



**VANDERBILT**  
School *of* Engineering

# CE 3300-01 – RISK, RELIABILITY, AND RESILIENCE ENGINEERING

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Continuous Random Variables  
Book Reference: Chapters 3-4

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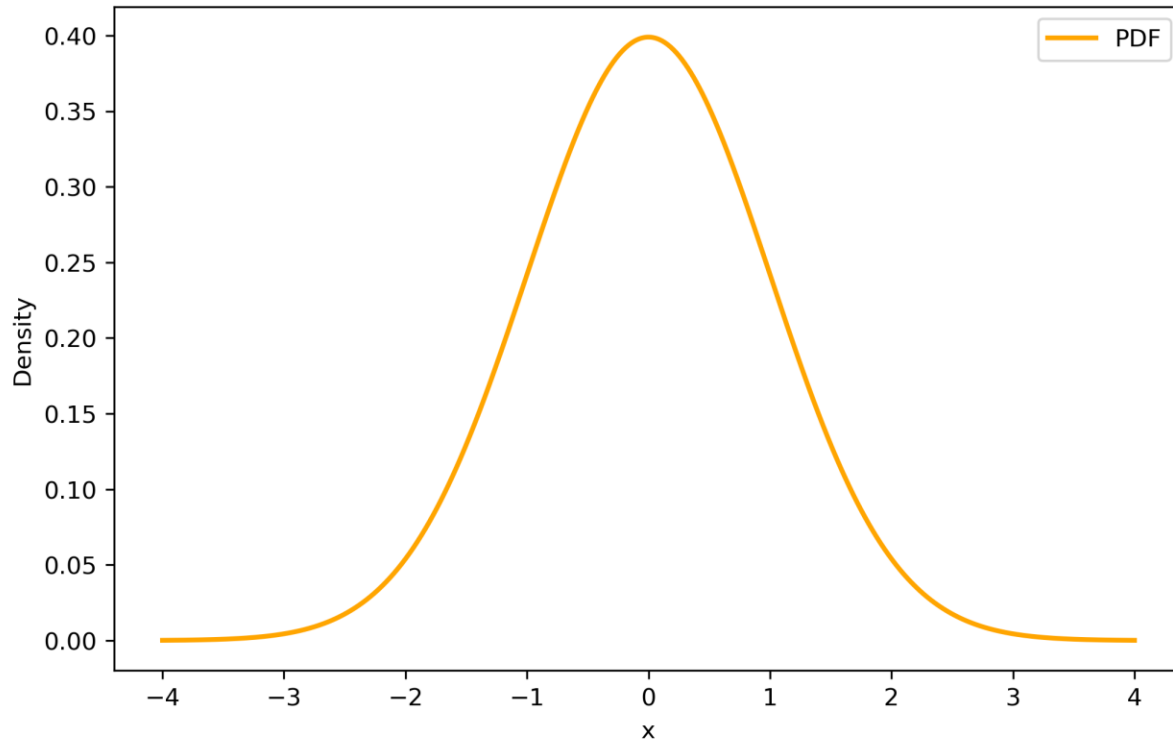
February 11<sup>th</sup>-12<sup>th</sup>, 2025

Instructor: Dr. Hiba Baroud

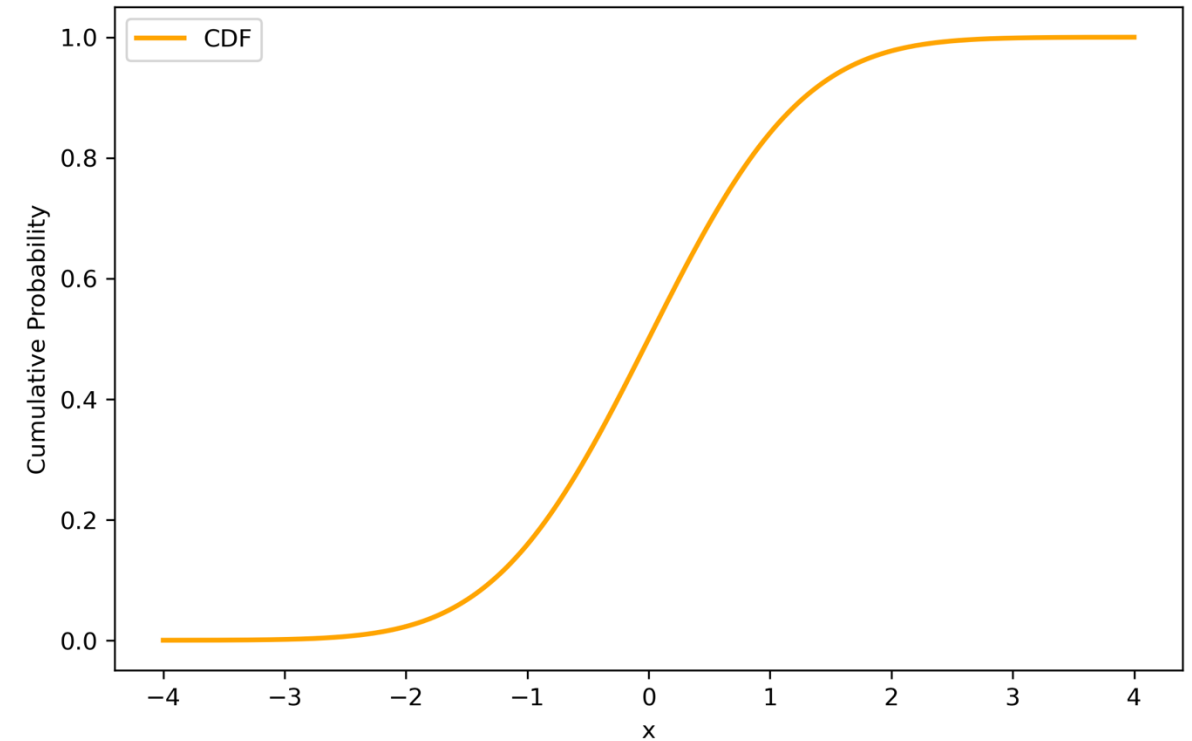
# Today: Continuous Random Variables



Probability Density Function (PDF) of a Normal Distribution



Cumulative Distribution Function (CDF) of a Normal Distribution





# Continuous RVs – Learning Objectives

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- Continuous RVs and Probability Distribution
  - **Describe** continuous probability distributions
  - **Calculate** probability and moments of continuous probability distributions
  - **Distinguish** between types of probability distributions
  - **Solve** problems with both discrete and continuous R.V.

# Recall: Discrete Vs. Continuous RVs



- A RV is a variable whose value can take on one of several realizations such that each realization is associated with a likelihood of occurrence

A **discrete** RV takes on a finite or countably infinite set of values. This means that the possible outcomes are distinct and can be listed individually.

A **continuous** RV can take on **any value** within an interval. Since there are infinitely many possible values, the probability of a single exact outcome is **zero**.

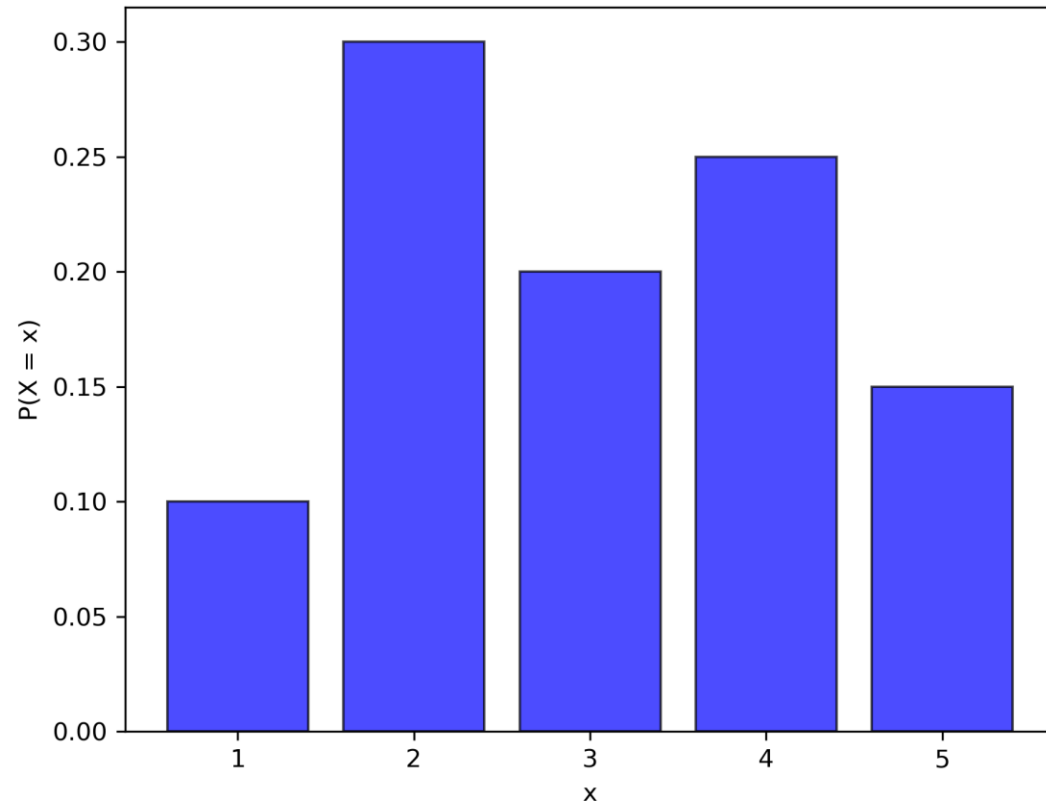
Probability is given by the probability mass function (PMF):  $p_X(x)$  **discrete** RV

Probability is described by the probability density function (PDF):  $f_X(x)$  **Continuous** RV

# Continuous Probability Distributions

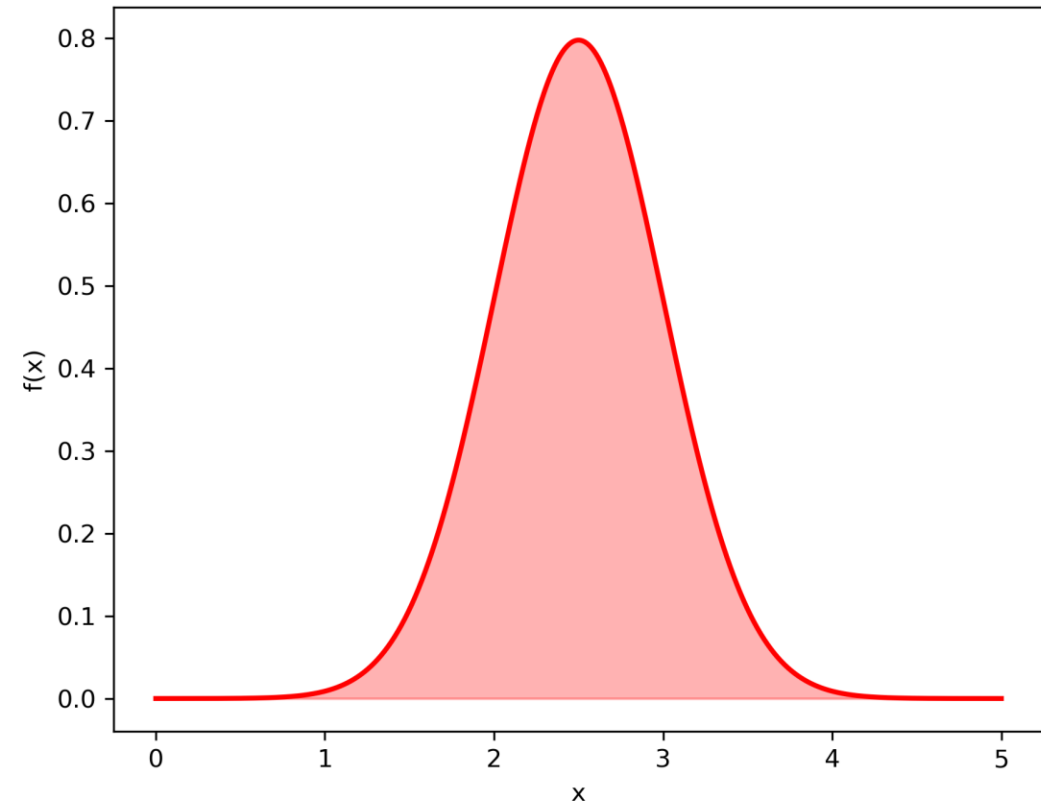


Discrete Random Variable Example



$$P(X = x)$$

Continuous Random Variable Example



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

# Probability Density Function – PDF



## Discrete RV

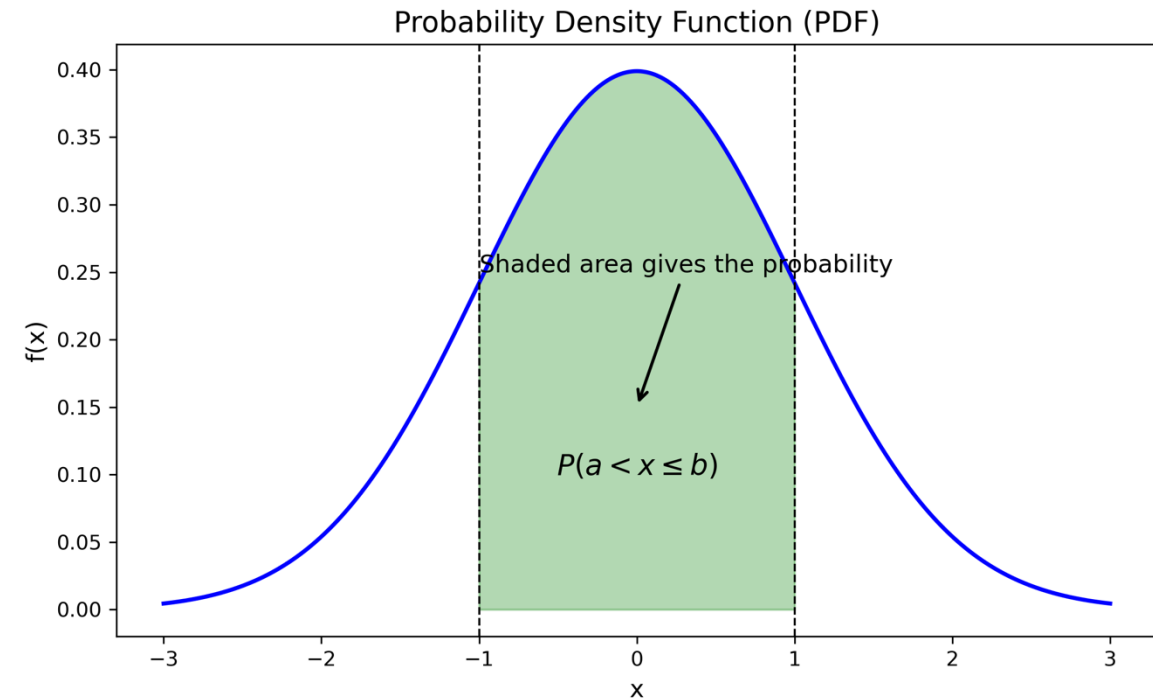
- Probability is given by the probability mass function (PMF)

$$f_x(x) = p_X(x_i) = \mathbf{P}(X = x_i)$$

## Continuous RV

- $f(x)$  is the probability density (distribution) function (PDF)
- The probability of the random variable taking a range of values is given by the area under the pdf

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

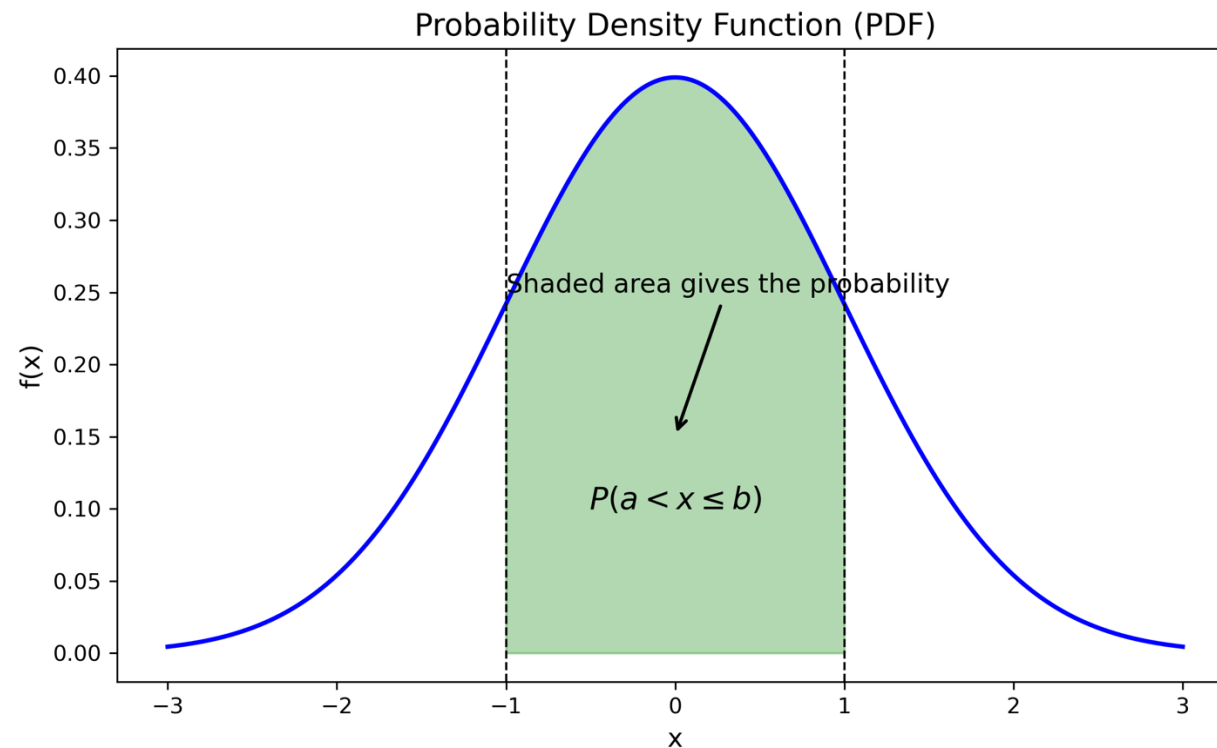


# Note the Equivalence



$$\mathbf{P}(X = a) = \int_a^a f_X(x) dx = 0$$

↪  $\mathbf{P}(a \leq X \leq b) = \mathbf{P}(a < X < b) = \mathbf{P}(a \leq X < b) = \mathbf{P}(a < X \leq b)$



# Cumulative Distribution Function – CDF



## Discrete RV

- CDF

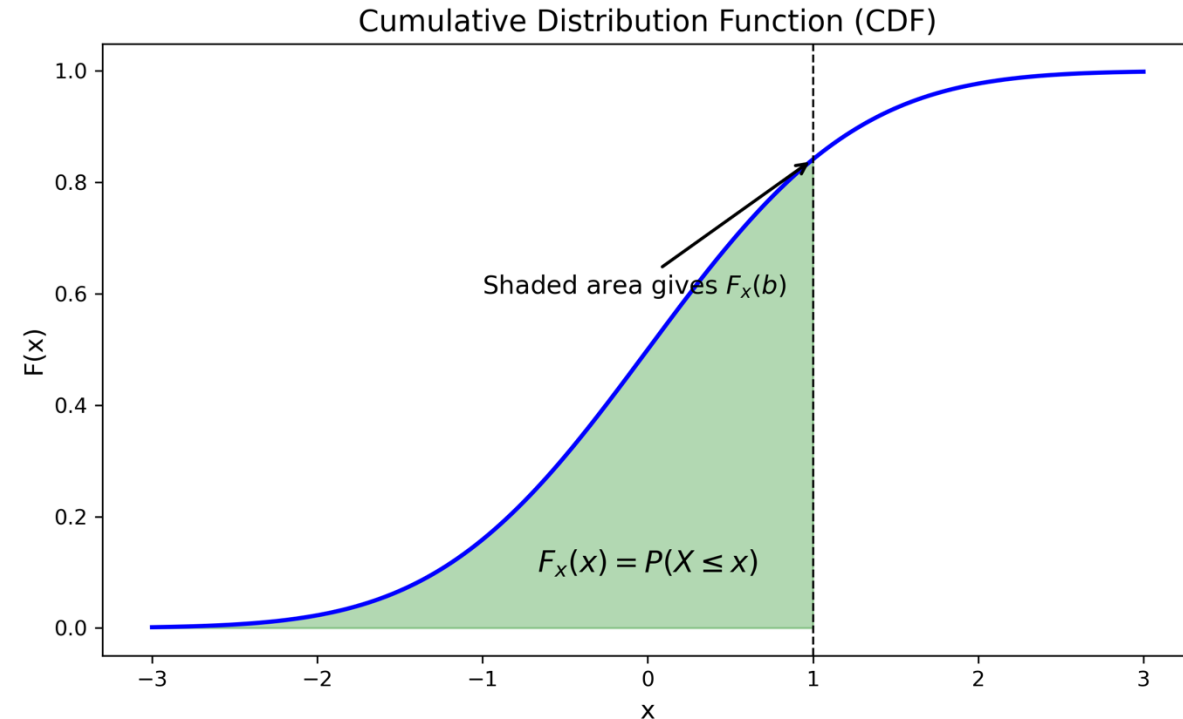
$$F_X(x) = \sum_{\text{all } x_i \leq x} P(X = x_i) = \sum_{\text{all } x_i \leq x} p_X(x_i)$$

## Continuous RV

- The CDF is obtained by integrating the PDF

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

Or whatever the domain/lower bound is for the distribution



## Axioms

$$\sum x_i p_X(x_i) = 1 \quad \int_{-\infty}^{+\infty} f_X(x) dx = 1$$

# Descriptors of a Continuous RV – Expected Value



The expected value represents the **average or mean** of the distribution.

Discrete RV

$$\mathbf{E}[X] = \sum_{x_i} x_i p_X(x_i)$$

Continuous RV

$$\mathbf{E}[X] = \int_{-\infty}^{+\infty} x f_X(x) dx$$

# Descriptors of a Continuous RV – Variance



The variance provides a measure of dispersion of  $X$  around its mean. How widely or narrowly the values of the random variable are dispersed.

$$\text{Var}[X] = \mathbf{E} [X^2] - (\mathbf{E}[X])^2 = \mathbf{E} [X^2] - \mu_x^2$$

Discrete RV

$$\text{Var}[X] = \sum x_i^2 p_X(x_i) - \left( \sum x_i p_X(x_i) \right)^2$$

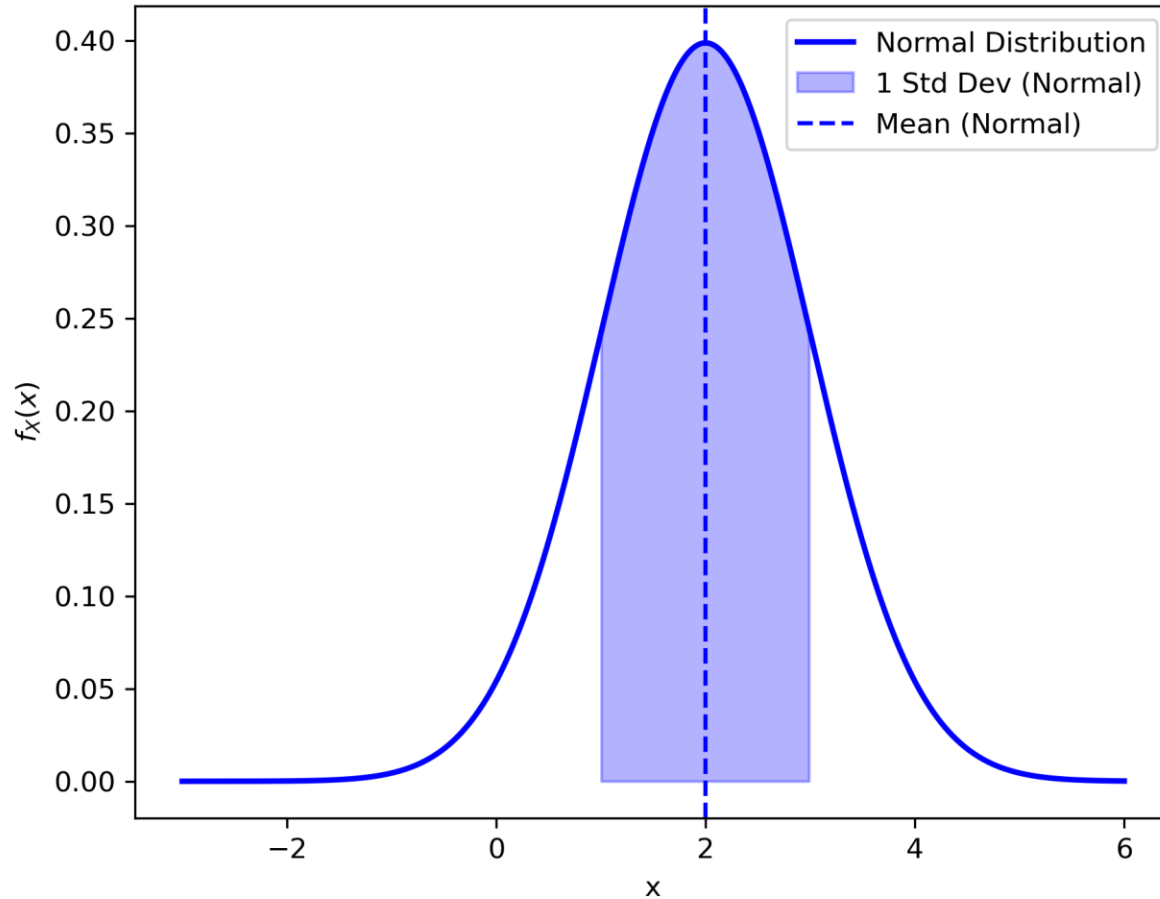
Continuous RV

$$\text{Var}[X] = \int_{-\infty}^{+\infty} (x - \mu_x)^2 f_X(x) dx = \int_{-\infty}^{+\infty} x^2 f_X(x) dx - \left( \int_{-\infty}^{+\infty} x f_X(x) dx \right)^2$$

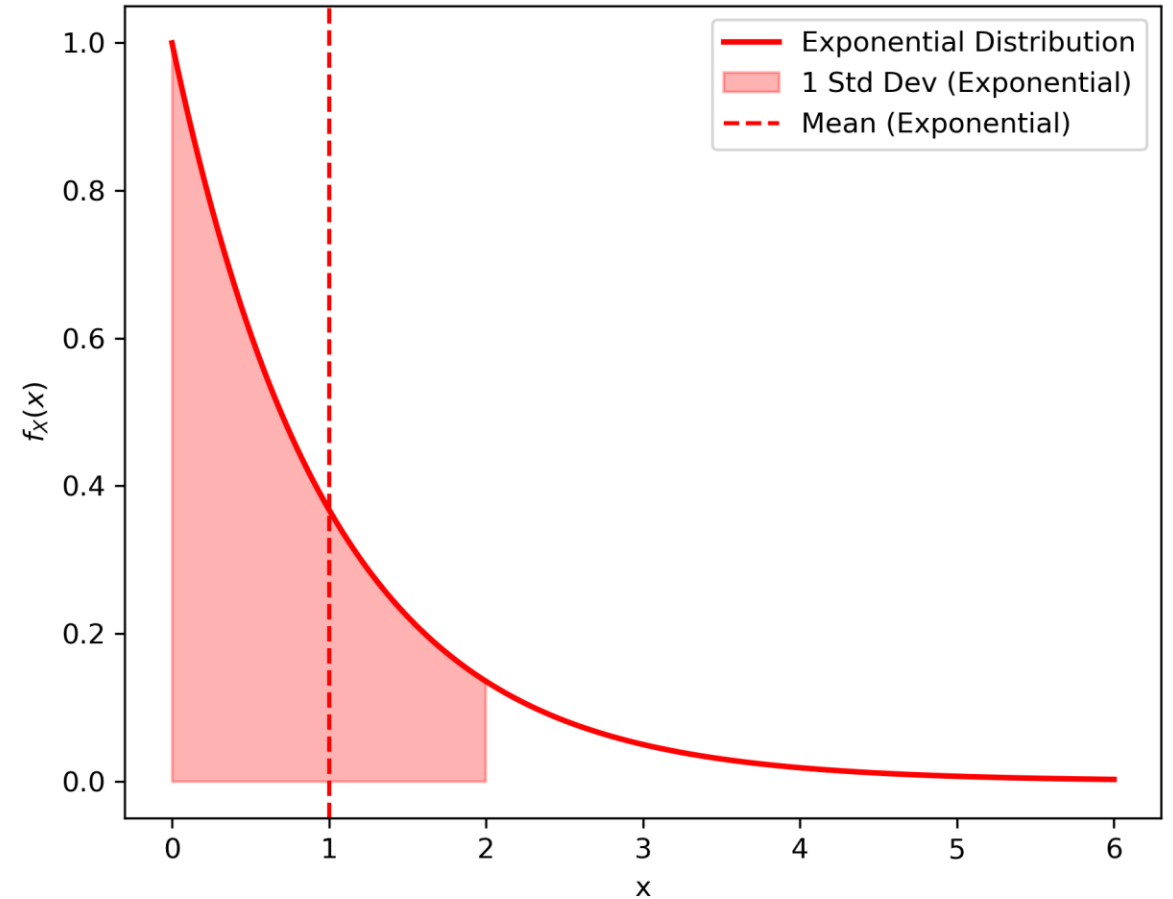
# Examples– Mean and Variance of a Continuous RV



Normal Distribution



Exponential Distribution



$$\sigma_X = \sqrt{\text{Var}(X)}$$

# Exponential Distribution - Definition



**Exponential Distribution** is a continuous probability distribution that models the **time between independent events** occurring at a constant average rate.

- The occurrence of an event constitutes a Poisson Process.
- It is often used to describe waiting times, such as time between customer arrivals or system failures. (**Recurrence time**)

## Real-world applications:

- Time between arrivals of customers in a queue.
- Time until the failure of a machine component.
- Time between earthquakes in a given region.
- Time between the occurrence of floods

## Recall:

Poisson distribution for “rate” or “# occurrences per unit”

# Exponential Distribution – Properties



The main property of the exponential distribution is the fact that it's **MEMORYLESS**

$$P(X \geq x_0 + x_1 \mid X \geq x_0) = P(X \geq x_1)$$

- Such a property is useful for calculations but may not represent reality in many applications
- Example: The probability of waiting additional time does not depend on how much time has already elapsed.



# Exponential Distribution – PDF and Parameters



## PDF Exponential

$$X \sim \text{Exp}(\lambda)$$

The PDF of an exponentially distributed random variable  $X$  is:

$$f(x) = \lambda e^{-\lambda x}, \quad x \geq 0$$

$\lambda$  is the mean number of occurrences in one interval (same as Poisson)

Another way of describing the exponential distribution is using  $\lambda = \frac{1}{\beta}$

- Continuous random variable
- Models waiting times between events
- Defined only for  $x > 0$
- Memoryless property

# Exponential Distribution – CDF



## PDF Exponential

$$X \sim \text{Exp}(\lambda)$$

The PDF of an exponentially distributed random variable  $X$  is:

$$f(x) = \lambda e^{-\lambda x}, \quad x \geq 0$$

## CDF Exponential

$$\begin{aligned} F_X(x) &= P(X \leq x) = \int_0^x f_X(x) dx = \int_0^x \lambda e^{-\lambda x} dx = \\ &= -e^{-\lambda x} \Big|_0^x = -e^{-\lambda x} - (-e^0) = 1 - e^{-\lambda x} \end{aligned}$$

# Exponential Distribution – Moments



The mean is given by  $E[X] = \frac{1}{\lambda}$ , indicating the average time between events.

$$E[X] = \frac{1}{\lambda} = \beta$$

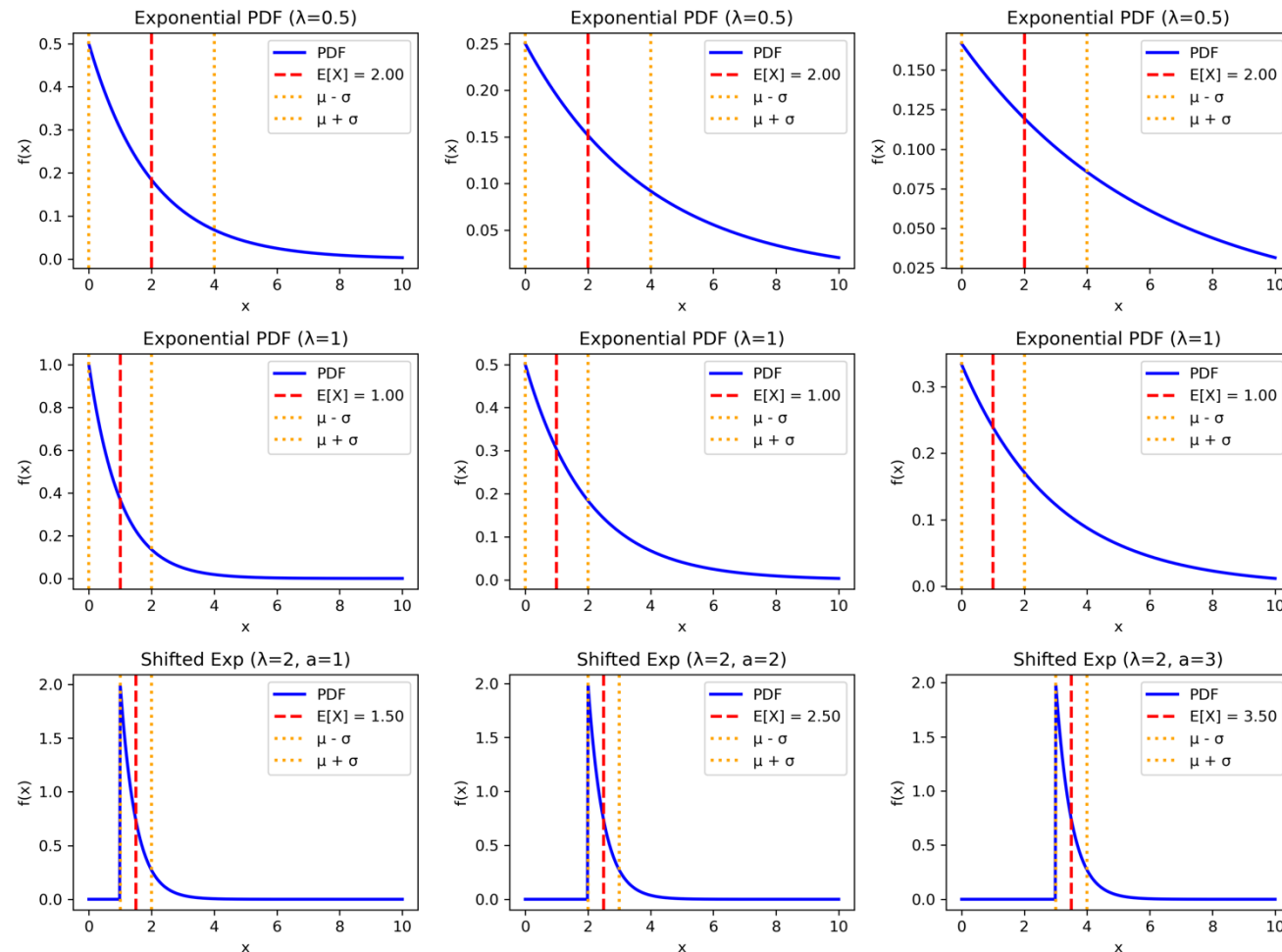
The variance is  $V[X] = \frac{1}{\lambda^2}$ , reflecting the spread of inter-event times.

$$Var[X] = \frac{1}{\lambda^2} = \beta^2$$

# Exponential Distributions



Parameter	Effect when increased	Effect when decreased
$\lambda$ (rate)	Steeper decay, shorter waiting times, lower mean and variance	Flatter curve, longer waiting times, higher mean and variance
$a$ (shift)	Distribution shifts right (delayed start)	Distribution shifts left (earlier start)




# Example 1 – Earthquake



There were 16 high intensity earthquakes that occurred in San Francisco between 1836 and 1961. If we assume that the occurrence of such events follows a Poisson process, what is the probability that the next earthquake will occur within 2 years?

Let  $T$  be time until the next earthquake

$$T \sim \text{Exp} \left( \lambda = \frac{16}{1961-1836} = 0.128 \text{ earthquakes/year} \right)$$

A gold-colored L-shaped arrow pointing from the left towards the equation.
$$P(T \leq 2) = 1 - e^{-0.128 \times 2} = 0.226$$

# Differentiate between Poisson and Exponential



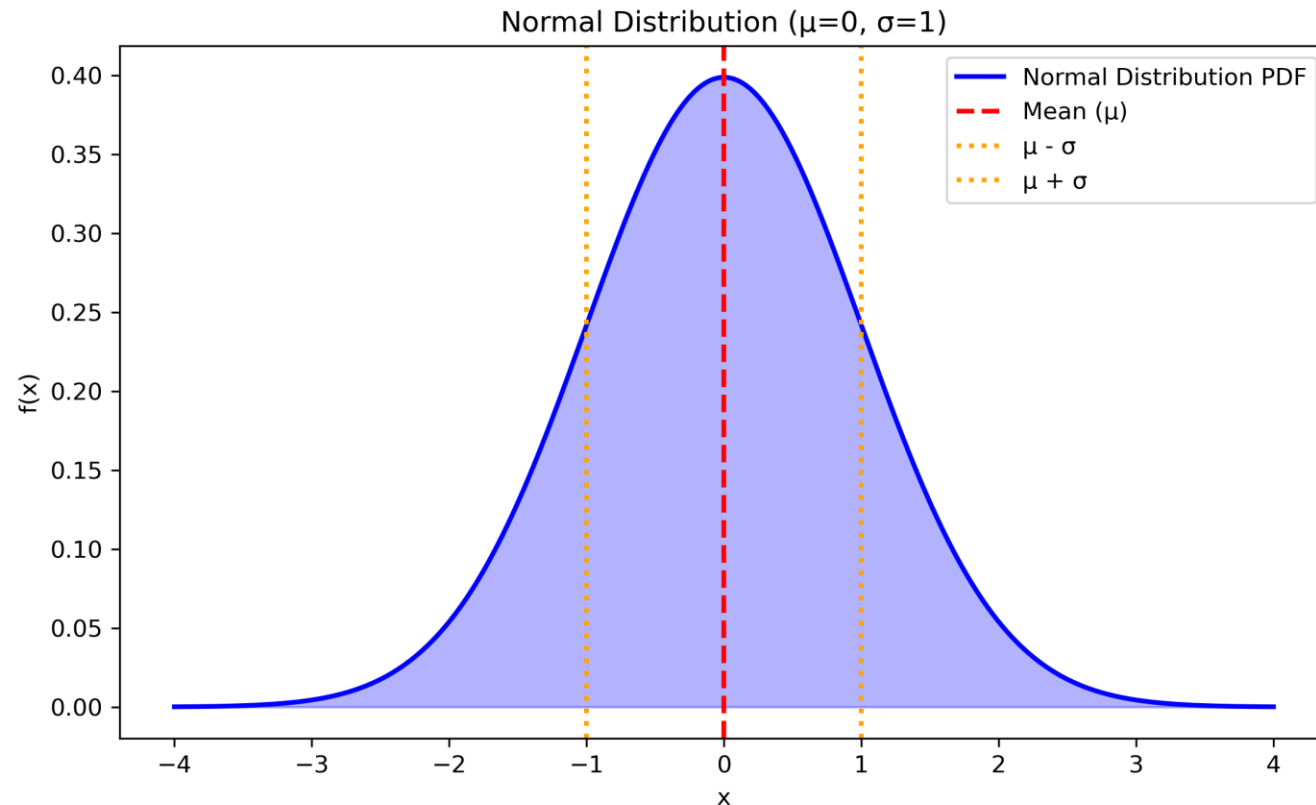
Exponential	Poisson
P(it takes 15 minutes for the next call)	P(3 to 5 calls will take place in the next 15 minutes)
P(10 years until the next earthquake to occur)	P(1 or more earthquakes in the next 20 years)

# Normal Distribution – Definition



The best known and most widely used probability distribution.

- Also referred to as **Gaussian distribution**
- Describes a lot of real-world phenomena
- Continuous probability distribution characterized by its **symmetric, bell-shaped curve**.
- It is widely used in statistics, natural sciences, and engineering due to its properties.



# Normal Distribution – PMF and Parameters



The PDF of a normally distributed random variable  $X$  is:  $X \sim \mathcal{N}(\mu, \sigma^2)$

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2 / 2\sigma^2} \quad -\infty \leq x \leq \infty$$

- $\mu$  (mean) determines the center of the distribution.
  - $\sigma$  (standard deviation) determines the spread of the distribution.
  - The normal distribution is bell-shaped and symmetric.
  - The total area under the curve equals 1 .
- Continuous random variable
  - Symmetric bell curve
  - Defined for all real values of  $x$
  - Mean = Median = Mode

# Normal Distribution – CDF and Moments



CDF of a normal distribution

$$F_X(x) = P(a < X \leq b) = \int_a^b \frac{1}{\sigma\sqrt{2\pi}} e^{-(1/2)[(x-\mu)/\sigma]^2} dx$$

- No closed form
- Use tables to calculate probabilities

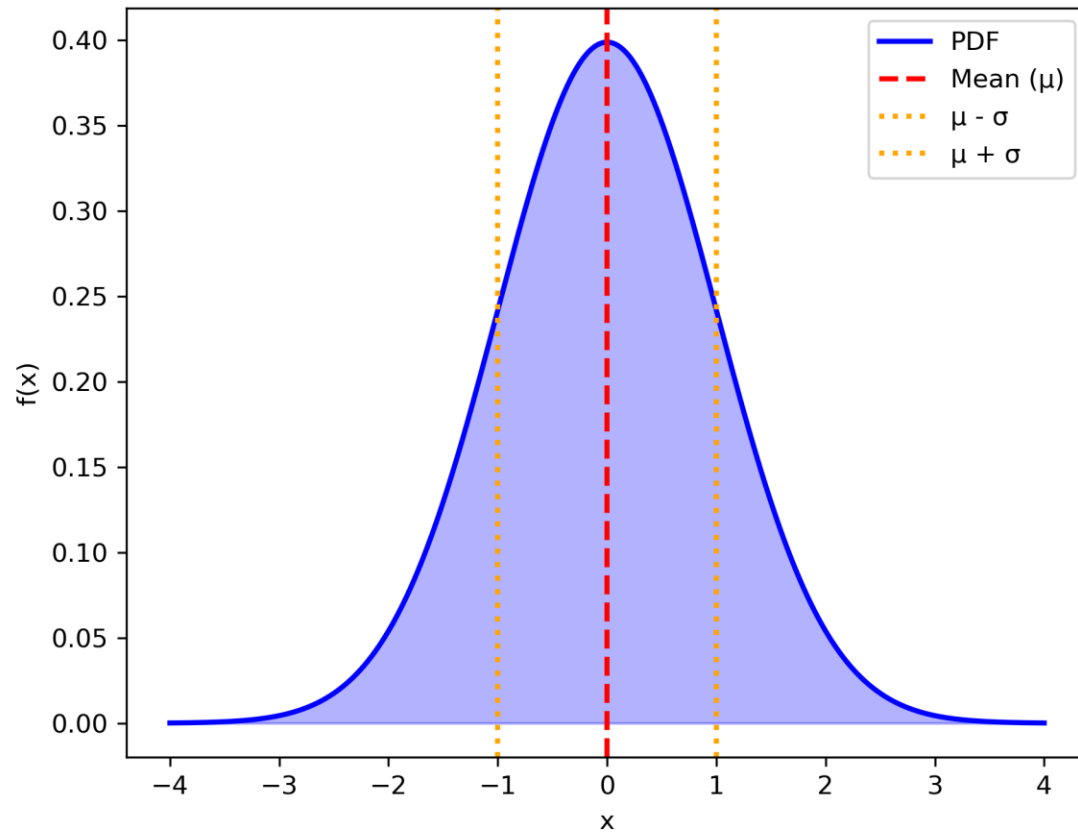
The mean and the variance can be calculated to be

$$\mathbf{E}[X] = \mu, \quad \text{var}(X) = \sigma^2$$

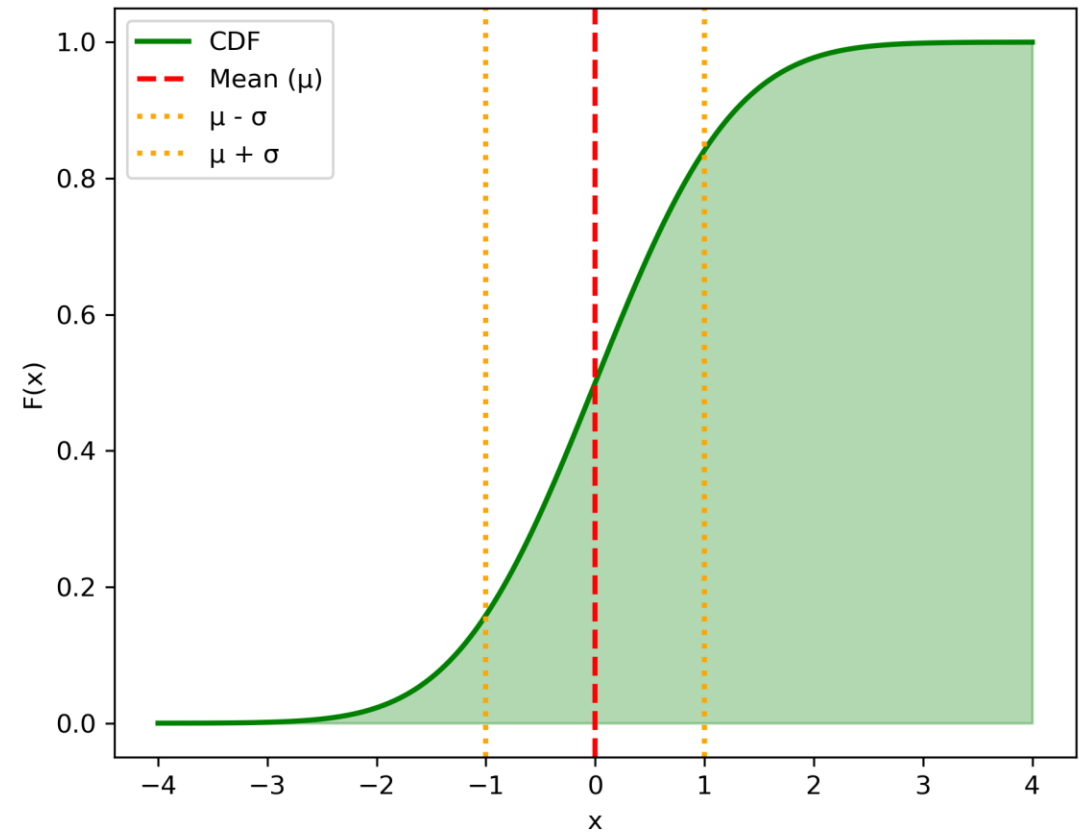
# Normal Distribution



Normal Distribution PDF



Normal Distribution CDF



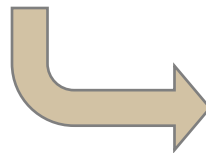
# Quiz 2

# Standard Normal Distribution



Let  $X$  be a normal random variable with mean  $\mu$  and variance  $\sigma^2$ .

We "standardize"  $X$  by defining a new random variable  $Y$  given by

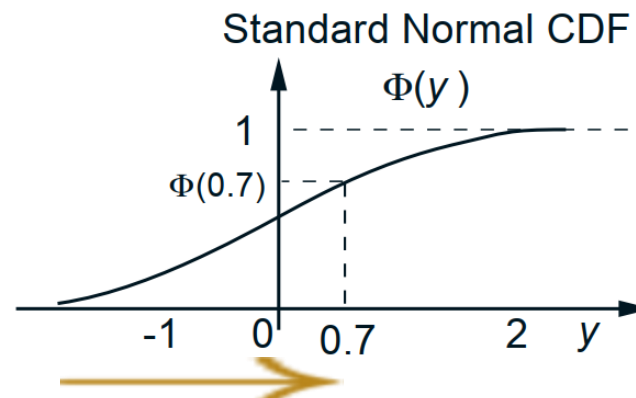
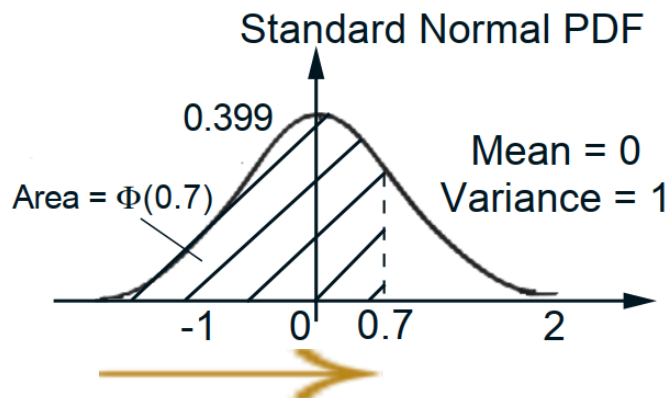

$$Y = \frac{X - \mu}{\sigma} \quad Y \sim \mathcal{N}(\mu = 0, \sigma^2 = 1)$$

A normal random variable  $Y$  with zero mean and unit variance is said to be a standard normal. Its CDF is denoted by  $\Phi$ ,

$$\Phi(y) = \mathbf{P}(Y \leq y) = \mathbf{P}(Y < y) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^y e^{-t^2/2} dt$$

Complement

$$\mathbf{P}(Y > y) = 1 - \mathbf{P}(Y \leq y)$$



Negative Values

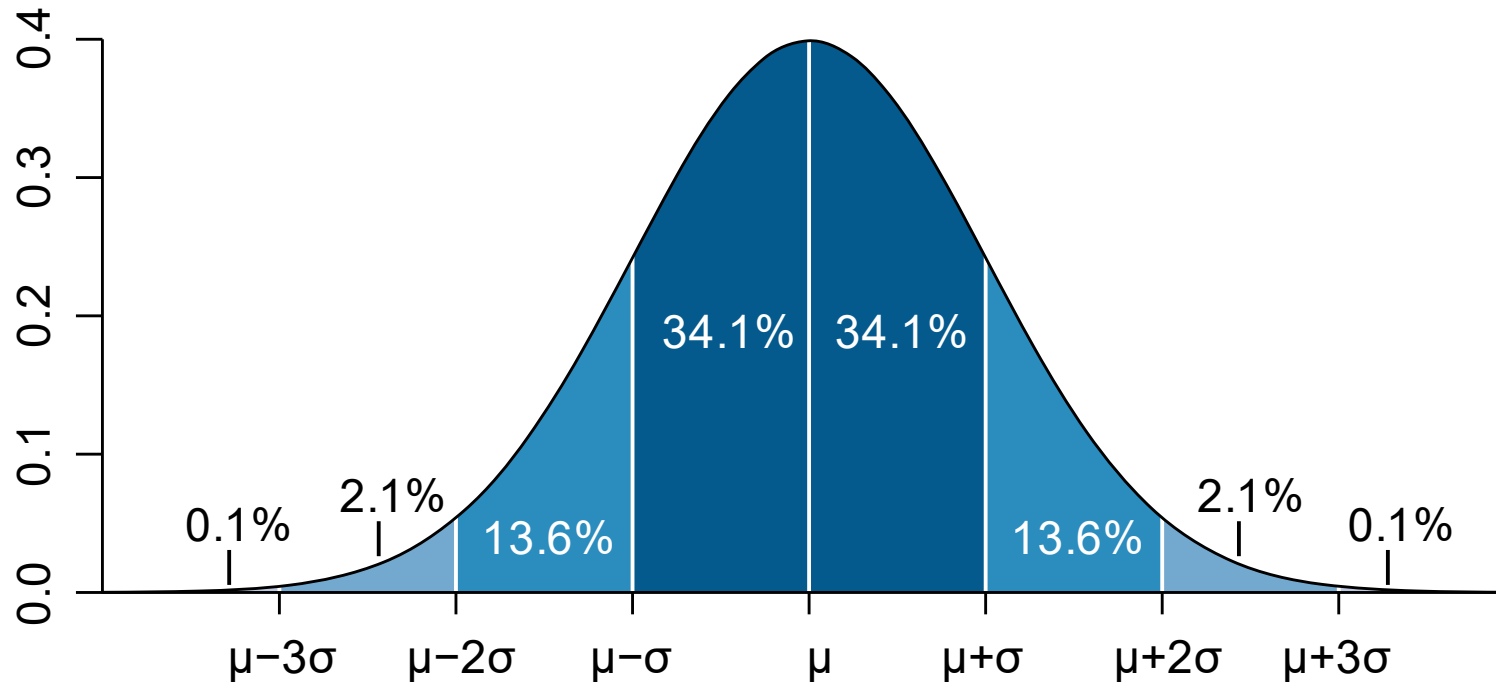
$$\Phi(-y) = 1 - \Phi(y)$$

# The 68-95-99.7 Rule



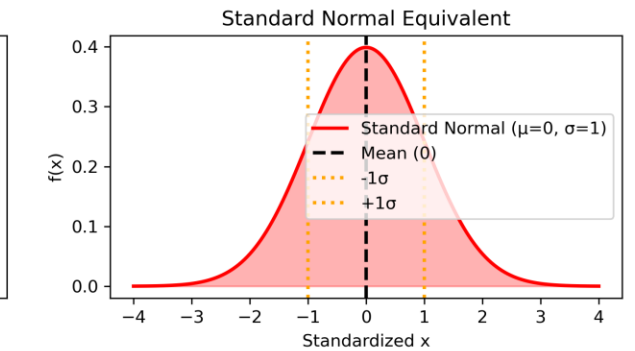
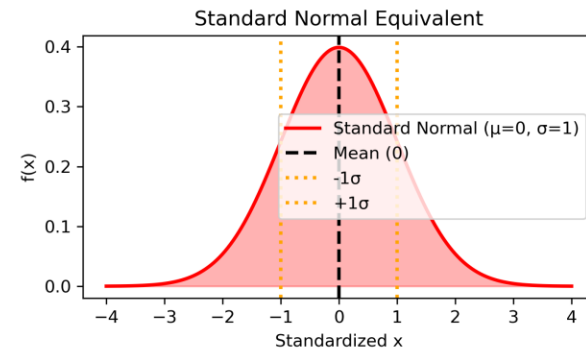
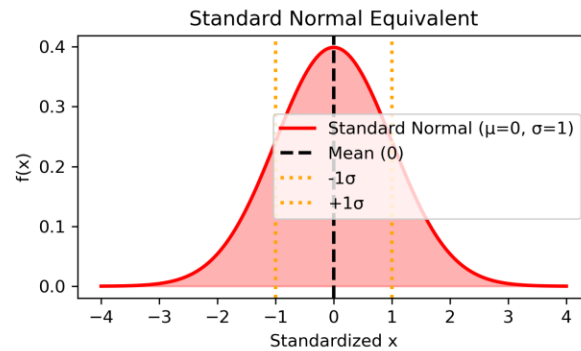
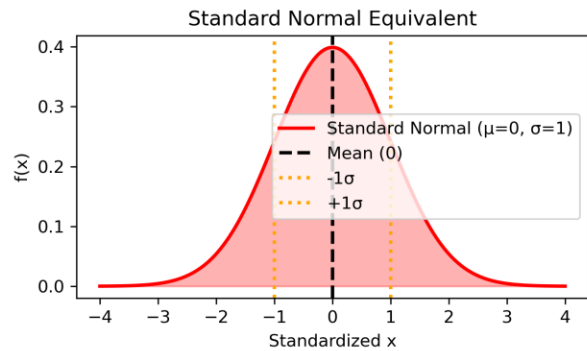
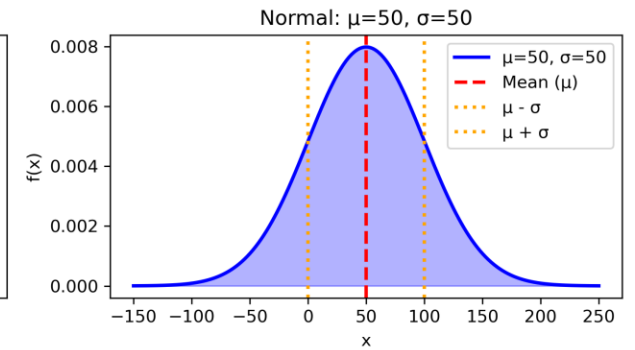
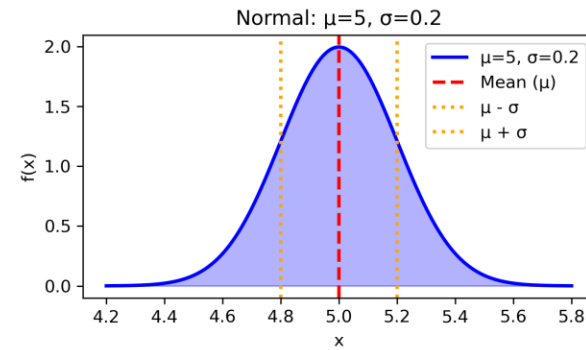
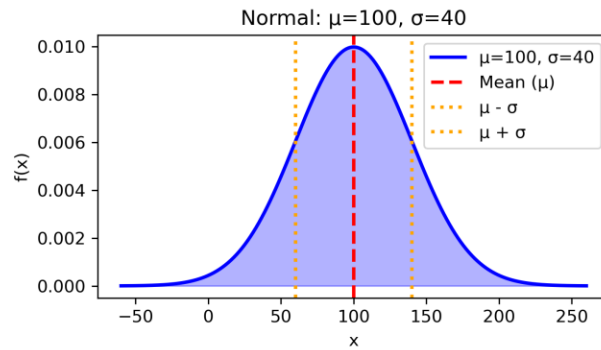
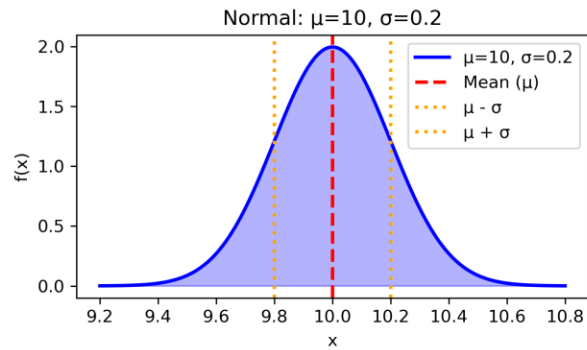
The 68-95-99.7 Rule:

- 68% of data falls within 1 standard deviation ( $\mu \pm \sigma$ ).
- 95% falls within 2 standard deviations ( $\mu \pm 2\sigma$ ).
- 99.7% falls within 3 standard deviations ( $\mu \pm 3\sigma$ ).



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

# Normal to Standard Normal



# Recall: Special Cases for Binomial Distribution

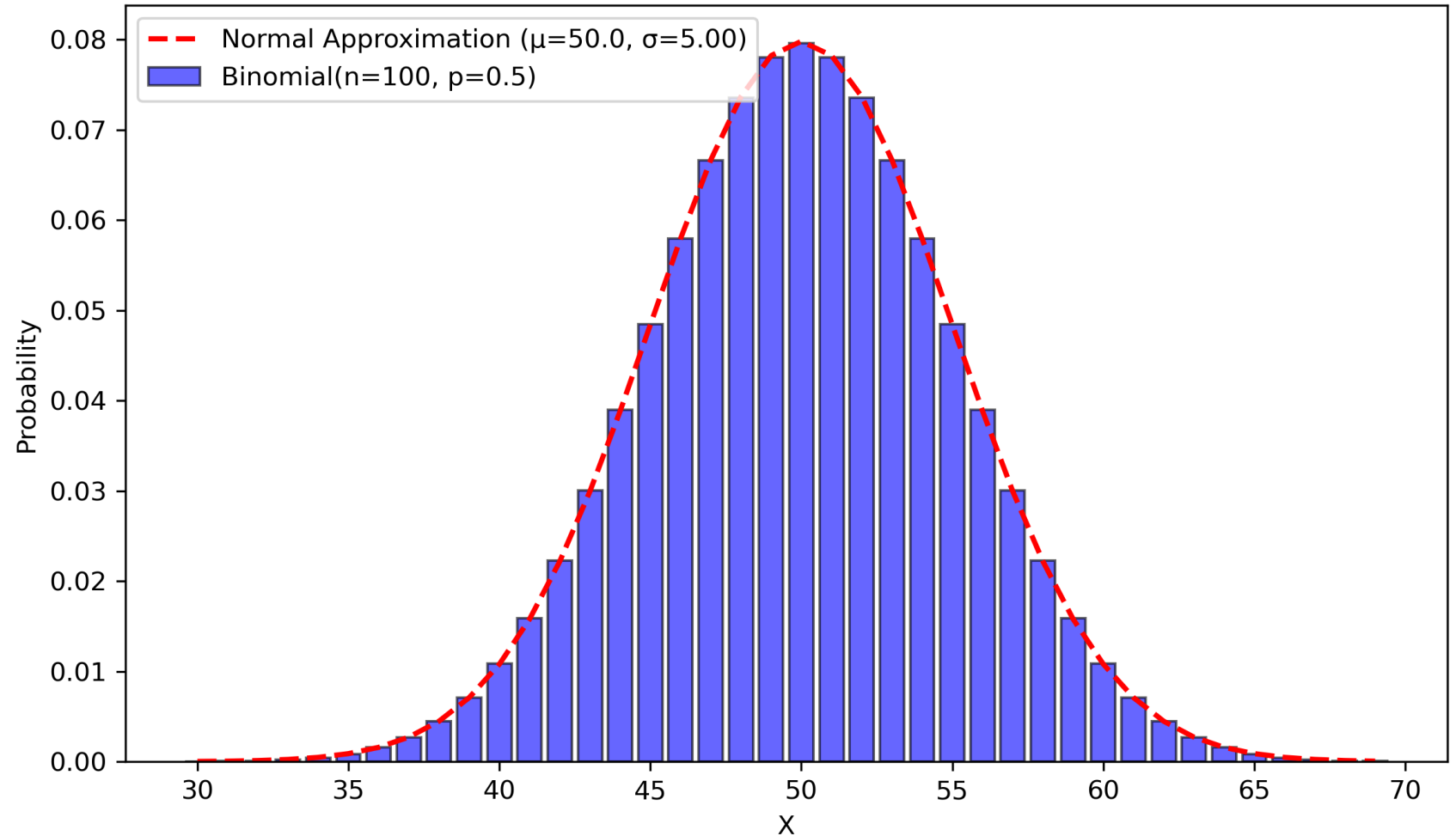


$$X \sim \text{binomial}(n, p)$$

$$X \sim \text{normal}(np, \sqrt{npq}) \quad \begin{array}{l} \text{if } npq \\ \text{not small} \end{array}$$

$$X \sim \text{poisson}(\lambda) \quad \lambda = np \quad \text{if } np \text{ small}$$

Normal Approximation to the Binomial Distribution



# Example 2 – Standard Normal



Consider a RV:  $Z \sim \text{normal}(0, 1)$   
 Calculate and draw the following:

$$P(Z < 0) = 0.5$$

$$P(0 < Z < 1.12) = F(1.12) - F(0) = 0.86864 - 0.5 = 0.36864$$

TABLE A.1 Standard Normal Probabilities (pg. 1 of 4)  $\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-y^2/2} dy$

x	$\Phi(x)$	x	$\Phi(x)$	x	$\Phi(x)$
0.00	0.500000000	0.40	0.655421742	0.80	0.788144601
0.01	0.503989356	0.41	0.659097026	0.81	0.791029912
0.02	0.507978314	0.42	0.662757273	0.82	0.793891946
0.03	0.511966473	0.43	0.666402179	0.83	0.796730608
0.04	0.515953437	0.44	0.670031446	0.84	0.799545807
0.05	0.519938806	0.45	0.673644780	0.85	0.802337457
0.06	0.523922183	0.46	0.677241890	0.86	0.805105479
0.07	0.527903170	0.47	0.680822491	0.87	0.807849798
0.08	0.531881372	0.48	0.684386303	0.88	0.810570345
0.09	0.535856393	0.49	0.687933051	0.89	0.813267057
0.10	0.539827837	0.50	0.691462461	0.90	0.815939875
0.11	0.543795313	0.51	0.694974269	0.91	0.818588745
0.12	0.547758426	0.52	0.698468212	0.92	0.821213602
0.13	0.551716787	0.53	0.701944035	0.93	0.823814458
0.14	0.555670005	0.54	0.705401484	0.94	0.826391220
0.15	0.559617692	0.55	0.708840313	0.95	0.828943874
0.16	0.563559463	0.56	0.712260281	0.96	0.831472393
0.17	0.567494932	0.57	0.715661151	0.97	0.833976754
0.18	0.571423716	0.58	0.719042691	0.98	0.836456941
0.19	0.575345435	0.59	0.722404675	0.99	0.838912940
0.20	0.579259709	0.60	0.725746882	1.00	0.841344746
0.21	0.583166163	0.61	0.729069096	1.01	0.843752355
0.22	0.587064423	0.62	0.732371107	1.02	0.846135770
0.23	0.590954115	0.63	0.735652708	1.03	0.848494997
0.24	0.594834872	0.64	0.738913700	1.04	0.850830050
0.25	0.598706326	0.65	0.742153889	1.05	0.853140944
0.26	0.602568113	0.66	0.745373085	1.06	0.855427700
0.27	0.606419873	0.67	0.748571105	1.07	0.857690346
0.28	0.610261248	0.68	0.751747770	1.08	0.859928910
0.29	0.614091881	0.69	0.754902906	1.09	0.862143428
0.30	0.617911422	0.70	0.758036348	1.10	0.864333939
0.31	0.621719522	0.71	0.761147932	1.11	0.866500487
0.32	0.625515835	0.72	0.764237502	1.12	0.868643119
0.33	0.629300019	0.73	0.767304908	1.13	0.870761888
0.34	0.633071736	0.74	0.770350003	1.14	0.872856849
0.35	0.636830651	0.75	0.773372648	1.15	0.874928064
0.36	0.640576433	0.76	0.776372708	1.16	0.876975597
0.37	0.644308755	0.77	0.779350054	1.17	0.878999516
0.38	0.648027292	0.78	0.782304562	1.18	0.880999893
0.39	0.651731727	0.79	0.785236116	1.19	0.882976804

# Example 2 – Standard Normal



Consider a RV:  $Z \sim \text{normal}(0, 1)$   
Calculate and draw the following:

$$P(-2.17 < Z < 0) = F(0) - F(-2.17) = F(0) - (1 - F(2.17)) = 0.5 - 1 + 0.8577 = 0.48499$$

$$P(Z < -1.17) = 1 - F(1.17) = 1 - 0.87899 = 0.12101$$

$$P(-1.56 < Z < 1.31) = F(1.31) - (1 - F(1.56))$$

# Example 3– Normal Distribution



The heights of male adults in the US are approximately normal, with mean 70 in. and standard deviation 3.0 in.

- What is the percentage of male adults in the US who are at least as tall as
  - Kevin Durant, 6'9" (i.e., 81 in.)
  - Manute Bol, 7'7" (i.e., 91 in.)
  - Muggsy Bogues, 5'3" (i.e., 63 in.)

$$X \sim N(\mu, \sigma) \quad Z \sim N(0, 1) \quad x \sim N(\mu = 70, \sigma = 3)$$

$$\text{Kevin: } P(X > 81) = P\left(Z > \frac{(81-70)}{3}\right) = P(Z > 3.67) = 1 - F(3.67) = 1 - 0.999878 = 0.000122$$

$$\text{Manute: } P(X > 91) = P\left(Z > \frac{(91-70)}{3}\right) = P(Z > 7) = 1 - F(7) = 1.28e-12$$

$$\text{Muggsy: } P(X > 63) = P\left(Z > \frac{(63-70)}{3}\right) = P(Z > 2.3) = 1 - F(2.3) = 1 - 0.98927 = 0.01073$$

# Example 3 – Continued



The heights of male adults in the US are approximately normal, with mean 70 in. and standard deviation 3.0 in.

- What is the percentage of male adults in the US who are at least as tall as
  - Kevin Durant, 6'9" (i.e., 81 in.)
  - Manute Bol, 7'7" (i.e., 91 in.)
  - Muggsy Bogues, 5'3" (i.e., 63 in.)

If there are approximately 100 million male adults in the US, roughly how many in the population does the above relate to?

Kevin: 12,200 are at least as tall as KD

Manute: 0.000128

Muggsy: 1,073,000 as tall as Manute

# Example 4 – Exam Scores



A university professor gives an exam where the scores are **normally distributed** with **mean** of 75 and **standard deviation** of 8.

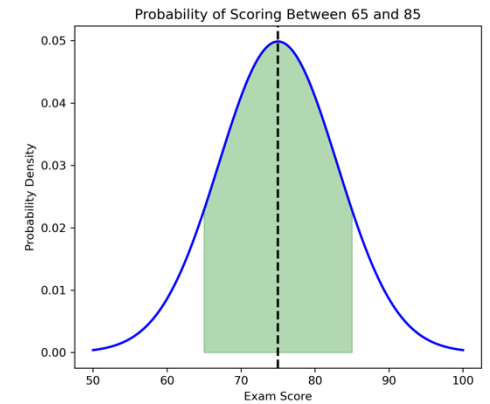
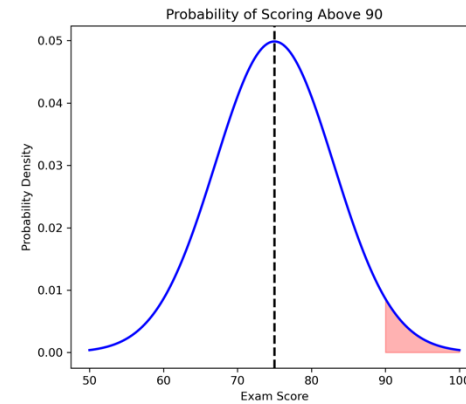
- What percentage of students score **above 90**?
- What proportion of students score **between 65 and 85**?

Let  $X \sim \mathcal{N}(\mu = 75, \sigma^2 = 64)$

Then,  $Z \sim \mathcal{N}(\mu = 0, \sigma^2 = 1)$

$$\text{a. } z = \frac{x - \mu}{\sigma} = \frac{90 - 75}{8} = 1.875 \rightarrow P(Z > 1.875) = 1 - P(Z < 1.875) = 1 - 0.9693 = 0.0307$$

$$\begin{aligned} \text{b. } P(65 < X < 85) &= P(-1.25 < Z < 1.25) = \Phi(1.25) - \Phi(-1.25) \\ &= 0.8944 - (1 - 0.8944) = 0.8944 - 0.1056 = 0.7888 \end{aligned}$$



# Example 4 – Lifespan of Lightbulbs



A company manufactures lightbulbs, and their lifespan follows a normal distribution with mean of 1000 hours and standard deviation of 200 hours.

- a. What is the probability that a randomly selected lightbulb lasts less than 800 hours?
- b. What should the warranty period be if the company wants to cover only the bottom 5% of bulbs?

Let  $X \sim \mathcal{N}(\mu = 1000, \sigma^2 = 200^2)$

Then,  $Z \sim \mathcal{N}(\mu = 0, \sigma^2 = 1)$

a. 
$$P(X < 800) = P\left(Z < \frac{800 - 1000}{200}\right) = P(Z < -1)$$
$$= (1 - \Phi(1)) = 1 - 0.8413 = 0.1587$$

# Example 4 – Lifespan of Lightbulbs



b. What should the warranty period be if the company wants to cover only the bottom 5% of bulbs?

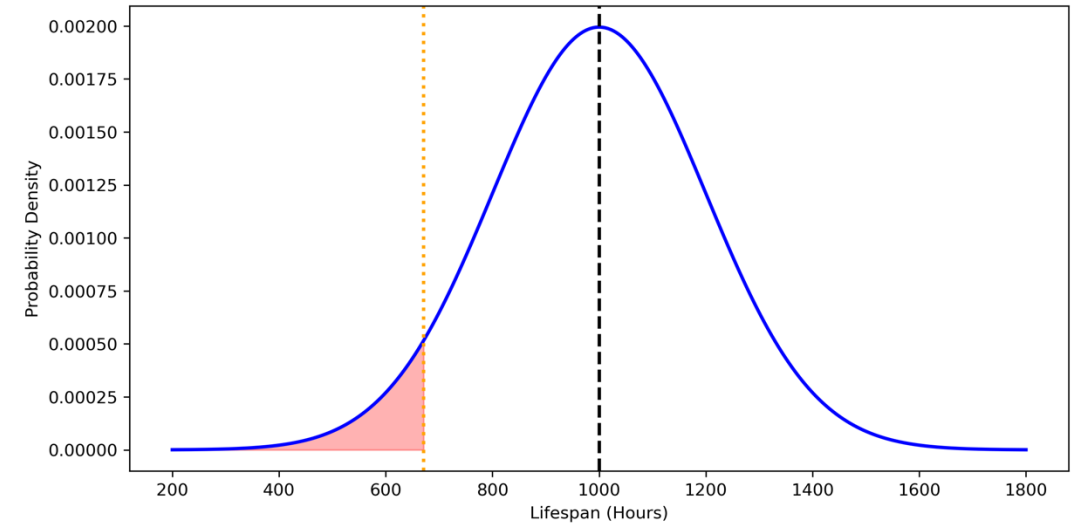
We want to find the value of  $X$  where 5% of the data is below it.

Let  $X \sim \mathcal{N}(\mu = 1000, \sigma^2 = 200^2)$

Then,  $Z \sim \mathcal{N}(\mu = 0, \sigma^2 = 1)$

b. We are looking for the value of  $P(Z < z) = 0.05$

From the  $Z$ -table, what is the  $Z$ -score corresponding to  $P(Z) = 0.05$



# Example 4 – Lifespan of Lightbulbs



b. What should the warranty period be if the company wants to cover only the bottom 5% of bulbs?

If  $P(Z < z)$  is to be 0.05  
then, we can say given the symmetry of the normal distribution that  
 $P(Z > z)$  is to be 0.95

Then to find  $z$  for the probability of 0.95 we refer to Appendix A.

From Appendix A, for  $\Phi(z) = 0.95$ , we have  $z = 1.645$

we now refer to the relation  $\rightarrow \Phi(-y) = 1 - \Phi(y)$

As such,  $0.05 = 1 - \Phi(z) = 1 - \Phi(1.645) = \Phi(-1.645) \rightarrow z = -1.645$

Then,  $X = \mu + Z\sigma = 1000 + (-1.645)(200) = 670$

