

Marginal and Conditional Probability Distributions

Just the univariate density, emphasizing that we look one variable only.

Y_1, Y_2 : continuous r.v. with $f(y_1, y_2)$

(Marginal) density of Y_1 (or Y_2)

$$f_1(y_1) = \int_{-\infty}^{\infty} f(y_1, y_2) dy_2 \quad \text{and} \quad f_2(y_2) = \int_{-\infty}^{\infty} f(y_1, y_2) dy_1.$$

Must not depend on Y_2

Conditional density of Y_1 given $Y_2 = y_2$

$$f(y_1|y_2) = \frac{f(y_1, y_2)}{f_2(y_2)}$$

*Y_1
: a ft of (Y_2)*

provided that $f_2(y_2) > 0$.

$$f_{Y_1, Y_2}(y_1, y_2)$$

f/

$$f(y_1, y_2) = 24y_1y_2 \quad 0 \leq y_1 \leq 1, \quad 0 \leq y_2 \leq 1, \quad y_1 + y_2 \leq 1 \quad \frac{P(5)}{P(2)P(3)}$$

marginal: $\underline{f(y_1)} = f_{Y_1}(y_1) = \int_0^{1-y_1} f(y_1, y_2) dy_2 = \underline{12y_1(y_1-1)^2}$

Beta(2, 3)

: nothing to do with Y_2 .

Conditional density of $Y_1 | Y_2 = y_2$.

$$f(y_1 | y_2) = f_{Y_1|Y_2=y_2}(y_1 | y_2) = \frac{f(y_1, y_2)}{f(y_2)} = \frac{24y_1y_2}{12y_2(y_2-1)^2}$$

r.v. ← a fixed value, not a r.v.

$$= \frac{2y_1}{(y_2-1)^2}, \quad \underline{0 \leq y_1 \leq 1-y_2}$$

: a f.t. of y_1 , but also depends on y_2 .
(also a f.t. of y_2).

Check: $\int_0^{1-y_2} \frac{2y_1}{(y_2-1)^2} dy_1 = 1$.

$X \sim$ Some distribution of height

$$\arg \min_m E(X - m)^2 = \mu = E(X)$$

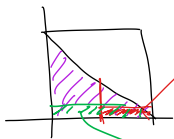
$$\arg \min_m E |X - m| = \text{median of } X$$

$$P(Y_1 > .5 | Y_2 = .1)$$

$$= \int_{.5}^{.9} f(y_1 | .1) dy_1$$

$$P(Y_1 > .5 | Y_2 < .1)$$

$$= \frac{P(Y_1 > .5, Y_2 < .1)}{P(Y_2 < .1)}$$



$$\iint 24 y_1 y_2 dy_1 dy_2 \dots \dots$$

Ex 40 | $Y_1 \sim B(n_1, p)$ $Y_2 \sim B(n_2, p)$

indep

$$W = Y_1 + Y_2 \sim B(n_1 + n_2, p)$$

$$P(Y_1 = y_1 | W = w) = \frac{\binom{n_1}{y_1} p^{y_1} (1-p)^{n_1-y_1} \binom{n_2}{w-y_1} p^{w-y_1} (1-p)^{n_2-w+y_1}}{\binom{n_1+n_2}{w} p^w (1-p)^{n_1+n_2-w}}$$

$$\frac{P(Y_1 = y_1, W = w)}{P(W = w)}$$

$$P(Y_1=y_1, Y_2=w-y_1) / P(W=w)$$

$$= \frac{\binom{n_1}{y_1} \binom{n_2}{w-y_1}}{\binom{n_1+n_2}{w}} : \text{HG}$$

$$Y_1 \sim \text{Poisson}(\lambda_1) \quad Y_2 \sim \text{Poisson}(\lambda_2) \quad (\text{indep})$$

$$W = Y_1 + Y_2 \sim \text{Poisson}(\lambda_1 + \lambda_2)$$

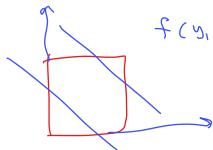
$$P(Y_1=y_1 | W=w) = \dots = \binom{w}{y_1} \left(\frac{\lambda_1}{\lambda_1 + \lambda_2} \right)^{y_1} \left(\frac{\lambda_2}{\lambda_1 + \lambda_2} \right)^{w-y_1}$$

$$: \text{Binomial} \left(w, \frac{\lambda_1}{\lambda_1 + \lambda_2} \right)$$

In general, the distribution of $Y_1 + Y_2$, we can find the CDF of $W = Y_1 + Y_2$ using

$$P(Y_1 + Y_2 \leq u) =$$

.....



e.g. $Y_1 \sim \text{Unif}(0, 1)$
 $Y_2 \sim \text{Unif}(0, 1)$) indep

$$P(Y_1 + Y_2 \leq u) = \int_0^u \int_0^{u-y_2} 1 \, dy_1 \, dy_2 = \begin{cases} 1 - \frac{1}{2}(2-u)^2 & 1 \leq u \leq 2 \\ \frac{1}{2} u^2 & 0 \leq u \leq 1 \end{cases}$$

Independent Random Variables

$$f(u, v) = \begin{cases} 2-u & 1 \leq u \leq 2 \\ u & 0 \leq u \leq 1 \end{cases}$$

Y_1 and Y_2 : independent if and only if $F(y_1, y_2) = F_1(y_1)F_2(y_2)$.
Equivalently,

- ▶ Discrete: $p(y_1, y_2) = p_1(y_1)p_2(y_2)$.
- ▶ Continuous: $f(y_1, y_2) = f_1(y_1)f_2(y_2)$. Joint = product of marginals.

- ↑
- ▶ $f(y_1, y_2) = g(y_1)h(y_2)$ where $g(y_1)$ is a nonnegative function of y_1 alone and $h(y_2)$ is a nonnegative function of y_2 alone.
 (Note: $g(y_1) \geq 0$ and $h(y_2) \geq 0$ are implied by the context of probability density functions.)

Eg. $f(y_1, y_2) = \frac{1}{8} y_1 e^{-(y_1 + y_2)/2}$
 $0 < y_1 < \infty$
 $0 < y_2 < \infty$

$$\begin{cases} Y_1 \sim \text{Gamma}(2, 2) = \chi^2(4) \\ Y_2 \sim \text{Exp}(2) \end{cases}$$

Bayesian

$$Y|\lambda \sim \text{Poisson}(\lambda)$$

$$\lambda \sim \text{Exp}(1) \rightarrow \text{prior}$$

$$f(y, \lambda) = f(y|\lambda) f(\lambda)$$

$$= \frac{e^{-\lambda} \lambda^y}{y!} \cdot e^{-\lambda} = \frac{e^{-2\lambda} \lambda^y}{y!}, \quad \lambda > 0, \quad y = 0, 1, 2, \dots$$

$$\underline{f(y)} = \int_0^{\infty} f(y, \lambda) d\lambda = \int_0^{\infty} \frac{1}{y!} \underbrace{\lambda^{y+1-1} e^{-\lambda/\frac{1}{2}}}_{\text{Gamma}(y+1, \frac{1}{2})} d\lambda = \dots$$

$$= \left(\frac{1}{2}\right)^{y+1}, \quad y = 0, 1, \dots$$

: Geometric

$f(\lambda|y)$: posterior density

Expected Value of a Function of Random Variables

There are k variables

Joint density

$$E[g(Y_1, Y_2, \dots, Y_k)] = \int_{y_k} \cdots \int_{y_2} \int_{y_1} \underbrace{g(y_1, y_2, \dots, y_k)}_{\text{any fct of } Y_1, \dots, Y_k} \underbrace{f(y_1, y_2, \dots, y_k)}_{\text{Joint density}} dy_1 dy_2 \cdots dy_k.$$

a and b : constants

▶ $E(ag(Y_1, Y_2) + b) = aE[g(Y_1, Y_2)] + b$

▶ $E[\sum_{i=1}^k g_i(Y_1, Y_2)] = \sum_{i=1}^k E[g_i(Y_1, Y_2)]$

▶ $E[g(Y_1)h(Y_2)] = E[g(Y_1)]E[h(Y_2)]$ if Y_1 and Y_2 are independent. \Rightarrow

$E(Y_1 Y_2) = E(Y_1) E(Y_2)$ if $Y_1 \perp Y_2$