Goals

We have a dataset contain axon diameters of neurons from the optic nerve of control and mutant zebrafish. We'd like to know if the mean axon diameter, or the distribution of axon diameters, differs between groups. We want to implement tests that take account of within and between animal variance.

Here, we focus on the myRF data set.

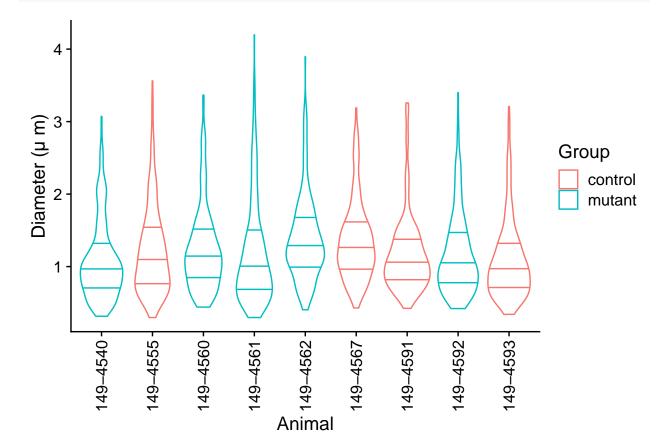
Load and format data

```
df <- read_excel("Shiverer Axon Diameter.xlsx", range = "A2:J293") %>%
    pivot_longer(cols = 1:10) %>%
    drop_na() %>%
    mutate(group = as_factor(ifelse(name %in% c("149-4555", "149-4567", "149-4591", "149-4593"), "contr
```

Plot the data

Focus here on plot of individual mice, colour coded by group.

```
(plot_by_id <- ggplot(data = df, aes(name, value)) +
    geom_violin(aes(colour = group), draw_quantiles = c(0.25, 0.5, 0.75)) +
    theme_cowplot(font_size = 14) +
    theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1)) +
    labs(x = 'Animal', y = 'Diameter (\u000B5 m)', colour = "Group"))</pre>
```



```
ggsave('Plots/violins_shiv.jpeg', plot_by_id)
## Saving 6.5 x 4.5 in image
Tests for differences in means
mm_t <- lmer(value ~ group + (1 | name), data = df)</pre>
mm_9t_null <- lmer(value ~ (1 | name), data = df)
summary(mm_t)
## Linear mixed model fit by REML ['lmerMod']
## Formula: value ~ group + (1 | name)
##
     Data: df
##
## REML criterion at convergence: 4273.8
##
## Scaled residuals:
      Min
              1Q Median
                               3Q
## -1.6545 -0.7044 -0.2186 0.4247 5.1681
##
## Random effects:
## Groups
            Name
                        Variance Std.Dev.
## name
            (Intercept) 0.01154 0.1074
## Residual
                        0.33984 0.5830
## Number of obs: 2415, groups: name, 9
## Fixed effects:
              Estimate Std. Error t value
## (Intercept) 1.206465
                         0.056751
                                   21.26
## groupmutant 0.005307
                         0.075981
                                     0.07
##
## Correlation of Fixed Effects:
              (Intr)
## groupmutant -0.747
anova(mm_t, mm_t_null)
## refitting model(s) with ML (instead of REML)
## Data: df
## Models:
## mm_t_null: log(value) ~ (1 | name)
## mm_t: value ~ group + (1 | name)
                           BIC logLik deviance Chisq Df Pr(>Chisq)
            npar AIC
## mm_t_null 3 3084.0 3101.4 -1539.0
                                         3078.0
## mm t
               4 4273.5 4296.7 -2132.8
                                         4265.5
Same test but with log transformed data
```

```
mm_t <- lmer(log(value) ~ group + (1 | name), data = df)
mm_t_null <- lmer(log(value) ~ (1 | name), data = df)
summary(mm_t)</pre>
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: log(value) ~ group + (1 | name)
     Data: df
##
## REML criterion at convergence: 3086.5
## Scaled residuals:
##
       Min
                 1Q
                      Median
                                    3Q
## -2.84380 -0.68071 -0.02389 0.63836 3.12308
##
## Random effects:
## Groups
                        Variance Std.Dev.
            Name
## name
             (Intercept) 0.01067 0.1033
## Residual
                         0.20754 0.4556
## Number of obs: 2415, groups: name, 9
##
## Fixed effects:
              Estimate Std. Error t value
                                   1.667
## (Intercept) 0.08933
                          0.05360
## groupmutant -0.01302
                          0.07181 -0.181
##
## Correlation of Fixed Effects:
##
               (Intr)
## groupmutant -0.746
anova(mm_t, mm_t_null)
## refitting model(s) with ML (instead of REML)
## Data: df
## Models:
## mm_t_null: log(value) ~ (1 | name)
## mm_t: log(value) ~ group + (1 | name)
                        BIC logLik deviance Chisq Df Pr(>Chisq)
            npar AIC
               3 3084 3101.4 -1539
## mm_t_null
                                         3078
                4 3086 3109.2 -1539
                                         3078 0.0429 1
## mm t
                                                             0.836
```

Generate histograms for all animals

```
### Make histograms for each animal
### Use log transformed data
names = unique(df$name)
### If submean = 1 then will substract means before making histograms
histfun <- function(name, df, submean = 0) {
    sub <- ifelse(submean == 1, mean(df$value[df$name==name]), 0)
        hist(log(df$value[df$name==name]-sub), seq(-2,2,0.1), plot = FALSE)
}
hists <- sapply(names, histfun, df, submean=0)

### Convert results to tibble for use with tidyverse functions
rns <- rownames(hists)
hists_tib <- as_tibble(hists) %>%
    rownames_to_column(var = "rowname") %>%
    pivot_longer(-rowname, names_to = "column", values_to = "value") %>%
```

```
pivot_wider(names_from = rowname, values_from = value)
colnames(hists_tib) <- c("animal", rns)</pre>
ggconvfun <- function(mids, density) {</pre>
    gghist <- cbind(mids, density)</pre>
    ggplot(gghist, aes(mids, density)) +
         geom_col() +
         theme_cowplot()
}
gghists <- map2(hists_tib$mids, hists_tib$density, ggconvfun)</pre>
plot_grid(plotlist = gghists)
     8.0
                                                                   density
0.0
0.3
                                      1.00
     0.6
     0.4
                                     0.50
0.25
     0.2
     0.0
                                     0.00
                                                                      0.0
         -2
              -1
                    0
                             2
                                            -2
                                                     0
                                                              2
                                                                           -2
                                                                                     0
                                                                                               2
                                                -1
                                                                                -1
                 mids
                                                   mids
                                                                                   mids
                                      1.2
                                                                       1.00
    0.9
                                      0.9
                                                                   densitv
                                                                       0.75
     0.6
                                     0.6
                                                                      0.50
     0.3
                                     0.3
                                                                      0.25
                                     0.0
                                                                      0.00
     0.0
                             2
                   Ó
                                                    Ó
                                               -1
                                                                            -2 -1
         -2
              _1
                                          -2
                                                                                      0
                 mids
                                                  mids
                                                                                    mids
     0.8 -
 density
                                                                      0.75
                                  density
     0.6
                                      1.0
                                                                      0.50
     0.4
                                     0.5
                                                                      0.25
     0.2
                                      0.0
                                                                       0.00
     0.0
                   0
                                                     0
                                                              2
                             2
                                                                                _1
                                                                                      0
                                                                                               2
         -2
              -1
                                          -2
                                               _1
                                                                            -2
                 mids
                                                  mids
                                                                                    mids
```

Evaluate distributions

##

Use package lqmm (https://www.jstatsoft.org/article/view/v057i13) to evaluate potential differences in the distributions.

```
fit.lqmm <- lqmm(fixed = value ~ group, random = ~1, group = name, tau = c(0.25,0.5, 0.75), nK = 7, typ
summary(fit.lqmm, R = 500, seed = 2)

## Call: lqmm(fixed = value ~ group, random = ~1, group = name, tau = c(0.25,
## 0.5, 0.75), nK = 7, type = "normal", data = df, control = c(LP_max_iter = 5000))</pre>
```

```
## tau = 0.25
##
## Fixed effects:
                 Value Std. Error lower bound upper bound Pr(>|t|)
##
## (Intercept) 0.51508
                           1.46366
                                      -2.36061
                                                    3.3908
                                                             0.7251
                           0.72869
                                      -1.68954
                                                    1.1738
                                                             0.7236
## groupmutant -0.25786
## tau = 0.5
##
## Fixed effects:
                   Value Std. Error lower bound upper bound Pr(>|t|)
## (Intercept) 1.095003
                           0.621789
                                      -0.126644
                                                     2.3167 0.07884 .
## groupmutant -0.029004
                           0.472751
                                      -0.957832
                                                     0.8998 0.95110
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## tau = 0.75
##
## Fixed effects:
                   Value Std. Error lower bound upper bound Pr(>|t|)
                                                    3.2921
## (Intercept) 2.388583
                           0.459854
                                       1.485094
                                                               3e-07 ***
                           0.296071
                                      -0.021642
                                                     1.1418 0.05912 .
## groupmutant 0.560056
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## AIC:
## [1] 3690 (df = 4) 4214 (df = 4) 5407 (df = 4)
fit.log.lqmm <- lqmm(fixed = log(value) ~ group, random = ~1, group = name, tau = c(0.25,0.5, 0.75), nK
summary(fit.log.lqmm, R = 500, seed = 2)
## Call: lqmm(fixed = log(value) ~ group, random = ~1, group = name, tau = c(0.25,
      0.5, 0.75), nK = 7, type = "normal", data = df, control = c(LP_max_iter = 5000))
##
## tau = 0.25
## Fixed effects:
##
                  Value Std. Error lower bound upper bound Pr(>|t|)
                           0.48290
                                      -2.31428
                                                   -0.4168 0.004876 **
## (Intercept) -1.36552
                                      -2.16249
                                                   -0.3061 0.009254 **
## groupmutant -1.23431
                           0.47242
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## tau = 0.5
##
## Fixed effects:
                   Value Std. Error lower bound upper bound Pr(>|t|)
## (Intercept) 0.090755
                           0.056518
                                      -0.020287
                                                     0.2018
                                                              0.1090
## groupmutant -0.026201
                           0.081327
                                      -0.185987
                                                     0.1336
                                                              0.7475
##
## tau = 0.75
##
## Fixed effects:
                 Value Std. Error lower bound upper bound Pr(>|t|)
## (Intercept) 1.49105
                          0.48872
                                      0.53084
                                                   2.4513 0.002403 **
```

```
## groupmutant 1.19001  0.38079  0.44185  1.9382 0.001881 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## AIC:
## [1] 3741 (df = 4) 3445 (df = 4) 3822 (df = 4)
```

Hack together additional tests for differences in distributions

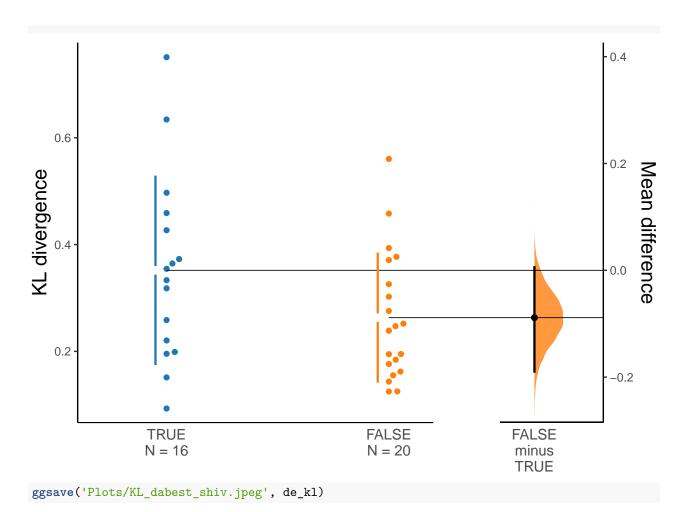
```
### Make histograms compatible with comparison tools
hists_as_matrix <- function(density, mids) {matrix(c(density, mids), ncol=2)}
hists_tib <- hists_tib %>%
        mutate(mat = map2(density, mids, hists_as_matrix))

### List all combinations of histograms
combinations <- combn(1:length(names), 2, simplify = FALSE)

### Calculate KL divergence for all combinations
kl_on_comb <- function(comb, mat) {
    P <- mat[[comb[[1]]]][,1] / sum(mat[[comb[[1]]]][,1])
    Q <- mat[[comb[[2]]]][,1] / sum(mat[[comb[[2]]]][,1])
    x <- rbind(P,Q)
    KL(x)
}
kls <- lapply(combinations, kl_on_comb, hists_tib$mat)</pre>
```

```
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
```

```
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
## Metric: 'kullback-leibler' using unit: 'log2'; comparing: 2 vectors.
### Put everything together for analysis
collected <- tibble(pairs = combinations, kl = unlist(kls))</pre>
### Add columns to identify animals
a1_func <- function(pair, names, pos) {</pre>
    names[pair[[pos]][1]]
collected$pair1 <- sapply(collected$pairs, a1_func, names, 1)</pre>
collected$pair2 <- sapply(collected$pairs, a1_func, names, 2)</pre>
### Reorganise
get_group <- function(name, df) {as.character(df$group[[grep(name, df$name)[[1]]]])}</pre>
grouplist <- lapply(names, get_group, df)</pre>
group_lookup <- function(id, names, grouplist) {grouplist[[grep(id, names)]]}</pre>
compare_groups <- function(g1, g2) {g1 == g2}</pre>
collected <- collected %>%
    mutate(group1 = map_chr(pair1, group_lookup, names, grouplist),
           group2 = map_chr(pair2, group_lookup, names, grouplist),
           samegroup = map2_lgl(group1, group2, compare_groups))
### Compare KL divergece for pairs that are from the same group with pairs from different groups
wilcox.test(kl ~ samegroup, data = collected)
##
## Wilcoxon rank sum exact test
##
## data: kl by samegroup
## W = 107, p-value = 0.09495
## alternative hypothesis: true location shift is not equal to 0
Make dabest plots for the above comparisons. Use dabest_plot.
dabest_obj_kl.mean_diff <- load(</pre>
 data = collected,
 x = samegroup,
 y = kl,
 idx = c("TRUE", "FALSE")
) %>%
 mean_diff()
(de_kl <- dabest_plot(dabest_obj_kl.mean_diff, TRUE,</pre>
                       swarm_label = 'KL divergence'))
```



Saving 6.5×4.5 in image