



香港中文大學(深圳)

The Chinese University of Hong Kong, Shenzhen

**DDA2001: Introduction to Data Science**

# **Lecture 8: Continuous Random Variable**

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# Recap of Continuous Random Variable

# Continuous R.V.

- A continuous random variable can take any value within its range (an interval or a union of multiple intervals of real numbers).
- We cannot list all the possible values and their probabilities as in the discrete case.

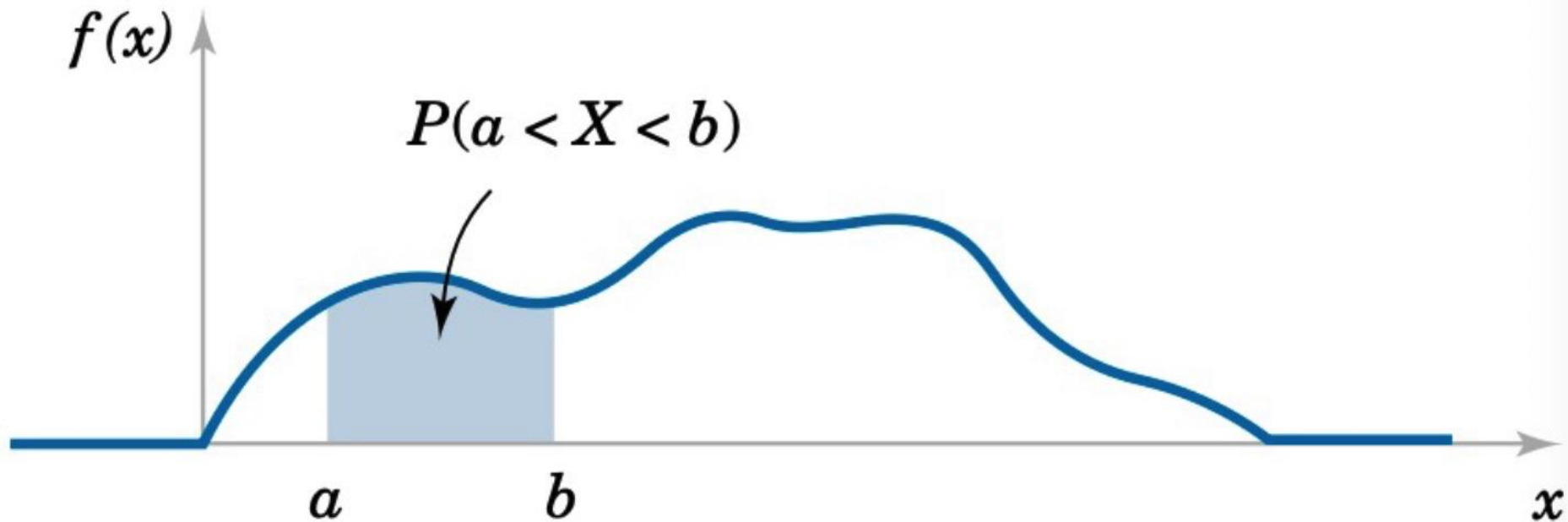
# How to describe the probability?

- If  $P(E) = 0$ , then  $E$  is a **zero-probability** event.
- If  $E$  is empty, then  $E$  is **impossible**.

- For a continuous RV  $X$ ,  $P(X=x) = 0$  but  $\{x\}$  is not an **impossible** event.
- We will not use the probability **mass** function (pmf), namely  $P(X=x)$ .
- Instead, we introduce a function  $f(\omega)$ , called the probability **density** function (pdf).
  - $f(\omega) > 0$ , if  $\omega \in S$
  - $f(\omega) = 0$ , if  $\omega \notin S$
  - $\int_{-\infty}^{\infty} f(x)dx = 1$ .

Probability of  $X \in [a, b]$

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



# Properties of PDF

- For  $x$  that is not in the sample space,  $f(x)=0$
- A large value of  $f(x)$  means that the values around  $x$  is more likely to be observed. (remember this implication)
- As a pdf,  $f(x)$  can be larger than 1, while as a pmf,  $f(x)$  cannot be larger than 1.
  - $f(\omega) = 2$  , if  $\omega \in [0, 0.5]$
  - $f(\omega) = 0$ , if  $\omega \notin [0, 0.5]$

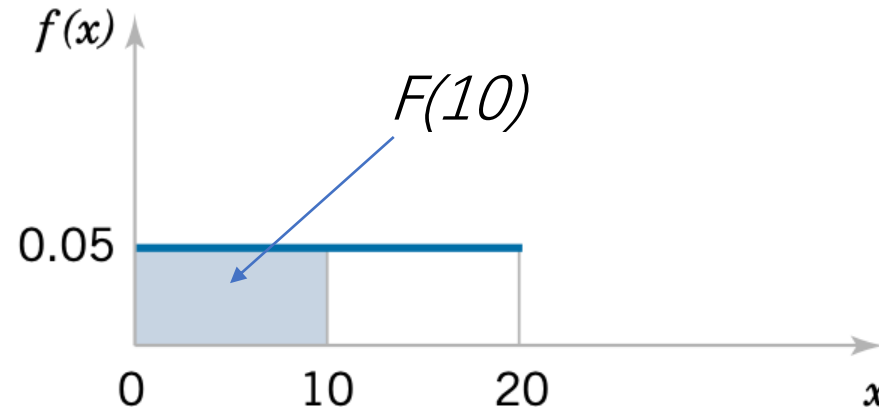
# CDF

- Recall: the CDF of a discrete random variable  $X$  is

$$F(x) = P(X \leq x) = \sum_{\tilde{x} \leq x} f(\tilde{x})$$

- CDF for continuous random variable is defined as:

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



# CDF

- Recall: the CDF of a discrete random variable  $X$  is

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- CDF for continuous random variable is defined as:

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✓  $0 \leq F(x) \leq 1$

✓ If  $x \leq y$ , then  $F(x) \leq F(y)$

} For both discrete and continuous RVs



# Mean and Variance

- Discrete:
  - ✓ Probability mass function.
- Continuous
  - ✓ Probability density function.

Summation  $\leftrightarrow$  Integration

- Mean

$$E[X] = \sum x f(x)$$

- Variance

$$\text{Var}[X] = \sum (x - E[X])^2 f(x)$$

- Mean

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

- Variance

$$\text{Var}[X] = \int_{-\infty}^{\infty} (x - E(X))^2 f(x) dx$$

# Expectation of $g(X)$

$$E[g(X)] = \int_{-\infty}^{\infty} g(x)f(x)dx$$

# Uniform Distribution

- With the same probability,  $X$  takes a value within  $[a, b]$ , where  $b > a$ .  
Discrete version: toss a coin, roll a dice.
- What's the pdf?

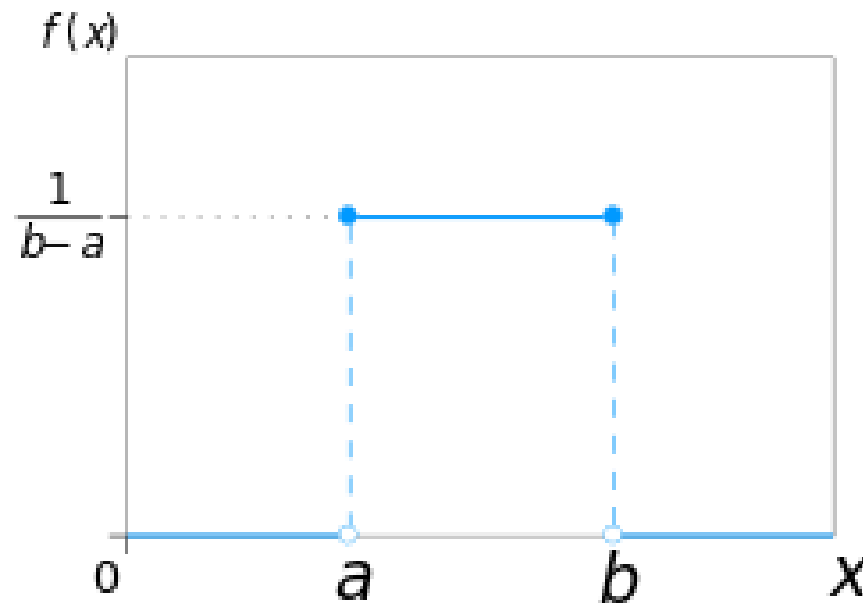
# Uniform Distribution

- With the same probability,  $X$  takes a value within  $[a, b]$ , where  $b > a$ .
- What's the pdf?
- $f(x) = c$  for  $x \in [a, b]$  and  $f(x) = 0$  for  $x \notin [a, b]$
- As  $\int_{-\infty}^{\infty} f(x) dx = c(b - a) = 1$ , we have

$$c = \frac{1}{b - a}$$

# Uniform Distribution

- With the same probability,  $X$  takes a value within  $[a, b]$
- $X \sim \text{Uniform}(a, b)$



$$\text{Mean} = (a + b)/2$$

$$\text{Variance} = (b - a)^2/12$$

# Applications

- Given  $X \sim \text{Uniform}(0,2)$
- What's the value of  $E[2 e^{X^2 + \cos(X)}]$ ?

# Applications

- Given  $X \sim \text{Uniform}(0,2)$
  - What's the value of  $E[2 e^{X^2 + \cos(X)}]$ ?
- 
- $f(x) = 1/2$  for  $x \in [0,2]$
  - $E[2 e^{X^2 + \cos(X)}] = \int_0^2 2 e^{x^2 + \cos(x)} f(x) dx = \int_0^2 e^{x^2 + \cos(x)} dx$

How to approximate  $\int_0^2 e^{x^2 + \cos(x)} dx$ ?



Given  $X \sim \text{Uniform}(0,2)$ ,  $E[2 e^{X^2 + \cos(X)}] = \int_0^2 e^{x^2 + \cos(x)} dx$

- Draw  $N$  samples of  $X \sim \text{Uniform}(0,2)$ :  $X_1, X_2, X_3, \dots, X_N$
- Calculate  $\frac{\sum_i 2 e^{X_i^2 + \cos(X_i)}}{N}$

Why? Expectation can be approximated by long-run average.

# General Case

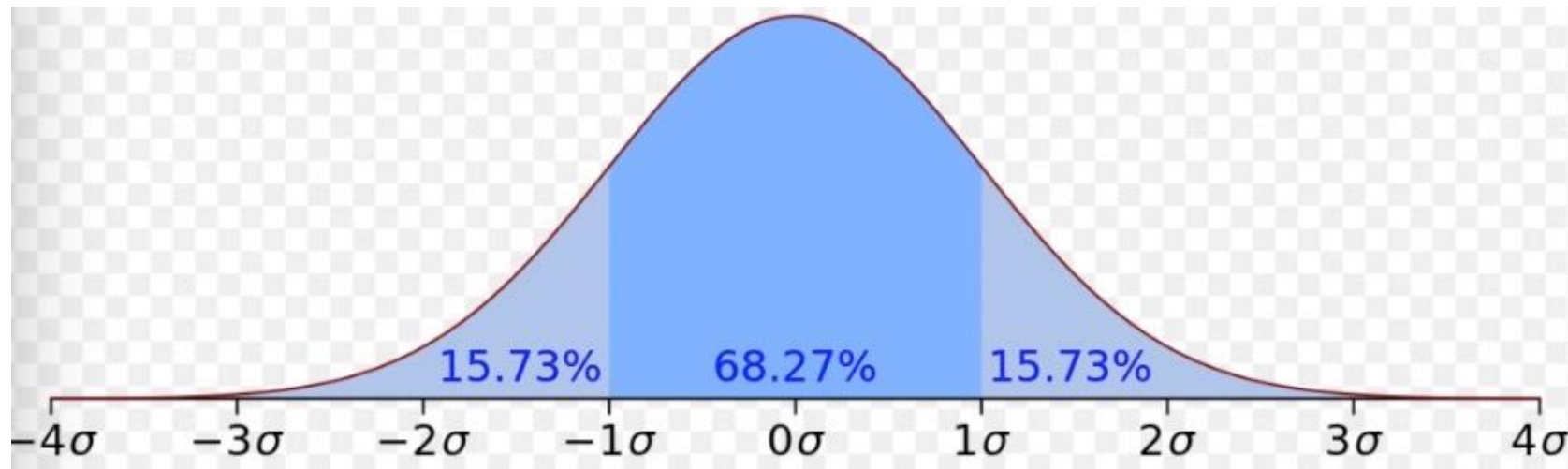
- How to calculate  $\int_a^b h(x)dx$  ?
  - Draw  $N$  samples of  $X \sim \text{Uniform}(a, b)$ :  $X_1, X_2, X_3, \dots, X_N$
  - Calculate  $\frac{\sum_i (b-a) h(X_i)}{N}$ 
    - $E[h(x)]$  only gives you the average “height” of  $h(x)$
    - In order to get  $\int_a^b h(x)dx$ , which is the area, we need to multiply  $E[h(x)]$  by  $(b - a)$
- Let  $X \sim \text{Uniform}(a, b)$
- $f(x) = 1/(b-a)$  for  $x \in [a, b]$
- $E[(b - a)h(x)] = \int_a^b (b - a)h(x)f(x)dx = \int_a^b h(x)dx$

Most important:  
Normal distribution

- $X$  can be any real number
- Parameters:  $\mu$  and  $\sigma$

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

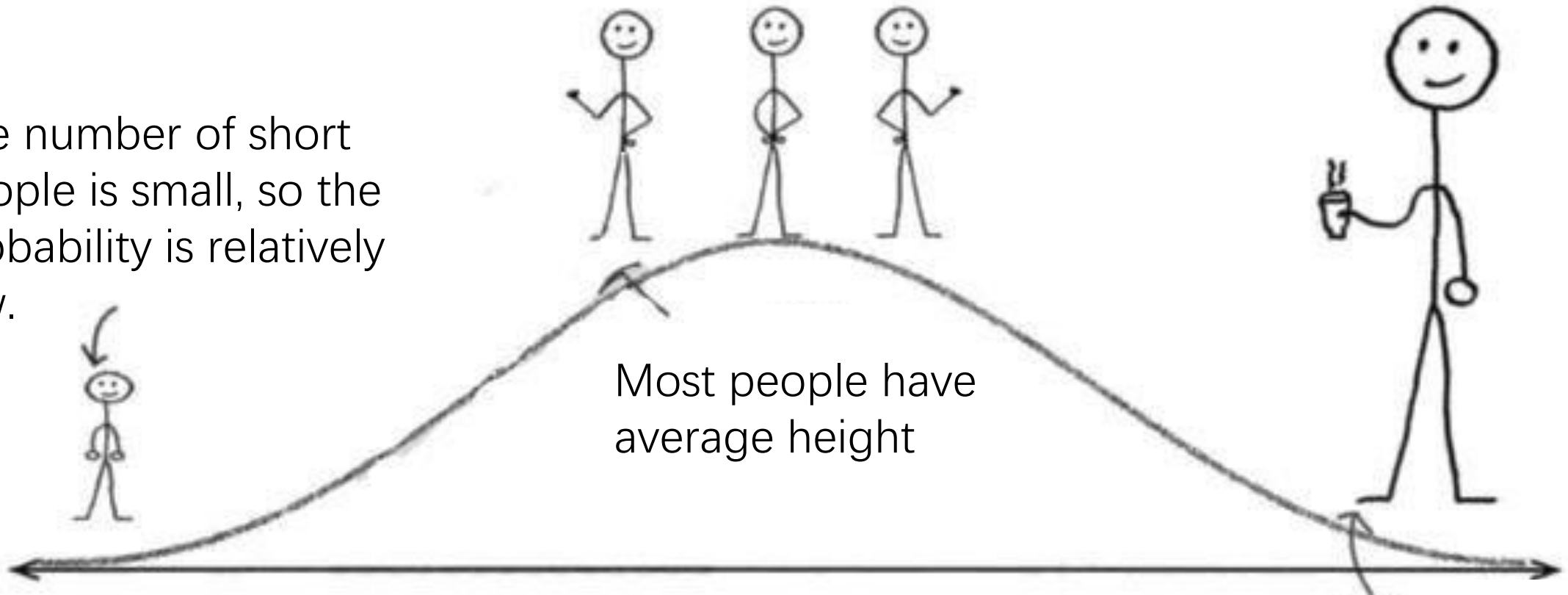
- $X \sim \text{Normal}(\mu, \sigma)$



Why we have this  
distribution?

# Normal Distribution: examples

The number of short people is small, so the probability is relatively low.



Most people have average height

**Human Being's Height**

There are not many tall people

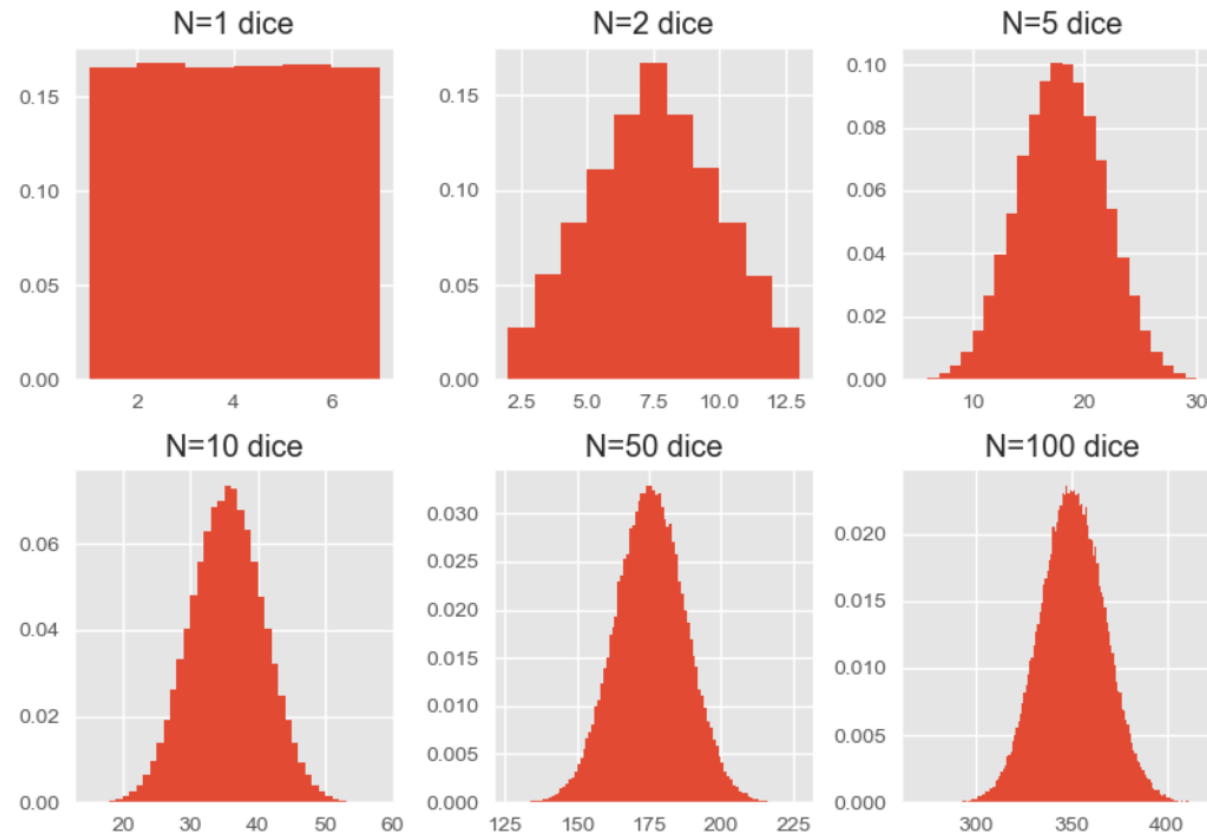
# Normal Distribution: examples

- A large number of layers
- When a ball goes through each layer, it randomly goes left or right



# An example

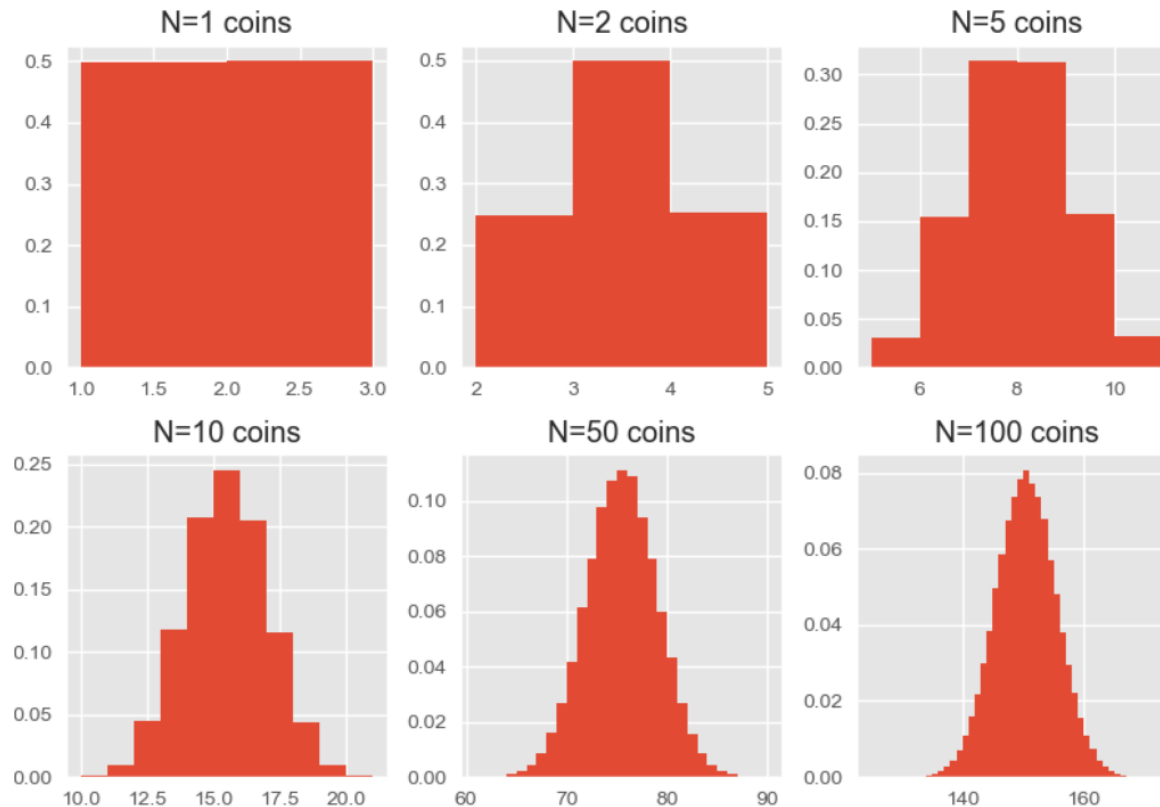
- Toss a die  $N$  times
- Let  $X$  be the sum
- A demo:  $N = 1, 2, \dots, 100$ , see the pmf of  $X$





# An example

- Flip a fair coin  $N$  times
- Let  $X$  be the sum (head: 1; tail: 2)
- A demo:  $N = 1, 2, \dots, 100$ , see the pmf of  $X$



# Normal Distribution

## Central limit theorem

**Lindeberg–Lévy CLT.** Suppose  $\{X_1, \dots, X_n\}$  is a sequence of **i.i.d.** random variables with  $\mathbb{E}[X_i] = \mu$  and  $\text{Var}[X_i] = \sigma^2 < \infty$ . Then as  $n$  approaches infinity, the random variables  $\sqrt{n}(\bar{X}_n - \mu)$  **converge in distribution** to a **normal**  $\mathcal{N}(0, \sigma^2)$ :

$$\sqrt{n}(\bar{X}_n - \mu) \xrightarrow{d} \mathcal{N}(0, \sigma^2).$$

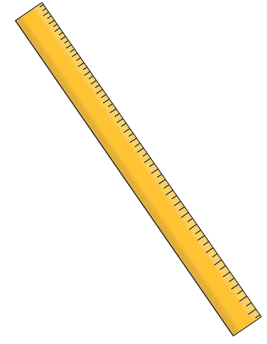
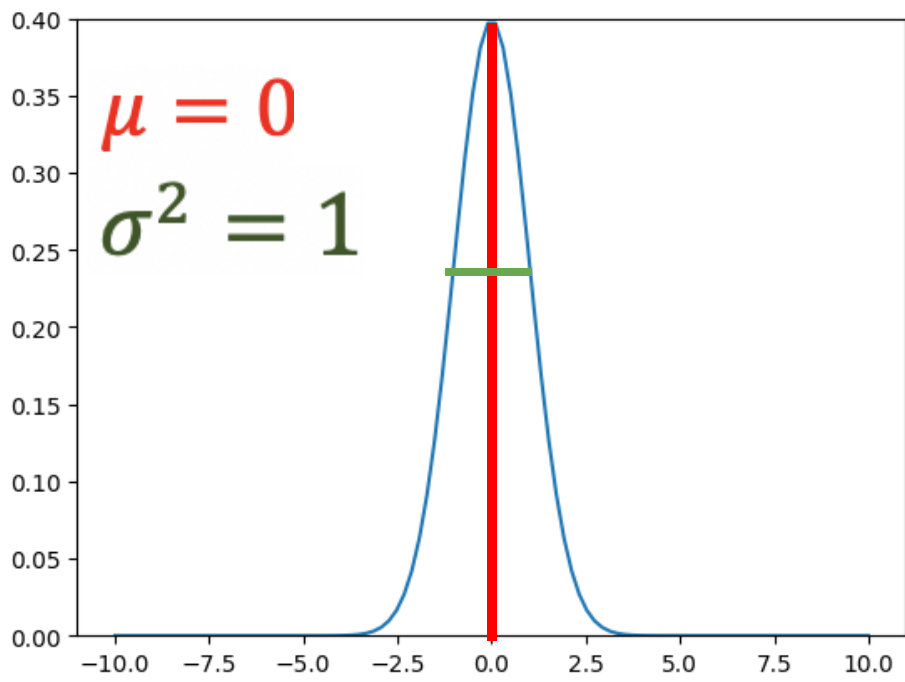
**no need to grasp!!!**

What is the meaning of the  
parameters?

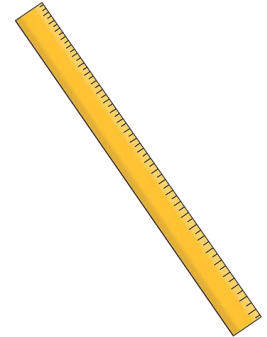
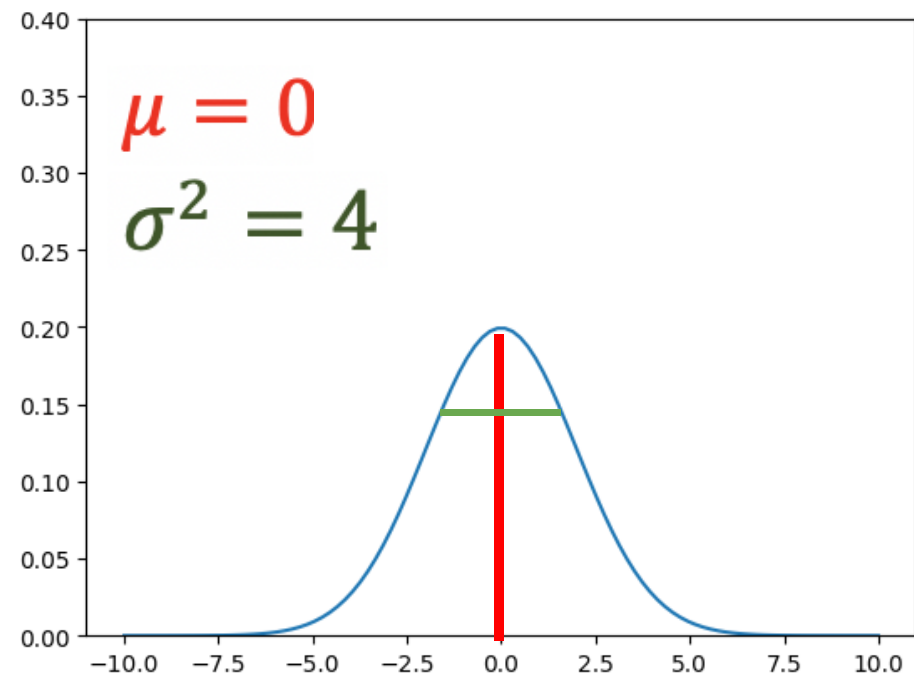
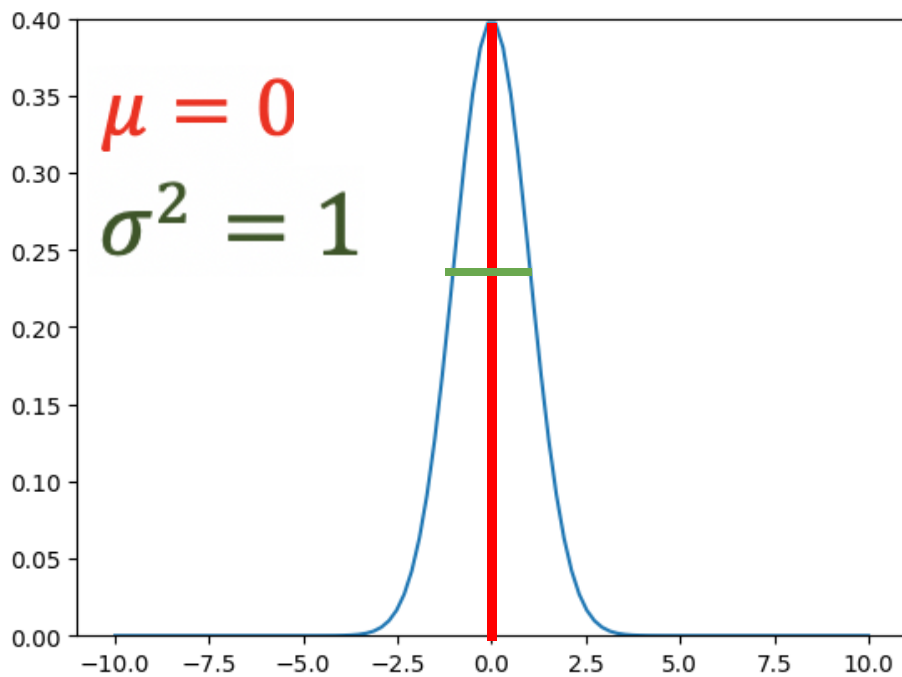
# Mean and Variance

- Mean:  $\mu$
- Variance:  $\sigma^2$

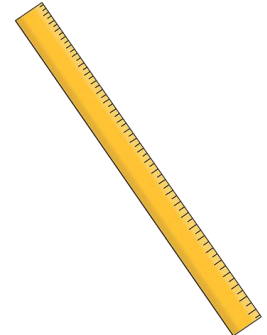
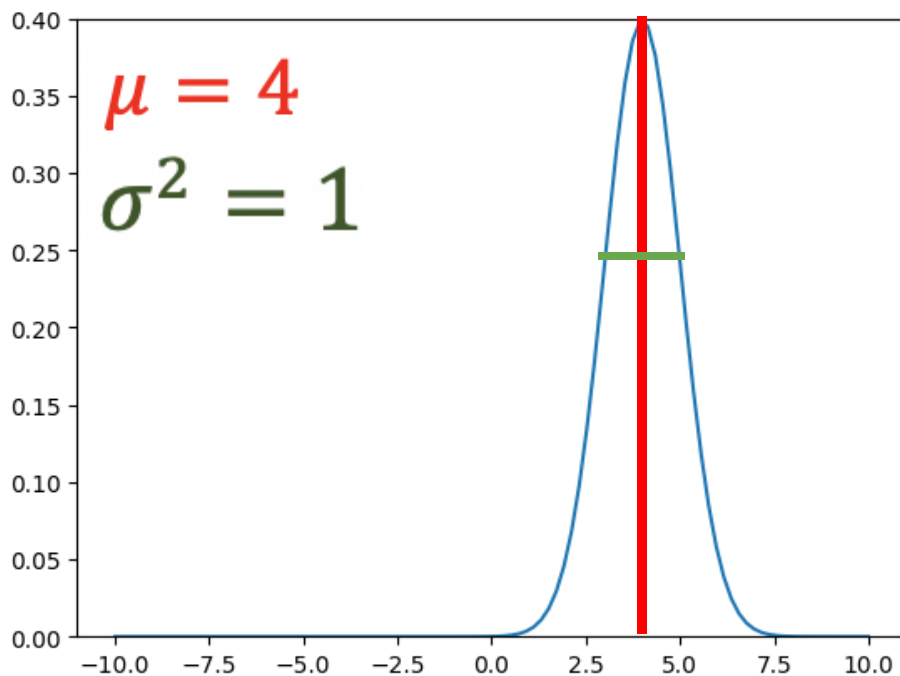
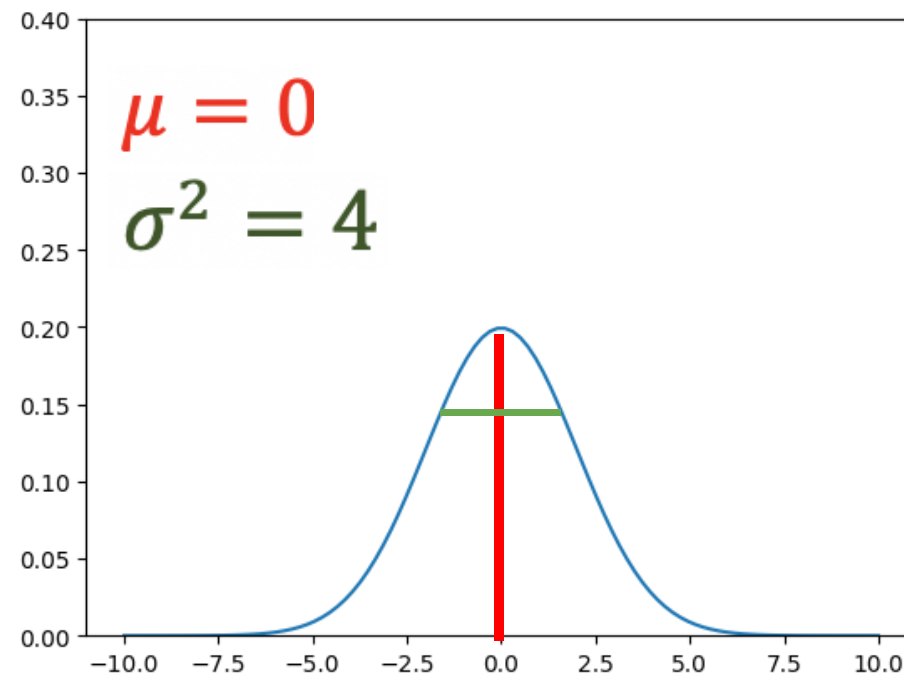
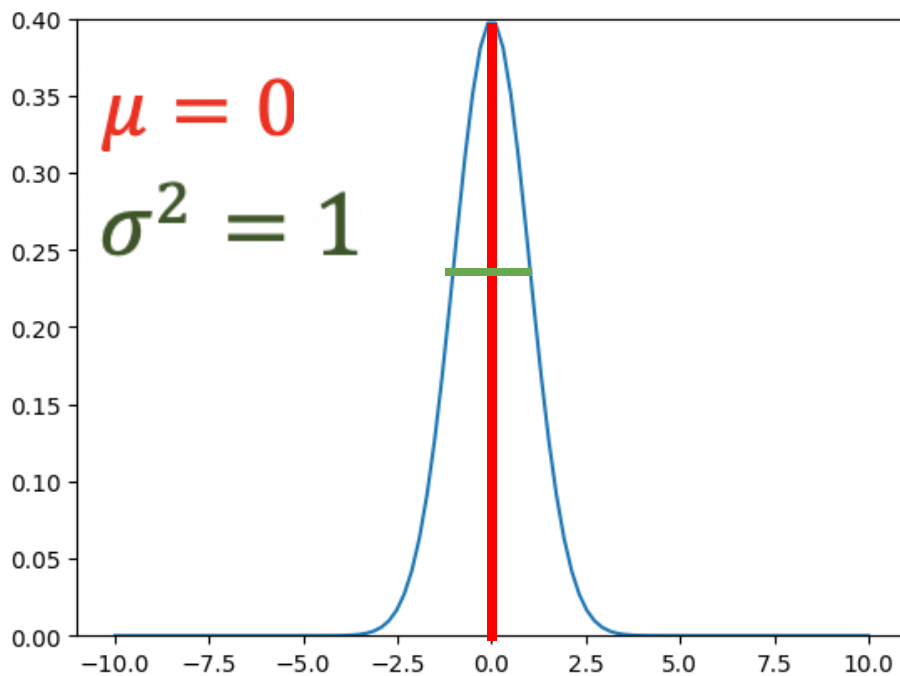
# The Normal PDF



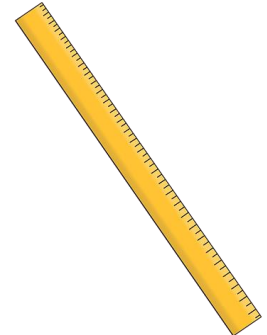
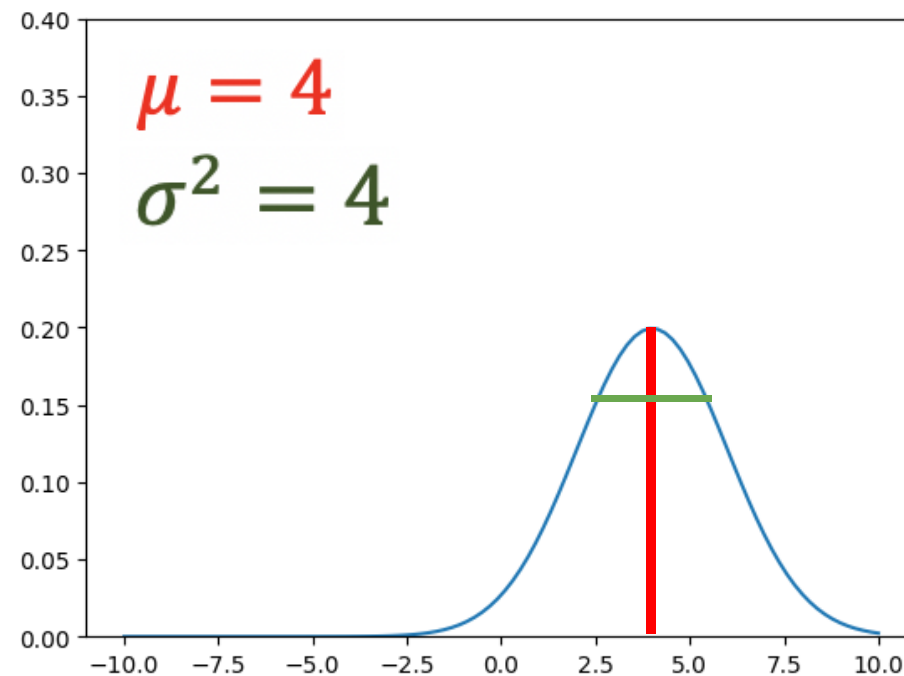
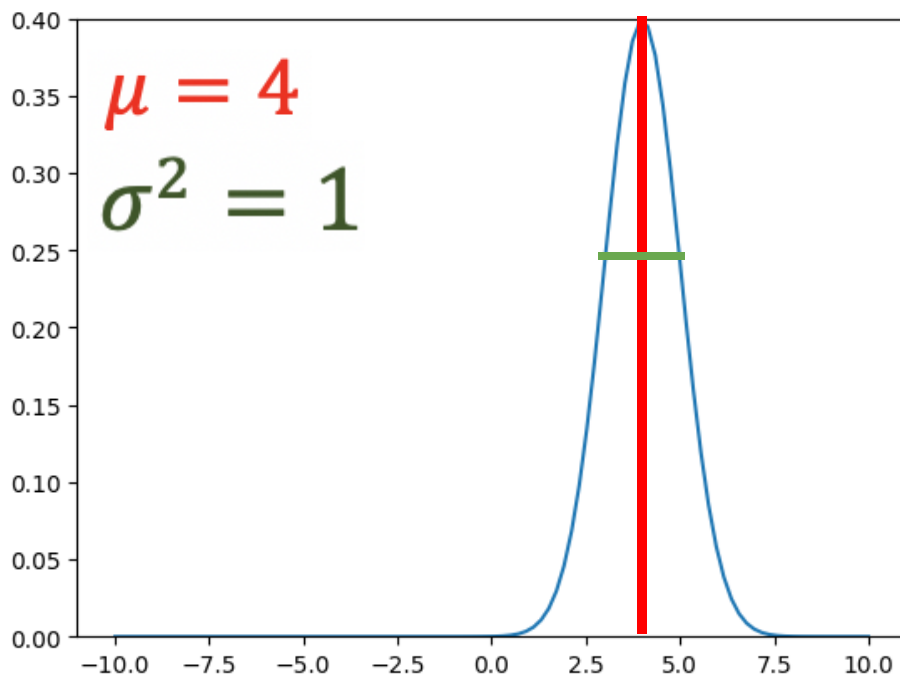
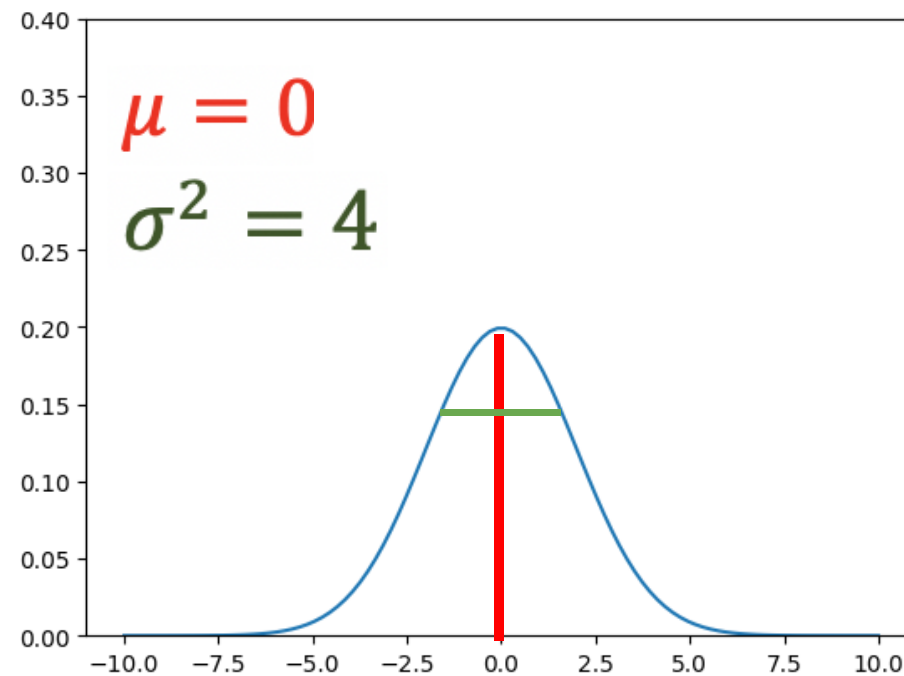
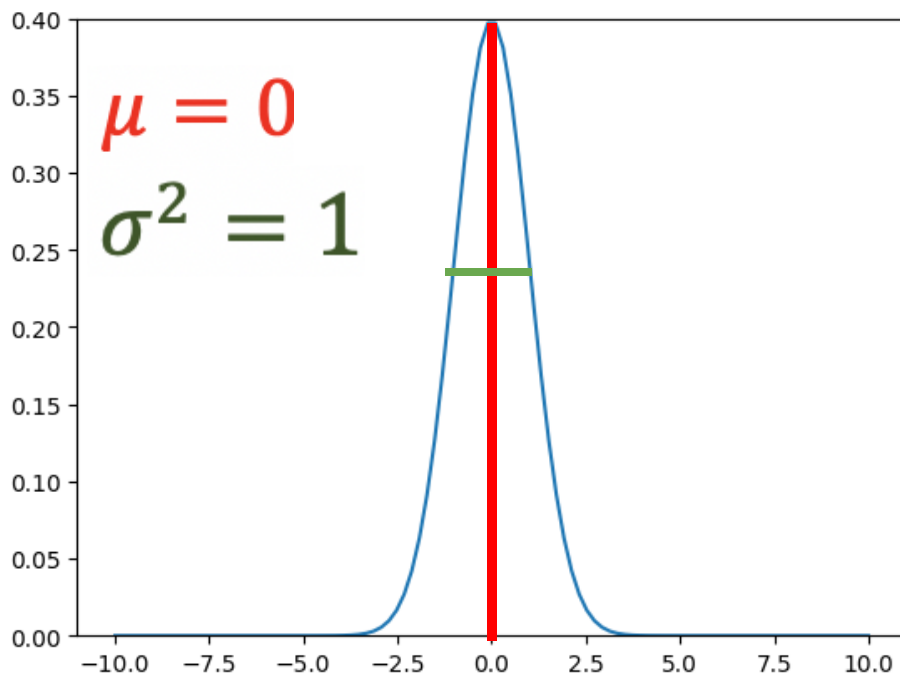
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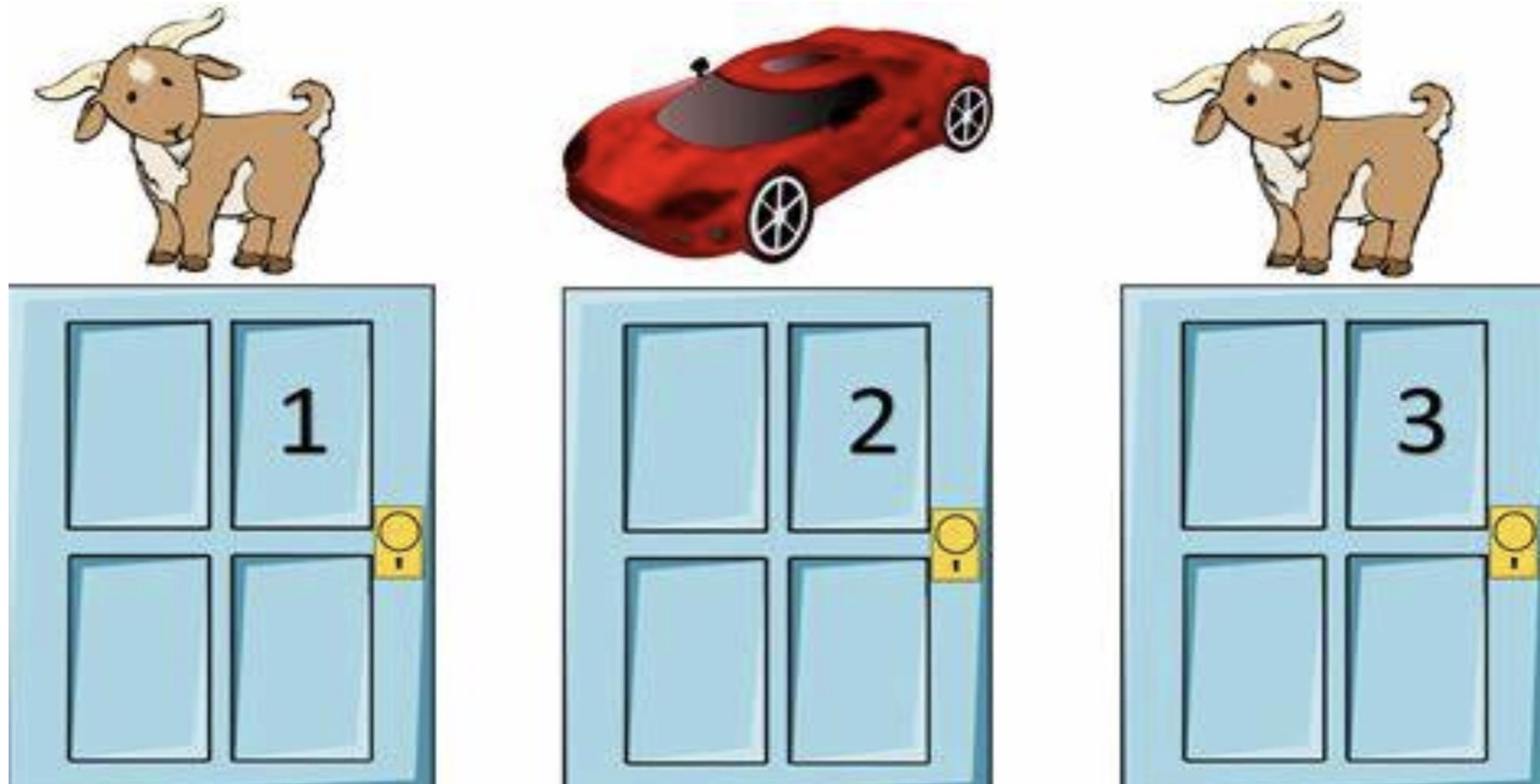
# The Normal PDF





# **Advanced Concepts: Conditional Probability**

# Monty Hall problem



# Monty Hall problem

Suppose you're on a game show, and you're given the choice of three doors:

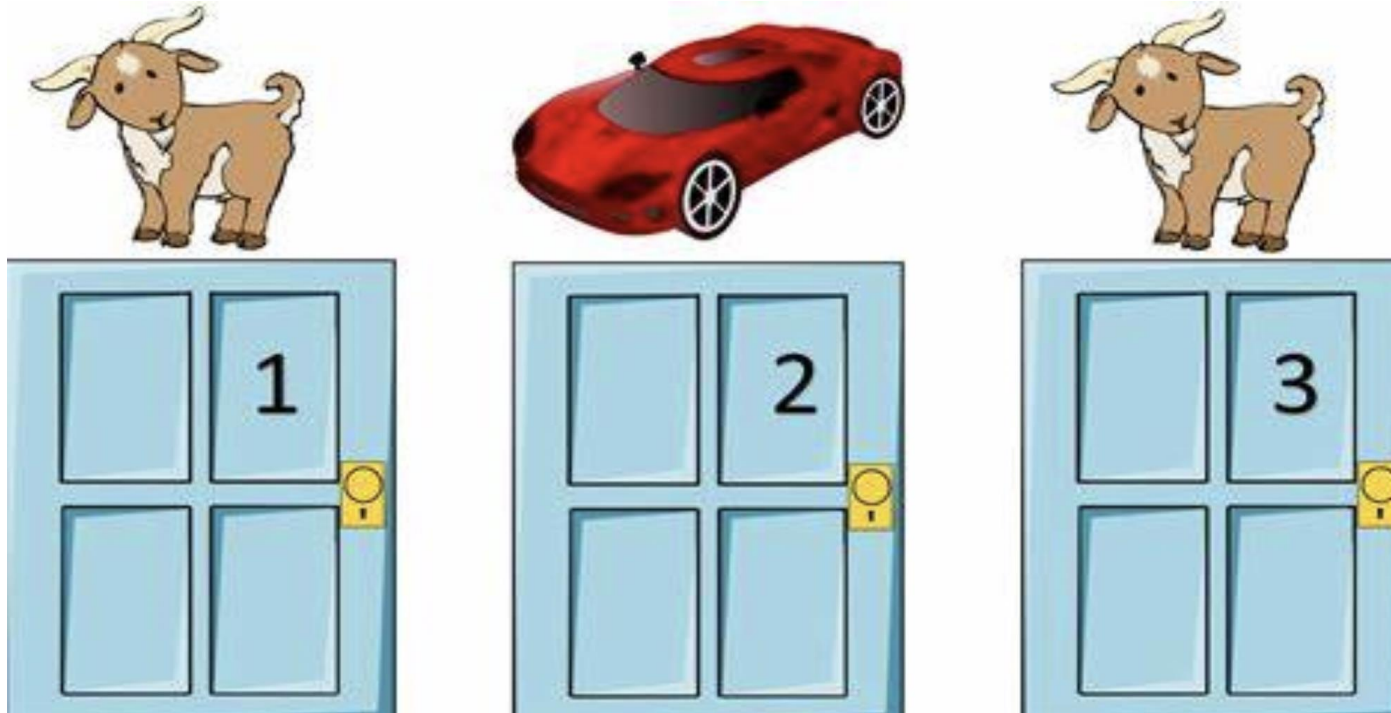
- Behind one door is a car;
- Behind the others, goats.

The car is randomly placed behind one door.

Which door should you choose to open?



- After you choose No. 1, I open a door (among the other two doors) with a goat behind,.
- Would you like to switch to the other door?
- Now you have additional information\event!



Behind door 1	Behind door 2	Behind door 3	Result if staying at door #1	Result if switching to the other door
Goat	Goat	<b>Car</b>	Wins goat	<b>Wins car</b>
Goat	<b>Car</b>	Goat	Wins goat	<b>Wins car</b>
<b>Car</b>	Goat	Goat	<b>Wins car</b>	Wins goat

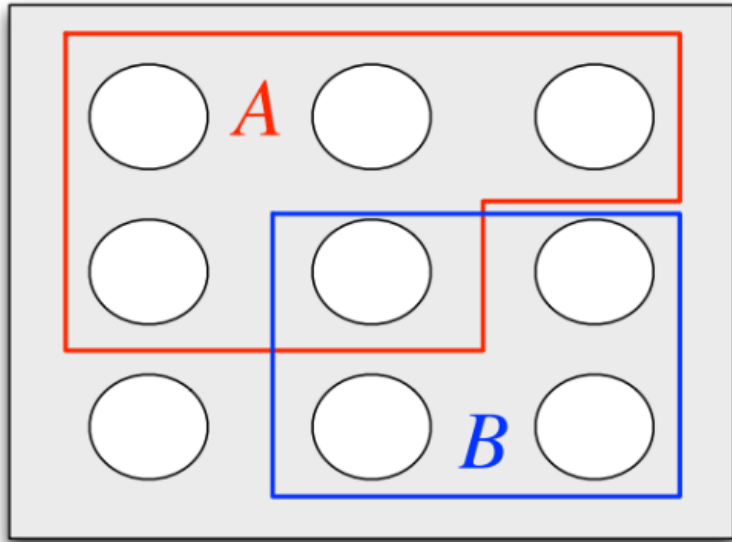
$P(\text{win when stay}) = 1/3$

$P(\text{win when switch}) = 2/3$

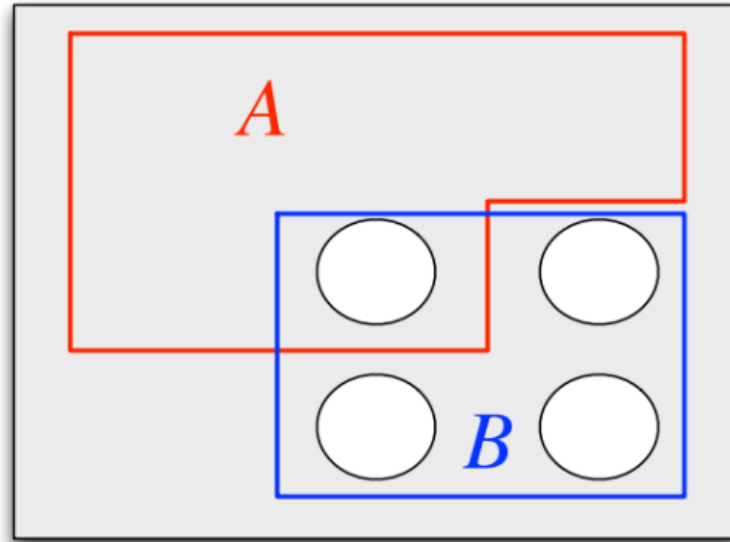
# Conditional Probability

- Given the realization of event A, the probability of event B may change
- (Conditional probability) If A and B are events with  $P(B) > 0$ , then the conditional probability of A given B, denoted by  $P(A|B)$ , is defined as 
$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

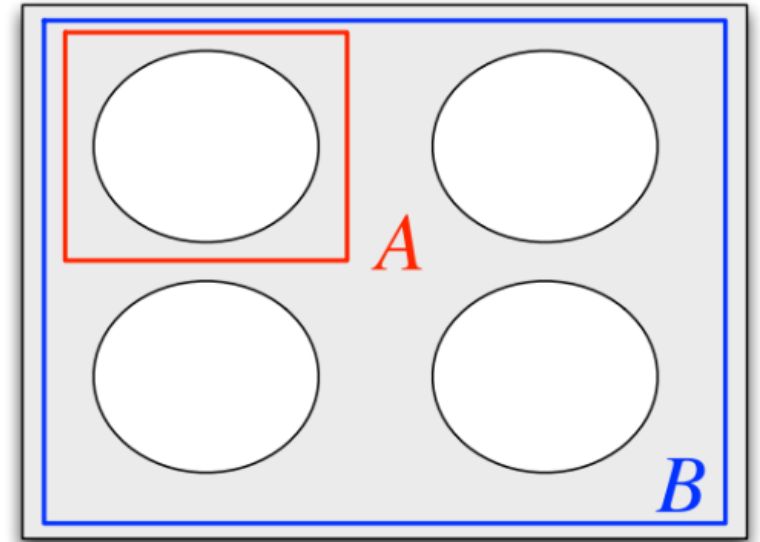
$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$



$$P(A|B)=?$$



$$P(A|B)=?$$



$$P(A|B)=?$$



- Given the realization of event A, the probability of event B may change
- (Conditional probability) If A and B are events with  $P(B) > 0$ , then the conditional probability of A given B, denoted by  $P(A|B)$ , is defined as  $P(A|B) = \frac{P(A \cap B)}{P(B)}$
- (Independence) Two events A and B are called independent if and only if  $P(A \cap B) = P(A)P(B)$

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

# Conditional Probability in NLP

- H: mention “Interesting” in message
- D: mention “DDA2001” in message

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

- $P(H) = .1$
- $P(D) = .1$
- $P(H \cap D) = .08$
- $P(H|D) = ??$

Known Information from data



# Conditional Probability in NLP

- H: mention “Interesting” in message
- D: mention “DDA2001” in message

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

- $P(H) = .1$
  - $P(D) = .1$
  - $P(H \cap D) = .08$
- } Known Information from data
- $P(H|D) = 0.08/0.1 = 0.8$

