Replication Bayes Factors

Bayes factors to assess whether a study replicates

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Psychological Methods
University of Amsterdam

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Overview

Open Science Framework (OSF): Reproducibility Project

- JEP:LMC, JPSP, and Psychological Science
- 167 replication attempts (22 April 2015)

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- Successful replication?

Example: Successful Replications?

Replication result

- $p_{\text{orig}} = .047, n_{\text{orig}} = 100$ & $p_{\text{rep}} = .047, n_{\text{rep}} = 100$

Conclusion: *p*-values and replications

Example: Successful Replications?

Replication result

- $p_{\text{orig}} = .047, n_{\text{orig}} = 100$ & $p_{\text{rep}} = .047, n_{\text{rep}} = 100$
- $p_{\text{orig}} = .047, n_{\text{orig}} = 100$ & $p_{\text{rep}} = .757, n_{\text{rep}} = 100$

Conclusion: *p*-values and replications

Example: Successful Replications?

Replication result

- $p_{\text{orig}} = .047, n_{\text{orig}} = 100$ & $p_{\text{rep}} = .047, n_{\text{rep}} = 100$
- $p_{\text{orig}} = .047, n_{\text{orig}} = 100$ & $p_{\text{rep}} = .757, n_{\text{rep}} = 100$
- $p_{\text{orig}} = .047, n_{\text{orig}} = 25$ & $p_{\text{rep}} = .051, n_{\text{rep}} = 100$

Conclusion: *p*-values and replications

Example: Successful Replications?

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- $p_{\text{orig}} = .047, n_{\text{orig}} = 100$ & $p_{\text{rep}} = .757, n_{\text{rep}} = 100$
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Conclusion: *p*-values and replications

- Typically, $n_{\text{orig}} < n_{\text{rep}}$
- Typically, not informative: $p_{\text{orig}} < .05$ and $p_{\text{rep}} > .05$. Need a continuous measure of evidence.

Bayes Factors

The pros of Bayes factors

- Evidence for $\mathcal{M}_1$ *and* $\mathcal{M}_0$
- $\text{BF}_{10}(d) = 7$, the data d are seven times more likely to be generated from the alternative model $\mathcal{M}_1$
- $\text{BF}_{10}(d) = 1/7$, the data d are seven times more likely to be generated from the null model $\mathcal{M}_0$, as $\text{BF}_{01}(d) = 7$

The cons of Bayes factors

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The cons of Bayes factors

- Comparative measure of evidence
- Computationally hard
- Sensitive to the prior choice

Example: Successful Replications?

Replication result

- $\text{BF}_{10}(d_{\text{orig}}) = 7, n_{\text{orig}} = 100$ & $\text{BF}_{10}(d_{\text{rep}}) = 7, n_{\text{rep}} = 100$

Conclusion: Default Bayes factors and replications

Example: Successful Replications?

Replication result

- $BF_{10}(d_{orig}) = 7, n_{orig} = 100$ & $BF_{10}(d_{rep}) = 7, n_{rep} = 100$
- $BF_{10}(d_{orig}) = 7, n_{orig} = 100$ & $BF_{10}(d_{rep}) = 0.1, n_{rep} = 100$

Conclusion: Default Bayes factors and replications

Example: Successful Replications?

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- $\text{BF}_{10}(d_{\text{orig}}) = 7, n_{\text{orig}} = 100$ & $\text{BF}_{10}(d_{\text{rep}}) = 7, n_{\text{rep}} = 100$
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- $\text{BF}_{10}(d_{\text{orig}}) = 7, n_{\text{orig}} = 25$ & $\text{BF}_{10}(d_{\text{rep}}) = 3, n_{\text{rep}} = 100$

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Conclusion: Default Bayes factors and replications

- Not informative
- Need to link the two d_{orig} to d_{rep}.

The Verhagen and Wagenmakers (2014) Proposal

- Replication Bayes factor defined as a modification of a default Bayes factor

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- Linking d_{orig} to d_{rep}: Use $\pi(\phi, \theta \mid d_{\text{orig}})$ within $\mathcal{M}_1$ as a prior for the new data d_{rep}

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- Computational method to approximate $\pi(\phi, \theta \mid d_{\text{orig}})$, sampling method.

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- Linking d_{orig} to d_{rep}: Use $\pi(\phi, \theta \mid d_{\text{orig}})$ within $\mathcal{M}_1$ as a prior for the new data d_{rep}
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- Generalisations? Theoretical properties? Well-behaved? Relationship to default Bayes factor?

Default Bayes Factors

$$\mathrm{BF}_{10}(d) = \frac{p(d \mid \mathcal{M}_1)}{p(d \mid \mathcal{M}_0)}$$

- $p(d \mid \mathcal{M}_0)$ marginal likelihood

Default Bayes Factors

$$\text{BF}_{10}(d) = \frac{\int_\Phi \int_\Theta f(d \mid \phi, \theta)\pi(\phi, \theta)\text{d}\theta\text{d}\phi}{\int_\Phi f(d \mid \phi, \theta_0)\pi(\phi)\text{d}\phi}$$

- User: Likelihood functions $f(d \mid \phi, \theta)$ and $f(d \mid \phi, \theta_0)$. Example: Binomial rate $\theta_0 = 1/2$, correlation test $\theta_0 = \rho = 0$, etc.

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- User: Likelihood functions $f(d \mid \phi, \theta)$ and $f(d \mid \phi, \theta_0)$. Example: Binomial rate $\theta_0 = 1/2$, correlation test $\theta_0 = \rho = 0$, etc.
- Statistician: Priors $\pi(\phi, \theta)$ and $\pi(\phi)$ Example: uniform on θ Jeffreys (1961), scaled beta distribution on θ in a correlation test (Ly, Verhagen & Wagenmakers, in press), etc.

Default Bayes Factors

$$\mathrm{BF}_{10}(d) = \frac{\int_\Phi \int_\Theta f(d \mid \phi, \theta)\pi(\phi, \theta)\mathrm{d}\theta\mathrm{d}\phi}{\int_\Phi f(d \mid \phi, \theta_0)\pi(\phi)\mathrm{d}\phi}$$

- Statistician: Priors $\pi(\phi, \theta)$ and $\pi(\phi)$ Example: uniform on θ Jeffreys (1961), scaled beta distribution on θ in a correlation test (Ly, Verhagen & Wagenmakers, in press), etc.
- Model selection consistency: If d of size n is generated from $\mathcal{M}_1$, $\mathrm{BF}_{10}(d) \to \infty$ as $n \to \infty$ and when d is generated from $\mathcal{M}_0$, $\mathrm{BF}_{10}(d) \to 0$ as $n \to \infty$.

Replication Bayes Factor: Linking Data

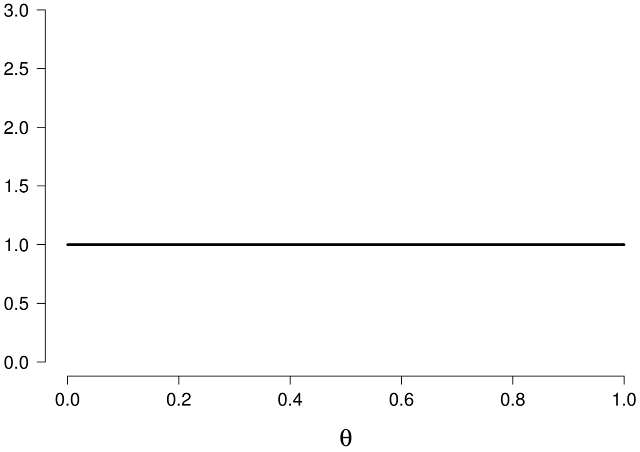
Default Bayes factor applied to d_{rep}

$$\text{BF}_{10}(d_{\text{rep}}) = \frac{\int_\Phi \int_\Theta f(d_{\text{rep}} \mid \phi, \theta) \pi(\phi, \theta) \text{d}\theta \text{d}\phi}{\int_\Phi f(d_{\text{rep}} \mid \phi, \theta_0) \pi(\phi) \text{d}\phi}$$

- Answers: “Is there an effect?”
- Want: to answer “Is the experiment replicated?”
- Need: Link with d_{orig}

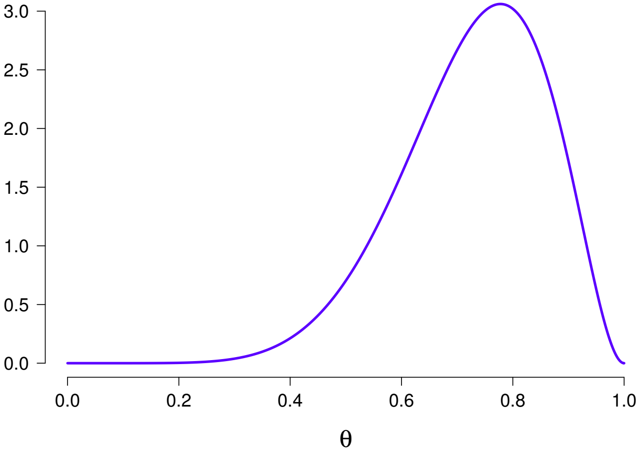
Replication Bayes Factor: Linking Data

Default prior for binomial:



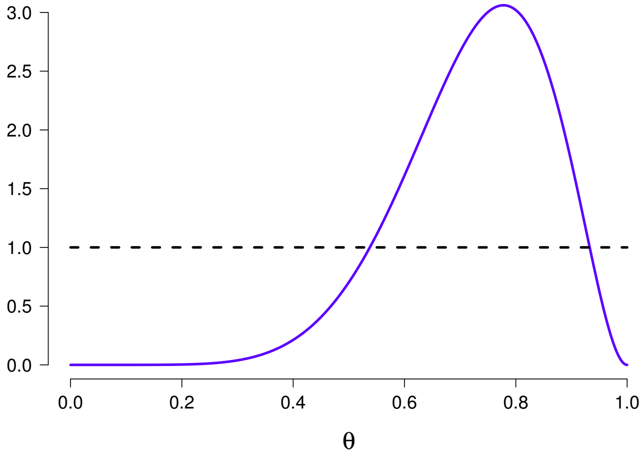
Replication Bayes Factor: Linking Data

Original data $y_{\text{orig}} = 7$ successes in n_{orig} trials



Replication Bayes Factor: Linking Data

Comparison between the two priors



Replication Bayes Factor: Linking Data

Linking d_{orig} to d_{rep} within a default Bayes factor

$$\tilde{\text{BF}}_{r0}(d_{\text{rep}}) = \frac{\int_\Phi \int_\Theta f(d_{\text{rep}} \mid \phi, \theta)\pi(\phi, \theta \mid d_{\text{orig}})\text{d}\theta\text{d}\phi}{\int_\Phi f(d_{\text{rep}} \mid \phi, \theta_0)\pi(\phi)\text{d}\phi}$$

- Answers “Is the experiment replicated?”

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- Answers “Is the experiment replicated?”
- $\pi(\phi, \theta \mid d_{\text{orig}})$ proponents’ idealised beliefs

Replication Bayes Factor: Linking Data

Linking d_{orig} to d_{rep} within a default Bayes factor

$$\tilde{\text{BF}}_{\text{r0}}(d_{\text{rep}}) = \frac{\int_\Phi \int_\Theta f(d_{\text{rep}} \mid \phi, \theta)\pi(\phi, \theta \mid d_{\text{orig}})\text{d}\theta\text{d}\phi}{\int_\Phi f(d_{\text{rep}} \mid \phi, \theta_0)\pi(\phi)\text{d}\phi}$$

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- Computationally: Verhagen and Wagenmakers (2014) approximate $\pi(\phi, \theta \mid d_{\text{orig}})$ and use a sampling method

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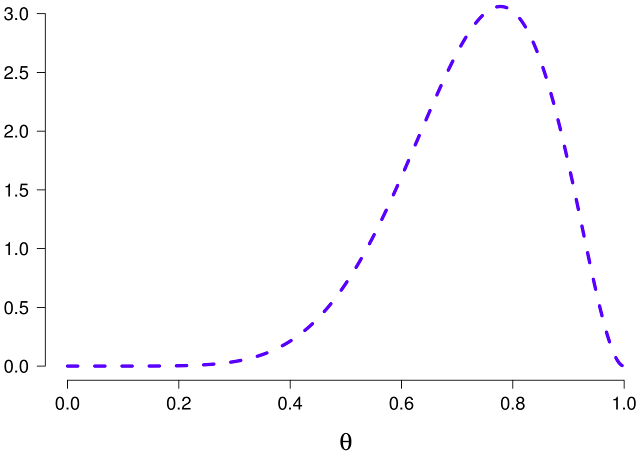

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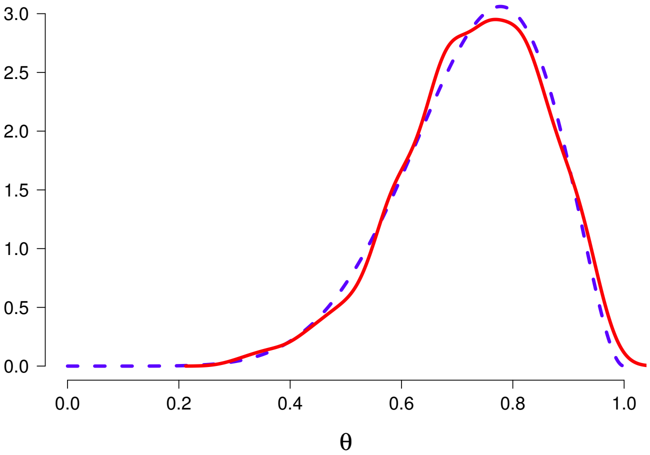

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$$\tilde{\text{BF}}_{r0}(d_{\text{rep}}) = \frac{\int_\Phi \int_\Theta f(d_{\text{rep}} \mid \phi, \theta)\pi(\phi, \theta \mid d_{\text{orig}})\text{d}\theta\text{d}\phi}{\int_\Phi f(d_{\text{rep}} \mid \phi, \theta_0)\pi(\phi)\text{d}\phi}$$

- Answers "Is the experiment replicated?"
- $\pi(\phi, \theta \mid d_{\text{orig}})$ proponents' idealised beliefs
- Computationally: Verhagen and Wagenmakers (2014) approximate $\pi(\phi, \theta \mid d_{\text{orig}})$ and use a sampling method
- $\pi(\phi)$ skeptics' totally unmoved beliefs

The Replication Bayes Factor

$$\mathrm{BF}_{r0}(d_{\mathrm{rep}}) = \frac{\int_{\Phi}\int_{\Theta} f(d_{\mathrm{rep}} \mid \phi, \theta)\pi(\phi, \theta \mid d_{\mathrm{orig}})\mathrm{d}\theta\mathrm{d}\phi}{\int_{\Phi} f(d_{\mathrm{rep}} \mid \phi, \theta_0)\pi(\phi \mid d_{\mathrm{orig}})\mathrm{d}\phi}$$

- Answers: Is the experiment replicated?
- $\pi(\phi, \theta \mid d_{\mathrm{orig}})$ updated
- $\pi(\phi \mid d_{\mathrm{orig}})$ also updated
- Simplies dramatically

Main Result:

$$\mathrm{BF}_{r0}(d_{\mathrm{rep}}) = \mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) = \frac{\mathrm{BF}_{10}(d_{\mathrm{rep}}, d_{\mathrm{orig}})}{\mathrm{BF}_{10}(d_{\mathrm{orig}})}$$

- Philosophically: Model selection consistent if $\mathrm{BF}_{10}(d)$ is

Main Result:

$$\mathrm{BF}_{r0}(d_{\mathrm{rep}}) = \mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) = \frac{\mathrm{BF}_{10}(d_{\mathrm{rep}}, d_{\mathrm{orig}})}{\mathrm{BF}_{10}(d_{\mathrm{orig}})}$$

- Philosophically: Model selection consistent if $\mathrm{BF}_{10}(d)$ is
- Computationally: Use the computational method of the default Bayes factor

Main Result:

$$\mathrm{BF}_{r0}(d_{\text{rep}}) = \mathrm{BF}_{10}(d_{\text{rep}} \mid d_{\text{orig}}) = \frac{\mathrm{BF}_{10}(d_{\text{rep}}, d_{\text{orig}})}{\mathrm{BF}_{10}(d_{\text{orig}})}$$

- Philosophically: Model selection consistent if $\mathrm{BF}_{10}(d)$ is
- Computationally: Use the computational method of the default Bayes factor
- Interpretation: A replication is successful, if the combined data $d_{\text{all}} = (d_{\text{rep}}, d_{\text{orig}})$ yield at least as much evidence for the alternative as d_{orig} alone

Binomial Test

Default Bayes factor (Jeffreys, 1961; Wagenmakers et al., 2014) with a uniform prior on θ

$$\text{BF}_{10}(d) = \frac{\mathcal{B}(y+1, n-y+1)}{(1/2)^n}$$

- Good theoretical behaviour: Model selection consistent and more.

Binomial Test

Default Bayes factor (Jeffreys, 1961; Wagenmakers et al., 2014) with a uniform prior on θ

$$\text{BF}_{10}(y, n) = \text{1/dbeta(1/2, y+1, n-y+1)}$$

- Computational implementation in R
- Need: $y_{\text{orig}}, n_{\text{orig}}$ and $y_{\text{all}}, n_{\text{all}}$

Combining Artificial Data

Data

- $d_{\text{orig}} : (y_{\text{orig}} = 10, n_{\text{orig}} = 10)$
- $d_{\text{rep}} : (y_{\text{orig}} = 0, n_{\text{rep}} = 10)$
- $d_{\text{all}} : (y_{\text{all}} = 10, n_{\text{all}} = 20)$ (Typical for $\mathcal{M}_0$)

Bayes factors

Combining Artificial Data

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- $d_{\text{orig}} : (y_{\text{orig}} = 10, n_{\text{orig}} = 10)$
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Bayes factors

- $\text{BF}_{10}(y_{\text{orig}}, n_{\text{orig}}) = 93.09$

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Bayes factors

- $\text{BF}_{10}(y_{\text{orig}}, n_{\text{orig}}) = 93.09$
- $\text{BF}_{10}(y_{\text{rep}}, n_{\text{rep}}) = 93.09$ (opposite direction)

Combining Artificial Data

Data

- $d_{\text{orig}} : (y_{\text{orig}} = 10, n_{\text{orig}} = 10)$
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- $\text{BF}_{10}(y_{\text{rep}}, n_{\text{rep}}) = 93.09$ (opposite direction)
- $\text{BF}_{10}(y_{\text{all}}, n_{\text{all}}) = 0.27$

Combining Artificial Data

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Bayes factors

- $\text{BF}_{10}(y_{\text{orig}}, n_{\text{orig}}) = 93.09$
- $\text{BF}_{10}(y_{\text{rep}}, n_{\text{rep}}) = 93.09$ (opposite direction)
- $\text{BF}_{10}(y_{\text{all}}, n_{\text{all}}) = 0.27$
- $\text{BF}_{10}(d_{\text{all}} \mid d_{\text{orig}}) = 0.0029$. Hence, evidence against replication; $\text{BF}_{10}(d_{\text{orig}})$ works as a penalty.

Replication Bayes Factor and Penalty

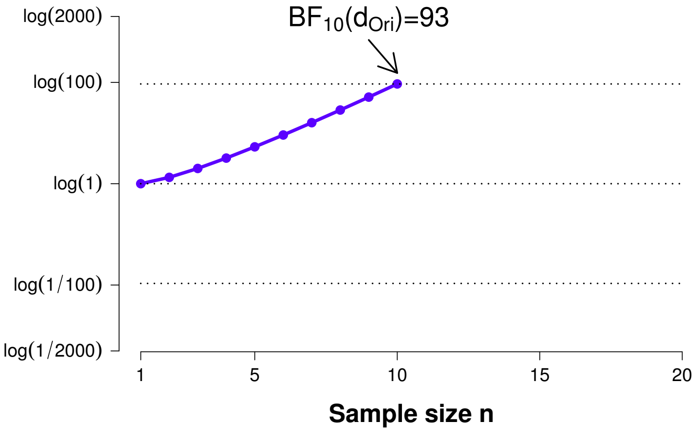
Recall

$$\text{BF}_{r0}(d_{\text{rep}}) = \text{BF}_{10}(d_{\text{rep}} \mid d_{\text{orig}}) = \frac{\text{BF}_{10}(d_{\text{all}})}{\text{BF}_{10}(d_{\text{orig}})}$$

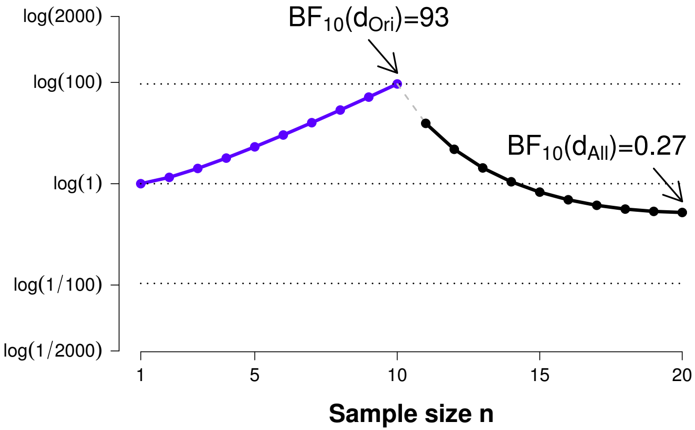
Taking the logarithm

$$\log \text{BF}_{10}(d_{\text{rep}} \mid d_{\text{orig}}) = \log \text{BF}_{10}(d_{\text{all}}) - \overbrace{\log \text{BF}_{10}(d_{\text{orig}})}^{\text{penalty}}$$

Sequential View of the Replication Bayes Factor



Sequential View of the Replication Bayes Factor



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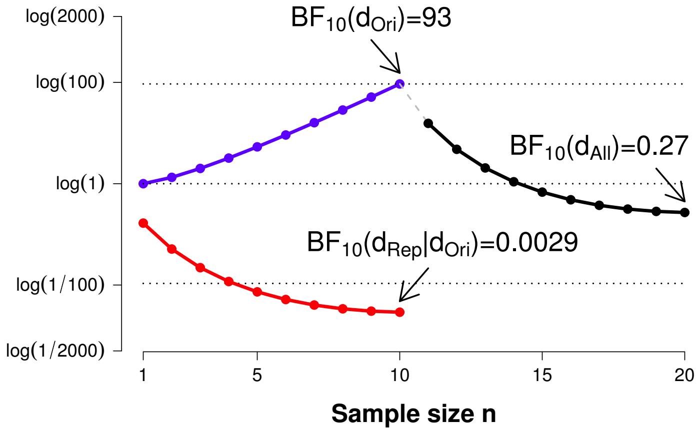

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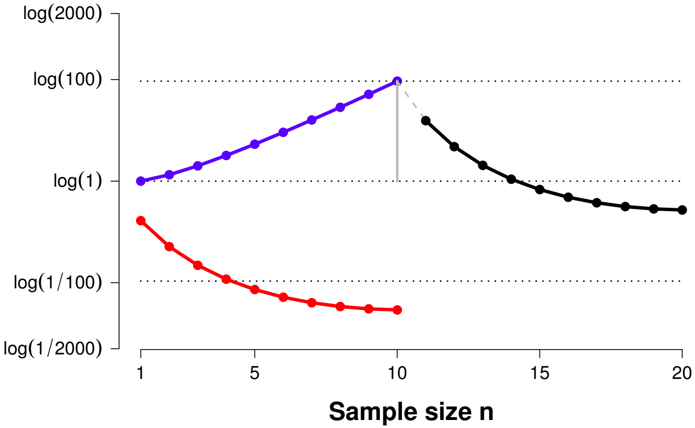

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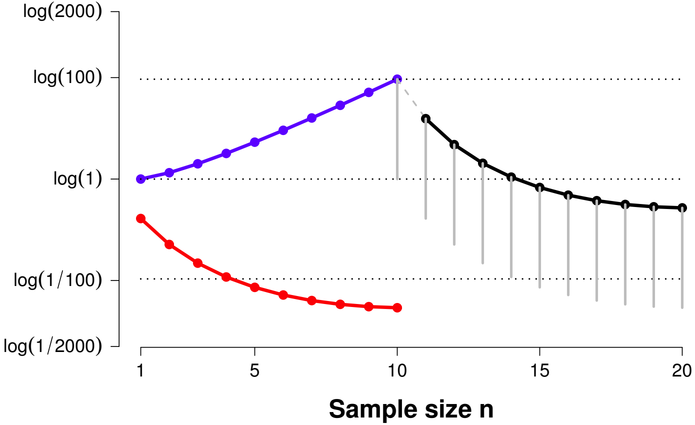

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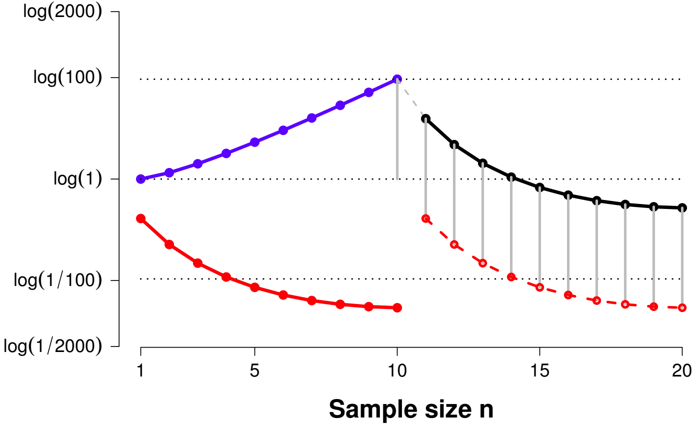

Correlation Test

Default Bayes factor (Jeffreys, 1948; Ly, Verhagen & Wagenmakers, in press), scaled-beta prior on $\theta = \rho$, Jeffreys prior on $\mu_x, \sigma_x, \mu_y, \sigma_y$ (nuisance).

$$\mathrm{BF}_{10}(d) = \sqrt{\frac{\pi}{2}} \frac{\Gamma\left(\frac{n-1}{2}\right)}{\Gamma\left(\frac{n+2}{2}\right)} \, {}_2F_1\left(\frac{n-1}{2}, \frac{n-1}{2}\,;\, \frac{n+2}{2}\,;\, r^2\right)$$

- Good theoretical behaviour: Model selection consistent and more.

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$$\mathrm{BF}_{10}(n, r) = \text{bf10Corrie(n, r)}$$

- Implemented in R and used in JASP
- Need: $r_{\text{orig}}, n_{\text{orig}}$ and and $r_{\text{all}}, n_{\text{all}}$

Donellan et al. (2015). Lonely people do NOT shower longer

Replication of a null hypothesis

Data

- $d_{\text{orig}} : (n_{\text{orig}} = 1153, r_{\text{orig}} = -0.03)$
- $d_{\text{rep}} : (n_{\text{rep}} = 1920, r_{\text{rep}} = 0.01)$

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- $d_{\text{all}} : (n_{\text{all}} = 3073, r_{\text{all}} = -0.001)$ (Raw data thanks to Donellan et al.)

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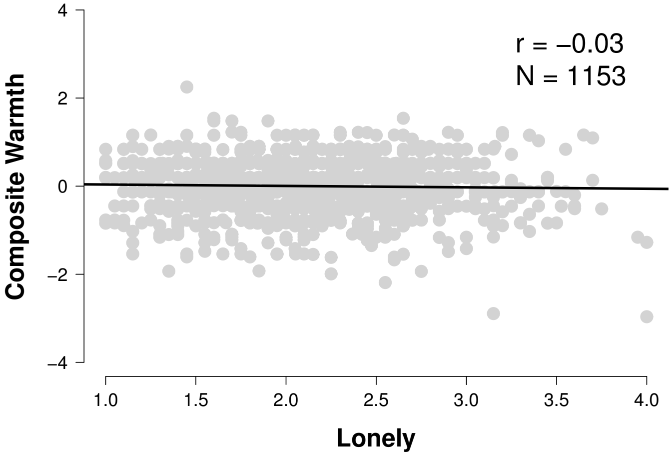
Replication of a null hypothesis



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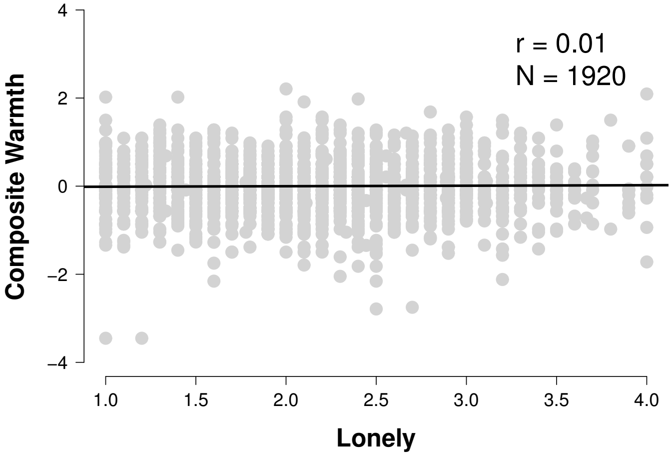

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Bayes factors

- $\text{BF}_{01}(d_{\text{orig}}) = 16.17$

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Bayes factors

- $\text{BF}_{01}(d_{\text{orig}}) = 16.17$
- $\text{BF}_{01}(d_{\text{all}}) = 44.08$
- $\text{BF}_{01}(d_{\text{all}} \mid d_{\text{orig}}) = 2.73$. Hence, evidence for a replication of the null hypothesis

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