Random Variables and Expectation (III)

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Jensen's inequality

Recall $f : \mathbb{R} \to \mathbb{R}$ is convex if, for all $x_1, x_2 \in \mathbb{R}$ and for all $t \in [0, 1]$, we have

$$f(t\,x_1 + (1-t)x_2) \leqslant t\,f(x_1) + (1-t)\,f(x_2).$$

If f is twice differentiable, a necessary and sufficient condition for f to be convex is that $f''(x) \geqslant 0$ for $x \in \mathbb{R}$.

Lemma

If f is convex then $\mathbb{E}[f(X)] \geqslant f(\mathbb{E}[X])$.

Jensen's inequality

Proof

Let $\mu = \mathbb{E}[X]$ ($\mu \in \mathbb{R}$). Using Taylor to expand f at $X = \mu$,

$$\begin{aligned} f(X) &= f(\mu) + f'(\mu)(X - \mu) + \frac{f''(\mu)(X-\mu)^2}{2} + \cdots \\ &\geqslant f(\mu) + f'(\mu)(X - \mu) \\ \mathbb{E}[f(X)] &\geqslant \mathbb{E}\big[f(\mu) + f'(\mu)(X - \mu)\big] \\ &= \mathbb{E}[f(\mu)] + f'(\mu)(\mathbb{E}[X] - \mu) = f(\mu) \end{aligned}$$

i.e., $\mathbb{E}[f(X)] \geqslant f(\mathbb{E}[X])$. □

Expectation of combinations of r.v.

Consider the following experiment:

$X = \text{Uniform}(\{1,2\})$ and $Y = \text{Uniform}(\{1, X+1\})$

Thus Y depends on X.

What is the expectation of the r.v. XY?

$\Omega = \{(1,1),(1,2),(2,1),(2,2),(2,3)\}$

$$\mathbb{E}[XY] = \sum_{\omega \in \Omega} X(\omega)Y(\omega)\,\mathbb{P}[\omega]$$

We have

$$\mathbb{P}[(1,1)] = \mathbb{P}[(1,2)] = 1/4;$$
$$\mathbb{P}[(2,1)] = \mathbb{P}[(2,2)] = \mathbb{P}[(2,3)] = 1/6.$$

$$\mathbb{E}[XY] = \frac{1}{4}\cdot 1\cdot 1 + \frac{1}{4}\cdot 1\cdot 2 + \frac{1}{6}\cdot 2\cdot 1 + \frac{1}{6}\cdot 2\cdot 2 + \frac{1}{6}\cdot 2\cdot 3 = \frac{11}{4}.$$

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We have, $\mathbb{P}[X = 1] = 1/2$; $\mathbb{P}[X = 2] = 1/2$ and

$$\mathbb{P}[Y = 1] = \mathbb{P}[Y = 1|X = 1]\,\mathbb{P}[X = 1] + \mathbb{P}[Y = 1|X = 2]\,\mathbb{P}[X = 2] = 1/4 + 1/6 = 5/12;$$
$$\mathbb{P}[Y = 2] = \mathbb{P}[Y = 2|X = 1]\,\mathbb{P}[X = 1] + \mathbb{P}[Y = 2|X = 2]\,\mathbb{P}[X = 2] = 1/4 + 1/6 = 5/12;$$
$$\mathbb{P}[Y = 3] = \mathbb{P}[Y = 3|X = 1]\,\mathbb{P}[X = 1] + \mathbb{P}[Y = 3|X = 2]\,\mathbb{P}[X = 2] = 0 + 1/6 = 1/6.$$

Then $\mathbb{E}[X] = 3/2$ and $\mathbb{E}[Y] = 7/4$ so $\mathbb{E}[X]\,\mathbb{E}[Y] = 21/8$.
Therefore,

$$\mathbb{E}[XY] \neq \mathbb{E}[X]\,\mathbb{E}[Y]\,.$$

Joint Probability Mass Function

The joint PMF of r.v. X, Y is the function $p_{XY} : \mathbb{R}^2 \to \mathbb{R}$ defined by $p_{XY}(x, y) = \mathbb{P}[X = x \wedge Y = y]$.

With the joint PMF of r.v. X, Y you can compute the expectation of any function $f(X, Y)$:

$$\mathbb{E}[f(X,Y)] = \sum_{x,y} f(x,y) \cdot p_{XY}(x,y).$$

Compute $\mathbb{E}\left[\frac{X}{Y}\right]$ for the previous r.v. X, Y

$$\begin{aligned}\mathbb{E}\left[\frac{X}{Y}\right] &= p_{XY}(1,1)\frac{1}{1} + p_{XY}(1,2)\frac{1}{2} \\ &\quad + p_{XY}(2,1)\frac{2}{1} + p_{XY}(2,2)\frac{2}{2} + p_{XY}(2,3)\frac{2}{3} \\ &= \frac{1}{4}\cdot(1 + 1/2) + \frac{1}{3}\cdot(2 + 1 + 2/3) = \frac{3}{8} + \frac{11}{3} = \frac{97}{24} = 4\frac{1}{24}\end{aligned}$$

Independent r.v.: Main result

Theorem

If X and Y are independent r.v. then $\mathbb{E}[XY] = \mathbb{E}[X]\,\mathbb{E}[Y]$.

Proof

$$
\begin{aligned}
\mathbb{E}[X \cdot Y] &= \sum_{x,y} p_{XY}(x,y) \cdot x \cdot y \\
&= \sum_{x,y} p_X(x) \cdot p_Y(y) \cdot x \cdot y \text{ (by independence)} \\
&= \sum_{x,y} x \cdot p_X(x) \cdot y \cdot p_Y(y) \\
&= \left(\sum_{x} x \cdot p_X(x)\right) \cdot \left(\sum_{y} y \cdot p_Y(y)\right) \\
&= \mathbb{E}[X] \cdot \mathbb{E}[Y]
\end{aligned}
$$

□

The Poisson approximation to the Binomial

For $X \sim \text{Bin}(n, p)$, for large n, computing the PMF $\mathbb{P}[X = x]$ could be quite nasty.

It turns out that for large n and small p, $\text{Bin}(n, p)$ can be easily approximated by the PMF of a simpler Poisson random variable.

A discrete r.v. X is Poisson with parameter λ ($X \sim \text{Poisson}(\lambda)$), if it has PMF $\mathbb{P}[X = i] = \frac{\lambda^i e^{-\lambda}}{i!}$, for $i \in \{0, 1, 2, 3, \ldots\}$

If $X \sim \text{Poisson}(\lambda)$ then $\mathbb{E}[X] = \lambda$.

This is the reason that sometimes λ is denoted μ.

Proof

$$\mathbb{E}[X] = \sum_{i=1}^{\infty} i \frac{\lambda^i e^{-\lambda}}{i!} = e^{-\lambda} \lambda \underbrace{\sum_{i=1}^{\infty} \frac{\lambda^{i-1}}{(i-1)!}}_{\text{Taylor for } e^{\lambda}} = e^{-\lambda} \lambda e^{\lambda} = \lambda$$

$\square$

The Poisson approximation to the Binomial

Theorem

If $X \in$ *Bin*(n, p), *with* $\mu = pn$, *then as* $n \to \infty$, *for each fixed* $i \in \{0, 1, 2, 3, \ldots\}$,

$$\mathbb{P}[X = i] \sim \frac{\mu^i e^{-\mu}}{i!}.$$

Proof

As $\mu = np$,

$$\begin{aligned}
\mathbb{P}[X = i] &= \binom{n}{i}\left(\frac{\mu}{n}\right)^i\left(1 - \frac{\mu}{n}\right)^{n-i} \\
&= \frac{n(n-1)\cdots(n-i+1)}{i!}\frac{\mu^i}{n^i}\left(1 - \frac{\mu}{n}\right)^n\left(1 - \frac{\mu}{n}\right)^{-i} \\
&= \frac{\mu^i}{i!}\left(1 - \frac{\mu}{n}\right)^n \frac{n(n-1)\cdots(n-i+1)}{n^i}\left(1 - \frac{\mu}{n}\right)^{-i} \\
&\sim \frac{\mu^i}{i!} e^{-\mu} \text{ as } n \to \infty.
\end{aligned}$$

Example

The population of Catalonia is around 7 million people. Assume that the probability that a person is killed by lightning in a year is $p = \frac{1}{5\times 10^8}$.

a) Let's compute the exact probability that 3 or more people will be killed by lightning next year in Catalonia.
Let X be a r.v. counting the number of people that will be killed in Cat. next year by a lightning.
We want to compute
$\mathbb{P}[X \geqslant 3] = 1 - \mathbb{P}[X = 0] - \mathbb{P}[X = 1] - \mathbb{P}[X = 2]$, where
$X \sim \text{Bin}(7 \times 10^6, \frac{1}{5\times 10^8})$.
Then,
$\mathbb{P}[X \geqslant 3] = 1 - (1-p)^n - np(1-p)^{n-1} - \binom{n}{2}p^2(1-p)^{n-2} = 1.65422 \times 10^{-7}$

Example

b) Use Poisson approximation to approximate $\mathbb{P}[X \geqslant 3]$.
$\lambda = np = 7/500$ so
$\mathbb{P}[X \geqslant 3] \sim 1 - e^{\lambda} - \lambda e^{-\lambda} - \frac{\lambda^2}{2} e^{-\lambda} = 1.52558 \times 10^{-7}$

c) Approximate the probability that 2 or more people will be killed by lightning the first 6 months of the year
Notice we are considering λ as a rate. Then we have now
$\lambda = (7/500)/2$
$\mathbb{P}[X \geqslant 2 \text{ during 6 months}] \sim 1 - e^{\lambda} - \lambda e^{-\lambda} = 5.79086 \times 10^{-7}$

d) Approximate the probability that in 3 of the next 10 years exactly 3 people will be killed
We have $\lambda = 7/500$, then the probability that in any particular year 3 people are killed is $= \frac{e^{-\lambda}\lambda^3}{3!}$. Let Y be a r.v. counting the number of years with exactly 3 kills.
Assuming independence between years, $Y \sim \text{Bin}(10, \frac{e^{-\lambda}\lambda^3}{3!})$,
therefore the answer is $\binom{10}{3}(\frac{e^{-\lambda}\lambda^3}{3!})^3(1 - \frac{e^{-\lambda}\lambda^3}{3!})^7 \approx 1.1 \cdot 10^{-17}$