STA286 Lecture 23

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roadmap

probability/statistics

I said probability was "done", but it really wasn't.

In statistics we use a sample to make statements about what is unknown about an underlying distribution.

Then we did more probability - but not for the purpose of modeling actual random processes in the wild.

The purpose of the additional probability was to determine some properties of functions of samples—with a focus on the properties of $\overline{X}$

Now we are actually going to do statistics.

parameter estimation

point estimation

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Open questions about point estimators:

- what desirable properties should they have?

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Open questions about point estimators:

- what desirable properties should they have?
- how do I know which one to use? (To be addressed later.)

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We would like $\hat{\theta}$ to be *unbiased* ("for θ"):

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Another desirable property (that $\overline{X}$ has, for example) is *consistency*, which means the

[redacted]

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and the expected value of a Gamma(α, λ) is $\frac{\alpha}{\lambda}$, we get:

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[redacted]

$Exp(\lambda)$

How to estimate the rate parameter λ?