

# **Mathematical Statistics**

**Anna Janicka**

**Lecture VIII, 19.04.2021**

**CONFIDENCE INTERVALS**

# Plan for Today

---

Interval estimation – confidence intervals, different models



# Summary: basic (point) estimator properties

---

Point estimators – statistics which are designed to provide a single value of the estimator. We can evaluate them in terms of:

- bias
- variance
- MSE
- efficiency
- asymptotic unbiasedness
- consistency
- asymptotic normality
- asymptotic efficiency



# Interval estimation – confidence intervals

---

- We do not provide a single value estimate, but rather a lower and an upper bound for the estimate (the true value will fit into these bounds with given probability)
- We estimate with given precision



# Confidence interval

---

Let  $g(\theta)$  be a function of unknown parameter  $\theta$ , and let  $\bar{g} = \bar{g}(X_1, X_2, \dots, X_n)$  and  $\underline{g} = \underline{g}(X_1, X_2, \dots, X_n)$  be statistics

Then,  $[\underline{g}, \bar{g}]$  is a **confidence interval** for  $g(\theta)$  with a confidence level  $1-\alpha$ , if for any  $\theta$

$$P_{\theta}(\underline{g}(X_1, X_2, \dots, X_n) \leq g(\theta) \leq \bar{g}(X_1, X_2, \dots, X_n)) \geq 1 - \alpha$$



# Confidence intervals – use and interpretation

---

- Typically:  $\alpha$  is a small number, for example  $1-\alpha = 0,95$  or  $1-\alpha = 0,99$
- The condition from the definition means: the random interval  $[\underline{g}, \bar{g}]$  includes the unknown value  $g(\theta)$  with given (high) probability.
- If we calculate the *realization* of the confidence interval (e.g.  $\underline{g} = 1, \bar{g} = 3$ ) then we CAN'T say that the unknown parameter is included in the range with probability  $1-\alpha$  anymore!

---

the parameter is either in the interval or not – the event is not random, it is just something we don't know.



# Confidence intervals – construction

---

- The confidence interval depends on the underlying probability distribution
- Usually, normal samples are considered (the distribution most frequently observed in nature)



# Confidence intervals – construction cont.

---

- Convenient method: we look for random variables which depend on sample data and parameter values, but whose *distributions* do not depend on unknown parameters (*pivotal method*)
- If  $U = U(X_1, X_2, \dots, X_n, \theta)$  is such a function, then we look for confidence intervals  $[a, b]$  such that

$$P_{\theta}(a \leq U \leq b) \geq 1 - \alpha$$

- Usually we look for „symmetric” CI

$$P_{\theta}(U < a) \leq \frac{\alpha}{2}, \quad P_{\theta}(U > b) \leq \frac{\alpha}{2}$$





# Most commonly used models

---

- Model I (normal): CI for the mean, variance known
- Model II (normal): CI for the mean, variance unknown
- Model II (normal): CI for the variance
- Model III (asymptotic): CI for the mean
- Model IV (asymptotic): CI for the fraction
- Asymptotic model: CI based on MLE



## CI for the mean – Model I

---

Normal model:  $X_1, X_2, \dots, X_n$  are an IID sample from  $N(\mu, \sigma^2)$ ,  $\sigma^2$  is **known**.

The CI for  $\mu$ , for a confidence level  $1-\alpha$  :

$$\left[ \bar{X} - u_{1-\alpha/2} \frac{\sigma}{\sqrt{n}}, \bar{X} + u_{1-\alpha/2} \frac{\sigma}{\sqrt{n}} \right]$$

where  $u_{1-\alpha/2}$  is a quantile of rank  $1-\alpha/2$  for the  $N(0,1)$  distribution



# CI for the mean – Model I, justification:


---

Point estimate for  $\mu$ :  $MLE(\mu) = \bar{X}$

We know the distribution of  $\bar{X}$ :

$$\bar{X} \sim N(\mu, \sigma^2/n), \quad \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim N(0,1)$$

distribution  
does not  
depend on  
 $\mu$



We want: a CI symmetric around the point estimate (the distribution of the normalized average is symmetric around 0). We have:

$$P_{\mu} \left( \left| \sqrt{n}(\bar{X} - \mu) / \sigma \right| \leq u \right) = \Phi(u) - \Phi(-u) = 2\Phi(u) - 1$$
$$= 1 - \alpha$$

$$\text{so } u = u_{1-\alpha/2}$$



# CI for the mean – Model I, properties

---

□ Error:  $d = u_{1-\alpha/2} \frac{\sigma}{\sqrt{n}}$

□ Length of CI:  $2d$

□ Sample size allowing to obtain a given *precision* (error)  $d$ :

$$n \geq \frac{\sigma^2 u_{1-\alpha/2}^2}{d^2}$$



## CI Model I – example phrasing

---

In a survey of food expenditures for  $n=400$  randomly chosen respondents, the average weekly amount spent on fruit amounted to \$30. ***From previous research, we know that the variance of fruit expenditures is equal to 5.*** Assuming that food expenditures are distributed normally, find a 95% CI for the average weekly amount spent.



## CI for the mean – Model II

---

Normal model:  $X_1, X_2, \dots, X_n$  are an IID sample from  $N(\mu, \sigma^2)$ ,  $\sigma^2$  is **unknown**.

The CI for  $\mu$ , for a confidence level  $1-\alpha$  :

$$\left[ \bar{X} - t_{1-\alpha/2}(n-1) \frac{S}{\sqrt{n}}, \bar{X} + t_{1-\alpha/2}(n-1) \frac{S}{\sqrt{n}} \right]$$

where  $t_{1-\alpha/2}(n-1)$  is a quantile of rank  $1-\alpha/2$  for a  $t$ -Student distribution with  $n-1$  degrees of freedom  $t(n-1)$ , and  $S = \sqrt{S^2}$  for the unbiased variance estimator  $S^2$ .

---



## CI for the mean – Model II, justification:

---

Point estimate for  $\mu$ :  $MLE(\mu) = \bar{X}$

We know the distribution of  $\bar{X}$  :

$$\bar{X} \sim N(\mu, \sigma^2/n), \quad \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim N(0,1), \quad T = \frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t(n-1)$$

We want: a CI symmetric around the point estimate (the distribution of  $T$  is symmetric around 0). We have:

$$P_{\mu, \sigma} \left( \left| \sqrt{n}(\bar{X} - \mu) / S \right| \leq t \right) = 1 - \alpha$$

$$\text{so } t = t_{1-\alpha/2}(n-1)$$

---



## CI for the mean – Model II, properties

---

□ Error: 
$$d = t_{1-\alpha/2}(n-1) \frac{S}{\sqrt{n}}$$

□ Length of CI:  $2d$

□ Sample size allowing to obtain a given *precision* (error)  $d$ :

*to be determined on the base of the so-called Stein's two-stage procedure – we need a preliminary assessment of the variance first*





# Stein's two-stage procedure

1. We collect a preliminary sample  $X_1, X_2, \dots, X_{n_0}$  and estimate the variance:

$$S_0^2 = \frac{1}{n_0 - 1} \sum_{i=1}^{n_0} (X_i - \bar{X}_0)^2$$

2. We check whether the sample fulfills the given condition: we calculate  $k = \frac{S_0^2 [t_{1-\alpha/2}(n_0 - 1)]^2}{d^2}$

- a) if  $n_0 \geq k$  then we take the CI

$$\left[ \bar{X}_0 - t_{1-\alpha/2}(n_0 - 1) \frac{S_0}{\sqrt{n_0}}, \bar{X}_0 + t_{1-\alpha/2}(n_0 - 1) \frac{S_0}{\sqrt{n_0}} \right]$$

- b) if  $n_0 < k$  then we choose  $n \geq k$  and draw an additional sample of  $X_{n_0+1}, X_{n_0+2}, \dots, X_n$ . We calculate the mean for the *whole* sample  $X_1, X_2, \dots, X_n$ , and take the CI

$$\left[ \bar{X} - t_{1-\alpha/2}(n_0 - 1) \frac{S_0}{\sqrt{n}}, \bar{X} + t_{1-\alpha/2}(n_0 - 1) \frac{S_0}{\sqrt{n}} \right]$$



## CI Model II – example phrasing

---

In a survey of food expenditures for  $n=400$  randomly chosen respondents, the average weekly amount spent on fruit amounted to \$30, ***and the variance of fruit expenditures amounted to 5.*** Assuming that food expenditures are distributed normally, find a 95% CI for the average weekly amount spent.



## CI for the variance – Model II

---

Normal model:  $X_1, X_2, \dots, X_n$  are an IID sample from  $N(\mu, \sigma^2)$

CI for  $\sigma^2$ , for a confidence level  $1-\alpha$  :

$$\left[ \frac{(n-1)S^2}{\chi_{1-\alpha/2}^2(n-1)}, \frac{(n-1)S^2}{\chi_{\alpha/2}^2(n-1)} \right]$$

where  $\chi_{\alpha/2}^2(n-1)$  and  $\chi_{1-\alpha/2}^2(n-1)$  are quantiles of rank  $\alpha/2$  and  $1-\alpha/2$ , respectively, for a chi-squared distribution with  $n-1$  degrees of freedom



## CI for the variance – Model II, justification

---

Point estimate for  $\sigma^2$ :  $S^2$

We know the distr.:  $U = \frac{(n-1)}{\sigma^2} S^2 \sim \chi^2(n-1)$

The chi-squared distribution is not symmetric. We want a „symmetric” CI, i.e. we look for  $[a, b]$  such that

$$P_{\sigma^2}(U < a) = \frac{\alpha}{2}, \quad P_{\sigma^2}(U > b) = \frac{\alpha}{2}$$

so

$$a = \chi_{\alpha/2}^2(n-1) \text{ and } b = \chi_{1-\alpha/2}^2(n-1)$$



## CI for the mean – Model III

---

Asymptotic model:  $X_1, X_2, \dots, X_n$  are an IID sample from a distr. with mean ( $\mu$ ) and variance,  $n$  – large.

*Approximate* CI for  $\mu$ , for a confidence level  $1-\alpha$  :

$$\left[ \bar{X} - u_{1-\alpha/2} \frac{S}{\sqrt{n}}, \bar{X} + u_{1-\alpha/2} \frac{S}{\sqrt{n}} \right]$$

where  $u_{1-\alpha/2}$  is a quantile of rank  $1-\alpha/2$  from the  $N(0,1)$  distribution,  $S = \sqrt{S^2}$  for the unbiased estimator of the variance  $S^2$ .

Justification: from CLT, when  $n \rightarrow \infty$  we have

$$\frac{\bar{X} - \mu}{S/\sqrt{n}} \xrightarrow{D} N(0,1)$$



## CI for the fraction – Model IV

---

Asymptotic model:  $X_1, X_2, \dots, X_n$  are an IID sample from a two-point distribution,  $n$  – large.

$$P_p(X = 1) = p = 1 - P_p(X = 0)$$

*Approximate* CI for  $p$ , for a confidence level  $1 - \alpha$  :

$$\left[ \hat{p} - u_{1-\alpha/2} \frac{\sqrt{\hat{p}(1-\hat{p})}}{\sqrt{n}}, \hat{p} + u_{1-\alpha/2} \frac{\sqrt{\hat{p}(1-\hat{p})}}{\sqrt{n}} \right]$$

where  $u_{1-\alpha/2}$  is a quantile of rank  $1 - \alpha/2$  from the  $N(0,1)$  distribution



# CI for the fraction – Model IV, justification

---

The point estimate for the fraction  $p$ :

$$\hat{p} = MLE(p) = \bar{X}$$

We know the asymptotic distribution: from CLT, when  $n \rightarrow \infty$ , we have

$$U = \frac{\hat{p} - p}{\sqrt{\hat{p}(1 - \hat{p})}} \sqrt{n} \xrightarrow{D} N(0,1)$$

Using  $U$ , just like in model I, we get the formula.



## CI for the fraction – Model IV, properties

---

- Assessment error:  $d = u_{1-\alpha/2} \frac{\sqrt{\hat{p}(1-\hat{p})}}{\sqrt{n}}$
- Sample size allowing to obtain a given *precision* (error)  $d$ :

$$n \geq \frac{\hat{p}(1-\hat{p})u_{1-\alpha/2}^2}{d^2}$$

if we do not know anything about  $p$ , we need to consider the worst scenario

where  $p=1/2$ :  $n \geq \frac{u_{1-\alpha/2}^2}{4d^2}$





# CI on the base of the MLE – Asymptotic model

---

Asymptotic model:  $X_1, X_2, \dots, X_n$  are an IID sample from a distr. with unknown parameter  $\theta$ ,  $n$  – large.

If  $\hat{\theta} = MLE(\theta)$  is asymptotically normal with an asymptotic variance equal to  $1/I_1(\theta)$ , i.e.

$$(\hat{\theta} - \theta)\sqrt{n} \xrightarrow{D} N(0, 1/I_1(\theta))$$

and if  $I(\hat{\theta}) = MLE(I(\theta))$  is consistent:

$$(\hat{\theta} - \theta)\sqrt{nl(\hat{\theta})} \xrightarrow{D} N(0,1)$$

*Approximate* CI for  $\theta$ , for a confidence level  $1-\alpha$  :

$$\left[ \hat{\theta} - u_{1-\alpha/2} \frac{1}{\sqrt{nl_1(\hat{\theta})}}, \hat{\theta} + u_{1-\alpha/2} \frac{1}{\sqrt{nl_1(\hat{\theta})}} \right]$$

where  $u_{1-\alpha/2}$  is a quantile of rank  $1-\alpha/2$  from  $N(0,1)$



# CI on the base of the MLE – Asymptotic model, general case

---

Asymptotic model:  $X_1, X_2, \dots, X_n$  are an IID sample from a distr. with unknown parameter  $\theta$ ,  $n$  – large.

If  $g(\hat{\theta}) = g(MLE(\theta))$  is asymptotically normal with an asymptotic variance equal to  $(g'(\theta))^2 / I_1(\theta)$ , i.e.

$$(\hat{\theta} - \theta)\sqrt{n} \xrightarrow{D} N(0, (g'(\theta))^2 / I_1(\theta))$$

and if  $I(\hat{\theta}) = MLE(I(\theta))$  is consistent:

$$(\hat{\theta} - \theta)\sqrt{nl(\hat{\theta})} \xrightarrow{D} N(0,1)$$

Approximate CI for  $g(\theta)$ , for a confidence level  $1-\alpha$ :

$$\left[ g(\hat{\theta}) - u_{1-\alpha/2} \frac{|g'(\hat{\theta})|}{\sqrt{nl_1(\hat{\theta})}}, g(\hat{\theta}) + u_{1-\alpha/2} \frac{|g'(\hat{\theta})|}{\sqrt{nl_1(\hat{\theta})}} \right]$$

where  $u_{1-\alpha/2}$  is a quantile of rank  $1-\alpha/2$  from  $N(0,1)$



# CI on the base of the MLE – Example

---

Let  $X_1, X_2, \dots, X_n$  be an IID sample from a Poisson distr. with unknown parameter  $\theta$ ,  $n$  – large.

$\hat{\theta} = MLE(\theta) = \bar{X}$  is asymptotically normal (CLT) with an asymptotic variance equal to  $1/I_1(\theta) = \theta$

$\hat{I}(\theta) = 1/\hat{\theta}$  behaves well.

*Approximate* CI for  $\theta$ , for a confidence level  $1-\alpha$  :

$$\left[ \bar{X} - u_{1-\alpha/2} \frac{\sqrt{\bar{X}}}{\sqrt{n}}, \bar{X} + u_{1-\alpha/2} \frac{\sqrt{\bar{X}}}{\sqrt{n}} \right]$$

where  $u_{1-\alpha/2}$  is a quantile of rank  $1-\alpha/2$  from  $N(0,1)$

For example, if for  $n=900$  we had  $\bar{X} = 4$ , then the 90% CI for  $\theta$  would be

---

$$\approx \left[ 4 - 1.645 \sqrt{4/900}, 4 + 1.645 \sqrt{4/900} \right] \approx [3.89, 4.11]$$


## CI on the base of the MLE – Example cont.

---

If we wanted to approximate the probability of the outcome = 0, we would look for  $g(\theta) = e^{-\theta}$

$$g(\hat{\theta}) = g(MLE(\theta)) = e^{-\bar{X}}$$

And the *approximate* CI for  $g(\theta)$ , for a confidence level  $1-\alpha$  :

$$\left[ e^{-\bar{X}} - u_{1-\alpha/2} \frac{\sqrt{\bar{X}}}{\sqrt{n}} e^{-\bar{X}}, e^{-\bar{X}} + u_{1-\alpha/2} \frac{\sqrt{\bar{X}}}{\sqrt{n}} e^{-\bar{X}} \right]$$

where  $u_{1-\alpha/2}$  is a quantile of rank  $1-\alpha/2$  from  $N(0,1)$

For example, if for  $n=900$  we had  $\bar{X} = 4$ , then the 90% CI for  $g(\theta)$  would be

$$\approx \left[ e^{-4} - 1.645 \sqrt{4/900} e^{-4}, e^{-4} + 1.645 \sqrt{4/900} e^{-4} \right] \approx [0.016, 0.020]$$



