

Normalization Analysis

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```
library(metagenomeSeq)
library(tidyverse)
```

Objective

- Assessment of count table values for different pipelines.
- Impact of normalization methods on count performance

Loading Pipeline Data

```
mrex_files <- list(
  dada2 = "../data/mrex_dada2.RDS",
  mothur = "../data/mrex_mothur.RDS",
  qiime = "../data/mrex_qiime_refclus_nochimera.RDS"
)
mrex <- mrex_files %>% map(readRDS)
```

Extracting metadata

```
meta_dat <- mrex$mothur %>% pData()

##labeling PCR replicates
half1 <- paste(rep(c("A","B","C","D","E","F","G","H"), each = 6),1:6, sep = "_")
sam_dat <- meta_dat %>%
  mutate(pcr_half = if_else(pos %in% half1, "1","2"),
         pcr_rep = paste0(pcr_16S_plate,":",pcr_half)) %>%
  select(sampleID, dilution,sam_names, pcr_rep) %>%
  rename(samID = sam_names)
```

Subsetting data to focus on one biological replicate

Keeping biological replicate E01JH0004

```
E01JH004_sams <- meta_dat %>%
  filter(sampleID == "E01JH0004") %>% .$sam_names
mrex_004 <- mrex %>% map(~.[,which(colnames(.) %in% E01JH004_sams)])
```

Raw, Normalized, and Transformed Count Data

Question - does the order of the normalization and log transformation matter?

```
calc_raw_counts <- function(mrex){
  mrex@assayData$counts %>% as_tibble() %>%
    rownames_to_column(var = "otuID") %>%
```

```

      gather("samID", "count", -otuID) %>%
      left_join(sam_dat)
}

calc_css_counts <- function(mrexp, p = 0.75){
  ## col_id is the name of the col in the output
  ## dataframe with the css normalized counts
  mrexp %>% cumNormMat(p = p) %>% as_tibble() %>%
    rownames_to_column(var = "otuID") %>%
    gather("samID", "count", -otuID) %>%
    left_join(sam_dat)
}

# TSS from http://mixomics.org/mixmc/normalisation/
TSS.divide = function(x){ x/sum(x) }

calc_tss_counts <- function(mrexp){
  mrexp@assayData$counts %>% {apply(., 2, TSS.divide)} %>%
    as_tibble() %>% rownames_to_column(var = "otuID") %>%
    gather("samID", "count", -otuID) %>%
    left_join(sam_dat)
}

calc_tsslog_counts <- function(mrexp){
  mrexp@assayData$counts %>%
    {log2(. + 1)} %>% {apply(., 2, TSS.divide)} %>%
    as_tibble() %>% rownames_to_column(var = "otuID") %>%
    gather("samID", "count", -otuID) %>%
    left_join(sam_dat)
}

raw_counts <- mrexp_004 %>% map_df(calc_raw_counts, .id = "pipe")
rawlog_counts <- mrexp_004 %>% map_df(calc_raw_counts, .id = "pipe") %>%
  mutate(count = log2(count + 1))

css_counts <- mrexp_004 %>% map_df(calc_css_counts, .id = "pipe")
csslog_counts <- mrexp_004 %>% map_df(calc_css_counts, .id = "pipe") %>%
  mutate(count = log2(count + 1))

tss_counts <- mrexp_004 %>% map_df(calc_tss_counts, .id = "pipe")
tsslog_counts <- mrexp_004 %>% map_df(calc_tsslog_counts, .id = "pipe")

Combine into a single data frame

count_df <- list(raw = raw_counts, rawlog = rawlog_counts,
                css = css_counts, csslog = csslog_counts,
                tss = tss_counts, tsslog = tsslog_counts) %>%
  bind_rows(.id = "norm_method")

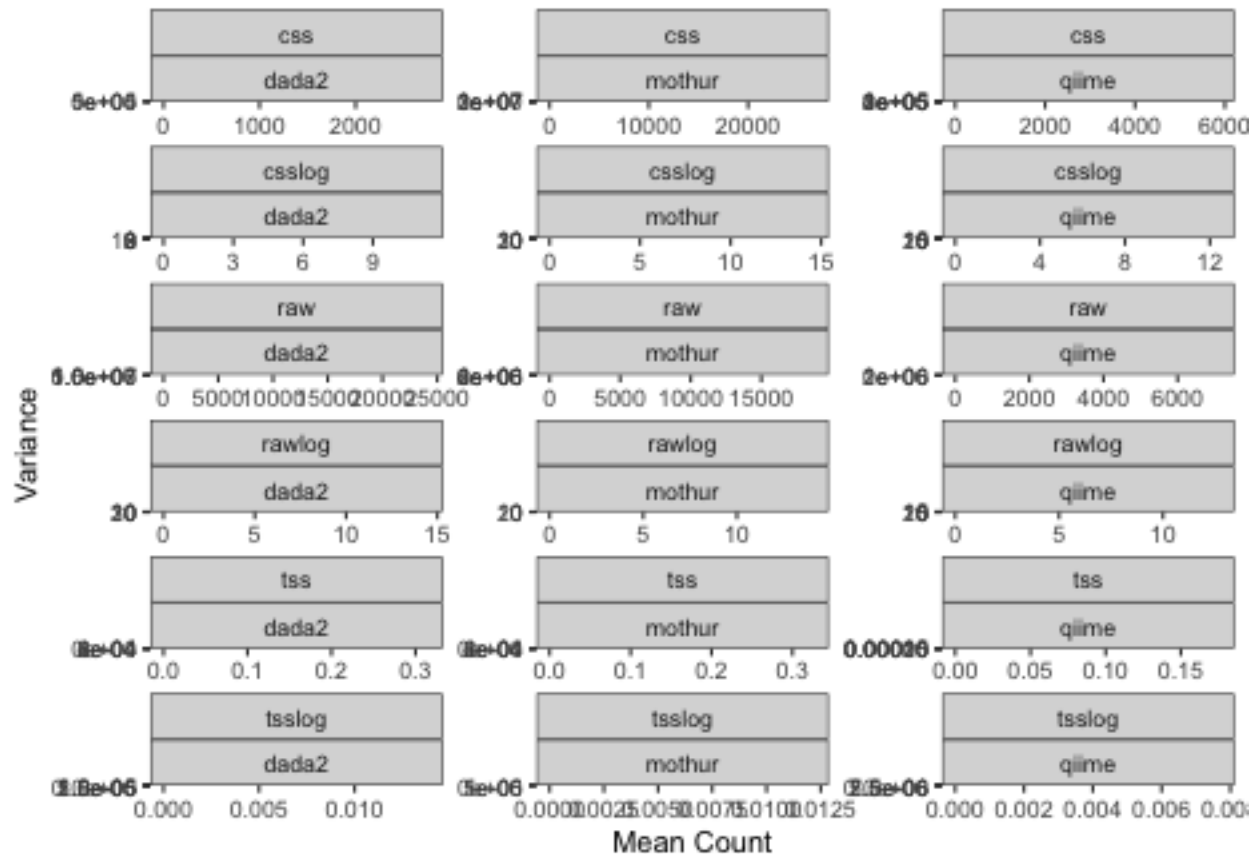
```

Count Value Variance

Relationship between the mean count and variance for the four PCR replicates. Note the heteroscedasticity, increase in variance with mean counts. Will want to look into log2 transforming count values. For tss normalization does order of operations impact the values.

```
count_var_df <- count_df %>% group_by(pipe, norm_method, dilution, otuID) %>%
  summarise(mean_count = mean(count), var_count = var(count))
```

```
ggplot(count_var_df) +
  geom_point(aes(x = mean_count, y = var_count), alpha = 0.5) +
  facet_wrap(norm_method~pipe, nrow = 6, scales = "free") +
  theme_bw() + labs(x = "Mean Count", y = "Variance")
```



Count Value Bias

Relationship between the expected count values calculated using the unmixed sample count values and proportions.

Calculating expected values based on pre and post unmixed samples by replicate (defined as half of PCR plate).

```
# pre_post_count <- count_df %>% filter(dilution %in% c(-1,0)) %>%
#   mutate(unmixed = if_else(dilution == 0, "post", "pre")) %>%
#   select(-dilution, -samID) %>%
#   spread(unmixed, count)
pre_count <- count_df %>% filter(dilution == -1) %>%
  rename(pre = count) %>% select(-dilution, -samID)
post_count <- count_df %>% filter(dilution == 0) %>%
  rename(post = count) %>% select(-dilution, -samID)
pre_post_count <- left_join(pre_count, post_count)
```

```
## Joining, by = c("norm_method", "pipe", "otuID", "sampleID", "pcr_rep")
rm(pre_count, post_count)

count_exp_obs <- count_df %>%
  filter(!(dilution %in% c(0,-1))) %>%
  left_join(pre_post_count) %>%
  mutate(p = 2^(-dilution), exp_count = post * (1-p) + pre * p)

## Joining, by = c("norm_method", "pipe", "otuID", "sampleID", "pcr_rep")
```

Metrics for evaluating count values

```
count_rmse <- count_exp_obs %>% mutate(residual = (exp_count - count)^2) %>%
  group_by(pipe, norm_method) %>%
  summarise(mse = mean(residual),
            rmse = sqrt(mse),
            nrmse = rmse/mean(exp_count))
```

RMSE - pipeline and normalization method

```
count_rmse %>% select(-mse, -nrmse) %>%
  spread(norm_method, rmse) %>% knitr::kable()
```

pipe	css	csslog	raw	rawlog	tss	tsslog
dada2	11.94749	0.4107282	137.43043	0.8659248	0.0015081	0.0006963
mothur	51.66372	0.2219331	36.87206	0.1887412	0.0004973	0.0001438
qiime	18.31263	0.3928529	25.22429	0.4248141	0.0004745	0.0002183
NRMSE - p	ipeline and	normalizati	on mehod			

```
count_rmse %>% select(-mse, -rmse) %>%
  spread(norm_method, nrmse) %>% knitr::kable()
```

pipe	css	csslog	raw	rawlog	tss	tsslog
dada2	6.976880	2.439084	7.538342	2.707173	5.566477	2.570212
mothur	20.076203	4.963514	20.758012	4.802844	15.887853	4.594221
qiime	8.305818	2.496649	10.318790	2.578011	5.400798	2.484070

```
count_exp_obs %>% filter(norm_method %in% c("csslog", "tsslog")) %>%
  ggplot() + geom_point(aes(x = count, y = exp_count,
                           color = factor(dilution)), alpha = 0.5) +
  geom_abline(aes(intercept = 0, slope = 1)) +
  facet_wrap(pipe~norm_method, scales = "free") +
  theme_bw() + labs(x = "Observed Counts", y = "Expected Counts")
```

