

Linear Regression Models

Segment 1 - Simple Linear Regression Model

Topic 1 – Data Generation Process: Sample and Population

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Topics



- 1. Questions from Data
- 2. Output & Input Variables in Linear Regression
- 3. Population & Sample
- 4. Population Model
- 5. A Linear Population Model





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- Is the relationship approximately linear? Linear Regression.





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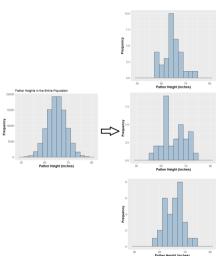
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- Example of a sample statistic: the average height of *n* randomly chosen biological females in a city.
- Note that sample statistic (or just statistic) is a random variable.

Population & Sample - Example with Sample Size = 32









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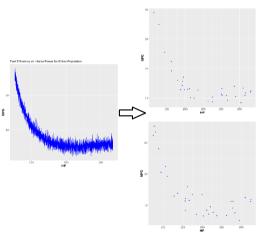
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- Population models are typically nonlinear: $Y = f(X) + \epsilon$ for an unknown nonlinear function f, where ϵ is a random error term.
- Example of a population model for mpg and hp: $Y = \frac{1.8}{V} 0.03X + \epsilon$.

Population & Sample - Another Example with Sample Size = 32





A Linear Population Model







 For a random father-son pair in a population, let Y represent the son's height and X represent the father's height.





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- Suppose that in the population, father's heights are normally distributed with mean 65 inches and standard deviation 4 inches: $X \sim N(\mu = 65, \sigma^2 = 16)$.
- Given the father's height X=x, suppose the son's height Y is also normally distributed with mean $42+0.4\times x$ and standard deviation 3 inches:





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- For a random father-son pair in a population, let *Y* represent the son's height and *X* represent the father's height.
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- The population model for Y as a function of X is a linear one: $Y = 42 + 0.4X + \epsilon$, where $\epsilon \sim N(\mu = 0, \sigma^2 = 9)$.