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Degrees of freedom

Consider the observations $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} D(\mu, \sigma)$.

When we assume a distribution for the observations, we are assuming values of the parameters how in this case is μ and σ .

For every parameter we estimate **we lost one degree of freedom.**

Estimator 1: $(n - 1)$ degrees of freedom.

$$\hat{S}_1 = \frac{1}{(n - 1)} \cdot \sum_{i=1}^n (x_i - \bar{x})^2$$

We are going to demonstrate that estimator is unbiased.

$$\mathbb{E}[\hat{S}_1] = \mathbb{E}\left[\frac{1}{(n - 1)} \cdot \sum_{i=1}^n (x_i - \bar{x})^2\right] = \frac{1}{(n - 1)} \cdot \sum_{i=1}^n \mathbb{E}[(x_i - \bar{x})^2]$$

\Rightarrow

$$\boxed{\mathbb{E}[\hat{S}_1] = \frac{1}{(n - 1)} \cdot \sum_{i=1}^n \mathbb{E}[(x_i - \bar{x})^2]} \quad (1)$$

Note:

$$\begin{aligned} \mathbb{E}[(x_i - \bar{x})^2] &= \mathbb{E}[(x_i)^2 - 2 \cdot x_i \cdot \bar{x} + (\bar{x})^2] \\ &= \mathbb{E}\left[(x_i)^2 - 2 \cdot x_i \cdot \frac{1}{n} \cdot \sum_{j=1}^n x_j + \frac{1}{n} \cdot \sum_{j=1}^n x_j \cdot \frac{1}{n} \cdot \sum_{k=1}^n x_k\right] \\ &= \mathbb{E}\left[(x_i)^2 - \frac{2}{n} \cdot \sum_{j=1}^n x_i \cdot x_j + \frac{1}{n^2} \cdot \sum_{k=1}^n \sum_{j=1}^n x_j \cdot x_k\right] \end{aligned}$$

$$\begin{aligned}
&= \mathbb{E}[(x_i)^2] - \frac{2}{n} \cdot \sum_{j=1}^n \mathbb{E}[x_i \cdot x_j] + \frac{1}{n^2} \cdot \sum_{k=1}^n \sum_{j=1}^n \mathbb{E}[x_j \cdot x_k] \\
&= \mathbb{E}[(x_i)^2] - \frac{2}{n} \cdot \left(\sum_{j=1: j \neq i}^n \mathbb{E}[x_i \cdot x_j] + \mathbb{E}[x_i \cdot x_i] \right) + \frac{1}{n^2} \cdot \left(\sum_{k=1: k \neq j}^n \sum_{j=1}^n \mathbb{E}[x_j \cdot x_k] + \sum_{j=1}^n \mathbb{E}[x_j \cdot x_j] \right)
\end{aligned}$$

Now we can see that:

$$\mathbb{E}[(x_i)^2] = \mathbb{V}[x_i] + \mathbb{E}[x_i]^2 = \sigma^2 + \mu^2$$

On the other hand:

$$\begin{aligned}
\sum_{j=1: j \neq i}^n \mathbb{E}[x_i \cdot x_j] + \mathbb{E}[x_i \cdot x_i] &= \sum_{j=1: j \neq i}^n (\text{Cov}(x_i, x_j) + \mathbb{E}[x_i] \cdot \mathbb{E}[x_j]) + \mathbb{V}[x_i] + (\mathbb{E}[X_i])^2 \\
\sum_{j=1: j \neq i}^n (\mu \cdot \mu) + \sigma^2 + \mu^2 &= (n-1) \cdot \mu^2 + \sigma^2 + \mu^2 = n \cdot \mu^2 + \sigma^2
\end{aligned}$$

And finally:

$$\begin{aligned}
&\sum_{k=1: k \neq j}^n \sum_{j=1}^n \mathbb{E}[x_j \cdot x_k] + \sum_{j=1}^n \mathbb{E}[x_j \cdot x_j] \\
&= \sum_{k=1: k \neq j}^n \sum_{j=1}^n (\text{Cov}(x_j, x_k) + \mathbb{E}[x_j] \cdot \mathbb{E}[x_k]) + \sum_{j=1}^n (\mathbb{V}[x_j] + \mathbb{E}[x_j]^2) \\
&= \sum_{k=1: k \neq j}^n \sum_{j=1}^n \mu^2 + \sum_{j=1}^n (\sigma^2 + \mu^2) = (n^2 - n) \cdot \mu^2 + n \cdot \sigma^2 + n \cdot \mu^2 = n \cdot [n \cdot \mu^2 + \sigma^2]
\end{aligned}$$

Thus:

$$\begin{aligned}
\mathbb{E}[(x_i - \bar{x})^2] &= \mathbb{E}[(x_i)^2] - \frac{2}{n} \cdot \left(\sum_{j=1: j \neq i}^n \mathbb{E}[x_i \cdot x_j] + \mathbb{E}[x_i \cdot x_i] \right) + \frac{1}{n^2} \cdot \left(\sum_{k=1: k \neq j}^n \sum_{j=1}^n \mathbb{E}[x_j \cdot x_k] + \sum_{j=1}^n \mathbb{E}[x_j \cdot x_j] \right) \\
&= (\sigma^2 + \mu^2) - \frac{2}{n} \cdot (n \cdot \mu^2 + \sigma^2) + \frac{1}{n^2} \cdot n \cdot [n \cdot \mu^2 + \sigma^2] \\
&= \sigma^2 + \mu^2 - 2 \cdot \mu^2 - \frac{2}{n} \cdot \sigma^2 + \mu^2 + \frac{\sigma^2}{n} = \sigma^2 - \frac{\sigma^2}{n} = \frac{(n-1)}{n} \cdot \sigma^2
\end{aligned}$$

\Rightarrow

$$\mathbb{E}[(x_i - \bar{x})^2] = \frac{(n-1)}{n} \cdot \sigma^2$$

Substituting this on (1) we have that:

$$\begin{aligned}\mathbb{E} \left[\hat{S}_1 \right] &= \frac{1}{(n-1)} \cdot \sum_{i=1}^n \mathbb{E}[(x_i - \bar{x})^2] = \frac{1}{(n-1)} \cdot \sum_{i=1}^n \frac{(n-1)}{n} \cdot \sigma^2 \\ &= \frac{1}{(n-1)} \cdot \frac{(n-1)}{n} \cdot n \cdot \sigma^2 = \sigma^2\end{aligned}$$

\Rightarrow

$$\boxed{\mathbb{E} \left[\hat{S}_1 \right] = \sigma^2}$$

Estimator 2: n degrees of freedom.

$$\hat{S}_2 = \frac{1}{n} \cdot \sum_{i=1}^n (x_i - \mu)^2$$

We are going to demonstrate that estimator is unbiased.

$$\begin{aligned}\mathbb{E} \left[\hat{S}_2 \right] &= \mathbb{E} \left[\frac{1}{n} \cdot \sum_{i=1}^n (x_i - \mu)^2 \right] = \frac{1}{n} \cdot \sum_{i=1}^n \mathbb{E} [(x_i - \mu)^2] = \frac{1}{n} \cdot \sum_{i=1}^n \mathbb{E} [(x_i)^2 - 2 \cdot \mu \cdot x_i + \mu^2] \\ &= \frac{1}{n} \cdot \left(\sum_{i=1}^n (\mathbb{E} [(x_i)^2] - 2 \cdot \mu \cdot \mathbb{E} [x_i] + \mu^2) \right) = \frac{1}{n} \cdot \left(\sum_{i=1}^n (\mathbb{V} [x_i] + \mathbb{E}[x_i]^2 - 2 \cdot \mu \cdot \mu + \mu^2) \right) \\ &= \frac{1}{n} \cdot \left(\sum_{i=1}^n (\sigma^2 + \mu^2 - 2 \cdot \mu^2 + \mu^2) \right) = \frac{1}{n} \cdot \left(\sum_{i=1}^n \sigma^2 \right) = \frac{1}{n} \cdot n \cdot \sigma^2 = \sigma^2\end{aligned}$$

\Rightarrow

$$\boxed{\mathbb{E} \left[\hat{S}_2 \right] = \sigma^2}$$
