

Lecture 29: Bayesian Statistics

Chapter 2.2.7

1 / 25

Recall Conditional Probability

2 / 25

Back to Midterm: New Notation

Back to Midterm

Back to Midterm

So recall from the midterm we have the following 2×2 table of possible outcomes:

		Test conclusion	
		\ominus	\oplus
Truth	H_0 true	$(1 - 0.05) \times 900 = 855$	$0.05 \times 900 = 45$
	H_A true	$(1 - 0.8) \times 100 = 20$	$0.8 \times 100 = 80$

5 / 25

Different Set-Up

Now say for the same machine H_A is true 40% of the time. i.e.
 $P(H_A) = 0.4$

		Test conclusion	
		\ominus	\oplus
Truth	H_0 true	$(1 - 0.05) \times 600 = 570$	$0.05 \times 600 = 30$
	H_A true	$(1 - 0.8) \times 400 = 80$	$0.8 \times 400 = 320$

6 / 25

How Reliable Are Your Test Results?

7 / 25

How Reliable Are Your Test Results?

The probability that a positive result is right depends on how likely H_A is. Same goes for negative results.

Question 2 from Quiz 9: (Nature article) Say a scientist obtains a p-value of 0.01. An incorrect interpretation of this is that it is the probability of a “false alarm” (type I error)... If one wants to make a statement about this being a false alarm, what additional piece of information is required?

Answer 2: The plausibility of the hypothesis being tested for.

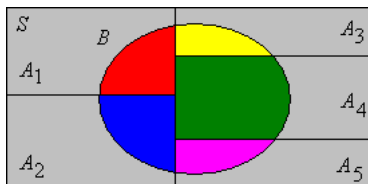
8 / 25

Bayes Theorem

9 / 25

Illustration

- ▶ The sample space S is the overall grey box
- ▶ A_1, \dots, A_5 are the five blocks that partition S .
- ▶ B is the oval



10 / 25

Tailored to our Situation

Tailored to our Situation

The Debate

In the midterm you applied Bayes Theorem from scratch/intuition.

Why isn't everybody taking into account $P(H_A)$ when testing H_0 vs H_A ?

In this example, we assumed we **knew** the true $P(H_A)$. In real life however, we don't.

13 / 25

Statistics In General

Statistics is inferring about some unknown parameter θ .

- ▶ **Frequentist Statistics**: the true θ is a single value.
- ▶ **Bayesian Statistics**: the true θ is a **distribution** of values that reflects our **belief** in the plausibility of different values.

Ex: Coin Flips

14 / 25

The Bayesian Procedure

To express our belief about θ from as a Bayesian, we have:

1. A prior distribution $\Pr(\theta)$. It reflects our **prior** belief about θ .
2. The likelihood function $\Pr(X|\theta)$. This is the mechanism that generates the **data**.
3. A posterior distribution $\Pr(\theta|X)$. We **update** our belief about θ after observing data X .

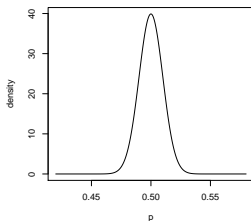
$$\Pr(\theta|X) = \frac{\Pr(X|\theta) \cdot \Pr(\theta)}{\Pr(X)}$$

The Issue: The Bayesian Procedure

Where do you come up with $\Pr(\theta)$? It's completely **subjective**! You decide!

Prior Distribution

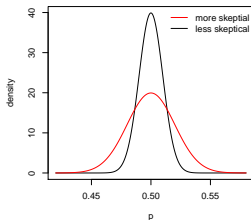
This distribution can reflect someone's **prior belief** of p .



17 / 25

Prior Distribution

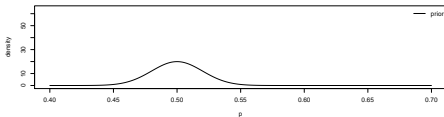
Say someone is more skeptical that $p = 0.5$, we can lower it.



18 / 25

The Bayesian Procedure

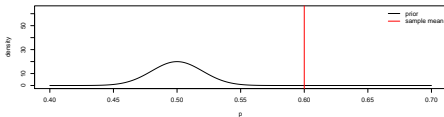
Say we have the following prior belief centered at $p = 0.5$



19 / 25

The Bayesian Procedure

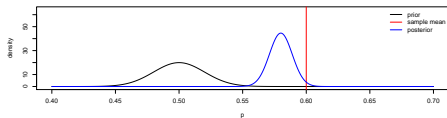
Say we collect data, represented by the red line, suggesting $p = 0.6$



20 / 25

The Bayesian Procedure

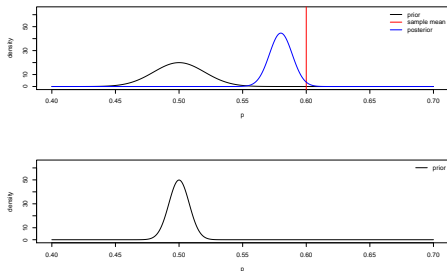
We then **update** our belief, as reflected in the posterior distribution!



21 / 25

The Bayesian Procedure

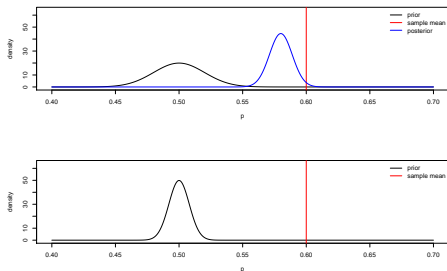
Now say we have a stronger prior belief that $p = 0.5$



22 / 25

The Bayesian Procedure

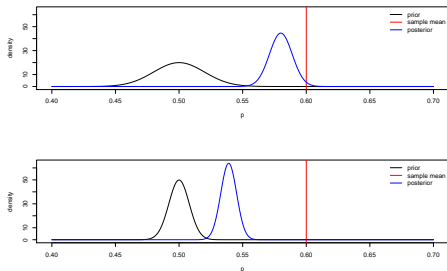
Say we observed the same data (as represented in red).



23 / 25

The Bayesian Procedure

The posterior in this case is pulled left due to the sharper prior.



24 / 25

Back to Debate

Frequentists believe statistics should be completely **objective** and therefore do not accept the premise of a subjective prior.

Back to Hypothesis Testing Machine example. In order to use such a procedure in real life, we would need to specify some prior belief $\Pr(H_A)$ that H_A is true.