

# **Radial-Basis Function Networks**

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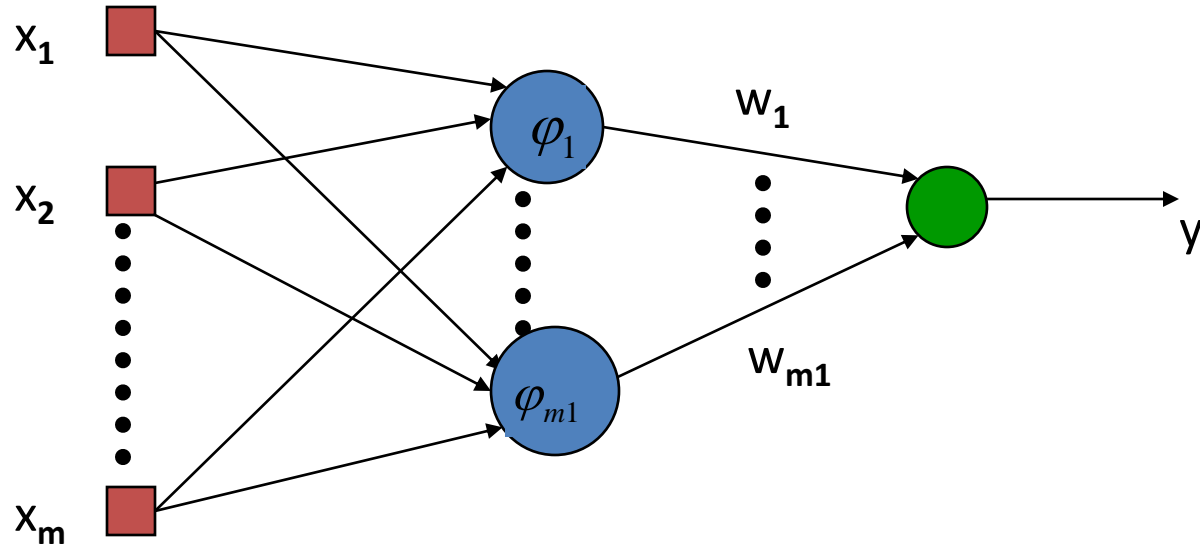
**IIT Allahabad**

# Radial-Basis Function Networks

Radial-Basis Function network (RBF) is a three layers architecture:

- **Input Layer:** The input layer is made up of source nodes that connect the network to its environment.
- **Hidden Layer:** In this layer a nonlinear transformation is applied from the input space to the hidden space.
- **Output Layer:** The output layer is linear, supplying the response of the network to the activation pattern applied to the input layer.

# RBF ARCHITECTURE



- **One hidden layer with RBF activation functions**

$$\varphi_1 \dots \varphi_{m1}$$

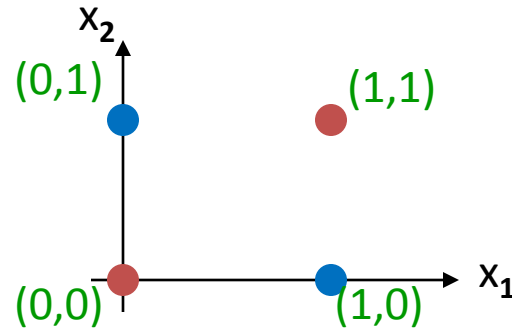
- **Output layer with linear activation function.**

$$y = w_1 \varphi_1(\|x - t_1\|) + \dots + w_{m1} \varphi_{m1}(\|x - t_{m1}\|)$$

$\|x - t\|$  distance of  $x = (x_1, \dots, x_m)$  from vector  $t$

# Example: XOR Problem

- Input space:



- Output space:



- Construct an RBF pattern classifier such that:
  - $(0,0)$  and  $(1,1)$  are mapped to 0, class C1
  - $(1,0)$  and  $(0,1)$  are mapped to 1, class C2

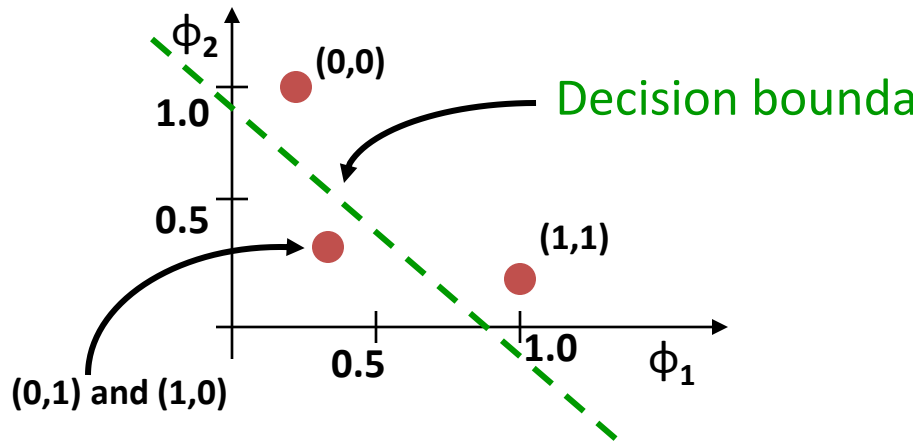
# Example: the XOR problem

- In the feature (hidden layer) space:

$$\varphi_1(\|x - t_1\|) = e^{-\|x - t_1\|^2}$$

$$\varphi_2(\|x - t_2\|) = e^{-\|x - t_2\|^2}$$

with  $t_1 = (1,1)$  and  $t_2 = (0,0)$



**TABLE 5.1** Specification of the Hidden Functions for the XOR Problem of Example 5.1

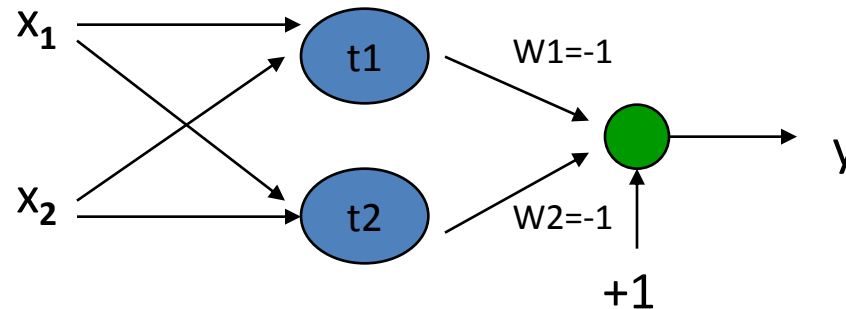
Input Pattern, $\mathbf{x}$	First Hidden Function, $\varphi_1(\mathbf{x})$	Second Hidden Function, $\varphi_2(\mathbf{x})$
(1,1)	1	0.1353
(0,1)	0.3678	0.3678
(0,0)	0.1353	1
(1,0)	0.3678	0.3678

- When mapped into the feature space  $\langle \varphi_1, \varphi_2 \rangle$  (hidden layer), C1 and C2 become *linearly separable*. So a linear classifier with  $\varphi_1(\mathbf{x})$  and  $\varphi_2(\mathbf{x})$  as inputs can be used to solve the XOR problem.

# RBF NN for the XOR problem

$$\varphi_1(\|x - t_1\|) = e^{-\|x - t_1\|^2} \quad \text{with } t_1 = (1,1) \text{ and } t_2 = (0,0)$$

$$\varphi_2(\|x - t_2\|) = e^{-\|x - t_2\|^2}$$



$$y = -e^{-\|x - t_1\|^2} - e^{-\|x - t_2\|^2} + 1$$

If  $y > 0$  then class 1 otherwise class 0

# Generalized Radial-Basis Function Networks

- When  $x_i$ ,  $i=1..N$  is large, the one-to-one correspondence between the training input data and the Green's function produces a regularisation network that may be considered expensive.
- An approximation of the regularized network.

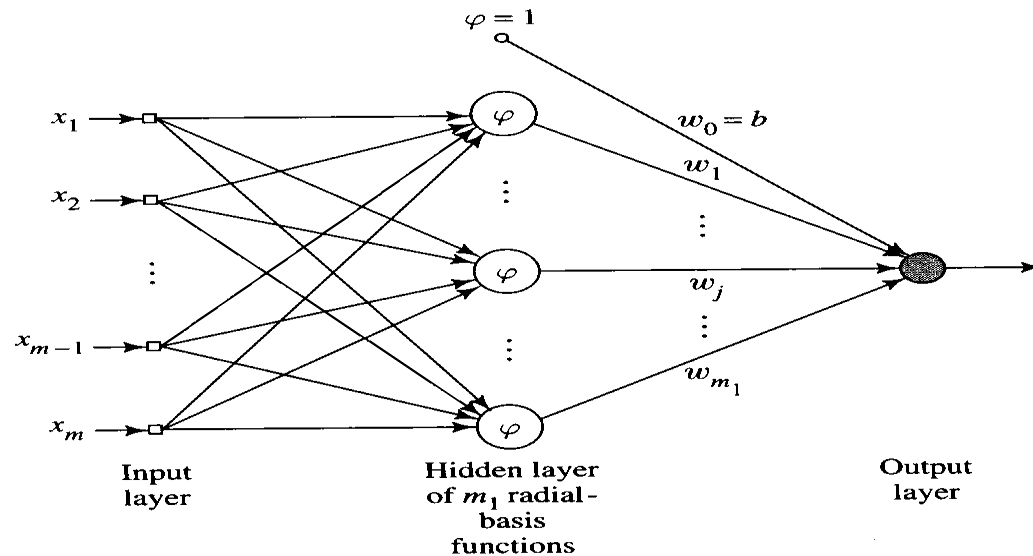


FIGURE 5.5 Radial-basis function network.

# Example: XOR Problem

**Table: Input output Transformation Computed for XOR problem**

Data point, j	Input pattern, $X_j$	Desired output, $d_j$
1	(1, 1)	0
2	(0,1)	1
3	(0,0)	0
4	(1,0)	1

Where G is green's function defined as:

$$G = \begin{bmatrix} G(X_1, t_1) & G(X_1, t_2) & \dots & G(X_1, t_m) \\ G(X_2, t_1) & G(X_2, t_2) & \dots & G(X_2, t_m) \\ G(X_3, t_1) & G(X_3, t_2) & \dots & G(X_3, t_m) \\ G(X_N, t_1) & G(X_N, t_2) & \dots & G(X_N, t_m) \end{bmatrix} \quad G = \begin{bmatrix} 1 & 0.1353 & 1 \\ 0.3678 & 0.3678 & 1 \\ 0.1353 & 1 & 1 \\ 0.3678 & 0.3678 & 1 \end{bmatrix}$$

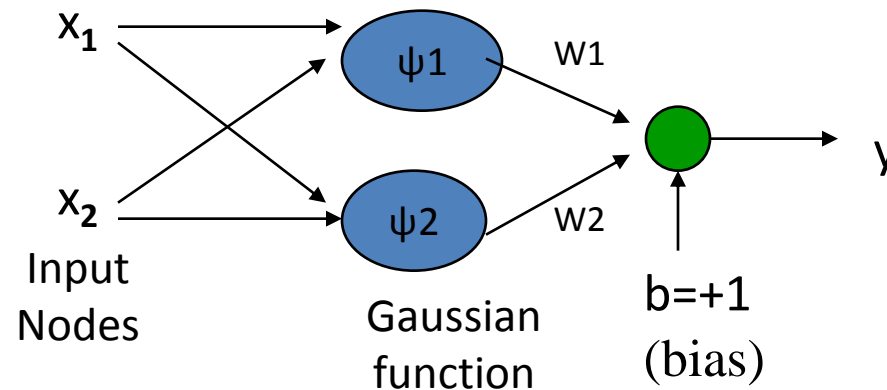
Calculated as  $G(\| \mathbf{x} - \mathbf{t}_i \|) = \exp(-(\| \mathbf{x} - \mathbf{t}_i \|)^2)$   $i=1,2$



# Example: XOR Problem

$$d = [0 \ 1 \ 0 \ 1]^T \quad W = [w_1 \ w_2 \ b]^T$$

Where  $W = G^+ d = (G^T G)^{-1} G^T d$  And  $G^+$  is a pseudo inverse of  $G$



Thus the final input output relation of the network is defined as:

$$y(x) = \sum_{i=1}^2 w_i G(\|x - t_i\|) + b$$