# AUA CS 108, Statistics, Fall 2019 Lecture 21

Michael Poghosyan
YSU, AUA
michael@ysu.am, mpoghosyan@aua.am

11 Oct 2019

### Contents

► Bias and Biasedness/Unbiasedness

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• the CDF of  $X + \frac{1}{n^2}$  is not  $F_X(x) + \frac{1}{n^2}$ .

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- Define the Bias of an Estimator.
- What is the definition of the Unbiased/Biased Estimator?

**Example:** Now, let's not forget that we can have  $\bf R$  in our Midterm 2 or Final  $\ddot{-}$ . So let's do an experiment with Biased and Unbiased Estimators.

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#### **UnBiased Estimator Case**

We consider the Poisson Model:

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Easy to se that  $\hat{\lambda}$  is an Unbiased Estimator for  $\lambda$  (OTB!).

## Example, cont'd

Now, the code

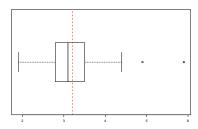
observing once: ganarating a Sample just once and calculating one Estimate:

```
lambda <- 3.21
x <- rpois(10, lambda = lambda)
lambda.hat <- mean(x)
lambda.hat</pre>
```

```
## [1] 3.4
```

observing many times: ganarating Samples many times, calculating Estimates, and then averaging:

```
lambda <- 3.21; n <- 10; m <- 200
x <- rpois(n*m, lambda = lambda)
x <- as.data.frame(matrix(x, ncol = m))
lambda.hats <- sapply(x, mean)
boxplot(lambda.hats, horizontal = T);
abline(v = lambda, col="red", lwd = 2, lty = 2)</pre>
```

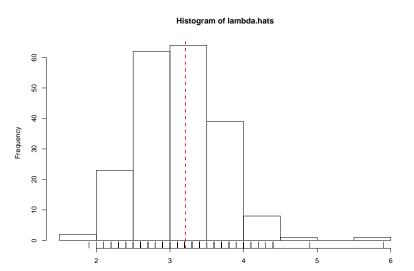


mean(lambda.hats)

## [1] 3.172

### With a Histogram:

```
hist(lambda.hats)
rug(lambda.hats)
abline(v = lambda, col="red", lwd = 2, lty = 2)
```



#### Biased Estimator Case

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Easy to se that  $\hat{\lambda}$  is an Biased Estimator for  $\lambda$  (OTB!).

## Example, cont'd

Now, the code:

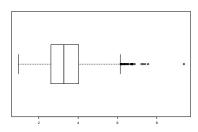
observing once: ganarating a Sample just once and calculating one Estimate:

```
lambda <- 0.3
x <- rexp(10, rate = lambda)
lambda.hat <- mean(x)
lambda.hat</pre>
```

```
## [1] 2.3389
```

observing many times: ganarating Samples many times, calculating Estimates, and then averaging:

```
lambda <- 0.3; n <- 10; m <- 2000
x <- rexp(n*m, rate = lambda)
x <- as.data.frame(matrix(x, ncol = m))
lambda.hats <- sapply(x, mean)
boxplot(lambda.hats, horizontal = T);
abline(v = lambda, col="red", lwd = 2, lty = 2)</pre>
```

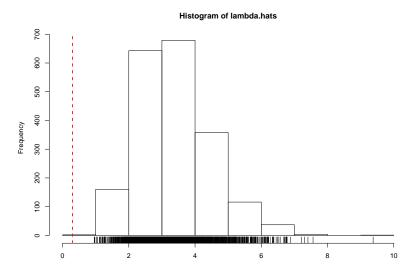


mean(lambda.hats)

## [1] 3.380309

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**Idea:** If the Sample size is very large, then the behaviour of our Asymptotic Unbiased Estimator is close to an Unbiased one,  $Bias(\hat{\theta}_n,\theta)\approx 0$ 

**Example:** Say, for the Mean  $\mu$  of the Population,

$$\hat{\mu} = \frac{X_1 + X_2 + \dots + X_n}{n+1}$$

is a Biased, but Asymptotically Unbiased Estimator. OTB, please!

# Bias-Variance Decomposition

This is an important result:

Theorem(Bias-Variance Decomposition of the MSE): If  $\hat{\theta}$  is an Estimator for  $\theta$ , then

$$MSE(\hat{\theta}, \theta) = \left(Bias(\hat{\theta}, \theta)\right)^2 + Var_{\theta}(\hat{\theta}).$$

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**Proof:** OTB