

# Analysing Bergman's rule with TaxMeta

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```
## Warning: package 'ggplot2' was built under R version 3.2.3
```

## Estimating Bergman's rule for mammals

Using the supplied Bergman dataset:

```
data('Bergman')
head(Bergman)
```

```
##           species      genus  corr  N  z_response      se
## 1      Alces alces      Alces  0.35  8  0.36544375 0.4472136
## 2    Anoura cultrata    Anoura  0.95  4  1.83178082 1.0000000
## 3  Blarina brevicauda  Blarina  0.01  6  0.01000033 0.5773503
## 4 Chaetodipus penicillatus Chaetodipus  0.10 16  0.10033535 0.2773501
## 5    Dipodomys agilis   Dipodomys  0.57  4  0.64752284 1.0000000
## 6  Dipodomys californicus Dipodomys -0.33 38 -0.34282825 0.1690309
```

?Bergman gives info about the data. First, to apply the hierarchical model, we need to get the taxonomy using the taxize package:

```
taxonomy = c('species', 'genus', 'family', 'order')
Bergman_full <- get_tax(Bergman, taxonomy)
```

We can now apply the meta-analysis:

```
bergman_res_full <- TaxMeta(Bergman_full,
  'z_response',
  distribution = 'norm',
  study_epsilon = 'se',
  taxonomy = taxonomy,
  type='full',
  loo_waic = T,
  n.chains = 3,
  n.iter = 150e3,
  n.thin=3,
  n.burnin=25e3,
  return_MCMC=T)
```

```
## Compiling model graph
##   Resolving undeclared variables
##   Allocating nodes
## Graph information:
##   Observed stochastic nodes: 40
##   Unobserved stochastic nodes: 178
```

```
## Total graph size: 939
##
## Initializing model
```

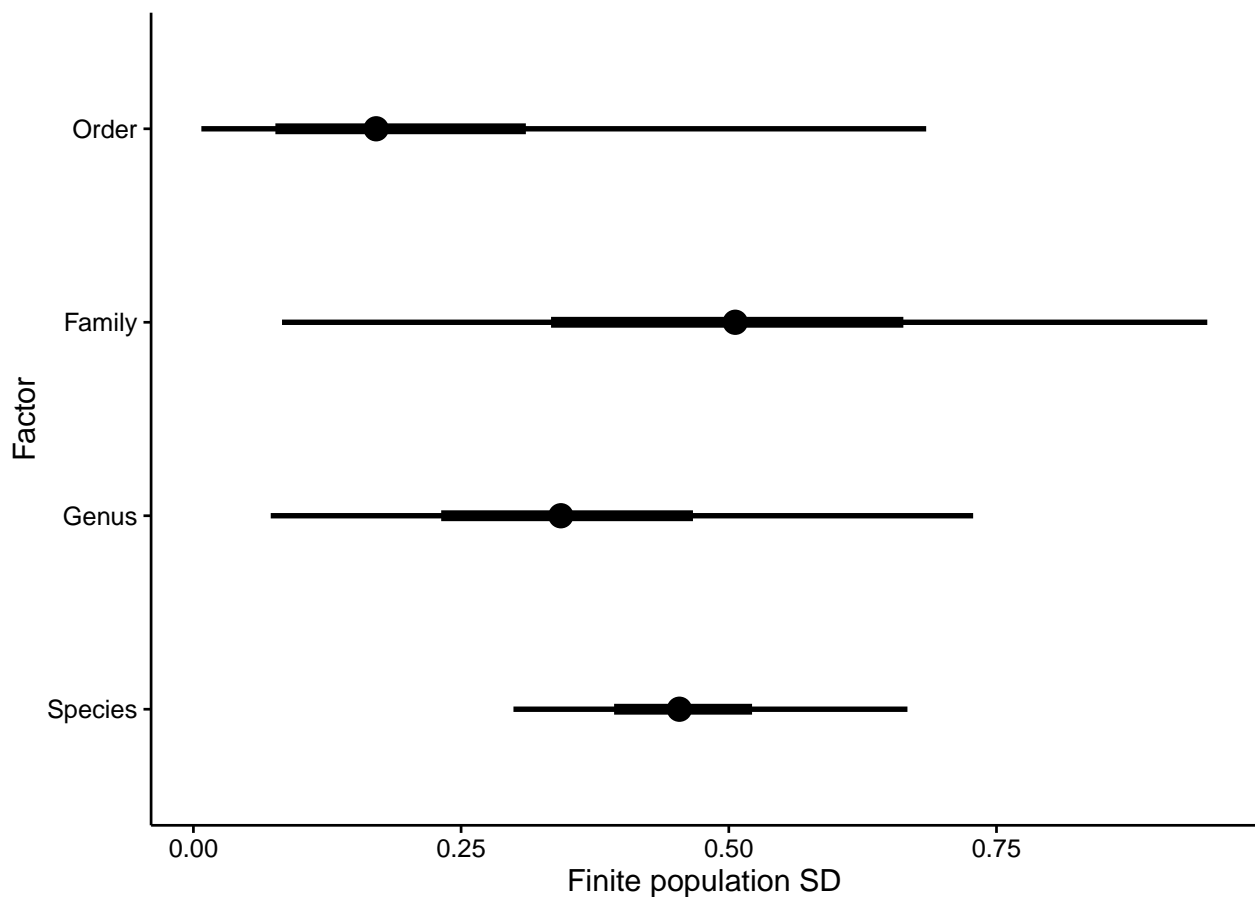
```
bergman_res_full
```

```
##
## Iterations = 26003:176000
## Thinning interval = 3
## Number of chains = 3
## Sample size per chain = 50000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##      Mean      SD Naive SE Time-series SE
## Intercept  0.3087 0.28361 0.0007323      0.005524
## family_scale 9.3461 24.52737 0.0633294      0.344576
## genus_scale 8.1521 20.12186 0.0519544      0.337556
## hyper_scale 0.7988 1.04108 0.0026881      0.014159
## order_scale 8.5506 21.92537 0.0566111      0.316305
## sd.family 0.5018 0.22946 0.0005925      0.002326
## sd.genus 0.3571 0.17118 0.0004420      0.001700
## sd.order 0.2180 0.18641 0.0004813      0.002227
## sd.species 0.4616 0.09516 0.0002457      0.000624
## species_scale 9.0767 28.15061 0.0726846      0.355813
##
## 2. Quantiles for each variable:
##
##      2.5%      25%      50%      75%      97.5%
## Intercept -0.234897 0.13720 0.3111 0.4850 0.8523
## family_scale 0.421807 1.81810 4.0042 9.0323 49.6240
## genus_scale 0.546535 1.87578 3.7752 8.0972 40.9338
## hyper_scale 0.044082 0.22301 0.4781 0.9746 3.5039
## order_scale 0.353079 1.62921 3.6392 8.3352 45.6604
## sd.family 0.082755 0.33400 0.5060 0.6630 0.9468
## sd.genus 0.072224 0.23141 0.3432 0.4665 0.7282
## sd.order 0.007446 0.07656 0.1707 0.3105 0.6843
## sd.species 0.298900 0.39290 0.4539 0.5217 0.6668
## species_scale 0.226921 1.36539 3.3743 8.2622 51.0307
##
## Potential scale reduction factors:
##
##      Point est. Upper C.I.
## Intercept      1.00      1.01
## family_scale    1.01      1.02
## genus_scale     1.00      1.00
## hyper_scale     1.00      1.00
## order_scale     1.01      1.01
## sd.family       1.00      1.00
## sd.genus        1.00      1.00
## sd.order        1.00      1.00
## sd.species      1.00      1.00
## species_scale   1.01      1.01
```

```
##
## Multivariate psrf
##
## 1
##
##
## waic 41.30119 waic SE 8.436146
##
##
## loo 68.31956 loo SE 8.512628
```

To plot the contributions of different taxonomic levels, simply plot the result:

```
plot(bergman_res_full)
```



To generate predictions at other taxonomic levels, simply add some bogus data to the data. Say, we need an estimate for a species for which the genus was not in the original dataset, but the family was part of the dataset:

```
Bergman_pred <- Bergman_full
Bergman_pred[length(Bergman_pred)+1,] <- Bergman_pred[11,]
Bergman_pred[length(Bergman_pred)+2,] <- Bergman_pred[11,]

Bergman_pred[length(Bergman_full)+1, 'genus'] <- 'bogus_genus'
Bergman_pred[length(Bergman_full)+1, 'species'] <- 'Bogus species'
```

```
Bergman_pred[length(Bergman_full)+1,'z_response'] <- NA
Bergman_pred[length(Bergman_full)+2,'species'] <- 'Bogus species'
Bergman_pred[length(Bergman_full)+2,'z_response'] <- NA
```

```
bergman_res_pred <- TaxMeta(Bergman_pred,
  'z_response',
  distribution = 'norm',
  study_epsilon = 'se',
  taxonomy = taxonomy,
  type='full',
  loo_waic = T,
  n.chains = 3,
  n.iter = 150e3,
  n.thin=30,
  n.burnin=25e3,
  return_MCMC=T)
```

```
## Compiling model graph
##   Resolving undeclared variables
##   Allocating nodes
## Graph information:
##   Observed stochastic nodes: 38
##   Unobserved stochastic nodes: 180
##   Total graph size: 942
##
## Initializing model
```

```
bergman_res_pred
```

```
##
## Iterations = 26030:176000
## Thinning interval = 30
## Number of chains = 3
## Sample size per chain = 5000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##           Mean      SD Naive SE Time-series SE
## Intercept      0.33677 0.2831 0.0023118      0.0053266
## family_scale  10.03887 25.0154 0.2042497      0.5407525
## genus_scale    9.27884 28.6032 0.2335438      0.6920907
## hyper_scale    0.73569 0.9382 0.0076605      0.0140853
## order_scale    9.43829 36.4366 0.2975035      0.5898891
## pred[1]        0.00645 0.8176 0.0066760      0.0068823
## pred[2]       -0.11394 0.6758 0.0055180      0.0055179
## sd.family      0.52492 0.2232 0.0018223      0.0024998
## sd.genus       0.35853 0.1735 0.0014165      0.0020685
## sd.order       0.21703 0.1843 0.0015046      0.0023249
## sd.species     0.43642 0.1067 0.0008712      0.0009835
## species_scale 10.05286 35.8544 0.2927498      0.6322678
##
## 2. Quantiles for each variable:
```

```
##
##           2.5%      25%      50%      75%      97.5%
## Intercept    -0.212000  0.16193  0.33685  0.5126  0.8774
## family_scale  0.466772  2.00368  4.35525  9.8490 51.1339
## genus_scale   0.583186  2.05407  4.20043  8.9619 47.0983
## hyper_scale   0.040627  0.20640  0.43891  0.8915  3.2648
## order_scale   0.376918  1.74971  3.90966  8.8528 48.0171
## pred[1]       -1.578032 -0.46169 -0.01657  0.4603  1.6729
## pred[2]       -1.449752 -0.46143 -0.12484  0.2305  1.2738
## sd.family      0.098188  0.36928  0.53246  0.6799  0.9510
## sd.genus       0.074464  0.22882  0.34084  0.4717  0.7367
## sd.order       0.007081  0.07719  0.17014  0.3083  0.6849
## sd.species     0.257955  0.36065  0.42686  0.4999  0.6701
## species_scale  0.238670  1.46074  3.66265  9.0405 53.8473
##
## Potential scale reduction factors:
##
##           Point est. Upper C.I.
## Intercept           1.00      1.01
## family_scale        1.11      1.12
## genus_scale         1.23      1.27
## hyper_scale         1.00      1.01
## order_scale         1.22      1.24
## pred[1]            1.00      1.00
## pred[2]            1.00      1.00
## sd.family          1.00      1.00
## sd.genus           1.00      1.00
## sd.order           1.00      1.00
## sd.species         1.00      1.00
## species_scale      1.13      1.13
##
## Multivariate psrf
##
## 1
##
##
## waic 44.45657 waic SE 8.712652
##
##
## loo 66.54654 loo SE 8.362529
```

We can also compare alternative model formulations:

```
bergman_res_fixed <- TaxMeta(Bergman_full,
                             'z_response',
                             distribution = 'norm',
                             study_epsilon = 'se',
                             taxonomy = taxonomy,
                             type='fixed',
                             scale=0.1,
                             loo_waic = T,
                             n.chains = 3,
                             n.iter = 150e3,
                             n.thin=3,
```

```
n.burnin=20e3,  
return_MCMC=F)
```

```
## Compiling model graph  
##   Resolving undeclared variables  
##   Allocating nodes  
## Graph information:  
##   Observed stochastic nodes: 40  
##   Unobserved stochastic nodes: 92  
##   Total graph size: 656  
##  
## Initializing model
```

```
bergman_res_gamma <- TaxMeta(Bergman_full,  
  'z_response',  
  distribution = 'norm',  
  study_epsilon = 'se',  
  taxonomy = taxonomy,  
  type='gamma',  
  loo_waic = T,  
  n.chains = 3,  
  n.iter = 150e3,  
  n.thin=3,  
  n.burnin=25e3,  
  return_MCMC=F)
```

```
## Compiling model graph  
##   Resolving undeclared variables  
##   Allocating nodes  
## Graph information:  
##   Observed stochastic nodes: 40  
##   Unobserved stochastic nodes: 93  
##   Total graph size: 658  
##  
## Initializing model
```

```
bergman_res_unif <- TaxMeta(Bergman_full,  
  'z_response',  
  distribution = 'norm',  
  study_epsilon = 'se',  
  taxonomy = taxonomy,  
  type='uniform',  
  loo_waic = T,  
  n.chains = 3,  
  n.iter = 150e3,  
  n.thin=3,  
  n.burnin=25e3,  
  return_MCMC=F)
```

```
## Compiling model graph  
##   Resolving undeclared variables  
##   Allocating nodes
```

```
## Graph information:
##   Observed stochastic nodes: 40
##   Unobserved stochastic nodes: 93
##   Total graph size: 658
##
## Initializing model
```

And compare the results:

```
loo_comp <- loo::compare(bergman_res_fixed$loo,
  bergman_res_gamma$loo,
  bergman_res_unif$loo,
  bergman_res_full$loo)

loo_comp <- data.frame(loo_comp)
loo_comp$model <- do.call('rbind',strsplit(rownames(loo_comp),split = '\\\\$'))[,1]
loo_comp$loo_weight = loo_comp$weight

waic_comp <- loo::compare(bergman_res_fixed$waic,
  bergman_res_gamma$waic,
  bergman_res_unif$waic,
  bergman_res_full$waic)

waic_comp <- data.frame(waic_comp)
waic_comp$model <- do.call('rbind',strsplit(rownames(waic_comp),split = '\\\\$'))[,1]
waic_comp$waic_weight = waic_comp$weight

comp_tab <- dplyr::inner_join(loo_comp,waic_comp,by='model')

knitr::kable(comp_tab[,c('model','looic','se_looic','loo_weight','waic','se_waic','waic_weight')],
  row.names=F,
  digits=c(0,1,1,2,1,1,2),
  align=c('l','r','r','r','r','r','r'))
```

model	looic	se_looic	loo_weight	waic	se_waic	waic_weight
bergman_res_fixed	65.6	7.9	0.58	39.4	8.1	0.46
bergman_res_gamma	67.8	8.3	0.19	40.9	8.4	0.22
bergman_res_full	68.3	8.5	0.15	41.3	8.4	0.18
bergman_res_unif	69.3	8.5	0.09	41.8	8.6	0.14

This comparison does not give a good idea of model performance, so lets try a plot:

```
plot(Full=bergman_res_full,
  Fixed =bergman_res_fixed,
  Gamma =bergman_res_gamma,
  Uniform=bergman_res_unif)
```

