

Defn: Expectation / Expected Value / Mean

(i) Discrete: $E[X] = \sum_x x f(x)$

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

Ex. $X \sim \text{Bin}(n, p)$ ← independent
 = flip n coins w/ prob p of H,
 $X = \#$ of heads

$\text{Support}(X) = \{0, 1, 2, \dots, n\}$

the pmf is

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

Note: to show this is a valid pmf

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

(2) $\sum_x f(x) = 1$ (Binomial Theorem)
 $(x+y)^n = \sum_{x=0}^n \binom{n}{x} x^x y^{n-x}$

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

$$= \sum_{x=0}^n x \binom{n}{x} p^x (1-p)^{n-x}$$

→ $x \neq 0$

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

aside:

$$x \binom{n}{x} = x \frac{n!}{x!(n-x)!} = \frac{n!}{(x-1)!(n-x)!}$$

$$= \frac{n!}{(x-1)!(n-x)!}$$

$$\begin{aligned}
 & x = \emptyset 1 \\
 & \text{define } y = x - 1 \Leftrightarrow x = y + 1 \\
 & = \sum_{y=0}^{n-1} n \binom{n-1}{y} p^{y+1} (1-p)^{n-y-1} = n \binom{n-1}{x-1} p^x (1-p)^{n-x} \\
 & = np \sum_{y=0}^{n-1} \underbrace{\binom{n-1}{y} p^y (1-p)^{(n-1)-y}}_{\text{pmf of Bin}(n-1, p)} \\
 & \quad \underbrace{\text{Sum of pmf of Bin}(n-1, p) \text{ over support}}_{= 1}
 \end{aligned}$$

$$\begin{aligned}
 Y & \sim \text{Bin}(n-1, p) \\
 f(y) & = \binom{n-1}{y} p^y (1-p)^{(n-1)-y} \\
 \text{Support}(Y) & = \{0, 1, \dots, n-1\}
 \end{aligned}$$

$$\boxed{= np} = (\# \text{ of trials}) (\text{prds. of success for each})$$

↑ doesn't have to be in the support (integer)

General trick:

Convert tricky sums/integrals to sums/integrals of pmf/pdfs.

Theorem: Law of the Unconscious Statistician

$$E[g(X)] = \begin{cases} \sum_x g(x) f(x) & \text{discrete} \\ \int g(x) f(x) dx & \text{continuous} \end{cases}$$

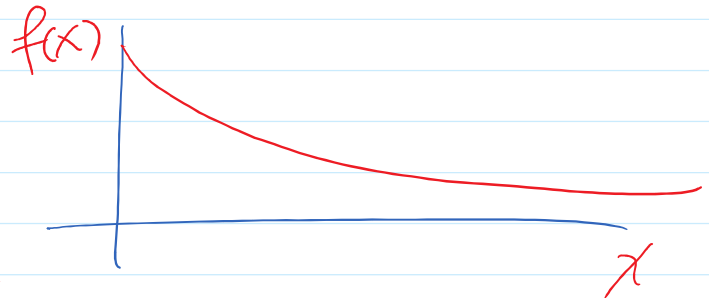
$$\int_{\mathbb{R}} g(x) f(x) dx$$

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

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

Saw

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



Q: $E[X^2] = \int x^2 f(x) dx$

$$= \int_0^{\infty} x^2 \lambda e^{-\lambda x} dx = \int u dv$$

by Parts: $u = x^2$ $v = -e^{-\lambda x}$
 $du = 2x dx$ $dv = \lambda e^{-\lambda x} dx$

$$= uv - \int v du$$

$$= \left[-x^2 e^{-\lambda x} \right]_0^{\infty} - \int_0^{\infty} -e^{-\lambda x} 2x dx$$

$$= 0 + 2 \int_0^{\infty} \lambda x e^{-\lambda x} dx$$

$$E[X] = \int x f(x) dx$$

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

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

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

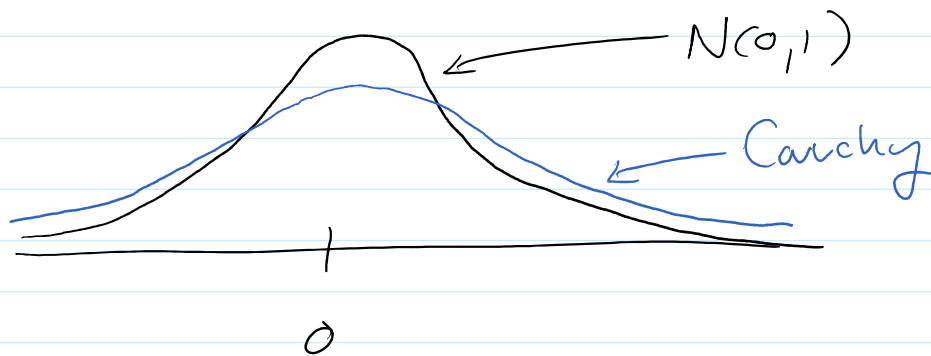
improper integral:

$\int_0^{\infty} \frac{1}{x^2} dx$ has a meaningful value

$\int_0^{\infty} \frac{1}{x} dx$ no meaningful value

Ex. X has a Cauchy distribution

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



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

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

$\underbrace{\frac{x}{1+x^2}}_{\text{asymptotically } \frac{1}{x}}$

Theorem: Properties of E

$a, b \in \mathbb{R}$

(a) $E[aX + b] = aE[X] + b$
(linearity)

p.f.

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

(b) If $X \geq 0$ (Support(X) is non-neg.)
then $E[X] \geq 0$.

p.f.

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

(c) If g_1 and g_2 are functions and
 $g_1(x) \leq g_2(x) \quad \forall x$

then $E[g_1(X)] = E[g_2(X)]$

pf. Combine (a) and (b)

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



$$E[g_1(X)] - E[g_2(X)] \leq 0$$

\Updownarrow (linearity)

$$E[\underbrace{g_1(X) - g_2(X)}_{\text{call this } Y}] \leq 0$$

$$E[Y] \leq 0 \quad \text{where } Y \leq 0$$

(d) Furthermore if $a \leq X \leq b$ then

$$a \leq E[X] \leq b.$$

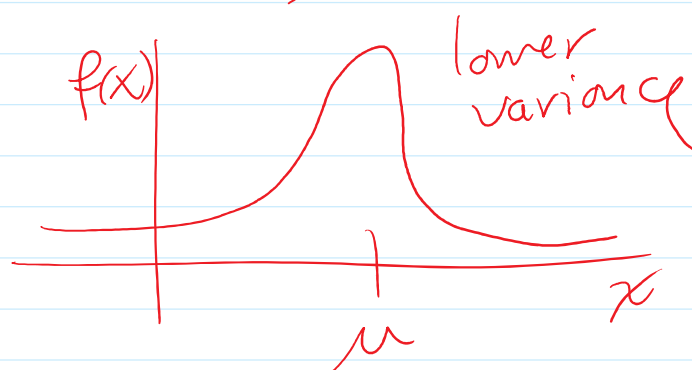
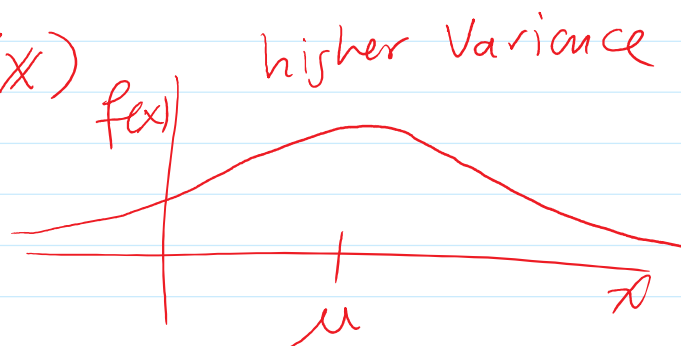
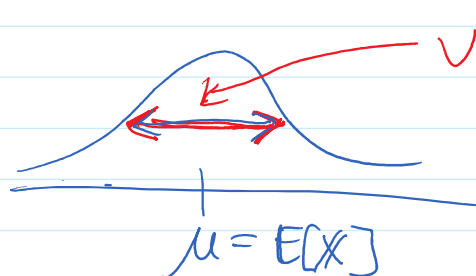
pf use previous Theorems.

Defn: Variance

Variance of a r.v. tells you how spread the mass/density is around the mean.

— $\text{Var}(X)$

higher Variance



Mathematically,

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

Note:

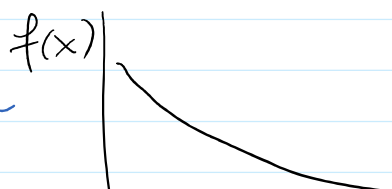
$$Y = X - E[X]$$

same number
 $X - \mu$ $\mu = E[X]$

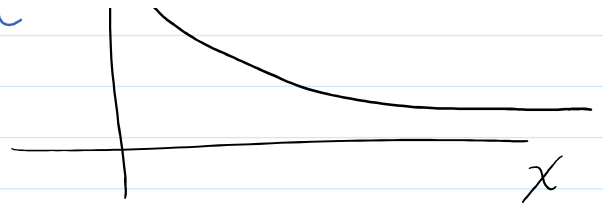
$$\begin{aligned} E[Y] &= E[X - E[X]] = E[X] - E[E[X]] \\ &= E[X] - E[X] \\ &= 0 \end{aligned}$$

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

recall: $E[X] = 1/\lambda = \mu$



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

$$= \int (x - \mu)^2 f(x) dx$$

$$= \int (x - 1/\lambda)^2 \lambda e^{-\lambda x} dx$$

$$= \int (x^2 - \frac{2x}{\lambda} + \frac{1}{\lambda^2}) \lambda e^{-\lambda x} dx$$

$$= \underbrace{\int x^2 \lambda e^{-\lambda x} dx}_{E[X^2]} - \frac{2}{\lambda} \underbrace{\int x \lambda e^{-\lambda x} dx}_{E[X]} + \frac{1}{\lambda^2} \underbrace{\int \lambda e^{-\lambda x} dx}_1$$

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

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

Theorem 1 Short-cut Theorem For Variance

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

pf.

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

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

$E[c] = c$
when c is

$$= E[X^2] - E[2X\mu] + E[\mu^2] \quad \text{a const.}$$

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

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

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

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

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

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

So

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

Theorem:

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

pf.

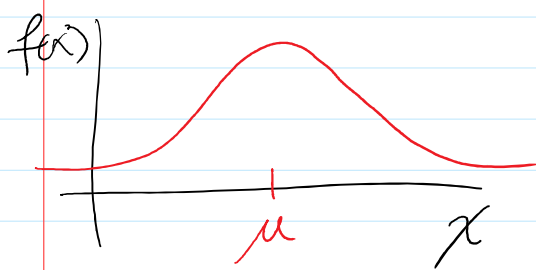
$$\text{Var}(aX + b)$$

$$= E[(aX + b)^2] - E[aX + b]^2 \quad (\text{short-cut})$$

$$= E[a^2X^2 + 2abX + b^2] - (aE[X] + b)^2$$

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

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



add b
→



multiply
 a
→

