

10/13

Last time: Expectation $E(X)$

Discrete $\sum_i x_i p(x_i)$

Continuous, $\int_{-\infty}^{\infty} x f(x) dx$

Today:

Theorem:

Suppose that $Y = g(X)$

g : "Nice" function.

(a) If X is discrete with p.m.f. $p(x)$

Then, $\checkmark E(Y) = \sum_x g(x) p(x)$ $\checkmark E(X) = \sum_x x p(x)$

(provided $\sum_x |g(x)| p(x) < \infty$)

(b) If X is continuous with pdf $f(x)$

Then $\checkmark E(Y) = \int_{-\infty}^{\infty} g(x) f(x) dx$ $\checkmark E(X) = \int_{-\infty}^{\infty} x f(x) dx$

(provided $\int_{-\infty}^{\infty} |g(x)| f(x) dx < \infty$)

Example:

X : the magnitude of the velocity of gas molecule

Then it is known (Maxwell's distribution)
that

$$f_X(x) = \begin{cases} \frac{\sqrt{2/\pi}}{\sigma^3} \cdot x^2 e^{-\frac{x^2}{2\sigma^2}} & x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Average kinetic energy $= Y = \frac{1}{2} m X^2$

New random variable

Question: What is the average kinetic energy? $E(Y)$

Solution: $E(Y) = \int_{-\infty}^{\infty} \left(\frac{1}{2} m x^2 \right) f_X(x) dx$

$$= \int_0^{\infty} \frac{1}{2} m x^2 \cdot \frac{\sqrt{2/\pi}}{\sigma^3} x^2 e^{-\frac{x^2}{2\sigma^2}} dx$$

$$= \frac{\sqrt{2/\pi}}{2\sigma^3} m \int_0^{\infty} x^4 e^{-\frac{x^2}{2\sigma^2}} dx$$

$$= \frac{\sqrt{2/\pi}}{2\sigma^3} m \cdot \int_0^{\infty} x^4 e^{-\frac{x^2}{2\sigma^2}} dx$$

(2)

$$= \frac{\sqrt{2/\pi}}{2\sigma^3} m \int_0^{\infty} x^4 e^{-x^2/2\sigma^2} dx$$

$$= \frac{\sqrt{2/\pi}}{2\sigma^3} m \int_0^{\infty} 4\sigma^2 u^2 e^{-u} \frac{\sigma}{\sqrt{2u}} du$$

$$\Gamma(x) = \int_0^{\infty} e^{-u} u^{x-1} du$$

$x \neq -1, -2, -3, \dots$

$$\begin{aligned} u &= \frac{x^2}{2\sigma^2} \\ du &= \frac{2x dx}{2\sigma^2} \\ dx &= \frac{\sigma^2}{x} du \\ &= \frac{\sigma^2}{\sqrt{2\sigma^2 u}} du \end{aligned}$$

$$= \frac{\sqrt{2/\pi}}{2} \sigma^2 m \frac{4}{\sqrt{2}} \int_0^{\infty} u^{3/2-1} e^{-u} du$$

$$= \frac{4m\sigma^2}{2\sqrt{\pi}} \int_0^{\infty} u^{5/2-1} e^{-u} du$$

$$= \frac{4m\sigma^2}{2\sqrt{\pi}} \cdot \Gamma\left(\frac{5}{2}\right)$$

$$= \frac{4m\sigma^2}{2\sqrt{\pi}} \cdot \frac{3}{4} \sqrt{\pi}$$

$$= \frac{3}{2} m \sigma^2$$

$$\begin{aligned} \Gamma\left(\frac{5}{2}\right) &= \frac{3}{2} \Gamma\left(\frac{3}{2}\right) \\ &= \frac{3}{2} \cdot \frac{1}{2} \Gamma\left(\frac{1}{2}\right) \\ &= \frac{3}{4} \cdot \sqrt{\pi} \end{aligned}$$

Theorem:

Suppose that X_1, X_2, \dots, X_n are jointly distributed random variables and

$$Y = g(X_1, X_2, \dots, X_n)$$

(a) If the X_i are discrete with joint p.m.f. $p(x_1, x_2, \dots, x_n)$, then

$$E(Y) = \sum_{x_1, x_2, \dots, x_n} g(x_1, x_2, \dots, x_n) \cdot p(x_1, x_2, \dots, x_n)$$

(b) If X_i are continuous with joint density function $f(x_1, x_2, \dots, x_n)$, then

$$E(Y) = \underbrace{\int \int \dots \int}_n g(x_1, x_2, \dots, x_n) f(x_1, x_2, \dots, x_n) dx_1 dx_2 \dots dx_n$$

Corollary: If X and Y are independent random variables and g and h are fixed functions, then

$$E[g(X) h(Y)] = E[g(X)] \cdot E[h(Y)]$$

(3)

Theorem: If X_1, X_2, \dots, X_n are jointly distributed random variables with expectations $E(X_i)$ and

Y is given by

$$Y = a + \sum_{i=1}^n b_i X_i \quad \text{then}$$

$$E(Y) = a + \sum_{i=1}^n b_i E(X_i)$$

Where a, b_1, b_2, \dots, b_n are constants.

Proof: (Continuous case)

$n=2$

$$Y = a + b_1 X_1 + b_2 X_2 = g(X_1, X_2)$$

$$E(Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (a + b_1 x_1 + b_2 x_2) f(x_1, x_2) dx_1 dx_2$$

$$= a \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x_1, x_2) dx_1 dx_2 + b_1 \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 f(x_1, x_2) dx_1 dx_2 + b_2 \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_2 f(x_1, x_2) dx_1 dx_2$$

$$= a + b_1 \int_{-\infty}^{\infty} x_1 \left(\int_{-\infty}^{\infty} f(x_1, x_2) dx_2 \right) dx_1 + b_2 \int_{-\infty}^{\infty} x_2 \left(\int_{-\infty}^{\infty} f(x_1, x_2) dx_1 \right) dx_2$$

(6)

$$= a + b_1 \int_{x_1=-\infty}^{\infty} x_1 f_{X_1}(x_1) dx_1 + b_2 \int_{x_2=-\infty}^{\infty} x_2 f_{X_2}(x_2) dx_2$$

pdf of X_1
(marginal pdf)

$$= a + b_1 E(X_1) + b_2 E(X_2)$$

$n=2$ is done.
By induction check the rest //

Example: $X \sim \text{Binomial}(n, p)$
 $E(X) = np$

To get this

$$E(X) = \sum_{k=0}^n k \cdot P(X=k)$$

||

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

Homework

Another way:

If $X \sim \text{Binomial}(n, p)$
 then we can think of X as

$$X = X_1 + X_2 + X_3 + \dots + X_n$$

where X_i 's are (independent)
 and (identically distributed) (i.i.d.)

Bernoulli distribution

~~$E(X_i) =$~~

X_i	Prob.
1	p
0	$1-p$

$$E(X_i) = 1 * p + 0 * (1-p) = p$$

for all i

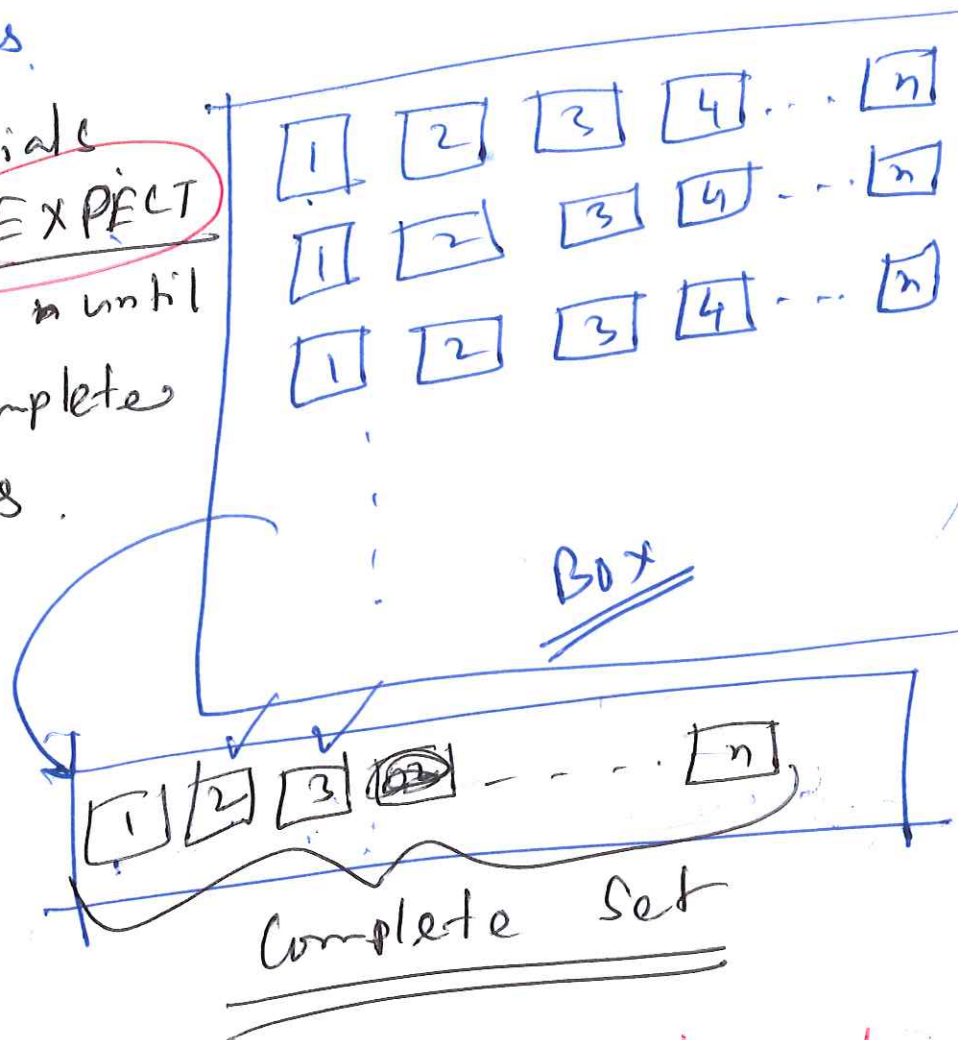
Therefore, using the last theorem

$$\begin{aligned} \checkmark E(X) &= E(X_1) + E(X_2) + \dots + E(X_n) \\ &= \underbrace{p + p + \dots + p}_{n \text{ times}} \\ &= \boxed{np} \checkmark \end{aligned}$$

Example: (Coupon Collection)

- Suppose that you collect coupons.
- There are n - distinct types of coupons.
- On each trial you are equally likely to get a coupon of any of the types.

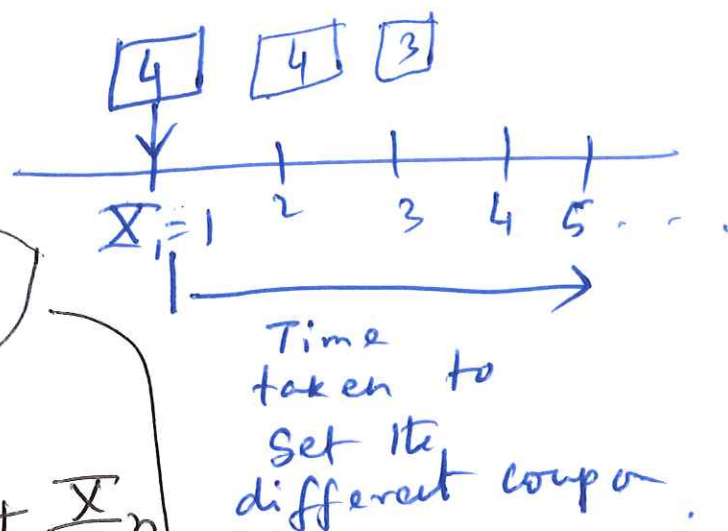
How many trials would you EXPECT to go through until you had a complete set of coupons.



Solution: X_i : # of trials up to and including the trial on which the first coupon is collected $X_i = 1$

X_2 : # of trials from the ~~that~~ point ⁽⁹⁾
 (picking up the first coupon) up to
 and including the trial on which
 the next coupon DIFFERENT FROM
 the first is obtained

Similarly X_3 etc.



Then the total # of trials \bar{X}

$$= X_1 + X_2 + X_3 + \dots + X_n$$

$$\text{So, } E(\bar{X}) = E(X_1) + E(X_2) + E(X_3) + \dots + E(X_n)$$

$$X_1 = 1 \quad \left| \quad E(X_1) = 1$$

~~Supp~~

Consider

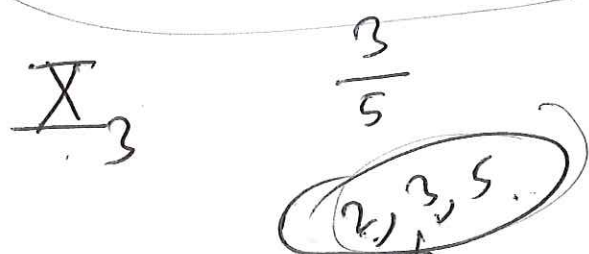
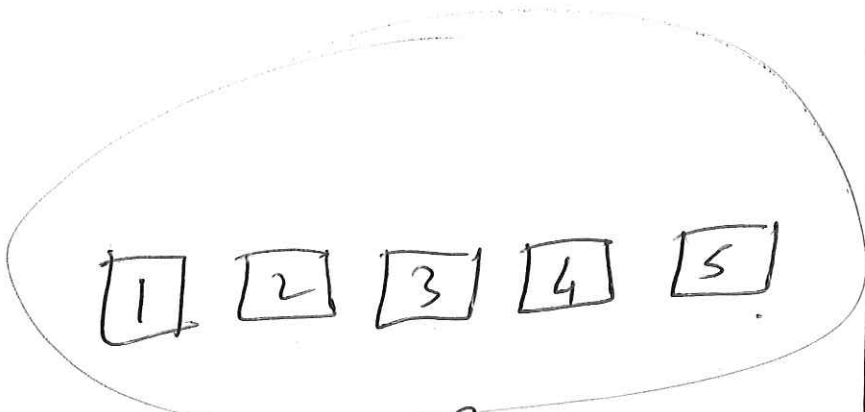
X_r

\sim Geometric distribution
 probability of success

$(r-1)$ coupons are picked up

$n - (r-1) = n - r + 1$ coupons left

$$\text{Probability of success} = \frac{n - r + 1}{n}$$



So,
 $E(X_r) = \frac{n}{n-r+1}$
(By the property of geometric distribution)

Hence $E(\bar{X}) = E(X_1) + E(X_2) + \dots + E(X_n)$
 $= \frac{n}{n} + \frac{n}{n-1} + \frac{n}{n-2} + \dots + \frac{n}{1}$

$= n \sum_{r=1}^n \frac{1}{r}$

//

Variance and Standard Deviation

Definition: If X is a random variable with expectation $E(X)$, then the variance of X is

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

Suppose X is continuous with pdf $f(x)$.

Think

$$Y = (X - E(X))^2 = g(X)$$

$$E(Y) = E((X - E(X))^2)$$

$$= \int_{-\infty}^{\infty} g(x) \cdot f(x) dx$$

def

$$= \int_{-\infty}^{\infty} (x - \underbrace{E(X)}_{\text{(a number)}})^2 f(x) dx$$

So,

$$\text{Var}(X) = \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx$$

Theorem:Suppose $Y = a + bX$ Then $\text{Var}(Y) = b^2 \text{Var}(X)$,

Proof: $\text{Var}(Y) \stackrel{\text{def}}{=} E((Y - E(Y))^2)$

$$= E\left(\left(\cancel{a} + \cancel{b}X - (\cancel{a} + \cancel{b}E(X))\right)^2\right)$$

$$= E\left(b^2 (X - E(X))^2\right)$$

$$= b^2 E(X - E(X))^2$$

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

Bernoulli distribution:

X	Prob.
✓ 1	p
✓ 0	$(1-p)$

$$E(X) = 1 \cdot p + 0 \cdot (1-p)$$

$$= p$$

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

$$= (1-p)^2 \cdot P(X=1) + (0-p)^2 \cdot P(X=0)$$

$$\begin{aligned}
 &= (1-p)^2 \cdot p + (-p)^2 \cdot (1-p) \\
 &= (1+p^2-2p)p + p^2(1-p) \\
 &= p + \cancel{p^3} - 2p^2 + \cancel{p^2} - \cancel{p^3} \\
 &= p - p^2 = \boxed{p(1-p)}
 \end{aligned}$$

Variance
 Bernoulli

for
distribution

Normal distribution

$X \sim N(\mu, \sigma^2)$

$E(X) = \mu$ (done last time)

$$\begin{aligned}
 \text{Var}(X) &= E((X - E(X))^2) \\
 &= E[(X - \mu)^2] \\
 &= \int_{-\infty}^{\infty} (x - \mu)^2 \cdot f_X(x) dx \\
 &= \int_{-\infty}^{\infty} (x - \mu)^2 \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} dx
 \end{aligned}$$

(14)

$$\int_{-\infty}^{\infty} \sigma^2 u^2 \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}u^2} du$$

Sub. $u = \frac{x-\mu}{\sigma}$

$$du = \frac{dx}{\sigma}$$

② $x = -\infty, u = -\infty$
 $x = +\infty, u = +\infty$

$$= \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} u^2 \cdot e^{-\frac{1}{2}u^2} du \quad \text{even}$$

$$= \frac{\sigma^2}{\sqrt{2\pi}} \cdot (2) \int_0^{\infty} u^2 \cdot e^{-\frac{1}{2}u^2} du$$

$$= \frac{2\sigma^2}{\sqrt{2\pi}} \int_0^{\infty} (2z) \cdot e^{-z} \cdot \frac{dz}{\sqrt{2z}}$$

Sub $z = \frac{u^2}{2}$

$$dz = u du$$

$$du = \frac{dz}{\sqrt{2z}}$$

$$= \frac{2\sigma^2}{\sqrt{2\pi}} \int_0^{\infty} z^{1/2} e^{-z} dz$$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \int_0^{\infty} z^{\frac{3}{2}-1} e^{-z} dz$$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \Gamma\left(\frac{3}{2}\right)$$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \cdot \frac{1}{2} \sqrt{\pi}$$

$$= \boxed{\sigma^2}$$

Variance
of
 $N(\mu, \sigma^2)$