

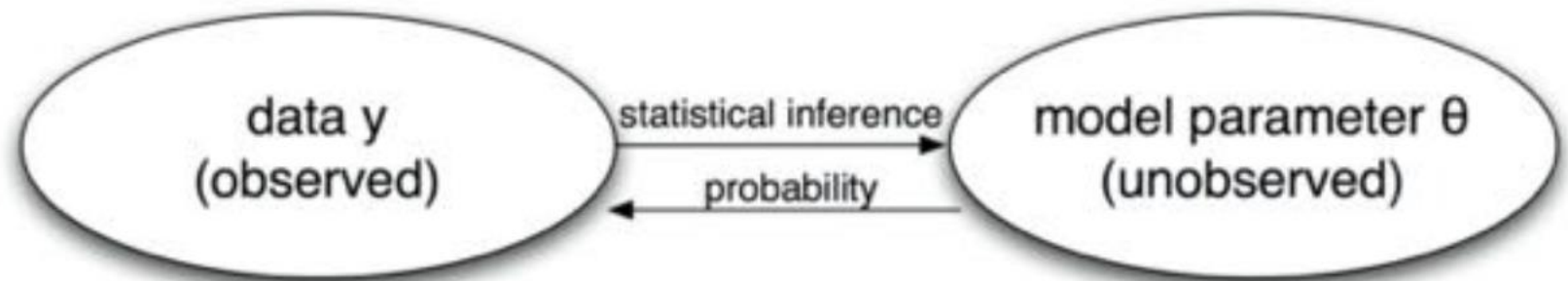
# Statistical Models

Instructor, Nero Chan Zhen Yu



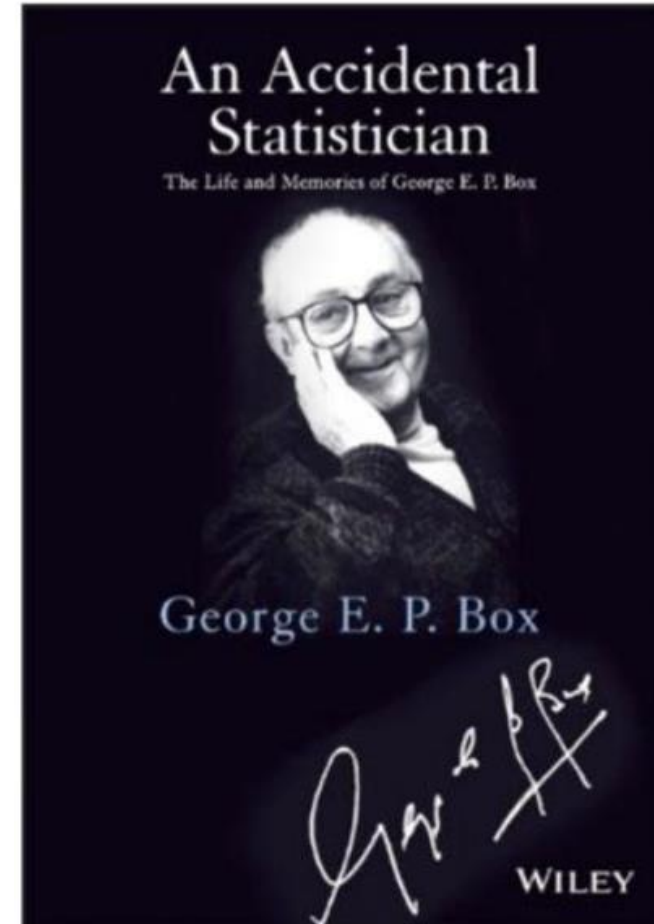
# What is statistical models?

- A family of distributions, indexed by parameters
- Sharpens distinction between data and parameters, and between estimators and estimands.
- Parametric (eg. Based on Normal, Binomial) vs Non-parametric (eg. Methods like bootstrap, KDE)



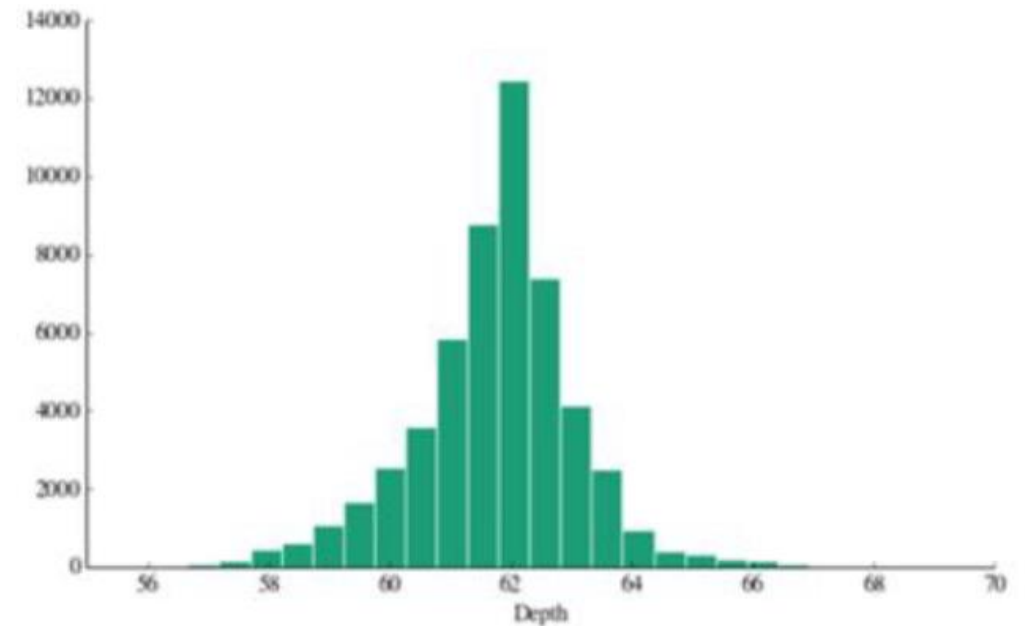
# What good is a statistical model?

- “All models are wrong, but some models are useful.” – George Box (1919-2013)



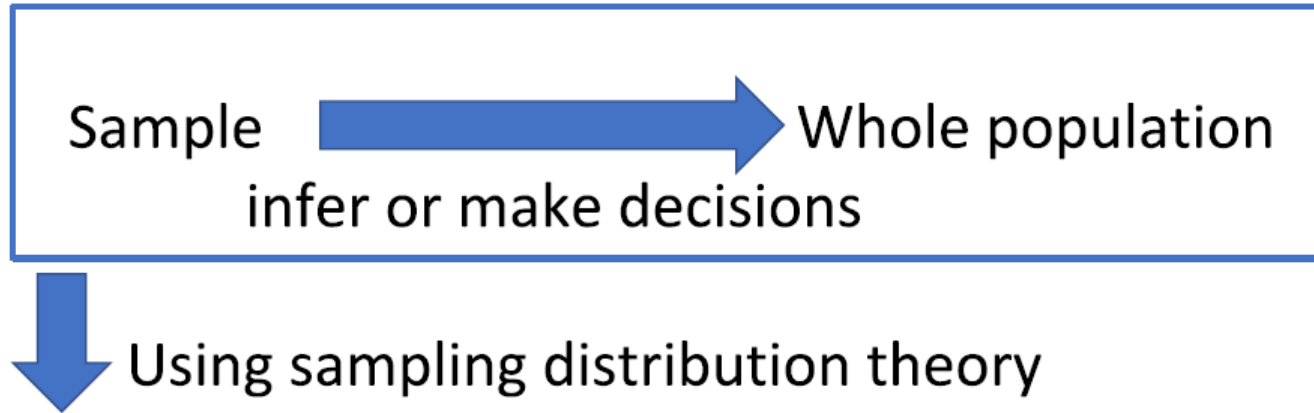
# Parametric vs Non-parametric

- Parametric: finite-dimensional parameter space (eg. Mean and Variance for a Normal)
- Non-Parametric: infinite-dimensional parameter space
- Is there anything in between?
- Non-parametric is very general, but no free lunch!
- Remember to plot and explore the data!



# Statistical Inference

- The basic idea of Statistical Inference:



Application in

- Confidence Intervals:
  - What is the population value?
- Tests of Significance:
  - Is the population value really what is proposed?

# Term used in Probability

- Probability:
  - The study of randomness and uncertainty. In other words, probability is a numerical measure of chance for the occurrence of an event.
- Experiment:
  - A repeatable procedure with a well-defined set of possible outcomes. Eg. Tossing a coin, Rolling a die.
- Observation:
  - Data collected only by monitoring what occurs.
- Sample space:
  - The set of all possible outcomes of an experiment.
- Event:
  - A set of outcomes, subset of sample space.

# Example

Consider an experiment of rolling a 6-sided die.

Sample space,  $S$ : {1, 2, 3, 4, 5, 6}

- A: even number is rolled
  - Equivalently to {2, 4, 6}
  - $P(A) = 3/6$
- B: number less than three is rolled
  - Equivalently to {1, 2}
  - $P(B) = 2/6$

# Basic Rules of Probability Theory

1) For an event  $A$ :  $0 \leq P(A) \leq 1$

2)  $P(A) + P(A^c) = 1 \Rightarrow P(A) = 1 - P(A^c)$

$A^c$ : the complement event of event  $A$

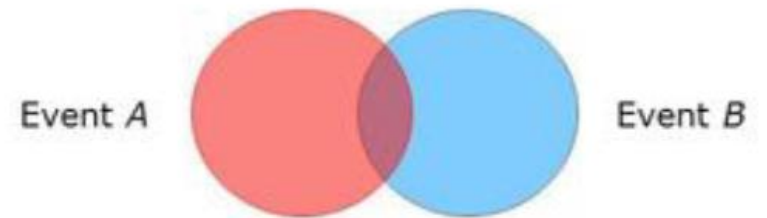
3)  $P(A \text{ or } B) = P(A \cup B) = P(A) + P(B) - P(A \cap B)$

if  $A, B$  are mutually exclusive, then

$P(A \cup B) = P(A) + P(B)$  since  $P(A \cap B) = 0$

4)  $P(A \cap B) = P(A) P(B)$  if  $A$  and  $B$  are independent

independent : occurrence of  $A$  is not depend on  $B$  and vice versa





# Example

- Lets assume that if we choose a young adult aged 25 to 30 from Malaysia population, the probability that the person chosen has a diploma is 0.46, 0.35 that the person chosen has a bachelor's degree, and 0.13 that the person chosen has both diploma and bachelor's degree.
- What is the probability that a randomly selected Malaysian young adult has a diploma or bachelor's degree?

# Example

$$P(\text{Diploma}) = 0.46$$

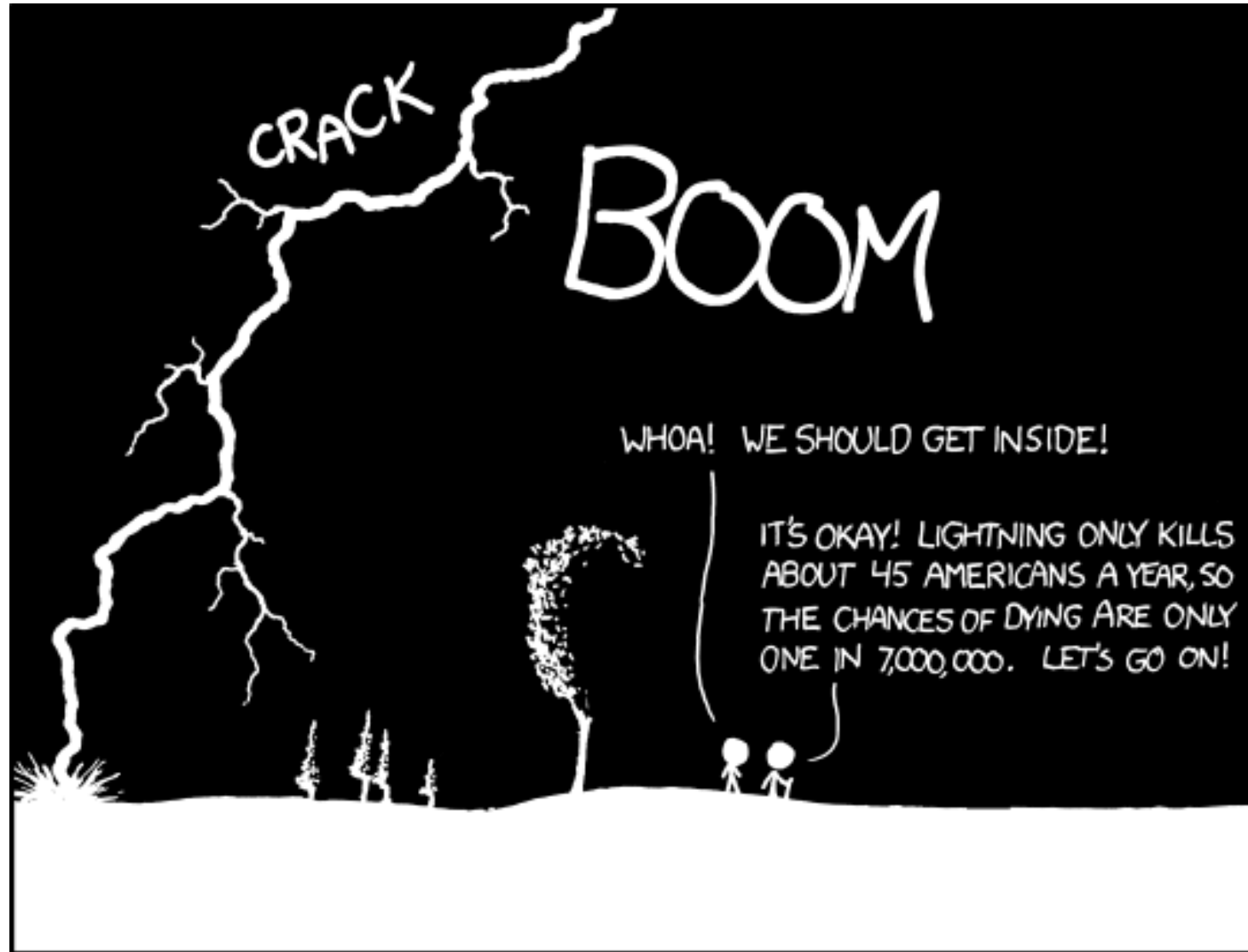
$$P(\text{Bachelor}) = 0.35$$

$$P(\text{Diploma} \cap \text{Bachelor}) = 0.13$$

$$P(\text{Diploma} \cup \text{Bachelor}) = P(\text{Diploma}) + P(\text{Bachelor}) - P(\text{Diploma} \cap \text{Bachelor})$$

$$= 0.46 + 0.35 - 0.13$$

$$= 0.68$$



THE ANNUAL DEATH RATE AMONG PEOPLE  
WHO KNOW THAT STATISTIC IS ONE IN SIX.

# Conditional Probability

- The probability of an event B occurring when it is known that some event A has occurred is called **conditional probability** and is denoted by  $P(B|A)$ .
- For any two events A and B (with  $P(A) > 0$ ), the **conditional probability** of B given A, denoted by  $P(B|A)$ , is defined as

$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$

- If we are interested in the **conditional probability** of A given B (with  $P(B) > 0$ ), then

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

# Bayes' Theorem

$$\underbrace{P(B | A)}_{\text{Posterior}} = \frac{\overbrace{P(A | B)}^{\text{Likelihood}} \overbrace{P(B)}^{\text{Prior}}}{\underbrace{P(A)}_{\text{Model Evidence}}}$$

# Conditional Probability

- $P(B|A) = \frac{P(A \cap B)}{P(A)} \Rightarrow P(A \cap B) = P(B|A) P(A)$   
Likelihood
- $P(A|B) = \frac{P(A \cap B)}{P(B)} \Rightarrow P(A \cap B) = P(A|B) P(B)$   
Prior

# Law of Total Probability

- Suppose there are 2 possible events A and B: What are the total possibilities of B happening?

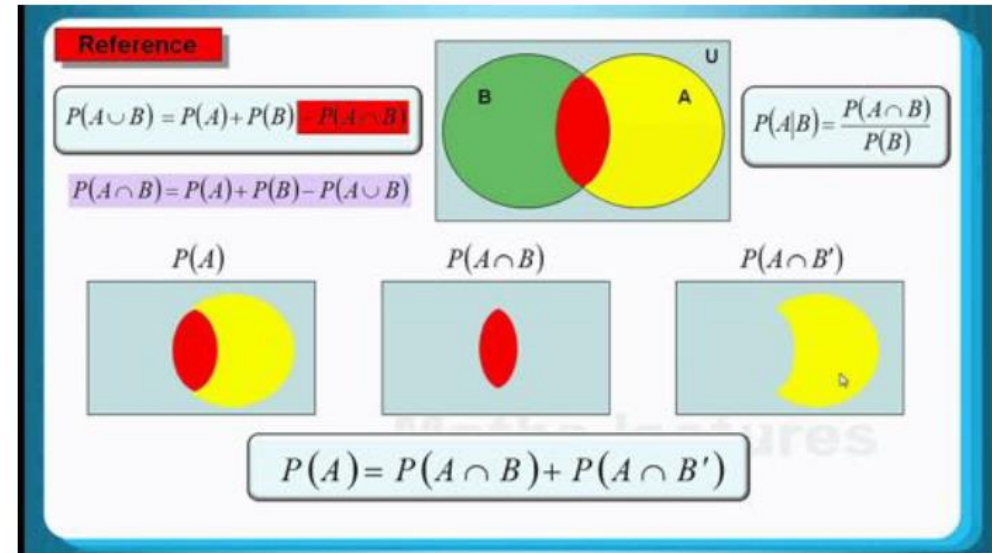
$$P(B) = P(B \cap A) + P(B \cap A^c)$$

- Since  $P(B \cap A) = P(B|A) P(A)$

- $P(B \cap A^c) = P(B|A^c) P(A^c)$

- **The Law of Total Probability:**

$$P(B) = P(B|A) P(A) + P(B|A^c) P(A^c)$$



# Example

- Draw 2 cards without replacement from a standard pack of cards. What is the probability of getting an Ace in the second draw?
- Pack of cards = 52 cards, of which 4 are Aces

A = Get an Ace in first draw

B = Get an Ace in second draw

- $P(A) = 4/52 = 0.077$
- $P(B|A) = 3/51 = 0.069$
- $P(B|A^c) = 4/51 = 0.078$

$$\begin{aligned}\text{So } P(B) &= P(B \cap A) + P(B \cap A^c) \\ &= P(B|A) P(A) + P(B|A^c) P(A^c) \\ &= (0.069)(0.077) + (0.078)(1-0.077) \\ &= 0.0053 + 0.072 \\ &= \mathbf{0.077}\end{aligned}$$



# Bayes' Rule

$$\begin{aligned} P(A | B) &= \frac{P(A \cap B)}{P(B)} \\ &= \frac{P(B | A)P(A)}{P(B)} \\ &= \frac{P(B | A)P(A)}{P(B | A)P(A) + P(B | A^c)P(A^c)} \end{aligned}$$

- Where the denominator uses **The Law of Total Probability**

# Example

- A patient with certain symptoms consulted her doctor to be checked for a disease, and she undergoes a test.
- With this test there is a probability of 0.90 that a woman with the disease shows a positive result, and a probability of only 0.99 that a healthy woman shows a negative result.
- Historical information also suggests that the prevalence of this disease in the population is 2 in 10000.
- Find the probability that a woman has the disease given the test says she does (i.e. does the test diagnose true patient status?)

# Example

Let  $D$  be the event 'woman has the cancer' and  $+$  be the event 'biopsy is positive'.

$$P(D) = 2/10000 = 0.0002 \text{ (disease prevalence)}$$

$$P(+ | D) = 0.90 \text{ (sensitivity)}$$

$$P(- | D^c) = 0.99 \text{ (specificity)} \quad > (0.9) \cdot (0.0002) / ((0.9) \cdot (0.0002) + (1 - 0.99) \cdot (1 - 0.0002))$$

0.0176852

Need to find the positive predictive value,  $P(D | +)$

$$\begin{aligned} P(D | +) &= \frac{P(D \cap +)}{P(+)} = \frac{P(+ | D)P(D)}{P(+ | D)P(D) + P(+ | D^c)P(D^c)} \\ &= \frac{(0.9)(0.0002)}{(0.9)(0.0002) + (1 - 0.99)(1 - 0.0002)} \end{aligned}$$

# Important Point on Notation:

- A numerical value associated with a population is called a “parameter”: (FIXED)
  - population mean:  $\mu$ (mu)
  - population standard deviation:  $\sigma$ (sigma)
  - population proportion:  $p$
- A numerical value associated with a sample is called a “statistic”: (VARIABLE)
  - sample mean:  $\bar{x}$ (x-bar)
  - sample standard deviation:  $s$
  - sample proportion:  $\hat{p}$  (p-hat)

# Random Variable

- A random variable has values which depend on the outcome of a random experiment
- Random variables are labelled with capital letter. (e.g.  $X$  = sum of numbers on 2 throws of a die)
- The values of random variable is labelled with small letters. ( $x = 2, 3, 4, \dots, 12$ )
- Random variables can be discrete or continuous.

# Discrete Random Variable

- **Discrete random variable** is a **random variable** whose possible values can be listed in a **finite** or an **infinite sequence**
- E.g.
  - number of students attend this class,
  - number of students in this family,
  - number of cars pass through a toll in given day

# Continuous Random Variable

- **Continuous random variable** are **random variables** that are measured on a **continuous scale**.
- They can usually take on any value over some interval
- E.g.
  - heights,
  - weights,
  - time spending on reading a statistics book

# Probability Mass Function (PMF)

- This function evaluates the probability of a discrete random variable  $X$  takes certain value  $x$ .

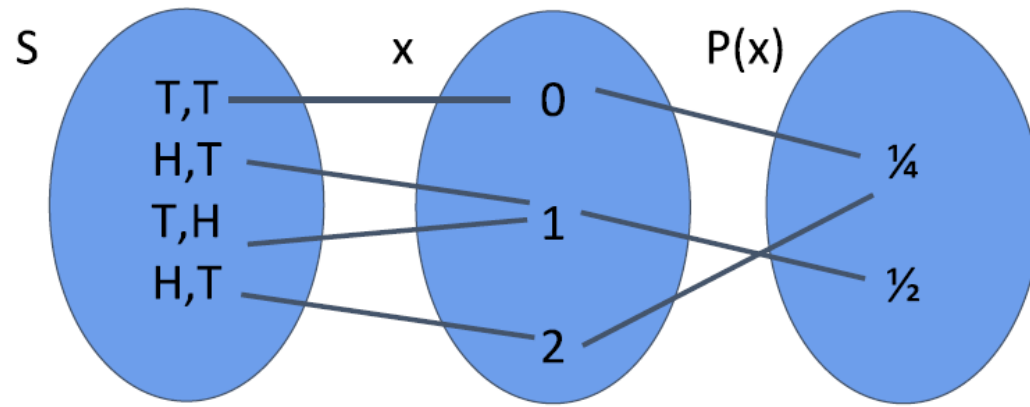
$$P(x) = P(X = x)$$

- The following conditions are required for any pmf:
  1.  $p(x) > 0$
  2.  $\sum p(x) = 1$



# Probability Mass Function (PMF)

Toss of a coin, and Random Variable,  $x$  is HEAD



Function  $P(x)$ : Random Variable  $\rightarrow$  Probability

**Probability Mass Function (PMF)**

What is the probability of getting:

a) No HEAD

$$P(x=0) = \frac{1}{4}$$

b) One HEAD

$$P(x=1) = P(HT) + P(TH) = \frac{2}{4} = \frac{1}{2}$$

c) Two HEADs

$$P(x=2) = \frac{1}{4}$$

# Probability Mass Function (PMF)

- The PMF of a random variable  $X$  is:

$$p(x) = x/36 \quad \text{for} \quad x = 1, 2, 3, \dots, 8$$

$$P(X = 1) = p(1) = 1/36$$

$$P(X = 2) = p(2) = 2/36$$

.

.

.

$$P(X = 8) = p(8) = 8/36$$

# Example

$x$	$P(x)$
1	$1/36$
2	$2/36$
3	$3/36$
4	$4/36$
5	$5/36$
6	$6/36$
7	$7/36$
8	$8/36$

Sum =

1

# Cumulative Distribution Function (CDF)

- This function evaluates the probability of a random variable  $X$  takes value less or equal to  $x$

$$F(x) = P(X \leq x)$$

For the example in the previous slide:

$$F(3) = P(X \leq 3) = 1/36 + 2/36 + 3/36 = 6/36 = 1/6$$

# Probability Density Function (PDF)

- This function associates with the probability of a continuous random variable
- The probability that the continuous random variable takes on a value between  $a$  and  $b$  is the area under the curve between  $a$  and  $b$ .
- For continuous random variable

$$P(X < a) = P(X \leq a)$$

- That is with or without equal sign makes no difference to the probability, this also apply to greater than

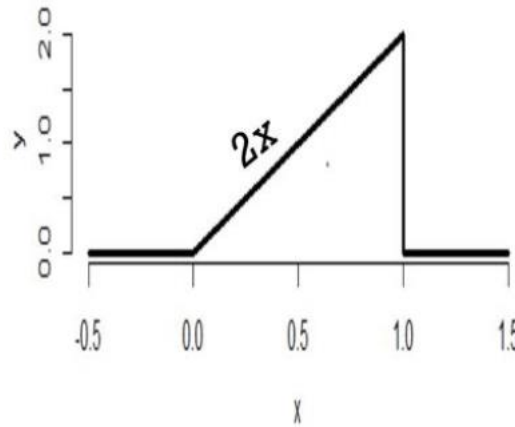
# Example

- Suppose that the proportion of help calls that get addressed in a random day by a help line is given by:

$$f(x) = \begin{cases} 2x, & 0 < x < 1 \\ 0, & \text{otherwise} \end{cases}$$

# Example

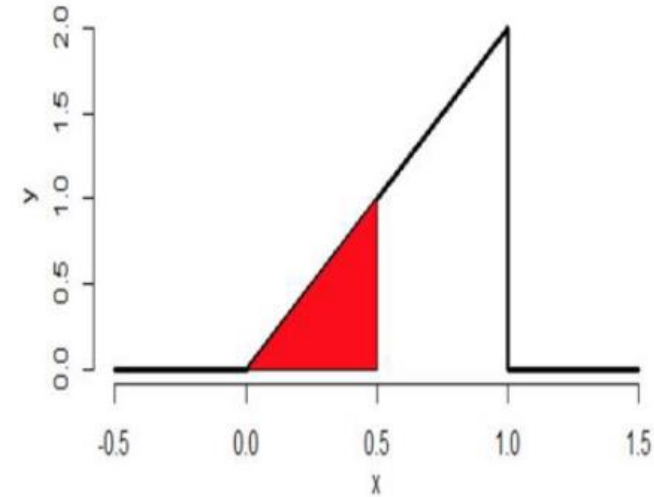
- If this is a mathematically valid density, then the total probability (area under curve) should equal to 1



- Area under the curve (triangle) =  $(1/2)(\text{base})(\text{height})$   
=  $(1/2)(1)(2) = 1$
- Total probability = 1, it is valid density

# Example

- What is the  $P(X < 0.5)$ ?



- Area under the curve (red color triangle)  
=  $(1/2)(\text{base})(\text{height}) = (1/2)(0.5)(1) = 0.25$
- Or if we know that this is a beta distribution with parameter 2 and 1, just type in python

```
from scipy.stats import beta  
beta.cdf(0.5, 2, 1)  
[1] 0.25
```



# Percentile

The  $\alpha$ th percentile of a distribution is the value  $x$  such that

- The probability that a random variable drawn from the population is less than  $x$  is  $\alpha$  %

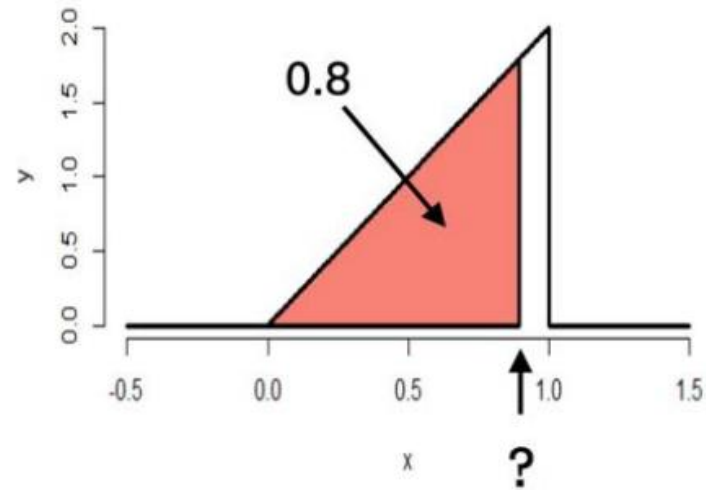
$$P(X < x) = \alpha\%$$

- The probability that a random variable drawn from the population is more than  $x$  is  $(1 - \alpha)\%$

$$P(X > x) = (1 - \alpha)\%$$

# Example

- What is the 80th percentile of this pdf?



$$P(X < ?) = 0.8$$

$$\left(\frac{1}{2}\right)(x)(2x) = 0.8 \Rightarrow x^2 = 0.8 \Rightarrow x = 0.89$$

Or by using scipy:

```
> beta.ppf(0.8, 2, 1)
```

# Quartiles

- The first quartile is the 25<sup>th</sup> percentile

$$P(X < x) = 0.25$$

```
## 1st quartile  
beta.ppf(0.25, 2, 1)
```

- The second quartile is the 50<sup>th</sup> percentile (the median)

$$P(X < x) = 0.5$$

```
## 2nd quartile  
beta.ppf(0.5, 2, 1)
```

- The third quartile is the 75<sup>th</sup> percentile

$$P(X < x) = 0.75$$

```
## 3rd quartile  
beta.ppf(0.75, 2, 1)
```

# The Population Mean

- Mean, also known as expected value
- Expected value of a random variable  $X$ ,  $E(X)$  or  $\mu$
- For discrete random variable, if we know the PMF then the mean can be determined
- The mean of a discrete random variable  $X$  is:

$$\mu = E(X) = \sum xp(x)$$

# Example

$X$  = face value when we throw a die

Pmf of  $X$ :

$x$	$P(x)$
1	1/6
2	1/6
3	1/6
4	1/6
5	1/6
6	1/6

$$\begin{aligned} E(X) &= \sum xp(x) = (1)(1/6) + (2)(1/6) + \dots + (6)(1/6) \\ &= 3.5 \end{aligned}$$

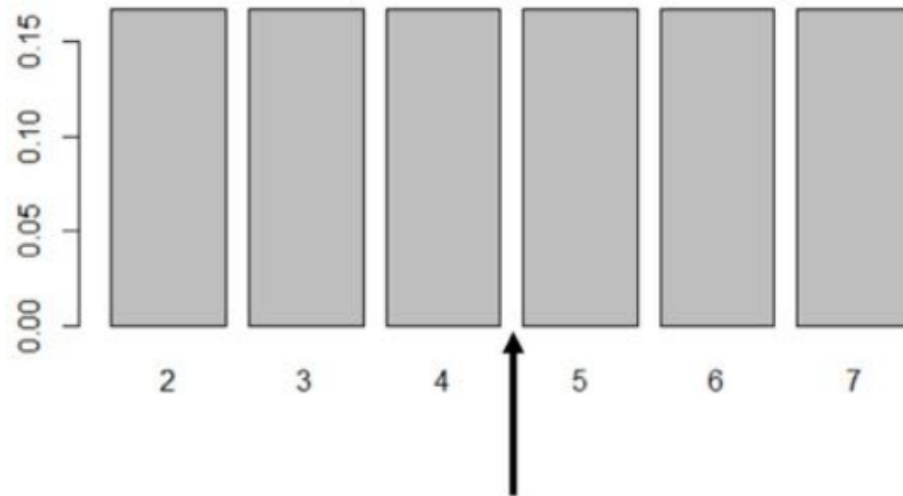
# Sample Mean

- The mean calculated from sample data
- It estimates the population mean
- Sample mean :  $\bar{x}$
- Population mean :  $\mu$
- E.g. sample data value: 4, 6, 2, 5, 3, 7

$$\bar{x} = \frac{4+6+2+5+3+7}{6} = 4.5$$

# Mean

- The sample mean is the center of mass of the sample data
- For the sample data: 4, 6, 2, 5, 3, 7
- Let's assume that they are build of solid bar and we arrange them on a level surface. The mean will be point that we can put a stick that balance these bars.

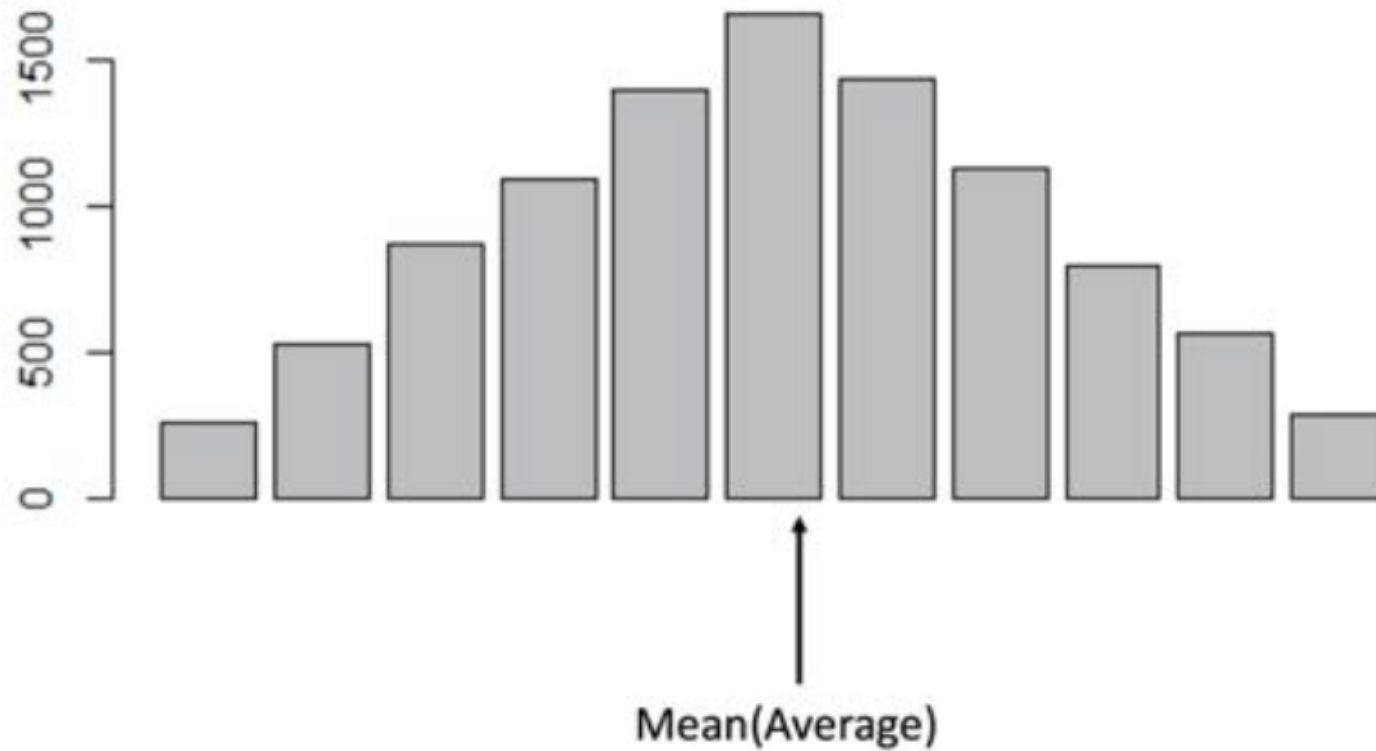


# Behaviour of Sample Mean

- Sample Mean is a random variable
- When we take different sample from the same population, the sample mean might be different
- Let's take a look on how these sample mean behave
- Imagine we roll a die 2 times, calculate the mean of the 2 outcomes, now we have 1 sample mean of die roll with sample size 2
- We repeat this procedure for 10000 times, so we will have 10000 sample mean of die roll with sample size 2



# Behaviour of Sample Mean

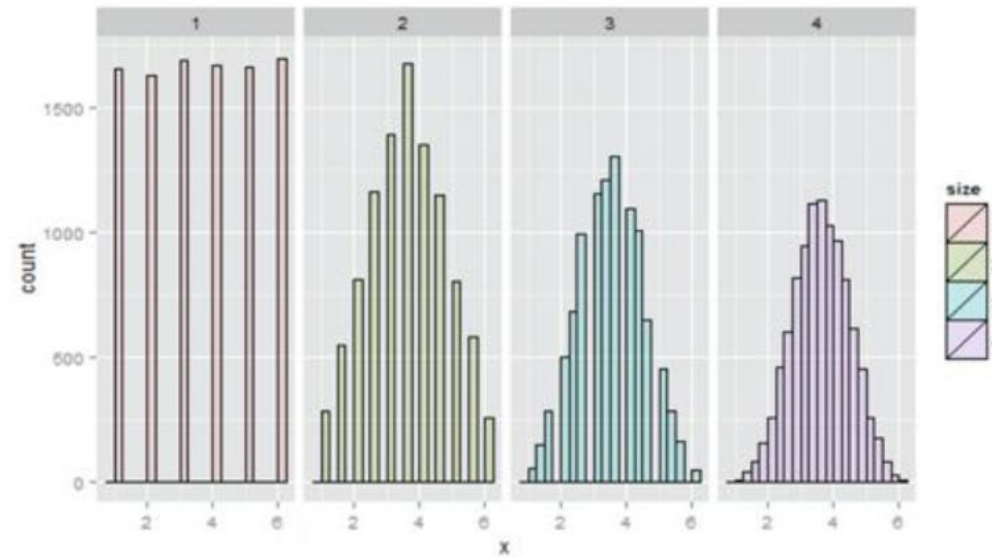


# Behaviour of Sample Mean

- Let's repeat the above steps with larger sample size, say  $n=3$ , and  $n=4$
- $n=3$ :
  - We roll the die 3 times, calculate the mean of the 3 outcomes, now we have 1 sample mean of die roll with sample size 3
  - We repeat this procedure 10000 times, so we will have 10000 sample mean of die roll with sample size 3
- $n=4$ :
  - We roll the die 4 times, calculate the mean of the 4 outcomes, now we have 1 sample mean of die roll with sample size 4
  - We repeat this procedure 10000 times, so we will have 10000 sample mean of die roll with sample size 4

# Behaviour of Sample Mean

- Plot the distributions of the sample mean side by side:



- When  $n$  increases:
  - The distribution of the sample mean become more concentrated and more Gaussian (symmetric)
  - The center of mass remain unchanged

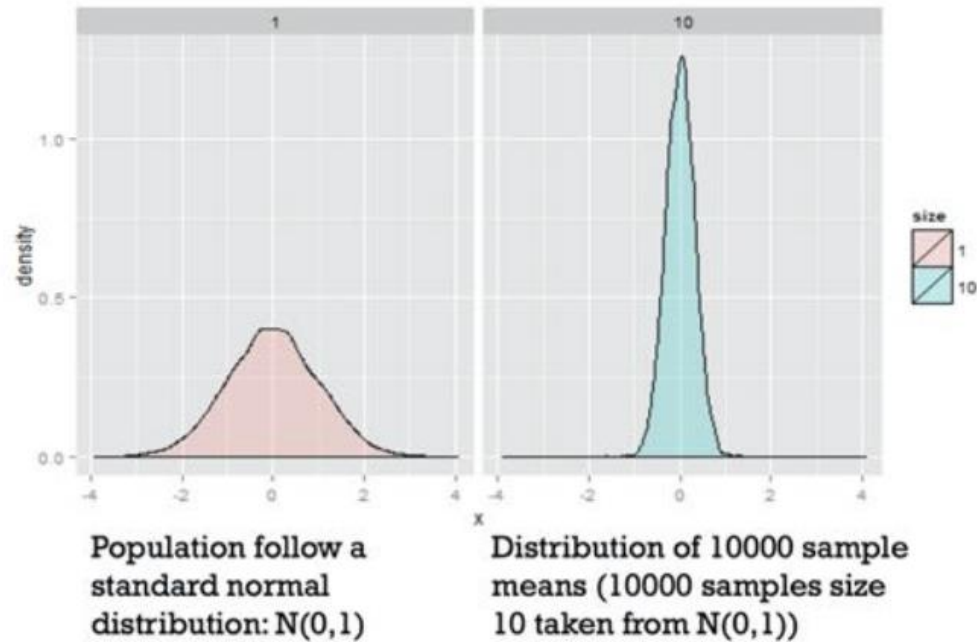
# Behaviour of Sample Mean

- When  $n$  increases:
  - The distribution of the sample mean become more concentrated and more Gaussian (symmetric)
  - The center of mass remain unchanged

Center of the mass = population mean

- Sample mean is an unbiased estimator for the population mean

# Behaviour of Sample Mean



- The distribution of the sample mean (blue) is Gaussian, more concentrated than the population distribution and has mean = 0

# Behaviour of Sample Mean

- When the population is normal, the distribution of the sample mean is exactly normal with mean  $\mu$  and variance  $\frac{\sigma^2}{n}$
- When the population is not normal (eg. Toss coin), the distribution of the sample mean is approximately normal with mean  $\mu$  and variance  $\frac{\sigma^2}{n}$  if  $n$  is large enough

# Summary

- Expected values are properties of distributions
- The population mean is the center of mass of population
- The sample mean is the center of mass of the observed data (sample)
- The sample mean is an estimate of the population mean
- The sample mean is unbiased
  - The mean of its distribution is the mean that it's trying to estimate
  - The more data that goes into the sample mean (*n increase*), the more concentrated its density / mass function is around the population mean

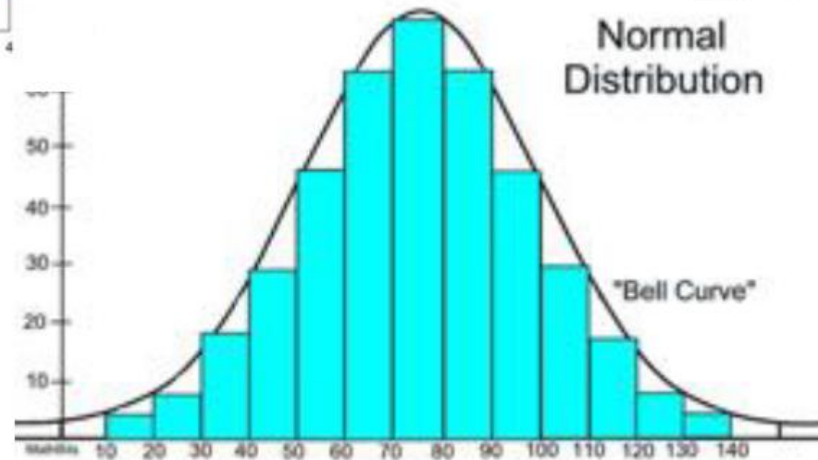
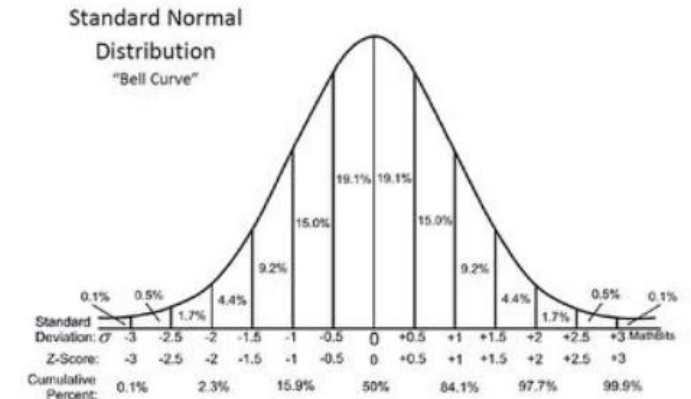
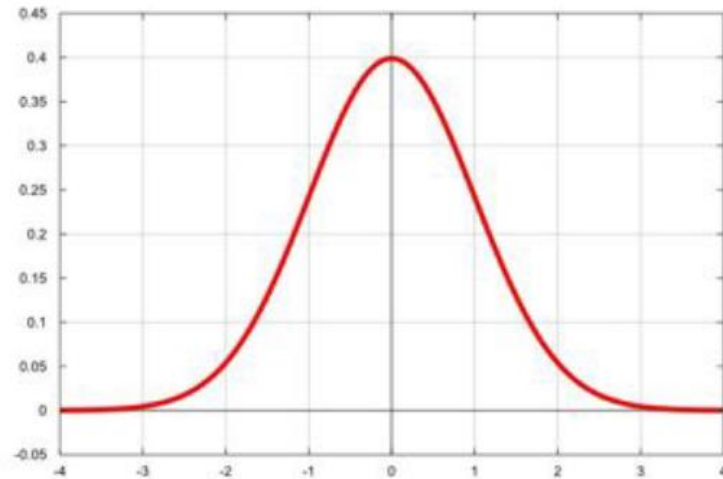
# Normal Distribution

Instructor, Nero Chan Zhen Yu





# Have you seen this shape before?



# The Normal Distribution

- Often times data is described as being “normal” (in statistical sense)
- As known as (or Gaussian or Gauss or Laplace-Gauss)
- The frequency by which some events occur; both natural and man-made:
  - Natural: human height, temperature, blood pressure etc.
  - Man-made: machine products, financial data, sales etc.
- For these measures, the average (mean) tends to be very frequent while measures away from the mean are less and less frequent

# Standard Normal Distribution

- Take any Normal Distribution and convert it to The Standard Normal Distribution



# Standard Normal Distribution

- The number of standard deviations from the mean is also called the “Standard Score”, “Sigma” or “z-score”.
- Here is the formula for z-score that we have been using:

$$z = \frac{x - \mu}{\sigma}$$

- **z** is the "z-score" (Standard Score)
- **x** is the value to be standardized
- **μ** is the mean
- **σ** is the standard deviation

# The Standard Normal Curve

Mean,  
Median, Mode

Z distribution

$$\mu = 0$$

$$\sigma = 1$$

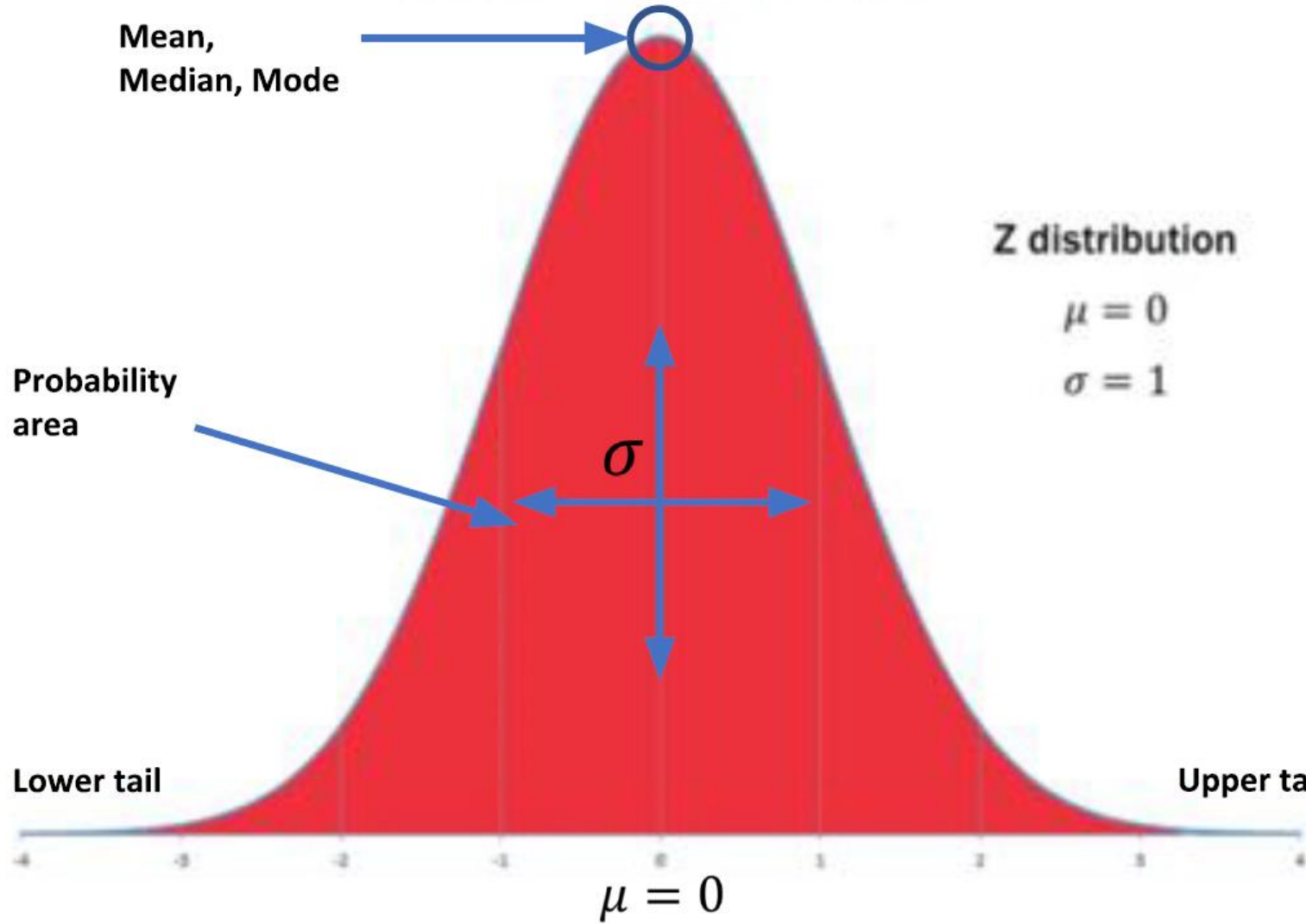
Probability  
area

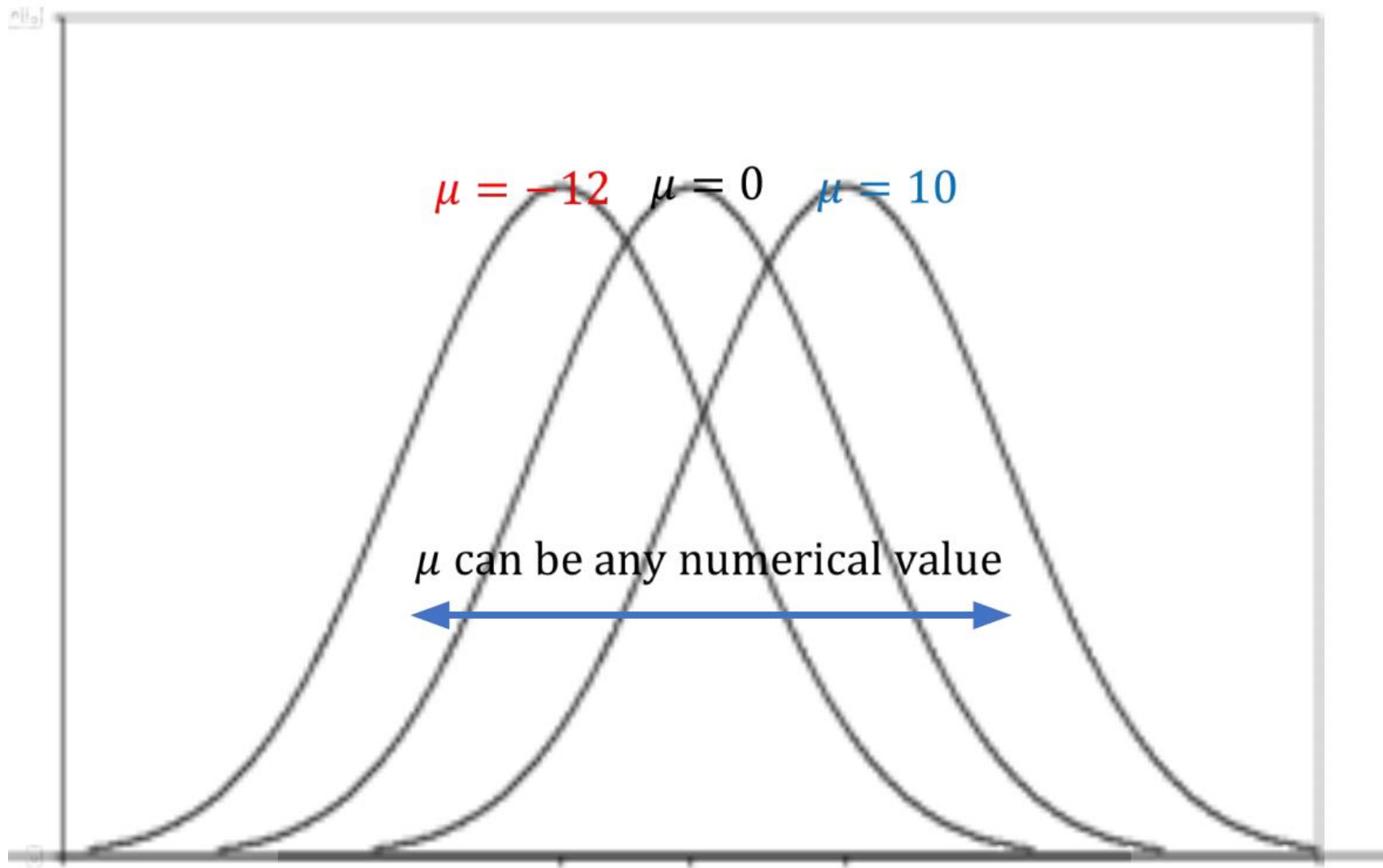
$\sigma$

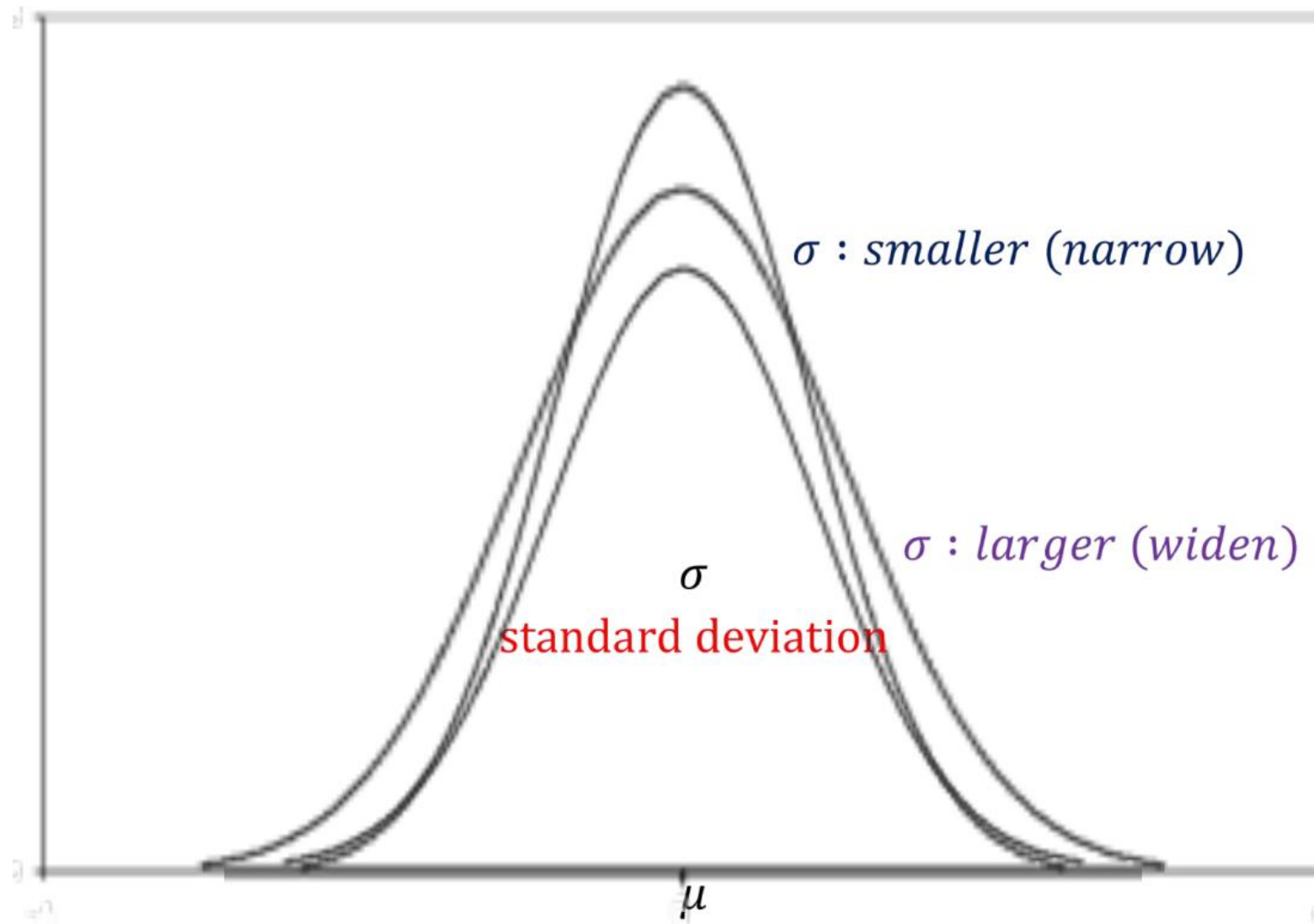
Lower tail

Upper tail

$$\mu = 0$$

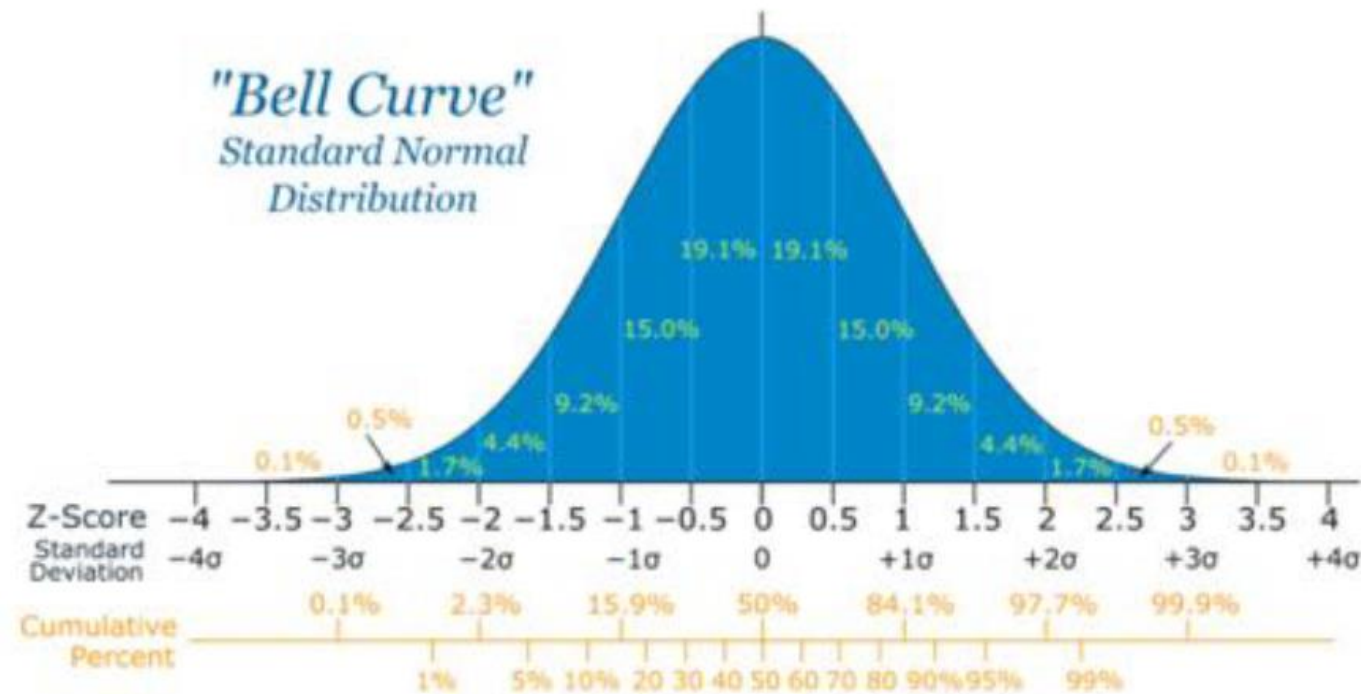






# Standard Normal Distribution

- Here is the Standard Normal Distribution with percentages for every half of a standard deviation and cumulative percentages:





# The Standard Normal Curve

Area under the curve

1

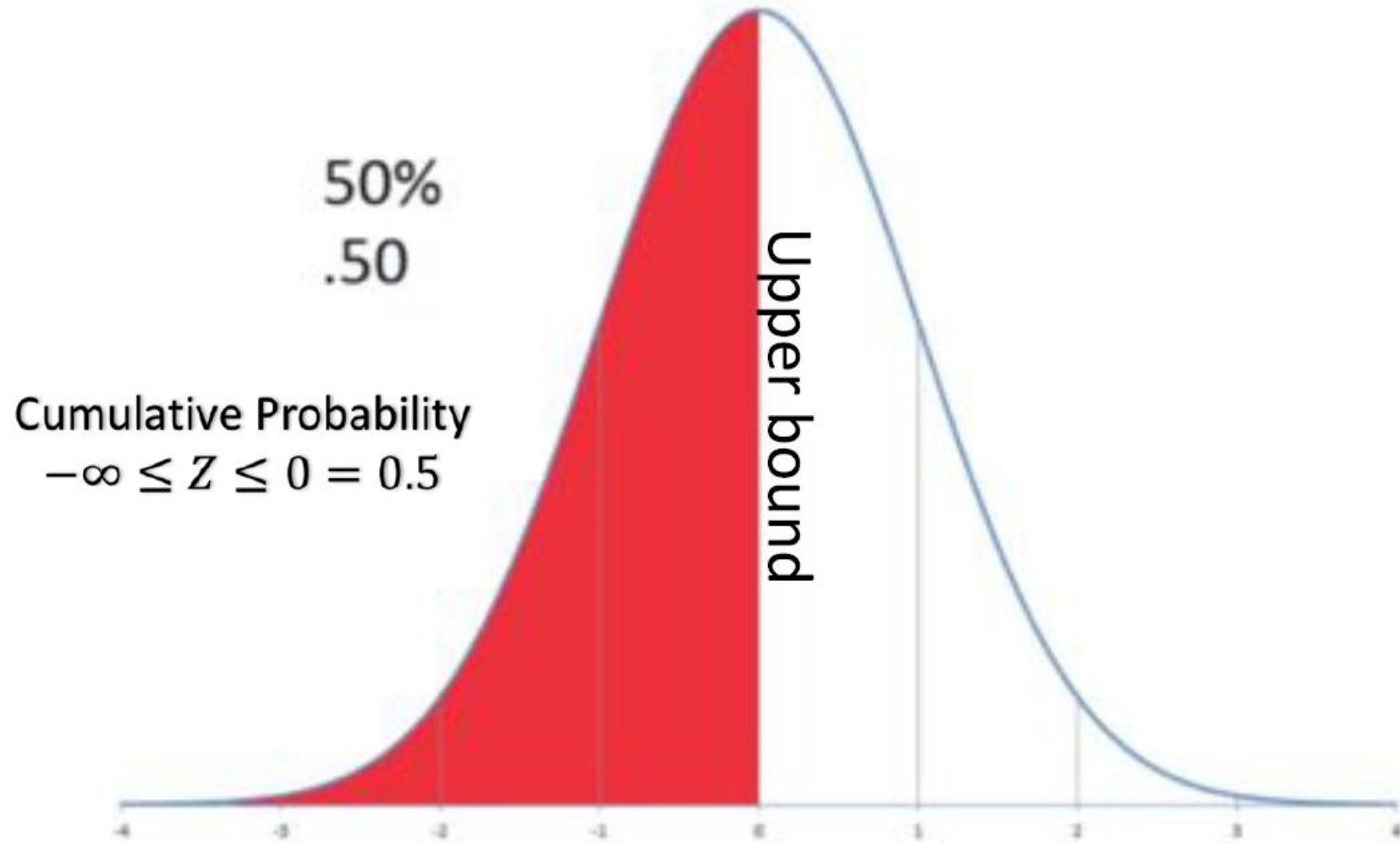
Z distribution

$$\mu = 0$$

$$\sigma = 1$$



The Standard Normal Curve

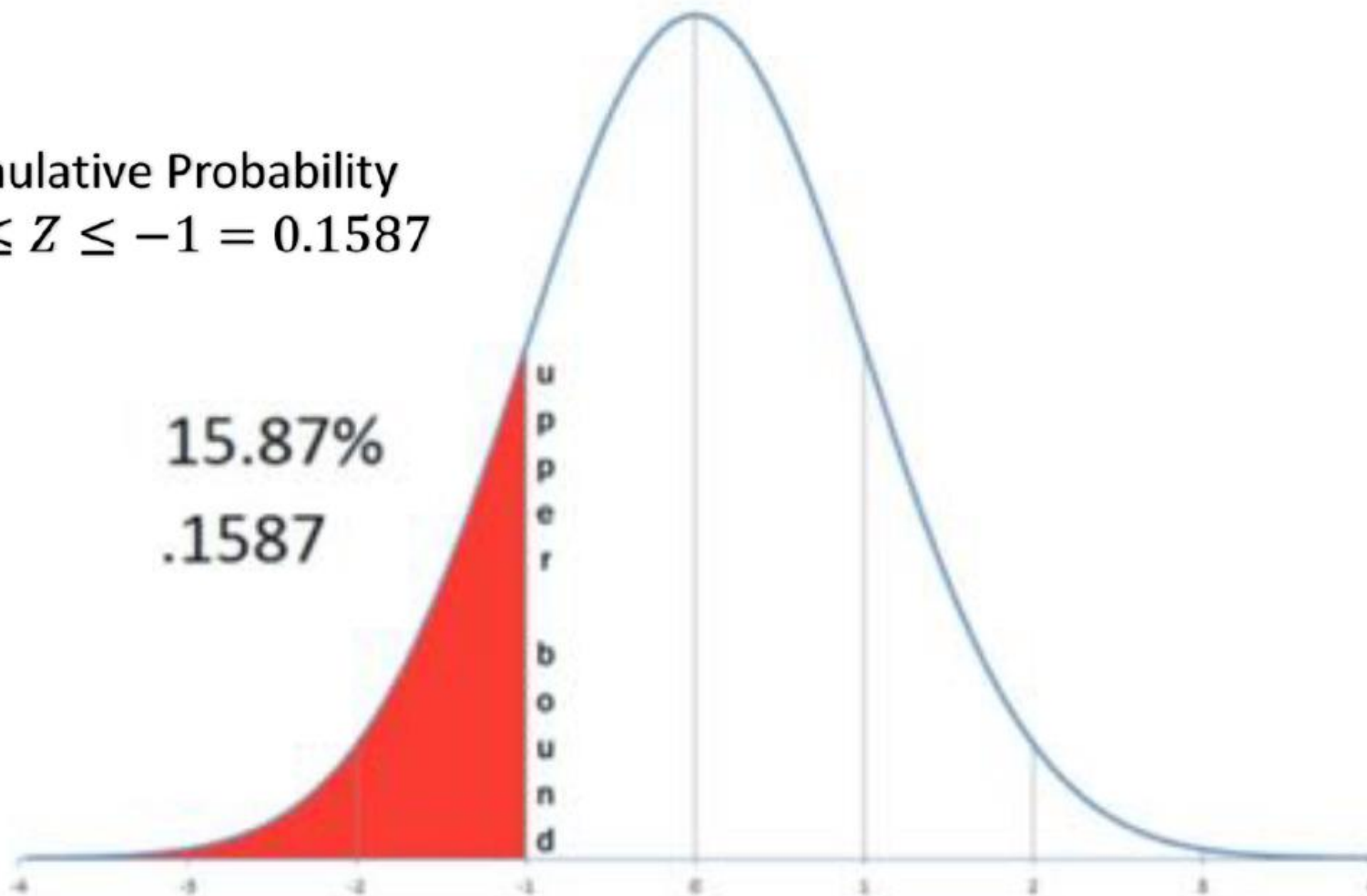


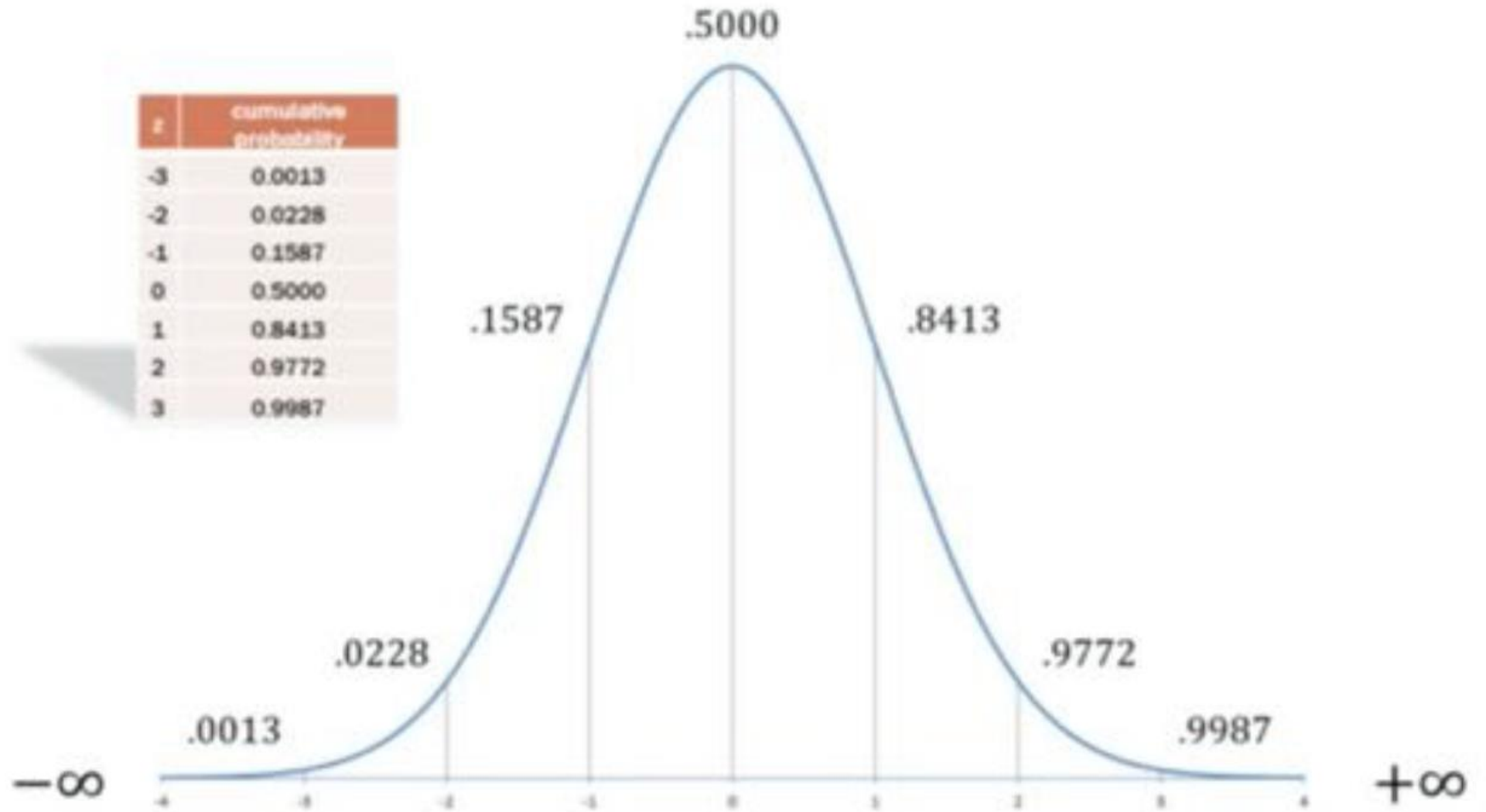
## The Standard Normal Curve

Cumulative Probability  
 $-\infty \leq Z \leq -1 = 0.1587$

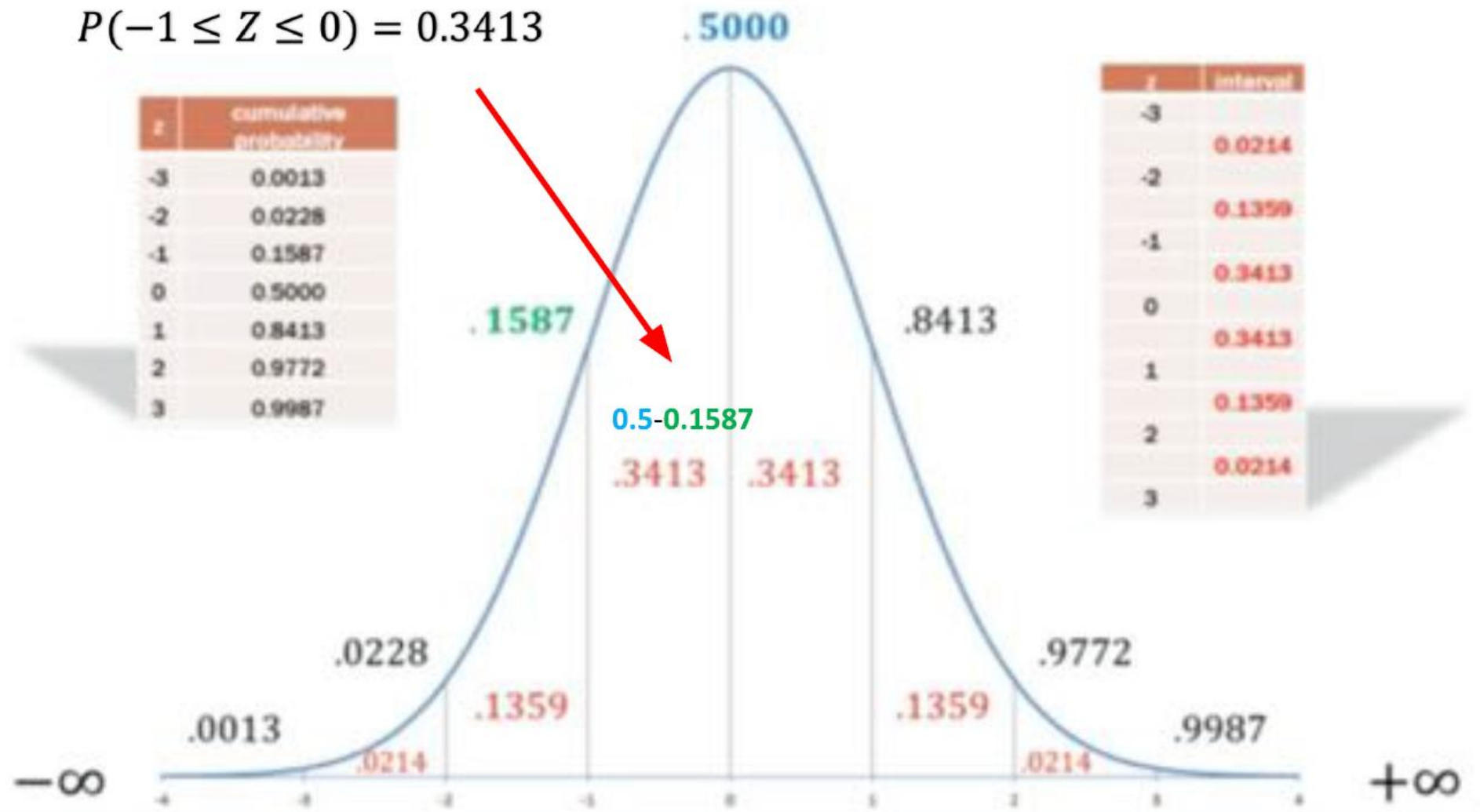
15.87%  
.1587

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a  
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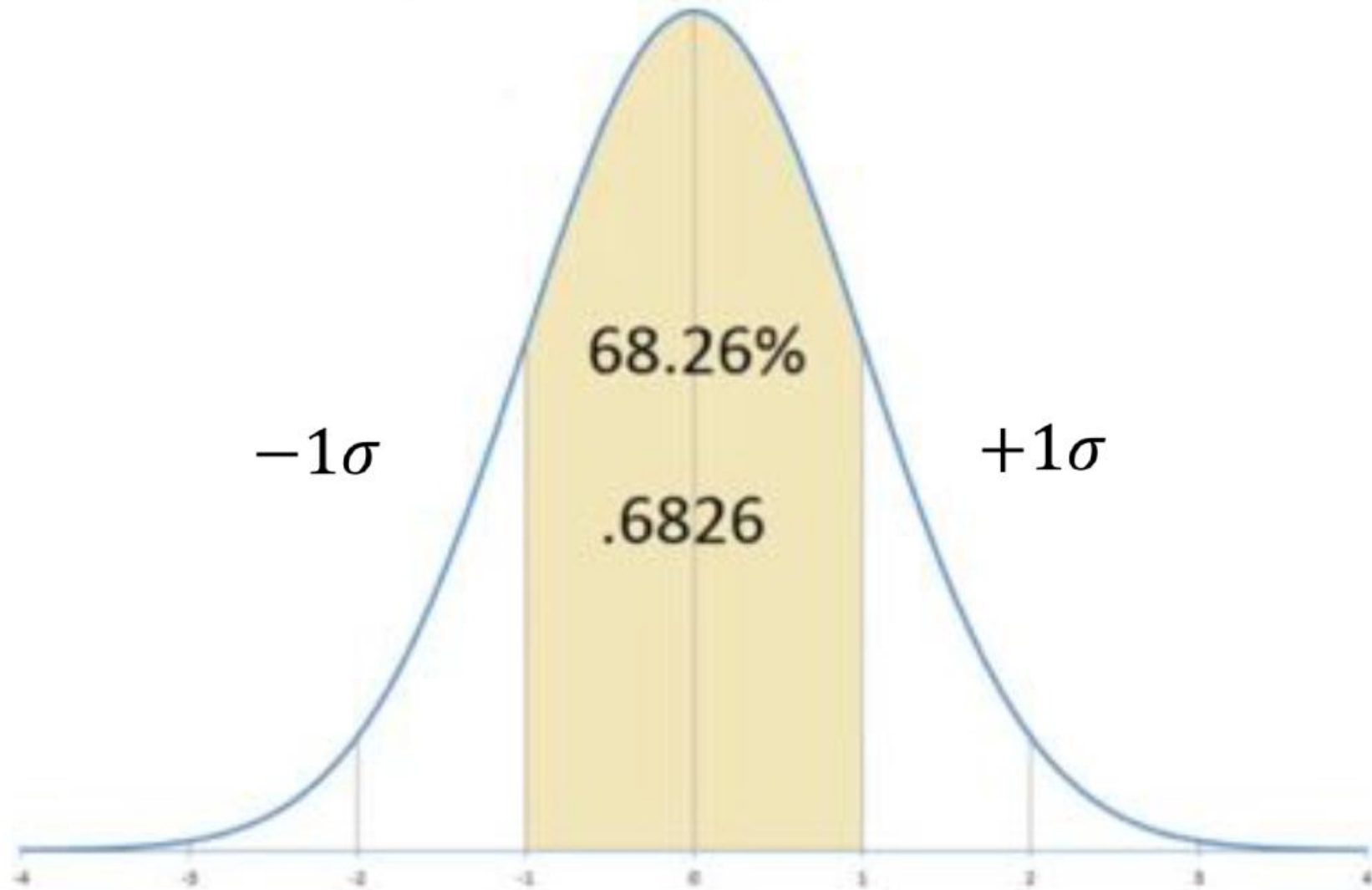




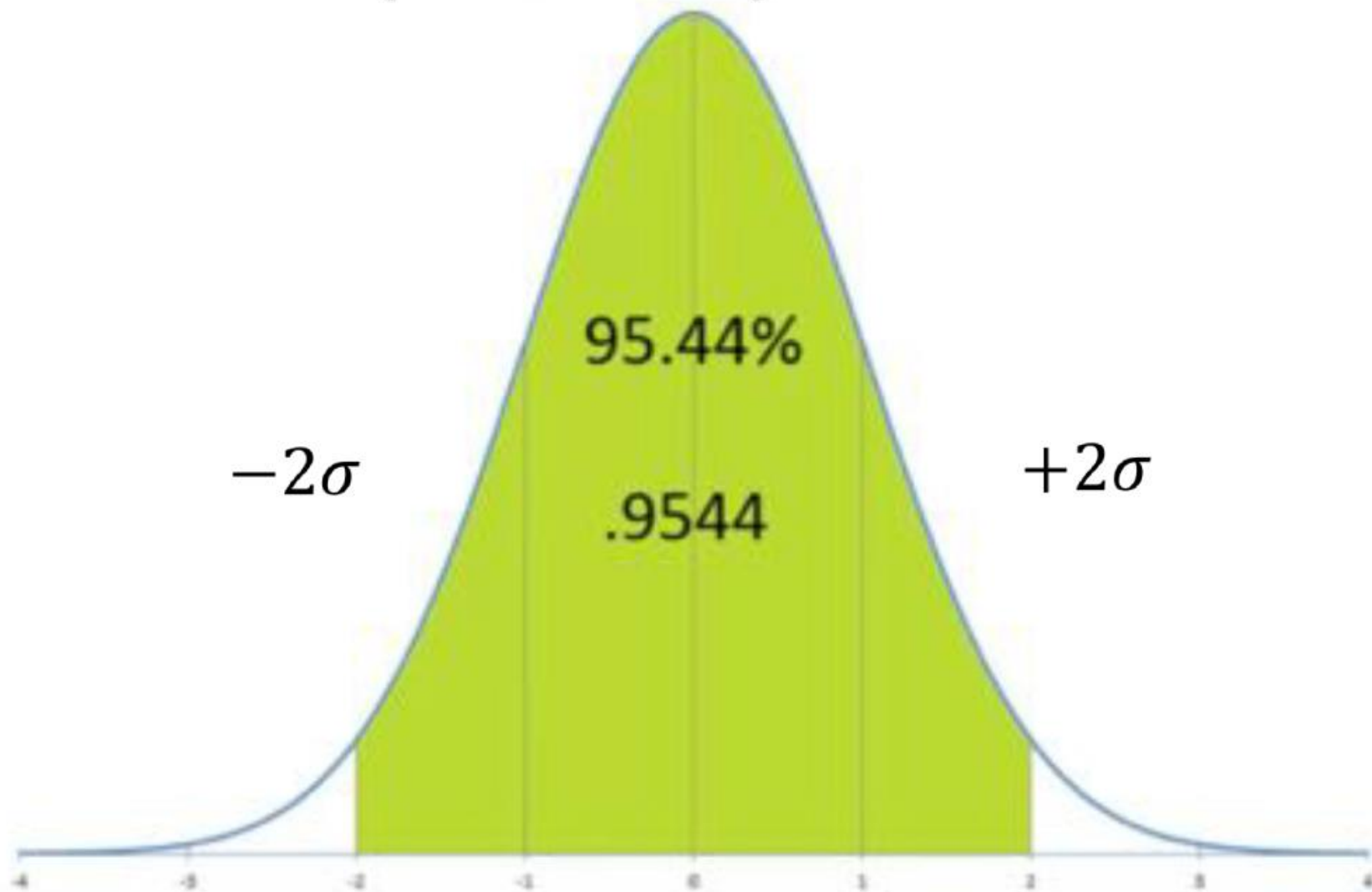
$$P(-1 \leq Z \leq 0) = 0.3413$$



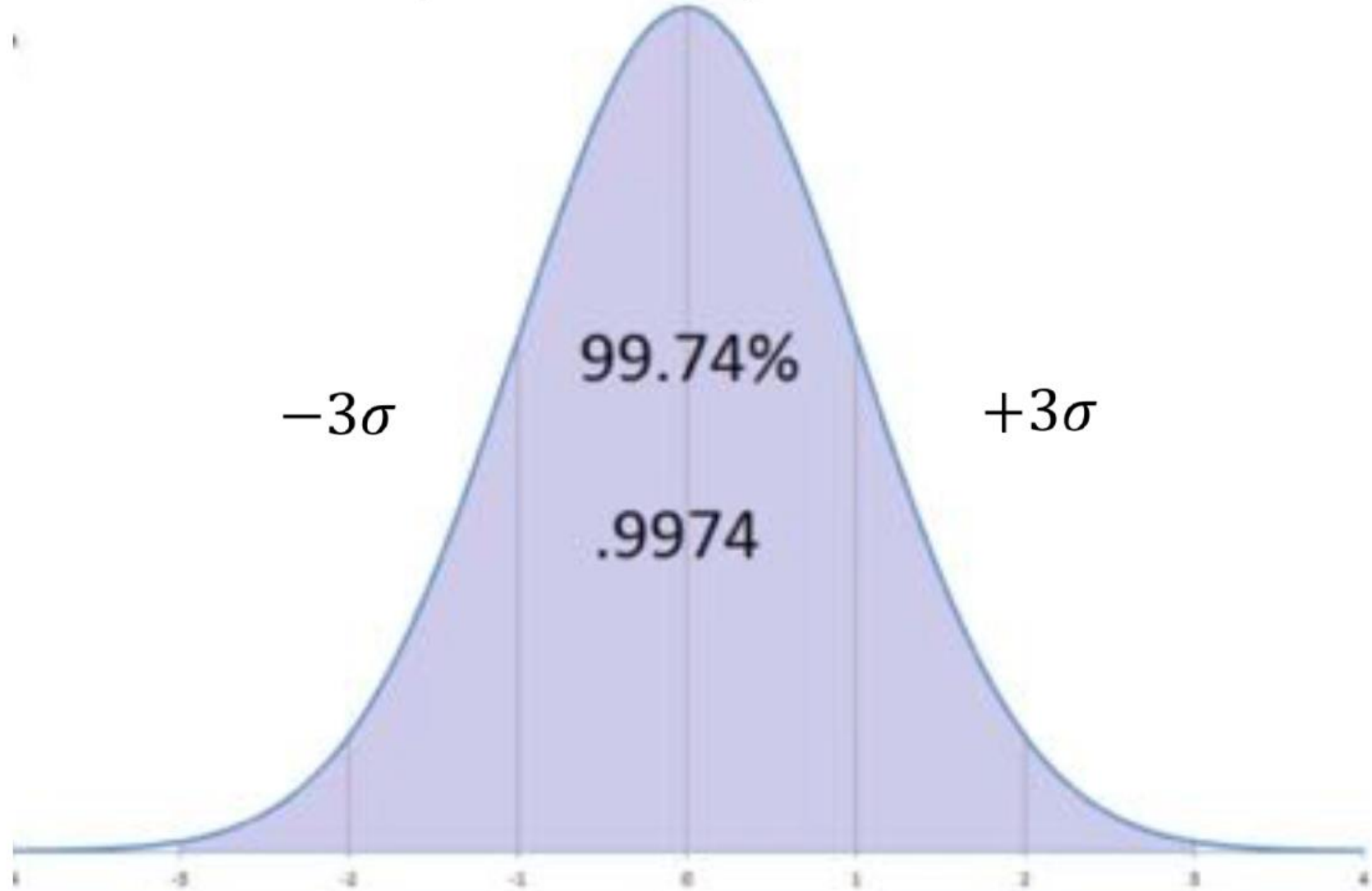
$$P(-1 \leq Z \leq 1) = 0.6826$$



$$P(-2 \leq Z \leq 2) = 0.9544$$

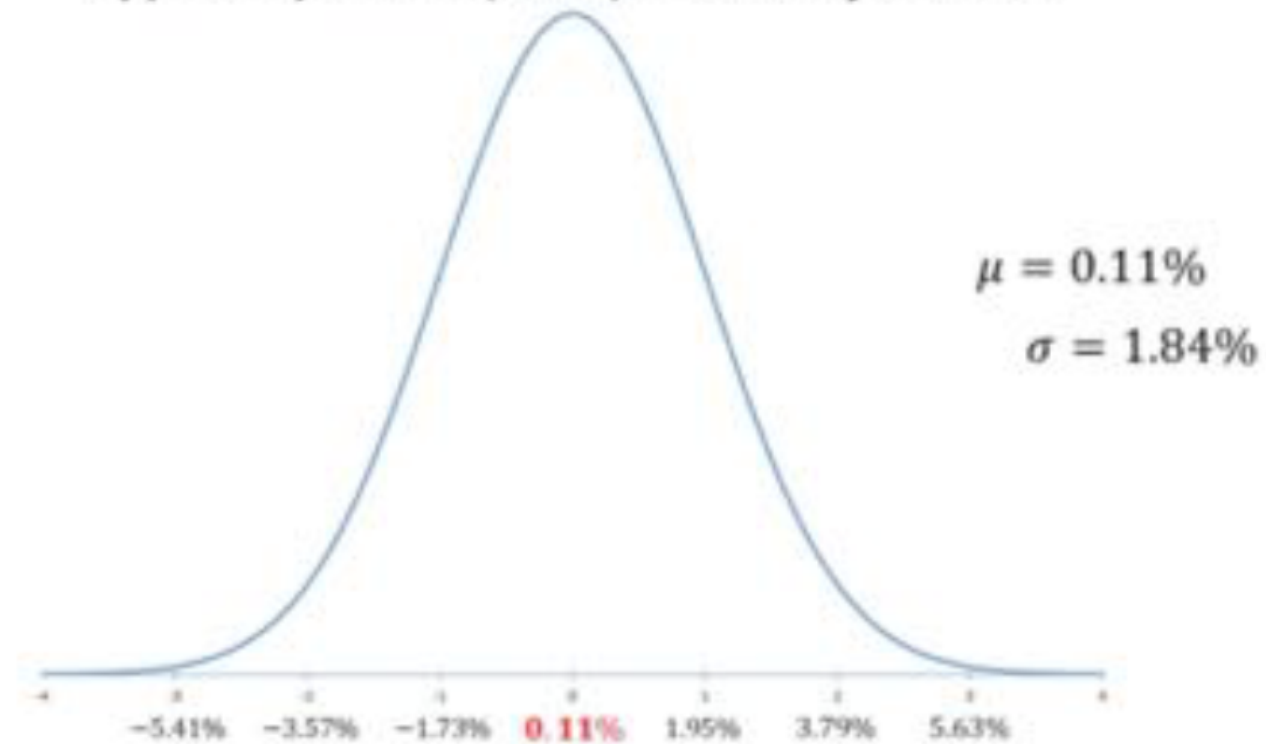


$$P(-3 \leq Z \leq 3) = 0.9974$$





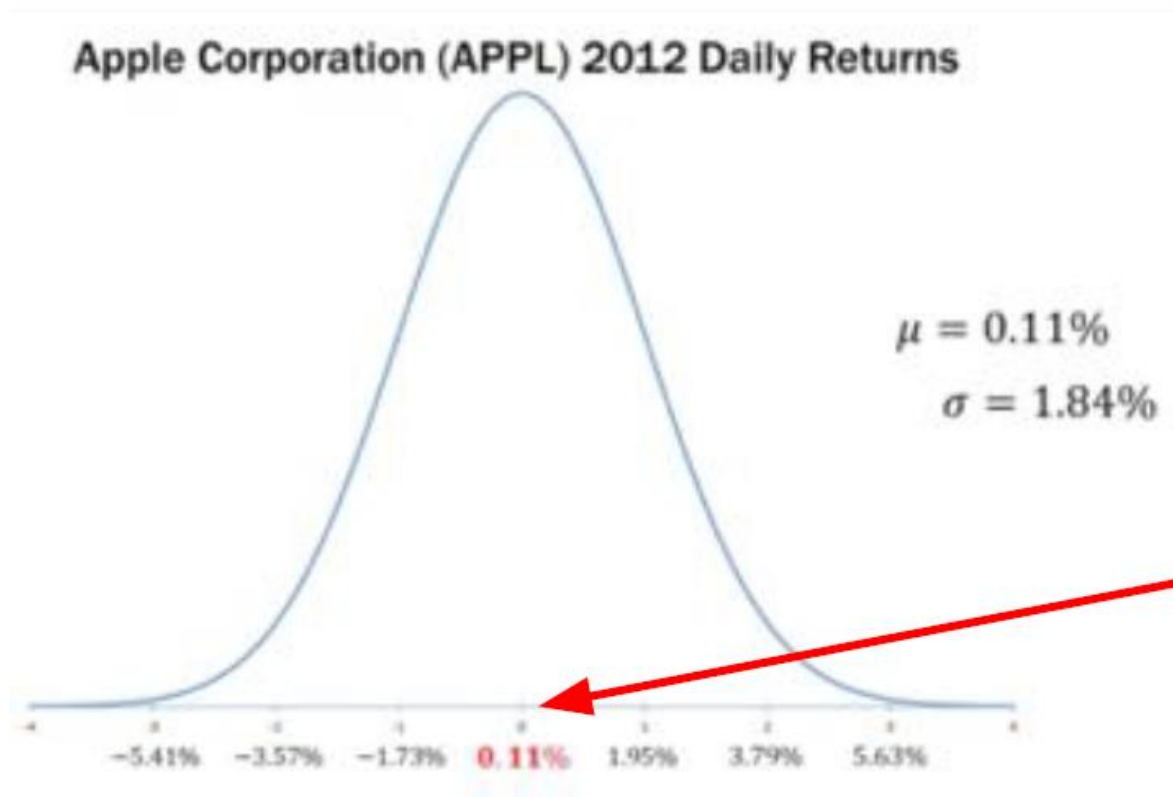
### Apple Corporation (APPL) 2012 Daily Returns



Questions:

1. What is the probability, for any given day, of a return greater than 0.5%?
2. What is the probability, for any given day, of a loss greater than 2%?
3. What is the probability, for any given day, of a return between 0% and 1%?
4. What is the probability, for any given day, of a return OR loss greater than 3%?

What is the probability, for any given day, of a return greater than 0.5%?



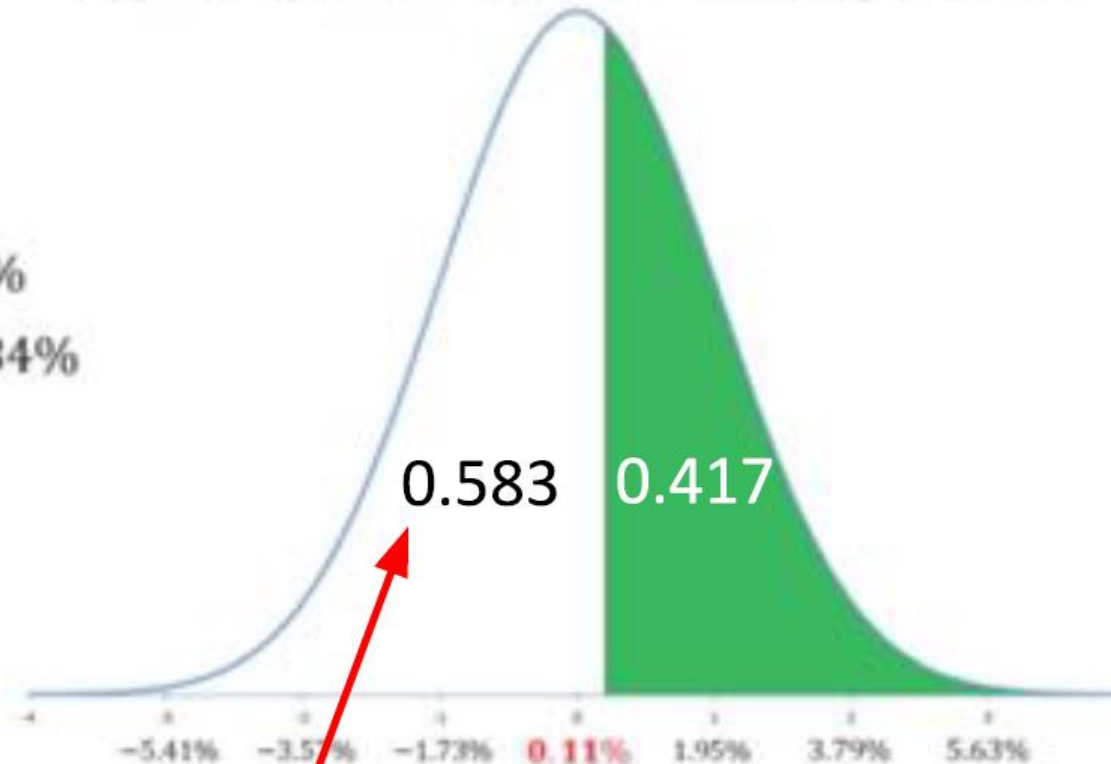
$$Z = \frac{x - \mu}{\sigma}$$

$$Z = \frac{0.5 - 0.11}{1.84}$$

$$Z = 0.21$$

## Apple Corporation (APPL) 2012 Daily Returns

$\mu = 0.11\%$   
 $\sigma = 1.84\%$



$$z = \frac{x - \mu}{\sigma}$$

$$z = \frac{0.5 - .11}{1.84}$$

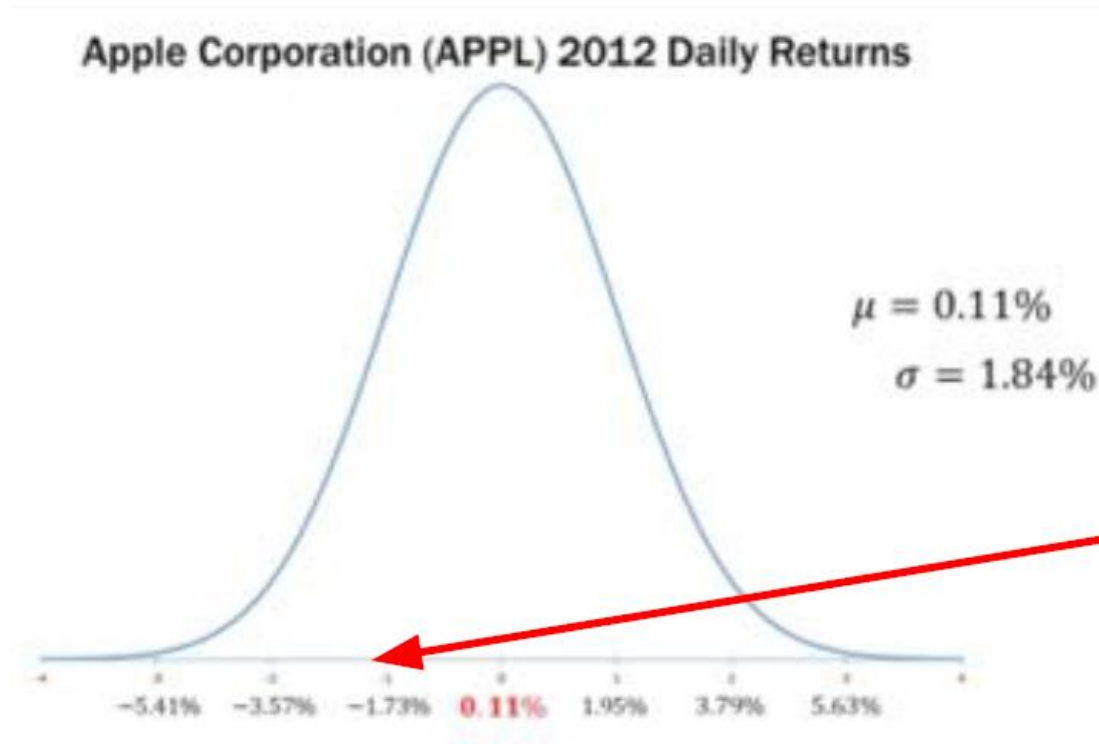
$$z = .21$$

What is the probability, for any given day, of a return greater than 0.5%?

`norm.cdf(0.21,0,1)`      $1 - 0.583 = 0.417$   
`norm.cdf(0.5, 0.11, 1.84)`

42%

What is the probability, for any given day, of a loss greater than 2%?



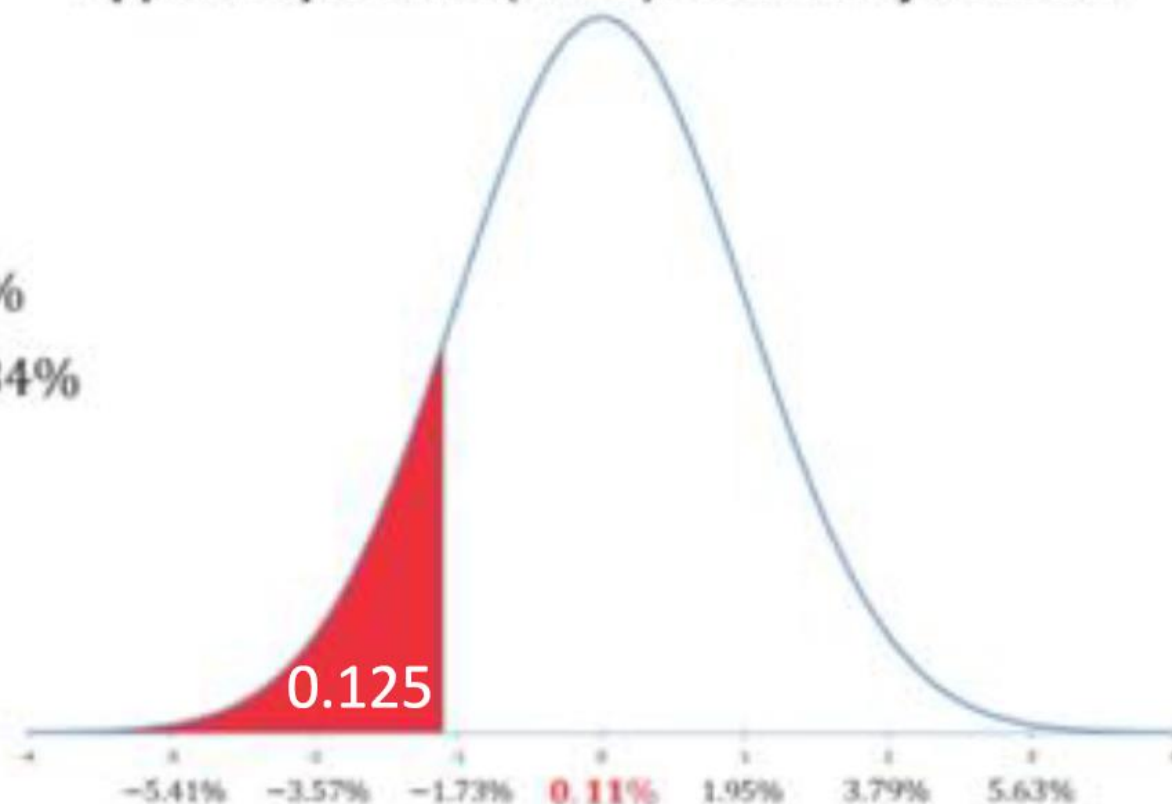
$$Z = \frac{x - \mu}{\sigma}$$

$$Z = \frac{-2 - 0.11}{1.84}$$

$$Z = -1.15$$

## Apple Corporation (APPL) 2012 Daily Returns

$\mu = 0.11\%$   
 $\sigma = 1.84\%$



$$z = \frac{x - \mu}{\sigma}$$

$$z = \frac{-2 - .11}{1.84}$$

$$z = -1.15$$

What is the probability, for any given day, of a loss greater than 2%?

`norm.cdf(-1.15,0,1) = 0.125`

`norm.cdf(-2,0.11,1.84)`

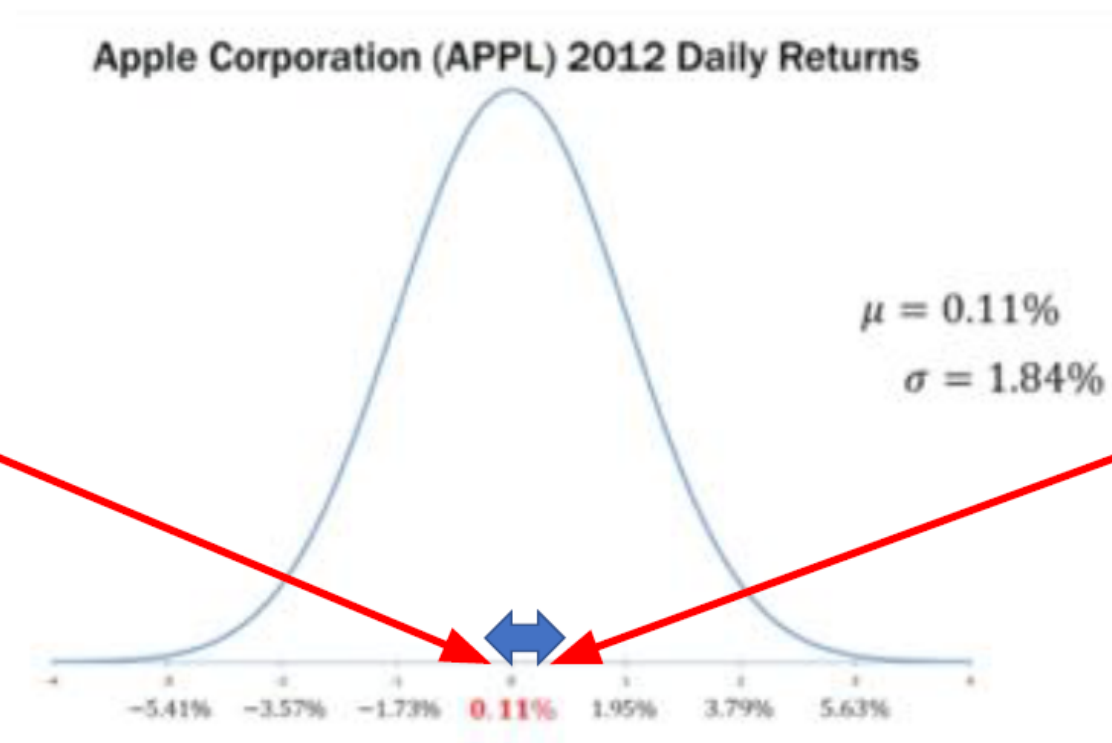
**12.5%**

What is the probability, for any given day, of a return between 0% and 1%?

$$Z = \frac{x - \mu}{\sigma}$$

$$Z = \frac{0 - 0.11}{1.84}$$

$$Z = -0.06$$

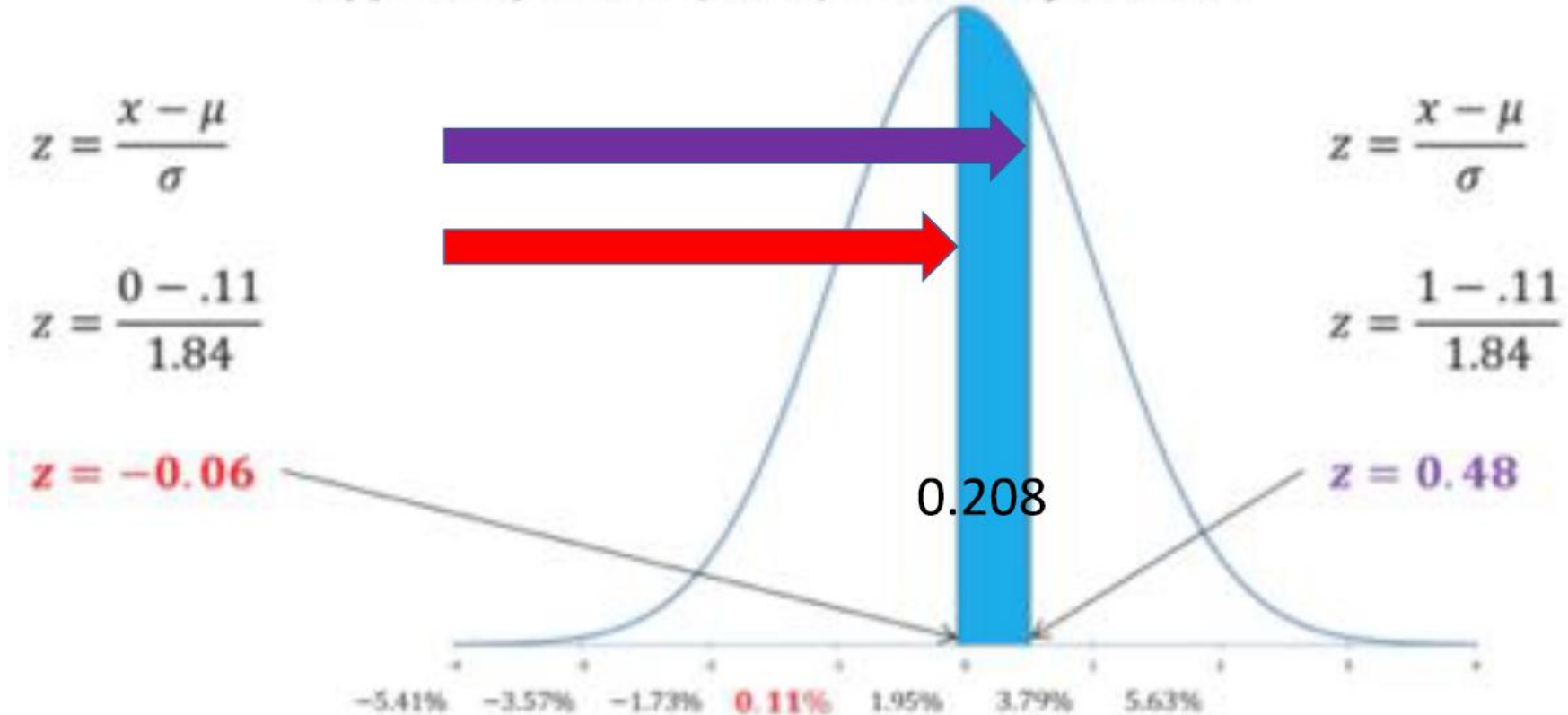


$$Z = \frac{x - \mu}{\sigma}$$

$$Z = \frac{1 - 0.11}{1.84}$$

$$Z = 0.48$$

## Apple Corporation (APPL) 2012 Daily Returns



What is the probability, for any given day, of a return between 0% and 1%?

$$\text{norm.cdf}(0.48, 0, 1) = 0.684 - \text{norm.cdf}(-0.06, 0, 1) = 0.476 = 0.208$$

$$\text{norm.cdf}(1, 0.11, 1.84) - \text{norm.cdf}(0, 0.11, 1.84)$$

21%

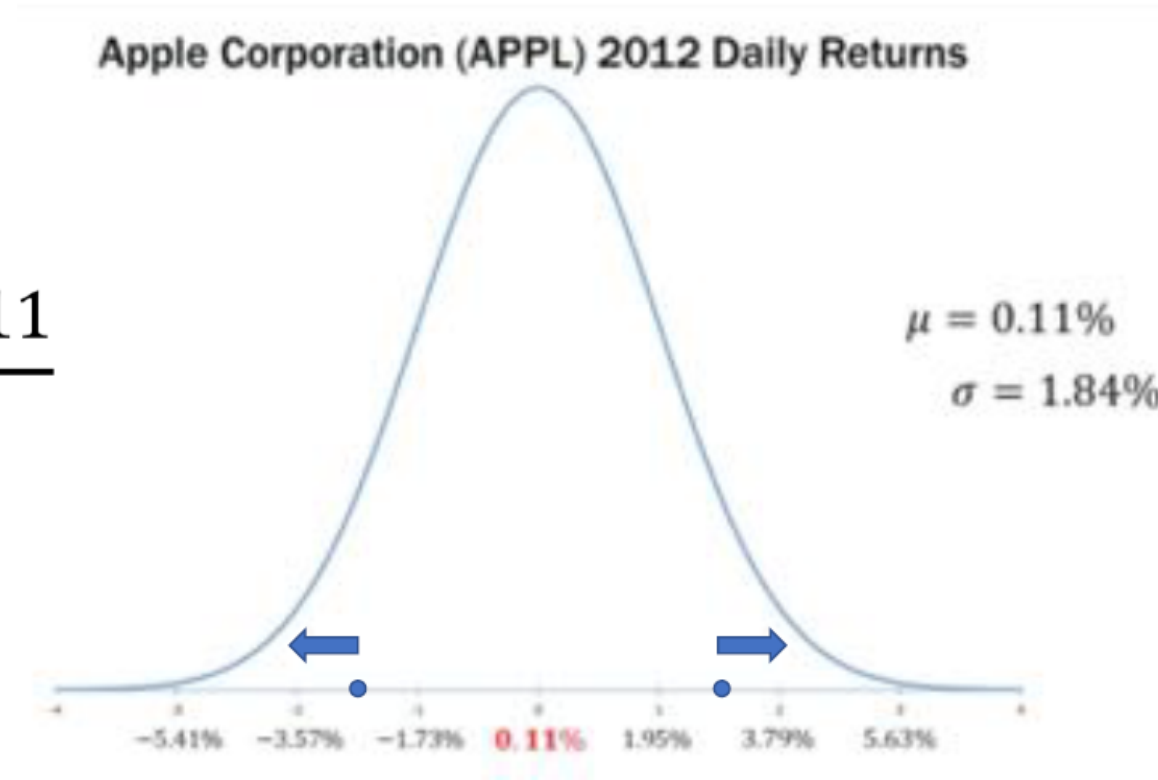


What is the probability, for any given day, of a return OR loss greater than 3%?

$$Z = \frac{x - \mu}{\sigma}$$

$$Z = \frac{-3 - 0.11}{1.84}$$

$$Z = -1.69$$



$$Z = \frac{x - \mu}{\sigma}$$

$$Z = \frac{3 - 0.11}{1.84}$$

$$Z = 1.57$$



## Apple Corporation (APPL) 2012 Daily Returns

$$z = \frac{x - \mu}{\sigma}$$

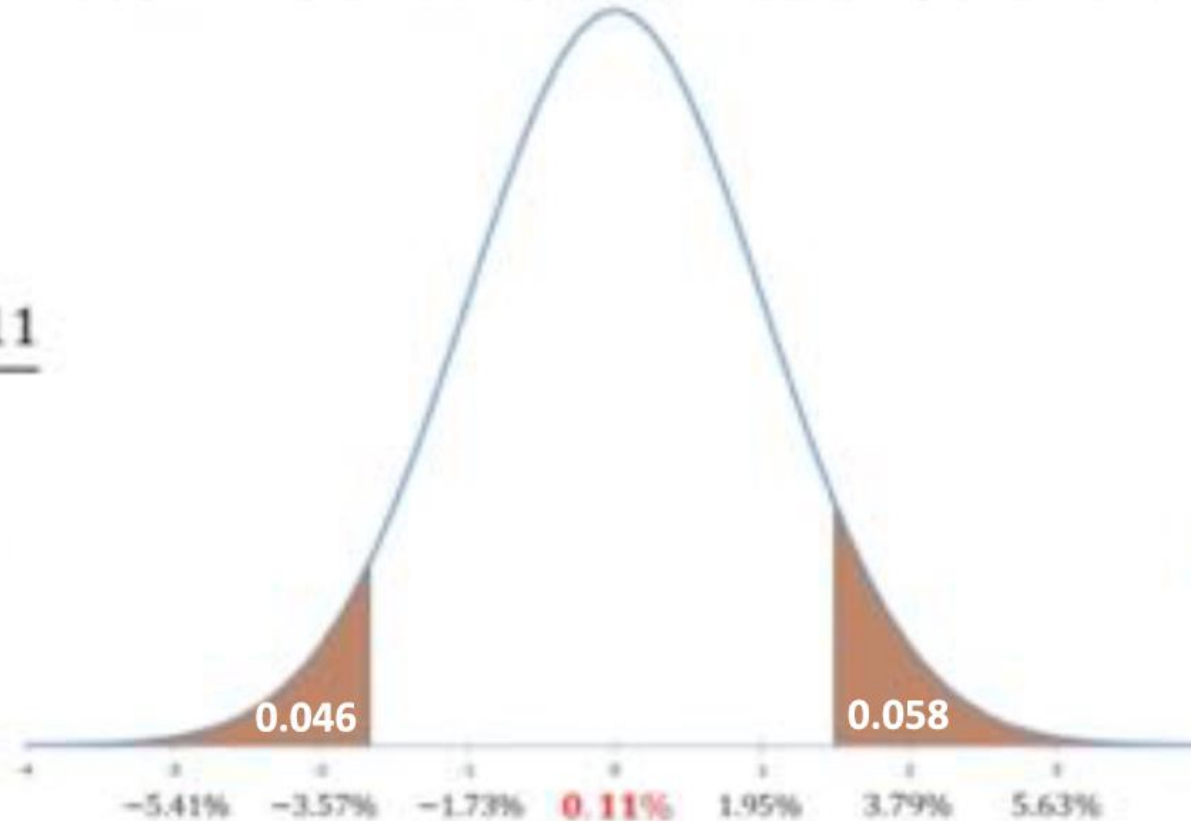
$$z = \frac{-3 - .11}{1.84}$$

$$z = -1.69$$

$$z = \frac{x - \mu}{\sigma}$$

$$z = \frac{3 - .11}{1.84}$$

$$z = 1.57$$



10.4%

What is the probability, for any given day of a return OR loss greater than 3%?

$$\text{norm.cdf}(-1.69, 0, 1) = 0.046 \quad + \quad 1 - \text{norm.cdf}(1.57, 0, 1) = 0.058$$

$$0.046 + 0.058 = 0.104 \text{ or } 10.4\% \quad \text{norm.cdf}(-3, 0.11, 1.84) + (1 - \text{norm.cdf}(3, 0.11, 1.84))$$

# Normal Distribution with Scipy

- <https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.norm.html>
- The normal distribution is defined by the following probability density function, where  $\mu$  is the population mean and  $\sigma^2$  is the variance.
- In particular, the normal distribution with  $\mu = 0$  and  $\sigma = 1$  is called standard normal distribution and denoted as  $N(0, 1)$ .
- The normal distribution is important because of the Central Limit Theorem, which states that the population of all possible samples of size  $n$  from a population with mean  $\mu$  and variance  $\sigma^2$  approaches a normal distribution with mean  $\mu$  and  $\sigma^2 / n$  when  $n$  approaches infinity.

`norm.pdf(x, loc = 0, scale = 1)` Probability Density Function

`norm.cdf(x, loc = 0, scale = 1)` Cumulative Density Function

`norm.ppf(x, loc = 0, scale = 1)` Percent Point Function

`norm.rvs(loc=0, scale=1, size=1, random_state=None)` Generate random normal numbers

```
norm.pdf(x, loc = 0, scale = 1)
```

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

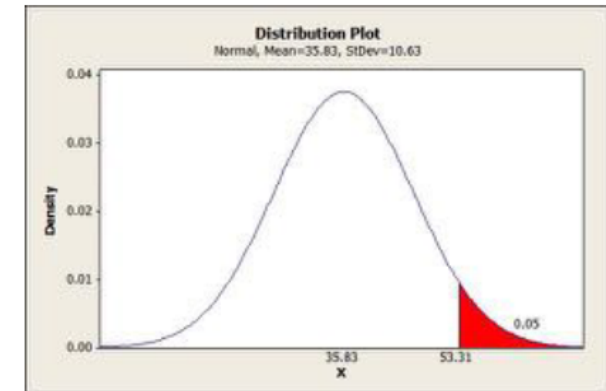
- The function `pdf` returns the value of the probability density function for the normal distribution given parameters for `x`, `μ`, and `σ`.
- Although `x` represents the independent variable of the pdf for the normal distribution, it's also useful to think of `x` as a Z-score.

```
norm.pdf(2, loc = 5, scale = 3)
```

```
norm.cdf(x, loc = 0, scale = 1)
```

- The function `cdf` returns the integral from  $-\infty$  to  $x$  of the pdf of the normal distribution where  $x$  is a Z-score.
- The `cdf` function also takes the argument `lower tail`. For **upper tail**, it is equivalent to `cdf` returns the integral from  $x$  to  $\infty$  of the pdf of the normal distribution. Note that **upper tail** for `norm.cdf(x)` is the same as `1 - norm.cdf(x)`

```
norm.cdf(2, 5, 3)
```



```
norm.ppf(x, loc = 0, scale = 1)
```

- The `norm.ppf` function is simply the inverse of the cdf, which you can also think of as the inverse of `norm.cdf`

```
# What is the Z-score of the 50th quantile of the normal  
distribution?
```

```
> norm.ppf(0.5)
```

```
# [1] 0
```

```
# What is the Z-score of the 99th quantile of the normal  
distribution?
```

```
> norm.ppf(0.99)
```

```
# [1] 2.326348
```

	PURPOSE	SYNTAX	EXAMPLE
<b>norm.rvs</b>	Generates random numbers from normal distribution	<code>norm.rvs(loc=0, scale=1, size=1, rand om_state=None)</code>	<code>norm.rvs(1000, 3, .25)</code>  Generates 1000 numbers from a normal with mean 3 and sd=.25
<b>norm.pdf</b>	Probability Density Function (PDF)	<code>norm.pdf(x, loc = 0, scale = 1)</code>	<code>norm.pdf(0, 0, .5)</code>  Gives the density (height of the PDF) of the normal with mean=0 and sd=.5.
<b>norm.cdf</b>	Cumulative Distribution Function (CDF)	<code>norm.cdf(x, loc = 0, scale = 1)</code>	<code>norm.cdf(1.96, 0, 1)</code>  Gives the area under the standard normal curve to the left of 1.96,  i.e. ~0.975
<b>norm.ppf</b>	Quantile Function – inverse of pnorm	<code>norm.ppf(x, loc = 0, scale = 1)</code>	<code>norm.ppf(0.975, 0, 1)</code>  Gives the value at which the CDF of the standard normal is .975, i.e. ~1.96

# Exercise 1

- With a normal random variable with mean 22 and variance 25, find put the following probabilities:
  - Lies between 16.2 and 27.5
  - Is greater than 29
  - Is less than 17
  - Is less than 15 or greater than 25

## Exercise 2

- Assume that the test scores of a college entrance exam fits a normal distribution. Furthermore, the mean test score is 72, and the standard deviation is 15.2. What is the percentage of students scoring 84 or more in the exam?