



# Bayesian Neural Network and its application in ATLAS

Jiahang ZHONG (*Academia Sinica*)



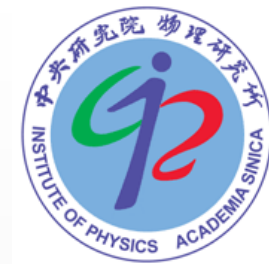
# BNN



- Neural Network following Bayesian statistical interpretation
- Features:
  - Fitting of probability function
  - Regulator to avoid overtraining
  - Uncertainty estimation
- Based on the MLP algorithm
  - Configurable as options of the algorithm
  - Available in rel. 4.1.0 (ROOT 5.28)



# Statistical interpretation of MLP



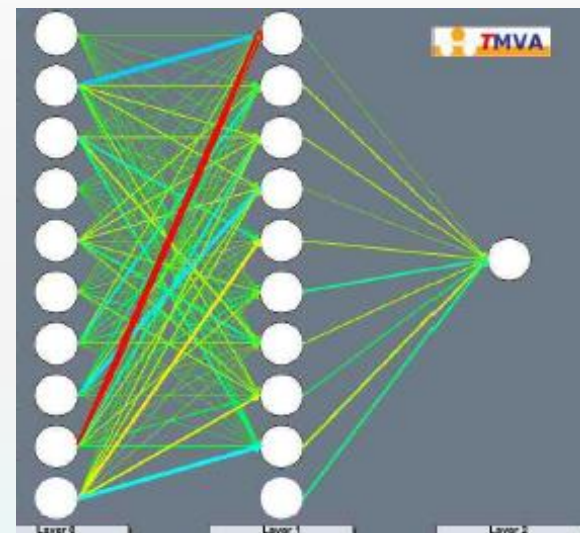
- Generic multivariate function approximator  
(Think of polynomial in 1D)

- Training:

- Unbinned fitting with  $D = \{\mathbf{x}_i, t_i\}$
- Cost function  $(y(\mathbf{x}, \mathbf{w}) - t)^2 = -\log(L)$ ,  $L = P(D|\mathbf{w})$
- Min cost function = Max likelihood

- Prediction:

- Obtained fitted value in the phase space
- Classification: cut at the fitted value for discrimination



$$a_j^{(1)} = \sum_l w_{jl}^{(1)} x_l$$

$$h_j = f^{(1)}(a_j^{(1)})$$

$$f^{(1)}(x) = \tanh(x)$$

$$a_i^{(2)} = \sum_j w_{ij}^{(2)} x_j$$

$$y_i = f^{(2)}(a_i^{(2)})$$

$$f^{(2)}(x) = x$$

# Bayesian implementation (I)

- Fitting probability function

- Probability  $y \in [0,1]$  is more useful than proposition  $y \in \{0,1\}$

- Not for probability density function  $\int y d\mathbf{x} = 1 \Rightarrow$  PDERS

- To constrain  $y$  between 0 and 1, transform  $y$  by  
 $f^{(2)}(x) = 1/(1 + \exp(-x))$

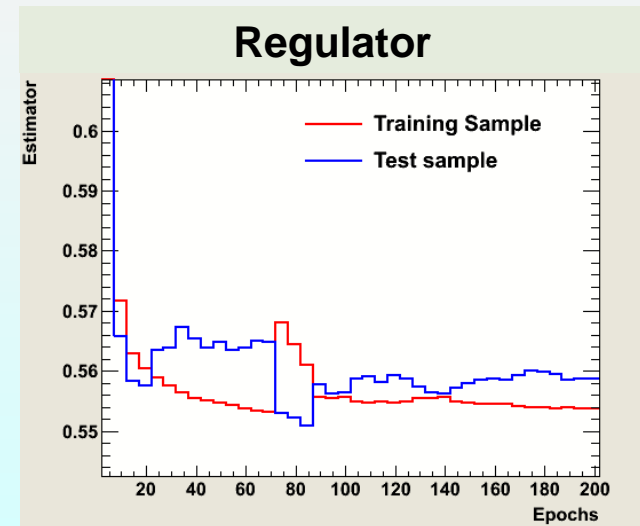
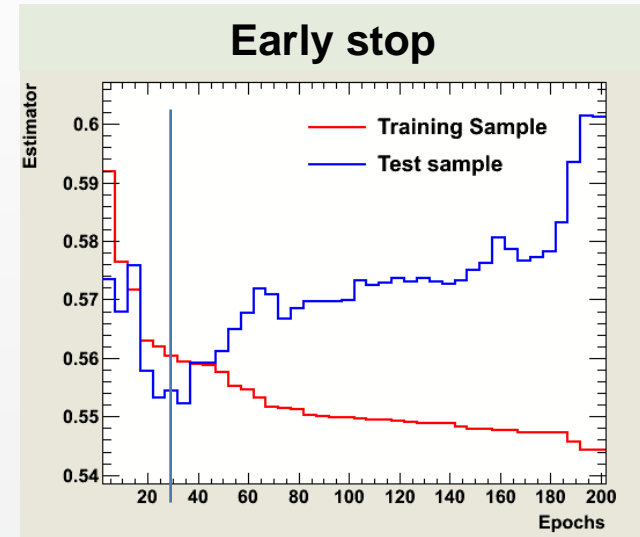
- To make  $y=P(t==1)$ .  
Bernoulli likelihood  $\Leftrightarrow$  Cross entropy cost function

$$-\log(L) = \sum_i (-t_i * \log y(x_i) - (1 - t_i) * \log(1 - y(x_i)))$$

- MLP option: EstimatorType=CE

# Bayesian implementation (II)

- Regulator to avoid overtraining
  - Overtraining is caused by excessive complexity of NN
  - A prior knowledge prefer “simpler” model  $\Leftrightarrow$  small  $w$ 
    - Gaussian prior  $-\log(P(\mathbf{w})) = \sum_m (\alpha_m \times w_m^2)$
    - $P(\mathbf{w}|\mathbf{D})=P(\mathbf{D}|\mathbf{w})P(\mathbf{w})$ . Add to the log likelihood (cost function)
  - Optimize  $\alpha$  during training
    - $\Leftrightarrow$  Adaptive complexity control
  - MLP option: UseRegulator



# Bayesian implementation (III)

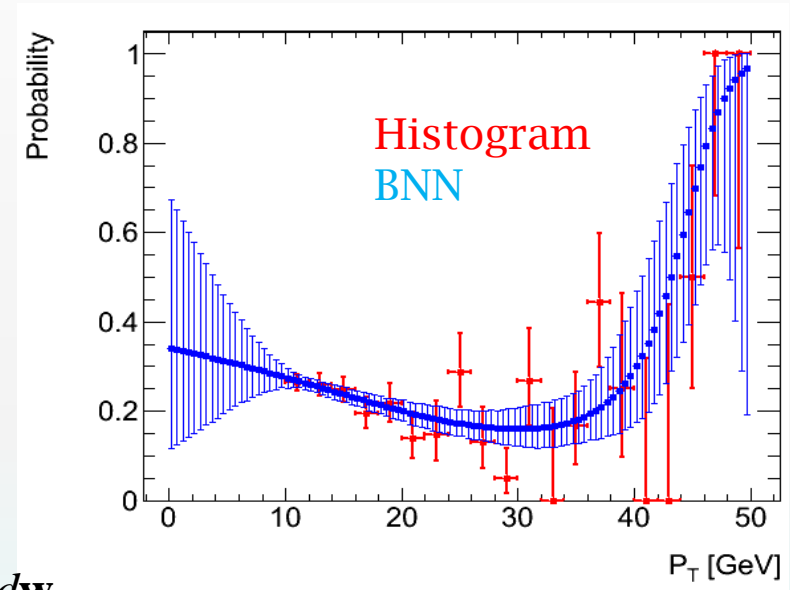
## ● Uncertainty estimation

### ● Training:

- Most probable value  $\mathbf{w}_{\text{MP}}$
- $P(\mathbf{w}|\mathbf{D})$   
Probability of other  $\mathbf{w}$

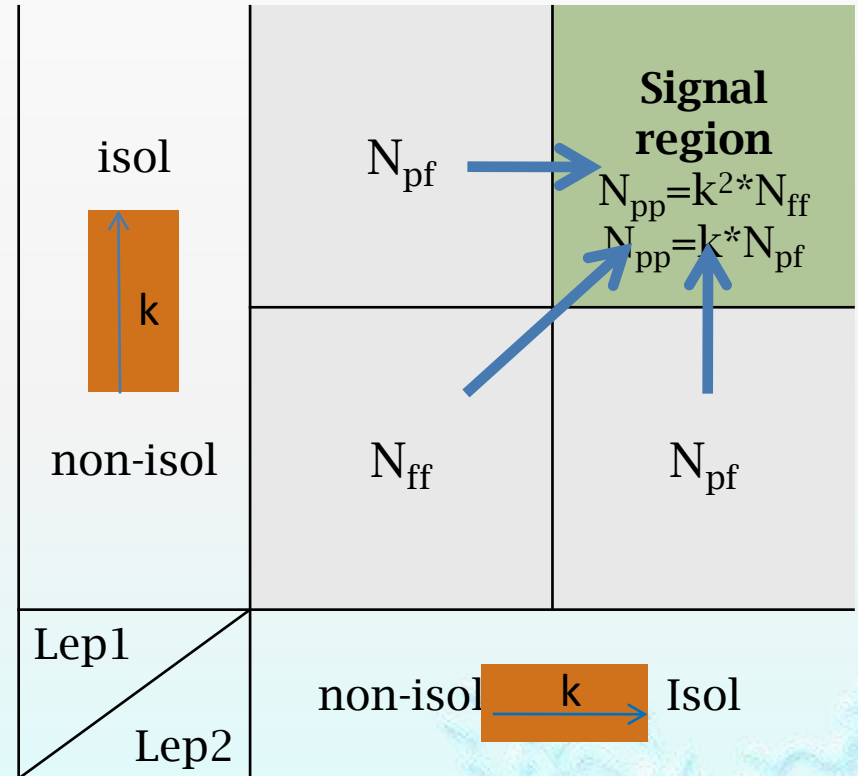
### ● Prediction

- Probability  
$$P(y | \mathbf{x}') = \int P(y | \mathbf{x}', \mathbf{w}) * P(\mathbf{w} | \mathbf{D}) d\mathbf{w}$$
- Uncertainty of  $y$
- Avoid excessive extrapolation (non-trivial for multivariate analysis)
- MLP option: CalculateErrors (interface need to be completed)



# Application in ATLAS analysis(I)

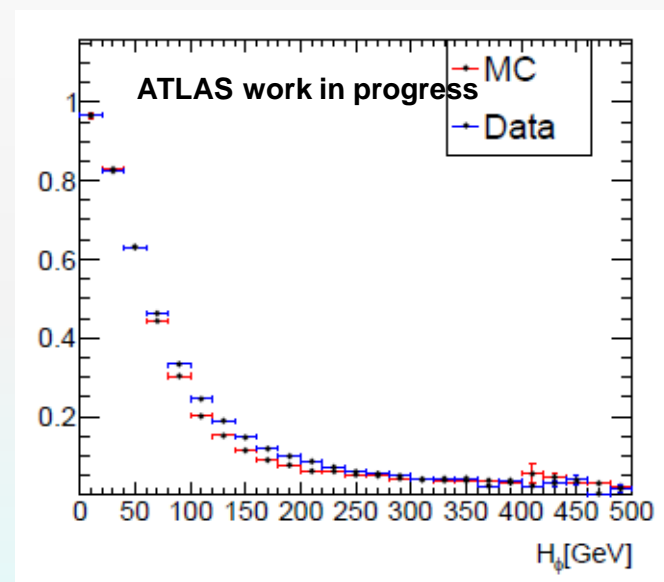
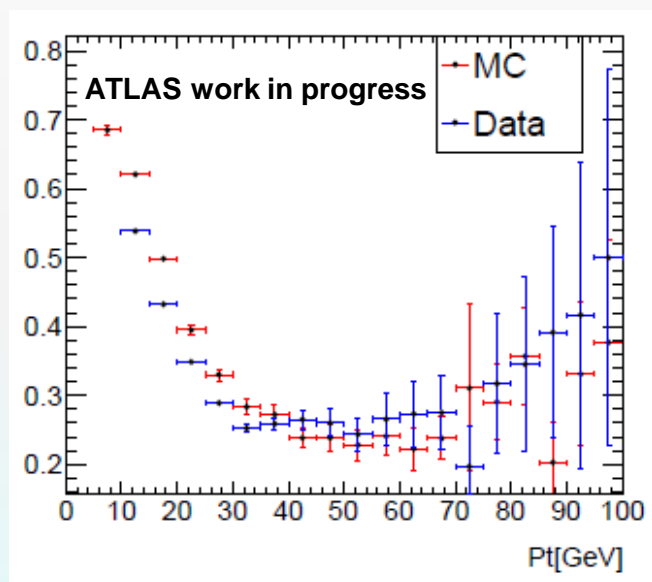
- Isolated di-lepton search (Exotic/SUSY)
  - Double-fake bkg: bb/cc
  - True-fake bkg: W/Z+jet
- Data-driven estimation
  - Extrapolate from non-isolated control samples to signal region
  - Weight each event by the (product of ) pass/fail ratio  $k$  of the failed muon(s)



$$k = \frac{P(\text{pass})}{1 - P(\text{pass})}$$

# Application in ATLAS analysis(II)

- P(pass) is obtained from a single-muon control sample
- Strong dependence of P(pass) over kinematics  $\chi$

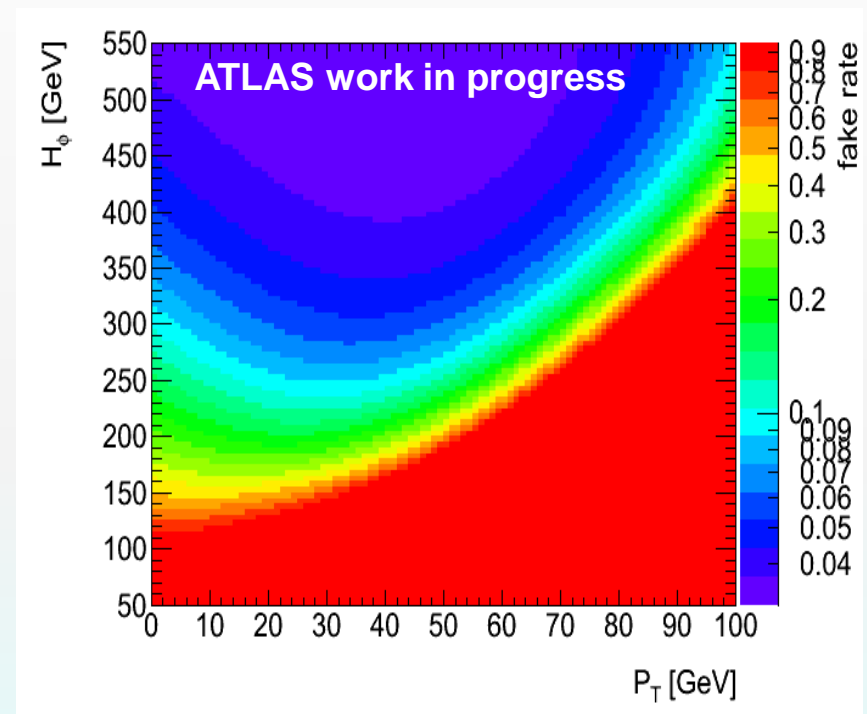


- Different distributions between control samples
- Correlation between the two leptons
- Proper parameterization of P(pass| $\chi$ ) is crucial



# Application in ATLAS analysis(III)

- The BNN is used for unbinned fitting of  $P(\text{pass}|\mathbf{x})$
- Training sample:
  - Single muons in background control region,
  - $D=\{\mathbf{x}_i, t_i\}$ 
    - $\mathbf{x}=\{p_T, H_\phi\}$
    - $t=1$  (pass isolation cut )  
 $t=0$  (fail isolation cut)
  - Could add more variables for parameterization: Eta,  $n_{\text{vertex}}$

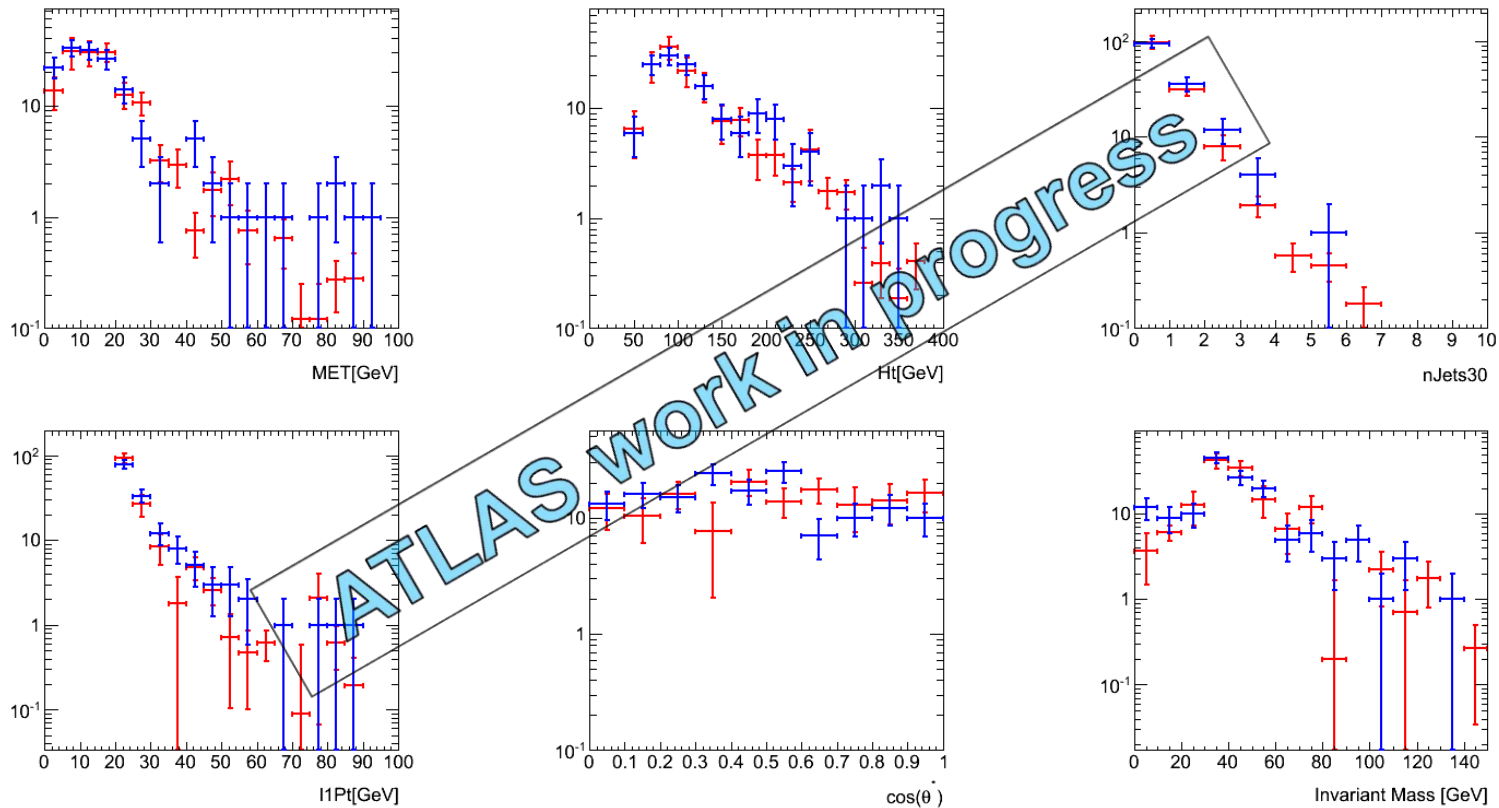


2D fake rate fitted by BNN

# Data-driven background estimation(V)

- Number of observed events= 149
- Number of predicted background yield=  $141 \pm 15$

Observation  
Prediction



# Summary

- The Bayesian implementations
  - As easy as polynomial fitting !!
  - Fitting of probability function
  - Regulator to avoid overtraining
  - Uncertainty estimation
- Probability fitting in data analysis
  - Shows good performance in one ATLAS application
  - Open the door to more delicate study
  - Could be applied to many other analysis:  
Trigger/Charge/ParticleID