

# Bayes Factors via Serial Tempering

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## 1 Introduction

### 1.1 Bayes Factors

Let  $\mathcal{M}$  be a finite or countable set of models (here we only deal with finite  $\mathcal{M}$  but Bayes factors make sense for countable  $\mathcal{M}$ ). For each model  $m \in \mathcal{M}$  we have the prior probability of the model  $\text{pri}(m)$ . It does not matter if this prior on models is unnormalized.

Each model  $m$  has a parameter space  $\Theta_m$  and a prior

$$g(\theta \mid m), \quad \theta \in \Theta_m$$

The spaces  $\Theta_m$  can and usually do have different dimensions. That's the point. These within model priors must be normalized proper priors. The calculations to follow make no sense if these priors are unnormalized or improper.

Each model  $m$  has a data distribution

$$f(y \mid \theta, m)$$

and the observed data  $y$  may be either discrete or continuous (it makes no difference to the Bayesian who treats  $y$  as fixed after it is observed and treats only  $\theta$  and  $m$  as random).

The unnormalized posterior for everything (for models and parameters within models) is

$$f(y \mid \theta, m)g(\theta \mid m)\text{pri}(m)$$

To obtain the conditional distribution of  $y$  given  $m$ , we must integrate out the nuisance parameter  $\theta$

$$\begin{aligned} q(y \mid m) &= \int_{\Theta_m} f(y \mid \theta, m)g(\theta \mid m)\text{pri}(m) d\theta \\ &= \text{pri}(m) \int_{\Theta_m} f(y \mid \theta, m)g(\theta \mid m) d\theta \end{aligned}$$

These are the unnormalized posterior probabilities of the models. The normalized posterior probabilities are

$$\text{post}(m \mid y) = \frac{q(y \mid m)}{\sum_{m \in \mathcal{M}} q(y \mid m)}$$

It is considered useful to define

$$b(y \mid m) = \int_{\Theta_m} f(y \mid \theta, m) g(\theta \mid m) d\theta$$

so

$$q(y \mid m) = b(y \mid m) \text{pri}(m)$$

Then the ratio of posterior probabilities of models  $m_1$  and  $m_2$  is

$$\frac{\text{post}(m_1 \mid y)}{\text{post}(m_2 \mid y)} = \frac{q(y \mid m_1)}{q(y \mid m_2)} = \frac{b(y \mid m_1)}{b(y \mid m_2)} \cdot \frac{\text{pri}(m_1)}{\text{pri}(m_2)}$$

This ratio is called the *posterior odds* of the models (a ratio of probabilities is called an *odds*) of these models.

The *prior odds* is

$$\frac{\text{pri}(m_1)}{\text{pri}(m_2)}$$

The term we have not yet named in

$$\frac{\text{post}(m_1 \mid y)}{\text{post}(m_2 \mid y)} = \frac{b(y \mid m_1)}{b(y \mid m_2)} \cdot \frac{\text{pri}(m_1)}{\text{pri}(m_2)}$$

is called the *Bayes factor*

$$\frac{b(y \mid m_1)}{b(y \mid m_2)} \tag{1}$$

the ratio of posterior odds to prior odds.

The prior odds tells how the prior compares the probability of the models. The Bayes factor tells us how the data shifts that comparison going from prior to posterior via Bayes rule. Bayes factors are the primary tool Bayesians use for model comparison, the competitor for frequentist  $P$ -values in frequentist hypothesis tests of model comparison.

Note that our clumsy multiple letter notation for priors and posteriors  $\text{pri}(m)$  and  $\text{post}(m \mid y)$  does not matter because neither is involved in the actual calculation of Bayes factors (1). Priors and posteriors are involved in motivating Bayes factors but not in calculating them.

## 1.2 Tempering

Simulated tempering (Marinari and Parisi, 1992; Geyer and Thompson, 1995) is a method of Markov chain Monte Carlo (MCMC) simulation of many distributions at once. It was originally invented with the primary aim of speeding up MCMC convergence, but was also recognized to be useful for sampling multiple distributions (Geyer and Thompson, 1995). In the latter role it is sometimes referred to as “umbrella sampling” which is a term coined by Torrie and Valleau (1977) for sampling multiple distributions not necessarily via MCMC or simulated tempering (which was invented long after they wrote).

We have a finite set of unnormalized distributions we want to sample, all related in some way. The R function `temper` in the CRAN package `mcmc` requires all to have continuous distributions for random vectors of the same dimension (all distributions have the same domain  $\mathbb{R}^p$ ). Let  $h_i$ ,  $i \in \mathcal{I}$  denote the unnormalized densities of these distributions. Simulated tempering (called “serial tempering” by the `temper` function to distinguish from a related scheme not used in this document called “parallel tempering” and in either case abbreviated ST) runs a Markov chain whose state is a pair  $(i, x)$  where  $i \in \mathcal{I}$  and  $x \in \mathbb{R}^p$ .

The unnormalized density of stationary distribution of the ST chain is

$$h(i, x) = h_i(x)c_i \tag{2}$$

where the  $c_i$  are arbitrary constants chosen by the user (more on this later).

The equilibrium distribution of the ST state  $(I, X)$  — both bits random — is such that conditional distribution of  $X$  given  $I = i$  is the distribution with unnormalized density  $h_i$ . This is obvious from  $h(i, x)$  being the unnormalized conditional density — the same function thought of as a function of both variables is the unnormalized joint density and thought of as a function of just one of the variables is an unnormalized conditional density — and  $h(i, x)$  thought of as a function of  $x$  for fixed  $i$  being proportional to  $h_i$ . The equilibrium unnormalized marginal distribution of  $I$  is

$$\int h(i, x) dx = c_i \int h_i(x) dx = c_i d_i \tag{3}$$

where

$$d_i = \int h_i(x) dx$$

is the normalizing constant for  $h_i$ , that is,  $h_i/d_i$  is a normalized distribution.

It is clear from (3) being the unnormalized marginal distribution that in order for the marginal distribution to be uniform we must choose the tuning constants  $c_i$  to be proportional to  $1/d_i$ . It is not important that the marginal distribution be exactly uniform, but unless it is approximately uniform, the sampler will not visit each distribution frequently. Thus we do need to have the  $c_i$  to be approximately proportional to  $1/d_i$ . This is accomplished by trial and error (one example is done in this document) and is easy for easy problems and hard for hard problems (Geyer and Thompson, 1995, have much to say about adjusting the  $c_i$ ). For the rest of this section we will assume the tuning constants  $c_i$  have been so adjusted: we do not have the  $c_i$  exactly proportional to  $1/d_i$  but do have them approximately proportional to  $1/d_i$ .

### 1.3 Tempering and Bayes Factors

Bayes factors are very important in Bayesian inference and many methods have been invented to calculate them. No method except the one described here using ST is anywhere near as accurate and straightforward. Thus no competitors will be discussed.

In using ST for Bayes factors we identify the index set  $\mathcal{I}$  with the model set  $\mathcal{M}$  and use the integers  $1, \dots, k$  for both. We would like to identify the within model parameter vector  $\theta$  with the vector  $x$  that is the continuous part of the state of the ST Markov chain, but cannot because the dimension of  $\theta$  depends on  $m$  and this is not allowed. Thus we have to do something a bit more complicated. We “pad”  $\theta$  so that it always has the same dimension, doing so in a way that does not interfere with the Bayes factor calculation. Write  $\theta = (\theta_{\text{actual}}, \theta_{\text{pad}})$ , the dimension of both parts depending on the model  $m$ . Then we insist on the following conditions:

$$f(y \mid \theta, m) = f(y \mid \theta_{\text{actual}}, m)$$

so the data distribution does not depend on the “padding” and

$$g(\theta \mid m) = g_{\text{actual}}(\theta_{\text{actual}} \mid m) \cdot g_{\text{pad}}(\theta_{\text{pad}} \mid m)$$

so the two parts are *a priori* independent and both parts of the prior are

normalized proper priors. This assures that

$$\begin{aligned}
b(y | m) &= \int_{\Theta_m} f(y | \theta, m) g(\theta | m) d\theta \\
&= \iint f(y | \theta_{\text{actual}}, m) g_{\text{actual}}(\theta_{\text{actual}} | m) g_{\text{pad}}(\theta_{\text{pad}} | m) d\theta_{\text{actual}} d\theta_{\text{pad}} \\
&= \int_{\Theta_m} f(y | \theta_{\text{actual}}, m) g_{\text{actual}}(\theta_{\text{actual}} | m) d\theta_{\text{actual}}
\end{aligned} \tag{4}$$

so the calculation of the unnormalized Bayes factors is the same whether or not we “pad”  $\theta$ , and we may then take

$$\begin{aligned}
h_m(\theta) &= f(y | \theta, m) g(\theta | m) \\
&= f(y | \theta_{\text{actual}}, m) g_{\text{actual}}(\theta_{\text{actual}} | m) g_{\text{pad}}(\theta_{\text{pad}} | m)
\end{aligned}$$

to be the unnormalized densities for the component distributions of the ST chain, in which case the unnormalized Bayes factors are proportional to the normalizing constants  $d_i$  in Section 1.2.

#### 1.4 Tempering and Normalizing Constants

Let  $d$  be the normalizing constant for the joint equilibrium distribution of the ST chain (2). When we are running the ST chain we know neither  $d$  nor the  $d_i$  but we do know the  $c_i$ , which are constants we have chosen based on the results of previous runs but are fixed known numbers for the current run. Let  $(I_t, X_t)$ ,  $t = 1, 2, \dots$  be the sample path of the ST chain. Recall that (somewhat annoyingly) we are using the notation  $(i, x)$  for the state vector of a general ST chain and the notation  $(m, \theta)$  for ST chains used to calculate Bayes factors, identifying  $i = m$  and  $x = \theta$ .

Let  $\text{ind}(\cdot)$  denote the function that maps logical values to numerical values, false to zero and true to one. Normalizing constants are estimated by averaging the time spent in each model

$$\hat{\delta}_n(m) = \frac{1}{n} \sum_{t=1}^n \text{ind}(I_t = m) \tag{5}$$

For the purposes of approximating Bayes factors the  $X_t$  are ignored. The  $X_t$  may be useful for other purposes, such as Bayesian model averaging (Hoeting, Madigan, Raftery, and Volinsky, 1999), but this is not discussed here.

The Monte Carlo approximations (5) converge to their expected values under the equilibrium distribution

$$E\{\text{ind}(I_t = m)\} = \int \frac{h(m, x)}{d} dx = \frac{c_m d_m}{d} = \delta(m) \quad (6)$$

We want to estimate the unnormalized Bayes factors (4), which are in this context proportional to the  $d_m$ . The  $c_m$  are known,  $d$  is unknown but does not matter since we only need to estimate the  $d_m = b(m | y)$  up to an overall unknown constant of proportionality, which cancels out of Bayes factors (1).

Note that our discussion here applies unchanged to the general problem of estimating normalizing constants up to an unknown constant of proportionality, which has applications other than Bayes factors, for example, missing data maximum likelihood (Thompson and Guo, 1991; Geyer, 1994; Sung and Geyer, 2007). The ST method approximates normalizing constants up to an overall constant of proportionality with high accuracy regardless of how large or small they are (whether they are  $10^{100}$  or  $10^{-100}$ ), and no other method that does not use essentially the same idea can do this.

The key is what seems at first sight to be a weakness of ST, the need to adjust the tuning constants  $c_i$  by trial and error. In this context the weakness is actually a strength: the adjusted  $c_i$  contain most of the information about the size of the normalizing constants  $d_i$  and the Monte Carlo averages (5) add only the finishing touch. Thus multiple runs of the ST chain with different choices of the  $c_i$  used in each run are needed (the “trial and error”), but the information from all are incorporated in the final run used for final approximation of the normalizing constants (Bayes factors). It is perhaps surprising that the Monte Carlo error approximation is trivial. In the context of the last run of the ST chain the  $c_i$  are known constants and contribute no error. The Monte Carlo error of the averages (5) is straightforwardly estimated by batch means or competing methods.

Geyer and Thompson (1995) note that the  $c_i$  enter formally like a prior: one can think of  $h_i(x)c_i$  as likelihood times prior. But one should not think of the  $c_i$  as representing prior information, informative, non-informative, or in between. The  $c_i$  are adjusted to make the ST distribution sample all the models  $h_i$ , and that is the only criterion for the adjustment. For this reason Geyer and Thompson (1995) call the  $c_i$  the *pseudoprior*. This is a special case of a general principle of MCMC. When doing MCMC one should forget the statistical motivation (in this case Bayes factors). One should set up a Markov chain that does a good job of simulating the required equilibrium distribution, whatever it is. Thinking about the statistical motivation of the

equilibrium does not help and can hurt (if one thinks of the pseudoprior as an actual prior, one may be tempted to adjust it to represent prior information).

## 2 R Package MCMC

We use the R statistical computing environment (R Development Core Team, 2010) in our analysis. It is free software and can be obtained from <http://cran.r-project.org>. Precompiled binaries are available for Windows, Macintosh, and popular Linux distributions. We use the contributed package `mcmc` (Geyer., 2009) If R has been installed, but this package has not yet been installed, do

```
install.packages("mcmc")
```

from the R command line (or do the equivalent using the GUI menus if on Apple Macintosh or Microsoft Windows). This may require root or administrator privileges.

Assuming the `mcmc` package has been installed, we load it

```
> library(mcmc)
```

The version of the package used to make this document is 0.7-5 (which is available on CRAN). The version of R used to make this document is 2.11.0.

We also set the random number generator seed so that the results are reproducible.

```
> set.seed(42)
```

To get different results, change the setting or don't set the seed at all.

## 3 Logistic Regression Example

We use the same logistic regression example used in the `mcmc` package vignette for the `metrop` function (file `demo.pdf`). Simulated data for the problem are in the data set `logit`. There are five variables in the data set, the response `y` and four predictors, `x1`, `x2`, `x3`, and `x4`.

A frequentist analysis for the problem is done by the following R statements

```
> data(logit)
> out <- glm(y ~ x1 + x2 + x3 + x4, data = logit, family = binomial,
+          x = TRUE)
> summary(out)
```

```

Call:
glm(formula = y ~ x1 + x2 + x3 + x4, family = binomial, data = logit,
     x = TRUE)

Deviance Residuals:
      Min       1Q   Median       3Q      Max
-1.7461  -0.6907   0.1540   0.7041   2.1943

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.6328     0.3007   2.104  0.03536 *
x1              0.7390     0.3616   2.043  0.04100 *
x2              1.1137     0.3627   3.071  0.00213 **
x3              0.4781     0.3538   1.351  0.17663
x4              0.6944     0.3989   1.741  0.08172 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 137.628  on 99  degrees of freedom
Residual deviance:  87.668  on 95  degrees of freedom
AIC: 97.668

Number of Fisher Scoring iterations: 6

```

But this example isn't about frequentist analysis, we want a Bayesian analysis. For our Bayesian analysis we assume the same data model as the frequentist, and we assume the prior distribution of the five parameters (the regression coefficients) makes them independent and identically normally distributed with mean 0 and standard deviation 2.

Moreover, we wish to calculate Bayes factors for the  $16 = 2^4$  possible submodels that include or exclude each of the predictors, `x1`, `x2`, `x3`, and `x4`.

### 3.1 Setup

We set up a matrix that indicates these models.

```

> varnam <- names(coefficients(out))
> varnam <- varnam[varnam != "(Intercept)"]

```



```

> nvar <- length(varnam)
> models <- NULL
> foo <- seq(0, 2^nvar - 1)
> for (i in 1:nvar) {
+   bar <- foo%%2^(i - 1)
+   bar <- bar%%2
+   models <- cbind(bar, models, deparse.level = 0)
+ }
> colnames(models) <- varnam
> models

```

```

      x1 x2 x3 x4
[1,]  0  0  0  0
[2,]  0  0  0  1
[3,]  0  0  1  0
[4,]  0  0  1  1
[5,]  0  1  0  0
[6,]  0  1  0  1
[7,]  0  1  1  0
[8,]  0  1  1  1
[9,]  1  0  0  0
[10,] 1  0  0  1
[11,] 1  0  1  0
[12,] 1  0  1  1
[13,] 1  1  0  0
[14,] 1  1  0  1
[15,] 1  1  1  0
[16,] 1  1  1  1

```

In each row, 1 indicates the predictor is in the model and 0 indicates it is out.

The function `temper` in the `mcmc` package that does tempering requires a notion of neighbors among models. It attempts jumps only between neighboring models. Here we choose models to be neighbors if they differ only by one predictor.

```

> neighbors <- matrix(FALSE, nrow(models), nrow(models))
> for (i in 1:nrow(neighbors)) {
+   for (j in 1:ncol(neighbors)) {
+     foo <- models[i, ]
+     bar <- models[j, ]

```

```

+           if (sum(foo != bar) == 1)
+             neighbors[i, j] <- TRUE
+       }
+ }

```

Now we specify the equilibrium distribution of the ST chain. Its state vector is  $(i, x)$  or  $(m, \theta)$  in our alternative notations, where  $i$  is an integer between 1 and `nrow(models) = 16` and  $\theta$  is the parameter vector “padded” to always be the same length, so we take it to be the length of the parameter vector of the full model which is `length(out$coefficients)` or `ncol(models) + 1` which makes the length of the state of the ST chain `ncol(models) + 2`. We take the within model priors for the “padded” components of the parameter vector to be the same as those for the “actual” components, normal with mean 0 and standard deviation 2 for all cases. As is seen in (4) the priors for the “padded” components (parameters not in the model for the current state) do not matter because they drop out of the Bayes factor calculation. The choice does not matter much for this toy example. See the discussion section for more on this issue. It is important that we use normalized log priors, the term `dnorm(beta, 0, 2, log = TRUE)` in the function, unlike when we are simulating only one model as in the `mcmc` package vignette where it would be o. k. to use unnormalized log priors  $-\text{beta}^2 / 8$ . The `temper` function wants the log unnormalized density of the equilibrium distribution. We include an additional argument `log.pseudo.prior`, which is  $\log(c_i)$  in our mathematical development, because this changes from run to run as we adjust it by trial and error. Other “arguments” are the model matrix of the full model `modmat`, the matrix `models` relating integer indices (the first component of the state vector of the ST chain) to which predictors are in or out of the model, and the data vector `y`, but these are not passed as arguments to our function and instead are found in the R global environment.

```

> modmat <- out$x
> y <- logit$y
> ludfun <- function(state, log.pseudo.prior) {
+   stopifnot(is.numeric(state))
+   stopifnot(length(state) == ncol(models) + 2)
+   icomp <- state[1]
+   stopifnot(icomp == as.integer(icomp))
+   stopifnot(1 <= icomp && icomp <= nrow(models))
+   stopifnot(is.numeric(log.pseudo.prior))
+   stopifnot(length(log.pseudo.prior) == nrow(models))

```

```

+   beta <- state[-1]
+   inies <- c(TRUE, as.logical(models[icomp, ]))
+   beta.logl <- beta
+   beta.logl[!inies] <- 0
+   eta <- as.numeric(modmat %*% beta.logl)
+   logp <- ifelse(eta < 0, eta - log1p(exp(eta)),
+                 -log1p(exp(-eta)))
+   logq <- ifelse(eta < 0, -log1p(exp(eta)), -eta -
+                 log1p(exp(-eta)))
+   logl <- sum(logp[y == 1]) + sum(logq[y == 0])
+   logl + sum(dnorm(beta, 0, 2, log = TRUE)) + log.pseudo.prior[icomp]
+ }

```

### 3.2 Trial and Error

Now we are ready to try it out. We start in the full model at its MLE, and we initialize `log.pseudo.prior` at all zeros, having no idea *a priori* what it should be.

```

> state.initial <- c(nrow(models), out$coefficients)
> qux <- rep(0, nrow(models))
> out <- temper(ludfun, initial = state.initial, neighbors = neighbors,
+   nbatch = 1000, blen = 100, log.pseudo.prior = qux)
> names(out)

```

[1] "lud"	"initial"	"neighbors"	"nbatch"
[5] "blen"	"nspac"	"scale"	"outfun"
[9] "debug"	"parallel"	"initial.seed"	"final.seed"
[13] "time"	"batch"	"acceptx"	"accepti"
[17] "initial"	"final"	"ibatch"	

```

> out$time

```

```

      user  system elapsed
28.393   0.012  28.417

```

So what happened?

```

> ibar <- colMeans(out$ibatch)
> ibar

```

```

[1] 0.00000 0.00000 0.00000 0.00000 0.00524 0.06489 0.00754
[8] 0.06021 0.00033 0.00202 0.00008 0.00054 0.28473 0.31487
[15] 0.12478 0.13477

```

The ST chain did not mix well, several models not being visited even once. So we adjust the pseudo priors to get uniform distribution.

```

> qux <- qux + pmin(log(max(ibar)/ibar), 10)
> qux <- qux - min(qux)
> qux

[1] 10.0000000 10.0000000 10.0000000 10.0000000  4.0958384
[6]  1.5794663  3.7319377  1.6543214  6.8608225  5.0490623
[11]  8.2778885  6.3683460  0.1006185  0.0000000  0.9256077
[16]  0.8485902

```

The new pseudoprior should be proportional to  $1 / \text{ibar}$  if  $\text{ibar}$  is an accurate estimate of (6), but this makes no sense when the estimates are bad, in particular, when they are exactly zero. Thus we put an upper bound, chosen arbitrarily (here 10) on the maximum increase of the log pseudoprior. The statement

```
qux <- qux - min(qux)
```

is unnecessary. An overall arbitrary constant can be added to the log pseudoprior without changing the equilibrium distribution of the ST chain. We do this only to make qux more comparable from run to run.

Now we repeat this until the log pseudoprior “converges” roughly.

```

> qux.save <- qux
> time.save <- out$time
> repeat {
+   out <- temper(out, log.pseudo.prior = qux)
+   ibar <- colMeans(out$ibatch)
+   qux <- qux + pmin(log(max(ibar)/ibar), 10)
+   qux <- qux - min(qux)
+   qux.save <- rbind(qux.save, qux, deparse.level = 0)
+   time.save <- rbind(time.save, out$time, deparse.level = 0)
+   if (max(ibar)/min(ibar) < 2)
+     break
+ }
> qux.save

```

```

      [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
[1,] 10.00000 10.00000 10.00000 10.00000 4.095838 1.579466
[2,] 17.70751  9.999775 14.43037  9.714906 4.049512 1.539382
[3,] 18.76818  9.325494 14.43382  9.014132 3.972982 1.385058
[4,] 18.94703  9.733071 14.71371  9.478451 4.276229 1.490810
      [,7]      [,8]      [,9]     [,10]     [,11]     [,12]
[1,] 3.731938 1.654321 6.860822 5.049062 8.277888 6.368346
[2,] 3.349201 1.826804 6.024402 4.412902 6.607937 5.676098
[3,] 3.164068 1.401334 5.635094 4.145408 6.330649 5.173185
[4,] 3.229581 1.553204 6.186982 4.623995 6.881493 5.660156
      [,13]      [,14]      [,15]      [,16]
[1,] 0.1006185 0.000000000 0.9256077 0.8485902
[2,] 0.1475452 0.000000000 0.7369393 0.7865126
[3,] 0.0000000 0.003240203 0.4411160 0.6143926
[4,] 0.1095034 0.000000000 0.9146666 0.8328578

```

```
> qux
```

```

 [1] 18.9470263  9.7330707 14.7137106  9.4784515  4.2762293
 [6]  1.4908095  3.2295806  1.5532045  6.1869824  4.6239946
[11]  6.8814927  5.6601564  0.1095034  0.0000000  0.9146666
[16]  0.8328578

```

```
> apply(time.save, 2, sum)
```

```

user.self  sys.self    elapsed user.child  sys.child
  111.911    0.012    111.926    0.000    0.000

```

Now that the pseudoprior is adjusted well enough, we need to perhaps make other adjustments to get acceptance rates near 20%.

```
> out$accepti
```

```

      [,1]      [,2]      [,3]      [,4]      [,5]
[1,]      NA 0.2392567 0.2122222      NA 0.2207637
[2,] 0.2941989      NA      NA 0.2500000      NA
[3,] 0.2362003      NA      NA 0.2609254      NA
[4,]      NA 0.2775120 0.3292496      NA      NA
[5,] 0.2199747      NA      NA      NA      NA
[6,]      NA 0.1552463      NA      NA 0.2347826
[7,]      NA      NA 0.1579487      NA 0.2902893

```

[8,]	NA	NA	NA	0.1472192	NA
[9,]	0.3443478	NA	NA	NA	NA
[10,]	NA	0.2300469	NA	NA	NA
[11,]	NA	NA	0.2327448	NA	NA
[12,]	NA	NA	NA	0.2503864	NA
[13,]	NA	NA	NA	NA	0.2430998
[14,]	NA	NA	NA	NA	NA
[15,]	NA	NA	NA	NA	NA
[16,]	NA	NA	NA	NA	NA
	[,6]	[,7]	[,8]	[,9]	[,10]
[1,]	NA	NA	NA	0.2182030	NA
[2,]	0.1925287	NA	NA	NA	0.2299383
[3,]	NA	0.1992574	NA	NA	NA
[4,]	NA	NA	0.2157191	NA	NA
[5,]	0.2871537	0.3480454	NA	NA	NA
[6,]	NA	NA	0.2943005	NA	NA
[7,]	NA	NA	0.2502629	NA	NA
[8,]	0.3119266	0.2540193	NA	NA	NA
[9,]	NA	NA	NA	NA	0.2508651
[10,]	NA	NA	NA	0.2416107	NA
[11,]	NA	NA	NA	0.2125436	NA
[12,]	NA	NA	NA	NA	0.2960630
[13,]	NA	NA	NA	0.1707060	NA
[14,]	0.2347140	NA	NA	NA	0.1394892
[15,]	NA	0.3637902	NA	NA	NA
[16,]	NA	NA	0.2719072	NA	NA
	[,11]	[,12]	[,13]	[,14]	[,15]
[1,]	NA	NA	NA	NA	NA
[2,]	NA	NA	NA	NA	NA
[3,]	0.2065789	NA	NA	NA	NA
[4,]	NA	0.2503937	NA	NA	NA
[5,]	NA	NA	0.3187415	NA	NA
[6,]	NA	NA	NA	0.2373950	NA
[7,]	NA	NA	NA	NA	0.2285714
[8,]	NA	NA	NA	NA	NA
[9,]	0.1849427	NA	0.2535885	NA	NA
[10,]	NA	0.2768116	NA	0.2201550	NA
[11,]	NA	0.2859451	NA	NA	0.2173228
[12,]	0.2787402	NA	NA	NA	NA
[13,]	NA	NA	NA	0.3325688	0.2688889

```

[14,]      NA      NA 0.2721154      NA      NA
[15,] 0.2166934      NA 0.3615160      NA      NA
[16,]      NA 0.1775586      NA 0.3317536 0.2301496
      [,16]
[1,]      NA
[2,]      NA
[3,]      NA
[4,]      NA
[5,]      NA
[6,]      NA
[7,]      NA
[8,] 0.2508631
[9,]      NA
[10,]      NA
[11,]      NA
[12,] 0.2364532
[13,]      NA
[14,] 0.2659574
[15,] 0.2916053
[16,]      NA

```

```
> out$acceptx
```

```

[1] 0.19633658 0.09694989 0.07855559 0.05680561 0.10568032
[6] 0.05587045 0.05044360 0.03606650 0.10563674 0.06666667
[11] 0.05854701 0.03254552 0.06180666 0.03780718 0.03388525
[16] 0.02426036

```

The acceptance rates for swaps seem o. k.

```
> min(as.vector(out$accepti), na.rm = TRUE)
```

```
[1] 0.1394892
```

and there is nothing simple we can do to adjust them (adjustment is possible, see the discussion section for more on this issue). We adjust the acceptance rates for within model moves by adjusting the scaling.

```

> out <- temper(out, scale = 0.5, log.pseudo.prior = qux)
> time.save <- rbind(time.save, out$time, deparse.level = 0)
> out$acceptx

```

```

[1] 0.4003067 0.2870911 0.2511125 0.2217288 0.3143193 0.2468896
[7] 0.2245908 0.2063492 0.3088322 0.2260388 0.2026928 0.1677290
[13] 0.2470217 0.1932432 0.1964912 0.1526632

```

Looks o. k. now.

Inspection of autocorrelation functions for components of `out$ibatch` (not shown) says batch length needs to be at least 4 times longer. We make it 10 times longer for safety.

```

> out <- temper(out, blen = 10 * out$blen, log.pseudo.prior = qux)
> time.save <- rbind(time.save, out$time, deparse.level = 0)
> foo <- apply(time.save, 2, sum)
> foo.min <- floor(foo[1]/60)
> foo.sec <- foo[1] - 60 * foo.min
> c(foo.min, foo.sec)

```

```

user.self user.self
      6.000      58.602

```

The total time for all runs of the `temper` function was 6 minutes and 58.6 seconds.

### 3.3 Bayes Factor Calculations

Now we calculate log 10 Bayes factors relative to the model with the highest unnormalized Bayes factor.

```

> log.10.unnorm.bayes <- (qux - log(colMeans(out$ibatch)))/log(10)
> k <- seq(along = log.10.unnorm.bayes)[log.10.unnorm.bayes ==
+   min(log.10.unnorm.bayes)]
> models[k, ]

```

```

x1 x2 x3 x4
1  1  0  1

```

```

> log.10.bayes <- log.10.unnorm.bayes - log.10.unnorm.bayes[k]
> log.10.bayes

```

```

[1] 8.17814103 4.17098637 6.33069128 4.05292216 1.80254545
[6] 0.67203156 1.40468558 0.70498671 2.58875400 1.93202268
[11] 2.82341431 2.37170521 0.08004553 0.00000000 0.37357715
[16] 0.35242443

```



These are base 10 logarithms of the Bayes factors against the  $k$ -th model where  $k = 14$ . For example, the Bayes factor for the  $k$ -th model divided by the Bayes factor for the first model is  $10^{8.178}$ .

Now we calculate Monte Carlo standard errors two different ways. One is the way the delta method is usually taught. To simplify notation, denote the Bayes factors

$$b_m = b(y \mid m)$$

and their Monte Carlo approximations  $\hat{b}_m$ . Then the log Bayes factors are

$$g_i(b) = \log_{10} b_i - \log_{10} b_k$$

hence we need to apply the delta method with the function  $g_i$ , which has derivatives

$$\begin{aligned}\frac{\partial g_i(b)}{\partial b_i} &= \frac{1}{b_i \log_e(10)} \\ \frac{\partial g_i(b)}{\partial b_k} &= -\frac{1}{b_k \log_e(10)} \\ \frac{\partial g_i(b)}{\partial b_j} &= 0, \quad j \neq i \text{ and } j \neq k\end{aligned}$$

```
> fred <- var(out$ibatch)/out$nbatch
> sally <- colMeans(out$ibatch)
> mcse.log.10.bayes <- (1/log(10)) * sqrt(diag(fred)/sally^2 -
+      2 * fred[, k]/(sally * sally[k]) + fred[k, k]/sally[k]^2)
> mcse.log.10.bayes

[1] 0.02297789 0.02297554 0.02427784 0.02466045 0.02124325
[6] 0.01925444 0.02381757 0.02289809 0.02190834 0.01983693
[11] 0.02293685 0.02213382 0.01753144 0.00000000 0.02146088
[16] 0.01857454

> foompter <- cbind(models, log.10.bayes, mcse.log.10.bayes)
> round(foompter, 5)

      x1 x2 x3 x4 log.10.bayes mcse.log.10.bayes
[1,]  0  0  0  0         8.17814         0.02298
[2,]  0  0  0  1         4.17099         0.02298
[3,]  0  0  1  0         6.33069         0.02428
[4,]  0  0  1  1         4.05292         0.02466
[5,]  0  1  0  0         1.80255         0.02124
```

[6,]	0	1	0	1	0.67203	0.01925
[7,]	0	1	1	0	1.40469	0.02382
[8,]	0	1	1	1	0.70499	0.02290
[9,]	1	0	0	0	2.58875	0.02191
[10,]	1	0	0	1	1.93202	0.01984
[11,]	1	0	1	0	2.82341	0.02294
[12,]	1	0	1	1	2.37171	0.02213
[13,]	1	1	0	0	0.08005	0.01753
[14,]	1	1	0	1	0.00000	0.00000
[15,]	1	1	1	0	0.37358	0.02146
[16,]	1	1	1	1	0.35242	0.01857

An alternative calculation of the MCSE replaces the actual function of the raw Bayes factors with its best linear approximation

$$\frac{1}{\log_e(10)} \left( \frac{\hat{b}_i - b_i}{b_i} - \frac{\hat{b}_k - b_k}{b_k} \right)$$

and calculates the standard deviation of this quantity by batch means

```
> ibar <- colMeans(out$ibatch)
> herman <- sweep(out$ibatch, 2, ibar, "/")
> herman <- sweep(herman, 1, herman[, k], "-")
> mcse.log.10.bayes.too <- (1/log(10)) * apply(herman,
+      2, sd)/sqrt(out$nbatch)
> all.equal(mcse.log.10.bayes, mcse.log.10.bayes.too)

[1] TRUE
```

## 4 Discussion

We hope readers are impressed with the power of this method. The key to the method is pseudopriors adjusted by trial and error. The method could have been invented by any Bayesian who realized that the priors on models,  $\text{pri}(m)$  in our notation in Section 1.1, do not affect the Bayes factors and hence are irrelevant to calculating Bayes factors. Thus the priors (or pseudopriors in our terminology) should be chosen for reasons of computational convenience, as we have done, rather than to incorporate prior information.

The rest of the details of the method are unimportant. The `temper` function in R is convenient to use for this purpose, but there is no reason

to believe that it provides optimal sampling. Samplers carefully designed for each particular application would undoubtedly do better. Our notion of “padding” so that the within model parameters have the same dimension for all models follows Carlin and Chib (1995) but “reversible jump” samplers (Green, 1995) would undoubtedly do better. Unfortunately, there seems to be no way to code up a function like `temper` that uses “reversible jump” and requires no theoretical work from users that if messed up destroys the algorithm. The `temper` function is foolproof in the sense that if the log unnormalized density function written by the user (like our `ludfun`) is correct, then the ST Markov chain has the equilibrium distribution is supposed to have. There is nothing the user can mess up except this user written function. No analog of this for “reversible jump” chains is apparent (to your humble author).

Two issues remain where the text above said “see the discussion section for more on this issue.” The first was about within model priors for the “padding” components of within model parameter vectors  $g_{\text{pad}}(\theta_{\text{pad}} \mid m)$  in the notation in (4). Rather than choose these so that they do not depend on the data (as we did), it would be better (if more trouble) to choose them differently for each “padding” component, centering  $g_{\text{pad}}(\theta_{\text{pad}} \mid m)$  so the distribution of a component of  $\theta_{\text{pad}}$  is near to the marginal distribution of the same component in neighboring models (according to the `neighbors` argument of the `temper` function).

The other remaining issue is adjusting acceptance rates for jumps. There is no way to adjust this other than by changing the number of models and their definitions. But the models we have cannot be changed; if we are to calculate Bayes factors from them, then we must sample them as they are. But we can insert new models between old models. For example, if the acceptance for swaps between model  $i$  and model  $j$  is too low, then we can insert distribution  $k$  between them that has unnormalized density

$$h_k(x) = \sqrt{h_i(x)h_j(x)}.$$

This idea is inherited from simulated tempering; (Geyer and Thompson, 1995) have much discussion of how to insert additional distributions into a tempering network. It is another key issue in using tempering to speed up sampling. It is less obvious in the Bayes factor context, but still an available technique if needed.

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