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# Probability Distributions

## Week 11

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Yunkyu Sohn

School of Political Science and Economics

Waseda University

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- ▶ Random Variables and Probability Distributions (Chapter 6.3)
  - ▶ Overview
  - ▶ Bernoulli / Binomial distribution
  - ▶ Uniform / Normal distribution
  - ▶ Expectation

# Random Variables and Probability Distribution

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- ▶ **Random variable** assigns a **numeric value** to each **event** of the experiment.
  - ▶ Coin flip side: head = 1; tail = 0
  - ▶ #secs took for commuting: any value greater than 0.
- ▶ These values represent **mutually exclusive and exhaustive events**, together forming the entire sample space  $\Omega$ .
- ▶ A **discrete RV** takes a finite or at most countably infinite #distinct values.
  - ▶ coin flip; race; number of years of education
- ▶ A **continuous RV** assumes an uncountably infinite number of values.
  - ▶ height, distance from earth, gross domestic product
- ▶ Probability distribution: Probability that a random variable takes a certain value or range of values.
  - ▶  $P(\text{side}): P(\text{side}=1) = 0.5; P(\text{side}=0) = 0.5$
  - ▶  $P(\text{\#secs}): P(0 < \text{\#secs} < 1000) = 0.3; P(1000 < \text{\#secs} < 2000) = 0.4 \dots$

# Probability Density / Mass Function

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- ▶ Probability mass function (PMF):  $f(x)$  for a discrete random variable
- ▶ Probability density function (PDF):  $f(x)$  for a continuous random variable
- ▶ Recall  $P(\Omega) = 1$  : total sum of  $f(x)$  (PMF), or the area of  $f(x)$  (PDF), must equal to 1.
- ▶ Cumulative mass function (CMF):

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

- ▶ Cumulative density function (CDF):

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

- ▶ What is the probability that a random variable  $X$  takes a value equal to or less than  $x$ ?
- ▶ Area under the density curve
- ▶ Non-decreasing

# Bernoulli Distribution

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►  $\Omega = \{0, 1\}$

► PMF

$$f(x) = \begin{cases} p & \text{if } x = 1 \\ 1 - p & \text{if } x = 0 \\ 0 & \text{otherwise.} \end{cases}$$

► CMF

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



# Bernoulli Distribution

►  $\Omega = \{0, 1\}$

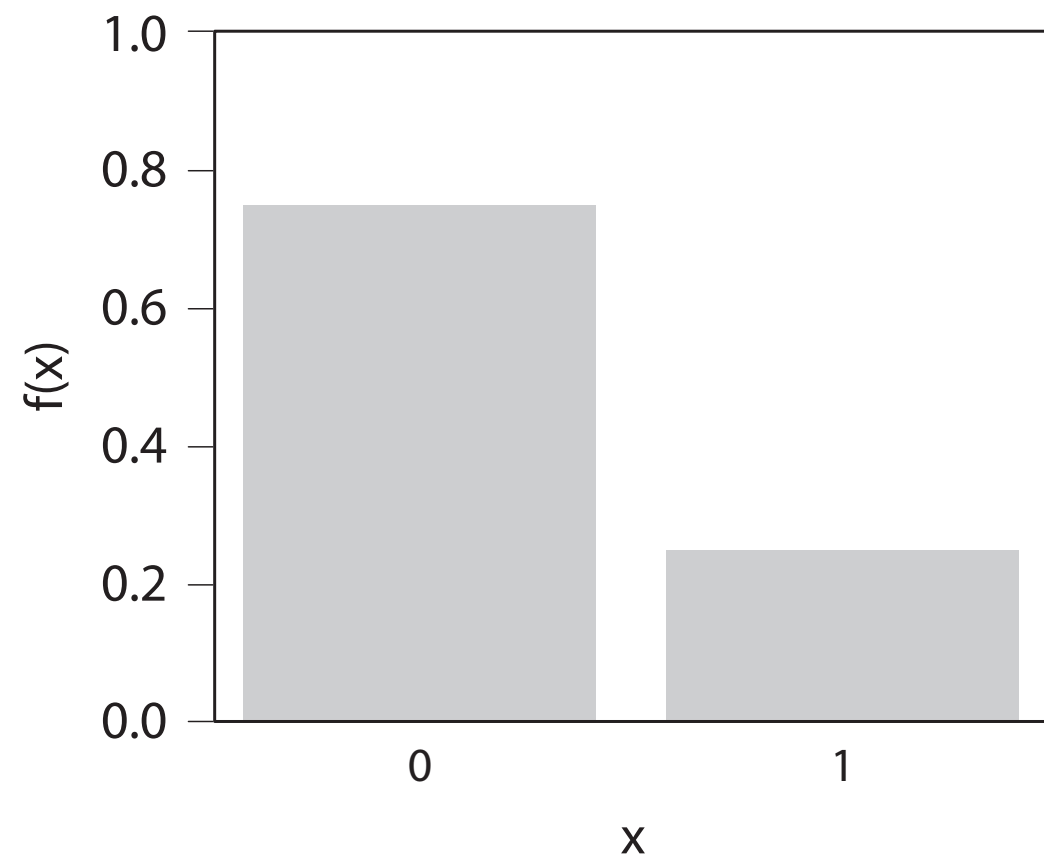
► PMF

$$f(x) = \begin{cases} p & \text{if } x = 1 \\ 1 - p & \text{if } x = 0 \\ 0 & \text{otherwise.} \end{cases}$$

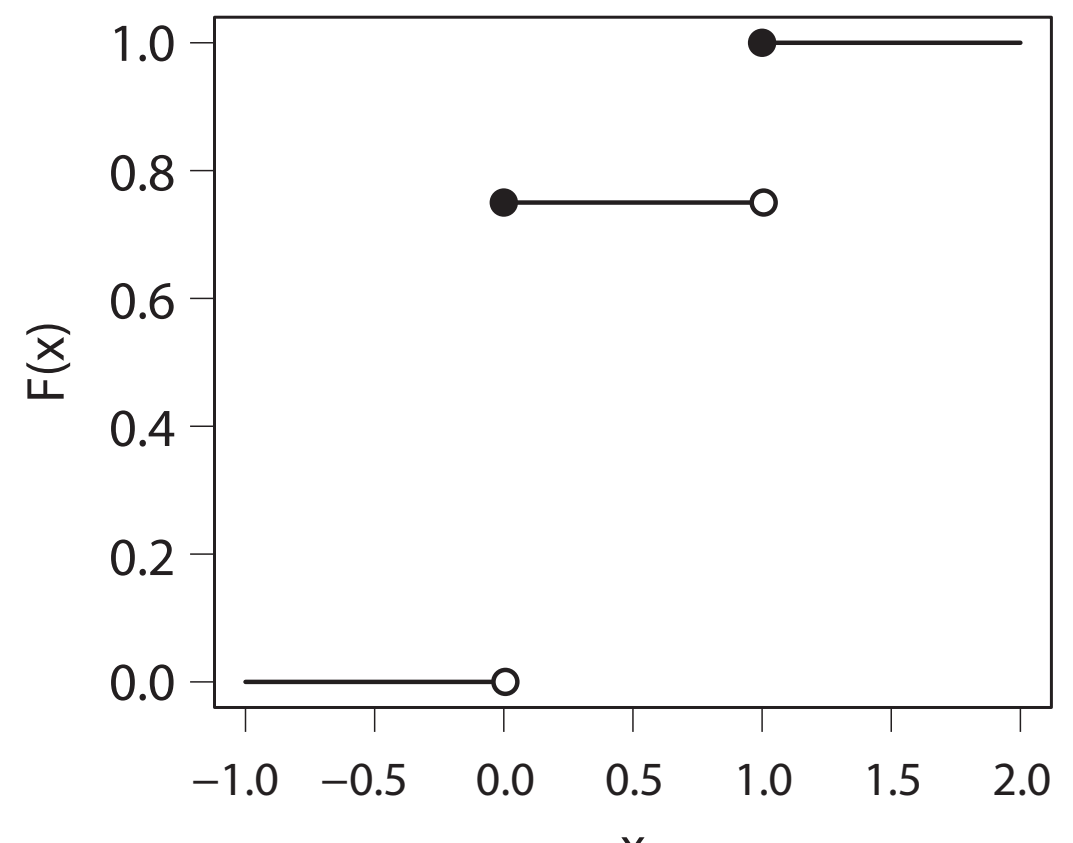


► PMF and CDF of Bernoulli distribution for  $p = 0.25$

Probability mass function

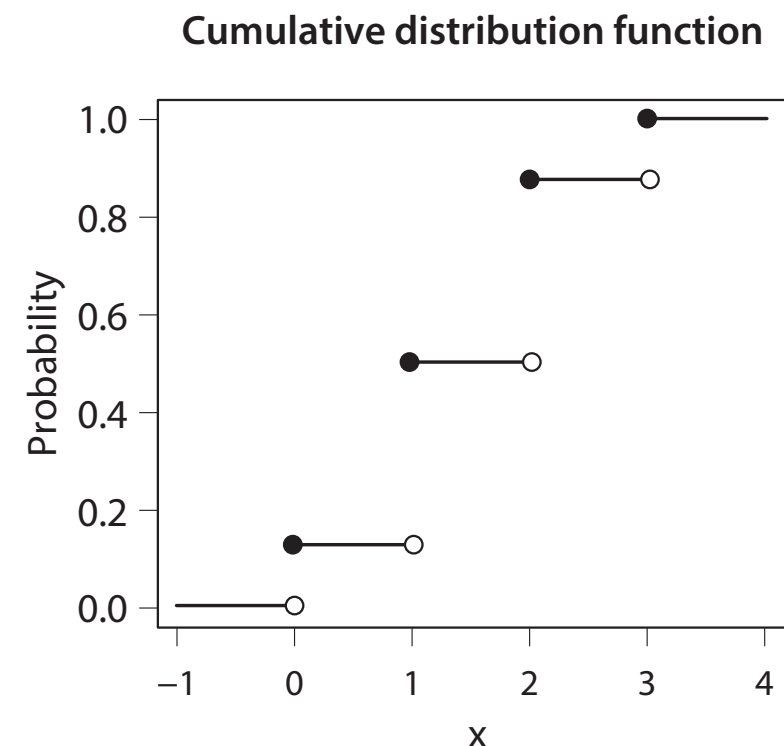
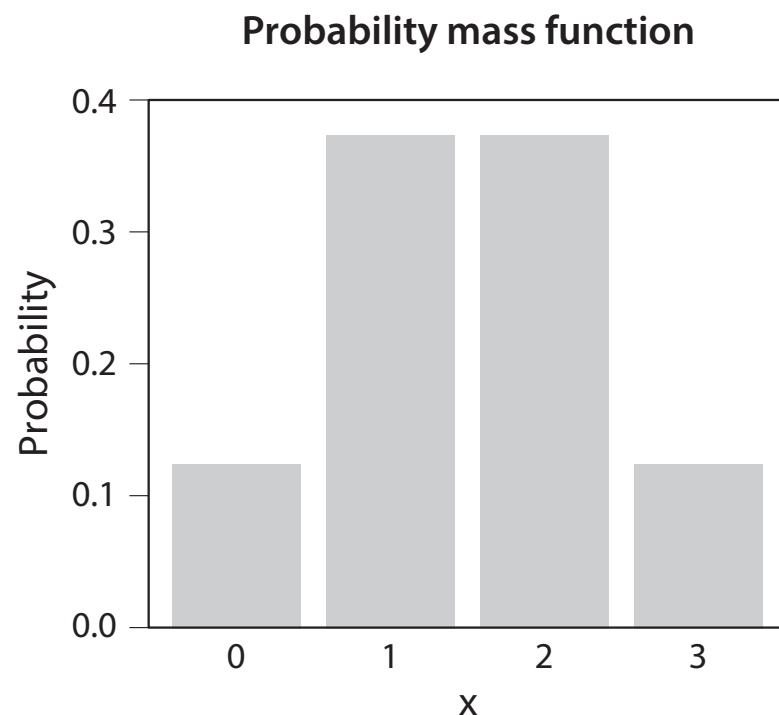


Cumulative distribution function



# Binomial Distribution

- ▶ The number of 1s (one of the binary outcomes) in **multiple** Bernoulli trials
- ▶  $\Omega = \{0, 1, \dots, n-1, n\}$
- ▶ PMF
$$f(x) = P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x} \quad \binom{n}{x} = {}_n C_x$$
- ▶ CMF
$$F(x) = P(X \leq x) = \sum_{k=0}^x \binom{n}{k} p^k (1 - p)^{n-k}$$
- ▶  $p = 0.5$  and  $n = 3$



# Binomial Distribution

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- ▶ ex1) In a small department: There are exactly 10 who support candidate A, another 10 people who support candidate B for electing the chair of the department. Suppose that we expect their individual turnout probability is equal to their previous overall turnout rate which was 70%. What is the chance that exactly 7 people vote for candidate A and 7 people vote for candidate B, and the election ends in a tie?
- ▶ ex2) In a small department: There are exactly 10 who support candidate A, another 10 people who support candidate B for electing the chair of the department. Suppose that we expect their individual turnout probability is equal to their previous overall turnout rate which was 70%. What is the chance that the election ends in a tie?



# Uniform Distribution

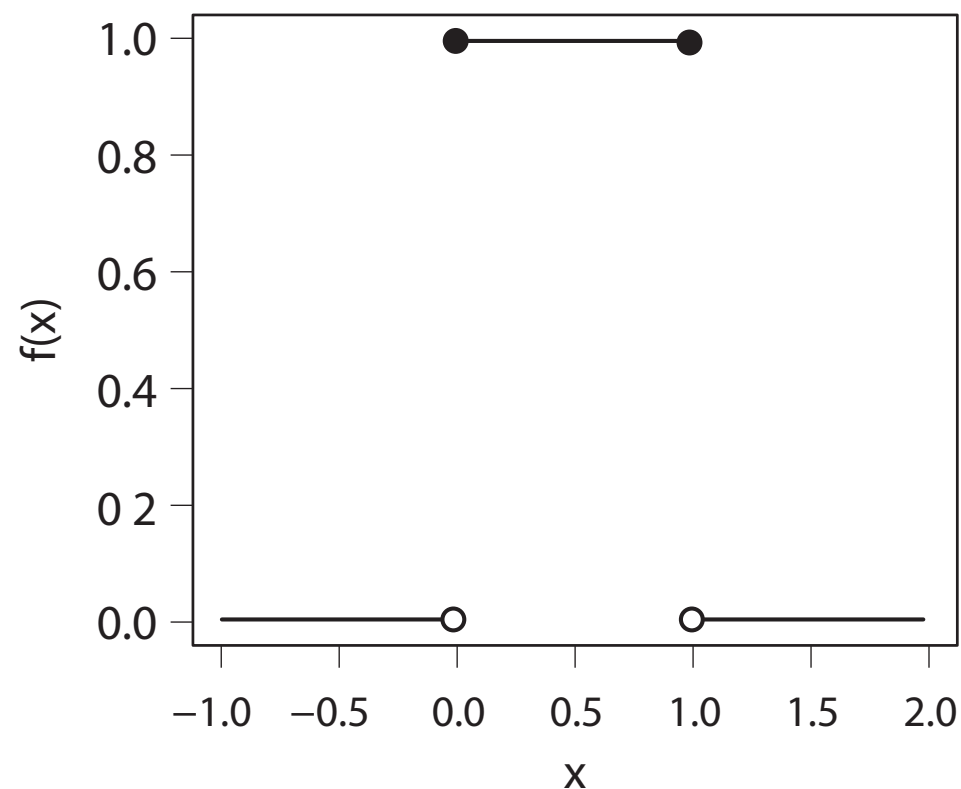
- ▶ Every number in an interval has an equal chance of appearance

- ▶  $\Omega =$  **set of real numbers in a range**  $[a, b]$

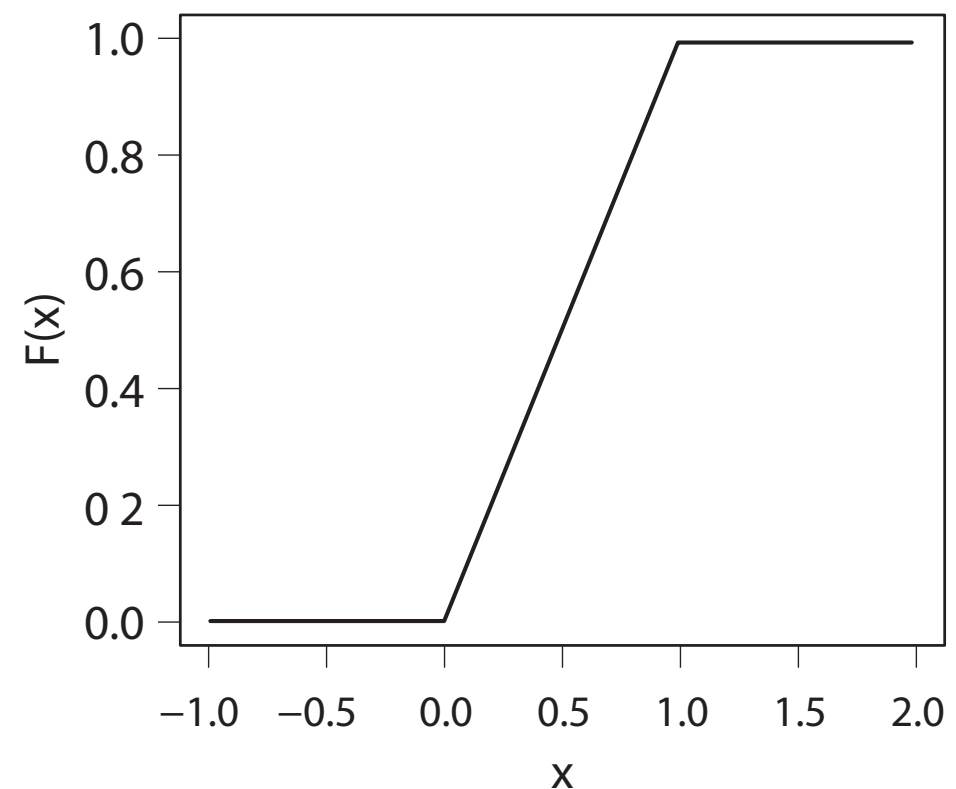
- ▶ PDF 
$$f(x) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq x \leq b \\ 0 & \text{otherwise.} \end{cases}$$
- ▶ CDF 
$$F(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & \text{if } a \leq x \leq b \\ 1 & x \geq b \end{cases}$$

- ▶ Uniform distribution for the interval  $[0,1]$

Probability density function



Cumulative distribution function



# Uniform Distribution

- ▶ Every number in an interval has an equal chance of appearance

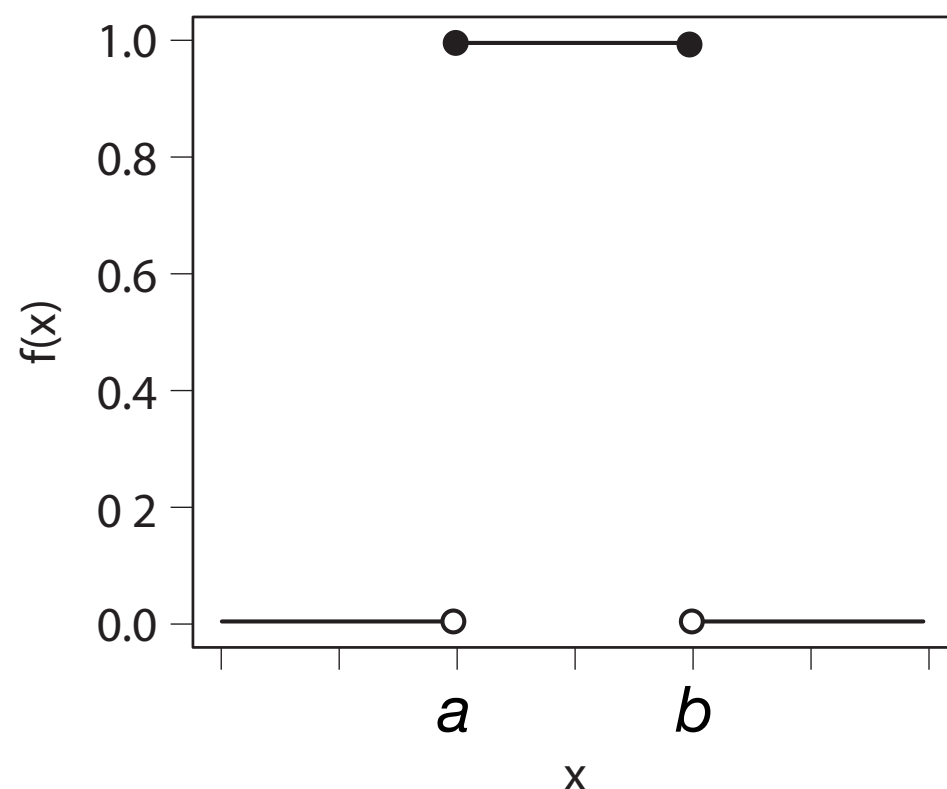
- ▶  $\Omega = \text{set of real numbers}$

- ▶ PDF
$$f(x) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq x \leq b \\ 0 & \text{otherwise.} \end{cases}$$

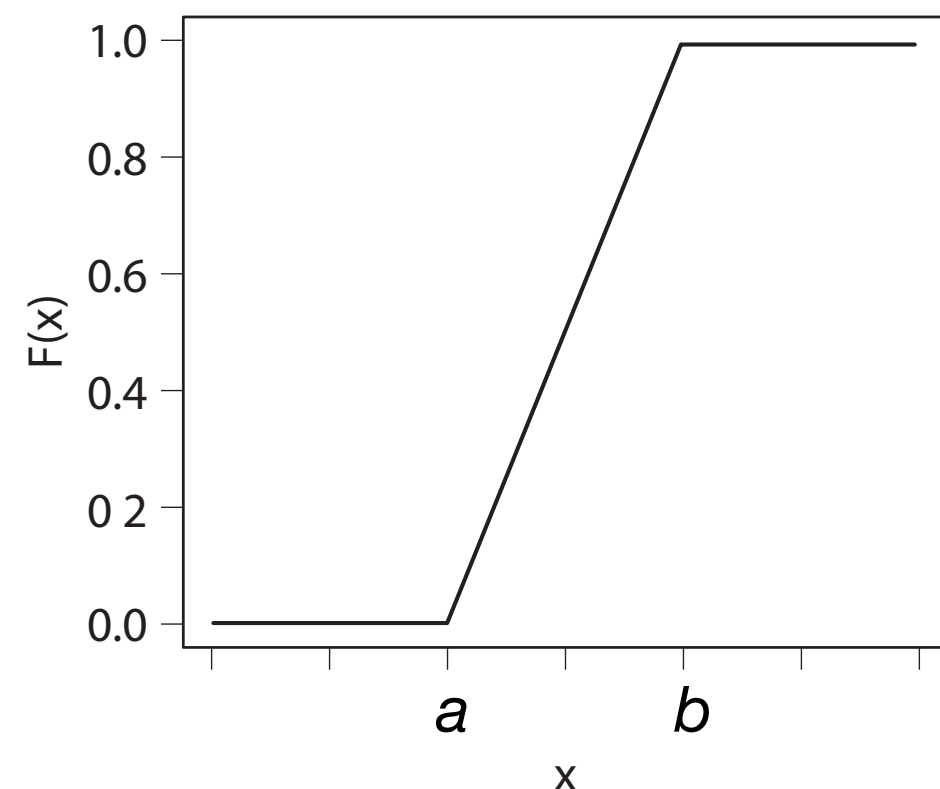
- ▶ CDF
$$F(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & \text{if } a \leq x \leq b \\ 1 & x \geq b \end{cases}$$

- ▶ Uniform distribution for the interval  $[a, b]$

Probability density function

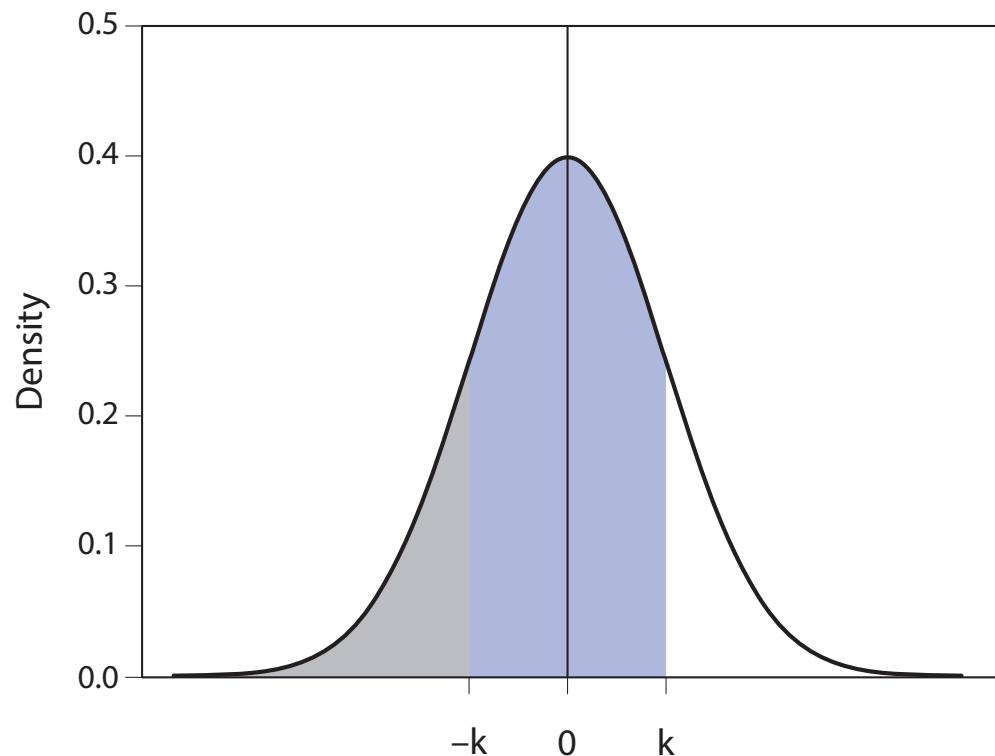


Cumulative distribution function



# Normal Distribution

- ▶ Most famous and frequently observed distribution (Why?)
- ▶  $\Omega$ =real numbers (continuous number)
- ▶  $X$  is normal RV with **mean  $\mu$**  and **standard deviation  $\sigma$** :  $X \sim \mathcal{N}(\mu, \sigma^2)$
- ▶ PDF
$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{1}{2\sigma^2} (x - \mu)^2 \right\}$$
- ▶ e.g.  $X \sim \mathcal{N}(0,1)$



- ▶ Singled peaked, symmetric
- ▶ about 2/3 are within 1 standard deviation ( $\sigma$ ) from the mean
- ▶ about 95% are within 2 standard deviations ( $2\sigma$ ) from the mean

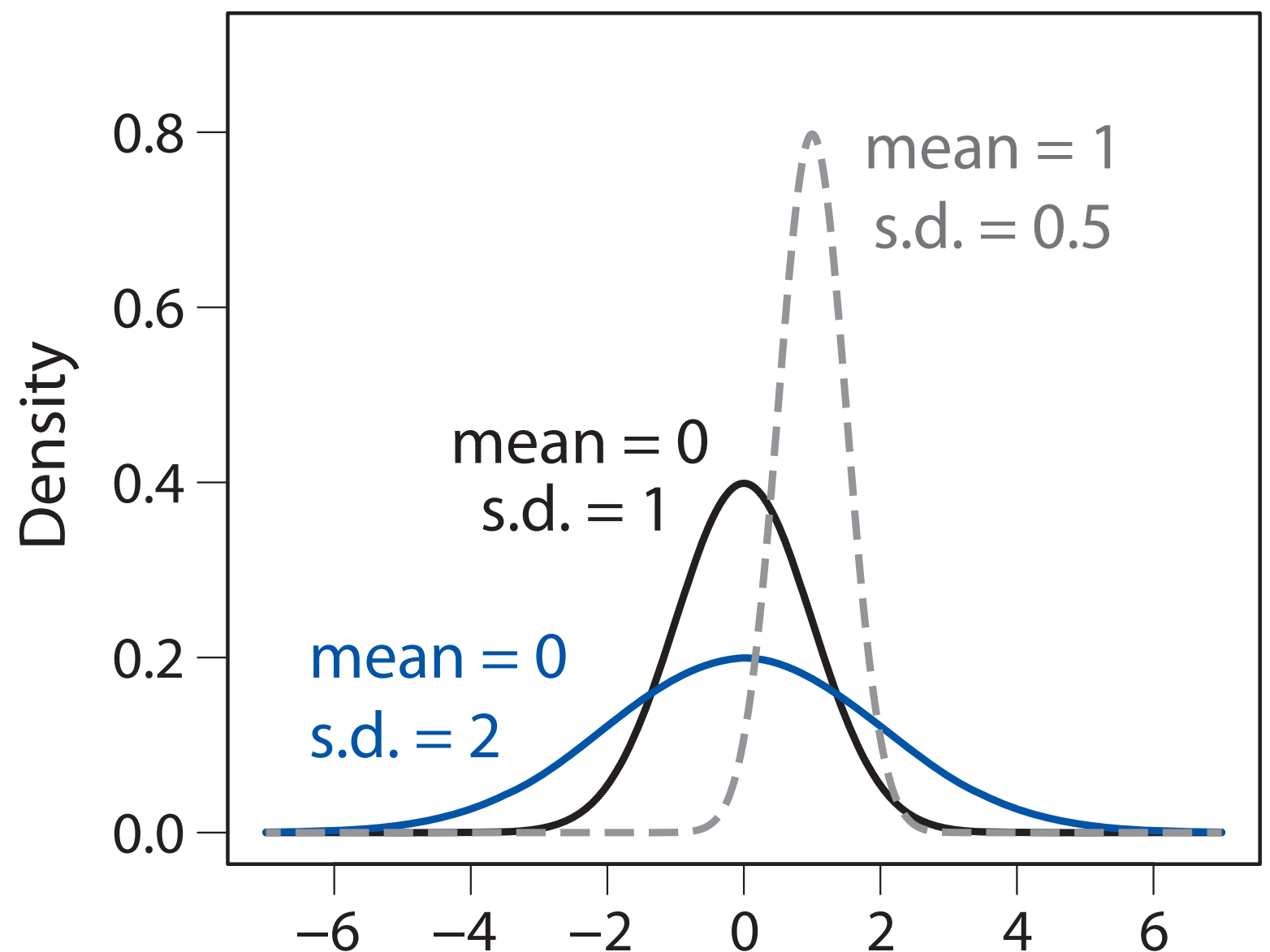
- ▶ CDF  $F(x) = P(X \leq x) = \int_{-\infty}^x f(t) dt = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{1}{2\sigma^2} (t - \mu)^2 \right\} dt$

# Normal Distribution

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

- ▶  $X \sim \mathcal{N}(\mu, \sigma^2)$
- ▶  $S = X + c \rightarrow S \sim \mathcal{N}(\mu + c, \sigma^2)$
- ▶  $Y = cX \rightarrow Y \sim \mathcal{N}(c\mu, (c\sigma)^2)$
- ▶  $T = aX + b \rightarrow T \sim \mathcal{N}(a\mu + b, (a\sigma)^2)$

## Probability density function



# Normal Distribution

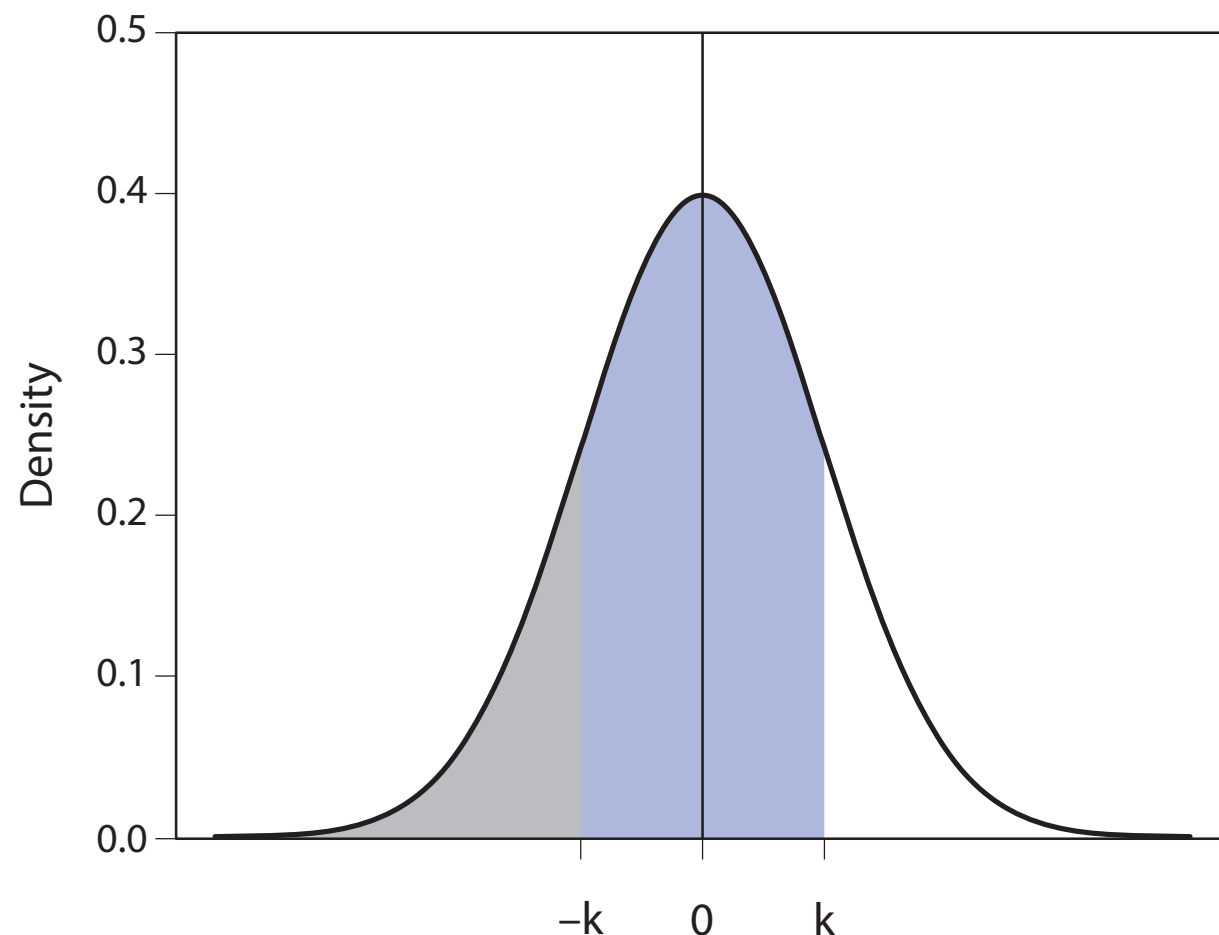
$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{1}{2\sigma^2} (x - \mu)^2 \right\}$$

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- ▶  $X \sim \mathcal{N}(\mu, \sigma^2)$
- ▶  $S = X + c \rightarrow S \sim \mathcal{N}(\mu + c, \sigma^2)$
- ▶  $Y = cX \rightarrow Y \sim \mathcal{N}(c\mu, (c\sigma)^2)$
- ▶  $T = aX + b \rightarrow T \sim \mathcal{N}(a\mu + b, (a\sigma)^2)$
- ▶ **z-score:**  $Z = (X - \mu)/\sigma \rightarrow Z \sim \mathcal{N}(0,1)$

# Normal Distribution

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



- Probability that a normal random variable with mean  $\mu$  and sdv  $\sigma$  lies within  $k$  standard deviations from the mean for a positive constant  $k > 0$

$$P(\mu - k\sigma \leq X \leq \mu + k\sigma) = P(-k\sigma \leq X - \mu \leq k\sigma)$$

$$= P\left(-k \leq \frac{X - \mu}{\sigma} \leq k\right)$$

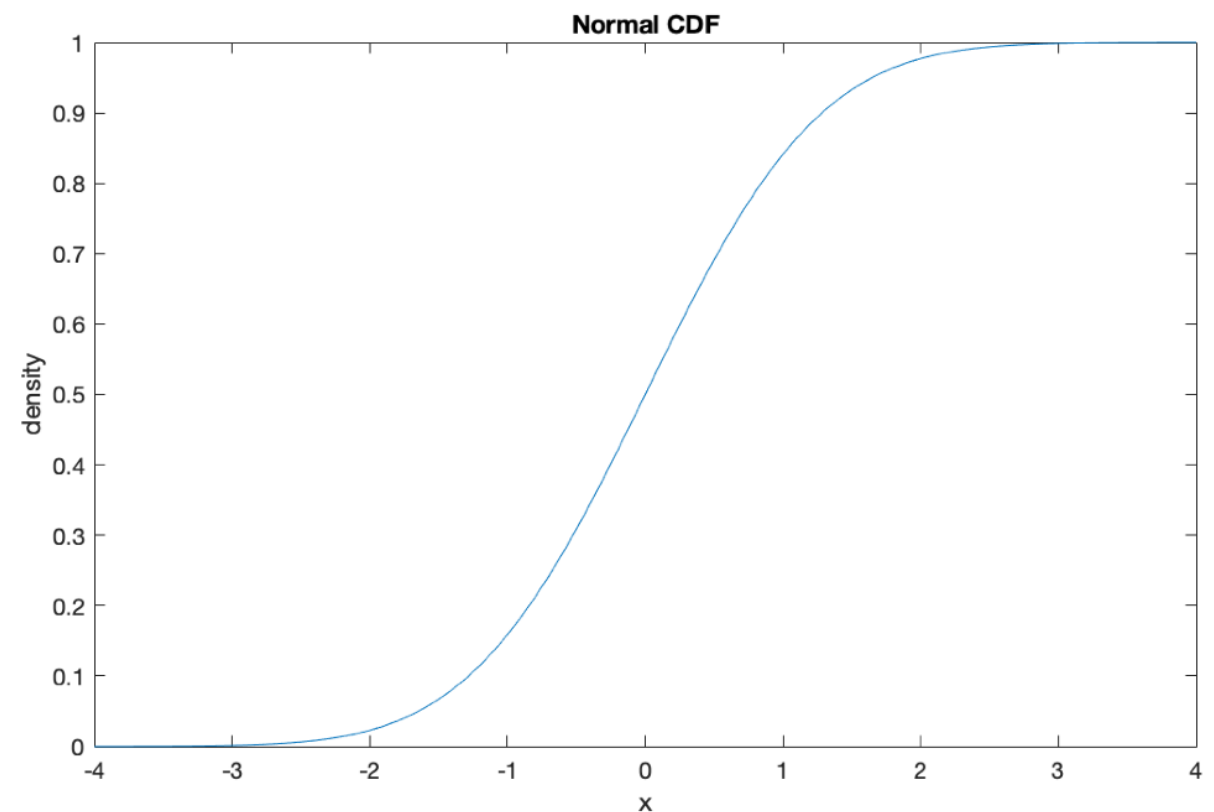
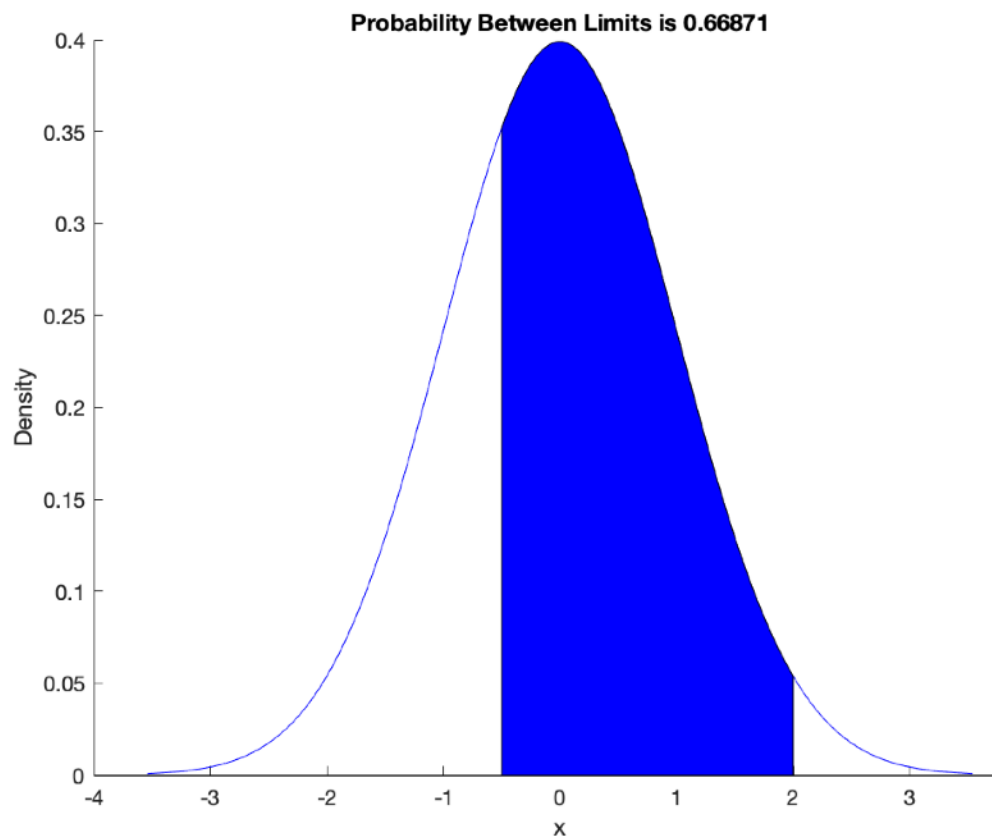
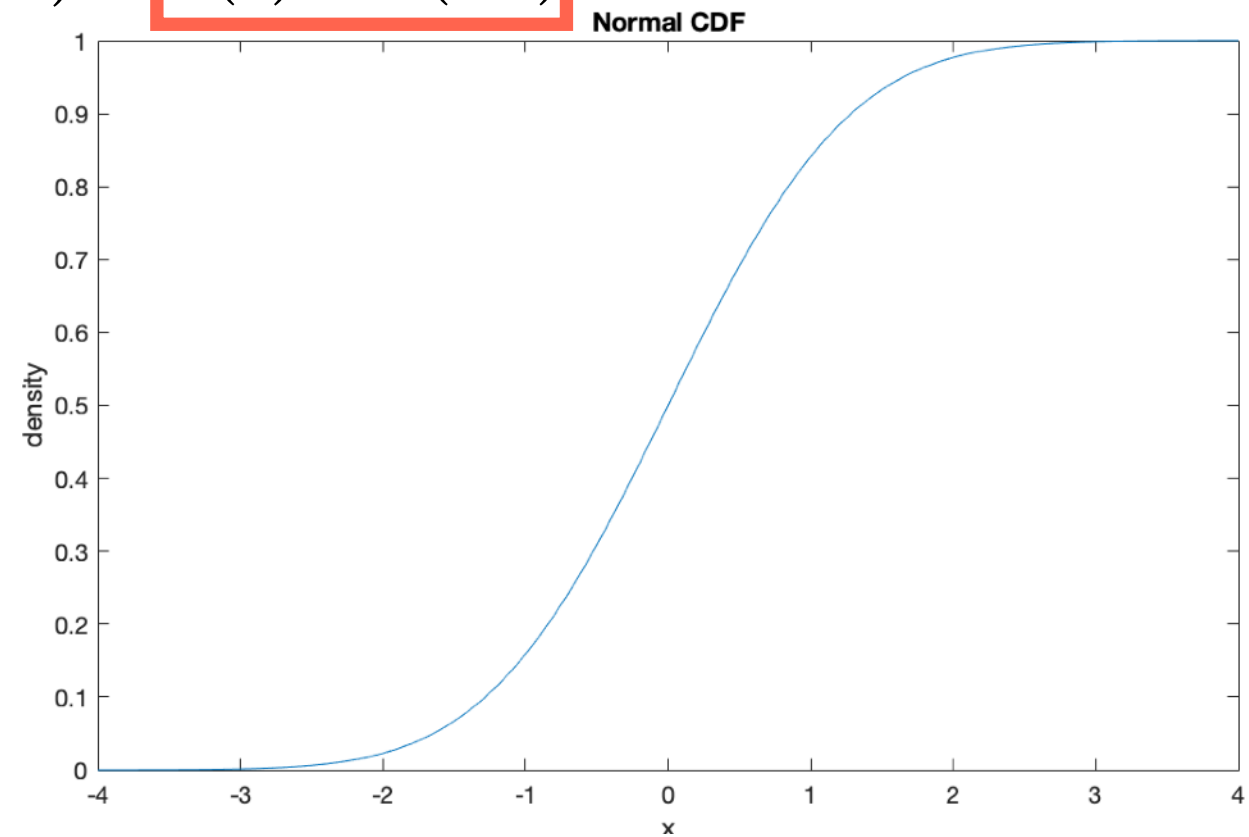
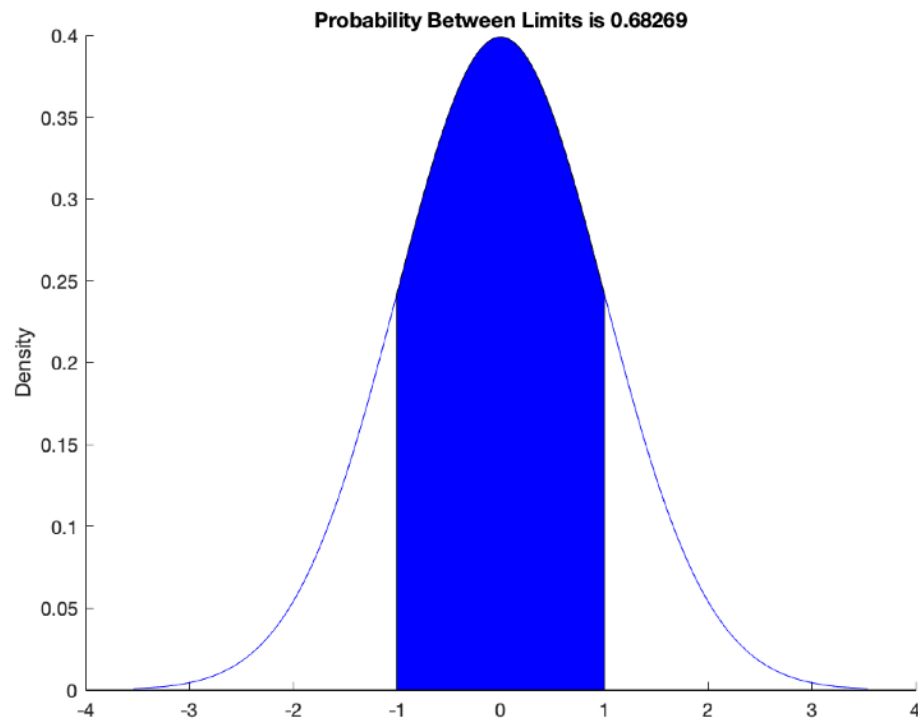
$$= P(-k \leq Z \leq k),$$

$$P(-k \leq Z \leq k) = P(Z \leq k) - P(Z \leq -k) = F(k) - F(-k)$$

# Normal Distribution

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

$$P(-k \leq Z \leq k) = P(Z \leq k) - P(Z \leq -k) = F(k) - F(-k)$$



# Normal Distribution

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- ▶ Singled peaked, symmetric
- ▶ about 2/3 are within 1 standard deviation ( $\sigma$ ) from the mean
- ▶ about 95% are within 2 standard deviations ( $2\sigma$ ) from the mean

```
## plus minus 1 standard deviation from the mean
```

```
pnorm(1) - pnorm(-1)
```

```
## [1] 0.6826895
```

```
## plus minus 2 standard deviations from the mean
```

```
pnorm(2) - pnorm(-2)
```

```
## [1] 0.9544997
```

```
mu <- 5
```

```
sigma <- 2
```

```
## plus minus 1 standard deviation from the mean
```

```
pnorm(mu + sigma, mean = mu, sd = sigma) - pnorm(mu - sigma, mean = mu, sd = sigma)
```

```
## [1] 0.6826895
```

```
## plus minus 2 standard deviations from the mean
```

```
pnorm(mu + 2*sigma, mean = mu, sd = sigma) - pnorm(mu - 2*sigma, mean = mu, sd = sigma)
```

```
## [1] 0.9544997
```



# Expectation: Definition and General Properties

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- Expectation (population mean) of a random variable  $X$ 
  - Fixed value given a probability distribution (different from sample means)

$$\mathbb{E}(X) = \begin{cases} \sum_x x \times f(x) & \text{if } X \text{ is discrete,} \\ \int x \times f(x) dx & \text{if } X \text{ is continuous} \end{cases}$$

- Properties of expectation ( $a, b$ : constant values;  $X, Y$ : independent RVs)
  1.  $\mathbb{E}(a) = a$ .
  2.  $\mathbb{E}(aX) = a\mathbb{E}(X)$ .
  3.  $\mathbb{E}(aX + b) = a\mathbb{E}(X) + b$ .
  4.  $\mathbb{E}(aX + bY) = a\mathbb{E}(X) + b\mathbb{E}(Y)$ .
  5. If  $X$  and  $Y$  are independent, then  $\mathbb{E}(XY) = \mathbb{E}(X)\mathbb{E}(Y)$ . But generally,  $\mathbb{E}(XY) \neq \mathbb{E}(X)\mathbb{E}(Y)$ .

# Expectation: Examples

$$\mathbb{E}(X) = \begin{cases} \sum_x x \times f(x) & \text{if } X \text{ is discrete,} \\ \int x \times f(x) dx & \text{if } X \text{ is continuous} \end{cases}$$

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► Expectation (population mean)

► Expected value of a random variable

► e.g. PMF: Bernoulli random variable

$$\mathbb{E}(X) = 0 \times P(X = 0) + 1 \times P(X = 1) = 0 \times f(0) + 1 \times f(1) = 0 \times (1 - p) + 1 \times p = p$$

► e.g. PMF: Binomial random variable

$$\mathbb{E}(X) = 0 \times f(0) + 1 \times f(1) + \cdots + n \times f(n) = \sum_{x=0}^n x \times f(x)$$

► e.g. PMF: Binomial random variable ( $Y_i$  is a Bernoulli RV with  $p$ )

$$\mathbb{E}(X) = \mathbb{E}\left(\sum_{i=1}^n Y_i\right) = \sum_{i=1}^n \mathbb{E}(Y_i) = np$$

► e.g. PDF: uniform random variable defined in the interval  $[a, b]$

$$\mathbb{E}(X) = \int_a^b x \times f(x) dx = \int_a^b \frac{x}{b-a} dx = \frac{x^2}{2(b-a)} \Big|_a^b = \frac{a+b}{2}$$

# Summary

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- ▶ Random Variables and Probability Distributions (Chapter 6.3)
  - ▶ Overview
  - ▶ Bernoulli / Binomial distribution
  - ▶ Uniform / Normal distribution
  - ▶ Expectation

**See you next week.**