

## Problem 1

No, three vectors  $u$ ,  $v$ , and  $w$  cannot have  $u \cdot v < 0$ ,  $u \cdot w < 0$ ,  $v \cdot w < 0$  in an  $xy$  plane. A negative dot product between two vectors means that the angle between them are greater than  $90^\circ$ . The three statements above cannot be true in an  $xy$  plane because the angle between any two vectors should be between  $0^\circ$  and  $180^\circ$ . Said differently, if  $u \cdot v < 0$ , then  $u$  and  $v$  point in nearly opposite directions (the angle is greater than  $90^\circ$ ). Similarly, if  $u \cdot w < 0$ , the angle between  $u$  and  $w$  will be greater than  $90^\circ$ . Coupling both of these statements is not possible in an  $xy$  plane since the angle between two vectors has to be between  $0^\circ$  and  $180^\circ$ .

We can prove this mathematically using dot products and trigonometry. Let  $\theta_{UV}$ ,  $\theta_{UW}$ , and  $\theta_{VW}$  be the angles between  $u$  and  $v$ ,  $u$  and  $w$ , and  $v$  and  $w$  respectively. Given that  $u \cdot v < 0$  and  $u \cdot w < 0$ ,

$$\begin{aligned}u \cdot v &= |u||v|\cos(\theta_{UV}) \\ u \cdot w &= |u||w|\cos(\theta_{UW})\end{aligned}$$

Since both  $u \cdot v$  and  $u \cdot w$  are negative, we have:

$$\begin{aligned}\cos(\theta_{UV}) &< 0 \\ \cos(\theta_{UW}) &< 0\end{aligned}$$

Similarly, for  $\theta_{VW}$ :

$$v \cdot w = |v||w|\cos(\theta_{VW})$$

If  $\cos(\theta_{UV}) < 0$  and  $\cos(\theta_{UW}) < 0$ , then the product of these two negative numbers should be positive. I.e.

$$\cos(\theta_{UV}) \times \cos(\theta_{UW}) > 0$$

The above statement contradicts with the last statement ( $v \cdot w < 0$ ) which implies that  $\cos(\theta_{VW}) < 0$ . Therefore, we cannot have  $u \cdot v < 0$ ,  $u \cdot w < 0$ ,  $v \cdot w < 0$  simultaneously for the three vectors in an  $xy$  plane.

## Problem 2

To find  $z_1$ ,  $z_2$ , and  $z_3$  in terms of  $b_1$ ,  $b_2$ , and  $b_3$ , we can solve  $\Delta z = b$  for  $z$  by using the inverse matrix ( $\Delta^{-1}$ ).

Since  $\Delta$  is an upper triangular matrix, we can find its inverse ( $\Delta^{-1}$ ) by taking the inverse of its diagonal elements. Given that the diagonal elements are all -1,

$$\Delta^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

Multiplying both sides of  $\Delta z = b$  by  $\Delta^{-1}$ , we get:

$$\Delta^{-1}\Delta z = \Delta^{-1}b$$

This allows us to find  $z_1$ ,  $z_2$ , and  $z_3$  in terms of  $b_1$ ,  $b_2$ , and  $b_3$ .

Since  $\Delta^{-1}\Delta$  is the identity matrix, we get:

$$z = \Delta^{-1}b$$

We can compute  $z_1$ ,  $z_2$ , and  $z_3$  in terms of  $b_1$ ,  $b_2$ , and  $b_3$  in Python (see the attached code below). Using random numbers to define  $b_1$ ,  $b_2$ , and  $b_3$  as 0.624, 1.557, and 9.667 respectively, we get  $z_1$ ,  $z_2$ , and  $z_3$  as 0.624, 2.181, and 11.849 respectively which verifies the forward difference matrix and its inverse.

### Problem 3

Since we don't know the population standard deviation, we can compute the sample standard error using `np.var()` in Python (see the attached code below).<sup>1</sup> We re-ran the same three cases in HW01 Problem 1 and report the estimates of  $\text{Var}[X]$  and standard error for each case below.

1.  $M = 1,000$ ; Mean = 15.071;  $\text{Var}[X] = 38.791$ ; Standard Error = 0.197
2.  $M = 10,000$ ; Mean = 14.625;  $\text{Var}[X] = 37.976$ ; Standard Error = 0.0616
3.  $M = 100,000$ ; Mean = 14.664;  $\text{Var}[X] = 38.341$ ; Standard Error = 0.0196

### Problem 4

Given that  $v + w = \begin{bmatrix} 5 \\ 1 \end{bmatrix}$  and  $v - w = \begin{bmatrix} 1 \\ 5 \end{bmatrix}$ , we can compute and draw  $v$  and  $w$  as follows:

$$v + w = \begin{bmatrix} 5 \\ 1 \end{bmatrix} \tag{1}$$

$$v - w = \begin{bmatrix} 1 \\ 5 \end{bmatrix} \tag{2}$$

Solving simultaneously:

$$v + w + v - w = \begin{bmatrix} 5 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 5 \end{bmatrix}$$

Simplifying:

$$2v = \begin{bmatrix} 5 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 5 \end{bmatrix}$$

$$2v = \begin{bmatrix} (5+1) \\ (1+5) \end{bmatrix}$$

$$2v = \begin{bmatrix} 6 \\ 6 \end{bmatrix}$$

$$v = \begin{bmatrix} 6 \\ 6 \end{bmatrix} \div 2$$

$$v = \begin{bmatrix} 36 \\ 6 \end{bmatrix} \div 2$$

$$v = \begin{bmatrix} 18 \\ 12 \end{bmatrix}$$

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<sup>1</sup>I included "ddof=1" parameter to get the unbiased estimate; omitting it yields quantitatively similar results.

Finding  $w$ :

$$v + w - (v - w) = \begin{bmatrix} 5 \\ 1 \end{bmatrix} - \begin{bmatrix} 1 \\ 5 \end{bmatrix}$$

Simplifying:

$$\begin{aligned} v + w - v + w &= \begin{bmatrix} 5 \\ 1 \end{bmatrix} - \begin{bmatrix} 1 \\ 5 \end{bmatrix} \\ 2w &= \begin{bmatrix} 5 \\ 1 \end{bmatrix} - \begin{bmatrix} 1 \\ 5 \end{bmatrix} \\ 2w &= \begin{bmatrix} (5-1) \\ (1-5) \end{bmatrix} \\ 2w &= \begin{bmatrix} 4 \\ -4 \end{bmatrix} \\ w &= \begin{bmatrix} 4 \\ -4 \end{bmatrix} \div 2 \\ w &= \begin{bmatrix} 16 \\ -4 \end{bmatrix} \div 2 \\ w &= \begin{bmatrix} 8 \\ -4 \end{bmatrix} \end{aligned}$$

Finding the angle between  $v$  and  $w$ ,

$$\cos(\theta) = (v \cdot w) \div (||v|| \times ||w||)$$

where,  $\cos(\theta)$  denotes the cosine of the angle,  $v \cdot w$  is the dot product of  $v$  and  $w$ ,  $||v||$  is the magnitude of  $v$ , and  $||w||$  is the magnitude of  $w$ .

$$\begin{aligned} v \cdot w &= \begin{bmatrix} 18 \\ 12 \end{bmatrix} \cdot \begin{bmatrix} 8 \\ -4 \end{bmatrix} \\ &= (18 \times 8) + (12 \times -4) \\ &= 144 - 48 \\ &= 96 \end{aligned}$$

$$||v|| = \sqrt{(18^2 + 12^2)} = \sqrt{324 + 144} = \sqrt{468} = 2\sqrt{117}$$

$$||w|| = \sqrt{(8^2 + -4^2)} = \sqrt{64 + 16} = \sqrt{80} = 4\sqrt{5}$$

$$\begin{aligned} \cos(\theta) &= \frac{v \cdot w}{||v|| \times ||w||} \\ &= \frac{96}{2\sqrt{117} \times 4\sqrt{5}} \\ &= \frac{96 \times 5}{2\sqrt{117} \times 4\sqrt{5} \times 5} \\ &= \frac{480}{10\sqrt{117} \times 4\sqrt{5}} \\ &= \frac{480}{40\sqrt{117}} \\ &= \frac{12}{\sqrt{117}} \end{aligned}$$

$$\theta = \arccos\left(\frac{12}{\sqrt{117}}\right) \approx 1.237 \text{ radians}$$

The angle between  $v$  and  $w$  is approximately 1.237 radians. We can fill the entire  $xy$  plane using linear combinations of  $v$  and  $w$  because  $v$  and  $w$  are linearly independent since they have different directions (meaning that they are not scalar multiples of each other). Given that  $v = [18, 12]$  and  $w = [8, -4]$ , we can draw vectors  $v$  and  $w$  and represent them as arrows on the  $xy$  plane (see Figure 1).

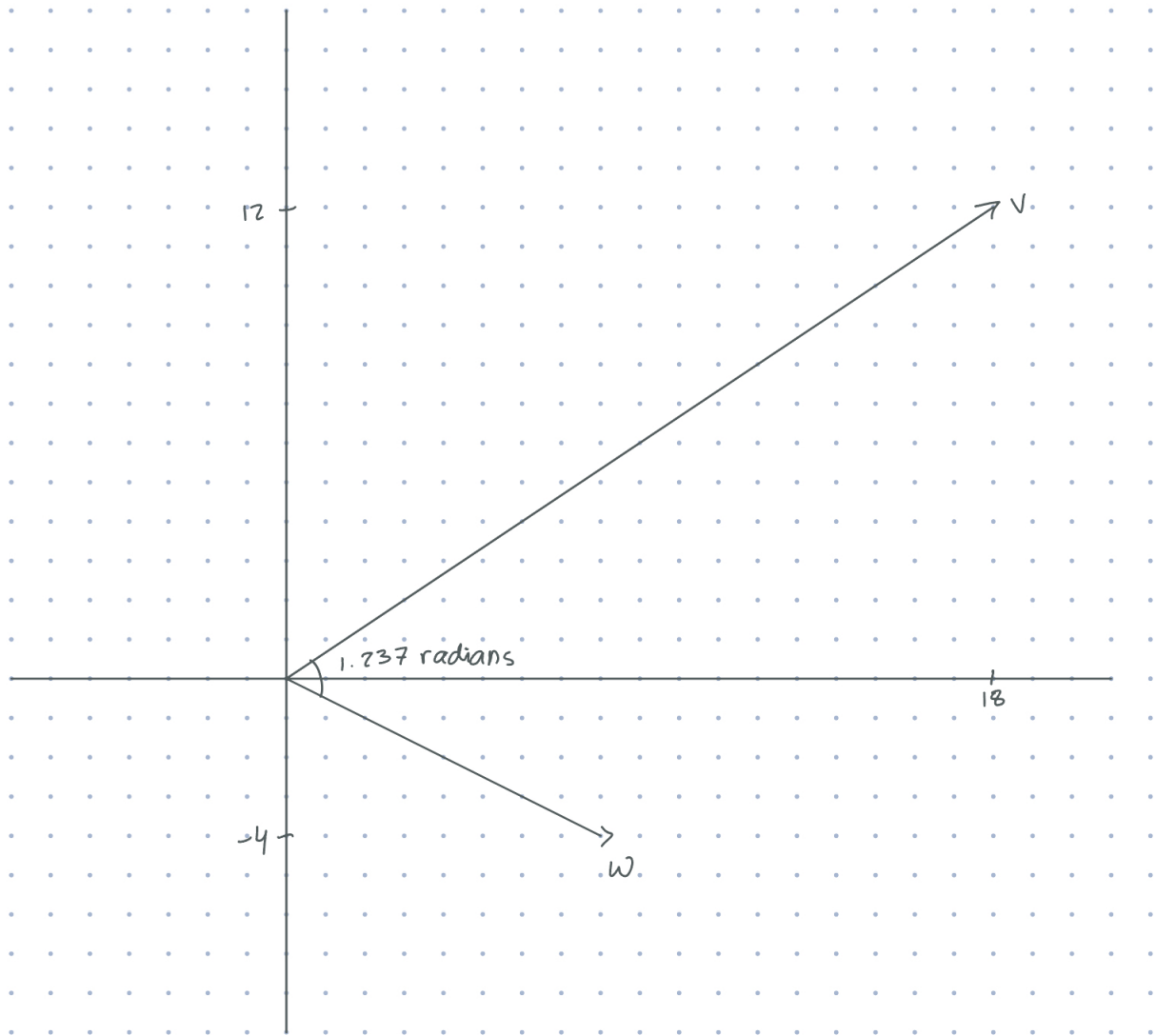


Figure 1: Vector  $V$  and  $W$

# Homework M2HW02

```
In [1]: ▶ # Problem 2

import numpy as np
import random

# Define the inverse upper triangular matrix
delta_inv = np.array([[1,0,0],[1,1,0],[1,1,1]])

# Define b1, b2, b3
#random.seed(42) #to check work; not part of the actual assignment.
b1 = random.uniform(0,10)
b2 = random.uniform(0,10)
b3 = random.uniform(0,10)

# Define b
b = np.array([b1,b2,b3])

# Solve for z
z = np.dot(delta_inv, b)

# Extract z1, z2, z3
z1, z2, z3 = z

# Print b1, b2, b3, z1, z2, z3
print(f"b1 = {b1}, b2 = {b2}, b3 = {b3}")
print(f"z1 = {z1}, z2 = {z2}, z3 = {z3}")
'''
b1 = 0.624363496349557, b2 = 1.5570660360057254, b3 = 9.667125194198464
z1 = 0.624363496349557, z2 = 2.181429532355282, z3 = 11.84855472655374
'''

b1 = 0.624363496349557, b2 = 1.5570660360057254, b3 = 9.667125194198464
z1 = 0.624363496349557, z2 = 2.181429532355282, z3 = 11.848554726553747
```

```
In [2]: ▶ import random
from numpy import array, mean, var, sqrt
```

```

In [3]: ▶ def M2HW02P3(M=100, N=6):
        """
        M: number of trials
        N: number of faces in a die, which should be set to 6 for this problem
        """

        """
        Fill in your Monte Carlo simulation code here.
        """

        # Initialize arrays to store trial results
        X_trials = np.zeros(M)

        # Monte Carlo Simulation for M trials
        #random.seed(42) #to check work; not part of the actual assignment.
        for i in range(M):
            die_numbers = set()
            rolls = 0
            while len(die_numbers) < N:
                roll = random.randint(1, N)
                die_numbers.add(roll)
                rolls += 1
            X_trials[i] = rolls

        # Sample mean
        m = np.mean(X_trials)

        # Sample variance (Var[X]) for X (r.v.)
        v = np.var(X_trials, ddof=1) #specify ddof=1 for unbiased estimate; no

        # Standard error
        s = np.sqrt(v/M)

        """
        You need to calculate and return the following three variables: m, v,
        m: sample mean, i.e., Monte Carlo estimate C.
        v: variance of the random variable X you are simulating.
        s: standard error, i.e., the standard deviation of C.
        """

        #m = 0.
        #v = 0.
        #s = 0.

        return m, v, s

```

```
In [4]: ▶ %time M2HW02P3(10000)

# Call M2HW02P3 for the three cases
num_trials = [1000, 10000, 100000]

for M in num_trials:
    mvs = M2HW02P3(M)
    print(f"M = {M}; mean, Var[X], standard error = {mvs}")
```

CPU times: total: 31.2 ms

Wall time: 74.8 ms

M = 1000; mean, Var[X], standard error = (15.071, 38.79074974974975, 0.19695367412097126)

M = 10000; mean, Var[X], standard error = (14.6245, 37.975897339733976, 0.061624587089678724)

M = 100000; mean, Var[X], standard error = (14.66415, 38.340778185281856, 0.019580801358800883)