# Statistical Inference

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## 1 Probability Theory

#### 1.5(a)

Solution. A U.S. birth results in female identical twins.

#### 1.5(b)

Solution.

$$P(A \cap B \cap C) = P(A|B \cap C)P(B|C)P(C) = P(A|B)P(B|C)P(C) = \frac{1}{2}\frac{1}{3}\frac{1}{90} = \frac{1}{540}.$$

#### 1.24(b)

Solution. Suppose  $E_i = \{\text{head first appears on } i \text{th toss} \}$ , then

$$P(A \text{ wins}) = P(\bigcup_{i=k}^{\infty} E_{2k+1}) = \sum_{k=0}^{\infty} P(E_{2k+1}) = \sum_{k=0}^{\infty} p(1-p)^{2k+1} = \frac{p}{1-(1-p)^2}.$$

#### 1.31(a)

*Proof.* To get the average  $(x_1+\cdots+x_n)/n$ , we need the unordered sample to be  $\{x_1,x_2,\ldots,x_n\}$ . The number of ordered samples which results in it is n! and there are  $n^n$  ordered samples in total. Hence, the probability is  $n!/n^n$ .

For any other resulted average, there will exist some double counting when counting the ordered samples. Therefore, the outcome with average  $(x_1 + \cdots + x_n)/n$  is most likely.

#### 1.33

Solution.

$$P(\text{male}|\text{color-blind}) = P(\text{color-blind}|\text{male}) \frac{P(\text{male})}{P(\text{color-blind})}$$
$$= 0.05 \times \frac{0.5}{0.5 \times 0.05 + 0.5 \times 0.0025}$$
$$= \frac{20}{21} = 0.9524.$$

#### 1.36

Solution. The probabilities of all shots being missed and the target being hit exactly once are  $(4/5)^5 = 0.32768$  and  $5 \times (1/5)(4/5)^4 = 0.4096$  respectively. Hence,

$$P(\text{being hit at least twice}) = 1 - 0.32768 - 0.4096 = 0.26272.$$

And

$$P(\text{being hit at least twice}|\text{being hit at least once})$$

$$= \frac{P(\text{being hit at least twice})}{P(\text{being hit at least once})} = \frac{0.26272}{0.4096} = 0.6414.$$

1.39(a)

*Proof.* A and B are mutually exclusive means that  $A \cap B = \emptyset$ . Hence,  $P(A \cap B) = 0$ . However, P(A), P(B) > 0. Therefore,  $P(A \cap B) \neq P(A)P(B)$ .

1.39(b)

*Proof.* As A and B are independent,  $P(A \cap B) = P(A)P(B) > 0$ , which implies that  $A \cap B \neq \emptyset$ .

**Notes on 1.39** An intuitive proof: Since A and B are mutually exclusive, if we know that A did not happen, then the possibility that B happened will increase. Hence, they are not independent.

#### 1.52

*Proof.* Clear that  $g(x) \geq 0$  for all  $x \in \mathbb{R}$  and

$$\int_{-\infty}^{\infty} g(x) dx = \int_{x_0}^{\infty} \frac{f(x)}{1 - F(x_0)} dx$$

$$= \frac{1}{1 - F(x_0)} \left( \int_{-\infty}^{\infty} f(x) dx - \int_{-\infty}^{x_0} f(x) dx \right)$$

$$= \frac{1}{1 - F(x_0)} (1 - F(x_0)) = 1.$$

Hence, by Theorem 1.6.5, g(x) is a pdf.

## 2 Transformations and Expectations

#### 1.(b)

Solution.  $f_X$  is continuous and  $g^{-1}(y) = (y-3)/4$  is continuously differentiable, therefore

$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{\mathrm{d}}{\mathrm{d}y} g^{-1}(y) \right| = \frac{7}{4} e^{-7(y-3)/4}.$$

 $\mathcal{Y} = (3, \infty)$  and

$$\int_{\mathcal{Y}} f_Y(y) = -\int_3^{\infty} \exp\left(-\frac{7}{4}y + \frac{21}{4}\right) d\left(-\frac{7}{4}y + \frac{21}{4}\right) = 1.$$

#### 3.

Solution.

$$f_Y(y) = P(Y = y) = P\left(\frac{X}{X+1} = y\right) = P\left(X = \frac{1}{1-y} - 1\right) = \frac{1}{3}\left(\frac{2}{3}\right)^{\frac{1}{1-y}-1},$$
  
where  $y = 0, 1/2, 2/3, \dots$ 

#### **5**.

Solution.  $g(x) = \sin^2 x$  is monotone on  $(0, \pi/2]$ ,  $[\pi/2, \pi)$ ,  $(\pi, 3\pi/2]$  and  $[3\pi/2, 2\pi)$  respectively and the ranges of g on the intervals are the same. Furthermore,

$$\begin{array}{ll} g_0^{-1}(y) = \arcsin \sqrt{y}, & g_1^{-1}(y) = -\arcsin(-\sqrt{y}) \\ g_2^{-1}(y) = \pi + \arcsin \sqrt{y}, & g_3^{-1}(y) = \pi - \arcsin(-\sqrt{y}), \end{array}$$

all of which are continuously differentiable. Hence,

$$f_Y(y) = \sum_{i=0}^{3} \frac{1}{2\pi} \left| \frac{\mathrm{d}}{\mathrm{d}y} g_i^{-1}(y) \right| = \frac{1}{\pi \sqrt{y(1-y)}}.$$

and vanishes elsewhere.

Next we show that the same answer can be obtained by differentiating (2.1.6). Note that d(x+c) = dx and  $x_2 - x_1 = 2(\pi - x)1$ , then we get

$$f_Y(y) = \frac{\mathrm{d}}{\mathrm{d}y} P(Y \le y) = \frac{2}{\pi} \frac{\mathrm{d}}{\mathrm{d}y} x_1 = \frac{2}{\pi} \frac{\mathrm{d}}{\mathrm{d}y} \arcsin \sqrt{y} = \frac{1}{\pi \sqrt{y(1-y)}}.$$

#### 9.

Solution. By Theorem 2.1.10, we only need to set  $u = F_X$ , that is,

$$u(x) = \int_{-\infty}^{x} f(x) dx = \begin{cases} 0, & x \le 1, \\ (x-1)^2/4, & 1 < x < 3, \\ 1, & x \ge 3, \end{cases}$$

and the monotonicity is obvious.

#### 11.(a)

Solution. Direct calculating yields

$$EX^2 = \int_{-\infty}^{\infty} x^2 \frac{1}{\sqrt{2\pi}} e^{-x^2} dx = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-x^2/2} dx = 1.$$

And by Example 2.1.17,

$$EY = \int_0^\infty y \frac{1}{2\sqrt{y}} (f_X(\sqrt{y}) + f_X(-\sqrt{y})) dy$$
$$= \frac{1}{\sqrt{2\pi}} \int_0^\infty \sqrt{y} e^{-y/2} dy = \sqrt{\frac{2}{\pi}} \int_0^\infty y^2 e^{-y^2/2} dy = 1.$$

13.

Solution.  $f_X(x) = P(X = x) = p^x(1-p) + (1-p)^x p \ (n = 1, 2, 3, ...)$  and

$$EX = \sum_{x=1}^{\infty} x f_X(x) = (1-p) \sum_{x=1}^{\infty} x p^x + p \sum_{x=1}^{\infty} x (1-p)^x = \frac{p}{1-p} + \frac{1-p}{p}.$$

15.

*Proof.* Clear that  $X + Y = (X \vee Y) + (X \wedge Y)$ . Hence,

$$E(X \vee Y) = E(X + Y - (X \wedge Y)) = EX + EY - E(X \wedge Y).$$

18.

Proof.

$$E|x - a| = \int_{-\infty}^{\infty} |x - a| f(x) dx$$

$$= \int_{-\infty}^{a} (a - x) f(x) dx + \int_{a}^{\infty} (x - a) f(x) dx$$

$$= a \int_{-\infty}^{a} f(x) dx - \int_{-\infty}^{a} x f(x) dx + \int_{a}^{\infty} x f(x) dx - a \int_{a}^{\infty} f(x) dx.$$

Differentiating the both sides yields

$$\frac{\mathrm{d}}{\mathrm{d}a} \mathbf{E}|x-a| = \left( \int_{-\infty}^{a} f(x) \mathrm{d}x + af(a) \right) - af(a) - af(a) - \left( \int_{a}^{\infty} f(x) \mathrm{d}x - af(a) \right)$$
$$= \int_{-\infty}^{a} f(x) \mathrm{d}x - \int_{a}^{\infty} f(x) \mathrm{d}x.$$

Meanwhile, the value at m of the twice derivative is greater than 0. Therefore, x=m is the minimum point.

### 24.(a)

Solution.

$$EX = \int_0^1 x a x^{a-1} dx = \frac{a}{a+1}.$$

$$E(X^2) = \int_0^1 x^2 a x^{a-1} dx = \frac{a}{a+2}.$$

$$VarX = (EX)^2 - E(X^2) = \frac{a}{(a+1)(a+2)}.$$

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Proof.

$$\frac{\mathrm{d}}{\mathrm{d}t}S(t) = \frac{\mathrm{d}}{\mathrm{d}t}\left(\log\int_{-\infty}^{\infty} e^{tx}f(x)\mathrm{d}x\right) = \frac{1}{\int_{-\infty}^{\infty} e^{tx}f(x)\mathrm{d}x}\int_{-\infty}^{\infty} xe^{tx}f(x)\mathrm{d}x.$$

Therefore,

$$S'(0) = \frac{1}{\int_{-\infty}^{\infty} f(x) dx} \int_{-\infty}^{\infty} x f(x) dx = EX.$$

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### 3 Common Families of Distributions

5.

Solution. Assuming that the two kinds of drugs are equally effective and let X = the number of effective cases. Then with the binomial distribution

$$P(X \ge 85 | n = 100, p = 0.8) = \sum_{k=85}^{100} {100 \choose k} 0.8^k 0.2^{100-k} = 0.1285.$$

Hence, there is still some possibility that the new drugs is no better than the old ones.

7.

Solution.

$$P(X \ge 2) > 0.99 \implies e^{-\lambda}(1+\lambda) < 0.01 \implies \lambda \ge 6.6384.$$

Hence, the mean of the distribution is  $\lambda = 6.6484$ .

13.(a)

Solution.  $P(X=0)=e^{-\lambda}$  and therefore  $P(X>0)=1-e^{-\lambda}$ . Hence,

$$P(X_T = x) = \frac{P(X = x)}{1 - P(X = 0)} = \frac{\lambda^x}{x!(e^{\lambda} - 1)},$$

$$EX_T = \frac{1}{P(X > 0)} \sum_{x=1}^{\infty} x P(X = x) = \frac{\lambda}{1 - e^{-\lambda}},$$

$$VarX_T = \frac{1}{1 - e^{-\lambda}} \lambda(\lambda + 1) - \left(\frac{\lambda}{1 - e^{-\lambda}}\right)^2.$$