

# Machine Learning in HEP

## (A gentle introduction)

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**Pre-school for ML4HEP V4**  
**Online host: TIFR Mumbai**

## Statement of the Problem

## Artificial Neural Networks (ANN)

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# Problems Types

Regression

Classification

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Need to **approximate/estimate** the said **function**.

# Approximating/Estimating the function

**Case 1:**

**Case 2:**



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Known function with unknown parameters

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Need a parametrized approximant.

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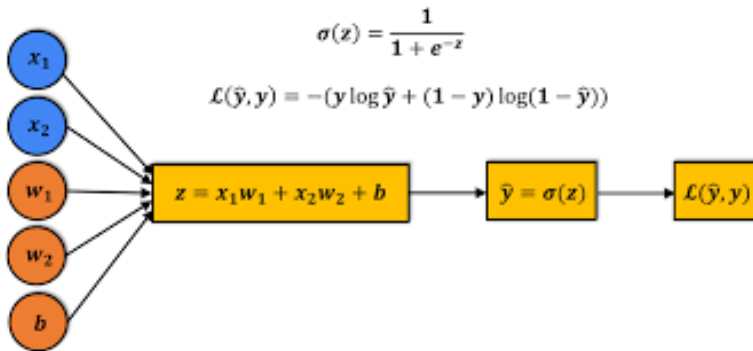
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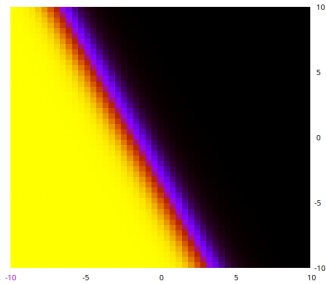
The approximant is alternating sequence of  
*linear maps* (**hyperplane**) and *non-linear maps* (**envelope**).

## Artifitial Neural Networks (ANN)

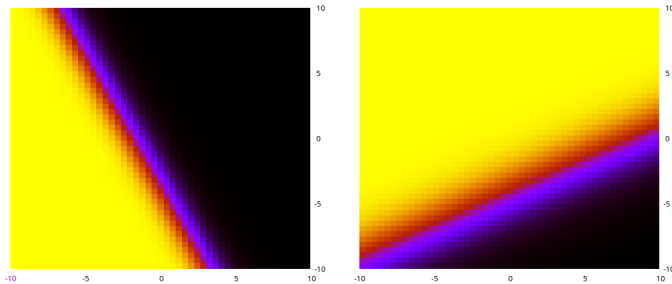
# Logistic Regression



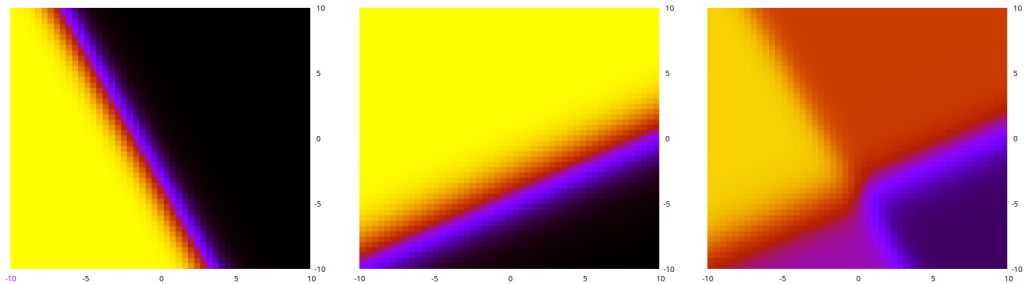
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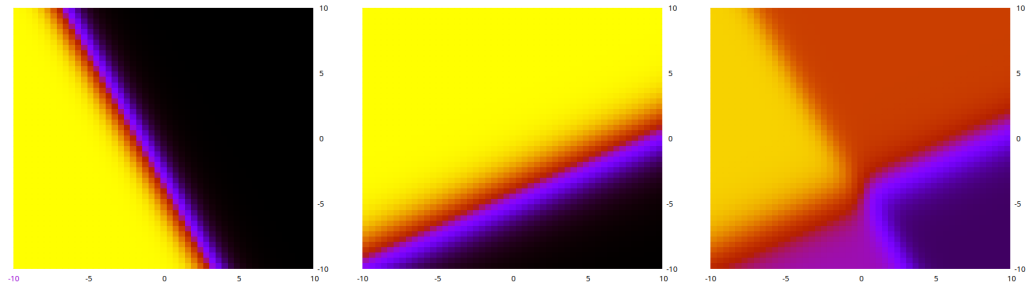


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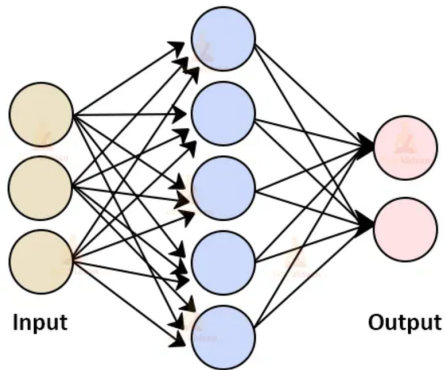


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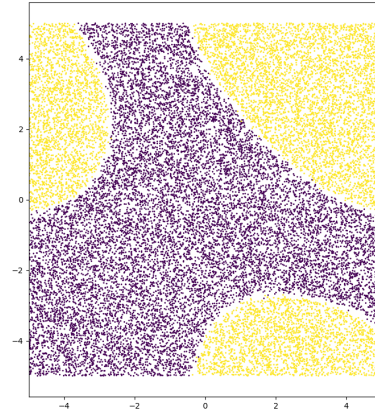
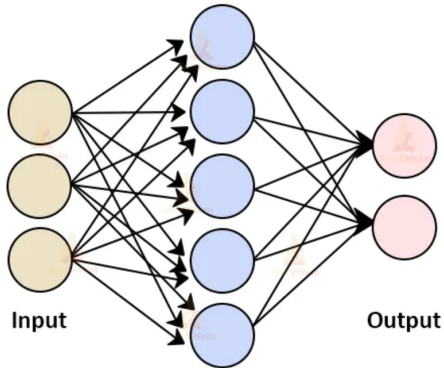


Combining several Logistic maps, we make an **ANN**.

## Artificial Neural Networks

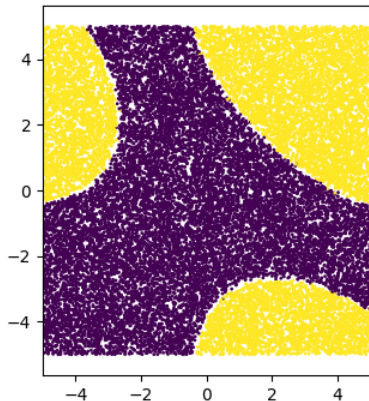


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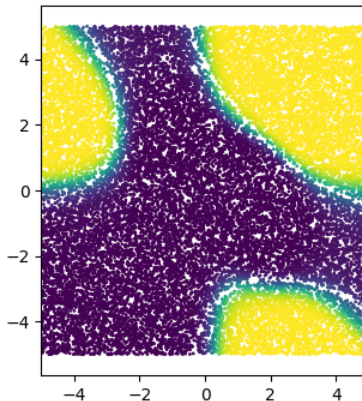


ANN:  $N_{\text{hidden}} = 4$ ,  $N_{\text{epoch}} = 10$ , Accuracy = **97.4%**

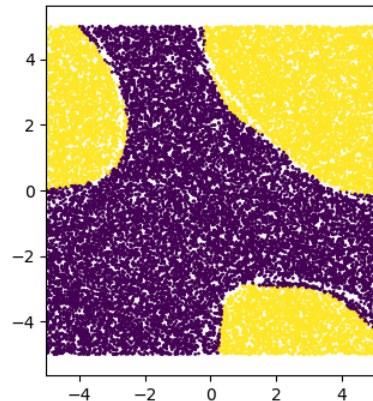
data



score

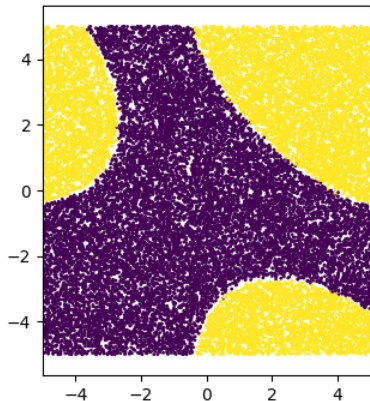


classification

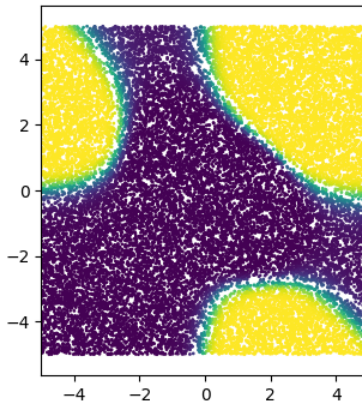


ANN:  $N_{\text{hidden}} = 4$ ,  $N_{\text{epoch}} = 20$ , Accuracy = **97.9%**

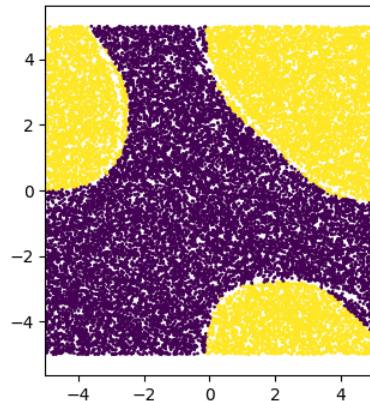
data



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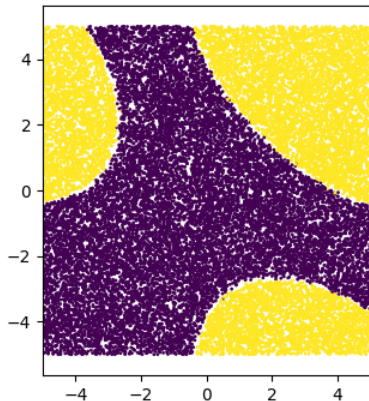


classification

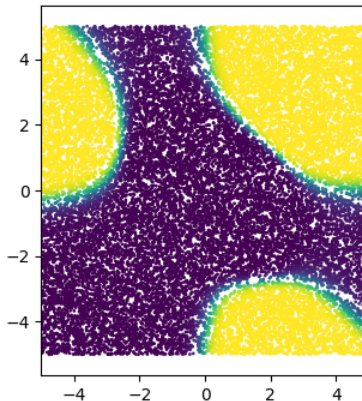


ANN:  $N_{\text{hidden}} = 4$ ,  $N_{\text{epoch}} = 30$ , Accuracy = **98.1%**

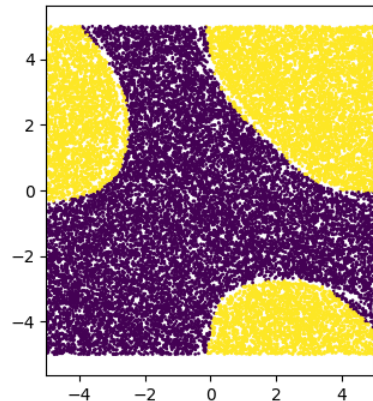
data



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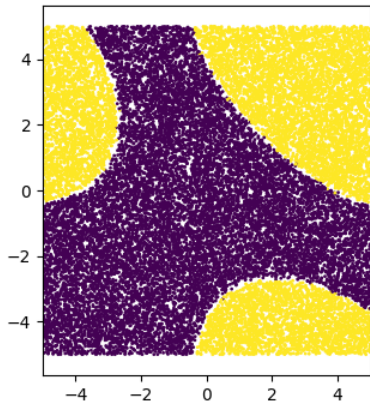


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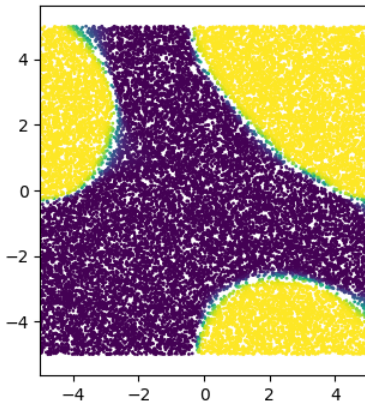


ANN:  $N_{\text{hidden}} = 10$ ,  $N_{\text{epoch}} = 10$ , Accuracy = **99.7%**

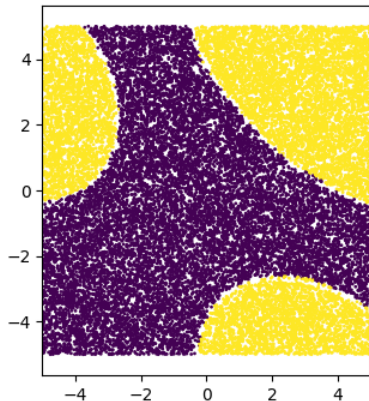
data



score



classification



## Feature Engineering

**Features:**  $(x, y)$

Decision boundary approximation with 4 neurons  $\Rightarrow \sim 98.0\%$  accuracy

About 15 parameters to fit. Improves slowly with  $N_{epoch}$

Decision boundary approximation with 10 neurons  $\Rightarrow \sim 99.7\%$  accuracy

About 40 parameters to fit. May get stuck in local minima. Less **interpretable**.

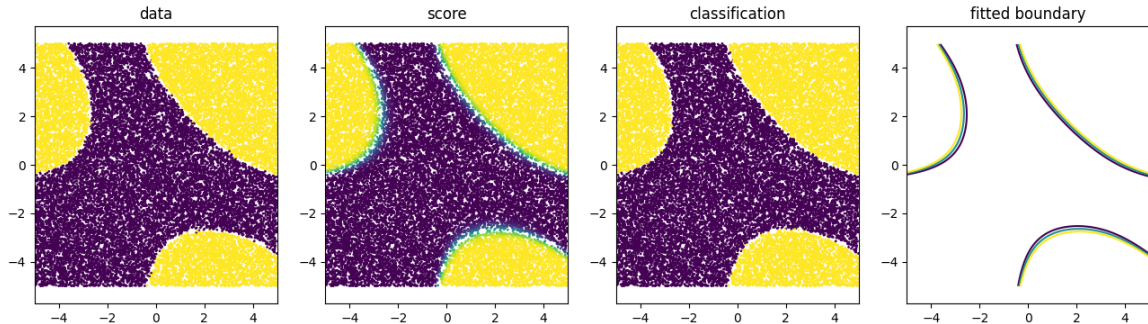
**Features:**  $(x, y, x^2, y^2, xy, x^2y, xy^2)$

Decision boundary approximation with **one neuron**  $\Rightarrow \sim 99.8\%$  accuracy

Less number of parameters to fit. Symmetries can help further. More **interpretable**.

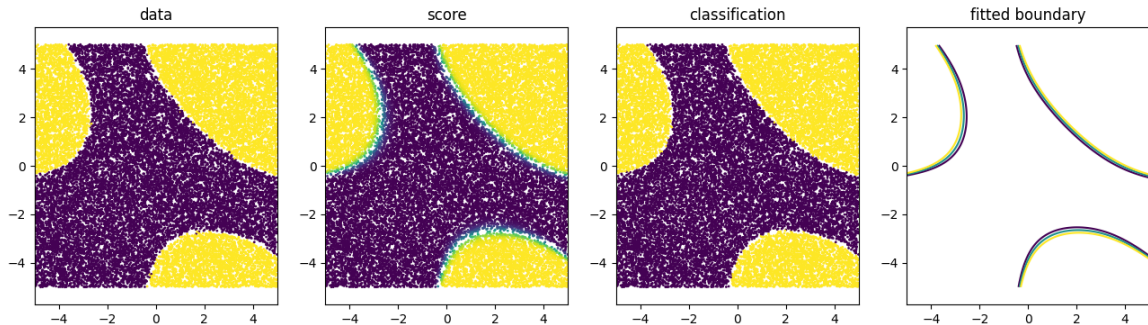


ANN:  $N_{\text{input}} = 7$ ,  $N_{\text{epoch}} = 10$ , Accuracy = **99.86%**, (non-linear)



$x$	$y$	$x^2$	$y^2$	$xy$	$x^2y$	$xy^2$
-0.031	0.055	<b>0.705</b>	<b>0.710</b>	0.051	<b>0.751</b>	<b>0.748</b>

ANN:  $N_{\text{input}} = 4$ ,  $N_{\text{epoch}} = 10$ , Accuracy = **99.87%**, (non-linear + sym)



$x + y$	$x^2 + y^2$	$xy$	$x^2y + xy^2$
0.0069	<b>0.711</b>	-0.025	<b>0.776</b>