

# SWPA Workshop

## Getting started in Bayesian Statistics with JASP

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### Outline:

- discuss differences between p-values & Bayes factors
- priors on models vs. priors on parameters
- correlation example using JASP, w/ reporting template.
- more resources!

\* These slides can be downloaded from

<https://tomfaulkenberry.github.io/talks.html>



Suppose we are interested in the relationship between math anxiety and performance on a standardized assessment.

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Define hypotheses about (population) correlation  $\rho$   
 $H_0: \rho = 0$ ,  $H_1: \rho \neq 0$

Collect data

Compute:  
 $p(\text{data} | H_0)$   
"p-value"

Interpretation:  
If  $p$  is small, data is rare under  $H_0$ , so we reject  $H_0$  in favor of  $H_1$ .

Compute:  
 $BF_{01} = \frac{p(\text{data} | H_0)}{p(\text{data} | H_1)}$   
"Bayes factor"

Interpretation:  
if  $BF_{01} > 1$ , data more likely under  $H_0$ .  
if  $BF_{01} < 1$ , data more likely under  $H_1$ .

$$\text{p-value} = p(\text{data} | H_0)$$

1) only considers fit of  $H_0$  as a potential model for data

2) ignores fit of  $H_1$

Thus, "support" for  $H_1$  is only indirect

$$\text{Bayes factor} = \frac{p(\text{data} | H_0)}{p(\text{data} | H_1)}$$

1) considers relative adequacy of both models as predictors of data.

2) can directly index support for either  $H_0$  or  $H_1$ .

Ex:  $BF_{01} = 8 \rightarrow$  "The observed data are 8 times more likely under  $H_0$  than  $H_1$ ."

Jeffreys (1961):

BF	Evidence*
1-3	anecdotal
3-10	moderate
10-30	strong
30-100	very strong
> 100	extreme

\* these are only guidelines!

## How does Bayes work?

for single model  $\mathcal{H}$ :

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

↪ posterior belief in  $\mathcal{H}$  = prior belief in  $\mathcal{H}$  × updating factor

for two models:

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

↪ posterior odds = prior odds × Bayes factor

What do we mean by prior?

Two types of "priors":

1) priors on models

2) priors on parameters within a given model

① Priors on models — before observing data, what is relative likelihood of competing models?

• common default:  $p(H_0) = p(H_1) = 1/2$

↳ i.e., "1-1 prior odds"

• these prior model probabilities must add to 1

$$\hookrightarrow p(H_0) + p(H_1) = \frac{1}{2} + \frac{1}{2} = \underline{1}$$

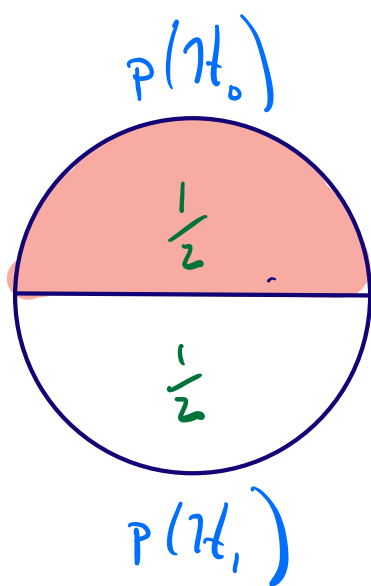
• prior model probabilities are updated after observing data:

$$p(H_0 | \text{data}) = \frac{BF_{01} \cdot p(H_0)}{BF_{01} \cdot p(H_0) + p(H_1)}$$

\* Note: if  $p(H_0) = p(H_1) = \frac{1}{2}$ ,

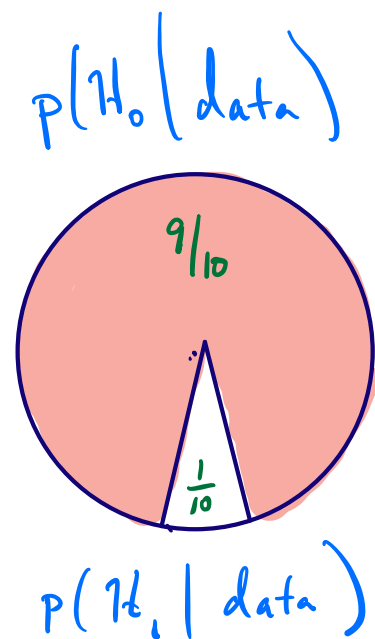
$$p(H_0 | \text{data}) = \frac{BF_{01}}{BF_{01} + 1}$$

Example:



Prior odds = 1:1

observe data  
→  
 $BF_{01} = 9$



Posterior odds = 9:1

$$\begin{aligned} * p(H_0 | \text{data}) &= \frac{BF_{01}}{BF_{01} + 1} \\ &= \frac{9}{9 + 1} \\ &= 0.9 \end{aligned}$$

② priors on parameters within a given model.

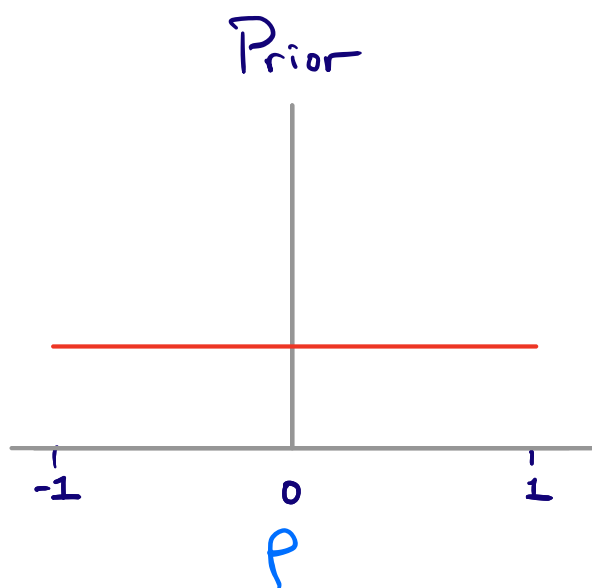
- model definitions:  $H_0: \rho = 0$

$H_1: \rho \neq 0$  ← what exactly do we mean here?

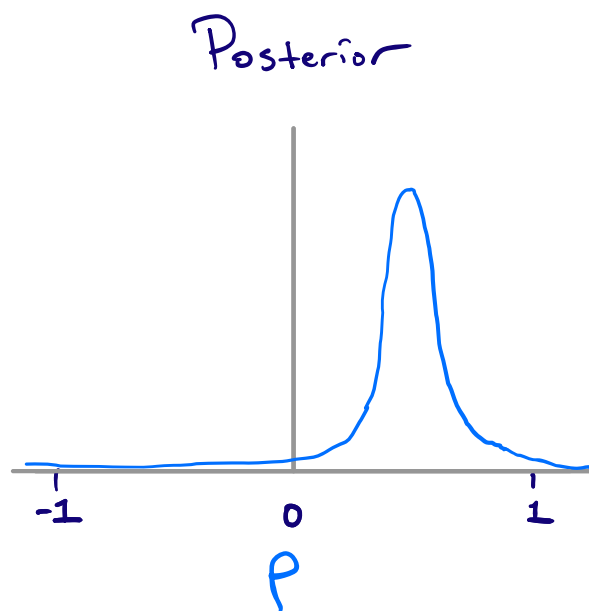
- we quantify our uncertainty about the correlation  $\rho$  under  $H_1$  by placing a distribution on  $\rho$

- suppose we have no idea what to expect. Here, we might believe any value of  $\rho$  is equally likely to occur.

↳ we say  $\rho$  is uniformly distributed on  $(-1, 1)$



observe data



Let's continue our working example. Suppose we tested  $N = 65$  participants and observed a correlation of  $r = 0.37$ .

- use JASP "Summary Statistics" module

## Elements to report:

### 1. report results of hypothesis test

- define  $H_0$ ,  $H_1$ , and specify prior under  $H_1$ .

"Under the null hypothesis we expect a correlation of 0 between maths anxiety and performance. Thus, we define  $H_0: \rho = 0$ . The alternative hypothesis is two-sided,  $H_1: \rho \neq 0$ , and we assigned a uniform prior probability to all values of  $\rho$  between -1 and +1."

- report and interpret Bayes factor

"We found a Bayes factor of  $BF_{10} = 13.93$ , which means that the observed data are approximately 14 times more likely under  $H_1$  than  $H_0$ . This result indicates strong evidence in favor of  $H_1$ ."



- (optional) calculate and report posterior model probability for preferred model.

- from earlier,

$$p(H_1 | \text{data}) = \frac{BF_{10}}{BF_{10} + 1}$$
$$= \frac{13.93}{13.93 + 1} = 0.93.$$

- "Assuming prior odds of 1-1 for  $H_1$  and  $H_0$ , our observed data updated these odds to 13.93-to-1 in favor of  $H_1$ . This is equivalent to a posterior model probability of  $p(H_1 | \text{data}) = 0.93$ ."

## 2. report results of parameter estimation

- only if  $H_1$  is the preferred model!

- specify parameter of interest and remind reader of prior under  $H_1$ ,

- "of interest is the posterior distribution for  $\rho$ , the population-level correlation between maths anxiety and performance. Under  $H_1$ ,  $\rho$  was assigned a uniform prior over the interval from -1 to +1."

- report the 95% credible interval.

- "The posterior distribution for  $p$  had a median of 0.356, with a central 95% credible interval that ranges from 0.134 to 0.554."

Let's do another example. Suppose we tested  $N = 175$  participants and observed a correlation of  $r = 0.15$ .

- ???

- frequentist p-value  $\rightarrow$  support for  $H_1$ ,  
but Bayes factor  $\rightarrow$  support for  $H_0$ !

$\hookrightarrow$  Jeffreys-Lindley Paradox



Everything You Always Wanted to Know About the Jeffreys-Lindley Paradox But Were Afraid to Ask

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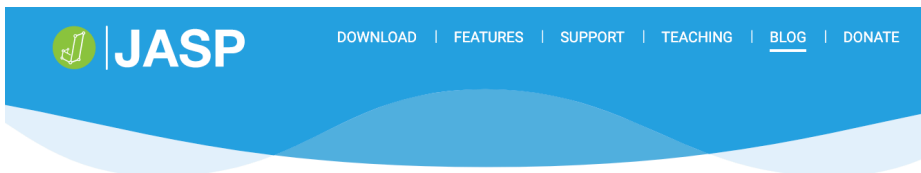
This post is a teaser for Wagenmakers, E.-J., & Ly, A. (2020). History and nature of the Jeffreys-Lindley paradox. Preprint available on ArXiv: <https://arxiv.org/abs/2111.10191>

# More resources

\* van Doorn et al. (2021). The JASP guidelines for conducting and reporting a Bayesian analysis. *Psychonomic Bulletin & Review*

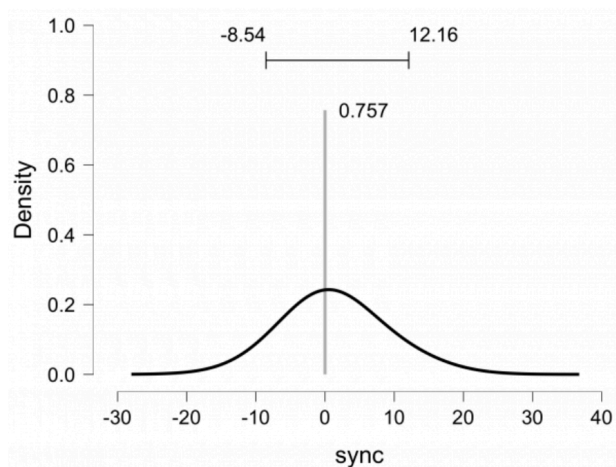


\* Faulkenberry, Ly, & Wagenmakers (2020). Bayesian inference in numerical cognition: A tutorial using JASP. *Journal of Numerical Cognition*



## How to do Bayesian Linear Regression in JASP – A Case Study on Teaching Statistics

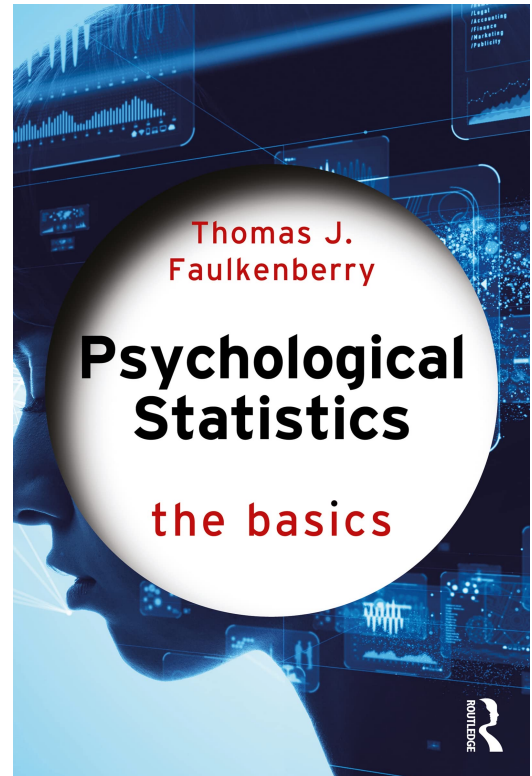
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This is a guest post by Tom Faulkenberry (Tarleton State University). [Click here](#) to access the supplementary materials.

# Before you go - a couple of shameless plugs!

1) My new book, covering the basics of psychological statistics from both the frequentist & Bayesian perspectives.



2) PsyStat - a free online Bayes factor calculator

<https://tomfaulkenberry.shinyapps.io/psystat>

PsyStat   Probability calculator   **Bayes factor calculator**   About

Bayes factor calculator

Summary   Help

Test:  
 t-test  
 ANOVA

Design:  
 Single sample  
 Independent samples

Predicted direction:  
 None  
 Positive effect  
 Negative effect

t-statistic:  
2.87

Sample size:  
25

Prior probability of null:  
0.5

Model definitions:  
 $\mathcal{H}_0$ : effect size is equal to 0  
 $\mathcal{H}_1$ : effect size is not equal to 0

Predictive adequacy:

Bayes factors:  
The Bayes factor for the alternative is  $BF_{10} = 5.52$   
This means that the observed data are approximately 5.52 times more likely under  $\mathcal{H}_1$  than under  $\mathcal{H}_0$



## Take home points:

- Bayes is easy, especially with the right software.
- Bayes answers the questions you thought you were asking
- testing or estimation? No need to choose -  
Bayes gives you both!

More questions - contact me!

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