

Chebyshev / Kolmogorov Inequalities

• Chebyshev's Inequality

$$\forall \text{ random variable } X \text{ and } \delta > 0 : P[|X - E[X]| \geq \delta] \leq \frac{\text{var}[X]}{\delta^2}$$

(*) Important application: For \bar{X}_n we get $P[|\bar{X}_n - E[\bar{X}_n]| \geq \delta] \leq \frac{\text{var}[\bar{X}_n]}{\delta^2} \Rightarrow P[|\bar{X}_n - \mu| \geq \delta] \leq \frac{\sigma^2}{n \cdot \delta^2}$

Now, we can answer to the question:

"How big must be the n -sample to ensure that the probability P of the estimate \bar{X}_n being further than $\pm \delta$ from the true μ , is less than or equal to P_0 ?"

$$P \leq P_0 \Rightarrow \frac{\sigma^2}{n \cdot \delta^2} \leq P_0 \Rightarrow n \geq \frac{\sigma^2}{\delta^2 \cdot P_0}$$

(+) result does not depend on distribution of X

(-) bound can be quite imprecise

(-) result varies significantly across distributions with very different σ^2

• Kolmogorov's Inequality

← strengthens Chebyshev's inequality

If X_i : independent
and
 $E[X] = 0$
 $E[X^2] < \infty$

$$\Rightarrow \forall \varepsilon > 0 \quad P\left[\max_{1 \leq j \leq n} \left| \sum_{i=1}^j X_i \right| > \varepsilon\right] \leq \frac{\sum_{i=1}^n E[X_i^2]}{\varepsilon^2}$$