

RCode - No evidence for a role of MHC class II genotype in the chemical encoding of heterozygosity and relatedness in Antarctic fur seals*

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Packages

```
if (!require("magrittr", quietly = TRUE)) {  
  install.packages("magrittr")  
  library(magrittr)  
} else {  
  library(magrittr) # pipe operators  
}  
  
if (!require("tidyverse", quietly = TRUE)) {  
  install.packages("tidyverse")  
  library(tidyverse)  
} else {  
  library(tidyverse) # package collection for easy and pretty data science with R  
}  
  
if (!require("phyloseq", quietly = TRUE)) {  
  if (!require("BiocManager", quietly = TRUE)) {  
    install.packages("BiocManager")  
  }  
  BiocManager::install(pkgs = "phyloseq")  
  library(phyloseq) # phyloseq objects  
} else {  
  library(phyloseq) # phyloseq objects  
}  
  
if (!require("GCalignR", quietly = TRUE)) {  
  install.packages("GCalignR")  
  library(GCalignR)  
} else {  
  library(GCalignR) # handling/aligning chromatograms  
}  
  
if (!require("inbreedR", quietly = TRUE)) {
```

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```

install.packages("inbreedR")
library(inbreedR)
} else {
  library(inbreedR) # population genetic analyses
}

if (!require("vegan", quietly = TRUE)) {
  install.packages("vegan")
  library(vegan)
} else {
  library(vegan) # statistical tools
}

if (!require("ggpubr", quietly = TRUE)) {
  install.packages("ggpubr")
  library(ggpubr)
} else {
  library(ggpubr) # ggplot grid and plot alignment functions
}

if (!require("ape", quietly = TRUE)) {
  install.packages("ape")
  library(ape)
} else {
  library(ape) # handling phylogenetic tree data
}

if (!require("performance", quietly = TRUE)) {
  install.packages("performance")
  library(performance)
} else {
  library(performance) # tools for models
}

if (!require("MuMIn", quietly = TRUE)) {
  install.packages("MuMIn")
  library(MuMIn)
} else {
  library(MuMIn) # tools for models
}

if (!require("partR2", quietly = TRUE)) {
  install.packages("partR2")
  library(partR2)
} else {
  library(partR2) # tools for models
}

if (!require("ggbeeswarm", quietly = TRUE)) {
  install.packages("ggbeeswarm")
  library(ggbeeswarm)
} else {
  library(ggbeeswarm)
}

```

```

}

# archived package as is dependent on `fts` package
# for execution of the code, users need to manually install Rtools to be able
# to install packages `Demerelate` and `fts`

library(fts)

library(Demerelate)

```

Packages for relatedness calculations

Not supported on newer versions of R, to execute code you must have Rtools installed on your machine in order to load older version of the Demerelate and fts package.

```

if (!require("remotes", quietly = TRUE)) {
  install.packages("remotes")
  library(remotes)
} else {
  library(remotes)
}

if (!require("fts", quietly = TRUE)) {
  install_version("fts", "0.9.9.2")
  library(fts)
} else {
  library(fts)
}

if (!require("Demerelate", quietly = TRUE)) {
  install_version("Demerelate", "0.9.9.2")
  library(Demerelate)
} else {
  library(Demerelate)
}

options(digits = 12)

```

Subset scent data to correlate same individuals

```

## read in meta data
meta <- read.table(file = "data/arga_metadata.txt", sep = "\t") %>%
  `colnames<-`(unlist(.[,1])) %>%
  .[-1,]

## normalise area and return a data frame
scent <- norm_peaks(aligned_peak_data,
  conc_col_name = "area",
  rt_col_name = "time",
  out = "data.frame")

## common transformation for abundance data to reduce the extent of mean-variance trends
scent <- log(scent + 1)

```

```

n_scnt <- rownames(scent)

keep_i <- match(meta$id, n_scnt)

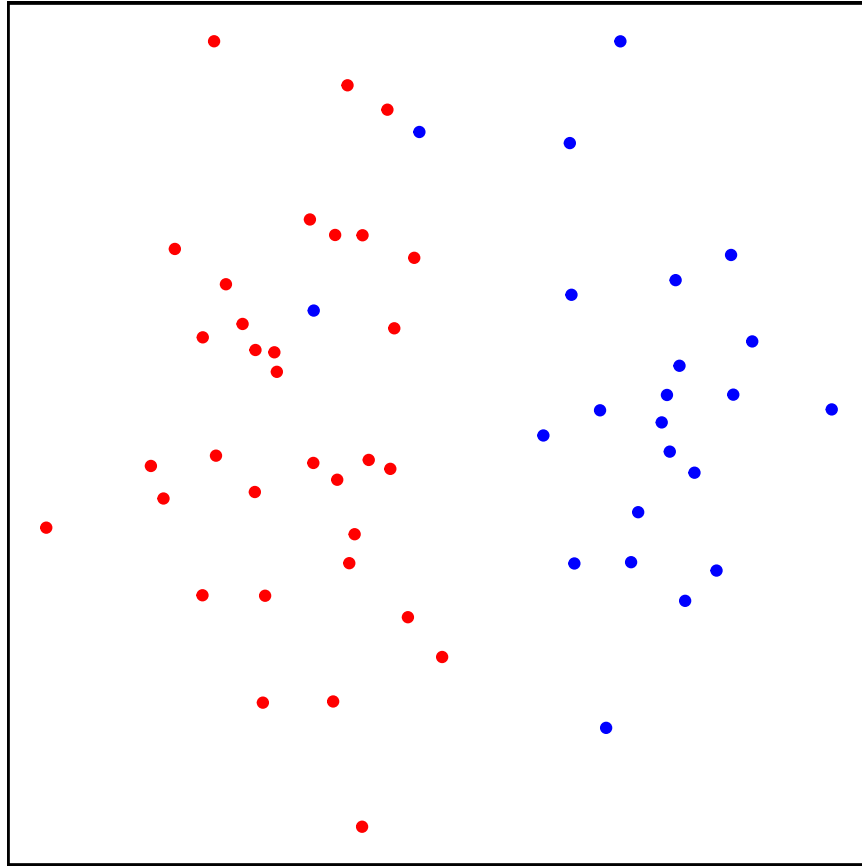
scent %<>%
  .[keep_i, ] %>%
  `rownames<-`(meta$real_id)

## NMDS with reduced data
## GCalignR contains factors for the chemical dataset
data("peak_factors")
peak_factors <- peak_factors[match(meta$id, rownames(peak_factors)),] %>%
  `rownames<-`(meta$real_id)

## keep order of rows consistent
scent <- scent[match(rownames(peak_factors), rownames(scent)),]
## NMDS using Bray-Curtis dissimilarities
scent_nmds.obj <- vegan::metaMDS(comm = scent, distance = "bray")
## get x and y coordinates
scent_nmds <- as.data.frame(scent_nmds.obj[["points"]])
## add the colony as a factor to each sample
scent_nmds <- cbind(scent_nmds, colony = peak_factors[["colony"]])

## quick plotting
scent_plot <- ggplot(data = scent_nmds, aes(MDS1, MDS2, color = colony)) +
  geom_point() +
  theme_void() +
  scale_color_manual(values = c("blue", "red")) +
  theme(panel.background = element_rect(colour = "black",
                                         linewidth = 1,
                                         fill = NA),
        aspect.ratio = 1,
        legend.position = "none")
scent_plot

```



Calculate MHC heterozygosity relatedness between individuals

```
## read in mhc genotype data
mhc_het_dat <- read.table("data/clone_mhc_het.txt")
## restructure `mhc_het_dat` to fit `Demerelate()::inputdata`
## id and colony as factors; alleles as integers or numeric
## otherwise `rxy` cannot handle computations
mhc_het_dat %<>%
  rownames_to_column(., var = "id") %>%
  # mutate(., a1 = str_pad(a1, 2, pad = "0")) %>%
  # mutate(., a2 = str_pad(a2, 2, pad = "0")) %>%
  mutate(., colony = as.factor(rep("col", 56))) %>%
  mutate(., id = as.factor(id)) %>%
  .[, -4] %>%
  relocate(., colony, .before = a1)
## order mhc_het_dat$id after meta$real_id
## so data is consistently ordered same in all data.frames

## get matching indeces
id_index <- match(meta$real_id, mhc_het_dat$id)
## sort correspondingly
mhc_het_dat %<>% .[id_index,]

## calculate relatedness after Queller & Goodnight
mhc_relatedness_res <- Demerelate(inputdata = mhc_het_dat,
```

```

value = "rxy",
object = T,
NA.rm = F,
Fis = F)

```

```

## Warning in Demerelate(inputdata = mhc_het_dat, value = "rxy", object = T, : Careful, bi-allelic markers
##   Especially, rxy and ritland estimator are not defined when bi-allelic estimates are used with alle
##   You should consider removing bi-allelics which tend to have very evenly distributed alleles or swi
##   Be careful even if allele frequencies are not perfectly 0.5, during randomizations problems may oc

```

```

mhc_relatedness <- unlist(mhc_relatedness_res$Empirical_Relatedness)

```

```

## fill distant matrix / make sure that it follows same systematics as previous distance matrices
## create empty matrix with equal rows and cols similar to sample size of individuals
relate_mat_mhc <- matrix(nrow = 56, ncol = 56)
## fill distance matrix row wise, thus fill upper.tri
relate_mat_mhc[upper.tri(relate_mat_mhc)] <- mhc_relatedness
## transpose to keep consistency with other distance matrices
relate_mat_mhc <- t(relate_mat_mhc)
relate_mat_mhc %<>% `colnames<-`(meta$real_id) %>% `rownames<-`(meta$real_id)

## vectorize again to identify whether relatedness pairs were consistent in the first place
a <- relate_mat_mhc %>% as.vector() %>% na.omit()

```

Create vectorized distance measurements for scent data

```

# bray-curtis distance measurement on scent profiles
scent_dist <- vegdist(scent) %>% as.matrix()
scent_dist[upper.tri(scent_dist, diag = T)] <- NA
b <- scent_dist %>% as.vector() %>% na.omit()

```

Generate UniFrac distances from MHC DQB II individual genotypes

```

# handle genotypes as otu table
phylo_mat <- read.table("data/phyloseq-mat.txt") %>%
  as.matrix()

# make sample names consistent
n <- match(meta$real_id, colnames(phylo_mat))

phylo_mat %<>% .[, n] %>%
  otu_table(., taxa_are_rows = T)

# create phylogenetic tree from file
phylo_tree <- ape::read.tree("data/unifrac_tree_p.nwk")

# merge into Formal class phyloseq
arga_phyloseq <- merge_phyloseq(phylo_mat, phylo_tree)

# create UniFrac as genetic diversity measurement for single locus data
mhc_dqb2_ufrac <- UniFrac(arga_phyloseq, weighted = F) %>%
  # distances to distance matrix
  as.matrix()

```

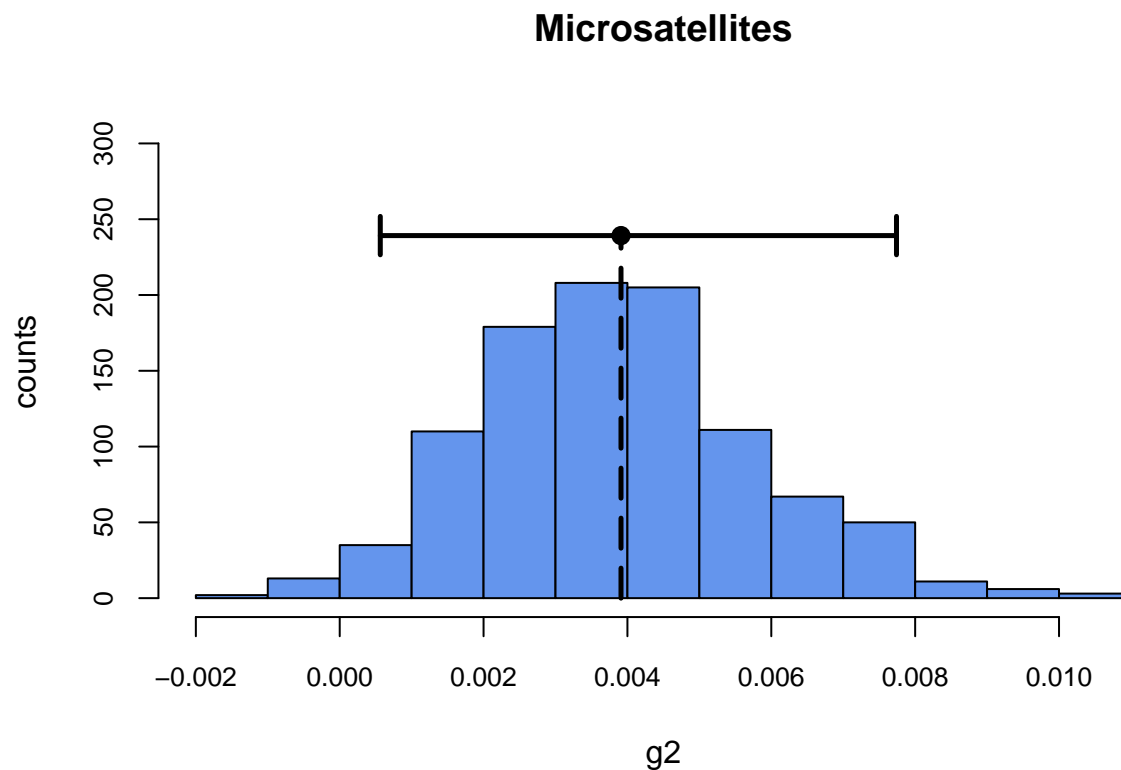
```
# vectorize distances matrices
mhc_dqb2_ufrac[upper.tri(mhc_dqb2_ufrac, diag = T)] <- NA
c <- mhc_dqb2_ufrac %>% as.vector() %>% na.omit()
```

Calculate identity disequilibrium g2

```
msats_g2 <- read.table("data/msats_genotypes_inbreedR.txt", sep = "\t") %>%
  convert_raw()

g2 <- g2_microsats(msats_g2, nperm = 1000, nboot = 1000, CI = 0.95)

plot(g2, main = "Microsatellites",
     col = "cornflowerblue", cex.axis=0.85)
```



Calculate microsatellite relatedness values

create data.frame in correspondence to Demerelate input format

```
# read in genotype data table
msats_df <- read.table("data/msats_genotypes_inbreedR.txt", sep = "\t")

# update data.frame with additional info
# "delete" colony info, otherwise relatedness is only calculated for individuals
# within their own colonies -> no complete pairwise comparison
msats_df <- cbind(id = as.factor(rownames(msats_df)),
```

```

        # colony = meta$colony,
        colony = rep("col", 56),
        msats_df[1:56,]) %>%
# clear df from rownames/ only keep colnames/ variable names
`rownames<-`(NULL)

msats_df[is.na(msats_df)] = 0

str(msats_df)

write.table(msats_df, file = "data/msats_genotypes_demerelate.txt",
            sep = "\t",
            row.names = F)

```

Calculate relatedness of individuals based on Queller & Goodnight

```

relatedness_results <- Demerelate(inputdata = msats_df,
                                value = "rxy",
                                object = T,
                                NA.rm = F,
                                Fis = F)

```

Coerce output to a vector

```

relatedness <- unlist(relatedness_results$Empirical_Relatedness)

## fill distant matrix / make sure that it follows same systematics as previous distance matrices
## create empty matrix with equal rows and cols similar to sample size of individuals
relate_mat <- matrix(nrow = 56, ncol = 56)
## fill distance matrix row wise, thus fill upper.tri
relate_mat[upper.tri(relate_mat)] <- relatedness
## transpose to keep consistency with other distance matrices
relate_mat <- t(relate_mat)
relate_mat %<>% `colnames<-`(meta$real_id) %>% `rownames<-`(meta$real_id)

## vectorize again to identify whether relatedness pairs were consistent in the first place
d <- relate_mat %>% as.vector() %>% na.omit()

```

Analyse Odour and genetic association by MHC DQB II and neutral genomic background

Create data.frame to plot in ggplot2

```

## substitute once tested correctly
## scent_mds shall contain similarity values but `b` contains
## dissimilarity values based on Bray-Curtis -> subtracting
## dissimilarities from 1 returns similarities

model_rel.df <- cbind(mhc_rel = a, scent_mds = 1-b, ufrac = c, rel = d) %>%
  as.data.frame()

```


Custom theme to make plot aesthetics consistent

```
# custom theme to ease figure creation
custom_theme <- ggplot2::theme_classic(base_size = 20,
                                       base_line_size = 1,
                                       base_rect_size = 1) +

ggplot2::theme(
  #c(top, right, bottom, left)
  plot.margin = margin(5.5, 6.5, 8, 5.5, "pt"),
  panel.grid = element_blank(),
  axis.text = element_text(color = "black"),
  axis.title.x = element_text(vjust = -.75),
  axis.title.y = element_text(vjust = +2),
  axis.ticks = element_line(color = "black"),
  aspect.ratio = 1,
  legend.position = "none"
)
```

Plot odour by mhc similarity

```
# odour by mhc sim
panel1.a <- ggplot(data = model_rel.df,
  aes(x = ufrac, y = scent_mds)) +
  geom_point(size = 3.5,
    alpha = 0.25) +
  # geom_smooth(method = "lm",
  #             color = "orange") +
  scale_x_continuous(name = "MHC Unifrac distance") +
  scale_y_continuous(name = "Chemical similarity") +
  # labs(tag = "A") +
  custom_theme
```

Plot odour by relatedness

```
# odour by relatedness
panel1.b <- ggplot(data = model_rel.df,
  aes(x = rel, y = scent_mds)) +
  geom_point(size = 3.5,
    alpha = 0.25) +
  # geom_smooth(method = "lm",
  #             color = "orange") +
  scale_x_continuous(name = "Relatedness") +
  scale_y_continuous(name = "Chemical similarity") +
  custom_theme
```

Model odour relationship on MHC and neutral genetic background

Pool underlying data dependencies

Create a function that generates pairwise variables in a systematic matter for pairwise comparisons

```
create_pair_vars <- function(row_cross, col_cross, split_vars = F){
  require(stringr)
```

```

rc <- row_cross
cc <- col_cross

# create empty matrix
# keep row and col names from existing distance matrices

empty_mat <- matrix(nrow = length(rc),
                    ncol = length(cc)) %>%
  `colnames<-`(cc) %>%
  `rownames<-`(rc)

# fill each matrix i,j-th cell with the crossing from their corresponding
# i-th rowname and j-th colname
for (i in 1:dim(empty_mat)[1]) {
  for (j in 1:dim(empty_mat)[2]) {

    empty_mat[i,j] <- paste0(rc[i], "/", cc[j])

  } # end j
} # end i

# delete `upper.tri()` of `empty_mat` to resemble structure of the other
# distance matrices in use

empty_mat[upper.tri(empty_mat, diag = T)] <- NA
pair_vars <- empty_mat %>% as.vector() %>% na.omit()

# split `pair_vars` if needed
if (split_vars == T) {

  pair_vars1 <- sapply(pair_vars,
                      function(x){
                        str_split(x, pattern = "/")[[1]][1]
                      })

  pair_vars2 <- sapply(pair_vars,
                      function(x){
                        str_split(x, pattern = "/")[[1]][2]
                      })

  pair_vars_split <- list(pair_variable1 = pair_vars1,
                        pair_variable2 = pair_vars2)

  return(pair_vars_split)

} else {
  return(pair_vars)
}

} #end create_pair_vars

```

Helper function to combine double entries

```
## for x, overwrite specified replacer with specified value
f <- function(x, replacer, overwrite){
  if (x == replacer) {
    x <- overwrite
  } else {
    x <- x
  }
}
```

Transform model variables

```
agePaired <- create_pair_vars(row_cross = meta$maturity,
                             col_cross = meta$maturity) %>%
  sapply(., f, "P/M", "M/P")

colonyPaired <- create_pair_vars(row_cross = meta$colony,
                                col_cross = meta$colony) %>%
  sapply(., f, "FWB/SSB", "SSB/FWB")

colonyID1 <- create_pair_vars(row_cross = meta$colony,
                              col_cross = meta$colony,
                              split_vars = T)[1] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

colonyID2 <- create_pair_vars(row_cross = meta$colony,
                              col_cross = meta$colony,
                              split_vars = T)[2] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

colonyBool <- ifelse(colonyID1 == colonyID2, 1, 0)

familyPaired <- create_pair_vars(row_cross = meta$family,
                                 col_cross = meta$family)

familyID1 <- create_pair_vars(row_cross = meta$family,
                              col_cross = meta$family,
                              split_vars = T)[1] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

familyID2 <- create_pair_vars(row_cross = meta$family,
                              col_cross = meta$family,
                              split_vars = T)[2] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

pairID1 <- create_pair_vars(row_cross = meta$real_id,
                           col_cross = meta$real_id,
```

```

                                split_vars = T)[1] %>%
  unlist() %>%
  as.vector()

pairID2 <- create_pair_vars(row_cross = meta$real_id,
                           col_cross = meta$real_id,
                           split_vars = T)[2] %>%
  unlist() %>%
  as.vector()

familyBool <- ifelse(familyID1 == familyID2, 1, 0)

```

Update data.frame with model variables

```

model_rel.df <- data.frame(model_rel.df,
  agePaired = as.factor(agePaired),
  colonyPaired = as.factor(colonyPaired),
  colonyBool = as.factor(colonyBool),
  familyPaired = as.factor(familyPaired),
  familyID1 = as.factor(familyID1),
  familyID2 = as.factor(familyID2),
  familyBool = as.factor(familyBool),
  pairID1 = as.factor(pairID1),
  pairID2 = as.factor(pairID2))

```

Color Chemical similarity by same or different beach

‘colonyBool’ encodes whether individual from same colonies (SSB vs SSB and FWB vs FWB) are compared or from different colonies

Chemical similarity models

```

# mhc
a1 <- lmerTest::lmer(scent_mds ~ ufrac + colonyBool + agePaired + (1|familyBool) +
  (1|pairID1) + (1|pairID2),
  data = model_rel.df)

# relatedness
a2 <- lmerTest::lmer(scent_mds ~ rel + colonyBool + agePaired + (1|familyBool) + (1|pairID1) +
  (1|pairID2),
  data = model_rel.df)

# mhc & relatedness
a3 <- lmerTest::lmer(scent_mds ~ rel + ufrac + colonyBool + agePaired + (1|familyBool) +
  (1|pairID1) + (1|pairID2),
  data = model_rel.df)

# no genetic effect
a4 <- lmerTest::lmer(scent_mds ~ colonyBool + agePaired + (1|familyBool) + (1|pairID1) +
  (1|pairID2),
  data = model_rel.df)

# compare model performance scores
compare_performance(a1, a2, a3, a4, rank = T) %>%
  arrange(Name)

```

```
## # Comparison of Model Performance Indices
##
## Name | Model | R2 (cond.) | R2 (marg.) | ICC | RMSE | Sigma | AIC weights | AICc weights
## -----
## a1 | lmerModLmerTest | 0.696 | 0.140 | 0.646 | 0.060 | 0.062 | 0.198 | 0.19
## a2 | lmerModLmerTest | 0.690 | 0.143 | 0.638 | 0.060 | 0.062 | 0.212 | 0.21
## a3 | lmerModLmerTest | 0.689 | 0.144 | 0.636 | 0.060 | 0.062 | 0.082 | 0.08
## a4 | lmerModLmerTest | 0.698 | 0.139 | 0.649 | 0.060 | 0.062 | 0.508 | 0.51
```

```
summary(a2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: scent_mds ~ rel + colonyBool + agePaired + (1 | familyBool) +
## (1 | pairID1) + (1 | pairID2)
## Data: model_rel.df
##
## REML criterion at convergence: -3928.2
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.108444259 -0.690869875 -0.068233408  0.583996354  3.762633304
##
## Random effects:
## Groups      Name      Variance    Std.Dev.
## pairID2     (Intercept) 0.00136165106 0.0369005564
## pairID1     (Intercept) 0.00132283514 0.0363708006
## familyBool  (Intercept) 0.00404648919 0.0636120208
## Residual                0.00381948877 0.0618020126
## Number of obs: 1540, groups: pairID2, 55; pairID1, 55; familyBool, 2
##
## Fixed effects:
##              Estimate      Std. Error      df    t value Pr(>|t|)
## (Intercept) 3.15186662e-01 4.73683692e-02 1.14156516e+00  6.65395 0.074931 .
## rel         8.71026170e-03 2.08593513e-02 1.33740535e+03  0.41757 0.676328
## colonyBool1 8.37421175e-02 8.06181663e-03 1.20111837e+02 10.38750 < 2e-16 ***
## agePairedM/P 2.39466928e-03 8.06276850e-03 1.28046621e+02  0.29700 0.766945
## agePairedP/P 1.21988991e-02 1.53157945e-02 1.03077423e+02  0.79649 0.427577
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) rel      clnyB1 agPM/P
## rel         -0.090
## colonyBool1 -0.152  0.012
## agePairedM/P -0.145 -0.016 -0.023
## agePairedP/P -0.137 -0.004 -0.026  0.915
```

```
summary(a4)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: scent_mds ~ colonyBool + agePaired + (1 | familyBool) + (1 |
## pairID1) + (1 | pairID2)
## Data: model_rel.df
```

```
##
## REML criterion at convergence: -3933.9
##
## Scaled residuals:
##      Min           1Q       Median           3Q      Max
## -3.113665362 -0.687292046 -0.067704903  0.586076727  3.745905490
##
## Random effects:
##   Groups      Name      Variance    Std.Dev.
##   pairID2      (Intercept) 0.00136551721 0.0369529053
##   pairID1      (Intercept) 0.00132698089 0.0364277489
##   familyBool   (Intercept) 0.00435745709 0.0660110377
##   Residual                0.00381639653 0.0617769903
## Number of obs: 1540, groups: pairID2, 55; pairID1, 55; familyBool, 2
##
## Fixed effects:
##              Estimate      Std. Error      df    t value Pr(>|t|)
## (Intercept)  3.17056257e-01 4.87992888e-02 1.13632796e+00  6.49715 0.077614 .
## colonyBool1  8.36965038e-02 8.07029419e-03 1.20281473e+02 10.37094 < 2e-16 ***
## agePairedM/P 2.44412815e-03 8.07041285e-03 1.28202135e+02  0.30285 0.762495
## agePairedP/P 1.22231134e-02 1.53347232e-02 1.03314754e+02  0.79709 0.427228
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) clnyB1 agPM/P
## colonyBool1 -0.147
## agePairedM/P -0.142 -0.023
## agePairedP/P -0.134 -0.026  0.915
# if interested
# check model performance by
# check_model(a2)
#
```

Correlations of genetic main effects

```
# correlation of ufrac and relatedness
u_r_model1 <- lmerTest::lmer(ufrac ~ rel + (1|pairID1) + (1|pairID2),
                             data = model_rel.df)
summary(u_r_model1)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: ufrac ~ rel + (1 | pairID1) + (1 | pairID2)
##   Data: model_rel.df
##
## REML criterion at convergence: -663.8
##
## Scaled residuals:
##      Min           1Q       Median           3Q      Max
## -4.441714289 -0.385476875  0.272592692  0.681993885  1.501197368
##
## Random effects:
##   Groups      Name      Variance    Std.Dev.
##
```

```

## pairID1 (Intercept) 0.00216331204 0.0465114183
## pairID2 (Intercept) 0.00101136839 0.0318020186
## Residual 0.03589648773 0.1894636844
## Number of obs: 1540, groups: pairID1, 55; pairID2, 55
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) 7.97297459e-01 9.69913681e-03 6.44203957e+01 82.20293 < 2.22e-16
## rel -2.38911481e-01 5.12089926e-02 1.42412461e+03 -4.66542 3.3692e-06
##
## (Intercept) ***
## rel ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr)
## rel -0.009
u_r_model2 <- lmerTest::lmer(ufrac ~ rel + (1|pairID1) + (1|pairID2) + (1|familyBool),
                             data = model_rel.df)
summary(u_r_model2)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: ufrac ~ rel + (1 | pairID1) + (1 | pairID2) + (1 | familyBool)
## Data: model_rel.df
##
## REML criterion at convergence: -674.6
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -4.473364209 -0.379228923 0.272204191 0.676906270 2.150144511
##
## Random effects:
## Groups Name Variance Std.Dev.
## pairID1 (Intercept) 0.00215194602 0.0463890722
## pairID2 (Intercept) 0.00107608003 0.0328036587
## familyBool (Intercept) 0.01743074553 0.1320255488
## Residual 0.03554491277 0.1885335853
## Number of obs: 1540, groups: pairID1, 55; pairID2, 55; familyBool, 2
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) 0.7107349721 0.0967753027 0.9921110956 7.34418 0.087397 .
## rel -0.1266874397 0.0594151597 922.8588459187 -2.13224 0.033251 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr)
## rel -0.126

```

```
compare_performance(u_r_model1, u_r_model2, rank = T)
```

```
## Some of the nested models seem to be identical and probably only vary in
## their random effects.
```

```
## # Comparison of Model Performance Indices
```

```
##
## Name | Model | R2 (cond.) | R2 (marg.) | ICC | RMSE | Sigma | AIC weights | AICc
## -----
## u_r_model2 | lmerModLmerTest | 0.369 | 0.003 | 0.368 | 0.185 | 0.189 | 0.874 |
## u_r_model1 | lmerModLmerTest | 0.095 | 0.015 | 0.081 | 0.186 | 0.189 | 0.126 |
```

```
u_r_model3 <- lmerTest::lmer(ufrac ~ rel + colonyBool + (1|pairID1) + (1|pairID2) + (1|familyBool),
                             data = model_rel.df)
```

```
summary(u_r_model3)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
```

```
## lmerModLmerTest]
```

```
## Formula: ufrac ~ rel + colonyBool + (1 | pairID1) + (1 | pairID2) + (1 |
```

```
## familyBool)
```

```
## Data: model_rel.df
```

```
##
```

```
## REML criterion at convergence: -667.8
```

```
##
```

```
## Scaled residuals:
```

```
##      Min      1Q      Median      3Q      Max
## -4.473094103 -0.378995809  0.272905728  0.676506794  2.148306764
```

```
##
```

```
## Random effects:
```

```
## Groups      Name      Variance      Std.Dev.
## pairID1      (Intercept) 0.00217394338 0.0466255657
## pairID2      (Intercept) 0.00108902249 0.0330003408
## familyBool   (Intercept) 0.01740183944 0.1319160318
## Residual              0.03555503513 0.1885604283
```

```
## Number of obs: 1540, groups: pairID1, 55; pairID2, 55; familyBool, 2
```

```
##
```

```
## Fixed effects:
```

```
##              Estimate      Std. Error      df t value Pr(>|t|)
## (Intercept)  7.11336570e-01  9.72959228e-02  1.01443951e+00  7.31106 0.084313 .
## rel          -1.26595370e-01  5.94527269e-02  9.16826722e+02 -2.12935 0.033492 *
## colonyBool1  -7.42382735e-04  1.31644657e-02  2.09024905e+02 -0.05639 0.955083
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## Correlation of Fixed Effects:
```

```
##      (Intr) rel
```

```
## rel      -0.126
```

```
## colonyBool1 -0.110  0.013
```

```
compare_performance(u_r_model1, u_r_model2, u_r_model3, rank = T)
```

```
## Some of the nested models seem to be identical and probably only vary in
## their random effects.
```

```
## # Comparison of Model Performance Indices
```

```
##
```


## Name	Model	R2 (cond.)	R2 (marg.)	ICC	RMSE	Sigma	AIC weights	AICc
## u_r_model2	lmerModLmerTest	0.369	0.003	0.368	0.185	0.189	0.661	
## u_r_model3	lmerModLmerTest	0.369	0.003	0.368	0.185	0.189	0.243	
## u_r_model1	lmerModLmerTest	0.095	0.015	0.081	0.186	0.189	0.096	

```
summary(u_r_model2) # colony effect unsubstantial but family important!
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: ufrac ~ rel + (1 | pairID1) + (1 | pairID2) + (1 | familyBool)
## Data: model_rel.df
##
## REML criterion at convergence: -674.6
##
## Scaled residuals:
##      Min           1Q       Median           3Q          Max
## -4.473364209 -0.379228923  0.272204191  0.676906270  2.150144511
##
## Random effects:
## Groups      Name      Variance    Std.Dev.
## pairID1     (Intercept) 0.00215194602 0.0463890722
## pairID2     (Intercept) 0.00107608003 0.0328036587
## familyBool  (Intercept) 0.01743074553 0.1320255488
## Residual                    0.03554491277 0.1885335853
## Number of obs: 1540, groups: pairID1, 55; pairID2, 55; familyBool, 2
##
## Fixed effects:
##              Estimate      Std. Error      df    t value Pr(>|t|)
## (Intercept)  0.7107349721  0.0967753027  0.9921110956  7.34418 0.087397 .
## rel          -0.1266874397  0.0594151597 922.8588459187 -2.13224 0.033251 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##      (Intr)
## rel -0.126
```

```
(aov_u_r <- anova(u_r_model2))
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##      Sum Sq      Mean Sq NumDF      DenDF F value    Pr(>F)
## rel 0.1616032287 0.1616032287      1 922.8588459 4.54645 0.033251 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

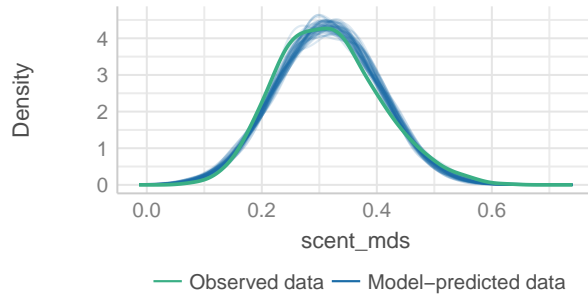
Adressing collinearity

```
# use performance tools to check model goodness

# model with all genetic effects that were
# evaluated in chemical similarity associations:
check_model(a3)
```

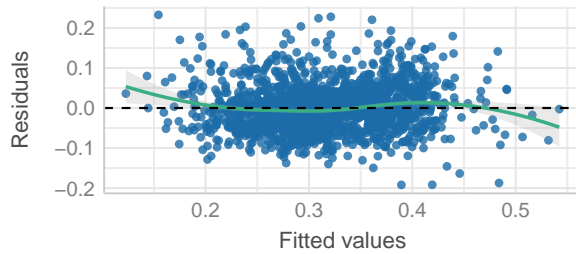
Posterior Predictive Check

Model-predicted lines should resemble observed data line



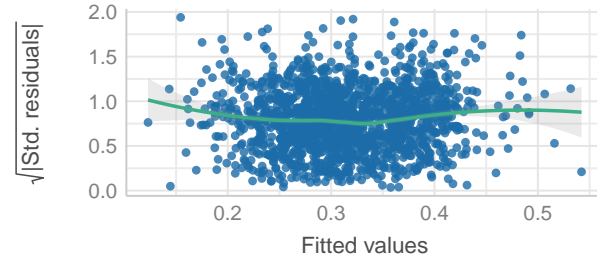
Linearity

Reference line should be flat and horizontal



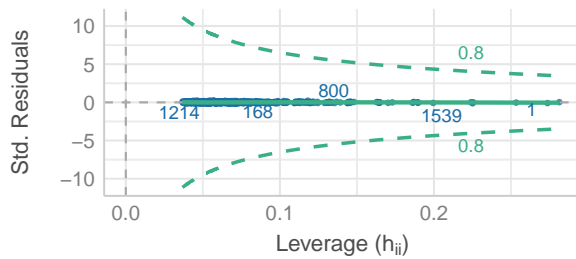
Homogeneity of Variance

Reference line should be flat and horizontal



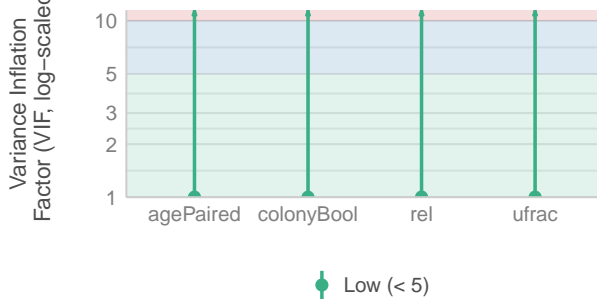
Influential Observations

Points should be inside the contour lines



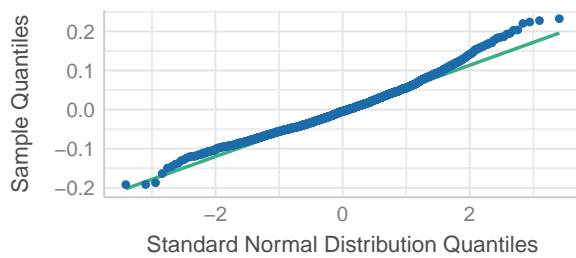
Collinearity

High collinearity (VIF) may inflate parameter uncertainty



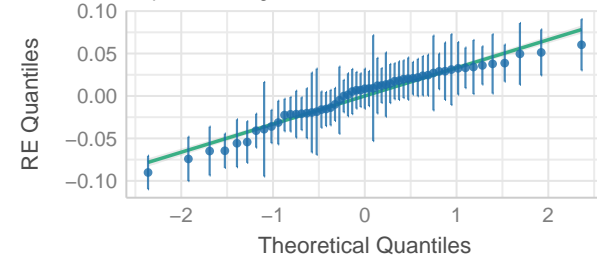
Normality of Residuals

Dots should fall along the line



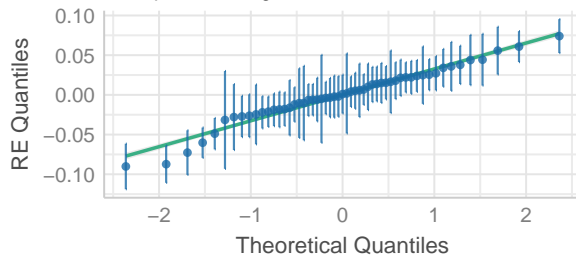
Normality of Random Effects (pairID2)

Dots should be plotted along the line



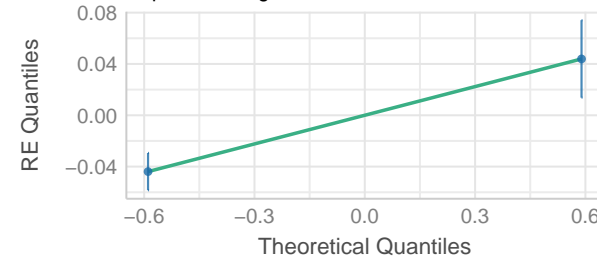
Normality of Random Effects (pairID1)

Dots should be plotted along the line



Normality of Random Effects (familyBool)

Dots should be plotted along the line



```

# check by re-running a3 model with residuals for relatedness effect
res_u_r <- residuals(u_r_model2)

temp_df <- cbind(model_rel.df, col_residuals = res_u_r)

a3_residual <- lmerTest::lmer(scent_mds ~ col_residuals + rel + colonyBool + agePaired +
                             (1|familyBool) + (1|pairID1) + (1|pairID2),
                             data = temp_df)

summary(a3_residual)

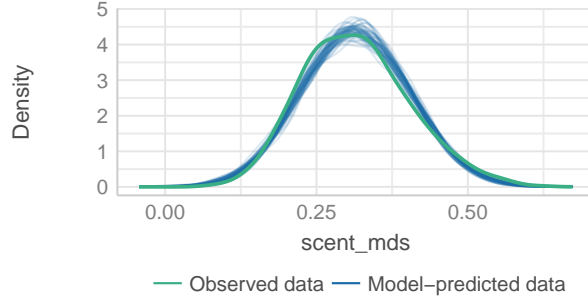
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: scent_mds ~ col_residuals + rel + colonyBool + agePaired + (1 |
##      familyBool) + (1 | pairID1) + (1 | pairID2)
## Data: temp_df
##
## REML criterion at convergence: -3920.6
##
## Scaled residuals:
##      Min           1Q       Median           3Q          Max
## -3.103258827 -0.690769473 -0.068686908  0.585558921  3.761156979
##
## Random effects:
## Groups      Name      Variance      Std.Dev.
## pairID2     (Intercept) 0.00136213257 0.0369070802
## pairID1     (Intercept) 0.00132201584 0.0363595358
## familyBool  (Intercept) 0.00404272164 0.0635824004
## Residual                0.00382206362 0.0618228406
## Number of obs: 1540, groups: pairID2, 55; pairID1, 55; familyBool, 2
##
## Fixed effects:
##              Estimate      Std. Error      df    t value Pr(>|t|)
## (Intercept)  3.15169410e-01  4.73489770e-02  1.14124101e+00  6.65631 0.074941
## col_residuals -1.72524676e-03  8.62343567e-03  1.43952773e+03 -0.20006 0.841458
## rel          8.77922600e-03  2.08681133e-02  1.33588284e+03  0.42070 0.674041
## colonyBool1  8.37532200e-02  8.06204794e-03  1.20109868e+02 10.38858 < 2e-16
## agePairedM/P 2.38288843e-03  8.06317648e-03  1.28076263e+02  0.29553 0.768070
## agePairedP/P 1.21929643e-02  1.53155887e-02  1.03075963e+02  0.79611 0.427795
##
## (Intercept) .
## col_residuals
## rel
## colonyBool1 ***
## agePairedM/P
## agePairedP/P
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##      (Intr) cl_rsd rel      clnyB1 agPM/P
## col_residls  0.002
## rel          -0.090 -0.014
## colonyBool1 -0.152 -0.008  0.012

```

```
## agePairedM/P -0.145  0.008 -0.016 -0.023
## agePairedP/P -0.137  0.002 -0.004 -0.026  0.915
check_model(a3_residual)
```

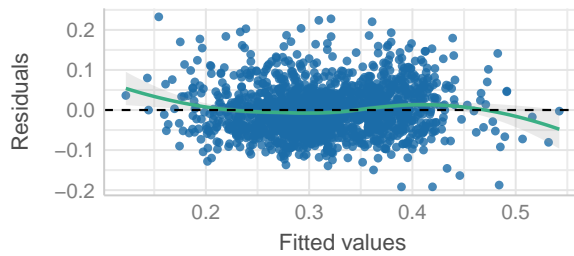
Posterior Predictive Check

Model-predicted lines should resemble observed data line



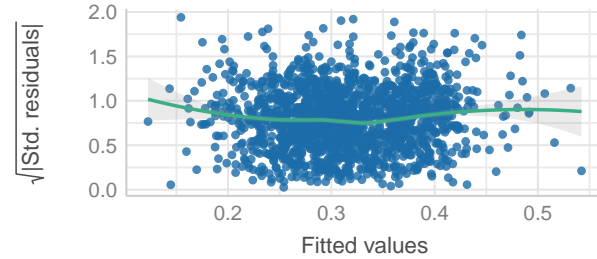
Linearity

Reference line should be flat and horizontal



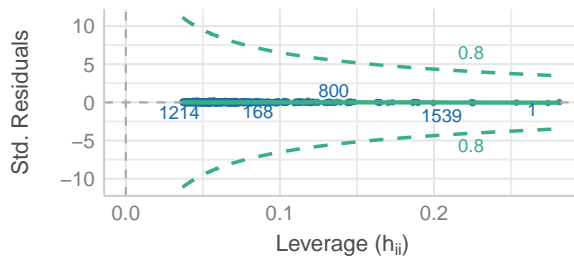
Homogeneity of Variance

Reference line should be flat and horizontal



Influential Observations

Points should be inside the contour lines



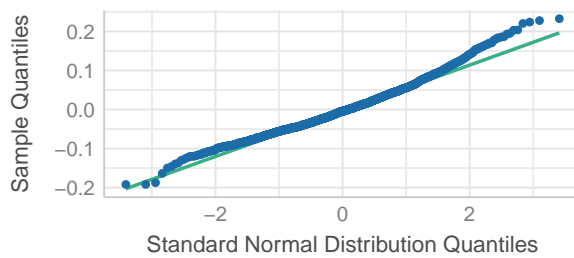
Collinearity

High collinearity (VIF) may inflate parameter uncertainty



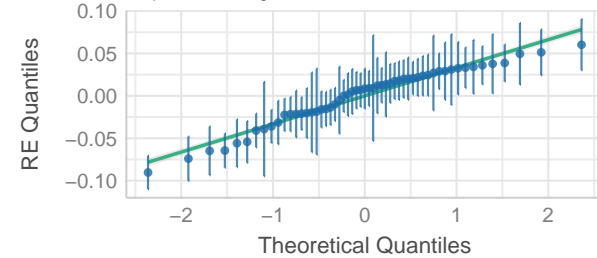
Normality of Residuals

Dots should fall along the line



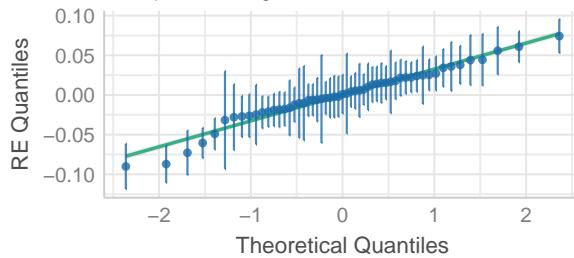
Normality of Random Effects (pairID2)

Dots should be plotted along the line



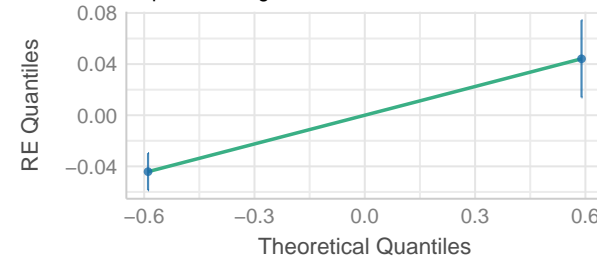
Normality of Random Effects (pairID1)

Dots should be plotted along the line



Normality of Random Effects (familyBool)

Dots should be plotted along the line

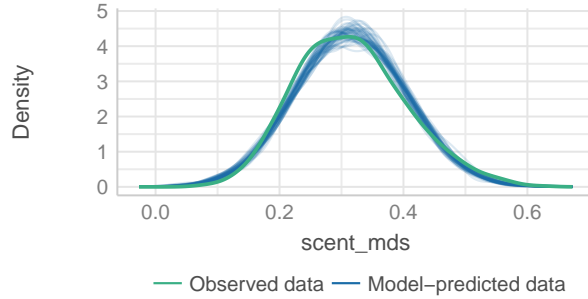


Neither model, performs noticeably better, and by VIC both models (with and without residuals fitted) show no high amount of collinearity. However, 'a4' is within this same goodness and while retaining the same information with less fixed effects, thus being more parsimonious.

```
check_model(a4)
```

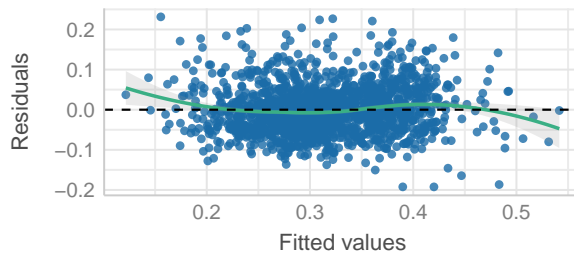
Posterior Predictive Check

Model-predicted lines should resemble observed data line



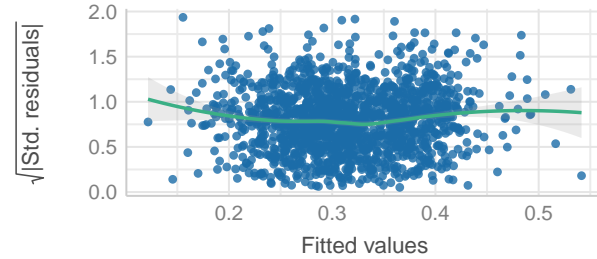
Linearity

Reference line should be flat and horizontal



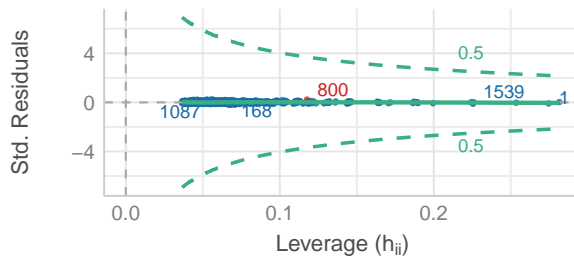
Homogeneity of Variance

Reference line should be flat and horizontal



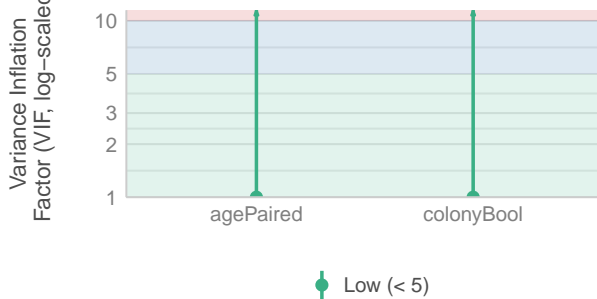
Influential Observations

Points should be inside the contour lines



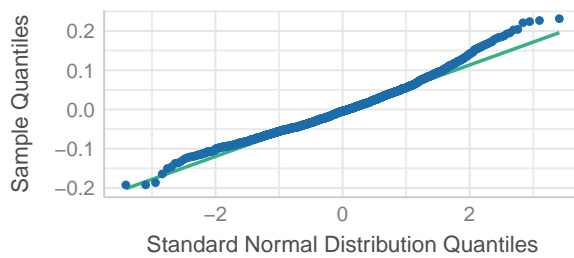
Collinearity

High collinearity (VIF) may inflate parameter uncertainty



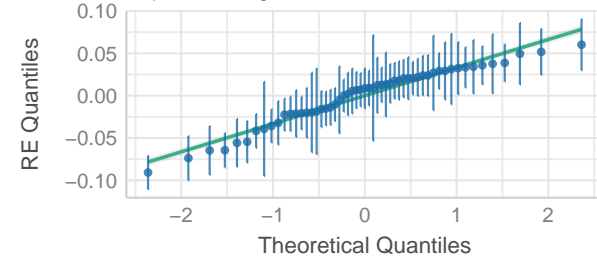
Normality of Residuals

Dots should fall along the line



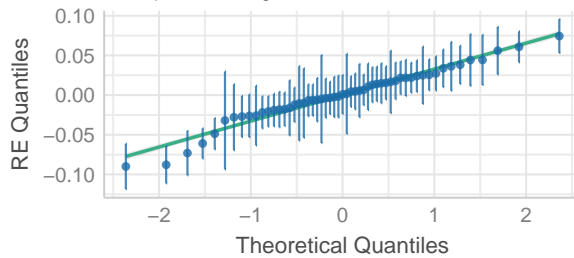
Normality of Random Effects (pairID2)

Dots should be plotted along the line



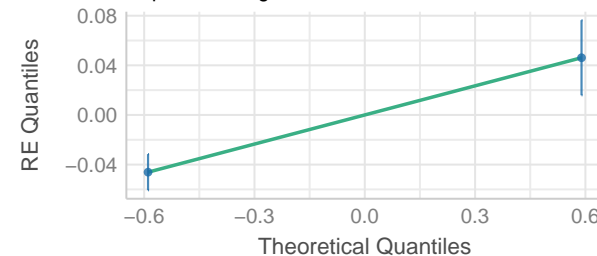
Normality of Random Effects (pairID1)

Dots should be plotted along the line



Normality of Random Effects (familyBool)

Dots should be plotted along the line



Model relationship between chemical diversity and mhc plus msats diversity

update data frame with meta data

Include information about MHC heterozygosity, sMLH from microsatellite data and chemical diversity by number of compounds per individual

```
scent.abs <- ifelse(scent != 0, 1, 0)
compound_n <- apply(scent.abs, 1, sum)

names(compound_n) == meta$real_id

## [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [16] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [31] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [46] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE

# read in heterozygosity information
het_table <- read.table("data/arga_mhc_het.txt", sep = "\t")

# keep names consistent
match_het <- match(meta$real_id, rownames(het_table))
het_table %<>% .[match_het,]

# generate sMLH with microsatellite data
# table is pre-prepped, thus rows correspond to same individuals in meta data
smlh_res <- read.table("data/msats_genotypes_inbreedR.txt", sep = "\t") %>%
  # convert to inbreedR format
  convert_raw() %>%
  # generate sMLH
  sMLH()

meta %<>% cbind(., compound_n = compound_n,
               mhc_het = het_table$het,
               smlh = smlh_res)

meta %<>% mutate(
  real_id = as.factor(real_id),
  colony = as.factor(colony),
  maturity = as.factor(maturity),
  family = as.factor(family)
)
```

General meta data information

```
# 32 adult female individuals
meta_mom <- meta %>% filter(maturity == "M")

# check n for each beach colony
n_fwb_mom <- meta_mom %>% filter(colony == "FWB") %>% dim() %>% .[1]
n_ssb_mom <- meta_mom %>% filter(colony == "SSB") %>% dim() %>% .[1]

# test for difference in number of chemicals by beach
chems_fwb_mom <- meta_mom %>% filter(., colony == "FWB") %>%
  select(compound_n) %>%
  unlist()
```



```

chems_ssb_mom <- meta_mom %>% filter(., colony == "SSB") %>%
  select(compound_n) %>%
  unlist()

(colony_t_test_mom <- t.test(chems_fwb_mom, chems_ssb_mom))

##
## Welch Two Sample t-test
##
## data: chems_fwb_mom and chems_ssb_mom
## t = -1.522037389, df = 22.29327201, p-value = 0.142058931
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -29.16483741389 4.46483741389
## sample estimates:
## mean of x mean of y
## 52.15 64.50

# 24 pups (mixed sexes)
meta_pup <- meta %>% filter(maturity == "P")

# check n for each beach colony
n_fwb_pup <- meta_pup %>% filter(colony == "FWB") %>% dim() %>% .[1]
n_ssb_pup <- meta_pup %>% filter(colony == "SSB") %>% dim() %>% .[1]

# test for difference in number of chemicals by beach
chems_fwb_pup <- meta_pup %>% filter(., colony == "FWB") %>%
  select(compound_n) %>%
  unlist()

chems_ssb_pup <- meta_pup %>% filter(., colony == "SSB") %>%
  select(compound_n) %>%
  unlist()

(colony_t_test_pup <- t.test(chems_fwb_pup, chems_ssb_pup))

##
## Welch Two Sample t-test
##
## data: chems_fwb_pup and chems_ssb_pup
## t = 1.175783211, df = 20.29290702, p-value = 0.253292061
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -6.90357099378 24.77769686791
## sample estimates:
## mean of x mean of y
## 58.8461538462 49.9090909091

# standard error function
se <- function(x) sd(x)/sqrt(length(x))

mean_chems_by_colony <- list(chems_fwb_mom, chems_fwb_pup, chems_ssb_mom, chems_ssb_pup)
sapply(mean_chems_by_colony, mean)

## [1] 52.1500000000 58.8461538462 64.5000000000 49.9090909091

```

```

supply(mean_chems_by_colony, se)

## [1] 4.80037005153 6.31324021184 6.54182348779 4.23288971884
mean(meta$compound_n)

## [1] 55.9107142857
se(meta$compound_n)

## [1] 2.80714265061
# neither in pups nor moms compound_n differs for colony, calculate anova
# check whether compound number varies for different ages and different colonies

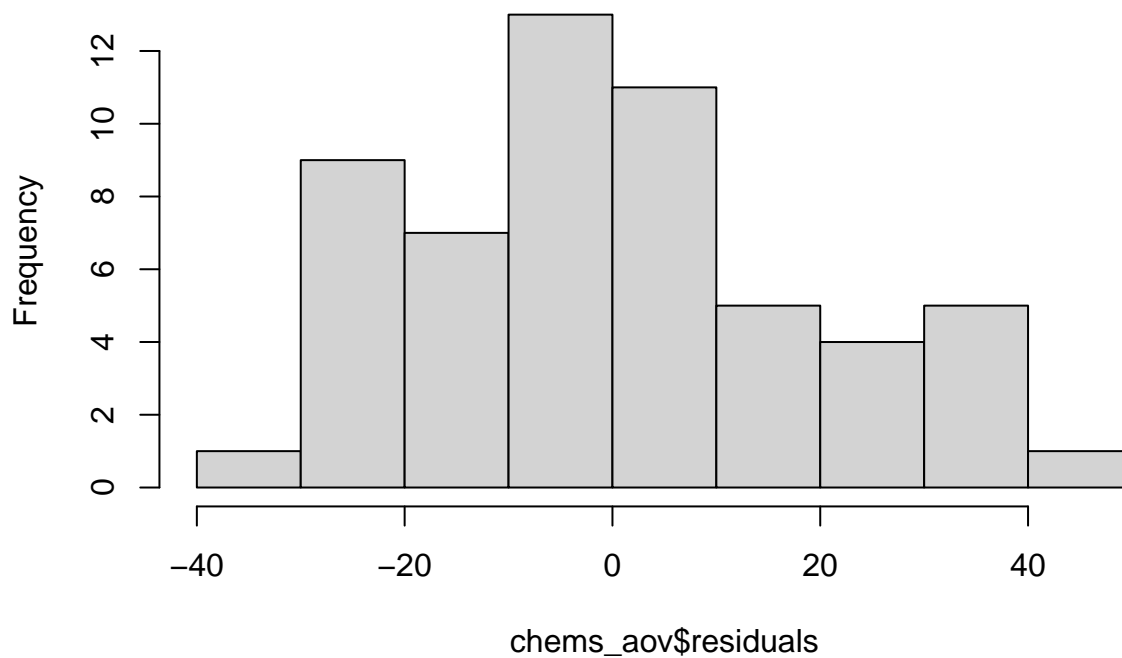
chems_aov <- aov(compound_n ~ maturity * colony, data = meta)
summary(chems_aov)

##              Df      Sum Sq   Mean Sq F value    Pr(>F)
## maturity      1    56.58482    56.58482  0.13023  0.71966
## colony        1   115.19930   115.19930  0.26513  0.60880
## maturity:colony 1  1504.61805  1504.618048  3.46285  0.06842 .
## Residuals    52  22594.15140   434.502912
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

hist(chems_aov$residuals)

```

Histogram of chems_aov\$residuals



```

# post-hoc analysis
TukeyHSD(chems_aov)

## Tukey multiple comparisons of means
## 95% family-wise confidence level
##
## Fit: aov(formula = compound_n ~ maturity * colony, data = meta)
##
## $maturity
##      diff      lwr      upr      p adj
## P-M -2.03125 -13.326105701 9.26360570104 0.7196568197
##
## $colony
##      diff      lwr      upr      p adj
## SSB-FWB 2.90513833992 -8.45648556259 14.2667622424 0.610058289387
##
## $`maturity:colony`
##      diff      lwr      upr      p adj
## P:Fwb-M:Fwb 6.69615384615 -13.01371483797 26.40602253028 0.803961243091
## M:SSB-M:Fwb 12.35000000000 -7.85146210548 32.55146210548 0.375145035385
## P:SSB-M:Fwb -2.24090909091 -23.00834798997 18.52652980816 0.991714931867
## M:SSB-P:Fwb 5.65384615385 -16.49347177283 27.80116408052 0.905141795957
## P:SSB-P:Fwb -8.93706293706 -31.60181836421 13.72769249008 0.723034927926
## P:SSB-M:SSB -14.59090909091 -37.68444251969 8.50262433787 0.346056221246

#### Permanova

perm_chem_data <- vegan::adonis2(
  # term
  scent ~ colony + family + smlh + maturity,
  by = "terms",
  # data for grouping
  data = meta)

perm_chem_data

## Permutation test for adonis under reduced model
## Terms added sequentially (first to last)
## Permutation: free
## Number of permutations: 999
##
## vegan::adonis2(formula = scent ~ colony + family + smlh + maturity, data = meta, by = "terms")
##      Df      SumOfSqs      R2      F Pr(>F)
## colony  1  1.671427973 0.1273987963 11.47634 0.001 ***
## family 34  8.546158183 0.6514012466  1.72587 0.001 ***
## smlh    1  0.120713508 0.0092009682  0.82884 0.687
## maturity 1  0.159812162 0.0121811274  1.09730 0.341
## Residual 18  2.621540965 0.1998178615
## Total    55 13.119652790 1.0000000000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Compare chemical diversity models

Correlate Chemical diversity per sample with their sMLH and MHC, respectively. Also accounting maturity and family as fixed and random effect.

```
b1 <- lmerTest::lmer(compound_n ~ mhc_het + maturity + colony +(1|family),  
  data = meta)
```

```
b2 <- lmerTest::lmer(compound_n ~ smlh + maturity + colony + (1|family),  
  data = meta)
```

```
b3 <- lmerTest::lmer(compound_n ~ mhc_het + smlh + maturity + colony + (1|family),  
  data = meta)
```

```
b4 <- lmerTest::lmer(compound_n ~ maturity + colony + (1|family),  
  data = meta)
```

```
compare_performance(b1, b2, b3, b4, rank = T) %>% arrange(Name)
```

```
## # Comparison of Model Performance Indices
```

```
##
```

```
## Name | Model | R2 (cond.) | R2 (marg.) | ICC | RMSE | Sigma | AIC weights | AICc weigh
```

```
## -----
```

```
## b1 | lmerModLmerTest | 0.747 | 0.006 | 0.746 | 7.248 | 10.847 | 0.005 | 0.0
```

```
## b2 | lmerModLmerTest | 0.772 | 0.119 | 0.741 | 6.696 | 9.994 | 0.713 | 0.7
```

```
## b3 | lmerModLmerTest | 0.769 | 0.117 | 0.738 | 6.706 | 10.127 | 0.269 | 0.2
```

```
## b4 | lmerModLmerTest | 0.752 | 0.006 | 0.751 | 7.202 | 10.670 | 0.014 | 0.0
```

```
summary(b2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
```

```
## lmerModLmerTest]
```

```
## Formula: compound_n ~ smlh + maturity + colony + (1 | family)
```

```
## Data: meta
```

```
##
```

```
## REML criterion at convergence: 450.6
```

```
##
```

```
## Scaled residuals:
```

```
## Min 1Q Median 3Q Max
```

```
## -1.1174803761 -0.5102355060 -0.0397205379 0.2311200062 2.1221413149
```

```
##
```

```
## Random effects:
```

```
## Groups Name Variance Std.Dev.
```

```
## family (Intercept) 285.8932945 16.90837942
```

```
## Residual 99.8834741 9.99417201
```

```
## Number of obs: 56, groups: family, 36
```

```
##
```

```
## Fixed effects:
```

```
## Estimate Std. Error df t value Pr(>|t|)
```

```
## (Intercept) -21.15641099 24.20114640 44.84179770 -0.87419 0.3866725
```

```
## smlh 76.53192951 24.10779559 43.94521713 3.17457 0.0027408 **
```

```
## maturityP -4.62266359 3.17801210 24.39984244 -1.45458 0.1585308
```

```
## colonySSB 4.10983380 6.36424962 34.10616354 0.64577 0.5227505
```

```
## ---
```

```
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation of Fixed Effects:
##           (Intr) smlh   mtrtyP
## smlh      -0.984
## maturityP  0.257 -0.303
## colonySSB -0.165  0.055 -0.076

Correlate zygotity effects

smlh_het_m1 <- lmerTest::lmer(smlh ~ mhc_het + (1|family), data = meta)
summary(smlh_het_m1)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: smlh ~ mhc_het + (1 | family)
## Data: meta
##
## REML criterion at convergence: -98.4
##
## Scaled residuals:
##           Min           1Q           Median           3Q           Max
## -2.193649022 -0.656470901  0.102448217  0.718635430  1.907640611
##
## Random effects:
## Groups   Name      Variance    Std.Dev.
## family   (Intercept) 0.00131322013 0.0362383793
## Residual                0.00720048654 0.0848556806
## Number of obs: 56, groups: family, 36
##
## Fixed effects:
##           Estimate    Std. Error      df    t value Pr(>|t|)
## (Intercept)  1.0286614945  0.0268377389  51.3350533536  38.32892 < 2e-16 ***
## mhc_het      -0.0381338548  0.0301679498  53.0219141496  -1.26405  0.21174
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr)
## mhc_het -0.876

# check performance for including colony as fixed effect, as well
smlh_het_m2 <- lmerTest::lmer(smlh ~ mhc_het + colony + (1|family), data = meta)
summary(smlh_het_m2)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: smlh ~ mhc_het + colony + (1 | family)
## Data: meta
##
## REML criterion at convergence: -93.1
##
## Scaled residuals:
##           Min           1Q           Median           3Q           Max
## -2.095136459 -0.653315112  0.113695726  0.687418314  1.847436161
##
## Random effects:
```

```
## Groups      Name      Variance      Std.Dev.
## family      (Intercept) 0.00154644902 0.0393249160
## Residual                0.00714119814 0.0845056101
## Number of obs: 56, groups: family, 36
##
## Fixed effects:
##              Estimate      Std. Error      df    t value Pr(>|t|)
## (Intercept)  1.03101391140  0.02871644361 45.35909433637 35.90326   <2e-16 ***
## mhc_het      -0.03679744212  0.03054090182 52.11941131342 -1.20486   0.2337
## colonySSB    -0.00838946614  0.02680960458 26.33503941544 -0.31293   0.7568
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) mhc_ht
## mhc_het      -0.799
## colonySSB    -0.329 -0.074
```

```
(aov <- anova(smlh_het_m2))
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##              Sum Sq      Mean Sq NumDF      DenDF F value Pr(>F)
## mhc_het 0.010366750137 0.010366750137      1 52.11941131 1.45168 0.2337
## colony  0.000699292576 0.000699292576      1 26.33503942 0.09792 0.7568
```

```
compare_performance(smlh_het_m1, smlh_het_m2, rank = T)
```

```
## # Comparison of Model Performance Indices
```

```
##
## Name | Model | R2 (cond.) | R2 (marg.) | ICC | RMSE | Sigma | AIC weights | AICc
## -----|-----|-----|-----|-----|-----|-----|-----|-----
## smlh_het_m2 | lmerModLmerTest | 0.202 | 0.029 | 0.178 | 0.076 | 0.085 | 0.277 |
## smlh_het_m1 | lmerModLmerTest | 0.178 | 0.028 | 0.154 | 0.077 | 0.085 | 0.723 |
```

Plot chemical complexity by mhc heterozygosity

```
panel2.a <- ggplot(data = meta,
  aes(y = compound_n,
    x = as.factor(mhc_het),
    fill = as.factor(mhc_het),
    color = as.factor(mhc_het))) +
  scale_fill_manual(values = c("darkgrey", "orange")) +
  geom_boxplot(width = 0.4,
    color = "black",
    size = 1) +
  geom_jitter(height = 0.02,
    width = 0.1,
    color = "black",
    size = 3.5,
    alpha = 0.25) +
  scale_x_discrete(name = "MHC heterozygosity",
    breaks = c(0,1),
    labels = c("homozygous", "heterozygous")) +
  scale_y_continuous(name = "Chemical diversity") +
  custom_theme
```

Plot chemical complexity by sMLH

```
panel2.b <- ggplot(data = meta,
  aes(y = compound_n,
      x = smlh)) +
  geom_point(size = 3.5,
    alpha = 0.25) +
  geom_smooth(method = "lm",
    se = T,
    color = "orange") +
  scale_x_continuous(name = "sMLH") +
  scale_y_continuous(name = "Chemical diversity") +
  scale_color_manual(name = "Senescence",
    values = c("#E8B54D", "#000000"),
    labels = c("Mother", "Pup")) +
  scale_fill_manual(name = "Senescence",
    values = c("#E8B54D", "#000000"),
    labels = c("Mother", "Pup")) +
  custom_theme
```

Effect size bootstrap of linear mixed effects models

Demanding code and results are prerendered to optimize run-time of this markdown script. Bootstraps take several hours, only run, if you're interested in a different seed as a different randomization should switch up the data points but not overall results.

```
# subsample 30 individuals

model_r2_btrap <- function(x){

  n <- 1:dim(meta)[1]
  n_btrap <- sample(n, 30, replace = F)
  btrap_meta <- meta[n_btrap, ]
  div_trap <- lmerTest::lmer(compound_n ~ mhc_het + smlh + maturity + colony + (1|family),
    data = btrap_meta)

  # bootstrap effect size with partR2
  partR2(div_trap, partvars = c("mhc_het", "smlh", "maturity", "colony"), nboot = 100, CI = 0.95)

}

# amount of times bootstrap shall be repeated
nbtrap <- 1000

# repeat function call as often as specified for bootstrap iterations
system.time(
  div_r2_btrap <- lapply(1:nbtrap, model_r2_btrap)
)

sim_r2_btrap <- function(x){

n <- 1:dim(model_rel.df)[1]
```

```

n_btrap <- sample(n, 800, replace = F)
btrap_sim_df <- model_rel.df[n_btrap, ]

sim_trap <- lmerTest::lmer(scent_mds ~ rel + ufrac + colonyBool + agePaired + (1|familyBool) +
  (1|pairID1) + (1|pairID2),
  data = btrap_sim_df)

partR2(sim_trap, partvars = c("rel", "ufrac", "colonyBool", "agePaired"),
  nboot = 100, CI = 0.95)
}

nboot = 1000
sim_r2_btrap_res <- lapply(1:nboot, sim_r2_btrap)

```

Plot effect size results

Load in the pre-rendered data.

```

load(file = "RData/div_r2_btrap.RData")
load(file = "RData/sim_r2_btrap_res.RData")

```

Create a ggplot workable data frame

```

# extract r2 values only for the mhc heterozygosity fixed effect
r2_mhc_het <- sapply(1:length(div_r2_btrap), function(i) div_r2_btrap[[i]]$R2$estimate[2])
r2_smlh <- sapply(1:length(div_r2_btrap), function(i) div_r2_btrap[[i]]$R2$estimate[3])
r2_relatedness <- sapply(1:length(sim_r2_btrap_res), function(i) sim_r2_btrap_res[[1]]$R2$estimate[2])
r2_ufrac <- sapply(1:length(sim_r2_btrap_res), function(i) sim_r2_btrap_res[[1]]$R2$estimate[3])

group_factor <- c(rep("mhc_het", 1000),
  rep("r2_smlh", 1000),
  rep("relatedness", 1000),
  rep("ufrac", 1000)) %>%
  factor(., c("r2_smlh", "mhc_het", "relatedness", "ufrac"))

boot_estimate <- c(r2_mhc_het,
  r2_smlh,
  r2_relatedness,
  r2_ufrac)

plot_div_btrap_df <- data.frame(boot_estimate = boot_estimate,
  group = as.factor(group_factor))

```

Plot effect sizes

```

effectsize_best_model_gg <- ggplot(plot_div_btrap_df, aes(y = boot_estimate,
  x = group,
  color = group)) +
  # this arranges the points according to their density
  geom_quasirandom(alpha = 0.2, size = 3, width = 0.3, bandwidth = .95) +
  scale_color_manual(values = c("darkgrey", "darkgrey", "orange", "orange")) +
  # makes the boxplots

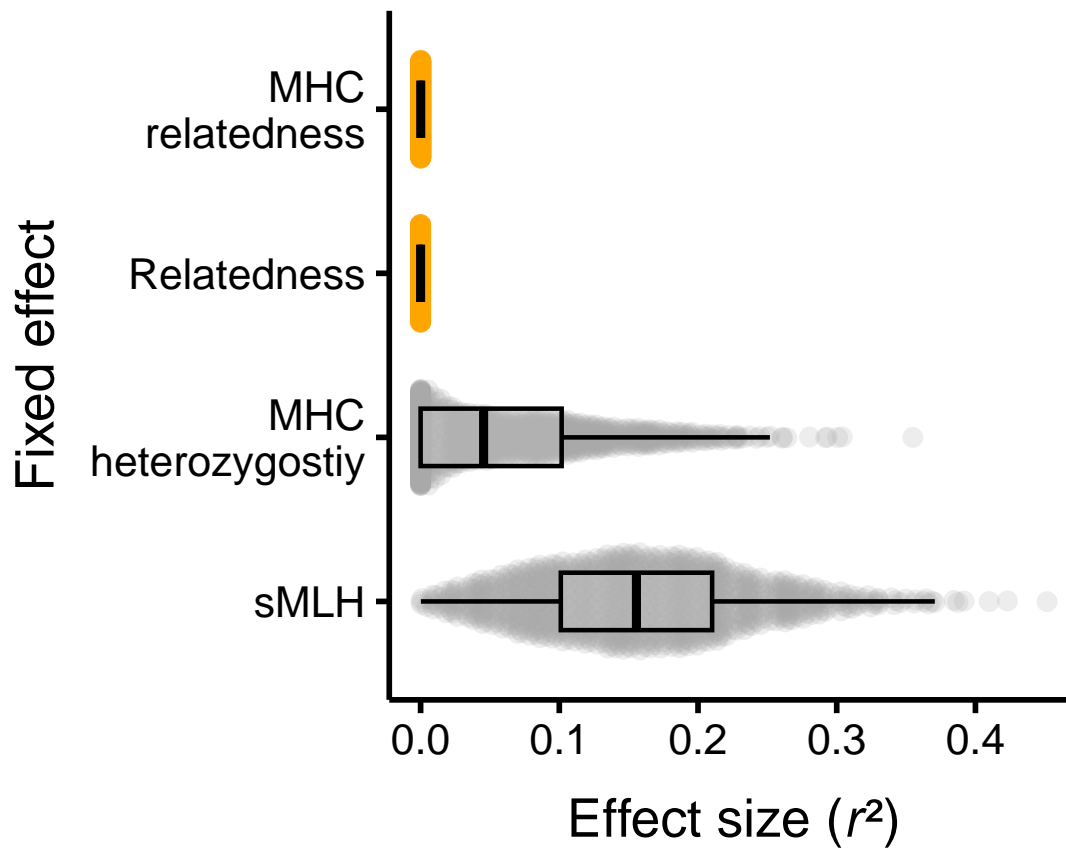
```



```

geom_boxplot(width = 0.35, outlier.shape = NA, color = "black",
             alpha = 0.1, lwd=0.8, notch = F) +
labs(y = expression(paste("Effect size (", italic("r"), "^2)")),
     x = "Fixed effect") +
scale_x_discrete(labels = c(
  "ufrac" = "MHC\\nrelatedness",
  "relatedness" = "Relatedness",
  "r2_smlh" = "sMLH",
  "mhc_het" = "MHC\\nheterozygosity")) +
coord_flip() +
custom_theme
effectsize_best_model_gg

```



```

ggsave(filename = "figures/figure3.png", dpi = 400,
       width = 22, height = 20,
       units = "cm",
       bg = "white")

```

Addition to model selection process by ‘dredge’ and ‘partR2’

Similarity model selection and power

```

# premise for 'dredge' to work correctly
options(na.action = "na.fail")

```

```
# model with all effects
sim_m <- lmerTest::lmer(scent_mds ~ rel + ufrac + colonyBool + agePaired + (1|familyBool) +
                        (1|pairID1) + (1|pairID2),
                        data = model_rel.df)

# calculate different versions
m1 <- dredge(sim_m)
```

Find appropriate models

```
## Warning in dredge(sim_m): comparing models fitted by REML
```

```
## Fixed term is "(Intercept)"
```

```
subset(m1, delta < 4)
```

```
## Global model call: lmerTest::lmer(formula = scent_mds ~ rel + ufrac + colonyBool +
##   agePaired + (1 | familyBool) + (1 | pairID1) + (1 | pairID2),
##   data = model_rel.df)
## ---
## Model selection table
##   (Intercept) clnyB df    logLik    AICc delta weight
## 3  0.3197      + 6 1974.155 -3936.3      0      1
## Models ranked by AICc(x)
## Random terms (all models):
##   1 | familyBool, 1 | pairID1, 1 | pairID2
```

```
# chose best
summary(get.models(m1, 1)[[1]])
```

select best

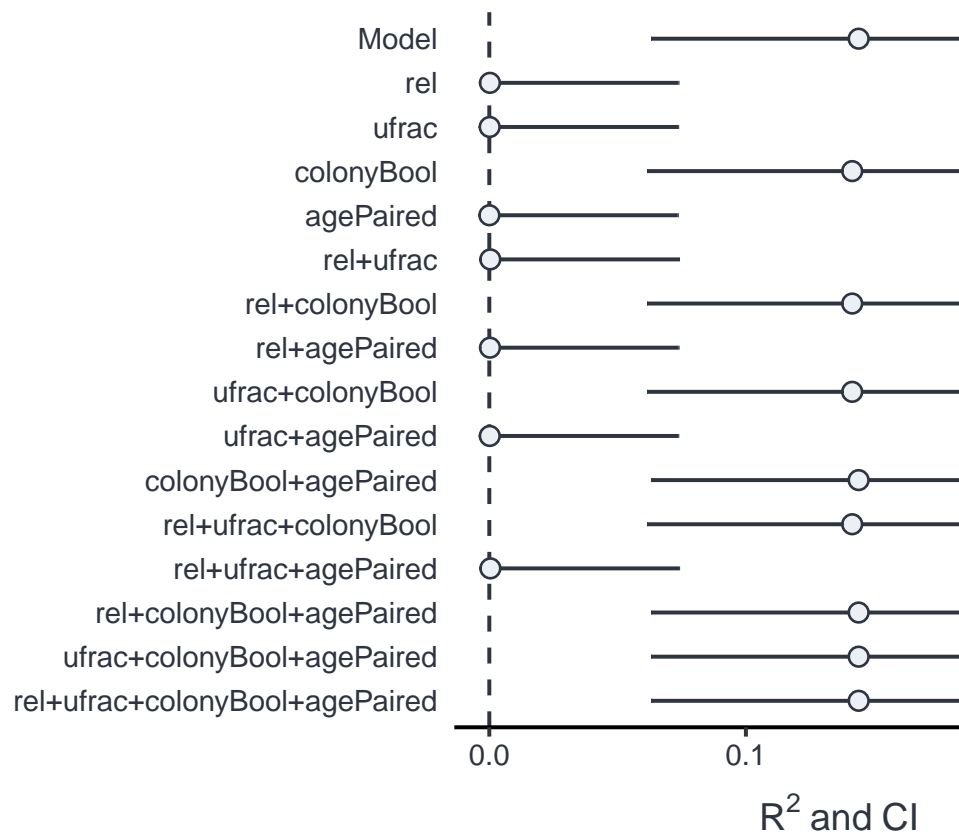
```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: scent_mds ~ colonyBool + (1 | familyBool) + (1 | pairID1) + (1 |
##   pairID2)
## Data: model_rel.df
##
## REML criterion at convergence: -3948.3
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.138411025 -0.682850860 -0.075254444  0.581948282  3.762734892
##
## Random effects:
##   Groups      Name      Variance  Std.Dev.
## pairID2  (Intercept) 0.00134929136 0.0367327015
## pairID1  (Intercept) 0.00132586922 0.0364124872
## familyBool (Intercept) 0.00421404024 0.0649156394
## Residual              0.00381737000 0.0617848687
## Number of obs: 1540, groups: pairID2, 55; pairID1, 55; familyBool, 2
##
## Fixed effects:
##              Estimate      Std. Error      df    t value Pr(>|t|)
## (Intercept) 3.19681994e-01 4.75484750e-02 1.09434933e+00 6.72329 0.080084 .
```

```
## colonyBool1 8.39162891e-02 8.04874742e-03 1.22040771e+02 10.42601 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##      (Intr)
## colonyBool1 -0.154
```

```
r2_sim_m <- partR2(sim_m, partvars = c("rel", "ufrac", "colonyBool", "agePaired"),
  nboot = 100, CI = 0.95)
```

Calculate effect size by partR2

```
forestplot(r2_sim_m, type = "R2", line_size = 0.7, text_size = 14, point_size = 3)
```



Visualize effect sizes of fixed effects

```
r2_sim_m
```

```
##
##
## R2 (marginal) and 95% CI for the full model:
## R2      CI_lower CI_upper nboot ndf
## 0.1439 0.0631   0.2727   100   6
##
## -----
##
```

```
## Part (semi-partial) R2:
## Predictor(s)          R2      CI_lower CI_upper nboot ndf
## Model                  0.1439 0.0631   0.2727   100   6
## rel                    0.0002 0.0000   0.0737   100   5
## ufrac                  0.0001 0.0000   0.0736   100   5
## colonyBool             0.1414 0.0615   0.2691   100   5
## agePaired              0.0000 0.0000   0.0735   100   4
## rel+ufrac              0.0004 0.0000   0.0739   100   4
## rel+colonyBool         0.1414 0.0615   0.2691   100   4
## rel+agePaired          0.0003 0.0000   0.0738   100   3
## ufrac+colonyBool       0.1414 0.0615   0.2691   100   4
## ufrac+agePaired        0.0002 0.0000   0.0737   100   3
## colonyBool+agePaired   0.1439 0.0631   0.2726   100   3
## rel+ufrac+colonyBool   0.1414 0.0615   0.2691   100   3
## rel+ufrac+agePaired    0.0004 0.0000   0.0740   100   2
## rel+colonyBool+agePaired 0.1439 0.0631   0.2727   100   2
## ufrac+colonyBool+agePaired 0.1439 0.0631   0.2727   100   2
## rel+ufrac+colonyBool+agePaired 0.1439 0.0631   0.2727   100   1
```

Diversity model selection

```
div_m <- lmerTest::lmer(compound_n ~ mhc_het + smlh + maturity + colony + (1|family),
                        data = meta)

m3 <- dredge(div_m)
```

Find appropriate models

```
## Warning in dredge(div_m): comparing models fitted by REML
```

```
## Fixed term is "(Intercept)"
```

```
subset(m3, delta < 4)
```

```
## Global model call: lmerTest::lmer(formula = compound_n ~ mhc_het + smlh + maturity +
##      colony + (1 | family), data = meta)
## ---
## Model selection table
##      (Int) cln mtr mhc_het   sml df   logLik   AICc delta weight
## 16 -22.62  +   +   1.1860 77.18  7 -222.645 461.6  0.00  0.620
## 12 -21.16  +   +           76.53  6 -225.280 464.3  2.65  0.165
## 15 -20.32      +   1.2930 76.51  6 -225.621 465.0  3.33  0.117
## 14 -12.22  +   -0.2606 66.23  6 -225.800 465.3  3.69  0.098
## Models ranked by AICc(x)
## Random terms (all models):
##      1 | family
```

```
summary(get.models(m3, 1)[[1]])
```

select best

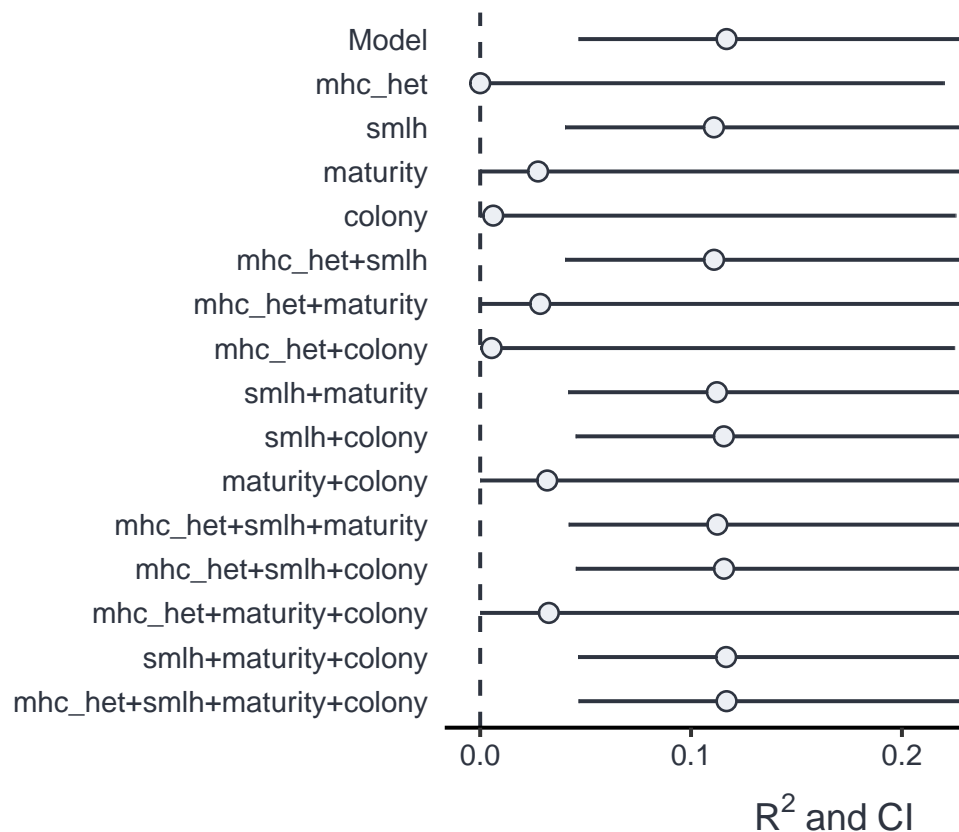
```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: compound_n ~ colony + maturity + mhc_het + smlh + (1 | family)
##      Data: meta
```

```
##
## REML criterion at convergence: 445.3
##
## Scaled residuals:
##      Min           1Q       Median           3Q      Max
## -1.0928313033 -0.4734130794 -0.0457156417  0.2360966398  2.0910996889
##
## Random effects:
##   Groups   Name      Variance  Std.Dev.
##   family   (Intercept) 289.098507 17.0028970
##   Residual              102.550738 10.1267338
## Number of obs: 56, groups: family, 36
##
## Fixed effects:
##              Estimate   Std. Error      df    t value   Pr(>|t|)
## (Intercept) -22.62052081  25.23757770  41.63258609 -0.89630 0.3752445
## colonySSB    4.06383229   6.41330434  33.84088527  0.63366 0.5305648
## maturityP   -4.75717833   3.27180878  24.21976233 -1.45399 0.1587859
## mhc_het      1.18588993   5.45889047  42.15362665  0.21724 0.8290693
## smlh        77.17560246  24.48424644  42.14207673  3.15205 0.0029835 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##      (Intr) clnSSB mtrtyP mhc_ht
## colonySSB -0.152
## maturityP  0.289 -0.068
## mhc_het    -0.247 -0.034 -0.181
## smlh       -0.973  0.051 -0.313  0.100
```

```
r2_div_m <- partR2(div_m,
  partvars = c("mhc_het", "smlh", "maturity", "colony"),
  nboot = 100, CI = 0.95)
```

Calculate effect size by partR2

```
forestplot(r2_div_m, type = "R2", line_size = 0.7, text_size = 14, point_size = 3)
```



Visualize effect sizes of fixed effects

r2_div_m

```
##
##
## R2 (marginal) and 95% CI for the full model:
## R2      CI_lower CI_upper nboot ndf
## 0.1168 0.0467   0.3359   100   5
##
## -----
##
## Part (semi-partial) R2:
## Predictor(s)      R2      CI_lower CI_upper nboot ndf
## Model              0.1168 0.0467   0.3359   100   5
## mhc_het            0.0000 0.0000   0.2199   100   4
## smlh               0.1108 0.0402   0.3310   100   4
## maturity           0.0275 0.0000   0.2440   100   4
## colony             0.0062 0.0000   0.2254   100   4
## mhc_het+smlh       0.1109 0.0403   0.3310   100   3
## mhc_het+maturity   0.0285 0.0000   0.2451   100   3
## mhc_het+colony     0.0054 0.0000   0.2248   100   3
## smlh+maturity      0.1122 0.0417   0.3322   100   3
## smlh+colony        0.1155 0.0453   0.3349   100   3
## maturity+colony    0.0318 0.0000   0.2486   100   3
## mhc_het+smlh+maturity 0.1125 0.0420   0.3323   100   2
## mhc_het+smlh+colony 0.1156 0.0453   0.3349   100   2
## mhc_het+maturity+colony 0.0326 0.0000   0.2494   100   2
```

```
## smlh+maturity+colony          0.1166 0.0464  0.3357  100  2
## mhc_het+smlh+maturity+colony 0.1168 0.0467  0.3359  100  1
```

Correlation of genetic effects

```
gen_m <- lmerTest::lmer(ufrac ~ rel + colonyBool + agePaired + (1|pairID1) + (1|pairID2) + (1|familyBool),
                        data = model_rel.df)

m2 <- dredge(gen_m)
```

Find appropriate models

```
## Warning in dredge(gen_m): comparing models fitted by REML
```

```
## Fixed term is "(Intercept)"
```

```
subset(m2, delta < 4)
```

```
## Global model call: lmerTest::lmer(formula = ufrac ~ rel + colonyBool + agePaired +
## (1 | pairID1) + (1 | pairID2) + (1 | familyBool), data = model_rel.df)
## ---
## Model selection table
## (Intrc)      rel df logLik   AICc delta weight
## 1  0.6825          5 337.011 -664.0  0.00  0.675
## 5  0.7107 -0.1267  6 337.288 -662.5  1.46  0.325
## Models ranked by AICc(x)
## Random terms (all models):
## 1 | pairID1, 1 | pairID2, 1 | familyBool
```

```
summary(get.models(m2, 1)[[1]])
```

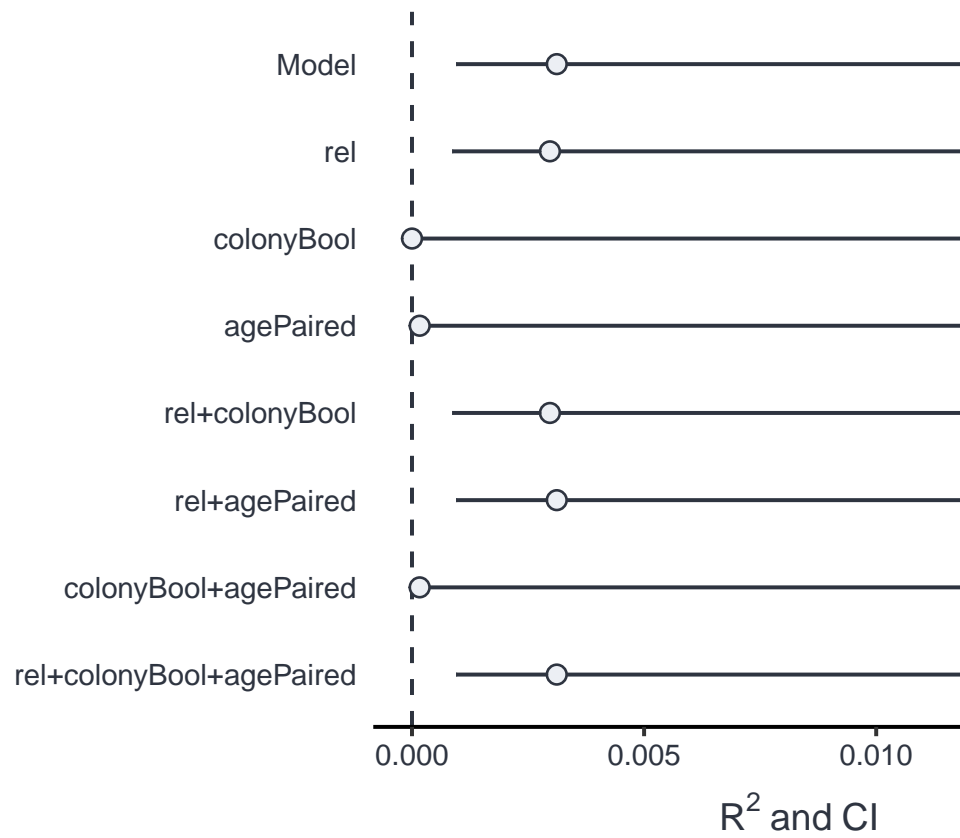
select best

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: ufrac ~ (1 | pairID1) + (1 | pairID2) + (1 | familyBool)
## Data: model_rel.df
##
## REML criterion at convergence: -674
##
## Scaled residuals:
##      Min       1Q       Median       3Q      Max
## -4.485507072 -0.371589025  0.270089938  0.677691079  2.138879974
##
## Random effects:
## Groups      Name      Variance  Std.Dev.
## pairID1     (Intercept) 0.00218749622 0.0467706769
## pairID2     (Intercept) 0.00115356500 0.0339641723
## familyBool  (Intercept) 0.02938341728 0.1714159190
## Residual    0.03556353542 0.1885829669
## Number of obs: 1540, groups: pairID1, 55; pairID2, 55; familyBool, 2
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept) 0.682529592 0.123310856 1.004398662 5.53503  0.11302
```

```
r2_gen_m <- partR2(gen_m, partvars = c("rel", "colonyBool", "agePaired"),
  nboot = 100, CI = 0.95)
```

Calculate effect size by partR2

```
forestplot(r2_gen_m, type = "R2", line_size = 0.7, text_size = 14, point_size = 3)
```



Visualize effect sizes of fixed effects

```
r2_gen_m
```

```
##
##
## R2 (marginal) and 95% CI for the full model:
## R2      CI_lower CI_upper nboot ndf
## 0.0031 0.001    0.0167   100   5
##
## -----
##
## Part (semi-partial) R2:
## Predictor(s)      R2      CI_lower CI_upper nboot ndf
## Model              0.0031 1e-03    0.0167   100   5
## rel                 0.0030 9e-04    0.0165   100   4
## colonyBool          0.0000 0e+00    0.0125   100   4
## agePaired           0.0002 0e+00    0.0127   100   3
## rel+colonyBool      0.0030 9e-04    0.0165   100   3
## rel+agePaired       0.0031 1e-03    0.0167   100   2
```



```
## colonyBool+agePaired      0.0002 0e+00    0.0127   100    2
## rel+colonyBool+agePaired 0.0031 1e-03    0.0167   100    1
```

PERMANOVA for individual genotypes and alleles respectively

Create workable dataframe

```
# create data frame containing of:
# individual substance count for every animal
# an animals individual genotype, represented by 0 and 1 for a given number
# of alleles (here ranging from 1 to 19)
idv_allele <- t(phylo_mat) %>%
  # coerce to data.frame
  as.data.frame() %>%
  # combine individual compound number with mhc genotype
  cbind(., compound_n) %>%
  # rename columns
  `colnames<-`(c(paste0("a",1:19), "compound_n"))
```

Run PERMANOVA on each allele

```
# run permanova to associate individual alleles to compound complexity
allele_permanova <-
  vegan::adonis2(compound_n ~ a1 + a2 + a3 + a4 + a5 + a6 + a7 + a8 + a9 + a10 +
    a11 + a12 + a13 + a14 + a15 + a16 + a17 + a18 + a19,
    data = idv_allele)
# View results
allele_permanova
```

```
## Permutation test for adonis under reduced model
```

```
## Terms added sequentially (first to last)
```

```
## Permutation: free
```

```
## Number of permutations: 999
```

```
##
```

```
## vegan::adonis2(formula = compound_n ~ a1 + a2 + a3 + a4 + a5 + a6 + a7 + a8 + a9 + a10 + a11 + a12 +
```

```
##      Df      SumOfSqs      R2      F Pr(>F)
```

```
## a1      1 0.0151593876 0.0084655024 0.46315 0.543
```

```
## a2      1 0.0096098366 0.0053664500 0.29360 0.645
```

```
## a3      1 0.0069896633 0.0039032587 0.21355 0.748
```

```
## a4      1 0.0378931425 0.0211607815 1.15771 0.274
```

```
## a5      1 0.0026201425 0.0014631741 0.08005 0.883
```

```
## a6      1 0.0442421031 0.0247062507 1.35169 0.255
```

```
## a7      1 0.0221723994 0.0123817997 0.67741 0.421
```

```
## a8      1 0.0564621645 0.0315303363 1.72503 0.180
```

```
## a9      1 0.0022475191 0.0012550888 0.06867 0.904
```

```
## a10     1 0.0239470526 0.0133728246 0.73163 0.382
```

```
## a11     1 0.0201670701 0.0112619576 0.61615 0.462
```

```
## a12     1 0.0751690749 0.0419768926 2.29657 0.130
```

```
## a13     1 0.0171102090 0.0095549055 0.52275 0.499
```

```
## a14     1 0.0578941065 0.0323299800 1.76878 0.191
```

```
## a15     1 0.1338806176 0.0747633560 4.09033 0.035 *
```

```
## a16     1 0.0026532032 0.0014816363 0.08106 0.866
```

```
## a17     1 0.0129836481 0.0072504976 0.39668 0.570
```

```
## a18     1 0.0591946266 0.0330562334 1.80852 0.195
```

```
## a19     1 0.0120118860 0.0067078336 0.36699 0.584
```

```
## Residual 36 1.1783172402 0.6580112405
```

```
## Total      55 1.7907250935 1.0000000000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# give out p-values for each individual allele
pvals <- allele_permanova[1:19,5]

# correct p-values by fdr
pvals_corrected <- p.adjust(pvals, method = "fdr") %>% as.data.frame()
pvals_corrected
```

```
##
## 1  0.792571428571
## 2  0.817000000000
## 3  0.888250000000
## 4  0.743714285714
## 5  0.904000000000
## 6  0.743714285714
## 7  0.792571428571
## 8  0.741000000000
## 9  0.904000000000
## 10 0.792571428571
## 11 0.792571428571
## 12 0.741000000000
## 13 0.792571428571
## 14 0.741000000000
## 15 0.665000000000
## 16 0.904000000000
## 17 0.792571428571
## 18 0.741000000000
## 19 0.792571428571
```

PERMANOVA for associated odour nmbs profiles with genotypes

```
# combine individuals alleles for each individual to genotype in same dataframe
het_table %<>% mutate(gtype = as.factor(paste0(a1, "/", a2)))

vegan::adonis2(scent ~ het_table$gtype)
```

```
## Permutation test for adonis under reduced model
## Terms added sequentially (first to last)
## Permutation: free
## Number of permutations: 999
##
## vegan::adonis2(formula = scent ~ het_table$gtype)
##              Df      SumOfSqs      R2      F Pr(>F)
## het_table$gtype 36  8.803613197 0.6710248615 1.07653  0.175
## Residual        19  4.316039594 0.3289751385
## Total           55 13.119652790 1.0000000000

scent_nmbs %<>% cbind(., gtype = as.factor(het_table$gtype))
```

Plot PERMANOVA results

```
# create color palette for the plot
clr <- c("#D55E00", "#0000ff", "#56B4E9", "#009E73", "#000000", "#CC79A7", "#a4805c",
        "turquoise", "#ed0c2e", "#8000ff", "#ffb700", "#ffff00", "#0a0c2e", "#db5e71")
```

```

# assign pch values for plotting
shp <- c(17, 15, 16, 18)

color_shape_pairs <- crossing(clr,shp)

shape_pair_df <- data.frame(fam = levels(scent_nmds$gtype),
                           color_shape_pairs[1:length(levels(scent_nmds$gtype)),])

cross_ref <- match(scent_nmds$gtype, shape_pair_df$fam)

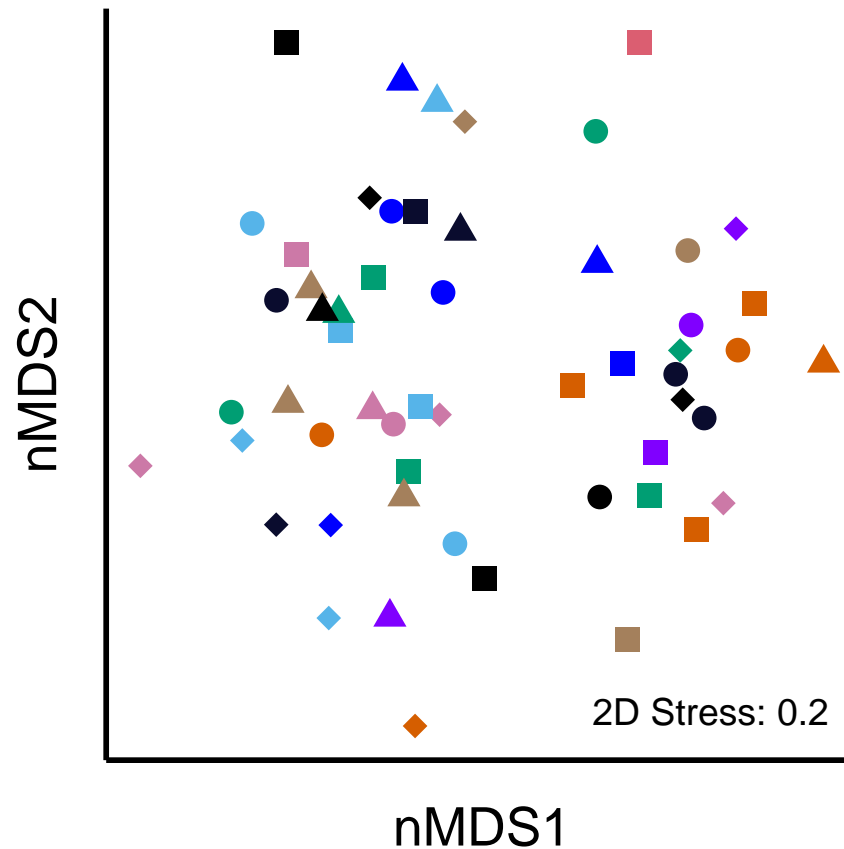
shape_pair_df %<>% .[cross_ref,]

scent_nmds %<>% cbind(.,
                    shape_pair_df[,2:3])

scent_nmds %<>% mutate(across(clr:shp, as.factor))

ggplot(data = scent_nmds,aes(MDS1,MDS2, color = clr, shape = shp)) +
  geom_point(size = 4) +
  scale_shape_manual(values = as.numeric(levels(scent_nmds$shp))) +
  theme_void() +
  scale_color_manual(values = levels(as.factor(scent_nmds$clr))) +
  annotate("text", x = 0.48, y = -0.75, label = "2D Stress: 0.2", size = 5) +
  scale_x_continuous(name = "nMDS1") +
  scale_y_continuous(name = "nMDS2") +
  custom_theme +
  theme(
    legend.position = "none",
    axis.ticks = element_blank(),
    axis.text = element_blank()
  )

```



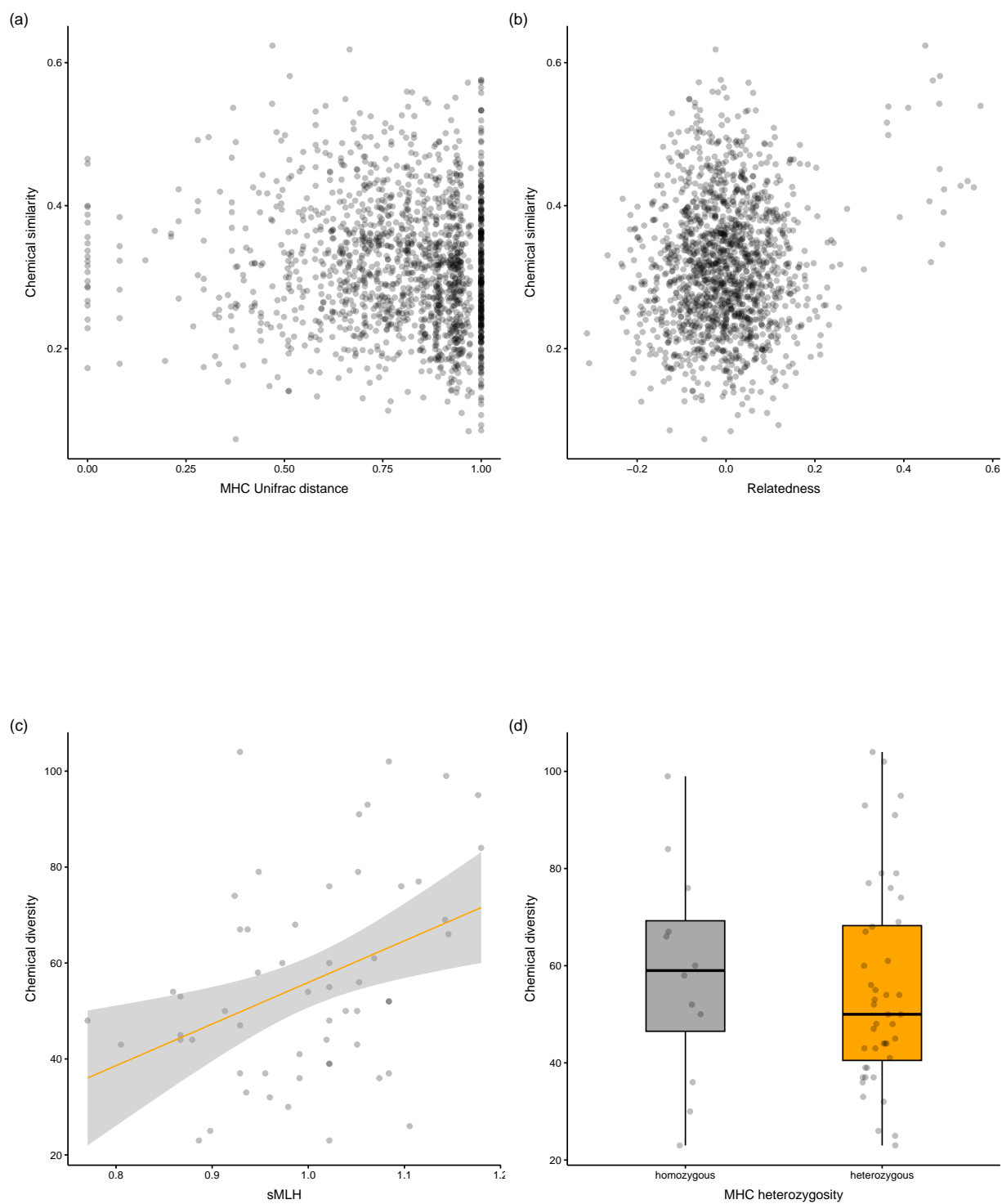
```
# save output
ggsave(filename = "figures/supplementary_figure1.png",
        width = 32, height = 16,
        units = "cm", dpi = 400)
```

Create manuscript panel figure

```
# tag is according to final manuscript structure
panel1.a <- panel1.a + labs(tag = "(a)")
panel1.b <- panel1.b + labs(tag = "(b)")
panel2.b <- panel2.b + labs(tag = "(c)")
panel2.a <- panel2.a + labs(tag = "(d)")

# arrange figures in 2x2 grid and align horizontally and vertically
panel_final <- ggpubr::ggarrange(panel1.a, panel1.b,
                                panel2.b, panel2.a,
                                nrow = 2, ncol = 2, align = "hv")

## `geom_smooth()` using formula = 'y ~ x'
# print
panel_final
```



```
# save high resolution
ggsave(filename = "figures/figure2.png",
        panel_final, dpi = 400,
        width = 33.97, height = 31.04,
        units = "cm",
        bg = "white"
)
```

Repeat for best subset by SIMPER analysis

```
# simper analysis
min_range <- 12
max_range <- 42
scent_range <- scent[,as.numeric(colnames(scent)) >= min_range & as.numeric(colnames(scent)) <= max_range]

simp_colony <- vegan::simper(scent_range, meta$colony)

# getting best substances and their contribution to colony dissimilarity

# set numbers of best compounds to retain
keep_compounds <- 15

simp_colony_names <- summary(simp_colony, ordered = T)[[1]] %>%
  rownames(.) %>%
  .[1:keep_compounds]

contribution <- summary(simp_colony, ordered = TRUE)[[1]] %>%
  .$average %>%
  .[1:keep_compounds]

# indices of colony substances (58,62,68,74,86,89,90,98,106,107,110,164,181,189,211)
ind_col <- which(names(scent) %in% simp_colony_names)
# connect to data frame and compute contribution in percent
col_simp <- data.frame(comp = simp_colony_names, contrib = contribution*100, stringsAsFactors = FALSE)
col_simp
```

```
##           comp      contrib
## 1 15.4498717948718 3.05575894307
## 2 19.7148780487805 2.48839019949
## 3 19.5174358974359 2.37671240496
## 4 16.3895238095238 2.30226998568
## 5 26.7808450704225 2.27321897210
## 6 21.3982051282051 2.06493210540
## 7          21.34 1.87869623710
## 8 30.7885294117647 1.51069283280
## 9 37.5734782608696 1.49482594047
## 10 38.4982142857143 1.47661837144
## 11 17.4137142857143 1.38914137040
## 12 20.509347826087 1.35687404025
## 13 15.5008108108108 1.27741681524
## 14          38.5256 1.23455984162
## 15 19.6568571428571 1.21537246870
```

```
print(
  paste0(
    "Subset of ", keep_compounds, " chemicals accounts for ", round(sum(col_simp$contrib), digits = 2),
    "% of colony similarity"))
```

```
## [1] "Subset of 15 chemicals accounts for 27.4% of colony similarity"
```

cumulative contribution plot

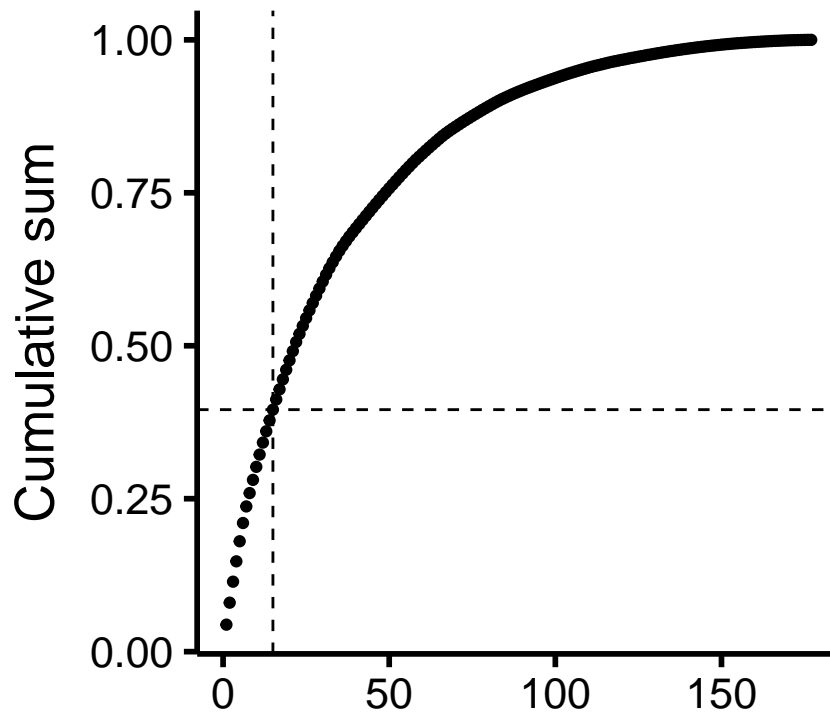
```
# contribution that's already ordered for cumulative sum of best contributing
contribution_cusum <- simp_colony$FWB_SSB$cusum %>% as.vector()

max_on_15 <- contribution_cusum[15]

plot_simper_cusum_df <- data.frame(cusum = contribution_cusum,
                                   pos = 1:length(contribution_cusum))

plot_simper_cusum <- ggplot(data = plot_simper_cusum_df,
                           aes(x = pos,
                               y = cusum)) +

  geom_point() +
  geom_vline(xintercept = 15, linetype = "dashed") +
  geom_hline(yintercept = max_on_15, linetype = "dashed") +
  labs(x = "\nSubstances in SIMPER",
       y = "Cumulative sum") +
  custom_theme
plot_simper_cusum
```



Substances in SIMPER

```
ggsave("figures/supplementary_figure2.png", dpi = 400,
       plot = plot_simper_cusum)
```

```
## Saving 6.5 x 4.5 in image
```

```
adjust scent matrix, include only 15 most explanatory compounds
```

```
scent_simper <- scent[, ind_col]
```

```
## keep order of rows consistent
```

```
scent <- scent[match(rownames(peak_factors), rownames(scent)),]
```

```
## NMDS using Bray-Curtis dissimilarities
```

```
scent_nmds_simper.obj <- vegan::metaMDS(comm = scent, distance = "bray")
```

```
## Run 0 stress 0.237312208882
```

```
## Run 1 stress 0.265264584858
```

```
## Run 2 stress 0.237259771339
```

```
## ... New best solution
```

```
## ... Procrustes: rmse 0.00455459699277 max resid 0.0175743807085
```

```
## Run 3 stress 0.23724653326
```

```
## ... New best solution
```

```
## ... Procrustes: rmse 0.00329465441673 max resid 0.0184418499811
```

```
## Run 4 stress 0.237312208063
```

```
## ... Procrustes: rmse 0.0032871656428 max resid 0.0177210836637
```

```
## Run 5 stress 0.272455802099
```

```
## Run 6 stress 0.237259771282
```



```
## ... Procrustes: rmse 0.00329460147083 max resid 0.0184563298893
## Run 7 stress 0.247185188618
## Run 8 stress 0.260803509876
## Run 9 stress 0.237246533347
## ... Procrustes: rmse 3.40524953281e-06 max resid 2.11006052797e-05
## ... Similar to previous best
## Run 10 stress 0.237312208561
## ... Procrustes: rmse 0.00328712544992 max resid 0.017719791264
## Run 11 stress 0.237319083569
## ... Procrustes: rmse 0.00470931669268 max resid 0.0192677607849
## Run 12 stress 0.237259787024
## ... Procrustes: rmse 0.00329486087486 max resid 0.018451660086
## Run 13 stress 0.272821623191
## Run 14 stress 0.237246533289
## ... Procrustes: rmse 2.38427808995e-06 max resid 8.68711840498e-06
## ... Similar to previous best
## Run 15 stress 0.261703636107
## Run 16 stress 0.257209600538
## Run 17 stress 0.237246533433
## ... Procrustes: rmse 4.27976217777e-06 max resid 1.65355319758e-05
## ... Similar to previous best
## Run 18 stress 0.292412991286
## Run 19 stress 0.268877071645
## Run 20 stress 0.247186205737
## *** Best solution repeated 3 times

## get x and y coordinates
scent_nmds_simper <- as.data.frame(scent_nmds.obj[["points"]]) %>%
## add the colony as a factor to each sample
cbind(.,colony = peak_factors[["colony"]])
```

Create vectorized distance measurements for scent data

```
# bray-curtis distance measurement on scent profiles
scent_dist_simper <- vegdist(scent_simper) %>% as.matrix()
scent_dist_simper[upper.tri(scent_dist_simper, diag = T)] <- NA
b_simper <- scent_dist_simper %>% as.vector() %>% na.omit()
```

Repeat chemical similarity models with best chemicals subset

```
model_rel.df %<>% cbind(., scent_simper_mds = b_simper)

# mhc
z1 <- lmerTest::lmer(scent_simper_mds ~ ufrac + colonyBool + agePaired + (1|familyBool) +
  (1|pairID1) + (1|pairID2),
  data = model_rel.df)

# relatedness
z2 <- lmerTest::lmer(scent_simper_mds ~ rel + colonyBool + agePaired + (1|familyBool) + (1|pairID1) +
  (1|pairID2),
  data = model_rel.df)

# mhc & relatedness
z3 <- lmerTest::lmer(scent_simper_mds ~ rel + ufrac + colonyBool + agePaired + (1|familyBool) +
  (1|pairID1) + (1|pairID2),
  data = model_rel.df)
```

```

# no genetic effect
z4 <- lmerTest::lmer(scent_simper_mds ~ colonyBool + agePaired + (1|familyBool) + (1|pairID1) +
                    (1|pairID2),
                    data = model_rel.df)

# compare model performance scores
compare_performance(z1, z2, z3, z4, rank = T) %>%
  arrange(Name)

## # Comparison of Model Performance Indices
##
## Name | Model | R2 (cond.) | R2 (marg.) | ICC | RMSE | Sigma | AIC weights | AICc weights
## -----
## z1 | lmerModLmerTest | 0.670 | 0.350 | 0.493 | 0.096 | 0.099 | 0.157 | 0.15
## z2 | lmerModLmerTest | 0.658 | 0.365 | 0.461 | 0.096 | 0.099 | 0.304 | 0.30
## z3 | lmerModLmerTest | 0.658 | 0.365 | 0.462 | 0.096 | 0.099 | 0.113 | 0.11
## z4 | lmerModLmerTest | 0.670 | 0.351 | 0.492 | 0.096 | 0.099 | 0.426 | 0.43

summary(z2)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: scent_simper_mds ~ rel + colonyBool + agePaired + (1 | familyBool) +
## (1 | pairID1) + (1 | pairID2)
## Data: model_rel.df
##
## REML criterion at convergence: -2489.9
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -3.361727005 -0.601762806 0.044879466 0.656512064 4.481398163
##
## Random effects:
## Groups Name Variance Std.Dev.
## pairID2 (Intercept) 0.00371962719 0.0609887464
## pairID1 (Intercept) 0.00222537088 0.0471738368
## familyBool (Intercept) 0.00248148577 0.0498145136
## Residual 0.00985985813 0.0992968183
## Number of obs: 1540, groups: pairID2, 55; pairID1, 55; familyBool, 2
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) 0.5656545688 0.0416705362 1.4157079114 13.57445 0.018025
## rel -0.0339705052 0.0329143620 473.1835094380 -1.03209 0.302558
## colonyBool1 -0.2041643091 0.0118146357 112.2879453844 -17.28063 < 2e-16
## agePairedM/P -0.0165814738 0.0119597238 128.9256179904 -1.38644 0.168005
## agePairedP/P -0.0317056901 0.0224867649 99.4223955740 -1.40997 0.161669
##
## (Intercept) *
## rel
## colonyBool1 ***
## agePairedM/P
## agePairedP/P
## ---

```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) rel      clnyB1 agPM/P
## rel      -0.149
## colonyBool1 -0.256  0.016
## agePairedM/P -0.250 -0.024 -0.002
## agePairedP/P -0.237 -0.009 -0.003  0.900
summary(z4)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: scent_simper_mds ~ colonyBool + agePaired + (1 | familyBool) +
##          (1 | pairID1) + (1 | pairID2)
## Data: model_rel.df
##
## REML criterion at convergence: -2493.8
##
## Scaled residuals:
##          Min           1Q           Median           3Q           Max
## -3.369275911 -0.607272157  0.045559137  0.657635847  4.508880002
##
## Random effects:
## Groups      Name      Variance      Std.Dev.
## pairID2      (Intercept) 0.00373524835 0.0611166781
## pairID1      (Intercept) 0.00223267976 0.0472512409
## familyBool   (Intercept) 0.00356932632 0.0597438392
## Residual                0.00985536801 0.0992742062
## Number of obs: 1540, groups: pairID2, 55; pairID1, 55; familyBool, 2
##
## Fixed effects:
##              Estimate      Std. Error      df    t value Pr(>|t|)
## (Intercept)  0.5579296640  0.0474009636  1.3493551125  11.77043 0.025259
## colonyBool1  -0.2038667903  0.0118300291 112.1681349190 -17.23299 < 2e-16
## agePairedM/P -0.0167874180  0.0119726612 128.7456942475  -1.40215 0.163278
## agePairedP/P -0.0318598080  0.0225198624  99.4410644101  -1.41474 0.160268
##
## (Intercept) *
## colonyBool1 ***
## agePairedM/P
## agePairedP/P
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) clnyB1 agPM/P
## colonyBool1 -0.224
## agePairedM/P -0.224 -0.001
## agePairedP/P -0.210 -0.003  0.900

# if interested
# check model performance by
# check_model(z2)
#

```

Repeat analyses for moms only

empty workspace to repeat analyses for moms

```
rm(list=ls())
```

Subset scent data to correlate same individuals

```
## read in meta data
meta <- read.table(file = "data/arga_metadata.txt", sep = "\t") %>%
  `colnames<-`(unlist(.[,1])) %>%
  .[-1,] %>%
  # subset for only moms
  filter(., maturity == "M")

## normalise area and return a data frame
scent <- norm_peaks(aligned_peak_data,
                    conc_col_name = "area",
                    rt_col_name = "time",
                    out = "data.frame")

## common transformation for abundance data to reduce the extent of mean-variance trends
scent <- log(scent + 1)

n_scent <- rownames(scent)

keep_i <- match(meta$id, n_scent)

scent %<>%
  .[keep_i, ] %>%
  `rownames<-`(meta$real_id)

## NMDS with reduced data
## GCalignR contains factors for the chemical dataset
data("peak_factors")
peak_factors <- peak_factors[match(meta$id, rownames(peak_factors)),] %>%
  `rownames<-`(meta$real_id)

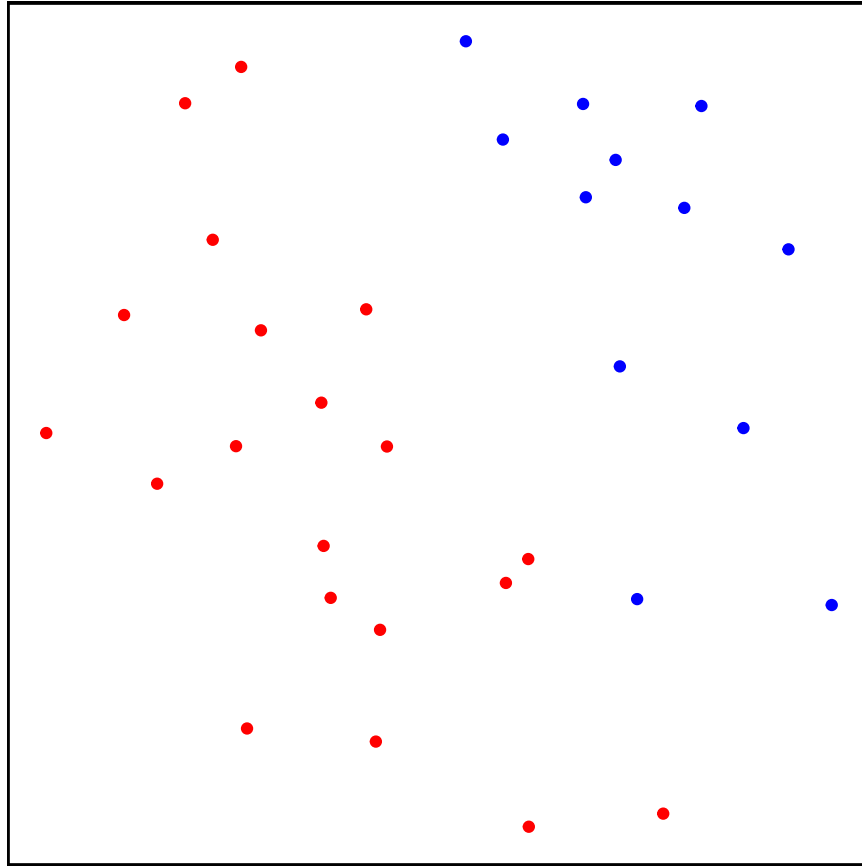
## keep order of rows consistent
scent <- scent[match(rownames(peak_factors), rownames(scent)),]
## NMDS using Bray-Curtis dissimilarities
scent_nmds.obj <- vegan::metaMDS(comm = scent, distance = "bray")

## Run 0 stress 0.236250449583
## Run 1 stress 0.273896000443
## Run 2 stress 0.236250429503
## ... New best solution
## ... Procrustes: rmse 5.1038556819e-05 max resid 0.000244449699983
## ... Similar to previous best
## Run 3 stress 0.26439479565
## Run 4 stress 0.235715137028
## ... New best solution
```

```
## ... Procrustes: rmse 0.0604219246538 max resid 0.209409276007
## Run 5 stress 0.273397308431
## Run 6 stress 0.277291055707
## Run 7 stress 0.269029016895
## Run 8 stress 0.254929173724
## Run 9 stress 0.234377760291
## ... New best solution
## ... Procrustes: rmse 0.020029646673 max resid 0.0770581727136
## Run 10 stress 0.234560649699
## ... Procrustes: rmse 0.0769586220157 max resid 0.336866947374
## Run 11 stress 0.234397995757
## ... Procrustes: rmse 0.0831069979267 max resid 0.341319618348
## Run 12 stress 0.234290238615
## ... New best solution
## ... Procrustes: rmse 0.00830399067539 max resid 0.0364622872984
## Run 13 stress 0.233612593051
## ... New best solution
## ... Procrustes: rmse 0.0796424569836 max resid 0.314081677123
## Run 14 stress 0.23361259392
## ... Procrustes: rmse 7.57242802129e-06 max resid 2.80427885109e-05
## ... Similar to previous best
## Run 15 stress 0.23694577347
## Run 16 stress 0.23361259285
## ... New best solution
## ... Procrustes: rmse 1.22898278309e-05 max resid 3.99724237402e-05
## ... Similar to previous best
## Run 17 stress 0.235605100621
## Run 18 stress 0.254928644085
## Run 19 stress 0.233785519159
## ... Procrustes: rmse 0.00876323931581 max resid 0.0371269987634
## Run 20 stress 0.25744705675
## *** Best solution repeated 1 times
```

```
## get x and y coordinates
scent_nmds <- as.data.frame(scent_nmds.obj[["points"]])
## add the colony as a factor to each sample
scent_nmds <- cbind(scent_nmds,colony = peak_factors[["colony"]])
## quick plotting
ggplot(data = scent_nmds,aes(MDS1,MDS2,color = colony)) +
  geom_point() +
  theme_void() +
  scale_color_manual(values = c("blue","red")) +
  theme(panel.background = element_rect(colour = "black",
                                         size = 1,
                                         fill = NA),
        aspect.ratio = 1,
        legend.position = "none")
```

```
## Warning: The `size` argument of `element_rect()` is deprecated as of ggplot2 3.4.0.
## i Please use the `linewidth` argument instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```



Calculate MHC heterozygosity relatedness between individuals

```
## read in mhc genotype data
mhc_het_dat <- read.table("data/clone_mhc_het.txt")
## restructure `mhc_het_dat` to fit `Demerelate()::inputdata`
## id and colony as factors; alleles as integers or numeric
## otherwise `rxy` cannot handle computations
mhc_het_dat %<>%
  rownames_to_column(., var = "id") %>%
  # mutate(., a1 = str_pad(a1, 2, pad = "0")) %>%
  # mutate(., a2 = str_pad(a2, 2, pad = "0")) %>%
  mutate(., colony = as.factor(rep("col", 56))) %>%
  mutate(., id = as.factor(id)) %>%
  .[, -4] %>%
  relocate(., colony, .before = a1)
## order mhc_het_dat$id after meta$real_id
## so data is consistently ordered same in all data.frames

## get matching indeces
id_index <- match(meta$real_id, mhc_het_dat$id)
## sort correspondingly
mhc_het_dat %<>% .[id_index,]

## calculate relatedness after Queller & Goodnight
mhc_relatedness_res <- Demerelate(inputdata = mhc_het_dat,
```

```

value = "rxy",
object = T,
NA.rm = F,
Fis = F)

```

```

## Warning in Demerelate(inputdata = mhc_het_dat, value = "rxy", object = T, : Careful, bi-allelic markers
##   Especially, rxy and ritland estimator are not defined when bi-allelic estimates are used with alle
##   You should consider removing bi-allelics which tend to have very evenly distributed alleles or swi
##   Be careful even if allele frequencies are not perfectly 0.5, during randomizations problems may oc

```

```

mhc_relatedness <- unlist(mhc_relatedness_res$Empirical_Relatedness)

```

```

## fill distant matrix / make sure that it follows same systematics as previous distance matrices
## create empty matrix with equal rows and cols similar to sample size of individuals
relate_mat_mhc <- matrix(nrow = dim(mhc_het_dat)[1],
                        ncol = dim(mhc_het_dat)[1])
## fill distance matrix row wise, thus fill upper.tri
relate_mat_mhc[upper.tri(relate_mat_mhc)] <- mhc_relatedness
## transpose to keep consistency with other distance matrices
relate_mat_mhc <- t(relate_mat_mhc)
relate_mat_mhc %<>% `colnames<-`(meta$real_id) %>% `rownames<-`(meta$real_id)

## vectorize again to identify whether relatedness pairs were consistent in the first place
a <- relate_mat_mhc %>% as.vector() %>% na.omit()

```

Create vectorized distance measurements for scent data

```

# bray-curtis distance measurement on scent profiles
scent_dist <- vegdist(scent) %>% as.matrix()
scent_dist[upper.tri(scent_dist, diag = T)] <- NA
b <- scent_dist %>% as.vector() %>% na.omit()

```

Generate UniFrac distances from MHC DQB II individual genotypes

```

# handle genotypes as otu table
phylo_mat <- read.table("data/phyloseq-mat.txt") %>%
  as.matrix()

# make sample names consistent
n <- match(meta$real_id, colnames(phylo_mat))

phylo_mat %<>% .[, n] %>%
  otu_table(., taxa_are_rows = T)

# create phylogenetic tree from file
phylo_tree <- ape::read.tree("data/unifrac_tree_p.nwk")

# merge into Formal class phyloseq
arga_phyloseq <- merge_phyloseq(phylo_mat, phylo_tree)

# create UniFrac as genetic diversity measurement for single locus data
mhc_dqb2_ufrac <- UniFrac(arga_phyloseq, weighted = F) %>%
  # distances to distance matrix
  as.matrix()

```

```
# vectorize distances matrices
mhc_dqb2_ufrac[upper.tri(mhc_dqb2_ufrac, diag = T)] <- NA
c <- mhc_dqb2_ufrac %>% as.vector() %>% na.omit()
```

Calculate microsatellite relatedness values

create data.frame in correspondence to Demerelate input format

```
# read in genotype data table
msats_df <- read.table("data/msats_genotypes_inbreedR.txt", sep = "\t")

# update data.frame with additional info
# "delete" colony info, otherwise relatedness is only calculated for individuals
# within their own colonies -> no complete pairwise comparison
msats_df <- cbind(id = as.factor(rownames(msats_df)),
                  # colony = meta$colony,
                  colony = rep("col", 56),
                  msats_df[1:56,]) %>%

# clear df from rownames/ only keep colnames/ variable names
`rownames<-`(NULL)

msats_df[is.na(msats_df)] = 0

str(msats_df)

# write.table(msats_df, file = "data/msats_genotypes_demerelate.txt",
#           sep = "\t",
#           row.names = F)

msats_df %<>% .[match(meta$real_id, .$id),]
```

Calculate relatedness of individuals based on Queller & Goodnight

```
relatedness_results <- Demerelate(inputdata = msats_df,
                                  value = "rxy",
                                  object = T,
                                  NA.rm = F,
                                  Fis = F)
```

```
## Warning in Demerelate(inputdata = msats_df, value = "rxy", object = T, NA.rm = F, : Careful, bi-allelic
##   Especially, rxy and ritland estimator are not defined when bi-allelic estimates are used with allelic
##   You should consider removing bi-allelics which tend to have very evenly distributed alleles or swi
##   Be careful even if allele frequencies are not perfectly 0.5, during randomizations problems may oc

## Warning in prop.test(c(emp, non), c(sum(table(empirical.list))),
## sum(table(related.non.X.mean))), : Chi-Quadrat-Approximation kann inkorrekt sein
```

Coerce output to a vector

```
relatedness <- unlist(relatedness_results$Empirical_Relatedness)

## fill distant matrix / make sure that it follows same systematics as previous distance matrices
## create empty matrix with equal rows and cols similar to sample size of individuals
```



```

relate_mat <- matrix(nrow = dim(msats_df)[1],
                    ncol = dim(msats_df)[1])
## fill distance matrix row wise, thus fill upper.tri
relate_mat[upper.tri(relate_mat)] <- relatedness
## transpose to keep consistency with other distance matrices
relate_mat <- t(relate_mat)
relate_mat %<>% `colnames<-`(meta$real_id) %>% `rownames<-`(meta$real_id)

## vectorize again to identify whether relatedness pairs were consistent in the first place
d <- relate_mat %>% as.vector() %>% na.omit()

```

Analyse Odour and genetic association by MHC DQB II and neutral genomic background

Create data.frame to plot in ggplot2

```

## substitute once tested correctly
## scent_mds shall contain similarity values but `b` contains
## dissimilarity values based on Bray-Curtis -> substracting
## dissimilarities from 1 returns similarities

model_rel.df <- cbind(mhc_rel = a, scent_mds = 1-b, ufrac = c, rel = d) %>% as.data.frame()

```

Custom theme to make plot aesthetics consistent

```

# custom theme to ease figure creation
custom_theme <- ggplot2::theme_classic(base_size = 16,
                                       base_line_size = 1,
                                       base_rect_size = 1) +

ggplot2::theme(
  # plot.margin = unit(c(5.5, 8.5, 5.5, 5.5), "pt"), #c(top, right, bottom, left)
  plot.margin = margin(5.5,6.5,5.5,5.5, "pt"),
  panel.grid = element_blank(),
  axis.text = element_text(color = "black"),
  axis.ticks = element_line(color = "black"),
  aspect.ratio = 1
)

```

Model odour relationship on MHC and neutral genetic background

Pool underlying data dependencies

Create a function that generates pairwise variables in a systematic matter for pairwise comparisons

```

create_pair_vars <-function(row_cross, col_cross, split_vars = F){
  require(stringr)

  rc <- row_cross
  cc <- col_cross

  # create empty matrix
  # keep row and col names from existing distance matrices

  empty_mat <- matrix(nrow = length(rc),

```

```

        ncol = length(cc)) %>%
`colnames<-`(cc) %>%
`rownames<-`(rc)

# fill each matrix i,j-th cell with the crossing from their corresponding
# i-th rowname and j-th colname
for (i in 1:dim(empty_mat)[1]) {
  for (j in 1:dim(empty_mat)[2]) {

    empty_mat[i,j] <- paste0(rc[i], "/", cc[j])

  } # end j
} # end i

# delete `upper.tri()` of `empty_mat` to resemble structure of the other
# distance matrices in use

empty_mat[upper.tri(empty_mat, diag = T)] <- NA
pair_vars <- empty_mat %>% as.vector() %>% na.omit()

# split `pair_vars` if needed
if (split_vars == T) {

  pair_vars1 <- sapply(pair_vars,
    function(x){
      str_split(x, pattern = "/")[1][1]
    })

  pair_vars2 <- sapply(pair_vars,
    function(x){
      str_split(x, pattern = "/")[1][2]
    })

  pair_vars_split <- list(pair_variable1 = pair_vars1,
    pair_variable2 = pair_vars2)

  return(pair_vars_split)

} else {
  return(pair_vars)
}

} #end create_pair_vars

```

Helper function to combine double entries

```

## for x, overwrite specified replacer with specified value
f <- function(x, replacer, overwrite){
  if (x == replacer) {
    x <- overwrite
  } else {
    x <- x
  }
}

```

```
}
```

Transform model variables

```
agePaired <- create_pair_vars(row_cross = meta$maturity,
                              col_cross = meta$maturity) %>%
  sapply(., f, "P/M", "M/P")

colonyPaired <- create_pair_vars(row_cross = meta$colony,
                                 col_cross = meta$colony) %>%
  sapply(., f, "FWB/SSB", "SSB/FWB")

colonyID1 <- create_pair_vars(row_cross = meta$colony,
                              col_cross = meta$colony,
                              split_vars = T)[1] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

colonyID2 <- create_pair_vars(row_cross = meta$colony,
                              col_cross = meta$colony,
                              split_vars = T)[2] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

colonyBool <- ifelse(colonyID1 == colonyID2, 1, 0)

familyPaired <- create_pair_vars(row_cross = meta$family,
                                 col_cross = meta$family)

familyID1 <- create_pair_vars(row_cross = meta$family,
                              col_cross = meta$family,
                              split_vars = T)[1] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

familyID2 <- create_pair_vars(row_cross = meta$family,
                              col_cross = meta$family,
                              split_vars = T)[2] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

pairID1 <- create_pair_vars(row_cross = meta$real_id,
                            col_cross = meta$real_id,
                            split_vars = T)[1] %>%
  unlist() %>%
  as.vector()

pairID2 <- create_pair_vars(row_cross = meta$real_id,
                            col_cross = meta$real_id,
                            split_vars = T)[2] %>%
```

```

unlist() %>%
as.vector()

familyBool <- ifelse(familyID1 == familyID2, 1, 0)

```

Update data.frame with model variables

```

model_rel.df <- data.frame(model_rel.df,
  agePaired = as.factor(agePaired),
  colonyPaired = as.factor(colonyPaired),
  colonyBool = as.factor(colonyBool),
  familyPaired = as.factor(familyPaired),
  familyID1 = as.factor(familyID1),
  familyID2 = as.factor(familyID2),
  familyBool = as.factor(familyBool),
  pairID1 = as.factor(pairID1),
  pairID2 = as.factor(pairID2))

```

update data frame with meta data

Include information about MHC heterozygosity, sMLH from microsatellite data and chemical diversity by number of compounds per individual

```

scent.abs <- ifelse(scent != 0, 1, 0)
compound_n <- apply(scent.abs, 1, sum)

names(compound_n) == meta$real_id

## [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [16] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [31] TRUE TRUE

# read in heterzygosity information
het_table <- read.table("data/arga_mhc_het.txt", sep = "\t")

# keep names consistent
match_het <- match(meta$real_id, rownames(het_table))
het_table %<>% .[match_het,]

# generate sMLH with microsatellite data
# table is pre-prepped, thus rows correspond to same individuals in meta data
smlh_res <- read.table("data/msats_genotypes_inbreedR.txt", sep = "\t")
smlh_res <- smlh_res[match(meta$real_id, rownames(smlh_res)), ] %>%
  # convert to inbreedR format
  convert_raw() %>%
  # generate sMLH
  sMLH()

meta %<>% cbind(., compound_n = compound_n,
  mhc_het = het_table$het,
  smlh = smlh_res)

meta %<>% mutate(
  real_id = as.factor(real_id),

```

```

colony = as.factor(colony),
maturity = as.factor(maturity),
family = as.factor(family)
)

```

Repeat models for chemical similarity

```

# without age and indicator for family groupings
# as grouping factors must have >1 sampled level

```

```

# mhc
c1 <- lmerTest::lmer(scent_mds ~ ufrac + colonyBool + (1|pairID1) + (1|pairID2),
  data = model_rel.df)

# relatedness
c2 <- lmerTest::lmer(scent_mds ~ rel + colonyBool + (1|pairID1) + (1|pairID2),
  data = model_rel.df)

# mhc & relatedness
c3 <- lmerTest::lmer(scent_mds ~ rel + ufrac + colonyBool + (1|pairID1) + (1|pairID2),
  data = model_rel.df)

# no genetic effect
c4 <- lmerTest::lmer(scent_mds ~ colonyBool + (1|pairID1) + (1|pairID2),
  data = model_rel.df)

```

```

# compare model performance scores
compare_performance(c1, c2, c3, c4, rank = T) %>%
  arrange(Name)

```

```
## # Comparison of Model Performance Indices
```

```
##
## Name | Model | R2 (cond.) | R2 (marg.) | ICC | RMSE | Sigma | AIC weights | AICc weights
## -----|-----|-----|-----|-----|-----|-----|-----|-----
## c1 | lmerModLmerTest | 0.524 | 0.245 | 0.370 | 0.060 | 0.064 | 0.200 | 0.196
## c2 | lmerModLmerTest | 0.524 | 0.245 | 0.370 | 0.060 | 0.064 | 0.196 | 0.196
## c3 | lmerModLmerTest | 0.524 | 0.244 | 0.369 | 0.060 | 0.064 | 0.074 | 0.074
## c4 | lmerModLmerTest | 0.525 | 0.245 | 0.370 | 0.060 | 0.064 | 0.531 | 0.531

```

```
summary(c2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: scent_mds ~ rel + colonyBool + (1 | pairID1) + (1 | pairID2)
## Data: model_rel.df
##
## REML criterion at convergence: -1211.3
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.434739031 -0.668546769 -0.125072431  0.516608517  3.362588564
##
## Random effects:
## Groups Name Variance Std.Dev.
## pairID1 (Intercept) 0.00129394285 0.0359714171
## pairID2 (Intercept) 0.00108030441 0.0328679845

```

```

## Residual          0.00404600916 0.0636082475
## Number of obs: 496, groups: pairID1, 31; pairID2, 31
##
## Fixed effects:
##              Estimate      Std. Error      df    t value    Pr(>|t|)
## (Intercept) 2.64239187e-01 1.31288102e-02 4.08268587e+01 20.12667 < 2.22e-16
## rel         1.70656495e-03 3.59170911e-02 4.83363527e+02 0.04751 0.96212
## colonyBool1 9.11773096e-02 1.13258476e-02 7.04830509e+01 8.05037 1.4125e-11
##
## (Intercept) ***
## rel
## colonyBool1 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) rel
## rel          0.030
## colonyBool1 -0.666 0.045
summary(c4)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: scent_mds ~ colonyBool + (1 | pairID1) + (1 | pairID2)
## Data: model_rel.df
##
## REML criterion at convergence: -1216.1
##
## Scaled residuals:
##              Min           1Q           Median           3Q           Max
## -2.438554364 -0.669736096 -0.127401072  0.518947513  3.362266186
##
## Random effects:
## Groups Name      Variance Std.Dev.
## pairID1 (Intercept) 0.00129455037 0.0359798606
## pairID2 (Intercept) 0.00108126826 0.0328826437
## Residual          0.00403675432 0.0635354572
## Number of obs: 496, groups: pairID1, 31; pairID2, 31
##
## Fixed effects:
##              Estimate      Std. Error      df    t value    Pr(>|t|)
## (Intercept) 0.2642215710 0.0131250678 41.6332801738 20.13106 < 2.22e-16 ***
## colonyBool1 0.0911511887 0.0113126069 71.5115810251 8.05749 1.2502e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr)
## colonyBool1 -0.668

```

Repeat models for chemical diversity

```
# exclude family as random effects (no accounting of same family in different
# individuals)
# exclude age as only one 'age' group being moms is modelled
```

```
d1 <- lm(compound_n ~ mhc_het + colony , data = meta)
```

```
d2 <- lm(compound_n ~ smlh + colony, data = meta)
```

```
d3 <- lm(compound_n ~ mhc_het + smlh + colony, data = meta)
```

```
d4 <- lm(compound_n ~ colony, data = meta)
```

```
compare_performance(d1, d2, d3, d4, rank = T) %>% arrange(Name)
```

```
## # Comparison of Model Performance Indices
```

```
##
```

```
## Name | Model | R2 | R2 (adj.) | RMSE | Sigma | AIC weights | AICc weights | BIC weights | Perf
```

```
## -----
```

```
## d1 | lm | 0.091 | 0.029 | 21.014 | 22.075 | 0.086 | 0.086 | 0.079 |
```

```
## d2 | lm | 0.190 | 0.134 | 19.841 | 20.842 | 0.540 | 0.543 | 0.500 |
```

```
## d3 | lm | 0.191 | 0.104 | 19.831 | 21.200 | 0.202 | 0.134 | 0.090 |
```

```
## d4 | lm | 0.074 | 0.043 | 21.217 | 21.913 | 0.172 | 0.236 | 0.331 |
```

```
summary(d2)
```

```
##
```

```
## Call:
```

```
## lm(formula = compound_n ~ smlh + colony, data = meta)
```

```
##
```

```
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -36.56900864 -15.29316134 -0.55473784  12.51322130  45.43810011
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) -27.91731762  39.51389375 -0.70652 0.485504
```

```
## smlh         80.82602303  39.60992119  2.04055 0.050493 .
```

```
## colonySSB    10.39704337   7.67024625  1.35550 0.185721
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## Residual standard error: 20.8416688 on 29 degrees of freedom
```

```
## Multiple R-squared:  0.189883606,    Adjusted R-squared:  0.13401351
```

```
## F-statistic:  3.3986626 on 2 and 29 DF,  p-value: 0.0471995222
```

Repeat analyses for pups only

Empty Workspace to analyse pups isolated

```
rm(list=ls())
```

Subset scent data to correlate same individuals

```
## read in meta data
meta <- read.table(file = "data/arga_metadata.txt", sep = "\t") %>%
  `colnames<-`(unlist(.[,1])) %>%
  .[-1,] %>%
  # subset for only pups
  filter(., maturity == "P")

## normalise area and return a data frame
scent <- norm_peaks(aligned_peak_data,
  conc_col_name = "area",
  rt_col_name = "time",
  out = "data.frame")

## common transformation for abundance data to reduce the extent of mean-variance trends
scent <- log(scent + 1)

n_scent <- rownames(scent)

keep_i <- match(meta$id, n_scent)

scent %<>%
  .[keep_i, ] %>%
  `rownames<-`(meta$real_id)

## NMDS with reduced data
## GCalignR contains factors for the chemical dataset
data("peak_factors")
peak_factors <- peak_factors[match(meta$id, rownames(peak_factors)),] %>%
  `rownames<-`(meta$real_id)

## keep order of rows consistent
scent <- scent[match(rownames(peak_factors), rownames(scent)),]
## NMDS using Bray-Curtis dissimilarities
scent_nmds.obj <- vegan::metaMDS(comm = scent, distance = "bray")
```

```
## Run 0 stress 0.212491025469
## Run 1 stress 0.257378638662
## Run 2 stress 0.238092493952
## Run 3 stress 0.211374909057
## ... New best solution
## ... Procrustes: rmse 0.0907533352972 max resid 0.287862328273
## Run 4 stress 0.217888945627
## Run 5 stress 0.212862773777
## Run 6 stress 0.216780269732
## Run 7 stress 0.238043625053
## Run 8 stress 0.216780443807
## Run 9 stress 0.218956812636
## Run 10 stress 0.239730576085
## Run 11 stress 0.384094848795
## Run 12 stress 0.236168559556
```

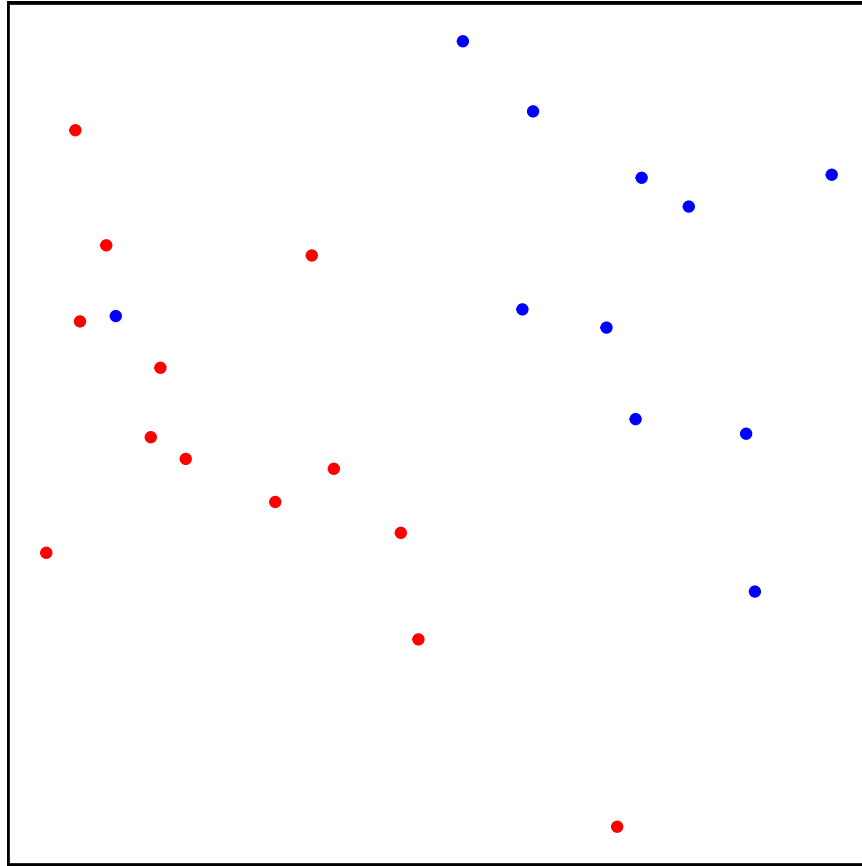


```

## Run 13 stress 0.218956783145
## Run 14 stress 0.218956812431
## Run 15 stress 0.246729269165
## Run 16 stress 0.211477467526
## ... Procrustes: rmse 0.00867756151392  max resid 0.0298711275109
## Run 17 stress 0.211477456022
## ... Procrustes: rmse 0.00866770930371  max resid 0.0298709926633
## Run 18 stress 0.238043604548
## Run 19 stress 0.233549099578
## Run 20 stress 0.211374918481
## ... Procrustes: rmse 5.57321404878e-05  max resid 0.000166639654834
## ... Similar to previous best
## *** Best solution repeated 1 times

## get x and y coordinates
scent_nmds <- as.data.frame(scent_nmds.obj[["points"]])
## add the colony as a factor to each sample
scent_nmds <- cbind(scent_nmds,colony = peak_factors[["colony"]])
## quick plotting
ggplot(data = scent_nmds,aes(MDS1,MDS2,color = colony)) +
  geom_point() +
  theme_void() +
  scale_color_manual(values = c("blue","red")) +
  theme(panel.background = element_rect(colour = "black",
                                         size    = 1,
                                         fill    = NA),
        aspect.ratio    = 1,
        legend.position = "none")

```



Calculate MHC heterozygosity relatedness between individuals

```
## read in mhc genotype data
mhc_het_dat <- read.table("data/clone_mhc_het.txt")
## restructure `mhc_het_dat` to fit `Demerelate()::inputdata`
## id and colony as factors; alleles as integers or numeric
## otherwise `rxy` cannot handle computations
mhc_het_dat %<>%
  rownames_to_column(., var = "id") %>%
  # mutate(., a1 = str_pad(a1, 2, pad = "0")) %>%
  # mutate(., a2 = str_pad(a2, 2, pad = "0")) %>%
  mutate(., colony = as.factor(rep("col", 56))) %>%
  mutate(., id = as.factor(id)) %>%
  .[, -4] %>%
  relocate(., colony, .before = a1)
## order mhc_het_dat$id after meta$real_id
## so data is consistently ordered same in all data.frames

## get matching indeces
id_index <- match(meta$real_id, mhc_het_dat$id)
## sort correspondingly
mhc_het_dat %<>% .[id_index,]

## calculate relatedness after Queller & Goodnight
mhc_relatedness_res <- Demerelate(inputdata = mhc_het_dat,
```

```

value = "rxy",
object = T,
NA.rm = F,
Fis = F)

```

```

## Warning in Demerelate(inputdata = mhc_het_dat, value = "rxy", object = T, : Careful, bi-allelic markers
##   Especially, rxy and ritland estimator are not defined when bi-allelic estimates are used with alle
##   You should consider removing bi-allelics which tend to have very evenly distributed alleles or swi
##   Be careful even if allele frequencies are not perfectly 0.5, during randomizations problems may oc

```

```

mhc_relatedness <- unlist(mhc_relatedness_res$Empirical_Relatedness)

## fill distant matrix / make sure that it follows same systematics as previous distance matrices
## create empty matrix with equal rows and cols similar to sample size of individuals
relate_mat_mhc <- matrix(nrow = dim(mhc_het_dat)[1],
                        ncol = dim(mhc_het_dat)[1])
## fill distance matrix row wise, thus fill upper.tri
relate_mat_mhc[upper.tri(relate_mat_mhc)] <- mhc_relatedness
## transpose to keep consistency with other distance matrices
relate_mat_mhc <- t(relate_mat_mhc)
relate_mat_mhc %<>% `colnames<-`(meta$real_id) %>% `rownames<-`(meta$real_id)

## vectorize again to identify whether relatedness pairs were consistent in the first place
a <- relate_mat_mhc %>% as.vector() %>% na.omit()

```

Create vectorized distance measurements for scent data

```

# bray-curtis distance measurement on scent profiles
scent_dist <- vegdist(scent) %>% as.matrix()
scent_dist[upper.tri(scent_dist, diag = T)] <- NA
b <- scent_dist %>% as.vector() %>% na.omit()

```

Generate UniFrac distances from MHC DQB II individual genotypes

```

# handle genotypes as otu table
phylo_mat <- read.table("data/phyloseq-mat.txt") %>%
  as.matrix()

# make sample names consistent
n <- match(meta$real_id, colnames(phylo_mat))

phylo_mat %<>% .[, n] %>%
  otu_table(., taxa_are_rows = T)

# create phylogenetic tree from file
phylo_tree <- ape::read.tree("data/unifrac_tree_p.nwk")

# merge into Formal class phyloseq
arga_phyloseq <- merge_phyloseq(phylo_mat, phylo_tree)

# create UniFrac as genetic diversity measurement for single locus data
mhc_dqb2_ufrac <- UniFrac(arga_phyloseq, weighted = F) %>%
  # distances to distance matrix
  as.matrix()

```

```
# vectorize distances matrices
mhc_dqb2_ufrac[upper.tri(mhc_dqb2_ufrac, diag = T)] <- NA
c <- mhc_dqb2_ufrac %>% as.vector() %>% na.omit()
```

Calculate microsatellite relatedness values

create data.frame in correspondence to Demerelate input format

```
# read in genotype data table
msats_df <- read.table("data/msats_genotypes_inbreedR.txt", sep = "\t")

# update data.frame with additional info
# "delete" colony info, otherwise relatedness is only calculated for individuals
# within their own colonies -> no complete pairwise comparison
msats_df <- cbind(id = as.factor(rownames(msats_df)),
                  # colony = meta$colony,
                  colony = rep("col", 56),
                  msats_df[1:56,]) %>%

  # clear df from rownames/ only keep colnames/ variable names
  `rownames<-`(NULL)

msats_df[is.na(msats_df)] = 0

str(msats_df)

# write.table(msats_df, file = "data/msats_genotypes_demerelate.txt",
#           sep = "\t",
#           row.names = F)

msats_df %<>% .[match(meta$real_id, .$id),]
```

Calculate relatedness of individuals based on Queller & Goodnight

```
relatedness_results <- Demerelate(inputdata = msats_df,
                                  value = "rxy",
                                  object = T,
                                  NA.rm = F,
                                  Fis = F)
```

```
## Warning in Demerelate(inputdata = msats_df, value = "rxy", object = T, NA.rm = F, : Careful, bi-allelic
##   Especially, rxy and ritland estimator are not defined when bi-allelic estimates are used with allelic
##   You should consider removing bi-allelics which tend to have very evenly distributed alleles or swi
##   Be careful even if allele frequencies are not perfectly 0.5, during randomizations problems may oc

## Warning in prop.test(c(emp, non), c(sum(table(empirical.list))),
## sum(table(related.non.X.mean))), : Chi-Quadrat-Approximation kann inkorrekt sein
```

Coerce output to a vector

```
relatedness <- unlist(relatedness_results$Empirical_Relatedness)

## fill distant matrix / make sure that it follows same systematics as previous distance matrices
## create empty matrix with equal rows and cols similar to sample size of individuals
```

```

relate_mat <- matrix(nrow = dim(msats_df)[1],
                    ncol = dim(msats_df)[1])
## fill distance matrix row wise, thus fill upper.tri
relate_mat[upper.tri(relate_mat)] <- relatedness
## transpose to keep consistency with other distance matrices
relate_mat <- t(relate_mat)
relate_mat %<>% `colnames<-`(meta$real_id) %>% `rownames<-`(meta$real_id)

## vectorize again to identify whether relatedness pairs were consistent in the first place
d <- relate_mat %>% as.vector() %>% na.omit()

```

Analyse Odour and genetic association by MHC DQB II and neutral genomic background

Create data.frame to plot in ggplot2

```

## substitute once tested correctly
## scent_mds shall contain similarity values but `b` contains
## dissimilarity values based on Bray-Curtis -> substracting
## dissimilarities from 1 returns similarities

model_rel.df <- cbind(mhc_rel = a, scent_mds = 1-b, ufrac = c, rel = d) %>% as.data.frame()

```

Custom theme to make plot aesthetics consistent

```

# custom theme to ease figure creation
custom_theme <- ggplot2::theme_classic(base_size = 16,
                                       base_line_size = 1,
                                       base_rect_size = 1) +

ggplot2::theme(
  # plot.margin = unit(c(5.5, 8.5, 5.5, 5.5), "pt"), #c(top, right, bottom, left)
  plot.margin = margin(5.5,6.5,5.5,5.5, "pt"),
  panel.grid = element_blank(),
  axis.text = element_text(color = "black"),
  axis.ticks = element_line(color = "black"),
  aspect.ratio = 1
)

```

Model odour relationship on MHC and neutral genetic background

Pool underlying data dependencies

Create a function that generates pairwise variables in a systematic matter for pairwise comparisons

```

create_pair_vars <-function(row_cross, col_cross, split_vars = F){
  require(stringr)

  rc <- row_cross
  cc <- col_cross

  # create empty matrix
  # keep row and col names from existing distance matrices

  empty_mat <- matrix(nrow = length(rc),

```

```

        ncol = length(cc)) %>%
`colnames<-`(cc) %>%
`rownames<-`(rc)

# fill each matrix i,j-th cell with the crossing from their corresponding
# i-th rowname and j-th colname
for (i in 1:dim(empty_mat)[1]) {
  for (j in 1:dim(empty_mat)[2]) {

    empty_mat[i,j] <- paste0(rc[i], "/", cc[j])

  } # end j
} # end i

# delete `upper.tri()` of `empty_mat` to resemble structure of the other
# distance matrices in use

empty_mat[upper.tri(empty_mat, diag = T)] <- NA
pair_vars <- empty_mat %>% as.vector() %>% na.omit()

# split `pair_vars` if needed
if (split_vars == T) {

  pair_vars1 <- sapply(pair_vars,
    function(x){
      str_split(x, pattern = "/")[1][1]
    })

  pair_vars2 <- sapply(pair_vars,
    function(x){
      str_split(x, pattern = "/")[1][2]
    })

  pair_vars_split <- list(pair_variable1 = pair_vars1,
    pair_variable2 = pair_vars2)

  return(pair_vars_split)

} else {
  return(pair_vars)
}

} #end create_pair_vars

```

Helper function to combine double entries

```

## for x, overwrite specified replacer with specified value
f <- function(x, replacer, overwrite){
  if (x == replacer) {
    x <- overwrite
  } else {
    x <- x
  }
}

```

```
}
```

Transform model variables

```
agePaired <- create_pair_vars(row_cross = meta$maturity,
                             col_cross = meta$maturity) %>%
  supply(., f, "P/M", "M/P")

colonyPaired <- create_pair_vars(row_cross = meta$colony,
                                col_cross = meta$colony) %>%
  supply(., f, "FWB/SSB", "SSB/FWB")

colonyID1 <- create_pair_vars(row_cross = meta$colony,
                             col_cross = meta$colony,
                             split_vars = T)[1] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

colonyID2 <- create_pair_vars(row_cross = meta$colony,
                             col_cross = meta$colony,
                             split_vars = T)[2] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

colonyBool <- ifelse(colonyID1 == colonyID2, 1, 0)

familyPaired <- create_pair_vars(row_cross = meta$family,
                                 col_cross = meta$family)

familyID1 <- create_pair_vars(row_cross = meta$family,
                              col_cross = meta$family,
                              split_vars = T)[1] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

familyID2 <- create_pair_vars(row_cross = meta$family,
                              col_cross = meta$family,
                              split_vars = T)[2] %>%
  unlist() %>%
  paste0("f", .) %>%
  as.vector()

pairID1 <- create_pair_vars(row_cross = meta$real_id,
                           col_cross = meta$real_id,
                           split_vars = T)[1] %>%
  unlist() %>%
  as.vector()

pairID2 <- create_pair_vars(row_cross = meta$real_id,
                           col_cross = meta$real_id,
                           split_vars = T)[2] %>%
```

```

unlist() %>%
as.vector()

familyBool <- ifelse(familyID1 == familyID2, 1, 0)

```

Update data.frame with model variables

```

model_rel.df <- data.frame(model_rel.df,
  agePaired = as.factor(agePaired),
  colonyPaired = as.factor(colonyPaired),
  colonyBool = as.factor(colonyBool),
  familyPaired = as.factor(familyPaired),
  familyID1 = as.factor(familyID1),
  familyID2 = as.factor(familyID2),
  familyBool = as.factor(familyBool),
  pairID1 = as.factor(pairID1),
  pairID2 = as.factor(pairID2))

```

update data frame with meta data

Include information about MHC heterozygosity, sMLH from microsatellite data and chemical diversity by number of compounds per individual

```

scent.abs <- ifelse(scent != 0, 1, 0)
compound_n <- apply(scent.abs, 1, sum)

names(compound_n) == meta$real_id

## [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [16] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE

# read in heterzygosity information
het_table <- read.table("data/arga_mhc_het.txt", sep = "\t")

# keep names consistent
match_het <- match(meta$real_id, rownames(het_table))
het_table %<>% .[match_het,]

# generate sMLH with microsatellite data
# table is pre-prepped, thus rows correspond to same individuals in meta data
smlh_res <- read.table("data/msats_genotypes_inbreedR.txt", sep = "\t")
smlh_res <- smlh_res[match(meta$real_id, rownames(smlh_res)), ] %>%
  # convert to inbreedR format
  convert_raw() %>%
  # generate sMLH
  sMLH()

meta %<>% cbind(., compound_n = compound_n,
  mhc_het = het_table$het,
  smlh = smlh_res)

meta %<>% mutate(
  real_id = as.factor(real_id),
  colony = as.factor(colony),

```



```

maturity = as.factor(maturity),
family = as.factor(family)
)

```

Repeat models for chemical similarity

```

# without age and indicator for family groupings
# as grouping factors must have >1 sampled level

```

```

# mhc

```

```

e1 <- lmerTest::lmer(scent_mds ~ ufrac + colonyBool + (1|pairID1) + (1|pairID2),
  data = model_rel.df)

```

```

# relatedness

```

```

e2 <- lmerTest::lmer(scent_mds ~ rel + colonyBool + (1|pairID1) + (1|pairID2),
  data = model_rel.df)

```

```

# mhc & relatedness

```

```

e3 <- lmerTest::lmer(scent_mds ~ rel + ufrac + colonyBool + (1|pairID1) + (1|pairID2),
  data = model_rel.df)

```

```

# no genetic effect

```

```

e4 <- lmerTest::lmer(scent_mds ~ colonyBool + (1|pairID1) + (1|pairID2),
  data = model_rel.df)

```

```

# compare model performance scores

```

```

compare_performance(e1, e2, e3, e4, rank = T) %>%
  arrange(Name)

```

```

## # Comparison of Model Performance Indices

```

```

##

```

```

## Name | Model | R2 (cond.) | R2 (marg.) | ICC | RMSE | Sigma | AIC weights | AICc weights

```

```

## -----

```

```

## e1 | lmerModLmerTest | 0.517 | 0.188 | 0.404 | 0.058 | 0.062 | 0.287 | 0.287

```

```

## e2 | lmerModLmerTest | 0.525 | 0.186 | 0.417 | 0.058 | 0.062 | 0.207 | 0.207

```

```

## e3 | lmerModLmerTest | 0.520 | 0.191 | 0.407 | 0.058 | 0.062 | 0.228 | 0.211

```

```

## e4 | lmerModLmerTest | 0.522 | 0.184 | 0.414 | 0.058 | 0.062 | 0.278 | 0.291

```

```

summary(e2)

```

```

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [

```

```

## lmerModLmerTest]

```

```

## Formula: scent_mds ~ rel + colonyBool + (1 | pairID1) + (1 | pairID2)

```

```

## Data: model_rel.df

```

```

##

```

```

## REML criterion at convergence: -669.2

```

```

##

```

```

## Scaled residuals:

```

```

## Min 1Q Median 3Q Max

```

```

## -2.8734024086 -0.6551149100 -0.0127392185 0.5907406140 2.6919018000

```

```

##

```

```

## Random effects:

```

```

## Groups Name Variance Std.Dev.

```

```

## pairID1 (Intercept) 0.00114373121 0.0338190954

```

```

## pairID2 (Intercept) 0.00158812032 0.0398512273

```

```

## Residual 0.00382618866 0.0618561934

```

```

## Number of obs: 276, groups: pairID1, 23; pairID2, 23
##
## Fixed effects:
##           Estimate      Std. Error      df    t value    Pr(>|t|)
## (Intercept)  0.2930925713   0.0159793884  29.8480662643  18.34191 < 2.22e-16
## rel          0.0634645257   0.0534097404  267.2637395374   1.18826   0.23579
## colonyBool1  0.0761977589   0.0136127102  51.9474648776   5.59755 8.2768e-07
##
## (Intercept) ***
## rel
## colonyBool1 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr) rel
## rel          0.108
## colonyBool1 -0.639 -0.031
summary(e4)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: scent_mds ~ colonyBool + (1 | pairID1) + (1 | pairID2)
## Data: model_rel.df
##
## REML criterion at convergence: -671.8
##
## Scaled residuals:
##           Min           1Q           Median           3Q           Max
## -2.8754878831 -0.6724901336 -0.0272566346  0.5651130445  2.6590829271
##
## Random effects:
## Groups   Name      Variance  Std.Dev.
## pairID1  (Intercept) 0.00114074594 0.0337749306
## pairID2  (Intercept) 0.00156895325 0.0396100145
## Residual                0.00383649427 0.0619394403
## Number of obs: 276, groups: pairID1, 23; pairID2, 23
##
## Fixed effects:
##           Estimate      Std. Error      df    t value    Pr(>|t|)
## (Intercept)  0.2910051000   0.0158359198  29.1599058492  18.37627 < 2.22e-16 ***
## colonyBool1  0.0767098586   0.0135826001  52.0344825538   5.64766 6.8802e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr)
## colonyBool1 -0.640

```

Repeat models for chemical diversity

```

# exclude family as random effects (no accounting of same family in different
# individuals)

```

```
# exclude age as only one 'age' group being moms is modelled
```

```
f1 <- lm(compound_n ~ mhc_het + colony , data = meta)
```

```
f2 <- lm(compound_n ~ smlh + colony, data = meta)
```

```
f3 <- lm(compound_n ~ mhc_het + smlh + colony, data = meta)
```

```
f4 <- lm(compound_n ~ colony, data = meta)
```

```
compare_performance(f1, f2, f3, f4, rank = T) %>% arrange(Name)
```

```
## # Comparison of Model Performance Indices
```

```
##
```

```
## Name | Model | R2 | R2 (adj.) | RMSE | Sigma | AIC weights | AICc weights | BIC weights | Perf
```

```
## -----
```

```
## f1 | lm | 0.055 | -0.035 | 18.471 | 19.746 | 0.071 | 0.070 | 0.067 |
```

```
## f2 | lm | 0.201 | 0.125 | 16.980 | 18.152 | 0.536 | 0.526 | 0.503 |
```

```
## f3 | lm | 0.202 | 0.082 | 16.973 | 18.593 | 0.199 | 0.106 | 0.104 |
```

```
## f4 | lm | 0.055 | 0.012 | 18.471 | 19.293 | 0.193 | 0.298 | 0.327 |
```

```
summary(f2)
```

```
##
```

```
## Call:
```

```
## lm(formula = compound_n ~ smlh + colony, data = meta)
```

```
##
```

```
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
```

```
## -33.84774747 -10.72822530 -2.63667025  13.89024838  32.64888040
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) -32.76603326  46.95021186 -0.69789  0.49290
```

```
## smlh          89.23084048  45.46613021  1.96258  0.06308 .
```

```
## colonySSB    -3.59128851   7.91958429 -0.45347  0.65486
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## Residual standard error: 18.1520925 on 21 degrees of freedom
```

```
## Multiple R-squared:  0.201400231,    Adjusted R-squared:  0.12534311
```

```
## F-statistic: 2.64801282 on 2 and 21 DF,  p-value: 0.0942879933
```

Session information

```
sessionInfo()
```

```
## R version 4.3.1 (2023-06-16 ucrt)
```

```
## Platform: x86_64-w64-mingw32/x64 (64-bit)
```

```
## Running under: Windows 11 x64 (build 22621)
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##
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## Matrix products: default
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##
##
## locale:
## [1] LC_COLLATE=German_Germany.utf8 LC_CTYPE=German_Germany.utf8
## [3] LC_MONETARY=German_Germany.utf8 LC_NUMERIC=C
## [5] LC_TIME=German_Germany.utf8
##
## time zone: Europe/Berlin
## tzcode source: internal
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods   base
##
## other attached packages:
## [1] remotes_2.4.2.1   Demerelate_0.9-3   fts_0.9.9.2       zoo_1.8-12
## [5] ggbeeswarm_0.7.2  partR2_0.9.1       MuMIn_1.47.5       performance_0.10.4
## [9] ape_5.7-1         ggpubr_0.6.0       vegan_2.6-4        lattice_0.21-8
## [13] permute_0.9-7     inbreedR_0.3.3     GCalignR_1.0.5     phyloseq_1.44.0
## [17] lubridate_1.9.2   forcats_1.0.0      stringr_1.5.0      dplyr_1.1.2
## [21] purrr_1.0.1       readr_2.1.4        tidyr_1.3.0        tibble_3.2.1
## [25] ggplot2_3.4.2     tidyverse_2.0.0    magrittr_2.0.3
##
## loaded via a namespace (and not attached):
## [1] rstudioapi_0.15.0   jsonlite_1.8.7      datawizard_0.8.0
## [4] farver_2.1.1        nloptr_2.0.3         rmarkdown_2.23
## [7] ragg_1.2.5          zlibbioc_1.46.0     vctrs_0.6.3
## [10] multtest_2.56.0     minqa_1.2.5         RCurl_1.98-1.12
## [13] rstatix_0.7.2       htmltools_0.5.5     broom_1.0.5
## [16] Rhdf5lib_1.22.0     Formula_1.2-5       rhdf5_2.44.0
## [19] plyr_1.8.8          sfsmisc_1.1-15      igraph_1.5.0.1
## [22] lifecycle_1.0.3     iterators_1.0.14    pkgconfig_2.0.3
## [25] Matrix_1.6-0        R6_2.5.1            fastmap_1.1.1
## [28] GenomeInfoDbData_1.2.10 rbibutils_2.2.13    digest_0.6.33
## [31] numDeriv_2016.8-1.1 colorspace_2.1-0    patchwork_1.1.2
## [34] S4Vectors_0.38.1    textshaping_0.3.6   labeling_0.4.2
## [37] fansi_1.0.4         timechange_0.2.0    abind_1.4-5
## [40] mgcv_1.8-42         compiler_4.3.1      withr_2.5.0
## [43] backports_1.4.1     carData_3.0-5       mlogit_1.1-1
## [46] highr_0.10          ggsignif_0.6.4      MASS_7.3-60
## [49] biomformat_1.28.0    tools_4.3.1         vipor_0.4.5
## [52] lmtest_0.9-40       beeswarm_0.4.0      glue_1.6.2
## [55] nlme_3.1-162        rhdf5filters_1.12.1 grid_4.3.1
## [58] cluster_2.1.4       reshape2_1.4.4      ade4_1.7-22
## [61] see_0.8.0           generics_0.1.3      gtable_0.3.3
## [64] tzdb_0.4.0          data.table_1.14.8    hms_1.1.3
## [67] car_3.1-2           utf8_1.2.3          XVector_0.40.0
## [70] BiocGenerics_0.46.0 ggrepel_0.9.3        foreach_1.5.2
## [73] pillar_1.9.0        splines_4.3.1       survival_3.5-5
## [76] tidyselect_1.2.0    pbapply_1.7-2        Biostrings_2.68.1
## [79] knitr_1.43          IRanges_2.34.1      stats4_4.3.1
## [82] xfun_0.39           Biobase_2.60.0      statmod_1.5.0
## [85] dfidx_0.0-5         stringi_1.7.12      yaml_2.3.7
## [88] boot_1.3-28.1       evaluate_0.21        codetools_0.2-19
## [91] cli_3.6.1           systemfonts_1.0.4    Rdpack_2.4

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## [94] munsell_0.5.0	Rcpp_1.0.11	GenomeInfoDb_1.36.1
## [97] parallel_4.3.1	bayestestR_0.13.1	bitops_1.0-7
## [100] lme4_1.1-34	lmerTest_3.1-3	scales_1.2.1
## [103] insight_0.19.3	crayon_1.5.2	rlang_1.1.1
## [106] cowplot_1.1.1		

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