



U N I V E R S I T Y O F B E R G E N

Department of Physics and Technology

Separating heavy Higgses using machine learning

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Theoretical motivation

- In the Standard Model, we have one scalar SU(2) doublet Φ , and the Higgs potential

$$V_H = \mu^2 \Phi^\dagger \Phi + \lambda (\Phi^\dagger \Phi)^2 \quad (1)$$

with

- 3 d.o.f. to be absorbed by W^\pm and Z^0

$$\Phi \sim \begin{pmatrix} \eta_1(x) + i\eta_2(x) \\ v + \sigma(x) + i\eta_3(x) \end{pmatrix} \quad (2)$$

- 1 Higgs boson h and VEV v






Theoretical motivation

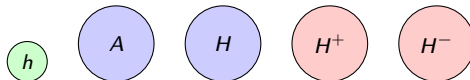
- Add an SU(2) doublet, call it a Higgs, and we have Φ_1 and Φ_2 and a much larger V_H .

$$\Phi = \Phi_1 + \Phi_2 \sim \begin{pmatrix} \phi_{11}(x) + i\phi_{12}(x) \\ \phi_{13}(x) + i\phi_{14}(x) \end{pmatrix} + \begin{pmatrix} \phi_{21}(x) + i\phi_{22}(x) \\ \phi_{23}(x) + i\phi_{24}(x) \end{pmatrix} \quad (3)$$

- 3 d.o.f. must still be absorbed by W^\pm and Z^0
- 1 Higgs boson h and VEV v
- 4 d.o.f. left! \Rightarrow 4 new Higgs bosons H , A , H^+ and H^- .

Theoretical motivation

- Two Higgs doublet model (2HDM)
- A total of five physical states:
 - One light scalar h , this one we know 
 - Two charged ones, which are easily separable  
 - Two neutral ones, A and H , which have opposite charge under CP  
 - Expect some mass-degeneracy among the heavy states
 - After EWSB: v sets scale for SM-like Higgs, one mass parameter left (m_{12}^2)
 - Heavy states are split by mass contributions $\sim \lambda_i v$
 - Large mass splittings possible at tree-level through fine-tuned cancellations among the λ_i 's.
 - Cancellations spoiled by loop corrections.



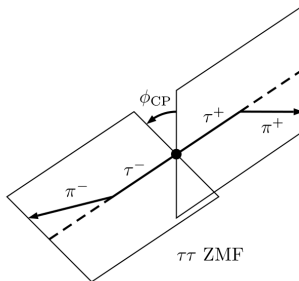
The measurement

- Typical searches (ATLAS [1], CMS [2]) look for *any* particle decaying to ditau, but don't attempt to distinguish them [1] CERN-EP-2016-164, [2] CMS PAS HIG-13-021
 - ... mainly because it's difficult. No direct access to the *CP* numbers
 - Miss out on vital information this way

- Look at the decay

$$A/H \rightarrow \tau\tau \rightarrow \pi^+\pi^0\nu\pi^-\pi^0\nu \quad (4)$$

- One angle of particular importance: Angle between decay planes



Conventional method

- Use φ^* observable [3] [ArXiv:1510.03850](#)
- One-dimensional template fit to φ^* distribution

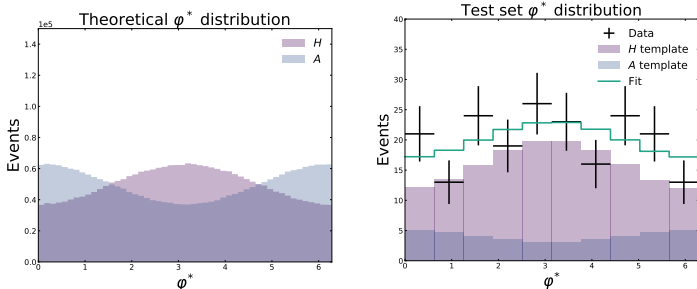
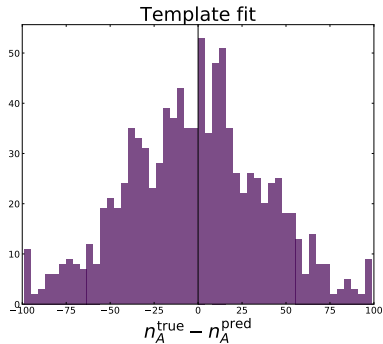


Figure: Theoretical and test set φ^* distributions, $m_A = m_H = 450$ GeV

- Find n_A and n_H , i.e. measure cross section times branching ratio for the two

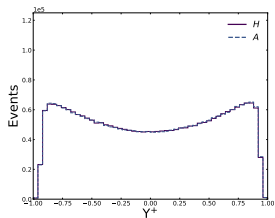
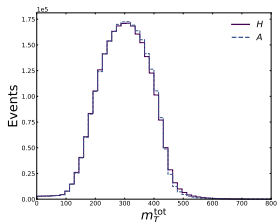
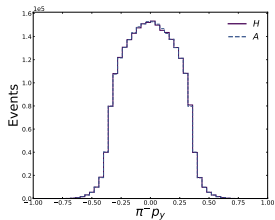
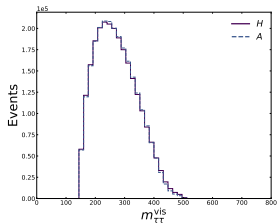
Conventional method

- Using φ^* method on 200 test sets



ML method

- Feature distributions

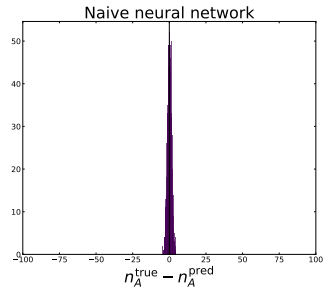
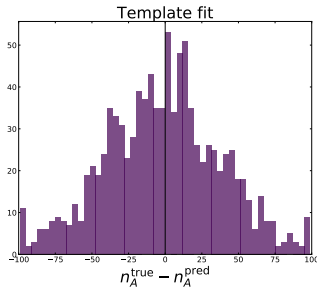


Neural network

- Implemented a fully-connected feed-forward neural network in Keras and TensorFlow
- Leaky ReLu activation functions, Adam optimiser, batch normalisation included
- Use 2-4 hidden layers with ~ 300 nodes each
- Not the easiset problem ever attempted with machine learning
 - Extremely overlapping feature distributions, no single 'killer' feature. Need to rely on correlations
 - Achieve up to ~ 0.63 ROC AUC

ML vs conventional method

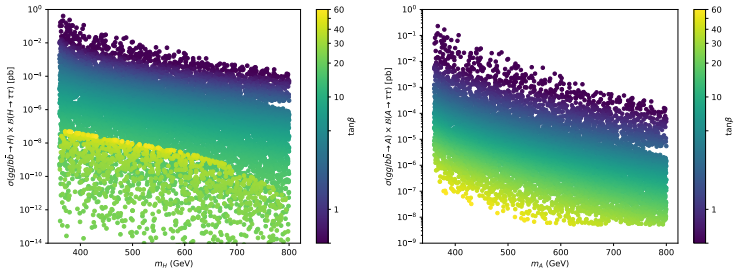
- Again, 200 test sets each



- Not sure whether to publish in Science or Nature

Too good to be true classification?

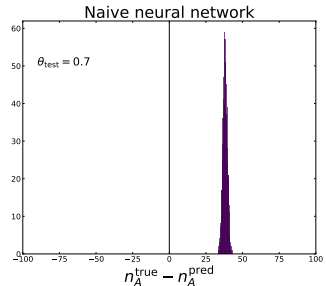
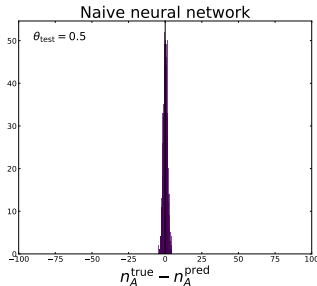
- Yes.
- Train set distribution depends on theory parameters



- \Rightarrow Can't make a train set without making assumptions about the theory!

Too biased to be good classification.

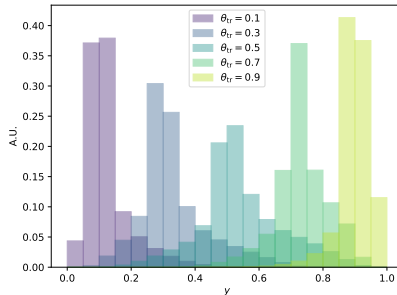
- Define $\theta = \frac{n_A}{n_A + n_H}$, $\theta \in [0, 1]$.
- Evenly distributed train set has $\theta_{\text{train}} = 0.5$



- Very overlapping features \Rightarrow all points lie close to decision surface \Rightarrow very strong prior dependence.

Get rid of bias...

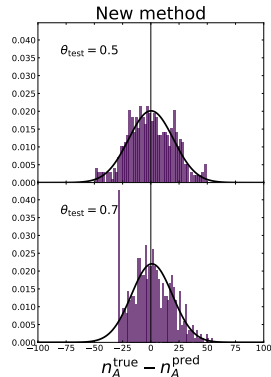
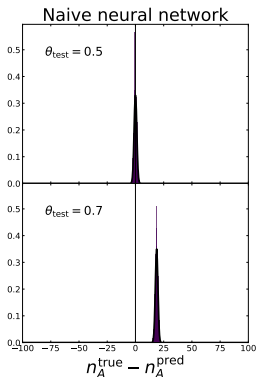
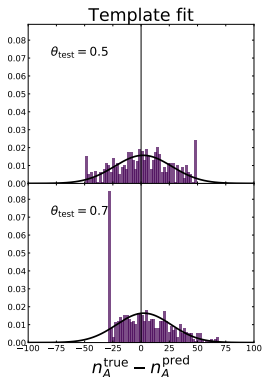
- Train as many networks as you want for different $\theta_{\text{train}} = 0.1, 0.2, \dots$
- Make a template for each θ_{train}



- Do a template fit on network output
- The network which achieves the best fit wins!

Get rid of bias...

PRELIMINARY



- $\sim 20\%$ improvement
 - 200 test sets with 100 events (that's not very much)
 - Not optimised network (Christmas went by so quickly)



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Questions

- Other classifiers tested, no immediate success

