

Soc 30005: Statistical Methods of Research 2

Notes on Probability

I. Probability for Discrete Variables

Joint Probability:

$$\Pr(Y = y, X = x), x \in \{0,1,\dots\}, y \in \{0,1,\dots\}$$

Marginal Probability

$$\begin{aligned}\Pr(Y = y) &= \sum_x \Pr(Y = y, X = x) \\ \Pr(X = x) &= \sum_y \Pr(Y = y, X = x)\end{aligned}\tag{1}$$

Conditional Probability

$$\Pr(Y = y \mid X = x) = \frac{\Pr(Y = y, X = x)}{\Pr(X = x)}\tag{2}$$

$$\Pr(X = x \mid Y = y) = \frac{\Pr(Y = y, X = x)}{\Pr(Y = y)}$$

Decompositions

Joint Probability: From (2),

$$\begin{aligned}\Pr(Y = y, X = x) &= \Pr(Y = y \mid X = x) \Pr(X = x) \\ &= \Pr(X = x \mid Y = y) \Pr(Y = y)\end{aligned}$$

Marginal Probability: From (1) and (2)

$$\begin{aligned}\Pr(Y = y) &= \sum_x \Pr(Y = y \mid X = x) \Pr(X = x) \\ \Pr(X = x) &= \sum_y \Pr(Y = y \mid X = x) \Pr(X = x)\end{aligned}$$

Bayes Theorem

$$\begin{aligned}\Pr(Y = y | X = x) &= \frac{\Pr(Y = y, X = x)}{\Pr(X = x)} \\ &= \frac{\Pr(X = x | Y = y) \Pr(Y = y)}{\Pr(X = x)} \\ &= \frac{\Pr(X = x | Y = y) \Pr(Y = y)}{\sum_y \Pr(X = x | Y = y) \Pr(Y = y)}\end{aligned}$$

Independence

If X and Y are independent, $\Pr(Y = y | X = x) = \Pr(Y = y)$.

Therefore,

$$\begin{aligned}\Pr(Y = y, X = x) &= \Pr(Y = y | X = x) \Pr(X = x) \\ &= \Pr(Y = y) \Pr(X = x)\end{aligned}$$

II. Probability for Continuous Variables

Henceforth, we shall refer to $\text{Prob}(Y=y)$ as $f(y)$.

Marginal Probability

$$\begin{aligned}\Pr(a < X < b) &\approx \sum_{i=1}^n f(x_i) \Delta \\ \Pr(a < X < b) &= \lim_{\substack{n \rightarrow \infty \\ \Delta \rightarrow 0}} \left(\sum_{i=1}^n f(x_i) \Delta \right) = \int_a^b f(x) dx \\ &\quad [\text{where } x_i = a + i \Delta; \Delta = (b - a)/n].\end{aligned}$$

$$\text{We must have } f(x) \geq 0, \quad \int_{-\infty}^{\infty} f(x) dx = 1.$$

Probability density function

In the continuous case, $f(x)$ is called the *probability density* function.

Joint Probability

$$\Pr(a < X < b, c < Y < d) = \int_c^d \int_a^b f(x, y) dx dy$$

Note: $f(x) = \int \int f(x, y) dy$; $f(y) = \int \int f(x, y) dx$ (3)

Joint probability density

$f(x, y)$ is the *joint density* function

Conditional Probability

$$\Pr(c < Y < d \mid a < X < b) = \frac{\int_a^b \int_c^d f(x, y) dx dy}{\int_a^b f(x) dx} = \frac{\int_c^d \int_a^b f(x, y) dx dy}{\int_{-\infty}^{\infty} f(y) dy}$$

Conditional probability density

$$f(y \mid x) = \frac{f(x, y)}{f(x)} \text{ is the } \textit{conditional density} \text{ function.} \quad (4)$$

Decompositions

Joint Probability: From (4),

$$f(x, y) = f(y \mid x) f(x) = f(x \mid y) f(y)$$

Marginal Probability: From (3) and (4)

$$f(x) = \int f(x, y) dy = \int f(y \mid x) f(x) dy$$

$$f(y) = \int f(x, y) dx = \int f(x \mid y) f(y) dx$$

Bayes Theorem

$$f(y \mid x) = \frac{f(x, y)}{f(x)} = \frac{f(x \mid y) f(y)}{f(x)} = \frac{f(x \mid y) f(y)}{\int f(x \mid y) f(y) dy}$$

Independence

If X and Y are independent, $f(x, y) = f(x) f(y)$.

III. Expectation

$$\text{Discrete case: } E(X) = \sum_{i=1}^n x_i f(x_i)$$

$$\text{Continuous case: } E(X) = \int x f(x) dx$$

Sums of Expectations

$$E(X + Y) = E(X) + E(Y); \text{ therefore } E(kX) = kE(X) \quad (5)$$

Conditional Expectation

$$E(Y | X) = \begin{cases} \sum y_i f(y_i | x) & \text{discrete case} \\ \int y f(y | x) dy & \text{continuous case} \end{cases}$$

Independence

$$\text{If } X \perp Y, E(Y | X) = E(Y)$$

Proof (discrete case): Recall that if $X \perp Y$, $f(y | x) = f(y)$. Then

$$E(Y | X) = \sum y_i f(y_i | x) = \sum y_i f(y_i) = E(Y).$$

III. Variance

$$\text{Var}(X) = E(X - \mu_x)^2, \text{ where } \mu_x = E(X).$$

$$\text{Note } E(X - \mu_x)^2 = E(X^2) - \mu_x^2$$

IV. Covariance

$$\text{Cov}(X, Y) = E(X - \mu_x)(Y - \mu_y)$$

$$\text{Note if } X \perp Y, \text{Cov}(X, Y) = \text{Cov}(X, Y) = E(X - \mu_x)E(Y - \mu_y) = 0 \quad (6)$$

V. Variance of a Sum

$$\begin{aligned} \text{Var}(X + Y) &= E[(X + Y) - (\mu_x + \mu_y)]^2 \\ &= E[(X - \mu_x) + (Y - \mu_y)]^2 \\ &= E[(X - \mu_x)^2 + (Y - \mu_y)^2 + 2(X - \mu_x)(Y - \mu_y)] \\ &= \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y) \end{aligned}$$

From (6), if $X \perp Y$, $Var(X + Y) = Var(X) + Var(Y)$

Common notation

$$Var(X) = \sigma_x^2; \quad Var(Y) = \sigma_y^2, \quad Cov(X, Y) = \sigma_{xy}$$

Or

$$Var(X) = \sigma_{xx}; \quad Var(Y) = \sigma_{yy}, \quad Cov(X, Y) = \sigma_{xy}$$