

Lecture 7, MATH-57091 Probability and Statistics for High-School Teachers.

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NOTE: \bar{X} is a **random variable!**. It is good point to remark that

$$\mathbb{E}\bar{X} = \mu \text{ and } \text{Var}\bar{X} = \frac{\sigma^2}{n}$$

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Central Limit Theorem (and restatement for sample mean).

Central Limit Theorem

Let X_1, X_2, \dots be a sequence of independent random variables having common distribution and let $\mathbb{E}X_i = \mu$ and $\text{Var}(X_i) = \sigma^2$. Then, the distribution of

$$\frac{X_1 + X_2 + \dots + X_n - n\mu}{\sigma\sqrt{n}}$$

tends to the standard normal distribution $N(0, 1)$ as $n \rightarrow \infty$. That is

$$P\left(\frac{X_1 + X_2 + \dots + X_n - n\mu}{\sigma\sqrt{n}} < a\right) \rightarrow P(N(0, 1) < a) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^a e^{-\frac{x^2}{2}} dx$$

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We notice that $\bar{X} = (X_1 + X_2 + \dots + X_n)/n$ and thus

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$$P(\bar{X} \leq a) = P\left(\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \leq \frac{a - \mu}{\sigma/\sqrt{n}}\right) \approx P\left(N(0, 1) \leq \frac{a - \mu}{\sigma/\sqrt{n}}\right).$$

Example.

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So as we were expected, when we increase the sample size the probability that the sample mean will be close to the population mean increases!

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So with 10 measurements there is about 40 percent chance that the estimates distance will be within .5 light -years of the actual distance.