Improving a search for heavy neutral Higgs bosons in the $t\bar{t}Z$ final state at CMS using parameterized neural networks

DPG Frühjahrstagung 2025, Göttingen

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Two Higgs Doublet Models (2HDM)

- Second Higgs doublet → 5 different Higgs bosons (h , H, A, $H^{\pm}$)
- Free parameters
  - Masses of the Higgs bosons (m_h, m_H, m_A, $m_{H^{\pm}}$)
  - Ratio of the vacuum expectation values: $\tan(\beta) = \frac{v_1}{v_2}$
  - Mixing angle α between the CP-even Higgs bosons
- "Alignment limit": $\cos(\beta - \alpha) \to 0$
  - Beyond the standard model h boson couples like the standard model Higgs boson

h H

Neutral CP-even

A

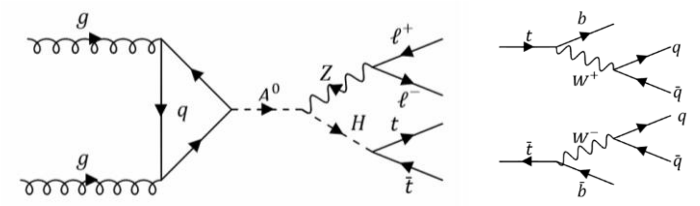
Neutral CP-odd

H^{+} H^{-}

Charged

Overview

- Search targets $A \rightarrow ZH$ with decay of $H \rightarrow t\bar{t}$ (see previous talk by Yannick Fischer)
- Focus on hadronic decay of $t\bar{t}$
- CMS result with 138/fb of Run 2 data at 13 TeV [1]
- Now: analysis of Run 3 data
- Here: study of neural network to separate signal of heavy Higgs boson events from background



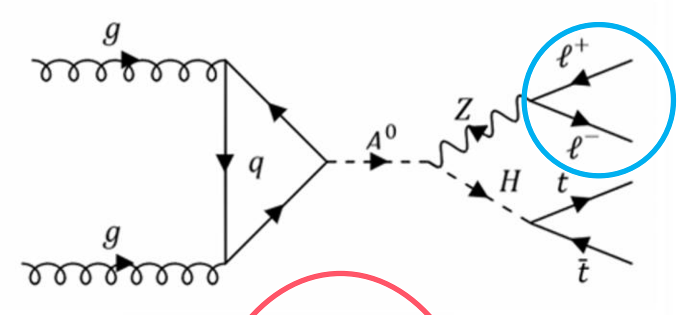
Limit plot Yannick

[1] [arXiv: 2412.00570 (subm. to PLB)]

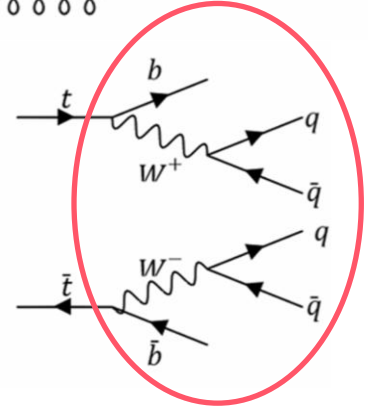
Setup for the analysis

Monte Carlo simulated events
(Run 2 – 2017)

$$\frac{\Gamma_{A/H}}{m_{A/H}} = 0.03$$



Exactly two leptons
(ee / $\mu\mu$)
$|m_{ll} - m_Z| \leq 5$ GeV



5 jets,
$\geq$ 1 b tagged jet

Mass range:
$330 \text{ GeV} \leq m_H \leq 850 \text{ GeV}$
$430 \text{ GeV} \leq m_A \leq 950 \text{ GeV}$
$\triangle m \geq 100 \text{ GeV}$

Background processes:
Drell-Yan, $t\bar{t}$, $t\bar{t}Z$

Characteristics of the neural networks (NN)

Network structure

→ 5 hidden dense layers
→ Leaky ReLU, Sigmoid activation function
→ Vs weight initializer

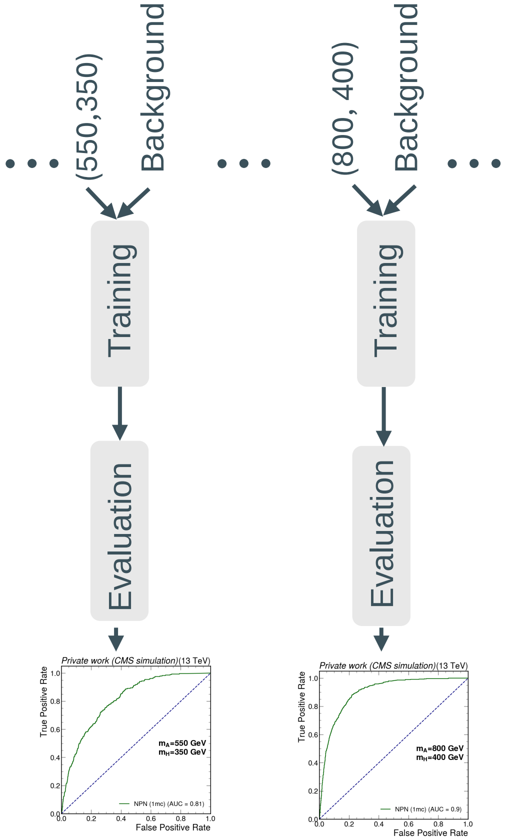
Tuned hyperparameters (Keras Hyperband Optimizer)

→ Number of nodes in the layers
→ Dropout rate
→ Learning rate

Input features

p_T, η, ϕ of the jets, leptons, A, Z, H, $\mathrm{M_A}$, $\mathrm{M_H}$, $\Delta\mathrm{M}$, b tagging scores, $\Delta\mathrm{R}$ leptons, $\Delta\mathrm{R}$ leading b jet and Z

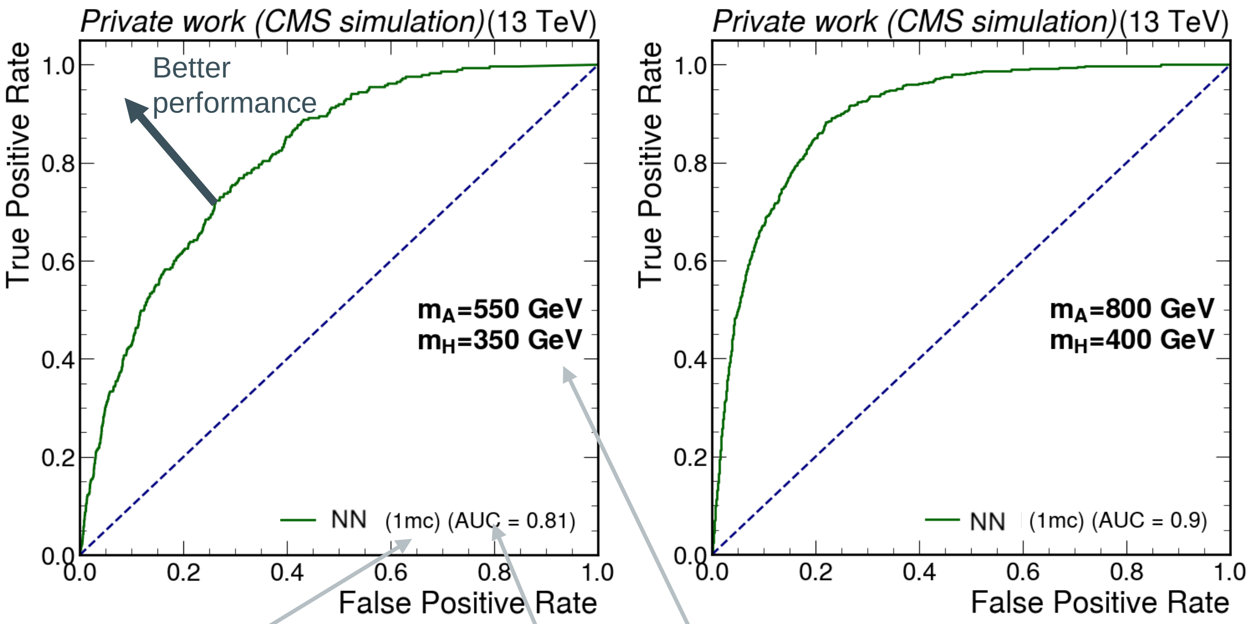
Training of individual NN



Input features: p_T, ϕ, η, M_A, M_H ….

(in total 79 different mass combinations considered)

ROC dedicated NN per mass combination



NN (1 mc): trained with 1 mass combination

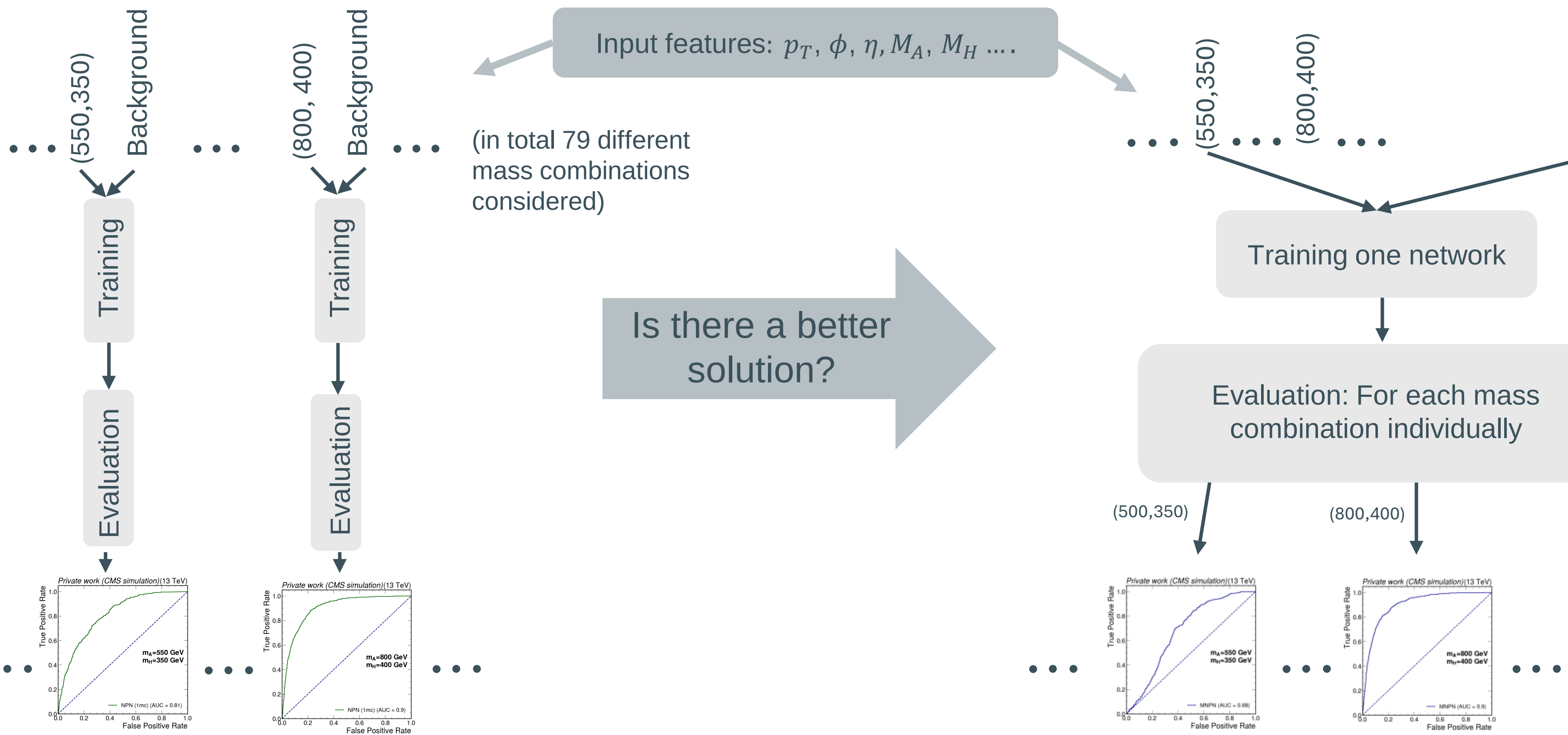
- Performance is good, but it is impractical
- For each mass combination a separate network is necessary

mc: number of mass combinations included in the training

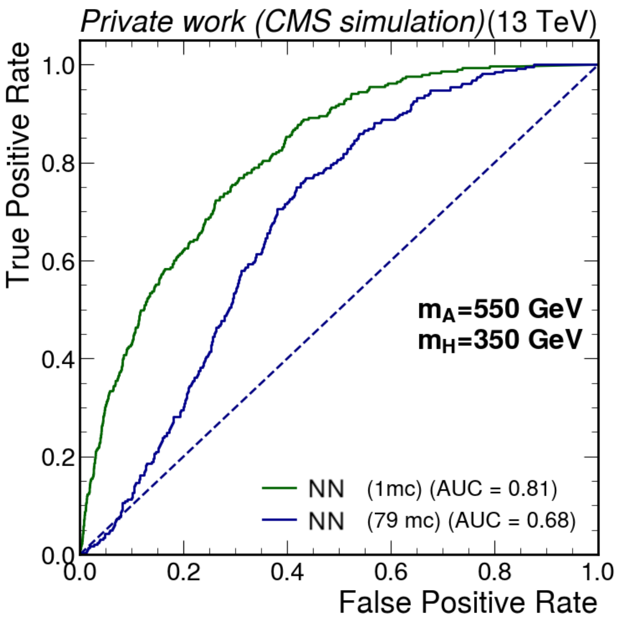
Mass combination used for evaluation of the network

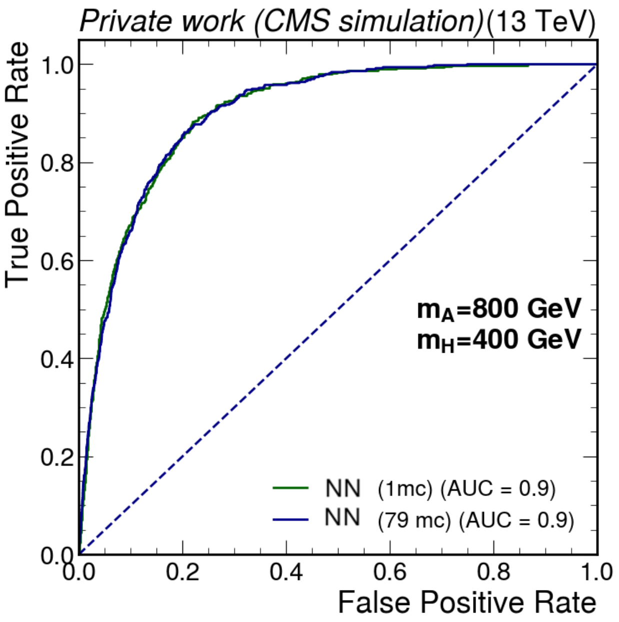
AUC: area under the ROC curve

Training of individual NN



NN trained with all masses





NN (1 mc): trained with 1 mass combination

NN (79 mc): trained with 79 different mass combinations

→ The inclusion of all signal events into a NN leads to a decrease in performance for some mass combinations

Training of individual NN

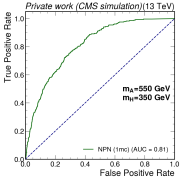
Input features: $p_T, \phi, \eta, M_A, M_H$ ….

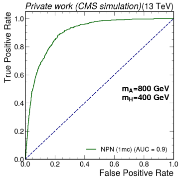
… (550,350) Background … (800, 400) Background …

(in total 79 different mass combinations considered)

Training

Evaluation





Is there a better solution?

… (550,350) … (800,400) … Background

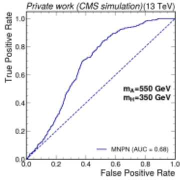
Training one network

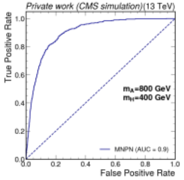
combination individually

Lower performance than before
→ inadequate solution!

(500,350)

(800,400)





Parameterized neural network (PNN)

Input features: $p_T, \phi, \eta, M_A, M_H$ ….

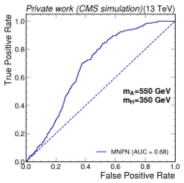
… (550,350) … (800,400) … Background

Training one network

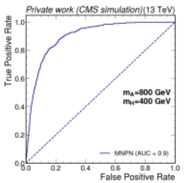
Lower performance than before
→ inadequate solution!

combination individually

(500,350)



(800,400)



Parameterized neural network

Signals: true masses (m_A, m_H)

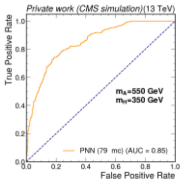
Background: random true mass combinations (m_A, m_H)

… (550,350) … (800,400) … Background

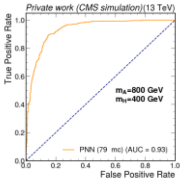
Training one network with parametrization

Evaluation: For each mass combination individually

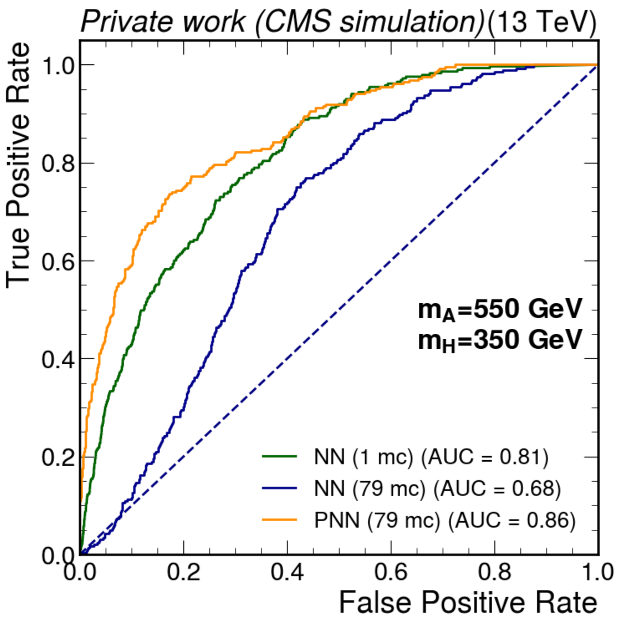
(500,350)

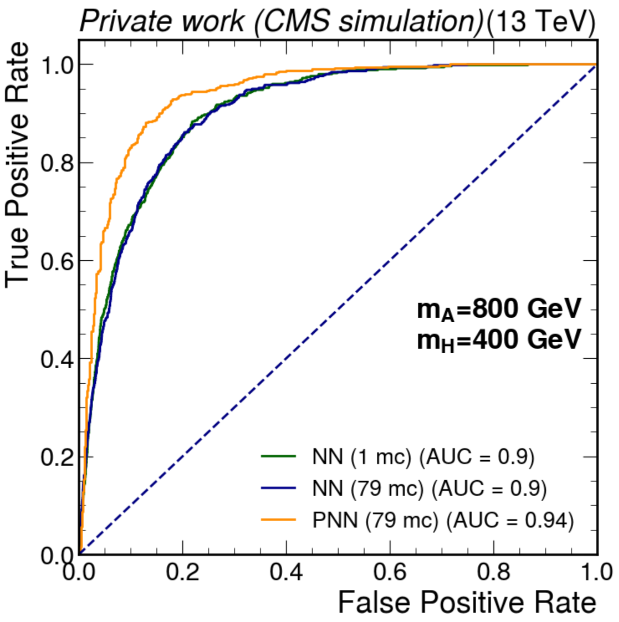


(800,400)



Comparison of ROC for NN and PNN





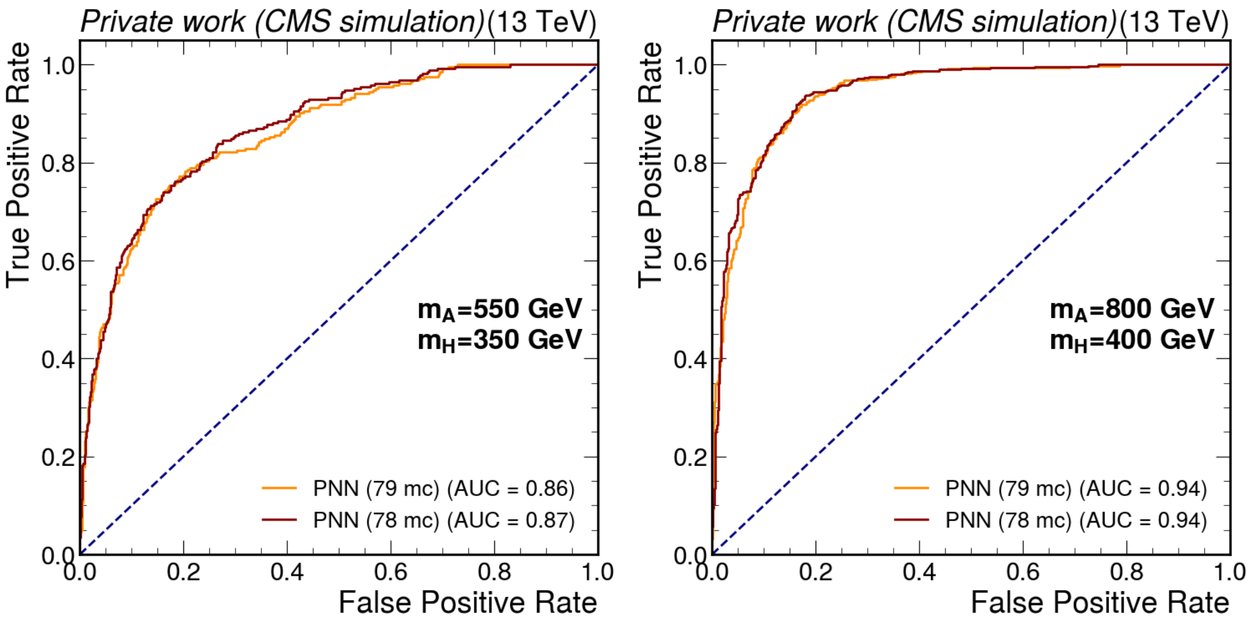
NN (1 mc): trained with 1 mass combination

NN (79 mc): trained with 79 different mass combinations

PNN (79 mc): trained with 79 different mass combinations

→ The inclusion of all signal events with parameterization leads to an increase in performance

Extrapolation for unseen mass combinations



PNN (79 mc): trained with 79 different mass combinations

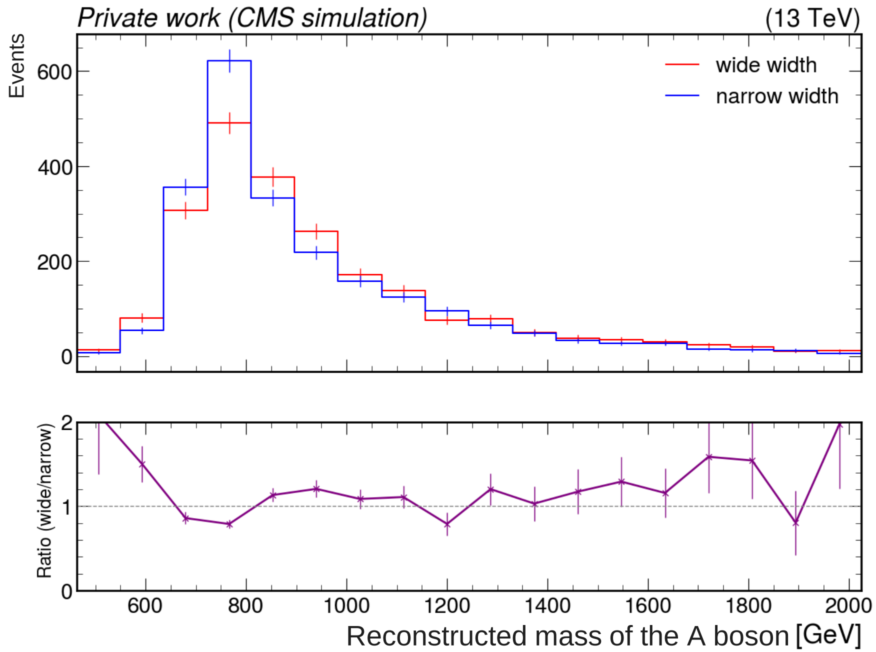
PNN (78 mc): trained with 78 different mass combinations; the mass combination used for evaluation is not included in the training

➔ PNN can generalize and extrapolate for mass combinations not included in the training

Advantages of PNNs

- One network can be used to evaluate all mass combinations
- Better performance than NN
- Evaluation of mass combinations not included in the training is possible; performance is better than NN (for considered examples)

Impact of changes of the decay width



Narrow width:

$$\frac{\Gamma_{A/H}}{m_{A/H}} = 0.03$$

Wide width:

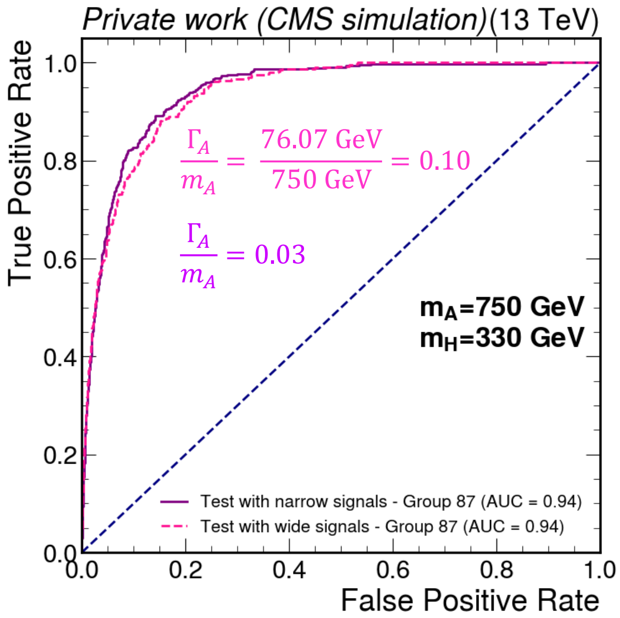
As predicted in 2HDM e.g.

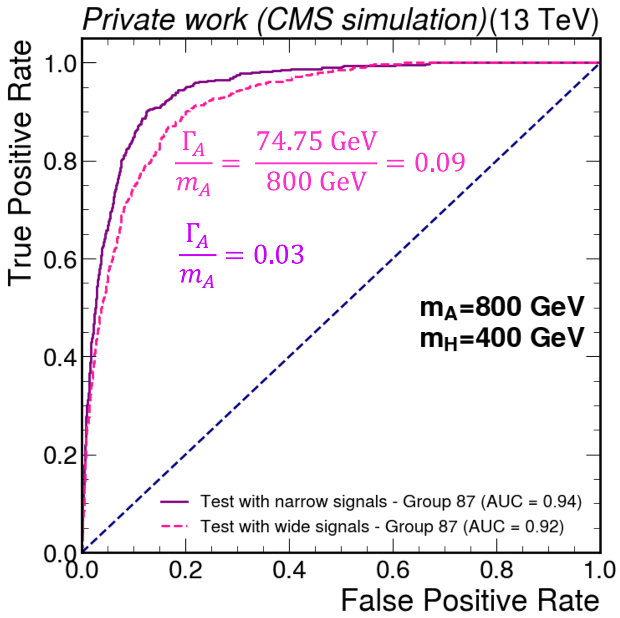
$m_A = 800$ GeV, $\Gamma_A = 74.75$ GeV (for $\tan(\beta) = 2$)

$$\frac{\Gamma_A}{m_A} = \frac{74.75 \text{ GeV}}{800 \text{ GeV}} = 0.09$$

→ Decay width of the A boson is no longer neglectable compared to detector resolution

Impact of changes of the decay width





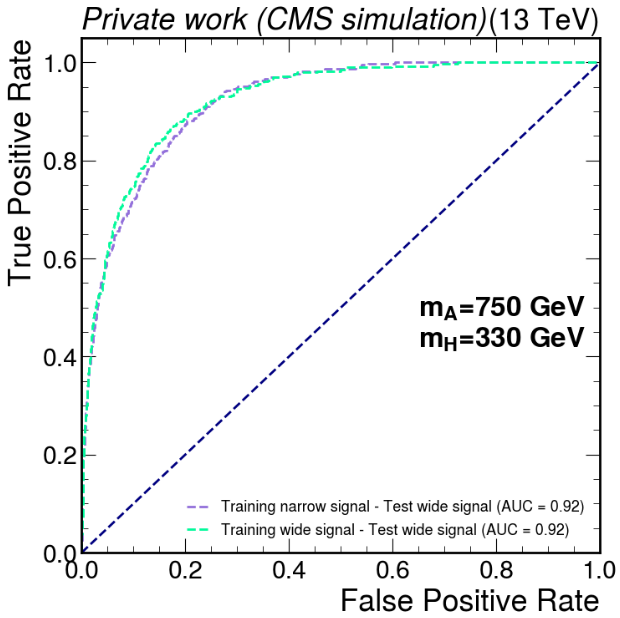
Training: narrow signal events

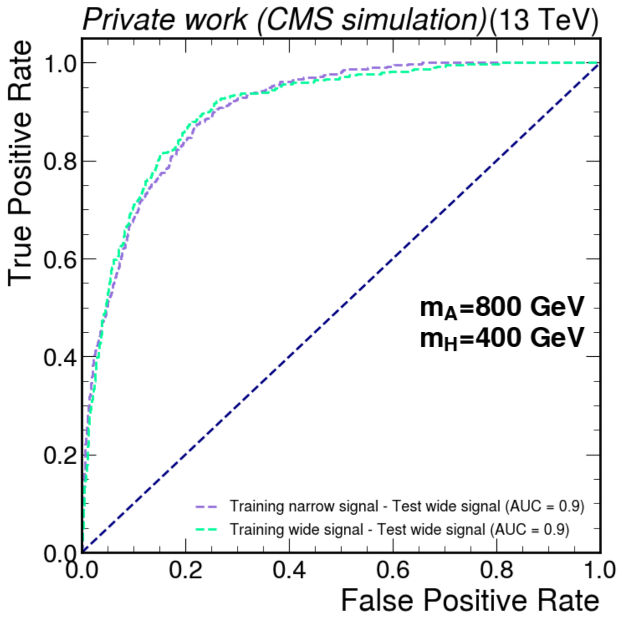
Testing: narrow or wide signal events in comparison

→ Even if we train the network with narrow signal events, the network performs nearly similar for testing with wide signal events

→ Neural network performs robust when the signal width is changed

Impact of changes of the decay width





Training: narrow or wide signal events in comparison

Testing: wide signal events

→ Using wide signal events for training does not lead to an increase in performance compared to training with narrow signals when testing with wide signal events

Summary

- Search for heavy Higgs bosons ($A \rightarrow ZH \rightarrow l\bar{l}\,t\bar{t}$)
- Studied neutral networks for signal/background classification
- Network performance measured using ROC and AUC score
- Parameterized network trained on several mass points performs better than several individual networks
- Parameterized neural network is robust to the effects of a change in the width of the A boson