

Neural Networks for Erasmus

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dr hab. inż. Michał Bereta
room 144 / 8, Institute of Computer Science

mbereta@pk.edu.pl
www.michalbereta.pl/nn

Classification problems

Linearly separable data

- Two classes
 - One perceptron needed
- More than two classes
 - Each class has its own neuron
 - For this neuron, its class is “1”, all other classes are “-1”
 - Multi-class problem is decomposed into several two class problems

Classification problems

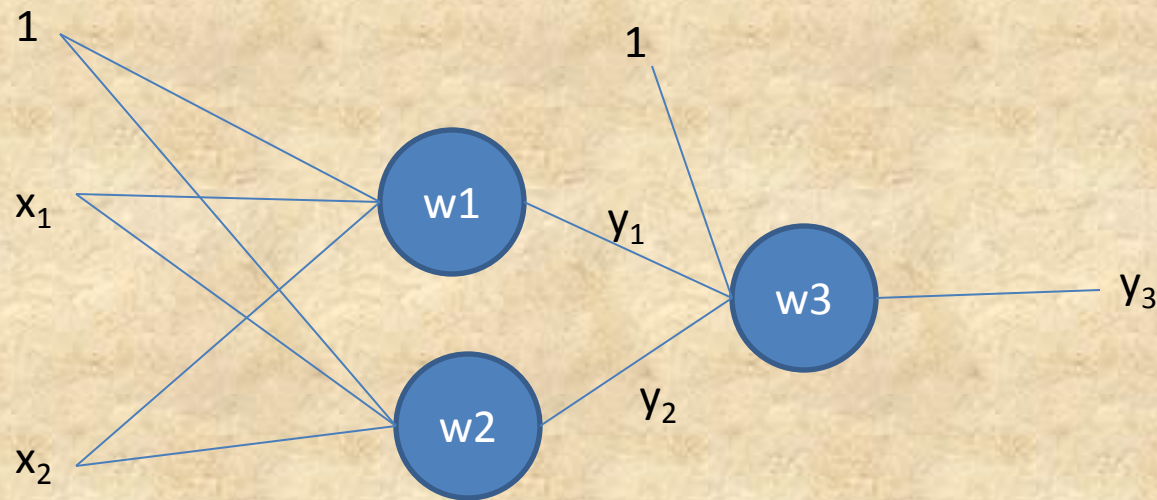
- Linearly nonseparably data (nonlinear problem)
 - You can try one neuron
 - Adding nonlinear features by hand
 - **Use network of neurons**

For regression

- Linear
 - Widrow-Hoff model
- Nonlinear functions
 - Adding nonlinear features by hand
 - **Use network of neurons**

Neural Nets

- Can we use only linear neurons to create a net?



$$\mathbf{w}_1 = [w_{10}, w_{11}, w_{12}]$$

$$\mathbf{w}_2 = [w_{20}, w_{21}, w_{22}]$$

$$\mathbf{w}_3 = [w_{30}, w_{31}, w_{32}]$$

Neural Nets

$$y_1 = w_{10} + w_{11}x_1 + w_{12}x_2$$

$$y_2 = w_{20} + w_{21}x_1 + w_{22}x_2$$

$$y_3 = w_{30} + w_{31}y_1 + w_{32}y_2 =$$

$$w_{30} + w_{31} * (w_{10} + w_{11}x_1 + w_{12}x_2) + w_{32} * (w_{20} + w_{21}x_1 + w_{22}x_2) =$$

$$(w_{30} + w_{31}w_{10} + w_{32}w_{20}) + x_1 * (w_{31}w_{11} + w_{32}w_{21}) + x_2 * (w_{31}w_{12} + w_{32}w_{22})$$

$$= w_{40} + w_{41}x_1 + w_{42}x_2$$

Neural Nets

$$y_1 = w_{10} + w_{11}x_1 + w_{12}x_2$$

$$y_2 = w_{20} + w_{21}x_1 + w_{22}x_2$$

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$$= w_{40} + w_{41}x_1 + w_{42}x_2$$

Linear combination of linear combinations
is also a linear combination.

Activation functions

Neurons in hidden layers should have a nonlinear activation functions.

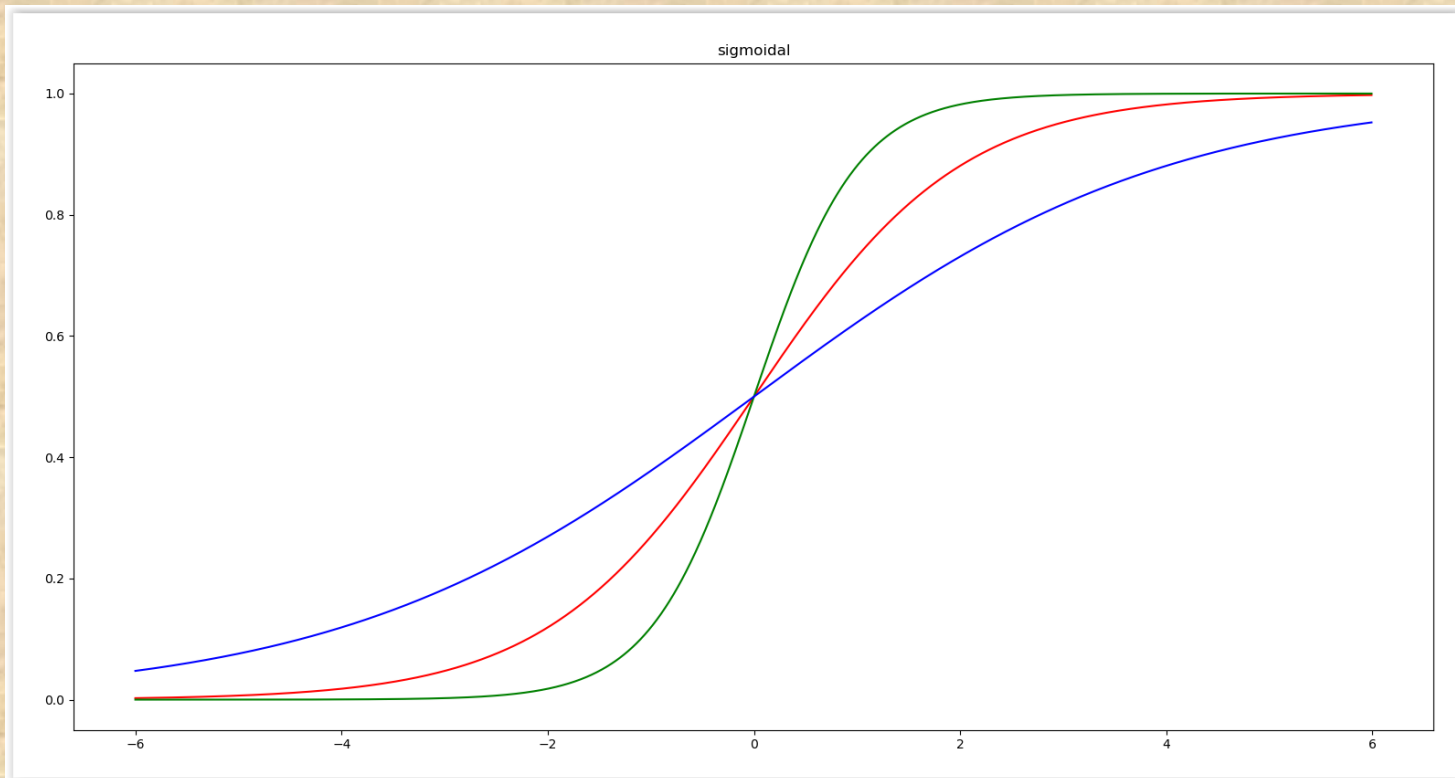
$$f(u_i) = \begin{cases} 1 & u_i > 0 \\ 0 & u_i \leq 0 \end{cases}$$

Unipolar activation function

Problem:

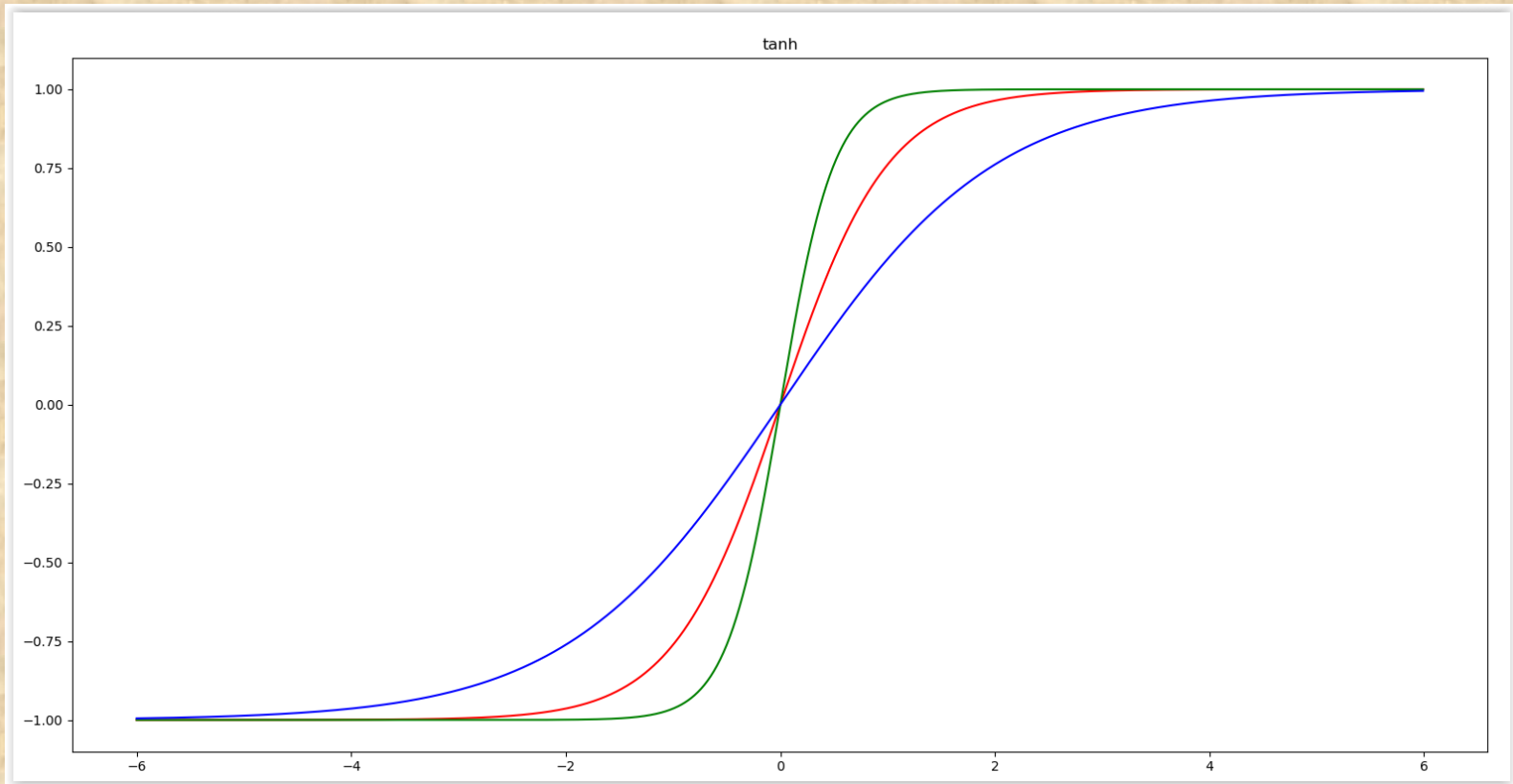
- It is not continuous
- There will be problems with calculation of gradients

Activation functions



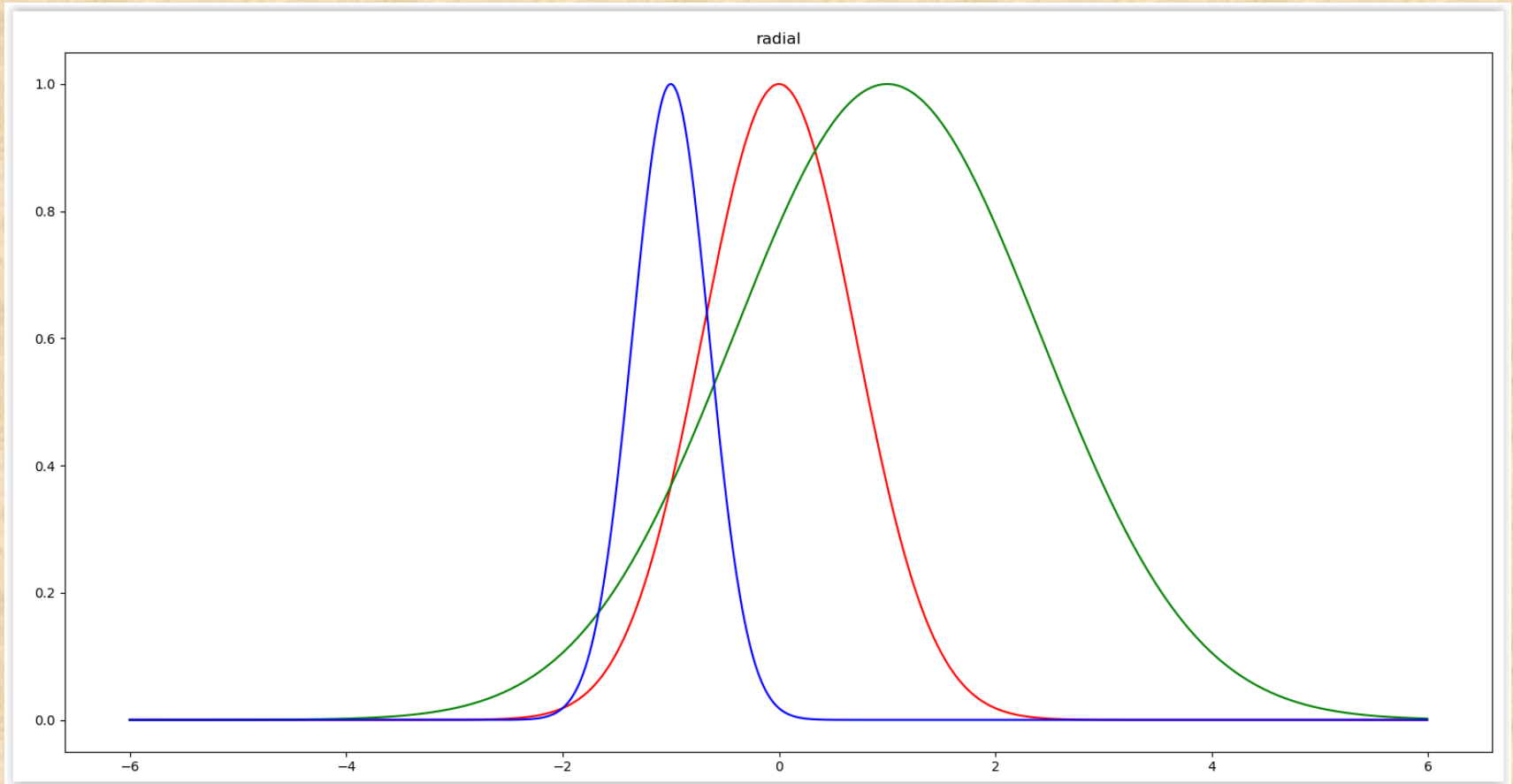
$$f(x) = \frac{1}{1 + e^{-\beta x}}$$

Activation functions



$$f(x) = \tanh(\beta x)$$

Activation functions



$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

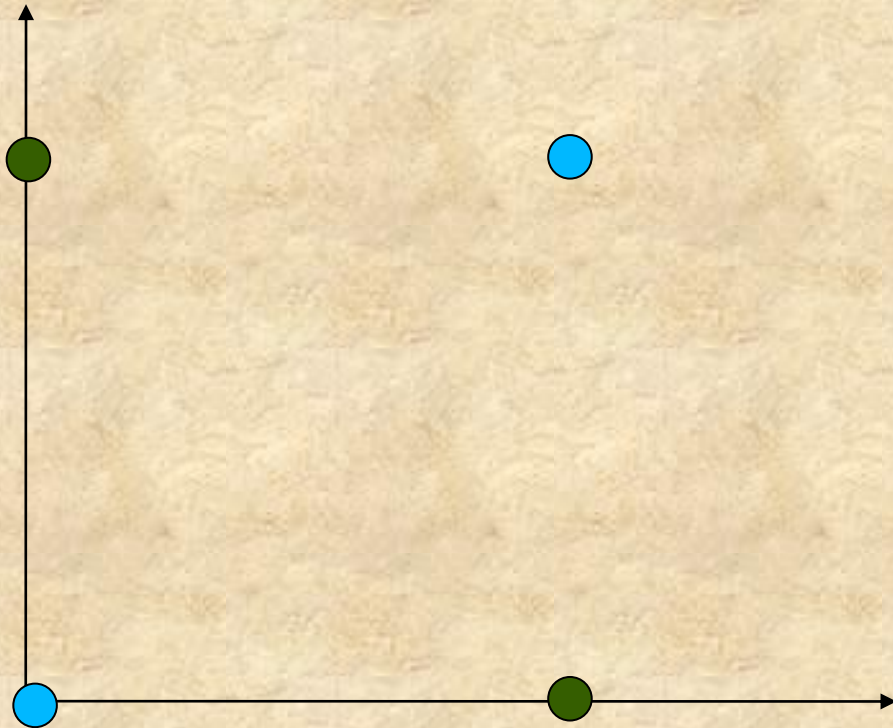
As in the normal distribution

Neural Nets

- Hidden layers, due to the nonlinear transformations, transfer the problem into a new space.
- Linear neurons from output layer solve a linear problem (in the new space)

XOR problem

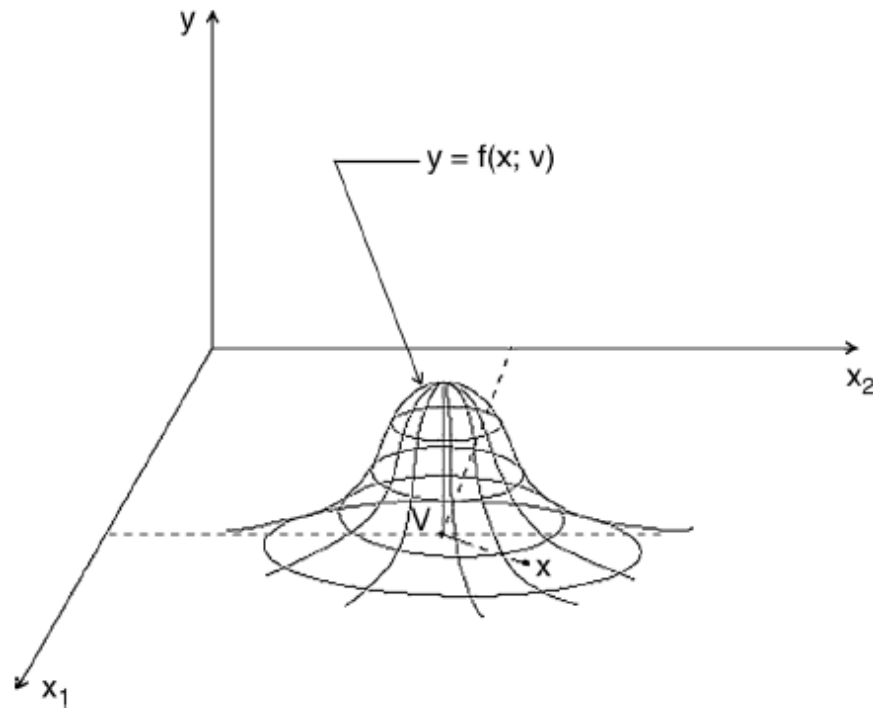
XOR		
x	y	x xor y
0	0	0
1	0	1
0	1	1
1	1	0



Cannot be solved with linear model

XOR problem

Nets with radial basis functions (RBF)

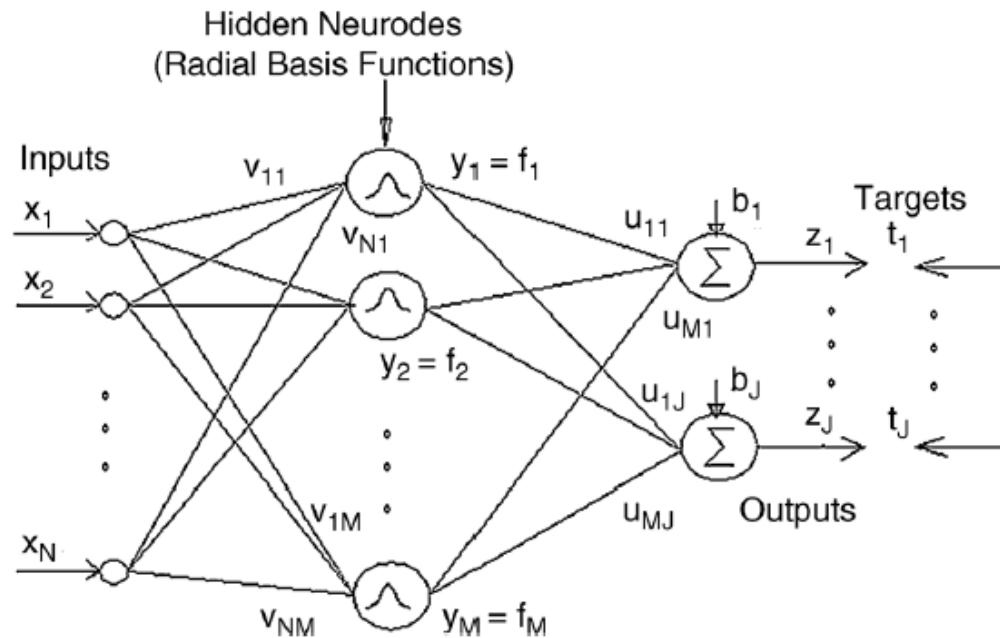


A radial basis function centered on v .

Gaussian Radial basis function:
$$k(\mathbf{x}, \mathbf{x}') = \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}'\|^2}{2\sigma^2}\right)$$

RBF

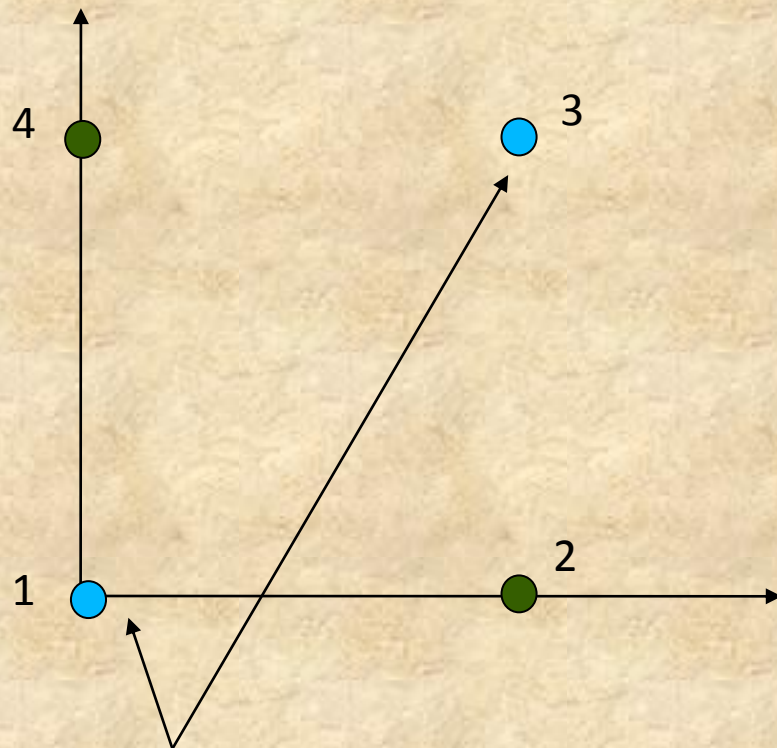
Radial basis functions networks



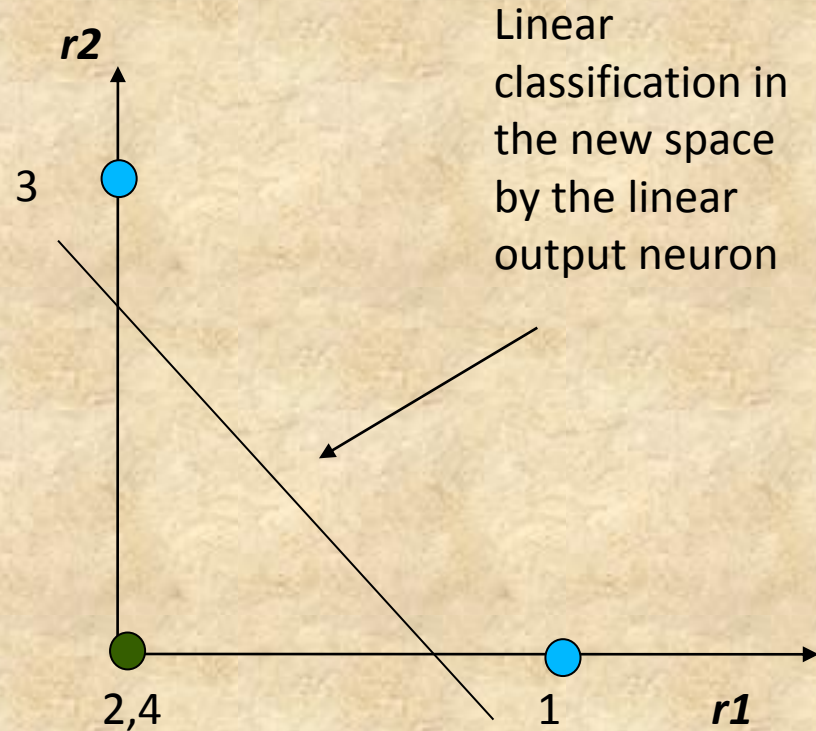
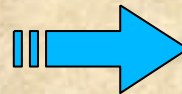
The radial basis function neural network architecture.

XOR problem

Nets with radial basis functions (RBF)



There we place two radial neurons $r1$ and $r2$



Linear classification in the new space by the linear output neuron

In the new space, the problem is linear!

Nets with radial basis functions (RBF)

- Also for regression

Gaussian functions

- We can decide where to place them
 - They are fixed, not changed during training of output layer
- Their positions and widths can be learned from data
 - Random initialization
 - Training modifies the whole network, both layers