

# ECEN 303: Random Signals and Systems

## Chapter 4: Conditional Probability

# References

- Chapter 4, Class Notes
- D. Bertsekas and J. Tsitsiklis, *Introduction to Probability*, Chapter 1.3-1.5
- M. Harchol-Balter, *Introduction to Probability for Computing*, Chapter
- S. Ross, *A First Course in Probability*, Chapter 3

# Conditional Probability

- Two successive rolls of a die:

# Conditional Probability

- Two successive rolls of a die:
  - ▶ What is the probability that the first roll is 6?

# Conditional Probability

- Two successive rolls of a die:
  - ▶ What is the probability that the first roll is 6?
  - ▶ ... given that the sum of the rolls is 9

# Conditional Probability

- Two successive rolls of a die:
  - ▶ What is the probability that the first roll is 6?
  - ▶ ... given that the sum of the rolls is 9
- Word guessing game:

# Conditional Probability

- Two successive rolls of a die:
  - ▶ What is the probability that the first roll is 6?
  - ▶ ... given that the sum of the rolls is 9
- Word guessing game:
  - ▶ What is the probability that the second letter is 'h'?

# Conditional Probability

- Two successive rolls of a die:
  - ▶ What is the probability that the first roll is 6?
  - ▶ ... given that the sum of the rolls is 9
- Word guessing game:
  - ▶ What is the probability that the second letter is 'h'?
  - ▶ ... given that the first letter is 't'?



# Conditional Probability

- Two successive rolls of a die:
  - ▶ What is the probability that the first roll is 6?
  - ▶ ... given that the sum of the rolls is 9
- Word guessing game:
  - ▶ What is the probability that the second letter is 'h'?
  - ▶ ... given that the first letter is 't'?
- Medical diagnosis:

# Conditional Probability

- Two successive rolls of a die:
  - ▶ What is the probability that the first roll is 6?
  - ▶ ... given that the sum of the rolls is 9
- Word guessing game:
  - ▶ What is the probability that the second letter is 'h'?
  - ▶ ... given that the first letter is 't'?
- Medical diagnosis:
  - ▶ What is the probability that a person has a certain disease?

# Conditional Probability

- Two successive rolls of a die:
  - ▶ What is the probability that the first roll is 6?
  - ▶ ... given that the sum of the rolls is 9
- Word guessing game:
  - ▶ What is the probability that the second letter is 'h'?
  - ▶ ... given that the first letter is 't'?
- Medical diagnosis:
  - ▶ What is the probability that a person has a certain disease?
  - ▶ ... given that the medical test is positive?

# Conditional Probability

- Two successive rolls of a die:
  - ▶ What is the probability that the first roll is 6?
  - ▶ ... given that the sum of the rolls is 9
- Word guessing game:
  - ▶ What is the probability that the second letter is 'h'?
  - ▶ ... given that the first letter is 't'?
- Medical diagnosis:
  - ▶ What is the probability that a person has a certain disease?
  - ▶ ... given that the medical test is positive?
  - ▶ ... given that the medical test is negative?

# Conditional Probability

- Conditional probability provides a way to compute the probability of an event based on partial information

# Conditional Probability

- Conditional probability provides a way to compute the probability of an event based on partial information
- Suppose that we know that the outcome is within some given event  $B$ . We wish to quantify the probability that the outcome also belongs to some other event  $A$  given event  $B$

# Conditional Probability

- Conditional probability provides a way to compute the probability of an event based on partial information
- Suppose that we know that the outcome is within some given event  $B$ . We wish to quantify the probability that the outcome also belongs to some other event  $A$  given event  $B$
- Conditional probability of  $A$  given  $B$ , denoted as  $P(A|B)$

# Conditional Probability

- Consider the experiment of rolling a fair die. We want to compute

$$P(\text{outcome is 5} \mid \text{outcome is odd})$$



# Conditional Probability

- Consider the experiment of rolling a fair die. We want to compute

$$P(\text{outcome is 5} \mid \text{outcome is odd})$$

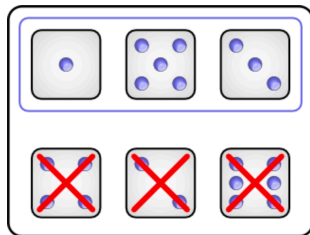
- $\Omega = \{1, 2, \dots, 6\}$ ,  $A = \{5\}$ ,  $B = \{1, 3, 5\}$ . We want to compute  $P(A|B)$

# Conditional Probability

- Consider the experiment of rolling a fair die. We want to compute

$$P(\text{outcome is 5} \mid \text{outcome is odd})$$

- $\Omega = \{1, 2, \dots, 6\}$ ,  $A = \{5\}$ ,  $B = \{1, 3, 5\}$ . We want to compute  $P(A|B)$

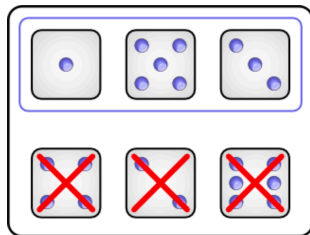


# Conditional Probability

- Consider the experiment of rolling a fair die. We want to compute

$$P(\text{outcome is 5} \mid \text{outcome is odd})$$

- $\Omega = \{1, 2, \dots, 6\}$ ,  $A = \{5\}$ ,  $B = \{1, 3, 5\}$ . We want to compute  $P(A|B)$



- In this example,

$$P(A|B) = \frac{\text{number of elements in } A \cap B}{\text{number of elements in } B}$$

# Conditional Probability

For any events  $A, B$

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

# Conditional Probability: Examples

- We toss a fair coin three successive times. We wish to find the conditional probability  $P(A|B)$  when  $A$  and  $B$  are the events  
 $A = \{\text{more heads than tails come up}\}$ ,  $B = \{\text{1st toss is a head}\}$ .

# Conditional Probability: Examples

- We toss a fair coin three successive times. We wish to find the conditional probability  $P(A|B)$  when  $A$  and  $B$  are the events  
 $A = \{\text{more heads than tails come up}\}$ ,  $B = \{\text{1st toss is a head}\}$ .

$$B = \{HHH, HHT, HTH, HTT\},$$
$$A \cap B = \{HHH, HHT, HTH\}$$

# Conditional Probability: Examples

- We toss a fair coin three successive times. We wish to find the conditional probability  $P(A|B)$  when  $A$  and  $B$  are the events  
 $A = \{\text{more heads than tails come up}\}$ ,  $B = \{\text{1st toss is a head}\}$ .

$$B = \{HHH, HHT, HTH, HTT\},$$
$$A \cap B = \{HHH, HHT, HTH\}$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{3/8}{4/8} = \frac{3}{4}$$

# Conditional Probability: Examples

- A fair coin is flipped twice. What is the conditional probability that both flips land on heads, given that *the first flip lands on heads*?



# Conditional Probability: Examples

- A fair coin is flipped twice. What is the conditional probability that both flips land on heads, given that *the first flip lands on heads*?

$$A = \{\text{both flips land on heads}\} = \{HH\}$$

# Conditional Probability: Examples

- A fair coin is flipped twice. What is the conditional probability that both flips land on heads, given that *the first flip lands on heads*?

$$A = \{\text{both flips land on heads}\} = \{HH\}$$

$$B = \{\text{first flip lands on heads}\} = \{HT, HH\}$$

# Conditional Probability: Examples

- A fair coin is flipped twice. What is the conditional probability that both flips land on heads, given that *the first flip lands on heads*?

$$A = \{\text{both flips land on heads}\} = \{HH\}$$

$$B = \{\text{first flip lands on heads}\} = \{HT, HH\}$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{1/4}{2/4} = \frac{1}{2}$$

# Conditional Probability: Examples

- A fair coin is flipped twice. What is the conditional probability that both flips land on heads, *given that at least one flip lands on heads*?

# Conditional Probability: Examples

- A fair coin is flipped twice. What is the conditional probability that both flips land on heads, *given that at least one flip lands on heads*?

$$A = \{\text{both flips land on heads}\} = \{HH\}$$

# Conditional Probability: Examples

- A fair coin is flipped twice. What is the conditional probability that both flips land on heads, *given that at least one flip lands on heads*?

$$A = \{\text{both flips land on heads}\} = \{HH\}$$

$$B = \{\text{at least one flips land on heads}\} = \{HT, TH, HH\}$$

# Conditional Probability: Examples

- A fair coin is flipped twice. What is the conditional probability that both flips land on heads, *given that at least one flip lands on heads*?

$$A = \{\text{both flips land on heads}\} = \{HH\}$$

$$B = \{\text{at least one flips land on heads}\} = \{HT, TH, HH\}$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{1/4}{3/4} = \frac{1}{3}$$

# Conditional Probabilities Specify a Probability Law

- Conditional probability law  $P(\cdot|B)$  satisfies all three axioms for any given event  $B$



# Conditional Probabilities Specify a Probability Law

- Conditional probability law  $P(\cdot|B)$  satisfies all three axioms for any given event  $B$ 
  - 1 (Nonnegativity)

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \geq 0$$

# Conditional Probabilities Specify a Probability Law

- Conditional probability law  $P(\cdot|B)$  satisfies all three axioms for any given event  $B$

① (Nonnegativity)

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \geq 0$$

② (Normalization)

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

# Conditional Probabilities Specify a Probability Law

- Conditional probability law  $P(\cdot|B)$  satisfies all three axioms for any given event  $B$

① (Nonnegativity)

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \geq 0$$

② (Normalization)

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

③ (Countable Additivity) Consider disjoint sets  $A_1$  and  $A_2$ . then  $A_1 \cap B$  and  $A_2 \cap B$  are disjoint. Now,

# Conditional Probabilities Specify a Probability Law

- Conditional probability law  $P(\cdot|B)$  satisfies all three axioms for any given event  $B$

❶ (Nonnegativity)

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \geq 0$$

❷ (Normalization)

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

❸ (Countable Additivity) Consider disjoint sets  $A_1$  and  $A_2$ . then  $A_1 \cap B$  and  $A_2 \cap B$  are disjoint. Now,

$$\begin{aligned} P(A_1 \cup A_2|B) &= \frac{P((A_1 \cup A_2) \cap B)}{P(B)} = \frac{P((A_1 \cap B) \cup (A_2 \cap B))}{P(B)} \\ &= \frac{P(A_1 \cap B) + P(A_2 \cap B)}{P(B)} = \frac{P(A_1 \cap B)}{P(B)} + \frac{P(A_2 \cap B)}{P(B)} \end{aligned}$$

# Conditional Probability: Examples

- A conservative design team, call it C, and an innovative design team, call it N, are asked to separately design a new product within a month. From past experience we know that:
  - ▶ The probability that team C is successful is  $2/3$
  - ▶ The probability that team N is successful is  $1/2$
  - ▶ The probability that at least one team is successful is  $3/4$

Assuming that exactly one successful design is produced, what is the probability that it was designed by team N?

# Conditional Probability: Examples

There are four possible outcomes here, corresponding to the four combinations of success and failure of the two teams:

$SS$  : both succeed,

$SF$  : C succeeds, N fails,

$FF$  : both fail,

$FS$  : C fails, N succeeds.

## Conditional Probability: Examples

There are four possible outcomes here, corresponding to the four combinations of success and failure of the two teams:

$SS$  : both succeed,

$FF$  : both fail,

$SF$  : C succeeds, N fails,

$FS$  : C fails, N succeeds.

We are given that the probabilities of these outcomes satisfy

$$P(SS) + P(SF) = \frac{2}{3}, P(SS) + P(FS) = \frac{1}{2}, P(SS) + P(SF) + P(FS) = \frac{3}{4}.$$

## Conditional Probability: Examples

There are four possible outcomes here, corresponding to the four combinations of success and failure of the two teams:

$SS$  : both succeed,

$FF$  : both fail,

$SF$  : C succeeds, N fails,

$FS$  : C fails, N succeeds.

We are given that the probabilities of these outcomes satisfy

$$P(SS) + P(SF) = \frac{2}{3}, P(SS) + P(FS) = \frac{1}{2}, P(SS) + P(SF) + P(FS) = \frac{3}{4}.$$

From these relations, together with the normalization equation

$P(SS) + P(SF) + P(FS) + P(FF) = 1$ , we can obtain the probabilities of all the outcomes:

$$P(SS) = \frac{5}{12}, P(SF) = \frac{1}{4}, P(FS) = \frac{1}{12}, P(FF) = \frac{1}{4}.$$



## Conditional Probability: Examples

There are four possible outcomes here, corresponding to the four combinations of success and failure of the two teams:

$SS$  : both succeed,

$FF$  : both fail,

$SF$  : C succeeds, N fails,

$FS$  : C fails, N succeeds.

We are given that the probabilities of these outcomes satisfy

$$P(SS) + P(SF) = \frac{2}{3}, P(SS) + P(FS) = \frac{1}{2}, P(SS) + P(SF) + P(FS) = \frac{3}{4}.$$

From these relations, together with the normalization equation

$P(SS) + P(SF) + P(FS) + P(FF) = 1$ , we can obtain the probabilities of all the outcomes:

$$P(SS) = \frac{5}{12}, P(SF) = \frac{1}{4}, P(FS) = \frac{1}{12}, P(FF) = \frac{1}{4}.$$

The desired conditional probability is

$$P(\{FS\}|\{SF, FS\}) = \frac{P(\{FS\})}{P(\{SF, FS\})} = \frac{\frac{1}{12}}{\frac{1}{4} + \frac{1}{12}}$$

# Chain Rule of Probability

# Chain Rule of Probability

Let  $A_1$  and  $A_2$  be any two events. Then,

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

# Chain Rule of Probability

Let  $A_1$  and  $A_2$  be any two events. Then,

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

Let  $A_1, A_2, \dots, A_n$  be a collection of events. Then,

$$P\left(\bigcap_{k=1}^n A_k\right) = P(A_1)P(A_2|A_1)P(A_3|A_1 \cap A_2) \cdots P\left(A_n \middle| \bigcap_{k=1}^{n-1} A_k\right).$$

# Chain Rule of Probability

- An urn contains eight blue balls and four green balls. Three balls are drawn from this urn without replacement. We wish to compute the probability that all three balls are blue.

# Chain Rule of Probability

- An urn contains eight blue balls and four green balls. Three balls are drawn from this urn without replacement. We wish to compute the probability that all three balls are blue.

We can compute the answer through combinatorial approach as

## Chain Rule of Probability

- An urn contains eight blue balls and four green balls. Three balls are drawn from this urn without replacement. We wish to compute the probability that all three balls are blue.

We can compute the answer through combinatorial approach as

$$\frac{\binom{8}{3}}{\binom{12}{3}} = \frac{8!}{3!5!} \frac{3!9!}{12!} = \frac{8 \cdot 7 \cdot 6}{12 \cdot 11 \cdot 10}$$

## Chain Rule of Probability

- An urn contains eight blue balls and four green balls. Three balls are drawn from this urn without replacement. We wish to compute the probability that all three balls are blue.

We can compute the answer through combinatorial approach as

$$\frac{\binom{8}{3}}{\binom{12}{3}} = \frac{8!}{3!5!} \frac{3!9!}{12!} = \frac{8 \cdot 7 \cdot 6}{12 \cdot 11 \cdot 10}$$

We can also compute this using the chain rule. Let  $B_i$  be the event of getting a blue ball at  $i$ th draw.



## Chain Rule of Probability

- An urn contains eight blue balls and four green balls. Three balls are drawn from this urn without replacement. We wish to compute the probability that all three balls are blue.

We can compute the answer through combinatorial approach as

$$\frac{\binom{8}{3}}{\binom{12}{3}} = \frac{8!}{3!5!} \frac{3!9!}{12!} = \frac{8 \cdot 7 \cdot 6}{12 \cdot 11 \cdot 10}$$

We can also compute this using the chain rule. Let  $B_i$  be the event of getting a blue ball at  $i$ th draw. We can easily infer the following

$$P(B_1) = \frac{8}{12}, \quad P(B_2|B_1) = \frac{7}{11}, \quad P(B_3|B_1 \cap B_2) = \frac{6}{10}$$

## Chain Rule of Probability

- An urn contains eight blue balls and four green balls. Three balls are drawn from this urn without replacement. We wish to compute the probability that all three balls are blue.

We can compute the answer through combinatorial approach as

$$\frac{\binom{8}{3}}{\binom{12}{3}} = \frac{8!}{3!5!} \frac{3!4!}{12!} = \frac{8 \cdot 7 \cdot 6}{12 \cdot 11 \cdot 10}$$

We can also compute this using the chain rule. Let  $B_i$  be the event of getting a blue ball at  $i$ th draw. We can easily infer the following

$$P(B_1) = \frac{8}{12}, \quad P(B_2|B_1) = \frac{7}{11}, \quad P(B_3|B_1 \cap B_2) = \frac{6}{10}$$

Then, the probability of getting three blue balls is

$$P(\cap_{i=1}^3 B_i) = P(B_1)P(B_2|B_1)P(B_3|B_1 \cap B_2) = \frac{8}{12} \cdot \frac{7}{11} \cdot \frac{6}{10}$$

# Conditional Probability: Examples

- If an aircraft is present in a certain area, a radar correctly registers its presence with probability 0.99. If it is not present, the radar falsely registers an aircraft presence with probability 0.10. We assume that an aircraft is present with probability 0.05. What is the probability of false alarm (a false indication of aircraft presence), and the probability of missed detection (nothing registers, even though an aircraft is present)?

# Conditional Probability: Examples

- If an aircraft is present in a certain area, a radar correctly registers its presence with probability 0.99. If it is not present, the radar falsely registers an aircraft presence with probability 0.10. We assume that an aircraft is present with probability 0.05. What is the probability of false alarm (a false indication of aircraft presence), and the probability of missed detection (nothing registers, even though an aircraft is present)?

Consider the events

$A = \{\text{aircraft is present}\},$

$B = \{\text{radar registers an aircraft presence}\}$

$A^c = \{\text{aircraft is not present}\},$

$\bar{B} = \{\text{radar does not register an aircraft presence}\}$

# Conditional Probability: Examples

- If an aircraft is present in a certain area, a radar correctly registers its presence with probability 0.99. If it is not present, the radar falsely registers an aircraft presence with probability 0.10. We assume that an aircraft is present with probability 0.05. What is the probability of false alarm (a false indication of aircraft presence), and the probability of missed detection (nothing registers, even though an aircraft is present)?

Consider the events

$A = \{\text{aircraft is present}\},$

$B = \{\text{radar registers an aircraft presence}\}$

$A^c = \{\text{aircraft is not present}\},$

$B^c = \{\text{radar does not register an aircraft presence}\}$

We have

$$P(B|A) = 0.99 \quad P(B|A^c) = 0.1, P(A) = 0.05, P(A^c) = 0.95.$$

## Conditional Probability: Examples

- If an aircraft is present in a certain area, a radar correctly registers its presence with probability 0.99. If it is not present, the radar falsely registers an aircraft presence with probability 0.10. We assume that an aircraft is present with probability 0.05. What is the probability of false alarm (a false indication of aircraft presence), and the probability of missed detection (nothing registers, even though an aircraft is present)?

Consider the events

$A = \{\text{aircraft is present}\},$

$B = \{\text{radar registers an aircraft presence}\}$

$A^c = \{\text{aircraft is not present}\},$

$B^c = \{\text{radar does not register an aircraft presence}\}$

We have

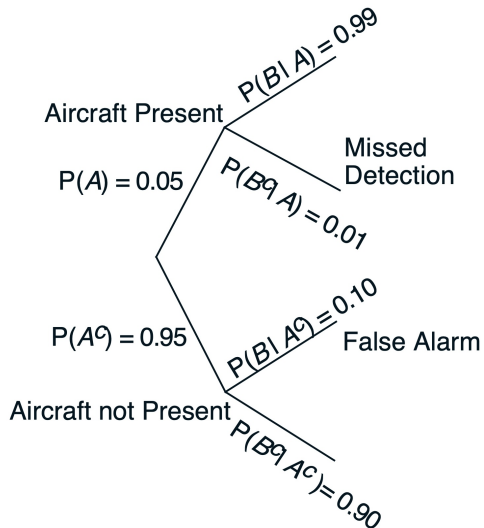
$$P(B|A) = 0.99 \quad P(B|A^c) = 0.1, P(A) = 0.05, P(A^c) = 0.95.$$

Now, we can compute

$$\begin{aligned} P(\text{false alarm}) &= P(A^c \cap B) = P(A^c)P(B|A^c) = 0.95 \cdot 0.1 = 0.095, \\ P(\text{missed detection}) &= P(A \cap B^c) = P(A)P(B^c|A) = 0.05 \cdot 0.01 = 0.0005. \end{aligned}$$

# Conditional Probability: Examples

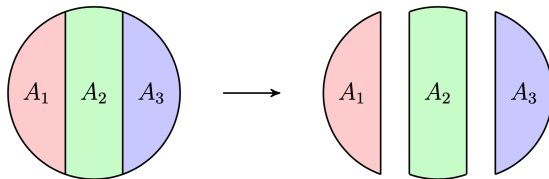
# Conditional Probability: Examples





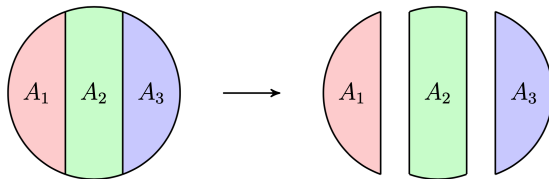
# Total Probability Theorem

- Consider the set  $A$  and its partition  $A_1, A_2, A_3$ 
  - Since  $A_i$ s are disjoint and  $A = \cup_{i=1}^3 A_i$ , we get  $P(A) = \sum_{i=1}^3 P(A_i)$

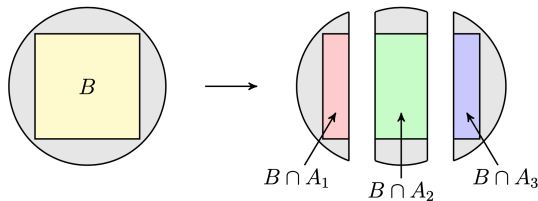


# Total Probability Theorem

- Consider the set  $A$  and its partition  $A_1, A_2, A_3$ 
  - Since  $A_i$ s are disjoint and  $A = \cup_{i=1}^3 A_i$ , we get  $P(A) = \sum_{i=1}^3 P(A_i)$

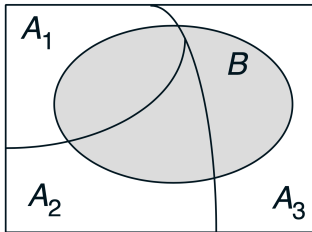


- Now consider the set  $B \subset A$  and its partitions  $B_1, B_2, B_3$ , where  $B_i = B \cap A_i$



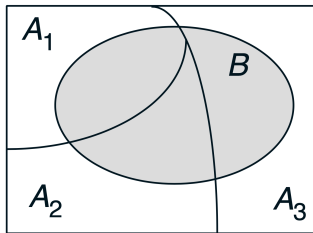
# Total Probability Theorem

- Another visualization is as



# Total Probability Theorem

- Another visualization is as

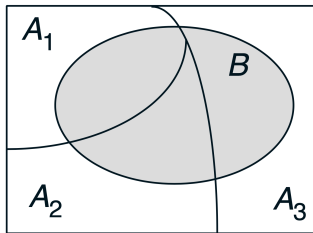


- From the previous figures, it is easy to see that

$$P(B) = \sum_{i=1}^3 P(B_i) = \sum_{i=1}^3 P(B \cap A_i) = \sum_{i=1}^3 P(B|A_i)P(A_i)$$

# Total Probability Theorem

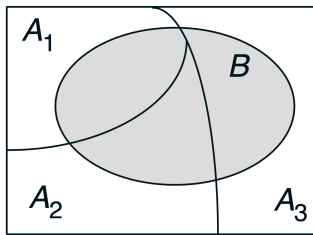
- Another visualization is as



- From the previous figures, it is easy to see that

$$P(B) = \sum_{i=1}^3 P(B_i) = \sum_{i=1}^3 P(B \cap A_i) = \sum_{i=1}^3 P(B|A_i)P(A_i)$$

# Total Probability Theorem



## Total Probability Theorem

Let  $A_1, A_2, \dots, A_n$  be a collection of events that forms a partition of the sample space  $\Omega$ . Suppose that  $P(A_k) > 0$  for all  $k$ . Then, for any event  $B$ , we can write

$$\begin{aligned} P(B) &= P(A_1 \cap B) + P(A_2 \cap B) + \dots + P(A_n \cap B) \\ &= P(A_1)P(B|A_1) + P(A_2)P(B|A_2) + \dots + P(A_n)P(B|A_n). \end{aligned}$$

# Total Probability Theorem

**Proof:** The collection of events  $A_1, A_2, \dots, A_n$  forms a partition of the sample space  $\Omega$ . We can therefore write

$$B = B \cap \Omega = B \cap \left( \bigcup_{k=1}^n A_k \right).$$

# Total Probability Theorem

**Proof:** The collection of events  $A_1, A_2, \dots, A_n$  forms a partition of the sample space  $\Omega$ . We can therefore write

$$B = B \cap \Omega = B \cap \left( \bigcup_{k=1}^n A_k \right).$$

Since  $A_1, A_2, \dots, A_n$  are disjoint sets, the events  $A_1 \cap B, A_2 \cap B, \dots, A_n \cap B$  are also disjoint.



# Total Probability Theorem

**Proof:** The collection of events  $A_1, A_2, \dots, A_n$  forms a partition of the sample space  $\Omega$ . We can therefore write

$$B = B \cap \Omega = B \cap \left( \bigcup_{k=1}^n A_k \right).$$

Since  $A_1, A_2, \dots, A_n$  are disjoint sets, the events  $A_1 \cap B, A_2 \cap B, \dots, A_n \cap B$  are also disjoint. Combining these two facts, we get

$$\begin{aligned} P(B) &= P \left( B \cap \left( \bigcup_{k=1}^n A_k \right) \right) = P \left( \bigcup_{k=1}^n (B \cap A_k) \right) \\ &= \sum_{k=1}^n P(B \cap A_k) = \sum_{k=1}^n P(A_k) P(B|A_k), \end{aligned}$$

where the fourth equality follows from the third axiom of probability. □

## Total Probability Theorem: Examples

- An urn contains five green balls and three red balls. A second urn contains three green balls and nine red balls. One of the two urns is picked at random, with equal probabilities, and a ball is drawn from the selected urn. We wish to compute the probability of obtaining a green ball.

## Total Probability Theorem: Examples

- An urn contains five green balls and three red balls. A second urn contains three green balls and nine red balls. One of the two urns is picked at random, with equal probabilities, and a ball is drawn from the selected urn. We wish to compute the probability of obtaining a green ball.

Let  $U_i$  be the event of choosing urn  $i$ .

Also, let  $G$  be the event of getting a green ball.

# Total Probability Theorem: Examples

- An urn contains five green balls and three red balls. A second urn contains three green balls and nine red balls. One of the two urns is picked at random, with equal probabilities, and a ball is drawn from the selected urn. We wish to compute the probability of obtaining a green ball.

Let  $U_i$  be the event of choosing urn  $i$ .

Also, let  $G$  be the event of getting a green ball.

We can observe that

$$P(G|U_1) = \frac{5}{8}, \quad P(G|U_2) = \frac{3}{12}, \quad P(U_i) = \frac{1}{2}, i = 1, 2$$

## Total Probability Theorem: Examples

- An urn contains five green balls and three red balls. A second urn contains three green balls and nine red balls. One of the two urns is picked at random, with equal probabilities, and a ball is drawn from the selected urn. We wish to compute the probability of obtaining a green ball.

Let  $U_i$  be the event of choosing urn  $i$ .

Also, let  $G$  be the event of getting a green ball.

We can observe that

$$P(G|U_1) = \frac{5}{8}, \quad P(G|U_2) = \frac{3}{12}, \quad P(U_i) = \frac{1}{2}, i = 1, 2$$

Using this, we can compute

$$\begin{aligned} P(G) &= P(G \cap U_1) + P(G \cap U_2) \\ &= P(G|U_1)P(U_1) + P(G|U_2)P(U_2) \\ &= \frac{5}{8} \frac{1}{2} + \frac{3}{12} \frac{1}{2} = \frac{7}{16} \end{aligned}$$

# Total Probability Theorem: Examples

- Alice is taking a probability class and at the end of each week she can be either up-to-date or she may have fallen behind. If she is up-to-date in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.8 (or 0.2, respectively). If she is behind in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.4 (or 0.6, respectively). Alice is (by default) up-to-date when she starts the class. What is the probability that she is up-to-date after three weeks?

# Total Probability Theorem: Examples

- Alice is taking a probability class and at the end of each week she can be either up-to-date or she may have fallen behind. If she is up-to-date in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.8 (or 0.2, respectively). If she is behind in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.4 (or 0.6, respectively). Alice is (by default) up-to-date when she starts the class. What is the probability that she is up-to-date after three weeks?

Let  $U_i$  and  $B_i$  be the events that Alice is up-to-date or behind, respectively, after  $i$  weeks.

# Total Probability Theorem: Examples

- Alice is taking a probability class and at the end of each week she can be either up-to-date or she may have fallen behind. If she is up-to-date in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.8 (or 0.2, respectively). If she is behind in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.4 (or 0.6, respectively). Alice is (by default) up-to-date when she starts the class. What is the probability that she is up-to-date after three weeks?

Let  $U_i$  and  $B_i$  be the events that Alice is up-to-date or behind, respectively, after  $i$  weeks.

$$P(U_3) = P(U_3|U_2)P(U_2) + P(U_3|B_2)P(B_2) = 0.8P(U_2) + 0.4P(B_2)$$



# Total Probability Theorem: Examples

- Alice is taking a probability class and at the end of each week she can be either up-to-date or she may have fallen behind. If she is up-to-date in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.8 (or 0.2, respectively). If she is behind in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.4 (or 0.6, respectively). Alice is (by default) up-to-date when she starts the class. What is the probability that she is up-to-date after three weeks?

Let  $U_i$  and  $B_i$  be the events that Alice is up-to-date or behind, respectively, after  $i$  weeks.

$$P(U_3) = P(U_3|U_2)P(U_2) + P(U_3|B_2)P(B_2) = 0.8P(U_2) + 0.4P(B_2)$$

$$P(U_2) = P(U_2|U_1)P(U_1) + P(U_2|B_1)P(B_1) = 0.8P(U_1) + 0.4P(B_1)$$

# Total Probability Theorem: Examples

- Alice is taking a probability class and at the end of each week she can be either up-to-date or she may have fallen behind. If she is up-to-date in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.8 (or 0.2, respectively). If she is behind in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.4 (or 0.6, respectively). Alice is (by default) up-to-date when she starts the class. What is the probability that she is up-to-date after three weeks?

Let  $U_i$  and  $B_i$  be the events that Alice is up-to-date or behind, respectively, after  $i$  weeks.

$$P(U_3) = P(U_3|U_2)P(U_2) + P(U_3|B_2)P(B_2) = 0.8P(U_2) + 0.4P(B_2)$$

$$P(U_2) = P(U_2|U_1)P(U_1) + P(U_2|B_1)P(B_1) = 0.8P(U_1) + 0.4P(B_1)$$

Since Alice starts her class up-to-date, we have  $P(U_1) = 0.8$ ,  $P(B_1) = 0.2$

# Total Probability Theorem: Examples

- Alice is taking a probability class and at the end of each week she can be either up-to-date or she may have fallen behind. If she is up-to-date in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.8 (or 0.2, respectively). If she is behind in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.4 (or 0.6, respectively). Alice is (by default) up-to-date when she starts the class. What is the probability that she is up-to-date after three weeks?

Let  $U_i$  and  $B_i$  be the events that Alice is up-to-date or behind, respectively, after  $i$  weeks.

$$P(U_3) = P(U_3|U_2)P(U_2) + P(U_3|B_2)P(B_2) = 0.8P(U_2) + 0.4P(B_2)$$

$$P(U_2) = P(U_2|U_1)P(U_1) + P(U_2|B_1)P(B_1) = 0.8P(U_1) + 0.4P(B_1)$$

Since Alice starts her class up-to-date, we have  $P(U_1) = 0.8$ ,  $P(B_1) = 0.2$

From this, we can compute  $P(U_2) = 0.72$ ,  $P(B_2) = 0.28$ .

# Total Probability Theorem: Examples

- Alice is taking a probability class and at the end of each week she can be either up-to-date or she may have fallen behind. If she is up-to-date in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.8 (or 0.2, respectively). If she is behind in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.4 (or 0.6, respectively). Alice is (by default) up-to-date when she starts the class. What is the probability that she is up-to-date after three weeks?

Let  $U_i$  and  $B_i$  be the events that Alice is up-to-date or behind, respectively, after  $i$  weeks.

$$P(U_3) = P(U_3|U_2)P(U_2) + P(U_3|B_2)P(B_2) = 0.8P(U_2) + 0.4P(B_2)$$

$$P(U_2) = P(U_2|U_1)P(U_1) + P(U_2|B_1)P(B_1) = 0.8P(U_1) + 0.4P(B_1)$$

Since Alice starts her class up-to-date, we have  $P(U_1) = 0.8$ ,  $P(B_1) = 0.2$

From this , we can compute  $P(U_2) = 0.72$ ,  $P(B_2) = 0.28$ .

From this , we can compute  $P(U_3) = 0.688$ ,  $P(B_3) = 0.312$

# Independence

- Conditional probability  $P(A|B)$  can be intuitively interpreted as the partial information that event B provides about event A.

# Independence

- Conditional probability  $P(A|B)$  can be intuitively interpreted as the partial information that event B provides about event A.
- Sometimes, the occurrence of B provides no information and does not alter the probability that A, i.e,  $P(A|B) = P(A)$

# Independence

- Conditional probability  $P(A|B)$  can be intuitively interpreted as the partial information that event  $B$  provides about event  $A$ .
- Sometimes, the occurrence of  $B$  provides no information and does not alter the probability that  $A$ , i.e,  $P(A|B) = P(A)$ 
  - ▶ We then say that  $A$  is **independent** of  $B$

# Independence

- Conditional probability  $P(A|B)$  can be intuitively interpreted as the partial information that event B provides about event A.
- Sometimes, the occurrence of B provides no information and does not alter the probability that A, i.e,  $P(A|B) = P(A)$ 
  - ▶ We then say that  $A$  is **independent** of  $B$

Two events are **independent** if

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



# Independence: Example

- Suppose that two dice are rolled at the same time, a red die and a blue die. We observe the numbers that appear on the upper faces of the two dice. The sample space for this experiment is composed of thirty-six equally likely outcomes. Verify if the following events are independent:
  - ▶ Getting a four on the red die and six on the blue die.

## Independence: Example

- Suppose that two dice are rolled at the same time, a red die and a blue die. We observe the numbers that appear on the upper faces of the two dice. The sample space for this experiment is composed of thirty-six equally likely outcomes. Verify if the following events are independent:
  - ▶ Getting a four on the red die and six on the blue die.

The probability of getting a four on the red die given that the blue die shows a six,

$$P(\{R = 4\} \cap \{B = 6\}) = \frac{1}{36}, \quad P(\{R = 4\}) = \frac{6}{36} \quad P(\{B = 6\}) = \frac{6}{36}$$

## Independence: Example

- Suppose that two dice are rolled at the same time, a red die and a blue die. We observe the numbers that appear on the upper faces of the two dice. The sample space for this experiment is composed of thirty-six equally likely outcomes. Verify if the following events are independent:
  - ▶ Getting a four on the red die and six on the blue die.

The probability of getting a four on the red die given that the blue die shows a six,

$$P(\{R = 4\} \cap \{B = 6\}) = \frac{1}{36}, \quad P(\{R = 4\}) = \frac{6}{36} \quad P(\{B = 6\}) = \frac{6}{36}$$

So,  $P(\{R = 4\} \cap \{B = 6\}) = P(\{R = 4\}) \cdot P(\{B = 6\})$

## Independence: Example

- Suppose that two dice are rolled at the same time, a red die and a blue die. We observe the numbers that appear on the upper faces of the two dice. The sample space for this experiment is composed of thirty-six equally likely outcomes. Verify if the following events are independent:
  - ▶ Getting a four on the red die and six on the blue die.

The probability of getting a four on the red die given that the blue die shows a six,

$$P(\{R = 4\} \cap \{B = 6\}) = \frac{1}{36}, \quad P(\{R = 4\}) = \frac{6}{36} \quad P(\{B = 6\}) = \frac{6}{36}$$

So,  $P(\{R = 4\} \cap \{B = 6\}) = P(\{R = 4\}) \cdot P(\{B = 6\})$

- ▶ Getting a four on the red die and getting the sum of the two dice is eleven

## Independence: Example

- Suppose that two dice are rolled at the same time, a red die and a blue die. We observe the numbers that appear on the upper faces of the two dice. The sample space for this experiment is composed of thirty-six equally likely outcomes. Verify if the following events are independent:

- ▶ Getting a four on the red die and six on the blue die.

The probability of getting a four on the red die given that the blue die shows a six,

$$P(\{R = 4\} \cap \{B = 6\}) = \frac{1}{36}, \quad P(\{R = 4\}) = \frac{6}{36} \quad P(\{B = 6\}) = \frac{6}{36}$$

So,  $P(\{R = 4\} \cap \{B = 6\}) = P(\{R = 4\}) \cdot P(\{B = 6\})$

- ▶ Getting a four on the red die and getting the sum of the two dice is eleven

$$P(\{R = 4\} \cap \{R + B = 11\}) = 0, \quad P(\{R = 4\}) = \frac{6}{36} \quad P(\{R + B = 11\}) = \frac{2}{36}$$

In this case, we conclude that getting a four on the red die and a sum total of eleven are not independent events.

## Independence: Example

- If events  $A$  and  $B$  are independent, then  $A^c$  and  $B^c$  are independent.

# Independence of Multiple Events

The events  $A_1, A_2, \dots, A_n$  are **independent** provided that

$$P\left(\bigcap_{i \in \mathbb{I}} A_i\right) = \prod_{i \in \mathbb{I}} P(A_i),$$

for every subset  $\mathbb{I}$  of  $\{1, 2, \dots, n\}$ .

# Independence of Multiple Events

The events  $A_1, A_2, \dots, A_n$  are **independent** provided that

$$P\left(\bigcap_{i \in \mathbb{I}} A_i\right) = \prod_{i \in \mathbb{I}} P(A_i),$$

for every subset  $\mathbb{I}$  of  $\{1, 2, \dots, n\}$ .

Consider a collection of three events,  $A$ ,  $B$  and  $C$ . These events are independent whenever



# Independence of Multiple Events

The events  $A_1, A_2, \dots, A_n$  are **independent** provided that

$$P\left(\bigcap_{i \in \mathbb{I}} A_i\right) = \prod_{i \in \mathbb{I}} P(A_i),$$

for every subset  $\mathbb{I}$  of  $\{1, 2, \dots, n\}$ .

Consider a collection of three events,  $A$ ,  $B$  and  $C$ . These events are independent whenever

$$P(A \cap B) = P(A)P(B), \quad P(A \cap C) = P(A)P(C), \quad P(B \cap C) = P(B)P(C) \quad (1)$$

and, in addition,

$$P(A \cap B \cap C) = P(A)P(B)P(C).$$

# Independence of Multiple Events

The events  $A_1, A_2, \dots, A_n$  are **independent** provided that

$$P\left(\bigcap_{i \in \mathbb{I}} A_i\right) = \prod_{i \in \mathbb{I}} P(A_i),$$

for every subset  $\mathbb{I}$  of  $\{1, 2, \dots, n\}$ .

Consider a collection of three events,  $A$ ,  $B$  and  $C$ . These events are independent whenever

$$P(A \cap B) = P(A)P(B), \quad P(A \cap C) = P(A)P(C), \quad P(B \cap C) = P(B)P(C) \quad (1)$$

and, in addition,

$$P(A \cap B \cap C) = P(A)P(B)P(C).$$

The three equalities in (1) assert that  $A$ ,  $B$  and  $C$  are **pairwise independent**.

# Independence of Multiple Events

The events  $A_1, A_2, \dots, A_n$  are **independent** provided that

$$P\left(\bigcap_{i \in \mathbb{I}} A_i\right) = \prod_{i \in \mathbb{I}} P(A_i),$$

for every subset  $\mathbb{I}$  of  $\{1, 2, \dots, n\}$ .

Consider a collection of three events,  $A$ ,  $B$  and  $C$ . These events are independent whenever

$$P(A \cap B) = P(A)P(B), \quad P(A \cap C) = P(A)P(C), \quad P(B \cap C) = P(B)P(C) \quad (1)$$

and, in addition,

$$P(A \cap B \cap C) = P(A)P(B)P(C).$$

The three equalities in (1) assert that  $A$ ,  $B$  and  $C$  are **pairwise independent**. Note that the fourth equation does not follow from the first three conditions, nor does it imply any of them.

# Independence of Multiple Events

The events  $A_1, A_2, \dots, A_n$  are **independent** provided that

$$P\left(\bigcap_{i \in \mathbb{I}} A_i\right) = \prod_{i \in \mathbb{I}} P(A_i),$$

for every subset  $\mathbb{I}$  of  $\{1, 2, \dots, n\}$ .

Consider a collection of three events,  $A$ ,  $B$  and  $C$ . These events are independent whenever

$$P(A \cap B) = P(A)P(B), \quad P(A \cap C) = P(A)P(C), \quad P(B \cap C) = P(B)P(C) \quad (1)$$

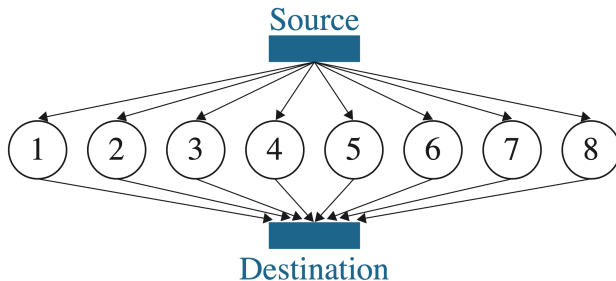
and, in addition,

$$P(A \cap B \cap C) = P(A)P(B)P(C).$$

The three equalities in (1) assert that  $A$ ,  $B$  and  $C$  are **pairwise independent**. Note that the fourth equation does not follow from the first three conditions, nor does it imply any of them. **Pairwise independence does not necessarily imply independence.**

## Independence: Example

- Suppose you are routing a packet from the source node to the destination node, as shown in the Figure below. On the plus side, there are 8 possible paths on which the packet can be routed. On the minus side, each of the 16 edges in the network independently only works with probability  $p$ . What is the probability that the transmitted packet will be received successfully at the destination?



# Independence: Example

Let  $E_i$  denote the event that the packet transmission through the  $i$ th two-hop paths is successful. What is  $P(E_i)$ ?

# Independence: Example

Let  $E_i$  denote the event that the packet transmission through the  $i$ th two-hop paths is successful. What is  $P(E_i)$ ?

$E_i = E_{i1} \cap E_{i2}$ , and  $E_{i1}$  and  $E_{i2}$  are independent.

# Independence: Example

Let  $E_i$  denote the event that the packet transmission through the  $i$ th two-hop paths is successful. What is  $P(E_i)$ ?

$E_i = E_{i1} \cap E_{i2}$ , and  $E_{i1}$  and  $E_{i2}$  are independent. Then,  $P(E_i) = P(E_{i1})P(E_{i2}) = p^2$



# Independence: Example

Let  $E_i$  denote the event that the packet transmission through the  $i$ th two-hop paths is successful. What is  $P(E_i)$ ?

$E_i = E_{i1} \cap E_{i2}$ , and  $E_{i1}$  and  $E_{i2}$  are independent. Then,  $P(E_i) = P(E_{i1})P(E_{i2}) = p^2$

Let  $E$  be the event that the transmitted packet is received successfully at the destination.

# Independence: Example

Let  $E_i$  denote the event that the packet transmission through the  $i$ th two-hop paths is successful. What is  $P(E_i)$ ?

$E_i = E_{i1} \cap E_{i2}$ , and  $E_{i1}$  and  $E_{i2}$  are independent. Then,  $P(E_i) = P(E_{i1})P(E_{i2}) = p^2$

Let  $E$  be the event that the transmitted packet is received successfully at the destination. So,  $E$  is the event that **at least one** of the eight paths works.

# Independence: Example

Let  $E_i$  denote the event that the packet transmission through the  $i$ th two-hop paths is successful. What is  $P(E_i)$ ?

$E_i = E_{i1} \cap E_{i2}$ , and  $E_{i1}$  and  $E_{i2}$  are independent. Then,  $P(E_i) = P(E_{i1})P(E_{i2}) = p^2$

Let  $E$  be the event that the transmitted packet is received successfully at the destination. So,  $E$  is the event that **at least one** of the eight paths works.

$$E = E_1 \cup E_2 \cup \dots \cup E_8.$$

## Independence: Example

Let  $E_i$  denote the event that the packet transmission through the  $i$ th two-hop paths is successful. What is  $P(E_i)$ ?

$E_i = E_{i1} \cap E_{i2}$ , and  $E_{i1}$  and  $E_{i2}$  are independent. Then,  $P(E_i) = P(E_{i1})P(E_{i2}) = p^2$

Let  $E$  be the event that the transmitted packet is received successfully at the destination. So,  $E$  is the event that **at least one** of the eight paths works.

$$E = E_1 \cup E_2 \cup \dots \cup E_8.$$

$$P(\text{at least one path works}) = 1 - P(\text{no (zero) path works}) = 1 - P(E^c)$$

## Independence: Example

Let  $E_i$  denote the event that the packet transmission through the  $i$ th two-hop paths is successful. What is  $P(E_i)$ ?

$E_i = E_{i1} \cap E_{i2}$ , and  $E_{i1}$  and  $E_{i2}$  are independent. Then,  $P(E_i) = P(E_{i1})P(E_{i2}) = p^2$

Let  $E$  be the event that the transmitted packet is received successfully at the destination. So,  $E$  is the event that **at least one** of the eight paths works.

$$E = E_1 \cup E_2 \cup \dots \cup E_8.$$

$$P(\text{at least one path works}) = 1 - P(\text{no (zero) path works}) = 1 - P(E^c)$$

$$P(E^c) = P(E_1^c \cap E_2^c \cap \dots \cap E_8^c) = P(E_1^c) \cdot P(E_2^c) \cdot \dots \cdot P(E_8^c) = (1 - p^2)^8$$

## Independence: Example

- A fair coin is flipped twice. Let  $A$  denote the event that heads is observed on the first toss. Let  $B$  be the event that heads is obtained on the second toss. Finally, let  $C$  be the event that the two coins show distinct sides. Verify if  $A, B, C$  are independent.

## Independence: Example

- A fair coin is flipped twice. Let  $A$  denote the event that heads is observed on the first toss. Let  $B$  be the event that heads is obtained on the second toss. Finally, let  $C$  be the event that the two coins show distinct sides. Verify if  $A, B, C$  are independent.

$$P(A) = P(B) = P(C) = \frac{1}{2}$$

## Independence: Example

- A fair coin is flipped twice. Let  $A$  denote the event that heads is observed on the first toss. Let  $B$  be the event that heads is obtained on the second toss. Finally, let  $C$  be the event that the two coins show distinct sides. Verify if  $A, B, C$  are independent.

$$P(A) = P(B) = P(C) = \frac{1}{2}$$

$$P(A \cap B) = P(A \cap C) = P(B \cap C) = \frac{1}{4}$$

and, therefore, these events are *pairwise independent*.



## Independence: Example

- A fair coin is flipped twice. Let  $A$  denote the event that heads is observed on the first toss. Let  $B$  be the event that heads is obtained on the second toss. Finally, let  $C$  be the event that the two coins show distinct sides. Verify if  $A, B, C$  are independent.

$$P(A) = P(B) = P(C) = \frac{1}{2}$$

$$P(A \cap B) = P(A \cap C) = P(B \cap C) = \frac{1}{4}$$

and, therefore, these events are *pairwise independent*. However, we can verify that

$$P(A \cap B \cap C) = 0 \neq \frac{1}{8} = P(A)P(B)P(C).$$

This shows that events  $A$ ,  $B$  and  $C$  are not independent.

# Conditional Independence

We say that events  $A_1$  and  $A_2$  are **conditionally independent**, given event  $B$ , if

$$P(A_1 \cap A_2 | B) = P(A_1 | B)P(A_2 | B).$$

# Conditional Independence

- By definition of conditional independence,

$$\begin{aligned}P(A_1 \cap A_2 | B) &= \frac{P(A_1 \cap A_2 \cap B)}{P(B)} = \frac{P(B)P(A_1|B)P(A_2|A_1 \cap B)}{P(B)} \\&= P(A_1|B)P(A_2|A_1 \cap B).\end{aligned}$$

# Conditional Independence

- By definition of conditional independence,

$$\begin{aligned}P(A_1 \cap A_2|B) &= \frac{P(A_1 \cap A_2 \cap B)}{P(B)} = \frac{P(B)P(A_1|B)P(A_2|A_1 \cap B)}{P(B)} \\&= P(A_1|B)P(A_2|A_1 \cap B).\end{aligned}$$

- If  $A_1$  and  $A_2$  are conditionally independent, given event  $B$ , then

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

# Conditional Independence

- By definition of conditional independence,

$$\begin{aligned}P(A_1 \cap A_2 | B) &= \frac{P(A_1 \cap A_2 \cap B)}{P(B)} = \frac{P(B)P(A_1|B)P(A_2|A_1 \cap B)}{P(B)} \\&= P(A_1|B)P(A_2|A_1 \cap B).\end{aligned}$$

- If  $A_1$  and  $A_2$  are conditionally independent, given event  $B$ , then

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

- Under the assumption that  $P(A_1|B) > 0$ , we then get

$$P(A_2|A_1 \cap B) = P(A_2|B).$$

# Conditional Independence

- By definition of conditional independence,

$$\begin{aligned}P(A_1 \cap A_2 | B) &= \frac{P(A_1 \cap A_2 \cap B)}{P(B)} = \frac{P(B)P(A_1|B)P(A_2|A_1 \cap B)}{P(B)} \\&= P(A_1|B)P(A_2|A_1 \cap B).\end{aligned}$$

- If  $A_1$  and  $A_2$  are conditionally independent, given event  $B$ , then

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

- Under the assumption that  $P(A_1|B) > 0$ , we then get

$$P(A_2|A_1 \cap B) = P(A_2|B).$$

- This implies that, given event  $B$  has taken place, the additional information that  $A_1$  has also occurred does not affect the likelihood of  $A_2$ .

## Conditional Independence: Example

- Two dice are rolled at the same time, a red die and a blue die. Let  $A_1$  be the event of getting two on red die and  $A_2$  be the event of getting 6 on blue die. Let  $B$  be the event of getting the an odd number as the sum of the two dice.
  - ▶ Verify if  $A_1$  and  $A_2$  are independent

## Conditional Independence: Example

- Two dice are rolled at the same time, a red die and a blue die. Let  $A_1$  be the event of getting two on red die and  $A_2$  be the event of getting 6 on blue die. Let  $B$  be the event of getting the an odd number as the sum of the two dice.
  - Verify if  $A_1$  and  $A_2$  are independent

$$P(A_1) = \frac{1}{6}, \quad P(A_2) = \frac{1}{6}, \quad P(A_1 \cap A_2) = \frac{1}{36}. \text{ So, } A_1 \text{ and } A_2 \text{ are independent.}$$



## Conditional Independence: Example

- Two dice are rolled at the same time, a red die and a blue die. Let  $A_1$  be the event of getting two on red die and  $A_2$  be the event of getting 6 on blue die. Let  $B$  be the event of getting the an odd number as the sum of the two dice.
  - Verify if  $A_1$  and  $A_2$  are independent

$$P(A_1) = \frac{1}{6}, \quad P(A_2) = \frac{1}{6}, \quad P(A_1 \cap A_2) = \frac{1}{36}. \text{ So, } A_1 \text{ and } A_2 \text{ are independent.}$$

- Verify if  $A_1$  and  $A_2$  are conditionally independent given  $B$

## Conditional Independence: Example

- Two dice are rolled at the same time, a red die and a blue die. Let  $A_1$  be the event of getting two on red die and  $A_2$  be the event of getting 6 on blue die. Let  $B$  be the event of getting the an odd number as the sum of the two dice.
  - Verify if  $A_1$  and  $A_2$  are independent

$$P(A_1) = \frac{1}{6}, \quad P(A_2) = \frac{1}{6}, \quad P(A_1 \cap A_2) = \frac{1}{36}. \text{ So, } A_1 \text{ and } A_2 \text{ are independent.}$$

- Verify if  $A_1$  and  $A_2$  are conditionally independent given  $B$

$$P(A_1|B) = \frac{P(A_1 \cap B)}{P(B)} = \frac{3/36}{18/36} = \frac{1}{6}, \quad P(A_2|B) = \frac{P(A_2 \cap B)}{P(B)} = \frac{3/36}{18/36} = \frac{1}{6}$$

$$P(A_1 \cap A_2|B) = 0 \neq P(A_1|B) \cdot P(A_2|B)$$

So, these two events are not conditionally independent.

## Conditional Independence: Example

- Two dice are rolled at the same time, a red die and a blue die. Let  $A_1$  be the event of getting two on red die and  $A_2$  be the event of getting 6 on blue die. Let  $B$  be the event of getting the an odd number as the sum of the two dice.
  - Verify if  $A_1$  and  $A_2$  are independent

$$P(A_1) = \frac{1}{6}, \quad P(A_2) = \frac{1}{6}, \quad P(A_1 \cap A_2) = \frac{1}{36}. \text{ So, } A_1 \text{ and } A_2 \text{ are independent.}$$

- Verify if  $A_1$  and  $A_2$  are conditionally independent given  $B$

$$P(A_1|B) = \frac{P(A_1 \cap B)}{P(B)} = \frac{3/36}{18/36} = \frac{1}{6}, \quad P(A_2|B) = \frac{P(A_2 \cap B)}{P(B)} = \frac{3/36}{18/36} = \frac{1}{6}$$

$$P(A_1 \cap A_2|B) = 0 \neq P(A_1|B) \cdot P(A_2|B)$$

So, these two events are not conditionally independent.

- Two events that are independent with respect to an unconditional probability law may not be conditionally independent.

# Bayes' Rule

## Bayes' Rule

Then, for any events  $A, B$  with  $P(B) > 0$ , we can write

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

# Bayes' Rule

## Bayes' Rule

Then, for any events  $A, B$  with  $P(B) > 0$ , we can write

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

**Proof:** Bayes' rule is easily verified. We can write the probability of  $A \cap B$  as  $P(A \cap B) = P(A|B)P(B)$ . Rearranging the terms yields the first equality. □

# Bayes' Rule

## Bayes' Rule

Let  $A_1, A_2, \dots, A_n$  be a collection of events that forms a partition of the sample space  $\Omega$ . Suppose that  $P(A_k) > 0$  for all  $k$ . Then, for any event  $B$  such that  $P(B) > 0$ , we can write

$$\begin{aligned} P(A_i|B) &= \frac{P(B|A_i)P(A_i)}{P(B)} \\ &= \frac{P(A_i)P(B|A_i)}{\sum_{k=1}^n P(A_k)P(B|A_k)}. \end{aligned}$$

# Bayes' Rule

## Bayes' Rule

Let  $A_1, A_2, \dots, A_n$  be a collection of events that forms a partition of the sample space  $\Omega$ . Suppose that  $P(A_k) > 0$  for all  $k$ . Then, for any event  $B$  such that  $P(B) > 0$ , we can write

$$\begin{aligned} P(A_i|B) &= \frac{P(B|A_i)P(A_i)}{P(B)} \\ &= \frac{P(A_i)P(B|A_i)}{\sum_{k=1}^n P(A_k)P(B|A_k)}. \end{aligned}$$

**Proof:** Bayes' rule is easily verified. We can write the probability of  $A_i \cap B$  as

$$P(A_i \cap B) = P(A_i|B)P(B) = P(B|A_i)P(A_i).$$

Rearranging the terms yields the first equality.

# Bayes' Rule

## Bayes' Rule

Let  $A_1, A_2, \dots, A_n$  be a collection of events that forms a partition of the sample space  $\Omega$ . Suppose that  $P(A_k) > 0$  for all  $k$ . Then, for any event  $B$  such that  $P(B) > 0$ , we can write

$$\begin{aligned} P(A_i|B) &= \frac{P(B|A_i)P(A_i)}{P(B)} \\ &= \frac{P(A_i)P(B|A_i)}{\sum_{k=1}^n P(A_k)P(B|A_k)}. \end{aligned}$$

**Proof:** Bayes' rule is easily verified. We can write the probability of  $A_i \cap B$  as

$$P(A_i \cap B) = P(A_i|B)P(B) = P(B|A_i)P(A_i).$$

Rearranging the terms yields the first equality. The second equality is obtained by applying 'Total Probability Theorem' to the denominator  $P(B)$ . □

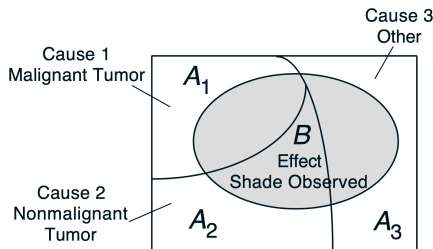


# Bayes' Rule: Example

- Bayes' rule is often used for inference. There are a number of *causes* that may result in a certain *effect*. We observe the effect, and wish to infer the cause.

# Bayes' Rule: Example

- Bayes' rule is often used for inference. There are a number of *causes* that may result in a certain *effect*. We observe the effect, and wish to infer the cause.
- We observe a shade in a person's X-ray (this is event  $B$ , the *effect*) and we want to estimate the likelihood of three mutually exclusive and collectively exhaustive potential *causes*: cause 1 (event  $A_1$ ) is that there is a malignant tumor, cause 2 (event  $A_2$ ) is that there is a nonmalignant tumor, and cause 3 (event  $A_3$ ) corresponds to reasons other than a tumor. We assume that we know the probabilities  $P(A_i)$  and  $P(B|A_i)$ ,  $i = 1, 2, 3$ . We want to compute  $P(A_1|B)$



## Bayes' Rule: Example

- (Example) If an aircraft is present in a certain area, a radar correctly registers its presence with probability 0.99. If it is not present, the radar falsely registers an aircraft presence with probability 0.10. We assume that an aircraft is present with probability 0.05. Compute  $P(\text{aircraft present} \mid \text{radar registers})$ .

## Bayes' Rule: Example

- (Example) If an aircraft is present in a certain area, a radar correctly registers its presence with probability 0.99. If it is not present, the radar falsely registers an aircraft presence with probability 0.10. We assume that an aircraft is present with probability 0.05. Compute  $P(\text{aircraft present} \mid \text{radar registers})$ .

$A = \{\text{aircraft is present}\},$

$B = \{\text{radar registers an aircraft presence}\}$

$A^c = \{\text{aircraft is not present}\},$

$B^c = \{\text{radar does not register an aircraft presence}\}$

## Bayes' Rule: Example

- (Example) If an aircraft is present in a certain area, a radar correctly registers its presence with probability 0.99. If it is not present, the radar falsely registers an aircraft presence with probability 0.10. We assume that an aircraft is present with probability 0.05. Compute  $P(\text{aircraft present} \mid \text{radar registers})$ .

$A = \{\text{aircraft is present}\}, \quad B = \{\text{radar registers an aircraft presence}\}$

$A^c = \{\text{aircraft is not present}\}, \quad B = \{\text{radar does not register an aircraft presence}\}$

$$P(B|A) = 0.99, P(B|A^c) = 0.10, P(A) = 0.05, P(A^c) = 0.95$$

## Bayes' Rule: Example

- (Example) If an aircraft is present in a certain area, a radar correctly registers its presence with probability 0.99. If it is not present, the radar falsely registers an aircraft presence with probability 0.10. We assume that an aircraft is present with probability 0.05. Compute  $P(\text{aircraft present} \mid \text{radar registers})$ .

$A = \{\text{aircraft is present}\}, \quad B = \{\text{radar registers an aircraft presence}\}$

$A^c = \{\text{aircraft is not present}\}, \quad B = \{\text{radar does not register an aircraft presence}\}$

$$P(B|A) = 0.99, P(B|A^c) = 0.10, P(A) = 0.05, P(A^c) = 0.95$$

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|A^c)P(A^c)} = \frac{0.05 \cdot 0.99}{0.05 \cdot 0.99 + 0.95 \cdot 0.1} \approx 0.3426.$$

## Bayes' Rule: Example

- April, a biochemist, designs a test for a latent disease. If a subject has the disease, the probability that the test results turn out positive is 0.95. Similarly, if a subject does not have the disease, the probability that the test results come up negative is 0.95. Suppose that one percent of the population is infected by the disease. We wish to find the probability that a person who tested positive has the disease.

# Bayes' Rule: Example

- April, a biochemist, designs a test for a latent disease. If a subject has the disease, the probability that the test results turn out positive is 0.95. Similarly, if a subject does not have the disease, the probability that the test results come up negative is 0.95. Suppose that one percent of the population is infected by the disease. We wish to find the probability that a person who tested positive has the disease.

Let  $D$  denote the event that a person has the disease, and let  $A$  be the event that the test results are positive.



## Bayes' Rule: Example

- April, a biochemist, designs a test for a latent disease. If a subject has the disease, the probability that the test results turn out positive is 0.95. Similarly, if a subject does not have the disease, the probability that the test results come up negative is 0.95. Suppose that one percent of the population is infected by the disease. We wish to find the probability that a person who tested positive has the disease.

Let  $D$  denote the event that a person has the disease, and let  $A$  be the event that the test results are positive. Using Bayes' rule,

$$\begin{aligned} P(D|A) &= \frac{P(D)P(A|D)}{P(D)P(A|D) + P(D^c)P(A|D^c)} \\ &= \frac{0.01 \cdot 0.95}{0.01 \cdot 0.95 + 0.99 \cdot 0.05} \\ &\approx 0.1610. \end{aligned}$$

## Bayes' Rule: Example

- April, a biochemist, designs a test for a latent disease. If a subject has the disease, the probability that the test results turn out positive is 0.95. Similarly, if a subject does not have the disease, the probability that the test results come up negative is 0.95. Suppose that one percent of the population is infected by the disease. We wish to find the probability that a person who tested positive has the disease.

Let  $D$  denote the event that a person has the disease, and let  $A$  be the event that the test results are positive. Using Bayes' rule,

$$\begin{aligned} P(D|A) &= \frac{P(D)P(A|D)}{P(D)P(A|D) + P(D^c)P(A|D^c)} \\ &= \frac{0.01 \cdot 0.95}{0.01 \cdot 0.95 + 0.99 \cdot 0.05} \\ &\approx 0.1610. \end{aligned}$$

Although the test may initially appear fairly accurate, the probability that a person with a positive test carries the disease remains small.