UNIVERSITY OF BERGEN
Department of Physics and Technology

Studying two Higgs doublet models using machine learning

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Theoretical motivation

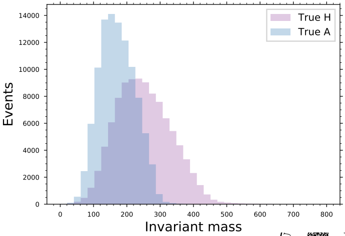
- In the Standard Model, we have an SU(2) doublet ϕ corresponding to one physical particle, the Higgs boson (h, 125 GeV)

$$\mathscr{L} = -\frac{1}{4}F_{\mu\nu}F^{\mu\nu} + i\bar{\psi}\not{D}\psi + \psi_i y_{ij}\psi_j\phi + |D_\mu\phi|^2 - V(\phi) \tag{1}$$

- A minimal extension of the Higgs sector is to add one more doublet - i.e. a *two Higgs doublet model* (2HDM)
- This addition results in 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, but can be degenerate in mass

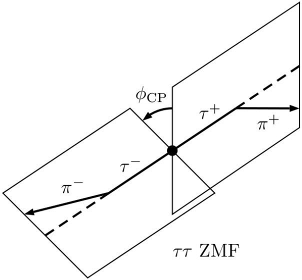
Main idea

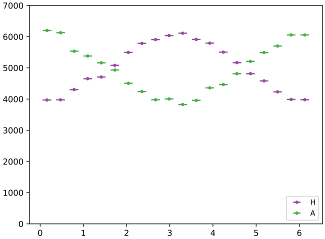
- Typical searches (ATLAS [1], CMS [2]) look for *any* particle decaying to ditaus, but don't attempt to distinguish them [1] CERN-EP-2016-164, [2] CMS PAS HIG-13-021
  - ... mainly because it's difficult. No direct access to the *CP* numbers
  - Miss out on vital information this way
- We propose to:
  - Use machine learning to separate A and H
  - From the classified events, deduce model parameters in two different cases:
    - *Both A and H have the same mass:* Measure cross section times branching ratio for the two, separately
    - *A and H have unequal, but similar mass:* Measure the mass difference



Inputs

- Look at the decay $A/H \to \tau\tau \to \pi^+\pi`0\nu\,\pi^-\pi^0\nu$
- Fundamental info: 4-momenta of 4 particles, plus missing transverse energy
- Derived info: various angles, energy ratios, impact parameters
  - One angle of particular importance: Angle between decay planes



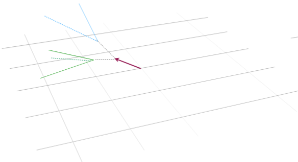


- Generating all datasets using Pythia8.2

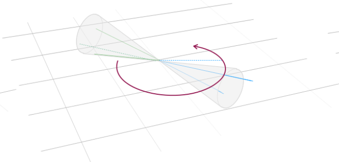
Processing inputs

- Need to choose a standard frame of reference
- When doing so, the 16 4-vector components are reduced to 11 independent variables

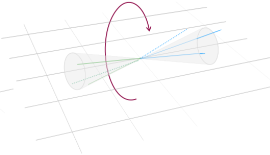
1: Boost to visible rest frame



2: Rotate to align with z axis



3: Rotate so that pi- has zero x-component



τ-	px	py	pz	E
τ+	px	py	pz	E
π-	px	py	pz	E
π0(-)	px	py	pz	E
π+	px	py	pz	E
π0(+)	px	py	pz	E

τ-	0	0	pz	E
τ+	0	0	-pz	E
π-	px	py	pz	E
π0(-)	px	py	pz	E
π+	px	py	pz	E
π0(+)	px	py	pz	E

τ-	0	0	pz	E
τ+	0	0	-pz	E
π-	0	py	pz	E
π0(-)	0	-py	pz	E
π+	px	py	pz	E
π0(+)	-px	-py	pz	E

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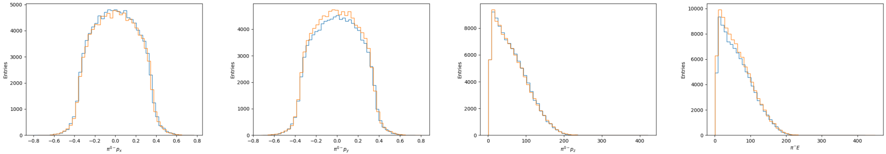
Neural network

- Implemented a fully-connected feed-forward neural network in Keras (i.e. standard Dense() layers)
- ReLu activation functions, Adam optimiser, batch normalisation included
- so far tested 2-4 hidden layers with $\sim$ 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
    - Simple-ish network implementation achieves $\sim$ 0.61 ROC AUC



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Summary

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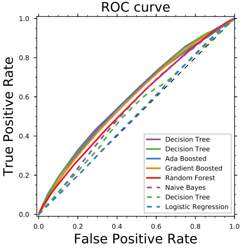
- Currenlty optimising network structure
- Other
  classifiers tested, no immediate success
- Still thinking
  through some open issue, related to
  - Feature engineering
  - Feature scaling
  - Uncertainty estimation



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