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Lecture 10



ISE | Industrial & Enterprise Systems Engineering GRAINGER COLLEGE OF ENGINEERING

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Figure: Throwing 1 die.

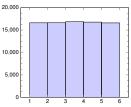




Figure: Throwing 1 die.

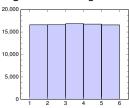


Figure: Throwing 2 dies.

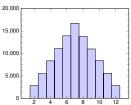






Figure: Throwing 1 die.

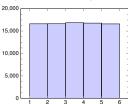


Figure: Throwing 5 dies.

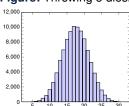


Figure: Throwing 2 dies.

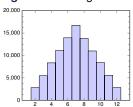






Figure: Throwing 1 die.

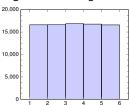


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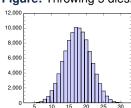


Figure: Throwing 2 dies.

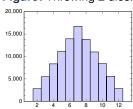
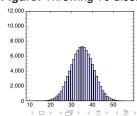


Figure: Throwing 10 dies.





The central limit theorem: attempt 1

Theorem

Let X_i , i = 1, ..., n be a series of independent, identically distributed random variables (continuous or discrete, Bernoulli, binomial, geometric, Poisson, exponential, uniform, normal – any of them). Also, define:

- \blacksquare $Y = \sum_{i=1}^{n} X_i / n$ (i.e., as the average of all X_i).
- $Z = \sum_{i=1}^{n} X_i$ (i.e., as the summation of all X_i).

Then Y and Z follow a normal distribution when n is large enough

- The implication? Say we are measuring some random variable that is an average of independent random variables with same distributions, then it is likely to be normally distributed!
- That's the reason why the normal distribution appears so ofter in real life.



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Example

The time you have to wait for a bus every day is uniformly distributed between 0 and 4 minutes. What is the probability you have to wait for more than 3 minutes for the bus today?

Answer: Based on our knowledge of the uniform distribution, the probability is $\frac{1}{4} = 0.25$.

Example

The time you have to wait for a bus every day is uniformly distributed between 0 and 4 minutes. What is the probability you have to wait for more than 3 minutes for the bus on average in the next 300 days?

Answer: We can now use the central limit theorem, as 300 days is a big enough sample. Hence, we know that the average time you have to wait for the bus is normally distributed!



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we'll see later how to compute this probability.

Theorem

Let X_i , $i=1,\ldots,n$ be a series of independent, identically distributed random variables with expected value $E[X_i] = \mu$ and variance $Var[X_i] = \sigma^2$. Define $Z = \sum_{i=1}^n X_i$ (i.e., as the summation of all random variables X_i) and $Y = \sum_{i=1}^n X_i/n$ (i.e., as the average of all X_i). Then:

Z follows a normal distribution when n is large enough with parameters $\mu_Z = \sum_{i=1}^{n} E[X_i] = n \cdot \mu$ and $\sigma_Z^2 = \sum_{i=1}^{n} Var[X_i] = n \cdot \sigma^2$.

$$Z \sim \mathcal{N}\left(n \cdot \mu, n \cdot \sigma^2\right)$$
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Y tollows a normal distribution when n is large enough with parameters $\mu_Y = \frac{1}{n} \sum_{i=1}^n E[X_i] = \mu \text{ and } \sigma_2^2 = \frac{1}{n} \sum_{i=1}^n Var[X_i] = \frac{\sigma^2}{n}.$

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Example

The time you have to wait for a bus every day is uniformly distributed between 0 and 4 minutes. What is the probability you have to wait for more than or equal to 2.2 minutes for the bus on average in the next 300 days?

Answer: We can now fully use the central limit theorem.

- Average time you wait for the bus is normally distributed.
- Each of the times you wait for the bus has mean 2 minutes and variance $\frac{4}{3}$ minutes².
- Hence, the average time you wait for the bus is $\mathcal{N}(2, \frac{4}{900})$. We are looking for P(T > 2.2) = 1 P(T < 2.2). First let us convert to the proper z value:

$$Z = \frac{X - \mu}{\sigma} = \frac{2.2 - 2}{2/30} = 3$$

Looking at the z-table:

 $P(T < 2.2) = 0.9987 \implies P(T \ge 2.2) = 1 - 0.9987 = 0.0013.$

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