

RBFN

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1. If we take the r 1-4 as our 4 basis vectors, then the weight matrix is assigning the classifiers associated with each basis vector and a bias of zero because the data is already centered around the origin. In the weight vector r_1 and r_2 are 1 because their two inputs match, while r_3 and r_4 are -1 because their inputs don't match. If we plug these basis vectors into the $\phi(x)$ equation from the lecture notes ($\exp(x-r_i)$) then we get W .

2. In a multi-class classification setting one could perform a nearest neighbor classification by RBFN by taking each input vector of size K (dimension of input space), appending the correct classification $(K+1)$, transposing to make each column a basis vector and we have L basis vectors (number of input vectors). This $[K+1][L]$ matrix could then be used to perform nearest neighbor classification by computing the distance of the new input vector to each basis vector.

3. $D(y^*, M, \phi(x)) = -(y^* \log(\sigma(w^T \phi(x))) + (1 - y^*) \log(1 - \sigma(w^T \phi(x))))$

First, we derive the derivative with respect to $\phi_k(x)$

$$\begin{aligned}\nabla_{\phi_k(x)} D(y^*, M, \phi(x)) &= (-y^*) \left(\frac{1}{\sigma(w^T \phi(\tilde{x}))} \right) (\sigma(w^T \phi(\tilde{x})) (1 - \sigma(w^T \phi(\tilde{x}))) w_k - (1 \\ &\quad - y^*) \left(\frac{1}{\sigma(w^T \phi(\tilde{x}))} \right) (-1) (\sigma(w^T \phi(\tilde{x})) (1 - \sigma(w^T \phi(\tilde{x}))) w_k \\ \nabla_{\phi_k(x)} D(y^*, M, \phi(x)) &= -y^* (1 - \sigma(w^T \phi(\tilde{x}))) w_k + (1 - y^*) (\sigma(w^T \phi(\tilde{x}))) w_k \\ \nabla_{\phi_k(x)} D(y^*, M, \phi(x)) &= [-y^* + y^* \sigma(w^T \phi(\tilde{x})) + \sigma(w^T \phi(\tilde{x})) - y^* \sigma(w^T \phi(\tilde{x}))] w_k \\ \nabla_{\phi_k(x)} D(y^*, M, \phi(x)) &= -(y^* - \sigma(w^T \phi(\tilde{x}))) w_k\end{aligned}$$

Next, we take a look at $\phi_k(x) = \exp(-(x - r^k)^2)$

Solving for $\frac{\partial \phi_k(x)}{\partial r^k}$ allows us to use the chain rule to find $\nabla_{\phi_k(x)} D(y^*, M, \phi(x))$.

$$\frac{\partial \phi_k(x)}{\partial r^k} = \exp(-(x - r^k)^2) * (-2(x - r^k)) * (-1)$$

$$\frac{\partial \phi_k(x)}{\partial r^k} = 2 * \exp(-(x - r^k)^2) * (x - r^k)$$

Therefore,

$$\nabla_{r^k} D(y^*, M, \phi(x)) = -(y^* - \sigma(w^T \phi(\tilde{x}))) w_k * 2 * \exp(-(x - r^k)^2) * (x - r^k)$$

And if we re-write the equation and substitute back in $\phi_k(x)$ matches the equation in our notes:

$$\nabla_{r^k} D(y^*, M, \phi(x)) = -2(y^* - \sigma(w^T \phi(\tilde{x}))) w_k * \phi_k(x) * (x - r^k)$$