

MINE AUTOMATION AND DATA ANALYTICS





SWAYAM NPTEL COURSE ON MINE AUTOMATION AND DATA ANALYTICS

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Module 8: Inferential Statistics

**Lecture 20 A: Continuous Random Variable
Part I**

CONCEPTS COVERED

1. Continuous random variable
2. Probability Distribution Function
3. Uniform distribution
4. Exponential distribution
5. Normal distribution



Discrete and Continuous Random Variables

Definition:

A discrete random variable is characterized by its ability to assume, at most, a countable number of possible values.

Consequently, any random variable capable of adopting either a finite number or a countably infinite number of distinct values qualifies as a discrete random variable.

It's worth noting that there are also random variables whose set of potential values is uncountably infinite.

Definition:

Continuous random variables pertain to scenarios where outcomes of random events are numerical, yet cannot be enumerated and are infinitely divisible.

Discrete Random Variable

- A discrete random variable is characterized by having possible values that are distinct points along the real number line.
- Discrete random variables are often associated with counting scenarios

Continuous Random Variable

- A continuous random variable is defined by its possible values spanning an interval along the real number line.
- Continuous random variables typically involve measurement scenarios.

Probability density function (pdf)

- A Probability Density Function (pdf) is a mathematical function that describes the likelihood of a continuous random variable falling within a particular range of values.
- In other words, it provides a way to represent the probability distribution of a continuous random variable. It is denoted by $f(x)$

Probability density function (pdf)

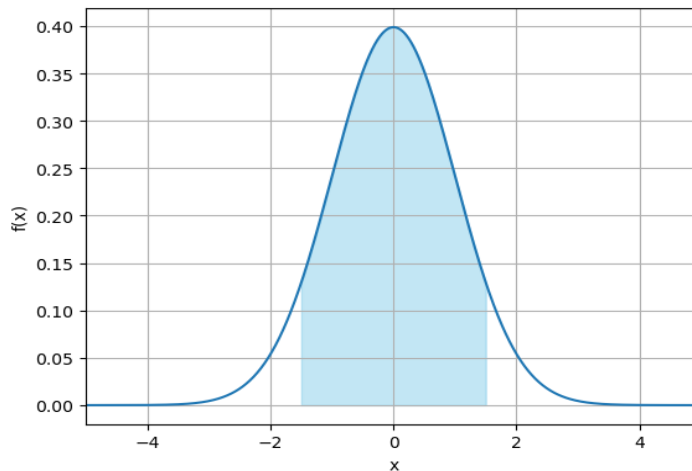
- The integral of the Probability Density Function curve signifies the likelihood of the random variable existing within a specific interval.
- In mathematical terms, for a continuous random variable X with Probability Density Function ($f(x)$),

The **probability of X lying within the range $[a, b]$** is calculated by integrating the Probability Density Function over that interval.

$P(X \in [a, b]) = P(a \leq X \leq b)$ is area under curve between a and b

$$P(a \leq X \leq b) = \int_a^b f(x) dx$$

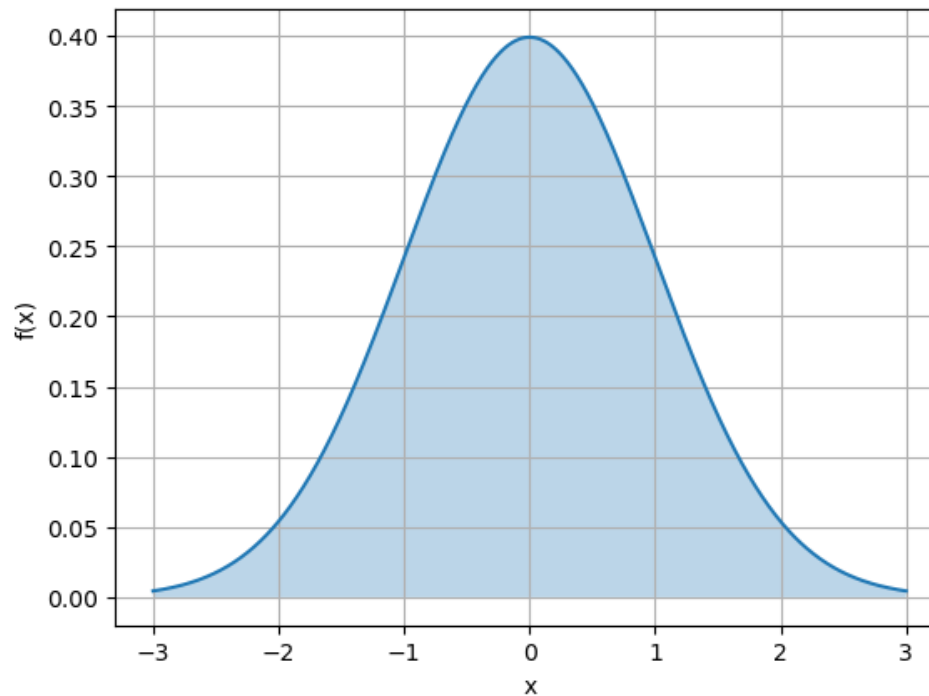
$P(-1.5 \leq X \leq 1.5) :$



Properties of pdf

- The total area under the curve equals 1, ensuring the probabilities encompass all potential outcomes.

$$\int f(x)dx = 1$$



Properties of pdf

- Therefore, the area beneath the probability distribution curve of a continuous random variable between any two points falls within the range of 0 to 1.

$$0 \leq P(X = xi) \leq 1$$

- The area beneath the probability density function graph between points a and b remains constant, irrespective of whether the endpoints a and b are inclusive or exclusive.

$$P(a \leq X \leq b) = P(a < X < b) = \int_a^b f(x) dx$$

Cumulative Distribution Function

- For a continuous random variable X

$$F(a) = P(X \leq a) = \int_{-\infty}^a f(x) dx$$

- Given that a probability of continuous random variable (X) taking any single value is zero , we consequently have

$$P(X \leq a) = P(X < a) = \int_{-\infty}^a f(x) dx$$

Expectation and Variance of any continuous random variable

$$\text{Expectation } E(X) = \int x f(x) dx$$

$$\text{Variance } \text{Var}(X) = \int (x - E(X))^2 f(x) dx$$

Expectation and Variance of any discrete random variable

$$\text{Expectation } E(X) = \sum_{i=1}^{\infty} x_i P(x_i)$$

$$\text{Variance } \text{Var}(X) = E(X - \mu)^2$$

Continuous Random Variable Distributions

- **Uniform Distribution**
- **Standard Uniform Distribution**
- **Exponential Distribution**
- **Normal Distribution**
- **Standard Normal Distribution**
- **T distribution**
- **Chi Squared Distribution**



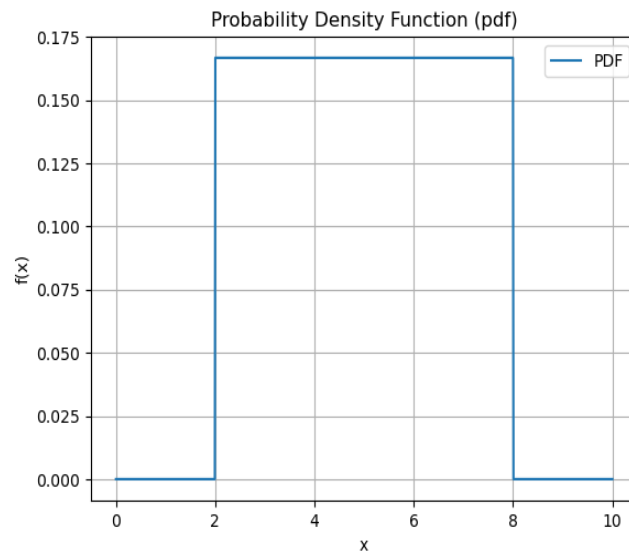
Continuous random variable

Uniform Distribution

A uniform distribution is assigned to a continuous random variable, denoted as $X \sim U(a, b)$.

The Probability Density Function for a uniform distribution is expressed as : $f(x) = \begin{cases} \frac{1}{b-a} & a < x < b \\ 0 & \text{otherwise} \end{cases}$

We know that the total area under the probability density curve of any continuous distribution equals 1



$$\int_a^b f(x) dx = 1$$

$$f(x) \int_a^b dx = 1$$

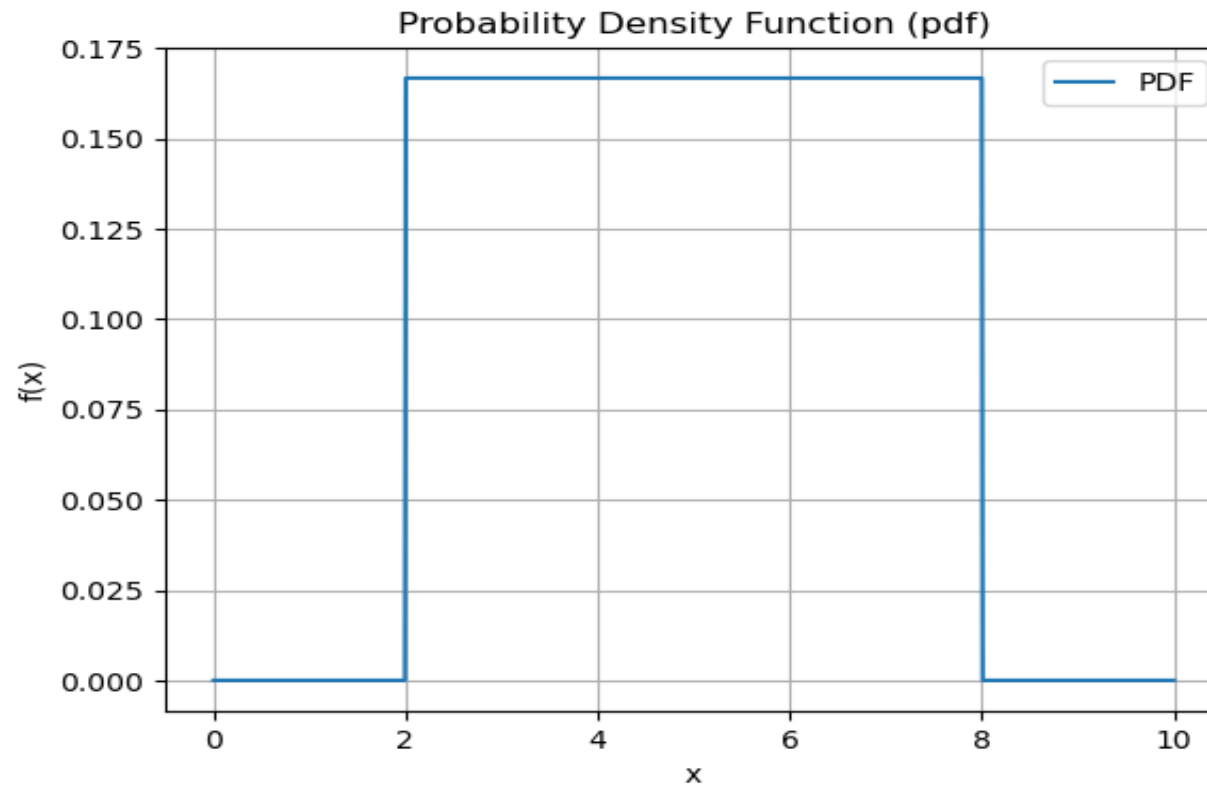
$$f(x) (b - a) = 1$$

$$f(x) = \frac{1}{b-a}$$

Continuous random variable

Uniform Distribution

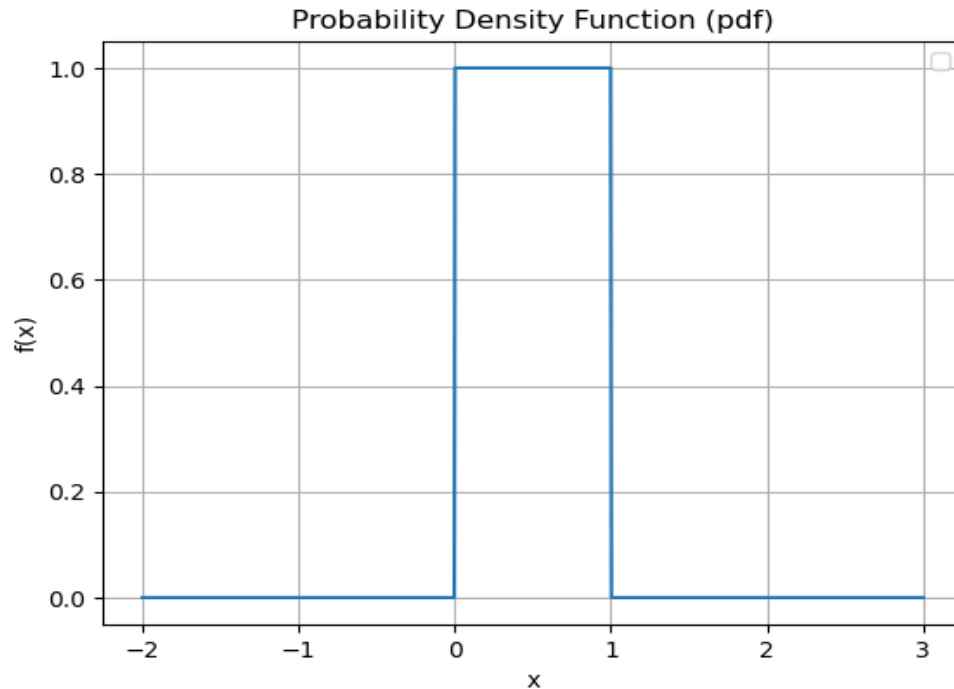
Example: Uniform Distribution $U(2,8)$



Standard Uniform Distribution

A continuous random variable follows the standard uniform distribution with a minimum value of 0 and a maximum value of 1, represented as $X \sim U(0, 1)$.

Probability Density Function of uniform distribution is given by : $f(x) = \begin{cases} 1 & 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$



$$\int_0^1 f(x) dx = 1$$

$$f(x) \int_0^1 dx = 1$$

$$f(x) (1 - 0) = 1$$

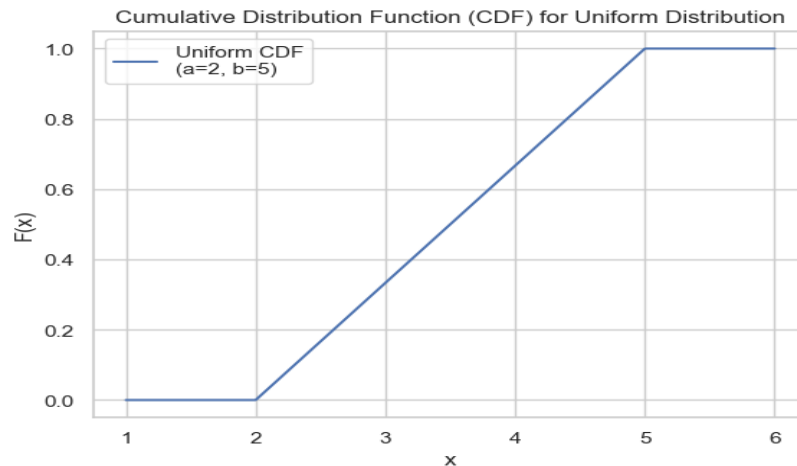
$$f(x) = 1$$

Cumulative Distribution Function Uniform Distribution

The cumulative distribution function for a uniform distribution, denoted by $F(x)$, is given by:

$$F(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x < b \\ 1 & x \geq b \end{cases}$$

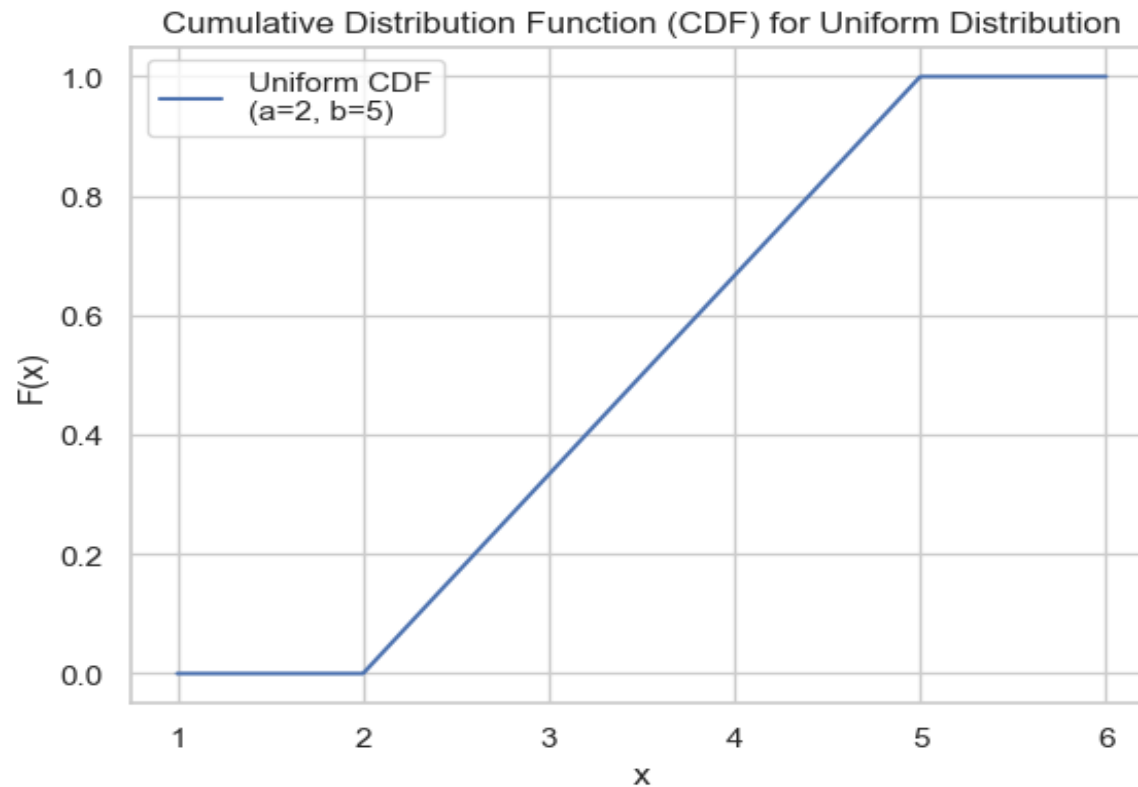
- We know for any continuous random variable X : $F(a) = P(X \leq a) = \int_{-\infty}^a f(x)dx$



$$\begin{aligned} F(x) &= P(X \leq x) = \int_{-\infty}^x f(x)dx \\ &= \int_{-\infty}^a f(x)dx + \int_a^x f(x)dx \\ &= 0 + \int_a^x f(x)dx \\ &= \int_a^x \frac{1}{b-a} dx \\ &= \frac{x-a}{b-a} \end{aligned}$$

Cumulative Distribution Function Uniform Distribution

Example : cumulative distribution function for uniform distribution $U(2,5)$

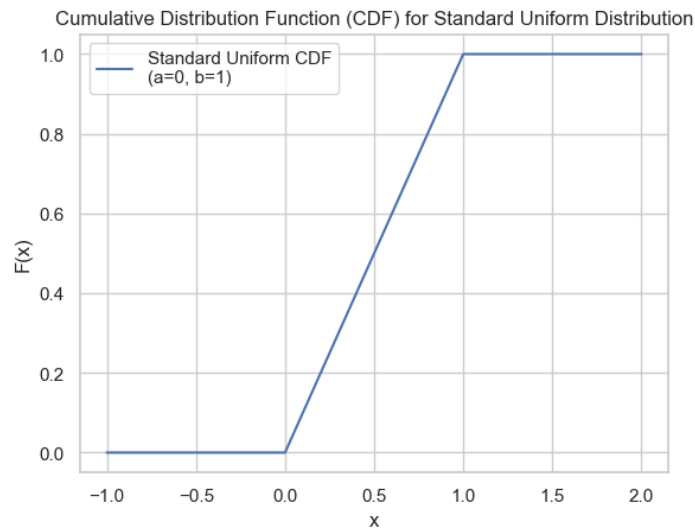


Cumulative Distribution Function Standard Uniform Distribution

The cumulative distribution function for the standard uniform distribution is denoted by $F(x)$.

$$F(x) = \begin{cases} 0 & x < 0 \\ x & 0 \leq x < 1 \\ 1 & x \geq 1 \end{cases}$$

- We know for any continuous random variable X : $F(a) = P(X \leq a) = \int_{-\infty}^a f(x) dx$



$$F(x) = P(X \leq x) = \int_{-\infty}^x f(x) dx$$

$$= \int_{-\infty}^0 f(x) dx + \int_0^x f(x) dx$$

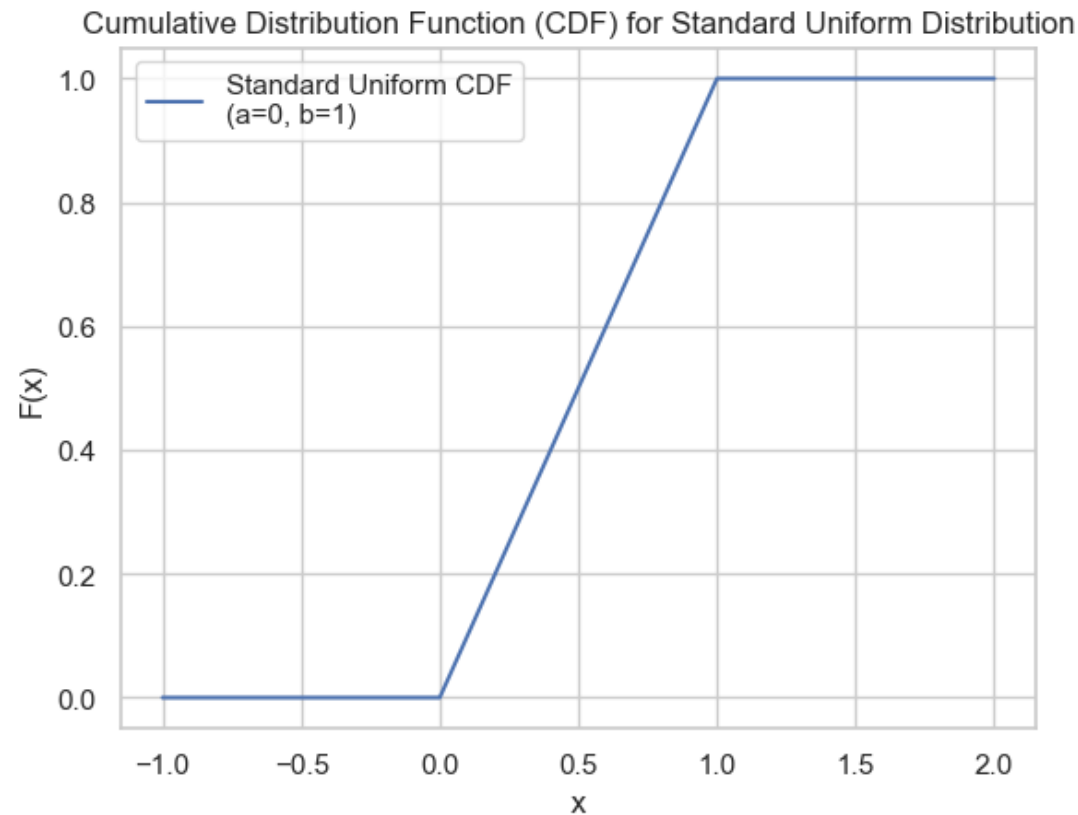
$$= 0 + \int_0^x f(x) dx$$

$$= \int_0^x 1 dx$$

$$= x$$

Cumulative Distribution Function Standard Uniform Distribution

Example : cumulative distribution function for uniform distribution $U(0,1)$



Expectation

Expectation of continuous random variable

$X \sim U(a, b)$

$$E(X) = \frac{a + b}{2}$$

We know

$$E(X) = \int_a^b x f(x) dx$$

$$= \int_a^b x \frac{1}{b-a} dx = \frac{1}{b-a} \int_a^b x dx$$

$$= \frac{1}{b-a} \frac{b^2 - a^2}{2}$$

Expectation of Uniform Continuous random variable = $\frac{b+a}{2}$



Variance

Variance of continuous random variable

$X \sim U(a, b)$

$$V(X) = \frac{(b-a)^2}{12}$$

$$V(X) = E(X^2) - (E(X))^2$$

$$E(X^2) = \int_a^b x^2 f(x) dx$$

$$= \int_a^b x^2 \frac{1}{b-a} dx = \frac{1}{b-a} \int_a^b x^2 dx$$

$$= \frac{1}{b-a} \frac{b^3 - a^3}{3}$$

$$= \frac{b^2 + a^2 + ab}{3}$$



Variance

Variance of continuous random variable

$X \sim U(a, b)$

$$V(X) = \frac{(b-a)^2}{12}$$

$$\begin{aligned} V(X) &= E(X^2) - (E(X))^2 \\ &= \frac{b^2+a^2+ab}{3} - \left(\frac{b+a}{2}\right)^2 \\ &= \frac{b^2+a^2+ab}{3} - \frac{a^2+b^2+2ab}{4} \\ &= \frac{b^2+a^2-2ab}{12} \end{aligned}$$

Variance of Uniform Continuous random variable $= \frac{(b-a)^2}{12}$



Example

X is a uniform random variable over (0,1). Find the probabilities as follows:

1. $P(X < 0.5) = 0.5$

$$\begin{aligned} P(X \leq x) &= P((X \leq x) = P((X < 0.5) = \int_0^{0.5} f(x) dx \\ &= \int_0^{0.5} 1. dx \\ &= 0.5 \end{aligned}$$

[We know pdf value for standard uniform distribution is 1]

1. $P(X \geq 0.8) = 1 - 0.8 = 0.2$

$$\begin{aligned} P((X \geq 0.8) &= 1 - P((X < 0.8) = 1 - \int_0^{0.8} f(x) dx \\ &= 1 - \int_0^{0.8} 1. dx \\ &= 1 - 0.8 \\ &= 0.2 \end{aligned}$$

Example

X is a uniform random variable over (0,1). Find the probabilities as follows:

1. $P(0.2 \leq X < 0.9) = 0.9 - 0.2 = 0.7$

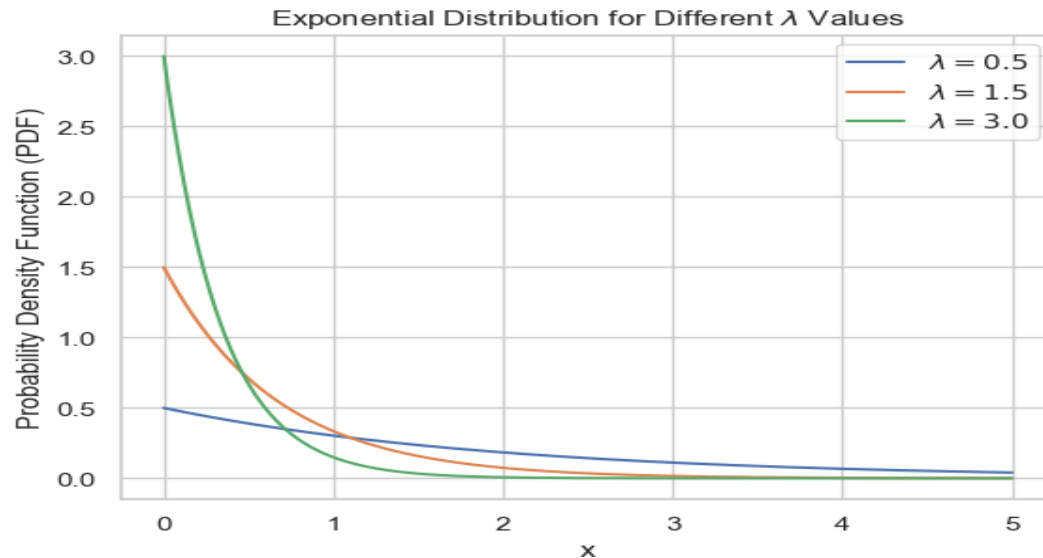
$$\begin{aligned} P(y \leq X \leq x) &= P((X \leq x) - P((X \leq y) = P((X \leq 0.9) - P((X \leq 0.2) \\ &= \int_0^{0.9} f(x)dx - \int_0^{0.2} f(x)dx \\ &= 0.9 - 0.2 \\ &= 0.7 \end{aligned}$$

Continuous Random Variable

Exponential Distribution

For some $\lambda > 0$, the probability density function (denoted by $f(x)$) of an exponential continuous random variable is defined as:

$$X \sim \text{Exp}(\lambda)$$
$$f(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$



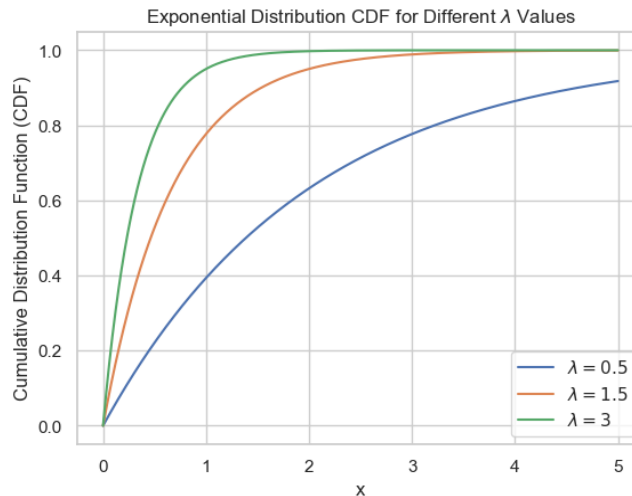
Cumulative Distribution Function Exponential Distribution

The cumulative distribution function of the exponential distribution is denoted as $F(a)$.

We know cumulative distribution function for any continuous random variable, $F(a) = P(X \leq a) = \int_{-\infty}^a f(x) dx$

$$= \int_{-\infty}^0 f(x) dx + \int_0^a f(x) dx$$

We Know $f(x) = 0$ for x less than zero in exponential distribution, So



$$= \int_0^a \lambda e^{-\lambda x} dx$$

$$F(a) = 1 - e^{-\lambda a}$$

Expectation Exponential Distribution

The Expectation of exponential distribution is given by $E(X)$

$$\begin{aligned} E(X^n) &= \int_0^{\infty} x^n f(x) dx \\ &= \int_0^{\infty} x^n \lambda e^{-\lambda x} dx \\ &= \lambda \int_0^{\infty} x^n e^{-\lambda x} dx \end{aligned}$$

By applying integration by parts formula: $\int u dv = uv - \int v du$

$$E(X^n) = \frac{n}{\lambda} E(X^{n-1})$$

$$\text{For } n = 1, E(X^1) = \frac{1}{\lambda} E(X^{1-1}) = \frac{1}{\lambda}$$

$$\text{Expectation of a Exponential Distribution } \text{Exp}(\lambda) = \frac{1}{\lambda}$$

Variance

Exponential Distribution

The Variance of exponential distribution is given by $V(X)$

$$\text{For } n = 1, E(X^1) = \frac{1}{\lambda} E(X^{1-1}) = \frac{1}{\lambda}$$

$$\text{For } n = 2, E(X^2) = \frac{2}{\lambda} E(X^{2-1}) = \frac{2}{\lambda^2}$$

$$E(X) = \frac{1}{\lambda}$$

$$\begin{aligned} V(X) &= E(X^2) - (E(X))^2 \\ &= \frac{2}{\lambda^2} - \left(\frac{1}{\lambda}\right)^2 \\ &= \frac{1}{\lambda^2} \end{aligned}$$

The Variance $V(x)$ of an exponential distribution defined by $\text{Exp}(\lambda) = \frac{1}{\lambda^2}$

Normal Distribution

- The normal distribution, alternatively referred to as the Gaussian distribution or bell curve, is a continuous probability distribution exhibiting symmetry around its mean, which coincides with its median and mode.
- Defined by its mean (μ) and standard deviation (σ), the normal distribution takes on a bell-shaped form.
- Considered paramount in statistics for both theoretical understanding and practical application, the normal distribution holds significant importance.

Probability Density Function (pdf) Normal Distribution

The continuous random variable X follows a normal distribution, denoted as $X \sim N(\mu, \sigma^2)$, where μ is the mean and σ^2 is the variance.

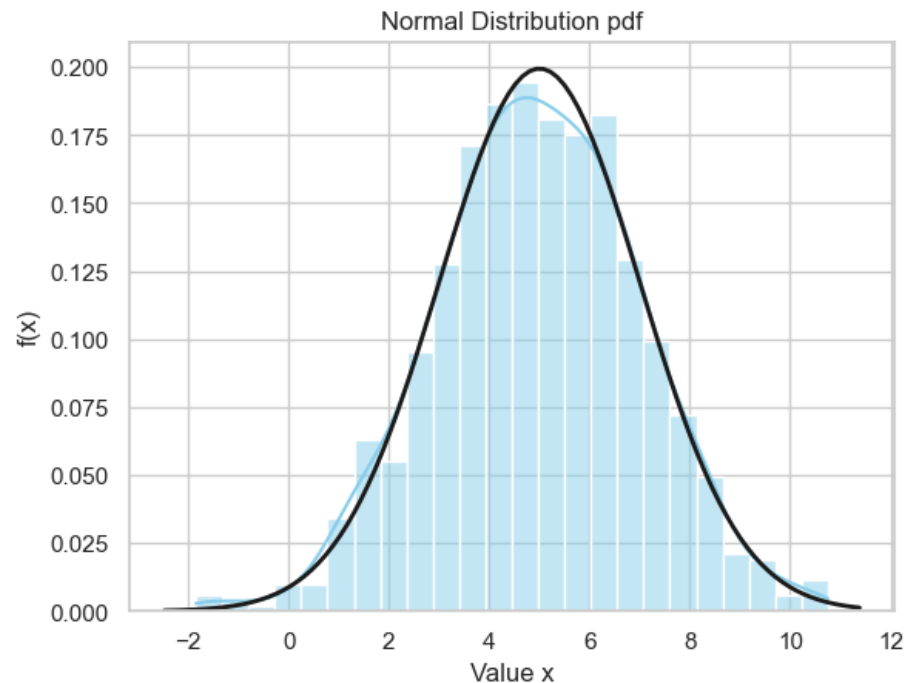
where μ = expected value i.e. mean

σ^2 = variance

Pdf of normal distribution is given by $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad -\infty < x < \infty$

Shape of Normal Probability Density Function (pdf)

Pdf of normal distribution is given by $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$ $-\infty < x < \infty$



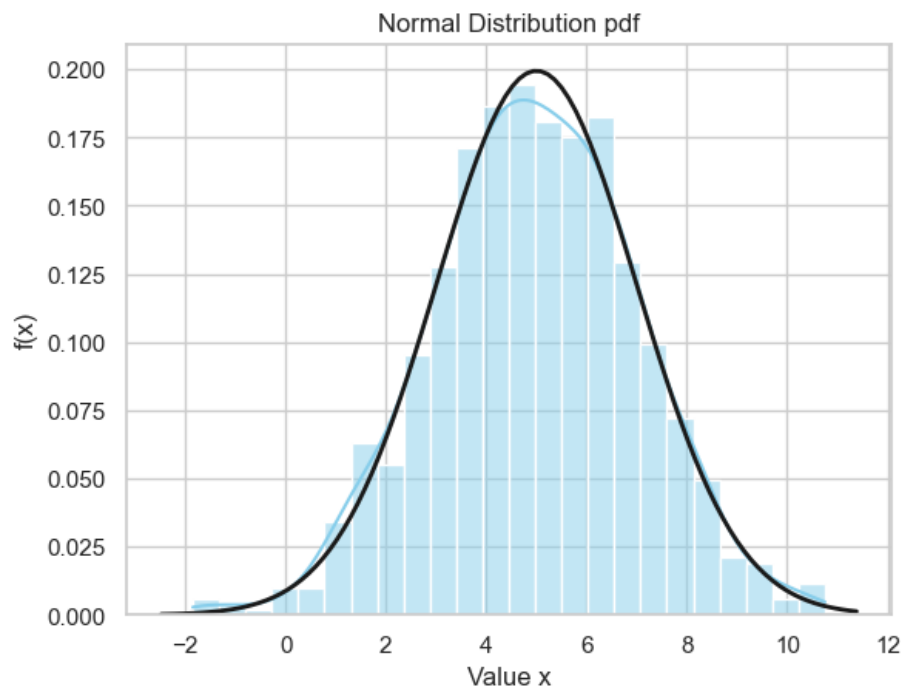
μ = expected value i.e. mean = 5

σ = Standard deviation = 2

Height of the graph

Pdf of normal distribution is given by $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2} \quad -\infty < x < \infty$

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2}$$



$$f(x) = 0.199 \text{ for}$$

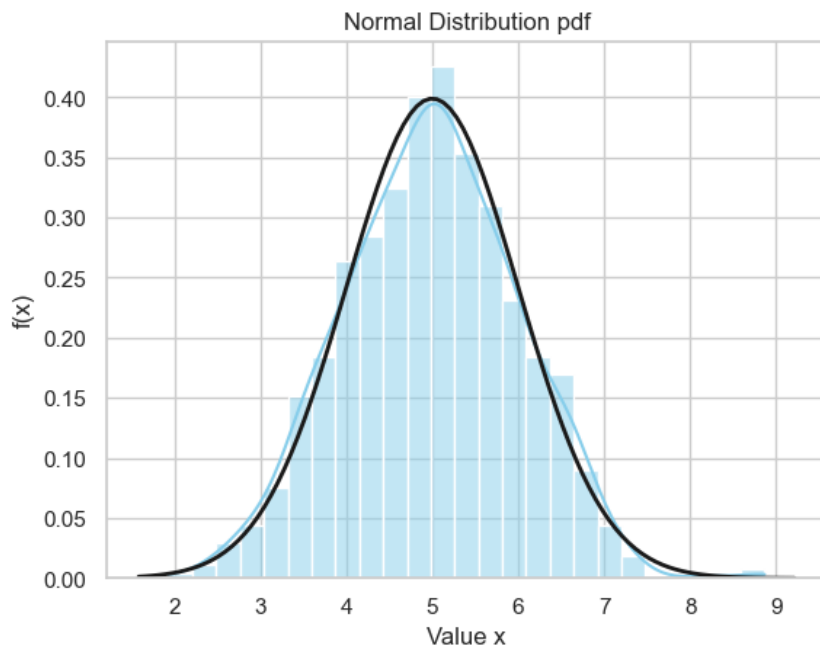
μ = expected value i.e. mean = 5

σ = Standard deviation = 2

Height of the graph

Pdf of normal distribution is given by $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2}$ $-\infty < x < \infty$

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2}$$



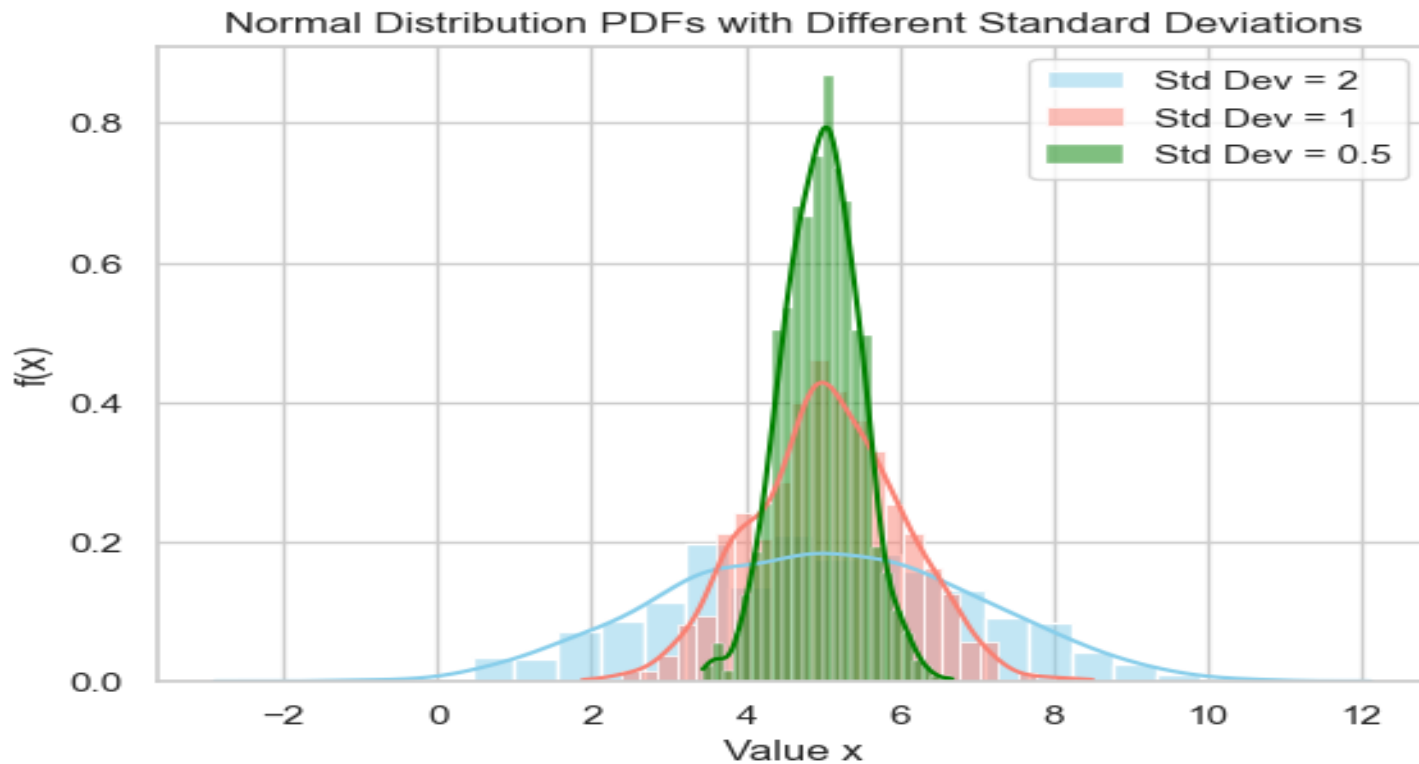
$$f(x) = 0.399 \text{ for}$$

μ = expected value i.e. mean = 5

σ = Standard deviation = 1

Same Mean and Different Standard Deviation

Pdf of normal distribution is given by $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$ $-\infty < x < \infty$

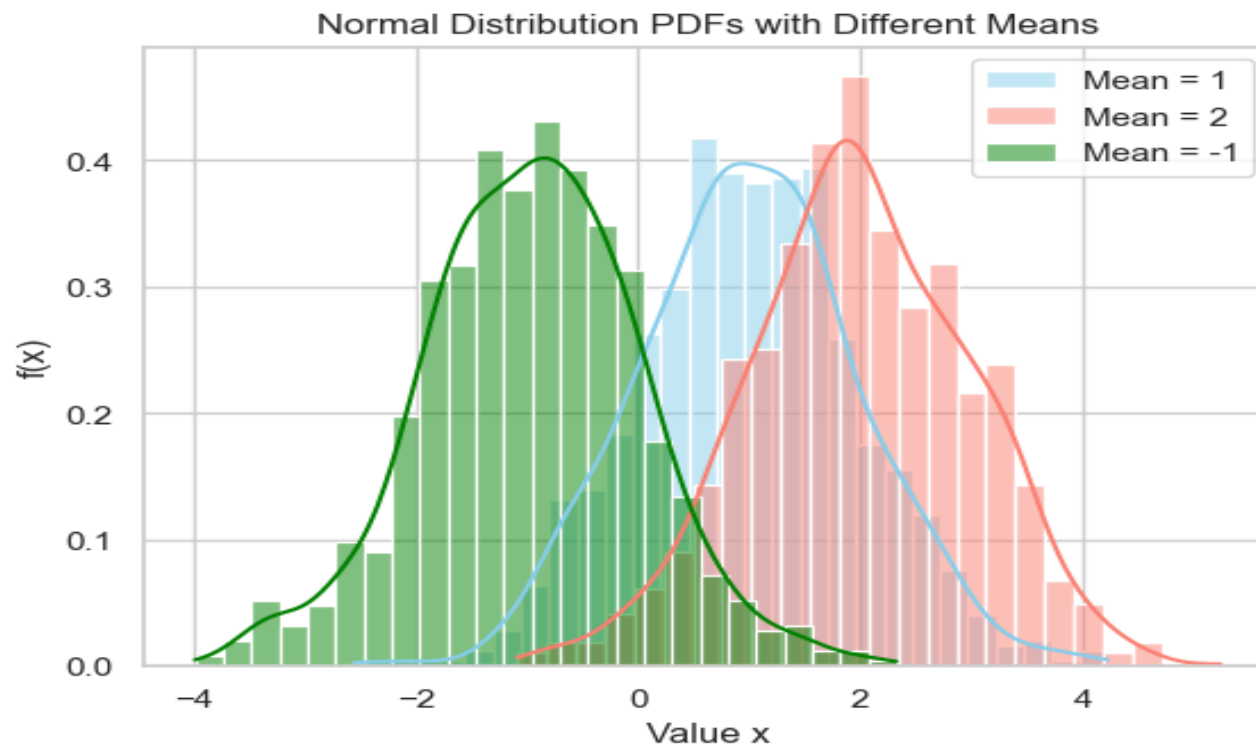


μ = expected value i.e. mean = 5
 σ = Standard deviation = 2, 1, 0.5

The larger the standard deviation , the flatter the graph becomes.

Same Standard Deviation and Different Mean

Pdf of normal distribution is given by $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$ $-\infty < x < \infty$

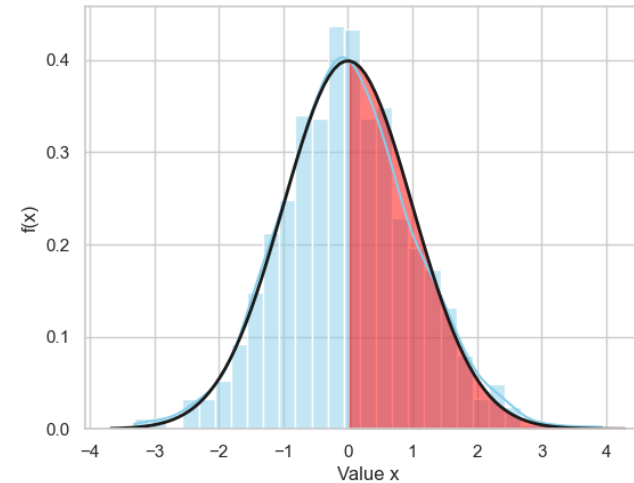
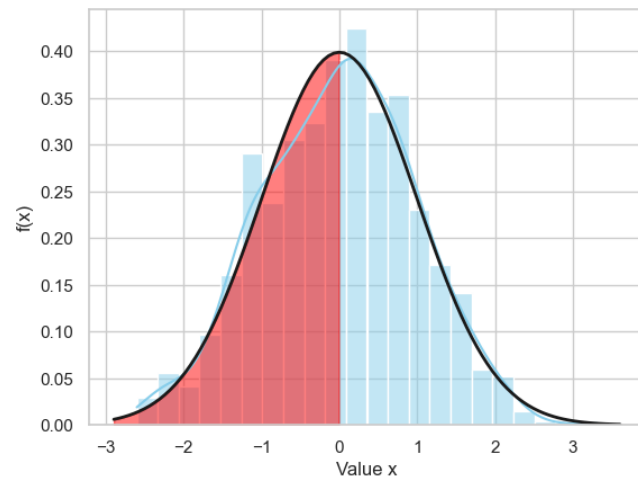


μ = expected value i.e. mean = 1 , 2, -1
 σ = Standard deviation = 1

Symmetric around Mean

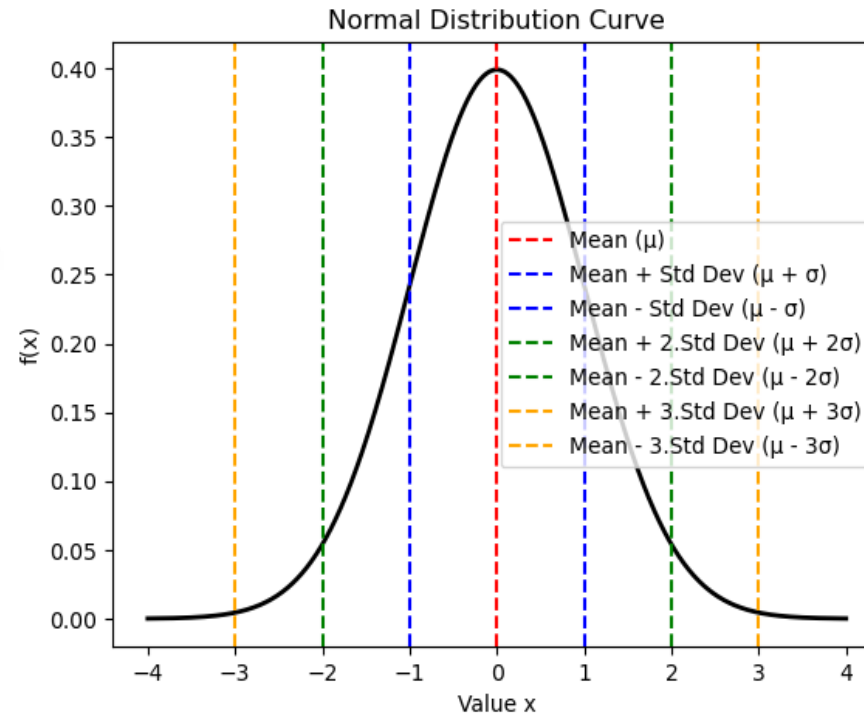
- Pdf of normal distribution is given by $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$ $-\infty < x < \infty$
- The probability density function of a normal random variable X exhibits symmetry around its mean.
- This means that X is equally likely to occur on either side of the mean (μ).

$$P(X \leq \mu) = P(X \geq \mu) = 0.5$$



Normal Distribution

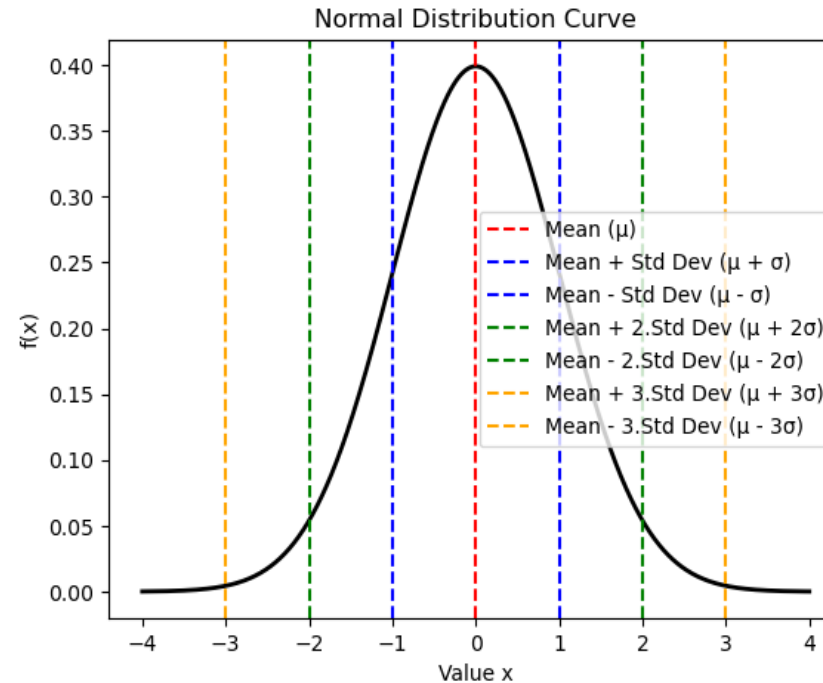
1. Bell Shaped
2. Centered at mean i.e., the expected value
3. Close to the horizontal axis outside the range from $\mu + 3\sigma$ and $\mu - 3\sigma$



Approximation rule for Normal Distribution

For a continuous random variable following a normal distribution with mean μ and standard deviation σ :

- The interval between $\mu + \sigma$ and $\mu - \sigma$ encompasses approximately 68% of the distribution.
- The interval between $\mu + 2\sigma$ and $\mu - 2\sigma$ encompasses approximately 95% of the distribution.
- The interval between $\mu + 3\sigma$ and $\mu - 3\sigma$ encompasses approximately 99% of the distribution.

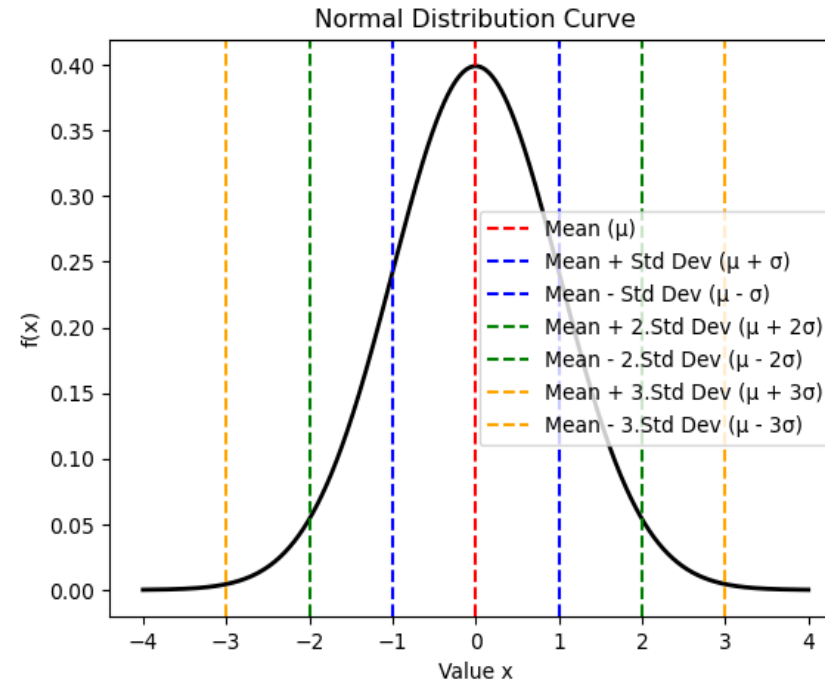


Example of Normal Distribution $N(\mu, \sigma^2)$

$X \sim N(10, 16)$

What is the probability that X is between 6 and 14 ?

Using the Approximation rule Answer is 0.68

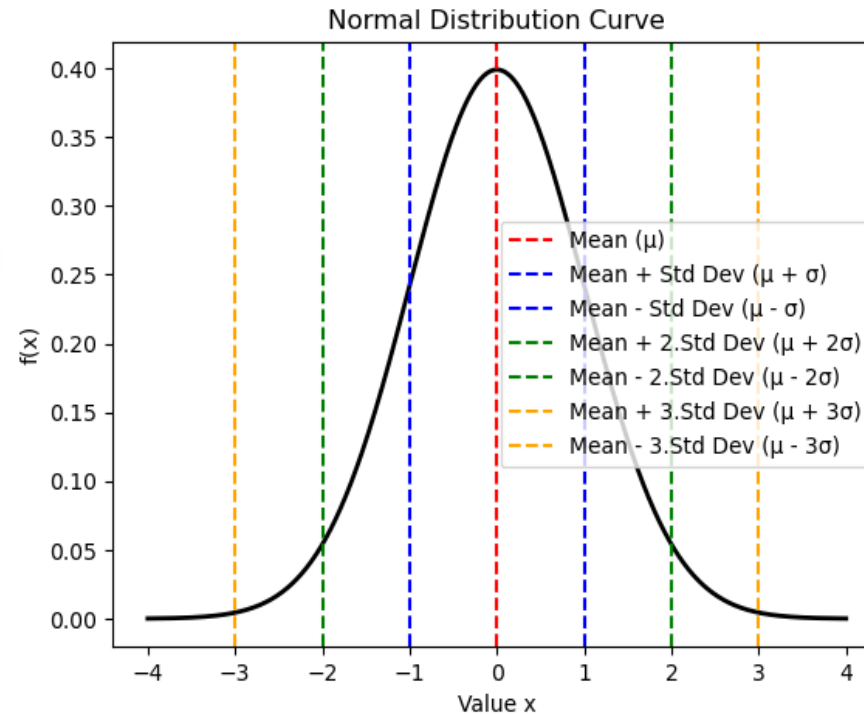


Example of Normal Distribution $N(\mu, \sigma^2)$

$X \sim N(10, 16)$

What is the probability that X is less than 6 ?

Using the Approximation rule Answer is 0.16

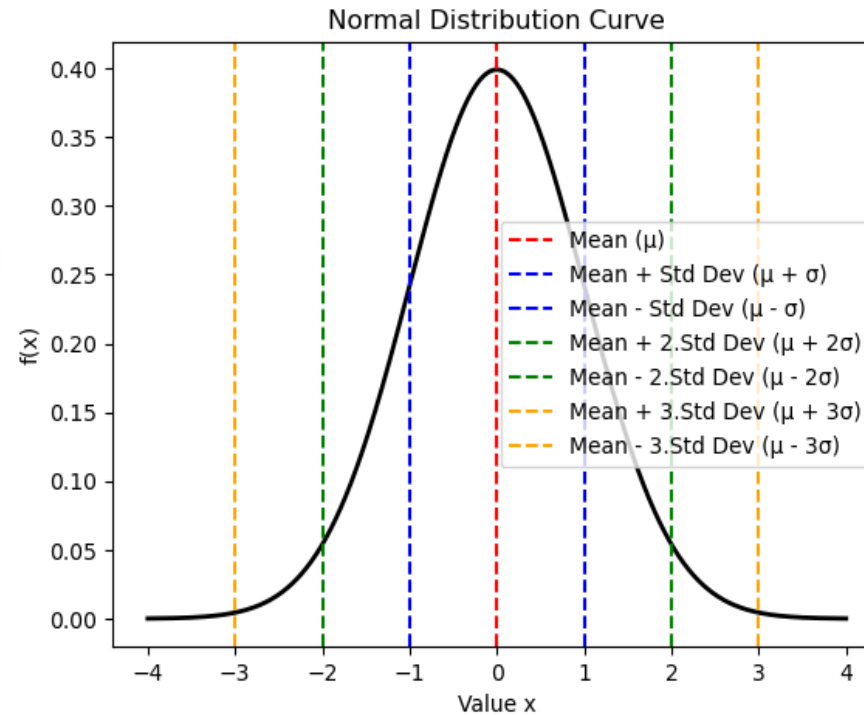


Example of Normal Distribution $N(\mu, \sigma^2)$

$X \sim N(10, 16)$

What is the probability that X is greater than 14 ?

Using the Approximation rule, the Answer is 0.16

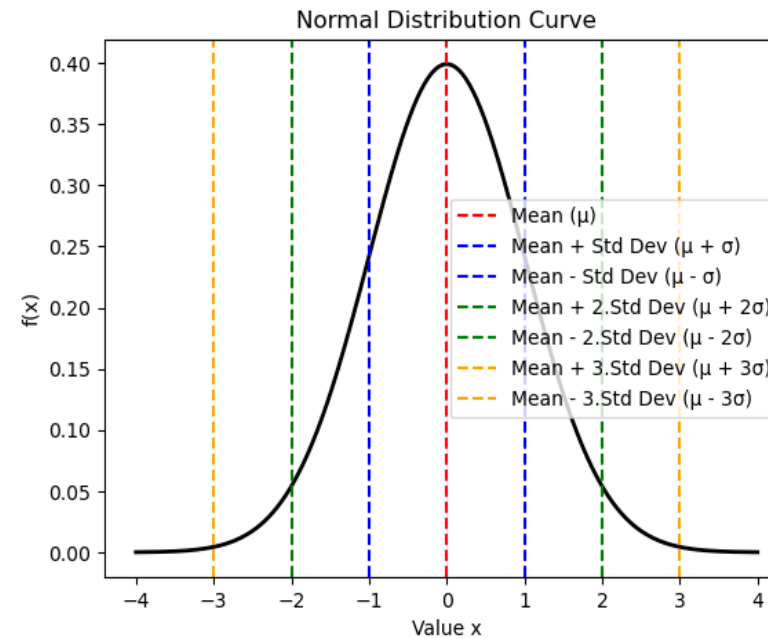


Example of Normal Distribution $N(\mu, \sigma^2)$

$X \sim N(10, 16)$

What is the probability that X is greater than 22 ?

Using the Approximation rule, the Answer is 0



REFERENCES

- Introduction to Probability and Statistics for Engineers and Scientists, Sixth Edition, Sheldon M. Ross
- Statistical Methods Combined Edition (Volume I& II), N G Das



CONCLUSION

- Continuous random variable
- Probability Distribution Function
Properties of pdf
- Cumulative Distribution Function
- Uniform and Standard Uniform distribution
Expectation and Variance
- Exponential distribution
Expectation and Variance
- Normal distribution
Approximation Rule



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