

Lecture 15: Fri Oct 26 (a): Joint densities L & M 3.7

15.1 Joint and marginal (cumulative) distribution functions

For two random variables X and Y the *joint cdf* is $F_{X,Y}(a,b) = P(X \leq a, Y \leq b)$, $-\infty < a, b < \infty$.

Note that the *marginal cdfs* of X and of Y are given by

$$\begin{aligned} F_X(a) &= P(X \leq a) = P(\lim_{b \rightarrow \infty} \{X \leq a, Y \leq b\}) \quad (\text{increasing sequence of sets}) \\ &= \lim_{b \rightarrow \infty} P(X \leq a, Y \leq b) = \lim_{b \rightarrow \infty} F_{X,Y}(a,b) \equiv F_{X,Y}(a, \infty) \end{aligned}$$

$$\text{Similarly, } F_Y(b) = P(Y \leq b) = \lim_{a \rightarrow \infty} F_{X,Y}(a,b) \equiv F_{X,Y}(\infty, b)$$

Just as in 1 dimension, we can get all other probabilities from $F_{X,Y}$. For example (draw picture):

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$

15.2 Joint and marginal probability mass functions

If X and Y are discrete random variables the *joint pmf* is $p_{X,Y}(x,y) = P(X = x, Y = y)$ for $x \in \mathcal{X}$, $y \in \mathcal{Y}$.

Then the *marginal pmfs* of X and of Y are

$$p_X(x) = P(X = x) = \sum_{y \in \mathcal{Y}} p_{X,Y}(x,y), \quad \text{and } p_Y(y) = \sum_{x \in \mathcal{X}} p_{X,Y}(x,y).$$

Note $p_X(x) > 0$ for $x \in \mathcal{X}$, and $p_Y(y) > 0$ for $y \in \mathcal{Y}$, but $p_{X,Y}(x,y)$ can be 0 for some $x \in \mathcal{X}$, $y \in \mathcal{Y}$.

15.3 The multinomial distribution

If we take a sample size n (with replacement) and there are r types, with type i having probability p_i , $i = 1, \dots, r$ and $\sum_{i=1}^r p_i = 1$. Let X_i be the number of type i in the sample ($i = 1, \dots, r$): $\sum_{i=1}^r X_i = n$:

$$P(X_1 = n_1, X_2 = n_2, \dots, X_r = n_r) = \frac{n!}{n_1! n_2! \dots n_r!} p_1^{n_1} p_2^{n_2} \dots p_r^{n_r}$$

Recall (Lecture 3), number of ways of arranging n_1 objects type-1, n_2 objects type-2, ... n_k objects type-k, where $n_1 + n_2 + \dots + n_k = n$ is $n!/(n_1! n_2! \dots n_k!)$.

Example: There are 4 ABO blood types, A , B , AB and O . For the USA population, roughly, $P(A) = 0.41$, $P(B) = 0.16$, $P(AB) = 0.07$, and $P(O) = 0.36$. Twelve students go to donate blood: what is the probability 5 are type A , 2 are type B , one is AB , and 4 are type O ? Answer:

$$12!/(5! \times 2! \times 1! \times 4!)(0.41)^5(0.16)^2(0.07)^1(0.36)^4 = 914760 \times 3.487^{-7} \approx 0.319$$

What is the (marginal) pmf of the number of students with type A blood? Answer: $\text{Bin}(12, 0.41)$. (Why?)

15.4 Joint and marginal probability density functions

(i) Random variables X and Y are *jointly continuous* if there is a function $f_{X,Y}(x,y)$ defined for all real x and y , such that for every (? not quite?) set C in \mathbb{R}^2 , $P((X,Y) \in C) = \int \int_{(x,y) \in C} f_{X,Y}(x,y) dx dy$.

Then $f_{X,Y}(x,y)$ is the *joint pdf* of X and Y .

$$(ii) \quad F_{X,Y}(a,b) = P(X \in (-\infty, a], Y \in (-\infty, b]) = \int_{y=-\infty}^b \int_{x=-\infty}^a f_{X,Y}(x,y) dx dy$$

$$\text{so } f_{X,Y}(a,b) = \frac{\partial^2}{\partial a \partial b} F_{X,Y}(a,b)$$

$$(iii) \quad P(X \in A) = P(X \in A, Y \in (-\infty, \infty)) = \int_{X \in A} \int_{y=-\infty}^{\infty} f_{X,Y}(x,y) dx dy = \int_{X \in A} f_X(x) dx$$

$$\text{where } f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy$$

So $f_X(x)$ is pdf of X and similarly pdf of Y is $f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx$

Lecture 16: Oct 26 (b). Independent random variables (L & M 3.7,3.8)

X and Y are *independent* if for any subsets A and B of \mathcal{R} , $P(X \in A \cap Y \in B) = P(X \in A) \times P(Y \in B)$.

16.1 Independence of two r.vs: discrete case

Theorem: Independence is equivalent to $p_{X,Y}(x,y) = P(X = x, Y = y) = P(X = x) \cdot P(Y = y) = p_X(x)p_Y(y)$.

Proof: Clearly this is *necessary*: take $A = \{x\}$ and $B = \{y\}$.

Conversely, if $p_{X,Y}(x,y) = p_X(x)p_Y(y)$, then for any A, B :

$$\begin{aligned} P(X \in A, Y \in B) &= \sum_{x \in A} \sum_{y \in B} p_{X,Y}(x,y) = \sum_{x \in A} \sum_{y \in B} p_X(x)p_Y(y) \\ &= \sum_{x \in A} p_X(x) \sum_{y \in B} p_Y(y) = P(X \in A) P(Y \in B) \end{aligned}$$

Note this must hold for all $x \in \mathcal{X}$, $y \in \mathcal{Y}$. Thus independence implies $p_{X,Y}(x,y) > 0$ for all $x \in \mathcal{X}$, $y \in \mathcal{Y}$.

If X and Y are independent, the ranges of the r.v.s cannot depend on each other.

Example: X is value on first die, Y on second: these are independent. But if we throw out doubles (i.e. points with $x = y$) they are no longer independent: if $X = 4$ we know $Y \neq 4$.

16.2 Independence of two r.vs: continuous case

With $A = (-\infty, x)$ and $B = (-\infty, y)$ we see

$$F_{X,Y}(x,y) = P(X \leq x, Y \leq y) = P(X \leq x)P(Y \leq y) = F_X(x)F_Y(y).$$

$$\text{Then } f_{X,Y}(x,y) = \frac{\partial^2}{\partial x \partial y} F_{X,Y}(x,y) = \frac{\partial^2}{\partial x \partial y} F_X(x)F_Y(y) = f_X(x)f_Y(y).$$

Conversely: If $f_{X,Y}(x,y) = f_X(x)f_Y(y)$ then

$$P(X \in A, Y \in B) = \int_{X \in A} \int_{Y \in B} f_{X,Y}(x,y) dx dy = \int_{X \in A} \int_{Y \in B} f_X(x)f_Y(y) dx dy = P(X \in A)P(Y \in B)$$

That is: X and Y are independent if and only if $f_{X,Y}(x,y) = f_X(x)f_Y(y)$ for all x, y .

Integrating f back to F : X and Y are independent if and only if $F_{X,Y}(x,y) = F_X(x)F_Y(y)$ for all x, y .

Also, if $f_{X,Y} = g_1(x)g_2(y)$ for all x, y , then X and Y are independent, and $f_X(x) \propto g_1(x)$, $f_Y(y) \propto g_2(y)$.

Note again these must hold for all x, y : the ranges of the r.vs cannot depend on each other.

16.3 Examples of independence and dependence

(i) **Example:** $f_{X,Y}(x,y) = x + y$ on $0 < x < 1, 0 < y < 1$.

X and Y are not independent: why not? What is $f_X(x)$?

(ii) **Example:** $f_{X,Y}(x,y) = 24xy$ on $0 < x, 0 < y, x + y < 1$

X and Y are not independent: why not? What is $f_X(x)$?

(Compare this with $f_{X,Y}(x,y) = 4xy$ on $0 < x < 1, 0 < y < 1$, where X and Y are independent.)

(iii) **Example:** $f_{X,Y}(x,y) = \exp(-(x+y))$ on $0 < x < \infty, 0 < y < \infty$

$$\text{or } f_{X,Y}(x,y) = \exp(-(x+y))I_{(0,\infty)}(x)I_{(0,\infty)}(y)$$

X and Y are independent: why? What is $f_X(x)$? (Note: $I_A(x) = 1$ if $x \in A$ and 0 otherwise.)

(iv) **Example:** $f_{X,Y}(x,y) = 2 \exp(-(4x + \frac{1}{2}y))$ on $0 < x < \infty, 0 < y < \infty$.

X and Y are independent: why? What is $f_X(x)$?

How would you compute $f_X(x)$ if you did not see X and Y are independent?

(v) **Example:** $f_{X,Y}(x,y) = 1/6$ on $0 < x < 2, 0 < y < 3$, or $f_{X,Y}(x,y) = (1/6)I_{(0,2)}(x)I_{(0,3)}(y)$

X and Y are independent: why? What is $f_X(x)$?

17: Examples of computing probabilities

17.1 Computing probabilities with joint pdf's

Recall: $P((X, Y) \in A) = \int \int_A f_{X,Y}(x, y) dx dy$.

(i) **Example:** $f(x, y) = x + y$ on $0 < x < 1, 0 < y < 1$. (Ch 6: # 22)

$$\begin{aligned} P(X + Y < 1) &= \int_{y=0}^1 \int_{x=0}^{1-y} (x + y) dx dy = \int_{y=0}^1 \left[\frac{1}{2}x^2 + yx \right]_0^{1-y} dy \\ &= \int_{y=0}^1 \left(\frac{1}{2}(1-y)^2 + y(1-y) \right) dy = \int_{y=0}^1 \frac{1}{2}(1-y^2) dy = \frac{1}{2}(1 - (1/3)) = 1/3. \end{aligned}$$

(ii) **Example:** $f(x, y) = 2$ on $0 < x, 0 < y, x + y < 1$

$$\begin{aligned} P(X < 3Y) &= \int_{y=0}^1 \int_{x=0}^{\min(1-y, 3y)} 2 dx dy = \int_{y=0}^{1/4} 6y dy + \int_{y=1/4}^1 2(1-y) dy \\ &= [3y^2]_0^{1/4} + [-(1-y)^2]_{1/4}^1 = 3/16 + 9/16 = 3/4. \end{aligned}$$

Easier: Draw a picture. For a constant density. Probability \equiv area.

17.2: Sum of two independent U(0,1)

Let $X \sim U(0, 1)$ and $Y \sim U(0, 1)$ with X and Y independent.

So $f_{X,Y}(x, y) = 1$ on $0 < x < 1, 0 < y < 1$.

(a) What is the range of $W = X + Y$?

(b) Compute $P(X + Y < w)$ where $0 < w < 1$.

Or, draw a picture. (Answer: $w^2/2$)

(c) Hence show $f_W(w) = w$ if $0 < w < 1$. (This is only part of $f_W(w)$.)

(c) Note $(2 - W) = (1 - X) + (1 - Y)$.

Why does this tell me that $f_W(w)$ is symmetric about $w = 1$?

Because of its shape, $f_W(w)$ is known as a triangular density.

17.3 Buffon's needle: a classic example of estimating π . (For interest only)

Parallel lines distance D apart; needle length L , with $L \leq D$.

Let X be distance from needle midpoint to nearest line; θ be angle of needle to X . X is $U(0, D/2)$, θ is $U(0, \pi/2)$ and they are *independent*. We want the probability

$$\begin{aligned} P(X \leq (L/2) \cos(\theta)) &= \int \int_{2x < L \cos(y)} f_X(x) f_\theta(y) dx dy = \frac{2}{\pi} \frac{2}{D} \int_0^{\pi/2} \int_0^{L/2 \cos(y)} dx dy \\ &= \frac{4}{\pi D} \int_0^{\pi/2} \frac{L}{2} \cos(y) dy = \frac{2L}{\pi D} [\sin(y)]_0^{\pi/2} = 2L/\pi D \end{aligned}$$

17.4 The variance of a Normal N(0,1): For interest only.

A $N(0, 1)$ r.v. had p.d.f. $f_Z(z) = \frac{1}{\sqrt{2\pi}} \exp(-z^2/2)$ on $-\infty < z < \infty$ is a *standard Normal random variable*.

$$\begin{aligned} \left(\int_{-\infty}^{\infty} \exp(-z^2/2) dz \right)^2 &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp(-(x^2 + y^2)/2) dx dy = \int_0^{\infty} \int_0^{2\pi} \exp(-r^2/2) r dr d\theta \\ &= [-\exp(-r^2/2)]_0^{\infty} [\theta]_0^{2\pi} = 2\pi \quad \text{using polar coordinates} \end{aligned}$$

$$E(Z) = \int_{-\infty}^{\infty} z f_Z(z) dz = 0 \quad \text{since } f_Z(-z) = f_Z(z).$$

$$\begin{aligned} \text{var}(Z) = E(Z^2) &= \int_{-\infty}^{\infty} z^2 f_Z(z) dz = \frac{1}{\sqrt{2\pi}} \left([-z \exp(-z^2/2)]_{-\infty}^{\infty} + \int_{-\infty}^{\infty} \exp(-z^2/2) dz \right) \\ &= \int_{-\infty}^{\infty} z f_Z(z) dz = 1 \end{aligned}$$

Lecture 18: Transforming random variables Wed Oct 31 L & M 3.8

18.1 Linear transformations: Location and scale

Let X have pdf $f_X(x)$, $E(X) = \mu$, $\text{var}(X) = \sigma^2$, and $Y = aX + b$, $X = (Y - b)/a$.

(a) **Location:** ($a = 1$): $Y = X + b$, $E(Y) = \mu + b$, $\text{var}(Y) = \sigma^2$:

$$F_Y(y) = P(Y \leq y) = P(X \leq y - b) = F_X(y - b). \text{ So } f_Y(y) = f_X(y - b).$$

(b) **Scale:** ($b = 0$, $a > 0$): $Y = aX$, $E(Y) = a\mu$, $\text{var}(Y) = a^2\sigma^2$:

$$F_Y(y) = P(Y \leq y) = P(X \leq y/a) = F_X(y/a). \text{ So } f_Y(y) = (1/a)f_X(y/a).$$

(c) **Location and scale:** ($a > 0$): $Y = aX + b$, $E(Y) = a\mu + b$, $\text{var}(Y) = a^2\sigma^2$:

$$F_Y(y) = P(Y \leq y) = P(X \leq (y - b)/a) = F_X((y - b)/a). \text{ So } f_Y(y) = (1/a)f_X((y - b)/a).$$

18.2 Exponential random variables have scale only

Note that exponential densities have scale λ^{-1} , where λ is the rate parameter.

Instead of a density $(1/a)f(y/a)$ with scale parameter a , we have a density of form $\lambda f(\lambda y)$. (i.e. $a = (1/\lambda)$)

If $Y \sim \mathcal{E}(\lambda)$, then $\lambda Y \sim \mathcal{E}(1)$.

If buses come at rate 0.1 per minute, they come at rate $60 \times 0.1 = 6$ per hour.

My expected waiting time is 10 minutes, or $10/60 = 1/6$ hours.

18.3 Normal random variables have location and scale

The Normal r.v. $X \sim N(\mu, \sigma^2)$ has pdf $f_X(x) = (1/\sqrt{2\pi})(1/\sigma) \exp(-(1/2)((x - \mu)/\sigma)^2)$.

So $f_X(x) = (1/\sigma)f_Z((x - \mu)/\sigma)$ where $f_Z(z) = (1/\sqrt{2\pi}) \exp(-(1/2)z^2)$ is pdf of $N(0, 1)$.

Recall, $X \sim N(\mu, \sigma^2)$ gives $Z = (X - \mu)/\sigma \sim N(0, 1)$.

Conversely, $Z \sim N(0, 1) \Rightarrow X = \mu + \sigma Z \sim N(\mu, \sigma^2)$.

If we assume $E(Z) = 0$ and $\text{var}(Z) = 1$ (we haven't shown it yet), then $E(X) = \mu$ and $\text{var}(X) = \sigma^2$.

That is, the two parameters that define the Normal pdf are the mean and the variance.

Now let $Y = aX + b = a(\mu + \sigma Z) + b = (a\mu + b) + a\sigma Z$. So $Y \sim N(a\mu + b, a^2\sigma^2)$.

18.4 Uniform random variables have location and scale

Uniform random variables, $U(a, b)$ have both location and scale: linear functions of uniforms are uniform.

Let X be $U(0, 1)$: $f_X(u) = 1$ for $0 \leq u \leq 1$ and 0 otherwise. Or $f_X(x) = I_{(0,1)}(x)$.

Note $E(X) = 1/2$, $\text{var}(X) = 1/12$.

Note $F_X(u) = 0$ for $u \leq 0$, $F_X(u) = u$ for $0 \leq u \leq 1$, and $F_X(u) = 1$ for $u \geq 1$.

Now let $Y = c + (k - c)X$ where $c < k$: $0 \leq X \leq 1$ so $c \leq Y \leq k$. Consider $c \leq y \leq k$.

Then $F_Y(y) = P(Y \leq y) = P(c + (k - c)X \leq y) = P(X \leq (y - c)/(k - c)) = (y - c)/(k - c)$.

So $f_Y(y) = 1/(k - c)$, if $c \leq y \leq k$ and 0 otherwise.

That is

$$f_Y(y) = \frac{1}{(k - c)} I_{(c,k)}(y) = \frac{1}{k - c} I_{(0,1)}\left(\frac{y - c}{k - c}\right)$$

So we have a location-scale family with location c and scale $(k - c)$.

18.5 Example: Do the triangular densities of **17.2** form a location/scale family?