

March 13

Let there is a coin
with prob. of getting
head in single toss be
 $p \in (0, 1)$.

Our goal is to "approximate" p .

We toss the coin n -times
independently in identical
condition.

Let X_n be the

$X_1, \dots, X_n$ are
RVs associated with
those tosses, where
$$X_i = \begin{cases} 1 & \text{if } i^{\text{th}} \text{ outcome is head} \\ 0 & \text{otherwise} \end{cases}$$

An approximation of p
from here is the sample mean
$$\bar{X}_n = \frac{X_1 + \dots + X_n}{n}$$

$$\begin{aligned} \textcircled{1} \quad E(\bar{X}_n) &= E\left(\frac{X_1 + \dots + X_n}{n}\right) \\ &= \frac{1}{n} [E(X_1) + \dots + E(X_n)] \end{aligned}$$

$$= \frac{1}{n} n E(X_1) = E(X_1)$$

$$= p$$

(11) We know sum of
IID Bernoulli RVs is
a Binomial RV.

$$X_1 + X_2 + \dots + X_n =: Y_n$$

Then
 $Y_n \sim \text{Binomial}(n, p)$

Observe that

$$Y_n = n \bar{X}_n$$

$$\Rightarrow \bar{X}_n = \frac{1}{n} Y_n$$

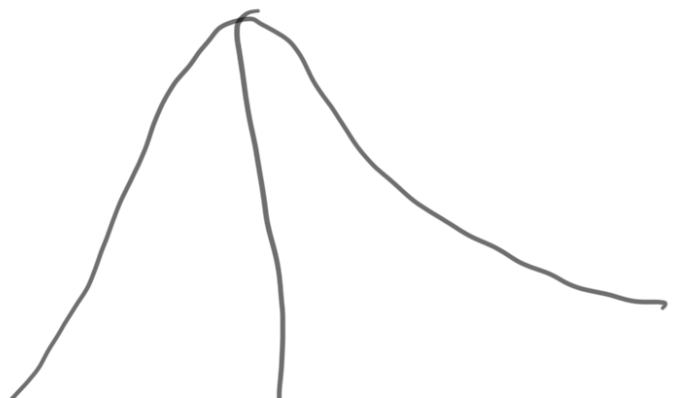
where $Y_n \sim \text{Binomial}(n, p)$

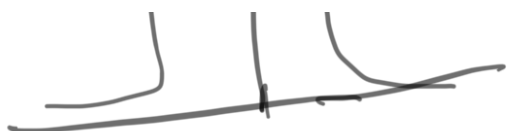
$$\text{Var}(\bar{X}_n) = \text{Var}\left(\frac{1}{n} Y_n\right)$$

$$= \frac{1}{n^2} \text{Var}(Y_n)$$

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

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





$$N(0, 0.1)$$

less variance
more concentrated



$$N(0, 2)$$

high variance
scattered.

eg:

let $x_1, \dots, x_n$ are
IID observations from

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

μ is unknown
 σ^2 is known

An approximation of μ

$\bar{x}$

$$\frac{x_1 + \dots + x_n}{n}$$

$$\bar{X}_n = \frac{\sum_{i=1}^n X_i}{n}$$

$$(i) E(\bar{X}_n) = \mu$$

(ii) Using MGF,

$$\bar{X}_n \sim N\left(\mu, \underbrace{\sigma^2/n}\right)$$

Next, when variance is unknown.

Eg: Let $X_1, \dots, X_n$ are IID RVs with mean μ and variance σ^2 .

Define

$$\bar{X}_n = \frac{1}{n} (X_1 + \dots + X_n)$$

$$S_n^2 = \frac{1}{n} \sum_{i=1}^n X_i^2 - (\bar{X}_n)^2$$

$$(1) E(S_n^2)$$

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

$$= \frac{E[(\bar{X}_n)^2]}{n}$$

Observe that

$$\text{Var}(X_1) = E(X_1^2) - [E(X_1)]^2$$

$$= E(X_1^2) - \mu^2$$

$$\Rightarrow \boxed{E(x_1^2) = \sigma^2 + \mu^2}$$

Next

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

$$\Rightarrow \frac{\sigma^2}{n} = E[(\bar{X}_n)^2] - \mu^2$$

$$\Rightarrow \boxed{E[(\bar{X}_n)^2] = \frac{\sigma^2}{n} + \mu^2}$$

Therefore,

$$E(S_n^2) = \frac{1}{n} \sum_{i=1}^n (\sigma^2 + \mu^2)$$

$$= \sigma^2 + \mu^2 - \frac{\sigma^2}{n} - \mu^2$$

$$= \sigma^2 \left(1 - \frac{1}{n}\right)$$

$$\Rightarrow E(S_n^2) = \sigma^2 \left(1 - \frac{1}{n}\right)$$

$$= \left(\frac{n-1}{n}\right) \sigma^2$$

↓
for large n

$\frac{n-1}{n}$ is close to 1.

Claim: $\frac{1}{n-2} \sum_{i=1}^n (x_i - \bar{x}_n)^2$

$$\text{Let } S_{n-1}^2 = \frac{1}{n-1} \sum_{i=1}^{n-1} (x_i - \bar{x})^2$$

$$\text{Then } E(S_{n-1}^2) = \sigma^2$$

$$\begin{aligned} \text{proof: } S_{n-1}^2 &= \frac{n}{n-1} \cdot \underbrace{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}_{S_n^2} \\ &= \frac{n}{n-1} \cdot S_n^2 \end{aligned}$$

$$\Rightarrow E(S_{n-1}^2) = \frac{n}{n-1} E(S_n^2)$$

$$= \frac{n}{n-1} \cdot \frac{n-1}{n} \sigma^2$$

$$= \sigma^2$$

