

OCT 16

Review: homework 03

Review: central limit theorem

What is the distribution of \bar{X} ?

What is $E(\bar{X})$?

What is $Var(\bar{X})$?

X_1, \dots, X_n IID

$$E X_i = \mu$$

$$Var(X_i) = \sigma^2$$

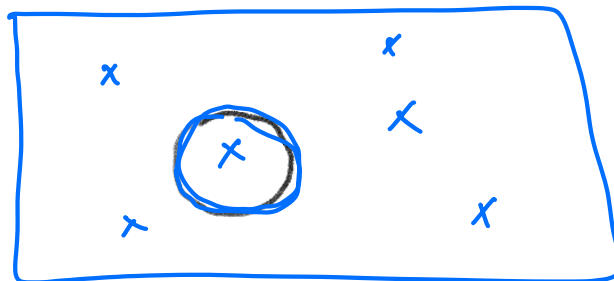
Today: Estimating parameters

X_1, X_2, \dots IID $N(\mu, \sigma)$ How do we find μ ?

→ Poisson (λ) DISTRIBUTION HOW & WHERE

→ Normal (μ, σ) DISTRIBUTION (CLT)

Normal approx to \bar{X}
to $\sum_{i=1}^n X_i = S_n$



$N = \#$ interval of length l
 $N \sim \text{Poisson}(l \times \lambda)$

$\#$ falling / unit time in tile

$$N \approx \text{Poisson}(\lambda t)$$

$$S = EN = \lambda t$$

Last time: x_1, x_2, \dots, x_n IID

$$\bar{x} = (x_1 + x_2 + \dots + x_n) / n \quad \mathbb{E}x_i = \mu \quad \text{Var}(x_i) = \sigma^2 \\ \text{SD} = \sigma$$

$$\bar{X} \approx \text{Normal}(\mu, \sigma/\sqrt{n})$$

$$\mathbb{E}(\bar{X}) = \mathbb{E}\left[\frac{1}{n} \sum_{i=1}^n x_i\right] = \frac{1}{n} \sum_{i=1}^n \mathbb{E}x_i = \frac{1}{n} \sum_{i=1}^n \mu = \mu$$

$$\text{Var}(\bar{X}) = \text{Var}\left(\frac{1}{n} \sum_{i=1}^n x_i\right) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}(x_i) = \frac{n\sigma^2}{n^2} \\ = \frac{\sigma^2}{n}$$

$$\text{SD}(\bar{X}) = \sigma/\sqrt{n}$$

HW03 PR3

$$S_{100} = \sum_{i=1}^{100} x_i$$

$$x_i \sim \mathbb{E}(x_i) = 49 \text{ cm} \\ \text{SD}(x_i) = 30 \text{ cm}$$

(a) What is Dist'n of S_{100} ?

$$\bar{X} \approx N(\mu, \sigma/\sqrt{n})$$

$$S_n \approx N(n\mu, \sqrt{n}\sigma)$$

$$S_n = \sum_{i=1}^n x_i$$

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

$$\mathbb{E}S_n = n \mathbb{E}\bar{X} \stackrel{?}{=} n\mu$$

$$n=100$$

$$\text{SD}(S_n) = n \text{SD}(\bar{X}) = n \frac{\sigma}{\sqrt{n}} = \sqrt{n} \sigma$$

$$\mathbb{P}(S_n > 55)$$

Estimating parameters

→ fixed unknown

Toss a coin w/ $p = \mathbb{P}(\text{"heads"})$

toss 100 times. $X = 62$ # Heads

If p is unknown, want to guess its values based on data

DATA = 62 HEADS

Guess at $p \Leftrightarrow \hat{p} = 62/100$

\hat{p} is the outcome of experiment so it has a prob distribution
 \hat{p} is a statistic: depends on data

\hat{p} is an estimator of p

X_1, X_2, \dots, X_{100} IID $EX_i = \mu$ $Var(X_i) = \sigma^2$
Guess μ : \uparrow unknown \uparrow fixed constants
Goal: guess μ is \bar{X}
 \hookrightarrow statistic

General for finding estimates of parameters given data

Likelihood estimation

Coin example: $X = \#$ heads in 100 tosses

$$P(X=k | p) = \binom{100}{k} p^k (1-p)^{100-k}$$

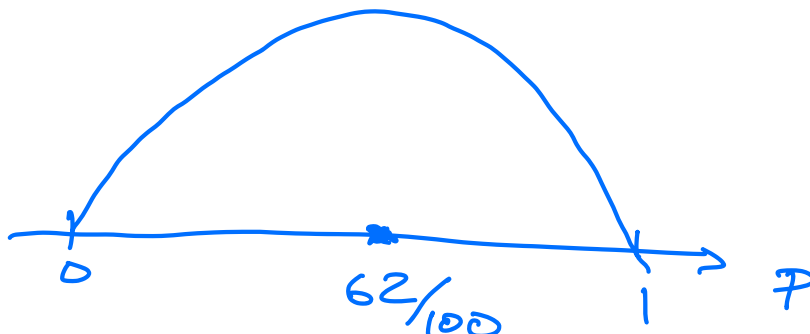
\hookrightarrow Binomial (100, p)

Observe $X=62$ want to know value of p

Likelihood function

$$L(p | X=62) = \binom{100}{62} p^{62} (1-p)^{38}$$

Likelihood principle: pick value of p making this
as large as possible



$$l(p) = \log L(p) = \log \binom{100}{62} + 62 \log p + 38 \log(1-p)$$

$$l'(p) = 0 + 62/p - 38/(1-p)$$

$$l'(p) = 0 \Leftrightarrow 62/p - 38/(1-p) = 0 \quad p(1-p)$$

$$62(1-p) - 38p = 0$$

$$62 - 62p - 38p = 0$$

$$62 - 100p = 0$$

$$62 = 100p$$

$$p = 62/100$$

Max. Likelihood estimate of unknown parameter $p \Leftrightarrow$
 $\hat{p} = 62/100$

In general: If p is unknown $X \sim \text{Bin}(n, p)$

$$\hat{p} = X/n$$

$$\lambda = EX_i$$

Example: X_1, \dots, X_n IID Poisson(λ)

Don't know λ but want to estimate from data

$$P(X_1 = k_1, \dots, X_n = k_n | \lambda)$$

Suppose 5 data points $X_1 = 2, X_2 = 0, X_3 = 3, X_4 = 3, X_5 = 1$

$$P(X_1 = 2, X_2 = 0, X_3 = 3, X_4 = 3, X_5 = 1 | \lambda)$$

$$= P(X_1 = 2 | \lambda) P(X_2 = 0 | \lambda) P(X_3 = 3 | \lambda) P(X_4 = 3 | \lambda) P(X_5 = 1 | \lambda)$$

$$= \frac{e^{-\lambda} \lambda^2}{2!} \frac{e^{-\lambda} \lambda^0}{0!} \frac{e^{-\lambda} \lambda^3}{3!} \frac{e^{-\lambda} \lambda^3}{3!} e^{-\lambda} \lambda^1 / 1!$$

$$= \frac{e^{-5\lambda} \lambda^{2+0+3+3+1}}{2! 0! 3! 3! 1!} = \frac{e^{-5\lambda} \lambda^9}{2! 0! 3! 3! 1!}$$

$$L(\lambda) =$$

$$l(\lambda) = \log L(\lambda) = -5\lambda + 9 \log \lambda - \sum_{i=1}^5 \log k_i$$

$$l'(\lambda) = -5 + 9/\lambda$$

$$= 0$$

$$\Leftrightarrow$$

$$-5 + 9/\lambda = 0$$

$$9/\lambda = 5$$

$$\lambda = 9/5$$

Value maximizing $L(\lambda) \Leftrightarrow \hat{\lambda} = 9/5$

In general $\hat{\lambda} = \frac{\sum_{i=1}^n k_i}{n}$ maximum likelihood estimator
 $\hat{\lambda} = \bar{X}$

Example

Note: If x_1, \dots, x_n IID r.v.s

$$\mathbb{E}X_i = \mu, \quad \text{Var}(X_i) = \sigma^2$$

Want to estimate μ always \bar{X} is a reasonable estimator

$$\mathbb{E}(\bar{X}) = \mu$$

$$\text{Var}(\bar{X}) = \frac{\sigma^2}{n}$$

$$\text{SD}(\bar{X}) = \sigma/\sqrt{n}$$

Fundamental Theorem
of Statistics

x_1, \dots, x_n Poisson(λ)

$$\mathbb{E}X_i = \lambda$$

Good estimator of λ should be: \bar{X}

Maximum Likelihood estimator is \bar{X}

X_1, X_2, \dots, X_n IID $N(\mu, \sigma)$

estimator of μ is \bar{X}

$\mu = E X_i$
= pop mean

\bar{X} as best guess at μ

How certain are we of this estimate?

In this example: estimate μ by $\hat{\mu} = 113$.

How likely is $\hat{\mu}$ to be more than 5 gm from truth?

$P(|\hat{\mu} - \mu| > 5)$? Suppose know $\sigma = 3$

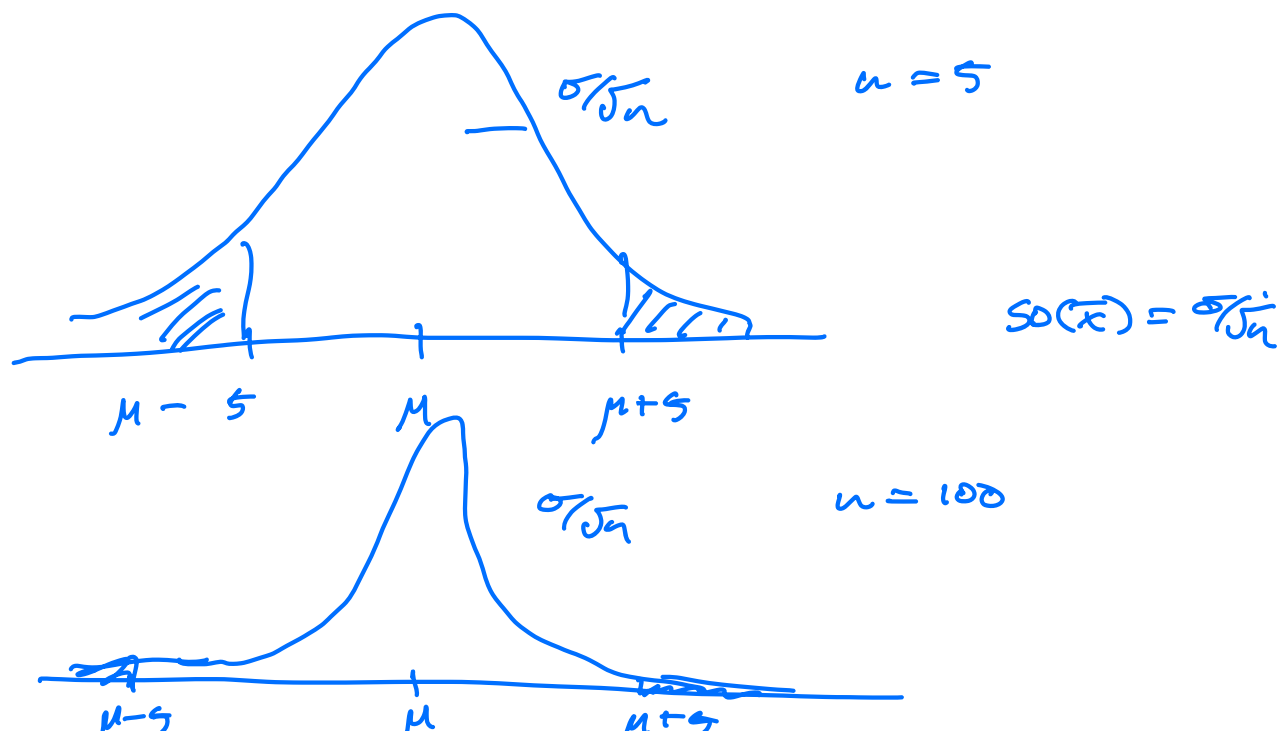
$$P(|\bar{X} - \mu| > 5)$$

$$\hookrightarrow \bar{X} \sim N(\mu, \frac{\sigma}{\sqrt{n}})$$

$$\bar{X} - \mu \sim N(0, \frac{\sigma}{\sqrt{n}})$$

$$P(\bar{X} - \mu < -5) + P(\bar{X} - \mu > 5)$$

What is advantage of taking sample bigger than 5?



$$\mathbb{P}(|\bar{x} - \mu| > \epsilon) \rightarrow 0 \text{ as } n \rightarrow \infty$$