

# Exercise 2

## Probability Theory 2020 Autumn

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October 10, 2020

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## 1 Problem 1

Define the number of each dice as  $X_1, X_2, X_3$  and event  $A$  as  $X_1 > X_2 > X_3$  and  $B$  as  $X_1, X_2, X_3$ . Obviously there are  $6^3 = 216$  possible combinations of  $(X_1, X_2, X_3)$  with equal probability. So we just need to find the size of  $A = \{(X_1, X_2, X_3) | X_1 > X_2 > X_3, X_1, X_2, X_3 \in \{1, 2, \dots, 6\}\}$

Fix  $X_1 = i, X_2 = j < i$ , there are  $j - 1$  possible choices of  $X_3$ . So the size of  $A$  is

$$\sum_{i=1}^6 \left( \sum_{j=1}^{i-1} (j-1) \right) = \sum_{i=1}^6 \left( \frac{(i-1)(i-2)}{2} \right) = 20 \quad (1)$$

Symmetrically,  $|A| = |B| = 20$ . So  $P(X_1 > X_2 > X_3) = P(X_1 < X_2 < X_3) = \frac{20}{216} = \frac{5}{54}$

## 2 Problem 2

### 2.1 (i)

Using the Lagrange Multiplier method,

$$L = H(X) + \lambda_1 \left( \sum_{k=1}^n p_k - 1 \right) + \lambda_2 \left( \sum_{k=1}^n p_k x_k - \mu \right) \quad (2)$$

To maximize  $L$ ,

$$\begin{cases} \frac{\partial L}{\partial p_k} = 0 & (k = 1, 2, \dots, n) \\ \frac{\partial L}{\partial \lambda_1} = 0 \\ \frac{\partial L}{\partial \lambda_2} = 0 \end{cases} \quad (3)$$

And

$$\frac{\partial L}{\partial p_k} = -1 - \log(p_k) + \lambda_1 + \lambda_2 x_k = 0 \iff p_k = e^{\lambda_2 x_k + \lambda_1 - 1} = C r^{x_k} \quad (4)$$

where  $C = e^{\lambda_1 - 1}, r = e^{\lambda_2}$  which are constants determined by  $\sum_{k=1}^n p_k = 1$  and  $\sum_{k=1}^n x_k p_k = \mu$ .

### 2.2 (ii)

For a countable support set, let  $n \rightarrow \infty$ ,

$$L = H(X) + \lambda_1 \left( \sum_{k=1}^{\infty} p_k - 1 \right) + \lambda_2 \left( \sum_{k=1}^{\infty} p_k x_k - \mu \right) \quad (5)$$

To maximize  $L$ ,

$$\begin{cases} \frac{\partial L}{\partial p_k} = 0 & (k = 1, 2, \dots, \infty) \\ \frac{\partial L}{\partial \lambda_1} = 0 \\ \frac{\partial L}{\partial \lambda_2} = 0 \end{cases} \quad (6)$$

And

$$\frac{\partial L}{\partial p_k} = -1 - \log(p_k) + \lambda_1 + \lambda_2 x_k = 0 \iff p_k = e^{\lambda_2 x_k + \lambda_1 - 1} = Cr^{x_k} \quad (7)$$

where  $C = e^{\lambda_1 - 1}$ ,  $r = e^{\lambda_2}$  which are constants determined by  $\sum_{k=1}^{\infty} p_k = 1$  and  $\sum_{k=1}^{\infty} x_k p_k = \mu$ .

For the case of  $x_k = k$ ,

$$\begin{cases} \sum_{i=1}^{\infty} p_k = \sum_{i=1}^{\infty} Cr^k = \frac{Cr}{1-r} = 1 \\ \sum_{k=1}^{\infty} x_k p_k = \sum_{i=1}^{\infty} Ckr^k = \frac{Cr}{(1-r)^2} = \mu \end{cases} \quad (8)$$

So  $C = \mu - 1$ ,  $r = \frac{\mu-1}{\mu}$  and  $P(X = k) = Cr^k$  is a geometric distribution.

### 3 Problem 3 (Conditionally convergent series)

#### 3.1 (i)

According to Leibniz's test,  $S_n = \sum_{n=1}^{\infty} \frac{(-1)^{n+1}}{n}$  converges, thus

$$\lim_{n \rightarrow \infty} S_n = \lim_{n \rightarrow \infty} S_{2n} = \lim_{n \rightarrow \infty} \sum_{k=1}^n \frac{1}{n+k} = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n \frac{1}{1+k/n} = \int_0^1 \frac{1}{1+x} dx = \ln 2 \quad (9)$$

#### 3.2 (ii)

Notice that  $1 - \frac{1}{2} - \frac{1}{4} = \frac{1}{2}(1 - \frac{1}{2})$ ,  $\frac{1}{3} - \frac{1}{6} - \frac{1}{8} = \frac{1}{2}(\frac{1}{3} - \frac{1}{4})$  and so on. Thus,

$$1 - \frac{1}{2} - \frac{1}{4} + \frac{1}{3} - \frac{1}{6} - \frac{1}{8} + \frac{1}{5} - \frac{1}{10} - \frac{1}{12} + \dots = \frac{1}{2} \sum_{n=1}^{\infty} \frac{(-1)^{n+1}}{n} = \frac{\ln 2}{2} \quad (10)$$

#### 3.3 (iii)

$\frac{1}{n} > \ln(1 + \frac{1}{n}) = \ln(n+1) - \ln(n)$ , so  $\sum_{k=1}^n \frac{1}{k} > \ln(n+1)$ , and the infinite sum converges. So the series  $\frac{(-1)^{(n+1)}}{n}$  is conditionally convergent but not absolutely convergent.

## 4 Problem 4

### 4.1 (i)

For  $X \sim \text{Geometric}(p)$ , we have  $E(X) = \frac{1}{p}$  and  $E(X^2) = \frac{2-p}{p^2}$ .

Because  $P(X-1 = k | X > 1) = P(X = k)$ ,

$$\begin{aligned} E[X^3 | X > 1] &= E[(X-1)^3 + 3(X-1)^2 + 3(X-1) + 1 | X > 1] \\ &= E[X^3] + 3E[X^2] + 3E[X] + 1 \\ &= E[X^3] + \frac{6-3p}{p^2} + \frac{3}{p} + 1 \end{aligned} \tag{11}$$

Also,  $E[X^3] = E[X^3 | X > 1](1-p) + p$ .

$$E[X^3] = \frac{(\frac{6}{p^2} + 1)(1-p) + p}{p} = \frac{6-6p+p^2}{p^3} \tag{12}$$