

# ESE 417 Homework 1

Problem 1, Problem 3, Problem 5(c) are completed using python.

Problem 2, Problem 4, Problem 5(a)(b) are written by hand.

## Problem 1

(Use Python numpy package to finish this)

Consider the following two real vectors:  $\mathbf{x} = [-2.4, 1.5, 0.0, 3.2]^T$  and  $\mathbf{y} = [1.3, 4.2, 3.0, -2.5]^T$

a) Find the 1-norm, 2-norm, 3-norm and infinity-norm of  $\mathbf{x}$ , then sort them in a descending order.

b) Find the distance between  $\mathbf{x}$  and  $\mathbf{y}$ ,  $d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|$ , using 1-norm, 2-norm, and infinity-norm, then sort them in an ascending order.

In [21]:

```
# a)

import numpy as np

# Define the two vectors
x = np.array([-2.4, 1.5, 0.0, 3.2])
y = np.array([1.3, 4.2, 3.0, -2.5])

print("x = ", x)
print("y = ", y)

# Calculate norms of x
norm_1_x = np.linalg.norm(x, ord=1)
norm_2_x = np.linalg.norm(x, ord=2)
norm_3_x = np.linalg.norm(x, ord=3)
norm_inf_x = np.linalg.norm(x, ord=np.inf)

print("Norms of x:")
print("L1 norm: ", norm_1_x)
print("L2 norm: ", norm_2_x)
print("L3 norm: ", norm_3_x)
print("L_inf norm: ", norm_inf_x)

# Sort norms of x in descending order
norms_x = np.array([norm_1_x, norm_2_x, norm_3_x, norm_inf_x])
norms_x_sorted = np.sort(norms_x)[::-1]
print("Sorted norms of x: ", norms_x_sorted)
```

```
x = [-2.4  1.5   0.    3.2]
y = [ 1.3   4.2   3.   -2.5]
Norms of x:
L1 norm:  7.1
L2 norm:  4.272001872658765
L3 norm:  3.683220833338153
L_inf norm:  3.2
Sorted norms of x:  [7.1          4.27200187  3.68322083  3.2         ]
```

In [22]:

```
# Cauculate the distance between x and y in L1, L2 and L_inf norms
dist_1 = np.linalg.norm(x - y, ord=1)
dist_2 = np.linalg.norm(x - y, ord=2)
dist_inf = np.linalg.norm(x - y, ord=np.inf)

print("Distance between x and y:")
print("L1 distance: ", dist_1)
print("L2 distance: ", dist_2)
print("L_inf distance: ", dist_inf)
```

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# Sort distances in ascending order
dists = np.array([dist_1, dist_2, dist_inf])
dists_sorted = np.sort(dists)
print("Sorted distances: ", dists_sorted)

Distance between x and y:
L1 distance: 15.100000000000001
L2 distance: 7.903796556086196
L_inf distance: 5.7
Sorted distances: [ 5.7           7.90379656 15.1           ]

```

### Problem 3

(use Numpy package in this problem)

Consider the following matrix:

$$B = \begin{bmatrix} 2 & 2 & 4 \\ 1 & 4 & 7 \\ 2 & 5 & 4 \end{bmatrix}$$

Find the eigenvalues and corresponding eigenvectors of matrix  $B$  and then find the eigendecomposition of matrix  $B$ . Verify that  $B=Q\Lambda Q^{-1}$

```

In [23]: import numpy as np

# Define the matrix B
B = np.array([[2, 2, 4],
              [1, 4, 7],
              [2, 5, 4]])

print("Matrix B:")
print(B)

# Calculate eigenvalues and eigenvectors of B
eigenvalues, eigenvectors = np.linalg.eig(B)

print("Eigenvalues of B:")
print(eigenvalues)
print("Eigenvectors of B:")
print(eigenvectors)

```

```

Matrix B:
[[2 2 4]
 [1 4 7]
 [2 5 4]]
Eigenvalues of B:
[10.93777843 1.25234419 -2.19012261]
Eigenvectors of B:
[[-0.42228933 -0.92515036 -0.29500861]
 [-0.67326244 0.37923364 -0.69446846]
 [-0.6069509 -0.01669331 0.65626479]]

```

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In [24]: # Find the eigendecomposition of B
Q = eigenvectors
Lambda = np.diag(eigenvalues)
Q_inv = np.linalg.inv(Q)

print("Eigendecomposition of B:")
print("Q:")
print(Q)
print("Lambda:")
print(Lambda)
print("Q_inv:")
print(Q_inv)

```

```

Eigendecomposition of B:
Q:
[[ -0.42228933 -0.92515036 -0.29500861]
 [ -0.67326244  0.37923364 -0.69446846]
 [ -0.6069509  -0.01669331  0.65626479]]
Lambda:
[[ 10.93777843  0.          0.          ]
 [  0.          1.25234419  0.          ]
 [  0.          0.          -2.19012261]]
Q_inv:
[[ -0.24458613 -0.63090205 -0.77757728]
 [ -0.88991249  0.47022663  0.09756081]
 [ -0.24884369 -0.57153292  0.80710925]]

```

```

In [25]: # Verify the equation B = Q * Lambda * Q_inv
B_reconstructed = Q @ Lambda @ Q_inv

print("Reconstructed matrix B:")
print(B_reconstructed)

# Find B and B_reconstructed are equal
print("Are B and B_reconstructed equal? " + str(np.allclose(B, B_reconstructed)))

```

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Reconstructed matrix B:
[[ 2.  2.  4.]
 [ 1.  4.  7.]
 [ 2.  5.  4.]]
Are B and B_reconstructed equal? True

```

## Problem 5

Consider the following objective function:  $f(x, y) = x^2 + 2y^2 - 2xy$

- Compute the Hessian matrix H of function f, and find the definiteness of matrix H.
- Use calculus method to find the minimum value of  $f(x,y)$
- Use Python to implement the gradient descent search method to find the global minimum value of function f, suppose the initial values of  $[x, y]$  are  $[1,1]$ . Show the convergence curve of  $x$  and  $y$  with learning rate: 0.1, 0.01, and 0.001. (Don't use sk-learn package)

```

In [26]: import numpy as np
import matplotlib.pyplot as plt

# Function f(x, y)
def f(x, y):
    return x**2 + 2*y**2 - 2*x*y
# Gradient of f(x, y)
def grad_f(x, y):
    df_dx = 2*x - 2*y
    df_dy = 4*y - 2*x
    return np.array([df_dx, df_dy])

# Gradient descent implementation returning x and y values
def gradient_descent(initial_values, learning_rate, num_iterations):
    # Initialize lists to store x and y values
    x_vals = [initial_values[0]]
    y_vals = [initial_values[1]]
    for _ in range(num_iterations):
        # Calculate gradient at current point
        grad = grad_f(x_vals[-1], y_vals[-1])
        # Update x and y values
        new_x = x_vals[-1] - learning_rate * grad[0]
        new_y = y_vals[-1] - learning_rate * grad[1]
        # Append new x and y values to the lists
        x_vals.append(new_x)
        y_vals.append(new_y)
    return np.array(x_vals), np.array(y_vals)

```

```

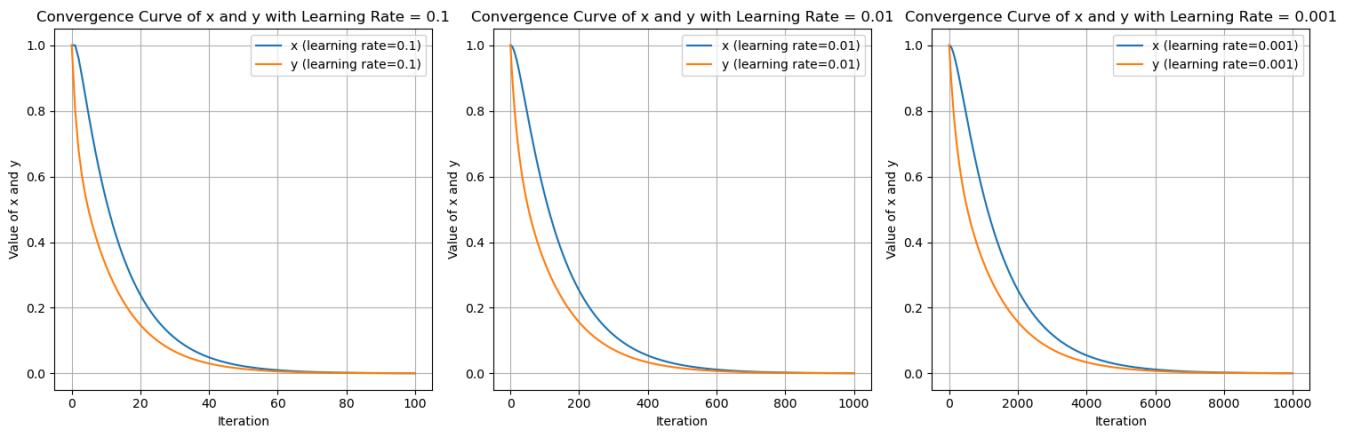
# Initial values for (x, y)
initial_values = [1, 1]

# Learning rates and number of iterations
learning_rates = [0.1, 0.01, 0.001]
num_iterations_list = [100, 1000, 10000]

# Plot convergence for different learning rates
fig, axes = plt.subplots(1, 3, figsize=(15, 5))
for i, (lr, num_iterations) in enumerate(zip(learning_rates, num_iterations_list)):
    # Run gradient descent and store x and y values
    x_vals, y_vals = gradient_descent(initial_values, lr, num_iterations)
    axes[i].plot(x_vals, label=f'x (learning rate={lr})')
    axes[i].plot(y_vals, label=f'y (learning rate={lr})')
    axes[i].set_title(f'Convergence Curve of x and y with Learning Rate = {lr}')
    axes[i].set_xlabel('Iteration')
    axes[i].set_ylabel('Value of x and y')
    axes[i].legend(loc='upper right')
    axes[i].grid(True)

plt.tight_layout()
plt.show()

```



In [ ]:

## Problem 2

$$(a) \quad A - \lambda I = \begin{pmatrix} 5-\lambda & 4 \\ 4 & 5-\lambda \end{pmatrix}$$

$$|A - \lambda I| = (5-\lambda)^2 - 16 = 0$$

$$\Rightarrow 5-\lambda = \pm 4$$

$$\Rightarrow \lambda_1 = 1, \lambda_2 = 9$$

$$A\vec{x} = \lambda \vec{x} \Rightarrow (A - \lambda I)\vec{x} = 0$$

$$\text{For } \lambda_1 = 1, (A - \lambda_1 I)\vec{x}_1 = (A - I)\vec{x}_1 = 0$$

$$\begin{pmatrix} 4 & 4 \\ 4 & 4 \end{pmatrix} \begin{pmatrix} x_1' \\ x_1'' \end{pmatrix} = 0$$

$$4x_1' + 4x_1'' = 0 \Rightarrow x_1' = -x_1''$$

$$\Rightarrow \vec{x}_1 = \begin{pmatrix} 1 \\ -1 \end{pmatrix}$$

$$\text{For } \lambda_2 = 9 (A - 9I)\vec{x}_2 = 0$$

$$\begin{pmatrix} -4 & 4 \\ 4 & -4 \end{pmatrix} \begin{pmatrix} x_2' \\ x_2'' \end{pmatrix} = 0$$

$$-4x_2' + 4x_2'' = 0 \Rightarrow x_2' = x_2''$$

$$\vec{x}_2 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

b)  $A = Q \Lambda Q^T$ , where  $Q$  is formed by the normalized eigenvectors

$$Q = \begin{pmatrix} \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} \\ -\frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} \end{pmatrix} \quad Q^T = \begin{pmatrix} \frac{\sqrt{2}}{2} & -\frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} \end{pmatrix} \quad \Lambda = \begin{pmatrix} 1 & 0 \\ 0 & 9 \end{pmatrix}$$

$$\begin{aligned} Q \Lambda Q^T &= \begin{pmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 9 \end{pmatrix} \begin{pmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix} \\ &= \begin{pmatrix} \frac{1}{\sqrt{2}} & \frac{9}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} & \frac{9}{\sqrt{2}} \end{pmatrix} \begin{pmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix} = \begin{pmatrix} 5 & 4 \\ 4 & 5 \end{pmatrix} = A \end{aligned}$$

c) Since  $\lambda_1 = 1 > 0$ ,  $\lambda_2 = 9 > 0$  and  $A$  is a symmetric matrix,

$\Rightarrow$  the matrix  $A$  is positive definite

### Problem 4

$$f(\vec{x}) = \vec{a}^T \vec{x} + b, \quad \vec{a}, \vec{x} \in \mathbb{R}^n, \quad b \in \mathbb{R}$$

$$f(t\vec{x}_1 + (1-t)\vec{x}_2) = \vec{a}^T [t\vec{x}_1 + (1-t)\vec{x}_2] + b = t\vec{a}^T \vec{x}_1 + (1-t)\vec{a}^T \vec{x}_2 + b, \quad \vec{x}_1, \vec{x}_2 \in \mathbb{R}$$

$$\begin{aligned} t f(\vec{x}_1) + (1-t) f(\vec{x}_2) &= t(\vec{a}^T \vec{x}_1 + b) + (1-t)(\vec{a}^T \vec{x}_2 + b) = t\vec{a}^T \vec{x}_1 + tb + (1-t)\vec{a}^T \vec{x}_2 + (1-t)b \\ &= t\vec{a}^T \vec{x}_1 + (1-t)\vec{a}^T \vec{x}_2 + b \end{aligned}$$

$$\implies f(t\vec{x}_1 + (1-t)\vec{x}_2) = t f(\vec{x}_1) + (1-t) f(\vec{x}_2)$$

Thus,  $f(\vec{x}) = \vec{a}^T \vec{x} + b$  is convex

### Problem 5

$$(a) \quad f(x, y) = x^2 + 2y^2 - 2xy$$

$$Hf = \begin{pmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial y \partial x} & \frac{\partial^2 f}{\partial y^2} \end{pmatrix} = \begin{pmatrix} 2 & -2 \\ -2 & 4 \end{pmatrix}$$

$$Hf - \lambda I = \begin{pmatrix} 2-\lambda & -2 \\ -2 & 4-\lambda \end{pmatrix}$$

$$|Hf - \lambda I| = (2-\lambda)(4-\lambda) - 4 = 8 - 2\lambda - 4\lambda + \lambda^2 - 4 = \lambda^2 - 6\lambda + 4 = 0$$

$$\lambda_1 = \frac{6 + \sqrt{36 - 4 \cdot 4}}{2} = 3 + \sqrt{5} \quad \lambda_2 = 3 - \sqrt{5}$$

Since  $\lambda_1 = 3 + \sqrt{5} > 0$ ,  $\lambda_2 = 3 - \sqrt{5} > 0$ ,  $Hf$  is positive definite

$$(b) \quad \begin{cases} \frac{\partial f}{\partial x} = 2x - 2y = 0 \\ \frac{\partial f}{\partial y} = 4y - 2x = 0 \end{cases} \Rightarrow \begin{cases} x = y \\ x = 2y \end{cases} \Rightarrow \begin{cases} x = 0 \\ y = 0 \end{cases}$$

$$f(0, 0) = 0$$

Since  $Hf$  is positive definite.  $f$  is strictly convex. Then,  $(0, 0)$  is the global minimum of  $f$ .