

CS2 107 10-22-24

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• mid-term 1 : Thur. 10/24

- test : 9:50 - 10:55

- break : 10:55 - 11:00

- lecture : 11:00 - 11:25

2.7 Independence of r.v.s

Defn

We say r.v.s X, Y are independent iff events

$$\{X=x\} \text{ and } \{Y=y\}$$

are independent for all $x \in \text{range}(X)$ and $y \in \text{range}(Y)$. i.e.

$$P(X=x, Y=y) = P(X=x) \cdot P(Y=y)$$

i.e.

$$P_{X,Y}(x,y) = P_X(x) \cdot P_Y(y)$$

for all possible x, y .

$\Rightarrow$ If $P_Y(y) > 0$ for all $y \in \text{range}(Y)$,

then

$$\frac{P_{X,Y}(x,y)}{P_Y(y)} = P_X(x)$$

i.e.

$$P_{X|Y}(x|y) = P_X(x)$$

for all
poss. x, y

As usual, extend defn. to
conditional Probability law:

$$P(\cdot | A) \text{ where } P(A) > 0$$

Defn

We say X, Y are conditionally independent given A iff

$$P(X=x, Y=y | A) = P(X=x | A) \cdot P(Y=y | A)$$

for all $x \in \text{range}(X), y \in \text{range}(Y)$.

i.e.

$$P_{X,Y|A}^{(x,y)} = P_{X|A}^{(x)} \cdot P_{Y|A}^{(y)}$$

Theorem

If X, Y are independent,
then

$$E[X \cdot Y] = E[X] \cdot E[Y]$$

Proof

$$E[X \cdot Y] = \sum_x \sum_y xy P_{X,Y}(x,y)$$

$$= \sum_x \sum_y xy \cdot P_X(x) \cdot P_Y(y)$$

$$= \left(\sum_x x P_X(x) \right) \cdot \left(\sum_y y P_Y(y) \right)$$

$$= E[X] \cdot E[Y].$$



Theorem

If X, Y are independent r.v.s,
then so are $g(X)$ and $h(Y)$

See Problem #44 on P. 134 of text.

Thus

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

Theorem

If X, Y are independent, then

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

Proof

let X, Y be independent, and

let

$$U = X - E[X], \quad V = Y - E[Y].$$

Then

$$E[U] = E[X - E[X]] = E[X] - E[X] = 0$$

and

$$E[V] = \dots = 0.$$

Also

$$\text{Var}(U) = \text{Var}(X)$$

$$\text{Var}(V) = \text{Var}(Y).$$

$\rightarrow 0$

$$\begin{aligned}u + v &= (X - E[X]) + (Y - E[Y]) \\&= (X + Y) - E[X + Y]\end{aligned}$$

Thus

$$\begin{aligned}\text{Var}(X + Y) &= E[(u + v)^2] \\&= E[u^2 + 2uv + v^2] \\&= E[u^2] + 2E[uv] + E[v^2] \\&= E[u^2] + 2\overset{0}{\cancel{E[u]}} \cdot \overset{0}{\cancel{E[v]}} + E[v^2] \\&= \text{Var}(X) + \text{Var}(Y).\end{aligned}$$



we can do this for 3, 4, 5...

r.v.s. For instance, let

X, Y, Z be r.v.s. They are independent iff

$$P_{X,Y,Z}(x,y,z) = P_X(x) \cdot P_Y(y) \cdot P_Z(z)$$

If X, Y, Z are ind., then so are

$f(X), g(Y), h(Z)$ (or any other

functional combinations of X, Y, Z .)

we have $E[XYZ] = E[X]E[Y]E[Z]$

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

Variance of Binomial r.v.

Recall, if X is Binomial with Param. n, p , then

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

independent, identically distributed (i.i.d) Bernoulli r.v. $\&$

Thus

$$\text{Var}(X) = \text{Var}(X_1) + \dots + \text{Var}(X_n)$$

$$= p(1-p) + \dots + p(1-p)$$

$$= np(1-p).$$

Ex.

suppose we flip a weighted coin,
but we don't know

$$P(\text{head}) = p$$

How can we estimate p ?

we compute the sample mean

$$\bar{S}_n = \frac{X_1 + X_2 + \dots + X_n}{n}$$

where $X_i = \begin{cases} 1 & \text{if } i^{\text{th}} \text{ flip is heads} \\ 0 & \dots \dots \dots \text{tails} \end{cases}$

we have $E[X_i] = p$, we have

$$E[S_n] = E\left[\frac{1}{n}X_1 + \frac{1}{n}X_2 + \dots + \frac{1}{n}X_n\right]$$

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

$$= \sum_{i=1}^n \frac{1}{n} \cdot p = n \cdot \frac{1}{n} \cdot p = p$$

so S_n is an estimate for p .

since X_i are ind., so are the $\frac{1}{n} \cdot X_i$. Hence

$$\text{Var}(S_n) = \text{Var}\left(\sum_{i=1}^n \frac{1}{n} X_i\right)$$

$$= \sum_{i=1}^n \text{Var}\left(\frac{1}{n} X_i\right)$$

$$= \sum_{i=1}^n \frac{1}{n^2} \text{Var}(X_i)$$

$$= n \cdot \frac{1}{n^2} p(1-p)$$

$$= \frac{p(1-p)}{n}$$

$$\therefore \text{Var}(S_n) \rightarrow 0 \text{ as } n \rightarrow \infty$$

Since $E[S_n] = p$, we have

$$S_n \rightarrow p \text{ as } n \rightarrow \infty.$$

Note: "X

Even if X_i are not Bernoulli,

the same calculation gives

$$\text{Var}(S_n) = \frac{\text{Var}(X)}{n}$$

provided X_i are i.i.d. Since

$$E[S_n] = E[X_i],$$

so S_n is a good approx. to
mean $E[X]$.

Ex. (#38 on p. 132, ch 2)

Alice Passes through 4 traffic lights, each equally likely to be Red or Green independently.

1a) find ^{PMF,} mean & variance of # of Red lights encountered.

Solution

Let $X = \# \text{ red lights}$. Then

X is binomial with param.

$$n = 4$$

$$p = \frac{1}{2}$$

so

$$P_X(k) = \binom{4}{k} \left(\frac{1}{2}\right)^k \left(\frac{1}{2}\right)^{4-k} \quad k=0,1,2,3,4$$

$$= \binom{4}{k} \left(\frac{1}{2}\right)^4$$

$$= \frac{4!}{k!(4-k)!} \cdot \frac{1}{16}$$

$$= \frac{24}{16 \cdot k!(4-k)!}$$

$$= \boxed{\frac{3}{2k!(4-k)!} \quad k=0,1,2,3,4}$$

$$E[X] = np = 4 \cdot \frac{1}{2} = \boxed{2}$$

$$\text{Var}(X) = n \cdot p(1-p) = 4 \cdot \frac{1}{2} \cdot \frac{1}{2} = \boxed{1}$$

(b) Suppose Alice is delayed by 2 minutes for each red light. Find the Variance of her commute time.

Solution

Let $\overline{T}$ be her commute time.

Then

$$\overline{T} = \overline{T}_0 + 2X$$

where $\overline{T}_0$ is her commute time with no red lights.

$$\text{Var}(\bar{T}) = \text{Var}(\bar{T}_0 + 2X)$$

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

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

$$= 4 \cdot 1 = \boxed{4}$$