

Variance and Covariance

July, 23, 2020

1) Applications of Linearity of Expectation

2) Variance

3) Covariance and Correlation

Last time:

Distributions:

$$X \sim \text{Bernoulli}(p), \quad \Pr[X] = \begin{cases} p & \text{if } x=1 \\ 1-p & \text{if } x=0 \end{cases}$$

$$X \sim \text{Bin}(n, p), \quad \Pr[X=i] = \binom{n}{i} p^i (1-p)^{n-i}$$

Linearity of Expectation:

$$E[c_1x_1 + \dots + c_nx_n] = c_1E[x_1] + \dots + c_nE[x_n]$$

I) Applications of Linearity of Expectation:

Example: Hand back assignments to n students at random.

Expected number of students who get back their hw?

X_n : the number of students who get back their hw.

Use indicator r.v.

$$I_i = \begin{cases} 1 & \text{1 } i^{\text{th}} \text{ student get back } \frac{1}{n} \text{ their own assignment} \\ 0 & \text{others} \end{cases}$$
$$\Pr[I_i=1] = \frac{1}{n}$$

$$X_n = I_1 + \dots + I_n$$

$$E[X_n] = E[I_1 + \dots + I_n] = E[I_1] + \dots + E[I_n]$$

↑
linearity

$$= \sum_{i=1}^n E[I_i] = \sum_{i=1}^n \frac{1}{n} = n \cdot \frac{1}{n} = 1$$

$$E[I_i] = \sum_{a \in \{0,1\}} a \Pr[I_i=a] = 1 \times \Pr[I_i=1] + 0 \times \Pr[I_i=0]$$
$$= \frac{1}{n}$$

The expected number of students who get their own home works in a class size n is $\underline{\underline{1}}$.

Example: Throw m balls in n bins.

The expected number of empty bins.

X : number of empty bins

Help Indicators, help!

$$I_i = \begin{cases} 1 & i^{\text{th}} \text{ bin is empty} \\ 0 & \text{otherwise} \end{cases} \xrightarrow{\text{PR}} E[I_i] = \Pr[I_i=1]$$

$$X = \sum_{i=1}^n I_i \quad \text{linearity}$$

$$E[X] = E\left[\sum_{i=1}^n I_i\right] = \sum_{i=1}^n E[I_i] = \sum_{i=1}^n \left(\frac{n-1}{n}\right)^m = \left(\frac{n-1}{n}\right)^m \sum_{i=1}^n 1$$

$$E[I_i] = \sum_{a \in \{0,1\}} a \cdot \Pr[I_i=a] = 1 \cdot \Pr[I_i=1] + 0 \cdot \Pr[I_i=0] = \left(\frac{n-1}{n}\right)^m$$

For $n=m$ and $n \rightarrow \infty$?

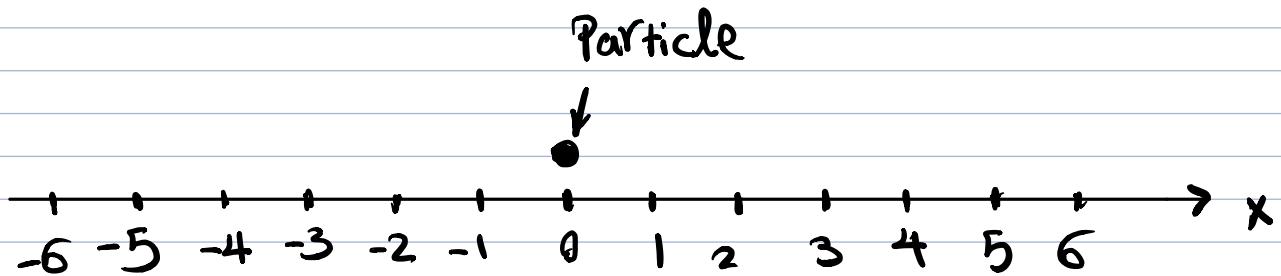
$$E[X] = n \left(\frac{n-1}{n}\right)^n = n \left(1 - \frac{1}{n}\right)^n = \frac{n}{e} \approx 0.37n$$

$$\lim_{n \rightarrow \infty} \left(1 - \frac{1}{n}\right)^n = \frac{1}{e}$$

$\sim 37\%$ of bins will be empty.

2) Variance:

Example: Random Walk



- The Particle moves in one dimension.
- At each time step, Particle moves to the right or left with equal probability.

S_n = The position of the Particle after n moves

$$X_i = \text{the } i^{\text{th}} \text{ movement} \Rightarrow X = \begin{cases} +1 & \Pr[1] = \frac{1}{2} \\ -1 & \Pr[-1] = \frac{1}{2} \end{cases}$$

$$S_n = 0 + X_1 + X_2 + \dots + X_n = \sum_{i=1}^n X_i$$

$$E[S_n] = E\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n E[X_i] = 0 \rightarrow \text{not useful}$$

$$E[X_i] = \sum_{a \in \{1, -1\}} a \times \Pr[X_i = a] = 1 \times \Pr[X_i = 1] + (-1) \times \Pr[X_i = -1]$$

$$= 1 \times \frac{1}{2} + (-1) \times \frac{1}{2} = 0$$

what is the expected distance from 0? $|S_n|$

We work $\boxed{S_n^2}$

Hint:

$$\underline{(x_1 + \dots + x_n)}^2 = \sum_{i=1}^n x_i^2 + 2 \sum_{i < j} x_i x_j$$

$$E[S_n^2] = E[(x_1 + \dots + x_n)^2]$$

$$= E\left[\sum_{i=1}^n x_i^2 + 2 \sum_{i < j} x_i x_j\right]$$

$$= \sum_{i=1}^n E[x_i^2] + 2 \sum_{i < j} E[x_i x_j] = \sum_{i=1}^n 1 = n$$

$$E[x_i^2] = \sum_{a \in \{\pm 1\}} a^2 \times \Pr[x_i = a] = (1)^2 \Pr[x_i = 1] + (-1)^2 \Pr[x_i = -1]$$

$$= 1 \times \frac{1}{2} + 1 \times \frac{1}{2} = 1$$

$$E[\underbrace{x_i x_j}] = \sum_{a,b \in \{\pm 1\}} a b \times \Pr[x_i = a, x_j = b] \rightarrow \Pr[x_i = a] \times \Pr[x_j = b]$$

$$= (1)(1) \Pr[x_i = 1] \Pr[x_j = 1]$$

$$+ (1)(-1) \Pr[x_i = 1] \Pr[x_j = -1]$$

$$+ (-1)(1) \Pr[x_i = -1] \Pr[x_j = 1]$$

$$+ (-1)(-1) \Pr[x_i = -1] \Pr[x_j = -1]$$

$$= 1 \times \frac{1}{4} - 1 \times \frac{1}{4} - 1 \times \frac{1}{4} + 1 \times \frac{1}{4} = 0$$

so
 $E[S_n^2] = n$
 \downarrow

Variance
of S_n

Definition: For a r.v. X with expectation $E[X] = \mu$

the variance of X is defined to be

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

what does variance measure? The deviation from mean value.

The square root $\sigma(X) := \sqrt{\text{Var}(X)}$ is

the standard deviation of variable X .

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

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

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

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

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

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

Some Properties of Variance:

$$\text{Var}(X + c) = \text{Var}(X) \rightarrow \underline{\text{exercise}}$$

$$\text{Var}(cX) = c^2 \text{Var}(X) \rightarrow \underline{\text{exercise.}}$$

More Examples:

• Uniform distribution

X is a uniform random variable on the set $\{1, \dots, n\}$

$$X \sim \text{Uniform}\{1, \dots, n\}, \quad \underbrace{\Pr[X=i] = \frac{1}{n}}_{\text{for } i \in \{1, \dots, n\}}$$

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

$$\left\{ \begin{array}{l} E[X] = \sum_{a \in \{1, \dots, n\}} a \times \Pr[X=a] = \sum_{a=1}^n \frac{a}{n} = \frac{1}{n} \sum_{a=1}^n a = \frac{1}{n} \frac{n(n+1)}{2} \\ \\ E[X^2] = \sum_{a \in \{1, \dots, n\}} a^2 \times \Pr[X=a] = \sum_{a=1}^n \frac{a^2}{n} = \frac{1}{n} \sum_{a=1}^n a^2 = \frac{1}{n} \frac{n(n+1)(2n+1)}{6} \\ \\ = \frac{(n+1)(2n+1)}{6} \end{array} \right.$$

$$\text{Var}(X) \leq \frac{n^2-1}{12}.$$

Example: Hand back assignments to n Students at random.

X_n : the number of students who get back their hw.

use indicators! $I_i = \begin{cases} 1 & \text{student } i \text{ gets their hw} \\ 0 & \text{otherwise} \end{cases}$ $\Pr \frac{1}{n}$

$$- X_n = I_1 + I_2 + \dots + I_n = \sum_{i=1}^n I_i, \quad \underline{\text{exercise}}$$

$$- E[X_n] = 1 \quad \downarrow$$

$$\text{Hint: } (I_1 + \dots + I_n) = \sum_{i=1}^n I_i^2 + 2 \sum_{i < j} I_i I_j$$

$$\text{Var}(X) = E[X^2] - E[X]^2 = E[X^2] - 1$$

$$E[X^2] = E\left[\left(\sum_{i=1}^n I_i\right)^2\right] = \sum_{i=1}^n E[I_i^2] + 2 \sum_{i < j} E[I_i I_j]$$

$$1) E[I_i^2] = 1 \times \Pr[I_i = 1] + 0 \times \Pr[I_i = 0] = \frac{1}{n}$$

$$2) E[\underbrace{I_i I_j}_{i \neq j}] = 1 \times \Pr[I_i = 1] \times \Pr[I_j = 1] = \frac{1}{n(n-1)}$$

$$\hookrightarrow E[X^2] = \sum_{i=1}^n \frac{1}{n} + 2 \sum_{i < j} \frac{1}{n(n-1)} \quad \text{Choose a Pair of indecis}$$

$$= n \cdot \frac{1}{n} + 2 \binom{n}{2} \frac{1}{n(n-1)} = 2$$

$$\Rightarrow \boxed{\text{Var}(X) = 2 - 1 = 1}$$

Independent Random Variables:

Theorem: For independent random variables X, Y we have

$$E[XY] = E[X]E[Y]$$

Proof:

$$\begin{aligned}
 E[\underline{XY}] &= \sum_a \sum_b ab \Pr[X=a, Y=b] \\
 &= \sum_a \sum_b ab \Pr[X=a] \Pr[Y=b] \\
 &= \left(\sum_a a \Pr[X=a] \right) \times \left(\sum_b b \Pr[X=b] \right) \\
 &= E[X] \times E[Y]. \quad \square
 \end{aligned}$$

independent
 X and Y

Theorem: For independent random variables X, Y

we have

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$$

Proof:

$$\begin{aligned}
 \text{Var}(X+Y) &= E[(X+Y)^2] - (E[X+Y])^2 \\
 &= E[\underline{X^2} + 2XY + Y^2] - (E[X]^2 + 2E[X]E[Y] + E[Y]^2) \\
 &\stackrel{\text{linearity}}{=} E[X^2] + 2E[XY] + E[Y^2] - E[X]^2 - 2E[X]E[Y] - E[Y]^2 \\
 &= (E[X^2] - E[X]^2) + (E[Y^2] - E[Y]^2) + 2(E[XY] - E[X]E[Y])
 \end{aligned}$$

$$= \text{Var}(X) + \text{Var}(Y) + 2(\underbrace{E[XY] - E[X]E[Y]}_{=0})$$

If X and Y are independent \rightarrow

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y).$$

If X and Y are independent, then

$$\text{Var}(X-Y) = ?$$

remember

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

$$\begin{aligned} \text{Var}(X+(-Y)) &= \text{Var}(X) + \text{Var}(-Y) \\ &\leq \text{Var}(X) + (-1)^2 \text{Var}(Y) \\ &= \text{Var}(X) + \text{Var}(Y) \end{aligned}$$

Example: X_n is the number of heads in n tosses of a biased coin with heads probability P .

$$\underset{i\text{th toss}}{\underline{X_n}} \sim ? \quad \text{Bin}(n, P)$$

$$\rightarrow I_i = \begin{cases} 1 & \text{heads } P \\ 0 & \text{tails } 1-P \end{cases}$$

$$X_n = \sum_{i=1}^n I_i$$

$$E[X_n] = E[\sum_{i=1}^n I_i] = \sum_{i=1}^n E[I_i] = \sum_{i=1}^n P = nP$$

$$\text{Var}(X_n) = \text{Var}\left(\sum_{i=1}^n I_i\right) = \sum_{i=1}^n \text{Var}(I_i) = \sum_{i=1}^n P(1-P)$$

\uparrow
 $= nP(1-P)$

$$\begin{aligned}\text{Var}(I_i) &= E[I_i^2] - \underline{E[I_i]}^2 \\ &= 1 \times \Pr[I_i=1] + 0^2 \times \Pr[I_i=0] - P^2 = P - P^2 = \underline{P(1-P)}\end{aligned}$$

3) Covariance and Correlation:

Definition: The covariance of random variables

X and Y is

$$\text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)] = E[XY] - E[X]E[Y]$$

Remarks:

1. If X, Y are independent. $\text{Cov}(X, Y) = 0$

• Can we say

if $\text{Cov}(X, Y) = 0$ \Rightarrow X, Y are independent? No

The converse of $\frac{1}{2}$ is not true.

$$\begin{aligned}2. \text{Cov}(X, X) &= E[X \cdot X] - E[X]E[X] \\ &= E[X^2] - \underline{E[X]}^2 = \text{Var}(X)\end{aligned}$$

3. Covariance is bilinear

For any collection of random variables

$\{x_1, \dots, x_n\}$, $\{y_1, \dots, y_m\}$ and fixed constants

$\{a_1, \dots, a_n\}$, $\{b_1, \dots, b_m\}$ then

$$\text{Cov}\left(\sum_{i=1}^n a_i x_i, \underbrace{\sum_{j=1}^m b_j y_j}_Y\right) = \sum_{i=1}^n \sum_{j=1}^m a_i b_j \text{Cov}(x_i, y_j)$$

About $\text{Cov}(X, Y)$

1. The sign of X, Y determines how X and Y are related
2. The magnitude is hard to interpret.

Definition: Correlation.

Suppose X and Y are random variables

with $\sigma(X) > 0$ and $\sigma(Y) > 0$. The correlation of X and Y is

$$\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma(X) \sigma(Y)}.$$

Theorem:

$$-1 \leq \text{Corr}(x, y) \leq 1$$

$$X = \alpha Y + b \quad \begin{cases} \text{if } \alpha > 0 \Rightarrow \text{Corr}(x, y) \leq 1 \\ \text{if } \alpha < 0 \Rightarrow \text{Corr}(x, y) \geq -1 \end{cases}$$

$$\text{- Corr}(\underline{x}, \underline{x}) = 1$$

$$\text{- Corr}(x, -x) = -1$$

$$\left\{ \begin{array}{l} \text{Corr}(x, y) = \frac{\text{Cov}(x, y)}{\sigma(x)\sigma(y)} = \frac{E[xy] - E[x]E[y]}{\sigma(x)\sigma(y)} \\ \boxed{y = \alpha x + b} \end{array} \right. \quad \left\{ \begin{array}{l} = \frac{E[x(\alpha x + b)] - E[x]E[\alpha x + b]}{\sigma(x) |\alpha| \sigma(x)} \\ = \frac{\alpha E[x^2] + b E[x] - a E[x] - b E[x]}{|\alpha| \text{Var}(x)} \\ = \frac{\alpha (E[x^2] - E[x]^2)}{|\alpha| \text{Var}(x)} = \frac{\alpha \text{Var}(x)}{|\alpha| \text{Var}(x)} \end{array} \right.$$

$$\sigma(y) = \sigma(\alpha x + b) = \sqrt{\text{Var}(\alpha x + b)}$$

$$= \sqrt{\alpha^2 \text{Var}(x)}$$

$$= |\alpha| \sqrt{\text{Var}(x)}$$

$$x = |\alpha| \sigma(x)$$

$$= \frac{\alpha}{|\alpha|} = \begin{cases} 1 & \alpha > 0 \\ -1 & \alpha < 0. \end{cases}$$