

## Recall

Independence of discrete rvs.

$\hookrightarrow X_1, \dots, X_n$  independent means  $p_{X_1, \dots, X_n}(x_1, \dots, x_n)$  is the product  $p_{X_1}(x_1) p_{X_2}(x_2) \dots p_{X_n}(x_n)$

Showed if  $X_1, X_2$  independent, then  $E(X_1 X_2) = E(X_1) E(X_2)$ .

Another useful fact: If  $X, Y$  independent, then  
$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$$

Proof of fact:

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

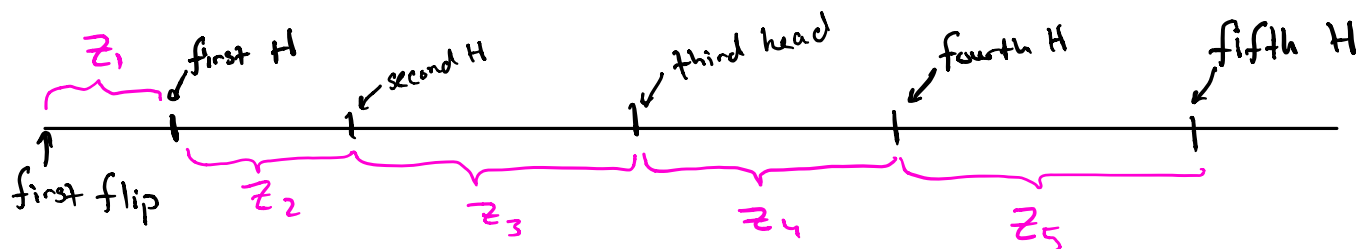
This generalizes to  $n$  independent rvs

$$\text{i.e. } \text{Var}(X_1 + \dots + X_n) = \text{Var}(X_1) + \dots + \text{Var}(X_n)$$

**Example** - where this property helps

Have a coin,  $P(\{H\}) = p$ . Flip it; let  $X =$  index of 5<sup>th</sup> head.  
Find  $IE(X)$ ,  $Var(X)$ .

One approach: use a "stretchy timeline"



All these marked times -  $Y_1, Y_2, Y_3, Y_4, Y_5 = X$  - are random.

write  $X$  as

$$X = Z_1 + Z_2 + Z_3 + Z_4 + Z_5$$

$\uparrow \quad \uparrow \quad \uparrow \quad \uparrow \quad \uparrow$   
 $Y_1 \quad Y_2 - Y_1 \quad Y_3 - Y_2 \quad Y_4 - Y_3 \quad Y_5 - Y_4$

All  $Z$ 's are geometric rvs w/ parameter  $p$  - and they're independent.

(Aside: computing pmf of  $X$  would be UGLY)

$$IE(Z_k) = \frac{1}{p}, \quad Var(Z_k) = \frac{1-p}{p^2} \quad \text{for } k \in \{1, 2, 3, 4, 5\}$$

$$IE(X) = \sum_{k=1}^5 Z_k = \frac{5}{p}, \quad Var(X) = \sum_{k=1}^5 Var(Z_k) = \frac{5(1-p)}{p^2}$$

## Example - Binomial r.v

Let's find  $\text{Var}(X)$  when  $X$  is  $\text{binomial}(n, p)$

$$P_X(k) = \begin{cases} \binom{n}{k} p^k (1-p)^{n-k} & ; 0 \leq k \leq n \\ 0 & ; \text{else} \end{cases}$$

Saw  $IE(X) = np$  - saw by writin  $X = Z_1 + \dots + Z_n$  where

$$Z_m = \begin{cases} 1 & \text{if H on flip } m \\ 0 & \text{if T on flip } m \end{cases} ; IE(Z_m) = p$$

↑ independent Bernoulli  $p$  rvs

Meanwhile,  $\text{Var}(Z_k) = p(1-p)$  - by independence,

$$\text{Var}(X) = \sum_{m=1}^n \text{Var}(Z_m) = np(1-p)$$

This is **WAY EASIER** than

$$\text{Var}(X) = \sum_{k=0}^n (k-np)^2 \binom{n}{k} p^k (1-p)^{n-k}$$

One last independence-related item: **estimating stats by sample means.**

Have a sequence  $X_1, X_2, \dots, X_n$  of independent rvs (can think of them as Bernoulli  $p$  but don't have to).

For every  $n > 0$ , let

$$S_n = \frac{1}{n} \sum_{m=1}^n X_m$$

← Note:  $S$  is a rv

If all the  $X_m$  have the same IE (let's use the case when the  $X_m$  are Bernoulli  $p$ ), we have

$$\text{IE}(S_n) = \frac{1}{n} \sum_{m=1}^n \text{IE}(X_m) \stackrel{\text{by independence}}{=} \frac{1}{n} (np) = p \quad \forall n$$

← assumes  $X$  is Bernoulli  $p$

$$\text{Var}(S_n) \stackrel{\text{by independence}}{=} \sum_{m=1}^n \text{Var}\left(\frac{1}{n} X_m\right) = \frac{1}{n^2} \sum_{m=1}^n \text{Var}(X_m)$$

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

Summary:

- $\text{IE}(S_n) = \text{common IE of all } X_m \text{'s}, \forall n > 0$
- $\text{Var}(S_n) \rightarrow 0$  as  $n \rightarrow \infty$

- This helps at estimating an unknown  $p$  for a  $p$ -coin by flipping
- This is an elementary instance of a law of large numbers