

# Unit 01 notes

## Events and outcomes

### 01 Theory

#### 📖 Events and outcomes – informally

- An **event** is a *description* of something that can happen.
- An **outcome** is a *complete description* of something that can happen.

All outcomes are events. An event is usually a *partial* description. Outcomes are events given with a *complete* description.

Here ‘complete’ and ‘partial’ are within the context of the **probability model**.

- ⚠️ It can be misleading to say that an ‘outcome’ is an ‘observation’.
  - ‘Observations’ occur in the *real world*, while ‘outcomes’ occur in the *model*.
  - To the extent the model is a good one, and the observation conveys *complete* information, we can say ‘outcome’ for the observation.

Notice:

- 💡 Because outcomes are *complete*, no two distinct outcomes could *actually happen* in a run of the experiment being modeled.

When an event happens, the *fact* that it has happened constitutes **information**.

#### 📖 Events and outcomes – mathematically

- The **sample space** is the *set of possible outcomes*, so it is the set of the complete descriptions of everything that can happen.
- An **event** is a *subset* of the sample space, so it is a *collection of outcomes*.
- ☞ For mathematicians: some “wild” subsets are not *valid* events. Problems with infinity and the continuum...

#### 📖 Notation

- Write  $S$  for the set of possible outcomes,  $s \in S$  for a single outcome in  $S$ .
- Write  $A, B, C, \dots \subset S$  or  $A_1, A_2, A_3, \dots \subset S$  for some events, subsets of  $S$ .
- Write  $\mathcal{F}$  for the collection of all events. This is frequently a *huge* set!
- Write  $|A|$  for the **cardinality** or *size* of a set  $A$ , i.e. the *number of elements it contains*.

Using this notation, we can consider an *outcome itself as an event* by considering the “singleton” subset  $\{\omega\} \subset S$  which contains that outcome alone.

### 02 Illustration

#### ☰ Example - Coin flipping

Flip a fair coin two times and record both results.

- **Outcomes:** sequences, like  $HH$  or  $TH$ .
- **Sample space:** all possible sequences, i.e. the set  $S = \{HH, HT, TH, TT\}$ .
- **Events:** for example:
  - $A = \{HH, HT\} = \text{“first was heads”}$
  - $B = \{HT, TH\} = \text{“exactly one heads”}$
  - $C = \{HT, TH, HH\} = \text{“at least one heads”}$

With this setup, we may combine events in various ways to generate other events:

- **Complex events:** for example:
  - $A \cap B = \{HT\}$ , or in words:  
“first was heads” AND “exactly one heads” = “heads-then-tails”  
  
Notice that the last one is a **complete description**, namely the **outcome**  $HT$ .
  - $A \cup B = \{HH, HT, TH\}$ , or in words:  
“first was heads” OR “exactly one heads”  
= “starts with heads, else it’s tails-then-heads”

### Exercise - Coin flipping: counting subsets

Flip a fair coin five times and record the results.

How many elements are in the sample space? (How big is  $S$ ?)

How many events are there? (How big is  $\mathcal{F}$ ?)

[Solution](#)

## 03 Theory

### New events from old

Given two events  $A$  and  $B$ , we can form new events using set operations:


$$A \cup B \longleftrightarrow \text{“event } A \text{ OR event } B\text{”}$$

$$A \cap B \longleftrightarrow \text{“event } A \text{ AND event } B\text{”}$$

$$A^c \longleftrightarrow \text{not event } A$$

We also use these terms for events  $A$  and  $B$ :

- They are **mutually exclusive** when  $A \cap B = \emptyset$ , that is, they have *no elements in common*.
- They are **collectively exhaustive**  $A \cup B = S$ , that is, when they jointly *cover all possible outcomes*.

-  In probability texts, sometimes  $A \cap B$  is written “ $A \cdot B$ ” or even (frequently!) “ $AB$ ”.

## ☰ Rules for sets

### Algebraic rules

- Associativity:  $(A \cup B) \cup C = A \cup (B \cup C)$ . Analogous to  $(A + B) + C = A + (B + C)$ .
- Distributivity:  $A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$ . Analogous to  $A(B + C) = AB + AC$ .

### De Morgan's Laws

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

In other words: you can distribute “ $c$ ” but must simultaneously do a switch  $\cap \leftrightarrow \cup$ .

## Probability models

### 04 Theory

#### ☰ Axioms of probability

A **probability measure** is a function  $P : \mathcal{F} \rightarrow \mathbb{R}$  satisfying:

#### Kolmogorov Axioms:

- **Axiom 1:**  $P[A] \geq 0$  for every event  $A$   
(probabilities are not negative!)
- **Axiom 2:**  $P[S] = 1$   
(probability of “anything” happening is 1)
- **Axiom 3:** additivity for any *countable collection* of *mutually exclusive* events:

$$P[A_1 \cup A_2 \cup A_3 \cup \dots] = P[A_1] + P[A_2] + P[A_3] + \dots$$

$$\text{when: } A_i \cap A_j = \emptyset \text{ for all } i \neq j$$

- %& Notation: we write  $P[A]$  instead of  $P(A)$ , even though  $P$  is a function, to emphasize the fact that  $A$  is a set.

#### ☰ Probability model

A **probability model** or **probability space** consists of a triple  $(S, \mathcal{F}, P)$ :

- $S$  the sample space
- $\mathcal{F}$  the set of valid events, where every  $A \in \mathcal{F}$  satisfies  $A \subset S$
- $P : \mathcal{F} \rightarrow \mathbb{R}$  a probability measure satisfying the Kolmogorov Axioms

#### 👉 Finitely many exclusive events

It is a consequence of the Kolmogorov Axioms that additivity also works for finite collections of mutually exclusive events:

$$P[A \cup B] = P[A] + P[B]$$

$$P[A_1 \cup \dots \cup A_n] = P[A_1] + \dots + P[A_n]$$

## 📄 Inferences from Kolmogorov

A probability measure satisfies these rules.  
They can be deduced from the Kolmogorov Axioms.

- **Negation:** Can you find  $P[A^c]$  but not  $P[A]$ ? Use negation:

$$P[A] = 1 - P[A^c]$$

- **Monotonicity:** Probabilities grow when outcomes are added:

$$A \subset B \implies P[A] \leq P[B]$$

- **Inclusion-Exclusion:** A trick for resolving unions:

$$P[A \cup B] = P[A] + P[B] - P[A \cap B]$$

(even when  $A$  and  $B$  are *not exclusive*!)

## ☰ Inclusion-Exclusion

The principle of inclusion-exclusion generalizes to three events:

$$P[A \cup B \cup C] = P[A] + P[B] + P[C] - P[A \cap B] - P[A \cap C] - P[B \cap C] + P[A \cap B \cap C]$$

The same pattern works for any number of events!

The pattern goes: “include singles” then “exclude doubles” then “include triples” then ...

Include, exclude, include, exclude, include, ...

## 05 Illustration

### ☰ Example - Lucia is Host or Player

The professor chooses three students at random for a game in a class of 40, one to be Host, one to be Player, one to be Judge. What is the probability that Lucia is either Host or Player?

#### ☰ Solution

1. ☰ Set up the probability model.

- Label the students 1 to 40. Write  $L$  for Lucia's number.
- **Outcomes:** assignments such as  $(H, P, J) = (2, 5, 8)$   
These are ordered triples with *distinct* entries in 1, 2, ..., 40.
- **Sample space:**  $S$  is the collection of all such distinct triples
- **Events:** any subset of  $S$
- **Probability measure:** assume all outcomes are equally likely, so  $P[(i, j, k)] = P[(r, l, p)]$  for all  $i, j, k, r, l, p$
- In total there are  $40 \cdot 39 \cdot 38$  triples of distinct numbers.
- Therefore  $P[(i, j, k)] = \frac{1}{40 \cdot 39 \cdot 38}$  for any *specific* outcome  $(i, j, k)$ .
- Therefore  $P[A] = \frac{|A|}{40 \cdot 39 \cdot 38}$  for any event  $A$ . (Recall  $|A|$  is the *number* of outcomes in  $A$ .)

2. ➡ Define the desired event.

- Want to find  $P[\text{“Lucia is Host or Player”}]$
- Define  $A = \text{“Lucia is Host”}$  and  $B = \text{“Lucia is Player”}$ . Thus:

$$A = \{(L, j, k) \mid \text{any } j, k\}, \quad B = \{(i, L, k) \mid \text{any } i, k\}$$

- So we seek  $P[A \cup B]$ .

3. ➡ Compute the desired probability.

- Importantly,  $A \cap B = \emptyset$  (mutually exclusive).  
There are no outcomes in  $S$  in which Lucia is *both* Host and Player.
- By *additivity*, we infer  $P[A \cup B] = P[A] + P[B]$ .
- Now compute  $P[A]$ .
  - There are  $39 \cdot 38$  ways to choose  $j$  and  $k$  from the students besides Lucia.
  - Therefore  $|A| = 39 \cdot 38$ .
  - Therefore:

$$P[A] \gg \gg \frac{|A|}{40 \cdot 39 \cdot 38} \gg \gg \frac{39 \cdot 38}{40 \cdot 39 \cdot 38} \gg \gg \frac{1}{40}$$

- Now compute  $P[B]$ . It is similar:  $P[B] = \frac{1}{40}$ .
- Finally compute that  $P[A] + P[B] = \frac{1}{20}$ , so the answer is:

$$P[A \cup B] \gg \gg P[A] + P[B] \gg \gg \frac{1}{20}$$

### Example - iPhones and iPads

At Mr. Jefferson’s University, 25% of students have an iPhone, 30% have an iPad, and 60% have neither.

What is the probability that a randomly chosen student has *some* iProduct? (Q1)

What about *both*? (Q2)

#### Solution

1. ➡ Set up the probability model.

- A student is chosen at random: an *outcome* is the chosen student.
- *Sample space*  $S$  is the set of all students.
- Write  $O = \text{“has iPhone”}$  and  $A = \text{“has iPad”}$  concerning the chosen student.
- All students are equally likely to be chosen: therefore  $P[E] = \frac{|E|}{|S|}$  for any event  $E$ .
- Therefore  $P[O] = 0.25$  and  $P[A] = 0.30$ .
- Furthermore,  $P[O^c A^c] = 0.60$ . This means 60% have “not iPhone AND not iPad”.

2. ➡ Define the desired event.

- Q1: desired event =  $O \cup A$
- Q2: desired event =  $OA$

3. ➡ Compute the probabilities.

- We do not believe  $O$  and  $A$  are exclusive.

- Try: apply inclusion-exclusion:

$$P[O \cup A] = P[O] + P[A] - P[OA]$$

- We know  $P[O] = 0.25$  and  $P[A] = 0.30$ . So this formula, with given data, RELATES Q1 and Q2.
- Notice the complements in  $O^c A^c$  and try *Negation*.
- *Negation*:

$$P[(OA)^c] = 1 - P[OA]$$

DOESN'T HELP.

- Try again: *Negation*:

$$P[(O^c A^c)^c] = 1 - P[O^c A^c]$$

- And De Morgan (or a Venn diagram!):

$$(O^c A^c)^c \gg \gg O \cup A$$

- Therefore:

$$P[O \cup A] \gg \gg P[(O^c A^c)^c]$$

$$\gg \gg 1 - P[O^c A^c] \gg \gg 1 - 0.6 = 0.4$$

- We have found Q1:  $P[O \cup A] = 0.40$ .
- Applying the RELATION from inclusion-exclusion, we get Q2:

$$P[O \cup A] = P[O] + P[A] - P[OA]$$

$$\gg \gg 0.40 = 0.25 + 0.30 - P[OA]$$

$$\gg \gg P[OA] = 0.15$$

## Conditional probability

### 06 Theory

#### Conditional probability

The **conditional probability** of “ $B$  given  $A$ ” is defined by:

$$P[B \mid A] = \frac{P[B \cap A]}{P[A]}$$

This conditional probability  $P[B \mid A]$  represents the probability of event  $B$  taking place *given the assumption* that  $A$  took place. (All within the given probability model.)

By letting the actuality of event  $A$  be taken as a fixed hypothesis, we can define a *conditional probability measure* by plugging events into the slot of  $B$ :

$$P[- \mid A] = \frac{P[- \cap A]}{P[A]}$$

It is possible to verify each of the Kolmogorov axioms for this function, and therefore  $P[- \mid A]$  itself defines a bona fide *probability measure*.

### ☰ Conditioning

What does it really mean?

Conceptually,  $P[B \mid A]$  corresponds to *creating a new experiment* in which we run the old experiment and record data *only those times that A happened*. Or, it corresponds to finding ourselves with *knowledge* or *data* that A happened, and we seek our best estimates of the likelihoods of other events, based on our existing model and the actuality of A.

Mathematically,  $P[B \mid A]$  corresponds to *restricting* the probability function to outcomes in A, and *renormalizing* the values (dividing by  $p[A]$ ) so that the total probability of all the outcomes (in A) is now 1.

The definition of conditional probability can also be turned around and reinterpreted:

### ☰ Multiplication rule

$$P[AB] = P[A] \cdot P[B \mid A]$$

“The probability of A AND B equals the probability of A *times* the probability of B-given-A.”

This principle generalizes to any events in sequence:

### ☰ Generalized multiplication rule

$$P[A_1 A_2 A_3] = P[A_1] \cdot P[A_2 \mid A_1] \cdot P[A_3 \mid A_1 A_2]$$

$$P[A_1 \cdots A_n] = P[A_1] \cdot P[A_2 \mid A_1] \cdot P[A_3 \mid A_1 A_2] \cdots P[A_n \mid A_1 \cdots A_{n-1}]$$

The generalized rule can be verified like this. First substitute  $A_2$  for B and  $A_1$  for A in the original rule. Now repeat, substituting  $A_3$  for B and  $A_1 A_2$  for A in the original rule, and combine with the first one, and you find the rule for triples. Repeat again with  $A_4$  and  $A_1 A_2 A_3$ , combine with the triples, and you get quadruples.

## 07 Illustration

### ✍ Exercise - Simplifying conditionals

Let  $A \subset B$ . Simplify the following values:

$$P[A \mid B], \quad P[A \mid B^c], \quad P[B \mid A], \quad P[B \mid A^c]$$

[Solution](#)

### ☰ Example - Coin flipping: at least 2 heads

Flip a fair coin 4 times and record the outcomes as sequences, like *HHTH*.

Let  $A_{\geq 2}$  be the event that there are at least two heads, and  $A_{\geq 1}$  the event that there is at least one heads.

First let's calculate  $P[A_{\geq 2}]$ .

Define  $A_2$ , the event that there were exactly 2 heads, and  $A_3$ , the event of exactly 3, and  $A_4$  the event of exactly 4. These events are exclusive, so:

$$P[A_{\geq 2}] = P[A_2 \cup A_3 \cup A_4] \gg \gg P[A_2] + P[A_3] + P[A_4]$$

Each term on the right can be calculated by counting:

$$P[A_2] = \frac{|A_2|}{2^4} \gg \gg \frac{\binom{4}{2}}{16} \gg \gg \frac{6}{16}$$

$$P[A_3] = \frac{|A_3|}{2^4} \gg \gg \frac{\binom{4}{3}}{16} \gg \gg \frac{4}{16}$$

$$P[A_4] = \frac{|A_4|}{2^4} \gg \gg \frac{\binom{4}{4}}{16} \gg \gg \frac{1}{16}$$

Therefore,  $P[A_{\geq 2}] = \frac{11}{16}$ .

Now suppose we find out that “at least one heads definitely came up”. (Meaning that we know  $A_{\geq 1}$ .) For example, our friend is running the experiment and tells us this fact about the outcome.

Now what is our estimate of likelihood of  $A_{\geq 2}$ ?

The formula for conditioning gives:

$$P[A_{\geq 2} \mid A_{\geq 1}] = \frac{P[A_{\geq 2} \cap A_{\geq 1}]}{P[A_{\geq 1}]}$$

Now  $A_{\geq 2} \cap A_{\geq 1} = A_{\geq 2}$ . (Any outcome with at least two heads automatically has at least one heads.) We already found that  $P[A_{\geq 2}] = \frac{11}{16}$ . To compute  $P[A_{\geq 1}]$  we simply *add* the probability  $P[A_1]$ , which is  $\frac{4}{16}$ , to get  $P[A_{\geq 1}] = \frac{15}{16}$ .

Therefore:

$$P[A_{\geq 2} \mid A_{\geq 1}] = \frac{11/16}{15/16} \gg \gg \frac{11}{15}$$

### ≡ Example: Flip a coin, then roll dice

Flip a coin. If the outcome is heads, roll two dice and add the numbers. If the outcome is tails, roll a single die and take that number. What is the probability of getting a tails AND a number at least 3?

#### ≡ Solution

This “two-stage” experiment lends itself to a solution using the multiplication rule for conditional probability.

##### 1. ≡ Label the events of interest.

- Let  $H$  and  $T$  be the events that the coin showed heads and tails, respectively.
- Let  $A_1, \dots, A_{12}$  be the events that the final number is 1,  $\dots$ , 12, respectively.
- The value we seek is  $P[TA_{\geq 3}]$ .

##### 2. ≡ Observe known (conditional) probabilities.

- We know that  $P[H] = \frac{1}{2}$  and  $P[T] = \frac{1}{2}$ .
- We know that  $P[A_5 \mid T] = \frac{1}{6}$ , for example, or that  $P[A_2 \mid H] = \frac{1}{36}$ .

##### 3. ≡ Apply “multiplication” rule.



- This rule gives:

$$P[TA_{\geq 3}] = P[T] \cdot P[A_{\geq 3} | T]$$

- We know  $P[T] = \frac{1}{2}$  and can see by counting that  $P[A_{\geq 3} | T] = \frac{2}{3}$ .
- Therefore  $P[TA_{\geq 3}] = \frac{1}{3}$ .

### ≡ Multiplication: draw two cards

Two cards are drawn from a standard deck (without replacement).

What is the probability that the first is a 3, and the second is a 4?

#### ≡ Solution

This “two-stage” experiment lends itself to a solution using the multiplication rule for conditional probability.

##### 1. ≡ Label events.

- Write  $T$  for the event that the first card is a 3
- Write  $F$  for the event that the second card is a 4.
- We seek  $P[TF]$ .

##### 2. ≡ Write down knowns.

- We know  $P[T] = \frac{4}{52}$ . (It does not depend on the second draw.)
- Easily find  $P[F | T]$ .
  - If the first is a 3, then there are four 4s remaining and 51 cards.
  - So  $P[F | T] = \frac{4}{51}$ .

##### 3. ≡ Apply multiplication rule.

- Multiplication rule:

$$P[TF] = P[T] \cdot P[F | T]$$

$$P[TF] = \frac{4}{52} \cdot \frac{4}{51} \gg \gg \frac{4}{13 \cdot 51}$$

- Therefore  $P[TF] = \frac{4}{663}$

## 08 Theory

### ≡ Division into Cases

For any events  $A$  and  $B$ :

$$P[B] = P[A] \cdot P[B | A] + P[A^c] \cdot P[B | A^c]$$

Interpretation: event  $B$  may be *divided along the lines of  $A$* , with some of  $P[B]$  coming from the part in  $A$  and the rest from the part in  $A^c$ .

### ≡ Total Probability - Explanation

- First divide  $B$  itself into parts in and out of  $A$ :

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

- These parts are exclusive, so in probability we have:

$$P[B] = P[BA] + P[BA^c]$$

- Use the Multiplication rule to break up  $P[BA]$  and  $P[BA^c]$ :

$$P[BA] \gg P[A] \cdot P[B | A]$$

$$P[BA^c] \gg P[A^c] \cdot P[B | A^c]$$

- Now substitute in the prior formula:

$$P[B] \gg P[BA] + P[BA^c] \gg P[A] \cdot P[B | A] + P[A^c] \cdot P[B | A^c]$$

This law can be generalized to any **partition** of the sample space  $S$ . A partition is a collection of events  $A_i$  which are *mutually exclusive* and *jointly exhaustive*:

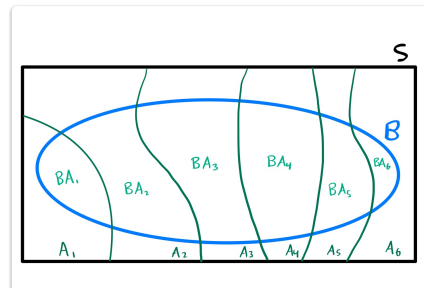
$$A_i \cap A_j = \emptyset, \quad \bigcup_i A_i = S$$

The generalized formulation of Total Probability for a partition is:

### 📦 Law of Total Probability

For a partition  $A_i$  of the sample space  $S$ :

$$P[B] = \sum_i P[A_i] \cdot P[B | A_i]$$



*Division into Cases* is just the *Law of Total Probability* after setting  $A_1 = A$  and  $A_2 = A^c$ .

## 09 Illustration

### 🔪 Exercise - Marble transferred, marble drawn

Setup:

- Bin 1 holds five red and four green marbles.
- Bin 2 holds four red and five green marbles.

Experiment:

- You take a random marble from Bin 1 and put it in Bin 2 and shake Bin 2.
- Then you draw a random marble from Bin 2 and look at it.

What is the probability that the marble you look at is red?

[Solution](#)

## Bayes' Theorem

### 10 Theory

#### 📖 Bayes' Theorem

For any events  $A$  and  $B$ :

$$P[B | A] = P[A | B] \cdot \frac{P[B]}{P[A]}$$

- ⚠ Bayes' Theorem is also called Bayes' Rule sometimes.

#### 📖 Bayes' Theorem - Derivation

Start with the observation that  $AB = BA$ , or event “ $A$  AND  $B$ ” equals event “ $B$  AND  $A$ ”.

Apply the *multiplication rule* to each of order:

$$P[AB] = P[A] \cdot P[B | A]$$

$$P[BA] = P[B] \cdot P[A | B]$$

Equate them and rearrange:

$$P[AB] = P[BA] \quad \gg \gg \quad P[A] \cdot P[B | A] = P[B] \cdot P[A | B]$$

$$\gg \gg \quad P[B | A] = P[A | B] \cdot \frac{P[B]}{P[A]}$$

The main application of Bayes' Theorem is to calculate  $P[A | B]$  when it is easy to calculate  $P[B | A]$  from the problem setup. Often this occurs in **multi-stage experiments** where event  $A$  describes outcomes of an intermediate stage.

Note: these notes use *alphabetical order*  $A, B$  as a mnemonic for *temporal or logical order*, i.e. that  $A$  comes *first* in time, or that otherwise that  $A$  is the *prior* conditional from which it is easier to calculate  $B$ .

### 11 Illustration

#### 📖 Example - Bayes' Theorem - COVID tests

Assume that 0.5% of people have COVID. Suppose a COVID test gives a (true) positive on 96% of patients who have COVID, but gives a (false) positive on 2% of patients who do not have COVID. Bob tests positive. What is the probability that Bob has COVID?

#### 📖 Solution

1. 📖 Label events.

- Event  $A_P$ : Bob is actually positive for COVID

- Event  $A_N$ : Bob is actually negative; note  $A_N = A_P^c$
- Event  $T_P$ : Bob tests positive
- Event  $T_N$ : Bob tests negative; note  $T_N = T_P^c$

## 2. ➡ Identify knowns.

- Know:  $P[T_P | A_P] = 96\%$
- Know:  $P[T_P | A_N] = 2\%$
- Know:  $P[A_P] = 0.5\%$  and therefore  $P[A_N] = 99.5\%$
- We seek:  $P[A_P | T_P]$

## 3. 📄 Translate Bayes' Theorem.

- Using  $A = T_P$  and  $B = A_P$  in the formula:

$$P[A_P | T_P] = P[T_P | A_P] \cdot \frac{P[A_P]}{P[T_P]}$$

- We know all values on the right except  $P[T_P]$

## 4. ⚠ Use Division into Cases.

- Observe:

$$T_P = T_P \cap A_P \cup T_P \cap A_N$$

- Division into Cases yields:

$$P[T_P] = P[A_P] \cdot P[T_P | A_P] + P[A_N] \cdot P[T_P | A_N]$$

- ⚠ Important to notice this technique!

- It is a common element of Bayes' Theorem application problems.
- It is frequently needed *for the denominator*.

- Plug in data and compute:

$$\gg \gg P[T_P] = \frac{5}{1000} \cdot \frac{96}{100} + \frac{995}{1000} \cdot \frac{2}{100} \gg \gg \approx 0.0247$$

## 5. ≡ Compute answer.

- Plug in and compute:

$$P[A_P | T_P] = P[T_P | A_P] \cdot \frac{P[A_P]}{P[T_P]}$$

$$\gg \gg 0.96 \cdot \frac{0.005}{0.0247} \gg \gg \approx 19\%$$

## 👉 Intuition - COVID testing

Some people find the low number surprising. In order to repair your intuition, think about it like this: roughly 2.5% of tests are positive, with roughly 2% coming from *false* positives, and roughly 0.5% from *true* positives. The true ones make up only 1/5 of the positive results!

(This rough approximation is by assuming  $96\% = 100\%$ .)

If *two* tests both come back positive, the odds of COVID are now 98%.

If *only people with symptoms* are tested, so that, say, 20% of those tested have COVID, that is,  $P[A_P | T_P] = 20\%$ , then one positive test implies a COVID probability of 92%.

### Exercise - Bayes' Theorem and Multiplication: Inferring bin from marble

There are marbles in bins in a room:

- Bin 1 holds 7 red and 5 green marbles.
- Bin 2 holds 4 red and 3 green marbles.

Your friend goes in the room, shuts the door, and selects a random bin, then draws a random marble. (Equal odds for each bin, then equal odds for each marble in that bin.) He comes out and shows you a red marble.

What is the probability that this red marble was taken from Bin 1?

[Solution](#)

## Independence


### 12 Theory

Two events are independent when information about one of them does not change our probability estimate for the other. Mathematically, there are three ways to express this fact:

#### Independence

Events  $A$  and  $B$  are **independent** when these (logically equivalent) equations hold:

- $P[B \mid A] = P[B]$
- $P[A \mid B] = P[A]$
- $P[BA] = P[B] \cdot P[A]$

-  The last equation is symmetric in  $A$  and  $B$ .
  - Check:  $BA = AB$  and  $P[B] \cdot P[A] = P[A] \cdot P[B]$
  - This symmetric version is the preferred definition of the concept.

#### Multiple-independence

A **collection** of events  $A_1, \dots, A_n$  is **mutually independent** when every subcollection  $A_{i_1}, \dots, A_{i_k}$  satisfies:

$$P[A_{i_1} \cdots A_{i_k}] = P[A_{i_1}] \cdots P[A_{i_k}]$$

A potentially **weaker condition** for a collection  $A_1, \dots, A_n$  is called **pairwise independence**, which holds when all 2-member subcollections are independent:

$$P[A_i A_j] = P[A_i] \cdot P[A_j] \quad \text{for all } i \neq j$$

One could also define 3-member independence, or  $n$ -member independence. Plain 'independence' means **any**-member independence.

### 13 Illustration

#### Exercise - Independence and complements

Prove that these are logically equivalent statements:

- $A$  and  $B$  are independent
- $A$  and  $B^c$  are independent
- $A^c$  and  $B^c$  are independent

Make sure you demonstrate both directions of each equivalency.

[Solution](#)

### ≡ Example - Checking independence by hand

A bin contains 4 red and 7 green marbles. Two marbles are drawn.

Let  $R_1$  be the event that the first marble is red, and let  $G_2$  be the event that the second marble is green.

- (a) Show that  $R_1$  and  $G_2$  are independent if the marbles are drawn *with replacement*.
- (b) Show that  $R_1$  and  $G_2$  are not independent if the marbles are drawn *without replacement*.

#### ≡ Solution

(a) With replacement.

1. ≡ Identify knowns.

- Know:  $P[R_1] = \frac{4}{11}$
- Know:  $P[G_2] = \frac{7}{11}$

2. ≡ Compute both sides of independence relation.

- Relation is  $P[R_1 G_2] = P[R_1] \cdot P[G_2]$
- Right side is  $\frac{4}{11} \cdot \frac{7}{11}$
- For  $P[R_1 G_2]$ , have  $4 \cdot 7$  ways to get  $R_1 G_2$ , and  $11^2$  total outcomes.
- So left side is  $\frac{4 \cdot 7}{11^2}$ , which equals the right side.

(b) Without replacement.

1. ≡ Identify knowns.

- Know:  $P[R_1] = \frac{4}{11}$  and therefore  $P[R_1^c] = \frac{7}{11}$
- We seek:  $P[G_2]$  and  $P[R_1 G_2]$

2. ⇨ Find  $P[G_2]$  using Division into Cases.

- Division into cases:

$$G_2 = G_2 \cap R_1 \cup G_2 \cap R_1^c$$

- Therefore:

$$P[G_2] = P[R_1] \cdot P[G_2 | R_1] + P[R_1^c] \cdot P[G_2 | R_1^c]$$

- Find these by counting and compute:

$$\gg \gg \quad P[G_2] = \frac{4}{11} \cdot \frac{7}{10} + \frac{7}{11} \cdot \frac{6}{10} \gg \gg \quad \frac{70}{110}$$

3.  $\equiv$  Find  $P[R_1 G_2]$  using Multiplication rule.

- Multiplication rule (implicitly used above already):

$$P[R_1 G_2] = P[R_1] \cdot P[G_2 | R_1] \gg \gg \frac{4}{11} \cdot \frac{7}{10} \gg \gg \frac{28}{110}$$

4.  $\equiv$  Compare both sides.

- Left side:  $P[R_1 G_2] = \frac{28}{110}$
- Whereas, right side:

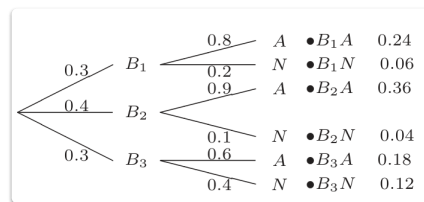
$$P[R_1] \cdot P[G_2] = \frac{4}{11} \cdot \frac{70}{110} = \frac{28}{121}$$

- But  $\frac{28}{110} \neq \frac{28}{121}$  so  $P[R_1 G_2] \neq P[R_1] \cdot P[G_2]$  and they are *not independent*.

## Tree diagrams

### 14 Theory

A **tree diagram** depicts the components of a **multi-stage experiment**. Nodes, or *branch points*, represent sources of randomness.



An *outcome* of the experiment is represented by a *pathway* taken from the root (left-most node) to a leaf (right-most node). The branch chosen at a given node junction represents the outcome of the “sub-experiment” constituting that branch point. So a pathway encodes the outcomes of all sub-experiments.

Each branch from a node is labeled with a probability number. This is the probability that the sub-experiment of that node has the outcome of that branch.

- The probability label on some branch is the conditional probability of that branch, assuming the pathway from root to prior node.
  - In the example:  $0.8 = P[A | B_1]$ .
  - Therefore, branch labels from given node sum to 1. (Law of Total Probability)
- The probability of a given (overall) outcome is the *product* of the probabilities on each branch of the pathway to that outcome.
  - Makes sense, because (e.g.):  $P[AB_1] = P[A] \cdot P[B_1 | A]$
  - More generally: remember that (e.g.):  $P[ABCD] = P[ABC] \cdot P[D | ABC]$
  - This overall outcome probability may be written at the leaf.

One can also use a tree diagram to remember quickly how to calculate certain probabilities.

For example, what is  $P[A]$  in the diagram?

Answer: add up the pathway probabilities (leaf numbers) terminating in *A*. That makes  $0.24 + 0.36 + 0.18 = 0.78$

For example, what is  $P[B_1 | N]$ ?

Answer: divide the leaf probability of  $B_1N$  by the total probability of *N*. That makes:

$$P[B_1 | N] = \frac{0.06}{0.06 + 0.04 + 0.12} \approx 0.27$$

## 15 Illustration

### Example - Tree diagrams: Marble transferred, marble drawn

Setup:

- Bin 1 holds five red and four green marbles.
- Bin 2 holds four red and five green marbles.

Experiment:

- You take a random marble from Bin 1 and put it in Bin 2 and shake Bin 2.
- Then you draw a random marble from Bin 2 and look at it.

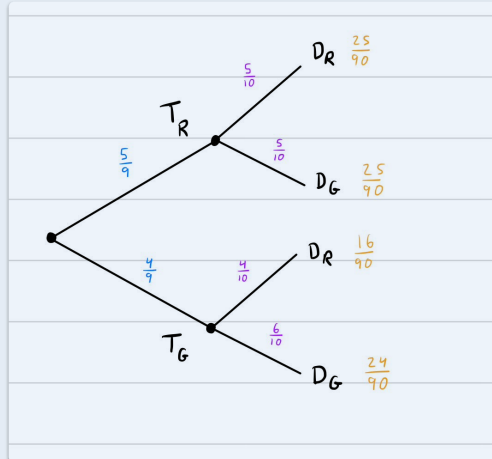
Questions:

- (a) What is the probability you *draw* a red marble?
- (b) Supposing that you drew a red marble, what is the probability that a red marble was *transferred*?

### Solution

#### 1. Construct the tree diagram.

- Identify sub-experiments, label events, compute probabilities:



#### 2. For (a), compute $P[D_R]$ .

- Add up leaf numbers for  $D_R$  at leaf:

$$P[D_R] = \frac{25}{90} + \frac{16}{90} = \frac{41}{90}$$

#### 3. For (b), compute $P[T_R | D_R]$ .

- Conditional probability:

$$P[T_R | D_R] = \frac{P[T_R D_R]}{P[D_R]}$$

- Plug in data and compute:

$$\gg \gg \frac{25/90}{41/90} \gg \gg \frac{25}{41}$$



- Interpretation: mass of desired pathway over mass of possible pathways.

## Counting

### 16 Theory

In many “games of chance”, it is assumed by symmetry principles that all outcomes are equally likely. From this assumption we infer the rule for  $P[-]$ :

$$P[A] = \frac{|A|}{|S|}$$

In words: the probability of event  $A$  is the number of outcomes in  $A$  divided by the number of possible outcomes.

When this formula applies, it is important to be able to count total outcomes, as well as outcomes satisfying various conditions.

#### ▣ Permutations

**Permutations** count the number of *ordered lists* one can form from some items. For a list of  $r$  items taken from a total collection of  $n$ , the number of permutations is:

$$\frac{n!}{(n-r)!}$$

To see where this comes from:

There are  $n$  choices for the first item, then  $n-1$  for the second, then ... then  $n-r+1$  for the  $r^{\text{th}}$  item. So the number is  $n(n-1)(n-2)\cdots(n-r+1)$ . Observe:

$$\begin{aligned} \frac{n!}{(n-r)!} &= \frac{n(n-1)(n-2)\cdots(n-r+1)(n-r)(n-r-1)\cdots 1}{(n-r)(n-r-1)\cdots 1} \\ &\gg \gg n(n-1)(n-2)\cdots(n-r+1) \end{aligned}$$

#### ▣ Combinations, binomial coefficient

**Combinations** count the number of *sets* (ignoring order) one can form from some items. We define a notation for it like this:

$$\binom{n}{r} = \frac{n!}{r!(n-r)!}$$

This counts the number of sets of  $r$  distinct elements taken from a total collection of  $n$  items.

Another name for combinations is the **binomial coefficient**.

This formula can be derived from the formula for permutations. The possible permutations can be partitioned into combinations: each combination gives a set, and by specifying an ordering of elements in the set, we get a permutation. For a set of  $r$  elements taken from  $n$  items, there are  $r!$  ways to put them into a specific order. So the number of permutations must be a factor of  $r!$  greater than the number of combinations.

This notation,  $\binom{n}{r}$ , is also called the **binomial coefficient** because it provides the coefficients of a binomial expansion:

$$(x + y)^n = \sum_{i=1}^n \binom{n}{i} x^{n-i} y^i$$

For example:

$$(x + y)^4 = x^4 + 4x^3y + 6x^2y^2 + 4xy^3 + y^4$$

There are also 'higher' combinations:

### Multinomial coefficient

The general multinomial coefficient is defined by the formula:

$$\binom{n}{r_1, r_2, \dots, r_k} = \frac{n!}{r_1! r_2! \dots r_k!}$$

where  $r_1 + r_2 + \dots + r_k = n$ .

The multinomial coefficient measures the number of ways to partition  $n$  items into sets with sizes  $r_1, r_2, \dots, r_k$ , respectively.

Notice that  $\binom{5}{3, 2} = \binom{5}{2, 3}$  so we already defined these values ( $k = 2$ ) with binomial coefficients.

But with  $k > 2$ , we have new values. They correspond to the coefficients in multinomial expansions. For example  $k = 3$  gives coefficients for  $(x + y + z)^n$ .

## 17 Illustration

### Exercise - Combinations: Counting teams with Cooper


A team of 3 student volunteers is formed at random from a class of 40. What is the probability that Cooper is on the team?

[Solution](#)


### Example - Combinations: Groups with Haley and Hugo

The class has 40 students. Suppose the professor chooses 3 students Wednesday at random, and again 3 on Friday. What is the probability that Haley is chosen today and Hugo on Friday?

#### Solution

1.  Count total outcomes.

- Have  $\binom{40}{3}$  possible groups chosen Wednesday.
- Have  $\binom{40}{3}$  possible groups chosen Friday.
- Therefore  $\binom{40}{3} \times \binom{40}{3}$  possible groups in total.

2.  Count desired outcomes.

- Groups of 3 with Haley are same as groups of 2 taken from others.
- Therefore have  $\binom{39}{2}$  groups that contain Haley.

- Have  $\binom{39}{2}$  groups that contain Hugo.
- Therefore  $\binom{39}{2} \times \binom{39}{2}$  total desired outcomes.

### 3. $\Rightarrow$ Compute probability.

- Let  $E$  label the desired event.
- Use formula:

$$P[E] = \frac{|E|}{|S|}$$

- Therefore:

$$\begin{aligned} P[E] &\gg \gg \frac{\binom{39}{2} \times \binom{39}{2}}{\binom{40}{3} \times \binom{40}{3}} \\ &\gg \gg \left( \frac{\frac{39 \cdot 38}{2!}}{\frac{40 \cdot 39 \cdot 38}{3!}} \right)^2 \gg \gg \left( \frac{3}{40} \right)^2 \end{aligned}$$

## $\equiv$ Example - Counting VA license plates

A VA license plate has three letters (with no I, O, or Q) followed by four numerals. A random plate is seen on the road.

- (a) What is the probability that the numerals are in increasing order?
- (b) What is the probability that at least one number is repeated?

### $\equiv$ Solution

(a)

#### 1. $\equiv$ Count ways to have 4 numerals in increasing order.

- Any four distinct numerals have a single order that's increasing.
- There are  $\binom{10}{4}$  ways to choose 4 numerals from 10 options.

#### 2. $\equiv$ Count ways to have 3 letters in order except I, O, Q.

- 26 total letters, 3 excluded, thus 23 options.
- Repetition allowed, thus  $23 \cdot 23 \cdot 23 = 23^3$  possibilities.

#### 3. $\equiv$ Count total plates with increasing numerals.

- Multiply the options:

$$23^3 \cdot \binom{10}{4}$$

#### 4. $\equiv$ Count total plates.

- Have  $23 \cdot 23 \cdot 23$  options for letters.
- Have  $10 \cdot 10 \cdot 10 \cdot 10$  options for numbers.
- Thus  $23^3 \cdot 10^4$  possible plates.

#### 5. $\equiv$ Compute probability.

- Let  $E$  label the event that a plate has increasing numerals.

- Use the formula:

$$P[E] = \frac{|E|}{|S|}$$

- Therefore:

$$P[E] \gg \gg \frac{23^3 \cdot \binom{10}{4}}{23^3 \cdot 10^4} \gg \gg \frac{\frac{10!}{4!6!}}{10000} \gg \gg \frac{21}{1000}$$

(b)

1. ➡ Count plates with at least one number repeated.

- 🗨 “At least” is hard! Try *complement*: “no repeats”.

- Let  $E^c$  be event that *no* numbers are repeated. All distinct.
- Count possibilities:

$$|E^c| = 23 \cdot 23 \cdot 23 \cdot 10 \cdot 9 \cdot 8 \cdot 7$$

- Total license plates is still  $23^3 \cdot 10^4$ .
- Therefore, license plates with *at least one number repeated*:

$$|E| = |S| - |E^c|$$

$$\gg \gg 23^3 \cdot 10^4 - 23^3 \cdot 10 \cdot 9 \cdot 8 \cdot 7 \gg \gg 60348320$$

2. ➡ Compute probability.

- Desired outcomes over total outcomes:

$$\frac{|E|}{|S|} \gg \gg \frac{60348320}{23^3 \cdot 10^4} \gg \gg 0.496$$