

Communication Systems II

[KECE322_01]

<2012-2nd Semester>

Lecture #2

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School of Electrical Engineering

Korea University

Prof. Young-Chai Ko

Outline

- Review of probability and random variables (Secs. 5.1.1 - 5.1.4)
 - sample space, events, and probability
 - conditional probability
 - random variables
 - functions of random variable

Experiment, Outcome, and Sample space

random experiment

- flipping a coin
- drawing a card from a deck of cards
- throwing a die

possible outcomes

- H or T
- one of 52 cards
- 1,2,3,4,5,6

■ Sample space Ω

- the set of all possible outcomes

$$\Omega = \{H, T\}$$

$$\Omega = \{1, 2, 3, 4, 5, 6\}$$

- Denote an outcome as ω , then $\omega \in \Omega$

Continuous vs. Discrete Sample Space

- Continuous sample space
 - Received signal
 - Temperature
- Discrete sample space
 - Flipping a coin
 - bits generated from the source

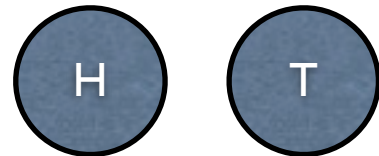
Events

■ Events, E

- subsets of the sample space
- Example: In the experiment of throwing a die,
 - ◆ the event “the outcome is odd” consists of outcomes 1, 3, and 5.
 - ◆ the event “the outcome is greater than 3” consists of outcomes 4, 5 and 6.
 - ◆ the event “the outcome divides 4” consists of the single outcome 4.
- Example: In the experiment of picking a number between 0 and 1,
 - ◆ we can define an event as “the outcome is less than 0.7”, “the outcome is between 0.2 and 0.5”, “the outcome is 0.5”.
- Events are disjoint if their intersection is empty
 - ◆ In throwing a die, the events “the outcome is odd” and “the outcome divides 4” are disjoint.

Intuitive Concept of Probability

- Experiment: Flipping a coin

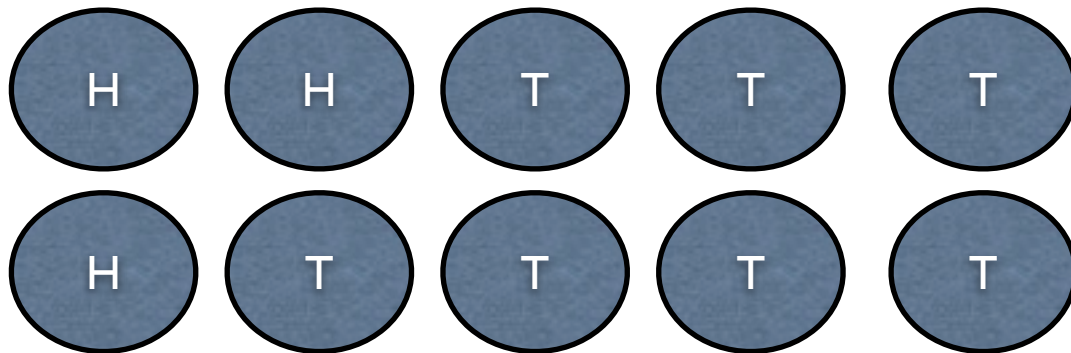


- Head or Tail

- What is the probability of 'Head' or 'Tail' to occur in the event of flipping a coin?

$$P(H) = \frac{1}{2}, \quad P(T) = \frac{1}{2}$$

- Experiment: Flipping a coin 10 times

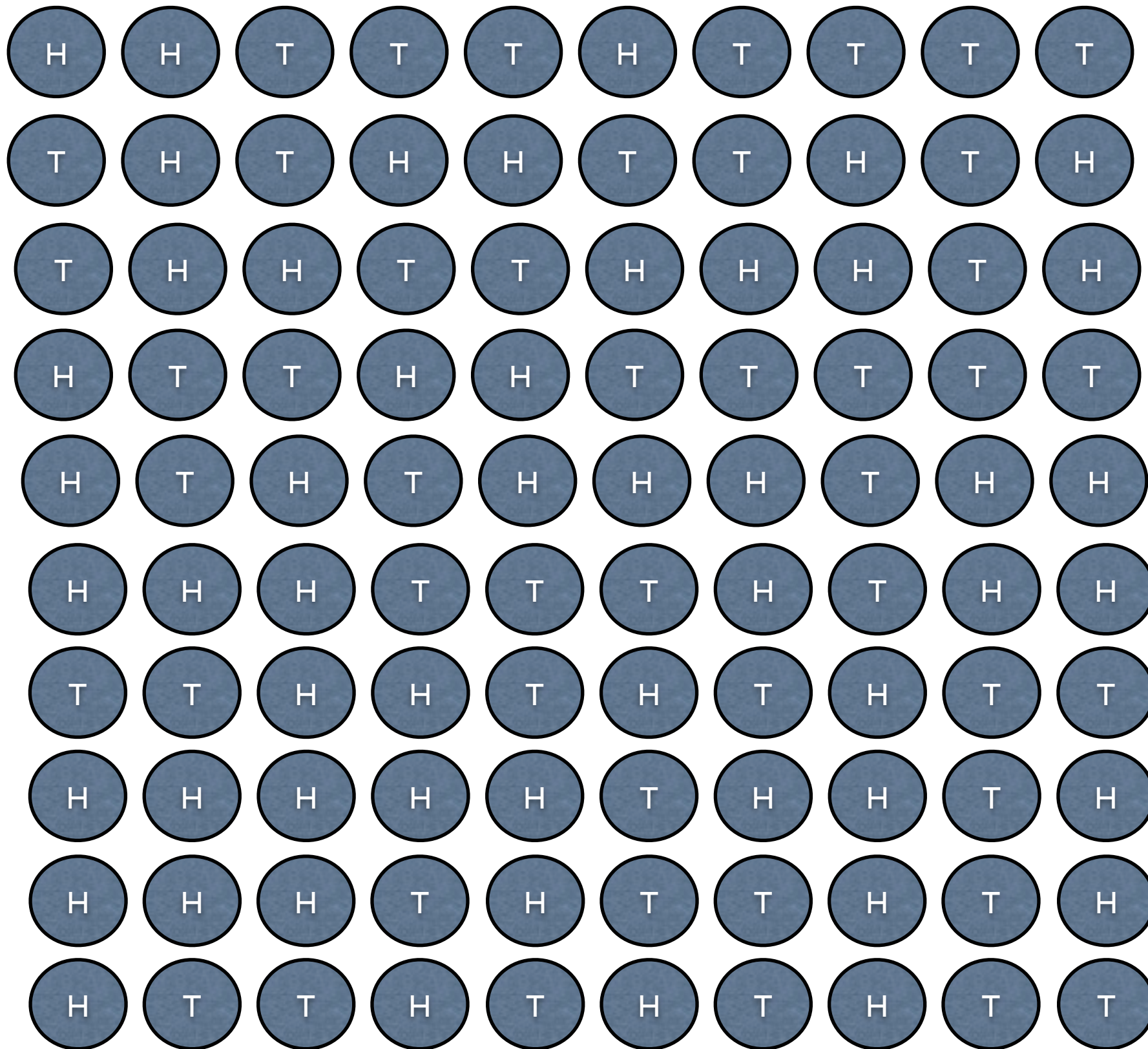


Did you get 1/2 of probability for 'H' or 'T'?

$$P(H) = \frac{3}{10}$$
$$P(T) = \frac{7}{10}$$

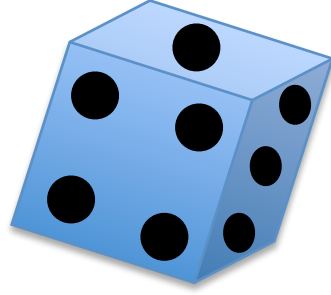


Experiment: Flipping a coin 100 times



$$P(H) = \frac{51}{100}$$
$$P(T) = \frac{49}{100}$$

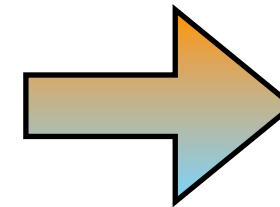
● Experiment: Tossing a die



- Possible outcomes=1,2,3,4,5,6

● Experiment: Toss a die two times then the total possible outcomes are

{(1, 1), (1, 2), (1, 3), (1, 4), (1, 5), (1, 6),
(2, 1), (2, 2), (2, 3), (2, 4), (2, 5), (2, 6),
(3, 1), (3, 2), (3, 3), (3, 4), (3, 5), (3, 6),
(4, 1), (4, 2), (4, 3), (4, 4), (4, 5), (4, 6),
(5, 1), (5, 2), (5, 3), (5, 4), (5, 5), (5, 6),
(6, 1), (6, 2), (6, 3), (6, 4), (6, 5), (6, 6)}



36 possible outcomes

● Toss a die two times then the total possible outcomes of the sum are

{2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12}

- In the experiment of tossing a die two times and observing the sum more than 8

$\{(3, 6), (4, 5), (4, 6), (5, 4), (5, 5), (5, 6), (6, 3), (6, 4), (6, 5), (6, 6)\}$

- 10 outcomes out of 36 possible outcomes

- Now what do you say about the probability of the **event** that the sum is more than 8?

$$P(\text{event of more than 8}) = \frac{10}{36}$$

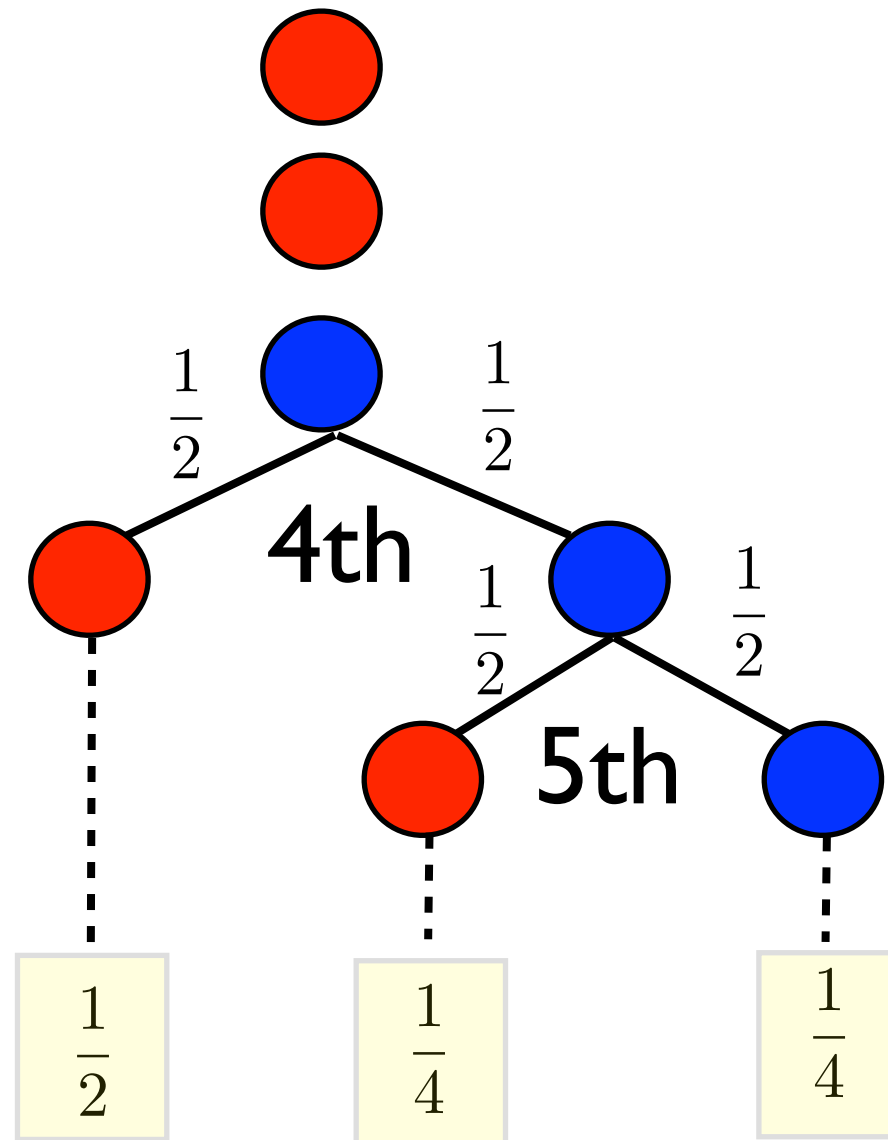
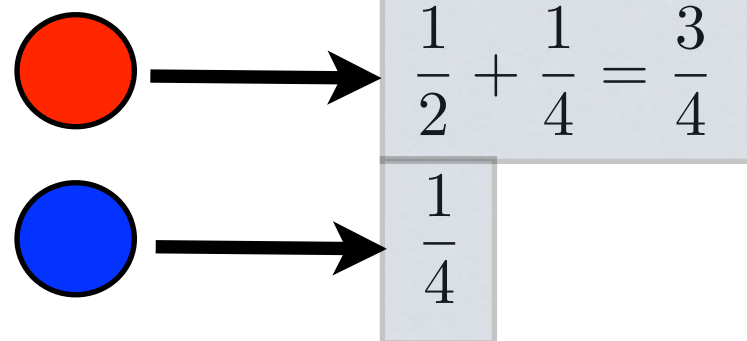
Origin of the Probability Theory: Gambling and Probability



Blaise Pascal (1623-1662)



Pierre de Fermat (1601-1665)



Gambler, Chevalier de Mere

■ Mere's questions:

- ~ Two gamblers, A and B, are gambling. The game rule is that one who wins the three times wins the game.
- ~ How do we can distribute the money if the game is sopped and A won 2 times and B won one time?

Probability

■ We define a probability P as a set of function assigning nonnegative values to all events E such that the following conditions are satisfied:

1. $0 \leq P(E) \leq 1$ for all events

2. $P(\Omega) = 1$.

3. For disjoint events E_1, E_2, E_3, \dots (i.e., events for which $E_i \cap E_j \neq \phi$ for all $i \neq j$, where ϕ is the empty set), we have $P(\cup_{i=1}^{\infty} E_i) = \sum_{i=1}^{\infty} P(E_i)$.

■ Law of large number and definition of probability

$$\lim_{n \rightarrow \infty} \left(\frac{\text{number of the occurrence of event } A}{\text{number of experiments, } n} \right) = P(A)$$

■ We can also define the probability such as

$$P(A) = \frac{\text{length of event}}{\text{length of sample space}}$$

Example of tossing two dice

•(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)
•(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)
•(3,1)	(3,2)	(3,3)	(3,4)	(3,5)	(3,6)
•(4,1)	(4,2)	(4,3)	(4,4)	(4,5)	(4,6)
•(5,1)	(5,2)	(5,3)	(5,4)	(5,5)	(5,6)
•(6,1)	(6,2)	(6,3)	(6,4)	(6,5)	(6,6)

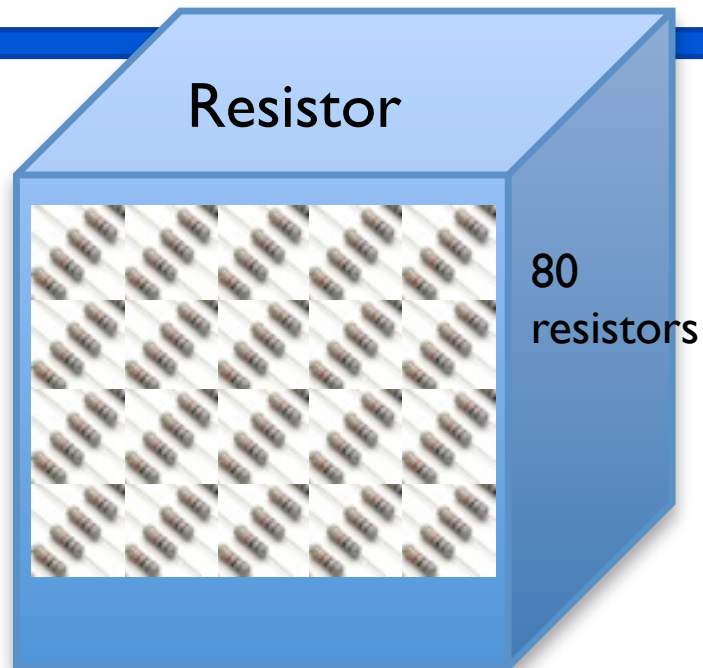
$A = \{\text{sum}=7\}$, $B = \{8 < \text{sum} \leq 11\}$, and, $C = \{10 < \text{sum}\}$

■ events $A_{ij} = \{\text{sum for outcome } (i, j) = i + j\}$

$$P(A) = P\left(\bigcup_{i=1}^6 A_{i,7-i}\right) = \sum_{i=1}^6 P(A_{i,7-i}) = 6 \left(\frac{1}{36}\right) = \frac{1}{6}$$

$$P(B) = 9 \left(\frac{1}{36}\right) = \frac{1}{4} \quad P(C) = 3 \left(\frac{1}{36}\right) = \frac{1}{12}$$

Example

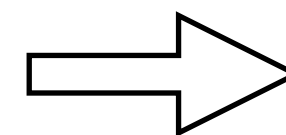


Suppose a 22 Ohm resistor is drawn from the box and not replaced. A second resistor is then drawn from the box.

- In a box there are 80 resistors with the same size and shape, we have for the second drawing

$$P(\text{draw } 10\Omega | 22\Omega) = 18/79,$$
$$P(\text{draw } 27\Omega | 22\Omega) = 33/79,$$

$$P(\text{draw } 22\Omega | 22\Omega) = 12/79$$
$$P(\text{draw } 47\Omega | 22\Omega) = 17/79$$



Conditional probability

- In a box there are 80 resistors with the same size and shape.
 - 18 are 10 Ohm
 - 12 are 22 Ohm
 - 33 are 27 Ohm
 - 17 are 47 Ohm
- Experiment: randomly draw out one resistor from the box with each one being “equally likely” to be drawn.

$$P(\text{draw } 10\Omega) = 18/80, \quad P(\text{draw } 22\Omega) = 12/80$$
$$P(\text{draw } 27\Omega) = 33/80, \quad P(\text{draw } 47\Omega) = 17/80$$

Joint Probability

- Joint probability for two events A and B

$$P(A \cap B) = P(A) + P(B) - P(A \cup B)$$

- Equivalently

$$P(A \cup B) = P(A) + P(B) - P(A \cap B) \leq P(A) + P(B)$$

- Mutually exclusive events if $A \cap B = \phi$, and therefore, $P(A \cap B) = P(\phi) = 0$

Conditional Probability

- Given some event B with nonzero probability $P(B) > 0$ we define the conditional probability of an event A , given B , by

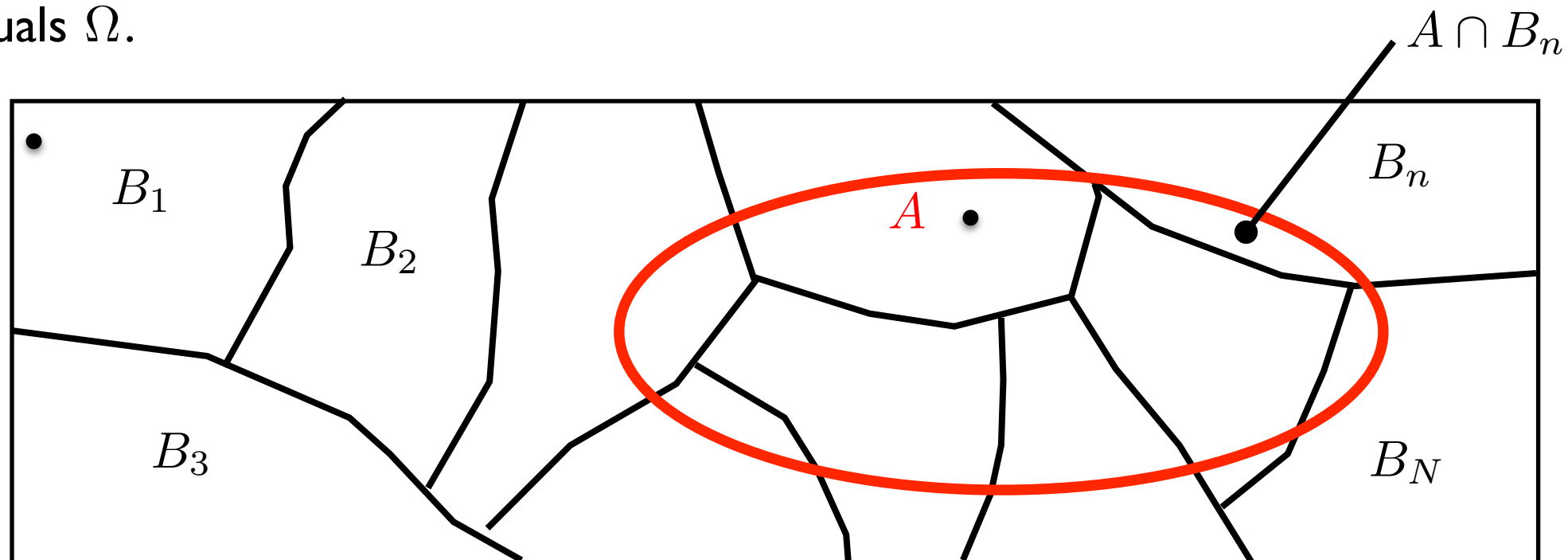
$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

- The probability $P(A|B)$ simply reflects the fact that the probability of an event A may depend on a second event B .
- If A and B are mutually exclusive, $A \cap B = \phi$, and $P(A|B) = 0$.
- Conditional probability is a defined quantity and cannot be proven.
 - ◆ However, as a probability it must satisfy the three axioms.
 - ◆ From axiom 2,

$$P(\Omega|B) = \frac{P(\Omega \cap B)}{P(B)} = \frac{P(B)}{P(B)} = 1$$

Total Probability

- The probability $P(A)$ of any event A depends on a sample space Ω can be expressed in terms of conditional probabilities.
- Suppose we are given N mutually exclusive events $B_n, n = 1, 2, \dots, N$, whose union equals Ω .



$$P(A) = \sum_{n=1}^N P(A \cap B_n) = \sum_{n=1}^N P(A|B_n)P(B_n)$$

Bayes' Theorem

■ Bayes' theorem

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

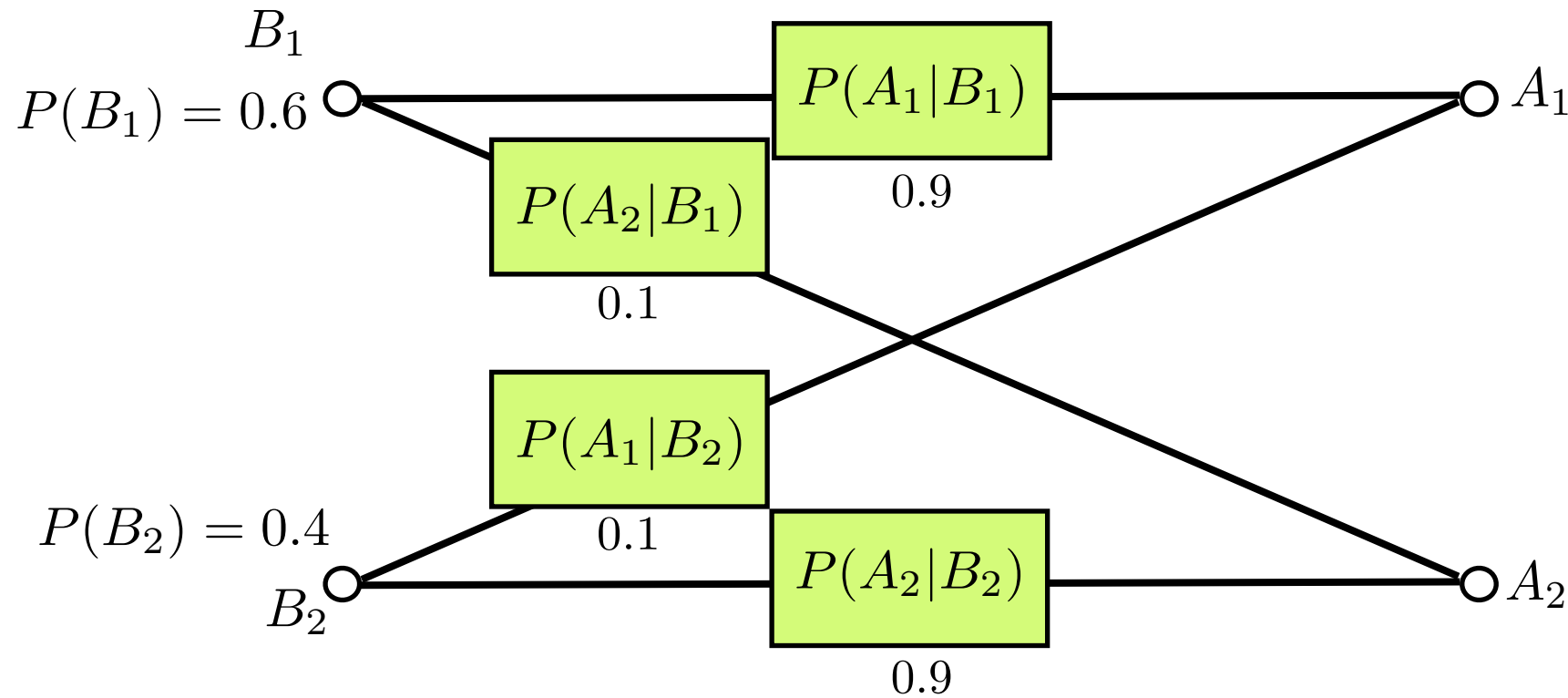
$$P(A|B_n) = \frac{P(A \cap B_n)}{P(B_n)} = \frac{P(B_n|A)P(A)}{P(B_n)}$$

■ We can also rewrite

$$\begin{aligned} P(B_n|A) &= \frac{P(A \cap B_n)}{P(A)} = \frac{P(A|B_n)P(B_n)}{P(A)} = \frac{P(A|B_n)P(B_n)}{P(A|B_1)P(B_1) + \cdots + P(A|B_N)P(B_N)} \\ &= \frac{P(A|B_n)P(B_n)}{\sum_{j=1}^N P(A|B_j)P(B_j)}. \end{aligned}$$

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

Example: Binary Symmetric Channel (BSC)



$P(A_1)$ and $P(A_2)$?

$P(B_1|A_1)$ and $P(B_2|A_2)$?

$P(B_1|A_2)$ and $P(B_2|A_1)$?

$$P(A_1) = P(A_1|B_1)P(B_1) + P(A_1|B_2)P(B_2) = 0.9(0.6) + 0.1(0.4) = 0.58$$

$$P(A_2) = P(A_2|B_1)P(B_1) + P(A_2|B_2)P(B_2) = 0.1(0.6) + 0.9(0.4) = 0.42$$

$$P(B_1|A_1) = \frac{P(A_1|B_1)P(B_1)}{P(A_1)} = \frac{0.9(0.6)}{0.58} = \frac{0.54}{0.58} \approx 0.931$$

$$P(B_2|A_2) = \frac{P(A_2|B_2)P(B_2)}{P(A_2)} = \frac{0.9(0.4)}{0.42} = \frac{0.36}{0.42} \approx 0.857$$

$$P(B_1|A_2) = \frac{P(A_2|B_1)P(B_1)}{P(A_2)} = \frac{0.1(0.6)}{0.42} = \frac{0.06}{0.42} \approx 0.143$$

$$P(B_2|A_1) = \frac{P(A_1|B_2)P(B_2)}{P(A_1)} = \frac{0.1(0.4)}{0.58} = \frac{0.04}{0.58} \approx 0.069$$

Independent Events

- Statistically independent if

$$P(A|B) = P(A) \qquad P(B|A) = P(B)$$

- We also have for statistically events

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

- If A and B are statistically independent,

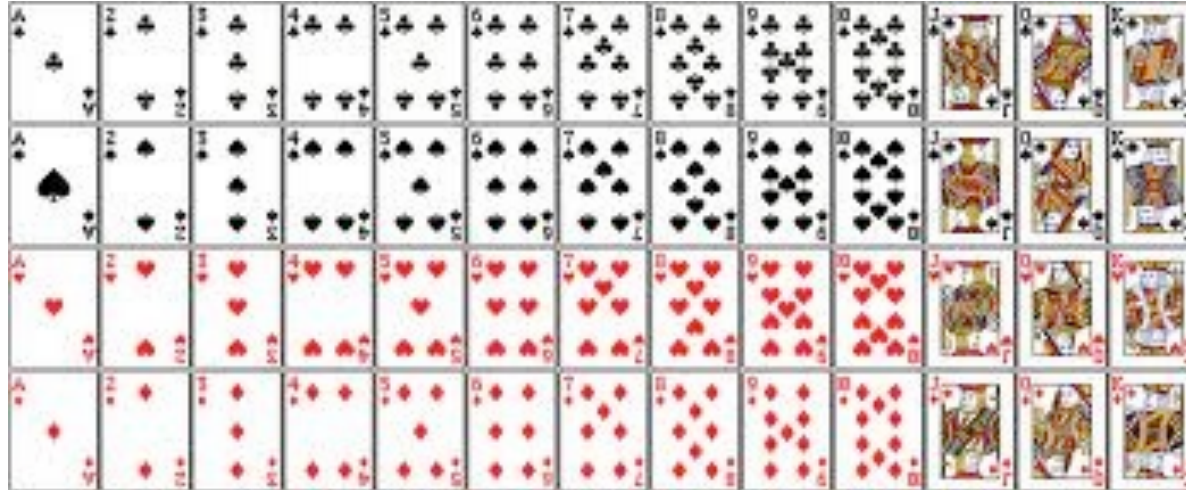
$$P(A \cap B) = P(A|B)P(B) = P(A)P(B) \neq 0$$

- Note

- ◆ If A and B are nonzero probabilities of occurrences and statistically independent,
- ◆ which means $A \cap B \neq \phi$.

- In order for two events to be independent they must have an intersection $A \cap B \neq \phi$

Example



Define events as follows:

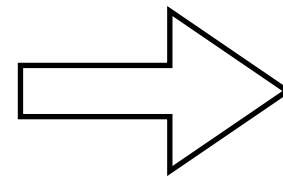
Event A : select a king

Event B: select a jack or queen

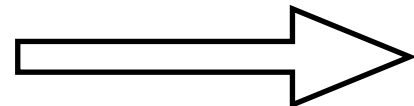
Event C: select a heart

Joint probabilities

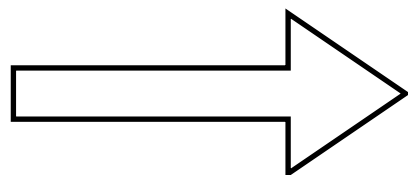
Independent?



$$P(A) = \frac{4}{52}, P(B) = \frac{8}{52}, \text{ and } P(C) = \frac{13}{52}$$



$$P(A \cap B) = 0, P(A \cap C) = \frac{1}{52}, P(B \cap C) = \frac{2}{52}$$



$$P(A \cap B) = 0 \neq P(A)P(B) = \frac{32}{52^2}$$

$$P(A \cap C) = \frac{1}{52} = P(A)P(C) = \frac{1}{52}$$

$$P(B \cap C) = \frac{2}{52} = P(B)P(C) = \frac{2}{52}$$

Multiple Independent Events

- Three independents

$$P(A_1 \cap A_2) = P(A_1)P(A_2)$$

$$P(A_1 \cap A_3) = P(A_1)P(A_3)$$

$$P(A_2 \cap A_3) = P(A_2)P(A_3)$$

$$P(A_1 \cap A_2 \cap A_3) = P(A_1)P(A_2)P(A_3)$$

Permutation and Combination

■ Permutation

$$\begin{aligned} \text{ordering of } r \text{ elements taken from } n &= n(n-1)(n-2)\cdots(n-r+1) \\ &= \frac{n!}{(n-r)!} = P_r^n \quad r = 1, 2, \dots, n \end{aligned}$$

■ Combination

binomial coefficient

$$r \text{ elements taken from } n = \binom{n}{r} = \frac{n!}{(n-r)!r!} = {}_n C_r$$

■ Binomial coefficient

$$(x+y)^n = \sum_{r=0}^n \binom{n}{r} x^r y^{n-r}$$

■ Symmetry of binomial coefficient

$$\binom{n}{r} = \binom{n}{n-r}$$

The Random Variable (RV)

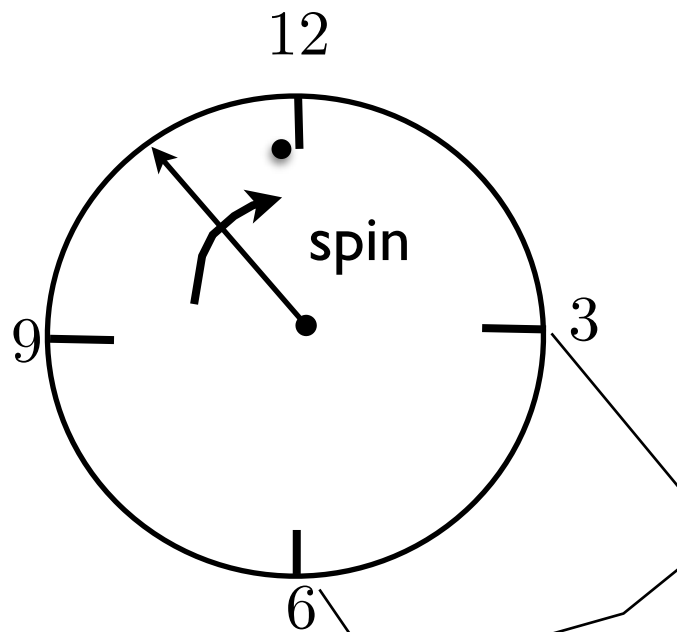
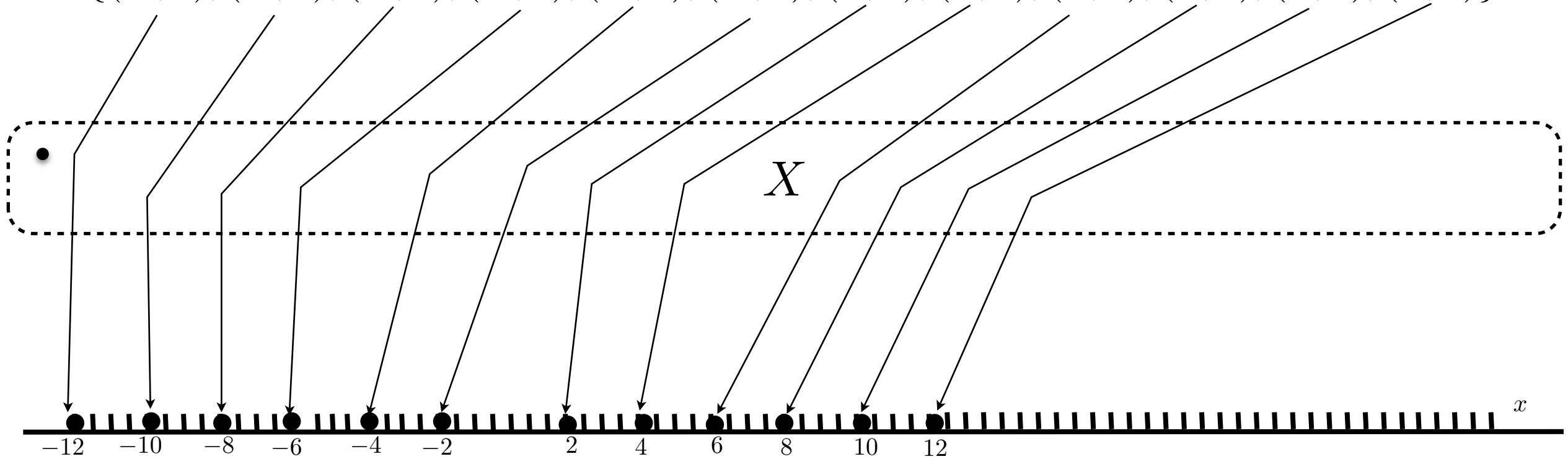
- A real random variable is defined as
 - a real function of the elements of a sample space Ω

- Represent a random variable by a capital letter such as W , X , or Y and any particular value of the random variable by a lowercase letter such as w , x , or y .

- Thus, given an experiment defined by a sample space Ω with elements ω , we assign to every ω a real number $X(\omega)$
 - according to some rule and call $X(\omega)$ a **random variable**.

Example

$$\Omega = \{(H, 1), (H, 2), (H, 3), (H, 4), (H, 5), (H, 6), (T, 1), (T, 2), (T, 3), (T, 4), (T, 5), (T, 6)\}$$



Conditions for a Function to be a Random

■ First condition

- The set $\{X \leq x\}$ shall be an event for any real number x .
- The probability of this event, denoted by $P\{X \leq x\}$ is equal to the sum of the probabilities of all the elementary events corresponding to $\{X \leq x\}$.

■ Probabilities of the events $\{X = \infty\}$ and $\{X = -\infty\}$

$$P\{X = \infty\} = 0 \text{ and } P\{X = -\infty\} = 0$$

■ Probabilities of the events $\{X \leq \infty\}$

$$P\{X \leq \infty\} = 1$$

Categorization of Random Variables

- Continuous random variable
- Discrete random variable
- Mixed random variable

Bernoulli Trials

- There exist two outcomes in the experiment.

- Example:

- ◆ binary bit 1 or 0 is generated
- ◆ Head or tail

- Denote each of two outcomes as A and \bar{A}

- Repeat experiments N times and A is observed k times out of the N trials.

- Such repeated experiments are called *Bernoulli trials*.

- Probability

$$P(A) = p \text{ then } P(\bar{A}) = 1 - p$$

- k times out of N trials for the event A

- one particular sequence is k times of A and $N - k$ times of \bar{A} and its probability is

$$\underbrace{P(A)P(A) \cdots P(A)}_{k \text{ terms}} \underbrace{P(\bar{A})P(\bar{A}) \cdots P(\bar{A})}_{N - k \text{ terms}} = p^k (1 - p)^{N - k}$$

- Probability that A occurs exactly k times

$$P(A \text{ occurs exactly } k \text{ times}) = \binom{N}{k} p^k (1 - p)^{N-k}$$

Distribution Function

■ Cumulative distribution function (CDF)

$$F_X(x) = P\{X \leq x\}$$

■ Properties of CDF

(1) $F_X(-\infty) = 0$

(2) $F_X(\infty) = 1$

(3) $0 \leq F_X(x) \leq 1$

(4) $F_X(x_1) \leq F_X(x_2)$, if $x_1 < x_2$

(5) $P\{x_1 < X \leq x_2\} = F_X(x_2) - F_X(x_1)$

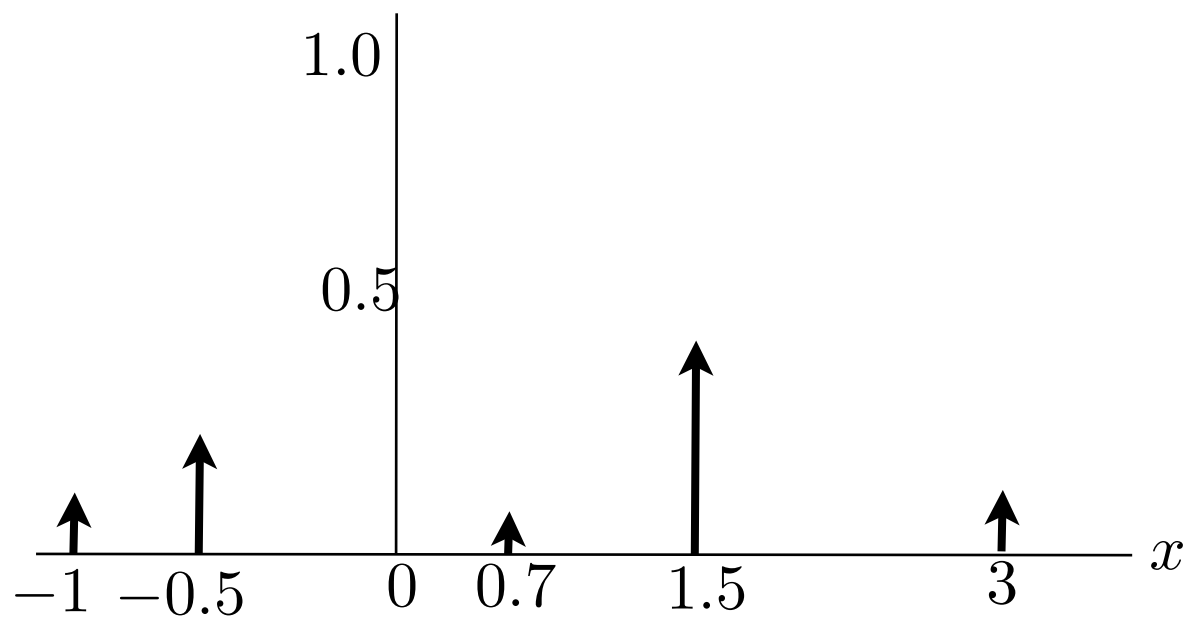
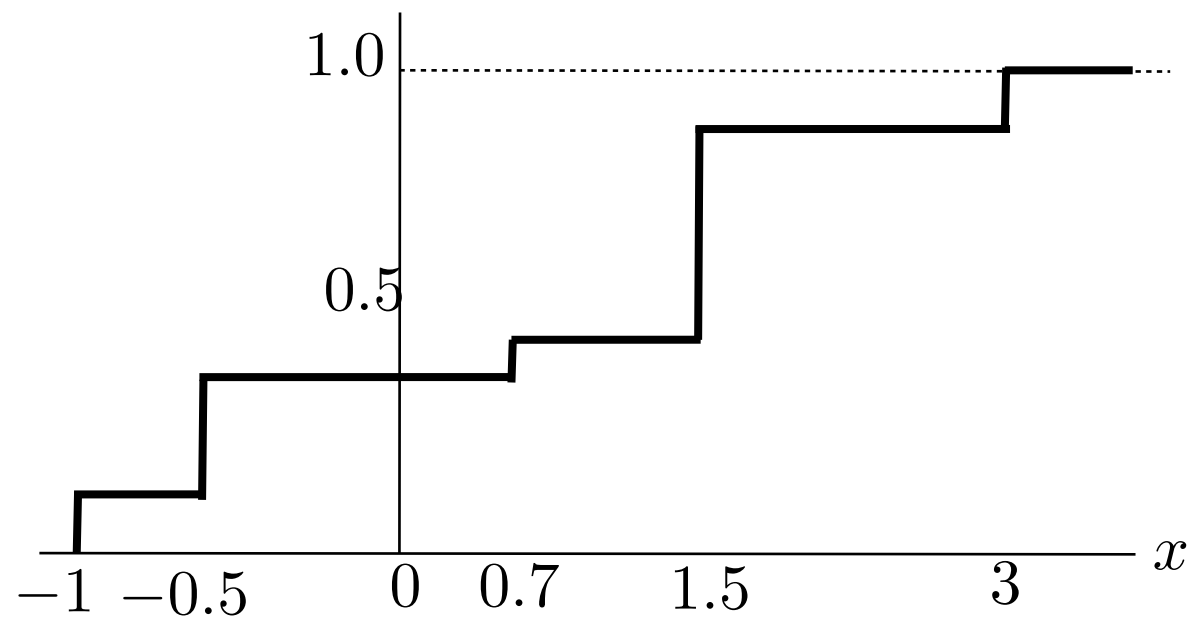
(6) $F_X(x^+) = F_X(x)$

■ If the values of x_i , we may write $F_X(x)$

$$F_X(x) = \sum_{i=1}^N P\{X = x_i\}u(x - x_i)$$

- If the values of x_i , we may write $F_X(x)$

$$F_X(x) = \sum_{i=1}^N P\{X = x_i\}u(x - x_i)$$



Probability Density Function (PDF)

- PDF is defined as the derivative of CDF.

$$f_X(x) = \frac{dF_X(x)}{dx}$$

- Properties of PDF

(1) $0 \leq f_X(x)$ all x

(2) $\int_{-\infty}^{\infty} f_X(x) dx = 1$

(3) $F_X(x) = \int_{-\infty}^x f_X(\zeta) d\zeta$

(4) $P\{x_1 < X \leq x_2\} = \int_{x_1}^{x_2} f_X(x) dx$

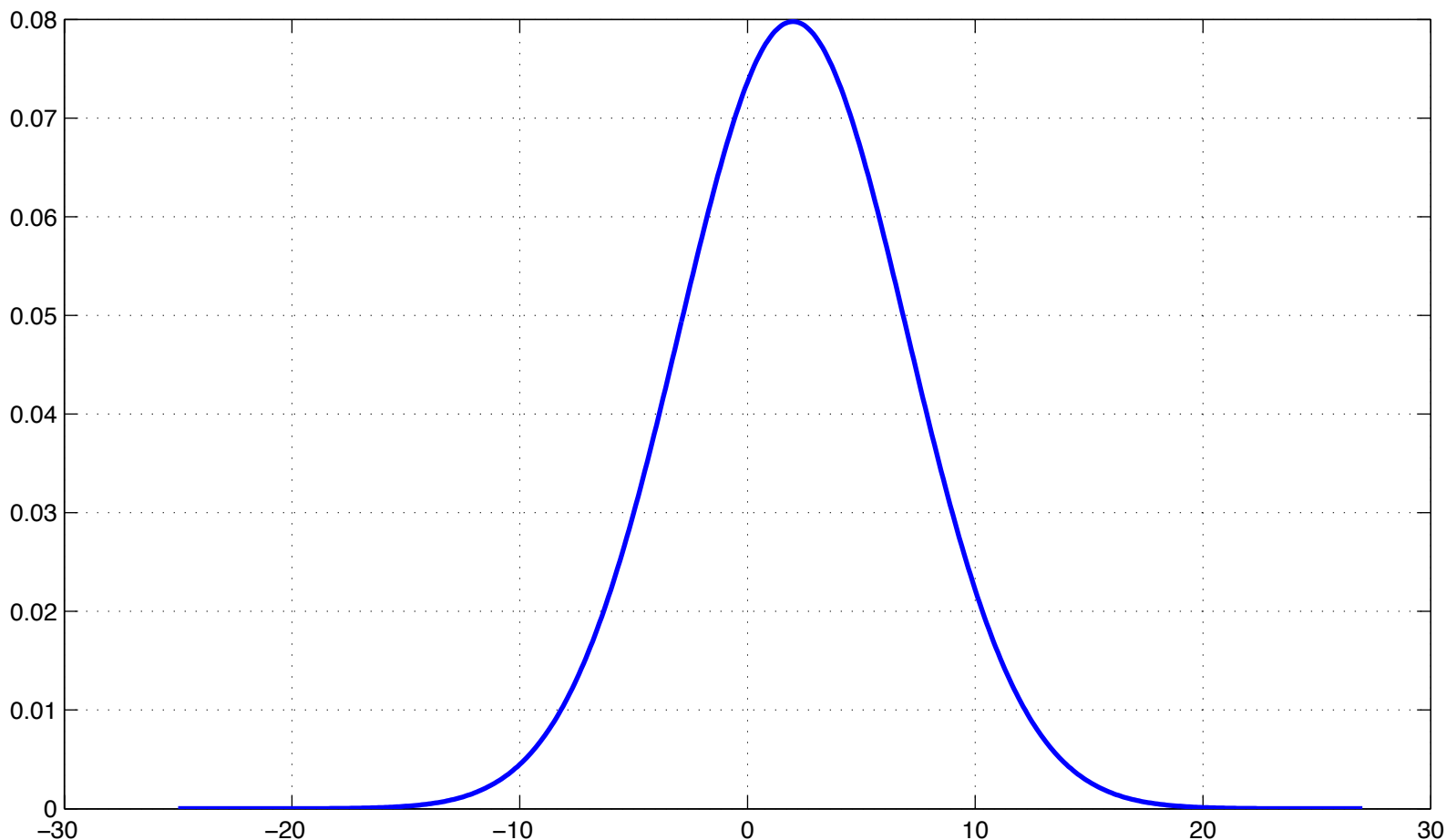
Gaussian Random Variable

- A random variable X is called gaussian if its density function has the form

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(x-m)^2}{2\sigma_x^2}\right] \quad \sigma_X > 0 \text{ and } -\infty < m < \infty$$

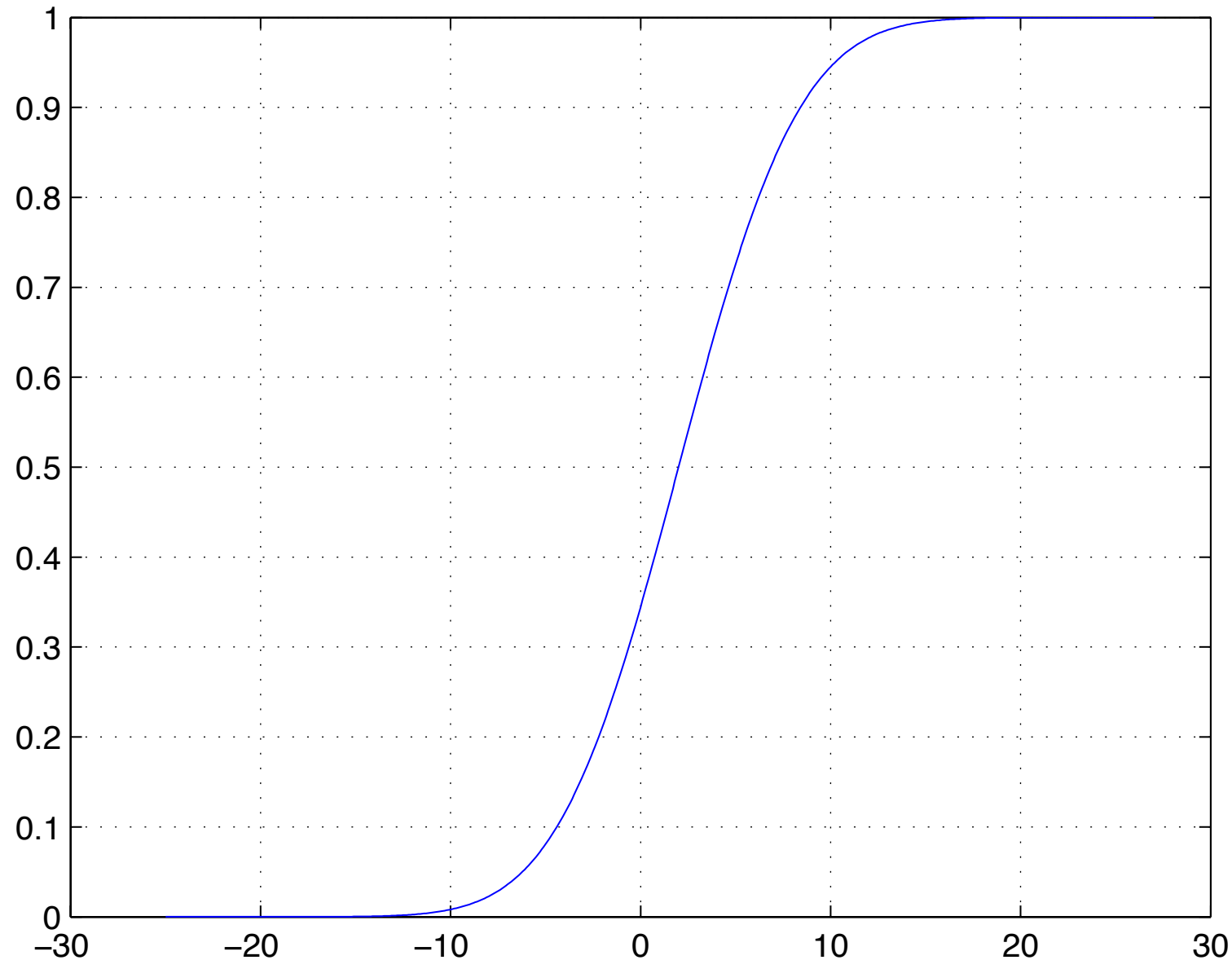
- Example

$$m = 2 \text{ and } \sigma = 5$$



■ CDF

$$\begin{aligned} F_X(x) = \Pr[X \leq x] &= \int_{-\infty}^x f_X(\zeta) d\zeta = \int_{-\infty}^x \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(\zeta - m)^2}{2\sigma_X^2}\right] d\zeta \\ &= \int_{-\infty}^{\frac{(x-m)}{\sigma_X}} \exp\left[-\frac{t^2}{2}\right] dt = 1 - \int_{\frac{(x-m)}{\sigma_X}}^{\infty} \exp\left[-\frac{t^2}{2}\right] dt \\ &= 1 - Q\left(\frac{x-m}{\sigma_X}\right) \end{aligned}$$



where

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt$$

Some Special Functions

■ Q-function

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt$$

■ Error function

$$\text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt$$

● Properties of error function

◆ symmetry relation: $\text{erf}(-x) = -\text{erf}(x)$

◆ As x approaches infinity, $\text{erf}(x)$ approaches unity; that is,

$$\frac{2}{\sqrt{\pi}} \int_0^{\infty} e^{-t^2} dt = 1$$

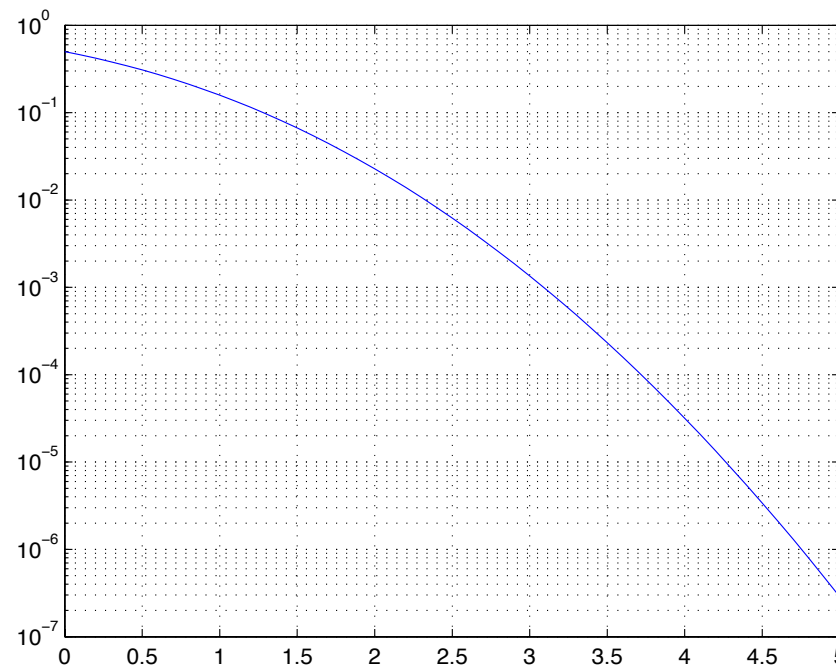
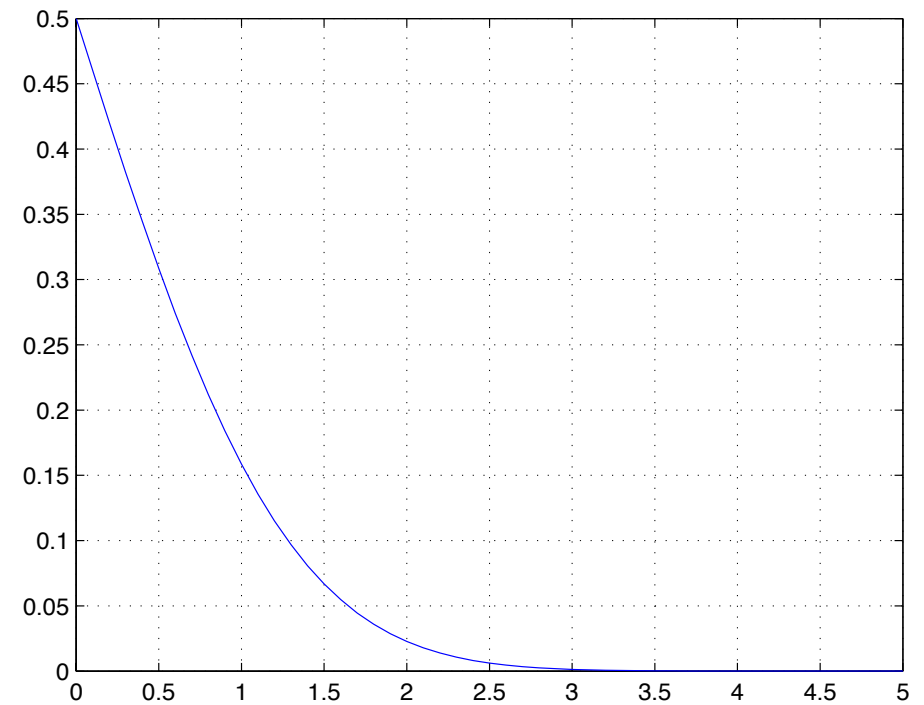
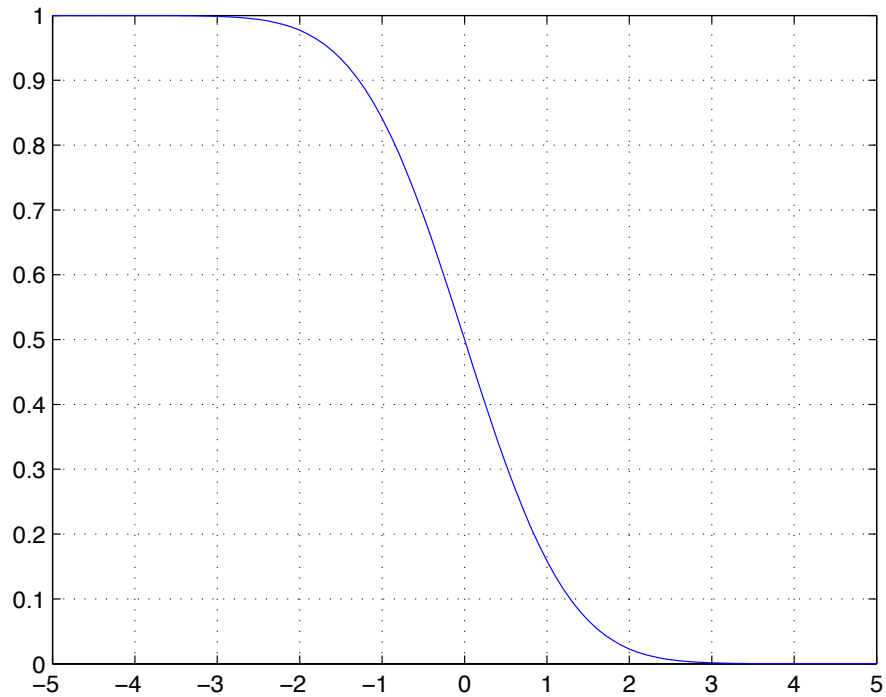
◆ Complementary error function

$$\text{erfc}(x) = 1 - \text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_x^{\infty} e^{-t^2} dt = 1$$

■ Relation between Q and erfc functions

$$Q(x) = \frac{1}{2} \operatorname{erfc} \left(\frac{x}{\sqrt{2}} \right)$$
$$\operatorname{erfc}(x) = 2Q(\sqrt{2}x)$$

Q-function Plot



semilog plot

Binomial Distribution and Density

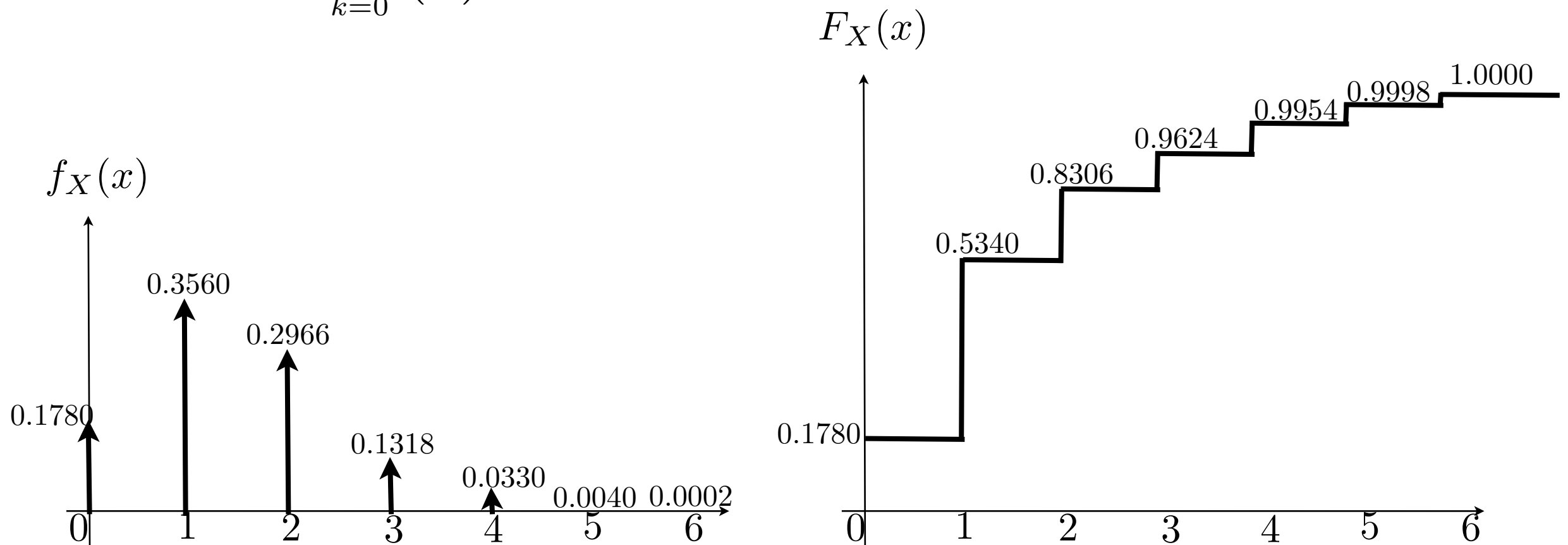
Let $0 < p < 1$, and $N = 1, 2, \dots$. Then,

PDF

$$f_X(x) = \sum_{k=0}^N \binom{N}{k} p^k (1-p)^{N-k} \delta(x-k)$$

CDF

$$F_X(x) = \sum_{k=0}^N \binom{N}{k} p^k (1-p)^{N-k} u(x-k)$$



Uniform Distribution and Density

■ PDF

$$f_X(x) = \begin{cases} \frac{1}{b-a}, & a \leq x \leq b \\ 0, & \text{elsewhere} \end{cases}$$

■ CDF

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

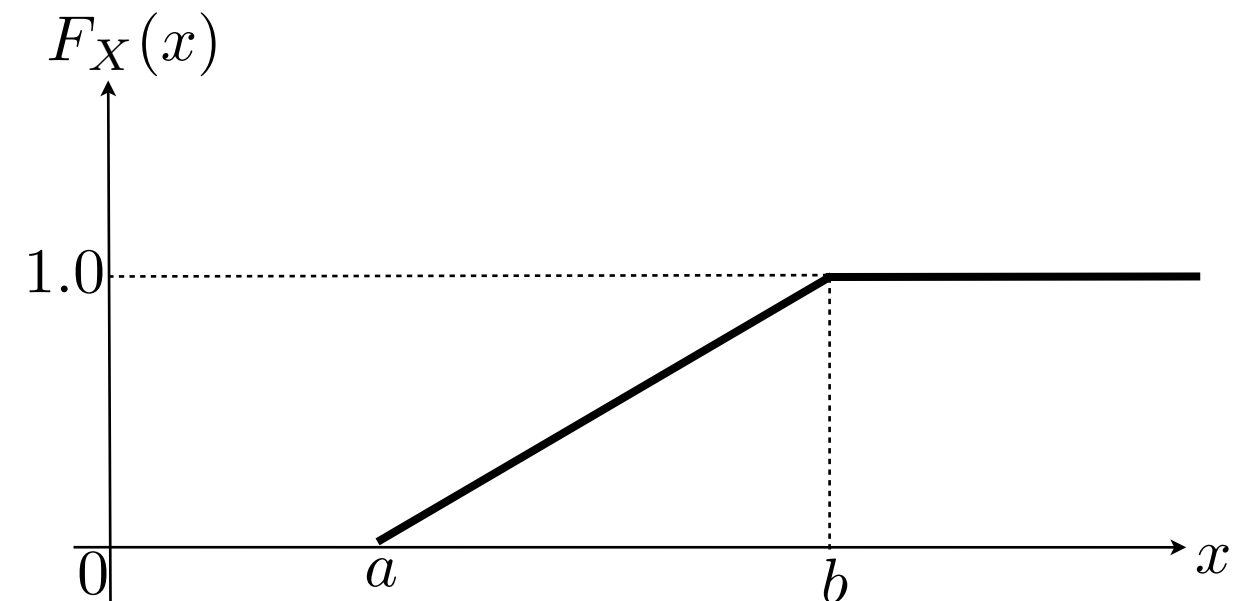
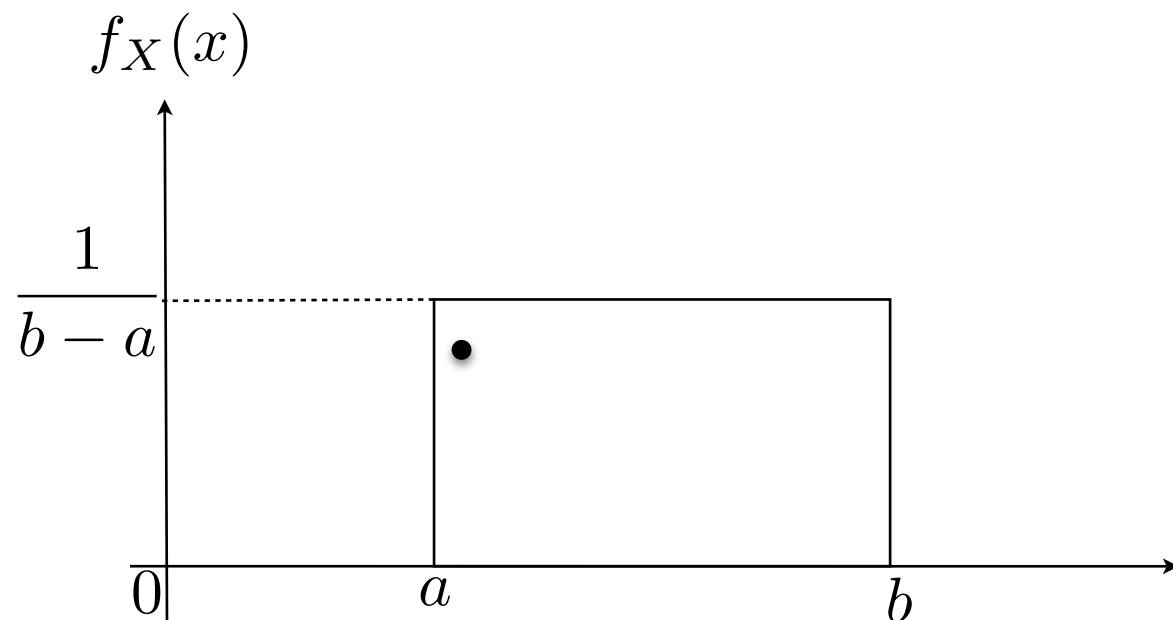
Uniform Distribution and Density

■ PDF

$$f_X(x) = \begin{cases} \frac{1}{b-a}, & a \leq x \leq b \\ 0, & \text{elsewhere} \end{cases}$$

■ CDF

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



Uniform Random Samples in Matlab

- In matlab, “rand(N)” generates the N random samples distributed uniformly between zero and one.

- For example,

```
u=rand(10); % generates 10 uniformly distributed random samples
```

```
u = 0.8147 0.9058 0.1270 0.9134 0.6324 0.0975 0.2785 0.5469 0.9575 0.9649
```

- Binary random sample generation with probability of half for zero and one, respectively.

```
u=rand(1,1);
```

```
if (u<0.5)
```

```
    b=0;
```


Exponential Distribution and Density

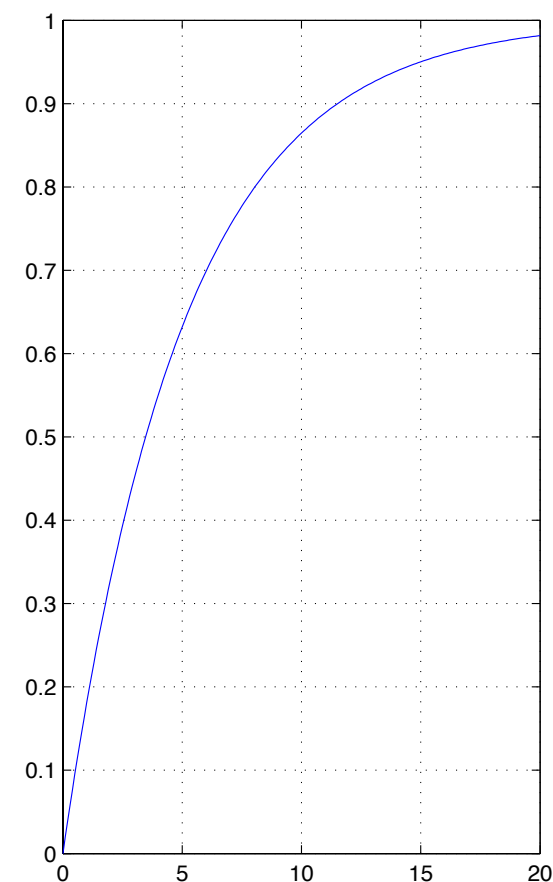
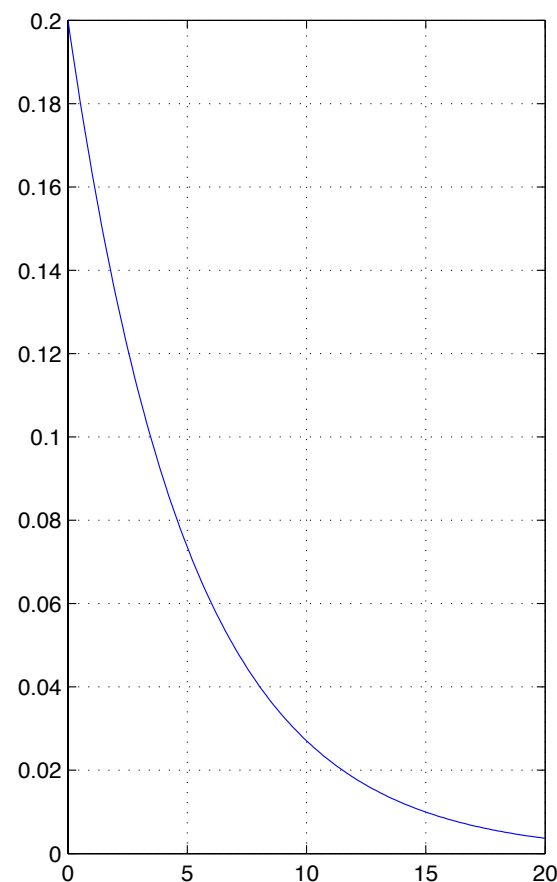
■ PDF

$$f_X(x) = \frac{1}{\lambda} e^{-\frac{x}{\lambda}} \quad \text{for } x \geq 0$$

■ CDF

$$F_X(x) = 1 - e^{-\frac{x}{\lambda}} \quad \text{for } x \geq 0$$

■ Example for $\lambda = 5$



Rayleigh Distribution and Density

■ PDF

$$f_X(x) = \frac{2}{\lambda} x e^{-\frac{x^2}{\lambda}} \quad \text{for } x \geq 0$$

■ CDF

$$F_X(x) = 1 - e^{-\frac{x^2}{\lambda}} \quad \text{for } x \geq 0$$

■ Example for $\lambda = 5$

