# STA2112H: Probability I

### Problem 1

Prove each of the following statements. Assume that any conditioning event has positive probability.

(a) If P(B) = 1, then P(A|B) = P(A) for any A.

**Solution** 

$$P(B) = 1 \implies P(B^c) = 1 - P(B) = 1 - 1 = 0$$

$$P(B^c) = 0 \implies P(B^c \cap A) = 0$$

$$P(A) = P(A \cap B) + P(A \cap B^c) = P(A \cap B)$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = P(A \cap B) = P(A)$$

(b) If  $A \subset B$ , then P(B|A) = 1 and P(A|B) = P(A)/P(B).

**Solution**  $A \subset B \iff x \in A \implies x \in B$ . Therefore all elements of A are also in B. This implies that  $A = A \cap B$ . Then

$$P(B|A) = \frac{P(A \cap B)}{P(A)} = \frac{P(A)}{P(A)} = 1$$
  
and 
$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(A)}{P(B)}.$$

(c) If A and B are mutually exclusive, then

$$P(A|A \cup B) = \frac{P(A)}{P(A) + P(B)}.$$

Solution

$$A, B \text{ mutually exclusive } \Longrightarrow P(A \cap B) = 0$$

$$P(A \cup B) = P(A) + P(B)$$

$$P(A|A \cup B) = \frac{P(A \cap (A \cup B))}{P(A \cup B)} = \frac{P((A \cap A) \cup \overbrace{(A \cap B)}^{\text{the empty set}})}{P(A) + P(B)}$$

$$= \frac{P(A)}{P(A) + P(B)}.$$

(e)  $P(A \cap B \cap C) = P(A|B \cap C)P(B|C)P(C)$ .

### Solution

$$P(A\cap B\cap C)=P(A\cap (B\cap C))=P(A|(B\cap C))P(B\cap C)=P(A|(B\cap C))P(B|C)P(C).$$

(d) If  $P(A) = \frac{1}{2}$  and  $P(B^c) = \frac{1}{4}$ , can A and B be disjoint?

**Solution** No, because if A and B be disjoint then

$$P(A \cup B) = P(A) + P(B) = P(A) + (1 - P(B^c)) = \frac{1}{2} + \frac{3}{4} > 1.$$

More generally, if A and B are disjoint then  $A \subset B^c$  so  $P(A) \leq P(B^c)$ . In this example,  $P(A) > P(B^c)$ .

Consider a clinical trial with two treatment groups and a binary outcome of success/failure. Assume the outcomes of different subjects are independent. In a 'play the winner' rule for assigning treatments, you randomly assign the first subject to either treatment group 1 or 2 with probability  $\frac{1}{2}$ . If that subject is a success, you assign the next subject to that same group, otherwise you assign the next subject to the other group. Suppose you continue assigning subjects in this manner indefinitely. Let  $p_1 > 0$  be the probability of success in group 1 and  $p_2 > 0$  be the probability of success in group 2.

(a) Suppose that the first subject is randomized to group 1. Let X be the random variable for number of subjects that are assigned to group 1 before switching over to group 2. What is the pmf of X?

**Solution** We may equivalently define X as the random variable for the number of trials until there is a failure in treatment group 1. The treatment for group 1 fails with probability  $1 - p_1$ . It then follows that  $X \sim Geom(1 - p_1)$ , which has pmf

$$p(X = k) = (p_1)^{k-1}(1 - p_1)$$
 for  $k = 1, 2...$ 

(b) Suppose you are blinded to the first treatment group assignment, but you observe that the first n outcomes are successes. What is the probability that the first treatment assignment was group 1?

**Solution** Let A be the event that the first treatment assignment was group 1 and B be the event that the first n outcomes are successes. By Bayes' rule,

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|A^c)P(A^c)}.$$

From the problem statement we have,  $P(B|A) = p_1^n$ ,  $P(B|A^c) = p_2^n$ , and P(A) = 1/2. It then follows that

$$P(A|B) = \frac{\frac{1}{2}(p_1^n)}{\frac{1}{2}(p_1^n + p_2^n)} = \frac{p_1^n}{p_1^n + p_2^n}$$

(c) Discuss a pro and a con of using the play the winner rule as the method of treatment allocation in a clinical trial as opposed to randomly choosing assignments.

#### **Solution**

Pro: More patients receive the more effective treatment.

Con: We can't start treatment for the next subject until we've observed the outcome of the previous subject which could be impractical if response times are slow.

Suppose you are making trail mix for a hike and have  $n \geq 2$  unique ingredients to use. You decide to make the mix by picking an ingredient uniformly at random from each of the n ingredients n times. What is the most likely combination of ingredients you'll end up with?

**Solution** In this example, you are taking a uniform random sample of size n from the n ingredients with replacement. If we let  $X_i$  denote the random variable for the number of ingredients of type i for i = 1, ..., n, then  $(X_1, ..., X_n)$  follows a Multinomial  $(n, p_1, p_2, ..., p_n)$  where  $p_i = 1/n$  for i = 1, ..., n. Using the definition of the multinomial distribution,

$$P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) = \frac{n!}{x_1! x_2! \dots x_n!} n^{-n}$$

This probability is maximized when  $x_1 = x_2 = \cdots = x_n = 1$  so the most likely combination for your trail mix is the one that includes all of the ingredients.

Looking ahead: In a few weeks, we will learn about the bootstrap. The same calculations can be used to show that the most likely bootstrap resample is the original sample.

Suppose that  $X_1, \ldots, X_n$  are iid continuous random variables with cdf F(x) and pdf f(x). Define the random variables

$$U = min(X_1, \dots, X_n)$$
 and  $V = max(X_1, \dots, X_n)$ 

.

a) Find the cdf of U.

**Solution** 

$$P(U \le u) = P(\min(X_1, ..., X_n) \le u)$$

$$= 1 - P(\min(X_1, ..., X_n) \ge u)$$

$$= 1 - P(X_1 \ge u, X_2 \ge u, ..., X_n \ge u)$$

$$= 1 - (P(X_1 \ge u)P(X_2 \ge u) ... P(X_n \ge u))$$

$$= 1 - (1 - F(u))^n$$

b) Find the cdf of V.

**Solution** 

$$P(V \le v) = P(\max(X_1, \dots, X_n) \le v)$$

$$= P(X_1 \le v, \dots, X_n \le v)$$

$$= (P(X_1 \le v)P(X_2 \le v) \dots P(X_n \le v))$$

$$= (F(v))^n$$

c) Find the joint cdf of U and V.

**Solution** By definition  $U \leq V$ , so f(u,v) = 0 for u > v. When  $u \leq v$ , we have

$$P(U \le u, V \le v) = P(V \le v) - P(U > u, V \le v)$$

$$= P(V \le v) - (P(u < X_1 \le v)P(u < X_2 \le v) \dots P(u < X_n \le v))$$

$$= (F(v))^n - (F(v) - F(u))^n$$

The first equality follows from the fact that

$$P(V < v) = P(V < v, U < u) + P(V < v, U > u)$$

.

Let X and Y be two random variables with mean 0 and variance 1. The correlation between X and Y is then given by

$$\rho = E(XY) = Cov(X, Y) = Cor(X, Y)$$

In the subsequent exercises, we will verify some of the properties of correlation and covariance we saw in class.

## Part A

Find  $E[(X - \rho Y)^2]$  and then use this result, together with the fact that  $(X - \rho Y)^2$  is a nonnegative random variable, to show that  $-1 \le \rho \le 1$ .

#### **Solution**

$$E[(X - \rho Y)^{2}] = E(X^{2} - 2XY\rho + Y^{2}\rho^{2})$$

$$= E(X^{2}) - 2\rho E(XY) + \rho^{2} E(Y^{2})$$

$$= 1 - 2\rho^{2} + \rho^{2} = 1 - \rho^{2}$$

Since  $(X - \rho Y)^2$  is nonnegative,

$$0 \le E[(X - \rho Y)^2] = 1 - \rho^2$$

implying that

$$\rho^2 \le 1 \to -1 \le \rho \le 1$$

#### Part B

Suppose that Y = aX + b for some positive constants a and b. Find Cor(X, Y).

#### Solution

$$\begin{split} Cor(X,Y) &= \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}} \\ &= \frac{E[X(aX+b)] - E(X)E(aX+b)}{\sqrt{Var(X)Var(aX+b)}} \\ &= \frac{E(aX^2 + bX) - E(X)E(aX+b)}{\sqrt{Var(X)Var(aX+b)}} \\ &= \frac{a}{\sqrt{a^2}} = 1 \end{split}$$

# Part C

Using your result from Part A, show that X and Y are linearly dependent when  $|\rho|=1$ .

#### **Solution**

From Part A, we have

$$E[(X - \rho Y)^2] = 1 - \rho^2$$

If  $|\rho| = 1$ ,

$$E[(X - \rho Y)^2] = 0$$

Because  $(X - \rho Y)^2$  is nonnegative, it follows that  $(X - \rho Y)^2 = 0$  with probability 1 and therefore  $X = \rho Y$ . Since  $|\rho| = 1$ ,

$$X = Y$$
 or  $X = -Y$ .

## Part D

Let U = X - Y and V = X + Y. Find Cov(U, V) and Cor(U, V).

#### **Solution**

$$Cov(U, V) = Cov(X - Y, X + Y)$$

$$= E[(X - Y)(X + Y)] + E(X - Y)E(X + Y)$$

$$= E[X^{2} - Y^{2}]$$

$$= E[X^{2}] - E[Y^{2}] = 0$$

Since Cov(U, V) = 0, Cor(U, V) = 0. This example shows that a correlation of zero between two random variables does not imply that they are independent. We also saw an example of this in class.