

Applied Probability and Statistics I - STAT400

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Mestiyage - Fall 2024

Syllabus

Grading

- Homework — 28% (7% each)
- R Projects — 12% (4% each)
- Two exams — 30% (15% each)
- Final exam — 30%

Office Hours

- Tuesday: 1:00 PM - 1:50 PM (in person, MTH 4106)
- Wednesday: 11:00 AM - 11:50 AM (online)

Exams

- 2 midterms and a final exam

Lecture 1: Tuesday 8/27/2024

Course Overview: STAT400

We study:

1. Probability
2. Descriptive Statistics
3. Inferential Statistics

1. Probability

Probability is the mathematical study of uncertainty.

2. Descriptive Statistics

Descriptive Statistics involves methods for summarizing and describing the important characteristics of a dataset.

3. Inferential Statistics

Inferential Statistics involves methods for using data from a subset (sample) of a larger group (population) to make meaningful conclusions. Note that each time you pick a subset, you lose out on certain information, leading to uncertainty.

Setting: Conducting an Experiment

In this course, we will often assume we are about to conduct an experiment. The possible outcomes of the experiment are known, but the exact outcome is not.

Examples:

- Tossing a coin
- Rolling a die

To study these types of situations, we introduce a *model for probability*.

Ordered Triples (Ω, \mathcal{F}, P)

- Ω is the **sample space**: The set of all possible outcomes of the experiment.
- \mathcal{F} is the **event space**:
 - An **event** is a subset of Ω .
 - An event captures the idea that in many situations, we care about collections of outcomes rather than a single outcome.
 - The event space contains collections of outcomes for which we can assign probabilities.
- P is the **probability measure**:

$$P : \mathcal{F} \rightarrow \mathbb{R}$$

where P assigns probabilities to events.

Example 1: Tossing a Fair Coin

Consider the simple experiment of tossing a **fair** coin.

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

$$\mathcal{F} = \{\emptyset, \{H\}, \{T\}, \{H, T\}\}$$

- $P(\emptyset) = 0$
(“A probability of 0 represents an outcome/collection of outcomes that never takes place.”)
- $P(\{H, T\}) = 1$
(“A probability of 1 represents an outcome/collection of outcomes that always takes place.”)
- $P(\{H\}) = \frac{1}{2}$
(Requires the coin to be fair.)
- $P(\{T\}) = \frac{1}{2}$
(Requires the coin to be fair.)

Example 2: Rolling a Fair Die

Consider the experiment of rolling a fair die. Note: ($\mathcal{P}(\Omega)$ is the Powerset of Ω)

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

$$\mathcal{F} = \mathcal{P}(\Omega) =$$

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

- $P(\{i\}) = \frac{1}{6}$ for $i = 1, 2, 3, 4, 5, 6$
- $P(\emptyset) = 0$
- $P(\Omega) = 1$
- $P(\{1, 2\}) = ?$
(Listing out probabilities for each event is **not** feasible.)

We would want a way to calculate the probability of a particular event by using the “base” probabilities.

We will look at these rules for computing probabilities of complicated events in terms of basic ones in a bit.

Example 3: Tossing a Fair Coin Until We See Heads for the First Time

Consider the experiment of tossing a fair coin repeatedly until we observe heads for the first time, then we stop.

$$\Omega = \{(H), (T, H), (T, T, H), (T, T, T, H), \dots\}$$

$$\mathcal{F} = \mathcal{P}(\Omega)$$

Let A_i be the event of seeing heads on the i th toss.

$$P(A_i) = \frac{1}{2^i}$$

Question: What is the probability of seeing heads on an even-numbered toss?

$$Q = P(\text{seeing heads on an even-numbered toss}) = ?$$

Example 4: Picking a Number from the Interval $[0, 1]$

Consider picking a number from the interval $[0, 1]$ such that the probabilities of selecting numbers from two subintervals I_1 and I_2 of $[0, 1]$ are the same whenever I_1 and I_2 have the same length.

$$\Omega = [0, 1]$$

$$\mathcal{F} = \mathcal{P}(\Omega)$$

$$P(\text{selecting a number from a subinterval } I \text{ of } [0, 1]) = \text{length}(I)$$

$$P([0, \frac{1}{4}]) = \frac{1}{4} - 0 = \frac{1}{4}$$

$$P([0, \frac{1}{2}]) = \frac{1}{2} - 0 = \frac{1}{2}$$

$$P\left(\left\{\frac{1}{2}\right\}\right) = P\left(\left[\frac{1}{2}, \frac{1}{2}\right]\right) = \frac{1}{2} - \frac{1}{2} = 0$$

“The probability of 0 indicates an event that does not take place or an event that is so unlikely that the only reasonable value to assign to it is 0, i.e., an event that almost surely does not take place.”

On Thursday will learn how to compute problems similar to $P(\mathbb{Q} \cap [0, 1]) = ?$

Lecture 2: Thursday 8/29/2024

Probability

- Mathematical study of uncertainty.

Probability Space

$$(\Omega, F, P)$$

- Ω - All possible outcomes of the experiment of interest.
- F - Contains events, i.e., collections of outcomes we would like to assign probabilities to.
- P - Probability measure.

$$P : F \rightarrow \mathbb{R}$$

On Tuesday, we discussed examples and introduced some formulas to compute probabilities of “basic” events.

Goal for Today

Explore how to compute probabilities of “complicated” events in terms of basic events.

Two Questions

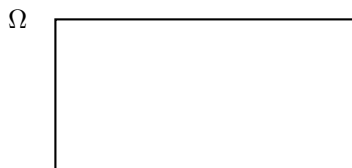
1. How do we express a complicated event in terms of basic ones?
 2. What rules can be used to compute probabilities once Question 1 has been answered?
- Question 1 is best answered by using tools from set theory.

→ We treat Ω as the list of all possible outcomes.

→ Events are sublists of Ω .

Since we are only interested in outcomes (or combinations thereof) of the experiment, we treat Ω as the universal set (i.e., we pretend that nothing outside of Ω exists).

Pictorial Representation

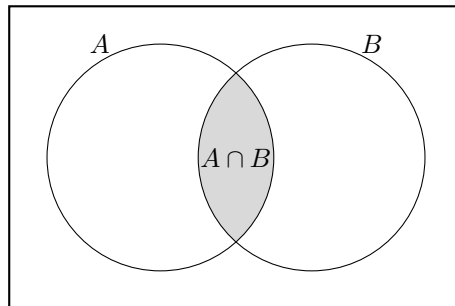


We can manipulate collections of events to obtain new events in various ways:

- Intersections
- Unions
- Relative complements

Given events A and B , the intersection is the event that contains all outcomes common to both A and B . We denote this by $A \cap B$.

Intersection of Two Events



Example

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

Let $A = \{1, 3, 5\}$ and $B = \{4, 5\}$. Then, the intersection of A and B is:

$$A \cap B = \{5\}$$

Extending the Intersection to Families of Events

The idea of the intersection of events can be extended to families of events.

$$\bigcap_{i=1}^3 A_i = (A_1 \cap A_2) \cap A_3$$

For an infinite family of events:

$$\bigcap_{i=1}^{\infty} A_i = A_1 \cap A_2 \cap A_3 \cap A_4 \cap A_5 \cap \dots$$

Disjoint Events

Two events are said to be disjoint if $A \cap B = \emptyset$.

- Events A_1, \dots, A_n are said to be disjoint if $\bigcap_{i=1}^n A_i = \emptyset$.
- Events A_1, \dots, A_n, \dots are said to be disjoint if $\bigcap_{i=1}^{\infty} A_i = \emptyset$.
- Events A_1, A_2, \dots are said to be pairwise disjoint if $A_i \cap A_j = \emptyset$ for all $i \neq j$.

Example

Consider the sample space $\Omega = \{1, 2, 3, 4, 5, 6\}$ with the following events:

$$A = \{1, 3, 5\}, \quad B = \{4, 5\}, \quad C = \{6\}$$

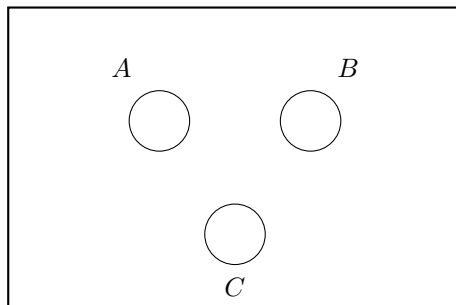
Here, A , B , and C are disjoint events, meaning:

$$A \cap B \cap C = \emptyset$$

However, they are not pairwise disjoint, because:

$$A \cap B = \{5\} \neq \emptyset$$

Pairwise Disjoint Sets

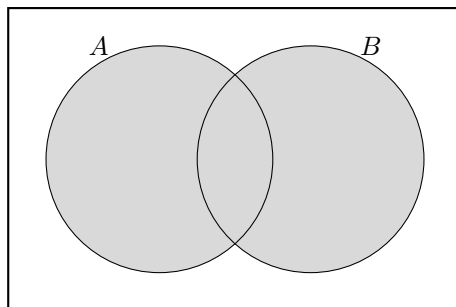


The word “and” usually translates to intersection when discussing sets or events. Conversely, the word “or” translates to a union.

Unions

The union of two events A and B , denoted by $A \cup B$, is the event that contains all outcomes that are in A , B , or both.

Venn Diagram: Union of Two Sets



$A \cup B$ (shaded region)

Example

Consider the sample space $\Omega = \{1, 2, 3, 4, 5, 6\}$ with the following events:

$$A = \{1, 3, 5\}, \quad B = \{2, 3, 5\}$$

The union of A and B is:

$$A \cup B = \{1, 2, 3, 5\}$$

Infinite and Finite Unions

Infinite versions of unions and finite versions of unions with more than two sets can be similarly defined.

$$\bigcup_{i=1}^3 A_i = A_1 \cup A_2 \cup A_3$$

Similarly, the union of more than two finite sets can be defined as:

$$\bigcup_{i=1}^n A_i = A_1 \cup A_2 \cup \dots \cup A_n$$

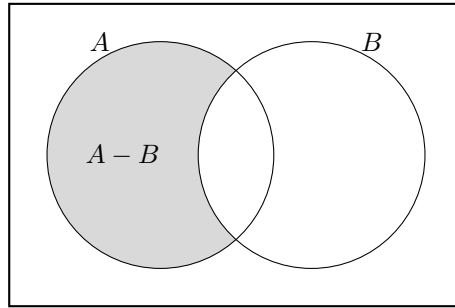
Unions can also be extended to infinite collections of sets. For example, the union of an infinite sequence of sets A_1, A_2, \dots is denoted as:

$$\bigcup_{i=1}^{\infty} A_i = A_1 \cup A_2 \cup \dots$$

Relative Complements

Given events A and B , the relative complement $A - B$ is the event that contains only the outcomes that are **unique** to A .

Venn Diagram: Unique to A ($A - B$)



Example

Consider the sample space $\Omega = \{1, 2, 3, 4, 5, 6\}$ with the following events:

$$A = \{1, 2, 3\}, \quad B = \{2, 4, 5\}$$

The relative complements are:

$$A - B = \{1, 3\}, \quad B - A = \{4, 5\}$$

Complement of A

We use A^c to denote the complement of A within the universal set Ω , which is the set of outcomes that are not in A :

$$A^c = \Omega - A = \{4, 5, 6\}$$

The word **not** is associated with complements and the phrases “and not”, “but not” are associated with relative compliments

Aside (for the HW): Verifying Set Identities with Venn Diagrams

We can use Venn diagrams to verify set identities. For example, let's verify the identity:

$$(A \cap B)^c = A^c \cup B^c$$

Venn diagrams representing set operations of (left hand side) LHS and (right hand side) RHS respectively are shown below:

LHS

$A \cap B$



RHS

A^c



$(A \cap B)^c$



B^c



$A^c \cup B^c$



Conclusion

Both sides of the identity are visually represented by the same shaded region, thus confirming that:

$$(A \cap B)^c = A^c \cup B^c$$

The shaded regions for $(A \cap B)^c$ and $A^c \cup B^c$ match. Therefore, $(A \cap B)^c = A^c \cup B^c$.

Note: (we are not worrying about edges cases, for example, where A and B are disjoint but the identity still holds true)

Now that the terminology is in place, we start to answer Q2.

Axioms

1. $P(\Omega) = 1, P(\emptyset) = 0$
2. $P(A) \geq 0$ for all $A \in \mathcal{F}$
3. If $A_1, A_2, \dots, A_n, \dots \in \mathcal{F}$ are pairwise disjoint, then

$$P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i)$$

Example: Consider the problem of tossing a fair coin until we observe heads. We want to find $P(\text{heads on an even numbered toss})$

Let A be the event that heads appears for the first time on an even-numbered toss.

Thus, A can be expressed as:

$$A = \{(T, H), (T, T, T, H), (T, T, T, T, T, H), \dots\}$$

Recall, A_i is heads on the i th toss.

$$P(A_i) = \frac{1}{2^i}$$

Notice that we can describe A as the union of disjoint events where heads occurs for the first time on the $2i$ -th toss:

$$A = A_2 \cup A_4 \cup A_6 \cup \dots = \bigcup_{i=1}^{\infty} A_{2i}$$

where A_{2i} is the event that heads first appears on the $2i$ -th toss. The probability of A_{2i} can be computed as:

$$P(A_{2i}) = \left(\frac{1}{2}\right)^{2i}$$

Since the events A_{2i} are pairwise disjoint, we can use axiom 3 to see the probability of A is given by:

$$P(A) = P\left(\bigcup_{i=1}^{\infty} A_{2i}\right) = \sum_{i=1}^{\infty} P(A_{2i}) = \sum_{i=1}^{\infty} \left(\frac{1}{2}\right)^{2i} = \sum_{i=1}^{\infty} \left(\frac{1}{4}\right)^i$$

This series is an infinite geometric series with the first term $a = \frac{1}{4}$ and common ratio $r = \frac{1}{4}$:

Recall, that a the sum of a converging infinite geometric series where $|r| < 1$ is:

$$S = a + ar + ar^2 + \dots = \sum_{i=0}^{\infty} (ar^i) = \frac{a}{1-r}$$

Therefore:

$$\sum_{i=1}^{\infty} \left(\frac{1}{4}\right)^i = \frac{\frac{1}{4}}{1 - \frac{1}{4}} = \frac{\frac{1}{4}}{\frac{3}{4}} = \frac{1}{3}$$

Thus, the probability that the first occurrence of heads is on an even-numbered toss is $\boxed{\frac{1}{3}}$.

Derived rule: If $A_1, \dots, A_N \in \mathcal{F}$ are pairwise disjoint, then

$$P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i)$$

Example: Consider a fair die roll. What is the probability of rolling a 1, 3, or 5?

$$P(\{i\}) = \frac{1}{6} \quad \text{for } i = 1, \dots, 6$$

$$P(\{1, 3, 5\}) = P(\{1\}) + P(\{3\}) + P(\{5\}) = \frac{1}{6} + \frac{1}{6} + \frac{1}{6} = \frac{1}{2}$$

Lecture 3: Thursday 9/3/2024

1 Probability

Definition: Probability is the mathematical framework for quantifying and analyzing uncertainty.

A probability space is defined by the triple (Ω, \mathcal{F}, P) , where:

- Ω is the sample space (set of all possible outcomes)
- \mathcal{F} is the event space (sigma-algebra of subsets of Ω)
- P is the probability measure (function assigning probabilities to events)

Axioms of Probability

The probability measure P satisfies the following axioms:

1. $P(\Omega) = 1$ and $P(\emptyset) = 0$
2. For all $A \in \mathcal{F}$, $P(A) \geq 0$
3. (Countable additivity) If $A_1, A_2, \dots \in \mathcal{F}$ are pairwise disjoint events (i.e. $A_i \cap A_j = \emptyset$ for all $i \neq j$):

$$P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i)$$

Note: Understanding and being able to derive properties from these axioms is crucial for the first midterm and for building a solid foundation in probability theory.

Important Results

1. **Decomposition of Probability:** For any two events $A, B \in \mathcal{F}$:

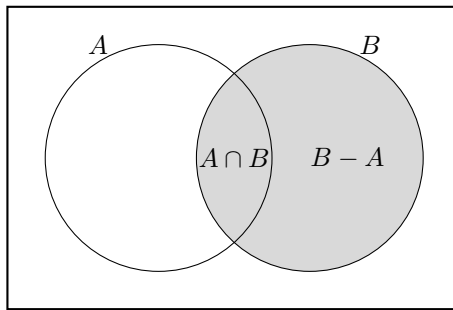
$$P(B) = P(B - A) + P(A \cap B)$$

Proof:

- Observe that B can be partitioned into two disjoint sets: $B = (B - A) \cup (A \cap B)$
- Note that $(B - A) \cap (A \cap B) = \emptyset$ (these sets are mutually exclusive)
- By the axiom of countable additivity (which implies finite additivity for disjoint events):

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

This result is fundamental in probability theory and is often used in solving complex probability problems. It allows us to break down the probability of an event into mutually exclusive parts, which can be easier to calculate individually.



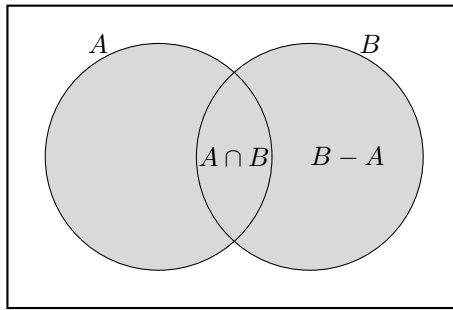
2. **Finite Additivity:** For any two events $A, B \in \mathcal{F}$:

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

Proof:

- Observe that $A \cup B = A \cup (B - A)$ and $A \cap (B - A) = \emptyset$
- Since A and $B - A$ are disjoint, $P(A \cup B) = P(A) + P(B - A)$ (finite additivity)
- From the decomposition result: $P(B) = P(B - A) + P(A \cap B)$
- Rearranging: $P(B - A) = P(B) - P(A \cap B)$
- Substituting into our earlier equation:

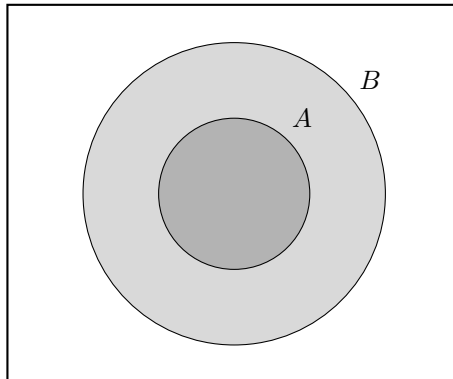
$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$



3. **Monotonicity:** If $A \subseteq B$, then $P(A) \leq P(B)$

Proof:

- If $A \subseteq B$, then:
 - $B = A \cup (B - A)$
 - $A \cap (B - A) = \emptyset$
- By finite additivity: $P(B) = P(A \cup (B - A)) = P(A) + P(B - A)$
- Since probabilities are non-negative, $P(B - A) \geq 0$
- Therefore, $P(B) \geq P(A)$

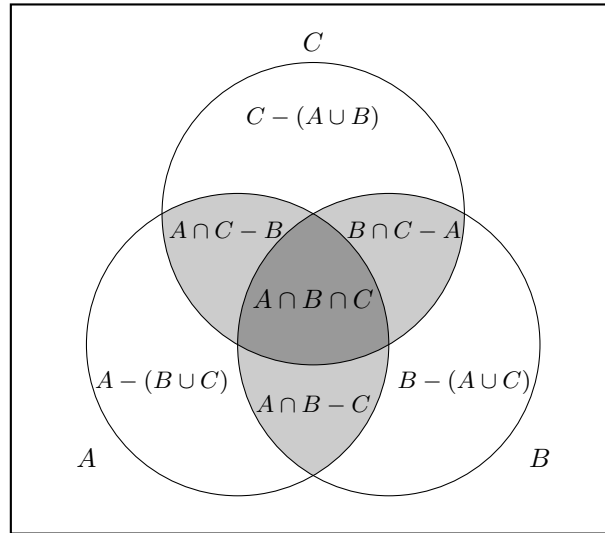


4. **Union of Three Sets:** For $A, B, C \in \mathcal{F}$:

$$P(A \cup B \cup C)$$

How to compute:

$$\begin{aligned}
 P(A \cup B \cup C) &= P(A) + P(B \cup C) - P(A \cap (B \cup C)) \\
 &= P(A) + [P(B) + P(C) - P(B \cap C)] - P(A \cap (B \cup C)) \quad (\text{decompose the union}) \\
 &= P(A) + P(B) + P(C) - P(B \cap C) - P((A \cap B) \cup (A \cap C)) \quad (\text{by distributive law}) \\
 &= P(A) + P(B) + P(C) - P(B \cap C) - (P(A \cap B) + P(A \cap C) - P((A \cap B) \cap (A \cap C))) \\
 &= P(A) + P(B) + P(C) - P(B \cap C) - (P(A \cap B) + P(A \cap C) - P(A \cap B \cap C)) \\
 &= P(A) + P(B) + P(C) - P(B \cap C) - P(A \cap B) - P(A \cap C) + P(A \cap B \cap C)
 \end{aligned}$$



Example: Suppose that A and B are events with $P(A) = 0.5$ and $P(B) = 0.6$. Find numbers a and b such that $a \leq P(A \cup B) \leq b$ and $a \leq P(A \cap B) \leq b$.

1. Using the addition rule of probability:

$$P(A \cup B) = P(A) + P(B) - P(A \cap B) = 0.5 + 0.6 - P(A \cap B) = 1.1 - P(A \cap B)$$

2. Since $A \cup B \subseteq \Omega$ and $P(\Omega) = 1$, we have:

$$P(A \cup B) \leq P(\Omega) \leq 1$$

3. From steps 1 and 2:

$$1.1 - P(A \cap B) \leq 1 \implies P(A \cap B) \geq 0.1$$

4. The maximum value for $P(A \cap B)$ is $\min(P(A), P(B)) = 0.5$, because:

- $A \cap B \subseteq A$ and $A \cap B \subseteq B$
- Therefore, $P(A \cap B) \leq P(A)$ and $P(A \cap B) \leq P(B)$

5. We can conclude:

$$0.1 \leq P(A \cap B) \leq 0.5$$

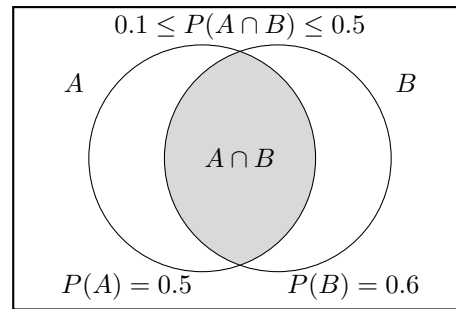
$$0.6 \leq P(A \cup B) \leq 1.0$$

6. To verify the lower bound for $P(A \cup B)$:

$$\begin{aligned} P(A \cup B) &= P(A) + P(B) - P(A \cap B) \\ &\geq P(A) + P(B) - \min(P(A), P(B)) \\ &= 0.5 + 0.6 - 0.5 = 0.6 \end{aligned}$$

Conclusion: We have found that $a = 0.1$ and $b = 0.5$ satisfy $a \leq P(A \cap B) \leq b$, while $a = 0.6$ and $b = 1.0$ satisfy $a \leq P(A \cup B) \leq b$.

Visualization: To better understand the relationship between A and B , consider the following Venn diagram:



This visualization illustrates why $0.1 \leq P(A \cap B) \leq 0.5$ and $0.6 \leq P(A \cup B) \leq 1.0$.

Example: When Alice visits a certain grocery store, she:

- buys apples with probability 0.4
- buys bananas with probability 0.7
- buys both with probability 0.25

Compute the probability that on her next visit to the store, Alice:

1. buys either apples or bananas
2. buys bananas but not apples
3. buys neither apples nor bananas

Step 1: Define notation and given probabilities

A : Alice buys apples

B : Alice buys bananas

$$P(A) = 0.4$$

$$P(B) = 0.7$$

$$P(A \cap B) = 0.25$$

Note: Symbol correspondences

- \cup corresponds to “or” (union)
- \cap corresponds to “and” (intersection)
- \complement corresponds to “not” (complement)
- $-$ corresponds to “and not”, or “but not” (relative complement)

Step 2: Calculate probabilities

1. $P(A \cup B) = P(A) + P(B) - P(A \cap B) = 0.4 + 0.7 - 0.25 = 0.85$

2. $P(B - A) = P(B) - P(A \cap B) = 0.7 - 0.25 = 0.45$

3. $P(A^c \cap B^c) = P((A \cup B)^c) = 1 - P(A \cup B) = 1 - 0.85 = 0.15$

Note: Important probability relationships:

$$P(A) = 1 - P(A^c)$$

$$\Omega = A \cup A^c$$

$$P(\Omega) = P(A) + P(A^c) = 1$$

$$P(A^c) = 1 - P(A)$$

Computing probabilities for finite, equally likely outcomes: For any event $A \subseteq \Omega$, where Ω is a finite sample space with equally likely outcomes, the probability of A is given by:

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

where $|A|$ denotes the cardinality (number of elements) of set A .

Lecture 4: Thursday 9/5/2024

Probability for Finite, Equally Likely Outcomes

Consider an experiment with finitely many outcomes, each of which is equally likely. This scenario is often referred to as “fair” or “uniformly at random” (with finite outcomes).

In this situation:

- $\mathcal{F} = \mathcal{P}(\Omega)$
- For any event $A \in \mathcal{F}$, $P(A) = \frac{|A|}{|\Omega|}$

Proof that $P(A) = \frac{|A|}{|\Omega|}$ satisfies the axioms of probability:

1. For any outcome $\omega \in \Omega$, we show $P(\{\omega\}) = \frac{1}{|\Omega|}$

Let $\Omega = \{\omega_1, \omega_2, \dots, \omega_n\}$. Then:

- $P(\{\omega_1\}) = P(\{\omega_2\}) = \dots = P(\{\omega_n\})$ (equally likely)
- $\{\omega_i\}$ are pairwise disjoint for $i = 1, \dots, n$
- $\Omega = \bigcup_{i=1}^n \{\omega_i\}$
- $P(\Omega) = P(\bigcup_{i=1}^n \{\omega_i\}) = \sum_{i=1}^n P(\{\omega_i\})$ (finite additivity)

Let $x = P(\{\omega_i\})$ for any i . Then:

$$\begin{aligned} 1 &= P(\Omega) = nx \\ x &= \frac{1}{n} = \frac{1}{|\Omega|} \end{aligned}$$

Therefore, $P(\{\omega_1\}) = P(\{\omega_2\}) = \dots = P(\{\omega_n\}) = \frac{1}{|\Omega|}$

2. For any event $A \subseteq \Omega$, we prove $P(A) = \frac{|A|}{|\Omega|}$

Let $A = \{\omega_{i_1}, \omega_{i_2}, \dots, \omega_{i_k}\}$ where $k = |A|$. Then:

$$\begin{aligned} P(A) &= P(\{\omega_{i_1}\} \cup \{\omega_{i_2}\} \cup \dots \cup \{\omega_{i_k}\}) \\ &= \sum_{j=1}^k P(\{\omega_{i_j}\}) \quad (\text{finite additivity}) \\ &= \sum_{j=1}^k \frac{1}{n} \\ &= \frac{k}{n} = \frac{|A|}{|\Omega|} \end{aligned}$$

To properly use the probability formula, we need to be able to count effectively. There are two fundamental principles of counting:

- Additive principle of counting

- Multiplicative principle of counting

Additive Principle of Counting: If we have n ways of doing one thing and m ways of doing another thing, where both actions cannot be performed simultaneously, then there are $n + m$ ways of selecting an action.

Example (Additive Principle): Suppose you own:

- 6 pairs of jeans
- 5 pairs of slacks

Then there are $6 + 5 = 11$ ways of selecting an article of clothing.

Multiplicative Principle of Counting: If we have n ways of doing one thing and m ways of doing another thing, then there are $n \times m$ ways of performing both actions.

Example (Multiplicative Principle): Continuing from the previous example, if you are packing for a trip and want to pack:

- 1 pair of jeans
- 1 pair of slacks

There are $6 \times 5 = 30$ ways of selecting a pair of jeans and a pair of slacks.

Problems we study in this class can be categorized according to two main features:

1. Replacement
2. Order

Examples:

- Passwords: Replacement allowed, order matters
- Card games: Usually no replacement, order may or may not matter (depends on the situation)

We can visualize these categories in a 2x2 grid:

	Replacement	No Replacement
Order Matters	✓	✓
Order Doesn't Matter	×	✓

This grid helps us classify different probability problems based on their characteristics. The ✓ and × are used to indicate what we will study in this class.

Problem: Suppose that a password consists of 10 characters. The character set contains 256 possible characters. If characters are chosen uniformly at random, what is the probability of picking a password that starts with an 'A'?

Analysis:

- Replacement: ✓
- Order matters: ✓

Visualization:

- All possible passwords:

$$256, 256, 256, \dots, 256$$

(256 choices for each of the 10 slots)

- Passwords starting with 'A':

$$A, 256, 256, \dots, 256$$

A-----

(1 choice for first slot ('A'), 256 choices for each of the remaining 9 slots)

Calculation:

- Total number of possible passwords: 256^{10} (256 choices for each of 10 slots)
- Number of passwords starting with 'A': 1×256^9 (1 choice for first slot, 256 choices for each of 9 slots)
- Probability = $\frac{\text{Favorable outcomes}}{\text{Total outcomes}} = \frac{1 \times 256^9}{256^{10}} = \frac{1}{256}$

Conclusion: The probability of picking a password that starts with an 'A' is $\frac{1}{256}$.

General Rule: If you have a list of n things to choose from, replacement is allowed, order matters, and you choose k times, then there are n^k possible choices.

New Problem: Using the previous example (where $n = 256$ and $k = 10$), what is the probability of randomly picking a password that repeats at least one character?

Strategy: It is sometimes easier to calculate the probability of the complement of an event.

Approach: We will count the number of passwords where each character is unique.

Let A be the event that the randomly chosen password has no repeated characters.

$$P(A^c) = 1 - P(A)$$

Number of passwords with unique characters:

- Visualization:

$$\underbrace{256 \cdot 255 \cdot 254 \cdot 253 \cdot 252 \cdot 251 \cdot 250 \cdot 249 \cdot 248 \cdot 247}_{10 \text{ positions}}$$

- Mathematical representation: $\prod_{i=0}^9 (256 - i)$
- Probability calculation: $P(A^c) = 1 - \frac{\prod_{i=0}^9 (256 - i)}{256^{10}}$

General Formula: When picking k things out of n things while keeping track of the order (where $k \leq n$):

Number of different ways:

$$\begin{aligned}
 &= n \cdot (n-1) \cdot (n-2) \cdot \dots \cdot (n-k+1) \\
 &= n \cdot (n-1) \cdot (n-2) \cdot \dots \cdot (n-k+1) \cdot \frac{(n-k) \cdot (n-k-1) \cdot \dots \cdot 1}{(n-k) \cdot (n-k-1) \cdot \dots \cdot 1} \\
 &= \frac{n!}{(n-k)!}
 \end{aligned}$$

Where $n!$ is defined as:

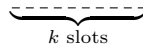
$$n! = \prod_{i=1}^n i \quad \text{and} \quad 0! = 1$$

$\frac{n!}{(n-k)!}$ is known as “ n permute k ”, denoted as ${}^n P_k$.

No replacement, order does not matter:

The trick is to solve the problem assuming order matters, then adjust by dividing by the number of ways to order the k things.

Consider the following slots:



First, we count the number of ways to fill these slots while keeping track of the order:

- This is given by ${}^n P_k = \frac{n!}{(n-k)!}$
- It represents the number of ways to choose and arrange k items from n options

However, this count includes permutations of the same k items, which we don't want to distinguish. To adjust for this overcounting:

- We divide by the number of ways to order k items, which is $k!$
 - $k!$ represents all possible permutations of the k chosen items
- This adjustment gives us the following formula:

$$\frac{{}^n P_k}{k!} = \frac{n!}{k!(n-k)!} = {}^n C_k = \binom{n}{k}$$

The result, $\binom{n}{k}$, is known as “ n choose k ”. It represents the number of ways to choose k items from n options when the order doesn't matter.

Lecture 5: Tuesday 9/10/2024

No Replacement, Order Does Not Matter

A common source of examples for this scenario is card games like poker.

Example: Suppose you are dealt 5 cards from a well-shuffled deck of cards. What is the probability that you are dealt a straight (5 cards in sequence)?

- A well-shuffled deck means all 52 cards are equally likely to be drawn (uniformly at random).
- A straight has 5 consecutive ranks but not all of the same suit.

Common Strategy: Undercount and Adjust

- We count a specific case and adjust for the number of cases.
- Recall: For $\binom{n}{k} = \frac{n P_k}{k!}$, we overcounted and adjusted by dividing by $k!$.

Let's consider a specific type of straight: one containing the ranks 9, 10, J, Q, K.

- There are 4 different suits, so there are four ways to choose each rank.
- Total number of ways for a specific straight: $4^5 = 1024$
- Subtract straight flushes: $1024 - 4 = 1020$ (4 straight flushes, one for each suit)

The number of all straights is equal to $(4^5 - 4) \times$ number of options for the starting rank.

- Ace can be considered the highest or lowest rank, but not both:
 - A, 2, 3, 4, 5 ✓
 - 10, J, Q, K, A ✓
 - J, Q, K, A, 2 ✗
- There are 10 possible starting ranks (Ace(1) through 10)

Therefore, the total number of straights is:

$$10 \times (4^5 - 4) = 10 \times 1020 = 10,200$$

The required probability is:

$$\begin{aligned} P(\text{Straight}) &= \frac{\text{Number of straights}}{\text{Number of possible hands}} \\ &= \frac{10(4^5 - 4)}{\binom{52}{5}} \end{aligned}$$

Conditional Probability

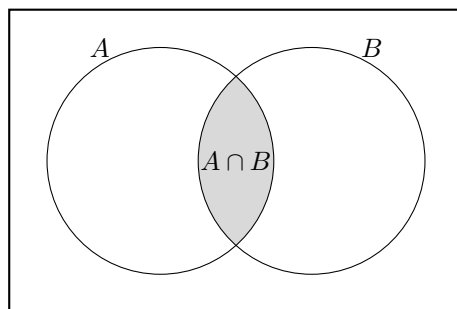
Conditional probability measures the likelihood of an event occurring given that another event has already occurred. It allows us to update our probability estimates based on new information.

Definition: Given two events A and B , where $P(A) > 0$, the conditional probability of B given that A has occurred is denoted by $P(B|A)$. This probability is defined as:

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

Example: Suppose you buy a lottery ticket and the first four numbers drawn match the numbers on your ticket. Your chances of winning have increased because we now have additional information.

The formula for conditional probability can be interpreted as the proportion of outcomes in A that also belong to B . This is visually represented in the Venn diagram below:



In this diagram, $P(B|A)$ represents the proportion of the area of A that overlaps with B .

Independence

Two events A and B are independent if:

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

Note: This definition holds for all values of $P(A)$ and $P(B)$, including when either or both equal zero.

In the case where $P(A) > 0$, independence implies:

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

Which is equivalent to $P(B|A) = P(B)$, meaning the occurrence of A does not affect the probability of B .