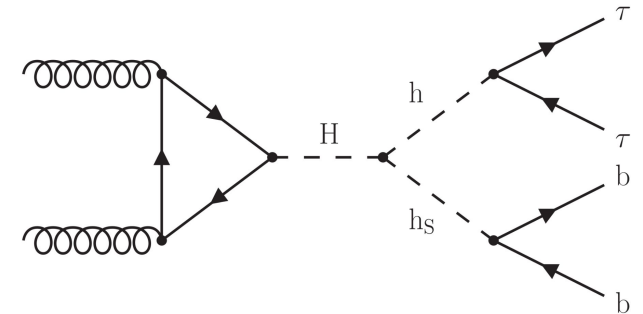
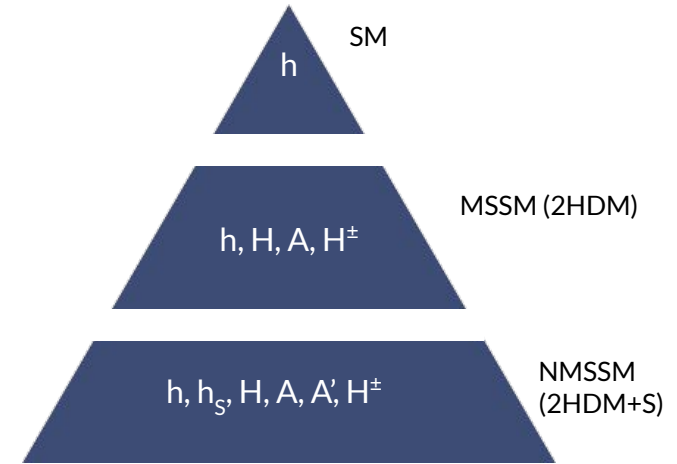


# Studies of neural network architectures in the search for di-Higgs events in the context of NMSSM in the $\tau\tau+bb$ final state

Ralf Schmieder

# NMSSM phenomenology

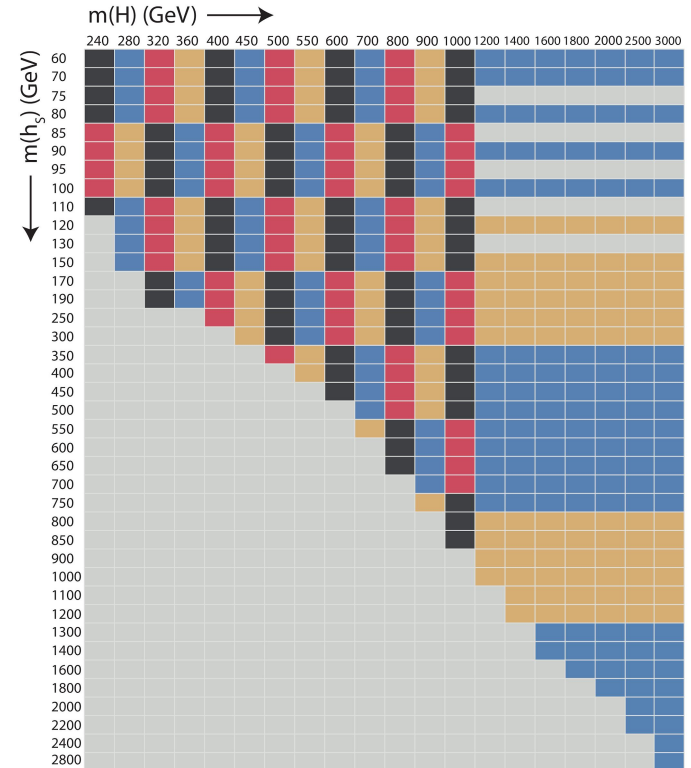
- Decays of a heavy Higgs boson into two lighter bosons: Motivated e.g. by the next-to-minimal-supersymmetric standard model (NMSSM)
- Light Higgs boson  $h_s$  assumed to have significant admixture of the singlet field  $S$
- In this case  $H \rightarrow hh_s$  is the dominant production process for  $h_s$
- $H \rightarrow h(\tau\tau)h_s(bb)$  combines high branching ratio through  $bb$  decay with the lower bkg from the  $\tau\tau$  decay



2HDM+S = 2 Higgs doublet model + Singlet

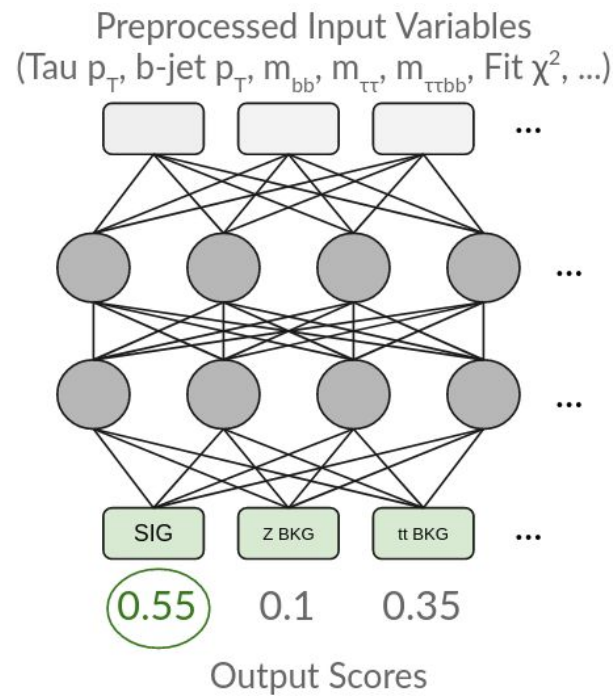
# Analysis strategy in a nutshell

- In  $H \rightarrow hh_s$   $m(H)$  and  $m(h_s)$  are unknown
- A grid of 420 mass hypotheses are simulated with up to 500k events each between  $m(H) = 240$  GeV and 3000 GeV
- Event categorization with the help of neural network (NN) multiclassification
- Grouping of mass hypotheses in individual trainings (color code on right figure)  $\rightarrow$  resulting in **68 trainings per  $\tau\tau$  final state**
- Depending on the  $\tau\tau$  final state,  $\sim 45$ -95% of **backgrounds estimated from data**



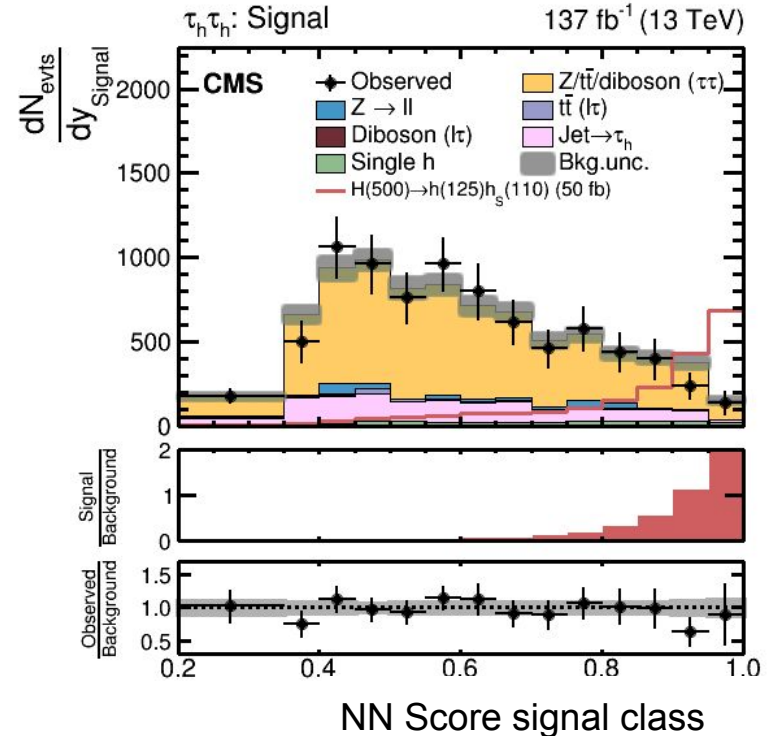
# Event Categorisation

- Multiclassification based on neural networks (**NNs**) with one signal and four background categories
  - NN returns probability-like score for each category. The event is assigned to the category with the highest NN score
  - NN score used as final discriminator for signal extraction
- Mass hypotheses have different kinematic properties → NN training in 68 groups of signals



# Example distribution of NN score

- Training group comprising the signal samples with  $m(H)=500$  GeV,  $m(h_S)=[110, 120, 130, 150]$  GeV
- Signal with  $m(H)=500$  GeV,  $m(h_S)=150$  GeV indicated by red unstacked histogram
- Total of 45 such histograms enter 420 combined maximum likelihood fits, one for each mass hypothesis, for signal extraction

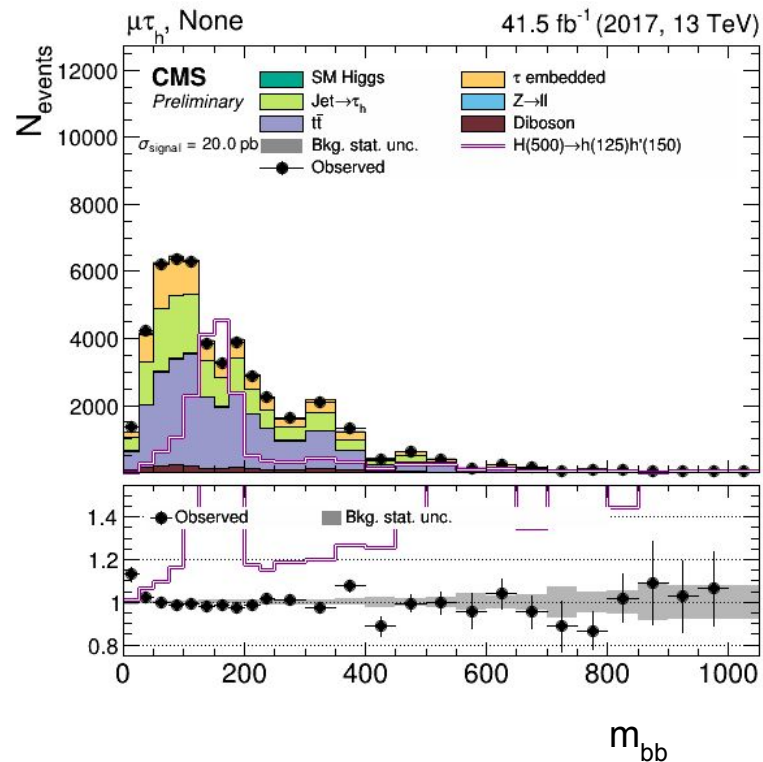


# Analysis of the invariant bb mass as input to the NN

- Best possible setup: individual training per mass hypothesis
- Study of possible loss of sensitivity due to the grouping of hypotheses
  - Most groups contain four signal hypotheses
- Compare the results of individual training and grouped training
- Study of impact of mass estimator of di-b-system to the NN categorization

# Analysis of the invariant bb mass as input to the NN

- Two informations from bb mass estimator:
  - Signal is peaking
  - Signal peak is fixed
- Hypothesis:  
In groups of 4 or more hypothesis this character is washed out



# NN - Taylor coefficient analysis

- Designed to get a hint on the impact of the input features  $\mathbf{x}$  (Tau  $p_T$ ,  $m_{\tau\tau}$ , ...) on the NN output function  $f(\mathbf{x})$
- Expand  $f(\mathbf{x})$  in its input features  $x_i$  up to the second order
- For each event  $\mathbf{a}$  with input feature values  $a_i$ ,  $f(\mathbf{x})$  is expanded around  $\mathbf{a}$
- Taylor coefficients  $t_i$



Study impact of the input feature  $m_{bb}$

$$f(\mathbf{x}) \approx f(\mathbf{a}) + (x_1 - a_1)t_{x_1} + (x_2 - a_2)t_{x_2} + (x_1 - a_1)^2 t_{x_1 x_1} + (x_1 - a_1)(x_2 - a_2)t_{x_1 x_2} + \dots$$



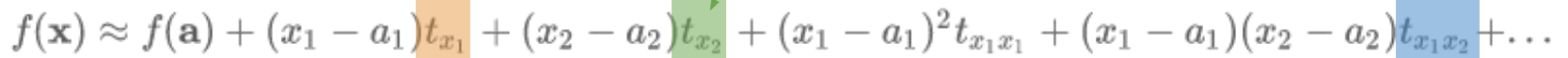
# NN - Taylor coefficient analysis

Example:  $x_1 = m_{\tau\tau}$ ,  $x_2 = m_{bb}$

Impact of the correlation of  $m_{\tau\tau}$  and  $m_{bb}$  on the NN output function

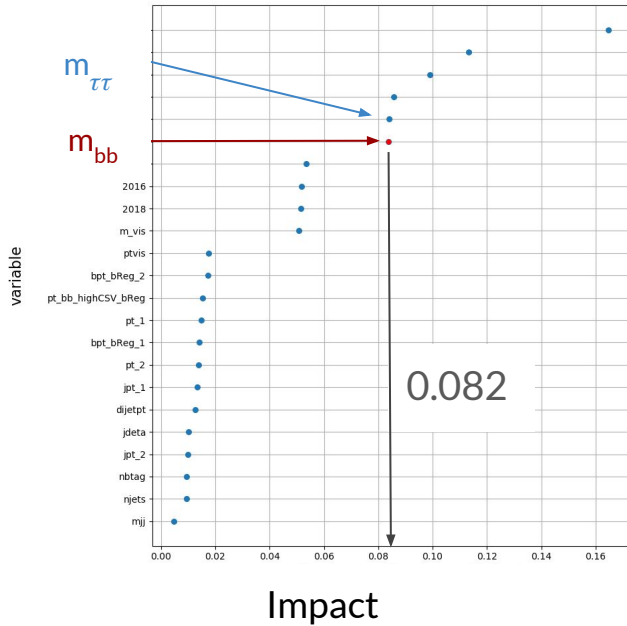
Impact of  $m_{\tau\tau}$  on the NN output function

Impact of  $m_{bb}$  on the NN output function

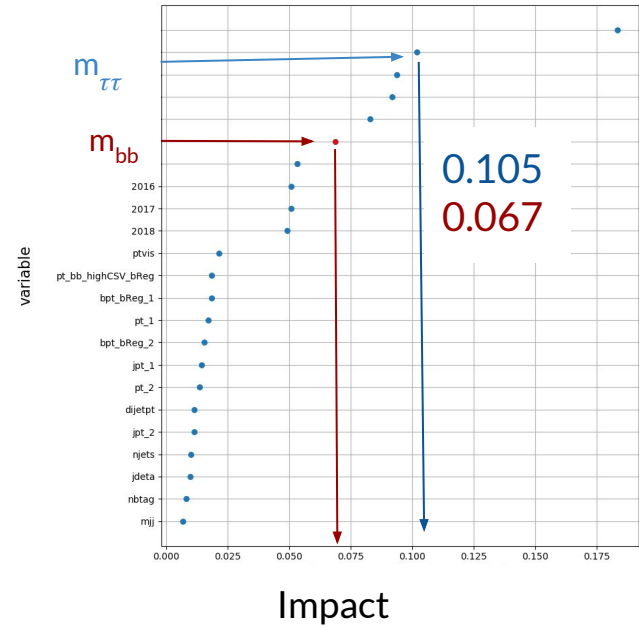
$$f(\mathbf{x}) \approx f(\mathbf{a}) + (x_1 - a_1)t_{x_1} + (x_2 - a_2)t_{x_2} + (x_1 - a_1)^2 t_{x_1 x_1} + (x_1 - a_1)(x_2 - a_2)t_{x_1 x_2} + \dots$$
The diagram shows the Taylor expansion of the NN output function f(x) around the point a. The terms are: f(a), (x1 - a1)t\_x1, (x2 - a2)t\_x2, (x1 - a1)^2 t\_x1x1, and (x1 - a1)(x2 - a2)t\_x1x2. The term (x1 - a1)t\_x1 is highlighted with an orange box, and an orange arrow points from the text 'Impact of m\_tau tau on the NN output function' to it. The term (x2 - a2)t\_x2 is highlighted with a green box, and a green arrow points from the text 'Impact of m\_bb on the NN output function' to it. The term (x1 - a1)(x2 - a2)t\_x1x2 is highlighted with a blue box, and a blue arrow points from the text 'Impact of the correlation of m\_tau tau and m\_bb on the NN output function' to it.

# Impact of mass estimators to the signal class

## Single mass hypothesis

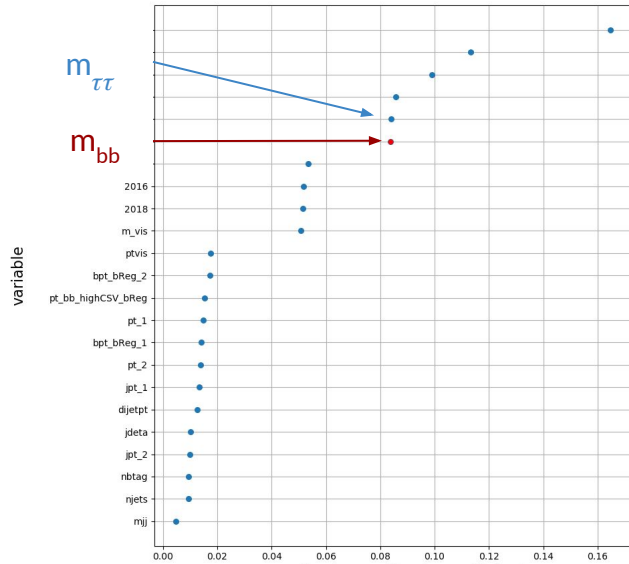


## Four mass hypotheses

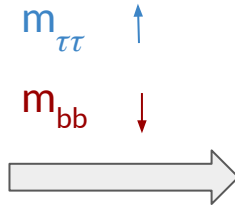


# Impact of mass estimators to the signal class

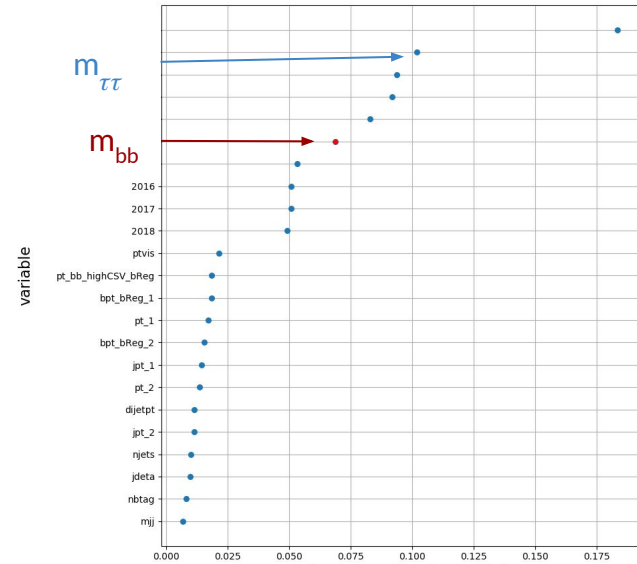
## Single mass hypothesis



Impact



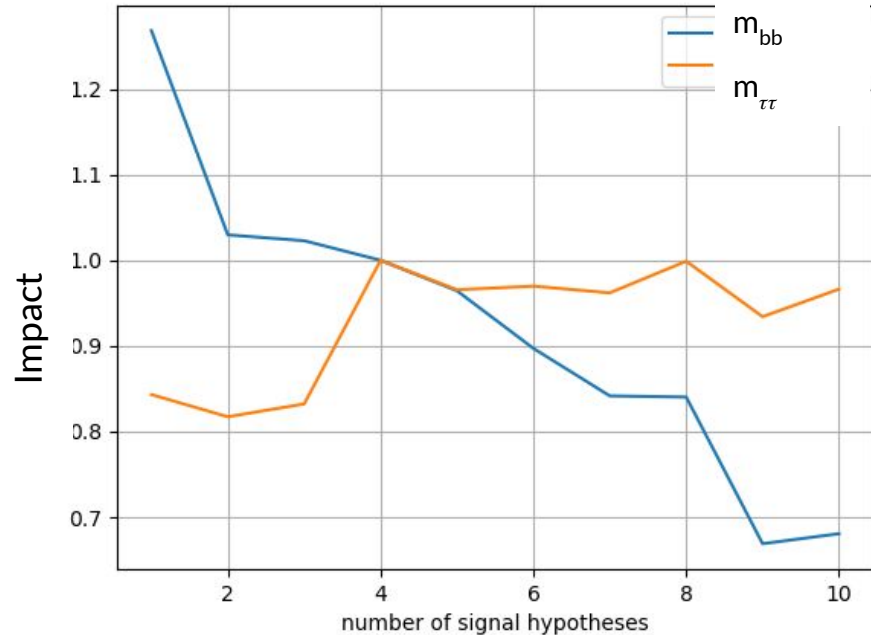
## Four mass hypotheses



Impact

# Impact of mass estimators to the signal class

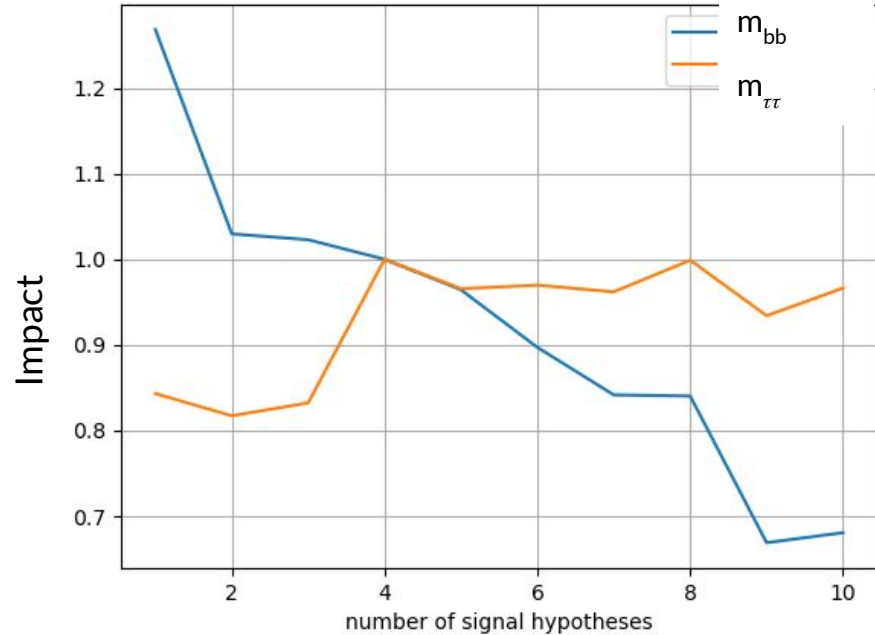
- Investigate inverse trends of impact of  $m_{bb}$  and  $m_{\tau\tau}$
- vary number of signal hypotheses that form signal class
- Impact normalized to the impact with 4 signal hypotheses



# Impact of mass estimators to the signal class

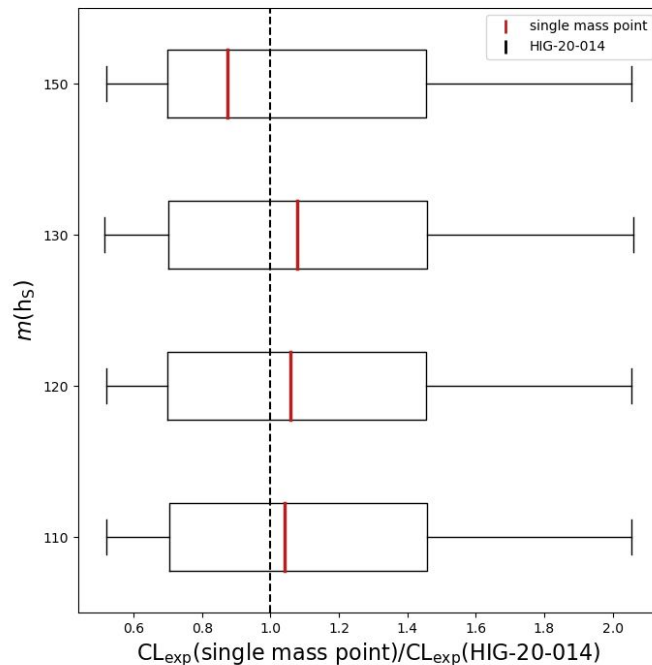
Impact of  $m_{bb}$  increases with the number of signals

Impact of  $m_{\tau\tau}$  stagnates after 4 signals



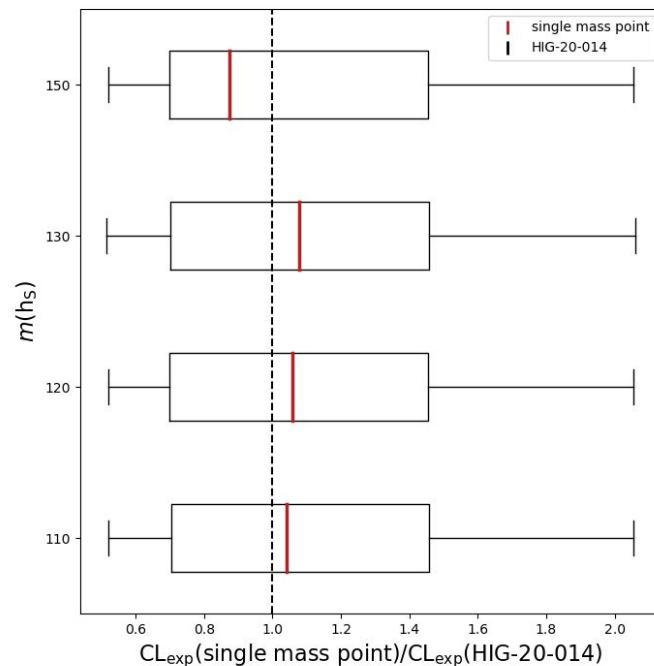
# Analysis of the invariant bb mass as input to the NN

- No signal excess -> result is an exclusion limit
- Compare two results -> compare two exclusion limits
- Ratio plot:
  - Expected limits normalized to the limits of the base analysis
  - Boxes represent the  $1\sigma$  band of the base analysis
  - Whiskers represent the  $2\sigma$  band of the base analysis



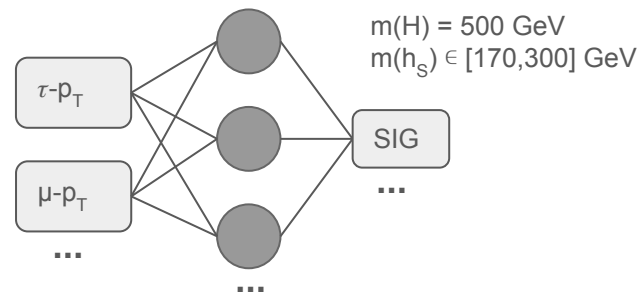
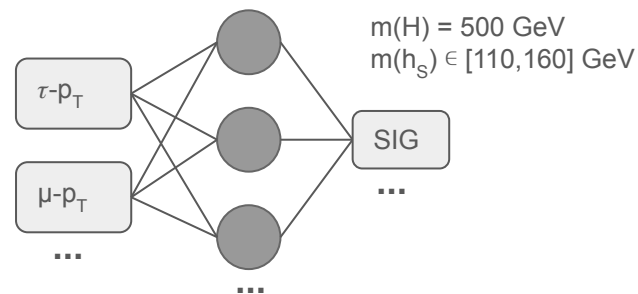
# Analysis of the invariant bb mass as input to the NN

Grouping of four different but similar signal signatures to a signal class has no significant effect to the limits



# Parameterized NN

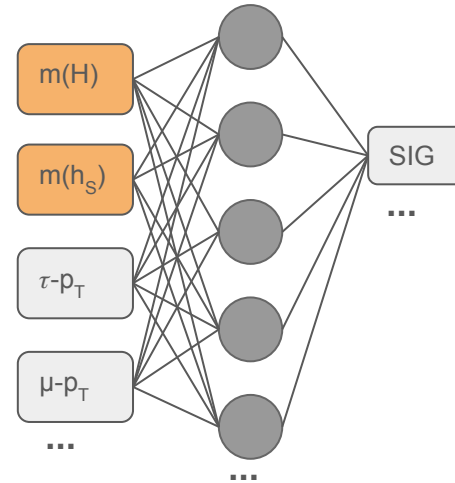
- Goal: replace 68 trainings per final state with a single training
- Idea: expand the input vector by parameters  $\rightarrow m(H), m(h_S)$
- Replace the NNs for different masspoints by a single NN, which trains on the same samples but has the parameters  $m(H), m(h_S)$  as input





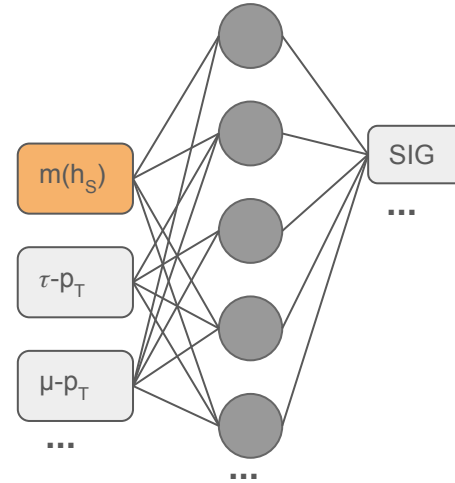
# Parameterized NN

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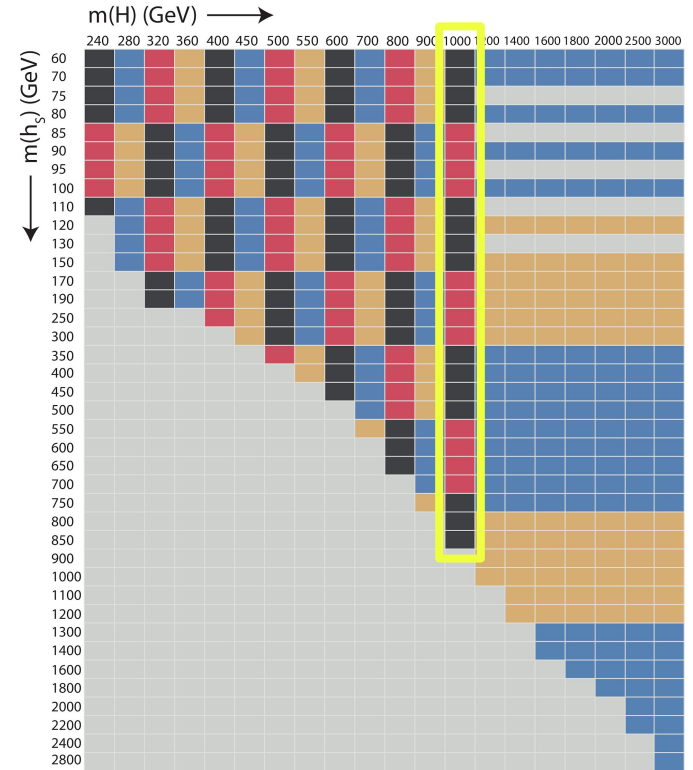
# Parameterized NN

- First test: fix heavy Higgs boson mass  $m(H)$  to  $m(H)=1000$  GeV and pass only  $m(h_S)$
- Pass random value to backgrounds and true value to signal event
- Compare exclusion limits with the limits of the presented analysis



# Parameterized NN

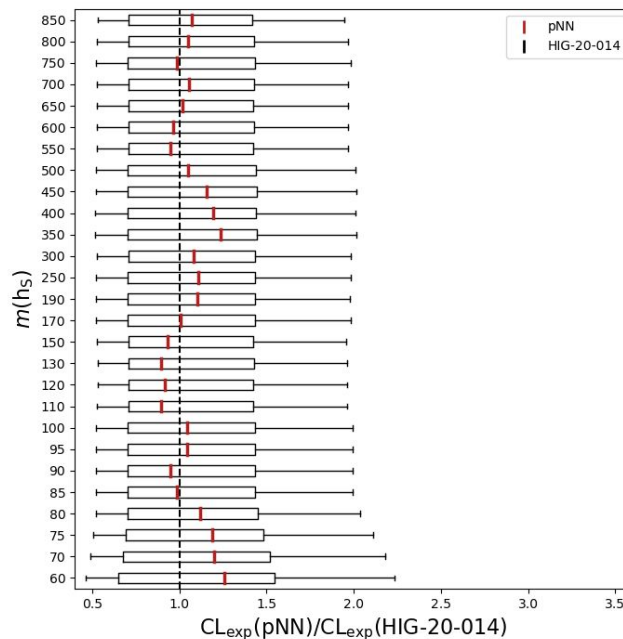
- First test: fix heavy Higgs boson mass  $m(H)$  to  $m(H)=1000$  GeV and pass only  $m(h_s)$  as an input parameter
- 27 mass hypotheses tested in a single NN  
→ replace 7 individual NN



# Parameterized NN

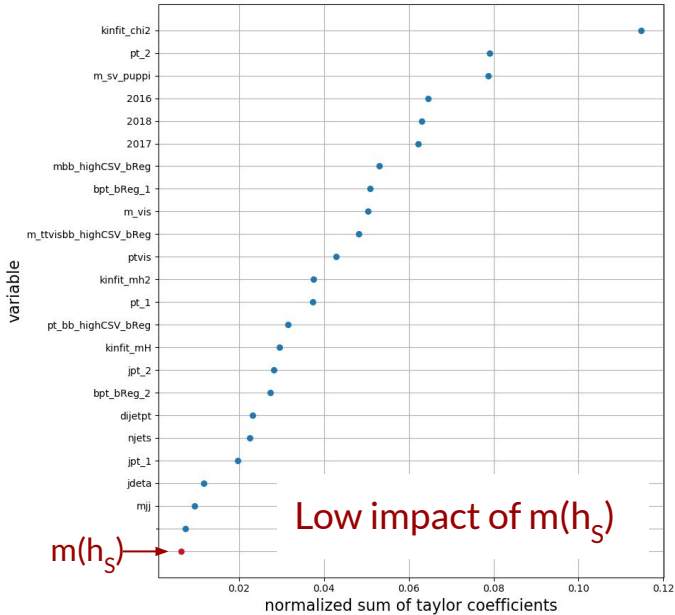
- Ratio plot:
  - Expected limits normalized to the limits of the base analysis
  - Boxes represent the  $1\sigma$  band of the base analysis
  - Whiskers represent the  $2\sigma$  band of the base analysis

**All tested mass hypotheses are within the  $1\sigma$  band of the base analysis (HIG-20-014)**

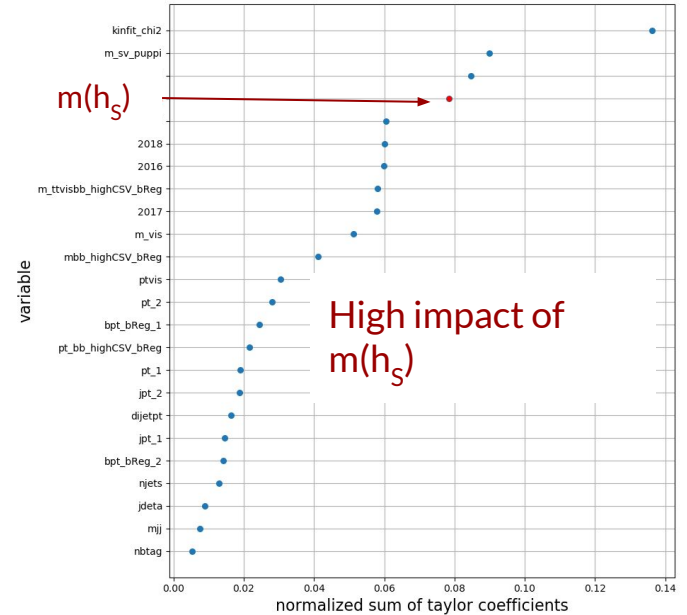


# Parameterized NN - Taylor coefficient analysis

## Background classes

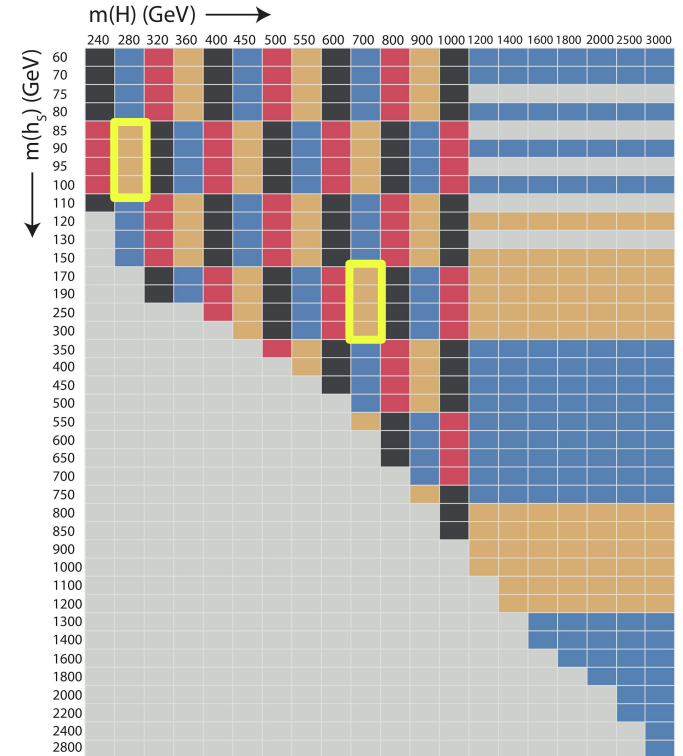


## Signal class



# Parameterized NN with sub NNs

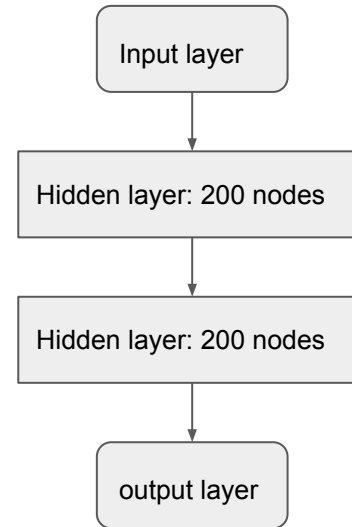
- Goal: single NN with a several sub NNs
- **First test:** pick two batches from the 68, implement a functional NN and compare the limits with the base analysis
  - $m(H) = 280$  GeV, batch 2
  - $m(H) = 700$  GeV, batch 4



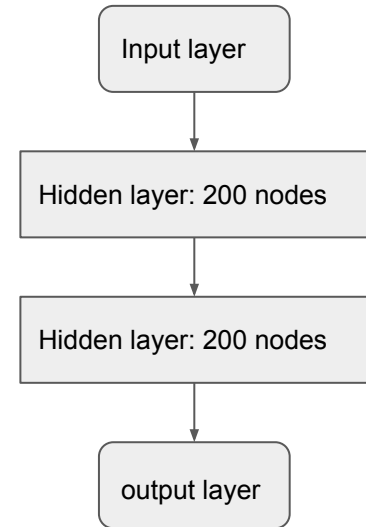
# Parameterized NN with sub NNs

- Build a single NN with multiple input and multiple output tensors, each for one batch
- Each sub NN has the same architecture as the base analysis
- Sub NNs are independent → no shared layers

$m(H) = 280 \text{ GeV}$   
 $m(h_s) = [85, 100] \text{ GeV}$

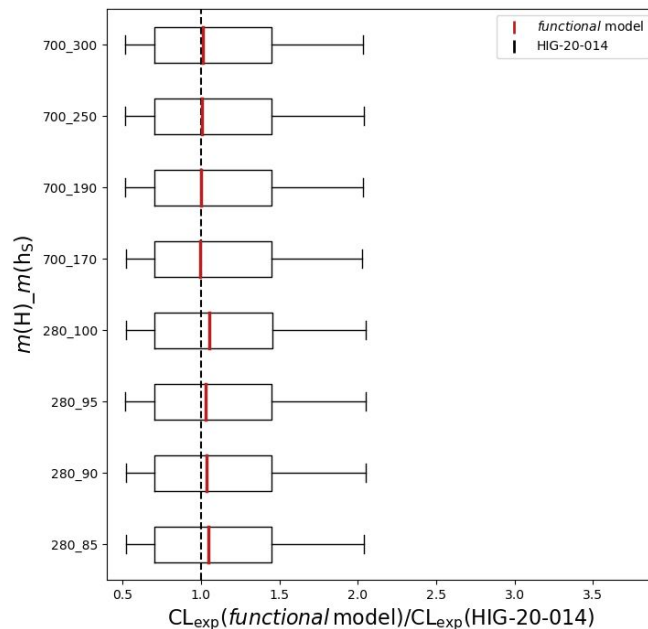


$m(H) = 700 \text{ GeV}$   
 $m(h_s) = [170, 300] \text{ GeV}$



# Parameterized NN with sub NNs

- Build a single NN with multiple input and multiple output tensors, each for one batch
- Each sub NN has the same architecture as the base analysis
- Sub NNs are independent → no shared layers



**Both NNs lead to the same exclusion limits**



# Summary

- Base analysis: search for  $H \rightarrow hh_s$  decays in the context of the NMSSM
- No significant loss of discrimination power with grouping signals hypotheses
- PNN as a single NN to replace 68 individual NNs
- PNN reaches same sensitivity as base analysis setup in tested parameter space and is able to interpolate between mass hypotheses
- PNN with sub NNs leads to the same exclusion limits as base analysis