

**Assignment 1 Task 2: Probability****Student ID = 31237223****Name = Yee Darren Jer Shien****Question 4.1 Fruits Experiment Python Implementation**

```
In [8]: import numpy as np

def construct_boxes (boxes,card):
    temp = []
    for i in range (len(card)):
        temp.append (['apple']*card[i][0] + ['orange']*card[i][1])
    return temp

def fruits_experiment (num):
    boxes = ['red','blue','green']
    card = [[3,8],[4,4],[9,1]]
    contents = construct_boxes(boxes,card)
    rng = np.random.default_rng()
    boxes_picked = []
    fruits_picked = []
    for i in range (num):
        box_picked = rng.integers(len(boxes))
        fruit_picked = rng.integers(len(contents[box_picked]))
        boxes_picked.append(boxes[box_picked])
        fruits_picked.append(contents[box_picked][fruit_picked])
    return np.array(boxes_picked), np.array(fruits_picked)
```

```
In [9]: print (fruits_experiment(5))

(array(['blue', 'blue', 'red', 'blue', 'green'], dtype='<U5'), array(['apple', 'orange', 'orange', 'apple', 'apple'], dtype='<U6'))
```

**Question 4.2 Probability Calculation**

To calculate the probability of picking from Yellow Box given the fruit picked was an apple, we first denote:

**Y = Picking Yellow Box, A = Picking an Apple**

where  $P(Y|A) = \frac{P(A|Y) \cdot P(Y)}{P(A)}$  according to Bayes Rule

Firstly, we derive  $P(A|Y) = \frac{9}{10}$  according to the given data and  $P(Y) = \frac{1}{3}$  derived from question due to uniform nature

Then, we can derive  $P(A) = P(A|Y) \cdot P(Y) + P(A|\text{not } Y) \cdot P(\text{not } Y)$

$$P(A|\text{not } Y) = \frac{7}{16}$$

$$P(\text{not } Y) = \frac{2}{3}$$

$$\text{So } P(A) = \frac{9}{10} \cdot \frac{1}{3} + \frac{7}{16} \cdot \frac{2}{3} = \frac{71}{124}$$

$$P(A|B) = \frac{\frac{9}{10} \cdot \frac{1}{3}}{\frac{71}{124}}$$

Final Probability of  $P(A|B) = 0.524$

### Question 5.1 Die Experiment Python Implementation

```
In [10]: def die_experiment (reps):
    final_results = []
    for _ in range (reps):
        Z = 0
        rng = np.random.default_rng()
        X1 = rng.integers(1,7)
        X2 = rng.integers(1,7)
        Y = X1 + X2
        for _ in range (Y):
            Z += rng.integers(1,7)
        final_results.append(Z)
    return final_results
```

```
In [11]: reps = 10000
experiment = die_experiment(10000)
```

### Question 5.2 Die Experiment Expected Value Confidence Interval Calculation

```
In [12]: expected = np.mean(experiment) - ((1.96*np.std(experiment))/np.sqrt(reps))
print (expected)
```

24.403483555601007

### Question 5.3 Derivation

For a discrete  $X$ , formula is as given below according to lecture slides

$$E[Z|X_1 = x_1, X_2 = x_2] = \sum_z z \cdot P(Z = z|X_1 = x_1, X_2 = x_2)$$

According to law of marginal probability, we can get  $E[Z]$  from using the formular below by incorporating the conditional expectation above:

$$E[Z] = \sum_{x_1, x_2} E[Z|X_1 = x_1, X_2 = x_2] \cdot P(X_1 = x_1, X_2 = x_2)$$

Which is equivalent to,

$$E[Z] = \sum_{x_1, x_2} \left( \sum_z z \cdot P(Z = z|X_1 = x_1, X_2 = x_2) \right) \cdot P(X_1 = x_1, X_2 = x_2)$$

Thus allowing us to calculate the expected value of  $Z$

$$E[Z|X_1 = x_1, X_2 = x_2] = (x_1 + x_2) \cdot 3.5 \text{ (Average value across all die rolls)}$$

Then,  $P(X_1 = x_1, X_2 = x_2) = \frac{1}{6} \cdot \frac{1}{6}$

$$\text{Which means } E[Z] = \sum_{x_1, x_2} (x_1 + x_2) \cdot 3.5 \cdot \frac{1}{6} \cdot \frac{1}{6}$$

```
In [13]: expected_value = 0
for i in range(1, 7):
    for j in range(1, 7):
        expected_value+= (i + j) * 3.5 * (1/6) * (1/6)
print (expected_value)
```

24.499999999999996