

Investigating the Relationship Between the Bayes Factor and the Separation of Credible Intervals

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Outline

1. Motivation
2. Method
3. Graphical Results
4. Concluding Remarks

Motivation

- Null-hypothesis significance testing and p -value
- Bayes factor and credible interval for within-subject designs

Problems with p -Values

- ▶ p -values depend on **hypothetical data** that were never observed,
e.g., uncensored data from a *censored* volt-meter.
- ▶ p -values depend on possibly unknown **subjective intentions**,
e.g., optional stopping.
- ▶ p -values do **not quantify** statistical evidence,
e.g., p -postulate.

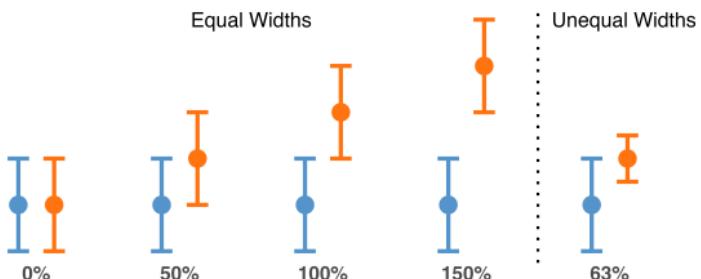
(Wagenmakers, 2007;
Wasserstein and Lazar, 2016;
Greenland et al., 2016;
Goodman, 2008)

Method

- ▶ Bayes factor (**BF**) → measure of evidence → model selection

$$\underbrace{\frac{p(H_0 \mid \text{Data})}{p(H_1 \mid \text{Data})}}_{\text{posterior odds}} = \underbrace{\frac{p(\text{Data} \mid H_0)}{p(\text{Data} \mid H_1)}}_{\text{Bayes factor } BF_{01}} \cdot \underbrace{\frac{p(H_0)}{p(H_1)}}_{\text{prior odds}} \quad (1)$$

- ▶ Interval estimates of effect sizes (rather than the p -value dichotomy)
 - ▷ Frequentist: confidence interval (**CI**)
 - ▷ Bayesian: credible interval (**Crl**)
 - e.g., highest-density interval (**HDI**)
- ▶ Graphical display
 - ▷ Two intervals' separation percentage



Experimental Designs

- A one-way **between-subjects design**

$$\mathcal{M}_1 : Y_{ij} = \mu + \tau_i + \epsilon_{ij} \quad (\text{let } \tau_i = \sigma_\epsilon t_i) \quad (2)$$

versus $\mathcal{M}_0 : Y_{ij} = \mu + \epsilon_{ij}$,

$$\epsilon_{ij} \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma_\epsilon^2) \text{ for } i = 1, \dots, a; j = 1, \dots, n.$$



- A “one”-way **within-subject** (repeated-measures) **design**

$$\mathcal{M}_1 : Y_{ij} = \mu + \sigma_\epsilon(t_i + b_j) + \epsilon_{ij} \quad (3)$$

versus $\mathcal{M}_0 : Y_{ij} = \mu + \sigma_\epsilon b_j + \epsilon_{ij}$



Image: Nielsen Norman Group

Variance Partitioning

Remove the between-subjects variability in within-subject designs

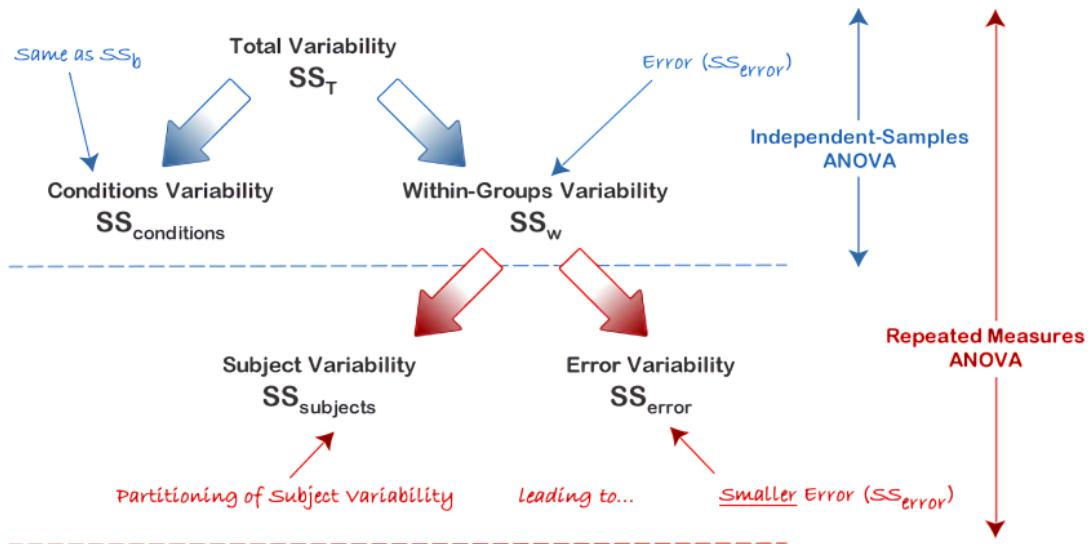


Image: Laerd Statistics

Within-Subject Interval Estimates

- Significant difference between two sample means: **both designs**

$|M_{p.} - M_{q.}| > \sqrt{2} \times \text{CI width}$ (Loftus & Masson, 1994) (4)

$\sqrt{2}/2 \approx 71\% \text{ CI separation}$ (5)

- **Four within-subject interval estimates**

Label	Equation	Description
CI	$M_{i.} \pm \sqrt{\frac{SS_W}{n(n-1)a}} \cdot t^*_{1-\frac{\alpha}{2}, a(n-1)}$	standard confidence interval
HDI	Markov chain Monte Carlo sampling of μ_i	standard highest-density interval
LM-CI	$M_{i.} \pm \sqrt{\frac{SS_{S\times C}}{n(n-1)(a-1)}} \cdot t^*_{1-\frac{\alpha}{2}, (n-1)(a-1)}$	within-subject CI
NKM-HDI	$M_{i.} \pm \sqrt{\frac{SS_{S\times C}}{n(n-1)a}} \cdot t^*_{1-\frac{\alpha}{2}, a(n-1)}$	conditional within-subject HDI
LH- or JZS-HDI	$\mathbb{E} \left[\mu_i \pm \frac{\sigma_\epsilon}{\sqrt{n}} \cdot t^*_{1-\frac{\alpha}{2}, a(n-1)} \mid \text{Data} \right]$	modification of NKM-HDI

Hierarchical Specification

Priors (Rouder et al., 2012 & 2017)

- ▶ Jeffreys prior, $\pi(\mu, \sigma_\epsilon^2) \propto \frac{1}{\sigma_\epsilon^2}$; (6)

- ▶ $t_i | g \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, g); b_j | g_b \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, g_b);$ (7)

which treat the effect sizes as random effects and allow for shrinkage;

- ▶ $g \sim \text{Scale-inv-}\chi^2(1, h^2); g_b \sim \text{Scale-inv-}\chi^2(1, h_b^2);$ (8)

- ▶ By default, $h = 0.5$ for the fixed effects
and $h = 1, h_b = 1$ for the random effects (9)

The marginal prior density of the column vector $(t_1, \dots, t_a)^\top$ is a multivariate Cauchy distribution.

Bayes factor

$$BF_{10} = \frac{p(\text{Data} | \mathcal{M}_1)}{p(\text{Data} | \mathcal{M}_0)} (10)$$

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Modeling Fixed Effects

Projecting a set of a effects (t_1, \dots, t_a)

into $a - 1$ parameters $(t_1^*, \dots, t_{a-1}^*)$

with the property that the marginal prior on all a effects is identical

$$\blacktriangleright t_i^* \mid g \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, g); \quad (7')$$

$$\blacktriangleright (t_1^*, \dots, t_{a-1}^*) = (t_1, \dots, t_a) \cdot \mathbf{Q}; \quad (11)$$

$$\blacktriangleright \mathbf{I}_a - a^{-1} \mathbf{J}_a = \mathbf{Q} \cdot \mathbf{Q}^\top; \quad (12)$$

$$\text{e.g., } t_1^* = \frac{\sqrt{2}}{2}(t_1 - t_2) \text{ when } a = 2;$$

where \mathbf{Q} is an $a \times (a - 1)$ matrix of the $a - 1$ eigenvectors of unit length corresponding to the nonzero eigenvalues of the left side term in (12).

Jeffreys-Zellner-Siow Bayes Factor

The resulting $JZS-BF_{10}$ from (6)-(9) avoids critical issues:

- ▶ Bartlett's paradox

The Bayes factor approaches zero as the prior variance increases.

- ▶ Information paradox

The Bayes factor tends to be bounded, given overwhelming information.

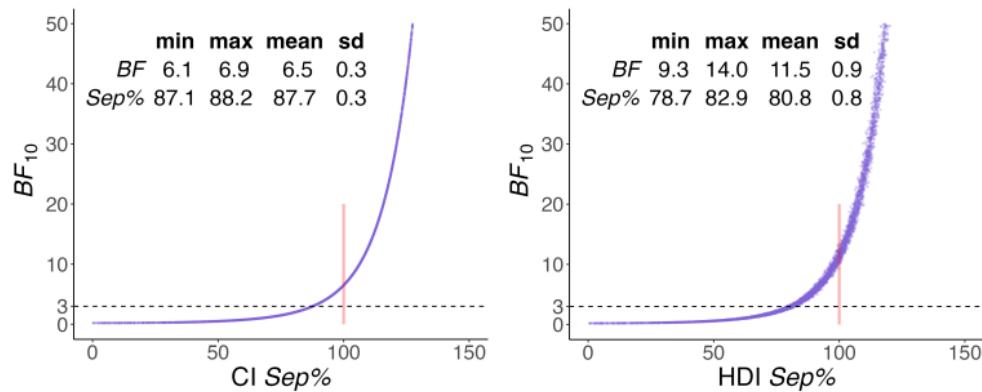
Another consideration is the Pearson Bayes factor
(in an analytic form; Faulkenberry, 2021).

Results: Between-Subjects Designs

71% CI separation (based on $\alpha = .05$)

(5)

Between-Subjects Design, Report 4: power=0.8, $n=48$

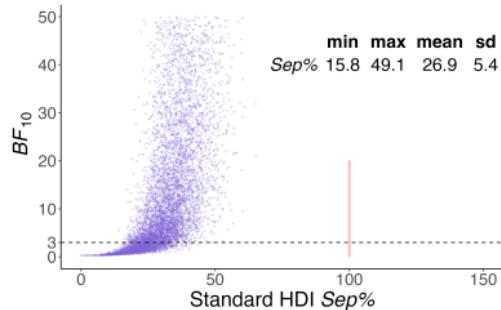
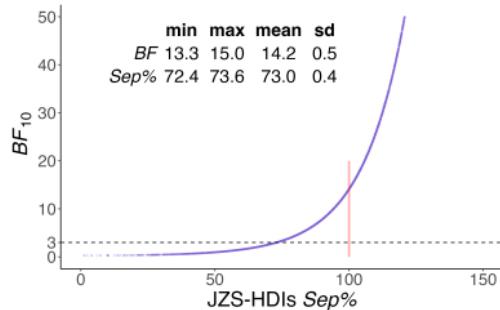
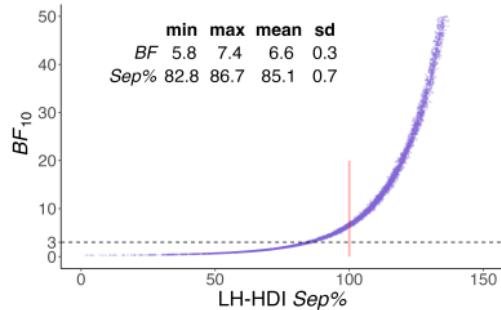
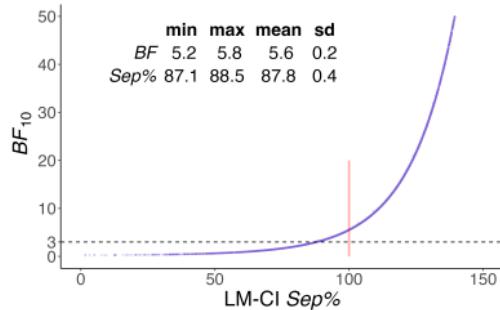


Why is Bayesian inference more conservative?

The p -value of **.01** may correspond to the Bayes factor value of 3 for some n .

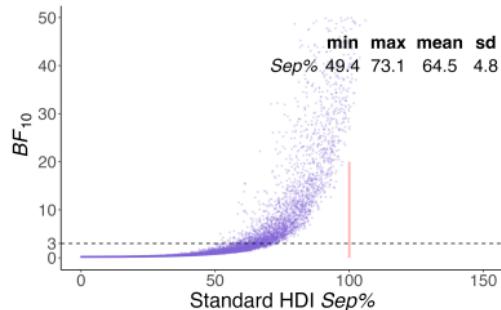
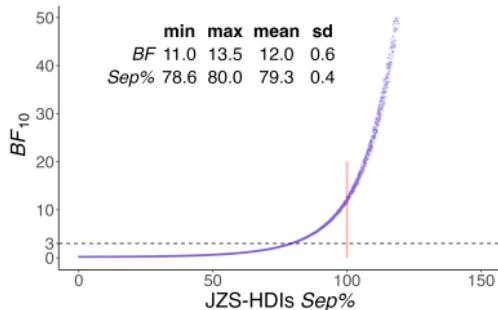
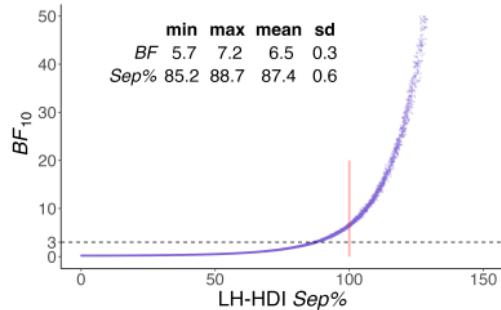
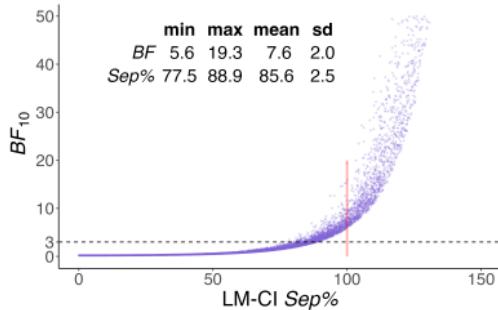
Results: Within-Subject Designs

Within-Subject Design, Report 1: $p=0.9$, power=0.8, $n=24$



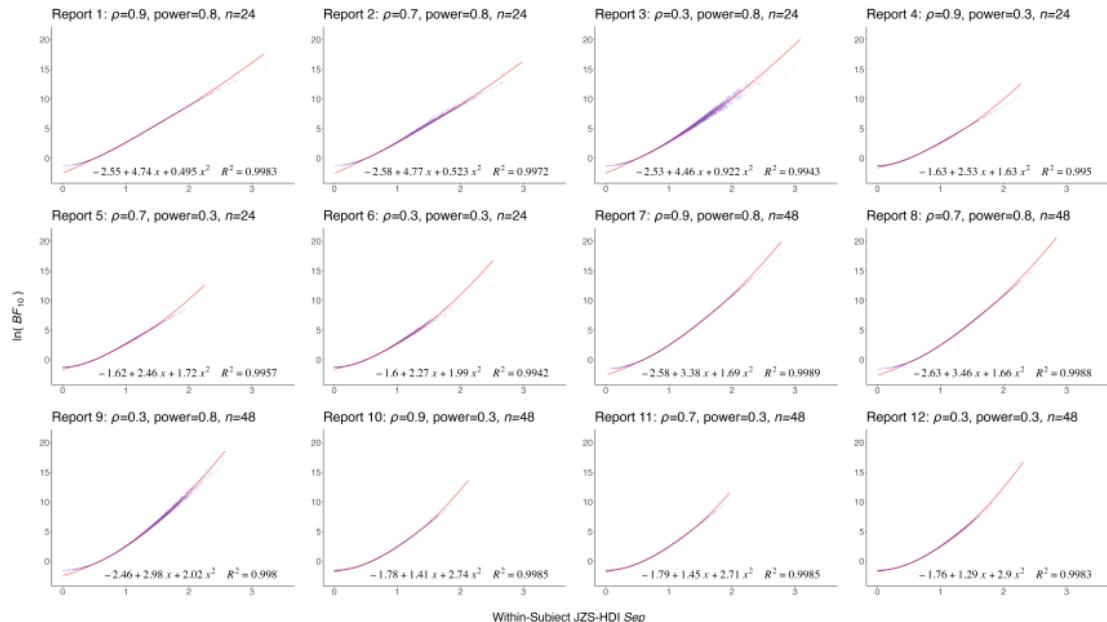
Results: Within-Subject Designs (continued)

Within-Subject Design, Report 12: $\rho=0.3$, power=0.3, $n=48$

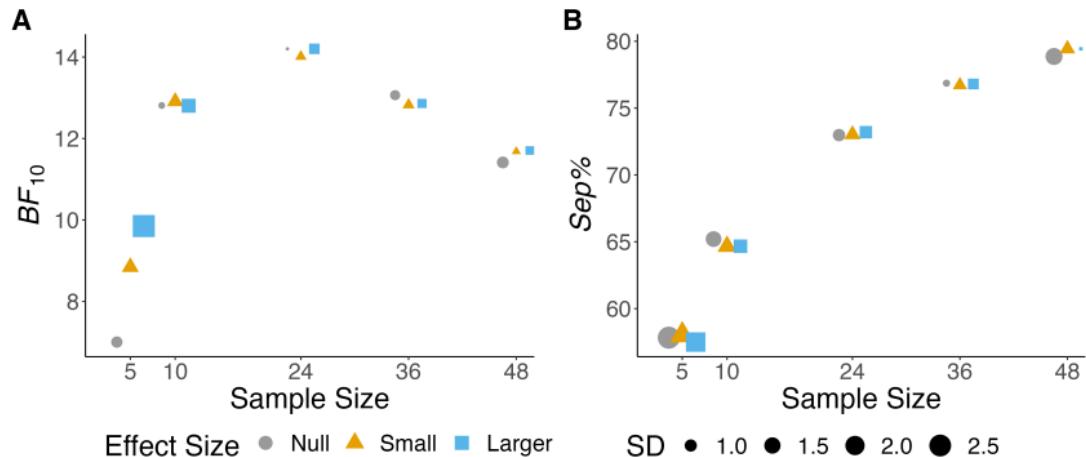


Curve Fitting for Case JZS-HDI

$$\ln BF \sim a + b \times Sep + c \times Sep^2$$



Varying Sample Sizes



Where We Were

Initiated Sept. 23, 2020

- ▶ Open Science Framework

<https://osf.io/x2pvw/>

- ▶ *Statistics Jan. 19, 2022* and *CaBS Oct. 1, 2021* seminars
- ▶ *WNAR Jun. 14, 2021* and *SSC Jun. 7, 2021* conferences

- ▶ ‘rmBayes’ R package

CRAN

GitHub

pkgdown

RPubls

Submitted Sept. 14, 2021; Accepted Sept. 15, 2021

> install.packages("rmBayes", type = "binary")

- ▶ *Psychonomic Bulletin & Review journal*

Submitted May 10, 2022; Accepted Apr. 16, 2023

Concluding Remarks

- ▶ We discovered a **quadratic exponential** relationship, **dependent on sample size**, between the Bayes factor and the separation of credible intervals in the linear mixed-effects model for a within-subject design.

Contribution

- ▶ Practitioners can adopt our approach, the modified within-subject Bayesian interval using JZS-HDI (which has less Monte Carlo variability compared to the existing methods) and examine the separation percentage to assess the strength of evidence for effects.

Limitation

- ▶ Our current method assumes the equal variance. We further examine the subject-centering transformation, *i.e.*, subtracting from the original response a corresponding subject mean minus the overall mean, to tackle the heteroscedastic data.

Future Work

When it comes to multiway ANOVA

- ▶ Model specifications

Two-factor factorial design with blocking

$$Y_{ijk} = \mu + s_k + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk} \quad (13)$$

Two-way repeated-measures design

$$Y_{ijk} = \mu + s_k + \alpha_i + \beta_j + (\alpha\beta)_{ij} + (\alpha s)_{ik} + (\beta s)_{jk} + \epsilon_{ijk} \quad (14)$$

- ▶ Assumptions

Compound symmetry \implies Sphericity (Circularity)

- ▶ Bayes factor strategies

Top-down analysis violates the principle of marginality

References

- Faulkenberry, T. J. (2021). The Pearson Bayes factor: An analytic formula for computing evidential value from minimal summary statistics. *Biom. Lett.*, 58, 1-26.
<https://doi.org/10.2478/bile-2021-0001>
- Heck, D. W. (2019). Accounting for estimation uncertainty and shrinkage in Bayesian within-subject intervals: A comment on Nathoo, Kilshaw, and Masson (2018). *J. Math. Psychol.*, 88, 27–31. <https://doi.org/10.31234/osf.io/whp8t>
- Loftus, G. R., & Masson, M. E. J. (1994). Using confidence intervals in within-subject designs. *Psychon. Bull. Rev.*, 1, 476–490. <https://doi.org/10.3758/BF03210951>
- Morey, R. D., & Rouder, J. N. (2023). *BayesFactor: Computation of Bayes factors for common designs*. R package version 0.9.12-4.5.
<https://cran.r-project.org/package=BayesFactor>
- Nathoo, F. S., Kilshaw, R. E., & Masson, M. E. J. (2018). A better (Bayesian) interval estimate for within-subject designs. *J. Math. Psychol.*, 86, 1–9.
<https://doi.org/10.1016/j.jmp.2018.07.005>
- Rouder, J. N., Morey, R. D., Speckman, P. L., & Province, J. M. (2012). Default Bayes factors for ANOVA designs. *J. Math. Psychol.*, 56, 356–374.
<https://doi.org/10.1016/j.jmp.2012.08.001>
- Rouder, J. N., Morey, R. D., Verhagen, J., Swagman, A. R., & Wagenmakers, E.-J. (2017). Bayesian analysis of factorial designs. *Psychol. Methods*, 22, 304-321.
<https://doi.org/10.1037/met0000057>
- Wagenmakers, E.-J. (2007). A practical solution to the pervasive problems of *p* values. *Psychon. Bull. Rev.*, 14, 779–804. <https://doi.org/10.3758/BF03194105>
- Wei, Z., Nathoo, F. S., & Masson, M. E. J. (2022). *rmBayes: Performing Bayesian inference for repeated-measures designs*. R package version 0.1.15.
<https://cran.r-project.org/package=rmBayes>

Thank you.

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Farouk Nathoo holds a Tier II Canada Research Chair in Biostatistics for Spatial and High-Dimensional Data.

Backup

Two Approaches in Parameter Estimation

BACK

Frequentist

- ▶ Probability is “long-run frequency of repeated events”
- ▶ $\mathbb{P}(X | \theta)$ is a sampling distribution
 - function of X with θ fixed
 - Assuming repetitive sampling from the population to find the single true value for a parameter governing the population
- ▶ Null-hypothesis significance testing (NHST) and p -value
- ▶ Confidence interval

Bayesian

- ▶ Probability is “degree of certainty about values”
- ▶ $\mathbb{P}(X | \theta)$ is a likelihood
 - function of θ with X fixed
 - Assuming the probability distribution of a parameter value and its reliability is increased by increasing the sample size
- ▶ Prior
- ▶ Posterior \propto Prior \times Likelihood
- ▶ Credible interval

Confidence Interval (CI)

parameters are fixed but unknown and data are random;
the lower and upper bounds are random

A 95% confidence interval means that with a large number of repeated samples, 95% of such calculated confidence intervals would include the true value of the parameter.

Credible Interval (CrI)

parameters are random and data are fixed;
the lower and upper bounds are fixed

A 95% credible interval is an interval within which an unobserved parameter value falls with a 95% probability.

Within-subject (6,180,000 results)

Bub et al. (2021); Cousineau (2019); Nathoo et al. (2018);
Rouder et al. (2012); Loftus and Masson (1994).

Within-subjects (3,410,000 results)

Rouder et al. (2017); Franz and Loftus (2012); Wagenmakers (2010).

Both

Heck (2019); Masson and Loftus (2003).



BACK

```
> summary(aov(Response~Level, recall.long)) #between-subjects
      Df Sum Sq Mean Sq F value Pr(>F)
Level       2   52.3   26.13    0.74  0.487
Residuals  27  953.6   35.32
> summary(aov(Response~Level+Error(Subject/Level), recall.long)) #within-subject

Error: Subject
      Df Sum Sq Mean Sq F value Pr(>F)
Residuals  9  942.5   104.7

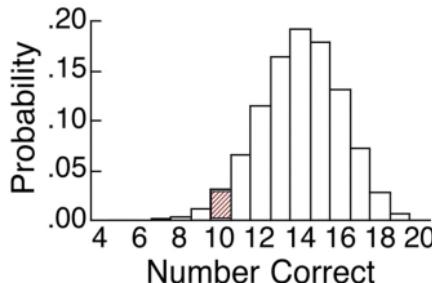
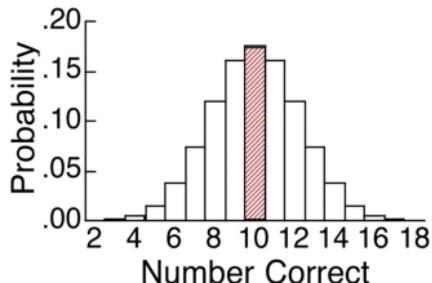
Error: Subject:Level
      Df Sum Sq Mean Sq F value   Pr(>F)
Level       2  52.27  26.133   42.51 1.52e-07 ***
Residuals 18  11.07   0.615
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> set.seed(277); anovaBF(Response~Level, recall.long, progress=F) #between-subjects
Bayes factor analysis
-----
[1] Level : 0.3410478 ±0.01%  
  
Against denominator:
Intercept only
---
Bayes factor type: BFBayesianModel, JZS
  
  
> set.seed(277); anovaBF(Response~Level+Subject, recall.long, whichRandom="Subject",
progress=F) #within-subject
Bayes factor analysis
-----
[1] Level + Subject : 35959.93 ±0.56%
  
  
Against denominator:
Response ~ Subject
---
Bayes factor type: BFBayesianModel, JZS
```

Example 1 of Computing the Bayes Factor

[BACK](#)

H_0 : the probability of correctly guessing the outcome $\theta = .5$ versus

$H_1 : \theta = .7$. Data: 10 outcomes out of 20 coin flips are predicted correctly.

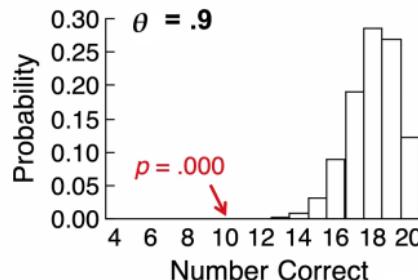
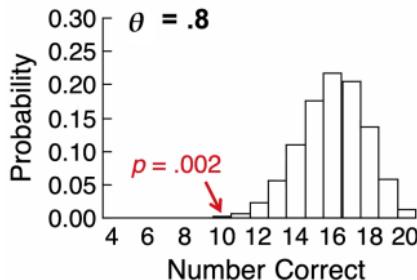
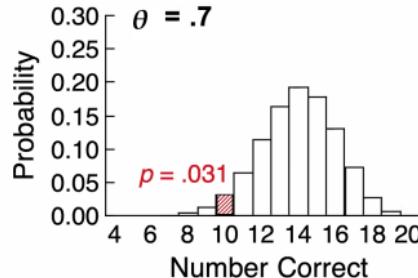
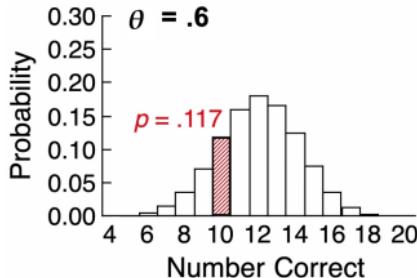


$$LR = BF_{01} = \frac{p(\text{Data} | H_0)}{p(\text{Data} | H_1)} = \frac{\binom{20}{10} \cdot 0.5^{20}}{\binom{20}{10} \cdot 0.7^{10} \cdot 0.3^{10}} = 5.718$$

- **Evidence** (supporting H_0) is anecdotal (BF 1-3), moderate (BF 3-10), strong (BF 10-30), or very strong (BF 30-100).

Example 2 of Computing the Bayes Factor

Now, $H_1 : \theta \in \{.6, .7, .8, .9\}$ and they are equally plausible.



$$p(\text{Data} | H_1) = (.117).25 + (.031).25 + (.002).25 + (.000).25 = .037$$

$$BF_{01} = \frac{p(\text{Data} | H_0)}{p(\text{Data} | H_1)} = 4.699$$

Discrete Data

$$BF_{01} = \frac{\sum_i p(\text{Data} \mid H_0, \theta_i) \cdot p(\theta_i \mid H_0)}{\sum_j p(\text{Data} \mid H_1, \theta_j) \cdot p(\theta_j \mid H_1)} \quad (\text{A1})$$

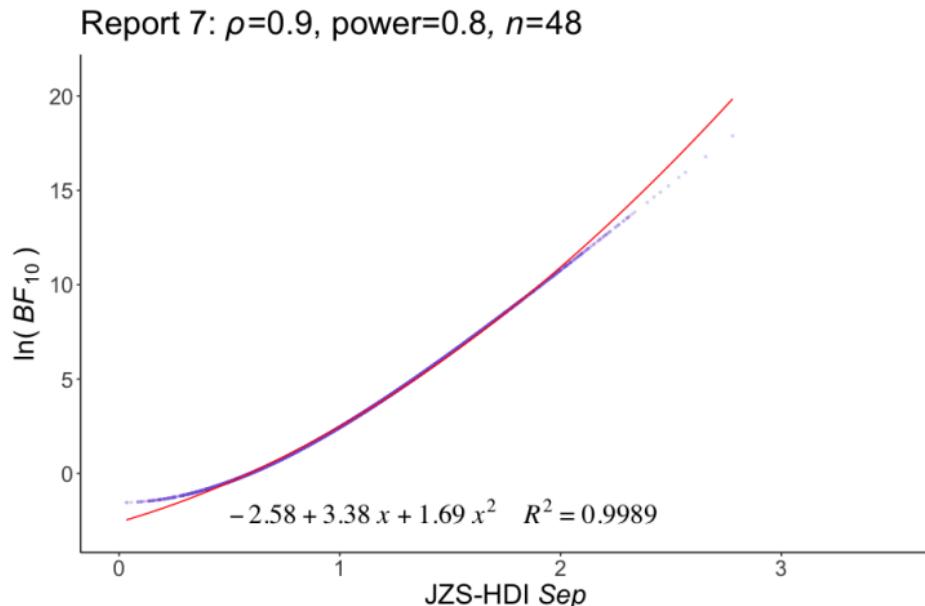
Continuous Data

$$BF_{01} = \frac{\int_{\boldsymbol{\theta} \in \Theta_0} p(\text{Data} \mid H_0, \boldsymbol{\theta}) \cdot p(\boldsymbol{\theta} \mid H_0) d\boldsymbol{\theta}}{\int_{\boldsymbol{\theta} \in \Theta_1} p(\text{Data} \mid H_1, \boldsymbol{\theta}) \cdot p(\boldsymbol{\theta} \mid H_1) d\boldsymbol{\theta}} \quad (\text{A2})$$

Log Bayes Factor Versus Separation

ZOOM OUT

$$\ln BF \sim a + b \times Sep + c \times Sep^2$$



Log Bayes Factor Versus Separation

ZOOM OUT

$$\ln BF \sim a + b \times Sep + c \times Sep^2$$

