Behavioural Economics

PSYC3310: Specialist Topics In Psychology

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Seminar 4: Judgement Under Risk & Uncertainty

CSIRO-UWA BEL Behavioural Economics Laboratory

Last week

- Last week, we focused on preferences and choices—components **1** and **4** in the standard model

(1)	**(2)**	**(3)**	**(4)**
$\max\limits_{x_i^t \in X_i}$	$\sum\limits_{t=0}^{\infty} \delta^t$	$\sum\limits_{s_t \in S_t} p(s_t)$	$U(x_i^t \mid s_t)$

Today

- Examine probabilities and beliefs in the standard model—**component 3**

$$\underbrace{\max_{x_i^t \in X_i}}_{(1)} \underbrace{\sum_{t=0}^{\infty} \delta^t}_{(2)} \underbrace{\sum_{s_t \in S_t} p(s_t)}_{(3)} \underbrace{U(x_i^t \mid s_t)}_{(4)}$$

- Judgement under risk & uncertainty
  - confront the model with empirical data

Today

- Examine probabilities and beliefs in the standard model—**component 3**

(1) **(2)** **(3)** **(4)**

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- Judgement under risk & uncertainty
  - confront the model with empirical data

The standard model: An example

Suppose you have to choose between two 3310 topics:

(1) Behavioural Economics (BE)
(2) Cognition and Emotion (CE)

Choice	State of world $s \in S$	Probability $p(s)$	Utility $U(x\|s)$
BE	Exciting	0.8	60
	Dull	0.2	30
CE	Exciting	0.05	60
	Dull	0.95	30

U(BE) = (0.8 $\times$ 60) + (0.2 $\times$ 30) = **54**
U(CE) = (0.05 $\times$ 60) + (0.95 $\times$ 30) = **31.5**

The standard model: An example

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Choice	State of world $s \in S$	Probability $p(s)$	Utility $U(x\|s)$
BE	Exciting	0.3	60
	Dull	0.7	30
CE	Exciting	0.75	60
	Dull	0.25	30

U(BE) = (0.3 $\times$ 60) + (0.7 $\times$ 30) = **39**
U(CE) = (0.75 $\times$ 60) + (0.25 $\times$ 30) = **52.5**

The standard model: An example

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The standard model: Main assumptions

- In terms of beliefs, the standard model makes two central assumptions
  - **Perfect rationality**
  - **Bayesian probability estimation**
- Let's look at each in turn ...

The standard model: Perfect rationality

- We've already discussed this in the past two seminars
- The basic assumptions here are that
  - people have all the relevant information they need when they make a decision
  - they have the cognitive resources to process it instantly and without cost
- **Bounded rationality** (Simon, 1955) is the term we use if these assumptions do not hold

The standard model: Bayesian probability estimation

- People are assumed to be **Bayesian probability estimators**
- This means that
  - they are able to estimate probabilities correctly, given the relevant information
  - they are able to update these probabilities in light of new information
- In order to understand this assumption, we need to introduce **Bayes' rule**

Bayes' rule

- Bayes' rule is a rigorous method for interpreting evidence in the context of previous experience or knowledge
- It was discovered by the English statistician and minister, Thomas Bayes (1701-1761)

Bayes' rule

- Bayes' rule, or *Bayes' theorem*, constitutes a mathematical foundation for reasoning
- It is not a matter of conjecture—as a theorem it has been proved to be true
- In essence, Bayes' rule is used to combine *prior* experience with observed data to interpret these data
- This process is known as *Bayesian inference*

Bayes' rule

- Bayes' rule can be specified as follows

$$p(hypothesis|data) = \frac{p(data|hypothesis) \times p(hypothesis)}{p(data)}, \quad (1)$$

Where:

- $p(hypothesis|data)$ = *posterior probability*
- $p(data|hypothesis)$ = *likelihood*
- $p(hypothesis)$ = *prior probability*
- $p(data)$ = *marginal likelihood*
  - calculated as $\sum p(data|hypothesis_i) \times p(hypothesis_i)$

Bayes' rule

- **Posterior probability**
  - the probability the hypothesis is true given the data
- **Likelihood**
  - the likelihood of observing the data if the hypothesis is true
- **Prior probability**
  - the prior probability of the hypothesis
- **Marginal likelihood**
  - the *a priori* probability of witnessing the data under all hypotheses

Example 1: Medical diagnosis

- You wake up one day with spots on your face
- Your doctor informs you the symptoms (*data*) are consistent with two Poxy diseases (*hypotheses*): smallpox and chickenpox
- She knows 80% of people with chickenpox have spots, but also that 90% of people with smallpox have spots
- How should she decide between the two diagnoses?

Example 1: Medical diagnosis

- Although the probability of spots given you have chickenpox or smallpox is comparable, your doctor knows the former disease is common, but the latter is rare
- This *prior information* can be used to determine which disease you might have
- Reaching a decision requires the doctor to combine the possible diagnoses (hypotheses) implied by your symptoms (data) with her prior knowledge (prior information)

Example 1: Medical diagnosis

- Based on medical reports, your doctor knows the following
- The conditional probability a patient has spots given they have smallpox is 90% or 0.9
  - $p(spots|smallpox) = 0.9$,
- The conditional probability a patient has spots given they have chickenpox is 80% or 0.8
  - $p(spots|chickenpox) = 0.8$,
- So far this does not take into account prior information about the relative prevalence of the two diseases

Example 1: Medical diagnosis

- Public health statistics indicate the prevalence of smallpox in the general population is 0.001
  - $p(smallpox) = 0.001$,
- The prevalence of chickenpox in the general population is 0.1
  - $p(chickenpox) = 0.1$,
- The probability that a randomly chosen person in the population has spots—the marginal likelihood—is $(0.9 \times 0.001) + (0.8 \times 0.1) = 0.081$
  - $p(spots) = 0.081$,
- Your doctor now has the prior information she needs to make a diagnosis using Bayes' rule

Example 1: Medical diagnosis

Using Bayes' rule, the *posterior probability* that you have smallpox, given your symptoms, can be calculated as:

$$p(smallpox|spots) = \frac{p(spots|smallpox) \times p(smallpox)}{p(spots)}, \tag{2}$$

Plugging in the values from the previous slides we get

$$p(smallpox|spots) = 0.9 \times 0.001/0.081 \tag{3}$$

$$p(smallpox|spots) = \textbf{0.011.} \tag{4}$$

Example 1: Medical diagnosis

Now let's calculate the *posterior probability* that you have chickenpox:

$$p(chickenpox|spots) = \frac{p(spots|chickenpox) \times p(chickenpox)}{p(spots)}, \tag{5}$$

Plugging in the values from the previous slides we get

$$p(chickenpox|spots) = 0.8 \times 0.1/0.081 \tag{6}$$

$$p(chickenpox|spots) = \mathbf{0.988.} \tag{7}$$

Example 1: Medical diagnosis

The two posterior probabilities are:

$$p(smallpox|spots) = \mathbf{0.011.} \tag{8}$$

$$p(chickenpox|spots) = \mathbf{0.988.} \tag{9}$$

Using these values we can create a posterior ratio

$$R_{post} = \frac{p(chickenpox|spots)}{p(smallpox|spots)} \tag{10}$$

$$R_{post} = \frac{0.988}{0.011} \tag{11}$$

$$R_{post} = 89.81 \tag{12}$$

Example 2: Spoken word recognition

Let's consider another example, but before that some light hearted relief Two Ronnies Sketch

Example 2: Spoken word recognition

- Suppose you are a shopkeeper and a customer asks you *have you got forkandles?*
- The acoustic input is ambiguous: did the customer ask for *four candles* or *fork handles*?
- To adjudicate between the two hypotheses, you may use prior information to infer the correct interpretation
- You sell many more candles than fork handles
- Thus, you may not hear the words *fork handles* and instead hear *four candles*

Example 2: Spoken word recognition

- Lets make the following assumptions for our example
- The probability that the phrase spoken was *four candles* is 0.6
  - $p(data|four\, candles)$ = 0.6,
- The probability that the phrase spoken was *fork handles* is 0.7
  - $p(data|fork\, handles)$ = 0.7,

Example 2: Spoken word recognition

- You have been asked 90 times in the past for four candles and only 10 times for fork handles
- Before the customer speaks, you estimate that the probability he will say each phrase is
  - $p(four\ candles) = 0.9$,
  - $p(fork\ handles) = 0.1$,
- The marginal likelihood is $(0.6 \times 0.9) + (0.7 \times 0.1) = 0.61$
  - $p(data) = 0.61$

Example 2: Spoken word recognition

Using Bayes' rule, the posterior probability that the customer said *four candles* is: -

$$p(four\,candles|data) = \frac{p(data|four\,candles) \times p(four\,candles)}{p(data)}, \tag{13}$$

Plugging in the values from the previous slides we get

$$p(four\,candles|data) = 0.6 \times 0.9/0.61 \tag{14}$$

$$p(four\,candles|data) = \mathbf{0.885} \tag{15}$$

Example 2: Spoken word recognition

The posterior probability that the customer said *fork handles* is: -

$$p(fork\,handles|data) = \frac{p(data|fork\,handles) \times p(fork\,handles)}{p(data)}, \tag{16}$$

Plugging in the values from the previous slides we get

$$p(fork\,handles|data) = 0.7 \times 0.1/0.61 \tag{17}$$

$$p(fork\,handles|data) = \mathbf{0.115} \tag{18}$$

Example 2: Spoken word recognition

The two posterior probabilities are:

$$p(four\,candles|data) = \mathbf{0.885} \tag{19}$$

$$p(fork\,handles|data) = \mathbf{0.115} \tag{20}$$

Using these values we can create a posterior ratio

$$R_{post} = \frac{p(four\,candles|data)}{p(fork\,handles|data)} \tag{21}$$

$$R_{post} = \frac{0.885}{0.115} \tag{22}$$

$$R_{post} = 7.69 \tag{23}$$

Next... are people Bayesian probability estimators?

- Do people behave according to the rules of logic and probability theory as the standard model predicts?
- Do they update their beliefs using Bayes' rule (so-called **Bayesian updating**)?
- We consider instances where this is not the case
    - speaker 1: gambler's and conjunction fallacies
    - speaker 2: base-rate neglect and planning fallacy
    - speaker 3: confirmation bias
    - speaker 4: availability heuristic and hindsight bias