JOHNS HOPKINS
BLOOMBERG SCHOOL
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Lecture 6

The classical linear regression model: Maximum likelihood estimates = least square solution, Distributions of key results, vector notation

Maximum likelihood estimation under gaussian residuals

- Model:
- Likelihood function:
- Log Likelihood function:

Maximum likelihood estimation under gaussian residuals

- Solution for β_j

Maximum likelihood estimation under gaussian residuals

- Solution for β_j

Maximum likelihood estimation under gaussian residuals

- Solution for σ^2

MLEs for simple linear regression

MLEs for simple linear regression

MLEs for simple linear regression

Take away messages

Take away messages

Properties of sums of independent Gaussian random variables

Distribution of $\hat{\beta}_1$ in SLR assuming Gaussian residuals

Distribution of $\hat{\beta}_1$ in SLR assuming Gaussian residuals

Implications for data analysis

MLR model expressed in vector notation

MLR model expressed in vector notation

MLR model expressed in vector notation

MLE or LS solution expressed in vector notation

MLE or LS solution expressed in vector notation

Next time....

- We will use vector notation to derive the distribution of key results including the estimated regression coefficient vector, predicted values and residuals
- Geometry of least squares
- What happens to our inferences when the Gaussian assumption is violated? We will explore this via simulation study