

Applying Artificial Neural Networks in Data Analysis

Jacek Biernat



UPPSALA
UNIVERSITET

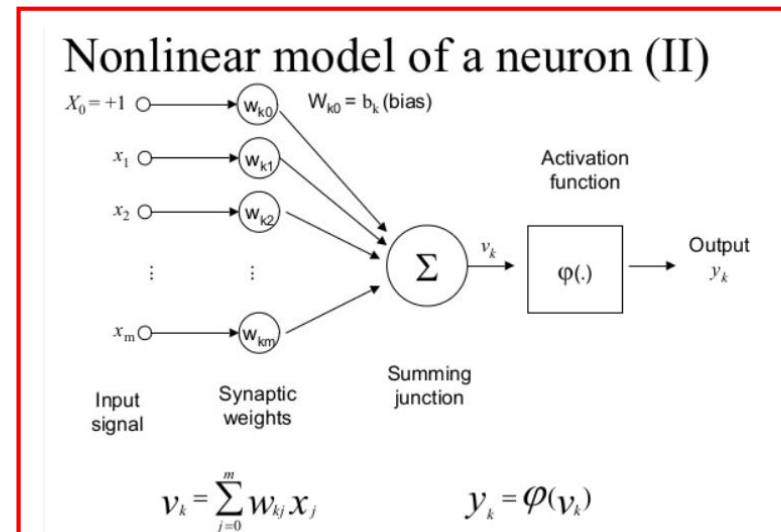
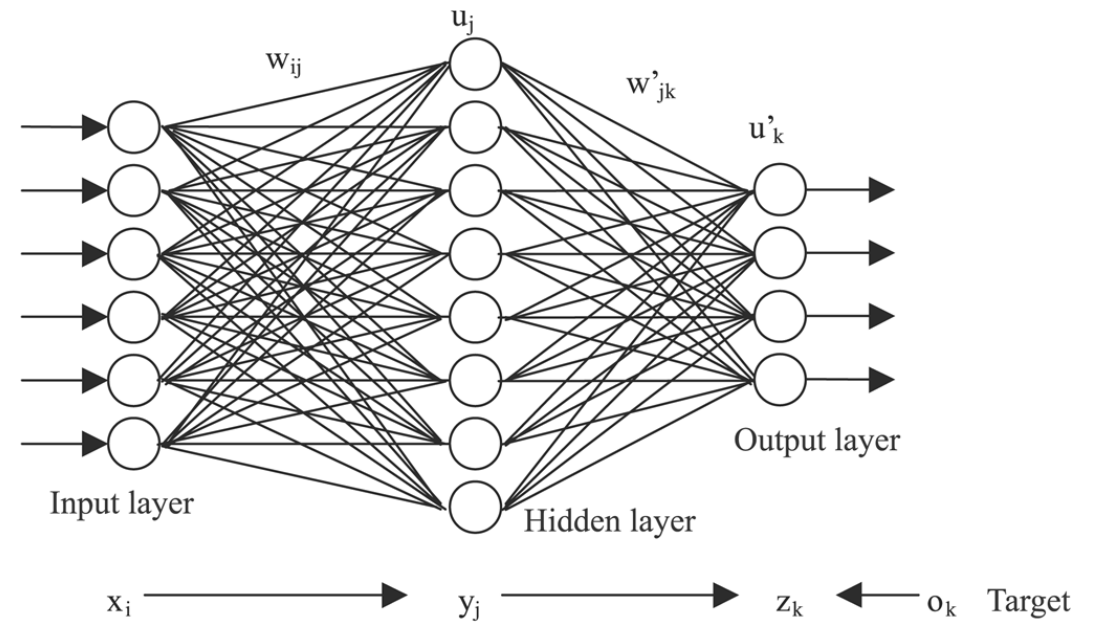


The Menu:

- What is a neural network ?
- Types of neural networks
- Available interfaces
- Few words about BESIII
- BNN for background suppression:
 - Analysis Steps
 - Results
 - Conclusions

Neural Network

- Mathematical tool
- Suitable for finding patterns in big data sets
- Similar to a “human brain” 😊



Neural Networks

$$a_{t+1,j}(\mathbf{X}) = \sum_{r: (v_{t,r}, v_{t+1,j}) \in E} w((v_{t,r}, v_{t+1,j})) o_{t,r}(\mathbf{X}),$$

Output of a ANN where:
 V_{ti} – is the i 'th neuron of the t 'th layer
 O_{ti} – neuron output
 X – input vector

One can define the neuron output as:

$$o_{t+1,j}(\mathbf{X}) = \sigma(a_{t+1,j}(\mathbf{X})).$$

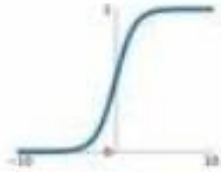
σ – neuron activation function (ϕ – in previous slide)

Neural Networks – activation functions

Activation Functions

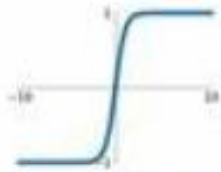
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



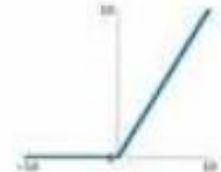
tanh

$$\tanh(x)$$



ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$



Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



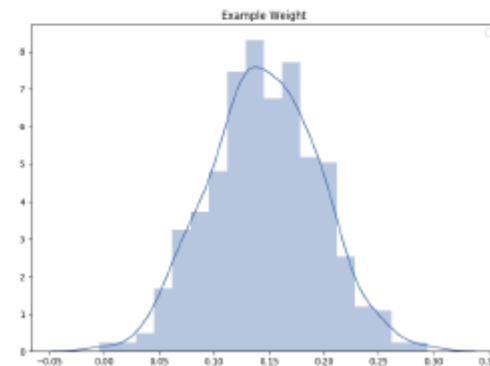
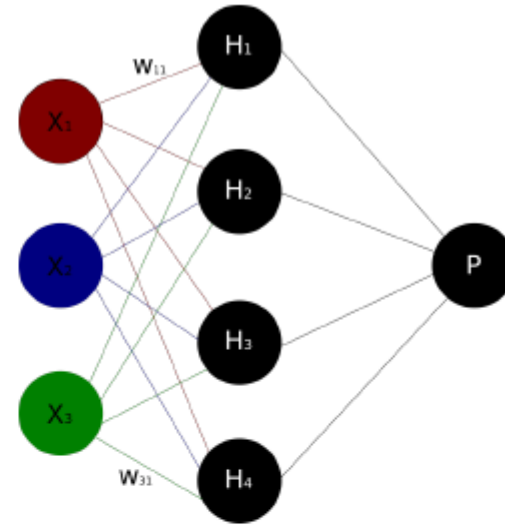
Types of Neural Networks

Conventional NNs

- ▶ Convolutional NN (require Image-Data)
- ▶ Multi-Layer Perceptron (MLP)

Bayesian NN¹

- ▶ weights are distributions
- ▶ gives a set of NNs in one Model



Interfaces

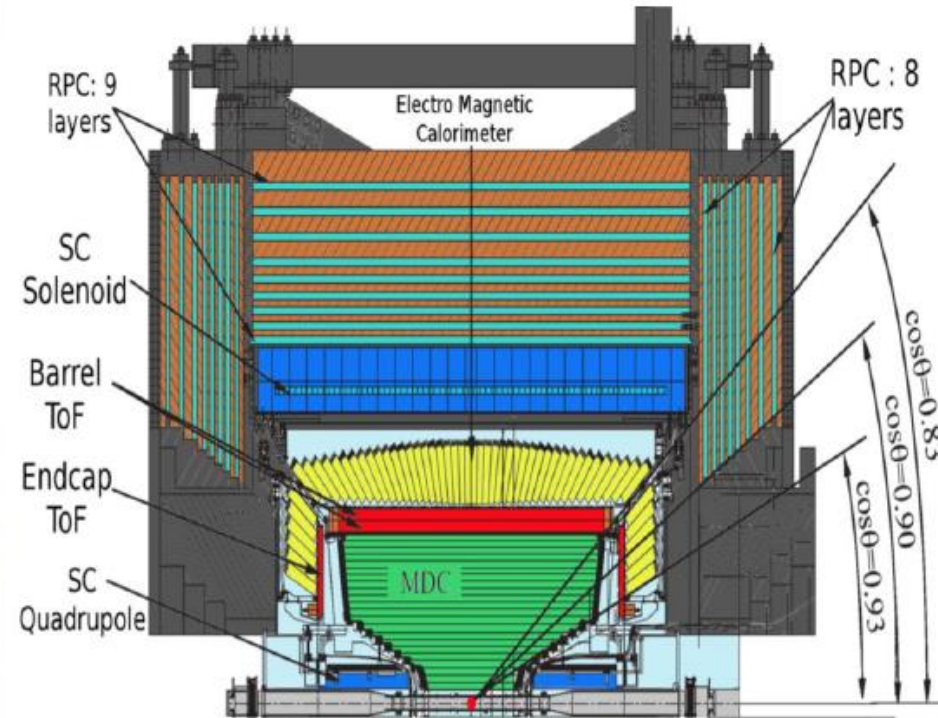
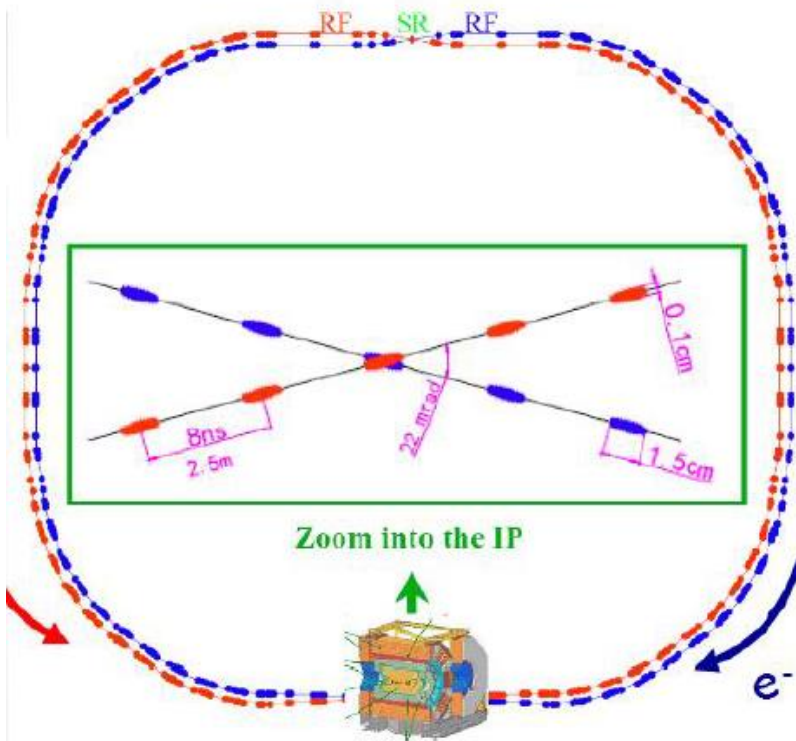
ROOT and TMVA

- ▶ ROOT: tool for Data Analysis
- ▶ widely used in physics
- ▶ TMVA: Toolkit for Multivariate Analysis

Tensorflow and Keras

- ▶ Keras simplifies construction of NN-models
- ▶ with Python: Quick way to test your model
- ▶ Additional Tensorflow Libraries for Bayesian Approach
- ▶ NVIDIA GPU Cards with CUDA-capability are supported
- ▶ GPU computations improve training and inference process

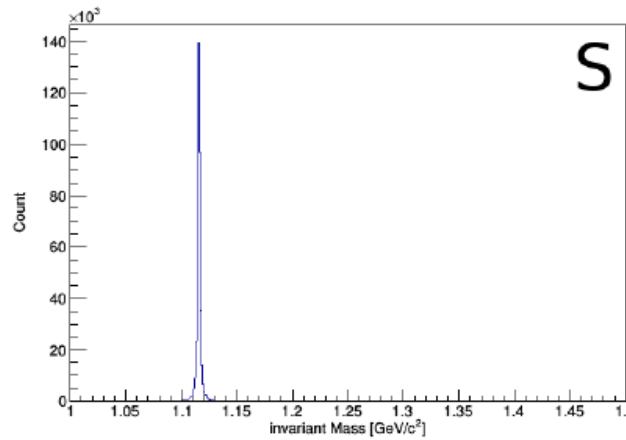
- BEPC = Beijing Electron Positron Collider.
- Operates in the τ -charm mass region



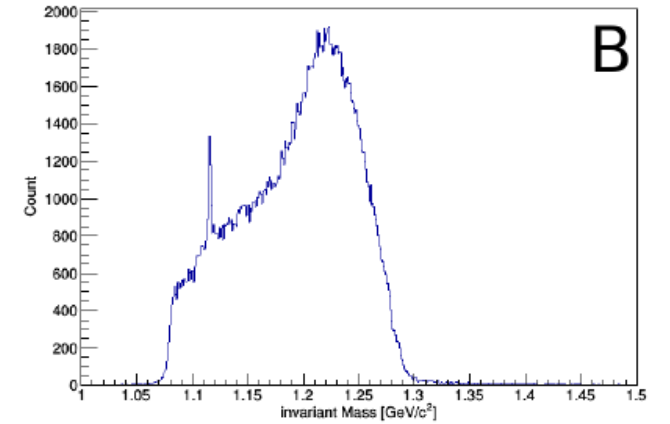
- Charmonium physics
- Light hadron
- Hyperon physics:
 - Hyperon form factors
 - Decay asymmetry parameters of hyperons

The Analysis

- Training Model:
 - Input vector ?
 - Signal Sample
 - Background Sample
- Principal Component Analysis
- Training the NN
- Application on unlabelled data



S : Signal labelled



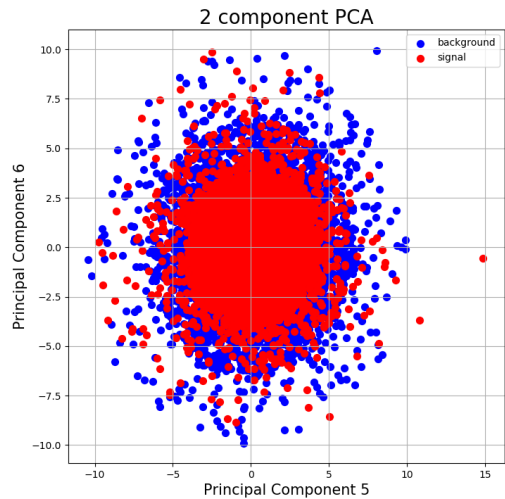
B : Background labelled

S + B = Training Set

$$y' [i] = vertex_{x,y,z}[i] + DecayLength[i] + MDC_{x,y,z}[i](\pi; p)$$

Principle Component Analysis

- Decorrelation
- Dimensionality reduction
- Separation (Unsupervised Learning)



Full overlap – no separation, a more advanced method required BNN

For example:

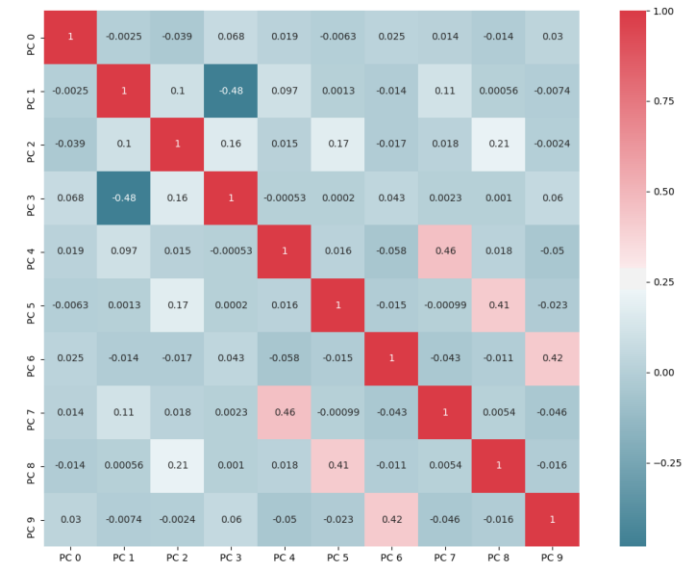
Principal component analysis

Jake Lever, Martin Krzywinski & Naomi Altman *Nature Methods* volume14, pages641–642 (2017)

Original



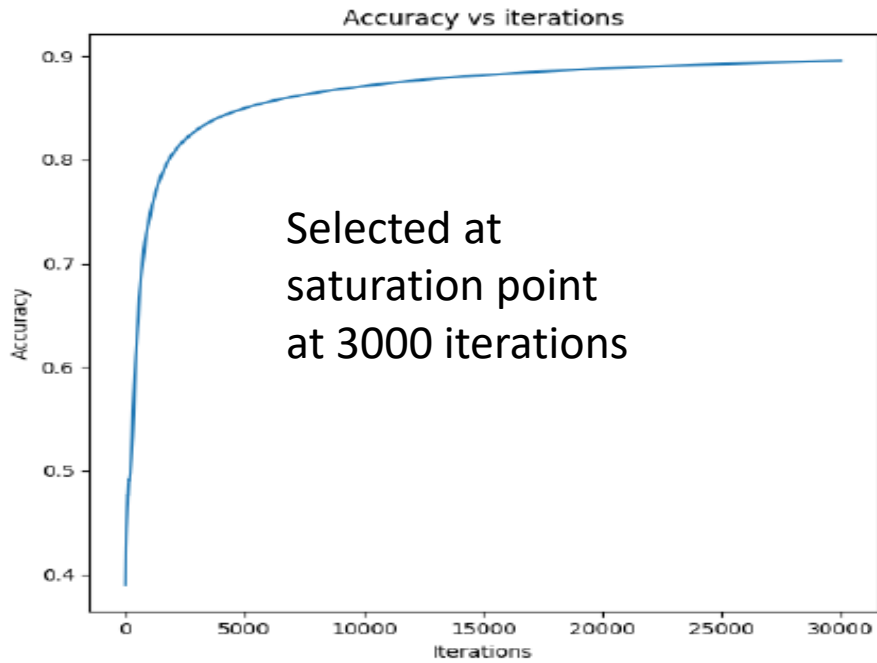
After PCA



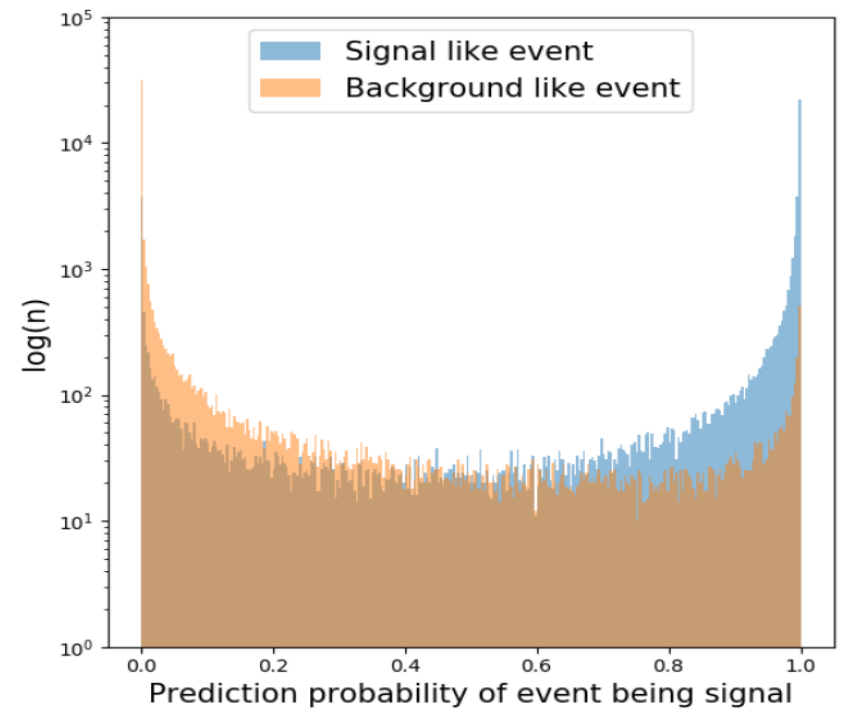
The Analysis – Bayesian Neural Network

- BNN for S/B separation (background suppression):
 - ✓ 10 element input vector
 - ✓ 22 nodes (neurons) in hidden layer (simple architecture = stability)
 - ✓ 2 output nodes

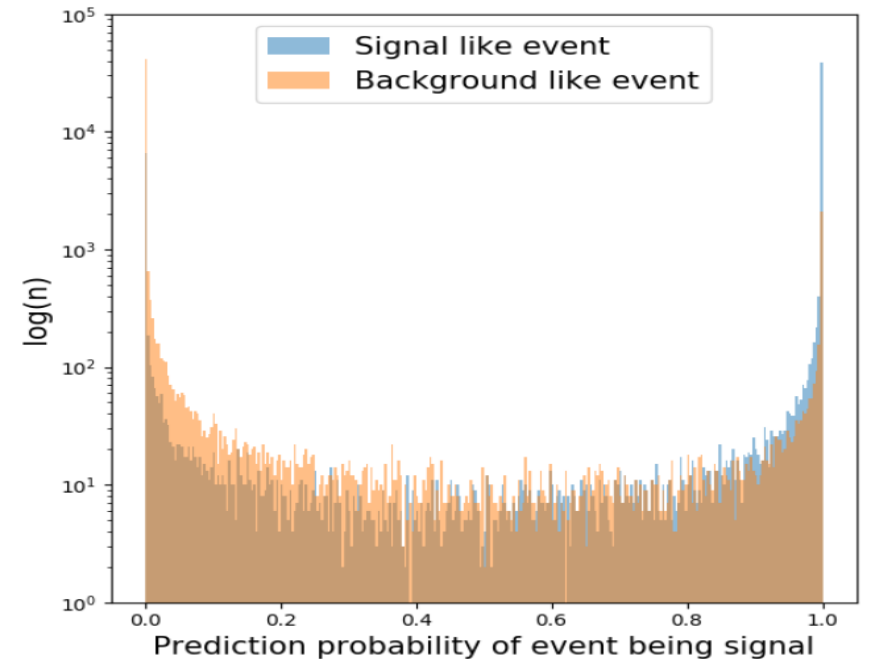
The analysis – training the NN



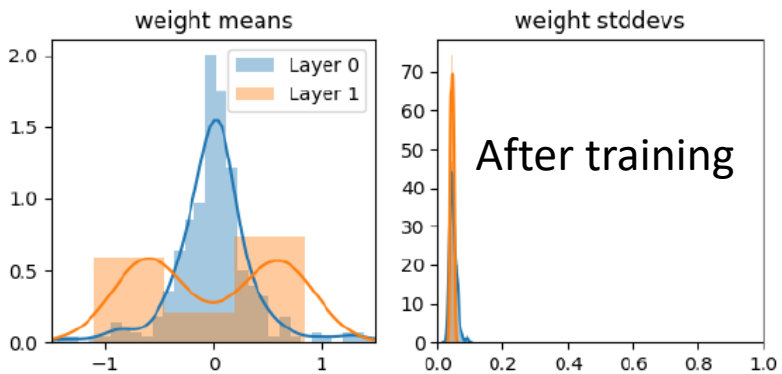
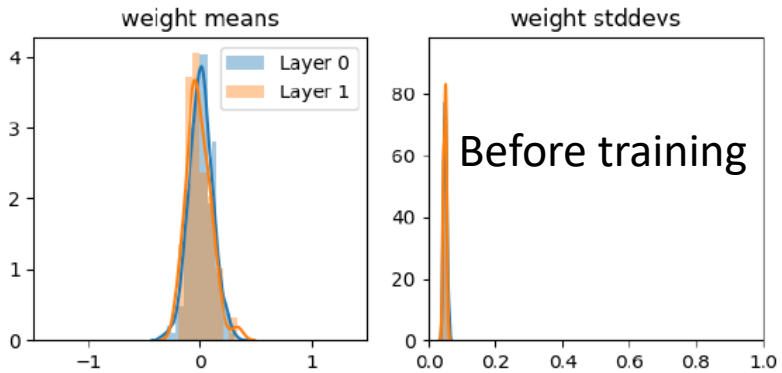
Network trained at 3000 iterations



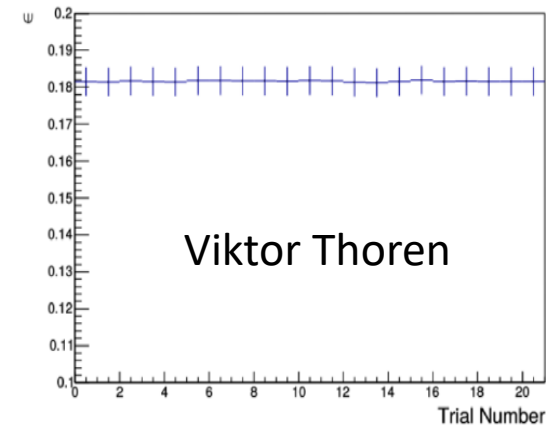
Network trained at 30000 iterations.
Over trained



The Analysis- Sampling Weight distributions



- Instability coming from sampling weight distributions?
- ✓ Evaluate this effect with MC sample for 20 applications!

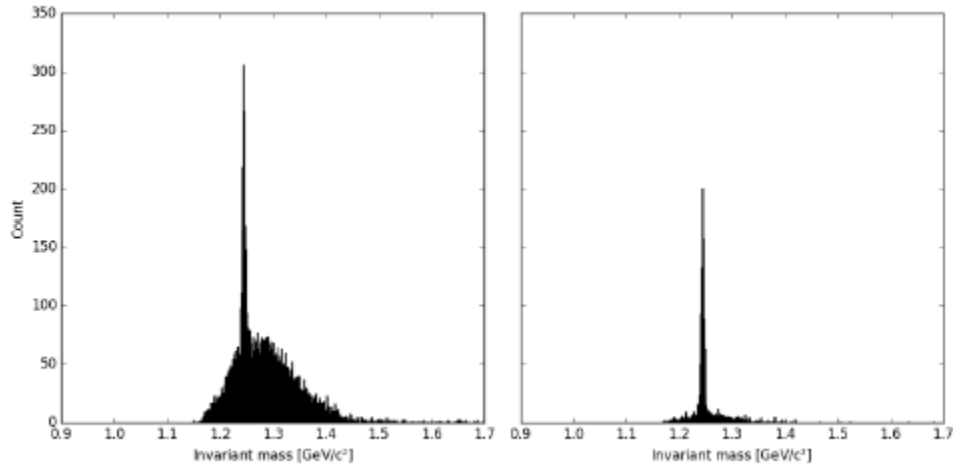


$$\sqrt{\frac{\epsilon_i(1-\epsilon_i)}{N_i(MCtruth)}}$$

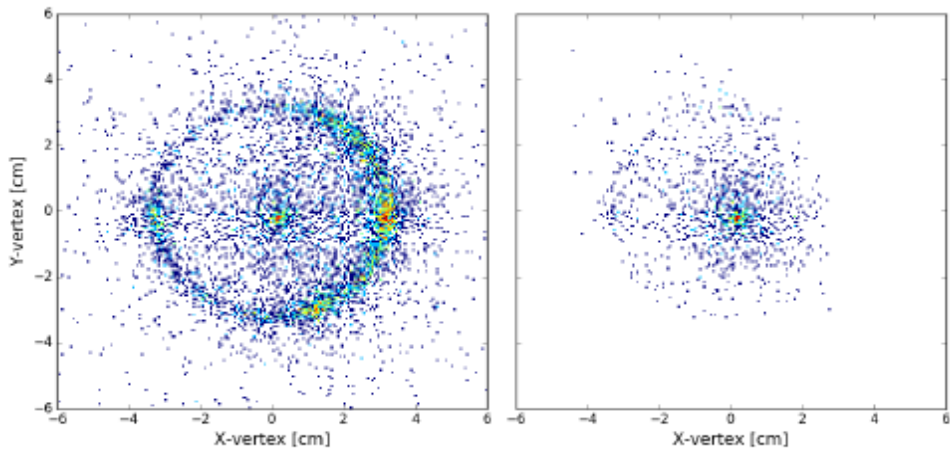
The Results

Before

After



Decay points of a given object
projected on a X vs Y plane



Decay points of a given object
projected on a X vs Y plane

Conclusions

- The method provides background reduction in the signal region
- The applied neural network infrastructure is simple therefore the training and application does not require a lot of computing power or time
- This method has been used and verified by Viktor Thoren (For BESIII members -> see plenary talk at Shanghai CM meeting)