

# Estimating the population variance from a random sample

Nguyen Duc Thanh

(Introduction to Probability - Spring 2021)

## 1 Problem

Let  $X_1, X_2, \dots$  be uncorrelated random variables, each having mean  $\mu$  and variance  $\sigma^2$ . If  $\bar{X} = n^{-1}(X_1 + X_2 + \dots + X_n)$ , show that

$$\mathbb{E} \left( \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 \right) = \sigma^2$$

This fact is of importance in statistics and is used when estimating the population variance from knowledge of a random sample.

## 2 Proof

Since  $\mathbb{E}(X_i) = \mu$  for any  $i = 1, 2, \dots$ , one has

$$\begin{aligned} \mathbb{E}(\bar{X}) &= \mathbb{E} \left( \frac{1}{n} \sum_{i=1}^n X_i \right) \\ &= \frac{1}{n} \mathbb{E} \left( \sum_{i=1}^n X_i \right) \\ &= \frac{n\mu}{n} \\ &= \mu \end{aligned}$$

Consider  $\sum_{i=1}^n (X_i - \bar{X})^2$

$$\begin{aligned} \sum_{i=1}^n (X_i - \bar{X})^2 &= \sum_{i=1}^n [(X_i - \mu) - (\bar{X} - \mu)]^2 \\ &= \sum_{i=1}^n [(X_i - \mu)^2 - 2(X_i - \mu)(\bar{X} - \mu) + (\bar{X} - \mu)^2] \\ &= \sum_{i=1}^n (X_i - \mu)^2 - 2(\bar{X} - \mu) \sum_{i=1}^n (X_i - \mu) + n(\bar{X} - \mu)^2 \\ &= \sum_{i=1}^n (X_i - \mu)^2 - 2(\bar{X} - \mu)(n\bar{X} - n\mu) + n(\bar{X} - \mu)^2 \\ &= \sum_{i=1}^n (X_i - \mu)^2 - n(\bar{X} - \mu)^2 \end{aligned}$$

Because  $\mathbb{E}(X_i) = \mathbb{E}(\bar{X}) = \mu$

$$\sum_{i=1}^n (X_i - \bar{X})^2 = \sum_{i=1}^n [X_i - \mathbb{E}(X_i)]^2 - n [\bar{X} - \mathbb{E}(\bar{X})]^2$$

Then

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

Notice that  $\mathbb{E}\left([X_i - \mathbb{E}(X_i)]^2\right) = \text{var}(X_i) = \sigma^2$  and  $\mathbb{E}\left([\bar{X} - \mathbb{E}(\bar{X})]^2\right) = \text{var}(\bar{X})$ , the equation can then be simplified as

$$\mathbb{E}\left(\frac{1}{n-1}\sum_{i=1}^n(X_i - \bar{X})^2\right) = \frac{n}{n-1}[\sigma^2 - \text{var}(\bar{X})]$$

Consider  $\text{var}(\bar{X})$

$$\begin{aligned}\text{var}(\bar{X}) &= \text{var}\left(\frac{1}{n}\sum_{i=1}^n X_i\right) \\ &= \frac{1}{n^2}\text{var}\left(\sum_{i=1}^n X_i\right) \\ &= \frac{1}{n^2}\left[\mathbb{E}\left(\left[\sum_{i=1}^n X_i\right]^2\right) - \mathbb{E}\left(\sum_{i=1}^n X_i\right)^2\right] \\ &= \frac{1}{n^2}\left[\mathbb{E}\left(\sum_{i=1}^n \sum_{j=1}^n X_i X_j\right) - \left[\sum_{i=1}^n \mathbb{E}(X_i)\right]^2\right] \\ &= \frac{1}{n^2}\left[\sum_{i=1}^n \sum_{j=1}^n \mathbb{E}(X_i X_j) - \sum_{i=1}^n \sum_{j=1}^n \mathbb{E}(X_i)\mathbb{E}(X_j)\right] \\ &= \frac{1}{n^2}\sum_{i=1}^n \sum_{j=1}^n [\mathbb{E}(X_i X_j) - \mathbb{E}(X_i)\mathbb{E}(X_j)]\end{aligned}$$

Given that  $X_1, X_2, \dots$  are uncorrelated, one has

$$\text{cov}(X_i, X_j) = \mathbb{E}(X_i X_j) - \mathbb{E}(X_i)\mathbb{E}(X_j) = 0 \quad \text{whenever } i \neq j$$

Then

$$\begin{aligned}\text{var}(\bar{X}) &= \frac{1}{n^2}\sum_{i=1}^n [\mathbb{E}(X_i^2) - \mathbb{E}(X_i)^2] \\ &= \frac{1}{n^2}\sum_{i=1}^n \text{var}(X_i) \\ &= \frac{n\sigma^2}{n^2} \\ &= \frac{\sigma^2}{n}\end{aligned}$$

Hence

$$\mathbb{E}\left(\frac{1}{n-1}\sum_{i=1}^n(X_i - \bar{X})^2\right) = \frac{n}{n-1}\left(1 - \frac{1}{n}\right)\sigma^2 = \sigma^2$$

□