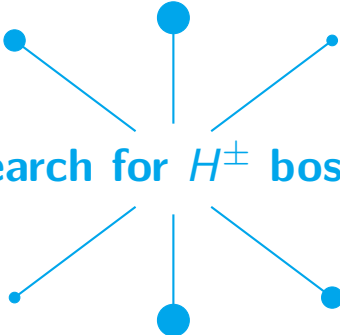




Search for $H^\pm$ boson

DESY Summer Student Programme 2019

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Deutsches Elektronen-Synchrotron

28.8.2019

Two higgs doublet model as a SM extension

SM: one doublet Φ of complex scalar fields

THDM: two doublets Φ_1 and $\Phi_2 \rightarrow$ five Higgs-sector particles

α – mixing angle of neutral CP even Higgs-particles

β : $\tan \beta = v_1/v_2$, where v_1 and v_2 are vacuum expectation values, corresponding to each of doublets



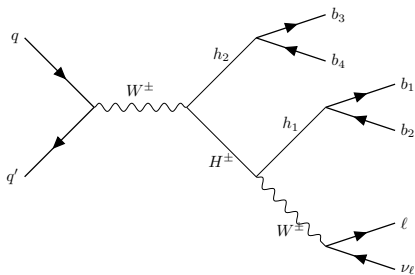
Model specification:

- Type I ($\Phi_1 \rightarrow -\Phi_1$) (no FCNC)
- $m_H = 125.09$ GeV
- $\sin(\alpha - \beta) = 0 \rightarrow m_h < m_H$
- $m_{H^\pm} = m_A, \tan(\beta) = 3$

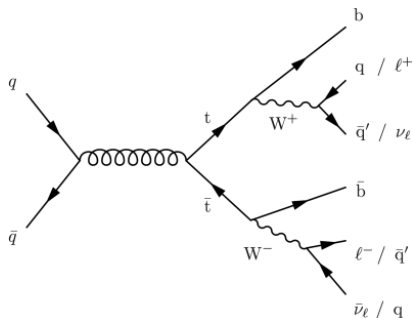
Features of this specification:

- High $\text{BR}(H^\pm \rightarrow W^\pm h)$
- h decays to fermions (b, τ)
- Large unexcluded region for high $\text{BR}(H^\pm \rightarrow W^\pm h)$

Feynman diagrams

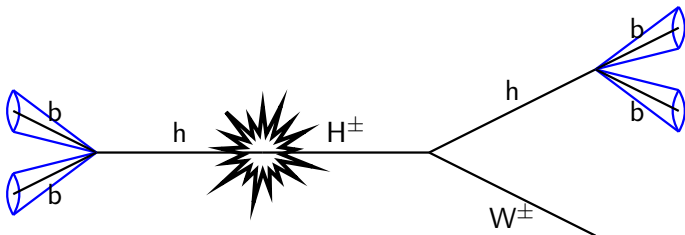


Studied process

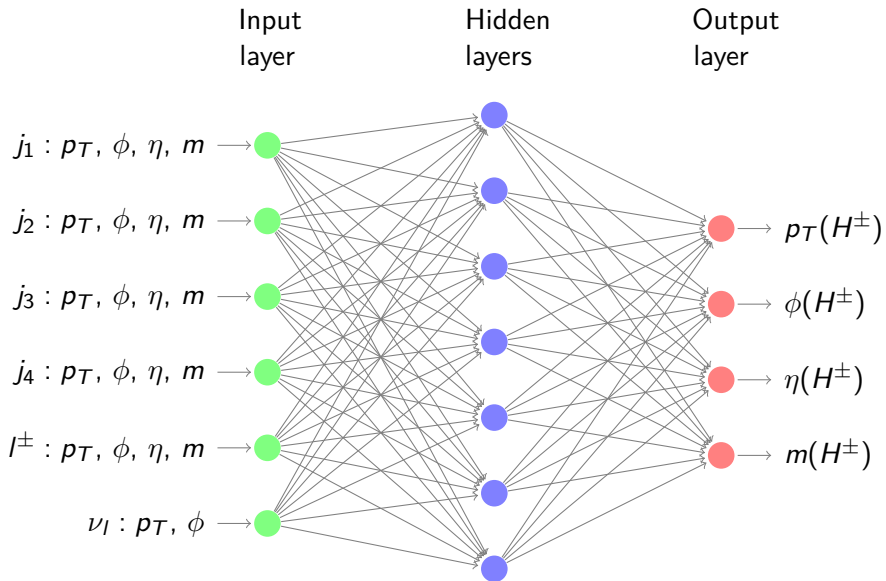


Background process

Non-boosted topology:



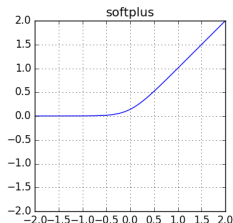
Combinatorial problem: only two of four jets origin from a charged Higgs, and one has to choose these jets correctly to reconstruct the four-momenta of the intermediate particle $H^\pm$



Parameters of the neural network

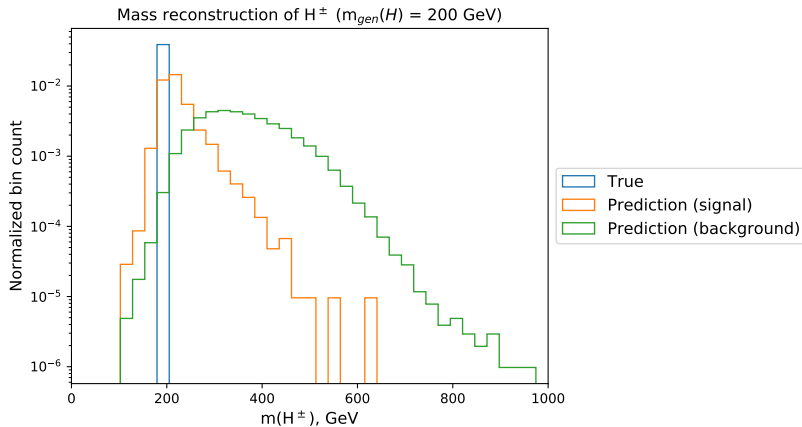
During the network's hyperparameters tuning (random search in the grid) the following set of parameters turned out to be optimal:

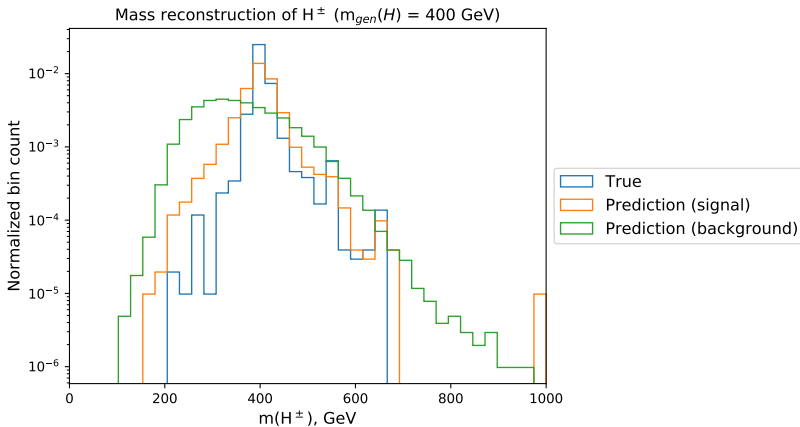
- Number of hidden layers: 5
- Nodes in each hidden layer: 200
- Batch size: 100
- Activation function for nodes in hidden layers: softplus

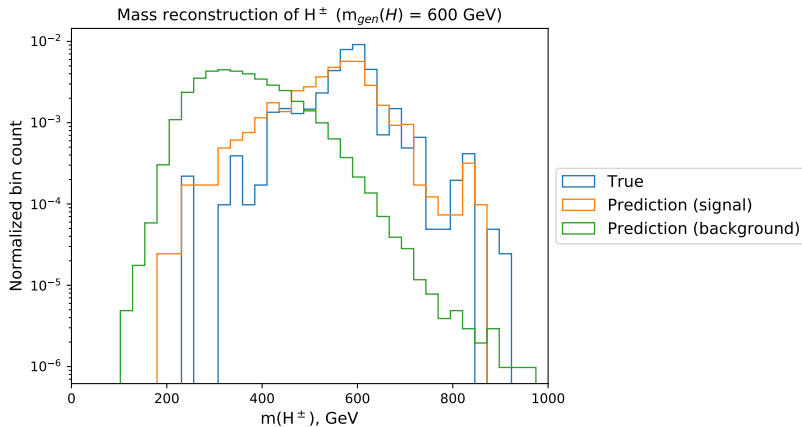


MC-generated events with $m(h_1) = 100$ GeV and $m(H^\pm) = 200, 250, \dots, 600$ GeV were used for training

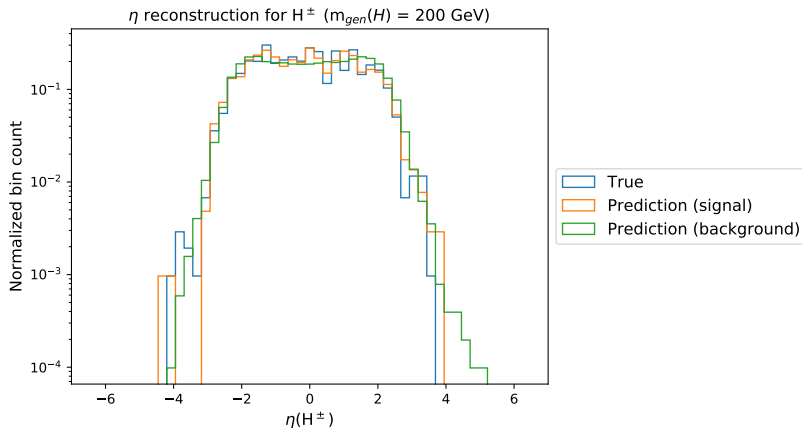
- $\sim 3 \cdot 10^5$ events
- unbalanced data (from $\sim 36 \cdot 10^3$ events for $m(H^\pm) = 200$ GeV to $\sim 14 \cdot 10^3$ events for $m(H^\pm) = 600$ GeV) → using *weighted* MSE as a loss function
- training : test : validation = 81 : 10 : 9



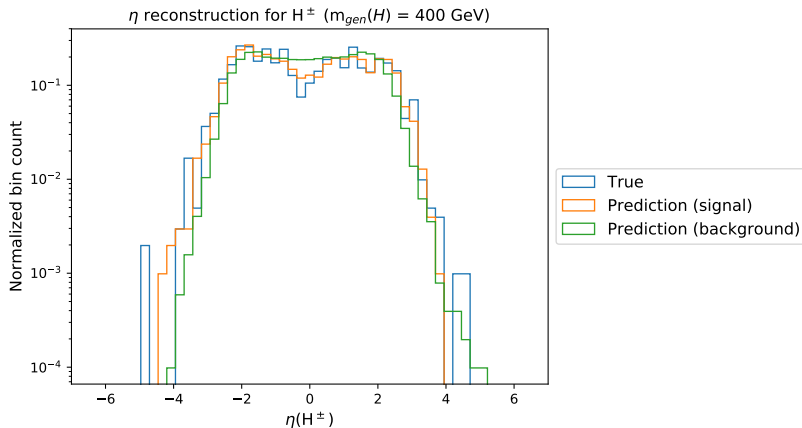




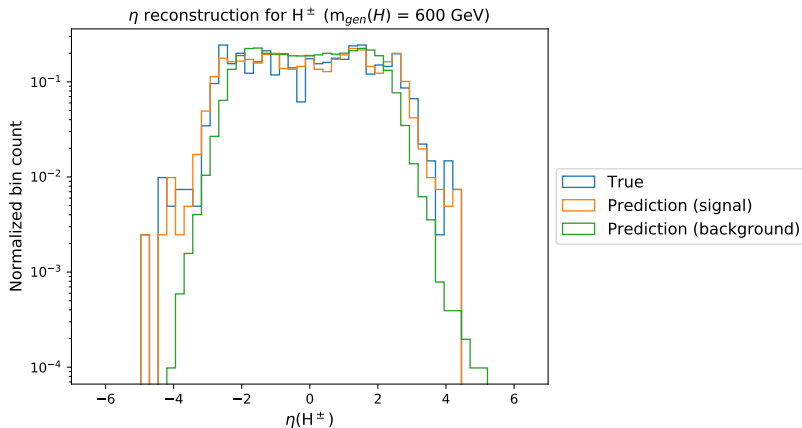
Predictions of pseudorapidity



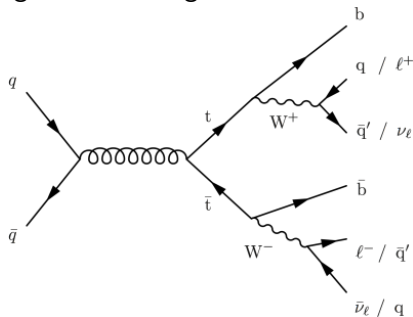
Predictions of pseudorapidity



Predictions of pseudorapidity

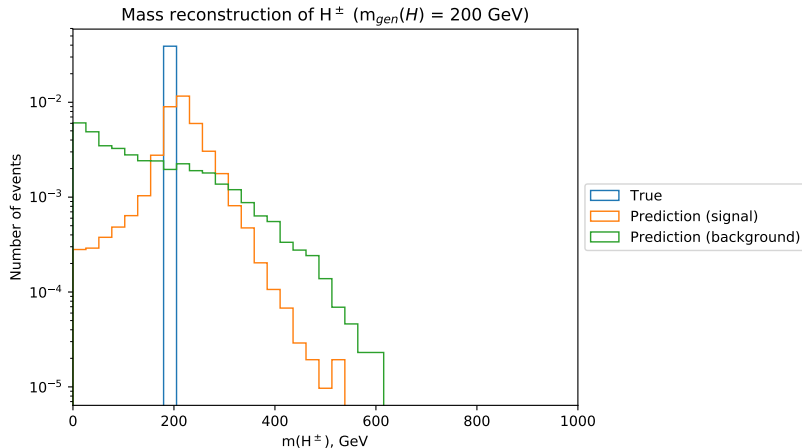


Significant background to deal with:

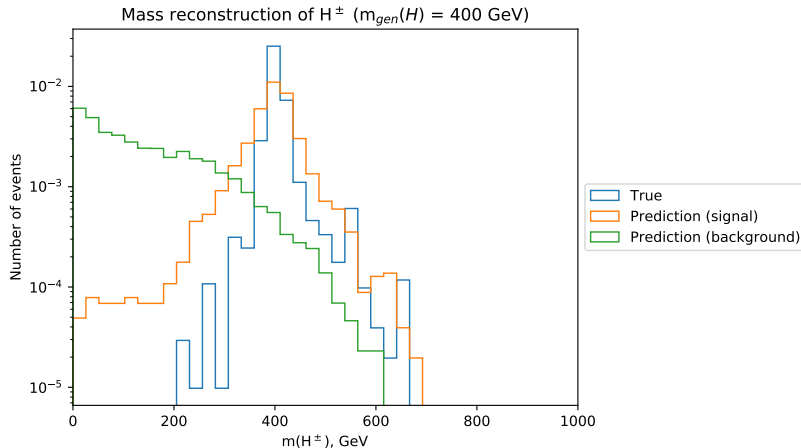


Solution: include background events into training and train the network such that it will predict for them vector $(p_T, \phi, \eta, m) = (0, 0, 0, 0)$.

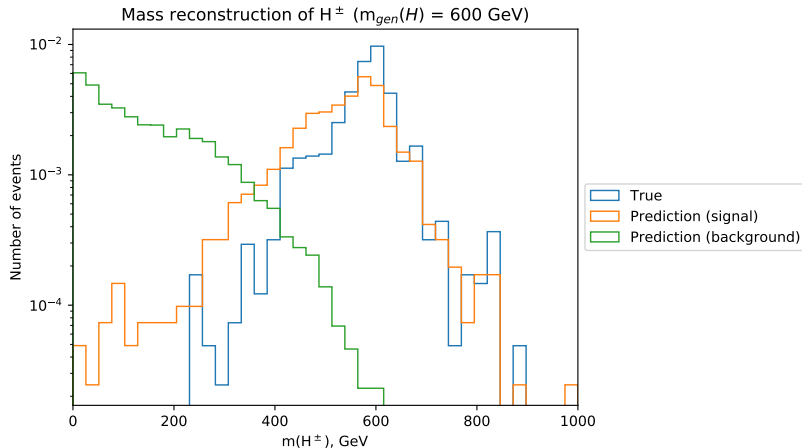
Dense NN with $\text{bkg} \rightarrow 0$



Dense NN with $\text{bkg} \rightarrow 0$



Dense NN with $\text{bkg} \rightarrow 0$





What is done:

- Dense neural network is implemented
- Hyperparameters tuning is performed
- Architectures with LSTM and convolutional layers are tested
- Successful reconstruction of $H^\pm$ with mass in a broad spectrum (from 200 GeV to 600 GeV) is accomplished
- Different approaches of background suppression are tested
- $t\bar{t}$ -background suppression is achieved

What can be improved:

- Architecture (researches on more complicated layers are needed)

Higgs Mechanism is included into the SM to generate masses of the gauge bosons ($W^\pm$ and Z).

Recipe:

- Introduce a complex doublet Φ of scalar fields into the Electroweak Lagrangian $\mathcal{L}_{EW}$:

$$\mathcal{L}_{EW} = -\frac{1}{4}W_{\mu\nu}^a W_a^{\mu\nu} - \frac{1}{4}B_{\mu\nu}B^{\mu\nu} + (D_\mu\Phi)^\dagger(D_\mu\Phi) - \mu^2\Phi^\dagger\Phi - \lambda(\Phi\Phi^\dagger)^2,$$

where W_μ^i and B_μ are massless boson fields and D_μ is the covariant derivative, defined as

$$D_\mu = \partial_\mu - ig_2 \frac{\tau_a}{2} W_\mu^a - ig_1 \frac{Y_h}{2} B_\mu$$

- Break symmetry $\rightarrow$ massive bosons – W^+ , W^- and Z , massless boson γ and massive CP-even neutral particle – Higgs boson.

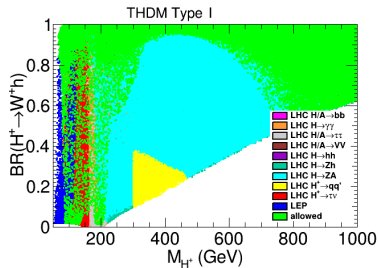
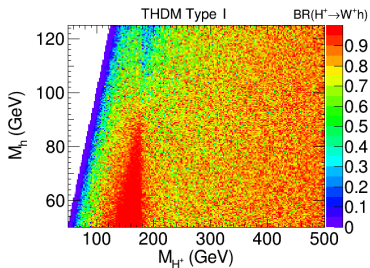


Two higgs doublet model – extension of the SM

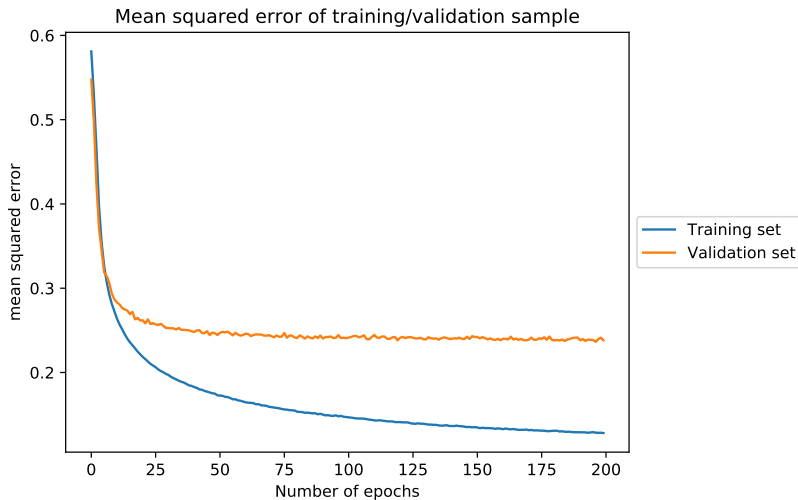
Why don't we introduce another complex scalar doublet?
2 doublets $\rightarrow$ five Higgs-sector particles, angle α – the mixing angle of neutral CP even Higgs-particles, β – angle which is responsible for the ratio of the vacuum expectation values v_1 and v_2 , corresponding to the doublets Φ_1 and Φ_2 : $\tan \beta = v_1/v_2$.



Features of the specification in plots

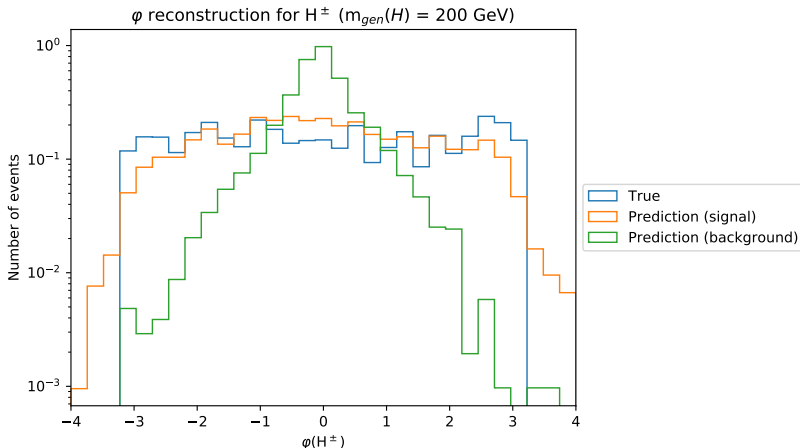


Training curve



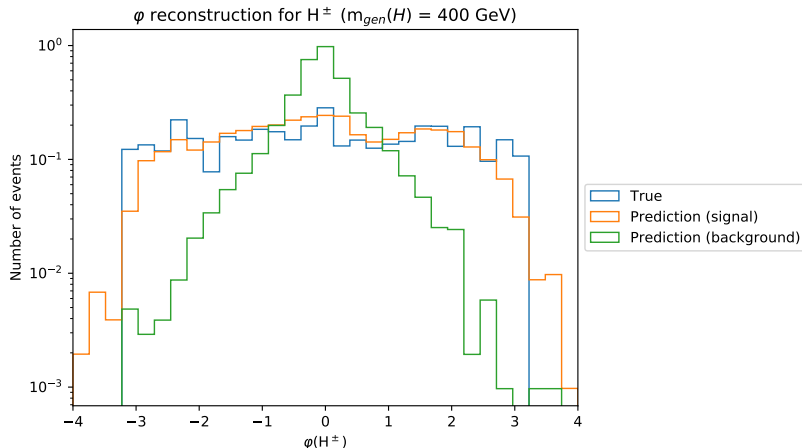
Results ($\phi^{pred}(H^\pm)$ for $m^{gen}(H^\pm) = 200$ GeV)

Angle reconstruction (dense NN with bkg $\rightarrow$ 0)



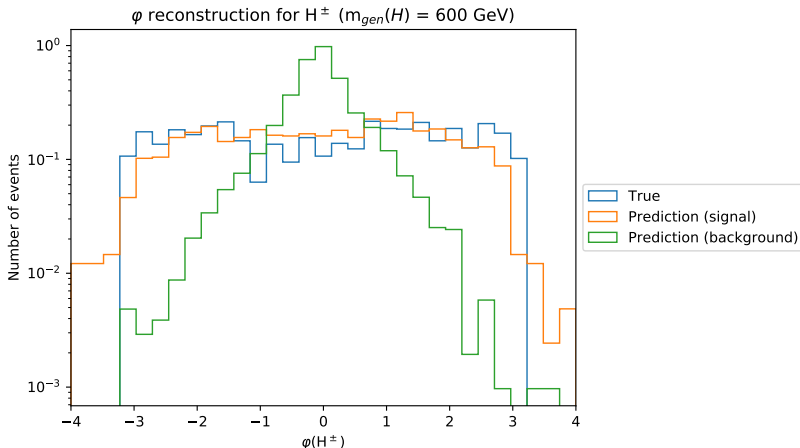
Results ($\phi^{pred}(H^\pm)$ for $m^{gen}(H^\pm) = 400$ GeV)

Angle reconstruction (dense NN with bkg $\rightarrow$ 0)

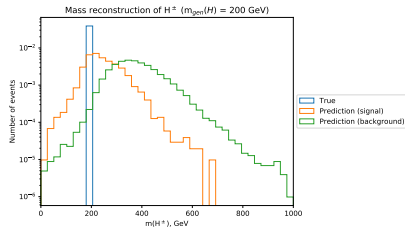
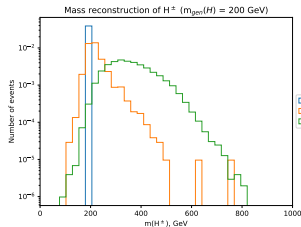


Results ($\phi^{pred}(H^\pm)$ for $m^{gen}(H^\pm) = 600$ GeV)

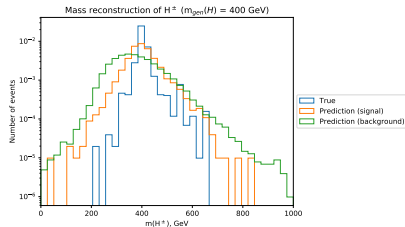
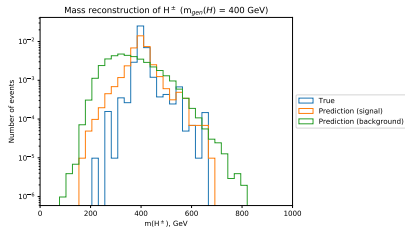
Angle reconstruction (dense NN with bkg $\rightarrow$ 0)



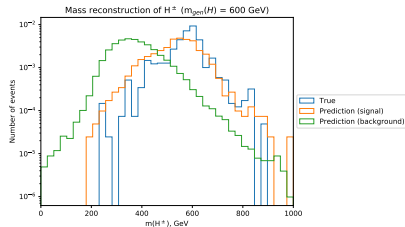
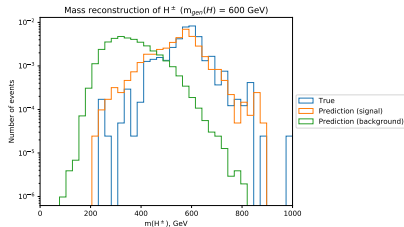
$m(H^\pm)$ predictions ($m^{\text{gen}}(H^\pm) = 200 \text{ GeV}$)



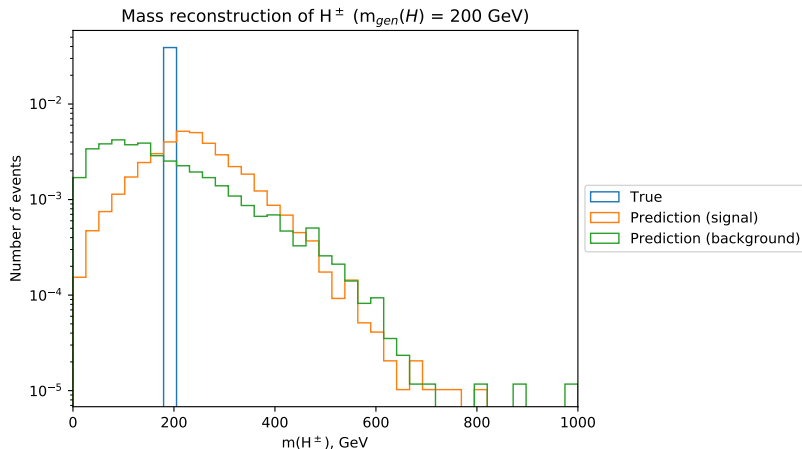
$m(H^\pm)$ predictions ($m^{\text{gen}}(H^\pm) = 400 \text{ GeV}$)



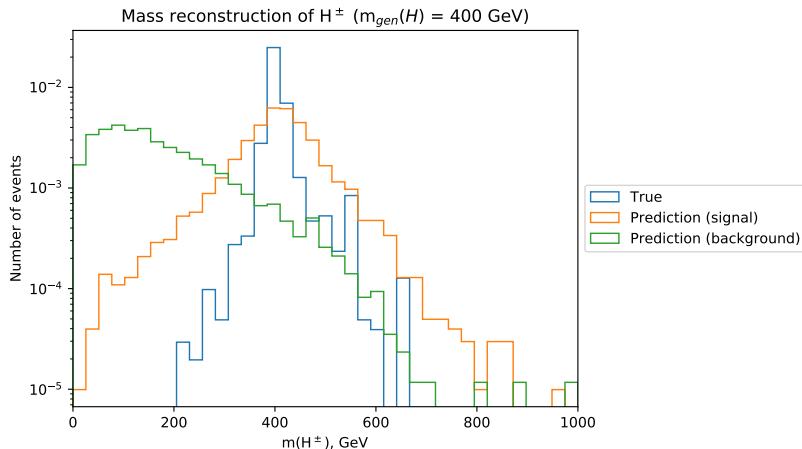
$m(H^\pm)$ predictions ($m^{\text{gen}}(H^\pm) = 600 \text{ GeV}$)



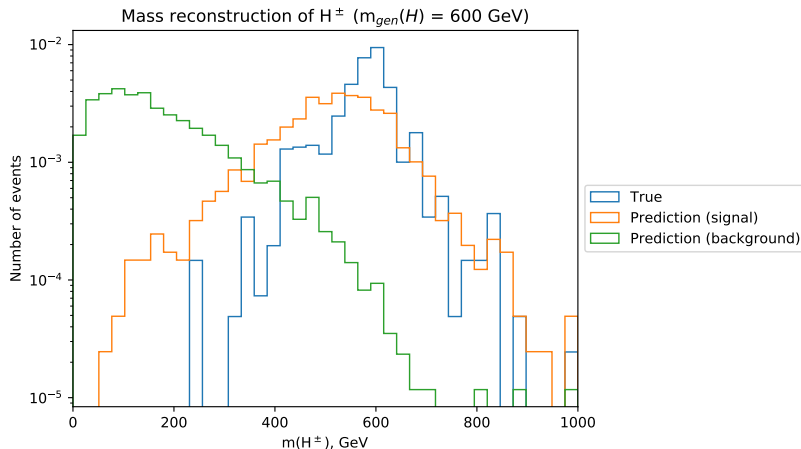
Dense NN with $\text{bkg} \rightarrow 0$



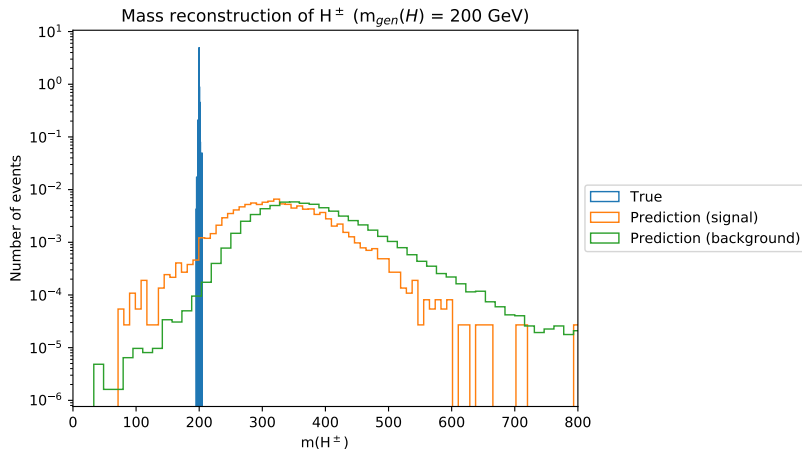
Dense NN with $\text{bkg} \rightarrow 0$



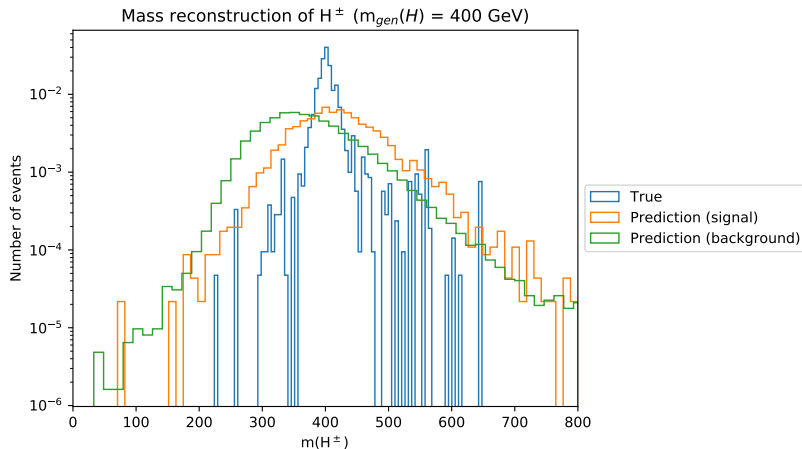
Dense NN with $\text{bkg} \rightarrow 0$



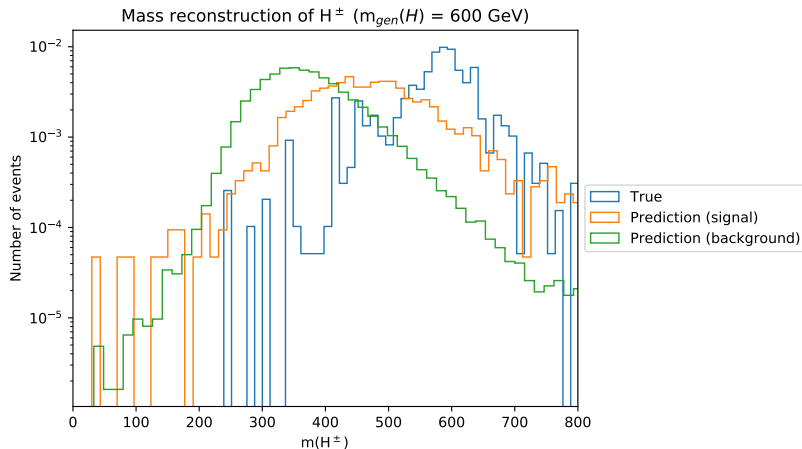
Convolutional input layer + 4 dense fully-connected layers



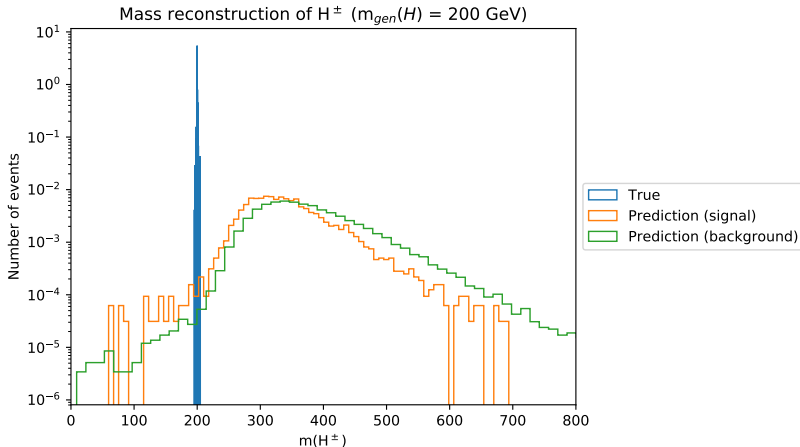
Convolutional input layer + 4 dense fully-connected layers



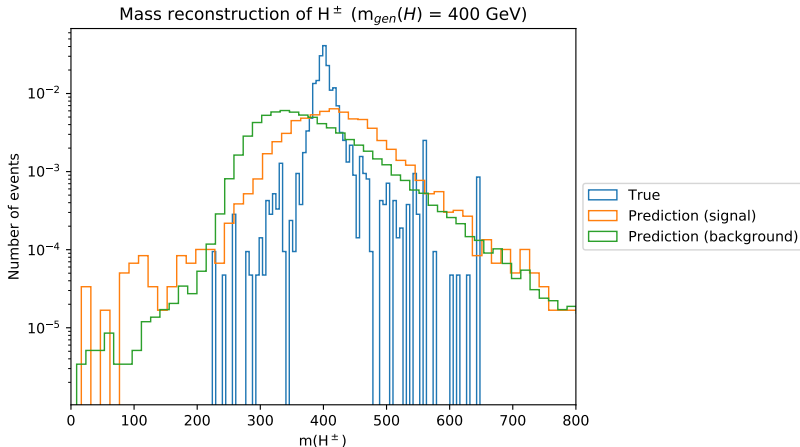
Convolutional input layer + 4 dense fully-connected layers



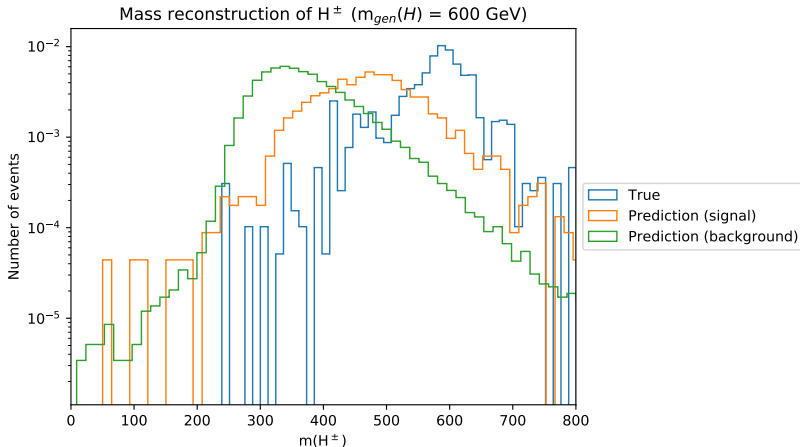
2 convolutional input layers (32 kernels $6 \times 1 + 4$ dense fully-connected layers)



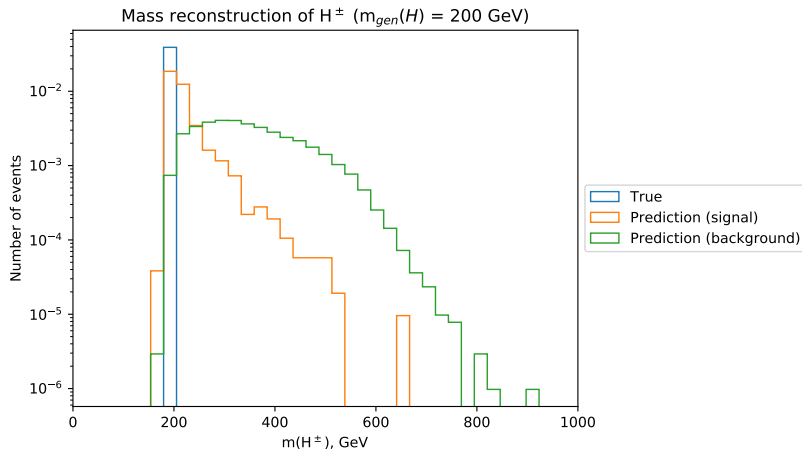
2 convolutional input layers (32 kernels $6 \times 1 + 4$ dense fully-connected layers)



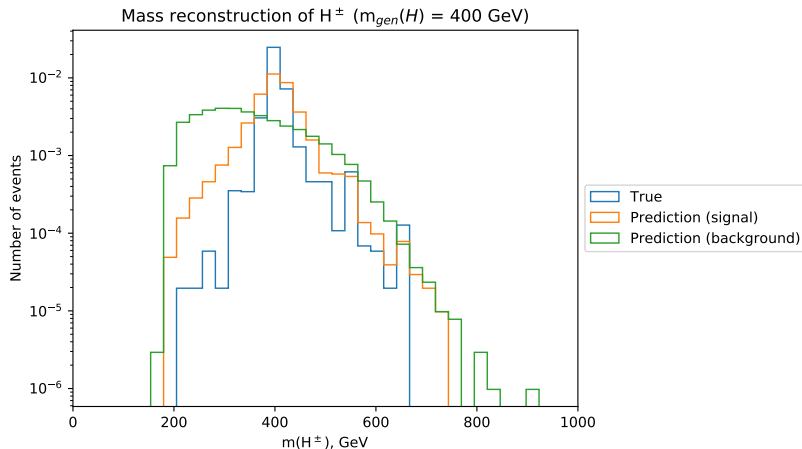
2 convolutional input layers (32 kernels $6 \times 1 + 4$ dense fully-connected layers)



LSTM input layer + 4 dense fully-connected layers



LSTM input layer + 4 dense fully-connected layers



LSTM input layer + 4 dense fully-connected layers

