

Lecture 10: Expectation

General trick: PMF/PDF trick

If I can recognize part of a calculation as either

$$\sum_x f(x) \quad \text{or} \quad \int_{\mathbb{R}} f(x) dx$$

I can replace them w/ 1.

Functions of RVs

Any function of a RV is itself a RV.

e.g. if X is a RV then so is

X^2 , $\log X$, \sqrt{X} , etc.

Theorem: Law of the Unconscious Statistician

If $g: \mathbb{R} \rightarrow \mathbb{R}$ and X is a RV then

$$\mathbb{E}[g(X)] = \begin{cases} \sum_x g(x) f(x) & \text{discrete} \\ \int_{\mathbb{R}} g(x) f(x) dx & \text{cts} \end{cases}$$

Ex. Let $X \sim \text{Exp}(\lambda)$ ↗ $\lambda > 0$

$$f(x) = \lambda e^{-\lambda x}, \text{ for } x > 0$$

$$E[X] = 1/\lambda$$

$$E[X^2] = \int_{\mathbb{R}} x^2 f(x) dx = \int_0^{\infty} \underbrace{x^2}_{u} \underbrace{\lambda e^{-\lambda x}}_{dv} dx$$

$$u = x^2 \\ du = 2x dx$$

$$v = -e^{-\lambda x} \\ dv = \lambda e^{-\lambda x} dx$$

$$= uv - \int v du = \underbrace{-x^2 e^{-\lambda x}}_0^{\infty} + 2 \int_0^{\infty} e^{-\lambda x} x dx$$

$$= 0 - 0 + \frac{2}{\lambda} \underbrace{\int_0^{\infty} x e^{-\lambda x} dx}_{E[X]}$$

$$= \frac{2}{\lambda} \frac{1}{\lambda}$$

$E[X^2] = 2/\lambda^2$

Ex. Cauchy Distribution

$$f(x) = \frac{1}{\pi} \frac{1}{1+x^2} \quad \text{for } x \in \mathbb{R}$$

$$E[X] = \int_{\mathbb{R}} x f(x) dx$$

$$= \int_{-\infty}^{\infty} x \frac{1}{\pi} \frac{1}{1+x^2} dx$$

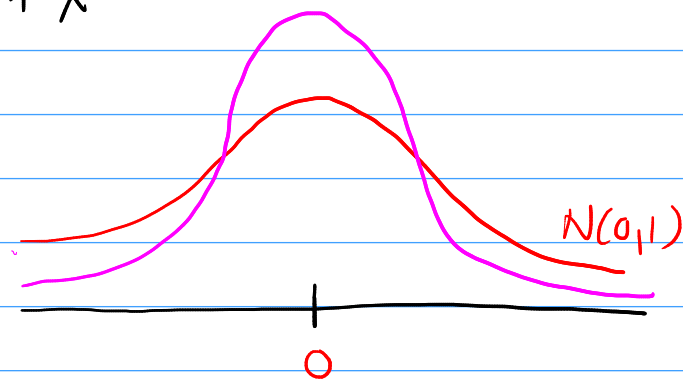
$$= \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x}{1+x^2} dx$$

$$= \frac{2}{\pi} \lim_{T \rightarrow \infty} \int_0^T \frac{x}{1+x^2} dx = \infty$$

$$\frac{x}{1+x^2} \sim \frac{x}{x^2} = \frac{1}{x} \quad \lim_{T \rightarrow \infty} \int_0^T \frac{1}{x} dx$$

$\sum_{i=1}^{\infty} \frac{1}{i^2} < \infty$	$\int_0^{\infty} \frac{1}{x^2} dx < \infty$
$\sum_{i=1}^{\infty} \frac{1}{i} = \infty$	$\int_0^{\infty} \frac{1}{x} dx = \infty$

So $E[X] = \infty$.



Theorem: Properties of Expectation

① Expectation is linear

$$E[aX + b] = aE[X] + b$$

pf (cts)

$$E[aX + b] = \int (aX + b) \overset{g(x)}{f(x)} dx$$

$$g(x) = aX + b$$

$$= \int aX f(x) dx + \int b f(x) dx$$

$$= a \underbrace{\int X f(x) dx}_{E[X]} + b \underbrace{\int f(x) dx}_1$$

$$= aE[X] + b$$

② If $\underbrace{X \geq 0}_{\text{support} \geq 0}$ then $E[X] \geq 0$

pf (cts)

$$E[X] = \int \underbrace{x}_{\geq 0} \underbrace{f(x)}_{\geq 0} dx \geq 0$$

$\underbrace{\hspace{10em}}_{\geq 0}$

③ If g_1 and g_2 are functions then

① $E[g_1(X) + g_2(X)] = E[g_1(X)] + E[g_2(X)]$

② If $g_1(x) \leq g_2(x)$ then

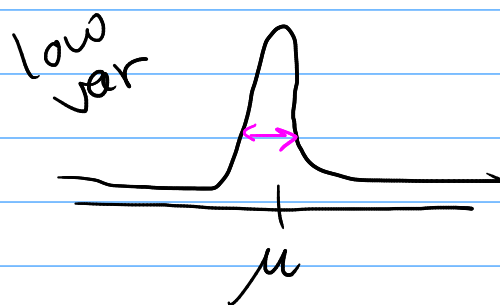
$$Eg_1(X) \leq Eg_2(X)$$

④ If $a \leq X \leq b$ then $a \leq EX \leq b$.

Defn: Variance

$\mu = EX =$ location of dist

$\sigma^2 = \text{Var}(X) =$ spread of dist



$$\begin{aligned}\text{Var}(X) &= E[(X - \mu)^2] \\ &= E[(X - E(X))^2]\end{aligned}$$

Standard deviation: $\text{Sd}(X) = \sqrt{\text{Var}(X)}$

Ex. $X \sim \text{Exp}(\lambda)$

$$f(x) = \lambda e^{-\lambda x} \quad \text{for } x > 0$$

$$\mu = \mathbb{E}X = 1/\lambda \quad \text{and} \quad \mathbb{E}[X^2] = 2/\lambda^2$$

$$\text{Var}(X) = \mathbb{E}[(X - \mu)^2] = \int g(x) f(x) dx$$

$$g(x) = (x - \mu)^2 = \int_0^{\infty} (x - \mu)^2 \lambda e^{-\lambda x} dx$$

↑ correct, but I'm lazy

$$\mathbb{E}[X^2 - 2\mu X + \underbrace{\mu^2}_{(\mathbb{E}X)^2}]$$

$$= \mathbb{E}[X^2] - 2\mu \mathbb{E}X + \mu^2$$

$$= 2/\lambda^2 - 2\left(\frac{1}{\lambda}\right)\left(\frac{1}{\lambda}\right) + \left(\frac{1}{\lambda}\right)^2$$

$$= \frac{2}{\lambda^2} - \frac{2}{\lambda^2} + \frac{1}{\lambda^2} = \boxed{\frac{1}{\lambda^2} = \text{Var}(X)}$$

Theorem: Short-Cut formula for Variance

$$\text{Var}(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2.$$

pf

$$\begin{aligned} \text{Var}(X) &= \mathbb{E}[(X - \mu)^2] \\ &= \mathbb{E}[X^2 - 2\mu X + \mu^2] \end{aligned}$$

$$= E[X^2] - 2\mu EX + \mu^2$$

$$= E[X^2] - 2(EX)(EX) + (EX)^2$$

$$= E[X^2] - E[X]^2.$$

Revisit ex, $EX = 1/\lambda$, $E[X^2] = 2/\lambda^2$

$$\begin{aligned} \text{Var}(X) &= E[X^2] - (EX)^2 \\ &= 2/\lambda^2 - (1/\lambda)^2 \\ &= 1/\lambda^2. \end{aligned}$$

ex. $X \sim \text{Bin}(n, p)$

$$EX = np$$

$$E[X^2] = np(np - p + 1)$$

$$\begin{aligned} \text{Var}(X) &= E[X^2] - (EX)^2 \\ &= np(np - p + 1) - (np)^2 \\ &= \hat{\quad} \hat{\quad} \hat{\quad} \\ &= np(1-p) \end{aligned}$$

$$\text{sd}(X) = \sqrt{np(1-p)}$$

Theorem:

$$\text{Var}(aX + b) = a^2 \text{Var}(X).$$

two rules!

① multiply by const \rightarrow var goes like const^2

② ignore additive consts

pf. $\text{Var}(\underbrace{aX + b}_Y) = \underbrace{E[(aX + b)^2]}_{E[Y^2]} - \underbrace{E[aX + b]^2}_{E[Y]^2}$

$$= E[a^2X^2 + 2aXb + b^2] - (aEX + b)^2$$

$$= a^2 E[X^2] + \cancel{2abEX} + \cancel{b^2} - (a^2(EX)^2 + \cancel{2abEX} + \cancel{b^2})$$

$$= a^2 (E[X^2] - (EX)^2)$$

$$= a^2 \text{Var}(X).$$
