AUA CS 108, Statistics, Fall 2019 Lecture 27

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Last Lecture ReCap

▶ Give a good Estimator for p in Bernoulli(p) Model and justify your choice.

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- ▶ Give a good Estimator for λ in $Pois(\lambda)$ Model and justify your choice.

Examples, MoM

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So assume $\theta=(\theta_1,\theta_2)$. Then we need 2 Equations to find θ_1 and θ_2 . The MoM says: first try to solve the following system:

1-st order Theoretical Moment = 1-st order Empirical Moment
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So assume $\theta = (\theta_1, \theta_2)$. Then we need 2 Equations to find θ_1 and θ_2 . The MoM says: first try to solve the following system:

$$\begin{array}{l} \hbox{1-st order Theoretical Moment} = \hbox{1-st order Empirical Moment} \\ \hbox{2-nd order Theoretical Moment} = \hbox{2-nd order Empirical Moment} \\ \end{array}$$

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Example: Find the MoM Estimator for (μ, σ^2) in the $\mathcal{N}(\mu, \sigma^2)$ Model.

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Example: Find the MoM Estimator for (a, b) in the Unif[a, b]

Model.

Solution: OTB

Example: Let us do an experiment in **R**, concerning the last example:

```
a <- 2.5; b <- 3.24
x <- runif(10, min = a, max = b)
x.bar <- mean(x)
z <- sqrt(3* (mean(x^2) - x.bar^2))
a.hat.MoM<- x.bar - z
b.hat.MoM <- x.bar + z
c(a.hat.MoM, b.hat.MoM)</pre>
```

```
## [1] 2.529413 3.219274
```

Example: Let us do an experiment in **R**, concerning the last example:

```
a < -2.5; b < -3.24
x \leftarrow runif(10, min = a, max = b)
x.bar <- mean(x)
z \leftarrow sqrt(3* (mean(x^2) - x.bar^2))
a.hat.MoM < -x.bar - z
b.hat.MoM <- x.bar + z
c(a.hat.MoM, b.hat.MoM)
## [1] 2.529413 3.219274
Of course, we can just take \hat{a} = X_{(1)} and \hat{b} = X_{(n)}:
c(min(x), max(x))
```

[1] 2.520091 3.170063

Note: If you do not want to obtain the *MoM Estimator*, but just the *MoM Estimate*, just plug the Observations into the Empirical Moments, and then solve the Moments Equality Equations.

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Note: Sometimes we are interested not in the Estimate of the Parameter itself, but in the Estimate for some function of that Parameter. Say, we want to Estimate $h(\theta)$, where θ is our unknown Parameter. Then one of the approaches is the Plug-in Principle: find an Estimator $\hat{\theta}$ for θ , say, using the MoM, and then plug that in h, to obtain $h(\hat{\theta})$ as an Estimator for $h(\theta)$.

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Indeed, to find the MoM Estimator for θ , we need to solve

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Now, by the WLLN, $\overline{X}_n \stackrel{\mathbb{P}}{\longrightarrow} \mathbb{E}(X_1) = e(\theta)$, so

$$\hat{\theta}_n = e^{-1}(\overline{X}_n) \stackrel{\mathbb{P}}{\longrightarrow} e^{-1}(e(\theta)) = \theta.$$

The Maximum Likelihood Method

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Well, of course, you are correct, best guess is p=1. But it is possible also that this outcome is obtained from a coin with p=0.9. Or with p=0.8.

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So our guess was to select the value of *p* giving the highest likelihood to our outcome.