

# Probability

CS 220 — Applied Discrete Mathematics

{April 30, May 5}, 2025



# Terminology

Everything you have learned about **counting** constitutes the basis for computing the **probability** of **events** to happen.

## Definitions

An **experiment** is a task, procedure, **generative process**, etc.

Each time the **experiment** is performed, it yields one **outcome**. If it is performed multiple times, it may yield a different **outcome** each time.

The set of possible **outcomes** is called the **sample space**.

An **event** is a subset of the **sample space**.

## Example

**Experiment:** Roll two dice (one red, one green).

**Sample space:**  $\{(1, 1), (1, 2), (2, 1), (1, 3), (2, 2), (3, 1), \dots, (6, 6)\}$

“The dice sum to 7” corresponds to an **event**.

“The red result is larger than the green result” is another **event**.

“Both dice show 6s” is another **event** (containing a single **outcome**).

# Probability of an Event

If all outcomes in the sample space are equally likely, the following definition of probability applies:

## Definition (Probability)

Suppose  $S$  is a finite **sample space** of **equally likely outcomes**.

The **probability** of an **event**  $E$ , where  $E \subseteq S$ , is

$$p(E) = \frac{|E|}{|S|}$$

**Probability** values range from 0 to 1.

- ▶ A 0 probability means the **event** will never happen.
- ▶ A 1 probability means the **event** will always happen.

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- ▶ An urn contains 4 green balls and 5 red balls.  
What is the probability that a ball chosen from the urn is green?
  
- ▶ What is the probability of winning the lottery “6/49” — that is, picking the correct set of 6 numbers out of 49?

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What is the probability that a ball chosen from the urn is green?  
**Solution:** The **sample space** has 9 possible **outcomes**.  
The **event** “chosen ball is green” contains 4 of these outcomes.  
Therefore, the **probability** of this **event** is  $4/9$  or approximately 44.44%.
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**Solution:** The **sample space** has  $C(49, 6)$  possible **outcomes**.  
Only 1 of these outcomes actually wins the lottery.

$$p(\text{Win}) = \frac{1}{C(49, 6)} = \frac{1}{13\,983\,816}$$

# Complementary Event

## Definition (Complementary Event)

Let  $E$  be an **event** in a sample space  $S$ .

Its **complementary event**, written  $\overline{E}$ , is defined as  $S - E$ , meaning “ $E$  does not happen”. Its **probability** is the following:

$$p(\overline{E}) = 1 - p(E)$$

The probability of  $\overline{E}$  can be calculated from the definition:

$$p(\overline{E}) = p(S - E) = \frac{|S - E|}{|S|} = \frac{|S| - |E|}{|S|} = 1 - \frac{|E|}{|S|} = 1 - p(E)$$

This rule is useful if it is easier to determine the probability of the **complementary event** than the probability of the event itself.

# Examples



$$p(E) = 1 - p(\overline{E})$$

- ▶ A sequence of 10 bits is randomly generated.  
What is the probability that at least one of these bits is zero?
  
  
  
  
  
  
  
  
  
  
- ▶ In a group of 36 people, what is the probability that at least 2 of them have the same birthday? (Assume all birthdays are equally likely.)



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What is the probability that at least one of these bits is zero?

**Solution:** The sample space  $S$  has  $2^{10} = 1024$  outcomes.

Let  $E$  refer to the event “at least one of the bits is zero”.

The complementary event  $\bar{E}$  means “none of the bits is zero”.

It has only one outcome, namely 11111 11111. Thus  $p(\bar{E}) = 1/1024$ .

$$p(E) = 1 - p(\bar{E}) = 1 - \frac{1}{1024} = \frac{1023}{1024}$$

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- ▶ In a group of 36 people, what is the probability that at least 2 of them have the same birthday? (Assume all birthdays are equally likely.)

**Solution:** The sample space  $S$  contains all possibilities for the birthdays of the 36 people, so  $|S| = 365^{36}$ . Event  $E$  is “at least 2 people share a birthday”.

Consider  $\bar{E}$ : “all 36 people have a different birthday”.

The event  $\bar{E}$  contains  $P(365, 36)$  outcomes (365 possibilities for the first person's birthday, 364 for the second, and so on).

$$p(E) = 1 - p(\bar{E}) = 1 - \frac{P(365, 36)}{365^{36}} \approx 1 - 0.168 \approx 0.832, \text{ or } 83.2\%$$

# Unions of Events

Let  $E_1$  and  $E_2$  be **events** in the **sample space**  $S$ .

If  $E_1$  and  $E_2$  are **disjoint**, then we have

$$p(E_1 \cup E_2) = p(E_1) + p(E_2)$$

Otherwise, we have

$$p(E_1 \cup E_2) = p(E_1) + p(E_2) - p(E_1 \cap E_2)$$

Does this remind you of something?

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Of course, the **sum rule** and **inclusion-exclusion**.

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### **Solution:**

Let  $E_2$  be “divisible by 2”; that is,  $E_2 = \{2, 4, 6, \dots, 100\}$ , and so  $|E_2| = 50$

Let  $E_5$  be “divisible by 5”; that is,  $E_5 = \{5, 10, \dots, 100\}$ , and so  $|E_5| = 20$ .

Then  $p(E_2) = 0.5$  and  $p(E_5) = 0.2$ . But these **events** overlap:

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What is  $E_2 \cap E_5$ ? It is “divisible by both 2 and 5” which is just “divisible by 10”.

So  $E_2 \cap E_5 = \{10, 20, 30, \dots, 100\}$ , and so  $|E_2 \cap E_5| = 10$ , so  $p(E_2 \cap E_5) = 0.1$

Now we can calculate using **inclusion-exclusion**:

$$p(E_2 \cup E_5) = p(E_2) + p(E_5) - p(E_2 \cap E_5) = 0.5 + 0.2 - 0.1 = 0.6$$

## Example: Unions of Events

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We get the same result if we use **inclusion-exclusion** to calculate  $|E_2 \cup E_5|$ :

$$p(E_2 \cup E_5) = \frac{|E_2 \cup E_5|}{|S|} = \frac{50 + 20 - 10}{100} = 0.6$$



# Discrete Probability Distributions

What if the **outcomes** of an **experiment** are not equally likely?

## Definition (Discrete Probability Distribution)

Let  $S$  be a finite **sample space**.

A **discrete probability distribution** directly assigns a **probability** to every **outcome** in  $S$ . It must satisfy two conditions:

1.  $0 \leq p(s) \leq 1$  for every  $s \in S$ , and
2.  $\sum_{s \in S} p(s) = 1$ .

If we consider the **distribution** as the function  $p : S \rightarrow [0, 1]$ , then that function is called a **probability mass function**.

If an **experiment** on  $S$  has the **discrete probability distribution**  $p$ , then the probability of an **event**  $E \subseteq S$  is defined as follows:

$$p(E) = \sum_{s \in E} p(s)$$

# Notation

In this course, we'll generally talk about only one **experiment** at a time. Each **experiment** has

- ▶ a **sample space**  $S$ , and
- ▶ a **(discrete) probability distribution** on  $S$

We will typically “overload” the notation  $p(\ )$ :

- ▶  $p(s)$  where  $s \in S$  — the probability of the single **outcome**  $s$
- ▶  $p(E)$  where  $E \subseteq S$  — the probability of the **event**  $E$
- ▶  $p(E|F)$  where  $E, F \subseteq S$  — the conditional probability of  $E$  given  $F$

All implicitly depend on the **experiment** and its **probability distribution**.

Other courses and literature might use slightly different notations, especially to talk about multiple **experiments** at a time.

# Uniform Distribution

## Definition (Uniform Distribution)

Let  $S$  be a finite **sample space**. The **uniform distribution** on  $S$  is defined by

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(Does this satisfy the conditions on **discrete probability distributions**?)

If an **experiment** on  $S$  has a **uniform distribution**  $p$ ,  
then the probability of an **event**  $E \subseteq S$  is

$$p(E) = \sum_{s \in E} p(s) = \sum_{s \in E} \frac{1}{|S|} = \frac{|E|}{|S|}$$

In other words, all of our examples so far have been assuming that the **sample space** is **uniformly distributed** (“outcomes are equally likely”).

## Example: A Non-Uniform Distribution (1)



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**Solution:** There are 6 possible **outcomes**:  $S = \{s_1, \dots, s_6\}$ .

Let  $p$  be the **discrete probability distribution** for this **experiment**.

$$p(s_1) = p(s_2) = p(s_4) = p(s_5) = p(s_6) = x \qquad p(s_3) = 2x$$

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Since the probabilities must add up to 1, we have:

$$1 = \sum_{s \in S} p(s) = 7x$$

And therefore:

$$p(s_1) = p(s_2) = p(s_4) = p(s_5) = p(s_6) = \frac{1}{7} \qquad p(s_3) = \frac{2}{7}$$

## Example: A Non-Uniform Distribution (2)

$$p(E) = \sum_{s \in E} p(s)$$

For the biased die from the previous example, what is the probability that an odd number appears when we roll the die?



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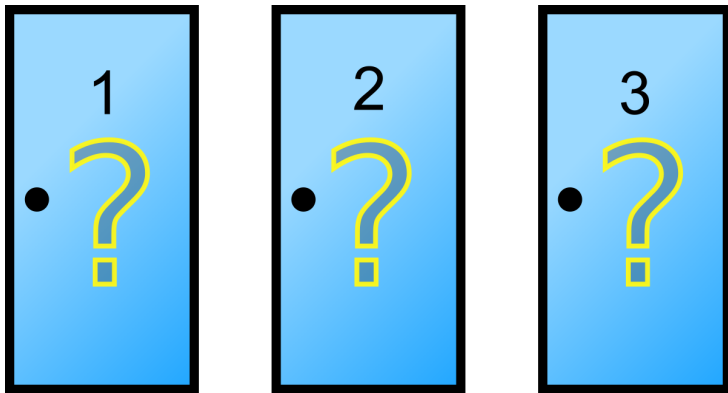
**Solution:** Let  $E_{\text{odd}} = \{s_1, s_3, s_5\}$ . We want to calculate  $p(E_{\text{odd}})$ :

$$p(E_{\text{odd}}) = \sum_{s \in E_{\text{odd}}} p(s) = \frac{1}{7} + \frac{2}{7} + \frac{1}{7} = \frac{4}{7} \approx 57.14\%$$

# Conditional Probability

# The Monty Hall Problem

You are on a TV show.<sup>1</sup> There are three doors, and you must pick one. Behind one door is a brand new **car**. Behind the other two are **goats**.



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<sup>1</sup>[https://en.wikipedia.org/wiki/Monty\\_Hall\\_problem](https://en.wikipedia.org/wiki/Monty_Hall_problem)

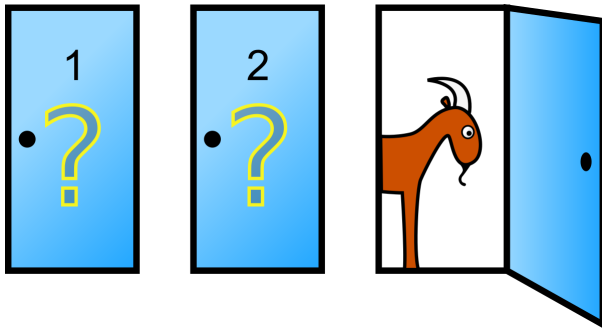
# The Monty Hall Problem — The Twist

You pick a door; let's say it's Door #1.

The host, who knows which doors have which prizes, must open one of the other doors, revealing a goat; let's say it's Door #3.

The host then says, "Do you want to stay with #1 or switch to #2?"

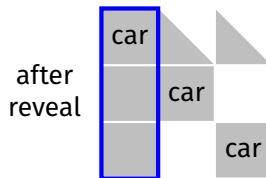
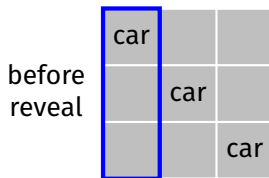
Should you stay or should you switch? Does it matter?



# The Monty Hall Problem — Solution

The answer is, surprisingly, yes you should switch!

Here's how possibilities change, **given** that you picked Door #1 and then Monty revealed a door with a goat:



The **effective** sample space has shrunk!

Door #1	Door #2	Door #3	Revealed	Stay	Switch
Car	Goat	Goat	2 or 3	Car	Goat
Goat	Car	Goat	3	Goat	Car
Goat	Goat	Car	2	Goat	Car

# Conditional Probability

Suppose that we toss a coin 3 times.

What is the probability that we get tails at least twice?

Solution:

- ▶ There are  $2^3 = 8$  different **outcomes**.
- ▶ Tails at least twice: {HTT, THT, TTH, TTT}
- ▶ So  $\frac{4}{8} = \frac{1}{2}$ . Equivalently,  $\frac{C(3,2)+C(3,3)}{2^3} = \frac{3+1}{8} = \frac{1}{2}$ .

What is the probability that we get tails at least twice  
*if the first toss landed heads?*

Solution:

- ▶ If the first toss is H, the possible outcomes are {HHH, HHT, HTH, HTT}.
- ▶ Tails occurs at least twice in only one of those: {HTT}.
- ▶ So the **conditional probability** is  $\frac{1}{4}$ .

# Conditional Probability

## Definition (Conditional Probability)

Let  $S$  be a **sample space** and let  $E$  and  $F$  be **events** in  $S$ .

The **conditional probability** of  $E$  given  $F$ , written  $p(E|F)$ , is defined as

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

It is the probability that  $E$  occurs assuming that  $F$  occurs.

That is, to measure the **conditional probability** of  $E$  given  $F$ :

- ▶ we use  $F$  as the effective **sample space** (it must be possible!)
- ▶ we must “trim”  $E$  down to the parts that fit in  $F$ : that is  $E \cap F$

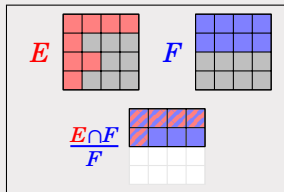
# Example: Calculating Conditional Probability

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

What is the probability that a random string of 4 bits contains at least 2 consecutive zeroes, given that its first bit is a zero?

## Solution:

- ▶  $S$  is “bit strings of length 4”; there are  $2^4 = 16$  of them
- ▶  $E$  is “bit string contains at least two consecutive zeroes”
- ▶  $F$  is “first bit of the string is a zero”
- ▶  $E \cap F = \{0000, 0001, 0010, 0011, 0100\}$
- ▶  $p(E \cap F) = \frac{|E \cap F|}{|S|} = \frac{5}{16}$
- ▶  $p(F) = \frac{|F|}{|S|} = \frac{8}{16}$
- ▶  $p(E|F) = \frac{5/16}{8/16} = \frac{5}{8} = 0.625$





# Using Conditional Probability

From the definition of **conditional probability**:

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

we can rewrite it in the following form:

$$p(A \cap B) = p(A) \cdot p(B|A)$$

which we can interpret as follows:

*The probability that both  $A$  and  $B$  both happen is the probability that, first,  $A$  happens, times the **conditional probability** that  $B$  happens given  $A$ .*

It is not necessary that  $A$  causes  $B$ .

It is not even necessary that  $A$  happens before  $B$  in time!

# Example: Using Conditional Probability

$$p(A \cap B) = p(A) \cdot p(B|A)$$

A gambler has a fair die and a biased die in her pocket.  
(Recall, the biased die rolls 3 twice as often as any other number.)  
She takes out a random die for a game. We can't tell which one.  
How likely is it that she rolls a 3?

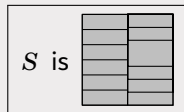
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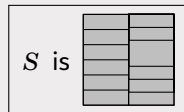
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- ▶ Let  $E$  be “rolled a 3”.



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- ▶ Let  $F$  be “used fair die” and  $\bar{F}$  be “used biased die”. So  $p(F) = \frac{1}{2}, p(\bar{F}) = \frac{1}{2}$ .
- ▶ Let  $E$  be “rolled a 3”. It can be split into two parts:  $E = (E \cap F) \cup (E \cap \bar{F})$ . That is, “rolled a 3” could be “rolled a 3 with fair die” or “rolled a 3 with biased die”.

$$p(E \cap F) = p(F) \cdot p(E|F) = \frac{1}{2} \cdot \frac{1}{6} = \frac{1}{12}$$

$$p(E \cap \bar{F}) = p(\bar{F}) \cdot p(E|\bar{F}) = \frac{1}{2} \cdot \frac{2}{7} = \frac{1}{7}$$

- ▶ Then  $p(E) = p(E \cap F) + p(E \cap \bar{F}) = \frac{1}{12} + \frac{1}{7} = \frac{19}{84} \approx 0.226$ .

This is the **marginal probability** of  $E$  — the **total** over all the possible “causes”.

# Inference

You are standing in a dark kitchen, in front of the sink.

You can barely see two switches on the wall. One is for the lights, and one is for the garbage disposal, but you don't know which is which.

You pick a switch at random.

What is the probability that you chose the light switch?



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What is the probability that you chose the light switch? **evidence**  
**posterior prob.**

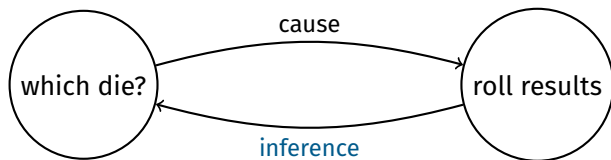
In this example, the evidence is conclusive. What if it isn't?

# Probabilistic Inference

A gambler has both a fair die and a biased die in her pocket.  
(Recall, the biased die rolls 3 twice as often as any other number.)

She selects a random die for a game. We can't tell which one.  
She rolls the die, and the result is a 3.

How likely is it that she is using the fair die?



# Probabilistic Inference

- ▶ Let  $F$  be the event that the gambler selects the fair die. Then  $\bar{F}$  is the event that she selects the biased die.

$$p(F) = \frac{1}{2} \qquad p(\bar{F}) = \frac{1}{2}$$

- ▶ Let  $X$  be the event that the die comes up 3. We know the **conditional probabilities** of  $X$  given  $F$  and  $\bar{F}$ :

$$p(X|F) = \frac{1}{6} \qquad p(X|\bar{F}) = \frac{2}{7}$$

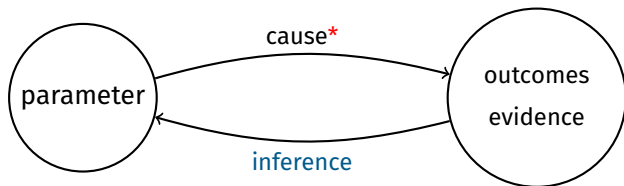
- ▶ We **want** the **conditional probability** of  $F$  given  $X$  — that is,  $p(F|X)$ ! That is, we have **observed** a roll result of 3 (event  $X$ ). Given that **evidence**, we want to **infer** what die she is using.

(Note: The probability  $p(F)$  doesn't *change*; it refers to the probability at an earlier point in time, before the die was actually chosen.)

# Bayes' Theorem

**Bayes' Theorem** provides a way to reason about the likelihood that the die is biased based on the evidence of the outcomes.

Bayes' Theorem is the cornerstone of many algorithms in machine learning where the goal is to determine the likelihood of some event based on data obtained from observations.



# Bayes' Theorem

## Bayes' Theorem

Let  $A$  and  $B$  be events. Then

$$p(A|B) = \frac{p(A) \cdot p(B|A)}{p(B)}$$

Bayes' Theorem is usually applied when  $A$  is a “hidden cause” and  $B$  is an “observable effect”. Then we say

- ▶  $p(A)$  is the **prior probability** of  $A$ .
- ▶  $p(B|A)$  is the **conditional probability** of  $B$  given  $A$ .
- ▶  $p(B)$  is the **marginal probability** of  $B$ , sometimes\* calculated by

$$p(B) = p(B \cap A) + p(B \cap \bar{A}) = p(A) \cdot p(B|A) + p(\bar{A}) \cdot p(B|\bar{A})$$

- ▶  $p(A|B)$  is the **posterior probability** of  $A$  given  $B$ .

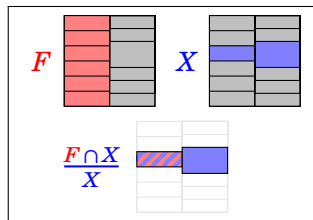
# Using Bayes' Theorem

The **prior probability** of  $F$  ("fair die"):

$$p(F) = \frac{1}{2}$$

The **conditional probability** of  $X$  ("rolled 3") given  $F$ :

$$p(X|F) = \frac{1}{6}$$



The **marginal probability** of  $X$ :

$$p(X) = p(F) \cdot p(X|F) + p(\bar{F}) \cdot p(X|\bar{F}) = \frac{1}{2} \cdot \frac{1}{6} + \frac{1}{2} \cdot \frac{2}{7} = \frac{19}{84}$$

Then by **Bayes' Theorem** the **posterior probability** of  $F$  given  $X$  is

$$p(F|X) = \frac{p(F) \cdot p(X|F)}{p(X)} = \frac{1/2 \cdot 1/6}{19/84} = \frac{7}{19} \approx 0.37$$

# Exercise: Bayes' Theorem

$$p(A|B) = \frac{p(B|A) \cdot p(A)}{p(B)}$$

Suppose an elven paladin has one 6-sided die, one 10-sided die, and one 20-sided die. The paladin selects a die at random, rolls it out of our view, and reports a 2. How likely is it that the 6-sided die was selected?

## Hints:

- ▶ There are *three* choices for the die this time. Let the events be called  $D_6$ ,  $D_{10}$ , and  $D_{20}$ . They are disjoint, and  $D_6 \cup D_{10} \cup D_{20} = S$ .
- ▶ Let  $X$  be the event “rolled a 2”.



# Independent Events

# Independent Events

## Example

A die is rolled.

- ▶ What is the probability that its result is a multiple of 3?
- ▶ What is the probability that its result is a multiple of 3, given that the result is even?

# Independent Events

## Example

A die is rolled.

- ▶ What is the probability that its result is a multiple of 3?

Solution:  $\frac{2}{6} = \frac{1}{3}$ .

- ▶ What is the probability that its result is a multiple of 3, given that the result is even?

Solution:  $\frac{1}{3}$ .

Even vs odd does not affect whether the result is a multiple of 3.

We say these events are **independent** — despite being based on the same “physical action”!

# Independent Events

## Definition (Independent)

Let  $E$  and  $F$  be events in  $S$ . Then  $E$  and  $F$  are **independent** if and only if

$$p(E \cap F) = p(E) \cdot p(F)$$

Equivalently:

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

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

# Independent Bernoulli Trials

## Definition (Bernoulli Trial)

A **Bernoulli trial** is an **experiment** whose set of **outcomes** is partitioned into an **event** labeled “success” and an event labeled “failure”.

## Examples

- ▶ Experiment: Flipping a coin.  
Success = {H}, failure = {T}.
- ▶ Experiment: Rolling a die.  
Success = {2, 4, 6}, failure = {1, 3, 5}.
- ▶ Experiment: Rolling a die.  
Success = {1, 2, 3, 4, 5}, failure = {6}.
- ▶ Experiment: Randomly picking a number from  $\{1, \dots, 100\}$ .  
Success = “prime”, failure = “not prime”.

# Example: Bernoulli Trials

When we roll a die, we consider a result of 1–5 a success, and 6 is a failure.

- ▶ If we roll the die 3 times, what is the probability we get a success, a failure, and then another success?

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**Solution:** Each roll is **independent**, so

$$p(sfs) = p(s) \cdot p(f) \cdot p(s) = \frac{5}{6} \cdot \frac{1}{6} \cdot \frac{5}{6} = \frac{25}{216}$$

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- ▶ What is the probability of 2 successes and 1 failure, in any order?

**Solution:** Generalizing from the previous solution, the probability of any sequence of 2 successes and 1 failure is  $\frac{25}{216}$ . But there are 3 ways to choose which 2 of the 3 trials are successful.

$$p(2s, 1f) = p(ssf) + p(sfs) + p(fss) = 3 \cdot \frac{25}{216} = \frac{25}{72}$$

# Bernoulli Trials

## Bernoulli Trials

The probability of  $k$  successes in  $n$  independent Bernoulli trials is

$$C(n, k) \cdot s^k (1 - s)^{n-k}$$

where  $s$  is the probability of success in each trial.

Let  $f = 1 - s$ . Apply the Binomial Theorem to  $(s + f)^n$ :

$$(s + f)^n = 1s^n f^0 + \dots + C(n, k) \cdot s^k f^{n-k} + \dots + 1s^0 f^n$$

# Random Variables

# Random Variables

We want to do math on **experiments**, but some **outcomes** are not numbers. So we introduce an indirection: the **random variable**.

## Definition (Random Variable)

Let  $S$  be the **sample space** for an experiment.

A **random variable** is a function  $S \rightarrow \mathbb{R}$ .

That is, a **random variable** assigns a real number to each **outcome**.

**Note:** A **random variable** is a function, not a variable, and it is not random, but maps “random” results from experiments onto real numbers in a well-defined manner.

# Examples: Random Variables

- ▶ **Experiment:** Two dice are rolled. An outcome is a pair of numbers 1–6. Suppose we're interested in the sum of the faces of the two dice.

**Random Variable:**  $X(a, b) = a + b$ .

- ▶ **Experiment:** A card is drawn from a standard deck. An outcome is a pair of face and suit, like  $9\heartsuit$  or  $K\spadesuit$ . Suppose we're counting cards (Hi-Lo).

**Random Variable:** 
$$X(f, s) = \begin{cases} +1 & \text{if } f \in \{2, 3, 4, 5, 6\} \\ 0 & \text{if } f \in \{6, 7, 8, 9\} \\ -1 & \text{if } f \in \{10, J, Q, K, A\} \end{cases}$$

- ▶ **Experiment:** A single die is rolled. An outcome is a number 1–6. If it shows 1–5, then player A wins \$1 from player B. If it shows 6, then player B wins \$5 from player A.

**Random Variable:** 
$$X(d) = \begin{cases} 1 & \text{if } d \in \{1, 2, 3, 4, 5\} \\ -5 & \text{if } d = 6 \end{cases}$$

$X$  represents player A's gain;  $-X$  represents player B's gain.

# Expected Value

Once we have defined **random variables** for the **experiment**, we can analyze their numeric properties. For example:

## Definition (Expected Value)

Let  $S$  be a **sample space** and let  $X$  be a **random variable**.

The **expected value** of  $X$ , written  $E[X]$ , is defined as follows:

$$E[X] = \sum_{s \in S} X(s) \cdot p(s)$$

That is,  $E[X]$  is the average value of  $X$  weighted by the probability of each **outcome**.

The expectation represents what we would expect to get as the **mean** value of  $X$  for a large number of repetitions of the experiment.

## Example: Expected Value (1)

$$E[X] = \sum_{s \in S} X(s) \cdot p(s)$$

A six-sided die is rolled.

If it shows 1–5, then player A wins \$1.

If it shows 6, then player B wins \$5.

$$X(d) = \begin{cases} 1 & \text{if } d \in \{1, 2, 3, 4, 5\} \\ -5 & \text{if } d = 6 \end{cases}$$

What is player A's **expected** gain per round? That is, what is  $E[X]$ ?

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What is player A's **expected** gain per round? That is, what is  $E[X]$ ?

**Solution:** There are 6 outcomes, each equally likely (probability  $\frac{1}{6}$ ).

$$\begin{aligned} E[X] &= \sum_{d \in \{1, 2, 3, 4, 5, 6\}} X(d) \cdot p(d) \\ &= \frac{1}{6} (X(1) + X(2) + X(3) + X(4) + X(5) + X(6)) \\ &= \frac{1}{6} (1 + 1 + 1 + 1 + 1 + -5) = 0 \end{aligned}$$



## Example: Expected Value (2)

$$E[X] = \sum_{s \in S} X(s) \cdot p(s)$$

Two six-sided dice are rolled. Let the **random variable**  $X$  be the sum of the two faces. There are 36 outcomes ( $S$  is pairs of numbers from 1 to 6). Each outcome is equally likely (probability  $\frac{1}{36}$ ). What is  $E[X]$ ?

## Example: Expected Value (2)

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$$\begin{aligned} E[X] &= \sum_{(a,b) \in S} p(a,b) \cdot X(a,b) = \frac{1}{36} \sum_{(a,b) \in S} (a+b) = \frac{1}{36} \sum_{a=1}^6 \sum_{b=1}^6 (a+b) \\ &= \frac{1}{36} \left( \sum_{a=1}^6 \sum_{b=1}^6 a + \sum_{a=1}^6 \sum_{b=1}^6 b \right) = \frac{1}{36} \left( 6 \sum_{a=1}^6 a + 6 \sum_{b=1}^6 b \right) \\ &= \frac{1}{36} (6 \cdot 21 + 6 \cdot 21) = \frac{252}{36} = 7 \end{aligned}$$

This means that if we roll the dice many times, sum all the numbers that appear and divide the sum by the number of trials, we expect to find a value of 7.

# Linearity of Expected Value

## Theorem

Suppose that  $X$  and  $Y$  are **random variables** on a **sample space**  $S$ .

Then  $X + Y$  is itself a **random variable**, and  $E[X + Y] = E[X] + E[Y]$ .

Furthermore, if  $a, b \in \mathbb{R}$ , then  $E[aX + b] = a E[X] + b$ .

The theorem also generalizes to more than two **random variables**:

*If  $X_1, \dots, X_n$  are **random variables**, then so is  $X_1 + \dots + X_n$ ,  
and  $E[X_1 + \dots + X_n] = E[X_1] + \dots + E[X_n]$ .*

## Example: Expected Value (2')

With this theorem, we can solve the previous example more easily.

Let  $X_1$  and  $X_2$  be the results of the first and the second die, respectively. For each die, there is an equal probability for each of the six numbers to appear. Therefore,

$$E[X_1] = E[X_2] = \frac{1 + 2 + 3 + 4 + 5 + 6}{6} = \frac{21}{6} = \frac{7}{2}$$

Now we have

$$E[X_1 + X_2] = E[X_1] + E[X_2] = \frac{7}{2} + \frac{7}{2} = 7$$

# Summary

- ▶ experiment, sample space, outcome, event
- ▶ probability of event
- ▶ complementary event
- ▶ unions of events (disjoint, non-disjoint)
- ▶ discrete probability distributions, uniform distribution
- ▶ conditional probability, marginal probability
- ▶ Bayes' Theorem, prior vs posterior probability
- ▶ independent events, Bernoulli trials
- ▶ random variables, expected value