

Statistical Inference

Def

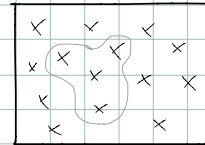
Statistics is the science of collecting, summarizing and analyzing experimental data to provide the basis for inference of decisions concerning the true nature of the population at study.

Ex

Height of a Chalmers female student.

Pick 10 students at random, measure their heights.

Results: 182, 171, 177, 174, 186, 187, 193, 172, 180, 181



Def

A random sample of size n from the distribution of X is a collection of n independent r.v.'s, each with the same distribution as X .

Notes

μ = the "true" average heights?

$$\bar{x} = \frac{1}{10} \sum_{i=1}^{10} x_i = 179.9$$

Def

A parameter of probability distribution (of population) is a number associated with the distribution (and in some way descriptive of that distribution).

Ex

μ - expectation and σ_x^2 - variance

Def

A statistic is some specified numerical function of observed sample values x_1, \dots, x_n .

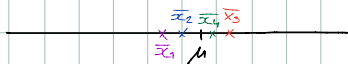
Def

A statistic used to approximate/estimate a distribution parameter θ is called point estimator for θ and is denoted $\hat{\theta}$. A numerical value obtained on a given data is called estimate.

Def

An estimator $\hat{\theta}$ is an unbiased estimator of parameter θ iff $E[\hat{\theta}] = \theta$.

Picture



Def

Let X_1, \dots, X_n be a random sample of size n from the distribution of X . Then $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$ is called sample mean.

Proposition

\bar{X} is an unbiased estimator of μ with $\sigma_{\bar{X}}^2 = \frac{\sigma_x^2}{n}$, n = number of observations.

Proof

$$E[\bar{X}] = E\left[\frac{1}{n} \sum_{i=1}^n X_i\right] = \frac{1}{n} E\left[\sum_{i=1}^n X_i\right] = \frac{1}{n} \sum_{i=1}^n E[X_i] = \frac{1}{n} \cdot n \cdot \mu_x = \mu_x$$

$$\text{Var}[\bar{X}] = \text{Var}\left[\frac{1}{n} \sum_{i=1}^n X_i\right] = \frac{1}{n^2} \text{Var}\left[\sum_{i=1}^n X_i\right] = \frac{1}{n^2} \sum_{i=1}^n \text{Var}[X_i] = \frac{1}{n^2} \cdot n \cdot \sigma_x^2 = \frac{\sigma_x^2}{n}$$

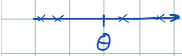
$\{X_1, \dots, X_n \text{ are independent}\}$
 $\text{Var}[\bar{X}] = \sigma_{\bar{X}}^2$

Ex

$$\begin{aligned} \bar{X} &= X_1 & \bar{X} &= \frac{1}{n} \sum_{i=1}^n X_i \\ E[\bar{X}] &= E[X_1] = \mu_x & E[\bar{X}] &= \mu_x \\ \text{Var}[\bar{X}] &= \text{Var}[X_1] = \sigma_x^2 & \text{Var}[\bar{X}] &= \frac{\sigma_x^2}{n} \end{aligned}$$



$$E[\hat{\theta}_1] = \theta$$



$$E[\hat{\theta}_2] - \theta = b > 0$$



$$\text{Var}[\hat{\theta}_1] \gg \text{Var}[\hat{\theta}_2]$$

Intuition

We need to estimate $E[X - \mu_x]^2 = \sigma_x^2$

$$\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \text{ - estimator for } \sigma_x^2$$

$$\begin{aligned} E\left[\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2\right] &= E\left[\frac{1}{n} \sum_{i=1}^n ((X_i - \mu_x) - (\bar{X} - \mu_x))^2\right] = E\left[\frac{1}{n} \sum_{i=1}^n ((X_i - \mu_x)^2 - 2(X_i - \mu_x)(\bar{X} - \mu_x) + (\bar{X} - \mu_x)^2)\right] \\ &= \frac{1}{n} E\left[\sum_{i=1}^n (X_i - \mu_x)^2 - 2(\bar{X} - \mu_x) \sum_{i=1}^n (X_i - \mu_x) + n(\bar{X} - \mu_x)^2\right] = \frac{1}{n} E\left[\sum_{i=1}^n (X_i - \mu_x)^2 - 2n(\bar{X} - \mu_x)^2 + n(\bar{X} - \mu_x)^2\right] \\ &= \frac{1}{n} E\left[\sum_{i=1}^n (X_i - \mu_x)^2 - n(\bar{X} - \mu_x)^2\right] = \frac{1}{n} E\left[\sum_{i=1}^n (X_i - \mu_x)^2 - n E[(\bar{X} - \mu_x)^2]\right] = \frac{1}{n} (n\sigma_x^2 - \sigma_x^2) = \frac{n-1}{n} \sigma_x^2 \end{aligned}$$

Def

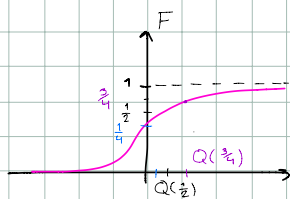
Let X_1, \dots, X_n be a random sample of size n from the distribution X . The statistic $S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$ is called a sample variance.

$$\text{For computing: } S^2 = \frac{1}{n-1} \sum_{i=1}^n X_i^2 - n(\bar{X})^2$$

Def

Given a CDF F we can define the quantile function $Q(p) = \inf\{x: F(x) \geq p\}$ for $p \in (0, 1)$.

Pic



$$\begin{aligned} P\left(\frac{1}{2}\right) & \quad Q\left(\frac{1}{2}\right) = \text{median} \\ P\left(\frac{3}{4}\right) & \quad Q\left(\frac{3}{4}\right) = \text{upper quartile} \\ P\left(\frac{1}{4}\right) & \quad Q\left(\frac{1}{4}\right) = \text{lower quartile} \end{aligned}$$