

## Assignment 27

Similarities between RBF and MLP:

- feed forward networks
- universal function approximators.
- similar application areas.

Differences between RBF and MLP:

RBF	MLP
The outputs of the hidden units are monotonic functions of the weighted linear sum of the inputs => constant on the (d-1)D hyperplanes.	Hidden unit outputs are functions of distance from prototype vector (centre) => constant on concentric (d-1)D hyper ellipsoids.
Distributed representation => interference between units => non-linear training => slow convergence.	Localised hidden units mean that few contribute to output => lack of interference => faster convergence.
More than one hidden layer.	One hidden layer.
Global supervised learning of all weights.	Hybrid learning with supervised learning in one set of weights.
Global approximations to nonlinear mappings.	Localised approximations to nonlinear mappings.
Can be partially connected	Is mandatorily fully connected.

## Assignment 28

There are 3 approaches to set, adjust centers and sizes of the RBF network.

- 1) We choose the case when there is little or no information about the input data because of this it is often suitable to cover the input space uniformly; therefore the values of the centers are set so that the space is covered in this way. The parameter size should allow a moderate coverage of the input area. The shape of the radial basis function determines the size (width) and thereby the degree of overlapping for the center functions.
- 2) This paradigm is based on the input data. To determine the centers and sizes for the RBF network it is used a clustering algorithm. Such algorithms could be k—means clustering algorithm. The main idea is that the centers are placed only in those regions

that have input data space. Other methods use subset of the input data; statistical analysis.

- 3) This is an error driven approach using gradient decent. The idea is to compare the achieved output with the teacher and to adapt the center and sizes by gradient decent.

$$\frac{\partial^p E(c_{nk})}{\partial c_{nk}} \quad \frac{\partial^p E(s_k)}{\partial s_k}$$

Assignment 29

$$G = R^+ \hat{Y} = (R^T R)^{-1} R^T \hat{Y}$$

Calculating number of multiplication for each matrix multiplication:

$$R_{K \times P}^T R_{P \times K} \rightarrow K P K = K^2 P$$

$$(R^T R)_{K \times K}^{-1} \rightarrow K K K = K^3$$

$$(R^T R)_{K \times K}^{-1} R_{K \times P}^T \rightarrow K K P = K^2 P$$

$$((R^T R)^{-1} R^T)_{K \times P} \hat{Y}_{P \times M} \rightarrow K P M$$

Number of multiplications needed to calculate all RBF outputs is  $NPK$ . To sum up, total number of multiplications is  $2K^2P + K^3 + KPM + NPK$ .

# Assignment 32

## Assignment 32

$$p y_m = \sum_{k=1}^K \omega_{km} v_k, \quad v_k(p_x) = \exp\left(-\frac{\|p_x - c_k\|^2}{2s_k^2}\right)$$

$$v_k = \exp\left(-\frac{\|p_x - c_k\|^2}{2s_k^2}\right)$$

$$v_k = \exp\left(-\frac{(p_x - c_k)(p_x - c_k)^T}{2s_k^2}\right)$$

$$v_k = \exp\left(-\frac{\sum_{i=1}^m (x_i - c_{ki})^2}{2s_k^2}\right)$$

$$v_k = \exp\left(-\frac{\sum_{i=1}^m (x_i - c_{ki})^2}{2s_k^2}\right)$$

$$F = \frac{1}{2} \sum_{i=1}^p \sum_{j=1}^m \left( p y_m - \sum_{k=1}^K \omega_{km} \cdot \exp\left(-\frac{\sum_{i=1}^m (x_i - c_{ki})^2}{2s_k^2}\right) \right)^2$$

$$\frac{\partial F}{\partial s_k} = \frac{1}{2} \left[ \sum_{i=1}^p \sum_{j=1}^m \left( \frac{p y_m}{2} + \sum_{k=1}^K \omega_{km} \exp\left(-\frac{\sum_{i=1}^m (x_i - c_{ki})^2}{2s_k^2}\right) \right)^2 \right]$$

$$\frac{\partial F}{\partial c_k} = \frac{1}{2} \sum_{i=1}^p \sum_{j=1}^m \left( p y_m - \sum_{k=1}^K \omega_{km} \cdot \exp\left(-\frac{\sum_{i=1}^m (x_i - c_{ki})^2}{2s_k^2}\right) \right)^2$$