ASDS Statistics, YSU, Fall 2020

Lecture 16

Michael Poghosyan

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Contents

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So if you want to generate a sample of size 100 from $\mathcal{N}(2, 9)$, use the command `rnorm(100, mean = 2, sd = 3)`.

Normal (Gaussian) Distribution

Additional Properties:

- If $X \sim \mathcal{N}(\mu, \sigma^2)$, then $Z = \dfrac{X - \mu}{\sigma} \sim \mathcal{N}(0, 1)$ and

$$\mathbb{P}(a < X < b) = \mathbb{P}\left(\frac{a-\mu}{\sigma} < \frac{X-\mu}{\sigma} < \frac{b-\mu}{\sigma}\right) =$$

$$= \Phi\left(\frac{b-\mu}{\sigma}\right) - \Phi\left(\frac{a-\mu}{\sigma}\right).$$

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- If $X_k \sim \mathcal{N}(\mu_k, \sigma_k^2)$ for $k = 1, ..., n$ are independent, then $X_1 + X_2 + ... + X_n \sim \mathcal{N}(\mu_1 + \mu_2 + ... + \mu_n, \sigma_1^2 + \sigma_2^2 + ... + \sigma_n^2)$.

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- If $X \sim \mathcal{N}(\mu, \sigma^2)$, then

$$\mathbb{P}(\mu - \sigma < X < \mu + \sigma) \approx 0.6827,$$

$$\mathbb{P}(\mu - 2\sigma < X < \mu + 2\sigma) \approx 0.9545$$

and

$$\mathbb{P}(\mu - 3\sigma < X < \mu + 3\sigma) \approx 0.9973.$$

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I know, almost all examples are examples of *finite* sequences, but for theoretical (and practical) reasons we can assume they are infinite.

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Also, we will use a lot the CLT, say, to construct Confidence Intervals and design Tests for Hypotheses, so we need to know the CLT, and CLT is about the limit of a r.v. sequence.

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Aha, that's the problem - it is not so easy to define the closedness $\ddot\smile$

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$$\mathbb{P}\Big(\omega \in \Omega : \lim_{n\to+\infty} X_n(\omega) = X(\omega)\Big) = 1,$$

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Equivalently, we can write

$$X_n \xrightarrow{a.s.} X \qquad \text{iff} \qquad \mathbb{P}\Big(X_n \not\to X\Big) = 0.$$