Axis_analysis_19_June

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Lets source our packages etc.

```
library(popbio)
library(popdemo)
## Welcome to popdemo! This is version 1.3-0
## Use ?popdemo for an intro, or browseVignettes('popdemo') for vignettes
## Citation for popdemo is here: doi.org/10.1111/j.2041-210X.2012.00222.x
## Development and legacy versions are here: github.com/iainmstott/popdemo
library(ape)
library(caper)
## Loading required package: MASS
## Loading required package: mvtnorm
library(phytools)
## Loading required package: maps
## Loading required package: rgl
library(MCMCglmm)
## Loading required package: Matrix
##
## Attaching package: 'Matrix'
## The following object is masked from 'package:phytools':
##
##
       expm
## Loading required package: coda
library(mulTree)
## Loading required package: hdrcde
## This is hdrcde 3.3
## Loading required package: snow
library(ineq)
library(pspline)
library(paran)
library(SIBER)
library(ggplot2)
#devtools to get the Mage package
library(devtools)
source("Demography_functions.R")
```

You should have calulated all the population matrics and created a dataset to upland for the analysis here.

```
pop_data <- read.csv("axis_analysis_data_6_march_2019.csv",</pre>
                                                      sep = ",", header = T)
axis_trees <- read.tree("axis_analysis_phylo.tre")</pre>
Ok now lets do the circular bar plot
#First make a named vector of the mean trait value.
plot_gini <- vector()</pre>
plot_sd <- vector()</pre>
plot_T <- vector()</pre>
plot_repo <- vector()</pre>
plot_matrix <- vector()</pre>
for(i in 1:length(axis_trees[[1]]$tip.label)){
    plot_matrix[i] <- mean(pop_data[pop_data$species == axis_trees[[1]]$tip.label[i] ,"matrix_size"])</pre>
  plot_gini[i] <- mean(pop_data[pop_data$species == axis_trees[[1]]$tip.label[i] ,"gini"])</pre>
  plot_sd[i] <- mean(pop_data[pop_data$species == axis_trees[[1]]$tip.label[i] ,"surv_sd"])</pre>
 plot_T[i] <- mean(pop_data[pop_data$species == axis_trees[[1]]$tip.label[i] ,"gen_time"])</pre>
 plot_repo[i] <- mean(pop_data[pop_data$species == axis_trees[[1]]$tip.label[i] ,"mean_repo_rate_stabl</pre>
}
names(plot_gini) <- axis_trees[[1]]$tip.label</pre>
names(plot_sd) <- axis_trees[[1]]$tip.label</pre>
names(plot_T) <- axis_trees[[1]]$tip.label</pre>
names(plot_repo) <- axis_trees[[1]]$tip.label</pre>
#pdf("phylobar_gini.pdf")
\#plotTree.wBars(tree = axis\_trees[[1]], x = plot\_gini, scale= 100, type="fan", cex = 0.2, tip.labels = 100, type="fan", cex = 0.2, type="
#dev.off()
#pdf("phylobar_sd_surv.pdf")
\#plotTree.wBars(tree = axis\_trees[[1]], x = plot\_sd, scale = 500, type = "fan", cex = 0.2, tip.labels = T,
#dev.off()
#pdf("phylobar_genT.pdf")
\#plotTree.wBars(tree = axis\_trees[[1]], x = plot\_T, scale = 0.8, type = "fan", cex = 0.2, tip.labels = T,
#dev.off()
#pdf("phylobar repo.pdf")
#dev.off()
Log10 the non index based metrics
log list <- c("life time La",</pre>
                              "mean_repo_rate_stable_state",
                               "mean repo rate",
```

```
"gen_time",
               "M_rep_lif_exp",
               "gini",
              "surv_sd",
              "mass g",
              "mxlxsd",
               "matrix size")
pop_data_log <- pop_data
pop_data_log[,log_list] <- sapply(pop_data[,log_list], function(x) log10(x))</pre>
Now let mean center all the data
mean_c_list <- c("life_time_La",</pre>
                   "mean_repo_rate_stable_state",
                   "mean_repo_rate",
                   "gen_time",
                   "M_rep_lif_exp",
                   "matrix_size",
                   "gini",
                   "surv_sd",
                   "mxlxsd",
                   "mass g")
pop_data_log_mc <- pop_data_log</pre>
pop_data_log_mc[,mean_c_list] <- sapply(pop_data_log[,mean_c_list], function(x) mean_center(x))</pre>
First we make a multree object so we can loop each of the models through the trees
pop_multree <- as.mulTree(data = pop_data_log_mc, tree = axis_trees, taxa = "animal", rand.terms = ~animal
All the diagnostices look good, lets read that back in.
La_models <- read.mulTree("la_run")</pre>
summary(La_models)
                          Estimates(mode hdr) lower.CI(2.5) lower.CI(25)
##
## (Intercept)
                                    0.19719722 -1.50849226 -0.36690480
## mass_g
                                    0.59886150 0.38364714
                                                                0.52569761
                                    0.06146704
## matrix_size
                                                 -0.01051303
                                                                0.03715196
                                    2.03182521
                                                  0.92568227
                                                                1.57138252
## phylogenetic.variance
## residual.variance
                                    0.29105041
                                                  0.17437996
                                                                0.24779073
                          upper.CI(75) upper.CI(97.5)
## (Intercept)
                            0.76240368
                                            1.9105662
## mass_g
                            0.67352314
                                             0.8166247
## matrix_size
                            0.08761245
                                             0.1367521
## phylogenetic.variance
                                             3.8375286
                            2.54299781
## residual.variance
                            0.34484386
                                            0.4648104
## attr(,"class")
## [1] "matrix" "mulTree"
La models variance terms
la_var <- read.mulTree("la_run", extract = "VCV")</pre>
la_phlyo <- list()</pre>
```

```
la_spec <- list()</pre>
la_unit <- list()</pre>
for(i in 1:length(names(la_var))){
  la_phlyo[[i]] <- la_var[[1]][,1]</pre>
  la_spec[[i]] <- la_var[[1]][,2]</pre>
  la_unit[[i]] <- la_var[[1]][,3]</pre>
la_phlyo <- unlist(la_phlyo)</pre>
la_spec <- unlist(la_spec)</pre>
la_unit <- unlist(la_unit)</pre>
la_prop_phlyo <- la_phlyo/(la_phlyo + la_spec + la_unit)</pre>
la_prop_spec <- la_spec/(la_phlyo + la_spec + la_unit)</pre>
la_prop_residuals <- la_unit/(la_phlyo + la_spec + la_unit)</pre>
hdr(la_prop_phlyo)
## $hdr
##
             [,1]
                        [,2]
                                   [,3]
                                             [,4]
                                                        [,5]
                                                                   [.6]
                                                                              [,7]
## 99% 0.6406183 0.6434432 0.6503685 0.6568608 0.6704964 0.6970627 0.7004244
## 95% 0.7332508 0.7464076 0.7483361 0.9558327
                                                          NA
                                                                     NA
                                                                                NA
## 50% 0.8324944 0.8330940 0.8451230 0.9092764 0.9138267 0.9171321
                                                                                NA
##
             [,8]
                        [,9]
                                  [,10]
## 99% 0.9619999 0.9624982 0.9644117
## 95%
                          NΑ
                                    NΑ
               MΔ
## 50%
               NA
                          NA
                                    NA
##
## $mode
## [1] 0.8937473
##
## $falpha
                               50%
##
          1%
                     5%
## 0.2469906 0.9254727 5.6389922
hdr(la_prop_spec)
## $hdr
##
              [,1]
                          [,2]
                                      [,3]
                                                 [,4]
                                                            [,5]
                                                                       [,6]
## 99% 0.03478366 0.26431852 0.26583073 0.2845250 0.2911740 0.3008965
## 95% 0.03738579 0.03901049 0.04092025 0.2137509 0.2151911 0.2294792
## 50% 0.07665461 0.08087969 0.08282138 0.1419366 0.1501532 0.1514604
##
             [,7]
                        [,8]
                                   [,9]
                                            [,10]
                                                       [,11]
                                                                  [,12]
## 99% 0.3050153 0.3089759 0.3125572 0.3140130 0.3234217 0.3241761 0.3260958
## 95% 0.2321272 0.2371634 0.2399997 0.2467182 0.2484158 0.2530036 0.2707032
## 50%
                          NA
                                    NA
               NA
                                               NA
                                                          NA
                                                                     NA
                                                                                NΑ
            [,14]
                       [,15]
                                  [,16]
                                            [,17]
                                                       [,18]
## 99% 0.3293287 0.3405726 0.3429459 0.3702027 0.3705973
## 95% 0.2714517
                          NA
                                    NA
                                               NA
                                                          NA
## 50%
                                               NA
                                                          NA
                          NA
                                    NA
               NA
## $mode
```

```
## [1] 0.09529242
##
## $falpha
                   5%
##
                           50%
         1%
## 0.330040 1.073751 5.984917
hdr(la_prop_residuals)
## $hdr
##
               [,1]
                           [,2]
                                        [,3]
                                                     [,4]
                                                                  [,5]
## 99% 0.004173126 0.004208015 0.004438841 0.004482253 0.004713095
## 95% 0.005449061 0.017740518 0.017926165 0.018072369 0.018290177
## 50% 0.007896610 0.007922972 0.008196460 0.008254788 0.008456136
##
               [,6]
                           [,7]
                                        [,8]
                                                     [,9]
                                                                           [,11]
## 99% 0.020977529 0.021066973 0.021428959 0.022145687 0.02245146 0.02297645
## 95% 0.018471928 0.018837176 0.019134845 0.019515459 0.01961413
## 50% 0.008609794 0.008666226 0.008783359 0.008893645 0.01190254 0.01204487
##
            [,12]
## 99% 0.02313278
## 95%
               NA
## 50% 0.01285248
##
## $mode
## [1] 0.01031497
##
## $falpha
##
                              50%
          1%
                     5%
##
    4.607315 15.866655 95.350920
Now we need to calulate the residuals
La_resids <- mul_resids(mul_output = La_models,</pre>
                         mul_data = pop_multree,
                         Y_data_col = c("life_time_La")
)
All the diagnostices look good, lets read that back in.
repo_models <- read.mulTree("mean_repo_rate_run")</pre>
summary(repo_models)
##
                          Estimates (mode hdr) lower.CI(2.5) lower.CI(25)
## (Intercept)
                                    -0.3821457
                                                  -1.9569788
                                                                -0.8931508
## mass_g
                                    -0.3269210
                                                  -0.5526147
                                                                -0.4028722
                                                  -0.3864657
                                    -0.2602216
                                                                -0.3039546
## matrix_size
## phylogenetic.variance
                                     1.3396644
                                                    0.4631444
                                                                 0.9726397
                                                    0.2280802
## residual.variance
                                     0.3852071
                                                                 0.3277389
                          upper.CI(75) upper.CI(97.5)
## (Intercept)
                            0.08567504
                                            1.02958316
## mass_g
                           -0.24661572
                                           -0.09573343
## matrix_size
                           -0.21771048
                                           -0.13614979
                            1.80301263
                                            2.99722644
## phylogenetic.variance
## residual.variance
                            0.45870537
                                            0.61795971
## attr(,"class")
## [1] "matrix" "mulTree"
```

repo_models variance terms

```
repo_var <- read.mulTree("mean_repo_rate_run", extract = "VCV")</pre>
repo_phlyo <- list()</pre>
repo_spec <- list()</pre>
repo_unit <- list()</pre>
for(i in 1:length(names(repo_var))){
  repo_phlyo[[i]] <- repo_var[[1]][,1]
  repo_spec[[i]] <- repo_var[[1]][,2]</pre>
  repo_unit[[i]] <- repo_var[[1]][,3]</pre>
  }
repo_phlyo <- unlist(repo_phlyo)</pre>
repo_spec <- unlist(repo_spec)</pre>
repo_unit <- unlist(repo_unit)</pre>
repo_prop_phlyo <- repo_phlyo/(repo_phlyo + repo_spec + repo_unit)</pre>
repo_prop_spec <- repo_spec/(repo_phlyo + repo_spec + repo_unit)</pre>
repo_prop_residuals <- repo_unit/(repo_phlyo + repo_spec + repo_unit)</pre>
hdr(repo_prop_phlyo)
## $hdr
                        [,2]
##
             [,1]
                                   [,3]
                                              [,4]
                                                         [,5]
                                                                    [,6]
## 99% 0.3304617 0.3459109 0.4338728 0.4455735 0.4634407 0.9298817
## 95% 0.5272801 0.9034334
                                    NA
                                               NA
## 50% 0.6979054 0.7100960 0.7214446 0.8228251 0.8236185 0.8337907
##
## $mode
## [1] 0.749791
##
## $falpha
                               50%
##
          1%
                     5%
## 0.1606762 0.6014679 3.4860705
hdr(repo_prop_spec)
## $hdr
                         [,2]
##
              [,1]
                                    [,3]
                                               [,4]
                                                          [,5]
                                                                     [,6]
                                                                                [,7]
## 99% 0.03816652 0.4286204 0.4428340 0.4458482 0.4687746 0.4732355 0.4988469
## 95% 0.06328580 0.3678677 0.3764072 0.3789635
                                                            NA
                                                                      NA
                                                                                 NA
## 50% 0.11387528 0.2159938
                                      NA
                                                 NA
                                                            NA
                                                                      NA
                                                                                 NA
                                  [,10]
##
             [,8]
                        [,9]
## 99% 0.5063282 0.5460005 0.5493642
## 95%
               NA
                          NA
                                     NΔ
## 50%
               NA
                          NA
                                     NA
##
## $mode
## [1] 0.1711385
##
## $falpha
                     5%
                               50%
          1%
## 0.1619615 0.9029375 4.3120476
```

```
hdr(repo_prop_residuals)
## $hdr
                         [,2]
                                     [,3]
##
              [,1]
                                                 [,4]
                                                             [,5]
                                                                        [,6]
## 99% 0.02545950 0.12921964 0.13539426 0.13726320
                                                              NΑ
                                                                          NA
## 95% 0.03275220 0.10838396 0.11150978 0.11345735 0.11495791 0.11545449
## 50% 0.04929815 0.04989975 0.05220181 0.07652539 0.08142521 0.08371029
##
## $mode
## [1] 0.06141387
##
## $falpha
                                  50%
##
           1%
                       5%
               2.6031406 15.7228361
    0.6010618
Now we need to calulate the residuals
repo resids <- mul resids(mul output = repo models,
                         mul_data = pop_multree,
                         Y_data_col = c("mean_repo_rate_stable_state")
)
Lets run it for mean reproductive rate that is just the mean of the positive F values (not stable state nst)
All the diagnostices look good, lets read that back in.
repo_nst_models <- read.mulTree("mean_repo_rate_nst_run")</pre>
summary(repo_nst_models)
##
                          Estimates (mode hdr) lower.CI(2.5) lower.CI(25)
## (Intercept)
                                    0.20592155
                                                   -1.9870386 -0.50275160
## mass_g
                                   -0.01381715
                                                   -0.2666515
                                                               -0.09754541
                                   -0.18379369
                                                   -0.2820744 -0.21757472
## matrix_size
## phylogenetic.variance
                                    3.02559729
                                                    1.3125387
                                                                2.25238180
## residual.variance
                                    0.35172675
                                                    0.1496779
                                                                0.27277813
##
                          upper.CI(75) upper.CI(97.5)
## (Intercept)
                            0.90936349
                                             2.3362077
## mass_g
                            0.07771676
                                             0.2478755
## matrix_size
                           -0.15030131
                                            -0.0860611
## phylogenetic.variance
                            4.00089887
                                             6.5208370
## residual.variance
                            0.42885374
                                             0.5987622
## attr(,"class")
## [1] "matrix" "mulTree"
repo nst models variance terms
repo_nst_var <- read.mulTree("mean_repo_rate_nst_run", extract = "VCV")
repo_nst_phlyo <- list()
repo_nst_spec <- list()
repo_nst_unit <- list()</pre>
for(i in 1:length(names(repo_nst_var))){
  repo_nst_phlyo[[i]] <- repo_nst_var[[1]][,1]</pre>
  repo_nst_spec[[i]] <- repo_nst_var[[1]][,2]</pre>
  repo_nst_unit[[i]] <- repo_nst_var[[1]][,3]</pre>
```

```
}
repo_nst_phlyo <- unlist(repo_nst_phlyo)</pre>
repo_nst_spec <- unlist(repo_nst_spec)</pre>
repo_nst_unit <- unlist(repo_nst_unit)</pre>
repo_nst_prop_phlyo <- repo_nst_phlyo/(repo_nst_phlyo + repo_nst_spec + repo_nst_unit)</pre>
repo_nst_prop_spec <- repo_nst_spec/(repo_nst_phlyo + repo_nst_spec + repo_nst_unit)</pre>
repo_nst_prop_residuals <- repo_nst_unit/(repo_nst_phlyo + repo_nst_spec + repo_nst_unit)
hdr(repo_nst_prop_phlyo)
## $hdr
            [,1]
                       [,2]
                                  [,3]
                                            [,4]
                                                       [,5]
                                                                            [,7]
##
                                                                 [,6]
## 99% 0.6889961 0.6989034 0.7008208 0.7041441 0.7078575 0.7125583 0.7137018
## 95% 0.7327639 0.7359139 0.7441847 0.7477584 0.7511318 0.7535076 0.7581548
## 50% 0.8668325 0.8694338 0.8699654 0.8811941 0.8926059 0.9511400
                                                                              NA
            [,8]
                       [,9]
                                 [,10]
## 99% 0.9818997
                         NA
                                   NA
## 95% 0.7667052 0.7729678 0.9760557
## 50%
              NA
                         NA
##
## $mode
## [1] 0.929044
##
## $falpha
##
                  5%
                           50%
## 0.338572 0.978501 5.687038
hdr(repo_nst_prop_spec)
## $hdr
                          [,2]
                                      [,3]
##
               [,1]
                                                [,4]
                                                           [,5]
                                                                      [,6]
## 99% 0.009671813 0.26809147 0.26811030 0.2816910
                                                             NA
                                                                       NA
## 95% 0.013831219 0.20400063 0.21016320 0.2261061 0.2379580 0.2398576
## 50% 0.040367925 0.09278263 0.09979294 0.1084204 0.1097175 0.1146234
##
## $mode
   [1] 0.08173958
##
##
## $falpha
                              50%
##
          1%
                     5%
## 0.3011703 0.9476453 6.3711450
hdr(repo_nst_prop_residuals)
## $hdr
##
               [,1]
                           [,2]
                                        [,3]
                                                   [,4]
                                                               [.5]
## 99% 0.005755433 0.005772303 0.006592023 0.02915650 0.02933019 0.02986175
## 95% 0.007131696 0.023125620 0.023273812 0.02584850 0.02619559 0.02642302
## 50% 0.009637023 0.010018068 0.010177768 0.01224453 0.01266264 0.01356451
##
             [,7]
                         [,8]
                                     [,9]
                                               [,10]
                                                           [,11]
                                                                       [,12]
## 99% 0.03040132 0.03147881 0.03304289 0.03326004 0.03597439 0.03603415
## 95%
               NA
                           NA
                                       NA
                                                  NA
                                                              NA
                                                                          NA
## 50% 0.01365827 0.01483560 0.01501015 0.01652746 0.01672665 0.01720037
```

```
##
## $mode
## [1] 0.01408839
##
## $falpha
##
                     5%
                               50%
          1%
    3.244211 13.899985 65.475867
Now we need to calulate the residuals
repo nst resids <- mul resids(mul output = repo nst models,
                         mul_data = pop_multree,
                         Y_data_col = c("mean_repo_rate")
)
standard deviation of mxlx
All the diagnostices look good, lets read that back in.
mxlxsd_models <- read.mulTree("mxlxsd_logged_10_run")</pre>
summary(mxlxsd models)
                           Estimates(mode hdr) lower.CI(2.5) lower.CI(25)
##
## (Intercept)
                                    -0.1639072 -1.65326400 -0.63006258
## mass_g
                                    -0.1924591
                                                  -0.43282306 -0.27444884
                                     0.1277970
                                                  -0.03112928
## matrix_size
                                                                 0.07252109
## phylogenetic.variance
                                     1.1075544
                                                   0.30275387
                                                                  0.75209887
## residual.variance
                                     0.3782147
                                                   0.16402751
                                                                 0.29921755
                           upper.CI(75) upper.CI(97.5)
## (Intercept)
                              0.2940136
                                             1.21802434
## mass_g
                             -0.1085908
                                             0.05379142
                              0.1801878
                                             0.28327663
## matrix_size
## phylogenetic.variance
                              1.5471337
                                             2.85791220
                                             0.66387348
## residual.variance
                              0.4665206
## attr(,"class")
## [1] "matrix" "mulTree"
gen_time_models variance terms
mxlxsd_var <- read.mulTree("mxlxsd_logged_10_run", extract = "VCV")</pre>
mxlxsd_phlyo <- list()</pre>
mxlxsd spec <- list()</pre>
mxlxsd_unit <- list()</pre>
for(i in 1:length(names(mxlxsd_var))){
  mxlxsd_phlyo[[i]] <- mxlxsd_var[[1]][,1]</pre>
  mxlxsd_spec[[i]] <- mxlxsd_var[[1]][,2]</pre>
  mxlxsd_unit[[i]] <- mxlxsd_var[[1]][,3]</pre>
  }
mxlxsd_phlyo <- unlist(mxlxsd_phlyo)</pre>
mxlxsd spec <- unlist(mxlxsd spec)</pre>
mxlxsd_unit <- unlist(mxlxsd_unit)</pre>
```

mxlxsd_prop_phlyo <- mxlxsd_phlyo/(mxlxsd_phlyo + mxlxsd_spec + mxlxsd_unit)</pre>

```
mxlxsd_prop_spec <- mxlxsd_spec/(mxlxsd_phlyo + mxlxsd_spec + mxlxsd_unit)</pre>
mxlxsd_prop_residual <- mxlxsd_unit/(mxlxsd_phlyo + mxlxsd_spec + mxlxsd_unit)
hdr(mxlxsd_prop_phlyo)
## $hdr
##
            [,1]
                       [,2]
                                  [,3]
                                            [,4]
## 99% 0.2643258 0.8910551
                                   NA
## 95% 0.3640159 0.3750883 0.3814946 0.8586202
## 50% 0.5703276 0.5965176 0.6024163 0.7475046
##
## $mode
## [1] 0.6704041
##
## $falpha
##
          1%
                     5%
                              50%
## 0.1378582 0.6119429 2.4023317
hdr(mxlxsd_prop_spec)
## $hdr
##
             [,1]
                        [,2]
                                   [,3]
                                             [,4]
                                                        [,5]
                                                                  [,6]
## 99% 0.02268929 0.4579201 0.4628629 0.4792459 0.5072331 0.5102751
## 95% 0.04017092 0.3847158 0.3882358 0.3969752
                                                          NA
## 50% 0.10300596 0.2050351 0.2088769 0.2214962
                                                          NA
                                                                    NA
##
## $mode
## [1] 0.1697693
##
## $falpha
                              50%
##
                     5%
## 0.1703277 0.7297996 3.5800693
hdr(mxlxsd_prop_residual)
## $hdr
##
                        [,2]
                                   [,3]
                                             [,4]
             [,1]
## 99% 0.06980017 0.3120442 0.3422491 0.3432030
## 95% 0.07923663 0.2560268 0.2625259 0.2720485
## 50% 0.12536900 0.1850378 0.1884294 0.1941885
##
## $mode
## [1] 0.164099
##
## $falpha
          1%
                     5%
                              50%
## 0.3983083 1.2794866 6.2070687
Now we need to calulate the residuals
mxlxsd_resids <- mul_resids(mul_output = mxlxsd_models,</pre>
                         mul_data = pop_multree,
                         Y_data_col = c("mxlxsd")
)
```

All the diagnostices look good, lets read that back in.

```
gen_time_models <- read.mulTree("gen_time_run")</pre>
summary(gen_time_models)
                          Estimates(mode hdr) lower.CI(2.5) lower.CI(25)
##
## (Intercept)
                                    0.60230035 -1.421124979 -0.07966155
## mass_g
                                    0.58946186
                                                 0.383169243
                                                                 0.51837202
                                   -0.03398890 -0.121445851 -0.06351646
## matrix_size
## phylogenetic.variance
                                    3.02631924
                                                 1.685164647
                                                                 2.50951070
## residual.variance
                                    0.07253635 -0.001593354
                                                                 0.04181541
                          upper.CI(75) upper.CI(97.5)
## (Intercept)
                           1.268497685
                                            2.61019863
                           0.658244045
                                            0.79282154
## mass_g
                                            0.05672399
                          -0.002310072
## matrix_size
## phylogenetic.variance 3.695077886
                                            5.18098858
## residual.variance
                           0.105109650
                                            0.17293323
## attr(,"class")
## [1] "matrix" "mulTree"
gen_time_models variance terms
gen_time_var <- read.mulTree("gen_time_run", extract = "VCV")</pre>
gen_time_phlyo <- list()</pre>
gen_time_spec <- list()</pre>
gen_time_unit <- list()</pre>
for(i in 1:length(names(gen_time_var))){
  gen_time_phlyo[[i]] <- gen_time_var[[1]][,1]</pre>
  gen_time_spec[[i]] <- gen_time_var[[1]][,2]</pre>
  gen_time_unit[[i]] <- gen_time_var[[1]][,3]</pre>
gen_time_phlyo <- unlist(gen_time_phlyo)</pre>
gen_time_spec <- unlist(gen_time_spec)</pre>
gen_time_unit <- unlist(gen_time_unit)</pre>
gen_time_prop_phlyo <- gen_time_phlyo/(gen_time_phlyo + gen_time_spec + gen_time_unit)</pre>
gen_time_prop_spec <- gen_time_spec/(gen_time_phlyo + gen_time_spec + gen_time_unit)</pre>
gen_time_prop_residual <- gen_time_unit/(gen_time_phlyo + gen_time_spec + gen_time_unit)</pre>
hdr(gen_time_prop_phlyo)
## $hdr
                       [,2]
                                  [,3]
                                             [,4]
                                                       [,5]
                                                                  [,6]
                                                                             [,7]
##
             [,1]
## 99% 0.8249987 0.8257493 0.8488786 0.8508666 0.8570096 0.8577666 0.8620359
## 95% 0.8914276 0.8928867 0.8947280 0.8966186 0.8977921 0.8983582 0.9014317
## 50% 0.9403439 0.9412924 0.9432609 0.9437884 0.9497649 0.9743616 0.9765054
##
             [,8]
                       [,9]
                                 [,10]
                                            [,11]
                                                      [,12]
                                                                [,13]
## 99% 0.8627734 0.8643483 0.8665584 0.8695865 0.8713434 0.873064 0.8741273
## 95% 0.9025613 0.9043517 0.9069714 0.9083974 0.9877568
                                                                   NΑ
                                                                             NΑ
## 50% 0.9772085
                         NA
                                    NA
                                               NA
                                                                   NA
                                                                             NA
                                                         NΑ
           [,15]
                      [,16]
                                 [,17]
                                            [,18]
## 99% 0.8763387 0.8784535 0.8807454 0.9897361
## 95%
                         NA
              NA
                                    NΑ
```

```
## 50%
               NA
                         NA
                                    NA
                                               NA
##
## $mode
   [1] 0.9690783
##
##
## $falpha
##
                       5%
                                  50%
           1%
    0.5662276 2.2701398 14.0133108
##
hdr(gen_time_prop_spec)
## $hdr
##
                 [,1]
                             [,2]
                                         [,3]
                                                    [,4]
                                                                 [,5]
                                                                            [,6]
## 99% -0.0018585027 0.08395070 0.08544532 0.08693469 0.08866977 0.09434585
  95% -0.0009924721 0.06700528 0.06891456 0.06988070 0.07837194 0.07912414
## 50% 0.0065698578 0.02883896
                                          NA
                                                      NA
                                                                  NA
                                                                              NA
                                                                   [,12]
##
              [,7]
                         [8,]
                                   [,9]
                                             [,10]
                                                        [,11]
## 99% 0.09968784 0.1042189 0.1092902 0.1096494 0.1207809 0.1227524
##
  95%
                NA
                          NA
                                     NA
                                                NA
                                                           NA
                                                                      NA
##
  50%
                NA
                          NA
                                     NA
                                                NA
                                                           NA
                                                                      NA
##
## $mode
##
   [1] 0.01622625
##
##
  $falpha
                       5%
                                  50%
##
           1%
    0.5012662 3.0375745 18.3937212
hdr(gen_time_prop_residual)
## $hdr
                          [,2]
                                      [,3]
##
              [,1]
                                                 [,4]
                                                             [,5]
                                                                         [,6]
## 99% 0.00996279 0.03728400 0.03746791 0.03901980 0.03905797 0.04003358
## 95% 0.01189825 0.03351992 0.03379308 0.03546167
## 50% 0.01640808 0.02327199 0.02365737 0.02412280 0.02534696 0.02538581
##
              [,7]
                          [,8]
                                      [,9]
                                                [,10]
## 99% 0.04197632 0.04230088 0.04409717 0.04451534
## 95%
                NA
                            NA
                                       NA
                                                   NA
## 50%
                NA
                           NA
                                       NA
                                                   NA
##
## $mode
  [1] 0.02177171
##
## $falpha
##
                     5%
                               50%
          1%
    2.731566 10.579572 54.341345
Now we need to calulate the residuals
gen_time_resids <- mul_resids(mul_output = gen_time_models,</pre>
                         mul_data = pop_multree,
                         Y_data_col = c("gen_time")
)
```

Lets run it for life expectancy conditional on reaching sexual maturity

All the diagnostices look good, lets read that back in.

```
M_rep_lif_exp_models <- read.mulTree("M_rep_lif_exp_run")</pre>
summary(M_rep_lif_exp_models)
##
                          Estimates(mode hdr) lower.CI(2.5) lower.CI(25)
## (Intercept)
                                   0.31576098 -1.439073720 -0.26028877
## mass_g
                                   0.58795591
                                                 0.386373547
                                                                0.51712000
## matrix_size
                                   0.05466011 -0.049173230
                                                                0.02086836
## phylogenetic.variance
                                   2.24965729
                                                 1.100292031
                                                                1.78280700
## residual.variance
                                   0.07459563 -0.005804658
                                                                0.03870326
                          upper.CI(75) upper.CI(97.5)
## (Intercept)
                            0.90913886
                                             2.0895082
## mass g
                            0.65293404
                                             0.7840524
## matrix_size
                            0.09396632
                                             0.1641846
## phylogenetic.variance
                            2.78690064
                                             4.0508399
## residual.variance
                            0.11422760
                                             0.1933473
## attr(,"class")
## [1] "matrix" "mulTree"
M_rep_lif_exp_models variance terms
M_rep_lif_exp_var <- read.mulTree("M_rep_lif_exp_run", extract = "VCV")</pre>
M_rep_lif_exp_phlyo <- list()</pre>
M_rep_lif_exp_spec <- list()</pre>
M_rep_lif_exp_unit <- list()</pre>
for(i in 1:length(names(M_rep_lif_exp_var))){
  M_rep_lif_exp_phlyo[[i]] <- M_rep_lif_exp_var[[1]][,1]</pre>
  M_rep_lif_exp_spec[[i]] <- M_rep_lif_exp_var[[1]][,2]</pre>
  M_rep_lif_exp_unit[[i]] <- M_rep_lif_exp_var[[1]][,3]</pre>
M_rep_lif_exp_phlyo <- unlist(M_rep_lif_exp_phlyo)</pre>
M_rep_lif_exp_spec <- unlist(M_rep_lif_exp_spec)</pre>
M_rep_lif_exp_unit <- unlist(M_rep_lif_exp_unit)</pre>
M_rep_lif_exp_prop_phlyo <- M_rep_lif_exp_phlyo/(M_rep_lif_exp_phlyo + M_rep_lif_exp_spec + M_rep_lif_e.
M_rep_lif_exp_prop_spec <- M_rep_lif_exp_spec/(M_rep_lif_exp_phlyo + M_rep_lif_exp_spec + M_rep_lif_ex
M_rep_lif_exp_prop_residuals <- M_rep_lif_exp_unit/(M_rep_lif_exp_phlyo + M_rep_lif_exp_spec + M_rep_l
hdr(M_rep_lif_exp_prop_phlyo)
## $hdr
                       [,2]
                                  [,3]
                                            [,4]
                                                                 [,6]
                                                                            [,7]
##
             [,1]
                                                       [,5]
## 99% 0.7202008 0.7212668 0.7679105 0.7713399 0.7747669 0.7794336 0.7811104
## 95% 0.8127583 0.8193569 0.8206474 0.8237017 0.8260872 0.9663523
                                                                              NΑ
## 50% 0.8899500 0.8911998 0.8923896 0.8953435 0.9016716 0.9443826
                                                                              NA
##
             [,8]
                      [,9]
                                [,10]
                                          [,11]
                                                     [,12]
## 99% 0.7877129 0.789438 0.7924834 0.7985336 0.9735319
## 95%
              NA
                        NA
                                  NA
                                             NA
                                                       NA
## 50%
              NA
                        NA
                                  NA
                                             NA
                                                        NA
##
## $mode
## [1] 0.9303792
```

```
##
## $falpha
##
          1%
                     5%
                               50%
## 0.4426789 1.4154873 8.4976864
hdr(M_rep_lif_exp_prop_spec)
## $hdr
##
                              [,2]
                                          [,3]
                                                      [,4]
                                                                  [,5]
                                                                              [,6]
                 [,1]
## 99% -1.366250e-03 0.109124638 0.111073405 0.11837650 0.11972427 0.12135369
## 95% -9.676678e-04 0.089412696 0.092463889 0.09369499 0.09597386 0.09951742
## 50% -4.301442e-05 0.002933646 0.005060425 0.01037997 0.01285116 0.02535762
                         [,8]
                                     [,9]
                                                [,10]
                                                         [,11]
              [,7]
## 99% 0.12169578 0.12189725 0.12431492 0.12591678 0.127305 0.1302091
## 95%
               NA
                           NA
                                       NA
                                                   NA
                                                            NA
                                                                       NA
## 50% 0.02768163 0.03657883 0.04016347 0.04088809
                                                            NA
                                                                       NA
                                        [,16]
          [,13]
                     [,14]
                              [,15]
                                                   [,17]
                                                              [,18]
## 99% 0.143484 0.1450535 0.14733 0.1488654 0.1526898 0.1529817
                                 NA
## 95%
             NA
                        NA
                                           NA
                                                      NA
                                                                NA
## 50%
             NA
                        NA
                                 NA
                                           NA
                                                      NA
                                                                NA
##
## $mode
##
  [1] 0.01846302
##
## $falpha
                                  50%
##
           1%
                       5%
   0.6167438 2.4424673 13.7450488
hdr(M_rep_lif_exp_prop_residuals)
## $hdr
                         [,2]
##
              [,1]
                                    [,3]
                                                [,4]
                                                           [,5]
                                                                       [,6]
## 99% 0.02452006 0.11055279 0.1115022 0.11287259 0.11596625 0.11605916
## 95% 0.02858911 0.02922202 0.0300296 0.09365835 0.09550034 0.09706253
## 50% 0.04125548 0.04202726 0.0431870 0.06162428 0.06348429 0.06527947
##
             [,7]
                       [,8]
## 99% 0.1277325 0.1284555
## 95%
              NA
                         NA
## 50%
              NA
                         NA
##
## $mode
## [1] 0.05578845
##
## $falpha
##
                       5%
                                  50%
           1%
    0.7355868
               3.2571590 19.7733814
Now we need to calulate the residuals
M_rep_lif_exp_resids <- mul_resids(mul_output = M_rep_lif_exp_models,</pre>
                         mul_data = pop_multree,
                         Y_data_col = c("M_rep_lif_exp")
)
```

Lets run it for the gini index

All the diagnostices look good, lets read that back in.

```
gini_models <- read.mulTree("gini_logged_run")</pre>
summary(gini_models)
##
                           Estimates (mode hdr) lower.CI(2.5) lower.CI(25)
## (Intercept)
                                   -0.42792607
                                                   -2.0464245
                                                                 -0.9689465
## mass_g
                                   -0.19601910
                                                   -0.4244734
                                                                 -0.2745834
## matrix_size
                                   -0.09997738
                                                   -0.2324761
                                                                 -0.1452911
## phylogenetic.variance
                                    1.79675072
                                                    0.9171706
                                                                   1.4300623
## residual.variance
                                    0.25784403
                                                    0.1276057
                                                                   0.2086542
##
                          upper.CI(75) upper.CI(97.5)
## (Intercept)
                             0.11276264
                                             1.19790393
                                             0.03280158
                            -0.11832226
## mass_g
## matrix_size
                            -0.05474631
                                             0.03184344
## phylogenetic.variance
                             2.19375023
                                             3.26168320
## residual.variance
                             0.31350049
                                             0.44078588
## attr(,"class")
## [1] "matrix" "mulTree"
Since the read in seems to miss the species variance term we need to read that in seperate.
gini_var <- read.mulTree("gini_logged_run", extract = "VCV")</pre>
gini_phlyo <- list()</pre>
gini_spec <- list()</pre>
gini_unit <- list()</pre>
for(i in 1:length(names(gini_var))){
  gini_phlyo[[i]] <- gini_var[[1]][,1]
  gini_spec[[i]] <- gini_var[[1]][,2]</pre>
  gini_unit[[i]] <- gini_var[[1]][,3]</pre>
gini_phlyo <- unlist(gini_phlyo)</pre>
gini_spec <- unlist(gini_spec)</pre>
gini_unit <- unlist(gini_unit)</pre>
gini_prop_phlyo <- gini_phlyo/(gini_phlyo + gini_spec + gini_unit)</pre>
gini_prop_spec <- gini_spec/(gini_phlyo + gini_spec + gini_unit)</pre>
gini_prop_residuals <- gini_unit/(gini_phlyo + gini_spec + gini_unit)</pre>
hdr(gini_prop_phlyo)
## $hdr
##
             [,1]
                        [,2]
                                  [,3]
                                             [, 4]
                                                        [,5]
                                                                   [,6]
                                                                              [,7]
## 99% 0.6014925 0.6029427 0.6221889 0.9106813 0.9162405 0.9182208
                                                                                NΑ
## 95% 0.6456083 0.6483562 0.6543877 0.6557645 0.6656940 0.8893681 0.8922537
## 50% 0.7476243 0.7500067 0.7643972 0.7686894 0.7699635 0.8292471 0.8322060
##
             [,8]
                       [,9]
                                 [,10]
## 99%
              NA
                         NA
                                    NA
## 95% 0.8942774
                                    NA
                         NA
## 50% 0.8383279 0.8402843 0.8453827
##
## $mode
```

```
## [1] 0.7922497
##
## $falpha
                               50%
##
                     5%
          1%
## 0.1915535 1.1621993 5.1429723
hdr(gini_prop_spec)
## $hdr
##
                         [,2]
                                   [,3]
                                              [,4]
                                                         [,5]
                                                                    [,6]
              [,1]
## 99% 0.02806573 0.2233123 0.2255779 0.2487039 0.2528714 0.2532666
## 95% 0.04264019 0.2066662 0.2123950 0.2183107
                                                           NA
                                                                     NA
## 50% 0.07666218 0.1326623 0.1401001 0.1410701
                                                                     NA
                                                           NA
##
## $mode
  [1] 0.1046461
##
##
## $falpha
                     5%
                               50%
##
          1%
## 0.3773721 1.5087452 6.9429816
hdr(gini_prop_residuals)
## $hdr
##
              [,1]
                          [,2]
                                      [,3]
                                                 [,4]
                                                             [,5]
                                                                         [,6]
## 99% 0.03954057 0.04124459 0.04760719 0.15339161 0.15505207 0.15617927
## 95% 0.05207554 0.05331253 0.05379206 0.05529746 0.05595720 0.13625517
## 50% 0.06714741 0.06832185 0.07228855 0.08253943 0.08342508 0.09522928
                                   [,9]
                                             [,10]
                                                        [,11]
                                                                   [,12]
                                                                             [,13]
##
              [,7]
                         [,8]
## 99% 0.15802543 0.1611068 0.1754038 0.1777230
                                                           NA
                                                                      NA
                                                                                NA
## 95% 0.13765449 0.1394366 0.1406215 0.1426684 0.1436330 0.1449316
## 50% 0.09609703 0.1004976 0.1044944 0.1051261 0.1067461 0.1077285 0.1089811
##
            [,14]
## 99%
              NA
## 95%
               NA
## 50% 0.1092551
##
## $mode
##
  [1] 0.09190319
##
## $falpha
##
          1%
                     5%
                               50%
    0.817346 2.895939 13.641542
Now we need to calulate the residuals
gini_resids <- mul_resids(mul_output = gini_models,</pre>
                         mul_data = pop_multree,
                         Y_data_col = c("gini")
)
Lets run it for the standard deviation of mortality rates
All the diagnostices look good, lets read that back in.
surv_sd_models <- read.mulTree("surv_sd_logged_run")</pre>
```

summary(surv sd models)

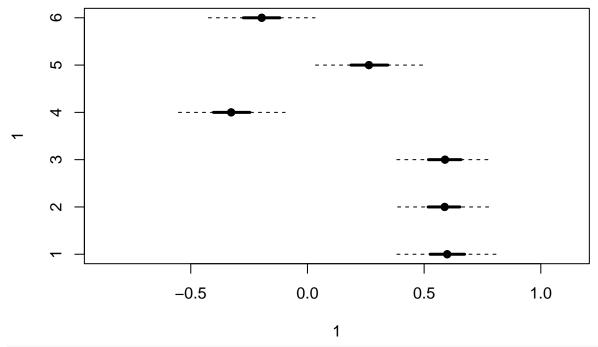
```
##
                          Estimates (mode hdr) lower.CI(2.5) lower.CI(25)
## (Intercept)
                                     0.2919404
                                                 -1.17657834
                                                                 -0.1883169
## mass_g
                                     0.2633088
                                                   0.03469285
                                                                  0.1864593
## matrix_size
                                    -0.3503768
                                                  -0.50536667
                                                                 -0.4040565
## phylogenetic.variance
                                     1.1714224
                                                   0.38878793
                                                                  0.8386725
## residual.variance
                                     0.2431978
                                                   0.09919949
                                                                  0.1882855
                           upper.CI(75) upper.CI(97.5)
## (Intercept)
                              0.7439635
                                              1.7092974
                                              0.5007707
## mass_g
                              0.3445202
                             -0.2995984
                                             -0.1995481
## matrix_size
## phylogenetic.variance
                              1.6285572
                                              2.8397630
                                              0.4565594
## residual.variance
                              0.3083809
## attr(,"class")
## [1] "matrix" "mulTree"
Since the read in seems to miss the species variance term we need to read that in seperate.
surv_sd_var <- read.mulTree("surv_sd_logged_run", extract = "VCV")</pre>
surv_sd_phlyo <- list()</pre>
surv_sd_spec <- list()</pre>
surv_sd_unit <- list()</pre>
for(i in 1:length(names(surv_sd_var))){
  surv_sd_phlyo[[i]] <- surv_sd_var[[1]][,1]</pre>
  surv_sd_spec[[i]] <- surv_sd_var[[1]][,2]</pre>
  surv_sd_unit[[i]] <- surv_sd_var[[1]][,3]
surv_sd_phlyo <- unlist(surv_sd_phlyo)</pre>
surv_sd_spec <- unlist(surv_sd_spec)</pre>
surv_sd_unit <- unlist(surv_sd_unit)</pre>
surv_sd_prop_phlyo <- surv_sd_phlyo/(surv_sd_phlyo + surv_sd_spec + surv_sd_unit)</pre>
surv_sd_prop_spec <- surv_sd_spec/(surv_sd_phlyo + surv_sd_spec + surv_sd_unit)</pre>
surv_sd_prop_residuals <- surv_sd_unit/(surv_sd_phlyo + surv_sd_spec + surv_sd_unit)</pre>
hdr(surv_sd_prop_phlyo)
## $hdr
##
                       [,2]
                                  [,3]
                                             [,4]
             [,1]
## 99% 0.3335133 0.8827036
                                    NA
                                               NA
## 95% 0.4348327 0.8563945
                                    NA
                                               NΑ
## 50% 0.5956603 0.6192499 0.6318059 0.7555922
##
## $mode
## [1] 0.7194289
##
## $falpha
##
                     5%
                               50%
          1%
## 0.1542353 0.6181539 2.9152680
```

```
hdr(surv_sd_prop_spec)
## $hdr
                         [,2]
                                    [,3]
                                              [,4]
##
                                                        [,5]
                                                                   [,6]
              [,1]
## 99% 0.02104198 0.29423689 0.2950760 0.3136595 0.3196814 0.3358598
## 95% 0.03162066 0.25883345 0.2590323 0.2638300 0.2700172 0.2750848
## 50% 0.06736595 0.09728116 0.1002710 0.1462048 0.1493806 0.1515445
##
## $mode
## [1] 0.1070557
##
## $falpha
##
                    5%
                              50%
          1%
## 0.3454369 0.9256044 5.2555032
hdr(surv_sd_prop_residuals)
## $hdr
##
             [,1]
                         [,2]
                                    [,3]
                                               [,4]
                                                          [,5]
                                                                    [,6]
## 99% 0.07410689 0.07412768 0.08114927 0.3632304 0.3804389 0.3810536
## 95% 0.09362128 0.09870303 0.10104871 0.3168509 0.3355439 0.3385396
## 50% 0.14705875 0.14858537 0.15431778 0.1721416 0.1752069 0.1937691
                       [,8]
                                 [,9]
                                           [,10]
##
            [,7]
## 99% 0.4394676 0.4413945
                                   NA
                                              NA
                                              NA
## 95%
              NA
                         NA
                                   NA
## 50% 0.1966278 0.2164779 0.2182223 0.2363943
##
## $mode
## [1] 0.2247078
## $falpha
          1%
                    5%
                              50%
## 0.2207477 1.1501733 5.5529351
Now we need to calulate the residuals
surv_sd_resids <- mul_resids(mul_output = surv_sd_models,</pre>
                         mul_data = pop_multree,
                         Y data col = c("surv sd")
)
Lets plot out these allometries.
par(mfrow=c(2,3))
##la
plot(pop_multree$data$life_time_La ~ pop_multree$data$mass_g, pch = 16,
     xlab = expression('log'[10]*" mass"),
     ylab = "Age at sexual maturity")
abline(summary(La_models)[1],summary(La_models)[2])
#M_rep_lif_exp
plot(pop_multree$data$M_rep_lif_exp ~ pop_multree$data$mass_g, pch = 16,
          xlab = expression('log'[10]*" mass"),
          ylab = "Life expectancy post maturity")
```

abline(summary(M_rep_lif_exp_models)[1],summary(M_rep_lif_exp_models)[2])

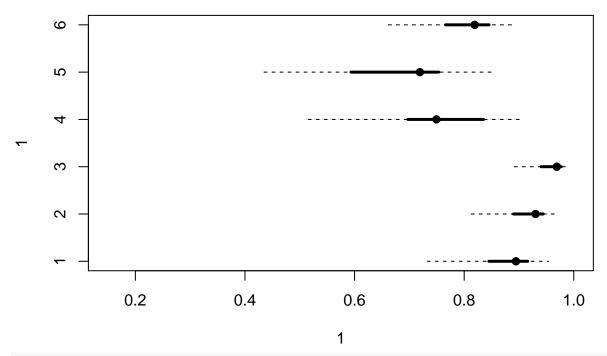
```
#generation time
plot(pop_multree$data$gen_time ~ pop_multree$data$mass_g, pch = 16,
            xlab = expression('log'[10]*" mass"),
            ylab = "Generation time")
abline(summary(gen_time_models)[1],summary(gen_time_models)[2])
##mean repo rate
plot(pop_multree$data$mean_repo_rate_stable_state ~ pop_multree$data$mass_g, pch = 16,
            xlab = expression('log'[10]*" mass"),
            ylab = "Mean reproductive rate")
abline(summary(repo_models)[1],summary(repo_models)[2])
#Gini
plot(pop_multree$data$gini ~ pop_multree$data$mass_g, pch = 16,
            xlab = expression('log'[10]*" mass"),
            ylab = "Spread of reproduction")
abline(summary(gini_models)[1],summary(gini_models)[2])
#SD of survival
plot(pop_multree$data$surv_sd ~ pop_multree$data$mass_g, pch = 16,
      xlab = expression('log'[10]*" mass"),
      ylab = "Distribution of survival")
abline(summary(surv_sd_models)[1],summary(surv_sd_models)[2])
                                     Life expectancy post maturity
Age at sexual maturity
                                                                          Generation time
    N
                                         \alpha
                   0
                                                        0
                       1
                                                                                     -2
                                                                                             0
               log<sub>10</sub> mass
                                                     log<sub>10</sub> mass
                                                                                          log_{10}\ mass
Mean reproductive rate
                                    Spread of reproduction
                                                                          Distribution of survival
                                         7
    ī
                                         4
                                                                              က
                                         ဖှ
                                                        0
                                                                2
          -2
                                                                                        -1
                                                                                             0
                                                                                          log_{10} \, mass
               log<sub>10</sub> mass
                                                    log<sub>10</sub> mass
```

Lets plot out these model cooficents into a table



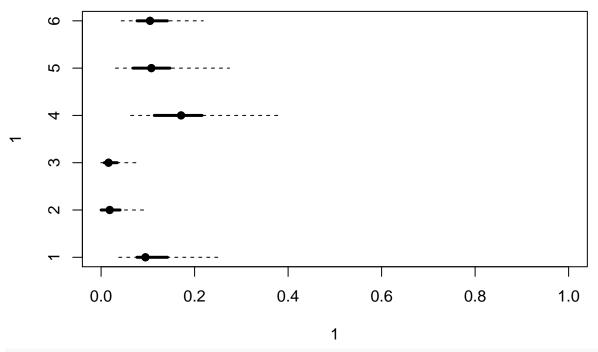
#dev.off()

And the variance terms



#dev.off()

Warning in if (xlim == "auto") $\{: \text{ the condition has length} > 1 \text{ and only the}$ ## first element will be used



#dev.off()

Now lets creata a new dataset of these residuals

```
predicted_data <- data.frame(</pre>
                         SD_mort = surv_sd_resids,
                         La_r = La_resids,
                         gen_r = gen_time_resids,
                         M_repo = repo_resids,
                         M_suv = M_rep_lif_exp_resids,
                         gini_r = gini_resids
predicted_data_M_repo_nst <- data.frame(</pre>
                          SD_mort = surv_sd_resids,
                         La_r = La_{resids},
                         gen_r = gen_time_resids,
                         M_repo_nst = repo_nst_resids,
                         M_suv = M_rep_lif_exp_resids,
                         gini_r = gini_resids
predicted_data_mxlxsd <- data.frame(</pre>
                         SD_mort = surv_sd_resids,
                         La_r = La_resids,
                         gen_r = gen_time_resids,
                         M_repo = repo_resids,
                         M_suv = M_rep_lif_exp_resids,
                         mxlxsd = mxlxsd_resids
                         )
```

```
predicted_data_noT <- data.frame(</pre>
                        SD_mort = surv_sd_resids,
                       La_r = La_resids,
                       M_repo = repo_resids,
                       M_suv = M_rep_lif_exp_resids,
                       gini = gini_resids
                       )
predicted_data_justT <- data.frame(</pre>
                       SD_mort = surv_sd_resids,
                       M_repo = repo_resids,
                       gen_r = gen_time_resids,
                       gini = gini_resids
And run a PCA
pca_res <- prcomp(predicted_data)</pre>
pca_nst <- prcomp(predicted_data_M_repo_nst)</pre>
pca_mxlxsd <- prcomp(predicted_data_mxlxsd)</pre>
pca_noT <- prcomp(predicted_data_noT)</pre>
horn_res <- paran(predicted_data)</pre>
##
## Using eigendecomposition of correlation matrix.
## Computing: 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
##
##
## Results of Horn's Parallel Analysis for component retention
## 180 iterations, using the mean estimate
##
## Component Adjusted Unadjusted
                                     Estimated
             Eigenvalue Eigenvalue Bias
## -----
             2.614513 2.804697
## 1
                                      0.190183
             1.383173 1.481387 0.098213
## 2
## Adjusted eigenvalues > 1 indicate dimensions to retain.
## (2 components retained)
horn_nst <- paran(predicted_data_M_repo_nst)</pre>
##
## Using eigendecomposition of correlation matrix.
## Computing: 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
##
## Results of Horn's Parallel Analysis for component retention
```

```
## 180 iterations, using the mean estimate
##
## -----
## Component Adjusted
                    Unadjusted
                              Estimated
                              Bias
          Eigenvalue Eigenvalue
## -----
           2.561541 2.759154
                              0.197612
                             0.097472
           1.312938 1.410411
##
## Adjusted eigenvalues > 1 indicate dimensions to retain.
## (2 components retained)
horn_mxlx <- paran(predicted_data_mxlxsd)
##
## Using eigendecomposition of correlation matrix.
## Computing: 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
##
## Results of Horn's Parallel Analysis for component retention
## 180 iterations, using the mean estimate
## -----
## Component Adjusted
                    Unadjusted Estimated
           Eigenvalue Eigenvalue Bias
## -----
           2.710939 2.911046
                              0.200107
          1.332993 1.437757 0.104764
##
## Adjusted eigenvalues > 1 indicate dimensions to retain.
## (2 components retained)
horn_noT <- paran(predicted_data_noT)</pre>
##
## Using eigendecomposition of correlation matrix.
## Computing: 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
##
##
## Results of Horn's Parallel Analysis for component retention
## 150 iterations, using the mean estimate
##
## -----
## Component Adjusted
                    Unadjusted
                              Estimated
           Eigenvalue Eigenvalue
##
                              Bias
## -----
          1.7687131.9340800.1653671.3960901.4669760.070885
## 1
## -----
## Adjusted eigenvalues > 1 indicate dimensions to retain.
## (2 components retained)
PLOTS
```

Lets make some beter plots. First we can flip the PCA axis so that it reads with increases towards slow lifestyles on the right and increasing towards tye 1 survorship curves upwards

```
results <- pca_res
results$rotation[,"PC1"] <- -results$rotation[,"PC1"]
results$x[,"PC1"] <- -results$x[,"PC1"]
results$rotation[,"PC2"] <- -results$rotation[,"PC2"]
results$x[,"PC2"] <- -results$x[,"PC2"]</pre>
```

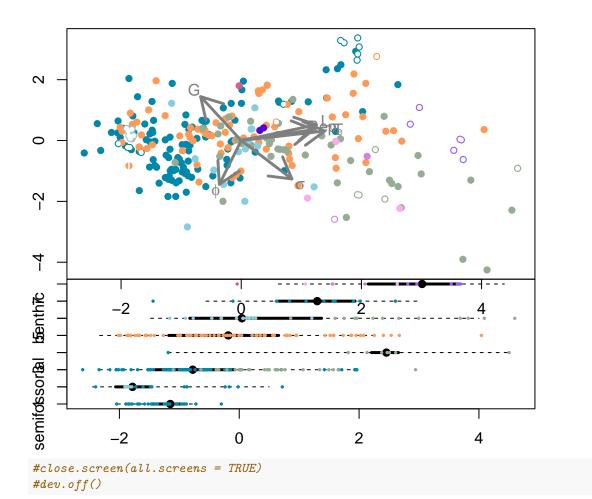
Now lets make a nicer looking PCA graph

```
result <- results
loadings <- as.data.frame(result$rotation)</pre>
#loadings_nst <- as.data.frame(results_nst$rotation)</pre>
loadings[,"col"]=c("gray50",
                    "gray50",
                    "gray50",
                    "gray50",
                    "gray50",
                    "gray50"
loadings$LHT=rownames(loadings)
loadings$LHT=c("surv_sd",
                "La",
                "gen_time",
                "mean_repo_rate",
                "M_suv"
                , "gini_r"
loadings$LHTexpr <- list(</pre>
                            expression(sigma),
                            expression("L"[alpha]),
                            expression("T"),
                            expression(phi),
                            expression(Rep["e"]),
                            expression("G")
arrowThickness=2.9
sizeArrowLetters=1
scalingArrows=2.5
scalingLetters=2.9
class_match <- vector()</pre>
species_match <- vector()</pre>
loads_taxa <- data.frame(results$x)</pre>
```

```
for(i in 1:length(loads_taxa[,1])){
   class match[i] <- as.vector(pop multree$data[i,"taxa name"])</pre>
   species match[i] <- as.vector(pop multree$data[i, "species"])</pre>
   }
pca_data <- cbind(loads_taxa,class_match, species_match)</pre>
##rename some of the mode of life levels
PCA1 <- pca_data[,1]</pre>
PCA2 <- pca_data[,2]
mobility_PCA <- pop_multree$data$mobility</pre>
mobility_PCA <- as.vector(mobility_PCA)</pre>
mobility_PCA[mobility_PCA == "fw_benthic"] <- "benthic"</pre>
mobility_PCA[mobility_PCA == "m_benthic"] <- "benthic"</pre>
mobility_PCA[mobility_PCA == "fw_pelagic"] <- "pelagic"</pre>
mobility_PCA[mobility_PCA == "m_pelagic"] <- "pelagic"</pre>
mobility_PCA[mobility_PCA == "fw_river"] <- "benthic"</pre>
mobility_PCA <- factor(mobility_PCA, levels = c("sessile", "arboreal", "benthic", "volant",</pre>
                                             "semiaquatic", "terrestrial", "pelagic", "semifossorial"))
pca_data$mobility_PCA <- mobility_PCA</pre>
PCA_moblist <- list(semifossorial = pca_data[pca_data$mobility_PCA == "semifossorial",1],
                      pelagic = pca_data[pca_data$mobility_PCA == "pelagic",1],
                      terrestrial = pca_data[pca_data$mobility_PCA == "terrestrial",1],
                      semiaquatic = pca_data[pca_data$mobility_PCA == "semiaquatic",1],
                      volant = pca_data[pca_data$mobility_PCA == "volant",1],
                      benthic = pca_data[pca_data$mobility_PCA == "benthic",1],
                      arboreal = pca_data[pca_data$mobility_PCA == "arboreal",1],
                      sessile = pca data[pca data$mobility PCA == "sessile",1]
                      )
mam_col <- rgb(0,136,170, max = 255)
bird_col <- rgb(255,153,85, max= 255)
rep_col <- rgb(147,172,147, max= 255)
fish_col <- rgb(135,205,222, max= 255)
sponge_col <- rgb(211,95,141, max= 255)
coral_col <- rgb(153,85,255, max= 255)</pre>
gast_col <- rgb(255,170,238, max= 255)</pre>
biv_col <- rgb(205,135,222, max= 255)
```

```
shark_col <- rgb(85,0,212, max= 255)</pre>
Now let do the actual plot
#pdf("Figure2_PCA.pdf")
split \leftarrow rbind(c(0.15,0.9, 0.4,0.98), c(0.15,0.9, 0.1, 0.4))
split.screen(split)
## [1] 1 2
screen(1)
par(mar = c(0, 0, 0, 0))
plot(pca_data[,1], pca_data[,2], pch=16, cex = 0.1, col = "white", xlab= "PCA",
     ylab= "PCA 2")
points(pca_data[pca_data$class_match == "Mammalia",1], pca_data[pca_data$class_match == "Mammalia",2],
points(pca_data[pca_data$class_match == "Aves",1], pca_data[pca_data$class_match == "Aves",2], pch=16,
points(pca_data[pca_data$class_match == "Reptilia",1], pca_data[pca_data$class_match == "Reptilia",2],
points(pca_data{pca_data$class_match == "Actinopterygii",1], pca_data[pca_data$class_match == "Actinopterygii",1]
points(pca_data[pca_data$class_match == "Gastropoda",1], pca_data[pca_data$class_match == "Gastropoda",
points(pca_data{pca_data$class_match == "Demospongiae",1], pca_data[pca_data$class_match == "Demospongiae",1]
points(pca_data[pca_data$class_match == "Anthozoa",1], pca_data[pca_data$class_match == "Anthozoa",2],
points(pca_data[pca_data$class_match == "Bivalvia",1], pca_data[pca_data$class_match == "Bivalvia",2],
points(pca data[pca data$class match == "Elasmobranchii",1], pca data[pca data$class match == "Elasmobr
###And lets add Humans
points(pca_data[pca_data$species_match == "Homo_sapiens",1], pca_data[pca_data$species_match == "Homo_s
##and other points
points(pca_data[pca_data$species_match == "Elephas_maximus",1], pca_data[pca_data$species_match == "Ele
points(pca_data[pca_data$species_match == "Fulmarus_glacialis",1], pca_data[pca_data$species_match == ".
points(pca_data[pca_data$species_match == "Tympanuchus_cupido",1], pca_data[pca_data$species_match == "
points(pca_data[pca_data$species_match == "Gyps_coprotheres",1], pca_data[pca_data$species_match == "Gy
points(pca_data[pca_data$species_match == "Crocodylus_johnsoni",1], pca_data[pca_data$species_match ==
points(pca_data[pca_data$species_match == "Urocitellus_armatus",1], pca_data[pca_data$species_match ==
points(pca_data[pca_data$species_match == "Paramuricea_clavata",1], pca_data[pca_data$species_match == "Paramuricea_clavata",1]
points(pca_data[pca_data$species_match == "Oncorhynchus_tshawytscha",1], pca_data[pca_data$species_match
points(pca_data[pca_data$species_match == "Mya_arenaria",1], pca_data[pca_data$species_match == "Mya_ar
```

```
points(pca_data[pca_data$species_match == "Clemmys_guttata",1], pca_data[pca_data$species_match == "Clemmys_guttata",1]
arrows(x0=0,y0=0,x1=loadings[,1]*scalingArrows,y1=loadings[,2]*scalingArrows,col="black", lwd=2)
arrows(x0=0,y0=0,x1=loadings[,1]*scalingArrows,y1=loadings[,2]*scalingArrows,col=as.character(loadings
\#arrows(x0=0,y0=0,x1=loadings[,1]*scalingArrows,y1=loadings[,2]*scalingArrows,col="black", lwd=arrowThicksequents for the state of th
 \#arrows(x0=0,y0=0,x1=loadings[,1]*scalingArrows,y1=loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*scalingArrows,col=as.character(loadings[,2]*
text(loadings[1,"PC1"]*scalingLetters-.0,loadings[1,"PC2"]*scalingLetters,loadings$LHTexpr[[1]],col = 1
text(loadings[2,"PC1"]*scalingLetters-.0,loadings[2,"PC2"]*scalingLetters,loadings$LHTexpr[[2]],col = 1
text(loadings[3,"PC1"]*scalingLetters+.0,loadings[3,"PC2"]*scalingLetters,loadings$LHTexpr[[3]],col = 1
text(loadings[4,"PC1"]*scalingLetters-.0,loadings[4,"PC2"]*scalingLetters,loadings$LHTexpr[[4]],col = 1
text(loadings[5,"PC1"]*scalingLetters-.0,loadings[5,"PC2"]*scalingLetters,loadings$LHTexpr[[5]],col = 1
text(loadings[6,"PC1"]*scalingLetters+.0,loadings[6,"PC2"]*scalingLetters,loadings$LHTexpr[[6]],col = 1
 #text(loadings[7, "PC1"]*scalingLetters+.0,loadings[7, "PC2"]*scalingLetters,loadings$LHTexpr[[7]],col =
screen(2)
par(mar = c(0, 0, 0, 0))
MultiDisPlot(PCA_moblist)
tick_lables <- names(PCA_moblist)</pre>
axis(2, 1:length(tick_lables), labels = tick_lables)
mob_match <- as.vector(mobility_PCA)</pre>
for(i in 1:(length(tick_lables))){
mob_match[mob_match == tick_lables[i]] <- i</pre>
}
mob_match <- as.numeric(mob_match)</pre>
pca_data$mob_match <- mob_match</pre>
points(pca_data[pca_data$class_match == "Mammalia", "mob_match"] ~ pca_data[pca_data$class_match == "Mammalia", "mob_match == "
points(pca_data[pca_data$class_match == "Aves", "mob_match"] ~ pca_data[pca_data$class_match == "Aves", 1
points(pca_data[pca_data$class_match == "Reptilia", "mob_match"] ~ pca_data[pca_data$class_match == "Rep
points(pca_data[pca_data$class_match == "Actinopterygii", "mob_match"] ~ pca_data[pca_data$class_match ==
points(pca_data[pca_data$class_match == "Gastropoda", "mob_match"] ~ pca_data[pca_data$class_match == "G
points(pca_data[pca_data$class_match == "Demospongiae", "mob_match"] ~ pca_data[pca_data$class_match == "Demospongiae", "mob_match == "Demospongiae", "mob_
points(pca_data[pca_data$class_match == "Anthozoa", "mob_match"] ~ pca_data[pca_data$class_match == "Ant
points(pca_data[pca_data$class_match == "Bivalvia", "mob_match"] ~ pca_data[pca_data$class_match == "Biv
```



Now lets do some more plots

```
##needs to run longer
aquatic_pc1 <- MCMCglmm(PC1 ~ mobility_PCA,</pre>
                     data = aquatic_res,
                     random=~animal + species match,
                     pedigree = axis_trees[[1]],
                     prior = prior,
                     nitt = c(1100000), burnin = 100000, thin = 500, verbose = F)
summary(aquatic pc1)
##
   Iterations = 100001:1099501
##
## Thinning interval = 500
## Sample size = 2000
##
## DIC: 142.0543
##
## G-structure: ~animal
##
##
          post.mean 1-95% CI u-95% CI eff.samp
              2.604 0.001246
                                6.407
##
##
                  ~species_match
##
##
                 post.mean 1-95% CI u-95% CI eff.samp
## species_match
                    0.7562 2.027e-05
                                         1.66
                                                   2000
##
##
   R-structure: ~units
##
##
         post.mean 1-95% CI u-95% CI eff.samp
## units
            0.4102
                     0.2044
                               0.645
                                          2000
##
  Location effects: PC1 ~ mobility_PCA
##
##
##
                       post.mean 1-95% CI u-95% CI eff.samp pMCMC
## (Intercept)
                        -1.03391 -3.78979 1.48484
                                                        2000 0.363
                                                        1870 0.062 .
## mobility_PCAsessile
                         2.66368 0.12352 5.50703
## mobility_PCAbenthic
                         1.66644 0.09585 3.01360
                                                        2000 0.030 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
aquatic_pc1_vcv_phylo <- aquatic_pc1$VCV[,1]</pre>
aquatic_pc1_vcv_spec <- aquatic_pc1$VCV[,2]</pre>
aquatic_pc1_vcv_units <- aquatic_pc1$VCV[,3]</pre>
aquatic_pc1_phylo <- aquatic_pc1_vcv_phylo/c(aquatic_pc1_vcv_phylo + aquatic_pc1_vcv_spec + aquatic_pc1
aquatic_pc1_spec <- aquatic_pc1_vcv_spec/c(aquatic_pc1_vcv_phylo + aquatic_pc1_vcv_spec + aquatic_pc1_v
aquatic_pc1_units <- aquatic_pc1_vcv_units/c(aquatic_pc1_vcv_phylo + aquatic_pc1_vcv_spec + aquatic_pc1
hdr(aquatic_pc1_phylo)
## $hdr
                       [,2]
##
             [,1]
## 99% 0.05957729 1.0423730
```

95% 0.26955221 0.9798612

```
## 50% 0.57278798 0.8243079
##
## $mode
## [1] 0.7089488
##
## $falpha
                    5%
                              50%
          1%
## 0.1138648 0.3942820 1.6427459
hdr(aquatic_pc1_spec)
## $hdr
              [,1]
## 99% -0.06273573 0.7629974
## 95% -0.03255971 0.5562057
## 50% 0.04895875 0.2486875
##
## $mode
## [1] 0.1622204
##
## $falpha
##
          1%
                    5%
                              50%
## 0.1118308 0.4249094 2.0653048
hdr(aquatic_pc1_units)
## $hdr
##
              [,1]
                        [,2]
## 99% 0.001403337 0.3368995
## 95% 0.019487762 0.2506065
## 50% 0.071472859 0.1425920
##
## $mode
## [1] 0.1065099
##
## $falpha
                              50%
##
          1%
                    5%
## 0.2161613 0.9167200 5.6960532
##terrestiral species
ter_res <- pca_data[pca_data$mobility_PCA == "terrestrial" | pca_data$mobility_PCA == "arboreal"
                        | pca_data$mobility_PCA == "volant" | pca_data$mobility_PCA == "semiaquatic" | p
ter_res$mobility_PCA <- factor(ter_res$mobility_PCA, levels = c("terrestrial", "arboreal", "volant", "s
ter_pc1 <- MCMCglmm(PC1 ~ mobility_PCA,
                     data = ter_res,
                     random=~animal + species_match,
                     pedigree = axis_trees[[1]],
                     prior = prior,
                     nitt = c(1100000), burnin = 100000, thin = 500, verbose = F)
summary(ter_pc1)
```

##

```
Iterations = 100001:1099501
##
    Thinning interval = 500
##
    Sample size = 2000
##
##
   DIC: 319.4125
##
    G-structure: ~animal
##
##
##
          post.mean 1-95% CI u-95% CI eff.samp
              10.57
                                 15.75
                                            1671
##
   animal
                        5.382
##
##
                   ~species_match
##
##
                 post.mean 1-95% CI u-95% CI eff.samp
                    0.1377 1.37e-06
                                       0.3342
                                                   1721
##
   species_match
##
##
    R-structure: ~units
##
         post.mean 1-95% CI u-95% CI eff.samp
##
## units
            0.1753
                      0.1353
                               0.2183
                                           2000
##
   Location effects: PC1 ~ mobility_PCA
##
                              post.mean 1-95% CI u-95% CI eff.samp pMCMC
##
## (Intercept)
                                                                2000 0.885
                                0.30402 -5.04768 5.47766
## mobility_PCAarboreal
                                0.22312 -0.69394
                                                   1.05826
                                                                2000 0.610
## mobility_PCAvolant
                                0.08002 -1.72926
                                                   2.47692
                                                                2000 0.962
## mobility_PCAsemiaquatic
                                0.02463 -1.62026
                                                                2000 0.966
                                                   1.77493
## mobility_PCAsemifossorial -0.40542 -1.78345
                                                  0.87149
                                                                2000 0.560
ter_pc1_vcv_phylo <- ter_pc1$VCV[,1]</pre>
ter_pc1_vcv_spec <- ter_pc1$VCV[,2]</pre>
ter_pc1_vcv_units <- ter_pc1$VCV[,3]</pre>
ter_pc1_phylo <- ter_pc1_vcv_phylo/c(ter_pc1_vcv_phylo + ter_pc1_vcv_spec + ter_pc1_vcv_units)
ter_pc1_spec <- ter_pc1_vcv_spec/c(ter_pc1_vcv_phylo + ter_pc1_vcv_spec + ter_pc1_vcv_units)</pre>
ter_pc1_units <- ter_pc1_vcv_units/c(ter_pc1_vcv_phylo + ter_pc1_vcv_spec + ter_pc1_vcv_units)</pre>
hdr(ter_pc1_phylo)
## $hdr
            [,1]
                       [,2]
                                [,3]
                                          [,4]
                                                   [,5]
                                                              [,6]
## 99% 0.9062223 0.9073376 0.911247 0.916007 0.919754 0.9937795
## 95% 0.9371836 0.9914065
                                  NA
                                            NA
                                                     NA
                                                                NA
## 50% 0.9694404 0.9848373
                                  NA
                                            NA
                                                     NA
                                                                NA
##
## $mode
## [1] 0.9791207
##
## $falpha
           1%
                       5%
                                 50%
   0.5745123 3.4329950 25.4838910
```

```
hdr(ter_pc1_spec)
## $hdr
                             [,2]
                                                                [,5]
##
                [,1]
                                        [,3]
                                                    [,4]
                                                                            [,6]
## 99% -0.001719918 0.054466799 0.05514227 0.05893179 0.07841291 0.07902547
## 95% -0.001319937 0.038627601
                                                      NA
                                                                  NΑ
                                                                              NA
## 50% 0.000112596 0.009962863 0.01055440 0.01217742
                                                                  NA
                                                                              NA
##
## $mode
## [1] 0.005006542
##
## $falpha
                              50%
##
                     5%
          1%
    1.055593 3.667939 37.374994
hdr(ter_pc1_units)
## $hdr
##
               [,1]
                          [,2]
                                      [,3]
                                                  [,4]
## 99% 0.007000206 0.03085296 0.03306523 0.03351056
## 95% 0.008719491 0.02648578
                                        NA
                                                    NA
## 50% 0.012772645 0.01838083
                                        NA
                                                    NA
##
## $mode
## [1] 0.01482833
## $falpha
##
                     5%
                               50%
          1%
    2.104418 11.940251 71.139024
Metabolic rate analysis
met_PCA <- pop_multree$data$met_rate_Wg</pre>
pca_data$met_PCA <- met_PCA</pre>
pca_data$animal <- pca_data$species_match</pre>
pca_data$met_rate <- as.numeric(as.vector(pca_data$met_PCA))</pre>
pca_data_met <- na.omit(pca_data[,c("species_match","animal","PC1","class_match","met_rate")])</pre>
met_mod <- MCMCglmm(PC1 ~ log10(met_rate) ,</pre>
                      data = pca_data_met,
                      random=~animal + species_match,
                      pedigree = axis_trees[[1]],
                      prior = prior,
                      nitt = c(1100000), burnin = 100000, thin = 500, verbose = F)
summary(met mod)
##
    Iterations = 100001:1099501
##
## Thinning interval = 500
## Sample size = 2000
```

```
##
   DIC: 220.4934
##
##
    G-structure: ~animal
##
##
          post.mean 1-95% CI u-95% CI eff.samp
##
              7.331
                        3.354
                                  11.5
  animal
##
##
                   ~species_match
##
##
                 post.mean 1-95% CI u-95% CI eff.samp
                   0.05729 2.672e-08
                                                    2000
##
   species_match
                                        0.2166
##
##
    R-structure: ~units
##
##
         post.mean 1-95% CI u-95% CI eff.samp
            0.2063
                    0.1587
                              0.2729
                                           2000
##
   units
##
    Location effects: PC1 ~ log10(met_rate)
##
##
##
                   post.mean 1-95% CI u-95% CI eff.samp pMCMC
## (Intercept)
                      -2.5216 -7.4268
                                         2.2588
                      -1.0381 -1.8828 -0.1241
                                                     2000 0.024 *
## log10(met_rate)
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
met_mod_phylo <- met_mod$VCV[,1]</pre>
met_mod_spec <- met_mod$VCV[,2]</pre>
met_mod_units <- met_mod$VCV[,3]</pre>
met_mod_phylo_H <- met_mod_phylo/c(met_mod_phylo + met_mod_spec + met_mod_units)</pre>
met_mod_spec_H <- met_mod_spec/c(met_mod_phylo + met_mod_spec + met_mod_units)</pre>
met_mod_units_H <- met_mod_units/c(met_mod_phylo + met_mod_spec + met_mod_units)</pre>
hdr(met_mod_phylo_H)
## $hdr
##
                       [,2]
            [,1]
## 99% 0.8816459 0.9947336
## 95% 0.9253472 0.9903859
## 50% 0.9616506 0.9773326
## $mode
## [1] 0.9696589
##
## $falpha
##
                      5%
                                 50%
           1%
  0.3646195 2.0960558 25.4189342
hdr(met_mod_spec_H)
## $hdr
##
                [,1]
                             [,2]
                                          [,3]
                                                      [,4]
                                                                  [,5]
                  NA 0.033308755 0.034383345 0.039792336 0.04144077
## 99%
## 95%
                  NA 0.026763158 0.027103884 0.028248672 0.02877469
```

```
## 50% -0.0003043433 0.003089078 0.003591603 0.004062234
##
            [,6]
                       [,7]
                                 [,8]
                                           [,9] [,10]
                                                                [,11]
## 99% 0.04407108 0.04408625 0.04490320 0.04636180 0.04710839 0.04942646
## 95% 0.02902732 0.02994748 0.02996134 0.03037664 0.03126559 0.03156201
## 50%
           NA
                       NA
                                  NA
                                            NA
                                                        NA
                                [,14]
##
           [,12]
                      [,13]
                                           [,15]
                                                     [,16]
                                                                [,17]
## 99% 0.05011109 0.05025058 0.05115680 0.05265059 0.05281274 0.05313354
## 95% 0.03286971 0.03589365 0.03630552 0.03697813 0.03743899 0.03920592
## 50%
         NA
                        NA
                               NA
                                            NA
                                                        NA
                                                                  NA
##
           [,18]
                      [,19]
                                [,20]
                                           [,21]
                                                     [,22]
## 99% 0.05316924 0.05413300 0.05463529 0.05703074 0.05775910 0.05780200
## 95% 0.03945526 0.04431918 0.04467045 0.04976583 0.04978382 0.05064565
                 NA
                            NA
                                          NA
          NA
                                                    NA
                                [,26]
           [,24]
                      [,25]
                                           [,27]
                                                     [,28]
## 99% 0.05891637 0.05923707 0.05977589 0.06104226 0.06172311 0.06222158
## 95% 0.05092723
                    NA
                                 NA
                                             NA
                                                        NA
## 50%
                        NA
                                  NA
                                             NA
                                                        NA
             NA
                                                                   NA
                                [,32]
##
           [,30]
                      [,31]
                                           [,33]
                                                     [,34]
## 99% 0.06324565 0.06388036 0.06396064 0.06496085 0.06496638 0.06555822
              NA
                        NA
                                  NA
                                             NA
                                                        NA
## 50%
              NA
                        NΑ
                                   NA
                                             NA
                                                        NΔ
                                                                   NΔ
                     [,37]
                               [,38]
                                          [,39]
                                                   [,40]
## 99% 0.0656272 0.06657396 0.06703433 0.06789169 0.0679228 0.06976292
## 95%
       NA
                       NA
                                  NA
                                            NA
                                                      NA
## 50%
            NA
                       NA
                                  NA
                                            NA
                                                                 NΑ
                                                      NA
           [,42]
                      [,43]
                                [,44]
                                           Γ.45]
                                                     [,46]
## 99% 0.07077877 0.07131389 0.07236617 0.07591353 0.07596655 0.07710538
                        NA
## 95%
       NA
                                   NA
                                             NA
                                                        NA
                                                                   NA
## 50%
              NA
                        NA
                                   NA
                                             NA
                                                        NA
                                                                   NA
                                                     [,52]
           [,48]
                     [,49]
                               [,50]
                                           [,51]
## 99% 0.07735182 0.07746284 0.07766832 0.08349839 0.08355331 0.08643088
## 95%
             NA
                        NA
                                  NΑ
                                             NA
                                                        NΑ
                                                                   NA
## 50%
                        NA
             NA
                                   NA
                                                                   NA
##
           [,54]
                     [,55]
                              [,56]
                                        [,57]
                                                  [,58]
## 99% 0.08649149 0.1127854 0.1128587 0.2100523 0.2100712
## 95%
              NA
                       NA
                                 NA
                                          NA
                                                    NA
## 50%
              NA
                       NA
                                 NA
                                          NA
                                                    NA
##
## $mode
## [1] 0.0002158479
## $falpha
## 1%
                 5%
## 1.013906 3.153052 59.871183
hdr(met_mod_units_H)
## $hdr
                       [,2]
##
             [,1]
## 99% 0.009775394 0.05859375
## 95% 0.012647033 0.04893915
## 50% 0.020942363 0.03193002
##
## $mode
## [1] 0.02613693
```

```
##
## $falpha
                              50%
##
                    5%
    1.786117 6.419047 37.081706
##
plot(log10(pca_data_met$met_rate), pca_data_met$PC1, pch = 16, col = "white", cex = 0.1)
points(log10(pca_data_met[pca_data_met$class_match == "Mammalia", "met_rate"]), pca_data_met[pca_data_met
points(log10(pca_data_met[pca_data_met$class_match == "Aves", "met_rate"]), pca_data_met[pca_data_met$class_match
points(log10(pca_data_met[pca_data_met$class_match == "Reptilia", "met_rate"]), pca_data_met[pca_data_met
points(log10(pca data met[pca data met$class match == "Actinopterygii", "met rate"]), pca data met[pca d
points(log10(pca_data_met[pca_data_met$class_match == "Gastropoda", "met_rate"]), pca_data_met[pca_data_met
points(log10(pca_data_met[pca_data_met$class_match == "Demospongiae", "met_rate"]), pca_data_met[pca_dat
points(log10(pca_data_met[pca_data_met$class_match == "Anthozoa", "met_rate"]), pca_data_met[pca_data_met
points(log10(pca_data_met[pca_data_met$class_match == "Bivalvia", "met_rate"]), pca_data_met[pca_data_met
abline(hdr(met_mod$Sol[,1])$mode, hdr(met_mod$Sol[,2])$mode)
      က
pca_data_met$PC1
      \sim
     0
      7
     7
```

reproduction productivity on PC2 axis Need to allow this data and the met date flow through the scripts properly.

-3.0

log10(pca_data_met\$met_rate)

-2.5

-2.0

-4.0

-3.5

```
r_size_g <- vector()
notes <- vector()
trophic_again <- read.csv("Trophic_data_June16_2017.csv")

for(k in 1:length(pca_data$species_match)){</pre>
```

```
r_size_g[k] <- ((trophic_again[trophic_again$species == as.vector(pca_data$species_match[k]), "repo_siz
notes[k] <- as.character((trophic_again[trophic_again$species == as.vector(pca_data$species_match[k]),
}
## Warning: NAs introduced by coercion
## Warning: NAs introduced by coercion
egg_size_data0 <- data.frame(PC1 = pca_data$PC1,</pre>
                             r_size_g,
                             species = pca_data$species_match,
                             animal = pca_data$species_match,
                             taxa = pca_data$class_match,
                             notes = notes)
egg_size_data <- na.omit(egg_size_data0)</pre>
egg_size <- MCMCglmm(PC1 ~ r_size_g,
                     data = egg_size_data,
                     random=~animal + species,
                     pedigree = axis_trees[[1]],
                     prior = prior,
                     nitt = c(1100000), burnin = 10000, thin = 50, verbose = F)
egg_size_phylo <- egg_size$VCV[,1]/(egg_size$VCV[,1] +</pre>
                                          egg size$VCV[,2] +
                                          egg_size$VCV[,3])
egg_size_species <- egg_size$VCV[,2]/(egg_size$VCV[,1] +
                                          egg_size$VCV[,2] +
                                          egg_size$VCV[,3])
egg_size_units <- egg_size$VCV[,3]/(egg_size$VCV[,1] +
                                          egg_size$VCV[,2] +
                                          egg_size$VCV[,3])
hdr(egg_size_phylo)
## $hdr
##
            [,1]
                       [,2]
                                 [,3]
                                           [, 4]
                                                      [,5]
                                                                [,6]
## 99% 0.8951514 0.8972206 0.8987438 0.9015902 0.9047617 0.9908595
## 95% 0.9264072 0.9291886 0.9294333 0.9892499
## 50% 0.9660125 0.9835624
                                             NA
                                                       NA
                                                                  NA
##
## $mode
## [1] 0.9780624
##
## $falpha
                      5%
                                 50%
##
## 0.5945475 2.8591756 22.7179454
hdr(egg_size_species)
```

```
## $hdr
##
                 [,1]
                             [,2]
                                          [,3]
                                                     [,4]
                                                                 [,5]
                                                                             [,6]
## 99%
                  NA 0.062819057 0.063162674 0.06485098 0.06625850 0.06771723
## 95% -0.0006862196 0.042476363 0.043181378 0.04429806 0.04493563 0.04565082
## 50% -0.0003194662 0.008894888 0.009047336 0.01021854 0.01049438 0.01115119
##
             [,7]
                         [,8]
                                     [,9]
                                               [,10]
## 99% 0.06890145 0.06924265 0.07144036 0.07174806
## 95%
               NA
                           NA
                                       NA
## 50%
               NA
                           NA
                                       NA
                                                  NA
##
## $mode
## [1] 0.0001587444
##
## $falpha
##
           1%
                                 50%
                       5%
    0.6843343 3.5753145 33.1714577
hdr(egg_size_units)
## $hdr
                          [,2]
##
              [,1]
## 99% 0.009300005 0.03930224
## 95% 0.010616915 0.03263813
## 50% 0.015133330 0.02228768
##
## $mode
## [1] 0.01818734
##
## $falpha
##
                     5%
                              50%
          1%
   2.674841 9.018205 58.498888
```

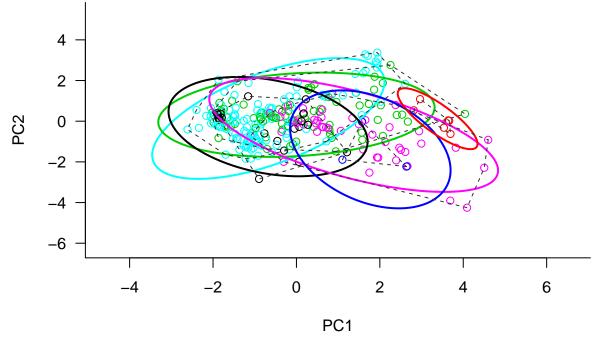
Next up plot the ellipses.

Adding some ellipses for taxinomic groups

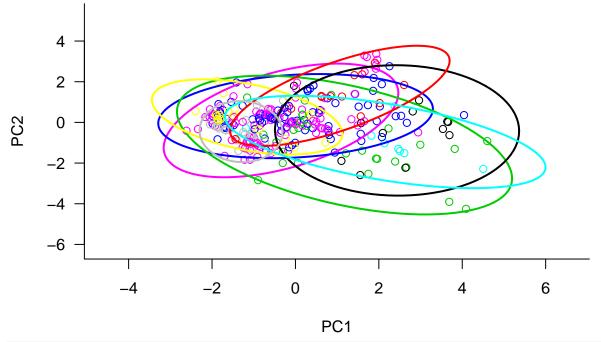
```
pca_data$class_match == "Reptilia",]
sidpca <- data.frame(iso1 = siber_pca_data$PC1,</pre>
                     iso2 = siber_pca_data$PC2,
                      group = as.numeric(siber_pca_data$class_match),
                      community = rep(1,length(siber_pca_data$class_match)))
##we need to get rid of the
sidmob <- data.frame(iso1 = pca_data$PC1,</pre>
                     iso2 = pca_data$PC2,
                      group = as.numeric(pca_data$mobility_PCA),
                      community = rep(1,length(pca_data$class_match)))
sidtherm <- data.frame(iso1 = pca_data$PC1,</pre>
                     iso2 = pca_data$PC2,
                      group = as.numeric(pca_data$therm_PCA),
                      community = rep(1,length(pca_data$class_match)))
pca_data$iucn_statue <- factor(pca_data$iucn_statue, levels = c("NA", "CE", "E", "LC", "LR", "NT", "V")
pca data$iucn statue[is.na(pca data$iucn statue)] <- "NA"</pre>
sired <- na.omit(data.frame(iso1 = pca_data$PC1,</pre>
                     iso2 = pca_data$PC2,
                      group = as.numeric(pca_data$iucn_statue),
                      community = rep(1,length(pca_data$class_match))))
siber.plots <- createSiberObject(sidpca)</pre>
## Warning in createSiberObject(sidpca): At least one of your groups has less than 5 observations.
             The absolute minimum sample size for each group is 3 in order
##
             for the various ellipses and corresponding metrics to be
##
             calculated. More reasonably though, a minimum of 5 data points
##
             are required to calculate the two means and the 2x2 covariance
##
             matrix and not run out of degrees of freedom. Check the item
##
##
             named 'sample.sizes' in the object returned by this function
             in order to locate the offending group. Bear in mind that NAs in
##
##
             the sample.size matrix simply indicate groups that are not
##
             present in that community, and is an acceptable data structure
             for these analyses.
siber.mob <- createSiberObject(sidmob)</pre>
siber.therm <- createSiberObject(sidtherm)</pre>
siber.iucn<- createSiberObject(sired)</pre>
## Warning in createSiberObject(sired): At least one of your groups has less than 5 observations.
##
             The absolute minimum sample size for each group is 3 in order
##
             for the various ellipses and corresponding metrics to be
             calculated. More reasonably though, a minimum of 5 data points
##
```

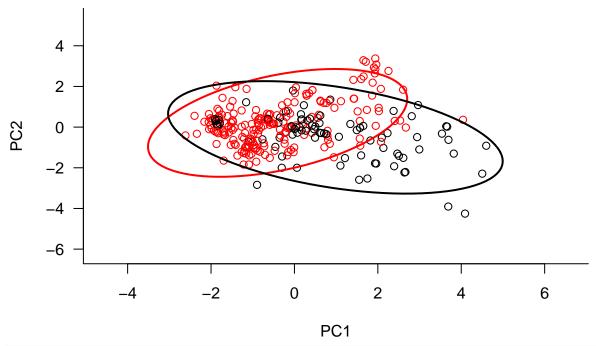
```
## are required to calculate the two means and the 2x2 covariance
## matrix and not run out of degrees of freedom. Check the item
## named 'sample.sizes' in the object returned by this function
## in order to locate the offending group. Bear in mind that NAs in
## the sample.size matrix simply indicate groups that are not
## present in that community, and is an acceptable data structure
## for these analyses.
```

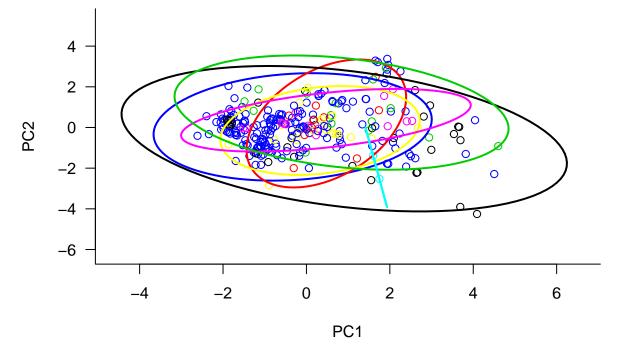
```
# Create lists of plotting arguments to be passed onwards to each
# of the three plotting functions.
community.hulls.args <- list(col = 1, lty = 1, lwd = 1)</pre>
group.ellipses.args <- list(n = 100, p.interval = 0.95,</pre>
                              lty = 1, lwd = 2)
                     <- list(lty = 2, col = "grey20")
group.hull.args
#plot for taxa
plotSiberObject(siber.plots,
                  ax.pad = 2,
                  hulls = F, community.hulls.args,
                  ellipses = T, group.ellipses.args,
                  group.hulls = T, group.hull.args,
                  bty = L'',
                  iso.order = c(1,2),
                  xlab = "PC1",
                  ylab = "PC2"
```



```
ellipses = T, group.ellipses.args,
group.hulls = F, group.hull.args,
bty = "L",
iso.order = c(1,2),
xlab = "PC1",
ylab = "PC2"
)
```



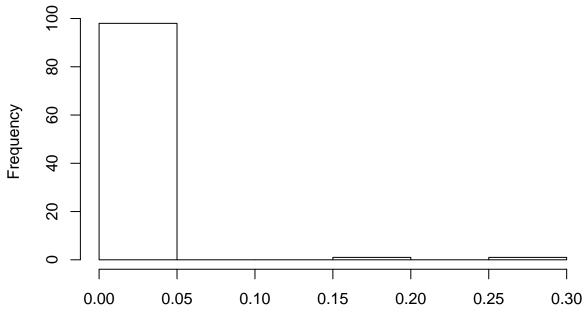


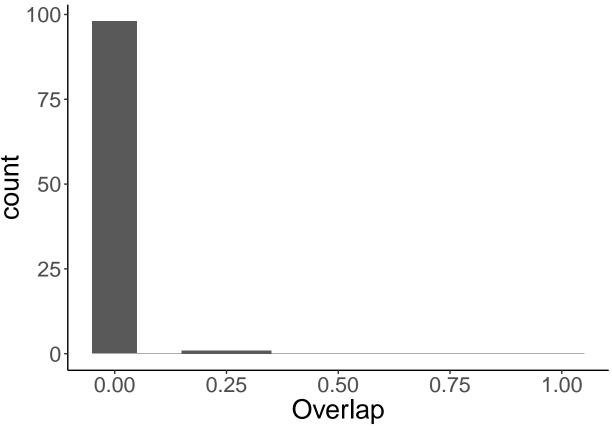


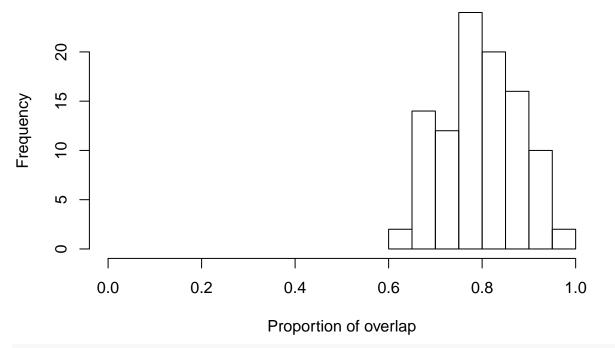
Ellipse overlap calculations for taxa

```
group.MLtaxa <- groupMetricsML(siber.plots)</pre>
group.MLmob <- groupMetricsML(siber.mob)</pre>
# options for running jags
parms <- list()</pre>
parms$n.iter <- 2 * 10^4 # number of iterations to run the model for
parms$n.burnin <- 1 * 10^3 # discard the first set of values
parms$n.thin <- 10
                        # thin the posterior by this many
parms$n.chains <- 2</pre>
                            # run this many chains
# define the priors
priors <- list()</pre>
priorsR < 1 * diag(2)
priors$k <- 2
priors$tau.mu <- 1.0E-3</pre>
ellipses.posterior <- siberMVN(siber.plots, parms, priors)</pre>
## Compiling model graph
      Resolving undeclared variables
##
      Allocating nodes
##
## Graph information:
##
      Observed stochastic nodes: 121
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 136
##
## Initializing model
##
## Compiling model graph
##
      Resolving undeclared variables
##
      Allocating nodes
## Graph information:
      Observed stochastic nodes: 81
##
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 96
##
## Initializing model
##
## Compiling model graph
      Resolving undeclared variables
##
      Allocating nodes
##
## Graph information:
##
      Observed stochastic nodes: 21
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 36
##
## Initializing model
##
## Compiling model graph
##
      Resolving undeclared variables
```

```
##
      Allocating nodes
## Graph information:
      Observed stochastic nodes: 48
##
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 63
##
## Initializing model
##
## Compiling model graph
##
      Resolving undeclared variables
##
      Allocating nodes
## Graph information:
      Observed stochastic nodes: 3
##
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 18
##
## Initializing model
##
## Compiling model graph
      Resolving undeclared variables
##
##
      Allocating nodes
## Graph information:
##
      Observed stochastic nodes: 6
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 21
## Initializing model
# The first ellipse is referenced using a character string representation where
# in "x.y", "x" is the community, and "y" is the group within that community.
# So in this example: community 1, group 1
#Actinopteryqii
ellipse_Actinopterygii <- "1.1"
#Anthozoa
ellipse_Anthozoa <- "1.2"
#Aves
ellipse_Aves <- "1.3"
#Gastropoda
ellipse_Gastropoda <- "1.7"
#Mammalia
ellipse_Mammalia <- "1.8"
#Reptilia
ellipse_Reptilia <- "1.9"
####fish - coral
AAn_95.overlap <- bayesianOverlap(ellipse_Actinopterygii,
                                    ellipse_Anthozoa,
```

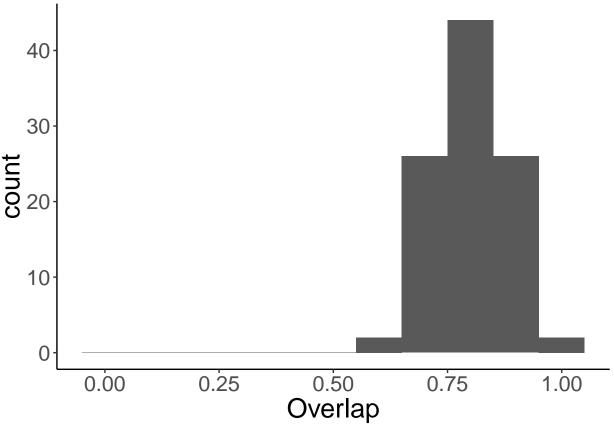






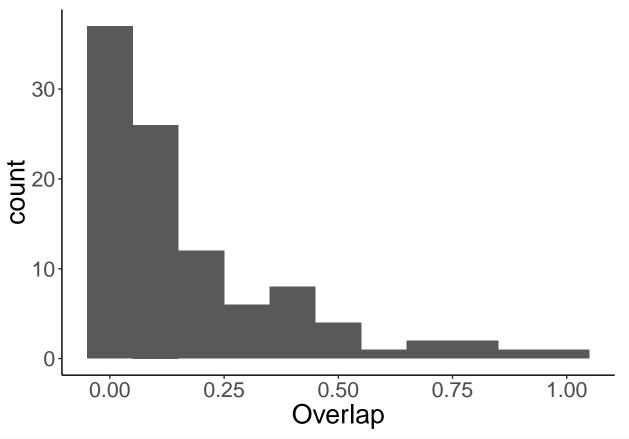
hdr(AAv_95_overlap_prop)

```
## $hdr
##
            [,1]
                      [,2]
## 99% 0.6351274 0.9531334
## 95% 0.6466299 0.9409581
## 50% 0.7479998 0.8574179
##
## $mode
## [1] 0.8015085
##
## $falpha
                          50%
##
         1%
                  5%
## 1.136424 1.411099 3.481389
myplot_Aav = ggplot(data.frame(Overlap = AAv_95_overlap_prop),
                    aes(Overlap)) +
  geom_histogram(binwidth=0.1) +
  scale_x_continuous(limits = c(-0.05, 1.05))
myplot_Aav + theme_bw() + theme(panel.border = element_blank(), panel.grid.major = element_blank(),
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"),
text = element_text(size=20))
```



```
ggsave("fish_aves.png", dpi=300, width=4, height=3)
####fish - gastropod
AG95.overlap <- bayesianOverlap(ellipse_Actinopterygii,
                                   ellipse_Gastropoda,
                                   ellipses.posterior,
                                   draws = 100,
                                  p.interval = 0.95,
                                   n = 100)
AG_95_overlap_prop <- vector()
for(i in 1:length(AG95.overlap$)){
AG_95_overlap_prop[i] <- AG95.overlap$overlap[i]/min(AG95.overlap[i,1:2])
}
myplot_AG = ggplot(data.frame(Overlap = AG_95_overlap_prop),
                    aes(Overlap)) +
  geom_histogram(binwidth=0.1) +
  scale_x_continuous(limits = c(-0.05, 1.05))
myplot_AG + theme_bw() + theme(panel.border = element_blank(), panel.grid.major = element_blank(),
```

```
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"),
text = element_text(size=20))
```

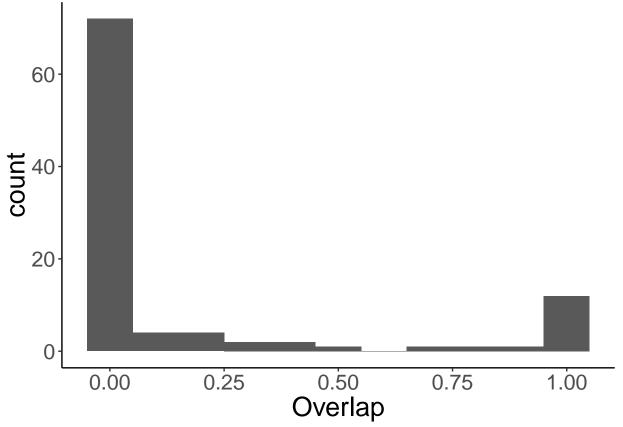


```
ggsave("fish_gastropod.png", dpi=300, width=4, height=3)
#hdr(AG_95_overlap_prop)
##fish - mammal
AM95.overlap <- bayesianOverlap(ellipse_Actinopterygii,
                                   ellipse_Mammalia,
                                   ellipses.posterior,
                                   draws = 100,
                                   p.interval = 0.95,
                                   n = 100)
Am_95_overlap_prop <- vector()</pre>
for(i in 1:length(AM95.overlap$)){
Am_95_overlap_prop[i] <- AM95.overlap$overlap[i]/min(AM95.overlap[i,1:2])</pre>
}
myplot_AM = ggplot(data.frame(Overlap = Am_95_overlap_prop),
                    aes(Overlap)) +
  geom_histogram(binwidth=0.1) +
 scale_x_continuous(limits = c(-0.05, 1.05))
```

```
myplot_AM + theme_bw() + theme(panel.border = element_blank(), panel.grid.major = element_blank(),
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"),
text = element_text(size=20))
   60
   40
   20
     0
                            0.25
                                             0.50
            0.00
                                                             0.75
                                                                              1.00
                                         Overlap
ggsave("fish_mammal.png", dpi=300, width=4, height=3)
hdr(Am_95_overlap_prop)
## $hdr
##
            [,1]
                      [,2]
                                [,3]
                                          [,4]
                                                  [,5]
                                                            [,6]
## 99% 0.8375788 1.0171641
                                  NA
                                            NA
                                                    NA
                                                             NA
## 95% 0.8446865 0.8538227 0.8781512 0.8871702 0.89052 1.015364
## 50% 0.9814695 1.0111432
                                            NA
                                                    NA
                                                             NA
##
## $mode
## [1] 0.9991794
##
## $falpha
##
                  5%
                          50%
## 1.184232 2.145753 6.716224
###fish and reptiles
AR95.overlap <- bayesianOverlap(ellipse_Actinopterygii,
                                   ellipse_Reptilia,
                                   ellipses.posterior,
                                   draws = 100,
                                   p.interval = 0.95,
```

```
n = 100)
AR_95_overlap_prop <- vector()</pre>
for(i in 1:length(AR95.overlap$)){
AR_95_overlap_prop[i] <- AR95.overlap$overlap[i]/min(AR95.overlap[i,1:2])
}
myplot_AR = ggplot(data.frame(Overlap = AR_95_overlap_prop),
                    aes(Overlap)) +
  geom_histogram(binwidth=0.1) +
  scale_x_continuous(limits = c(-0.05, 1.05))
myplot_AR + theme_bw() + theme(panel.border = element_blank(), panel.grid.major = element_blank(),
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"),
text = element_text(size=20))
   30
    10
     0
                                            0.50
                            0.25
                                                            0.75
            0.00
                                                                             1.00
                                         Overlap
ggsave("fish_reptile.png", dpi=300, width=4, height=3)
#hdr(AR_95_overlap_prop)
###coral-gastropod
AnG95.overlap <- bayesianOverlap(ellipse_Anthozoa,</pre>
```

ellipse_Gastropoda,



```
ggsave("coral_gastropod.png", dpi=300, width=4, height=3)
#hdr(AnG95_overlap_prop)
##coral mammal
```

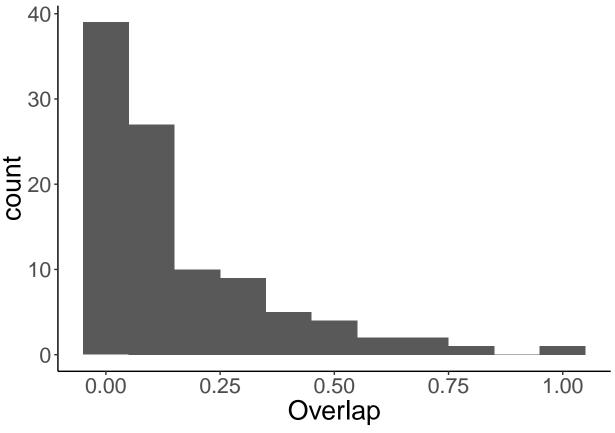
```
AnM95.overlap <- bayesianOverlap(ellipse_Anthozoa,</pre>
                                   ellipse_Mammalia,
                                   ellipses.posterior,
                                   draws = 100,
                                   p.interval = 0.95,
                                   n = 100)
AnM95_overlap_prop <- vector()</pre>
for(i in 1:length(AnG95.overlap$overlap)){
AnM95_overlap_prop[i] <- AnM95.overlap$overlap[i]/min(AnM95.overlap[i,1:2])
}
myplot_AnM = ggplot(data.frame(Overlap = AnM95_overlap_prop),
                    aes(Overlap)) +
  geom_histogram(binwidth=0.1) +
  scale_x_continuous(limits = c(-0.05, 1.05))
myplot_AnM + theme_bw() + theme(panel.border = element_blank(), panel.grid.major = element_blank(),
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"),
text = element_text(size=20))
     50
                              0.25
             0.00
                                              0.50
                                                              0.75
                                                                               1.00
```

```
ggsave("coral_mammal.png", dpi=300, width=4, height=3)
#hdr(AnM95_overlap_prop, h = 100)
```

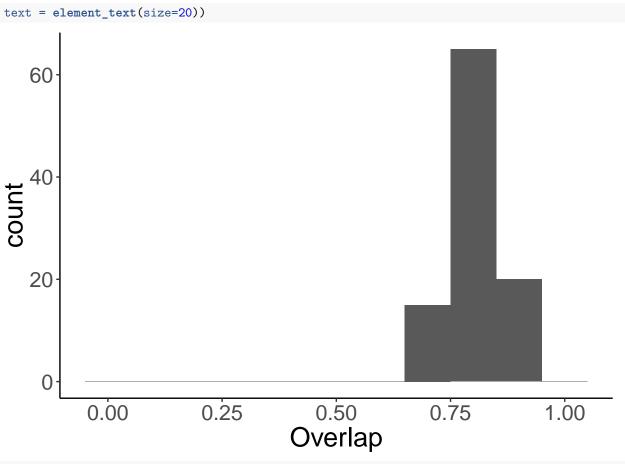
Overlap

```
##coral reptile
AnR95.overlap <- bayesianOverlap(ellipse_Anthozoa,</pre>
                                   ellipse_Reptilia,
                                   ellipses.posterior,
                                   draws = 100,
                                   p.interval = 0.95,
                                   n = 100)
AnR95_overlap_prop <- vector()</pre>
for(i in 1:length(AnR95.overlap$overlap)){
AnR95_overlap_prop[i] <- AnR95.overlap[i]/min(AnR95.overlap[i,1:2])
}
myplot_AnR = ggplot(data.frame(Overlap = AnR95_overlap_prop),
                    aes(Overlap)) +
  geom_histogram(binwidth=0.1) +
  scale_x_continuous(limits = c(-0.05, 1.05))
myplot_AnR + theme_bw() + theme(panel.border = element_blank(), panel.grid.major = element_blank(),
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"),
text = element_text(size=20))
   80
   60
   20
                                            0.50
           0.00
                            0.25
                                                            0.75
                                                                             1.00
                                         Overlap
```

```
ggsave("coral_reptile.png", dpi=300, width=4, height=3)
#hdr(AnR95_overlap_prop)
###bird - gastropd
AvG95.overlap <- bayesianOverlap(ellipse_Aves,</pre>
                                    ellipse_Gastropoda,
                                    ellipses.posterior,
                                   draws = 100,
                                   p.interval = 0.95,
                                   n = 100)
AvG95_overlap_prop <- vector()</pre>
for(i in 1:length(AvG95.overlap$)){
AvG95_overlap_prop[i] <- AvG95.overlap$overlap[i]/min(AvG95.overlap[i,1:2])</pre>
}
myplot_AvG = ggplot(data.frame(Overlap = AvG95_overlap_prop),
                    aes(Overlap)) +
  geom_histogram(binwidth=0.1) +
  scale_x_continuous(limits = c(-0.05, 1.05))
myplot_AvG + theme_bw() + theme(panel.border = element_blank(), panel.grid.major = element_blank(),
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"),
text = element_text(size=20))
```

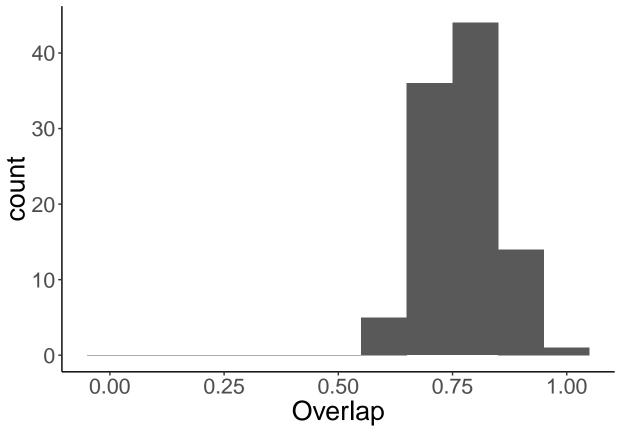


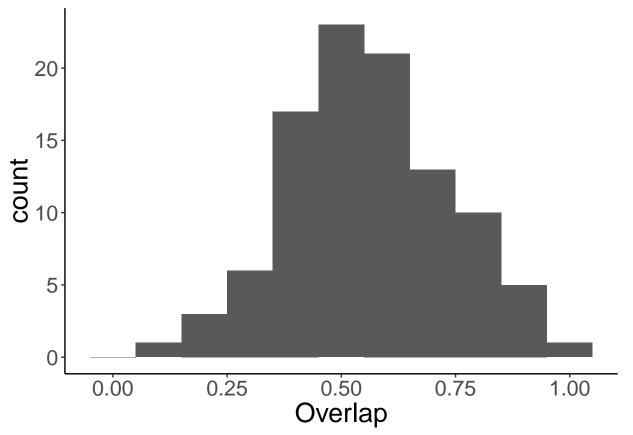
```
ggsave("aves_gastorpod.png", dpi=300, width=4, height=3)
#hdr(AvG95_overlap_prop)
####aves mammal
AvM95.overlap <- bayesianOverlap(ellipse_Aves,</pre>
                                   ellipse_Mammalia,
                                   ellipses.posterior,
                                   draws = 100,
                                   p.interval = 0.95,
                                   n = 100)
AvM95_overlap_prop <- vector()</pre>
for(i in 1:length(AvM95.overlap$overlap)){
AvM95_overlap_prop[i] <- AvM95.overlap[i]/min(AvM95.overlap[i,1:2])
}
myplot_AvM = ggplot(data.frame(Overlap = AvM95_overlap_prop),
                    aes(Overlap)) +
  geom_histogram(binwidth=0.1) +
  scale_x_continuous(limits = c(-0.05, 1.05))
myplot_AvM + theme_bw() + theme(panel.border = element_blank(), panel.grid.major = element_blank(),
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"),
```

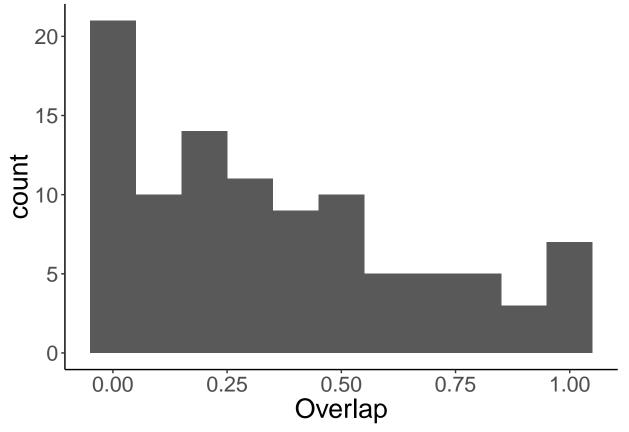


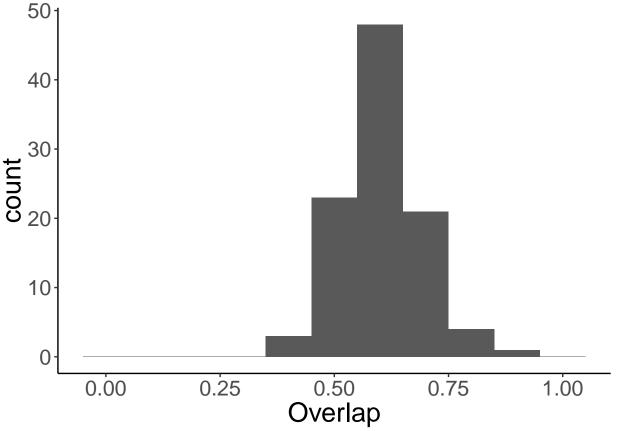
```
ggsave("aves_mammal.png", dpi=300, width=4, height=3)
#hdr(AvM95_overlap_prop)
##### Aves reptile
AvRR95.overlap <- bayesianOverlap(ellipse_Aves,</pre>
                                    ellipse_Reptilia,
                                    ellipses.posterior,
                                    draws = 100,
                                    p.interval = 0.95,
                                    n = 100)
AvR95_overlap_prop <- vector()</pre>
for(i in 1:length(AvRR95.overlap$overlap)){
AvR95_overlap_prop[i] <- AvRR95.overlap$overlap[i]/min(AvRR95.overlap[i,1:2])
}
myplot_AvR = ggplot(data.frame(Overlap = AvR95_overlap_prop),
                    aes(Overlap)) +
  geom_histogram(binwidth=0.1) +
  scale_x_continuous(limits = c(-0.05, 1.05))
```

```
myplot_AvR + theme_bw() + theme(panel.border = element_blank(), panel.grid.major = element_blank(),
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"),
text = element_text(size=20))
```







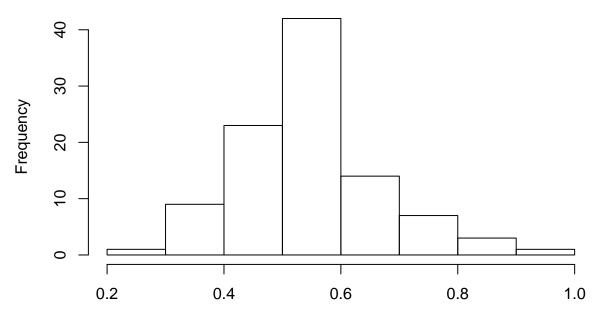


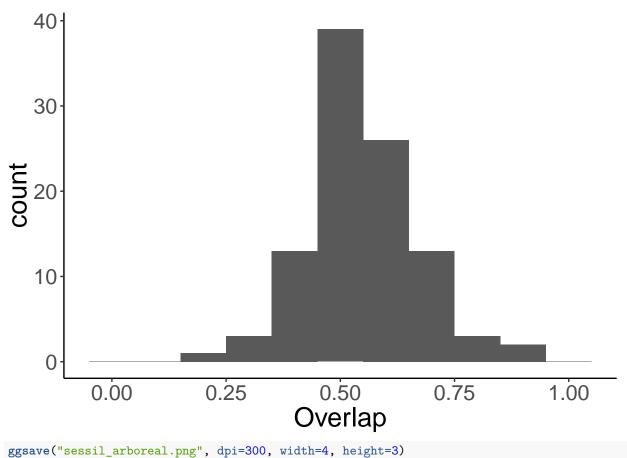
```
draws = 100,
                                   p.interval = 0.95,
                                   n = 100)
MG95_overlap_prop <- vector()</pre>
for(i in 1:length(RG95.overlap$overlap)){
MG95_overlap_prop[i] <- MG95.overlap$overlap[i]/min(MG95.overlap[i,1:2])
}
myplot_MG = ggplot(data.frame(Overlap = MG95_overlap_prop),
                    aes(Overlap)) +
  geom_histogram(binwidth=0.1) +
  scale_x_continuous(limits = c(-0.05, 1.05))
myplot_MG + theme_bw() + theme(panel.border = element_blank(), panel.grid.major = element_blank(),
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"),
text = element_text(size=20))
   30
   20
    10
     0
                            0.25
                                            0.50
           0.00
                                                             0.75
                                                                              1.00
                                         Overlap
ggsave("mammal_gastropod.png", dpi=300, width=4, height=3)
hdr(MG95_overlap_prop)
## $hdr
              [,1]
                        [,2]
                                  [,3]
                                            [,4]
## 99% -0.08654210 0.5607515 0.6224771 0.6749137
```

```
## 95% -0.08073216 0.4201050 0.4506731 0.5324460
## 50% -0.01683704 0.1000328
##
## $mode
## [1] 0.0209193
##
## $falpha
                               50%
##
          1%
                     5%
## 0.2394809 0.3297246 2.9250461
Ellipse overlap calculations for mode of life
group.ML <- groupMetricsML(siber.plots)</pre>
group.MLmob <- groupMetricsML(siber.mob)</pre>
# options for running jags
parms <- list()</pre>
parms$n.iter <- 2 * 10^4 # number of iterations to run the model for
parms$n.burnin <- 1 * 10^3 # discard the first set of values
parms$n.thin <- 10
                       # thin the posterior by this many
                            # run this many chains
parms$n.chains <- 2
# define the priors
priors <- list()</pre>
priors R \leftarrow 1 * diag(2)
priors$k <- 2</pre>
priors$tau.mu <- 1.0E-3
ellipses.posterior_mob <- siberMVN(siber.mob, parms, priors)</pre>
## Compiling model graph
##
      Resolving undeclared variables
##
      Allocating nodes
## Graph information:
##
      Observed stochastic nodes: 95
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 110
##
## Initializing model
##
## Compiling model graph
      Resolving undeclared variables
##
      Allocating nodes
##
## Graph information:
##
      Observed stochastic nodes: 82
##
      Unobserved stochastic nodes: 3
      Total graph size: 97
##
##
## Initializing model
##
## Compiling model graph
      Resolving undeclared variables
```

```
Allocating nodes
## Graph information:
      Observed stochastic nodes: 28
##
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 43
##
## Initializing model
##
## Compiling model graph
##
      Resolving undeclared variables
##
      Allocating nodes
##
   Graph information:
      Observed stochastic nodes: 12
##
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 27
##
## Initializing model
##
##
  Compiling model graph
      Resolving undeclared variables
##
##
      Allocating nodes
## Graph information:
      Observed stochastic nodes: 21
##
##
      Unobserved stochastic nodes: 3
      Total graph size: 36
##
## Initializing model
##
##
  Compiling model graph
      Resolving undeclared variables
##
##
      Allocating nodes
## Graph information:
      Observed stochastic nodes: 12
##
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 27
##
## Initializing model
##
## Compiling model graph
      Resolving undeclared variables
##
##
      Allocating nodes
## Graph information:
      Observed stochastic nodes: 8
##
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 23
##
## Initializing model
##
##
  Compiling model graph
      Resolving undeclared variables
##
##
      Allocating nodes
## Graph information:
##
      Observed stochastic nodes: 27
      Unobserved stochastic nodes: 3
##
```

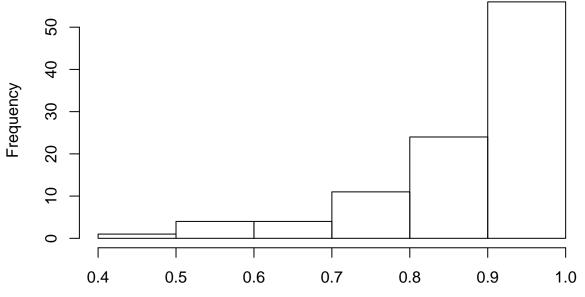
```
Total graph size: 42
##
##
## Initializing model
# The first ellipse is referenced using a character string representation where
\# in "x.y", "x" is the community, and "y" is the group within that community.
# So in this example: community 1, group 1
#ellipse group numbers
ellipse_sessile <- "1.1"
ellipse_arboreal <- "1.2"
ellipse_benthic <- "1.3"
ellipse_volant <- "1.4"
ellipse_semiaquatic <- "1.5"
ellipse_terrestrial <- "1.6"
ellipse_pelagic <- "1.7"
ellipse_semifossorial <- "1.8"
####sessile - arboreal
SA_95.overlap <- bayesianOverlap(ellipse_sessile,</pre>
                                   ellipse_arboreal,
                                   ellipses.posterior_mob,
                                   draws = 100,
                                   p.interval = 0.95,
                                   n = 100)
SA_95.overlap_prop <- vector()</pre>
for(i in 1:length(SA_95.overlap$overlap)){
SA_95.overlap_prop[i] <- SA_95.overlap[i]/min(SA_95.overlap[i,1:2])
}
hist(SA_95.overlap_prop, xlab = "Proportion of overlap", main = "")
```

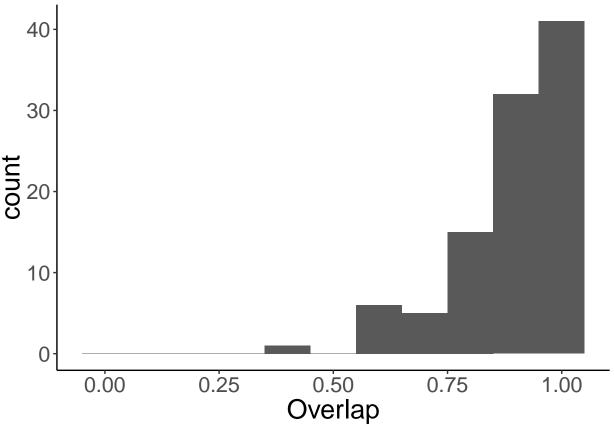


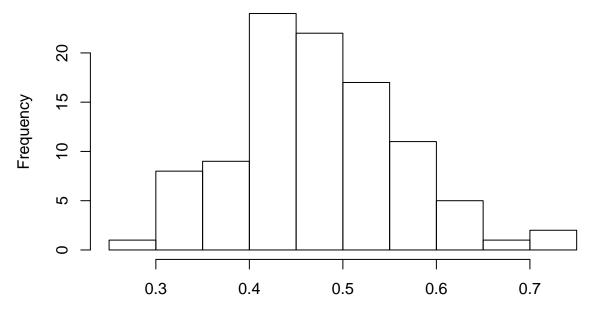


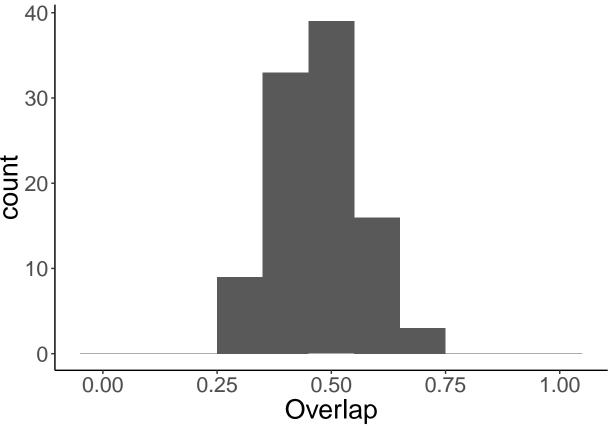
```
hdr(SA_95.overlap_prop, h = 10)
## $hdr
##
            [,1]
                       [,2]
## 99% 0.2066101 0.8871577
## 95% 0.3013192 0.7942679
## 50% 0.4858807 0.6159243
##
## $mode
## [1] 0.494468
##
## $falpha
##
           1%
                       5%
                                 50%
## 0.03986693 0.03987784 0.03988960
#####sessile - benthic
SB_95.overlap <- bayesianOverlap(ellipse_sessile,</pre>
                                    ellipse_benthic,
                                    ellipses.posterior_mob,
                                    draws = 100,
                                    p.interval = 0.95,
                                    n = 100)
SB_95.overlap_prop <- vector()</pre>
for(i in 1:length(SB_95.overlap$)overlap)){
SB_95.overlap_prop[i] <- SB_95.overlap$overlap[i]/min(SB_95.overlap[i,1:2])
```

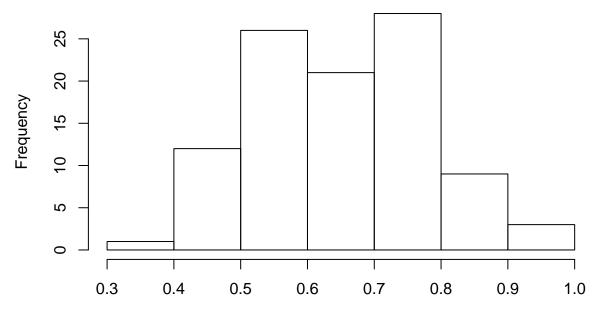
```
hist(SB_95.overlap_prop, xlab = "Proportion of overlap", main = "")
```

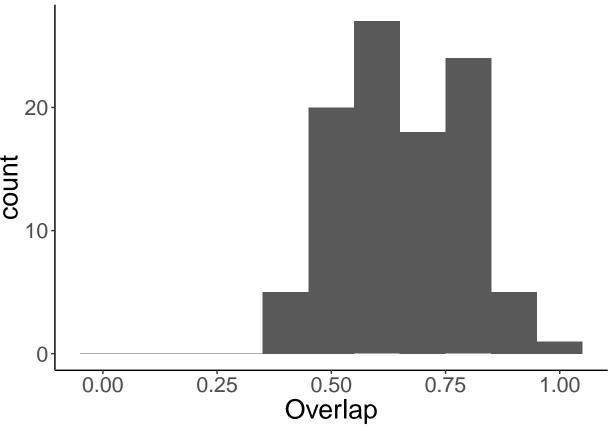


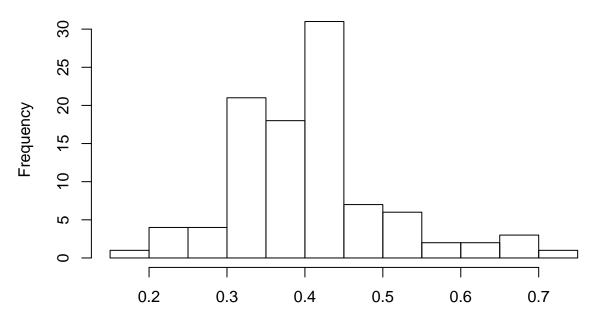


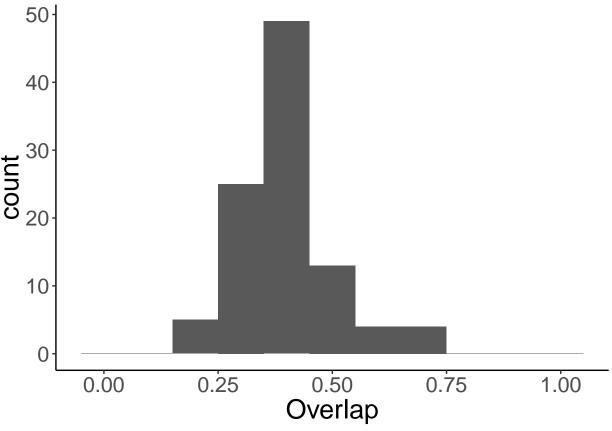


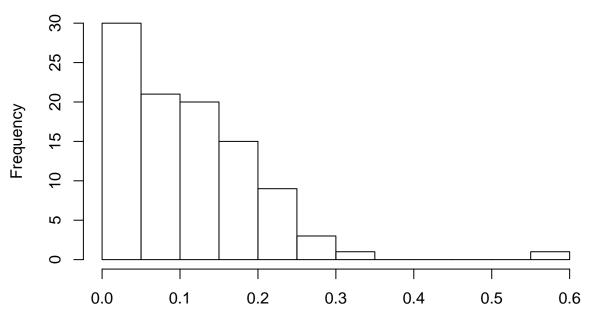


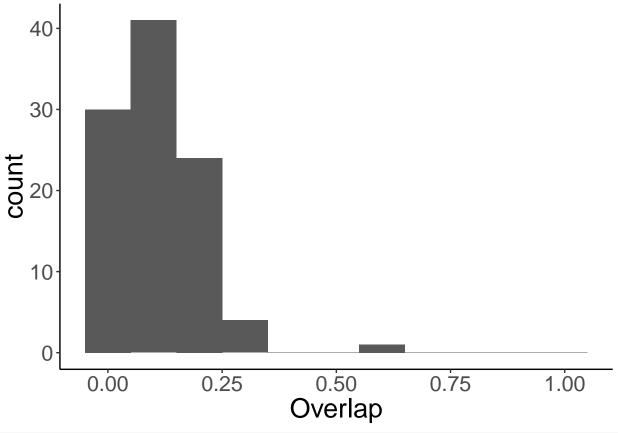


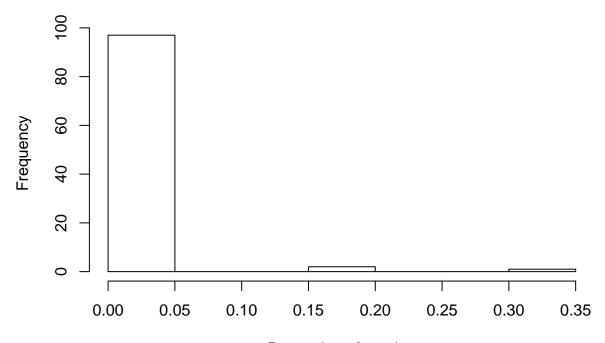


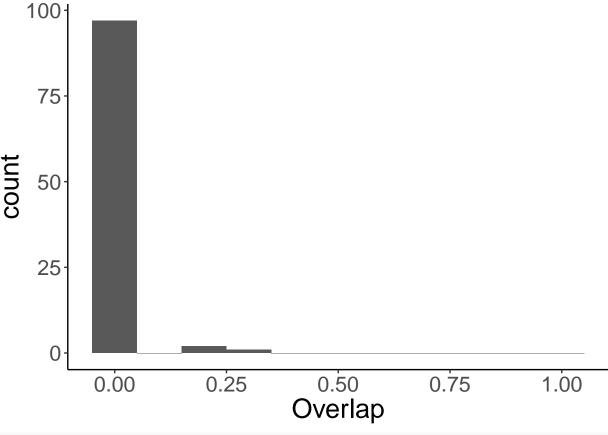


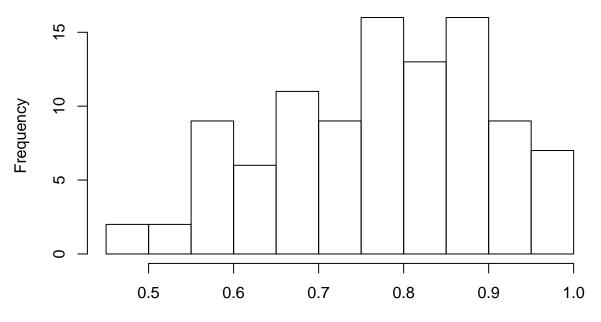


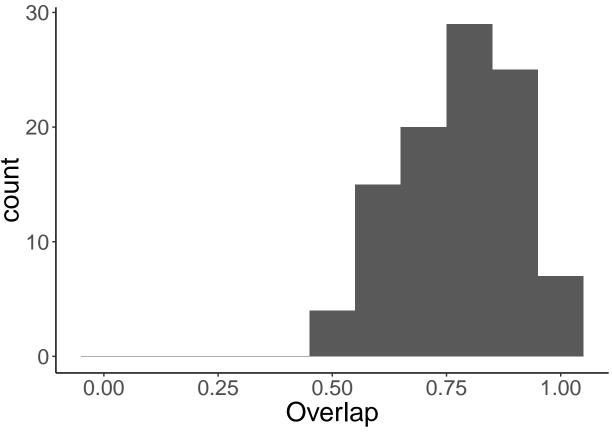


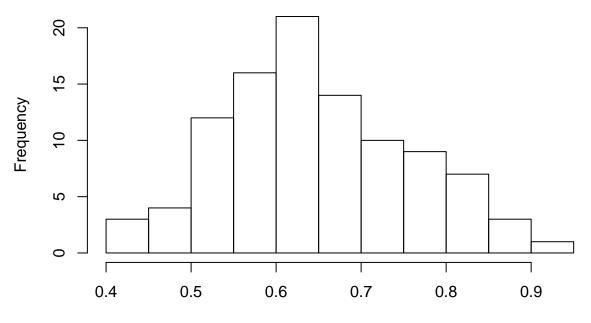


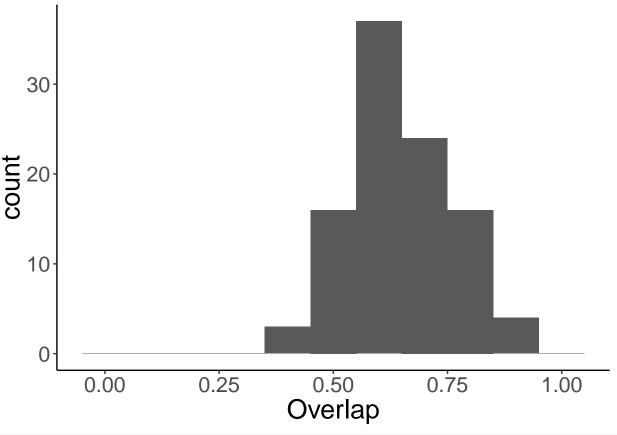


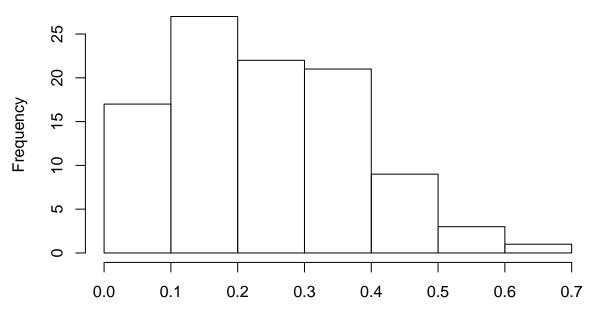


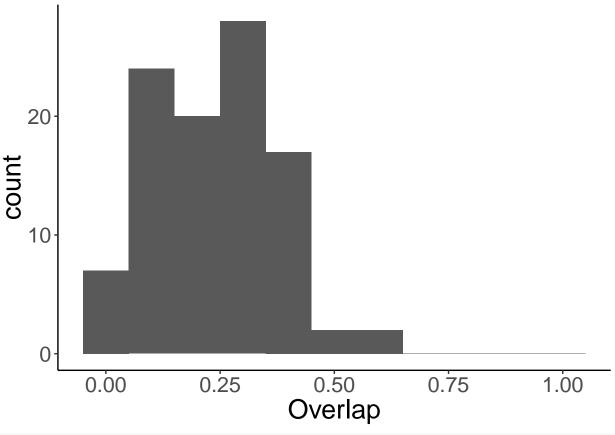


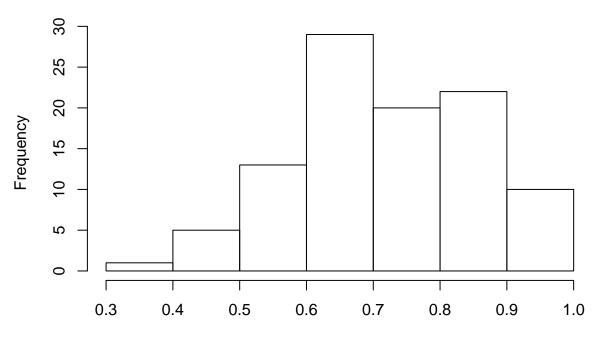


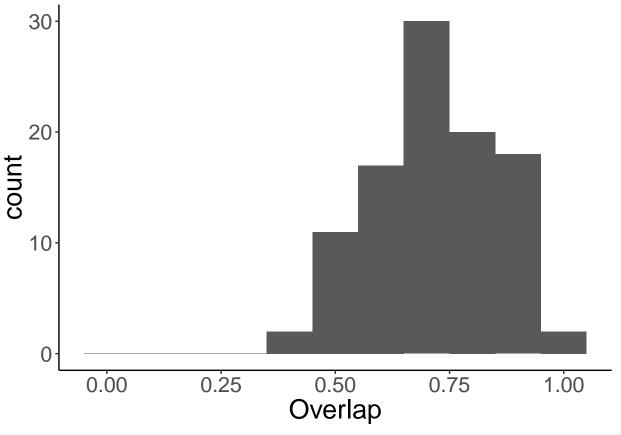


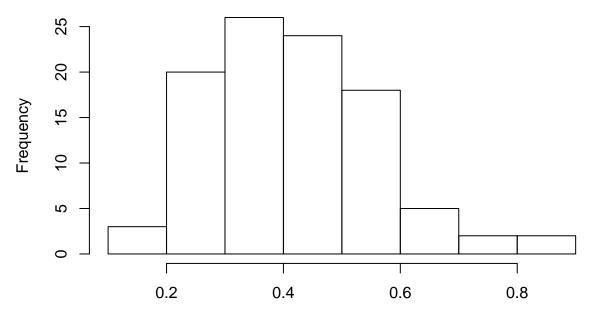


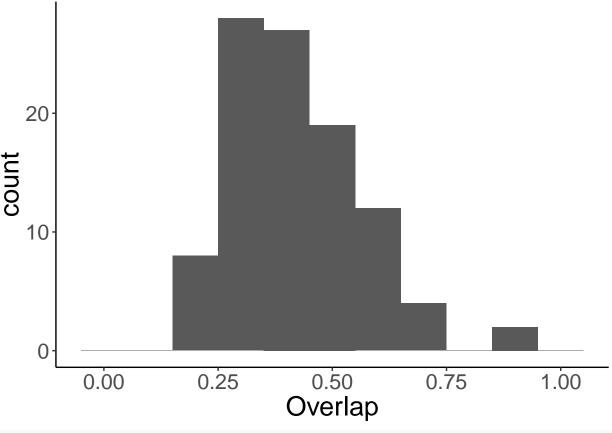


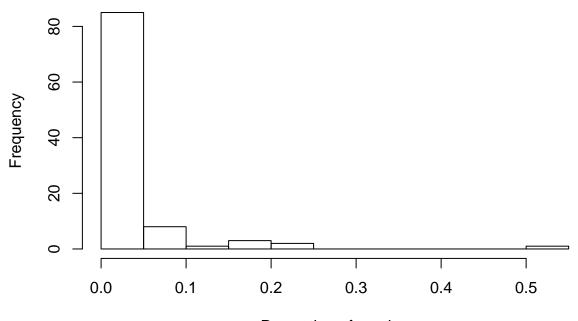


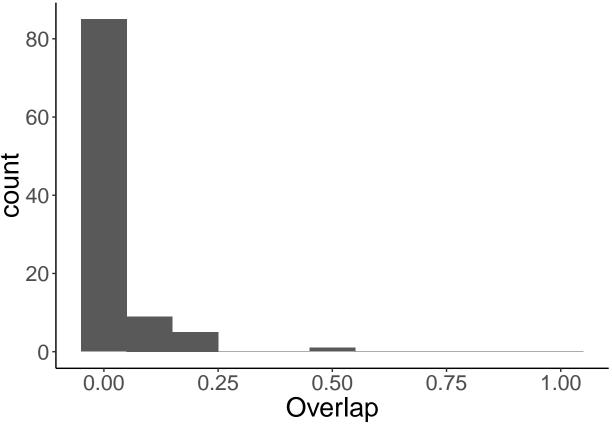


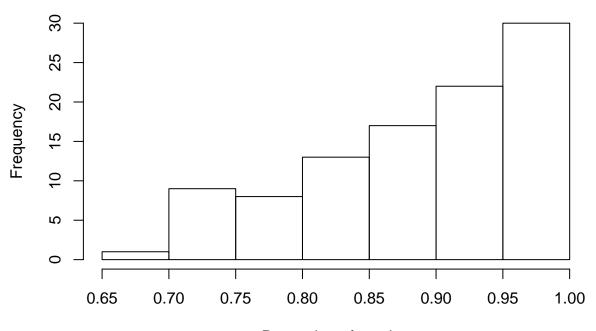


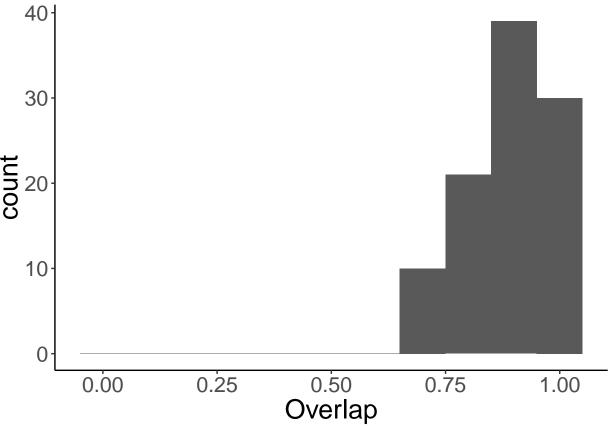


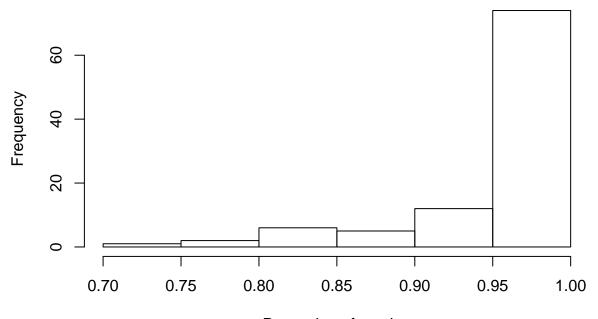


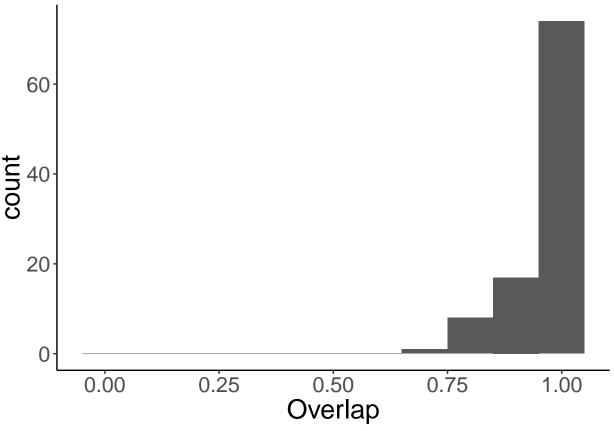


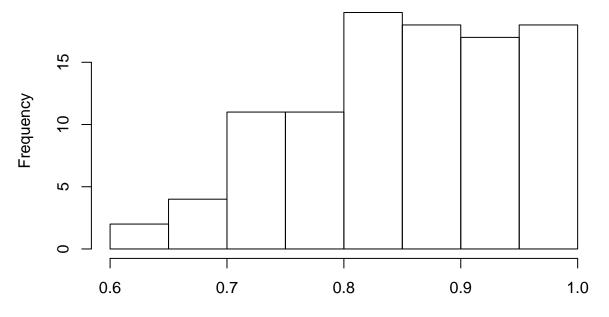


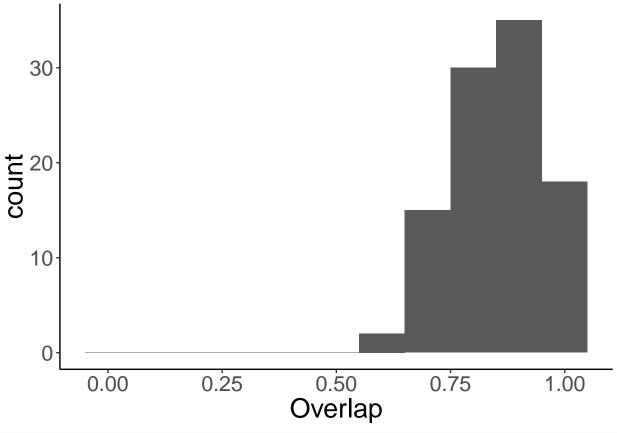


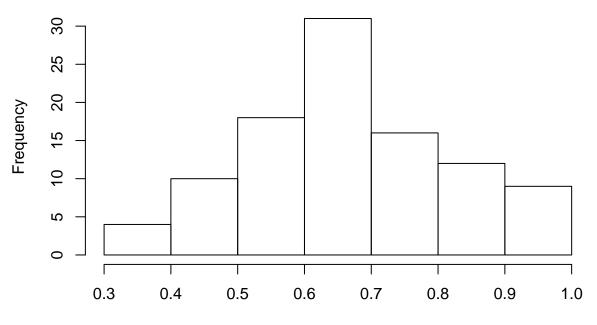


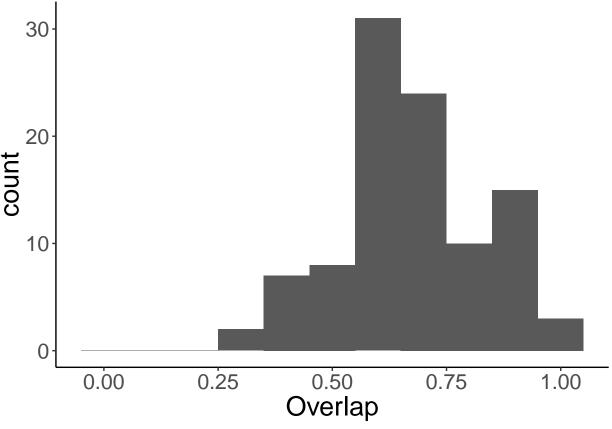


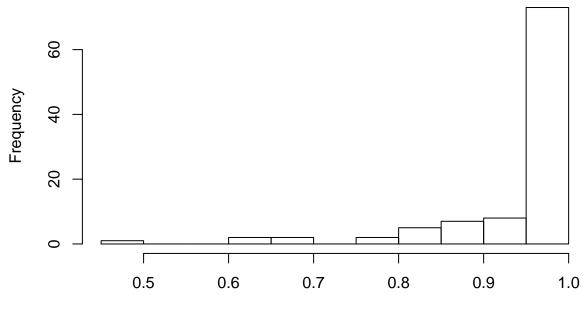


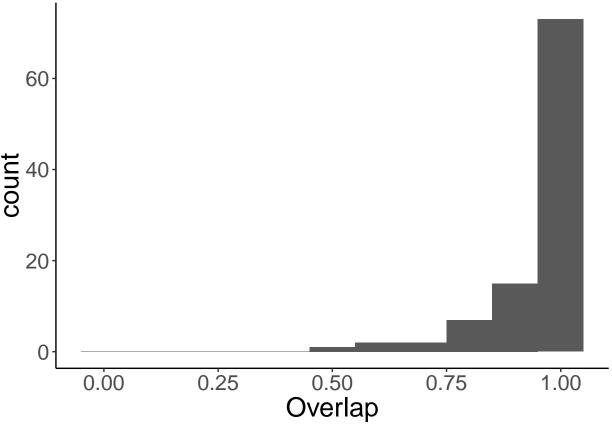


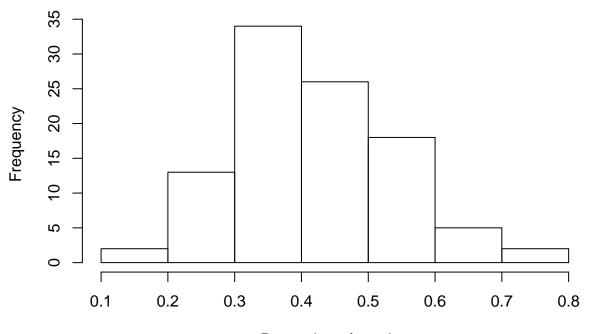


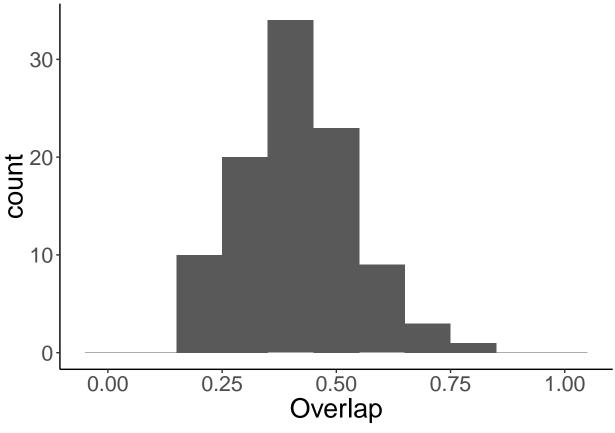


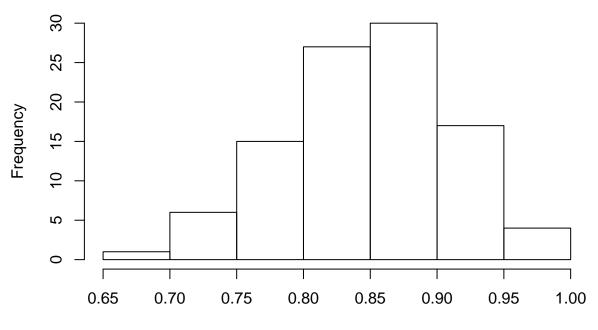


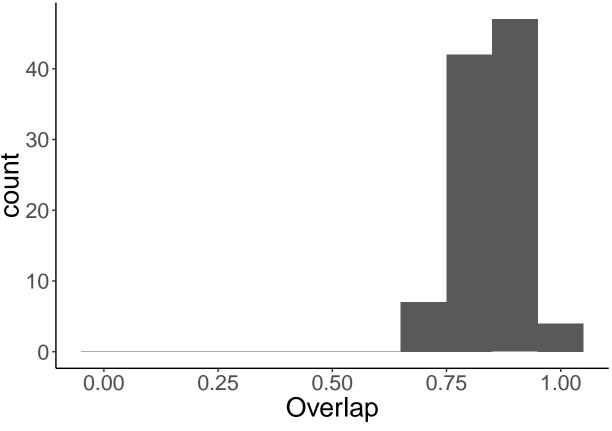


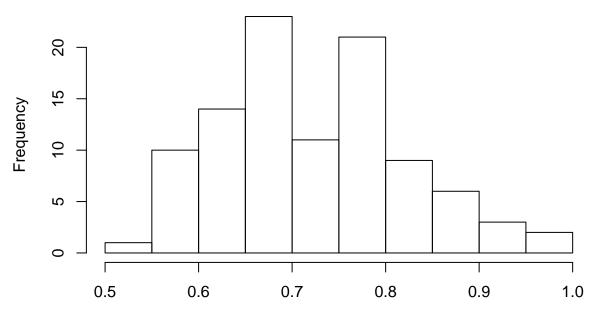


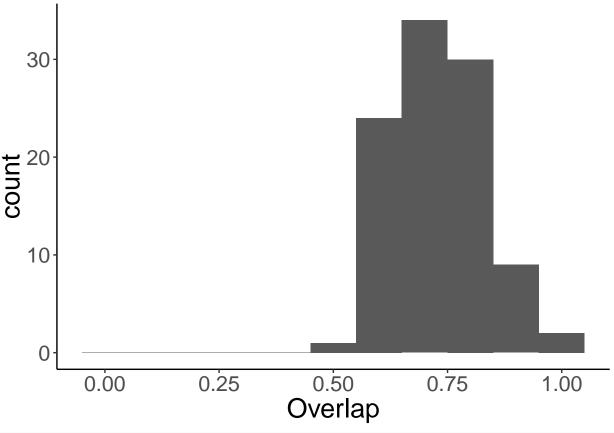


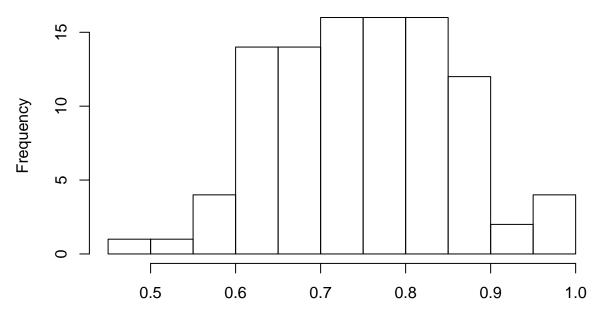


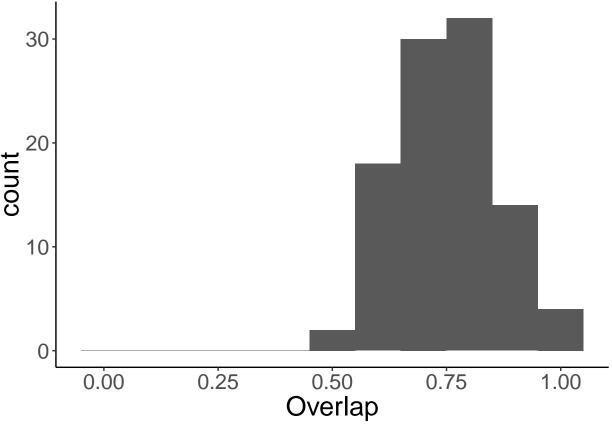


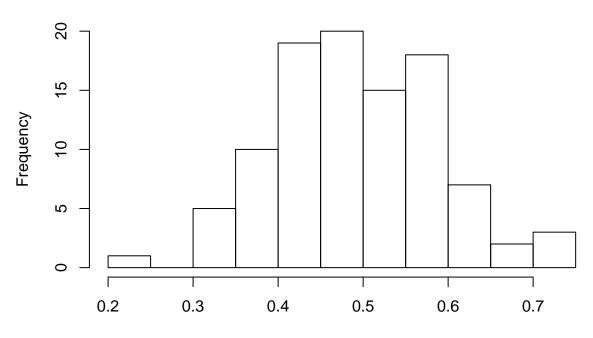


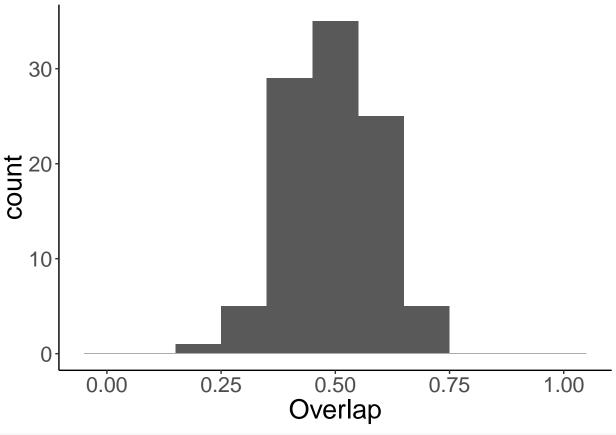


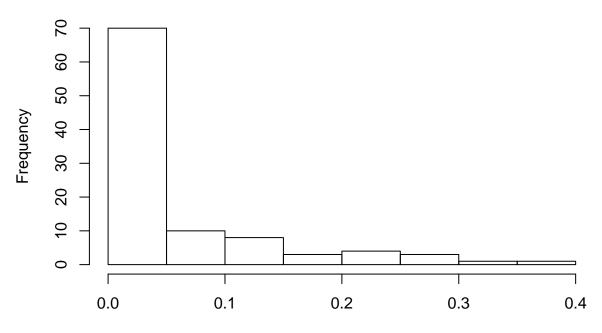


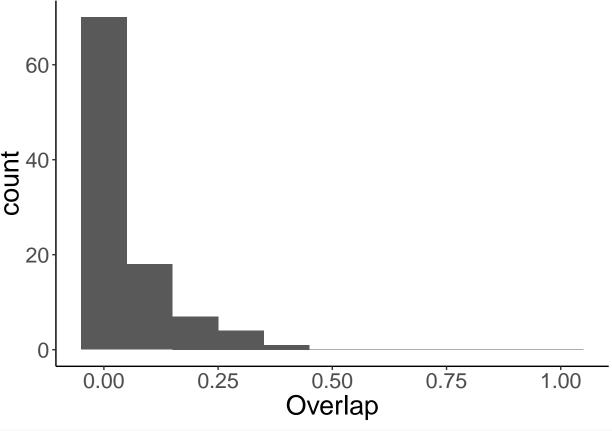


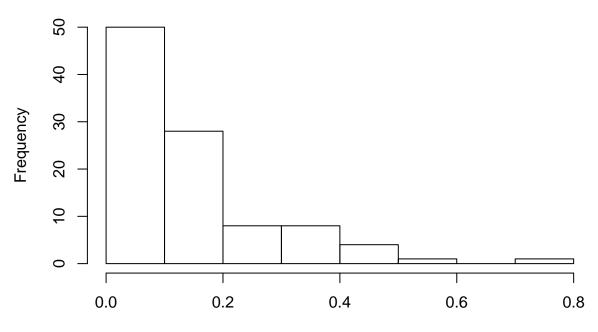


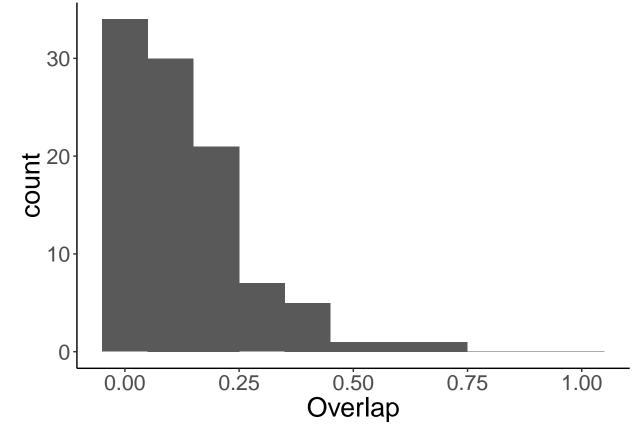


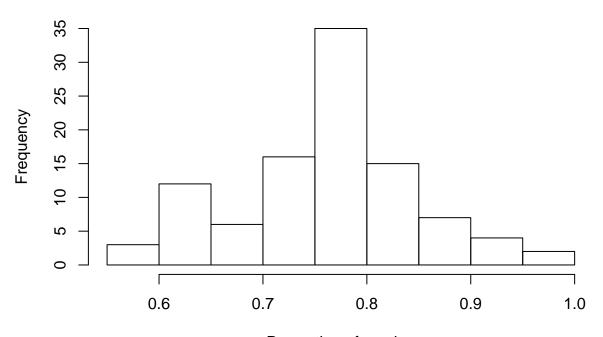


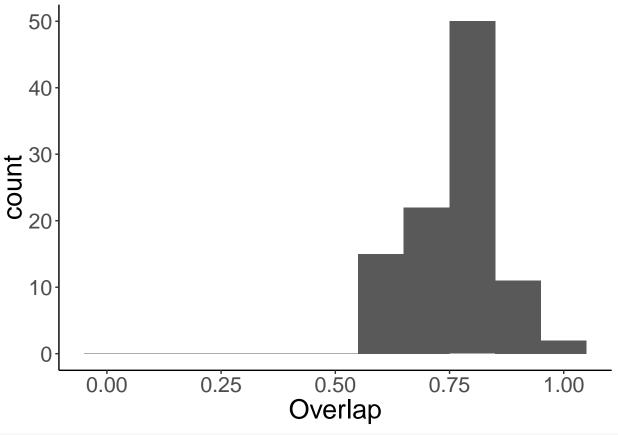


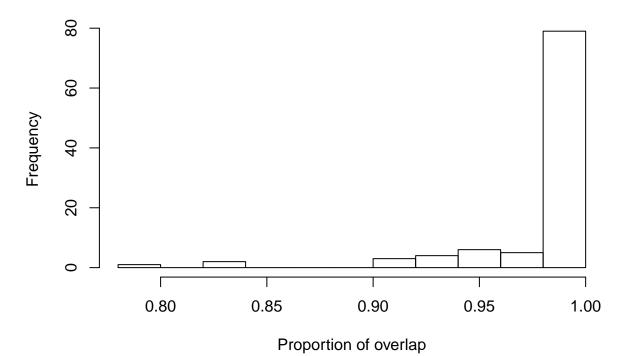


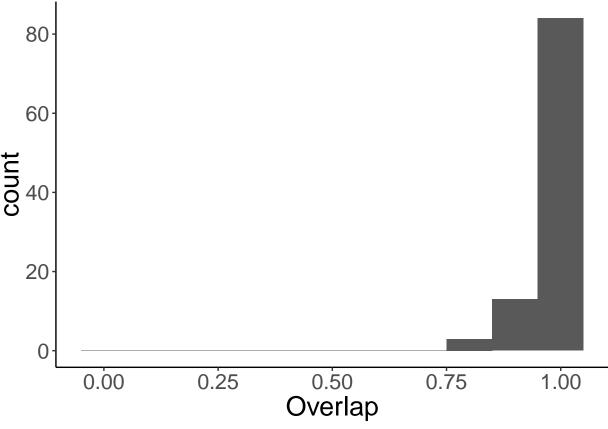


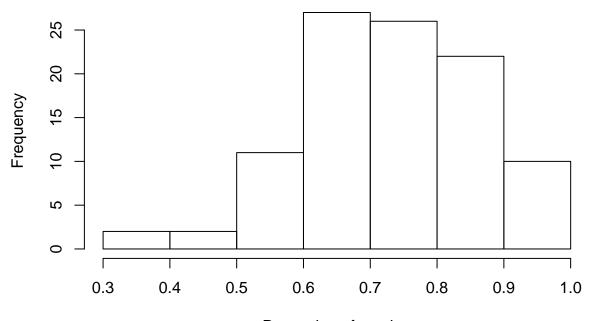


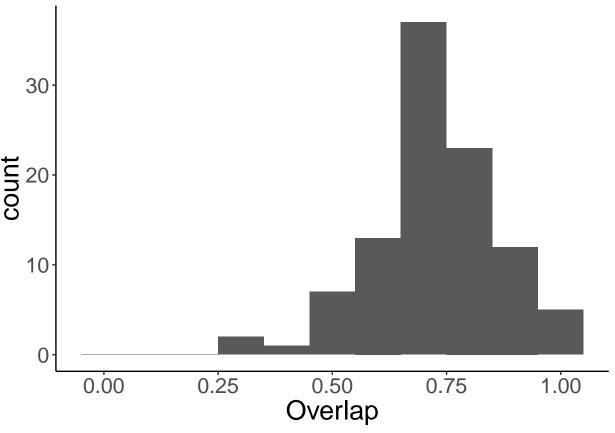












```
ggsave("pelegic_semifoss.png", dpi=300, width=4, height=3)
#hdr(Psfoss_95.overlap_prop, h = 10)
```

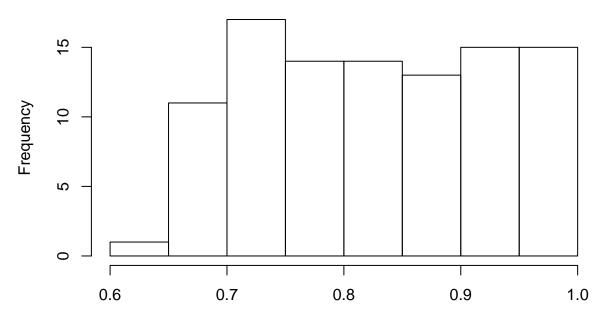
IUCN overlap calculations for mode of life

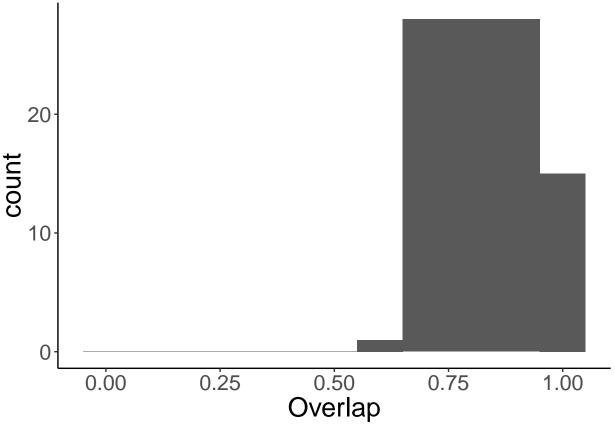
```
group.ML <- groupMetricsML(siber.plots)</pre>
group.ML_iucn <- groupMetricsML(siber.iucn)</pre>
# options for running jags
parms <- list()</pre>
parms$n.iter <- 2 * 10^4 # number of iterations to run the model for
parms$n.burnin <- 1 * 10^3 # discard the first set of values
parms$n.thin <- 10
                        # thin the posterior by this many
                              # run this many chains
parms$n.chains <- 2</pre>
# define the priors
priors <- list()</pre>
priors$R <- 1 * diag(2)</pre>
priors$k <- 2</pre>
priors$tau.mu <- 1.0E-3</pre>
ellipses.posterior_iucn <- siberMVN(siber.iucn, parms, priors)</pre>
```

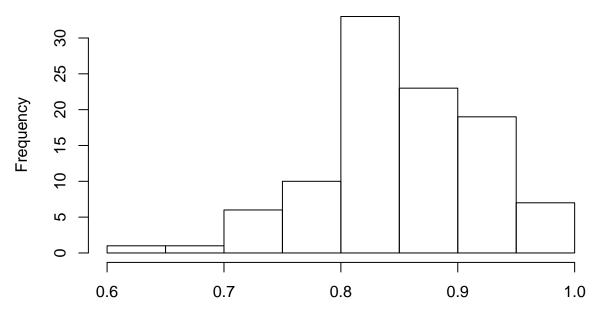
Compiling model graph

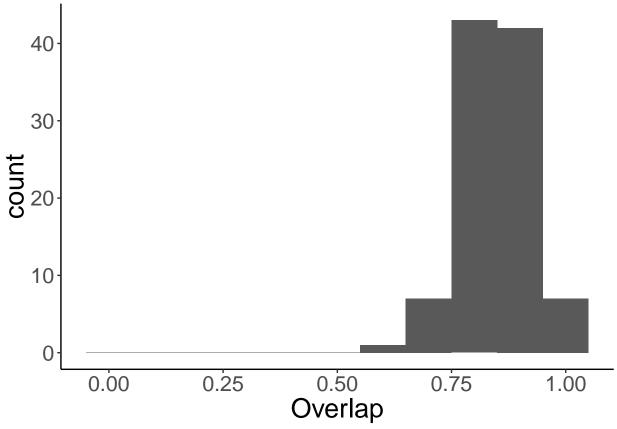
```
##
      Resolving undeclared variables
##
      Allocating nodes
##
  Graph information:
      Observed stochastic nodes: 191
##
##
      Unobserved stochastic nodes: 3
      Total graph size: 206
##
## Initializing model
##
##
   Compiling model graph
      Resolving undeclared variables
##
      Allocating nodes
##
  Graph information:
      Observed stochastic nodes: 10
##
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 25
##
## Initializing model
##
##
  Compiling model graph
##
      Resolving undeclared variables
##
      Allocating nodes
## Graph information:
##
      Observed stochastic nodes: 31
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 46
##
## Initializing model
##
  Compiling model graph
##
      Resolving undeclared variables
##
      Allocating nodes
##
   Graph information:
##
      Observed stochastic nodes: 21
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 36
##
## Initializing model
##
  Compiling model graph
##
      Resolving undeclared variables
##
      Allocating nodes
## Graph information:
      Observed stochastic nodes: 14
##
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 29
##
## Initializing model
##
##
  Compiling model graph
##
      Resolving undeclared variables
##
      Allocating nodes
## Graph information:
##
      Observed stochastic nodes: 16
```

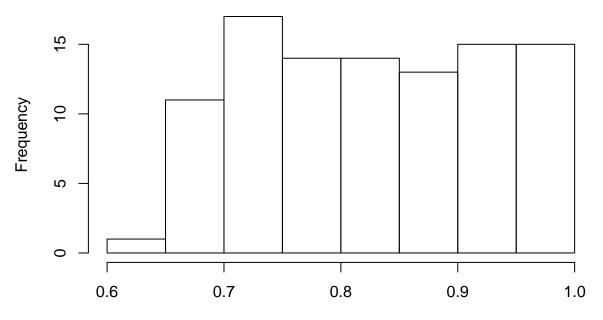
```
##
      Unobserved stochastic nodes: 3
##
      Total graph size: 31
##
## Initializing model
##
## Compiling model graph
      Resolving undeclared variables
      Allocating nodes
##
## Graph information:
##
      Observed stochastic nodes: 2
##
      Unobserved stochastic nodes: 3
      Total graph size: 17
##
##
## Initializing model
# The first ellipse is referenced using a character string representation where
# in "x.y", "x" is the community, and "y" is the group within that community.
# So in this example: community 1, group 1
#ellipse group numbers
ellipse_NA <- "1.1"
ellipse_CE <- "1.2"
ellipse_E <- "1.3"
ellipse_LC <- "1.4"
ellipse_LR <- "1.5"
ellipse NT <- "1.6"
ellipse_V <- "1.7"
#####LC - NT
LC_NT_95.overlap <- bayesianOverlap(ellipse_LC,</pre>
                                    ellipse_E,
                                    ellipses.posterior_iucn,
                                    draws = 100,
                                    p.interval = 0.95,
                                    n = 100)
LC_NT_95.overlap_prop <- vector()</pre>
for(i in 1:length(LC_NT_95.overlap$overlap)){
LC_NT_95.overlap_prop[i] <- LC_NT_95.overlap$overlap[i]/min(LC_NT_95.overlap[i,1:2])
}
hist(LC_NT_95.overlap_prop, xlab = "Proportion of overlap", main = "")
```

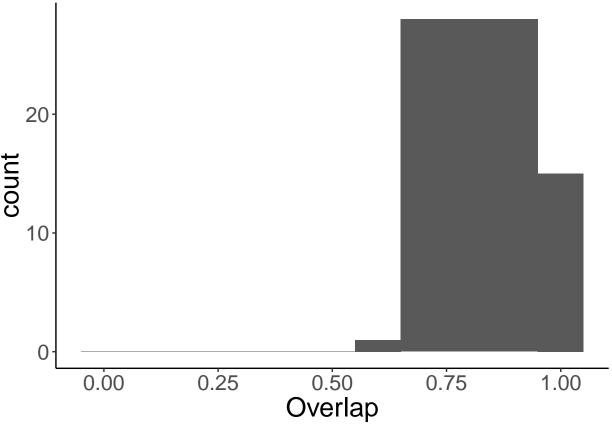


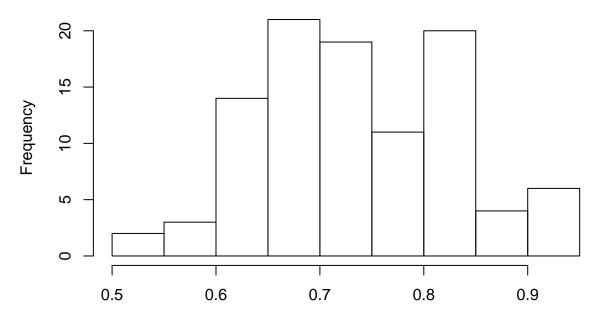


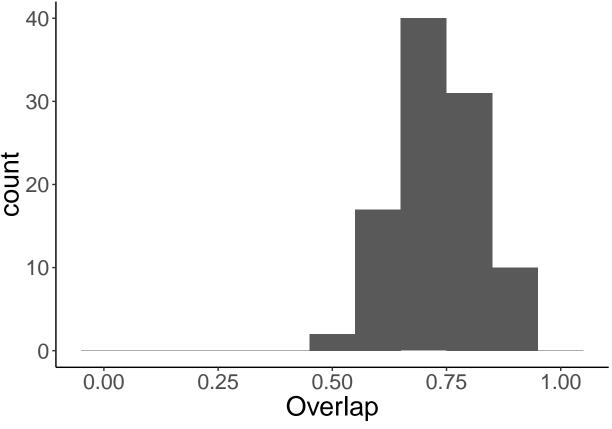


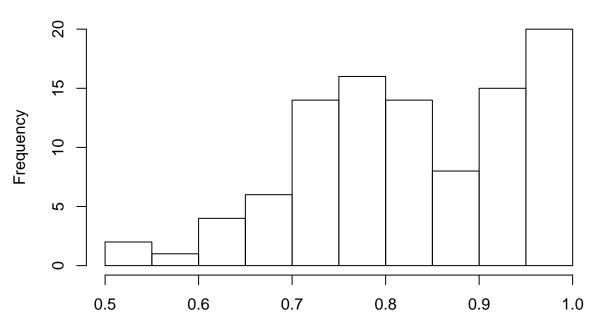


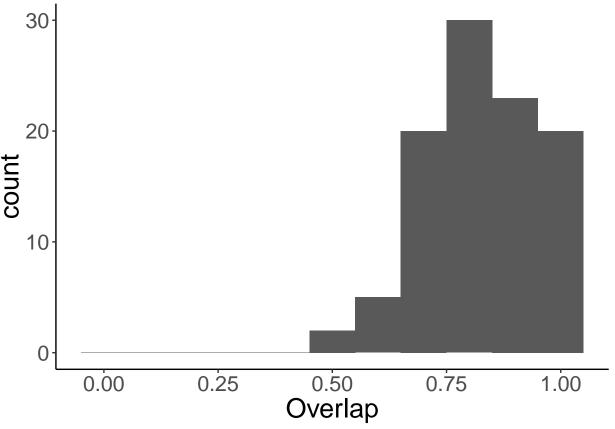


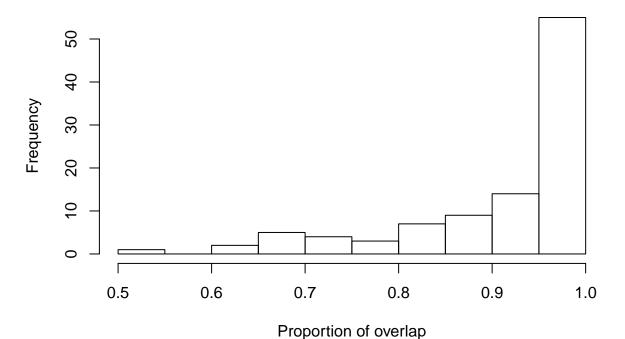




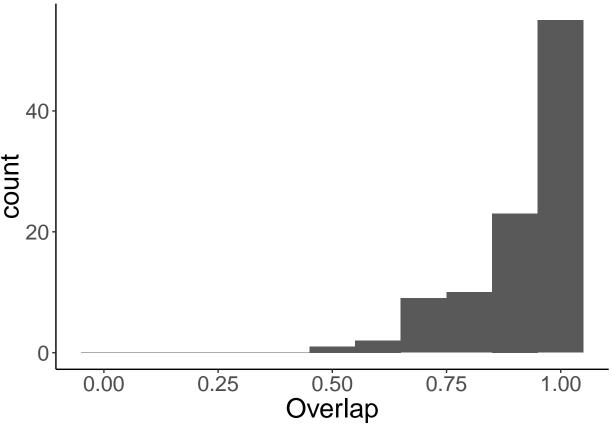


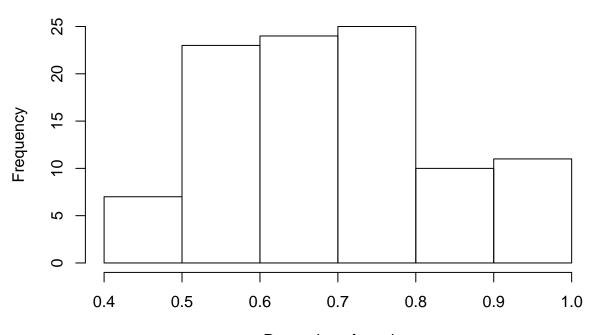


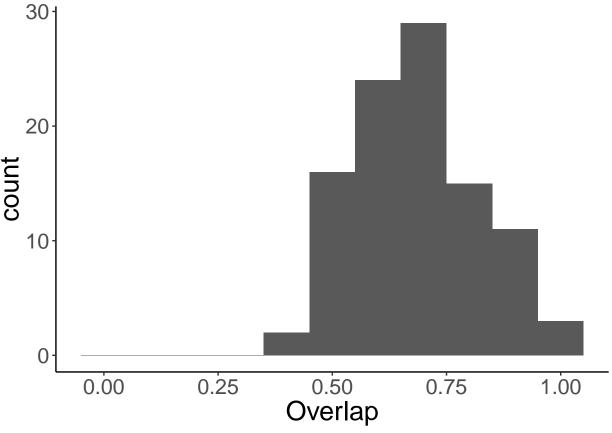


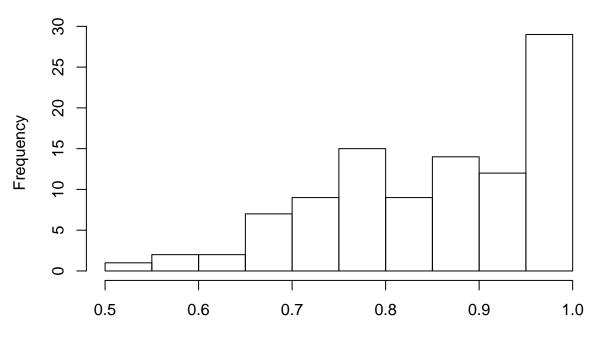


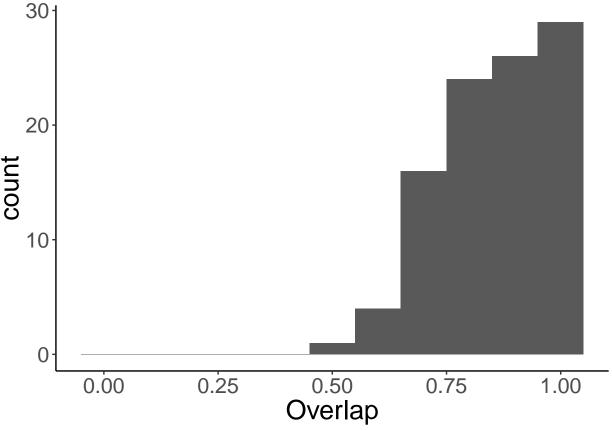
text = element_text(size=20))

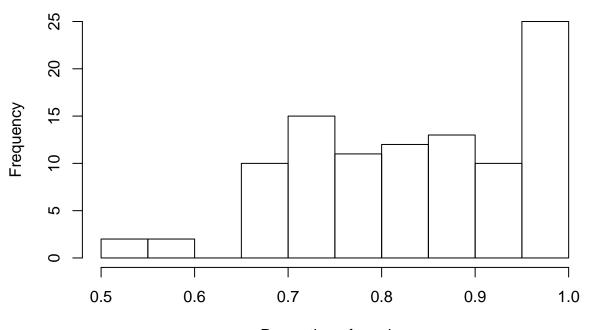


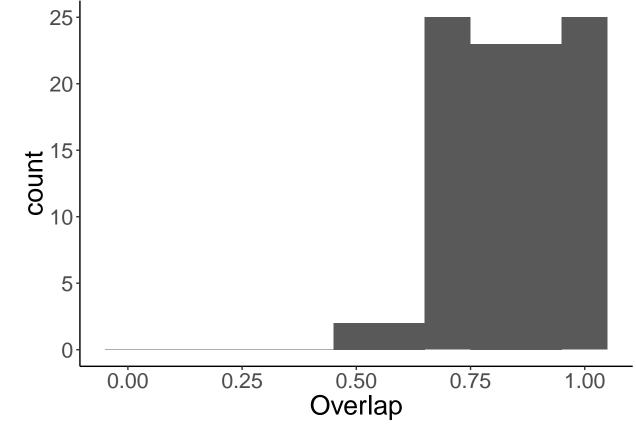


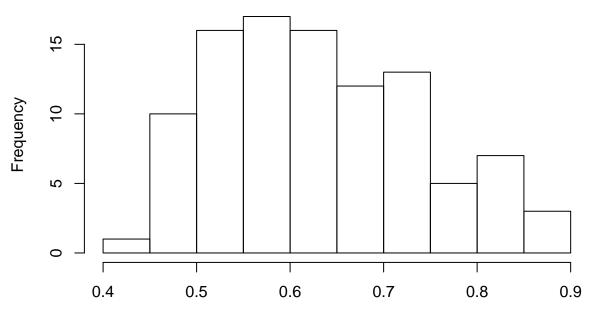


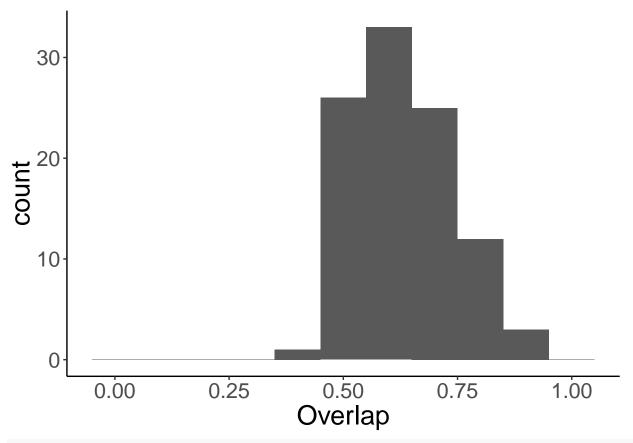












ggsave("CE_V.png", dpi=300, width=4, height=3)
#hdr(CE_V_95.overlap_prop)