Closed-Form Power and Sample Size Calculations for Bayes Factors

Samuel Pawel, Leonhard Held

Department of Biostatistics, Center for Reproducible Science and Research Synthesis
University of Zurich
samuel.pawel@uzh.ch, https://orcid.org/0000-0003-2779-320X

September 4, 2025 – SISBAYES 2025 – Padova

Sample Size Determination

$$n = ?$$

Sample Size Determination

$$n = ?$$

How large should the sample size be?

- Too large: Unethical and/or waste of resources
- Too small: High chance of inconclusive results

$\rightarrow$ **Accurately estimating sample size is crucial!**

Sample Size Determination

$$n = ?$$

How large should the sample size be?

- Too large: Unethical and/or waste of resources
- Too small: High chance of inconclusive results

$\rightarrow$ **Accurately estimating sample size is crucial!**

How to estimate sample size?

- “*As ye shall analyse is as ye shall design*” (Julious, 2023, p. 179)

$\rightarrow$ **Design needs to take into account the planned analysis**

Frequentist Hypothesis Testing

- **Closed-form solutions** for power and sample size of z-test:

$$1-\beta = 1-\Phi\left(\frac{z_{1-\alpha/2}-\mu+\theta_0}{2\sigma^2/n}\right) \quad \text{and} \quad n = \frac{2\sigma^2(z_{1-\alpha/2}+z_{1-\beta})^2}{(\mu-\theta_0)^2}$$

Frequentist Hypothesis Testing

- **Closed-form solutions** for power and sample size of z-test:

$$1 - \beta = 1 - \Phi\left(\frac{z_{1-\alpha/2} - \mu + \theta_0}{2\sigma^2/n}\right) \quad \text{and} \quad n = \frac{2\sigma^2(z_{1-\alpha/2} + z_{1-\beta})^2}{(\mu - \theta_0)^2}$$

- **Numerical solutions** for many common tests:

```
power.t.test(...)
power.prop.test(...)
power.anova.test(...)
```

Bayes Factor Hypothesis Testing

$$\mathrm{BF}_{01} = \frac{\Pr(H_0 \mid \text{data})}{\Pr(H_1 \mid \text{data})} \Bigg/ \frac{\Pr(H_0)}{\Pr(H_1)} = \frac{p(\text{data} \mid H_0)}{p(\text{data} \mid H_1)}$$

Bayes Factor Hypothesis Testing

$$\mathrm{BF}_{01} = \frac{\Pr(H_0 \mid \text{data})}{\Pr(H_1 \mid \text{data})} \bigg/ \frac{\Pr(H_0)}{\Pr(H_1)} = \frac{p(\text{data} \mid H_0)}{p(\text{data} \mid H_1)}$$

- **Closed-form power** for z-test Bayes factor (Weiss, 1997; De Santis, 2004)
  - $\rightarrow$ Relatively unknown among users of Bayes factors
  - $\rightarrow$ Not implemented in accessible software
  - $\rightarrow$ No closed-form sample size

Bayes Factor Hypothesis Testing

$$\mathrm{BF}_{01} = \frac{\Pr(H_0 \mid \text{data})}{\Pr(H_1 \mid \text{data})} \bigg/ \frac{\Pr(H_0)}{\Pr(H_1)} = \frac{p(\text{data} \mid H_0)}{p(\text{data} \mid H_1)}$$

- **Closed-form power** for z-test Bayes factor (Weiss, 1997; De Santis, 2004)
  $\rightarrow$ Relatively unknown among users of Bayes factors
  $\rightarrow$ Not implemented in accessible software
  $\rightarrow$ No closed-form sample size
- **Monte Carlo simulation approaches** (Gelfand and Wang, 2002; Schönbrodt and Wagenmakers, 2018)
  $\rightarrow$ BFDA R package (Schönbrodt and Stefan, 2019)
  $\rightarrow$ Time-consuming, computationally expensive, non-deterministic
  $\rightarrow$ Less intuitive than a formula

Bayes Factor Hypothesis Testing

$$\mathrm{BF}_{01} = \frac{\Pr(H_0 \mid \text{data})}{\Pr(H_1 \mid \text{data})} \bigg/ \frac{\Pr(H_0)}{\Pr(H_1)} = \frac{p(\text{data} \mid H_0)}{p(\text{data} \mid H_1)}$$

- **Closed-form power** for z-test Bayes factor (Weiss, 1997; De Santis, 2004)
  $\rightarrow$ Relatively unknown among users of Bayes factors
  $\rightarrow$ Not implemented in accessible software
  $\rightarrow$ No closed-form sample size
- **Monte Carlo simulation approaches** (Gelfand and Wang, 2002; Schönbrodt and Wagenmakers, 2018)
  $\rightarrow$ BFDA R package (Schönbrodt and Stefan, 2019)
  $\rightarrow$ Time-consuming, computationally expensive, non-deterministic
  $\rightarrow$ Less intuitive than a formula

$\Rightarrow$ **Reasons why Bayes factors rarely used by researchers?**

This Talk

THE AMERICAN STATISTICIAN
2025, VOL. 79, NO. 3, 330–344: General
https://doi.org/10.1080/00031305.2025.2467919

OPEN ACCESS

Closed-Form Power and Sample Size Calculations for Bayes Factors

Samuel Pawel and Leonhard Held

- Synthesize and extend previous results on **closed-form power**
- Derive **closed-form sample size** formulae for *z*-test Bayes factor
- Implement in **R package bfpwr** (doi.org/10.32614/CRAN.package.bfpwr)

z-test Bayes Factor

- **Parameter estimate** $\hat{\theta}$ with **standard error** $\boldsymbol{\sigma_{\hat{\theta}}/\sqrt{n}}$ where $\sigma^2_{\hat{\theta}}$ a unit variance and n the effective sample size
  $\rightarrow$ Assume **approximate normality**: $\hat{\theta} \mid \theta \sim \mathrm{N}(\theta, \sigma^2_{\hat{\theta}}/n)$

z-test Bayes Factor

- **Parameter estimate** $\hat{\theta}$ with **standard error** $\boldsymbol{\sigma_{\hat{\theta}}/\sqrt{n}}$ where $\sigma^2_{\hat{\theta}}$ a unit variance and n the effective sample size
  $\rightarrow$ Assume **approximate normality**: $\hat{\theta} \mid \theta \sim \mathrm{N}(\theta, \sigma^2_{\hat{\theta}}/n)$
- $\boldsymbol{H_0: \theta = \theta_0}$ versus $\boldsymbol{H_1: \theta \neq \theta_0}$

z-test Bayes Factor

- **Parameter estimate** $\hat{\theta}$ with **standard error** $\sigma_{\hat{\theta}}/\sqrt{n}$ where $\sigma^2_{\hat{\theta}}$ a unit variance and n the effective sample size
  $\rightarrow$ Assume **approximate normality**: $\hat{\theta} \mid \theta \sim \mathrm{N}(\theta, \sigma^2_{\hat{\theta}}/n)$
- $H_0: \theta = \theta_0$ versus $H_1: \theta \neq \theta_0$
- **Normal prior** for effect: $\theta \mid H_1 \sim \mathrm{N}(\mu, \tau^2)$

z-test Bayes Factor

- **Parameter estimate $\hat{\theta}$** with **standard error $\sigma_{\hat{\theta}}/\sqrt{n}$** where $\sigma^2_{\hat{\theta}}$ a unit variance and n the effective sample size
  $\rightarrow$ Assume **approximate normality:** $\hat{\theta} \mid \theta \sim \mathrm{N}(\theta, \sigma^2_{\hat{\theta}}/n)$
- $\boldsymbol{H_0: \theta = \theta_0}$ versus $\boldsymbol{H_1: \theta \neq \theta_0}$
- **Normal prior** for effect: $\theta \mid H_1 \sim \mathrm{N}(\mu, \tau^2)$
- **Bayes factor**

$$\mathrm{BF}_{01} = \sqrt{1 + \frac{n\tau^2}{\sigma^2_{\hat{\theta}}}} \exp\left[-\frac{1}{2}\left\{\frac{(\hat{\theta} - \theta_0)^2}{\sigma^2_{\hat{\theta}}/n} - \frac{(\hat{\theta} - \mu)^2}{\tau^2 + \sigma^2_{\hat{\theta}}/n}\right\}\right]$$

$\rightarrow$ Point prior at μ when $\tau \downarrow 0$ and Bayes factor becomes likelihood ratio

Types of Parameter Estimates

Outcome	**Parameter estimate** $\hat{\theta}$	**Interpretation of** n	**Unit variance** $\sigma^2_{\hat{\theta}}$
Continuous	Mean	Sample size	σ^2
Continuous	Mean difference	Sample size per group	$2\sigma^2$
Continuous	Standardized mean difference	Sample size per group	2
Continuous	z-transformed correlation	Sample size minus 3	1
Binary	Arcsine square root difference	Sample size per group	1/2
Binary	Log odds ratio	Total number of events	4
Survival	Log hazard ratio	Total number of events	4
Count	Log rate ratio	Total count	4

Parameters based on two groups assume equal allocation

Power Calculations for the z-test Bayes Factor

- **Normal design prior $\theta \sim \mathrm{N}(\mu_d, \tau_d^2)$**
  $\rightarrow$ not necessarily the same as analysis prior $\theta \mid H_1 \sim \mathrm{N}(\mu, \tau^2)$

Power Calculations for the z-test Bayes Factor

- **Normal design prior $\theta \sim \mathrm{N}(\mu_d, \tau_d^2)$**
  $\to$ not necessarily the same as analysis prior $\theta \mid H_1 \sim \mathrm{N}(\mu, \tau^2)$
- **Bayes factor threshold k**, e.g., $k = 1/10$

Power Calculations for the z-test Bayes Factor

- **Normal design prior $\theta \sim \mathrm{N}(\mu_d, \tau_d^2)$**
  $\rightarrow$ not necessarily the same as analysis prior $\theta \mid H_1 \sim \mathrm{N}(\mu, \tau^2)$
- **Bayes factor threshold k**, e.g., $k = 1/10$
- **Probability of evidence for H_1**

$$\Pr(\mathrm{BF}_{01} \leq k \mid \mu_d, \tau_d^2)$$

$\rightarrow$ When $\mu_d = \theta_0$ and $\tau_d \downarrow 0$ this is the frequentist **type I error rate**
$\rightarrow$ Otherwise the **(predictive) power**

Power Calculations for the z-test Bayes Factor

- **Normal design prior $\theta \sim \mathrm{N}(\mu_d, \tau_d^2)$**

  $\rightarrow$ not necessarily the same as analysis prior $\theta \mid H_1 \sim \mathrm{N}(\mu, \tau^2)$
- **Bayes factor threshold k**, e.g., $k = 1/10$
- **Probability of evidence for H_1**

$$\Pr(\mathrm{BF}_{01} \leq k \mid \mu_d, \tau_d^2)$$

  $\rightarrow$ When $\mu_d = \theta_0$ and $\tau_d \downarrow 0$ this is the frequentist **type I error rate**

  $\rightarrow$ Otherwise the **(predictive) power**
- **Probability of evidence for H_0**

$$\Pr(\mathrm{BF}_{01} > k_0 \mid \mu_d, \tau_d^2)$$

  $\rightarrow$ Symmetric thresholds $k_0 = 1/k$

  $\rightarrow$ When $\mu_d = \theta_0$ and $\tau_d \downarrow 0$ this is the "power for H_0"

Closed-Form Power Functions

- **Normal analysis prior** (Weiss, 1997; De Santis, 2004)

$$\Pr(\mathrm{BF}_{01} \leq k \mid n, \mu_d, \tau_d, \boldsymbol{\tau > 0}) = \Phi(-\sqrt{X} - M) + \Phi(-\sqrt{X} + M)$$

with $M = \left\{\mu_d - \theta_0 - \frac{\sigma^2_{\hat{\theta}}}{n\tau^2}(\theta_0 - \mu)\right\} \frac{1}{\sqrt{\tau_d^2 + \sigma^2_{\hat{\theta}}/n}}$,

$$X = \left\{\log\left(1 + \frac{n\tau^2}{\sigma^2_{\hat{\theta}}}\right) + \frac{(\theta_0 - \mu)^2}{\tau^2} - \log k^2\right\}\left(1 + \frac{\sigma^2_{\hat{\theta}}}{n\tau^2}\right)\frac{\sigma^2_{\hat{\theta}}}{n\tau_d^2 + \sigma^2_{\hat{\theta}}}$$

Closed-Form Power Functions

- **Normal analysis prior** (Weiss, 1997; De Santis, 2004)

$$\Pr(\mathrm{BF}_{01} \leq k \mid n, \mu_d, \tau_d, \boldsymbol{\tau > 0}) = \Phi(-\sqrt{X} - M) + \Phi(-\sqrt{X} + M)$$

$$\text{with } M = \left\{\mu_d - \theta_0 - \frac{\sigma^2_{\hat{\theta}}}{n\tau^2}(\theta_0 - \mu)\right\} \frac{1}{\sqrt{\tau_d^2 + \sigma^2_{\hat{\theta}}/n}},$$

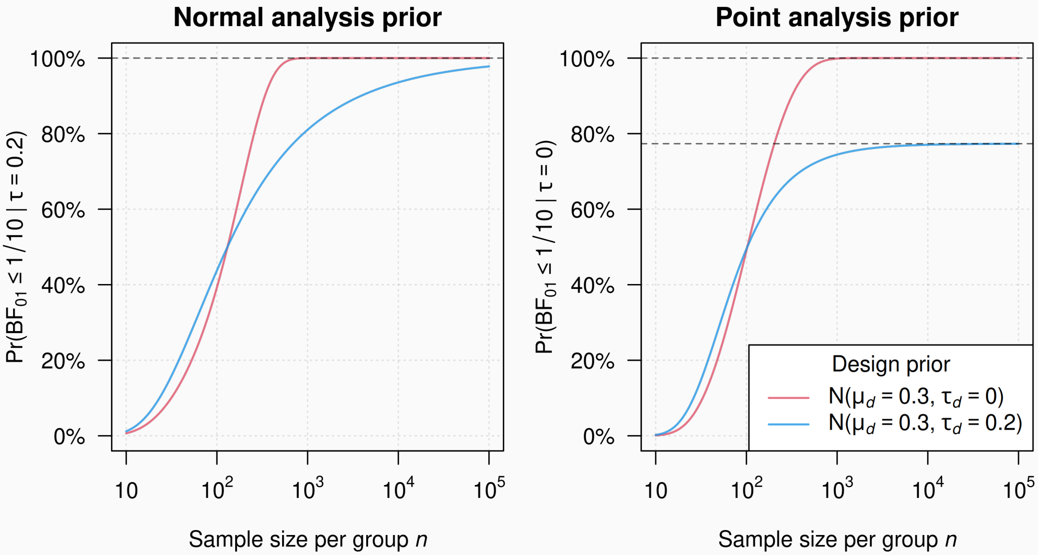
$$X = \left\{\log\left(1 + \frac{n\tau^2}{\sigma^2_{\hat{\theta}}}\right) + \frac{(\theta_0 - \mu)^2}{\tau^2} - \log k^2\right\}\left(1 + \frac{\sigma^2_{\hat{\theta}}}{n\tau^2}\right)\frac{\sigma^2_{\hat{\theta}}}{n\tau_d^2 + \sigma^2_{\hat{\theta}}}$$

- **Point analysis prior**

$$\Pr(\mathrm{BF}_{01} \leq k \mid n, \mu_d, \tau_d, \boldsymbol{\tau = 0}) = \begin{cases} 1 - \Phi(Z) & \text{if } \mu - \theta_0 > 0 \\ \Phi(Z) & \text{if } \mu - \theta_0 < 0 \end{cases}$$

$$\text{with } Z = \frac{1}{\sqrt{\tau_d^2 + \sigma^2_{\hat{\theta}}/n}}\left\{\frac{\sigma^2_{\hat{\theta}} \log k}{n(\theta_0 - \mu)} + \frac{\theta_0 + \mu}{2} - \mu_d\right\}$$

Example Power Calculations



Availability of Closed-Form Sample Size

- Sample size can be easily computed with **numerical root-finding**
- Is there also a **closed-form solution**? YES, in some cases!

Availability of Closed-Form Sample Size

- Sample size can be easily computed with **numerical root-finding**
- Is there also a **closed-form solution**? YES, in some cases!

	Analysis prior	
Design prior	Point prior (likelihood ratio)	Normal prior (Bayes factor)
Point prior (conditional power)	✓	✗
Normal prior (predictive power)	✓	✓ (for local normal priors)

Closed-Form Sample Size – Point Analysis Prior ($\tau = 0$)

- **General formula**

$$n = \left[\left\{ z_{1-\beta} + \sqrt{z_{1-\beta}^2 - \frac{\Delta_{\mu_d} \log k^2}{\Delta_\mu} + \left(\frac{\tau_d \log k^2}{\Delta_\mu} \right)^2} \right\}^2 - \left(\frac{\tau_d \log k^2}{\Delta_\mu} \right)^2 \right] \times \frac{\sigma_{\hat{\theta}}^2}{\Delta_{\mu_d}^2 - 4 z_{1-\beta}^2 \tau_d^2}$$

where $\Delta_{\mu_d} = 2\mu_d - \mu - \theta_0$ is the generalized effect size

Closed-Form Sample Size – Point Analysis Prior ($\tau = 0$)

- **General formula**

$$n = \left[\left\{z_{1-\beta} + \sqrt{z_{1-\beta}^2 - \frac{\Delta_{\mu_d} \log k^2}{\Delta_\mu} + \left(\frac{\tau_d \log k^2}{\Delta_\mu}\right)^2}\right\}^2 - \left(\frac{\tau_d \log k^2}{\Delta_\mu}\right)^2\right] \times \frac{\sigma_{\hat{\theta}}^2}{\Delta_{\mu_d}^2 - 4 z_{1-\beta}^2 \tau_d^2}$$

  where $\Delta_{\mu_d} = 2\mu_d - \mu - \theta_0$ is the generalized effect size

- **Simplified formula** assuming $\mu_d = \mu$ and $\tau_d = 0$

$$n = \frac{\sigma_{\hat{\theta}}^2 \left\{z_{1-\beta} + \sqrt{z_{1-\beta}^2 - \log k^2}\right\}^2}{(\mu - \theta_0)^2}$$

Closed-Form Sample Size – Point Analysis Prior ($\tau = 0$)

- **General formula**

$$n = \left[\left\{z_{1-\beta} + \sqrt{z_{1-\beta}^2 - \frac{\Delta_{\mu_d} \log k^2}{\Delta_\mu} + \left(\frac{\tau_d \log k^2}{\Delta_\mu}\right)^2}\right\}^2 - \left(\frac{\tau_d \log k^2}{\Delta_\mu}\right)^2\right] \times \frac{\sigma_{\hat{\theta}}^2}{\Delta_{\mu_d}^2 - 4 z_{1-\beta}^2 \tau_d^2}$$

  where $\Delta_{\mu_d} = 2\mu_d - \mu - \theta_0$ is the generalized effect size

- **Simplified formula** assuming $\mu_d = \mu$ and $\tau_d = 0$

$$n = \frac{\sigma_{\hat{\theta}}^2 \left\{z_{1-\beta} + \sqrt{z_{1-\beta}^2 - \log k^2}\right\}^2}{(\mu - \theta_0)^2}$$

  $\rightarrow$ **Related to frequentist sample size**: $z_{1-\alpha/2}$ replaced by $\sqrt{z_{1-\beta}^2 - \log k^2}$

Closed-Form Sample Size – Point Analysis Prior ($\tau = 0$)

- **General formula**

$$n = \left[\left\{z_{1-\beta} + \sqrt{z_{1-\beta}^2 - \frac{\Delta_{\mu_d}\log k^2}{\Delta_\mu} + \left(\frac{\tau_d \log k^2}{\Delta_\mu}\right)^2}\right\}^2 - \left(\frac{\tau_d \log k^2}{\Delta_\mu}\right)^2\right] \times \frac{\sigma_{\hat{\theta}}^2}{\Delta_{\mu_d}^2 - 4z_{1-\beta}^2\tau_d^2}$$

where $\Delta_{\mu_d} = 2\mu_d - \mu - \theta_0$ is the generalized effect size

- **Simplified formula** assuming $\mu_d = \mu$ and $\tau_d = 0$

$$n = \frac{\sigma_{\hat{\theta}}^2 \left\{z_{1-\beta} + \sqrt{z_{1-\beta}^2 - \log k^2}\right\}^2}{(\mu - \theta_0)^2}$$

$\rightarrow$ **Related to frequentist sample size**: $z_{1-\alpha/2}$ replaced by $\sqrt{z_{1-\beta}^2 - \log k^2}$

$\rightarrow$ Matches with **likelihoodist sample size** (Royall, 1997; Strug et al., 2007)

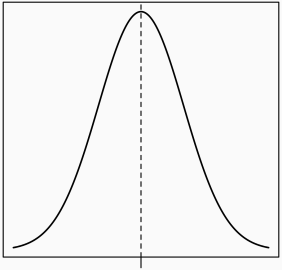
$\rightarrow$ Enables **hybrid Bayesian-likelihoodist design**

Closed-Form Sample Size – Normal Analysis Prior ($\tau > 0$)

- Assuming the **same local analysis and design prior** ($\mu = \mu_d = \theta_0$ and $\tau_d = \tau$) leads to

$$n = \frac{\sigma^2_{\hat{\theta}}}{\tau^2} \underbrace{k^2 \exp\left\{-W_{-1}\left(-k^2\, z^2_{(1-\beta)/2}\right)\right\}}_{n_{k,\beta}}$$

with $W_{-1}(\cdot)$ the Lambert W function (Corless et al., 1996)

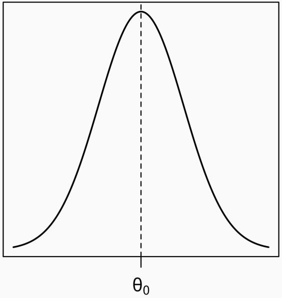


Closed-Form Sample Size – Normal Analysis Prior ($\tau > 0$)

- Assuming the **same local analysis and design prior** ($\mu = \mu_d = \theta_0$ and $\tau_d = \tau$) leads to

$$n = \frac{\sigma^2_{\hat{\theta}}}{\tau^2} \underbrace{k^2 \exp\left\{-\mathrm{W}_{-1}\left(-k^2\, z^2_{(1-\beta)/2}\right)\right\}}_{n_{k,\beta}}$$

with $\mathrm{W}_{-1}(\cdot)$ the Lambert W function (Corless et al., 1996)
$\rightarrow$ **Unit-information sample size** $n_{k,\beta}$ for $\tau^2 = \sigma^2_{\hat{\theta}}$

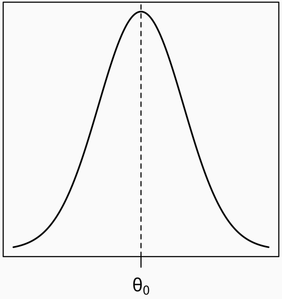


Closed-Form Sample Size – Normal Analysis Prior ($\tau > 0$)

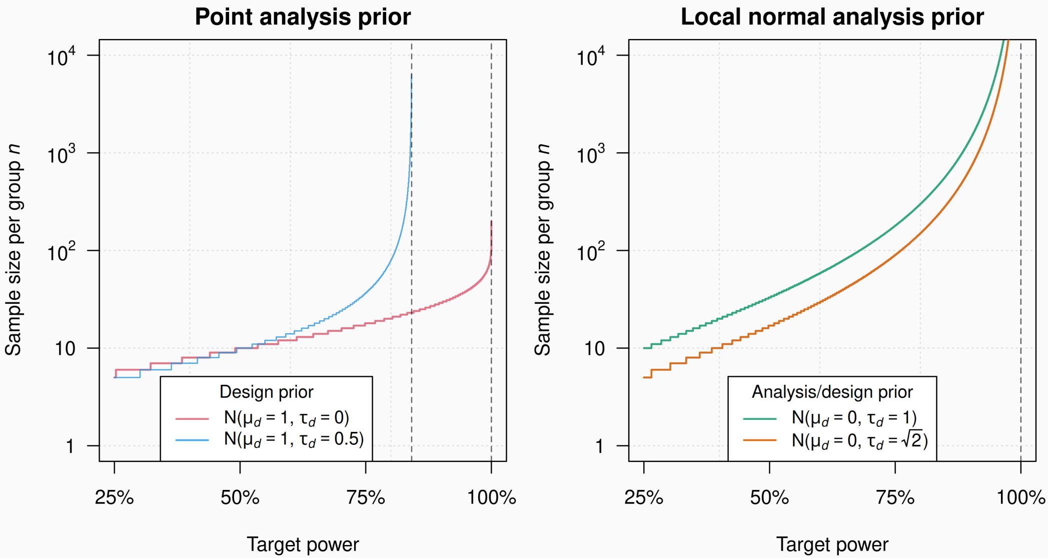
- Assuming the **same local analysis and design prior** ($\mu = \mu_d = \theta_0$ and $\tau_d = \tau$) leads to

$$n = \frac{\sigma^2_{\hat{\theta}}}{\tau^2} \underbrace{k^2 \exp\left\{-W_{-1}\left(-k^2 z^2_{(1-\beta)/2}\right)\right\}}_{n_{k,\beta}}$$

with $W_{-1}(\cdot)$ the Lambert W function (Corless et al., 1996)
$\rightarrow$ **Unit-information sample size** $n_{k,\beta}$ for $\tau^2 = \sigma^2_{\hat{\theta}}$
$\rightarrow$ Local normal design prior may be **unrealistic** in practice



Closed-Form Sample Size Determination

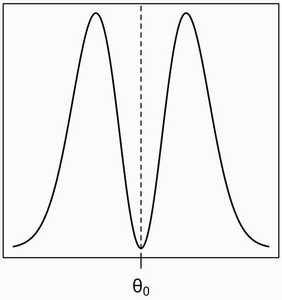


Extensions – Nonlocal Analysis Priors

- **Normal moment prior** (Johnson and Rossell, 2010)

$$p(\theta) = \mathrm{N}(\theta \mid \theta_0, \tau^2) \times (\theta - \theta_0)^2/\tau^2$$

$\rightarrow$ Faster accumulation of evidence for H_0



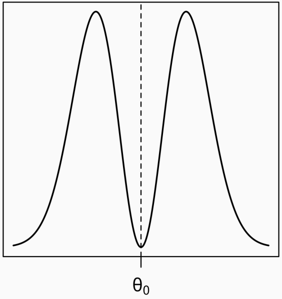
Extensions – Nonlocal Analysis Priors

- **Normal moment prior** (Johnson and Rossell, 2010)

$$p(\theta) = \mathrm{N}(\theta \mid \theta_0, \tau^2) \times (\theta - \theta_0)^2/\tau^2$$

$\rightarrow$ Faster accumulation of evidence for H_0

- **Power** available in **closed-form**
- **Sample size** computable with **root-finding**

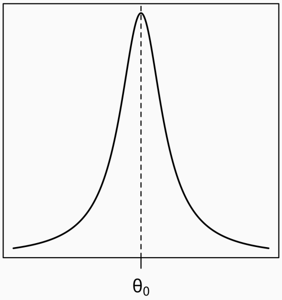


Extensions – Bayesian *t*-Test

- **Truncated location-scale *t* prior** (Gronau et al., 2020)

$$\mathrm{BF}_{01} = \frac{\mathrm{T}_{\nu}(t \mid 0, 1)}{\int_{-\infty}^{+\infty} \mathrm{NCT}_{\nu}(t \mid \theta\sqrt{n})\, \mathrm{T}_{\kappa}(\theta \mid \mu, \tau)_{[a,b]}\, \mathrm{d}\theta}$$

$\rightarrow$ Generalizes popular **Jeffreys-Zellner-Siow BF**



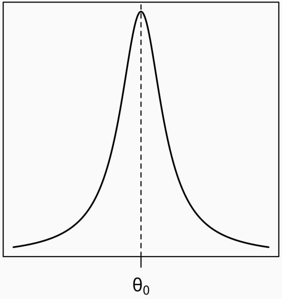
Extensions – Bayesian *t*-Test

- **Truncated location-scale *t* prior** (Gronau et al., 2020)

$$\mathrm{BF}_{01} = \frac{\mathrm{T}_\nu(t \mid 0, 1)}{\int_{-\infty}^{+\infty} \mathrm{NCT}_\nu(t \mid \theta\sqrt{n})\, \mathrm{T}_\kappa(\theta \mid \mu, \tau)_{[a,b]}\, \mathrm{d}\theta}$$

$\rightarrow$ Generalizes popular **Jeffreys-Zellner-Siow BF**

- **Power and sample size** computable with **root-finding**



Example: Bayesian *t*-Test (1)

```r
install.packages("bfpwr")
library("bfpwr")
result <- powertbf01(power = 0.8, k = 1/10, plocation = 0,
                     pscale = 1, pdf = 1, dpm = 0.5,
                     dpsd = 0.3, alternative = "greater")
result
```

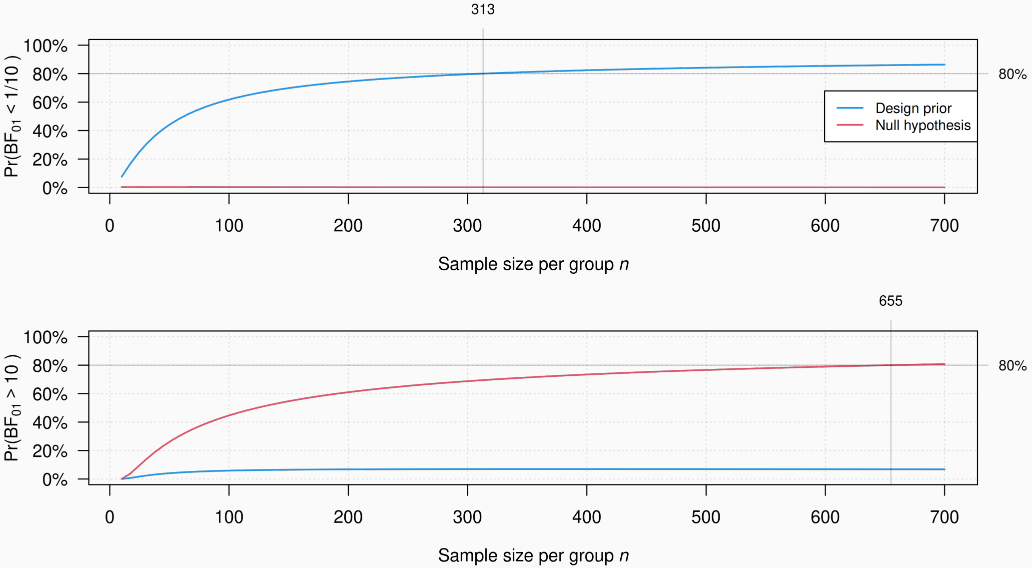
Example: Bayesian *t*-Test (2)

```
##
##      Two-sample t-test Bayes factor power calculation
##
##                           n = 312.1429
##                       power = 0.8
##                          sd = 1
##                        null = 0
##                 alternative = greater
##       analysis prior location = 0
##          analysis prior scale = 1
##             analysis prior df = 1
##             design prior mean = 0.5
##               design prior sd = 0.3
##                BF threshold k = 1/10
##
## NOTE: BF oriented in favor of H0 (BF01 < 1 indicates evidence for H1 over H0)
##       n is number of *observations per group*
##       sd is standard deviation of one observation (assumed equal in both groups)
```

Example: Bayesian t-Test (3)

```r
plot(result, nlim = c(10, 700))
```

Example: Bayesian *t*-Test (4)



Discussion

THE AMERICAN STATISTICIAN
2025, VOL. 79, NO. 3, 330–344: General
https://doi.org/10.1080/00031305.2025.2467919

OPEN ACCESS

Closed-Form Power and Sample Size Calculations for Bayes Factors

Samuel Pawel and Leonhard Held

- **Bayes factor power and sample size calculations can be done without simulation in many common settings**
  $\longrightarrow$ Fast, deterministic, requires no simulation parameters
  $\longrightarrow$ More familar and easier to use for applied researchers
- Main limitation: **Asymptotic normality assumption**
  $\longrightarrow$ Student t likelihood (Wong and Tendeiro, 2025)
  $\longrightarrow$ Binomial likelihood (Kelter and Pawel, 2025)
- Still left to do: **Sequential designs** and **multivariate parameters**

References i

Corless, R. M., Gonnet, G. H., Hare, D. E. G., Jeffrey, D. J., and Knuth, D. E. (1996). On the Lambert W function. *Advances in Computational Mathematics*, 5(1):329–359. doi:10.1007/bf02124750.

De Santis, F. (2004). Statistical evidence and sample size determination for Bayesian hypothesis testing. *Journal of Statistical Planning and Inference*, 124(1):121–144. doi:10.1016/S0378-3758(03)00198-8.

Gelfand, A. E. and Wang, F. (2002). A simulation-based approach to Bayesian sample size determination for performance under a given model and for separating models. *Statistical Science*, 17(2):193–208. doi:10.1214/ss/1030550861.

Gronau, Q. F., Ly, A., and Wagenmakers, E.-J. (2020). Informed Bayesian *t*-tests. *The American Statistician*, 74(2):137–143. doi:10.1080/00031305.2018.1562983.

Johnson, V. E. and Rossell, D. (2010). On the use of non-local prior densities in Bayesian hypothesis tests. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 72(2):143–170. doi:10.1111/j.1467-9868.2009.00730.x.

Julious, S. A. (2023). *Sample Sizes for Clinical Trials*. Wiley, Chichester, 2nd edition.

Kelter, R. and Pawel, S. (2025). Bayesian power and sample size calculations for Bayes factors in the binomial setting. doi:10.48550/ARXIV.2502.02914. arXiv preprint.

References ii

Pawel, S. and Held, L. (2025). Closed-form power and sample size calculations for Bayes factors. *The American Statistician*, 79(3):330–344. doi:10.1080/00031305.2025.2467919.

Royall, R. (1997). *Statistical Evidence: A Likelihood Paradigm*. Chapman & Hall, London New York.

Schönbrodt, F. D. and Wagenmakers, E.-J. (2018). Bayes factor design analysis: Planning for compelling evidence. *Psychonomic Bulletin & Review*, 25(1):128–142. doi:10.3758/s13423-017-1230-y.

Schönbrodt, F. D. and Stefan, A. M. (2019). *BFDA: An R package for Bayes factor design analysis (version 0.5.0)*. URL `https://github.com/nicebread/BFDA`.

Strug, L. J., Rohde, C. A., and Corey, P. N. (2007). An introduction to evidential sample size calculations. *The American Statistician*, 61(3):207–212. doi:10.1198/000313007x222488.

Weiss, R. (1997). Bayesian sample size calculations for hypothesis testing. *Journal of the Royal Statistical Society: Series D (The Statistician)*, 46(2):185–191. doi:10.1111/1467-9884.00075.

Wong, T. K. and Tendeiro, J. N. (2025). On a generalizable approach for sample size determination in Bayesian t tests. *Behavior Research Methods*, 57(5). doi:10.3758/s13428-025-02654-x.