

monotonically increasing for non-negative arguments.

$$\mathbf{c}^* = \arg \min_{\mathbf{c}} \|\mathbf{x} - g(\mathbf{c})\|_2^2. \quad (2.55)$$

The function being minimized simplifies to

$$(\mathbf{x} - g(\mathbf{c}))^\top (\mathbf{x} - g(\mathbf{c})) \quad (2.56)$$

(by the definition of the L^2 norm, equation 2.30)

$$= \mathbf{x}^\top \mathbf{x} - \mathbf{x}^\top g(\mathbf{c}) - g(\mathbf{c})^\top \mathbf{x} + g(\mathbf{c})^\top g(\mathbf{c}) \quad (2.57)$$

(by the distributive property)

$$= \mathbf{x}^\top \mathbf{x} - 2\mathbf{x}^\top g(\mathbf{c}) + g(\mathbf{c})^\top g(\mathbf{c}) \quad (2.58)$$

(because the scalar $g(\mathbf{c})^\top \mathbf{x}$ is equal to the transpose of itself).

We can now change the function being minimized again, to omit the first term, since this term does not depend on \mathbf{c} :

$$\mathbf{c}^* = \arg \min_{\mathbf{c}} -2\mathbf{x}^\top g(\mathbf{c}) + g(\mathbf{c})^\top g(\mathbf{c}). \quad (2.59)$$

To make further progress, we must substitute in the definition of $g(\mathbf{c})$:

$$\mathbf{c}^* = \arg \min_{\mathbf{c}} -2\mathbf{x}^\top \mathbf{D}\mathbf{c} + \mathbf{c}^\top \mathbf{D}^\top \mathbf{D}\mathbf{c} \quad (2.60)$$

$$= \arg \min_{\mathbf{c}} -2\mathbf{x}^\top \mathbf{D}\mathbf{c} + \mathbf{c}^\top \mathbf{I}_l \mathbf{c} \quad (2.61)$$

(by the orthogonality and unit norm constraints on \mathbf{D})

$$= \arg \min_{\mathbf{c}} -2\mathbf{x}^\top \mathbf{D}\mathbf{c} + \mathbf{c}^\top \mathbf{c} \quad (2.62)$$

We can solve this optimization problem using vector calculus (see section 4.3 if you do not know how to do this):

$$\nabla_{\mathbf{c}}(-2\mathbf{x}^\top \mathbf{D}\mathbf{c} + \mathbf{c}^\top \mathbf{c}) = \mathbf{0} \quad (2.63)$$

$$-2\mathbf{D}^\top \mathbf{x} + 2\mathbf{c} = \mathbf{0} \quad (2.64)$$

$$\mathbf{c} = \mathbf{D}^\top \mathbf{x}. \quad (2.65)$$