University of BRISTOL

WEEK 1

Course motivation and overview

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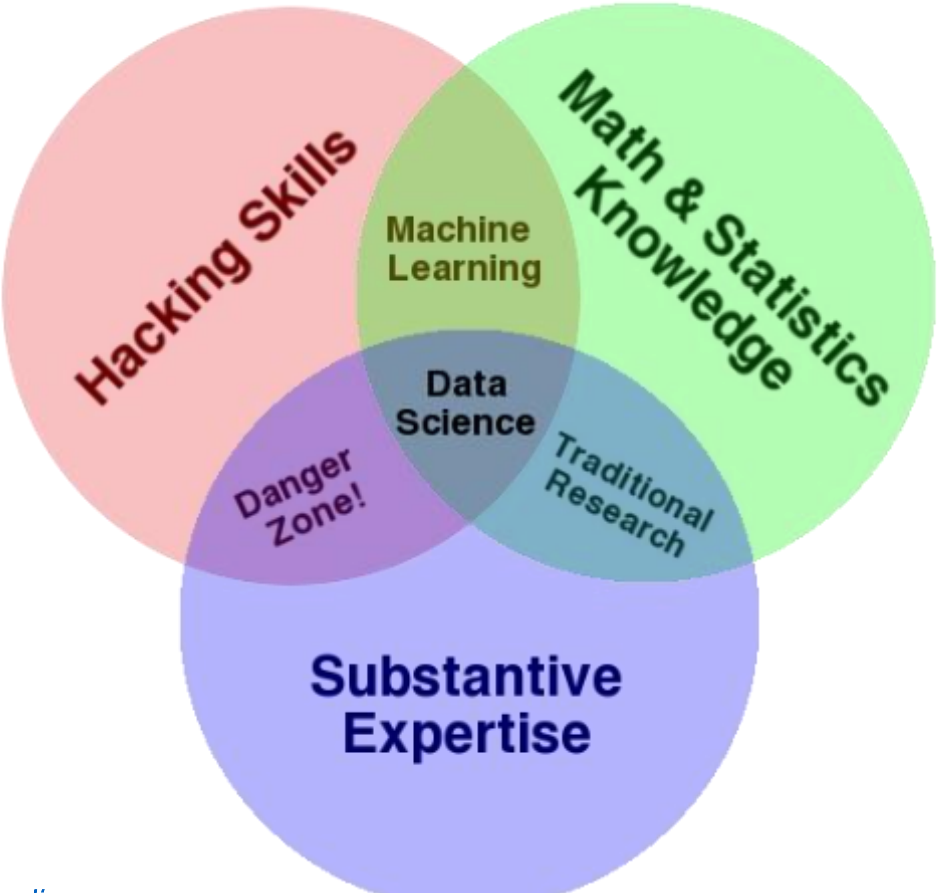
Statistical Computing and Empirical Methods

What's this course about?

In this course you'll gain a broad understanding of some of the fundamental ***statistical principles and methods*** *necessary for a successful career in* ***Data Science****.*



How is this useful?

Let's do a quick experiment…

Image: http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram

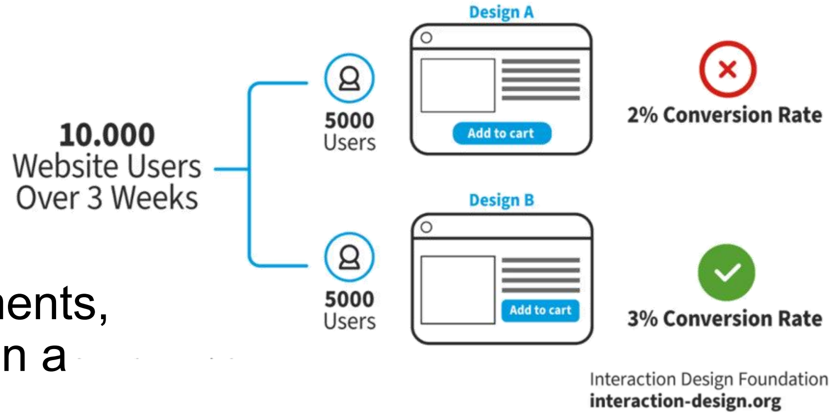
Data gathering

Please take 15 seconds to answer 2 simple questions using this link.

(please do it – it's more fun when we have live data)

https://forms.office.com/e/J5qJw7d4CG

A/B testing

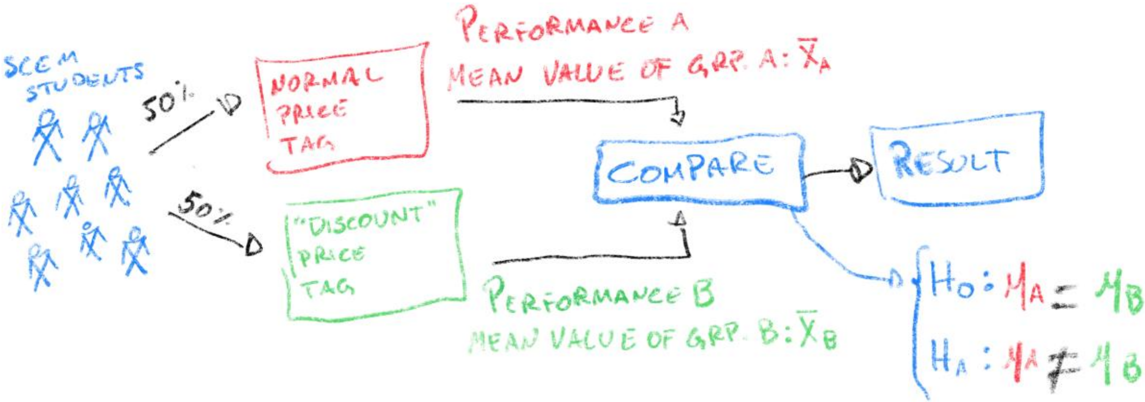


A/B testing (also know as split testing) is a common technique used to run *online* experiments, usually to assess user responses to changes in a system (e.g., changes in click-through rates, average sales value, etc.).

Methodologically speaking, there's nothing new about A/B testing – they are just one example of coupling classic ***statistical methods*** with modern data-gathering capabilities, to reach ***statistically sound conclusions***.

We have just run our first A/B test (sort of).

Let's walk through it.



Step 1: Defining a question of interest

The form you just completed was designed to test what is known as the *anchoring bias*[1] – the tendency of people to rely on some initial piece of information (even if irrelevant) when trying to estimate a quantity.

In this case, the same question about the oven price was presented with two different images, randomly presented (with the birth date used to randomise the allocation). Is there an effect of the perception of a "promotion"? (which could affect how much a person would be willing to pay for the product)

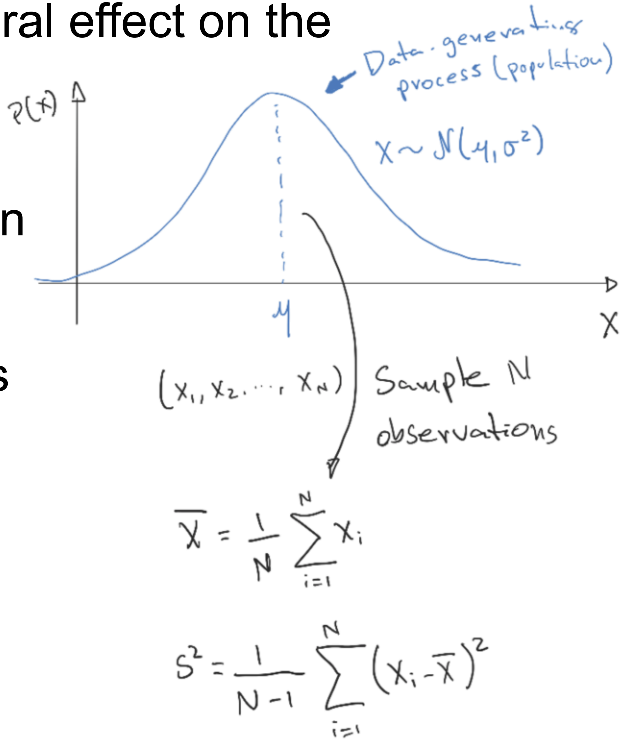
How can we **measure** the differences and **test** if the differences are due to a real effect of the options given, or just random noise?

[1]Tversky and Kahneman (1974). [Judgment under Uncertainty: Heuristics and Biases](). Science 184.

Step 2: Formalising the question

Each person will have their own opinion on the actual value of the item. Predicting an individual's reaction is almost impossible with the information we have. However, we are instead interested in the general effect on the **population**, not on a specific person.

Estimating **populational parameters** from information contained in a **sample** is the realm of ***statistical estimation*** (which you'll be learning in a few weeks). Reaching solid conclusions based on those estimates is the realm of ***statistical inference / hypothesis testing*** (which you'll also be learning soon).



(*We will learn about* ***point estimation*** *in week 3*)

Step 2: Formalising the question

In the case of our A/B test, the "performance" of each picture option can be measured as the *mean attributed value* in that group, μ_A or μ_B.
These quantities can be estimated by their respective *sample means*, $\bar{X}_A$ and $\bar{X}_B$, which we use to test our question of interest: ***Is the mean value attributed to the product greater when the picture shows a "promotion" tag?***

In statistical terms, this is commonly formalised as a pair of ***statistical hypotheses***:

Null hypothesis
(no effect)

$$\begin{cases} H_0: \mu_A = \mu_B \\ H_A: \mu_A \neq \mu_B \end{cases}$$

Alternative hypothesis
(some effect)

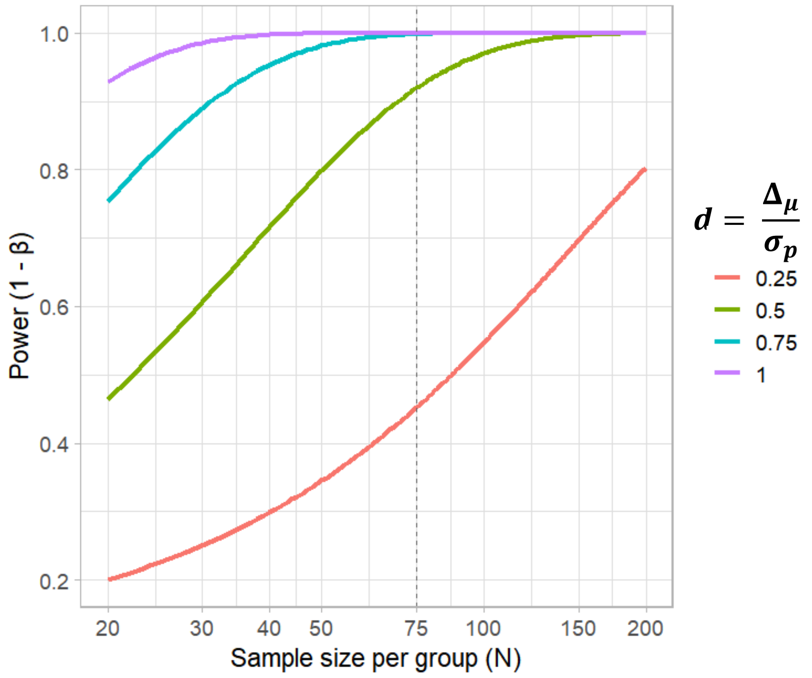
(*We will learn about comparative experiments in week 6*)

3. Designing the experiment

Given a question of interest, formalised as statistical hypotheses, how to go about testing those hypotheses?

This includes considerations about:

- Which **statistical test** to use?
- What is the desired level of **confidence**?
- What is the **smallest relevant difference** we want to be able to detect?
- What is the desired sensitivity (a.k.a. **statistical power**) of the experiment?
- What are the required (or the available) **sample sizes**?

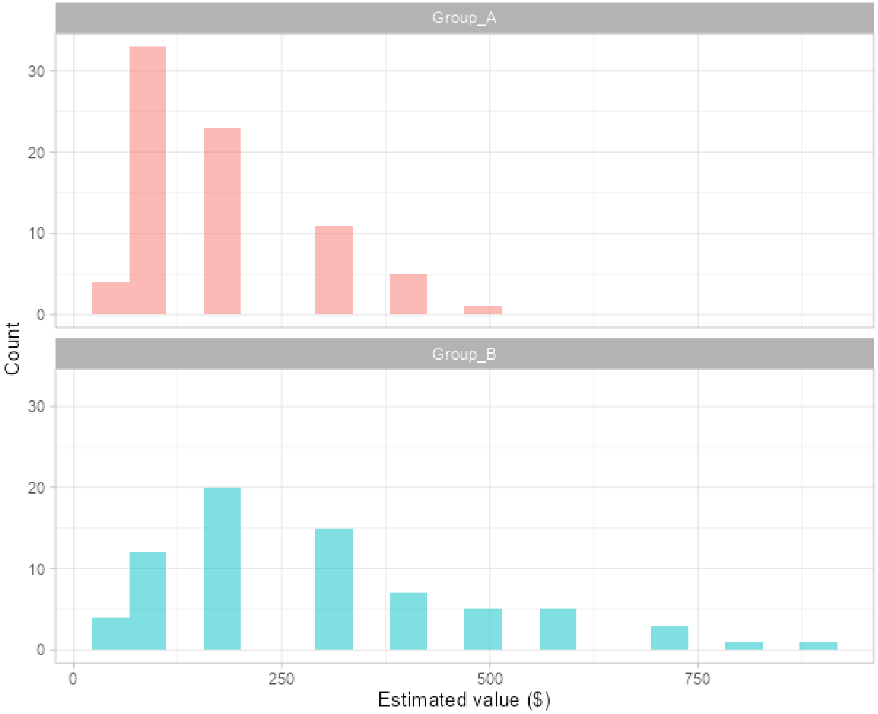


(We will learn about experimental design in weeks 5-7)

4. Exploratory Data Analysis

An important part of any data analysis task is to get a sense of what the data "looks like" – to check for data inconsistencies, missing values, the general shape of the data distributions, etc.

This process is known as ***Exploratory Data Analysis*** (EDA). It commonly combines visuals and summary statistics.



Group	n	mean	median	sd
Group_A	77	180.52	200	102.00
Group_B	73	301.37	300	195.07

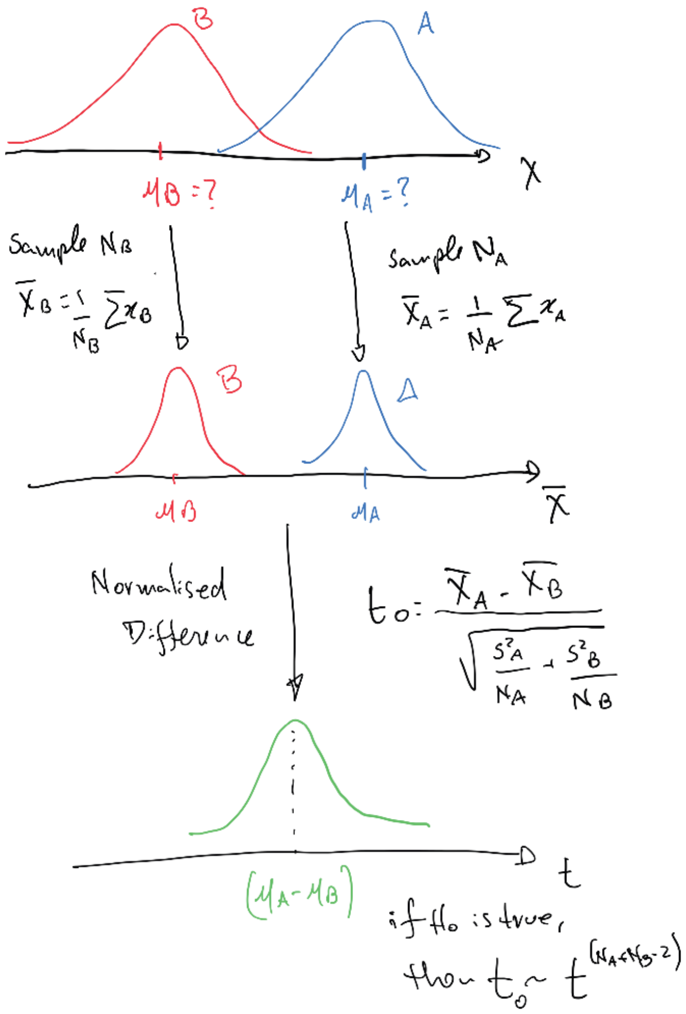
(*We will learn about EDA in weeks 8-9*)

5. Testing hypotheses

Hypothesis testing is used to extract conclusions about (unknown) ***populational parameters*** based on (known) ***sample statistics***.

Broadly speaking, statistical hypothesis testing works by comparing the value of some ***test statistic*** (calculated from the data) with what values would be expected under the ***null hypothesis*** ("no effect").

If the observed scenario is inconsistent with the expected "no effects" behaviour, it is said that the null hypothesis is **rejected.**

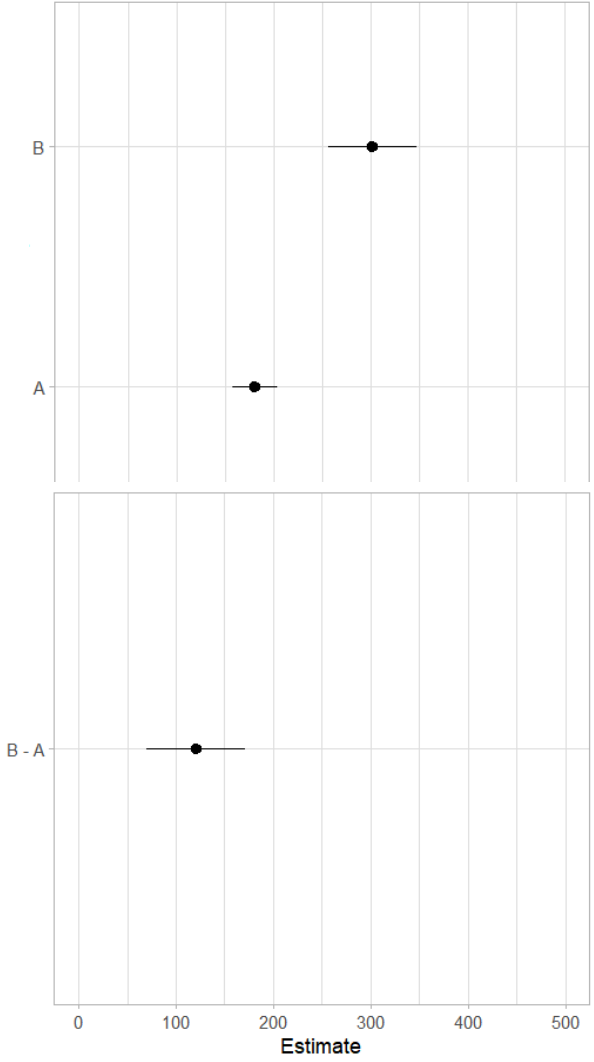


(We will learn about hypothesis testing in weeks 5-7)

6. Reporting

Once we finish our analyses, it is important to adequately report the results, including the estimated differences (and the precision associated with those estimates, e.g., in the form of ***confidence intervals***), the results of the hypothesis testing, etc.

In practice it is important to report the statistics, but also to step back and describe what the results mean in the context of the problem – for instance, what does it mean to have a significant difference in perceived value, in the context of that online store?



(We will learn about statistical intervals in week 4)

Tying these concepts to the course structure

In this course, you will learn about *statistical computing and empirical methods* through two main learning modes:

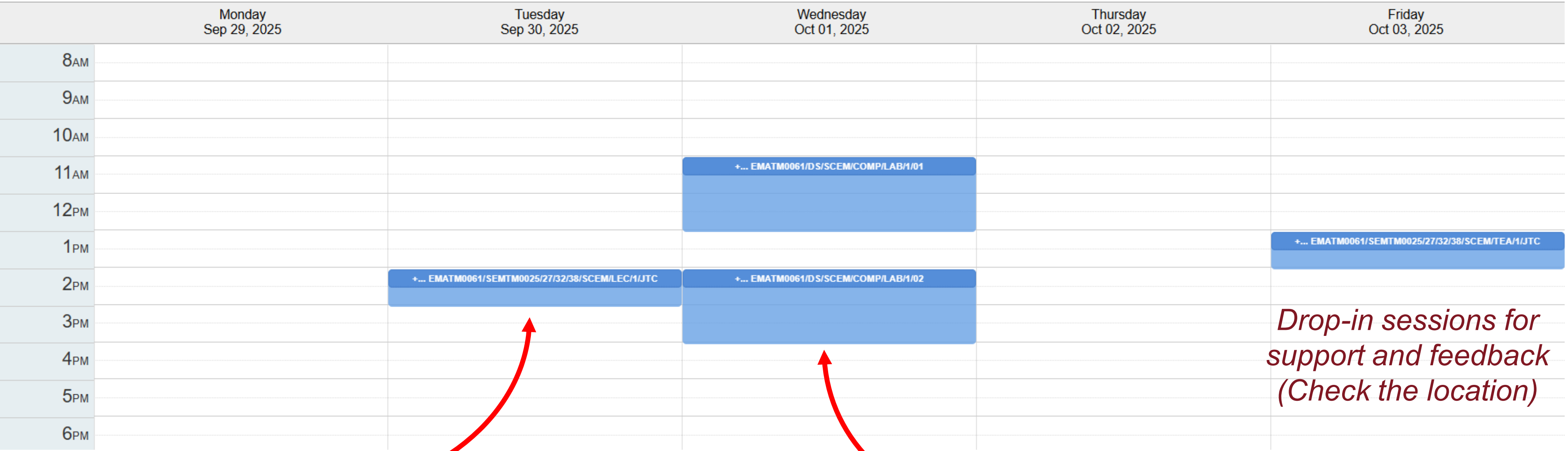
- ***learn-by-watching***: weekly live lectures (every Tuesday) + asynchronous video content. In these sessions, concepts are introduced and discussed.

Important*: keeping up with the video contents is just as important as attending the lectures - some items are only covered in the lectures, others only in the videos*.

- ***learn-by-doing***: weekly lab sessions (every Wednesday). In these sessions you'll consolidate your learning and, as the course advances, get some hands-on experience with more complex computational statistical methods.

Important*: don't neglect the lab activities. Besides getting some practical knowledge in R, these sessions are a great opportunity to ask questions about the unit and get some* ***feedback*** to check your understanding, and they'll also prepare you for the final coursework.

A typical week:



Drop-in sessions for support and feedback (Check the location)

Lecture (Check the location)

Labs (Check your slot) (Check the location)

A typical week:

Each week there will also be one or more ***videos.***

They can be viewed at a time of your choosing, but it is **recommended** to do so before the in-person lectures and computer labs. I **suggest** adding a fixed time slot into your calendar (maybe on Monday or Tuesday morning?) and making it a habit.

If you don’t come prepared, you are likely to benefit less from the sessions.

Assessment

Formative assignments (does not count towards your final score)

Type: Weekly lab assignments (computational and theoretical).

Feedback: Live discussions during the lab sessions. Cohort-wide discussion of previous week assignment at the start of each lab.

Summative assessment (counts towards your final score)

Type: Final coursework (100%). Composed of a series of tasks (computational and/or theoretical) to assess the knowledge and skills acquired in the unit. More details released in October. *Deadline: early December.*

Feedback: Provided after marking. Summary of marks + marker feedback on specific questions.

The one-stop shop: our Blackboard page

SEMTM_61_32_27_25_2025_TB-1

CLOSED

Statistical Computing and Empirical Methods (EMATM0061 + SEMTM0038 + SEMTM0032 + SEMTM0027 + SEMTM0025) 2025

Content Calendar Announcements Discussions Gradebook Messages Groups

Course Content

Welcome
Please read this document before exploring the unit.

Unit Information and Resources
Here you will find a comprehensive guide on what you can expect from the course, including contact information, learning objectives, and the lecture schedule, as well as a range of important resources such as your resource list and the collection of Re/Play recordings for this unit.

Unit Assessment

Course Staff

Zahraa Abdallah
INSTRUCTOR

Maria Aspinall
INSTRUCTOR

Show more

Details & Actions

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