

Deep learning for automatic RF-modulation classification



- 1 *Artificial intelligence*
- 2 *Wave reconstruction*
- 3 *ANN training*
- 4 *Results*
- 5 *Conclusions*



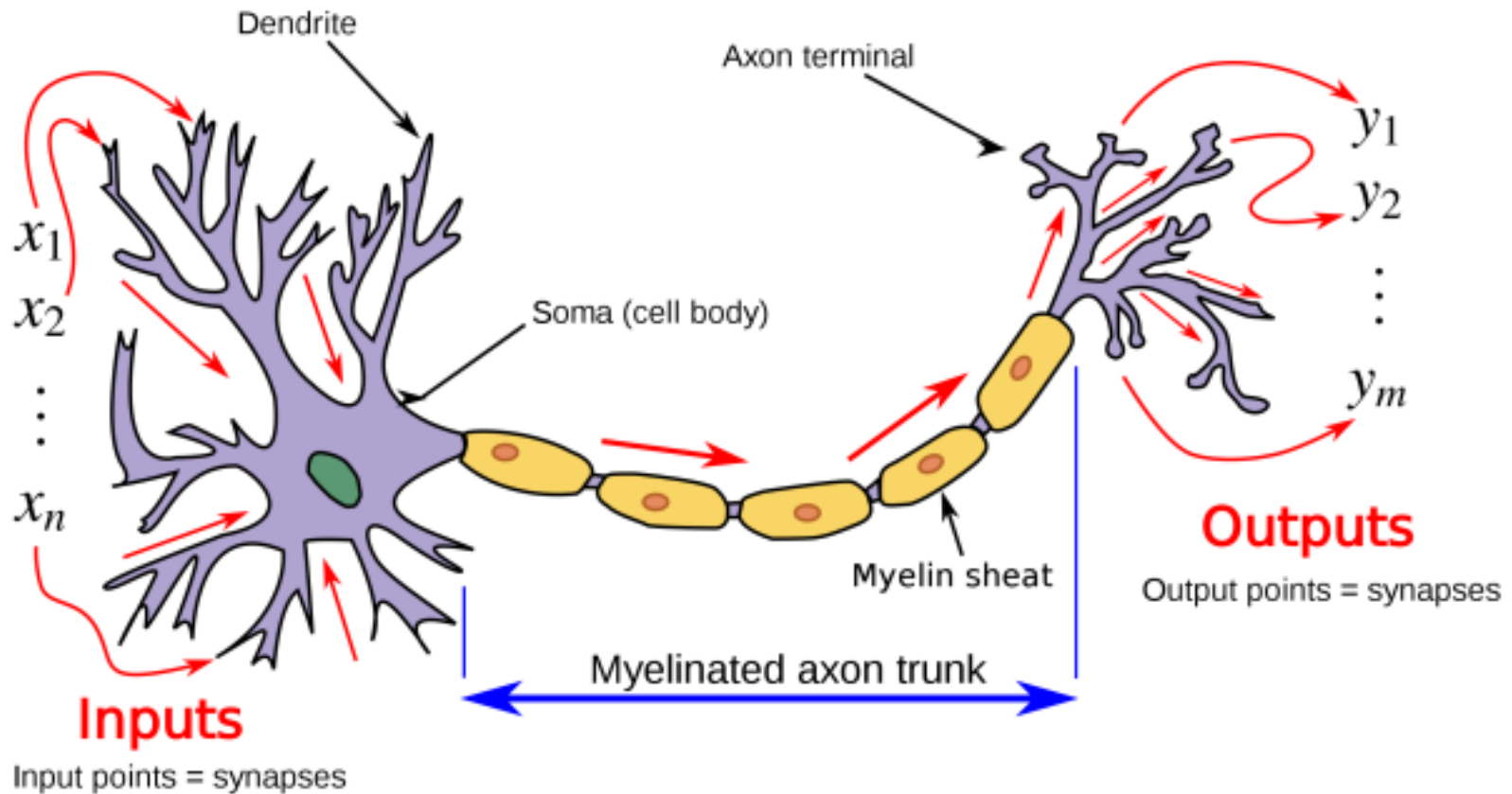
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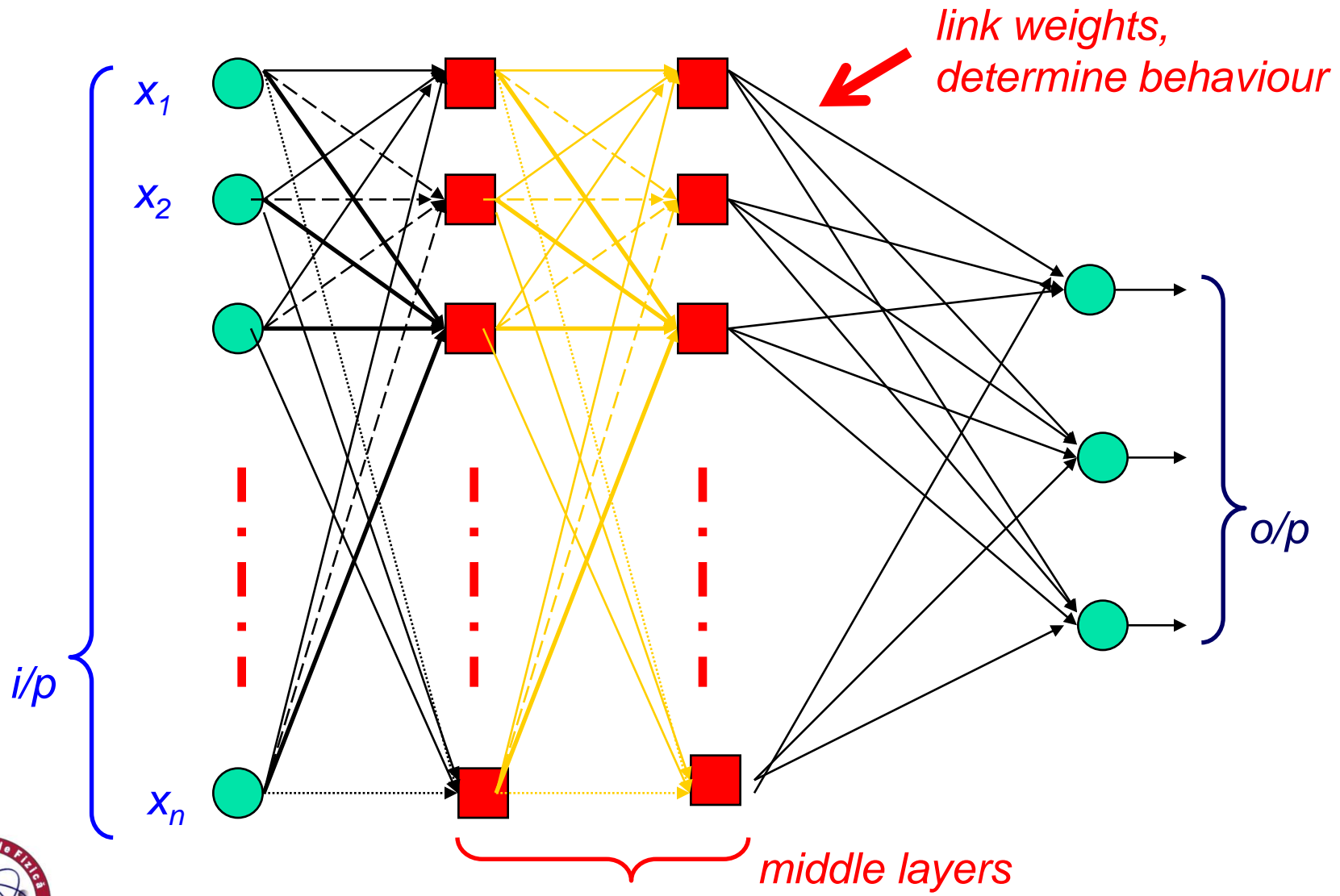
Bio-analogy

- representation of data selection with:

- *sum*
- *threshold*



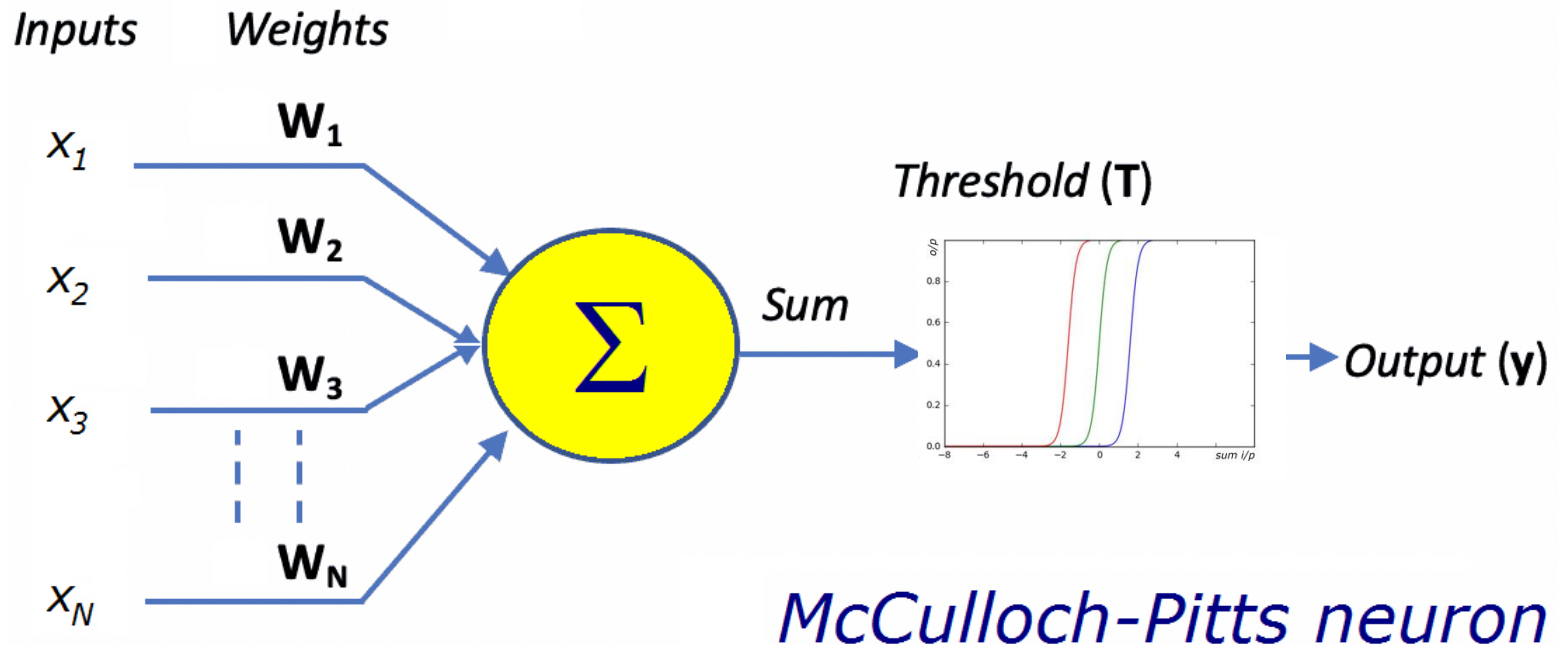
Multi-layer perceptron



Artificial Intelligence

- representation of data selection with:

- *sum*
- *threshold*



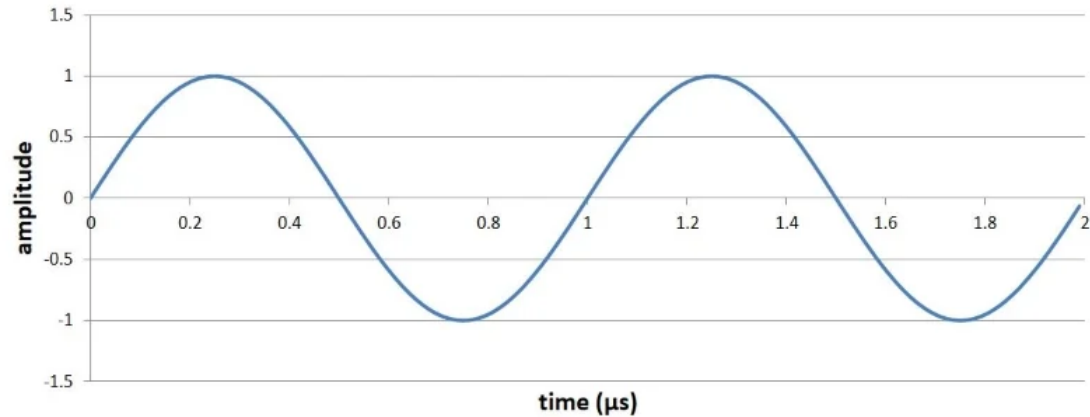
McCulloch-Pitts neuron

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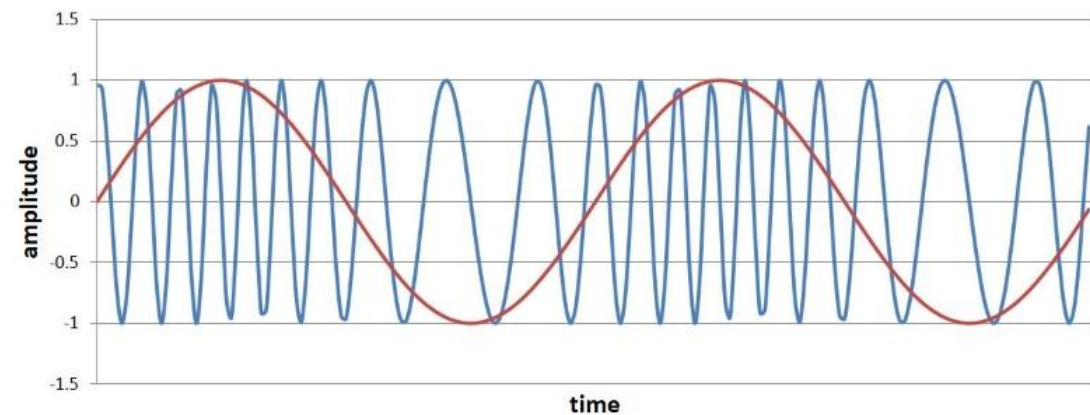


Radio frequency modulation

Baseband Signal



Frequency Modulation



Shift keying:

- ASK, *amplitude*
- FSK, *frequency*
- PSK, *phase*
- ASK-LSB
- ASK-USB



Magic sample number

- RF wave $y = p + A \sin(2\pi ft + \phi)$

sampling **1 : 3.675**

f_0 **12000 Hz**

Δ **1 / 44100 s**

- **pedestal**: find from average

$$\langle y \rangle = p + A_e \sin\left(2\pi ft \frac{t_i + t_f}{2} + \phi\right) \operatorname{sinc}\left(\frac{2\pi f \Delta t}{2}\right)$$

$$A_e = \frac{A}{\operatorname{sinc}(\pi f \Delta)}$$

- **magic N**: $\Delta t = 11\Delta \dots \delta p = 0.0023 A_e$



Amplitude

- same $N = 11$: $\langle \delta^2 y \rangle = A_e \langle \delta^2(\sin) \rangle$

Frequency

- same $N = 11$: $\langle y(y - y_{k\Delta}) \rangle = pA_e(\langle \sin \rangle - \langle \sin_{k\Delta} \rangle)$
+
 $A_e^2(\langle \sin^2 \rangle - \langle \sin \cdot \sin_{k\Delta} \rangle)$
 $\simeq A_e^2 \sin^2\left(\frac{2\pi f k \Delta}{2}\right)$
 $\simeq \pi k \Delta A_e^2 \sin(2\pi f k \Delta) \cdot \delta f$

($k = 1$; max sensitivity)



Phase

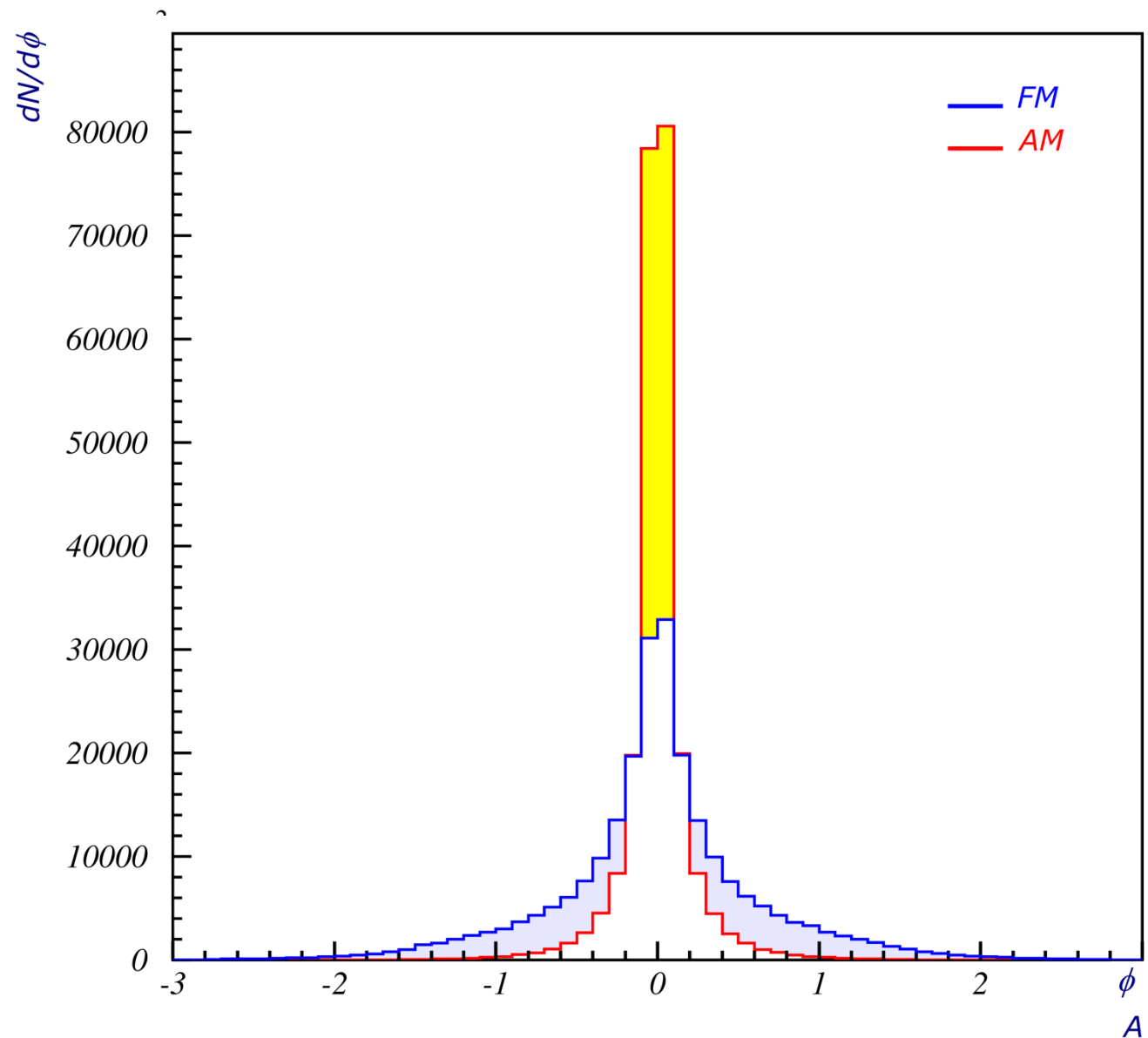
$$- \delta\phi = \phi_{\text{current}} - \phi_{\text{previous}}$$

$$\langle y \cdot \cos(\pi ft) \rangle \simeq \frac{A_e}{2} \sin\phi$$

- next: form *features*



Distributions



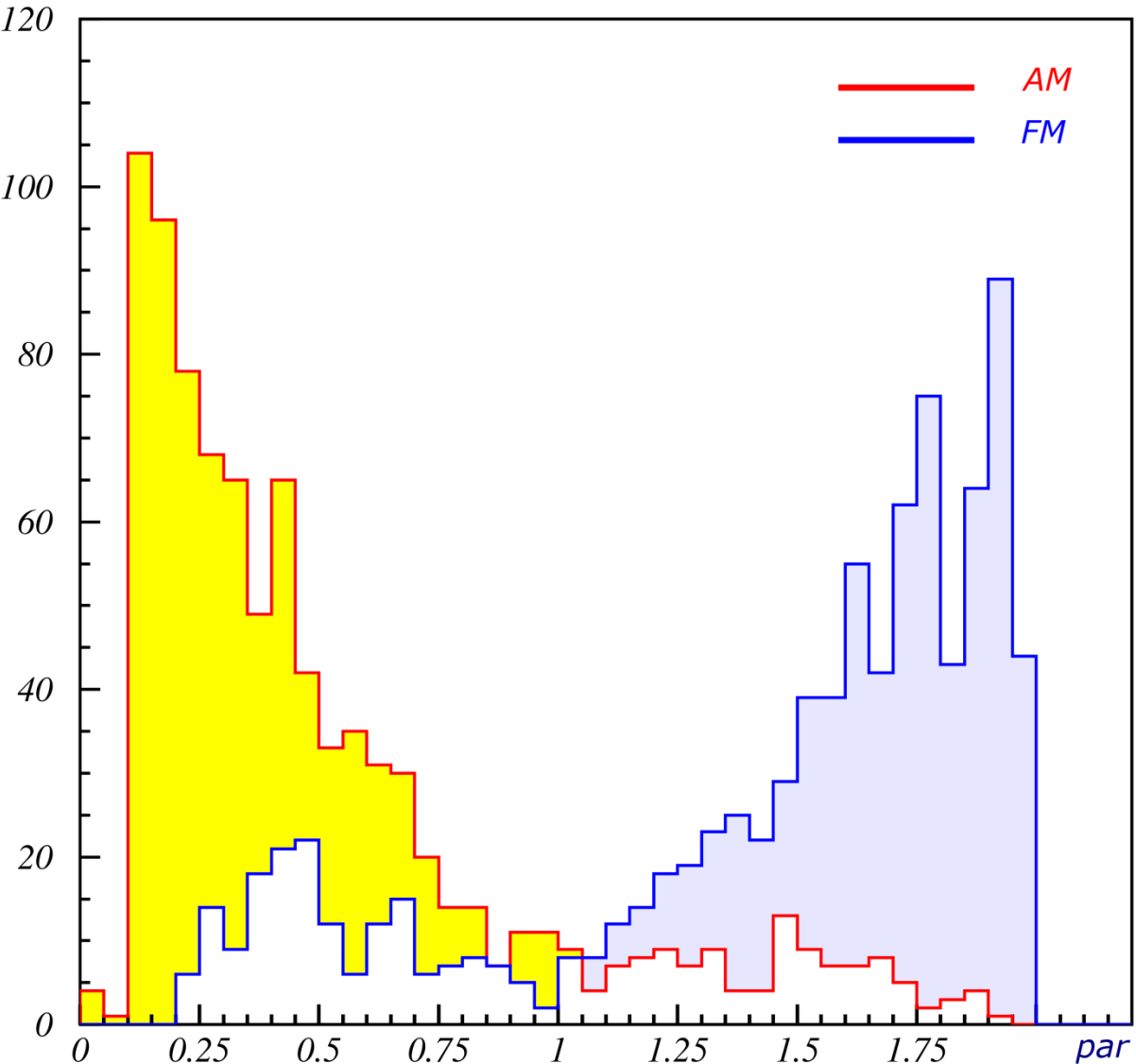
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Parameter - 11

$\phi_1 = (L_2 - L_1) * d_p$
 $L_1 = \text{where } d$
 $L_2 =$
 $2 = \langle \text{distr.} \rangle \text{ in } t$
 $3 = \langle N_{\phi} \rangle - \langle 1/$
 $4 = \langle N_{\phi} * \delta t \wedge$

$\frac{N_{\phi}}{d(par)}$



Parameter - 13

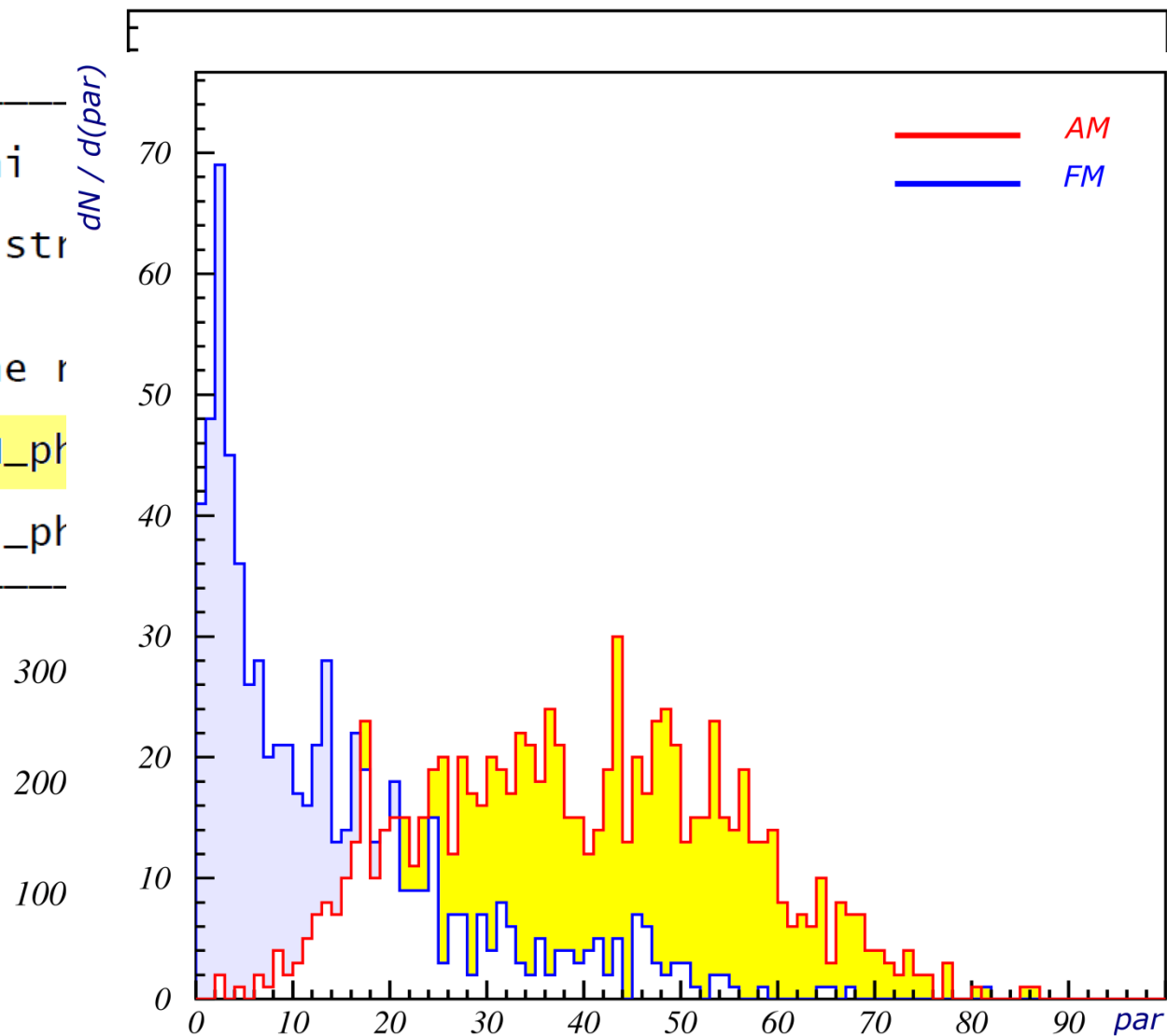
 $N/d\phi$

$$\phi_1 = (L_2 - L_1) * d_\phi$$

 $L_1 = \text{where distr}$
 $L_2 =$
 $2 = \langle \text{distr.} \rangle \text{ in the } r$

$$3 = \langle N_\phi \rangle - \langle 1/N_\phi \rangle$$

$$4 = \langle N_\phi * \delta^2_\phi \rangle$$



MLP run-through

Input Layer

bias	X1	X2
1	0	1
1	0	0
1	0	0
1	1	0

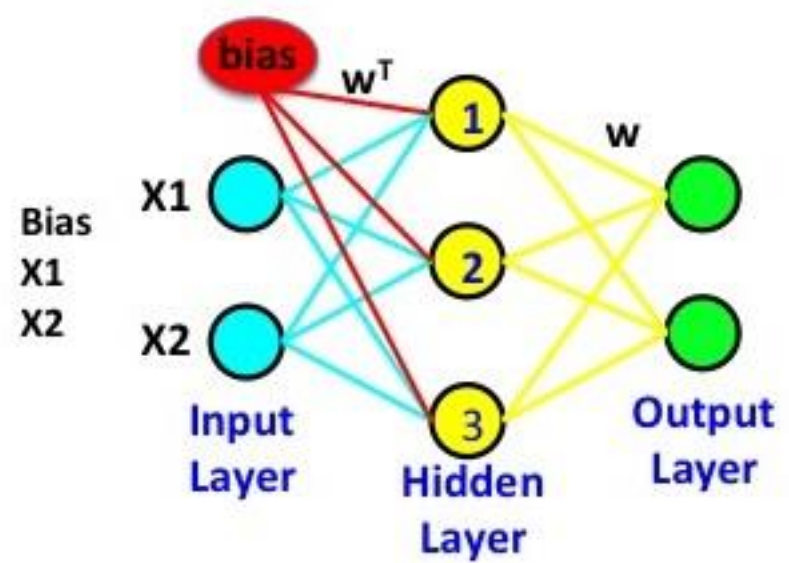
4 x 3

Weights w^T (transposed)

.5	.5	.5
.5	.5	.5
.5	.5	.5

3 x 3

Go to Hidden Nodes



Hidden Layer

Bias	Node 1	Node 2	Node 3
1	.5	.5	.5
1	.5	.5	.5
1	.5	.5	.5

4 x 3

Sigmoid Function

$\frac{1}{1 + e^{-(wx+b)}}$

Weights

.2	.1
.4	.1
.4	.1

3 x 2

Output Layer

1	.3
.5	.15
.5	.15
1	.3

4 x 2

Sigmoid Function

$\frac{1}{1 + e^{-(wx+b)}}$

Output

1	0
1	0
1	0
1	0





Public Types

enum **EDataSet** { kTraining, kTest }

enum **ELearningMethod** {
 kStochastic, kBatch, kSteepestDescent, kRibierePolak,
 kFletcherReeves, kBFGS
}

► Public Types inherited from **TObject**

Public Member Functions

TMultiLayerPerceptron ()

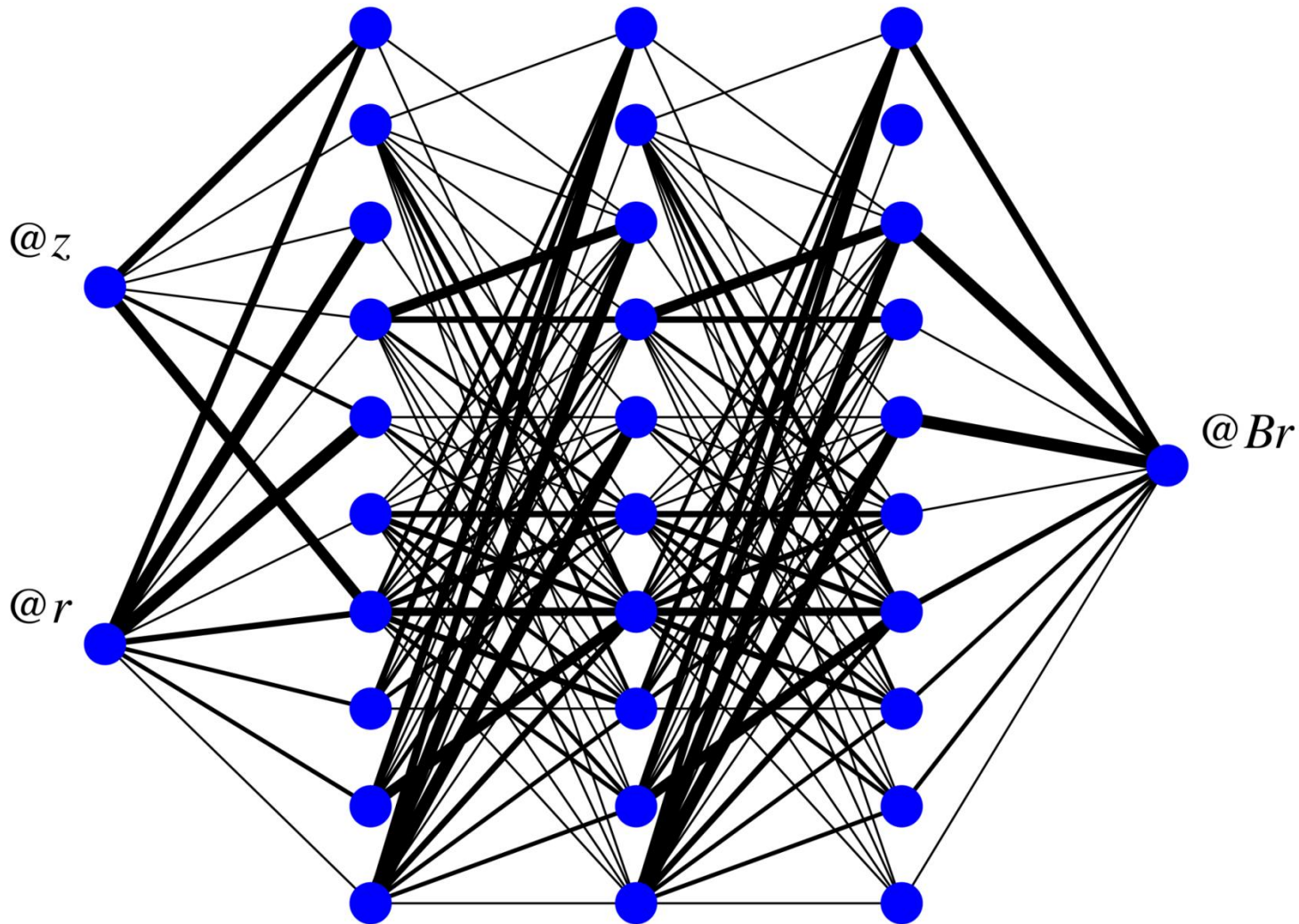
Default constructor. [More...](#)

TMultiLayerPerceptron (const char *layout, const char *weight, **TTree** *data, **TEventList** *training, **TEventList** *test, **TNeuron::ENeuronType** type=**TNeuron::kSigmoid**, const char *extF="", const char *extD="")

The network is described by a simple string: The input/output layers are defined by giving the branch names separated by comas. [More...](#)



```
// show network structure _____  
m1p->Draw() ;
```



Define ANN parameters

- learning method

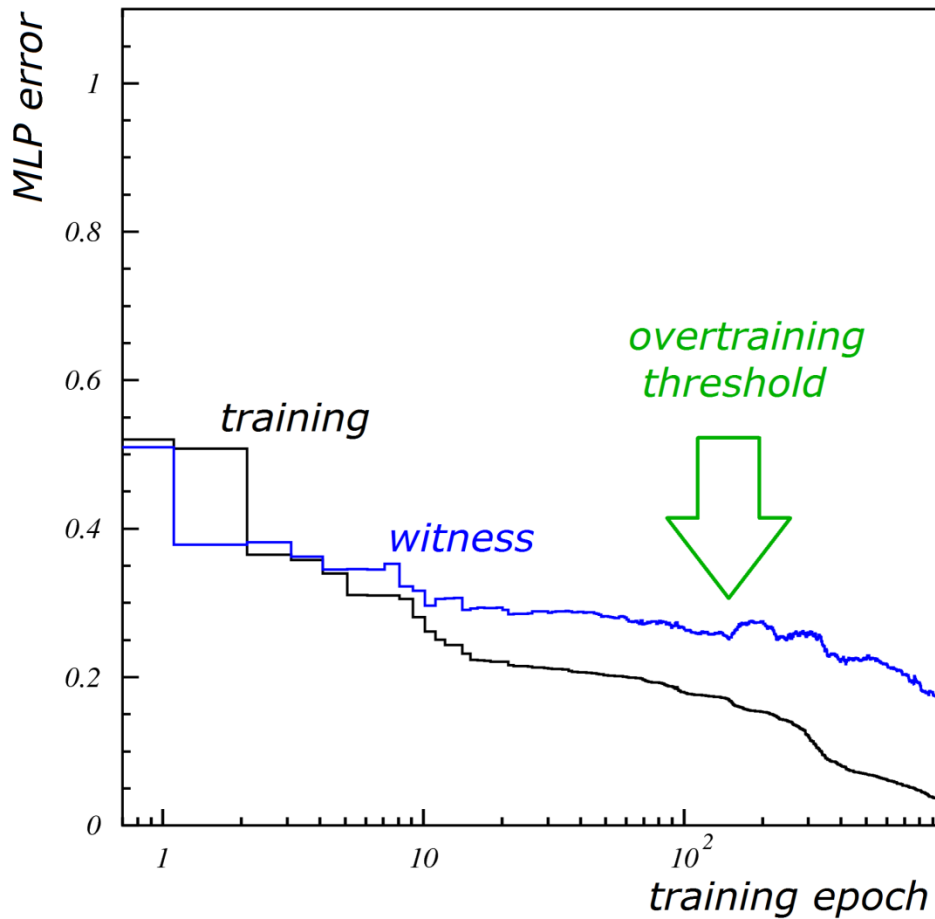
```
// set learn method _____  
mlp->SetLearningMethod(TMULTILayerPerceptron::kBFGS ) ;  
  
// kStochastic = default  
// kBatch  
// kSteepestDescent  
// kRibierePolak  
// kFletcherReeves  
// kBFGS
```

- # training epochs and error plot updates

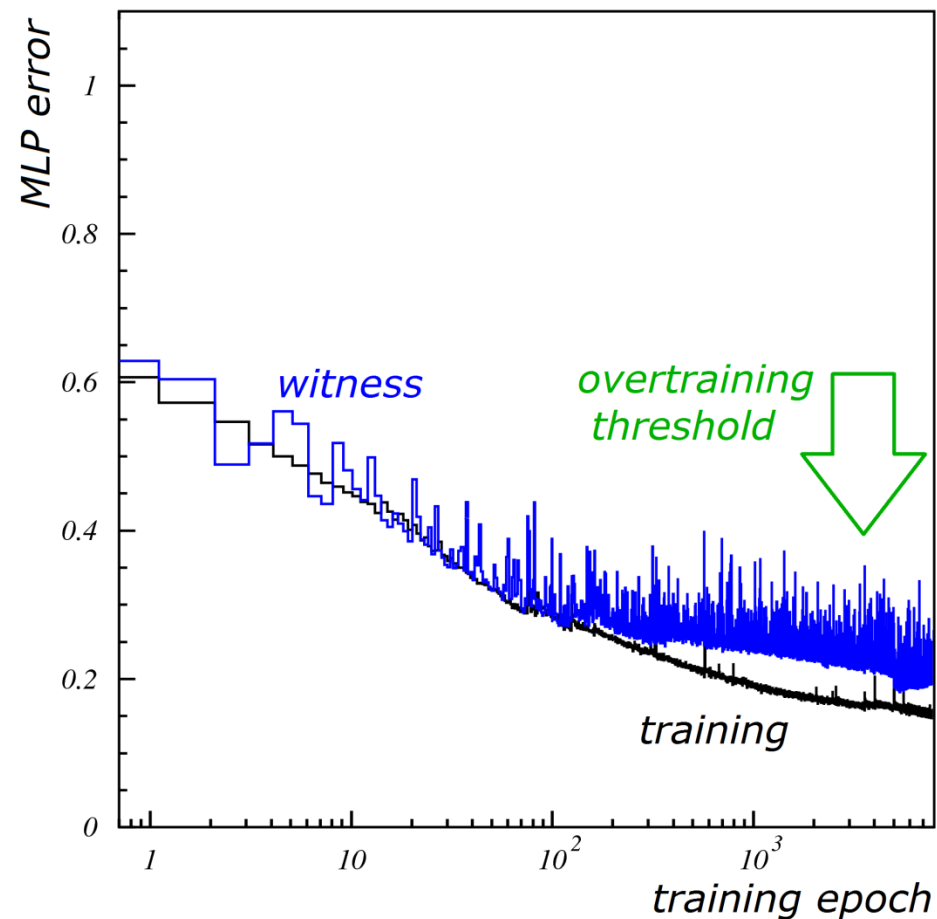
```
// training _____  
mlp->Train( 1000  
           "text,update=100" ) ;  
  
// 1000 events  
// write text to console  
// updates every 100 epochs
```



AM vs. FM: *BFGS*



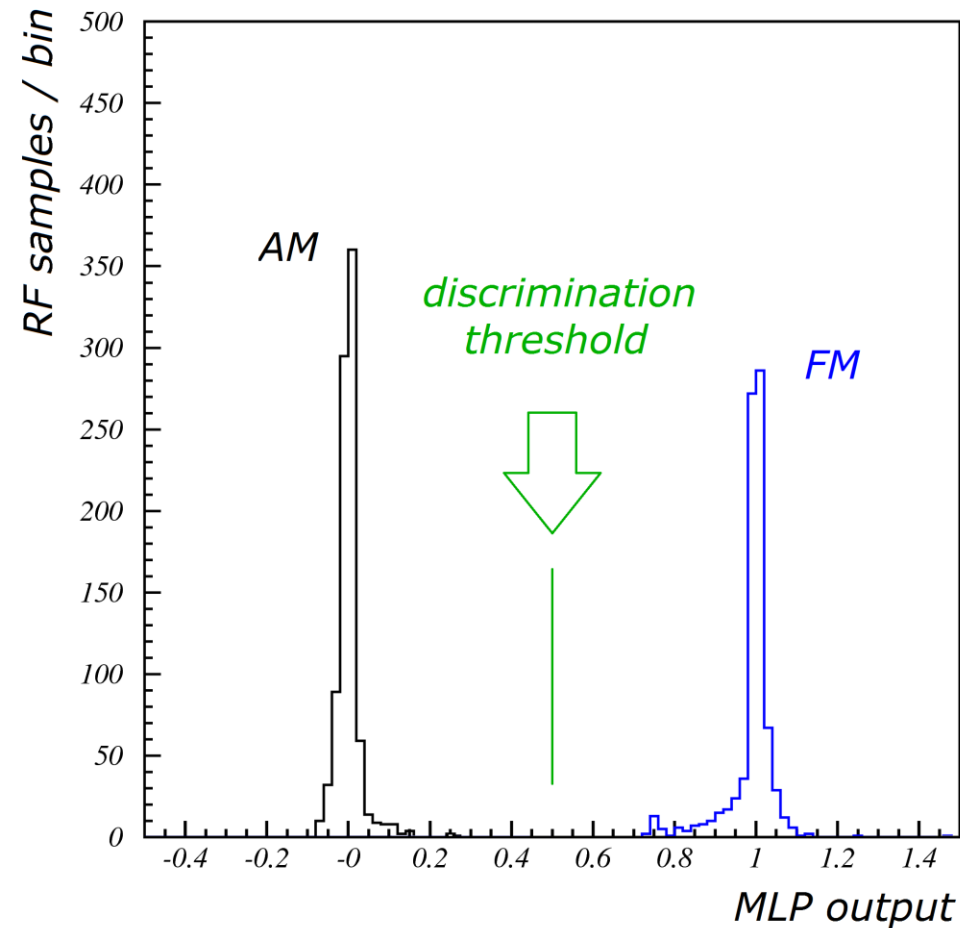
AM-LSB vs. AM-USB: *stochastic*



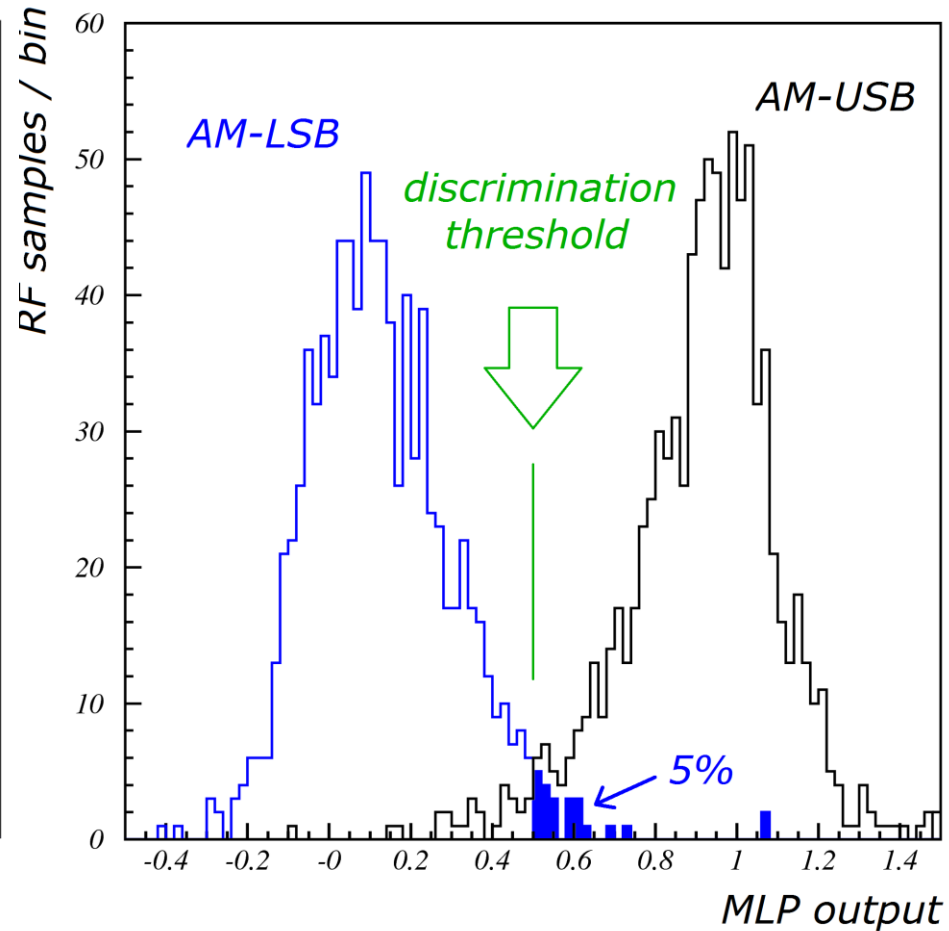
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AM vs. FM: *BFGS*



AM-LSB vs. AM-USB: *stochastic*



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Neuromorphic software

- *advantageous for classification of signals*
 - *excellent* performance on AM vs. FM
 - *very good* even on the difficult AM-LSB vs. AM-USB case
- *additive*
 - *can join sub-task networks to form master-network*
- *ROOT*
 - *easy to use implementation of Multi-Layer Perceptrons*
 - *helpful user-analysis features*

