

**Concepts of parameter estimation - confidence interval estimation**

In confidence interval parameter estimation based on the sample  $\mathbf{V} = (X_1, X_2, \dots, X_n)$  a **confidence interval**  $[l, u]$  is determined for which it is trusted with a **confidence coefficient**  $(1 - \alpha)$  or a **risk coefficient**  $\alpha$  that it contains the true value of the estimated parameter  $\theta$ :

$$P(l \leq \theta \leq u) = 1 - \alpha. \quad (1)$$

Confidence intervals can be two-sided or left and right one-sided:

$$l \leq \theta \leq u \quad \text{or} \quad l \leq \theta \quad \text{and} \quad \theta \leq u. \quad (2)$$

Error of interval estimation is  $|l - \theta|$  or  $|u - \theta|$ .

When the distribution of  $X_i$  in the sample is *normal with known variance*  $\sigma^2$ , the two-sided confidence interval on **mean**  $m$  of this distribution is:

$$\langle x \rangle - z_{\alpha/2} \frac{\sigma}{\sqrt{n}} < m < \langle x \rangle + z_{\alpha/2} \frac{\sigma}{\sqrt{n}}. \quad (3)$$

It is taken into account that the random variable

$$Z = \frac{\langle X \rangle - m}{\sigma/\sqrt{n}} \quad (4)$$

has a normal distribution. The value  $z_{\alpha/2}$  is determined by  $\Phi(z_{\alpha/2}) = (1 - \alpha)/2$ .

When the distribution of  $X_i$  in the sample is *arbitrary with unknown variance*  $\sigma^2$  and the *sample is large* ( $n > 30$ ), the two-sided confidence interval on **mean**  $m$  of this distribution is:

$$\langle x \rangle - z_{\alpha/2} \frac{s}{\sqrt{n}} < m < \langle x \rangle + z_{\alpha/2} \frac{s}{\sqrt{n}}, \quad (5)$$

where the unknown variance  $\sigma^2$  is replaced by the corrected sample variance  $S^2$  which is a random variable. In the above equation its realisation  $s^2$  is used which is determined from the sample. It is taken into account that the random variable

$$Z = \frac{\langle X \rangle - m}{S/\sqrt{n}} \quad (6)$$

has a normal distribution based on the central limit theorem for large  $n$ . The value  $z_{\alpha/2}$  is determined as above.

When the distribution of  $X_i$  in the sample is *normal with unknown variance*  $\sigma^2$  and the *sample is small* ( $n < 30$ ), the two-sided confidence interval on **mean**  $m$  of this distribution is:

$$\langle x \rangle - t_{n-1; \alpha/2} \frac{s}{\sqrt{n}} < m < \langle x \rangle + t_{n-1; \alpha/2} \frac{s}{\sqrt{n}}, \quad (7)$$

where the unknown variance  $\sigma^2$  is replaced by the corrected sample variance  $S^2$ . It is taken into account that the random variable

$$T = \frac{\langle X \rangle - m}{S/\sqrt{n}} \quad (8)$$

has a Student (or "t") distribution with  $n - 1$  degrees of freedom. The value  $t_{n-1; \alpha/2}$  is found in Table A.2.

When the distribution of  $X_i$  in the sample is *normal*, the two-sided confidence interval on **variance**  $\sigma^2$  of this distribution is:

$$\frac{(n-1)s^2}{\chi_{n-1;\alpha/2}^2} < \sigma^2 < \frac{(n-1)s^2}{\chi_{n-1;1-\alpha/2}^2}. \quad (9)$$

It is taken into account that the random variable

$$\chi^2 = \frac{(n-1)S^2}{\sigma^2} \quad (10)$$

has a  $\chi^2$  distribution with  $n-1$  degrees of freedom. The values  $\chi_{n-1;\alpha/2}^2$  and  $\chi_{n-1;1-\alpha/2}^2$  are found in Table A.3.

The approximate two-sided confidence interval on **proportion  $p$  of the population** having a *large sample* is:

$$\hat{p} - z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}} < p < \hat{p} + z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}. \quad (11)$$

Here it is assumed that the binomial distribution can be approximated by a normal distribution.

The two-sided confidence interval on **sum (difference) of the means**  $m_1$  and  $m_2$  of the *normally distributed* populations with *known variances* is:

$$\langle x_1 \rangle \pm \langle x_2 \rangle - z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}} < m_1 \pm m_2 < \langle x_1 \rangle \pm \langle x_2 \rangle + z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}. \quad (12)$$

If the populations have *arbitrary distributions* with *unknown variances* and the *samples are large*, the above confidence interval is used with variances  $\sigma_1^2$  and  $\sigma_2^2$  replaced by sample variances  $s_1^2$  and  $s_2^2$ .

The two-sided confidence interval on **sum (difference) of the means**  $m_1$  and  $m_2$  of the *normally distributed* populations with *unknown variances* and having *small samples* is:

$$\langle x_1 \rangle \pm \langle x_2 \rangle - t_{n_1+n_2-2;\alpha/2} s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}} < m_1 \pm m_2 < \langle x_1 \rangle \pm \langle x_2 \rangle + t_{n_1+n_2-2;\alpha/2} s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}, \quad (13)$$

where  $s_p$  is a realisation of the combined sample standard deviation  $S_p$ :

$$S_p^2 = \frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1 + n_2 - 2}. \quad (14)$$

The approximate two-sided confidence interval on **sum (difference) of the proportions**  $p_1$  and  $p_2$  **of the populations** when the *samples are large* is:

$$\hat{p}_1 \pm \hat{p}_2 - z_{\alpha/2} \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}} < p_1 \pm p_2 < \hat{p}_1 \pm \hat{p}_2 + z_{\alpha/2} \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}. \quad (15)$$

Here it is assumed that the binomial distributions can be approximated by normal distributions.