Lecture 33: Nov. 30

Last time

- Conditional Distributions

Today

- Course evaluations
- Final exam format poll
- Bivariate Transformation

Example: Buffon's Needle A table is ruled with lines distance 1 unit apart. A needle of length $L \leqslant 1$ is thrown randomly on the table. What is the probability that the needle intersects a line?
Solution:
Define two random variables:

- X: distance from low end of the needle to the nearest line above
- θ: angle from the vertical to the needle.

By "random", we assume X and θ are independent, and

$$X \sim U(0,1) \quad \text{and} \quad \theta \sim U[-\pi/2, \pi/2].$$

This means that

$$f_{X,\theta}(x,\theta) = 1/\pi, \quad 0 \leqslant x \leqslant 1, -\pi/2 \leqslant \theta \leqslant \pi/2$$

For the needle to intersect a line, we need $X < L\cos(\theta)$.

Expectations of Independent RVs (Theorem 4.2.10) Let X and Y be independent rvs.

- For any $A \subset \mathbb{R}$ and $B \subset \mathbb{R}$,

$$\Pr(X \in A, Y \in B) = \Pr(X \in A)\Pr(Y \in B)$$

  i.e. the events $\{X \in A\}$ and $\{Y \in B\}$ are independent.

- Let $g(x)$ be a function only of x and $h(y)$ be a function only of y. Then

$$E\left[g(X)h(Y)\right] = \left[Eg(X)\right]\left[Eh(Y)\right]$$

Proof:

$$
\begin{aligned}
E\left[g(X)h(Y)\right] &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x)h(y)f_{XY}(x,y)dxdy \\
&= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x)h(y)f_X(x)f_Y(y)dxdy \\
&= \left(\int_{-\infty}^{\infty} g(x)f_X(x)dx\right)\left(\int_{-\infty}^{\infty} h(y)f_Y(y)dy\right) \\
&= \left[Eg(X)\right]\left[Eh(Y)\right]
\end{aligned}
$$

Example X, Y are independent

$$
\begin{aligned}
E(X^2Y^3) &= (EX^2)(EY^3) \\
E(Y^2Y^3) &\neq (EY^2)(EY^3)
\end{aligned}
$$

Bivariate Transformation

Functions of random variables Let (X,Y) be a bivariate rv with known distributions. Define (U,V) by

$$U = g_1(X,Y), \quad V = g_2(X,Y)$$

Probability mapping For any Borel set $B \subset \mathbb{R}^2$,

$$\Pr\left[(U,V) \in B\right] = \Pr\left[(X,Y) \in A\right]$$

where A is the inverse mapping of B, i.e.

$$A = \{(x,y) \in \mathbb{R}^2 : (g_1(x,y), g_2(x,y)) \in B\}$$

The inverse is well defined even if the mapping is not bijective.

Example Let $g_1(x,y) = x, g_2(x,y) = x^2 + y^2$.

Discrete RVs Suppose that (X,Y) is a discrete rv, i.e. the pmf is positive on a countable set $\mathcal{A}$. Then (U,V) is also discrete and takes values on a countable set $\mathcal{B}$. Define

$$A_{u,v} = \{(x,y) \in \mathcal{A} : g_1(x,y) = u, g_2(x,y) = v\}$$

Then

$$f_{UV}(u,v) = \Pr(U = u, V = v) = \sum_{(x,y)\in A_{u,v}} f_{XY}(x,y)$$

Sum of two independent Poissons Let $X \sim Poisson(\lambda_1)$, $Y \sim Poisson(\lambda_2)$, independent, and define

$$U = X + Y, \quad V = Y$$

- (X,Y) takes values in $\mathcal{A} = \{0,1,2,\dots\}^2$

- (U, V) takes values on $\mathcal{B} = \{(u, v) : v = 0, 1, 2, \dots, u = v, v+1, v+2, \dots\}$.
- For a particular (u, v), $A_{uv} = \{(x, y) \in \mathcal{A} : x + y = u, y = v\} = (u - v, u)$.

The joint pmf of U and V is

$$f_{UV}(u, v) = f_{XY}(u - v, v) = \frac{e^{-\lambda_1}\lambda_1^{u-v}}{(u-v)!}\frac{e^{-\lambda_2}\lambda_2^{v}}{(v)!}$$

The distribution of $U = X + Y$ is the marginal

$$\begin{aligned} f + U(u) &= \sum_{v=0}^{u} \frac{e^{-\lambda_1}\lambda_1^{u-v}}{(u-v)!}\frac{e^{-\lambda_2}\lambda_2^{v}}{(v)!} \\ &= \frac{e^{-(\lambda_1+\lambda_2)}}{u!} \sum_{v=0}^{u} \binom{u}{v} \lambda_1^{u-v}\lambda_2^{v} \\ &= \frac{e^{-(\lambda_1+\lambda_2)}}{u!} (\lambda_1 + \lambda_2)^u \end{aligned}$$

We obtain that U is Poisson with parameter $\lambda = \lambda_1 + \lambda_2$.

Bivariate Transformations of Continuous RVs Suppose (X, Y) is continuous and the joint transformation

$$u = g_1(x, y), \quad v = g_2(x, y)$$

is one-to-one and differentiable. Define the inverse mapping

$$x = h_1(u, v), \quad y = h_2(u, v)$$

Then

$$f_{UV}(u, v) = f_{XY}\left(h_1(u, v), h_2(u, v)\right) |J(u, v)|$$

where $J(u, v)$ is the Jacobian of the transformation $(x, y) \to (u, v)$ given by

$$J(u, v) = \frac{\partial(x, y)}{\partial(u, v)} = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix}$$

Example: Rotation of a bivariate normal vector Let $X \sim N(0, 1)$, $Y \sim N(0, 1)$, independent. Define the rotation

$$\begin{aligned} U &= X\cos\theta - Y\sin\theta \\ V &= X\sin\theta + Y\cos\theta \end{aligned}$$

for fixed θ. Then $U \sim N(0, 1)$, $V \sim N(0, 1)$, independent.

Proof:
The range of (X, Y) is $\mathbb{R}^2$. The range of (U, V) is $\mathbb{R}^2$. Need the inverse transformation

$$\begin{aligned} X &= U\cos\theta + V\sin\theta \\ Y &= -U\sin\theta + V\cos\theta \end{aligned}$$

with Jacobian

$$J(u,v) = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{vmatrix} = 1$$

The joint pdf of (X,Y) is

$$f_{XY}(x,y) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \cdot \frac{1}{\sqrt{2\pi}} e^{-y^2/2} = \frac{1}{2\pi} e^{-(x^2+y^2)/2}$$

The joint pdf of (U,V) is

$$\begin{aligned} f_{UV}(u,v) &= \frac{1}{2\pi} e^{-\left[(u\cos\theta+v\sin\theta)^2+(-u\sin\theta+v\cos\theta)^2\right]/2} \cdot |1| \\ &= \frac{1}{2\pi} e^{-(u^2+v^2)/2} = \frac{1}{\sqrt{2\pi}} e^{-u^2/2} \cdot \frac{1}{\sqrt{2\pi}} e^{-v^2/2} \end{aligned}$$

so $U \sim N(0,1)$, $V \sim N(0,1)$, and U and V are independent.

Functions of independent random variables (Theorem 4.3.5) Let X and Y be independent rvs. Let $g : \mathbb{R} \to \mathbb{R}$ and $h : \mathbb{R} \to \mathbb{R}$ be functions. Then the random variables $U = g(X)$ and $V = h(Y)$ are independent.

Sum of two independent rvs Suppose X and Y are independent. What is the distribution of $Z = X + Y$? In general:

$$F_Z(z) = \Pr(X + Y \leqslant z) = \Pr(\{(x,y) \text{ such that } x + y \leqslant z\})$$

Various approaches:

- bivariate transformation method (continuous and discrete)
- Discrete convolution

$$f_Z(z) = \sum_{x+y=z} f_X(x) f_Y(y) = \sum_x f_X(x) f_Y(z-x)$$

- Continuous convolution (Section 5.2)
- MGF method (continuous and discrete)

Example (Sum of two independent Poissons) Define X, Y to be two independent random variables having Poisson distributions with parameters λ_i, $i = 1,2$. Then:

$$f_{X,Y}(x,y) = \frac{e^{-\lambda_1}\lambda_1^x}{x!} \frac{e^{-\lambda_2}\lambda_2^y}{y!}, x, y = 0, 1, 2, \ldots$$

The distribution of $S = X + Y$ is

$$
\begin{aligned}
f_S(s) &= \sum_{x=0}^{s} \frac{e^{-\lambda_1}\lambda_1^x}{x!}\frac{e^{-\lambda_2}\lambda_2^{s-x}}{(s-x)!} \\
&= \frac{e^{-(\lambda_1+\lambda_2)}}{s!}\sum_{x=0}^{s}\binom{s}{x}\lambda_1^x\lambda_2^{s-x} \\
&= \frac{e^{-(\lambda_1+\lambda_2)}}{s!}(\lambda_1+\lambda_2)^s
\end{aligned}
$$

Again, S is Poisson with parameter $\lambda = \lambda_1 + \lambda_2$.

Moment generating function (Theorem 4.2.12) Let X and Y be independent rvs with mgfs $M_X(\cdot)$ and $M_Y(\cdot)$, respectively. Then the mgf of $Z = X + Y$ is

$$M_Z(t) = M_X(t)M_Y(t)$$

Proof:

$$
\begin{aligned}
M_Z(t) &= E\exp(Zt) & &= E\{\exp[(X+Y)t]\} \\
&= E[\exp(Xt)\exp(Yt)] & &= E[\exp(Xt)]\cdot E[\exp(Yt)] \\
&= M_X(t)M_Y(t)
\end{aligned}
$$

Corollary: If X and Y are independent and $Z = X - Y$,

$$M_Z(t) = M_X(t)M_Y(-t)$$

Example (sum of two independent Poissons) Suppose $X \sim Poisson(\lambda_X)$ and $Y \sim Poisson(\lambda_Y)$ and put $Z = X + Y$. Then, $Z \sim Poisson(\lambda_X + \lambda_Y)$. *Proof:*

$$
\begin{aligned}
M_Z(t) &= \exp\left[\lambda_X(e^t-1)\right]\exp\left[\lambda_Y(e^t-1)\right] \\
&= \exp\left[(\lambda_X+\lambda_Y)(e^t-1)\right]
\end{aligned}
$$

Example (sum of two independent normals) Suppose $X \sim N(\mu_x, \sigma_x^2)$ and $Y \sim N(\mu_y, \sigma_y^2)$ and X and Y are independent and $Z = X + Y$. Then

$$Z \sim N(\mu_x + \mu_y, \sigma_x^2 + \sigma_y^2)$$

Proof:

$$
\begin{aligned}
M_Z(t) &= \exp\left(\mu_x t + \frac{1}{2}\sigma_x^2 t^2\right)\exp\left(\mu_y t + \frac{1}{2}\sigma_y^2 t^2\right) \\
&= \exp\left[(\mu_x+\mu_y)t + \frac{1}{2}(\sigma_x^2+\sigma_y^2)t^2\right]
\end{aligned}
$$

Example (sum of two independent gammas) Suppose $X \sim \Gamma(\alpha_x, \beta)$ and independently $Y \sim \Gamma(\alpha_y, \beta)$. Let $Z = X + Y$. Then $Z \sim \Gamma((\alpha_x + \alpha_y), \beta)$.
Proof:

$$\begin{aligned} M_Z(t) &= \left(\frac{1}{1-\beta t}\right)^{\alpha_x} \left(\frac{1}{1-\beta t}\right)^{\alpha_y} \\ &= \left(\frac{1}{1-\beta t}\right)^{\alpha_x+\alpha_y} \end{aligned}$$

Remember that

- If $\alpha = 1$ we have an exponential with parameter β.
- If $\alpha = n/2$ and $\beta = 2$, we have a $\chi^2(n)$ (with n d.f.). The above result states that $\chi^2(n_1) + \chi^2(n_2) = \chi^2(n_1 + n_2)$.