MA369

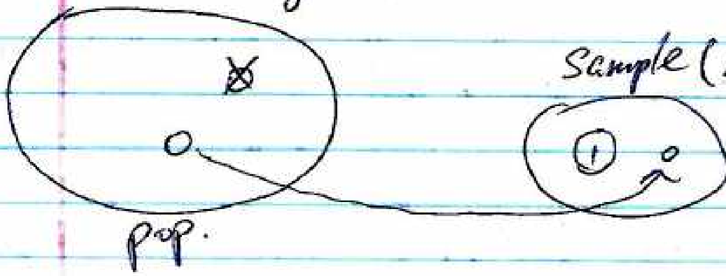
08/31/2020.

Lecture 02

$X_1 \sim Bern(\theta) = Bern\left(\frac{x}{N}\right)$

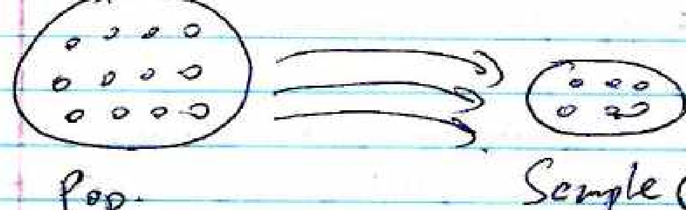
Let's draw a second sample from the population assuming $X_1 = 1$.

Not Independent



$$P(X_2 = 1 \mid X_1 = 1) = \frac{x-1}{N-1} < \frac{x}{N} = \theta$$

$$\Rightarrow X_2 \mid X_1 = 1 \sim Bern\left(\frac{x-1}{N-1}\right)$$



$$T_n = X_1 + \cdots + X_n \sim Hyper(n, x, N)$$

$$P(T_n = t) = \frac{\binom{x}{t}\binom{N-x}{n-t}}{\binom{N}{n}}$$

Hypergeometric Distribution.

Dealing with the hypergeometric is complicated (but doable).

What can we assume to make this go away?

$\rightarrow$ Let $x, N \rightarrow \infty$ but $\theta = \frac{x}{N}$

$$\lim P(X_2 = 1 \mid X_1 = 1) = \lim \frac{x-1}{N-1} = \theta$$

$$\rightarrow \theta = \frac{x}{N} \xrightarrow{\text{simplifying assumption}} X_1, X_2, \cdots, X_n \overset{iid}{\sim} Bern(p)$$

Pretend you work at the iphone factory, they sample new iphones to ensure they work to ensure the manufacturing is working properly. You check the first one $x_1 = 1, x_2 = 1, \ldots, x_{100} = 1$

What population are you sampling from? What is N?

When you estimate θ, you're estimating θ in a "process", ie a "data generating process" (DGP), iid Bern(θ).

DGPs and infinite population sampling is the same thing. We no longer care about whether the population is "real". we just assume an iid DGP from now on...

Returning to our main goal: inference i.e. knowing something about θ from the data. First subgoal: point estimation. Recall,

$$\hat{\hat{\theta}} = \frac{1}{n}(x_1 + \cdots + x_n)$$

$\bar{x}$ $\hat{p}$

$x_1, \ldots, x_n$ are random realizations from
$X_1, \ldots, X_n \overset{iid}{\sim} \text{Bern}(\theta)$

e.g. $\vec{x} = [10010] \Rightarrow \hat{\hat{\theta}} = 0.4$

but e.g. $\vec{x} = [11101] \Rightarrow \hat{\hat{\theta}} = 0.8$

$\Rightarrow \hat{\hat{\theta}}$ random.

$\hat{\hat{\theta}}$ is a realization from the r.v $\hat{\theta} := \frac{1}{n}\sum_{i=1}^{n} X_i$ $= w(X_1, \dots, X_2)$

called a "statistical estimator" or "just "estimator".
The statistic (statistical estimate, estimate) is
a realization from the estimator. The distribution
of the estimator, $\hat{\theta}$ is called the "sampling distribution".
This sampling distribution and its properties are very
important b/c ~~they~~ it tells us a lot about our
estimates

One property is the estimator's expectation, the mean
It would be nice if $E[\hat{\theta}] = \theta$ over all sample of size n.

$$E[\hat{\theta}] = E\left[\frac{1}{n}(X_1 + \dots + X_n)\right]$$

over all $X_1, \dots, X_n$

$$= \frac{1}{n}\sum E[X_i] = \frac{1}{n} \cdot n\, E[X_i] = \theta.$$

in $\theta \overset{iid}{\sim} \text{Bern}(\theta)$ setting

$\Rightarrow$ "$\hat{\theta}_n$" is unbiased.

$\text{Bias}[\hat{\theta}] := E[\hat{\theta}] - \theta$. If $\text{Bias}[\hat{\theta}] = 0 \Rightarrow \hat{\theta}$ is unbiased

If $\text{Bias}[\hat{\theta}] \neq 0 \Rightarrow \hat{\theta}$ is biased.

How far is $\hat{\theta}$ from θ?

we define a distance function AKA "loss function" ("error function")

$\ell(\hat{\theta}, \theta)$. $\ell : \Theta \times \Theta \to [0, \infty)$

$\ell = 0$ only if $\hat{\theta} = \theta$.

There are many loss functions e.g.

$\ell(\hat{\theta}, \theta) := |\hat{\theta} - \theta|$ Absolute error loss (L_1 loss)

Default * $\ell(\hat{\theta}, \theta) := |\hat{\theta} - \theta|^2$ Squared error loss (L_2 loss)

$\ell(\hat{\theta}, \theta) := |\hat{\theta} - \theta|^p, p > 0$ (L_p loss)

$$\ell(\hat{\theta}, \theta) := \int_{\vec{x} \in \mathcal{X}} \ln\left(\frac{f(x; \theta)}{f(x; \hat{\theta})}\right) f(x; \theta)\, d\vec{x}$$

Kullblack - Leibler (KL) loss for continuous rv's.

How far away on average are we?

$$\underset{\text{over } X_1, \dots, X_n}{E}[\ell(\theta, \hat{\theta})] := R(\hat{\theta}; \theta)$$

Risk of an estimator.

If we use squared error loss, $R(\hat{\theta}, \theta) = MSE[\hat{\theta}]$

"mean squared error" (MSE) $= E[(\hat{\theta} - \theta)^2]$

~~under squared error loss~~

If the estimator is unbiased, does its MSE simplify?

$$MSE[\hat{\theta}] = E[(\hat{\theta} - \theta)^2] = E[(\hat{\theta} - E[\hat{\theta}])^2]$$

if θ is unbiased, $E[\hat{\theta}] = \theta$.

$$= var[\hat{\theta}].$$

For a biased estimator (ie the general case)

$$MSE[\hat{\theta}] = E[(\hat{\theta} - \theta)^2] = E[\hat{\theta}^2 - 2\hat{\theta}\theta + \theta^2]$$

$$= E[\hat{\theta}^2] - 2\theta E[\hat{\theta}] + \theta^2$$

Recall $Var[\hat{\theta}] = E[\hat{\theta}^2] - E[\hat{\theta}]^2$

$$= Var[\hat{\theta}] + E[\hat{\theta}]^2 - 2\theta E[\hat{\theta}] + \theta^2$$

$$= Var[\hat{\theta}] + (E[\hat{\theta}] - \theta)^2$$

$$= Var[\hat{\theta}] + Bias[\hat{\theta}]^2.$$

Bias - variance decomposition of MSE.

$SE[\hat{\theta}] := \sqrt{var[\hat{\theta}]}$ "standard error of the estimator".

Note

r.v. $x \sim p(x)$.

$$\mu = E[x] = \sum_{x \in Supp[X]} x \, p(x).$$

$$\sigma^2 = Var[x] = E[(x-\mu)^2].$$

the square of the distance.
that How far am I away from μ.

If $\hat{\theta} = \bar{x}$,

$$\underbrace{\theta = E[\theta]}_{\hat{\theta} \text{ is unbiased}} = \sum_{\hat{\hat{\theta}} \in Supp[\hat{\theta}]} \hat{\hat{\theta}} \, p(\hat{\hat{\theta}}).$$

$$R(\hat{\theta}, \theta) = MSE$$

$$MSE = Var(\hat{\theta}) = E[\overbrace{(\hat{\theta}-\theta)^2}^{l(\hat{\theta}, \theta)}].$$

$$\hat{\theta} = \bar{X} = \frac{X_1 + \cdots + X_2}{n}.$$

$\hat{\hat{\theta}} = \bar{x}$ realization from $\bar{X}$