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of PUBLIC HEALTH

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



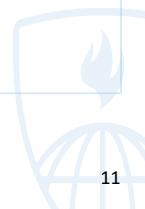
Take away messages



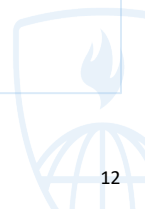
Take away messages



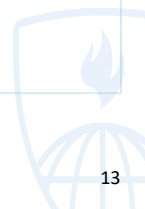
Properties of sums of independent Gaussian random variables



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



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



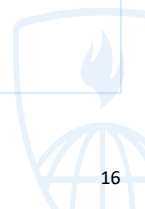
Implications for data analysis



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

