

# Bayesian Data Analysis

Dr Niamh Cahill (she/her)

Bayes' Rule

# Bayes' rule

Thomas Bayes' famous theorem was published in 1763.



For events A and B:

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

- ▶ The branch of statistics that you are probably most familiar with up to now is called *frequentist* statistics.
- ▶ Bayesian statistics uses Bayes' rule for inference and decision making, frequentist statistics does not.

## Toy example

Suppose that you are interested in the probability of rain in the afternoon in your location.

Let's assume 30% of days have rain in the afternoon.

$$(1) \quad P(\text{rain}) = 0.3$$

Let's assume you have additional information which is that in the morning it's cloudy.

Now assume you have an updated probability of rain which is conditional on the morning being cloudy.

$$(2) \quad P(\text{rain}|\text{cloudy}) = 0.6$$

What information did we need to get from (1) to (2)?

## Toy example

We added some information (data) about clouds. We need to know the probability of observing that data given what we know about rain.

$$(3) \quad P(\text{cloudy}|\text{rain}) = 0.8$$

We also need to know what the marginal probability of being cloudy is.

$$(4) \quad P(\text{cloudy}) = 0.4$$

Now we can put (1), (3) and (4) together using Bayes' rule

$$P(\text{rain}|\text{cloudy}) = \frac{P(\text{cloudy}|\text{rain})P(\text{rain})}{P(\text{cloudy})}$$

$P(A|B)$                        $P(B|A)$      $P(A)$                        $P(B)$

## Disease screening example

- ▶ Suppose there is a test for a disease that has a sensitivity of 80% (i.e., if 100 people that have the disease take the test then 80 of them will get a positive result).

$$P(+iv|disease) = 0.8$$

- ▶ Suppose the chance of having this disease is 2%.

$$P(disease) = 0.02$$

- ▶ Suppose we also know that the test gives false positive results 5% of the time (this relates to specificity of the test).

$$P(+iv|no\ disease) = 0.05$$

What is the probability you have the disease given that you receive a positive test result?

$$P(disease|+iv) = \frac{P(+ive|disease)P(disease)}{P(+ive)}$$

## Disease screening example

Find the probability that a person has the disease given they get a positive test result.

$$(1) P(+ive|disease)P(disease) = 0.8 \times 0.02$$

$$(2) P(+ive) = P(+ive|disease)P(disease) + P(+ive|no disease)P(no disease) = 0.065$$

$$P(disease|+ive) = \frac{0.8 \times 0.02}{0.065} = 0.25$$

- ▶ So even with a positive test result for a test with an 80% “hit rate”, the probability of having the disease is only 25%
- ▶ The lower probability is a consequence of the low *prior* probability of the disease and the non-negligible false positive rate.

# Bayes' rule applied to parameters and data

Given a set of observed data points  $Y$  and a set of parameters  $\theta$ , we write Bayes' rule as

$$P(\theta|Y) = \frac{\overset{\text{likelihood}}{P(Y|\theta)} \overset{\text{prior}}{P(\theta)}}{\underset{\text{marginal likelihood}}{P(Y)}}$$

Where the denominator is

$P(Y) = \sum_{\theta^*} P(Y|\theta^*)P(\theta^*)$  for discrete-valued variables, or

$P(Y) = \int P(Y|\theta^*)P(\theta^*)d\theta^*$  for continuous variables.

$P(Y)$  is often difficult to calculate (more on this later) and Baye's rule is often written more simply as a proportional statement

$$P(\theta|Y) \propto \overset{\text{likelihood}}{P(Y|\theta)} \overset{\text{prior}}{P(\theta)}$$

# Likelihood, Prior & Posterior

$$\underset{\text{posterior}}{P(\theta|Y)} \propto \underset{\text{likelihood}}{P(Y|\theta)} \underset{\text{prior}}{P(\theta)}$$

- ▶  $P(Y|\theta)$  which is the probability distribution of the data given the parameters is known as the *likelihood*
- ▶  $P(\theta)$  which is the probability distribution of the parameters is known as the *prior*. The prior represents what we know about the parameters before the data are observed.
- ▶  $P(\theta|Y)$  which is the probability distribution of the parameters given the data is known as the *posterior*. The posterior represents our updated knowledge about parameters after the data are observed.