Assignment 4:

1. (a) Using the method of Lagrange multipliersⁱ to find **y**, such that

min_y {
$$\sum_{1 \le i \le n} |\mathbf{a}_i - \mathbf{y}|^2$$
, subject to $\mathbf{y}^T \mathbf{x} = 0$ }, (2)

let $f(\mathbf{y})$ be the vector-valued objective function $f(y_1, ..., y_n) = \sum_{1 \le i \le n} |\mathbf{a}_i - \mathbf{y}|^2$, and $g(\mathbf{y}) = \mathbf{y}^{\mathrm{T}} \mathbf{x} = 0$ be the constraint function. Taking the gradient of f vields

$$\nabla f(\mathbf{y}) = \sum_{1 \leq j \leq n} f_j(y_1, \dots, y_n) \mathbf{e}_j,$$

where f_i is the partial derivative of f with respect to the j-th component, and \mathbf{e}_i is the unit basis vector of the *j*-th component namely $\mathbf{e}_i = [0, \dots, \mathbf{e}_i = 1, \dots, 0]^T$. With $|\mathbf{a}_i - \mathbf{y}|^2 = \mathbf{a}_i^T \mathbf{a}_i - 2\mathbf{a}_i^T \mathbf{y} + \mathbf{y}^T \mathbf{y}$ for each *i*, then

$$\nabla f(\mathbf{y}) = \sum_{1 \le j \le n} \partial/\partial y_j \left[\sum_{1 \le i \le n} |\mathbf{a}_i - \mathbf{y}|^2 \right] \mathbf{e}_j$$
$$= \sum_{1 \le j \le n} \partial/\partial y_j \left[\sum_{1 \le i \le n} \mathbf{a}_i^{\mathsf{T}} \mathbf{a}_i - 2\mathbf{a}_i^{\mathsf{T}} \mathbf{y} + \mathbf{y}^{\mathsf{T}} \mathbf{y} \right] \mathbf{e}_j$$

Since we are in \mathbf{R}^{n} , and the 2-norm is an assignment from \mathbf{R}^{n} to $\mathbf{R} (|\mathbf{a}_{i} - \mathbf{y}|^{2})$ is the Euclidean norm assigning the *n*-vector **y** to a real number), then from a theorem in real analysisⁱⁱ, f is continuous. So, from another property of analysis, we can interchange the summand with partial derivative, yielding

$$\nabla f(\mathbf{y}) = \sum_{1 \le j \le n} \sum_{1 \le i \le n} \partial \partial y_j \left[\mathbf{a}_i^{\mathrm{T}} \mathbf{a}_i - 2 \mathbf{a}_i^{\mathrm{T}} \mathbf{y} + \mathbf{y}^{\mathrm{T}} \mathbf{y} \right] \mathbf{e}_j$$

$$= \sum_{1 \le j \le n} \sum_{1 \le i \le n} \partial \partial y_j \left[\mathbf{a}_i^{\mathrm{T}} \mathbf{a}_i - 2(a_{ji}y_j) + y_j^2 \right] \mathbf{e}_j$$

$$= \sum_{1 \le j \le n} \left[\sum_{1 \le i \le n} (-2a_{ji} + 2y_j) \mathbf{e}_j \right]$$

$$= \sum_{1 \le j \le n} \left[\sum_{1 \le i \le n} (-a_{ji}) \mathbf{e}_j + \sum_{1 \le i \le n} y_j \mathbf{e}_j \right]$$

$$= 2 \left[\sum_{1 \le i \le n} (-\mathbf{a}_i) + \sum_{1 \le i \le n} \mathbf{y} \right]$$

$$= 2n\mathbf{y} - 2 \sum_{1 \le i \le n} \mathbf{a}_i.$$

Now, taking the gradient of g, gives

$$\nabla g(\mathbf{y}) = \sum_{1 \le j \le n} \partial \partial y_j [y_j x_j] \mathbf{e}_j$$
$$\nabla g(\mathbf{y}) = \partial \partial y_j [y_1 x_1 + \dots + y_n x_n] \mathbf{e}_j$$

$$= \sum_{1 \leq j \leq n} (x_j) \mathbf{e}_j$$
$$= \mathbf{x}.$$

Employing the Lagrange multiplier, and solving the system for lambda yields

$$\nabla f(\mathbf{y}) = \lambda \nabla g(\mathbf{y}) \implies 2n\mathbf{y} - 2\sum_{1 \le i \le n} \mathbf{a}_i = \lambda \mathbf{x}$$

Now, left-multiplying by \mathbf{x}^{T} , and using the conditions $\mathbf{y}^{T}\mathbf{x} = 0 \Rightarrow \mathbf{x}^{T}\mathbf{y} = 0$, and $\mathbf{x}^{\mathrm{T}}\mathbf{x} = 1$,

$$\mathbf{x}^{\mathrm{T}} (2n\mathbf{y} - 2\sum_{1 \le i \le n} \mathbf{a}_i) = \mathbf{x}^{\mathrm{T}} \lambda \mathbf{x}$$

$$\Rightarrow \mathbf{x}^{\mathrm{T}} (2n)\mathbf{y} - \mathbf{x}^{\mathrm{T}} (2) \sum_{1 \le i \le n} \mathbf{a}_i = \lambda (\mathbf{x}^{\mathrm{T}} \mathbf{x})$$

$$\Rightarrow (2n)\mathbf{x}^{\mathrm{T}} \mathbf{y} - 2\mathbf{x}^{\mathrm{T}} \sum_{1 \le i \le n} \mathbf{a}_i = \lambda (\mathbf{x}^{\mathrm{T}} \mathbf{x})$$

$$\Rightarrow \lambda = -2\mathbf{x}^{\mathrm{T}} \sum_{1 \le i \le n} \mathbf{a}_i.$$

Substituting for lambda gives

$$2n\mathbf{y} - 2\sum_{1 \le i \le n} \mathbf{a}_i = -2\mathbf{x}^{\mathrm{T}} \left(\sum_{1 \le i \le n} \mathbf{a}_i \right) \mathbf{x}$$

$$\Rightarrow \qquad \mathbf{y} = 1/n \left[\sum_{1 \le i \le n} \mathbf{a}_i - \mathbf{x}^{\mathrm{T}} \left(\sum_{1 \le i \le n} \mathbf{a}_i \right) \mathbf{x} \right],$$

with x and its transpose as known entities. So, to minimize (2),

$$\mathbf{y} = 1/n \left[\sum_{1 \le i \le n} \mathbf{a}_i - \mathbf{x}^{\mathrm{T}} \left(\sum_{1 \le i \le n} \mathbf{a}_i \right) \mathbf{x} \right].$$

ⁱ Larson, *Calculus: Early Transcendental Functions*, 6th Ed. ⁱⁱ Marsden, Hoffman, *Elementary Classical Analysis*, 2nd Ed.