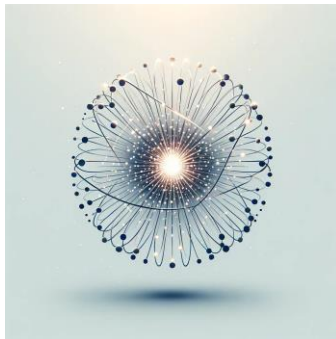




FAIR Universe



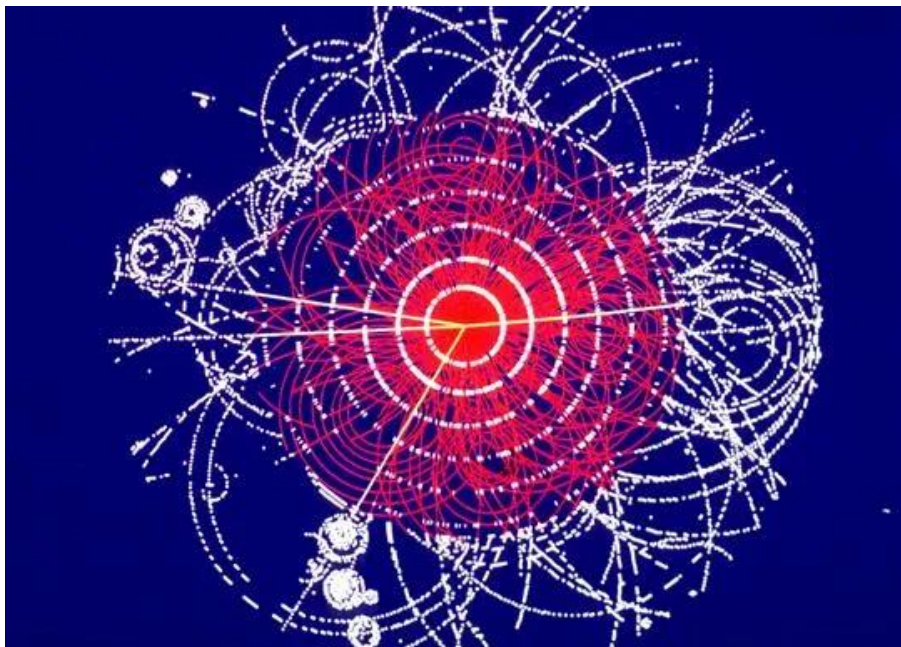
# Fair Universe

HiggsML Uncertainty Challenge

## Sample Submission



# Introduction

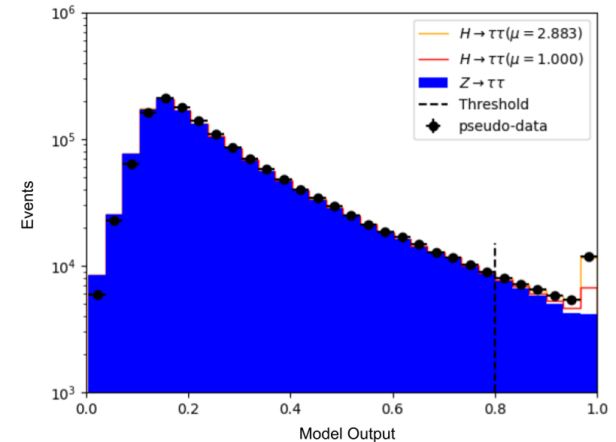


This is a brief summary of the baseline method for the Higgs ML Uncertainty Challenge

The method is a simple ML Classifier with NLL for estimation

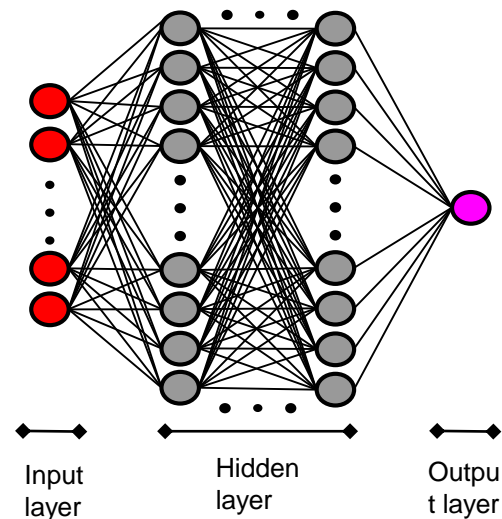
# Basic Algorithm

1. Start
2. Divide data into *train\_set* and *holdout\_set*
3. Use *train\_set* to Train the ML Classifier
4. Construct for S and B functions from *holdout\_set*
5. Combine Define Negative Log Likelihood function as function of TES and  $\mu$
6. For Each pseudo experiment
  - a. Predict score for pseudo experiment
  - b. Use Minuit to find value of  $\mu$ ,  $\sigma_{\mu}$  and TES
  - c. Returns
    - $\mu$
    - $p16 = \mu - \sigma_{\mu}$
    - $p84 = \mu + \sigma_{\mu}$
7. End

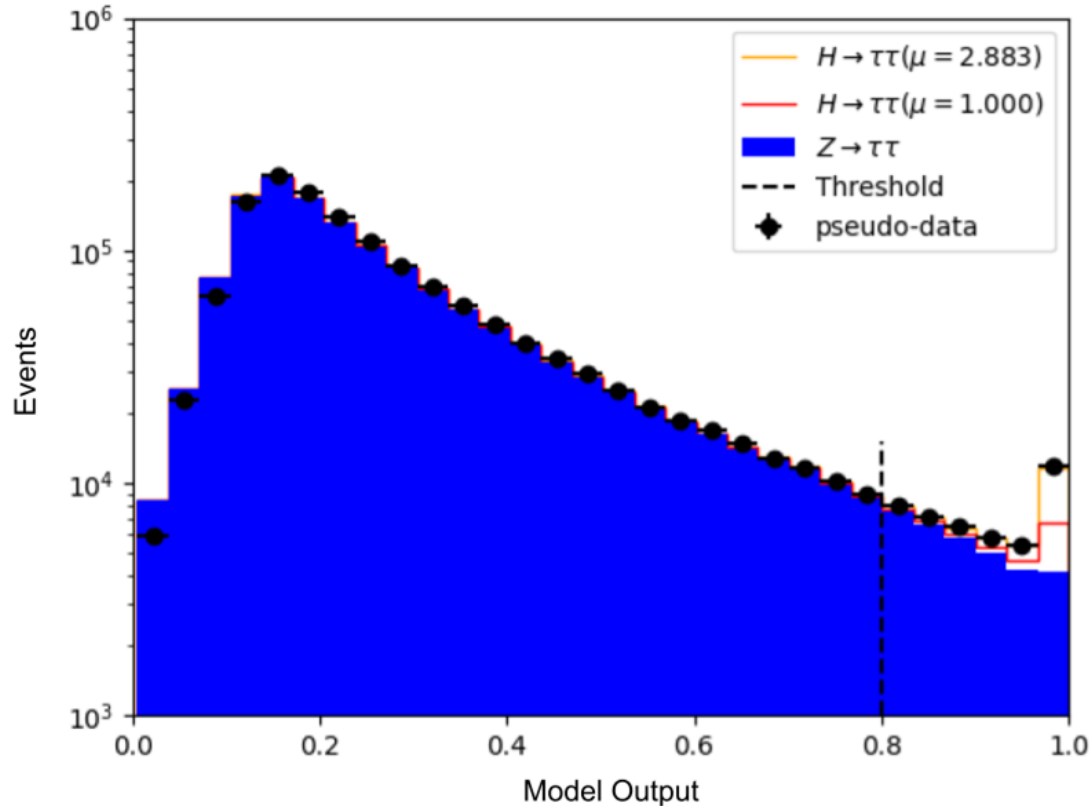


# NN with L2 regularization using PyTorch

- PyTorch NN Classifier is Trained to distinguish Signal (Higgs) from Background (Z)
- 32 features,
- Architecture
  - 4 Hidden layers with 200 nodes
  - 1 Output node
  - Sigmoid Activation between layers
  - L2 Regularization during training
- Model return score between 0 (background) and 1(signal),



# Histograms on Model Score

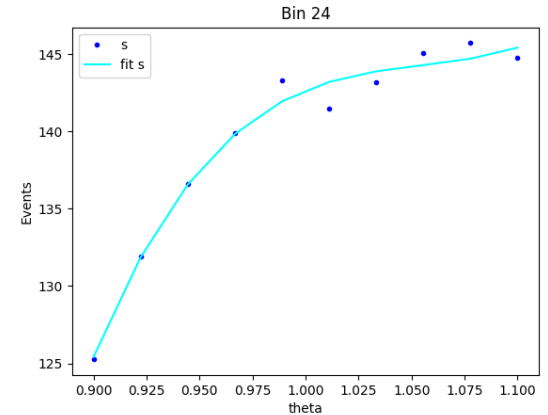
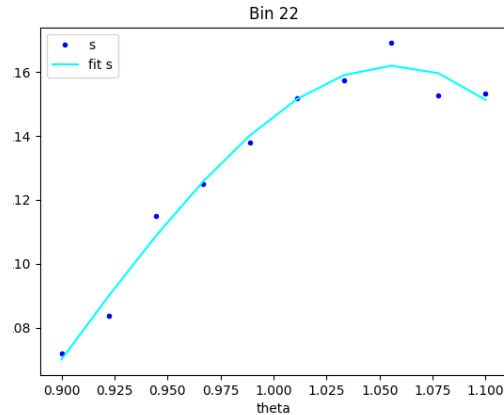
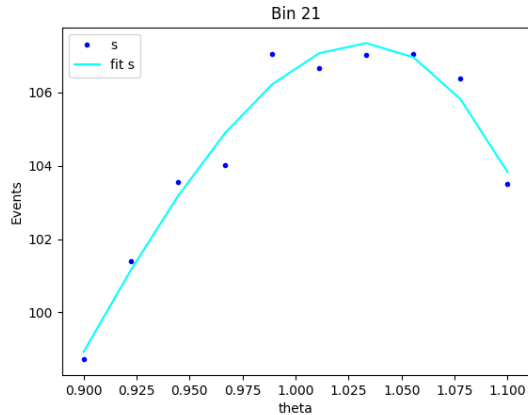


For each value of TES,  
The transformed  
*holdout\_set* is  
evaluated by the model  
and histogram is build on  
the model score

# Parameterisation of $S(\alpha)$

With the help of the *holdout\_set* for we get values of S and B for each TES in each bin.

A polynomial function is used to fit them. This function is later used in the NLL formalism



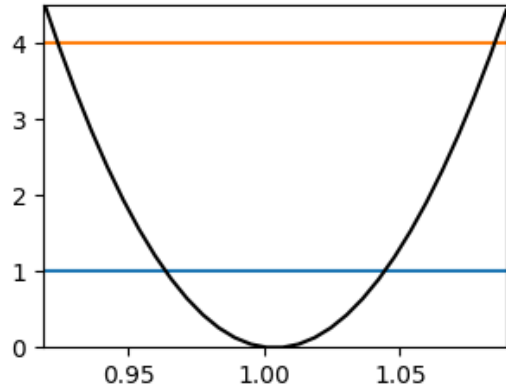
## Profile $\mu$ and $\alpha$ simultaneously

$$L(\mu, \alpha | \mathcal{D}) = \prod_{i=1}^{N_{\text{bins}}} \frac{(\mu S_i(\alpha) + B_i(\alpha))^{n_i} e^{-(\mu S_i(\alpha) + B_i(\alpha))}}{n_i!}$$

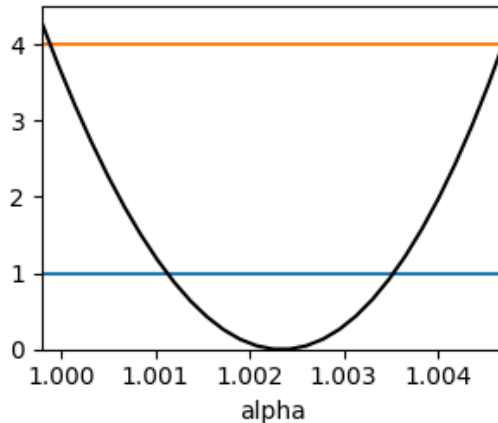
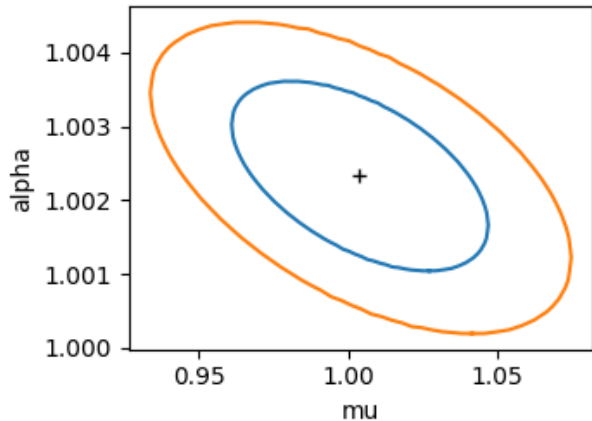
$$\begin{aligned} t_{\mu, \alpha} &= -2 \log(L(\mu, \alpha | \mathcal{D})) \\ &= -2 \sum_i^{N_{\text{bins}}} n_i \log(\mu S_i(\alpha) + B_i(\alpha)) + (\mu S_i(\alpha) + B_i(\alpha)) \end{aligned}$$

$L$  here is the likelihood estimator which depends on  $\mu$  and  $\alpha$ , thus the  $\mu$  at which  $L$  is maximum or  $t_{\mu, \alpha}$  is minimum is the predicted  $\hat{\mu}$ ,

# NLL ( $t_{\mu,\alpha}$ ) curve and contour

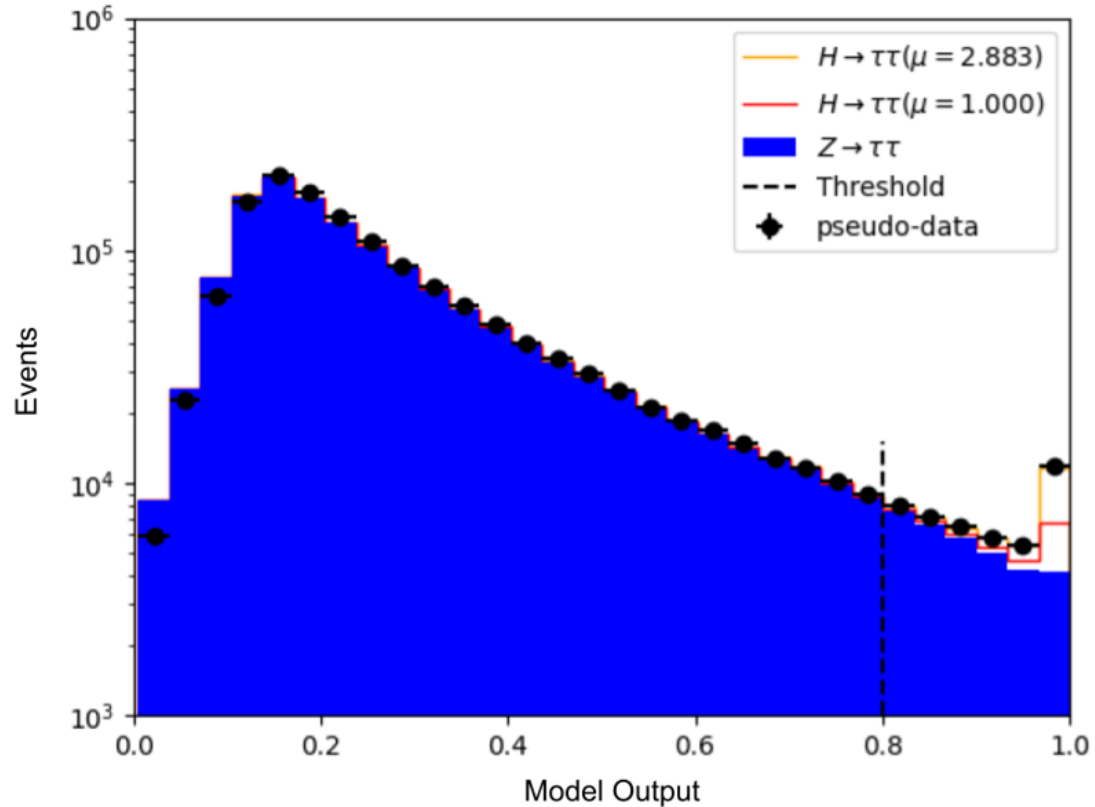


We use *iminuit* package to find the minimum of  $t_{\mu,\alpha}$  with high accuracy and the 1-sigma width, the 1-sigma width is width between points on the parabola for  $t_{\mu,\alpha} = 1$

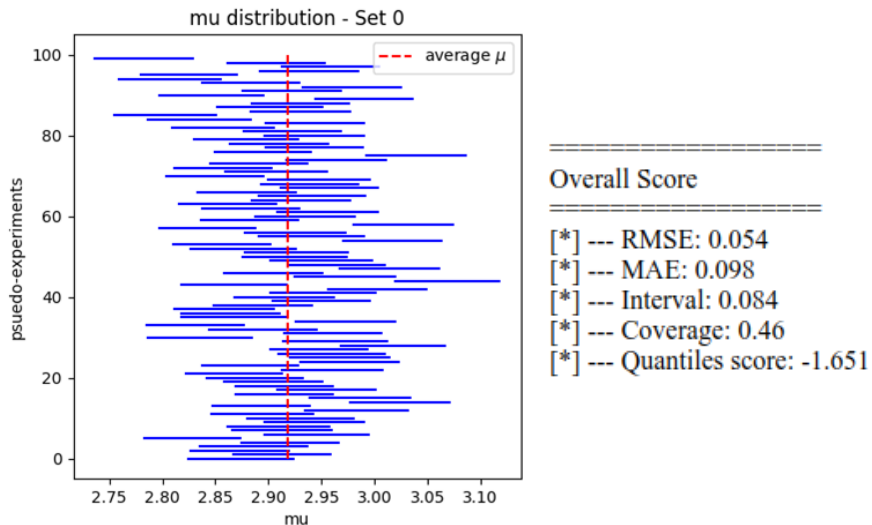




# Fit on one pseudo Experiments



# Signal Strength and Coverage - Pytorch



Coverage plot for NN pytorch (syst) [100 PX]

## Other Remarks

- The model is designed to train for 100 epochs with a early stop
- It's recommended to be trained outside codabench.
- The model has a method to detect trained model, to avoid unnecessary re-training.
- Please comment it out or delete the trained model from the `sample_code_submission`, if you want to retrain.
- The starting kit has option to run on `sample_data` or `public_data`  
The `sample_data` is ~ 1% of the `public_data` so be cautious about it while training.
- All models should be serializable to be compatible with ingestion.

# Back-up

# Parameterisation of B(alpha)

