

$$\text{Expected value: } E[X] = \begin{cases} \int x f(x) dx & \text{cts} \\ \sum x f(x) & \text{discrete} \end{cases}$$

Q: Does expected value always exist? **No.**

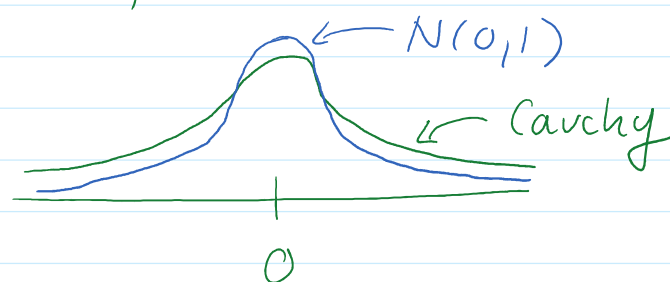
Ex. Cauchy Distribution

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

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

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

looks like  $\int_{-\infty}^{\infty} \frac{x}{x^2} dx = \int_{-\infty}^{\infty} \frac{1}{x} dx = \infty$



Facts from calc II:

$$\sum_k \frac{1}{k^2} < \infty \quad \text{but} \quad \sum_k \frac{1}{k} = \infty$$

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

## Theorem: Properties of Expectation

① Expectation is linear

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

pf. (cts)

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

② If  $X \geq 0$  then  $E[X] \geq 0$ .

support  $\subseteq [0, \infty)$

pf. (cts)

$$E[X] = \int_{-\infty}^{\infty} xf(x) dx = \int_0^{\infty} \underbrace{x}_{\geq 0} \underbrace{f(x)}_{\geq 0} dx \geq 0$$

③ If  $g_1$  and  $g_2$  are functions then

$$(i) \mathbb{E}[g_1(X) + g_2(X)] = \mathbb{E}[g_1(X)] + \mathbb{E}[g_2(X)]$$

(ii) if  $g_1(x) \leq g_2(x)$  then

$$\mathbb{E}[g_1(X)] \leq \mathbb{E}[g_2(X)]$$

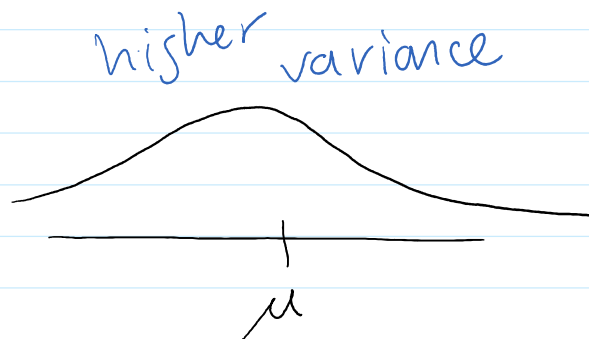
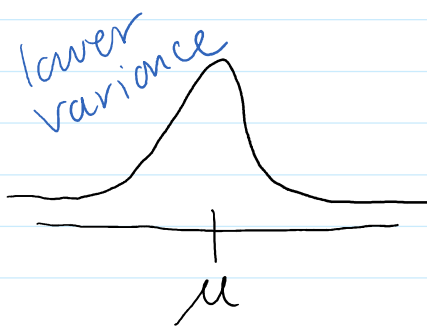
pf. Use (1), (2), Law of Unconscious Stat.

(4) If  $a \leq X \leq b$  then  $a \leq \mathbb{E}[X] \leq b$ .

pf apply (2) twice

Defn: Variance

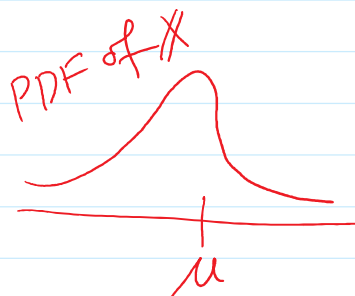
$$\mu = \mathbb{E}[X] \in \mathbb{R} = \text{mean}$$



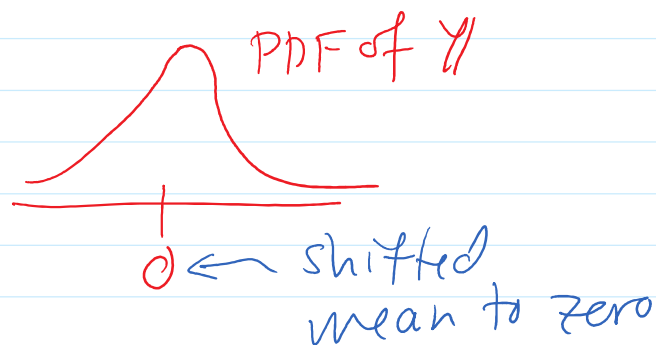
Variance = how spread out values around mean

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

$$\underline{Y = X - \mu}$$



$$Y = X - \mu$$



$$\mathbb{E}[Y] = \mathbb{E}[X - \mu] = \mathbb{E}[X] - \mu = \mu - \mu = \underline{0}$$

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


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

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

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

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

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

$$= \underbrace{\mathbb{E}[X^2]}_{\frac{2}{\lambda^2}} - 2\mu \underbrace{\mathbb{E}[X]}_{\frac{1}{\lambda}} + \mu^2$$

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

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

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

Notice: only needed to know  $E[X]$ ,  $E[X^2]$ .

Theorem: Short-cut Formula For Variance

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

expected square - sq. of expectation

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

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

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

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

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

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

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

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


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Theorem:

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

① multiply by const  $\rightsquigarrow$  multiply var by sq

② ignore additive constants

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

$$\rightarrow \mathbb{E}[a^2X^2 + 2abX + b^2] - (a\mathbb{E}[X] + b)^2$$

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

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

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

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


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

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

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

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

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

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

$$= \sum_{x=1}^n x^2 \binom{n}{x} p^x (1-p)^{n-x}$$

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

$$= \sum_{y=0}^{n-1} (y+1) \underline{n} \binom{n-1}{y} p^{y+1} (1-p)^{(n-1)-y}$$

$$= np \sum_{y=0}^{n-1} (y+1) \binom{n-1}{y} p^y (1-p)^{(n-1)-y}$$

$$= np \left[ \sum_{y=0}^{n-1} y \binom{n-1}{y} p^y (1-p)^{(n-1)-y} + \sum_{y=0}^{n-1} \binom{n-1}{y} p^y (1-p)^{(n-1)-y} \right]$$

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

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

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

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

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

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

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Defn: Moments of a RV

If  $r$  is a pos. integer then the  $r^{\text{th}}$  moment of  $X$  is defined as

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


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Ex.

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

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



$$\mu_3 = \mathbb{E}[X^3]$$

Defn: Moment Generating Function (MGF)

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

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

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

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

$$\mathbb{E}[g(X)] = \begin{cases} \int g(x) f(x) dx \\ \sum g(x) f(x) \end{cases}$$

In our case  $g(x) = e^{tx}$

For discrete:

$$M(t) = \mathbb{E}[e^{tX}] = \sum_x e^{tx} f(x)$$

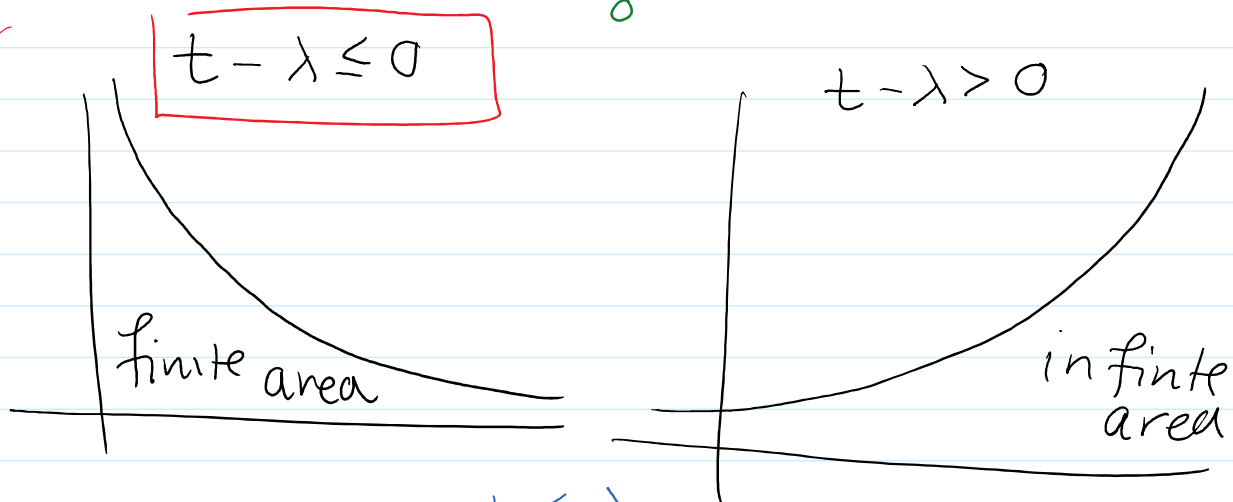
For continuous:

$$M(t) = \mathbb{E}[e^{tX}] = \int_{\mathbb{R}} e^{tx} f(x) dx$$

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

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

$$\begin{aligned} M(t) &= E[e^{tX}] = \int e^{tx} f(x) dx \\ &= \int_0^{\infty} e^{tx} \lambda e^{-\lambda x} dx \\ &= \int_0^{\infty} \lambda e^{(t-\lambda)x} dx \end{aligned}$$



If  $t - \lambda \leq 0 \rightarrow t \leq \lambda$

$$= \lambda \int_0^{\infty} e^{(t-\lambda)x} dx = \lambda \left[ \frac{e^{(t-\lambda)x}}{t-\lambda} \right]_0^{\infty} = \frac{\lambda}{t-\lambda} [0 - 1]$$

$$M(t) = \begin{cases} \frac{\lambda}{\lambda - t} & \text{for } t \leq \lambda \end{cases}$$

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

consider:

consider:

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

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