

# Statistics

We will typically be in a situation where we find some

$$X_1, X_2, \dots, X_n \text{ iid with Common pdf } f_{X_i}(x_i)$$

We should think of this as a "repeated experiment"

Some Notation:  $f_X(x; \theta)$   $\theta$  is an unknown parameter.  
 ↳ there could also be multiple unknown parameters.

we say  $\theta \in \Theta$ , where  $\Theta$  encompasses all possible values of our unknown parameter  $\theta$ .

remember that A statistic is a function of the data.

eg.  $h(X_1, X_2, \dots, X_n)$  & notice we do not need to know  $\theta$ .

Examples:  $N(\mu=2, \sigma^2)$  where  $\sigma$  is unknown

here, we say  $\sum (x_i - \mu)^2$  is a statistic  
 because we know  $\mu$  &  $x_i$ 's.

↳ & if  $\mu$  was unknown then this would not be a statistic

A Sampling Distribution  $X_1, X_2, \dots, X_n \text{ iid } \sim f_{X_i}(x_i, \theta)$

$y = h(X_1, \dots, X_n)$  is a statistic

Then the distribution of  $y$ ,  $f_Y(y)$  is a sampling distribution.

We can reference this 'more precisely' as  $f_Y(y; \theta)$

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Consider our usual situation...

What we may want to do is estimate our parameter  $\theta$

We say a statistic,  $y = h(\text{data})$ , whose purpose is to estimate  $\theta$ , is referred to as an ESTIMATOR

Example:  $\bar{X} = \frac{\sum_{i=1}^n X_i}{n}$  is an estimator of  $\mu$ .  
"sample mean" | | | "population mean"

$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$  is an estimator of  $\sigma^2$ .  
"sample variance" | | | "population variance"

Assume we are working with  $X_1, \dots, X_n$  iid  $\sim N(\mu, \sigma^2)$

↳ We know that  $\bar{X} \sim N(\mu, \frac{\sigma^2}{n})$

↳ We also know that  $\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$

↳ so we then know the pdf of  $S^2$

Some Facts:  $E[\chi_{n-1}^2] = n-1$  &  $V[\chi_{n-1}^2] = 2(n-1)$

Thus  $E[S^2] = \sigma^2$

&  $V[S^2] = \frac{2\sigma^4}{n-1}$

As  $\frac{(n-1)}{\sigma^2} E[S^2] = n-1$

$$E\left[\frac{(n-1)S^2}{\sigma^2}\right]$$

As  $\frac{(n-1)^2}{\sigma^4} V[S^2] = 2(n-1)$   
 $V\left[\frac{(n-1)S^2}{\sigma^2}\right]$

We can pull  
constants out of  
our Expected Value  
& our Variance \*

Some Additional Notation: We say that  $T$  is an unbiased estimator of  $\theta$  if  $E[T] = \theta \quad \forall \theta \in \Theta$

For example  $\bar{X}$ , regardless of  $f_X(X, \theta)$ , so long as  $E[X]$  exists,

$$\text{then } E[\bar{X}] = E\left(\frac{X_1 + \dots + X_n}{n}\right) = \frac{n\mu}{n} = \mu.$$

$\therefore \bar{X}$  is an unbiased estimator of  $\mu$ .

Likewise, so long as  $E[X^2]$  exists, then

$$E[S^2] = E\left[\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2\right] = \sigma^2 \quad \& \quad \text{then}$$

$S^2$  is an unbiased estimator of  $\sigma^2$ .

Note; in general,  $S$  is not an unbiased estimator of  $\sigma$ .

We will often want to find unbiased estimators.

Ex. Given  $X_1, \dots, X_n$  are iid  $\sim \text{Exp}[\beta]$   $\therefore \left\{ f_{X_i}(x_i) = \frac{1}{\beta} e^{-\frac{x}{\beta}}, E[X_i] = \beta, V[X_i] = \beta^2 \right\}$

$\hookrightarrow$  We would like to find an unbiased estimator of  $\frac{1}{\beta}$

$\hookrightarrow$  We know that  $\bar{X}$  is a good estimator of  $\mu$

$\hookrightarrow$  thus  $\bar{X}$  is a good estimator of  $\beta$ .

$\hookrightarrow$  Naturally, let's try to use  $T = \frac{1}{\bar{X}}$  as an estimator of  $\frac{1}{\beta}$ .

Notice  $T = \frac{1}{\bar{X}} = \frac{n}{\sum_{i=1}^n X_i} = \frac{n}{Z} \quad (\Sigma \text{ as shorthand for } \sum_{i=1}^n X_i)$

So let's find the pdf of  $\frac{1}{Z}$

Recall:  $X_1, \dots, X_n$  are iid  $\text{Exp}(\beta)$  so  $\Sigma$  is  $\text{Gamma}(\alpha=n, \beta=\beta)$

The pdf of  $\text{Gamma}(\alpha, \beta) = \frac{1}{\Gamma(\alpha)\beta^\alpha} x^{\alpha-1} e^{-\frac{x}{\beta}}$ ,  $x > 0$

Recall: If  $\alpha$  is a positive integer, then,  $\Gamma(\alpha) = (\alpha-1)!$

Also:  $\int_0^\infty x^{\alpha-1} e^{-\frac{x}{\beta}} dx = \Gamma(\alpha)\beta^\alpha = (\alpha-1)!\beta^\alpha$

Now we can try to find  $E[\frac{1}{\Sigma}]$ :

$$\begin{aligned} E\left[\frac{1}{\Sigma}\right] &= \int_0^\infty \left(\frac{1}{x}\right) \cdot \frac{1}{\Gamma(n)\beta^n} x^{n-1} e^{-\frac{x}{\beta}} dx \\ &= \int_0^\infty \frac{1}{\Gamma(n)\beta^n} x^{n-2} e^{-\frac{x}{\beta}} dx \\ &= \frac{1}{\Gamma(n)\beta^n} \cdot \int_0^\infty x^{n-2} e^{-\frac{x}{\beta}} dx \\ &= \frac{1}{\Gamma(n)\beta^n} \cdot \Gamma(n-1)\beta^{n-1} \end{aligned}$$

$$E\left[\frac{1}{\sum_{i=1}^n x_i}\right] = E\left[\frac{1}{\Sigma}\right] = \frac{(n-2)!}{(n-1)!} \cdot \frac{\beta^{n-1}}{\beta^n} = \frac{1}{(n-1)\beta}$$

Note:  $(n-1) \cdot E\left[\frac{1}{\Sigma}\right] = \frac{1}{\beta}$

So our question is: is  $\frac{1}{\bar{x}} = \frac{n}{\Sigma}$  an unbiased estimator of  $\frac{1}{\beta}$ ?

$\bar{x} = \frac{\Sigma}{n}$  well:  $E\left[\frac{n}{\Sigma}\right] = \frac{n}{(n-1)\beta} = E\left[\frac{1}{\bar{x}}\right]$

↳ this is not as we want  $\frac{1}{\beta}$

Thus, a true unbiased estimator of  $\frac{1}{\beta}$  is  $\frac{n-1}{n} \cdot \frac{1}{\bar{x}} = T$

Note:  $T = \frac{n-1}{n} \cdot \frac{n}{\Sigma} = \frac{n-1}{\Sigma}$

thus we use  $T = \frac{n-1}{\sum_{i=1}^n x_i}$  to estimate  $\frac{1}{\beta}$

This is A Common Technique We will be using!

- \* Guess the Estimator
- \* Figure out a fudge factor
- \* Construct the Estimator