

# Introduction to Bayesian Inference for the Psychological Sciences

Thomas J. Faulkenberry, Ph.D.

Tarleton State University

# Plan for today's workshop

- convince you that  $p$ -values are problematic (20 min)
- introduce Bayesian inference (15 min)
- show you some free software for conducting Bayesian inference (JASP) (5 min)
- do some examples together (50 min)

All materials can be found at:

- <http://github.com/tomfaulkenberry/bayesWorkshop>

## An exercise

Suppose you have a treatment that you suspect may alter performance on a certain task. You find that the experimental group **significantly** outperforms the control group,  $t(18) = 2.7$ ,  $p = 0.01$ .

How many of the following are True statements?

- The probability that the null hypothesis is true is 1%
- The probability that the research hypothesis is true is 99%
- If you reject the null, the probability that you are making the wrong decision is 1%
- If you repeated the experiment over and over, then you would get a significant result 99% of the time.

## An exercise

Suppose you have a treatment that you suspect may alter performance on a certain task. You find that the experimental group **significantly** outperforms the control group,  $t(18) = 2.7$ ,  $p = 0.01$ .

**They're all false!**

## So what is a $p$ -value?

The  $p$ -**value** is the probability of obtaining a test statistic at least as extreme as the one that was observed, given that the null hypothesis is true. . . i.e.,  $P(D \mid \mathcal{H}_0)$ .

Core logic:

- suppose the opposite of what we want (i.e., that there is no effect)
- show that this *under this null hypothesis*, our data is very unlikely (our  $p$ -value is very small)
- conclude that there must be an effect

# Formal logic

This argument is similar to the *modus tollens* syllogism from formal logic:

- **Premise:** If A, then B;
- **Premise:** not B;
- **Conclusion:** therefore, not A.

# Formal logic

Example of modus tollens:

- **Premise:** If Anabel is happy, then she is smiling;
- **Premise:** Anabel is not smiling;
- **Conclusion:** therefore, Anabel is not happy.

# Formal logic

Fisher's disjunction (logic of hypothesis testing):

- **Premise:** If  $\mathcal{H}_0$ , then not data;
- **Premise:** data;
- **Conclusion:** therefore, not  $\mathcal{H}_0$ .



# Hypothesis testing

In hypothesis testing, we use a *probabilistic* version of Fisher's disjunction:

- **Premise:** If  $\mathcal{H}_0$ , then data very unlikely;
- **Premise:** data;
- **Conclusion:** therefore,  $\mathcal{H}_0$  very unlikely.

# Hypothesis testing

In hypothesis testing, we use a *probabilistic* version of Fisher's disjunction:

- **Premise:** If  $\mathcal{H}_0$ , then data very unlikely;
- **Premise:** data;
- **Conclusion:** therefore,  $\mathcal{H}_0$  very unlikely.

*Problem: this is not logically valid!*

# Hypothesis testing

- **Premise:** If an individual is a man, he is unlikely to be Pope;
- **Premise:** Francis is the Pope;
- **Conclusion:** therefore Francis is probably not a man.

## "Marginal" $p$ -values

You conduct a high powered experiment and find  $p = 0.045$ .

- What do you do?
- What do you conclude?

## "Marginal" $p$ -values

Some context: suppose we want to test whether a *brain training* program had a significant effect on IQ scores. Let  $\mu$  equal the population mean IQ score **after** training. Recall that IQ scores are normally distributed with mean 100 and standard deviation 15.

We can define two competing hypotheses:

1.  $\mathcal{H}_0: \mu = 100$
2.  $\mathcal{H}_1: \mu \neq 100$

Suppose further that the training had a moderate effect (i.e., Cohen's  $d = 0.6$ ). This would imply that under  $\mathcal{H}_1$ ,  $\mu$  would be equal to \_\_\_\_\_

## What $p$ -values should we *expect*?

We'll run a simulation in R. On each run, we'll:

- take a sample of  $n = 50$  IQ scores
- compare the sample mean to hypothesized mean of 100
- save the  $p$ -value from the test

Let's do this 50,000 times and plot the **distribution of  $p$ -values**:

- assuming  $\mathcal{H}_0$  is true
- assuming  $\mathcal{H}_1$  is true

# Simulation in R

## Question

You conduct a high powered experiment and find  $p = 0.045$ .

- How surprised should we be to see  $p = 0.045$ ?



## How surprising?

From simulation, we see:

- $p = 0.045$  is surprising when there is no effect
- $p = 0.045$  is EVEN MORE SURPRISING when there IS an effect!

## A paradox?

This is known as *Lindley's Paradox*

- do I **reject**  $\mathcal{H}_0$  (since  $p < 0.05$ )?
- or do I **accept**  $\mathcal{H}_0$ , since  $p = 0.045$  is twice as likely under  $\mathcal{H}_0$  as it is under  $\mathcal{H}_1$ ?

# Criticisms

Nelder (1999)

"The most important task before us in developing statistical science is to demolish the  $p$ -value culture, which has taken root to a frightening extent in many areas of both pure and applied science, and technology. (p. 261)"

Nelder, J. A. (1999). From statistics to statistical science. *Journal of the Royal Statistical Society: Series D (The Statistician)*, 48, 257-269. 10.1111/1467-9884.00187

# Criticisms

Lindley (1999)

"My personal view is that  $p$ -values should be relegated to the scrap heap and not considered by those who wish to think and act coherently. (p. 75)"

Lindley, D.V. (1999). Comment on Bayarri and Berger. In J.M. Bernardo, J.O. Berger, A.P. Dawid, & A.F.M. Smith (Eds.), *Bayesian Statistics* (Vol. 6, p. 75). Oxford: Clarendon.

# Criticisms

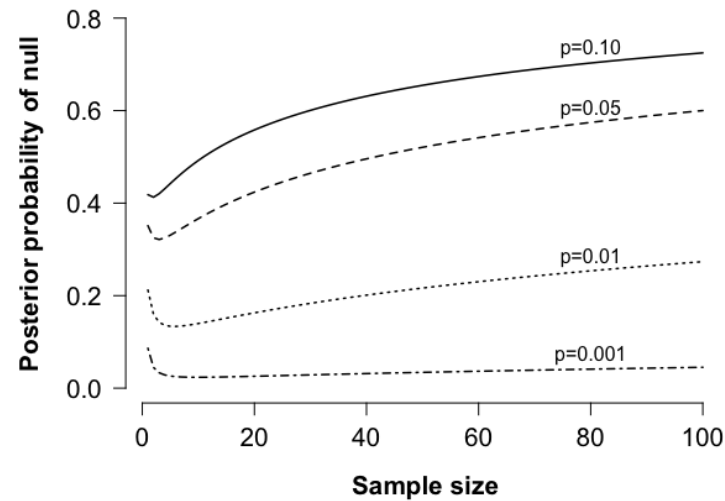
Townsend (2008)

"[R]ecent years have seen a lively debate about the value of null hypothesis testing, in addition to various means of improving the strategy and avoiding its threatening sloughs of despond. (p. 271)"

Townsend, J. T. (2008). Mathematical Psychology: Prospects For The 21st Century: A Guest Editorial. *Journal of Mathematical Psychology*, 52, 269–280. 10.1016/j.jmp.2008.05.001

# Criticisms

Berger & Sellke (1987) -  $p$ -values **overstate** evidence against the null



Note: for a given  $p$ -value, that  $p$ -value becomes **less evidential** against  $\mathcal{H}_0$  as sample size increases

## An alternative

Use *Bayesian* inference

# Bayesian inference

The machinery underlying Bayesian inference is *Bayes Theorem*:

$$p(\mathcal{H} \mid \text{data}) = \frac{p(\text{data} \mid \mathcal{H}) \cdot p(\mathcal{H})}{p(\text{data})}$$



# Bayesian inference

Perhaps this is a more useful presentation:

$$\underbrace{p(\mathcal{H} \mid \text{data})}_{\text{Posterior beliefs about hypothesis}} = \underbrace{p(\mathcal{H})}_{\text{Prior beliefs about hypothesis}} \times \underbrace{\frac{p(\text{data} \mid \mathcal{H})}{p(\text{data})}}_{\text{predictive updating factor}}$$

# Bayesian inference

Natural action in our discipline is to *compare* two hypotheses  $\mathcal{H}_0$  and  $\mathcal{H}_1$ .

- Bayes theorem gives us a natural way to do this by computing **relative** likelihoods

$$\frac{p(\mathcal{H}_1 \mid \text{data})}{p(\mathcal{H}_0 \mid \text{data})} = \frac{\frac{p(\text{data}|\mathcal{H}_1) \cdot p(\mathcal{H}_1)}{p(\text{data})}}{\frac{p(\text{data}|\mathcal{H}_0) \cdot p(\mathcal{H}_0)}{p(\text{data})}}$$

# Bayesian inference

Natural action in our discipline is to *compare* two hypotheses  $\mathcal{H}_0$  and  $\mathcal{H}_1$ .

- Bayes theorem gives us a natural way to do this by computing **relative** likelihoods

$$\frac{p(\mathcal{H}_1 \mid \text{data})}{p(\mathcal{H}_0 \mid \text{data})} = \frac{p(\text{data} \mid \mathcal{H}_1) \cdot p(\mathcal{H}_1)}{p(\text{data} \mid \mathcal{H}_0) \cdot p(\mathcal{H}_0)}$$

# Bayesian inference

Natural action in our discipline is to *compare* two hypotheses  $\mathcal{H}_0$  and  $\mathcal{H}_1$ .

- Bayes theorem gives us a natural way to do this by computing **relative** likelihoods

$$\underbrace{\frac{p(\mathcal{H}_1 \mid \text{data})}{p(\mathcal{H}_0 \mid \text{data})}}_{\text{posterior beliefs about hypotheses}} = \underbrace{\frac{p(\mathcal{H}_1)}{p(\mathcal{H}_0)}}_{\text{prior beliefs about hypotheses}} \times \underbrace{\frac{p(\text{data} \mid \mathcal{H}_1)}{p(\text{data} \mid \mathcal{H}_0)}}_{\text{predictive updating factor}}$$

# Bayesian inference

The predictive updating factor

$$B_{10} = \frac{p(\text{data} \mid \mathcal{H}_1)}{p(\text{data} \mid \mathcal{H}_0)}$$

tells us how much better  $\mathcal{H}_1$  predicts our observed data than  $\mathcal{H}_0$ .

This ratio is called the **Bayes factor** (Jeffreys, 1961)

## Bayes factors

Example: suppose  $B_{10} = 5$ .

Interpretation: the observed data are 5 times more likely under the alternative hypothesis  $\mathcal{H}_1$  than the null hypothesis  $\mathcal{H}_0$ .

This is taken as **positive evidence** for the alternative  $\mathcal{H}_1$

# Bayes factors

Jeffreys (1961) proposed the following thresholds for evidence:

Bayes factor	Evidence
1-3	anecdotal
3-10	moderate
10-30	strong
30-100	very strong
>100	extreme

[www.jasp-stats.org](http://www.jasp-stats.org)

The image shows the JASP software interface on a computer monitor. The background is a blue gradient with the JASP logo and the text "A Fresh Way to Do Statistics". A navigation bar at the top includes links for DOWNLOAD, SUPPORT, TEACHING, BLOG, and DONATE. The software window displays a "CorrectIdentify" analysis. The left sidebar shows a list of analyses: Descriptives, T-Tests, ANOVA, Regression, Frequencies, and Factor. The main window shows the "CorrectIdentify - 1" analysis results. The "Prior and Posterior" section displays a density plot with a solid line for the posterior and a dashed line for the prior. The plot shows a peak at a median of 0.731. The Bayes Factor (BF) is 112.646, and the 95% Credible Interval (CrI) is [0.610, 0.833]. The "Hypothesis" section shows the test value as 0.5. The "Plots" section has checkboxes for "Prior and posterior", "Additional info", and "Sequential analysis". The "Bayes Factor" section has radio buttons for "BF<sub>10</sub>", "BF<sub>01</sub>", and "Log(BF<sub>10</sub>)". The "Prior" section has input fields for "Beta prior: parameter a" and "Beta prior: parameter b", both set to 1. A green circular badge in the bottom right corner of the monitor displays the text "0.8.6 NEW RELEASE" and "BAS, Multinomial Analysis, Flatpak support & more".

**JASP**

A Fresh Way to Do Statistics

DOWNLOAD | SUPPORT | TEACHING | BLOG | DONATE

Download JASP

CorrectIdentify - 1

Prior and Posterior

BF<sub>10</sub> = 112.646  
BF<sub>01</sub> = 0.009

median = 0.731  
95% CrI: [0.610, 0.833]

Density

Posterior  
Prior

0.8.6  
NEW RELEASE  
BAS, Multinomial Analysis, Flatpak support & more



# JASP demo

# Ex 1 - Does problem format affect arithmetic performance?

9 + 5	<input type="text"/>	7 + 8	<input type="text"/>
8 + 6	<input type="text"/>	6 + 5	<input type="text"/>
8 + 8	<input type="text"/>	6 + 7	<input type="text"/>
9 + 4	<input type="text"/>	6 + 8	<input type="text"/>
3 + 9	<input type="text"/>	7 + 9	<input type="text"/>
5 + 6	<input type="text"/>	8 + 4	<input type="text"/>
4 + 8	<input type="text"/>	7 + 4	<input type="text"/>
9 + 6	<input type="text"/>	6 + 9	<input type="text"/>
7 + 7	<input type="text"/>	4 + 9	<input type="text"/>
5 + 9	<input type="text"/>	5 + 7	<input type="text"/>
9 + 8	<input type="text"/>	8 + 9	<input type="text"/>
9 + 7	<input type="text"/>	5 + 8	<input type="text"/>
7 + 6	<input type="text"/>	8 + 5	<input type="text"/>
9 + 9	<input type="text"/>	9 + 3	<input type="text"/>
6 + 6	<input type="text"/>	4 + 7	<input type="text"/>
8 + 7	<input type="text"/>	7 + 5	<input type="text"/>

five + seven	<input type="text"/>	six + eight	<input type="text"/>
seven + five	<input type="text"/>	seven + four	<input type="text"/>
eight + eight	<input type="text"/>	five + nine	<input type="text"/>
six + seven	<input type="text"/>	eight + six	<input type="text"/>
eight + nine	<input type="text"/>	nine + six	<input type="text"/>
eight + five	<input type="text"/>	nine + five	<input type="text"/>
six + five	<input type="text"/>	seven + eight	<input type="text"/>
nine + eight	<input type="text"/>	nine + three	<input type="text"/>
six + nine	<input type="text"/>	five + six	<input type="text"/>
seven + seven	<input type="text"/>	three + nine	<input type="text"/>
nine + seven	<input type="text"/>	seven + six	<input type="text"/>
four + nine	<input type="text"/>	four + seven	<input type="text"/>
eight + four	<input type="text"/>	six + six	<input type="text"/>
four + eight	<input type="text"/>	eight + seven	<input type="text"/>
nine + nine	<input type="text"/>	five + eight	<input type="text"/>
seven + nine	<input type="text"/>	nine + four	<input type="text"/>

## Ex 1 - Does problem format affect arithmetic performance?

Your task:

- load `mental_arithmetic.csv` into JASP
- conduct an independent samples  $t$ -test
  - DV = completed
  - Grouping variable = format

## Ex 1 - Does problem format affect arithmetic performance?

Now, let's do the Bayesian version

## Ex 1 - Does problem format affect arithmetic performance?

Example writeup:

"We computed a Bayesian independent samples  $t$ -test to quantify the evidence for the hypothesis that participants can complete more problems in digit format than word format. We found a Bayes factor of  $B_{10} = 19.2$ , indicating that the observed data are approximately 19 times more likely under the alternative hypothesis than the null hypothesis. According to the classification scheme of Jeffreys (1961), this constitutes strong evidence for a format effect in arithmetic performance"

## Ex 2 - Do horizontal saccades improve recall?

Several studies have shown that making horizontal eye movements after list learning improves episodic memory, possibly due to *interhemispheric interaction* (e.g., Christman & Propper, 2010).

We will look at some data from Matzke et al. (2015, JEP:G) and test two competing hypotheses:

- $\mathcal{H}_1$ : horizontal  $>$  fixation
- $\mathcal{H}_0$ : horizontal  $\leq$  fixation

## Ex 2 - Do horizontal saccades improve recall?

First, let's do the traditional  $t$ -test

- load `data_eye_movements.csv` into JASP
- conduct an independent samples  $t$ -test
  - DV = recall
  - Grouping variable = condition
  - be sure to select "Group 1 < Group 2" for hypothesis

## Ex 2 - Do horizontal saccades improve recall?

Now lets do the Bayesian version



## Ex 2 - Do horizontal saccades improve recall?

Example writeup:

"We computed a Bayesian independent samples  $t$ -test to quantify the evidence for the hypothesis that making horizontal saccades after initial study will increase memory recall. We found a Bayes factor of  $B_{0+} = 11.7$ , indicating that the observed data are approximately 12 times more likely under the null hypothesis than the alternative hypothesis. According to the classification scheme of Jeffreys (1961), this constitutes strong evidence for the null hypothesis that horizontal saccades have no effect on memory recall"

## Ex 3 - Turning the hands of time

Topolinski and Sparenberg (2012): clockwise movements induce psychological states of temporal progression and an orientation toward the future and novelty.

## Ex 3 - Turning the hands of time



Participants who turned kitchen rolls *clockwise* reported more "openness to experience" than participants who turned the kitchen rolls *counterclockwise*

## Ex 3 - Turning the hands of time

Wagenmakers et al. (2015) performed a confirmatory replication of the original experiment. Let's look at their data:

- load `kitchen_rolls.csv` into JASP
- conduct an independent samples *t*-test
  - DV = `mean_NEO`
  - Grouping variable = `Rotation`
  - be sure to select "Group 1 > Group 2" for hypothesis

## Ex 3 - Turning the hands of time

Now lets do the Bayesian version

## Ex 3 - Turning the hands of time

Example writeup:

"We computed a Bayesian independent samples  $t$ -test to quantify the evidence for the hypothesis that participants who turn kitchen rolls clockwise will report increased openness. We found a Bayes factor of  $B_{0+} = 7.8$ , indicating that the observed data are approximately 8 times more likely under the null hypothesis than the alternative hypothesis. According to the classification scheme of Jeffreys (1961), this constitutes strong evidence for the null hypothesis that there is no difference in openness between people rotating clockwise versus counterclockwise"

# Questions

- Email: `faulkenberry@tarleton.edu`
- Twitter: `@tomfaulkenberry`