

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

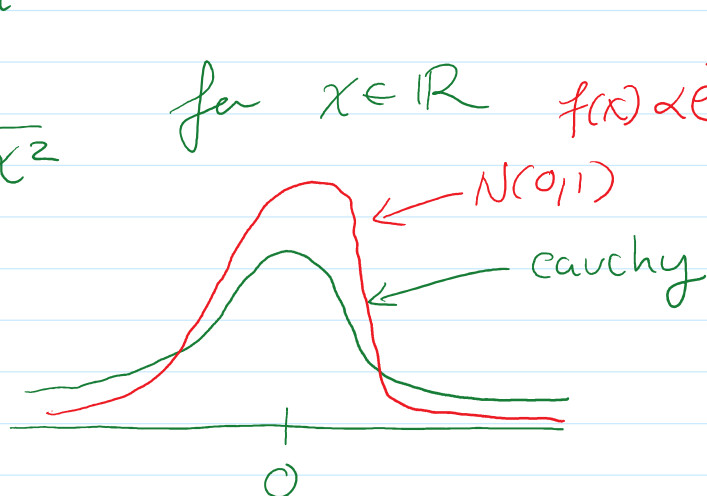
Q: Does expectation always exist? No.

Ex. Cauchy Distribution

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

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

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



looks like

$$\int_{-\infty}^{\infty} \frac{x}{x^2} dx = \int_{-\infty}^{\infty} \frac{1}{x} dx \quad \text{doesn't converge}$$

analogy

$$\sum_i \frac{1}{i^2} < \infty \quad \text{but} \quad \sum_i \frac{1}{i} = \infty$$

$$\int \frac{1}{x^2} dx < \infty \quad \text{but} \quad \int \frac{1}{x} dx = \infty$$

$$\int_0^1 \frac{1}{x^2} dx < \infty \quad \text{but} \quad \int_0^1 \frac{1}{x} dx = \infty$$

Theorem: Properties of Expectation

① Expectation is linear:

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

pf. (cts)

$$\begin{aligned} E[aX + b] &= \int (ax + b)f(x) dx = \int [axf(x) + bf(x)] dx \\ &= \int axf(x) dx + \int bf(x) dx \\ &= \underbrace{a \int xf(x) dx}_{E[X]} + \underbrace{b \int f(x) dx}_1 \\ &= aE[X] + b \end{aligned}$$

② If $X \geq 0$ then $E[X] \geq 0$.

↑ support $\subseteq [0, \infty)$

pf. (cts)

$$E[X] = \int_0^{\infty} x f(x) dx \geq 0$$

\uparrow $x \geq 0$ \uparrow $f(x) \geq 0$

③ If g_1 and g_2 are functions

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

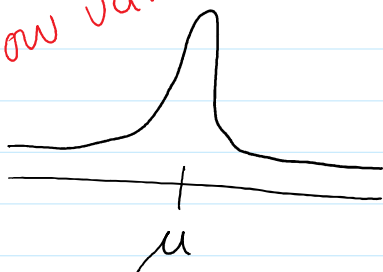
$$E[g_1(X)] \leq E[g_2(X)]$$

④ If $a \leq X \leq b$ then $a \leq E[X] \leq b$.

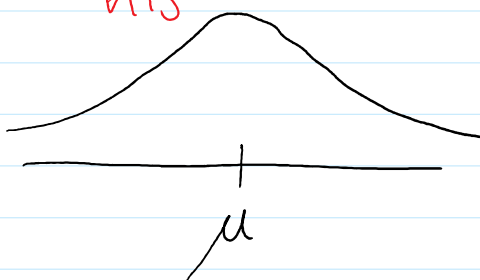
Defn: Variance

$$\mu = E[X] = \text{mean}$$

low variance



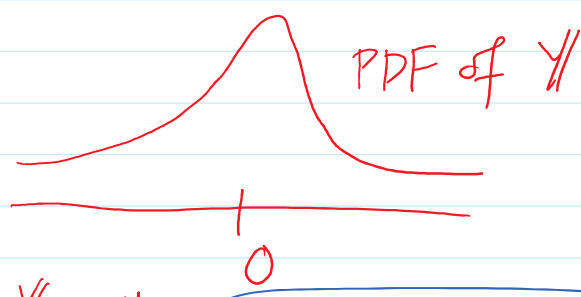
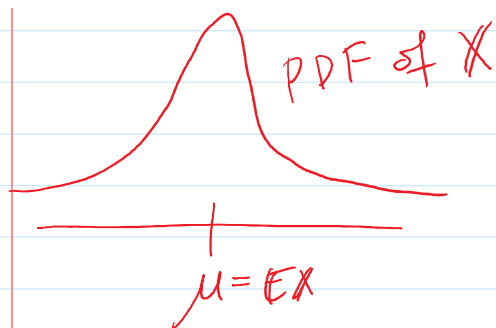
high variance



variance \approx how spread are values around the mean.

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

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



$$Y = X - \mu$$

then $\text{Var}(X) = E[Y^2]$

$$\begin{aligned} E[Y] &= E[X - \mu] \\ &= E[X] - \mu \\ &= \mu - \mu = 0 \end{aligned}$$

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

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

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

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

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

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

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

OK, ... but
takes a lot
of effort

$$= \frac{2}{\lambda^2} - \frac{2}{\lambda^2} + \frac{1}{\lambda^2}$$

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

Theorem: Short-Cut Formula for Variance

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

expected sq - sq of expectation

pf.

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

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

$$\begin{aligned} \text{Var}(X) &= \mathbb{E}[X^2] - \mathbb{E}[X]^2 \\ &= \frac{2}{\lambda^2} - \left(\frac{1}{\lambda}\right)^2 = \frac{1}{\lambda^2} \end{aligned}$$

Theorem:

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

- ① multiply X by $a \rightsquigarrow$ Var is mult. by a^2
- ② ignore additive shifts

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

$$= \mathbb{E}[a^2X^2 + 2abX + b^2] - (a\mathbb{E}[X] + b)^2$$
$$= a^2\mathbb{E}[X^2] + \cancel{2ab\mathbb{E}[X]} + \cancel{b^2} - (a^2\mathbb{E}[X]^2 + \cancel{2ab\mathbb{E}[X]} + \cancel{b^2})$$
$$= a^2(\mathbb{E}[X^2] - \mathbb{E}[X]^2)$$
$$= a^2 \text{Var}(X).$$

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

recall: $\mathbb{E}[X] = np$

$$f(x) = \binom{n}{x} p^x (1-p)^{n-x}$$

$$\mathbb{E}[X^2] = \sum_{x=0}^n x^2 f(x) = \sum_{x=1}^n x^2 \binom{n}{x} p^x (1-p)^{n-x}$$



trick 1: $x \binom{n}{x} = n \binom{n-1}{x-1}$

$$= \sum_{x=1}^n x n \binom{n-1}{x-1} p^x (1-p)^{n-x}$$

trick 2: $y = x-1$

$$= \sum_{x=1}^n x \binom{n-1}{x-1} p^x (1-p)^{n-x}$$

trick 2: $y = x - 1$
 $x = y + 1$

$$= \sum_{y=1}^{n-1} (y+1) \binom{n-1}{y} p^{y+1} (1-p)^{(n-1)-y}$$

$$= np \sum_{y=1}^{n-1} (y+1) \binom{n-1}{y} p^y (1-p)^{(n-1)-y}$$

$$= np \left[\underbrace{\sum_{y=1}^{n-1} y \binom{n-1}{y} p^y (1-p)^{(n-1)-y}}_{f(y)} + \underbrace{\sum_{y=1}^{n-1} \binom{n-1}{y} p^y (1-p)^{(n-1)-y}}_{\text{Sum of PMF of Bin}(n-1, p)} \right]$$

$$\mathbb{E}[\text{Bin}(n-1, p)]$$

$$= (n-1)p$$

Sum of PMF of
 $\text{Bin}(n-1, p)$
 $= 1$

$$= np \left[(n-1)p + 1 \right] = np(np - p + 1) = \mathbb{E}[X^2]$$

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

$$= np(np - p + 1) - (np)^2$$

$$= \cancel{n^2 p^2} - np^2 + np - \cancel{n^2 p^2}$$

$$= np(1-p)$$

Standard Deviation: $sd(X) = \sqrt{\text{Var}(X)}$

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

Defn: Moments of RVs

If r is a pos. integer we define the r^{th} moment of X as

$$\mu_r = E[X^r].$$

Ex

$$\mu_1 = \mu = E[X]$$

$$\mu_2 = E[X^2]$$

$$\mu_3 = E[X^3] \dots$$

Defn: Moment Generating Function (MGF)

If X is a RV the MGF of X is a function

$$M: \mathbb{R} \rightarrow \mathbb{R}$$

defined for $t \in \mathbb{K}$ as

$$M(t) = \mathbb{E}[e^{tX}].$$

For discrete:

$$M(t) = \sum_x e^{tx} f(x)$$

continuous:

$$M(t) = \int e^{tx} f(x) dx$$

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

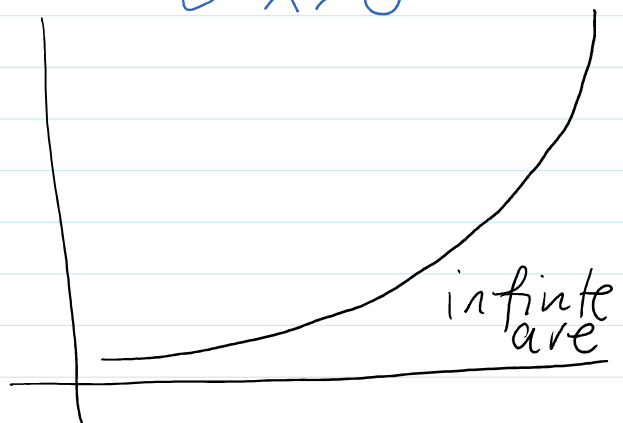
$$f(x) = \lambda e^{-\lambda x} \text{ for } x \geq 0$$

$$M(t) = \mathbb{E}[e^{tX}] = \int_0^{\infty} e^{tx} \lambda e^{-\lambda x} dx$$

$$= \lambda \int_0^{\infty} e^{(t-\lambda)x} dx$$

$$\boxed{t - \lambda \leq 0}$$

$$t - \lambda > 0$$



$$\text{If } t - \lambda \leq 0 \Leftrightarrow \boxed{t \leq \lambda}$$

$$\text{If } t - \lambda \leq 0 \Leftrightarrow \boxed{t \leq \lambda}$$

then

$$M(t) = \lambda \int_0^{\infty} e^{(t-\lambda)x} dx = \lambda \left[\frac{e^{(t-\lambda)x}}{t-\lambda} \right]_0^{\infty}$$

$$= \frac{\lambda(0-1)}{t-\lambda}$$

$$= \frac{\lambda}{\lambda-t} \quad \text{for } t \leq \lambda$$

$$M(t) = \frac{\lambda}{\lambda-t} \quad \text{for } t \leq \lambda$$

Recall: $E[X] = \frac{1}{\lambda}$; $E[X^2] = \frac{2}{\lambda^2}$

$$\textcircled{1} \quad \frac{dM}{dt} = \frac{\lambda}{(\lambda-t)^2} \Rightarrow \left. \frac{dM}{dt} \right|_{t=0} = \frac{\lambda}{\lambda^2} = \frac{1}{\lambda}$$

$$\textcircled{2} \quad \frac{d^2M}{dt^2} = \frac{2\lambda}{(\lambda-t)^3} \Rightarrow \left. \frac{d^2M}{dt^2} \right|_{t=0} = \frac{2\lambda}{\lambda^3} = \frac{2}{\lambda^2}$$