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

Chapter 2: Probability

The aim of this chapter is to revise the basic rules of probability. By the end of this chapter, you should be comfortable with:

- conditional probability, and what you can and can't do with conditional expressions;
- the Partition Theorem and Bayes' Theorem;
- First-Step Analysis for finding the probability that a process reaches some state, by conditioning on the outcome of the first step;
- calculating probabilities for continuous and discrete random variables.

2.1 Sample spaces and events

Definition: A **sample space**, Ω, is a *set of possible outcomes of a random experiment.*

Definition: An **event**, A, is a *subset of the sample space.*

This means that event A is simply *a collection of outcomes.*

Example:

Random experiment: Pick a person in this class at random.
Sample space: $\Omega = \{$*all people in class*$\}$
Event A: $A = \{$*all males in class*$\}$.

Definition: Event A **occurs** if *the outcome of the random experiment is a member of the set A.*

In the example above, event A occurs if *the person we pick is male.*

2.2 Probability Reference List

The following properties hold for all events A, B.

- $\mathbb{P}(\emptyset) = 0$.
- $0 \leq \mathbb{P}(A) \leq 1$.
- **Complement:** $\mathbb{P}(\overline{A}) = 1 - \mathbb{P}(A)$.
- **Probability of a union:** $\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \cap B)$.

  For three events A, B, C:

  $$\mathbb{P}(A \cup B \cup C) = \mathbb{P}(A) + \mathbb{P}(B) + \mathbb{P}(C) - \mathbb{P}(A \cap B) - \mathbb{P}(A \cap C) - \mathbb{P}(B \cap C) + \mathbb{P}(A \cap B \cap C)\,.$$

  If A and B are **mutually exclusive**, then $\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B)$.

- **Conditional probability:** $\mathbb{P}(A \mid B) = \dfrac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}$.
- **Multiplication rule:** $\mathbb{P}(A \cap B) = \mathbb{P}(A \mid B)\mathbb{P}(B) = \mathbb{P}(B \mid A)\mathbb{P}(A)$.
- **The Partition Theorem:** if $B_1, B_2, \ldots, B_m$ form a partition of Ω, then

  $$\mathbb{P}(A) = \sum_{i=1}^{m} \mathbb{P}(A \cap B_i) = \sum_{i=1}^{m} \mathbb{P}(A \mid B_i)\mathbb{P}(B_i) \quad \text{for any event } A.$$

  As a special case, B and $\overline{B}$ partition Ω, so:

  $$\begin{aligned} \mathbb{P}(A) &= \mathbb{P}(A \cap B) + \mathbb{P}(A \cap \overline{B}) \\ &= \mathbb{P}(A \mid B)\mathbb{P}(B) + \mathbb{P}(A \mid \overline{B})\mathbb{P}(\overline{B}) \quad \text{for any } A,\ B. \end{aligned}$$

- **Bayes' Theorem:** $\mathbb{P}(B \mid A) = \dfrac{\mathbb{P}(A \mid B)\mathbb{P}(B)}{\mathbb{P}(A)}$.

  More generally, if $B_1, B_2, \ldots, B_m$ form a partition of Ω, then

  $$\mathbb{P}(B_j \mid A) = \frac{\mathbb{P}(A \mid B_j)\mathbb{P}(B_j)}{\sum_{i=1}^{m} \mathbb{P}(A \mid B_i)\mathbb{P}(B_i)} \quad \text{for any } j.$$

- **Chains of events:** for any events $A_1, A_2, \ldots, A_n$,

  $$\mathbb{P}(A_1 \cap A_2 \cap \ldots \cap A_n) = \mathbb{P}(A_1)\mathbb{P}(A_2 \mid A_1)\mathbb{P}(A_3 \mid A_2 \cap A_1) \ldots \mathbb{P}(A_n \mid A_{n-1} \cap \ldots \cap A_1).$$

2.3 Conditional Probability

Suppose we are working with sample space $\Omega = \{\text{people in class}\}$. I want to find the proportion of people in the class who ski. What do I do?

Count up the number of people in the class who ski, and divide by the total number of people in the class.

Now suppose I want to find the proportion of *females* in the class who ski. What do I do?

Count # females in class who ski, and divide by # females.

$$\mathbb{P}(\text{female skis}) = \frac{\#\text{ female skiers in class}}{\#\text{ females in class.}} \leftarrow \text{intersection}$$

conditional prob

$\mathbb{P}(S \mid F)$

By changing from asking about everyone to asking about females only, we have:

- restricted our attention to the set of females only,

or: reduced the sample space from the set of everyone to the set of females,

or: conditioned on the event {females}.

We could write the above as:

$$\mathbb{P}(\text{skis} \mid \text{female}) = \frac{\#\text{ female skiers in class}}{\#\text{ females in class}}.$$

Conditioning is like changing the sample space: we are now working in a new sample space of females in class.

In the above example, we could replace 'skiing' with *any* attribute B. We have:

$$\mathbb{P}(\text{skis}) = \frac{\#\text{ skiers in class}}{\#\text{ class}}; \qquad \mathbb{P}(\text{skis} \mid \text{female}) = \frac{\#\text{ female skiers in class}}{\#\text{ females in class}};$$

so:

$$\mathbb{P}(B) = \frac{\#\text{ B's in class}}{\#\text{ class}}.$$

and:

$$\mathbb{P}(B \mid \text{female}) = \frac{\#\text{ female B's in class}}{\#\text{females in class}}$$

$$= \frac{\#\text{ in class who are both B and female}}{\#\text{ in class who are female.}}$$

Likewise, we could replace 'female' with any attribute A:

$$\mathbb{P}(B \mid A) = \frac{\#\text{ in class who are both B and A}}{\#\text{ in class who are A}}$$

This is how we get the definition of conditional probability:

$$\mathbb{P}(B \mid A) = \frac{\mathbb{P}(B \text{ and } A)}{\mathbb{P}(A)} = \frac{\mathbb{P}(B \cap A)}{\mathbb{P}(A)}.$$

Think of $\mathbb{P}(B \mid A)$ as "Prob B OUT OF the A's"

By conditioning on event A, we have changed the sample space to the set of A's only.

Definition: Let A and B be events on the same sample space: so
The **conditional probability of event B, given event A**, is

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

this prob is in the sample space of A

these two probs are both in the sample space Ω.

$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$ if indept.

Multiplication Rule: (Immediate from above). For any events A and B,

$$\boxed{\mathbb{P}(A \cap B) = \mathbb{P}(A \mid B)\mathbb{P}(B) = \mathbb{P}(B \mid A)\mathbb{P}(A) = \mathbb{P}(B \cap A)}$$

Conditioning as 'changing the sample space'

The idea that "conditioning" = "changing the sample space" can be very helpful in understanding how to manipulate conditional probabilities.

Any 'unconditional' probability can be written as a conditional probability:

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

Writing $\mathbb{P}(B) = \mathbb{P}(B \mid \Omega)$ just means that we are looking for the probability of event B, out of all possible outcomes in the set Ω.

In fact, the symbol $\mathbb{P}$ ***belongs*** to the set Ω: it has ***no meaning without*** Ω. To remind ourselves of this, we can write

$$\mathbb{P} = \mathbb{P}_\Omega$$

Then $\mathbb{P}(B) = \mathbb{P}(B \mid \Omega) = \mathbb{P}_\Omega(B)$

Similarly, $\mathbb{P}(B \mid A)$ means that we are looking for the probability of event B, out of all possible outcomes in the set A.

So A is just another sample space. Thus we can manipulate conditional probabilities $\mathbb{P}(\cdot \mid A)$ just like any other probabilities, as long as we always stay inside the same sample space A.

The trick: Because we can think of A as just another sample space, let's write

$$\mathbb{P}(\cdot \mid A) = \mathbb{P}_A(\cdot)$$

Note: NOT standard notation

Then ***we can use*** $\mathbb{P}_A$ ***just like*** $\mathbb{P}$***, as long as we remember to keep the*** A ***subscript on EVERY*** $\mathbb{P}$ ***that we write.***

$$\mathbb{P}_A(B \mid C) = \mathbb{P}(B \mid C \cap A)$$

$$\mathbb{P}_{X_0}(X_2 = x_2 \mid X_1 = x_1)$$

This helps us to make quite complex manipulations of conditional probabilities without thinking too hard or making mistakes. There is only one rule you need to learn to use this tool effectively:

$$\mathbb{P}_A(B \mid C) = \mathbb{P}(B \mid C \cap A).$$ for any A, B, C.

prob of B conditioned on BOTH A AND C [by different notations]

(Proof: Exercise).

The rules:

$$\boxed{\begin{aligned} &\mathbb{P}(\,\cdot \mid A) = \mathbb{P}_A(\,\cdot\,) \\ &\mathbb{P}_A(B \mid C) = \mathbb{P}(B \mid C \cap A) \text{ for any } A,\ B,\ C. \end{aligned}}$$

Examples:

1. Probability of a union. In general,

$$\mathbb{P}(B \cup C) = \mathbb{P}(B) + \mathbb{P}(C) - \mathbb{P}(B \cap C)$$

So, $\mathbb{P}_A(B \cup C) = \mathbb{P}_A(B) + \mathbb{P}_A(C) - \mathbb{P}_A(B \cap C)$ ← line of rough work

Thus, $\mathbb{P}(B \cup C \mid A) = \mathbb{P}(B \mid A) + \mathbb{P}(C \mid A) - \mathbb{P}(B \cap C \mid A)$

2. Which of the following is equal to $\mathbb{P}(B \cap C \mid A)$?

(a) $\mathbb{P}(B \mid C \cap A)$.

(b) $\dfrac{\mathbb{P}(B \mid C)}{\mathbb{P}(A)}$.

(c) $\mathbb{P}(B \mid C \cap A)\mathbb{P}(C \mid A)$.

(d) $\mathbb{P}(B \mid C)\mathbb{P}(C \mid A)$.

Exercise (Solutions in filled-in notes on website)

Solution:

3. Which of the following is true?

(a) $\mathbb{P}(\overline{B} \mid A) = 1 - \mathbb{P}(B \mid A)$.

(b) $\mathbb{P}(\overline{B} \mid A) = \mathbb{P}(B) - \mathbb{P}(B \mid A)$.

Solution:

$$\text{LHS} = \mathbb{P}(\overline{B} \mid A)$$
$$= \mathbb{P}_A(\overline{B})$$
$$= 1 - \mathbb{P}_A(B)$$
Rough work
$$= 1 - \mathbb{P}(B \mid A) = \text{answer (a)}$$
← back to standard notation.

4. Which of the following is true?

Exercise

(a) $\mathbb{P}(\overline{B} \cap A) = \mathbb{P}(A) - \mathbb{P}(B \cap A)$.

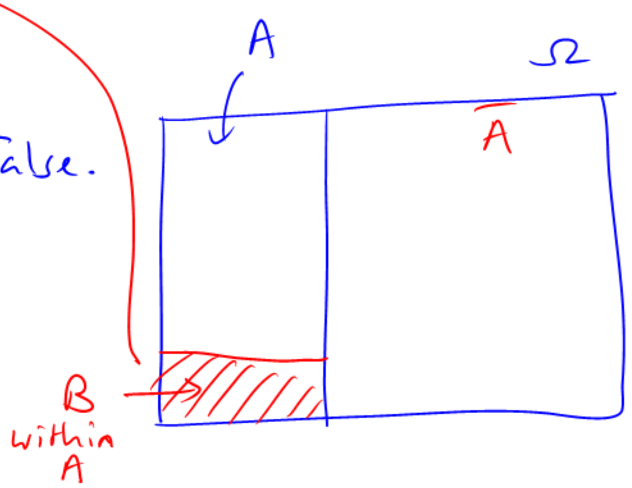
(b) $\mathbb{P}(\overline{B} \cap A) = \mathbb{P}(B) - \mathbb{P}(B \cap A)$.

Solution:

5. True or false: $\mathbb{P}(B \mid A) = 1 - \mathbb{P}(B \mid \overline{A})$?

False.

Answer:

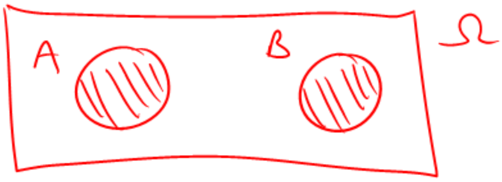


Exercise: if we wish to express $\mathbb{P}(B \mid A)$ in terms of only B and $\overline{A}$, show that
$$\mathbb{P}(B \mid A) = \frac{\mathbb{P}(B) - \mathbb{P}(B \mid \overline{A})\mathbb{P}(\overline{A})}{1 - \mathbb{P}(\overline{A})}.$$
Note that this does not simplify nicely!

2.4 The Partition Theorem (Law of Total Probability)

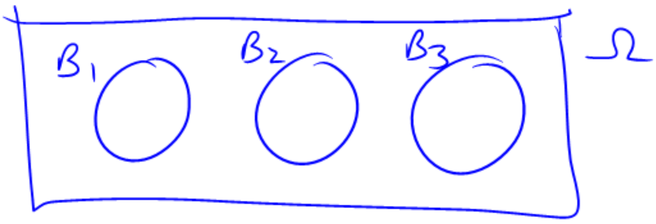
Definition: Events A and B are **mutually exclusive**, or **disjoint**, if $A \cap B = \phi$.

This means events A and B cannot happen together. If A happens, it excludes B from happening, and vice-versa.



If A and B are mutually exclusive, $\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B)$
For all other A and B, $\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \cap B)$.

Definition: Any number of events $B_1, B_2, \ldots, B_k$ are **mutually exclusive** if every pair of the events is mutually exclusive: ie. $B_i \cap B_j = \emptyset$ *for all* i, j *with* $i \neq j$.



Definition: A **partition** of Ω is a collection of mutually exclusive events whose union is Ω.

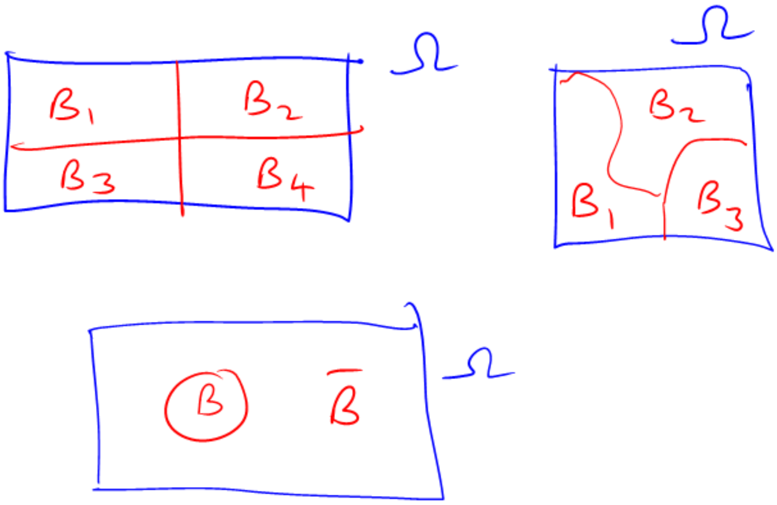
That is, sets $B_1, B_2, \ldots, B_k$ form a partition of Ω if

$$B_i \cap B_j = \emptyset \quad \text{for all } i, j \text{ with } i \neq j,$$

$$\textbf{and} \quad \bigcup_{i=1}^{k} B_i = B_1 \cup B_2 \cup \ldots \cup B_k = \Omega.$$

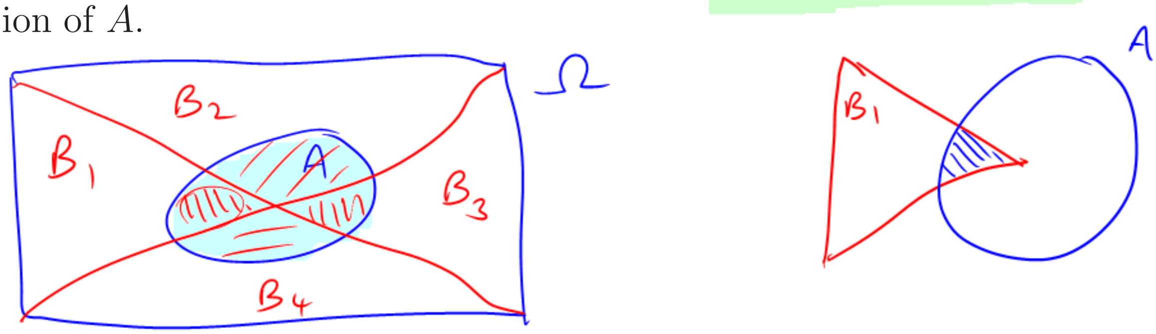
$B_1, \ldots, B_k$ form a partition of Ω if they have no overlap and collectively cover all outcomes in Ω.

Examples:



Partitioning an event A

Any set A can be partitioned: it doesn't have to be Ω.
In particular, if $B_1, \ldots, B_k$ form a partition of Ω, then $(A \cap B_1), \ldots, (A \cap B_k)$ form a partition of A.



Theorem 2.4: The Partition Theorem (Law of Total Probability)

Let $B_1, \ldots, B_m$ form a partition of Ω. Then for any event A,

$$\boxed{\mathbb{P}(A) = \sum_{i=1}^{m} \mathbb{P}(A \cap B_i) = \sum_{i=1}^{m} \mathbb{P}(A \mid B_i)\,\mathbb{P}(B_i)}$$

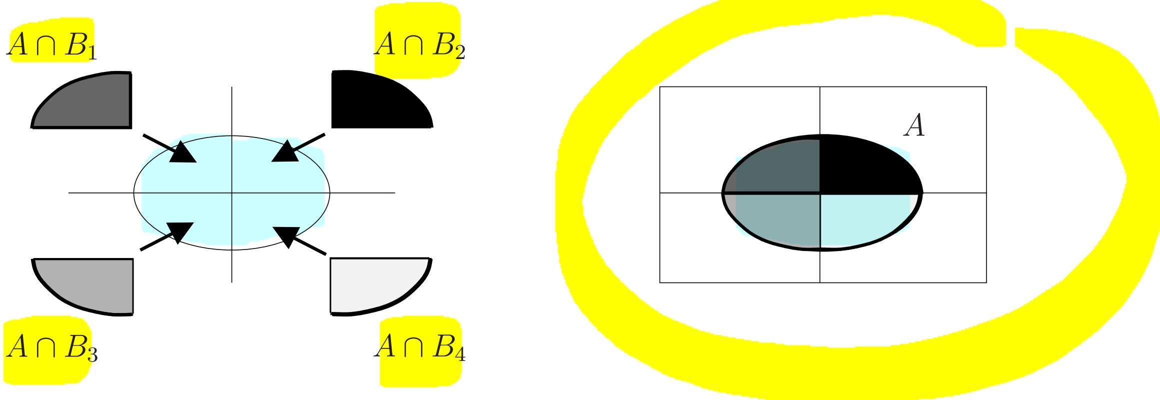
intuition (picture)

practical one for calculations

Both formulations of the Partition Theorem are very widely used, but especially the conditional formulation $\sum_{i=1}^{m} \mathbb{P}(A \mid B_i)\mathbb{P}(B_i)$.

Intuition behind the Partition Theorem:

The Partition Theorem is easy to understand because it simply states that "the whole is the sum of its parts."



$$\mathbb{P}(A) = \mathbb{P}(A \cap B_1) + \mathbb{P}(A \cap B_2) + \mathbb{P}(A \cap B_3) + \mathbb{P}(A \cap B_4).$$

2.5 Bayes' Theorem: inverting conditional probabilities

Bayes' Theorem allows us to "invert" a conditional statement, ie. *to express* $\mathbb{P}(B \mid A)$ *in terms of* $\mathbb{P}(A \mid B)$.

Theorem 2.5: Bayes' Theorem

For any events A and B:
$$\boxed{\mathbb{P}(B \mid A) = \frac{\mathbb{P}(A \mid B)\mathbb{P}(B)}{\mathbb{P}(A)}.}$$

Proof:

$$\begin{aligned}
\mathbb{P}(B \cap A) &= \mathbb{P}(A \cap B) \\
\mathbb{P}(B \mid A)\mathbb{P}(A) &= \mathbb{P}(A \mid B)\mathbb{P}(B) \qquad \text{(multiplication rule)} \\
\therefore \qquad \mathbb{P}(B \mid A) &= \frac{\mathbb{P}(A \mid B)\mathbb{P}(B)}{\mathbb{P}(A)}. \qquad \square
\end{aligned}$$

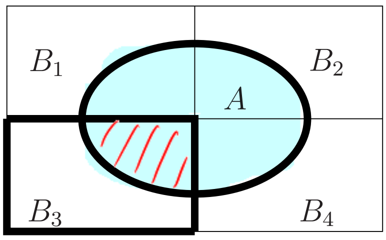
Extension of Bayes' Theorem

Suppose that $B_1, B_2, \ldots, B_m$ form a partition of Ω. By the Partition Theorem,

$$\mathbb{P}(A) = \sum_{i=1}^{m} \mathbb{P}(A \mid B_i)\mathbb{P}(B_i).$$

Thus, for ***any single partition member*** B_j, put $B = B_j$ in Bayes' Theorem to obtain:

$$\boxed{\mathbb{P}(B_j \mid A) = \frac{\mathbb{P}(A \mid B_j)\mathbb{P}(B_j)}{\mathbb{P}(A)} = \frac{\mathbb{P}(A \mid B_j)\mathbb{P}(B_j)}{\sum_{i=1}^{m} \mathbb{P}(A \mid B_i)\mathbb{P}(B_i)}.}$$



$B_j = B_3$ here

Special case: $m = 2$

Given any event B, the events B and $\overline{B}$ form a partition of Ω. Thus:

$$\boxed{\mathbb{P}(B \mid A) = \frac{\mathbb{P}(A \mid B)\mathbb{P}(B)}{\mathbb{P}(A \mid B)\mathbb{P}(B) + \mathbb{P}(A \mid \overline{B})\mathbb{P}(\overline{B})}.}$$

Example: In screening for a certain disease, the probability that a healthy person wrongly gets a positive result is 0.05. The probability that a diseased person wrongly gets a negative result is 0.002. The overall rate of the disease in the population being screened is 1%. If my test gives a positive result, what is the probability I actually have the disease?

1) Define events: $\Omega = \{\text{popn being screened}\}$

$D = \{\text{have disease}\}$ $\bar{D} = \{\text{don't have disease}\}$

$P = \{\text{positive test result}\}$ $N = \bar{P} = \{\text{negative test}\}$.

2) Information given:

False positive rate is 0.05 $\Rightarrow$ $\mathbb{P}(P \mid \bar{D}) = 0.05$

False negative rate is 0.002 $\Rightarrow$ $\mathbb{P}(N \mid D) = 0.002$

Disease rate is 1% $\Rightarrow$ $\mathbb{P}(D) = 0.01$

3) Looking for: $\mathbb{P}(D \mid P)$.

We have $\mathbb{P}(D \mid P) = \dfrac{\mathbb{P}(P \mid D)\,\mathbb{P}(D)}{\mathbb{P}(P)}$ (*)

Now $\mathbb{P}(P \mid D) = 1 - \mathbb{P}(N \mid D) = 1 - 0.002 = 0.998$.

Also $\mathbb{P}(P) = \mathbb{P}(P \mid D)\mathbb{P}(D) + \mathbb{P}(P \mid \bar{D})\mathbb{P}(\bar{D})$

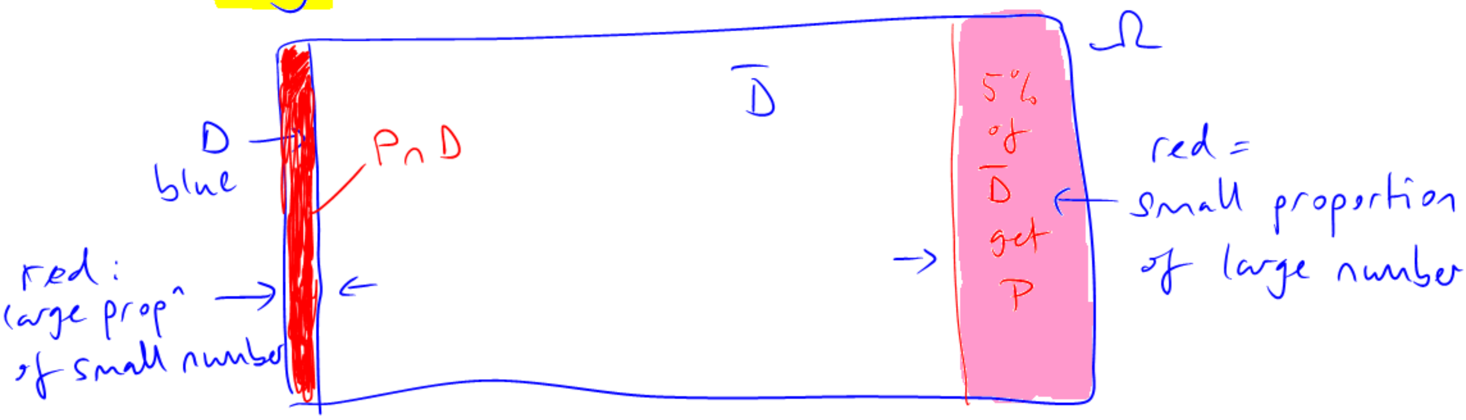
$= 0.998 * 0.01 + 0.05 * (1 - 0.01)$

$= 0.05948$.

Subst in (*):

$\rightarrow \mathbb{P}(D \mid P) = \dfrac{0.998 * 0.01}{0.05948} = 0.168$.

Given a positive test, my chance of having the disease is only 16.8%.



Ass Bonus Q's: completely optional top-up assignment total.

Complete Solutions Only

Total assign mark 280/300

A+ / A → no help before hand-in.

2.6 First-Step Analysis for calculating probabilities in a process

In a stochastic process, what happens at the next step depends upon the current state of the process. We often wish to know the probability of *eventually* reaching some particular state, given our current position.

Throughout this course, we will tackle this sort of problem using a technique called First-Step Analysis.

The idea is to consider all possible first steps away from the current state. We derive a system of equations that specify the probability of the eventual outcome given each of the possible first steps. We then try to solve these equations for the probability of interest.

First-Step Analysis depends upon ***conditional probability*** and the ***Partition Theorem.*** Let $S_1, \ldots, S_k$ be the k possible first steps we can take away from our current state. We wish to find the probability that event E happens eventually. First-Step Analysis calculates $\mathbb{P}(E)$ as follows:

e.g. $E = \{\text{Venus Wins eventually}\}$

$$\mathbb{P}(E) = \mathbb{P}(E \mid S_1)\mathbb{P}(S_1) + \ldots + \mathbb{P}(E \mid S_k)\mathbb{P}(S_k).$$

Here, $\mathbb{P}(S_1), \ldots, \mathbb{P}(S_k)$ give the probabilities of taking the different first steps $1, 2, \ldots, k$.

Example: Tennis game at Deuce.

Venus and Serena are playing tennis, and have reached the score Deuce (40-40). (*Deuce* comes from the French word *Deux* for 'two', meaning that each player needs to win two consecutive points to win the game.)

For each point, let:

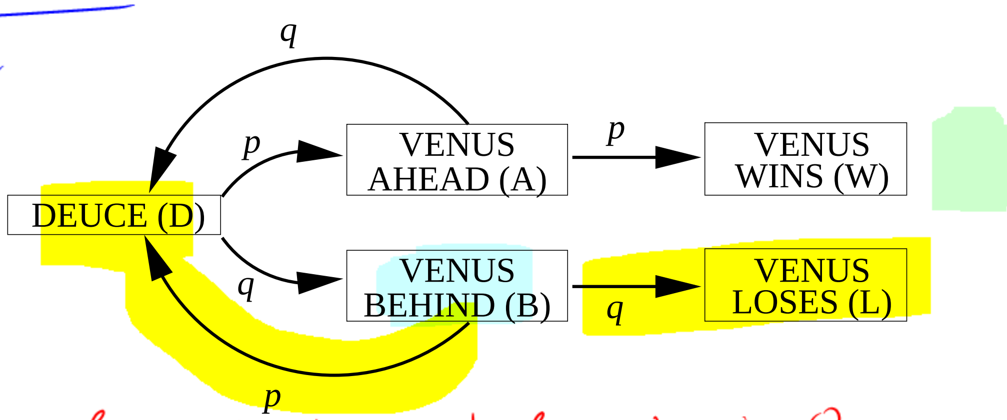
$$p = \mathbb{P}(\text{Venus wins point}), \qquad q = 1 - p = \mathbb{P}(\text{Serena wins point}).$$

Assume that all points are independent.

Let v be the probability that Venus wins the game eventually, starting from Deuce. Find v.

Transition Diagram (single-step transitions)

"States" are the things in the boxes.



First notation: for explanation, not for using in Qs

Use First-step analysis. The possible steps, starting from Deuce, are:

1) Venus wins next point (probability p) : move to state A.

2) Venus loses " " (" $q = 1-p$) : " " " B.

Let V = {Venus wins EVENTUALLY, starting from Deuce}.

So $v = \mathbb{P}(\text{Venus wins} \mid D_1)$

$= \mathbb{P}_{D_1}(V)$ using the subscript notation from §2.3

$= \mathbb{P}_{D_1}(V \mid A_2)\underbrace{\mathbb{P}_{D_1}(A_2)}_{} + \mathbb{P}_{D_1}(V \mid B_2)\underbrace{\mathbb{P}_{D_1}(B_2)}_{},$ (Partition Thm)

$v = \mathbb{P}(V \mid A_2)\, p + \mathbb{P}(V \mid B_2)\, q$ (*)

NB: dropped subscript D_1 because it doesn't make any difference: all that matters is being in state A. $\mathbb{P}(V \mid A_2 \cap D_1) = \mathbb{P}(V \mid A_2)$.

Now we need to find $\mathbb{P}(V \mid A_2)$ and $\mathbb{P}(V \mid B_2)$.

Use First-step Analysis (FSA) again:

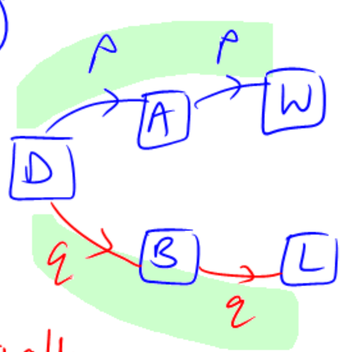
$$\mathbb{P}(V \mid A_2) = \mathbb{P}_{A_2}(V) = \underbrace{\mathbb{P}_{A_2}(V \mid W_3)}_{\text{Venus already won! so this prob} = 1}\, p + \overbrace{\mathbb{P}_{A_2}(V \mid D_3)}^{\text{this is the same as } v\text{, what we want}}\, q$$

So $\mathbb{P}(V \mid A_2) = 1 * p + v * q = p + qv$. (a)

Similarly, $\mathbb{P}(V \mid B_2) = \mathbb{P}_{B_2}(V)$

$$= \mathbb{P}_{B_2}(V \mid L_3)\, q + \mathbb{P}_{B_2}(V \mid D_3)\, p$$

$$= 0 * q + v * p \quad (b)$$



Substitute (a) and (b) into (*):

$$v = (p + qv)\,p + (vp)\,q$$

$$v = p^2 + 2pqv$$

$$v(1-2pq) = p^2$$

$$\therefore \boxed{v = \frac{p^2}{1-2pq}}$$

prob Venus wins eventually, starting from Deuce.

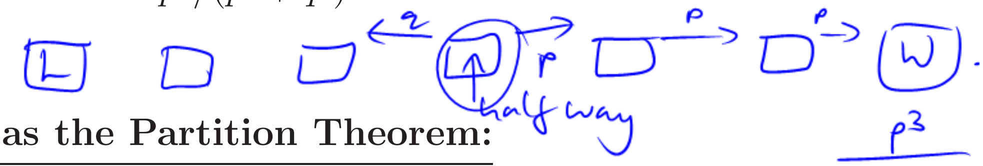
Note: Because $p + q = 1$, we have:

$$1 = 1^2 = (p+q)^2 = p^2 + q^2 + 2pq \Rightarrow 1 - 2pq = p^2 + q^2.$$

So the final probability that Venus wins the game is:

$$v = \frac{p^2}{1-2pq} = \frac{p^2}{p^2+q^2}.$$

Note how this result makes intuitive sense. For the game to finish from Deuce, either Venus has to win two points in a row (probability p^2), or Serena does (probability q^2). The ratio $p^2/(p^2 + q^2)$ describes Venus's 'share' of the winning probability.



$$\frac{p^3}{p^3+q^3}.$$

First-step analysis as the Partition Theorem:

Our approach to finding $v = \mathbb{P}(\text{Venus wins})$ can be summarized as:

$$\mathbb{P}(\text{Venus wins eventually}) = v = \sum_{\text{first steps}} \mathbb{P}\left(\text{Venus wins eventually} \,\middle|\, \text{first step}\right) \mathbb{P}(\text{first step}).$$

First-step analysis is just the **Partition Theorem:**

The sample space is $\Omega = \{$all possible routes from Deuce to the end$\}$

An example of a sample point is: $D_1 \to A_2 \to D_3 \to B_4 \to D_5 \to B_6 \to L_7$.

Another example is: $D_1 \to B_2 \to D_3 \to A_4 \to W_5$.

The **partition** of the sample space that we use in first-step analysis is:

$R_1 = \{$all possible routes from Deuce to the end that start $D_1 \to A_2\}$

$R_2 = \{$ " " " " " " " " " " $D_1 \to B_2\}$

R_1 and R_2 are disjoint sets: $R_1 \cap R_2 = \phi$

and union is Ω (all routes must be in R_1 or R_2).

$V = \{\text{Venus wins eventually}\}$

Then first-step analysis simply states:

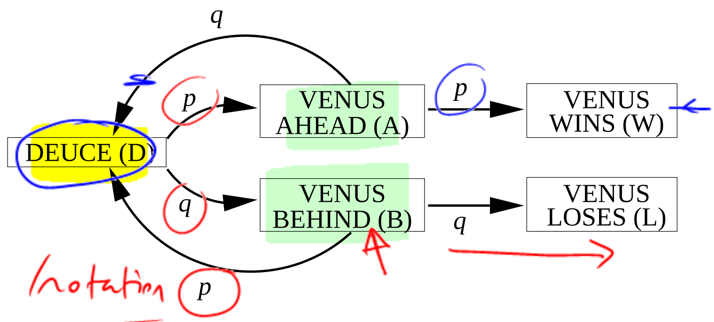
$$\mathbb{P}(V) = \mathbb{P}(V \mid R_1)\,\mathbb{P}(R_1) + \mathbb{P}(V \mid R_2)\,\mathbb{P}(R_2)$$

$$= \mathbb{P}_{D_1}(V \mid A_2)\,\mathbb{P}_{D_1}(A_2) + \mathbb{P}_{D_1}(V \mid B_2)\,\mathbb{P}_{D_1}(B_2)$$

Notation for quick solutions of first-step analysis problems

Defining a helpful notation is central to modelling with stochastic processes. Setting up well-defined notation helps you to solve problems quickly and easily. Defining your notation is one of the most important steps in modelling, because it provides the conversion from words (which is how your problem starts) to mathematics (which is how your problem is solved).

Several marks are allotted on first-step analysis questions for setting up a well-defined and helpful notation.



Use this method / notation

Here is the correct way to formulate and solve this first-step analysis problem.

Need the probability that Venus wins eventually, starting from Deuce.

1) Define notation:

Let
$V_D = \mathbb{P}(\text{Venus wins eventually} \mid \text{start at state } D)$
$V_A = \mathbb{P}(\;\text{"}\quad\text{"}\quad\text{"} \mid \text{"}\quad\text{"}\quad\text{"}\; A)$
$V_B = \mathbb{P}(\;\text{"}\quad\text{"}\quad\text{"} \mid \text{"}\quad\text{"}\quad\text{"}\; B)$

destination (final aim) remains the same

starting point changes

2) FSA:

$V_D = p\,V_A + q\,V_B$ (a)
$V_A = p * 1 + q\,V_D$ (b)
$V_B = p\,V_D + q * 0$ (c)

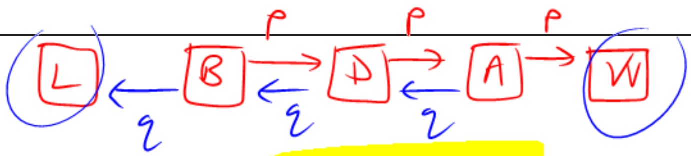
3. Solve simultaneous eqns :

Subst ⓑ and ⓒ into ⓐ :

$$v_D = p(p + q v_D) + q(p v_D)$$

$$\Rightarrow v_D \{1 - pq - pq\} = p^2$$

$$\Rightarrow v_D = \frac{p^2}{1-2pq} \quad \text{as before.}$$



2.7 Special Process: the Gambler's Ruin

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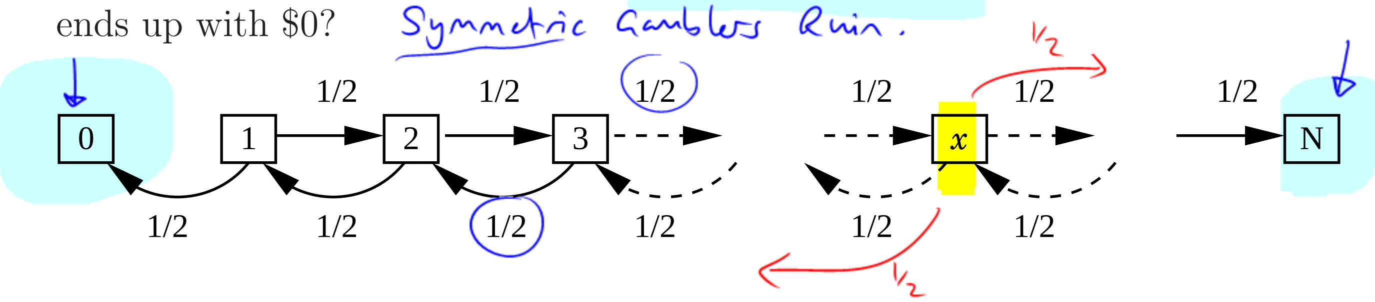
This is a famous problem in probability. A gambler starts with $\$x$. She tosses a fair coin repeatedly.

If she gets a Head, she wins $1. If she gets a Tail, she loses $1.

The coin tossing is repeated until the gambler has either $0 or $\$N$, when she stops. What is the probability of the Gambler's Ruin, i.e. that the gambler ends up with $0? Symmetric Gamblers Ruin.



Want to find $\mathbb{P}(\text{ends with } \$0 \mid \text{starts with } \$x)$.

Define event : $R = \{\text{eventual Ruin}\} = \{\text{ends with } \$0\}$.

We want to find $\mathbb{P}(R \mid \text{starts with } \$x)$.

FSA Notation :

Let $p_x = \mathbb{P}(R \mid \text{currently has } \$x)$ for $x = 0, 1, \dots, N$.

single final destination

changing start point

Information Given:

$p_0 = \mathbb{P}(\text{Ruin} \mid \text{reached state } 0) = 1$

$p_N = \mathbb{P}(\text{Ruin} \mid \text{reached state } N) = 0$ (stops at N).

FSA equations:

$$\boxed{x-1} \xleftarrow{1/2} \boxed{x} \xrightarrow{1/2} \boxed{x+1}$$

$p_x = \mathbb{P}(\text{Ruin} \mid \text{has } \$x)$

$p_x = \frac{1}{2} p_{x+1} + \frac{1}{2} p_{x-1}$ (*) for $x = 1, \ldots, N-1$

Boundaries $p_0 = 1$ and $p_N = 0$.

Difference equation.

Solution of difference equation $(\star)$:

$$\left\{ \begin{array}{rcll} p_x & = & \frac{1}{2} p_{x+1} \; + \; \frac{1}{2} p_{x-1} & \text{for } x = 1, 2, \ldots, N-1\,; \\ p_0 & = & 1 & \\ p_N & = & 0. & \end{array} \right. \qquad (\star)$$

We usually solve equations like this using the theory of 2nd-order difference equations. For this special case we will also verify the answer by two other methods.

1. Theory of linear 2nd order difference equations

Symmetric Gamblers Ruin

325 ⇒ told this

Theory tells us that the general solution of $(\star)$ *is* $p_x = A + Bx$ *for some constants* A, B *and for* $x = 0, 1, \ldots, N$. *Our job is to find* A *and* B *using the boundary conditions:*

721 ⇒ find it

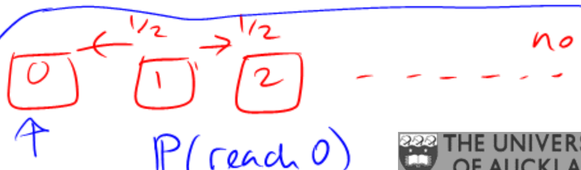
$p_x = A + Bx$ for constants A and B and for $x = 0, \ldots, N$.

Solve with boundary conditions

So $p_0 = A + B * 0 = 1 \Rightarrow A = 1$

$p_N = A + BN = 1 + BN = 0$

$\Rightarrow B = -\frac{1}{N}$.



no finish state N, goes on forever

$P(\text{reach } 0) = 1$ [definitely lose!]

$A = 1$
$B = -\frac{1}{N}$

Ass Q3 example

So our solution is: $\boxed{p_x = A + Bx = 1 - \frac{x}{N} \text{ for } x = 0, 1, \ldots, N.}$

For Stats 325, you will be told the general solution of the 2nd-order difference equation and expected to solve it using the boundary conditions.

For Stats 721, we will study the theory of 2nd-order difference equations. You will be able to derive the general solution for yourself before solving it.

Question: What is the probability that the gambler wins (ends with \$N), starting with \$x?

$\mathbb{P}(\text{ends with } \$N \mid \text{starts with } \$x) = 1 - \mathbb{P}(\text{ends with } \$0 \mid \text{starts with } \$x)$
$= 1 - p_x$
$= \frac{x}{N}$ for $x = 0, 1, \ldots, N.$

2. Solution by inspection

The problem shown in this section is the ***symmetric*** Gambler's Ruin, where the probability is $\frac{1}{2}$ of moving up or down on any step. For this special case, we can solve the difference equation by inspection.

We have:

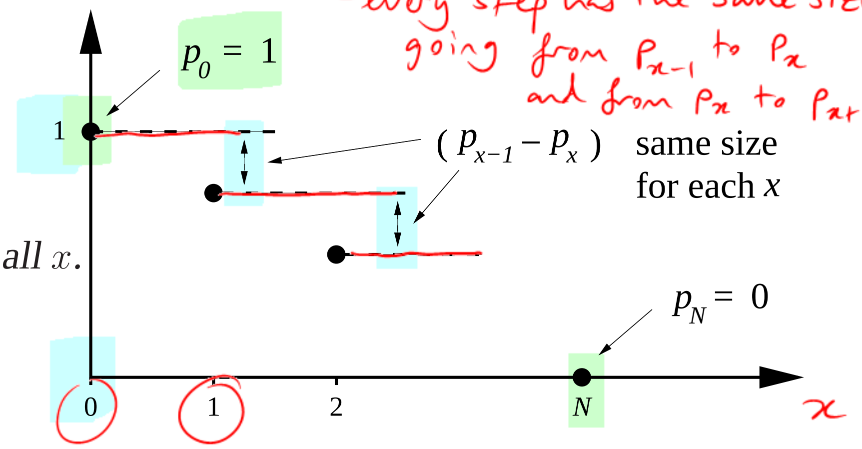
$$p_x = \tfrac{1}{2}p_{x+1} + \tfrac{1}{2}p_{x-1}$$ FSA

$$\tfrac{1}{2}p_x + \tfrac{1}{2}p_x = \tfrac{1}{2}p_{x+1} + \tfrac{1}{2}p_{x-1}$$

Rearranging: $\quad p_{x-1} - p_x = p_x - p_{x+1}.$ *Boundaries:* $p_0 = 1, p_N = 0.$

every step has the same size. going from p_{x-1} to p_x and from p_x to p_{x+1}, ...

There are N steps to go down from $p_0 = 1$ to $p_N = 0$.
Each step is the same size, because
$(p_{x-1} - p_x) = (p_x - p_{x+1})$ *for all x.*
So each step has size $1/N$,
$\Rightarrow \quad p_0 = 1,\ p_1 = 1 - 1/N,$
$\qquad p_2 = 1 - 2/N$, *etc.*



So

$$p_x = 1 - \frac{x}{N} \quad \textit{as before.}$$

3. Solution by repeated substitution.

Have a look.

In principle, all systems could be solved by this method, but it is usually too tedious to apply in practice.

We just had simultaneous eqns (N+1 of them)

Rearrange $(\star)$ *to give:*

$$
\begin{array}{llcl}
 & p_{x+1} & = & 2p_x - p_{x-1} \\
\Rightarrow \quad (x=1) & p_2 & = & 2p_1 - 1 \qquad \textit{(recall } p_0 = 1\textit{)} \\
(x=2) & p_3 & = & 2p_2 - p_1 = 2(2p_1 - 1) - p_1 = 3p_1 - 2 \\
(x=3) & p_4 & = & 2p_3 - p_2 = 2(3p_1 - 2) - (2p_1 - 1) = 4p_1 - 3 \qquad \textit{etc} \\
 & & \vdots & \\
\textit{giving} & p_x & = & x p_1 - (x-1) \qquad \textit{in general,} \qquad (\star\star) \\
\textit{likewise} & p_N & = & N p_1 - (N-1) \qquad \textit{at endpoint.}
\end{array}
$$

Boundary condition: $p_N = 0 \quad \Rightarrow \quad Np_1 - (N-1) = 0 \quad \Rightarrow \quad p_1 = 1 - 1/N.$

Induction (Ch 5).

Substitute in $(\star\star)$*:*

$$
\begin{aligned}
p_x &= x p_1 - (x-1) \\
&= x\left(1 - \tfrac{1}{N}\right) - (x-1) \\
&= x - \tfrac{x}{N} - x + 1 \\
p_x &= 1 - \tfrac{x}{N} \qquad \textit{as before.} \qquad \square
\end{aligned}
$$

2.8 Independence

Read.

Definition: Events A and B are **statistically independent** if and only if

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B).$$

This implies that A and B are statistically independent if and only if $\mathbb{P}(A \mid B) = \mathbb{P}(A)$.

Note: If events are *physically* independent, they will also be statistically indept.

For interest: more than two events

Definition: For more than two events, $A_1, A_2, \ldots, A_n$, we say that $A_1, A_2, \ldots, A_n$ are **mutually independent** if

$$\mathbb{P}\left(\bigcap_{i \in J} A_i\right) = \prod_{i \in J} \mathbb{P}(A_i) \qquad \textit{for ALL finite subsets } J \subseteq \{1, 2, \ldots, n\}.$$

Example: events A_1, A_2, A_3, A_4 are mutually independent if

i) $\mathbb{P}(A_i \cap A_j) = \mathbb{P}(A_i)\mathbb{P}(A_j)$ for all i, j with $i \neq j$; AND

ii) $\mathbb{P}(A_i \cap A_j \cap A_k) = \mathbb{P}(A_i)\mathbb{P}(A_j)\mathbb{P}(A_k)$ for all i, j, k that are all different; AND

iii) $\mathbb{P}(A_1 \cap A_2 \cap A_3 \cap A_4) = \mathbb{P}(A_1)\mathbb{P}(A_2)\mathbb{P}(A_3)\mathbb{P}(A_4)$.

Note: For mutual independence, it is ***not*** enough to check that $\mathbb{P}(A_i \cap A_j) = \mathbb{P}(A_i)\mathbb{P}(A_j)$ for all $i \neq j$. Pairwise independence does not imply mutual independence.

2.9 The Continuity Theorem

New : subtle
We use it maybe twice later in the course

The Continuity Theorem states that probability is a *continuous set function*:

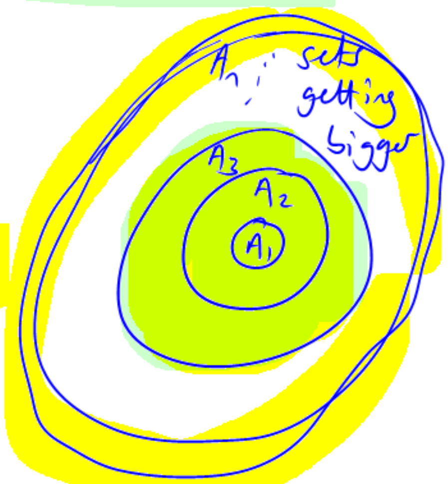
Theorem 2.9: The Continuity Theorem

a) Let $A_1, A_2, \ldots$ be an *increasing sequence of events*: i.e.

$$A_1 \subseteq A_2 \subseteq \ldots \subseteq A_n \subseteq A_{n+1} \subseteq \ldots.$$

Then

$$\mathbb{P}\left(\lim_{n\to\infty} A_n\right) = \lim_{n\to\infty} \mathbb{P}(A_n).$$



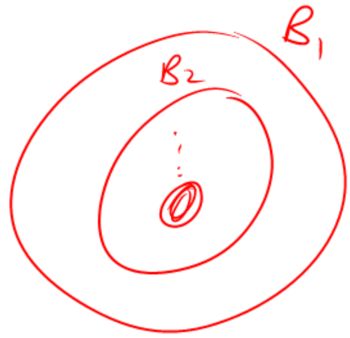
Note: because $A_1 \subseteq A_2 \subseteq \ldots$, we have: $\displaystyle\lim_{n\to\infty} A_n = \bigcup_{n=1}^{\infty} A_n.$

$P_1, P_2, P_3, \ldots$

$\mathbb{P}$(limiting event)

limit of probabilities,
i.e. limit of a sequence of numbers

b) Let $B_1, B_2, \ldots$ be a *decreasing sequence of events*: i.e.



$$B_1 \supseteq B_2 \supseteq \ldots \supseteq B_n \supseteq B_{n+1} \supseteq \ldots .$$

Then

$$\mathbb{P}\left(\lim_{n\to\infty} B_n\right) = \lim_{n\to\infty} \mathbb{P}(B_n).$$

Note: because $B_1 \supseteq B_2 \supseteq \ldots$, we have: $\displaystyle \lim_{n\to\infty} B_n = \bigcap_{n=1}^{\infty} B_n$.

Proof (a) only: for (b), take complements and use (a).

Define $C_1 = A_1$, and $C_i = A_i \backslash A_{i-1}$ for $i = 2, 3, \ldots$. Then $C_1, C_2, \ldots$ are mutually exclusive, and $\bigcup_{i=1}^n C_i = \bigcup_{i=1}^n A_i$, and likewise, $\bigcup_{i=1}^\infty C_i = \bigcup_{i=1}^\infty A_i$.

Thus

$$\begin{aligned}
\mathbb{P}(\lim_{n\to\infty} A_n) = \mathbb{P}\left(\bigcup_{i=1}^{\infty} A_i\right) = \mathbb{P}\left(\bigcup_{i=1}^{\infty} C_i\right) &= \sum_{i=1}^{\infty} \mathbb{P}(C_i) \quad (C_i \text{ mutually exclusive}) \\
&= \lim_{n\to\infty} \sum_{i=1}^{n} \mathbb{P}(C_i) \\
&= \lim_{n\to\infty} \mathbb{P}\left(\bigcup_{i=1}^{n} C_i\right) \\
&= \lim_{n\to\infty} \mathbb{P}\left(\bigcup_{i=1}^{n} A_i\right) = \lim_{n\to\infty} \mathbb{P}(A_n). \quad \square
\end{aligned}$$

2.10 Random Variables

Revision: Read

Definition: A **random variable**, X, is defined as *a function from the sample space to the real numbers:* $X : \Omega \to \mathbb{R}$.

A random variable therefore *assigns a real number to every possible outcome of a random experiment.*

A random variable is essentially *a rule or mechanism for generating random real numbers.*

The Distribution Function

Definition: The **cumulative distribution function** of a random variable X is given by

$$F_X(x) = \mathbb{P}(X \leq x)$$

$F_X(x)$ is often referred to as simply the **distribution function**.

Properties of the distribution function

1) $F_X(-\infty) = \mathbb{P}(X \leq -\infty) = 0.$
   $F_X(+\infty) = \mathbb{P}(X \leq \infty) = 1.$

2) $F_X(x)$ is a non-decreasing function of x:
   if $x_1 < x_2$, *then* $F_X(x_1) \leq F_X(x_2)$.

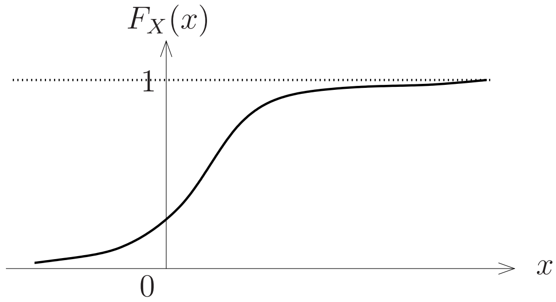
3) If $b > a$, then $\mathbb{P}(a < X \leq b) = F_X(b) - F_X(a)$.

4) F_X is right-continuous: i.e. $\lim_{h \downarrow 0} F_X(x+h) = F_X(x)$.

2.11 Continuous Random Variables

Definition: The random variable X is **continuous** if *the distribution function $F_X(x)$ is a continuous function.*

In practice, this means that a continuous random variable *takes values in a continuous subset of $\mathbb{R}$: e.g. $X : \Omega \to [0, 1]$ or $X : \Omega \to [0, \infty)$.*

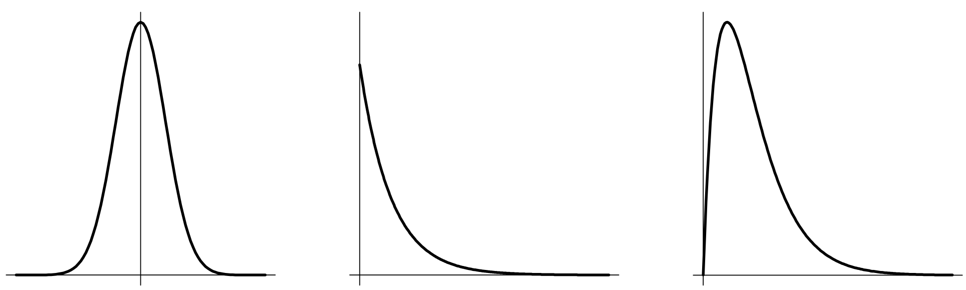


Probability Density Function for continuous random variables

Definition: Let X be a continuous random variable with continuous distribution function $F_X(x)$. The **probability density function (p.d.f.)** of X is defined as

$$f_X(x) = F'_X(x) = \frac{d}{dx}(F_X(x))$$

> The pdf, $f_X(x)$, gives the *shape* of the distribution of X.



Normal distribution Exponential distribution Gamma distribution

By the Fundamental Theorem of Calculus, the distribution function $F_X(x)$ can be written in terms of the probability density function, $f_X(x)$, as follows:

$$\boxed{F_X(x) = \int_{-\infty}^{x} f_X(u)\, du}$$

Endpoints of intervals

For continuous random variables, every point x has $\mathbb{P}(X = x) = 0$. This means that the endpoints of intervals are not important for continuous random variables.

Thus, $\mathbb{P}(a \le X \le b) = \mathbb{P}(a < X \le b) = \mathbb{P}(a \le X < b) = \mathbb{P}(a < X < b)$.

This is ***only*** true for ***continuous*** random variables.

Calculating probabilities for continuous random variables

X continuous r.v.

To calculate $\mathbb{P}(a \le X \le b)$, use ***either***

$$\mathbb{P}(a \le X \le b) = \overbrace{F_X(b) - F_X(a)}^{\text{cdf}}$$

or

$$\mathbb{P}(a \le X \le b) = \int_a^b \underbrace{f_X(x)}_{\text{pdf}}\, dx$$

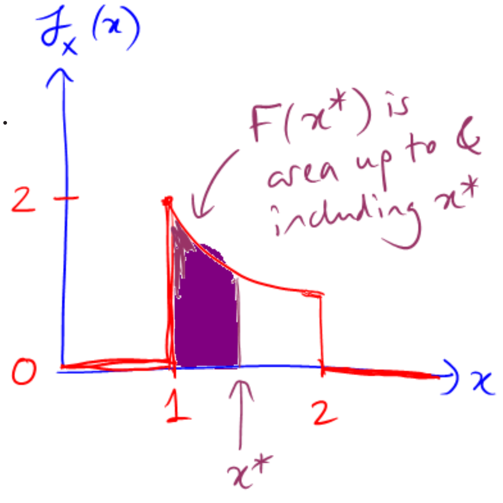
Example: Let X be a continuous random variable with p.d.f. probability density function

$$f_X(x) = \begin{cases} 2x^{-2} & \text{for } 1 < x < 2, \\ 0 & \text{otherwise.} \end{cases}$$

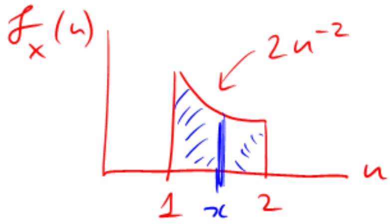
(a) Find the cumulative distribution function, $F_X(x)$.

(b) Find $\mathbb{P}(X \le 1.5)$.

$F_X(x) = \mathbb{P}(X \le x)$



a) $F_X(x) = \int_{-\infty}^{x} f_X(u)\,du$



$= \int_{1}^{x} 2u^{-2}\,du$ for $1 < x < 2$

$= \left[-2u^{-1}\right]_1^x$

$\therefore F_X(x) = 2 - \frac{2}{x}$ for $1 < x < 2$

So overall:

$$F_X(x) = \begin{cases} 0 & \text{for } x \leq 1 \\ 2 - \frac{2}{x} & \text{for } 1 < x < 2 \\ 1 & \text{for } x \geq 2. \end{cases}$$

b) $\mathbb{P}(X \leq 1.5) = F_X(1.5)$

$= 2 - \frac{2}{1.5}$

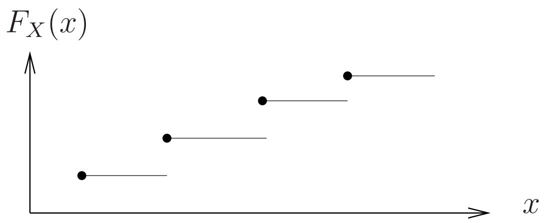
$= \frac{2}{3}$

2.12 Discrete Random Variables

Read.

Definition: The random variable X is **discrete** if X *takes values in a finite or countable subset of* $\mathbb{R}$*: thus,* $X : \Omega \to \{x_1, x_2, \ldots\}$.

When X is a discrete random variable, the distribution function $F_X(x)$ is a *step function.*



Probability function

Definition: Let X be a discrete random variable with distribution function $F_X(x)$. The **probability function** of X is defined as

$$f_X(x) = \mathbb{P}(X = x).$$

Endpoints of intervals

For discrete random variables, *individual points can have* $\mathbb{P}(X = x) > 0$.

This means that *the endpoints of intervals ARE important for discrete random variables.*

For example, if X takes values $0, 1, 2, \ldots$, and a, b are integers with $b > a$, then

$\mathbb{P}(a \leq X \leq b) = \mathbb{P}(a-1 < X \leq b) = \mathbb{P}(a \leq X < b+1) = \mathbb{P}(a-1 < X < b+1)$.

Calculating probabilities for discrete random variables

To calculate $\mathbb{P}(X \in A)$ for any countable set A, use

$$\mathbb{P}(X \in A) = \sum_{x \in A} \mathbb{P}(X = x).$$

Partition Theorem for probabilities of discrete random variables

Recall the Partition Theorem: for any event A, and for events $B_1, B_2, \ldots$ that form a ***partition*** of Ω,

$$\mathbb{P}(A) = \sum_y \mathbb{P}(A \mid B_y)\,\mathbb{P}(B_y).$$

A, B_y are events (sets).

We can use the Partition Theorem to find probabilities for random variables. Let X and Y be **discrete** random variables.

- Define event A as $A = \{X = x\}$.
- Define event B_y as $B_y = \{Y = y\}$ for $y = 0, 1, 2, \ldots$ (or whatever other values Y takes).
- Then, by the Partition Theorem,

$$\mathbb{P}(X = x) = \sum_y \mathbb{P}(X = x \mid Y = y)\,\mathbb{P}(Y = y).$$

conditional prob fn of X given Y.

If X, Y are independent (discrete), r.v.s then $\mathbb{P}(X=x \mid Y=y) = \mathbb{P}(X=x)$ for all x, y.

2.13 Independent Random Variables

Random variables X and Y are independent if they have no effect on each other. This means that the probability that they both take specified values simultaneously is the product of the individual probabilities.

Definition: Let X and Y be random variables. The **joint distribution function** of X and Y is given by

$$F_{X,Y}(x, y) = \mathbb{P}(X \leq x \text{ and } Y \leq y) = \mathbb{P}(X \leq x, Y \leq y).$$

Definition: Let X and Y be any random variables (continuous or discrete). X and Y are **independent** if

$$F_{X,Y}(x, y) = F_X(x)F_Y(y) \text{ for ALL } x, y \in \mathbb{R}.$$

If X and Y are ***discrete***, they are independent if and only if their joint probability function is the product of their individual probability functions:

$$\begin{aligned} \textit{Discrete } X, Y \textit{ are indept} \quad &\iff \quad \mathbb{P}(X = x \textit{ AND } Y = y) = \mathbb{P}(X = x)\mathbb{P}(Y = y) \\ &\qquad\qquad \textit{for ALL } x, y \\ &\iff \quad f_{X,Y}(x, y) = f_X(x)f_Y(y) \quad \textit{for ALL } x, y. \end{aligned}$$