Problem Set #1

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Question 3.1

1.
$$g(w) = w \log w + (1 - w) \log(1 - w), w \in (0, 1)$$

$$\frac{dg}{dw} = \log w \frac{dw}{dw} + w \frac{d \log w}{dw} + \log(1 - w) \frac{d(1 - w)}{dw} + (1 - w) \frac{d \log(1 - w)}{dw}$$

$$= \log w + \frac{w}{w} + \log(1 - w) \cdot -1 + \frac{(1 - w)}{(1 - w)} \cdot -1$$

$$= \log w - \log(1 - w)$$

Stationary points occur when dg/dw = 0:

$$0 = \log \frac{w}{1 - w}$$
$$1 = \frac{w}{1 - w}$$

$$w = 1/2$$

The plot (at end of the homework) shows that this point is a minimum.

2.
$$g(w) = \log(1 + e^w)$$

$$\frac{dg}{dw} = \frac{\log(1 + e^w)}{d(1 + e^w)} \frac{d(1 + e^w)}{dw}$$
$$= \frac{e^w}{(1 + e^w)}$$

$$w = -\infty$$

The plot shows that the derivative function tending toward $w=-\infty$ is a minimum.

3. $g(w) = w \tanh w$

$$\frac{dg}{dw} = \tanh w \frac{dw}{dw} + w \frac{d \tanh w}{dw}$$

$$= \tanh w + w \operatorname{sech}^{2} w$$

$$0 = \sinh w \cosh w + w$$

$$= \frac{1}{2} \sinh 2w + w$$

$$w = 0$$

The plot shows that this stationary point is a minimum.

4.
$$g(w) = \frac{1}{2}\mathbf{w}^T \mathbf{C} \mathbf{w} + \mathbf{b}^T \mathbf{w}$$

$$\nabla_{w}g(w) = \frac{1}{2}\nabla(\mathbf{w}^{T}\mathbf{C}\mathbf{w}) + \nabla(\mathbf{b}^{T}\mathbf{w})$$
$$= \frac{1}{2}(\mathbf{C} + \mathbf{C}^{T})\mathbf{w} + \mathbf{b}, \qquad \mathbf{C}^{T} = \mathbf{C}$$
$$\mathbf{0} = \mathbf{C}\mathbf{w} + \mathbf{b}$$
$$-\mathbf{b} = \mathbf{C}\mathbf{w}$$

The problem states that:

$$\mathbf{C} = \begin{bmatrix} 2 & 1 \\ 1 & 3 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$
$$\begin{bmatrix} 2 & 1 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} -1 \\ -1 \end{bmatrix}$$
$$\begin{bmatrix} (w_1 & w_2)^T = (-2/5 & -1/5)^T \end{bmatrix}$$

The plot shows this stationary point is a minimum.

Question 3.3

Start with Rayleigh's quotient:

$$g(\mathbf{w}) = \frac{\mathbf{w}^T \mathbf{C} \mathbf{w}}{\mathbf{w}^T \mathbf{w}}.$$

Taking the gradient of the numerator and denominators separately:

$$\nabla(\mathbf{w}^T \mathbf{C} \mathbf{w}) = (\mathbf{C} + \mathbf{C}^T) \mathbf{w},$$
$$\nabla(\mathbf{w}^T \mathbf{w}) = 2\mathbf{w}.$$

Now taking the gradient of g:

$$\nabla g(\mathbf{w}) = \frac{\nabla (\mathbf{w}^T \mathbf{C} \mathbf{w}) \mathbf{w}^T \mathbf{w} - \nabla (\mathbf{w}^T \mathbf{w}) \mathbf{w}^T \mathbf{C} \mathbf{w}}{(\mathbf{w}^T \mathbf{w})^2}$$
$$= \frac{(\mathbf{C} + \mathbf{C}^T) \mathbf{w} \mathbf{w}^T \mathbf{w} - 2 \mathbf{w} \mathbf{w}^T \mathbf{C} \mathbf{w}}{||\mathbf{w}||_2^4}.$$

The stationary points occur when $\nabla g = \mathbf{0}$:

$$\mathbf{0} = (\mathbf{C} + \mathbf{C}^T)\mathbf{w}(\mathbf{w}^T\mathbf{w}) - 2\mathbf{w}(\mathbf{w}^T\mathbf{C}\mathbf{w}).$$

Since $\mathbf{w}^T \mathbf{w} \in \mathbb{R}$, it can freely be divided:

$$\mathbf{0} = (\mathbf{C} + \mathbf{C}^{T})\mathbf{w} - 2\mathbf{w}\frac{\mathbf{w}^{T}\mathbf{C}\mathbf{w}}{\mathbf{w}^{T}\mathbf{w}}$$

$$= (\mathbf{C} + \mathbf{C}^{T})\mathbf{w} - 2g(\mathbf{w})\mathbf{w}$$

$$= (\mathbf{C} + \mathbf{C}^{T} - 2g(\mathbf{w})\mathbf{I})\mathbf{w}$$
(1)

There, the last equation is multiplied by the identity matrix **I** to make the sum inside of the parenthesis a matrix. This is the classic eigenvalue problem which can more easily been shown if $\mathbf{C} = \mathbf{C}^T$:

$$\mathbf{0} = (2\mathbf{C} - 2g(\mathbf{w})\mathbf{I})\mathbf{w} \implies \det(\mathbf{C} - 2g(\mathbf{w})\mathbf{I}) = 0.$$

Consider $\mathbf{C} \in \mathbb{R}^{N \times N}$. This implies that $|\mathbf{C} + \mathbf{C}^T - 2g(\mathbf{w})\mathbf{I}| = 0$ can be solved to determine N eigenvalues, each of which correspond to one eigenvectors (N total eigenvectors). Therefore, the stationary points of Rayleigh's quotient correspond to the N eigenvectors of the matrix \mathbf{C} .

Question 3.5

Here we start with the function:

$$g(w) = \frac{w^4 + w^2 + 10w}{50}$$

The derivative of this is trivial:

$$\frac{dg}{dw} = \frac{4w^3 + 2w + 10}{50}$$

The cost function plots for this problem are at the end of this document. With this combination of step length and initial position, $\alpha = 1$ converges the quickest to the minimum $w \sim -1.234, g(w) \sim -0.17$.

Question 3.6

See end of document for plot. Please note that the fixed-step line stops at k=4 where it encounters the minimum which is a non-differentiable point.

Question 3.8

The cost function we're trying to minimize is:

$$g(\mathbf{w}) = \mathbf{w}^T \mathbf{w}$$

and has a gradient of the form:

$$\nabla_{\mathbf{w}} g(\mathbf{w}) = 2\mathbf{w}.$$

The cost function history plots are below and a step length of $\alpha = 0.1$ converges quickest to the minimum located at $\mathbf{w} = \mathbf{0}$.