Search for $H^{\pm}$ boson

DESY Summer Student Programme 2019

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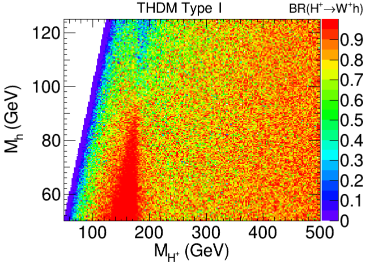
Two higgs doublet model

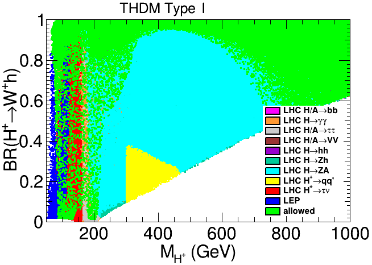
Model specification:

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

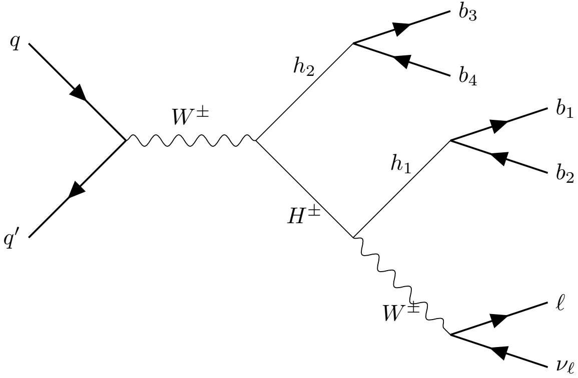
Features of this specification:

- High BR($H^\pm \to W^\pm h$) (first plot)
- h decays to fermions (b, τ)
- Large unexcluded region for high BR($H^\pm \to W^\pm h$) (second plot)



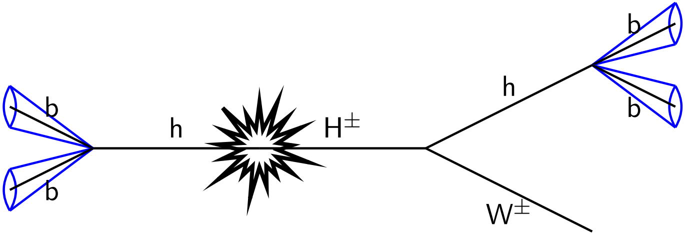


Feynman diagram of analysis process



Signal jet kinematic

Non-boosted topology:

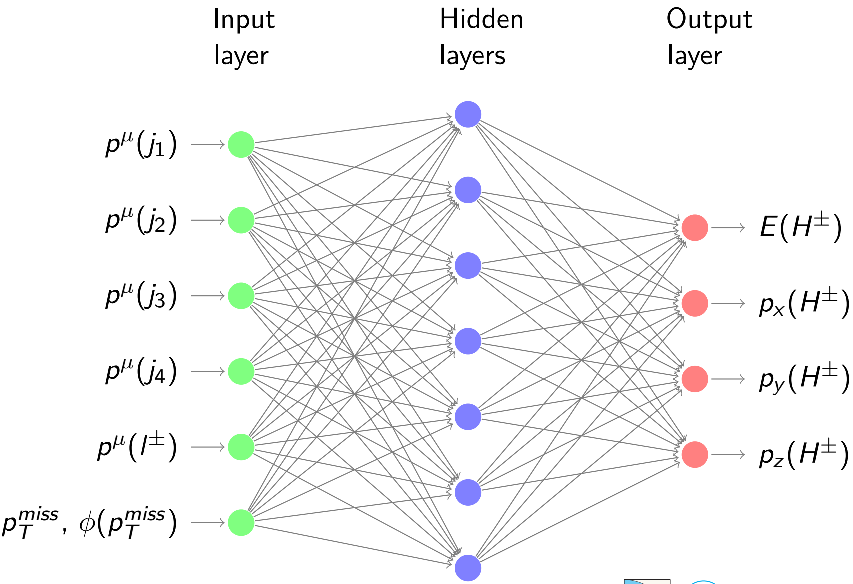


Data for training a DNN

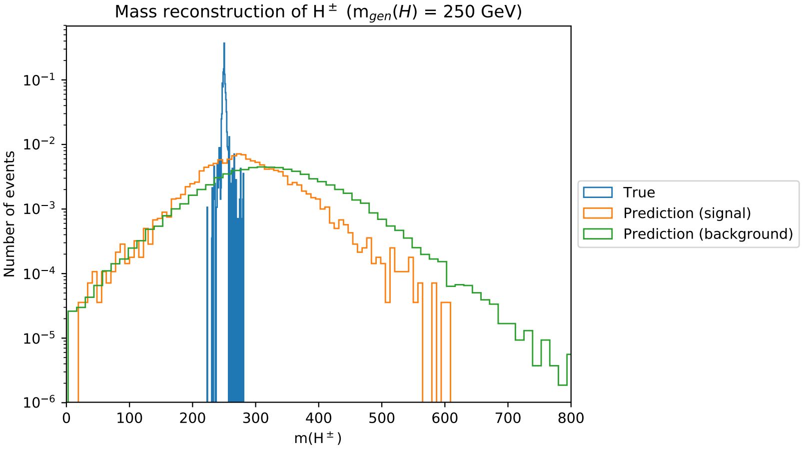
MC-generated events with $m(h_1) = 100$ GeV and $m(H^{\pm}) = 200, 250, ..., 600$ GeV were used for training

- $\rightarrow$ $\sim 3 \cdot 10^5$ events
- $\rightarrow$ 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) $\rightarrow$ using *weighted* MSE as a loss function
- $\rightarrow$ training : test : validation $= 81 : 10 : 9$

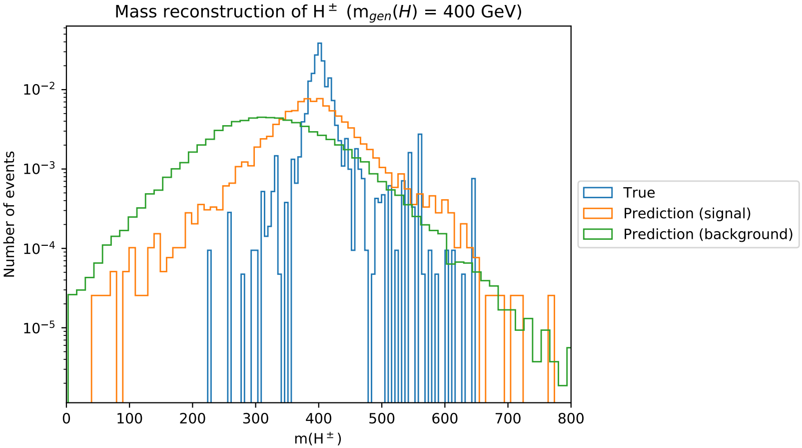
Dense neural network for $m(H^{\pm})$ reconstruction



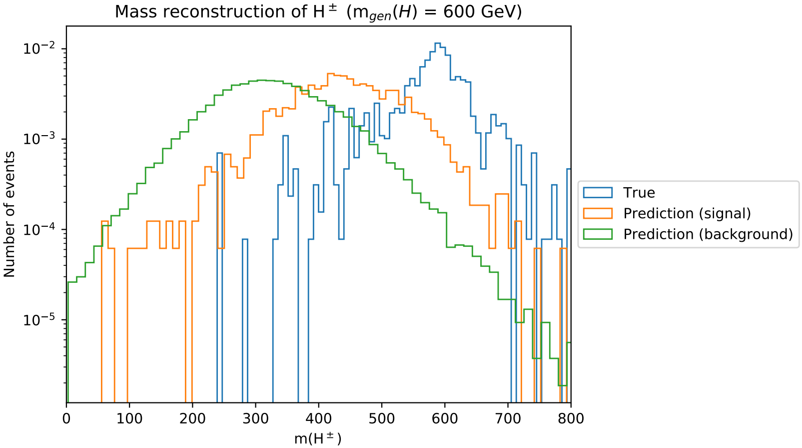
Results ($m^{pred}(H^{\pm})$ for $m^{gen}(H^{\pm}) = 250$ GeV)



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



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



Analysis status (07.08)

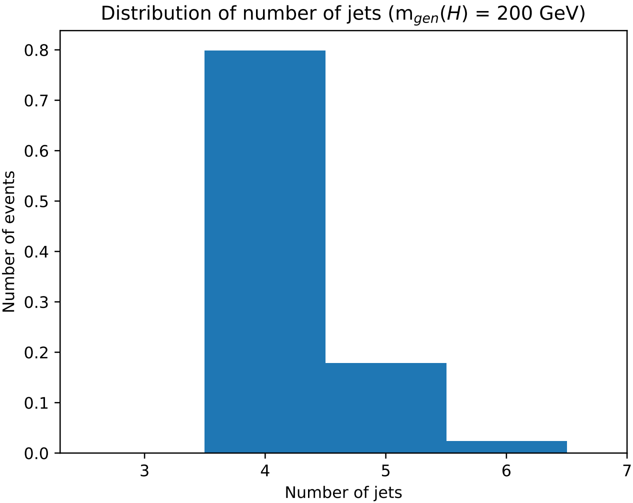
What was achieved/figured out:

- → Neural network is implemented
- → Trained *dense neural network* is able to predict $m(H^{\pm})$ for low masses and gives shifted results for higher masses
- → Dense neural network performs *worse* if it has some *convolutional layers* among the first layers
- → Naive attempts to include background events into training are not successful ...

Plans:

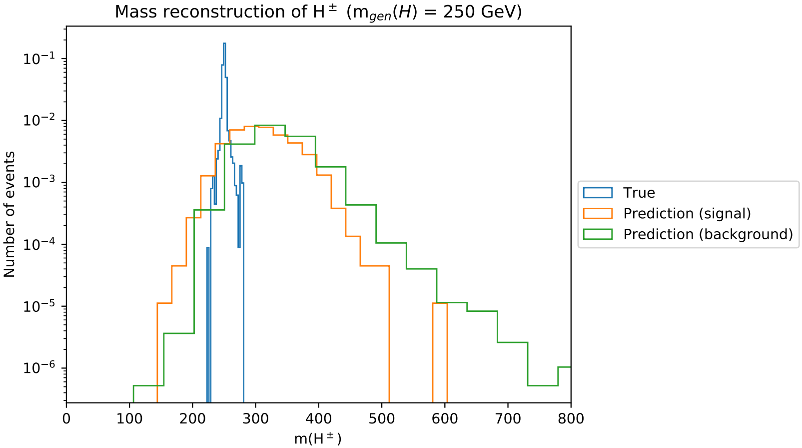
- → Remove (temporarily?) background events from training
- → Include more information about the event in the input (more than 4 jets in each)

Distribution of the total number of jets (in MC)



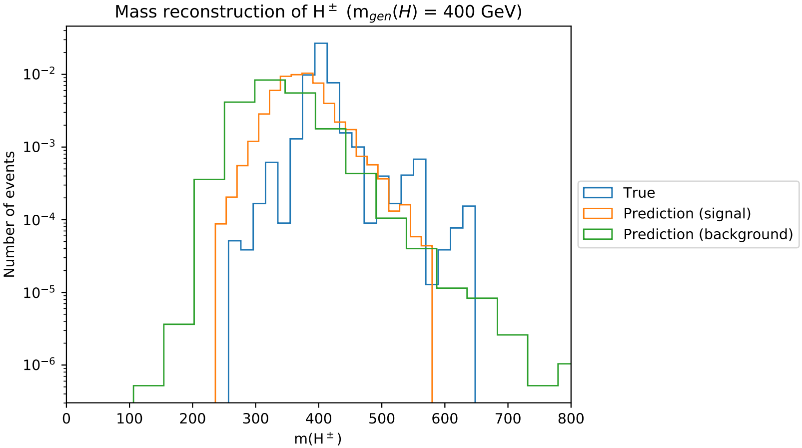
Results ($m^{pred}(H^{\pm})$ for $m^{gen}(H^{\pm}) = 250$ GeV)

Dense neural network with null padding



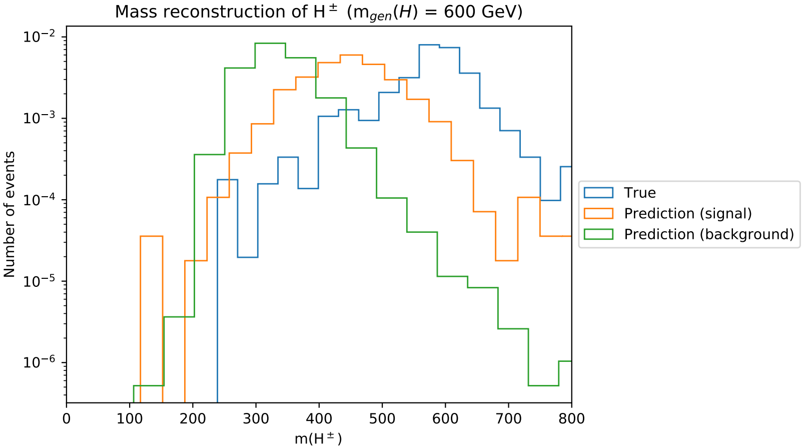
Results ($m^{pred}(H^{\pm})$ for $m^{gen}(H^{\pm}) = 400$ GeV)

Dense neural network with null padding

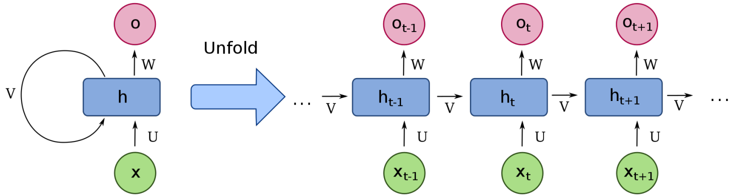


Results ($m^{pred}(H^{\pm})$ for $m^{gen}(H^{\pm}) = 600$ GeV)

Dense neural network with null padding



New approach: recurrent neural network

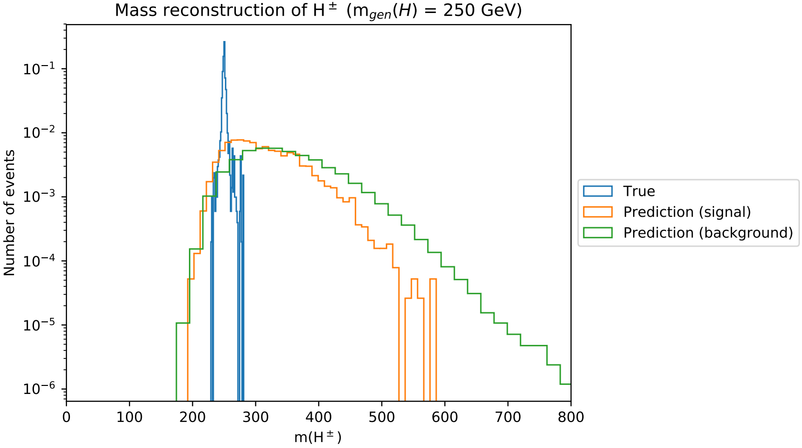


The data can be interpreted as a *sequence* of 4-momenta of the «particles» in the final states

We decided to use the one of the most popular kinds of RNN - LSTM (long short term memory)

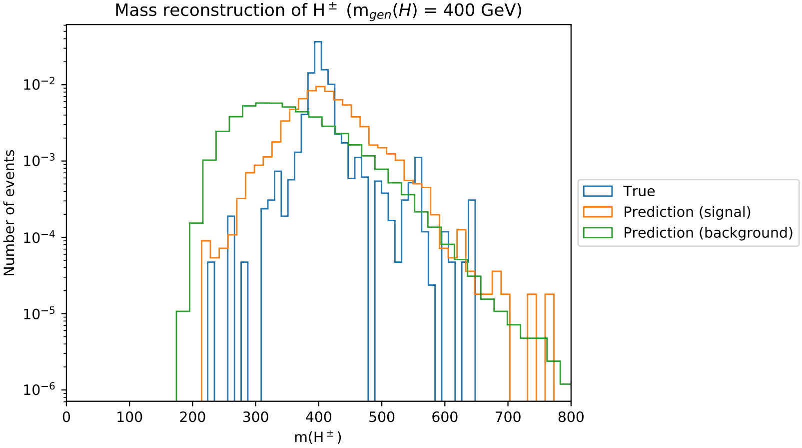
Results ($m^{pred}(H^{\pm})$ for $m^{gen}(H^{\pm}) = 250$ GeV)

LSTM with dense layers (null padding for inputs)



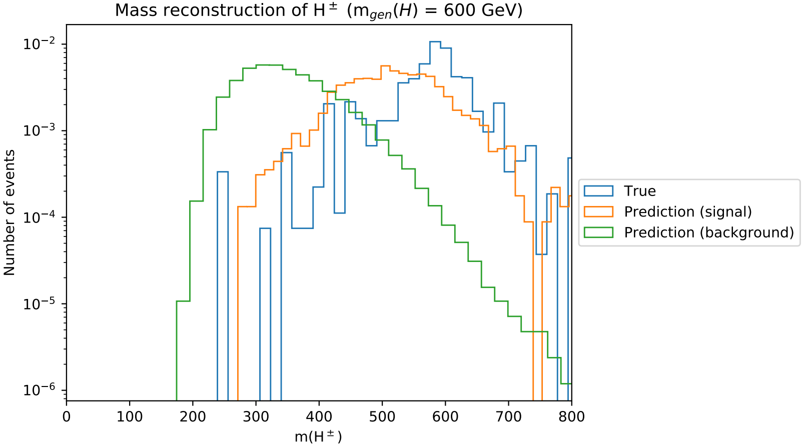
Results ($m^{pred}(H^{\pm})$ for $m^{gen}(H^{\pm}) = 400$ GeV)

LSTM with dense layers (null padding for inputs)



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

LSTM with dense layers (null padding for inputs)



Analysis status (14.08)

What was achieved for this week:

- → Information about all the jets (from 4 to 6) in the MC-generated event was included in the set of input-features
- → Dense NN with 30 inputs was used (with null padding)
- → Convolutional 8×4-dimensional (particle $\times$ momentum) input layer was tested (unsuccessfully)
- → LSTM with null padding was trained

Plans:

- → Train LSTM without null padding
- → More architectures?
- → Compare with the existing solution (based on BDT)

Thank you for your attention

Don't use the GPU's! Otherwise I'll shoot you