# 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  $\mathbf{w} = \mathbf{0}$ .

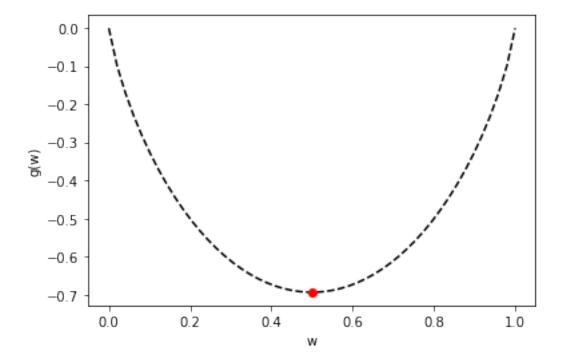
## HW 1

April 14, 2020

```
[1]: #Import modules
import numpy as np
import matplotlib
matplotlib.rcParams['font.size'] = 16
import matplotlib.pyplot as plt
```

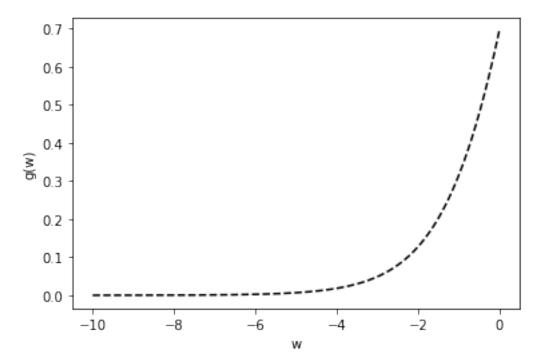
```
[2]: #Part A
    xs = np.linspace(0.0001, 0.9999)

    plt.plot(xs, xs * np.log(xs) + (1 - xs) * np.log(1 - xs), 'k--')
    plt.plot(0.5, np.log(0.5), 'ro')
    plt.xlabel("w")
    plt.ylabel("g(w)")
    plt.show()
```



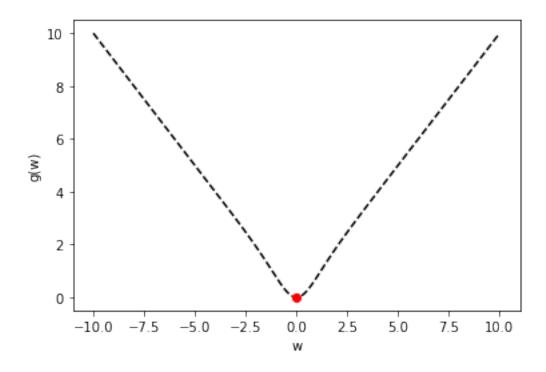
```
[3]: #Part B: Minimum is at -infinity
xs = np.linspace(-10, 0, num=10000)

plt.plot(xs, np.log(1 + np.exp(xs)), 'k--')
plt.xlabel("w")
plt.ylabel("g(w)")
plt.show()
```

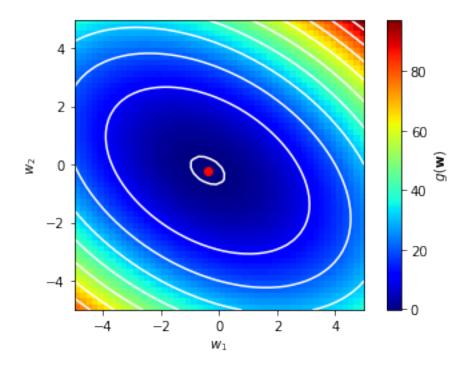


```
[4]: #Part C
    xs = np.linspace(-10, 10, num=10000)

    plt.plot(xs, xs * np.tanh(xs), 'k--')
    plt.plot(0, 0, 'ro')
    plt.xlabel("w")
    plt.ylabel("g(w)")
    plt.show()
```



```
[5]: #Part D
     def g(x, y):
         C = np.matrix('2 1; 1 3')
         w = np.matrix([[x], [y]])
         b = np.matrix('1; 1')
         return np.sum(0.5 * w.T*C*w + b.T * w)
     xs, ys = np.linspace(-5.0, 5.0), np.linspace(-5.0, 5.0)
     xm, ym = np.meshgrid(xs, ys)
     gs = np.zeros((xs.size, xs.size))
     for i, x in enumerate(xs):
         for j, y in enumerate(ys):
             gs[j, i] = g(x, y)
     plt.imshow(gs, origin='lower', cmap='jet', extent=[-5.0, 5.0, -5.0, 5.0])
     cbar = plt.colorbar()
     plt.contour(xm, ym, gs, levels=10, colors='white')
     cbar.set_label("$g(\\mathbf{w})$")
     plt.plot(-2/5, -1/5, 'ro')
     plt.xlabel("$w_1$")
     plt.ylabel("$w_2$")
     plt.show()
```

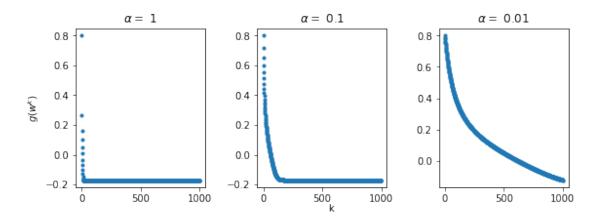


```
[6]: def g(w):
         return (w**4.0 + w**2.0 + 10 * w) / 50.0
     def grad_g(w):
         return (4 * w**3.0 + 2 * w + 10) / 50.0
     def grad_descent(w0, alpha, n_iter):
         ws = np.array([])
         for i in range(n_iter):
             ws = np.append(ws, w0)
             w0 = w0 - alpha * grad_g(w0)
         return ws
     fig, ax = plt.subplots(1, 3, figsize=(9, 3))
     ax[0].plot(np.arange(1000), g(grad_descent(2, 1, 1000)), '.')
     ax[0].set_ylabel("$g(w^k)$")
     ax[0].set_title("$\\lambda = $ 1")
     ax[1].plot(np.arange(1000), g(grad_descent(2, 0.1, 1000)), '.')
     ax[1].set_title("$\\lambda = $ 0.1")
     ax[2].plot(np.arange(1000), g(grad_descent(2, 0.01, 1000)), '.')
```

```
ax[2].set_title("$\\alpha = $ 0.01")

plt.subplots_adjust(left=0.1, right=0.88, wspace=0.4)
fig.text(0.5, 0.01, "k")
```

#### [6]: Text(0.5, 0.01, 'k')

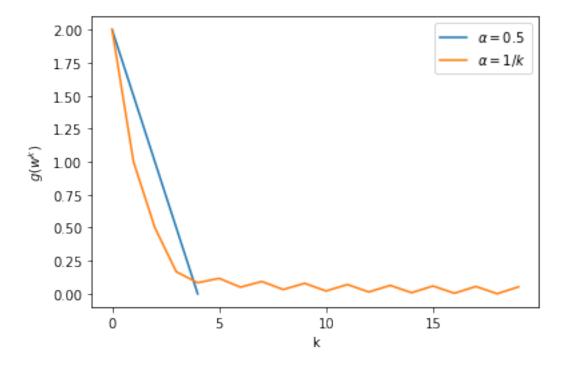


```
[7]: def g(w):
         return np.abs(w)
     def grad_g(w):
         if w < 0:
             return -1.0
         elif w > 0:
             return 1.0
         else:
             return np.nan #Stop if we hit a non-differentiable point
     # Diminshing step length
     def grad_descent_diminish(w0, n_iter):
         ws = []
         for i in range(1, n_iter+1):
             ws.append(w0)
             w0 = w0 - (1 / i) * grad_g(w0)
         return ws
     def grad_descent(w0, alpha, n_iter):
         ws = []
         for i in range(n_iter):
```

```
ws.append(w0)
    w0 = w0 - alpha * grad_g(w0)
    return ws

plt.plot(g(grad_descent(2.0, 0.5, 20)), label="$\\alpha = 0.5$")
plt.plot(g(grad_descent_diminish(2, 20)), label="$\\alpha = 1/k$")
plt.xlabel("k")
plt.ylabel("$g(w^k)$")
plt.xticks(np.arange(0, 20, 5))
plt.legend()
```

#### [7]: <matplotlib.legend.Legend at 0x2bc9a7e2608>



```
[8]: def g(w):
    return np.sum(w**2.0)

def grad_w(w):
    return 2 * w

def grad_descent(w0, alpha, n_iter):
    ws = []
    for i in range(n_iter):
```

```
ws.append(g(w0))
    w0 = w0 - alpha * grad_w(w0)
    return ws

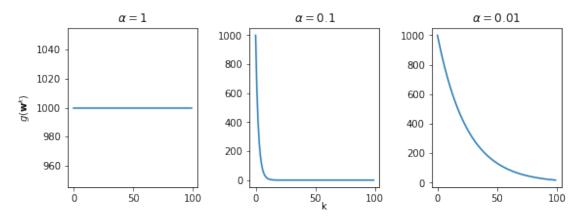
fig, ax = plt.subplots(1, 3, figsize=(9, 3))
ax[0].plot(grad_descent(10*np.ones((10, 1)), 1.0, 100))
ax[0].set_ylabel("$g(\\mathbf{w}^k)$")
ax[0].set_title("$\\alpha = 1$")

ax[1].plot(grad_descent(10*np.ones((10, 1)), 0.1, 100))
ax[1].set_title("$\\alpha = 0.1$")

ax[2].plot(grad_descent(10*np.ones((10, 1)), 0.01, 100))
ax[2].set_title("$\\alpha = 0.01$")

fig.text(0.5, 0.02, "k")

plt.subplots_adjust(left=0.1, right=0.88, wspace=0.4)
```



[]: