Integration in the hyper2 package

Robin K. S. Hankin

Auckland University of Technology

Abstract

The hyper2 package presented a new formulation of the hyperdirichlet package, offering speed advantages and the ability to deal with higher-dimensional datasets. However, hyper2 was based on likelihood methods and as originally uploaded did not have the ability to integrate over the unit-sum simplex. This functionality has now been incorporated into the package which is documented here, by reproducing earlier analysis.

Keywords: Dirichlet distribution, hyperdirichlet, **hyper2**, combinatorics, R, multinomial distribution, constrained optimization, integration, simplex, unit-sum constraint.

1. Introduction

The **hyper2** package (Hankin 2017) presented a new formulation of the hyperdirichlet distribution (Hankin 2010) which offered speed advantages over the original **hyperdirichlet** package, and the ability to deal with higher-dimensional datasets. However, **hyper2** was based on likelihood methods and as originally uploaded did not have the ability to integrate over the unit-sum simplex. This functionality has now been incorporated into the package which is documented here, by reproducing earlier analysis.

2. Chess

Consider Table 1 in which matches between three chess players are tabulated; this dataset was analysed by Hankin (2010).

$$C \frac{p_1^{30} p_2^{36} p_3^{22}}{\left(p_1 + p_2\right)^{35} \left(p_2 + p_3\right)^{35} \left(p_1 + p_3\right)^{18}}$$

(the symbol 'C' consistently stands for an undetermined constant). This likelihood function is provided in the **hyper2** package as the **chess** dataset:

```
> data(chess)
> chess
```

```
Topalov^30 * (Topalov + Anand)^-35 * (Topalov + Karpov)^-18 * Anand^36
* (Anand + Karpov)^-35 * Karpov^22
```

We can calculate the normalizing constant:

Topalov	Anand	Karpov	total
22	13	-	35
-	23	12	35
8	-	10	18
30	36	22	88

Table 1: Results of 88 chess matches (dataset chess in the aylmer package) between three Grandmasters; entries show number of games won up to 2001 (draws are discarded). Topalov beats Anand 22-13; Anand beats Karpov 23-12; and Karpov beats Topalov 10-8

> B(chess)

[1] 1.442828e-28

comparing well with the value given by the **hyperdirichlet** package of 1.47×10^{-28} . Hankin (2010) went on to calculate the *p*-value for $H_0: p = (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$ as 0.395, a calculation which may be performed in the **hyper2** package as follows:

```
> f <- function(p){loglik(chess,indep(p)) > loglik(chess,c(1,1)/3)}
> probability(chess, disallowed=f,tol=0.01)
```

[1] 0.3785911

Again comparing well with the older result (smaller values of tol give closer agreement at the expense of increased computation time). Finally, we can calculate the probability that Topalov is a better player than Anand:

```
> T.lt.A <- function(p){p[1]<p[2]}
> probability(chess, disallowed=T.lt.A,tol=0.001)
```

```
[1] 0.7127539
```

again showing reasonable agreement with the 2010 value of 0.701.

3. Verification

In a breathtaking display of arrogance and/or incompetence, Hankin (2010) did not actually provide any evidence that the integration suite of **hyperdirichlet** was accurate. Here I compensate for that inexcusable lapse by comparing numerical results with analytical formulae. Consider the standard Dirichlet distribution:

$$\frac{p_1^{\alpha_1-1}\dots p_k^{\alpha_k-1}}{B\left(\alpha_1,\dots,\alpha_k\right)}\tag{1}$$

where it is understood that the $p_i > 0$ and $\sum p_i = 1$; here $B = \frac{\Gamma \sum \alpha_i}{\prod \Gamma \alpha_i}$ is the normalization constant. We can verify that hyper2::B() is operating as expected for the case $\alpha_1 = 1, \alpha_2 = 2, \alpha_3 = 3, \alpha_4 = 4$:

```
> prod(gamma(1:4))/gamma(sum(1:4))
```

[1] 3.306878e-05

> B(dirichlet(alpha=1:4))

[1] 3.306878e-05

Further, consider a Dirichlet distribution with $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 3$. Then, by symmetry, the probability that $p_1 < p_2$ should be exactly $\frac{1}{2}$:

```
> f <- function(p){p[1]<p[2]}
> H <- dirichlet(alpha=rep(2,4))
> probability(H,f,tol=0.1)
```

[1] 0.5045785

Further, $\mathsf{P}(p_1 < p_2 < p_3)$ should be exactly $\frac{1}{6}$:

> g <- function(p){(p[1]<p[2]) & (p[2]<p[3])}
> 1-probability(H,disallowed=g,tol=0.1)

[1] 0.1644873

4. More results: icons dataset

Consider the icons dataset, shown in table 2, and the following hypotheses, again following Hankin (2010), and reproduced here for convenience.

```
> data("oneill")
                                       # load the dataset
> icons
NB^32 * (NB + L + THC + OA)^-20 * (NB + L + THC + WAIS)^-15 * (NB + L +
OA + WAIS)^-9 * (NB + PB + THC + OA)^-18 * (NB + PB + THC + WAIS)^-18 *
(NB + PB + OA + WAIS)<sup>-8</sup> * L<sup>24</sup> * (L + PB + THC + OA)<sup>-11</sup> * (L + PB +
THC + WAIS)^-16 * (L + PB + OA + WAIS)^-18 * PB^30 * THC^24 * OA^14 *
WAIS^9
> maxp(icons)
        NB
                                PB
                     L
                                           THC
                                                        OA
                                                                  WAIS
0.25230411 0.17364433 0.22458188 0.17011281 0.11068604 0.06867083
```

For reference, the other hypotheses were:

icon						
NB	L	PB	THC	OA	WAIS	total
5	3	-	4	-	3	15
3	-	5	8	-	2	18
-	4	9	2	-	1	16
1	3	-	3	4	-	11
4	-	5	6	3	-	18
-	4	3	1	3	-	11
5	1	-	-	1	2	9
5	-	1	-	1	1	8
-	9	7	-	2	0	18
23	24	30	24	14	9	124

Table 2: Experimental results from O'Neill (2007) (dataset icons in the package): respondents' choice of 'most concerning' icon of those presented. Thus the first row shows results from respondents presented with icons NB, L, THC, and WAIS; of the 15 respondents, 5 chose NB as the most concerning (see text for a key to the acronyms). Note the "0" in row 9, column 6: this option was available to the 18 respondents of that row, but none of them actually chose WAIS

- $H_1: p_1 \ge \frac{1}{6}$
- $H_2: p_1 \ge \max\{p_2, \dots, p_6\}$
- $H_3: p_5 + p_6 \ge \frac{1}{3}$
- $H_4: \max\{p_5, p_6\} \ge \min\{p_1, p_2, p_3, p_4\}$

```
> f1 <- function(p){p[1] > 1/6}
```

- > f2 <- function(p){p[1] > max(fillup(p)[-1])}
- > f3 <- function(p){sum(fillup(p)[5:6]) > 1/3}
- > f4 <- function(p){max(fillup(p)[1:2]) > min(fillup(p)[3:6])}

Here I will analyse just the first hypothesis, that is $H_1: p_1 \leq \frac{1}{6}$ using the integration facilities of the **hyper2** package, and compare with previous results. Here we perform a Bayesian analysis, made possible by the efficient coding of **hyper2**:

> probability(icons, disallowed=function(p){p[1] > 1/6}, tol=0.1)

```
[1] 0.01501733
```

See how the disallowed region is the *expected* bit of the parameter space. Thus the probability that the p_i are unexpected (that is, $p_1 < 1/6$) is about 1.5% or conversely, $P(H_1) \simeq 0.985$. The likelihood ratio reported was about 2.608, which would correspond to a *p*-value of about

> pchisq(2*2.608,df=1,lower.tail=FALSE)

[1] 0.02237997

or just over 2% under an asymptoic distribution; thus this frequentist technique gives comparable strength of evidence for H_1 to the Bayesian approach.

5. Incomplete survey data

This section performs the analysis originally presented in Altham and Hankin (2010). The data, given here in table 4 arises from 69 medical malpractice claims, and are the two surgeons' answers to the question: was there a communication breakdown in the hand-off between physicians caring for the patient?

Reviewer 1	Reviewer 2			
	Yes	No	Missing	Total
Yes	26	1	2	29
No	5	18	9	32
Missing	4	4	0	8
Total	35	23	11	69

Table 3: Two surgeon reviews of malpractice claims data

Reviewer 1	Reviewer 2				
	Yes	No	Missing	Total	
Yes	y_{11}	y_{10}	z_{1+}	$y_{1+} + z_{1+}$	
No	y_{01}	y_{00}	z_{0+}	$y_{0+} + z_{0+}$	
Missing	$u_{\pm 1}$	$u_{\pm 0}$	0	u_{++}	
Total	$y_{+1} + u_{+1}$	$y_{+0} + u_{+0}$	z_{++}	n	

Table 4: Notation for the data

We may implement an appropriate likelihood function as follows:

```
> H <- hyper2(d=4)
> pnames(H) <- c("t00", "t10", "t01", "t11")
> H["t00"] <- 18
> H["t10"] <- 01
> H["t01"] <- 05
> H["t11"] <- 26
> H[c("t11", "t10")] <- 2
> H[c("t01", "t00")] <- 9
> H[c("t11", "t01")] <- 4
> H[c("t10", "t00")] <- 4
> H
t00^18 * (t00 + t10)^4 * (t00 + t01)^9 * t10 * (t10 + t11)^2 * t01^5 *
(t01 + t11)^4 * t11^26
```

(object H is provided as handover in the package). Then we may estimate the probability that reviewer 2 is more likely to give a 'yes' than reviewer 1 as follows:

Then the constrained optimization:

```
> obj <- function(p){-loglik(H,p)} # objective func
> gr <- function(p){-gradient(H,p)} # gradient, needed for speed
> UI <- rbind(diag(3),-1) # UI and CI specify constraints
> CI <- c(rep(0,3),-1) # p_i >= 0 and sum p_i <= 1</pre>
```

We will test $H_A: p_2 < p_3$ using the method of support.

```
> ml_HA <- constrOptim(theta=c(0.1,0.2,0.1), f = obj,grad=gr,
+ ui = rbind(UI,c(0,1,-1)), # p2 > p3
+ ci = c(CI,0))
> ml_HA$value
```

[1] 66.14453

Thus the support for H_A is

> ml_HA\$value - free\$value

[1] 130.2899

thus agreeing almost exactly with Altham and Hankin (2010).

References

Altham PME, Hankin RKS (2010). "Using recently developed software on a 2x2 table of matched pairs with incompletely classified data." Journal of the Royal Statistical Society, series C, 59(2), 377–379.

- Hankin RKS (2010). "A Generalization of the Dirichlet Distribution." Journal of Statistical Software, **33**(11), 1–18. URL http://www.jstatsoft.org/v33/i11/.
- Hankin RKS (2017). "Partial rank data with the **hyper2** package: likelihood functions for generalized Bradley-Terry models." *The R Journal*, **9**(2), 429–439.
- O'Neill S (2007). An Iconic Approach to Representing Climate Change. Ph.D. thesis, School of Environmental Science, University of East Anglia.

Affiliation:

Robin K. S. Hankin Auckland University of Technology E-mail: hankin.robin@gmail.com