

Am I going too fast in lecture? Your responses are anonymous.

<https://pollev.com/annakarlin185>

- A. Yes, you are going **way too fast**.
- B. Yes, you are going a **little bit too fast**.
- C. No, your pace is **about right**.
- D. No, your pace is **too slow**.

The Birthday Paradox, Conditional Probability and more

CSE 312 Spring 26
Lecture 5

Many of the slides in this lecture were created by Mor Harchol-Balter for her book: "Introduction to Probability for Computing", Harchol-Balter '24

Review - Probability

Definition. A **sample space** Ω is the set of all possible outcomes of an experiment.

Definition. An **event** $E \subseteq \Omega$ is a subset of possible outcomes.

Examples:

- Single coin flip: $\Omega = \{H, T\}$
- Two coin flips: $\Omega = \{HH, HT, TH, TT\}$
- Roll of a die: $\Omega = \{1, 2, 3, 4, 5, 6\}$

Examples:

- Getting at least one head in two coin flips:
 $E = \{HH, HT, TH\}$
- Rolling an even number on a die :
 $E = \{2, 4, 6\}$

Probability space - more

Either finite or infinite countable (e.g., integers)

Definition. A (discrete) **probability space** is a pair (Ω, \mathbb{P}) where:

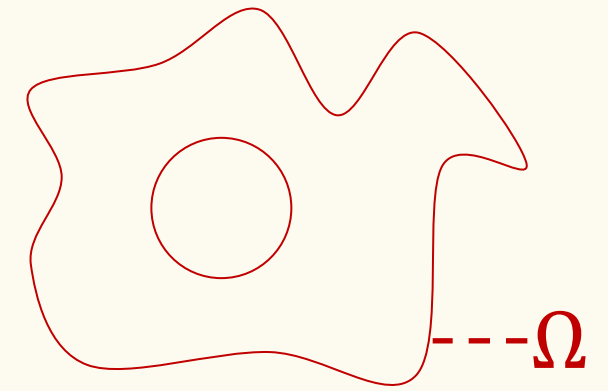
- Ω is a set called the **sample space**.

- \mathbb{P} is the **probability measure**, a function $\mathbb{P}: \Omega \rightarrow [0,1]$ such that:

- $\mathbb{P}(\omega) \geq 0$ for all $\omega \in \Omega$

- $\sum_{\omega \in \Omega} \mathbb{P}(\omega) = 1$

Set of possible elementary outcomes



Specify Likelihood (or probability) of each elementary outcome

Some outcome must show up

The likelihood (or probability) of each outcome is non-negative.

Review Axioms of Probability

Let Ω denote the sample space and $E, F \subseteq \Omega$ be events.

Axiom 1 (Non-negativity): $P(E) \geq 0$

Axiom 2 (Normalization): $P(\Omega) = 1$

Axiom 3 (Countable Additivity): If E and F are mutually exclusive events, then $P(E \cup F) = P(E) + P(F)$

Corollary 1 (Complementation): $P(E^c) = 1 - P(E)$

Corollary 2 (Monotonicity): If $E \subseteq F$, $P(E) \leq P(F)$

Corollary 3 (Inclusion-Exclusion): $P(E \cup F) = P(E) + P(F) - P(E \cap F)$

Review: Equally Likely Outcomes

If (Ω, P) is a **uniform** probability space, then for any event $E \subseteq \Omega$, then

$$P(E) = \frac{|E|}{|\Omega|}$$

Examples:

- Two coin flips: $\Omega = \{HH, HT, TH, TT\}$
- Roll of a die: $\Omega = \{1, 2, 3, 4, 5, 6\}$

Events:

- Getting at least one head in two coin flips: $E = \{HH, HT, TH\}$

$$P(E) = \frac{3}{4}$$

- Rolling an even number on a die: $E = \{2, 4, 6\}$

$$P(E) = \frac{3}{6} = \frac{1}{2}$$

Example: Birthday “Paradox”

Suppose we have a collection of n people in a room. What is the probability that at least 2 people share a birthday? Assume that there are exactly 365 possible birthdays, and each possibility is equally likely.

Say the people’s names are 1, 2, 3,..n

Sample space: all possible assignments of birthdays to these people =

$$\Omega = \{(b_1, b_2, \dots, b_n) : b_i \in \{1, \dots, 365\}\}$$

($b_i = 25$ means person i was born on the 25th day of the year)

$$|\Omega| =$$

Uniform probability space: $\mathbb{P}(\omega) =$

Example: Birthday “Paradox”

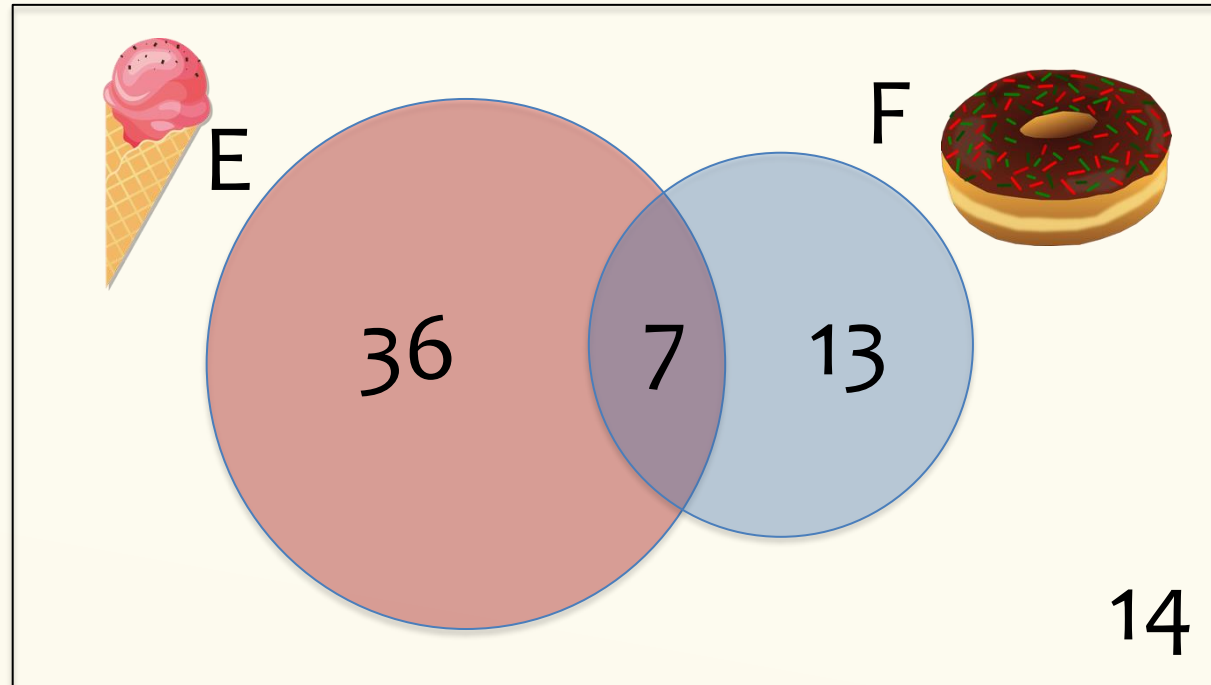
$E = \{ \text{at least 2 people share a birthday} \}$

What is $\mathbb{P}(E)$?

Agenda (1)

- Conditional Probability
- Chain Rule
- Independence
- Law of Total Probability
- Bayes Theorem

Conditional Probability (Idea)



What's the probability that a uniformly random person likes ice cream **given** they like donuts?

Conditional Probability

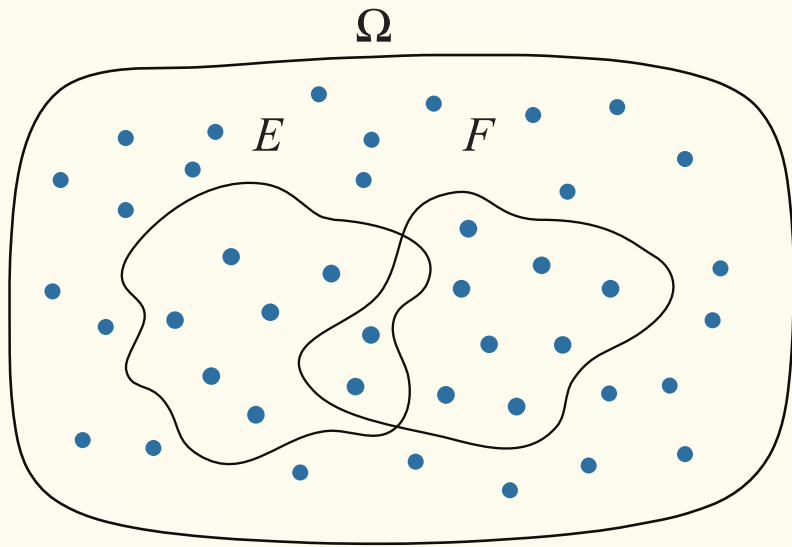
Definition. The **conditional probability** of event E given an event F happened (assuming $P(F) > 0$) is

$$P(E|F) = \frac{P(E \cap F)}{P(F)}$$

Conditional Probability

Definition. The **conditional probability** of event E **given** an event F happened (assuming $P(F) \neq 0$) is

$$P(E|F) = \frac{P(E \cap F)}{P(F)}$$



Two equivalent views for **equally likely outcomes**:

$$P\{E | F\} = \frac{2}{10} \quad (\text{of the 10 outcomes in set } F, \text{ only 2 of these are in set } E)$$

$$P\{E | F\} = \frac{P\{E \cap F\}}{P\{F\}} = \frac{\frac{2}{42}}{\frac{10}{42}} = \frac{2}{10}$$

Conditional Probability on Events



Q: What is $P\{\text{both are colts}\}$?

The offspring of a horse is called a foal.
Horse couples have one foal at a time and each foal is either a “colt” or a “filly.”

We’re told that a horse couple had 2 foals and that each outcome is equally likely.

Conditional Probability on Events



Definition. The **conditional probability** of event E **given** an event F happened (assuming $P(F) \neq 0$) is

$$P(E|F) = \frac{P(E \cap F)}{P(F)}$$

Q: What is $P\{\text{both are colts} \mid \geq 1 \text{ colt}\}$?

The offspring of a horse is called a foal.
Horse couples have one foal at a time and each foal is either a “colt” or a “filly.”

We’re told that a horse couple had 2 foals and that each outcome is equally likely. We are also told that at least one of these is a colt.

Conditional Probability on Events - Answer



The offspring of a horse is called a foal.
Horse couples have one foal at a time and each foal is either a “colt” or a “filly.”

We’re told that a horse couple had 2 foals and that each outcome is equally likely. We are also told that at least one of these is a colt.

$$\begin{aligned} & P\{\text{both are colts} \mid \geq 1 \text{ colt}\} \\ &= \frac{P\{\text{both are colts} \& \geq 1 \text{ colt}\}}{P\{\geq 1 \text{ colt}\}} \\ &= \frac{P\{\text{both are colts}\}}{P\{\geq 1 \text{ colt}\}} \\ &= \frac{\frac{1}{4}}{\frac{3}{4}} \\ &= \frac{1}{3} \end{aligned}$$

Conditional Probability on Events - picture



$$P\{\text{both are colts} \mid \geq 1 \text{ colt}\} \\ = \frac{1}{3}$$

The offspring of a horse is called a foal.
Horse couples have one foal at a time and each foal is either a “colt” or a “filly.”

We’re told that a horse couple had 2 foals and that each outcome is equally likely. We are also told that at least one of these is a colt.

	Colt	Filly
Colt	✓	
Filly		

Conditional Probability in a uniform probability space

Definition. The **conditional probability** of event E given an event F happened (assuming $P(F) \neq 0$) is

$$P(E|F) = \frac{P(E \cap F)}{P(F)}$$

If the probability space is uniform, then $P(E|F) = \frac{|E \cap F|}{|F|}$

Agenda (2)

- Conditional Probability
- Chain Rule
- Independence
- Law of Total Probability
- Bayes Theorem

Chain Rule

If $P\{E_1 \cap E_2\} > 0$, then:

$$P\{E_2|E_1\} = \frac{P\{E_1 \cap E_2\}}{P\{E_1\}}$$

Equivalently, we can write:

If $P\{E_1 \cap E_2\} > 0$, then:

$$P\{E_1 \cap E_2\} = P\{E_1\} \cdot P\{E_2|E_1\}$$

$$\text{Likewise: } P\{E_1 \cap E_2\} = P\{E_2\} \cdot P\{E_1|E_2\}$$

Probability
outcome
is in both
 E_1 and E_2

Probability
outcome
is in E_1

Probability
outcome
is in E_2 given
that it's in E_1

Chain Rule for Conditioning – general case.

If $P\{E_1 \cap E_2\} > 0$, then:

$$P\{E_1 \cap E_2\} = P\{E_1\} \cdot P\{E_2|E_1\}$$

This can be generalized!

Theorem: [**Chain Rule for Conditioning**]

If $P\{E_1 \cap E_2 \cap E_3 \cap \dots \cap E_n\} > 0$, then

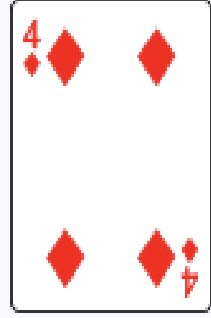
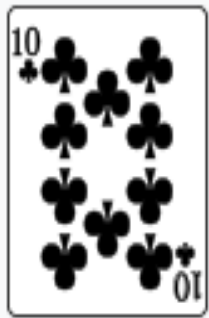
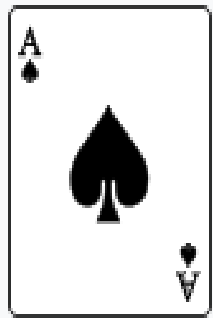
$$P\{E_1 \cap E_2 \cap E_3 \cap \dots \cap E_n\}$$

$$= P\{E_1\} \cdot P\{E_2 | E_1\} \cdot P\{E_3 | E_1 \cap E_2\} \cdots P\{E_n | E_1 \cap E_2 \cap E_3 \cap \dots \cap E_{n-1}\}$$

Chain Rule Example

Have a Standard 52-Card Deck. Shuffle It, and draw the top 3 cards **in order**. (uniform probability space).

What is $P(\text{Ace of Spades First, 10 of Clubs Second, 4 of Diamonds Third}) = P(\mathbf{A} \cap \mathbf{B} \cap \mathbf{C})$?

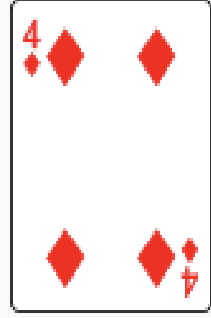
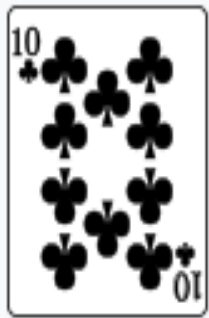
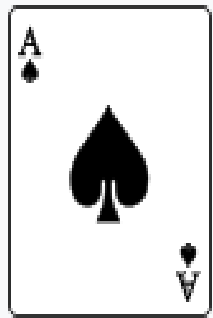


- A:** Ace of Spades First
- B:** 10 of Clubs Second
- C:** 4 of Diamonds Third

Chain Rule Example

Have a Standard 52-Card Deck. Shuffle It, and draw the top 3 cards **in order**. (uniform probability space).

What is $P(\text{Ace of Spades First, 10 of Clubs Second, 4 of Diamonds Third}) = P(\mathbf{A} \cap \mathbf{B} \cap \mathbf{C})?$



A: Ace of Spades First

B: 10 of Clubs Second

C: 4 of Diamonds Third

$$\mathbb{P}(A) \cdot \mathbb{P}(B|A) \cdot \mathbb{P}(C|A \cap B)$$

$$= \frac{1}{52} \cdot \frac{1}{51} \cdot \frac{1}{50}$$

Agenda (3)

- Conditional Probability
- Chain Rule
- Independence
- Law of Total Probability
- Bayes Theorem

Independent Events

Defn: Events E and F are **independent**, written $E \perp F$, if:

$$P\{E \cap F\} = P\{E\} \cdot P\{F\}$$

Here's an equivalent and perhaps more intuitive definition:

Defn: Assuming $P\{F\} > 0$, Events E and F are **independent**, if:

$$P\{E \mid F\} = P\{E\}$$

If E and F are **independent**, so are \bar{E} and F , E and \bar{F} , and \bar{E} and \bar{F}

Independent Events – example 1

Defn: Events E and F are **independent**, written $E \perp F$, if:

$$P\{E \cap F\} = P\{E\} \cdot P\{F\}$$

Here's an equivalent and perhaps more intuitive definition:

Defn: Assuming $P\{F\} > 0$, Events E and F are **independent**, if:

$$P\{E \mid F\} = P\{E\}$$

Q1: Can two mutually exclusive, non-null events be independent?

Independent Events – example 2

Defn: Events E and F are **independent**, written $E \perp F$, if:

$$P\{E \cap F\} = P\{E\} \cdot P\{F\}$$

Here's an equivalent and perhaps more intuitive definition:

Defn: Assuming $P\{F\} > 0$, Events E and F are **independent**, if:

$$P\{E | F\} = P\{E\}$$

Q2: Suppose we roll a die twice. Each outcome equally likely.

Which of these pairs of events are independent:

- Let E = "1st roll is 6." Let F = "2nd roll is 6"
- Let E = "Sum of rolls is 7." Let F = "2nd roll is 4"

Independent Events - answers

Defn: Events E and F are **independent**, written $E \perp F$, if:

$$P\{E \cap F\} = P\{E\} \cdot P\{F\}$$

Here's an equivalent and perhaps more intuitive definition:

Defn: Assuming $P\{F\} > 0$, Events E and F are **independent**, if:

$$P\{E | F\} = P\{E\}$$

Q1: Can two mutually exclusive, non-null events be independent?

No!

Q2: Suppose we roll a die twice. Which of these pairs of events are independent:

a. Let E = "1st roll is 6." Let F = "2nd roll is 6"

b. Let E = "Sum of rolls is 7." Let F = "2nd roll is 4"

Both!

More Independence Definitions

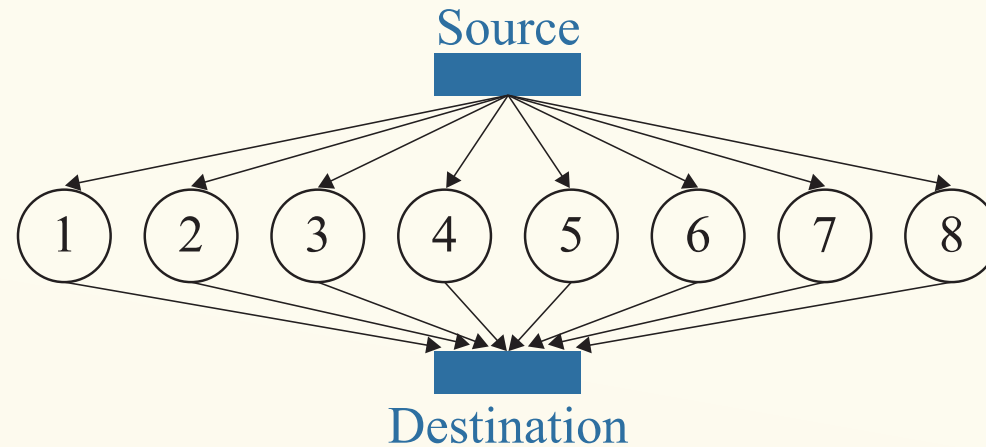
Defn: Events A_1, A_2, \dots, A_n are **independent** if, for every subset S of $\{1, 2, \dots, n\}$:

$$\mathbf{P}\left\{\bigcap_{i \in S} A_i\right\} = \prod_{i \in S} \mathbf{P}\{A_i\}$$

Another example

You are routing a packet from the source to the destination.

But each of the 16 edges in the network works with probability p , independently.



Q: What is the probability that you can get the packet from the source to the destination?

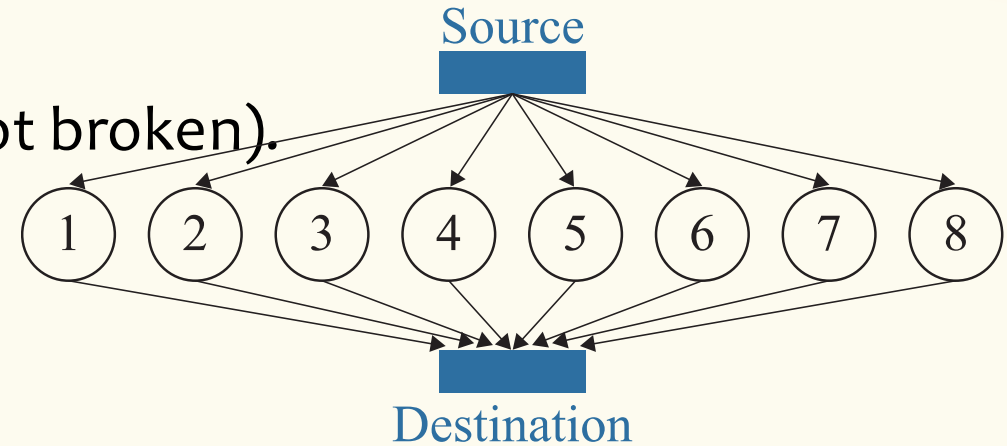
Let's break it down

Each edge works with probability p , independently of other edges. There are 8 paths.

Let E_i denote the event that the i^{th} path is usable (not broken).

Q1: What is $P\{E_i\}$?

Q2: What is $P\{\bar{E}_i\}$?



More calculations

Each edge works with probability p , independently of other edges. There are 8 paths.

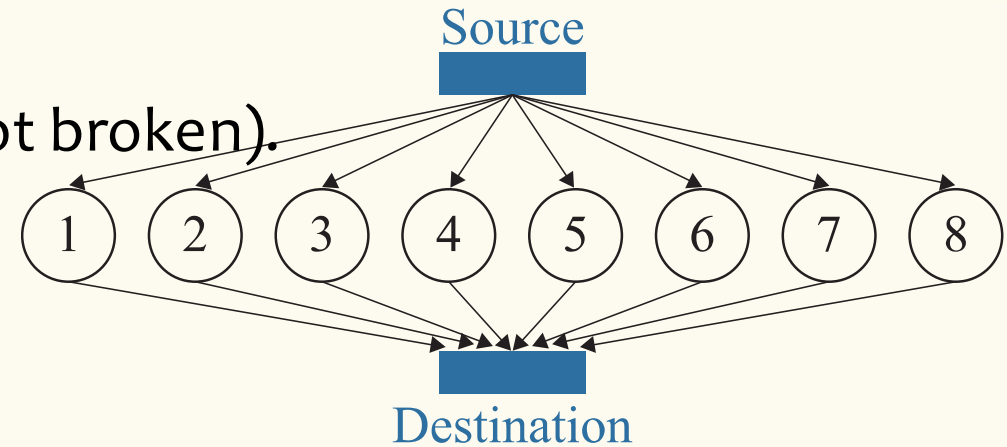
Let E_i denote the event that the i^{th} path is usable (not broken).

$$P\{E_i\} = p^2$$

$$P\{\bar{E}_i\} = 1 - p^2$$

What is $P\{\text{Can get from source to destination}\}$?

$P\{\text{Can get from source to destination}\} =$



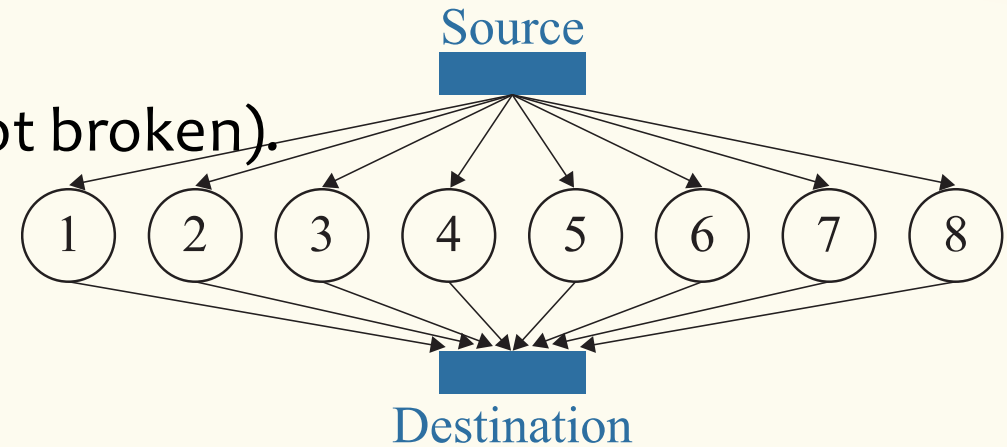
Answer

Each edge works with probability p , independently of other edges. There are 8 paths.

Let E_i denote the event that the i^{th} path is usable (not broken).

$$P\{E_i\} = p^2$$

$$P\{\bar{E}_i\} = 1 - p^2$$



What is $P\{\text{Can get from source to destination}\}$?

$$P\{\text{Can get from source to destination}\} = P\{\text{At least one path works}\}$$

$$= P\{E_1 \cup E_2 \cup \dots \cup E_8\}$$

$$= 1 - P\{\text{All paths are broken}\}$$

$$= 1 - P\{\bar{E}_1\} \cdot P\{\bar{E}_2\} \dots P\{\bar{E}_8\} = 1 - (1 - p^2)^8$$

Agenda (4)

- Conditional Probability
- Chain Rule
- Independence
- Law of Total Probability
- Bayes Theorem

Law of Total Probability

For any sets E and F :

$$F = (F \cap E) \cup (F \cap \bar{E})$$

$$P\{F\} = P\{F \cap E\} + P\{F \cap \bar{E}\}$$

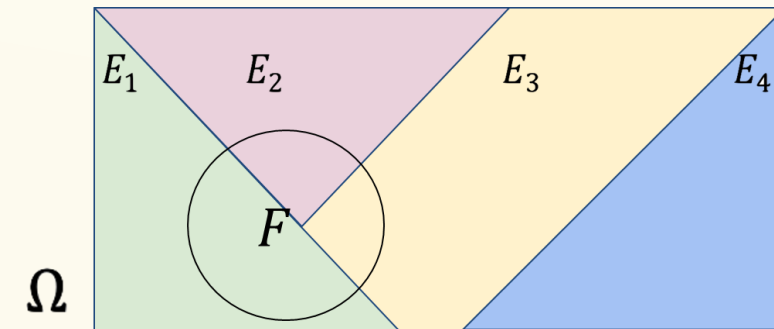
$$= P\{F|E\} \cdot P\{E\} + P\{F|\bar{E}\} \cdot P\{\bar{E}\}$$

Generalizing, we have:

Theorem: [Law of Total Probability]

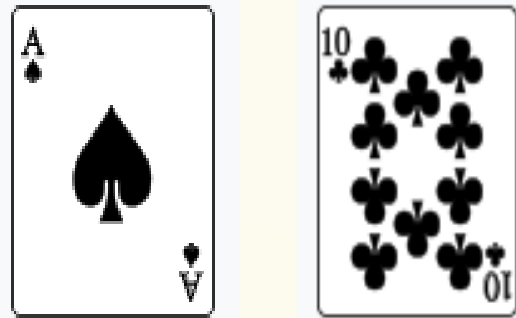
Let E_1, E_2, \dots, E_n partition the state space Ω . Then:

$$P\{F\} = \sum_{i=1}^n P\{F \cap E_i\} = \sum_{i=1}^n P\{F|E_i\} \cdot P\{E_i\}$$



Are A and B independent?

Have a Standard 52-Card Deck. Shuffle It, and draw the top 2 cards **in order**. (uniform probability space).



A: Ace of Spades First

B: 10 of Clubs Second

Are the events A and B independent?

$$\mathbb{P}(B|A) = \frac{1}{51}$$

$$\mathbb{P}(B) =$$

Agenda (5)

- Conditional Probability
- Chain Rule
- Independence
- Law of Total Probability
- **Bayes Theorem**

Our First Machine Learning Task: Spam Filtering

Subject: “FREE \$\$\$ CLICK HERE”

Suppose you know that 80% of emails you receive are spam.

So a priori, our belief is that any email has an 80% chance of being spam.

How do you update that belief when you see that the subject line contains the phrase “FREE \$\$\$”?

Bayes Theorem



A formula to let us “reverse” the conditional.

Theorem. (Bayes Rule) For events A and B , where $P(A), P(B) > 0$,

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

$P(A)$ is called the **prior** (our belief without knowing anything)

$P(A|B)$ is called the **posterior** (our belief after learning B)

Bayes Theorem follows from the definition of conditional probability

Definition. The **conditional probability** of event A given an event B happened (assuming $P(B) \neq 0$) is

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

Bayes Theorem Proof

By definition of conditional probability

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

Swapping A, B gives

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

But $P(A \cap B) = P(B \cap A)$, so

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

Dividing both sides by $P(B)$ gives

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

Back to Spam Filtering

Subject: “FREE \$\$\$ CLICK HERE”

What is the probability this email is spam, given the subject contains “FREE”?

Some useful stats:

- 10% of ham (i.e., not spam) emails contain the word “FREE” in the subject.
- 70% of spam emails contain the word “FREE” in the subject.
- 80% of emails you receive are spam.

You receive a random email:

- Let S be event that the email is spam
- Let F be the event that the email contains the word “FREE”.

Bayes Theorem with Law of Total Probability

Bayes Theorem with LTP: Let E_1, E_2, \dots, E_n be a partition of the sample space, and F an event. Then,

$$P(E_1|F) = \frac{P(F|E_1)P(E_1)}{P(F)} = \frac{P(F|E_1)P(E_1)}{\sum_{i=1}^n P(F|E_i)P(E_i)}$$

Simple Partition: In particular, if E is an event with non-zero probability, then

$$P(E|F) = \frac{P(F|E)P(E)}{P(F|E)P(E) + P(F|E^c)P(E^c)}$$