

Psychological Methods University of Amsterdam

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Overview



- 2 Bayes factors
- 3 Replication Bayes factors 1
- 4 Replication Bayes factors 2
- 5 Conclusion

Conclusion

Open Science Framework (OSF): Reproducibility project

- JEP:LMC, JPSP, and Psychological Science
- 167 replication attempts

Open Science Framework (OSF): Reproducibility project

- JEP:LMC, JPSP, and Psychological Science
- 167 replication attempts
- Successful replication?

Replication results:

- *p*_{orig} = .032 < .05
- p_{rep} = .032 < .05

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- p_{orig} = .032 < .05, r_{orig} = 0.2
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Conclusion: *p*-values and replications

 p-values alone not informative, also need the direction of the effect

Replication results:

- p_{orig} = .032 < .05, r_{orig} = 0.2
- p_{rep} = .032 < .05, r_{rep} = 0.2

- *p*-values alone not informative, also need the direction of the effect
- To what extend? Need: Continues measure of evidence

Replication results:

- $p_{\rm orig} = .032 < .05, r_{\rm orig} = 0.2, n_{\rm orig} = 50$
- p_{rep} = .046 < .05, r_{rep} = 0.1, n_{rep} = 100

- *p*-values alone not informative, also need the direction of the effect
- To what extend? Need: Continues measure of evidence

Replication results:

- $p_{\rm orig} = .032 < .05, r_{\rm orig} = 0.2, n_{\rm orig} = 50$
- p_{rep} = .051 > .05, r_{rep} = 0.11, n_{rep} = 101

- p-values alone not informative, also need the direction of the effect
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- p-values alone not informative, also need the direction of the effect
- To what extend? Need: Continues measure of evidence
- Sample sizes are relevant.
- More general, use all data d_{orig} and d_{rep}

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- Slides will be online www.Alexander-Ly.com.

The pros

• Evidence for \mathcal{M}_1 and \mathcal{M}_0

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- Evidence for \mathcal{M}_1 and \mathcal{M}_0
- BF₁₀(*d*) = 7, the data *d* are seven times more likely to be generated from the alternative model *M*₁
- BF₁₀(d) = 1/7, the data d are seven times more likely to be generated from the null model M₀, as BF₀₁(d) = 7

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The cons

• Comparative measure of evidence.

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- BF₁₀(*d*) = 7, the data *d* are seven times more likely to be generated from the alternative model *M*₁
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The cons

- Comparative measure of evidence.
- Computationally hard, but we can use computers and now JASP
- Sensitive to prior choice

For each model (\mathcal{M}_0 and \mathcal{M}_1) do the following:

O Prior: Express our uncertain about the parameter θ .

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- Observe data: Learn from the observed data, say, *d*orig.
- **Obstraints** Posterior: Revise our uncertainty about the parameter θ .
- Repeat Go to step 2.

Prior

Prior Predictive







Experimental set up

 We plan to get a participant to respond to n = 10 items yielding y number of correct and n - y incorrect responses.

Experimental set up

- We plan to get a participant to respond to n = 10 items yielding y number of correct and n - y incorrect responses.
- The participant's ability θ drives the number of correct responses y; the closer the ability θ is to one, the closer the number of correct responses y is to n.

Experimental set up

We plan to get the participant to respond *another* n = 10 items yielding *y* number of correct and n - y incorrect responses.

The null model \mathcal{M}_0

Standard null hypothesis: The ability is known \mathcal{M}_0 : $\theta = 1/2$

Experimental set up

We plan to get the participant to respond *another* n = 10 items yielding *y* number of correct and n - y incorrect responses.

The null model \mathcal{M}_0

Standard null hypothesis: The ability is known M_0 : $\theta = 1/2$ Implicit prior with zero uncertainty.

Binomial case: Null model \mathcal{M}_0 predictions



Experimental set up

We plan to get the participant to respond *another* n = 10 items yielding *y* number of correct and n - y incorrect responses.

The null model \mathcal{M}_0

Standard null hypothesis: The ability is known M_0 : $\theta = 1/2$ Implicit prior with zero uncertainty.

The alternative model \mathcal{M}_1

Standard alternative hypothesis: The ability is unknown: M_1 : θ is in (0, 1). Choose a prior in JASP.
The default prior in JASP: 1. Load "binomialOri.csv"

0	0 0		binomia	IA	R _M
	File Variables	Common SE	A R11t Learn		IΞ
	Descriptives	ANOVA Regression	Frequencies BF from t		
	👶 Outcome				
1	Correct				- 1
2	Correct			· · · · · · · · · · · · · · · · · · ·	- 1
3	Incorrect			Welcome to JASP!	- 1
4	Correct			Version 0.7.5.5	- 11
5	Correct			Hi and welcome to JASP, a fresh and new way to do statistics that we're sure you'll like.	
6	Correct			JASP aims to be a complete and full featured	
7	Correct			alternative to SPSS, and it's well on its way there! In fact, it aims to be a lot more than SPSS, which is	
8	Correct			why it implements some of the latest Bayesian analyses. So load up a data file, and take a look.	
9	Incorrect			Also remember, this is an early preview release and there are a number of features missing. So if it	
10	Correct			doesn't do all you need today, then check back tomorrow; JASP is being developed at break-neck	
				speed!	
				()	

The default prior in JASP: 1. Load "binomialOri.csv"

0	00				binomialA		R _M
	File Variables	Common	SEM	R11t Lea	ırn		IΞ
	Descriptives		Regression	Frequencies	BF from t		
	\delta Outcome						
1	Correct						
2	Correct						
3	Incorrect					Welcome to JASP!	
4	Correct					Version 0.7.5.5	
5	Correct					Hi and welcome to JASP, a fresh and new way to do statistics that we're sure you'll like.	
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8	Correct					analyses. So load up a data file, and take a look.	
9	Incorrect					Also remember, this is an early preview release and there are a number of feature micring. So if it	
10	Correct					doesn't do all you need today, then check back tomorrow: IASP is being developed at break-neck	
						speed	
						زJ	

Conclusion

The default prior in JASP: 2. Choose "Bayesian Binomial Test"

00		binomialA*		R _M
File Variables	Common SEM R11t Learn	n		E
Descriptives	ANOVA Regression Frequencies	₽ F from t		
\delta Outcome		ОК	Results	
			Bayesian Binomial Test]
			Bayesian Binomial Test	
Test value: 0.5			Level Counts	Total Proportion BF10
Hypothesis	Plots		Note. Proportions tested against value	ue: 0.5.
● # Test value	Prior and posterior			
> Test value	Additional info			
🔾 < Test value	Sequential analysis			
Bayes Factor	Prior			
 BF10 	Beta prior: parameter a 1			
O BF01	Beta prior: parameter b 1			
O Log(BF10)				

The default prior in JASP: 3. Setting

00	binomialA	*
File Variables	Common SEM R11t Learn	II
Descriptives	ANDVA Regression Frequencies BF from t	
뤐 Outcome	ОК	Results
		Bayesian Binomial Test
Test value: 0.5		Level Counts Total Proportion BF10
Hypothesis	Plots	Note. Proportions tested against value: 0.5.
● # Test value	Prior and posterior	
> Test value	Additional info	
🔾 < Test value	Sequential analysis	
Bayes Factor BF ₁₀ BF ₀₁ Log(BF ₁₀)	Prior Beta prior: parameter a 1 Beta prior: parameter b 1	

The default prior in JASP: 3. Setting

Prior

Beta prior: parameter a



Beta prior: parameter b



Meaning of the default prior: Beta a = 1, b = 1

 Interpretation: Pre-experimentally, we saw a – 1 correct and b – 1 incorrect responses before the data collection.

Meaning of the default prior: Beta a = 1, b = 1

- Interpretation: Pre-experimentally, we saw a 1 correct and b – 1 incorrect responses before the data collection.
- The default specification implies 0 correct and 0 incorrect pre-responses.

Meaning of the default prior: Beta a = 1, b = 1



Binomial case: Alternative model \mathcal{M}_1 predictions



Example: Binomial case

Bayes factor

A Bayes factor compares the predictions of the two models at the observed data $y_{\rm orig}$

Recall: Null model \mathcal{M}_0 predictions



Recall: Alternative model \mathcal{M}_1 predictions



The \mathcal{M}_0 vs \mathcal{M}_1 predictions



Null model \mathcal{M}_0 "wins": BF₁₀(d_{orig}) < 1



Alternative model \mathcal{M}_1 "wins": BF₁₀(d_{orig}) > 1



Observing data: $y_{\text{orig}} = 8$ correct and $n_{\text{orig}} - y_{\text{orig}} = 2$ incorrect responses

00		binomialA*		R _M
File Variables	Common SEM R11t Lea	rn		i≡
Descriptives	ANOVA Regression Frequencies	BF from t		
🔥 Outcome		ОК	lesults	
			ayesian Binomial Test	
			ayesian Binomial Test	- 1
Test value: 0.5			Level Counts Total Proportion B	F ₁₀
Hypothesis	Plots		lote. Proportions tested against value: 0.5.	_
● # Test value	Prior and posterior			
> Test value	Additional info			
🔾 < Test value	Sequential analysis			
Bayes Factor	Prior			
 BF10 	Beta prior: parameter a 1			
O BF01	Beta prior: parameter b 1			
O Log(BF10)				

Observing data: $y_{\text{orig}} = 8$ correct and $n_{\text{orig}} - y_{\text{orig}} = 2$ incorrect responses

00		binomialA*		N ^M
File Variables	Common SEM R11t Lear	rn		i≡
Descriptives	ANOVA Regression Frequencies	BF from t		
뤔 Outcome		ОК	lesults	
			ayesian Binomial Test	
			ayesian Binomial Test	- 1
Test value: 0.5			Level Counts Total Proportion E	F ₁₀
Hypothesis	Plots		lote. Proportions tested against value: 0.5.	
● # Test value	Prior and posterior			
> Test value	Additional info			
🔾 < Test value	Sequential analysis			
Bayes Factor	Prior			
 BF10 	Beta prior: parameter a 1			
O BF01	Beta prior: parameter b 1			
O Log(BF10)				
l				

Observing data: $y_{\text{orig}} = 8$ correct and $n_{\text{orig}} - y_{\text{orig}} = 2$ incorrect responses

00		binomialA*						R _M
File Variables	Common SEM R11t Lear	rn						IE
Descriptives	ANOVA Regression Frequencies	BF from t						
	💰 Outcome	ОК	lesults					
			ayesian	Binomia	al Test			
			ayesian Binc	mial Test				
				Level	Counts	Total	Proportion	BF ₁₀
Test value: 0.5			Outcome	Correct	8	10	0.800	2.069
Hypothesis	Plots			Incorrect	2	10	0.200	2.069
 ✓ Test value 	Prior and posterior		lote. Proport	tions tested a	gainst value:	0.5.		
> Test value	Additional info							
🔾 < Test value	Sequential analysis							
Bayes Factor	Prior							
BF10	Beta prior: parameter a 1							
BF01	Beta prior: parameter b 1							
O Log(BF10)								
			-	_	_	_	_	

Explaining the result



Explaining the result



Default Bayes factor $BF_{10}(d_{orig})$



Default Bayes factor $BF_{10}(d_{orig})$



Replication Bayes factor $BF_{10}(d_{orig} | d_{rep})$



a. Revise the prior: Learn from the original data



b. Revise the predictions



a. Learning from the original data d_{orig} : $y_{\text{orig}} = 8$, $n_{\text{orig}} = 10$

Experimental set up

After observing d_{orig} , we plan to get the participant to respond another n = 10 items yielding y number of correct and n - yincorrect responses.

The null model \mathcal{M}_0

Revised null hypothesis: The ability is still known; $M_0: \theta = 1/2$. Same "no-uncertainty" prior.

b. Revised: Null model \mathcal{M}_0 predictions



a. Learning from the original data d_{orig} : $y_{\text{orig}} = 8$, $n_{\text{orig}} = 10$

Experimental set up

After observing d_{orig} , we plan to get the participant to respond another n = 10 items yielding y number of correct and n - yincorrect responses.

The null model \mathcal{M}_0

"Revised" null hypothesis: The ability is still known $\theta = 1/2 \leftarrow$ Same prior.

The alternative model \mathcal{M}_1

Revised alternative hypothesis: The ability is still unknown and $\mathcal{M}_1: \theta$ in (0, 1), but we are less uncertain about it.

Recall: Beta prior implies that we saw *a* – 1 correct and *b* – 1 incorrect responses before the new data.

- Recall: Beta prior implies that we saw a 1 correct and b – 1 incorrect responses before the new data.
- With y_{orig} = 8 and n_{orig} y_{orig} = 2, this yields a = 9 and b = 3, before seeing the replication data.





Revising the prior in JASP: 1. Load "binomialRepA.csv"

0	0 0			binomialRepA		H.
	File Variables 0	Common	SEM R11t	Learn		E
D	escriptives	NOVA Regressi	on Frequencies	BF from t		
	👶 Outcome					
1	Incorrect					
2	Correct					
3	Correct				Welcome to JASP!	
4	Correct				Version 0.7.5.5	
5	Correct				Hi and welcome to JASP, a fresh and new way to do statistics that we're sure you'll like.	
6	Correct				JASP aims to be a complete and full featured	
7	Correct				alternative to SPSS, and it's well on its way there! in fact, it aims to be a lot more than SPSS, which is	
8	Correct				analyses. So load up a data file, and take a look.	
9	Correct				Also remember, this is an early preview release and there are a number of features mission. So if it	
10	Incorrect				doesn't do all you need today, then check back tomorrow; JASP is being developed at break-neck speed!	
					Lj	

Revising the prior in JASP: 1. Load "binomialRepA.csv"

0	0 0			binomialRep	1	R.
	File Variables	Common	SEM R11t	Learn		iΞ
D	escriptives	ANOVA Reg	gression Frequencies	BF from t		
	👶 Outcome					
1	Incorrect					
2	Correct)	
3	Correct				Welcome to JASP!	
4	Correct				Version 0.7.5.5	
5	Correct				Hi and welcome to JASP, a fresh and new way to do statistics that we're sure you'll like.	
6	Correct				JASP aims to be a complete and full featured	
7	Correct				fact, it aims to be a lot more than SPSS, which is	
8	Correct				analyses. So load up a data file, and take a look.	
9	Correct				Also remember, this is an early preview release and there are a number of features mirsing. So if it	
10	Incorrect				doesn't do all you need today, then check back tomorrow; JASP is being developed at break-neck speed!	
					L	

Conclusion

Revising the prior in JASP: 2. Choose "Bayesian Binomial Test"

00	binomialRepA*	R _M
File Variables	Common SEM R11t Learn	E
Descriptives	ANDVA Regression Frequencies BF from t	
🎝 Outcome	■ OK Results ▼	
	Bayesian Binomial Test	
	Bayesian Binomial Test	
Testurius 0.5	Level Counts Total Proportion	3F
Test value: 0.5		
Hypothesis	Plots Note. Proportions tested against value: 0.5.	
 	Prior and posterior	
> Test value	Additional info	
🔾 < Test value	Sequential analysis	
Bayes Factor	Prior	
 BF10 	Beta prior: parameter a 1	
O BF01	Beta prior: parameter b 1	
O Log(BF10)		

Revising the prior in JASP: 3. Change the prior

00	binomialRepA*	R _M
File Variables	Common SEM R11t Learn	I≡
Descriptives	ANOVA Regression Frequencies BF from t	
🚓 Outcome	OK Results	
	Bayesian Binomial Test Bayesian Binomial Test	
Testuslus: 0.5	Level Counts Total Proporti	on BF
Test value: 0.5		
Hypothesis	Plots Note. Proportions tested against value: 0.5.	
● ≠ Test value	Prior and posterior	
> Test value	Additional info	
🔾 < Test value	Sequential analysis	
Bayes Factor	Prior	
 BF10 	Beta prior: parameter a 9	
⊖ BF ₀₁	Beta prior: parameter b 3	
O Log(BF10)		
Revising the prior in JASP: 3. Change the prior



b. Revised: Alternative model \mathcal{M}_1 predictions



Replication Bayes factor

Bayes factor

The replication Bayes factor compares the revised predictions (based on d_{orig}) of the two models at the observed data y_{rep}

b. Recall revised null model \mathcal{M}_0 predictions



b. Recall revised alternative model \mathcal{M}_1 predictions



c. The revised \mathcal{M}_0 vs \mathcal{M}_1 predictions



c. The revised null \mathcal{M}_0 wins: $\mathsf{BF}_{10}(d_{\mathsf{rep}} | d_{\mathsf{orig}}) < 1$



c. The revised alternative M_1 wins: $BF_{10}(d_{rep} | d_{orig}) > 1$



00	binomialRep/	X *	H.
File Variables	Common SEM R11t Learn		IΞ
Descriptives	ANOVA Regression Frequencies		
🔥 Outcome	ОК	Results	
		Bayesian Binomial Test	
		Bayesian Binomial Test	
Test value: 0.5		Level Counts Total Proportion	BF
Hypothesis	Plots	Note. Proportions tested against value: 0.5.	-
● ≠ Test value	Prior and posterior		
> Test value	Additional info		
🔾 < Test value	Sequential analysis		
Bayes Factor	Prior		
 BF10 	Beta prior: parameter a 9		
○ BF ₀₁	Beta prior: parameter b 3		
O Log(BF10)			

00	binomialRepA*
File Variables	Common SEM R11t Learn
Descriptives	Image: And Via Regression Frequencies Image: And Via
	Outcome OK esults
	ayesian Binomial Test vesian Binomial Test
	Level Counts Total Proportion BF10
Test value: 0.5	Dutcome Correct 8 10 0.800 4.982
Hypothesis	Plots
● ≠ Test value	Prior and posterior
> Test value	Additional info
🔾 < Test value	Sequential analysis
Bayes Factor	Prior
 BF10 	Beta prior: parameter a 9
O BF01	Beta prior: parameter b 3
O Log(BF10)	



Load "binomialRepB.csv"

0	0 0			binor	nialRepB	Mar.
	File Variables	Common	SEM	R11t Learn		i≡
	escriptives		egression Frequ	encies BF from	i t	
	👶 Outcome					
1	Incorrect					- 1
2	Incorrect					- 1
3	Incorrect				Welcome to JASP!	- 1
4	Incorrect				Version 0.7.5.5	- 1
5	Incorrect				Hi and welcome to JASP, a fresh and new way to do statistics that we're sure you'll like.	
6	Correct				JASP aims to be a complete and full featured	
7	Incorrect				fact, it aims to be a lot more than SPSS, which is	
8	Incorrect				analyses. So load up a data file, and take a look.	
9	Incorrect				Also remember, this is an early preview release and there are a number of features missing. So if it	
10	Correct				doesn't do all you need today, then check back tomorrow; JASP is being developed at break-neck	
					speed!	

0 0	binomialR	ep8* 2
File Variables	Common SEM R11t Learn	I=
Descriptives	ANOVA Regression Frequencies BF from t	
🍰 Outcome	ОК	Results
		Bayesian Binomial Test
		Bayesian Binomial Test
		Level Counts Total Proportion BF
Test value: 0.5		
Hypothesis	Plots	Note. Proportions tested against value: 0.5.
 	Prior and posterior	
> Test value	Additional info	
🔾 < Test value	Sequential analysis	
Bayes Factor	Prior	
 BF10 	Beta prior: parameter a 9	
O BF01	Beta prior: parameter b 3	
O Log(BF10)		

00	binomialRepB*	R _M
File Variables	Common SEM R11t Learn	IΞ
Descriptives	ANOVA Regression Frequencies BF from t	
🌧 Outcome	COK Results	
	Bayesian Binomial Test Bayesian Binomial Test	
	Level Counts Total Proportion	BF
Test value: 0.5		
Hypothesis	Plots Note. Proportions tested against value: 0.5.	-
● ≠ Test value	Prior and posterior	
> Test value	Additional info	
🔾 < Test value	Sequential analysis	
Bayes Factor	Prior	
 BF10 	Beta prior: parameter a 9	
○ BF ₀₁	Beta prior: parameter b 3	
O Log(BF10)		

0 0	binomialRepE)*
File Variables	Common SEM R11t Learn	
Descriptives	ANOVA Regression Frequencies BF from t	
	🔥 Outcome 🛛 🛛 🐼	sults
		yesian Binomial Test
		Level Counts Total Proportion BF10
Test value: 0.5		utcome Correct 2 10 0.200 0.131 Incorrect 8 10 0.800 4.982
Hypothesis	Plots	e. Proportions tested against value: 0.5.
● ≠ Test value	Prior and posterior	
> Test value	Additional info	
🔾 < Test value	Sequential analysis	
Bayes Factor	Prior	
 BF10 	Beta prior: parameter a 9	
O BF01	Beta prior: parameter b 3	
O Log(BF10)		



Load "binomialRepC.csv"

0	0 0		binomialRe	pC 🔬
	File Variables	Common	SEM R11t Learn	I
	lescriptives	ANOVA Regressio	on Frequencies BF from t	
	👶 Outcome			
1	Incorrect			
2	Incorrect			
3	Correct			Welcome to JASP!
4	Correct			Version 0.7.5.5
5	Correct			Hi and welcome to JASP, a fresh and new way to do statistics that we're sure you'll like.
6	Correct			JASP aims to be a complete and full featured
7	Correct			alternative to SPSS, and it's well on its way there! In fact, it aims to be a lot more than SPSS, which is
8	Correct			why it implements some of the latest Bayesian analyses. So load up a data file, and take a look.
9	Incorrect			Also remember, this is an early preview release and there are a number of features mission. So if it
10	Correct			doesn't do all you need today, than dis back tomorrow; JASP is being developed at break-neck speed

00	binomialRep0	*
File Variables	Common SEM R11t Learn	
Descriptives	ANOVA Regression Frequencies BF from t	
\delta Outcome	ОК	Results
		Bayesian Binomial Test
		Bayesian Binomial Test
Test value: 0.5		Level Counts Total Proportion B
Hypothesis	Plots	Note. Proportions tested against value: 0.5.
● # Test value	Prior and posterior	
> Test value	Additional info	
🔾 < Test value	Sequential analysis	
Bayes Factor	Prior	
 BF10 	Beta prior: parameter a 9	
O BF01	Beta prior: parameter b 3	
O Log(BF10)		

00	binomialRepC*	H.
File Variables	Common SEM R11t Learn	IΞ
Descriptives	Y Image: Second secon	
\delta Outcome	OK Results	
	Bayesian Binomial Test	
	Bayesian Binomial Test	
	Level Counts Total Proportion	BF
Test value: 0.5		
Hypothesis	Plots Note. Proportions tested against value: 0.5.	_
● # Test value	Prior and posterior	
> Test value	Additional info	
🔾 < Test value	Sequential analysis	
Bayes Factor	Prior	
 BF10 	Beta prior: parameter a 9	
⊖ BF01	Beta prior: parameter b 3	
O Log(BF10)		

00	binomialRep	C* 2
File Variables	Common SEM R11t Learn	I
Descriptives	ANOVA Regression Frequencies BF from t	
	💰 Outcome 🛛 🔿	sults
		yesian Binomial Test
		sian Binomial Test
		Level Counts Total Proportion BF10
Test value: 0.5		stcome Correct 7 10 0.700 1.557
Hypothesis	Plots	Been the second
● # Test value	Prior and posterior	e. Proportions tested against value: 0.5.
> Test value	Additional info	
< Test value	Sequential analysis	
Bayes Factor	Prior	
 BF10 	Beta prior: parameter a 9	
O BF01	Beta prior: parameter b 3	
O Log(BF10)		



 Replication Bayes factor as a two step method. First find the posterior based on d_{orig}, use this as prior for d_{rep}. Input in "Prior" part of JASP

- Replication Bayes factor as a two step method. First find the posterior based on d_{orig}, use this as prior for d_{rep}. Input in "Prior" part of JASP
- Prior is not always easily updated.

• Alternative: Calculate the replication Bayes factor as

$$\mathsf{BF}_{10}(d_{\mathsf{rep}} \,|\, d_{\mathsf{orig}}) = \frac{\mathsf{BF}_{10}(d_{\mathsf{orig}}, d_{\mathsf{rep}})}{\mathsf{BF}_{10}(d_{\mathsf{orig}})} \tag{1}$$

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Interpretation

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The replication Bayes factor is the additional evidence for \mathcal{M}_1 in the new data d_{rep} given that we already know d_{orig} .

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- BF₁₀(*d*_{rep} | *d*_{orig}) > 1, the contribution of *d*_{rep} to the total evidence grows.

Total Bayes factor $BF_{10}(d_{orig}, d_{rep})$



Default Bayes factor $BF_{10}(d_{orig})$



Replication Bayes factor $BF_{10}(d_{orig} | d_{rep})$



Example: Orig contingency table Dai et al. (2008)

	Perce		
Endowed	Fewer flowers	Fewer birds	Total
Flowers endowed	15	12	27
Birds endowed	8	21	29
Total	23	33	56

Table: Dai, Wertenbroch & Brendl (2008). "The Value Heuristic in Judgments of Relative Frequency"

Result

Bayes factor $BF_{10}(d_{orig}) = 2.880$

Example: Rep contingency table Fuchs et al. (2015)

	Perce		
Endowed	Fewer flowers	Fewer birds	Total
Flowers endowed	11	16	27
Birds endowed	14	10	24
Total	25	26	51

Table: Fuchs, Estel & Göllner (2015). Replication of Dai et al. (2008) (https://osf.io/q7f6w/)

Result

Bayes factor $BF_{10}(d_{rep}) = 0.720$

Example: Combined contingency table

	Percei		
Endowed	Fewer flowers	Fewer birds	Total
Flowers endowed	26	28	54
Birds endowed	22	31	53
Total	48	59	107

Table: Fuchs et al. (2015) and Dai et al. (2008) (https://osf.io/q7f6w/)

Result Bayes factor $BF_{10}(d_{orig}, d_{rep}) = 0.298$





(4)

thus,

$$\mathsf{BF}_{01}(\mathit{d}_{\mathsf{rep}}\,|\,\mathit{d}_{\mathsf{orig}}) pprox 9.6$$

in favour of the null.

1. Load "contingencyComb.csv"

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	\delta Endowed	\delta Perceived	👶 Count					
1	Flowers endowed	Fewer flowers	26					
2	Birds endowed	Fewer birds	31		()			
3	Flowers endowed	Fewer birds	28		Welcome to JASP!			
4	Birds endowed	Fewer flowers	22		Version 0.7.5.5			
Γ					Hi and welcome to JASP, a fresh and new way to do statistics that we're sure you'll like.			
					JASP aims to be a complete and full featured alternative to SPSS, and it's well on its way there in fact, it aims to be a to more than 595, which is why it implements some of the latest Bayesian analyses. So load up a data file, and take a look.			
					Also remember, this is an early preview release and there are a number of features missing. So if it doesn't do all you need today, then check back tomorrow, JASP is being developed at break-neck speed!			
					()			

2. Choose "Bayesian Contingency Tables"

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4. Fill in table



5. Write down result



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2	Birds endowed	Fewer birds	21			[]	
3	Flowers endowed	Fewer birds	12			Welcome to JASP!	
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- We need to automatise the calculation and develop an interface for this.

Workshop



Theory and Practice of Bayesian Hypothesis Testing A JASP Workshop, August 22–23, 2016 Amsterdam https://jasp-stats.org