# Math 156 Project 1

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## Problem 1

#### Part 1

Let  $k_a(\mathbf{x}_a, \mathbf{x}'_a) = \Phi_a(\mathbf{x}_a)^T \Phi_a(\mathbf{x}'_a)$ ,  $k_b(\mathbf{x}_b, \mathbf{x}'_b) = \Phi_b(\mathbf{x}_b)^T \Phi_b(\mathbf{x}'_b)$  so that

$$k(\mathbf{x}, \mathbf{x}') = \Phi_a(\mathbf{x}_a)^T \Phi_a(\mathbf{x}'_a) + \Phi_b(\mathbf{x}_b)^T \Phi_b(\mathbf{x}'_b).$$

We claim that k is defined by a nonlinear feature space mapping

$$\psi\left(\mathbf{x}\right) = \left(\Phi_a\left(\mathbf{x}_a\right), \Phi_b\left(\mathbf{x}_b\right)\right).$$

where the subscripts a and b define the disjoint subsets of  $\mathbf{x}$  as in the problem statement. This feature space mapping is valid as all components of  $\mathbf{x}$  are present in the union of the sets  $\mathbf{x}_a$ ,  $\mathbf{x}_b$ .

Evaluating an inner product as block matrices, we get that

$$\psi(\mathbf{x})^{T} \psi(\mathbf{x}') = (\Phi_{a}(\mathbf{x}_{a}), \Phi_{b}(\mathbf{x}_{b}))^{T} (\Phi_{a}(\mathbf{x}'_{a}), \Phi_{b}(\mathbf{x}'_{b})).$$

Note here that inner product is valid since we can transpose the block vector components individually to get valid inner products in the expansion of the above expression. i.e.

$$\psi\left(\mathbf{x}\right)^{T}\psi\left(\mathbf{x}'\right) = \left(\Phi_{a}\left(\mathbf{x}_{a}\right), \Phi_{b}\left(\mathbf{x}_{b}\right)\right)^{T}\left(\Phi_{a}\left(\mathbf{x}_{a}'\right), \Phi_{b}\left(\mathbf{x}_{b}'\right)\right) = \Phi_{a}\left(\mathbf{x}_{a}\right)^{T}\Phi_{a}\left(\mathbf{x}_{a}'\right) + \Phi_{b}\left(\mathbf{x}_{b}\right)^{T}\Phi_{b}\left(\mathbf{x}_{b}'\right),$$

which is exactly  $k(\mathbf{x}, \mathbf{x}')$ .

#### Part 2

Let  $\mathbf{x} = (x_1, x_2), \mathbf{y} = (y_1, y_2), \text{ so}$ 

$$k(\mathbf{x}, \mathbf{y}) = (x_1y_1 + x_2y_2)^2 = x_1^2y_1^2 + 2x_1x_2y_1y_2 + x_2^2y_2^2.$$

From here it is clear that the mapping

$$\Phi\left(\mathbf{x}\right) = \left(x_1^2, \sqrt{2}x_1x_2, x_2^2\right)$$

produces the expression for k when taking  $\Phi\left(\mathbf{x}\right)^{T}\Phi\left(\mathbf{y}\right)$ .

## Problem 2

The log likelihood of the model is

$$F(\mathbf{w}) = \frac{-\beta}{2} \sum_{n=1}^{N} [y(x_n, \mathbf{w}) - t_n]^2 + \frac{N}{2} \ln \beta - \frac{N}{2} \ln 2\pi.$$

To maximize we differentiate F with respect to each component of  $\mathbf{w}$   $w_1, \ldots, w_M$ . To compute this we compute the general partial derivatives of y with respect to each of the components  $w_1, \ldots, w_M$ .

$$\frac{\partial y}{\partial w_i} = x^i \qquad i = 0, \dots, M.$$

Therefore

$$\frac{\partial F}{\partial x} = -\beta \sum_{n=1}^{N} \left[ y\left(x_{n}, \mathbf{w}\right) - t_{n} \right] x_{n}^{i} \qquad i = 1, \dots, M.$$

Setting each of these partials equal to 0 we get

$$0 = -\beta \sum_{n=1}^{N} [y(x_n, \mathbf{w}) - t_n] x_n^i \qquad i = 1, ..., M$$

$$\sum_{n=1}^{N} t_n x_n^i = \sum_{n=1}^{N} x_n^i y(x_n, \mathbf{w}) \qquad i = 1, ..., M$$

$$\sum_{n=1}^{N} t_n x_n^i = \sum_{n=1}^{N} x_n^i \sum_{j=0}^{M} w_j x_n^j \qquad i = 1, ..., M$$

$$\sum_{n=1}^{N} t_n x_n^i = \sum_{n=1}^{N} \sum_{j=0}^{M} w_j x_n^{i+j} \qquad i = 1, ..., M$$

$$\sum_{n=1}^{N} t_n x_n^i = \sum_{j=0}^{M} \sum_{i=1}^{N} w_j x_n^{i+j} \qquad i = 1, ..., M$$

$$\iff T_i = \sum_{j=0}^{M} A_{ij} w_j$$

## Problem 3

Let  $A \in M_n(\mathbf{R})$ . Suppose  $v \in \text{Im}(A)$  so there exists  $w \in \mathbf{R}^n$  such that v = Aw. Then

$$A(A^{T}A)^{-1}A^{T}v = A(A^{T}A)^{-1}A^{T}Aw = A\mathbf{1}_{n}w = Aw = v$$

so the claimed projection matrix leaves elements in the image of A alone. Now suppose  $v \in \text{Im}(A)^{\perp}$ . By rank nullity theorem this means that  $v \in \text{Ker}(A^T)$ . So

$$A\left(A^TA\right)^{-1}A^Tw = 0,$$

which is consistent with the behavior of orthogonal projections of vectors onto orthogonal spaces.

## Problem 4

We differentiate in  ${\bf w}$  and set equal to  ${\bf 0},$  solving for  ${\bf w}$  :

$$E_{D}(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^{N} r_{n} \{t_{n} - \mathbf{w}^{T} \phi(\mathbf{x}_{n})\} :$$

$$E'_{D}(\mathbf{w}) = \left(\sum_{n=1}^{N} r_{n} \{t_{n} - \mathbf{w}^{T} \phi(\mathbf{x}_{n})\}\right) \left(-2 \left(t_{n} - \mathbf{w}^{T} \phi(\mathbf{x}_{n})\right) \phi(\mathbf{x}_{n})\right)$$

$$\mathbf{0} = \left(\sum_{n=1}^{N} r_{n} \{t_{n} - \mathbf{w}^{T} \phi(\mathbf{x}_{n})\}\right) \left(-2 \left(t_{n} - \mathbf{w}^{T} \phi(\mathbf{x}_{n})\right) \phi(\mathbf{x}_{n})\right)$$

$$\mathbf{0} = \left(\sum_{n=1}^{N} r_{n} \{t_{n} - \mathbf{w}^{T} \phi(\mathbf{x}_{n})\}\right) \left(-2t_{n} + 2\mathbf{w}^{T} \phi(\mathbf{x}_{n})\right) \phi(\mathbf{x}_{n})$$

$$\mathbf{0} = \left(\sum_{n=1}^{N} r_{n} \{t_{n} - \mathbf{w}^{T} \phi(\mathbf{x}_{n})\}\right) \phi(\mathbf{x}_{n})$$

$$\mathbf{0}^{T} = \left(\sum_{n=1}^{N} r_{n} \{t_{n} - \mathbf{w}^{T} \phi(\mathbf{x}_{n})\}\right) \phi(\mathbf{x}_{n})^{T}$$

$$\mathbf{0}^{T} = \sum_{n=1}^{N} r_{n} t_{n} \phi^{T}(\mathbf{x}_{n}) - \sum_{n=1}^{N} r_{n} \mathbf{w}^{T} \phi(\mathbf{x}_{n}) \phi(\mathbf{x}_{n})^{T}$$

$$\sum_{n=1}^{N} r_{n} t_{n} \phi(\mathbf{x}_{n})^{T} = \sum_{n=1}^{N} r_{n} \mathbf{w}^{T} \phi(\mathbf{x}_{n}) \phi(\mathbf{x}_{n})^{T}$$

$$\sum_{n=1}^{N} r_{n} t_{n} \phi(\mathbf{x}_{n}) = \sum_{n=1}^{N} r_{n} \phi(\mathbf{x}_{n}) \phi(\mathbf{x}_{n})^{T} \mathbf{w}$$

$$\mathbf{w} = \left(\sum_{n=1}^{N} r_{n} \phi(\mathbf{x}_{n}) \phi(\mathbf{x}_{n})^{T}\right)^{-1} \left(\sum_{n=1}^{N} r_{n} t_{n} \phi(\mathbf{x}_{n})\right)$$

## Problem 4

#### Final part

Using equation (1) we have

$$\left(w_n^{(k+1)}\right)^T \mathbf{x}_n = \left(\left(\mathbf{w}^{(k)}\right)^T + \frac{\left(t_n - \left(\mathbf{w}^{(k)}\right)^T\right) \mathbf{x}_n}{\|\mathbf{x}_n\|^2} \mathbf{x}_n^T\right) \mathbf{x}_n$$

$$\left(w_n^{(k+1)}\right)^T \mathbf{x}_n = \left(\mathbf{w}^{(k)}\right)^T \mathbf{x}_n + \frac{\left(t_n - \left(\mathbf{w}^{(k)}\right)^T \mathbf{x}_n\right)}{\|\mathbf{x}_n\|^2} \mathbf{x}_n^T \mathbf{x}_n$$

$$\left(w_n^{(k+1)}\right)^T \mathbf{x}_n = \left(\mathbf{w}^{(k)}\right)^T \mathbf{x}_n + \left(t_n - \left(\mathbf{w}^{(k)}\right)^T \mathbf{x}_n\right)$$

$$\left(w_n^{(k+1)}\right)^T \mathbf{x}_n = t_n$$