

# Report

## A study of machine learning algorithms for reconstruction of missing energy in particle physics experiments.

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## 1 Introduction and Objective

## 2 The Dataset

### 2.1 Structure

The dataset consists of simulated  $pp$  collision events, in which a charged Higgs is produced and decays as  $H^+ \rightarrow \tau\nu$ . Each event is described by one set of observable variables and one set of unobservable variables.

Observable variables:

- $E_x^{\text{miss}}, E_y^{\text{miss}}$  — The  $x$ - and  $y$ -components of the missing energy.
- $P_{\tau_{\text{vis.}}}$  — The 4-momentum of the visible (hadronic) part of the  $\tau$  decay.
- $P_{b_0}, P_{b_1}, P_{q_0}, P_{q_1}$  — The 4-momenta of the two  $b$ -jets and two light jets.

Unobservable variables:

- $P_{\nu_\tau}$  — The 4-momentum of the neutrino from the charged Higgs decay.
- $P_{\bar{\nu}_\tau}$  — The 4-momentum of the neutrino from the  $\tau$  decay.

### 2.2 Production

MG5\_aMC@NLO [1] is used for the matrix element computation of  $gg/q\bar{q} \rightarrow H^+$  and the event simulation. The events are then passed to PYTHIA8 [2] for the showering and hadronization, and for the  $H^+ \rightarrow \tau\nu$  decay. Finally, the detector response is simulated using DELPHES [3] with an ATLAS-like geometry.

### 2.3 Estimated and true quantities

The true quantities for both the observable and the unobservable variables are available as output from the event simulation. The estimated values for the observable variables are reconstructed from the output from the detector response simulation.

## 3 Methods and Implementation

### 3.1 Predictor selection

### 3.2 Artificial Neural Network

The data needs to be scaled to avoid the tails of the Artificial Neural Network (ANN) activation functions and improve the learning rate. The method used here is to scale it such that the minimum is -1 and the maximum is 1 for each training set variable. The test set data is scaled using the scaling parameters computed from the training set. Another scaling method would be to scale the mean to 0 and the standard deviation to 1, but this was found to slow down the training and give worst result.

The ANN implemented here uses Python with SciPy [4], Numpy [5], and Pandas [6] for general data processing, and Keras [7] for the actual neural network. The number of input nodes is restricted to the 19 selected predictor variables and the output to the target dimension of 1. Since the network is used for regression, the activation functions between the last hidden layer and the output must be linear.

Training is performed using stochastic gradient descent with the Nesterov method [8] and a mean-squared-error loss function. The learning rate was set to 0.1, the learning rate decay to  $1 \times 10^{-6}$ , and the momentum to 0.9.

A large number of configurations of the hidden layers were tested by varying the number of layers, the number of perceptrons in each layer, and the activation functions (sigmoid, tanh, and softmax). Sigmoid activation functions produced the best result for a fixed training period. A network with two hidden layers (i.e. 4 layers counting the 19 node input layer and 1 node output layer) with 25 and 10 perceptrons was found to be sufficiently complex. Using deeper networks, e.g. one with 4 hidden layer with 20, 35, 25, and 15 perceptrons, did not improve the result.

## 4 Results

## 5 Discussion

Out of all the Machine Learning (ML) methods tried, ANN showed the best performance in terms of resolution and predicting the  $p_T$  of the tau neutrino.

This project focused on predicting the transverse momentum  $p_T$  of the tau neutrino  $\nu_\tau$  by using the reconstructed four-momenta and missing energy seen by the detector as input and training on the true  $p_T$  given by the Monte-Carlo simulation. In the end it is the mass of the  $H^+$  that is interesting, which means that one option is to target the

$H^+$  mass directly. This would require Monte-Carlo for a range of possible  $H^+$  masses (3 mass-points were used in this study). Another option is to target the complete three-vector of the missing energy or the (combined or separate) four-vectors of the two neutrinos. These options were briefly looked at but were considered to be out of the scope of this project. They will be pursued in more detail in future studies.

To compute the missing transverse mass  $M_T$  (described in sec. 4) from the  $p_T$  predicted by the ML methods, the angle  $\phi$  of the  $p_T$  is needed. However, since we are only predicting the  $p_T$ , the angle  $\phi$  is unknown and is instead taken from the angle of  $M_T$ . It would have been better to also predict  $\phi$ . This will also be studied in the future.

## References

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