

part 3

Asher Christian 006-150-286

2024-05-28

1 Discrete

X : eye color of random person

Y : hair

$N(x, y)$ = # of people of eye color x and hair color y

$$p(x, y) = P(X = x, Y = y) = \frac{N(x, y)}{N}$$

N = total #

$$N(x) = \sum_y N(x, y)$$

$$N(x, \cdot) = \sum_y N(x, y)$$

$$N(\cdot, y) = \sum_x N(x, y)$$

$$p(x) = P(X = x) = \frac{N(x, \cdot)}{N} = \frac{\sum_y N(x, y)}{N} = \sum_y \frac{N(x, y)}{N} = \sum_y p(x, y).$$

$$p(y) = \sum_x p(x, y).$$

Conditional:

$$p(y|x) = P(X = x|Y = y) = \frac{N(x, y)}{N(\cdot, y)} = \left(\frac{\frac{N(x, y)}{N}}{\frac{N(\cdot, y)}{N}} \right) = \frac{p(x, y)}{p(y)}.$$

$$p(y|x) = \frac{p(x, y)}{p(x)}.$$

$$p(x, y) = p(x)p(y|x) = p(y)p(x|y).$$

$$p(x|y) = \frac{p(x, y)}{p(y)} = \frac{p(x, y)}{\sum_x p(x, y)} = \frac{p(x)p(y|x)}{\sum_x p(x)p(y|x)}.$$

$$p(y) = \sum_x p(x, y) = \sum_x p(x)p(y|x).$$

$$E(h(x)) = \sum_x h(x)p(x).$$

$$E(h(x, y)) = \sum_x \sum_y h(x, y) p(x, y) = \sum_{x, y} h(x, y) \frac{N(x, y)}{N} = \frac{1}{N} \sum_{x, y} h(x, y) N(x, y).$$

The population average of h

Continuous random variables
 X = height of random person
 Y = weight

$$\begin{aligned} f(x, y) &= \frac{\# \text{ of points in } (x, x + \Delta x) \cdot (y, y + \Delta y) / N}{\Delta x \Delta y} = \frac{P(X \in (x, x + \Delta x) \& Y \in (y, y + \Delta y))}{\Delta x \Delta y} \\ &= \frac{\frac{N(x, y)}{N}}{\Delta x \Delta y}. \end{aligned}$$

$$\begin{aligned} f(x) &= \frac{\text{Proportion}}{\text{size}} \\ &= \frac{N(X, \cdot) / N}{\Delta x} \\ &= \frac{P(X \in (x, x + \Delta x))}{\Delta x} \\ &= \frac{\sum_y \frac{N(x, y)}{N}}{\Delta x} \\ &= \frac{\sum_y f(x, y) \Delta x \Delta y}{\Delta x} \\ &= \sum_y f(x, y) \Delta y \\ &= \int f(x, y) dy \\ f(y) &= \int f(x, y) dx. \end{aligned}$$

Conditional

$$\begin{aligned}
 f(x|y) &= \frac{\text{Proportion}}{\text{Size}} \\
 &= \frac{P(X \in (x, x + \Delta x) | Y \in (y, y + \Delta y))}{\Delta x} \\
 &= \frac{\frac{N(x, y)}{N(\cdot, y)}}{\Delta x} \\
 &= \frac{\frac{N(x, y)}{N} / \frac{N(\cdot, y)}{N}}{\Delta x} \\
 &= \frac{\frac{f(x, y) \Delta x \Delta y}{f(y) \Delta y}}{\Delta x} \\
 &= \frac{f(x, y)}{f(y)}
 \end{aligned}$$

$$\begin{aligned}
 f(x, y) &= f(x)f(y|x) \\
 &= f(y)f(x|y)
 \end{aligned}$$

$$\begin{aligned}
 E(h(x, y)) &= \int_x \int_y h(x, y) f(x, y) dx dy \\
 &= \frac{1}{N} \sum_x \sum_y h(x, y) N(x, y)
 \end{aligned}$$

$p(x, y)$ prob mass function or probability density function
 Rule 1: Marginalization

$$\begin{aligned}
 p(x) &= \sum_y p(x, y) \\
 &= \int p(x, y) dy \\
 p(y) &= \sum_x p(x, y) \\
 &= \int p(x, y) dx
 \end{aligned}$$

Rule 2: Conditioning

$$\begin{aligned}
 p(x|y) &= \frac{p(x, y)}{p_y(y)} \\
 p(y|x) &= \frac{p(x, y)}{P_x(x)}
 \end{aligned}$$

Rule 3: Chain

$$\begin{aligned} P(x, y) &= p(x)p(y|x) \\ &= P(y)p(x|y) \end{aligned}$$

Independence X orthogonal Y

$$P(x, y) = p_x(x)p_y(y), p(x|y) = p_x(x), p(y|x) = p_y(y).$$

2 Day 2

$$E(h(x, y)) = \int_y \int_x h(x, y) f(x, y) dx dy.$$

independence:

$$p(x, y) = p_x(x)p_y(y).$$

Standardization

$$\mu = E(x), \sigma^2 = Var(x), X < -\frac{x-\mu}{\sigma}$$

$$X \sim N(0, 1).$$

$$f_x(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

$[Y|X = x] \sim N(\rho x, 1 - \rho^2)$ regression model.

$$f(Y|x) = \frac{1}{\sqrt{2\pi(1 - \rho^2)}} e^{-\frac{(y - \rho x)^2}{2(1 - \rho^2)}}.$$

$\rho < 1$ $y = \rho x$ is the regression line

1. Conditional expectation & variance

$$E(Y|X = x) = \rho x$$

$$Var(Y|X = x) = 1 - \rho^2 \text{ regression towards the mean}$$

$$Y = \rho X + \epsilon \text{ and epsilon is indep of } x$$

$$\epsilon \sim N(0, 1 - \rho^2) \text{ } \epsilon \text{ is independant of } X$$

$$Y = \rho x + \epsilon \sim N(\rho x, 1 - \rho^2)$$

$$E(Y) = E(\rho X + \epsilon) = \rho E(x) + E(\epsilon) = \rho$$

$$Var(Y) = Var(\rho X) + Var(\epsilon) = \rho^2 Var(X) + (1 - \rho^2) = 1$$

2. Modern meaning of regression $E(Y|X) = f(x)$

- 3.

$$(x, y) \sim f(x, y).$$

$$Cov(x, y) = E((X - E(X))(Y - E(Y))).$$

$$Cov(x, x) = E((X - E(X))^2) = Var(X).$$

Covariance changes units depending on the measure - to fix that we standardize

$$\begin{aligned}
 \text{Cov}\left(\frac{X - \mu_X}{\sigma_X}, \frac{Y - \mu_Y}{\sigma_Y}\right) &= E((X_s)(Y_s)). \\
 &= \frac{E((X - \mu_X)(Y - \mu_Y))}{\sigma_X \sigma_Y} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)}\sqrt{\text{Var}(Y)}}. \\
 &= \rho = \text{Corr}(X, Y).
 \end{aligned}$$