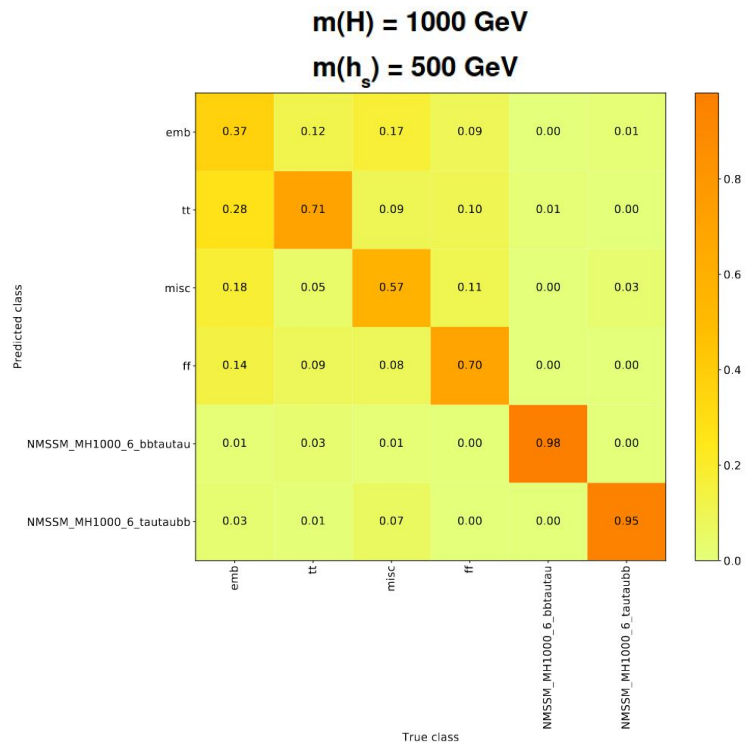
- Fully connected feed-forward network
- 2 hidden layers with 200 nodes
- Minimise the empirical risk function (*balanced batches, $N = 600$*)

$$R_{\text{emp}} = - \sum_{j=1}^N w^j \sum_{i=1}^C t_i^j \cdot \log(y_i^j)$$



Event Classification (3)

Comparison of different $m(h_s)$ mass points:



Statistical Inference

Calculate 95% CL CL_s limits on $H \rightarrow hh_s$ assuming absence of signal:

- Calculate likelihood function based on a poisson ansatz for individual bin content

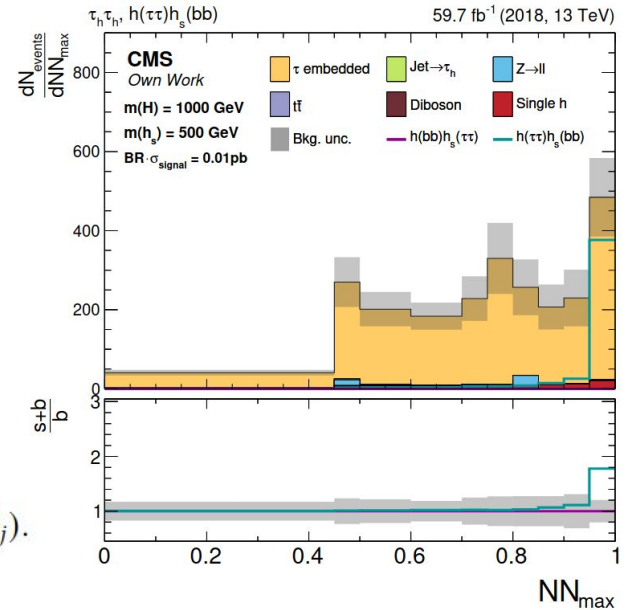
$$\mathcal{P}(k; \lambda) = \frac{\lambda^k e^{-\lambda}}{k!} \quad \mathcal{L}(d | \mu \cdot s(\theta) + b(\theta)) = \prod_{i \in \text{bins}} \mathcal{P}(d_i | \mu \cdot s(\theta) + b(\theta)) \times \prod_{j \in \text{nuis.}} \mathcal{C}(\hat{\theta}_j | \theta_j).$$

- Profile likelihood test statistic

$$q_\mu = -2 \ln \left(\frac{\mathcal{L}(d | \mu \cdot s(\hat{\theta}_\mu) + b(\hat{\theta}_\mu))}{\mathcal{L}(d | \hat{\mu} \cdot s(\hat{\theta}) + b(\hat{\theta}))} \right)$$

- CL_s method

$$CL_s = \frac{p_\mu}{1 - p_0}$$



- Analysis is model-independent until this point
- Can be interpreted in terms of any $X \rightarrow xh$ model by scaling expected yields of the signal final states (assume equal yields here)

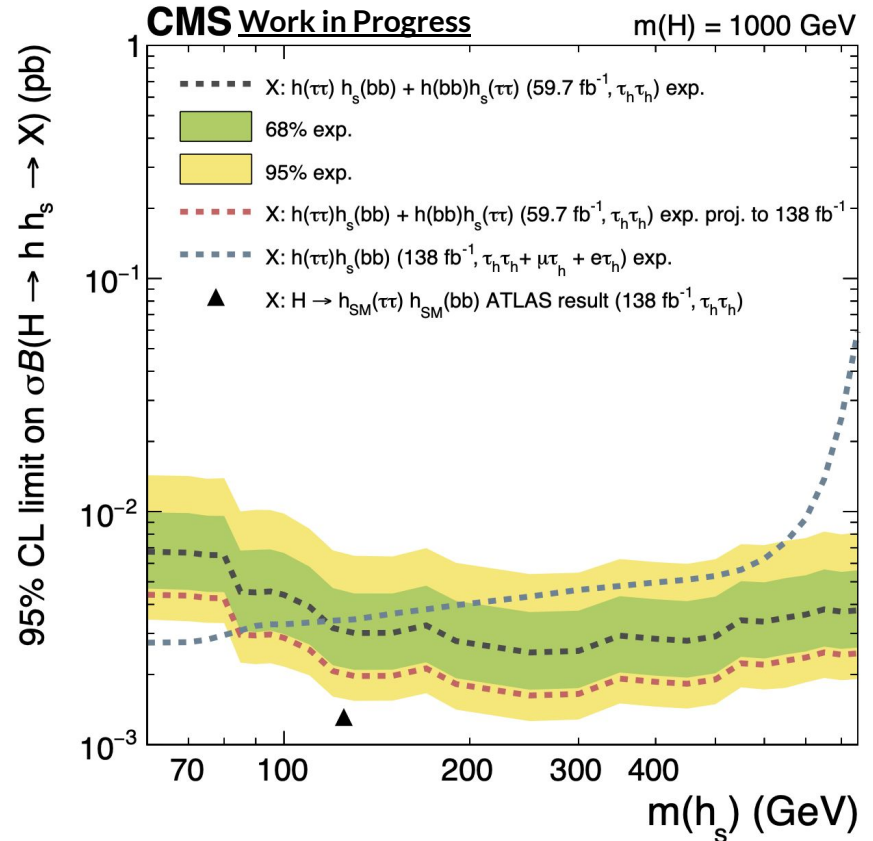
Results (1)

Analysis sensitivity is gauged by the calculated expected exclusion limits on

$$\sigma B(H \rightarrow hh_s \rightarrow bb + \tau\tau)$$

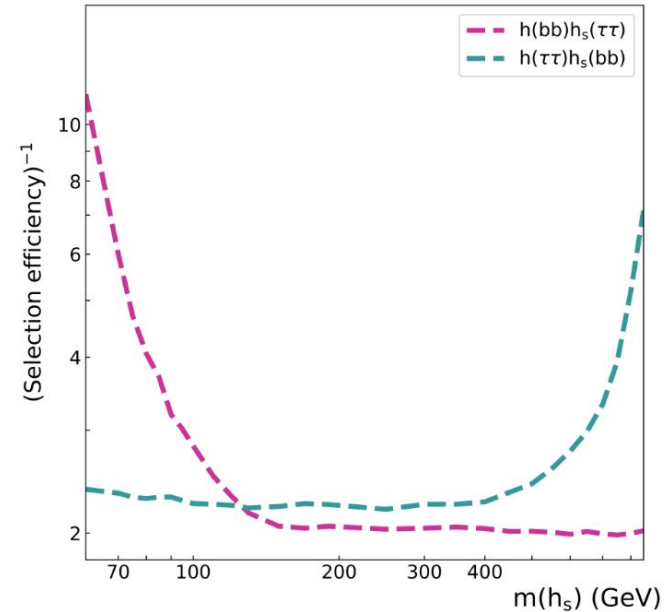
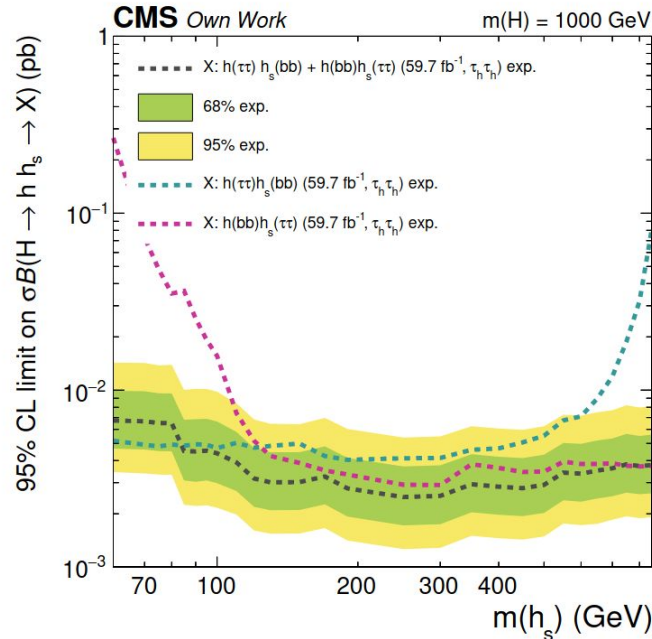
Combination of $h(bb)h_s(\tau\tau) + h(\tau\tau)h_s(bb)$ final states (**red**) improves upon sensitivity of $h(\tau\tau)h_s(bb)$ analysis (**blue**) significantly for $m(h_s) > 80$ GeV

[2] <http://cdsweb.cern.ch/record/2777236/files/ATLAS-CONF-2021-030.pdf>



Results (2)

Taking a look at the results split by signal final states:



→ Analysis sensitivity is driven by selection efficiency

Conclusion

A novel search for $\mathbf{H} \rightarrow \mathbf{h}h_s$ decays was presented:

- NMSSM inspired but largely model independent
- Employs background estimation methods such as τ -embedding and the F_F method
- Multiclassification is performed using multivariate NN with two signal classes
- Significant improvement in exclusion sensitivity is achieved when $\mathbf{h}(\mathbf{b}\mathbf{b})h_s(\tau\tau) + \mathbf{h}(\tau\tau)h_s(\mathbf{b}\mathbf{b})$ final states are considered simultaneously

Thank you!

Backup - F_F Method

