Replication Bayes factors from JASP output

Alexander Ly, Alexander Etz, Maarten Marsman, Quentin Gronau, Sacha Epskamp, Dora Matzke, Ravi Selker, Tahira Jamil and Eric-Jan Wagenmakers

Psychological Methods
University of Amsterdam

Heidelberg, 21 March 2016

Overview

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?

Example: Successful Replications?

Replication results:

- $p_{\text{orig}} = .032 < .05$
- $p_{\text{rep}} = .032 < .05$

Example: Successful Replications?

Replication results:

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

Example: Successful Replications?

Replication results:

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

Conclusion: *p*-values and replications

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

Example: Successful Replications?

Replication results:

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

Conclusion: *p*-values and replications

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

Example: Successful Replications?

Replication results:

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

Conclusion: *p*-values and replications

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

Example: Successful Replications?

Replication results:

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

Conclusion: *p*-values and replications

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

Example: Successful Replications?

Replication results:

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

Conclusion: *p*-values and replications

- *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}

Take home message

- Better method to asses hypotheses: Bayes factors that are continuous and take into account all the data.

Take home message

- Better method to asses hypotheses: Bayes factors that are continuous and take into account all the data.
- Better method to asses replications: Replication Bayes factors.

Take home message

- Better method to asses hypotheses: Bayes factors that are continuous and take into account all the data.
- Better method to asses replications: Replication Bayes factors.
- Here instructions how to calculate them in JASP (http://jasp-stats.org/).

Take home message

- Better method to asses hypotheses: Bayes factors that are continuous and take into account all the data.
- Better method to asses replications: Replication Bayes factors.
- Here instructions how to calculate them in JASP (http://jasp-stats.org/).
- Slides will be online www.Alexander-Ly.com.

Bayes Factors

The pros

- Evidence for $\mathcal{M}_1$ *and* $\mathcal{M}_0$

Bayes Factors

The pros

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

Bayes Factors

The pros

- 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

- Comparative measure of evidence.

Bayes Factors

The pros

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

The cons

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

Bayes Factors

The pros

- 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

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

Basics of Bayesian learning

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

1. Prior: Express our uncertain about the parameter θ.

Basics of Bayesian learning

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

1. Prior: Express our uncertain about the parameter θ.
2. Predictive: The uncertainty about θ yields expectations about future data.

Basics of Bayesian learning

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

1. Prior: Express our uncertain about the parameter θ.
2. Predictive: The uncertainty about θ yields expectations about future data.
3. Observe data: Learn from the observed data, say, d_{orig}.

Basics of Bayesian learning

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

1. Prior: Express our uncertain about the parameter θ.
2. Predictive: The uncertainty about θ yields expectations about future data.
3. Observe data: Learn from the observed data, say, d_{orig}.
4. Posterior: Revise our uncertainty about the parameter θ.

Basics of Bayesian learning

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

1. Prior: Express our uncertain about the parameter θ.
2. Predictive: The uncertainty about θ yields expectations about future data.
3. Observe data: Learn from the observed data, say, d_{orig}.
4. Posterior: Revise our uncertainty about the parameter θ.
5. Repeat Go to step 2.

The default prior kickstarts learning

Prior

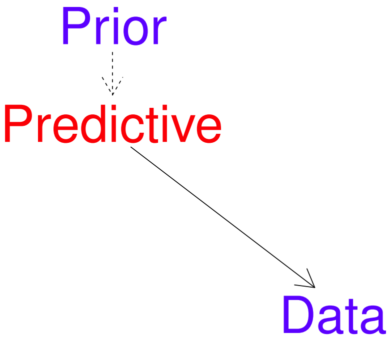
The default prior kickstarts learning

Prior

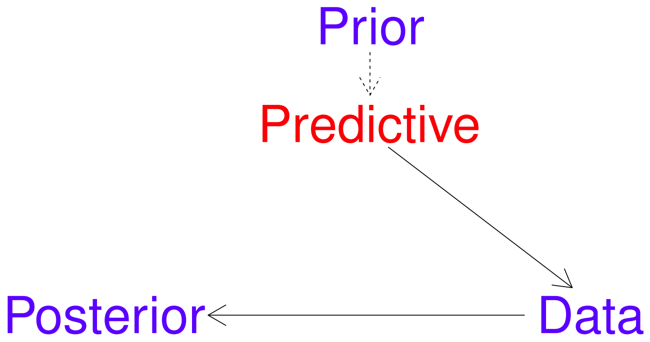
$\downarrow$

Predictive

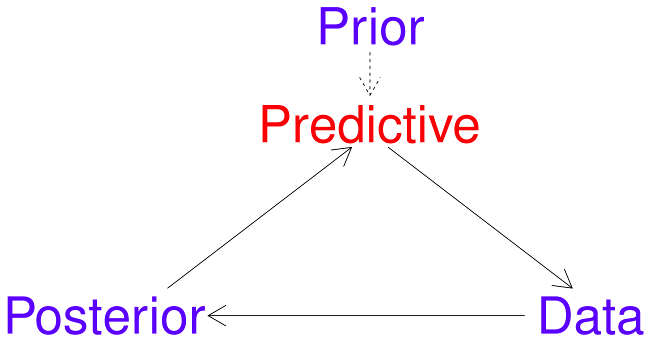
The default prior kickstarts learning



The default prior kickstarts learning



The default prior kickstarts learning



Example: Binomial case

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.

Example: Binomial case

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.

Example: Binomial case

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 $\mathcal{M}_0 : \theta = 1/2$

Example: Binomial case

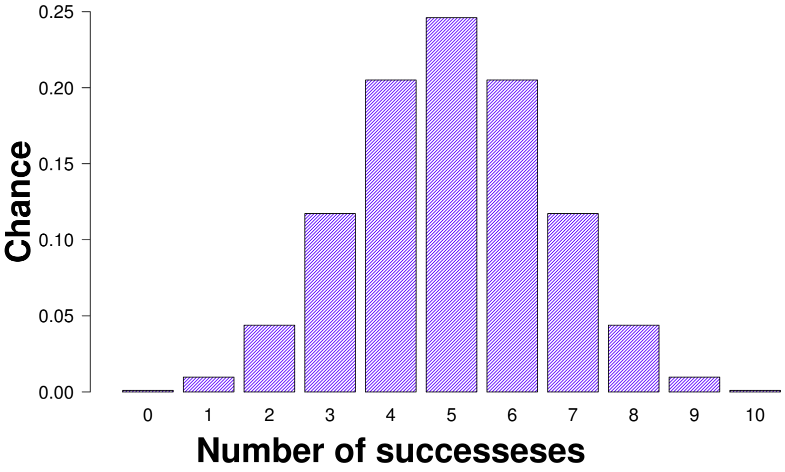
Experimental set up

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 $\mathcal{M}_0 : \theta = 1/2$
Implicit prior with zero uncertainty.

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



Example: Binomial case

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.

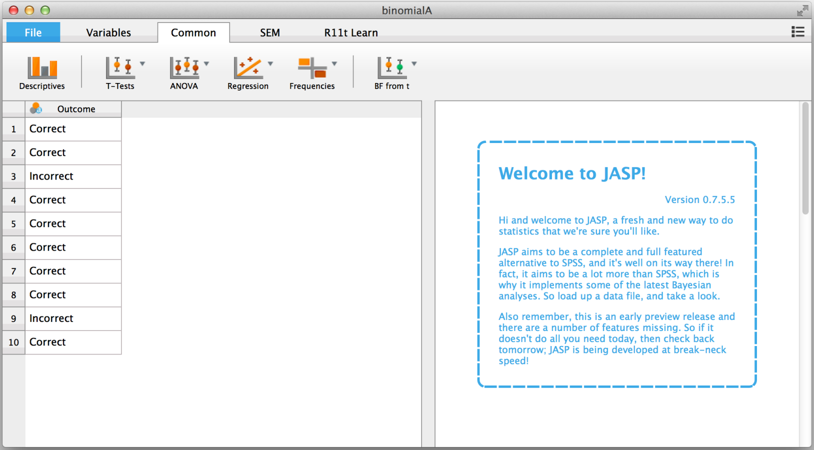
The null model $\mathcal{M}_0$

Standard null hypothesis: The ability is known $\mathcal{M}_0 : \theta = 1/2$
Implicit prior with zero uncertainty.

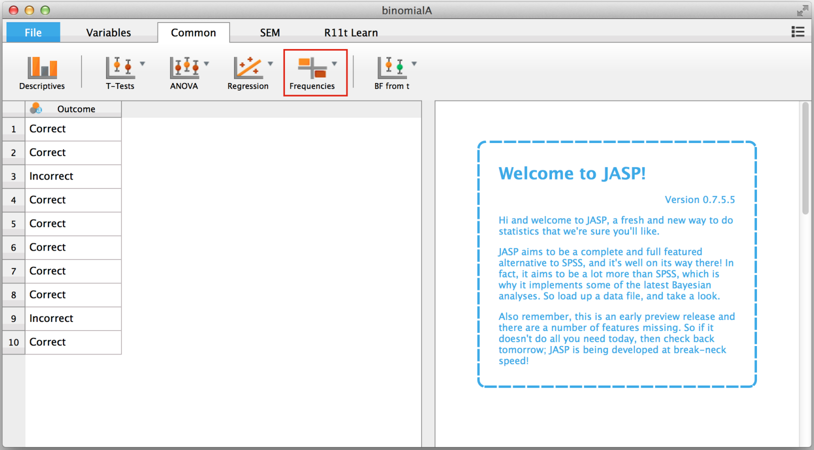
The alternative model $\mathcal{M}_1$

Standard alternative hypothesis: The ability is unknown: $\mathcal{M}_1 : \theta$ is in $(0, 1)$. Choose a prior in JASP.

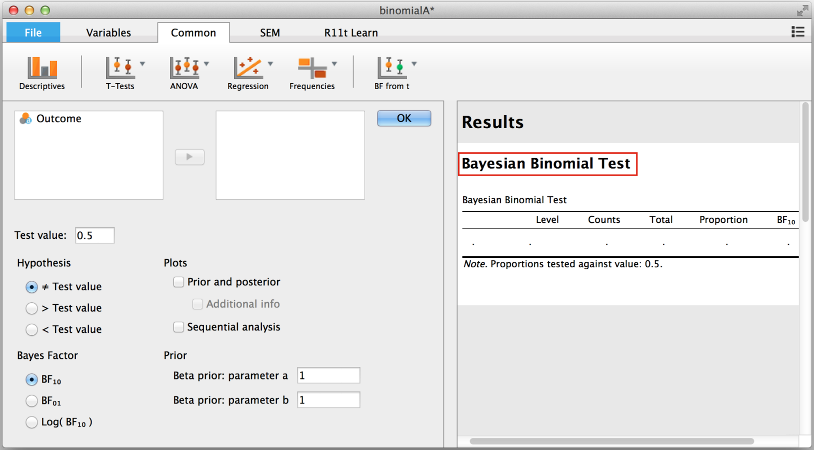
The default prior in JASP: 1. Load "binomialOri.csv"



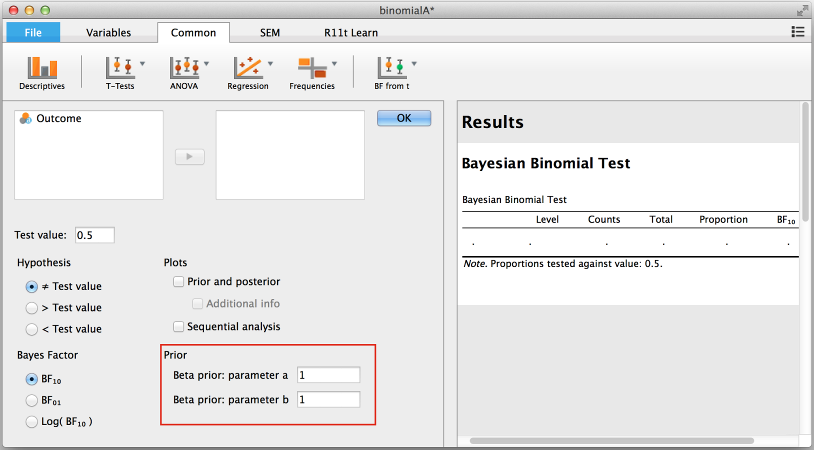
The default prior in JASP: 1. Load "binomialOri.csv"



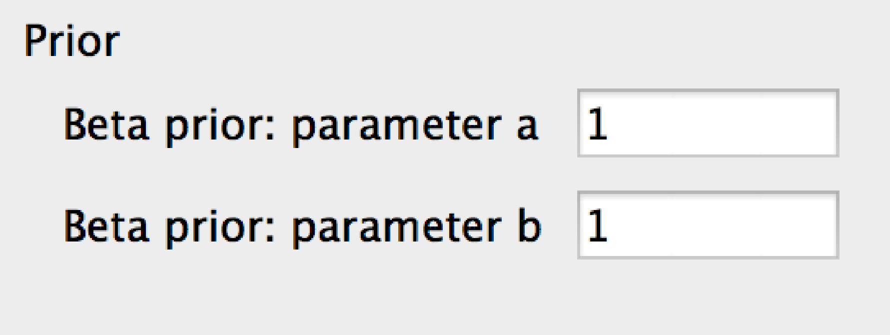
The default prior in JASP: 2. Choose "Bayesian Binomial Test"



The default prior in JASP: 3. Setting



The default prior in JASP: 3. Setting



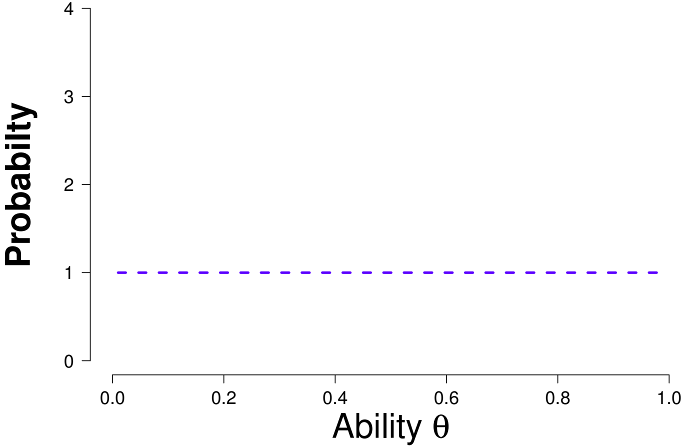
Meaning of the default prior: Beta $a = 1, b = 1$

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

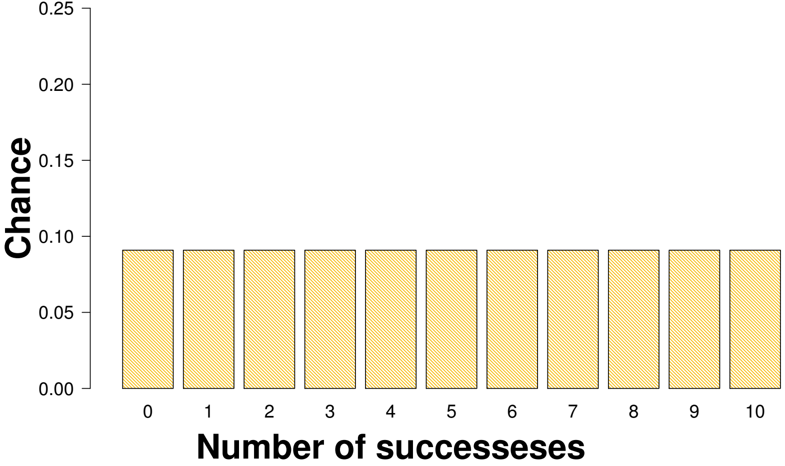
Meaning of the default prior: Beta $a = 1, b = 1$

- 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

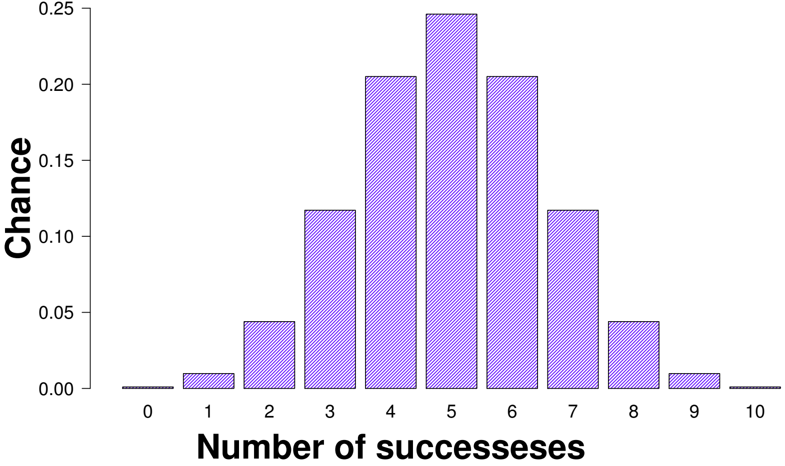


Example: Binomial case

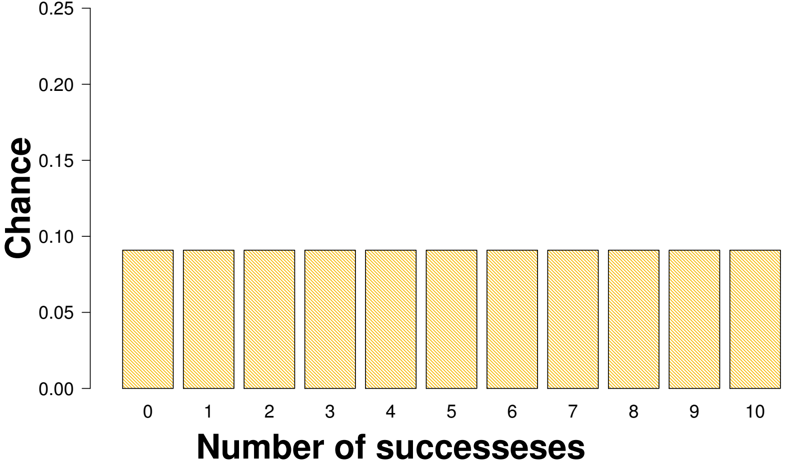
Bayes factor

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

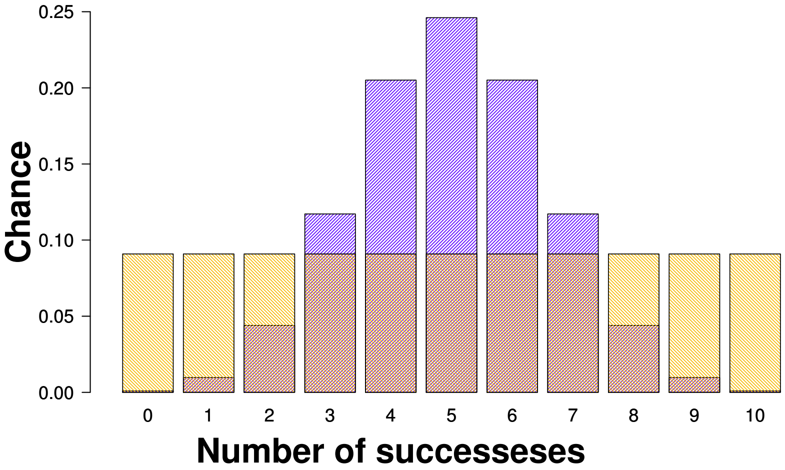
Recall: Null model $\mathcal{M}_0$ predictions



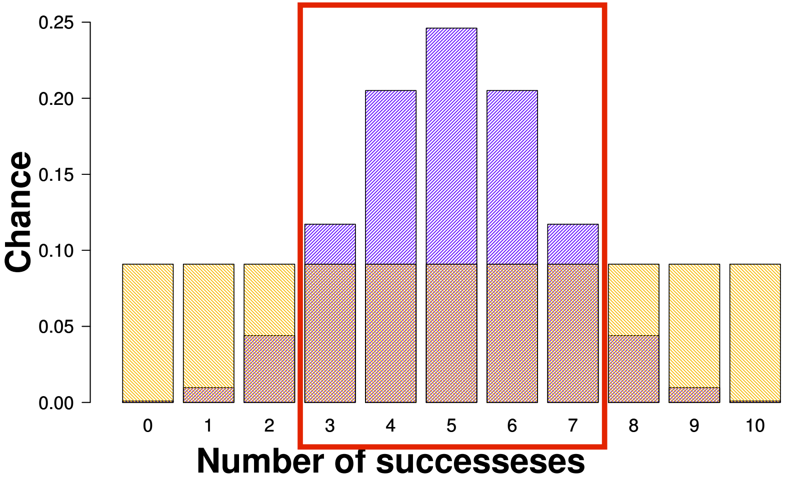
Recall: Alternative model $\mathcal{M}_1$ predictions



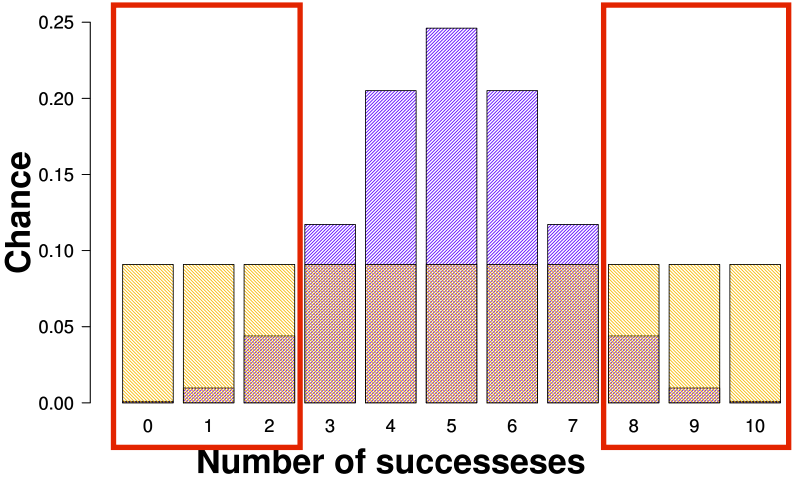
The $\mathcal{M}_0$ vs $\mathcal{M}_1$ predictions



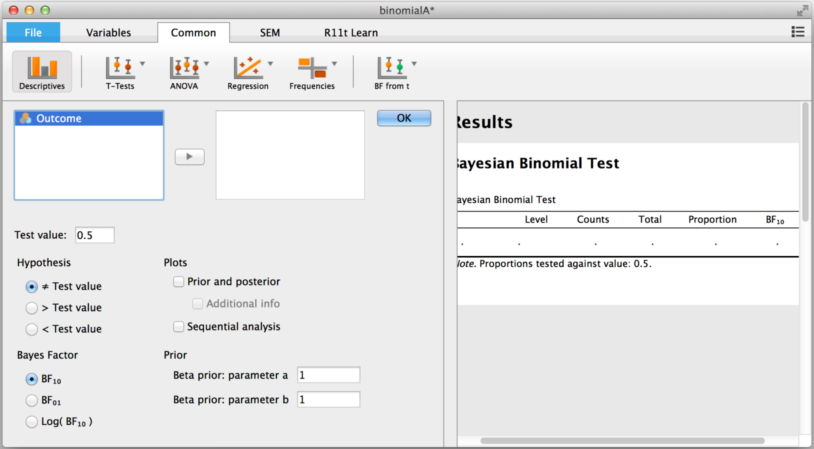
Null model $\mathcal{M}_0$ "wins": $\text{BF}_{10}(d_{\text{orig}}) < 1$



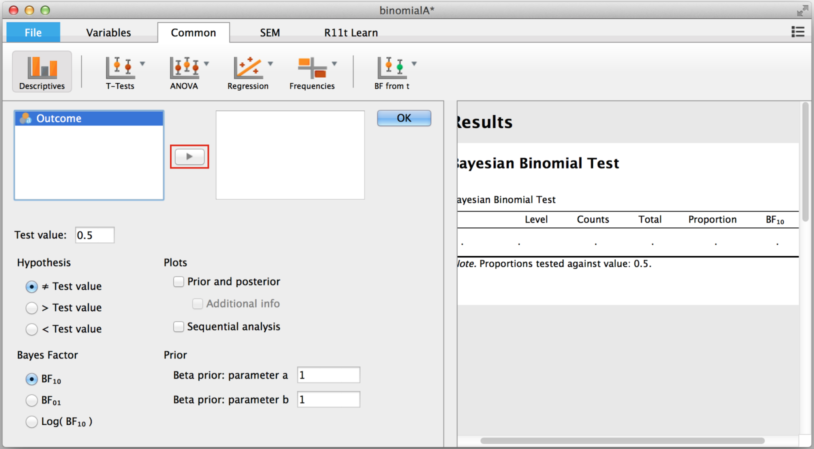
Alternative model $\mathcal{M}_1$ "wins": $\text{BF}_{10}(d_{\text{orig}}) > 1$



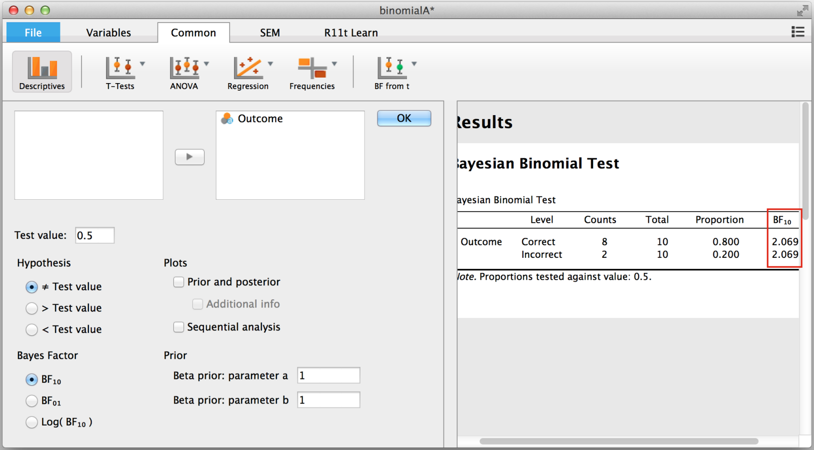
Observing data: $y_{orig} = 8$ correct and $n_{orig} - y_{orig} = 2$ incorrect responses



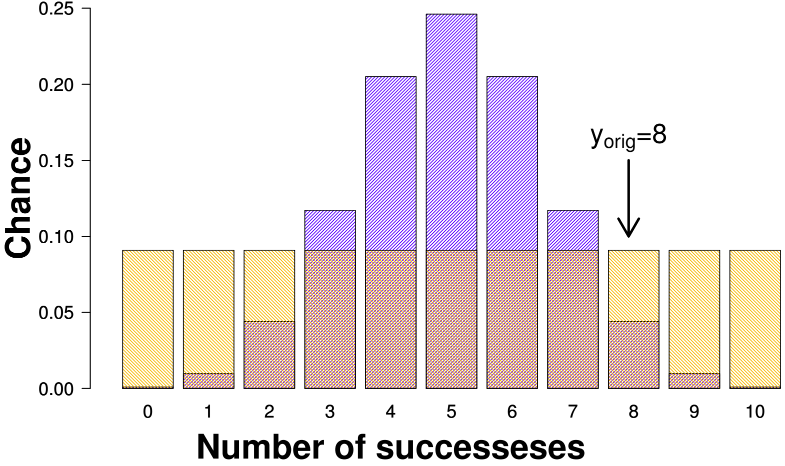
Observing data: $y_{\text{orig}} = 8$ correct and $n_{\text{orig}} - y_{\text{orig}} = 2$ incorrect responses



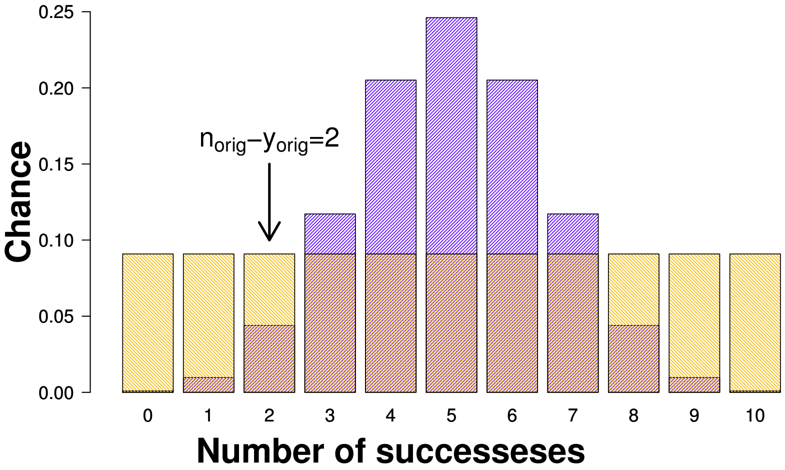
Observing data: $y_{\text{orig}} = 8$ correct and $n_{\text{orig}} - y_{\text{orig}} = 2$ incorrect responses



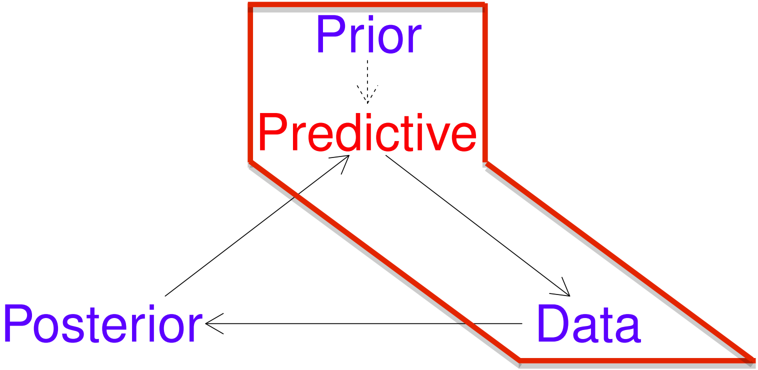
Explaining the result



Explaining the result



Default Bayes factor $\mathrm{BF}_{10}(d_{\text{orig}})$



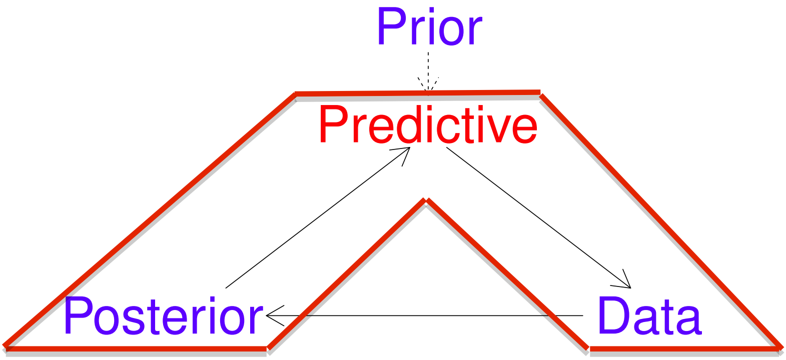
Default Bayes factor $\mathrm{BF}_{10}(d_{\mathrm{orig}})$

Prior

Predictive

d_{orig}

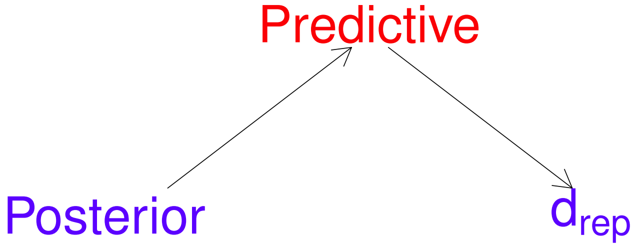
Replication Bayes factor $BF_{10}(d_{orig} \mid d_{rep})$



a. Revise the prior: Learn from the original data

$$\text{Posterior} \longleftarrow d_{\text{orig}}$$

b. Revise the predictions



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

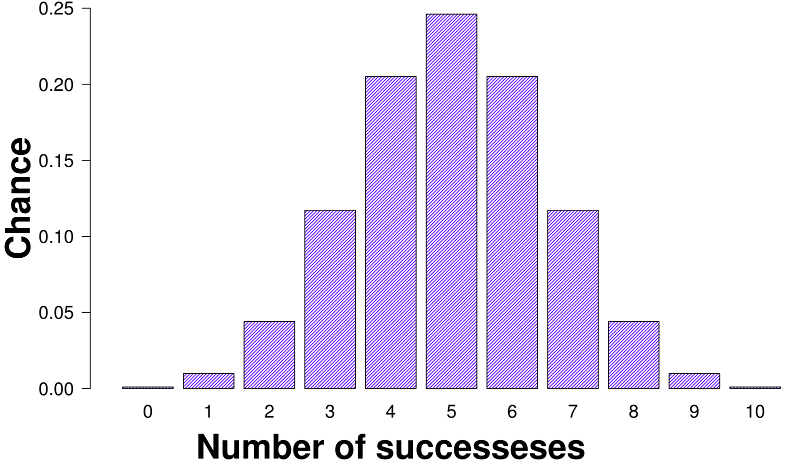
Experimental set up

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

The null model $\mathcal{M}_0$

Revised null hypothesis: The ability is still known;
$\mathcal{M}_0 : \theta = 1/2$. Same "no-uncertainty" prior.

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



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

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 $n - y$ incorrect 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.

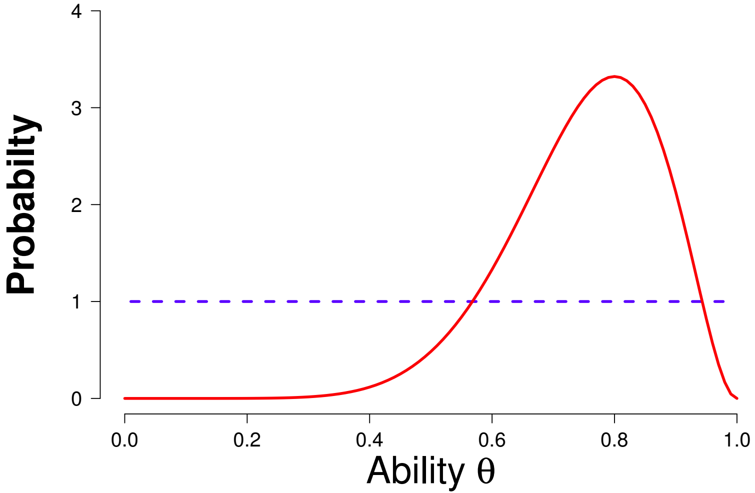
a. Revising the prior in $\mathcal{M}_1$

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

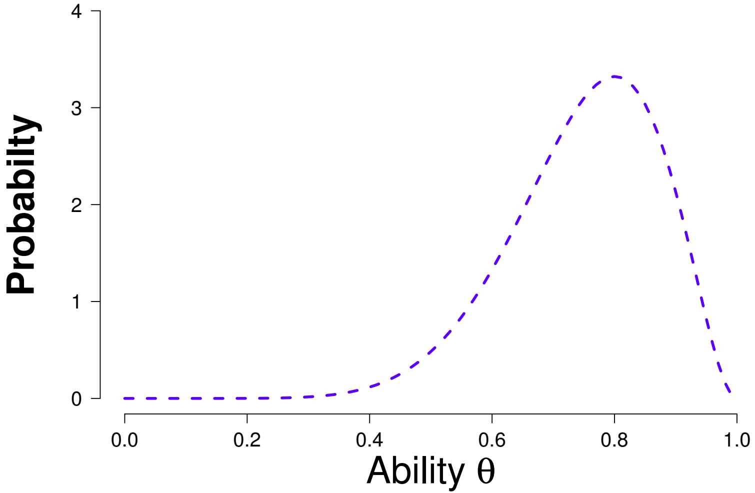
a. Revising the prior in $\mathcal{M}_1$

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

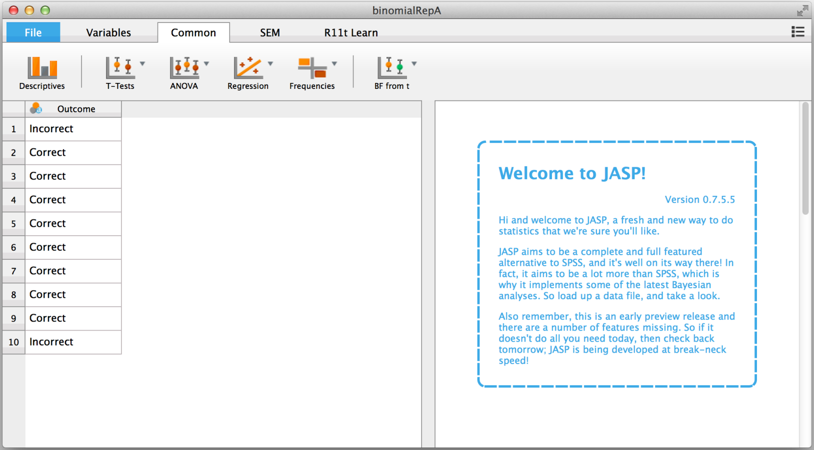
a. Revising the prior in $\mathcal{M}_1$



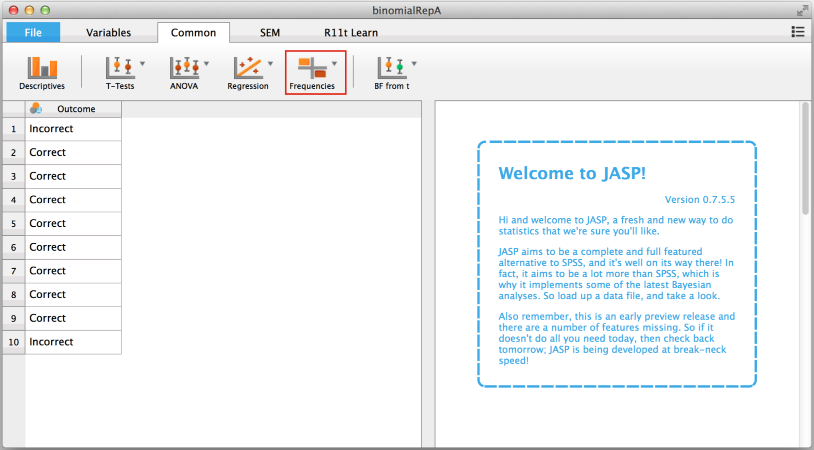
a. Revising the prior in $\mathcal{M}_1$



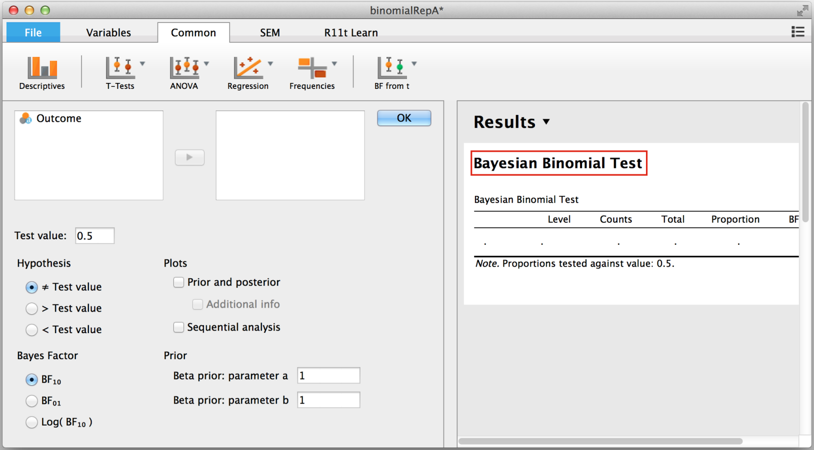
Revising the prior in JASP: 1. Load "binomialRepA.csv"



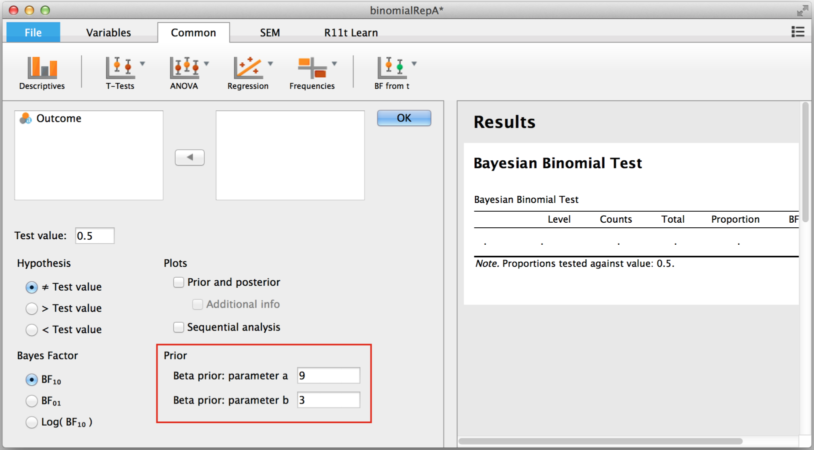
Revising the prior in JASP: 1. Load "binomialRepA.csv"



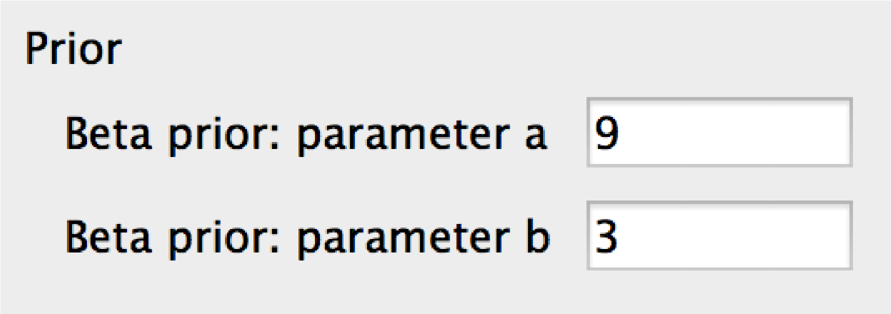
Revising the prior in JASP: 2. Choose "Bayesian Binomial Test"



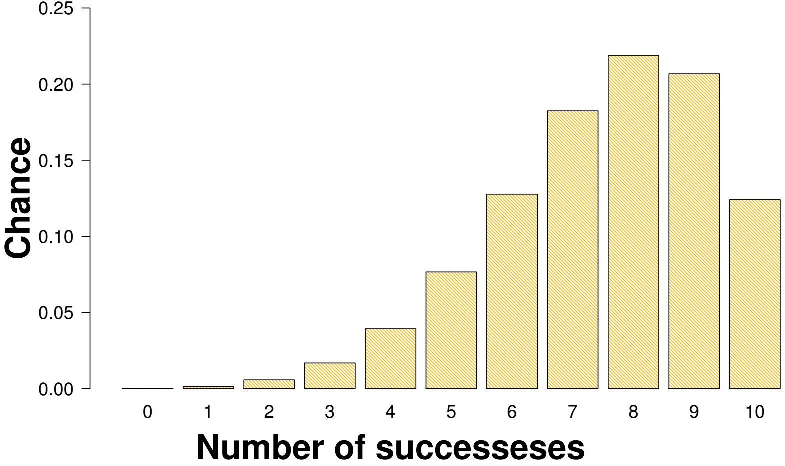
Revising the prior in JASP: 3. Change the prior



Revising the prior in JASP: 3. Change the prior



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

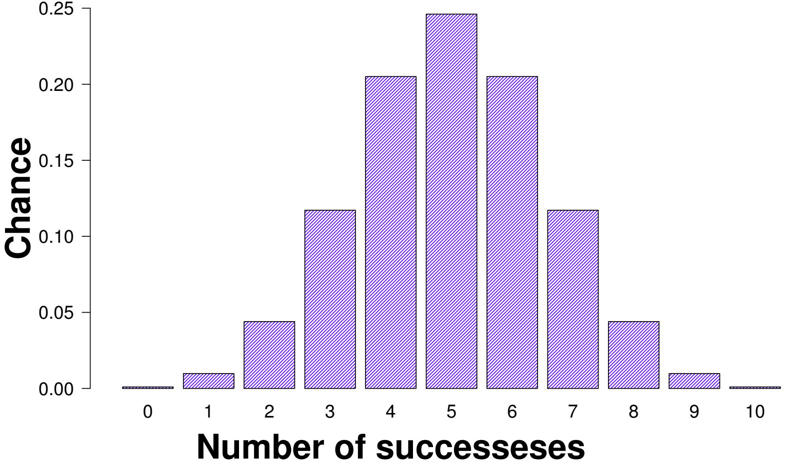


Replication Bayes factor

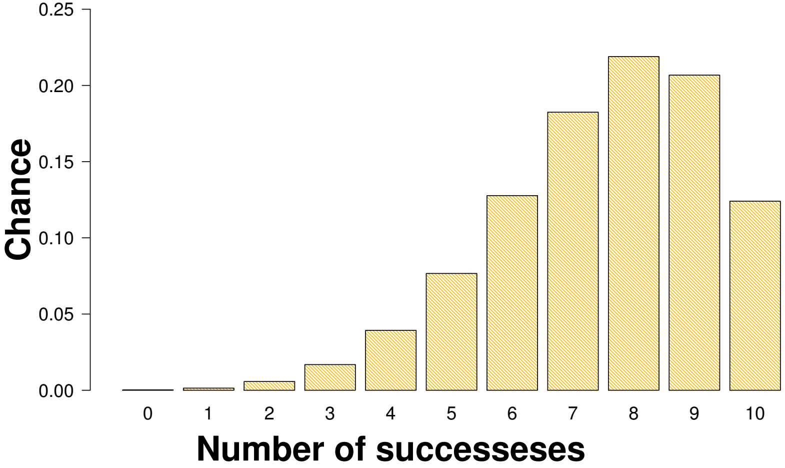
Bayes factor

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

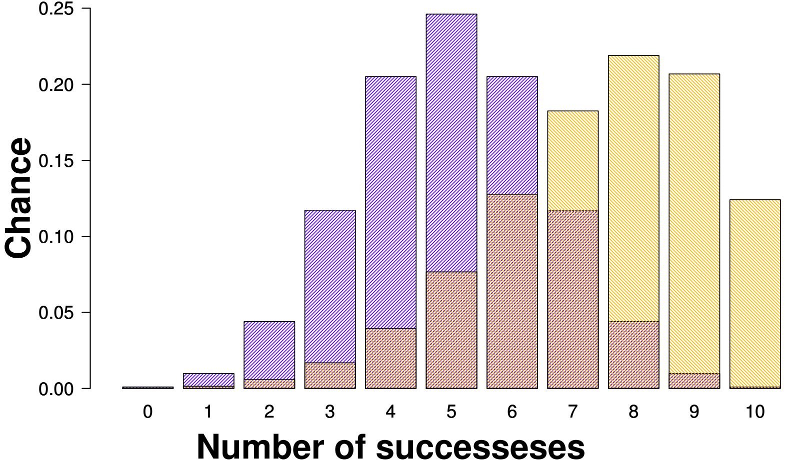
b. Recall revised null model $\mathcal{M}_0$ predictions



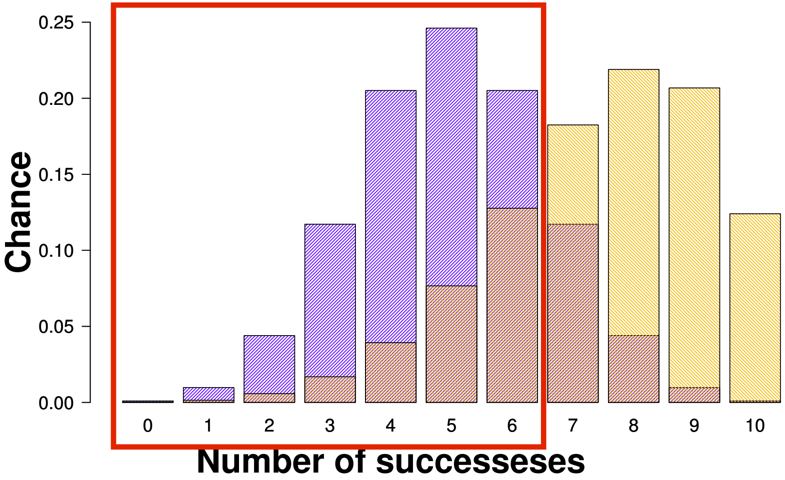
b. Recall revised alternative model $\mathcal{M}_1$ predictions



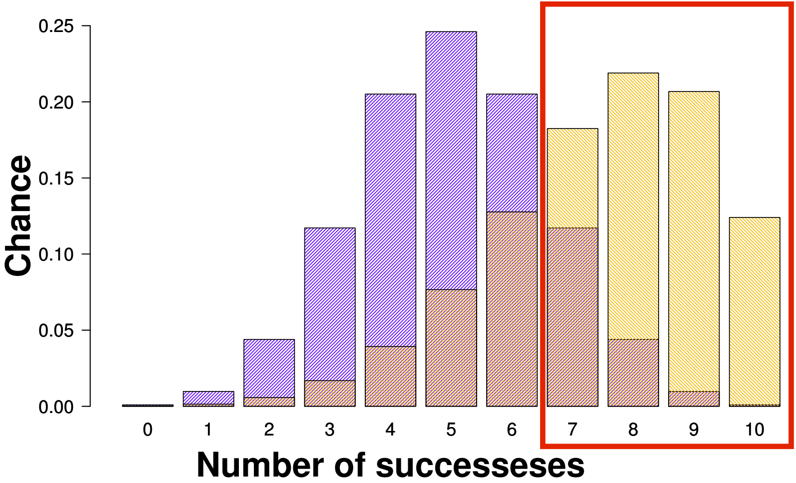
c. The revised $\mathcal{M}_0$ vs $\mathcal{M}_1$ predictions



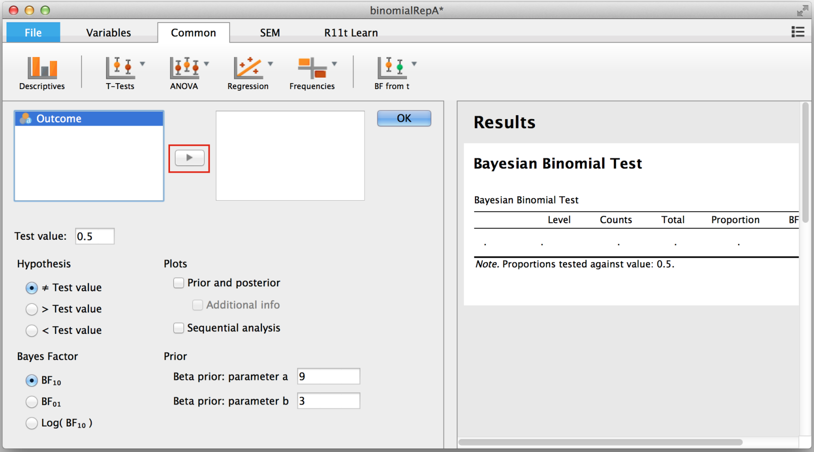
c. The revised null $\mathcal{M}_0$ wins: $\text{BF}_{10}(d_{\text{rep}} \mid d_{\text{orig}}) < 1$



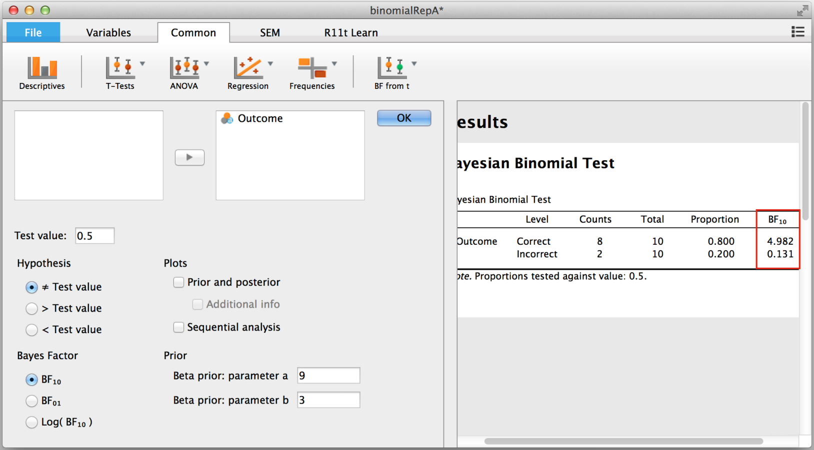
c. The revised alternative $\mathcal{M}_1$ wins: $\mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) > 1$



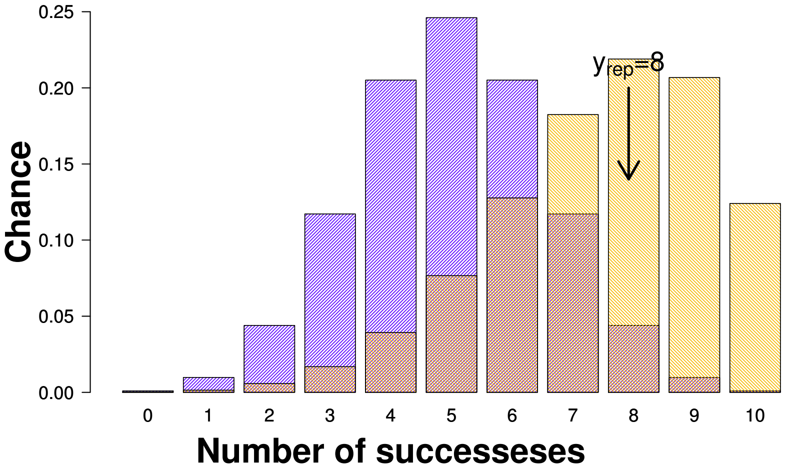
Example A: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 8, n_{\text{rep}} = 10$



Example A: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 8, n_{\text{rep}} = 10$

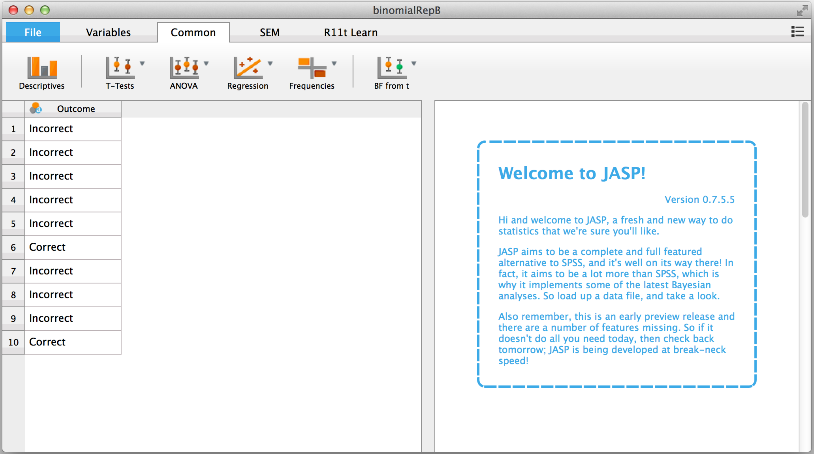


Example A: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 8, n_{\text{rep}} = 10$

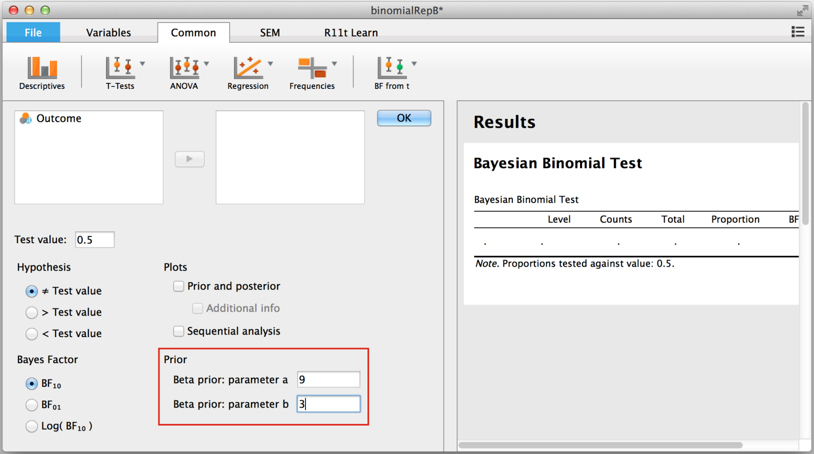


Example B: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 2, n_{\text{rep}} = 10$

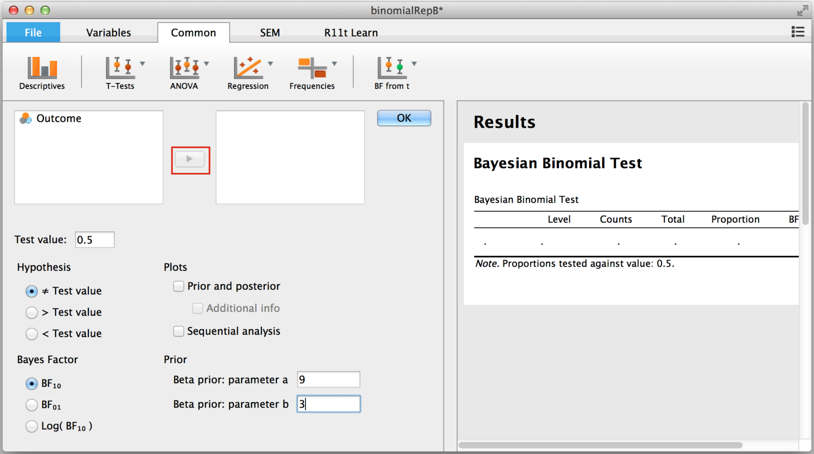
Load "binomialRepB.csv"



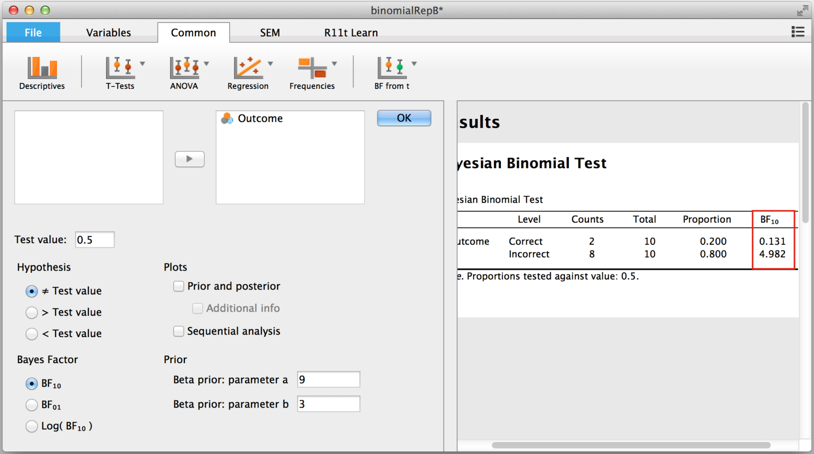
Example B: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 2, n_{\text{rep}} = 10$



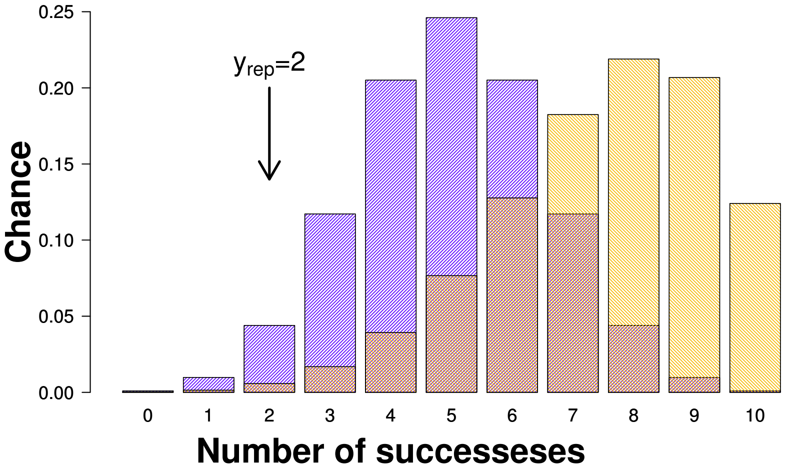
Example B: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 2, n_{\text{rep}} = 10$



Example B: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 2, n_{\text{rep}} = 10$

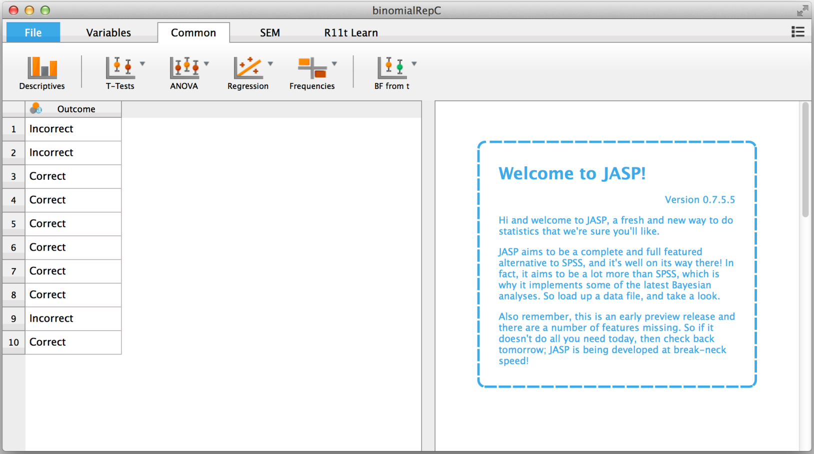


Example B: $y_{orig} = 8, n_{orig} = 10$ and $y_{rep} = 2, n_{rep} = 10$

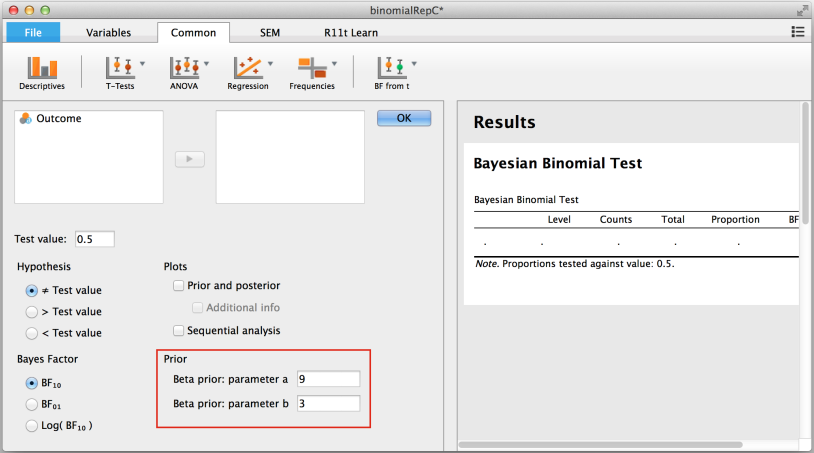


Example C: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 7, n_{\text{rep}} = 10$

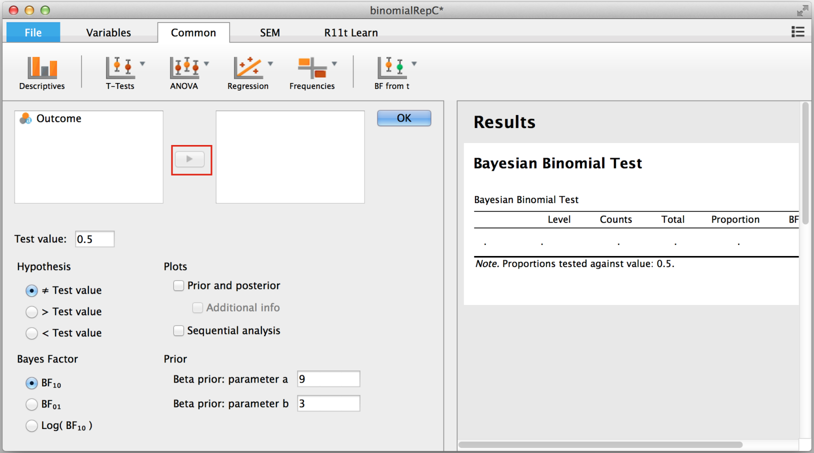
Load "binomialRepC.csv"



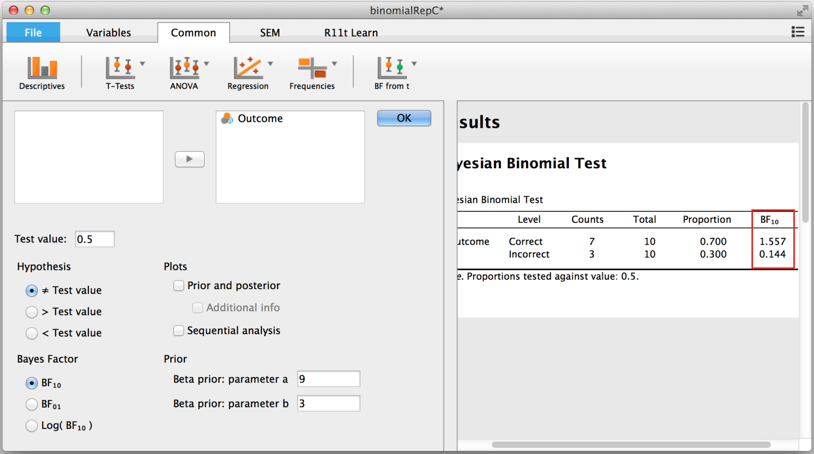
Example C: $y_{orig} = 8, n_{orig} = 10$ and $y_{rep} = 7, n_{rep} = 10$



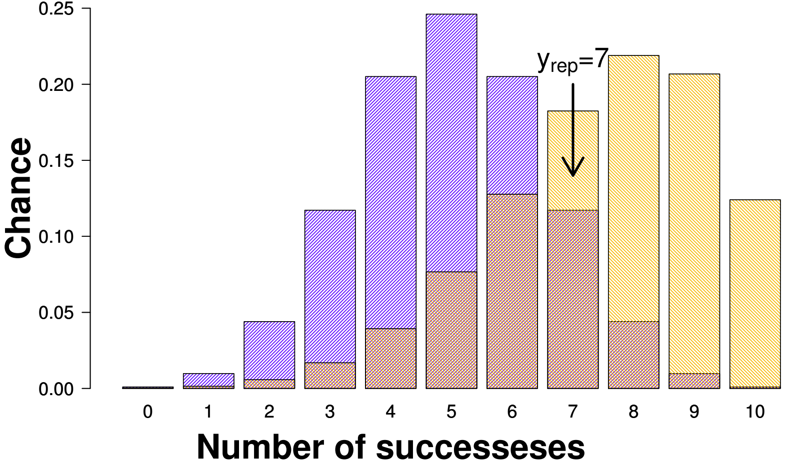
Example C: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 7, n_{\text{rep}} = 10$



Example C: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 7, n_{\text{rep}} = 10$



Example C: $y_{\text{orig}} = 8, n_{\text{orig}} = 10$ and $y_{\text{rep}} = 7, n_{\text{rep}} = 10$



Alternative method of calculation

- 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

Alternative method of calculation

- 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 method of calculation

- Alternative: Calculate the replication Bayes factor as

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

Alternative method of calculation

- Alternative: Calculate the replication Bayes factor as

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

- Interpretation

$$\mathrm{BF}_{10}(d_{\mathrm{orig}}, d_{\mathrm{rep}}) = \mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}})\mathrm{BF}_{10}(d_{\mathrm{orig}}) \tag{2}$$

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}.

Alternative method of calculation

- Alternative: Calculate the replication Bayes factor as

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

- Interpretation

$$\mathrm{BF}_{10}(d_{\mathrm{orig}}, d_{\mathrm{rep}}) = \mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}})\mathrm{BF}_{10}(d_{\mathrm{orig}}) \tag{2}$$

  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}.

- $\mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) < 1$, the contribution of d_{rep} to the total evidence shrinks.

Alternative method of calculation

- Alternative: Calculate the replication Bayes factor as

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

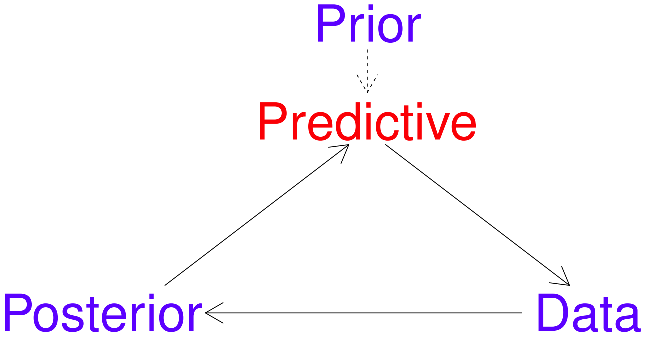
- Interpretation

$$\mathrm{BF}_{10}(d_{\mathrm{orig}}, d_{\mathrm{rep}}) = \mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}})\mathrm{BF}_{10}(d_{\mathrm{orig}}) \tag{2}$$

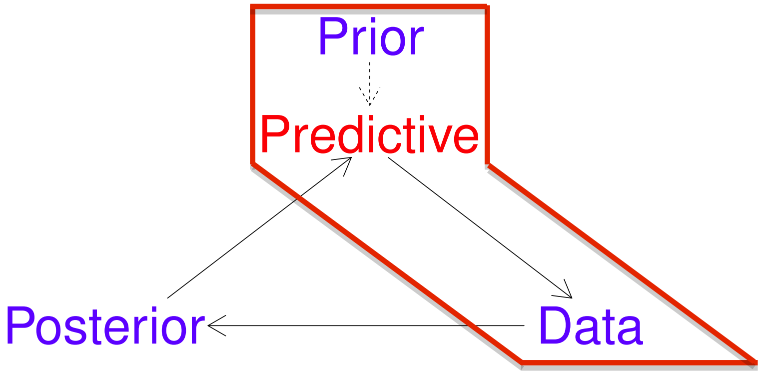
  The replication Bayes factor is the additional evidence for $\mathcal{M}_1$ in the new data d_{rep} given that we already know d_{orig}.

- $\mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) < 1$, the contribution of d_{rep} to the total evidence shrinks.
- $\mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) > 1$, the contribution of d_{rep} to the total evidence grows.

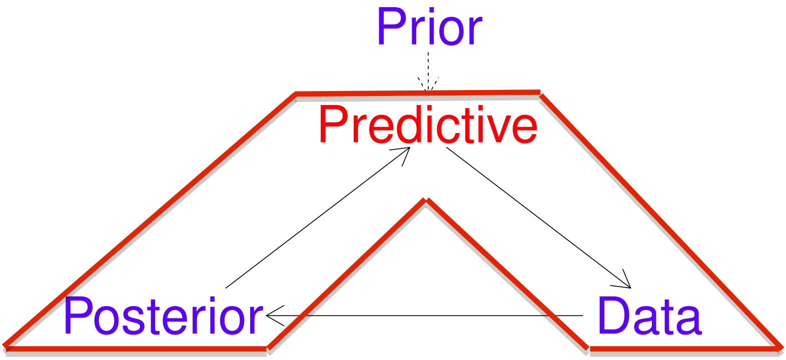
Total Bayes factor $\mathrm{BF}_{10}(d_{\mathrm{orig}}, d_{\mathrm{rep}})$



Default Bayes factor $\mathrm{BF}_{10}(d_{\mathrm{orig}})$



Replication Bayes factor $\mathrm{BF}_{10}(d_{\mathrm{orig}} \mid d_{\mathrm{rep}})$



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

	Perceived		
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 $\mathrm{BF}_{10}(d_{\text{orig}}) = 2.880$

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

	Perceived		
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 $\mathrm{BF}_{10}(d_{\mathrm{rep}}) = 0.720$

Example: Combined contingency table

	Perceived		
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 $\mathrm{BF}_{10}(d_{\text{orig}}, d_{\text{rep}}) = 0.298$

Results

Result

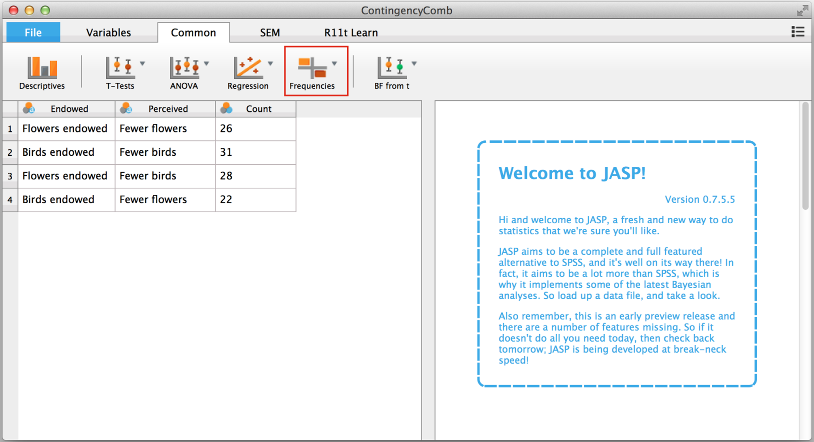
$$\mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) \approx 0.10 \tag{3}$$

thus,

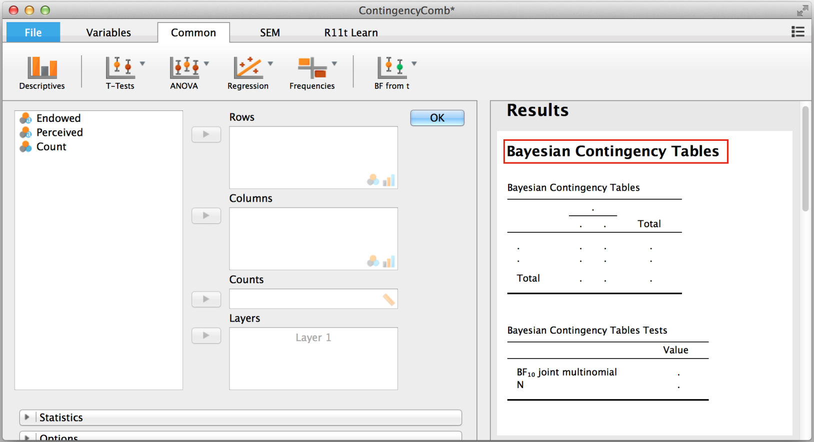
$$\mathrm{BF}_{01}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) \approx 9.6 \tag{4}$$

in favour of the null.

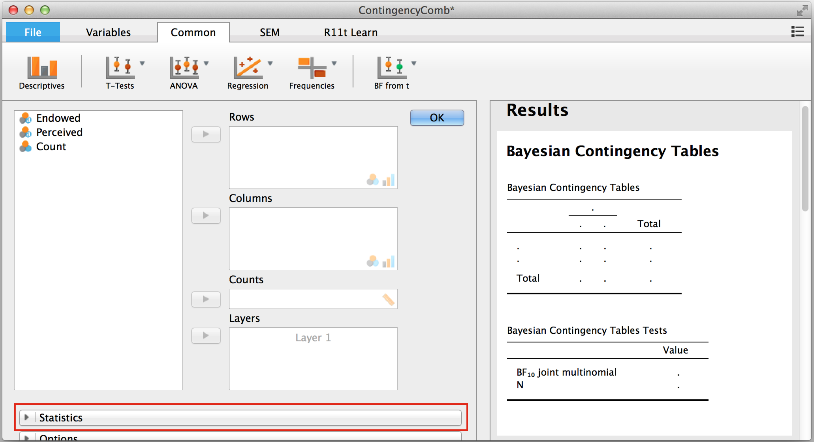
1. Load "contingencyComb.csv"



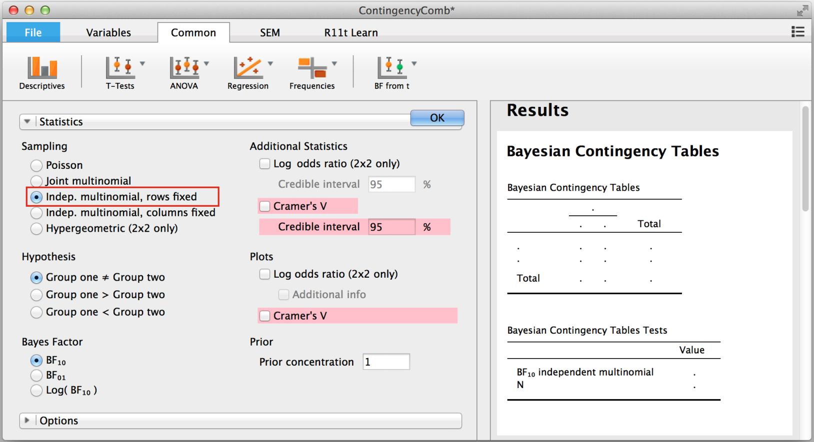
2. Choose "Bayesian Contingency Tables"



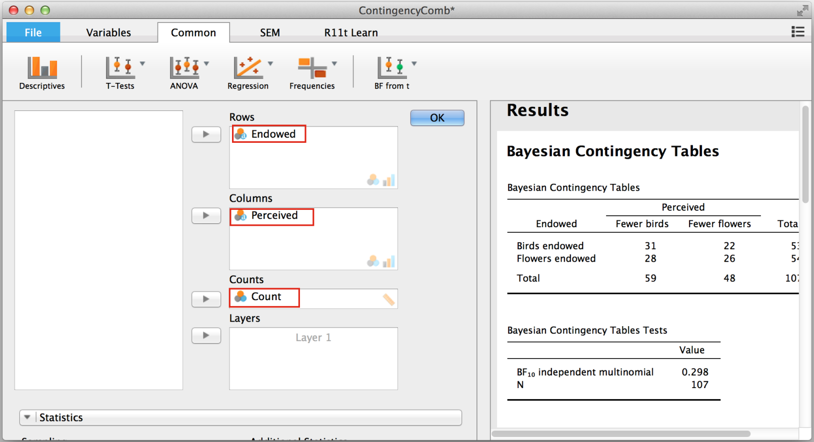
3. Choose right analysis



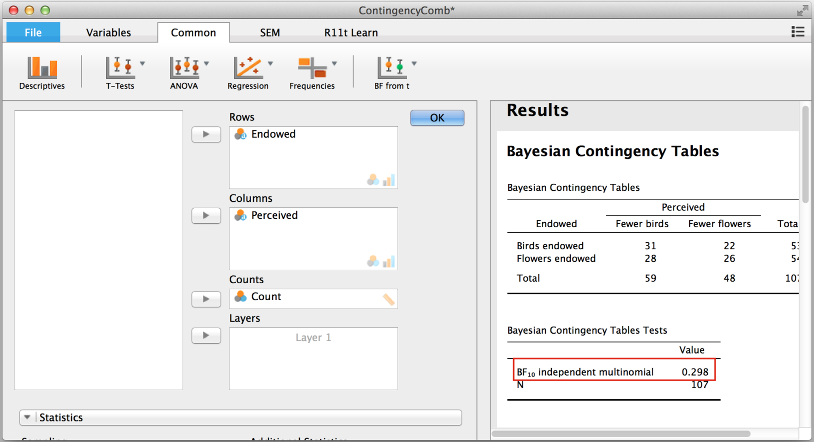
3. Choose right analysis



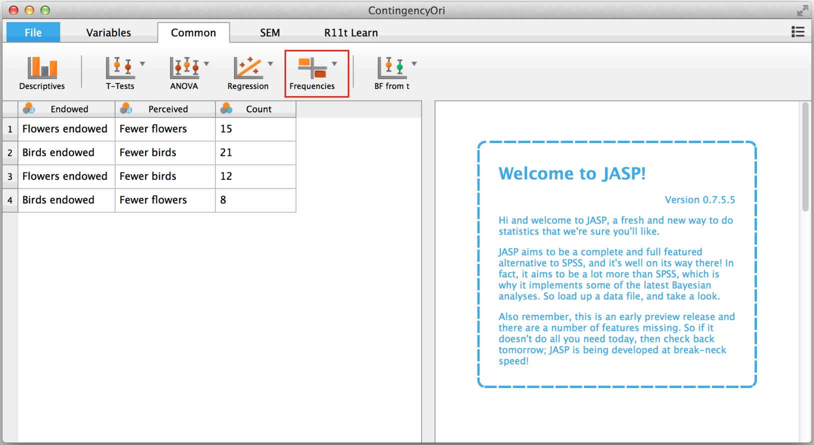
4. Fill in table



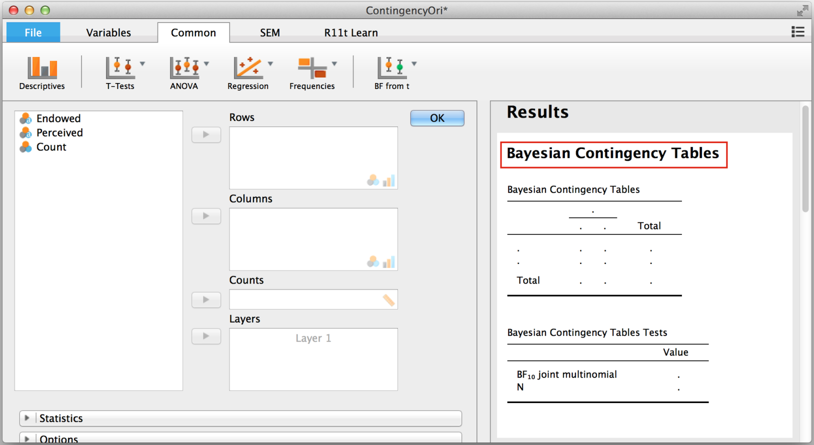
5. Write down result



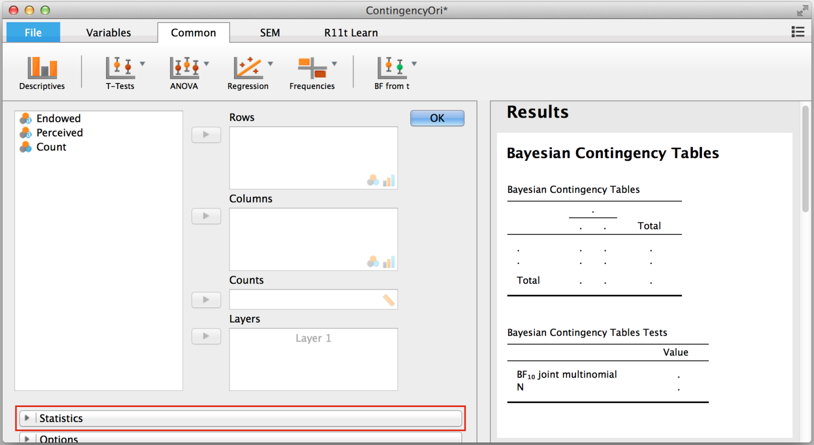
1. Load "contingencyOri.csv"



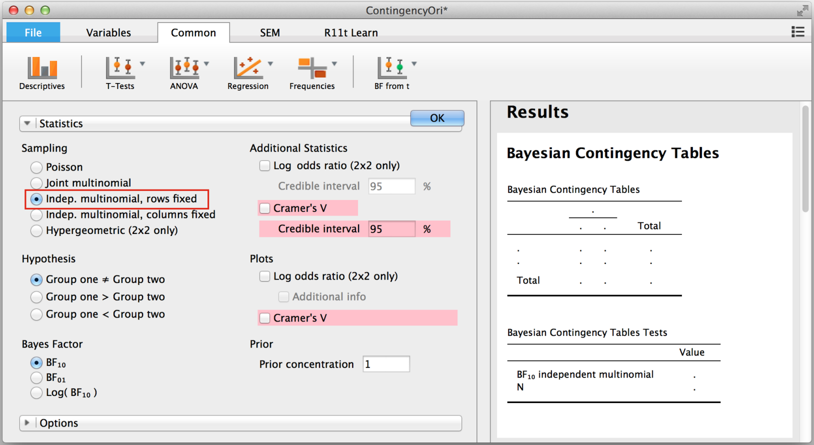
2. Choose "Bayesian Contingency Tables"



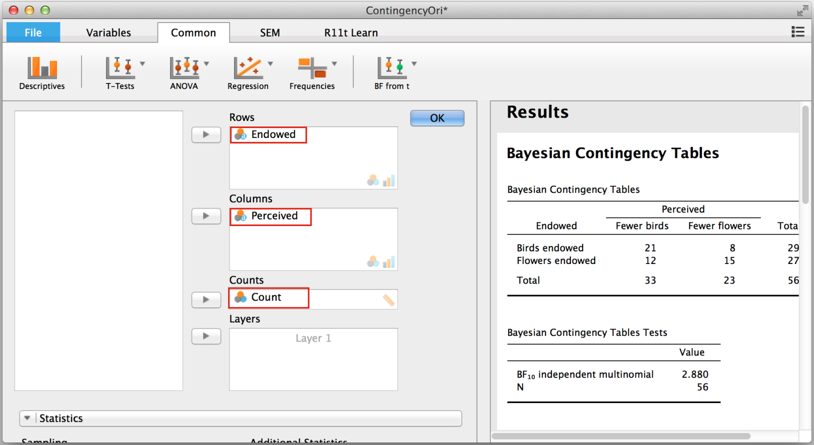
3. Choose right analysis



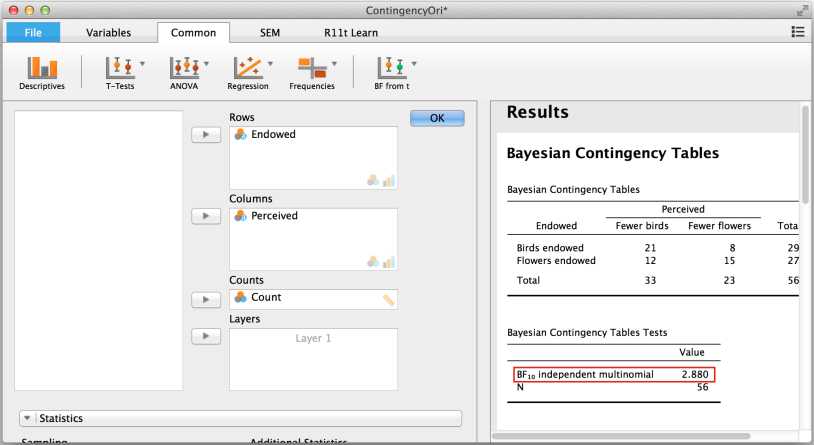
3. Choose right analysis



4. Fill in table



5. Write down result



Calculate

- Combined data: $\mathrm{BF}_{10}(d_{\mathrm{orig}}, d_{\mathrm{rep}}) = 0.298$
- Original data: $\mathrm{BF}_{10}(d_{\mathrm{orig}}) = 2.880$

Calculate

- Combined data: $\mathrm{BF}_{10}(d_{\mathrm{orig}}, d_{\mathrm{rep}}) = 0.298$
- Original data: $\mathrm{BF}_{10}(d_{\mathrm{orig}}) = 2.880$
- Calculate replication Bayes factor

$$\mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) = \frac{0.298}{2.880} \approx 0.10 \tag{5}$$

Calculate

- Combined data: $\mathrm{BF}_{10}(d_{\mathrm{orig}}, d_{\mathrm{rep}}) = 0.298$
- Original data: $\mathrm{BF}_{10}(d_{\mathrm{orig}}) = 2.880$
- Calculate replication Bayes factor

$$\mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) = \frac{0.298}{2.880} \approx 0.10 \tag{5}$$

- Thus,

$$\mathrm{BF}_{01}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}}) = \frac{1}{\mathrm{BF}_{10}(d_{\mathrm{rep}} \mid d_{\mathrm{orig}})} \approx 9.6 \tag{6}$$

in favour of the null.

Conclusion and future endeavours

- You can already calculate replication Bayes factors in JASP.

Conclusion and future endeavours

- You can already calculate replication Bayes factors in JASP.
- i. By changing the priors.

Conclusion and future endeavours

- You can already calculate replication Bayes factors in JASP.
- i. By changing the priors.
- ii. Or by combining the data (this can be tricky).

Conclusion and future endeavours

- You can already calculate replication Bayes factors in JASP.
- i. By changing the priors.
- ii. Or by combining the data (this can be tricky).
- Requires full data: Social problem (publish raw data).

Conclusion and future endeavours

- You can already calculate replication Bayes factors in JASP.
- i. By changing the priors.
- ii. Or by combining the data (this can be tricky).
- Requires full data: Social problem (publish raw data).
- Replication Bayes factors depend on the (quality) of the data (pre-registration).

Conclusion and future endeavours

- You can already calculate replication Bayes factors in JASP.
- i. By changing the priors.
- ii. Or by combining the data (this can be tricky).
- Requires full data: Social problem (publish raw data).
- Replication Bayes factors depend on the (quality) of the data (pre-registration).
- 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