## Statistical Learning for Engineers (EN.530.641) Homework 1

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Out: 09/09/2022Due: 09/16/2022 by midnight EST

This is exclusively used for Fall 2022 EN.530.641 SLE students, and is not to be posted, shared, or otherwise distributed.

1 (a) In the class, we have discussed the properties that define a vector space. Let  $\mathbf{x} \in \mathbb{R}^n$ . Prove that

$$0 x = 0$$

only by using those properties. Do not use component form calculations. Here 0 denotes scalar zero, while  $\mathbf{0}$  means the zero vector in  $\mathbb{R}^n$ .

- (b) Using part (a), prove that  $-\mathbf{x} = (-1)\mathbf{x}$ . Note that through this, one can define the difference between two vectors  $\mathbf{x}$ ,  $\mathbf{y}$  in a vector space, i.e.,  $\mathbf{x} \mathbf{y}$ .
- (c) Prove that  $\mathbb{R}^{m \times n}$  (the set of all real  $m \times n$  matrices) with matrix addition, +, and scalar multiplication, ·, forms a vector space.
- **2** (a) Let's consider a system of equations

$$\begin{pmatrix} 1 & 1 & 2 \\ 1 & -1 & 2 \\ 2 & 0 & 4 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 3 \\ 2 \\ 1 \end{pmatrix}.$$

Does this system of equations have a solution? How do you know?

- (b) Suppose that, for  $\mathbb{R}^2$ , we have a basis set  $\{\mathbf{v}_1, \mathbf{v}_2\}$  that is not orthonormal. How do you obtain the orthonormal basis set? Can you generalize the process into  $\mathbb{R}^n$ ?
- **3** In the class, we have learned FONC as  $\mathbf{v}^T \nabla f(\mathbf{x}^*) \geq 0$  for a local minimizer  $\mathbf{x}^*$  ( $\mathbf{v}$  is a feasible direction). If  $\mathbf{x}^*$  is located inside the domain, then FONC becomes

$$\nabla f(\mathbf{x}^*) = \mathbf{0}.$$

Prove that this is indeed true.

- **4** Given a function  $f: \mathbb{R}^2 \to \mathbb{R}$  which is explicitly written as  $f(x_1, x_2) = x_1^2 + 2x_1x_2 + x_2^3$ ,
  - (a) Compute the gradient  $\nabla f$ .
  - (b) Compute the Hessian  $D^2f$ .

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(c) Expand  $f(x_1, x_2)$  by using the Taylor series  $\mathbf{a}$  out the point (1, 2) up to the second order.

**5** Let  $f: \mathbb{R}^2 \to \mathbb{R}$  have the following form

$$\frac{3}{8} = 200(\times_2 - \times_1^2) \times -2X_1 - 2(1 - X_1)$$

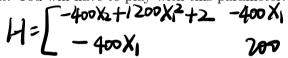
$$f(\mathbf{x}) = f(x_1, x_2) = 100(x_2 - x_1^2)^2 + (1 - x_1)^2$$
 -4 $(\mathbf{x}_2 - \mathbf{x}_1^2) \mathbf{x}_1 - 2 + 2\mathbf{x}_1$ 

where  $\mathbf{x} = [x_1, x_2]^T$ .

(a) Draw a contour plot using python. (Hint: look for contourf in numpy). -450 X2X1 +450X1 -2+2X1

- (b) Can you find any minimum point? (do it analytically you are to do it numerically in the next problem). Is it a local or a global minimizer?
- 6 Now you are asked to write your python code for finding a minimum of the function given in Problem 5. Choose any initial point that is not close to the minimum. Then implement the following algorithms:
  - (a) Gradient descent algorithm, where  $\alpha_k$  is constant. You will have to play with this parameter.
  - (b) Newton's algorithm.

As the outcomes:



- Report min f and  $\mathbf{x}^*$  (the corresponding minimum point). And compare it with the results in Problem 5 (b).
- Generate the plot of function values vs. step numbers.
- Generate plots that looks like Fig. 1.

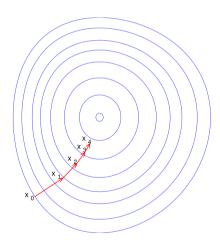


Figure 1: Problem 6: An exemplary figure that shows the steps and movements during the gradient-based optimization process, with contour plot of the function. This is from wikipedia.

## Submission Guideline

- Submit the analytic parts of the homework (Problem 1 to 5) in pdf format, including plots, to "HW1\_analytical" on Gradescope.
  - No more than two (2) homework problems may be on the same page. In other words, for each problem your answers should be on a separate set of pages (e.g., for Problem 1, your answer is on page 1–3, and for Problem 2, your answer is on page 4-5, and so on).

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- When submitting, you should assign the pages to each problem on Gradescope. You can scan your answers or use an app (e.g., Adobe Scan) to generate a pdf file. Show your work.

- Submit to "HW1\_computational" on Gradescope a single zip file that contains all the codes for each computational problem (if any, codes for analytic parts as well). Name your single zip file as "YourName\_HW1.zip". For example, "JinSeobKim\_HW1.zip" for a single zip file. Submission will be done through the Gradescope.
- Just in case you have related separate files, please make sure to include *all the necessary files*. If TAs try to run your function and it does not run, then your submission will have a significant points deduction.
- Make as much comments as possible so that the TAs can easily read your codes.
- 1 (a) In the class, we have discussed the properties that define a vector space. Let  $\mathbf{x} \in \mathbb{R}^n$ . Prove that

$$0 \, {\bf x} = {\bf 0}$$

only by using those properties. Do not use component form calculations. Here 0 denotes scalar zero, while  $\mathbf{0}$  means the zero vector in  $\mathbb{R}^n$ .

- (b) Using part (a), prove that  $-\mathbf{x} = (-1)\mathbf{x}$ . Note that through this, one can define the difference between two vectors  $\mathbf{x}$ ,  $\mathbf{y}$  in a vector space, i.e.,  $\mathbf{x} \mathbf{y}$ .
- (c) Prove that  $\mathbb{R}^{m \times n}$  (the set of all real  $m \times n$  matrices) with matrix addition, +, and scalar multiplication, ·, forms a vector space.

a) For any 
$$X \in \mathbb{R}^n$$
, there  $\exists -X \in \mathbb{R}^n$ ,  $\exists + (-X) = 0$ .

By dishibitively  $0 = X + (-X) = (1 + (-1)) \times = 0$ .

b) For any  $X \in \mathbb{R}^n$ .  $\exists -X \in \mathbb{R}^n \Rightarrow + (-X) = 0$ .

 $(1 + (-1)) \times = 0$ .

 $(1 + (-1)) \times = (1 +$ 

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3 there 20

St any AER Mxn
$$\begin{bmatrix}
0 \\
0
\end{bmatrix}
+
\begin{bmatrix}
a_{11} & a_{12} & a_{1n} \\
0 & a_{1n}
\end{bmatrix}
=
\begin{bmatrix}
0 + a_{11} & 0 + a_{1n} \\
0 + a_{n1} & 0 + a_{nn}
\end{bmatrix}
= A$$

4 For any ACD min there exist 
$$\begin{bmatrix} -a_{11} - -a_{1n} \\ -a_{m1} - -a_{mn} \end{bmatrix}$$
 5t  $\begin{bmatrix} a_{11} - a_{1n} \\ -a_{m1} - a_{mn} \end{bmatrix} + \begin{bmatrix} -a_{11} - a_{m1} \\ -a_{m1} - a_{mn} \end{bmatrix} = \begin{bmatrix} a_{11} - a_{11} \\ a_{11} - a_{m1} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = 0$ 

(a) 
$$(\alpha\beta)$$
  $\begin{bmatrix} a_{11} - a_{1n} \\ a_{m1} - a_{mn} \end{bmatrix} = \begin{bmatrix} \alpha\beta a_{11} - \alpha\beta a_{m1} \\ \alpha\beta a_{m1} - \alpha\beta a_{mn} \end{bmatrix} = \alpha \begin{bmatrix} \beta a_{11} & \beta a_{11} \\ \beta a_{m1} & \beta a_{mn} \end{bmatrix} = \alpha (\beta A)$ 

2 (a) Let's consider a system of equations

$$\begin{pmatrix} 1 & 1 & 2 \\ 1 & -1 & 2 \\ 2 & 0 & 4 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 3 \\ 2 \\ 1 \end{pmatrix}.$$

Does this system of equations have a solution? How do you know?

(b) Suppose that, for  $\mathbb{R}^2$ , we have a basis set  $\{\mathbf{v}_1, \mathbf{v}_2\}$  that is not orthonormal. How do you obtain the orthonormal basis set? Can you generalize the process into  $\mathbb{R}^n$ ?

> No solution since [0 0 0 12] is inconsistent.

$$\overrightarrow{u} = \overrightarrow{V}_{2} - \frac{\langle \overrightarrow{u}_{1}, \overrightarrow{V}_{1} \rangle \overrightarrow{u}}{|\overrightarrow{u}_{1}|^{2}}$$

$$|\overrightarrow{v}_{1}| = |\overrightarrow{V}_{2}| - \frac{\langle \overrightarrow{u}_{1}, \overrightarrow{V}_{1} \rangle \overrightarrow{u}}{|\overrightarrow{u}_{1}|^{2}}$$

$$|\overrightarrow{v}_{2}| = |\overrightarrow{V}_{k}| - \frac{|\overrightarrow{k}|}{|\overrightarrow{u}_{1}|^{2}} - \frac{|\overrightarrow{u}_{k}|}{|\overrightarrow{u}_{1}|^{2}} |\overrightarrow{u}_{1}|$$

**3** In the class, we have learned FONC as  $\mathbf{v}^T \nabla f(\mathbf{x}^*) \geq 0$  for a local minimizer  $\mathbf{x}^*$  ( $\mathbf{v}$  is a feasible direction). If  $\mathbf{x}^*$  is located inside the domain, then FONC becomes

$$\nabla f(\mathbf{x}^*) = \mathbf{0}.$$

Prove that this is indeed true.

If 
$$x^{\mu}$$
 is located inside the domain, then every differtion is feasible,  $V^{T}Vf(x^{*}) = 0$   $V^{T}Vf(x^{*}) = 0$   $V^{T}Vf(x^{*}) = 0$   $V^{T}Vf(x^{*}) = 0$   $V^{T}Vf(x^{*}) = 0$ .

- **4** Given a function  $f: \mathbb{R}^2 \to \mathbb{R}$  which is explicitly written as  $f(x_1, x_2) = x_1^2 + 2x_1x_2 + x_2^3$ ,
  - (a) Compute the gradient  $\nabla f$ .
  - (b) Compute the Hessian  $D^2f$ .
  - (c) Expand  $f(x_1, x_2)$  by using the Taylor series about the point (1, 2) up to the second order.

a) 
$$\nabla f = \begin{bmatrix} 2x_1 + 2x_2 \\ 2x_1 + 3x_2^2 \end{bmatrix}$$

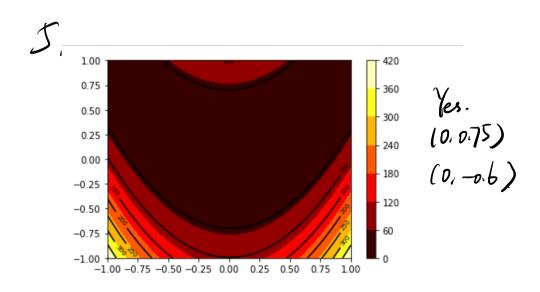
b) 
$$D^2 f = \begin{bmatrix} \frac{\partial f}{\partial x_i} & \frac{\partial f}{\partial x_i \partial x_i} \\ \frac{\partial f}{\partial x_i \partial x_i} & \frac{\partial f}{\partial x_i^2} \end{bmatrix} = \begin{bmatrix} 2 & 2 \\ 2 & 6x_2 \end{bmatrix}$$

c) 
$$f(x+v) = f(x) + \langle \nabla f(x), V \rangle + \frac{1}{2} \langle v, D^2 f(x), V \rangle$$
  
 $f(x, x_0) = 1 + 2 \times 2 + 2^3 = 1 + 4 + 8 = 13$ 

$$\mathcal{P}f(1/2) = \begin{bmatrix} 2+2x^2 \\ 2+3x^2 \end{bmatrix} = \begin{bmatrix} 6 \\ 14 \end{bmatrix}$$

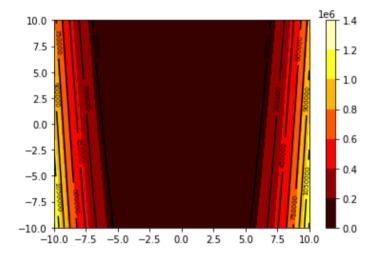
$$\mathcal{P}f(x) = \begin{bmatrix} 2 & 2 \\ 2 & 12 \end{bmatrix}$$

f(x+v)= 13+ 6v+141/2+ 2V+4V11/2+121/2



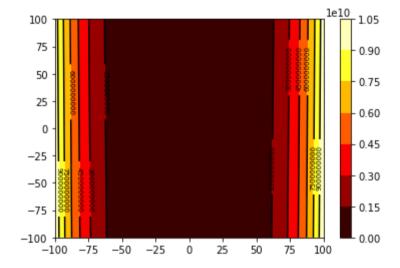
```
import matplotlib.pyplot as plt
import numpy as np
from matplotlib import cm

fig = plt.figure()
    ax = fig.add_subplot(111)
    u = np.linspace(-10, 10, 100)
    x, y = np.meshgrid(u, u)
    z = 100*(y-x**2)**2+(1-x)**2
    cset = plt.contourf(x,y,z,6, cmap = plt.cm.hot)
    contour = plt.contour(x,y,z,8, colors = 'k')
    plt.clabel(contour, fontsize = 7, colors = 'k')
    plt.show()
```



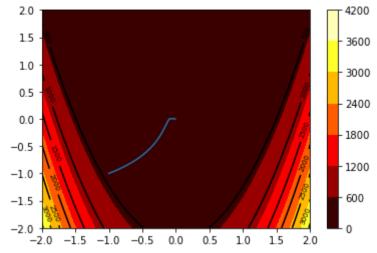
```
In [2]: ##5
    import matplotlib.pyplot as plt
    import numpy as np
    from matplotlib import cm

fig = plt.figure()
    ax = fig.add_subplot(111)
    u = np.linspace(-100, 100, 100)
    x, y = np.meshgrid(u, u)
    z = 100*(y-x**2)**2+(1-x)**2
    cset = plt.contourf(x,y,z,6, cmap = plt.cm.hot)
    contour = plt.contour(x,y,z,8, colors = 'k')
    plt.clabel(contour, fontsize = 7, colors = 'k')
    plt.colorbar(cset)
    plt.show()
```



```
In [4]: ###the direction of arrow
        import math
        import numpy as np
        start point = np.array([-1,-1])
        alpha = 0.0001
        def z value(x,y):
            z = 100*(y-x**2)**2+(1-x)**2
        def f prime(x,y):
            x \text{ prime} = -400*x*y+400*x**3+2*x-2
            y \text{ prime} = 200*(y-x**2)
            return np.array([x_prime,y_prime])
        def point_update(x,y,alpha):
            grad = f prime(x,y)
            grad x = grad[0]
            grad y = grad[1]
            x_new = x-alpha*grad_x
            y_new = y-alpha*grad_y
            return np.array([x_new,y_new])
        point update(start point[0],start point[1],alpha)
        def gradient decent(start point, alpha, precision = 1, max_iters = 10000):
            z_list = []
            ite_list = [0]
            fig = plt.figure()
            x1 list = []
            x2_list = []
            ax = fig.add subplot(111)
            u = np.linspace(-2, 2, 100)
            x, y = np.meshgrid(u, u)
            z = 100*(y-x**2)**2+(1-x)**2
            cset = plt.contourf(x,y,z,6, cmap = plt.cm.hot)
            contour = plt.contour(x,y,z,8, colors = 'k')
            plt.clabel(contour, fontsize = 7, colors = 'k')
            plt.colorbar(cset)
            previous = start point
            update = point update(previous[0],previous[1],alpha)
            x1 list.append(previous[0])
            x2 list.append(previous[1])
            ite = 1
            z list.append(z value(previous[0],previous[1]))
            ite list.append(ite)
            while np.linalg.norm(f_prime(update[0],update[1]))>precision and np.lin
                previous = update
                update = point update(previous[0],previous[1],alpha)
                ite +=1
                x1 list.append(previous[0])
                x2 list.append(previous[1])
                ite list.append(ite)
                 z_list.append(z_value(previous[0],previous[1]))
            z list.append(z value(update[0],update[1]))
            x1 list.append(update[0])
            x2 list.append(update[1])
```

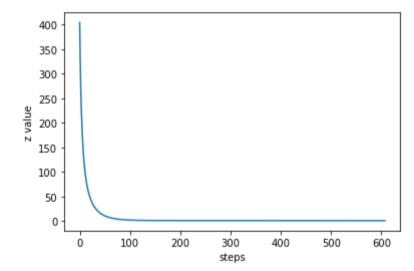
```
ax.plot(x1_list, x2_list)
  plt.show()
  return update, z_list, ite_list
z, y, x = gradient_decent(start_point, 0.0001)
print("end_point: ", z)
```



end point: [-0.00997581 0.00050599]

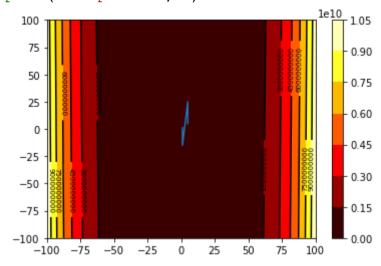
```
In [5]: fig = plt.figure()
   plt.plot(y)
   plt.xlabel("steps")
   plt.ylabel("z value")
```

## Out[5]: Text(0, 0.5, 'z value')



```
In [6]: |import math
        import numpy as np
        def z value(x,y):
            z = 100*(y-x**2)**2+(1-x)**2
            return z
        def hess inv(x,y):
            m = np.array([
                 [-400*y+1200*x**2+2, -400*x],
                                      2001
                 [-400*x,
            ])
            return np.linalg.inv(m)
        def f prime(x,y):
            x \text{ prime} = -400*x*y+400*x**3+2*x-2
            y \text{ prime} = 200*(y-x**2)
            return np.array([x prime,y prime]).reshape(2,1)
        def point update newton(x,y):
            grad = f prime(x,y)
            point = np.array([x,y]).reshape(2,1)
            new = point-np.matmul(hess inv(x,y),grad)
            return new
        def Newtons method(start point, precision = 1, max iters = 100):
            z list = []
            ite list = []
            fig = plt.figure()
            ax = fig.add subplot(111)
            u = np.linspace(-100, 100, 100)
            x, y = np.meshgrid(u, u)
            z = 100*(y-x**2)**2+(1-x)**2
            x1_list = []
            x2_list = []
            cset = plt.contourf(x,y,z,6, cmap = plt.cm.hot)
            contour = plt.contour(x,y,z,8, colors = 'k')
            plt.clabel(contour, fontsize = 7, colors = 'k')
            plt.colorbar(cset)
            previous = start point
            update = point update newton(previous[0][0],previous[1][0])
            x1_list.append(previous[0][0])
            x2 list.append(previous[1][0])
            ite = 0
            ite list.append(ite)
            z list.append(z value(previous[0][0],previous[1][0]))
            while np.linalg.norm(f prime(update[0][0],update[1][0]))>precision and
                previous = update
                update = point update newton(previous[0][0],previous[1][0])
                ite +=1
                ite_list.append(ite)
                z list.append(z value(previous[0][0],previous[1][0]))
                x1 list.append(previous[0][0])
                x2_list.append(previous[1][0])
```

```
z_list.append(z_value(update[0][0], update[1][0]))
x1_list.append(update[0][0])
x2_list.append(update[1][0])
ax.plot(x1_list, x2_list)
plt.show()
return update, z_list, ite_list
z, y, x = Newtons_method(np.array([5,5]).reshape(2,1))
print("end_point: ", z)
```

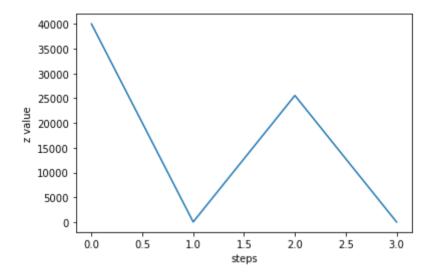


```
end point: [[1.00079899]
  [1.00159862]]
```

```
In [7]: fig = plt.figure()
    plt.plot(y)
    print(y)
    plt.xlabel("steps")
    plt.ylabel("z value")
```

[40016, 15.992002999100214, 25553.976901245092, 6.383860142168448e-07]

## Out[7]: Text(0, 0.5, 'z value')



In [ ]: