1   multibridge: An R Package To Evaluate Informed Hypotheses in Binomial and

2   Multinomial Models

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9   Abstract

10   The **multibridge** R package allows a Bayesian evaluation of informed hypotheses $\mathcal{H}_r$

11   applied to frequency data from an independent binomial or multinomial distribution.

12   **multibridge** uses bridge sampling to efficiently compute Bayes factors for the following

13   hypotheses concerning the latent category proportions $\boldsymbol{\theta}$: (a) hypotheses that postulate

14   equality constraints (e.g., $\theta_1 = \theta_2 = \theta_3$); (b) hypotheses that postulate inequality

15   constraints (e.g., $\theta_1 < \theta_2 < \theta_3$ or $\theta_1 > \theta_2 > \theta_3$); (c) hypotheses that postulate combinations

16   of inequality constraints and equality constraints (e.g., $\theta_1 < \theta_2 = \theta_3$); and (d) hypotheses

17   that postulate combinations of (a)–(c) (e.g., $\theta_1 < (\theta_2 = \theta_3), \theta_4$). Any informed hypothesis

18   $\mathcal{H}_r$ may be compared against the encompassing hypothesis $\mathcal{H}_e$ that all category

19   proportions vary freely, or against the null hypothesis $\mathcal{H}_0$ that all category proportions are

20   equal. **multibridge** facilitates the fast and accurate comparison of large models with

21   many constraints and models for which relatively little posterior mass falls in the restricted

22   parameter space. This paper describes the underlying methodology and illustrates the use

23   of **multibridge** through fully reproducible examples.

₂₄   multibridge: An R Package To Evaluate Informed Hypotheses in Binomial and

₂₅   Multinomial Models

₂₆   **Introduction**

₂₇   The most common way to analyze categorical variables is to conduct either binomial

₂₈ tests, multinomial tests, or chi-square goodness of fit tests. These tests compare the

₂₉ encompassing hypothesis to a null hypothesis that all underlying category proportions are

₃₀ either exactly equal, or follow a specific distribution. Accordingly, these tests are suitable

₃₁ when theories predict either the invariance of all category proportions or specific values. For

₃₂ instance, chi-square goodness of fit tests are commonly used to test Benford's law, which

₃₃ predicts the distribution of leading digits in empirical datasets (Benford, 1938; Newcomb,

₃₄ 1881). Often, however, the predictions that researchers are interested in are of a different

₃₅ kind. Consider for instance the weak-order mixture model of decision-making (Regenwetter

₃₆ & Davis-Stober, 2012). The theory predicts that individuals' choice preferences are weakly

₃₇ ordered at all times, that is, if they prefer choice A over B and B over C then they will

₃₈ also prefer A over C (Regenwetter, Dana, & Davis-Stober, 2011)—a well-constrained

₃₉ prediction of behavior. The theory is, however, silent about the exact values of each choice

₄₀ preference. Hence, the standard tests that compare $\mathcal{H}_e$ to $\mathcal{H}_0$ are unsuited to test the

₄₁ derived predictions. Instead, the predictions need to be translated into an informed

₄₂ hypothesis $\mathcal{H}_r$ that reflects the predicted ordinal relations among the parameters. Only

₄₃ then is it possible to adequately test whether the theory of weakly-ordered preference

₄₄ describes participants' choice behavior. Of course, researchers may be interested in more

₄₅ complex hypotheses, including ones that feature combinations of equality constraints,

₄₆ inequality constraints, and unconstrained category proportions. For instance, Nuijten,

₄₇ Hartgerink, Assen, Epskamp, and Wicherts (2016) hypothesized that articles published in

₄₈ social psychology journals would have higher error rates than articles published in other

₄₉ psychology journals. As in the previous example, the authors had no expectations about

the exact error rate distribution across journals. Here, again, the standard tests are inadequate. Generally, by specifying informed hypotheses researchers and practitioners are able to "add theoretical expectations to the traditional alternative hypothesis'' (Hoijtink, Klugkist, & Boelen, 2008, p. 2) and thus test hypotheses that relate more closely to their theories (Haaf, Klaassen, & Rouder, 2019; Rijkeboer & van den Hout, 2008).

In the Bayesian framework, researchers may test hypotheses of interest by means of Bayes factors (Jeffreys, 1935; Kass & Raftery, 1995). Bayes factors quantify the extent to which the data change the prior model odds to the posterior model odds, that is, the extent to which one hypothesis outpredicts the other. Specifically, Bayes factors are the ratio of marginal likelihoods of the respective hypotheses. For instance, the Bayes factor for the informed hypothesis versus the encompassing hypothesis is defined as:

$$\mathrm{BF}_{re} = \frac{\overbrace{p(\mathbf{x} \mid \mathcal{H}_r)}^{\substack{\text{Marginal likelihood} \\ \text{under } \mathcal{H}_r}}}{\underbrace{p(\mathbf{x} \mid \mathcal{H}_e)}_{\substack{\text{Marginal likelihood} \\ \text{under } \mathcal{H}_e}}},$$

where the subscript r denotes the informed hypothesis and e denotes the encompassing hypothesis. Several available R packages compute Bayes factors for informed hypotheses. For instance, the package **multinomineq** (Heck & Davis-Stober, 2019) evaluates informed hypotheses for multinomial models as well as models that feature independent binomials. The package **BFpack** (Joris Mulder et al., 2021) evaluates informed hypotheses for statistical models such as univariate and multivariate normal linear models, generalized linear models, special cases of linear mixed models, survival models, and relational event models. The package **bain** (Gu, Hoijtink, Mulder, & Rosseel, 2019) evaluates informed hypotheses for structural equation models. Outside of R, the Fortran 90 program **BIEMS** (Joris Mulder, Hoijtink, & de Leeuw, 2012) evaluates informed hypotheses for multivariate linear models such as MANOVA, repeated measures, and multivariate regression. All these packages rely on one of two implementations of the encompassing prior approach (Klugkist, Kato, & Hoijtink, 2005; Sedransk, Monahan, & Chiu, 1985) to approximate order

68 constrained Bayes factors: the unconditional encompassing method (Klugkist et al., 2005 ;

69 Hoijtink, 2011; Hoijtink et al., 2008) and the conditional encompassing method (Gu,

70 Mulder, Deković, & Hoijtink, 2014; Laudy, 2006; Joris Mulder, 2014; J. Mulder, 2016; J.

71 Mulder et al., 2009). Even though the encompassing prior approach is currently the most

72 common method to evaluate informed hypotheses, it becomes increasingly unreliable and

73 inefficient as the number of restrictions increases or the parameter space of the restricted

74 model decreases (Sarafoglou et al., 2021). For instance, simulation studies conducted by

75 Sarafoglou et al. (2021) have illustrated that the unconditional encompassing approach is

76 not able to produce Bayes factors when hypotheses with a large number of constrained

77 parameters are considered (i.e., they considered 18 categories). For hypotheses with fewer

78 categories (i.e., 5 or 6), the method worked well when the data provided either weak or

79 moderate evidence in favor of or against the informed hypothesis. However, when the data

80 provided extreme evidence against the predicted constraints, the method again failed to

81 compute Bayes factors.

82   As alternative to the encompassing prior approach, Sarafoglou et al. (2021) recently

83 proposed a bridge sampling routine (Bennett, 1976; Meng & Wong, 1996) that computes

84 Bayes factors for informed hypotheses more reliably and efficiently. This routine is

85 implemented in **multibridge** (https://CRAN.R-project.org/package=multibridge) and is

86 suitable to evaluate inequality constraints for multinomial and binomial models as well as

87 combinations between equality and inequality constraints.

88   Here we showcase how the proposed bridge sampling routine by Sarafoglou et al.

89 (2021) can be performed with **multibridge**. In the remainder of this article, we will

90 introduce the package and its functionalities and describe the methods used to compute

91 the informed hypotheses in binomial and multinomial models. We will illustrate its core

92 functions using three examples and end with a brief discussion and future directions.

₉₃   **Multibridge**

₉₄   The general workflow of **multibridge** is illustrated in Figure 1. The core functions of

₉₅ **multibridge**, that is `mult_bf_informed` and `binom_bf_informed`, return the Bayes factor

₉₆ estimate in favor of or against the informed hypothesis. To compute a Bayes factor, the

₉₇ core functions require the observed counts, the informed hypothesis, the parameters of the

₉₈ prior distribution under $\mathcal{H}_e$, and the category labels. An overview of the basic required

₉₉ arguments of the two core functions are provided in Table 1.

₁₀₀   When calling `mult_bf_informed` or `binom_bf_informed`, the user specifies the data

₁₀₁ values (`x` and `n` for binomial models and `x` for multinomial models, respectively), the

₁₀₂ informed hypothesis (`Hr`), the α and β parameters of the binomial prior distributions (`a`

₁₀₃ and `b`) or the concentration parameters for the Dirichlet prior distribution (`a`), respectively,

₁₀₄ and the category labels of the factor levels (`factor_levels`). The functions then return

₁₀₅ the estimated Bayes factor for the informed hypothesis relative to the encompassing

₁₀₆ hypothesis that imposes no constraints on the category proportions or the null hypothesis

₁₀₇ which states that all category proportions are equal. Based on these results different S3

₁₀₈ methods can be used to get more detailed information on the individual components. For

₁₀₉ instance, users can extract the Bayes factor with the `bayes_factor`-method, visualize the

₁₁₀ posterior parameter estimates under the encompassing hypothesis using the `plot`-method,

₁₁₁ or get more detailed information on how the Bayes factor is composed using the

₁₁₂ `summary`-method. Table 2 summarizes all S3 methods currently available in **multibridge**.

₁₁₃ **Supported Hypotheses**

₁₁₄   The following hypotheses are supported in **multibridge**. Users can test hypotheses

₁₁₅ on equality and inequality constraints among parameters (left column in Figure 2). We

₁₁₆ consider inequality constraints, for instance, in Example 3 of this manuscript, when we test

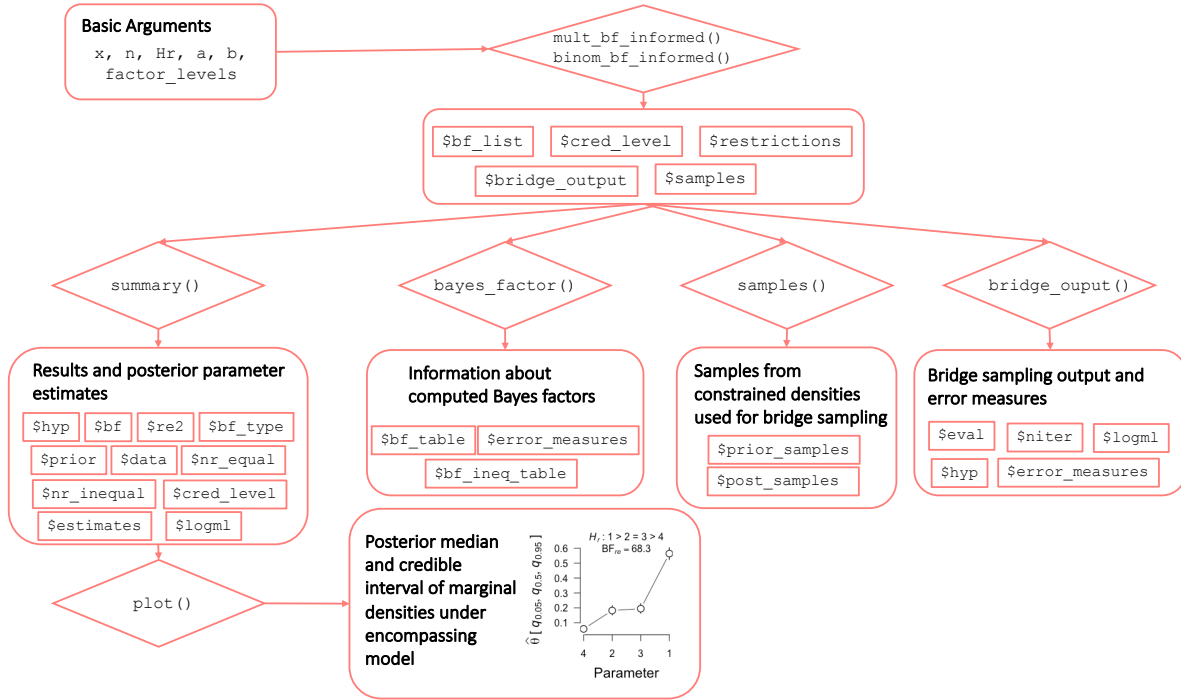₁₁₇ whether the probability to violate stochastic dominance decreases for persons with higher

Figure 1. The **multibridge** workflow. The functions `mult_bf_informed` or `binom_bf_informed` return the estimated Bayes factor for the informed hypothesis relative to the encompassing or the null hypothesis. Based on these results different S3 methods can be used to get more detailed information on the individual components of the analysis (e.g., `summary`, `bayes_factor`), and parameter estimates of the encompassing distribution (`plot`).

118 education levels (Myung, Karabatsos, & Iverson, 2005).

119 Additionally, **multibridge** supports the evaluation of combinations of equality

120 constraints, inequality constraints, and free parameters (middle column). As an example,

121 the hypothesis in the top middle panel identifies a largest parameter (θ_1) and a smallest

122 parameter (θ_5), and equates the remaining parameters ($\theta_2 = \theta_3 = \theta_4$). Combinations of

123 constraints are considered, for instance, in Example 2 of this manuscript. Based on Nuijten

124 et al. (2016) we test whether the proportion of statistical reporting errors is higher for

125 articles published in the *Journal of Personality and Social Psychology* (JPSP) than for

126 articles published in seven other high-profile psychology journals.

₁₂₇   The package also supports the computation of Bayes factors for multiple independent

₁₂₈ constraints, representing, for instance, two main effects (right column). For instance, the

₁₂₉ hypothesis in the bottom right panel describes an inequality constraint on the first three

₁₃₀ category proportions ($\theta_1 > \theta_2 > \theta_3$) and an equality constraint on the fourth and fifth
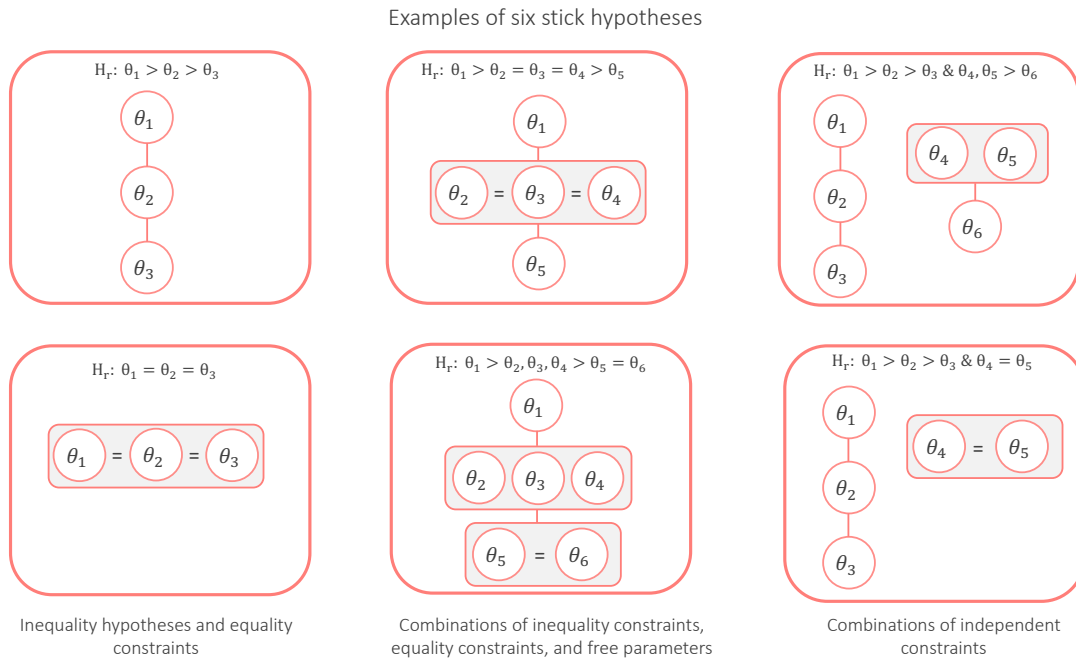
₁₃₁ category proportion ($\theta_4 = \theta_5$).

Examples of six stick hypotheses

Inequality hypotheses and equality constraints

Combinations of inequality constraints, equality constraints, and free parameters

Combinations of independent constraints

Figure 2. **multibridge** supports informed hypotheses including inequality and equality constraints (left column), combinations of inequality and equality constraints and free parameters (middle column), and multiple independent constraints (right column). Parameters with larger values appear higher in the drawing. A prerequisite of **multibridge** is that all elements within a constraint can be arranged as a linearly ordered set.

₁₃₂   An important requirement for the hypotheses supported in **multibridge** is that

₁₃₃ within each independent constraint, all elements are arranged as a linearly ordered set.

₁₃₄ Elements can refer to individual parameters as shown in the top left panel of Figure 2. In

₁₃₅ this example, for each pair of elements one precedes the other in the sequence (i.e., θ_1

₁₃₆ precedes θ_2 and θ_2 precedes θ_3). Elements can also refer to a group of equality constrained

137   parameters or a group of free parameters as shown in the middle panel of Figure 2. In the

138   top middle panel, too, for each pair of elements one precedes the other in the sequence

139   (e.g., θ_1 precedes $(\theta_2 = \theta_3 = \theta_4)$ and $(\theta_2 = \theta_3 = \theta_4)$ precedes θ_5). That is, if the constraint

140   was to be drawn as a Hasse diagram or specified as a character vector, the constrained

141   elements should string together like a chain, ranging from the smallest element to the

142   largest. We refer to these hypotheses as "stick hypotheses".

143   Conversely, "branched hypotheses'', are hypotheses in which elements are not

144   arranged as a linearly ordered set but as a partial order, meaning that some but not all

145   pairs of elements precede one another. These hypotheses are *not* supported in

146   **multibridge**. Examples for branched hypotheses are shown in Figure 3. For instance, the

147   hypothesis illustrated in the left panel states that θ_1 precedes all other parameters. In

148   addition, the hypothesis orders the branches $(\theta_2, \theta_3, \theta_4)$ and $(\theta_5, \theta_6, \theta_7)$. However, it

149   remains unclear whether, for instance, θ_3 or θ_5 precede the other in the sequence. Thus,

150   not all pairs of elements are comparable. Similarly, in all three examples of branched

151   hypotheses it is unclear whether θ_3 precedes or follows θ_6. Researchers whose theories give

152   rise to branched hypotheses and wish to test them can do so using one of the alternative `R`

153   packages, for instance, **multinomineq** by Heck and Davis-Stober (2019).

154   When an informed hypothesis includes combinations of equality and inequality

155   constraints, the core functions in **multibridge** split the hypothesis to compute Bayes

156   factors separately for imposed equality constraints (for which the Bayes factor has an

157   analytic solution) and inequality constraints (for which the Bayes factor is estimated using

158   bridge sampling). Hence, for hypotheses that include combinations of equality and

159   inequality constraints the `bayes_factor` method separately returns the Bayes factor for

160   the equality constraints and the conditional Bayes factor for the inequality constraints

161   given the equality constraints.

162   The informed hypothesis `Hr` can be conveniently specified as a string or a character
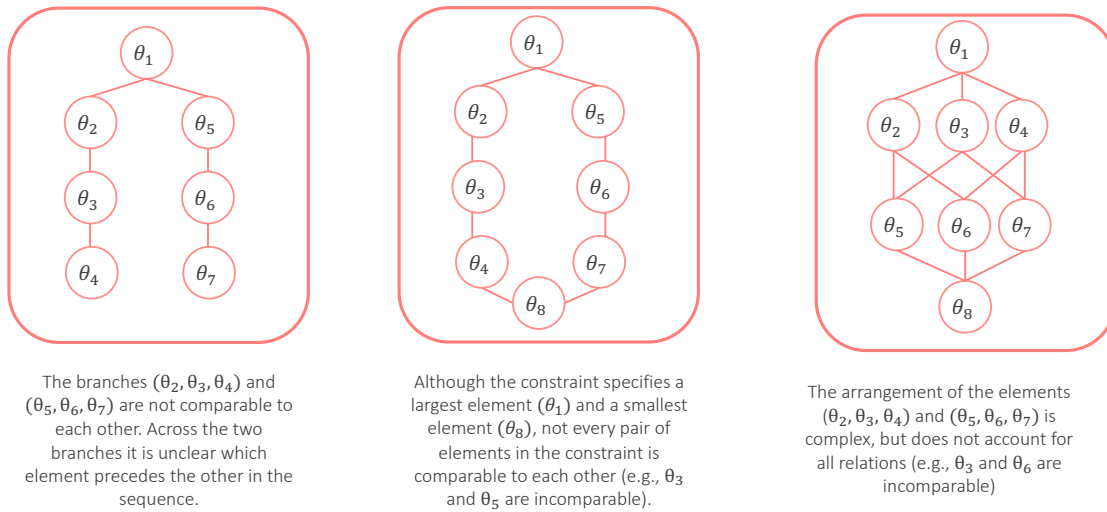
Examples of three branched hypotheses

The branches ($\theta_2, \theta_3, \theta_4$) and ($\theta_5, \theta_6, \theta_7$) are not comparable to each other. Across the two branches it is unclear which element precedes the other in the sequence.

Although the constraint specifies a largest element (θ_1) and a smallest element (θ_8), not every pair of elements in the constraint is comparable to each other (e.g., θ_3 and θ_5 are incomparable).

The arrangement of the elements ($\theta_2, \theta_3, \theta_4$) and ($\theta_5, \theta_6, \theta_7$) is complex, but does not account for all relations (e.g., θ_3 and θ_6 are incomparable)

Figure 3. Examples of three hypotheses in which elements in a constraint are arranged as a partial order. In each panel there exist elements that are not comparable with each other, that is, for which neither element precedes the other in the sequence. The partial order shows itself in the branching of the Hasse diagram. These branched hypotheses are currently not supported in **multibridge**.

163   vector describing the relations among the category proportions. A simple ordering of three

164   category proportions, $\theta_1 > \theta_2 > \theta_3$, can be specified either as `c("t1", ">", "t2", ">",`

165   `"t3")`, or as `"t1 > t2 > t3"`. To assign labels to the parameters, they must be passed to

166   the argument `factor_levels`. **multibridge** then assumes that the order within the

167   category labels correspond to the order of the data vector. Alternatively, the informed

168   hypotheses can be specified using indices (e.g., `"1 > 2 > 3"`). To avoid circularity, an

169   index or category label can be used only once within an informed hypothesis.

Table 1

To estimate the Bayes factor in favor for or against the specified informed hypothesis, the user provides the core functions `mult_bf_informed` and `binom_bf_informed` with the basic required arguments listed below.

Argument	Description
x	`numeric`. Vector with data (for multinomial models) or a vector of counts of successes, or a two-dimensional table (or matrix) with 2 columns, giving the counts of successes and failures, respectively (for binomial models).
n	`numeric`. Vector with counts of trials. Must be the same length as `x`. Ignored if `x` is a matrix or a table. Included only in binom_bf_informed.
Hr	`string` or `character`. String or a character vector with the user specified informed hypothesis. Parameters may be referenced by the specified `factor_levels` or by numerical indices.
a	`numeric`. Vector with concentration parameters of Dirichlet distribution (for multinomial models) or α parameters for independent beta distributions (for binomial models). Must be the same length as `x`. Default sets all parameters to 1.
b	`numeric`. Vector with β parameters. Must be the same length as `x`. Default sets all β parameters to 1. Included only in binom_bf_informed.
factor_levels	`character`. Vector with category labels. Must be the same length as `x`.

170   Signs permitted to specify informed hypotheses are the `$<$''-sign and`>''-sign for
171   inequality constraints, the `$=$''-sign for equality constraints, the,''-sign for
172   parameters that vary freely within a constraint, and the "&"-sign to connect multiple
173   independent constraints. For instance, the informed hypothesis in the top right panel in
174   Figure 2, that is, `"t1 > t2 > t3 & t4 , t5 > t6"`, states that `t1` is bigger than `t2`,
175   and that `t2`, is bigger than `t3`. In addition, the hypothesis states that `t4` and `t5` are bigger
176   than `t6`, with no further constraints imposed among `t4` and `t5`.

177   When testing equality constrained hypotheses, users should be aware that there is a
178   difference between assuming equality of category proportions and adding categories
179   together, that is, the hypothesis $\mathcal{H}_r : \theta_1 = \theta_2 > \theta_3 = \theta_4$ differs from the hypothesis
180    $\mathcal{H}_r : \theta_1 + \theta_2 > \theta_3 + \theta_4$. The first hypothesis concerns four category proportions of which two
181   pairs are expected to be equal; as a result, we assign a $K = 4$ Dirichlet prior to this
182   distribution. The second hypothesis concerns only two categories since we assume that θ_1
183   and θ_2 belong to one group and θ_3 and θ_4 belong to the other. Consequently, one assigns a
184    $K = 2$ Dirichlet prior to this distribution. Therefore, to test the second hypothesis, the
185   respective counts of the categories should first be combined and the analysis should be
186   performed on the basis of these new data.

Table 2

*S3 methods available in **multibridge**.*

Function Name(s)	S3 Method	Description
`mult_bf_informed`, `binom_bf_informed`	`print`	Prints model specifications and descriptives.
	`summary`	Prints and returns the Bayes factor and associated hypotheses for the full model, and all equality and inequality constraints.
	`plot`	Plots the posterior median and credible interval of the parameter estimates of the encompassing model. Default sets credible interval to 95%.
	`bayes_factor`	Contains all Bayes factors and log marginal likelihood estimates for inequality constraints.
	`samples`	Extracts prior and posterior samples from constrained densities (if bridge sampling was applied).
	`bridge_output`	Extracts bridge sampling output and associated error measures.
	`restriction_list`	Extracts restriction list and associated informed hypothesis.
`mult_bf_inequality`, `binom_bf_inequality`	`print`	Prints the bridge sampling estimate for the log marginal likelihood and the corresponding percentage error.
	`summary`	Prints and returns the bridge sampling estimate for the log marginal likelihood and associated error terms.

In **multibridge**, the functions `mult_bf_informed` and `binom_bf_informed` perform all necessary analysis steps. Other available functions compute Bayes factors for hypotheses that postulate only equality or only inequality constraints, and draw from constrained multinomial distributions and distributions of multiple independent binomials. A list of all currently available functions and data sets is given in Table 3.

Table 3

*Core functions available in **multibridge**.*

Function Name(s)	Description
`mult_bf_informed`	Evaluates informed hypotheses on multinomial parameters.
`mult_bf_inequality`	Estimates the marginal likelihood of a constrained prior or posterior Dirichlet distribution.
`mult_bf_equality`	Computes Bayes factor for equality constrained multinomial parameters using the standard Bayesian multinomial test.
`mult_tsampling`	Samples from constrained prior or posterior Dirichlet density.
`lifestresses`, `peas`	Data sets associated with informed hypotheses in multinomial models.
`binom_bf_informed`	Evaluates informed hypotheses on binomial parameters.
`binom_bf_inequality`	Estimates the marginal likelihood of constrained prior or posterior beta distributions.
`binom_bf_equality`	Computes Bayes factor for equality constrained binomial parameters.
`binom_tsampling`	Samples from constrained prior or posterior beta densities.
`journals`	Data set associated with informed hypotheses in binomial models.
`generate_restriction_list`	Encodes the informed hypothesis.

Methodological Background

In this section we provide background information on the methods implemented in **multibridge**. Specifically, we formalize multinomial models and models that feature independent binomial probabilities, and define Bayes factors for the Bayesian multinomial test and testing equality of multiple independent binomial probabilities. Furthermore, the section discusses the influence of priors on the Bayes factors, illustrates how to compute posterior model probabilites and how to compare two informed hypotheses with each other, and provides a non-technical introduction into the bridge sampling routine implemented in **multibridge**. Mathematical details of the methods and principles discussed here can be found in Sarafoglou et al. (2021) and Gronau et al. (2017).

In the binomial model, we assume that the elements in the vector of successes $\mathbf{x}$ and the elements in the vector of total number of observations $\mathbf{n}$ in the K categories follow independent binomial distributions $\mathbf{x} \sim \prod_{k=1}^{K} \mathrm{Binomial}(\theta_k, n_k)$, where θ_k is the kth category proportion. From this distribution we can derive the likelihood of the data given the parameters:

$$p(\mathbf{x} \mid \boldsymbol{\theta}) = \prod_{k=1}^{K} \binom{n_k}{x_k} \theta_k^{x_k} (1 - \theta_k)^{n_k - x_k}.$$

The parameter vector of the binomial success probabilities $\boldsymbol{\theta}$ contains the underlying category proportions and assume that categories are independent. Therefore, a suitable choice for a prior distribution for $\boldsymbol{\theta}$ is a vector of independent beta distributions with parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, thus $\boldsymbol{\theta} \sim \prod_{k=1}^{K} \mathrm{Beta}(\alpha_k, \beta_k)$. The prior density is given by:

$$p(\boldsymbol{\theta}) = \prod_{k=1}^{K} \frac{\theta_k^{\alpha_k - 1} (1 - \theta_k)^{\beta_k - 1}}{\mathrm{B}(\alpha_k, \, \beta_k)},$$

where $\mathrm{B}(\alpha_k, \, \beta_k)$ is the beta function:

$$\mathrm{B}(\alpha_k, \, \beta_k) = \frac{\Gamma(\alpha_k) \Gamma(\beta_k)}{\Gamma(\alpha_k + \beta_k)}.$$

The multinomial model generalizes the binomial model for cases where $K > 2$. In this model, we assume that the vector of observations $\mathbf{x}$ in the K categories follows a

214 multinomial distribution in which the parameters of interest, $\boldsymbol{\theta}$, represent the underlying

215 category proportions, thus $\mathbf{x} \sim \text{Multinomial}(x_+, \boldsymbol{\theta})$, where $x_+ = \sum_{k=1}^{K} x_k$.

216   Since the K categories are dependent, the vector of probability parameters is

217 constrained to sum to one, such that $\sum_{k=1}^{K}(\theta_1, \cdots, \theta_K) = 1$. Therefore, a suitable choice for

218 a prior distribution for $\boldsymbol{\theta}$ is the Dirichlet distribution with concentration parameter vector

219 $\boldsymbol{\alpha}$, $\boldsymbol{\theta} \sim \text{Dirichlet}(\boldsymbol{\alpha})$:

$$p(\boldsymbol{\theta}) = \frac{1}{\text{B}(\boldsymbol{\alpha})} \prod_{k=1}^{K} \theta_k^{\alpha_k - 1},$$

220 where $\text{B}(\boldsymbol{\alpha})$ is the multivariate beta function:

$$\text{B}(\boldsymbol{\alpha}) = \frac{\prod_{k=1}^{K} \Gamma(\alpha_k)}{\Gamma\left(\sum_{k=1}^{K} \alpha_k\right)}.$$

221   In `multibridge`, we have deliberately chosen to leave the priors at the original scale

222 (i.e., in the probability space), because it makes it easier to express ones expectations

223 about data patterns. Alternative approaches transform the model parameters into the

224 probit space, which has the advantage that correlations can be specified for hierarchical

225 models (e.g., as in the latent-trait model for multinomial processing tree models, Klauer,

226 2010; Matzke, Dolan, Batchelder, & Wagenmakers, 2015). However, these transformations

227 make the development of priors more difficult and can lead to unintended consequences; for

228 instance, a uniform prior on the probit scale does not translate to a uniform prior on the

229 probability scale (as discussed in Heck & Wagenmakers, 2016).

230 **Developing Suitable Prior Distributions**

231   In the binomial and multinomial model, the concentration parameters have an

232 intuitive interpretation. In the binomial model, the parameters α_k can be interpreted as

233 vector of *a priori* successes that observations fall within the various categories and β_k can

234 be interpreted as vector of *a priori* failures. Likewise, in the multinomial model, α_k can be

235 interpreted as vector of *a priori* category counts. It follows, that the higher the number of

236 concentration parameters is, the information the prior contains and the more influence it

237 has on parameter estimation and hypothesis testing.

238   Developing suitable prior distributions for Bayesian inference is a much discussed

239 topic involving various theoretical and computational considerations (see Consonni,

240 Fouskakis, Liseo, and Ntzoufras (2018) for a review paper on prior distributions for

241 objective Bayesian analysis). Therefore, recommending approaches for developing

242 appropriate prior distributions is, in our view, a difficult undertaking. In this section, we

243 therefore present a selected subset of approaches that we consider particularly suitable for

244 assigning adequate priors for the multiple binomials model and the multinomial model.

245   If researchers possess no knowledge or expectations about the plausible parameter

246 values, a uniform distribution can be assigned across the parameter space. This prior

247 assumes that before seeing the data, each category contains one observation, that is, all

248 concentration parameters are set to one. A uniform prior distribution, puts equal

249 probability mass on all permitted parameter values, similar to the adjusted priors for

250 reparametrized models proposed by Heck and Wagenmakers (2016) (see Figure 4).

251 However, **multibridge** allows priors to be set on the original scale.

252   We recommend incorporating prior knowledge into the models whenever possible.

253 Based on theories, expert knowledge, or informed guesses, researchers often have

254 expectations about plausible and implausible parameter values. In these cases, the prior

255 should match these expectations (Lee & Vanpaemel, 2018). For instance, in the case of

256 informed hypotheses, prior counts can be chosen to match a particular expected ordinal

257 trend. To determine whether the chosen priors are consistent with the theory, researchers

258 can visualize and assess prior predictive distributions, that is, the distribution of the model

259 parameters and data patterns predicted by the priors (Gabry, Simpson, Vehtari,

260 Betancourt, & Gelman, 2019; Schad, Betancourt, & Vasishth, 2021; Wagenmakers et al.,

261 2021). The developed priors should reflect expectations about the parameters and make
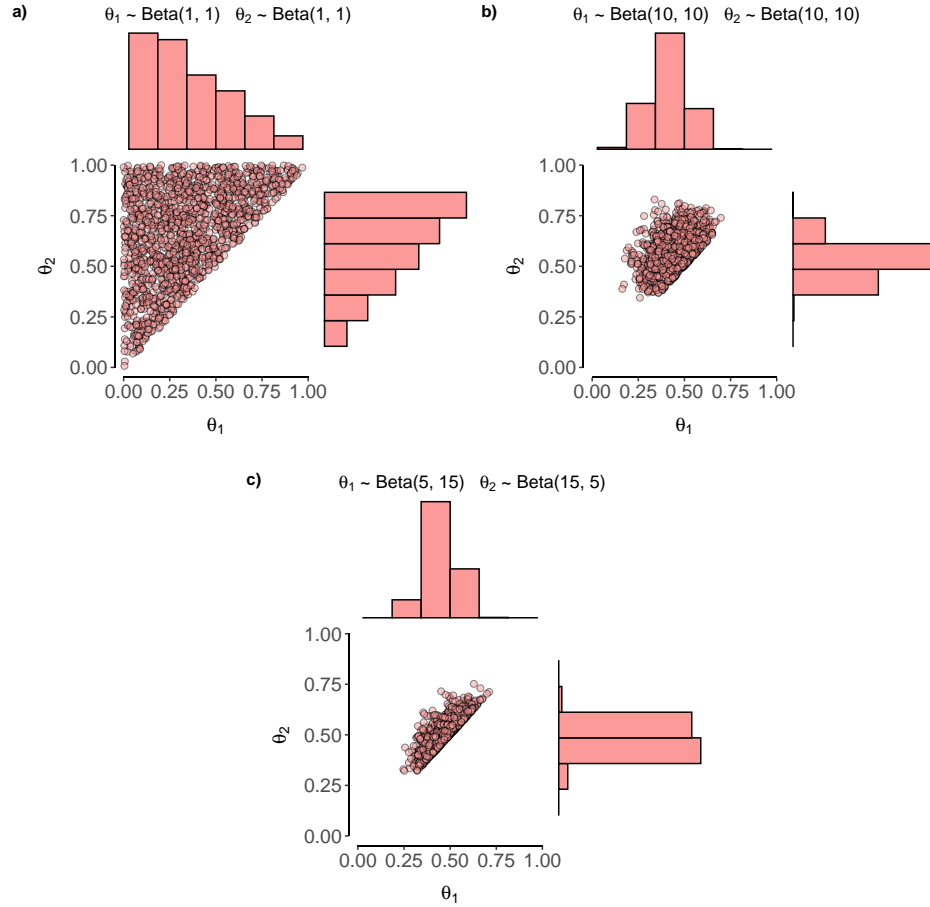
Figure 4. The development of a prior distribution should be accompanied by a visual inspection of the prior predictive. Here we display three prior distributions on two binomial probabilities that are constrained to be $\theta_1 < \theta_2$. The uniform distribution (panel a) assigns equal mass to all permissible values of the constrained space. A symmetric prior (panel b) concentrates the mass in the center of the distribution. A prior describing a constraint in the opposite direction (panel c), puts most of the density along the diagonal.

262 sensible predictions. This is particularly important for Bayes factor hypothesis testing;

263 when the purpose is parameter estimation, however, it may be more informative to assign

264 prior parameter distributions that are relatively wide (e.g., Doorn et al., 2021).

265   Furthermore, one can choose the observed category counts of previous studies as

266 priors for the current one, as is often suggested for replication studies and referred to as

267 "Bayesian learning'' (e.g., Verhagen & Wagenmakers, 2014). This approach constructs

268 highly informative priors; instead of describing the new data as precisely as possible, the

269 goal with this approach is quantify the additional knowledge gained by the new data.

270 Finally, priors can be constructed using a fraction of the likelihood of the data while

271 centering it on the the mean of the parameter range (Gu, Mulder, & Hoijtink, 2018; Joris

272 Mulder, 2014).

273 **Bayes factor**

274   **multibridge** features two different methods to compute Bayes factors: one method

275 computes Bayes factors for equality constrained parameters (which can be computed

276 analytically) and one method computes Bayes factors for inequality constrained parameters

277 (which needs to be approximated). In cases where informed hypotheses feature

278 combinations between inequality and equality constraints, **multibridge** computes the

279 overall Bayes factor BF_{re} by multiplying the individual Bayes factors for both constraint

280 types. This is motivated by the fact that the Bayes factor for combinations (BF_{re}) will

281 factor into a Bayes factor for the equality constraints (BF_{1e}) and a conditional Bayes factor

282 for the inequality constraints given the equality constraints $(\text{BF}_{2e|1e})$. For instance, to

283 evaluate the hypothesis $\mathcal{H}_r : \theta_1 > \theta_2 = \theta_3$, **multibridge** factors the Bayes factor as follows:

$$\text{BF}_{re} = \underbrace{\frac{p(\theta_1 > \theta_{23} \mid \theta_2 = \theta_3, \, \mathbf{x}, \, \mathcal{H}_e)}{p(\theta_1 > \theta_{23} \mid \theta_2 = \theta_3, \, \mathcal{H}_e)}}_{\text{BF}_{2e|1e}} \times \underbrace{\frac{p(\theta_2 = \theta_3 \mid \mathbf{x}, \, \mathcal{H}_e)}{p(\theta_2 = \theta_3 \mid \mathcal{H}_e)}}_{\text{BF}_{1e}},$$

284   where the subscript 1 denotes the hypothesis that only features equality constraints,

285   the subscript 2 denotes the hypothesis that only features inequality constraints, and

286    $p(\theta_1 > \theta_{23} \mid \theta_2 = \theta_3)$ refers to a Dirichlet integral, where the category proportions θ_2 and θ_3

287   are collapsed. See Sarafoglou et al. (2021) for the proof and a detailed account of this

288   method.

289   **Testing Equality Constraints.**   For equality constrained binomial models

290   **multibridge** supports two null hypotheses, one stating that all parameters are equal and

291   one stating that all parameters are equal to a specific value. Both null hypotheses are

292   tested against an encompassing hypothesis. Under the encompassing hypothesis, we specify

293   a Beta(α_k, β_k) prior on each of the θ_k that yields the following marginal likelihood:

$$p(\mathbf{x} \mid \mathcal{H}_e) = \frac{\prod_{k=1}^{K} \binom{n_k}{x_k} \times \mathrm{B}(x_k + \alpha_k,\, n_k - x_k + \beta_k)}{\prod_{k=1}^{K} \mathrm{B}(\alpha_k,\, \beta_k)}.$$

294   Under the first null hypothesis which states that all binomial probabilities are set

295   equal without a constraint on a specific value, we collapse all individual Beta(α_k, β_k) priors

296   and correct for the change in categories; if K categories are collapsed, $K - 1$ is subtracted

297   from the concentration parameters. The resulting prior is a

298   Beta$(\alpha_+ - (K - 1), \beta_+ - (K - 1))$ distribution on θ, where $\alpha_+ = \sum_{k=1}^{K} \alpha_k$ and

299    $\beta_+ = \sum_{k=1}^{K} \beta_k$. Hence, a Beta$(1, 1)$ prior on each individual category proportion yields

300   again a Beta$(1, 1)$ prior on the categories that are collapsed. When the prior is more

301   informative, say a Beta$(2, 2)$ prior on three individual category proportions, it would result

302   in a Beta$(4, 4)$ prior on θ as the information available is added together. The

303   corresponding marginal likelihood takes the following form:

$$p(\mathbf{x} \mid \mathcal{H}_{01}) = \frac{\prod_{k=1}^{K} \binom{n_k}{x_k} \times \mathrm{B}(x_+ + \alpha_+ - (K - 1),\, n_+ - x_+ + \beta_+ - (K - 1))}{\mathrm{B}(\alpha_+ - (K - 1),\, \beta_+ - (K - 1))}.$$

We can now compute the Bayes factor BF_{01e} as follows:

$$\text{BF}_{0e} = \frac{p(\mathbf{x} \mid \mathcal{H}_0)}{p(\mathbf{x} \mid \mathcal{H}_e)}$$

$$= \frac{\frac{\prod_{k=1}^{K} \binom{n_k}{x_k} \times \text{B}(x_+ + \alpha_+ - (K-1),\, n_+ - x_+ + \beta_+ - (K-1))}{\text{B}(\alpha_+ - (K-1),\, \beta_+ - (K-1))}}{\frac{\prod_{k=1}^{K} \binom{n_k}{x_k} \times \text{B}(x_k + \alpha_k,\, n_k - x_k + \beta_k)}{\prod_{k=1}^{K} \text{B}(\alpha_k,\, \beta_k)}}$$

$$= \frac{\prod_{k=1}^{K} \text{B}(x_+ + \alpha_+ - (K-1),\, n_+ - x_+ + \beta_+ - (K-1))}{\prod_{k=1}^{K} \text{B}(x_k + \alpha_k,\, n_k - x_k + \beta_k)} \times \frac{\prod_{k=1}^{K} \text{B}(\alpha_k,\, \beta_k)}{\text{B}(\alpha_+ - (K-1),\, \beta_+ - (K-1))}$$

The second null hypothesis states that all binomial probabilities in a model are assumed to be exactly equal *and* equal to a predicted value θ_0. Under this hypothesis, the prior reduces to a single point and the marginal likelihood simplifies to the likelihood function:

$$p(\mathbf{x} \mid \mathcal{H}_{02}) = \theta_0^{x_+} (1 - \theta_0)^{n_+ - x_+} \times \prod_{k=1}^{K} \binom{n_k}{x_k}.$$

The Bayes factor for the second null hypothesis is then defined as:

$$\text{BF}_{02e} = \frac{\prod_{k=1}^{K} \text{B}(\alpha_k,\, \beta_k)}{\prod_{k=1}^{K} \text{B}(\alpha_k + x_k,\, \beta_k + n_k - x_k)} \times \theta_0^{x_+} (1 - \theta_0)^{n_+ - x_+}.$$

Note that **multibridge** only supports the specification of one predicted value for all binomial probabilities.

```r
x <- c(3, 4, 10, 11)
n <- c(15, 12, 12, 12)
a <- c(1, 1, 1, 1)
b <- c(1, 1, 1, 1)
# assuming all binomial proportions are equal
binom_bf_equality(x=x, n=n, a=a, b=b)
# assuming all binomial proportions are equal
# and equal to a predicted value
binom_bf_equality(x=x, n=n, a=a, b=b, p = 0.5)
```

311   The Bayes factor BF_{0e} for the multinomial test is defined as:

$$\text{BF}_{0e} = \frac{\text{B}(\boldsymbol{\alpha})}{\text{B}(\boldsymbol{\alpha} + \mathbf{x})} \times \prod_{k=1}^{K} \theta_{0k}^{x_k},$$

312   where θ_{0k} represent the predicted category proportions (see Sarafoglou et al., 2021 for the

313   derivation). For multinomial models, under the null hypothesis, category probabilities can

314   either all be set equal (i.e., all category probabilities are $\frac{1}{K}$) or can replaced with the

315   user-specified predicted values.

```
x <- c(3, 4, 10, 11)

a <- c(1, 1, 1, 1)

# assuming all category proportions are exactly equal

mult_bf_equality(x=x, a=a)

# specifying predicted values

mult_bf_equality(x=x, a=a, p = c(0.1, 0.1, 0.3, 0.5))
```

316   **Testing Inequality Constraints.**   For inequality constrained binomial and

317   multinomial models, users can specify informed hypotheses that are either tested against a

318   null hypothesis postulating that all parameters are equal or against the encompassing

319   hypothesis which lets all parameters free to vary. Generally, to obtain the marginal

320   likelihood of the informed hypothesis, it is necessary to integrate over the restricted

321   parameter space, which is difficult to compute. As a solution to the problem of computing

322   marginal likelihood of the informed hypothesis, Klugkist et al. (2005) derived an identity

323   that defines the Bayes factor BF_{re} as the ratio of proportions of posterior and prior

324   parameter space consistent with the restriction. This identity forms the basis of the

325   encompassing prior approach. Recently, Sarafoglou et al. (2021) highlighted that these

326   proportions can be reinterpreted as the marginal likelihoods (i.e., the normalizing

327   constants) of the constrained posterior and constrained prior distribution. The prior

328   distribution consistent with the restriction takes the following form:

$$p(\boldsymbol{\theta} \mid \mathcal{H}_r) = \frac{p(\boldsymbol{\theta} \mid \mathcal{H}_e)\,\mathbb{I}(\boldsymbol{\theta} \in \mathcal{R}_r)}{\int_{\mathcal{R}_e} p(\boldsymbol{\theta} \mid \mathcal{H}_r)\,\mathrm{d}\boldsymbol{\theta}},$$

where $\mathbb{I}(\boldsymbol{\theta} \in \mathcal{R}_r)$ is an indicator function that is one for parameter values in the that obey

the constrained and zero otherwise. The constrained posterior distribution of the

parameters under the informed hypothesis can be represented in the same way,

$$p(\boldsymbol{\theta} \mid \mathbf{x},\, \mathcal{H}_r) = \frac{p(\boldsymbol{\theta} \mid \mathbf{x},\, \mathcal{H}_e)\,\mathbb{I}(\boldsymbol{\theta} \in \mathcal{R}_r)}{\int_{\mathcal{R}_e} p(\mathbf{x} \mid \boldsymbol{\theta})\,p(\boldsymbol{\theta} \mid \mathcal{H}_r)\,\mathrm{d}\boldsymbol{\theta}}.$$

The Klugkist identity (Klugkist et al., 2005) can be derived from the marginal likelihoods

of the two distributions as follows:

$$\mathrm{BF}_{re} = \frac{\overbrace{p(\boldsymbol{\theta} \in \mathcal{R}_r \mid \mathbf{x},\, \mathcal{H}_e)}^{\substack{\text{Marginal likelihood of} \\ \text{constrained posterior distribution}}}}{\underbrace{p(\boldsymbol{\theta} \in \mathcal{R}_r \mid \mathcal{H}_e)}_{\substack{\text{Marginal likelihood of} \\ \text{constrained prior distribution}}}}. \tag{1}$$

The Klugkist identity made it possible to utilize numerical sampling methods such as

bridge sampling to compute the Bayes factor. The following section provides a conceptual

introduction to bridge sampling and how it is used in the context of evaluating informed

hypotheses.

Bridge Sampling Routine

The bridge sampling routine implemented in **multibridge** is a numerical method to

estimate the marginal likelihood of a target density (cf., Gronau et al., 2017; Overstall &

Forster, 2010). The identity used in bridge sampling is displayed in Equation 2; it considers

the unnormalized target density, a proposal density with known normalizing constant, and

an arbitrary bridge function. The numerator in Equation 2 describes the expected value of

the unnormalized target density evaluated with samples from the proposal density. The

345 denominator is the expected value of the proposal density and a bridge function evaluated

346 with samples from the target density. The bridge function serves the purpose of increasing

347 the overlap between the two densities, thus increasing the efficiency and accuracy of the

348 method. The bridge sampling identity can then be expressed as follows:

$$p(\boldsymbol{\theta} \in \mathcal{R}_r \mid \mathcal{H}_e) = \frac{\mathbb{E}_{g(\boldsymbol{\theta})}\left(p(\boldsymbol{\theta} \mid \mathcal{H}_e)\mathbb{I}(\boldsymbol{\theta} \in \mathcal{R}_r)h(\boldsymbol{\theta})\right)}{\mathbb{E}_{\text{prior}}\left(g(\boldsymbol{\theta})h(\boldsymbol{\theta})\right)}, \tag{2}$$

349 where the term $h(\boldsymbol{\theta})$ refers to the bridge function proposed by Meng and Wong (1996),

350 $g(\boldsymbol{\theta})$ refers to a proposal density (in this application we choose the multivariate normal

351 density), and $p(\boldsymbol{\theta} \mid \mathcal{H}_e)\mathbb{I}(\boldsymbol{\theta} \in \mathcal{R}_r)$ is the unnormalized target density; in this case it

352 represents the part of the prior parameter space under the encompassing hypothesis that is

353 in accordance with the constraint. In the conventional application of bridge sampling, the

354 marginal likelihoods of the two competing hypotheses are estimated, that is, the marginal

355 likelihood of the informed hypothesis and the marginal likelihood of the encompassing

356 hypothesis. But on the basis of Equation 1, the routine implemented in **multibridge**

357 estimates the marginal likelihood of the restricted prior and restricted posterior density.

358   It should be noted that the bridge sampling algorithm implemented in **multibridge**

359 is an adapted version of the algorithm implemented in the `R` package **bridgesampling**

360 (Gronau, Singmann, & Wagenmakers, 2020) and allows for the specification of informed

361 hypotheses on probability vectors.[1]

362   A schematic representation of the bridge sampling routine is displayed in Figure 5.

363 To estimate the marginal likelihood, bridge sampling requires samples from the target

364 distribution, that is, the constrained Dirichlet distribution for multinomial models and

365 constrained beta distributions for binomial models, and samples from the proposal

366 distribution which in principle can be any distribution with a known marginal likelihood;

---

[1] In addition, the function to compute the relative mean square error for bridge sampling estimates in
multibridge is based on the code of the `error_measures`-function from the **bridgesampling** package.

367 in **multibridge** the proposal distribution is the multivariate normal distribution. Samples

368 from the target distribution are generated using the Gibbs sampling algorithms proposed

369 by Damien and Walker (2001). For binomial models, we apply the suggested Gibbs

370 sampling algorithm for constrained beta distributions. In the case of the multinomial

371 models, we apply an algorithm that simulates values from constrained Gamma

372 distributions which are then transformed into Dirichlet random variables. To sample

373 efficiently from these distributions, **multibridge** provides a `C++` implementation of this

374 algorithm. Samples from the proposal distribution are generated using the standard

375 `rmvnorm`-function from the `R` package **mvtnorm** (Genz et al., 2020).

376   Despite the bridge function, the efficiency of the bridge sampling method is optimal

377 only if the target and proposal distribution operate on the same parameter space and have

378 sufficient overlap. We therefore probit transform the samples of the constrained

379 distributions to move the samples from the probability space to the entire real line.

380 Subsequently, we use half of these draws to construct the proposal distribution using the

381 method of moments. Then, samples are drawn from the proposal density and transformed

382 back into the probability space, ensuring that the samples correspond to the informed

383 hypothesis. These transformed samples are then used to evaluate the unnormalized target

384 density.

385   The numerator in Equation 2 evaluates the unnormalized density for the constrained

386 prior distribution with samples from the proposal distribution. The denominator evaluates

387 the normalized proposal distribution with samples from the constrained prior distribution.

388 Since the optimal bridge function proposed by Meng and Wong (1996) contains the

389 marginal likelihood of the target density –the quantity we wish to compute– an iterative

390 scheme is applied to obtain the estimate. **multibridge** then runs the iterative scheme until

391 the tolerance criterion suggested by Gronau et al. (2017) is reached. The sampling from

392 the target and proposal distribution, the transformations and computational steps are

393 performed automatically within the core functions of **multibridge**. The user only needs to
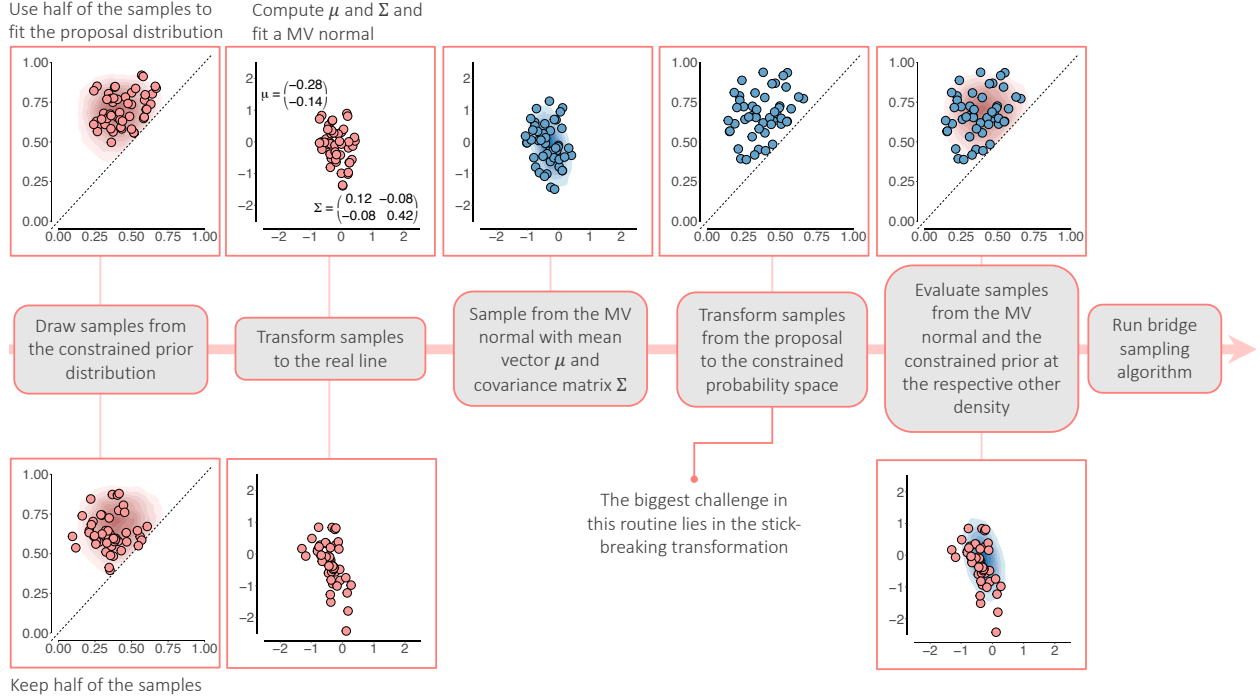
Figure 5. A schematic illustration of the steps taken to estimate the marginal likelihood of the constrained prior distribution of two binomial probabilities under $\mathcal{H}_r : \theta_1 < \theta_2$. As starting point, the routine requires samples from the constrained prior distribution (red). Following a transformation to the real line, a multivariate normal distribution (blue) is fit to half of the samples. The results from evaluating the samples from the multivariate normal distribution and the constrained prior distribution at the respective other density are needed to compute the expected values displayed in Equation 2. As final step, the bridge sampling algorithm estimates the marginal likelihood of the constrained prior distribution using an iterative scheme.

394 provide the functions with the data, a prior and a specification of the informed hypothesis.

395 As part of the standard output of `binom_bf_informed` and `mult_bf_informed`, the

396 functions return the bridge sampling estimate for the log marginal likelihood of the target

397 distribution, its associate relative mean square error and the number of iterations needed

398 to until the bridge sampling estimator reached the tolerance criterion.

399   To summarize, in order to implement the bridge sampling method we only need to be

400 able to sample from the constrained densities. Crucially, when using bridge sampling, it

401 does not matter how small the constrained parameter space is in proportion to the

402 encompassing density. This gives the method a decisive advantage over the encompassing

403 prior approach in terms of accuracy and efficiency especially (1) when binomial and

404 multinomial models with moderate to high number of categories (i.e., $K > 10$) are

405 evaluated and (2) when relatively little posterior mass falls in the constrained parameter

406 space.

407 **Stick-Breaking Transformation**

408   The bridge sampling routine in **multibridge** uses the multivariate normal

409 distribution as proposal distribution, which requires moving samples from target

410 distribution to the real line and conversely, moving samples from the real line to the

411 ordered probability space. Crucially, the transformation needs to retain the ordering of the

412 parameters, that is, it needs to take into account the lower bound and the upper bound of

413 each parameter. Elements from the real line to the ordered probability space are then

414 transformed as follows:

$$\theta_k = (u_k - l_k)\Phi(\xi_k) + l_k,$$

415 where ξ_k is kth the element on the real line, Φ is the cumulative density function of a

416 standard normal and u_k and l_k are the upper and lower bounds of ξ_k, respectively. The

largest element is simply the remainder of the stick. The inverse transformation is given by

$$\xi_k = \Phi^{-1}\left(\frac{\theta_k - l_k}{u_k - l_k}\right),$$

where Φ^{-1} denote the inverse cumulative density function. To determine the bounds,

multibridge uses a probit transformation, as proposed in Sarafoglou et al. (2021), which

transforms the elements by moving from the smallest to the largest value. A schematic

illustration of the stick-breaking transformation is given in Figure 6, detailed technical

details of the transformation are provided in the appendix.

Transform values from the real line (ξ_1, ξ_2, ξ_3) to an ordered probability vector
$(\theta_1 < \theta_2 < \theta_3)$ using the stick-breaking transformation

0 is the lower bound of the smallest element

With 3 elements in the stick, the smallest one cannot be larger than $\frac{1}{3}$

Stick of length 1

Step 1:
$\theta_1 = \left(\frac{1}{3} - 0\right)\phi(\xi_1) + 0$

θ_1 is the lower bound for the second element

The upper bound is the length of the remaining stick $(1 - \theta_1)$ divided by the number of remaining elements

θ_1

Step 2:
$\theta_2 = \left(\frac{(1-\theta_1)}{2} - \theta_1\right)\phi(\xi_1) + \theta_1$

θ_1 θ_2

Step 3:
The value of the last element is the remainder of the stick

θ_1 θ_2 θ_3

Figure 6. The stick-breaking transformation of elements on the real line to the ordered probability space. The stick-breaking transformation moves from the smallest to the largest element to determine its lower and upper bounds.

To perform the transformation from a parameter vector on the real line to an ordered

probability vector, we need to determine the lower and upper bound of each parameter.

Consider an increasing trend of four parameters, that is, $\theta_1 < \theta_2 < \theta_3$. The lower bound for

for the smallest element in the parameter vector, θ_1, is 0. For θ_2 and θ_3 the lower bound is

427 the preceding element in the vector. That is, the lower bound for θ_2 is θ_1, lower bound for

428 θ_3 is θ_2.

429   This definition holds for both binomial models and multinomial models. Differences

430 in these two models appear only when determining the upper bound for each parameter.

431 For binomial models, the upper bound for each parameter is 1. For multinomial models,

432 due to the sum-to-one constraint the upper bounds need to be computed differently. As

433 proposed in Frigyik, Kapila, and Gupta (2010) and Stan Development Team (2020) we

434 represent $\boldsymbol{\theta}$ as unit-length stick which we subsequently divide into as many elements as

435 there are parameters in the constraint (Stan Development Team, 2020). In this approach,

436 the upper bounds are derived from on the values of smaller elements as well as on the

437 number of remaining larger parameters in the stick. Concretely, for the smallest element in

438 the parameter vector, θ_1, the upper bound is $\frac{1}{3}$; if this element were larger than that it

439 would be impossible to create a probability vector with increasing values. For θ_2 and θ_3 the

440 upper bound is the proportion of the unit-length stick that has not yet been accounted for

441 in the transformation divided by the number of parameters in the remaining stick. For

442 instance, the upper bound for θ_2 is defined as $\frac{1-\theta_1}{2}$. This transformation allows us to

443 effectively transform elements from the real line to an constrained probability space and is

444 therefore a main component of the bridge sampling algorithm.

445   The drawback of this transformation is, however, that it can only be performed if all

446 elements in the constraint are arranged as a linearly ordered set, thus, only works for "stick

447 hypotheses". For hypotheses in which elements in a constraint are arranfed as a partial

448 order, the assumption is violated that for a given parameter smaller elements and the

449 number of parameters in the remaining stick determine their upper bound.

Poster Model Probabilites, and Bayes Factor Transitivity

Consider a scenario where researchers entertain more than two hypotheses that they wish to compare. For instance, they may entertain two informed hypotheses $\mathcal{H}_{r1}$ and $\mathcal{H}_{r2}$ as well as a null hypothesis $\mathcal{H}_0$ and the encompassing hypothesis $\mathcal{H}_e$. An overview of the relative plausibility of all $M = 4$ models simultaneously may be obtained by presenting the posterior model probabilities for all hypotheses, $p(\mathcal{H}_i \,|\, x)$, $i = 1, \cdots, 4$ Berger and Molina (2005). Posterior model probabilities are not automatically computed in **multibridge**; however, after computing the individual Bayes factors, the posterior model probabilities can be obtained easily. Denoting the prior model probability for hypothesis $\mathcal{H}_{r1}$ by $p(\mathcal{H}_{r1})$, the posterior model probability $p(\mathcal{H}_{r1} \,|\, \mathbf{x})$ is given by:

$$p(\mathcal{H}_{r1} \,|\, \mathbf{x}) = \frac{\frac{p(\mathbf{x}|\mathcal{H}_{r1})}{p(\mathbf{x}|\mathcal{H}_e)} \times p(\mathcal{H}_{r1})}{\sum_{i=1}^{M} \frac{p(\mathbf{x} \,|\, \mathcal{H}_i)}{p(\mathbf{x} \,|\, \mathcal{H}_e)} \times p(\mathcal{H}_i)}.$$

When all hypotheses are equally likely *a priori*, this simplifies to:

$$p(\mathcal{H}_{r1} \,|\, \mathbf{x}) = \frac{\mathrm{BF}_{r1e}}{\mathrm{BF}_{r1e} + \mathrm{BF}_{r2e} + \mathrm{BF}_{0e} + \mathrm{BF}_{ee}},$$

where BF_{ee} equals 1. In R, the posterior model probabilities can be computed as follows:

```r
# posterior model probability of Hr1 given three alternative hypotheses
p_Hr1_x <- bfr1e/(bfr1e + bfr2e + bf0e + 1) # bfee = 1
```

Posterior model probabilities are useful for comparing multiple hypotheses; however, they are relative quantities that change depending on which other hypotheses are included in the comparison. Thus, hypotheses that describe the data poorly may have high posterior model probabilities if the other hypotheses in the comparison set provide even worse descriptions of the data. In order to gain insight into whether a hypothesis describes the data adequately, we therefore consider so-called bookend hypotheses along with

theory-informed hypotheses. That is, we include a hypothesis that maximally constrains the parameter space (such as a point-null hypothesis $\mathcal{H}_0$) and the encompassing hypothesis $\mathcal{H}_e$ that does not constrain the parameter space (in this case, that makes no ordinal predictions, Lee & Vanpaemel, 2018). A hypothesis is then considered adequate if it outperforms these two bookend models.

In addition to posterior model probabilities, Bayes factors can also be calculated directly between two informed hypotheses. The comparison of any two informed hypotheses with one another follows from the fact that Bayes factors are transitive. For instance, the Bayes factor comparison between two informed hypotheses $\mathcal{H}_{r1}$ and $\mathcal{H}_{r2}$ can be obtained by first computing BF_{r1e} and BF_{r2e}, and then dividing out the common hypothesis $\mathcal{H}_e$:

$$\text{BF}_{r1r2} = \frac{\text{BF}_{r1e}}{\text{BF}_{r2e}}.$$

For this comparison to be feasible, the encompassing hypotheses must be identical, that is, the same prior distribution must be assigned to the category proportions.

Prior Sensitivity

Bayesian hypothesis testing has been criticised as the priors exert too much influence on the Bayes factors (e.g., Kass & Raftery, 1995). That is, even if the data are informative enough to overwhelm the prior for parameter estimation, priors can still influence the Bayes factors. The development of suitable priors is thus an important part of Bayesian hypothesis testing.

But even priors that are justified by theory are to a certain degree arbitrary. For instance, if one expects an increasing trend in the data, the parameters in the prior can be chosen to reflect that trend. The exact number of *a priori* category counts, however, is at the discretion of the analyst. It is therefore considered good research practice to conduct a sensitivity analysis on the final results Lee & Vanpaemel (2018). In a sensitivity analysis, a set of plausible priors are determined in addition to the prior chosen in the main analysis

492 for which the Bayes factors are calculated. The range of Bayes factors then gives an

493 indication of the extent to which the results are fragile or robust to different modeling

494 choices. In general, the prior on which the final analysis is performed as well as the set of

495 priors used to conduct the sensitivity analysis should be determined and preregistered

496 before seeing the data to ensure a fair comparison of the hypotheses of interest.

Usage and Examples

498 In the following, we will outline three examples on how to use **multibridge** to

499 compare an informed hypothesis to a null or encompassing hypothesis. The first example

500 concerns multinomial data and the second and third example concerns independent

501 binomial data. Additional examples are available as vignettes (see

502 \texttt{vignette(package = "multibridge")).

503 The two core functions of **multibridge**—`mult_bf_informed` and the

504 `binom_bf_informed`—can be illustrated schematically as follows:

```
mult_bf_informed(x, Hr, a, factor_levels)

binom_bf_informed(x, n, Hr, a, b, factor_levels)
```

Example 1: Applying A Benford Test to Greek Fiscal Data

506 The first-digit phenomenon, otherwise known as Benford's law (Benford, 1938;

507 Newcomb, 1881) states that the expected proportion of leading digits in empirical data can

508 be formalized as follows: for any given leading digit $d, d = (1, \cdots, 9)$ the expected

509 proportion is approximately equal to

$$\mathbb{E}_{\theta_d} = \log_{10}((d + 1)/d).$$

510 This means that in an empirical data set, numbers with smaller leading digits are more

511 common than numbers with larger leading digits. Specifically, a number has leading digit 1

in 30.1% of the cases, and leading digit 2 in 17.61% of the cases; leading digit 9 is the least

frequent digit with an expected proportion of only 4.58% (see Table 4 for an overview of the

expected proportions). Empirical data for which this relationship holds include population

sizes, death rates, baseball statistics, atomic weights of elements, and physical constants

(Benford, 1938). In contrast, artificially generated data, such as telephone numbers, do in

general not obey Benford's law (Hill, 1995). Given that Benford's law applies to empirical

data but not artificially generated data, a so-called Benford test can be used in fields like

accounting and auditing to check for indications for poor data quality (for an overview, see

e.g., Durtschi, Hillison, & Pacini, 2004; Nigrini, 2012; Nigrini & Mittermaier, 1997). Data

that do not pass the Benford test, should raise audit risk concerns, meaning that it is

recommended that they undergo additional follow-up checks (Nigrini, 2019).

Below we discuss four possible Bayesian adaptations of the Benford test. In a first

scenario we simply conduct a Bayesian multinomial test in which we test the point-null

hypothesis $\mathcal{H}_0$ which predicts a Benford distribution. In a second scenario we test the

informed hypothesis $\mathcal{H}_{r1}$, which predicts a decreasing trend in the proportions of leading

digits. The hypothesis $\mathcal{H}_{r1}$ exerts considerably more constraint than $\mathcal{H}_e$ and provides a

more sensitive test if our primary goal is to test whether data comply with Benford's law or

whether the data follow a similar but different trend. In the next two scenarios, our main

goal is to identify fabricated data. The third scenario therefore tests the null hypothesis

against the hypothesis that all proportions occur equally often. This hypothesis $\mathcal{H}_{r2}$ could

be considered if it is suspected that the data were generated randomly or could serve as a

bookend comparison hypothesis as it maximally constraints the parameter space. In a

fourth scenario we test a hypothesis which predicts a trend that is characteristic for

manipulated data. This hypothesis, which we denote as $\mathcal{H}_{r3}$, could be derived from

empirical research on fraud or be based on observed patterns from former fraud cases. For

instance, Hill (1995) instructed students to produce a series of random numbers; in the

resulting data the proportion of the leading digit 1 occurred most often and the digits 8

539 and 9 occurred least often which is consistent with the general pattern of Benford's law.

540 However, the proportion for the remaining leading digits were approximately equal. Note

541 that the predicted distribution derived from Hill (1995) is not currently used as a test to

542 detect fraud, however, for the sake of simplicity, we assume that this pattern could be an

543 indication of manipulated auditing data. All hypotheses will be tested against the

544 encompassing hypothesis $\mathcal{H}_e$, which too serves as a bookend comparison hypothesis, and

545 which imposes no constraints on the proportion of leading digits.

546   **Data and Hypothesis.**   The data we use to illustrate the computation of Bayes

547 factors were originally published by the European statistics agency "Eurostat" and served

548 as basis for reviewing the adherence to the Stability and Growth Pact of EU member

549 states. Rauch, Göttsche, Brähler, and Engel (2011) conducted a Benford test on data

550 related to budget deficit criteria, that is, public deficit, public dept and gross national

551 products. The data used for this example features the proportion of first digits from Greek

552 fiscal data in the years between 1999 and 2010; a total of $N = 1{,}497$ numerical data were

553 included in the analysis. We choose this data, since the Greek government deficit and debt

554 statistics states has been repeatedly criticized by the European Commission in this time

555 span (European Commision, 2004, 2010). In particular, the commission has accused the

556 Greek statistical authorities to have misreported deficit and debt statistics. For further

557 details on the data set see Rauch et al. (2011). The observed and expected proportions are

558 displayed in Table 4; the expected proportions versus the posterior parameter estimates

559 under the encompassing hypothesis are displayed in Figure 7.

Table 4

Observed counts, observed proportions, and expected proportions of first digits in the Greek fiscal data set. The total sample size was $N = 1{,}497$ observations. Note that the observed proportions and counts deviate slightly from those reported in Rauch et al. (2011) (probably due to rounding errors).

Leading digit	Observed Counts	Observed Proportions	Expected Proportions: Benford's Law
1	509	0.340	0.301
2	353	0.236	0.176
3	177	0.118	0.125
4	114	0.076	0.097
5	77	0.051	0.079
6	77	0.051	0.067
7	53	0.035	0.058
8	73	0.049	0.051
9	64	0.043	0.046

In this example, the parameter vector of the multinomial model, $\theta_1, \cdots, \theta_K$, reflects the probabilities of a leading digit in the Greek fiscal data being a number from 1 to 9. Each of the hypotheses above will be tested against the encompassing hypothesis $\mathcal{H}_e$ which imposes no constraints on the parameters. The hypotheses introduced above can then be

formalized as follows:

$$\mathcal{H}_e : \boldsymbol{\theta} \sim \mathrm{Dirichlet}(\mathbf{1})$$

$$\mathcal{H}_0 : \boldsymbol{\theta}_0 = (0.301, 0.176, 0.125, 0.097, 0.079, 0.067, 0.058, 0.051, 0.046),$$

$$\mathcal{H}_{r1} : \theta_1 > \theta_2 > \theta_3 > \theta_4 > \theta_5 > \theta_6 > \theta_7 > \theta_8 > \theta_9$$

$$\mathcal{H}_{r2} : \boldsymbol{\theta}_0 = \left(\frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{1}{9}\right)$$

$$\mathcal{H}_{r3} : \theta_1 > (\theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = \theta_7) > (\theta_8, \ \theta_9).$$

Method. Both BF_{0e} and BF_{r2e} may be readily computed by means of a Bayesian multinomial test which is implemented in the function `mult_bf_equality`. This function requires (1) a vector with observed counts, (2) a vector with concentration parameters of the Dirichlet prior distribution under $\mathcal{H}_e$, and (3) the vector of expected proportions under $\mathcal{H}_0$ and under $\mathcal{H}_{r2}$. In this example, we do not incorporate specific expectations about the distribution of leading digits in the Greek fiscal data and therefore assign a uniform Dirichlet distribution to the proportion of leading digits. That is, we set all concentration parameters under $\mathcal{H}_e$ to 1 (i.e., we assign $\boldsymbol{\theta}$ a uniform Dirichlet prior distribution). This prior supports all possible points equally, meaning that, if the data were completely random, none of the hypotheses under consideration should be favored over the other.

```r
# Observed counts
x <- c(509, 353, 177, 114,  77,  77,  53,  73,  64)
# Prior specification for Dirichlet prior distribution under H_e
a <-  c(1, 1, 1, 1, 1, 1, 1, 1, 1)
# Expected proportions for H_0 and H_r2
p0  <- log10((1:9 + 1)/1:9)
pr2 <- c(1/9, 1/9, 1/9, 1/9, 1/9, 1/9, 1/9, 1/9, 1/9)
# Execute the analysis
results_H0_He   <- mult_bf_equality(x = x, a = a, p = p0)
```

```
results_Hr2_He  <- mult_bf_equality(x = x, a = a, p = pr2)

logBFe0  <- results_H0_He$bf$LogBFe0

logBFer2 <- results_Hr2_He$bf$LogBFe0
```

570   The hypotheses $\mathcal{H}_{r1}$ and $\mathcal{H}_{r3}$ contain inequality constraints, and this necessitates the

571 use of the function `mult_bf_informed` to compute the Bayes factors BF_{r1e} and BF_{r3e}. This

572 function requires (1) a vector with observed counts, (2) a vector with concentration

573 parameters of the Dirichlet prior distribution under $\mathcal{H}_e$, (3) labels for the categories of

574 interest (i.e., leading digits), and (4) the informed hypothesis $\mathcal{H}_{r1}$ or $\mathcal{H}_{r3}$ (e.g., as a string).

575 In addition to the basic required arguments, we use two additional arguments here. The

576 first argument sets the Bayes factor type, that is, whether the output should print the

577 Bayes factor in favor of the informed hypothesis (i.e., BF_{re}) or in favor of the encompassing

578 hypothesis (i.e., BF_{er}). It is also possible to compute the log Bayes factor in favor of the

579 hypothesis, which is the setting we choose for this example. The purpose of the second

580 argument `seed` is to make the results reproducible:

```
# Observed counts
x <- c(509, 353, 177, 114,  77,  77,  53,  73,  64)
# Prior specification for Dirichlet prior distribution under H_e
a <-  c(1, 1, 1, 1, 1, 1, 1, 1, 1)
# Labels for categories of interest
factor_levels <- 1:9
# Specifying the informed hypotheses as a string
Hr1 <- c('1 > 2 > 3 > 4 > 5 > 6 > 7 > 8 > 9')
Hr3 <- c('1 > 2 = 3 = 4 = 5 = 6 = 7 > 8 , 9')
# Execute the analysis
results_He_Hr1 <- mult_bf_informed(x = x, Hr = Hr1, a = a,
                                   factor_levels = factor_levels,
```

```
                                        bf_type = 'LogBFer', seed = 2020)

results_He_Hr3 <- mult_bf_informed(x = x, Hr = Hr3, a = a,

                                   factor_levels = factor_levels,

                                   bf_type = 'LogBFer', seed = 2020)

logBFer1 <- summary(results_He_Hr1)$bf

logBFer3 <- summary(results_He_Hr3)$bf
```

581   We also compute the posterior model probabilities for all hypotheses. The results are

582 shown in Table 5.

Table 5

Prior model probabilities, posterior model probabilities, and Bayes factors for five rival
accounts of first digit frequencies in the Greek fiscal data set.

Hypothesis	$p(\mathcal{H}_.)$	$p(\mathcal{H}_. \mid \mathbf{x})$	$\log(\mathrm{BF}_{.e})$
$\mathcal{H}_0$	0.2	1.27×10^{-11}	-17.67
$\mathcal{H}_{r1}$	0.2	0.9994	7.42
$\mathcal{H}_e$	0.2	0.0006	0
$\mathcal{H}_{r3}$	0.2	5.97×10^{-79}	-172.70
$\mathcal{H}_{r2}$	0.2	2.71×10^{-212}	-479.73

583   The results indicate strong support for $\mathcal{H}_{r1}$ –the model in which the proportions are

584 assumed to decrease monotonically– over all other models. The log Bayes factor of $\mathcal{H}_{r1}$

585 against the encompassing hypothesis $\mathcal{H}_e$ is 7.42, which equates to a Bayes factor of 1,664

586 on a natural scale.

587   The strong Bayes factor support for $\mathcal{H}_{r1}$ translates to a relatively extreme posterior

588 model probability of 0.9994. By comparison, the posterior model probabilities for

589 hypotheses $\mathcal{H}_{r2}$ and $\mathcal{H}_{r3}$, that is, the bookend null-hypothesis and the hypothesis

590 predicting a data pattern typical of fraud, are only slightly greater than zero. The

591   posterior model probability for $\mathcal{H}_e$ is 0.0006. Thus, hypothesis $\mathcal{H}_{r1}$ can outperform the two

592   bookend hypotheses $\mathcal{H}_{r2}$ and $\mathcal{H}_e$. That $\mathcal{H}_{r1}$ outperforms the unconstrained model $\mathcal{H}_e$

593   demonstrates how a parsimonious model that makes precise predictions can be favored over

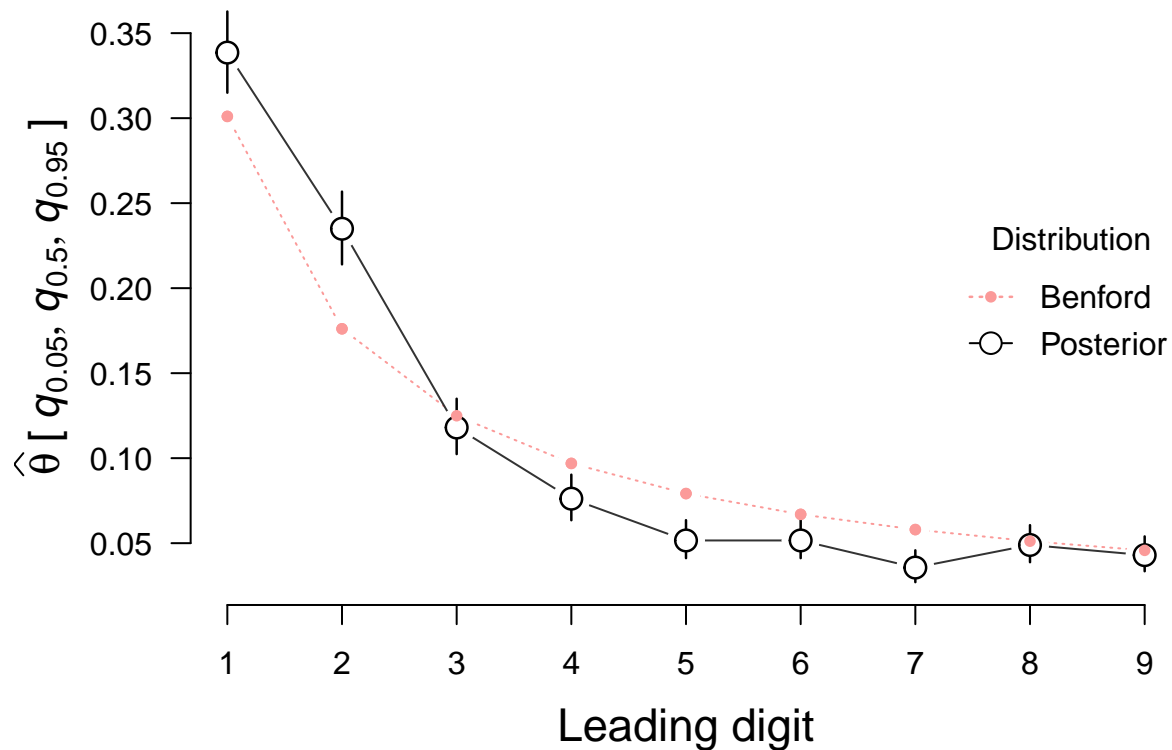594   a model that is more complex (e.g., Jefferys & Berger, 1992).

Figure 7. Predictions from Benford's law (in pink) show together with the posterior medians
(black circles) for the category proportions estimated under the encompassing model $\mathcal{H}_e$. The
circle skewers show the 95% credible intervals. Only three of nine intervals encompass the
expected proportions, suggesting that the data do not follow Benford's law. This plot was
created using the `plot`-S3-method for `summary.bmult` objects in **multibridge**.

595   **Sensitivity Analysis.**   In a sensitivity analysis we will determine whether our

596   results are robust against different prior choices. In the main analysis we chose a uniform

597   Dirichlet distribution on the category proportions as prior under $\mathcal{H}_e$. This prior assigns

598 equal probability to all possible parameter values, but alternative prior distributions are

599 seem also conceivable. Audit researchers may argue for the development of more

600 informative and theory-driven priors that resemble one of the hypotheses under

601 consideration. The Dirichlet parameters vectors specified below resemble the four

602 hypotheses, assuming $N = 54$ prior observations.

```r
# Alternative prior specifications

a0 <-  c(16, 10, 7, 5, 4, 3, 3, 3, 2) # Benford's law

a1 <-  c(10, 9, 8, 7, 6, 5, 4, 3, 2)  # Monotonically decreasing trend

a2 <-  c(6, 6, 6, 6, 6, 6, 6, 6, 6)   # Equal proportions

a3 <-  c(12, 6, 6, 6, 6, 6, 6, 3, 3)  # Fraud pattern
```

603   The sensitivity analysis is then carried out for each prior choice and will be compared

604 to the main results. For this analysis, we are particularly interested in the Bayes factors of

605 the hypothesis postulating a decreasing trend $\mathcal{H}_{r1}$ and Benford's law $\mathcal{H}_0$ to the

606 encompassing hypothesis $\mathcal{H}_e$.

```r
# Sensitivity analysis for log(BFe_r1)

sensitivity0 <- mult_bf_informed(x = x, Hr = Hr1, a = a0,

                                 factor_levels = factor_levels,

                                 bf_type = 'LogBFer', seed = 2020)
sensitivity1 <- mult_bf_informed(x = x, Hr = Hr1, a = a1,

                                 factor_levels = factor_levels,

                                 bf_type = 'LogBFer', seed = 2020)
sensitivity2 <- mult_bf_informed(x = x, Hr = Hr1, a = a2,

                                 factor_levels = factor_levels,

                                 bf_type = 'LogBFer', seed = 2020)
sensitivity3 <- mult_bf_informed(x = x, Hr = Hr1, a = a3,
```

```
                                   factor_levels = factor_levels,

                                   bf_type = 'LogBFer', seed = 2020)


# Sensitivity analysis for log(BFe_0)

sensitivity4   <- mult_bf_equality(x = x, a = a0, p = p0)

sensitivity5   <- mult_bf_equality(x = x, a = a1, p = p0)

sensitivity6   <- mult_bf_equality(x = x, a = a2, p = p0)

sensitivity7   <- mult_bf_equality(x = x, a = a3, p = p0)
```

₆₀₇   The results of the sensitivity analysis are displayed in Table 6. The general direction

₆₀₈ of the sensitivity analysis agrees with our conclusions drawn from the main analysis. That

₆₀₉ is, for the Bayes factors of $\mathcal{H}_{r1}$ compared to $\mathcal{H}_e$, the evidence points towards the informed

₆₁₀ hypothesis. However, the prior exerts an influence on BF_{r1e}; the evidence in favor for the

₆₁₁ informed hypothesis ranges from weak to extreme evidence. Specifically, when we choose

₆₁₂ priors that resemble a decreasing trend for the frequency of leading digits, as we did with

₆₁₃ $\boldsymbol{\alpha_0}$ and $\boldsymbol{\alpha_1}$, the Bayes factor becomes smaller and the evidence weak (i.e., $(\text{BF}_{r1e} \mid \boldsymbol{\alpha_0}) =$

₆₁₄ 1.87 on the natural scale) and moderate (i.e., $(\text{BF}_{r1e} \mid \boldsymbol{\alpha_1}) = 4.74$ on the natural scale).

₆₁₅ When the prior contrasts the data, the evidence becomes very strong or extreme. Thus, a

₆₁₆ prior that closely resembles the predictive trend reduces to some degree the diagnostic

₆₁₇ value of the data.

₆₁₈   By contrast, the Bayes factors for $\mathcal{H}_0$ compared to $\mathcal{H}_e$ are robust against different

₆₁₉ prior settings. Here too, the prior changes the Bayes factor estimate but in all cases the

₆₂₀ data suggests overwhelming evidence in favor of the encompassing hypothesis over

₆₂₁ Benford's law.

Table 6

Results of a sensitivity analysis for the Greek fiscal data set.

Description	Prior	$\log(\text{BF}_{r1e})$	$\log(\text{BF}_{0e})$
Uniform	$\boldsymbol{\alpha_e} = (1, 1, 1, 1, 1, 1, 1, 1, 1)$	7.42	-17.67
Benford's law	$\boldsymbol{\alpha_0} = (16, 10, 7, 5, 4, 3, 3, 3, 2)$	0.63	-26.00
Montonically decreasing	$\boldsymbol{\alpha_1} = (10, 9, 8, 7, 6, 5, 4, 3, 2)$	1.56	-20.94
Centered on mean	$\boldsymbol{\alpha_2} = (6, 6, 6, 6, 6, 6, 6, 6, 6)$	7.53	-11.35
Fraud pattern	$\boldsymbol{\alpha_3} = (12, 6, 6, 6, 6, 6, 6, 3, 3)$	3.93	-18.62

To summarize, the data offer overwhelming support for hypothesis $\mathcal{H}_{r1}$, which postulates a decreasing trend in the digit proportions. This model outperformed both simpler models (e.g., the Benford model and the bookend null-hypothesis) and a more complex model in which the proportions were free to vary. The results are sensitive to our prior choices as a sensitivity analysis showed: for moderately informative priors which resemble the predicted decreasing trend, the $\mathcal{H}_{r1}$ cannot outperform the encompassing model. On the other hand, the conclusion that Benford's law does not offer a good description of the data was robust to different prior settings. Detailed follow-up analyses are needed to discover why the Greek fiscal data fail to adhere to Benford's law (Nigrini, 2019).

Example 2: Prevalence of Statistical Reporting Errors

This section illustrates how **multibridge** may be used to evaluate models for independent binomial data rather than multinomial data. Our example concerns the prevalence of statistical reporting errors across eight different psychology journals. In any article that uses null hypothesis significance testing, there is a chance that the reported test statistic and degrees of freedom do not match the reported p-value, possibly because of copy-paste errors. To flag these errors, Epskamp and Nuijten (2014) developed the R

639 package `statcheck`, which scans the PDF of a given scientific article and automatically

640 detects statistical inconsistencies. This package allowed Nuijten et al. (2016) to estimate

641 the prevalence of statistical reporting errors in the field of psychology. In total, the authors

642 investigated a sample of 30,717 articles (which translates to over a quarter of a million

643 *p*-values) published in eight major psychology journals between 1985 to 2013:

644 *Developmental Psychology* (DP), the *Frontiers in Psychology* (FP), the *Journal of Applied*

645 *Psychology* (JAP), the *Journal of Consulting and Clinical Psychology* (JCCP), *Journal of*

646 *Experimental Psychology: General* (JEPG), the *Journal of Personality and Social*

647 *Psychology* (JPSP), the *Public Library of Science* (PLoS), *Psychological Science* (PS).

648   Based on several background assumptions, Nuijten et al. (2016) predicted that the

649 proportion of statistical reporting errors is higher for articles published in the *Journal of*

650 *Personality and Social Psychology* (JPSP) than for articles published in the seven other

651 journals.

652   **Data and Hypothesis.** Here we reuse the original data published by Nuijten et al.

653 (2016), which we also distribute with the package **multibridge** under the name `journals`.

```
data(journals)
```

654   The Nuijten et al. (2016) hypothesis of interest, $\mathcal{H}_r$, states that the prevalence for

655 statistical reporting errors is higher for JPSP than for the other journals.[2] We will consider

656 two specific versions of the Nuijten et al. (2016) $\mathcal{H}_r$ hypothesis. The first hypothesis, $\mathcal{H}_{r1}$,

657 stipulates that JPSP has the highest prevalence of reporting inconsistencies, whereas the

658 other seven journals share a prevalence that is lower. The second hypothesis, $\mathcal{H}_{r2}$, also

659 stipulates that JPSP has the highest prevalence of reporting inconsistencies, but does not

660 commit to any particular structure on the prevalence for the other seven journals.

———

[2] Nuijten et al. (2016) did not report inferential tests because they had sampled the entire population. We do report inferential tests here because we wish to learn about the latent data-generating process.

661   The **multibridge** package can be used to test $\mathcal{H}_{r1}$ and $\mathcal{H}_{r2}$ against the null

662 hypothesis $\mathcal{H}_0$ that all eight journals have the same prevalence of statistical reporting

663 errors. In addition, we will compare $\mathcal{H}_{r1}$, $\mathcal{H}_{r2}$, and $\mathcal{H}_0$ against the encompassing hypothesis

664 $\mathcal{H}_e$ that makes no commitment about the prevalence of reporting inconsistencies across the

665 eight journals. In this example, the parameter vector of the binomial success probabilities,

666 $\boldsymbol{\theta}$, reflects the probabilities that articles contain at least one statistical reporting

667 inconsistency across journals. Thus, the above hypotheses can be formalized as follows:

$$\mathcal{H}_e : \theta_{\text{JAP}} \cdots \theta_{\text{JPSP}} \sim \prod_{k=1}^{K} \text{Beta}(\alpha_k, \beta_k)$$

$$\mathcal{H}_0 : \theta_{\text{JAP}} = \theta_{\text{PS}} = \theta_{\text{JCCP}} = \theta_{\text{PLOS}} = \theta_{\text{DP}} = \theta_{\text{FP}} = \theta_{\text{JEPG}} = \theta_{\text{JPSP}}$$

$$\mathcal{H}_{r1} : (\theta_{\text{JAP}} = \theta_{\text{PS}} = \theta_{\text{JCCP}} = \theta_{\text{PLOS}} = \theta_{\text{DP}} = \theta_{\text{FP}} = \theta_{\text{JEPG}}) < \theta_{\text{JPSP}}$$

$$\mathcal{H}_{r2} : (\theta_{\text{JAP}}, \theta_{\text{PS}}, \theta_{\text{JCCP}}, \theta_{\text{PLOS}}, \theta_{\text{DP}}, \theta_{\text{FP}}, \theta_{\text{JEPG}}) < \theta_{\text{JPSP}}.$$

668   **Method.**   To compute the Bayes factor BF_{0r} we need to specify (1) a vector with

669 observed successes (i.e., the number of articles that contain a statistical inconsistency), (2)

670 a vector containing the total number of observations (i.e., the number of articles), (3) a

671 vector with prior parameter α_k for each binomial proportion of the beta prior distribution

672 under $\mathcal{H}_e$, (4) a vector with prior parameter β_k for each binomial proportion of the beta

673 prior distribution under $\mathcal{H}_e$, (5) the category labels (i.e., journal names), and (6) the

674 informed hypothesis $\mathcal{H}_{r1}$ or $\mathcal{H}_{r2}$ (e.g., as a string). We also change the Bayes factor type to

675 `LogBFr0` so that the function returns the log Bayes factor in favor for the informed

676 hypothesis compared to the null hypothesis. Since we have no specific expectations about

677 the distribution of statistical reporting errors in any given journal, we set all parameters α_k

678 and β_k to one which corresponds to uniform beta distributions. With this information, we

679 can now conduct the analysis with the function `binom_bf_informed`.

```r
# Since percentages are rounded to two decimal values, we round the
# articles with an error to obtain integer values
x <- round(journals$articles_with_NHST  *
           (journals$perc_articles_with_errors/100))
# Total number of articles
n <- journals$articles_with_NHST
# Prior specification for beta prior distributions under H_e
a <- c(1, 1, 1, 1, 1, 1, 1, 1)
b <- c(1, 1, 1, 1, 1, 1, 1, 1)
# Labels for categories of interest
journal_names <- journals$journal


# Specifying the informed Hypothesis
Hr1 <- c('JAP = PS = JCCP = PLOS = DP = FP = JEPG < JPSP')
Hr2 <- c('JAP , PS , JCCP , PLOS , DP , FP , JEPG < JPSP')


# Execute the analysis for Hr1
results_H0_Hr1 <- binom_bf_informed(x = x, n = n, Hr = Hr1, a = a, b = b,
                              factor_levels = journal_names,
                              bf_type = 'LogBFr0', seed = 2020)
# Execute the analysis for Hr2
results_H0_Hr2 <- binom_bf_informed(x = x, n = n, Hr = Hr2, a = a, b = b,
                              factor_levels = journal_names,
                              bf_type = 'LogBFr0', seed = 2020)
```

```r
LogBFe0  <- results_H0_Hr1$bf_list$bf0_table[['LogBFe0']]
LogBFr10 <- summary(results_H0_Hr1)$bf
```

```
LogBFr20 <- summary(results_H0_Hr2)$bf
```

Table 7

Prior model probabilities, posterior model probabilities, and Bayes factors for four hypotheses concerning the prevalence of statistical reporting errors across psychology journals.

Hypothesis	$p(\mathcal{H}_.)$	$p(\mathcal{H}_. \mid \mathbf{x})$	$\log(\mathrm{BF}_{.0})$
$\mathcal{H}_0$	0.25	1.6073×10^{-69}	0
$\mathcal{H}_{r2}$	0.25	0.8814	158.28
$\mathcal{H}_e$	0.25	0.1186	156.27
$\mathcal{H}_{r1}$	0.25	1.9517×10^{-37}	73.88

680   As the evidence is extreme in all four cases, we again report all Bayes factors on the

681   log scale. The Bayes factor $\log(\mathrm{BF}_{r20})$ indicates overwhelming evidence for the informed

682   hypothesis that JPSP has the highest prevalence for statistical reporting inconsistencies

683   compared to the null hypothesis that the statistical reporting errors are equal across all

684   eight journals; $\log(\mathrm{BF}_{r20}) = 158.28$.

685   For a clearer picture about the ordering of the journals we can investigate the

686   posterior distributions for the prevalence rates obtained under the encompassing model.

```
plot(summary(results_H0_Hr2), xlab = "Journal")
```

687   The posterior medians and 95% credible intervals are returned by the

688   `summary`-method and are shown in Figure 8. The figure strongly suggests that the

689   prevalence of reporting inconsistencies is not equal across all eight journals. This

690   impression may be quantified by comparing the null hypothesis $\mathcal{H}_0$ to the encompassing

691   hypothesis $\mathcal{H}_e$. The corresponding Bayes factor equals $\log(\mathrm{BF}_{e0}) = 156.27$, which confirms

Figure 8. Posterior medians for the prevalence of statistical reporting inconsistencies across eight psychology journals, as obtained using the encompassing model. The circle skewers show the 95% credible intervals. Analysis based on data from Nuijten et al. (2016). This plot was created using the `plot`-S3-method for `summary.bmult` objects.

692 that the data dramatically undercut the null hypothesis that the prevalence of statistical

693 reporting inconsistencies is equal across journals.

694   The data offer most support for the Nuijten hypothesis $\mathcal{H}_{r2}$, which posits that JPSP

695 has the highest prevalence but does not commit to any restriction on the prevalences for

696 the remaining seven journals. This hypothesis may be compared to the encompassing

697 hypothesis $\mathcal{H}_e$, which yields $\log(\mathrm{BF}_{r2e}) = 2.01$. This means that the observed data are

698 $\exp(2.01) \approx 7.45$ times more likely under $\mathcal{H}_{r2}$ than under $\mathcal{H}_e$; this is moderate evidence for

699 the restriction suggested by Nuijten et al. (2016). Under equal prior probability for the

700 models, this Bayes factor translates to a posterior probability on $\mathcal{H}_e$ of 0.119, an amount

701 that researchers may deem too large to discard in an all-or-none fashion.

702 To summarize, the data provide moderate evidence for the hypothesis stated by

703 Nuijten et al. (2016) that the prevalence of statistical reporting inconsistencies in JPSP is

704 higher than that in seven other psychology journals.

705 **Example 3: Effects of Gender and Education on the Violation of Stochastic**

706 **Dominance**

707 This section illustrates the comparison of four nested hypotheses concerning

708 independent binomial probabilities. In his study, Birnbaum (1999) presented new

709 possibilities of online testing for psychological science (in the late 1990s online testing was

710 still novel and rarely used). To compare data collected from an online research to

711 traditional lab research, Birnbaum (1999) collected experimental data from 1224

712 participants online and 124 participants in the lab. In his experiment participants played

713 20 rounds of a gambling game. In each round, they were presented with two gambles with

714 different probabilities and monetary values and were asked to indicate which gamble they

715 would rather play. The gamble chosen by the participants was then played once. Birnbaum

716 (1999) examined the characteristics of the two samples, for instance, in terms of their risk

717 aversion and their consistency with decision making axioms, such as stochastic violations,

718 and correlated them with different demographics.

719 The author analyzed the proportion of stochastic violations for different demographic

720 variables, noting a seemingly ordinal pattern for the probabilities to violate of stochastic

721 dominance for the factors gender (m=male, f=female) and education (1=doctorate degree,

722 2=postgraduate degree, 3=bachelor's degree, 4=less than bachelor's degree). In a later

723 study, Myung et al. (2005) presented a Bayesian inference framework to test decision

724 making axioms (using the "Bayesian p-value'') and used Birnbaum's data as an example

725 on how to assess violations of stochastic dominance and their relationship with covariates.

726 Concretely, Myung et al. (2005) reanalyzed the data from Birnbaum (1999) and tested the

727 informed hypothesis that stochastic dominance is violated more frequently in women

728 compared to men and more frequently in lower education levels than higher education

729 levels.

730   **Data and Hypothesis.**   We will use data from Birnbaum (1999) as presented in

731 Myung et al. (2005). The data show the stochastic violations of the online sample for one

732 of the gambling rounds featuring 1212 valid responses (see Table 8).

```
dat <- data.frame(gender = rep(c('male', 'female'), each = 4),

                  education = rep(c('1', '2', '3', '4'), 2),

                  levels = paste0(rep(c('m', 'f'), each = 4), 1:4),

                  violation = c(0.487, 0.477, 0.523, 0.601,

                               0.407, 0.555, 0.650, 0.622),

                  n = c(80, 88, 195, 163,

                        54, 108, 206, 318),

                  x = c(39, 42, 102, 98,

                        22, 60, 134, 198))
```

733   The parameter vector of the binomial success probabilities, $\theta_1, \cdots, \theta_K$, contains the

734 probabilities of observing a value in a particular category; here, it reflects the probabilities

735 of violating stochastic dominance for a particular subgroup (e.g., women with a doctorate).

736 We will compare three inequality-constrained hypotheses $\mathcal{H}_{r1}$, $\mathcal{H}_{r2}$, $\mathcal{H}_{r3}$ formulated by

737 Myung et al. (2005). The first hypothesis $\mathcal{H}_{r1}$ encodes the main effect for gender and

738 states that the probability to violate stochastic dominance is lower for men than for

739 women. The second hypothesis $\mathcal{H}_{r2}$ encodes the main effect of education and states that

740 the probability to violate stochastic dominance is lower for persons with higher education

741 levels. The third hypothesis $\mathcal{H}_{r3}$ combines hypotheses $\mathcal{H}_{r1}$ and $\mathcal{H}_{r2}$. We will test this

Table 8

Observed counts and observed proportions of stochastic dominance
violations for the N = 1,212 participants in Birnbaum (1999). The data are
split by gender and education level of the participants.

Education	Observed Counts	Observed Proportions
Male		
Doctorate Degree	39/80	0.49
Postgraduate Degree	42/88	0.48
Bachelor's Degree	102/195	0.52
Less than Bachelor's degree	98/163	0.60
Female		
Doctorate Degree	22/54	0.41
Postgraduate Degree	60/108	0.56
Bachelor's Degree	134/206	0.65
Less than Bachelor's degree	198/318	0.62

742 hypothesis against the encompassing hypothesis $\mathcal{H}_e$ without any constraints. In addition,

743 we will include a bookend null-hypothesis $\mathcal{H}_0$ predicting that all probabilities are equal.

744 The set of candidate hypotheses can therefore be written as follows:

$$\mathcal{H}_e : (\theta_{m1}, \theta_{m2}, \theta_{m3}, \theta_{m4}, \theta_{f1}, \theta_{f2}, \theta_{f3}, \theta_{f4})$$

$$\mathcal{H}_0 : \boldsymbol{\theta}_0 = \left(\frac{1}{8}, \frac{1}{8}, \frac{1}{8}, \frac{1}{8}, \frac{1}{8}, \frac{1}{8}, \frac{1}{8}, \frac{1}{8}\right),$$

$$\mathcal{H}_{r1} : (\theta_{m1}, \theta_{m2}, \theta_{m3}, \theta_{m4}) < (\theta_{f1}, \theta_{f2}, \theta_{f3}, \theta_{f4})$$

$$\mathcal{H}_{r2} : (\theta_{m1}, \theta_{f1}) < (\theta_{m2}, \theta_{f2}) < (\theta_{m3}, \theta_{f3}) < (\theta_{m4}, \theta_{f4})$$

$$\mathcal{H}_{r3} : \theta_{m1} < \theta_{f1} < \theta_{m2} < \theta_{f2} < \theta_{m3} < \theta_{f3} < \theta_{m4} < \theta_{f4}.$$

745   **Method.**   To evaluate the inequality-constrained hypothesis, we need to specify (1)

746   a vector with observed successes, and (2) a vector containing the total number of

747   observations, (3) the informed hypothesis, (4) a vector with prior parameters alpha for each

748   binomial proportion, (5) a vector with prior parameters beta for each binomial proportion,

749   and (6) the labels of the categories of interest (i.e., gender and education level). As with

750   the previous two example, we assign a uniform Beta prior to the binomial probabilities.

```r
# number of violations
x <- dat$x
# total number people in the category
n <- dat$n


# Specifying the informed hypotheses (step 3)


# null hypothesis
p0  <- c(1/8, 1/8, 1/8, 1/8, 1/8, 1/8, 1/8, 1/8)


# informed hypotheses
Hr1 <- c('m1, m2, m3, m4 < f1, f2, f3, f4')
Hr2 <- c('m1, f1 < m2, f2 < m3, f3 < m4, f4')
Hr3 <- c('m1 < f1 < m2 < f2 < m3 < f3 < m4 < f4')


# Prior specification (step 4 and 5)
# We assign a uniform beta distribution to each binomial propotion
a <- c(1, 1, 1, 1, 1, 1, 1, 1)
b <- c(1, 1, 1, 1, 1, 1, 1, 1)


# categories of interest (step 6)
```

```
gender_edu <- dat$levels
```

751 With this information, we can now conduct the analysis with the function
752 `binom_bf_informed()`. Since we are interested in quantifying evidence in favor of the
753 informed hypotheses compared to the encompassing hypothesis, we set the Bayes factor
754 type to `BFre`. For reproducibility, we are also setting a seed.

```
results_H0_He <- multibridge::mult_bf_equality(x = x, a = a, p = p0)


results_Hr1_He <- multibridge::binom_bf_informed(x=x, n=n, Hr=Hr1, a=a, b=b,
                                                 factor_levels=gender_edu,
                                                 bf_type = 'BFre',
                                                 seed = 2020)




results_Hr2_He <- multibridge::binom_bf_informed(x=x, n=n, Hr=Hr2, a=a, b=b,
                                                 factor_levels=gender_edu,
                                                 bf_type = 'BFre',
                                                 seed = 2020)




results_Hr3_He <- multibridge::binom_bf_informed(x=x, n=n, Hr=Hr3, a=a, b=b,
                                                 factor_levels=gender_edu,
                                                 bf_type = 'BFre',
                                                 seed = 2020)
```

755 The results are summarized in Table 9. We first inspect the Bayes factors for the
756 three informed hypotheses compared to the encompassing hypothesis. For hypotheses $\mathcal{H}_{r1}$,

the data suggest moderate evidence for the encompassing hypothesis compared to the

informed hypothesis, with a Bayes factor of 6.43. This hypothesis predicted a main effect

of gender, that is, men should have a lower probability of violating stochastic dominance

than women regardless of their education level. For hypotheses $\mathcal{H}_{r2}$ and $\mathcal{H}_{r3}$, the data

provide strong evidence in favor of the informed hypothesis compared to the encompassing

hypothesis, with Bayes factors of 17.82 and 22.36, respectively. However, there is no

predictive advantage of $\mathcal{H}_{r3}$ over $\mathcal{H}_{r2}$; the Bayes factor directly comparing these hypotheses

is $\mathrm{BF}_{r3r2} = \frac{\mathrm{BF}_{r3e}}{\mathrm{BF}_{r2e}} = 1.26$. The degree to which the data conforms to the predicted pattern

from $\mathcal{H}_{r3}$ becomes apparent when we plot the posterior estimates.

```
plot(summary(results_Hr3_He))
```


To compare all four hypotheses directly with each other, we computed the posterior

model probabilities:

```
post_probs <- data.frame(
    Hyps = c('p(He | x)', 'p(H0 | x)', 'p(Hr1 | x)', 'p(Hr2 | x)', 'p(Hr3 | x)'),
    Prob = c(1, BF0e, BFr1e, BFr2e, BFr3e)/sum(c(1, BF0e, BFr1e, BFr2e, BFr3e)))
```

769   The model that predicts only a gender effect performs worse than the baseline model

770 without any restrictions. Hypothesis $\mathcal{H}_{r3}$ outperforms all other models, including the

771 bookend hypotheses, with a posterior model probability of 54%. Here too, however, the

772 posterior probability of hypothesis $\mathcal{H}_{r2}$ is with 43% almost as high as $\mathcal{H}_{r3}$. To sum up,

773 even though $\mathcal{H}_{r3}$ yield the biggest Bayes factor and the highest posterior model probability,

774 the difference advantage to $\mathcal{H}_{r2}$ is slim. Note that Myung et al. (2005) and Birnbaum

775 (1999) concluded that hypothesis $\mathcal{H}_{r3}$ performs the best. In contrast, our analysis

776 suggested that here is strong evidence for an effect of education, but it is inconclusive

777 whether the effect is moderated by gender.

Table 9

Prior model probabilities, posterior model probabilities, and Bayes factors for four
hypotheses concerning the relationship between gender and education level on the probability
of violating stochastic dominance.

Hypothesis	$p(\mathcal{H}_{.})$	$p(\mathcal{H}_{.} \mid \mathbf{x})$	$\mathrm{BF}_{.e}$
$\mathcal{H}_e$	0.25	0.0242	1
$\mathcal{H}_0$	0.25	1.34×10^{-53}	5.55×10^{-52}
$\mathcal{H}_{r1}$	0.25	0.0038	0.16
$\mathcal{H}_{r2}$	0.25	0.4310	17.82
$\mathcal{H}_{r3}$	0.25	0.5410	22.36

778   **Discussion**

779   The R package **multibridge** facilitates the estimation of Bayes factors for informed

780 hypotheses in both multinomial and independent binomial models. The efficiency gains of

781 **multibridge** are particularly pronounced when the parameter restrictions are highly

782 informative or when the number of categories is large.

783   **multibridge** supports the evaluation of informed hypotheses that feature equality

784 constraints, inequality constraints, and free parameters, as well as combinations between

785 them. Moreover, users can choose to test the informative hypothesis against an

786 encompassing hypothesis that lets all parameters vary freely or against the null hypothesis

787 that states that category proportions are exactly equal. Beyond the core functions

788 currently implemented in **multibridge**, there are several natural extensions we aim to

789 include in future versions of this package. For instance, to compare several models with

790 each other we plan to implement functions that compute the posterior model probabilities.

791 Another extension is to facilitate the specification of hierarchical binomial and multinomial

792 models which would allow users to analyze data where responses are nested within a

793 higher-order structure such as participants, schools, or countries. Hierarchical multinomial

794 models can be found, for instance, in source memory research where people need to select a

795 previously studied item from a list (e.g., Arnold, Heck, Bröder, Meiser, & Boywitt, 2019); a

796 hierarchical binomial model was applied, for instance, in Hoogeveen, Sarafoglou, and

797 Wagenmakers (2020), to evaluate laypeople's accuracy in predicting replication outcomes

798 for social science studies.

799   Furthermore, to make the method accessible to a larger audience of users and

800 students, the informed Bayesian multinomial test and the informed Bayesian test for

801 multiple binomials will be made available in future versions of the software package JASP

802 (JASP Team, 2022). JASP offers an intuitive graphical user interface and does not require

803 extensive knowledge in programming.

804   In addition, we plan to expand the types of hypotheses that can be evaluated in

805 future versions of this package. Currently, **multibridge** only supports informed

806 hypotheses which are "stick hypotheses", that is, hypotheses in which all elements within a

constraint are linearly ordered. While the quantity shown in Equation 1 admits in principle

any constraint imposed on a vector of category proportions, this requirement is necessary

for the bridge sampling routine, in order to transform samples from the real line to the

probability space. To be able to evaluate more general ordinal constrains including

"branch-hypotheses" with bridge sampling in the future, the stick-breaking transformation

needs to be further refined. Arguably, this refinement can be realized more easily for

transformations of multiple binomials than for multinomials, since independent binomials

live in probability space but are not constrained by the sum-to-one condition.

Finally, we aim to enable the specification of more general informed hypotheses,

including hypotheses on the size ratios of the parameters (e.g., $\theta_1 < 2 \times \theta_2$) or on their

odds ratios (e.g., $\frac{\theta_1}{(\theta_1+\theta_2)} < \frac{\theta_3}{(\theta_3+\theta_4)}$). A framework to evaluate these constraints using the

unconditional encompassing approach has already been proposed (Klugkist, Laudy, &

Hoijtink, 2010). We believe that the bridge sampling method could also be extended to

test these hypotheses as in principle, as all the building blocks are already in place.

Specifically, **multibridge** takes size ratios into account when it evaluates hypotheses

featuring combinations of equality and inequality constraints. For these hypotheses,

multibridge first evaluates the equality constraints separately and then evaluates the

inequality constraints given the equality constraints hold. To do so, the algorithm merges

equality-constrained categories but tracks their initial number to effectively sample from

the constrained parameter space and to transform the parameters. For odds ratios, on the

other hand, a suitable sampling method and transformation has not yet been developed.

To facilitate the evaluation of these hypotheses, alternative methods to sample and

transform the parameters are required.

Declarations

Availability of data and code

The source code of the `R` package is available at:
https://github.com/ASarafoglou/multibridge/. In addition, readers can access the code for
reproducing all analyses and plots via our project folder on the Open Science Framework:
https://osf.io/2wf5y/.

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Author contributions

The authors made the following contributions. Alexandra Sarafoglou:
Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Methodology,
Project Administration, Software, Validation, Visualization, Writing - Original Draft
Preparation, Writing - Review & Editing; Frederik Aust: Conceptualization, Software,
Supervision, Validation, Visualization, Writing - Original Draft Preparation, Writing -
Review & Editing; Maarten Marsman: Funding Acquisition, Conceptualization,
Methodology, Supervision, Validation, Writing - Review & Editing; Frantisek Bartos:
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Validation, Writing - Review & Editing; Julia M. Haaf: Conceptualization, Formal
Analysis, Methodology, Software, Supervision, Validation, Writing - Original Draft
Preparation, Writing - Review & Editing.

Conflicts of interest

The authors declare that there were no conflicts of interest with respect to the authorship or the publication of this article.

Ethical Approval

This is a methodological contribution which requires no ethical approval.

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Appendix

Transforming an Ordered Probability Vector to the Real Line

The bridge sampling routine in **multibridge** uses the multivariate normal

distribution as proposal distribution, which requires moving the target distribution $\boldsymbol{\theta}$ to

the real line. Crucially, the transformation needs to retain the ordering of the parameters,

that is, it needs to take into account the lower bound l_k and the upper bound u_k of each θ_k.

To meet these requirements, **multibridge** uses a probit transformation, as proposed in

Sarafoglou et al. (2021), and subsequently transforms the elements in $\boldsymbol{\theta}$, moving from its

lowest to its highest value. In the binomial model, we move all elements in $\boldsymbol{\theta}$ to the real

line and thus construct a new vector $\boldsymbol{y} \in \mathbb{R}^K$. For multinomial models it follows from the

sum-to-one constraint that the vector $\boldsymbol{\theta}$ is completely determined by its first $K - 1$

elements, where θ_K is defined as $1 - \sum_{k=1}^{K-1} \theta_k$. Hence, for multinomial models we will only

consider the first $K - 1$ elements of $\boldsymbol{\theta}$ and we will transform them to $K - 1$ elements of a

new vector $\boldsymbol{y} \in \mathbb{R}^{K-1}$.

Let ϕ denote the density of a normal variable with a mean of zero and a variance of

one, Φ denote its cumulative density function, and Φ^{-1} denote the inverse cumulative

density function. Then for each element θ_k, the transformation is

$$\xi_k = \Phi^{-1}\left(\frac{\theta_k - l_k}{u_k - l_k}\right),$$

The inverse transformation is given by

$$\theta_k = (u_k - l_k)\Phi(\xi_k) + l_k.$$

To perform the transformations, we need to determine the lower bound l_k and the

upper bound u_k of each θ_k. Assuming $\theta_{k-1} < \theta_k$ for $k \in \{2 \cdots, K\}$ the lower bound for any

element in $\boldsymbol{\theta}$ is defined as

$$l_k = \begin{cases} 0 & \text{if } k = 1 \\ \theta_{k-1} & \text{if } 1 < k < K. \end{cases}$$

This definition holds for both binomial models and multinomial models. Differences in these two models appear only when determining the upper bound for each parameter. For binomial models, the upper bound for each θ_k is simply 1. For multinomial models, however, due to the sum-to-one constraint the upper bounds depend on the values of smaller elements as well as on the number of remaining larger elements in $\boldsymbol{\theta}$. To be able to determine the upper bounds, we represent $\boldsymbol{\theta}$ as unit-length stick which we subsequently divide into K elements Stan Development Team (2020). By using this so-called stick-breaking method we can define the upper bound for any θ_k as follows:

$$u_k = \begin{cases} \dfrac{1}{K} & \text{if } k = 1 \\ \dfrac{1 - \sum_{i<k} \theta_i}{ERS} & \text{if } 1 < k < K, \end{cases} \tag{C1}$$

where $1 - \sum_{i<k} \theta_i$ represents the length of the remaining stick, that is, the proportion of the unit-length stick that has not yet been accounted for in the transformation. The elements in the remaining stick are denoted as ERS, and are computed as follows:

$$ERS = K - 1 + k.$$

The transformations outlined above are suitable only for ordered probability vectors, that is, for informed hypotheses in binomial and multinomial models that only feature inequality constraints. However, when informed hypotheses also feature equality constrained parameters, as well as parameters that are free to vary we need to modify the formula. Specifically, to determine the lower bounds for any θ_k, we need to take into

1057 account how many parameters were set equal to it (denoted as e_k) and how many

1058 parameters were set equal to its preceding value θ_{k-1} (denoted as e_{k-1}):

$$
l_k = \begin{cases} 0 & \text{if } k = 1 \\[2ex] \frac{\theta_{k-1}}{e_{k-1}} \times e_k & \text{if } 1 < k < K. \end{cases} \tag{C2}
$$

1059 The upper bound for parameters in the binomial models still remains 1. To determine the

1060 upper bound for multinomial models we must, additionally for each element θ_k, take into

1061 account the number of free parameters that share common upper and lower bounds

1062 (denoted with f_k). The upper bound is then defined as:

$$
u_k = \begin{cases} \dfrac{1 - (f_k \times l_k)}{K} = \dfrac{1}{K} & \text{if } k = 1 \\[3ex] \left(\dfrac{1 - \sum_{i<k} \theta_i - (f_k \times l_k)}{ERS} \right) \times e_k & \text{if } 1 < k < K \text{ and } u_k \geq \max(\theta_{i<k}), \\[3ex] \left(2 \times \left(\dfrac{1 - \sum_{i<k} \theta_i - (f_k \times l_k)}{ERS} \right) - \max(\theta_{i<k}) \right) \times e_k & \text{if } 1 < k < K \text{ and } u_k < \max(\theta_{i<k}). \end{cases}
$$

$$\tag{C3}$$

1063   The elements in the remaining stick are then computed as follows

$$
ERS = e_k + \sum_{j>k} e_j \times f_j.
$$

1064 The rationale behind these modifications will be described in more detail in the following

1065 sections. In **multibridge**, information that is relevant for the transformation of the

1066 parameter vectors is stored in the generated `restriction_list` which is returned by the

1067 main functions `binom_bf_informed` and `mult_bf_informed` but can also be generated

1068 separately with the function `generate_restriction_list`. This restriction list features

1069 the sublist `inequality_constraints` which encodes the number of equality constraints

1070 collapsed in each parameter in `nr_mult_equal`. Similarly the number of free parameters

1071 that share common bounds are encoded under `nr_mult_free`.

1072 **Equality Constrained Parameters.** In cases where informed hypotheses feature

1073 a mix of equality and inequality constrained parameters, we compute the Bayes factor

1074 BF_{re}, by multiplying the individual Bayes factors for both constraint types with each other:

$$\text{BF}_{re} = \text{BF}_{1e} \times \text{BF}_{2e} \mid \text{BF}_{1e},$$

1075 where the subscript 1 denotes the hypothesis that only features equality constraints and

1076 the subscript 2 denotes the hypothesis that only features inequality constraints. To receive

1077 $\text{BF}_{2e} \mid \text{BF}_{1e}$, we collapse all equality constrained parameters in the constrained prior and

1078 posterior distributions into one category. This collapse has implications on the performed

1079 transformations.

1080 When transforming the samples from the collapsed distributions, we need to account

1081 for the fact that the inequality constraints imposed under the original parameter values

1082 might not hold for the collapsed parameters. Consider, for instance, a multinomial model

1083 in which we specify the following informed hypothesis

$$\mathcal{H}_r : \theta_1 < \theta_2 = \theta_3 = \theta_4 < \theta_5 < \theta_6,$$

where samples from the encompassing distribution take the values
$(0.05, 0.15, 0.15, 0.15, 0.23, 0.27)$. For these parameter values the inequality constraints hold
since 0.05 is smaller than 0.15, 0.23, and 0.27. However, the same constraint does not hold
when we collapse the categories θ_2, θ_3, and θ_4 into θ_*. That is, the collapsed parameter
$\theta_* = 0.15 + 0.15 + 0.15 = 0.45$ is now larger than 0.23 and 0.27. In general, to determine
the lower bound for a given parameter θ_k we thus need to take into account both the
number of collapsed categories in the preceding parameter e_{k-1} as well as the number of
collapsed categories in the current parameter e_k. Thus, lower bounds for the parameters

need to be adjusted as follows:

$$
l_k = \begin{cases} 0 & \text{if } k = 1 \\[2ex] \frac{\theta_{k-1}}{e_{k-1}} \times e_k & \text{if } 1 < k < K, \end{cases}
$$

which leads to Equation C2. In this equation, e_{k-1} and e_k refer to the number of equality

constrained parameters that are collapsed in θ_{k-1} and θ_k, respectively. In the example

above, this means that to determine the lower bound for θ_* we multiply the preceding

value θ_1 by three, such that the lower bound is $\left(\frac{0.05}{1}\right) \times 3 = 0.15$. In addition, to determine

the lower bound of θ_5 we divide the preceding value θ_* by three, that is, $\left(\frac{0.45}{3}\right) \times 1 = 0.15$.

Similarly, to determine the upper bound for a given parameter value θ_k, we need to

multiple the upper bound by the number of parameters that are collapsed within it:

$$
u_k = \begin{cases} \dfrac{1}{ERS} \times e_k & \text{if } k = 1 \\[3ex] \dfrac{1 - \sum_{i<k} \theta_i}{ERS} \times e_k & \text{if } 1 < k < K, \end{cases} \tag{C4}
$$

where $1 - \sum_{i<k} \theta_i$ represents the length of the remaining stick and the number of elements

in the remaining stick are computed as follows: $ERS = \sum_k^K e_k$. For the example above, the

upper bound for θ_* is $\dfrac{1 - 0.05}{5} \times 3 = 0.57$. The upper bound for θ_5 is then

$\dfrac{(1 - 0.05 - 0.45)}{2} \times 1 = 0.25$.

Corrections for Free Parameters.   Different adjustments are required for a

sequence of inequality constrained parameters that share upper and lower bounds.

Consider, for instance, a multinomial model in which we specify the informed hypothesis

$$
\mathcal{H}_r : \theta_1 < (\theta_2\,,\,\theta_3) < \theta_4.
$$

This hypothesis specifies that θ_2 and θ_3 have the shared lower bound θ_1 and the shared

upper bound θ_4, however, θ_2 can be larger than θ_3 or vice versa. To integrate these cases

within the stick-breaking approach one must account for these potential changes of order. For these cases, the lower bounds for the parameters remain unchanged. To determine the upper bound for θ_k, we need to subtract from the length of the remaining stick the lower bound from the parameters that are free to vary. However, only those parameters are included in this calculation that have not yet been transformed:

$$u_k = \begin{cases} \dfrac{1 - (f_k \times l_k)}{K} & \text{if } k = 1 \\ \dfrac{1 - \sum_{i<k} \theta_i - (f_k \times l_k)}{ERS} & \text{if } 1 < k < K, \end{cases} \tag{C5}$$

where f_k represents the number of free parameters that share common bounds with θ_k and that have been not yet been transformed. Here, the number of elements in the remaining stick is defined as the number of all parameters that are larger than θ_k: $ERS = 1 + \sum_{j>k} f_j$. To illustrate this correction, assume that samples from the encompassing distribution take the values $(0.15, 0.29, 0.2, 0.36)$. The upper bound for θ_1 is simply $\frac{1}{4}$. For θ_2, we need to take into account that θ_2 and θ_3 share common bounds. To compute the upper bound for θ_2, we subtract from the length of the remaining stick the lower bound of θ_3: $\dfrac{1 - 0.15 - (1 \times 0.15)}{1 + 1} = 0.35$.

A further correction is required if a preceding free parameter (i.e., a parameter with common bounds that was transformed already) is larger than the upper bound of the current parameter. For instance, in our example the upper bound for θ_3 would be $\dfrac{1 - 0.44 - 0}{1 + 1} = 0.28$, which is smaller than the value of the preceding free parameter, which was 0.29. If in this case θ_3 would actually take on the value close to its upper bound, for instance $\theta_3 = 0.275$, then—due to the sum-to-one constraint—θ_4 would violate the constraint (i.e., $0.15 < (0.29\,,\, 0.275) \not< 0.285$). In these cases, the upper bound for the current θ_k needs to be corrected downwards. To do this, we subtract from the current upper bound the difference to the largest preceding free parameter. Thus, if

$u_k < \max(\theta_{i<k})$, the upper bound becomes:

$$u_k = u_k - (\max(\theta_{i<k}) - u_k) \tag{C6}$$

$$= 2 \times u_k - \max(\theta_{i<k}). \tag{C7}$$

For our example the corrected upper bound for θ_3 would become $2 \times 0.28 - 0.29 = 0.27$ which secures the proper ordering for the remainder of the parameters. If in this case θ_3 would take on the value close to its upper bound, for instance $\theta_3 = 0.265$, θ_4—due to the sum-to-one constraint—would take on the value 0.295 which would be in accordance with the constraint (i.e., $0.15 < (0.29, 0.265) < 0.295$).